DEVELOPING A FUZYY INFERENCE SYSTEM BY USING GENETIC ALGORITHMS AND EXPERT KNOWLEDGE

(WITH A CASE STUDY FOR LANDSLIDES IN IRAN)

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February, 2014

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ABSTRACT

Meeting the need to produce hazard maps has become more urgent than ever due to recent natural disasters like earthquakes, tsunami and hurricanes. This urgent need makes the scientific community to work more and more on assessing and understanding such natural disasters to mitigate casualties. One of these major hazards is landslides, which may follow all the aforementioned disasters.

There are several methods for landslide susceptibility assessment. Most of them either use knowledge extracted from data or expert knowledge. Since all kinds of knowledge are not extractable from data and expert knowledge is inherently subjective, the need to develop a system for integrating knowledge is clearly tangible. Furthermore, spatial data contains uncertainty from different sources. Thus, it is necessary to consider uncertainty in the analysis. In this research, the purpose is to use computational intelligence and GIS for integrating knowledge extracted from data and experts into one system as well as adding the ability of learning and inference to the system. In this study, a fuzzy inference system is employed since it can simultaneously use extracted knowledge from data and expert knowledge, and it considers uncertainty in the essence of data by employing fuzzy logic concepts.

For developing such a fuzzy inference system, producing a fuzzy knowledge base is a significant step. For this step, C means fuzzy clustering and genetic algorithms are used to automatically extract knowledge from available data. Also, expert knowledge in form of membership functions and fuzzy rules are used to reinforce the fuzzy knowledge base. To have a better understanding of methods, comparisons are made between different situations.

Mazandaran province in the northern areas of Iran is selected as the case study of this research. The data used in this study contains related contributing parameters to landslide such as slope, curvature, aspect, lithology, landuse, distance to rivers, distance to faults and distance to roads.

The landslide susceptibility map of the area of interest is produced as the result of this study. And, comparisons are drawn between results in absence and presence of expert knowledge. For the system validation, RSE is computed as the precision of the system. The results show the superiority of the optimized fuzzy inference system by genetic algorithms in the presence of expert knowledge.

Keywords: fuzzy inference system, knowledge integration, landslide susceptibility mapping

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1. INTRODUCTION

1.1. Motivation and problem statement

Natural hazards such as earthquakes, floods, tsunamis, drought and landslides cause huge casualties including severe physical, psychological and financial damages every year (Erener., 2009; Venkatesan et al., 2013). Consequently, disaster management is gaining more importance among policy makers for taking preventive measures to mitigate vital and financial losses of future hazards (Pradhan et al., 2010). One of these recurrent widespread destructive natural hazards in mountainous areas is landslides. Statistical evidences show that 17 per cent of all fatalities from natural hazards are caused by landslides (Pourghasemi et al., 2012). Iran, subject of this study, is not an exception either. There, from 1967 to end of September 2007, 187 people were killed by landslides, and the financial loss is estimated around 12,700 million dollars (Pourghasemi et al., 2012).

Policy makers intend to prevent expanding urban and man-made structures into areas at risk due to climatologic and geologic conditions and high tectonic activities (Pourghasemi et al., 2012; Vahidnia et al., 2010). Thus, the significance of producing landslide susceptibility maps which portray the spatial distribution of landslide hazards and predict the location of probable slope failures becomes evident in overall landslide hazard management. Different methods have been employed to assess landslide hazard. The reliability and quality of landslide hazard maps depends on the adopted methods. Hence, it is necessary to further develop existing methods to improve the quality and reliability of these maps.

In early stages, the existence of uncertainty in spatial phenomena has drawn the attention of GIS experts to fuzzy logic. Fuzzy logic is a part of soft computing which was first developed by Zadeh in 1987 for the purpose of creating a new generation of computational intelligence to understand real world phenomena (such as landslide) by considering the uncertainty in their essence. Fuzzy inference systems are one of the most important applications of fuzzy logic which are widely used in recent years (Aslani, 2011). Their core is a fuzzy knowledge base consisting of fuzzy rules (A fuzzy rule is defined as a conditional statement in the form of *if-then* rules) and membership functions (A membership function assigns a value between 0 and 1 to particular items which are going to be classified, and these values show the degree of membership to that class) (Ishibuchi et al., 2004).

In most researches done in the field of GIS, fuzzy rules and membership functions are extracted in either knowledge-driven or data-driven approaches. In knowledge-driven approaches, experts' knowledge is converted to fuzzy rules and membership functions, which is a hard task and may produce not sound results (Herrera et al., 1998). In data-driven approaches, fuzzy rules and membership functions are mined from the data through training phases by using methods like soft computing procedures (Saridakis et al., 2008). But, data-driven approaches are not always applicable since the quantity, distribution and reliability of data should be acceptable, and some fuzzy rules are not directly extractable from the data (Aslani, 2011). For compensating the drawbacks of each approach, it is possible to integrate them into one system to produce more reliable knowledge base. Knowledge-driven approaches can make up for deficiencies in physical data, while data-driven approaches clear some of the subjectivity from individual views (Vahidnia et al., 2010).

For automatic knowledge extraction, different methods exist. It is not possible to define the most accurate method unless they are tried and compared for the desired application (Aslani, 2011). In this research,

fuzzy C means clustering is employed to extract initial knowledge since it has been effectively applied in a wide variety of geo-statistical analysis problems (Bezdek et al., 1984; Mingqin Liu et al., 2002). Fuzzy C means clustering is an algorithm for clustering crisp data with fuzzy boundaries and as a result of this clustering, fuzzy rules and membership functions are extractable (Liu et al., 2002; Wu et al., 2005).
Also, it is possible to integrate different aspects of soft computing on the basis of united frameworks to outperform conventional methods (Saridakis et al., 2008). For example, fuzzy inference systems have their own advantages like the ability of incorporating human expert knowledge. However, lacking a clear design methodology, and the absence of learning capabilities in these kinds of systems is known as an important downside of them (Cordón et al., 2001). For dealing with these problems, the ability of learning can be added to fuzzy inference systems by genetic algorithms as evolutionary algorithms through genetic fuzzy systems. Genetic algorithms are powerful tools for producing fuzzy rules, membership functions and the optimization of them.
In this study to form the fuzzy inference system, firstly, an initial fuzzy knowledge base is produced by fuzzy C means clustering algorithm. Then, genetic algorithm and fuzzy inference system are integrated into a genetic fuzzy inference system (with a case study for landslides in north Iran). Next, expert knowledge is added to this genetic fuzzy inference system to improve it where the rules are not directly extractable from data-driven methods.

1.2. Research identification

The main objective of this research is to integrate knowledge extracted from data and expert knowledge into one fuzzy inference system for landslide risk mapping. To achieve this goal, genetic algorithms and fuzzy inference system are combined into one genetic fuzzy inference system for extracting knowledge from data. Next, expert knowledge in the form of fuzzy rules is added to the system. Finally, this system is used to provide landslide susceptibility map for a vulnerable area located in north of Iran. The produced susceptibility map could be employed in many fields such as engineering geology, geomorphology and land use policy making.

1.2.1. Research objectives

The specific objectives of this research are:

- Extracting knowledge from data by producing elements of the initial fuzzy inference system
- Converting expert knowledge to fuzzy rules and membership functions
- Adding capability of learning to fuzzy inference systems by integrating fuzzy inference system and genetic algorithms for landslide hazard mapping
- Employing the produced fuzzy rules and membership functions for landslide hazard mapping

1.2.2. Research questions

The research questions of this research are:

1. How to extract knowledge from data (producing the initial fuzzy inference system and its elements)? What is the best method?
2. How and where to use the expert knowledge for this case study? How to integrate the expert knowledge and knowledge extracted from data into one system?
3. How to integrate the fuzzy inference system and genetic algorithm? Which method suits this case study best?
4. What are the inputs of the system for producing landslide hazard map in the region of interest? How to assess the degree of landslide vulnerability for other parts of the region according to the extracted fuzzy rules?

1.2.3. Innovation aimed at

One of the weaknesses of the common data mining methods is that they do not consider expert knowledge. In this research we are going to integrate expert knowledge with extracted knowledge from data to produce landslide susceptibility maps. The novelties of this research are:

- Employing the combination of evolutionary algorithms (genetic algorithm) and fuzzy inference system (and producing genetic fuzzy inference system) for landslide hazard mapping
- Integration of expert knowledge with extracted knowledge from data through genetic fuzzy inference system to produce landslide susceptibility maps.

1.3. Thesis structure

The thesis consists of six chapters. Chapter one includes the research background, problem statement, research objectives, research questions and innovation of the research. Chapter two reviews the available literature in landslide hazard mapping and presents the employed related methods to most important aspects of the research. Chapter three starts with a brief description to uncertainty, fuzzy inference systems and their related concepts, and this is completed by describing C means fuzzy clustering algorithm. Chapter four starts with introducing the genetic algorithm and its functionality, this is followed and completed by discussion about genetic fuzzy inference systems. Chapter five is about data description, suggested procedure and methodology. Chapter six includes experiments about extracting knowledge from data and converting expert knowledge to fuzzy rule, results and discussion. And, chapter seven is all about conclusion and recommendations for future works.

2. LITERATURE REVIEW

Various methods are employed for landslide hazard mapping. These methods and applied techniques are classified into quantitative and qualitative approaches (Bui et al., 2012; Xie et al., 2004). These classes are briefly introduced in section 2.1 and 2.2. In these sections, we try to show the path leading to choose a genetic fuzzy inference system as a quantitative method for landslide hazard mapping.

2.1. Qualitative methods

Qualitative approaches delineate the hazard zones in descriptive terms by relying on the expert opinion (Xie et al., 2004). These subjective methods include mapping of spatial distribution of mass movements by using total stations, aerial photo interpretations, global satellite navigation systems, field surveying and catalogue of historical landslides in the region (Erener, 2009). Erener (2009) presented an overview of qualitative methods employed by different researchers in different areas during last years.

In all these methodologies, experts of geomorphology decide on the degree of hazard for each zone usually based on their experience directly in the field (Qualitative approaches are classified as direct and indirect methods. This method of producing the map in the field is called direct), and after fieldwork interpretation of detailed geomorphological maps (Indirect methods). In these methods, the index maps are weighted based on expert knowledge and combined by some processes such as overlay. The main disadvantage of all these methods is that they are time-consuming, expensive, expert knowledge dependent and hardly reproducible (Erener, 2009; Xie et al., 2004). The quantitative methods introduced in the next section are suggested to deal with these drawbacks.

2.2. Quantitative methods

These methods got attention in last decades due to the prevalence of computers. Quantitative methods are data dependent, and these methods usually do not use expert knowledge. The success of these methods is dependent on the quality, quantity and reliability of the data. Quantitative methods predict numerical estimations for the likelihood of landslide occurrence in the regions of interest. These methods are indirect and they usually use a landslide inventory map in combination with the landslide conditioning factors for landslide susceptibility mapping (Bui et al., 2012). Quantitative approaches use mathematical solutions. The main mathematical framework used for these approaches are classified into statistical methods, geotechnical models and soft computing approaches. All these methods estimate the likelihood of landslide incidence numerically at every point in the region of interest (Ercanoglu et al., 2002; Erener, 2009). These three classes are described in following paragraphs.

Many studies used statistical models. These are the most popular quantitative methods because of their adaptability to GIS environment (Akgün et al., 2007; Erener, 2009). These methods are based on finding the relationship of each factor and the distribution of the landslides (Akgün et al., 2007; Erener, 2009). The statistical methods are categorized into bivariate (Fernández et al., 2003) and multivariate methods. Multivariate methods consider that all contributing factors to landslide are correlated to each other, but bivariate methods consider them independent (Huabin et al., 2005). Statistical models require systematic collection and analysis of data for different factors which is quite expensive and demanding, and that is known as drawback of these models (Aleotti et al., 1999).

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Geotechnical models are widely used in civil engineering and engineering geology for slope stability analysis of a single slide (Xie et al., 2004). These approaches are based on physical laws, and that help to understand the cause of landslides. But, collecting reasonable geotechnical data is quite costly (Erener, 2009) and that is known as drawback of these methods.

Recently, using soft computing techniques for landslide mapping became popular. Soft computing as a multi-branch scientific domain is firstly introduced by professor Zadeh in 1981 to produce a new generation of artificial intelligence (Aslani, 2011; Saridakis et al., 2008). Soft computing areas include fuzzy logic, neural networks, evolutionary algorithms and probabilistic computing. The main purpose of soft computing is developing intelligent systems for solving nonlinear and complex problems (Saridakis et al., 2008). One of the most important parts of soft computing is fuzzy logic which was firstly introduced by Zadeh (1965). The purpose of fuzzy logic is to investigate spatial phenomena by considering the existent uncertainty in them. This uncertainty stems from different sources including random observation, shortage of data and the nature of the phenomena (Brimicombe, 2010). One of the important applications of fuzzy logic in inference machines are fuzzy rule-based inference systems (FRBIS) (Wang, 1996). In the literature, they are also called: fuzzy inference systems, fuzzy rule-based systems, fuzzy expert systems and fuzzy systems (Elsayed, 2009). The existence of uncertainty in spatial phenomena and the need of GIS systems to inference, brought FRBISs in the attention of GIS experts in recent years (Cay et al., 2011; Reshmidevi et al., 2009). Thus, in this research, a FRBIS is employed for landslide susceptibility mapping due to uncertain nature of the landslide data. Therefore, it is necessary to be familiar with basic concepts of fuzzy logic, uncertainty, expert systems and FRBISs. All concepts, structures, characteristics and applications related to abovementioned terms are comprehensively introduced in chapter three.
The core of a fuzzy inference system is a fuzzy knowledge base consisting of fuzzy rules and membership functions. As described in chapter one, these fuzzy rules and membership functions are produced by either expert knowledge or automatic knowledge extraction from data in the previous studies (Vahidnia et al., 2010).
In the following paragraphs, a number of studies employing these concepts for landslide susceptibility mapping and their week points are reviewed to reach the suggested solution of this study.

Wang et al. (2009) produced a landslide susceptibility map for an area in China by using fuzzy logic. They used expert knowledge about the importance of layers. But, not using fuzzy logic concepts for the integration of spatial layers caused to have an impaired uncertainty modelling and precision reduction.

Fatemi et al. (2005) employed a fuzzy inference system for landslide susceptibility mapping in northern regions in Iran. In their system, membership functions and fuzzy rules are extracted by interviewing landslide experts. This non-automatic method of producing fuzzy inference system elements is time consuming, subjective and difficult. In addition, it usually does not lead to logical results. Thus, it is necessary to produce fuzzy rules and membership functions in an automatic way.

Sezer et al. (2011) used neural networks for automatic extraction of fuzzy rules and membership functions. Their proposed system is an integration of fuzzy inference system and neural network. In their research, this system is used for landslide susceptibility mapping in Malaysia. The complexity of their system is known as its drawback. To avoid complexity in the present study, C means fuzzy clustering is used to generate the fuzzy rules and membership functions automatically (Ramze Rezaee et al., 1998). The comprehensive introduction to this method is presented in chapter three.

For compensating the drawbacks of common data-driven approaches (applications of fuzzy logic, neural networks, etc., and their combinations), their integration with knowledge-driven approaches for landslide hazard mapping and other spatial and non-spatial applications is also used in many researches (Dong, 1986; Melchiorre et al., 2008; Zhu et al., 2004; Xie et al., 2004). Since the quantity of landslide data is not sufficient, it is quite possible that the fuzzy inference system based on available datasets does not show suitable functionality. Thus, by converting expert knowledge to fuzzy rules and membership functions in chapter five, it is tried to reform the functionality of the system.

3. FUZZY INFERENCE SYSTEMS

3.1. Expert systems

Expert systems are intelligent computer programs that use knowledge and inference methods for solving complicated problems that need human expertise and skill (Durkin, 1994). These systems have many advantages. They are fast, cost effective and can be used in dangerous environments for humans (Durkin, 1994). Expert systems are weak in modelling complex problems since they are dependent on true and false values. But, there are fewer problems in real world that can be defined by certain values, since these problems are associated with uncertainty. For increasing the capability of expert systems, they are combined with fuzzy logic and named fuzzy inference systems (Wang, 1996). Fuzzy logic is proposed for solving complex problems by considering uncertainty in their nature. Thus, it is necessary to be familiar with uncertainty definition, sources and solutions. In this chapter, uncertainty is introduced in section 3.2. Then, basic concepts of fuzzy logic are introduced in chapter 3.3. In the next sections, the fuzzy inference systems, their design, applications and related concepts are introduced.

