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Optimizing Landfill Site Selection Using Fuzzy-AHP and GIS for Sustainable Urban Planning

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Abstract

Careful landfill selection with minimal environmental impact is vital for urban planners. This study aims to identify suitable sites for controlled landfills using Fuzzy-AHP integrated with Remote Sensing and GIS, considering a 20-year projection of population and solid waste generation. Initially, twelve sub-criteria were identified, grouped into environmental, socio-economic, and physical categories, and then weighted using paired comparison matrices involving nine experts. The sub-criteria were rasterized and classified into four suitability levels. The weighted overlay of sub-criteria maps generated a territorial suitability model. Within the Alto Utcubamba Commonwealth (Amazonas, Peru), 0.069%, 41.70%, 66.934%, 0.20%, and 12.4% of the territory are suitable, moderately suitable, less suitable, unsuitable, and restricted, respectively, for landfill establishment. Subsequently, 16 highly suitable sites were selected based on the required area (S4 polygons ≥ 0.505 ha) in line with the projected solid waste generation over 20 years. Of the 16 selected areas, only 15 met the shape index. The model showed high accuracy (AUC = 0.784) during validation. Furthermore, this study provides a comprehensive framework for making decisions about waste management in developing countries, enhancing understanding of key factors in selecting landfill sites. It also offers a deeper insight into global and local factors that determine the suitability of landfill sites.

Keywords: Landfill Locations; F-AHP; Remote Sensing; Geographic Information Systems; Suitability Model.

1. Introduction

The efficient handling of solid waste is a pressing worldwide issue, given its impact on public health and the environment [1]. Economic and demographic growth, along with urbanization and technological advancements, have

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exacerbated this issue, especially in developing countries [2]. The limited availability of space and other socio-economic dilemmas add complexity to this management, making it a focal point of environmental policies globally [1, 3]. The need to adopt a holistic and sustainable approach to managing solid waste is evident, which implies strategies that include recycling, reusing, and reducing [4]. Despite the prevalence of landfills due to their practicality, the exponential increase in waste threatens their viability worldwide [5], posing a potential global crisis along with environmental degradation. Therefore, it is imperative to adopt advanced technologies to minimize the impact of waste, especially in developing nations, without endangering public health or the environment, in line with the Sustainable Development Goals (SDGs) [6, 7].

Over the years, a variety of techniques have been used for waste disposal, including landfilling, burning, and composting [8]. Among these, landfills are the most prevalent because of their straightforwardness, affordability, and lower environmental effects [9–11]. Nonetheless, the careful choice of landfill sites is vital for efficient waste management and the development of sustainable infrastructure [12, 13]. Identifying optimal landfill sites is essential to ensuring sustainable development, which requires a detailed analysis of geographical, sanitary, economic, and physical variables [14]. These factors include topography, geology, land use, climate, proximity to urban areas, and major communication routes [7]. The careful choice of these locations is fundamental to minimizing negative impacts and ensuring safe waste disposal [3].

Lately, several methods of multi-criteria analysis have been utilized for the selection of landfill sites [15]. These methods include Analytical Hierarchy (AHP), the Preference Ranking Organization Method (PROMETHEE), and fuzzy TOPSIS, among others [5, 16–19]. Among them, the FAHP has gained prominence in decision-making related to waste management [20]. Despite the limited number of studies that have combined GIS and Fuzzy-AHP for the selection of landfill sites [2, 9, 15, 21–24]. Advancements in technology have made it easier to combine multi-criteria decision-making with Geographic Information Systems (GIS) and remote sensing for assessing potential landfill sites [25, 26]. Specifically, the Fuzzy-AHP has demonstrated its effectiveness in handling uncertainty and subjectivity in environmental decision-making [10, 22, 24]. Its capacity to transform linguistic variables into a measurable scale offers a flexible method for qualitative data [10, 24]. By integrating fuzzy set theory with GIS, potential landfill locations can be evaluated based on multiple criteria [2, 9, 10, 23, 27, 28].

In Peru, there is a technical standard that outlines the procedure and variables to consider for the selection of landfill sites, especially in the Amazon region, where the application of new tools in land use planning presents an opportunity for sustainable development with minimal impact. In this context, a preliminary study was conducted for the Chachapoyas-Huancas Commonwealth, using criteria adapted to the local reality and evaluating them according to the technical requirements established by Peruvian regulations. Likewise, in the Alto Utcubamba Commonwealth (AUCo), the suitability of the territory was assessed through the analysis of multiple criteria and compared with the community's current landfill. Variables such as quantity, Per Capita Generation (PCG), and population growth rate were considered to evaluate the suitability of the landfill through a multi-criteria analysis and compare it with the existing landfill in the commonwealth. Additionally, the Receiver Operating Characteristic (ROC) curve, a proven effective method in this field of research, was employed to assess the effectiveness of the final suitability model.

The literature review highlighted that most previous studies overlooked population growth and the projection of municipal solid waste generation. Generally, they focused on defining different criteria, performing pair comparisons using a model, and assigning weights to the layers of the problem to determine the suitability of the location map for landfills through the algebraic sum of the map weights. Despite the absence of research into the spatial and temporal aspects of population growth as a crucial part of managing municipal solid waste, the decision to place landfills in areas where the cities are physically expanding can result in environmental and financial issues. Therefore, this study incorporates population growth over a 20-year period and its future projections, in addition to the aspects mentioned in previous research.

The AUCo, comprising seven rural districts in the Amazonas region of Peru, is notable for its biodiversity, hosting numerous endemic species of flora and fauna. With the aim of promoting sustainable development through productive and tourist activities, it seeks to improve the quality of life of its inhabitants. Although the AUCo has an operational landfill in the Durazno Pampa district, most of the waste is disposed of in illegal landfills due to the imminent capacity limit of the current landfill. Therefore, it is imperative to identify new areas for controlled final waste disposal in the AUCo.

This study identifies the best potential sites for future solid waste landfills in the AUCo using a Fuzzy-AHP and GIS-based approach. This methodology involves the integration of spatial data, quantitative analysis, environmental regulations, and technical criteria. A five-phase procedure was used to assess the criteria and sub-criteria, generate criteria and sub-criteria layers through GIS, weigh the significance of the criteria and sub-criteria via MCDA-FAHP, create a suitability model, and evaluate the most appropriate sites based on future area and shape needs, taking into account population growth and projected municipal solid waste generation. This scientific approach provides a grounded and reproducible methodology that can be applied in other local and regional studies, thus contributing to waste management in the AUCo.

2. Material and Methods

2.1. Study Area

The Commonwealth spans a region of 106,625.1 km^2, is located on inclines reaching up to 77.6°, and has an altitude that varies between 1,817 and 4,275 meters above sea level (m.a.s.l) (Figure 1). Its administrative boundaries are as follows: to the North (N), it borders the districts of Longuita, Trita, and Magdalena; to the South (S), it borders the regions of San Martín and La Libertad; to the East (E), it borders the districts of María, Cocabamba, Balsas, and Chuquibamba; and finally, to the West (W), it borders the districts of Limabamba and Cochamal.

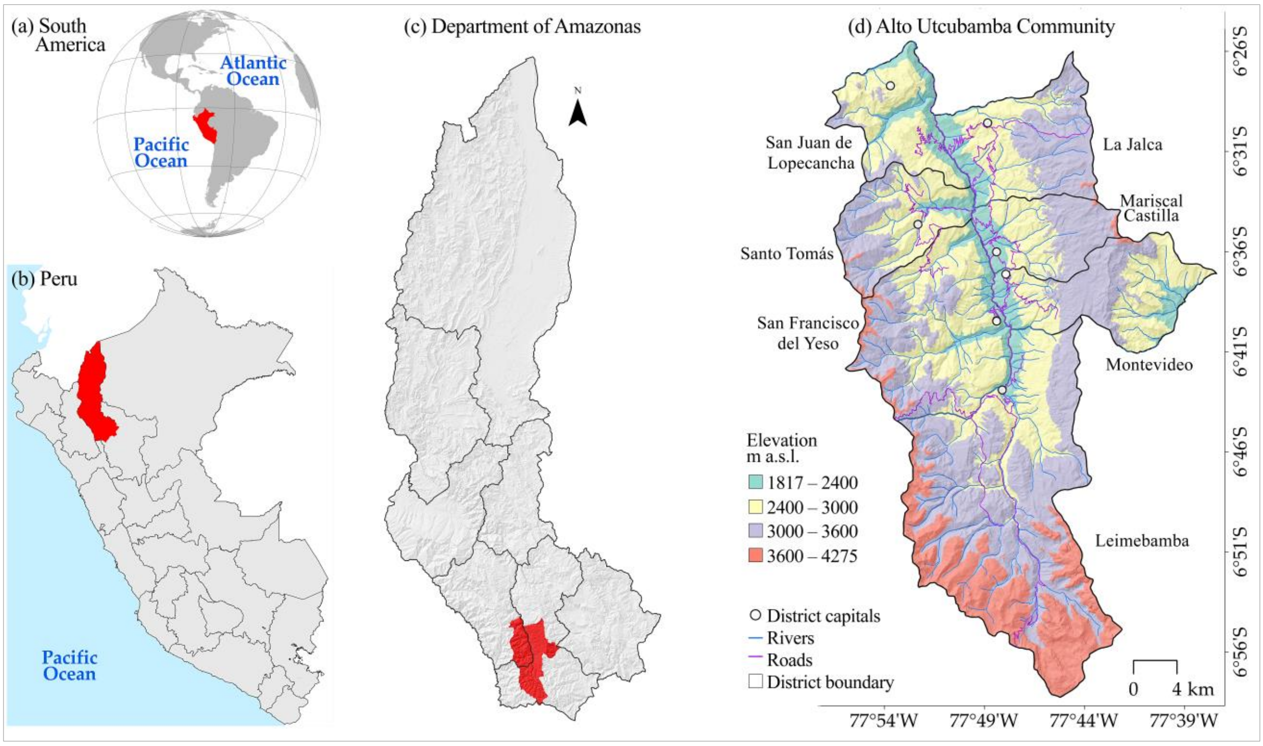


Figure 1. The geographic location of the AUCo is a) Peru, which contains the Amazonas region; b) the Amazonas department, which contains the AUCo; and c) AUCo

2.2. Methodological Process

Figure 2 illustrates the procedure for identifying suitable sites for installing a landfill. To do so, criteria and sub-criteria determining the landfill location were identified through a literature review of research and Peruvian legal regulations. Sub-criteria layers were then constructed by accessing free GIS information portals. The layers for each sub-criteria were also reclassified using GIS and suitability thresholds generated through a literature review. At the same time, the significance of the criteria and sub-criteria was evaluated using a pairwise comparison matrix via Fuzzy-AHP, which included a panel of experts to ascertain the importance weights. Ultimately, the territorial suitability model was derived from the weighted overlay of maps according to their importance. The most suitable sites were evaluated considering area and shape requirements, taking into account the projected lifespan of the landfill and population.

