Agricultural Water Management 218 (2019) 82–93

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Fuzzy inference system for site suitability evaluation of water harvesting structures in rainfed regions

Vamsikrishna Vema[a], K.P. Sudheer[a,b,*], I. Chaubey[b,c]

[a] Department of Civil Engineering, Indian Institute of Technology Madras, Chennai, India
[b] Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, IN, USA
[c] Department of Earth, Atmospheric and Planetary Sciences, Purdue University, West Lafayette, IN, USA

ARTICLE INFO

Keywords:
Fuzzy inference system
Water harvesting structures
Watershed management
Site suitability

ABSTRACT

Watershed management (WM) aims at enhancing the water availability in rainfed areas through water conservation structures, which facilitate storage of water and recharge to ground water. Identification of suitable locations for placing these structures play a major role in the effectiveness of the water conservation. Site suitability evaluation of water conservation structures is performed through an assessment of various biophysical and socio-economic factors. Many of these factors are expressed in linguistic terms rather than precise numeric values, and therefore the output of the evaluation gets subjective. In this study, a fuzzy inference system (FIS) is developed for site selection of water harvesting structures (check dams, farm ponds, and percolation tanks), owing to its capability to handle linguistic data effectively. The suitability zones were identified using the slope, soil permeability and runoff potential as input variables to the FIS. Trapezoidal membership function (MF) was considered for the input and output variables for the fuzzy model and MF parameters were obtained from literature and expert knowledge. The developed FIS is illustrated through an application to Kondepi watershed, Andhra Pradesh, India. The FIS categorized the majority of the watershed area into high suitability class for both farm ponds and check dams. However, the watershed characteristics were not conducive for percolation tanks according to the FIS. A sensitivity analysis of the FIS parameters suggested that the check dam suitability was sensitive to the soil permeability classes. The suitability maps from the FIS were in good agreement with the location of the existing structures in the watershed, suggesting potential use of the developed FIS in WM decisions.

1. Introduction

Watershed management (WM) strategies, such as rain water harvesting (RWH), enhance the land productivity by enhancing the water availability for rainfed agriculture in arid and semi-arid regions (Adham et al., 2016a, 2016b; Kahinda et al., 2008; Singh et al., 2017; Wani and Garg, 2009). The success and sustainability of these WM programs depend on the identification of suitable sites and technical design of water harvesting structures (Adham et al., 2016a; Al-Adamat et al., 2012; de Winnaar et al., 2007). The Food and Agricultural Organization (FAO) suggested guidelines for site selection for RWH structures, based on six different criteria, which include climate, hydrology, topography, agronomy, soil, and socio-economics (Kahinda et al., 2008). In addition, many additional factors, based on the field conditions, have also been considered for site selection (de Winnaar et al., 2007; Kahinda et al., 2008; Mbilinyi et al., 2007; Padmavathy et al., 1993; Prinz et al., 1998; Senay and Verdin, 2004). These factors can be broadly classified into two categories: biophysical (rainfall, slope, soil type, drainage network etc.) and socio-economic (distance to streams, distance to settlements etc.). The biophysical characteristics of the site determine the RWH structures suitability in terms of their applicability and use to the stakeholders, and the socio-economic factors determine the intended beneficiaries, and equitable distribution of resources among the various stakeholders etc. In the recent years, the socio-economic factors are considered through participatory watershed management approaches, while biophysical factors are considered for developing suitability maps that help in taking WM decisions.

Since the site suitability for RWH structures require handling and analysing different criteria, multi criteria analysis (MCA) appraoch is used by many researchers (de Winnaar et al., 2007; Durbude and Venkatesh, 2004; Mwenge Kahinda et al., 2009; Sekar and Randhir, 2007). Some of the common MCA methods, such as analytical hierarchy

* Corresponding author at: 521, ED Building, Department of Civil Engineering, IIT Madras, Chennai, 600036, India.
E-mail address: sudheer@iitm.ac.in (K.P. Sudheer).

https://doi.org/10.1016/j.agwat.2019.03.028
Received 8 November 2017; Received in revised form 31 January 2019; Accepted 19 March 2019
Available online 25 March 2019

process, weighted overlay process, weighted linear combination and Boolean method, have been employed in different WM studies (Adham et al., 2016a; Al-Adamat, 2008; Al-Adamat et al., 2010; Krois and Schulte, 2014; Mwenge Kahinda et al., 2009; Sekar and Randhir, 2007). One of the limitation for MCA techniques in site suitability analysis for RWH structures is that MCA require the inputs to be in the form of numerical values, while most of the attributes considered for the site suitability analysis are generally in qualitative forms. Thus, for application of MCA methods the qualitative information needs to be converted to numerical values. Consequently, the effectiveness of the decisions arrived using MCA methods is influenced by the accuracy of the input data and the expertise of the decision maker. Hence, the conversion of the qualitative information into quantitative input data needs careful consideration, and fuzzy logic based MCA approaches have been proven to be very effective in such cases (Nayak et al., 2005; Reshmidevi et al., 2009; Ross, 2004; Sasikala et al., 1996).

Fuzzy inference systems (FIS) is one such approach that has the ability to deal with an evaluation and assessment of imprecise and uncertain data, and thus have an advantage over traditional MCA techniques (Reshmidevi et al., 2009; Tsiko and Haile, 2011). As mentioned earlier, most of the attributes for site suitability analysis of the RWH structures are qualitative in nature, and a quantitative classification of these attributed to various classes is difficult to achieve. The FIS adopts a fuzzy set theory as opposed to the classical set theory adopted by traditional MCA techniques. A variable/element in classical set theory adopts only two values: true (one), if the variable belongs to the set or false (zero), if the variable does not belong to the set. While in fuzzy set theory the sharp boundaries between the sets is replaced by the concept of degree of membership, thus, a variable can belong to the fuzzy set with its membership ranging from 0 to 1. Hence, with the concept of degree of membership, the fuzzy sets and FIS account for the linguistic uncertainty in the qualitative input data. In addition, FIS simplifies the MCA process by splitting complex decisions into small criteria (Reshmidevi et al., 2009; Ross, 2004). Each criterion of the MCA problem or knowledge is expressed using IF-THEN rules in the FIS. The IF part contains the conditions to be satisfied, and THEN part contains the conclusions. The final decision is arrived at by aggregating the output from each rule. FIS approach is reported to be successful in problems involving multi criteria based decision making, that use qualitative information, such as land suitability evaluations for agriculture and identification of potential soil erosion zones (Adriaenssens et al., 2004; Dixon, 2005; Kweon, 2012; Reshmidevi et al., 2009; Sasikala et al., 1996; Tsiko and Haile, 2011).

In this paper, a FIS for site suitability evaluation of RWH techniques in rainfed agricultural watershed is presented. This study considered only biophysical factors for site suitability in FIS, as it is envisaged that the FIS output will complement the participatory approach of decision making. Accordingly, attributes related to the biophysical criteria (soil permeability, runoff potential, and slope) were considered for site suitability evaluation of RWH structures. The developed site suitability maps would aid the decision makers and local stakeholders in arriving at more efficient decisions. The FIS approach is demonstrated through a case study of RWH structures' (check dams, farm ponds and percolation tanks) site suitability in Kondepi watershed, Prakasam district of Andhra Pradesh, India.

2. Fuzzy inference system

The FIS is a rule based system comprising of three components: a rule base that consists of a collection of fuzzy IF-THEN rules; a database that defines the membership function (MF) of the input-output variables used in the fuzzy rules; and a reasoning procedure that aggregates the output from fuzzy rules to arrive at a reasonable conclusion (Nayak et al., 2005). While the input variables can be presented to the FIS either as crisp values or fuzzy set, the output from an FIS is generally a fuzzy set. Consequently, the fuzzy output requires *defuzzificaiton* in order to take decisions based on FIS output. The IF-THEN rules in the FIS facilitate a nonlinear mapping between the input and output space of the system being modeled. The fuzzy rules split the total input-output space into a number of local regions, and each rule represents the local behavior of the nonlinear mapping. Therefore, the efficacy of the FIS is largely dependent on the number of fuzzy rules. It is to note that while the efficacy of the FIS increases with increase in number of rules as the inference space increases with rules, formulating high number of rules is a tedious task.

There are two approaches in the FIS development: (i) the Mamdani approach (Mamdani and Assilian, 1975), and (ii) the Takagi-Sugeno approach (Takagi and Sugeno, 1985). For the Mamdani approach there are three clear procedures, i.e. fuzzification of the input variables, logic decision, and defuzzification of the FIS output. The Takagi-Sugeno approach, however, does not have an explicit defuzzification procedure. Rather, it amalgamates the logic decision and defuzzification procedures into one composite procedure. Application of the Takagi-Sugeno approach in hydrology has been mostly to function approximation (Nayak et al., 2005). The Mamdani approach has been used in some site suitability applications (Reshmidevi et al., 2009), and is also employed in this study. In the Mamdani approach, the first procedure of fuzzification assigns the degree of membership of various classes to the input variables. The second procedure evaluates the fuzzy rules from the rule base for the degree of membership of input variables. The degree of membership of the input variables to different classes determines the contribution of a rule to the possible value of the output variable. The third procedure of defuzzification involves conversion of the fuzzified output to a crisp value. The detailed procedures and methodology for the three processes is described in the subsequent sections.

