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An efficient approach for source-terminal reliability analysis of roadways network infrastructure system against flood hazard

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Abstract
Infrastructure damage from flooding can have detrimental social, environmental, and economic repercussions. Flood risks can have an impact on road networks, which are made up of interconnected linkages designed to meet public transportation needs. Flood-related damage to the road surface can raise questions about the dependability and connection of the road network. In this study, flood simulation was performed, and the information gathered was then analysed to determine the flood depth, followed by Monte Carlo simulation to determine the Source-Terminal (S-T) reliability. This research creates a novel method written in a comprehensive programming language, allowing decision-makers to be aware of the S-T reliability of road networks. When planning, this developed approach helps decision-makers make informed choices that will improve the reliability of road networks.

Keywords: Source-terminal reliability, road network, network reliability, Monte Carlo simulations, flood fragility

INTRODUCTION
Floods are amongst the most devastating natural hazards causing significant loss to infrastructure systems, such as road networks. According to the consequences of their disruption, road networks are regarded as vital infrastructure systems for socio-economic activities in a community. Flooding is a serious risk to roads since it can cause significant traffic congestion, damage/disruption to the road network, and often have

long-term adverse impacts. Flooding results in high repair expenses for road control authorities, access issues for emergency services, and inconvenience for both the community and road users. The effects on enterprises and the economy as a whole may be profound. Planning for long-term preventive measures against disaster and sustainability is essential due to the time and money needed for recovery. As a result, flood-induced reliability may be considered as a crucial factor in the decision-making process when designing these systems. The ability to withstand stressors due to natural disasters increases as the reliability of the road network rises.

Problem statement and motivation

Transport infrastructure has substantial social benefits and a considerable impact on economic growth and development. They are crucial to the expansion and development of a region or city. Flood risks can have an impact on road transport networks, which are made up of interconnected links designed to satisfy public transit needs[1,2]. Road pavement damage caused by flood events can lead to disruption in the connectivity of road networks[3]. Probabilistic pavement flooding damage analysis is illustrated by fragility models[1], which provide an estimation of the conditional probability of exceeding the specific pavement damage state (DS), given a flood event using developed fragility curves. To correlate the system fragility corresponding to average/maximum flood depth values, the probability of failure at every node/link in a road network is obtained. For every link in a road network, there will be two connected nodes[4]. Thus, applying probabilistic concepts, we get the fragility of every link in a road network and, consequently, Source-Terminal (S-T) node reliability. In evaluating the capacity of transportation networks, to maintain their operational continuity, the evaluation of network reliability is crucial[4]. Recent natural disasters (earthquakes, floods, and fires), hostility (terrorist attacks, sabotage, and wars), the expansion of the human habitat, and primarily the expansion of urban areas and traffic congestion on road networks have all generated interest in studies on the reliability of transportation networks[5]. The impact of nodes or link disruption has significant adverse effects on functionality. The evaluation of risks to the infrastructure of the transportation network and the assessment of the effects of a disruption in the functionality of the network and the failure of its components demands robust and resilient designs with informed decision support tools for enhanced serviceability.

