Judul Artikel: **Spatial data modeling on GIS for classification of measles-prone region using multiple attribute decision making**

1) Paper Submission to the International Journal of Intelligent Engineering and Systems by Email ijies@inass.org (10 Nov 2018 - Indonesia's time)
2) Editor confirm to Paper ID is " ijies1985" (10 Nov 2018 - Japan time and 10 Nov 2018 - Indonesia's time)
3) ijies1985: review result: **Accept after Major Revision** and Revised Paper (6 Desember 2018 - 15 Februari 2019)
4) ijies1985: review result and Revised Paper (28 Februari 2019 – 2 Maret 2019)
5) ijies1985: acceptance letter (1 Maret 2019 - Indonesia's time and 2 Maret 2019 - Japan time)
6) ijies1985: camera-ready (1-3 Maret 2019)
7) ijies1985: camera-ready was finished (4 Maret 2019 - Japan time and 3 Maret 2019 - Indonesia's time)

1) Paper Submission to the International Journal of Intelligent Engineering and Systems by Email ijies@inass.org
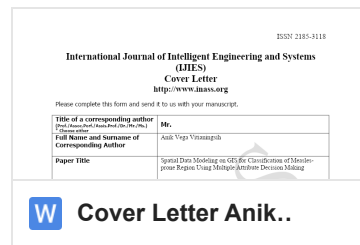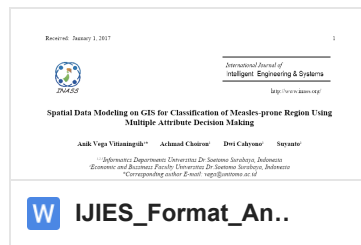(10 Nov 2018 - Indonesia's time)

Paper Submission

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

kepada ijies

Sab, 10 Nov 2018, 00.09

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3 Lampiran • Dipindai dengan Gmail

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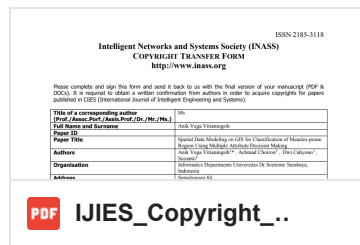
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Kei Eguchi <eguti@fit.ac.jp>   Sab, 10 Nov 2018, 15.42
kepada saya

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Thank you for your interest and support to IJIES.
I am hereby to confirm the delivery of your paper, Paper ID is " ijies1985".
It has been sent for reviewing.
The notification will be feedback within 1 month.
Appreciate your patiently wait.

If you have any question, please contact us with your paper ID.

Best regards,
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From: ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>
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3) ijies1985: review result: **Accept after Major Revision** and
   Revised Paper
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ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>

ijies1985: review result
13 pesan

Kei Eguchi <eguti@fit.ac.jp>   6 Desember 2018 pukul 16.35
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>

Dear author(s),

Congratulations!
The 1st review for your paper was accepted.
However, we are sorry to inform you that your paper cannot be recommended for publication in IJIES, in its current form.
Please revise your paper according to the attached reviewers' comments.

Please note that if your paper is still not satisfactorily revised or cannot be returned to us within TWO months from the date of this letter, your paper will not be recommended
to the journal above.

Thanks for your understanding and cooperation.

Kind Regards,
IJIES Editors.

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Thanks for reviewing my paper, I will do the revision according to the comment from the reviewer.

[Kutipan teks disembunyikan]

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   6 Februari 2019 pukul 17.19
Kepada: Kei Eguchi <eguti@fit.ac.jp>

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Pada tanggal Kam, 6 Des 2018 pukul 16.35 Kei Eguchi <eguti@fit.ac.jp> menulis:
[Kutipan teks disembunyikan]

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

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_____
差出人: ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>
送信日時: 2019年2月6日 19:19
宛先: 江口 啓
件名: Re: ijies1985: review result

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Yes Sir, ready.
Thanks for your information.
[Kutipan teks disembunyikan]

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   11 Februari 2019 pukul 12.53

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amphawan julsereewong <amphawan.ju@kmitl.ac.th>   11 Februari 2019 pukul 13.23
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>
Cc: Kei Eguchi <eguti@fit.ac.jp>, sawai pongswatd <sawai.po@kmitl.ac.th>

Dear Author(s),

Thank you for submitting your revised version.
However, the response letter is not attached to your e-mail.

To clarify the revised points, authors have a duty to submit the response letter.
Otherwise, the reviewers will be confused.
This is a general form of paper reviews in international journals.
There is no format for the response letter.

Please be kindly reminded that your revised manuscript may not to be reconsidered for IJIES publication due to late response.

Thanks for your understanding and cooperation.

Best regards,
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[Kutipan teks disembunyikan]

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   12 Februari 2019 pukul 14.21
Kepada: amphawan julsereewong <amphawan.ju@kmitl.ac.th>

Yes Sir, soon I'll make a response later.

Thanks for Your information.

[Kutipan teks disembunyikan]

Kei Eguchi <eguti@fit.ac.jp>   14 Februari 2019 pukul 18.50
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>

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There is no format for the response letter.

P.S.
The editor-in-chief is hospitalized now.
Please do not send a reply message to this e-mail address.
If you are in a hurry, please withdraw and submit your paper to other journals.

Best regards,
IJIES Editors.

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差出人: ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>
送信日時: 2019年2月6日 19:19
宛先: 江口 啓
件名: Re: ijies1985: review result

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[Kutipan teks disembunyikan]

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   14 Februari 2019 pukul 19.10
Kepada: Kei Eguchi <eguti@fit.ac.jp>

Yes Sir, i have to running response letter. Thanks for your information

[Kutipan teks disembunyikan]

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   15 Februari 2019 pukul 11.10
Kepada: amphawan julsereewong <amphawan.ju@kmitl.ac.th>, ijies@inass.org, Kei Eguchi <eguti@fit.ac.jp>

Dear Editor

I sent a response to my revised letter and paper from the Review Form 1985 Revision.

Thank You

Pada tanggal Sen, 11 Feb 2019 pukul 13.23 amphawan julsereewong <amphawan.ju@kmitl.ac.th> menulis:
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Kei Eguchi <eguti@fit.ac.jp>   15 Februari 2019 pukul 15.58
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>

Dear author(s),

Thank you for your interest and support to IJIES.
We received your revised version.
It has been sent for reviewing.
The notification will be feedback within 1 month.
Appreciate your patiently wait.

If you have any question, please contact us with your paper ID.

P.S.
The editor-in-chief is hospitalized now.
Please do not send a reply message to this e-mail address.
If you are in a hurry, please withdraw and submit your paper to other journals.

Best regards,
IJIES Editors

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差出人: ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>
送信日時: 2019年2月15日 13:10
宛先: amphawan julsereewong; ijies@inass.org; 江口 啓
件名: Re: ijies1985: review result

Dear Editor

I sent a response to my revised letter and paper from the Review Form 1985 Revision.

Thank You

Pada tanggal Sen, 11 Feb 2019 pukul 13.23 amphawan julsereewong <amphawan.ju@kmitl.ac.th<mailto:amphawan.ju@kmitl.ac.th>> menulis:
Dear Author(s),

Thank you for submitting your revised version.
However, the response letter is not attached to your e-mail.

To clarify the revised points, authors have a duty to submit the response letter.
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On Mon, Feb 11, 2019 at 12:54 PM ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id<mailto:vega@unitomo.ac.id>> wrote:
Dear Editor,

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Thank you for your attention.

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From: ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id<mailto:vega@unitomo.ac.id>>
Date: Rab, 6 Feb 2019 pukul 17.19
Subject: Re: ijies1985: review result
To: Kei Eguchi <eguti@fit.ac.jp<mailto:eguti@fit.ac.jp>>

Dear Editor,

Here I am sending a revised paper (Paper ID 1985), in accordance with the revised request dated December 6, 2018.

Thank you for your attention.

[Kutipan teks disembunyikan]

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   15 Februari 2019 pukul 16.07
Kepada: Kei Eguchi <eguti@fit.ac.jp>

Your welcome,

I hope there is good news for my paper.

Thanks for Your guide.

[Kutipan teks disembunyikan]

Review Form

Paper ID	ijies1985
Paper Title	Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

Recommendation for Publication	
☐(Evaluation A:) Accept	☐(Evaluation B:) Accept after Minor Revision
☐(Evaluation C:) Accept after Major Revision	☐(Evaluation D:) Reject

Comments from reviewers 1 & 2:

Comments from reviewers:

1. This seems a making report, because there is no comparison with existing techniques. As you know, there are some spatial data models in GIS. You should demonstrate the difference between the proposed technique and existing techniques by scientific data.

2. Don't use acronym, such as MMR, etc., without explanation.

3. The problem definition of this work is not clear. In Sect.1, the drawbacks of each conventional technique should be described clearly. In p.2, spatial data modeling techniques have been described. However, there is no explanation about these techniques. You should emphasize the difference with other methods to clarify the position of this work further.

4. In the Introduction part, strong points of this proposed method should be further stated and organization of this whole paper is supposed to be provided in the end.

5. In figures, letters are too small. Unify the font size of letters (more than 10pt). Enlarge or Redraw figures. e.g. Fig.1 and 4. Do not place 3 figures in one column.

6. The width of Eq.(11) is too wide.

7. Please improve the reference format. **This is very important for indexing service**. If you did not follow the following format, your paper will automatically rejected.
   *Do not use "et al." in author names.
   e.g.
   [1] R. Ruskone, S. Airault, and O. Jamet, "Vehicle Detection on Aerial Images", *International Journal of Intelligent Engineering and Systems*, Vol.1, No.1, pp.123-456, 2009.
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   [2] R. Ruskone, L. Guigues, S. Airault, and O. Jamet, "Vehicle Detection on Aerial Images", In: *Proc. of International Conf. On Pattern Recognition*, Vienna, Austria, pp.900-904, 1996.
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*Note: e.g. In the case of the author name:"John Doe", express as "J. Doe". ("John" is the first name and "Doe" is the family name.)

* * Please send your revised manuscript with the response letter for the 2nd review. (Please highlight modifications and additions inside the paper by red font.)

** The extra page charge USD50 per extra page will be charged if the paper length exceeds 10 pages.

Intelligent Networks and Systems Society

Review Form

Evaluation of Paper		
Contents	**Innovation**	☐Highly Innovate ☐Sufficiently Innovate ☐Slightly Innovate ☐Not Novel
	Integrality	☐Poor ☐Fair ☐Good ☐Outstanding
	Presentation	☐Totally Accessible ☐Mostly Accessible ☐Partially Accessible ☐Inaccessible
	Technical depth	☐Superficial ☐Suitable for the non-specialist ☐Appropriate for the generally knowledgeable individual working in the field ☐Suitable only for an expert
Presentation & English		☐Satisfactory ☐Needs improvement ☐Poor
Overall organization		☐Satisfactory ☐Could be improved ☐Poor

Response Letter of Review Form 1985 Revision

Author Name: Anik Vega Vitianingsih
Co-Authors: Achmad Choiron, Dwi Cahyono, Azizul Umam, Suyanto
Informatics Departments Universitas Dr.Soetomo Surabaya, Indonesia
Economic and Bussiness Faculty Universitas Dr.Soetomo Surabaya, Indonesia
Corresponding author E-mail: vega@unitomo.ac.id

Dear Editors
Intelligent Networks and Systems Society
International Journal of Intelligent Engineering and Systems (IJIES)
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Fukuoka, 811-0295 Japan
ijies@inass.org

Comments from reviewers: 1. This seems a making report, because there is no comparison with existing techniques. As you know, there are some spatial data models in GIS. You should demonstrate the difference between the proposed technique and existing techniques by scientific data.

Reply:

I give a description of the answers in Sect.3 and 4 in the Introduction, where:

Spatial data modeling was the process of spatial analysis results data to determine the decisions and policies of stakeholders. The resulting process included geocoding and mapping to produce a decision-making system [11][12] through the application of artificial intelligence (AI) methods [13]. The AI method used to map measles has been applied including fuzzy inference system [14], Data mining techniques [15], Bayesian mixture model [16], hierarchical Bayesian model [17], Bayesian spatial modeling [18]. The AI fuzzy inference system method is used to determine the symptoms of measles based on the input variable rule in the inference engine [14]. Artificial Neural Network (ANN), Decision Tree Algorithm and Naïve Bayes Classifier on Data Mining techniques, are used to predict disease trends. One of them is measles based on time series database disease [15]. Bayesian Normal mixture models were used to estimate the prevalence of measles through age factor [16]. Spatial hierarchical Bayesian models are used to map the risk of measles based on data on the number of measles, unemployment, birth rates, education level and age of immunization [17]. Bayesian spatial modeling is used to determine the mapping of disease populations based on disease statistics [18].

According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19]. Bayesian regression spatial model was used to identify the risk of measles spread at the regional level using data series in 2005-2014, the results obtained indicate the parameters of birth rate, number of measles cases, unemployment rate and the proportion of children immunized at 12 months to be a determinant in prevention of measles [17]. Socio-economic disparity had become a separate problem in the success of measles immunization programs, using multiple spatial regression methods mapping is done to

identify the distribution of immunization coverage based on socio-economic inequality. This was a step in mitigating the spread of measles virus [20]. Web-based GIS technology was developed as a web-based health surveillance system [21]. However, the research that has been done has not used the approach and parameters that would be proposed in the discussion of this paper, that is, with a multi-criteria parameter approach to explore the need for supporting factors in the analysis process, interview experts in the field of disease prevention and control of the Indonesian East Java Provincial Health Office, and analyze the behavior of data to determine AI methods through mathematical modeling that is suitable for producing distribution multi-class classification vulnerable area. The results of measles data processing based on the AI method are still presented in graphical form [14][15][16], Multi-criteria parameters that will be proposed for spatial data modeling with SAW and WPM methods in the discussion of this paper, have not been used in previous studies [17] [18].

Comments from reviewers: 2. Don't use acronym, such as MMR, etc., without explanation.

Reply:

I have repairs in Sect.4 on the introduction, dimana:

According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19].

Comments from reviewers: 3. The problem definition of this work is not clear. In Sect.1, the drawbacks of each conventional technique should be described clearly. In p.2, spatial data modeling techniques have been described. However, there is no explanation about these techniques. You should emphasize the difference with other methods to clarify the position of this work further.

Reply:

I give a description of the answers in Sect.1 and 5 in the Introduction, Sect.3.3 and Abstact, where:

Sect.1

Measles is one of the diseases that often becomes an extraordinary event in the tropics, such as Indonesia. The spread of measles is a global problem in the health sector. The problems, information on the incidence of measles is still based on risk factors for immunization status in the measles surveillance technique manual. Research studies are still descriptive statistics and there are no system applications that globally can identify areas prone to measles disease based on multi-criteria parameters to determine the distribution of vulnerable categories of regions. Measles control in this decade has been done by giving complete immunization to every baby or child, as a mitigation measure by the public health authority [1], measles is one type of disease that breeds in regions with tropical climates [2]. Based on the World Health Organization (WHO), measles incidence rate per million, Indonesia is a country with 6345 cases at a rate of 24.30. In 2017 the number of confirmed 11389 cases increased compared to 2016 which only reached 7204 confirmed cases [3]. Spatial patterns can be used to identify patterns of behavior of measles spreading, based on local seasonal factors in each region [4].

[**Sect.5,** I purpose SAW and WPM method, I using Method Consistency Test Cohen's Kappa, because it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field.]

The purpose of this paper was to propose an approach through spatial data modeling to determine the distribution of measles-prone areas based on immunization status coverage. Multiple attribute decision making (MADM) was used in the modeling of spatial data because alternative results in regional coverage use multi-parameter criteria including diseases preventable by immunization (PD3I), epidemic and nutritional status of infants taken from basic data on the health profile book of East Java Province of Indonesia in 2011-2016 obtained at the regional level [22][23][24][25][26][27]. The multi-class classification was obtained from the results of spatial data modeling using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method in the form of immunization status coverage: good, average, fair, and poor.

The spatial analysis produced spatial data modeling which was used to determine relationship between the basic data to be processed, with the parameters used as a factor of an area categorized in the classification of measles-prone areas based on immunization status coverage. Analysis and design of the built system have been described in advance according to the needs of spatial data that would be processed to become modeling [28].

The results of the spatial data modeling with the SAW method and WPM method obtained the preference value using The Guttman Scale Assessment. The alternative good category on the SAW method if the V_i preference value is above 0,875, the average category with the V_i preference value between 0,75 to 0,875, the V_i preference value between 0,625 to 0.75 for the fair alternative category, and poor for the preference V_i below 0,625. The Guttman Scale Assessment in the WPM method that is if the vector value V_i more than 0,001488 for good category, an average category for value V_i between 1,001274 to 0,001488, the value of V_i 0,00106 to 0,001274 for the value category V_i and smaller value than V_i 0,00106 for the poor category.

The results of trials which conducted on data layer (*.shp*) coverage each district for the 657 sub-district the East Java Province of Indonesia using the SAW method and WPM method for 2011-2016 data. Mapping the areas prone to measles by the SAW method, for the good category obtained 449, 488, 423, 442, 409, and 432 regions, the average category was obtained 113, 79, 94, 134, 108, and 134 regions, the fair category was 82, 56, 117, 69, 125, and 77 regions, and the poor category obtained 13, 34, 23, 12, 15, and 14 regions, respectively. In the WPM method, the results of mapping for regions with good categories were 299, 531, 494, 299, 306, and 315, the average category was 340, 92, 140, 337, 333, and 324 regions. from 12, 7, 13, 8, 5, and 5, and 6, 27, 10, 13, 13, and 13 in the number of regions in the poor category, respectively.

In Abstract:

This paper discusses the geographical information system (GIS) technology by analyzing spatial data modeling to determine the classification of measles-prone areas based on immunization status coverage using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method. Some parameters are used consist of immunization status data for multiple attribute decision making (MADM), diseases preventable by immunization (PD3I), epidemic and nutritional status of infants. The SAW method in modeling spatial data analysis processes data according to the parameters to determine the scale in comparing all alternative data on the scope of classification of immunization status areas, namely: good, average, fair and poor. The test results with the Cohen's Kappa Method Consistency Test (MCT) is obtained an average coefficient of 0.41 for consistent measurements for the chosen method. It can be concluded that the two measurements using the SAW and WPM methods have a moderate for the strength of agreement category, for using in spatial data modeling on the GIS for classification of measles prone regions using MADM.

Keywords: GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa tropical diseases, measles.

In Sect. 3.3

Method Consistency Test Cohen's Kappa is used to test consistency in measuring two methods, this measurement can be done for qualitative data based Eq. (14) [47].

$$K = \frac{Pr(a) - Pr(e)}{1 - Pr(e)} \qquad (14)$$

where, the variable K is the coefficient of the results of the measurement between methods. The variable *Pr(a)* is the percentage of the number of measurements that are consistent in making comparisons between methods, and the variable *Pr(e)* is the percentage change. Range of coefficient values in variable K [47], where if the variable value K <20, the value K 0,21 to 0,40, the value K is 0,41 to 0,60, the value K= 0,61 to 0,80, dan K 0,81 to 1,00, then strength of agreement are poor, fair, moderate, good, and very good, respectively.

It is in Conclusion Sect.5

Based on the discussion on testing data with MTC, it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field. Results from MTC have a moderate category strength of agreement for use in spatial data modeling on the GIS for classification of measles-prone regions using MADM. They have results that are not much different.

Comments from reviewers: 4. In the Introduction part, strong points of this proposed method should be further stated and organization of this whole paper is supposed to be provided in the end.

Reply:

In Sect 4. Results and Discussion

The results of the SAW method in the area with more good categories were 66.5 (15%) compared to the results of the WPM method. The area in the average category for the results of the WPM method is 58% greater than the results of the SAW method. Regions with a fair category have more than 90% of the results of the WMP method rather than the results of the SAW method, and more than 26% of the results of the SAW method for regions with the poor category rather than the results of the WPM method.

Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 2 is done on the same spatial datasets as the SAW method. Epidemic scores were 0, PD3I was 1, the category of nutrition status was good, and the number of infants in the Subdistrict was 152 infants with immunization status of 147 infants or 94,079% of infants with immunization status. The level of importance includes 3, 2, 3, and 3, respectively. The priority value for each parameter includes 2, 3, 4, and 1, respectively. The number of priority value in the Tb_{Pre} is 10, where the weight value in the W variable for each parameter is 0.2, 0.3, 0.4, and 0.1, respectively. Calculation of the value of Vector in the S variable for each parameter variable, namely is 1,390389, 1,148698, 1,551846, and 1,116123. V_s variable value is obtained by multiplying all T_V values is 1670,478685, then the total V_s obtained from all calculated data is 2,766324. The value of vector V by dividing the value of V_s by the value of T_{Vs}, then the value of V is 0,001656, based on Eq. (13) and flow on Fig. (1), then the classification of regions with good categories

The test results using Cohen's Kappa for the feasibility of using the SAW method and the WPM method for modeling spatial data on GIS for classification of measles-prone areas using MADM, obtained kappa coefficients from the K variable -0.42, 0,67, 0,519367011, 0,15, 0,215627097, and 0,253130142 for 2011-2016, respectively.

Comments from reviewers: 5. In figures, letters are too small. Unify the font size of letters (more than 10pt). Enlarge or Redraw figures. e.g. Fig.1 and 4. Do not place 3 figures in one column.