3. FIS for site suitability of RWH structures

Water harvesting structures in WM program are aimed at increasing land productivity by improving the soil moisture and water availability for agriculture. The commonly employed water harvesting structures include check dams, farm ponds, percolation tanks, recharge wells and injection wells. These structures serve the dual purpose of facilitating recharge to ground water as well as for direct use of water.

In this study, we have considered check dams, farm ponds, and percolation tanks for the site suitability analysis. The criteria for site suitability for these RWH structures based on biophysical factors (Napoli et al., 2014; Ramakrishnan et al., 2009; Rao and Bhaumik, 2003) is presented in Table 1. It is evident from the Table 1 that the defined criteria for different variables are in qualitative terms, and therefore the class definition for each variable may be highly subjective in different applications. Consequently, no consistency is observed in the site selection criteria across different studies.

As described, the development of FIS involves fuzzification of attributes, generation of fuzzy rules, aggregation of rules and defuzzification to find crisp suitability class. In this study, three biophysical criteria (soil permeability, runoff potential and slope) were considered as input variables to the FIS for evaluating the site suitability of check dams, farm ponds, and percolation tanks. The three input variables were classified into 3 fuzzy classes in terms of suitability viz. low, medium and high, to pair with the suggested site suitability criteria (Table 1). Fuzzy rules were generated based on the selection criteria for

Table 1
Selection Criteria for Different Water Harvesting Techniques.

Structure	Slope (%)	Permeability	Runoff Potential	Stream Order
Farm Ponds	Low	Low	Medium/high	1
Check dams	Medium	Low	Medium/high	1-4
Percolation Ponds	Medium	High	Low	1 – 4

check dams, farm ponds and percolation tanks. Detailed description of different components of the FIS is presented in the following sections.

3.1. Fuzzification

Fuzzification is the process by which the crisp attribute values are mapped into common range [0, 1] by using MF. A MF used within the FIS is a function, which returns the degree of the truth (membership grade/possibility) for a given variable, and it indicates the degree of belongingness of the variable to a specific class. The MF for a variable needs to be defined in terms of its crisp quantitative value. While there are various choices for the MF, trapezoidal MF (Eq. (1)) is assumed for all the variables in this study. Trapezoidal MF has a flat top and has 4 parameters (a, b, c, and d); 2 shoulder and 2 base parameters; a and d correspond to the base of the trapezoid, b and c correspond to the shoulder of the trapezoid. Class boundaries of the fuzzy variables for trapezoidal MF are defined as (Ross, 2004; Zadeh, 1965):

$$f(x;\, a,\, b,\, c,\, d) = \left\{ \begin{matrix} 0,\ d \le x \le a \\ \frac{x-a}{b-a},\ a \le x \le b \\ 1,\ b \le x \le c \\ \frac{d-x}{d-c},\ c \le x \le d \end{matrix} \right\} \tag{1}$$

where, f is the trapezoidal MF of a variable x; a, b, c, and d are the four parameters, which depict the shape of the trapezoidal function.

3.2. Description of MF for the input attributes for site suitability

3.2.1. Slope

Slope is an important factor in selection of the suitable site for RWH structures, as it controls the size of the structure and the quantity of water that can be stored. Areas with high slope are not suitable for surface storage structures, as it requires a large structure (in terms of height) to store a significant amount of water. Areas with medium or low slope are more suitable sites, as storage capacity can be increased even with smaller structures. In this study, slope is classified into 3 classes as mentioned earlier: low, medium, and high. The MF for each class of slope can be computed from Eqs. ((2)–(4)) for various values of the slope. In this equation, slope is expressed in terms of percentage. If $\mu_s(L)$, $\mu_s(M)$, and $\mu_s(H)$ are the MF for the classes low, medium, and high, then,

$$\mu_s(L) = f(s;\, a_{sL},\, b_{sL},\, c_{sL},\, d_{sL}) \tag{2}$$

$$\mu_s(M) = f(s;\, a_{sM},\, b_{sM},\, c_{sM},\, d_{sM}) \tag{3}$$

$$\mu_s(H) = f(s;\, a_{sH},\, b_{sH},\, c_{sH},\, d_{sH}) \tag{4}$$

where, the function f(s; a, b, c, d) is as defined in Eq. (1), s is the slope (%) and the subscripts (sL, sM, and sH) indicate that MF parameters a, b, c, and d belong to the low, medium and high classes of slope.

3.2.2. Soil permeability

Soil permeability is the physical property of the soil, which shows the readiness of soil to transport water through the soil. Soil permeability is also an important factor in the effectiveness of water harvesting structure. The water harvesting structures for surface water storage to aid rainfed agriculture are more suitable in areas with low values of soil permeability. Similar to slope, the soil permeability is also classified into low, medium and high classes. If $\mu_p(L)$, $\mu_p(M)$, and $\mu_p(H)$ are the MF for the classes low, medium, and high, then,

$$\mu_p(L) = f(p;\, a_{pL},\, b_{pL},\, c_{pL},\, d_{pL}) \tag{5}$$

$$\mu_p(M) = f(p;\, a_{pM},\, b_{pM},\, c_{pM},\, d_{pM}) \tag{6}$$

$$\mu_p(H) = f(p;\, a_{pH},\, b_{pH},\, c_{pH},\, d_{pH}) \tag{7}$$

where, the function f(p; a, b, c, d) is as defined in Eq. (1), p is the soil permeability (cm/day) and the subscripts (pL, pM, and pH) indicate that MF parameters a, b, c, and d belong to the low, medium and high classes of soil permeability.

3.2.3. Runoff potential

Runoff potential of a location implies the ability of the location to generate runoff and consequently the volume of water that can be captured by the RWH structures. The runoff volume from a location/catchment can be estimated using the Soil Conservation Service (SCS) curve number (CN) method. Generally, runoff potential maps are generated by simulating the runoff using the SCS-CN method for a 67% dependable rainfall (67% dependable rainfall is the amount of rainfall with an average recurrence interval of 1.5 years) (de Winnaar et al., 2007; Mwenge Kahinda et al., 2009; Ramakrishnan et al., 2009). The runoff generated for this rainfall at various locations is then categorized into different classes to generate the runoff potential maps. It is to note, the CN is a function of hydrologic soil group, land use, and antecedent moisture condition, and the runoff potential of an area is directly proportional to the value of CN, i.e. a higher CN indicates a higher runoff potential. Hence, the runoff potential map generated from the simulated runoff would be similar to the CN map of the catchment. Therefore, it is rational to use CN directly as an indicator of runoff potential, and is employed in this study. Similar to other variables, runoff potential also is divided into 3 classes, namely low, medium, and high in this study. If $\mu_r(L)$, $\mu_r(M)$, and $\mu_r(H)$ are the MF for the classes low, medium, and high, then,

$$\mu_r(L) = f(r;\, a_{rL},\, b_{rL},\, c_{rL},\, d_{rL}) \tag{8}$$

$$\mu_r(M) = f(r;\, a_{rM},\, b_{rM},\, c_{rM},\, d_{rM}) \tag{9}$$

$$\mu_r(H) = f(r;\, a_{rH},\, b_{rH},\, c_{rH},\, d_{rH}) \tag{10}$$

where, the function f(r; a, b, c, d) is as defined in Eq. (1) and r is the runoff potential and the subscripts (rL, rM, and rH) indicate that MF parameters a, b, c, and d belong to the low, medium, and high classes of runoff potential.

3.2.4. Parameters of MF for the input variables

The MF parameters define the structure of the trapezoid curve with a minimum value of 0 and a maximum value of 1. Generally, the MF parameters are determined by the expert knowledge and/or are generated using measured data, and the procedure depends on the availability of data and proposed application. Various researchers have used optimization techniques to identify the best set of MF parameters for the specific application of FIS (Adriaenssens et al., 2004; Dai et al., 2016; Li and Guo, 2015). However, in this study, due to the limitation of available data to validate the developed FIS output with the observed data, MF parameters are determined based on literature survey and expert knowledge.