Current practice and challenges

In response to growing demands for better and more dependable services, many critical infrastructure systems, such as transport, transmission lines, water supply, telecommunication, *etc*., now incorporate reliability analysis as an integral part of their planning, design, and operation[6]. For example, concerned with the likelihood that the network nodes stay connected, Iida and Wakabayashi (1989) performed a reliability study, which examined the presence of a path between a particular origin-destination (OD) pair as a special case of connectivity reliability[7]. The network operationality was checked on the basis of the binary state approach. Their methodology, however, precludes the application to real-world scenarios where arcs are operating between these two extremes. As a result, the outcome of this approach to assessing road network risk and reliability may be less accurate. Further, Javanbarg *et al*. (2010) performed a terminal-pair reliability analysis of infrastructure and lifeline networks using Binary Decision Diagrams (BDD)[8]. They used a DNA software tool developed by Xing (2007) to perform the analysis[9]. Networks were modeled as undirected graphs in every case study they undertook. Nodes were considered to be reliable, while the failures of links were presumed to be statistically correlated. The OD connectivity reliability was found, followed by the Monte Carlo simulation. However, to be able to cope with large-scale networks, a more efficient algorithm, as presented in this paper, may be helpful. Thorsten Neumann and Michael Behrisch (2018) applied the well-known idea of terminal reliability, given the situation with several potential destinations[10]. They applied an algorithm based on Boolean algebra. The entire idea was illustrated using an example that took several levels of network node risk and discussed the importance of each network link in terms of preserving connectivity between supply nodes and other nodes. Consequently, by detecting crucial connections and calculating the overall node isolation risk of the network, reliability was estimated. However, the problem of scalability remained as computation expenses ought to arise for large-scale applications.

Novelty and advantages of the proposed approach

The few reliability metrics currently in use are discussed above, which are helpful for evaluating many aspects of the functioning of transportation networks. But, few of them accurately measure the problem of S-T reliability considering real case studies, simulation, and algorithm development in an integrated and comprehensive manner. Therefore, the current study aims to address these research bottlenecks and finds their significance. Moreover, this study also focuses on investigating the reliability between any two nodes of a given network in the event of stochastic link failures.

Natural disasters, such as floods, create disruption in the functionality of roadway infrastructure systems. During disasters, it is crucial for communities to have access to essential services and commodities. Communities rely on (potentially damaged) road infrastructure, which may be represented as a graphical network model. All nodes in the network must provide connections to at least one critical node of each kind, even if some network links are temporarily unavailable. The current contribution analyses the probability of failure of a specific road network node based on the topological structure of the network, assuming that there are many nodes of each type throughout the network. For this reason, the scenario is adjusted to fit the concept of S-T reliability. In many applications using a real road network, selecting an appropriate method as well as algorithm from the multiple analytic approaches documented in the literature is a crucial step. This work considers a blend of physical, computational, and statistical simulation to be able to achieve a wider picture and reliable results of the defined problem statement that evaluates the S-T reliability of road networks against floods. The study area chosen for this research was the Barak River at Sadarghat bridge location in Silchar city of North-East India, and this study considers urban flooding.

Objectives

In this work, a road network was considered, and a flood simulation was done to find out the flood depths. To statistically correlate flood depths with fragility based on the DS and, consequently, find the S-T reliability, the betweenness centrality is a good measure. In graph theory, basically, betweenness centrality is a way of detecting the amount of influence a node has over the flow of information in a graph. It is often used to find nodes that serve as a bridge from one part of a graph to another. The algorithm calculates the shortest paths between all pairs of nodes in a graph. The same concept is applied to our work.

The objectives of this work may be broadly categorised as follows: (1) To develop a flood simulation model for determining the flood depth at the critical location of the considered road network, (2) To quantify the fragilities of components of the road network, and (3) To develop an algorithm to compute the S-T reliability of the road network based on Monte Carlo simulations.

The rest of the paper is organised as follows: literature review, methodology, results obtained, and, lastly, some conclusions and limitations of the study are discussed with possible future scopes. The research flow or summary is shown in Figure 1.

Literature review

Various research papers have studied and applied those strategies sequentially to find the reliability of road networks against floods. Karduni *et al.* (2016) discovered a tool to convert spatial polyline [Figure 2] data to a network [Figure 3] format[11]. Open Street Maps (OSM) has created geographic information, including on-road networks. With the help of Geographic Information Systems (GIS), this tool converts polyline data

