Article

A Fuzzy Logic-Based Approach for Modelling Uncertainty in Open Geospatial Data on Landfill Suitability Analysis

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Abstract: Besides OpenStreetMap (OSM), there are other local sources, such as open government data (OGD), that have the potential to enrich the modeling process with decision criteria that uniquely reflect some local patterns. However, both data are affected by uncertainty issues, which limits their usability. This work addresses the imprecisions on suitability layers generated from such data. The proposed method is founded on fuzzy logic theories. The model integrates OGD, OSM data and remote sensing products and generate reliable landfill suitability results. A comparison analysis demonstrates that the proposed method generates more accurate, representative and reliable suitability results than traditional methods. Furthermore, the method has facilitated the introduction of open government data for suitability studies, whose fusion improved estimations of population distribution and land-use mapping than solely relying on free remotely sensed images. The proposed method is applicable for preparing decision maps from open datasets that have undergone similar generalization procedures as the source of their uncertainty. The study provides evidence for the applicability of OGD and other related open data initiatives (ODIs) for land-use suitability studies, especially in developing countries.

Keywords: GIS; remote sensing; open data; open government data; uncertainty; fuzzy logic; suitability analysis; landfill modeling; developing countries

1. Introduction

A major bottleneck of suitability studies is the availability of data suitable to generate representative and sufficient criteria that satisfy the area's local characteristics under investigation. Criteria requirements for a given study problem and data availability for the proposed criteria are two very challenging questions to be answered in developing countries that fall short of financial resources to acquire commercial data. Hence, the need for assessing the applicability of various local and global data sources that are freely available in these regions cannot be overemphasized.

Even though satellite data have been the primary source for mapping and monitoring the earth's features [1,2], integration of multiple data sources results in higher completeness concerning geometric,

spatial, temporal and thematic coverage and quality [3–5]. The urge to explore various open data sources to capture local characteristics has prompted a more in-depth exploration of two available data sources—Open Street Map (OSM) and open government data (OGD).

OSM is one of the prominent free Volunteered geographic information (VGI) data sources common in developing countries. Some recent works in different research domains have shown interest in using these data [6]. Government Data (GD) is another precious resource whose potential is yet to be explored for suitability studies, especially in developing countries. OGD, as a form of authoritative data, is regarded as of higher quality data than VGI [7,8]. Various open government data contain points of interest (POI), which offer a useful reflection of the spatial distribution, spatial pattern, and categories of infrastructures, which are an important source of suitability indicators. The uniqueness of POIs is that a single POI may contain much information compared to common points' features of an ordinary map or point data. POIs data offers a variety of choices to be presented by the same points. However, each of the data sources has its related challenges.

Uncertainty in remotely sensed images is experienced as a mixed pixel problem and intra-class variability, causing difficulty in image classification [9]. In open spatial data, OSM data features and OGD POIs information usually undergo some kind of generalization or simplification to represent actual features on the ground [8,10]. While this is a common practice, OGD data are often more sensitive and often undergo further preprocessing procedures for privacy reasons. Processes such as smoothing and aggregation may introduce errors in the data [7]. Any dataset which has undergone some generalization operations experience either spatial or attributes transformations or both [11]. Therefore, suitability maps derived from these data will possess some degree of uncertainty. Generally, every type of data has some degree of uncertainty, but open datasets suffer the most as they have great variations in quality and modeling schemes applied. The integration of these data for land-use suitability studies requires a reliable approach to work with them. This paper will focus more on circumventing uncertainty in suitability layers derived from OSM and OGD datasets.

Considering the issues revealed above, this paper relies on fuzzy logic theories to derive meaningful suggestions for modeling suitability layers from open data sources for application in areas with insufficient data. Fuzzy set theories are chosen to model fuzzy regions' imprecision in criteria maps derived from the open data. According to [10,12–14], fuzzy logic can be useful to model inexact and data with imprecise boundaries. The model will integrate OGD, OSM with other remote sensing products. In this paper, we use landfills as a case study research; however, the proposed approach will also apply to other land-use suitability studies. The accuracy of our case study's final suitability map was evaluated by using the Google earth map system, and ground surveys in Dodoma, the capital city of Tanzania.

2. Materials

2.1. Case Study

This study will use landfill suitability analysis as a case study to analyze and evaluate the proposed Model. The study location is Dodoma, the capital city of Tanzania. Dodoma city is located at the center of the country between longitude 35°28′55″ E to 36°6′55″ E and latitude 5°49′49″ S to 6°28′32″ S. The city is 453 km west of the former capital, Dar es Salaam. It covers an area of about 2669 square kilometers, with a total population of 410,956 residents, according to the 2012 census [15]. Dodoma region features a semi-arid type of weather with warm to hot temperatures all year round with a minimum of 13 °C in July [16]. The rainy season is typically between November and April, with an average rainfall of 570 mm, but the city is usually dry the rest of the time [17].

According to national statistics, more than 100,000 tons of municipal solid waste is generated countrywide daily [18]. Dodoma Municipal is estimated to produce 305 tons of solid waste daily, but 67% of waste is improperly dumped, increasing health risks and diseases such as malaria, bacillary,

dysentery, and cholera [19,20]. An estimation of future landfill area for this city derived from cumulative waste volume based on population growth of 20 years (2020–2040) is 2.01 km^2.

2.2. Data Preprocessing

Evaluation criteria for waste disposal site suitability were derived by considering hydro-geological, topographical and social-economical information. Data issuing authorities, names, and web links are as listed in Table 1.

Table 1. Source of data.

No.	Criteria Map	Source
1	Surface water bodies	United States Geological Survey (USGS) Earth Explorer, Landsat 8 Operational Land Imager (OLI)
2	Soil type	Government data
3	Roads	OpenStreetMap (OSM)
4	Railways	OpenStreetMap (OSM)
5	Elevation	Digital Elevation Model (DEM) with 30 m pixel size downloaded from Earth data NASA website
6	Land use land cover (LULC)	United States Geological Survey (USGS) Earth Explorer, Landsat 8 Operational Land Imager (OLI)
7	Slope	Digital Elevation Model (DEM) converted to slope map using GIS
8	Water points	Ministry of Water: Open Government Data (http://wpm.maji.go.tz/, http://opendata.go.tz/)
9	Schools	Ministry of Education: Open Government Data (http://opendata.go.tz/)
10	Health facilities	Ministry of Health: Open Government Data (http://opendata.go.tz/)
11	Lineament density	USGS Earth Explorer, Landsat 8 Operational Land Imager (OLI.)
12	Drainage density	Digital Elevation Model (DEM) with 30 m pixel size downloaded from Earth data NASA website

2.2.1. Digital Elevation Model (DEM)

ASTER global digital elevation model with 30 m resolution from Earth data NASA website was used to extract information on the study area's terrain surface and drainage network. DEM is a useful tool for terrain analysis. We derived terrain attributes such as elevation, slope with the help of GIS software.

Drainage density or stream density is calculated as the total length of all the streams divided by the total area [21]. To map streams correctly, we applied some necessary preprocessing procedures to remove errors, such as filling artificial sinks in the digital elevation models. A stream network was extracted from a digital elevation model (DEM) by using ArcGIS tools such as fill, flow direction, and flow accumulation. Our model takes the stream network raster file as the input parameter in the focal statistics spatial analyst tool to produce a drainage density distribution map in a suitable format ready for further analysis.

2.2.2. Landsat 8 OLI Imagery

Lineament density map is prepared from band-8 of Landsat imagery using different GIS and remote sensing techniques. This band was chosen because it has a higher spatial resolution (15 m). The main steps involved in lineament analysis include lineament extraction, correction, and classification by density. We initially used a computer-aided method to automatically extract lineaments by a LINE module algorithm of PCI Geomatica. After that correction of the lines, a lineament density map was constructed using a line density tool in ArcGIS. A standard method to calculate lineament density is based on the number of lineaments per unit area (number/km^2) [22]. The line density tool calculates a magnitude per unit area from polyline features that fall within each cell's radius. The higher intensity of the lineament feature increases the probability of contaminant movement to the groundwater area [23].

LULC map was another product of Landsat 8 image analysis, which resulted from the classification results of four classes, namely built-up, waterbody, thick vegetation, and bare land or light vegetation. As each band file is provided unlayered in GeoTIFF output format, the band 2, 3, and 4 layers stacked in ERDAS Imagine, then clipped to contain the study area. The classification was performed using a combination of ERDAS Imagine and Google Earth system using a maximum-likelihood method. Moreover, we obtained acceptable results with accuracy overall accuracy of 0.83 for land use and land cover classification, with a 0. 77 kappa value.

2.2.3. OpenStreetMap (OSM) Data

Current literature on evaluating temporal accuracy, up-to-datedness, and lineage quality parameters of OSM data suggests that Tanzania OSM datasets are of higher quality in cities than in peripheral areas [24]. Furthermore, [25] concluded the completeness and positional accuracy of OSM road network datasets of Tanzania.

OpenStreetMap (OSM) was found to be the most mature and reliable crowdsource data in the region for this kind of data [24]. Hence, it was proposed to be the source of roads and railway network data. The datasets are a simplified representation of highways and railways as polylines. The data were downloaded via the QuickOSM tool in QGIS. Our road network layer, in this work, is a result of a merging of four OSM roads of several categories, which include highway trunk layer, highway secondary layer, highway tertiary layer, and highway turning circle layer of Dodoma city. The resulted layers were exported into a shapefile for further suitability analysis with other criteria in ArcGIS software to produce the final output map.

2.2.4. Open Government Data (OGD)

The majority of open government data (OGD) in developing countries remains mostly untouched in geospatial applications. This study acquires open government data from Tanzania's official websites, as shown in Table 1. In this resource, we are interested in spatial information that can help us filter sensitive areas that should be excluded from landfill siting. Therefore, we will consider open data issued by the Ministry of Water, the Ministry of Health, and the education sector.

