Spatially Explicit Sensitivity and Uncertainty Analysis for the landslide risk assessment of the Gas Pipeline Networks

Omid Ghorbanzadeh
Department of Geoinformatics – Z_GIS, University of Salzburg, Austria
omid.ghorbanzadeh@stud.sbg.ac.at

Bakhtiar Feizizadeh
Department of Remote Sensing and GIS, University of Tabriz, Iran
feizizadeh@tabrizu.ac.ir

Thomas Blaschke
Department of Geoinformatics – Z_GIS, University of Salzburg, Austria
thomas.blaschke@sbg.ac.at

Rasa Khosravi
Department of Remote Sensing and GIS, University of Tabriz, Iran
rasasomi@yahoo.com

Abstract

Gas pipeline networks are linear features that may cross regions susceptible to some land deformation processes such as landslides. Spatial multi-criteria decision-making (S-MCDM) is widely used for landslide susceptibility mapping (LSM). In this study, we used an analytical hierarchy process (AHP), one of the most commonly used MCDA techniques, in combination with a spatially explicit sensitivity and uncertainty analysis (SESUA) technique. This approach was implemented for a LSM application and identifies the highly susceptible areas that threaten gas pipeline networks in north-western Iran. The methodology consisted of three distinct phases. The AHP technique was used in the first phase to derive the weightings of related criteria, namely: lithology, land cover, rainfall, elevation, slope, aspect, and distance to faults and streams. In the second phase, a Monte Carlo simulation (MCS) was used to evaluate the uncertainty and sensitivity of areas susceptible to landslides based on the derived criteria weightings. Finally, a landslide inventory database was used to validate the results. The integrated SESUA technique indicated 7.1 % of gas pipeline networks cross highly susceptible landslide areas in our case study.
Keywords: Gas pipeline network, Landslide, Analytical Hierarchy Process (AHP), Spatially Explicit Sensitivity and Uncertainty Analysis (SESUA).

1 Introduction

Gas pipeline networks are often threatened by the impacts of land displacement and deformation caused by landslides (Kenny et al., 2105). The long linear shape of these networks makes them prone to being affected by land deformations. Especially those that pass through mountainous areas are more vulnerable to the consequences of this phenomenon (Baum et al., 2008). S-MCDM models are powerful methodologies that support decision makers in natural hazard risk assessment through the mapping of highly susceptible areas (Erlacher et al., 2017). They are used to combine geographical data into a single index of assessment. The AHP is one of the most common techniques of S-MCDM and has been used for a number of complex spatial decision-making problems (Cabrera-Barona, and Ghorbanzadeh, 2018). However, this technique requires experts with highly relevant knowledge to prepare pairwise comparison matrices in a professional manner (Franek and Kresta, 2014). The criteria weightings resulting from the AHP strongly depend on the decisions provided by the experts, which can be a major source of uncertainty in this technique (Ghorbanzadeh et al., 2017). In response to this drawback of the AHP, some researchers have started to use an integrated approach of sensitivity and uncertainty analysis for S-MCDA (Feizizadeh and Kienberger, 2017; Erlacher et al., 2017; Ghorbanzadeh et al., 2017). Sensitivity analysis measures the response of the model to variations in the input dataset (Neshat et al., 2017). This process can indicate the confidence level. Uncertainty analysis can also reduce uncertainties associated with S-MCDA techniques, and it is able to parameterize the stability of the resulting criteria weightings (Feizizadeh and Kienberger, 2017). In this study, we aim to address the improvement of the resulting LSM through the SESUA technique in Marand County, north-western Iran, and identify areas in which gas pipeline networks are threatened by landslides.