2.3. Hierarchical Structure Construction

The initial process involved constructing a Fuzzy-AHP model that encompasses objectives, criteria, sub-criteria, and alternatives [29]. Specifically, this study evaluated the territorial suitability of installing a landfill in Alto Utcubamba Commonwealth, Amazonas, Peru. Numerous influential criteria are involved in the selection of an area for landfill installation, considering all of them are impractical. This study selected twelve sub-criteria (see Table 1) after reviewing the literature and consulting with experts: (B1) Environmental Criteria: (C1) proximity to surface water, (C2) proximity to conservation areas, (C3) Land Use / Land Cover - LULC; (B2) Socioeconomic Criteria: (C4) proximity to access roads, (C5) proximity to populated centers, (C6) proximity to archaeological sites; (B3) Physical Criteria: (C7) elevation, (C8) slope, (C9) precipitation, (C10) temperature, (C11) soil texture, and (C12) proximity to geological faults. The expert team included employees from the Solid Waste Units of the Chachapoyas municipality, local district municipalities, and researchers from national and international universities related to the research topic. Four levels of territorial suitability classification were defined: Unsuitable (S1), Less Suitable (S2), Moderately Suitable (S3), and Suitable (S4) [30].

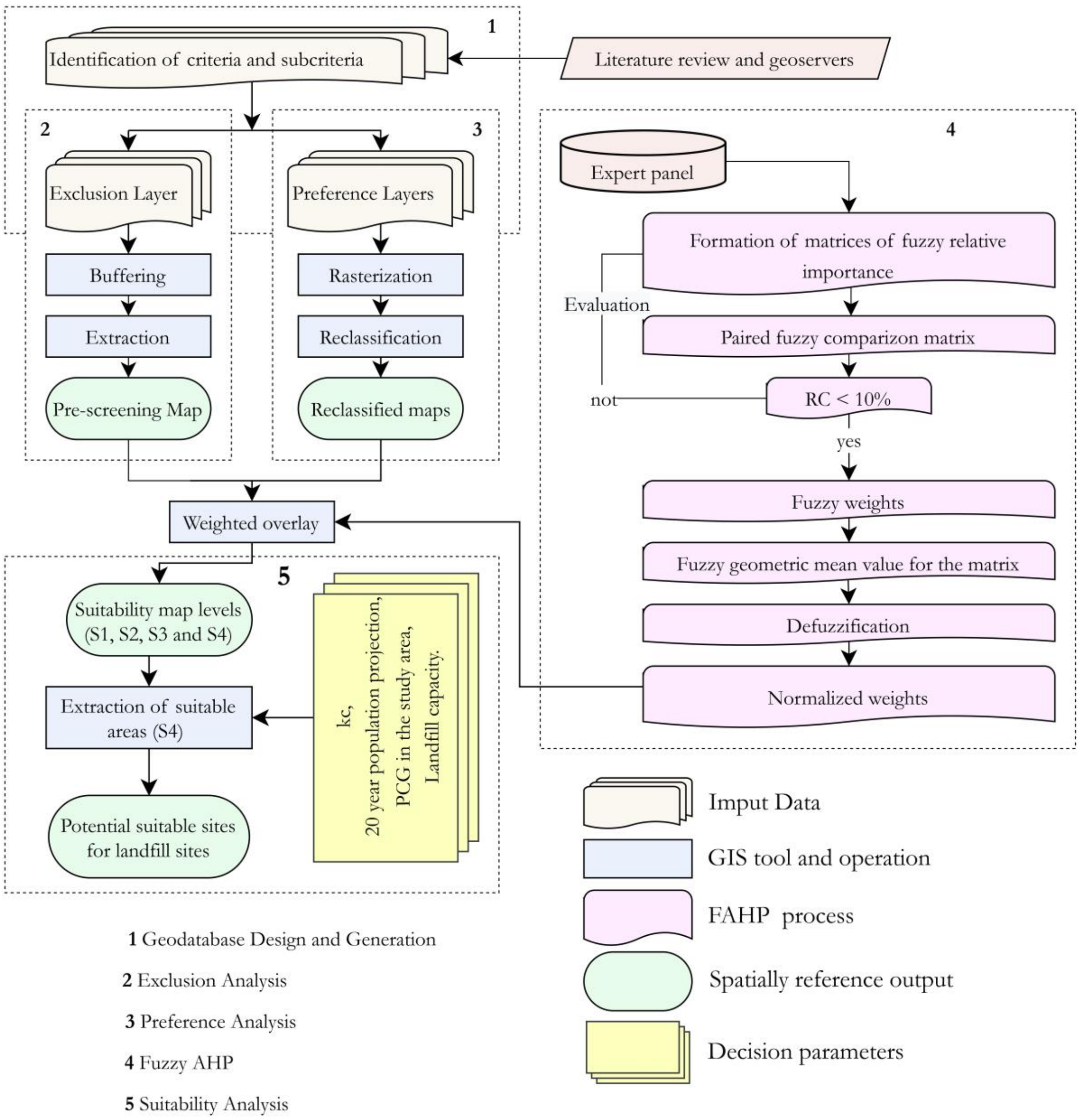


Figure 2. Flowchart methodology for identifying appropriate sites for setting up a landfill

Table 1. Territorial suitability thresholds for sub-criteria in the location of a landfill

Sub-criteria	S1	S2	S3	S4	Adapted on
			Environmental (B1)		
C1 (km)	< 0.4	0.4-0.7	0.7-1	> 1	[25, 31]
C2 (km)	<0.5	0.5-2	2-3	>3	[26, 32]
C3 (Class)	Built-up Areas, Forests, Water Bodies	Thickets	Crops and Pastures	Bare soil	[33]
			Socioeconomic (B2)		
C4 (km)	<0.3	>2	1-2	0.3 - 1	[34–36]
C5 (km)	< 0.5	0.5-1	1-2	>2	[31, 37, 38]
C6 (km)	<1	1-2	2-3	>3	[39, 40]
			Physical (B3)		
C7 (m.a.s.l.)	>3300	2800-3300	1000- 2000	2000- 2800	[41]
C8 (°)	>15	10-15	5- 10	< 5	[25, 30, 33, 38]
C9 (mm /year)	2450 >	1000 – 2 450	400 - 1000	< 400	[33, 42, 43]
C10 (°C)	< 11	11-14	14-17	17-21	[26]
C11 (Class)	Sand, Sandy clay, Sandy loam	Clay loam, Loamy clay loam, silty clay loam	Silty clay, silt	Clay	[32]
C12 (km)	< 0.3	0.3-1	1-2	> 2	[25, 44]

2.4. GIS Database of Criteria and Sub-Criteria

The management and processing of spatial data (vector and raster format) to generate maps of the 12 sub-criteria (Figure 3) and respective suitability levels (Appendix I, Table A1). This was accomplished using tools like ArcGIS Pro, Google Earth Pro v. 7.3, and Google Earth Engine (GEE). In the end, all layers were standardized into a raster format with a pixel resolution of 30 meters.

