Land Suitability Analysis for Agricultural Crops: A Fuzzy Multicriteria Decision Making Approach

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by

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ಮತ್ತು ಮುದ್ದಿನ ಪುಟಾಣಿಗಳಿಗೆ,

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Abstract

Land suitability analysis is a prerequisite for sustainable agricultural production. It involves evaluation of the criteria ranging from soil, terrain to socio-economic, market and infrastructure. Many of these factors are vaguely defined and characterised by their inherent vagueness. Multicriteria decision-making techniques like ranking, rating etc. are employed for suitability analysis. As this process incorporates expert knowledge and judgement by decision makers at various levels, it is very much subjective in nature. Although techniques like Analytic Hierarchy Process (AHP) incorporate experts' knowledge but fails to address the inherent uncertainty in them. Many parameters like soil pH, fertility, etc., which vary continuously over the space and it is not possible to model as it is. This research focuses on addressing uncertainty in the process of land suitability analysis for agricultural crops. Three approaches, AHP, Ideal Vector Approach (IVA) and Fuzzy AHP are followed. It is found that Fuzzy AHP performs better than rest of the two techniques. Fuzzy AHP is a hybrid approach. The techniques AHP, fuzzy numbers, fuzzy extent analysis, alpha cut and lambda function are involved in it. As stated the process of decision-making involves a range of criteria and good amount of expert knowledge and judgements. These factors influence the outcomes greatly. The ability of three techniques to model the sensitivity of decision-making process is investigated. Alpha cut and lambda values provide and facilitate good sensitivity analysis. All the three methodologies are implemented to analyse the suitability of the Rice crop in the Doiwala Block of the Dehradun District, Uttataranchal, India.

Keywords: Land suitability; IVA; fuzzy AHP; Alpha cut; lambda value; MCDM; Fuzzy extent analysis

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LIST OF ABBREVIATIONS

AHP:	Analytic Hierarchy Process
FAO:	Food and Agriculture Organisation
IVA:	Ideal Vector Approach
MCDM:	Multi-Criteria Decision Making
MCE:	Multi Criteria Evaluation
PCM:	Pairwise Comparison Matrix
PC:	Pairwise Comparison
TOPSIS:	Technique for Order Preference by Similarity to Ideal Solution

1. Introduction

1.1. Agriculture and Land Suitability

Agriculture, being the most primitive occupation of the civilized man, draws much on its development starting from shifting cultivation to advanced precision farming. With the advancement in the civilization man came to know about more crops and started to cultivate many crops. Population increase and advancement in the civilization made man to settle at one place and to cultivate the same area year after year. Now agriculture became a profession is given the name commercial agriculture, and precision agriculture and sustainable agriculture as being the part of it.

Nowadays, the population of the planet is growing dramatically. In order to meet the increasing demand for the food the farming community has to produce more and more. Under present situations, where the land is a limiting factor, it is impossible to bring more area under cultivation (*extensive farming*), so farming community should tackle this challenge of producing more and more food with the available land only (*intensive farming*). On the contrary, the increasing global concern towards the health of mankind and environment protests the use of higher amount of pesticides and fertilizers, genetically manipulated plants etc. However, latter are the current technologies having the potentiality to increase the food production. To overcome this concern the farming community has to produce *more and more, high quality food using eco-friendly practices*. This need for eco-friendly practices have paved the way for the concepts like precision farming, sustainable farming, organic farming etc. Higher productivity, profitability and health of mankind as well as environment are the concerns of the present agriculture. Hence much attention is shifted on selection of a crop, which suits an area the best.

This suitability is a function of crop requirements and soil/land characteristics. Matching the land characteristics with the crop requirements gives the suitability. So, *'Suitability is a measure of how well the qualities of a land unit match the requirements of a particular form of land use.'* (FAO). Besides the land/soil characteristics socio-economic, market and infrastructure characteristics are the other driving forces that can influence the crop selection.

1.2. Need for Land Suitability Analysis

Land suitability analysis is needed for various purposes in the context of present day agriculture.

1.2.1. Crop-Land suitability and Precision Farming

Precision farming aims to optimise the use of soil resources and external inputs (fertilizers and herbicides) on a site-specific basis. Precision farming involves the use of most advanced technologies like GPS, GIS, Remote Sensing and VRT (Variable Rate Technologies). Such systems are designed to monitor, analyse and control plant production with the aim to optimise expenses and ecological effects and to increase the income. To fulfil such contrasting aims the first prerequisite is to select the best suitable crop for the area. The land suitability analysis will best suffice such a basic need.

1.2.2. Crop-Land suitability and Sustainable Agriculture

The concept of sustainable agriculture or farming (SA / SF) involves producing *quality* products in an environmentally benign, socially acceptable and economically efficient way (Addeo et al. 2001), i.e. optimum utilization of the available natural resource for efficient agricultural production. In order to comply these principles of SA one has to grow the crops where they suit best and for which first and the foremost requirement is to carry out land suitability analysis (Nisar Ahamed et al. 2000). Land Suitability Analysis has to be carried out in such a way that local needs and conditions are reflected well in the final decisions.

1.3. Problem Definition

1.3.1. Land Suitability Analysis

As stated above, land suitability is the ability of a given type of land to support a defined use. The process of land suitability classification is the evaluation and grouping of specific areas of land in terms of their suitability for a defined use. The main objective of the land evaluation is the prediction of the inherent capacity of a land unit to support a specific land use for a long period of time without deterioration, in order to minimize the socio-economic and environmental costs (de la Rosa 2000). Land suitability analysis is an interdisciplinary approach by including the information from different domains like soil science, crop science, meteorology, social science, economics and management. Being interdisciplinary, land suitability analysis deals with information, which is measured in different scales like ordinal, nominal, ratio scale etc.

Based on the scope of suitability there are two types of classifications in FAO framework.

- ***Current suitability***: refers to the suitability for a defined use of land in its present condition, without any major improvements in it.
- ***Potential suitability***: for a defined use, of land units in their condition at some future date, after specified major improvements have been completed where necessary.

Current research aims at developing a methodology to analyse the *Current suitability* using fuzzy logic.

1.3.2. Need For Multi Criteria Decision Making

Agricultural land suitability is an interdisciplinary approach. Determination of optimum land use type for an area involves integration of data from various domains and sources like soil science to social science, meteorology to management science. All these major streams can be considered as separate groups; further each group can have various parameters (criteria) in itself. However all the criteria are not equally important, every criteria will contribute towards the suitability at different degrees. The relative degree of contribution of various criteria can be addressed well when they are grouped into various groups and organised at various hierarchies. Agricultural land suitability also involves major decisions at various levels starting from choosing a major land use types (LUT), selection of criteria, organisation of the criteria, deciding suitability limits for each class of the criteria, deciding the preferences (qualitative and quantitative). Relative importance of these parameters can be well evaluated to determine the suitability by *multi-criteria evaluation techniques* (Ceballos-Silva and Lopez-Blanco 2003)

The present popular methods that are followed for land suitability analysis include ranking and ratings, weighted summation, requirement matching etc. Here the weights are arbitrarily chosen, and are aggregated using simple Boolean overlay methods. Although these methods are simple and straightforward they lack solid mathematical foundations.

Ceballos-Silva and Lopez-Blanco (2003), used matrix pair wise comparison for land suitability. This method overcomes the problem of determining the weights.

1.3.3. Fuzziness in Land Suitability Decision Making

Land suitability analysis deals with many factors that are continuous in nature, like soil characteristics, and climatic parameters. And it also deals with many socio-economic parameters, which lack proper measurement scale, and are depicted using some linguistic parameters like; market is near, nearer, far away, very far etc. Using Boolean logic it is impossible to model such a vagueness and imprecision of environmental and socio-economic factors. Probabilistic approach can be used when the information regarding a phenomenon is completely unknown, but it cannot be applied when it is imprecise and incomplete. Under such an uncertain situation fuzzy (probabilistic) logic comes handy. Fuzzy logic aids in most precise representation of such imprecise, incomplete and vague information.

Land suitability analysis involves incorporation of expert knowledge at various levels of decision-making. Expert can't be certain all the time, uncertainty and imprecision involved in expert knowledge can be well addressed using fuzzy logic. Many researchers (Burrough 1989; Burrough et al. 1992; McBratney and Odeh 1997) have used fuzzy logic in the land evaluation but to address only the uncertainty associated with the data, they have not taken into account the uncertainty that can be associated with the expert knowledge.

1.4. Role of GIS and Remote Sensing

GIS is the tool for input, storage and retrieval, manipulation and analysis, and out put of spatial data (Marble et al. 1984). GIS functionality can play a major role in spatial decision-making. Considerable effort is involved in information collection for the suitability analysis for crop production. This information should present both opportunities and constraints for the decision maker(Ghafari et al. 2000). GIS have the ability to perform numerous tasks utilizing both spatial and attribute data stored in it. It has the ability to integrate variety of geographic technologies like GPS, Remote Sensing etc. The ultimate aim of GIS is to provide support for spatial decisions making process (Foote and Lynch 1996). In multi-criteria evaluation many data layers are to be handled in order to arrive at the suitability, which can be achieved conveniently using GIS.

Remote sensing provides the information about the various spatial criteria/factors under consideration. RS can provide us the information like land use/cover, drainage density, topography etc. Many of the non-spatial parameters can also be inferred by looking at the various spatial parameters. RS in combination with GIS will be a powerful tool to integrate and interpret real word situation in most realistic and transparent way. Research by Leingsakul et al. (1993) shown that integrated GIS and Remote Sensing technology apart from saving time and yielding good data quality have the ability to locate potential new cropland sites.

1.5. Research Objective

The aim of this research is to explore the role of fuzzy logic in multi-criteria evaluation of land suitability for different agricultural crops and compare the results with those of existing standard methodologies. Specific objective is to

- ❖ develop multi-criteria decision making technique using fuzzy logic for land suitability analysis for agricultural crops.

1.6. Research Questions

Present study aims at answering the following questions framed in order to achieve the above-mentioned objective.

- What are the required *evaluation criteria* to assess the crop-land suitability model?
- How are different land suitability parameter or criteria classes standardized?
- How are the class boundaries defined and integrated?
- How and where to incorporate the expert knowledge?
- How the sensitivity of the process can be measured?
- How can fuzzy logic approach improve the process compared to existing standard methods?

1.7. Thesis Structure

This research work is explained in six chapters. Chapter 1 dealt with introduction, need for the land suitability analysis, need for fuzzy decision making approach, research objective and research questions. Chapter 2 makes the survey of previous research work in connection with present research work. Chapter 3 shows the chosen study area to implement the methodology thus developed. Chapter 4 first introduces the framework of decision-making, basic principles of the spatial decision-making, and next get into the methodologies developed and followed in the research. Chapter 5 presents, analyse and discuss the results thus obtained. In the end, Chapter 6 gives conclusions on the present study and recommendations for future work.

2. Literature review

2.1. Land Suitability Analysis and Land use Planning

Determining suitable land for a particular use is a complex process involving multiple decisions that may relate to biophysical, socio-economic and institutional/organisational aspects. A structured and consistent approach to Land Suitability Analysis (LSA) is therefore essential. Abiotic, biotic, and socio-economic factors decide the success of a crop. Judgments regarding crop value should include the abiotic, biotic and socio-economic factors that determine the profitability.

The FAO Framework of land evaluation is developed from earlier land capability approaches. Here, overall land suitability of a land area for a certain land use is evaluated from a set of more-or-less independent land qualities, which may each limit the land-use potential. These evaluations often classify map units of natural resource inventories. Hereby, legend categories of a soil survey are classified into suitability subclasses, based on the number and severity of limitations to land use.

The FAO Framework identifies four categories of increasing details, as shown in table 2-1.
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Table 2.1 FAO Structure of Land Suitability Classification

Sl.No.	Categories	Explanation
1	Land Suitability Orders	reflecting kinds of suitability.
2	Land Suitability Classes	reflecting degrees of suitability within Orders.
3	Land Suitability Subclasses	reflecting kinds of limitation, or main kinds of improvement measures required, within Classes.
4	Land Suitability Units	reflecting minor differences in required management within Subclasses.

Based on the scale of measurement of the suitability there are two types of classifications in FAO framework

- ***Qualitative:*** the classes are evaluated based on physical production potential of the land, commonly employed in reconnaissance studies. It is used to evaluate environmental, social and economical criteria
- ***Quantitative:*** the classes are defined in common numerical terms; where comparison between the objectives is possible. Here considerable amount of economic criteria are used.

Quantified land evaluation (Beek et al. 1987) made an evolution in land suitability evaluation by introducing quantification of the indicators of land suitability over an entire area. The area is divided into small grid cells and made an initiation of cell based modelling. However, the Indicators must be quantifiable. In such land suitability analysis geographical information systems and geostatistical techniques are widely used.

Land suitability is a component of sustainability evaluation of a land use. Suitability together with vulnerability defines the sustainability of a land use. The sustainable land use should have maximum suitability and minimum vulnerability (de la Rosa 2000).

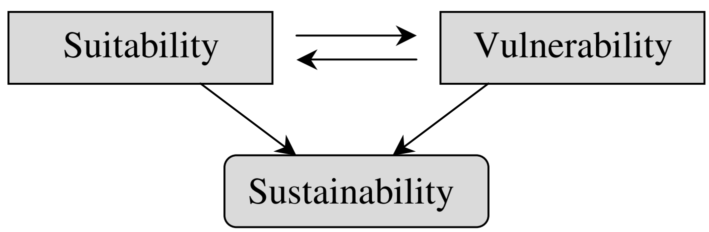

Figure 2.1 Land Use Sustainability (after de la Rosa 2000)

According to (Rossiter 1996), land is unique at every place and the land uses are affected by this uniqueness. He also states that land evaluation can be useful for agricultural support services.

2.2. Multi-Criteria Decision Making (MCDM)

Agricultural crop suitability involves integration information from various streams of science. There are many criteria upon which land suitability depends. The suitability analysis evaluates many alternative land use types under the light of various criteria from various streams. Alternatives here are competing with one another; criteria are both qualitative and quantitative. Decisions have to be taken at various levels starting from selecting the LUTs till the allocation of the LUTs for area that suit best. So the suitability analysis is a multiple criteria decision-making process.

Earlier, the multi-criteria land suitability was assessed more non-spatially, assuming the spatial homogeneity over the area under consideration. This, however, is unrealistic in cases like land suitability studies, where decisions are made using criteria which vary across in space (Malczewski 1999). Non-spatial conventional MCDM techniques average or total the impacts that are judged appropriate for the whole area under consideration (Tkach and Simonovic 1997). To address the spatial decision making, MCE and GIS can be integrated (Jankowski 1995). MCE seems to be applicable in GIS-based land suitability analysis (Pereira and Duckstein 1993) for different crops.

Widely used MCE methods in the land suitability analysis are ranking and rating. These methods lack theoretical foundation in deciding the weights. These methods assign the weights rather arbitrarily. They don't take comparison among the criteria and classes into considerations. Moreover, the outcomes of such analysis are aggregated using simple Boolean overlay or weighted aggregation. Both the methods are supposed to yield similar results, which they never do. The reason is being with the logic of aggregation. The Boolean method of characterising the criteria is too *black and white*. *Boolean intersection* (AND) results in a very strict output, i.e. if it fails to fulfil single criteria a region will be excluded from the results (Black). In contrast, *Boolean union* (OR) will include an area in the result if that area fulfils a single criteria (White). Where as in the weighted linear combination the higher score of the rest can compensate low score on one criterion (Jiang and Eastman 2000). These ranking and rating methods are criticized for not reflect the decision maker's views clearly and also for not having any rationale behind the approach.

