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Assessment of the Suitability of Rain Water Harvesting Areas Using Multi-Criteria Analysis and Fuzzy Logic

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Authors' contributions

This work was carried out in collaboration between all authors. Author ENM designed the study, collected and analyzed the data. Author BK wrote the first draft of the manuscript. Author RT prepared the study protocol and managed literature searches. Author MT edited the first draft of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Rain Water Harvesting (RWH) is any system that encompasses methods for collecting, concentrating and storing various forms of runoff for various purposes. Agriculture in semiarid tropics depends on the vagaries of weather, especially of the rain. Without doubt, the greatest climatic risk to sustained agricultural production in these areas, including Botswana, is rainfall variability. RWH has the potential to mitigate spatial and temporal variability of rainfall. Many methods of evaluating suitability for RWH, however, have limitations and/or drawbacks.

This study presents an approach that will enable water managers to assess suitability of RWH for any given area by taking advantage of the capabilities of Earth Observation (EO) techniques and fuzzy multi-criteria analysis. Literature shows that the incorporation of fuzzy logic to multi-criteria analysis can improve the results in suitability analysis hence the study to explore these capabilities in RWH.

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South East District of Botswana was used as the study area to identify suitable areas for macro RWH techniques using Analytical Hierarchical Process (AHP) and Fuzzy AHP integrated in GIS and RS. The study area was suitable for over 80% of the area, with AHP approach showing 87.1% suitable while Fuzzy AHP showing 92.2%, distributed between highly suitable (S1), moderately suitable (S2) and marginally suitable (S3). Validation process shows existing water bodies occupying only highly suitable area (44%) and moderately suitable (56%) and this was a good indication that the model has a good level of accuracy. Field visit showed an accuracy of 57% comparing model results with actual situation on the ground.

In conclusion, even though AHP is widely used in the decision analysis, it is not capable of modeling the uncertainties inherent in the criteria and the confidence of the decision maker. Fuzzy AHP is seen to perform better as it incorporates the techniques of AHP, fuzzy numbers, fuzzy extent analysis, alpha cut and Lambda functions which are able to model the uncertainties inherent in the criteria and confidence of the decision maker since the process of decision making involves a range of criteria and a good amount of expert knowledge and judgments which in turn affect the outcome greatly.

Keywords: Multi-criteria evaluation; AHP; fuzzy AHP; macro RWH; South East District.

1. INTRODUCTION

Rain Water Harvesting (RWH), described as the collection and concentration of runoff for productive purposes and domestic water supply [1,2,3,4] is very crucial in alleviating water shortages brought about by spatial and temporal variability of rainfall in the semiarid regions. This variability causes dry spells which result in crop yield reductions thus jeopardizing the success of rainfed agriculture [5]. Where practised, RWH has mitigated the impacts of dry spells and production has been increased. In addition, other crops that require more water such as rice and maize are now produced under RWH in areas where otherwise they would never do well [6].

RWH techniques for crop production are generally classified into three types namely: In-situ, Internal (micro) and External (macro) RWH. Implementation of these techniques requires assessment of the area for their suitability [7] since they are not suitable everywhere. Conventional methods such as land surveys, though accurate, are very expensive and time consuming to implement [7,8,9,10]. There is therefore, a need for methods that are easy to use, yet accurate, to identify potential areas.

Spatial techniques such as Geographical Information System (GIS) and Remote Sensing (RS) are vastly used in suitability evaluation [7] and have proven to be good for reconnaissance survey of any land assessment. Their results could then be used as a guideline for pinpointing areas that could be targeted. Like any land assessment process, RWH involves an appraisal of a lot of factors and constraints to be successful, and this renders it a multi criteria analysis (MCA) problem. Whereas classical GIS has been seen to have weaknesses when dealing with overlays [11,12], Multi Criteria Decision Making (MCDM) has been found to handle multi criteria well and thus its inclusion in land suitability assessments can render better results compared to those done with GIS alone.

Many factors dealt with in RWH such as soil texture, slope and rainfall are continuous in nature [13,14] and thus would be very difficult to be handled by GIS and/or MCDM. Previous methodologies used in identifying potential suitable areas for different RWH systems have either used GIS alone [15]; a combination of GIS and RS and to a limited extent MCDM [7,9,16]. To account for the continuous nature of different factors, fuzzy logic has been seen to produce better results compared to the above-mentioned methods. Fuzzy logic is an approach which takes into account the uncertainties in the criteria used and provides confidence to the decision maker. In addition, there is usually ambiguity and imprecision involved when selecting cut-offs in attributes associated with land use [13]. Under such uncertain situations fuzzy logic comes handy. Fuzzy logic aids in most precise presentation of such imprecise, incomplete and vague information [14,17]. The fuzzy logic approach has been used in site selection of many disciplines but has not been applied in the evaluation of suitable sites for RWH techniques.

The objective of this study was to explore the capabilities of fuzzy logic into MCA for the assessment of suitability of RWH sites in semiarid South East District of Botswana using GIS and RS.

2. MATERIALS AND METHODS

The study area is composed of arable and pastoral areas of South East District (25 - 27°S; 24 - 26°E) as shown in Fig. 1. The climate is semiarid with an average annual rainfall range of 459-761 mm. Most rainfall occurs in summer, which generally starts in late October and continues through March/April. Prolonged dry spells during the rainy season are common and rainfall tends to be localized. Mean maximum and minimum temperatures of the district vary between 22.5 – 33.0°C and 5.0 – 19.3°C, respectively. The underlying bedrock of South East District contains a number of different geological groups including granites, igneous and dolomite limestone. The areas exhibiting granitic bedrock are generally the flatter landscape and they usually form fertile soils in the district. Igneous rocks usually form shallow soils that are unsuitable for arable agriculture. The soils are also poor in terms of nutrient availability. The dolomite limestone is said to form fair to good soils for arable agriculture [18]. The formation of limestone also represents one of the best aquifers in the district. The vegetation structure of South East District is the *Croton gratismus* woodland and the species usually found in the area include *Croton gratismus*, *Combretum-apiculatum*, and *Combretum-molle*. The study area has a number of ephemeral rivers which experience flow and flash flooding during the rainy season.

The logical arrangement of procedures which were used in determining the suitability of RWH techniques are depicted in Fig. 2. Four phases were performed, namely, framework of land suitability evaluation decision making, data processing in MCE, data processing in GIS and the integration of GIS and MCE, to come up with suitability maps.

Phase I activities, that is, to prioritize criteria and/or constraints, were consecutively carried out as follows:

2.1 Selection of RWH Techniques

This step investigated possible RWH techniques in the study area by taking into account shortage of water, overexploitation of underground water, cropping patterns, soil patterns, agricultural markets, climate conditions and socioeconomic status of society. The study area was explored for its suitability of macro (ex-field, external) RWH technique.

2.2 Formulation of the Evaluation Criteria

After selecting the RWH technique, the next step was to identify relevant criteria (viz. factors and constraints) that were necessary for its spatial assessment. Criteria established in this phase were not unique, but the most relevant. The criteria established from literature on RWH assessment and RWH studies [9,16] included climate, hydrology, topography, agronomy, soils and socioeconomic factors. In addition, expert's opinions were solicited by the use of questionnaires. Relevant factors for Ex-field RWH included, among others, rainfall, land use, soil texture, drainage and topography. Each criterion was considered as a thematic layer in the GIS.

2.3 Hierarchical Organization of the Criteria

Criteria become manageable when they are arranged in a hierarchical structure [19]. In developing the hierarchy, the top level is the ultimate goal of the decision at hand and the hierarchy then descends from the general goal to the more specific elements of the problem until a level of attributes and alternatives are reached [19]. In this study a four level hierarchical structure that was followed is shown in Fig. 3. In a GIS based multi criteria analysis the alternatives are represented in GIS databases. Each layer contains the attribute values assigned to the alternatives, and each alternative (e.g. cell or polygon) is related to the higher-level elements (i.e. attributes) [19]. The above hierarchy (Fig. 3) was transformed to a spatial decision problem.

The next stage was to collect data to be used in the study. Some spatial data (including soil map) was obtained from the Ministry of Agriculture, Digital Elevation Model (DEM) from the African Monitoring of Environment for Sustainable Development (AMESD) project and aerial photographs from Department of Surveys and Mapping while rainfall data was obtained from Department of Meteorological services and AMESD project.

More spatial data was achieved by processing and manipulating data in ArcGIS Environment. Questioners were used to elicit expert knowledge on the ratings and ranking of the relevant criteria.

Phase II activities, that is, Multi Criteria Evaluation (MCE), involved the use of two approaches (after literature search): Analytical

Hierarchical Process (AHP) and Fuzzy AHP. AHP steps involved constructing/developing the pairwise comparison matrix (PCM) according to [19,20], standardization of the criteria according to expert knowledge and literature [7,9,15,21], assessing/estimation of relative weights according to [20,22], checking consistency according to [22] and obtaining the overall rating of criteria according to [19].

Fuzzy AHP steps [12,14,23] involved the following:

2.3.1 Acquisition of normal (crisp) pairwise comparison matrices (PCM)

The first step in Fuzzy AHP was the development of normal pairwise comparison matrices by decision makers as is done for AHP. The consistency property of the matrix was also checked to ensure the consistency of judgments in the pairwise comparison. The PCM developed in AHP and their consistency ratios were adopted for Fuzzy AHP in this study.

2.3.2 Fuzzifying the crisp PCM to fuzzy PCM

The above crisp PCM's were then converted into fuzzy matrices using pre-defined fuzzy triangular functions. The membership values of all the elements within the range were calculated as follows:

Fuzzy number	Membership function
$\overline{1}$	(1, 1, 3)
$\overline{x}$	(x-2, x, x+2) for x = 2, 3, 4, 5, 6, 7
$\overline{9}$	(7, 9, 11) (1)

Table 1 shows the pre-defined membership functions for triangular fuzzy numbers.

