Flood Resilience Quantification for Housing Infrastructure Using Analytic Hierarchy Process

Mrinal Kanti Sen, Subhrajit Dutta, and Golam Kabir

Abstract Natural hazards are severely damaging infrastructure systems, so it is essential to make the existing infrastructure more resilient to increase the considered infrastructure resisting ability. Resilience is the enduring capacity of an infrastructure system against natural disasters and quickly recover after the disaster. As the impact of any hazard cannot be stopped or reduced, and resilience depends on several parameters, it is essential to study the sensitivity of the resilience parameters. Additionally, a robust framework should be developed with the concept of resilience to enhance the resisting ability. The basic need of living is the housing infrastructure, so a practical resilience-based framework for housing infrastructure must be developed. In this work, a framework for quantification of resilience against flood hazard is developed by using a multi-criteria decision method (MCDM) tool, such as the analytic hierarchy process (AHP). Initially, several resilience parameters are considered based on literature and experts' knowledge. Then, a field survey is performed for the collection of required data. After getting the data needed, a flood resilience model is developed. Lastly, using AHP, the importance of each resilience parameter is identified, and also, the resilience is evaluated for all the surveyed places. The sensitivity of each parameter will help the decision-makers to focus on the most critical parameter/s to make the considered infrastructure more resilient for future hazards. Additionally, the evaluated resilience values will help the stakeholders by providing the surveyed places' real scenario against flood hazard.

Keywords Flood · Resilience quantification · Analytic hierarchy process · Housing infrastructure

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1 Introduction

The occurrence of hazards always interrupted the capability of any society or any infrastructure of a community, which also affects the functionality. Disasters types have been inspected, and it was discovered that natural, human-made, and a blend of both debacles spread a wide range of shocking occasions. Our discussion in the current context will be limited to flood only. The management of disaster is generally discussed after its occurrence, but practically, the preparation of disaster management should be effectively planned for future hazards. The concept of resilience has been applied in a broad scope of systems, including building, urban structure, financial matters, business, socio-biological, network, and psychological planning and preparation for future hazards [1–5]. Resilience is characterized as the capacity of a system to withstand peril and jump back to its ideal execution level after the event of any danger [6]. Infrastructure systems are broadly recognized as a lifesaver in the network and play a crucial job in continuing financial flourishing and urban versatility and manageability. For a practical, all-around sustainable development, the growing need of the hour is to invest importance in considering infrastructure resilience in the real-life community. However, little priority has been given to it in the past few decades since the inception of the concept of resilience. However, as of late, there is expanding acknowledgment that this individual-focused way to deal with resilience is full of limitations because it needs affectability to be social and the physical setting. Another assemblage of work is endeavoring to extend the emphasis on resilience as a trait of the individual to strength as a network and social process. This new spotlight on "community resilience" looks at how individuals conquer pressure, injury, and other life challenges by drawing from the cultural and social systems and rehearses that comprise networks.

Bruneau et al. [4] developed a framework to quantitatively resilience and enhance the seismic resilience of a community's infrastructure. Sen and Dutta [1] developed an integrated global information system (GIS) and the Bayesian belief network (BBN) framework and model for quantifying the resilience of roadway infrastructure. Further, the proposed framework is modified by performing interdependency among housing and roadway infrastructure using BBN [2]. Nan and Sansavini [7] developed a quantitative method for assessing the resilience of interdependent infrastructures. Sen et al. [3] studied the resilience of housing infrastructure in Barak Valley, Northeastern India. In that study, previous disaster data are collected by performing a field survey, and the resilience is quantified by using a variable elimination algorithm. The drawback of that study is that the weightage of parameters is not considered. Resilience depends on various parameters, so it is essential to study the importance of each resilience parameter.

Several multi-criteria decision-making (MCDM) tools are available for evaluating the importance, like analytic hierarchy process (AHP) [8], fault tree analysis (FTA) [9], and structural equation model (SEM) [10]. FTA cannot identify critical node/s of a network as the analysis is done without considering the nonlinear relationship among parameters. A considerable amount of questionnaires are needed for SEM to identify sensitive parameter/s of a network. Therefore, AHP can reduce the above-mentioned difficulty. This tool is generally considered a structured technique and used to organize or analyze mathematics-based complex decisions. This tool is developed in 1990 by Thomas Saaty [11]. Forman and Gass [12] discussed the structuring complexity, measurement on a ratio scale, and the principles of AHP tools. Kabir and Hasin [13] used an analytical hierarchal process (AHP) tool for finding the importance of power substation parameters. Saaty [14] discussed the applications and steps used in the AHP tool. Ho and Ma [15] discussed various literatures of AHP and compared all the published papers between 1997 and 2016. In this study, the AHP tool is used to evaluate the importance of resilience parameters, and a framework is developed for quantifying the resilience of housing infrastructure. The developed framework is implemented in a real community. Based on the above discussion, the objectives of the work are as follows;