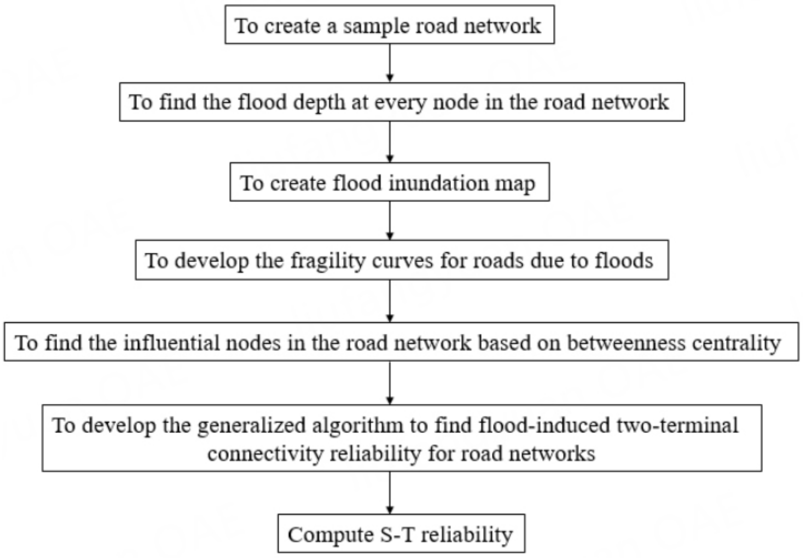

Figure 1. Summary of the entire process of computing source-terminal (S-T) reliability.

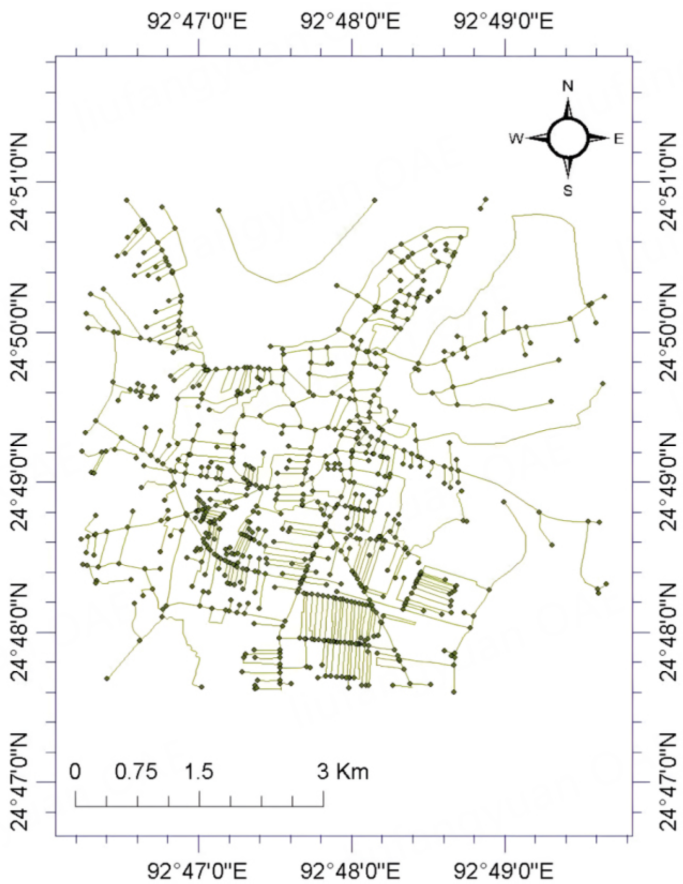

Figure 2. Example of Spatial polyline data.

