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RESEARCH ARTICLE

The Advantages of the Ordered Weighted Averaging (OWA) Method in Decision Making and Reliability Testing of Spatial Multi-Criteria Site Selection (SMCSS) Model

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Abstract A popular aggregation method known as the Weighted Linear Combination (WLC) is used in most SMCSS studies but it is observed to only provide one decision-making strategy. The review of the past studies also shows that most do not include reliability tests of the models applied. Therefore, this study aimed to provide a comprehensive description of different decision results obtained from the Ordered Weighted Averaging (OWA) method and show the unique sensitivity analysis (SA) process in the model. The retention pond site selection in Medan City, North Sumatra Province, Indonesia, was used as the case study. Moreover, the modeling was achieved through the steps of parameter determination, criteria map creation, map standardization, parameter weight determination, map combination, as well as model validation or sensitivity test measured by determining the changes caused in the outputs by the inputs. The variation of inputs was through the application of a set number of ordered weights which were part of the OWA method. The two outputs obtained included the results in the form of different decision strategies as well as the sensitivity or reliability of the SMCSS model.

1. Introduction

The problems associated with geographical information system (GIS)-based multi-criteria decision analysis (MCDA) are normally solved through 6 steps which include goal setting, criteria establishment, factors standardization, criteria weighting, criteria aggregation, and result validation (Estoque, 2011). It is important to state that the reliability of the Spatial Multi-Criteria Site Selection (SMCSS) Model is often tested during the final step. Moreover, the criteria map aggregation can be achieved using different methods such as the Weighted Linear Combination (WLC) or the Ordered Weighted Averaging (OWA).

The WLC is most widely in spatial MCDA (Malczewski and Rinner, 2015) due to some habit factors and a lack of understanding of the advantages associated with the OWA. This shows the need to provide comprehensive information on the ability of different OWA applications to produce diverse decision strategies. Moreover, the combination method used in GIS-MCDA is associated with the decision-making strategy characterized by two measures which include the risks to be taken and the trade-off. The measure normally used to determine the level of risks decisionmakers are willing to take is known as the degree of *OR*ness. The WLC can produce a special condition characterized by full trade-off and average risk at an *OR*ness value of 0.5 while the OWA offers different results with the *OR*ness range between 0 and 1.

The OWA is an improvement on the WLC aggregation method often applied in GIS. It was developed by Yager (1988) and was further expanded into the GIS environment by Eastman (2012). The overlaying value for each pixel or alternative in the method does not depend only on the criterion value and weight as in the WLC but also on the ordered weight (Yager, 1988). The OWA allows the determination of the certain level of trade-of and *OR*ness preferred based on the sets of ordered weights. It also provides opportunities to apply different strategies in the site selection model to produce several model outputs.

The reliability of the results or output from the GIS-MCDA model depends on the suitability of the formula used and the certainty of the inputs. A method for assessing uncertainty is the sensitivity analysis (SA) which is an integral part of GIS-based multi-criteria procedures due to its ability to examine the robustness of the output and provide a better understanding of the decision problem (Malczewski and Rinner, 2015). Meanwhile, it was observed that several studies conducted on the selection of locations did not test the feasibility of the model through SA (Alanbari et al., 2014; Buraihia and Sharif, 2015; Cradden et al., 2016; Shih, 2017; Kapilan and Elangovan, 2018; Manodhari, 2021; Raad et al., 2022; Magoura et al., 2023). This shows that only a limited number of GIS-MCDA studies have focused on the discussion related to model sensitivity despite the attention to different site selection objects.

Some reported that SA was based on the changes in the weight of input factors applied to determine whether the results were significantly different (Gómez & Boswue, 2004;

Ahmadisharaf et al., 2015). Moreover, the most common procedure was to vary the selected input components, return the model, and record the corresponding changes in the results. SA was further used to assess the reliability of a model by investigating the changes in the output based on the input parameters used to determine the criteria considered sensitive. It was also applied to determine the impact of variations in the weight of the factors on the output of the model in spatial size. The input factors most often analyzed include the number and values of the evaluation criteria (Chen et al., 2011; Tenerelli & Carver, 2012) as well as the weights of the criteria (Chen et al., 2013; Gorsevski et al., 2013). According to Ahmad (2017), the application of the OWA through the ordered weights was effective for the SA of the site selection criteria. This was associated with the ability of the method to offer varied evaluation results through different suitability index values. The concept simply shows that the application of ordered weights in OWA aggregation confirms the sensitivity of the criteria itself. Therefore, this study aimed to prove the advantages of using the OWA method in achieving decision-making objectives and simultaneously test the reliability or sensitivity of the model.

The background information provided showed that the main objectives of this study are to discuss the meaning of each result of several decision strategies in the OWA method, where one of them is the same as the result when using the WLC method; and to evaluate the aggregation results of the OWA method as a form of model sensitivity analysis.