OGD data are coming from trusted sources, unlike VGI. An official data source is a repository of valid or trusted data originated and is maintained by an appropriate governing body [26]. However, it is necessary to understand the reliability of these data sources for different stakeholders' intended use. Based on the literature, these data often undergo some preprocessing, such as smoothing and aggregation, for privacy reasons [7]. We would like to know if this phenomenon exists in our proposed datasets.

Summation of location deviation assessment between open and reference data returns a nonzero value proving that some shift exists in the open datasets. Points in polygon assessment is another approach for measuring uncertainty in vector data [27]. It shows a 75% chance of open data points to fall within the convex polygons of the reference data set. The majority of the points along boundaries are most likely to fall slightly outside of the polygons. The assessment shows a higher possibility that some smoothing procedures have taken place and introduced some uncertainties in the open dataset. However, both datasets (open and reference data) present a similar distribution pattern. Furthermore, there is no evidence of an aggregation procedure taking place in the open dataset; this helps preserve the public dataset's quality to some extent. Hence, these datasets will be useful for screening sensitive areas, and this paper proposes a reliable approach to work with them.

Waterpoints datasets contain POIs with many attributes, but for this study, we are interested in latitude, longitude, source type (wells, borehole, etc.), and water extraction methods. Due to variation of information, suitability requirements for water points should be determined based on more than one factor, such as coverage of the population served and source type information. These factors should be compared to assess constraint values for this layer. These aspects demonstrate the diverse nature of POIs data.

In the education sector, we extracted information about primary and secondary schools only. Therefore, the school dataset is a joint set of primary and secondary school data. Another resource is health facilities with fields like facility name, location, facility type (clinic, dispensary, health center, or a hospital) and their operational status. All healthy facility categories were treated the same.

The proposed datasets were downloaded and prepared accordingly. General steps for data preprocessing include filtering, merging, changing the coordinate system, and validate if data falls within the required region. Export them from.csv file to shapefile format for further analysis.

2.2.5. Other Government Data Sources

The last criteria added include soil media classes, which were defined and rated accordingly to their ability to transfer pollutants into the vadose zone. A review of the literature suggested that a landfill be placed in an area with a sufficient supply of heavy soil clay and fine-grained soils due to their low permeability [28–30]. Thus, this work assigns higher rates of clay related soils. Clay soil types were given higher rates due to their low permeability characteristics, as described in the literature. This fact accords with findings supporting the use of clay soil as a natural material landfill liner and as a cover material in most countries [31,32]. Hence, placing a landfill in an area with a good supply of such soil will minimize the facility's operational cost and protect underground water.

3. Methods

We develop a fuzzy logic model in three stages, standardization of fuzzy maps, aggregation, and defuzzification.

3.1. A Fuzzy Logic Approach for Criteria Standardization

3.1.1. Transition Boundaries

Determining appropriate transitions and boundaries values for membership functions can be done either with experts' knowledge (semantic import approach) or from cluster analysis with fuzzy k-means [33]. The semantic import (SI) approach is often utilized when the analyst has a good, general sense of where to put the boundaries between classes but has difficulty with the precision associated with these boundaries [34], as is the case in our study. Several research experts and international organizations have suggested landfill constraint requirements. Therefore, instead of relying on a single source of information, we review a collection of reference materials and define common class boundaries for landfill siting criteria. Reviewed references include journal articles, books, international guidelines, and reports, which were added in Mendeley software to simplify searching of information within the text. Appendix A1 contains a summary of the search results.

A common observation is that majority of the restrictions are expressed in vague linguistic terms of assessment, such as *about x km far from*, *at least x km, close to x*, etc. These are loosely defined boundaries.

3.1.2. Selection of Fuzzy Membership Functions (MFs)

First, we develop metrics for measuring fuzzy regions. Other layers will be evaluated based on distance, except for layers with continuous values like elevation, drainage density, and slope. Therefore, we first calculate Euclidean distance grids for POIs for schools, water points, and OSM roads and railways. A raster-based GIS is used for data representation and as a modeling platform.

Among possible choices, linear membership functions such as triangular or trapezoidal shapes are simple to implement and fast for computation [35,36]; hence, we consider them as a first choice whenever found fit to represent a scenario. Moreover, a trapezoidal fuzzy number can capture the vagueness of those linguistic assessments (Figure 1). For example, a *far* linguistic variable for proximity or distance will be represented by a left-side trapezoidal (LST) fuzzy number for school, waterpoints suitability maps. Therefore, we propose:

- a left-side trapezoidal (LST) fuzzy set if the fuzzy area is located in the left part of the support
- a right-side trapezoidal (RST) fuzzy set if the fuzzy area is located in the right part of the support;
- a full trapezoidal (T) fuzzy set if the fuzzy regions rise towards a certain range around a middle maximum value;
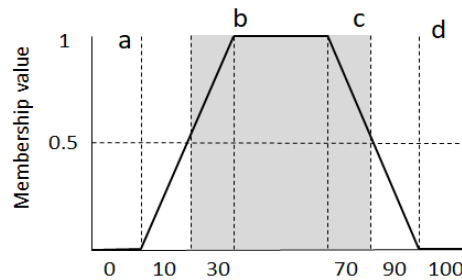- a discrete fuzzy function (D) for discrete fuzzy sets.

Figure 1. Linear membership function (source: [12]).

If the universe is discrete (D), a membership function can be defined by a finite set as follows [37]:

$$A = \sum \mu_i / x_i \tag{1}$$

where the symbol/separates the membership degrees from the elements of the universe $x_i \in X$.

The linear membership function has four parameters that determine the shape of the function. By choosing proper values for *a*, *b*, *c*, and *d* in Table 2, we can create LST, RST, and T membership functions.

$$\mu_A(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & b < x < c \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & x > d \end{cases} \tag{2}$$

3.1.3. Modification of Open Data Membership Functions

Since OGD POIs and OSM data have undergone some generalization procedures such as smoothing and simplification, we expect some spatial transformation of these features. To account for the uncertainty in feature boundaries, we propose the addition of modifiers such as *"very"* and *"somewhat"* to arrive at a more accurate representation of the scenarios. In the landfill modeling process, the boundary which matters most is that of a narrower protection zone because it is the minimum limit that must be observed.

For example, let us consider the school's layer with a minimum protection boundary of 300 m. Because of a little shift (or some uncertainty) in data, we are not very sure if, at 300 m distance, the school will actually have a 300 m protection zone on the ground, or maybe it will be so at 305 m or 310 m. Therefore, we discourage areas towards a narrower boundary through weakening modifiers.

A modifier *"somewhat"* reinforces, while *"very"* is a fuzzy hedge that reduces an area's suitability membership value (Figure 2a,b). Raising a fuzzy set to the second power is an operation called CONCENTRATION, which is taken to be equivalent to linguistically changing it through the modifier *very* (Figure 2a,b). Likewise, taking a square root of a fuzzy set is a procedure called DILATION, which is useful for representing a *somewhat* analytical modifier [38–40]. Such modifiers are also referred to as hedges [12].

Table 2. Suggested membership function for landfill decision criteria.

		Criteria	Boundary Parameters [1]				Type of Fuzzy Set
			a	*b*	*c*	*d*	
Landfill Siting Suitability	Socio Economical	Schools	0.3 km	3 km	n/a	n/a	LST
		Health facilities	0.3 km	3 km	n/a	n/a	LST
		Water points	0.2 km	2 km	n/a	n/a	LST
		Roads	0.05 km	1 km	4000 m	Avg distance [4]	T
		Railways	0.3 km	1.5 km	n/a	n/a	LST
		Urban centers	0.15 km	5 km	n/a	n/a	LST
	Geo-Hydrological	Surface water	0.305 km	2 km	n/a	n/a	LST
		Lineament density (m/m^2)	n/a	n/a	0.3	0.49	RST
	Topographical	Elevation (m.a.s.l.)	936	1070	1478	1964	T
		Slope (degree)	n/a	n/a	10	15	RST
		Drainage density (m/m^2)	n/a	n/a	50	76	RST
	Land Cover	Soil type	{0.2, 0.4, 1} [2]				D
		LULC	{0, 0, 0.6, 1} [3]				D

[1] boundary parameters are based on narrower and wider protection boundaries in Appendix A1). [2] listed in the order: more porous soil, low clay soil, higher clay related soil type. [3] listed in the order: built-up, waterbody, thick vegetation, low vegetation/bare land. [4] Average distance from the city center.
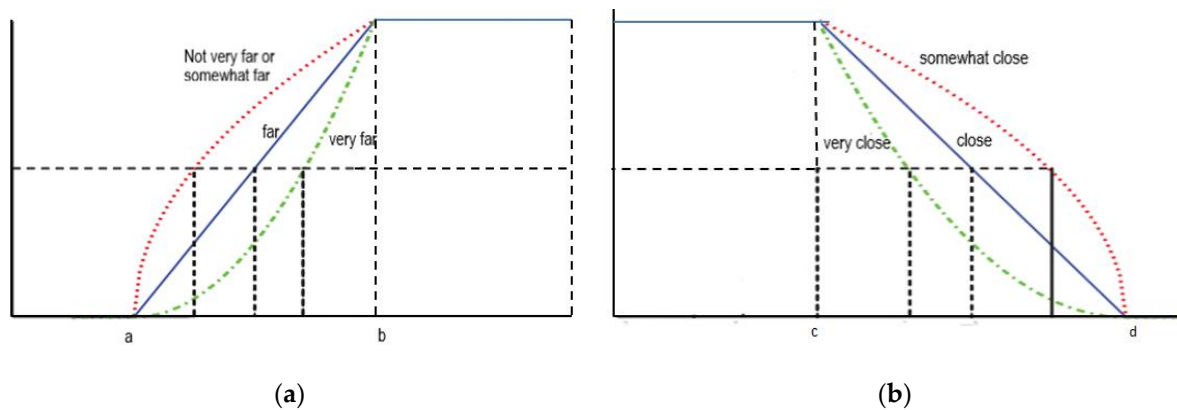

(a)　　　　　　　　　　　　　　　　　　　(b)

Figure 2. Reinforcing and weakening modifiers in fuzzy hedges (Source: [40]).

