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A Fuzzy Approach to Environmental Informatics Modeling and Data Classification in Land Selection

D.S.Kalana Mendis
Department of Information Technology, Advanced Technological Institute, Dehiwala, Sri Lanka.
Email: kalana@sliate.ac.lk

ABSTRACT

The project highlights usability of fuzzy logic for designing and implementation of an intelligent system by principal component analysis for environmental informatics modeling and data classification. However, problem of classifying a number of environmental objects into classes is one of the main problems of data analysis and arises in many areas of environmental informatics. The project contributesa new fuzzy approach for designing and implementation of a fuzzy system by principal component analysis for environmental informatics modeling and data classification.In the first instance of the methodology, it is mapped commonsense knowledge regarding to analysis of lands to a (land selection assessment) questionnaire with interaction of an Architect. The questionnaire will be analyzed by using Principal Component Analysis (PCA) to find dependencies by the fuzzy system based on Principal Component Analysis (PCA). In this sub phase of Fuzzification, it is basically analysis the fuzzy set and membership functions for commonsense knowledge modeling. Boundary values of membership functions has been defined by using output of PCA. Therefore this process can be concluded as a further classification for derived principal components by integrating PCA with fuzzy logic module. Membership functions for physical, functional and social parameters in land selection has been constructed by using the out puts of principal component analyzer. This intelligent land assessment tool based on a questionnaire to identify land types in percentages and dominated land type in archaeological sites. This enable a guide understand, instrumental values, operating values, and weak values of archaeological sites. The project highlights usability of fuzzy logic for designing and implementation of an intelligent system by principal component analysis for environmental informatics modeling and data classification. The system has been evaluated by an intelligent land assessment tool in a sub field of architecture domain of land selection in archaeological sites to come up with land classifications as physical, functional and social.

Keywords –**Sugeno Defuzzification, Principal Component Analysis, Tacit Knowledge, Fuzzy logic, Land selection**

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I. INTRODUCTION

Environmental Informatics aims at research and system development focusing on the environmental sciences relating to the creation, collection, storage, processing, modelling, interpretation, display and dissemination of data and information. Environmental Informatics (EI) uses environmental data to reveal, quantify, and validate scientific hypotheses. It does this with a panoply of tools from the Statistics, Mathematics, Computing, and Visualization disciplines.

1.2 Problem statement

The problem of classifying a number of environmental objects into classes is one of the main problems of data analysis and arises in many areas of environmental informatics. Conventional classification methods (e.g. clustering) based on Boolean logic ignore the continuous nature of environmental parameters and the imprecision and uncertainty of environmental data; this can result in misclassification.

2. REVIEW OF LITERATURE

A new discipline, known as Environmental Informatics, which combines research fields such as Artificial Intelligence, Geographical Information Systems (GIS), modelling and Simulation, User Interfaces, etc., is emerging. This exposition of environmental informatics is an attempt to bring current thinking about uncertainty quantification to the environmental sciences. EI, has the potential to be much broader than classical environmental statistics [1].

Fuzzy knowledge-based modelling can be particularly useful where there is no analytical model of the relationships to be examined or where there is an insufficient amount of data for statistical analysis. In these cases, the only basis for modelling is the expert knowledge that is often uncertain and imprecise. Fuzzy logic can be used here for the representation and processing of this vague knowledge [2]. The problem of classifying a number of environmental objects into classes is one of the main problems of data analysis and arises in many areas of environmental informatics. Conventional classification methods (e.g.

clustering) based on Boolean logic ignore the continuous nature of environmental parameters and the imprecision and uncertainty of environmental data; this can result in misclassification. Fuzzy clustering methods can be applied for fuzzy classification, which means the partition of objects into classes with not sharply formed boundaries [3]. Fuzzy classification is now widely accepted in remote sensing of spatial data. There are some examples of the analysis of remotely sensed data like satellite images in geo informatics [4].