2. Methods

2.1 Case and Study Area

From the many GIS applications on the location suitability analysis, the retention pond site selection was chosen to meet the objectives of this research. There were no specific requirements for the selection except for the mandatory need to pick a location and availability of data. The study area is located in the city of Medan, North Sumatra Province of Indonesia as presented in Figure 1. It is located at latitudes 3°27' to 3°77' N and longitudes 98°35' to 98°44' E and has elevations between 2.5 m to 37.5 m above sea level with a population density of 9,283 people/km² according to 2021 statistics. The area has 21 Sub-Districts with almost the entire edge bordered by the Deli Serdang district, except in the north where there is a sea, the Strait of Malacca (CBS-MC, 2018; FR-DMP, 2013).

2.2 Study Framework

The flow chart used in selecting the site through the OWA method applied in this study is presented in the following Figure 2. The aim was to develop a suitability map using a model with an approved sensitivity and this was achieved through several sequential steps which included criteria determination, criteria map collection, criteria standardization, criteria weights determination, and criteria map combination through the OWA method as explained in the next sub-sections. Meanwhile, ordered weights were first determined based on the decision strategy adopted before combining the criteria maps. The aggregation result maps were later compared to test the model sensitivity.

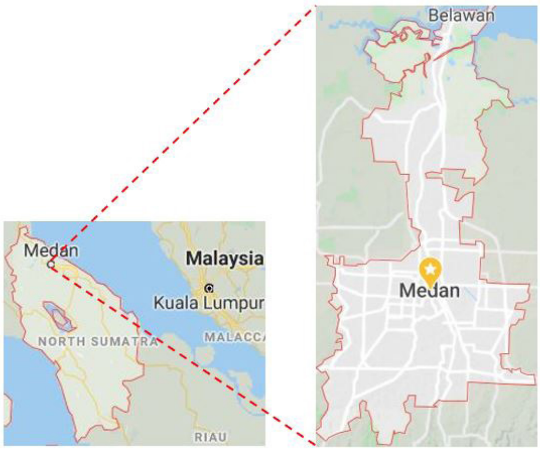

Figure 1. Map of Medan City in North Sumatra (Indonesia)

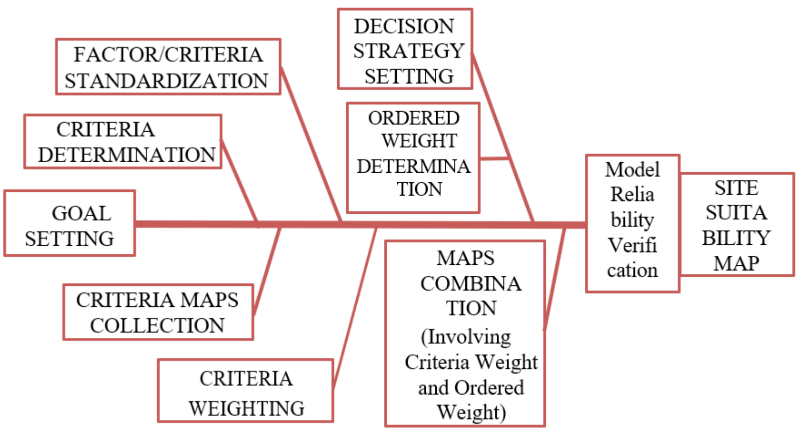

Figure 2. Framework of the OWA Site Selection Model

2.3 Evaluation Criteria for the Site Selection Model

The 2 types of criteria observed to be existing include factors and constraints. A factor is a criterion that enhances or detracts from the suitability of a specific alternative for the activity under consideration such as road distance where "near" is most suitable but "far" is least suitable. Meanwhile, a constraint is normally used to limit the alternatives under consideration in the form of an element or feature that represents limitations or restrictions on an area not preferred in any way or considered unsuitable such as a protected area, water body, and others (Malczewski and Rinner, 2015). The review of previous studies, literature, and guidelines led to the formulation of 12 factors in Table 1 and 7 constraints in Table 2 as the criteria for the proposed retention pond site selection (RPSS) model. The first 8 factors were grouped into the engineering factor group (EFG) while the remaining were classified as the socioeconomic factor group (SFG) (Saragih, 2020).

2.4 Data Collection and Maps Processing

Digital and hard copies of data were collected in different formats such as Tiff, Shp, JPG, Excel, and PDF from several sources including the Urban Development Planning Agency, Energy and Mineral Resources Office as well as Meteorological, Climatological, and Geophysical Agency, Medan. However, the secondary data could not be used directly for the analysis of site selection. This led to the application of several alternative stages to develop the factor map which included importation, conversion, overlay, geo-reference, digitization, cropping, re-classification, re-format, surface analysis, interpolation, distance analysis, and standardization of the data. Moreover, all the processing of the data and the map was conducted using the GIS software IDRISI-Selva version 17. MS Excel 2016 was also used to derive the criteria weights using the Analytical Hierarchy Process (AHP) and the "Solver" feature was further applied to calculate the ordered weights of the OWA model.