3.2. Uncertainty

Naturally, all kinds of data are associated with a degree of uncertainty and errors, and this comes from different sources (Brimicombe, 2010; Li et al., 2007). Uncertainty is defined as any aspect of the data, its collection, storage, manipulation, presentation, analysis, GIS functions and cartographic representation that may cast doubt to the results (Fisher, 1999; Openshaw, 1989).

Most common symbols of uncertainty mentioned in the literature are (Brimicombe, 2010):

Error is the deviation from the truth. The twin of error is *accuracy* which is the degree of accordance of observations with truth. *Precision* is the possible smallness degree of the observations. *Reliability* is the trust that is assigned to a set of input data according to available metadata and user control. *The fitness for use* is evaluated quality of the products of analysis employed in decision making.

The following figure shows main sources of uncertainty in spatial data.

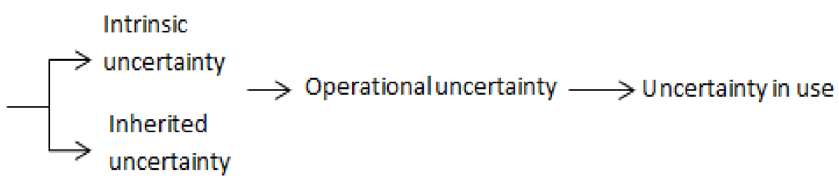


Figure 3-1: Uncertainty sources (Brimicombe, 2010)

In this figure, two branches of uncertainty are given. Intrinsic and inherited uncertainty are respectively attributed to primary and secondary methods of data acquisition (Brimicombe, 2010). The uncertainty emanated from software and hardware imperfection is named operational uncertainty (Brimicombe, 2010). Uncertainty in use is caused by misunderstanding of output by the user (Brimicombe, 2010).

3.2.1. Uncertainty reasons

All kinds of uncertainty arise from the fact that no observation from geographical phenomena is perfect (Brimicombe, 2010). The reasons given for the uncertainty in the literature are:

- **Imperfect measurement:** Very often, measurements are combined with blunders coupled with distributing around a truth value in relation to equipment's precision (Fisher, 1999).

- **Imperfect digital representation of phenomena:** Very often, the generalization of cartographic objects happens before, during and after the process of digitizing (Fisher, 1999).

- **Imperfect data entry and subjective judgement:** Very often, data collection methods are dependent on expert knowledge and data is miscoded during manual and electronic entry to GIS.

If the geographical object and its boundary are well defined, the uncertainty is just related to error (Abovementioned points), but if they are poor defined, the uncertainty is related to ambiguity and vagueness (Following points) (Fisher, 1999).

- **Ambiguity:** the suitability of the meaning of the geographical object is known as semantic accuracy or ambiguity. Semantic confusion occurs when commonly used words can have ambiguity and where precise definition of feature classes are not available (Brimicombe, 2010; Fisher, 1999).

- **Vagueness:** Because of numerous affecting factors and complexity of the systems at work, natural variations which exist in many areas make hard to give exact definition of the objects and their boundaries (Brimicombe, 2010). The solution to this problem is considering the phenomena imperfectly organized, incompletely structured and not exactly accurate (Morris, 2003; Schneider, 1999). Putting it another word, the phenomena are fuzzy. The best approach is keeping the data in fuzzy form, process them by fuzzy operators and producing fuzzy results (Morris, 2003; Schneider, 1999). In the present research, fuzzy logic is employed to deal with this type of uncertainty.

3.2.2. Solutions to deal with uncertainty

For modelling uncertainty, there is not a single best method for various data handling and transformation functions (Brimicombe, 2010; Li et al., 2007). Partly, this is known due to lack of a single, accepted theory of uncertainty in GIS (Brimicombe, 2010). And partly, it is because the fact that various GIS functions react to uncertainty in different ways (Brimicombe, 2010). Therefore, it is necessary to model uncertainty from the viewpoint of GIS functionality (topological overlay and interpolation), then move to more general issues like fuzzy concepts and uncertainty analysis (Morris, 2003).

For the first time, Zadeh (1965) proposed the concept of fuzzy sets and their associated logic. The advantage of fuzzy sets compared to traditional mathematics is their ability to describe classes of inexact objects (Brimicombe, 2010). Imprecisely defined classes play an important role in human thinking. Thus, fuzzy sets found early applications in engineering fields. In the next sections, the realm of fuzzy logic is briefly introduced.

3.3. Fuzzy logic and fuzzy sets

Suppose X is a universal set, for each fuzzy set like A, the membership function μ_A is defined as following (Dubois et al., 2000; Zadeh, 1965) : $A = \{(x, \mu_A(x) / x \in X\}$

The fuzzy set A is featured with the membership function μ_A. That means each point in x is attributed to a real number in the range of [0, 1] by this function. The nearer function values to one, the greater the membership grade to A (Dubois et al., 2000; Zadeh, 1965).

3.3.1. Common membership functions

Membership functions are used to map non-fuzzy input to fuzzy output and vice versa. There are different forms of membership functions such as triangular, trapezoidal, piecewise linear, Gaussian and singleton (Höhle et al., 1999). The most common types of membership function are triangular, trapezoidal, and Gaussian shapes which some of them are shown in the following figure:

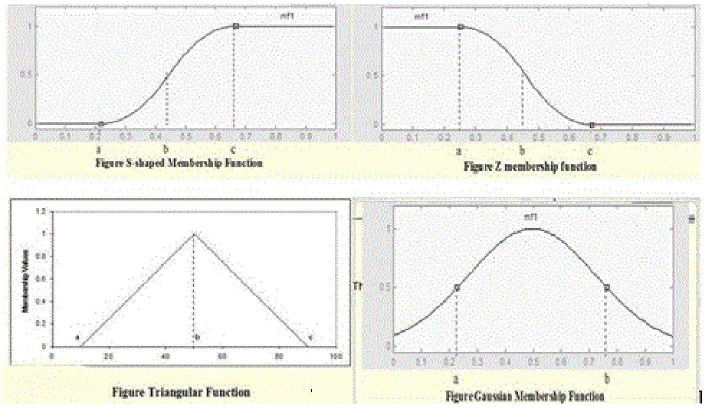


Figure 3-2: Common membership functions

3.3.2. Linguistic variables

If one variable can be assigned with natural words, it is named a linguistic variable. For example, temperatures can be understood by words like cold, mild and hot (Wang, 1996; Zadeh, 1965).

3.3.3. If-then fuzzy rules

If-then fuzzy rules are conditional phrases that show the association of one or more linguistic variables to each other. One simple if-then rule is shown as below (Dubois et al., 1996):

If<antecedent>then<consequence>

3.4. The structure of Mamdani-type fuzzy rule-based systems

Fuzzy inference systems or fuzzy rule-based systems (FRBS) are based on if-then rules, they can extract the relationship between some inputs and outputs by using these rules. These systems usually are used for modelling the phenomena containing high degrees of uncertainties. These systems are based on formulating the process of mapping from input to output by using the fuzzy logic which is named fuzzy reasoning (Cordón et al., 2001; Hamam et al., 2008; Wang, 1996). Two famous kinds of these systems are Takagi-Sugeno and Mamdani. In the following parts, the structure of these systems and their strong and weak points are described in order to decide which fuzzy inference system is suitable for this research.

The main components of Mamdani fuzzy inference system is shown in following figure (Abraham, 2005; Wang, 1996):

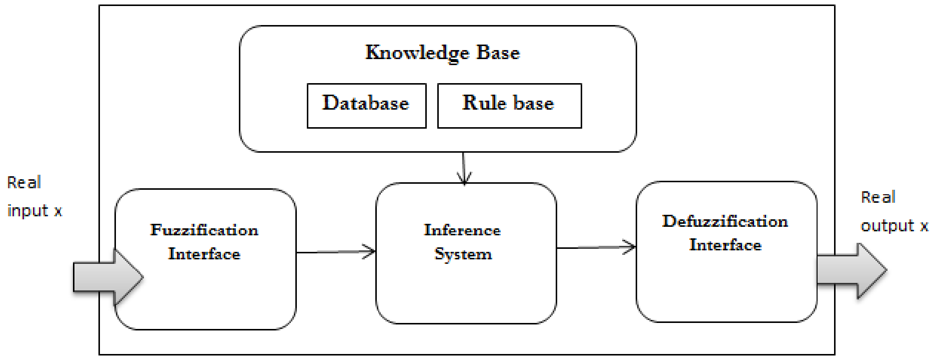


Figure 3-3: Mamdani fuzzy inference system (Cordón et al., 2001)

- **Knowledge Base:** knowledge base stores all data, information, rules and relationships which are used by expert system, and one of the methods for representing knowledge in knowledge base is using If-Then rules. Each rule is made of one antecedent (If-part) and one consequent (Then-part), and by combing these rules, it is possible to solve complicated problems.
- **Fuzzification interface:** Fuzzification interface receives the certain inputs and define how related they are to appropriate fuzzy sets in dependency rules.
- **Defuzzification interface:** The input of a defuzzifier is a fuzzy set, and the output is a certain amount.
- **The Inference engine:** Inference system is in fact the brain of the expert system which processes the stored rules and knowledge, the inference engine can be established based on different logics like fuzzy logic and it usually employ statistical computations for fulfilling its tasks.

3.4.1. Advantages and disadvantages of Mamdani-type fuzzy rule-based systems

A Mamdani-type FRBS shows several interesting characteristics. First of all, it prepares a natural framework to employ expert knowledge in the form of interpretable fuzzy rules (Cordón et al., 2001; Hamam et al., 2008). Because of the intuitive nature of their rule base, they are widely employed for decision support applications since they can present reasonable results with simple structure (Hamam et al., 2008). However, Mamdani FRBSs also have some disadvantages. One of the main problems is lack of accuracy due to the structure of the rules in some complex problems (Cordón et al., 2001).

DNF Mamdani fuzzy rule-based systems and Approximate Mamdani-type fuzzy rule-base systems have been proposed as alternatives when week points of Mamdani FRBSs are bold. The descriptions of these two systems are presented in Cordón et al. (2001).

3.5. Takagi—Sugeno—Kang Fuzzy Rule-Based Systems

A new idea is proposed in this model that antecedent is made of linguistic rules of the kind that is introduced previously, but consequent is symbolized by a function of the input variables (Chang et al., 2008; Cordón et al., 2001).

IF X_1 is A_1 and …and X_n is A_n THEN $Y=p_1.X_1+\ldots+p_n.X_n+ p_0$

In this formula, X_i is the system input variables, Y is the output variable and $P= (p_0, p_1, \ldots, p_n)$ is a vector of real parameters (Chang et al., 2008; Cordón et al., 2001).

The following figure shows a graphical representation of this kind of FRBS (Cordón et al., 2001).

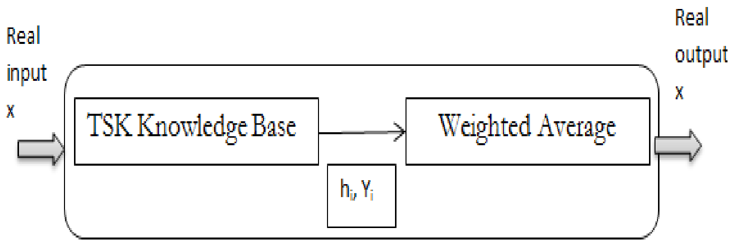


Figure 3-4: Basic structure of a TSK fuzzy rule base (Cordón et al., 2001)

The easier and more flexible design process is known as the main advantages of these systems since more parameters are allowed in the rules (Cordón et al., 2001; Hamam et al., 2008). Also, they provide higher computational efficiency and accuracy (Casillas, 2003; Chang et al., 2008; Cordón et al., 2001; Hamam et al., 2008). However, the drawback of this system is that the interpretation of TSK FRBSs is difficult compared to Mamdani FRBSs due to the complex structure of rule consequents to human experts (Casillas, 2003).

Keeping in mind the characteristics, weak and strong points of these two systems, in this research, Mamdani fuzzy inference system is used since it is more common and simple. In addition, it eases the simultaneous knowledge (from data and expert) employment and its interpretation. Moreover, to assess the functionality of this system, the concepts of the completeness and consistency of its rule set are considered, as it is suggested in the literature. These concepts are briefly introduced in section 3.6 and comprehensively described in section 3.9.

3.6. The functionality of a FRBS

The effectiveness of a FRBS is directly associated with the composition of the fuzzy rule set (Cordón et al., 2001; Gonzalez et al., 1998; Jin et al., 1999). The main characteristics of fuzzy rule sets which considerably affect the system functionality are introduced as following.

- **Completeness of a fuzzy rule set**

A FRBS should have the completeness property. That means each understandable system input corresponds to an output (Cordón et al., 2001; Jin et al., 1999). For each input x_0, at least one of the fuzzy rules has to be triggered.

- **Consistency of fuzzy rule set**

A fuzzy rule set is not consistent if it has rules with same antecedent and mutually exclusive consequent (Cordón et al., 2001; Jin et al., 1999).

3.7. Extracting initial fuzzy knowledge base

For forming a fuzzy inference system, the initial fuzzy membership functions and fuzzy rules should be produced. The initial fuzzy knowledge base can be produced either automatically (by using a training dataset) or non-automatically (by using expert knowledge). Each method has its advantages and disadvantages which were previously mentioned. For automatic initial fuzzy knowledge base extraction, different methods are suggested. Some of these methods based just on fuzzy logic concepts like fuzzy C means clustering, and others employ evolutionary algorithms as well. In this study, firstly, fuzzy C mean clustering is used to extract initial knowledge base. Next, genetic algorithms as evolutionary algorithms are used to optimize the knowledge base. To extract the initial knowledge base, other methods such as

Generating fuzzy rules by learning from examples is suggested by Wang et al. (1992). It is not possible to decide which method shows the best performance for this case study unless they are tested and compared. Considering the fact that fuzzy C means clustering is an algorithm for clustering crisp data with fuzzy boundaries (Liu et al., 2002; Wu et al., 2005), this method is used for initial extraction from data in this research.

3.8. Fuzzy C means clustering

By clustering a set of input and output data in a training dataset, it is possible to automatically produce initial membership functions and fuzzy rules. In this research, a model for one output (Landslide intensity) and several inputs (Eight contributing factors to landslide) is used. In this model, X is the vector of input data which have p dimensions (P is eight in this case), Y is the vector of output data by one dimension, and n is the number of training dataset records (Pal et al., 2002) (The training dataset used for this research contains 129 records. Thus, n is 129 for this research).

$X = \{x_1, x_2, x_3, \dots, x_n\} \subset R^p$

$Y = \{y_1, y_2, y_3, \dots, y_n\} \subset R$

If input and output vectors are integrated into one vector, dimension of this vector will be P+1.

$X^* = \begin{pmatrix} x_i \in R^p \\ y_i \in R \end{pmatrix} \in R^{p+1}$ (In practical terms, the size of X^* is 9 by 129 in this research)

By clustering along X^* and projecting each cluster on X and Y axis, it is possible to produce the initial fuzzy membership functions and rules. The following figure shows how initial fuzzy rules and membership functions are produced for two inputs and one output.

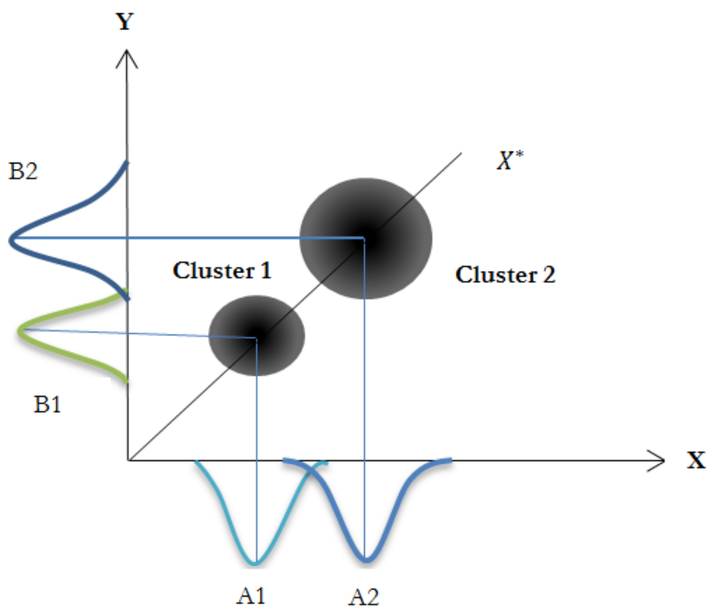


Figure 3-5: fuzzy C means clustering

Extracted rules: R1: IF X=A1 Then Y=B1
R2: IF X=A2 Then Y=B2

As it is visible in this picture, the number of fuzzy rules and memebership functions are equal to the number of clusters. Moreover, Gussian membership functions by equation (1) are fitted to the clusters.

