



Fuzzy modeling of farmers' knowledge for land suitability classification

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Abstract

In a case study, we demonstrate fuzzy modeling of farmers' knowledge (FK) for agricultural land suitability classification using GIS. Capture of FK was through rapid rural participatory approach. The farmer respondents consider, in order of decreasing importance, cropping season, soil color, soil texture, soil depth and slope as factors of suitability of their land for certain crops. Multi-class fuzzy sets using *S*-membership functions were generated for soil texture, soil depth and slope because of correlation or equivalence between farmers' definitions and scientific classifications of such land characteristics. In contrast, binary fuzzy relations, which are also fuzzy sets, were generated for cropping season and soil color because farmers' perceptions of such land characteristics are intrinsically binary. Despite variations in individual farmers' perceptions of land suitability, 12 unique FK rules for classifying land suitability were defined by hierarchical grouping of such different perceptions based on decreasing importance of factors. The FK rules form inference engines in combining fuzzy factor maps using appropriate fuzzy operators to create agricultural land suitability maps. Suitability maps resulting from application of Fuzzy AND and Fuzzy OR operators were found consistent with

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the FK rules. The FK-based suitability maps indicate either agreement or conflict with a land resource development plan (LRDP) for the case study area. Results of the study indicate usefulness of fuzzy modeling in FK-based classification of agricultural land suitability, which could provide useful information for optimum land-use planning.

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1. Introduction

Agricultural land suitability classification based on indigenous knowledge is vital to land-use planning – the systematic assessment of land and water potential, alternatives for land use and socio-economic conditions in order to select and put into practice those land uses that will best meet the needs of the people while safeguarding resources for the future (FAO, 1993). Authorities in top levels of government organizations usually develop land-use plans exclusive of indigenous knowledge. This non-participatory approach, however, commonly results in land-use plans that are poorly adopted by certain communities because such plans are often not agreeable with the desires of local people (FAO, 1997). On the other hand, farmers usually make their own agricultural land suitability classifications, which could also be socio-economically non-optimal due to a dichotomy of interests between farmers and the community to which they belong. Optimum land-use planning, therefore, should strive to identify improved and sustainable land-uses, through integration of the objectives and knowledge of the community and those of individual farmers.

It is generally agreed that the terms farmers' knowledge, indigenous knowledge, traditional knowledge, local knowledge, community knowledge, rural peoples' knowledge and indigenous technical knowledge all pertain to knowledge belonging to local people. While certain distinctions can be made, these terms often refer to the same thing (Mathias, 1995; Roach, 1994). In this paper, we use the term farmers' knowledge (FK) because it refers specifically to the knowledge of farmers in our study area, whether this knowledge is traditional, modern or mixed traditional–modern knowledge.

It has been shown that FK is important to agricultural land suitability classification (e.g., Habarurema and Steiner, 1997; Ryder, 2003; Steiner, 1998). It is even more useful when FK is integrated with scientific methods of land evaluation, which can be achieved effectively through application of geographic information systems or GIS (Cools et al., 2003; Gonzalez, 2002; Lawas and Luning, 1996; Messing and Fagerstrom, 2001; Oudwater and Martin, 2003; Wandahwa and Van Ranst, 1996; Zurayk et al., 2001). Common to previous works is the subjective or qualitative modeling of FK. However, FK is invariably portrayed as linguistic variables that are inherently vague or fuzzy, which could be inadequately modeled by subjective or qualitative approaches. A more adequate modeling of FK for agricultural land

suitability classification requires approaches capable of using vague or fuzzy concepts where a precise membership or non-membership in a land suitability class based on FK may be impossible or impractical to define.

Modeling of vague concepts is feasible by application of the theory of fuzzy sets (Zadeh, 1965). Fuzzy modeling of spatial data based on theoretical knowledge has been demonstrated to be useful in various GIS-based studies of land suitability classification (e.g., Ceballos-Silva and López-Blanco, 2003; Groenemans et al., 1997; Kollias and Kalivas, 1998; Liu and Samal, 2002; Malczewski, 2002; Nisar Ahamed et al., 2000; Triantafilis et al., 2001; Van Ranst et al., 1996). In addition, Beek (2000) avers that FK justifies fuzzy modeling in natural resource studies, in which certain properties are difficult to model, data are insufficient for statistical analysis or when relations between indicator variables are not clearly known. However, fuzzy modeling of spatial data based on FK to classify agricultural land suitability has not been reported yet.

In this paper, we demonstrate FK-based fuzzy modeling for agricultural land suitability classification using case spatial data sets from India. Firstly, we describe briefly theoretical concepts behind fuzzy sets, membership functions and operators. Secondly, we describe the case study area where local people, particularly farmers, have poorly adopted land-use plans developed through non-participatory approaches. Finally, we describe the knowledge bases and the spatial data captured into a GIS and the procedures followed for FK-based modeling of agricultural land suitability.

2. Fuzzy modeling

In classical set theory, membership in a set or a class is crisp and defined only as either non-complete (= 0) or complete (= 1). In fuzzy set theory, membership in a set or a class can range from non-complete (= 0) to complete (= 1) (Zadeh, 1965). Fuzzy sets are thus useful to classify attributes according to vague concepts of membership (e.g., Carranza and Hale, 2001; Lawry, 2001; McBratney and Odeh, 1997).

A fuzzy set X is a presupposed finite set (or space) of attributes. A fuzzy subset A of X is defined by a function, μ_A , in ordered pairs $A = \{x, \mu_A(x)\}$ for each $x \in X$. The relation $\mu_A(x)$ is a fuzzy membership function (FMF), which defines the grade of membership of x in A ; $x \in X$ indicates that x is in X . For all A , $\mu_A(x)$ is a value in the unit interval $[0,1]$ (i.e., a value in a set of all real numbers r with $0 \leq r \leq 1$). A grade of zero (0) means that an attribute has complete non-membership in a fuzzy set, while a grade of one (1) means that an attribute has complete membership in a fuzzy set and grades between 0 and 1 mean partial membership in a fuzzy set. Grades of membership are usually modeled by FMFs, which need not be linear or even continuous; indeed, many interesting fuzzy sets have extremely nonlinear FMFs (Zimmerman, 1991). Grades of membership in a fuzzy set always relate to a certain proposition. In this case, the FK-based proposition is: “This piece of land, based on a certain land characteristic, is suitable for agriculture”.

Fuzzy membership grades can be determined using S -membership functions, which are appropriate and robust for linguistic variables (e.g., FK). A S -membership function for x attributes can be defined as (Robinson, 2003):

$$S(x; \alpha, \beta, \gamma) = \begin{cases} 0, & x \in [-\infty, \alpha] \\ 2[(x - \alpha)/(\gamma - \alpha)]^2, & x \in [\alpha, \beta] \\ 1 - 2[(x - \beta)/(\gamma - \alpha)]^2, & x \in [\beta, \gamma] \\ 1, & x \in [\gamma, +\infty] \end{cases} \quad \text{or,} \quad (1)$$

$$S(x; \alpha, \beta, \gamma) = \begin{cases} 1, & x \in [-\infty, \alpha] \\ 1 - 2[(x - \alpha)/(\gamma - \alpha)]^2, & x \in [\alpha, \beta] \\ 2[(x - \beta)/(\gamma - \alpha)]^2, & x \in [\beta, \gamma] \\ 0, & x \in [\gamma, +\infty] \end{cases} \quad (2)$$

Eqs. (1) and (2) represent, respectively, increasing and decreasing FMFs (i.e., fuzzy values) for x attributes (e.g., soil depth) representing a factor S ; α and γ are lower or upper limits of x attributes, and β is $(\alpha + \gamma)/2$. In applying Eqs. (1) and (2) based on FK, the semantic import (SI) approach (McBratney and Odeh, 1997) can be employed to define multi-classes or fuzzy subsets based on conventionally imposed definitions or on experience (i.e., FK in this case). The SI approach can be seen as an extension of Boolean approaches and sensible comparisons can be made with strictly defined Boolean classes (Burrough et al., 1992). To illustrate how Eqs. (1) and (2) can be applied, suppose an area with soil depths (i.e., S) varying from 0 to 200 cm and suppose further that the soil depth data (i.e., x) has to be modeled into fuzzy subsets of ‘shallow’, ‘deep’ and ‘very deep’ soils according to a certain proposition. Fuzzy subset ‘shallow’ soils can be modeled by a decreasing FMF S -curve using Eq. (2) with $\alpha = 0$ cm and $\gamma = 100$ cm (Fig. 1). Fuzzy subset of ‘very deep’ soils can be modeled by an increasing FMF S -curve using Eq. (1) with $\alpha = 100$ cm and $\gamma = 200$