The MF parameters of the fuzzy sets map the input variable into a number of fuzzy regions with overlap unlike the classical sets having crisp boundaries (Nayak et al., 2005; Reshmidevi et al., 2009; Ross, 2004). The advantage of fuzzy sets is that the overlap of the fuzzy region makes the element to be partial in the set and also the transition from one region to another is gradual. Fig. 1 depicts the MF of the different classes considered for the input variables. As is evident from the figure, the MF of different classes overlap with each other and an element would have a membership in different classes. The MF of the input variables overlap each other, as shown in Fig. 1. For example, in Fig. 1 (a), a value of 8% slope falls in both low and medium class with varying degree of belongingness, as the MF for each class overlap. The value of 8% of slope would have a membership value of 0.2, 0.8, and 0 for low, medium, and high classes respectively. It is to note, the summation of the membership values for different classes of an element should be equal to one. Similarly, Figs. 1(b) and 1(c) depict the MF of soil permeability and runoff potential. The MF parameters of the three

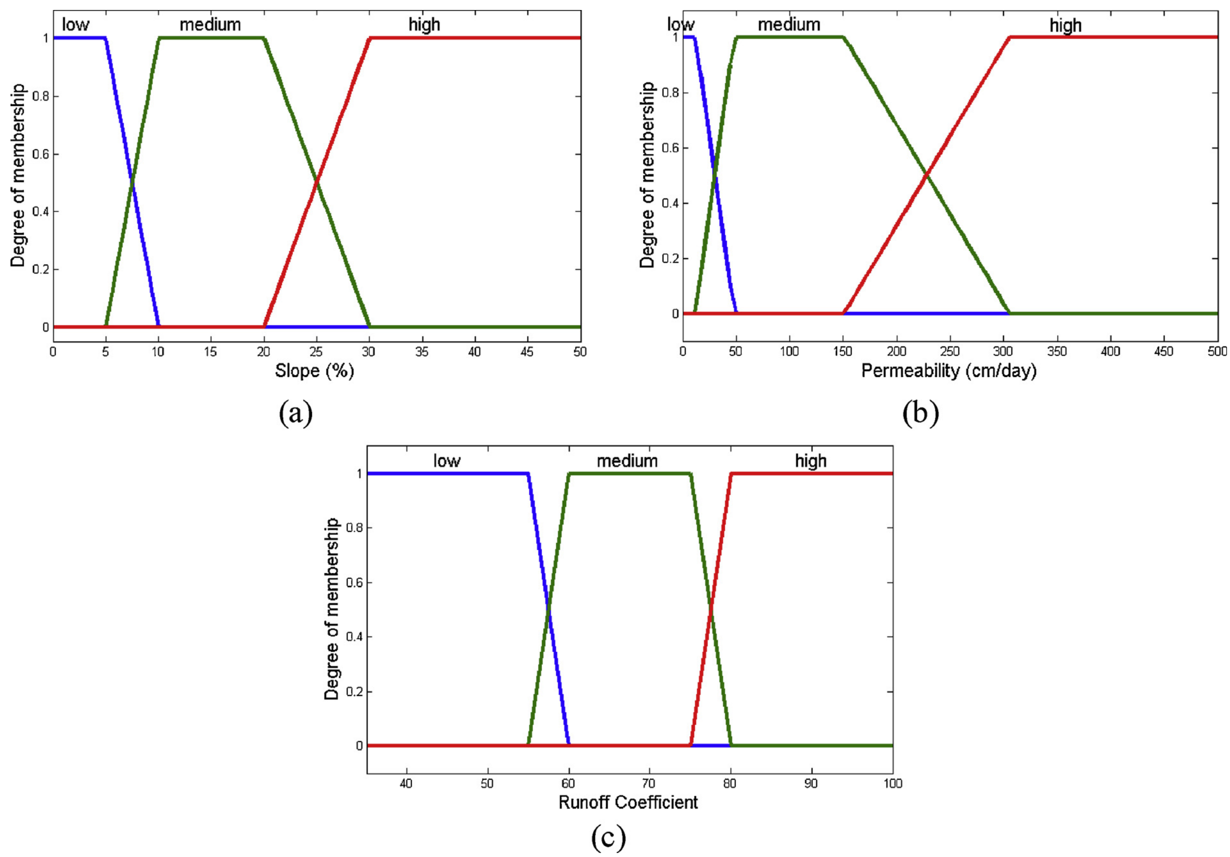

Fig. 1. Fuzzy MF for low, medium, and high classes of (a) slope, (b) soil permeability, and (c) runoff potential.

Table 2
Fuzzy Membership Function Parameters.

	Low				Medium				High			
	a	b	c	d	a	b	c	d	a	b	c	d
Slope (%)	0	0	5	10	5	10	20	30	20	30	100	100
Soil Permeability (cm/day)	0	0	12	48	12	48	151	305	151	305	900	1000
Runoff Potential (CN)	0	35	55	60	55	60	75	80	75	80	100	100

input variables for each class, derived from the expert knowledge, are presented in Table 2.

3.3. Development of the FIS for RWH suitability

3.3.1. Fuzzy rule base

The fuzzy rule base developed in this study is based on the literature (Adham et al., 2016a; Kadam et al., 2012; Ramakrishnan et al., 2009; Rao and Bhaumik, 2003) and the expert knowledge. As discussed earlier, each of the 3 input variables are classified into 3 classes, making a total of 27 IF-THEN rules in the FIS. The fuzzy outputs from the FIS are classified into 4 groups viz. not suitable, low suitability, medium suitability, and highly suitable. Note that all the three variables are given equal weightage in the FIS rules, and a typical example of FIS rules are:

IF soil permeability is low AND slope is low AND runoff potential is high THEN check dam suitability is high, farm pond is high, percolation tank is not suitable

IF soil permeability is low AND slope is low AND runoff potential is medium THEN check dam suitability is high, farm pond is high, percolation tank is not suitable

IF soil permeability is high AND slope is low AND runoff potential is low THEN check dam suitability is not suitable, farm pond is not suitable, percolation tank is medium

IF soil permeability is low AND slope is high AND runoff potential is low THEN check dam suitability is low, farm pond is not suitable, percolation tank is medium

Each rule in the rule base considers a combination of the fuzzy class of the input variables, and specifies the appropriate degree of membership in class of suitability for the water harvesting structure.

3.3.2. Aggregation of rules

The overall site suitability for the water harvesting structure is determined by combining the output from all the fuzzy rules. This process of obtaining the final output from the rule base is called aggregation of rules. In this study, Mamdani Implication method (Reshmidevi et al., 2009; Ross, 2004; Tsiko and Haile, 2011) is adopted, which is a maximum–minimum aggregation method. In this method, minimum among the attribute MF of a criterion is selected. The corresponding outputs from all the rules are aggregated using the fuzzy union operator, where the maximum values are selected from the set of outputs from each rule, as follows (Eq 11) (Reshmidevi et al., 2009; Ross, 2004):

$$suitability\,(\mu) = \max(\min(\mu_c^k\,(variable\ 1),\ \mu_c^k\,(variable\ 2),\ \mu_c^k\,(variable\ 3))) \tag{11}$$

