ORIGINAL ARTICLE

Efficiency of multiple hybrid techniques for the earthquake physical susceptibility mapping: the case of Abbottabad District, Pakistan

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Abstract
An earthquake is a natural event that causes serious intimidation to infrastructure and humans' life in northern Pakistan. Environmental, physical, and social dimensions effectively add to seismic vulnerability. The current study deals with seismic susceptibility by integrating various decisive supporting methods to generate more accurate outcomes in the Abbottabad District, Pakistan. Hybrid models: fuzzy-logistic regression (fuzzy-LR) and multi-criteria evaluation–logistic regression (MCE–LR) trained at 70 by multiple criteria decision analysis–multi-criteria evaluation (MCDA–MCE) and fuzzy-multiple criteria analysis (fuzzy-MCDA) are used to build hybrid training datasets at 30. High accuracy in the MCDA–MCE model is observed based on the model output. Seismic susceptibility maps are generated by implementing the resulting datasets and hybrid learning models (fuzzy-LR and MCE–LR). Finally, the area under the curve (AUC) and frequency ratio (FR) validate the outcomes of seismic susceptibility maps. In comparison, both MCDA–MCE hybrid model (AUC = 0.812) and MCE–LR hybrid model (AUC = 0.875) indicated more precision than fuzzy-MCDA model (AUC = 0.806) and fuzzy-LR hybrid model (AUC = 0.842), respectively. The current study concludes that training datasets are the responsible factor for defining the seismic susceptibility mapping and modelling accuracy. Moreover, this study helps to specify the high susceptible locations in the urbanized environment and facilitate policymakers to implement measures in the study area for better planning in future to avoid the effects of the earthquake.

Introduction

Catastrophic destructions are on the surge due to earthquakes, droughts, and floods, menacing major economic fatalities, structure framework and human life all around the world (Khan et al. 2019a). In the region of Asia, floods and earthquakes are considered major station of disasters (Khan et al. 2019a). South Asia has consistently stayed a target of earthquakes of various scales (Bilham 2009; Maqsood and Schwarz 2010). Major deaths and losses in this region have contributed to urbanization, scarcity, and illiteracy (Khan et al. 2019a; Shah et al. 2018). Earthquake effects can be influenced by different criteria such as the density of population, the density of building, building materials, the proximity of faults, proximity to treatment centres, numbers of floors in building, adjacent land uses, horizontal acceleration of land, remoteness and hazardous facilities and sites.

Different urban regions are susceptible to catastrophe due to the type of existing people in the region (Martins et al. 2012). Measures such as the number of flooring in structures, proximity to medical centres, faults distance and proximity, structure density, horizontal acceleration of land, remoteness, distance from hazardous sites and facilities, structure material, adjacent land uses, and population density have a considerable effect on increasing or decreasing the damage of earthquakes (Kumlu and Tüdeş 2019).

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Global causalities can be minimized by utilizing the hybrid techniques to find the vulnerability zones of any specific areas, which will minimize the hazard conditions of the soil. This will give us the necessary foresight in developing a sustainable structure on which we can trust its strength to avoid any threatening casualties.

Generally, in societies, the irregular effects and complex nature of earthquake penalties have a major turn, especially in the urbanized cities which are partially responsible due to certain factors when it comes to the irregular hazard spreading like the number of persons suffered, environmental susceptibility, amount of resilience from the community, and especially the seismic intensity (Wald et al. 2011). Mostly, the damage caused by such events on the physical and economic factor is mainly credited to the lack of planning and not following the policies of infrastructure standards and building codes (Yariyan et al. 2020). As urban societies are more sensitive to earthquake hazards due to their huge population and high density of infrastructure scope, there is a need for assessment of seismic susceptibility in the urbanized regions (Xing et al. 2015). A key measure that can express the damage reduction initiated by such natural hazards is the zoning of the natural catastrophes. To minimize risk, detailed and inclusive findings are required to recognize the influences of seismic activity in both rural and urban regions and to classify zones with high susceptibility (Merciu et al. 2018). The urban areas can be divided into three parts which can be affected by the disaster, i.e. social, physical and environmental facets. Most tangible is the physical dimension in the part of urbanized planning in minimizing the result of earthquakes hazards. Urban land use and urban construction are the most significant aspects of the physical dimension (Frigerio and De Amicis 2016).

Previous studies deal with the mapping of areas prone to the risk of an earthquake, such as Carreño et al. (2012) observed that only risk evaluation of economic and infrastructural damages is not enough, but there is a need to consider the environmental and social factors to assess the vulnerability of seismic risk. A study was conducted in New Zealand after 3 years of the earthquake in the country and showed the impact of assessment on people awareness about vulnerability and damage in their residential areas (McClure et al. 2015). Kumamoto and Masataka (2011) used statistical procedures and principal component analysis (PCA) on the basis of active fault, earthquake, gravity and seismic factors for seismic risk assessment in Japan. Asim et al. (2018) used an artificial neural network (ANN) for assessment and the outcomes illustrated that there is need to use valid methods for assessing the vulnerability of an area. Neural network algorithm (NNA) in integration with statistical clustering was used to investigate the earthquake susceptibility in northern area of Pakistan (Aslam et al. 2021). Several models and methods were used in different studies for seismic risk assessment including ordered weight averaging (OWA) (Asadi et al. 2019), support vector machine (SVM) (Abdollahi et al. 2019; Ghorbanzadeh et al. 2019a, b, c, d; Tavakkoli Piralilou et al. 2019), ANN (Ghorbanzadeh et al. 2019a, b, c, d; Tian et al. 2019), convolutional neural network (CNN) (Ghorbanzadeh et al. 2019a, b, c, d), adaptive neuron-fuzzy inference system (ANFIS) (Ghorbanzadeh et al. 2018a, b, c; Termeh et al. 2018), logistic regression (LR) (Bagheri et al. 2018), fuzzy quantifier algorithm (Pourghasemi et al. 2016), certainty factors (CF) (Dou et al. 2019) and various models of multiple criteria decision analysis (MCDA) like analytical network process (ANP) (Ghorbanzadeh and Blaschke 2018; Pirnazar et al. 2021) and analytic hierarchy process (AHP) (Guan et al. 2017; Gudiyangada Nachappa et al. 2019; Shahabi et al. 2014). The hybrid model was also used by integrating multiple methods and models for more efficient results (Pourghasemi and Rahmati 2018; Rahmati et al. 2019; Shahabi and Hashim 2015).

Due to a lack of awareness about seismic risk in urban areas, people are continuously investing in these areas, which results in high losses of people lives and property (Yariyan et al. 2020). In the recent past, Pakistan has become among the most active seismic regions because the Indian plate is continuously sub-ducting beneath the Eurasian plate (Khan et al. 2019b). It is impossible to control the natural hazards, but it is essential to plan strategies against the losses that may occur and to minimize their adverse impacts on society (Naseer et al. 2010). Seismic vulnerability assessment aids in figuring out the areas with high vulnerability and building infrastructure such as commercial and residential buildings, considering the impact of seismic waves in future. The structures built in Pakistan are mostly non-engineered structures or usually constructed without guidelines of earthquake-resistant structure policies. 90% of the total built structures of Pakistan come under non-engineered brickwork (Rafi et al. 2012). The research analysis done on the non-engineered structures is very limited as compared to the engineered structures (Solé et al. 2007). Normally, these non-engineered structures are acceptable under gravity loads, but when they are tested with lateral deformation, the structure faces less resistance against such conditions (Khan et al. 2019b). Many other studies also include earthquake seismic assessment in Pakistan (Aslam et al. 2021; Khan and Khan 2016; Qadri et al. 2017; Qadri and Malik 2021; Qadri et al. 2015a, b).