Ceballos-Silva and Lopez-Blanco (2003), used matrix pair wise comparison for land suitability. This method overcomes the problem of determining the weights. But they have not taken into consideration the hierarchical organisation of the criteria, which is the basic principle of Analytical Hierarchy Process (AHP). Hence it shows that they have just used the matrix pair wise comparison as a tool to derive weights. They have not implemented the AHP as a whole for decision-making. AHP is a widely used method in decision making and is introduced by Saaty (Saaty 1977; Saaty and Vargas 2001). It is developed to select the best from a number of alternatives with respect to several criteria. AHP allows for both the inconsistency in the decision and provide the means to improve the consistency. Here the decision maker or the user will perform simple Pairwise Comparison i.e. he/she will compare two elements at a time. The values of the Pairwise Comparison are determined according to the scale introduced by Saaty. The available values for the comparison are the member of the set: {9, 8, 7, 6, 5, 4, 3, 2, 1, 1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8, 1/9}, 9 representing absolute importance and 1/9 the absolute triviality (Saaty 1980; Triantaphyllou and Mann 1994). The AHP gained high popularity because of easiness in obtaining the weights and capacity to integrate heterogeneous data, and therefore AHP is applied in a wide variety of decision problems. The AHP is criticised by (Belton and Gear 1983; Dyer 1990; Triantaphyllou 2001) despite of its popularity. They focused mainly on four principal areas of AHP, the axiomatic foundation, the correct meaning of the priorities, the 1-9 measurement scale and the rank reversal (Mikhailov 2003). Mikhailov (2003) quote from (Lai 1995) that most of the problems are almost resolved at least for three level hierarchic structures. The requirement for the huge number of comparisons by AHP is also criticised (Triantaphyllou 1999). He quantifies the total number of comparisons needed by the approach if m numbers of alternatives are to be evaluated against n number of comparisons, {n (n-1)/2 + n*m (m-1)/2}. Jeganatan (2003) cite the major researches done by Lootsma, F.A. and Triantaphyllou to overcome the problems of rank reversal and requirement for large number of comparisons, respectively.

MCDM methods deal with real world problems that are multi dimensional in nature. When it comes to environmental issue the methods have to deal with heterogeneous criteria that are both qualitative and quantitative in nature. In order to incorporate heterogeneous information with different measurement scales, one has to bring them into a common domain of measurement. This process is called *Standardization*, a basic operation in MCE. Criteria should be standardized keeping in mind the goal and alternatives that are under evaluation. Standardization can change the outputs entirely if proper attention is not paid. For environmental criteria, there is a lack of valid and reliable standardization processes.

Decision-making is a subjective process, as the perception regarding a problem can diverge from person to person. One cannot expect a decision maker or an expert to be highly consistent while dealing with such a subjective process. The real world problems are influenced by many natural factors and processes, that are difficult to measure and model precisely. The decision situations are surrounded by uncertainty. *Sensitivity Analysis* is a way to address this uncertainty in estimating the parameters (Malczewski 1999). After the problem is evaluated for optimum conditions, sensitivity analysis assesses different conditions near the optimum values to check for the sensitivity of the criteria. Many decision-making methods lack a valid approach towards sensitivity analysis. Sensitivity analysis also aids in understanding the interaction between the criteria, dominant criterion and its effect, i.e. the variation in the final results when the weight of that criterion is varied. Triantaphyllou and Sanchez (1997) reviews the research on sensitivity analysis and presents a sensitivity analysis procedure in AHP, Weighted Product Model (WPM) and Weighted Sum Model (WSM). They state it as a complementary procedure that can be carried out together with the AHP method proposed by (Masuda 1990). This AHP method considers only the multiple levels of hierarchies, i.e. it considers only the single vector at a time and not the individual judgements.

However, AHP is also not the *panacea* for real world decision-making problems. As mentioned above, AHP is being criticized for its unbalanced measurement scale, and its inability to deal with uncertainty and imprecision of the decision maker’s perceptions (Deng 1999).

2.3. Fuzzy Decision Making

The inability of the normal decision making methods to address the imprecision and uncertainty paved the path for the fuzzy decision making techniques. Goals, constraints and consequences are known imprecisely in much of the real world decision-making processes and in such a situation fuzzy set theory becomes functional (Bellman and Zadeh 1970).

Important aspects of the soil, like internal heterogeneity, measurement error, complexity, imprecision etc. are ignored by traditional land evaluation classification (Burrough 1989). He states that the simple Boolean algebraic operations used in the evaluation process result in considerable loss of information and in such a cases fuzzy set theory will be a useful alternative. Burrough (1989), states that during 1970's numerical statistical methods like Principal Component Analysis, numerical taxonomy and discriminant analysis failed to draw the attention from the users of soil information. The reason is the difficulty relating their needs with the results that are obtained and the multivariate point of view, whereby these methods operate.

The use of fuzzy logic operations make it possible to improve analysis and simplification of the soil characteristics that are characterised by vague conception and/or subjectivity (McBratney and Odeh 1997). Land evaluators and experts can define the ideal requirements of a land use. They can distinguish an ideal value for a suitability class clearly, but are often unsure about boundaries between the classes. Besides, they are uncertain about the representing of soil characteristics in vague terms as "poorly drained", "fine textured", etc., (Burrough 1989).

But all of these researches are oriented towards addressing the uncertainty that is associated with the input data. Although these methods incorporate expert knowledge derived from the input data, still the uncertainty and ambiguity that can be associated with the expert knowledge left unanswered.

Triantaphyllou and Lin (1996) present the development and evaluation of five Multiattribute Decision-Making methods – Fuzzy Weighted-Sum Model, Fuzzy Weighted-Product Model, Fuzzy AHP, Revised Fuzzy AHP and Fuzzy TOPSIS *(Technique for Ordered Preference by Similarity to Ideal Solution).* Though none of these methods are perfect with respect to their evaluative criteria, they summarize that the revised fuzzy AHP is the best method. Saaty's AHP is first extended by Van Laarhoven and Pedrycz (1983). They use triangular fuzzy numbers for fuzzification of the pair wise comparison matrix. Later Buckley (1985) proposed some modifications over that where the normal equations is used to replace the fuzzy pairwise comparison ratios. Buckley (1985) also proposes the use of trapezoidal fuzzy numbers instead of triangular fuzzy numbers by criticizing that the algebraic operations on triangular fuzzy numbers do not necessarily produce triangular fuzzy numbers, in order to preserve the triangular shape of the numbers Van Laarhoven and Pedrycz (1983) are forced to employ approximate methods. Later, Boender et al. (1989) presented a modified method over Van Laarhoven and Pedrycz's method by criticizing the normalization procedure they followed to minimize the regression equation.

These methods involve complex process of comparison and ranking of fuzzy utilities and may produce unreliable results. These drawbacks can be attributed to considerable amount of calculations required, inconsistency among the results with different ranking approaches and rank reversal (Bortolan and Degani 1985; Zimmerman 1987; Chen and Hwang 1992; Deng and Yeh 1998) cited in Deng (1999). Deng (1999) proposes an outstanding method for multicriteria analysis that involves no complex calculations, which can be applied effectively for the problems involving qualitative information. He introduces α-cut analysis to avoid complex comparison of fuzzy utilities. This method is well designed to address all sorts of uncertainties. α-cut analysis allows to incorporate ambiguity in expert knowledge and the optimism index (λ) to address the decision makers attitude.

However, these methods derive priorities from the Pairwise Comparison Matrix (PCM) constructed using triangular fuzzy numbers. This Fuzzy PCM constructed using triangular fuzzy numbers will lead to some inaccuracies (Mikhailov 2003). He states that triangular fuzzy numbers are not always symmetric, and this skewness in reciprocals leads to the well-known phenomenon, the rank reversal. He proposes a new fuzzy decision making method; a fuzzy prioritisation approach with fuzzy preference programming. This method doesn't need construction of fuzzy PCMs; the priorities are derived directly from fuzzy comparisons and incomplete judgements can also be used. The calculation involved with this technique is complicated and time consuming

3. Study Area

The study area chosen for the research is Doiwala, a Community Development Block located in the southern part of the Dehradun district, Uttaranchal, INDIA. The area is situated in the Doon valley and located between latitude 29^0 58'N and 30^0 16'N and longitude 77^0 59'E and 78^0 19'E. The total area is 594.7 km^2.

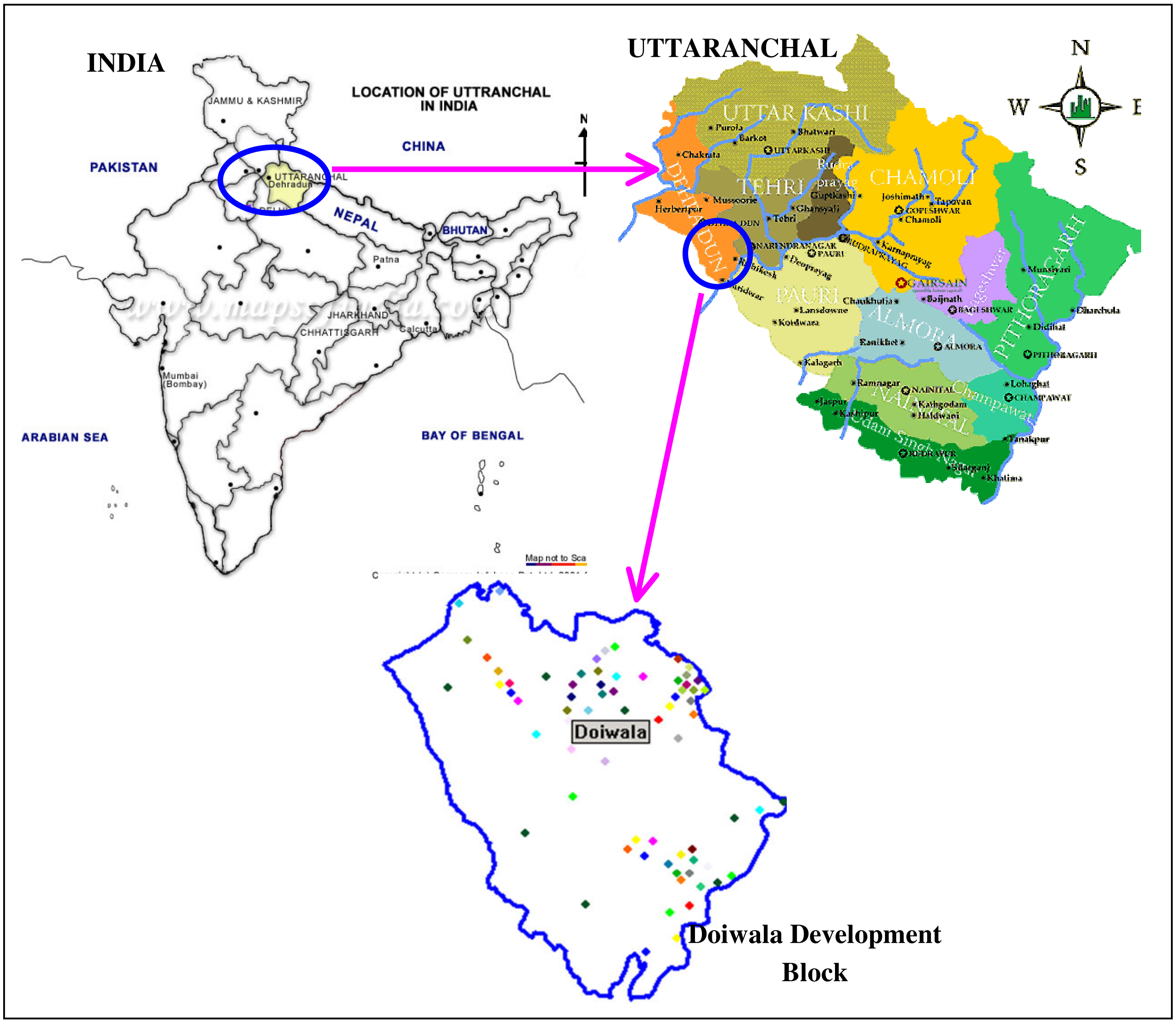

Figure 3.1 Location of the Study Area

The climate of the area is temperate. Average annual rainfall of the area is 2073.3 mm. Most of the annual rainfall is received within the period of June to September. There is a great variation in the temperature; it is hot during the summer and drops to freezing point during the winters. The average annual temperature is 20^0C (Max. 27.8^0C and Min. 13.3^0C).

The Dehradun district is nestled within the mountain ranges of the Himalayas and most of the area is comprised of hilly regions. Doiwala block consists in majority of fairly levelled land with altitude varying between 300 to 880 m above MSL. The Doiwala block is the major agriculture area of the Dehadrun district. Loam is the major soil type.

The well-known perennial river Ganges enters the block in the eastern part, facilitating irrigation only for a very small area. The river Song flows through the centre, but it is not perennial, flowing only in wet season. Irrigation canals are the major source of irrigation in the winter and / or summer.

Agriculture is the main source of income for the people. The majority of the agricultural area is under double cropping; the *kharif*, sown in June and reaped in September- October, and the *rabi* sown in October-November and reaped in March to May. Wherever there is irrigation during the summer, vegetable cultivation is common. The rice is the most important kharif food crop and wheat is the principal crop of rabi. Other major crops grown in the area are sugarcane, maize, pulses, vegetables and some fruits crops. Potato is the major crop among the vegetable; litchi, lemon, mango etc among the fruit crops and cowpea, pigeon pea etc among the pulses.

A sugar factory located near Doiwala is the major market for the sugarcane grown in the area.

4. Methodology

4.1. Framework for decision making

In the early days the use of remote sensing and GIS was confined only for the process of mapping. In time progress in the information technology developed tools to use these maps in the process of planning and decision-making. Land, being a precious resource, requires to be managed in a sustainable way to support life on earth. Sustainable management means the utilization of the available land resources in such a way that the occupation, which is conducted over a piece of land, is without or with least impact over the resources. For the sustainable use of the land, the area needs to be used for a specific purpose, which suits the local conditions best. An agricultural area needs to be characterized and evaluated over its potentiality, limitations and constraints that are influenced by different land use types (LUTs). The controlled performance of agriculture demands for the evaluation of the land for the specific land use types in it. This land suitability analysis involves the interdisciplinary criteria ranging from socio-economic to environmental. These multiple criteria that are influencing the LUT change over space, i.e. criteria values change from place to place, and are interrelated. Hence, there is a great need for the evaluation of these criteria in spatial domain. Several decisions need to be taken and expert knowledge must be incorporated at various stages in the suitability analysis.

Planning and decision making process is executed in three major phases, *intelligence, design* and *choice or decision* (Sharifi 2002) (see figure 4.1).

- Intelligence Phase: also called problem formulation phase, where the situation is analysed for the problem and prospects.

- Design Phase: involves problem understanding, generating alternatives, selecting criteria and establishing relationships among them.

- Choice/Decision Phase: involves the evaluation of the alternatives using the set criteria to achieve the objective.