$k = 1, 2, \ldots, 27\ (number\ of\ rules)\ \text{and}\ c = 1, 2, 3$

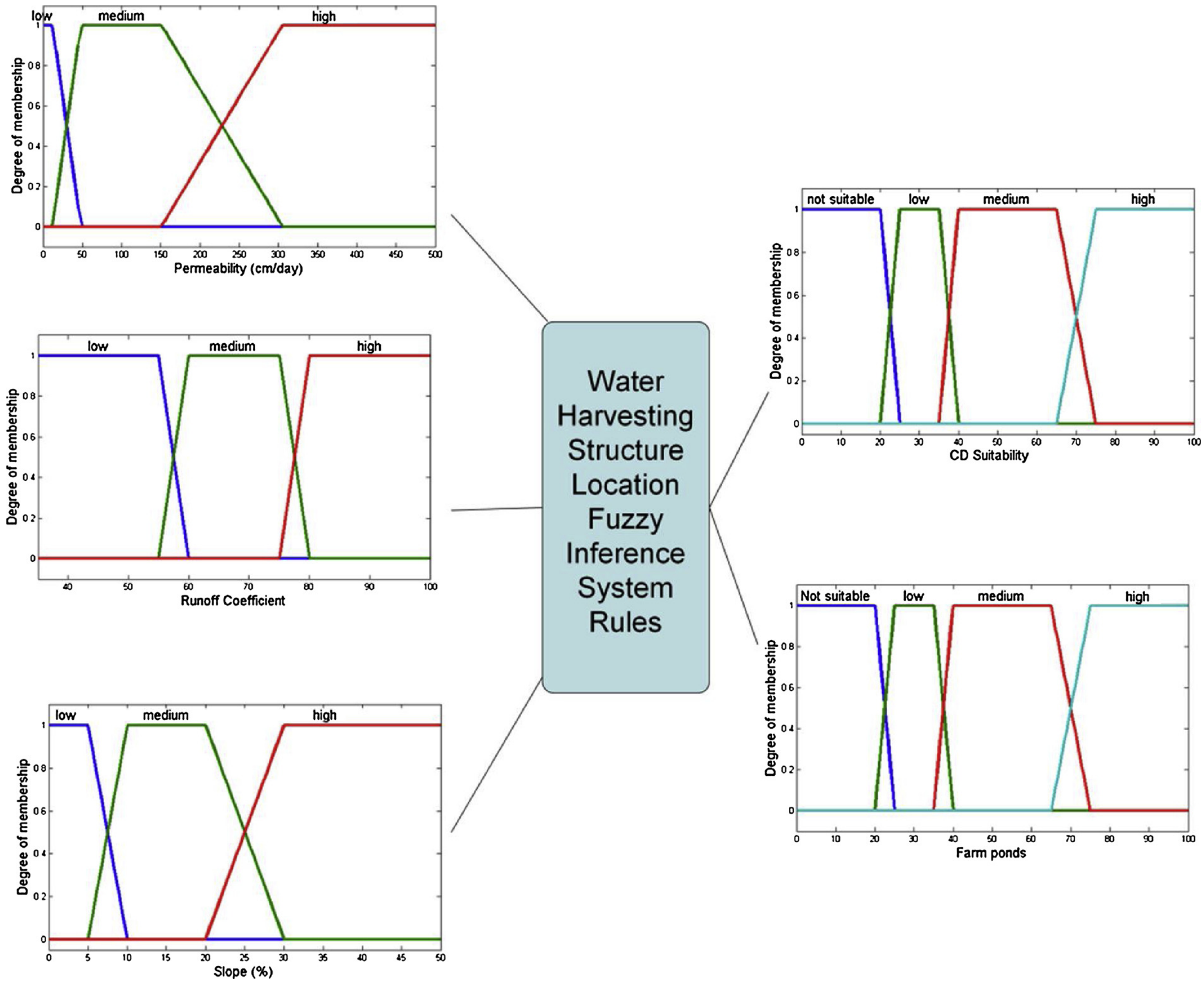

Fig. 2. Schematic diagram of the developed fuzzy inference system.

where, *suitability*(μ) is the membership grade of the suitability, μ is the MF of the input variable, c is the membership class of the input variable in rule k, and the variable1, variable 2, and variable 3 are the input variables to the FIS.

Schematic representation of the developed FIS is shown in Fig. 2. The inference engine considers the fuzzified input variables and evaluates all the fuzzy rules, and the output of the all rules is aggregated to get the fuzzified output, which are defuzzified to arrive at the suitability class

3.3.3. Defuzzification of the FIS output

In the Mamdani approach of aggregation of rules, the output of the FIS is a fuzzy variable, and needs to be defuzzified to the decision domain. Several defuzzification methods are available in the literature. Some of the commonly used methods are maximum membership principle, mean maximum membership (Ross, 2004), weighted average method (Reshmidevi et al., 2009), centroid method (Ross, 2004), and use of inflection points (Sicat et al., 2005). This study used maximum membership principle for defuzzification. In this method, the maximum of the largest membership value of suitability class is taken as the most representative value.

4. Demonstrative case example

The developed FIS is envisaged to be used for developing the site suitability maps of the water harvesting structures in a given watershed, to aid the participatory watershed management. The FIS is applied to a study watershed under rainfed agriculture in India, and is discussed in the following section.

4.1. Description of the study area

The developed FIS is applied to Kondepi watershed, near Kondepi Mandal, Prakasam district, Andhra Pradesh in India (Fig. 3). The watershed has a total geographical area of 4157 ha and a net cropped area of about 1100 ha. The watershed lies between latitudes 15°23′ N and 15°25′ N, and longitudes 79°48′ E and 79°53′ E, and falls under the subtropical climate with average annual rainfall of about 690 mm. Elevation of the watershed ranges from 18.8 m to 71.3 m. The agricultural practices are rainfed in this watershed, except 20 ha (~0.2% of the cropped area), which is cropped using drip irrigation with water drawn from groundwater. Only a few tube wells are in working condition in the watershed, with ground water level at 350 m below the surface. Primary crops grown in the watershed include tobacco (*Nicotiana tabcum)*, red gram (*Cajanus cajan*), bengal gram (*Cicer arietinum*), groundnut (*Arachis hypogaea*), and rice (*Oryza sativa)*. The watershed is plagued with agro-ecological problems such as soil erosion, poor crop productivity, land degradation etc., and these issues are exacerbated by spatio-temporal variability of rainfall. An integrated water management program (IWMP) is implemented by the Department of Rural Development, Andhra Pradesh in the watershed to increase the water availability for agriculture, and consequently mitigate ecological and socio-economic problems of the watershed. Various water conservation measures such as farm ponds, check dams, percolation tanks,

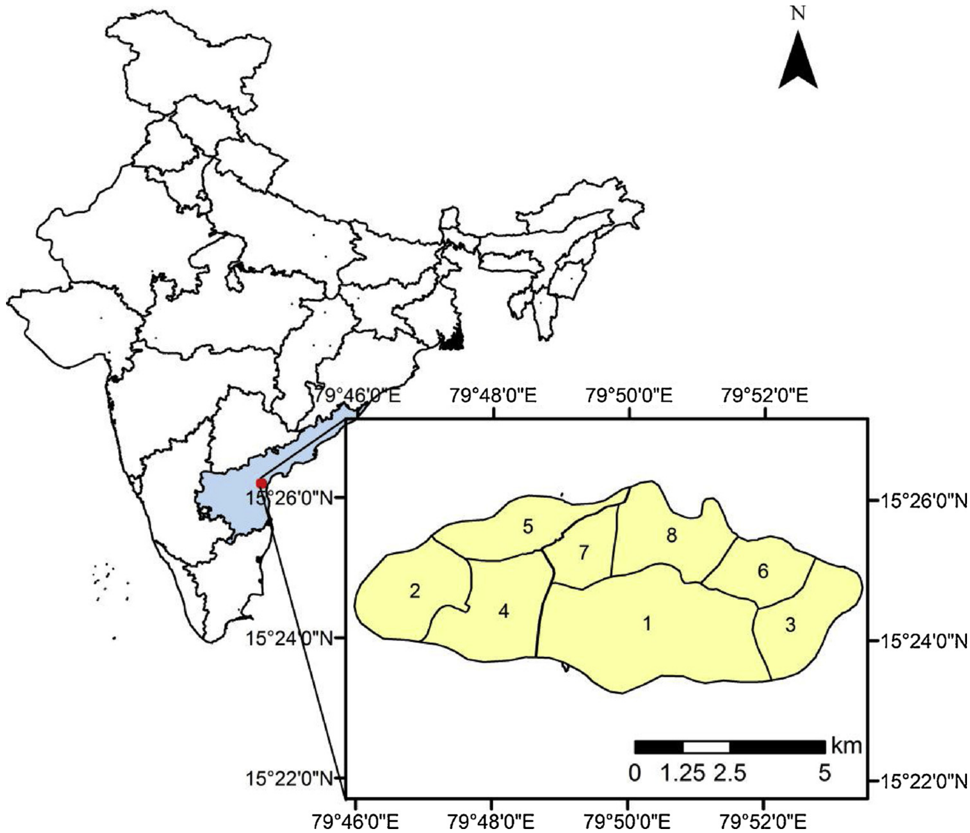

Fig. 3. Geographic location of Kondepi watershed in India. The Kondepi watershed along with the 8 microwatersheds is shown in the inset picture.

infiltration trenches, and rock filled dams are being implemented under IWMP in this watershed. These water conservation measures are essential in the watershed to maintain soil moisture levels during the crop growing period (July to January), as the majority of rainfall is received between mid-July to mid-October in the form of high intensity short duration storms.

The soil and land use maps used in this study are obtained from the Department of Rural Development, Andhra Pradesh. The soil in the watershed is classified into 10 different classes based on the percentage of sand, silt, and clay, and the majority of the area belongs to silty clay and silty clay loam. The physical properties of the soil are derived using pedo-transfer functions (Saxton and Rawls, 2006; Soundharajan and Sudheer, 2009) from the textural classification. Land use data from the global dataset of WaterBase was used to complement the land use information from Department of Rural Development. The DEM of 30 m resolution was obtained from Shuttle Radar Topography Mission (SRTM) database and slope map was derived using this DEM. The derived thematic layers of input variables (slope, runoff potential, and soil permeability) are shown in Fig. 4.

4.2. FIS model application

The derived thematic layers of the input variables (slope, soil permeability, and runoff potential) for the Kondepi watershed were in a raster format with a spatial resolution of 30 m. Each pixel (i.e. every 30 m × 30 m grid cell) of the raster had a specific value for the slope, soil permeability, and runoff potential. In the first step of fuzzification, the membership of the each pixel of the input variables was evaluated for different classes. Using the membership values for different classes, the fuzzy rules were evaluated for each pixel and the membership for the output classes was obtained. The obtained output membership value was defuzzified to get a crisp output for each pixel and the suitability maps were generated based on the defuzzified output.

The developed suitability maps were compared against the existing RWH structures in the watershed. The existing RWH structures were located and constructed by the IWMP considering only socio-economic factors through the participatory watershed management. The type of the structure and location of the structure were decided based on the stakeholders preference and biophysical factors were not considered in the decision making process. While, considering only socio-economic factors improves the maintenance of the RWH structures by the stakeholders, they may not perform the intended purpose.