Dilation:

$$\mu_{dil(A)}(x) = \mu_A{}^2(x) \tag{3}$$

Concentration:

$$\mu_{con(A)}(x) = \sqrt{\mu_A(x)} \tag{4}$$

In our model, we initially proposed a "*far*" linguistic variable for schools, health facilities, water points POIs, and railways, which is represented by a half trapezoidal membership function (LST). Then, through a fine-tuned procedure with a concentration modifier, the fuzzy number function changes from *far* to *very far.* On the other hand, roads were modeled by a combination of "*far*" and "*close to*" membership functions to obtain a fuzzy trapezoidal function (T). Now, after modification,

we arrive at expressions such as *"very far"* to increase the fuzziness of a region and make the proposed landfill area far from the road, and *"somewhat close to"* to make the site not very far from a given distance from the roads in order to reduce the cost of developing new routes for longer distances.

3.2. Aggregation Approach

3.2.1. Aggregation Rules

While there are a growing number of aggregation operations available, the choice depends on the model's objectives and its usefulness for analyzing decisions. This model's main goal is to combine decision criteria in a way that facilitates the ranking of the solution based on the risk of exposure for sensitive areas. For this purpose, we propose an ordered weighted averaging (OWA) operation.

Consider a set attribute maps n, *OWA* operators associate a set of order weight v and criterion weight w of an object in ith location. Where order weight for criterion $v_j \in [0,1]$, $j = 1, 2, \ldots, n$, and $\sum_{j=1}^{n} v_j = 1$; criterion weight $w_j \in [0,1]$ and $\sum_{j=1}^{n} w_j = 1$. Moreover, in this work, we apply the AHP model to determine criteria weights. Now, for a set of attribute values $x_{i1}, x_{i2}, \ldots, x_{in}$ at the ith location, the OWA operation is given by [41,42]:

$$OWA = \sum_{j=1}^{n} v_j z_{ij} \tag{5}$$

where $z_{i1} \geq z_{i2} \ldots \geq z_{in}$ is the set of reordered attribute values in descending order [43]. There are several methods suggested in the literature for determining the order weights v_j's, however, in this paper, we focus on the maximum entropy approach [44]. This method makes use of MAXness or ORness (α) and dispersion (ω) to determine optimal order weights for a given set of criteria [43,44]. Moreover, the set of optimal order weights is obtained by solving the following nonlinear programming equations:

Maximize ω:

$$\omega = -\sum_{j=1}^{n} \frac{v_j \ln v_j}{\ln n} \tag{6}$$

Subject to: $\sum_{j=1}^{n} \frac{n-j}{n-1} v_j = \alpha$, $\sum_{j=1}^{n} v_j = 1$, $0 \leq v_j \leq 1$, *for* $j = 1, 2, \ldots, n$. These two measures: ORness (α) and dispersion (ω), allow one to determine the position of an OWA operation on the continuum between the extreme cases from AND and OR operators, as shown in Figure 3. Again, [43] suggests that the range of ORness values can measure a decision-maker's attitude. Optimistic decision strategies take place from 0.5 to 1, and pessimistic plans are for values less than 0.5. In contrast, if the decision committee is neutral towards risk, they set ORness/Maxness value to 0.5. Therefore, OWA provides us with the capability to implement a wide range of different operations by choosing appropriate order weights.
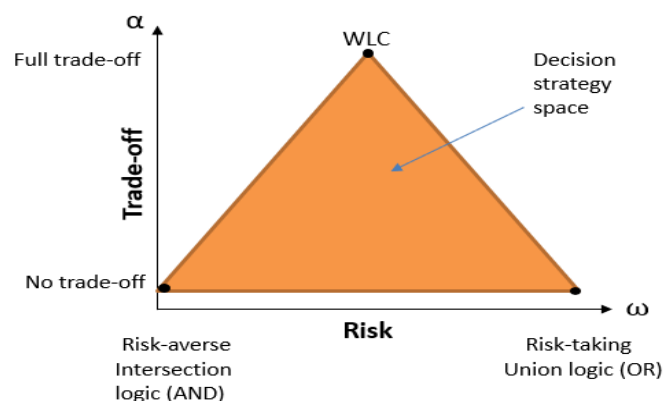

Figure 3. Decision strategy space in ordered weighted averaging (OWA) operations [45].

3.2.2. Criteria Weights

We propose using the analytic hierarchy process (AHP) method to determine the weights of the criteria. According to a literature review, AHP has proved to be a useful technique for generating criteria weights [46–48]. We estimate the criteria in the pairwise matrix based on an evaluation scale of importance from 1 to 9. AHP incorporates a useful technique for checking the consistency of the decision maker's evaluations [49]. The inconsistency of judgment throughout the matrix A can be captured using the maximum eigenvalue, λ_{max} [50]. The closer λ_{max} is to n the more consistent is the result. Saaty [51], proposed the Consistency Index (CI).

$$CI(A) = \frac{\lambda\mathrm{max} - n}{n - 1} \tag{7}$$

The consistency ratio (CR), is the rescaled version of CI. Given a matrix of order n, CR can be obtained by dividing CI by a real number Random Index (RI_n), which is nothing else, but an estimation of the average CI obtained from a large enough set of randomly generated matrices of size n. Estimated values for RI_n are reported in Table 3. RI value was used for this study 1.56 for the 13 criteria (including OGD criteria).

$$CR(A) = \frac{CI(A)}{RIn} \tag{8}$$

Table 3. Values of *RIn* [52,53].

n	1	2	3	4	5	6	7	8	9	10	11	12	13
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56

3.3. Defuzzification of the Output

Results generated in a fuzzy form cannot be applied in an environment where a decision must be taken on crisp values. Several defuzzification methods are known, including lambda-cut, weighted average, maxima, and centroid methods [48,54,55]. This study applies the lambda-cut defuzzification method for given threshold values. Precise thresholds should be determined by the user's requirements concerning output reliability after defuzzification.

Setting an initial suitability threshold μ0 is a common practice and one of the simple decision rules for defuzzification, where μ0 is the minimum grade for suitability classes. A defuzzification threshold of $0.5 < μ0 \leq 1.0$ is sensible [55,56]. The closer the threshold for μ0 is set to 1.0, the more certain and the less fuzzy the derived suitability classes can be regarded. Suitability vector $\vec{\mu} = (\mu_{BR}, \mu_{2nd}, \ldots, \mu_{nth})$ sorted in descending order of suitability, where μ_{BR} representing the best suitable class range with the highest membership degree, μ_{2nd} holds the membership degree of the second-best suitable class, and so on until the nth class. Avoiding the classification of areas less than 0.5 prevents defining areas with maximum fuzziness (uncertainty) as suitable.

4. Results

4.1. Decision Criteria Layers

Figure 4 consists of 13 criteria maps derived from four main sources, as described in Table 1. We can observe a relative variation in a given map's uncertainty increases with decreasing membership values. Therefore, areas with lower membership values are more uncertain (fuzzier) and vice versa. Membership grade values represent suitability values whose range is from 0 to 1.
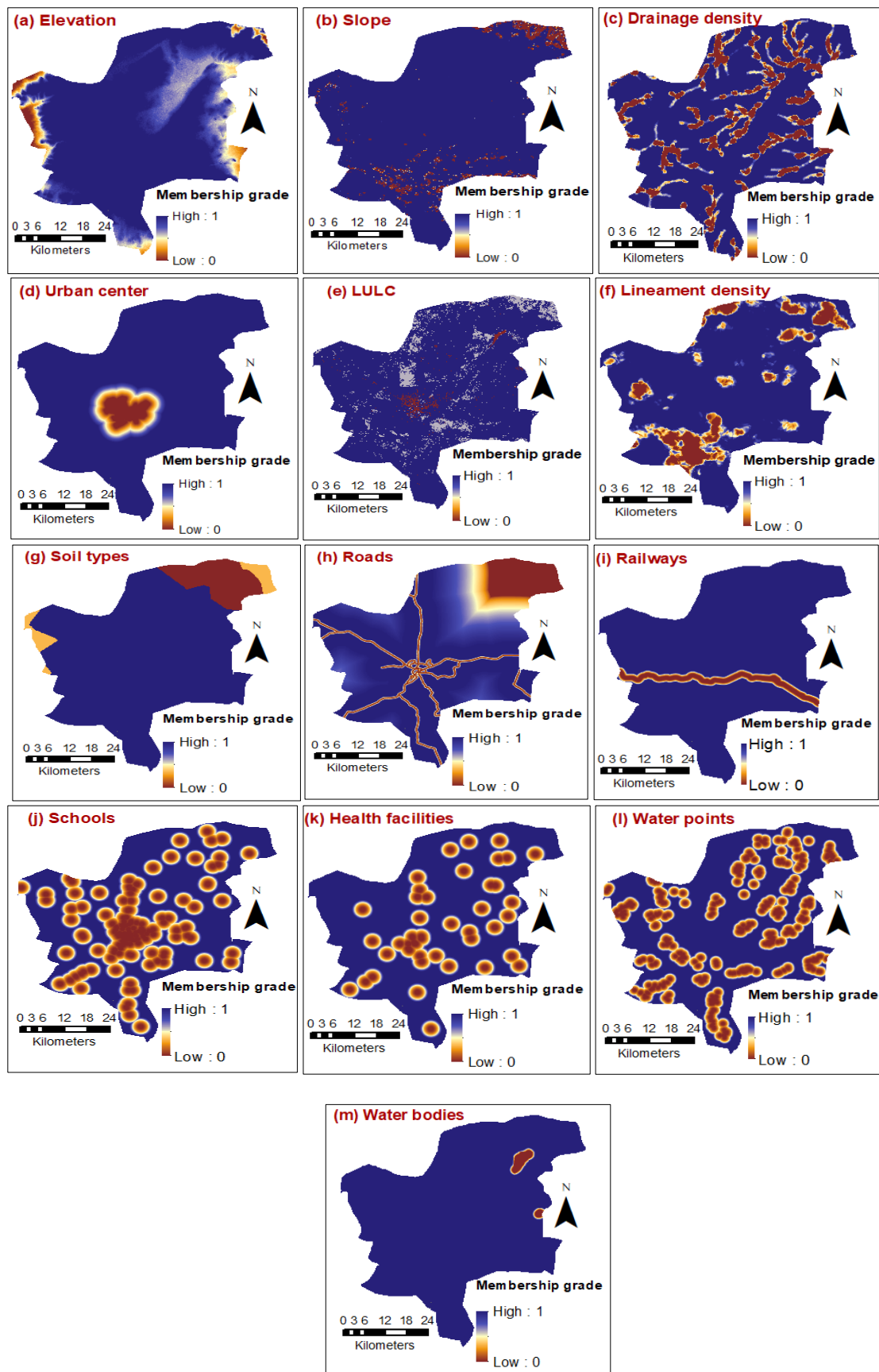
Figure 4. Membership grade of decision criteria (**a**–**m**).