2 Study Area and Dataset

The study area was Marand County, with an area of 3286 km2, in the northwest of Iran (Figure 1). The altitude of this mountainous County ranges from 900m in the stream beds to 3125m above mean sea level on mountain picks. Landslides are common in the northwest of Iran and in the Marand County in particular (Feizizadeh and Ghorbanzadeh, 2017). The convergence of the Arabian and Eurasian plates in this area leads to complex geological setting, intense faulting, extreme earthquakes and active volcanoes (Karakhanian et al., 2004). All these factors make the slopes of the study area potentially vulnerable to landslides. This county is located at the end of the ninth Iranian national gas pipelines. This pipeline is 56 inches in diameter and 1863 km in length, from Assalouyeh in the south of Iran to the border of Turkey in the northwest of Iran. The pipeline has a capacity of 110 million cubic meters per day, with 17 gas pressure booster stations. Because Marand County is at the end of the gas pipeline network, the gas pipeline is connected to a 40-inch gas pipeline of a neighboring county, to prevent the loss of sustained pressure (Khosravi, 2017). For our research, geology, topography, anthropogenic and climate factors were selected based on the knowledge of experts, according to the field studies of active landslides. We used a dataset of eight related causal criteria which prepared based on mentioned four main factors, along with considering related literature input datasets e.g., Khosravi (2017). Our input dataset consisted of rainfall, lithology, land cover, elevation, slope, aspect, and distance to faults and streams (Table 1). A landslide inventory dataset with a total of 26 landslides was separated randomly into two datasets for training and validation. The landslide inventory was collected within a field survey. All layers of input and inventory datasets were prepared in ArcGIS software as raster layers with a resolution of 30 m.

Figure 1: Location of Marand County, gas pipeline networks and landslide inventory.

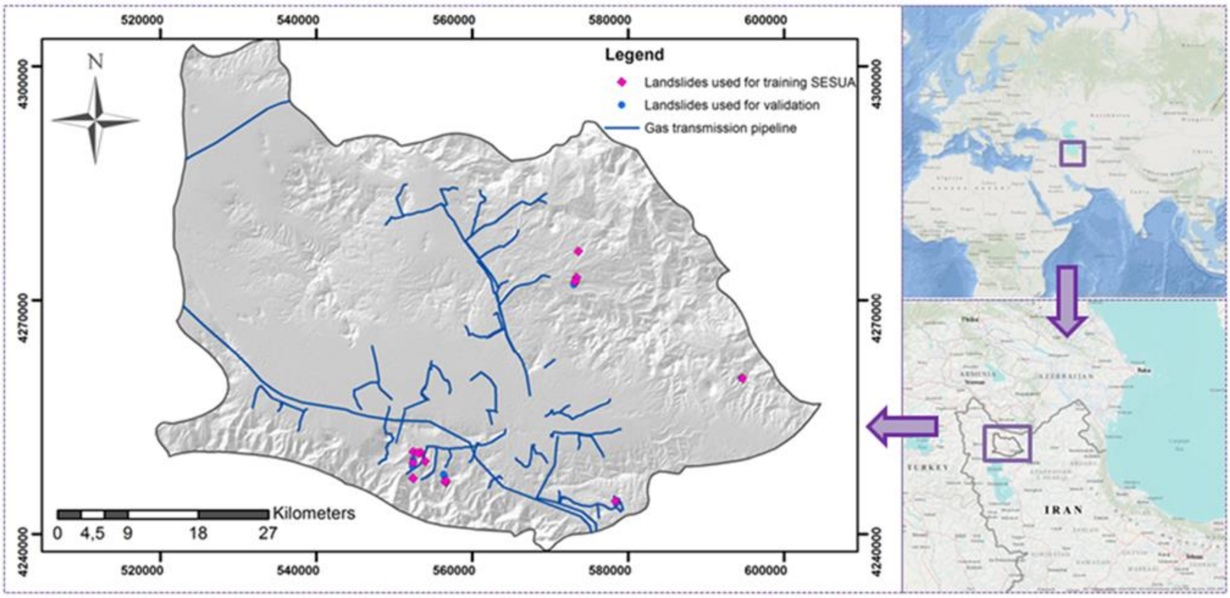


Table 1: Criteria, sub-criteria, pairwise comparison matrices, number of known landslides in each class and data source.

Criteria	Sub-criteria	Pairwise comparison matrices					Eigenvalues	CR	Land slides
Land use/cover									
	(1) Settlement	1					0.053		0
	(2) Irrigated agriculture	3	1				0.067		0
	(3) Orchard	8	7	1			0.235		0
	(4) Grassland	9	8	3	1		0.325		6
	(5) Bare soil & rock bodies	9	8	3	3	1	0.320	0.054	17
Rainfall (mm)									
	(1) 159.5 - 193.5	1					0.170		0
	(2) 193.5- 227.5	3	1				0.320		13
	(3) 227.5- 261.2	4	3	1			0.510	0.075	13
Geology									
	(1) Low / High terraces	1					0.061		10
	(2) Conglomerates	3	1				0.095		1
	(3) Volcanics	5	5	1			0.315		6
	(4) Limestones	6	6	2	1		0.527	0.069	7
Distance to fault (m)									
	(1) 0 -1000	1					0.641		7
	(2) 1000 - 2000	1⁄5	1				0.221		3