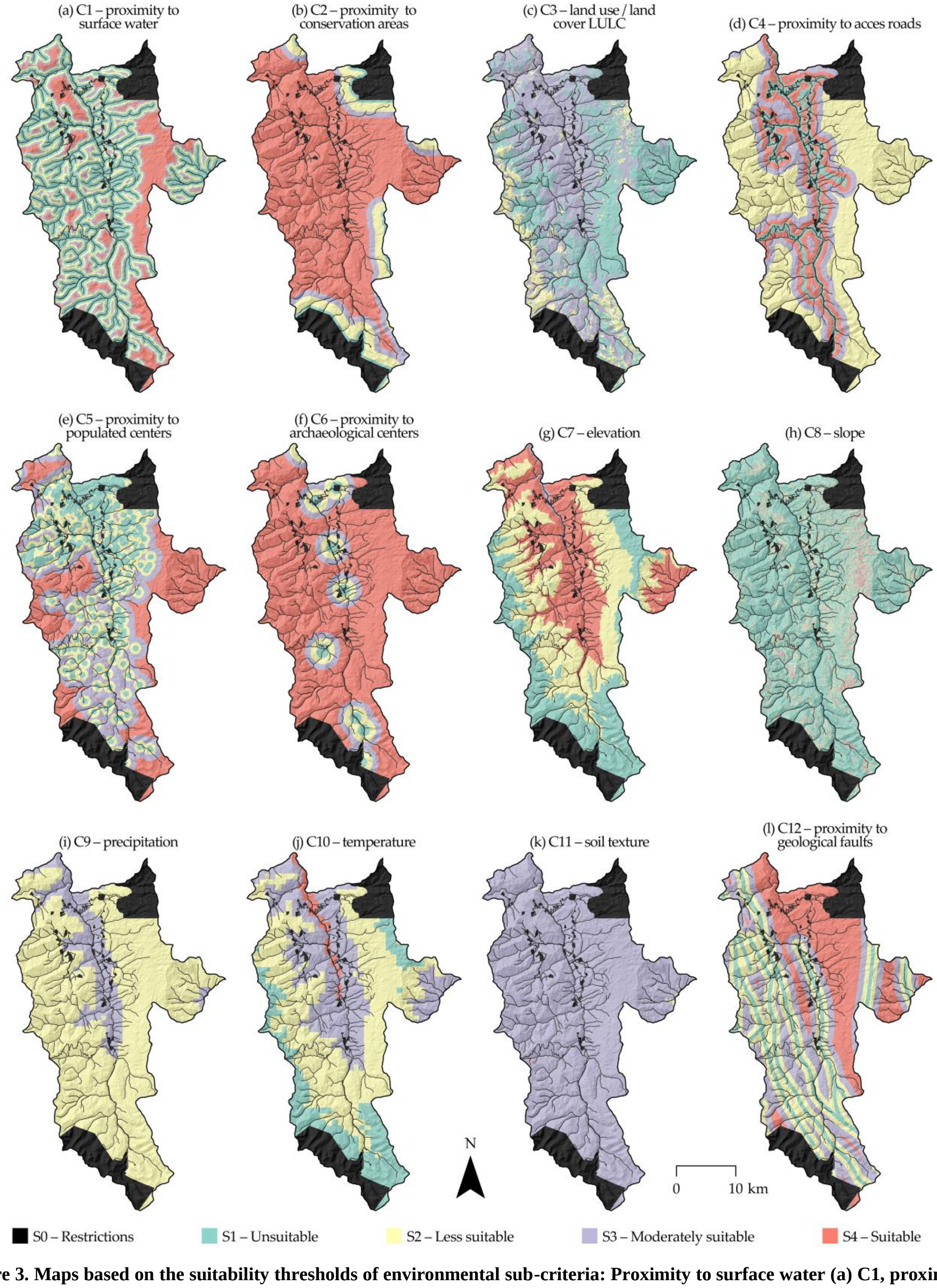


Figure 3. Maps based on the suitability thresholds of environmental sub-criteria: Proximity to surface water (a) C1, proximity to conservation areas (b) C2, and Land Use/Land Cover - LULC (c) C3; socioeconomic sub-criteria: Proximity to access roads (d) C4, proximity to populated centers (e) C5, and proximity to archaeological sites (f) C6; physical sub-criteria: Elevation (g) (C7), slope (h) (C8), precipitation (i) (C9), temperature (j) (C10), soil texture (k) (C11), and proximity to geological faults (l) (C12).

The "proximity to surface water" layer (C1) was generated from the vector layer of rivers from the National Map 13h (scale 1:100,000) of the National Geographic Institute (IGN), obtained from the Ministry of Education (MINEDU) database [45]. This layer was updated and complemented through manual digital mapping in Google Earth Pro and ArcGIS Pro. The "proximity to conservation areas" layer (C2) was obtained from the GeoServer of the National Service of Natural Protected Areas by the State (SERNANP) at a scale of 1:100,000 [46]. This data was initially obtained in vector format and then rasterized using the "Euclidean distance" tool in ArcGIS Pro.

The Land Use / Land Cover - "LULC" layer (C3) was developed in Google Earth Engine (GEE) following the procedure outlined by Silva López et al. [47]. This involved the use of Sentinel 2B satellite images (ID = COPERNICUS/S2_SR), which were filtered with a cloud cover percentage of 10.2% for the period from January 1, 2021, to January 20, 2022. Moreover, the average mosaic, including cloud masking, was categorized using a random forest (RF) algorithm and 144 training points across five classes: water, urban area, pasture, forest, and shrubland.

The "proximity to access roads" layer (C4) was generated from vector data provided by the Ministry of Transport and Communications (MTC) at a scale of 1:50,000 [48], updating all layers through manual mapping in Google Earth Pro and ArcGIS Pro. Similarly, for the "proximity to populated centers" layer (C5), the source of spatial vector data was INEI through https://www.geogpsperu.com/, where the data was downloaded at a scale of 1:100,000, identified and updated through manual digitization.

For the "proximity to archaeological sites" layer (C6), the source is the Ministry of Culture through the geoportal https://www.geogpsperu.com/ at a scale of 1:100,000 and in vector format. Finally, socio-economic sub-criteria layers was obtained through classification in ArcGIS Pro.

On the other hand, elevation and slope sub-criteria layers were generated from DEM (Digital Elevation Model) data from ALOS PALSAR RTC (Radiometrically Terrain-Corrected) with a resolution of 12.5 m [49]. ArcGIS Pro slope tools were used to obtain the slope map, and the DEM was reclassified to obtain the elevation map. The DEM was downloaded from the Alaska Satellite Facility Distributed Active Archive Data Center (ASF DAAC) (https://asf.alaska.edu/).

Precipitation and temperature layers were obtained from WorldClim 2.1 (*http://worldclim.org*), with a spatial resolution of (~1 km) [50], only performing reclassification functions. The soil texture sub-criterion layer data was obtained from the global soil digital mapping system SoilGrids (*https://soilgrids.org/*), with a spatial resolution of 250 m [51]. Soil texture was generated from layers of sand, silt, and clay content, averaging all layers from 0 to 5 cm, 5 to 10 cm, and 10 to 15 cm deep.

On the other hand, data for the geological faults sub-criterion layer was obtained from the National Geological Map 13h and 14h (scale 1:50,000) of the Geological, Mining, and Metallurgical Institute (INGEMMET).

Finally, to generate the sub-criterion layers, restrictions were considered (rivers, roads, urban areas), which were excluded in the reclassification of all layers.

2.5. Fuzzy Sets AHP Construction

Different fuzzy numbers can be utilized based on the specific characteristics of the study. In this research, triangular fuzzy numbers were chosen for their ease of computation and effectiveness in expressing and handling fuzzy logic [52]. At the beginning, a team of nine experts was assembled for decision-making purposes. Their task was to perform pairwise comparisons and articulate the relative significance of criteria and sub-criteria using the linguistic scale formulated by Gumus [53] (Table 2).

Table 2. Linguistic terms and the corresponding triangular fuzzy scale

Fuzzy number	Linguistic terms	Scale of triangular fuzzy number	Scale of triangular reciprocal fuzzy number
$\tilde{1}$	Equal	(1, 1, 1)	(1, 1, 1)
$\tilde{2}$	Weak advantage	(1, 2, 3)	(1/3, 1/2, 1)
$\tilde{3}$	Not bad	(2, 3, 4)	(1/4, 1/3, 1/2)
$\tilde{4}$	Preferable	(3, 4, 5)	(1/5, 1/4, 1/3)
$\tilde{5}$	Good	(4, 5, 6)	(1/6, 1/5, 1/4)
$\tilde{6}$	Fairly good	(5, 6, 7)	(1/7, 1/6, 1/5)
$\tilde{7}$	Very good	(6, 7, 8)	(1/8, 1/7, 1/6)
$\tilde{8}$	Absolute	(7, 8, 9)	(1/9, 1/8, 1/7)
$\tilde{9}$	Perfect	(8, 9, 10)	(1/10, 1/9, 1/8)

In particular, the coherence of the decision-making process was initially assessed using a standard AHP [30] via the Consistency Ratio (CR). The computation of the CR begins with the calculation of the Consistency Index (CI) (Equation 1) [5].

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

In this context, *'n'* represents the size or order of the matrix, while *'λ max'* corresponds to the priority vector in the decision matrix. In the end, the *CR* is calculated by dividing the CI by the aleatory consistency index (*AI*). The AI depends only on the number of compared elements or thematic criteria used; in this research, n=12, so the random index value (*AI* = 1.53) (Table 3). Equation 2 is used to obtain the value of the *CR*.

$$CR = \frac{CI}{AI} \tag{2}$$

Table 3. Random Consistency Index (AI) values for the weight of criteria 1-12 [54, 55]

n	3	4	5	6	7	8	9	10	11	12
AI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53

This does not suggest adequacy, yet significant results tend to be obtained [56]. If *CR* > 0.10, the pairwise comparison values are greater than 0.1, a new evaluation must be performed [57].

Once the consistency of the decision-making process was confirmed by ensuring the Consistency Ratio (CR) was less than 0.1, the experts reassessed each criterion using the linguistic terms outlined in Table S2. The linguistic terms used by each expert (Ex) in pairwise comparison matrices were transformed into Triangular Fuzzy Numbers (TFN) using operator (4).

$$\tilde{A} = \left(\tilde{a}_{ij}\right)_{nxn} = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \dots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, n_{21}) & (1,1,1) & \dots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1}, m_{n1}, n_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \dots & (1,1,1) \end{bmatrix}, \tag{4}$$

where $\tilde{a}_{ij} = \left(l_{ij,} m_{ij}, n_{ij}\right)$ y $\tilde{a}_{ij}{}^{-1} = \left(1/l_{ij,} 1/m_{ij}, 1/n_{ij}\right)$; for $i, j = 1, \dots., n$ y $i \neq j$.

