Landslide susceptibility mapping using geographically-weighted principal component analysis

Hassanali Faraji Sabokbar a, Majid Shadman Roodposhti b,⁎, Esmaeil Tazik b

a Dept. of Human Geography, Faculty of Geography, University of Tehran, Iran
b Dept. of RS and GIS, Faculty of Geography, University of Tehran, Iran

ARTICLE INFO

Article history:
Received 10 March 2014
Received in revised form 17 July 2014
Accepted 19 July 2014
Available online 31 July 2014

Keywords:
Geographically weighted principal component analysis (GWPCA)
Fuzzy gamma operator
Landslide susceptibility mapping (LSM)
Iran

ABSTRACT

Landslide susceptibility mapping (LSM) documents the extent of probable landslide events in a region to investigate the distribution, pattern, recurrence and statistics of slope failure and consequent mass movement. Similar to other analyses of quantitative sources of spatial data, LSM sometimes uses principal component analysis (PCA), a form of multivariate statistical analysis. This approach helps identify susceptibility by grouping locations or by measuring the variation between groups. The present study outlines the principles and examines the capability of the proposed methodology for landslide mapping, considers optimized shapes for spatial units, estimates an efficient kernel size using alternating least squares (ALS) analysis confirmed by cross-validation, and uses geographically-weighted principal component analysis (GWPCA) to calculate landslide susceptibility using a fuzzy gamma operator. RMSE and PBIAS statistical estimators were then used to assess operational efficiency of all LSMS using fuzzy gamma operators (0.1 to 0.9). ROC curves were drawn for the best result for LSM using a landslide inventory containing 82 landslide points, with an area under curve of 0.889. The new tools can improve the quality of landslide-related analyses, including erosion studies and landscape modeling, susceptibility and hazard assessments, and risk evaluation.

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1. Introduction

Landslides are geologic hazards that occur on spatial and temporal scales in mountainous landscapes (McKeen and Roering, 2004). They occur on all continents and represent serious hazards. They play an important role in the evolution of landscapes (Guzzetti et al., 2012). Although there has been increased understanding of slope instability mechanisms and mitigation techniques, landslides continue to cause human and financial loss. Landslide susceptibility mapping (LSM) is a solution to understanding and predicting hazards to mitigate their consequences (Feizizadeh and Blaschke, 2011). The degree of susceptibility is usually expressed cartographically using light-to-dark shades or sequences (Feizizadeh and Blaschke, 2011). The degree of susceptibility is measured by increasing dimensionality and identifying combinations of characteristics that delineate multivariate samples to identify spatial patterns. In this respect, PCA can be used to assess how far different landslide-related variables affect the landslide susceptibility of a study area. It also assists researchers to find a proper answer for questions like: “Is the landslide susceptibility of the study region more affected by topographic or by lithologic characteristics?”

Geographically weighted principal component analysis (GWPCA) can be applied as a quantitative solution to LSM when there is no known priority for landslide-related variables in the area of interest. The present study extended a data-driven LSM method using GWPCA where there was no prior expert knowledge for evaluation and weighting of variables.

Tessellation is required for neighborhood analysis; in this case hexagons were selected from the regular tessellations on a plane (hexagon, square, and triangle) (Carr et al., 1992; Birch et al., 2007). Triangular tessellation uses triangles with two orientations, which makes it unpopular for neighborhood analysis. Hexagons are considered to be more efficient spatial structures than square grids for continuously dividing a two-dimensional space, but a rectangle or square grid (Moore...
neighborhood) is more often used for LSM. Hexagonal shapes yield an isotropic neighborhood and result in better neighborhood analysis; however, the visual advantages of hexagonal shapes may be greater than their accuracy (Carr et al., 1992; Birch et al., 2007) (Fig. 2). We assume that GWPCA susceptibility maps using hexagonal grid neighborhood analysis tend to be less ambiguous and more accurate than those using a rectangular grid. We evaluate 12 landslide-related raster-based layers for LSM generation using an objective method with GWPCA.

