Spatial earthquake vulnerability assessment by using multi-criteria decision making and probabilistic neural network techniques in Odisha, India

Ratiranjan Jena[1], Biswajeet Pradhan[1,2*,] Ghassan Beydoun[1], Abdullah Alamri[3], Abdallah Shanableh[4]

[1]Center for Advanced Modeling and Geospatial Information Systems, Faculty of Engineering and Information Technology, University of Technology Sydney, NSW 2007, Australia; Email. Ratiranjan.Jena@uts.edu.au; Biswajeet.Pradhan@uts.edu.au; Ghassan.Beydoun@uts.edu.au

[2]Department of Energy and Mineral Resources Engineering, Sejong University, Choongmu-gwan, 209, Neungdong-ro Gwangin-gu, Seoul 05006, Korea; Email. biswajeet24@gmail.com;

[3]Department of Geology and Geophysics, College of Science, King Saud University, Riyadh 11451, Saudi Arabia; amsamri @ksu.edu.sa; alamri.geo@gmail.com

[4]Department of Civil and Environmental Engineering, College of Engineering, University of Sharjah, P. O. Box 27272, Sharjah, United Arab Emirates; shanableh@sharjah.ac.ae

*Email. Biswajeet.Pradhan@uts.edu.au and Bsiwajeet24@gmail.com (Corresponding author)

Abstract

In this study, the multi-criteria decision-making method was used to estimate the weights of several input factors such as slope, curvature, elevation, proximity to road, road density, proximity to land use, land use density, proximity to water bodies, river density, rail density, distance from rail, groundwater variation, lithology with amplification factors, peak ground acceleration (PGA) variation, and population density. An integrated analytic hierarchy process (AHP) and a probabilistic neural network (PNN) were applied for the Earthquake vulnerability assessment (EVA). The PNN model successfully explored the relationship between variables and weights obtained from the AHP approach. Validation results indicate that 92.5% accuracy was attained by the PNN model. According to the results, 24.26%, 15.26%, and 20.58% of the area fall under very-high, high, and moderate vulnerability category, respectively. The EVA map illustrates that high to very-high impact could be observed in coastal Odisha and few districts in the Mahanadi Graven.

Keywords: Earthquake vulnerability; MCDM; Bayesian classifier; probabilistic neural network; GIS

1. Introduction

Earthquake vulnerability assessment (EVA) has been a challenging subject (Peng 2015; Jena *et al.* 2020a). The evaluation of vulnerabilities of the physical, structural, geo-technical, and social components exposed to earthquake is ridden with problems. The main challenges in earthquake vulnerability estimation are (1) difficulties in identifying the suitable factors of vulnerability (Birkmann and Wisner 2006), (2) a lack of detailed and accurate data that can be implemented in feature selection for factor development (Thieken *et al.* 2008), and (3) the availability of data can only be found at highly aggregated levels (Notaro *et al.* 2014). Moreover, grouping of factors is challenging when establishing distinct categories. Some studies perceive geotechnical factors as part of structural vulnerability and vice versa (Yariyan *et al.* 2021). Challenges are also involved in incorporating temporal scales in vulnerability assessments of earthquakes (Baruah *et al.* 2020; Mohebbi *et al.* 2020).

Globally, several earthquake vulnerability studies have been conducted (Clark *et al.* 1998; Panahi 2014; Bankoff *et al.* 2013). Peng (2015) estimated earthquake vulnerability by using several multi-criteria decision-making (MCDM) methods, such as VIseKriterijumska Optimizacija I Kompromisno Resenje, Elimination et Choice Translating Reality, preference ranking organization method for enrichment evaluation, Weighted Sum Method, and Grey Relational Analysis. The studies were conducted in key Chinese locations using 11 criteria derived from built-up area, population, residential buildings, and industrial infrastructure. The author found that TOPSIS is the most selected method because of its efficiency. Rezaie and Panahi (2015) studied earthquake vulnerability by using Analytic Hierarchy Process (AHP) and Geographical Information System (GIS). Chen et al. (2013) described in their research that social vulnerability affects people's ability to handle pre- and post-disaster situations. Clark *et al.* (1998) described social vulnerability with respect to the range of destruction to specific communities, groups, or countries. Bankoff *et al.* (2013) emphasized that vulnerability is the key to estimate risk associated with the corresponding environment and societies. Vulnerability also deals with people, knowledge, and their perceptions (Bankoff *et al.* 2013). Therefore, vulnerability is a complex relationship embedded with processes within an environment. Wood et al. (2010) noted that social vulnerability is associated with individual, natural, and social changes that can expose lives to risk.