In archaeology, past twenty years archaeologists have discussed the potentials of, in particular, expert systems. Land selection depends on several independent criteria such as physical, functional and social. Thus, in addition to the GIS applications, one of multi-criteria evaluation (MCE) methods has to be integrated for the achievement of an optimal result through site selection process [5]. These methods can be evaluated as a major tool to assist decision makers, which divide the decision problems into smaller understandable parts, analyze each part separately and then integrate the parts in a logical manner. Land selection encourages critical reviews of ideas or behaviors that have been taken for granted, especially in heritage management [6]. Further, functional and social parameters describe significant evidence of cultural heritage

2.1 Imprecision, uncertainty and heterogeneity of environmental data

Ecologists collect and evaluate data from all possible data sources, sources of objective(mostly quantitative) data, like measurements and simulation results and sources of subjective (often only imprecise qualitative) information, like subjective estimations obtained from an expert. Not all ecological parameters are measurable, for example, the number and biomass of fish in a particular lake. Besides the usual problem of searching for effective methods for data analysis and modelling, there are some additional problems with handling ecological data. These problems result from some characteristic properties of environmental data, namely:

• Large data sets (spatial data with high resolution, long time series, etc.)
• Heterogeneity, which results from:
– different data sources,
– different types of data (e.g. quantitative and qualitative data) and
– different data structures and data formats (e.g. time series, spatial data).
• A large inherent uncertainty which results from:
– presence of random variables,
– incomplete or inaccurate data (inaccuracy of measurement),
– approximate estimations instead of measurements (due to technical or financial problems),
– incomparability of data (varying measurement or observation conditions),
– imprecise qualitative instead of quantitative information (due to technical or financial problems),
– incomplete or vague expert knowledge and
– subjectivity of the information obtained from expert

The requirements for the methods of ecological modelling and data analysis arise from the properties mentioned above. Thus, special methods for data analysis and modelling should be used to handle imprecision, uncertainty and heterogeneity of environmental data.

2.2 Fuzzy sets and fuzzy logic in ecological applications

There are a number of ways to deal with uncertainty problems (e.g. probabilistic inference networks or belief intervals), but the most successful method of dealing with the imprecision of data and vagueness of the expert knowledge is the fuzzy approach. The Fuzzy Set Theory is based on an extension of the conventional meaning of the term 'set' and deals with subsets of a given universe, where the transition between full membership and no membership is gradual [6]. That means an element of the universe can also only partly belong to this set, in the case of fuzzy sets with the membership value from the interval [0,1]. The membership of this element can be split up between different sets. Therefore, the boundaries of fuzzy sets are not sharp, which reflects better the continuous nature of ecological parameters. The Fuzzy Set Theory formulates specific logical and arithmetical operations for processing information defined in the form of fuzzy sets and fuzzy rules.

Fuzzy logic is the multi-value extension of the rules of conventional logic. This extensiondefines fuzzy inference methods, which are particularly useful for working with vague knowledge representation in the form of linguistic rules. The linguistic rules can contain imprecise terms, which can be represented by fuzzy sets. Compared with conventional methods of data analysis and modelling, the fuzzy approach enables us to make better use of imprecise ecological data and vague expert knowledge. Fuzzy sets can be used to handle the imprecision and uncertainty of data and fuzzy logic to handle inexact reasoning.

Fuzzy classification, spatial data analysis, modelling, decision-making and ecosystem management are the main application areas of the Fuzzy Set Theory in ecological research. Some examples for these application areas are mentioned below.

2.2.1 Fuzzy classification and spatial data analysis

The problem of classifying a number of ecological objects into classes is one of the main problems of data analysis and arises in many areas of ecology. Conventional classification methods (e.g. clustering) based on Boolean logic ignore the continuous nature of ecological parameters and the imprecision and uncertainty of ecological data; this can result in misclassification. Fuzzy clustering methods can be applied for fuzzy classification, which means the partition of objects into classes with not sharply formed boundaries. We can find many applications of fuzzy clustering in different topics of ecology. Compared with conventional classification methods the fuzzy clustering methods enable a better interpretation of data structure. Zhang et al. [7] apply the fuzzy approach to the classification of ecological habitats and Hollert et al. [8] to the eco toxicological contamination of aquatic sites. Fuzzy clustering was also used recently to examine the floristic and environmental similarity among reaches [4]. A fuzzy approach can be very useful for spatial data analysis when probabilistic approaches are inappropriate or impossible, e.g. for the classification of topo-climatic data. Burrough et al. [5] conclude that the fuzzy clustering procedure yields sensible topo-climatic classes that can be used for the rapid mapping of large areas. Liu and Samal [6] explored some fuzzy clustering approaches to the land use mapping (delineation of agro eco zones), whereas Rao and Srinivas [7] used fuzzy clustering for the regionalization of watersheds for flood frequency analysis.