1. To develop a framework for quantifying the housing infrastructure resilience against flood hazard.
2. To find out the importance of all resilience parameters by using AHP.
3. To find out the housing infrastructure resilience of a real community.

The paper is arranged as follows, in Sect. 2, the developed framework and the implementation of the developed framework in a real community are discussed, and finally, the results and conclusion section is discussed.

2 Implementation of the Developed Framework

2.1 The Resilience Quantification Framework

The developed framework for resilience quantification is shown in Fig. 1. In the framework, initially, all the resilience-dependent parameters are selected based on literature and experts' knowledge. A resilience model is then developed, and the

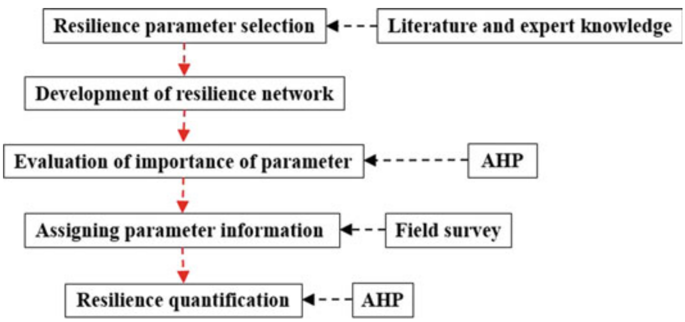

Fig. 1 Resilience quantification framework

importance of each resilience parameter is evaluated by using the AHP tool. The post-disaster information for each parameter is collected by performing a field survey. Then, the prior of each parent node is assigned based on collected data, and lastly, the housing infrastructure resilience is evaluated by using the AHP tool.

Analytic Hierarchy Process (AHP)

AHP is used to evaluate the importance of parameters or factors. It is an MCDM tool. The steps followed to study the significance of parameters in the AHP tool are as follows [16],

Step 1: Initially, a hierarchical network of an objective is developed with different levels (from top level to bottom level), where the objective is in top level, criteria are in intermediate levels, and alternatives are in the bottom level.

Step 2: Next, experts are asked to provide the score for relative importance between one parameter over another parameter to construct the initial pair-wise comparison matrix $A_{m\times n}$ of size $m \times n$ (shown in Eq. 1).

$$A_{m\times n} = \begin{pmatrix} a_{11} & \ldots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{1}$$

where $a_{11},\ldots a_{1n},\ldots,a_{m1},\ldots a_{nm}$ are the elements of $A_{m\times n}$ matrix. The diagonal of this matrix is always one, which means that the importance of an element over the same element is one. The ranges for the score are given in Table 1.

Step 3: Next, the initial pair-wise matrix is normalized by dividing a normalized factor (N.F.), where N.F. is the summation of each element of a column. The normalized column is shown in Eq. 2.

$$\begin{pmatrix} \frac{a_{11}}{\sum_{n=1}^{m} a_{n1}} & \cdots & \frac{a_{1n}}{\sum_{m=1}^{m} a_{mn}} \\ & \ddots & \\ \frac{a_{m1}}{\sum_{n=1}^{m} a_{n1}} & \cdots & \frac{a_{nm}}{\sum_{m=1}^{m} a_{mn}} \end{pmatrix} \tag{2}$$

Table 1 Scores for pair-wise matrix

Scale	Importance
1	Equal
3	Moderate
5	Strong
7	Very strong
9	Extreme
2, 4, 6, 8	Intermediate
1/3, 1/5, 1/7, 1/9	For inverse

where $\sum_{n=1}^{m} a_{n1}$ and $\sum_{m=1}^{m} a_{nm}$ is the summation of each element for the first and nth column.