In following formulas, C is the center of gussian membership functions, and σ is the standard deviation of these clusters. (N is the number of clusters):

$$\text{Gauss}\ (x; c, \sigma) = \exp\left(-\frac{(c-x)^2}{2\sigma^2}\right) \tag{1}$$

$$C_j^k = f_j^k \quad (k = 1, \ldots, p+1)\ and\ (j = 1, \ldots, N\ ) \tag{2}$$

$$\sigma_j^k = \sum_{i=1}^{n} \sqrt{\frac{\left(x_i^{*k} - f_j^k\right)^2}{2\log m_{ij}}} \tag{3}$$

As described previously, fuzzy C means clustering is an algorithm for clustering crisp data with fuzzy boundaries (Liu et al., 2002; Wu et al., 2005). In this method, every sample of data can be assigned to several clusters with various membership degrees. This algorithm receives the number of clusters (C parameter) as an input, and divides n objects to C clusters in a way that the inner similarity of clusters is high, and the outer similarity between clusters is low. The number of clusters (C) is defined by $c_{max} \leq \sqrt{n}$ (n is the number of training dataset records). In fact, the purpose of this algorithm is minimizing formula (4) and (5) (Pal et al., 2002). In these formulas, μ_{ik} is the membership degree of data k to cluster i, v_i is the centre of cluster i and weighted average of x_k.

$$j = \sum_{i=1}^{n} \sum_{k=1}^{n} (\mu_{ik}) \parallel x_k - v_i \parallel^2 \tag{4}$$

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m \ .x_k}{\sum_{k=1}^{n} \mu_{ik}} \qquad m > 1 \tag{5}$$

For assessing the different possible fuzzy inference systems generated by C means fuzzy clustering algorithm (According to the number of clusters introduced to the algorithm), it is necessary to design some defining factors. It is common to consider the best number of clusters according to the compactness and separation of them. But, these concepts consider the status of the clusters in relation to each other while it is necessary to consider the status of the clusters in a fuzzy inference system.

Therefore, incompleteness, inconsistency and RSE (Root Squared Error) of the fuzzy inference systems generated by different possible runs for the fuzzy C means algorithm are considered as criteria to choose the most functional fuzzy inference system in this study. A brief introduction to incompleteness and inconsistency of the fuzzy inference systems is given in section 3.6. The concept and mathematical expression behind these two factors are comprehensively described in section 3.9. Incompleteness and inconsistency assess the sensibility of the fuzzy inference systems and the RSE estimates the precision of these systems. Sections 5.3 clarifies how all these concepts are employed in different steps of the implementation to assess the system.

3.9. Completeness and consistency of fuzzy inference system

The membership functions produced from clustering should be fitted to the available data. If the distribution of training data is not normal, the membership functions will be unreal and the fuzzy inference system will be incomplete and incompatible (Jin et al., 1999). These criteria are used for assessing the functionality of different fuzzy inference systems produced by clustering (Jin et al., 1999).

- **Incompleteness**

If the membership functions and the rule structure of a fuzzy inference system are complete, the fuzzy inference system is called complete. For modelling the completeness in this study, the fuzzy similarity between membership functions is used. Fuzzy similarity between membership function A_i and A_{i+1} is defined as following formula (Jin et al., 1999):

$$\mathrm{S(Ai, Ai+1)} = \frac{M(\mathrm{Ai} \cap \mathrm{Ai+1})}{M(\mathrm{Ai} \cup \cap \mathrm{Ai+1})} \tag{7}$$

In this formula, the numerator is the area under graph and limited to intersection of A_i and A_{i+1}, and the denominator is the area under graph and limited to union of A_i and A_{i+1}. If the fuzzy similarity is near to zero, membership functions are incomplete and they do not have any overlap. But, if this amount is large, they are not distinguishable. Therefore, an upper and lower limit is defined for this index to control the similarity and distinguishability of the fuzzy membership functions (Jin et al., 1999).

$$LB \leq \mathrm{S(Ai, Ai+1)} \leq UL \tag{8}$$

If the fuzzy similarity is out of above range, the difference is considered as penalty for the fuzzy inference system, and the overall penalty is the summation of all penalties for all two adjacent membership functions (Jin et al., 1999).

- **Inconsistency**

The fuzzy rules are inconsistent, if the antecedents are similar but the consequents are different. For two rules R_i and R_k, the similarity of rule premise, similarity of rule consequent, consistency of two rules are respectively defined as (10), (11) and (12) (Jin et al., 1999):

$$R_i = If\ (x_1, A_{i1}(x_1) \ldots . And\ x_n, A_{in}(x_n))\ Then\ y, B_i(y)$$
$$R_k = If\ (x_1, A_{k1}(x_1) \ldots . And\ x_n, A_{kn}(x_n))\ Then\ y, B_k(y)$$
$$SRP(i,k) = min_{j=1}^{n} \mathrm{S}(\mathrm{A_{ij}}, \mathrm{A_{kj}}) \tag{10}$$
$$SRC(i,k) = \mathrm{S}(\mathrm{B_i}, \mathrm{B_k}) \tag{11}$$
$$\mathrm{Cons}(R_i, R_k) = \exp\left\{\frac{\left(\frac{SRP(i,k)}{SRC(i,k)} - 1\right)^2}{\frac{1}{SRP(i,k)}}\right\} \tag{12}$$

If the rules have the similar antecedents and consequents, the inconsistency of the rule i in rule base is computed as below (Jin et al., 1999):

$$\mathrm{Incons(i)} = \Sigma_{k=1}^{N} [1 - \mathrm{Cons}\ (R_i, R_k)] \tag{13}$$

Finally, the inconsistency of fuzzy rule base is computed as below (Jin et al., 1999):

$$\mathrm{Incons}_{\ \mathrm{RuleBase}} = \Sigma_{i=1}^{N} \mathrm{Incons\ (i)} \tag{14}$$

In above relations, N is the number of rules. The most ideal fuzzy inference system is the one by minimum inconsistency and incompleteness.

4. GENETIC FUZZY INFERENCE SYSTEMS

Currently, there is an increasing intention to hybridize different aspects of soft computing to reinforce their ability to solve the problems (Herrera, 2008). One of the most common approaches in this realm is hybridization of fuzzy systems and evolutionary algorithms like genetic algorithm leading to reach genetic fuzzy system (GFS) (Carse et al., 1996; Cordón et al., 2004; Delgado et al., 2004; Herrera, 2008; Lee et al., 1993). Different kinds of GFSs are introduced in the literature, but the most common type is genetic fuzzy rule-based systems (GFRBSs) (Cordón et al., 2004; Herrera, 2005). In GFRBSs, the genetic algorithm learns or tunes the various units of fuzzy rule-based systems. They can optimize either the whole fuzzy rule-based systems or some desired components of it. Following figure depicts the described idea.

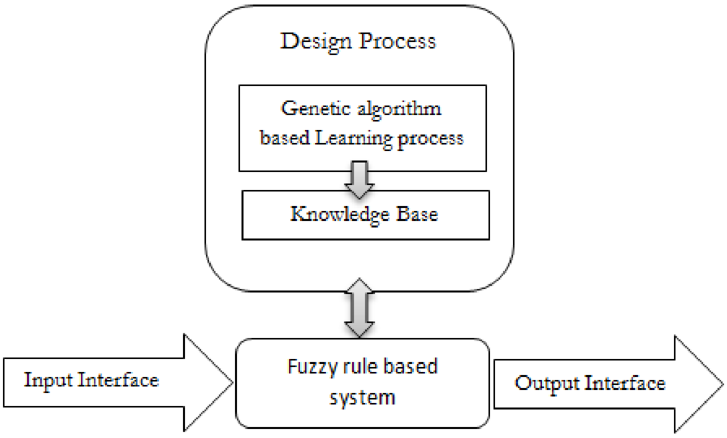


Figure 4-1: Genetic fuzzy systems

To understand GFSs, firstly, an overview of genetic algorithm is presented as following.

4.1. Genetic algorithms

Genetic algorithms (GAs) are designed for search purposes by inspiration of natural genetics to develop answers for questions (Affenzeller et al., 2009; Whitley, 1994). The general idea that genetic algorithms propose is suggesting a population of chromosomes that are candidates of solutions to the posed problem, and evolving this population through time and a process of competition (Man et al., 1996; Reeves, 1995). A portion of these chromosomes are used in forming new ones by considering their attributed fitness (Herrera et al., 1995; Whitley, 1994). The task of creation of these new chromosomes is done with genetic operators like crossover and mutation (Herrera et al., 1998).

This population experiences an evolution through the successful iterations called generations and a new population of chromosomes are formed (Whitley, 1994). To solve the problem, an evaluation or fitness function is required to be devised. By introducing chromosomes to the fitness function, it will return a single numerical fitness for each chromosome which shows the effectiveness of the solution proposed by the chromosome (Herrera et al., 1998). The basic essential steps of genetic algorithm are three operations: evaluation of individual fitness, formation of an intermediate population through selection step of GA and recombination by crossover and mutation operators (Herrera, 2005). The following figure illustrates this concept.

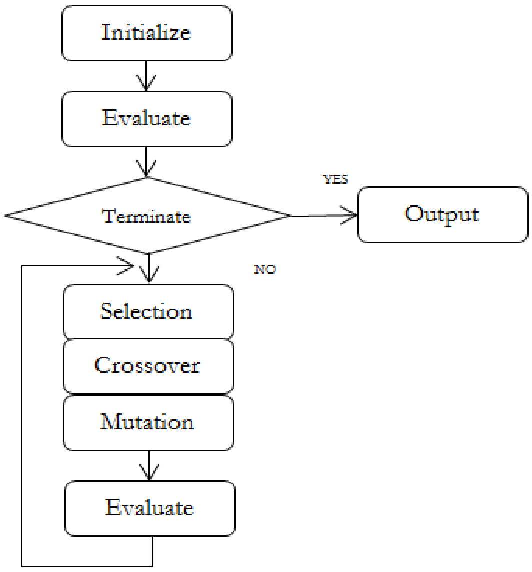


Figure 4-2: Genetic algorithm (Herrera, 2005)

4.1.1. GAs characteristics

Generally, the different components of GAs are listed as below (Herrera, 2005; Whitley, 1994):

- Encoding
- Evaluation or fitness function
- Reproduction function
- Selection mechanism
- Crossover and mutation mechanism
- Survival mechanism
- The stopping condition

These components are described in the following page.

4.1.2. Encoding

Encoding is the method of showing a single gene in genetic space. Different approaches are introduced for encoding, namely, permutation, value encoding (Mitchell, 1998).

- In permutation encoding, the chromosomes are developed in the form of a string of numbers. (Gen et al., 1997).

Chromosome A	1	5	3	2	4	7	9	8	6
Chromosome B	8	5	6	7	2	3	1	4	9

Table 4-1: Permutation encoding (Aslani, 2011)

- In value encoding, each chromosome is a string of values. These values can be floating numbers or coded objects.

Chromosome A	1.234	5.3243	0.4556	2.025 3
Chromosome B	Back	Right	Forward	Left

Table 4-2: Value encoding (Aslani, 2011)

In this research, value encoding is used to optimize Gaussian membership functions parameters (C and σ) and permutation encoding is used to optimize fuzzy rules.

4.1.3. Evaluation or fitness function

The fitness function defines the eligibility of a chromosome in the next generation. An ideal fitness function is closely related to the purpose of the genetic algorithm and feasibility of fast implementations (Srinivas et al., 1994).

4.1.4. Reproduction function

Reproduction function arbitrarily defines the initial population by a monotonous distribution. Reproduction is the first task which is implemented on the population. In this method, some chromosomes are selected from the population and are combined by crossover operation that leads to produce offspring.

4.1.5. Selection

If we consider p as a population of chromosomes C_1 to C_N, the selection procedure generates a new population (p') which contains copies of the first chromosomes in p. More suitable chromosomes with higher fitness value have the chance of being more copied (Whitley, 1994). There are different methods for selecting the parents described in the literature (Gen et al., 1997).

4.1.6. Crossover

Crossover is known as a method for information sharing between chromosomes. In fact, crossover chains the characteristics of two parent chromosomes to produce two children (Herrera et al., 1998; Srinivas et al., 1994; Whitley, 1994). In the first step, for choosing the parents, a random choice is applied according to the probability defined by a crossover rate (Herrera et al., 1998). Crossover rate is a value between zero and one and defines the proportion of next generation that is supposed to be created by crossover (the elite children are selected and transferred to the next generation before this). In the second step, a random place in the chromosome string is selected for crossover. In the third step, two strings are replaced with each other in the place of crossover.

- *Single sight crossover,* in this approach, first, one integer number (i) between one and n is selected (n is the number of the genes in the chromosome). Then, genes of the first chromosome up to i are added to genes of second chromosome from i onwards to produce the new chromosome. This concept is shown in the following figure (Melanie, 1999).

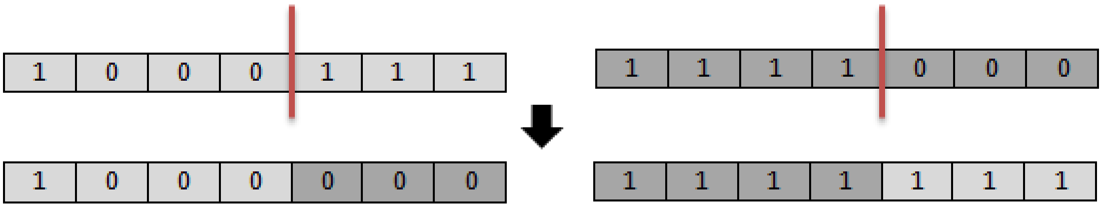


Figure 4-3: Single sight crossover operation(Aslani, 2011)

- *Two point crossover,* in this approach, two random numbers i and j are selected between one and n. Next, the child chromosome is formed by selecting genes less than i and greater than j in the first chromosome coupled with selecting genes between i and j from the second chromosome. In this method, from two parents, two chromosomes are produced. This concept is shown in the following figure (Melanie, 1999).

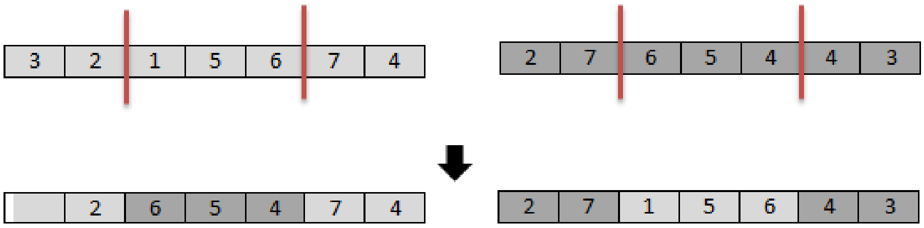


Figure 4-4: Two point crossover operation (Aslani, 2011)

4.1.7. Mutations

A mutation operator randomly changes some units of a chromosome to add variety to structure of the population. (Srinivas et al., 1994).

4.1.8. The stopping conditions

The stopping conditions are defined by considering the problem criteria and they have a huge impact on the final results. There are different stopping conditions which are listed as below (Gen et al., 1997):

- The algorithm can be stopped by a predefined number of iterations.
- The algorithm can be stopped when the difference between two chromosomes is less than a predefined threshold.
- The algorithm can be stopped when the desired factors reach to certain predefined amounts

4.1.9. Learning with GAs

GAs can function as domain independent search methods for a wide area of learning tasks (Srinivas et al., 1994). There are three approaches in which GAs are employed for learning procedures. These approaches are Michigan, Pittsburgh and Iterative Rule Learning approaches. In following sections, it is described how these approaches are used for optimization of knowledge bases.