Subsequently, the geometric mean method suggested by Buckley in 1985 [57] was employed to determine the fuzzy geometric means and fuzzy weights for each criterion and sub-criteria (See Appendix I, Table A2). The ensuing calculations were performed for this objective.

$$\tilde{r}_i = (\tilde{a}_{i1} * \tilde{a}_{i2} * \dots \dots \dots * \tilde{a}_{in})^{\frac{1}{n}} \tag{5}$$

$$\widetilde{w}_i = \tilde{r}_i * (\tilde{r}_1 + \tilde{r}_2 + \cdots \dots \dots + \tilde{r}_n)^{-1} \tag{6}$$

The fuzzy pairwise comparison value between criteria *i* and *n* is represented as $\tilde{a}_{in}$ is a fuzzy pairwise comparison value between criteria *i* and criteria n. The fuzzy geometric mean of the pairwise fuzzy comparison value of criteria *i* with each criterion is represented as $\tilde{r}_i$. The fuzzy weight of criteria *i*, expressed as $\widetilde{w}_i = (lw_{i,} mw_{i,} uw_{i,})$, is represented by lw_i, mw_i y uw_i, which denote the lower, middle, and upper values of the fuzzy weight of criteria *i*, respectively.

Following this, the fuzzy weights were made clear and transformed into actual numbers through a process known as defuzzification (refer to Appendix I, Table A3). This was achieved using the Center of Area (COA) method, a popular technique for defuzzification [58].

The optimal non-fuzzy performance value (BNP) of the fuzzy weight $\widetilde{w}_i$ was determined using the following calculation.

$$BNP_i = lw_i + \frac{(uw_i - lw_i) + (mw_i - lw_i)}{3}, \forall_1 \tag{7}$$

Finally, the normalized weights (Appendix I, Table A4) from the nine experts were obtained by normalizing the defuzzified weights. Then, a single normalized weight was obtained for each criterion and sub-criteria. Ultimately, these were combined to determine the importance of each sub-criteria.

2.6. Generation of the Territorial Suitability Model

Initially, the maps were reclassified based on the suitability levels outlined in Table 1 to create the suitability model. Following that, a Weighted Overlay Analysis (WOA) was performed to handle spatial complexity, a method that is commonly used [29]. In particular, the Weighted Overlay tool [59] in ArcGIS Pro was used. The calculation for the Land Suitability Index (LSI) is as follows:

$$LSI = \sum_{i=1}^{n} (Wi * Xi) \tag{8}$$

where: *Wi* represents the combined weight of the selected sub-criteria, *Xi* indicates the score of the sub-criteria of the *i* criteria, and n represents the total number of considered land suitability sub-criteria, with values assigned in the range of 1 to 4 [30], as indicated in Table 1 (corresponding to the areas in Figure 3). Higher scores were assigned to categories supporting land suitability for the installation of a landfill, while lower scores were given to those limiting it.

2.7. Determination of Suitable Areas, According to The Landfill and Population Life Span Projection

The landfill installation area must-have capabilities for waste accumulation and burial [60, 61]. Therefore, suitable areas (S4) were analyzed, considering the parameters in Table 4, with the aim of prioritizing areas (S4) that meet the requirements for the landfill's lifespan. For this study, quantitative data involved in the calculation were obtained through a literature review [60–65].

Table 4. Quantitative data for calculating landfill area

Description	Value	Based on:
Current beneficiary population (Hab)(Po)	11,798	[63]
Waste volume in 2022 (m^3)	1,515	[63]
Annual population growth rate (r) (%)	0.1	[65]
Average Per Capita Generation (PCG) (Kg/ hab.day)	0.52	[62]
Years of useful life (n)	20	[60, 61, 64]
Maximum landfill height in meters (m)	6	[61]

To calculate the amount of solid waste, the volume of waste generated over a 20-year period, and the required area according to the projection of generated solid waste, the equations from Table 5 were used [46].

Table 5. Technical requirements for landfill infrastructure

Description	Equation
Quantity of municipal solid waste (MSW) generated in a day (Q_0)	$Q_0 = P_0 \times GCP$
Solid Waste Density (**δ**) (kg/m^3)	$\delta = Q_{2042}/V_{diario}$
Future population by 2042	$Pf_{2042} = Pa(1+r)^n$
Quantity of MSW generated in a day by 2042	$Q_{2042} = Pf_{2042} \times GCP$
Total volume of MSW generated in a day	$V_{diario} = Q_{2042}/\delta$
Total volume of MSW generated in 20 years	$V_{2042} = V_{diario} \times 365 \times 20$
Minimum area for a landfill	$A_{min} = V_{2042}/m$

The compactness coefficient (Kc) was calculated to analyze the shape of the polygons and identify the regular shape of optimal areas. The Kc was determined using the perimeter (P) (km) and area (A) (km^2) of each polygon (Equation 9) [47]. If the Kc values are close to 1, it suggests that the polygons are similar to a circle ('Form I'). If the values are near 1.75, it indicates that the polygons are likely to be elongated ('Form II'), and values over 2 suggest irregular polygons ('Form III') [66].

$$\mathrm{Kc} = \frac{\mathrm{P}}{2\sqrt{\pi \mathrm{A}}} \tag{9}$$

2.8. Accuracy Assessment and Validation of Results

In this research, the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) were employed to evaluate the effectiveness and predictive power of the suitability model [67] for a landfill site. The ROC curve is a beneficial tool that depicts the quality of deterministic and probabilistic prediction and detection systems [68].

In the analysis of the ROC curve, the AUC reflects the precision of a prediction system by outlining its capacity to predict the occurrence or non-occurrence of specific 'events' [69]. The model's predictive efficiency improves as the AUC value rises (from 0.5 to 1) [70]. A value of 1 signifies flawless performance of the model [84], whereas 0.5 denotes a poor success rate for the model [70, 71]. As per Yesilnacar [72], the numerical-qualitative link between AUC and prediction accuracy can be ranked as follows: 0.5-0.6 (poor), 0.6-0.7 (fair), 0.7-0.8 (good), 0.8-0.9 (very good), and 0.9-1 (excellent). We validated this using point recording supported by a GPS navigator and a Mini Mavic drone.

3. Results and Discussion

3.1. Areas According to Suitability Levels of Sub-Criteria of The Territory with Restrictions

Figure 3 presents the reorganised maps of the environmental, socioeconomic and physical sub-criteria, according to the suitability thresholds (Table 1) with restrictions. Specifically, the unrestricted area is 933.62 km^2. In all sub-criteria, 12.4% (132.49 km^2) of the study area was restricted (S0), corresponding to urban areas, roads, surface water network and conservation areas. In addition, the environmental, socioeconomic and physical sub-criteria with the largest "Suitable" (S4) area were respectively Proximity to conservation areas (C2) (78.6%), Proximity to archaeological centers (C6) (80.0%) and Elevation (C7) (32.4%) (Table 6). On the other hand, those with the largest "Unsuitable" (S1) area were Proximity to the surface water network (C1) (43.9%), Proximity to populated centers (C5) (22.4%) and Slope (C8) (73.8%). Therefore, it is determined that Proximity to conservation areas (C2) (78.6%) is the sub-criterion that most benefits the site selection for a landfill establishment, while Slope is the one that most limits the territory.

Table 6. Areas according to suitability levels for each sub-criteria

Sub-criteria	S1		S2		S3		S4	
	Km^2	%	Km^2	%	Km^2	%	Km^2	%
Environmental Criteria								
C1	410.16	43.9	222.26	23.8	131.55	14.1	169.65	18.2
C2	26.57	2.8	93.37	10.0	80.30	8.6	733.38	78.6
C3	352.56	37.8	102.34	11.0	478.72	51.3	0.00	0.0
Socioeconomic Criteria								
C4	105.61	11.3	492.33	52.7	167.62	18.0	168.06	18.0
C5	208.70	22.4	224.71	24.1	237.71	25.5	262049	28.1
C6	22.14	2.4	67.48	7.2	97.25	10.4	746.75	80.0
Physical Criteria								
C7	251.35	26.9	371.51	39.8	7.95	0.9	302.81	32.4
C8	689.09	73.8	136.67	14.6	82.31	8.8	25.56	2.7
C9	0.00	0.0	791.38	84.8	142.25	15.2	0.00	0.0
C10	172.90	18.5	455.55	48.8	282.59	30.3	22.58	2.4
C11	0.00	0.0	1.49	0.2	931.69	99.8	0.45	0.0
C12	127.95	13.7	264.33	28.3	259.14	27.8	282.21	30.2

3.2. Fuzzy-AHP Weights of Criteria and Sub-criteria

The important weights of each criterion and sub-criterion were determined by a group of nine experts from different backgrounds and specialties. The preliminary expert evaluations successfully underwent the consistency test, with the CR value being below 10%. All expert viewpoints were scrutinized and the final weights were computed (Table A4). Table 7 presents the derived weights and the final mean weights for each criterion and its corresponding sub-criterion, based on the collective expert opinions. The most important sub-criteria within the hierarchical group were LULC (0.455), proximity to populated areas (0.544) and slope (0.242). Conversely, the least important were proximity to conservation area (0.181), proximity to roads (0.216) and elevation (0.062). On the other hand, according to the specialists, the most crucial criterion is Environmental. In addition, the overall impact was generally dominated by the LULC sub-criteria, the most crucial, followed by proximity to surface waters.