2. The study region

The study region is the Chehelchay Basin in central Golestan Province in northeastern Iran (Fig. 3). It is one of the most landslide-prone areas of Iran (Pourghasemi, 2008; Shadman et al., 2014). It lies between 36°59' and 37°13' N latitude and 55°23' to 55°38' E longitude and covers a surface area of 34,300 km². The minimum elevation is 770 m and the maximum elevation is 2550 m. The climate at higher elevations is temperate and mountainous, whereas a temperate semi-humid climate prevails in the plains. The Alborz Range to the west, the Kopedagh Range to the east, and the Caspian Sea to the north provide climatic diversity. The average annual precipitation in the basin is 766.5 mm and mainly consists of rainfall (~90%). The heaviest rainfall typically occurs between September and December because strong onshore winds blow from the Siberian High toward the Caspian Sea, although rainfall occurs throughout the year. The least rainfall occurs from April to July.

There are about 15 types of lithological outcrops throughout the study region within which fine-grained sedimentary rocks prevail. The general lithological properties of the Chehelchay Basin are shown in Fig. 4 and a detailed description is provided in Table 1. The prevailing

![Fig. 1. A schematic illustration of commonly used LSM methods.](image1)

![Fig. 2. Hexagonal versus rectangular (Moore) neighborhood for GWPCA based LSM.](image2)
constituents of the sedimentary rocks of the Chehelchay Basin are limestone, marl, shale, gypsum and siltstone. There are many discontinuities and weak planes, including a major fault to the southeast and several minor faults to the south and north (Fig. 4). It was found that the landslide frequency increased as the distance to a major or minor fault decreased, indicating the higher probability of landslides in the southeastern, southwestern and northern regions.

3. Material and methods

3.1. Landslide-influencing data

Twelve variables were selected for the LSM study area of the Chehelchay Basin: elevation, slope, aspect, erosion, distance-to-stream, distance-to-fault, distance-to-road, distance-to-village, mean annual precipitation, lithology, vegetation cover and soil type. These variables were selected because they have been successfully used in previous studies (Table 2). Further layer preprocessing was done in the ArcGIS environment. The data required to produce a susceptibility map of the study area was derived from various datasets (Table 2).

3.2. Landslide inventory

The Chehelchay Basin has experienced more than 80 landslides with different scales. Although there is no detailed temporal information on these events, the landslides provide data for the assessment and evaluation of landslide susceptibility in the region. The landslide inventory for the Chehelchay Basin was constructed using color aerial photographs and multi-source remote sensing imagery and verified by extensive field surveys using the global positioning system. A total of 82 rotational and translational landslides were detected and recorded in the point format. Fig. 4 shows the distribution of these landslides.

3.3. Methodology

Besides variable selection, data collection, preprocessing, regression analysis and collinearity calculation, the methodology used comprised eight steps. Step 1 was to prepare the basic hexagonal neighborhood shapes and evaluate their optimal size using root mean square error (RMSE) retrieved with MatLab. Hexagon sizes of 0.05, 0.075, 0.10, 0.25 and 0.50 km² were evaluated and 0.10 km² was selected because it offered the lowest RMSE value.

Step 2 increased the accuracy of the GWPCA-based LSM using an optimal k value and an alternating least squares (ALS) algorithm to determine the size of the kernel. The optimal k value was verified using a 10-fold cross-validation (CV) approach to decide how many neighbors will influence the neighborhood analysis in step 3. Although CV is computationally time consuming, it is useful to assist k optimization. In step 4, the measure of linear dependence (spatial co-linearity of landslide-related variables) was evaluated. GWPCA was implemented in step 5 to establish the relative importance of each landslide-related variable for geographic weighting determined by its contribution to overall susceptibility.

Step 6 used the results of the prior step for integration using fuzzy gamma operators. The results from step 6 were then used for validation and for creating the landslide inventory database in step 7. The best susceptibility map is further validated using the relative operating
characteristic (ROC) curve analysis in step 8. Fig. 5 is a schematic representation of the proposed methodology.