2.2.2 Fuzzy modelling, decision making and ecosystem management

Modelling is the next main application area of fuzzy sets and fuzzy logic in ecology. Fuzzy knowledge-based modelling can be particularly useful where there is no analytical model of the relationships to be examined or where there is an insufficient amount of data for statistical analysis. In these cases, the only basis for modelling is the expert knowledge that is often uncertain and imprecise. Fuzzy logic can be used here for the representation and processing of this vague knowledge [12, 13]. The knowledge-based models with the fuzzy IF-THEN rules are mostly based on the Mamdani-inference method [14]. The second type of fuzzy models is the Sugeno type model [15], which is well suited to modelling based on stipulated input–output data pairs.

2.2.3 Hybrid approaches to data analysis and ecological modelling

There are also a number of hybrid approaches, which result from linking the fuzzy approach with other techniques, e.g.:

• fuzzy approach with neural networks [2],
• fuzzy approach with linear programming for the optimization of land use scenarios [20],
• fuzzy approach with cellular automata [21],
• fuzzy approach with GIS [8],
• fuzzy approach with genetic algorithms [22].

A rapidly increasing number of hybrid approaches, which make use of the advantages of different techniques, can be expected in the near future.

3. METHODOLOGY

The problem of classifying a number of environmental objects into classes is one of the main problems of data analysis and arises in many areas of environmental informatics has been addressed the new fuzzy approach. It has been proposed a new fuzzy approach that contributes for enhancing the ability of modelling and classifying lands using an intelligent system based on principal component analysis and Fuzzy logic. This exploits the process of the new approach in following steps. The approach has been evaluated by using land selection in archaeological sites.

3.1 Informatics modeling

The approach begins by acquiring commonsense knowledge. This can be done as an interview between domain experts and the knowledge engineer. Using the interviewing process between expert and knowledge engineer, commonsense knowledge has been acquired and mapped in to a questionnaire based on Likert scale technology. Commonsense knowledge has been acquired into a questionnaire since it is more convenient for further analysis. On the other hand, the questionnaire can be automated to interact directly with the domain expert without involving a knowledge engineer. Once commonsense knowledge has been acquired, the questionnaire will be analyzed using Principal Component Analysis (PCA) to find dependencies. So PCA is mainly used to reduce dependencies among the questions in the questionnaire constructed for acquired commonsense knowledge. In the first instance it is mapped commonsense knowledge regarding to analysis of lands to a (land selection assessment) questionnaire with interaction of an Architect.

3.2 Data classification

This phase has been constructed by integrating output of model refinement with intelligent system. PCA derive a numerical out, which needs further analysis for knowledge classification. Therefore Fuzzy logic has been used to classify knowledge as a fine-tuning mechanism. This has been constructed by using membership functions defined for a fuzzy set in a commonsense domain. Boundary values of membership functions has been defined by using output of PCA. Therefore this process can be concluded as a further classification for derived principal components by integrating PCA with fuzzy logic module. Further, this will be described as an automated method for constructing membership functions in fuzzy logic module. This process has been concluded as knowledge classification and reasoning of commonsense knowledge modeling by using Fuzzy logic. It is consisted with following stages:

3.2.1Fuzzfication

In this sub phase of Fuzzification, it is basically analysis the fuzzy set and membership function for commonsense knowledge modeling. Membership functions has been constructed by using output of model refinement. Membership functions for physical, functional and social has been constructed by using the out puts of principal component analyzer.

3.2.2Fuzzy rule base

Fuzzy rule base has been constructed by using the membership functions defined in fuzzification process. Fuzzy rules has been constructed for classification of each of land's type.