Recently, Flanagan *et al.* (2011) proposed a method to estimate composite vulnerability by aggregating vulnerability factors. They understood that social vulnerability factors for storm surges are associated with natural hazards like hurricanes. Collins *et al.* (2009) worked on environmental vulnerability in El Paso, Texas (USA) and Ciudad Juarez (Mexico). They adopted the method proposed by Cutter *et al.* (2003) to estimate the vulnerability index. Bjarnadottir *et al.* (2011) generated a social vulnerability index on the basis of coastal community for hurricane-prone areas in Florida. Wood *et al.* (2010) converted community relations to social vulnerability associated with Cascadia tsunamis in the United States, and estimated block-level social vulnerability. Zhang *et al.* (2017) developed a model for social vulnerability estimation to evaluate earthquake vulnerability in Sichuan Province, China. Elimination of unimportant factors and optimization of the proposed model was performed by using an attribute reduction method. Thiri (2017) conducted an analysis on vulnerability estimation in 30 municipalities that were affected by the Great East Japan Earthquake that occurred in 2011. Disaster impact on environmental migration was evaluated by conducting interrupted time series analysis.

Several studies on earthquake vulnerability were carried out in India. One key research was conducted by the Indian Institute of Technology (Technical Document, IIT 2013). Sinha and Adarsh (1999) conducted a postulated vulnerability study for Mumbai City. Sinha and Goyal (2004) established a national policy for the earthquake vulnerability study for buildings in 2003. Likewise, Nath (2016) conducted a vulnerability study for Kolkata City. Some studies were also carried out for the north-eastern region of India, such as Guwahati City (Pathak *et al.* 2015) and Shillong City (Biswas *et al.* 2013).

However, only a few studies on earthquake vulnerability have been conducted in the state of Odisha (Jena *et al.* 2020d). Most of the focus has been given to local site-effect estimation and hazard mapping (Gupta *et al.* 2014; Mohanty *et al.* 2009). However, no recorded studies have been conducted for earthquake vulnerability assessment using a combined approach of MCDM and machine learning (ML) techniques. No comprehensive, large-scale earthquake vulnerability study has been conducted in Odisha by using ML and GIS. The major research questions that were addressed in this study are; (1) is good accuracy in vulnerability mapping possible? If so, how methodical are the obtained results?; (2) what are the main factors in the current model that help achieve good accuracy?; and (3) is the proposed PNN model good enough for future regional scale studies on earthquakes? Existing seismic studies concentrate on earthquake hazard assessment and local-scale vulnerability assessment. By contrast, many assumptions have been made for existing studies without considering the vulnerability index estimation. However, in this research, we have not gone through any assumption but followed the major factors that contribute to the vulnerability index. Previous works in Odisha were fully focused on probability and hazard assessment. However, in the current research, geological, geomorphological, structural, and social characteristics were integrated into GIS to generate an earthquake vulnerability map where implementation of the AHP and PNN technique provides a useful way to estimate vulnerability index. This work has three main objectives: (1) to estimate earthquake vulnerability by aggregating vulnerability factors with the addition of new factors by using MCDM; (2) to develop a PNN model to implement vulnerability prediction with good accuracy; and (3) to predict the site of spatial variation of vulnerable zones.