Table 7. Weights of criteria and sub-criteria based on F-AHP

Criteria	Normalized weights	Sub-criteria	Normalized weights	Combined weights	Importance
Environmental (B1)	0.493	Proximity to surface water (C1)	0.364	0.1795	2
		Proximity to conservation areas (C2)	0.181	0.0892	4
		LULC (C3)	0.455	0.2243	1
Socioeconomic (B2)	0.213	Proximity to roads (C4)	0.216	0.0460	10
		Proximity to populated centers (C5)	0.544	0.1159	3
		Proximity to archaeological centers (C6)	0.239	0.0509	8
Physical (B3)	0.294	Elevation (C7)	0.062	0.0182	12
		Slope (C8)	0.242	0.0711	5
		Precipitation (C9)	0.199	0.0585	7
		Temperature (C10)	0.114	0.0335	11
		Soil texture (C11)	0.226	0.0664	6
		Proximity to geological faults (C12)	0.157	0.0462	9

3.3. Territorial Suitability Model for Establishing a Landfill

The Figure 4 shows the final suitability map of the Alto Utcubamba Commonwealth (AUCo) territory, of which 0.069% (0.65 km^2) presents "Suitable" conditions (S4), 41.70% (306.20 km^2) "Moderately Suitable" (S3), 66.934% (624.91 km^2) "Less Suitable" (S2), and 0.20% (1.86 km^2) "Unsuitable" (S1), for the installation of a landfill. Likewise, the final suitability of the Commonwealth territory is divided into its seven districts (Table 8), of which the Santo Tomás and San Francisco del Yeso districts do not have any "Suitable" area (S4). In addition, the smallest surface area is occupied by Mariscal Castilla with a "Suitable" area (S4) of 0.0003% (0.0027 km^2). On the contrary, the Montevideo district, with 0.0505% (0.4713 km^2), has the largest "Suitable" (S4) surface area (Table 8). On the other hand, the Leimebamba district has the largest "Unsuitable" (S1) area with 0.1939% (1.8099 km^2), and the Santo Tomás, San Juan de Lopecancha, Mariscal Castilla, and Montevideo districts have the smallest "Unsuitable" (S1) area with 0.0% (0.00 km^2).

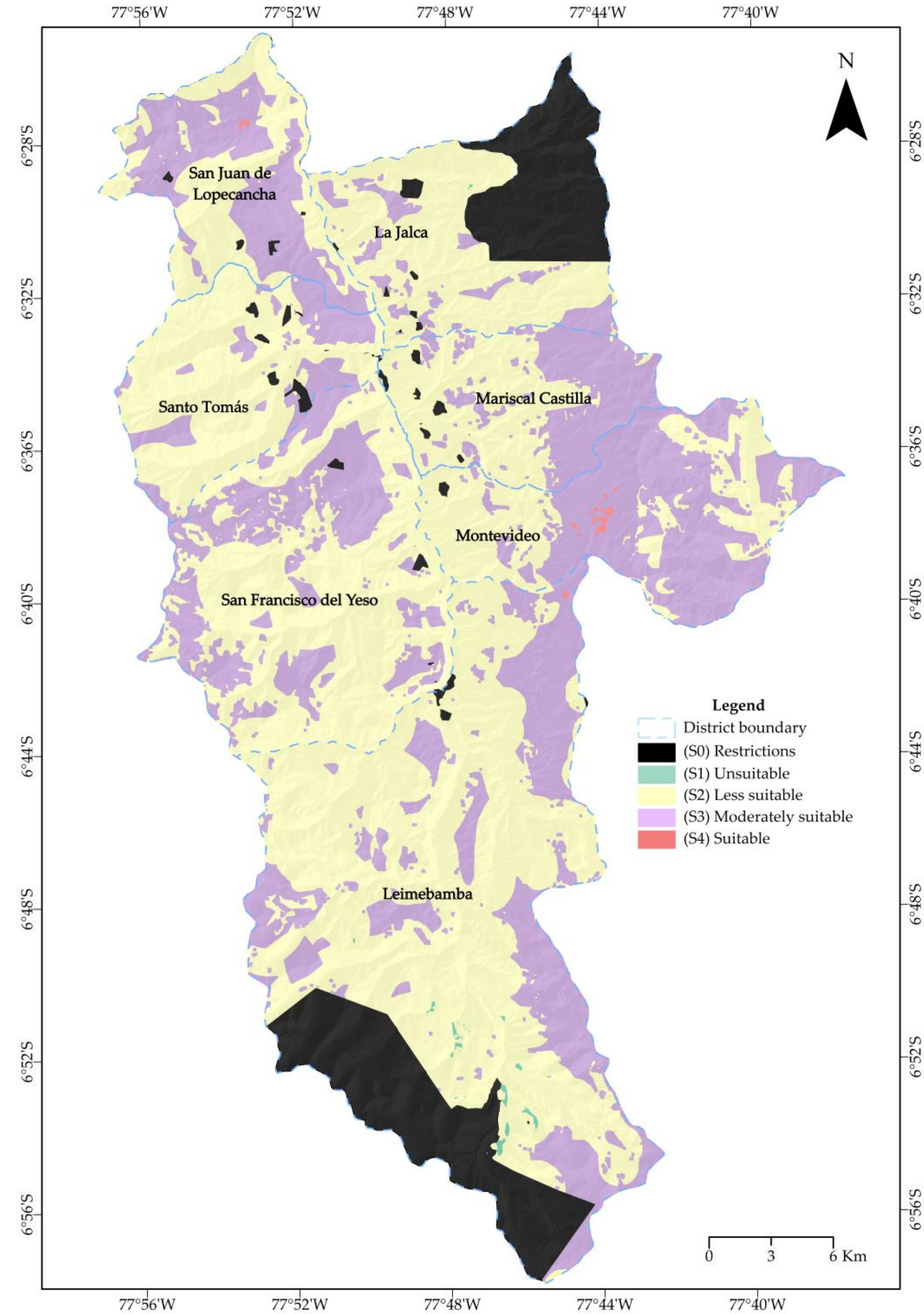


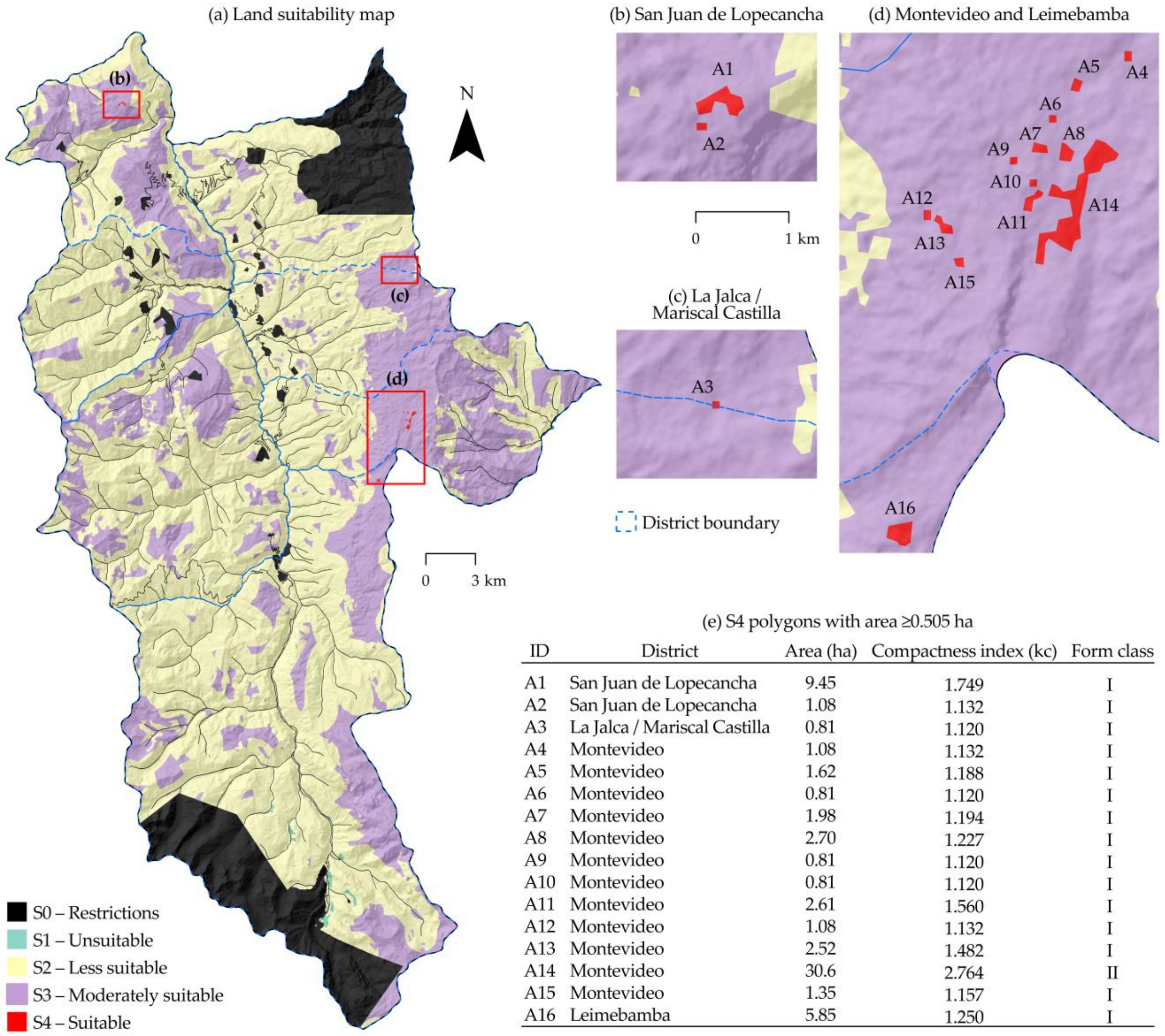
Figure 3. Land suitability map for the establishment of a landfill in the AUCo -Amazonas

