CHAPTER 7

ARTIFICIAL NEURAL NETWORKS

7.1 GENERAL

The methodology adopted in this research for Landslide Hazard Zonation can be used for the derivation of any specific themes using the preparatory for any locations based on expert’s knowledge and the neural networks. The study was carried out in the following manner, developing the LHZ Model using analytical hierarchical process and artificial neural networks, identifying the areas prone to landslide susceptibility in terms of very low, low, moderate, high and very high hazard and comparing the landslide hazard maps produced by neural networks with AHP model. Then, prioritization of landslide prone areas was identified for executing mitigation measures.

The following sections briefly explain the methodology adopted for this research work and also explains how the landslide susceptibility map has been generated using neural networks and analytical hierarchical process.

7.2 ARTIFICIAL NEURAL NETWORKS

An artificial neural network is a “computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping”. The back propagation training algorithm (BPN) is the most frequently used neural network method and is the method used in this study. The back propagation
training algorithm is trained using a set of examples of associated input and output values. The purpose of an artificial neural network is to build a model of the data-generating process, so that the network can generalize and predict outputs from inputs that it has not previously seen.

There are two stages involved in using neural networks for multi-source classification: the training stage, in which the internal weights are adjusted; and the classifying stage. Typically, the back-propagation algorithm trains the network until some targeted minimal error is achieved between the desired and actual output values of the network. Once the training is complete, the network is used as a feed-forward structure to produce a classification for the entire data.

The artificial neural network has many advantages compared with statistical methods. Firstly, the artificial neural network method is independent of the statistical distribution of the data and there is no need of specific statistical variables. Compared with the statistical methods, neural networks allow the target classes to be defined with much consideration to their distribution in the corresponding domain of each data source (Zhou 1999). Therefore, integration of remote sensing data or GIS data is convenient. Benediktsson et al (1990) improved classification accuracy using artificial neural network for integration of Landsat MSS imagery and a topographic database (altitude, slope, and aspect). Secondly, accurate analysis is possible though training area datasets are a few because of pixel-based calculations.

Compared with the statistical methods, neural networks need less training data for accurate analysis (Paola and Schowengerdt 1995). The basic element of a neural network is the processing node. This sum is then passed through an activation function to produce the node’s output value. An enhancement is to add a constant input to the summation at each processing
node. The corresponding weight, called the bias weight, effectively controls the threshold level of the activation function. The processing nodes are organized into layers, each generally fully interconnected to the following layer. There are no interconnections within a layer. However in addition, there is an input layer that serves as a distribution structure for the data being presented to the network. No processing is done at this layer. One or more actual processing layers follow the input layer. The final processing layer is called the output layer. Any layers in between the input and output layers are termed hidden layers (Paola and Schowengerdt 1995).

The multi-layer structure can separate data that are non-linear because it is ‘multi-layer’, and it generally consists of three types of layers. The first layer is the input layer, where the nodes are the elements of a feature vector. The second type of layer is the internal or ‘hidden’ layer since it does not contain an output unit. The third type of layer is the output layer and this presents the output data. Each node in the network is interconnected to the nodes in both the preceding and following layers shown in Figure 7.1.

![Figure 7.1 Architecture of Artificial Neural Networks](image-url)
These connections have associated weights with them (Atkinson and Tatnall 1997). There are two stages involved in using neural networks for a multisource classification: the training stage and the classification stage. The back propagation algorithm trains the network, typically, until some targeted minimal error is achieved between the desired and actual output values of the network. “Once training is complete, the network is used as a feed-forward structure to produce a classification for the entire image” (Paola and Schowengerdt 1995). In this research, we only use interlayer weights of training stage. A neural network consists of a number of interconnected nodes. Each node is a simple processing element that responds to the weighted inputs it received from other nodes. The arrangement of the nodes is referred to as the network architecture (Figure 7.1). The receiving node sums the weighted signals from all nodes to which it is connected in the preceding layer. Formally, the input that a single node \( j \) receives is weighted according to equation (7.1):

\[
net_j = \sum_i W_{ij} O_i
\]  

(7.1)

where \( W_{ij} \) represents the weights between nodes \( i \) and \( j \), and \( O_i \) is the output from node \( j \), given by

\[
O_j = f(net_j)
\]