	(3) 2000 - 3000	1⁄7	1⁄3	1			0.086		2
	(4) 3000 <	1⁄9	1⁄6	1⁄2	1		0.050	0.053	14
Elevation (m)									
	(1) 910 - 1.274	1					0.076		0
	(2) 1.274 -1.611	9	1				0.239		0
	(3) 1.611- 1.990	9	8	1			0.393		21
	(4) 1.990 - 2.429	8	7	7	1		0.173		5
	(5) 2.429 - 3.252	7	1⁄7	1⁄6	1⁄6	1	0.119	0.072	0
Slope (%)									
	(1) 0 - 5	1					0.053		0
	(2) 5 - 10	3	1				0.067		0
	(3) 10 - 15	8	7	1			0.235		7
	(4) 15 - 20	9	8	3	1		0.325		13
	(5) 20 <	9	8	3	3	1	0.320	0.054	6
Distance to stream (m)									
	(1) 0 -100	1					0.527		8
	(2) 100 - 200	1⁄3	1				0.315		9
	(3) 200 - 300	1⁄5	1⁄5	1			0.095		3
	(4) 300 <	1⁄6	1⁄6	1⁄2	1		0.061	0.069	6
Aspect									
	(1) Flat	1					0.046		1
	(2) North	9	1				0.059		2
	(3) East	1	1⁄8	1			0.109		7
	(4) West	4	1⁄7	3	1		0.269		6
	(5) South	9	7	7	7	1	0.517	0.061	11

Note: MWREP: Ministry of water resource for East Azerbaijan Province, MAREP: Ministry of agricultural resource for East Azerbaijan Province, GSDI: Geological survey department of Iran

3 Methodology

3.1 Workflow for AHP applied to LSM

The AHP technique is one of the most commonly used techniques in S-MCDA and was introduced and developed by Saaty (1980). Empirical studies of effective applications provide evidence of the acceptance of the AHP for S-MCDA. Suppose a decision-maker considers a multi-decision-making problem. Where $X = \{x_1, x_2, \dots, x_n\}$ is a set of n criteria. Experts should compare each pair of criteria (x_i and x_j) in X (Lan et al., 2009). A value (a_{ij}) can also be derived for the ratio of their weightings. If the criteria x_i is preferred to x_j then $a_{ij}>1$ and, conversely, if x_j is preferred to x_i then $a_{ij}<1$. Moreover, the reciprocal property $a_{ji} = {}^{1}/_{a_{ij}}$; $a_{ij}>0$, for $j = 1,2,\dots,n$, $i = 1,2,\dots,n$. The resulting criteria weightings (w_1, w_2, $w_3,\dots,w_n$) have two conditions, namely: $0 \le w_k \le 1$ and $\sum_{k=1}^{n} w_k = 1$

An underlying criterion ranking scale is used for pairwise comparisons in the AHP technique, with values from 1 for equal importance to 9 for extreme importance. The calculation of criteria weightings was broadly described by Malcezwski and Rinner (2016). If λ_{max} is the largest eigenvalue, the consistency ratio (CR) of weightings calculated by AHP is determined as equation 1:

$$CR = \frac{\lambda_{max} - n}{RI(n-1)} \qquad (1)$$

Where RI is the random index, which for n = 2, 3, 4, 5, 6, 7 and 8, RI = 0.00, 0.52, 0.89, 1.11, 1.25, 1.35 and 1.40, respectively. A $CR < 0.10$ indicates an acceptable consistency through the whole process of the AHP (Malczewski and Rinner, 2016). Using this process, we have calculated the pairwise comparison matrix for the decisions of our four experts in this field. The CR of the whole process was 0.016, and the derived AHP weightings are shown in Table 2.