Reply:

I made improvements in Figure 1, dimana:
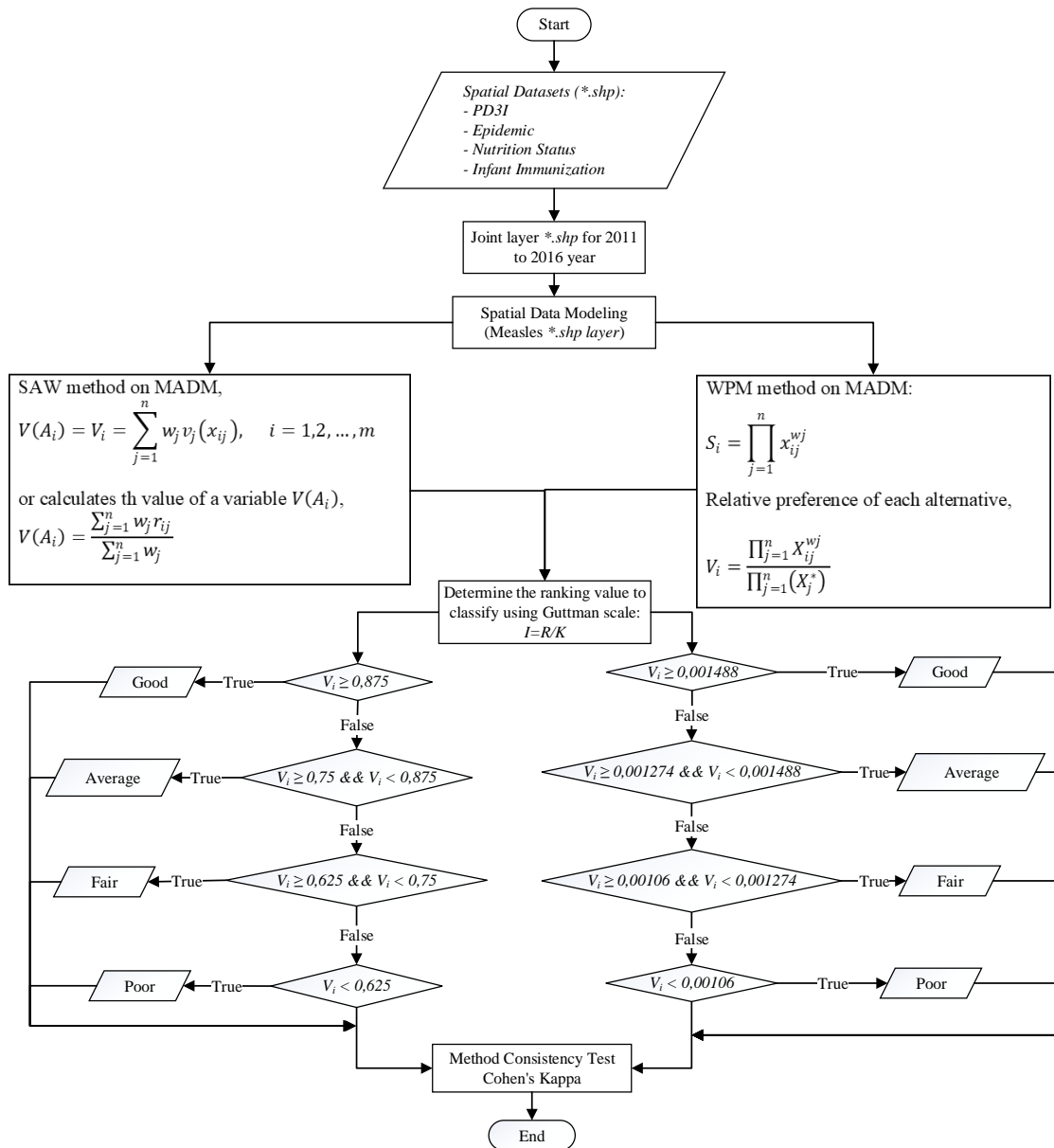
Figure. 1 Flow of Spatial Data Modelling with SAW and WPM Method

Comments from reviewers: 6. The width of Eq.(11) is too wide.

Reply:

I made improvements in Eq.(12)(13) and Table 2, where:

$$\begin{cases} good, if\ V_i \geq 0,875 \\ average, if\ V_i \geq 0,75\ and\ V_i < 0,875 \\ fair, if\ V_i \geq 0,625\ and\ V_i < 0,75 \\ poor, if\ V_i < 0,625 \end{cases} \qquad (12)$$

$$\begin{cases} good, if\ V_i \geq 0{,}001488 \\ average, if\ V_i \geq 0{,}001274\ and\ V_i < 0{,}001488 \\ fair, if\ V_i \geq 0{,}00106\ and\ V_i < 0{,}001274 \\ poor, if\ V_i < 0{,}00106 \end{cases} \quad (13)$$

Table 2. The Guttman Scale Assessment

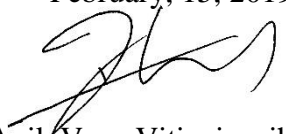| SAW Method	WPM Method
$R = V_{i_{maks}} - V_{i_{min}} = 1 - 0{,}5 = 0{,}5$ $K = 4$ $I = \dfrac{0{,}5}{4} = 0{,}125$	$R = V_{i_{maks}} - V_{i_{min}} = 0{,}001702 - 0{,}000846$ $= 0{,}000856$ $K = 4$ $I = \dfrac{0{,}000856}{4} = 0{,}000214$
$Assessment\ good\ criteria$ $= highest\ score - I$ $= 1 - 0{,}125 = 0{,}875$ $Assessment\ average\ criteria$ $= assesment\ good\ criteria - I$ $= 0{,}875 - 0{,}125 = 0{,}75$ $Assessment\ fair\ criteria$ $= assesment\ average\ criteria - I$ $= 0{,}75 - 0{,}125 = 0{,}625$ $Assessment\ poor\ criteria$ $= assesment\ fair\ criteria - I$ $= 0{,}625 - 0{,}125 = 0{,}5$	$Assessment\ good\ criteria$ $= highest\ score - I$ $= 0{,}001702 - 0{,}000214 = 0{,}001488$ $Assessment\ average\ criteria$ $= assesment\ good\ criteria - I$ $= 0{,}001488 - 0{,}000214 = 0{,}001274$ $Assessment\ fair\ criteria$ $= assesment\ average\ criteria - I$ $= 0{,}001274 - 0{,}000214 = 0{,}00106$ $Assessment\ poor\ criteria$ $= assesment\ fair\ criteria - I$ $= 0{,}00106 - 0{,}000214 = 0{,}000846$

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Surabaya, Indonesia
February, 15, 2019

Anik Vega Vitianingsih

Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

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Abstract: Indonesia is a country that has a tropical climate, so that many typical tropical climate diseases emerge. This disease is caused by viruses and parasites that breed during the dry season or the rainy season. One typical tropical disease is measles. This paper discusses the geographical information system (GIS) technology by analyzing spatial data modeling to determine the classification of measles-prone areas based on immunization status coverage using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method. Some parameters are used consist of immunization status data for multiple attribute decision making (MADM), diseases preventable by immunization (PD3I), epidemic and nutritional status of infants. The SAW method in modeling spatial data analysis processes data according to the parameters to determine the scale in comparing all alternative data on the scope of classification of immunization status areas, namely: good, average, fair and poor. The test results with the Cohen's Kappa Method Consistency Test (MCT) is obtained an average coefficient of 0.41 for consistent measurements for the chosen method. It can be concluded that the two measurements using the SAW and WPM methods have a moderate for the strength of agreement category, for using in spatial data modeling on the GIS for classification of measles prone regions using MADM.

Keywords: GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa tropical diseases, measles.

1. Introduction

Measles is one of the diseases that often becomes an extraordinary event in the tropics, such as Indonesia. The spread of measles is a global problem in the health sector. The problems, information on the incidence of measles is still based on risk factors for immunization status in the measles surveillance technique manual. Research studies are still descriptive statistics and there are no system applications that globally can identify areas prone to measles disease based on multi-criteria parameters to determine the distribution of vulnerable categories of regions. Measles control in this decade has been done by giving complete immunization to every baby or child, as a mitigation measure by the public health authority [1], measles is one type of disease that breeds in regions with tropical climates [2]. Based on the World Health Organization (WHO), measles incidence rate per million, Indonesia is a country with 6345 cases at a rate of 24.30. In 2017 the number of confirmed 11389 cases increased compared to 2016 which only reached 7204 confirmed cases [3]. Spatial patterns can be used to identify patterns of behavior of measles spreading, based on local seasonal factors in each region [4].

In the beginning, spatial data modeling was done by analyzing the needs of geospatial data to be processed for decision-making systems. The need for spatial data analysis was important in the field of research and policy making, provides a description of data needs, methods, and illustrations of case studies used [5], as well as in the health sector [6][7] measles field [8]. Analysis of spatial data as a mitigation measure for disease prevention and control had a very important role. This was developed based on the conditions of regional climate and social behavior of

the community, the method of Inverse Distance Weighting (IDW), the functions and weighted overlay functions were used to predict the location of disease spread [9]. The risk of spreading the disease to areas adjacent to the affected area has been carried out by using a spatial clustering method. In this method, a comparison was made on spatial grouping in heterogeneity. The resulting information would be beneficial for the Ministry of Health to formulate regional coping strategies as hotspots in epidemic diseases [10].

Spatial data modeling was the process of spatial analysis results data to determine the decisions and policies of stakeholders. The resulting process included geocoding and mapping to produce a decision-making system [11][12] through the application of artificial intelligence (AI) methods [13]. The AI method used to map measles has been applied including fuzzy inference system [14], Data mining techniques [15], Bayesian mixture model [16], hierarchical Bayesian model [17], Bayesian spatial modeling [18]. The AI fuzzy inference system method is used to determine the symptoms of measles based on the input variable rule in the inference engine [14]. Artificial Neural Network (ANN), Decision Tree Algorithm and Naïve Bayes Classifier on Data Mining techniques, are used to predict disease trends. One of them is measles based on time series database disease [15]. Bayesian Normal mixture models were used to estimate the prevalence of measles through age factor [16]. Spatial hierarchical Bayesian models are used to map the risk of measles based on data on the number of measles, unemployment, birth rates, education level and age of immunization [17]. Bayesian spatial modeling is used to determine the mapping of disease populations based on disease statistics [18].

According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19]. Bayesian regression spatial model was used to identify the risk of measles spread at the regional level using data series in 2005-2014, the results obtained indicate the parameters of birth rate, number of measles cases, unemployment rate and the proportion of children immunized at 12 months to be a determinant in prevention of measles [17]. Socio-economic disparity had become a separate problem in the success of measles immunization programs, using multiple spatial regression methods mapping is done to identify the distribution of immunization coverage based on

socio-economic inequality. This was a step in mitigating the spread of measles virus [20]. Web-based GIS technology was developed as a web-based health surveillance system [21]. However, the research that has been done has not used the approach and parameters that would be proposed in the discussion of this paper, that is, with a multi-criteria parameter approach to explore the need for supporting factors in the analysis process, interview experts in the field of disease prevention and control of the Indonesian East Java Provincial Health Office, and analyze the behavior of data to determine AI methods through mathematical modeling that is suitable for producing distribution multi-class classification vulnerable area. The results of measles data processing based on the AI method are still presented in graphical form [14][15][16], Multi-criteria parameters that will be proposed for spatial data modeling with SAW and WPM methods in the discussion of this paper, have not been used in previous studies [17] [18].

The purpose of this paper was to propose an approach through spatial data modeling to determine the distribution of measles-prone areas based on immunization status coverage. Multiple attribute decision making (MADM) was used in the modeling of spatial data because alternative results in regional coverage use multi-parameter criteria including diseases preventable by immunization (PD3I), epidemic and nutritional status of infants taken from basic data on the health profile book of East Java Province of Indonesia in 2011-2016 obtained at the regional level [22][23][24][25][26][27]. The multi-class classification was obtained from the results of spatial data modeling using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method in the form of immunization status coverage: good, average, fair, and poor.

The spatial analysis produced spatial data modeling which was used to determine relationship between the basic data to be processed, with the parameters used as a factor of an area categorized in the classification of measles-prone areas based on immunization status coverage. Analysis and design of the built system have been described in advance according to the needs of spatial data that would be processed to become modeling [28].

The results of the spatial data modeling with the SAW method and WPM method obtained the preference value using The Guttman Scale Assessment. The alternative good category on the SAW method if the V_i preference value is above 0,875, the average category with the V_i preference value between 0,75 to 0,875, the V_i preference value

between 0,625 to 0.75 for the fair alternative category, and poor for the preference V_i below 0,625. The Guttman Scale Assessment in the WPM method that is if the vector value V_i more than 0,001488 for good category, an average category for value V_i between 1,001274 to 0,001488, the value of V_i 0,00106 to 0,001274 for the value category V_i and smaller value than V_i 0,00106 for the poor category.

The results of trials which conducted on data layer (*.shp) coverage each district for the 657 sub-district the East Java Province of Indonesia using the SAW method and WPM method for 2011-2016 data. Mapping the areas prone to measles by the SAW method, for the good category obtained 449, 488, 423, 442, 409, and 432 regions, the average category was obtained 113, 79, 94, 134, 108, and 134 regions, the fair category was 82, 56, 117, 69, 125, and 77 regions, and the poor category obtained 13, 34, 23, 12, 15, and 14 regions, respectively. In the WPM method, the results of mapping for regions with good categories were 299, 531, 494, 299, 306, and 315, the average category was 340, 92, 140, 337, 333, and 324 regions. from 12, 7, 13, 8, 5, and 5, and 6, 27, 10, 13, 13, and 13 in the number of regions in the poor category, respectively.

The results of this study could be part of disaster mitigation measures to prevent the spread of measles [1][29] in developing countries with a tropical climate. The mapping results could provide a classification of prone red areas based on the coverage of poor immunization status. Policy makers such as the Health Office could make preventive measures based on the results of the classification.

2. Spatial Datasets

Spatial data sets are used to classify parameters that affect the spread of measles [8]. Spatial datasets consist of two components: spatial data and attribute data. Both become parameters to determine the classification of measles-prone areas based on immunization status coverage factors as in Table 1, including PD3I, epidemic, nutritional status, and infant immunization.

In each spatial datasets the weight value was given, to determine the level of importance/influence on the classification produced in each parameter criterion [30][31][31], This weighting used the fuzzification process, consisting of fuzzy sets indicators in giving a level description in the classification results [32].

Table 1. Description of the Multi-Criteria Parameter Spatial Datasets Measles Diseases

Spatial Datasets	The Priority Value	Weight	Incidence rate (annually)	Category of PD3I	Level of importance
PD3I	2	0.30	PD3I >12 months a year	Poor	1
			PD3I <12 months a year	Good	2
Epidemic	3	0.15	Epidemic > 60 cases a year	Poor	1
			Epidemic < 60 cases a year	Good	2
			Epidemic = 0 cases a year	Very good	3
Spatial Datasets	Value of the priority	Weight	The status	Range Standard Deviation (sd)	Level of importance
Nutrition Status	4	0.10	Very good nutrition	sd ≥ 2	4
			Good nutrition	sd < 2 && sd ≥ -2	3
			Less of nutrition	sd < -2 && sd ≥-3	2
			Poor nutrition	sd < -3	1
Infant Immunization (IM)	1	0.45	Good immunization	IM > 90%	3
			Average immunization	IM ≤ 90% && IM ≥ 80%	2
			Fair immunization	IM < 80%	1

3. Methods

Decision-making systems that involve GIS spatial data could be completed with MADM that be able to carry out integration in managing spatial data and attribute data to perform spatial data analysis [33]. Analysis of spatial data in the discussion of this paper resulted from spatial data modeling. the spatial datasets described in Table 1 be used as baseline data

to produce a classification of measles-prone areas based on immunization status coverage.

The process stages in spatial data modeling for classification of tropical disease prone areas based on immunization status coverage were shown in the flowchart Fig. 1. This stage gave a picture of how the system works. Starting from inputting or recording of all data needs, then the process of modeling spatial data by determining the AI method that matches the

behavior of the data obtained from the recording process, and the final process was to display the results of spatial data modeling in accordance with the functions and objectives to be achieved in GIS software development.
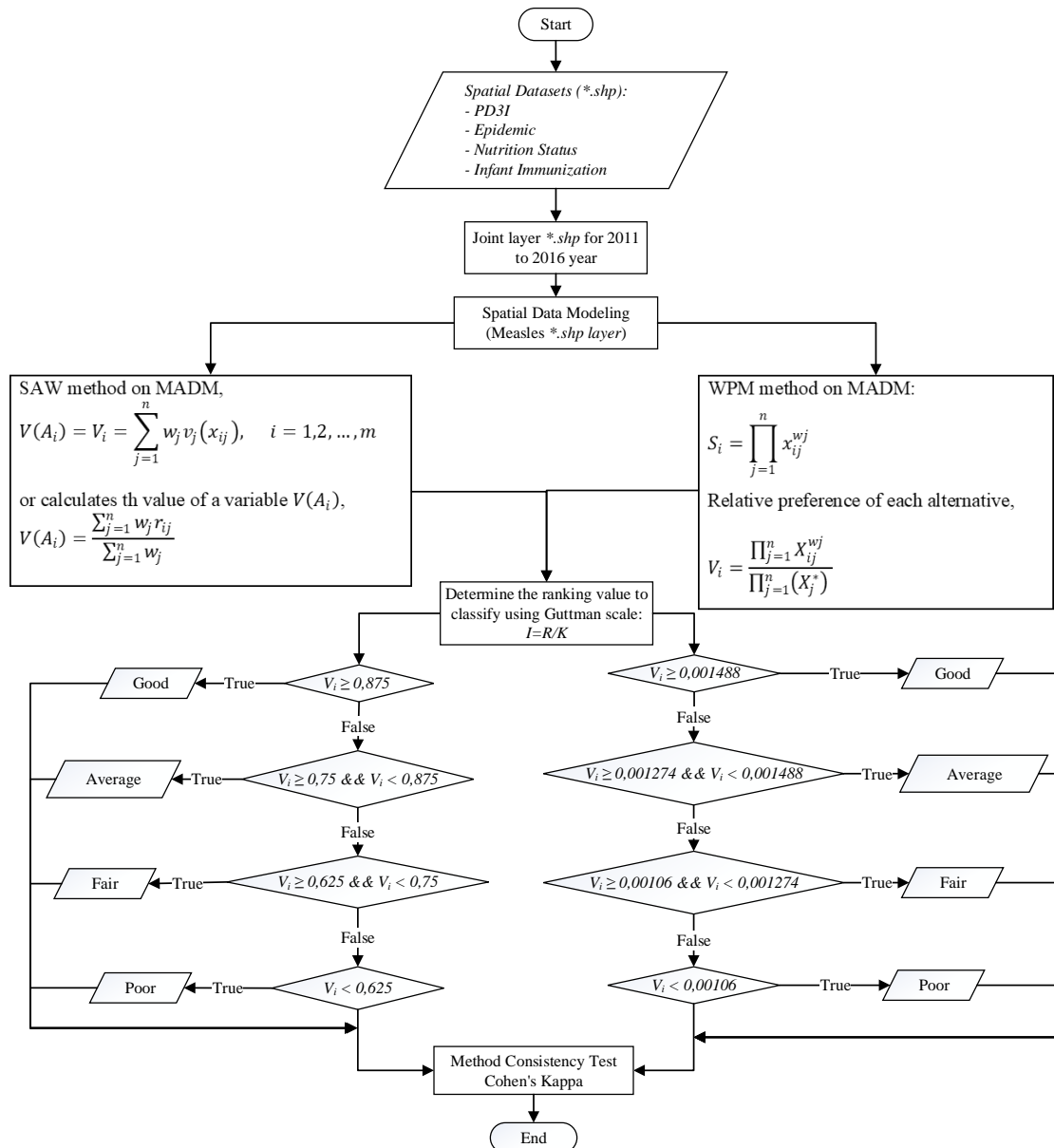

Figure. 1 Flow of Spatial Data Modelling with SAW and WPM Method

The first step, defining the spatial data requirements and layer attribute data in the spatial shapefile dataset (*.shp). The dataset includes a map of the East Java Province of Indonesia consisting of districts in each sub-district, including PD3I, epidemic, nutrition status, and infant immunization. The data used was qualitative [34] which was then cited [35] in each district with the concept of the overlay layer. This stage served to merge layers from 31 districts with data layers per sub-district to become a single layer.

The overlay layer results in one layer of measles (*measles*.*shp*) for each year. This was called spatial interpolation. The SAW and the WPM method through the MADM method would process the results of the regulation's layer to get the preference value of *Vi*. The Guttman method was used for classification of values with immunization status coverage categories with good, average, fair, and poor conditions in each sub-district.

The coverage of immunization status for the distribution of measles with the good category can be obtained if the V_i value increases compared to the previous year. It can be concluded that the state of immunization status is reached or exceeded the target, indicated by the description of the green area. In

regions with average immunization status coverage occurs if an area with immunization status reaches the minimum target which is represented by an area of orange color, where the value of V_i falls from the condition of the previous year. It could be seen from the value of V_i for the classification of regional categories with good immunization status. Fair classification occurs if in a region the value of V_i falls compared to the previous year in the area with the average category. This happened because the immunization target did not reach the minimum target with an orange description of the area. Regions with a V_i value below the average condition of good, average, and fair immunization status coverage, where the immunization target was not achieved, by mapping the red area.

3.1 Multiple Attribute Decision Making (MADM)

MADM is part of the Multi-criteria decision making (MCDM) decision-making system, as well as multi-objective decision making (MODM) [36]. MODM was used for decision making that be sustainable, as in computing programming [37]. MADM and MCDM were used for discrete retrieval, where the alternative of the support system of the decision was predetermined [37].

The Simple Additive Weighting Method (SAW) and the Weight Product Model (WPM) method is part of a decision-making system using multi-parameter criteria with a multiple attribute decision making (MADM) approach [38]. MADM describes the parameters/criteria that will be used to determine the best alternative based on several appropriate criteria, the characteristics of decision making using the MADM system will describe the attribute requirements in the spatial analysis process, make the decision weight from the data that has been described Table 1 to form a decision matrix produced [39][37][40].

Approach to the SAW method by giving a score on each alternative produced to be multiplied by the value weight for each parameter attribute [41], with the following steps:

1. The SAW method produces the final value of V_i in the Eq. (1) to obtain an alternative value from the classification that will be generated in the decision-making system [40].

$$V(A_i) = V_i = \sum_{j=1}^{n} w_j v_j(x_{ij}), \quad i = 1,2,\ldots,m \tag{1}$$

where $V(A_i)=V_i$ is the alternative result value in the classification generated in each attribute A_i, this value is obtained from the calculation of the preference value $v_j(x_{ij})$ on $V(A_i)$ and the w_j weight in each parameter. The value of $V(A_i)$ can also be calculated using Eq. (2), where r_{ij} is normalization from the calculation of the maximum value of the data on the parameter attribute.

$$V(A_i) = \frac{\sum_{j=1}^{n} w_j r_{ij}}{\sum_{j=1}^{n} w_j} \tag{2}$$

2. Calculating the preference value $v_j(x_{ij})$ on $V(A_i)$ for each parameter attribute by finding the maximum value in each parameter attribute value using Eq. (3) and normalizing the maximum value obtained using the Eq. (4) [40].

$$max = max\left(A_{ij}\right) \tag{3}$$

where, the max value (A_{ij}) is obtained from the parameter attribute, in this paper the parameter attribute value is described in Table 1 with the process on the spatial data input data *.shp as described in Fig. 1 which refers to Eq. (4).

$$
\begin{aligned}
max(a_i) &= max(a_{ij}) \\
max(b_i) &= \max(b_{ij}) \\
max(c_i) &= max(c_{ij}) \\
max(d_i) &= max(d_{ij})
\end{aligned} \tag{4}
$$

where, to declare parameter attributes *.shp spatial dataset on all data a_{ij}, $max(a_i)$ for PD3I, $max(b_i)$ for epidemic, $max(c_i)$ for nutritional status, and $max(d_i)$ for infant immunization.

