Chapter 2
Fuzzy Knowledge Based GIS for Zonation of Landslide Susceptibility

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2.1 Introduction

Landslides are among the major natural disasters in the world. It is a common phenomenon especially in a tectonically fragile and sensitive mountainous terrain like the lower Indian Himalayas [1]. Landslides cause loss of life and property, damage to natural resources, and hamper developmental projects like roads, dams, communication lines, bridges etc. The high susceptibility to landslides of the mountainous regions is mainly due to complex geological setting with the contemporary crustal adjustments, varying slopes and relief, heavy snow and rainfall along with ever-increasing human interference [2]. To take a quick and safer mitigation measure and strategic planning, identification of landslide prone areas and Landslide Susceptibility Zonation (LSZ) is important. A comparison of the distribution of different causative factors allows identifying the areas with varying landslide potential which is a complex task as the occurrence of landslide is dependent on many factors [3].

Several field-based hazard zonation techniques have been applied in the last few decades to the problem of landslide categorization [4]. These approaches have some drawbacks such as: repetitive coverage of area is difficult, manual overlay of thematic maps is a time consuming and tedious job, the extent of area covered is generally small, and in most of the cases landslide identification is close to road and thus interior parts are not covered. These problems are removed with the advent of satellite data and processing using geographical information system (GIS). It is now possible to efficiently and correctly collect and manipulate a variety of spatial

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Table 2.1 Causative factors and their associated uncertainty

Factors	Uncertainty
Rock composition	Low
Rock structure	Intermediate
Ground water conditions	High
Slope geometry	Low
Geomorphic processes	Intermediate/High
Land use	Low

Table 2.2 A sample from KB showing the variables and assignments

Sl no.	Fuzzy variable	Subvariable	Weightage	Function based rating
1.	Slope Angle	$> 45°$	0.7	(Signum function)
		36°–45°		9
		26°–35°		7
		16°–25°		5
		$< 16°$		3
				1
2.	Landuse/landcover	Barren Land	0.4	(Gaussian function)
		Sparse Vegetation		9
		Moderate Vegetation		8
		Agricultural land		6
		Dense Forest		4
		Water		3
				1
3.	Relative relief	> 110 m	0.3	(Signum function)
		81–110 m		9
		51–80 m		7
		21–50 m		5
		< 21 m		3
				1

attributes such as geology, structure, surface cover, vegetation cover, the variability of terrain parameters and, distribution of landslides of an area. Moreover repetitive coverage, synoptic overview, availability of data in digital format, multi-spectral information and 3-D view capability and analysis is possible through these techniques [5–7].

Various geo-structural as well as causative-factor based approaches have been proposed for landslide susceptibility zonation [4,8]. In recent times, GIS modeling of landslide phenomena has taken precedence, and digital landslide zonation maps at various scales are now being generated. Expert systems for landslide have also been proposed [9,10]. But wherever consideration of landslide causative factors comes up, a comprehensive methodology of defining the degree of association of the contributory factors towards landslide is still to be offered.

For a case study and testing of the system, a detailed landslide susceptibility zonation map has been prepared of a slide prone area, using the proposed modern fuzzy based GIS techniques. The system works on a selection of appropriate fuzzy variables and membership values to integrate various data layers in GIS towards preparation of landslide susceptibility zonation map. The system is designed with a knowledge-base (KB) capable of managing uncertainties (Table 2.1) with the knowledge (Table 2.2) stored in it. The difference with other such systems is in the use of fuzzy inferencing scheme, which effectively considers membership values of factors and sub-factors of landslide and the associated uncertainties.