Table 8. Territory of sub-criteria for each suitability alternative with potential for the establishment of a landfill per district of the AUCo – Amazonas

Districts	S1		S2		S3		S4		Total	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
San Juan de Lopecancha	0.0000	0.0000	44.7553	4.7937	40.5688	13.2491	0.1041	10.4098	85.4282	9.2%
La Jalca	0.0537	0.0057	64.3027	6.8875	10.6762	1.1435	0.0054	0.0006	75.0380	8.0%
Santo Tomás	0.0000	0.0000	70.3831	7.5387	17.2750	1.8503	0.0000	0.0000	87.6580	9.4%
Mariscal Castilla	0.0000	0.0000	47.0993	5.0448	30.8708	3.3066	0.0027	0.0003	77.9728	8.4%
San Francisco del Yeso	0.0000	0.0000	121.8045	13.0465	55.2075	5.9133	0.0000	0.0000	177.0121	19.0%
Montevideo	0.0000	0.0000	52.4156	5.6142	69.6173	7.4567	0.4713	0.0505	122.5042	13.1%
Leimebamba	1.8099	0.1939	224.1509	24.0088	81.9842	8.7813	0.0620	0.0066	308.0070	33.0%
total	1.86	19.96%	624.91	66.93	306.20	41.70	0.65	10.4678	933.62	100.0%

3.4. Potentially Suitable Sites for the Installation of a Landfill

Figure 5 shows the polygons S4 ≥ 0.505 hectares (ha) with compactness index (kc) and 'Suitability Class'. Thus, 15 'suitable' polygons (S4) were determined, which had a kc close to 1, that is, they are in the 'Suitability Class (I)'. Thus, 1 'suitable' polygon (S4) with kc ≥ 2 (Suitability Class III) was determined.



ID	District	Area (ha)	Compactness index (kc)	Form class
A1	San Juan de Lopecancha	9.45	1.749	I
A2	San Juan de Lopecancha	1.08	1.132	I
A3	La Jalca / Mariscal Castilla	0.81	1.120	I
A4	Montevideo	1.08	1.132	I
A5	Montevideo	1.62	1.188	I
A6	Montevideo	0.81	1.120	I
A7	Montevideo	1.98	1.194	I
A8	Montevideo	2.70	1.227	I
A9	Montevideo	0.81	1.120	I
A10	Montevideo	0.81	1.120	I
A11	Montevideo	2.61	1.560	I
A12	Montevideo	1.08	1.132	I
A13	Montevideo	2.52	1.482	I
A14	Montevideo	30.6	2.764	II
A15	Montevideo	1.35	1.157	I
A16	Leimebamba	5.85	1.250	I

Figure 4. Territorial map S4 ≥0.505 ha, according to Kc and form class with potential for the establishment of a landfill by district of the AUCo - Amazonas

The minimum area required to install a landfill in the Alto Utcubamba Commonwealth, with a projected population of urban solid waste generation by 2042, was estimated at 0.505 ha (Table 9). Thus, in the final suitability model (Figure 5), 16 'Suitable' polygons (S4) ≥ 0.505 ha were identified, of which the districts La Jalca-Mariscal Castilla and Leimebamba each occupy one polygon (area). In addition, San Juan de Lopecancha occupies two polygons (areas) and the remaining 12 areas correspond to the district of Montevideo.

Table 9. Calculating the smallest possible area for a future landfill for the UACo, projected to be operational for 20 years

Description	Result
Solid Waste Density	9,943.641 kg/m^3
City population by 2042	79,371 hab.
Quantity of MSW generated in a day	41,272.920 kg/day
Total volume of MSW generated in a day	4.151 m^3
Total volume of MSW generated in 20 years	30,300 m^3
Minimum area for a landfill	0.505 ha

3.5. Suitability Model Validated by AUC and ROC

Using a field visit, a GPS navigator, a Mini Mavic RPA (remotely piloted aircraft), and Planet Scope images (4.7 m spatial resolution), validation point data were collected to verify the generated models. Thus, 45 Georeferenced Points (GP) were recorded (Figure 6), in which each point was assigned a code of 0, for those where the adjacent area met the requirements to install a sanitary landfill; otherwise, a value of 1 was assigned. Consequently, the AUC-ROC was generated with the GPs, demonstrating a reliability of 0.784 (Figure 7), which is at the satisfactory level (0.7–0.8) [72] as the suitability model developed.

Figure 5. Field validation. a) and b) Visual inspection of potential areas. c) Inspection of the current landfill

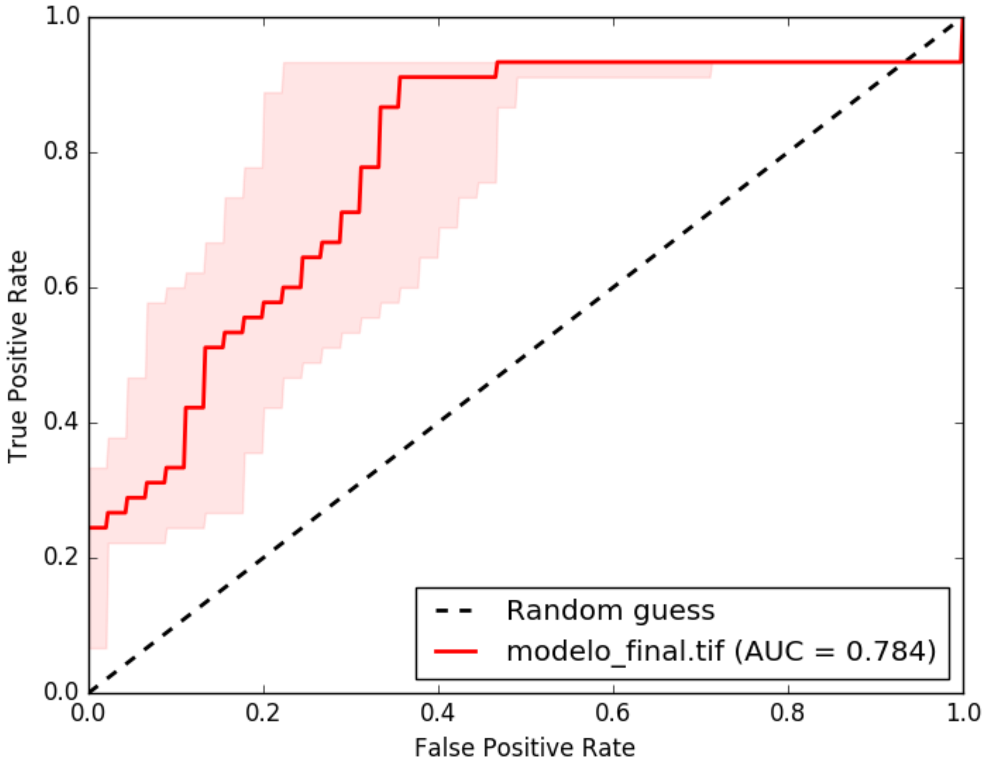


Figure 6. UAC-ROC graphs of the final suitability model

3.6. Discussion

Landfills are regarded as one of the most significant and economically efficient methods of waste disposal [73]. However, identifying a suitable location for solid waste disposal is a complex challenge for a municipality [74]. The selection of the site becomes a crucial aspect of urban planning, involving economic, physical, and social considerations [75] and potential environmental impacts [76].

In light of this, the existence of the methodology known as AHP-GIS applied to territorial suitability for establishing a landfill has become a useful and efficient tool worldwide [2, 22, 23]. In this study, a geospatial MCDA based on Fuzzy-AHP was used to determine the suitable areas for establishing a landfill. However, at the national level, the use of this approach in similar research is limited by the need for criteria established in the methodological guide of the Ministry of Environment [77]. Therefore, this study acknowledges that the system employs artificial values derived from pair comparisons. Nonetheless, Durú et al. [78] scrutinized various Fuzzy-AHP studies that did not exhibit a matrix consistency issue, despite the choices being inconsistent. The findings indicated that the fusion of fuzzy set theory with the AHP fulfills all the prerequisites.

In a localized context, the AHP-GIS technique was utilized to determine potential landfill sites in the districts of Chachapoyas & Huancas [47]. This study's methodology is noteworthy, as it adapted to local conditions and met MINAM's requirements [77], identifying 12 suitable landfill areas using 12 sub-criteria and three criteria, similar to other research [79, 80]. However, the AHP-GIS technique has a known bias due to its subjectivity during the paired comparison process conducted by the expert panel [5]. For the Commonwealth of Alto Utcubamba, 12 locally relevant sub-criteria were incorporated [47], in line with Peruvian regulations for landfill site identification [77]. Unlike previous research [81–83], this study employed the most sub-criteria (12). However, other research used more sub-criteria due to more available spatial data [25, 26, 40], a constraint in this study. Consequently, Dolui and Sarkar [2], considered proximity to railways; other authors [2, 80] considered power lines. Alkaradaghi et al. [40], considered proximity to oil and gas deposits, while Rezaeisabzevar et al. [84], used criteria like smell, property value reduction, and noise. These criteria were not included in our study due to limited local-scale spatial data on environmental, socioeconomic, and physical factors in Peru's Amazonas region. Additionally, acquiring high-resolution cartographic data for the study area was challenging, but this was mitigated by using simulated databases.