The present study deals with Abbottabad District, Khyber Pakhtunkhwa, Pakistan. The district lies under the Hazara division having coordinates 34°9′21″ north 73°13′10″ east as shown in Fig. 1. It is situated at an elevation of 1260 m and covers an area of 1969 square kilometres. The total population of the district is 1,332,912 and density 680/km2 (1800/sq mi). It includes three tehsils including Sherwan, Havelian and Abbottabad. To develop a procedure structure for the

Fig. 1 Map of the study area of
Abbottabad District
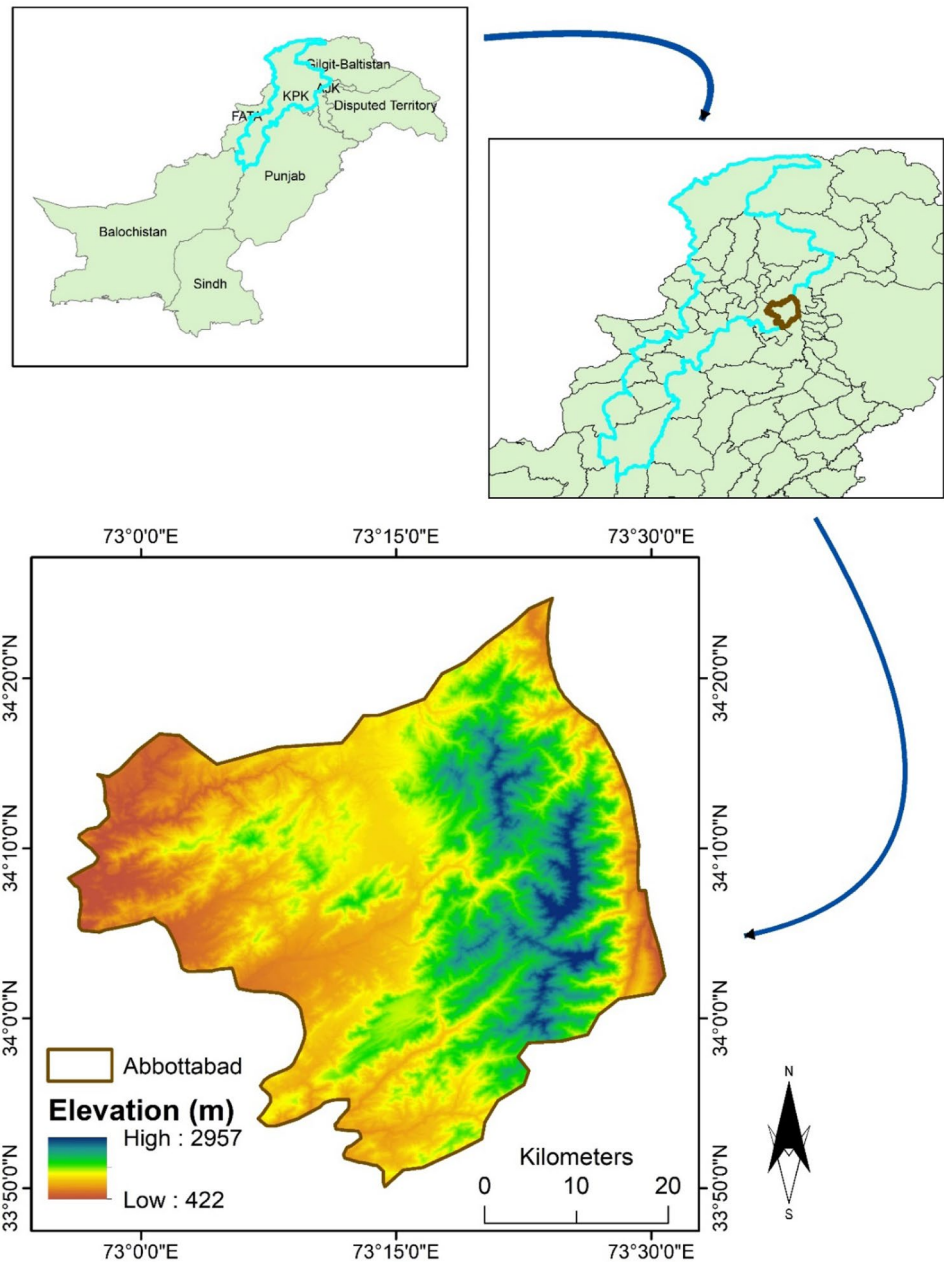
assessment of earthquake vulnerability, it is important to understand and eradicate the limitations of past researches, including not applying all the factors that influence the seismic activity; modelling with separate models comprising unpredictability; and so on. Furthermore, the population vulnerability and risk evaluation of various parts of the region in serious times was based on simple degrees like high, medium, low, and many other aspects of this research. In this valuation research, different procedures are used to analyse the susceptibility areas and to develop vulnerability maps of the earthquake. This includes five different models, named AHP, ANP, logistic regression (LR), OWA and fuzzy logic, and their four different hybrid procedures, named as (ANP–AHP)–OWA, (ANP–AHP)–fuzzy, OWA–LR, and fuzzy–LR, are prepared. Therefore, OWA and fuzzy procedures are created by the average weight rating of the ANP and AHP procedures. For easiness, we evaluated the (ANP–AHP)–OWA (A–OWA) and (ANP–AHP)–fuzzy (A–fuzzy) hybrid procedures to develop training sites, such that there would be two training datasets formed, and the fuzzy–LR and OWA–LR procedures would be formed independently. To conclude, seismic relative index (SRI), the confirmation process is conducted for initial authentication of two A–OWA and A–fuzzy hybrid procedures, whereas relative operating characteristic (ROC) curves are used for all four hybrid procedures, and finally, frequency ratio (FR)

methods are conducted to authenticate the final two-hybrid procedures of OWA–LR (OLR) and fuzzy–LR (FLR).

Methods and materials

In the present study, the methodology adopted consists of four stages as shown in Fig. 2. Different selected layers were edited and standardized in the first step. ANP and AHP were used to make pairwise comparison matrices and then hybrid models were generated. ANN in combination with hybrib models determine the seismic vulnerability assessment.

Training databases were used to create hybrid models. Severity classes were used to select each trading database point. In the last step, hybrid models were authenticated.

Table 1 The details of the faults present in the research region. It includes reverse and thrust faults type, namely: Gandghar fault, Panjal fault, Nathiagali fault, Kuzagali fault and MBT fault.

Data used

Seismic susceptibility assessment can be done based on the datasets which may influence the susceptability, which are
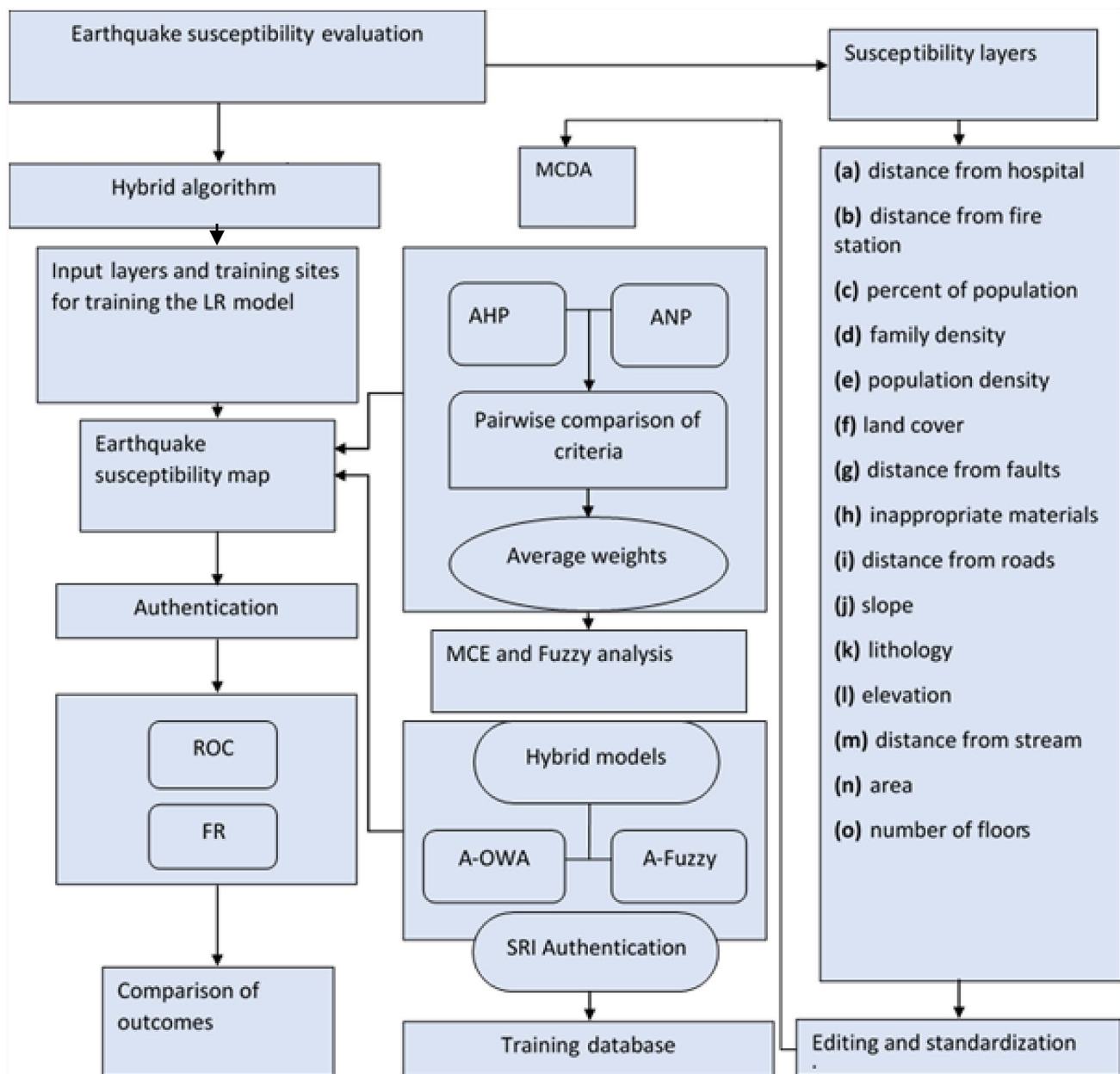