Normalize the value of each parameter attribute using Eq. (5), where X_j is the data value that is j and max is the value obtained from the calculation in Eq. (3) [40].

$$r_{ij} = X_j / max \tag{5}$$

In this spatial data modeling, normalization values refer to Eq. (5) with the implementation of spatial datasets using Eq. (6).

$$
\begin{aligned}
r(a_i) &= \frac{a_i}{max(a_{ij})} \; ; \; r(b_i) = \frac{b_i}{max(b_{ij})} \\
r(c_i) &= \frac{c_i}{max(c_{ij})} \; ; \; r(d_i) = \frac{d_i}{max(d_{ij})}
\end{aligned} \tag{6}
$$

3. Calculates the preference value $v_j(x_{ij})$ on $V(A_i)$ for all parameter attributes using Eq. (7) [40].

$$V_i = \sum_{j=1}^{n} w_j r_{ij}, \quad i = 1,2,\ldots,m \tag{7}$$

where, w_j is the weight of the parameter attribute value and r_{ij} is the normalization value obtained in Eq. (5). The discussion in the trial in this paper uses Eq. (8) based on a literature study on Eq. (7).

$$
\begin{aligned}
v(a_i) &= Norm(a_i) \; x \; weight(a_i) \\
v(b_i) &= Norm(b_i) \; x \; weight(b_i) \\
v(c_i) &= Norm(c_i) \; x \; weight(c_i) \\
v(d_i) &= Norm(d_i) \; x \; weight(d_i) \\
V_i &= v(a_i) + v(b_i) + v(c_i) + v(d_i)
\end{aligned} \tag{8}
$$

Approach to the WPM method use multiplication to connect the attribute rating. rating each attribute

must be raised first with the weight of the attribute [37][42]. The steps of the WPM method normalize to find out the alternative preferences of A_i in S_i vectors, according to Eq. (9) [37][42].

$$S_i = \prod_{j=1}^{n} x_{ij}^{wj} \qquad (9)$$

where, S variable is an alternative preference and is defined as a vector. X_{ij} variable is the variable value from the alternative on each attribute. The criteria or sub-criteria weight values are accommodated in the W_j variable. The N variable is used to represent the number of criteria in the multi-criteria parameters declared. Variable i is the desired alternative value, and variable j is the criteria value in the data. The value of the $\sum W_j$ variable is 1 with the rank positive for the profit attribute, and negative for the cost attribute. The relative preference of each alternative is calculated using Eq. (10) [37][42].

$$V_i = \frac{\prod_{j=1}^{n} X_{ij}^{wj}}{\prod_{j=1}^{n} (X_j^*)} \qquad (10)$$

where, V_i variable is an alternative preference defined as a vector with i-th data. Determine the weight value for each parameter used to set the priority value on the existing parameters that are accommodated in the Bpre variable, 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 $W=B_A$/Tb. Calculating the value of the variable S on each weight value in variable B is raised by the result of the variable W, with $S=B_a^W_a$. Calculating the value of V_s by multiplying all values in variable S, with V$_s$=S$_a$xS$_b$ x…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$_3$+…+V$_n$, then the variable value of V= V_{sa}/Tv_{sa}.

3.2 The Guttman Scale

Measurement of the classification values generated in this paper uses the Guttman scale [43], This scale is the basis of measurement to draw conclusions on qualitative data [44], and is used to provide an estimate of the value of the classification results in an intervention value that is still ambiguous because of uncertainty [45]. In the type of dataset that uses a score/weight in the analysis process, provides a value based on the uncertainty factor of the variable class described, it can be measured using the Guttman scale [46] in the Eq. (11).

$$I = \frac{R}{K} \qquad (11)$$

where I is the result of the interval value obtained from the variable R, is the range of data values and variable K with the number of alternative classifications that will be generated.

In the discussion of this paper, the variable value R is obtained from the range of values between the maximum value of V_i and the minimum value of V_i. K variable is the number of alternative classifications namely good, average, fair, and poor which refers to flow Fig. 1 and Table 2. Whereas, the determination of the scale for determining the classification value criteria for measles-prone areas based on the status of immunization coverage using Eq. (12) with SAW method and WPM method using Eq. (13).

$$\begin{cases} good, if\ V_i \geq 0,875 \\ average, if\ V_i \geq 0,75\ and\ V_i < 0,875 \\ fair, if\ V_i \geq 0,625\ and\ V_i < 0,75 \\ poor, if\ V_i < 0,625 \end{cases} \qquad (12)$$

$$\begin{cases} good, if\ V_i \geq 0,001488 \\ average, if\ V_i \geq 0,001274\ and\ V_i < 0,001488 \\ fair, if\ V_i \geq 0,00106\ and\ V_i < 0,001274 \\ poor, if\ V_i < 0,00106 \end{cases} \qquad (13)$$

Table 2. The Guttman Scale Assessment

SAW Method	WPM Method
$R = V_{i\,maks} - V_{i\,min} = 1 - 0,5 = 0,5$ $K = 4$ $I = \dfrac{0,5}{4} = 0,125$	$R = V_{i\,maks} - V_{i\,min} = 0,001702 - 0,000846 = 0,000856$ $K = 4$ $I = \dfrac{0,000856}{4} = 0,000214$
Assessment good criteria $= highest\ score - I$ $= 1 - 0,125 = 0,875$ *Assessment average criteria* $= assesment\ good\ criteria - I$ $= 0,875 - 0,125 = 0,75$ *Assessment fair criteria* $= assesment\ average\ criteria - I$ $= 0,75 - 0,125 = 0,625$ *Assessment poor criteria* $= assesment\ fair\ criteria - I$ $= 0,625 - 0,125 = 0,5$	*Assessment good criteria* $= highest\ score - I$ $= 0,001702 - 0,000214 = 0,001488$ *Assessment average criteria* $= assesment\ good\ criteria - I$ $= 0,001488 - 0,000214 = 0,001274$ *Assessment fair criteria* $= assesment\ average\ criteria - I$ $= 0,001274 - 0,000214 = 0,00106$ *Assessment poor criteria* $= assesment\ fair\ criteria - I$ $= 0,00106 - 0,000214 = 0,000846$

3.3 Method Consistency Test (MCT)

Method Consistency Test Cohen's Kappa is used to test consistency in measuring two methods, this measurement can be done for qualitative data based Eq. (14) [47].

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \qquad (14)$$

where, the variable K is the coefficient of the results of the measurement between methods. The variable $Pr(a)$ is the percentage of the number of measurements that are consistent in making comparisons between methods, and the variable $Pr(e)$ is the percentage change.

Range of coefficient values in variable K [47], where if the variable value K <20, the value K 0,21 to 0,40, the value K is 0,41 to 0,60, the value K= 0,61 to 0,80, dan K 0,81 to 1,00, then strength of agreement are poor, fair, moderate, good, and very good, respectively.

4. Results and Discussion

From the results of trials that have been carried out in 657 sub-districts in 38 regencies in 2011-2016 data obtained from the East Java Provincial Health Office of Indonesia [22] [23] [24] [25] [26] [27]. The results of the modeling spatial data on the number of districts with categories of classification of measles-prone areas based on the status of immunization coverage with MADM in the SAW method as in Table 2, Fig. 2 and WPM method as in Table 3, Fig.3.

Table 2. Distribution of Mapping Classification Results with the SAW Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	449	488	423	442	409	432
Average	113	79	94	134	108	134
Fair	82	56	117	69	125	77
Poor	13	34	23	12	15	14

Table 3. Distribution of Mapping Classification Results with the WPM Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	299	531	494	299	306	315
Average	340	92	140	337	333	324
Fair	12	7	13	8	5	5
Poor	6	27	10	13	13	13

The results of the SAW method in the area with more good categories were 66.5 (15%) compared to the results of the WPM method. The area in the average category for the results of the WPM method is 58% greater than the results of the SAW method. Regions with a fair category have more than 90% of the results of the WMP method rather than the results of the SAW method, and more than 26% of the results of the SAW method for regions with the poor category rather than the results of the WPM method.
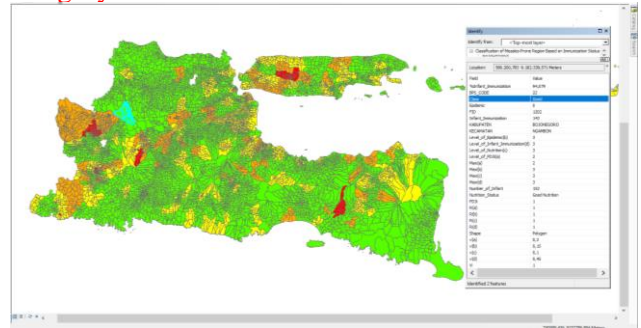

Figure. 2 The Results of the MADM Classification with the SAW Method

The Results of the MADM Classification with the SAW Method in Fig.2. The layer value of datasets PD3I is 1 incidence rate (annually) to months a year, epidemic is 0 annually to months a year, nutrition status is good, and number of infant = 152 infants with infant in immunization status is 143 infant for 94,079% infant immunization status, based on the level of importance referring to Table 1, the values are 2, 3, 3, and 3, so a =2 ; b =3; c =3; d=3, to get the max value in Eq. (3), the data input process is carried out based on Eq. (4), namely: $max(a_i) = 2$; $max(b_i) = 3$; $max(c_i) = 3$; $max(d_i) = 3$.

Normalization of the max value based on the theory in Eq. (5), the normalized value is obtained by dividing the value of the parameter variable with the max value of each variable referring to Eq. (6), namely: $r(a_i) = \frac{2}{2} = 1$; $r(b_i) = \frac{3}{3} = 1$; $r(c_i) = \frac{3}{3} = 1$; $r(d_i) = \frac{3}{3} = 1$.

The preference value is obtained from the reference in Eq. (7), which is multiplying between normalization value and weight in each parameter variable in Table 1 using Eq. (8).
$v(a_i) = 1 * 0,30 = 0,3$; $v(b_i) = 1 * 0,15 = 0,15$; $v(c_i) = 1 * 0,10 = 0,1$; $v(d_i) = 1 * 0,45 = 0,45$
Then, the final value of the preference is:
$$V_i = v(a_i) + v(b_i) + v(c_i) + v(d_i)$$
$$= 0,3 + 0,15 + 0,1 + 0,45 = 1$$
Based on Eq. (12) which refers to Eq. (11), the value of V_i is 1 entered in the range of good classification category in the area with green mapping, where the value of V_i is greater than 0.875.
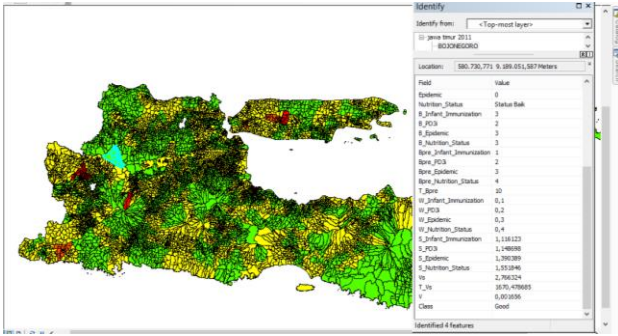
Figure. 3 The Results of the MADM Classification with the SAW Method

Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 2 is done on the same spatial datasets as the SAW method. Epidemic scores were 0, PD3I was 1, the category of nutrition status was good, and the number of infants in the Subdistrict was 152 infants with immunization status of 147 infants or 94,079% of infants with immunization status. The level of importance includes 3, 2, 3, and 3, respectively. The priority value for each parameter includes 2, 3, 4, and 1, respectively. The number of priority value in the Tb_{Pre} is 10, where the weight value in the W variable for each parameter is 0.2, 0.3, 0.4, and 0.1, respectively. Calculation of the value of Vector in the S variable for each parameter variable, namely is 1,390389, 1,148698, 1,551846, and 1,116123. V_s variable value is obtained by multiplying all T_V values is 1670,478685, then the total V_s obtained from all calculated data is 2,766324. The value of vector V by dividing the value of V_s by the value of T_{Vs}, then the value of V is 0,001656, based on Eq. (13) and flow on Fig. (1), then the classification of regions with good categories

The test results using Cohen's Kappa for the feasibility of using the SAW method and the WPM method for modeling spatial data on GIS for classification of measles-prone areas using MADM, obtained kappa coefficients from the K variable -0.42, 0,67, 0,519367011, 0,15, 0,215627097, and 0,253130142 for 2011-2016, respectively.

5. Conclusion

This paper examines the MADM technique in classifying multi-criteria parameters to produce spatial data modeling in its spatial process. The methods in MADM allows the results of comparative mapping in accordance with the level of importance, weight, and order of priority given to each of the parameter's multi-criteria variables in providing spatial sensitivity analysis.

This study resulted in the preference value of V_i in the SAW method and WPM method by considering quantitative data and the calculation of the Guttman scale classification parameter value scale, this matter becomes very important in the decision-making system as a step-in planning to provide classification in identifying areas affected by tropical diseases in measles-like the results in Eq. (12) and Eq. (13).

This finding provides a new direction for using the MADM technique with the SAW and WPM method as part of the planning for mitigation measures, this finding encourages further research to use other quantitative data to influence the results of spatial data modeling.

Regions that are classified as fair or poor are important for policymakers in the field of surveillance and immunization of the Health Office to take anticipatory steps as a form of mitigation measures [1] of disasters causing epidemics of measles. The results of this spatial data modeling answer the role of quantitative data types that can be used as a reference in displaying a mapping to produce a classification of vulnerable areas as part of decision making, for example providing understanding to communities in fair and poor categories to be more caring through self-awareness in order to immunize areas with high epidemics can be choked. This is important because prevention is not only the responsibility of the health sector, but the role of the socio-economic environment is also a driver of the spread of measles infectious diseases [7].

Based on the discussion on testing data with MTC, it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field. Results from MTC have a moderate category strength of agreement for use in spatial data modeling on the GIS for classification of measles-prone regions using MADM. They have results that are not much different.

Further research that can be developed is by collaborating the MADM method and data mining classification methods such as naïve Bayesian or decision tree, this function is to determine the comparison of the results of the classification given in each type of method used. Comparing the results of the classification of each method to be tested the level of accuracy of the method used through the method induction test.

Acknowledgments

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Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

Anik Vega Vitianingsih[1]*   **Achmad Choiron[2]**   **Dwi Cahyono[3]**   **Azizul Umam[4]**   **Suyanto[5]**

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Abstract: Indonesia is a country that has a tropical climate, so that many typical tropical climate diseases emerge. This disease is caused by viruses and parasites that breed during the dry season or the rainy season. One typical tropical disease is measles. This paper discusses the geographical information system (GIS) technology by analyzing spatial data modeling to determine the classification of measles-prone areas based on immunization status coverage using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method. Some parameters are used consist of immunization status data for multiple attribute decision making (MADM), diseases preventable by immunization (PD3I), epidemic and nutritional status of infants. The SAW method in modeling spatial data analysis processes data according to the parameters to determine the scale in comparing all alternative data on the scope of classification of immunization status areas, namely: good, average, fair and poor. The test results with the Cohen's Kappa Method Consistency Test (MCT) is obtained an average coefficient of 0.41 for consistent measurements for the chosen method. It can be concluded that the two measurements using the SAW and WPM methods have a moderate for the strength of agreement category, for using in spatial data modeling on the GIS for classification of measles prone regions using MADM.

Keywords: GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa tropical diseases, measles.

1. Introduction

Measles is one of the diseases that often becomes an extraordinary event in the tropics, such as Indonesia. The spread of measles is a global problem in the health sector. The problems, information on the incidence of measles is still based on risk factors for immunization status in the measles surveillance technique manual. Research studies are still descriptive statistics and there are no system applications that globally can identify areas prone to measles disease based on multi-criteria parameters to determine the distribution of vulnerable categories of regions. Measles control in this decade has been done by giving complete immunization to every baby or child, as a mitigation measure by the public health authority [1], measles is one type of disease that breeds in regions with tropical climates [2]. Based on the World Health Organization (WHO), measles incidence rate per million, Indonesia is a country with 6345 cases at a rate of 24.30. In 2017 the number of confirmed 11389 cases increased compared to 2016 which only reached 7204 confirmed cases [3]. Spatial patterns can be used to identify patterns of behavior of measles spreading, based on local seasonal factors in each region [4].

In the beginning, spatial data modeling was done by analyzing the needs of geospatial data to be processed for decision-making systems. The need for spatial data analysis was important in the field of research and policy making, provides a description of data needs, methods, and illustrations of case studies used [5], as well as in the health sector [6][7] measles field [8]. Analysis of spatial data as a mitigation measure for disease prevention and control had a very important role. This was developed based on the conditions of regional climate and social behavior of

the community, the method of Inverse Distance Weighting (IDW), the functions and weighted overlay functions were used to predict the location of disease spread [9]. The risk of spreading the disease to areas adjacent to the affected area has been carried out by using a spatial clustering method. In this method, a comparison was made on spatial grouping in heterogeneity. The resulting information would be beneficial for the Ministry of Health to formulate regional coping strategies as hotspots in epidemic diseases [10].

Spatial data modeling was the process of spatial analysis results data to determine the decisions and policies of stakeholders. The resulting process included geocoding and mapping to produce a decision-making system [11][12] through the application of artificial intelligence (AI) methods [13]. The AI method used to map measles has been applied including fuzzy inference system [14], Data mining techniques [15], Bayesian mixture model [16], hierarchical Bayesian model [17], Bayesian spatial modeling [18]. The AI fuzzy inference system method is used to determine the symptoms of measles based on the input variable rule in the inference engine [14]. Artificial Neural Network (ANN), Decision Tree Algorithm and Naïve Bayes Classifier on Data Mining techniques, are used to predict disease trends. One of them is measles based on time series database disease [15]. Bayesian Normal mixture models were used to estimate the prevalence of measles through age factor [16]. Spatial hierarchical Bayesian models are used to map the risk of measles based on data on the number of measles, unemployment, birth rates, education level and age of immunization [17]. Bayesian spatial modeling is used to determine the mapping of disease populations based on disease statistics [18].

According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19]. Bayesian regression spatial model was used to identify the risk of measles spread at the regional level using data series in 2005-2014, the results obtained indicate the parameters of birth rate, number of measles cases, unemployment rate and the proportion of children immunized at 12 months to be a determinant in prevention of measles [17]. Socio-economic disparity had become a separate problem in the success of measles immunization programs, using multiple spatial regression methods mapping is done to identify the distribution of immunization coverage based on

socio-economic inequality. This was a step in mitigating the spread of measles virus [20]. Web-based GIS technology was developed as a web-based health surveillance system [21]. However, the research that has been done has not used the approach and parameters that would be proposed in the discussion of this paper, that is, with a multi-criteria parameter approach to explore the need for supporting factors in the analysis process, interview experts in the field of disease prevention and control of the Indonesian East Java Provincial Health Office, and analyze the behavior of data to determine AI methods through mathematical modeling that is suitable for producing distribution multi-class classification vulnerable area. The results of measles data processing based on the AI method are still presented in graphical form [14][15][16], Multi-criteria parameters that will be proposed for spatial data modeling with SAW and WPM methods in the discussion of this paper, have not been used in previous studies [17] [18].

The purpose of this paper was to propose an approach through spatial data modeling to determine the distribution of measles-prone areas based on immunization status coverage. Multiple attribute decision making (MADM) was used in the modeling of spatial data because alternative results in regional coverage use multi-parameter criteria including diseases preventable by immunization (PD3I), epidemic and nutritional status of infants taken from basic data on the health profile book of East Java Province of Indonesia in 2011-2016 obtained at the regional level [22][23][24][25][26][27]. The multi-class classification was obtained from the results of spatial data modeling using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method in the form of immunization status coverage: good, average, fair, and poor.

The spatial analysis produced spatial data modeling which was used to determine relationship between the basic data to be processed, with the parameters used as a factor of an area categorized in the classification of measles-prone areas based on immunization status coverage. Analysis and design of the built system have been described in advance according to the needs of spatial data that would be processed to become modeling [28].

The results of the spatial data modeling with the SAW method and WPM method obtained the preference value using The Guttman Scale Assessment. The alternative good category on the SAW method if the V_i preference value is above 0,875, the average category with the V_i preference value between 0,75 to 0,875, the V_i preference value

The results of this study could be part of disaster mitigation measures to prevent the spread of measles [1][29] in developing countries with a tropical climate. The mapping results could provide a classification of prone red areas based on the coverage of poor immunization status. Policy makers such as the Health Office could make preventive measures based on the results of the classification.

2. Spatial Datasets

Spatial data sets are used to classify parameters that affect the spread of measles [8]. Spatial datasets consist of two components: spatial data and attribute data. Both become parameters to determine the classification of measles-prone areas based on immunization status coverage factors as in Table 1, including PD3I, epidemic, nutritional status, and infant immunization.

In each spatial datasets the weight value was given, to determine the level of importance/influence on the classification produced in each parameter criterion [30][31][31], This weighting used the fuzzification process, consisting of fuzzy sets indicators in giving a level description in the classification results [32].

Table 1. Description of the Multi-Criteria Parameter Spatial Datasets Measles Diseases

Spatial Datasets	The Priority Value	Weight	Incidence rate (annually)	Category of PD3I	Level of importance
PD3I	2	0.30	PD3I >12 months a year	Poor	1
			PD3I <12 months a year	Good	2
Epidemic	3	0.15	Epidemic > 60 cases a year	Poor	1
			Epidemic < 60 cases a year	Good	2
			Epidemic = 0 cases a year	Very good	3
Spatial Datasets	Value of the priority	Weight	The status	Range Standard Deviation (sd)	Level of importance
Nutrition Status	4	0.10	Very good nutrition	sd ≥ 2	4
			Good nutrition	sd < 2 && sd ≥ -2	3
			Less of nutrition	sd < -2 && sd ≥-3	2
			Poor nutrition	sd < -3	1
Infant Immunization (IM)	1	0.45	Good immunization	IM > 90%	3
			Average immunization	IM ≤ 90% && IM ≥ 80%	2
			Fair immunization	IM < 80%	1

3. Methods

Decision-making systems that involve GIS spatial data could be completed with MADM that be able to carry out integration in managing spatial data and attribute data to perform spatial data analysis [33]. Analysis of spatial data in the discussion of this paper resulted from spatial data modeling. the spatial datasets described in Table 1 be used as baseline data to produce a classification of measles-prone areas based on immunization status coverage.