2.5 Criteria Maps Standardization

Standardization or values scaling methods are normally used to convert raw data to comparable or proportional units (Malczewski & Rinner, 2015). The procedure was applied to each map derived as a prerequisite for the aggregation in this study as presented in Table 1. Moreover, all factors with continuous data were standardized by fuzzy membership function (FMF) while those with discrete data such as infiltration, runoff coefficient, and land cost were standardized by using a defined function. The method led to the mapping of each pixel value of the factor map to a membership value from 0 to 255. The standardization performed for the constraint maps using the Boolean images method is presented in Table 2.

Table 1. The OWA standardization of factor maps (Saragih, 2020)

Factors Group	Nr.	Factors	Function Shape Control point
Engineering Factor Group (EFG)	1	Infiltration	User-defined
	2	Rainfall (mm)	Sigmoidal Monotonically increasing a = 1800 mm, b = 2900 mm
	3	Runoff-coefficient	User-defined
	4	Ground Elevation (m)	Sigmoidal Monotonically decreasing c =1 m, d = 83 m
	5	Slope (%)	Sigmoidal Monotonically decreasing c = 0 %, d = 6 %
	6	Groundwater depth (m)	Linear Monotonically increasing a = 4 m, b = 20 m
	7	Distance to Channel (m)	Sigmoidal Monotonically decreasing c =50 m, d = 500 m
	8	Distance to River (m)	Sigmoidal Monotonically decreasing c =50 m, d = 500 m
Socio-economic Factor Group (SFG)	1	Distance to dense Residence (m)	Sigmoidal Monotonically decreasing c =50 m, d = 1000 m
	2	Distance to Road (m)	Sigmoidal Monotonically decreasing c =100 m, d = 1000 m
	3	Distance to Inundation (m)	Sigmoidal Monotonically decreasing c =50 m, d = 1000 m
	4	Land use-Land cost	User-defined

Table 2. OWA standardization of constraint maps (Saragih, 2020)

No.	Names of constraints (Parameter of Buffer)		Ratings of buffer (m)	Value
1	Distance to wells		>400	1
			<400	0
2	Distance to roads		>100	1
			<100	0
3	Strategic area		>500	1
			<500	0
4	Gas pipelines		>50	1
			<50	0
5	Freshwater pipelines		>50	1
			<50	0
6	Railway		>100	1
			<100	0
7	Land use	Ordinary residence	-	1
		Real estate	-	1
		Green area	-	1
		Schools/Universities	-	1
		Others	-	0

Table 3. Relative weights of 8 engineering factors, 4 socioeconomic factors, and 2 groups

Goal	Objectives: Factor groups	Factor group Weights	Factors	Factor Weights
Site selection for building of Retention Ponds	Engineering Factor Group (EFG)	0.754	1. Infiltration	0.174
			2. Rainfall	0.272
			3. Runoff-coefficient	0.237
			4. Slope	0.059
			5. Groundwater depth	0.099
			6. Ground elevation	0.064
			7. Distance to Channel	0.047
			8. Distance to River	0.048
	Socio-economic factor Group (SFG)	0.246	1. Distance to dense Residence	0.193
			2. Distance to Road	0.237
			3. Distance to Inundation	0.147
			4. Land use/Land cost	0.423

2.6 Factor and Group Weighting

The weights of the engineering and socio-economic factors and groups were determined using expert preferences through the pairwise comparison (PC) method from the Analytic Hierarchy Process (AHP). The experts used included 2 water resource planning consultants, 3 academics in the field of water resources engi neering, and 5 government officials from the three departments related to water resources management and urban drainage facilities. The AHP procedures were conducted through four steps in a row which were comparing the factors, completing the pairwise comparison matrix, normalizing and determining weight, and calculating the consistency ratio. The results showed that the consistency ratio of each participant satisfied the requirement by being smaller than 0.10 (Saaty, 2008). Furthermore, the weights of the factors and factor groups are presented in the following Table 3 (Saragih, 2020).

2.7 Aggregation using the OWA Rule Simultaneously with the Sensitivity Analysis

The information presented in Figure 2 was further explained using Figure 3 with a focus on the steps implemented before and during the combination of maps using the OWA method. It was observed that the OWA aggregation was followed by the analysis of the model sensitivity as presented in the following figure.

The first step for the OWA aggregation was to set the decision strategy in order to control the level of risk and the desired trade-off by altering the ordered weights in contrast to the WLC method. This led to the selection of 5 sets as the representatives of the large numbers of decision strategies (DSs), including (1) minimum risk and no trade-off with $\alpha = 0.00$, (2) low risk and some/average trade-off with $\alpha = 0.25$, (3) average risk and full trade-off with $\alpha = 0.5$, (4) high risk and some/average trade-off with $\alpha = 0.75$, and (5) maximum risk and no-trade-off with $\alpha = 1.00$. The symbol, α, was used to represent the degree of *OR*ness and the positions of the 5 decision points (DPs) in the decision strategy space are presented in the following Figure 4 (Saragih, 2020).