Fig. 2 Flowchart of the methodology used

Table 1 Fault characteristics in the research region

S. no	Fault name	Fault type	Fault length (m)
1	Gandghar fault	Reverse fault	5.78
2	Panjal fault	Thrust fault	54.89
3	Nathiagali thrust	Thrust fault	40.95
4	Kuzagali fault	Reverse fault	40.94
5	MBT (main bound-ary thrust)	Reverse fault	26.95

set upon three diverse dimensions, referred as environmental, social and physical aspects. It includes distance from the hospital, distance from the fire station, population percentage over 70 years old and under 4 years old, density of family, population density, land cover, distance from faults, inappropriate materials, distance from roads, slope, lithology, elevation, distance from the stream, area, and the number of floors (Rahmati et al. 2019). The equal interval method is used for classification and given below is the explanation of the data set used in this research (Fig. 3).

Closeness to the faults would have high risk, and serious damage of hazard and the risk will reduce as the distance increases with therefore having greater flexibility (Alizadeh et al. 2018). Recent history of the earthquake catastrophes around the globe projected that human faced the maximum damage and with the increasing human counting, it is expected that more deaths are expected in the coming future. Due to this nonserious development and planning of urbanization, the damage coefficient of the earthquake in modern regions is uncertain and more complicated (Rahman et al. 2015). Quick and appropriate contact to hospital services will surely improve earthquake pliability (Karimzadeh et al. 2014). Earthquake susceptibility is directly linked with the number of floors in a structure. Regardless of the quality of material used in the structure of buildings, greater the number of floors, greater will increase the susceptibility in the structure. If many numbers of floors are built with improper guideline principles, they will surely increase the danger of the building (Sivakumar et al. 2013).

The area of a structure also influences under the factors of earthquake susceptibility, meaning larger the area surrounded by the construction unit, less damage will be responsible for the structure and the path channels linking to it (Sinha et al. 2016). Under the town development codes, the consideration of land uses factors can drastically help decrease the economic damage, accidents and degree of susceptibility (Rimal et al. 2015). Copernicus land cover is used in this study. Most of the cases in the history of earthquake disasters, the causalities faced by the affected region, does not fully occur by the earthquake itself, but it often occurs due to the obstruction of the road networks during the time of emergency. Therefore, distance from the

roads should have importance while considering earthquake vulnerability (Amini et al. 2009). The reason of slope factor for susceptibility assessment earthquake is due to the fact that deterioration in landscape region with sharp slope is significantly amplified, mainly in the hilly areas and peaky regions. The guidelines on the building standards suggest that, for development, 5 to 9 percent slope angle is preferred (Alizadeh et al. 2018). In emergency situations during the earthquakes, every person is in a state of panic, but the children and older ones are highly sensitive groups of the public, meaning that we need to consider them in order to minimize the risk and damage (Armaş et al. 2017).

Easy Accessibility of fire station through the transportation networks will increase the saving operations of the public. Similarly, if the distant location of the fire station unit is from the operations, more damage susceptibility is possible (Duzgun et al. 2011). With the rivers occurrence, post-glacial alluvial sands would be generated, causing nearby land defenceless to lubrication and quivering (Potter et al. 2015). Therefore, structures considering near the river networks would be sensitive to slip. Each affected region is extremely associated with up heights and down heights of the structures with the susceptibility of landslides (Pachauri and Pant 1992). Therefore, due to anthropogenic activity and building corrosion, elevation with a higher degree would have a higher chance of earthquake susceptibility. Lithology is one of the main conditions in environmental investigating of the earthquake seismic vulnerability. This clarifies the ground formation in a particular region, where having harder geological minerals, would benefit in the resilience of the earthquake susceptibility and weaker the demolition influence of the earthquake. Family density is a social factor which has a significant impact in seismic susceptibility. Larger families are at more risk of earthquake damage than less dense families.

Earthquake vulnerability mapping

To check the vulnerability of the area to the earthquake, 16 different conditioning layers were selected in the first stage, and the considered layers were edited and standardized using software ArcGIS 10.4. Pairwise comparison matrices were created by using ANP and AHP models in the second stage of earthquake vulnerability mapping. Hybrid models were generated by obtaining average weights of both ANP and AHP models and use these weights to run the hybrid models (A-OWA and A-fuzzy) with five severity classes in the form of maps. Global Positioning System (GPS) was used to harvest different faulted locations for the validation of hybrid models in the investigation area.