5. Results and discussions

5.1. Map of fuzzified slope

As discussed earlier, the fuzzificaiton of the slope variable classifies the range of slope of watershed into different classes (using the criteria in Table 2), and accordingly the slope in the Kondepi watershed (Fig. 4(b) – slope ranges from 0 to 11.97%) is classified into classes: (a) Low and (b) Medium. Note that this watershed did not have slope in high class (above 20%, see Table 2). The Fig. 5 depicts the spatial distribution of fuzzified low and medium slope classes. As evident from Fig. 5(a), most of the watershed area falls into the low slope category, which is highly suitable for water harvesting structures. There are some areas of the watershed that have been classified into medium slope class. It can be seen from Fig. 5 (a) and 5(b) that some of the locations belong to both low and medium class, but with varying degree of belongingness according to the MF values. This indicates that these locations have varying degree of suitability of water harvesting structures according to the slope variable.

5.2. Map of fuzzified soil permeability

The soil permeability of the area defines the function of water

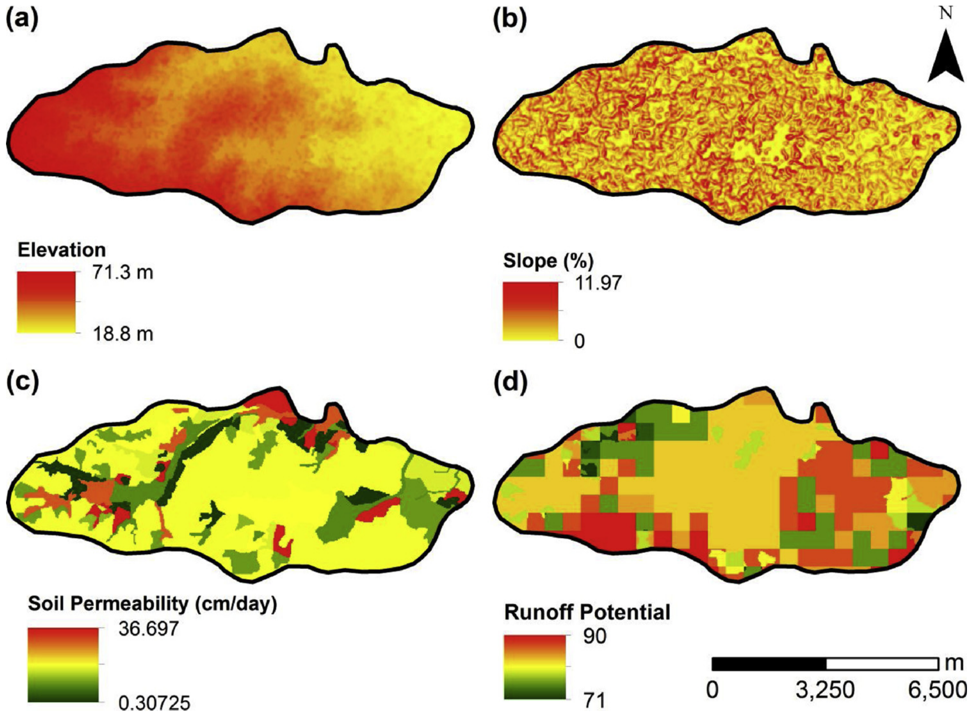

Fig. 4. Thematic layers of Kondepi watershed which is input to FIS: (a) DEM, (b) slope, (c) soil permeability, and (d) runoff potential.

harvesting structure as a surface storage structure or groundwater recharge structure. Since a major portion of the watershed has silty clay and silty clay loam, which have low soil permeability, the water harvesting structures will be mostly of surface storage structures. The soil permeability of the watershed varied from 0.3 cm/day to 31 cm/day (Fig. 4(c)) and is classified into 3 classes: (a) Low, (b) Medium, and (c) High. The Fig. 6 depicts the spatial distribution of the low and medium soil permeability classes for the watershed. As can be seen from the Fig. 6, whole of the watershed is classified into low category and more than 2/3rd of the watershed is also classified under the medium category, which indicates an overlap between categories for this variable too. However, degree of belongingness of the area to the low and medium categories is varying according to the MF values. It is to be noted that the watershed doesn't have any area under high soil permeability category.

5.3. Map of fuzzified runoff potential

The runoff potential of the area indicates the runoff generation capacity of the area. The runoff potential of the study area varied from 70 to 90, and is classified into 3 classes: (a) Low, (b) Medium, and (c) High. The spatial distribution of the runoff potential in the watershed (Fig. 7) show that most of the watershed is classified in high runoff potential class, with a limited area under medium class, and no area under low class. Similar to the slope and soil permeability, two of the runoff potential classes have overlapped, but with varying degree of belongingness. Surface storage water harvesting structures favor high and medium runoff potential classes, while groundwater recharge structures favor the low runoff potential areas.

5.4. Site suitability for water harvesting structures

The FIS generated site suitability map for check dam, farm pond, and percolation tank are presented in Fig. 8. Most of the area in the watershed falls in low slope category, and most of the locations have low permeability, a combination that is highly suitable for check dams. The FIS classified nearly 94% of the area as highly suitable for check dam installation. The remaining area is equally shared between low and medium suitability for the check dam. A cross examination of the maps of check dam suitability and soil indicates that the area that are classified as low suitability for check dams is with soil that has relatively more silt content compared to other soil types present in the watershed. The areas that have more silt content in the soil are relatively more permeable, and hence cannot hold water for a longer duration. A few

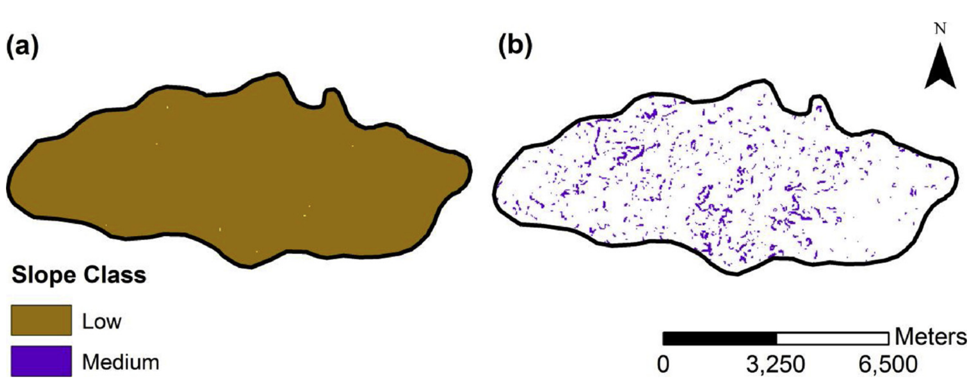

Fig. 5. Based on the fuzzy membership function and fuzzy classification of the slope, the watershed is classified into (a) Low and (b) Medium classes.

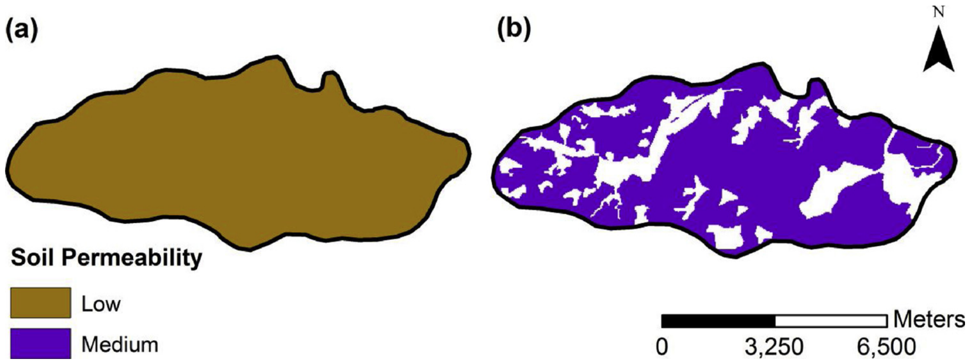

Fig. 6. Based on the fuzzy membership function and fuzzy classification of the soil permeability, the watershed is classified into (a) Low and (b) Medium classes.

locations under the medium suitability for check dams is due to the medium slope gradient in these areas. It should be noted that the check dams are constructed across a water course, and the locations have to be decided considering this factor. Therefore, even though 94% of the total area is classified under high suitability class for check dams, the actual potential locations are only along the drainage lines of the watershed. The existing check dams in the watershed showed a good agreement with the generated check dam suitability map as can be seen from Fig. 8(a).