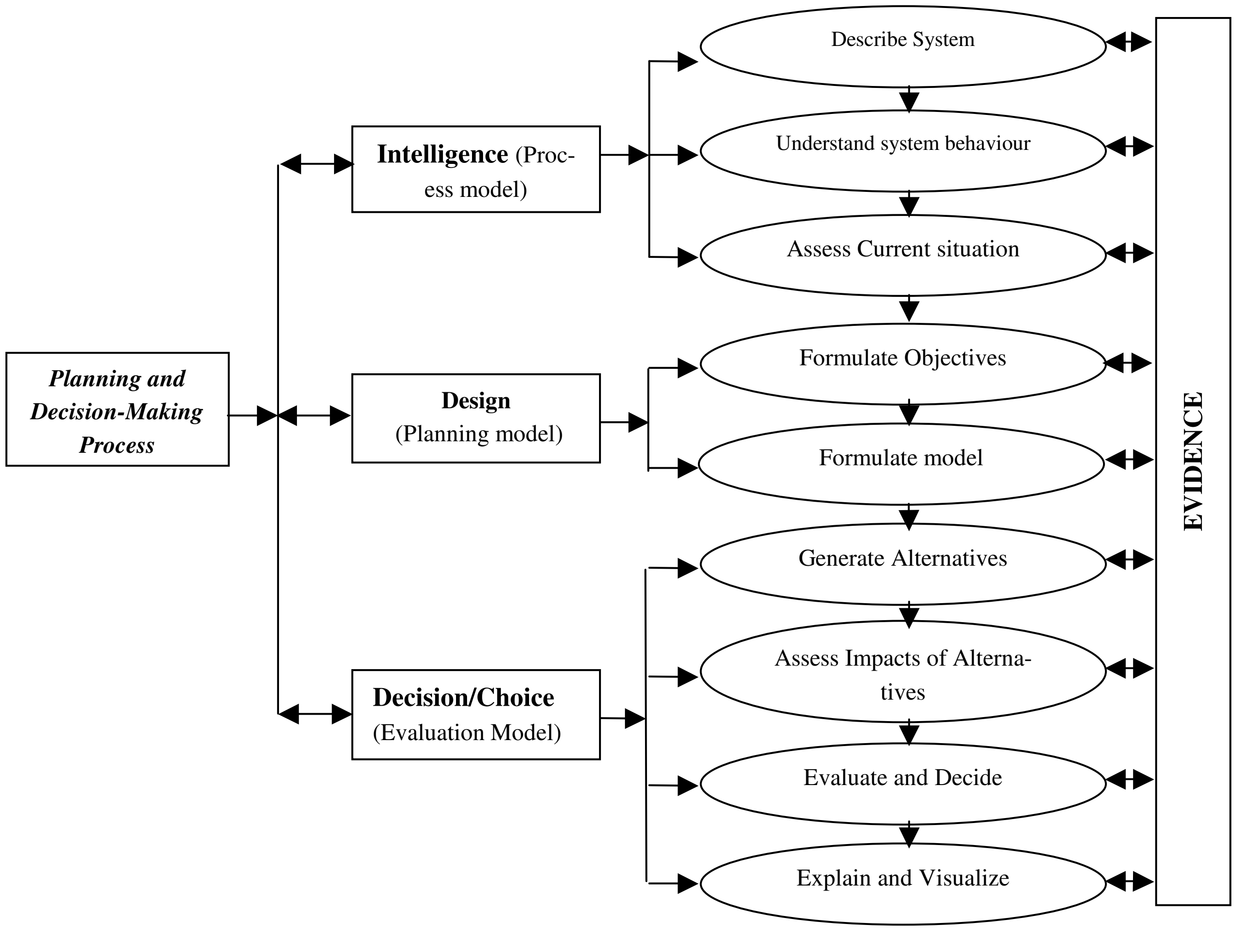

Figure 4.1 Framework for planning and decision making process. (After Sharifi et. al., 2002)

The process of Multicriteria Decision Making is classified on several criteria (Malczewski, 1999).

1. Multi Attribute Decision Making (MADM) and Multi Objective Decision Making (MODM), based on the way the criteria are being treated, as an attribute or an objective.
2. Individual Decision Making and Group Decision Making, based on the number of people involved in the decision-making process.
3. Decision Making under Certainty and Decision Making under Uncertainty, based on the situation under which decision making is being done and the nature of the criteria.

4.2. Spatial Multi-Criteria Decision Making

Spatial multi-criteria decision-making (MCDM) is a process where geographical data is combined and transformed into a decision. Multi-criteria decision-making involves input data, the decision maker's preferences and manipulation of both information using specified decision rules. In spatial MCDM, the input data is geographical data. Spatial MCDM is more complex and difficult in contrast to conventional MCDM, as large numbers of factors need to be identified and considered, with high correlated relationships among the factors (Malczewski 1999). According to Malczewski (1999) a spatial decision problem is the difference between the desired state in a geographical system and an existing state in real world.

Spatial MCDM aims to achieve solutions for spatial decision problems, derived from multiple criteria. These criteria, also called attribute must be identified carefully to arrive at the objectives and final goal. The performance of an objective is measured with the help of these attributes. These objectives and underlying attributes form a hierarchical structure of evaluation criteria for a particular decision problem. These evaluation criteria should be comprehensive and measurable. In a hierarchy, a set of criteria should be decomposable, non-redundant, complete, minimal, and computational. Further, a map layer in the GIS represents each criterion in the hierarchy (see figure 4.5). Most creative task in the decision-making is deciding what factors to include in the hierarchy structure. The hierarchy serves two purposes; 1) it provides the overall view of the complex relationships in the situation and 2) it allows decision makers to assess whether they are comparing the issues of same order or magnitude. The principal notion behind the hierarchical structuring of a decision problem is that the elements being compared should be homogeneous. One should be aware that the hierarchy does not need to be complete, i.e. an element in a given level does not have to function as criteria for all the elements in the level below. As mentioned above, hierarchy gives an opportunity to distinguish a criteria of greater importance from that of less importance: the criteria of greater importance is depicted in lower branches of the hierarchy, while the criteria of less importance is situated at the top or general level.

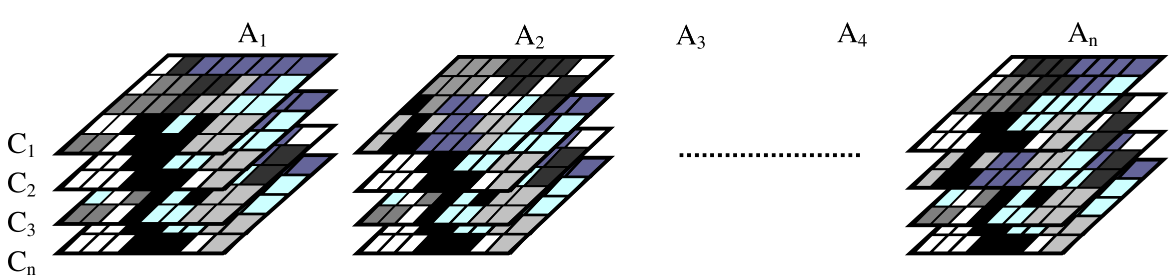

Figure 4.2 Schematic representation of the decision problem with spatial effect.

Being a case of spatial multi-criteria decision-making process, land suitability evaluation demands for visualization of the impact of the alternatives and criteria in the form of maps. This demands for visualization in the form of maps. This demand can be accomplished effectively by the integration of spatial analysis and conventional multi-criteria evaluation techniques, as shown in figure 4.3. Moreover, environmental decision problems are characterized of having multiple and often conflicting objectives. When evaluating such a complex phenomenon, the spatial dimension seems to be the big hurdle. Here, the integration of GIS and MCDM techniques becomes useful.

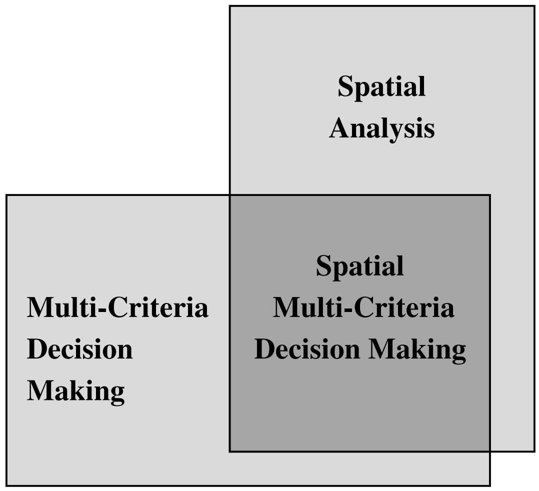

Figure 4.3 Integration of MCDM and GIS into Spatial MCDM

Most of the spatial decision problem area can be portrayed in many ways. Structuring a land use problem depends on the questions to be deal with (Malczewski, 1999).

1. Given a desired activity, which sites might be best for that activity? (Where to put something?)
2. Given a site or sites, what kind of activity might be most suitable here? (What to put here?)

Accordingly, four major land use problems are identified:

- *Site (Location) Selection*: Given a set of specific land use types, rank the set of sites for that land use and order them based on priority.
- *Location Allocation*: Situation where the functional relationship between the attributes of a land and the goals of decision making is stated.
- *Land use selection*: Given a set of sites, find the land use types (LUTs) that suits best and order them based on the priority. It can also be called as Alternative Uses.
- *Land use allocation*: Given a set of sites, which land use is the best for that site. It addresses the surface of land that should be allocated to a specific land use.

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From the discussion above it is clear that land suitability analysis for agricultural crops is a land use selection problem where LUTs are to be rated on priority basis. Here, alternative land uses are rated based on a set of criteria. The aim is not to find the exclusively suitable land use, but also to characterise and prioritise LUTs that suit the local condition. . In the context of agricultural crop suitability it is not possible to characterize a land use type that is suitable for a particular land explicitly.

4.3. Framework of Land suitability decision making

The decision-making problem of land suitability analysis for agricultural crops is analysed using the Simons model with required modifications. **Figure 4.4** depicts the conceptual flow of the research approach.

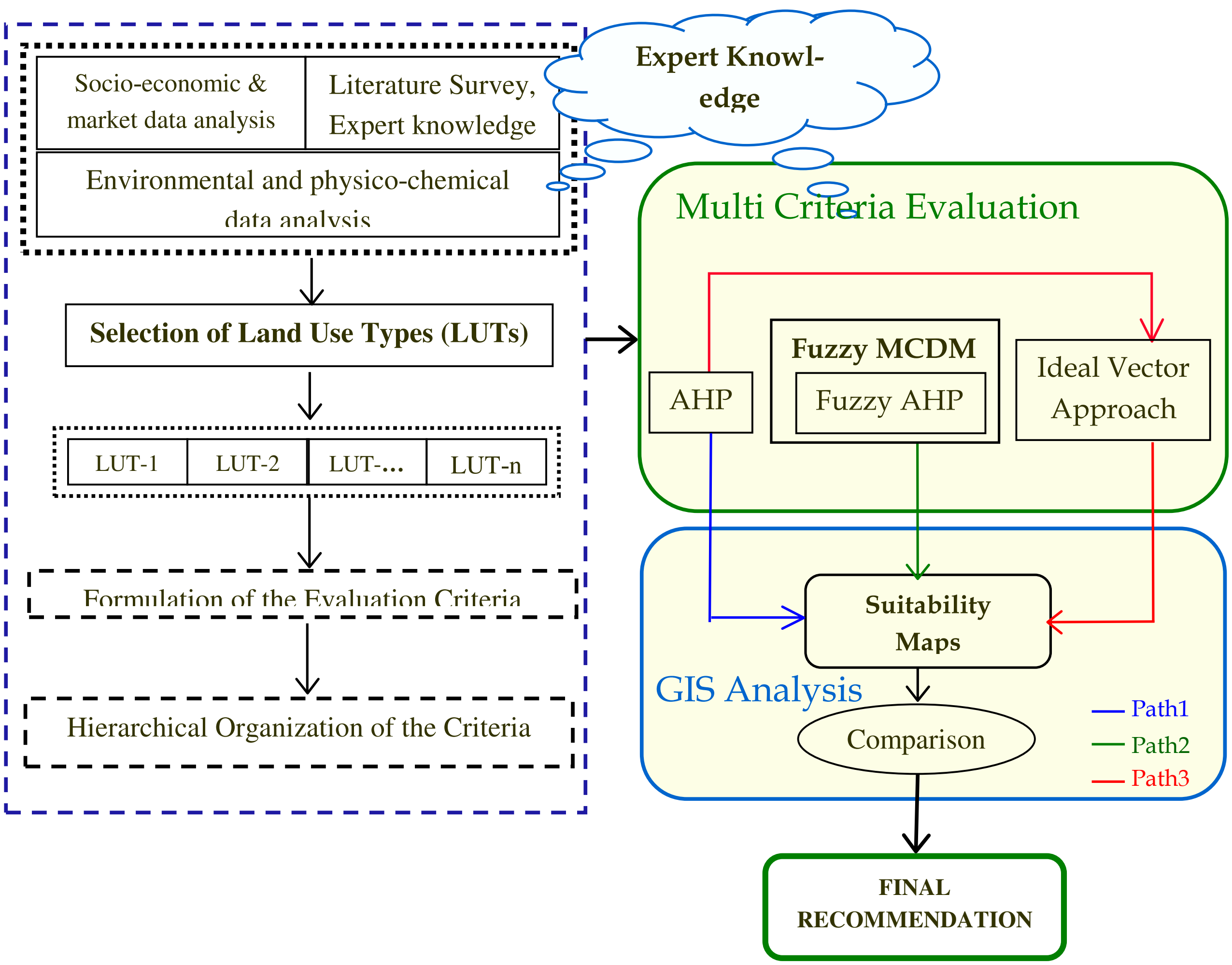

Figure 4.4 Conceptual flow of the research approach

4.3.1. Selection of Land Use Types

The aim of this research is to investigate the study area to arrive at the possible land use types. The parameters like agro-climatic (or agro-ecological) zone, present cropping-system, local food habit, major agricultural markets and facilities, processing industries in and around the area, population and economic status of the society and literacy are taken into account. Experts in the fields of agriculture, soil science and local policy-making are consulted to decide upon the potential land use types for the study area.

For this study area, the different land use types (crops) for evaluation that are considered, are:

- Rice
- Sugarcane
- Maize
- Vegetables
- Horticulture
- Pulses

4.3.2. Selection of the evaluation criteria

Evaluation criteria, objectives and attributes, should be identified with respect to the problem situation. A set of criteria selected should adequately represent the decision-making environment and must contribute towards the final goal. It is known that set of attributes or criteria depends upon the system that is being analysed. There is no set technique to select the evaluation criteria. The process of selecting the criteria is iterative in nature. Literature survey, analytical study and the opinion survey are tools that aid in the selection of evaluation criteria. The following evaluation criteria are considered to address the land suitability decision-making

1. Soil
    a. Chemical
        i. pH
        ii. Organic Carbon
        iii. Fertility
    b. Physical
        i. Texture
        ii. Drainage
        iii. Depth
2. Climate
    a. Temperature
    b. Rainfall
3. Irrigation

   a. Canal irrigation
   b. Ground water
4. Market and Infrastructure
   a. Roads
   b. Markets and Processing industries
5. Socio-economic (Population).

4.3.3. Hierarchical Organisation of the Criteria

Malczewiski (1999) states that relationship between the objectives and attributes has a hierarchical structure. At the highest level one can distinguish the objectives and at lower levels, the attributes can be decomposed. Figure 4.5 shows the hierarchical structure used in this study.