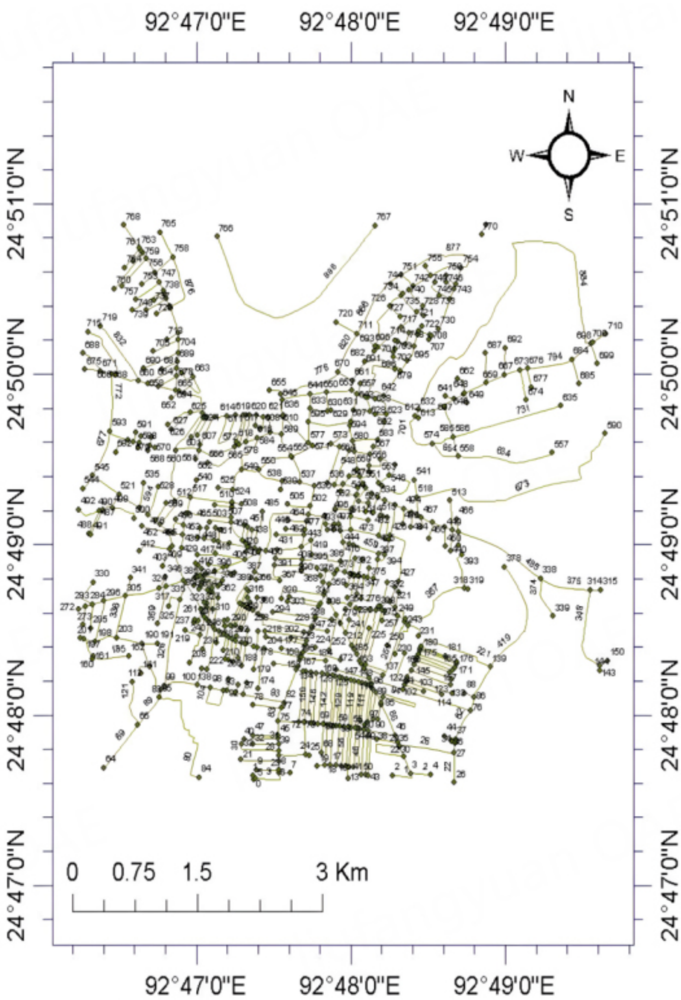

Figure 3. Network from Spatial polyline data.

into a format suitable for networks, including a node layer, an edge layer, and a list of nodes and edges. The tool can be accessed by adding it to ArcGIS. Porter (2019) published a guide that explains the concepts of fragility, vulnerability, and risk due to earthquakes[12]. It helps us to study the multi-hazard risk. In the present research, the concept of fragility is utilised to quantify the probability of exceedance. Lu *et al.* (2017) developed a framework for modeling pavement fragility against precipitation[13]. In this research, they developed fragility curves for both the flexible and rigid pavements against a depth of precipitation by considering International Roughness Index (IRI) as a damage factor.

Nazari and Bargi (2012) constructed a fragility curve for the Reinforced Cement Concrete (RCC) Bridge against earthquakes[14] and also explained the process of construction of a fragility curve with the help of MS Excel. Rogelis (2015) published technical notes on flood risk in road networks[15]. In this note, how the floods interact with the roads was explained, and also how these interactions lead to the failure or damage of roads and road networks.

A Technical Report and Atlas on remote sensing and GIS (2014)-based inputs for hazard risk vulnerability assessment of Silchar, Assam (case study area) helps us to understand how Silchar town is prone to flood hazards[16]. Pregnolato *et al.* (2017) explained the impact of flooding on road transport. The damage function was constructed based on the flood depth on the roads in this research paper[17]. Habermann and Hedel (2017) provided the damage functions for transport infrastructure[18]. This paper provided damage functions for roads, railways, and airports. Finally, the graphs were plotted for damage factors against flood inundation for roads, railways, and airports. Rosca *et al.* (2008) explained the reliability and vulnerability of transportation networks in large urban areas against disasters, such as floods, earthquakes, *etc.*, and also explained how the reliability of road networks was impacted by the disruption of their nodes and links[19]. Zhao *et al.* (2015) developed a Monte Carlo-based stochastic simulation technique to investigate the system reliability and component probabilistic importance of the road network where the components of the road network are nodes and links[20]. Iida (1999) explained the basic concepts and future directions for the reliability analysis of a road network[21]. The concepts of connectivity reliability and travel time reliability in normal and abnormal situations were given to understand how the reliability of the road network was affected due to the disasters, such as earthquakes and floods. Fishman (1986) introduced the Monte Carlo sampling plan for estimating the reliability of an undirected network[22]. This Monte Carlo approach replaces the deterministic approach for quantifying the reliability of a network. Gertsbakh and Shpungin (2019) explained how to find the reliability of an electrical network[23,24]. They discussed all the required basic to advanced concepts of reliability using Monte Carlo simulations. The dynamic reliability evaluation methods were also explained. Liu *et al.* (2017) have done a vulnerability analysis on Rail Transit Plans in Beijing-Tianjin-Hebei Region, considering the connectivity reliability of a network[25]. This paper analyses the impact of multiple attack modes on the network performance and also the vulnerability of the rail transit network[25]. Shang *et al.* (2020) have done community analysis on urban road networks to find the influential nodes based on Centrality measures, such as degree, clustering coefficient, closeness centrality, betweenness centrality, and average path length[26]. Finally, they concluded that the betweenness centrality measure, which is later on discussed and implemented in this paper, is the most efficient when compared to other centrality measures. Liu *et al.* (2019) approximated betweenness centrality to identify key nodes in a weighted urban complex transportation network to give more idea about this centrality measure[27]. The simulation results of betweenness centrality to identify key nodes were obtained within a short time with high accuracy.