2.2 Background

The requirement of this study is to evaluate multiple causative factors and their non-linear interactions to arrive at a decision. This could be achieved using a comprehensive input data set pertaining to the causative factors of the phenomena, fuzzy handling of the factors taking care of uncertainties and continuity, and multi-criteria evaluation of the contribution of the factors, all operating in a spatial domain of a GIS since the concerned problem is environmental, a geo-hazard called landslide. One common approach linking GIS, fuzzy logic and multi-criteria evaluation (MCE) [11,12] has been to utilize expert opinions on multiple criteria [13] and the resulting landslide maps are categorized into zones of "very low", "low", "medium", "high", and "very high" categories of susceptibility. In order to combine the selected landslide parameters and generate realistic output susceptibility maps, a GIS-based approach was developed using MCE and fuzzy sets. Each landslide contributory parameter affects the landslide process and final output maps so it is necessary to determine the relative importance of each parameter. The variabilities of the parameters have been captured effectively using fuzzy set membership functions [14] and the expert rules put down in the Indian Standard Code of Landslides [13] calculate the weight values for each parameter [15]. Final landslide susceptibility maps are then produced by using the weighted linear combination (WLC) method. A combination of the weighted parameterized maps using criteria weighting tools and criteria integration tools such as WLC lead to generate the landslide susceptibility maps [16].

2.2.1 GIS

Geographic information system (GIS) has rapidly developed from being a geographic database tool to now being able to provide sophisticated logical and mathematical analysis between multiple map layers. GIS gives the ability to store, handle, and transform spatial data efficiently and the integration of additional analytical techniques that can cope with multiple criteria problems has greatly enhanced the functionality of GIS. As a consequence, GIS is quickly evolving into a decision support system where decisions are made based on mapping outputs generated from the GIS analysis [16].

Spatial environmental problems with multiple criteria are easier to handle in a raster GIS. In the raster GIS data model, geographic space is represented as a grid of regular cells and each cell is coded with a single attribute value. With this raster GIS model, remote sensing data based on the pixel can now be easily integrated into the GIS as the spatial conceptualization of the pixel is analogous to that of the grid cell. Once in the GIS, remote sensing data can then be subjected to advanced spatial data analysis techniques at various scales of analysis [16].

2.2.2 Fuzzy MCE

Fuzzy set theory was developed to deal with the inherent uncertainty of data by allowing membership of data belonging to a set along a continuous scale, rather than a crisp binary set membership [14]. Compared to linear scaling, fuzzy sets are a more realistic standardization approach because using a fuzzy set membership represents a specific relation between the criteria and possible outcomes [17,18]. When Boolean overlay is used, membership values are reduced to 0 and 1, which assumes crisp boundaries meaning the final outcome is identical to those of Boolean overlay [19]. Once the fuzzification has been defined, it is important to assign the relative importance of each evaluation criterion with respect to the overall objective of the problem [13]. By varying and prioritizing criteria, it is possible to generate compromising alternatives and thus rank alternative outcomes by the different expert opinions [13,20]. Since varying the relative importance of criteria reflects the knowledge of experts, it allows for sensitivity analysis and validation of weights and rankings of alternatives [16].

In multi-criteria evaluation (MCE) or multi-criteria analysis (MCA) the aim is to scrutinize a number of alternative possibilities given numerous criteria and conflicting objectives. In other words, MCE is primarily concerned with how to combine information from several criteria by imparting consistency and continuity to form a single index of evaluation. Criteria are the evidence that the outcome is based on and can be in the form of either factors or constraints [16]. A factor increases or decreases the suitability of a specific alternative for the activity under consideration, while a constraint provides exclusions and limits the alternatives under consideration. The degree of suitability of factors can range from either Boolean unsuitable to suitable (i.e. zeros and ones) to varying levels of certainty (i.e. a continuous scale from zero and one), which can be attributable to the type of data used and the subjectiveness of each expert [16].

MCE provides many advantages for use in defining landslide susceptibility. Landslide studies often use MCE techniques because the types of data available are commonly qualitative (from expert opinion) and quantitative (from observed relationships between parameters and landslides), therefore requiring a semi-quantitative method that incorporates both types of data [21]. These methods involve assigning weights to the different parameters affecting landslide susceptibility and many techniques exist for determining weights [22]. The most common approach involves obtaining expert opinion to assigning weights in a procedure known as Analytical Hierarchy Process (AHP) and then combining weights additively by weighted linear combination (WLC) to produce landslide susceptibility maps [23,24].

2.2.3 Model

The purpose of the multi-criteria evaluation approach used is to classify landslide susceptibility based on numerous conditioning factors in order to classify degree of landslide hazard in a region. The most common MCE factor aggregation procedure is known as weighted linear combination (WLC), where continuous parameters are standardized to a common numeric range, weights are calculated for each parameter, and then combined by weighted averaging for the final landslide susceptibility map.