2. Study area

Odisha shares a coastline of 450 km with the Bay of Bengal (Figure 1a). It is located in Eastern India, which is famous for its history, culture, hot springs, and unique geography (Sarkar and Saha 1983). The state is located between the latitude and longitude of 20.9517° N and 85.0985° E, respectively. Bhubaneswar is Odisha's economic capital and the "temple city" of India. The state extends over 155,707 km^2 and has a population of 46 million. The GDP of Odisha in 2019–2020) was US$75 billion (Sarkar and Saha 1983; Dhar *et al.* 2017).

As stated in the seismic zonation map of India, Odisha falls under zones II and III (Narula *et al.* 2000). Although a considerable part of Odisha falls under zone III, much of the state is under zone III. Major cities that are encompassed by the Mahanadi Graben are Bhubaneswar, Cuttack, Talchir, Angul, Dhenkanal, Sambalpur, and Balasore (Figure 1c). Several moderate magnitude events have occurred in the Bonaigarh–Talchir area (Mw 5 and 4.8). In 1958 and 1962, two earthquake events of 5.2 Mw occurred in Rengali Province (Figure 1a). Several moderate events of Mw 4.4, 4.1, and 4.3 were also recorded in January 1986, because of the north Odisha boundary fault (NOBF) movement (Mahalik, 1994). Four major stations were established by the Geological Survey of India (GSI) for the measurement of micro-earthquake close to the NOBF. Nevertheless, many hypocenters, which indicate neo-tectonics, were also observed in the active NOBF.

This section presents the geological and tectonic settings in Odisha (Figure 1b). Approximately, 75% of the state is covered by Precambrian rocks. The rocks date back to 3,700 million year (M.Y.) of geological history (Gupta 2012). Consequently, 25% of the total rock deposits, including unconsolidated rocks, are from the Post-Cambrian age.

Figure 1. *Around here.*

Basement rocks are characterized by granites, gneisses, ultrabasic-basic rock types, khondalites, and charnockites (Gupta 2012). Studies have been conducted along the litho-contact between the Eastern Ghats Mobile Belt (EGMB) and North Odisha Craton (NOC), which is divided by the Mahanadi Shear Zone (MSZ) in east-west direction (Mahalik 1994). Gondwana graben is the basin known for coal deposits that have risen due to the fault zone generated between the cratons. Owing to the typical characteristics of fault slices, interpretation of sedimentation, intrusion, and litho-contact is difficult.

EGMB consists of granulite facies characterized by charnockites, khondalites, quartzites, gneiss, and garnet–biotite schists (Gupta 2012). The North Orissa craton is characterized by banded iron ore and supracrustal rocks of low-grade origin within granitic intrusion (Gupta 2012). Geologists believe that EGMB rocks are older than BIF-bearing granites. Amphibolite facies are located in the southern part of the Singhbhum craton. Migmatites are metamorphic rocks that are found in EGMB (Mahalik, 1994). The E–W oriented Mahanadi graben is sandwiched between NOC and EGMB, thus forming a basin (Mahalik 1994). Further, it can be considered as a half-graben composed of several normal faults. Thus, EGMB is trending in the WNW–ESE direction parallel to NOBF that is present in between NOC and Mahanadi basin. Moreover, the reactivation of NOBF and MSZ is directed towards tectonic basin development and seismicity.