- In *Pittsburgh* approach, each chromosome encodes the whole rule base or knowledge base. For example, suppose a fuzzy inference system has two inputs and one output, and three independent linguistic terms for each variable like it is outlined in the following table.

Input 1	**Input 2**	**Output**
Low=1	Low=1	Poor=1
Medium=2	Medium=2	Medium=2
High=3	High=3	High=3

Table 4-3: Example of a fuzzy inference system

Now, suppose that the following three rules exist in the rule base (x_1 and x_2 are the first and second input, and the Y is the output).

If x_1=low and x_2=medium then Y=poor.
If x_1=medium and x_2=medium then Y=medium.
If x_1=high and x_2=medium then Y=high.

These rules can be encoded to a chromosome as shown in the following figure.

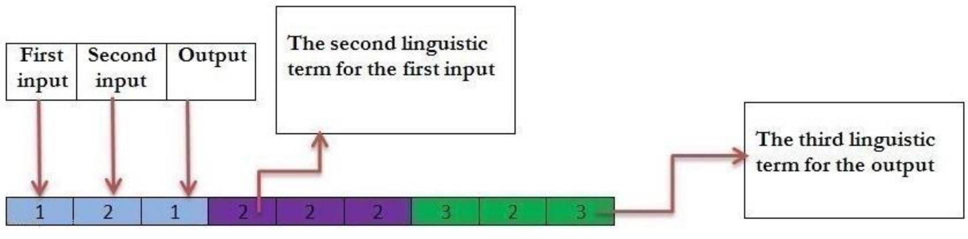


Figure 4-5: Rule encoding (Aslani, 2011)

If the purpose is to optimize the whole database, in addition to fuzzy rule base, the optimum form of membership functions should also be extracted. For example, the Gaussian membership functions have two parameters (C and σ). And, if each linguistic variable is expressed by four Gaussian membership functions, the following figure shows how the membership function parameters are coded into a chromosome and how linguistic variables are shown by these membership functions.

C_1	σ_1	C_2	σ_2	C_3	σ_3	C_4	σ_4	C_1	σ_1	C_2	σ_2	C_3	σ_3	C_4	σ_4	…

Table 4-4: Membership function parameters encoding

If the learning is done on the whole knowledge base, the both chromosomes of database and rule base should be attached.

- *Michigan learning approach,* in this method, each chromosome shows one rule, the whole rule base is the population and this population is optimized during the process (Herrera et al., 1998).
- *Iterative rule learning approach(IRL)*, in this model like Michigan method, each chromosome represents one rule, but despite to Michigan method, just the best individuals will be part of the solution and the rest of the chromosomes will be discarded (Herrera et al., 1998).

The abovementioned genetic learning methods (Pittsburgh, Michigan, IRL) have been known as methods for learning knowledge base components.

4.2. Genetic fuzzy systems

A genetic fuzzy system is a fuzzy system that is completed with evolutionary algorithms like genetic algorithm (Cordón et al., 2001). The common types of genetic fuzzy systems are genetic fuzzy inference systems. In these systems, genetic algorithms are used for optimizing the different components of the fuzzy inference system. However, genetic fuzzy systems have other types like genetic fuzzy clustering system, genetic fuzzy decision trees and genetic neuro-fuzzy systems (Cordón et al., 2001). But, in this research, focus is on genetic fuzzy inference systems. The birth of GFSs was in 1991. Karr (1991) proposed the pioneer work in genetic learning. Valenzuela-Rendón (1991) presented the first proposal dealing with GFS according to the Michigan approach for learning rule bases with DNF fuzzy rules (Herrera, 2008).

Numerous researchers made contribution to develop comprehensive systems and taxonomies after the abovementioned pioneer papers. The results of their works are widely available in the literature.

To better understand the methods and definitions suggested in these papers, it is necessary to be familiar with the general taxonomy of GFSs which is comprehensively discussed in part 4.2.1 and 4.2.2.

4.2.1. Taxonomy of genetic fuzzy systems

To design a genetic fuzzy system, the first step is to decide which parts of fuzzy systems are supposed to be optimized. The second step is coding them into chromosomes that should be optimized by genetic algorithm. In following sections, an introduction about the taxonomy of GFSs based on various parts of fuzzy systems coded by genetic algorithm is presented.

4.2.2. Taxonomy

GFS approaches are categorized into two classes: tuning and learning (Herrera, 2008). The first defining parameter for choosing between them is existing or not existing of an initial knowledge base (Herrera, 2008). By considering database and rule base, the framework of GFSs are briefly described as below (Herrera, 2008):

- *Genetic tuning:* if there is a knowledge base, a genetic tuning process for upgrading the system will be applied in a way that rule base remains the same, but the parameters of the FRBS will be adjusted.
- *Genetic learning:* another more complicated way to optimize just rule base or the whole knowledge base is genetic learning. This process does not need predefined rules, and the rule base will be created during genetic learning (Cordón et al., 2004).

Herrera (2008) Suggests the following taxonomy according to the mentioned points.

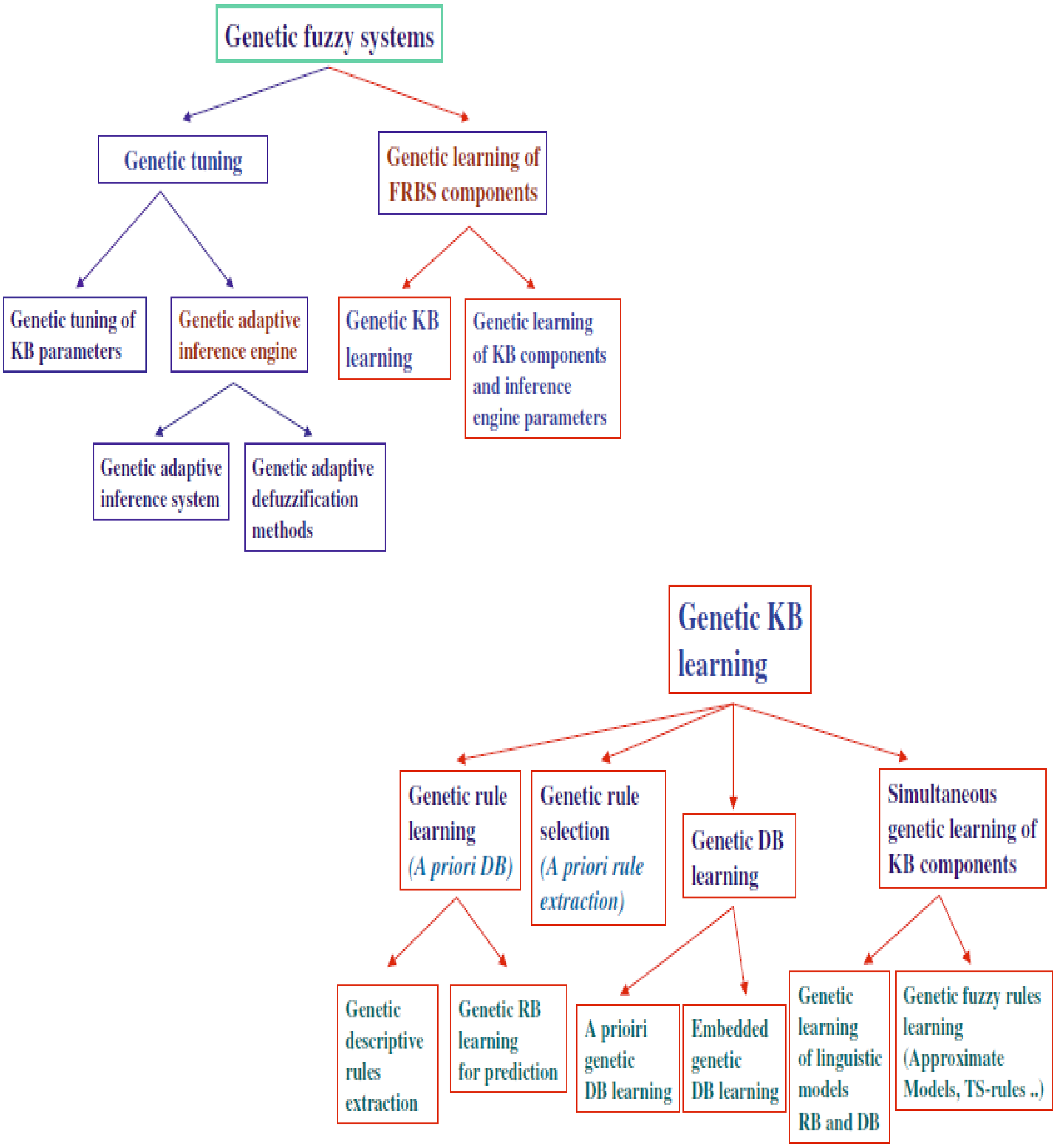


Figure 4-6: Genetic fuzzy systems taxonomy (Herrera, 2008)

4.2.3. Genetic tuning

When the rule base has been devised, some methods try to make FRBS implement more effectively. This purpose can be reached by adjusting initial database definition or the inference engine parameters (Herrera, 2008).

Three possibilities for tuning are suggested according to the sub-tree under genetic tuning:

1. *Genetic tuning of knowledge base parameters,* genetic tuning is used to adjust the membership function parameters. The learning process just changes the shape of the membership functions and it does not change the length of the chromosomes (Casillas et al., 2005).
2. *Genetic adaptive inference systems,* the main purpose of this method is to apply parameterized expressions in the inference systems which are called Adaptive Inference Systems for having more cooperation in fuzzy rules and consequently more precise fuzzy models (Alcalá-Fdez et al., 2007).

3. *Genetic adaptive defuzzification,* one of the ingredients of fuzzy inference systems is defuzzification interfaces as described in former chapter. This method uses genetic algorithm to optimize defuzzification unit of FIRBSs (Kim et al., 1999).

4.2.4. Genetic knowledge base learning

The second area in the realm of genetic fuzzy systems is genetic learning which is more complicated compared to genetic tuning. It can include learning of just the rule base or learning of the whole knowledge base (Cordón et al., 2001; Gonzblez et al., 1999). Therefore, the following four approaches are described for genetic learning:

1. *Genetic rule learning,* most of the methods which have suggested to automatic learn of knowledge base from numerical information, focus on rule base learning by employing a predefined database (Del Jesus et al., 2007; Herrera, 2008). Following figure shows this method more clearly.

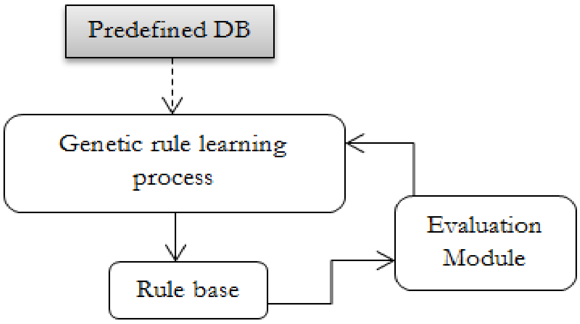


Figure 4-7: Genetic rule learning process (Herrera, 2008)

2. *Genetic rule selection,* data mining techniques sometimes lead to generate a huge number of rules. That would make difficult to understand the behavior of fuzzy inference systems. Some rules are irrelative, redundant, erroneous and conflictive. To avoid such rules, it is possible to use a genetic rule selection process to get an optimized abstract of rules (Alcalá et al., 2007; Casillas et al., 2005). Following figure shows this idea.

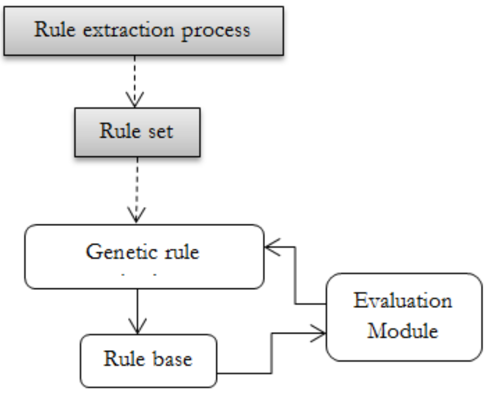


Figure 4-8: Genetic rule selection process (Herrera, 2008)

In addition, rule selection can be combined with tuning approaches. That helps to get good rule set accompanied with a tuned set of parameters (Herrera, 2008).

3. *Genetic database learning*, this method optimizes the whole knowledge base in two steps in a way that each time a database is extracted by the process of database definition, the rule base generation process will be employed to extract the rules (Cordon et al., 2001; Herrera, 2008). Next, the whole knowledge base will be validated. These concepts are shown in the following figure.

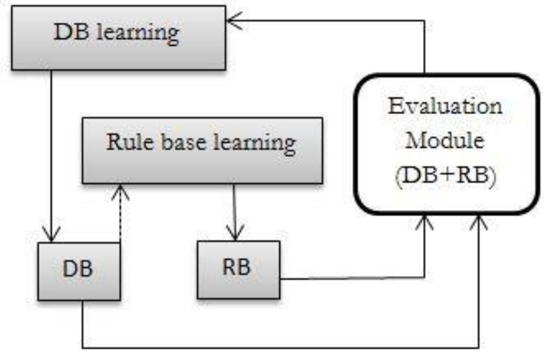


Figure 4-9: Genetic database learning (Herrera, 2008)

4. *Simultaneous genetic learning of knowledge base components,* as it sounds this method try to learn the two components of knowledge base at the same time (Herrera, 2008; Homaifar et al., 1995). This method has the advantage of generating better definitions and disadvantage of dealing with a larger search space that would make the learning progression slow and complicated (Herrera, 2008; Homaifar et al., 1995). This idea is depicted in the following figure.

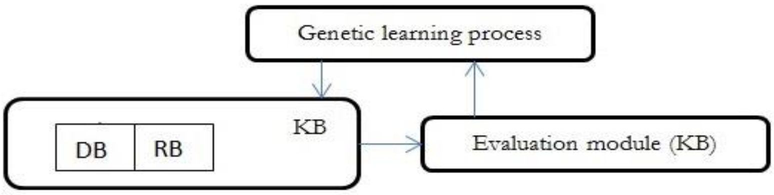


Figure 4-10: Genetic knowledge base learning (Herrera, 2008)

In this research, a fuzzy inference system is produced by fuzzy C means clustering. Next, just membership function parameters and rule base of this fuzzy inference system are encoded into different chromosomes (As described in section 4.1.9). Finally, these chromosomes are tuned in separated steps. The reason to choose tuning is the existence of an initial knowledge base and avoiding complexity of learning process.

5. DATA AND METHODS

5.1. The case study

For the purpose of this study, a part of Mazandaran province in the northern areas of Iran is selected. This region covers an area of 2938 square kilometres. The area lies between latitude of 52 31' 14.75" and 53 27' 15.57" N, and longitude of 35 51' 38.9" and 36 28' 38.78" E. The scale of maps used in this study is 1:100000. Figure 5-1 shows the study area and the locations of 129 records of landslide occurred there (These landslide records are used as training and control dataset for the study. Also, the location of the roads, rivers and faults are shown in this map since distance to these elements affect the landslide occurrence). The minimum and maximum altitudes in the region respectively are 47 and 2965 meters. The maximum slope in the region is around 63°. The most important landuse units in the region are forests with different densities, agricultural fields, gardens or a mixture of these units. The most important lithology units in this area are limestone, dolomite, siltstone, sandstone, stone clay or a mixture of them. This area is landslide vulnerable since it is mountainous, forested, located near fault lines and has high rainfall annually.