The second step was to determine the ordered weights using the maximum entropy method applied by Makropoulos et al. (2007). The method allowed determining the optimum ordered weights value by maximizing the entropy based on a

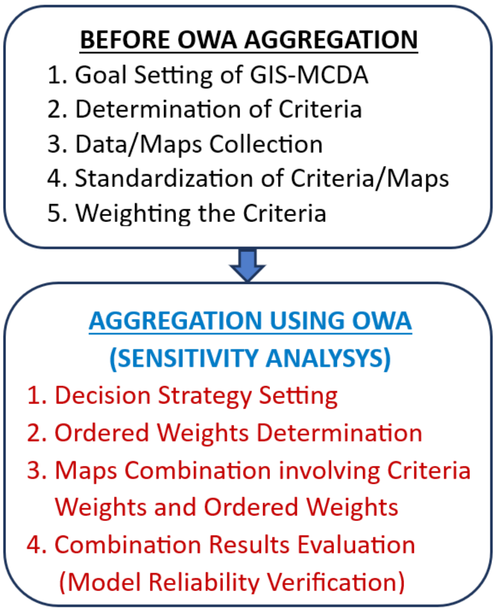

Figure 3. Steps of sensitivity analysis

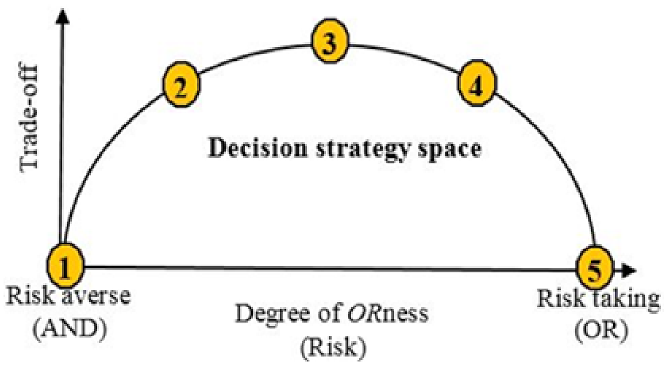

Figure 4. Decision strategy illustration

specified degree of *OR*ness. Moreover, the dispersion value of ordered weights was used as the measure of the trade-off as presented in Equation (1), and the measure of risk or *OR*ness value was calculated using Equation (3). The optimum ordered weights (λ_k) were later determined through the following optimization procedures:

Maximize: $\omega = -\sum_{k=1}^{n} \lambda_k \ln \lambda_k \;\; \omega = -\sum_{k=1}^{n} \lambda_k \ln \lambda_k$ (1)

Subject to: $\sum_{k=1}^{n} \lambda_k = 1\, 0 \leq \lambda_k \leq 1, \;\; j = 1, 2, \ldots n \sum_{k=1}^{n} \lambda_k = 1,$
$0 \leq \lambda_k \leq 1, \;\; j = 1, 2, \ldots n$ ' (2)

$\alpha = (n-1)^{-1} \sum_{k=1}^{n} (n-k)\lambda_k \; \alpha = (n-1)^{-1} \sum_{k=1}^{n} (n-k)\lambda_k,$ (3)

Where, ω is the dispersion of the ordered weights while α is the degree of *OR*ness.

The 5 selected sets of the ordered weights associated with 5 different decision strategies, DS-1 to DS-5 are presented in the following Table 4. It is important to state that DS-1, DS-3, and DS-5 are known as Boolean AND, WLC, and Boolean OR models respectively as shown in Figure 4. Moreover, the lists of the decision characteristics based on the decision point are presented in the table with the ordered weights applied between factors within each group.

Each set of the ordered weights was subjected to the maximum trade-off value ω listed in the last row of each table. The factor values presented in the top part of the table ranked from no.1 to no.8 based on the criterion that no. 1 was the highest while no.8 was the lowest in each pixel. Moreover, the bottom part showed the sequence number 1 as the factor with the highest value and number 4 as the lowest in each pixel.

The third step was to combine the maps involving the criteria and ordered weights. This was achieved in the OWA method by calculating the overlaying value for each pixel or alternative using the following Equation (4) [16].

$$V(A_i) = \sum_{k=1}^{n} \frac{\lambda_k u_k z_{ik}}{\sum_{k=1}^{n} \lambda_k u_k} \tag{4}$$

Where, $V(A_i)$ is the total factor map overlaying value in the i-th evaluation alternative (pixel), λ_k is a set of ordered weights ($0 \leq \lambda_k \leq 1$ and $\sum_{j=1}^{n} \lambda_j = 1 \sum_{j=1}^{n} \lambda_j = 1$), u_k is a set of reordered criterion weights corresponding to the ordered criterion values, and z_{ik} is a set of ordered criterion values. For the 5 decision strategies, 5 factor map aggregations were required and these were explained as follows.