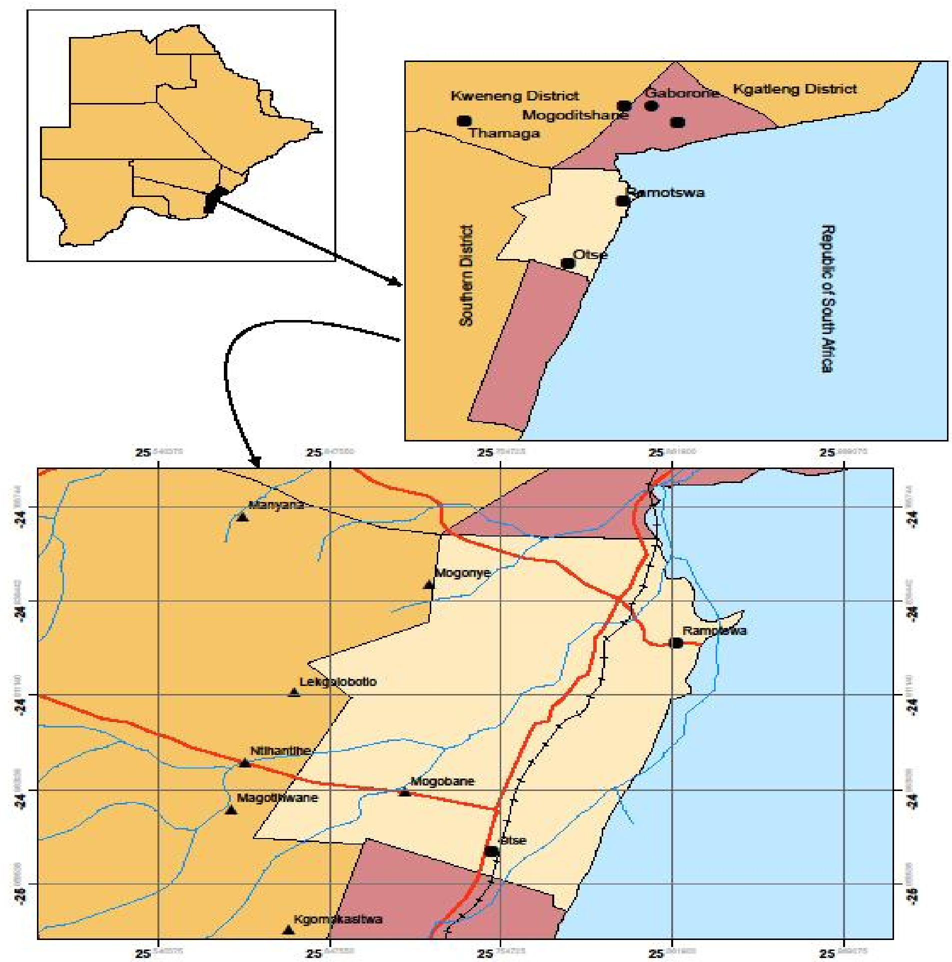

Fig. 1. Map of the study area in context of South East District and Botswana

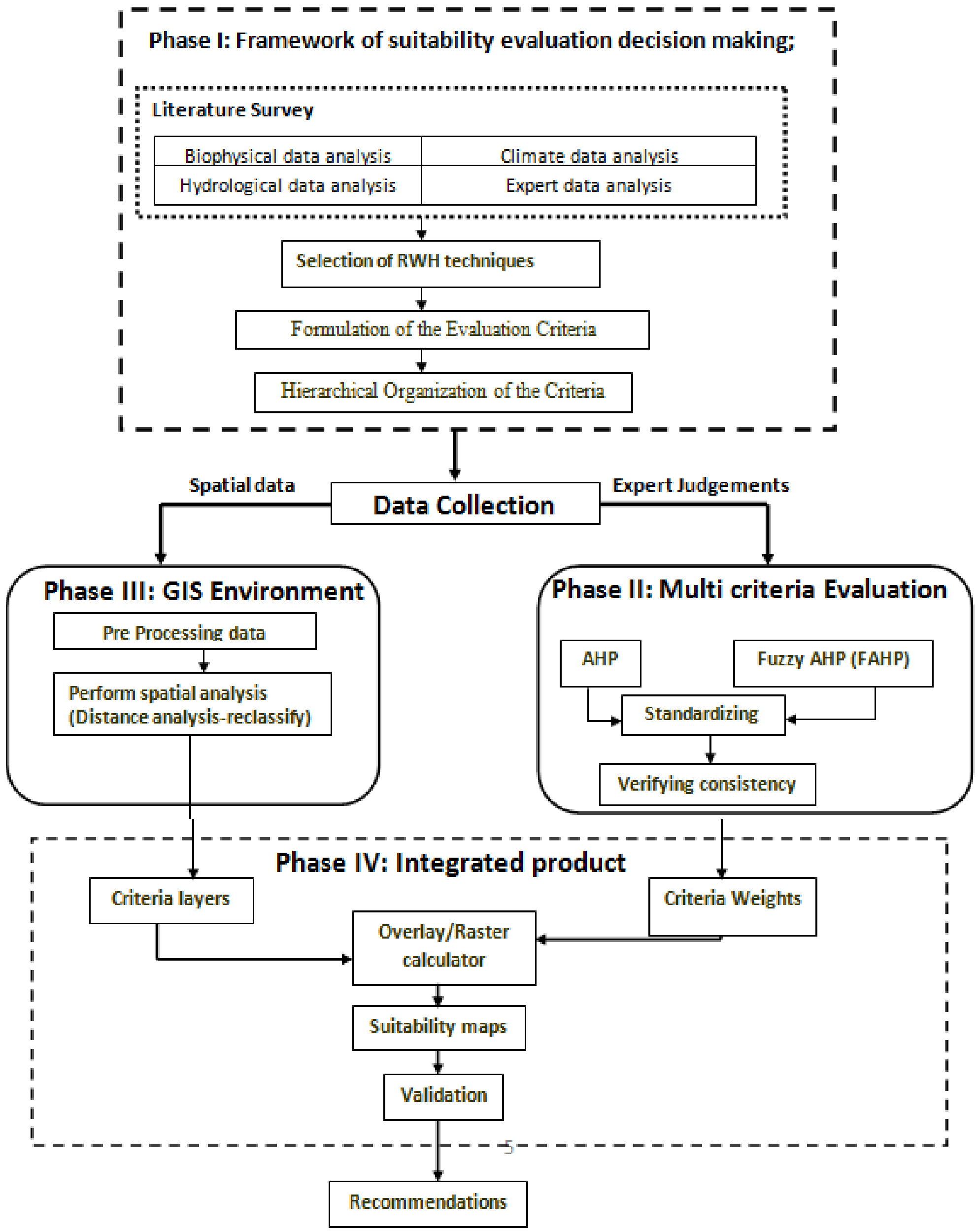

Fig. 2. Conceptual flow of suitability of RWH approach

Depending on the scores given for different criteria or alternatives fuzzy PCM is represented as follows:

$$\bar{A} = (\tilde{a}_{ij})_{nxn} = \begin{pmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \cdots & (1,1,1) \end{pmatrix} \qquad (2)$$

Where $\tilde{\alpha}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \tilde{\alpha}_{ij}^{-1} = (1/u_{ij}, 1/m_{ij}, 1/l_{ij})$

For $l,j = 1,\ldots,n$ and $1 \neq j$. l,m,u are the lower bound, middle bound and upper bound respectively.

2.3.3 Calculation of performance ratings and weights

After fixing the range, the next step was to find out the performance ratings (x_{ij}) and weights (w_j) of each of the alternatives with respect to all criteria. To achieve this, fuzzy extent analysis was employed as follows:

$$x_{ij} \text{ or } w_j = \frac{\sum_{j=1}^{k} \tilde{a}ij}{\sum_{i=1}^{k}\sum_{j=1}^{k} \tilde{a}ij} \tag{3}$$

where i = 1,2,…,n; j = 1,2…,m and k=m or n depending on whether the reciprocal judgment matrix was for assessing the performance ratings of alternatives or weights of the criteria involved. The result of applying the above formula yielded the decision matrix (X) and the weight vector (W) as follows:

$$X = \begin{pmatrix} (l_1, m_1, u_1) \\ (l_2, m_2, u_2) \\ \vdots \quad \vdots \quad \vdots \\ (l_n, m_n, u_n) \end{pmatrix}, \tag{4}$$

$W = (w1, w2, \ldots, wm)$

Where n is the number of alternatives and m is the number of criteria.

2.3.4 Weighting multiplication from hierarchy

After converting the fuzzy PCM to the performance ratings, the next step was to multiply them by the criterion weights which were obtained using the same step above. The result was a fuzzy weighted performance matrix (P) shown below, representing the overall performance of all alternatives with respect to each criterion.

$$P = \begin{pmatrix} (P_{1l}, P_{1m}, P_{1u}) \\ (P_{2l}, P_{2m}, P_{2u}) \\ (\vdots \quad \vdots \quad \vdots) \\ (P_{nl}, P_{nm}, U_{nu}) \end{pmatrix} \tag{5}$$

Where ($P_{1l} = w_l \times l_1$, $P_{1m} = w_m\, xm_1$, $P_{1u} = w_u\, xu_1$)

The results obtained above were the uncertain range of values over which any value could be considered as a performance value thus helping to decide on the certainty of the decision maker.