### 3.3.1. Cross-validation

CV is a well-established statistical technique to obtain estimations of optimized \( k \) in the neighborhood analysis. On the basis of optimization, the user must decide the best configuration for the \( k \)-nearest neighbors (\( k \)-NN) in terms of \( k \) and the distance unit. These settings are critical, since different \( k \)-NN configurations may produce different results in terms of prediction accuracy (Chirici et al., 2008).

CV divides the dataset into a number of \( v \) subsets. The \( k \)-NN model is applied for a fixed value of \( k \) to predict the \( v \)-th subset and evaluate the error using RMSE. This process is then implemented for all available choices for \( v \). The errors are then averaged for all \( v \) subsets (folds) to compute a measure of stability of the model which shows how well the model predicts points of interest. All steps are repeated for different \( k \) values and the value with the lowest RMSE is selected as the optimal value for \( k \).

### 3.3.2. k-NN

The k-NN algorithm is a simple machine algorithm (Yang and Jin, 2006; Bishop, 2007). In k-NN, members of the same geographic set that are located near each other will have similar characteristics. Using this algorithm, the expected value of a spatial object is estimated by majority vote of its neighbors. The object is then assigned to the class that is most common among the k-NN, where \( k \) is a positive integer that is typically small. If \( k = 1 \), then the object is assigned to the class of its nearest neighbor (Li et al., 2012).

In the proposed methodology, the choice of an optimal \( k \) value is essential to building the \( k \)-NN model because \( k \) strongly influences the quality of the susceptibility map. Perceiving \( k \) as a smoothing parameter is a way to evaluate the number of \( k \)-nearest neighbors. For any given problem, a small \( k \) leads to a large variance in prediction. Alternatively, setting \( k \) to a large value may lead to large model bias; thus, \( k \) should be set to an optimum value that is large enough to decrease the probability of misclassification but small enough (with respect to the number of cases in the sample) so that the \( k \)-nearest points are near to the point of interest. As for any smoothing parameter, the optimal \( k \) provides an optimum tradeoff between bias and variance of the model. k-NN can provide an estimation of \( k \) using CV (Bishop, 1995).

### 3.3.3. GWPCA

The concept of geographical weighting was introduced by Fotheringham et al. (2002) and initiated using geographically-weighted regression (GWR). Basic GWR technique examines the relationship between a dependent spatial variable \( (y) \) and one or a set of independent variables \( (x) \).

A number of studies have investigated multi-collinearity when applying GWR (Wheeler and Tiefelsdorf, 2005; Wheeler, 2007; Cho et al., 2009; Wheeler, 2009; Jiang et al., 2010; Lloyd, 2010; Wheeler and Páez, 2010). Additional limitations concern kernel bandwidth selection and multiple hypothesis testing. Geographical weights of landslide-related variables are used for LSM and GWPCA, and LPCA is used to extract the spatially variant susceptibility of each \( n \) dataset throughout the study region. A set of GW means, variances and covariances exists for each \( n \) data location around the means and should be calculated for GWPCA (Fotheringham et al., 2002; Lloyd, 2010). The geographically weighted mean can be computed as (Fotheringham et al., 2002; Lloyd, 2010):

\[
X_j = \frac{\sum_{i=1}^{n} X_i w_{ij}}{\sum_{i=1}^{n} w_{ij}}
\]

where \( x_i \) is a vector of independent variables for the jth observation and \( w_{ij} \) represents the weights of each hexagonal neighbor at ith row and the jth column of the kernel. A Gaussian weighting scheme can be