METHODOLOGY

General

The methodology of the present research involves flood modeling and construction of fragility curves against floods, quantification of fragilities of components of the road network, using a breadth-first search (BFS) algorithm to find the connectivity of the road network, and finally, finding the reliability of a road network using Monte Carlo simulations. Road networks consist of links and nodes. First, flood inundation maps were created using hydraulic modeling computer software[28]. The flood inundation maps were forwarded to Geographic information processing software[29] in raster format to find the flood depth at each node in the road network for various assumed discharges at the considered bridge location across the river. A suitable extraction tool in the Geographic information processing software was used to find the flood depth at each node in the road network. Then the average flood depth was computed at each node in the road network. These complex calculations were done with the help of a computer programming language[30]. The flood modeling was done using Geographic information processing software. The shapefile contains geospatial vector data for places, waterways, roads, railways, land use, and buildings. An online database extract service was used to get the road shapefile of Silchar, the proposed study area. The shapefile contains spatial polyline data visualising the shape of roads. Essentially, a road network consists of roadway segments modelled as edges and intersections modelled as nodes. The extracted road shapefile is given as input to the Geographic information processing software to get the Edgelist of the road network. The flood inundation maps were then prepared using the hydraulic modeling software. The flood inundation maps were prepared based on the assumed discharges at various cross-sections along the considered river site. The created flood inundation maps in appropriate format were forwarded to the Geographic information processing software to use a special tool to measure the flood depth at each node in the road network. Consider $d_{1,}$ $d_{2,}$ $d_{3,}$ ··············d_k the flood depths at node "i" in the road network from the "k" flood inundation maps. The Average Flood Depth AFD_i at node "i" in the road network is shown in equation (1).

$$AFD_i = \frac{d_1 + d_2 + d_3 \ldots\ldots\ldots\ldots d_k}{k}, \tag{1}$$

The Average Flood Depth AFD_i (where i = 1, 2 , 3··············n) at each node i of the road network is used in conjunction with the flood fragility curve (Major Damage) given in Figure 4. The obtained coordinates of this fragility curve are used as a reference to find the fragility of each node FR_i (i = 1, 2 , 3··············n) corresponding to the Average Flood Depth AFD_i in the road network with the help of a function in the computer programming language.

The road network is modeled as a graph $G = (V, E)$, where V is the set of nodes and $E \subseteq \{(i, j): i, j \in V\}$ is the set of edges[31]. It is very typical to find the fragility of each edge due to complex calculations. So, the fragility of each edge in the road network is considered as the maximum of the fragilities of the nodes connected. So, the fragility of each edge in the road network is $FRE \subseteq \{\max imum(FR_i, FR_j)\}$: FR_i and FR_j are the fragilities of end nodes i and j of that edge, respectively.