3. Data

Data for this study were collected from several sources. The open access catalog of earthquakes is obtained from national and international disaster management agencies. The sources are the United States Geological Survey (USGS), National Earthquake Information Center, and National Center for Seismology. Shape files, building information, and population data were collected to develop a geodatabase and to generate several layers for vulnerability assessment. The geological map was obtained from GSI and was used to prepare thematic layers. Geological data, including lithology, are the raw data used to derive vulnerability factors. For PGA estimation, this study chose the specific magnitudes ranging from 5.0 up to 7.5–8.5 which were experienced in and around Odisha using the ground motion equation developed by Campbell & Bozorgnia (2010). As most of the major earthquakes in Odisha falls within a distance ranging from 0–200 km, Campbell & Bozorgnia attenuation model best suits for the PGA estimation (Figure 3). The seismotectonic atlas and published papers were used as genuine referrals for locating earthquake sources and high-intensity locations for vulnerability identification purposes. In the current study, a digital elevation model with a spatial resolution of 30 m was used due to the unavailability of high-resolution data to generate major factors such as slope, elevation, curvature, and hill shade (USGS 2018). To prepare the thematic layers, a world geodetic system (WGS 1984) was used. The other thematic maps were derived from transportation data, groundwater and river data, and land use and land cover. Most of the researches explored only one side of the factors that is the proximity, however ignoring the other appealing side impacts on the model output (Yariyan *et al.* 2021, Alizadeh et al., 2018a,b). In "road density", dense locations were always prioritised and determined with all road contributing equally to a particular area. This is important for the main road junctions that is more significant than a single road (Jena *et al.* 2020b). However, individual roads are prioritized in "proximity to road factor". This signifies the importance of all other factors derived from single data for vulnerability assessment (Table 1). The thematic layers were presented by using natural break classification technique **(**Figure 2**)**. Table 1 lists down the raw data and the derived parameters implemented in the study.

Table 1. *Around here*

Figure 2. *Around here*

Figure 3. *Around here*

4. Methodology

An integrated AHP–PNN model was developed where 17 selected factors were chosen to estimate vulnerability. First, MCDM technique was implemented to understand the priority of thematic layers and considered as an input for the PNN classification of vulnerability. Second, a PNN model was developed for the prediction classification purposes. To generate the PNN-based earthquake vulnerability assessment, pre-processing, processing, and post-processing of data were conducted. Prediction of classification is the main task to generate vulnerable locations into points, and then post-processing was performed to generate maps. Finally, the GIS environment conversion of point-to-raster was conducted, thus generating the earthquake vulnerability map. Figure 4 presents the methodological flowchart.

Figure 4. *Around here*

4.1. AHP approach implementation

For the vulnerability assessment, 15 layers were selected on the basis of the literature (Jena *et al.* 2020a), and the AHP approach was implemented. The importance of thematic layers was presented with description in the data section (Table 1). Table 2 presents the pair-wise comparison and the relative importance of factors. Subsequently, normalization can be applied and the priority of all the layers can be estimated.

$$AW = l_{max}W, \qquad (1)$$

where pair-wise comparison matrix can be considered A and the eigenvector is W. l_{max} is the largest eigenvector as described in Eq (1). X is the eigenvector of matrix A, which could be presented through the expression in Eq. (2). For vulnerability assessment, the weighted sum tool was implemented to generate the map.

$$(A - l_{max}W) * X = 0 \qquad (2)$$

The consistency index (CI) can be presented by Eq. (3):

$$CI=\frac{(\lambda_{max}-n)}{n-1} \qquad (3)$$

Here, λ_{max} is the validation parameter. To check the consistency in the pairwise comparison, CI was used. If the consistency ratio (CR) is < 0.1, then it can be considered for the priority estimation and mathematically it can be written as:

$$CR = CI/RI. \qquad (4)$$

To the end, vulnerability map was developed in GIS using the factor’s priority values derived by using AHP approach (Table 2).

Table 2. *Around here.*

Table 3. *Around here*

4.2. Probabilistic neural network architecture and implementation

Specht (1990) first introduced the PNN model, which is established on the basis of Bayesian classifier technique that is most commonly implemented in solving pattern-recognition or classification problems (Figure 5).