### Table 1

<table>
<thead>
<tr>
<th>Code</th>
<th>Geologic era</th>
<th>Formation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qm</td>
<td>Quaternary</td>
<td>Dalichai</td>
<td>Swamp and marsh</td>
</tr>
<tr>
<td>Jd</td>
<td>Jurassic</td>
<td>Ruteh</td>
<td>Well-bedded to thin-bedded, greenish-gray argillaceous limestone with intercalations of calcareous shale</td>
</tr>
<tr>
<td>Pr</td>
<td>Permian</td>
<td>–</td>
<td>Dark gray medium-bedded to massive limestone</td>
</tr>
<tr>
<td>Jmnz</td>
<td>Late Jurassic</td>
<td>Mozduran</td>
<td>Gray thick-bedded limestone and dolomite</td>
</tr>
<tr>
<td>Qs.d</td>
<td>Quaternary</td>
<td>–</td>
<td>Unconsolidated windblown sand deposits including sand dunes</td>
</tr>
<tr>
<td>P21a.bv</td>
<td>Paleozoic</td>
<td>Paleozoic</td>
<td>Andesitic basaltic volcanic</td>
</tr>
<tr>
<td>Cm</td>
<td>Carboniferous</td>
<td>Mobarak</td>
<td>Dark gray to black fossiliferous limestone with subordinate black shale</td>
</tr>
<tr>
<td>DChk</td>
<td>Devonian</td>
<td>–</td>
<td>Yellowish, thin to thick-bedded, fossiliferous argillaceous limestone, greenish marl and shale, locally including gypsum</td>
</tr>
<tr>
<td>TRJs</td>
<td>Triassic–Jurassic</td>
<td>Shemshak</td>
<td>Dark gray shale and sandstone</td>
</tr>
<tr>
<td>Ku</td>
<td>Late Cretaceous</td>
<td>–</td>
<td>Upper cretaceous, undifferentiated rocks</td>
</tr>
<tr>
<td>Jch</td>
<td>Jurassic</td>
<td>Chaman Bid</td>
<td>Dark gray argillaceous limestone and marl</td>
</tr>
<tr>
<td>Jsc</td>
<td>Middle Jurassic</td>
<td>–</td>
<td>Conglomerate</td>
</tr>
</tbody>
</table>
employed to determine the geographical weights \((w_{ij})\) of each hexagonal neighbor as \((\text{Fotheringham et al., 2002; Lloyd, 2010})\):

\[
w_{ij} = e^{-0.5 \left( \frac{d_{ij}}{k} \right)^2}
\]

where \(k\) is the bandwidth and determines the size of the kernel and \(d_{ij}\) is the spatial distance between locations \(i\) and \(j\). If the weights are standardized to sum to one, Eq. (1) becomes:

\[
x_i = \sum_{j=1}^{n} x_j w_{ij}.
\]
Fotheringham et al. (2002) stated that the geographically-weighted variance in group \( i \) \((\sigma_i)\) can be computed as:

\[
\sigma_i = \left[ \sum_{j=1}^{n} \left( x_j - \bar{x}_i \right)^2 w_{ij} \right]^{0.5}.
\]  

(4)

The covariance of geographically-weighted variables (i.e., \( x_1 \) and \( x_2 \)) at location \( i \) is:

\[
\text{Cov} (x_1 - x_2) = \sum_{j=1}^{n} w_{ij} \left( x_{1j} \bar{x}_i \right) \left( x_{2j} \bar{x}_i \right)
\]

(5)

where \( x_{1j} \) and \( x_{2j} \) are the \( j \)-th case of variables \( x_1 \) and \( x_2 \), respectively. The next equation calculates the geographically-weighted correlation coefficient for the location \( i \) as:

\[
r_i = \frac{\text{Cov} (x_{1i} - x_{2i})}{\sqrt{\sigma(x_{1i}) \sigma(x_{2i})}}
\]

(6)

where \( \sigma(x_{1i}) \) and \( \sigma(x_{2i}) \) are the geographically-weighted variances for \( x_1 \) and \( x_2 \), respectively, at location \( i \). The correlation matrix of the estimated correlation coefficients can then be used for PCA.