A road network consists of edges. Each edge is regarded as a component of the road network. Let p_i (i = 1, 2 , 3··············n; $0 < p_i < 1$) be the fragility of i-th edge, n is the number of edges in the road network. Fragility is the probability of some undesirable event (damage) occurring as a function of some measure of environmental excitation (such as an earthquake, flood, *etc.*).

Let $a = (a_i{:}i$ = 1, 2 , 3··············n) denote a random vector to group the n random numbers. a_i (i = 1, 2 , 3··············n) is a random variable with a uniform distribution between 0 and 1. To calculate the S-T reliability, we use the Monte Carlo simulation approach to generate M realisations. If $a_i \leq p_i$ or $p_i = 0$, edge i is reliable; else, edge i fails when $a_i > p_i$ or $p_i = 1$. For each edge, x_i resents the state of edge i in the road network, as shown in equations (2) and (3).

$$x_i = 0 \text{ if edge } i \text{ is unreliable,} \tag{2}$$

$$x_i = 1 \text{ if edge } i \text{ is reliable,} \tag{3}$$

The edges with state 0 could be removed, and a path search algorithm could be used to judge whether the source S and terminal T are still connected. This process is repeated M times. In each test, a set of random numbers is generated, and the connectivity for each source S and Terminal T is checked. Considering m number of times, the source S and terminal T are not connected, then S - T Unreliability can be calculated as follows in equation (4)

$$\text{S} - \text{T Unreliability} = \frac{m}{M}, \tag{4}$$

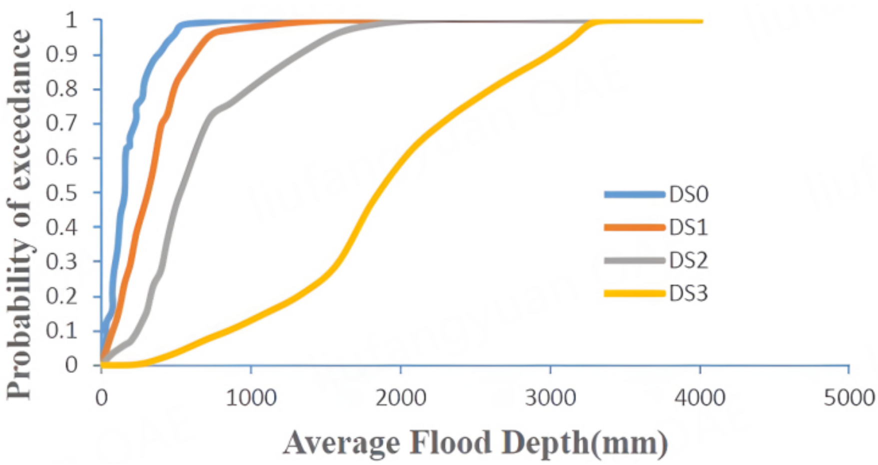

Figure 4. Flood fragility curve for road infrastructure.

Finally, S-T Reliability is measured as shown in equation (5)

$$\text{S} - \text{T Reliability} = 1 - (\text{S} - \text{T Unreliability}), \tag{5}$$

A Monte Carlo approach is followed to find the S-T Reliability[31]. The function random( ) delivers a random number a ϵ (0,1). Every link in the network has two states, "0" or "1". The state "0" means the link is failed, and the state "1" implies the link is working. Assign the state to the link as "1" when the fragility of the link is not zero and the random number "a" is less than the fragility of that link. Otherwise, assign the state "0" for that link. Then delete the links that state "0" and create the new network. Keep the failure counter as zero. Check the connectivity from the source node to the terminal node in the network. If there is no connectivity, increase the failure counter by one. A new algorithm was introduced in this paper to perform all the calculations explained above. And then, this algorithm is kept in a while loop to complete "n" number of simulations. Finally, Unreliability is the ratio of failure counter to "n" number of simulations. Then deduct Unreliability from "1" to get the S-T Reliability of the road network. The present algorithm explained in this paper is written using a computer programming language. The inputs required for this algorithm are Edgelist of a road network, ground levels of nodes in a network, Maximum Water level due to flood for previous years in that region, and an Excel sheet containing fragilities of nodes corresponding to flood depth. The other essential inputs are the Source node, the Terminal node, and the number of simulations. This algorithm finally gives the S-T Reliability of the road network as output.