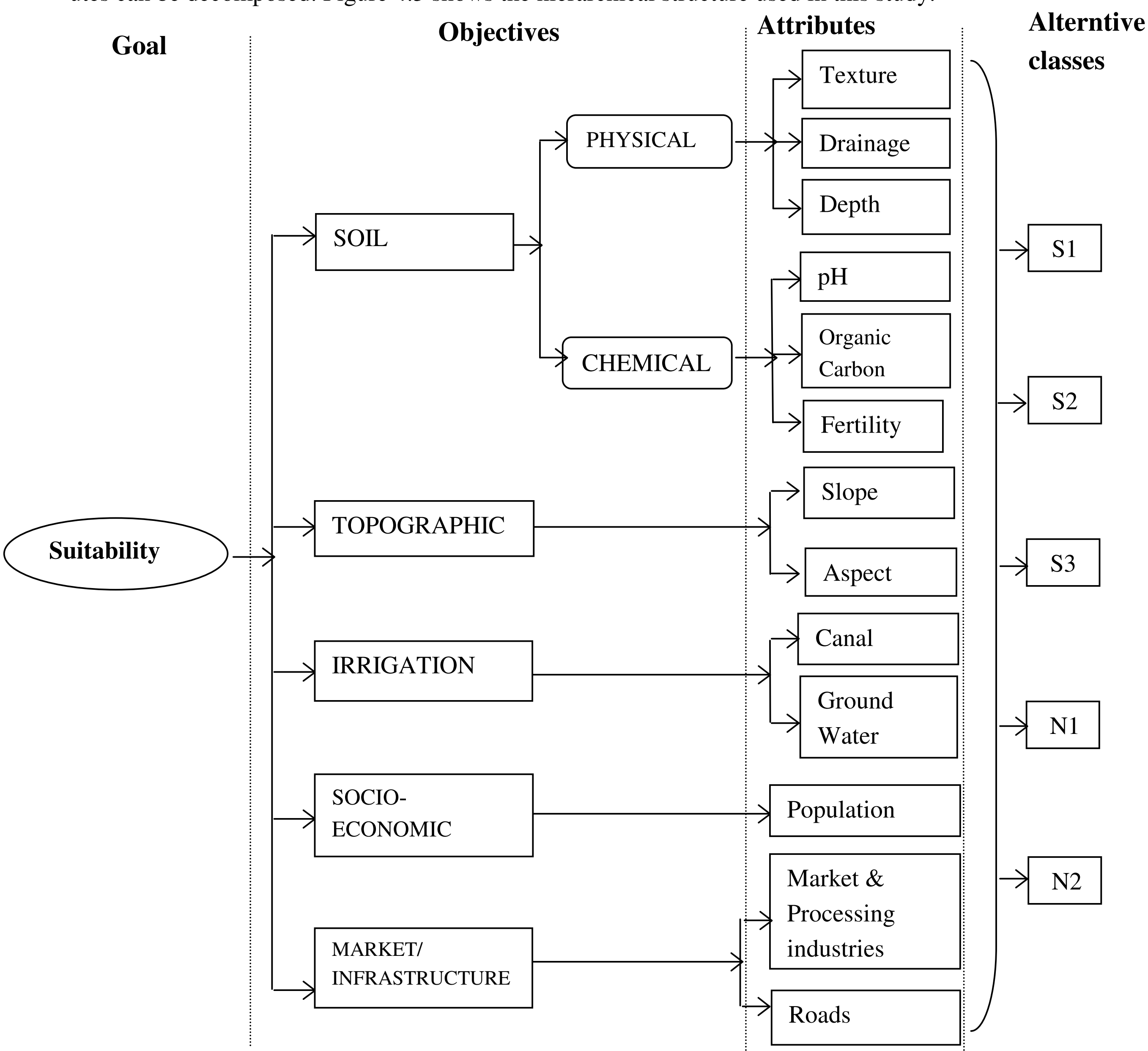

Figure 4.5 Hierarchical organisation of the criteria considered for the study.

4.3.4. Multi Criteria Evaluation

In the current study, the following three methods are applied to describe the multi criteria evaluation:

- Analytic Hierarchy Process (AHP)
- Ideal vector Approach
- Fuzzy AHP

Here, special emphasis is on the extended capabilities of the Fuzzy AHP for land suitability analysis. This study also compares the capabilities of these methods to address the drawbacks of conventional methods, as discussed in the earlier chapters.

4.4. Analytic Hierarchy Process (AHP)

Analytic Hierarchy Process is a widely used method in decision-making. AHP is introduced by Saaty (1977), with the basic assumption that comparison of two elements is derived from their relative importance. As the fuzzy methodology followed in this research is an extension of this Saaty's priority theory, it is necessary to introduce the basic concepts of the AHP. This section gives a brief introduction to the AHP.

Analytic means the separation of an entity into its constituents. This method decomposes the complex decision problems into simple groups and hierarchies.

Hierarchical organization of the criteria is common in large decision problems. This is advantageous in the decision making process, where relative importance of the criteria under evaluation is to be established consciously. It is proven that the human brain is not able to process more than seven stimuli at a time (Miller, 1956). Besides, empirical studies showed that people cannot compare more than three criteria at the same time (Rommelfanger 2003). Therefore, a hierarchical organization of the criteria helps to decompose the complex decision making processes, as suitability evaluation. A particular hierarchy or group helps to maintain the consistency among the comparisons and weightings of the criteria. Moreover, criteria that are comparable to each other are organized at the same level. Furthermore, the hierarchical structure has the ability to incorporate decisions or expert knowledge of people from various domains, especially while an environmental decision problem is an interdisciplinary terrain

The decision-making in AHP is a continuous process starting from analysing the decision environment to understand and arrange the criteria into different groups and levels till evaluating the criteria in its decision outputs.

The fundamental input for the AHP is the pairwise comparison matrix, which gives answers to a series of questions like: 'How important is criterion a relative to criterion B?' In AHP, comparisons are used to establish both weights for criteria and preference scores for classes on different criteria. The comparisons are measured on a ratio scale. First, a decision-maker has to make comparison between each element under evaluation. Here, the comparisons are made qualitatively, for example weak preference, moderate preference etc., and are termed as Pairwise Comparisons (PCs). Later, these preferences are converted to quantitative values using the scale designed by Saaty (1980). (Table 4.1).

4.4.1. Principles and axioms

By the prior discussion on AHP, it is clear that AHP is based on three basic principles (Sharifi and Herweijnen 2003):

- Decomposition: speaks: is to structure a complex problem into different clusters at various hierarchies
- Pairwise Comparisons: is to create Pairwise Comparison Matrices (PCMs) for all the elements or criteria under evaluation to derive the weights or the preferences, and
- Hierarchical composition, to aggregate these local comparisons over the hierarchy to arrive at the final evaluation

And the four simple axioms those constitute the theory of AHP are,

- Reciprocal axiom: If the pairwise comparison between two elements a and b with respect to an element c is Pc(xab), then the comparison between b and c must be 1/ Pc(xab).
- Homogeneity axiom: Elements clustered and arranged under a hierarchy must be homogeneous i.e. they must be comparable with an order of magnitude. It means that elements within a cluster should preferably be compared within the AHP scale, 1 to 9.
- Independency of judgment at each level: judgment at one level of hierarchy should be independent of the elements under it. One should carefully consider this axiom while making decisions, as the human tendency force one to look at the elements under the hierarchy during evaluation
- One should make sure that their ideas are adequately represented in or incorporated into process of decision making so that the results match their expectations.

Table 4.1 Fundamental Scale used in Pairwise Comparison (Saaty and Vargas 2001)

Intensity of Importance	Qualitative Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak	
3	Moderate importance	Experience and judgements slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another and dominance is demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation

4.4.2. AHP in the context of Land suitability analysis for Agricultural crops

4.4.2.1. Standardization of the Criteria Map

In land suitability analysis, a map represents each evaluation criterion with ordinal values (like S1, S2, S3, N1, N2 etc.) indicating the degree of suitability with respect to a criterion, based on the crop requirements (Sehgal 1996). These classes have to be rated, how important is the class S1 with respect to a particular criteria to contribute for the final goal or the objective? This process of setting the relative importance of the classes of criteria is called standardisation. Criteria standardization is normally done on 0 to 1 scale, or 0-10 or 0-100 etc. Pairwise comparison technique can be used for the purpose of rating or standardizing these ordinal values (Malczewski 2003). In this particular land suitability analysis the criteria are mainly related to soil, topography, climate, irrigation water resources, socio-economic, environment, market and infrastructural facilities. Some of them can be represented by the GIS layer and some are purely non spatial. These criteria at the lowest level having different suitability classes is standardised using the maximum Eigen vectors approach on 0 to 1 scale. By following this approach further process of standardising the performances is not required. The process will yield the yield the normalized score from the PCM (Table 4-2).

Table 4.2 Rating the classes of the pH using PCM (Ideal AHP)

pH	S1	S2	S3	N1	N2	Performances
S1	1	3	6	8	9	1
S2	1/3	1	3	4	5	0.4325
S3	1/6	1/3	1	2	3	0.1911
N1	1/8	1/4	1/2	1	2	0.1185
N2	1/9	1/5	1/3	1/2	1	0.0783

4.4.2.2. Assessing the Weights (Obtaining Decision Rules)

At higher levels of the hierarchy the criteria are required to be evaluated to derive the weights. Here the criteria weights need to be summed up to 1, so the well-established geometric mean method is used. In this approach all the elements in the row are multiplied and the nth root is calculated and are divided by their sum to get the normalized weights.

Table 4.3 Criteria weights using AHP (Geometric Mean method)

Chemical	pH	Fertility	OC	Weights
pH	1	1/4	3	0.2176
Fertility	4	1	6	0.6910
OC	1/3	1/6	1	0.0914

In this way the criteria over the hierarchy are obtained. Standardized Criteria maps are multiplied with these criteria weights at each level of the hierarchy as shown in Figure 4.6.

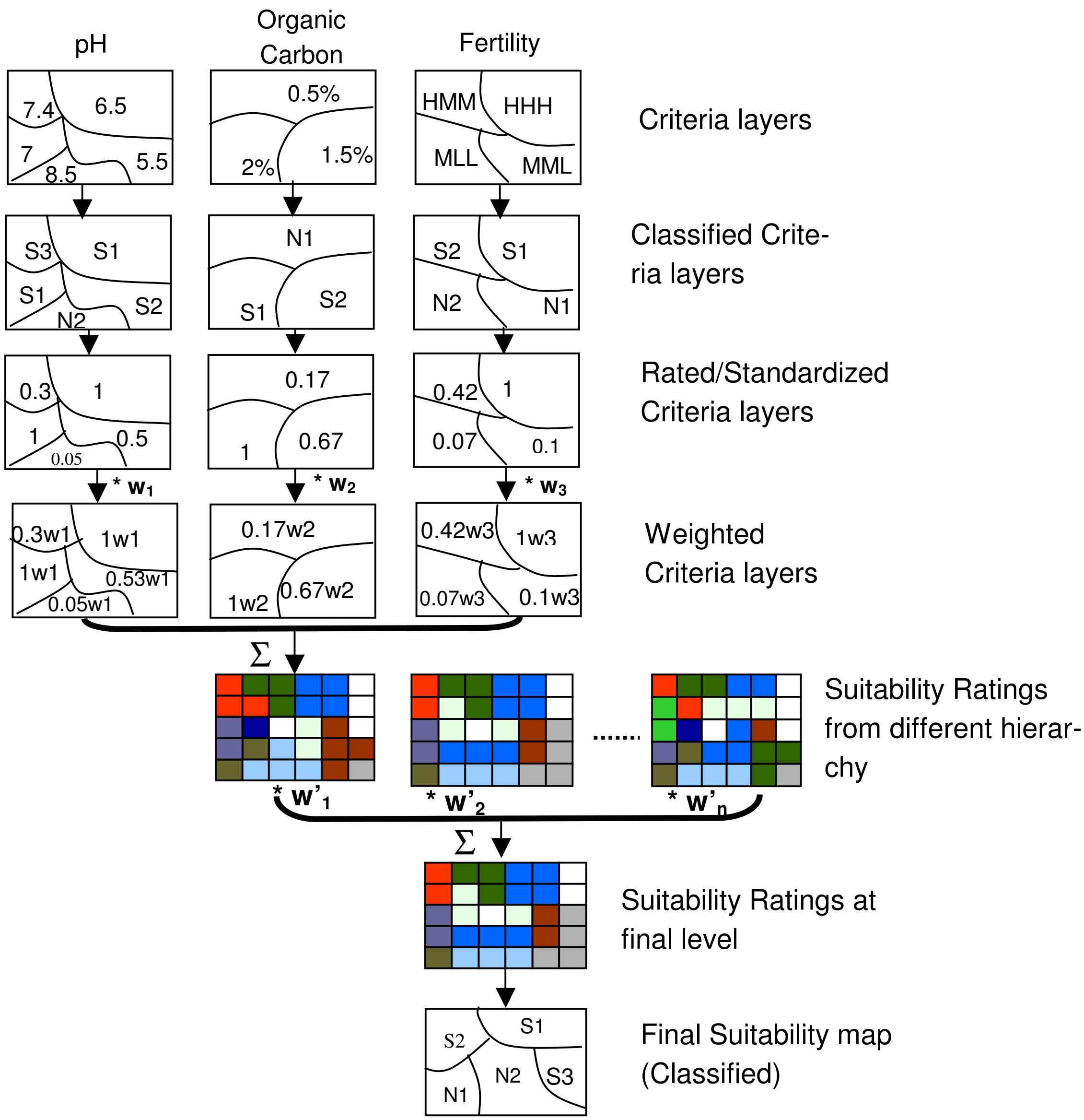

Figure 4.6 Aggregation of the ratings and weights over hierarchy

4.5. Ideal Vector Approach

The TOPSIS technique is based on the concept that the chosen alternative will have the shortest distance from the positive ideal solution and the longest from that of the negative ideal solution. The solution will be ideal, when the ideal scores in all attributes are collected (Hwang and Yoon, 1981 cited in (Fred. 2000)). This technique defines the similarity index, which is the combination of the proximity and remoteness to the positive and negative ideal solutions respectively.

In the agricultural crop suitability analysis the S1 is considered to be the ideal point and N2 the negative ideal. In AHP we determined the performances of these classes S1, S2, S3 N1 and N2. The performance of the S1 determined here is considered to be the positive ideal performance and that of the N2 is the negative ideal.

In the TOPSIS separation of each alternative from negative ideal and positive ideal is calculated using the n-dimensional Euclidean distance measure, where in present approach vector-matching function (Deng 1999) is applied. Here instead of the Euclidean distance the degree of similarity between each alternative and the negative and the positive ideal solution is measured using the following vector-matching functions.

Degree of similarity of the performances of the classes or the alternatives to the positive ideal performance, the S_{ij}^{+} is given by,

$$S_{ij}^{+} = \frac{A_{ij} A_j^{+}}{\max\left(A_{ij} A_{ij}, A_j^{+} A_j^{+}\right)}$$

Degree of similarity to the negative ideal performance, the S_{ij}^{-} is given by,

$$S_{ij}^{-} = \frac{A_{ij} A_j^{-}}{\max\left(A_{ij} A_{ij}, A_j^{-} A_j^{-}\right)}$$

Where, $A_{ij} = \left(a_{i1}, a_{i1}, ...a_{im}\right)$ is the overall performance matrix of the m classes or alternatives of that particular criteria. Larger the value of the S_{ij}^{+}, S_{ij}^{-} more is the similarity of the class or the alternative to positive and negative ideals, respectively. Measurement of the similarity needs performance matrices to be normalised. In our study we are looking to find the ideal class among the classes S1, S2, S3, N1 and N2. Though it is known that the class S1 is the ideal among them but we are not aware by what degree the other classes are deviating from the ideal and how much they contribute for the final suitability. So inputs into the IVA are the rating matrices of these classes in each attribute or criteria with respect to an objective and final goal. As the rating matrix is already a normalized one there is no further need to normalise the matrix.

The performance index of the class is then determined by comparing these similarity indices. A class that is having high positive similarity and low negative similarity will perform much better than those having less positive similarity index and high negative similarity index.

The performance index of the class is given by,

$$P_j = \frac{S_j^+}{S_j^+ + S_j^-} \quad \text{where j = 1, 2, ……n}$$

The earlier values (ratings) of the classes used in this calculation are replaced by these performance indices. Further the weights of the criteria obtained using AHP are multiplied over the hierarchy and aggregated to get the final suitability.