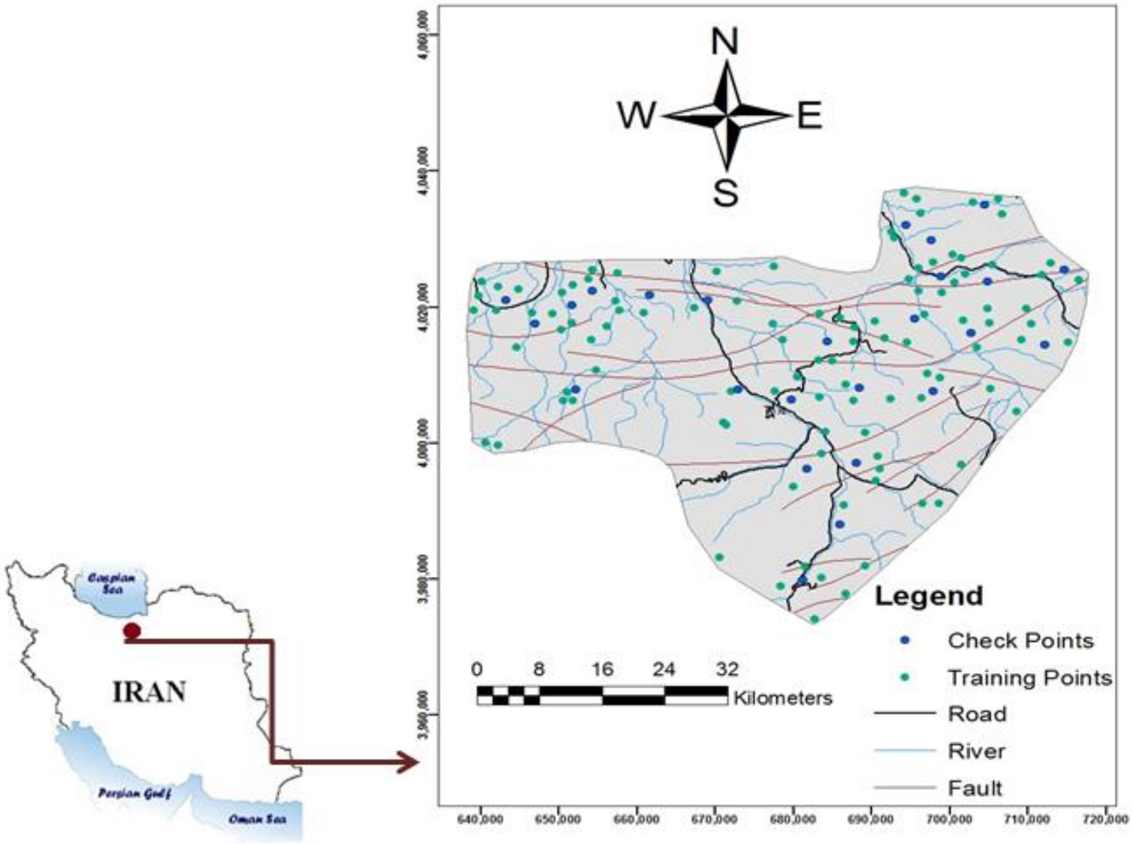


Figure 5-1: Study area

5.2. Data description

The data used in this research contains related contributing parameters to landslide such as slope, curvature, aspect, lithology, landuse, distance to rivers, distance to faults and distance to roads. These parameters are selected according to previous studies and expert points of view. Slope and aspect maps are derived from the digital elevation model of the area (DEM). Distance to river, distance to road and distance to fault raster datasets are respectively created by using river, road and fault maps. The initial maps are provided by National Geosciences Database of Iran (NGDIR). In this study, for each point in the study area one numerical estimation is computed for landslide intensity by a genetic fuzzy system, and to achieve this goal, the landslide contributing factor amounts in each point should be introduced to the system. Thus, all the data sources are rasterized. The following table gives information about the initial data, derived data and the methods used for data preparation.

Initial maps	Type of initial map	Scale	Source	Derived maps	Method	Type of derived map
DEM	vector (polygon)	1: 100000	NGDIR	Slope	Using the first derivative function	raster
				Curvature	Using the second derivative function	raster
				Aspect	Using the aspect (slope direction) function	raster
Landuse	vector (polygon)	1: 100000	NGDIR	Landuse	Vector to raster function	raster
Lithology	vector (polygon)	1: 100000	NGDIR	Lithology	Vector to raster function	raster
Fault	vector (polyline)	1: 100000	NGDIR	Distance to fault	Using Euclidean distance function	raster
Road	vector (polyline)	1: 100000	NGDIR	Distance to road	Using Euclidean distance function	raster
River	vector (polyline)	1: 100000	NGDIR	Distance to river	Using Euclidean distance function	raster

Table 5-1: Data preparation

The cell size of the output raster datasets is considered 50 meters, since very small cell size results in having large volume of the computations and the data sources are maps with small scales.

The nature of lithology and landuse layers is nominal. Thus, these layers are rated according to expert knowledge. That means each class in these layers are assigned a value between 0 and 100 in relation to their contribution to landslide occurrence. Next, all raster layers are normalized between 0 and 100. The following table shows the assigned weights to all classes in landuse layer.

Landuse class	**Weight**
Water body	100
Urban	90
High dense forest	80
Medium dense forest	70
Tea plantation	60
Garden	50
Agricultural fields	40
Mixture of Gardens and medium dense forest	30
Low dense forest	20
Barren land	10
Other	0

Table 5_2: Landuse classification

Also, a training dataset is prepared by using these raster datasets, in way that the values of the factor maps in the locations of landslide incidences are considered as input, and the landslide incidence is considered as output. Thus, this training dataset contains 129 records of landslides including their intensity and contributing factors amount for each record. In addition, 25 per cent of these records are considered as check dataset. A few rows of this training dataset are shown in the following table. In this table, NUM shows the number of the record and the other parameters cannot be assigned any unit since they are normalized values.

NUM	Fault	river	Road	Aspect	Curvature	Slope	landuse	lithology	Intensity
1	27.19	9.43	11.70	85.12	52.08	14.768	60	26.66	10.58
2	32.30	7.93	14.32	45.46	50	15.47	60	26.66	10.98
3	33.42	2.61	6.72	29.67	46.76	28.36	60	26.66	9.80
4	35.85	0.93	16.33	48.33	47.87	29.42	60	26.66	16.07
5	38.66	1.49	12.37	0.84	49.58	25.37	60	26.66	10.58
6	22.60	5.35	8.42	16.60	53.65	22.30	60	26.66	12.54
7	34.98	3.88	0.55	10.73	51.74	31.43	35	26.66	10.58
8	30.58	4.85	1.36	42.67	51.09	31.79	60	26.66	10.58
9	4.38	11.58	5.91	49.33	51.51	20.80	60	26.66	10.98

Table 5-3: Training dataset

The prepared input raster datasets (with resolution of 50 meters) for the case study of this research are shown in the following figure.

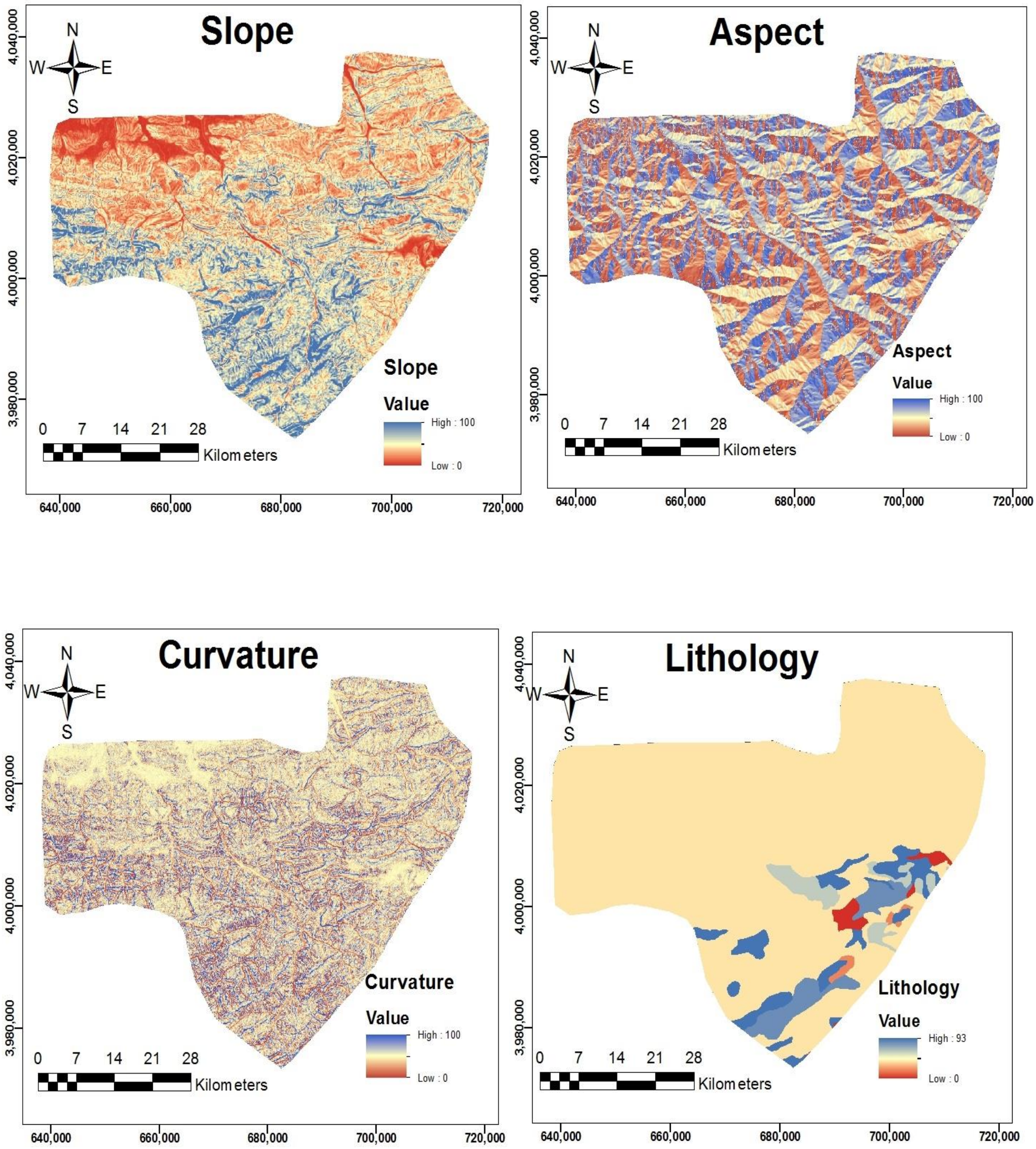


Figure 5-2: Prepared input datasets

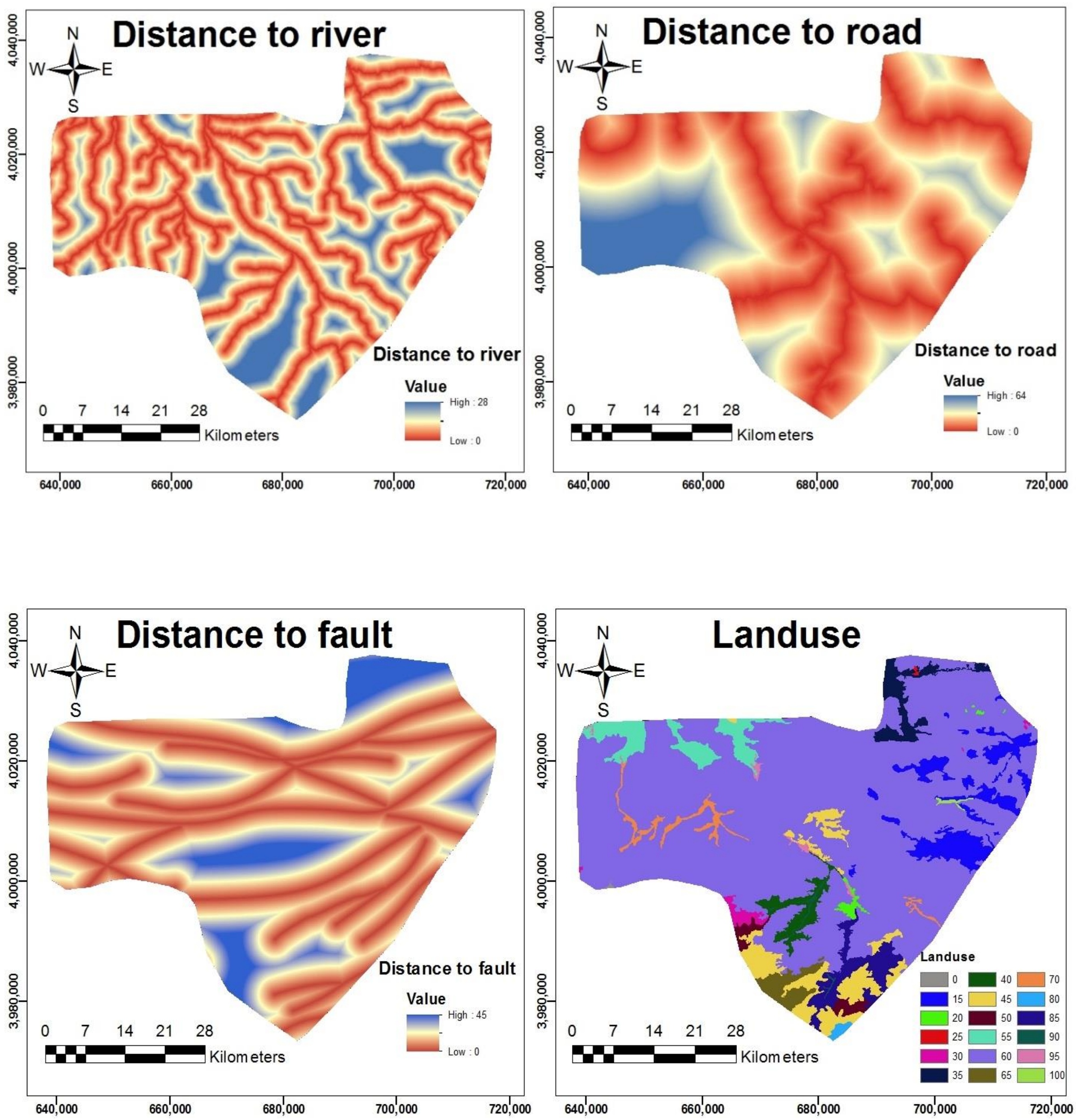


Figure 5-2: Prepared input datasets

5.3. Methods

5.3.1. Overview

Most of the existences in GIS have uncertain natures. Thus, it is necessary to develop a system that can infer from uncertain spatial data. Fuzzy inference systems are one of the most common systems that can deal with uncertain spatial data. In these systems, the elements of knowledge base (fuzzy rules and membership functions) can be extracted from training dataset (automatic) or by using expert knowledge (non-automatic). As it is described previously, each method has its own drawbacks and to reach a more reliable knowledge base, they are integrated into one system in this research. In this methodology, genetic algorithm is also employed to optimize knowledge base elements through a genetic fuzzy system.

For automatic knowledge base extraction from different available methods, C means fuzzy clustering is selected since it has been effectively applied in a wide variety of geo-statistical analysis problems (Bezdek et al., 1984; Mingqin Liu et al., 2002).

For integrating fuzzy inference system with genetic algorithm two procedures are possible. In the first procedure named Genetic Tuning, the elements of knowledge base are initially defined by methods like C means fuzzy clustering or expert knowledge. Next, genetic algorithm is employed to optimize these elements (fuzzy rules and membership function parameters). Unlikely, in the second procedure called Genetic Learning, the fuzzy rule base can be initially undefined and fuzzy rule base is produced during the process of learning.

In this research, the first procedure is used since the number of membership functions and fuzzy rules are consistent during this process, and it is less complicated compared to the second one. In order to implement the genetic tuning, firstly, by considering one consistent initial fuzzy rule base, the optimized form of membership functions is extracted. In the next step, the optimized membership functions are supposed consistent and extracting the optimized fuzzy rules is started.

Finally, those kinds of rules which are not directly extractable from the dataset are added to the system in form of fuzzy rules and membership functions by using landslide expert's knowledge.

The whole workflow of developing the genetic fuzzy system can be outlined in following steps:

1. Preparing the data, reference maps and training vectors (This step is comprehensively described in the sections 5.1 and 5.2).
2. Producing the initial knowledge base by using fuzzy C means clustering algorithm. As it is described in section 3.8, to evaluate the best fuzzy inference system produced by fuzzy C means clustering, three factors are considered: RSE (Root Squared Error), incompleteness and inconsistency of the systems. Incompleteness and inconsistency of fuzzy inference systems which defines the sensibility of the systems are previously described in chapter 3. For assessing the precision of the systems, RSE by following formula is considered.

$$RSE = \sqrt{\sum_{i=1}^{k}(y_{oi} - y_{ci})^2} \tag{15}$$

   In the RSE formula, k is the number of training/control data, y_{ci} is the output (Landslide intensity) computed by fuzzy inference system for the training/control dataset records and y_{oi} is the fixed real output (Landslide intensity) in the training/control dataset.