Seismic Vulnerability Assessment (SVA) was determined by combining ANN with hybrid models in this model. The model is planned in the third stage, and it contains mainly
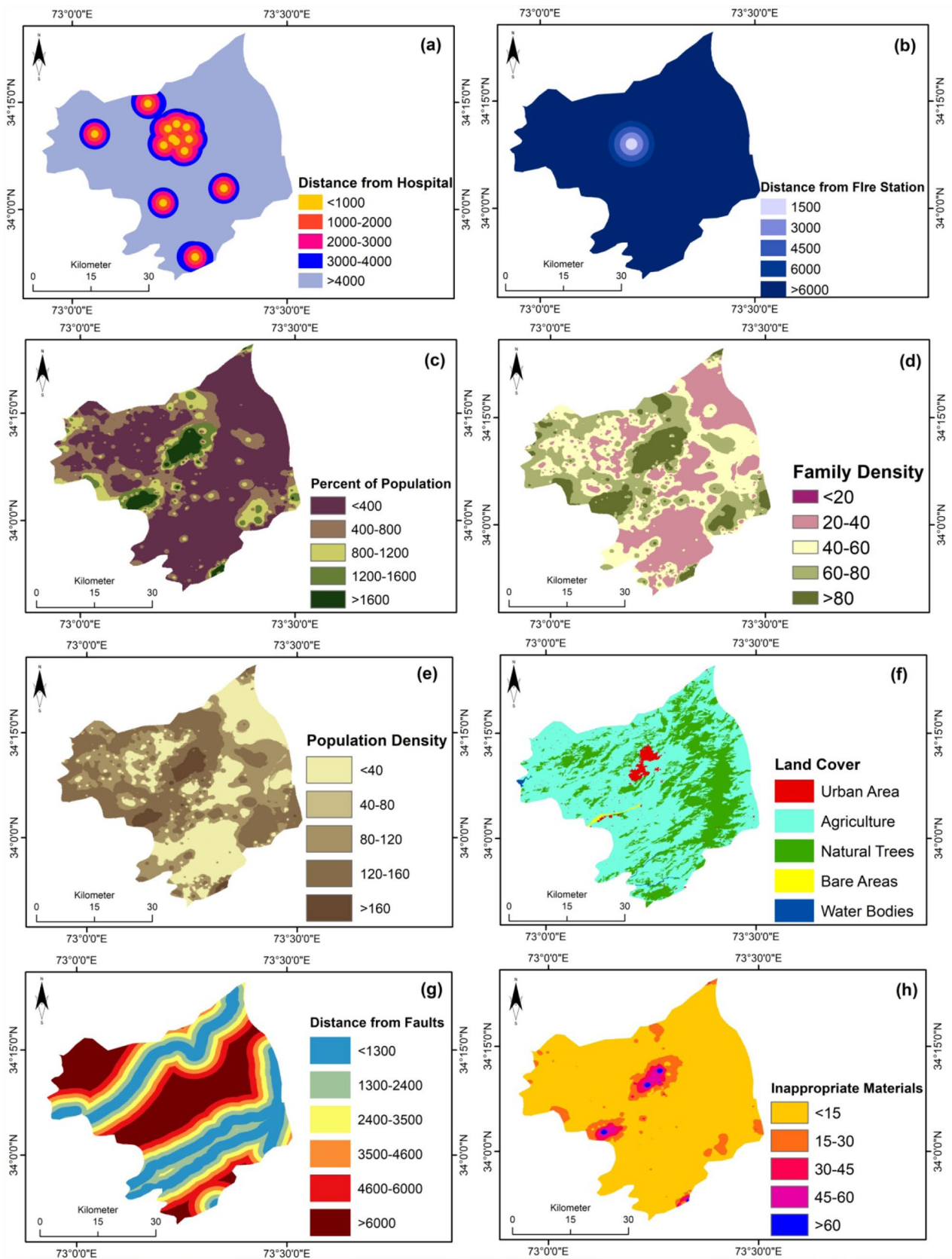
Fig. 3 Datasets used in the study: **a** distance from hospital, **b** distance from fire station, **c** percent of population, **d** family density, **e** population density, **f** land cover, **g** distance from faults, **h** inappropriate materials, **i** distance from roads, **j** slope, **k** lithology, **l** elevation, **m** distance from stream, **n** area, **o** number of floor
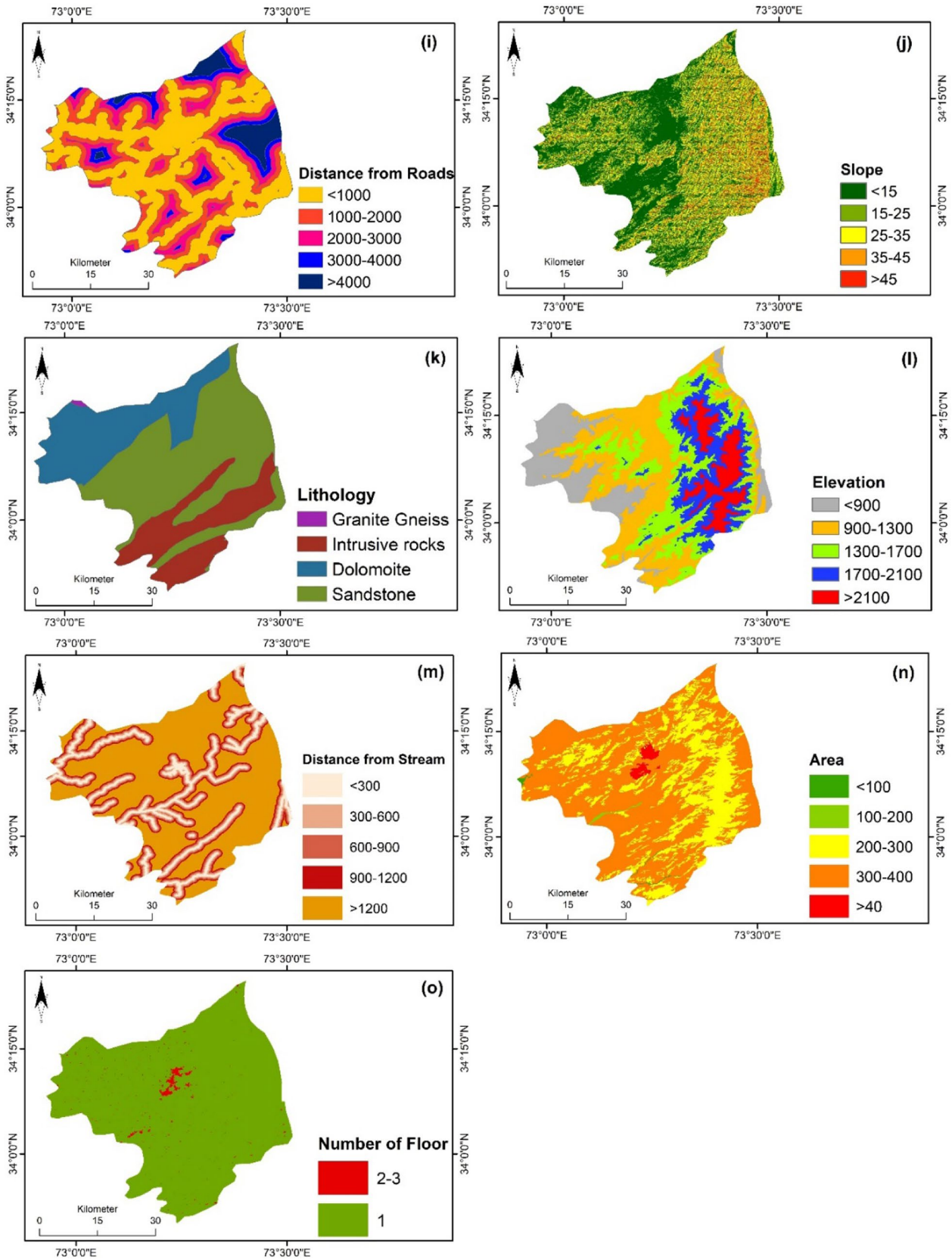
Fig. 3 (continued)

two stages, including ANN and hybrid models (A-OWA and A-fuzzy). LR model has been considered in methodology because (Chen et al. 2018) defined that the LR model has significant characteristics in the zoning of environmental hazard such as the ability of fast assessment and certainty in results. Training data and standardized parameter were necessary for the implementation of the LR model. So, hybrid models (A-OWA and A-fuzzy) were used to create two training databases. Five sensitivity classes (30 points in each class) were used to select the 150 points of each training database randomly. After this process, harvesting points were used for hybrid models authentication (OWA-LR and fuzzy-LR).

Multi-criteria decision and used statistical models

Fuzzy logic In fuzzy logic, all values between 0 and 1 can be taken by its variables and factors (Moslem et al. 2019). The ascription of each reference set member cannot define the subset, which indicates that it is uncertain to state the attribution of members to that sets. A number between 0 and 1 are assigned to the member in order to check the uncertainty. It can be claimed with certainty if the number is zero that the target member does not attribute to the set while one indicates the attribution of target member to the set. So above pattern is used by assigning values between 0 and 1 to specify the subset of fuzzy set (Theodoridou et al. 2017). Following steps are involved in the application of fuzzy logic including fuzzification (conversion of inputs into fuzzy information), rules base (decisions and rules to control the decision of 'decision system'), fuzzy inference (creation of different decisions on the basis of adapted percentage), aggregation (creation of fuzzy input set by combining all parallel results) and defuzzification (conversion of fuzzy sets into quantitative information and data). The most commonly used method provided by Centre Of Gravity (COG) for defuzzification is COG (relation 1), and the equation (Michael 2005) used for it is,

$$COG(A) = \frac{\int_a^b \mu_A(x)x dx}{\int_a^b \mu_A(x)dx}, \tag{1}$$

where $\mu_A(x)$ represents the aggregate membership function, x represents fuzzy system crisp output, a and b is the range of fuzzy set A. Table 2 shows the fuzzy operator.

Generally, the fuzzy set is represented in the form of,

$$A = \left\{ \left(\mu_A(x_i) | x_i \right) \mid x_i \epsilon X, i = 1, \dots .n_x \right\}. \tag{2}$$

Analytical Hierarchical Process (AHP) AHP is a commonly applied method used in MCDM (multi-criteria decision making) process (Ghorbanzadeh et al. 2019a, b, c, d). In

Table 2 Fuzzy operators (La 1965; Mamdani 1974)

Operator	Mathematical expression
X and Y	Min (X, Y)
X or Y	Max (X, Y)
Not X	1-X

Table 3 A basic scale for making judgments (Tang & Wen, 2009)

Classification	Class intensity
Extremely preferred	9
Very strongly preferred	7
Strongly preferred	5
Moderately preferred	3
Equally preferred	1
Intermediate values between	2, 4, 6, 8

this methods, ranking is assigned on the basis of influencing the importance of each parameter and develop a pairwise comparison matrices, but it is difficult to develop when a large number of options are available (Duleba and Moslem 2019). Verbal guesses of all comparisons are compared with each other in pairs. Two different values can be compared with each other on the basis of the comparison scale represented in Table 3 (Saaty 2008). Initially, alternatives are compared with criteria, and each alternative weights are assigned, and self-comparison of criteria is set up, and at the end, final weight is calculated by weighted linear combinations (Ghorbanzadeh et al. 2018a).

Calculation of the consistency ratio of these criteria is the next step in this process, and the resulting answer must be less than 0.1. Consistency ratio is the ratio of consistency index (CI) and average random consistency index (RI). Satty (Nik et al. 2009) defined the value of RI for different sizes where the equation for CI is,

$$CR = \frac{CI}{RI}, \tag{3}$$

$$CI = \mu_{Max} - \frac{n}{n-1}, \tag{4}$$

where μ_{Max} shows the maximum 8 value and n represents the number of factors considered. If CR exceeds 0.1 that weights should be corrected (Ghorbanzadeh et al. 2018b). It is noted that the comparison of factors in the AHP method is mostly dependent on the intellectual skills and experience of decision-makers, so this method is not more certain for exact analysis (Yariyan et al. 2020).

Analytic Network Process (ANP) ANP is the method used in MCDM (multi-criteria decision making) process, and like AHP, it also needs compensations in application (Pirnazar et al. 2021). The hierarchical analysis process is used to design this model, and the hierarchy is replaced by the network (Yariyan et al. 2020). An assumption was made in the process that lower sections and levels have no impact on higher sections and branches (Saaty 1999). However, in various decisions, it may happen that decisions are not independently and hierarchically modelled. Elements can be combined solve this nature problem. ANP method was suggested by Satty, and one-sided relationship is considered in different decision-making levels in the method of hierarchical analysis process (Saaty 1999; Zebardast 2013).