Table 4.4 Performance index of suitability classes for pH using Ideal vector Approach

pH	Ratings	IVA			
		Positive similarity (S+)	Negative Similarity (S^-)	Performance (P)	Weight *
S1	1	1	0.0783	0.9274	***0.0247***
S2	0.4325	0.4325	0.181	0.7049	***0.0188***
S3	0.1911	0.1911	0.4097	0.3181	***0.0085***
N1	0.1185	0.1185	0.6608	0.1521	***0.0040***
N2	0.0783	0.0783	1	0.0726	***0.0019***

* This final weight is calculated after the performance value is multiplied with the weights of the criteria over the hierarchy in the AHP technique, i.e. In this case
S1-weight = S1(performance) * W(pH) * W(chemical) * W(soil)
= 0.9274 * 0.2176 * 0.3333 * 0.3668 = 0.0247

Finally all the layers multiplied over hierarchy are summed up to yield the final suitability map.

4.6. Fuzzy AHP

One of the drawbacks of AHP is that it fails to address the uncertainty in expressing the preferences during pairwise comparison (PC). This paves the path for the incorporation of fuzzy logic in the AHP (Van Laarhoven and Pedrycz 1983; Buckley 1985; Deng 1999). Deng (1999) proposed a simple, improved, and sophisticated approach using fuzzy logic. This methodology has been recently modified by Jeganathan (2003).

4.6.1. A Brief Introduction to Fuzzy Logic

Dr. Lofti A. Zadeh in 1965 proposed a new theory called "Fuzzy Sets" (ZADEH A. LOTFI, 1965, Fuzzy Sets, Information and Control, 8, 338 – 353.) Accordingly a fuzzy set is a class of elements or objects without any definite boundaries between them. The fuzzy logic is useful to define the real world objects which are characterized by vagueness and uncertainty. Fuzzy logic is a multivalued theory where in intermediate values such as "moderate", "high", "low" instead of yes or no, true or false as it is in conventional crisp theory. The fuzzy sets are defined by the membership functions. The fuzzy sets represent the grade of any element x of X that have the partial membership to A. the degree to which an element belongs to a set is defined by the value between 0 and 1.

If an element x really belongs to A if $\mu A(x) = 1$, and clearly not if $\mu A(x) = 0$. Higher is the membership value μ, greater is the belongingness of an element x to a set A.

Fuzzy Numbers

Fuzzy numbers are the fuzzy sets with special considerations for easy calculation (Tanaka 1996). A fuzzy number will have the following characteristics.

- A fuzzy number is a convex fuzzy set;
- There is only one x0 that satisfies $\mu A(x0) = 1$;
- μA is continuous in an interval

Triangular Fuzzy Numbers

A triangular fuzzy number aare the special class of fuzzy number whose membership defined by three real numbers, expressed as (*l, m, u*). The triangular fuzzy numbers can be represented as follows.

$$\mu_A(x) = \begin{cases} (x - l) / (m - l), & l \le x \le m, \\ (u - x) / (u - m), & m \le x \le u, \\ 0, & \text{otherwise,} \end{cases}$$

where m is the most possible value of a fuzzy number A, and l and u are the lower and upper bounds, respectively before and beyond them the element will have no membership to the set.

Operations on triangular fuzzy numbers

Here are the few basic fuzzy arithmetic operations on triangular fuzzy numbers,

Let A = (l_a, m_a, u_a) and B = (l_b, m_b, u_b) be the two triangular fuzzy numbers, then

1. Addition
   $A + B = (l_a + l_b,\ m_a + m_b,\ u_a + u_b)$

2. Subtraction
   $A - B = (l_a - l_b,\ m_a - m_b,\ u_a - u_b)$

3. multiplication
   $AB = (l_a l_b,\ m_a m_b,\ u_a u_b)$

   - Scalar multiplication
     $\forall$ k >0, k$\in$ R, kA = (kl_a, km_a, ku_a),
     $\forall$ k >0, k$\in$ R, kB = (kl_b, km_b, ku_b)

4. Division

$$\frac{A}{B} = \left(\frac{l_a}{u_b}, \frac{m_a}{m_b}, \frac{u_a}{l_b}\right)$$

5. Inverse

$$A^{-1} = \left(\frac{1}{u_a}, \frac{1}{m_a}, \frac{1}{l_a}\right)$$

α-cuts: will yield an interval set of values from a fuzzy number. For example an $\alpha = 0.5$ will yield a set $\alpha_{0.5}$ = [0.3, 0.4, 0.5, 0.6, 0.7]. The operation is illustrated below (Figure 4.6).

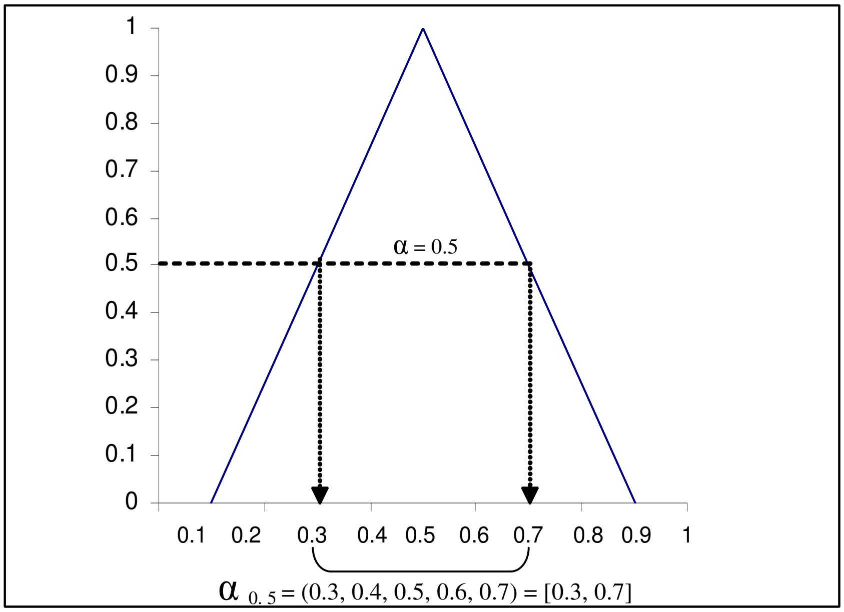

Figure 4.7 Alpha cut operation on triangular fuzzy number

4.6.2. Fuzzy AHP approach in Land Suitability Analysis

In the fuzzy AHP approach, we use triangular fuzzy numbers for the fuzzification of the crisp PCM. The basic concept of fuzzy extent analysis is to obtain the criteria importance and alternative performances by solving these fuzzified reciprocal PCMs. After obtaining the fuzzy performances, the ultimate aim will be to get the final results in crisp form. Therefore, the fuzzy performance matrices are transformed into interval performance matrices using the α-cut concept. Then, to obtain the crisp output, the concept of optimism index is introduced, λ.

Given a crisp PCM A, having the values ranging from 1/9 to 9

$$A = \begin{pmatrix} a_{11} & a_{12} \ldots\ldots\ldots\ldots\ldots & \ldots a_{1n} \\ a_{11} & a_{12} \ldots\ldots\ldots\ldots\ldots & \ldots a_{1n} \\ \ldots & \ldots \ldots\ldots\ldots\ldots\ldots & \ldots \\ & \ldots \ldots\ldots\ldots\ldots\ldots & \\ & & \\ \ldots & \ldots \ldots\ldots\ldots\ldots\ldots & \ldots \\ a_{m1} & a_{m2} \ldots\ldots\ldots\ldots\ldots & \ldots a_{mn} \end{pmatrix} \qquad (1)$$

The Crisp PCM A is fuzzified using the triangular fuzzy number f = (l, m, u), which fuzzifies the PCM as shown in table 4.5. The l *(lower bound)* and u (upper bound) represents the uncertain range that might exist in the preferences expressed by the decision maker or experts.

Table 4.5 Conversion of crisp PCM fuzzy PCM

Crisp PCM value	*Fuzzy PCM value*	*Crisp PCM value*	*Fuzzy PCM value*
1	(1,1,1), if diagonal (1, 1, 3), otherwise	1/1	(1/1, 1/1, 1/1), if diagonal (1/3, 1,1), otherwise
2	(1, 2, 4)	1/2	(1/4,1/2, 1/1)
3	(1, 3, 5)	1/3	(1/5,1/3, 1/1)
5	(3, 5, 7)	1/5	(1/7, 1/5, 1/3)
7	(5, 7, 9)	1/7	(1/9, 1/7, 1/5)
9	(7, 9, 11)	1/9	(1/11, 1/9, 1/7)

The fuzzy PCM $\overline{A}$ will be as follows,

$$\overline{A} = \begin{pmatrix} (a_{11l}\ a_{11m}\ a_{11u}) & (a_{12l}\ a_{12m}\ a_{12u}) \ldots\ldots\ldots\ \ldots\ldots & (a_{1nl}\ a_{1nm}\ a_{1nu}) \\ (a_{21l}\ a_{21m}\ a_{21u}) & (a_{22l}\ a_{22m}\ a_{22u})\ \ldots\ldots\ldots\ \ldots\ldots & (a_{2nl}\ a_{2nm}\ a_{2nu}) \\ : & :\ \ \ldots\ \ldots\ldots\ldots\ldots\ldots & : \\ : & :\ \ \ldots\ \ldots\ldots\ldots\ldots\ldots & : \\ : & :\ \ \ldots\ \ldots\ldots\ldots\ldots\ldots & : \\ (a_{m1\,l}\ a_{m1\,m}\ a_{m1u}) & (a_{m2\,l}\ a_{m2\,m}\ a_{m2\,u}) \ldots\ldots\ldots\ \ldots & (a_{mn\,l}\ a_{mn\,m} a_{mn\,u}) \end{pmatrix} \ldots \quad (2)$$

The fuzzy extent analysis is applied on the above fuzzy PCM to obtain the fuzzy performance matrix. To obtain only the fuzzy decision or performance matrix (X) and fuzzy weights (W) using the fuzzy extent analysis following formula is used

$$x_i \text{ or } w_j = \frac{\sum_{j=1}^{k} \bar{a}_j}{\sum_{i=1}^{k} \sum_{j=1}^{k} \bar{a}_{ij}} \qquad (3)$$

Where i =1, 2, 3……. p , j = 1, 2, 3…….q and k = p, or k = q, depending upon the element under operation, whether it is an alternative or criteria (the number of rows and columns in the PCM)

$$X_i = \begin{pmatrix} (x_{11l}\ x_{11m}\ x_{11u}) \\ (x_{21l}\ x_{21m}\ x_{21u}) \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ (x_{i1l}\ x_{ijm}\ x_{iju}) \end{pmatrix} \qquad (4)$$

Where j = number of classes in the sub criteria (lowest level) and no of criteria in the other upper levels

$$W_j = [(w_{1l}\ w_{1m}\ w_{1u})\ (w_{2l}\ w_{2m}\ w_{2u})\ \ldots\ldots\ (w_{nl}\ w_{nm}\ w_{nu})] \tag{5}$$

Where n = number of criteria or sub criteria under the hierarchy.

A fuzzy weighted performance matrix (P) can thus be obtained by multiplying the weight from the weight vector with the decision matrix.

$$P = X_i * W = \begin{pmatrix} (w_l x_{11l}\ w_m x_{11m}\ w_m x_{11u}) \\ (w_m x_{21l}\ w_m x_{21m}\ w_m x_{21u}) \\ \ldots\ldots\ldots \\ \ldots\ldots\ldots \\ \ldots\ldots\ldots \\ (w_m x_{i1l}\ w_m x_{ijm}\ w_m x_{iju}) \end{pmatrix} = \begin{pmatrix} p_{1l}\ \ p_{1m}\ p_{1u} \\ p_{2l}\ \ p_{2m}\ p_{2u} \\ \ldots\ldots \\ \ldots\ldots \\ \ldots\ldots \\ p_{il}\ \ p_{im}\ \ p_{iu} \end{pmatrix} \tag{6}$$

Next step is to obtain an interval performance matrix by applying the α-cut over these fuzzy numbers. α-cut is known to incorporate the experts or decision makers confidence over his preference or the judgements. Applying the α-cut will yield the interval performances. The α-cut value ranges from 0 to 1 stating that if the α-cut = 1 then the expert is highly certain about his knowledge regarding a phenomenon over which he express his preferences then the outcome will be a single value having the membership 1 in the fuzzy performance set. Then the further steps are not needed, but when the α-cut is less than 1, it indicates there exist uncertainty; the expert is obviously uncertain about the decisions he made. The α-cut = 0 express the highest level of uncertainty, and then the possible performance will be whole support of the fuzzy performance. Any value of α other than 1 needs further evaluation to get the crisp performance.

$$P_\alpha = \begin{pmatrix} [p_{1l\alpha}\ ,\ p_{1r\alpha}] \\ [p_{2l\alpha}\ ,\ p_{2r\alpha}] \\ \ldots\ldots \\ \ldots\ldots \\ \ldots\ldots \\ [p_{il\alpha}\ ,\ p_{ir\alpha}] \end{pmatrix} \tag{7}$$

where *l* and *r* represent the left and right value of the interval set.

Now the crisp performance matrix is obtained by applying the λ, the optimum index. In agricultural crop suitability studies this function is used to depict boundaries of suitability classes.

Optimism index λ is applied over the interval performance set as shown below resulting in a crisp performance matrix C.

$$c_\lambda = \lambda * p_{r\alpha} + (1-\lambda)*p_{l\alpha}, \qquad \text{where } \lambda = [0, 1]. \tag{8}$$

$$C_\lambda = \begin{pmatrix} c_{1\lambda} \\ c_{2\lambda} \\ \ldots \\ \ldots \\ c_{i\lambda}. \end{pmatrix} \tag{9}$$

4.6.3. Implementation the Fuzzy AHP in the context of land suitability analysis

Input to the fuzzy AHP methodology is the basic PCM (table 4.8) used in the Conventional AHP. The PCM given by the experts is fuzzified using triangular fuzzy numbers (table 4.5) to yield fuzzy PCM (table 4.7).

Table 4.6 Crisp Pairwise Comparison Matrix

pH	S1	S2	S3	N1	N2
S1	1	3	6	8	9
S2	1/3	1	3	4	5
S3	1/6	1/3	1	2	3
N1	1/8	1/4	1/2	1	2
N2	1/9	1/5	1/3	1/2	1

Table 4.7 Fuzzified Pairwise Comparison Matrix

pH	S1	S2	S3	N1	N2
S1	(1, 1, 1)	(1, 3, 5)	(4, 6, 8)	(6, 8, 10)	(7, 9, 11)
S2	(1/5, 1/3, 1/1)	(1, 1, 1)	(1, 3, 5)	(2, 4, 6)	(3, 5, 7)
S3	(1/8, 1/6, 1/4)	(1/5, 1/3, 1/1)	(1, 1, 1)	(1, 2, 4)	(1, 3, 5)
N1	(1/10, 1/8, 1/6)	(1/6, 1/4, 1/2)	(1/4 1/2 1/1)	(1, 1, 1)	(1, 2, 4)
N2	(1/11, 1/9, 1/7)	(1/7, 1/5, 1/3)	(1/5, 1/3, 1/1)	(1/4, 1/2, 1)	(1, 1, 1)

Fuzzy performance of the matrix is calculated as given by the equation (3) to yield a fuzzy performance matrix (table 4.8)

Table 4.8 Performances: AHP and fuzzy AHP

pH	Crisp performances	Fuzzy Performances		
		Lower	Middle	Upper
S1	0.5109	0.2487	0.5109	1.0378
S2	0.2523	0.0942	0.2523	0.5930
S3	0.1230	0.0435	0.1230	0.3336
N1	0.0733	0.0329	0.0733	0.1977
N2	0.0406	0.0220	0.0406	0.1031

Considering that the ph can be measured with moderate certainty alpha value of 0.6 is chosen. Which will yield a performance matrix with the range values (table 4.9).