Fig. 6. Obtained results of regression analysis between the first 5 local principal components of Chehelchay Basin and selected landslide related criteria for LSM.
3.3.4. Fuzzy gamma operator

A variety of fuzzy operators combine landslide-related variables that have been standardized using fuzzy membership functions. AND and OR are among the best-known operators; however, only one of the combined sets significantly affects the result of the combination, while the other sets have little influence. Fuzzy AND operator will return minimum of all values of the sets the cell location belongs to while, it is the maximum value in case of OR operator.

The fuzzy gamma operator was adopted in the present study as a better alternative. The fuzzy gamma operator is (Sandham and Leggett, 2003):

\[ \mu_i = \left(1 - \prod_{k=1}^{n} (1 - \mu_k)\right)^\gamma \prod_{k=1}^{n} \mu_k^{1-\gamma} \]  

(7)

where \(0 < \gamma < 1\), \(\mu_i\) is a susceptibility value, and \(\gamma\) is the fuzzy gamma operator. Different fuzzy gamma operators were used \((0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, \text{ and } 0.9)\) to evaluate the final susceptibility map of the study region. A fuzzy gamma value of 0.9 was selected as a compromise between the increasing and decreasing effects of the fuzzy gamma approach.

3.3.5. Model assessment

Two validation phases produced the prior and posterior map classifications (defuzzification) to assess the performance of the LSM using:

(1) RMSE and percent bias (PBIAS) and (2) the ROC curve. In the first validation phase, RMSE (quadratic mean) measures the difference between the value predicted by an estimator and the measured value (Hyndman and Koehler, 2006). PBIAS measures the average tendency of predicted values of an estimator to be systematically different (smaller or larger) from the observed values (Yapo et al., 1996).

In the second phase, the area under the curve (AUC) for ROC (0.5 to 1.0) is used to evaluate the accuracy of the model. AUC is a measure of the ability to discriminate landslide from non-landslide locations and is independent of a specific decision threshold for the model output. It is normally above 0.5 (random discrimination) and not higher than 1 (perfect separation of the classes) (Goetz et al., 2011; Pradhan, 2012).

4. Results

After ALS and 10-fold CV analysis, a standard GWPCA was constructed using the hexagonal neighbors. The results show that 2697 local components (hexagonal neighbors) were produced for every 12 calculated principal components (landslide-related variables). For most hexagonal neighborhoods, the first three components contained 55% to 70% of the variation and the first five principal components contained 61% to 76%.

Fig. 6 represents the results of regression analysis for the first five principal components and all 12 landslide-related variables. There was a noticeable spatial variation between the causative effects of the landslide-related variables. For the first principal component, the central to northern area had the most obvious spatial concentrations of vegetation and river variables. The southern and southwestern areas were mainly affected by soil and elevation variables. There was a clear distinction between the more and less susceptible areas for the first three principal components. The general pattern was strongly supported by the landslide inventory database of the region. The proposed GWPCA technique allowed detailed recognition of landslide-related contributing variables throughout the geographic boundaries of the study region (Fig. 7).

4.1. Validation of results using RMSE and PBIAS

RMSE and PBIAS were used to assess operational efficiency of the LSMS. Table 3 shows the estimator assessment results of each fuzzy gamma operator used for GWPCA susceptibility mapping.

<table>
<thead>
<tr>
<th>Gamma value</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.95</td>
<td>0.94</td>
<td>0.93</td>
<td>0.91</td>
<td>0.88</td>
<td>0.84</td>
<td>0.76</td>
<td>0.64</td>
<td>0.42</td>
</tr>
<tr>
<td>PBIAS</td>
<td>−0.94</td>
<td>−0.93</td>
<td>−0.91</td>
<td>−0.89</td>
<td>−0.86</td>
<td>−0.81</td>
<td>−0.74</td>
<td>−0.61</td>
<td>−0.40</td>
</tr>
</tbody>
</table>
Both estimators identified a gamma value of 0.9 as the best value for GWPCA-based LSM (Table 3). The \( \text{RMSE} \) value showed a decreasing trend that is statistically different from Fig. 8 which results from increased fuzzy gamma operator values. Increasing the fuzzy gamma operators led to an increase in \( PBIAS \). Positive \( PBIAS \) values indicate overestimation bias and negative underestimation bias.

