A Fuzzy Approach to Environmental Informatics Modelling and Data Classification for Cultural Heritage in Archaeological Sites

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Abstract

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 objectives should a) To construct fuzzy membership functions for effective classified output of environmental Informatics b) To use Fuzzy logic with PCA as the input can be used for developing an environmental information system for modeling commonsense knowledge c) To enable Knowledge modeling approach for modeling commonsense knowledge in, land selection which enables holistic approach for cultural heritage in archaeological sites. The 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 will be 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: ***Cultural Heritage, Environmental Informatics, Intelligent Systems***

Introduction

The research 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. The approach begins by acquiring commonsense knowledge. Commonsense knowledge will be acquired into a questionnaire since it is more convenient for further analysis. Once commonsense knowledge has been acquired, the questionnaire will be analyzed using Principal Component Analysis (PCA) to find dependencies. 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. In this sub phase of Fuzzification, it is basically analysis the fuzzy set and membership function 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.

Background and Justification

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.

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.

Research Objectives

a) To construct fuzzy membership functions for effective classified output of environmental Informatics

An important aspect of the fuzzy set application is that it can represent the subjective knowledge of the decision maker; different decision makers may have different perception for classified results. Although fuzzy membership functions considered as the most computationally effective data classification, but there is uncertainty about classified output because it generates boundary values of fuzzy membership functions objectively and not well evaluated.

b) To use Fuzzy logic with PCA as the input can be used for developing a environmental information system for modeling commonsense knowledge

Although rough set is considered as a formal approximation sets in terms of a pair of sets which give the lower and the upper approximation of crisp set, but in order to evaluate well defined lower and upper boundary values, output of principal component analysis will be considered. This will enable to develop a intelligent system for modeling environmental informatics in model refinement and knowledge classification for effective classified output for commonsense reasoning. Although Possibility theory is devoted to the handling of incomplete information, but the intelligent system will be used to handle complete information for modeling commonsense knowledge.

c) To enable Knowledge modeling approach for modeling commonsense knowledge in, land selection which enables holistic approach for cultural heritage in archaeological sites

This is further explained as development of intelligent system for archaeological sites. It is mainly concerned with the development of land selection assessment, model refinement and classification as features of the system to be developed by an intelligent system for cultural heritage in archaeological sites.

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

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.

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 extension defines 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.

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.

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.

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.

What is Principal Component Analysis?

The concept of Principal Component Analysis is based on the derivation of linear combinations of the p measured variables X1, X2...Xp to produce ‘derived variables’, that are uncorrelated and are such that explains a different ‘dimension’ within the data. Such derived variables are referred to as principal components (PCs).

Extracting Principal Components

The importance of each PC, in terms of level of data variation explained, is specified by its eigenvalue, the λ term, with Σ λ representing the total of the p eigen values. A measure of the proportion of data variation accounted for by each PC, based on the equivalence of eigenvalue and PC variance, is provided by the expression λ/ (Σ λ).

Generally, it is required to select those PCs, which account cumulatively for at least 80% to 90% of the data variation. In addition that each PC must exceed eigenvalue more than 1.However, if nearly all the correlations are less than 0.25, then there is probably no purpose in carrying out a PCA. However to reduce even that much of interdependency PCs can be computed.

Fuzzy Logic

Fuzzy logic deals with finding a truth ness of a concept in a range of values. It is not always considered the measurement for a degree of truth ness as an extreme value. Fuzzy logic underlying approximates, rather than exact, modules of reasoning – is finding applications that range from process control to medical diagnosis. In more specifications, what is central about fuzzy logic is that, unlike classical logic systems, it aims at modeling the imprecise models of reasoning that play an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision. This ability depends, in turn, on our ability to infer an approximate answer to a question based on a store of knowledge that is inexact, incomplete, or not totally reliable.

What Is A Fuzzy Set?

A fuzzy set can be simply defined as a set with fuzzy boundaries. Let X be the universe of discourse and its elements be denoted as x. Fuzzy set A of universe X is defined by function called membership function of set A.

This degree, a value between 0 and 1, represents the degree of membership, also named as membership value, of element x in set A.