Table 4.9 Application of Alpha Cut analyses

Suitability Class	Alpha Cut (60%)	
S1	0.0170	0.3347
S2	0.0083	0.1899
S3	0.0041	0.1062
N1	0.0024	0.0630
N2	0.0014	0.0329

To get crisp weight matrix from the range value matrix $\lambda = 0.5$ is applied (Eqn 8). Rationale behind is that λ measure how confident the expert is with respect the factor being evaluated. Value 0.5 indicate the expert is not that confident regarding his decisions or preferences, certain amount of uncertainty exist in his preferences.

Table 4.10 Crisp performance values obtained at three different lambda values

Suitability	Lambda (0)	Lambda (0.5)	Lambda (1)
S1	0.017	0.1759	0.3347
S2	0.0083	0.0991	0.1899
S3	0.0041	0.0552	0.1062
N1	0.0024	0.0327	0.063
N2	0.0014	0.0171	0.0329

Table 4.11 Illustration of fuzzy AHP over part of the Hierarchy

SOIL	Chemical		
	0.1786	0.3333	0.6154

Paddy	SOIL		
	0.1169	0.3216	0.8037

Chemical	pH			OC			Fertility		
	0.0912	0.2537	0.6195	0.2947	0.6567	1.4297	0.0558	0.0896	0.2145

Fuzzy performances

	pH			OC			Fertility		
S1	0.2487	0.5109	1.0378	0.1863	0.4331	1.0049	0.2293	0.4487	0.8867
S2	0.0942	0.2523	0.5930	0.0896	0.2490	0.6460	0.1227	0.2700	0.5700
S3	0.0435	0.1230	0.3336	0.0633	0.1895	0.4845	0.0763	0.1745	0.3863
N1	0.0329	0.0733	0.1977	0.0362	0.0830	0.2602	0.0296	0.0777	0.1908
N2	0.0220	0.0406	0.1031	0.0239	0.0453	0.1089	0.0184	0.0291	0.0657

Fuzzy weighted performances over the hierarchy

S1	0.0008	0.0278	0.7950	0.0002	0.0042	0.1066	0.0014	0.0316	0.6270
S2	0.0003	0.0137	0.4542	0.0001	0.0024	0.0685	0.0008	0.0190	0.4031
S3	0.0001	0.0067	0.2555	0.0001	0.0018	0.0514	0.0005	0.0123	0.2732
N1	0.0001	0.0040	0.1514	0.00001	0.0008	0.0276	0.0002	0.0055	0.1349
N2	0.0001	0.0022	0.0790	0.00001	0.0004	0.0116	0.0001	0.0020	0.0465

Interval performances
Alpha cut analysis. $\alpha = 0.6$, (60% confidence)

S1	0.0170	0.3347	0.0026	0.0451	0.0195	0.2698
S2	0.0083	0.1899	0.0015	0.0288	0.0117	0.1726
S3	0.0041	0.1062	0.0011	0.0217	0.0076	0.1166
N1	0.0024	0.0630	0.0005	0.0115	0.0034	0.0572
N2	0.0014	0.0329	0.0003	0.0049	0.0013	0.0198

Crisp Performance matrix using optimism index $\lambda = 0.5$

S1	0.1759	0.0239	0.1447
S2	0.0991	0.0152	0.0921
S3	0.0552	0.0114	0.0621
N1	0.0327	0.0060	0.0303
N2	0.0171	0.0026	0.0106

5. Results and Discussion

From the six major LUTs selected for the study area, rice crop is considered to explore the ability of three multi-criteria evaluation techniques under investigation. Evaluation criteria are framed and organised in a hierarchy, as shown in Figure 4.5. Discussions with relevant experts, literature survey and fieldwork are the major tools aided in deciding upon the LUTs, the evaluation criteria and their hierarchical structuring. First, each criterion is categorized into five suitability classes S1, S2, S3, N1 and N2, derived from rice crop requirements – Appendix C (London 1984; Sehgal 1996). Second, land suitability evaluation is executed by three multi-criteria evaluation techniques, as mentioned in chapter 4. The results of the three approaches are put together and discussed here. The input Pair wise Comparisons Matrices, the ratings of the classes of all the criteria and weights off all the criteria are listed in Appendix A and Appendix B.

5.1. Analytic hierarchy process (AHP)

5.1.1. Standardization

In the AHP approach, the criteria are standardized, using pairwise comparison techniques. The standardization of the criteria resulted in ratings ranging between 0 and 1. As an example, standardization results for slope are given in table 5.1. In Appendix A, all results for standardization of the criteria are given.

Table 5.1 Standardization of the suitability classes using pairwise comparison

Slope	S1	S2	S3	N1	N2	Ratings
S1	1	3	6	8	9	**1**
S2	0.333333	1	3	7	8	**0.5105**
S3	0.166667	0.333333	1	5	7	**0.2715**
N1	0.125	0.142857	0.2	1	3	**0.0948**
N2	0.111111	0.125	0.142857	0.333333	1	**0.0555**

For better understanding, the result of the criteria standardization for slope is plotted in a graph (Figure 5.1), as it is done in conventional linear scale transform, value function approach etc.

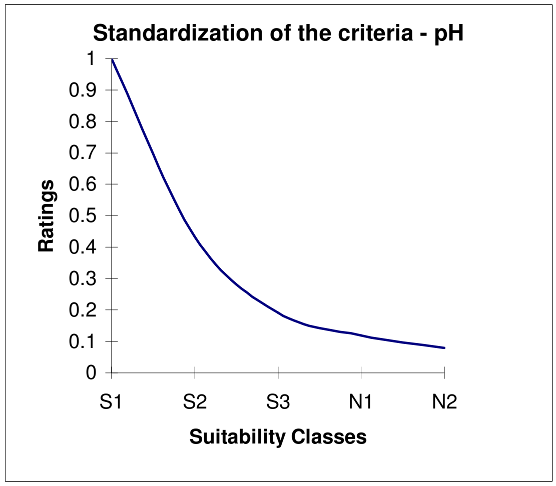

Figure 5.1 Visualization of standardized scores

5.1.2. Ranking

If the results from the standardization are satisfactory, the next step will be the ranking of the criteria. The geometric mean method is followed to obtain the criteria weights from the PCM. These weights are multiplied with the standardized criteria maps and aggregated over the hierarchy to obtain the suitability map. The results from ranking of the criteria in the group Chemical factors are given in Table 5.2.

Table 5.2 Criteria ranking or weights

Chemical	pH	Fertility	OC	Weights
pH	1	0.25	3	**0.2176**
Fertility	4	1	6	**0.691**
OC	0.333333	0.166667	1	**0.0914**

Suitability of the rice crop for the area is evaluated using this methodology. Accordingly 42.67 % of the total available area for agriculture is moderately suitable for rice crop and the results are summarized in the table 5.3. Figure 5.2 shows the final suitability map for rice, using an AHP approach.

Table 5.3 Rice Suitability Area under different classes (AHP)

Suitability Class	Area (in sq km)	Area (in %)
S1	35.19	28.23
S2	53.19	42.67
S3	16.67	13.37
N1	7.81	6.27
N2	11.79	9.46

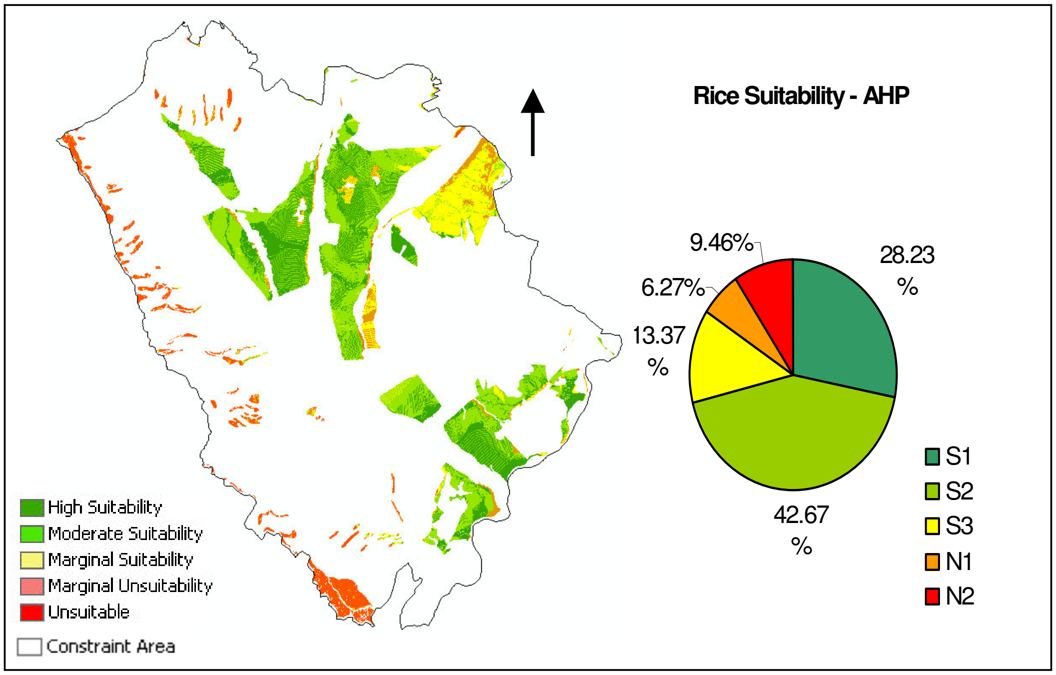

Figure 5.2 Suitability map for Rice from AHP technique

5.2. Ideal Vector Approach

Standardized scores of the previous methodology are the inputs for this approach. The score of class S1 is considered as the positive ideal vector and that of the N1 as the negative ideal vector. As described in the methodology (chapter 4), positive and negative similarity of the scores of each class is calculated using the vector matching function. Both the similarity indexes are used to calculate the performance index of each class.

The performance index thus obtained is multiplied with criteria weights (those obtained in AHP approach) and aggregated over the hierarchy to yield final suitability. Steps involved in this approach are briefed with example in the methodology chapter. (Table 4.4)

Results of the approach are summarised in table 5.4

Table 5.4 Rice suitability area under different classes (IVA)

Suitability Class	Area (in sq. km)	Area (in %)
S1	86.16	69.12
S2	16.80	13.47
S3	9.42	9.42
N1	5.2	4.18
N2	7.05	5.66

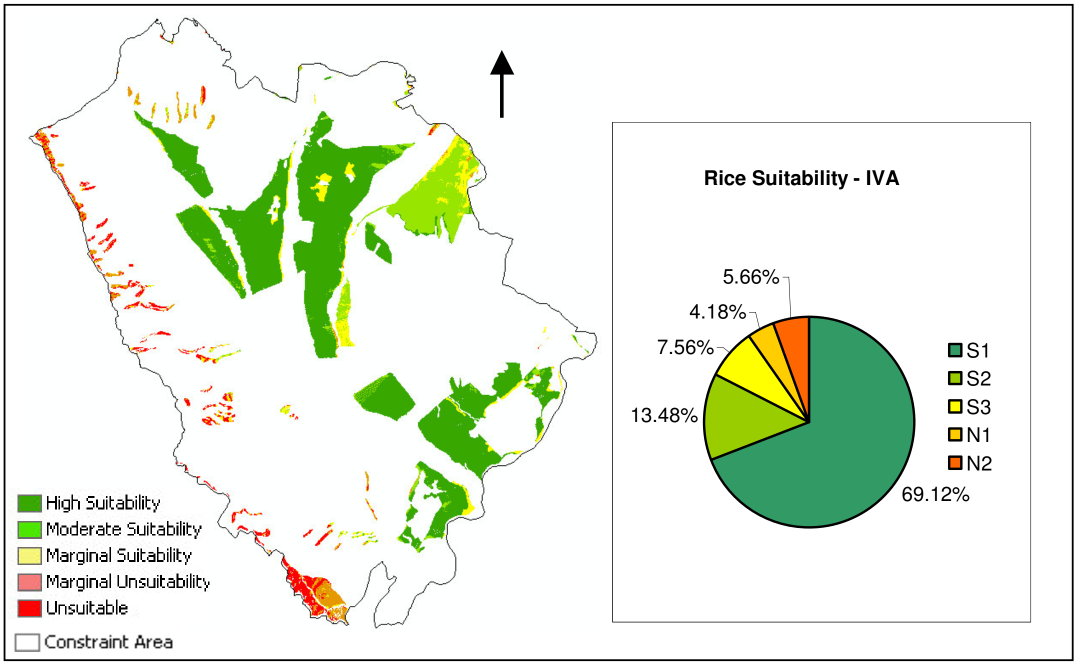

Figure 5.3 Suitability map for Rice from IVA

In this approach, rice is highly suitable (S1) over 86.16 km^2 area, which accounts for 69.12 % of the total area available for cultivation. Only 13.47% is moderately suitable (S2), where as, in the AHP approach, more area was under moderate suitability (S2). The explanation is due to the effect of the similarity index. When the similarity index is taken into consideration, even though the weightings in class S1 in both AHP and IVA are almost equal, the weightings of class S2 in IVA scores substantially greater than that of the AHP (see appendix B). Consequently, when weights of each criterion are aggregated over the hierarchy, class S2 of the IVA has a significantly greater contribution to the final score. Finally, when the final scores are classified into suitability classes, the greater number of pixels with high weightings, larger the area will be under class S1.

When maps from both the approaches (figure 5.2 and figure 5.3) are visually interpreted, class S1 in the suitability map from IVA occupies much of the area that was classified as S2 in the AHP method. Also, S2 occupies that of S3, but this is not the case for other suitability classes

5.3. Fuzzy AHP

Inputs for the fuzzy AHP approach are the crisp PCMs. The crisp PCMs are fuzzified using the triangular membership functions as described in paragraph 4.6. The Fuzzy PCMs for each suitability class are the inputs for fuzzy extent analysis to result in fuzzy performances per suitability class. In the same way, the PCMs constructed by the comparison among criteria in a group in the hierarchy are fuzzified to obtain fuzzy performances per criteria. The fuzzy performances for criteria are multiplied with the fuzzy performances for classes. The multiplication is executed over the hierarchy up to the first level. In the last stage, these performances are processed with alpha cut analysis and lambda functions. The results of the approach are described in table 5.5.

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Table 5.5 Rice suitability area under different classes by Fuzzy AHP

Suitability Class	Area (in sq km)	Area (%)
S1	65.86	52.83
S2	35.42	28.41
S3	7.36	5.91
N1	15.15	12.15
N2	0.86	0.69

The suitability of the rice suitability is analysed using fuzzy AHP, with alpha value of 0.6 indicating the 60% uncertainty in the expert knowledge about deciding upon the crop suitability parameters and their requirements by the crop and the uncertainty over deciding upon their importance is applied is incorporated through the optimism index, lambda. At lambda = 0.5 rice is highly suitable over 53% of the total area available for cultivation.28% of the area is under Moderate suitability, 6 % under marginal suitability.

5.3.1. Sensitivity analysis

To enlighten the effects of uncertainty in expert knowledge, we perform a sensitivity analysis on the fuzzy AHP technique. An alpha value of 0.6 and three different lambda values 0, 0.5 and 1 are used in this analysis. An alpha value of 0 indicates that the decision environment is highly uncertain and 1 indicates that the problem involves no uncertainty. Intermediate values indicate uncertainty between these two extreme ranges. Here, only one alpha value (0.6) is considered assuming that the decision environment is certain up to some extent. Because the process involves criteria, which is measured with comparatively good accuracies by advanced technology.