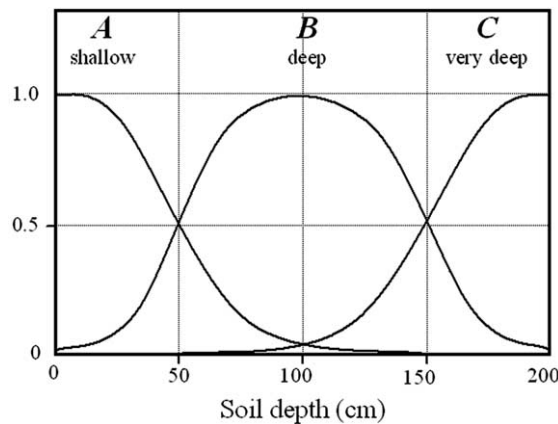


Fig. 1. Fuzzy membership functions fitted to fuzzy subsets of: (A) ‘shallow’ soils, (B) ‘deep’ soils and (C) ‘very deep’ soils (adapted from McBratney and Odeh, 1997).

cm. Fuzzy subset ‘deep’ soils can be modeled by an FMF with increasing and decreasing S -curves; the increasing S -curve can be modeled using Eq. (1) with $\alpha = 0$ cm and $\gamma = 100$ cm, while the decreasing S -curve can be modeled using Eq. (2) with $\alpha = 100$ cm and $\gamma = 200$ cm. The fuzzy subsets of ‘shallow’ and ‘very deep’ soils have asymmetrical FMFs while the fuzzy subset of ‘deep’ soils has a symmetrical FMF, representing a normal and convex FMF. Thus, for example, soils with depths of 100 cm have complete membership in the ‘deep’ soil fuzzy subset and have grades of membership of 1, whereas soils with depths of $0 \leq x < 100$ cm or $100 < x \leq 200$ cm have partial membership grades in this fuzzy subset. Fuzzy sets can thus overlap and the attribute value at the point where grades of membership equal 0.5 is called the ‘crossover point’, which illustrates that sets in the real world do not necessarily have sharply defined limits and that a continuum of attributes is not always classifiable with rigidly defined limits.

As in classical set theory, set-theoretic operations can be performed to integrate fuzzy sets, including equality, containment, union and intersection, all of which have meanings analogous to their crisp set equivalents. Hence, an integrated fuzzy land suitability index can be derived using appropriate fuzzy operators (e.g., Bonham-Carter, 1994; Carranza and Hale, 2001), weight factors (Tang, 1993) and joint membership functions (Davidson et al., 1994). Typically, fuzzy modeling of spatial data involves three main feedforward stages: (1) fuzzification; (2) logical inference procedures performed with fuzzy set operations; and (3) defuzzification (Fig. 2). Fuzzification, which can be knowledge-driven or data-driven, involves generation of FMFs for input categorical or numeric data. Inference procedures involve implementation of parallel and/or serial rules that sequentially combine fuzzy sets through fuzzy set operators into a synthesized fuzzy set. There are no general guidelines for designing a logical inference procedure except that as much as possible it should simulate the human decision-making process. Defuzzification involves transformation of a synthesized fuzzy set back to a crisp set, which expresses the result of modeling. Defuzzification can make use of a subjectively or objectively defined threshold fuzzy value. Hellendoorn and Thomas (1993) describe a number of criteria that an ideal defuzzification procedure should satisfy. The most important criterion is that a small change in inputs of a fuzzy model should not cause a significant change in output.

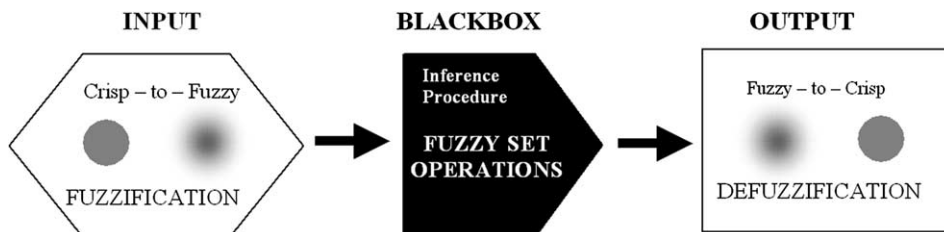


Fig. 2. Main stages in fuzzy modeling.

3. The case study area

Agricultural land suitability classification through FK-based (i.e., knowledge-driven) fuzzy modeling of spatial data was tested in an area in Nizamabad District of Andhra Pradesh State in India.

3.1. Background

In India, a GIS-based land-use planning project called the ‘Integrated Mission for Sustainable Development’ generates, analyzes and integrates 1:50,000 scale natural resource thematic data, together with satellite remote sensing data, to create land resources development plans (LRDPs) for alternate land-uses based on resource potential, groundwater exploration and recharge, surface water harvesting and soil conservation. The LRDPs were to be implemented by district level resource managers. However, such LRDPs were poorly adopted by several local communities (Harmsen and Nidumolu, 2002) because: (a) such plans failed to analyze the complete array of local circumstances and to diagnose the best points of local intervention and, consequently, (b) do not coincide with land-uses desired by primary stakeholders, particularly the local farmers. The Nizamabad District (Andhra Pradesh State, India) is one of the districts for which an LRDP was created. In this district, a suitable case area was found (i.e., soil database, digital elevation model, and a land-use map are available) for FK-based modeling of land suitability for comparison with the LRDP.

3.2. Geography and agricultural practices

The study area lies in the western part of Nizamabad District (Fig. 3). It lies between 18°10'N and 18°40'N latitudes and between 77°30'E and 78°00'E longitudes. It

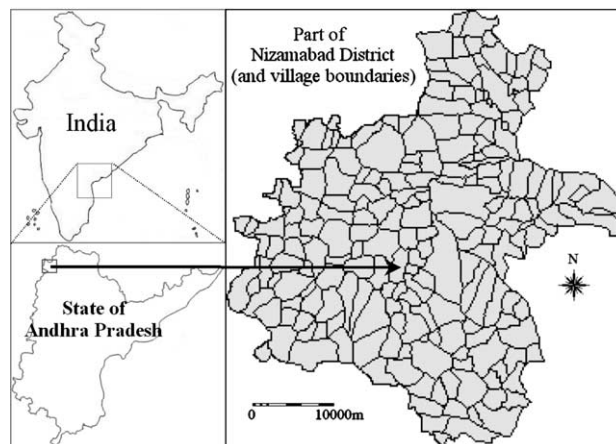


Fig. 3. Location of study area.

consists 220 villages belonging to six mandals (or administrative sub-divisions in a district) with a total area of about 1289 km², about 70–75% of which is used for agricultural purposes. Each village has its own Water Users Association (WUA), who, with the aid of the Mandal agriculture officer, determines which crops will be sown based on amount of available water. The Irrigation Office provides this information to the Mandal Office, which, in turn, provides information to the villages.

Generally, agricultural practices do not greatly vary from village to village although, socio-economically, the peasantry ranges from affluent farmers to subsistence farmers. Between these extreme groups, various intensities of agriculture are practiced. A major consideration is availability of and accessibility to water. Financially capable farmers have electricity-driven irrigation systems. In some villages, however, electricity is not always available throughout a day.

There are three cropping seasons when rain and groundwater are available: (1) *Kharif* (July–October); (2) '*Kharif + Rabi*' (October–December); and (3) *Rabi* (November–March). The summer cropping season is called *Zaid* (March–June) and depends on groundwater. In some villages, however, local farmers do not follow such distinct cropping seasons but have their own classification of cropping seasons. Whatever the cropping season, agricultural practice is either by mono-cropping, by multiple-cropping or by rotational cropping. The present trend is intensive rotational multiple-cropping in a year; however, relay-cropping (i.e., one crop sown in a standing crop) also occurs.