2.3.5 Embedding uncertainty of decision maker through alpha-cut analysis

Alpha cut (α cut) method was used to account for the uncertainty in the fuzzy range. It transformed the weighted performance matrix into an interval performance matrix. The value of α ranged from 0 to 1 and represented the decision maker's degree of confidence regarding the alternative ratings and criteria weights. A larger α value indicated a more confident decision maker while a lower value indicated an uncertain decision maker. The interval performance matrix took the form:

$$P_\alpha = \begin{pmatrix} [P_{11}^{\alpha}{}_{(l)}, P_{11}^{\alpha}{}_{(r)}] & [P_{12}^{\alpha}{}_{(l)}, P_{12}^{\alpha}{}_{(r)}] & \ldots & [P_{1n}^{\alpha}{}_{(l)}, P_{1n}^{\alpha}{}_{(r)}] \\ [P_{21}^{\alpha}{}_{(l)}, P_{21}^{\alpha}{}_{(r)}] & [P_{22}^{\alpha}{}_{(l)}, P_{22}^{\alpha}{}_{(r)}] & \ldots & [P_{3n}^{\alpha}{}_{(l)}, P_{3n}^{\alpha}{}_{(r)}] \\ \vdots & \vdots & & \vdots \\ [P_{n1}^{\alpha}{}_{(l)}, P_{n2}^{\alpha}{}_{(r)}] & [P_{n2}^{\alpha}{}_{(l)}, P_{n2}^{\alpha}{}_{(r)}] & \ldots & [P_{nn}^{\alpha}{}_{(l)}, P_{nn}^{\alpha}{}_{(r)}] \end{pmatrix} \tag{6}$$

Table 1. Fuzzy pairwise conversion

Linguistic variables	Crisp PCM value	Positive triangular fuzzy number	Positive reciprocal triangular fuzzy number
Equal	1	(1,1,1) if diagonal	(1,1,1)
Intermediate	2	(1,2,4)	(1/4,1/2,1)
Moderate	3	(1,3,5)	(1/5,1/3,1)
Intermediate	4	(2,4,6)	(1/6,1/4,1/2)
Strong	5	(3,5,7)	(1/7,1/5,1/3)
Intermediate	6	(4,6,8)	(1/8,1/6,1/4)
Very strong	7	(5,7,9)	(1/9,1/7,1/5)
Intermediate	8	(6,8,10)	(1/10,1/8,1/6)
Absolute	9	(7,9,11)	1/11,1/9,1/7)

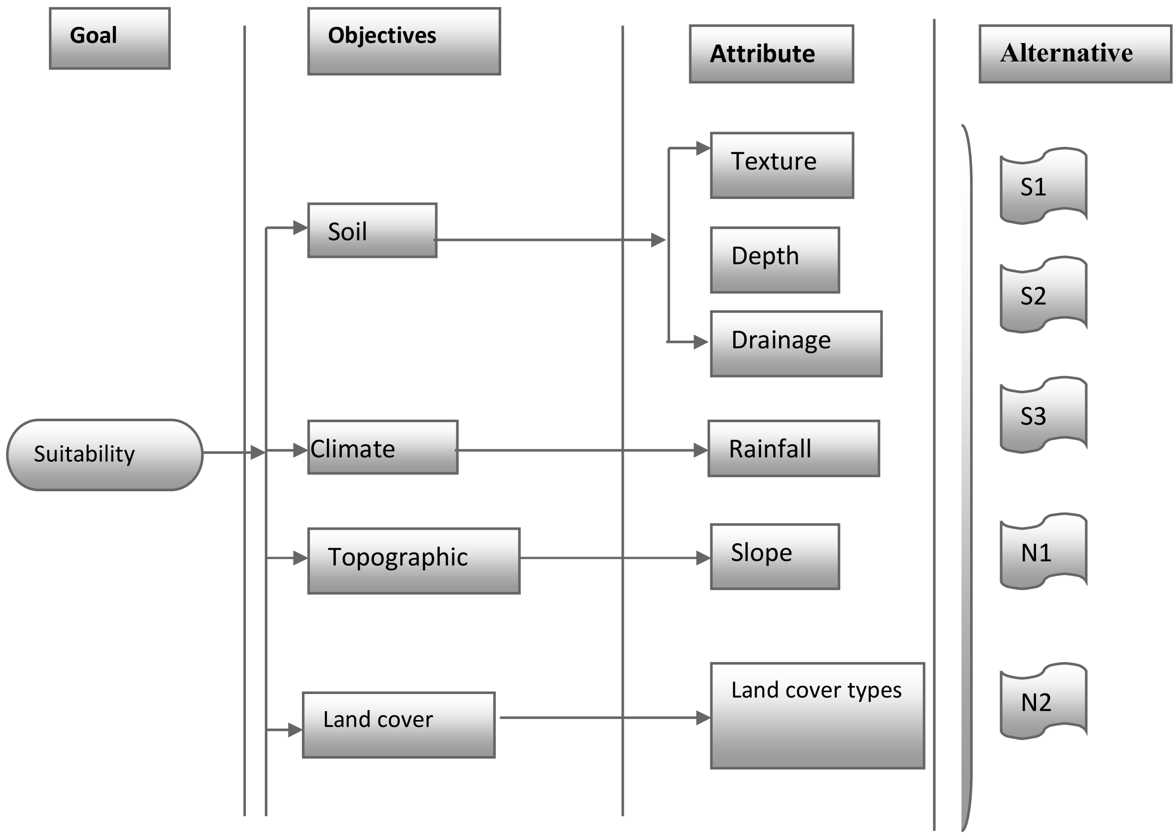

Fig. 3. Hierarchical structure for the suitability of RWH techniques [14,19]

2.3.6 Embedding attitude of the decision maker through lambda function

The attitude of the decision maker also played a role in deciding the performance value. After embedding the uncertainty of the decision maker, there still existed a range to pick from. This therefore brought the issue of decision maker being pessimistic, optimistic and neutral. Lambda function index (**λ**) which takes the values between 0 and 1 was used to capture decision maker's attitude. Decision maker with optimistic attitude would take the maximum Lambda; the moderate person would take the medium Lambda and the pessimistic person would take the minimum Lambda as follows:

$$C\lambda = \begin{pmatrix} C_{\lambda 1} \\ C_{\lambda 2} \\ \vdots \\ C_{\lambda n} \end{pmatrix} \quad (7)$$

$C\lambda = \lambda^*\alpha(R) + [(1-\lambda)^*\alpha L]$,

Where R is Right side and L is Left side; $C\ \lambda$ =crisp value.

The above steps were followed in this study to site suitable areas for macro rainwater harvesting.

Phase III activities, that is, GIS Environment, used GIS to map suitability derived from AHP and Fuzzy AHP approaches. Since many maps were produced (e.g. soil depth, soil texture, rainfall distribution, drainage, relief, etc.), overlaying in GIS proved handy. Fig. 4 shows a schematic representation used for the criteria chosen. All the maps, except those of land cover and spatial distribution of rainfall, were converted to raster layers and re-sampled to a resolution of 30 x 30 m to match the spatial resolution of Aster DEM. They were then re-classified as per the specifications of each RWH technique.

Phase IV activity, that is, integration of results from MCE and GIS environment, entailed the incorporation of the results from phase II and III. ArcGIS was used to achieve this and the raster calculator and overlay procedures were used. After calculating the weights, all the products were overlaid to come up with the final suitability maps.

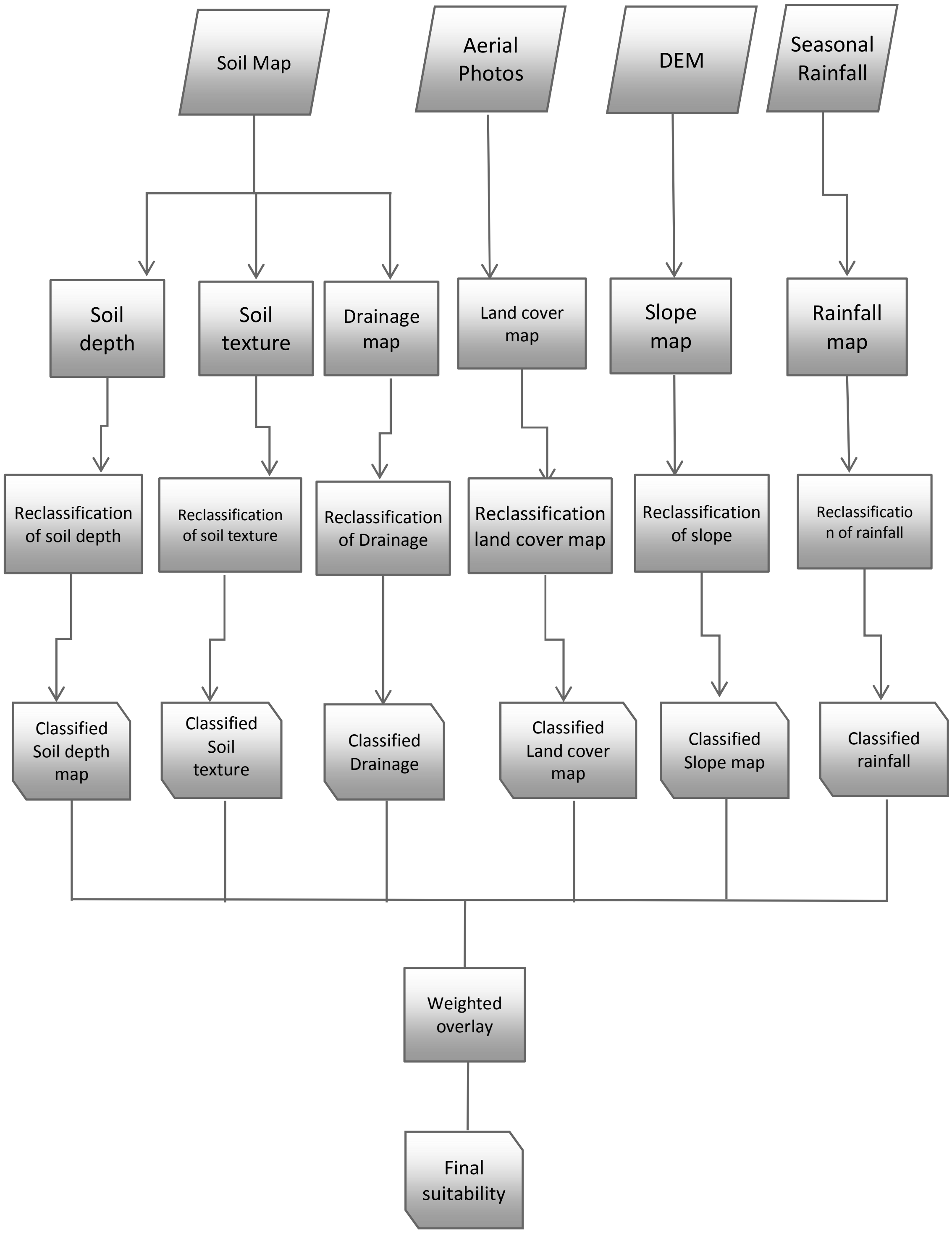

Fig. 4. Schematic representation of the procedures used to generate criteria maps in GIS