The process stages in spatial data modeling for classification of tropical disease prone areas based on immunization status coverage were shown in the flowchart Fig. 1. This stage gave a picture of how the system works. Starting from inputting or recording of

all data needs, then the process of modeling spatial data by determining the AI method that matches the behavior of the data obtained from the recording process, and the final process was to display the results of spatial data modeling in accordance with the functions and objectives to be achieved in GIS software development.
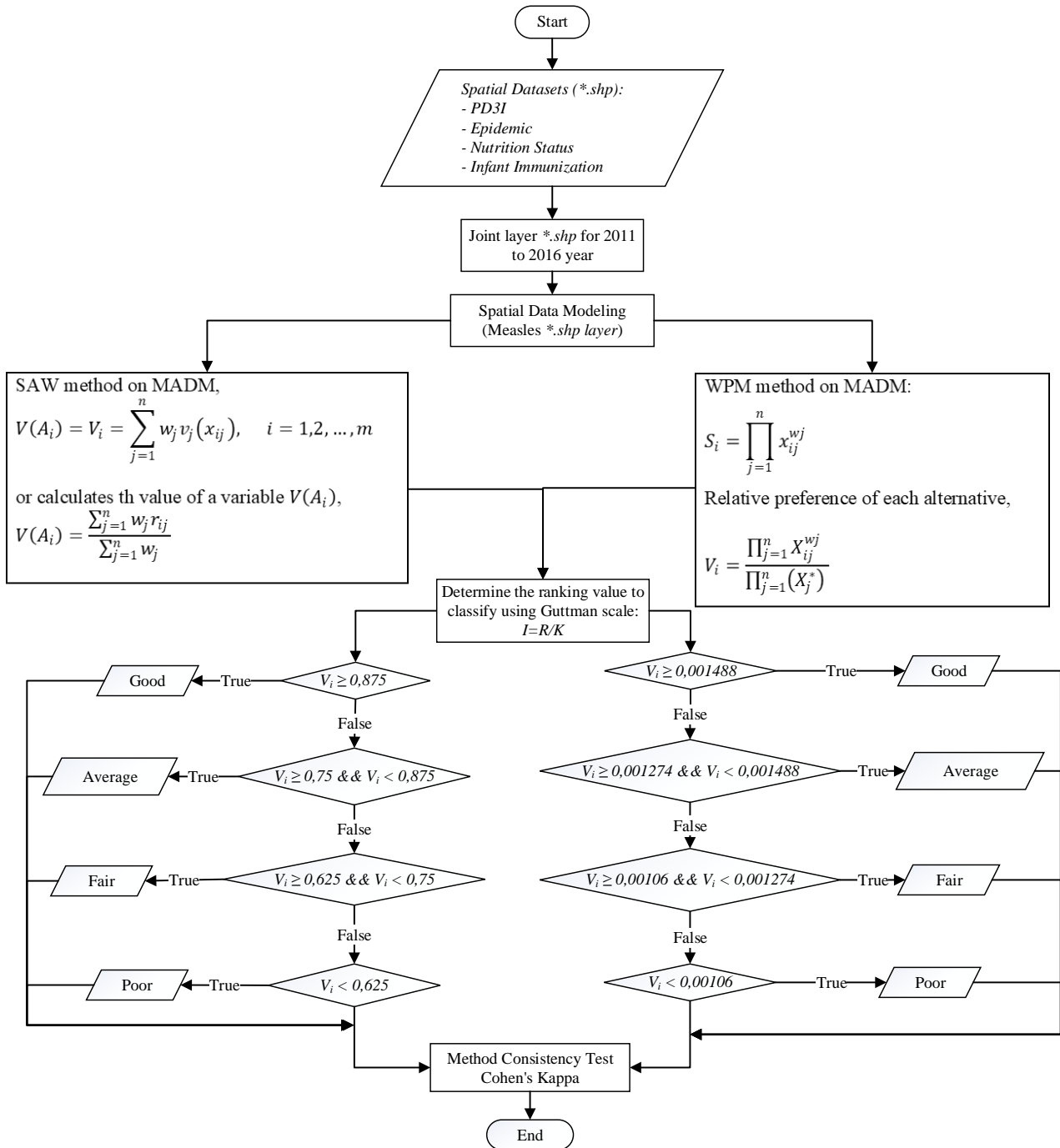

Figure. 1 Flow of Spatial Data Modelling with SAW and WPM Method

The first step, defining the spatial data requirements and layer attribute data in the spatial shapefile dataset (*.shp). The dataset includes a map of the East Java Province of Indonesia consisting of districts in each sub-district, including PD3I, epidemic, nutrition status, and infant immunization. The data used was qualitative [34] which was then cited [35] in each district with the concept of the overlay layer. This stage served to merge layers from 31 districts with data layers per sub-district to become a single layer.

The overlay layer results in one layer of measles (*measles*.shp*) for each year. This was called spatial interpolation. The SAW and the WPM method through the MADM method would process the results of the regulation's layer to get the preference value of *Vi*. The Guttman method was used for classification of values with immunization status coverage categories with good, average, fair, and poor conditions in each sub-district.

The coverage of immunization status for the distribution of measles with the good category can be obtained if the V_i value increases compared to the previous year. It can be concluded that the state of immunization status is reached or exceeded the target, indicated by the description of the green area. In regions with average immunization status coverage occurs if an area with immunization status reaches the minimum target which is represented by an area of orange color, where the value of V_i falls from the condition of the previous year. It could be seen from the value of V_i for the classification of regional categories with good immunization status. Fair classification occurs if in a region the value of V_i falls compared to the previous year in the area with the average category. This happened because the immunization target did not reach the minimum target with an orange description of the area. Regions with a V_i value below the average condition of good, average, and fair immunization status coverage, where the immunization target was not achieved, by mapping the red area.

3.1 Multiple Attribute Decision Making (MADM)

MADM is part of the Multi-criteria decision making (MCDM) decision-making system, as well as multi-objective decision making (MODM) [36]. MODM was used for decision making that be sustainable, as in computing programming [37]. MADM and MCDM were used for discrete retrieval, where the alternative of the support system of the decision was predetermined [37].

The Simple Additive Weighting Method (SAW) and the Weight Product Model (WPM) method is part of a decision-making system using multi-parameter criteria with a multiple attribute decision making (MADM) approach [38]. MADM describes the parameters/criteria that will be used to determine the best alternative based on several appropriate criteria, the characteristics of decision making using the MADM system will describe the attribute requirements in the spatial analysis process, make decision weight from the data that has been described

Table 1 to form a decision matrix produced [39][37][40].

Approach to the SAW method by giving a score on each alternative produced to be multiplied by the value weight for each parameter attribute [41], with the following steps:

1. The SAW method produces the final value of V_i in the Eq. (1) to obtain an alternative value from the classification that will be generated in the decision-making system [40].

$$V(A_i) = V_i = \sum_{j=1}^{n} w_j v_j(x_{ij}), \quad i = 1,2,\dots,m \qquad (1)$$

where $V(A_i)=V_i$ is the alternative result value in the classification generated in each attribute A_i, this value is obtained from the calculation of the preference value $v_j(x_{ij})$ on $V(A_i)$ and the w_j weight in each parameter. The value of $V(A_i)$ can also be calculated using Eq. (2), where r_{ij} is normalization from the calculation of the maximum value of the data on the parameter attribute.

$$V(A_i) = \frac{\sum_{j=1}^{n} w_j r_{ij}}{\sum_{j=1}^{n} w_j} \qquad (2)$$

2. Calculating the preference value $v_j(x_{ij})$ on $V(A_i)$ for each parameter attribute by finding the maximum value in each parameter attribute value using Eq. (3) and normalizing the maximum value obtained using the Eq. (4) [40].

$$max = max\,(A_{ij}) \qquad (3)$$

where, the max value (A_{ij}) is obtained from the parameter attribute, in this paper the parameter attribute value is described in Table 1 with the process on the spatial data input data **.shp* as described in Fig. 1 which refers to Eq. (4).

$$\begin{aligned} max(a_i) &= max(a_{ij}) \\ max(b_i) &= max(b_{ij}) \\ max(c_i) &= max(c_{ij}) \\ max(d_i) &= max(d_{ij}) \end{aligned} \qquad (4)$$

where, to declare parameter attributes **.shp* spatial dataset on all data a_{ij}, *max (a_i)* for PD3I, *max (b_i)* for epidemic, *max (c_i)* for nutritional status, and *max (d_i)* for infant immunization. Normalize the value of each parameter attribute using Eq. (5), where X_j is the data value that is j and max is the value obtained from the calculation in Eq. (3) [40].

$$r_{ij} = X_j / \max \qquad (5)$$

In this spatial data modeling, normalization values refer to Eq. (5) with the implementation of spatial datasets using Eq. (6).

$$r(a_i) = \frac{a_i}{max(a_{ij})} \; ; \; r(b_i) = \frac{b_i}{max(b_{ij})}$$
$$r(c_i) = \frac{c_i}{max(c_{ij})} \; ; \; r(d_i) = \frac{d_i}{max(d_{ij})} \qquad (6)$$

3. Calculates the preference value $v_j(x_{ij})$ on $V(A_i)$ for all parameter attributes using Eq. (7) [40].

$$V_i = \sum_{j=1}^{n} w_j r_{ij}, \qquad i = 1,2,\dots,m \qquad (7)$$

where, w_j is the weight of the parameter attribute value and r_{ij} is the normalization value obtained in Eq. (5). The discussion in the trial in this paper uses Eq. (8) based on a literature study on Eq. (7).

$$v(a_i) = Norm(a_i) \; x \; weight(a_i)$$
$$v(b_i) = Norm(b_i) \; x \; weight(b_i)$$
$$v(c_i) = Norm(c_i) \; x \; weight(c_i) \qquad (8)$$
$$v(d_i) = Norm(d_i) \; x \; weight(d_i)$$
$$V_i = v(a_i) + v(b_i) + v(c_i) + v(d_i)$$

Approach to the WPM method use multiplication to connect the attribute rating. rating each attribute must be raised first with the weight of the attribute [37][42]. The steps of the WPM method normalize to find out the alternative preferences of A_i in S_i vectors, according to Eq. (9) [37][42].

$$S_i = \prod_{j=1}^{n} x_{ij}^{wj} \qquad (9)$$

where, S variable is an alternative preference and is defined as a vector. X_{ij} variable is the variable value from the alternative on each attribute. The criteria or sub-criteria weight values are accommodated in the W_j variable. The N variable is used to represent the number of criteria in the multi-criteria parameters declared. Variable i is the desired alternative value, and variable j is the criteria value in the data. The value of the $\sum W_j$ variable is 1 with the rank positive for the profit attribute, and negative for the cost attribute. The relative preference of each alternative is calculated using Eq. (10) [37][42].

$$V_i = \frac{\prod_{j=1}^{n} X_{ij}^{wj}}{\prod_{j=1}^{n} (X_j^*)} \qquad (10)$$

where, V_i variable is an alternative preference defined as a vector with i-th data. Determine the weight value for each parameter used to set the priority value on the existing parameters that are accommodated in the Bpre variable, 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 $W=B_A/Tb$. Calculating the value of the variable S on each weight value in variable B is raised by the result of the variable W, with $S=B_a{}^{\wedge}W_a$. Calculating the value of V_s by multiplying all values in variable S, with $V_s=S_a x S_b$ x…n. calculating the total vector on variable V or Tv_s by adding up all the values of V_s, with $Tv_s=V_1+V_2+V_3+…+V_n$, then the variable value of $V= V_{sa}/Tv_{sa}$.

3.2 The Guttman Scale

Measurement of the classification values generated in this paper uses the Guttman scale [43], This scale is the basis of measurement to draw conclusions on qualitative data [44], and is used to provide an estimate of the value of the classification results in an intervention value that is still ambiguous because of uncertainty [45]. In the type of dataset that uses a score/weight in the analysis process, provides a value based on the uncertainty factor of the variable class described, it can be measured using the Guttman scale [46] in the Eq. (11).

$$I = \frac{R}{K} \qquad (11)$$

where I is the result of the interval value obtained from the variable R, is the range of data values and variable K with the number of alternative classifications that will be generated.

In the discussion of this paper, the variable value R is obtained from the range of values between the maximum value of V_i and the minimum value of V_i. K variable is the number of alternative classifications namely good, average, fair, and poor which refers to flow Fig. 1 and Table 2. Whereas, the determination of the scale for determining the classification value criteria for measles-prone areas based on the status of immunization coverage using Eq. (12) with SAW method and WPM method using Eq. (13).

$$\begin{cases} good, if\ V_i \geq 0,875 \\ average, if\ V_i \geq 0,75\ and\ V_i < 0,875 \\ fair, if\ V_i \geq 0,625\ and\ V_i < 0,75 \\ poor, if\ V_i < 0,625 \end{cases} \quad (12)$$

$$\begin{cases} good, if\ V_i \geq 0,001488 \\ average, if\ V_i \geq 0,001274\ and\ V_i < 0,001488 \\ fair, if\ V_i \geq 0,00106\ and\ V_i < 0,001274 \\ poor, if\ V_i < 0,00106 \end{cases} \quad (13)$$

Table 2. The Guttman Scale Assessment

SAW Method	WPM Method
$R = V_{i_{maks}} - V_{i_{min}} = 1 - 0,5 = 0,5$ $K = 4$ $I = \dfrac{0,5}{4} = 0,125$	$R = V_{i_{maks}} - V_{i_{min}} = 0,001702 - 0,000846 = 0,000856$ $K = 4$ $I = \dfrac{0,000856}{4} = 0,000214$
$Assessment\ good\ criteria$ $\quad = highest\ score - I$ $\quad = 1 - 0,125 = 0,875$ $Assessment\ average\ criteria$ $\quad = assesment\ good\ criteria - I$ $\quad = 0,875 - 0,125 = 0,75$ $Assessment\ fair\ criteria$ $\quad = assesment\ average\ criteria - I$ $\quad = 0,75 - 0,125 = 0,625$ $Assessment\ poor\ criteria$ $\quad = assesment\ fair\ criteria - I$ $\quad = 0,625 - 0,125 = 0,5$	$Assessment\ good\ criteria$ $\quad = highest\ score - I$ $\quad = 0,001702 - 0,000214 = 0,001488$ $Assessment\ average\ criteria$ $\quad = assesment\ good\ criteria - I$ $\quad = 0,001488 - 0,000214 = 0,001274$ $Assessment\ fair\ criteria$ $\quad = assesment\ average\ criteria - I$ $\quad = 0,001274 - 0,000214 = 0,00106$ $Assessment\ poor\ criteria$ $\quad = assesment\ fair\ criteria - I$ $\quad = 0,00106 - 0,000214 = 0,000846$

3.3 Method Consistency Test (MCT)

Method Consistency Test Cohen's Kappa is used to test consistency in measuring two methods, this measurement can be done for qualitative data based Eq. (14) [47].

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \quad (14)$$

where, the variable K is the coefficient of the results of the measurement between methods. The variable *Pr(a)* is the percentage of the number of measurements that are consistent in making comparisons between methods, and the variable *Pr(e)* is the percentage change.

Range of coefficient values in variable K [47], where if the variable value $K < 20$, the value K 0,21 to 0,40, the value K is 0,41 to 0,60, the value $K = 0,61$ to 0,80, dan K 0,81 to 1,00, then strength of agreement are poor, fair, moderate, good, and very good, respectively.

4. Results and Discussion

From the results of trials that have been carried out in 657 sub-districts in 38 regencies in 2011-2016 data obtained from the East Java Provincial Health Office of Indonesia [22] [23] [24] [25] [26] [27]. The results of the modeling spatial data on the number of districts with categories of classification of measles-prone areas based on the status of immunization coverage with MADM in the SAW method as in Table 2, Fig. 2 and WPM method as in Table 3, Fig.3.

Table 2. Distribution of Mapping Classification Results with the SAW Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	449	488	423	442	409	432
Average	113	79	94	134	108	134
Fair	82	56	117	69	125	77
Poor	13	34	23	12	15	14

Table 3. Distribution of Mapping Classification Results with the WPM Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	299	531	494	299	306	315
Average	340	92	140	337	333	324
Fair	12	7	13	8	5	5
Poor	6	27	10	13	13	13

The results of the SAW method in the area with more good categories were 66.5 (15%) compared to the results of the WPM method. The area in the

average category for the results of the WPM method is 58% greater than the results of the SAW method. Regions with a fair category have more than 90% of the results of the WMP method rather than the results of the SAW method, and more than 26% of the results of the SAW method for regions with the poor category rather than the results of the WPM method.
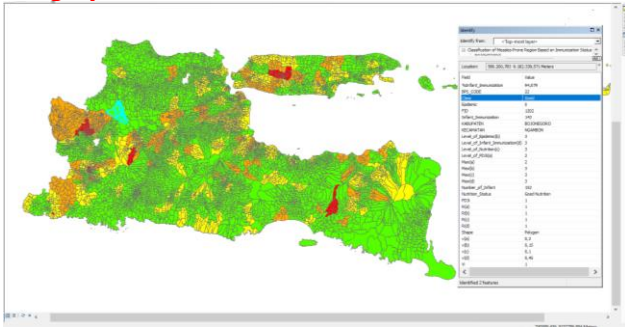

Figure. 2 The Results of the MADM Classification with the SAW Method

The Results of the MADM Classification with the SAW Method in Fig.2. The layer value of datasets PD3I is 1 incidence rate (annually) to months a year, epidemic is 0 annually to months a year, nutrition status is good, and number of infant = 152 infants with infant in immunization status is 143 infant for 94,079% infant immunization status, based on the level of importance referring to Table 1, the values are 2, 3, 3, and 3, so $a = 2$; $b = 3$; $c = 3$; $d = 3$, to get the max value in Eq. (3), the data input process is carried out based on Eq. (4), namely: $max(a_i) = 2$; $max(b_i) = 3$; $max(c_i) = 3$; $max(d_i) = 3$.

Normalization of the max value based on the theory in Eq. (5), the normalized value is obtained by dividing the value of the parameter variable with the max value of each variable referring to Eq. (6), namely: $r(a_i) = \frac{2}{2} = 1$; $r(b_i) = \frac{3}{3} = 1$; $r(c_i) = \frac{3}{3} = 1$; $r(d_i) = \frac{3}{3} = 1$.

The preference value is obtained from the reference in Eq. (7), which is multiplying between normalization value and weight in each parameter variable in Table 1 using Eq. (8).

$v(a_i) = 1 * 0,30 = 0,3$; $v(b_i) = 1 * 0,15 = 0,15$; $v(c_i) = 1 * 0,10 = 0,1$; $v(d_i) = 1 * 0,45 = 0,45$

Then, the final value of the preference is:

$V_i = v(a_i) + v(b_i) + v(c_i) + v(d_i)$
$= 0,3 + 0,15 + 0,1 + 0,45 = 1$

Based on Eq. (12) which refers to Eq. (11), the value of V_i is 1 entered in the range of good classification category in the area with green mapping, where the value of V_i is greater than 0.875.
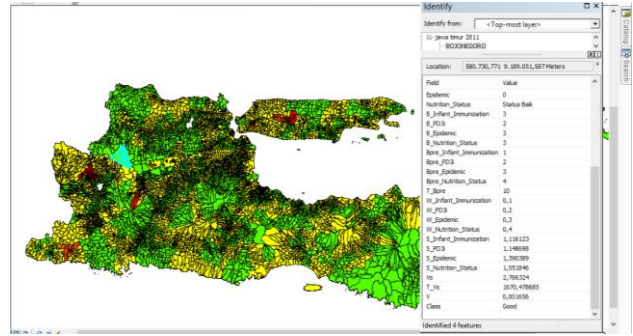

Figure. 3 The Results of the MADM Classification with the SAW Method

Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 2 is done on the same spatial datasets as the SAW method. Epidemic scores were 0, PD3I was 1, the category of nutrition status was good, and the number of infants in the Subdistrict was 152 infants with immunization status of 147 infants or 94,079% of infants with immunization status. The level of importance includes 3, 2, 3, and 3, respectively. The priority value for each parameter includes 2, 3, 4, and 1, respectively. The number of priority value in the Tb_{Pre} is 10, where the weight value in the W variable for each parameter is 0.2, 0.3, 0.4, and 0.1, respectively. Calculation of the value of Vector in the S variable for each parameter variable, namely is 1,390389, 1,148698, 1,551846, and 1,116123. V_s variable value is obtained by multiplying all T_V values is 1670,478685, then the total V_s obtained from all calculated data is 2,766324. The value of vector V by dividing the value of V_s by the value of T_{Vs}, then the value of V is 0,001656, based on Eq. (13) and flow on Fig. (1), then the classification of regions with good categories

The test results using Cohen's Kappa for the feasibility of using the SAW method and the WPM method for modeling spatial data on GIS for classification of measles-prone areas using MADM, obtained kappa coefficients from the K variable -0.42, 0,67, 0,519367011, 0,15, 0,215627097, and 0,253130142 for 2011-2016, respectively.

5. Conclusion

This paper examines the MADM technique in classifying multi-criteria parameters to produce spatial data modeling in its spatial process. The methods in MADM allows the results of comparative mapping in accordance with the level of importance, weight, and order of priority given to each of the parameter's multi-criteria variables in providing spatial sensitivity analysis.

This study resulted in the preference value of V_i in the SAW method and WPM method by

considering quantitative data and the calculation of the Guttman scale classification parameter value scale, this matter becomes very important in the decision-making system as a step-in planning to provide classification in identifying areas affected by tropical diseases in measles-like the results in Eq. (12) and Eq. (13).

This finding provides a new direction for using the MADM technique with the SAW and WPM method as part of the planning for mitigation measures, this finding encourages further research to use other quantitative data to influence the results of spatial data modeling.

Regions that are classified as fair or poor are important for policymakers in the field of surveillance and immunization of the Health Office to take anticipatory steps as a form of mitigation measures [1] of disasters causing epidemics of measles. The results of this spatial data modeling answer the role of quantitative data types that can be used as a reference in displaying a mapping to produce a classification of vulnerable areas as part of decision making, for example providing understanding to communities in fair and poor categories to be more caring through self-awareness in order to immunize areas with high epidemics can be choked. This is important because prevention is not only the responsibility of the health sector, but the role of the socio-economic environment is also a driver of the spread of measles infectious diseases [7].

Based on the discussion on testing data with MTC, it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field. Results from MTC have a moderate category strength of agreement for use in spatial data modeling on the GIS for classification of measles-prone regions using MADM. They have results that are not much different.

Further research that can be developed is by collaborating the MADM method and data mining classification methods such as naïve Bayesian or decision tree, this function is to determine the comparison of the results of the classification given in each type of method used. Comparing the results of the classification of each method to be tested the level of accuracy of the method used through the method induction test.

Acknowledgments

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Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

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Abstract: Indonesia is a country that has a tropical climate, so that many typical tropical climate diseases emerge. This disease is caused by viruses and parasites that breed during the dry season or the rainy season. One typical tropical disease is measles. This paper discusses the geographical information system (GIS) technology by analyzing spatial data modeling to determine the classification of measles-prone areas based on immunization status coverage using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method. Some parameters are used consist of immunization status data for multiple attribute decision making (MADM), diseases preventable by immunization (PD3I), epidemic and nutritional status of infants. The MADM method in modeling spatial data analysis processes data according to the parameters to determine the scale in comparing all alternative data on the scope of classification of immunization status areas, namely: good, average, fair and poor. The test results with the Cohen's Kappa Method Consistency Test (MCT) is obtained an average coefficient of 0.41 for consistent measurements for the chosen method. It can be concluded that the two measurements using the SAW and WPM methods have a moderate for the strength of agreement category, for using in spatial data modeling on the GIS for classification of measles prone regions using MADM.

Keywords: GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa, tropical diseases, measles.

1. Introduction

Measles is one of the diseases that often becomes an extraordinary event in the tropics, such as Indonesia. The spread of measles is a global problem in the health sector. The problems, information on the incidence of measles is still based on risk factors for immunization status in the measles surveillance technique manual. Research studies are still descriptive statistics and there are no system applications that globally can identify areas prone to measles disease based on multi-criteria parameters to determine the distribution of vulnerable categories of regions. Measles control in this decade has been done by giving complete immunization to every baby or child, as a mitigation measure by the public health authority [1], measles is one type of disease that breeds in regions with tropical climates [2]. Based on the World Health Organization (WHO), measles incidence rate per million, Indonesia is a country with 6345 cases at a rate of 24.30. In 2017 the number of confirmed 11389 cases increased compared to 2016 which only reached 7204 confirmed cases [3]. Spatial patterns can be used to identify patterns of behavior of measles spreading, based on local seasonal factors in each region [4].