(7.2)

The function \( f \) is usually a nonlinear sigmoid function that is applied to the weighted sum of inputs before the signal propagates to the next layer. One advantage of a sigmoid function is that its derivative can be expressed in terms of the function itself:

\[
f'(net_j) = f(net_j) * (1 - f(net_j))
\]

(7.3)

The network used in this research consisted of three layers. The first layer is the input layer, where the nodes are the elements of a feature vector. The
second layer is the internal or “hidden” layer. The third layer is the output layer that presents the output data. Each node in the hidden layer is interconnected to nodes in both the preceding and following layers by weighted connections (Atkinson and Tatnall 1997).

The error, \( E \), for an input training pattern, it is a function of the desired output vector, \( d \), and the actual output vector, \( o \), given by

\[
E = \frac{1}{2} \sum (d_k - o_k)^2
\]  
(7.4)

The error is propagated back through the neural network and is minimized by adjusting the weights between layers. The weight adjustment is expressed as

\[
W_{ij}(n+1) = \eta (\delta o_i) + \alpha \Delta W_{ij}
\]  
(7.5)

where \( \eta \) is the learning rate parameter (set to \( \eta = 0.01 \) in this study), \( \delta_j \) is an index of the rate of change of the error, and \( \alpha \) is the momentum parameter (set to \( \alpha = 0.01 \) in this study)

The factor \( \delta_j \) is dependent on the layer type. For example,

For hidden layers,

\[
\delta = (\sum \delta w_{jk}) f'(net_i)
\]  
(7.6)

And for output layer,

\[
\delta = (d_k - o_k) f'(net_k)
\]  
(7.7)

This process of feeding forward signals and back-propagating the error is repeated iteratively until the error of the network as a whole is minimized or reaches an acceptable magnitude. Using the back-propagation training algorithm, the weights of each factor can be determined and may be used for classification of data (input vectors) that the network has not seen before. Zhou (1999) described a method for determining the weights using back propagation.
From equation (7.2), the effect of an output, $o_j$, from a hidden layer node, $j$, on the output, $o_k$, from an output layer (node k) can be represented by the partial derivative of $o_k$ with respect to $o_j$ as

$$
\frac{\partial o_k}{\partial o_j} = f'(net_k) \times \frac{\partial (net_k)}{\partial o_j} = f'(net_k) \times W_{jk}
$$

(7.8)

Equation (7.8) produces both positive and negative values. If the effect’s magnitude is all that is of interest, then the importance (weight) of node $j$ relative to another node $O_j$ in the hidden layer may be calculated as the ratio of the absolute values derived from equation (7.9).

$$
\left| \frac{\partial o_k}{\partial o_j} \right| = \frac{|f'(net_k)W_{jk}|}{|f'(net_k)W_{jk}|} = \left| \frac{W_{jk}}{W_{jk}} \right|
$$

(7.9)

We should mention that $W_{jok}$ is simply another weight in $W_{jk}$ other than $W_{jk}$. For a given node in the output layer, the results of Equation (7.9) show that the relative importance of a node in the hidden layer is proportional to the absolute value of the weight connecting the node to the output layer. When the network consists of output layers with more than one node, then equation (7.9) cannot be used to compare the importance of two nodes in the hidden layer.

$$
W_{jok} = \frac{1}{J} \times \sum_{j=1}^{J} |W_{jk}|
$$

(7.10)

$$
t_{j} = \frac{|W_{jk}|}{\frac{1}{J} \sum_{j=1}^{J} |W_{jk}|} = J\left| W_{jk} \right| \sum_{j=1}^{J} |W_{jk}|
$$

(7.11)

Therefore, with respect to node k, each node in the hidden layer has a value that is greater or smaller than unity, depending on whether it is more or less important, respectively, than an average value. All the nodes in the hidden layer have a total importance with respect to the same node, given by
\[
\sum_{j=1}^{J} I_{jk} = J
\] (7.12)

Consequently, the overall importance of node \( j \) with respect to all the nodes in the output layer can be calculated by

\[
I_j = \frac{1}{K} \sum_{j=1}^{K} I_{jk}
\] (7.13)