The maximum ordered weight value of 1.0 was assigned to the factor with the lowest suitability value at each alternative pixel of DS-1 aggregation while all others had 0. For the DS-2 combination, several sets of ordered weight (λ_k) were calculated by setting the degree of *OR*ness (α) between 0 and 0.5. The

Table 4. The ordered weights and their decision strategies

Criteria	Rank and ω	DS-1 $\alpha = 0$	DS-2 $\alpha = 0.25$	DS-3 $\alpha = 0.5$	DS-4 $\alpha = 0.75$	DS-5 $\alpha = 1$
		Ordered weights with respect to selected decision strategy (DS) and corresponding degree of *OR*ness α				
Engineering Factors (EFG)	1	0	0.023	0.125	0.334	1
	2	0	0.033	0.125	0.228	0
	3	0	0.049	0.125	0.155	0
	4	0	0.072	0.125	0.106	0
	5	0	0.106	0.125	0.072	0
	6	0	0.155	0.125	0.049	0
	7	0	0.228	0.125	0.033	0
	8	1	0.334	0.125	0.023	0
	ω	0.00	1.77	2.08	1.77	0.00
Socio-economic Factors (SFG)	1	0	0.070	0.250	0.526	1
	2	0	0.137	0.250	0.268	0
	3	0	0.268	0.250	0.137	0
	4	1	0.526	0.250	0.070	0
	ω	0.00	1.45	1.39	1.45	0.00

values of the trade-off (ω) varied between 0 (minimum) and ln k (maximum), where k was the number of the factor. It was observed that the sequential aggregations produced a relatively higher level of suitability. As a representative, 2 sets of the ordered weights were applied for the value of $\alpha = 0.25$ and, the optimum trade-off (ω) values were 1.77 at λ_k ranging from 0.023 to 0.334 and 1.45 at 0.070 to 0.526 for the EFG and the SFG respectively as presented in Table 4.

In the DS-3 Aggregation, 2 sets of uniform ordered weights were applied for $\alpha = 0.50$, including 0.125 or 1/8 which was one divided by the number of factors of the EFG and 0.25 or ¼ representing one divided by the number of factors of the SFG as listed in Table 4. A similar trend was followed for the DS-4 combination where 2 sets of the ordered weights were applied as a representative for the value of $\alpha = 0.75$. These included the related optimum trade-off (ω) values of 1.77 at λ_k ranging from 0.334 to 0.023 and 1.45 at 0.526 to 0.070 for the EFG and the SFG respectively as presented in Table 4. Moreover, the maximum ordered weight value of 1.0 was provided for the factor with the highest suitability value at each alternative pixel of DS-5 aggregation while all others had 0.

The fourth step of the OWA aggregation was to evaluate the combination results simultaneously in assessing the reliability of the model. Moreover, SA of the proposed RPSS model was determined by altering the inputs through the inclusion of ordered weights and comparing the results as required in the OWA method.

3. Results and Discussion

3.1 Standardized Factor and Constraint Maps

The analysis of thematic data and processing of the maps with standardization led to the production of 8 maps for the engineering factor group, 4 maps for the socioeconomic factor group, and 7 constraint maps but only a few were presented in order to save space. Figures 5 and 6 show the factor suitability scores for each map ranging from the lowest, 0, to the highest, 255. It is important to state that a higher score represents a better factor in location suitability in all the maps produced from the analysis. An example of the constraint maps is presented in Figure 7 with each map pixel consisting of only 1 or 0, where, 1 represents an alternative while 0 signifies outside of the alternative.

3.2 The OWA Aggregation

The development of standardized criteria maps and the calculation of factor weights were followed by the aggregation process. The application of the 5 sets of ordered and related factor weights in the OWA aggregation procedure led to the generation of 5 conformity maps. Subsequently, each suitability map was overlaid with the total constraint map which was the combination of all to produce 5 final suitability score maps (FSSM) as presented in Figure 8.

The final suitability score maps for the retention pond in Medan City used as the case study are presented in Figure 8. In the legends of the maps, 0 represents the entire region not included as an alternative, 0.25 is the lowest suitability, and 255 is the highest as listed in Table 5. Moreover, the relationship between the decision strategy in column 1 marked by the degree of *OR*ness α in column 2 and the results of the OWA aggregation in the form of the suitability score range in column 3 is also presented in the table. It was observed that each DS-1 to DS-5 decision strategy produced a different suitability map as presented in column 4, showing the ability of the OWA to provide several solutions to the GIS-MCDA problem. The general conclusion from the table was that a greater degree of *OR*ness led to a higher suitability score for the map pixel.