Pattern vector $\boldsymbol{x}$ is considered with m dimensions, which belongs to K_1 or K_2 categories. Let us consider the F_1 (x) and F_2 (x) as the probability density functions (pdf) in the classification purposes of K_1 and K_2, respectively. Based on the decision rule of Bayes, $\boldsymbol{x}$ comes under K_1 if;

$$\frac{F_1(x)}{F_2(x)} > \frac{L_1}{L_2}\frac{P_2}{P_1}. \quad (5)$$

Conversely, $\boldsymbol{x}$ comes under K_2 if;

$$\frac{F_1(x)}{F_2(x)} < \frac{L_1}{L_2}\frac{P_2}{P_1}. \quad (6)$$

Here, loss function is L_1 linked with the vector misclassification that belongs to K_1category. When L_2 becomes the loss function, then it belongs to category K_2. Similarly, P_1 will be the prior probability when it belongs to category K_1, and for category K_2, P_2 will be the prior probability of occurrence. In several circumstances, the prior probabilities and the loss functions can be regarded as equal. Parzen window is a nonparametric estimation technique used in PNN to design class-dependent pdfs for each category on the basis of Bayes' theorem (Parzen 1962). Parzen window and Bayes' theorem have been implemented in a wide field of engineering applications, and they are featured in a number of statistical textbooks (Parzen 1962).

If $\boldsymbol{xj}$ is the *j*th pattern in K_1 category, then the Parzen estimate will be:

$$F_1(x) = \frac{1}{(2\pi)^{m/2}\sigma^m n}\sum_{j=1}^{n} exp\left[-\frac{(x-x_j)^T x-x_j}{2\sigma^2}\right]. \quad (7)$$

Here, *n* is the number of training patterns, *m* is the number of input space dimension, pattern number as *j*, and σ is the "smoothing parameter." Smoothing parameter σ can be determined experimentally. However, the choice of σ is not sensitive to its value variation (Specht 1990).

Figure 5. *Around here*

4.3. Model execution

The PNN architecture consists of four layers to implement the Bayesian network, as presented in Figure 5. The structure of PNN consists of four layers, namely, input, a pattern, a summation, and an output layer. A simple PNN is made of two categories, three independent variables, and five training cases (Meisel 1972). The first input layer primarily portrays *m* input variables$(x_1, x_2, \ldots, x_m)$. The input neurons simply spread all the variables of *x* to the neurons of the next layer known as the pattern layer. The fully connected pattern layer to the input layer allows one neuron for each pattern during the training purposes. In this layer, the neurons' weight values are set equal to the divergent training patterns. A dot product was performed by *j* as the neuron of pattern layer on the input pattern vector ***x***, where the weight vector is ***wj***, which can be presented as ***Zj*** = ***xwj***. A nonlinear function performance *exp* $\left[(Z_j - 1)/\sigma^2\right]$ is then conducted before outputting the summation neuron. Here, the value of ***x*** and ***wj*** are normalized; therefore, performing dot product is equivalent to this operation:

$$exp\left[-\frac{(w_j-x)^T w_j-x}{2\sigma^2}\right]. \qquad (8)$$

This is because,

$$exp\left[-\frac{(x-w_j)^T x-w_j}{2\sigma^2}\right]. \qquad (9)$$

Then, it can be rewritten as:

$$exp\left[-\frac{2x^T w_j-x^T x-w_j^T w_j}{2\sigma^2}\right]. \qquad (10)$$

Hence, nonlinear operation $exp\left[(Z_j - 1)/\sigma^2\right]$ is in the similar form as per the exponent function in Eq. (10). The exponential term in Eq. (10) can be computed for neurons in the pattern layer.

Each category has one summation-layer neuron. The neurons of the summation layer execute the exponential term in Eq. (10). The weights are fixed to the summation layer; therefore, the summation layer can easily add on the outputs that originated from the pattern layer. The outputs generated from the pattern layer come to the summation layer, which then can be classified by looking at the categories based on the selected training pattern. Binary output values can be resulted by the PNN model in the output-layer neurons. This model indicates a best classification option for each pattern in the data.