Similar, with respect to the node \( j \) in the hidden layer, the normalized importance of the node \( i \) in the input layer can be defined as equation (7.9).

\[
s_{ij} = \frac{|W_{ij}|}{\frac{1}{J} \sum_{j=1}^{J} |W_{ij}|} = \frac{|W_{ij}|}{\frac{1}{J} \sum_{j=1}^{J} |W_{ij}|}
\] (7.14)

The overall importance of node \( i \) with respect to the hidden layer is

\[
s_i = \frac{1}{J} \sum_{j=1}^{J} s_{ij}
\] (7.15)

Correspondingly, the overall importance of input node \( i \) with respect to output node \( k \) is given by

\[
s_{in} = \frac{1}{J} \sum_{j=1}^{J} s_{ij} \times I_j
\] (7.16)

### 7.2.1 Determination of Weight for Landslide Susceptibility Analysis using Artificial Neural Network

Artificial neural network methods have previously been applied to land use and cover classification using satellite imagery (Schaale and Furrer 1995, Serpico and Roli 1995). In particular, the multi-layer perceptron...
method using the back propagation algorithm was used widely in a supervised
classification with training area data (Atkinson and Tatnall 1997). The
supervised classification is assigned at the site where the information is well
known; this training site is classified by analysis of the input data for the site.
By this process, landslide susceptibility data were analyzed in this study using
artificial neural network methods.

Figure 7.2 is the flowchart of neural networks training for weight
determination. The weight between layers that acquired by training of neural
network calculated reversely and the contribution or importance of each factor
is calculated. So, the contribution or importance of each factor, weight, was
determined. A GIS spatial database was used as input data and landslide
locations were used as training sites.

The constructed landslide related factors do not have a Gaussian
distribution and are not statistically related or distributed amongst the
supervised classification, so the back propagation neural network method was
used. In the artificial neural network method, the 7 factors were used. The
program developed by Hines (1997) using MATLAB was partially modified
for the landslide analysis. It was modified in the input and output parts for the
use of GIS data.

In this analysis, the study area was divided into a 10 m x 10 m pixel
grid (ARC/INFO GRID format), which was converted to ASCII format for
use in the artificial neural network program. There were 4,85,01,300 cells in
the study area, and 3% of them experienced landslides. For analysis of
landslide susceptibility, the training sites were selected from the landslide-
related factors and the back propagation algorithm was applied to calculate
weights between the input layer and the hidden layer, and between the hidden
layer and the output layer, by modifying the number of hidden layers and the
learning rate. The weights were applied to the entire study area and the
landslide susceptibility index value was calculated. The calculated index values were converted into an ARC/INFO GRID using the GIS. Then the landslide susceptibility map was created using the GRID data.

Figure 7.2 Schematic diagram of weight determination for landslide factors using neural networks
The factors were inputted to a MATLAB-based application program that we had developed. Using the 8x15x2 (number of input, hidden, and output layers) structure and the formulae from equations 7.1–7.16, the weights were trained. A three-layered feed forward network was implemented in MATLAB on the basis of the framework provided by Hines (1997). Feed forward means that all the interconnections between the layers propagate forward to the next layer. The number of hidden layers and the number of nodes in a hidden layer required for a particular classification problem are not easy to deduce.

The input data has been normalized in the range 0.1–0.9. The reason for data normalization is that the eleven variables are different in dimensions and are not suitable for direct input for the ANN model. The common method (Choi et al., 2009) for the data processing is to transform the data to the values between 0 and 1. For example, for \( y_i (i = 1, 2, ..., n) \):

\[
Y_i = \frac{y_i - y_{\text{min}}}{y_{\text{max}} - y_{\text{min}}} \tag{7.17}
\]