Fuzzy Rules

A fuzzy rule can be defined as a conditional statement in the form: IF X= A THEN Y= B

Where X and Y are fuzzy sets on the universe of discourses X and Y, respectively

Land selection in Archaeology

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 (Khalid, 2013). 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. (van Pelt, M.J.F., 1994). Further, functional and social parameters describe significant evidence of cultural heritage in archaeological sites.

Methodology

I postulated a new approach enhancing the ability of 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 using land selection in archaeological sites.

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 will be 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. Once commonsense knowledge has been acquired then I should analyze the knowledge for finding dependencies. The questionnaire has been analyzed by using principal component analysis to find dependencies. 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.

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 using Fuzzy logic. It is consisted with following stages:

Fuzzfication

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.

Fuzzy 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.

Design

The questionnaire has been analyzed by removing dependencies among the questions that are modeled by principal component analysis based on survey results. Classification of the knowledge is processed through fuzzy logic module, which is constructed on the basis of principal components.

In the fuzzy logic modules, fuzzy sets have been constructed for environmental data based on the output of principal components analysis. Fuzzy rules have been constructed for classifying environmental data (Fig.1).

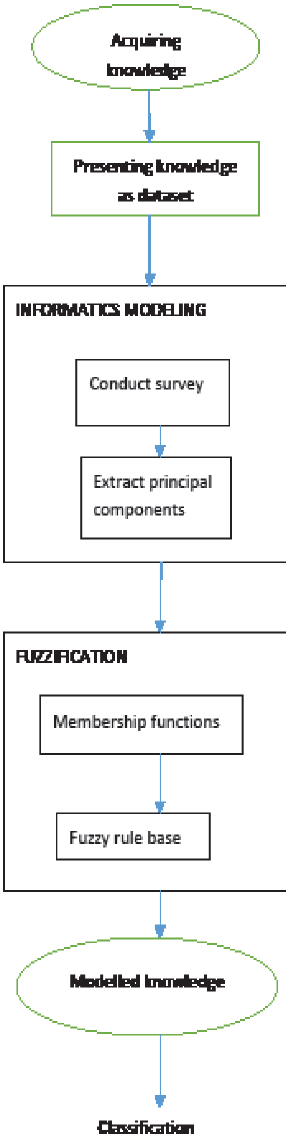

Fig.1: Knowledge modeling procedure

Therefore, this research presents a methodology to analyze environmental informatics modeling and data classification by using an intelligent system.

Intelligent land selection tool for land selection

The intelligent land selection tool is consisted of with modules such as principal component analyzer, database, knowledge base, and fuzzy logic (Fig.2),

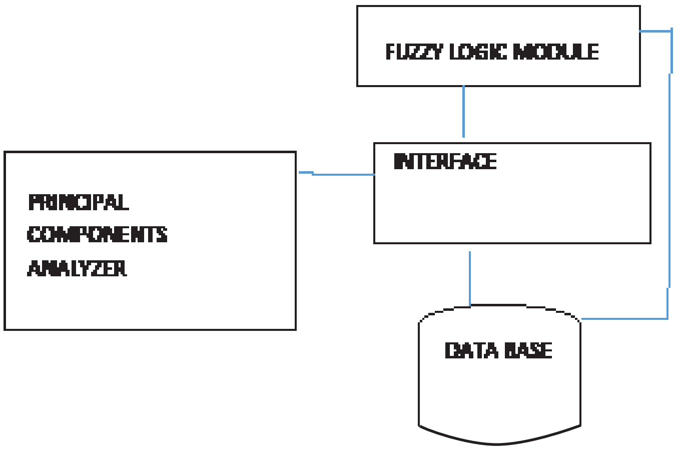

Fig.2: Top level architecture

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 Architect and knowledge engineer, commonsense knowledge has been acquired and mapped in to a questionnaire based on Likert scale technology. Commonsense knowledge will be 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. The questionnaire is based on Likert scale and stored in a MS ACCESS database (Appendix A).

Data from surveys has been analyzed by removing dependencies among the questions which are modelled by using principal component analysis based on sample of sites (Appendix A). So 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 4 number of principal components have been stored in a MS ACCESS database.