In contrast to these studies, our research combined AHP and fuzzy-AHP to identify appropriate landfill locations based on twelve geospatial characteristics. These include surface water, closeness to conservation areas, land use and cover, proximity to communication routes, proximity to population centers, closeness to archaeological centers, altitude, slope, precipitation, temperature, soil texture, and proximity to geological faults. Specifically, as a result, this study identified areas with potential for a joint landfill and evaluated the location of the current landfill, similar to the study by Najjari & Shayesteh [42]. Analyzing the criteria for the Alto Utcubamba Community, environmental criteria (49.3%) are the most important, followed by physical criteria (29.4%) and socioeconomic criteria (21.3%). Similarly, Silva López et al. [47], who used one more physical and socioeconomic sub-criterion, stated that environmental criteria are more important than socioeconomic and physical ones. Likewise, other authors [44, 85, 86] considered environmental criteria to be more important than socioeconomic ones in their research. On the other hand, for Najjari & Shayesteh [42], physical criteria are more important than environmental and socioeconomic ones. Therefore, discrepancies in importance may be due to the criteria used, which will vary depending on the number and type of sub-criteria and the average experience and knowledge of the expert group.

On the other hand, among all the sub-criteria, the most important were environmental, Land Use/Vegetation Cover (LULC) (22.42%), and proximity to the surface water network (17.94%). In contrast, elevation (1.82%) and temperature (3.35%) were the least important, according to expert opinions. The 'LULC' sub-criteria is the most important [36]. Additionally, Bilgilioglu et al. [87] and Abdelouhed et al. [16] also considered 'proximity to surface waters' as the second most important criteria. Meanwhile, Chabuk et al. [88] regarded 'proximity to surface waters' as the most important environmental criteria, emphasizing what was established by MINAM [77] about the importance of water sources for landfill location.

In the case of socioeconomic sub-criteria, the most important are 'Proximity to populated centers' (11.59%) and 'proximity to archaeological centers' (05.09%). Spigolon et al. [86]; Mohammed et al. [38]; Karabulut et al. [89]; and Ahire et al. [90] regard 'Proximity to populated centers' as the most important, while Mustafa and Bwadi [91], and Silva et al. [47] consider 'proximity to roads' as the most important, which is the least important socioeconomic sub-criteria in the study. Additionally, the sub-criteria 'proximity to archaeological centers' was considered, as in the study by Alkaradaghi et al. [40], due to the presence of archaeological remains in the study area. Among the physical sub-criteria, slope (07.11%) and soil texture (06.64%) were of greater importance. Randazzo et al. [40], due to the presence of archaeological remains in the study area.

Among the physical sub-criteria, slope (07.11%) and soil texture (06.64%) were of greater importance. Randazzo et al. [11] and Najjari & Shayesteh [42] highlight the slope as the most important criteria. Furthermore, Silva et al. [47] reaffirm the importance of considering soil texture as a physical criterion, as it guarantees the site for safe engineering construction.

Based on the evaluated criteria, 16 suitable sites with potential for a sanitary landfill installation were identified. These sites have the minimum surface area (≥0.505 ha) necessary for their operation until 2042. Out of these identified sites, 15 approximate to the 'Shape Class (I)' according to design parameters. Furthermore, the minimum analysis of the projected surface area of the future landfill [61, 77] and shape analysis [92] facilitated a better selection of sites than previous studies. Likewise, the reliability analysis carried out with the ROC-AUC curve showed a value of 0.784 (good) for the AUC [67], similar to the study conducted by Jaafari et al. [69], who obtained an AUC value of 0.7554, indicating a 'good' model. However, for the final selection of a single site, detailed field studies (soil, wind direction, and others) must be conducted.

On the other hand, the underlying mechanisms for selecting suitable landfill sites involve the evaluation of multiple factors. A careful selection of the site is essential to minimize the negative impacts on the environment and local community and ensure the long-term economic viability of the project. Therefore, it is important to take into account both public and governmental perspectives when selecting a suitable landfill. From the population's point of view, it is crucial to consider how the landfill installation will affect their quality of life. Residents in the vicinity may be concerned about noise, and potential water and air pollution caused by the landfill. From the administration's perspective, it is essential to select a safe site away from residential areas and bodies of water. It is also necessary to ensure that the landfill has enough space for future expansions and meets legal and environmental requirements.

4. Conclusions

The current analysis addressed multiple remote sensing data sets and decision-making methods to develop a unified scheme for the landfill suitability map for the Commonwealth of Alto Utcubamba, Amazonas, Peru. Following a thorough examination of the existing literature and the collection of expert opinions, twelve thematic layers were chosen for this study, which include proximity to surface water, closeness to conservation areas, land use and cover, proximity to communication routes, proximity to population centers, closeness to archaeological centers, altitude, slope, rainfall, temperature, soil structure, and proximity to geological faults. These layers were created using conventional and satellite data. Consequently, areas within the territory of the Commonwealth of Alto Utcubamba were identified based on their suitability: 0.069% (0.65 km^2) meet the 'Suitable' (S4) criteria, 41.70% (306.20 km^2) are 'Moderately Suitable' (S3), 66.934% (624.91 km^2) are 'Less Suitable' (S2), and 0.20% (1.86 km^2) are 'Unsuitable' (S1), with 12.43% (132.49 km^2) of the area restricted for a landfill. Additionally, 16 'Suitable' (S4) locations (A) were identified, each with a minimum surface area (≥0.505 ha), according to solid waste generation needs and population projections over 20 years. Of the 16 'Suitable' (S4) locations, 15 meet the shape criteria according to the compactness index (Kc). Among the seven districts that make up the Commonwealth of Alto Utcubamba, the Montevideo district has the highest number of suitable areas (12 sites).

In terms of spatial variation, suitable potential landfill sites were located in the eastern and northern areas of the commonwealth. This study concluded that, due to the abundance of water flows, high drainage network density, and a main river running from north to south throughout the commonwealth, there are no suitable locations for landfills in the central area.

This study provides a scientific basis for the analysis of urban landfill suitability, using the Fuzzy-AHP method with weighted overlay. This method is useful for assessing landfill suitability in Alto Utcubamba, and can be used by engineers and managers to discuss the need for new landfills. It is recommended to compare the results with field research to select the best locations for landfills.

The combination of AHP and Fuzzy-AHP methods can improve decision-making in complex and uncertain situations. This combination allows for consideration of multiple criteria, the incorporation of uncertain information, and enhancement of the accuracy of the decision-making process. Additionally, it can foster innovation and new solutions in decision-making.

This study's results are beneficial for waste management authorities in the Amazonas region, Peru. It emphasizes the necessity of thorough site evaluations and the consideration of diverse factors when choosing landfill sites. Furthermore, it stresses the importance of sustainable waste management methods that safeguard the environment and public health and take into account economic and social aspects.

In essence, this research highlights the need for a multifaceted approach to waste control and sustainable methods for safeguarding the environment and public health. Such methods can guide regions with similar issues and aid in global sustainable development goals. Waste management significantly impacts the environment, public health, and community welfare.

On the other hand, this research has a constraint in that it cannot perform a multicollinearity test due to the amalgamation of numerical and categorical input layers. Subsequent studies could concentrate on investigating techniques that are suitable for these two kinds of variables. Another drawback is the dependency on human discernment to determine the final AHP weights, which could result in mistakes or prejudice. The precision could be enhanced if the quantity of expert views is augmented.

5. Declarations

5.1. Author Contributions

Conceptualization, J.A.Z.S. and J.O.S.L.; methodology, J.A.Z.S., R.S.L., A.J.M.M., K.M.T.T., D.G.F., N.B.R.B., M.O.C., and J.O.S.L.; software, J.A.Z.S., R.S.L., J.O.S.L., and D.G.F.; validation, K.M.T.T., A.S.R.F., and J.L.C.; formal analysis, J.A.Z.S., D.G.F., and A.S.R.F.; investigation, J.A.Z.S., R.S.L., A.J.M.M., K.M.T.T., N.B.R.B., A.S.R.F., M.O.C., and D.G.F.; resources, R.S.L. and M.O.C.; data curation, J.A.Z.S., A.J.M.M., K.M.T.T., R.S.L., N.B.R.B., and J.O.S.L.; writing—original draft preparation, J.A.Z.S., J.L.C., and D.G.F.; writing—review and editing, J.A.Z.S. and J.O.S.L.; visualization, N.B.R.B., D.G.F., and K.M.T.T.; supervision, R.S.L.; project administration, R.S.L. and M.O.C. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

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5.5. Conflicts of Interest

The authors declare no conflict of interest.

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Appendix I

Table A-1. Area distribution and percentage of sub-criteria, and sub-criteria scores in the Alto Utcubamba Commonwealth, Amazonas

Sub-criteria	Class	Score	Area (km^2)	Area (%)	Sub-criteria	class	Score	Area (km^2)	Area (%)
C1	S4	4	169.65	18.2	C7	S4	4	302.81	32.4
	S3	3	131.55	14.1		S3	3	7.95	0.9
	S2	2	222.26	23.8		S2	2	371.51	39.8
	S1	1	410.16	43.9		S1	1	251.35	26.9
C2	S4	4	733.38	18.2	C8	S4	4	25.56	2.7
	S3	3	80.3	8.6		S3	3	82.31	8.8
	S2	2	93.37	10		S2	2	136.66	14.6
	S1	1	26.57	2.8		S1	1	689.09	73.8
C3	S4	4	0	0	C9	S4	4	0	0
	S3	3	478.72	51.3		S3	3	142.24	15.2
	S2	2	102.34	11		S2	2	791.38	84.8
	S1	1	352.56	37.8		S1	1	0	0
C4	S4	4	168.06	18	C10	S4	4	22.58	2.4
	S3	3	167.62	18		S3	3	282.59	30.3
	S2	2	492.33	52.7		S2	2	455.55	48.8
	S1	1	105.61	11.3		S1	1	172.9	18.5
C5	S4	4	262.49	28.1	C11	S4	4	0.44	0
	S3	3	237.71	25.5		S3	3	931.69	99.8
	S2	2	224.71	24.1		S2	2	1.49	0.2
	S1	1	208.7	22.4		S1	1	0	0
C6	S4	4	746.75	80	C12	S4	4	282.21	30.2
	S3	3	97.25	10.4		S3	3	259.14	27.8
	S2	2	67.48	7.2		S2	2	264.32	28.3
	S1	1	22.14	2.4		S1	1	127.95	13.7