Around 40% of the gross cropped area is not assured of irrigation and such areas are categorized as 'rain-fed drylands'. Agriculture in these 'rain-fed drylands' is characterized by: (a) lack of assured water supply for irrigation, (b) lack of technologies and cropping systems suited to dryland conditions, (c) poor resources and inadequate extension/support services, and (d) low productivity. Agriculture in these 'rain-fed drylands' are generally confined to relatively well-irrigated areas, where the traditional practice of subsistence multiple-cropping is shifting to commercial mono-cropping, largely because farmers feel it is the way to 'prosperity'. However, application of high doses of fertilizers and chemicals needed by certain crops hastens land degradation. Moreover, farmers with small land holdings tend to maximize utilization of their small plots in an unsustainable manner, thus depleting the full potential of the land for succeeding cropping activities. It is therefore not surprising that the 'rain-fed drylands' are among the least developed and poorest in the region.

3.3. *Farmers' knowledge of land suitability*

Farmers' knowledge and field data were gathered during a three-week fieldwork in September–October 2002. The FK was gathered through interviews using a semi-structured questionnaire (Appendix A). The farmers interviewed generally belong to 'rural Telangana farmers' who have common traits, traditions and culture with respect to agriculture. The interviews were limited to a rapid rural participatory approach and not based on village immersion methodologies (e.g., Lawas and Luning, 1996). The interviews were carried out in 26 randomly chosen localities representing zones that were classified, based on field verifications of existing land-uses, as

either: (a) agricultural land used to full potential, (b) agricultural land not used to full potential, or (c) non-agricultural land used to full agricultural potential. At each interview locality, at least 10 randomly chosen farmers were interviewed, each of who has land holdings of more than 3 ha situated about and beyond each of the interview localities. Field observations were made about and beyond each of the interview localities to determine areas used or not used for agriculture during different cropping seasons and to corroborate farmers' perceptions about land suitability based on certain land characteristics. From the several field observations in agricultural and non-agricultural lands, it is believed that the number of interview localities, number of farmer respondents, and locations of farmer respondents' land holdings provide a representative sampling of FK about agricultural land suitability.

The farmers classify suitability of their land for certain crops based mainly on cropping season, soil characteristics (i.e., color, texture, depth), and topographic slope (Table 1). The farmers' linguistic descriptions of soil characteristics (except color) and topographic slope are analogous with scientific descriptions (Table 2). The farmers categorize soil colors into only either *Nala regadi* ('black' colored) or *Chalka* ('red' colored) even when soils have varying degrees of 'blackness' or 'redness' as indicated on the soil color chart of Munsell and Birren (1969). The farmers' descriptions of soil texture are roughly equivalent to scientific classifications of soil texture based on clay content (Rao and Raj, 2001), while the farmers' classifications of soil depth and slope roughly correlate with the soil depth and slope classes of Venkateswarlu (2001).

There are variations in the way individual farmers perceive suitability of their land based on a combination of several land characteristics (Table 1). However, variations in farmers' perceptions about land suitability can be organized into discrete rules by grouping of individual farmers' perceptions hierarchically, in which a major factor (i.e., cropping season) is considered first followed by the minor factors in order of their decreasing ranks (Table 3). Note that cropping season is not presented in Table 3 because the farmers rank relative importance of soil characteristics and topographic slope based on crops they have to grow in a cropping season. Each of the farmers' knowledge rules thus defined applies to a unique combination of possible crops per cropping season in view of their classification of certain soil characteristics and topographic slope (Table 4). The farmers' knowledge rules indicate some form of 'logic' in regard to their land suitability classifications, which could be a function of the farmers' sharing of common traits, tradition and culture inherited from previous generations.

4. FK-based fuzzy modeling of land suitability

The farmers' definitions of cropping seasons, soil properties and topographic slopes (Table 2) and their rules for 'land suitability for certain crops' (Table 4) were the bases for fuzzy modeling of available spatial data for FK-based classification of agricultural land suitability. The spatial data consists of maps derived from the soil database (i.e., soil color map, soil clay content map, soil depth map), a slope map

Table 1
Summary of farmers' responses to questionnaire

Interview locales	Local soil color	Soil texture	Soils depth	Slope	<i>Kharif</i>	<i>Kharif + Rabi</i>	<i>Rabi</i>
1	<i>Nala Regadi</i>	Fine	Deep	Flat	Paddy	Paddy/Fallow	Groundnuts/Fallow
2	<i>Chalka</i>	Fine	Deep	Flat	Paddy/Jowar	Paddy/Fallow	Sugarcane/Fallow
3	<i>Nala Regadi</i>	Coarse	Moderately deep	Flat	Maize/Turmeric	Cotton/Groundnuts	Pulses/Jowar
4	<i>Chalka</i>	Fine	Moderately deep	Flat	Paddy	Sugarcane	Sugarcane
6	<i>Nala Regadi</i>	Fine	Moderately deep	Flat	Paddy	Paddy	Paddy
5	<i>Chalka</i>	Fine	Deep	Flat	Paddy/Fallow	Paddy/Fallow	Paddy/Fallow
8	<i>Chalka</i>	Moderately fine	Deep	Flat	Paddy/Turmeric	Paddy/Fallow	Paddy/Fallow
7	<i>Chalka</i>	Fine	Moderately deep	Flat	Paddy/Groundnuts	Paddy/Fallow	Paddy/Fallow
9	<i>Nala Regadi</i>	Fine	Deep	Flat	Paddy/Vegetables	Paddy/Fallow	Sugarcane/Fallow
10	<i>Chalka</i>	Fine	Deep	Flat	Paddy/Groundnuts	Paddy/Fallow	Sunflower
12	<i>Nala Regadi</i>	Fine	Moderately deep	Gentle	Paddy/Groundnuts	Paddy/Vegetables	Sunflower/Fallow
11	<i>Chalka</i>	Fine	Moderately deep	Gentle	Paddy/Jowar	Groundnuts/Turmeric	Sunflower/Fallow
13	<i>Nala Regadi</i>	Coarse	Deep	Flat	Cotton/Groundnuts	Paddy/Fallow	Jowar/Bajra
14	<i>Chalka</i>	Fine	Moderately deep	Flat	Paddy/Vegetables	Paddy/Fallow	Sunflower/Fallow
15	<i>Chalka</i>	Fine	Deep	Moderate	Paddy/Cotton	Maize/Fallow	Jowar/Fallow
17	<i>Nala Regadi</i>	Moderately fine	Moderately deep	Flat	Paddy/Sugarcane	Jowar/Maize	Paddy/Fallow
16	<i>Chalka</i>	Coarse	Deep	Moderate	Jowar/Maize	Jowar/Sunflower	Safflower/Fallow
19	<i>Nala Regadi</i>	Fine	Moderately deep	Flat	Paddy/Vegetables	Safflower/Sunflower	Jowar/Bajra
18	<i>Chalka</i>	Coarse	Moderately deep	Flat	Groundnuts/Turmeric	Jowar/Fallow	Sunflower/Fallow
20	<i>Nala Regadi</i>	Fine	Deep	Gentle	Paddy/Sunflower	Cotton/Fallow	Safflower/Fallow
21	<i>Chalka</i>	Fine	Moderately deep	Moderate	Paddy/Vegetables	Vegetables	Sugarcane/Fallow
23	<i>Nala Regadi</i>	Fine	Moderately deep	Moderate	Paddy/Fallow	Vegetables/Fallow	Cotton/Fallow
22	<i>Chalka</i>	Fine	Deep	Gentle	Paddy/Fallow	Groundnuts/Fallow	Sunflower/Fallow
24	<i>Nala Regadi</i>	Fine	Moderately deep	Moderate	Paddy/Vegetables	Sugarcane/Fallow	Sugarcane/Fallow
25	<i>Chalka</i>	Moderately fine	Moderately deep	Flat	Paddy/Sugarcane	Sugarcane/Fallow	Sugarcane/Fallow
26	<i>Chalka</i>	Fine	Deep	Gentle	Paddy/Sugarcane	Sugarcane/Vegetables	Groundnuts/Fallow

Table 2
Farmers' definitions versus scientific definitions of some soil properties and topographic slope

Farmers' soil color definition	Scientific soil color definition Munsell and Birren (1969)	
	Code	Description
<i>Nala regadi</i>	5YR 3/1	Very dark gray
<i>Nala regadi</i>	10R 2.5/1	Reddish black
<i>Chalka</i>	10R 4/6	Red
<i>Chalka</i>	10R 4/1	Dark reddish gray
<i>Chalka</i>	2.5YR 4/4	Reddish brown
Farmers' soil texture definition	Scientific soil texture definition Rao and Raj (2001)	
	Texture (% clay)	Description
Coarse	<10	Coarse
Moderately	10–20	Moderately coarse
	20–30	Moderately fine
Fine	>30	Fine
Farmers' soil depth definition	Scientific soil depth definition Venkateswarlu (2001)	
	Depth (cm)	Description
Shallow	<10	Very shallow
	10–25	Shallow
Medium deep	25–50	Medium deep
	50–100	Deep
Deep	>100	Very deep
Farmers' slope definition	Scientific slope definition Venkateswarlu (2001)	
	Slope (%)	Description
Flat	0–1	Nearly level
	1–3	Very gently sloping
	3–5	Gently sloping
Gentle	5–10	Moderately sloping
	10–15	Strongly sloping
Moderate	15–33	Steep
	>33	Very steep

(derived from a digital elevation model), and a land-use map other than the LRDP map (Fig. 4). Data for soil color and soil clay content pertain to tillable depth of soil (i.e., ~30 cm).