In the beginning, spatial data modeling was done by analyzing the needs of geospatial data to be processed for decision-making systems. The need for spatial data analysis was important in the field of research and policy making, provides a description of data needs, methods, and illustrations of case studies used [5], as well as in the health sector [6-7] measles field [8]. Analysis of spatial data as a mitigation measure for disease prevention and control had a very important role. This was developed based on the conditions of regional climate and social behavior of

the community, the method of Inverse Distance Weighting (IDW), the functions and weighted overlay functions were used to predict the location of disease spread [9]. The risk of spreading the disease to areas adjacent to the affected area has been carried out by using a spatial clustering method. In this method, a comparison was made on spatial grouping in heterogeneity. The resulting information would be beneficial for the Ministry of Health to formulate regional coping strategies as hotspots in epidemic diseases [10].

Spatial data modeling was the process of spatial analysis results data to determine the decisions and policies of stakeholders. The resulting process included geocoding and mapping to produce a decision-making system [11-12] through the application of artificial intelligence (AI) methods [13]. The AI method used to map measles has been applied including fuzzy inference system [14], Data mining techniques [15], Bayesian mixture model [16], hierarchical Bayesian model [17], Bayesian spatial modeling [18]. The AI fuzzy inference system method is used to determine the symptoms of measles based on the input variable rule in the inference engine [14]. Artificial Neural Network (ANN), Decision Tree Algorithm and Naïve Bayes Classifier on Data Mining techniques, are used to predict disease trends. One of them is measles based on time series database disease [15]. Bayesian Normal mixture models were used to estimate the prevalence of measles through age factor [16]. Spatial hierarchical Bayesian models are used to map the risk of measles based on data on the number of measles, unemployment, birth rates, education level and age of immunization [17]. Bayesian spatial modeling is used to determine the mapping of disease populations based on disease statistics [18].

According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19]. Bayesian regression spatial model was used to identify the risk of measles spread at the regional level using data series in 2005-2014, the results obtained indicate the parameters of birth rate, number of measles cases, unemployment rate and the proportion of children immunized at 12 months to be a determinant in prevention of measles [17]. Socio-economic disparity had become a separate problem in the success of measles immunization programs, using multiple spatial regression methods mapping is done to identify the distribution of immunization coverage based on

socio-economic inequality. This was a step in mitigating the spread of measles virus [20]. Web-based GIS technology was developed as a web-based health surveillance system [21]. However, the research that has been done has not used the approach and parameters that would be proposed in the discussion of this paper, that is, with a multi-criteria parameter approach to explore the need for supporting factors in the analysis process, interview experts in the field of disease prevention and control of the Indonesian East Java Provincial Health Office, and analyze the behavior of data to determine AI methods through mathematical modeling that is suitable for producing distribution multi-class classification vulnerable area. The results of measles data processing based on the AI method are still presented in graphical form [14-16], Multi-criteria parameters that will be proposed for spatial data modeling with SAW and WPM methods in the discussion of this paper, have not been used in previous studies [17-18].

The purpose of this paper was to propose an approach through spatial data modeling to determine the distribution of measles-prone areas based on immunization status coverage. Multiple attribute decision making (MADM) was used in the modeling of spatial data because alternative results in regional coverage use multi-parameter criteria including diseases preventable by immunization (PD3I), epidemic and nutritional status of infants taken from basic data on the health profile book of East Java Province of Indonesia in 2011-2016 obtained at the regional level [22-27]. The multi-class classification was obtained from the results of spatial data modeling using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method in the form of immunization status coverage: good, average, fair, and poor.

The spatial analysis produced spatial data modeling which was used to determine relationship between the basic data to be processed, with the parameters used as a factor of an area categorized in the classification of measles-prone areas based on immunization status coverage. Analysis and design of the built system have been described in advance according to the needs of spatial data that would be processed to become modeling [28].

The results of the spatial data modeling with the SAW method and WPM method obtained the preference value using The Guttman Scale Assessment. The alternative good category on the SAW method if the V_i preference value is above 0,875, the average category with the V_i preference value between 0,75 to 0,875, the V_i preference value

between 0,625 to 0,75 for the fair alternative category, and poor for the preference V_i below 0,625. The Guttman Scale Assessment in the WPM method that is if the vector value V_i more than 0,001488 for good category, an average category for value V_i between 1,001274 to 0,001488, the value of V_i 0,00106 to 0,001274 for the value category V_i and smaller value than V_i 0,00106 for the poor category.

The results of trials which conducted on data layer (*.shp) coverage each district for the 657 sub-district the East Java Province of Indonesia using the SAW method and WPM method for 2011-2016 data. Mapping the areas prone to measles by the SAW method, for the good category obtained 449, 488, 423, 442, 409, and 432 regions, the average category was obtained 113, 79, 94, 134, 108, and 134 regions, the fair category was 82, 56, 117, 69, 125, and 77 regions, and the poor category obtained 13, 34, 23, 12, 15, and 14 regions, respectively. In the WPM method, the results of mapping for regions with good categories were 299, 531, 494, 299, 306, and 315, the average category was 340, 92, 140, 337, 333, and 324 regions. from 12, 7, 13, 8, 5, and 5, and 6, 27, 10, 13, 13, and 13 in the number of regions in the poor category, respectively.

The results of this study could be part of disaster mitigation measures to prevent the spread of measles [1-29] in developing countries with a tropical climate. The mapping results could provide a classification of prone red areas based on the coverage of poor immunization status. Policy makers such as the Health Office could make preventive measures based on the results of the classification.

2. Spatial Datasets

Spatial data sets are used to classify parameters that affect the spread of measles [8]. Spatial datasets consist of two components: spatial data and attribute data. Both become parameters to determine the classification of measles-prone areas based on immunization status coverage factors as in Table 1, including PD3I, epidemic, nutritional status, and infant immunization.

In each spatial datasets the weight value was given, to determine the level of importance/influence on the classification produced in each parameter criterion [30-31], This weighting used the fuzzification process, consisting of fuzzy sets indicators in giving a level description in the classification results [32].

Table 1. Description of the Multi-Criteria Parameter Spatial Datasets Measles Diseases

Spatial Datasets	The Priority Value	Weight	Incidence rate (annually)	Category of PD3I	Level of importance
PD3I	2	0.30	PD3I >12 months a year	Poor	1
			PD3I <12 months a year	Good	2
Epidemic	3	0.15	Epidemic > 60 cases a year	Poor	1
			Epidemic < 60 cases a year	Good	2
			Epidemic = 0 cases a year	Very good	3
Spatial Datasets	**Value of the priority**	**Weight**	**The status**	**Range Standard Deviation (sd)**	**Level of importance**
Nutrition Status	4	0.10	Very good nutrition	$sd \geq 2$	4
			Good nutrition	$sd < 2$ && $sd \geq -2$	3
			Less of nutrition	$sd < -2$ && $sd \geq -3$	2
			Poor nutrition	$sd < -3$	1
Infant Immunization (IM)	1	0.45	Good immunization	IM > 90%	3
			Average immunization	IM ≤ 90% && IM ≥ 80%	2
			Fair immunization	IM < 80%	1

3. Methods

Decision-making systems that involve GIS spatial data could be completed with MADM that be able to carry out integration in managing spatial data and attribute data to perform spatial data analysis [33]. Analysis of spatial data in the discussion of this paper resulted from spatial data modeling. the spatial

datasets described in Table 1 be used as baseline data to produce a classification of measles-prone areas based on immunization status coverage.

The process stages in spatial data modeling for classification of tropical disease prone areas based on immunization status coverage were shown in the flowchart Fig. 1. This stage gave a picture of how the system works. Starting from inputting or recording of

all data needs, then the process of modeling spatial data by determining the AI method that matches the behavior of the data obtained from the recording process, and the final process was to display the results of spatial data modeling in accordance with the functions and objectives to be achieved in GIS software development.
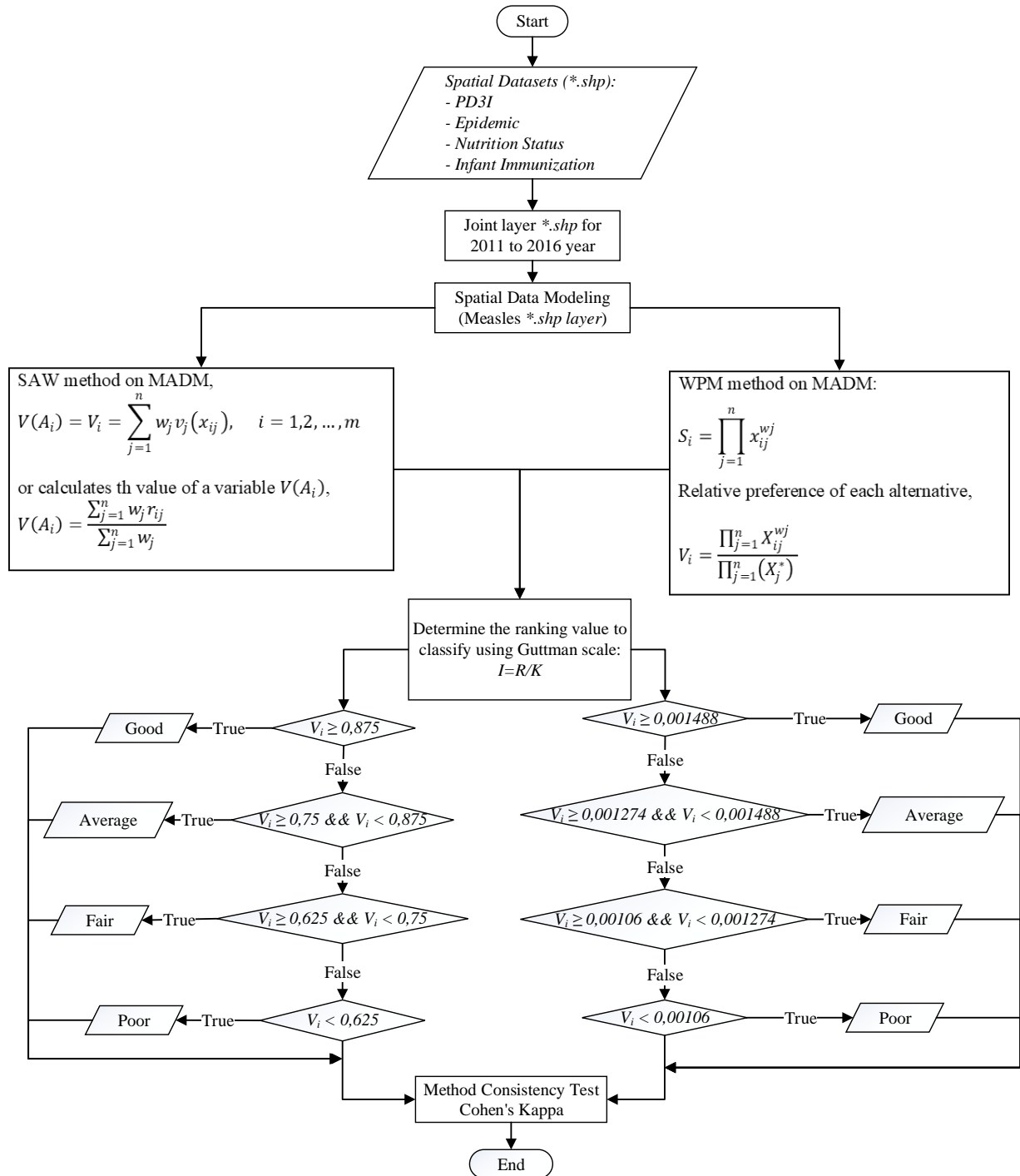

Figure. 1 Flow of Spatial Data Modeling with SAW and WPM Method

The first step, defining the spatial data requirements and layer attribute data in the spatial shapefile dataset (*.shp*). The dataset includes a map of the East Java Province of Indonesia consisting of districts in each sub-district, including PD3I, epidemic, nutrition status, and infant immunization. The data used was qualitative [34] which was then cited [35] in each district with the concept of the overlay layer. This stage served to merge layers from

31 districts with data layers per sub-district to become a single layer.

The overlay layer results in one layer of measles (*measles*.shp*) for each year. This was called spatial interpolation. The SAW and the WPM method through the MADM method would process the results of the regulation's layer to get the preference value of *Vi*. The Guttman method was used for classification of values with immunization status coverage categories with good, average, fair, and poor conditions in each sub-district.

The coverage of immunization status for the distribution of measles with the good category can be obtained if the V_i value increases compared to the previous year. It can be concluded that the state of immunization status is reached or exceeded the target, indicated by the description of the green area. In regions with average immunization status coverage occurs if an area with immunization status reaches the minimum target which is represented by an area of orange color, where the value of V_i falls from the condition of the previous year. It could be seen from the value of V_i for the classification of regional categories with good immunization status. Fair classification occurs if in a region the value of V_i falls compared to the previous year in the area with the average category. This happened because the immunization target did not reach the minimum target with an orange description of the area. Regions with a V_i value below the average condition of good, average, and fair immunization status coverage, where the immunization target was not achieved, by mapping the red area.

3.1 Multiple Attribute Decision Making (MADM)

MADM is part of the Multi-criteria decision making (MCDM) decision-making system, as well as multi-objective decision making (MODM) [36]. MODM was used for decision making that be sustainable, as in computing programming [37]. MADM and MCDM were used for discrete retrieval, where the alternative of the support system of the decision was predetermined [37].

The Simple Additive Weighting Method (SAW) and the Weight Product Model (WPM) method is part of a decision-making system using multi-parameter criteria with a multiple attribute decision making (MADM) approach [38]. MADM describes the parameters/criteria that will be used to determine the best alternative based on several appropriate criteria, the characteristics of decision making using the MADM system will describe the attribute requirements in the spatial analysis process, make the

decision weight from the data that has been described Table 1 to form a decision matrix produced [39,37,40].

Approach to the SAW method by giving a score on each alternative produced to be multiplied by the value weight for each parameter attribute [41], with the following steps:

1. The SAW method produces the final value of V_i in the Eq. (1) to obtain an alternative value from the classification that will be generated in the decision-making system [40].

$$V(A_i) = V_i = \sum_{j=1}^{n} w_j v_j(x_{ij}), \quad i = 1,2,\dots,m \quad (1)$$

where $V(A_i)=V_i$ is the alternative result value in the classification generated in each attribute A_i, this value is obtained from the calculation of the preference value $v_j(x_{ij})$ on $V(A_i)$ and the w_j weight in each parameter. The value of $V(A_i)$ can also be calculated using Eq. (2), where r_{ij} is normalization from the calculation of the maximum value of the data on the parameter attribute.

$$V(A_i) = \frac{\sum_{j=1}^{n} w_j r_{ij}}{\sum_{j=1}^{n} w_j} \quad (2)$$

2. Calculate the preference value $v_j(x_{ij})$ on $V(A_i)$ for each parameter attribute by finding the maximum value in each parameter attribute value using Eq. (3) and normalizing the maximum value obtained using the Eq. (4) [40].

$$max = max\left(A_{ij}\right) \quad (3)$$

where, the max value (A_{ij}) is obtained from the parameter attribute, in this paper the parameter attribute value is described in Table 1 with the process on the spatial data input data **.shp* as described in Fig. 1 which refers to Eq. (4).

$$\begin{aligned} max(a_i) &= max(a_{ij}) \\ max(b_i) &= max(b_{ij}) \\ max(c_i) &= max(c_{ij}) \\ max(d_i) &= max(d_{ij}) \end{aligned} \quad (4)$$

where, to declare parameter attributes **.shp* spatial dataset on all data a_{ij}, *max (a_i)* for PD3I, *max (b_i)* for epidemic, *max (c_i)* for nutritional status, and *max (d_i)* for infant immunization.

Normalize the value of each parameter attribute using Eq. (5), where X_j is the data value that is j and max is the value obtained from the calculation in Eq. (3) [40].

$$r_{ij} = X_j / \max \qquad (5)$$

In this spatial data modeling, normalization values refer to Eq. (5) with the implementation of spatial datasets using Eq. (6).

$$
\begin{aligned}
r(a_i) &= \frac{a_i}{\max(a_{ij})} \; ; \\
r(b_i) &= \frac{b_i}{max(b_{ij})} \\
r(c_i) &= \frac{c_i}{\max(c_{ij})} \; ; \\
r(d_i) &= \frac{d_i}{max(d_{ij})}
\end{aligned}
\qquad (6)
$$

3. Calculates the preference value $v_j(x_{ij})$ on $V(A_i)$ for all parameter attributes using Eq. (7) [40].

$$V_i = \sum_{j=1}^{n} w_j r_{ij}, \qquad i = 1,2,\dots,m \qquad (7)$$

where, w_j is the weight of the parameter attribute value and r_{ij} is the normalization value obtained in Eq. (5). The discussion in the trial in this paper uses Eq. (8) based on a literature study on Eq. (7).

$$
\begin{aligned}
v(a_i) &= Norm(a_i) \; x \; weight(a_i) \\
v(b_i) &= Norm(b_i) \; x \; weight(b_i) \\
v(c_i) &= Norm(c_i) \; x \; weight(c_i) \\
v(d_i) &= Norm(d_i) \; x \; weight(d_i) \\
V_i &= v(a_i) + v(b_i) + v(c_i) + v(d_i)
\end{aligned}
\qquad (8)
$$

Approach to the WPM method use multiplication to connect the attribute rating. rating each attribute must be raised first with the weight of the attribute [37-42]. The steps of the WPM method normalize to find out the alternative preferences of A_i in S_i vectors, according to Eq. (9) [37-42].

$$S_i = \prod_{j=1}^{n} x_{ij}^{wj} \qquad (9)$$

where, S variable is an alternative preference and is defined as a vector. X_{ij} variable is the variable value from the alternative on each attribute. The criteria or sub-criteria weight values are accommodated in the W_j variable. The N variable is used to represent the number of criteria in the multi-criteria parameters declared. Variable i is the desired alternative value, and variable j is the criteria value in the data. The value of the $\sum W_j$ variable is 1 with the rank positive for the profit attribute, and negative for the cost attribute. The relative preference of each alternative is calculated using Eq. (10) [37-42].

$$V_i = \frac{\prod_{j=1}^{n} X_{ij}^{wj}}{\prod_{j=1}^{n}(X_j^*)} \qquad (10)$$

where, V_i variable is an alternative preference defined as a vector with i-th data. Determine the weight value for each parameter used to set the priority value on the existing parameters that are accommodated in the Bpre variable, 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 $S = B_a \wedge W_a$. Calculating the value of V_s by multiplying all values in variable S, with $V_s = S_a x S_b x \dots n$. calculating the total vector on variable V or Tv_s by adding up all the values of V_s, with $Tv_s = V_1 + V_2 + V_3 + \dots + V_n$, then the variable value of $V = V_{sa}/Tv_{sa}$.

3.2 The Guttman Scale

Measurement of the classification values generated in this paper uses the Guttman scale [43], This scale is the basis of measurement to draw conclusions on qualitative data [44], and is used to provide an estimate of the value of the classification results in an intervention value that is still ambiguous because of uncertainty [45]. In the type of dataset that uses a score/weight in the analysis process, provides a value based on the uncertainty factor of the variable class described, it can be measured using the Guttman scale [46] in the Eq. (11).

$$I = \frac{R}{K} \qquad (11)$$

where I is the result of the interval value obtained from the variable R, is the range of data values and variable K with the number of alternative classifications that will be generated.

In the discussion of this paper, the variable value R is obtained from the range of values between the maximum value of V_i and the minimum value of V_i. The K variable is the number of alternative

classifications namely good, average, fair, and poor which refers to flow Fig. 1 and Table 2. Whereas, the determination of the scale for determining the classification value criteria for measles-prone areas based on the status of immunization coverage using Eq. (12) with SAW method and WPM method using Eq. (13).

$$\begin{cases} good, if\ V_i \geq 0,875 \\ average, if\ V_i \geq 0,75\ and\ V_i < 0,875 \\ fair, if\ V_i \geq 0,625\ and\ V_i < 0,75 \\ poor, if\ V_i < 0,625 \end{cases} \quad (12)$$

$$\begin{cases} good, if\ V_i \geq 0,001488 \\ average, if\ V_i \geq 0,001274\ and\ V_i < 0,00 \\ fair, if\ V_i \geq 0,00106\ and\ V_i < 0,001 \\ poor, if\ V_i < 0,00106 \end{cases} \quad (13)$$

Table 2. The Guttman Scale Assessment

SAW Method	WPM Method
$R = V_{i\,maks} - V_{i\,min} = 1 - 0,5 = 0,5$ $K = 4$ $I = \dfrac{0,5}{4} = 0,125$	$R = V_{i\,maks} - V_{i\,min} = 0,001702 - 0,000846 = 0,000856$ $K = 4$ $I = \dfrac{0,000856}{4} = 0,000214$
Assessment good criteria $= highest\ score - I$ $= 1 - 0,125 = 0,875$ *Assessment average criteria* $= assesment\ good\ criteria - I$ $= 0,875 - 0,125 = 0,75$ *Assessment fair criteria* $= assesment\ average\ criteria - I$ $= 0,75 - 0,125 = 0,625$ *Assessment poor criteria* $= assesment\ fair\ criteria - I$ $= 0,625 - 0,125 = 0,5$	*Assessment good criteria* $= highest\ score - I$ $= 0,001702 - 0,000214 = 0,001488$ *Assessment average criteria* $= assesment\ good\ criteria - I$ $= 0,001488 - 0,000214 = 0,001274$ *Assessment fair criteria* $= assesment\ average\ criteria - I$ $= 0,001274 - 0,000214 = 0,00106$ *Assessment poor criteria* $= assesment\ fair\ criteria - I$ $= 0,00106 - 0,000214 = 0,000846$

3.3 Method Consistency Test (MCT)

Method Consistency Test Cohen's Kappa is used to test consistency in measuring two methods, this measurement can be done for qualitative data based Eq. (14) [47].

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \quad (14)$$

where, the variable K is the coefficient of the results of the measurement between methods. The variable $Pr(a)$ is the percentage of the number of measurements that are consistent in making comparisons between methods, and the variable $Pr(e)$ is the percentage change.

Range of coefficient values in variable K [47], where if the variable value $K < 20$, the value K is 0,21 to 0,40, the value K is 0,41 to 0,60, the value $K = 0,61$ to 0,80, dan K 0,81 to 1,00, then strength of agreement are poor, fair, moderate, good, and very good, respectively.

4. Results and Discussion

From the results of trials that have been carried out in 657 sub-districts in 38 regencies in 2011-2016 data obtained from the East Java Provincial Health Office of Indonesia [22-27]. The results of the modeling spatial data on the number of districts with categories of classification of measles-prone areas based on the status of immunization coverage with MADM in the SAW method as in Table 2, Fig. 2 and WPM method as in Table 3, Fig.3.