3.2 Implementation of AHP-SESUA

In this study, the MCS and variance-based global sensitivity analysis (GSA) were used for modelling the error propagation and reducing the complexity of the model respectively. The training landslide inventory dataset is used for this aim. Criteria weightings of the AHP technique are used as reference weightings for the MCS (see Table 2). According to our small training data set, the simulation was run with epoch of 500. The GSA quantitatively determines input variables that have a high impact on the outputs. Two sensitivity parameters were generated by GSA, these being the first-order sensitivity index (S) and the total effect (ST) sensitivity index. The S and ST parameters estimate the individual effect of each input variable and the total effect of a single criterion on the output variance, respectively (Ghorbanzadeh et al., 2017). The resulted ST demonstrates non-important variables. By considering these variables as fixed nominal values, we can reduce the complexity of the model (Feizizadeh and Kienberger, 2017). The detailed process of GSA has been proven and broadly described by Norton, (2015). For the implementation of GSA, the significance of spatial bias in assessing option rank order by means of average shift in ranks (*ASR*) as equation 2:

$$ASR = \frac{1}{n}\sum_{a=1}^{n}\left|a\_rank_{ref} - a\_rank\right| \qquad (2)$$

Where a_rank_{ref} is the rank of an option in the reference ranking (e.g. equal weight case), and a_rank is the current rank of that option (Saisana et al., 2005). The weightings derived from the AHP technique are presented as the reference ranking column a in Table 2, and the results of the GSA are presented in columns b, c, d and e. The MCS and GSA were used to eliminate the uncertain criteria weights for LSM. According to the results of GSA, the slope, with a weighting of 23.2%, was identified to be the most important criterion of the landslide phenomenon.

Table 2: Results of AHP and AHP-SESUA

criteria	AHP weights	Rank	S	ST	S %	ST %	Rank
Land use	0.069	8	0.047	0.076	4.7	5.6	6
Aspect	0.162	3	0.01	0.246	1.0	18.1	3
Rainfall	0.071	7	-0.029	0.043	-2.9	3.2	7
Distance to fault	0.133	4	-0.053	0.227	-5.3	16.7	4
Lithology	0.114	5	-0.022	0.175	-2.2	12.9	5
Distance to stream	0.090	6	0.01	0.006	1.0	0.5	8
DEM	0.165	2	-0.053	0.248	-5.3	18.3	2
Slope	0.198	1	0.512	0.315	51.2	23.2	1