Traditional GIS applications have used crisp Boolean sets, where spatial information represented discrete objects in a discrete definition; however, transition from membership to non-membership is rarely a step function. Rather, there is a gradual change represented as fuzzy sets and it is characterized by a membership function ƒ(μ(x)) where μ(x) ε [0,1] is a degree of membership to a particular set. In this study, fuzzy sets were used to represent individual landslide conditioning parameters and their relationship to landslide susceptibility. This membership for each landslide parameter is standardized on a scale from 0 to 1, where 0 represents the least susceptible and 1 represents the most susceptible. The fuzzy membership function used in this study is the sigmoidal or s-shaped membership, which follows a cosine function. The sigmoidal membership function is most commonly used in GIS applications. The broad methodology of the system consists of development of a knowledge-based system having capability to categorize a given region into different intensity of landslide and to provide a hazard map as its output. The system has been developed on the basic assumptions that (1) the terrain lies in mountainous region of a particular seismicity, (2) landslide occurrence is based on the causative factors as envisaged by the experts, and (3) a landslide will occur in the future under similar geo-environmental conditions, necessary as per the expert knowledge laid down in IS 14496 Part 2–1998 [13] on which the knowledge base is built. These weights must sum to one and they represent the relative importance and contribution that each parameter has on landslide susceptibility. The methodology lies in the superimposition of maps of causative factors of slope instability as proclaimed by the experts in the IS 14496 Part 2–1998 [13], namely lithology (rock and soil type), structure, slope morphometry, relative relief, land use land cover (LULC) and ground-water condition/rainfall. Each of these categories is associated with an uncertainty rating on the basis of its significance in causing instability (Table 2.1). An expert rating scheme as available in [13] for the various sub-categories of individual causative factors has been included in this study. A sample of the rating scheme is as Table 2.2.

Once landslide-conditioning parameters were standardized by fuzzy sets, the procedure used to combine information from multiple criteria for continuous factors is WLC, which can be expressed by $S = \sum w_i . x_i$, where S is the landslide susceptibility, w_i is the weight of the parameter i, and x_i is the criterion score of parameter i. In other words, parameters are combined by applying a weight to each followed by a summation of the results to yield a susceptibility map.

2.3 Implementation

For developing landslide hazard zonation map, different spatial data sets have been collected from different sources which are grouped as follows.

1. Topographic map of Haridwar district, lower Indian Himalayas.
2. Satellite data in the form of ASTER VNIR (very near infra-red) image of the same area.

The data preparation involved the use of IDRISI Andes 15.00 and Arc GIS 9.0 for GIS analysis, RSI ENVI 4.7 and ERDAS Imagine 8.5 for thematic map generation.

2.3.1 Data Integration and Analysis

The topographical and geological maps obtained in analogue form were converted into digital form through digitization. Together with these vector maps, the landuse/landcover map prepared by digital image processing of Aster image is used for GIS analysis, which has been used in this study to convert analogue map to digital form, extraction of different thematic maps (e.g. slope map, relative relief map), analysis of these maps and final landslide hazard zonation map preparation using fuzzy technique. The various layers which were used for mapping in the area include:

(a) Landuse/Landcover (LULC) map (Fig. 2.1).
(b) DEM (digital elevation model) derivatives—Slope Angle Map, Relative Relief Map (Figs. 2.2 and 2.3).

2.3.1.1 Generation of LULC Map

The landuse/landcover map of the study area has been prepared using following datasets:

(a) F.C.C. (false color composite) of ASTER VNIR image of Haridwar district.
(b) Google earth image of the same area.

Aster image (after pre-processing and registration) has been classified using supervised classification using ERDAS Imagine 8.5. The analysis has been performed using IDRISI Andes software. A total of six classes of landuse/landcover have been selected from the entire study area based on the above sources.

(a) Water. The water body appears cyanish-white in F.C.C.
(b) Dense Forest. Dense forest appears deep-red in F.C.C.