where, \( Y_i \) means the normalized values of \( y_i \), \( y_{\text{min}} \) and \( y_{\text{max}} \) represent the minimum and maximum value of \( y_i \) respectively. In this way, the nominal and interval class group data were converted to continuous values ranging between 0.1 and 0.9. Therefore, the continuous values were not ordinal data, but nominal data, and the numbers denote the classification of the input data. The learning rate as 0.01 and the initial weights are randomly selected. The ASCII values are not directly used in the process but it has been converted into normalized weights. The weights for individual classes have been calculated by using the artificial neural network program. From each of the two classes (landslide and not landslide), 250 pixels are selected as training
pixels. The landslide prone (occurrence) locations and the landslide non-prone (non occurrence) locations are selected randomly as training sets. The 50 training sets are processed to recognize the changes in initial weights. The back propagation algorithm works the weights backwards and then controls the weights. The numbers of epochs are set to 1200 and Root Mean Square Error (RMSE) goal for stopping criterion was set to 0.01. Most of the iterations have met the 0.01 RMSE goals. The iteration might be stopped around 1200 epochs by default. After the training, the weights of each layer have been identified shown in Table 7.1. The landslide hazard map has been prepared using ArcMap software which is shown in Figure 7.3.

Once the networks were successfully trained and the weights computed, the trained network with the highest accuracy was used to categorize each and every pixel of the whole dataset to one of the landslide susceptibility zonation classes to produce the LSI classification. In other words, the landslide susceptibility index value was calculated from the weights determined from the back-propagation and the spatial datasets. The index values were between 0.1 and 0.9 for each pixel. The output indices were converted to GIS grid data. Using such values, the landslide susceptibility indices (LSI) were determined and used to create the landslide susceptibility maps. The value of susceptibility was classified by equal area and grouped into five classes for easy and visual interpretation. With an increase in the index, the landslide susceptibility also increases.
Landslide Susceptibility Map of Nilgiris District

Figure 7.3 Landslide Susceptibility Map Prepared through Neural Networks Model
Table 7.1 Initial weights assumed during the Determination of the weights of each factors

<table>
<thead>
<tr>
<th>Factors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Average</th>
<th>Std. Deviation</th>
<th>Normalized Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspect</td>
<td>0.1236</td>
<td>0.2322</td>
<td>0.1805</td>
<td>0.1685</td>
<td>0.1268</td>
<td>0.1568</td>
<td>0.1875</td>
<td>0.1609</td>
<td>0.0932</td>
<td>0.1642</td>
<td>0.1594</td>
<td>0.0386</td>
<td>1.0012</td>
</tr>
<tr>
<td>Curvature</td>
<td>0.0617</td>
<td>0.0923</td>
<td>0.0926</td>
<td>0.0697</td>
<td>0.0801</td>
<td>0.0531</td>
<td>0.0536</td>
<td>0.0932</td>
<td>0.0688</td>
<td>0.0780</td>
<td>0.0743</td>
<td>0.0155</td>
<td>1.3046</td>
</tr>
<tr>
<td>Geology</td>
<td>0.1446</td>
<td>0.1330</td>
<td>0.1648</td>
<td>0.2668</td>
<td>0.2105</td>
<td>0.1476</td>
<td>0.1833</td>
<td>0.1235</td>
<td>0.2430</td>
<td>0.1380</td>
<td>0.1751</td>
<td>0.0498</td>
<td>1.0983</td>
</tr>
<tr>
<td>Slope</td>
<td>0.5619</td>
<td>0.4038</td>
<td>0.4886</td>
<td>0.4007</td>
<td>0.4951</td>
<td>0.5429</td>
<td>0.4684</td>
<td>0.5247</td>
<td>0.5041</td>
<td>0.5304</td>
<td>0.4921</td>
<td>0.0546</td>
<td>3.0868</td>
</tr>
<tr>
<td>Landuse</td>
<td>0.0629</td>
<td>0.0760</td>
<td>0.0767</td>
<td>0.0747</td>
<td>0.0768</td>
<td>0.0730</td>
<td>0.0725</td>
<td>0.0762</td>
<td>0.0777</td>
<td>0.0787</td>
<td>0.0745</td>
<td>0.0042</td>
<td>1.3081</td>
</tr>
<tr>
<td>Socio</td>
<td>0.0408</td>
<td>0.0691</td>
<td>0.0692</td>
<td>0.0596</td>
<td>0.0546</td>
<td>0.0584</td>
<td>0.0604</td>
<td>0.0681</td>
<td>0.0633</td>
<td>0.0657</td>
<td>0.0609</td>
<td>0.0086</td>
<td>1.0693</td>
</tr>
<tr>
<td>Soil</td>
<td>0.0557</td>
<td>0.0667</td>
<td>0.0673</td>
<td>0.0662</td>
<td>0.0658</td>
<td>0.0610</td>
<td>0.0615</td>
<td>0.0666</td>
<td>0.0709</td>
<td>0.0575</td>
<td>0.0639</td>
<td>0.0048</td>
<td>1.1223</td>
</tr>
<tr>
<td>Rainfall</td>
<td>0.1389</td>
<td>0.1309</td>
<td>0.1263</td>
<td>0.1230</td>
<td>0.1207</td>
<td>0.1219</td>
<td>0.1258</td>
<td>0.1252</td>
<td>0.1188</td>
<td>0.1125</td>
<td>0.1244</td>
<td>0.0071</td>
<td>2.1840</td>
</tr>
</tbody>
</table>
The final weights between layers acquired during training of the neural networks and the contribution or importance of each of the 8 landslide causing factors used for predict landslide susceptibility are shown in Table 7.2. The results were not the same as the initial weights were assigned random values. Therefore, in this study, the calculations were repeated ten times, to allow the result to achieve similar values. The standard deviation of the results was in the range 0 to 0.015, and therefore, the random sampling did not have a large effect on the results. Average values were calculated for easy interpretation and these values were divided by the minimum value weighting. For easy interpretation, the average values were calculated and these values were divided by the average of the weights of the some factor that had a minimum value. Finally, the weights were applied to the entire study area, and the landslide susceptibility index value was calculated.