4.1. Generation of fuzzy factor maps

The farmers' perception of cropping season or soil color is intrinsically binary (Table 4). That is, 'this land is suitable when the cropping season is this and not that' and 'this land is suitable for certain crops because the soil color is this and not that'. 'Binary' fuzzy factor maps were thus generated for cropping season and for soil color.

Table 3
Farmers' ranking of factor importance, factor grades and weights for factors

Interview locales	Farmers' original rankings (from interviews)				Factor grades (converted ranks)			
	Soil color	Soil texture	Soil depth	Slope	Soil color (x_1)	Soil texture (x_2)	Soil depth (x_3)	Slope (x_4)
1, 2	2	1	3	4	3	4	2	1
3, 4	1	2	3	4	4	3	2	1
5, 6	1	2	3	4	4	3	2	1
7, 8	3	1	2	4	2	4	3	1
9, 10	1	2	3	4	4	3	2	1
11, 12	1	2	3	4	4	3	2	1
13, 14	1	2	3	4	4	3	2	1
15	1	3	2	4	4	2	3	1
16, 17	2	1	3	4	3	4	2	1
18, 19	1	2	3	4	4	3	2	1
20, 21	4	2	1	3	1	3	4	2
22, 23	1	2	3	4	4	3	2	1
24, 25	1	2	3	4	4	3	2	1
26	2	1	3	4	3	4	2	1
Sum of grades per factor ($\sum x_i$)					48	45	32	15
Sum of all grades ($\sum \sum x_i$)						140		
Weight per factor ($\sum x_i \div \sum \sum x_i$)					0.34	0.32	0.23	0.11

Based on the land-use map (Fig. 4), which was used in the fieldwork as reference map to determine zones cultivated by the farmers during different cropping seasons, binary *Kharif*, binary '*Kharif + Rabi*', and binary *Rabi* maps were created. In each of these binary maps, zones indicated by the farmers as suitable and non-suitable for agriculture in certain cropping seasons were assigned fuzzy membership of 0.95 and 0.05, respectively, instead of 1 and 0. Fuzzy membership of 1 and 0 were not assigned to suitable zones and non-suitable zones, respectively, based on cropping season because the farmers are not absolutely (say, only about 95%) certain that a zone is completely suitable or completely non-suitable.

The soil color map was re-classified into a binary map of *Nala regadi* soils and into a binary map of *Chalka* soils. In each of these binary maps, for example in the binary map of *Chalka* soils, *Chalka* zones and non-*Chalka* zones were assigned fuzzy membership of 0.95 and 0.05. Fuzzy membership of 1 and 0 were not assigned to zones with soil color considered suitable and non-suitable, respectively, because the farmers are not absolutely (say, only about 95%) certain whether all the soils in, for example, *Chalka* zones are completely *Chalka* or completely non-*Chalka*.

The farmers' perceptions of soil depth, soil texture and topographic slope (Table 2) are intrinsically non-binary. Thus, multi-class fuzzy factor maps were generated for: (a) soil depth, (b) soil texture and (c) topographic slope using either Eqs. (1) or (2). In using either Eqs. (1) or (2), we used a lowest and a highest fuzzy membership grade of 0.01 and 0.99, respectively, instead of 0 and 1. This is because the

Table 4
Farmers' knowledge rules of crop suitability of their land

Rule	IF	AND	OR			THEN
	Cropping season	Soil color	Soil texture	Soil depth	Slope	Crop*
1	<i>Kharif</i>	<i>Nala Regadi</i>	Fine to moderately fine	Moderately deep to deep	Flat to gentle	1
2	<i>Kharif</i>	<i>Nala Regadi</i>	Coarse	Moderately deep to deep	Gentle to moderate	2
3	<i>Kharif</i>	<i>Chalka</i>	Fine to moderately fine	Moderately deep to deep	Flat to gentle	5
4	<i>Kharif</i>	<i>Chalka</i>	Coarse	Moderately deep to deep	Gentle to moderate	6
5	' <i>Kharif + Rabi</i> '	<i>Nala Regadi</i>	Fine to moderately fine	Moderately deep to deep	Flat to gentle	1
6	' <i>Kharif + Rabi</i> '	<i>Nala Regadi</i>	Coarse	Moderately deep to deep	Gentle to moderate	2
7	' <i>Kharif + Rabi</i> '	<i>Chalka</i>	Fine to moderately fine	Moderately deep to deep	Flat or gentle	7
8	' <i>Kharif + Rabi</i> '	<i>Chalka</i>	Coarse	Moderately deep to deep	Flat to gentle	3
9	<i>Rabi</i>	<i>Nala Regadi</i>	Fine to moderately fine	Moderately deep to deep	Flat to gentle	3
10	<i>Rabi</i>	<i>Nala Regadi</i>	Coarse	Moderately deep to deep	Flat to gentle	4
11	<i>Rabi</i>	<i>Chalka</i>	Fine to moderately fine	Moderately deep to deep	Flat to gentle	8
12	<i>Rabi</i>	<i>Chalka</i>	Coarse	Moderately deep to deep	Gentle to moderate	3

* 1 = paddy, fallow, vegetables, groundnuts; 2 = maize, turmeric, cotton, groundnuts; 3 = jowar, maize, safflower, sunflower; 4 = jowar, pulses, bajra; 5 = paddy, sugarcane, cotton; 6 = jowar, maize, groundnuts, turmeric; 7 = paddy, vegetables, safflower, sunflower; 8 = jowar, bajra.

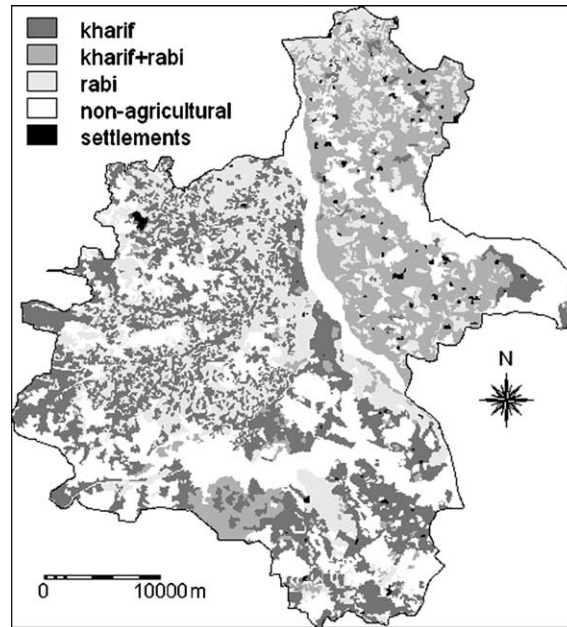


Fig. 4. Re-classified land-use map of study area.

farmers are not absolutely (say, at most 99%) certain about degree of agricultural suitability of their land based on soil depth, soil texture or slope.

The farmers consider 'medium deep' to 'deep' soils suitable for agriculture (Tables 1 and 4); their maximum 'deep' soil is about five times their minimum 'medium deep' or about 125 cm (Table 2). A fuzzy set of suitable soil depths (i.e., 'medium deep' to 'deep') with an increasing *S*-membership function was generated (Table 5); that is, soil depths less than 25 cm were assigned fuzzy membership of 0.01, soil depths greater than 125 cm were assigned fuzzy membership of 0.99, and soil depths ranging from 25 to 125 cm were assigned increasing fuzzy membership of 0.01–0.99.