Table 2. Distribution of Mapping Classification Results with the SAW Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	449	488	423	442	409	432
Average	113	79	94	134	108	134
Fair	82	56	117	69	125	77
Poor	13	34	23	12	15	14

Table 3. Distribution of Mapping Classification Results
with the WPM Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	299	531	494	299	306	315
Average	340	92	140	337	333	324
Fair	12	7	13	8	5	5
Poor	6	27	10	13	13	13

The results of the SAW method in the area with more good categories were 66,5 (15%) compared to the results of the WPM method. The area in the average category for the results of the WPM method is 58% greater than the results of the SAW method. Regions with a fair category have more than 90% of the results of the WMP method rather than the results of the SAW method, and more than 26% of the results of the SAW method for regions with the poor category rather than the results of the WPM method.

Figure. 2 The Results of the MADM Classification with the SAW Method

The Results of the MADM Classification with the SAW Method in Fig.2. The layer value of datasets PD3I is 1 incidence rate (annually) to months a year, epidemic is 0 annually to months a year, nutrition status is good, and number of infant = 152 infants with infant in immunization status is 143 infant for 94,079% infant immunization status, based on the level of importance referring to Table 1, the values are 2, 3, 3, and 3, so $a =2 ; b =3; c =3; d=3$, to get the max value in Eq. (3), the data input process is carried out based on Eq. (4).

Normalization of the max value based on the theory in Eq. (5), the normalized value is obtained by dividing the value of the parameter variable with the max value of each variable referring to Eq. (6).

The preference value is obtained from the reference in Eq. (7), which is multiplying between normalization value and weight in each parameter variable in Table 1 using Eq. (8). Based on Eq. (12) which refers to Eq. (11), the value of V_i is 1 entered in

the range of good classification category in the area with green mapping, where the value of V_i is greater than 0,875.

Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 3 is done on the same spatial datasets as the SAW method. Epidemic scores were 0, PD3I was 1, the category of nutrition status was good, and the number of infants in the Subdistrict was 152 infants with immunization status of 147 infants or 94,079% of infants with immunization status. The level of importance includes 3, 2, 3, and 3, respectively. The priority value for each parameter includes 2, 3, 4, and 1, respectively. The number of priority value in the Tb_{Pre} is 10, where the weight value in the W variable for each parameter is 0.2, 0.3, 0.4, and 0.1, respectively. Calculation of the value of Vector in the S variable for each parameter variable, namely is 1,390389, 1,148698, 1,551846, and 1,116123. The V_s variable value is obtained by multiplying all T_V values is 1670,478685, then the total V_s obtained from all calculated data is 2,766324. The value of vector V by dividing the value of V_s by the value of T_{Vs}, then the value of V is 0,001656, based on Eq. (13) and flow on Fig. 1, then the classification of regions with good categories.
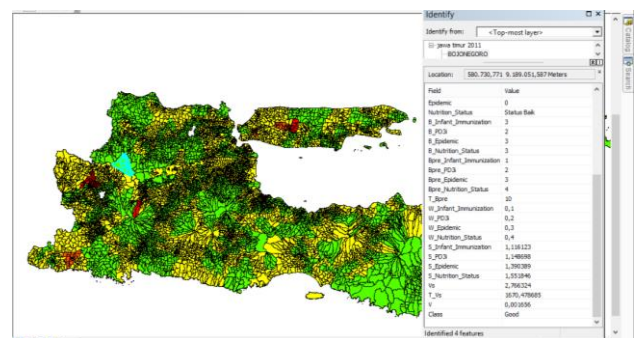

Figure. 3 The Results of the MADM Classification with the WPM Method

The test results using Cohen's Kappa for the feasibility of using the SAW method and the WPM method for modeling spatial data on GIS for classification of measles-prone areas using MADM, obtained kappa coefficients from the K variable -0.42, 0,67, 0,519367011, 0,15, 0,215627097, and 0,253130142 for 2011-2016, respectively.

5. Conclusion

This paper examines the MADM technique in classifying multi-criteria parameters to produce spatial data modeling in its spatial process. The methods in MADM allows the results of comparative mapping in accordance with the level of importance, weight, and order of priority given to each of the

parameter's multi-criteria variables in providing spatial sensitivity analysis.

This study resulted in the preference value of V_i in the SAW method and WPM method by considering quantitative data and the calculation of the Guttman scale classification parameter value scale, this matter becomes very important in the decision-making system as a step-in planning to provide classification in identifying areas affected by tropical diseases in measles-like the results in Eq. (12) and Eq. (13).

This finding provides a new direction for using the MADM technique with the SAW and WPM method as part of the planning for mitigation measures, this finding encourages further research to use other quantitative data to influence the results of spatial data modeling.

Regions that are classified as fair or poor are important for policymakers in the field of surveillance and immunization of the Health Office to take anticipatory steps as a form of mitigation measures [1] of disasters causing epidemics of measles. The results of this spatial data modeling answer the role of quantitative data types that can be used as a reference in displaying a mapping to produce a classification of vulnerable areas as part of decision making, for example providing understanding to communities in fair and poor categories to be more caring through self-awareness in order to immunize areas with high epidemics can be choked. This is important because prevention is not only the responsibility of the health sector, but the role of the socio-economic environment is also a driver of the spread of measles infectious diseases [7].

Based on the discussion on testing data with MTC, it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field. Results from MTC have a moderate category strength of agreement for use in spatial data modeling on the GIS for classification of measles-prone regions using MADM. They have results that are not much different.

Further research that can be developed is by collaborating the MADM method and data mining classification methods such as naïve Bayesian or decision tree, this function is to determine the comparison of the results of the classification given in each type of method used. Comparing the results of the classification of each method to be tested the level of accuracy of the method used through the method induction test.

Acknowledgments

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/ Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making Anik Vega Vitianingsih1* Achmad Choiron2 Dwi Cahyono3 Azizul Umam4 Suyanto Suyanto5 1,2,3,4Informatics Departments Universitas Dr. Soetomo Surabaya, Indonesia 5Economic and Bussiness Faculty Universitas Dr. Soetomo Surabaya, Indonesia *Corresponding author E-mail: vega@unitomo.ac.id
Abstract: Indonesia is a country that has a tropical climate, so that many typical tropical climate diseases emerge.

This disease is caused by viruses and parasites that breed during the dry season or the rainy season. One typical tropical disease is measles. This paper discusses the geographical information system (GIS) technology by analyzing spatial data modeling to determine the classification of measles-prone areas based on immunization status coverage using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method.

Some parameters are used consist of immunization status data for multiple attribute decision making (MADM), diseases preventable by immunization (PD3I), epidemic and nutritional status of infants. The MADM method in modeling spatial data analysis processes data according to the parameters to determine the scale in comparing all alternative data on the scope of classification of immunization status areas, namely: good, average, fair and poor.

The test results with the Cohen's Kappa Method Consistency Test (MCT) is obtained an average coefficient of 0.41 for consistent measurements for the chosen method. It can be concluded that the two measurements using the SAW and WPM methods have a moderate for the strength of agreement category, for using in spatial data modeling on

the GIS for classification of measles prone regions using MADM. Keywords: GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa, tropical diseases, measles.

Introduction Measles is one of the diseases that often becomes an extraordinary event in the tropics, such as Indonesia. The spread of measles is a global problem in the health sector. The problems, information on the incidence of measles is still based on risk factors for immunization status in the measles surveillance technique manual.

Research studies are still descriptive statistics and there are no system applications that globally can identify areas prone to measles disease based on multi-criteria parameters to determine the distribution of vulnerable categories of regions. Measles control in this decade has been done by giving complete immunization to every baby or child, as a mitigation measure by the public health authority [1], measles is one type of disease that breeds in regions with tropical climates [2].

Based on the World Health Organization (WHO), measles incidence rate per million, Indonesia is a country with 6345 cases at a rate of 24.30. In 2017 the number of confirmed 11389 cases increased compared to 2016 which only reached 7204 confirmed cases [3]. Spatial patterns can be used to identify patterns of behavior of measles spreading, based on local seasonal factors in each region [4].

In the beginning, spatial data modeling was done by analyzing the needs of geospatial data to be processed for decision-making systems. The need for spatial data analysis was important in the field of research and policy making, provides a description of data needs, methods, and illustrations of case studies used [5], as well as in the health sector [6-7] measles field [8].

Analysis of spatial data as a mitigation measure for disease prevention and control had a very important role. This was developed based on the conditions of regional climate and social behavior of the community, the method of Inverse Distance Weighting (IDW), the functions and weighted overlay functions were used to predict the location of disease spread [9].

The risk of spreading the disease to areas adjacent to the affected area has been carried out by using a spatial clustering method. In this method, a comparison was made on spatial grouping in heterogeneity. The resulting information would be beneficial for the Ministry of Health to formulate regional coping strategies as hotspots in epidemic diseases [10].

Spatial data modeling was the process of spatial analysis results data to determine the decisions and policies of stakeholders. The resulting process included geocoding and mapping to produce a decision-making system [11-12] through the application of artificial intelligence (AI) methods [13].

The AI method used to map measles has been applied including fuzzy inference system [14], Data mining techniques [15], Bayesian mixture model [16], hierarchical Bayesian model [17], Bayesian spatial modeling [18]. The AI fuzzy inference system method is used to determine the symptoms of measles based on the input variable rule in the inference engine [14].

Artificial Neural Network (ANN), Decision Tree Algorithm and Naïve Bayes Classifier on Data Mining techniques, are used to predict disease trends. One of them is measles based on time series database disease [15]. Bayesian Normal mixture models were used to estimate the prevalence of measles through age factor [16].

Spatial hierarchical Bayesian models are used to map the risk of measles based on data on the number of measles, unemployment, birth rates, education level and age of immunization [17]. Bayesian spatial modeling is used to determine the mapping of disease populations based on disease statistics [18]. According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19].

Bayesian regression spatial model was used to identify the risk of measles spread at the regional level using data series in 2005-2014, the results obtained indicate the parameters of birth rate, number of measles cases, unemployment rate and the proportion of children immunized at 12 months to be a determinant in prevention of measles [17].

Socio-economic disparity had become a separate problem in the success of measles immunization programs, using multiple spatial regression methods mapping is done to identify the distribution of immunization coverage based on socio-economic inequality. This was a step in mitigating the spread of measles virus [20]. Web-based GIS technology was developed as a web-based health surveillance system [21].

However, the research that has been done has not used the approach and parameters that would be proposed in the discussion of this paper, that is, with a multi-criteria parameter approach to explore the need for supporting factors in the analysis process, interview experts in the field of disease prevention and control of the Indonesian East Java Provincial Health Office, and analyze the behavior of data to determine AI methods through mathematical modeling that is suitable for producing distribution multi-class classification vulnerable area.

The results of measles data processing based on the AI method are still presented in graphical form [14-16], Multi-criteria parameters that will be proposed for spatial data modeling with SAW and WPM methods in the discussion of this paper, have not been used in previous studies [17-18]. The purpose of this paper was to propose an approach through spatial data modeling to determine the distribution of measles-prone areas based on immunization status coverage.

Multiple attribute decision making (MADM) was used in the modeling of spatial data because alternative results in regional coverage use multi-parameter criteria including diseases preventable by immunization (PD3I), epidemic and nutritional status of infants taken from basic data on the health profile book of East Java Province of Indonesia in 2011-2016 obtained at the regional level [22-27].

The multi-class classification was obtained from the results of spatial data modeling using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method in the form of immunization status coverage: good, average, fair, and poor. The spatial analysis produced spatial data modeling which was used to determine relationship between the basic data to be processed, with the parameters used as a factor of an area categorized in the classification of measles-prone areas based on immunization status coverage.

Analysis and design of the built system have been described in advance according to the needs of spatial data that would be processed to become modeling [28]. The results of the spatial data modeling with the SAW method and WPM method obtained the preference value using The Guttman Scale Assessment. The alternative good category on the SAW method if the Vi preference value is above 0,875, the average category with the Vi preference value between 0,75 to 0,875, the Vi preference value between 0,625 to 0.75 for the fair alternative category, and poor for the preference Vi below 0,625.

The Guttman Scale Assessment in the WPM method that is if the vector value Vi more than 0,001488 for good category, an average category for value Vi between 1,001274 to 0,001488, the value of Vi 0,00106 to 0,001274 for the value category Vi and smaller value than Vi 0,00106 for the poor category. The results of trials which conducted on data layer (*.shp) coverage each district for the 657 sub-district the East Java Province of Indonesia using the SAW method and WPM method for 2011-2016 data.

Mapping the areas prone to measles by the SAW method, for the good category obtained 449, 488, 423, 442, 409, and 432 regions, the average category was obtained 113, 79, 94, 134, 108, and 134 regions, the fair category was 82, 56, 117, 69, 125, and 77 regions, and the poor category obtained 13, 34, 23, 12, 15, and 14 regions, respectively.

In the WPM method, the results of mapping for regions with good categories were 299, 531, 494, 299, 306, and 315, the average category was 340, 92, 140, 337, 333, and 324 regions. from 12, 7, 13, 8, 5, and 5, and 6, 27, 10, 13, 13, and 13 in the number of regions in the poor category, respectively. The results of this study could be part of disaster mitigation measures to prevent the spread of measles [1,29] in developing countries with a tropical climate.

The mapping results could provide a classification of prone red areas based on the coverage of poor immunization status. Policy makers such as the Health Office could make preventive measures based on the results of the classification. Spatial Datasets Spatial data sets are used to classify parameters that affect the spread of measles [8].

Spatial datasets consist of two components: spatial data and attribute data. Both become parameters to determine the classification of measles-prone areas based on immunization status coverage factors as in Table 1, including PD3I, epidemic, nutritional status, and infant immunization.

In each spatial datasets the weight value was given, to determine the level of importance/influence on the classification produced in each parameter criterion [30-31], This weighting used the fuzzification process, consisting of fuzzy sets indicators in giving a level description in the classification results [32].

Table 1. Description of the Multi-Criteria Parameter Spatial Datasets Measles Diseases

Spatial Datasets	The Priority Value	Weight	Incidence rate (annually)	Category of PD3I	Level of importance
PD3I	2	0.30	PD3I >12 months a year	Poor	1
			PD3I <12 months a year	Good	2
Epidemic	3	0.15	Epidemic > 60 cases a year	Poor	1
			Epidemic < 60 cases a year	Good	2
			Epidemic = 0 cases a year	Very good	3

Spatial Datasets	Value of the priority	Weight	The status	Range Standard Deviation (sd)	Level of importance
Nutrition Status	4	0.10	Very good nutrition	sd = 2	4
			Good nutrition	sd < 2 && sd = -2	3
			Less of nutrition	sd < -2 && sd =-3	2
			Poor nutrition	sd < -3	1
Infant Immunization (IM)	1	0.45	Good immunization	IM > 90%	3
			Average immunization	IM = 90% && IM = 80%	2
			Fair immunization	IM < 80%	1

Methods Decision-making systems that involve GIS spatial data could be completed with MADM that be able to carry out integration in managing spatial data and attribute data to perform spatial data analysis [33]. Analysis of spatial data in the discussion of this paper resulted from spatial data modeling.

the spatial datasets described in Table 1 be used as baseline data to produce a classification of measles-prone areas based on immunization status coverage. The process stages in spatial data modeling for classification of tropical disease prone areas based on immunization status coverage were shown in the flowchart Fig. 1. This stage gave a picture of how the system works.

Starting from inputting or recording of all data needs, then the process of modeling spatial data by determining the AI method that matches the behavior of the data obtained from the recording process, and the final process was to display the results of spatial data modeling in accordance with the functions and objectives to be achieved in GIS software development.

_ Figure.

1 Flow of Spatial Data Modeling with SAW and WPM Method

The first step, defining the spatial data requirements and layer attribute data in the spatial shapefile dataset (*.shp). The dataset includes a map of the East Java Province of Indonesia consisting of districts in each sub-district, including PD3I, epidemic, nutrition status, and infant immunization. The data used was qualitative [34] which was then cited [35] in each district with the concept of the overlay layer.

This stage served to merge layers from 31 districts with data layers per sub-district to become a single layer. The overlay layer results in one layer of measles (measles*.shp) for each year. This was called spatial interpolation. The SAW and the WPM method through the MADM method would process the results of the regulation's layer to get the preference value of Vi.

The Guttman method was used for classification of values with immunization status coverage categories with good, average, fair, and poor conditions in each sub-district. The coverage of immunization status for the distribution of measles with the good category can be obtained if the Vi value increases compared to the previous year. It can be concluded that the state of immunization status is reached or exceeded the target, indicated by the description of the green area.

In regions with average immunization status coverage occurs if an area with immunization status reaches the minimum target which is represented by an area of ??orange color, where the value of Vi falls from the condition of the previous year. It could be seen from the value of Vi for the classification of regional categories with good immunization status.

Fair classification occurs if in a region the value of Vi falls compared to the previous year in the area with the average category. This happened because the immunization target did not reach the minimum target with an orange description of the area. Regions with a Vi value below the average condition of good, average, and fair immunization status coverage, where the immunization target was not achieved, by mapping the red area.

Multiple Attribute Decision Making (MADM) MADM is part of the Multi-criteria decision making (MCDM) decision-making system, as well as multi-objective decision making (MODM) [36]. MODM was used for decision making that be sustainable, as in computing programming [37]. MADM and MCDM were used for discrete retrieval, where the alternative of the support system of the decision was predetermined [37].

The Simple Additive Weighting Method (SAW) and the Weight Product Model (WPM) method is part of a decision-making system using multi-parameter criteria with a multiple attribute decision making (MADM) approach [38]. MADM describes the

parameters/criteria that will be used to determine the best alternative based on several appropriate criteria, the characteristics of decision making using the MADM system will describe the attribute requirements in the spatial analysis process, make the decision weight from the data that has been described Table 1 to form a decision matrix produced [37,39,40].

Approach to the SAW method by giving a score on each alternative produced to be multiplied by the value weight for each parameter attribute [41], with the following steps: The SAW method produces the final value of Vi in the Eq. (1) to obtain an alternative value from the classification that will be generated in the decision-making system [40].

?? ?? ?? = ?? ?? = ??=1 ?? ?? ?? ?? ?? ?? ???? , ??=1,2,...,?? _ (1) _ _ where V(Ai)=Vi is the alternative result value in the classification generated in each attribute Ai, this value is obtained from the calculation of the preference value vj(xij) on V(Ai) and the wj weight in each parameter. The value of V(Ai) can also be calculated using Eq. (2), where rij is normalization from the calculation of the maximum value of the data on the parameter attribute.

?? ?? ?? = ??=1 ?? ?? ?? ?? ???? ??=1 ?? ?? ?? _(2) _ _ Calculating the preference value vj(xij) on V(Ai) for each parameter attribute by finding the maximum value in each parameter attribute value using Eq. (3) and normalizing the maximum value obtained using the Eq. (4) [40]. ??????=??????? ?? ???? _(3) _ _ where, the max value (Aij) is obtained from the parameter attribute, in this paper the parameter attribute value is described in Table 1 with the process on the spatial data input data *.shp as described in Fig. 1 which refers to Eq. (4).

?????? ?? ?? =??????(?? ????) ?????? ?? ?? = max ?? ???? ?????? ?? ?? =??????(?? ????) ?????? ?? ?? =??????(?? ????) _ (4) _ _ where, to declare parameter attributes *.shp spatial dataset on all data aij, max (ai) for PD3I, max (bi) for epidemic, max (ci) for nutritional status, and max (di) for infant immunization. Normalize the value of each parameter attribute using Eq. (5), where Xj is the data value that is j and max is the value obtained from the calculation in Eq.

(3) [40. ?? ???? = ?? ?? / max _(5) _ _ In this spatial data modeling, normalization values refer to Eq. (5) with the implementation of spatial datasets using Eq. (6). ?? ?? ?? = ?? ?? max ?? ???? ; ?? ?? ?? = ?? ?? ??????(?? ????) ?? ?? ?? = ?? ?? max ?? ???? ; ?? ?? ?? = ?? ?? ??????(?? ????) _ (6) _ _ Calculates the preference value vj(xij) on V(Ai) for all parameter attributes using Eq. (7) [40].

$?? ?? = ??=1 ?? ?? ?? ?? ???? , ??=1,2,...,?? \_ (7) \_ \_$ where, wj is the weight of the parameter attribute value and rij is the normalization value obtained in Eq. (5). The discussion in the trial in this paper uses Eq. (8) based on a literature study on Eq. (7). $?? ?? ?? =???????? ?? ?? ?? ????????h??(?? ??) ?? ?? ?? =???????? ?? ?? ?? ????????h??(?? ??) ?? ?? ?? =???????? ?? ?? ?? ????????h??(?? ??) ?? ?? ?? =???????? ?? ?? ?? ????????h??(?? ??) ?? ?? = ?? ?? ?? +?? ?? ?? +?? ?? ?? +?? ?? ?? \_ (8) \_ \_$ Approach to the WPM method use multiplication to connect the attribute rating.

rating each attribute must be raised first with the weight of the attribute [37,42]. The steps of the WPM method normalize to find out the alternative preferences of Ai in Si vectors, according to Eq. (9) [37,42]. $?? ?? = ??=1 ?? ?? ???? ???? \_ (9) \_ \_$ where, S variable is an alternative preference and is defined as a vector.

Xij variable is the variable value from the alternative on each attribute. The criteria or sub-criteria weight values are accommodated in the Wj variable. The N variable is used to represent the number of criteria in the multi-criteria parameters declared. Variable i is the desired alternative value, and variable j is the criteria value in the data.

The value of the ?Wj variable is 1 with the rank positive for the profit attribute, and negative for the cost attribute. The relative preference of each alternative is calculated using Eq. (10) [37,42]. $?? ?? = ??=1 ?? ?? ???? ???? ??=1 ?? ?? ?? * \_ (10) \_ \_$ where, Vi variable is an alternative preference defined as a vector with i-th data.

Determine the weight value for each parameter used to set the priority value on the existing parameters that are accommodated in the Bpre variable, do the sum for all priority values Tbpre=Bprea+Bpreb+...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=BA/Tb.

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=Ba^Wa. Calculating the value of Vs by multiplying all values in variable S, with Vs=SaxSb x...n. calculating the total vector on variable V or Tvs by adding up all the values of Vs, with Tvs=V1+V2+V3+...+Vn, then the variable value of V= Vsa/Tvsa.

The Guttman Scale Measurement of the classification values generated in this paper uses the Guttman scale [43], This scale is the basis of measurement to draw conclusions on qualitative data [44], and is used to provide an estimate of the value of the classification results in an intervention value that is still ambiguous because of uncertainty [45].

In the type of dataset that uses a score/weight in the analysis process, provides a value based on the uncertainty factor of the variable class described, it can be measured using the Guttman scale [46] in the Eq. (11). ??= ?? ?? (11) where I is the result of the interval value obtained from the variable R, is the range of data values and variable K with the number of alternative classifications that will be generated.