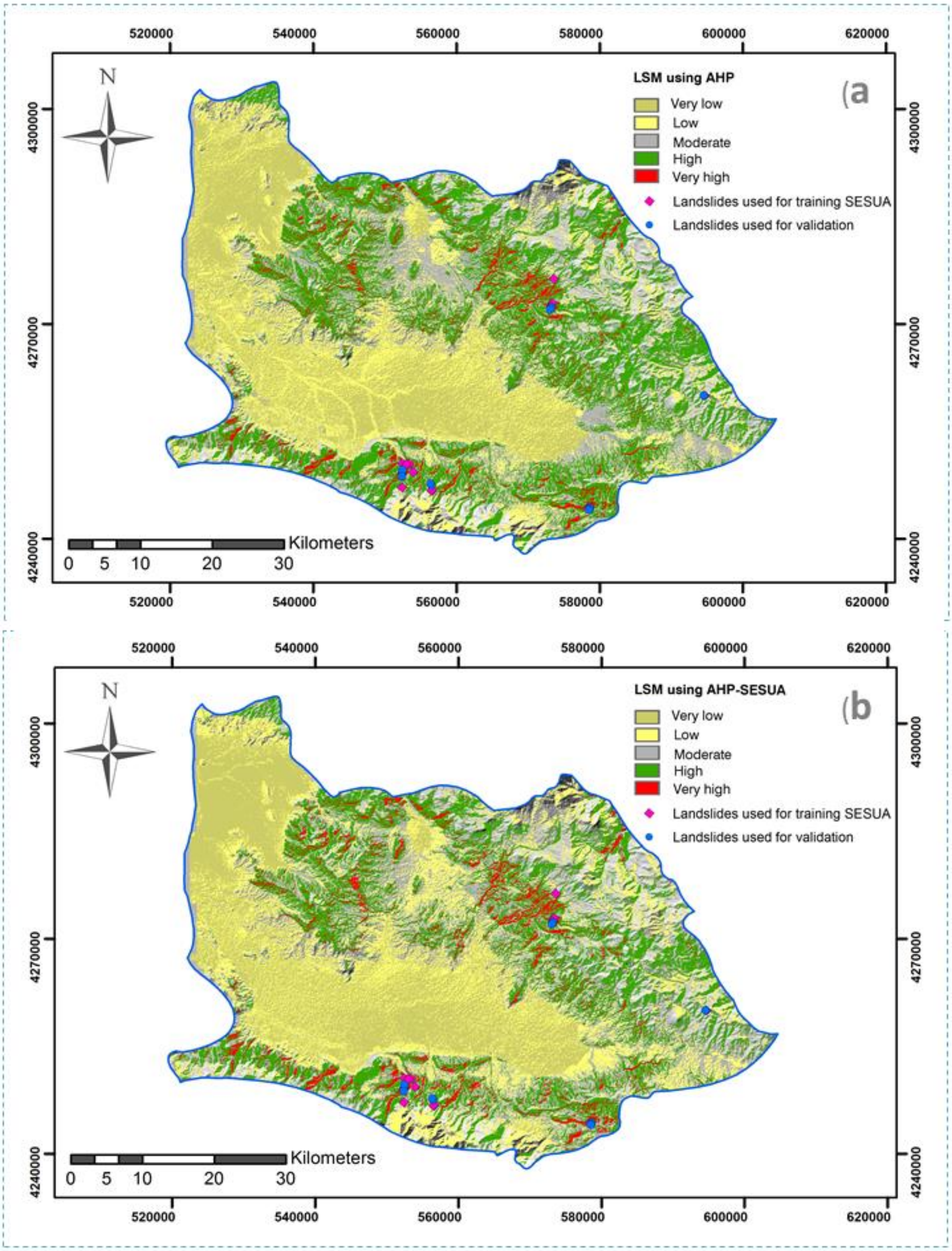
4 Results and Validation

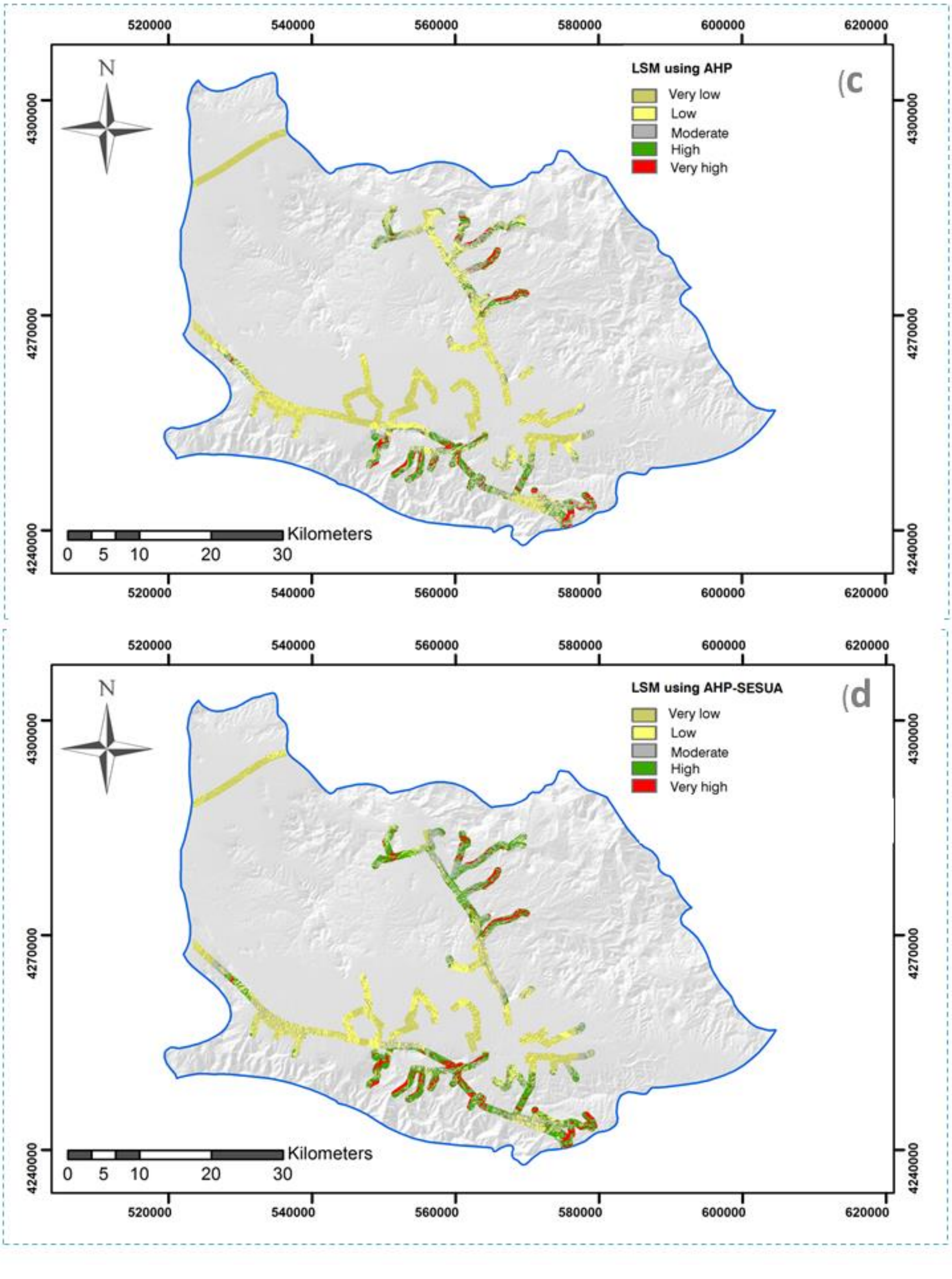
In order to generate LSM maps and identify the highly susceptible areas that threaten gas pipeline networks, the criteria weightings derived from both approaches were used for data aggregation within a GIS environment. Figures 2 (a) and (b) present the results of the LSM. Moreover, we considered a buffer of 500 meters around gas pipelines to identify the areas where potential landslides can affect the gas pipeline (Figures 3 (c) and (d)). The maps are classified into five classes of susceptibility using the natural breaks classification method. The natural breaks classification method applied in our study generates classes of similar values separated by some breakpoints. This is an effective technique for categorizing the susceptibility mapping results when we interpret pixel values close to each class boundary (e.g. values between ‘‘Moderate’’ and ‘‘High’’ susceptibility). In order to validate both resulting LSMs and identify the improvement in accuracy with using sensitivity analysis, a validation was carried out based on the known 13 landslides in the study area