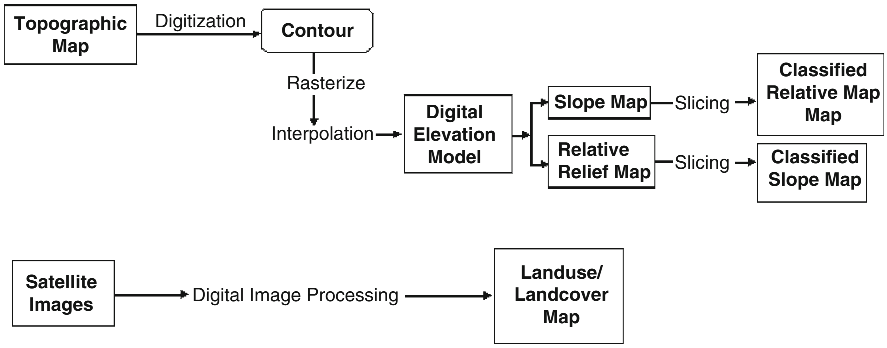

Fig. 2.1 Data preparation steps

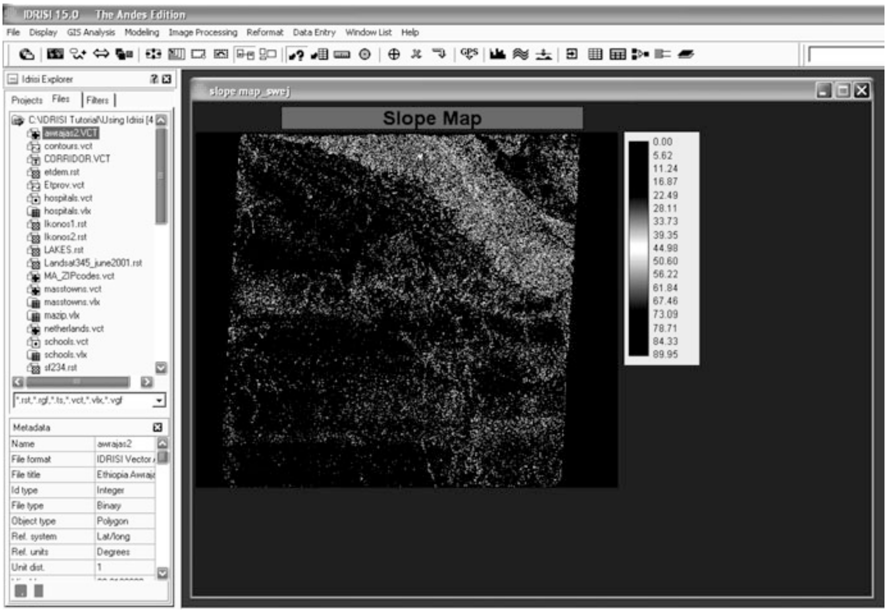

Fig. 2.2 DEM derivative slope map

(c) Moderate Vegetation. In ASTER F.C.C. moderate vegetation appears dull red.
(d) Agricultural Land. The agricultural fields are identified by pinkish-red in F.C.C. Mainly step-cultivation has been observed in this area surrounding small villages.
(e) Sparse Vegetation. The landcover where the vegetation density is very low with respect to the ground surface has been selected as sparse vegetation cover. Sparse vegetation shows up as dull red to green in F.C.C.
(f) Barren Land. Bluish-grey areas in F.C.C. have been chosen as barren areas.