In the discussion of this paper, the variable value R is obtained from the range of values between the maximum value of Vi and the minimum value of Vi. The K variable is the number of alternative classifications namely good, average, fair, and poor which refers to flow Fig. 1 and Table 2. Whereas, the determination of the scale for determining the classification value criteria for measles-prone areas based on the status of immunization coverage using Eq. (12) with SAW method and WPM method using Eq. (13).

????????, &???? ?? ?? =0,875 ?????????????????, &???? ?? ?? =0,75 ?????? ?? ?? <0,875 ????????, &???? ?? ?? =0,625 ?????? ?? ?? <0,75 ????????, &???? ?? ?? <0,625 _ (12) _ _ _ _ _ ????????, &???? ?? ?? =0,001488 ??????????????, &???? ?? ?? =0,001274 ?????? ?? ?? <0,001488 ????????, &???? ?? ?? =0,00106 ?????? ?? ?? <0,001274 ????????, &???? ?? ?? <0,00106 _ (13) _ _

Table 2.

The Guttman Scale Assessment SAW Method _WPM Method _ _$??$= $??$ $??$ $????????$ - $??$ $??$ $??????$ =1-0,5=0,5 $??$=4 $??$= $\frac{0,5}{4}$ =0,125 _$??$= $??$ $??$ $????????$ - $??$ $??$ $??????$ =0,001702-0,000846=0,000856 $??$=4 $??$= $\frac{0,000856}{4}$ =0,000214 _ _$???????????????????$ $????????$ $???????????????$ = h$????$h$??????$ $??????????$-$??$ =1-0,125=0,875 $??????????????????????$ $?????????????$ $???????????????$ =$??????????????????$ $????????$ $????????????????$-$??$ =0,875-0,125=0,75 $??????????????????????$ $????????$ $??????????????????$ =$????????????????$ $?????????????$ $???????????????$-$??$ =0,75-0,125=0,625 $??????????????????????$ $????????$ $???????????????$ =$?????????????????$ $????????$ $?????????????????$-$??$ =0,625-0,125=0,5 _$??????????????????????$ $????????$ $?????????????????$ = h$????$h$??????$ $??????????$-$??$ =0,001702-0,000214=0,001488 $???????????????????????$ $?????????????$ $??????????????$ =$????????????????$ $????????$ $???????????????$-$??$ =0,001488-0,000214=0,001274 $???????????????????????$ $????????$ $??????????????$ =$????????????????$ $?????????????$ $???????????????$-$??$ =0,001274-0,000214=0,00106 $??????????????????????$ $????????$ $??????????????$ =$?????????????????$ $????????$ $???????????????$-$??$ =0,00106-0,000214=0,000846 _ _

Method Consistency Test (MCT) Method Consistency Test Cohen's Kappa is used to test consistency in measuring two methods, this measurement can be done for qualitative data-based Eq. (14) [47].

$$?? = Pr\,?? - Pr?(??)\;1 - Pr?(??)\;\_(14)$$ _ _ where, the variable K is the coefficient of the results of the measurement between methods. The variable Pr(a) is the percentage of the number of measurements that are consistent in making comparisons between methods, and the variable Pr(e) is the percentage change.

Range of coefficient values in variable K [47], where if the variable value K <20, the value K is 0,21 to 0,40, the value K is 0,41 to 0,60, the value K= 0,61 to 0,80, dan K 0,81 to 1,00, then strength of agreement are poor, fair, moderate, good, and very good, respectively. Results and Discussion From the results of trials that have been carried out in 657 sub-districts in 38 regencies in 2011-2016 data obtained from the East Java Provincial Health Office of Indonesia [22-27].

The results of the modeling spatial data on the number of districts with categories of classification of measles-prone areas based on the status of immunization coverage with MADM in the SAW method as in Table 2, Fig. 2 and WPM method as in Table 3, Fig.3. Table 2. Distribution of Mapping Classification Results with the SAW Method Class _Sub-District _ _ _2011 _2012 _2013 _2014 _2015 _2016 _ _Good _449 _488 _423 _442 _409 _432 _ _Average _113 _79 _94 _134 _108 _134 _ _Fair _82 _56 _117 _69 _125 _77 _ _Poor _13 _34 _23 _12 _15 _14 _ _ Table 3.

Distribution of Mapping Classification Results with the WPM Method Class _Sub-District _ _ _2011 _2012 _2013 _2014 _2015 _2016 _ _Good _299 _531 _494 _299 _306 _315 _ _Average _340 _92 _140 _337 _333 _324 _ _Fair _12 _7 _13 _8 _5 _5 _ _Poor _6 _27 _10 _13 _13 _13 _ _ The results of the SAW method in the area with more good categories were 66.5 (15%) compared to the results of the WPM method.

The area in the average category for the results of the WPM method is 58% greater than the results of the SAW method. Regions with a fair category have more than 90% of the results of the WMP method rather than the results of the SAW method, and more than 26% of the results of the SAW method for regions with the poor category rather than the results of the WPM method. / Figure.

2 The Results of the MADM Classification with the SAW Method The Results of the MADM Classification with the SAW Method in Fig.2. The layer value of datasets PD3I is 1 incidence rate (annually) to months a year, epidemic is 0 annually to months a year, nutrition status is good, and number of infant = 152 infants with infant in immunization

status is 143 infant for 94,079% infant immunization status, based on the level of importance referring to Table 1, the values are 2, 3, 3, and 3, so a =2 ; b =3; c =3; d=3, to get the max value in Eq. (3), the data input process is carried out based on Eq. (4).

Normalization of the max value based on the theory in Eq. (5), the normalized value is obtained by dividing the value of the parameter variable with the max value of each variable referring to Eq. (6). The preference value is obtained from the reference in Eq.

(7), which is multiplying between normalization value and weight in each parameter variable in Table 1 using Eq. (8). Based on Eq. (12) which refers to Eq. (11), the value of Vi is 1 entered in the range of good classification category in the area with green mapping, where the value of Vi is greater than 0.875. / Figure. 3 The Results of the MADM Classification with the SAW Method Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig.

2 is done on the same spatial datasets as the SAW method. Epidemic scores were 0, PD3I was 1, the category of nutrition status was good, and the number of infants in the Subdistrict was 152 infants with immunization status of 147 infants or 94,079% of infants with immunization status. The level of importance includes 3, 2, 3, and 3, respectively.

The priority value for each parameter includes 2, 3, 4, and 1, respectively. The number of priority value in the TbPre is 10, where the weight value in the W variable for each parameter is 0.2, 0.3, 0.4, and 0.1, respectively. Calculation of the value of Vector in the S variable for each parameter variable, namely is 1,390389, 1,148698, 1,551846, and 1,116123.

Vs variable value is obtained by multiplying all TV values ??is 1670,478685, then the total Vs obtained from all calculated data is 2,766324. The value of vector V by dividing the value of Vs by the value of TVs, then the value of V is 0,001656, based on Eq. (13) and flow on Fig. (1), then the classification of regions with good categories The test results using Cohen's Kappa for the feasibility of using the SAW method and the WPM method for modeling spatial data on GIS for classification of measles-prone areas using MADM, obtained kappa coefficients from the K variable -0.42, 0,67, 0,519367011, 0,15, 0,215627097, and 0,253130142 for 2011-2016, respectively.

Conclusion This paper examines the MADM technique in classifying multi-criteria parameters to produce spatial data modeling in its spatial process. The methods in MADM allows the results of comparative mapping in accordance with the level of importance, weight, and order of priority given to each of the parameter's multi-criteria variables in providing spatial sensitivity analysis.

This study resulted in the preference value of Vi in the SAW method and WPM method by considering quantitative data and the calculation of the Guttman scale classification parameter value scale, this matter becomes very important in the decision-making system as a step-in planning to provide classification in identifying areas affected by tropical diseases in measles-like the results in Eq. (12) and Eq. (13).

This finding provides a new direction for using the MADM technique with the SAW and WPM method as part of the planning for mitigation measures, this finding encourages further research to use other quantitative data to influence the results of spatial data modeling. Regions that are classified as fair or poor are important for policymakers in the field of surveillance and immunization of the Health Office to take anticipatory steps as a form of mitigation measures [1] of disasters causing epidemics of measles.

The results of this spatial data modeling answer the role of quantitative data types that can be used as a reference in displaying a mapping to produce a classification of vulnerable areas as part of decision making, for example providing understanding to communities in fair and poor categories to be more caring through self-awareness in order to immunize areas with high epidemics can be choked.

This is important because prevention is not only the responsibility of the health sector, but the role of the socio-economic environment is also a driver of the spread of measles infectious diseases [7]. Based on the discussion on testing data with MTC, it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field.

Results from MTC have a moderate category strength of agreement for use in spatial data modeling on the GIS for classification of measles-prone regions using MADM. They have results that are not much different. Further research that can be developed is by collaborating the MADM method and data mining classification methods such as naïve Bayesian or decision tree, this function is to determine the comparison of the results of the classification given in each type of method used.

Comparing the results of the classification of each method to be tested the level of accuracy of the method used through the method induction test.

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Kei Eguchi <eguti@fit.ac.jp>   1 Maret 2019 pukul 18.30
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>
Cc: Amphawan Julsereewong <amphawan.ju@kmitl.ac.th>

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Best regards,
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Dear Editor of the International Journal of Intelligent Engineering and Systems,

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

- Manuscript number: IJIES-1895
- Title: Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

In more details, we include point-by-point changes that are done to revise ijies1985: camera-ready this paper.

Thank for your attention.

Best regards,
Anik Vega Vitianingsih

1. On page 97 for abstract line 7, I give the color red to the text, because there is something I have not added, which is correct, namely:
   #The SAW and WPM method.
2. In the keyword, I have a lack of punctuation ',', which is:
   #GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa, tropical diseases, measles.
3. On page 100, I increase the size of the text in picture 1 to make it clear
   #Figure 1
4. On step 1 page 101, V_i Variables need to be italic, namely:
   #V_i
5. On page 101 for step 2, equation 4, for the description of the variable there is an italic, namely:
   #j and max
6. On page 102 for equation (8) the variable description needs to be italicized, namely:
   #A_i in S_i vectors
7. On page 102 for equation (10) the variable description needs to be italicized, namely:
   #$Tbpre=Bpre_a+Bpre_b+…n$
   #$V_s=S_axS_b x…n$
8. On page 102 for equation (11) in the description of variable K, which is correct as follows:
   #The K variable
9. Caption in figure 3 page 104, which is correct as follows:
   #Figure. 3 The results of the MADM classification with the WPM method
10. Paragraph 4 on page 104, the sentence Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 3, correct as follows:
    #Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 3

Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

Anik Vega Vitianingsih[1]*   **Achmad Choiron[2]**   **Dwi Cahyono[3]**   **Azizul Umam[4]**   **Suyanto Suyanto[5]**

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Abstract: Indonesia is a country that has a tropical climate, so that many typical tropical climate diseases emerge. This disease is caused by viruses and parasites that breed during the dry season or the rainy season. One typical tropical disease is measles. This paper discusses the geographical information system (GIS) technology by analyzing spatial data modeling to determine the classification of measles-prone areas based on immunization status coverage using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method. Some parameters are used consist of immunization status data for multiple attribute decision making (MADM), diseases preventable by immunization (PD3I), epidemic and nutritional status of infants. The SAW and WPM method in modeling spatial data analysis processes data according to the parameters to determine the scale in comparing all alternative data on the scope of classification of immunization status areas, namely: good, average, fair and poor. The test results with the Cohen's Kappa Method Consistency Test (MCT) is obtained an average coefficient of 0.41 for consistent measurements for the chosen method. It can be concluded that the two measurements using the SAW and WPM methods have a moderate for the strength of agreement category, for using in spatial data modeling on the GIS for classification of measles prone regions using MADM.

Keywords: GIS, spatial data modeling, MADM, SAW, WPM, Cohen's Kappa, tropical diseases, measles.

1. Introduction

Measles is one of the diseases that often becomes an extraordinary event in the tropics, such as Indonesia. The spread of measles is a global problem in the health sector. The problems, information on the incidence of measles is still based on risk factors for immunization status in the measles surveillance technique manual. Research studies are still descriptive statistics and there are no system applications that globally can identify areas prone to measles disease based on multi-criteria parameters to determine the distribution of vulnerable categories of regions. Measles control in this decade has been done by giving complete immunization to every baby or child, as a mitigation measure by the public health authority [1], measles is one type of disease that breeds in regions with tropical climates [2]. Based on

the World Health Organization (WHO), measles incidence rate per million, Indonesia is a country with 6345 cases at a rate of 24.30. In 2017 the number of confirmed 11389 cases increased compared to 2016 which only reached 7204 confirmed cases [3]. Spatial patterns can be used to identify patterns of behavior of measles spreading, based on local seasonal factors in each region [4].

In the beginning, spatial data modeling was done by analyzing the needs of geospatial data to be processed for decision-making systems. The need for spatial data analysis was important in the field of research and policy making, provides a description of data needs, methods, and illustrations of case studies used [5], as well as in the health sector [6, 7] measles field [8]. Analysis of spatial data as a mitigation measure for disease prevention and control had a very important role. This was developed based on the conditions of regional climate and social behavior of

the community, the method of Inverse Distance Weighting (IDW), the functions and weighted overlay functions were used to predict the location of disease spread [9]. The risk of spreading the disease to areas adjacent to the affected area has been carried out by using a spatial clustering method. In this method, a comparison was made on spatial grouping in heterogeneity. The resulting information would be beneficial for the Ministry of Health to formulate regional coping strategies as hotspots in epidemic diseases [10].

Spatial data modeling was the process of spatial analysis results data to determine the decisions and policies of stakeholders. The resulting process included geocoding and mapping to produce a decision-making system [11, 12] through the application of artificial intelligence (AI) methods [13]. The AI method used to map measles has been applied including fuzzy inference system [14], Data mining techniques [15], Bayesian mixture model [16], hierarchical Bayesian model [17], Bayesian spatial modeling [18]. The AI fuzzy inference system method is used to determine the symptoms of measles based on the input variable rule in the inference engine [14]. Artificial Neural Network (ANN), Decision Tree Algorithm and Naïve Bayes Classifier on Data Mining techniques, are used to predict disease trends. One of them is measles based on time series database disease [15]. Bayesian Normal mixture models were used to estimate the prevalence of measles through age factor [16]. Spatial hierarchical Bayesian models are used to map the risk of measles based on data on the number of measles, unemployment, birth rates, education level and age of immunization [17]. Bayesian spatial modeling is used to determine the mapping of disease populations based on disease statistics [18].

According to previous research, geographical information system (GIS) technology was utilized through spatial analysis to identify groups of low or high for measles, mumps and rubella (MMR) immunization levels with spatial, temporal and spatial-temporal methods [19]. Bayesian regression spatial model was used to identify the risk of measles spread at the regional level using data series in 2005-2014, the results obtained indicate the parameters of birth rate, number of measles cases, unemployment rate and the proportion of children immunized at 12 months to be a determinant in prevention of measles [17]. Socio-economic disparity had become a separate problem in the success of measles immunization programs, using multiple spatial regression methods mapping is done to identify the distribution of immunization coverage based on

socio-economic inequality. This was a step in mitigating the spread of measles virus [20]. Web-based GIS technology was developed as a web-based health surveillance system [21]. However, the research that has been done has not used the approach and parameters that would be proposed in the discussion of this paper, that is, with a multi-criteria parameter approach to explore the need for supporting factors in the analysis process, interview experts in the field of disease prevention and control of the Indonesian East Java Provincial Health Office, and analyze the behavior of data to determine AI methods through mathematical modeling that is suitable for producing distribution multi-class classification vulnerable area. The results of measles data processing based on the AI method are still presented in graphical form [14-16], Multi-criteria parameters that will be proposed for spatial data modeling with SAW and WPM methods in the discussion of this paper, have not been used in previous studies [17, 18].

The purpose of this paper was to propose an approach through spatial data modeling to determine the distribution of measles-prone areas based on immunization status coverage. Multiple attribute decision making (MADM) was used in the modeling of spatial data because alternative results in regional coverage use multi-parameter criteria including diseases preventable by immunization (PD3I), epidemic and nutritional status of infants taken from basic data on the health profile book of East Java Province of Indonesia in 2011-2016 obtained at the regional level [22, 27]. The multi-class classification was obtained from the results of spatial data modeling using the Simple Additive Weighting (SAW) and Weight Product Model (WPM) method in the form of immunization status coverage: good, average, fair, and poor.

The spatial analysis produced spatial data modeling which was used to determine relationship between the basic data to be processed, with the parameters used as a factor of an area categorized in the classification of measles-prone areas based on immunization status coverage. Analysis and design of the built system have been described in advance according to the needs of spatial data that would be processed to become modeling [28].

The results of the spatial data modeling with the SAW method and WPM method obtained the preference value using The Guttman Scale Assessment. The alternative good category on the SAW method if the V_i preference value is above 0,875, the average category with the V_i preference value between 0,75 to 0,875, the V_i preference value

between 0,625 to 0,75 for the fair alternative category, and poor for the preference V_i below 0,625. The Guttman Scale Assessment in the WPM method that is if the vector value V_i more than 0,001488 for good category, an average category for value V_i between 1,001274 to 0,001488, the value of V_i 0,00106 to 0,001274 for the value category V_i and smaller value than V_i 0,00106 for the poor category.

The results of trials which conducted on data layer (*.shp) coverage each district for the 657 sub-district the East Java Province of Indonesia using the SAW method and WPM method for 2011-2016 data. Mapping the areas prone to measles by the SAW method, for the good category obtained 449, 488, 423, 442, 409, and 432 regions, the average category was obtained 113, 79, 94, 134, 108, and 134 regions, the fair category was 82, 56, 117, 69, 125, and 77 regions, and the poor category obtained 13, 34, 23, 12, 15, and 14 regions, respectively. In the WPM method, the results of mapping for regions with good categories were 299, 531, 494, 299, 306, and 315, the average category was 340, 92, 140, 337, 333, and 324 regions. from 12, 7, 13, 8, 5, and 5, and 6, 27, 10, 13, 13, and 13 in the number of regions in the poor category, respectively.

The results of this study could be part of disaster mitigation measures to prevent the spread of measles [1, 29] in developing countries with a tropical climate. The mapping results could provide a classification of prone red areas based on the coverage of poor immunization status. Policy makers such as the Health Office could make preventive measures based on the results of the classification.

2. Spatial Datasets

Spatial data sets are used to classify parameters that affect the spread of measles [8]. Spatial datasets consist of two components: spatial data and attribute data. Both become parameters to determine the classification of measles-prone areas based on immunization status coverage factors as in Table 1, including PD3I, epidemic, nutritional status, and infant immunization.

In each spatial datasets the weight value was given, to determine the level of importance/influence on the classification produced in each parameter criterion [30, 31], This weighting used the fuzzification process, consisting of fuzzy sets indicators in giving a level description in the classification results [32].

Table 1. Description of the Multi-Criteria Parameter Spatial Datasets Measles Diseases

Spatial Datasets	The Priority Value	Weight	Incidence rate (annually)	Category of PD3I	Level of importance
PD3I	2	0.30	PD3I >12 months a year	Poor	1
			PD3I <12 months a year	Good	2
Epidemic	3	0.15	Epidemic > 60 cases a year	Poor	1
			Epidemic < 60 cases a year	Good	2
			Epidemic = 0 cases a year	Very good	3
Spatial Datasets	Value of the priority	Weight	The status	Range Standard Deviation (sd)	Level of importance
Nutrition Status	4	0.10	Very good nutrition	$sd \geq 2$	4
			Good nutrition	$sd < 2$ && $sd \geq -2$	3
			Less of nutrition	$sd < -2$ && $sd \geq -3$	2
			Poor nutrition	$sd < -3$	1
Infant Immunization (IM)	1	0.45	Good immunization	$IM > 90\%$	3
			Average immunization	$IM \leq 90\%$ && $IM \geq 80\%$	2
			Fair immunization	$IM < 80\%$	1

3. Methods

Decision-making systems that involve GIS spatial data could be completed with MADM that be able to carry out integration in managing spatial data and attribute data to perform spatial data analysis [33]. Analysis of spatial data in the discussion of this paper resulted from spatial data modeling. the spatial datasets described in Table 1 be used as baseline data to produce a classification of measles-prone areas based on immunization status coverage.

The process stages in spatial data modeling for classification of tropical disease prone areas based on immunization status coverage were shown in the flowchart Fig. 1. This stage gave a picture of how the system works. Starting from inputting or recording of

all data needs, then the process of modeling spatial data by determining the AI method that matches the behavior of the data obtained from the recording process, and the final process was to display the

results of spatial data modeling in accordance with the functions and objectives to be achieved in GIS software development.
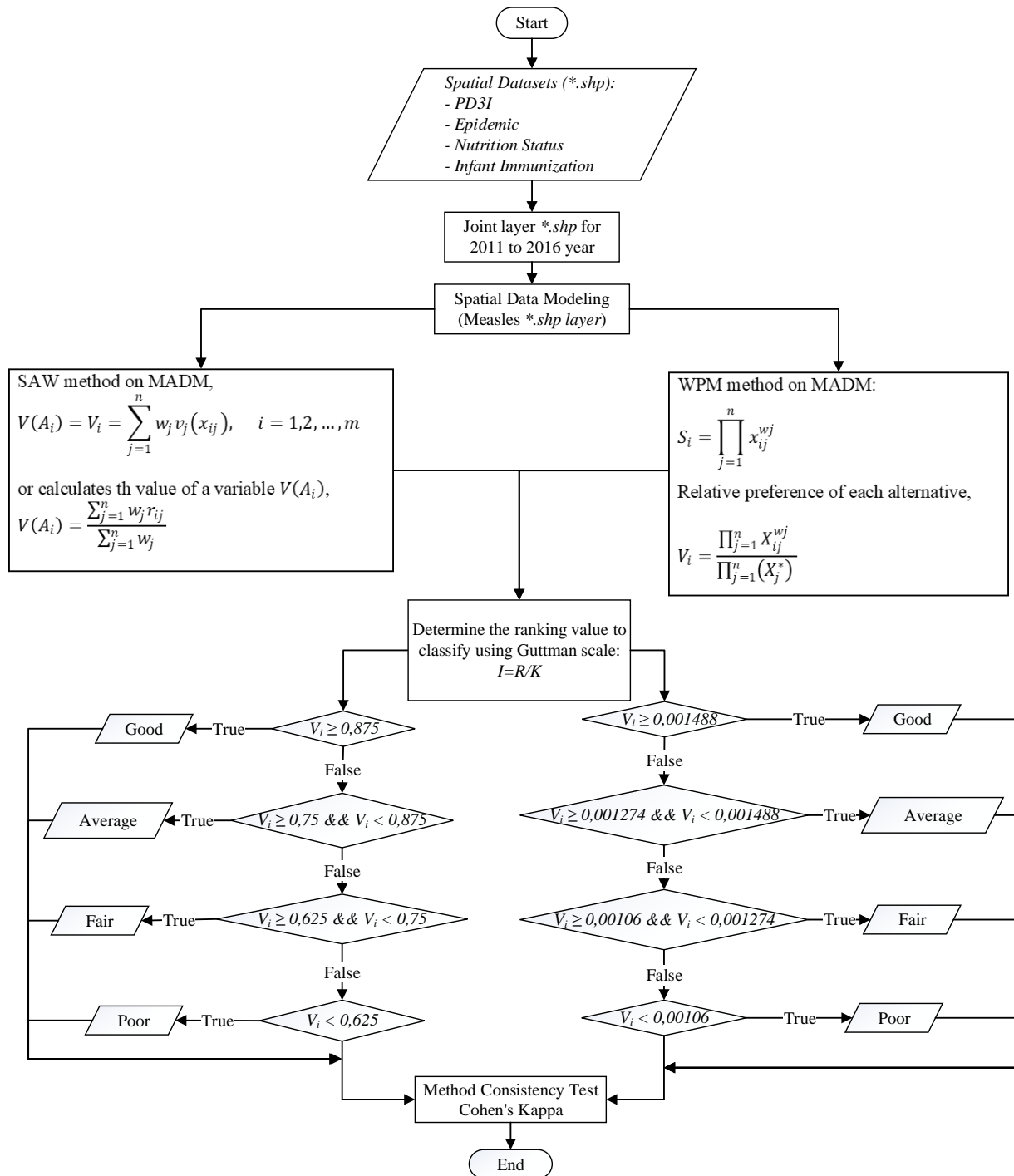

Figure. 1 Flow of Spatial Data Modeling with SAW and WPM Method

The first step, defining the spatial data requirements and layer attribute data in the spatial shapefile dataset (*.shp). The dataset includes a map of the East Java Province of Indonesia consisting of districts in each sub-district, including PD3I,

epidemic, nutrition status, and infant immunization. The data used was qualitative [34] which was then cited [35] in each district with the concept of the overlay layer. This stage served to merge layers from

31 districts with data layers per sub-district to become a single layer.