The farmers' definitions of soil texture (Table 2) were modeled using soil clay content data. The farmers' 'coarse' soils correspond to soils with minimum clay content of about 4% and maximum clay content of about 20%; thus, a fuzzy set of 'coarse' soils with a decreasing *S*-membership function was created (Table 5). The farmers' 'moderately fine' soils correspond to soils with 4–46% clay and their 'optimum moderately fine' soils correspond to soils with 20–30% clay; thus, a fuzzy set of 'moderately fine' soils defined by increasing and decreasing *S*-membership functions was created (Table 5) and soils with 20–30% clay were assigned fuzzy values of 0.99. The farmers' 'fine' soils correspond to soils with minimum clay content of about 30% and maximum clay content of about 46%; thus, a fuzzy set of 'fine soils' with an increasing *S*-membership function was created (Table 5).

The farmers' definitions of slopes were modeled based on the topographic slopes in the area, which vary from 0.8% to 24%. The minimum of the farmers' 'flat' slopes

Table 5
Parameters used to generate S -membership functions of multi-class fuzzy factor maps

Fuzzy factor	S -membership function	
	Type	Equation and parameters used
Soil depth 'Coarse' soils	Increasing	Eq. (1); with $\alpha = 25$ cm, $\beta = 75$ cm and $\gamma = 125$ cm
	Decreasing	Eq. (2); with $\alpha = 4\%$ clay, $\beta = 12\%$ clay and $\gamma = 20\%$ clay
'Moderately fine' soils	Increasing	Eq. (1); with $\alpha = 4\%$ clay, $\beta = 12\%$ clay and $\gamma = 20\%$ clay
	Decreasing	Eq. (2); with $\alpha = 30\%$ clay, $\alpha = 38\%$ clay and $\gamma = 46\%$ clay
'Fine' soils 'Flat' slopes	Increasing	Eq. (1); with $\alpha = 30\%$ clay, $\alpha = 38\%$ clay and $\gamma = 46\%$ clay
	Decreasing	Eq. (2); with $\alpha = 0.8\%$ slope, $\beta = 5.4\%$ slope and $\gamma = 10\%$ slope
'Gentle' slopes	Increasing	Eq. (1); with $\alpha = 0.8\%$ slope, $\beta = 5.4\%$ slope and $\gamma = 10\%$ slope
	Decreasing	Eq. (2); with $\alpha = 14\%$ slope, $\beta = 19\%$ slope and $\gamma = 24\%$ slope
'Moderate' slopes	Increasing	Eq. (1); with $\alpha = 14\%$ slope, $\beta = 19\%$ slope and $\gamma = 24\%$ slope

is about 10%; thus, a fuzzy set of 'flat' slopes was generated with a decreasing S -membership function (Table 5). The farmers' 'optimum gentle' slopes correspond to a gradient range of 10–14%; thus, a fuzzy set of 'gentle' slopes with increasing and decreasing S -membership functions was created (Table 5) and slopes of 10–14% were assigned fuzzy values of 0.99. The farmers' 'moderate' slopes have a minimum gradient of about 14%; thus, a fuzzy set of 'moderate' slopes was generated with an increasing S -membership function (Table 5).

The fuzzy factor maps were then assigned weights based on the farmers' ranking of importance of each land characteristic in regard to agricultural suitability. Aside from cropping season, the farmers rank soil color as the most important factor followed by soil texture, soil depth and slope (Table 3). To derive factor weights that are consistent with the FK (i.e., weights reflect importance), the original ranks were first converted to grades (x_i); i.e., rank 1 equals grade 4 (most important) while rank 4 equals grade 1 (least important) (Table 3). The grades per factor were added (i.e., $\sum x_i$) and the sums of grades per factor were then added (i.e., $\sum \sum x_i$). The weight per factor was derived by dividing sum of grades per factor by sum of all grades (i.e., $\sum x_i - \sum \sum x_i$). Each calculated weight was then multiplied to the pertinent fuzzy factor map (excluding the fuzzy maps based on cropping season).

4.2. Generation of land suitability maps

The FK rules (Table 4), each of which forms an inference engine for fuzzy modeling, axiomatically indicate combined applications of Fuzzy AND (FA) and Fuzzy OR (FO) operators and preclude applications of other fuzzy operators to integrate pertinent fuzzy factor maps. Suppose input fuzzy factor maps A , B and C with μ_A , μ_B and μ_C , respectively, as membership values of each of their attributes and with W_A , W_B and W_C , respectively, as map weights. Using the FA operator, output integrated fuzzy values $\mu_{\text{combination}}$ are obtained as:

$$\text{FA } \mu_{\text{combination}} = \text{MIN}(W_A\mu_A, W_B\mu_B, W_C\mu_C, \dots), \quad (3)$$

where the MIN operator looks for and takes as output the minimum fuzzy value at each point (or pixel) in any input map; it is equivalent but not equal to a Boolean AND operator. Using the FO operator, output integrated fuzzy values $\mu_{\text{combination}}$ are obtained as:

$$\text{FO } \mu_{\text{combination}} = \text{MAX}(W_A\mu_A, W_B\mu_B, W_C\mu_C, \dots), \quad (4)$$

where the MAX operator looks for and takes as output the maximum value at each point (or pixel) in any input map; it is equivalent but not equal to a Boolean OR operator.

However, the words AND and OR in the farmers' local dialect may not strictly mean the same as FA and FO, respectively. This suggests the need to apply and evaluate results of application of other fuzzy operators vis-à-vis the farmer respondents' perceptions of land suitability. The other fuzzy operator used was the fuzzy algebraic sum (FAS), by which output integrated fuzzy values $\mu_{\text{combination}}$ are obtained as:

$$\text{FAS } \mu_{\text{combination}} = 1 - \prod_{i=1}^n (1 - W_i\mu_i), \quad (5)$$

where W_i and μ_i are, respectively, the weight of and the fuzzy values in input fuzzy factor map i , and $i = 1, 2, \dots, n$ input fuzzy factor maps to be combined. The output of FAS for each point is always larger than, or equal to, the maximum fuzzy value at the same point in any input map (i.e., it has 'maximizing' effect). The FAS operator, due to its 'maximizing' effect, was tested because it may represent the fact that many farmers' 'overestimate' suitability of their land (i.e., they maximize utilization of their land in an unsustainable manner).

The output of integrating the FK fuzzy factor maps is a map of fuzzy values indicating degrees of suitability. The resulting fuzzy suitability maps were defuzzified to partition the fuzzy values into suitability classes by using inflection points along plots of cumulative frequency (i.e., cumulative percentage of pixels) of fuzzy values. These inflection points represent a sudden increase in number of pixels with a minor change in fuzzy values and were therefore interpreted to represent threshold fuzzy values, which allow differentiation between zones that are 'least suitable', 'moderately suitable', 'suitable' or 'most suitable' for agriculture.

4.3. Evaluation of land suitability maps

The FK-based suitability maps were compared with the LRDP map to: (a) determine degrees of similarity and (b) identify areas of agreement and conflict.

To determine degrees of similarity, a uniform classification was necessary because the FK-based maps represent agricultural land suitability zones with four classes while the LRDP map represent land-use units with 18 classes. The LRDP map and the FK-based suitability maps were therefore re-classified into two classes, 'agricultural' and 'non-agricultural' zones. For the LRDP map, the different land-use units were simply re-classified as either 'agricultural' or 'non-agricultural' zones

(Table 6). For the FK-based maps, zones initially mapped as ‘suitable’ and ‘most suitable’ were re-classified as ‘agricultural’ zones while zones mapped as ‘least suitable’ and ‘moderately suitable’ were re-classified as ‘non-agricultural’ zones. Then, the re-classified FK-based maps for a cropping season (Table 4) were combined, through a Boolean OR operation, into a map depicting zones suitable for agricultural and for non-agricultural purposes during a cropping season. To measure degrees of similarity, map overlay operations were performed to determine overlap between FK-based and LRDP ‘agricultural’ zones and overlap between FK-based and LRDP ‘non-agricultural’ zones. Degree of similarity (expressed in percent) between a seasonal FK-based suitability map and the LRDP map was calculated as the sum of number of pixels of overlap between ‘agricultural’ zones and number of pixels of overlap between ‘non-agricultural’ zones divided by total number of pixels and multiplied by 100. The measured degree of similarity is known in the geographic literature as the coefficient of areal association (Taylor, 1977).

To identify areas of agreement and/or conflict, each of the re-classified seasonal FK-based suitability maps were overlaid on the original LRDP map to determine percentages of mapped ‘agricultural’ zones in each of the LRDP land-use units.