4. Intelligent land selection tool for land selection

The intelligent land selection tool is consisted of with modules formodeling informatics, removing dependencies and classification of data as given below:

4.1 Informatics modeling in land selection

The questionnaire is based on Likert scale and stored in a MS ACCESS database. The survey results fromarcheological sites has been analyzed by removing dependencies among the questions which are modelled by using principal component analysis.

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Fig.1: construction of questionnaire and fuzzy sets window

4.2 Removing Dependencies

PCA is mainly used to reduce dependencies among the questions in the questionnaire constructed for acquired commonsense knowledge. Principal component analyzer has been used to remove dependencies using SPSS (Table 1). Extracted 9 number of principal components have been stored in a MS ACCESS database

F2	F3	F4	F5	F6	F7	F8	F9	F10
-0.208	0.344	-0.365	-0.395	0.485	-0.234	0.263	0.224	3.75E-01
-0.472	0.569	0.143	-0.247	-0.212	0.371	0.314	0.293	-6.69E-02
-0.372	0.607	-0.003444	0.524	0.218	-0.247	0.312	-0.112	-1.41E-02
0.174	-0.863	-0.16	-0.343	-0.01486	0.251	-0.0738	-0.003328	1.14E-01
-0.854	0.19	-0.07513	0.126	-0.04783	0.239	-0.181	0.104	3.31E-01
0.231	-0.389	-0.09243	0.624	-0.505	0.01066	0.359	0.103	4.42E-02
0.792	-0.05641	0.09766	0.274	0.346	0.403	0.01104	-0.04229	3.62E-02
-0.426	0.604	-0.00863	0.138	0.518	0.185	0.355	0.07632	2.46E-02
0.235	0.486	-0.394	-0.01722	-0.345	0.614	-0.143	-0.189	-1.85E-02
0.454	-0.147	-0.493	0.356	0.05348	-0.485	0.009768	0.23	-3.35E-01
-0.745	-0.212	-0.358	-0.0839	0.348	0.08552	0.158	0.02336	-3.32E-01
-0.846	-0.118	-0.196	0.185	-0.132	-0.08783	-0.399	0.109	-3.78E-02
-0.07458	0.07912	0.573	-0.655	-0.24	0.07187	0.402	0.07058	4.75E-02
0.359	-0.389	0.696	0.227	0.07641	-0.242	0.17	0.197	2.30E-01
0.189	0.857	-0.122	-0.152	0.183	-0.341	-0.178	-0.0625	8.33E-02

Table 1: Principal Component Matrix

4.3 Data classification

This phase has been constructed by integrating output of model refinement with intelligent system. PCA derive a numerical output, which needs further analysis for knowledge classification. Therefore Fuzzy logic has been used to classify knowledge as a fine-tuning mechanism. This has been constructed by using membership functions defined for a fuzzy set in a commonsense domain. Boundary values of membership functions has been defined by using output of PCA. Therefore this process can be concluded as a further classification for derived principal components by integrating PCA with fuzzy logic module. Further, this will be described as an automated method for constructing membership functions in fuzzy logic module. This process has been concluded as knowledge classification and

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reasoning of commonsense knowledge modeling using Fuzzy logic. It is consisted with following stages:

4.3.1 Fuzzy logic for classifying lands

In order for to determine the classification techniques for a given land type, it must receive inputs on the output of the Principal component analyzer. However, it is often not easy for users to specify these land types for the questionnaire. To provide crucial inputs, users need to deduce the principal components from the sampling data using a complex but comprehensive procedure. In this procedure, many subjective and uncertain conceptions orpreferences are involved and different users will classify a given land type differently.

The objective of the Fuzzy logic module is to deal with uncertainties inherent in the procedure of analysis of the available data using fuzzy set theory. Fuzzy logic module is a necessary component of the system because the task of analyzing the questionnaire to derive land types in combinations.