It is important to consider how to determine if an S-T pair is connected or disconnected when using the proposed Monte Carlo-based simulation method. From the source node to the destination node, a path is searched. A set of nodes connected from the Source node to the Terminal node may be found by using path search when the S-T pair is connected. Path search could discover network state 0 when the S-T pair is broken. Therefore, the issue simply becomes determining whether a new component, such as an edge or a node, will connect the S-T pair when it is introduced to the road network. The spatial polyline data are converted to network formats and applied to the road networks.

Finding flood depth at each node in the road network

The flood inundation maps of Silchar town were prepared using the hydraulic modeling software. The flood inundation maps were prepared based on the assumed discharges at various cross-sections along the Barak

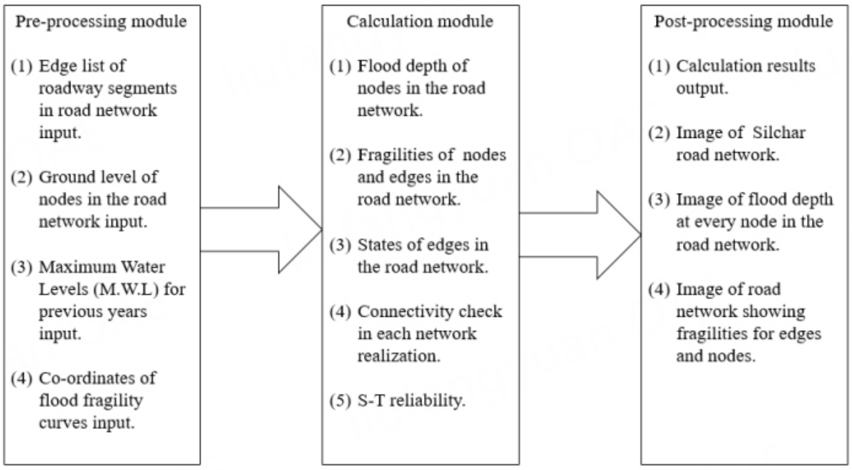

Figure 5. Modules to find S-T reliability of a road network.

River, which flows along Silchar town. The created flood inundation maps in raster format were forwarded to the Geographic information processing software to use the "Multi values to points" extraction tool to measure the flood depth at each node in the road network. The assumed discharges at the Sadarghat bridge location in the Barak River are shown in Table 1. The modules to find S-T reliability of a road network is shown in Figure 5.

Based on the discharge at the bridge across the river, the flood inundation maps were prepared with the help of the hydraulic modeling software. These flood inundation maps were forwarded to the Geographic information processing software in raster format. The "Multi values to points" extraction tool was used in the Geographic information processing software to get the flood depth at each node in the road network. The flood inundation map showing flood depth at each node in the road network is shown in Figure 6.

After obtaining flood depth at each node in the road network for various discharges, a flood depth matrix can be created with each row representing discharge and a column representing node number.

Construction of flood fragility curve for road infrastructure

The construction of fragility curves involves two stages. One defines the thresholds for different DS, and the other generates fragility functions.

Definition of thresholds for damage states

Definition of thresholds for damage states (DS) allows for the definition of various pavement damage levels. Road infrastructure damage from floods is mentioned in the descriptions of DS. According to the depth of the pavement flood, the damages are represented in this study. Damage levels, such as severe damage, medium damage, very slight damage, and insignificant or no damage, can be used to categorise different damage situations. Expert judgments based on experiences and observations may be used to define the threshold values in accordance with the damage levels. Examples of threshold values for various DS are shown in Table 2.