Table 7.2 Weights of each landslide causing factors after training

<table>
<thead>
<tr>
<th>Factors</th>
<th>Average</th>
<th>Standard Deviation</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspect</td>
<td>0.1594</td>
<td>0.0386</td>
<td>1.0012</td>
</tr>
<tr>
<td>Curvature</td>
<td>0.0743</td>
<td>0.0155</td>
<td>1.3046</td>
</tr>
<tr>
<td>Geology</td>
<td>0.1751</td>
<td>0.0498</td>
<td>1.0983</td>
</tr>
<tr>
<td>Slope</td>
<td>0.4921</td>
<td>0.0546</td>
<td>3.0868</td>
</tr>
<tr>
<td>Landuse</td>
<td>0.0745</td>
<td>0.0042</td>
<td>1.3081</td>
</tr>
<tr>
<td>Socio</td>
<td>0.0609</td>
<td>0.0086</td>
<td>1.0693</td>
</tr>
<tr>
<td>Soil</td>
<td>0.0711</td>
<td>0.0103</td>
<td>1.0821</td>
</tr>
<tr>
<td>Rainfall</td>
<td>0.1244</td>
<td>0.0071</td>
<td>2.1840</td>
</tr>
</tbody>
</table>
7.3 ANALYTICAL HIERARCHICAL PROCESS

Analytical Hierarchical Process (AHP), a theory for dealing with complex, technological, economical, and socio-political problems is an appropriate method for deriving the weight assigned to each factor. Basically, AHP is a multi-objective, multi-criteria decision-making approach to arrive at a scale of preference among a set of alternatives. AHP gained wide application in site selection, suitability analysis, regional planning, and landslide susceptibility analysis.

The AHP is employed to determine the weights of the available data to produce the landslide susceptibility map. With this method, the Weights of different subgroups are quantitatively determined. It has been shown that the use of the AHP method produces a practical and realistic result to define the factor weights in the landslide susceptibility model (Figure 7.4).

As shown in figure for Architecture of Analytical Hierarchical Process, the Data has been collected from satellite imagery and SRTM/contour maps. Landuse map has been prepared from satellite imagery, slope map from SRTM/contour, from the analysis of regional rainfall data the rainfall map has been prepared and geological map from geological studies has been prepared and then based on previous landslide studies the scores were assigned to each landslide causing factor through 5 point scale.

![Figure 7.4 Weighted overlay](image)

Figure 7.4 Weighted overlay
At the first stage, the data obtained from Remote Sensing and GIS are uploaded, including landslide inventory and database. The input parameter maps, and primary weight assigned parameter maps constructed with \( W_i \) values suggested by Van Westen (1997). The \( W_i \) value is expressed in the following equation:

\[
W_i = \frac{(N_{pix}(S_i)/N_{pix}(N_i))}{(\sum N_{pix}(S_i)/\sum N_{pix}(N_i))}
\]  \( \text{(7.17)} \)

where \( N_{pix}(S_i) \) the number of pixels is exposed to landslides for a subgroup of a parameter, and \( N_{pix}(N_i) \) is the total number of pixels for the related parameter.