5. Results

Fig. 5 shows the ‘binary’ fuzzy factor maps for *Kharif*, ‘*Kharif + Rabi*’ and *Rabi* and the ‘binary’ fuzzy factor maps for ‘dark-colored’ and for ‘red-colored’ soils. Fig. 6 shows the multi-class fuzzy factor maps based on soil depth, soil texture and slope. For illustration purposes and due to the limited space here, only the results of combining fuzzy factor maps pertinent to FK rule 1 (Table 4) are shown and described.

Fig. 7(a) shows the cumulative frequency plot of fuzzy values in the map resulting from combining fuzzy factor maps pertinent to FK rule 1 through applications of FA and FO. Fig. 7(b) shows the defuzzified map based on the inflection points. This map indicates that the farmers consider flat slopes with dark, fine-textured and deep soils as ‘most suitable’ for Crop Group 1 during *Kharif* (Table 4). In the northeastern part, many zones not considered suitable as *Kharif* crop zones (Fig. 5) are mapped as ‘suitable’ zones. This is due to the fuzzy factor map of ‘flat’ slopes and to the fuzzy factor map of ‘moderately fine’ soils (Fig. 6). This result is, however, coherent with the farmers’ perception that moderately fine soils in flat zones could adequately sustain water needed by crops in Crop Group 1 during *Kharif* (Table 4). This indicates that FK rule 1 is adequately modeled by application of FA and FO. The results of application of these operators to the other FK rules are also mostly coherent with the farmers’ perception of suitability of their land.

Fig. 7(c) shows the cumulative frequency plot of fuzzy values in the map resulting from combining fuzzy factor maps pertinent to FK rule 1 through application of FAS. Fig. 7(d) shows the defuzzified map based on the inflection points. In this map, there are very few zones classified as ‘most suitable’ and are not visible at

Table 6
Agreement and conflict between LRDP map and FK-based suitability maps

Land-use units in LRDP map			FK-based agricultural zones in LRDP land-use units (%)		
Original classification	% of study area	Reclassification*	<i>Kharif</i>	<i>Kharif+ Rabi</i>	<i>Rabi</i>
Agrohorticulture with soil conservation measures	21.2	A	84	9	65
Double cropping and/or agrohorticulture with ground water exploitation	17.4	A	82	4	71
Dry land horticulture	0.3	A	100	1	41
Existing agriculture in notified forest area	0.7	A	90	49	46
Horticulture	1.5	A	80	9	73
Hortipasture (non-irrigated)	7.9	A	55	23	57
Intensive agriculture	22.5	A	93	72	84
Rainfed agrohorticulture/Agroforestry	5.5	A	92	1	63
Silvi Pasture and/or Agroforestry	0.1	A	10	98	100
Afforestation	0.1	NA	74	6	99
Fodder and fuel wood plantation	2.6	NA	75	20	61
Forest conservation/protection	8.3	NA	66	21	76
Forestgap plantation	4.5	NA	45	13	53
Quarrying and mining activities	0.1	NA	94	25	100
Silvi Pasture and/or economic forest plantation	3.1	NA	62	37	68
Social forestry and pasture development	1.2	NA	75	12	95
Tank foreshore plantation	2.0	NA	54	2	50
Settlements	1.0	NA	–	12	–

* A = agricultural zones; NA = non-agricultural zones.

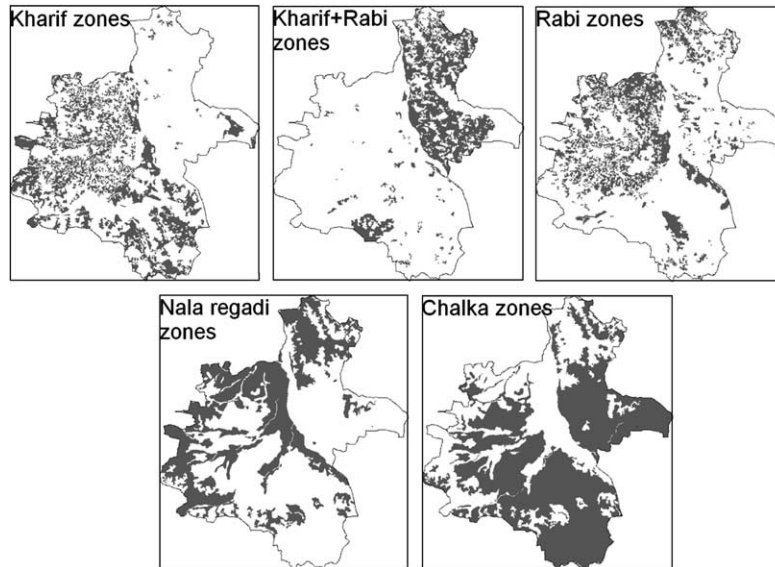


Fig. 5. 'Binary' fuzzy factor maps: *Kharif* zones; '*Kharif*+*Rabi*' zones; *Rabi* zones; *Nala Regadi* zones; and *Chalka* zones. Fuzzy values are 0.95 and 0.05 for black and white zones, respectively.

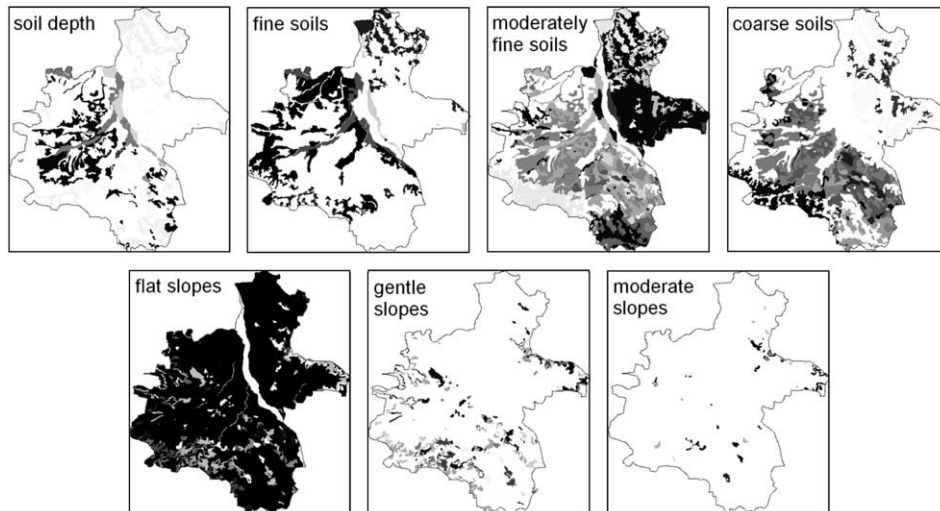


Fig. 6. Fuzzy factor maps based on soil depth, soil texture (fine, moderately fine, coarse) and slope (flat, gentle, moderate). Fuzzy values vary from 0.99 (black) to 0.01 (white).

the present map scale. 'Suitable' zones are characterized by *Nala regadi*, fine-textured and deep soils (Figs. 5 and 6). 'Moderately suitable' zones are characterized mainly by dark, fine-textured and deep soils on flat slopes. 'Least suitable' zones mostly per-