Removing Dependencies

At the initial stage, commonsense knowledge is converted into a questionnaire based on sample sites. Data from a sample of employees will be analyzed by removing dependencies among the questions which are modelled by using principal component analysis based on sample sites.

Table 1: Principal Component Matrix

Sheet1

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	-0.08243	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

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.

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

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 human constituents 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 or preferences 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 type in combinations.

Result & Discussion

This is further explained as development of intelligent land assessment tool for archaeological sites. It is mainly concerned with the development of land selection assessment, model refinement and classification as features of the system to be developed by an intelligent system for cultural heritage in archaeological sites (Table 2).

Table 2. Analysis of Land selection in archaeological sites

Land selection

District	Archaeological stic	Physical	Functional	Social
Trincomalee	Velagam Viharaya	4.04432	60.79982	35.15585
Mannar	Manthota Rajamaha Viharaya	17.31002	41.45678	41.2332
Jaffna	Kadurugoda Vihara	7.072626	44.11221	48.81516
Ratnapura	Divaguhawa	19.15861	37.91474	42.92664

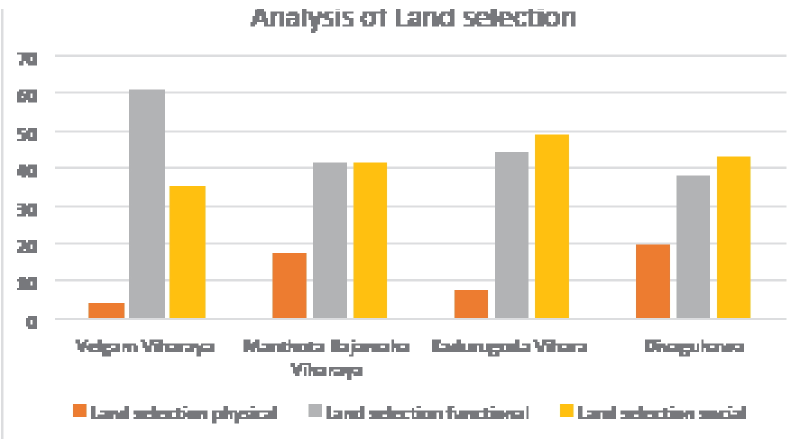

Fig. 3: Analysis of Land selection in archaeological sites

Physical	Functional	Social
11.896394	46.0708875	42.0327125

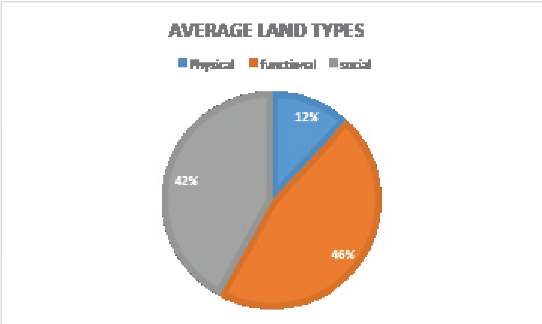

Fig.4: Average Land types

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

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 natural resource management in cultural heritage.

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VAR00001	1	2	3	4	1	6	1	1	1	1
VAR00002	3	3	4	3	3	3	3	3	2	3
VAR00003	3	1	5	2	5	5	2	2	3	4
VAR00004	2	5	2	5	2	2	5	5	5	2
VAR00005	2	3	6	6	6	4	2	6	2	5
VAR00006	1	2	3	2	3	1	6	2	5	6
VAR00007	3	6	3	1	2	2	2	1	6	3
VAR00008	2	2	5	2	3	4	1	2	2	2
VAR00009	2	6	3	1	4	3	3	3	1	4
VAR00010	4	3	2	2	2	6	5	4	6	6
VAR00011	2	2	4	3	3	4	3	5	3	2
VAR00012	2	1	3	4	4	3	2	6	2	4
VAR00013	6	4	6	6	3	2	6	2	1	1
VAR00014	4	2	3	4	2	1	3	1	5	3
VAR00015	5	4	3	3	4	6	2	2	2	4
VAR00016	4	3	6	2	5	3	1	3	5	5

Source: survey results