The overlay layer results in one layer of measles (*measles*.shp*) for each year. This was called spatial interpolation. The SAW and the WPM method through the MADM method would process the results of the regulation's layer to get the preference value of *Vi*. The Guttman method was used for classification of values with immunization status coverage categories with good, average, fair, and poor conditions in each sub-district.

The coverage of immunization status for the distribution of measles with the good category can be obtained if the V_i value increases compared to the previous year. It can be concluded that the state of immunization status is reached or exceeded the target, indicated by the description of the green area. In regions with average immunization status coverage occurs if an area with immunization status reaches the minimum target which is represented by an area of orange color, where the value of V_i falls from the condition of the previous year. It could be seen from the value of V_i for the classification of regional categories with good immunization status. Fair classification occurs if in a region the value of V_i falls compared to the previous year in the area with the average category. This happened because the immunization target did not reach the minimum target with an orange description of the area. Regions with a V_i value below the average condition of good, average, and fair immunization status coverage, where the immunization target was not achieved, by mapping the red area.

3.1 Multiple Attribute Decision Making (MADM)

MADM is part of the Multi-criteria decision making (MCDM) decision-making system, as well as multi-objective decision making (MODM) [36]. MODM was used for decision making that be sustainable, as in computing programming [37]. MADM and MCDM were used for discrete retrieval, where the alternative of the support system of the decision was predetermined [37].

The Simple Additive Weighting Method (SAW) and the Weight Product Model (WPM) method is part of a decision-making system using multi-parameter criteria with a multiple attribute decision making (MADM) approach [38]. MADM describes the parameters/criteria that will be used to determine the best alternative based on several appropriate criteria, the characteristics of decision making using the MADM system will describe the attribute requirements in the spatial analysis process, make the

decision weight from the data that has been described Table 1 to form a decision matrix produced [39, 37, 40].

Approach to the SAW method by giving a score on each alternative produced to be multiplied by the value weight for each parameter attribute [41], with the following steps:

1. The SAW method produces the final value of V_i in the Eq. (1) to obtain an alternative value from the classification that will be generated in the decision-making system [40].

$$V(A_i) = V_i = \sum_{j=1}^{n} w_j v_j(x_{ij}), \quad i = 1,2,\dots,m \quad (1)$$

where $V(A_i)=V_i$ is the alternative result value in the classification generated in each attribute A_i, this value is obtained from the calculation of the preference value $v_j(x_{ij})$ on $V(A_i)$ and the w_j weight in each parameter. The value of $V(A_i)$ can also be calculated using Eq. (2), where r_{ij} is normalization from the calculation of the maximum value of the data on the parameter attribute.

$$V(A_i) = \frac{\sum_{j=1}^{n} w_j r_{ij}}{\sum_{j=1}^{n} w_j} \quad (2)$$

2. Calculate the preference value $v_j(x_{ij})$ on $V(A_i)$ for each parameter attribute by finding the maximum value in each parameter attribute value using Eq. (3) and normalizing the maximum value obtained using the Eq. (4) [40].

$$max = max\left(A_{ij}\right) \quad (3)$$

where, the max value (A_{ij}) is obtained from the parameter attribute, in this paper the parameter attribute value is described in Table 1 with the process on the spatial data input data **.shp* as described in Fig. 1 which refers to Eq. (4).

$$\begin{aligned}
max(a_i) &= max(a_{ij}) \\
max(b_i) &= max(b_{ij}) \\
max(c_i) &= max(c_{ij}) \\
max(d_i) &= max(d_{ij})
\end{aligned} \quad (4)$$

where, to declare parameter attributes **.shp* spatial dataset on all data a_{ij}, *max (a_i)* for PD3I, *max (b_i)* for epidemic, *max (c_i)* for nutritional status, and *max (d_i)* for infant immunization.

Normalize the value of each parameter attribute using Eq. (5), where X_j is the data value that is j and *max* is the value obtained from the calculation in Eq. (3) [40].

$$r_{ij} = X_j / \max \qquad (5)$$

In this spatial data modeling, normalization values refer to Eq. (5) with the implementation of spatial datasets using Eq. (6).

$$r(a_i) = \frac{a_i}{\max(a_{ij})} \; ;$$
$$r(b_i) = \frac{b_i}{max(b_{ij})} \qquad (6)$$
$$r(c_i) = \frac{c_i}{\max(c_{ij})} \; ;$$
$$r(d_i) = \frac{d_i}{max(d_{ij})}$$

3. Calculates the preference value $v_j(x_{ij})$ on $V(A_i)$ for all parameter attributes using Eq. (7) [40].

$$V_i = \sum_{j=1}^{n} w_j r_{ij}, \qquad i = 1,2,\dots,m \qquad (7)$$

where, w_j is the weight of the parameter attribute value and r_{ij} is the normalization value obtained in Eq. (5). The discussion in the trial in this paper uses Eq. (8) based on a literature study on Eq. (7).

$$v(a_i) = Norm(a_i) \; x \; weight(a_i)$$
$$v(b_i) = Norm(b_i) \; x \; weight(b_i)$$
$$v(c_i) = Norm(c_i) \; x \; weight(c_i) \qquad (8)$$
$$v(d_i) = Norm(d_i) \; x \; weight(d_i)$$
$$V_i = v(a_i) + v(b_i) + v(c_i) + v(d_i)$$

Approach to the WPM method use multiplication to connect the attribute rating. rating each attribute must be raised first with the weight of the attribute [37-42]. The steps of the WPM method normalize to find out the alternative preferences of A_i in S_i vectors, according to Eq. (9) [37, 42].

$$S_i = \prod_{j=1}^{n} x_{ij}^{wj} \qquad (9)$$

where, S variable is an alternative preference and is defined as a vector. X_{ij} variable is the variable value from the alternative on each attribute. The criteria or sub-criteria weight values are accommodated in the

W_j variable. The N variable is used to represent the number of criteria in the multi-criteria parameters declared. Variable i is the desired alternative value, and variable j is the criteria value in the data. The value of the $\sum W_j$ variable is 1 with the rank positive for the profit attribute, and negative for the cost attribute. The relative preference of each alternative is calculated using Eq. (10) [37, 42].

$$V_i = \frac{\prod_{j=1}^{n} X_{ij}^{wj}}{\prod_{j=1}^{n} (X_j^*)} \qquad (10)$$

where, V_i variable is an alternative preference defined as a vector with i-th data. Determine the weight value for each parameter used to set the priority value on the existing parameters that are accommodated in the Bpre variable, 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 $S=B_a{}^\wedge W_a$. Calculating the value of V_s by multiplying all values in variable S, with *V_s=S_axS_bx…n*. calculating the total vector on variable V or Tv_s by adding up all the values of V_s, with $Tv_s=V_1+V_2+V_3+\dots+V_n$, then the variable value of $V= V_{sa}/Tv_{sa}$.

3.2 The Guttman Scale

Measurement of the classification values generated in this paper uses the Guttman scale [43], This scale is the basis of measurement to draw conclusions on qualitative data [44], and is used to provide an estimate of the value of the classification results in an intervention value that is still ambiguous because of uncertainty [45]. In the type of dataset that uses a score/weight in the analysis process, provides a value based on the uncertainty factor of the variable class described, it can be measured using the Guttman scale [46] in the Eq. (11).

$$I = \frac{R}{K} \qquad (11)$$

where I is the result of the interval value obtained from the variable R, is the range of data values and variable K with the number of alternative classifications that will be generated.

In the discussion of this paper, the variable value R is obtained from the range of values between the maximum value of V_i and the minimum value of V_i. The K variable is the number of alternative

classifications namely good, average, fair, and poor which refers to flow Fig. 1 and Table 2. Whereas, the determination of the scale for determining the classification value criteria for measles-prone areas based on the status of immunization coverage using Eq. (12) with SAW method and WPM method using Eq. (13).

$$\begin{cases} good, if\ V_i \geq 0{,}875 \\ average, if\ V_i \geq 0{,}75\ and\ V_i < 0{,}875 \\ fair, if\ V_i \geq 0{,}625\ and\ V_i < 0{,}75 \\ poor, if\ V_i < 0{,}625 \end{cases} \quad (12)$$

$$\begin{cases} good, if\ V_i \geq 0{,}001488 \\ average, if\ V_i \geq 0{,}001274\ and\ V_i < 0{,}00 \\ fair, if\ V_i \geq 0{,}00106\ and\ V_i < 0{,}001 \\ poor, if\ V_i < 0{,}00106 \end{cases} \quad (13)$$

Table 2. The Guttman Scale Assessment

SAW Method	WPM Method
$R = V_{i\ maks} - V_{i\ min} = 1 - 0{,}5 = 0{,}5$ $K = 4$ $I = \dfrac{0{,}5}{4} = 0{,}125$	$R = V_{i\ maks} - V_{i\ min} = 0{,}001702 - 0{,}000846 = 0{,}000856$ $K = 4$ $I = \dfrac{0{,}000856}{4} = 0{,}000214$
Assessment good criteria $= highest\ score - I$ $= 1 - 0{,}125 = 0{,}875$ *Assessment average criteria* $= assesment\ good\ criteria - I$ $= 0{,}875 - 0{,}125 = 0{,}75$ *Assessment fair criteria* $= assesment\ average\ criteria - I$ $= 0{,}75 - 0{,}125 = 0{,}625$ *Assessment poor criteria* $= assesment\ fair\ criteria - I$ $= 0{,}625 - 0{,}125 = 0{,}5$	*Assessment good criteria* $= highest\ score - I$ $= 0{,}001702 - 0{,}000214 = 0{,}001488$ *Assessment average criteria* $= assesment\ good\ criteria - I$ $= 0{,}001488 - 0{,}000214 = 0{,}001274$ *Assessment fair criteria* $= assesment\ average\ criteria - I$ $= 0{,}001274 - 0{,}000214 = 0{,}00106$ *Assessment poor criteria* $= assesment\ fair\ criteria - I$ $= 0{,}00106 - 0{,}000214 = 0{,}000846$

3.3 Method Consistency Test (MCT)

Method Consistency Test Cohen's Kappa is used to test consistency in measuring two methods, this measurement can be done for qualitative data based Eq. (14) [47].

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \quad (14)$$

where, the variable K is the coefficient of the results of the measurement between methods. The variable $Pr(a)$ is the percentage of the number of measurements that are consistent in making comparisons between methods, and the variable $Pr(e)$ is the percentage change.

Range of coefficient values in variable K [47], where if the variable value $K < 20$, the value K is 0,21 to 0,40, the value K is 0,41 to 0,60, the value $K = 0{,}61$ to 0,80, dan K 0,81 to 1,00, then strength of agreement are poor, fair, moderate, good, and very good, respectively.

4. Results and Discussion

From the results of trials that have been carried out in 657 sub-districts in 38 regencies in 2011-2016 data obtained from the East Java Provincial Health Office of Indonesia [22-27]. The results of the modeling spatial data on the number of districts with categories of classification of measles-prone areas based on the status of immunization coverage with MADM in the SAW method as in Table 2, Fig. 2 and WPM method as in Table 3, Fig.3.

Table 2. Distribution of Mapping Classification Results with the SAW Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	449	488	423	442	409	432
Average	113	79	94	134	108	134
Fair	82	56	117	69	125	77
Poor	13	34	23	12	15	14

Table 3. Distribution of Mapping Classification Results with the WPM Method

Class	Sub-District					
	2011	2012	2013	2014	2015	2016
Good	299	531	494	299	306	315
Average	340	92	140	337	333	324
Fair	12	7	13	8	5	5
Poor	6	27	10	13	13	13

The results of the SAW method in the area with more good categories were 66,5 (15%) compared to the results of the WPM method. The area in the average category for the results of the WPM method is 58% greater than the results of the SAW method. Regions with a fair category have more than 90% of the results of the WMP method rather than the results of the SAW method, and more than 26% of the results of the SAW method for regions with the poor category rather than the results of the WPM method.
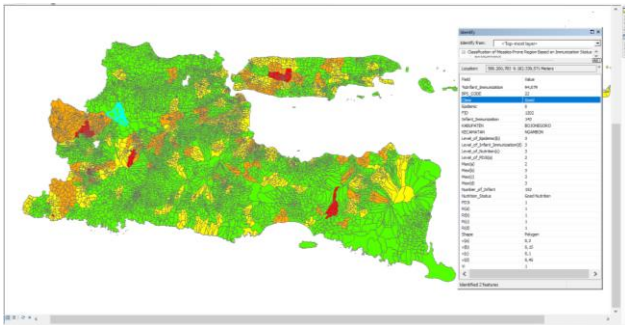

Figure. 2 The Results of the MADM Classification with the SAW Method
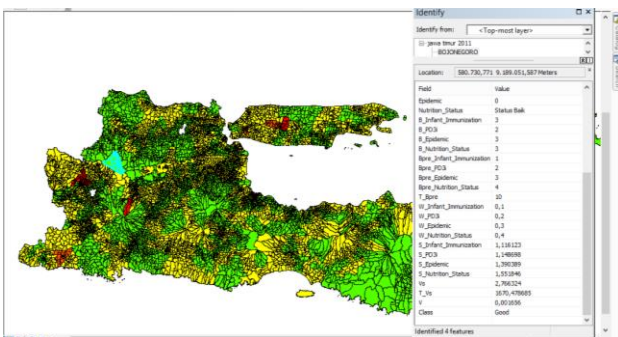

Figure. 3 The Results of the MADM Classification with the WPM Method

The Results of the MADM Classification with the SAW Method in Fig.2. The layer value of datasets PD3I is 1 incidence rate (annually) to months a year, epidemic is 0 annually to months a year, nutrition status is good, and number of infant = 152 infants with infant in immunization status is 143 infant for 94,079% infant immunization status, based on the

level of importance referring to Table 1, the values are 2, 3, 3, and 3, so $a = 2$; $b = 3$; $c = 3$; $d = 3$, to get the max value in Eq. (3), the data input process is carried out based on Eq. (4).

Normalization of the max value based on the theory in Eq. (5), the normalized value is obtained by dividing the value of the parameter variable with the max value of each variable referring to Eq. (6).

The preference value is obtained from the reference in Eq. (7), which is multiplying between normalization value and weight in each parameter variable in Table 1 using Eq. (8). Based on Eq. (12) which refers to Eq. (11), the value of V_i is 1 entered in the range of good classification category in the area with green mapping, where the value of V_i is greater than 0,875.

Testing with the WPM method is based on Eq. (9) and Eq. (10) on Fig. 3 is done on the same spatial datasets as the SAW method. Epidemic scores were 0, PD3I was 1, the category of nutrition status was good, and the number of infants in the Subdistrict was 152 infants with immunization status of 147 infants or 94,079% of infants with immunization status. The level of importance includes 3, 2, 3, and 3, respectively. The priority value for each parameter includes 2, 3, 4, and 1, respectively. The number of priority value in the Tb_{Pre} is 10, where the weight value in the W variable for each parameter is 0.2, 0.3, 0.4, and 0.1, respectively. Calculation of the value of Vector in the S variable for each parameter variable, namely is 1,390389, 1,148698, 1,551846, and 1,116123. The V_s variable value is obtained by multiplying all T_V values is 1670,478685, then the total V_s obtained from all calculated data is 2,766324. The value of vector V by dividing the value of V_s by the value of T_{Vs}, then the value of V is 0,001656, based on Eq. (13) and flow on Fig. 1, then the classification of regions with good categories.

The test results using Cohen's Kappa for the feasibility of using the SAW method and the WPM method for modeling spatial data on GIS for classification of measles-prone areas using MADM, obtained kappa coefficients from the K variable -0.42, 0,67, 0,519367011, 0,15, 0,215627097, and 0,253130142 for 2011-2016, respectively.

5. Conclusion

This paper examines the MADM technique in classifying multi-criteria parameters to produce spatial data modeling in its spatial process. The methods in MADM allows the results of comparative mapping in accordance with the level of importance, weight, and order of priority given to each of the

parameter's multi-criteria variables in providing spatial sensitivity analysis.

This study resulted in the preference value of V_i in the SAW method and WPM method by considering quantitative data and the calculation of the Guttman scale classification parameter value scale, this matter becomes very important in the decision-making system as a step-in planning to provide classification in identifying areas affected by tropical diseases in measles-like the results in Eq. (12) and Eq. (13).

This finding provides a new direction for using the MADM technique with the SAW and WPM method as part of the planning for mitigation measures, this finding encourages further research to use other quantitative data to influence the results of spatial data modeling.

Regions that are classified as fair or poor are important for policymakers in the field of surveillance and immunization of the Health Office to take anticipatory steps as a form of mitigation measures [1] of disasters causing epidemics of measles. The results of this spatial data modeling answer the role of quantitative data types that can be used as a reference in displaying a mapping to produce a classification of vulnerable areas as part of decision making, for example providing understanding to communities in fair and poor categories to be more caring through self-awareness in order to immunize areas with high epidemics can be choked. This is important because prevention is not only the responsibility of the health sector, but the role of the socio-economic environment is also a driver of the spread of measles infectious diseases [7].

Based on the discussion on testing data with MTC, it was concluded that the SAW method and the WPM method can be used for time series data types in spatial data modeling that do not have measurement data in the field. Results from MTC have a moderate category strength of agreement for use in spatial data modeling on the GIS for classification of measles-prone regions using MADM. They have results that are not much different.

Further research that can be developed is by collaborating the MADM method and data mining classification methods such as naïve Bayesian or decision tree, this function is to determine the comparison of the results of the classification given in each type of method used. Comparing the results of the classification of each method to be tested the level of accuracy of the method used through the method induction test.

Acknowledgments

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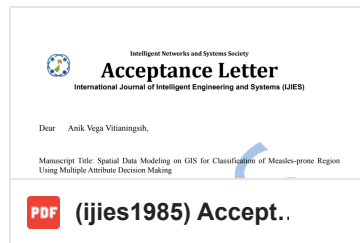
Intelligent Networks and Systems Society
Acceptance Letter
International Journal of Intelligent Engineering and Systems (IJIES)

Dear   Anik Vega Vitianingsih,

Manuscript Title: Spatial Data Modeling on GIS for Classification of Measles-prone Region
Using Multiple Attribute Decision Making

PDF (ijies1985) Accept..

Intelligent Networks and Systems Society
Official Receipt
International Journal of Intelligent Engineering and Systems (IJIES)

Received from
Anik Vega Vitianingsih
Universitas Dr. Soetomo Surabaya

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Dear   Anik Vega Vitianingsih,

Manuscript Title: Spatial Data Modeling on GIS for Classification of Measles-prone Region Using Multiple Attribute Decision Making

Author(s): Anik Vega Vitianingsih, Achmad Choiron, Dwi Cahyono, Azizul Umam, Suyanto Suyanto

Thank you for submitting your paper to the International Journal of Intelligent Engineering and Systems (IJIES). Based on double blind review process, we are pleased to inform you that our Review Committee has accepted your paper.

The paper will be included in the IJIES, which will be published with ISSN (ISSN: 2185-3118) in online on the website (http://www.inass.org/publications.html).
We are looking forward to your further contribution to our journal.

Kind regards

Prof. Dr. Kei EGUCHI
Editor-in-Chief, International Journal of Intelligent Engineering and Systems

Department of Information Electronics
Fukuoka Institute of Technology

E-mail: ijies@inass.org

Received from

Anik Vega Vitianingsih
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Description	Unit	Amount
IJIES formatting fee	1	USD 200
Total		USD 200

Prof. Dr. Kei EGUCHI
President, International Journal of Intelligent Engineering and Systems

Department of Information Electronics
Fukuoka Institute of Technology

E-mail: ijies@inass.org

7) ijies1985: camera-ready was finished
   (4 Maret 2019 - Japan time and 3 Maret 2019 - Indonesia's time)

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

Re: ijies1985: camera-ready was finished

2 pesan

Kei Eguchi <eguti@fit.ac.jp>   3 Maret 2019 pukul 07.09
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>
Cc: amphawan julsereewong <amphawan.ju@kmitl.ac.th>

Dear Authors,

The camera-ready was finished.
Please see the attached file.
On 30/4/2019 (tentative), your paper will appear on IJIES HP.

Appreciate your patiently wait.

Best regards,
IJIES Editors

_____
差出人: ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>
送信日時: 2019年3月3日 7:04
宛先: 江口 啓; amphawan julsereewong; ijies@inass.org
件名: Re: ijies1985: camera-ready

Dear Editor,

Here, I am sending the results of the correction '1985: camera-ready', I give the red color to the sentence text that needs to be fixed.

For more detailed information, I give it in the file attachment 'Response Letter-1985-Camera Ready.pdf'.

Thanks for your attention.

Best regards,

Pada tanggal Jum, 1 Mar 2019 pukul 18.30 Kei Eguchi <eguti@fit.ac.jp<mailto:eguti@fit.ac.jp>> menulis:
Dear author(s),

Thank you for your interest and support to IJIES.
I'd like to send the camera-ready version of your final manuscript.

Please check and confirm the attached file, and send the check result within THREE weeks.

If you have any question, please contact us with your paper ID.

Best regards,
IJIES Editors

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ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>   3 Maret 2019 pukul 07.25
Kepada: Kei Eguchi <eguti@fit.ac.jp>, amphawan julsereewong <amphawan.ju@kmitl.ac.th>

Yes IJIES Editors, I will wait patiently.

Thanks so much.

[Kutipan teks disembunyikan]