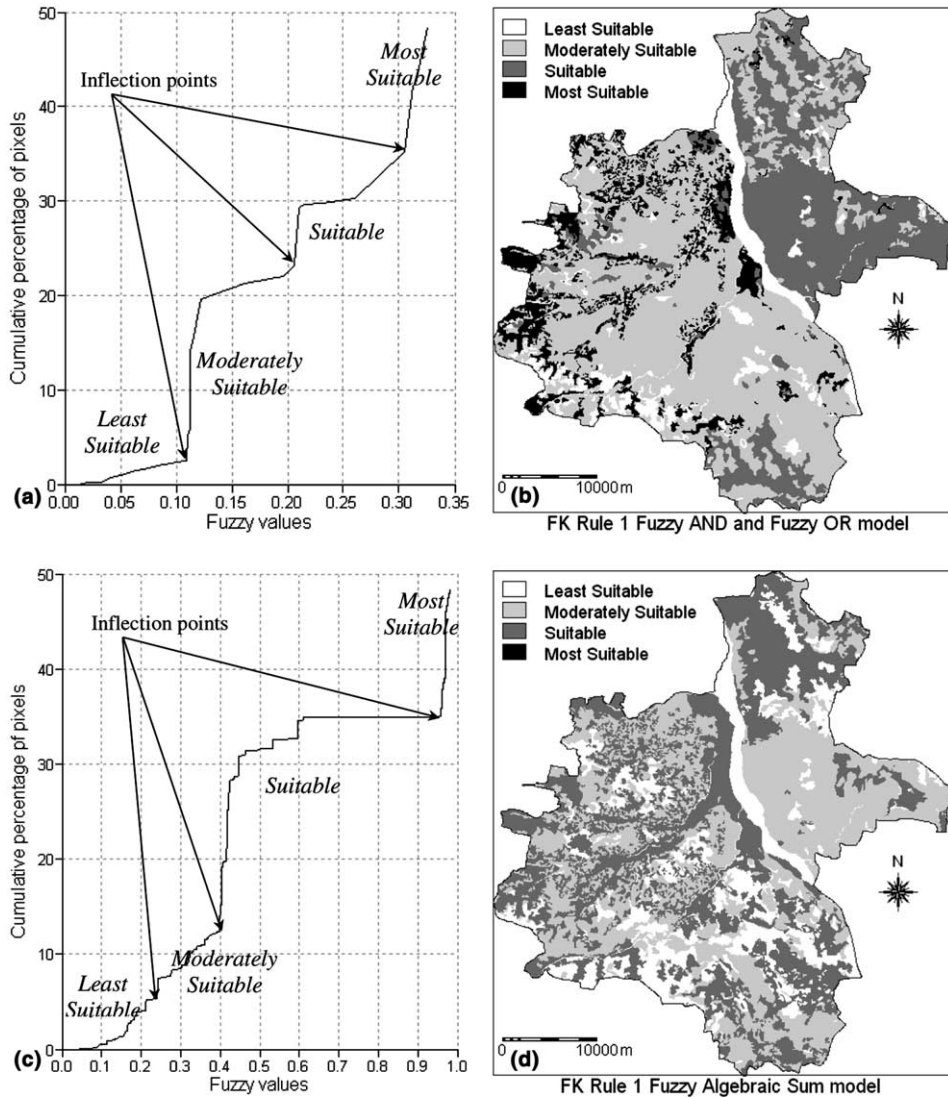


Fig. 7. Models of FK rule 1: (a) cumulative frequency plot of fuzzy values in FA–FO model; (b) defuzzified FA–FO model; (c) cumulative frequency plot of fuzzy values in FAS model; (d) defuzzified FAS model.

tain to flat slopes. Such classifications are non-coherent with the farmers’ perceptions of land suitability for Crop Group 1 during *Kharif*. This indicates that FAS inadequately models FK rule 1. The results of application of FAS to the other FK rules are also mostly non-coherent with the farmers’ perception of suitability of their land.

The degrees of similarity between the re-classified seasonal FK-based suitability maps derived from the combined applications of FA and FO and the re-classified LRDP map (Fig. 8) were then evaluated. The degrees of similarity of the re-classified FK-based suitability maps for *Kharif*, '*Kharif+Rabi*' and *Rabi* with the re-classified LRDP map are 73%, 40% and 62%, respectively. Table 6 further shows how the re-classified seasonal FK-based suitability maps agree/conflict with the LRDP map.

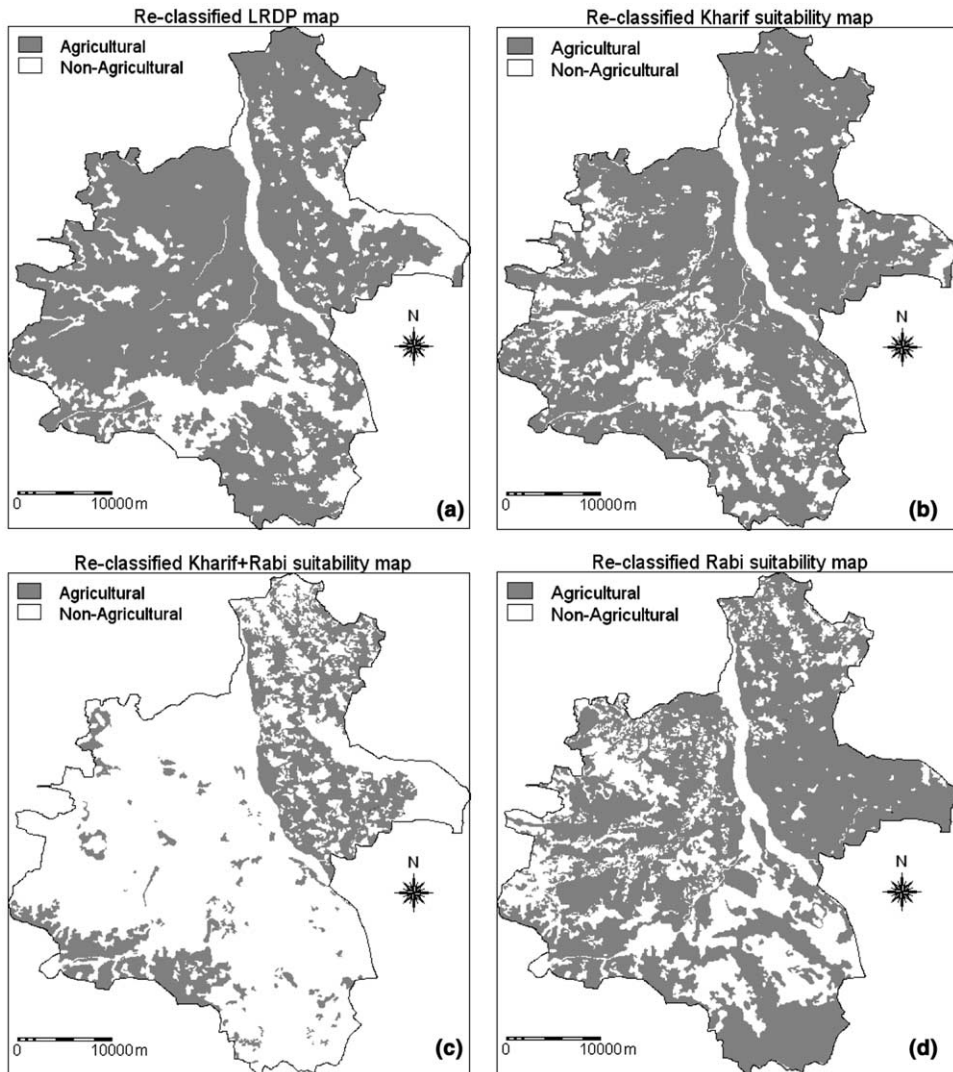


Fig. 8. Agricultural and non-agricultural zones based on: (a) LRDP map; (b) *Kharif* suitability maps; (c) '*Kharif+Rabi*' suitability maps; (d) *Rabi* suitability maps.

For *Kharif*, there is mostly very strong (>80%) agreement between FK-based ‘agricultural’ zones and most LRDP ‘agricultural’ zones (Table 6). Of the LRDP ‘agricultural’ zones, only the non-irrigated Hortipasture zones (i.e., grazing areas in plantations, orchards, etc.) moderately agree with FK-based ‘agricultural’ zones and only the Silvi Pasture and/or Agroforestry zones very weakly agree with FK-based ‘agricultural’ zones. However, there is moderate to strong (45–75%) conflict between FK-based ‘agricultural’ zones and LRDP ‘non-agricultural’ zones. This latter observation suggests that the farmers consider land characteristics in most LRDP ‘non-agricultural’ zones as suitable for agriculture during *Kharif*.

For ‘*Kharif + Rabi*’, there is mostly weak (<30%) to very weak (<10%) agreement between FK-based ‘agricultural’ zones and most LRDP ‘agricultural’ zones (Table 6). Of the LRDP ‘agricultural’ zones, only the existing agriculture in notified forest areas moderately agree with FK-based ‘agricultural’ zones while only the intensive agriculture areas and the Silvi Pasture and/or Agroforestry areas strongly agree with FK-based ‘agricultural’ zones. These observations suggest that the farmers consider land characteristics in most LRDP ‘agricultural’ zones as generally unsuitable for agriculture during ‘*Kharif + Rabi*’. It is, however, interesting to note that there is mostly very weak to weak (<30%) conflict between FK-based ‘agricultural’ zones and LRDP ‘non-agricultural’ zones. This observation suggests that the farmers consider land characteristics in LRDP ‘non-agricultural’ zones as generally unsuitable for agriculture during ‘*Kharif + Rabi*’.