In this process, relationship-based measurements are taken, and complication of different problems are considered and give better results. A pairwise comparison scale is also used in ANP method, and it does not imply a hierarchical structure on issues like in hierarchical analysis process, but decision problem is modelled with employing a system perspective with feedback (Yager 1988). Like AHP, in ANP method pairwise comparison matrices are formed on the basis of expert's intellectual skills and literature study, so this method also has chances of uncertainty in the final weights. In addition with these MCDM methods, some other factors like the integration of fuzzy theory with MCDAs (Ghorbanzadeh et al. 2019a, b, c, d) and interval-AHP decision support model (Ghorbanzadeh et al. 2018a, b, c) have been introduced, to make outputs more certain and accurate. Integration of ANP and AHP methods with fuzzy model proves to be more reliable and accurate than the single methods used.

Ordered Weight Average (OWA) OWA method is the most used method for calculating the final composition of weights in MCDM process. Yager (Malczewski 1999) proposed this method in which, weightings are combined with prioritization of valuation criterion and also prioritizing them. In this method, prioritization of weight directly controls the criterion and reclassification is considered as the main feature. For the selected alternative, weight coefficient is employed to the prioritize location of criterion like among the selected criterion having the highest values are assigned with the weight of the first-priority valuation criteria (Liu and Han 2008).

To one dimension, operator of OWA illustrates n dimension space (Shafapour Tehrany et al. 2017). On the basis of the bellman model for fuzzy set integration operations, three integration functions have been proposed, including fuzzy set community operators, average operators and fuzzy set sharing operators (Malczewski 1999).

The OWA operator contains the fuzzy minimum and maximum operators in line with logic OR and AND respectively (Liu and Han 2008).

$$F(X_{ij}) = (X1i * Y1i + X2i * Y2i + \cdots + Xni * Yni), \quad (5)$$

where X shows the criteria value for alternative i and Y shows the criteria weight.

Logistic Regression (LR) LR method is used to forecast the tendency of dependent variable applying independent variable. LR model used the logit function as a link function so it can be considered as a generalized linear model. The random event may occur in two conditions to remain two-sided. Flood occurring probability can be influenced by the physical factors considered in this model. Normal distribution of the data is not needed in LR, and there may be discrete or continuous effective parameters in this model (Ayalew and Yamagishi 2005). Building up the model to find the correlation between the dependent variable and parameters impacting the flood to create each variable coefficient is the key role of LR. The logistic regression at 0 and 1 for phenomenon, presence or absence prediction depends on predictor variables values. Generally, the correlation between the event and its dependency on some variables is shown as,

$$p(\text{event}) = \frac{\rceil^z}{(1 + \rceil^z)}, \quad (6)$$

where $p(\text{event})$ shows the flood occurring probability. The occurrence probability varies from zero to 1 as the Z value varies from $-\infty$ to $+\infty$. Z represents the function of linear combination for effective factors that show the linear relationship and b_0 show the model's origin width.

$$Z = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n. \quad (7)$$

The equation for logistic regression is,

$$Y = \text{logit}(p) = \ln(p|1 - p) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n, \quad (8)$$

where Y show the flood occurrence probability, b_n ($i = 0, 1, \ldots, n$) estimation coefficients, n number of independent variables, and X_n ($i = 0, 1, \ldots, n$) independent variables.

The positive coefficients signify the relationship between the dependent variable and effective parameters, and the negative coefficients signify effect of the opposite. The iterative algorithm is needed for estimation of factors because there is a nonlinear relationship between the occurrence probability and independent variables (Avand et al. 2019).

Authentication and accuracy evaluation

Relative operating characteristic (ROC)

ROC is used to evaluate the accuracy of the final vulnerability map of the earthquake. Using the Boolean method, in comparison with the actual map, it is a relative parameter that depicts the location and probability of this class (Avand et al. 2019; Chen et al. 2020a, b). Graph of AUC (Area under the curve) in this method shows the false positive percentage and actual positive percentage in the horizontal and vertical axis, respectively (Achour and Pourghasemi 2019). Larger values of AUC (which shows the area under the ROC curve) shows a more proficient assessment of final classification performance. AUC value normally ranged from 0.5 to 1. Prediction model accuracy is very high if the AUC value is approximately 1.

Seismic relative index (SRI)

The SRI is the criteria which validate the results of seismic susceptibility assessment in this study. The implemented hybrid model accuracy can be measured by using SRI and evaluating the seismic susceptibility point distribution in sensitivity class. The equation used to estimate this index is,

$$\text{RI} = \frac{100 * (p_i | P_i)}{\sum (p_i | P_i)}, \tag{9}$$

where P_i represents the seismic susceptibility point percentage and p_i represents the existing pixel percentage in each sensitivity class.

Frequency ratio (FR)

FR is used to evaluate the spatial relationship between classes and data of various parameters. A correlation with the rate of occurrence is represented by the data percentage in each class "i" of factor and "j" on the basis of FR numerical values (Jaafari et al. 2019). The equation to calculate FR index for each class is as follows,

$$\text{FR} = \frac{(L_i K j i * \sum pix)}{(li K j i * \sum L_i)}, \tag{10}$$

where L_i shows the occurrence point Kji criteria each class, $\sum pix$ represents pixels total number in the range, li shows the values of pixels Kji criteria each class and $\sum L_i$ total number of points of occurrence.

Results and analysis

For the formation of two hybrid procedures, A-fuzzy and A-MCE, sensitivity groups were graded in individual layers by computing the average weights of AHP and ANP decision procedures as shown in Table 4. These study factors were developed from the three major collections, social, environmental, and physical and then regimented on the basis of natural break procedure.

Considering the variances in the weight computations of the decision procedures of ANP and AHP models, for pairwise assessments, weighted methods were acknowledged. The fuzzy hybrid procedure was charted using the numerical values from 0 to 1 obtained from layer fuzzy, with the added combination of ranks attained from the MCDA method in the ArcGIS system. After that, by equalizing the layers on the purpose of the MAX and MIN technique, we developed the hybrid A-OWA procedure, which was executed by putting hybrid ranks in the IDRISI system.

Relying on Table 4 outcomes, the collective weight computed for the formation of functioning layers is built on normalized weights multi-criteria decision analysis (MCDA) procedure. Similarly, distance from the fault and population density aspects faced with the highest rank weight of 0.087 and 0.088. At the same time, elevation resulted in the lowest rank weight of 0.039 in this research.

Selectin of training sites used in modelling

Charted outcomes of the A-fuzzy and A-OWA hybrid procedures are listed upon five susceptibility groups named as, very high, high, moderate, low, and very low. For precision in the susceptibility maps, training facts plays a major part in the process. In order to acquire this process, it is important to choose the best suitable type of training stage data, because the most significant stages in the training sites procedure include gathering, choosing, and processing training information. With the lack of informative data records of earthquakes in the research area and deficient sampling, it is preferred to hire an advanced training system. For that, two apposite training records are created for the LR neural network training with the help of using the hybrid weight of AHP-ANP and hybrid A-fuzzy and A-OWA models present in the current study. Now at this stage, two new training records are formed with the help of the two-hybrid procedures. So, 150 random training positions were selected as final sites in each case of the hybrid base chart of A-OWA and A-fuzzy as shown in Fig. 4.

For accuracy comparison of two new hybrid procedures, 10 building damage points are selected from October 8,

Table 4 Parameters normalized weights based on multi-criteria decision analysis (MCDA) models

Group	Factors	Class	Pixels in Domain	Percentage of Domain	Weight of AHP-ANP	Eigenvalue AHP-ANP
Physical	Distance from hospital	< 1000	18,077	10	0.06863	0.10
		1000–2000	21,693	12		0.12
		2000–3000	28,924	16		0.16
		3000–4000	27,116	15		0.15
		> 4000	84,963	47		0.47
	Distance from fire station	1500	3615	2	0.06889	0.02
		3000	5423	3		0.03
		4500	9039	5		0.05
		6000	10,846	6		0.06
		> 6000	151,849	84		0.84
	Land cover	Urban area	25,308	14	0.07825	0.14
		Agriculture	79,540	44		0.44
		Natural trees	54,232	30		0.30
		Bare areas	14,462	8		0.08
		Water bodies	7231	4		0.04
	Inappropriate materials	< 15	115,695	64	0.05944	0.64
		15–30	19,885	11		0.11
		30–45	14,462	8		0.08
		45–60	18,077	10		0.10
		> 60	12,654	7		0.07
	Distance from roads	< 1000	75,925	42	0.06054	0.42
		1000–2000	23,500	13		0.13
		2000–3000	27,116	15		0.15
		3000–4000	14,462	8		0.08
		> 4000	39,770	22		0.22
	Area	< 100	3615	2	0.05945	0.02
		100–200	7231	4		0.04
		200–300	54,232	30		0.30
		300–400	83,156	46		0.46
		> 400	32,539	18		0.18
	Number of floors	2–3	28,924	16	0.06866	0.16
		1	151,849	84		0.84