Testing and validation of the approaches used in the study were carried out by adopting the approach of using existing areas of water impoundment [16]. Data was collected from the Ministry of Agriculture for water bodies and it was augmented by classifying LANDSAT and digitizing from aerial photographs of 1m x 1m resolution. The assumption made was that these areas are suitable for storing water that is why they are used as dams. Another assumption was that they have or are sited in places where there are drainage patterns to impound them therefore the drainage pattern in the study area was also used to validate the results obtained. The drainage pattern was obtained by using hydrology toolbox embedded in ArcGIS 10. The water bodies' layer was overlain with the final suitability map derived to check where the water bodies fell. Area covered by the different water bodies was calculated as per suitability classes. The area covered by water bodies was assumed to be highly suitable and those without water were said to be unsuitable. If the area within the water body falls within the area classified as suitable in the final suitability map, then the suitability model would be said to be good as it would be agreeing with the independent data.

Another way of validating the model was achieved by collecting points in the resultant suitability map and confirming them with field data (ground truthing). Points were collected by taking **x** and **y** coordinates at the confluence of the map grid reference. An error matrix was then constructed from the reference data and the classification data. Several measures of classification accuracy such as percentage correct, percent correct by category and both errors of commission and omission by category were calculated. Kappa statistic or coefficient was also calculated to determine the agreeability of the classified data compared to reference data.

3. RESULTS AND DISCUSSION

Figs. 5 a-h show the distribution of soil texture, soil depth, soil drainage, land cover, relief, slope (%), rainfall, and constraint areas, respectively, of the study area.