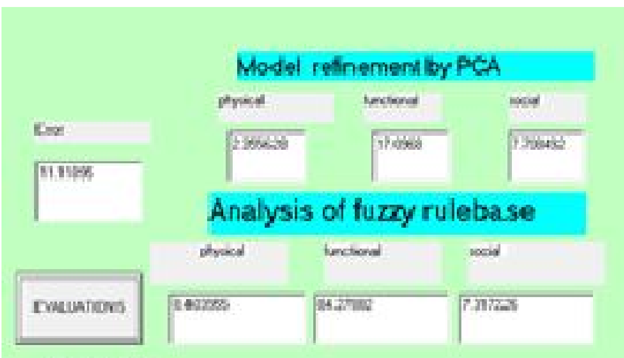

Fig. 2: Analysis window in land selection

4.3.1.1 Fuzzfication

In this module, it is aanalysis the fuzzy set and membership functions for modeling informatics in land selection. Membership functions has been constructed by using output of model refinement by PCA. Membership functions for physical, functional and social has been constructed by using the out puts of principal component analyzer (PCA).

Fuzzy membership for physical (p), functional (f) and social (s) of input fuzzy value (Land) have been constructed. For defining the fuzzy membership function, lower bound value is obtained using Likert scale (*LS*).

$$\Rightarrow LS = [L,..,U]$$

$$LS = [1,..,6]$$

Lower bound value is obtained when Marks = 1 (each question) for each land and upper bound value is obtained when Marks = 6 (each question) for each land respectively. Hence the fuzzy membership functions are for *physical*, *functional*, *social* can be defined as given below:

$$A(X) = \begin{cases} 0 & X => X_L \\ (X-X_L)/(X_U-X_L) & X_L < X < X_U \\ 1 & X <= XU \end{cases}$$

X_L and X_U values are derived from results of the filtered commonsense knowledge. It is computed as given below.

$$\Rightarrow X_L = L \sum_{i=1}^{n}\sum_{j=1}^{m} a_{ji}$$

$$\Rightarrow X_U = \mathrm{U} \sum_{i=1}^{n}\sum_{j=1}^{m} a_{ji}$$

- physical constitution

$$\because X_L = 1 \sum_{i=1}^{12}\sum_{j=1}^{9} a_{ij} = 1.952316$$

$$\because X_U = 6 \sum_{i=1}^{12}\sum_{j=1}^{9} a_{ij} = 11.71389$$

- Functionalconstitution

$$\because Y_L = 1 \sum_{i=13}^{23}\sum_{j=1}^{9} a_{ij} = 5.565917$$

$$\because Y_U = 6 \sum_{i=13}^{23}\sum_{j=1}^{9} a_{ij} = 33.3955$$

- Social *constitution*

$$\because Z_L = 1 \sum_{i=24}^{31}\sum_{j=1}^{9} a_{ij} = 6.533351$$

$$\because Z_U = 6 \sum_{i=24}^{31}\sum_{j=1}^{9} a_{ij} = 39.2001$$

4.3.1.2 Classifying lands

For classification of lands, *physical*, *functional* and *social* land typeshave been computed based on results derived from fuzzification module as given below:

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For *physical*: $\dfrac{p}{p+f+s}$

For *functional*: $\dfrac{f}{p+f+s}$

For *social*: $\dfrac{s}{p+f+s}$

5.RESULT & DISCUSSION

The intelligent land assessment tool has been evaluated in a sub field of architecture domain of land selection in archaeological sites to come up with land classifications as physical, functional and social for enhancing a guide to understand cultural recognition in archeological sites for cultural heritage.

District	Archaeological site	physical	functional	social
Trincomalee	VelgamViharaya	4.04432	60.79982	35.15585
Mannar	ManthotaRajamahaViharaya	17.31002	41.45678	41.2332
Jaffna	Kadurugoda Vihara	7.072626	44.11221	48.81516
Ratnapura	Divaguhawa	19.15861	37.91474	42.92664