Step 4: Then, the importance of each parameter is calculated by averaging all the elements in the row of A_N matrix (shown in Eq. 3).

$$\begin{pmatrix} \frac{a_{11}}{\sum_{n=1}^{m} a_{n1}} & \cdots & \frac{a_{1n}}{\sum_{m=1}^{m} a_{mn}} \\ & \ddots & \\ \frac{a_{m1}}{\sum_{n=1}^{m} a_{n1}} & \cdots & \frac{a_{nm}}{\sum_{m=1}^{m} a_{mn}} \end{pmatrix} = \begin{pmatrix} \text{Average of all the element of row} = W_1 \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \text{Average of all the element of row} = W_n \end{pmatrix} \tag{3}$$

Step 5: The consistency ratio is evaluated to check that the estimated importance is correct or not. Initially, each element in the column of $A_{m\times n}$ matrix is multiplied with its importance as shown in Eq. 4.

$$\begin{pmatrix} W_1 \times a_{11} & \cdots & W_n \times a_{1n} \\ \vdots & \ddots & \vdots \\ W_1 \times a_{m1} & \cdots & W_n \times a_{nm} \end{pmatrix} \tag{4}$$

Next, the weighted sum value for each row is calculated by adding each element in the row (shown in Eq. 5). Then, the ratio of weighted sum value with the importance of parameter (w_n/W_n, $n = 1, \ldots, n$) for each row is calculated, and $\lambda_{\max}$ is evaluated (shown in Eq. 6).

$$\begin{aligned} w_1 &= \sum_{n=1}^{n} W_n \times a_{1n} \\ &\vdots \\ w_m &= \sum_{n=1}^{n} W_n \times a_{mn} \end{aligned} \tag{5}$$

$$\lambda_{\max} = \frac{\sum_{n=1}^{n} \frac{w_n}{W_n}}{n} \tag{6}$$

The consistency index (C.I.) is evaluated using Eq. 7, and the consistency ratio (C.R.) is assessed using Eq. 8.

Table 2 Random index

# of parameter	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

$$\text{C.I.} = \frac{\lambda_{\max} - n}{n - 1} \tag{7}$$

$$\text{C.R.} = (\text{C.I.})/\text{Random Index}$$

where n is the number of parameters and random index (R.I.) is taken from Table 2. If the C.R. < 0.1, it means that the evaluated importance of the parameter is correct.

Step 6: The maximum probability value of a parameter is multiplied by the importance of that parameter to determine the weighted probability of that parameter. For example, parameter 1 having two states like "*yes*" or "*no,*" and probability of "*yes*" is 45% and "*no*" is 55%. Then, the weighted probability will be (shown in Eq. 8).

$$P_W(1) = W_1 \times P(\text{no}) \tag{8}$$

Finally, the probability of the objective is calculated by multiplying the importance of the parameters of the intermediate layer with the summation of the weighted probability of bottom layer parameters.

2.2 Implementation of the Framework

The developed framework is implemented in Barak Valley, Northeastern India. This region is selected because more than 30,000 houses get affected from 2015 to 2020 due to floods [17]. Initially, experts from the research-related domains are chosen. Here, a total of five experts is selected for construction of pair-wise matrix and selection of resilience parameter. Out of five experts, two are field officers in District Disaster Management Authority (DDMA), two are Assistant Professors from different institutions, and one is District Project Officer (DPO) of DDMA. Based on their knowledge and literature, a total of 12 resilience parameters is selected. The selected parameters are mainly based on two parameters: reliability and recoverability of housing infrastructure [1–3]. The selected resilience parameter for housing infrastructure for this work is as follows [3, 18], based on reliability, (R1) type of house, (R2) wall thickness, (R3) plinth level, (R4) flood depth, (R5) drainage, (R6) age of the building, and based on recoverability, (R7) income, (R8) insurance, (R9) resource availability, (R10) relief received, (R11) approachability, and (R12) education. Then, a resilience network model is developed based on selected parameters, as shown in Fig. 2.

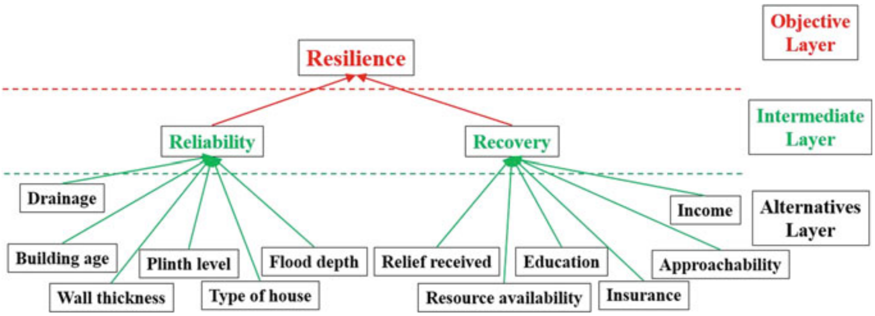

Fig. 2 Resilience network model

Experts are then asked to provide the scores for relative importance among parameters based on Table 1, and accordingly, an initial pair-wise comparison matrix $A_{m \times n}$ is developed using Eq. 1 (shown in Table 3).