3. Optimizing the membership functions parameters by genetic algorithm by considering consistent fuzzy rules. Pittsburgh approach (Described in 4.1.9) is selected to encode all the Gaussian membership functions parameters into one chromosome according to the table 4-2.
4. Optimizing the fuzzy rules by considering consistent membership function parameters. Pittsburgh approach (Described in 4.1.9) is selected to encode the initial extracted fuzzy rules into one chromosome according to Figure (4-8).

5. Adding expert knowledge in form of fuzzy rules to the system. To achieve this goal, Dr.Pedram introduced by NGDIR is interviewed as landslide expert, and according to his suggestions the fuzzy rules presented in section 6.3 are defined for the system where the distribution and quantity of the training dataset is not sufficient.
6. Producing the landslide susceptibility map of the region by the systems. In the final step, all prepared raster datasets are given to the fuzzy inference system, genetic fuzzy inference system and genetic fuzzy inference system completed by expert knowledge through different scenarios, and the landslide susceptibility map of the area in the form of raster datasets are produced for each scenario and comparisons are drawn.

In the following flowchart, the suggested methodology is shown.

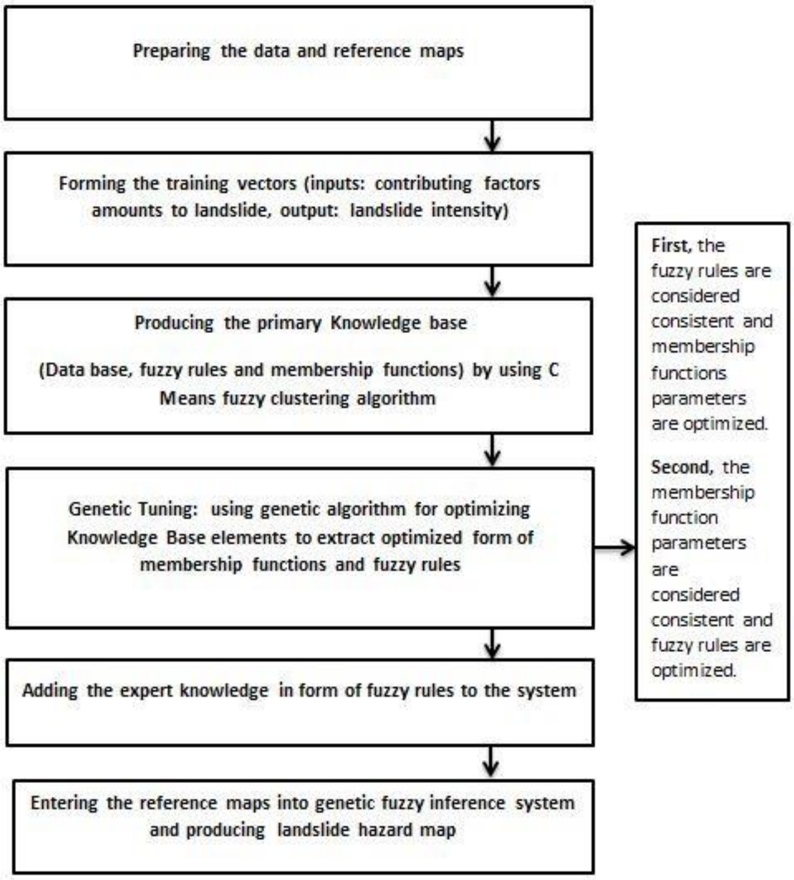


Figure 5-3: Methodology

The results and discussion related to each step of the suggested methodology is comprehensively described in the next chapter.

6. RESULTS AND DISCUSSION

6.1. Extracting initial fuzzy knowledge base by C mean fuzzy clustering

In this step, by using fuzzy C means clustering, the training dataset is clustered and each cluster is projected on the coordinate axis to create the fuzzy rules and membership functions. The input of the C means fuzzy clustering algorithm is the number of clusters (C) and it noticeably affects the precision and sensibility of the system. As it is described in section 3.8, the number of clusters is defined by $c_{max} \leq \sqrt{n}$ (n is the number of training dataset records). The training dataset provided for this research contains 129 records of landslide occurrence. 75 per cent of these records (96 records of landslide) are considered as training part. Thus, the maximum number of clusters can be 9.

fuzzy C means clustering is run for all possible input values from 2 to 9. For implementing the algorithm, *fismat* function of MATLAB is used.

To evaluate the best fuzzy inference system produced by C mean fuzzy clustering, three factors are considered: RSE (Root Squared Error), incompleteness and inconsistency of the systems. Incompleteness and inconsistency of fuzzy inference systems which defines the sensibility of the systems are previously described in chapter 3.9. For assessing the precision of the systems, RSE by the formula presented in equation (15) in section 5.3.1 is considered. Incompleteness and inconsistency of the systems are computed by the mathematical solutions and formulas given in section 3.9.

All abovementioned formulas are coded and computed in MATLAB. The results of all these computations are outlined in the following table.

Clusters	RSE-Training	RSE-Check	Incompleteness	Inconsistency
9	154.2399715	40.12578122	1.730784318	1.360861645
8	154.5275581	40.12497834	1.628267099	3.191880397
7	155.2128967	39.28666964	1.565601971	0.329931062
6	154.4437605	40.78168554	1.005448172	0.463955257
5	155.5599812	41.34318485	0.968055782	1.172996724
4	154.3357119	40.86932264	0.63730424	0.746936834
3	155.8810022	41.06216342	0.578556776	0.99999096
2	159.2948939	44.32250534	0.404235135	1

Table 6-1: Table of errors

The noticeable difference between $RSE_{Training\_dataset}$ and $RSE_{check\_dataset}$ is due to the number of records in these datasets and the nature of RSE formula (Check equation 15 in section 5.1.3) which accumulates the positive amounts consecutively. Thus, to clarify this point, $RMSE_{Training\_dataset}$ (Root Mean Square Error) and $RMSE_{check\_dataset}$ are computed for the FRBS generated with four clustering. These amounts respectively are 15.4 and 8.1. As it is noticeable in the table, none of the clusters show the minimum error for all the factors. To deal with this problem, each column of the table is normalized between 1 and 100. And, a weight is assigned to each factor by using expert knowledge. Next, weighted sum and sum of these factors are computed for each cluster. These steps are shown in the following tables.

Error	Weight
RSE for training data	4
RSE for check data	3
Incompleteness	1
Inconsistency	1

Table 6-2: Table of weights (Assigned by using expert knowledge)

Clusters	RSE-Training	RSE-Training	Incompleteness	Inconsistency	Weighted sum	Sum
9	1	17.49617886	100	36.6617521	193.1502887	155.15793
8	6.632346285	17.48039496	92.34916819	100	271.3197382	216.46191
7	20.05461393	1	87.67248696	1	171.8909427	109.7271
6	4.99118115	30.39066779	45.86836329	5.636139132	162.6412304	86.886351
5	26.85221888	41.42923914	43.07777953	30.16316495	304.9375374	141.5224
4	2.875063324	32.11353434	18.39388308	15.42498332	141.6597227	68.807464
3	33.13937355	35.90461061	14.00957603	24.17858289	278.459485	107.23214
2	100	100	1	24.1788956	725.1788956	225.1789

Table 6-3: Table of normalized errors

As, it is shown in the table, the fuzzy inference system with four clusters shows the best performance compared to others. This system shows the lowest weighted sum for the errors. Thus, the fuzzy inference system generated by fuzzy C means clustering with four clusters is considered as initial fuzzy inference system. The membership functions and fuzzy rules in this system are optimized by genetic algorithm in the next steps. The initial extracted membership functions and fuzzy rules from clustering phase are the knowledge extracted from data. The initial membership functions are shown as following:

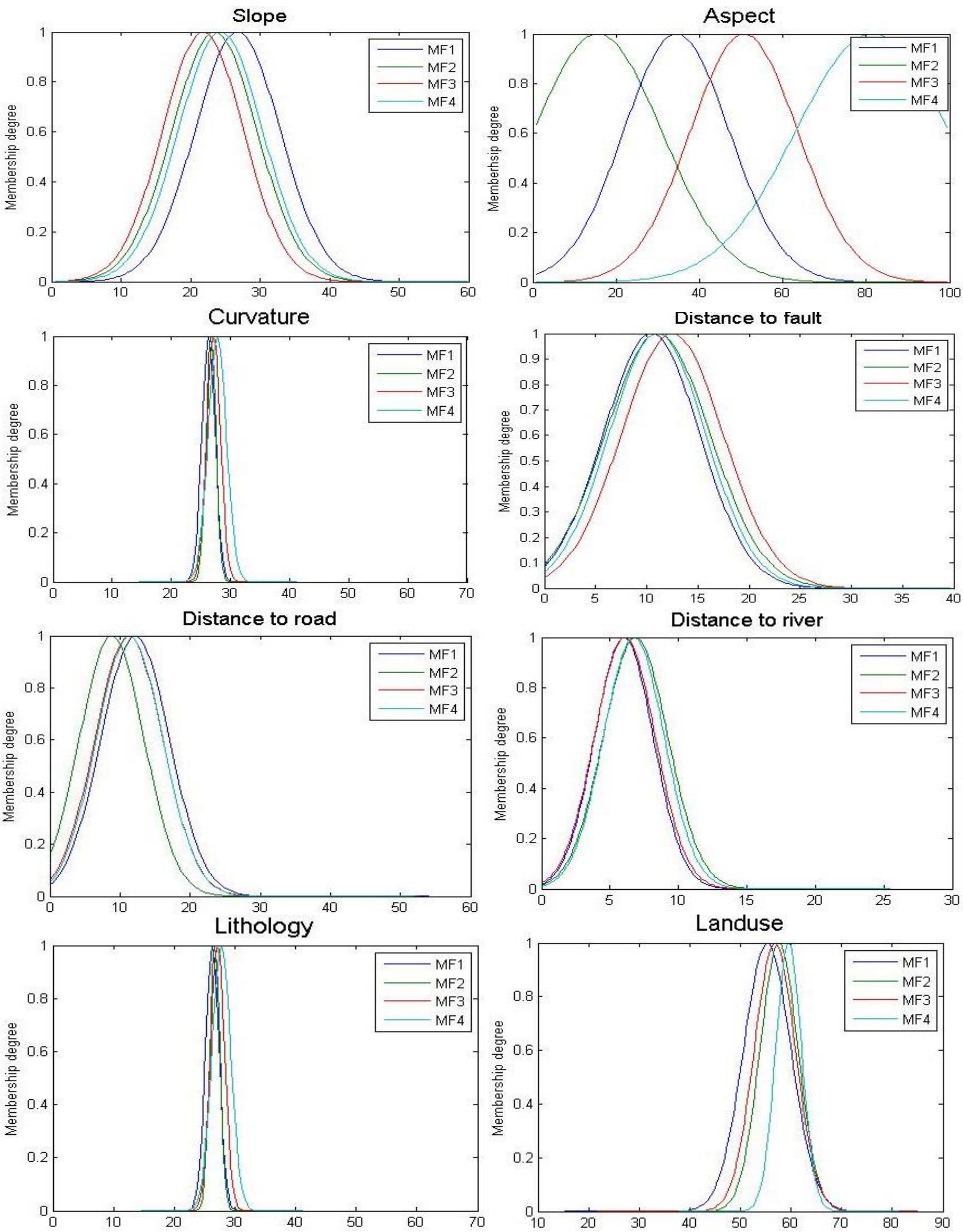


Figure 6-1: Initial membership functions (Generated by fuzzy C means clustering)

- **Rule1:** If (distance to fault=MF1) and (distance to river=MF1) and (distance to road=MF1) and (aspect=MF1) and (curvature =MF1) and (slope =MF1) and (lithology =MF1) and (landuse=MF1) then (intensity=MF1)
- **Rule2:** If (distance to fault=MF2) and (distance to river=MF2) and (distance to road=MF2) and (aspect=MF2) and (curvature =MF2) and (slope =MF2) and (lithology =MF2) and (landuse=MF2) then (intensity=MF2)
- **Rule3:** If (distance to fault=MF3) and (distance to river=MF3) and (distance to road=MF3) and (aspect=MF3) and (curvature=MF3) and (slope=MF3) and (lithology=MF3)and (landuse=MF3) then (intensity=MF3)
- **Rule4**: If (distance to fault=MF4) and (distance to river=MF4) and (distance to road=MF4) and (aspect=MF4) and (curvature =MF4) and (slope =MF4) and (lithology =MF4) and (landuse=MF4) then (intensity=MF4)

Figure 6-2: Knowledge extracted from data (Initial fuzzy rules)

6.2. Knowledge base optimization by genetic algorithm

In this step, genetic algorithm is used to extract the optimal form of membership functions and fuzzy rules. First, by considering consistent fuzzy rules, membership function parameters are optimized. In this research, Gaussian membership functions are considered. As it is described in section 3.8 (Equation 1), these functions have two parameters including C (The center of gussian membership functions) and σ (Standard deviation). Thus, in this step C and σ for all membership functions are optimized. In this research, the number of membership functions for each variable and the number of rules are considered to remain unchanged during the process of optimization. That means the number of genes of each chromosome will remain consistent during the process.

The selected fuzzy inference system from clustering phase in section 6.1 has four rules, eight inputs and one output. These four fuzzy rules are shown in Figure 6-2. The eight inputs of this system are slope, curvature, aspect, lithology, landuse, distance to rivers, distance to faults and distance to roads. The output is landslide intensity. As it is described in section 3.8, the number of clusters is equal to the number of membership functions for each input/output. Thus, for each input and output, four membership functions exist. Therefore, the number of membership functions and membership function parameters in the knowledge base are respectively 36 ((8 input + 1 output)*4) and 72 (36*2, each Gaussian membership function has two parameters).

After chromosome encoding is finished (Like the chromosome shown in table 4-2), it is supposed to be optimized by genetic algorithm. Thus, the genetic algorithm characteristics should be defined. In this part, the cross over and mutation operations are defined. Two point crossover by crossover rate of 0.7 is chosen, and the mutation rate is considered 0.1. The initial size of the population is considered 100 and the maximum number of generation is set 3000. All these numbers are decided by trial and error process.

The fitness function is the main part of genetic algorithm that should be defined. This function involves the optimization factors. The RSE of the training dataset is one of these factors. If only this factor is used in the fitness function of genetic algorithm, the fuzzy membership functions may lose their sensibility. To guarantee a sensible system, the incompleteness and inconsistency are introduced to the genetic algorithm in the form of some conditions. These two factors exert the sensibility to the system. It is also possible to include the inconsistency and incompleteness with RSE in the fitness function, that would help to minimize all sorts of errors simultaneously, but this approach add too much complexity to the system, and it leads to slow algorithm convergences. Thus, to avoid complexity and slowness, incompleteness and inconsistency are included as conditions of genetic algorithm.

Genetic algorithm finds the optimal membership function parameters by minimizing the fitness function (RSE) and meeting the conditions. These conditions are defined between the parameters of membership functions. The following figure shows how these conditions add sensibility to the system.