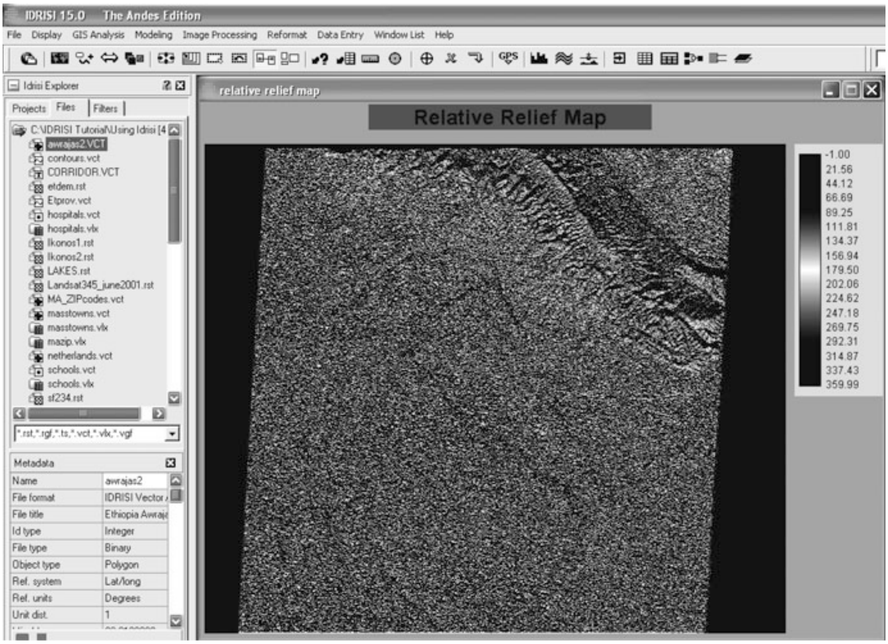

Fig. 2.3 DEM derivative relative relief map

Supervised Maximum Likelihood Classifier has been used to classify the Aster image. This classifier works on the principle that a given pixel may be assigned to that class for which it has the highest probability to be incorporated. It is assumed beforehand that the training data for each class in each band are normally (Gaussian) distributed.

The training data have been selected on per-pixel basis. The training pixels have been selected in such a way that these are well distributed over the entire area. From this training data set, various statistical parameters like mean and standard deviation to be used by Maximum Likelihood Classifier has been determined.

From the training data set statistics, each pixel in the image is allocated to one of the classes using the classifier. The pixel is allocated in that class with which it has the greatest probability of association. A classified map has thus been generated and area occupied by different classes has been calculated. An error matrix has been used to evaluate classification accuracy (Table 2.3). An unbiased set of test samples has been chosen from the reference data for assessment of classification accuracy. The overall accuracy has been calculated dividing the sum of diagonal element. The overall accuracy achieved is 69.13%.

Total Testing Pixels $= 2112$

Total Diagonal Elements $= 1460$

Overall Accuracy $= (1460/2112) \times 100 = 69.13\%$.

Table 2.3 Error matrix for assessment of classification accuracy

Classified data	Reference data (training set data)						
	Water	Dense forest	Moderate vegetation	Agricultural land	Sparse vegetation	Barren land	Total pixels
Water	387	3	0	0	3	9	402
Dense forest	0	288	51	3	27	0	369
Moderate vegetation	0	39	213	9	69	33	363
Agricultural land	0	0	9	228	9	6	252
Sparse vegetation	0	57	117	21	207	0	402
Barren land	9	3	21	12	42	237	324
Total pixels	396	390	411	273	357	285	2,112

2.3.1.2 Generation of DEM Derivatives

We have generated a contour map by digitizing the topographic map of Haridwar and its surrounding area using Arc GIS 9.0. Then the DEM has been generated using the contours and imported to IDRISI Andes for LSZ map preparation. Using the *Surface Analysis* in IDRISI Slope and Relative Relief maps have been created. Slope is an important parameter for stability consideration. The slope at any point is a gradient between the centre and neighborhood cell with maximum or minimum elevation. A slope map thus is a raster map in which the attribute of each pixel denotes the slope at a particular location. The slope map thus derived from DEM shows a range of variation of slope from 0° to 87° in the study area. It has been classified using "slicing" function into five classes as follows.

Slope Classes— $< 16°$ $> 16°$—25° 26°—35° 36°—45° $> 45°$

Relative relief is defined as the difference in maximum and minimum elevation values within an area or facet. In GIS the relative relief has been calculated by generating two maps using 3×3 rank order filter—one with maximum elevation and other with minimum elevation within a 3×3 window. The minimum elevation map is subtracted from maximum elevation map through "calculator" function to get to a relative relief map. The range of relative relief is found to be 0–174 m. On the basis of histogram and analyzing the spatial distribution, the map has been classified into five classes.

Relative Relief Classes— $>$ 110 m; 81–110 m; 51–80 m; 21–50 m; $<$ 21 m.