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**Fig. 9.** Resultant GWPCA based susceptibility maps of different fuzzy gamma operators.

Both estimators identified a gamma value of 0.9 as the best value for GWPCA-based LSM (Table 3). The \( \text{RMSE} \) value showed a decreasing trend that is statistically different from Fig. 8 which results from increased fuzzy gamma operator values. Increasing the fuzzy gamma operators led to an increase in \( PBIAS \). Positive \( PBIAS \) values indicate overestimation bias and negative underestimation bias.
A comparison of the nine gamma values (Fig. 8) shows that all proposed fuzzy gamma operators underestimated the bias for landslide susceptibility; the 0.9 gamma value for underestimation was much less severe (Table 3 and Fig. 8). The lower rate of underestimation and RMSE of each model yielded estimates with much greater accuracy and precision than did previous models. Fig. 9 shows susceptibility maps for the GWPCA method using fuzzy gamma operators from 0.1 to 0.9.

4.2. Validation of results using the ROC curve

A ROC curve was used to assess the accuracy of workflow. The proposed GWPCA-based LSM map with the lowest RMSE and PBIAS values (gamma 0.9) was evaluated by calculating the ROC curve (Fawcett, 2006; Nandi and Shakoor, 2009; Ballabio and Sterlacchini, 2012; Shadman et al., 2014) and the percentage of known landslides in various susceptibility classes.

Two concise and representative test datasets were used to implement the ROC curve analysis. The landslide inventory dataset comprises 82 recent and historic landslide points and 82 randomly-selected non-landslide locations in the study area. The ROC curves of the GWPCA-based LSM (AUC = 0.872) showed that GWPCA was a successful and promising model for susceptibility mapping. Fig. 10 shows the estimated AUC value and the standard error of the ROC curve for GWPCA-based LSM with a fuzzy gamma operator of 0.9.

5. Discussion and conclusions

Data on landslide-related variables are accessible with fair accuracy and a high degree of spatial detail in many countries. Such detailed databases include tens of landslide-related variables and can be used for detailed LSM. The present study introduced a quantitative approach for LSM using GWPCA and hexagonal neighborhood analysis which demonstrated its efficacy. The proposed LSM framework illustrates the key characteristics for slope instability in the Chehelchay Basin using GWPCA. It offers an efficient means of assessing spatial variations in susceptibility within a study region. Although a high GWPCA output signifies difficulty in summarization of resultant components, it also implies heterogeneity of the retrieved spatial information that can be used to develop detailed susceptibility models.

There also appear to be strong qualitative contrasts between rectangular and hexagonal grids. Compared with the rectangular grid, the hexagonal grid has a simpler and more symmetric nearest neighborhood, which truly avoids the ambiguities of the rectangular grid (Birch et al., 2007). Accordingly, it is thought that using hexagonal neighbors improves the accuracy of resultant susceptibility map. In this regard, although theoretical concept is approved by basic earlier studies (Rosenfeld, 1970; McNeill et al., 2006; Ray and Burgman, 2006; Birch et al., 2007), further comparative studies of LSM are needed for developing such hypothesis.

The analysis of slope instability and preparation of susceptibility maps is a promising option for planning agencies and preliminary hazard studies. GWPCA can help researchers assess how landslide-related variables differentiate the study region geographically. It also delineates variations in landslide susceptibility within the study region. It can be stated from a theoretical perspective that the results support the hypothesis of this research.

The different phases of accuracy assessment in the study provided encouraging results (AUC = 0.872) for the spatial prediction of landslide susceptibility based on GWPCA. More accurate findings and consolidated research are essential to the comprehensive development of such multivariate techniques. Without such development, GWPCA is unlikely to be applied effectively. It is hoped that this study will assist in delineating the advantages and disadvantages of the proposed technique for LSM and other geostatistical models.

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Fig. 10. ROC curve for the proposed GWPCA based susceptibility map of Chehelchay.
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