Three different scenarios of suitability for rice are obtained by this approach. These scenarios show how the uncertainties involved in land suitability decision-making process will influence the outcomes of the process. Figures 5.4, 5.5 and 5.6 show the results obtained with the lambda values 0, 0.5 and 1, respectively.

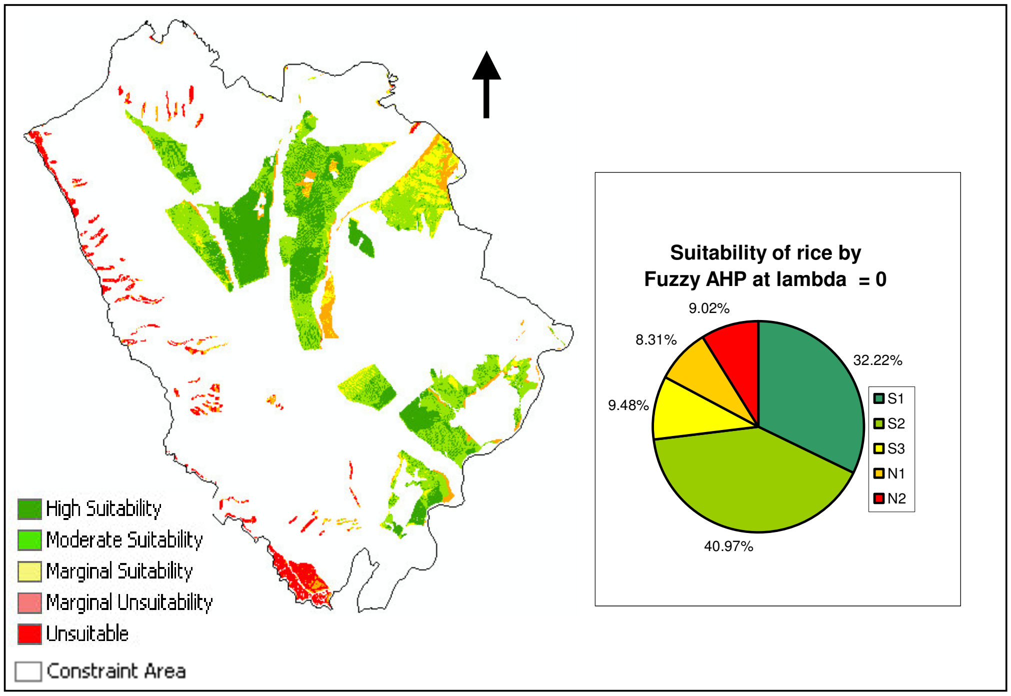

Figure 5.4 Suitability map of rice by Fuzzy AHP technique (at alpha = 0.6: Lambda = 0)

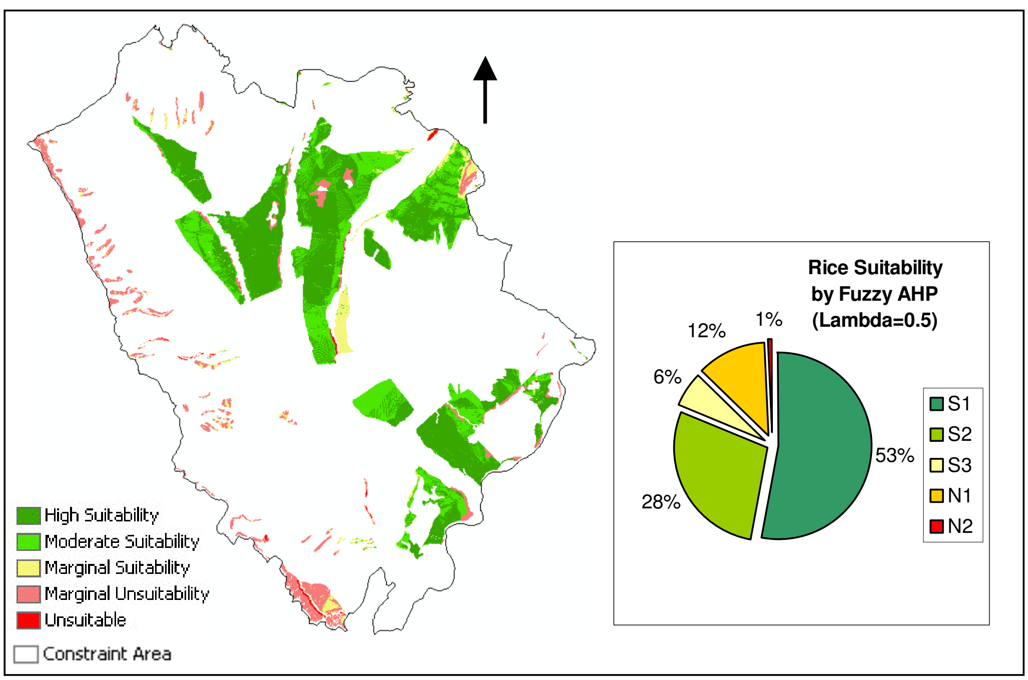

Figure 5.5 Suitability map of rice by Fuzzy AHP technique (at alpha = 0.6: Lambda = 0.5)

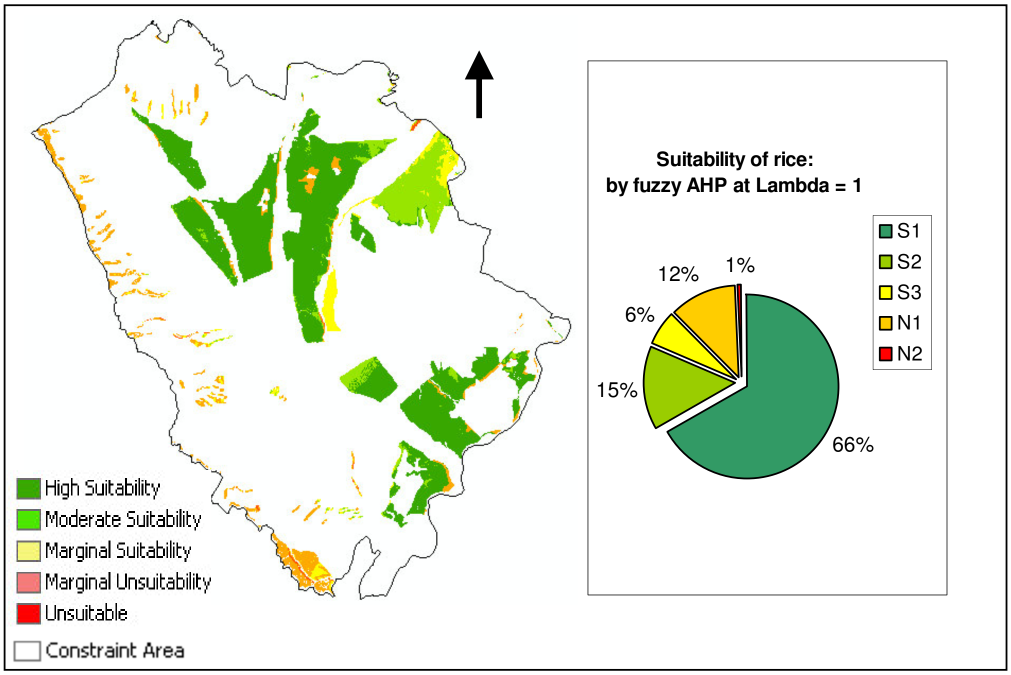

Figure 5.6 Suitability map of Rice by Fuzzy AHP technique (at alpha = 0.6: Lambda = 1)

With λ = 0, rice is highly suitable for 32.2% of the available area for cultivation and moderate suitable, for 40.97%. The three lower suitability classes score less than 10% each.

With λ = 0.5, class S1 dominates over 53% of the area and S2 is restricted only to the 28% of the area. The three lower suitability classes are squeezed down to a total of 18%. Here, it is noticeable that area under the class marginal unsuitability (N1) is increased in compare to λ = 0,. It is visually interpretable, that there has been a shift from areas under class N2 (at λ = 0) towards areas under class N1 (λ = 0.5) (see figure 5.4 and 5.5).

With λ = 1, area with high suitability is up to 66%. The S2 class squeezes itself to 15 %, but doesn't shift towards lower suitability classes. For λ = 1, the classes perform with the same magnitude as under λ = 0,5.

Here, we can conclude that λ can be used to measure the uncertainty of the expert's knowledge. λ = 0 is a measure for high uncertainty. The classes S3, N1 and N2 are no more sensitive for λ > 0.5. The expert knowledge is most uncertain in classes S1 and S2.

The variation in the fuzzy performances for each class can be depicted against the variations in the fuzzy performances for each criterion at different λ - values. Figures 5.7 and 5-8 present these variations for the final suitability classes.

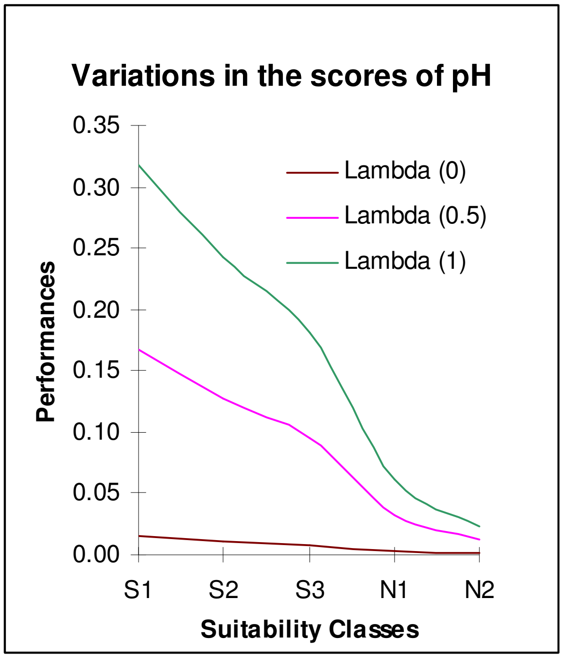

Figure 5.7 Sensitivity of the performances of the criterion pH for variations in lambda values

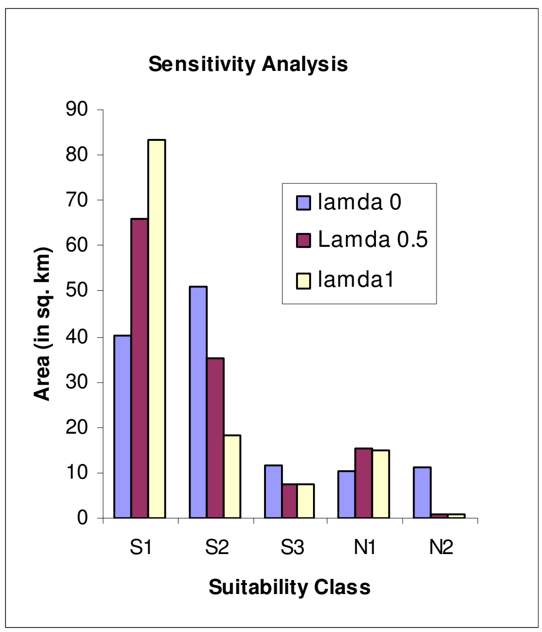

Figure 5.8 Uncertainty analysis by varying lambda value

5.4. Comparitive evaluation

The results of the three land suitability approaches are evaluated here for their abilities to model land suitability evaluation and addressing uncertainties involved in it.

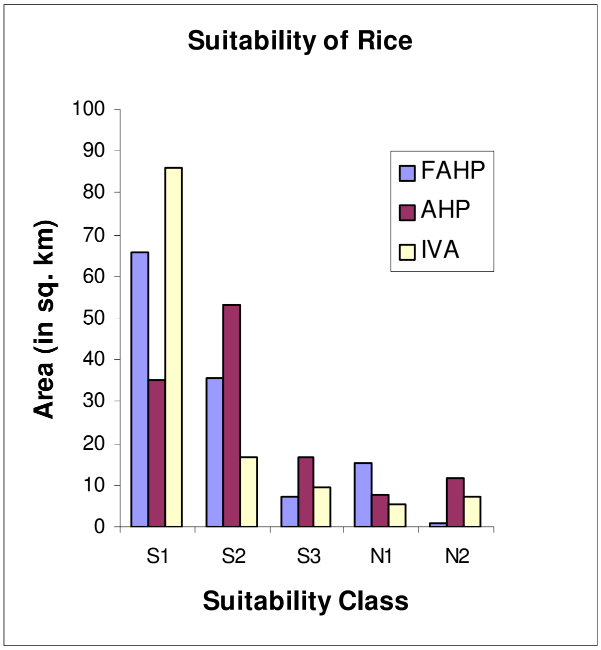

Figure 5.9 Comparison of the results of all the three techniques

It is evident from the results of all three approaches, that the majority of the area is suitable for the crop rice. At least more than 70% of the area is suitable for rice cultivation. Less of the area is under lower suitability classes.

It is observed from the results (Figure 5.3 and 5.9) that the ideal vector approach has some biasness towards negative and positive ideal values (S1 and N2). Positive ideal are exaggerated and the negative ideals suppressed, which is unrealistic. is the reason is that the similarity index, calculated from positive and negative ideals, leads to higher scores of S1 and lower scores of N2.

The results of the AHP approach are satisfactory. These results are comparable with that of the fuzzy AHP. Although AHP incorporates expert knowledge, it fails to incorporate the uncertainty involved in the expert knowledge, his judgment and opinions.

Fuzzy AHP gives considerably good results. The approach incorporates uncertainty of expert opinions, while comparing the criteria. Furthermore, this approach provides opportunity to incorporate uncertainty that might arise while expressing the preference over these criteria. For example one cannot express his preference of the drainage over texture with high certainty. One can express his opinion like drainage is more preferred to texture.

The alpha cut and λ - values used in the calculation of the fuzzy performances incorporate the uncertainty of various kinds. Alpha cut incorporates the uncertainty in determining the crop requirement ranges. For example, when the alpha value 0.6 is considered for pH it takes into consideration of the possible performances between the range 0.0170 and 0.3347 for the class S1, which include the values that might be scored by the class S2 (0.0083 - 0.1899). From this it can be inferred that the alpha cut function addresses the uncertainty involved in the input data (eg. pH map) and it also takes into consideration the uncertainty that might arise from definition of the class limits (S1, S2, S3 N1 and N2). If the criteria are measured with greater uncertainty then there is a chance that value of criterion in a particular pixel may have wider uncertain range than one measured with high uncertainty. So, value of the alpha cut towards 0 indicates the higher uncertainty and considers the higher uncertainty with criteria and those towards 1 represent the certainty and have narrow range of values

The λ - value also measures uncertainty. λ addresses the uncertainty that is involved in deciding upon the range of values obtained by the alpha cut. The value will be towards 1 if the expert or the decision maker is certain that the value of the criterion score is towards the maximum value of the uncertain range. The value will be towards 0 if the decision maker is more certain, that the value of the criteria score is towards the minimum value of the uncertain range.

6. Conclusions and Recommendations

Land suitability evaluation is being carried out without considering the uncertainty in the input data, expert knowledge. The land suitability evaluation involves the criteria, which are in different scales ranging from nominal to ratio. Many inputs into the GIS based land suitability evaluation are the maps of the criteria, which are representing the complex, continuous and uncertain information in a simple, classified map with the crisp boundaries among them. The Boolean methodologies and other simple technique are used for the land suitability evaluation, which aggravate outputs of the evaluation. In order to overcome these problems present research explores the potentiality of three approaches AHP, Ideal Vector Approach and Fuzzy AHP. The Objective of the study is to extend the potentialities of the Fuzzy AHP into Land suitability decision-making.