Table A-2. Fuzzy Geometric Mean Values of Criteria and Sub-criteria for Each Expert (Ex)

Criteria	Ex1	Ex2	Ex3	Ex4	Ex5	Ex6	Ex7	Ex8	Ex9
B1	(0.221, 0.493, 0.957)	(0.313, 0.571, 0.971)	(0.403, 0.630, 0.956)	(0.221, 0.493, 0.957)	(0.221, 0.466, 0.838)	(0.278, 0.540, 0.958)	(0.218, 0.458, 0.816)	(0.429, 0.648, 0.958)	(0.175, 0.268, 0.423)
B2	(0.106, 0.196, 0.460)	(0.088, 0.143, 0.273)	(0.097, 0.151, 0.280)	(0.106, 0.196, 0.460)	(0.084, 0.136, 0.254)	(0.097, 0.163, 0.332)	(0.079, 0.126, 0.230)	(0.082, 0.122, 0.209)	(0.402, 0.614, 0.911)
B3	(0.153, 0.311, 0.663)	(0.151, 0.286, 0.568)	(0.130, 0.218, 0.352)	(0.153, 0.311, 0.663)	(0.243, 0.398, 0732)	(0.153, 0.297, 0.603)	(0.259, 0.416, 0.751)	(0.135, 0.230, 0.380)	(0.081, 0.117, 0.185)
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C1	(0.181, 0.231, 0.300)	(0.194, 0.333, 0.627)	(0.081, 0.117, 0.185)	(0.197, 0.272, 0.392)	(0.153, 0.311, 0.663)	(0.569, 0.731, 0.934)	(0.187, 0.259, 0.367)	(0.190, 0.303, 0.514)	(0.886, 0.731, 0.467)
C2	(0.052, 0.060, 0.072)	(0.088, 0.140, 0.249)	(0.402, 0.614, 0.911)	(0.052, 0.067, 0.090)	(0.106, 0.196, 0.460)	(0.062, 0.081, 0.112)	(0.068, 0.090, 0.126)	(0.095, 0.146, 0.257)	(0.213, 0.188, 0.257)
C3	(0.586, 0.709, 0.848)	(0.280, 0.528, 0.905)	(0.175, 0.268, 0.423)	(0.475, 0.661, 0.899)	(0.221, 0.493, 0.957)	(0.137, 0.188, 0.257)	(0.461, 0.652, 0.905)	(0.301, 0.551, 0.934)	(0.097, 0.081, 0.112)
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C4	(0.152, 0.199, 0.262)	(0.073, 0.095, 0.129)	(0.081, 0.117, 0.185)	(0.540, 0.707, 0.916)	(0.135, 0.183, 0.248)	(0.052, 0.067, 0.090)	(0.064, 0.085, 0.120)	(0.149, 0.211, 0.300)	(0.15, 0.268, 0.423)
C5	(0.054, 0.068, 0.088)	(0.626, 0.816, 1.051)	(0.402, 0.614, 0.911)	(0.055, 0.070, 0.093)	(0.591, 0.742, 0.937)	(0.475, 0.661, 0.899)	(0.449, 0.644, 0.901)	(0.529, 0.705, 0.931)	(0.402, 0.614, 0.911)
C6	(0.582, 0.733, 0.919)	(0.069, 0.089, 0.123)	(0.175, 0.268, 0.423)	(0.165, 0.223, 0.305)	(0.059, 0.075, 0.090)	(0.197, 0.272, 0.392)	(0.189, 0.271, 0.403)	(0.064, 0.084, 0.119)	(0.081, 0.117, 0.185)
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C7	(0.016, 0.023, 0.036)	(0.018, 0.027, 0.044)	(0.029, 0.046, 0.083)	(0.157, 0.273, 0.474)	(0.023, 0.038, 0.070)	(0.023, 0.036, 0.062)	(0.032, 0.050, 0.082)	(0.016, 0.023, 0.035)	(0.024, 0.038, 0.068)
C8	(0.141, 0.298, 0.550)	(0.182, 0.336, 0.573)	(0.229, 0.380, 0.606)	(0.050, 0.083, 0.138)	(0.144, 0.296, 0.540)	(0.210, 0.366, 0.598)	(0.100, 0.157, 0.250)	(0.056, 0.089, 0.148)	(0.126, 0.222, 0.376)
C9	(0.121, 0.242, 0.467)	(0.086, 0.165, 0.314)	(0.086, 0.145, 0.246)	(0.142, 0.255, 0.450)	(0.075, 0.150, 0.297)	(0123, 0.199, 0.348)	(0.247, 0.388, 0.592)	(0.089, 0.151, 0.257)	(0.050, 0.087, 0.155)
C10	(0.053, 0.092, 0.187)	(0.061, 0.108, 0.200)	(0.045, 0.075, 0.138)	(0.179, 0.305, 0.521)	(0.066, 0.122, 0.240)	(0.049, 0.086, 0.150)	(0.026, 0.039, 0.066)	(0.069, 0.114, 0.206)	(0.036, 0.064, 0.120)
C11	(0.126, 0.220, 0.423)	(0.161, 0.284, 0.508)	(0.170, 0.273, 0.442)	(0.032, 0.052, 0.087)	(0.107, 0.201, 0.401)	(0.145, 0.256, 0.452)	(0.057, 0.091, 0.149)	(0.174, 0.276, 0.442)	(0.222, 0.386, 0.638)
C12	(0.068, 0.125, 0.245)	(0.046, 0.081, 0.166)	(0.045, 0.081, 0.141)	(0.020, 0.031, 0.051)	(0.103, 0.192, 0.384)	(0.036, 0.056, 0.096)	(0.178, 0.275, 0.427)	(0.204, 0.346, 0.556)	(0.115, 0.203, 0.389)

Table A- 3. Non-fuzzy Performance Values of Fuzzy Weights for Criteria and Sub-criteria for Each Expert (Ex)

Criteria	Ex1	Ex2	Ex3	Ex4	Ex5	Ex6	Ex7	Ex8	Ex9
B1	0.557	0.618	0.663	0.557	0.508	0.592	0.498	0.678	0.289
B2	0.254	0.168	0.176	0.254	0.158	0.197	0.145	0.138	0.642
B3	0.376	0.335	0.218	0.376	0.458	0.351	0.475	0.248	0.128
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C1	0.235	0.385	0.128	0.287	0.376	0.744	0.271	0.336	0.695
C2	0.061	0.159	0.642	0.070	0.254	0.085	0.094	0.166	0.219
C3	0.714	0.571	0.289	0.678	0.557	0.194	0.673	0.596	0.097
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C4	0.204	0.099	0.128	0.721	0.189	0.070	0.090	0.220	0.289
C5	0.070	0.831	0.942	0.073	0.757	0.678	0.665	0.722	0.642
C6	0.745	0.093	0.289	0.231	0.075	0.287	0.288	0.089	0.128
Sub-criterio	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C7	0.025	0.030	0.053	0.301	0.044	0.040	0.055	0.025	0.043
C8	0.330	0.364	0.405	0.090	0.327	0.392	0.169	0.098	0.241
C9	0.277	0.188	0.159	0.282	0.174	0.224	0.409	0.166	0.097
C10	0.111	0.123	0.086	0.335	0.143	0.095	0.043	0.130	0.073
C11	0.256	0.318	0.295	0.057	0.236	0.284	0.099	0.297	0.415
C12	0.146	0.098	0.089	0.034	0.227	0.063	0.293	0.369	0.236

Table A-4. Normalized Weights of Criteria and Sub-criteria for Each Expert (Ex)

Criteria	Ex1	Ex2	Ex3	Ex4	Ex5	Ex6	Ex7	Ex8	Ex9
B1	0.469	0.552	0.618	0.469	0.452	0.519	0.445	0.637	0.273
B2	0.214	0.150	0.164	0.214	0.141	0.173	0.130	0.129	0.607
B3	0.317	0.299	0.218	0.317	0.407	0.308	0.425	0.233	0.121
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C1	0.235	0.345	0.121	0.277	0.317	0.727	0.261	0.306	0.687
C2	0.061	0.143	0.607	0.067	0.214	0.083	0.091	0.151	0.217
C3	0.705	0.512	0.273	0.655	0.469	0.190	0.648	0.543	0.096
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C4	0.201	0.097	0.121	0.704	0.185	0.067	0.086	0.213	0.273
C5	0.069	0.812	0.607	0.071	0.742	0.655	0.638	0.700	0.607
C6	0.731	0.091	0.273	0.225	0.073	0.277	0.276	0.086	0.121
Sub-criteria	**Ex1**	**Ex2**	**Ex3**	**Ex4**	**Ex5**	**Ex6**	**Ex7**	**Ex8**	**Ex9**
C7	0.022	0.026	0.048	0.274	0.038	0.037	0.051	0.023	0.039
C8	0.288	0.325	0.373	0.082	0.284	0.357	0.158	0.090	0.218
C9	0.242	0.168	0.146	0.257	0.151	0.204	0.383	0.153	0.088
C10	0.097	0.110	0.079	0.304	0.124	0.086	0.041	0.120	0.066
C11	0.224	0.284	0.272	0.052	0.205	0.259	0.093	0.274	0.376
C12	0.127	0.087	0.082	0.031	0.197	0.057	0.274	0.340	0.213