This regards to generate the best smoothing parameter for a set of vectors $\boldsymbol{x}$ through the training of the PNN as σ, which makes the best use of the classification accuracy of an independent set of test vectors. The PNN model in this study was implemented to train and test the network reliability to classify the occurrence or non-occurrence of earthquake vulnerability accurately. This study treats the earthquake vulnerability problem as a classification problem whereby two categories of K_1 or K_2 need to be defined by a multivariate vector pattern $x = (x_1, x_2, \dots, x_m)$. Here, the components of vector $\boldsymbol{x}$ denote major thematic layers as factors to estimate vulnerability. Consequently, category K_1shows a case where vulnerability occurred and K_2 as a case of non-vulnerable locations. The training and testing set were considered that could predict the two categories and validate the performance of PNN. Figure 4 presents the overall flow chart of the study.

ROC curve

The receiver operating characteristic curve (ROC) is a graphical representation of the model performance, which has been plotted for binary classification. The false positive rate is shown in the x-axis, whereas the y-axis denotes the true positive rate.

$$True\ Positive\ Rate\ = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \qquad (11)$$

$$False\ Positive\ Rate\ = \frac{FalsePositives}{(False\ Positives + True\ Negatives)} \qquad (12)\ \ (12)$$

5. Results

A map of earthquake vulnerability was derived using several data of exposure and vulnerability factors based on AHP approach (Figure 6a). The consistency ratio achieved by using the AHP approach is 0.08, where 136 comparisons were performed. During the AHP priority scoring of factors, the principal eigenvalue of 19.06 was originated, whereas the eigenvector solution is seven iterations. However, the delta value achieved in this study is 1.0E-8 by using AHP approach. The CR displayed that the criteria scoring was assessed accurately. Several major factors including population density, peak ground acceleration, land use density and lithology with amplification factors ranked 1 to 4 with their approximate weights of 21.9%, 16.0%, 12.2% and 11.3%, respectively (Table 3). Other criteria were ranked medium to low. We evaluated 17 major factors for the purpose of vulnerability estimation, thus leading to an acceptable CR. Many criteria were considered as input thematic layers to assess the earthquake vulnerability of land use/cover and population density/km^2 of Odisha (Figure 2). At the end of the AHP analysis, a vulnerability map was developed and classified into five classes by using the natural break classification technique (Jena *et al.* 2020) (Figure 6b). The generated map denotes that 60.1% of the total area has very-high to moderate vulnerability, whereas 39.9% of the state has low to very-low areas vulnerability.

Figure 6. *Around here*

Very-high and high vulnerable zones based on AHP are covered by approximately 20.79% (32,287 km^2) and 19.99% (31,030 km^2) of the state, respectively. However, 23.79% (36,930 km^2), 14.72% (22,850 km^2), and 20.69% (32,130 km^2) are considered moderate, very-low, and low vulnerable areas, respectively, as shown in the Figure 6b. This map was taken as a target for the PNN prediction.

A prediction of vulnerable locations was organized by using the PNN model that predicts vulnerable areas (1) and non-vulnerable areas (0). This model predicted 494 data points successfully out of 534 events due to illogical values (negative or overestimated values) acquired from some pixels in the obtained layers of factors. In total, 11 positive cases and 29 negative cases were missed during the PNN prediction. The PNN model predicted a total area of 48,900 km^2 as the vulnerable location in Odisha with an accuracy of 92.5%. According to the PNN classification result, 24.26% (37,665 km^2), 15.26% (23,696 km^2), 20.58% (31,950 km^2), 22.52% (34,967 km^2) and 17.36% (26,949 km^2) are considered very-high, high, moderate, low, and very-low vulnerable locations. Training (70%) and testing (30%) were performed for 534 points, out of which 270 were vulnerable and 264 were non-vulnerable locations. The PNN model achieved 95.9% sensitivity and 89% specificity. The fitted ROC area (0.98) and empiric ROC area (0.96) were achieved in the PNN prediction (Table 4). Figure 7 shows the predicted vulnerability map. ROC was plotted to show the accuracy (Figure 8). All unpredicted vulnerable and non-vulnerable points displayed no discernible pattern.