The suitability problem is structured to fit into the framework of decision-making. The criteria are organised in the in the hierarchy (figure 4.5) to facilitate incorporation of expert knowledge from various disciplines. Keeping in mind the complexity of decision-making process the criteria are grouped at several stages over the hierarchy.

Research Question 1: What are the required *evaluation criteria* to assess model the crop-land suitability?

The FAO (1976) has given a framework for land suitability analysis for crops in terms of suitability classes from highly suitable to not suitable based on the crop specific soil, climatic and topographic data. The same framework has been incorporated in the study with addition of the more number of parameters like socio-economic, market-infrastructure and irrigation facilities, which influence the sustainable use of the land for the activity. Though, parameters considered under these category are not complete, the study augment the present framework by introducing the parameters those were not considered in the frame work and propose a methodology to deal with such information.

Research Question 2: How land suitability classes of a parameter are standardized?

The research follows pairwise comparison approach to standardize the criteria. This approach, as discussed in the section 5.1.1, provides opportunity to compare among the suitability classes to standardize them. The criteria are standardized using eigen value approach, which will standardize the class on 0 to 1 scale. The method also endowed with visualisation of the out comes of the process of standardization. It is known that comparative evaluation of the elements under consideration is very easy and effective as an element is being evaluated in comparison to its contenders. So, pairwise comparison looks more effective in the standardization of the values of criteria involved.

Research Question 3 and 4: 3) how are the class boundaries defined and integrated and uncertainty involved is addressed? 4) How and where to incorporate the expert knowledge and uncertainty involved in it?

Both the research questions are addressed collectively, as both are interrelated. Defining the class boundaries of the values of the criteria require considerable amount of experts knowledge. Boundaries of the each suitability class of a criterion are defined by looking into the crop specific requirements and expert knowledge. The Fuzzy AHP methodology provides opportunities at various stages to incorporate uncertainty in defining the class boundaries, expert knowledge and decision uncertainties involved in the process. At its first stage, fuzzificaion of the pairwise comparisons, the process incorporates the uncertainty that is involved in defining the class boundaries and that in the expert knowledge incorporated for the purpose of defining the class boundaries.

Alpha cut approach also incorporates the uncertainty that is involved in class boundaries and expert knowledge. The lambda function incorporates the uncertainty in the expert knowledge and decision making in deciding a single value among the range of values obtained by alpha cut analysis.

Research Question 5: How the sensitivity of the process can be measured?

Decision-making is a subjective process. There exists uncertainty even when highly technical skills are incorporated. The Fuzzy AHP provides elegant sensitivity analysis techniques. By changing in the values of the alpha and lambda which are the measures for addressing the uncertainty in the decision making process. Alpha and lambda values address the uncertainty in defining class boundaries and incorporating the expert knowledge, which are the possible sources of changing the entire decision scenario. The changes in alpha and lambda values will show the sensitivity of the process.

Research Question 6: How can fuzzy logic approach improve the process compared to existing standard methods?

From the results and discussions it is clear that the Fuzzy AHP approach is superior to other two methods, AHP and IVA. The techniques, fuzzy triangular number, fuzzy extent analysis, alpha cuts and lambda values employed in the fuzzy AHP help in addressing the uncertainty in the expert knowledge and class boundary definition. Fuzzy AHP also facilitate the sensitivity analysis. Alpha and lambda functions facilitate the visualisation of the consequences of the decisions and preferences made by the decision makers and experts, respectively.

Recommendations:

Present study is concentrated on a single crop that is dominant in the study area. The same methodology can be applied considering more crops. This study analyses the sensitivity of the process with single α value, further sensitivity can be analysed using different α values. Mikhailov (2003) presents a promising approach to make decisions from fuzzy PCMs, where construction of reciprocal comparison matrices. This methodology can be extended to land suitability analysis. This is also recommended to use AHP to standardize the criteria values.

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APPENDIX

APPENDIX A: Input PCMs of all the criteria and classes over complete hierarchy

Paddy	Soil	Topography	Socio-econ	Climate	Mrkt/infr	Irrigation	Weights
Soil	1	2	7	3	5	3	0.3668
Topography	0.5	1	6	3	5	2	0.2656
Socio-econ	0.142857	0.166667	1	0.25	0.5	0.25	0.0374
Climate	0.333333	0.333333	4	1	4	1	0.1387
Mrkt/infr	0.2	0.2	2	0.25	1	0.333333	0.0546
Irrigation	0.333333	0.5	4	1	3	1	0.137

Soil	Physical	Chemical	Weights
Physical	1	2	0.667
Chemical	0.5	1	0.333

Physical	Texture	Depth	Drainage	Weights
Texture	1	3	0.333333	0.2583
Depth	0.333333	1	0.2	0.1047
Drainage	3	5	1	0.637

TEXTURE	S1	S2	S3	N1	N2	Ratings
S1	1	3	5	8	9	1
S2	0.333333	1	3	7	8	0.538
S3	0.2	0.333333	1	6	7	0.3063
N1	0.125	0.142857	0.166667	1	3	0.096
N2	0.111111	0.125	0.142857	0.333333	1	0.0574

DRAINAGE	S1	S2	S3	N1	N2	Ratings
S1	1	3	5	8	9	1
S2	0.333333	1	2	4	6	0.4215
S3	0.2	0.5	1	3	4	0.2525
N1	0.125	0.125	0.333333	1	2	0.1021
N2	0.111111	0.166667	0.25	0.5	1	0.0737

DEPTH	S1	S2	S3	N1	N2	Ratings
S1	1	2	4	6	8	1
S2	0.5	1	3	5	7	0.6693
S3	0.25	0.333333	1	3	5	0.3209
N1	0.166667	0.2	0.333333	1	4	0.1684
N2	0.125	0.142857	0.2	0.25	1	0.077

Chemical	pH	Fertility	OC	Weights
pH	1	0.25	3	0.2176
Fertility	4	1	6	0.691
OC	0.333333	0.166667	1	0.0914

pH	S1	S2	S3	N1	N2	Ratings
S1	1	3	6	8	9	1
S2	0.333333	1	3	4	5	0.4325
S3	0.166667	0.333333	1	2	3	0.1911
N1	0.125	0.25	0.5	1	2	0.1185
N2	0.111111	0.2	0.333333	0.5	1	0.0783

FERTIL-ITY	S1	S2	S3	N1	N2	Ratings
S1	1	4	6	7	9	1
S2	0.25	1	3	5	7	0.4299
S3	0.166667	0.333333	1	3	6	0.225
N1	0.142857	0.2	0.333333	1	3	0.1091
N2	0.111111	0.142857	0.166667	0.333333	1	0.0567

OC	S1	S2	S3	N1	N2	Ratings
S1	1	2	4	6	7	1
S2	0.5	1	2	3	5	0.5297
S3	0.25	0.5	1	3	4	0.3419
N1	0.166667	0.333333	0.333333	1	2	0.1608
N2	0.142857	0.2	0.25	0.5	1	0.1011

Topography	Slope	Aspect	Weights
Slope	1	0.25	0.8
Aspect	4	1	0.2

Slope	S1	S2	S3	N1	N2	Ratings
S1	1	3	6	8	9	1
S2	0.333333	1	3	7	8	0.5105
S3	0.166667	0.333333	1	5	7	0.2715
N1	0.125	0.142857	0.2	1	3	0.0948
N2	0.111111	0.125	0.142857	0.333333	1	0.0555

Aspect	S1	S2	S3	N1	N2	Ratings
S1	1	3	6	8	9	1
S2	0.333333	1	3	7	8	0.5059
S3	0.166667	0.333333	1	6	6	0.2707
N1	0.125	0.142857	0.166667	1	1	0.0717
N2	0.111111	0.125	0.166667	1	1	0.0674

Mrkt/Infrastr	Market	Road	Weights
Mrkt	1	2	0.6667
Road	0.5	1	0.3333

Mkt/Pl	S1	S2	S3	N1	N2	Ratings
S1	1	2	4	6	9	1
S2	0.5	1	3	4	7	0.6311
S3	0.25	0.333333	1	4	6	0.3538
N1	0.166667	0.25	0.25	1	3	0.1494
N2	0.111111	0.142857	0.166667	0.333333	1	0.0732

Roads	S1	S2	S3	N1	N2	Ratings
S1	1	2	4	7	9	1
S2	0.5	1	2	6	8	0.6095
S3	0.25	0.5	1	4	6	0.3566
N1	0.142857	0.166667	0.25	1	3	0.1297
N2	0.111111	0.125	0.166667	0.333333	1	0.0694

Socio-econ	Population
Population	1

Climate	Rainfall	Temperature	Ratings
Rainfall	1	2	0.6667
Temperature	0.5	1	0.3333

Irrigation	canal	ground water	Weights
canal	1	3	0.75
ground water	0.333333	1	0.25

CANAL	S1	S2	S3	N1	N2	Ratings
S1	1	3	6	8	9	1
S2	0.333333	1	4	6	8	0.5405
S3	0.166667	0.25	1	4	6	0.2419
N1	0.125	0.166667	0.25	1	4	0.1114
N2	0.111111	0.125	0.166667	0.25	1	0.0553

Ground water	S1	S2	S3	N1	N2	Ratings
S1	1	3	6	8	9	1
S2	0.333333	1	4	6	8	0.5405
S3	0.166667	0.25	1	4	6	0.2419
N1	0.125	0.166667	0.25	1	4	0.1114
N2	0.111111	0.125	0.166667	0.25	1	0.0553

Appendix B: Weighted performance of each class over the Hierarchy By all the three methods. (AHP, Fuzzy AHP [at λ=0, λ=0.5 and λ=1] and IVA)

PHYSICAL

Texture	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0150	0.1667	0.3184	0.0632	0.0597
S2	0.0112	0.1272	0.2432	0.0340	0.0527
S3	0.0084	0.0946	0.1809	0.0193	0.0392
N1	0.0026	0.0321	0.0616	0.0061	0.0087
N2	0.0010	0.0122	0.0234	0.0036	0.0034

Depth	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0053	0.0618	0.1183	0.0256	0.0238
S2	0.0041	0.0490	0.0938	0.0171	0.0218
S3	0.0024	0.0307	0.0589	0.0082	0.0147
N1	0.0014	0.0181	0.0349	0.0043	0.0069
N2	0.0004	0.0047	0.0090	0.0020	0.0018

Drainage	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0385	0.4077	0.7768	0.0256	0.1451
S2	0.0197	0.2369	0.4541	0.0171	0.1101
S3	0.0128	0.1576	0.3025	0.0082	0.0722
N1	0.0053	0.0741	0.1429	0.0043	0.0193
N2	0.0030	0.0344	0.0658	0.0020	0.0107

CHEMICAL

pH	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0170	0.1759	0.3347	0.1558	0.0247
S2	0.0083	0.0991	0.1899	0.0657	0.0188
S3	0.0041	0.0552	0.1062	0.0393	0.0085
N1	0.0024	0.0327	0.0630	0.0159	0.0040
N2	0.0014	0.0171	0.0329	0.0115	0.0019

OC	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0026	0.0239	0.0451	0.0123	0.0101
S2	0.0015	0.0152	0.0288	0.0065	0.0082
S3	0.0011	0.0114	0.0217	0.0042	0.0060
N1	0.0005	0.0060	0.0115	0.0020	0.0023
N2	0.0003	0.0026	0.0049	0.0012	0.0010

Fertility	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0195	0.1447	0.2698	0.1690	0.0799
S2	0.0117	0.0921	0.1726	0.0726	0.0646
S3	0.0076	0.0621	0.1166	0.0380	0.0398
N1	0.0034	0.0303	0.0572	0.0184	0.0147
N2	0.0013	0.0106	0.0198	0.0096	0.0045

TOPOGRAPHIC

Slope	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0556	0.2288	0.4020	0.2125	0.2013
S2	0.0398	0.1685	0.2972	0.1085	0.1752
S3	0.0278	0.1181	0.2085	0.0577	0.1212
N1	0.0091	0.0423	0.0756	0.0201	0.0296
N2	0.0036	0.0160	0.0284	0.0118	0.0112

Aspect	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0146	0.0508	0.0870	0.0531	0.0498
S2	0.0104	0.0373	0.0643	0.0269	0.0420
S3	0.0073	0.0262	0.0451	0.0144	0.0277
N1	0.0014	0.0062	0.0109	0.0038	0.0038
N2	0.0013	0.0060	0.0108	0.0036	0.0034

INFRASTRUCTURE AND MARKET

Road	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0052	0.0229	0.0406	0.0182	0.0170
S2	0.0039	0.0176	0.0314	0.0111	0.0153
S3	0.0026	0.0120	0.0215	0.0065	0.0118
N1	0.0010	0.0050	0.0090	0.0024	0.0036
N2	0.0004	0.0019	0.0033	0.0013	0.0012

Market	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0102	0.0532	0.1060	0.0364	0.0339
S2	0.0072	0.0393	0.0775	0.0230	0.0307
S3	0.0054	0.0237	0.0581	0.0129	0.0230
N1	0.0021	0.0119	0.0253	0.0054	0.0085
N2	0.0008	0.0032	0.0091	0.0027	0.0025

Canal	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0293	0.1591	0.2889	0.1028	0.0974
S2	0.0210	0.1175	0.2139	0.0555	0.0864
S3	0.0124	0.0708	0.1293	0.0249	0.0528
N1	0.0060	0.0353	0.0647	0.0114	0.0188
N2	0.0018	0.0095	0.0171	0.0057	0.0054

Ground water	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
S1	0.0101	0.0532	0.0963	0.0343	0.0325
S2	0.0072	0.0393	0.0713	0.0185	0.0288
S3	0.0042	0.0237	0.0431	0.0083	0.0176
N1	0.0021	0.0119	0.0216	0.0038	0.0063
N2	0.0006	0.0032	0.0057	0.0019	0.0018

Climate	**Fuzzy AHP (at different Lambda values)**			**AHP**	**IVA**
	Lambda (0)	Lambda (0.5)	Lambda (1)		
Temperature	0.0725	0.2126	0.3526	0.0925	0.0925
Rainfall	0.0371	0.0924	0.1476	0.0462	0.0462

Population	Fuzzy AHP (at different Lambda values)			AHP	IVA
	Lambda (0)	Lambda (0.5)	Lambda (1)		
High	0.0138	0.0379	0.0620	0.0374	0.0315
Medium	0.0076	0.0218	0.0359	0.0199	0.0224
Low	0.0028	0.0074	0.0120	0.0374	0.0059

Soil Characteristics (Paddy)	Degrees of Limitation (L) and Suitability Class				
	0 (None)	***1 (Slight)***	***2 (Moderate)***	***3 (Severe)***	***4 (V.Severe)***
	S1	***S2***	***S3***	***N1***	***N2***
Rainfall (mm)	>1500	1000-1500	750-1000	<750	
Slope %	0-1	1-3	3-5	5-8	>8
Drainage Class	Imperfect	Mod. Well,	Well drained	Excessive	Excessive
Textural Class (% Clay)	Sic, coarse c(s) 40-60%	Sic, sc(s)	l, sl, sil (m)	Ls, fs	Sandy
DEPTH (cm)	*>80*	*50-80*	*30-50*	*15-30*	*<15*
NPK Rating	HHH	MMM	MML	LLL	-
Organic Carbon (%)	>1.5	1-1.5	0.5-1	0.2-0.5	<0.2
Temperature (^{0}C)	25-30	30-35	20-25	>35	<20
pH	6-7	5.5-6	7-7.5	5-5.5	<5.5, >7.5

Appendix C :
Crop requirements: Paddy

*Rest of the parameters are derived from population data, and other ancillary data