Results show that high elevation areas, high drainage concentration, and steeper slope have lower membership grades; this helps to avoid the risk of accelerating the runoff of pollutants to surrounding areas. In addition, it avoids the difficulty of waste transportation to the site [57]. Areas with very low elevations were also excluded to prevent flood risk. Zones with a higher risk of contaminating surface and underground water have low to zero membership values, including surface water bodies, water points, and higher lineament densities (Figure 4).

Furthermore, fuzziness decreases away from locations with a higher possibility or existence of human settlement or activities. This aspect satisfies the condition that landfills cannot be placed near a human settlement area to protect the general public from potential health hazards [58]. Criteria maps representing this phenomenon include built-up, urban centers, schools, hospitals (health facilities), water distribution points, roads, and railways (Figure 4).

4.2. Aggregation Results

The consistency ratio, CR, was 0.028 for 13 criteria; and the value is within the consistency range (i.e., less than 0.1). AHP pairwise comparison matrix values and weights are as shown in Table 4. OWA offers us a wide range of evaluation for decision criteria. Theoretically, we can obtain an infinite number of aggregation results by continuous adjustment of parameter α. In this study, seven α parameter values were selected 0,0.1, 0.3,0.5,0.7,0.9,1. The derived optimal order weights from these values are shown in Table 5 and their respective suitability maps in Figure 5.

We interpret the suitability of a given location based on its membership value. According, to our proposed defuzzification procedure, areas that can be considered for further suitability analysis are those whose membership grade is greater than 0.5. The more the value is closer to 1, the more suitable it is. It can be observed in Figure 5a–f how the size of a suitable area decreases from (a) to (f) by increasing the value of parameter α. Among the alternative solutions, we choose a low-risk with minimum tradeoff probabilities. In addition, suggested suitability threshold values to include 0.998 for the best results (most suitable), 0.9 for the second-best results (suitable), 0.8 for the 3rd best results (moderately suitable), and so forth.
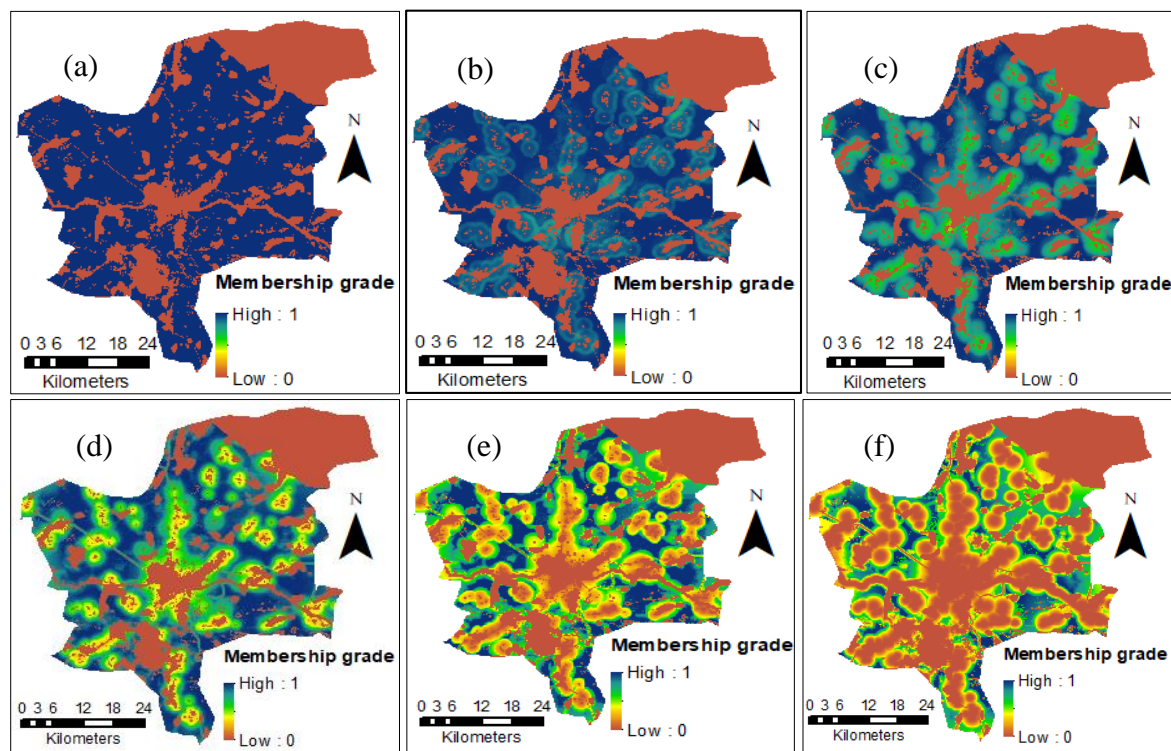
Table 4. A Pairwise comparison matrix.

	A	B	C	D	E	F	G	H	I	J	K	L	M	W_{13}
A	1	1	2	3	3	3	4	5	6	6	7	7	9	0.192
B	1	1	2	3	3	3	3	5	6	6	7	7	8	0.187
C	1/2	1/2	1	2	2	2	3	4	5	5	6	6	8	0.133
D	1/3	1/3	1/2	1	1	1	2	3	4	4	5	5	7	0.090
E	1/3	1/3	1/2	1	1	1	2	3	4	4	5	5	7	0.090
F	1/3	1/3	1/2	1	1	1	2	3	4	4	5	5	7	0.090
G	1/4	1/3	1/3	1/2	1/2	1/2	1	2	3	3	4	4	5	0.062
H	1/5	1/5	1/4	1/3	1/3	1/3	1/2	1	3	2	3	3	5	0.045
I	1/6	1/6	1/5	1/4	1/4	1/4	1/3	1/3	1	1	3	3	4	0.032
J	1/6	1/6	1/5	1/4	1/4	1/4	1/3	1/2	1	1	2	2	4	0.029
K	1/7	1/7	1/6	1/5	1/5	1/5	1/4	1/3	1/3	1/2	1	1	3	0.020
L	1/7	1/7	1/6	1/5	1/5	1/5	1/4	1/3	1/3	1/2	1	1	2	0.019
M	1/9	1/8	1/8	1/7	1/7	1/7	1/7	1/5	1/5	1/4	1/4	1/3	1	0.012

(**A**) surface waterbodies; (**B**) water points; (**C**) urban center; (**D**) schools; (**E**) hospitals; (**F**) LULC; (**G**) roads; (**H**) elevation; (**I**) soil type; (**J**) lineament density; (**K**) slope; (**L**) drainage density; (**M**)-railways; and W_{13}—relative weights for 13 criteria.

Table 5. Optimal order weights (v_j) for selected values of α parameter for n map layers.

Decision Strategy Space	Scenario 1 High Level of Risk, No Tradeoff	Scenario 2 High Level of Risk, Some Tradeoff	Scenario 3 High Level of Risk, Some Tradeoff	Scenario 4 Average Risk, Full Tradeoff	Scenario 5 Low Level of Risk, Some Tradeoff	Scenario 6 Low Level of Risk, Some Tradeoff	Scenario 7 Low Level of Risk, No Tradeoff
v_j \ α	0.0	0.1	0.3	0.5	0.7	0.9	1
v_1	0	0.000322	0.019679	0.076923	0.187611	0.453682	1
v_2	0	0.000589	0.023747	0.076923	0.155473	0.247934	0
v_3	0	0.001078	0.028656	0.076923	0.12884	0.135495	0
v_4	0	0.001973	0.03458	0.076923	0.106769	0.074047	0
v_5	0	0.003609	0.041728	0.076923	0.088479	0.040466	0
v_6	0	0.006605	0.050353	0.076923	0.073322	0.022115	0
v_7	0	0.012085	0.060762	0.076923	0.060762	0.012085	0
v_8	0	0.022115	0.073322	0.076923	0.050353	0.006605	0
v_9	0	0.040466	0.088479	0.076923	0.041728	0.003609	0
v_{10}	0	0.074047	0.106769	0.076923	0.03458	0.001973	0
v_{11}	0	0.135495	0.12884	0.076923	0.028656	0.001078	0
v_{12}	0	0.247934	0.155473	0.076923	0.023747	0.000589	0
v_{13}	1	0.453682	0.187611	0.076923	0.019679	0.000322	0
Dispersion (ω)	0	0.59083	0.91613	1.00000	0.91613	0.59083	0

Figure 5. Alternative decision strategies for suitability of landfill sites (**a**) scenario 1, (**b**) scenario 3, (**c**) scenario 4, (**d**) scenario 5, (**e**) scenario 6, (**f**) scenario 7.