2.4 Fuzzy System

The architecture of the proposed system has three functional modules—a GIS based Input Module, a Fuzzy Expert Module and an Output Module, wherein the expert module combines the knowledge module and the fuzzy inference module as sub-modules.

2.4.1 Proposed Architecture of the System

2.4.1.1 Input Module

The input module has been developed in IDRISI to accept layers of information of causative factors of landslides.

Table 2.4 Landslide susceptibility zonation on the basis of output fuzzy membership functions

Zone	Fuzzy membership function	Description	Function
I	<0.1	Very low hazard	Sigmoidal function
II	0.1–0.4	Low hazard	Sigmoidal function
III	0.4–0.6	Moderate hazard	Sigmoidal function
IV	0.6–0.75	High hazard	Sigmoidal function
V	>0.75	Very high hazard	Sigmoidal function

2.4.1.2 Expert Module

Knowledge-Base

The KB is derived from ground data and the Indian Standard Code [13]. The six causative factors with their sub-factors and ratings are stored in the Knowledge module, a sub-module of the expert module. Membership values and ratings are also defined in this sub-module with the appropriate fuzzy functions [14] as shown in Tables 2.2 and 2.4. The weighting and rating system is based on relative importance of various causative factors and the actual field knowledge on them. Table 2.2 describes the membership value and ratings given to each layer and their classes respectively. Theses membership and rating values have been re-adjusted using trial and error method [11,12] by matching it with the ground truth [13].

(a) Slope Angle: A very important parameter in landslide activity, in this area, the slopes greater than 45° are highly unstable [13,25].
(b) Landuse/landcover: Among all the classes, barren land is most prone to landslide activity. Hence, the highest rating is given to this class. As the vegetation density increases, the stability of slope increases [26].
(c) Relative Relief: The higher relative relief leads to greater landslide susceptibility. Therefore, the rating is given in increasing order as the relative relief increases.

Inference Engine

Computation of Landslide Hazard Index (LHI) is performed in this sub-module where LHI is given by:

$$\text{LHI} = \sum \text{weightage} \times \text{data layer (attribute)} = \sum \mu * X$$

For this study, the Landslide Hazard Index = [0.7 * Slope Angle + 0.4 * Landuse/landcover + 0.3 * Relative Relief]

2.4.1.3 The Output Module

The Output Module provides a grey coded (consisting of five different grey scale levels for the five levels of susceptibilities) digital map of the intensity of landslide susceptibility prevalent in the region of study, and a two-level binary map showing the entire region in two categories, susceptible or not susceptible.

2.4.2 Methodology

A decision support approach called Multi-Criteria Evaluation (MCE) using fuzzy system has been used [27]. A decision is a choice between alternatives. The basis for a decision is known as a criterion. In a Multi-Criteria Evaluation, an attempt is made to combine a set of criteria to achieve a single composite basis for a decision according to a specific objective. For example, a decision may need to be made about what areas are the most suitable for industrial development. Criteria might include proximity to roads, slope gradient, exclusion of reserved lands, and so on [28]. Through a Multi-Criteria Evaluation, these criteria images representing suitability may be combined to form a single suitability map from which the final choice will be made [29].

Criteria may be of two types: factors and constraints. Factors are generally continuous in nature such as slope gradient or road proximity factors; they indicate the relative suitability of certain areas [27,30]. Constraints, on the other hand, are always boolean in character such as reserved lands constraint. They serve to exclude certain areas from consideration. Factors and constraints can be combined in the MCE module and are characterized by different levels of control over tradeoff between factors and the level of risk assumed in the combination procedure where tradeoff is the degree to which one factor can compensate for another; how they compensate is governed by a set of factor weights sometimes called tradeoff weights [31,32]. Factor weights are given for each factor such that all factor weights, for a set of factors, sum to one; they indicate the relative importance of each factor to the objective under consideration. A factor with a high factor/tradeoff weight may compensate for low suitability in other factors that have lower factor/tradeoff weights [19,27].