After developing the matrix, using Eqs. 2 and 3, the importance of each parameter is evaluated, as shown in Fig. 3. It can be seen that R1 and R3 are the most sensitive against reliability, and R7 and R8 are the most sensitive against recovery of housing infrastructure.

After getting the weightage of all resilience parameters, a field survey is performed in the selected case study area. Total ten places are visited (all places are subdivided into various circle areas), in which a total of 212 houses are visited, and it took

Table 3 Initial pair-wise matrix for resilience parameters

Reliability parameters						
	R1	R2	R3	R4	R5	R6
R1	1	4	5	6	5	8
R2	1/4	1	3	2	3	5
R3	1/5	1/3	1	3	2	5
R4	1/6	1/2	1/3	1	2	4
R5	1/5	1/3	1/2	1/2	1	2
R6	1/8	1/5	1/5	1/4	1/2	1
Recovery parameters						
	R7	R8	R9	R10	R11	R12
R7	1	3	4	5	7	9
R8	1/3	1	2	3	5	7
R9	1/4	1/2	1	1	3	5
R10	1/5	1/3	1	1	2	4
R11	1/7	1/5	1/3	1/2	1	3
R12	1/9	1/7	1/5	1/4	1/3	1

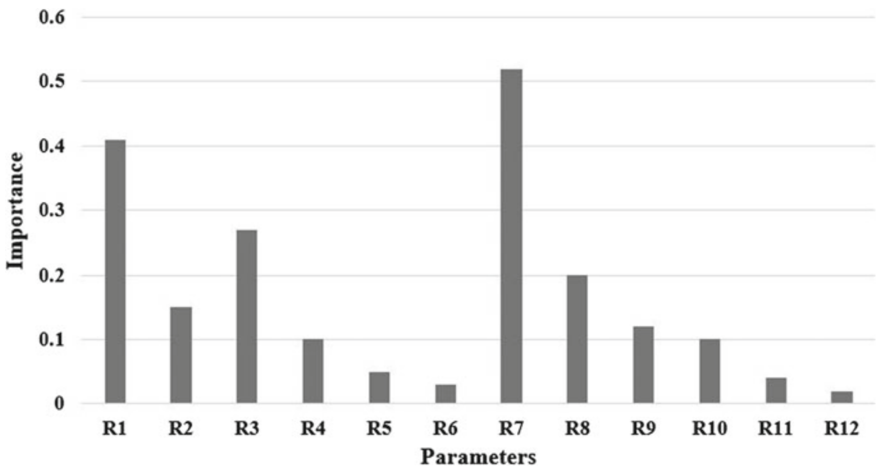

Fig. 3 Importance of resilience parameters

near about 25 min for each interview. Figure 4 shows the various surveyed places in Barak Valley, Northeastern India. All the required post-disaster data for resilience parameters are collected during the field survey, and the prior probability of all parent parameters is assigned accordingly. Using Eqs. 4–8 (Steps 5 to 6), resilience values for all surveyed places are quantified.

3 Results

In this study, all the parameters are assigned with two different probability states, such as resilient and non-resilient, based on experts' knowledge and field survey information. The quantified resilience values for all visited places are shown in Table 4. From the evaluated values, it can be observed that the housing infrastructure of areas like Dwabond, Algapur, Amjurghat, and Borbond of that valley is the most non-resilient, as 71.9, 68, 67.2, and 67% of housing infrastructure of those areas are non-resilient. It means that the stakeholders or decision-makers should give immediate attention to those places for strengthening the infrastructure to enhance the resilience against future hazards. All the surveyed areas are non-resilient, but Dullacherra is the least non-resilient compared to all other areas, as 60.3% of housing infrastructure are non-resilient. Non-resilient infrastructures surround the housing typology of this valley. Maximum of the houses of this valley are constructed with bamboo or wood with non-engineered construction. As the economic condition of maximum householders is weak, so they cannot build RCC houses or engineered houses. Every year, several homes get damaged, and due to which the government is paying a considerable amount for restoration. Nowadays, householders prefer RCC or Assam-type houses in rural areas by taking loans or help from various agenesis. Assam-type house is