After this, we selected a few potential landfill sites that fall under the most suitable regions. The results were evaluated via Google earth map service system and ground survey method and found to be reliable. All 12 potential site locations (in Figure 6) were found to be far away from the restricted environments for landfill use. Furthermore, during the validation process, we also found out that the most recent landfill site in the city (Chidaya landfill) also falls under the most suitable area class for landfill sites in our final suitability map (Figure 6). Therefore, other areas marked as potential sites

should be reserved for future landfill use as the city is expected to become one of the fastest-growing cities because of the relocation of government seats and its activities to this place.
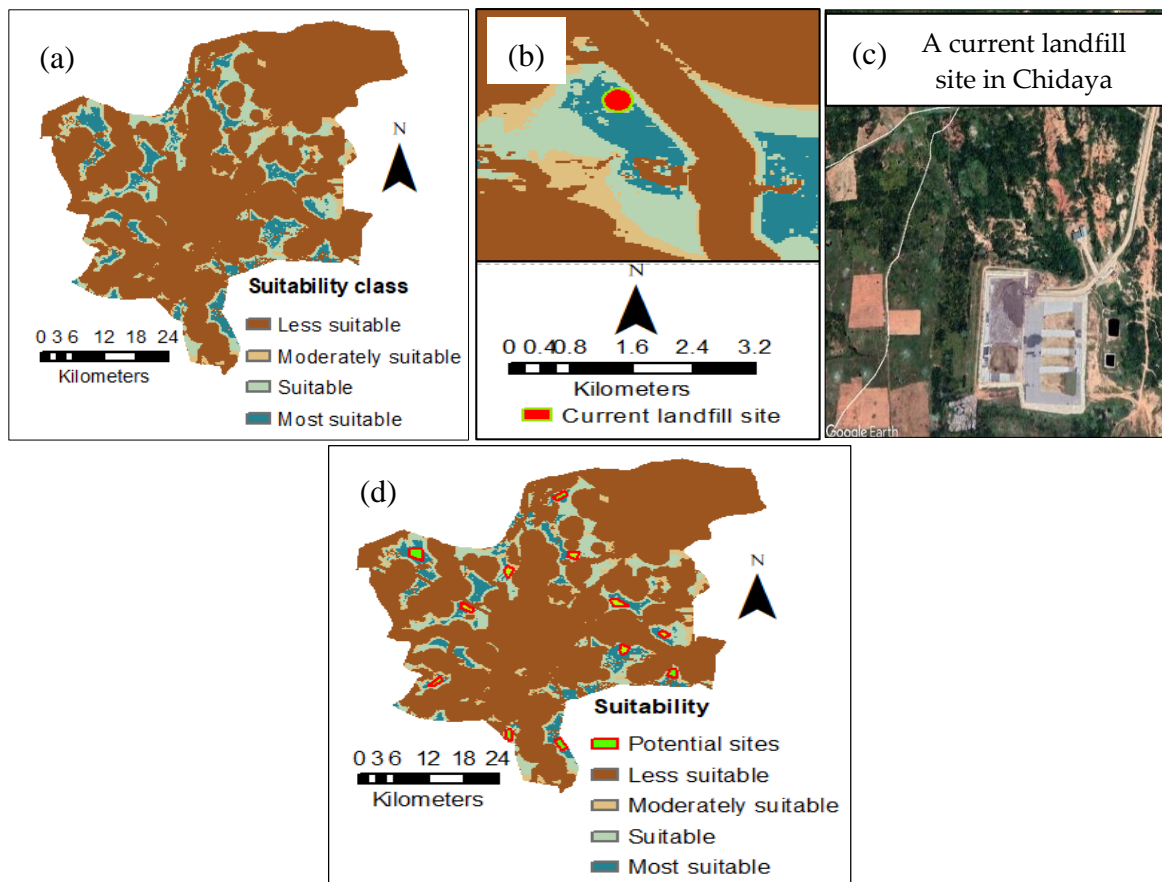

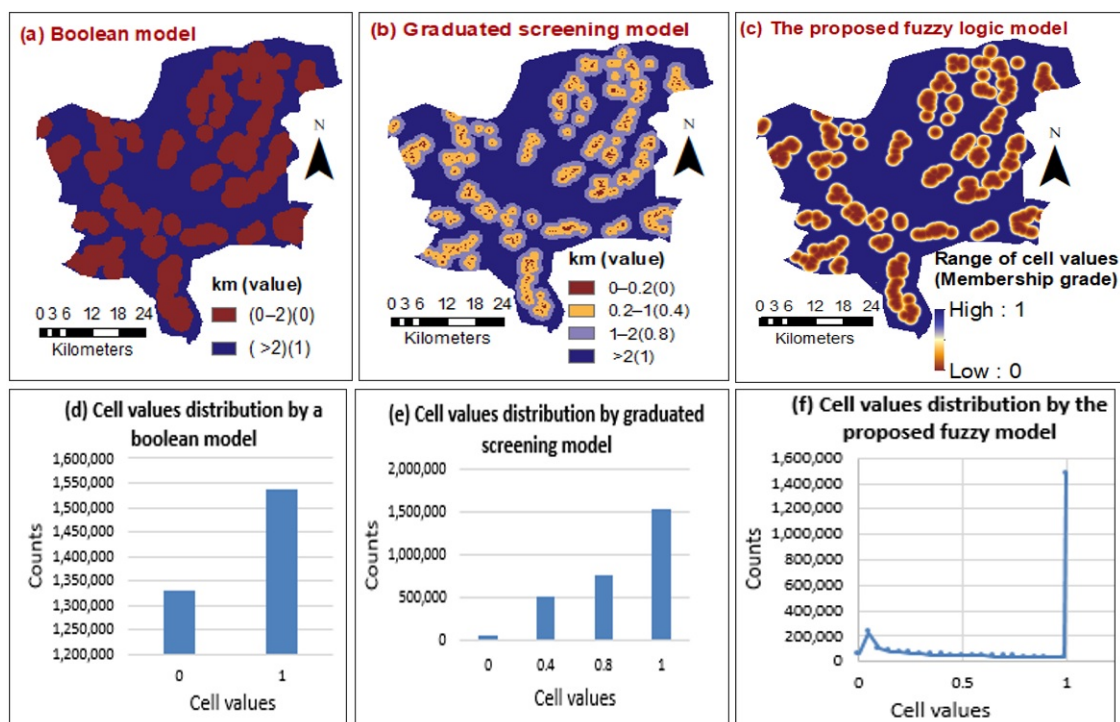**Figure 6.** Final landfill suitability map for scenario 6 where α = 0.9.

5. Discussion

5.1. Modeling of Uncertainties

The vagueness of landfill constraint variables offers a possibility for the accommodation of uncertainties in the decision criteria layers derived from the open data. The initial part of the model applies fuzzy membership functions that define decision criteria' suitability based on transition boundaries. However, to suppress areas with high uncertainty than others, we further degrade their membership values with weakening modifiers. Therefore, areas with high uncertainty values (maximum fuzziness) have very low suitability values, hence excluding them from subsequent considerations.

For example, in Figure 7c,f, we can observe a higher concentration of low membership values towards lower boundary distribution of cell values resulting from the proposed method. Areas whose cells have low membership values are areas with high uncertainty, which has resulted from a fuzzy concentration modifier, which has weakened the fuzziness of regions closer to the narrower protection zone. A similar case applies to schools, hospitals, railways, and water points. However, both weakening and strengthening modifiers were used to prepare a road suitability map. That is why, in Figure 4h, after a given distance, we observe a gradual decrease, not a sharp one, which is caused by *somewhat* a hedge modifier or dilation operation. This modifier reinforces an area's membership closer to the safe and required range, regions with low or no uncertainties.

Figure 7. Map standardization models: (**a,d**) Boolean logic; (**b,e**) graduated screening model; (**c,f**) modified fuzzy membership model.

In comparison with previous standardization procedures, our proposed approach (Figure 7c,f) outweighs the two classical models, namely Boolean logic (also known as pass/fail screening method) and graduated screening procedure. Boolean logic is based on a crisp set that allows only two-values {0,1}; it does not allow ranking. An area can only be considered either *suitable* or *not suitable* [59]. While graduated screening attempts to overcome the ranking problem by introducing multivalued suitability categories, it does not get away with the shortcomings associated with the pass/fail screening approach. Graduated screening converts raw values of a given criterion layer into discrete suitability classes, which replaces one clear-cut boundary (in Boolean logic) into multiple clear-cut boundaries [34]. Both of these two methods assume clear-cut boundaries for geographical phenomena, something which cannot be easily distinguished on many occasions, especially when dealing with imprecision in data.