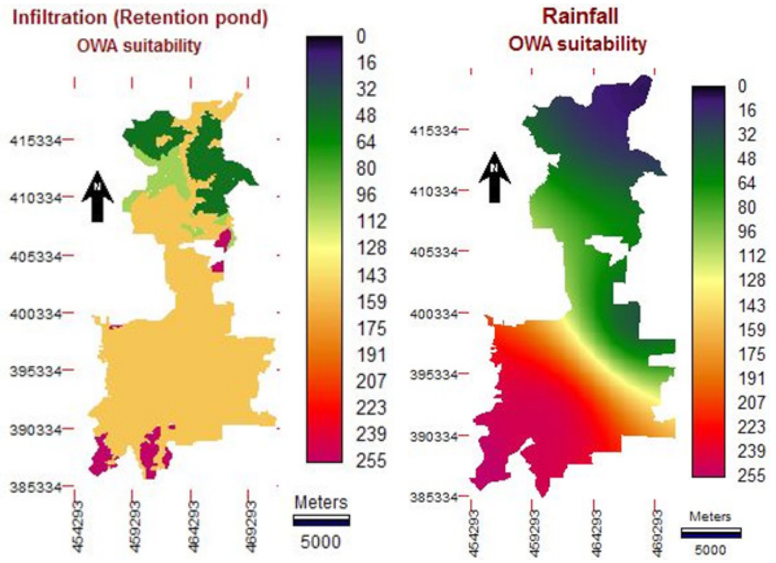

Figure 5. Factor maps for engineering factor group:
a) Infiltration and b) Rainfall

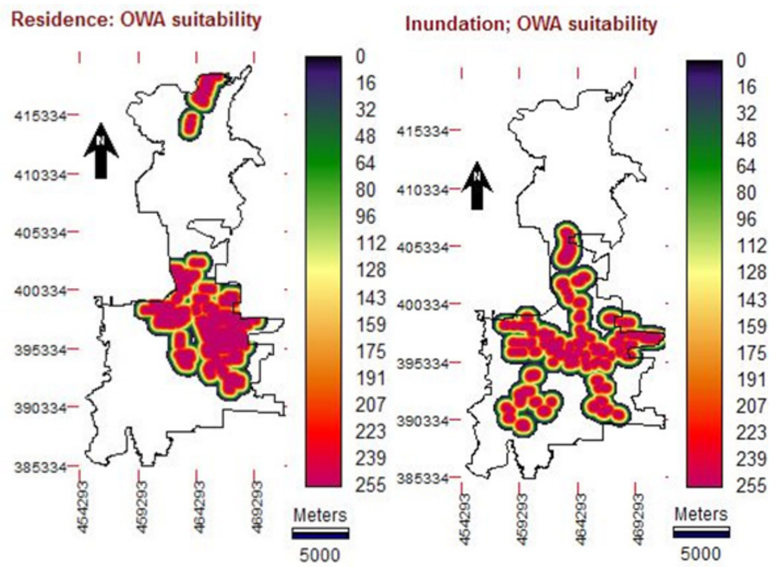

Figure 6. Factor maps for socio-economic factor group:
a) Residence and b) Inundation