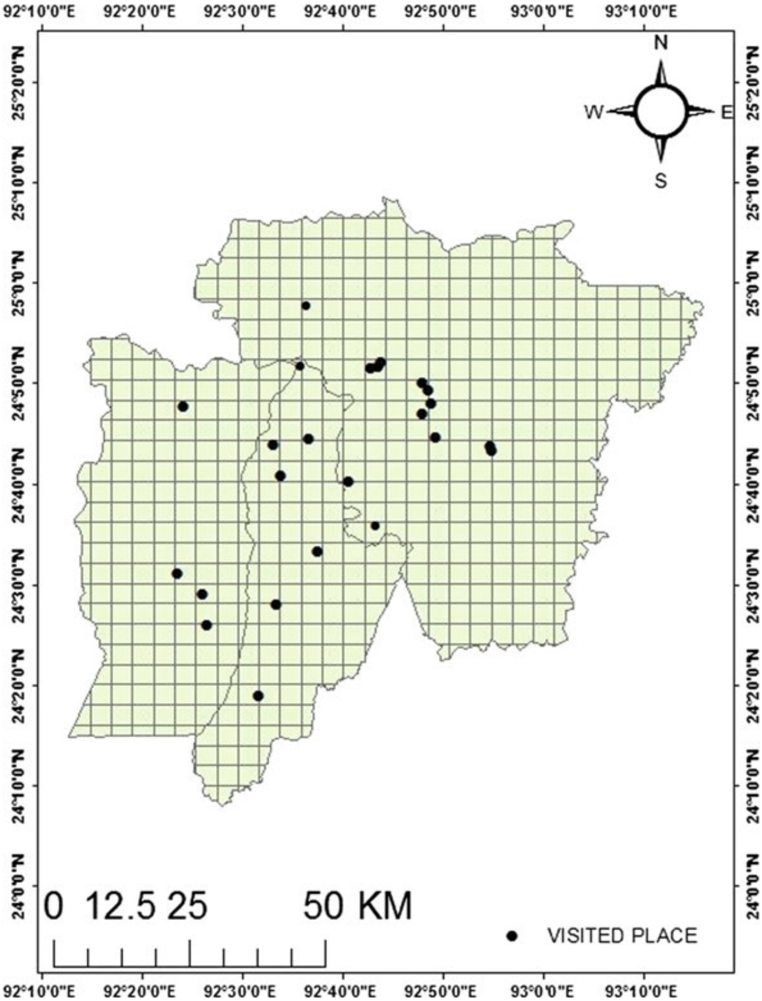

Fig. 4 Various surveyed areas in Barak Valley

also known as masonry house, which is more robust than bamboo or wooden house. There are two types of Assam-type house such as the half-wall house and full-wall house, where half-wall means the lower half is made up of the brickwork, and the upper half is made up of a mixture of bamboo-cement motor or bamboo-mud, and the full-wall means the whole wall is made up of brickwork.

Table 4 Visited places resilience values

Place name	Resilient	Non-resilient
Algapur	0.320	0.680
Amjurghat	0.328	0.672
Baleshwar	0.344	0.656
Bhatikupa	0.362	0.638
Borbond	0.330	0.670
Burunga	0.384	0.616
Dullacherra	0.397	0.603
Dwabond	0.281	0.719
Fanai cherra grant	0.392	0.608
Hailakandi town	0.374	0.626

4 Conclusion

In this work, a resilience quantification framework is developed, where various resilience parameters are selected. The importance of each parameter is evaluated. An extensive field survey is performed for the collection of information against each parameter. Then, the developed framework is implemented in a real case study area where a field survey is conducted. Using the AHP tool, the resilience of each surveyed area is evaluated. This framework can be applied to other critical infrastructure systems to assess that infrastructure's resiliency. The evaluated resilience values of Barak Valley will help the stakeholders to strengthen the housing infrastructure against a future hazard. The evaluated importance of each parameter will help the decision-makers to decide on giving attention to the sensitive parameters to make the considered infrastructure more resilient against a future hazard. In the future, more probability states will be considered for quantification of resilience value to get a more precise scenario. The developed framework can be updated by adding more information.

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