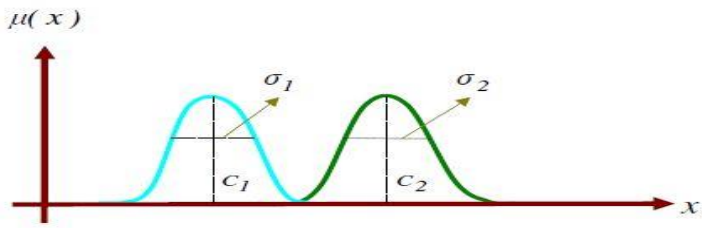


Figure 6-3: Sensibility conditions

$$\begin{cases} C_1 + 2\sigma_1 \le C_2 \\ C_2 - 2\sigma_2 \ge C_1 \end{cases}$$

For implementing the genetic algorithm, the *ga* function of MATLAB is used as below:

x = ga(fitnessfcn,nvars,A,b,Aeq,beq,LB,UB,nonlcon,options)

The parameters of the *ga* are outlined in the following table:

fitnessfcn	Fitness function
nvars	Number of design variables
A,b	Matrix and vector for linear inequality constraints
Aeq,beq	Matrix and vector for linear equality constraints
LB,UB	Lower bound and Upper bound on x
nonlcon	Nonlinear constraint function
options	Structure of GA

Table 6-4: GA function parameters

The structure of GA, number of design parameters and fitness function which are considered for this case are comprehensively explained in the former page. Lower and upper bounds for σ are considered 1 and 100 (Considering the fact that the ranges of variables are normalized between 0 and 100, and the standard deviation near to zero is not desired). Lower and upper bounds for C are considered 0 and 100. These boundaries are introduced to the *ga* by two matrixes of LB and UB. A and b are defined by transforming the inequality constraints shown in Figure (6-3) to the desired matrixes. Aeq, beq and nonlcon parameters are considered empty matrixes since linear equality constraints and nonlinear constraint function do not exist in this case.
The RSE of the fuzzy inference system selected from clustering phase (Generated by fuzzy C means algorithm with four clusters), is reduced from 154.33 (Check Table 6-1 in section 6-1) to 138.662 after the optimization of its Gaussian membership function parameters (σ, C) is done.

In the next page, membership functions after optimization are shown.

The membership functions after optimizations are shown in following figures.

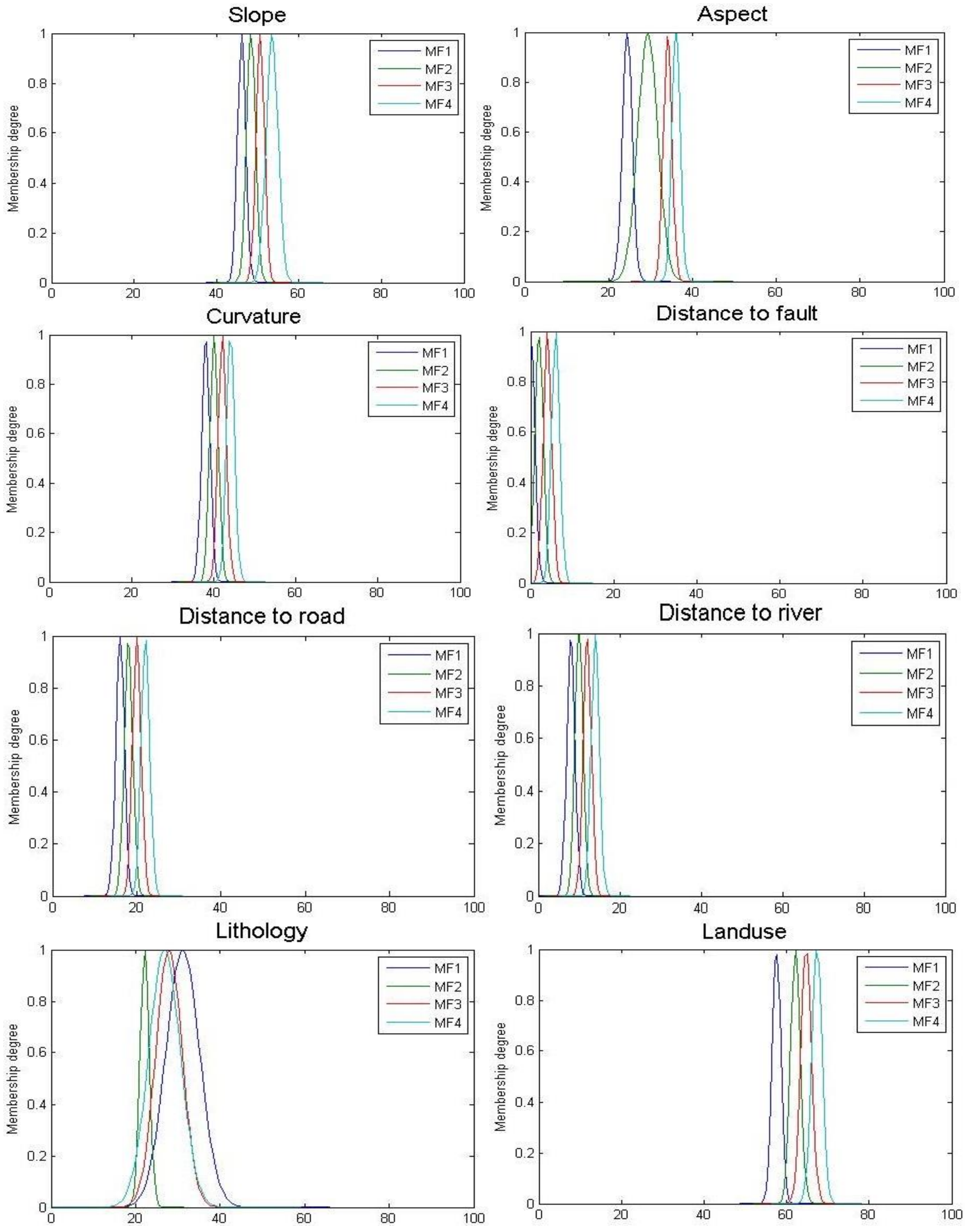


Figure 6-4: Membership functions after optimization

Next, the fuzzy rules are optimized by considering consistent membership function parameters. The coded chromosome for this part is shown in the following table. In section 4.1.9, it is described how it is possible to encode the fuzzy rules into chromosomes. In the following chromosome, each colour shows one rule. For each rule, 9 units exist. These 9 units include the 8 inputs and one output used in this system. And, the number shown in each unit is the number of the membership function assigned to that variable. (For instance, the first unit means if x_1=MF_1, the second unit means if x_2=MF_1, the tenth unit means if x_1=MF_2 and so on). Thus, the part of the chromosome shown with the lightest colour, transfer the concept of the first rule shown in Figure (6-2). And, the other three rules are shown by different colour degrees.

1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4

Table 6-5: Encoded chromosome for rule optimization

The optimization process for this part is different since the normal *ga* function of MATLAB optimizes variables into float numbers. In this case, the float numbers will cause the system to crash (For example, it will result in having 1.5 for the first cell of the chromosome. (That means to select input one from membership function number 1.5, since such a membership function does not exist, the system will crash). This problem is solved in higher versioned MATLAB, and a specific toolbox is suggested to optimize into integer values. The characteristics of this algorithm are designed in a way that forces the variables to be integer. This function uses its own default structure in *gaoptimset*, and adding new structure causes the algorithm to override.

IntCon = [1:36];
Opts=gaoptimset ('PlotFcns',@gaplotbestf,'initialpopulation',rulelist');
x = ga (fitnessfcn, nvar,[ ],[ ],[ ],[ ],lb,ub,[ ],IntCon,opts);

In this code, IntCon defines the matrix of variables which are supposed to be optimized. In this case, all 36 units in the chromosome of Table (6-5) are optimized. The lower and upper boundaries are considered 1 and 4 respectively since four membership functions are defined and variables have to be assigned to one of these membership functions. And, RSE is defined as fitness function of GA which is shown by penalty value in Figure 6-5. This figure shows the optimization process in this step.

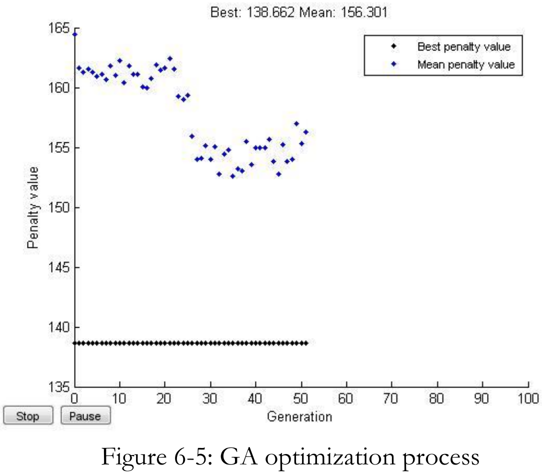


Figure 6-5: GA optimization process

The interesting point is that the fuzzy rules remained unchanged after optimization.

6.3. Adding expert knowledge in form of fuzzy rules to the system

In this section, we try to add expert knowledge in form of fuzzy rules to the system for the cases that system may face a failure to estimate the landslide vulnerability. To achieve these rules, firstly, the expert is asked to divide the contributing factors into overlapping ranges associated with linguistic variables and fuzzy membership functions (MF stands for membership function).
These ranges which are shown in the following table (Vahidnia et al., 2010) are mapped into the range of 0 and 100 to make them compatible with the system.

Input variables	Membership Function Ranges			
	Very low effective (MF1)	Low effective (MF2)	High effective (MF3)	Very high effective (MF4)
Slope (angle)	[0, 3]	[2, 14]	[13, 23]	[22, max]
Curvature		[min, -2]∪[2, max]	[-3, 3]	
Aspect(angle)	[20,160]	[110,250]	[230,270]	[260,340]
Landuse(class)	[1, 4]	[2, 6]	[4, 8]	[6, 10]
Lithology(class)	[1, 4]	[3, 9]	[6,12]	[9, 15]
Distance to river	[700, max]	[400, 800]	[100, 500]	[0, 200]
Distance to fault	[1750, max]	[1000, 2000]	[250, 1250]	[0, 500]

Table 6-6 : Suggested MFs by expert knowledge (Vahidnia et al., 2010)

The expert knowledge is employed in this system just where the rules are not directly extractable from data or training dataset is not sufficient. Accordingly, the following two rules are added to the system.

- *"If 'lithology' is 'MF1'and 'slope' is 'MF1' and 'aspect' is 'MF1' , then 'Landslide' is 'MF1"*
- *"If 'lithology' is 'MF1'and 'slope' is 'MF2' and 'Distance to fault' is 'MF5' , then 'Landslide' is 'MF2"*

In the first rule, it is tried to lessen the role of other contributing factors when slope, lithology and aspect are considerably low effective. That would help to reclassify regions at very low risk which are wrongly classified as higher risk regions under the impression of other factors (For example, closeness to the roads).
In the second rule, it is tried to reinforce the system in the locations that training dataset has not covered the spatial space for some input factors. This problem was noticeable in the layer of distance to fault. As it is shown in the following figure, the training dataset has not covered the red area for this layer. That means in the training dataset, there is not any record with values in the range of the red area (39 to 45) for the field of distance to fault. Thus, a fifth membership function for this range in the layer of distance to fault is defined, and the second rule is added to the system to support the GFS due to insufficient training dataset.

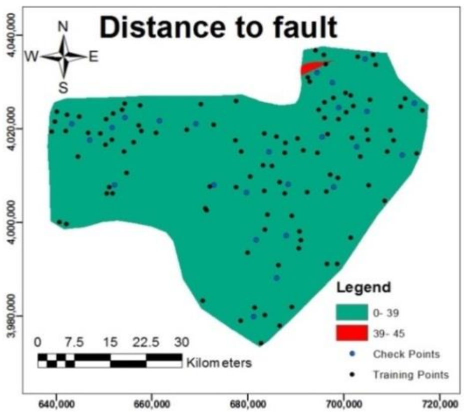


Figure 6-6: The deficiency of training dataset

For some of the other input factors, this problem does exist. In this research, other factors are not considered since they do not deal with a large area.

6.4. Landslide susceptibility map production

In the last step, three scenarios are introduced to present final results as following:

- Scenario A: Producing landslide susceptibility map by using fuzzy inference system generated by the best performance of C Means fuzzy clustering algorithm
- Scenario B: Producing landslide susceptibility map by using genetic fuzzy inference system (Optimized FRBS from previous scenario by genetic algorithm)
- Scenario C: Producing landslide susceptibility map by using GFS coupled with expert knowledge

The final landslide susceptibility maps produced by these scenarios are presented in the following figures. In the legends of these maps, bright colours show high susceptible areas (Greater landslide intensities) and dark colours show low susceptible areas (Smaller landslide intensities).

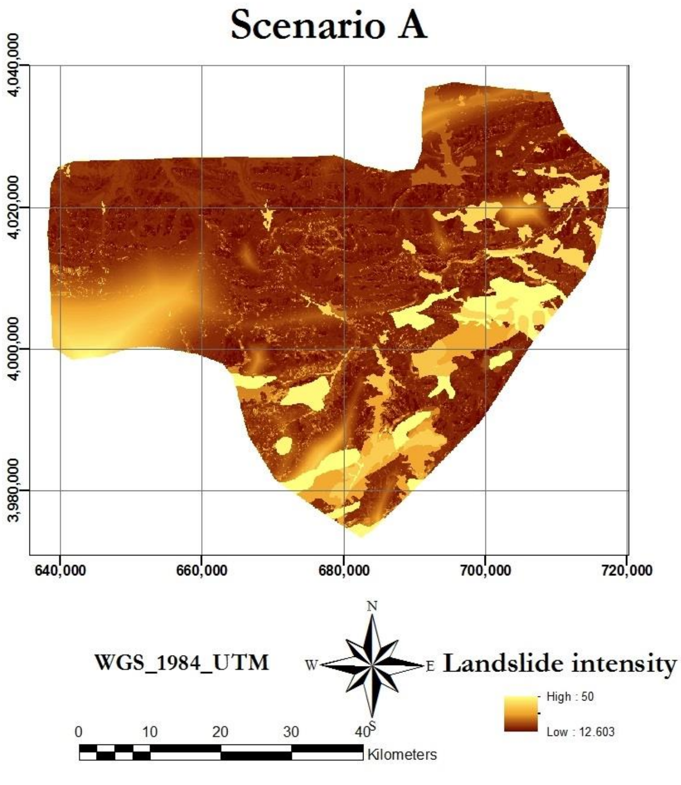


Figure 6-7: Landslide susceptibility map produced by fuzzy C means clustering

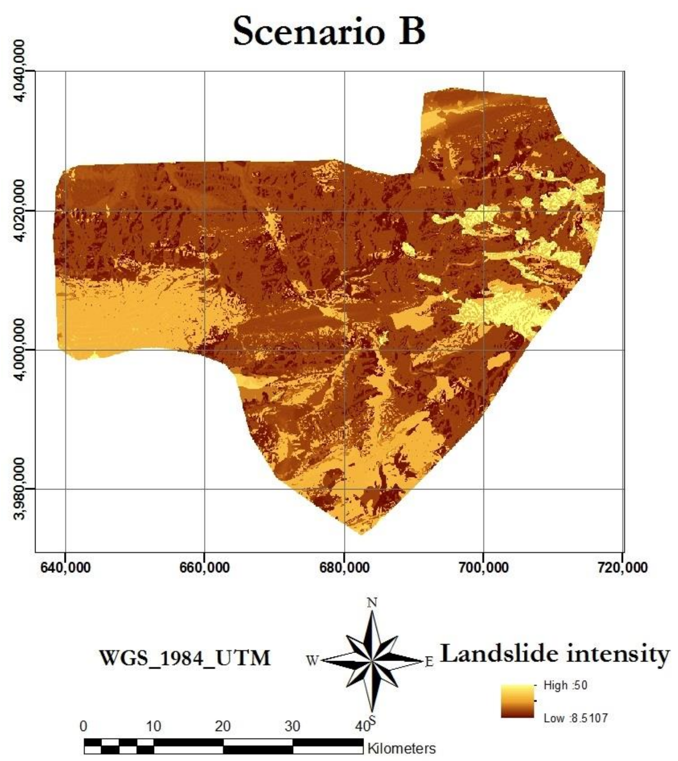


Figure 6-8: Landslide susceptibility map produced by genetic fuzzy inference system

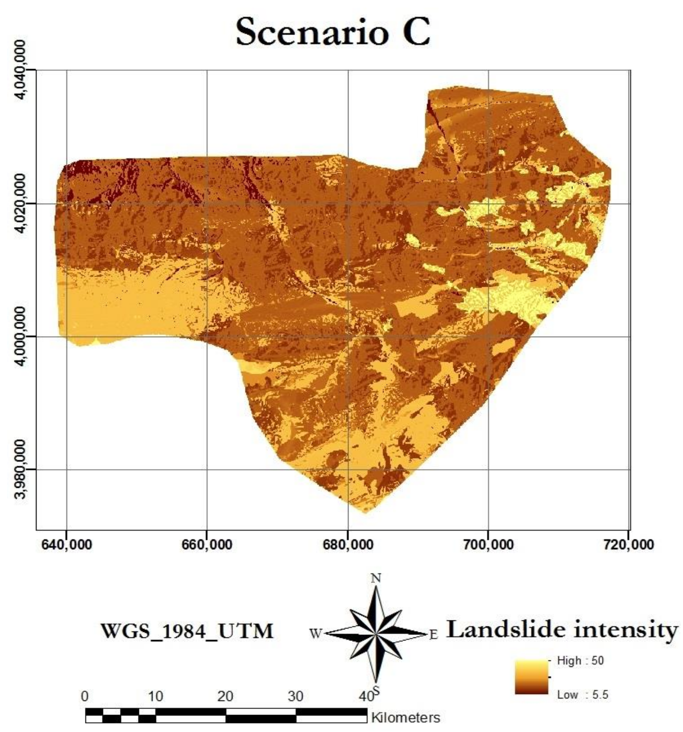


Figure 6-9: Landslide susceptibility map produced by genetic fuzzy inference system and expert knowledge

The maps produced by using these three scenarios are classified into four landslide susceptibility classes of very low, low, high and very high. The method used for this purpose is natural break classification. This method selects the points with intense changes as differentiation limits. The classified maps are shown in the following figure. The classes shown in all of the maps have the same range of landslide intensity. Thus, the same colours are assigned to these classes to provide visual comparisons. As it is noticeable, scenario A does not assign any area of the map to the class of very low susceptible with the yellow colour.