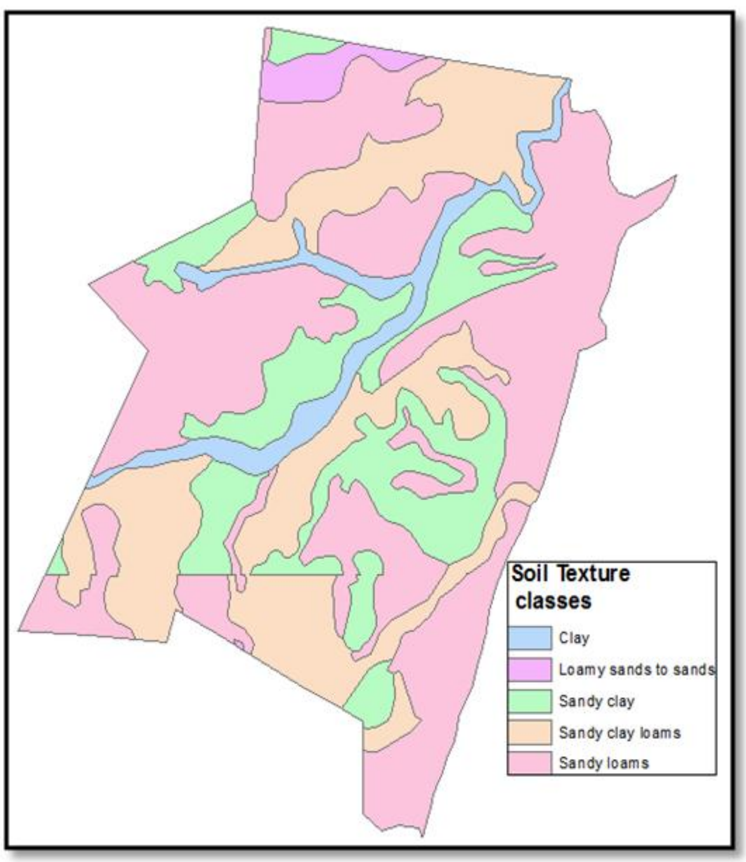

Fig. 5(a). Soil texture map

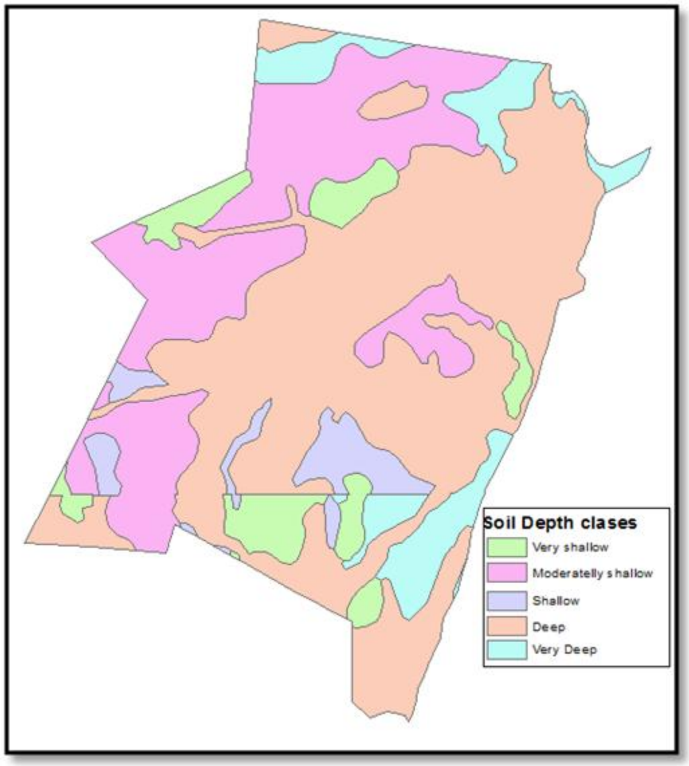

Fig. 5(b). Soil depth map

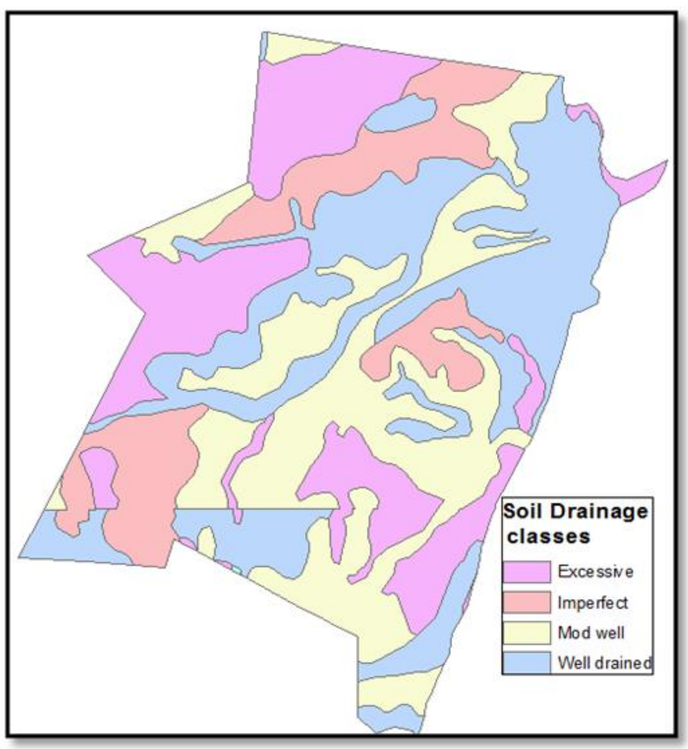

Fig. 5 (c). Soil drainage map

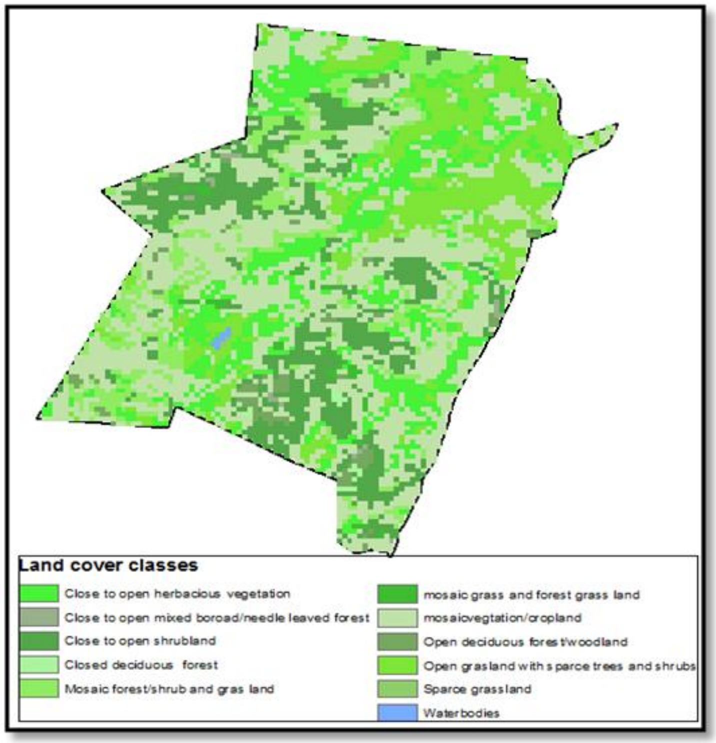

Fig. 5 (d). Land cover map

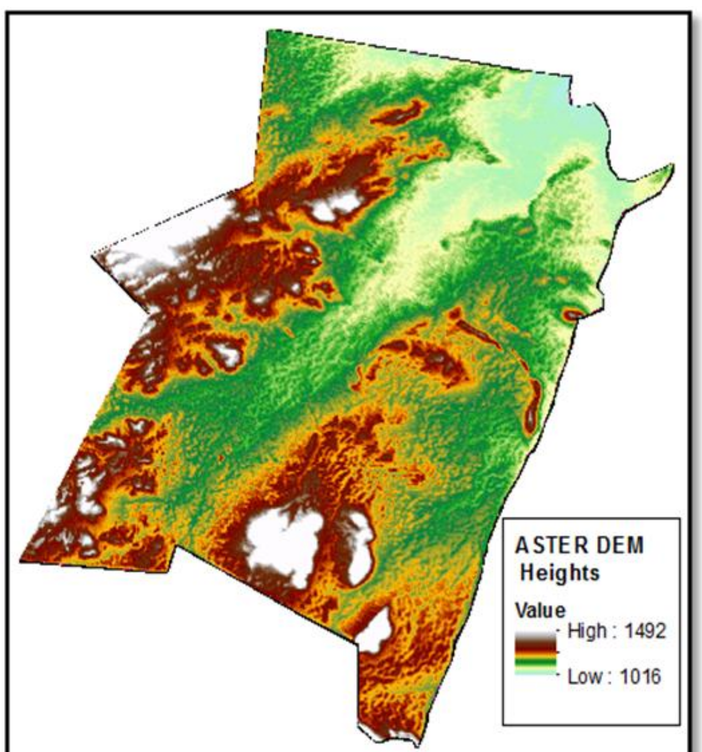

Fig. 5(e). Aster DEM

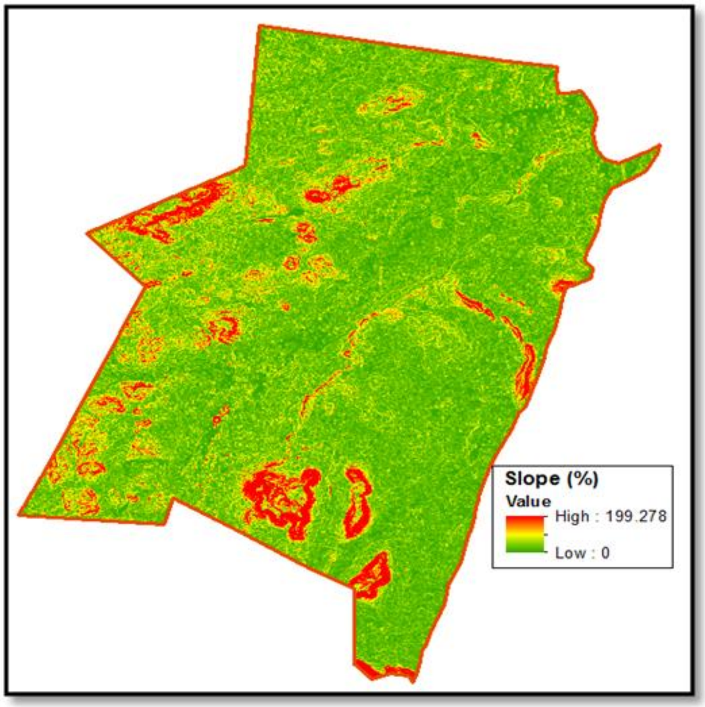

Fig. 5 (f). Slope map

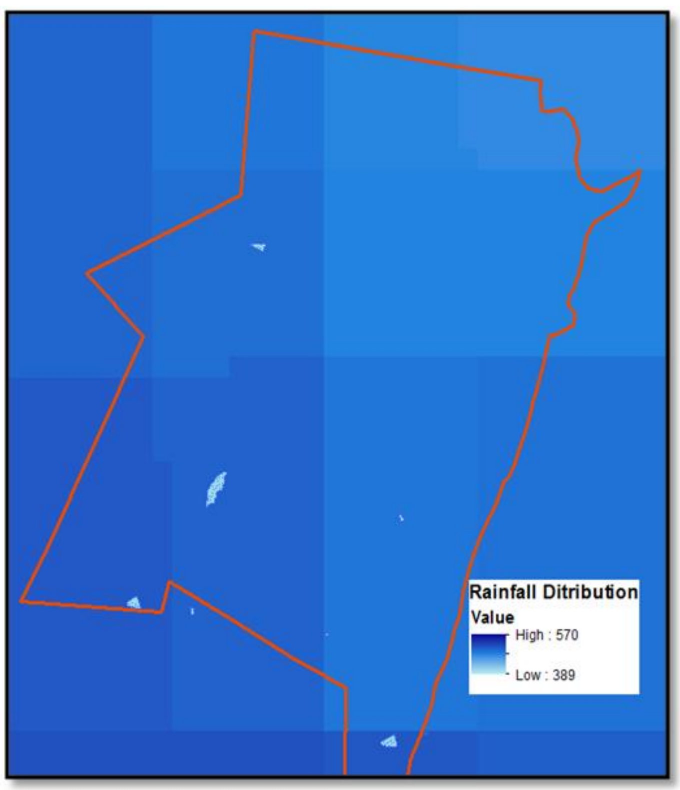

Fig. 5 (g). Rainfall distribution map

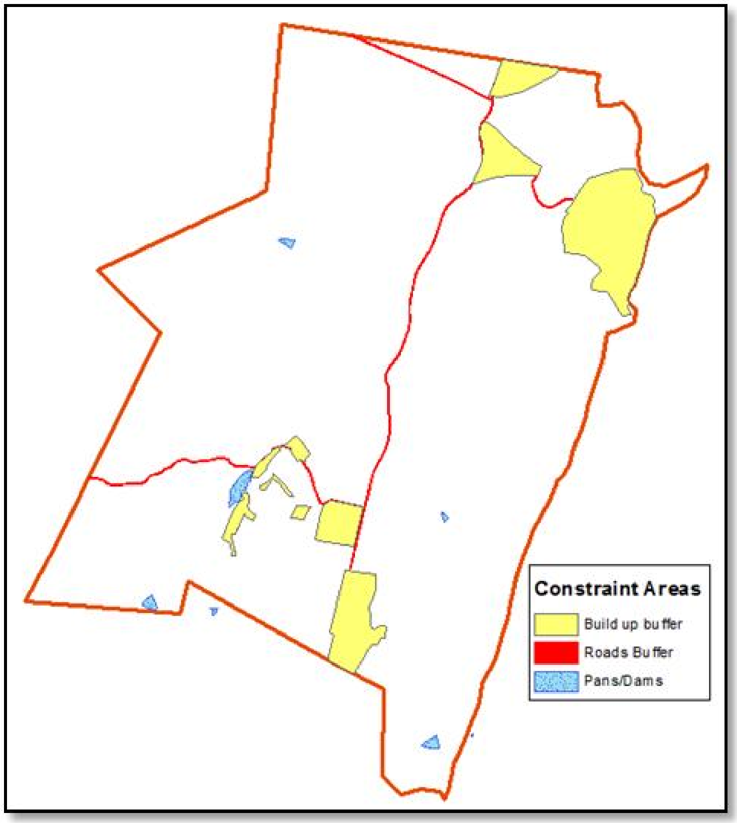

Fig. 5(h). Constraint areas for macro RWH

Table 2. Overall Pair-wise comparison matrix for macro RWH

Macro RWH	Climate	Topography	Soil	Land cover	Weights
Climate	1	2	3	5	0.4530
Topography		1	2	4	0.3089
Soil			1	2	0.1579
Land cover				1	0.0803
		C.I = 0.007		*R.I = 0.008*	

3.1 AHP

The pairwise comparison matrices shown in Tables 2 and 3 together with consistency index (CI) and consistency ratio (CR) of less than 0.10 indicate a reasonable level of consistency in the pairwise comparison.

Table 3. Pairwise comparison for soil attributes of macro RWH

Soil	Drainage	Texture	Weights
Drainage	1	2	0.6667
Texture	1/2	1	0.3333
	C.I = 0	*R.I = 0*	

The aggregation of relative weights of objectives and attribute levels to produce composite weights resulted in ratings and rankings shown in Table 4.

Table 4. Different criteria for macro RWH with their weights and their order of importance

Technique	Criteria	Weights	Ranking
Macro RWH	Climate	0.4530	1
	Topography	0.3089	2
	soil	0.1579	3
	Land cover	0.0803	4

Armed with weights for the whole criteria, the suitability map (using ArcGIS 10) for macro RWH techniques was obtained as shown in Fig. 6. From the map above, 87.1% of the total available area is suitable for macro RWH techniques with 21.3% being highly suitable (S1). The unsuitable area (N1 and N2) only occupies 12.9% of which 11.6% is occupied by N1. The results are summarized in Table 5.

3.2 Fuzzy AHP (FAHP)

As experts are not totally certain regarding suitability parameters of the RWH techniques in question and their requirements, an alpha cut value (α) of 0.6 (indicating 60%) of uncertainty in the experts' knowledge, and a lambda (ʎ) of 0.5 (indicating moderate attitude) of uncertainty over the range of their requirements, were applied in this study. Fig. 7 and Table 6 show the results of suitability for macro RWH techniques.

Fig. 7 and Table 6 show that macro RWH is highly suitable (S1) for 28.4% of the total area while 63.8% is distributed between other suitable classes (S2 and S3) with S3 dominating the area (33.8%). The unsuitable (N1 and N2) area only occupies 7.8% of the study area.