Table 4 (continued)

| Group	Factors	Class	Pixels in Domain	Percentage of Domain	Weight of AHP-ANP	Eigenvalue AHP-ANP
Environmental	Distance from fault	<1300	32,539	18	0.08766	0.18
		1300–2400	21,693	12		0.12
		2400–3500	23,500	13		0.13
		3500–4600	23,500	13		0.13
		4600–6000	21,693	12		0.12
		>6000	57,847	32		0.32
	Slope	<15	68,694	38	0.04609	0.38
		15–25	21,693	12		0.12
		25–35	25,308	14		0.14
		35–45	27,116	15		0.15
		>45	37,962	21		0.21
	Lithology	Granite Gneiss	3615	2	0.07935	0.02
		Mostly intrusive rocks	23,500	13		0.13
		Dolomite	57,847	32		0.32
		Sandstone	95,810	53		0.53
	Elevation	<900	43,386	24	0.03929	0.24
		900–1300	54,232	30		0.30
		1300–1700	36,155	20		0.20
		1700–2100	27,116	15		0.15
		>2100	19,885	11		0.11
	Distance from stream	<300	14,462	8	0.06054	0.08
		300–600	16,270	9		0.09
		600–900	16,270	9		0.09
		900–1200	16,270	9		0.09
		>1200	121,118	67		0.67
Social	Percent of population	<400	79,540	44	0.07809	0.44
		400–800	45,193	25		0.25
		800–1200	21,693	12		0.12
		1200–1600	14,462	8		0.08
		>1600	19,885	11		0.11
	Family density	<20	3615	2	0.04879	0.02
		20–40	57,847	32		0.32
		40–60	43,386	24		0.24
		60–80	39,770	22		0.22
		>80	36,155	20		0.20
	Population density	<40	50,616	28	0.0881	0.28
		40–80	36,155	20		0.20
		80–120	32,539	18		0.18
		120–160	37,962	21		0.21
		>160	23,500	13		0.13
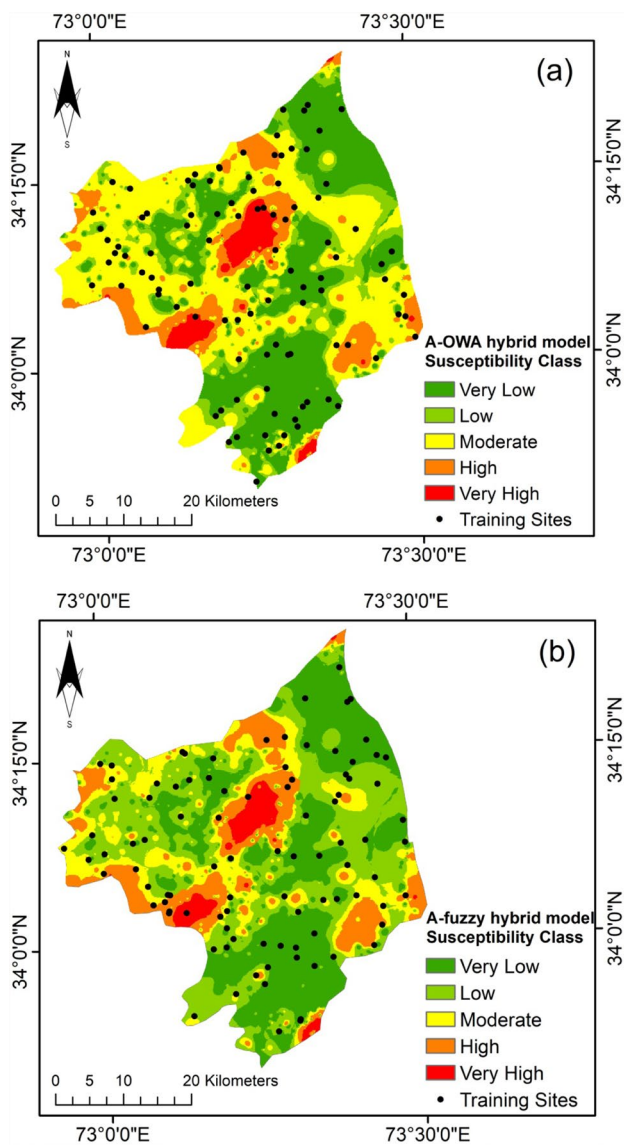
Fig. 4 Maps of training sets obtained from A-ordered weight averaging (OWA) and A-fuzzy hybrid models

2005 Kashmir earthquake and October 26, 2015 Afghanistan earthquake with the help of GPS during survey study of the research area. The precision of sensitivity outcomes of the procedures was computed with the seismic relative index (SRI) as shown in Table 5.

Benefiting from the arithmetic values in Table 5 and Fig. 5 for R-index with 10 damage points, for each group of A-OWA procedure and A-fuzzy procedure, the percentage amount of the dispersion points ranging from very low to very high susceptibility class was 86% and 84% correspondingly. SRI outcomes validate high precision in the earthquake susceptibility sensitivity groups of the A-OWA hybrid procedure based upon the existing points. This Validation analysis was used to assess training records in the study area.

Results

Seismic vulnerability map

LR procedure was conducted every time through each of the training groups by applying the input numbers (standardized information), after which two training records were developed with the use of the A-OWA hybrid procedure and the A-fuzzy hybrid procedure. While modelling the earthquake susceptibility in the study region, the classification approach of the LR procedure was executed with the use of IDRISI Selva version software (18th version). This classification model was also used to acquire the seismic susceptibility percentage. Since the training positions in the LR procedure must indicate 0 or 1 (binary), represented as an occurrence as 1 and non-occurrence as 1 in procedure implementation. With the help of the ANN test, the earthquake susceptibility charts were developed categorizing LR procedure into five groups very high, high, moderate, low, very low susceptibility ranks as shown in Fig. 6c, d. The map of earthquake vulnerability was formed with the combination of OWR-LR procedure, and fuzzy-LR procedure and these final charts were transported into the ArcGIS system.

Table 5 Assessment of Earthquake Vulnerability Maps Based on R Index

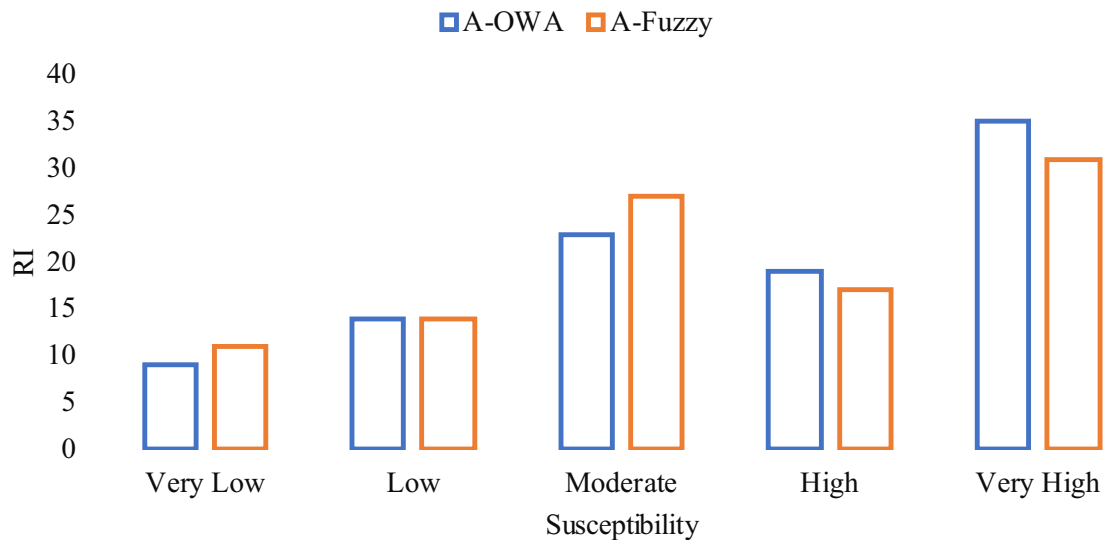| Hybrid model	Class	Pixel	Pi	SV (Occurrence)	Pi	RI
A-OWA	Very Low	34,340	19	0	0.00	0
	Low	56,039	31	1	10.00	5
	Moderate	48,807	27	3	30.00	12
	High	23,508	13	0	0.00	0
	Very High	18,079	10	6	60.00	84
A-fuzzy	Very Low	59,655	33	0	0.00	0
	Low	45,193	25	1	10.00	6
	Moderate	19,885	11	3	30.00	10
	High	34,347	19	0	0.00	0
	Very High	21,693	12	6	60.00	85

□ A-OWA □ A-Fuzzy

Fig. 5 R-Index for susceptibility classes

Authentication of the seismic susceptibility maps

This system includes the authentication of hybrid procedures named A-fuzzy, A-OWA, OWA-LR, and fuzzy-LR. These were used to appraise the seismic susceptibility charts precision in the research region. Moreover, the ROC graph was also used in this assessment, which decides the precision range of the susceptibility charts (Yariyan et al. 2019). ROC results exposed that AUC ranges for hybrid models A-OWA, A-fuzzy, OWA-LR, and fuzzy-LR were 0.812, 0.806, 0.875, and 0.842, respectively as shown in Fig. 7 and Table 6.