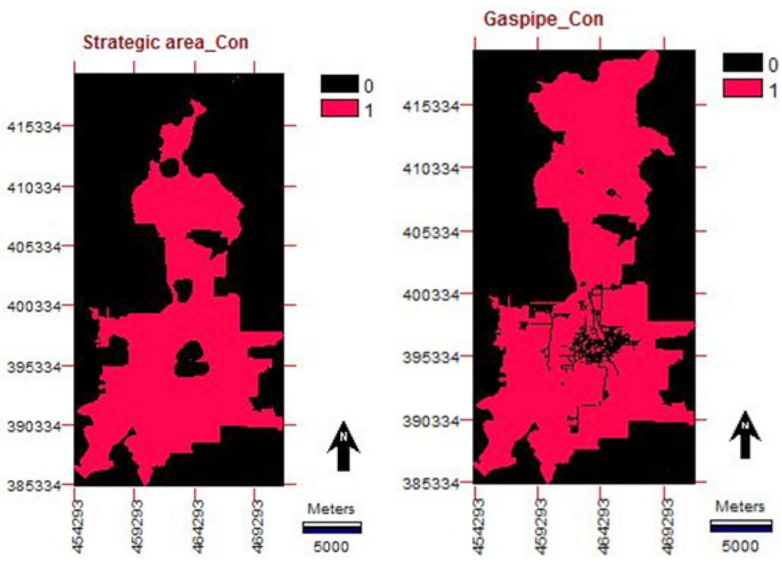

Figure 7. Constraint maps: a) Strategic area and b) Gas pipelines

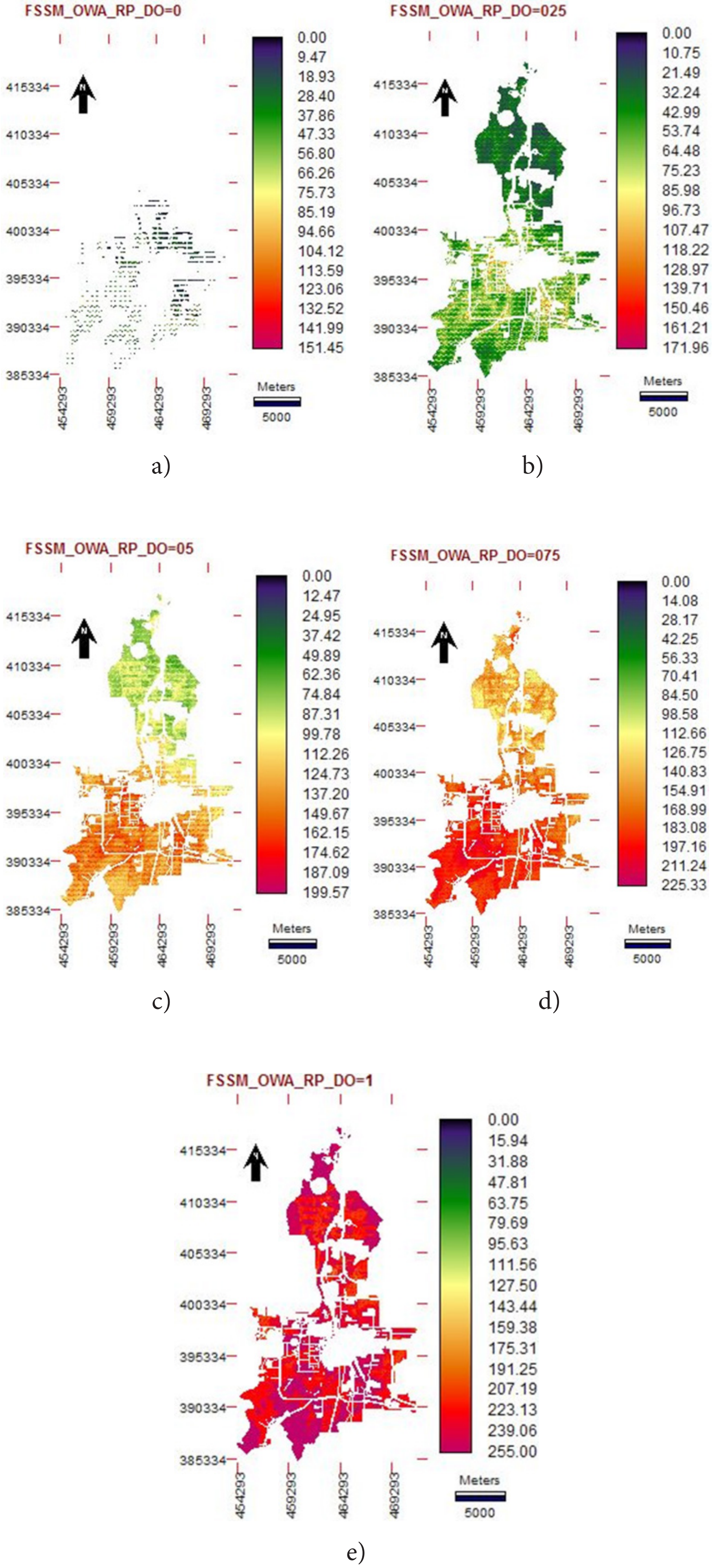

Figure 8. The Final Suitability Score Maps (FSSM): (a) For α = 0, (b) α = 0.25, (c) α = 0.5, (d) α = 0.75, and (e) for α = 1

3.3 Model Sensitivity Analysis through the Differences in the Outcomes

The information presented in Table 5 was assumed to be the sensitivity analysis (SA) result because it showed the significant differences between the outputs in columns 3 and 4 due to the changes made in the inputs in columns 1 and 2. Moreover, the variations were determined using the area of each suitability class ranging from the lowest or low suitability to the highest or very high suitability as observed in the values classified as smaller than 51, 51 to 100, 101 to 150, and greater than 150 in Table 6.

The area of each suitability class for DS-1 to DS-5 showed significant differences in the output of the OWA modeling presented in percentages in Table 6 as a consequence of the alterations in the inputs caused by the application of different sets of ordered weights represented by 5 types of decision strategies, DS-1 to DS-5. The results showed that the percentages of the area produced by these weights for the "very high suitability" level were 0.00, 0.05, 12.18, 83.35, and 100.00 respectively. A similar trend was also identified in other DSs and this further confirmed that the SMCSS model proposed was reliable.

The results presented in Figures 4 and 8 as well as Tables 4 to 6 were used to comprehensively describe the different meanings associated with each of the decision strategies selected. DS-1 was applied for decision-making concerning minimal risks in RPSS problems or other GIS-MCDA applications. It was observed in the *AND* (risk averse) position of the risk continuum in Figure 4 with the α value recorded to be 0 and this showed that there was no trade-off. Moreover, the DS-1 combination produced a minimum suitability score for the entire study area because only one factor, with the smallest value in each pixel, was considered in the aggregation process and the maximum score was 151.45 as presented in Figure 8a. This trend showed that DS-1 identified only a small portion as the appropriate location while the rest was declared unfeasible.