Table 5. Area suitable for macro RWH (AHP) under different classes

Suitability class	Area (km^2)	% Area
S1	107.32	21.3
S2	149.27	29.7
S3	181.53	36.1
N1	58.99	11.6
N2	6.31	1.3

Table 6. Area suitable for macro RWH (Fuzzy AHP 0.5) under different classes

Suitability class	Area (km^2)	% Area
S1	143.1	28.4
S2	150.8	30.0
S3	170.2	33.8
N1	38.1	7.6
N2	1.3	0.3

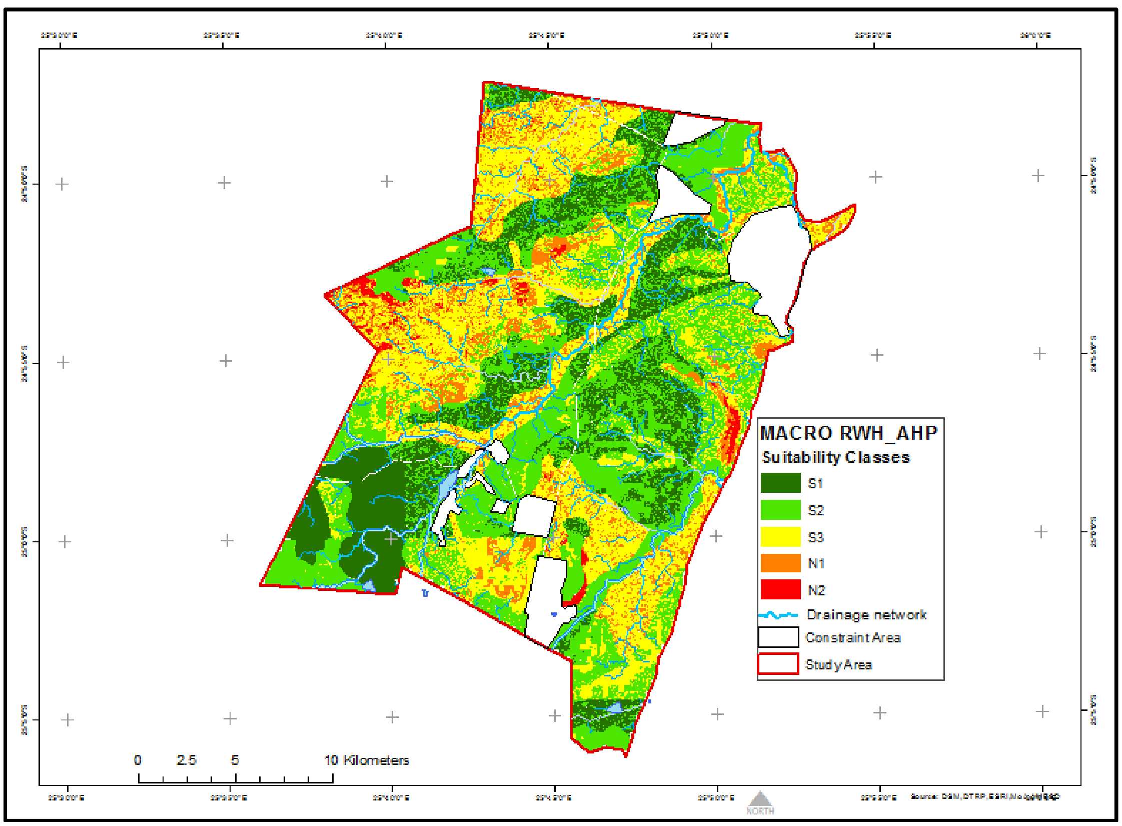

Fig. 6. Suitability map of macro RWH technique using AHP approach

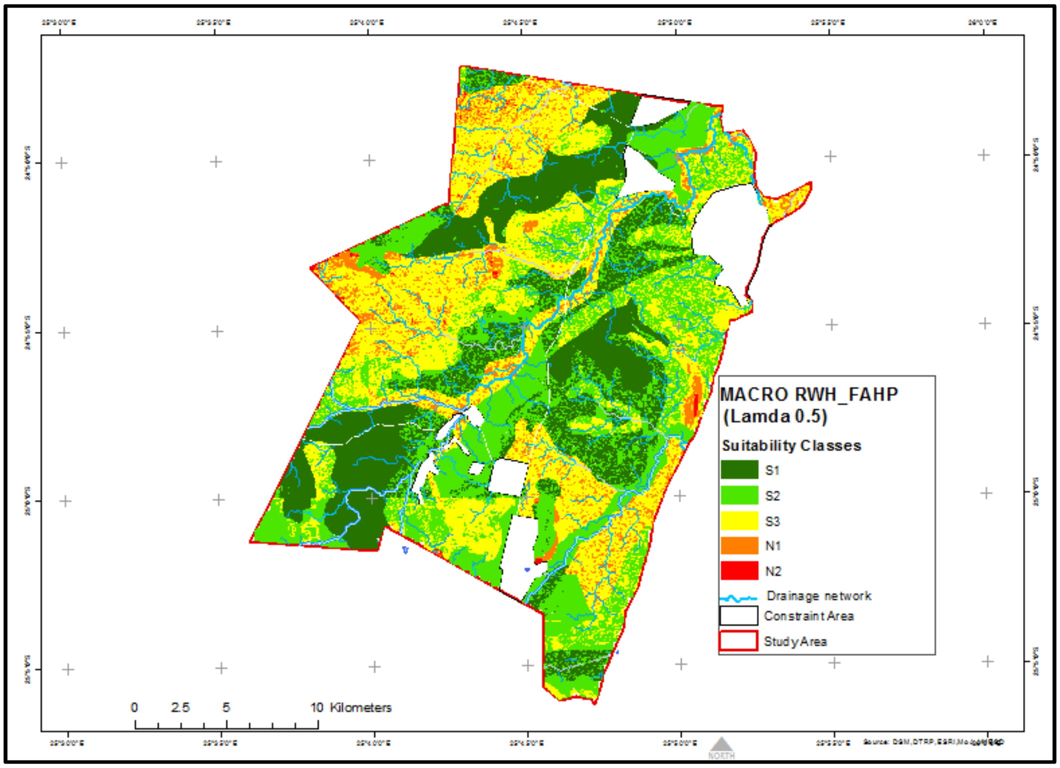

Fig. 7. Suitability map of macro RWH technique using Fuzzy AHP approach

In the overall it is evident from the results that the study area is mostly suitable for macro RWH techniques while less than quarter of the area is not suitable.

3.3 Sensitivity Analysis

In Fuzzy AHP approach, an Alpha-cut value of 0.6 was considered for this study assuming that the decision environment was certain to a certain level since the process involved criteria, which were measured with comparatively good accuracies by advanced technologies (e.g. slope derived from DEM). The decision maker on the other hand decides on the criteria selected and thus some level of uncertainty is involved. The sensitivity of the approach is therefore illustrated using Lambda 0, 0.5 and 1 for macro RWH technique. Figs. 8-10 show the results obtained using an Alpha cut of 0.6 and Lambda values of 0, 0.5 and 1 respectively.

The results for macro RWH at Lambda 0 show that the highly suitable area is 24.8% and that the unsuitable (N2) area is 1.0%. For Lambda 0.5, the most suitable area increased to 28.4% while that for highly unsuitable (N2) area is decreased to 0.3%. Comparisons of the results for the three Lambda values are shown in Table 7.The general trend is that the area under suitability classes S1 and S2 increases as the decision maker's attitude becomes optimistic but that of classes S3, N1 and N2 decreases.

Table 7. Comparison of results for macro RWH undertake by three Lambda values

Class	Lambda 0		Lambda 0.5		Lambda 1	
	Area	% Area	Area	% Area	Area	% Area
S1	124.8	24.8	143.1	28.4	152.1	30.2
S2	113.2	22.5	150.8	30.0	173.8	34.5
S3	199.3	39.6	170.2	33.8	148.6	29.5
N1	61.2	12.2	38.1	7.6	28.2	5.6
N2	5.0	1.0	1.3	0.3	0.7	0.1

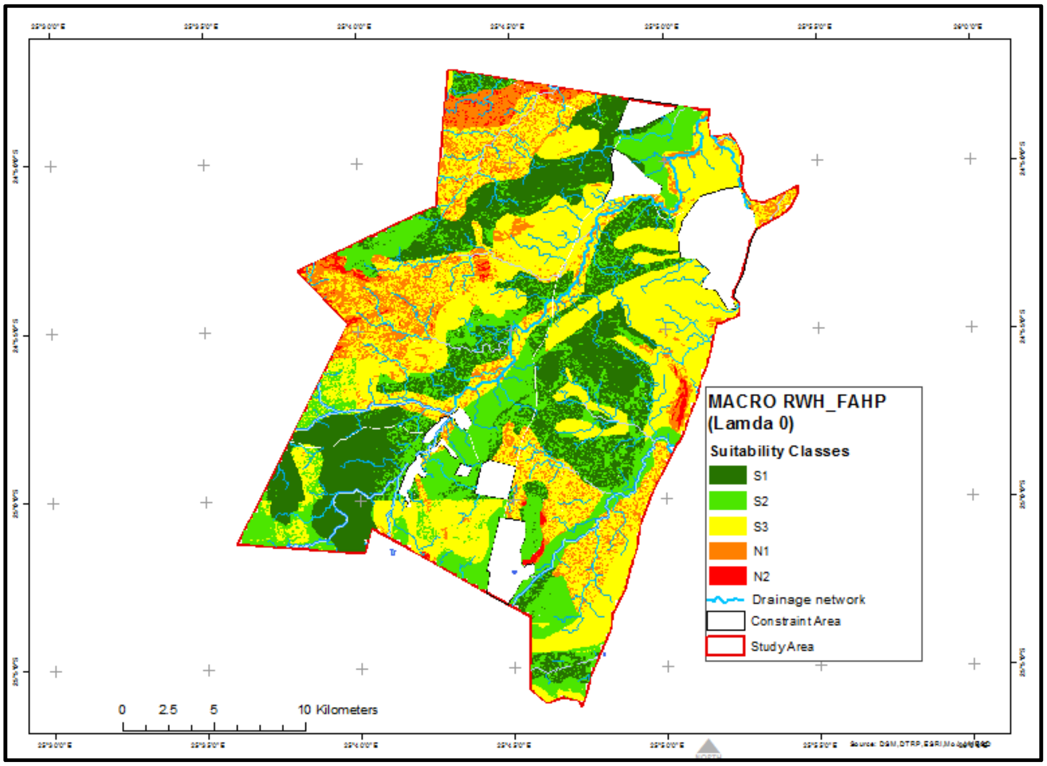

Fig. 8. Suitability of macro RWH technique using Fuzzy AHP approach (Lambda 0)