Fuzzy logic has better capabilities to handle imprecision and uncertainties involved in the suitability evaluation of spatial phenomena [10,60,61]. It can represent the extent to which a geographical aspect belongs to a given class with continuous partial membership values, which range from 0 to 1. Another added advantage of the fuzzy approach is its flexibility, which allows further modification of membership values. It can be observed in Figure 7f that there is a peak between 0 and 0.2, which is a result of dilation operation, which weakens (decreases suitability) of an area closer to the uncertain boundaries. In conclusion, the results suggest that the proposed fuzzy model is more efficient than the Boolean and graduated screening model in map standardization procedures when modeling data with ambiguity or vagueness or uncertainty.
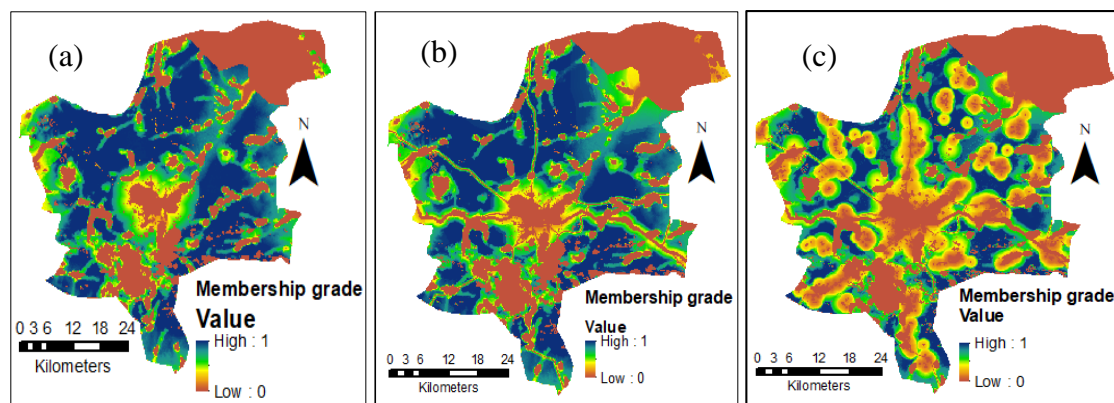
To embrace the benefits of characteristics of the derived criterion layers based on our model, we apply OWA aggregation operations to obtain a combined solution. In contrast, to many multi criteria decision analysis (MCDA) methods, which offer a single solution [49,62], the OWA aggregation rule gives a decision-maker control on risk-level and tradeoff among criteria via order weights in a decision strategy space [34,41,43,48,63]. Hence, it allows us to determine the level of risk, which will influence our final suitability results. A high-risk suitability map can be described as the one which is prepared from less strict rules which allow compensation of high uncertainty values in one layer

by low uncertainty values of another layer. However, a low-risk map is derived with more strict aggregation strategies, which limits compensation of a fuzzier value in one layer with a better value of another layer. A low-risk solution ensures that the final suitability map excludes most of the uncertain areas and therefore avoids the risk of exposure for sensitive areas, which are more likely to be found in fuzzier regions (areas with high uncertainty). Preventing the sensitive regions' exposure is very important, especially for the suitability assessment of undesirable facilities such as a landfill. Different types of land-use applications may consider the results of higher risk.

5.2. Contribution of Open Government Data (OGD)

The ability to model the uncertainties on suitability layers derived from open datasets, including the OGD, provides an opportunity to generate new and useful decision criteria from OGD that are not readily available from other sources, especially in developing countries. In traditional approaches, built-up areas in remote sensing images have been a well-known approach for population estimation. However, the efficiency in capturing this phenomenon is dependent on imagery resolution, which is limited in free satellite images [64]. Population census data are ideal for this task when the data are spatially disaggregated to a household or individual level; however, in most countries like Tanzania, these data are not publicly available for protection reasons [65]. The kind of census data that is made public is aggregated for relatively large administrative units such as regions or districts [15]; we found such data not helpful for spatial analysis on the micro-level. Selected population sensitive POIs such as water points, hospitals, and schools, provide a convenient measure to improve mapping of population distribution (Figure 8a–c).

Figure 8. Comparison of landfill suitability maps (**a**) results without including OpenStreetMap (OSM) and open government data (OGD) data (**b**) results including OSM (**c**) results including both OSM and OGD for scenario 6 where α = 0.9.

Another contribution from OGD datasets is based on the richness of POIs attributes information, which is useful for determining land-use constraints requirements. This kind of information is not readily available in other data sources. For example, buildings detected from remotely sensed imagery tell us less about these buildings' functions or uses. Without this information, it is not possible to enforce the required constraints. Using OGD POIs data, we can obtain such information and refine our results by adding required restrictions to the given points based on their functions, such as schools, hospitals, residential areas, or water source type. For example, water source data shows that about 80% of the water points are built on wells and boreholes. The local POIs data came in handy to enforce distance restrictions to prevent contamination of underground water. Thus, the proposed datasets do an excellent job of spatially distributing the suitability ranking indexes across the entire region, but when we do not use these data, more sensitive areas will be left exposed and classified as suitable (Figures 8a–c and 9).
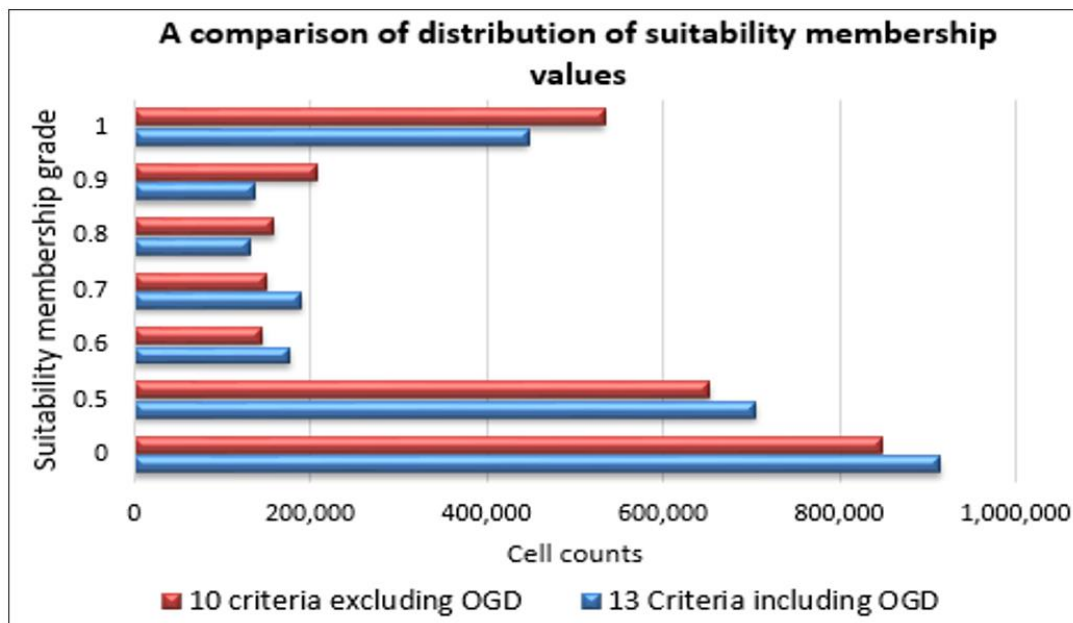
Figure 9. Comparison between landfill suitability maps with and without OGD data.

6. Conclusions

In this big data era, many open data initiatives (ODIs) have taken place and generate many free data. However, each data source has its challenge that limits its use. Local open data such as OSM and open government data (OGD) can assist in sustainable development by providing fine-grained solutions for efficient land-use suitability evaluation. However, these data have some uncertainties issues caused by smoothing and generalization procedures. We applied fuzzy logic theories to generate flexible and useful suitability layers from this type of data. The proposed method is applicable for preparing decision maps from open datasets that have undergone smoothing, generalization, or similar procedures. The approach is more effective for modeling dataset imprecision than traditional Boolean and graduated screening models.

Compared with other landfill suitability studies, this paper introduces OGD as a new data source and has proved to be very useful for landfill suitability analysis. Apart from freely available data like satellite images and DEMs, most of the remaining sources are not readily available or have limited accessibility in developing countries. That is why without the incorporation of OGD datasets, the overall suitability results in this region run a higher risk of leaving more sensitive areas exposed. We can use OGD to create various useful decision criteria to improve the results of our suitability analysis.

This study presents a systematic approach for integrating OGD, OSM, and other free remote sensing products for suitability assessment. This work has used landfill suitability analysis as a case study, but the approach is also applicable to other land-use suitability studies. We believe that this work largely contributes to awareness and provides a stepping stone for other researchers to work with such data. This work has focused more on handling uncertainties in open spatial data; future works will address different sources of uncertainty for layers generated from remotely sensed images.

The open government data movement in Tanzania began in 2014. During this time, similar efforts are observed in other developing countries in Africa, including Rwanda, Uganda, Malawi, Ghana, and Kenya [66]. We hope that this research's contribution brings awareness and stirs up more publications in this area and encourages the Government and individuals to engage more in such initiatives, thus increasing the sustainability of ODIs in these regions. Henceforth, researchers from different countries are encouraged to adapt and replicate the approach developed in this research work for similar studies to explore its generalizability.

Appendix A

Table A1. Landfill constraints' summary.

Criteria	Suggested	Applied (min, max) [1]
Roads	500 m–1000 m [67]; less than 1 km [29]; 50 m [68], 75 m (Chang et al. 2008), 100–500 m [69]	50 m, 1000 m
Railways	1500 m [70]; 300 m [71]; 500 m [66],	300 m, 1500 m
Waterbody	305 m [29]; minimum of 500 m [72]; 500 m to 1250 m [73]; 500 to about 2 km [67]	305 m, 2 km
Elevation	Exclude low and high elevations [74,75]	Exclude low and high elevations
Soil type	More preference for clay related soil [28,29]	High preference for clay soil, exclude high permeable soil
Slope	Allowed to 0 to 15 & exclude areas 15–50 degree [76]; terrains with an inclination of over 30% [74]	Exclude high slope values (15–51)
Drainage density	100 m from high drainage area [29]; far from high drainage network area [69]	Exclude areas with high drainage densities
LULC	150 m from residential [29]; exclude built-up, water bodies, agricultural land [76]	Exclude built-up and water bodies
Water supply points	Explanation of water points (see Section 2.2.4)	200 m, 2 km
Schools	about 300 m [77]; 500 m, 150 m [29]; 3000 m [69]	300 m, 3000 m
Hospitals	about 300 m [77], 450 m [78]; 3000 m [70]	300 m, 3000 m
Lineament density	at least 61 m [29]; 300 m [79]; exclude fault risk regions [75]	Exclude regions with high lineament densities
Urban centers	At least 150 m [29]; at least 1000 m, up to 4000 m [79]; exclude 0–5 km [76];	150 m, 5 km
Residential areas	150 m from residential [29]; 500 m to 2 km [67]; 500 m from dwellings [72]; 500 m or 1.5 km from settlements should be excluded [74]	150 m, 2 km
Underground water resources	300 m [29]; minimum 200 m to more than 1.5 km [74];	200 m, 1.5 km

[1] Min and max refers to the minimum and maximum protection boundaries.