Table 2. Analysis of Land selection in archaeological sites

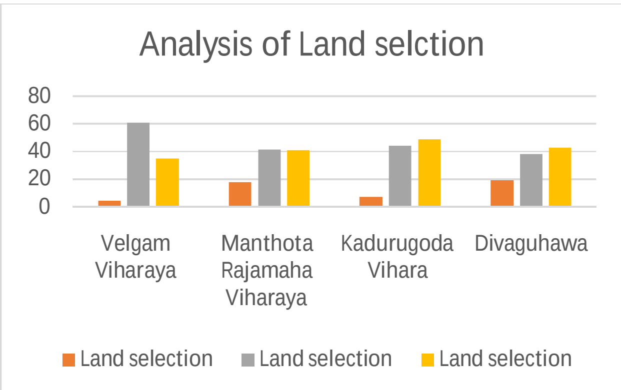

Fig. 3: Analysis of Land selection in archaeological sites

Physical	functional	social
11.896394	46.0708875	42.0327125

Table 3: Average land type of archaeological sites

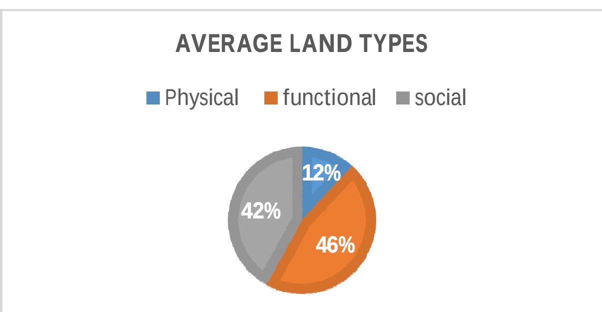

Fig.4: Average Land types

The results shows significant contribution of functional and social indicators respectively. This exploits a reliable assessment tool for cultural recognition in archaeological sites by showing significant contribution cultural heritage indicators such as functional and social. Results of the tool which guides cultural heritage in archeological sites one to find land types in percentages, dominated land types.

6. CONCLUSIONS, RECOMMENDATIONS & LIMITATIONS

Environmental Informatics aims at research and system development focusing on the environmental sciences relating to the creation, collection, storage, processing, modelling, interpretation, display and dissemination of data and information. The problem of classifying a number of environmental objects into classes is one of the main problems of data analysis and arises in many areas of environmental informatics. The project highlights usability of fuzzy logic for designing and implementation of an intelligent system by principal component analysis for environmental informatics modeling and data classification. The system has been evaluated by an intelligent land assessment tool in a sub field of architecture domain of land selection in archaeological sites to come up with land classifications as physical, functional and social.

This research project presents a tool for the systematic selection of lands, to assess the link between land selections for determination of cultural heritage. The land assessment tool analyze land that are found in archaeological sites. At the initial stage commonsense knowledge is converted into a questionnaire. Removing dependencies among the questions are modelled using principal component analysis based on a sample of sites. Classification of the knowledge is processed through fuzzy logic module, which is constructed on the basis of principal components. Results of the land assessment tool which guides cultural recognition in archaeological sites the one to find land types in percentages, dominated land types. This enable a guide understand, instrumental values, operating values, and weak values of cultural recognition for cultural heritage.

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Author Biography

Dr. D.S Kalana Mendis is a Senior lecturer at Department of Information Technology, Advanced Technological Institute, Dehiwala, Sri Lanka. He obtained BSc (Hons.) from University of Kelaniya, Sri Lanka.. He obtained his MPhil in Computer Science from Open University of Sri Lanka and obtained PhD in Engineering Technology (Fuzzy logic in Artificial Intelligence) from Open University of Sri Lanka. He is a Chartered Physicist. He has published more than 80 research publications and reviewed many research papers in IEEE Transaction of Fuzzy systems, Journal of Intelligent Information Management, International Conference on Industrial Information Systems, and Journal of Soft Computing in Image processing. He received presidential research award for scientific research in 2014. He was a Chairman of Environment committee in Sri Lanka Association for Advancement of Sciences in 2017 and council member for Institute of Physics Sri Lanka in 2014. He is a special issue organizer of WSEAS Transaction on Computers. He is a Life member and a council member (2023-2024) of Royal Asiatic Society of Sri Lanka and engaging research work on archaeology, history of science and technology of Sri Lanka for national and also international forums. His research fields are fuzzy modeling, fuzzy sets and systems, High performance computing,Knowledge engineering and Artificial Intelligence in general.