In addition to tradeoff, any MCE is also characterized by some level of assumed risk that will strongly influence the final suitability map. A low risk analysis is one where the area considered most suitable in the final result is minimized since it must be highly suitable in all factors. A high risk analysis is one where the area considered most suitable in the final result will be maximized since any area that is highly suitable for any one factor will be considered highly suitable in the result.

Constraints must be in byte or binary format and should be boolean maps with zeros in areas that are excluded from consideration and ones elsewhere. Factors must also be in byte or binary format with a standard scaling (i.e., all factors must use the same scaling system). For example, they might all have values that range from 0 to 255, or 0 to 99 which is to standardize the continuous factors into the desired range using one of a number of set membership functions (linear, sigmodal, J shaped, or user defined); it also allows for increasing, decreasing, or symmetric functions. Once the standardized factor images have been created, a set of weights have been developed that indicate the relative importance of each factor to the decision under consideration. These weights must sum to one.

By adding all the weight maps the Landslide Hazard Index [13,33,34] has been found to vary between the range of 0–1. Gamma values assigned for each gamma combination operation play the most important role on the output fuzzy membership functions [35]. Owing to the constant value for gamma, the outputs are essentially based on the fuzzy membership functions assessed to factor maps classes. Gamma values >0.94 moves the output fuzzy membership function values to high and very high landslide susceptibilities and eliminates the moderate susceptible zones. It is suggested to examine different values of gamma and evaluate the results based on the relationship between known landslides and the susceptibility zones. Landslide susceptibility zonation on the basis of output fuzzy membership functions is shown in Table 2.4.

2.5 Results

The present study is an attempt to prepare a detailed landslide susceptibility zonation map of Haridwar district, lower Himalayan foothills in India. From the distribution of various susceptibility classes in the landslide susceptibility zonation map (Figs. 2.4 and 2.5), following conclusions can be drawn.

(a) Very high susceptibility zone has a very high possibility of slope failure of as much as 9–12% of the area of study.
(b) High susceptibility zone occupies approximately 20–25% of the total study area.
(c) The study area is mainly falling in low hazard and moderate hazard zone.

A comparison between the landslide susceptibility class zones on the map and the landslides was carried out. All the three major known landslides were located in the high and very high susceptible zones.

2.6 Discussion and Conclusion

The fuzzy logic non-linear modeling approach used in this paper provides a flexible method with which to include expert opinion in developing an inference network. A variety of fuzzy operators are used to examine different combinations and produce an intermediate map, or add any new data layer to the model and to test its affect on the final possibility map. Because the fuzzy membership functions assessed for factor maps were mainly extracted from the field data, the procedure followed during the study should find locations of the known landslides. In order to control the performance of the produced susceptibility map, a comparison between the landslide susceptibility class zones on the map and the landslides has been carried out. All the three major known landslides were located in the high and very

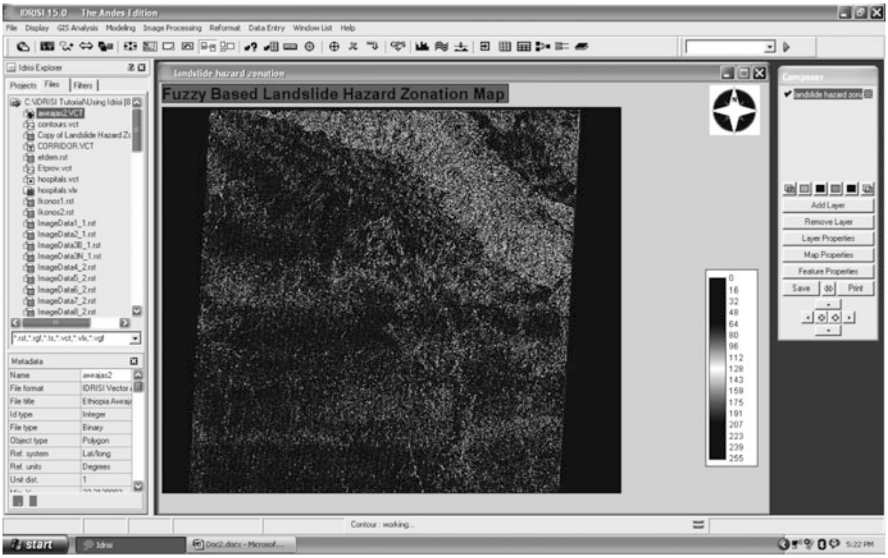

Fig. 2.4 Landslide susceptibility zonation map

high susceptible zones. This could be an acceptable result for a medium-scale landslide susceptibility map, and the use of fuzzy sigmoidal function in the generation of the landslide susceptibility map seems to be a reliable approach.