Similar to the check dam suitability, farm ponds are also suitable for areas with low slope and low soil permeability. Since most of the area in the watershed falls in the low slope and the low permeability category, majority of the area (~99%) is under high farm pond suitability class. There is a negligible area under low suitability in the watershed. A cross examination of the slope map and farm pond suitability map indicates that the areas with low suitability of farm ponds are the areas classified as medium slope. In medium and high slope areas, larger farm ponds need to be installed to increase the storage compared to the farm ponds installed in low slopes. Since farm ponds are on-farm structures and cropping area is lost for implementation of farm ponds, these structures are not preferred in medium to high slope areas. The existing farm ponds in the watershed showed a good agreement with the generated farm pond suitability map (Fig. 8b).

The purpose of percolation tanks in the watershed is to recharge the groundwater and improve the groundwater levels. Generally, these structures are implemented on permeable soils for easy recharge of groundwater. Since, the watershed is primarily consisting of silty clay and silty clay loam soils, which have low permeability, percolation tanks suitability is less. Similar results are obtained from the developed FIS, where the entire watershed area is classified under the not suitable category (Fig. 8(c)). There is a very small area (< 0.01%) under the medium suitability class. The watershed has few existing percolation tanks as shown in the Fig. 8(c), these tanks in reality serve the purpose of larger farm ponds rather than facilitating as groundwater recharge structures. Therefore, these percolation tanks will not work effectively for the purpose that it is intended to serve.

5.5. Sensitivity of FIS parameters on output

The classification of the watershed locations for water harvesting structure suitability by the FIS model for Kondepi watershed is in concurrence with the spatial variability of the input variables. The validity of the suitability maps is verified with the locations of the existing structures in this basin. Nonetheless, the output of the FIS is highly dependent of the fuzzy parameters of the fuzzy variables in the FIS, which categorizes the input variable into different classes. As mentioned earlier, the fuzzy MF parameters for the input variables in this study has been obtained from literature and expert knowledge. Therefore, there is certainly a level of subjectivity in these MF parameters. Consequently, an analysis was planned to check the sensitivity of these MF parameters on the final suitability maps. The impact of the MF parameters on the developed maps was evaluated through performing Monte Carlo simulations (1000 number) of the FIS model by perturbing the MF parameters within a range of -10% to +10% of the suggested value. The change in area of suitability (with the suggested value combination of MF parameters as reference) is considered as a measure of sensitivity, and 5% change is considered to be significant.

A plot of the percentage change in suitability area against the percentage change in the MF parameter is presented in Fig. 9, for all the three input variables. It is observed that a deviation of -3.5% for the permeability MF parameters results in a significant change in the locations that are suitable for check dams. The MF parameters for runoff potential did not exhibit any sensitivity on the output. However, slope showed a good degree of sensitivity in the final suitability maps, but with small amount (< 1%) of change in suitability area. The change in area from one suitability class to a different suitability class was increasing when the MF parameters for slope were perturbed from the expert suggested value.

To identify the spatial locations of the change in the areas in suitability classes, two random simulation results (Fig. 11), which had a

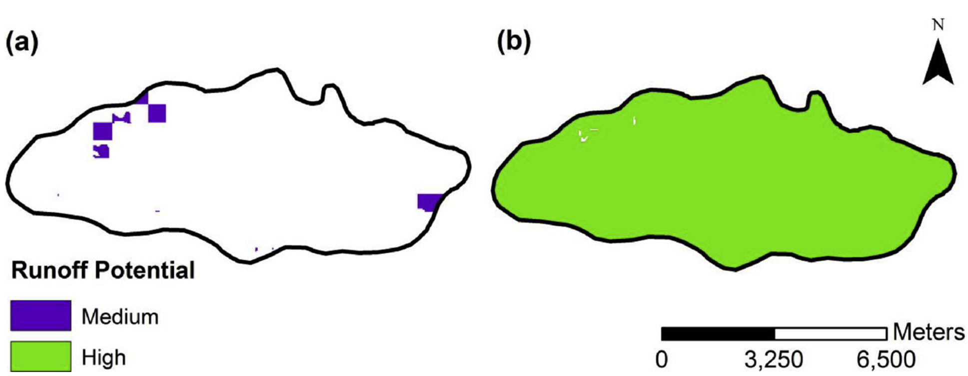

Fig. 7. Based on the fuzzy membership function and fuzzy classification of the runoff potential, the watershed is classified into (a) Medium and (b) High classes.

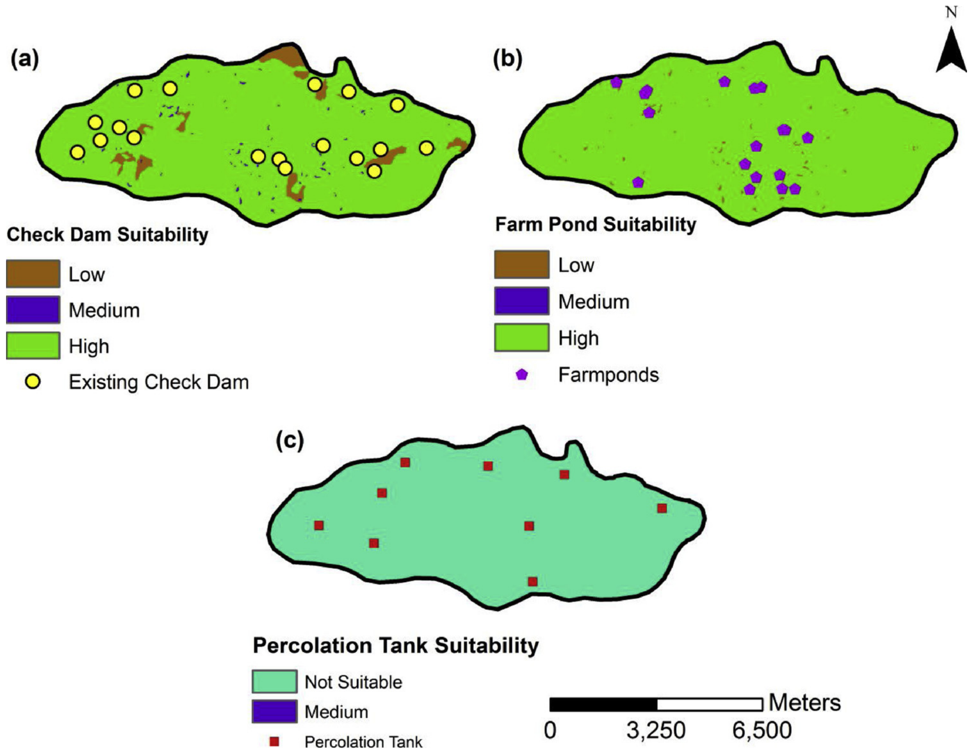

Fig. 8. Site suitability evaluation of Kondepi watershed by the developed fuzzy inference system for: (a) check dam suitability, (b) farm pond suitability, and (c) percolation tank suitability, and existing check dams and farm ponds in the Kondepi watershed.

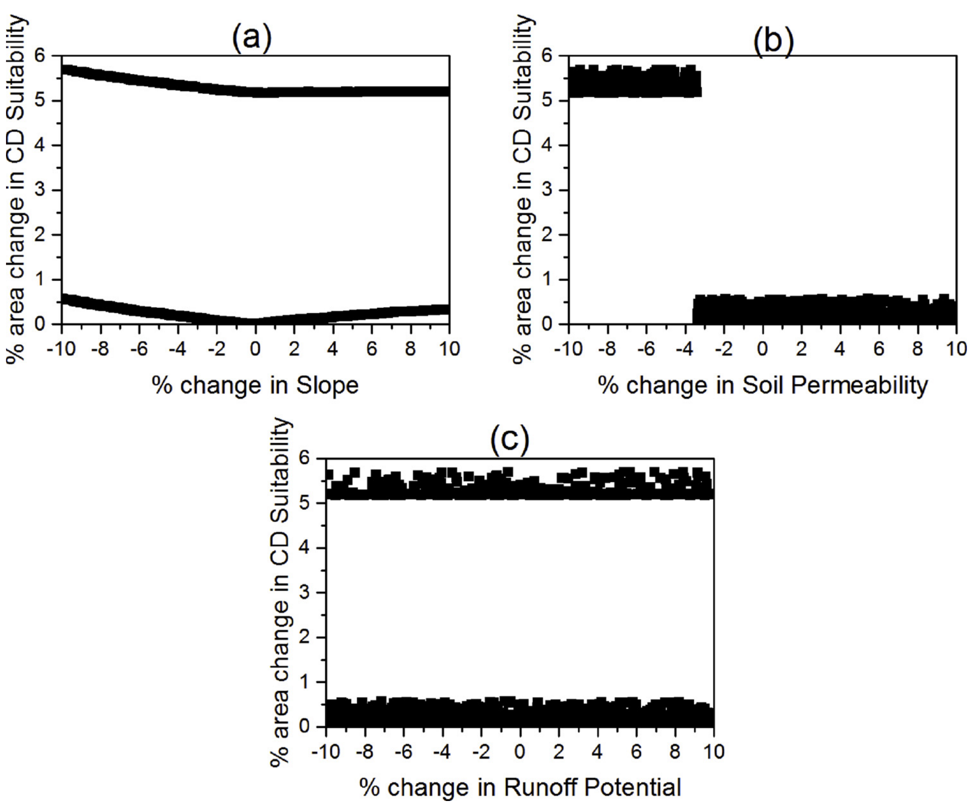

Fig. 9. Sensitivity analysis of the input membership function parameters for check dams. Plots of percentage change in suitability area vs. percentage change in membership function of (a) Soil permeability, (b)Runoff Potential, and (c) Slope.