The most precise model from the four models was the OWA-LR hybrid procedure having AUC = 0.875, making it more promising in computing the susceptibility chart.

In order to authorize the fuzzy-LR model and OWA-LR model, the frequency ration index was applied. Each of the model's very high-class values indicates the highest numerical of the FR, spotting the connection between the sensitivity groups and the susceptibility points with the most accuracy as compared with the other procedure as presented in Table 7. The analysis specifies a strong connection between the high vulnerability group and the percentage of indicating vulnerability positions.

Discussion

Recognizing the sensitive regions for earthquake susceptibility is a rising matter due to modern urbanization and lack of planning with respect to it. To this date, many types of research have concluded different methods and procedures to tackle the assessment of the earthquake vulnerable zones all around the globe, for the protection of the

economic sufferers and losses due to such natural disasters. Previously, investigators of the vulnerability assessment have been using single models for the seismic susceptibility charts, showing results with improvement voids of hybrid models. Recently, many new hybrid procedures have been conducted to chart the natural threats (Jaafari et al. 2019; Rahmati et al. 2019; Razandi et al. 2015). Lee et al. (2019) derived a hybrid approach that combines SWARA with radial basis function (RBF) along with the designs of (TLBO) teaching learning-based Optimization to encounter the susceptibility valuation of seismic waves. The factor of optimization algorithm was also used which was never integrated before for the susceptibility of seismic waves. This GIS-based engine learning program was beneficial for operators who have limited acquaintance of assessing the seismic vulnerability, they can efficiently valuate their office or home structure. The program for seismic susceptibility computation is superior at engaging powerful tools for geographic program design, e.g., Geographic Information System (GIS) and applying modernity weighting systems, like SWARA, RBF and TLBO, to deliver the susceptibility of the study area with higher accuracy results. Jena et al. (2020) estimated the seismic risk by applying cross-interrelation of parameters, SC (Silhouette clustering), PLC (pure locational clustering) grounded on HCA (hierarchical clustering analysis), CNN (convolutional neural network) and AHP (analytical hierarchy process) systems. Two risks, A and B were produced in which the EVA (earthquake vulnerability assessment), SSA (seismic amplification) and EPA (earthquake probability assessment) were engaged to make Risk A, while EVA (earthquake vulnerability assessment), SSA (seismic amplification) and EHA (earthquake hazard assessment) were engaged to make Risk B. After the risk charts
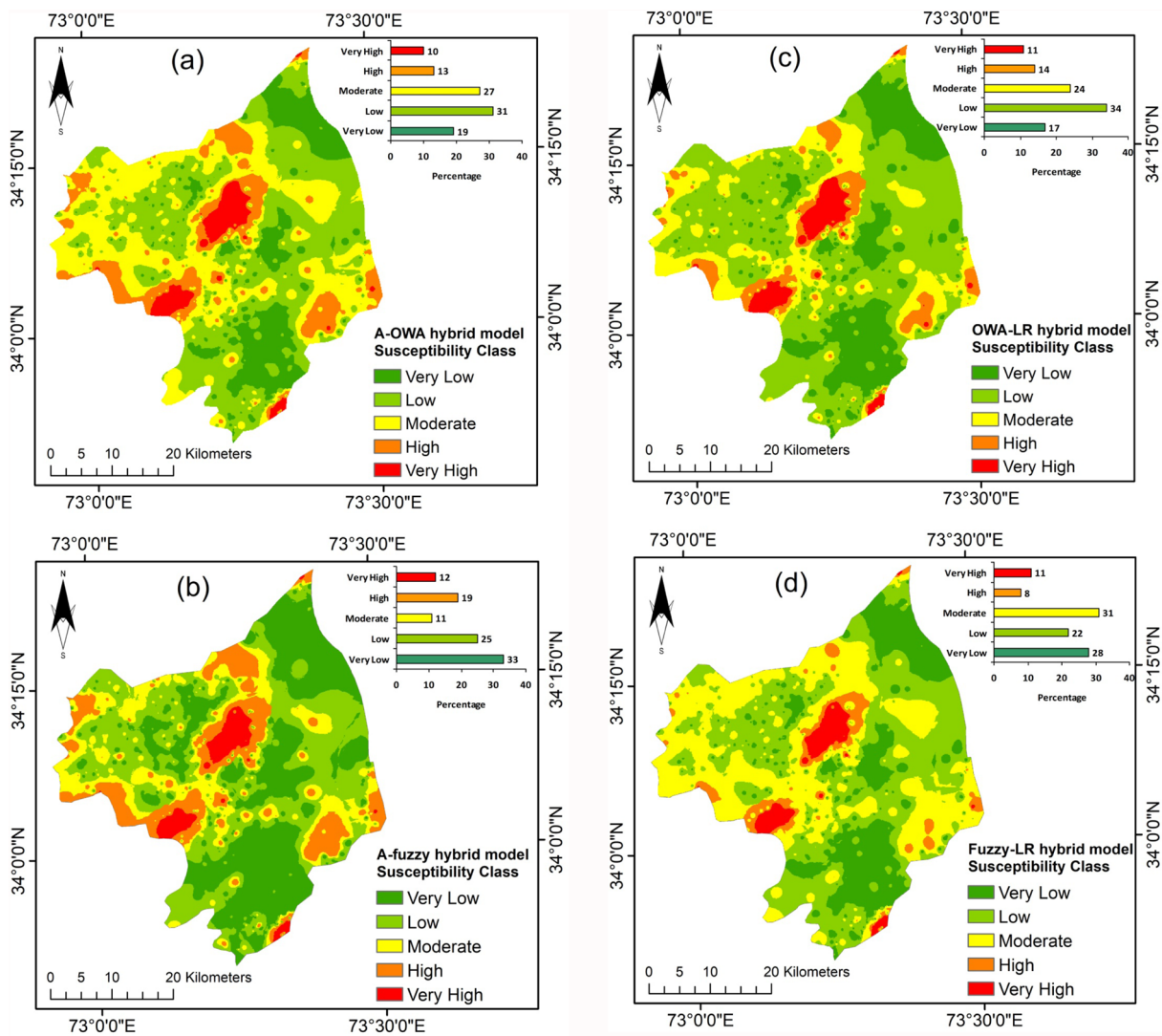
Fig. 6 Subsequent earthquake susceptibility maps based on hybrid models of **a** A-fuzzy, **b** A-OWA, **c** fuzzy-logistic regression (LR) and **d** OWA-LR

comparison, it resolved that in the case of EPA (earthquake risk assessment), results of risk B were preferable than risk A, giving 89.47 accuracy percentage for EPA and 0.07 consistency ratio for EVA. Yariyan et al. (2020) recognized earthquake susceptibility aspects to three extents: social, physical, and environmental. The parameter model they used to create the assessment approach included MCDA-MCE (multiple criteria decision analysis-multi-criteria evaluation) and fuzzy-MCDA (fuzzy-multiple criteria analysis), giving discipline to the MCE–LR (multi-criteria evaluation–logistic regression) and fuzzy-LR (fuzzy-logistic regression) hybrid systems. MCDA-MCE model exhibited higher precision after the validation of the dataset using ten damaged places from their location and the SRI (seismic relative index) system. Their assessment reports showed that the fuzzy-MCDA system showed lower accuracy (AUC = 0.80) than