References

1. Sumari, N.S.; Xu, G.; Ujoh, F.; Korah, P.I.; Ebohon, O.J.; Lyimo, N.N. A geospatial approach to sustainable urban planning: Lessons for Morogoro Municipal Council, Tanzania. *Sustainability* **2019**, *11*, 6508. [CrossRef]
2. Huang, H.; Li, Q.; Zhang, Y. Urban residential land suitability analysis combining remote sensing and social sensing data: A case study in Beijing, China. *Sustainability* **2019**, *11*, 2255. [CrossRef]

3. Zhao, L.; Zhang, D. Improving the Accuracy of Fine-Grained Population Mapping Using Population-Sensitive POIs. *Remote Sens.* **2019**, *11*, 2502. [CrossRef]

4. Twumasi, N.Y.D.; Shao, Z.; Altan, O. Mapping built-up areas using two band ratio on landsat imagery of accra in Ghana from 1980 to 2017. *Appl. Ecol. Environ. Res.* **2019**, *17*, 13147–13168. [CrossRef]

5. Shao, Z.; Cai, J.; Fu, P.; Hu, L.; Liu, T. Deep learning-based fusion of Landsat-8 and Sentinel-2 images for a harmonized surface reflectance product. *Remote Sens. Environ.* **2019**, *235*. [CrossRef]

6. Vargas-Muñoz, J.E.; Lobry, S.; Falcão, A.X.; Tuia, D. Correcting rural building annotations in OpenStreetMap using convolutional neural networks. *ISPRS J. Photogramm. Remote Sens.* **2019**, *147*, 283–293. [CrossRef]

7. Ceolin, D.; Moreau, L.; O'hara, K.; Schreiber, G.; Sackley, A.; Fokkink, W.; Robert van Hage, W.; Shadbolt, N. Reliability Analyses of Open Government Data. In Proceedings of the 9th International Conference on Uncertainty Reasoning for the Semantic Web, Sydney, Australia, 21 October 2013; pp. 34–39. Available online: http://www.theodi.org (accessed on 15 May 2020).

8. Stanislawski, L.V.; Buttenfield, B.; Bereuter, P.; Brewer, C. *Abstracting Geographic Information in a Data Rich World*; Springer: Cham, Switzerland, 2014. [CrossRef]

9. Zhang, Q.; Zhang, P. An uncertainty descriptor for quantitative measurement of the uncertainty of remote sensing images. *Remote Sens.* **2019**, *11*, 1560. [CrossRef]

10. Forghani, M.; Delavar, M.R. A quality study of the openstreetmap dataset for Tehran. *ISPRS Int. J. Geo-Inf.* **2014**, *3*, 750–763. [CrossRef]

11. Weibel, R.; Dutton, G. Generalising Spatial Data and Dealing with Multiple Representations. *Geogr. Inf. Syst.* **1999**, *1*, 125–155.

12. Kainz, W. *Fuzzy Logic and GIS*; University of Vienna: Vienna, Austria, 2001; pp. 1–21.

13. Burrough, P.A.; McDonnell, R.A. *Principles of Geographical Information Systems*; Oxford University Press: Oxford, UK, 1998.

14. Sadrykia, M.; Delavar, M.R.; Zare, M. A GIS-based fuzzy decision making model for seismic vulnerability assessment in areas with incomplete data. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 119. [CrossRef]

15. NBS. Tanzania Census Information. National Bureau of Statistics (NBS) Tanzania. 2013. Available online: http://www.dataforall.org/CensusInfoTanzania/libraries/aspx/Home.aspx (accessed on 14 February 2020).

16. Shemsanga, C.; Muzuka, A.N.N.; Martz, L.; Komakech, H.; Omambia, A.N. Statistics in climate variability, dry spells, and implications for local livelihoods in semiarid regions of Tanzania: The way forward. In *Handbook of Climate Change Mitigation and Adaptation*, 2nd ed.; Springer: Berlin, Germany, 2016; Volume 2, pp. 801–848. [CrossRef]

17. Deutscher Wetterdienst. Baseline Climate Means (1961–1990) from Stations All Over the world. Germany's National Meteorological Service. 2016. Available online: https://www.dwd.de/EN/ourservices/climate_data_abroad/klimadatenwelt.html (accessed on 5 February 2020).

18. National Bureau of Statistics. *Tanzania Experience on Compilation of Environment Statistics*; NBS: Dodoma, Tanzania, 2017.

19. Yhdego, M.; Kingu, A. Solid Waste Management in Urban Centers of Tanzania. Leapfrogging Towards a Circular Economy. *Affil. Environ. Resour. Consult.* **2016**, *1*. [CrossRef]

20. Mnyone, G.I.; Juma, M.S.; Mfinanga, F.A. Predicament in adoption of solid waste treatment technologies in developing countries: A Case of Majengo neighborhood in Dodoma City, Tanzania. *Int. J. Latest Eng. Manag. Res. (IJLEMR)* **2018**, *3*, 11–15.

21. Carlston, C.W.; Nolan, T.B. Drainage Density and Streamflow. *Geol. Surv. Prof. Pap.* **1963**. [CrossRef]

22. Hung, L.Q.; Batelaan, O.; De Smedt, F. Lineament extraction and analysis, comparison of Landsat ETM and ASTER imagery. Case study: Suoimuoi tropical karst catchment, Vietnam. In *Remote Sensing for Environmental Monitoring, GIS Applications, and Geology V*; SPIE: Bellingham, WA, USA, 2005; Volume 5983. [CrossRef]

23. Thannoun, R.G. Automatic Extraction and Geospatial Analysis of Lineaments and their Tectonic Significance in some areas of Northern Iraq using Remote Sensing Techniques and GIS. *Int. J. Enhanc. Res. Sci. Technol. Eng.* **2013**, *2*. Available online: www.erpublications.com (accessed on 24 February 2020).

24. Minghini, M.; Brovelli, M.A.; Frassinelli, F. An open source approach for the intrinsic assessment of the temporal accuracy, up-to-dateness and lineage of openstreetmap. *Int. Arch. Photogramm Remote Sens Spat. Inf. Sci. ISPRS Arch.* **2018**, *42*, 147–154. [CrossRef]

25. Jovanovic, S.; Jovanovic, D.; Bratic, G.; Brovelli, M.A. Analysis of free road data in Tanzania, Uganda and Kenya using free and open source software. *Int. Arch. Photogramm Remote Sens. Spat. Inf. Sci. ISPRS Arch.* **2019**, *42*, 1567–1572. [CrossRef]

26. Máchová, R.; Lněnička, M. Evaluating the quality of open data portals on the national level. *J. Theor. Appl. Electron. Commer. Res.* **2017**, *12*, 21–41. [CrossRef]

27. Lowell, K.; Jaton, A. Spatial Accuracy Assessment: Land Information Uncertainty in Natural Resources—Google Books. 2000. Available online: https://books.google.co.in/books?id=Q0hZDwAAQBAJ&pg=PA201&lpg=PA201&dq=Point+to+polygon+assessment+and+results?&source=bl&ots=LWmScAAJyM&sig=ACfU3U1uLCtHG3cfxyciRHBe0c_4NvQUNQ&hl=en&sa=X&ved=2ahUKEwiZxYiV8cjpAhV8zzgGHbYLAOkQ6AEwAnoECAoQAQ#v=onepage&q=Poin (accessed on 23 May 2020).

28. Chang, N.B.; Parvathinathan, G.; Breeden, J.B. Combining GIS with fuzzy multicriteria decision-making for landfill siting in a fast-growing urban region. *J. Environ. Manag.* **2008**, *87*, 139–153. [CrossRef]

29. Yazdani, M.; Monavari, S.M.; Omrani, G.A.; Shariat, M.; Hosseini, S.M. Landfill site suitability assessment by means of geographic information system analysis. *Solid Earth* **2015**, *6*, 945–956. [CrossRef]

30. Josimovi, B.; Mari, I. Methodology for the Regional Landfill Site Selection. In *Sustainable Development—Authoritative and Leading Edge Content for Environmental Management*; InTechOpen: London, UK, 2012. [CrossRef]

31. Williams, P.T. *Landfill Liner Materials. Waste Treatment and Disposal*; John Wiley & Sons: Hoboken, NJ, USA, 2013.

32. Rachael, Z. Clay Remains a Top Choice for Final Landfill Cover. *Waste360*. 2015. Available online: https://www.waste360.com/closure/clay-remains-top-choice-final-landfill-cover (accessed on 18 February 2020).

33. Metternicht, G. Assessing temporal and spatial changes of salinity using fuzzy logic, remote sensing and GIS. *Ecol. Modell.* **2001**, *144*, 163–179. [CrossRef]

34. Qiu, F.; Chastain, B.; Zhou, Y.; Zhang, C.; Sridharan, H. Modeling land suitability/capability using fuzzy evaluation. *GeoJournal* **2014**, *79*, 167–182. [CrossRef]

35. Barua, A.; Snigdha Mudunuri, L.; Kosheleva, O. *Why Trapezoidal and Triangular Membership Functions Work So Well: Towards a Theoretical Explanation*; 2014; Volume 8, Available online: http://digitalcommons.utep.edu/cs_techrephttp://digitalcommons.utep.edu/cs_techrep/783 (accessed on 27 May 2020).

36. Sadollah, A. Introductory Chapter: Which Membership Function is Appropriate in Fuzzy System? In *Fuzzy Logic. Based in Optimization Methods and Control. Systems and Its Applications Many*; InTech: London, UK, 2012; Volume 13. [CrossRef]

37. Wales, N.S. Application of Fuzzy Logic, GIS and Remote Sensing to the Assessment of Environmental Factors for Extensive Brackishwater Aquaculture in Indonesia Tarunamulia A thesis submitted in fulfillment of the requirements for Master of Science School of Biologica. Doctoral Dissertation, University of New South Wales, Sydney, NSW, Australia, 2008.