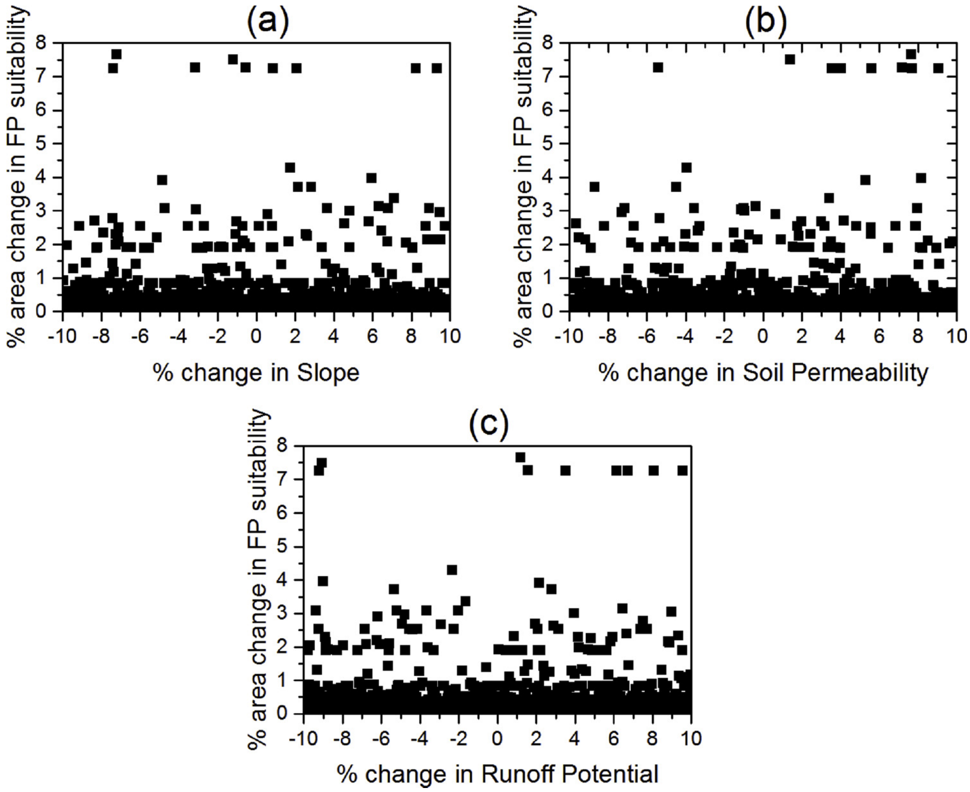

Fig. 10. Sensitivity analysis of the input membership function parameters for farm ponds. Plots of percentage change in suitability area vs. percentage change in membership function of (a) Soil permeability, (b)Runoff Potential, and (c) Slope.

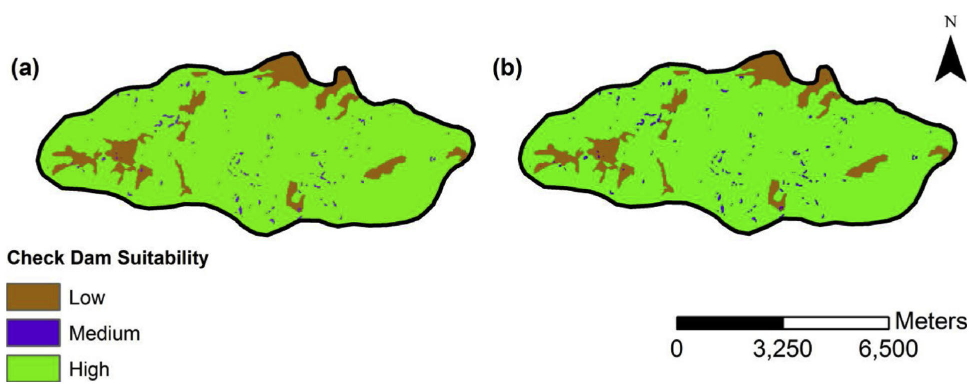

Fig. 11. Representative site suitability maps of check dams for the fuzzy membership function parameters whose percentage change in suitability class area is greater than 5%. Percentage change in suitability class is defined as the area of the watershed which has changed its class from one suitability class to another.

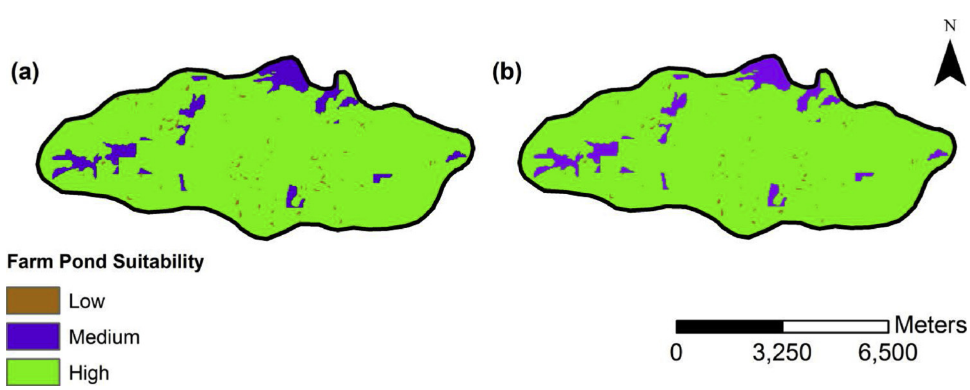

Fig. 12. Representative site suitability maps of farm ponds for the fuzzy membership function parameters whose percentage change in suitability class area is greater than 5%. Percentage change in suitability class is defined as the area of the watershed which has changed its class from one suitability class to another.

change in the suitability area > 5% were selected for analysis. A cross examination of the spatial distribution of the check dam suitable areas (where the suitability class of check dams has changed significantly) and the soil permeability map, indicated that the changed areas have the same soil group. The soil textural class of this area belonged to the silty clay loam with relatively more silt content. The permeability of this soil is 29 cm/day, which was classified to fall in both low and medium classes. A perturbation of -3.5% (and more) of the MF parameters resulted in a change of belongingness of the low and medium classes for these areas, thus resulting in change of suitability class from high to low. No clear trends were visible for farm pond suitability as can be seen from the Fig. 10. There are a few simulations that exhibit a change in suitability area for farm pond greater than 5% (Fig. 10), possibly due to the combined effect of change of parameters of all the three input variables. A few locations in the watershed experience a change in suitability from high to low for farm ponds (Fig. 12) (two randomly selected simulations from the Monte Carlo experiment), and similar to the check dams these areas also belong to the same soil class.

6. Summary and conclusions

A FIS model is developed in this study to identify suitable zone for check dams, farm ponds and percolation tanks in rainfed agricultural watersheds. The suitability zones were identified using the slope, soil permeability, and runoff potential as input variables to the FIS. Trapezoidal MF was considered for the input and output variables for the fuzzy model and MF parameters were obtained from literature and expert knowledge. The developed model was applied to Kondepi watershed, Andhra Pradesh, India to delineate the suitability zones for the three water harvesting structures. The FIS categorized the majority of the watershed area into high suitability class for both farm ponds and check dams. The watershed characteristics were not conducive for percolation tanks according to the FIS. A sensitivity analysis was carried out for the fuzzy model to evaluate the impacts of the MF parameters on the output suitability classes. Input MF parameters were perturbed between -10% to +10% of the expert suggested values. The results showed that check dam suitability zones was sensitive to the soil permeability classes. The other variables' classes were not sensitive to identify the check dam suitability. In the case of farm pond suitability, all the three variables did not show significant sensitivity, confirming the experts' suggestion for MF parameters. The FIS suggested suitability maps were in good agreement with the existing RWH structures in Kondepi watershed, except for percolation tanks. The percolation tanks in the watershed were probably constructed considering socio-economic factors. The FIS suggested suitability maps can hence be used to help take appropriate decisions in the participatory watershed management program.

References

Adham, A., Riksen, M., Ouessar, M., Ritsema, C., 2016a. Identification of suitable sites for rainwater harvesting structures in arid and semi-arid regions: a review. Int. Soil Water Conserv. Res. 4, 108–120. https://doi.org/10.1016/j.iswcr.2016.03.001.

Adham, A., Wesseling, J.G., Riksen, M., Ouessar, M., Ritsema, C.J., 2016b. A water harvesting model for optimizing rainwater harvesting in the wadi Oum Zessar watershed. *Tunisia*. Agric. Water Manag. 176, 191–202. https://doi.org/10.1016/j.agwat.2016.06.003.