Slope angle, slope aspect, topographical elevation and topographical shape parameters were obtained directly from the DEM. In order to express water condition, a DEM-based wetness index, otherwise known as compound topographic index (Moore et al 1988), is used to represent the spatial distribution of water flow across the study area. The wetness index represents a theoretical measure of the accumulation of flow at any point within a river basin and is calculated using the expression:

\[
w = \ln(A_s / \tan \beta)
\]  \( \text{(7.18)} \)

where \( w \) is the wetness index
\( A_s \) is the specific catchment area, and
\( \beta \) is the slope angle.

The second stage involved gathering the opinions of experts selected for their knowledge and experience about landslide concepts and their experience of landslides and their mechanisms in the study area. It was not considered appropriate to ask experts from abroad as landslide
characteristics vary from one region to another. The selected experts are professionals in geology and with academic backgrounds, particularly in engineering geology. They were asked to evaluate the pair wise comparison of the given parameters contributing to the regional landslide characteristics based on their experience and knowledge. This comparison was made based on the principles of the AHP method developed by Saaty (1977) which has been successfully employed in landslide susceptibility mapping by such workers as Barredo et al (2000), Ayalew et al (2005), Komac (2006) and Akgun and Bulut (2007) using GIS based multivariate statistics and logistic regression.

The AHP method is a multi-criteria decision-making process using the relative importance of the parameters contributing to the event to produce parameter weights and evaluates the consistency of pair wise comparison parameters (Barredo et al 2000). The scale proposed by Saaty (1977) involves a rating system ranging between 1/9 and 9 where 1/9 is the least important and 9 the most important parametric effect. These values are placed in a matrix based on the parametric pair wise importance. In our research the rating system ranges from 1 to 5.

The parametric pair wise ratings given by the experts are shown in Table 7.3. This is used to develop a set of relative weights for a group of parameters in a multicriteria evaluation. The weights are developed by providing a series of pair wise comparisons of the relative importance of parameters to the suitability of pixels for the activity being evaluated. The weights generated by this module are produced by means of the principal eigenvector of the pair wise comparison matrix.
The parameter weights are calculated by the ArcGIS software. In general the experts considered the most important parameter contributing to landslide occurrence in the study area is the slope angle and rainfall.

In other words, multi-criteria evaluation is a process in which several criteria are evaluated in order to meet a specific objective (Eastman 2003). Then involves multiplication of each parameter by its calculated weight and is selected as it has been successfully used in landslide assessment studies. Finally, taking into consideration of the experts’ opinions, landslide susceptibility maps of the study area were produced.

After having analyzed all the spatial data, a Model has been developed, using the Analytical Hierarchical Process method. The application of the AHP method, developed by Saaty (1977), for landslide susceptibility has been shown before and it was used to define the factors that govern landslide occurrence more transparently and to derive their weights. Figure 7.5 shows the final landslide hazard map prepared through Analytical Hierarchic Process method. This map has been prepared based on the scores of each landslide determinants multiplied with their assigned weights. In our chosen study area only three types of geological features has been found. The ranks have been assigned starting from 2 to 4. Since the rainfall is the major factor for causing landslide in our study area, the ranks have been assigned as 4 (rainfall from 1000 to 1600mm) and 5 (1600 to 2800mm).
Table 7.3 Weightages and Ranks for the layers based on their contribution for the landslide cause

<table>
<thead>
<tr>
<th>Layer</th>
<th>Weightage</th>
<th>Class</th>
<th>Rank in 5 point Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>40</td>
<td>0-8%</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8-15%</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>15-30%</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30-60%</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt;60%</td>
<td>5</td>
</tr>
<tr>
<td>Land use</td>
<td>36</td>
<td>Arable</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Forest</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>Metagabbro, Pyroxenite, Pyroxene granulite</td>
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<td>Charnockite</td>
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Figure 7.5 Landslide Hazard Mapping using AHP Model