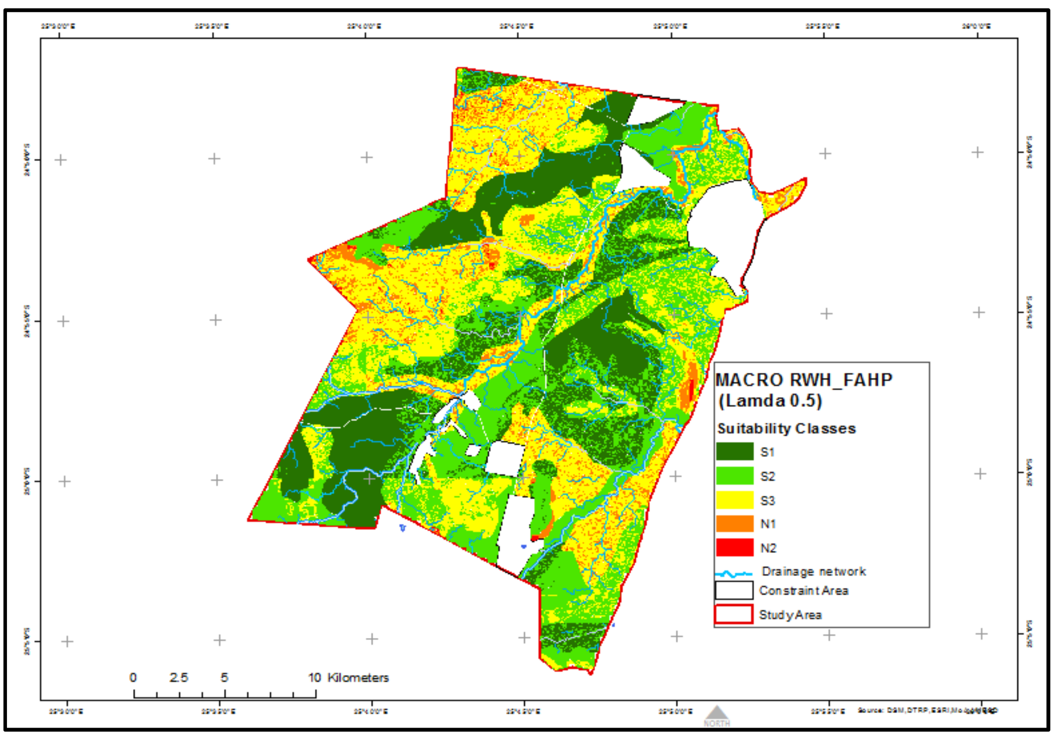

Fig. 9. Suitability of macro RWH technique using Fuzzy AHP approach (Lambda 0.5)

It is noticeable that there is a shift from lower suitability classes to higher classes when one moves from no confidence (pessimistic) to moderate and absolute confidence (optimistic) i.e. Lambda 0, 0.5 and 1.

It is thus concluded that Lambda can be used to measure the uncertainty of the expert knowledge. The analysis seems to be affected by the attitude of the decision maker as the results show significant changes in areas occupied by different classes. These shifts in the classes are also noticeable in Figs. 8-10.

3.4 Comparisons for AHP and Fuzzy AHP Approaches

The results of the two approaches are compared to see how they modeled suitability of macro RWH technique.

In Fig. 11, results of the two approaches can be said to be comparable. The highly suitable area is around 20-30% while N2 is around 1%. Fuzzy AHP has higher values than AHP for S1 and S2 while the reverse is true for S3, N1 and N2. It seems that fuzzy AHP shifts the area that was classified as unsuitable by AHP to suitable areas. In the overall, suitable area for macro RWH for both approaches is over 80%.

The results of the two approaches are somewhat comparable since moderate confidence and moderate attitude is used for Fuzzy AHP. Moderate confidence and attitude is modelled using the middle number in the fuzzy PCM, which could be reduced to classical AHP save for the effects of Lambda and Alpha cut. Although AHP incorporate expert knowledge, it fails to incorporate the uncertainty in the data used, expert knowledge, one's judgements and attitude.

Fuzzy AHP can give good results since it incorporates uncertainty of the expert and one's attitude while comparing criteria. This approach further incorporates uncertainty that arise while expressing the preference over these criteria. For instance when expressing the preference of topography over land use one can only express one's opinion such as topography is more preferred to land use. Where the decision maker is unable to be explicit about his/her judgements, Fuzzy AHP becomes handy since it gives interval judgements than fixed value judgements thereby allowing one to set one's level of confidence and the attitude of one's judgements.

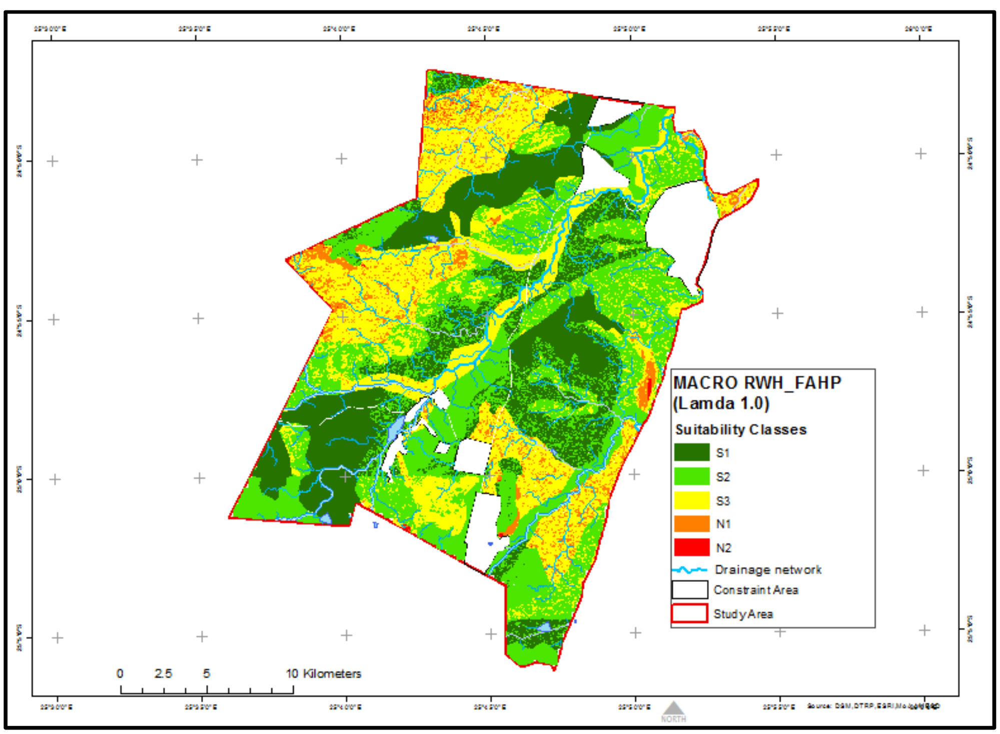

Fig. 10. Suitability of macro RWH technique using Fuzzy AHP approach (Lambda 1.0)