38. Zadeh, L.A. A fuzzy-set-theoretic interpretation of linguistic hedges. *J. Cybern.* **1972**, *2*, 4–34. [CrossRef]

39. Tsoukalas, L.H.; Uhrig, R.E. *Fuzzy and Neural Approaches in Engineering*; Wiley: Hoboken, NJ, USA, 1997.

40. Sallehuddin, M.H.; Wahab, A.F.; Gobithaasan, R.U. Generalizations of fuzzy linguistic control points in geometric design. In *AIP Conference Proceedings*; American Institute of Physics Inc.: College Park, MD, USA, 2014; Volume 1605, pp. 244–249. [CrossRef]

41. Malczewski, J. Integrating multicriteria analysis and geographic information systems: The ordered weighted averaging (OWA) approach. *Int. J. Environ. Technol. Manag.* **2006**, *6*, 7–19. [CrossRef]

42. Malczewski, J.; Chapman, T.; Flegel, C.; Walters, D.; Shrubsole, D.; Healy, M.A. GIS multicriteria evaluation with ordered weighted averaging (OWA): Case study of developing watershed management strategies. *Environ. Plan. A* **2003**, *35*, 1769–1784. [CrossRef]

43. Yager, R.R. On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decisionmaking. *IEEE Trans. Syst. Man. Cybern.* **1988**. [CrossRef]

44. O'Hagan, M. A fuzzy neuron based maximum entropy-ordered weighting averaging. In *Uncertainty in Knowledge Bases*; Bouchon-Meunier, B., Yager, R.R., Zadeh, L.A., Eds.; Springer: Berlin, Germany, 1990; pp. 598–609.

45. Patrick, R.; Pilling, M.J.; Rogers, G.J. IDRISI Selva Tutorial. *IDRISI* **2012**, *53*, 279–291. [CrossRef]

46. Mierzwiak, M.; Calka, B. Multi-Criteria Analysis for Solar Farm Location Suitability. *Rep. Geod. GeoInform.* **2017**, *104*, 20–32. [CrossRef]

47. Hassan, A.; Almatar, M.G.; Torab, M.; Allen, C.D. Environmental Urban Plan for Failaka Island, Kuwait: A Study in Urban Geomorphology. *Sustainability* **2020**, *12*, 7125. [CrossRef]

48. Sanga, C.; Venter, I. Algorithm for the evaluation of Free and Open Source Software when the Evaluator is "Uncertain". *Int. J. Manag. Sci. Inf. Technol.* **2015**, 36–55.

49. Memarbashi, E.; Azadi, H.; Barati, A.A.; Mohajeri, F.; Passel, S.V.; Witlox, F. Land-use suitability in Northeast Iran: Application of AHP-GIS hybrid model. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 396. [CrossRef]

50. Moutinho, L.; Hutcheson, G.; Beynon, M.J. Analytic Hierarchy Process. *SAGE Dict. Quant. Manag. Res.* **2014**, 9–12. [CrossRef]

51. Saaty, T.L. A scaling method for priorities in hierarchical structures. *J. Math. Psychol.* **1977**, *15*, 234–281. [CrossRef]

52. Isalou, A.A.; Zamani, V.; Shahmoradi, B.; Alizadeh, H. Landfill site selection using integrated fuzzy logic and analytic network process (F-ANP). *Environ. Earth Sci.* **2013**, *68*, 1745–1755. [CrossRef]

53. Chang, C.W.; Wu, C.R.; Lin, C.T.; Lin, H.L. Evaluating digital video recorder systems using analytic hierarchy and analytic network processes. *Inf. Sci.* **2007**, *177*, 3383–3396. [CrossRef]

54. Ross, T.J. Fuzzy relations. *Fuzzy Logic. Eng. Appl.* **2004**, *320*, 117–129. [CrossRef]

55. Hofmann, P. Defuzzification strategies for fuzzy classifications of remote sensing data. *Remote Sens.* **2016**, *8*, 467. [CrossRef]

56. William, S.; Buckeley, J.J. *Fuzzy Expert Systems*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2005.

57. Javaheri, H.; Nasrabadi, T.; Jafarian, M.H.; Rowshan, G.R.; Khoshnam, H. Site Selection of Municipal Solid Waste Landfills Using Analytical Hierarchy Process Method in a Geographical Information Technology Environment in Giroft. *Iran. J. Environ. Health Sci. Eng.* **2006**, *3*, 177–184.

58. Effat, H.A.; Hegazy, M.N. Mapping potential landfill sites for North Sinai cities using spatial multicriteria evaluation. *Egypt J. Remote Sens. Space Sci.* **2012**, *15*, 125–133. [CrossRef]

59. Adhikari, B.; Li, J. Modelling ambiguity in urban planning. *Ann. GIS* **2013**, *19*, 143–152. [CrossRef]

60. Schneider, M. Fuzzy Spatial Data Types for Spatial Uncertainty Management in Databases. In *Handbook of Research on Fuzzy Information Processing in Databases*; IGI Global: Hershey, PA, USA, 2011; pp. 490–515. [CrossRef]

61. Mironova, Y.N. Use of fuzzy sets in modeling of GIS objects. *J. Phys.* **2018**. [CrossRef]

62. Abujayyab, S.K.M.; Sanusi, M.; Yahya, A.S.; Alslaibi, T.M. GIS modeling for landfill site selection via multi-criteria decision analysis: A systematic review. *ACM Int. Conf. Proceeding Ser.* **2017**, 33–38. [CrossRef]

63. Yager, R.R. OWA aggregation of multi-criteria with mixed uncertain satisfactions. *Inf. Sci.* **2017**, *417*, 88–95. [CrossRef]

64. Rasul, A.; Balzter, H.; Ibrahim, G.; Hameed, H.; Wheeler, J.; Adamu, B.; Ibrahim, S.; Najmaddin, P. Applying Built-Up and Bare-Soil Indices from Landsat 8 to Cities in Dry Climates. *Land* **2018**, *7*, 81. [CrossRef]

65. Yu, W.; Wardrop, N.A.; Bain, R.; Wright, J.A. Integration of population census and water point mapping data—A case study of Cambodia, Liberia and Tanzania. *Int. J. Hyg. Environ. Health* **2017**, *220*, 888–899. [CrossRef]

66. United Nations. Unlocking the Potential of Open Government in Africa Policy. In *Legal and Technical Requirements for Open Government Implementation in Africa*; UN Economic Commission for Africa: Addis Ababa, Ethiopia, 2017.

67. Wang, G.; Qin, L.; Li, G.; Chen, L. Landfill site selection using spatial information technologies and AHP: A case study in Beijing, China. *J. Environ. Manag.* **2009**, *90*, 2414–2421. [CrossRef]

68. Baban, S.M.J.; Flannagan, J. Developing and implementing GIS- assisted constraints criteria for planning landfill sites in the UK. *Plan. Pract. Res.* **1998**, *13*, 139–151. [CrossRef]

69. Akinluyi, F.O. A GIS-Based Multi-Criteria Decision Analysis for Landfill Suitability Assessment in Ibadan Metropolis, Southwest, Nigeria. *J. Sustain. Technol.* **2019**, *10*, 130–141.

70. Alfy, Z.E.; Elhadary, R.; Elashry, A. Integrating GIS and MCDM to deal with landfill site selection. *Int. J. Eng. Technol.* **2018**, *10*, 33–40.

71. Akbari, V.; Rajabi, M.A.; Chavoshi, S.H.; Shams, R. Landfill Site Selection by Combining GIS and Fuzzy Multi Criteria Decision Analysis, Case Study: Bandar Abbas, Iran. *World Appl. Sci. J.* **2008**, *3*, 39–47.

72. ISWA. *International Guidelines for Landfill Evaluation*; GPML, 2011; Available online: https://www.gpmarinelitter.org/index.php/resources/information-documents/international-guidelines-landfill-evaluation-2011-international (accessed on 6 December 2020).

73. Uyan, M. MSW landfill site selection by combining AHP with GIS for Konya, Turkey. *Environ. Earth Sci.* **2014**, *71*, 1629–1639. [CrossRef]

74. Yu, C.; Chen, R.; Li, J.J.; Drahansky, M.; Paridah, M.; Moradbak, A.; Mohamed, A.; Owolabi, F.; Habdulwahab, T.; Asniza, M.; et al. Methodology for the Regional Landfill Site Selection. *Sustain. Dev.* **2012**, *13*. [CrossRef]

75. Chabuk, A.; Al-Ansari, N.; Hussain, N.; Hussain, M.; Sven, K.; Roland, P.; Jan, L. Combining GIS Applications and Method of Multi-Criteria Decision-Making AHp for Landfill Siting in Al-Hashimiyah Qadhaa Babylon Iraq. *Sustainability* **2017**, *9*, 1932. [CrossRef]

76. Alkaradaghi, K.; Ali, S.S.; Al-Ansari, N.; Laue, J.; Chabuk, A. Landfill site selection using MCDM methods and GIS in the Sulaimaniyah Governorate, Iraq. *Sustainability* **2019**, *11*, 4530. [CrossRef]

77. Taye, Z.H. GIS and Remote Sensing application in Solid Waste Management and optimal Site suitability assessment for landfill. *Nor. Univ. Sci. Technol.* **2018**, 1–86.

78. Public Health Act. Nuisance and General Sanitation Regulation. Province of Alberta, Canada. 2019. Available online: https://www.alberta.ca/waste-facilities-setbacks.aspx (accessed on 24 April 2020).

79. Randazzo, L.; Cusumano, A.; Oliveri, G.; Di Stefano, P.; Renda, P.; Perricone, M.; Zarcone, G. Landfill Site Selection for Municipal Solid Waste By Using Ahp Method in Gis Environment: Waste Management Decision-Support in Sicily (Italy). *Detritus* **2018**, *2*, 78. [CrossRef]

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