DS-2 was proposed for a situation when a low level of risk with some trade-off was desired as presented in Figure 4. The results showed that the aggregation produced a maximum score of 171.96 as presented in Figure 8b. This led to the production of more locations with higher suitability than DS-1 but lower than DS-3 as listed in Table 6. Meanwhile, DS-3 was observed to be identical to the WLC method because the level of risk was between the minimum and maximum, leading to a decision with average risk and maximum trade-off (ω) as presented in Figure 4. This was achieved using 2 sets of ordered weights determined at α = 0.5 and maximum trade-off values of 2.08 and 1.39, respectively, in Table 4. The results showed that DS-3 provided a full trade-off between factors with each having an effect proportional to the weight. The maximum score produced by DS-3 was 199.57 and the aggregation generated more locations with higher suitability than DS-2 but lower than DS-4 as presented in Table 6.

Decisions with high risk and some trade-offs were represented by DS-4 with sets of ordered weights applied using the risk value (α) between 0.5 and 1. Moreover, 2 sets of ordered weights were used for αn at 0.75 as a representative. The values of the related optimum trade-off (ω) were the same as those used for DS-2 which were 1.77 and 1.45 for EFG and SFG respectively as presented in Table 4. The maximum score produced was 225.33 as presented in Figure 8d which led to the generation of more locations with a higher suitability than DS-3 but lower than DS-5. Furthermore, DS-5 was applied for risk-taking problems in the SMCSS model by placing

Table 5. The OWA final suitability score range is based on decision strategy

Decision point/ strategy (DS) of OWA	Degree of *OR*ness (*a*)	Suitability score range	Presented in:
DS-1	0	0.25 - 151.45	Figure 7 a)
DS-2	0.25	15.18 - 171.96	Figure 7 b)
DS-3	0.5	56.73 - 199.57	Figure 7 c)
DS-4	0.75	102.66 - 225.33	Figure 7 d)
DS-5	1	173.77 - 255.00	Figure 7 e)

Table 6. Area of each category for the suitability class and decision strategy

Suitability Class	Unit	DS-1 (a = 0)	DS-2 (a = 0.25)	DS-3 (a = 0.5)	DS-4 (a = 0.75)	DS-5 (a = 1)
Low suitability	ha	1472.68	8960.52	0.00	0.00	0.00
	%	9.09	55.28	0.00	0.00	0.00
Moderate suitability	ha	113.93	6810.43	5230.75	0.37	0.00
	%	0.70	42.01	32.27	0.00	0.00
High suitability	ha	9.68	430.49	9004.75	2698.26	0.00
	%	0.06	2.66	55.55	16.65	0.00
Very high suitability	ha	0.06	8.18	1974.13	13510.99	16209.63
	%	0.0004	0.05	12.18	83.35	100.00
Alternative with value = 0	ha	14613.27	0.00	0.00	0.00	0.00
	%	90.15	0.00	0.00	0.00	0.00
Total	Ha	16209.63	16209.63	16209.63	16209.63	16209.63
	%	100.00	100.00	100.00	100.00	100.00

Table 7. Similarity test results

Site Selection Model	The identities of the compared map pair	Kappa value
OWA aggregated MCSS Model	DS-1 and DS-2	0.2442
	DS-2 and DS-3	0.4226
	DS-3 and DS-4	0.4223
	DS-4 and DS-5	0.4227

the OR in the risk continuum as presented in Figure 4. A maximum ordered weight of 1.0 was provided for the factor with the highest suitability value for each alternative pixel to produce the maximum score of 255 for the entire study area as presented in Figure 8e. The results showed that DS-5 provided the most alternatives with a very high suitability level in the study area as presented in Table 6.

The sensitivity of the model was further examined through the similarity test conducted on the 5 final site suitability maps (FSSMs) to determine the change in the evaluation results based on the variations in the input parameters. This was through the application of pairwise comparisons to calculate the Kappa index of agreement using the CROSSTAB GIS analysis tool. The results presented in Table 7 showed that all Kappa values were smaller than 0.5, thereby indicating the strengths of the agreement were below moderate level (Landis and Koch, 1977). This signified that the maps were significantly different from each other, leading to the consideration of the model as quite reliable.

4. Conclusion

In conclusion, every decision strategy in the GIS-MCDA model had risk value, and the level was determined using the OWA aggregation method. This was achieved by assessing 5 specific decision strategies at different risk levels including minimum or risk averse, low, medium, high, and maximum or risk-taking, respectively. Decisionmakers could select any of the strategies based on the goals and objectives. It was observed that the third decision strategy in the OWA which was associated with medium risk was similar to the outcome of the popular WLC aggregation method. However, the SA of the GIS-MCDA model using the OWA aggregation was found to be unique compared to the WLC. The uniqueness was based on the ability to alter the inputs at the criteria maps aggregation stage in order to complete the SA procedure which was expected to be followed by the evaluation of the results. This procedure was applied for the SA of the SMCSS model with the OWA aggregation method used in selecting retention pond locations. Furthermore, the results were evaluated by measuring differences in range, area, and similarity among the several model results. It was observed that the changes in the 5 inputs led to significant differences in the results of the model, indicating the SMCSS model developed was sensitive and reliable.

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