Table 4. *Around here*

Earthquake vulnerability is very-high in the eastern coastal parts, northwestern parts, and central locations of Mahanadi graben, as presented in Figure 7. Moreover, the several moderate magnitude earthquakes of 5.3 Mw have occurred in the northwestern part of Odisha. The earthquakes are most probably due to the active zone of NOBF fault. Most sections of the very-high vulnerable areas are covered in districts centered within the Mahanadi graben, which experienced high ground shaking. According to previously published articles, NOBF has the capacity to strike large events that makes the location more vulnerable. NOBF is associated with high vulnerable areas in Southern and Northwestern Odisha. Some parts in central and northern Odisha were characterized by medium vulnerability, whereas the western part and some scattered areas in central Odisha were characterized by low vulnerability. Several districts have very-high (0.85–1) to high (0.65–0.85) vulnerability. These districts are mostly located in Western and coastal Odisha, including Sundargarh, Jharsuguda, Sambalpur, Bargarh, Subarnapur, Balangir, Nuapada, Kalahandi, Nabarangpur, Cuttack, Kendrapada, Ganjam, Jagatsinghpur, Khordha and Puri. Many other districts fall under the moderate to very-low categories. Furthermore, the map shows that approximately 61,361 km^2 of Odisha falls in the very high-to-high category (Table 5).

Table 5. *Around here*

Figure 7. *Around here*.

Figure 8. *Around here*

6. Discussion

The study examines the implementation of PNN and MCDM for vulnerability estimation on a regional scale. In this study, natural break was implemented to derive the scale of vulnerability, which is important to properly translate the significance of vulnerability (Jena *et al.* 2020). The

AHP approach and PNN models were used as assessment techniques, which produced an acceptable vulnerability result. The FPF and TPF values were achieved with a CI of 95% (Table 6).

Table 6. *Around here.*

The NOBF trends east-west with a 250 km of strike length, whereas a 2–5 km of width range can be found. The NOBF is irregular and characterized by inter-linkage of rocks that make Northern Odisha non-uniform with complex geo-structures. Hahn *et al.* (2009) stated that the evaluation of vulnerability index could boost communities' engagement in vulnerable locations. Brooks (2003) described that community labelling is not suitable because vulnerability varies naturally with location and communities. The current study applied MCDM and PNN models, and the performance of the approach produced a good quality map that represents earthquake vulnerability in five classes. According to the outcome of this research, the state government should make the plan by considering key techniques throughout the period of disasters to minimize losses.

Major locations near and inside the Mahanadi River Valley are close to earthquake sources and fall under poorly consolidated sediment deposits. High to severe impact could be experienced in several districts such as Nayagarh, Khordha, Puri, Jagatsingpur, Kendrapada, Cuttack, Bhadrakh, Dhenkanal, Anugul, Sundargarh, Jharsuguda and Sambalpur because of both inland and offshore seismicity. The authors assume that a few locations are characterized by old buildings and constructed by using traditional methods, whereas some modern constructions that do not meet standards make buildings vulnerable to earthquakes (Figure 1c). This vulnerability assessment is necessary as the state was hit by many moderate magnitude events in the last decade.