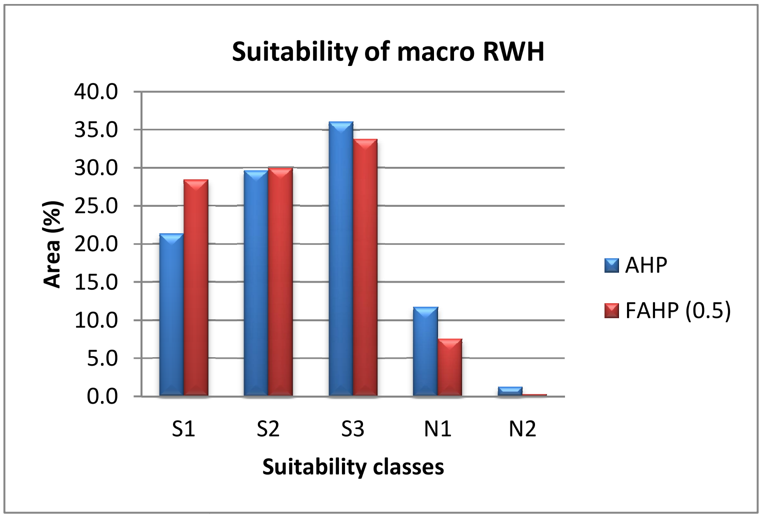

Fig. 11. Comparison of results for AHP and Fuzzy AHP for macro RWH

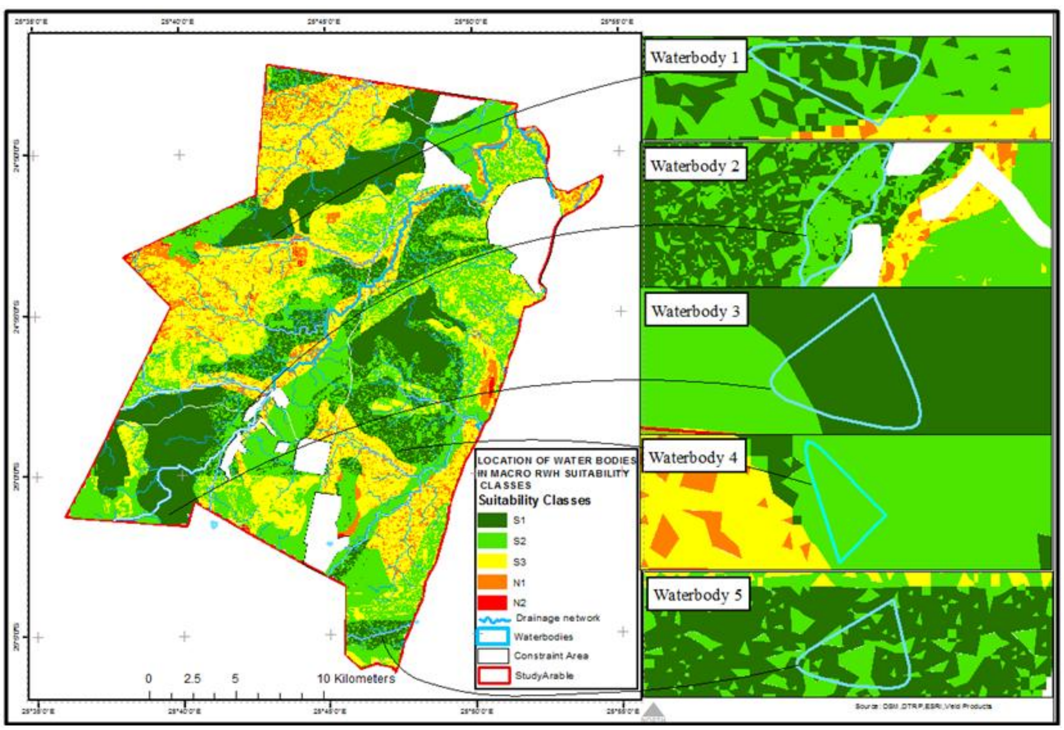

Fig. 12. Water bodies locations in the final suitability map for macro RWH techniques

3.5 Validation and Testing of the Results

Fig. 12 and Table 8 show the results of the validation process using existing water bodies. From the results, 44% of the dam area falls in the highly suitable area (S1) while 56% falls in S2 class. None of the area falls in classes S3, N1 and N2 which represent low suitability and non-suitability. From the results the model could be said to be reliable as it has made predictions that agree with the independent data.

Apart from using existing water bodies to validate the model, the study area was sampled at each confluence of the x and y coordinates in the grid (Fig. 13) to further validate the model. The points were then visited to assess the status of the area.

Table 8. Distribution of the area of water bodies in suitability levels of final suitability map

Independent data		Model output				
Water body ID	**Area (sq km)**	**S1**	**S2**	**S3**	**N1**	**N2**
1	0.18	0.11	0.07	0	0	0
2	0.74	0.13	0.61	0	0	0
3	0.25	0.23	0.02	0	0	0
4	0.05	0	0.05	0	0	0
5	0.29	0.20	0.09	0	0	0

In order to assess accuracy, an error matrix table was constructed (Table 9).

From the error matrix table, percent commission and omission errors, percent correct, Kappa coefficient and Kappa standard error at 95% confidence level were calculated. Table 10 shows a summary of the results obtained.

The percent Correct Observed (calculated by dividing the sum of the diagonal entries of the error matrix by the total number of reference entries) provided an overall accuracy assessment of the classification and for this study it was 57.14%. This could be said to be fair given the fact that few points (due to financial constraints) were considered.

Table 9. Error matrix

		Reference Data					
		S1	**S2**	**S3**	**N1**	**N2**	**Row total**
Data Classification	S1	1	0	0	0	0	**1**
	S2	0	1	1	0	0	**2**
	S3	0	1	1	1	0	**3**
	N1	0	0	0	1	0	**1**
	N2	0	0	0	0	0	**0**
	Column total	**1**	**2**	**2**	**2**	**0**	**7**

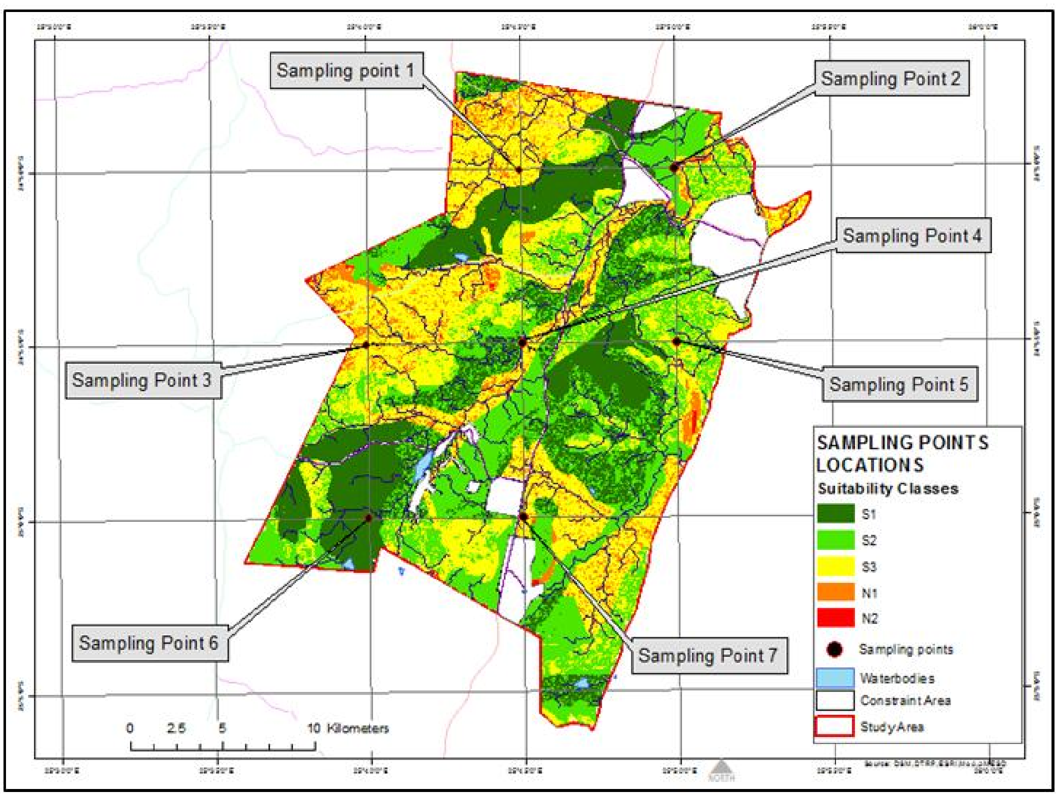

Fig. 13. Location of sampled points

Table 10. Summary of error matrix

Category	% Commission	% Omission	% correct category by category
S1	0	0	100
S2	50	50	50
S3	67	50	33
N1	0	50	100
N2	0	0	0
Weighted Kappa Coefficient	Kappa standard error (at 0.95 Confidence interval)		
0.604	0.2174		
Observed Correct	Total Observed	% Observed correct	
4	7	57.14%	

On the basis of category by category assessment, percent correct by category was calculated (Table 10) and the results show that the classification performed best for S1 and N1 categories with S1 having 0% omission and commission errors and N1 with 0% commission errors and 50% omission errors. S3 was least correctly classified (33%) with a commission error of 67% and omission error of 50%.

In addition to errors of commission and omission, Kappa coefficient was found to be 0.604 (Table 11), indicating the strength of agreement between classified data and reference data as being ‘’moderate’’ for this study.

Table 11. Interpretation of Kappa

Kappa coefficient	Strength of agreement
< 0.0	Poor
0.00 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	moderate
0.61 – 0.80	substantial
0.81 - 100	Almost perfect

In the overall, several measures of classification accuracy showed that the model performed well or moderate but a more rigorous accuracy exercise could be performed if more data was made available to improve the accuracy results.

4. CONCLUSIONS

GIS and Remote sensing techniques have been widely used in spatial assessments and spatial decision making, and have been found to perform well in modelling spatial data. However, the arbitrary choice of weights in spatial site suitability assessments has made the universal acceptance of results from geospatial techniques difficult.

To overcome the weight allocation problem MCE has been incorporated into these techniques. AHP, which is a comprehensive, logical and structured multi-criteria decision making technique, has been widely used in suitability evaluations including RWH assessments. In spite of its conceptual simplicity and computational efficiency in structuring the problem in a systematic manner and in calculating weights, the traditional AHP suffers some shortcomings. The major shortcoming is its inability to handle impression and attitude of the decision maker in deciding the criteria.

The current study proposed and demonstrated the use of Fuzzy AHP to deal with ambiguity in RWH assessments. Fuzzy AHP, with embedded techniques such as fuzzy numbers, fuzzy extent analysis, **α**-cut and **λ** index can adequately handle the inherent uncertainty and imprecision of the human decision making process and provide the flexibility and robustness needed for the decision maker to better understand the decision problem and their decision behaviours. With this approach, the decision maker’s attitude towards risk is adequately reflected by optimism index, **λ,** while their degree of confidence is handled using **α-**cut.

The above approaches can also be used to check the sensitivity of the model. For this study, **λ** index of 0, 0.5 and 1 were used and it was seen that there was a significant change between lambda 0, 0.5 and 1. Changing the values of alpha cut and Lambda showed the sensitivity of the process.

Suitability for macro RWH was achieved in the study area using AHP and fuzzy AHP. The results showed that over 80% of the study area is suitable for macro RWH distributed between S1, S2 and S3. S1 and S2 occupy a smaller area in AHP compared to results in Fuzzy AHP.

Several measures of classification accuracy were calculated including errors of commission and omission. In addition, statistical measures such as Kappa coefficient of agreement were calculated and the results showed a moderate accuracy with overall %age correct of 57.14 and Kappa coefficient of 0.604. Percent errors of omission and commission on category to category basis were also calculated and S1 had none of the errors while S3 performed least with 67% error of commission and 50% error of omission.

The suitability maps generated can be the first step in determining the viable water resource management option for the study area since the spatial context is captured. Furthermore, the maps generated can be used as an awareness tool to alert those who are interested in practicing RWH for crop production.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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