that have not used as training data. The ROC curve was used for validation. Based on the theory behind the ROC curve, the area under the curve (AUC) indicates the quality of a prediction model, whereby values close to 1.0 are considered to indicate the best results of a model. The calculated AUC for the LSM produced by the AHP was 89.2, and that of AHP-SESUA was 92.3 (Figures 3). Table 3 presents the area of each class of landslide susceptibility within the generated buffer zone for gas pipeline networks.

Table 3: The area of each category.

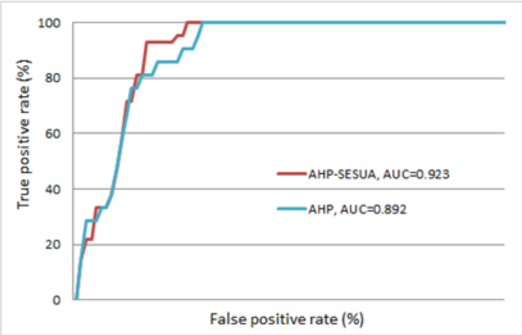
Landslide susceptibility	Area (km^2)		Percent of area	
	AHP	AHP-SESUA	AHP	AHP-SESUA
Very high	19.17	23.07	5.9	7.1
High	77.01	48.09	23.7	14.8
Medium	66.61	84.81	20.5	26.1
Low	104.95	95.85	32.3	29.5
Very low	60.43	73.11	18.6	22.5

Figure 2: Landslide susceptibility maps using (a) the AHP, (b) AHP-SESUA, (c) buffer zone of the AHP, (a) buffer zone of the AHP-SESUA.




520000
540000
560000
580000
600000
620000
4300000
4270000
4240000
N
LSM using AHP
(c
Very low
Low
Moderate
High
Very high
Kilometers
0 5 10 20 30
LSM using AHP-SESUA
(d

Figures 3: Results of ROC curves for the produced LSMs.