This landslide susceptibility map can be used as a planning tool but would rather not be recommended for individual site specific evaluation. Areas within the high and very high susceptibility categories should require further study by engineering geologists before development to determine the extent of possibly unstable conditions. Because the membership function approach has the nature of fuzzy rather than present-absent, or binary pattern, it may identify localities which previously have not been recognized by other methods, such as those based on known deposits. The fuzzy maps also have valuable data for other analysis methods, which apply some or all of the quantified factors. The fuzzy logic method is objective and repeatable, and can utilize varying reliability data, which commonly occur in geological descriptions.

Gamma values assigned for each gamma combination operation play the most important role on the output fuzzy membership functions. Owing to the constant value for gamma, the outputs are essentially based on the fuzzy membership functions assessed to factor maps classes. Gamma values >0.94 moves the output fuzzy membership function values to high and very high landslide susceptibilities and eliminates the moderate susceptible zones. It is suggested to examine different values of gamma and evaluate the results based on the relationship between known landslides and the susceptibility zones.

Apart from the spatial extents of landslide susceptibility that have come out with the result, it is seen that the very high and high hazard zones are mainly concentrated around the thrust.

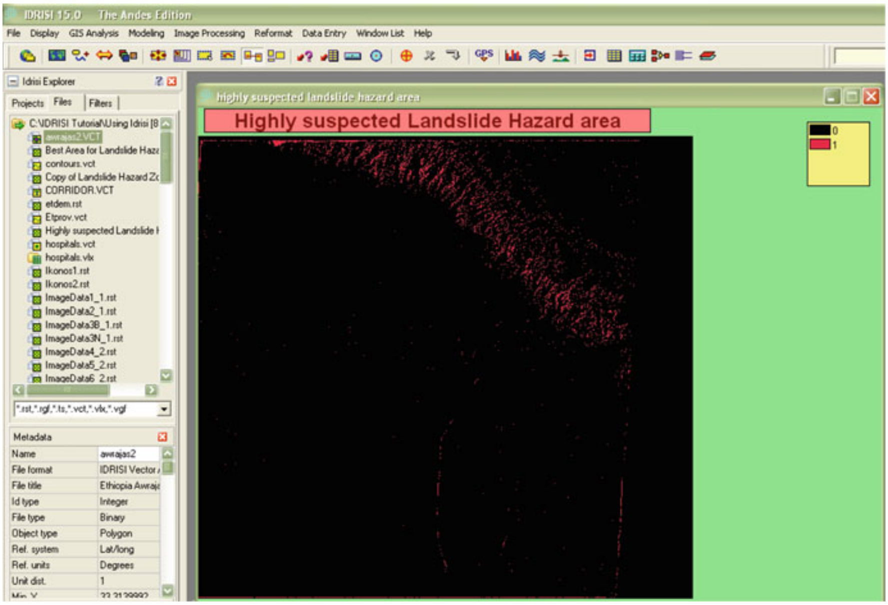

Fig. 2.5 Two level boolean landslide susceptibility zonation map showing high hazard

This method of landslide hazard zonation mapping depends mainly on the weights assigned to the parameters responsible for landslide. These weights and rating values should be re-adjusted using trial and error method. Here, from the above results it can be stated that the weighting-rating system adopted in this study is quite suitable for the study area. The landslide hazard zonation map depicts relative risk susceptibility of areas to landslides under natural conditions. The changes in natural environment (e.g. by human interference like road construction, deforestation etc.) may change the risk susceptibility of the area in terms of landslides.

Future scope of work is immense considering the fact that enhancements are possible in the knowledge base, use of still more efficient fuzzy operators and better implementation of non-linearity, and generalization of the system over national or even international extents. If susceptibility maps of larger scales are to be produced then site-specific parameters need to be taken into account which is another area of work.

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