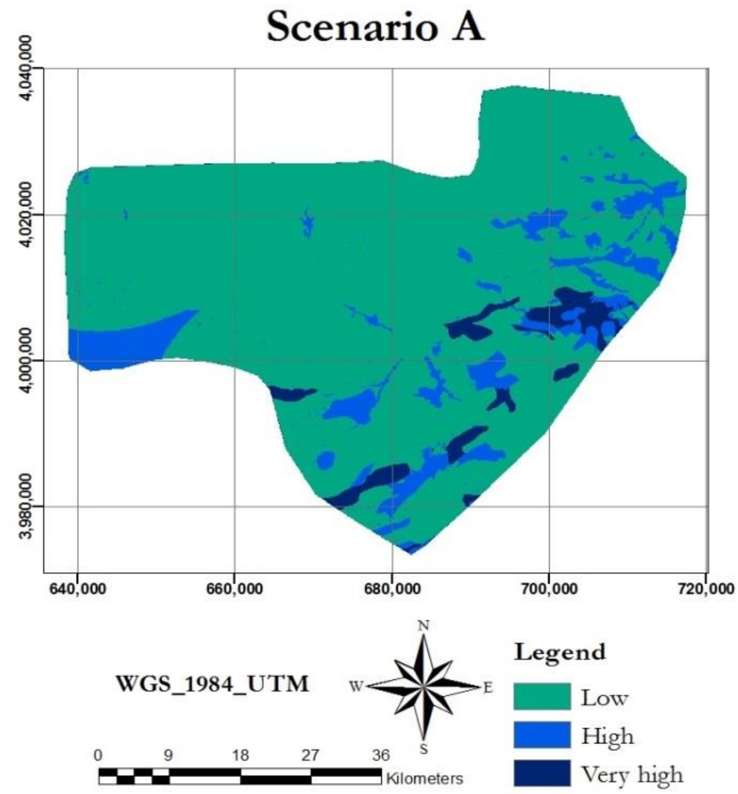


Figure 6-10: Classified landslide susceptibility map produced by scenario A

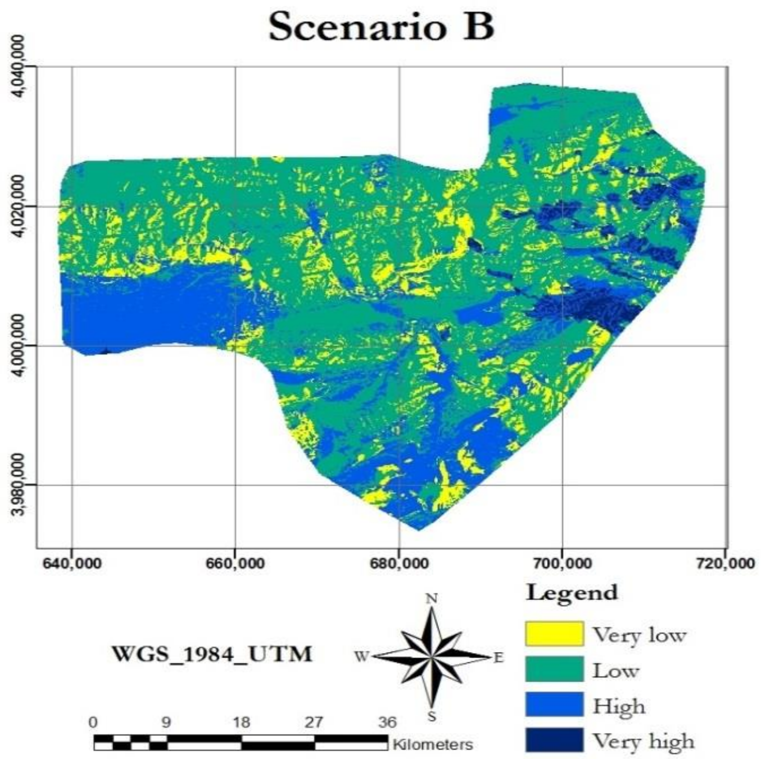


Figure 6-11: Classified landslide susceptibility map produced by scenario B

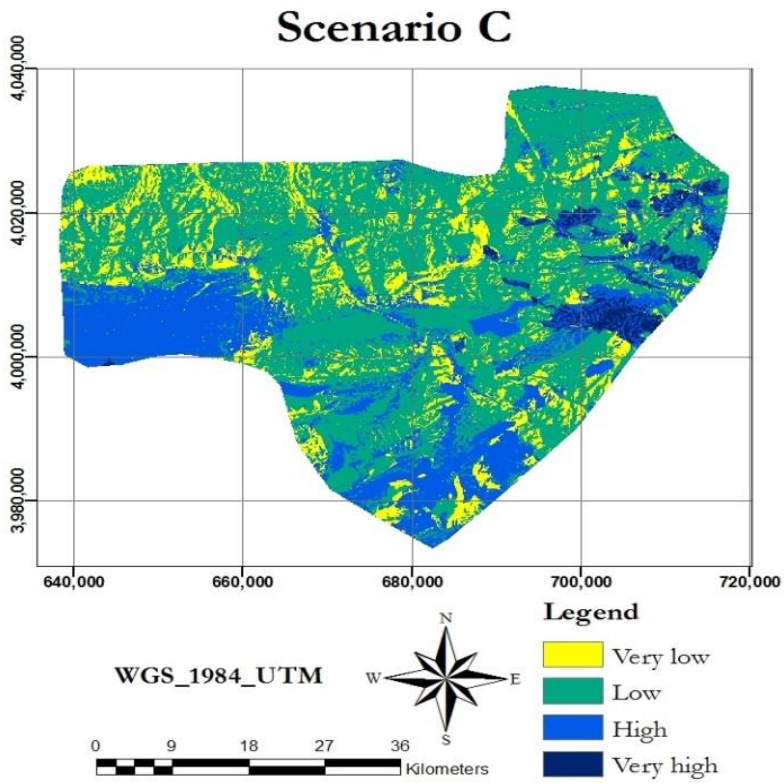
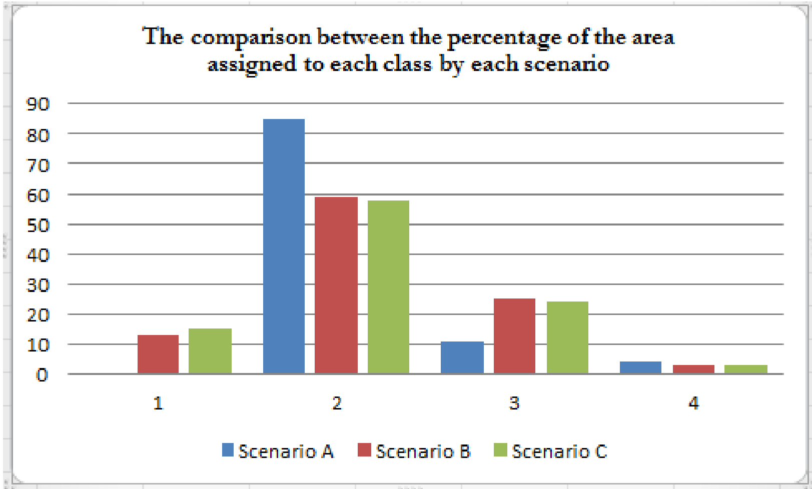


Figure 6-12: Classified landslide susceptibility map produced by scenario C

To compare these maps, following bar chart is presented. These bar chart represents the proportion of the area assigned to each class by these three scenarios (In the following figure, the landslide susceptibility classes of very low, low, high and very high are respectively shown by 1,2,3 and 4).



	1	2	3	4
Scenario A	0	85	11	4
Scenario B	13	59	25	3
Scenario C	15	58	24	3

Figure 6-13: Comparison of the classified regions by using different scenarios

As it can be understood from these figures, the scenario A classifies the 85 per cent of the area as low susceptible and 15 per cent as high and very high susceptible. Scenarios B and C respectively classify 72 and 73 per cent of the area as very low and low susceptible. Thus, 28 and 27 per cent of the area is classified as high and very high susceptible respectively by scenario B and C. Therefore, scenario A shows more optimistic landslide susceptibility estimation for this area compared with two other scenarios. Moreover, in comparison between the scenarios B and C, adding expert knowledge in scenario C caused one per cent reduction in the each class of low and high susceptible in favour of two per cent increment in the class of very low susceptible.

7. CONCLUSION AND RECOMMENDATION

7.1. Conclusion

Nowadays, spatial analysis and GIS are taking steps toward intelligence. In these problems, the nature of data calls uncertainty in the analysis and modelling. Therefore, employing soft computing methods like fuzzy computations is unavoidable to deal with these problems. Regarding to the case study of this research for producing the landslide susceptibility map of Mazandaran province in north of Iran, the modelling and methods of soft computing are presented to solve the problem. In this research, the emphasis is laid on using available datasets for an intelligent decision making especially for the problems like landslide susceptibility estimations. In addition, it is also tried to use expert knowledge (Dr.Pedram introduced by NGDIR) in a flexible way beside the training dataset. The fuzzy inference system is one of the solutions suggested by soft computing to deal with intelligent decision making problem in GIS environment.

The fuzzy inference systems provide the possibility to simultaneous employment of the expert knowledge and knowledge hidden in the data. The integration of fuzzy C means clustering and genetic algorithm is used to build an optimized fuzzy inference system from the available data. Following, to improve the functionality of the system, expert knowledge in form of fuzzy rules and membership functions is added to the system. As it was clear from the results, genetic algorithm has effectively optimized the membership functions in a way that after optimization they show logical overlaps and positions in relation to each other (Figure 6-1 and 6-4). However, the optimization process for fuzzy rules is stopped in almost half way and the fuzzy rules did not show any change after the end of the optimization process (Figure 6-5). It implies the fact that fuzzy rules generated from fuzzy C means clustering algorithm were optimal from the first stage. There is an underlying reason for this fact. In the first phase of optimization, fuzzy rules are considered consistent and membership functions are optimized while the membership functions are inseparable ingredients of fuzzy rules. Therefore, the simultaneous optimization of fuzzy rules and membership functions may produce better results. Simultaneous optimization of fuzzy rules and membership functions is possible by attaching both chromosomes of membership function parameters and fuzzy rules as previously described in section 4.1.9.

As it is clear, the weights of the contributing maps in the process of producing landslide susceptibility map are not extracted through the above mentioned scenarios. In this part, it is tried to evaluate the effect of the each input map on the produced output maps through different scenarios. To achieve this goal, the correlation coefficients (Equation 16) between the input maps and output maps are calculated.

$$\rho_{LSM,I}=\frac{\sigma_{LSM,I}}{\sqrt{\sigma_{LSM}\cdot\sigma_{I}}} \tag{16}$$

$\rho_{LSM,I}$, $\sigma_{LSM,I}$, σ_{LSM} and σ_I respectively are correlation coefficient of the landslide susceptibility map and the input map, covariance of the landslide susceptibility map and the input map, standard deviation of the landslide susceptibility map and standard deviation of the input map. In the following table, the results are presented.

Input maps	Correlation coefficient		
	Scenario A	Scenario B	Scenario C
Slope	0.131	0.035	0.085
Aspect	0.042	0.068	0.095
Curvature	0.005	0.049	0.050
Distance to fault	0.006	0.022	0.002
Distance to road	0.151	0.151	0.167
Distance to river	0.054	0.055	0.032
Lithology	0.675	0.283	0.287
Landuse	0.293	0.479	0.461

Table 7-1: Comparison between the association of the input maps and the output maps

The input maps with correlation coefficients near to one show higher association with the produced landslide susceptibility maps. For instance, the landslide susceptibility map produced by scenario A is more associated with lithology map for this dataset. Next, landuse, distance to road and slope maps are orderly more associated with the result of scenario A. Landslide susceptibility maps produced by scenarios B and C show more association with landuse, lithology and distance to road maps for this dataset, and scenario C is more associated with slope map compared to scenario B.

To compare the functionality of these scenarios, the root square error of the training dataset (RSE_{TR}) and the control dataset (RSE_{C}) and the summation of them are presented in the following table. This table clearly displays the reduction of the RSE in each step. Thus, scenario C is the most effective one as it was supposed to be.

Scenario	RSE_{TR}	RSE_{C}	$RSE_{TR} + RSE_{C}$
A	154.33	40.86	195.19
B	138.62	35.96	174.58
C	134.29	34.85	169.14

Table 7-2: Comparison between the RSE of the scenarios A, B and C

To have more comparison between the results of these scenarios, the percentage of the occurred landslides with low intensity classified in low susceptible classes (Classes of very low and low) and the percentage of the occurred landslides with high intensity classified in high susceptible classes (Classes of high and very high) are presented in the following table (Table 7-3). As it is clear from this table, the scenario A is weak in predicting high susceptible areas and strong in estimating low susceptible areas compared with the two other scenarios. By taking steps toward the scenario C, the ability of the system to predict high susceptible regions experiences a significant growth. As it can be observed, the overall precision of the prediction also increases considerably.

	Scenario A	Scenario B	Scenario C
The percentage of the landslide occurrence with low intensity classified in low susceptible classes	92%	88.99%	90.82%
The percentage of the landslide occurrence with high intensity classified in high susceptible classes	35%	65%	70%
Overall estimated precision	82.9%	85.2%	87.5%

Table 7-3: Comparison between the precisions of the scenarios A, B and C

Based on the experience learned from this research, the estimated percision can show an improvment by employing more contributing factor maps. However, the more training dataset records will not definitely improve the results.

7.2. Recommendations

By reviewing the results of this research and its strength and week points, the following recommendations are presented as future work.

First, it is recommended to include non-considered contributing factors to landslide occurrence in the analysis. For instance, rainfall and underground water quantities are known to be important contributing factors to landslide occurrence. These factors are not considered in this research due to lack of data for the study area. Thus, adding these factors to the system will help to improve landslide susceptibility predictions.

Second, investigating other methods of automatic knowledge extraction from knowledge base may help to find more efficient methods. In this research, fuzzy C means clustering is used for automatic knowledge extraction. For example, generating fuzzy rules by learning from examples suggested by Wang et al. (1992) may lead to better results.

Third, employing the genetic algorithm to optimize other parts of fuzzy inference system (Inference engine, fuzzification and defuzzification units) will help to improve the predictions. In this study, genetic algorithm is just used for knowledge base optimization. By optimizing other parts of the fuzzy inference system, it is possible to generate more reliable systems. In addition, simultaneous optimization of membership functions parameters and fuzzy rules can improve the results. Another way to achieve more reliable system is to include the incompleteness and incompatibility factors of the fuzzy inference system in the fitness function of genetic algorithm instead of placing them in the conditions of the algorithm. That will lead to simultaneous minimization of the all assessment criterions (Incompleteness, incompatibility and RSE).

Also, employing other forms of genetic fuzzy systems such as genetic fuzzy clustering system, genetic fuzzy decision trees and genetic neuro fuzzy systems is another suggested approach for future work.

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