For *Rabi*, there is moderate to very strong agreement between FK-based ‘agricultural’ zones and LRDP ‘agricultural’ zones (Table 6). However, there is also moderate (~50%) to very strong (>80%) conflict between FK-based ‘agricultural’ zones and LRDP ‘non-agricultural’ zones. This latter observation suggests that the farmers consider land characteristics in most LRDP ‘non-agricultural’ zones as generally suitable for agriculture during *Rabi*.

6. Discussion

Generation of fuzzy factor maps based on FK can be straightforward or problematical. Generation of a FK-based fuzzy factor map is relatively straightforward if correlation or equivalence between farmers’ definition and scientific classifications of certain land characteristics can be established. Establishment of correlation or equivalence between farmers’ definition and scientific classifications allows recognition of pertinent spatial data that could be used to generate FK-based fuzzy factor maps. Hence, FK-based fuzzy factor maps representing slope, soil depth, and soil texture were generated using slope map, soil depth data, and soil clay content data, respectively. In generating these fuzzy factor maps by application of appropriate *S*-membership function, a lower limit of 0.01 and an upper limit of 0.99, based on FK, were used instead of 0 (i.e., completely unsuitable) and 1 (i.e., completely suitable), respectively. This is because in knowledge-driven fuzzy modeling there are no matter-of-fact constraints on the choice of fuzzy membership functions or values except that such membership functions should reflect the context of the factor being

modeled (in this case based on FK context) and the membership values, inclusive of lower and upper limits, must lie in the range of 0–1 (i.e., lower and upper limits need not be strictly 0 and 1, respectively).

In contrast to the relative simplicity in generating FK-based fuzzy factor maps for slope, soil depth, and soil texture, creating FK-based fuzzy factor maps based on cropping season and soil color proved problematical. This is because: (a) sound correlation or equivalence between farmers' perceptions and scientific classifications of these factors was difficult to establish and/or (b) the farmers' perceptions of either of these factors are essentially binary yet fuzzy. The latter reason applies to cropping seasons while both reasons apply to soil color. Nevertheless, in recognition of the farmers' binary perceptions of these factors, 'binary' fuzzy factor maps for *Kharif*, '*Kharif+Rabi*', and *Rabi* were generated using the existing land-use map (Fig. 4) while 'binary' fuzzy factor maps for *Chalka* and *Nala regadi* soils were generated using the soil color map. These 'binary' fuzzy factor maps, in fact, represent binary fuzzy relations between farmers' perceptions of cropping season and existing land-use map and between farmers' perception of soil color and soil color data. A binary fuzzy relation R between a certain variable x (e.g., farmers' perceptions of soil color) and another variable y (e.g., scientific descriptions of soil color), whose domains are X and Y , respectively, is a fuzzy subset of $X \times Y$ characterized by its membership function $\mu_R(x, y) : X \times Y \rightarrow [0, 1]$ (Robinson, 2003). It can be argued that the delineated cropping season zones and soil color zones are very fuzzy and thus assignment of a single fuzzy membership value (i.e., 0.05 or 0.95) to each of these zones depending on certain farmers' proposition seems inappropriate. However, such rough fuzzification of cropping season zones and soil zones based on FK does not negate usefulness of the approach, but only indicates how farmers in the study area perceive reality, which should be considered in modeling pertinent spatial data based on FK.

The multi-class fuzzy factor maps of slope, soil depth, and soil texture can be considered fuzzy rough sets, while the binary fuzzy factor maps of cropping season and soil color can be considered rough fuzzy sets (Thiele, 1998). Since the binary fuzzy relations generated for cropping season and soil color are also fuzzy sets, they can also be combined with the fuzzy sets of slope, soil depth, and soil texture by applications of appropriate fuzzy operators. Of the eight criteria enumerated by Zimmerman (1991) for selecting appropriate fuzzy operators, 'axiomatic strength' and 'empirical fit' are more or less satisfied by the farmers' rules (Table 4). On one hand, the farmers' rules are self-evident (i.e., axiomatic) and therefore require operators that implicitly satisfy them (i.e., the rules or axioms). On the other hand, the farmers' rules represent practical experiences (i.e., through empirical association and/or commutation) and therefore require operators with certain formal qualities (such as associativity, commutativity) from a mathematical point of view to provide empirical testing. Thus, based on the 'axiomatic strength' criterion, the fuzzy factor maps were combined using FA and FO operators, which implicitly satisfy farmers' linguistic 'and' and 'or', respectively; whereas based on the 'empirical fit' criterion, the fuzzy factor maps were combined using FAS operator, which is associative and commutative.

Most of the land suitability maps resulting from applications of FA and FO operators were found more sound than the land suitability maps resulting from applications of FAS operator. The probable reason why most results of applications of FA and FO are sound is that these operators, respectively, ‘look’ for logical intersection and logical union of factors that indicate suitability, which are consistent with the FK rules. Most of the results of application of FAS, on the other hand, are unsound partly because this operator results in ‘maximized’ (or highly optimistic) models and partly because this operator is representative of the fact that many but not all farmers’ ‘overestimate’ (or are highly optimistic about) suitability of their land.

The degrees of similarity (ranging from about 40% to about 73%), the areas of agreement and the areas of conflict identified between the re-classified seasonal FK-based suitability maps and the re-classified or original LRDP map indicate mainly that local farmers’ perception of utilizing their land differ from the prescribed land-uses. Sound FK-based land suitability maps can thus be important sources of information indicating points of interventions or terms of reference that authorities need to consider in order to prepare optimum land-use plans. However, it is not the intention of our study to contest the LRDP map but to demonstrate FK-based modeling of relevant spatial data for land suitability classification with application of the theory of fuzzy sets, which is a tested theory for dealing with vague concepts. With adoption and/or further adaptations of fuzzy modeling of FK presented here, it is believed that FK or indigenous knowledge, in general, can be integrated properly with scientific models of land suitability derived also through fuzzy modeling (e.g., Ceballos-Silva and López-Blanco, 2003; Groenemans et al., 1997; Liu and Samal, 2002; Malczewski, 2002; Nisar Ahamed et al., 2000; Triantafilis et al., 2001; Van Ranst et al., 1996).

7. Conclusions

Farmers’ definitions of certain land characteristics, which they consider important in determining land suitability, are intrinsically vague. If correspondence between farmers’ definitions and scientific classifications of certain land characteristics can be established, then FK-based modeling of pertinent spatial data into fuzzy sets is relatively straightforward. If correspondence between farmers’ definitions and scientific classifications of certain land characteristics cannot be established and if farmers’ perceptions are binary, then relevant spatial data can be modeled by binary fuzzy relations, which are also fuzzy sets. Individual farmers’ perceptions about land suitability based on combinations of different factors can be organized into discrete rules by grouping such different perceptions hierarchically according to factors arranged in order of decreasing importance. The FK rules form inference engines and indicate which fuzzy operators are appropriate for combining fuzzy factor maps. For the study area, combined applications of Fuzzy AND and Fuzzy OR operators result in agricultural land suitability maps that are mostly consistent with the FK rules. FK-based fuzzy modeling of land suitability maps can

provide useful information that authorities need to consider in generating optimum land-use plans. The study further suggests that, in land suitability classifications, indigenous and scientific knowledge can be integrated properly through fuzzy modeling.

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Appendix A. Questionnaire to capture FK in study area

Village name:

Mandal name:

No. of respondents:

1. What kind of soils do you recognize in your farms?

Color	Munsell code	Texture	Depth	Other information
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2. What are the local names of these soils?

Color	Local name
-------	------------

3. Where are these soils normally found (in terms of slope)?

Color	Slope	Other information
-------	-------	-------------------

4. Of the four factors (color, texture, depth, slope), which of these do you consider most important?

Factor	Ranking	Remarks
Color		
Texture		
Depth		
Slope		

5. Are there any other special characteristics of type of soil, such as black soils normally have high fertility?

6. If irrigation water is available/not available, which crops and crop varieties are preferred in your farms based on the season?

Water availability	Crop	Season		
A	NA	Kharif	Kharif + Rabi	Rabi

7. Why, is it because of the soil or other factors? What are these other factors?

8. What crops are best grown or suitable on which soils?

Crop	Soil color	Soil texture	Soil depth	Slope	Season		
					Kharif	Kharif + Rabi	Rabi

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