5 Conclusion and Future Work

The main aim of this study is to evaluate the corresponding threat of probable future landslides for the gas pipeline network in Marand County. In addition to the conventional MCDA technique that was used for criteria weightings, the SESUA technique was also implemented for improving the accuracy of the results. Natural hazard susceptibility mapping is an effective approach to mitigating the adverse consequences they carry. The approach has often been used for the whole region of the case study. However, the evaluation of a natural hazard for a particular purpose can lead to more detailed results. In the presented study, we focused only on the areas that are a threat to gas pipeline networks. In this regard, a buffer of 500 meters is considered as a risk zone to the gas pipeline networks if a landslide occurs. The results indicate that landslides pose a greater threat to gas pipeline networks in the northern and southern regions of the County. Whereas, the central part of the County is a safer region for gas pipeline networks. It should be noted, however, that some parts of the central area are also prone to the other type land deformation, which is land subsidence. Therefore, our next study will consider the threat of both land deformations.

Acknowledgements

This research was partly funded by the Austrian Science Fund (FWF) through the Doctoral College GIScience (DK W 1237-N23) at the University of Salzburg.

References

Baum, R. L. Galloway, D. L. & Harp, E. L. (2008) Landslide and land subsidence hazards to pipelines (No. 2008-1164*). Geological Survey (US).*

Cabrera-Barona, P. & Ghorbanzadeh, O. (2018) Comparing Classic and Interval Analytical Hierarchy Process Methodologies for Measuring Area-Level Deprivation to Analyze Health Inequalities. *International journal of environmental research and public health,* 15(1), 140.

Erlacher, C. Jankowski, P. Blaschke, T. Paulus, G. & Anders, K. H. (2017) A GPU-based parallelization approach to conduct spatially-explicit uncertainty and sensitivity analysis in the application domain of landscape assessment. *GI_Forum 2017*, 1, 44-58.

Feizizadeh, B. & Ghorbanzadeh, O. (2017) GIS-based Interval Pairwise Comparison Matrices as a Novel Approach for Optimizing an Analytical Hierarchy Process and Multiple Criteria Weighting. *GI_Forum* 2017, 1, 27-35.

Feizizadeh, B. & Kienberger, S. (2017) Spatially explicit sensitivity and uncertainty analysis for multicriteria-based vulnerability assessment. *Journal of Environmental Planning and Management*, 60(11), 2013-2035.

Franek, J. & Kresta, A. (2014) Judgment scales and consistency measure in AHP. *Procedia Economics and Finance*, 12, 164-173.

Ghorbanzadeh, O. Feizizadeh, B. & Blaschke, T. (2017) Multi-criteria risk evaluation by integrating an analytical network process approach into GIS-based sensitivity and uncertainty analyses. *Geomatics, Natural Hazards and Risk*, 1-25.

Karakhanian, A. S., Trifonov, V. G., Philip, H., Avagyan, A., Hessami, K., Jamali, F., ... & Adilkhanyan, A. (2004) Active faulting and natural hazards in Armenia, eastern Turkey and northwestern Iran. *Tectonophysics,* 380(3-4), 189-219.

Kenny, S. & Jukes, P. (2015) Pipeline/Soil Interaction Modeling in Support of Pipeline Engineering Design and Integrity. Oil and Gas Pipelines: *Integrity and Safety Handbook*, 99-142.

Khosravi, R. (2017) Uncertainty analysis of multi-criteria decision making methods of GIS in zoning and modeling of landslide hazard and its destructive effects on gas transmission networks. *M.Sc. Thesis, University of Tabriz, Tabriz, Iran,* 2017.

Lan, J. Lin, J. & Cao, L. (2009) An information mining method for deriving weights from an interval comparison matrix. *Mathematical and Computer Modeling,* 50, 393-400.

Malczewski, J., & Rinner, C. (2016) Multicriteria decision analysis in geographic information science. *Springer.*

Neshat, A., Pradhan, B., & Javadi, S. (2015) Risk assessment of groundwater pollution using Monte Carlo approach in an agricultural region: an example from Kerman Plain, Iran. *Computers, Environment and Urban Systems*, 50, 66-73.

Norton, J. (2015) An introduction to sensitivity assessment of simulation models. *Environmental Modelling & Software*, 69, 166-174.

Saaty, T. L. (1980) The Analytical Hierarchy Process. *New York: McGraw Hill*, 641-658.

Saisana, M., Saltelli, A., & Tarantola, S. (2005) Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A (Statistics in Society),* 168(2), 307-323.