The importance of major factors and data limitations could help achieve the developed vulnerability map that has an important role in future risk mapping. The context of demographic analysis is vital in pre- and post-earthquake studies (Jena *et al.* 2020a). Therefore, social and structural characteristics are directly interlinked with damage, death, and relief facilities. Nonetheless, only a few works have been performed on the earthquake hazard assessment in Odisha. This study is a preliminary research for vulnerability assessment in Odisha. However, geotechnical and social attributes such as lithology with amplification factor, PGA variation and population density have more influence on the vulnerability assessment throughout a period. In Odisha, strong ground motion is particularly controlled by geotechnical specifications, which is the complex combination of frequency, duration, magnitude, distance from hypocenter, lithology, slope, distance from fault, and curvature. Thus, assessment of PGA is vital in infrastructure development, and it could minimize the vulnerability of damages (Panahi *et al.* 2014). If the foundation of structures fall over unstable steep slope, this condition could cause earthquakes, landslides, and liquefaction in loose lithotypes (Sarvar *et al.* 2011). Fan et al., (2019) conducted research on earthquake induced landslides that modify the landscapes. Their study suggest pathways towards an integrated research on the seismology with secondary effects on the Earth's surface. They have demonstrated the necessity for the joint consideration of earthquake-induced landslides into the co-seismic hazard and risk assessment. Karpouza et al., (2021) presented a study regarding an approach that is useful for the simultaneous hazard zonation mapping based on the earthquake-induced secondary effects. Their methodology applied an initial separate modeling process for the hazard estimation due to seismically induced soil liquefaction and landslides. Then, a subsequent stacking of the results into a single hazard map was conducted using an integrated assessment technique for exposed areas to earthquake-induced and seismic shaking phenomena. The detail integrated analysis could help in improving the earthquake vulnerability assessment.

A disabled male is less vulnerable than a disabled female, because the principal vulnerability lies in the weaknesses of people concentrating on their capabilities. Therefore, this assumption or ignorance could affect the results of vulnerability seriously (Jena *et al.* 2020b). Figure 7 presents the predicted vulnerable locations in the study area. Nevertheless, the analysis indicates that vulnerability increases with the increase in land use. In Figure 7, the predicted vulnerability shows that the model of PNN has a high capacity to predict locations precisely. As of now, very few casualties experienced due to earthquakes in Odisha still more fatalities and injuries could be experienced in future if the magnitude of more than Mw 5.5 experienced in the districts falling under Mahanadi graben (Jena *et al.* 2020d). Therefore, the principal center of attention must be on high to very-high vulnerable zones that could lead to high fatalities in coming future. The intensity is high with more poor building structure and in a greater number, which are located in the central and coastal parts of Odisha specifically in Cuttack, Khordha and Jagatsinghpur districts. Furthermore, the central region, coastal and north-western parts are highly vulnerable and have the capacity to mitigate and recover. This study was performed at a regional scale, but microzonation is necessary for each property. To the end, understanding the situations of earthquake vulnerabilities would help in mitigating future disasters. Vulnerability is complex to assess; therefore, a detailed indicator including building characteristics, geological factors, education level, and disability associated with persons are required. The proposed approach is useful for decision makers during the future risk assessment and has good variances in mapping the earthquake vulnerability. Table 7 presents the prediction values of 0 and 1.

Table 7. *Around here.*

7. Conclusions

We developed a PNN model for vulnerability prediction by using the MCDM results and ultimately produced an earthquake vulnerability map. This is a new approach to predict vulnerability as there is no earthquake vulnerability study have been conducted in Odisha. The conclusions that can be drawn from this research could be helpful for local residents and disaster management agencies. First, by using the AHP approach, vulnerability assessment was conducted using several input factors that include land use and population density. According to the AHP assessment in Odisha, 19.99% of the area fall under high, where 20.79% of the area comes under very-high vulnerability. Based on the PNN outcome, 15.26% and 24.26% of the area fall under high and very-high vulnerability category, respectively. Moreover, moderate vulnerable locations cover approximately 20.58% of area. Old buildings and poor ground conditions are seen along the northwest, central, and eastern coastal regions of the state. The EVA map illustrates earthquake vulnerability that could impact high to very-high for the districts such as Ganjam, Nayagarh, Khordha, Puri, Jagatsingpur, Kendrapada, Cuttack, Bhadrakh, Baleswar, Dhenkanal, Anugul, Sundargarh, Jharsuguda and Sambalpur. The EVA map validation was conducted successfully and PNN was implemented to predict the vulnerable locations keeping the AHP based map as the target. The study is limited to pre-earthquake vulnerability assessment. The criteria, which have not been considered in the current research, include soil liquefaction, building categories and seismic resonance. These aforementioned data were not included due to lack of data.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflict of Interest

The authors declare no conflict of interest.

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