Adriaenssens, V., De Baets, B., Goethals, P.L.M., De Pauw, N., 2004. Fuzzy rule-based models for decision support in ecosystem management. Sci. Total Environ. 319, 1–12. https://doi.org/10.1016/S0048-9697(03)00433-9.

Al-Adamat, R., 2008. GIS as a decision support system for siting water harvesting ponds in the basalt Aquifer/Ne Jordan. J. Environ. Assess. Policy Manag. 10, 189–206. https://doi.org/10.1142/S1464333208003020.

Al-Adamat, R., Diabat, A., Shatnawi, G., 2010. Combining GIS with multicriteria decision making for siting water harvesting ponds in Northern Jordan. J. Arid Environ. 74, 1471–1477. https://doi.org/10.1016/j.jaridenv.2010.07.001.

Al-Adamat, R., AlAyyash, S., Al-Amoush, H., Al-Meshan, O., Rawajfih, Z., Shdeifat, A., Al-Harahsheh, A., Al-Farajat, M., 2012. The combination of indigenous knowledge and geo-informatics for water harvesting siting in the Jordanian Badia. J. Geogr. Inf. Syst. 366–376. https://doi.org/10.4236/jgis.2012.44042. 2012.

Dai, C., Cai, Y.P., Ren, W., Xie, Y.F., Guo, H.C., 2016. Identification of optimal placements of best management practices through an interval-fuzzy possibilistic programming model. Agric. Water Manag. 165, 108–121. https://doi.org/10.1016/j.agwat.2015.10.016.

de Winnaar, G., Jewitt, G.P.W., Horan, M., 2007. A GIS-based approach for identifying potential runoff harvesting sites in the Thukela River basin, South Africa. Phys. Chem. Earth Parts A/B/C 32, 1058–1067. https://doi.org/10.1016/j.pce.2007.07.009.

Dixon, B., 2005. Groundwater vulnerability mapping: a GIS and fuzzy rule based integrated tool. Appl. Geogr. 25, 327–347. https://doi.org/10.1016/j.apgeog.2005.07.002.

Durbude, D.G., Venkatesh, B., 2004. Site suitability analysis for soil and water conservation structures. J. Indian Soc. Remote Sens. 32, 399–405. https://doi.org/10.1007/BF03030865.

Kadam, A.K., Kale, S.S., Pande, N.N., Pawar, N.J., Sankhua, R.N., 2012. Identifying potential rainwater harvesting sites of a semi-arid, basaltic region of Western India, using SCS-CN method. Water Resour. Manag. 26, 2537–2554. https://doi.org/10.1007/s11269-012-0031-3.

Kahinda, J.M., Lillie, E.S.B., Taigbenu, a.E., Taute, M., Boroto, R.J., 2008. Developing suitability maps for rainwater harvesting in South Africa. Phys. Chem. Earth, Parts A/B/C 33, 788–799. https://doi.org/10.1016/j.pce.2008.06.047.

Krois, J., Schulte, A., 2014. GIS-based multi-criteria evaluation to identify potential sites for soil and water conservation techniques in the Ronquillo watershed. northern Peru. Appl. Geogr. 51, 131–142. https://doi.org/10.1016/j.apgeog.2014.04.006.

Kweon, G., 2012. Delineation of site-specific productivity zones using soil properties and topographic attributes with a fuzzy logic system. Biosyst. Eng. 112, 261–277. https://doi.org/10.1016/j.biosystemseng.2012.04.009.

Li, M., Guo, P., 2015. A coupled random fuzzy two-stage programming model for crop area optimization—a case study of the middle Heihe River basin, China. Agric. Water Manag. 155, 53–66. https://doi.org/10.1016/j.agwat.2015.03.013.

Mamdani, E.H., Assilian, S., 1975. An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man. Mach. Stud. 7, 1–13. https://doi.org/10.1016/S0020-7373(75)80002-2.

Mbilinyi, B.P., Tumbo, S.D., Mahoo, H.F., Mkiramwinyi, F.O., 2007. GIS-based decision support system for identifying potential sites for rainwater harvesting. Phys. Chem. Earth, Parts A/B/C 32, 1074–1081. https://doi.org/10.1016/j.pce.2007.07.014.

Mwenge Kahinda, J., Taigbenu, a.E., Sejamoholo, B.B.P., Lillie, E.S.B., Boroto, R.J., 2009. A GIS-based decision support system for rainwater harvesting (RHADESS). Phys. Chem. Earth, Parts A/B/C 34, 767–775. https://doi.org/10.1016/j.pce.2009.06.011.

Napoli, M., Cecchi, S., Orlandini, S., Zanchi, C.A., 2014. Determining potential rainwater harvesting sites using a continuous runoff potential accounting procedure and GIS techniques in central Italy. Agric. Water Manag. 141, 55–65. https://doi.org/10.1016/j.agwat.2014.04.012.

Nayak, P.C., Sudheer, K.P., Ramasastri, K.S., 2005. Fuzzy computing based rainfall-runoff model for real time flood forecasting. Hydrol. Process. 19, 955–968. https://doi.org/10.1002/hyp.5553.

Padmavathy, A.S., Ganesha Raj, K., Yogarajan, N., Thangavel, P., Chandrasekhar, M.G., 1993. Checkdam site selection using GIS approach. Adv. Space Res. 13, 123–127. https://doi.org/10.1016/0273-1177(93)90213-U.

Prinz, D., Oweis, T., Oberle, A., 1998. Rainwater harvesting for dry Land agriculture - developing a methodology based on remote sensing and GIS. Proceedings of XIII International Congress of Agricultural Engineering. ANAFAD. pp. 1–12.

Ramakrishnan, D., Bandyopadhyay, A., Kusuma, K.N., 2009. SCS-CN and GIS-based approach for identifying potential water harvesting sites in the Kali watershed, Mahi River Basin, India. J. Earth Syst. Sci. 118, 355–368. https://doi.org/10.1007/s12040-009-0034-5.

Rao, K.H.V.D., Bhaumik, M.K., 2003. Spatial expert support system in selecting suitable sites for water harvesting structures — a case study of song watershed, Uttaranchal, India a case study of the song w. Geocarto Int. 18, 43–50. https://doi.org/10.1080/10106040308542288.

Reshmidevi, T.V., Eldho, T.I., Jana, R., 2009. A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds. Agric. Syst. 101, 101–109. https://doi.org/10.1016/j.agsy.2009.04.001.

Ross, T.J., 2004. Fuzzy Logic with Engineering Applications. McGraw-Hill, inc, Singapore.

Sasikala, K.R., Petrou, M., Kittler, J., 1996. Fuzzy classification with a GIS as an aid to decision making. Adv. Remote Sens. 4, 97–105.

Saxton, K.E., Rawls, W.J., 2006. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. Soil Sci. Soc. Am. J. 70, 1569. https://doi.org/10.2136/sssaj2005.0117.

Sekar, I., Randhir, T.O., 2007. Spatial assessment of conjunctive water harvesting potential in watershed systems. J. Hydrol. 334, 39–52. https://doi.org/10.1016/j.jhydrol.2006.09.024.

Senay, G.B., Verdin, J.P., 2004. Developing index maps of water-harvest potential in Africa. Appl. Eng. Agric. 20, 789–799.

Sicat, R.S., Carranza, E.J.M., Nidumolu, U.B., 2005. Fuzzy modeling of farmers' knowledge for land suitability classification. Agric. Syst. 83, 49–75. https://doi.org/10.1016/j.agsy.2004.03.002.

Singh, L.K., Jha, M.K., Chowdary, V.M., 2017. Multi-criteria analysis and GIS modeling for identifying prospective water harvesting and artificial recharge sites for sustainable water supply. J. Clean. Prod. 142, 1436–1456. https://doi.org/10.1016/j.jclepro.2016.11.163.

Soundharajan, B., Sudheer, K.P., 2009. Deficit irrigation management for rice using crop growth simulation model in an optimization framework. Paddy Water Environ. 7, 135–149. https://doi.org/10.1007/s10333-009-0156-z.

Takagi, T., Sugeno, M., 1985. Fuzzy identification of systems and its applications to modeling and control. Syst. Man Cybern. IEEE Trans. SMC-15 116–132. https://doi.

org/10.1109/TSMC.1985.6313399.
Tsiko, R.G., Haile, T.S., 2011. Integrating geographical information systems, fuzzy logic and analytical hierarchy process in modelling optimum sites for locating water reservoirs. A case study of the debub district in Eritrea. Water 3, 254–290. https://doi.org/10.3390/w3010254.
Wani, S.P., Garg, K.K., 2009. Watershed Management Concept and Principles. [WWW Document]. ICRISAT. URL (accessed 5.10.14). http://oar.icrisat.org/3914/1/1._Watershed_Management_Concept.pdf.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.