the MCDA-MCE hybrid system (AUC = 0.85), while the fuzzy-LR hybrid system showed lower accuracy in the susceptibility map production (AUC = 0.85) than the MCE-LR hybrid system (AUC = 0.90). The outcomes demonstrate that the precision value of the seismic susceptibility modelling and charting is directly associated with the training dataset precision. The investment of this research was to present modern hybrid procedures for such hazard susceptibility in the present study area. The vulnerable zones of the seismic hazards were based on the operation of new hybrid procedures and with the help of artificial neural net training in the process. In the effectiveness of the factors to earthquake exposure, fifteen factors were selected for the system. The direction of this study with applying new hybrid procedures was to produce comprehensive analysis and eradicating the deficiency in the individual procedures. A synthetic neural
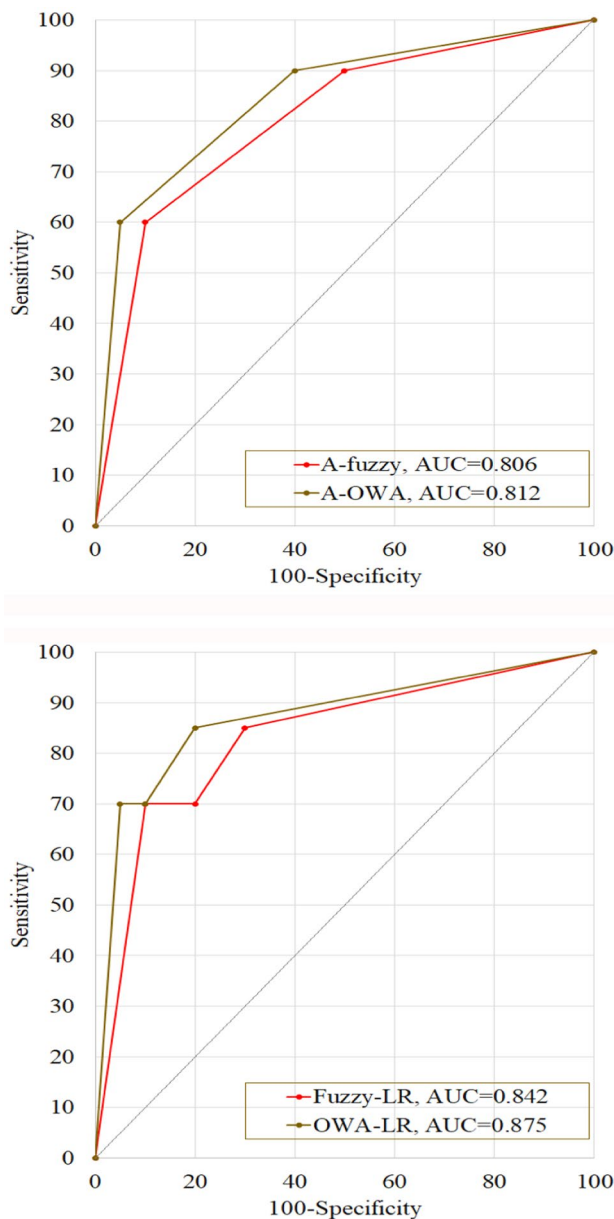
Fig. 7 The area under the ROC curve (AUC) for hybrid models

Table 6 Validation results of the ROC curve

Model	AUC	Std. error	Confidence interval (95%)	
			Lower	Upper
A-fuzzy	0.806	0.0974	0.527	0.924
A-OWA	0.812	0.0845	0.586	0.952
Fuzzy-LR	0.842	0.0758	0.617	0.953
OWA-LR	0.875	0.0685	0.657	0.962

system can be applied to classify the charts of estimating earthquake hazards with more precision globally. The fuzzy-LR hybrid system and OWA-LR hybrid system were executed after making the hybrid A-OWA model, and A-fuzzy model and the addition of databases of training sets. The accuracy results from the AUC and FR of the hybrid models disclosed that the A-OWA hybrid procedure is more exact with $AUC = 0.812$ than the A-fuzzy hybrid procedure with the value of $AUC = 0.806$.

Moreover, when comparing different hybrid procedures accuracy, the OWA-LR procedure had significantly greater accuracy in higher class sensitivity of $AUC = 0.875$ with STD error $= 0.0845$ and frequency ratio (FR) $= 11.52$ index value than $AUC = 0.842$ and $FR = 9.58$ of the Fuzzy-LR hybrid procedure. A-fuzzy procedure and A-OWA procedure also ended showing comparatively higher accuracy in seismic sensitivity, proving influential procedure for this research (Table 7). In this subject, two different hybrid procedures have been conducted in this research to compose training information for assimilation with synthetic neural networks. Thus, the procedures conducted in this research may acquire lower precision when operated individually. This research following the hybrid procedures, provide definite predictions concerning the earthquake sensitivity assessment. Still, the outcomes of the test recommend that the high precision of the A-OWA hybrid method with a minor standard error of 0.0845 increase the precision of the training record. Hence, training record validation combined with the concluding accuracy of damage points procedures indicates stable accuracy. Based on the outcomes from the hybrid OWA-LR model, reflecting an ideal model, 51% of the research area follows in the low and very low susceptibility range, while 24% reigns in the moderate zone. Around 25% of the urban region characterizes by susceptible zones.

In order to minimize the catastrophe produced by seismic waves, the susceptibility charts can illustrate vulnerable zones for infrastructure precautions and can be utilized by urban developers. Our technology and science still cannot resist the natural seismic disasters from happening, so humans can only adjust themselves and can only reduce the after damage to the least with its expertise. As a result of limited access, it is impossible to properly consider all the possible aspects relating to the seismic sensitivity, but the current update from the ground reviews and professional thoughts, this research is held responsible with the maximum sum of pointers for precise assessment. So, this research indicates three aspects influencing susceptibility in the three social, environmental, and physical scopes. A new approach is developed in this study due to a lack in the determination of ANP and AHP weight values, which gives the average weight values of each model, to gain the ideal weight of each model. At last, for improved AHP and ANP systems and to develop two new hybrid systems, seismic susceptibility chart

Table 7 Models seismic vulnerability based on Frequency Ratio Index

Hybrid model	Class	Pixel	Pixel %	No of SV	SV%	FR
Fuzzy-LR	Very Low	30,731.41	17	0	0	0.00
	Low	61,462.82	34	1	10	2.45
	Moderate	43,385.52	24	3	20	3.14
	High	25,308.22	14	0	0	0.00
	Very High	19,885.03	11	6	20	9.58
OWA-LR	Very Low	50,616.44	28	0	0	0.00
	Low	39,770.06	22	1	10	1.28
	Moderate	56,039.63	31	3	20	2.14
	High	14,461.84	8	0	0	0.00
	Very High	19,885.03	11	6	20	11.52

was formed by merging the weight values of multi-criteria decision-making systems of AHP, ANP, and linking these with OWA and fuzzy systems. To discipline the LR neural network system for conquering the access points limitations of earthquake susceptibility in the study area, new hybrid methods were developed. Therefore, hybrid A-OWA and A-fuzzy models, as the foundation for informative records, can conquer the limits of information access. For the precision of the hybrid systems, 10 points susceptibility records were used for the earthquake relative index verification. As a result, two charts were prepared by uniting the LR system (logistic regression) and hybrid MCDA-fuzzy and MCDA-OWA systems. Finally, accuracy data from the initial hybrid A-OWA and A-fuzzy systems in helping the training record were correlated with the exactness of the new hybrid OWA-LR and Fuzzy-LR systems (developed through them). The crux of the study was to estimate the vulnerability zones of different hazard areas with the most precise technique possible, which would benefit people in developing structures resistant to cataphoric events in the future. For such, the OWA-LR model and fuzzy-LR model were analyzed and it was identified that OWA-LR is a more positive approach in evaluating susceptibility zones.

Conclusions

Outcomes of the hybrid assessment models revealed that the model A-OWA and OWA-LR resulted in the most precise model results of AUC = 0.812 and AUC = 0.875 for earthquake sensitivity mapping. Thus, it can be concluded that the precision of the hybrid system resonates with the educational catalogue accuracy. So, in this research, the new model OWA-LR hybrid is recognized as the highly required system. In the opinion of this system, 11% of the total selected area is in the group of very high vulnerability. Moreover, the factors disturbing the susceptibility of the earthquake, containing physical and social aspects produced by inappropriate material quality, large population density, fewer passages width had an immense part in the seismic susceptibility. We also have compulsory post-emergency services such as fire stations and medical centre, but these factors hinder the services due to insufficient structure network performance and human emergency efficiency. As the charts of vulnerability represent the alert locations of the research region, it is essential to acknowledge proper threat reduction strategies and a prepared approach.

Contributions and future directions

This study helped to map the seismic susceptibility of Abbottabad district, in which areas at high risk to the earthquake were identified on the basis of their intensity. Outcomes of the current research will facilitate planners and management authorities to make well-grounded decisions in areas at high risk to seismic waves. This study also validates the integration of hybrid models, and the accuracy of results was justified in the current study.

In future, it is suggested to imply the same methodology in other earthquake susceptible zones of the world. It is also possible to integrate some other models for the accuracy of results already generated. Along with mapping, research can be conducted in the study area to investigate the current condition of the infrastructure. Earthquake resistant buildings should be proposed in the high susceptible zones. In future, the hybrid methods presented in this study can also be integrated with different possible models to enhance its capability in analyzing the earthquake susceptibility hazard globally, which can further provide insights for more truthful results and hazard free environment.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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