Generation of fragility functions

Fragility functions predict a given level of damage to the pavement structure or even more. A fragility function is frequently defined as a lognormal cumulative distribution function. Though the lognormal

Table 1. Data of assumed discharges at bridges across the river

Flood inundation map No	Discharge (m^3/s)
1	14,000
2	20,000
3	22,000
4	26,000
5	29,500
6	32,000
7	35,500
8	38,000
9	39,500
10	41,000
11	45,000
12	46,500
13	48,000
14	50,000
15	52,000
16	56,000
17	60,000
18	63,000
19	66,000
20	70,000

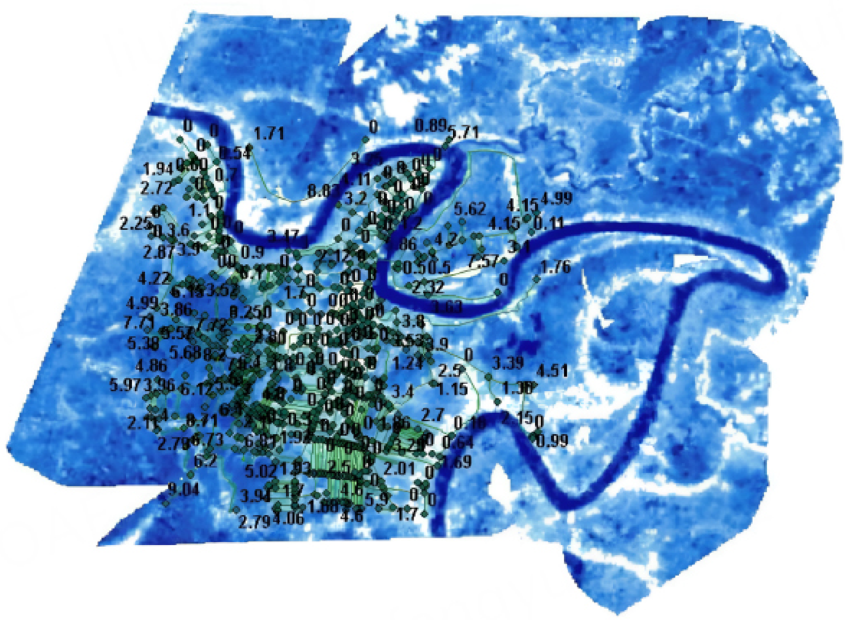

Figure 6. Flood inundation map showing flood depth at each node in the road network.

distribution is not absolutely accurate nor universal for its basic applications, its usage, in this case, is justified for at least four factors: (1) Simplicity: It just requires an estimate of the central value and uncertainty to approximate an uncertainty quantity that must take on a positive value; (2) Precedent: It has been extensively used for many years in natural disaster engineering applications; (3) Maximum entropy principle: If all that is known is that the variable is positively valued with a given median and logarithmic standard deviation, the distribution is assumed to have the maximum entropy. (4) Fit data: The observed distributions are frequently rather well fit. The fragility function is produced by the lognormal cumulative distribution function, as shown in equation (6)

$$P_{fragility} = P(DS / FH = x) = \phi\left(\frac{\ln x - \alpha}{\beta}\right), \tag{6}$$

where

DS = damage state,

$FH = x$ is the level of flood hazard (m),

ϕ (function) = cumulative distribution function of standard normal distribution,

α = logarithmic mean, and

β = logarithmic standard deviation.

In the present problem, the flood hazard considered was the average flood depth at each node in the road network for various discharges at the Sadarghat bridge. The damage factor taken in the present study involves flood depth values at each node for the previous years. The availability of data on the flood depth values at nodes, damage factors, and the fragility functions leads us to develop the fragility curves. The example fragility curve is shown in Figure 4.

The procedure to find the coordinates of the fragility curve is given briefly in the steps below.

Step 1: Create flood depth matrix Dij with rows representing discharge and columns representing node number, as shown below.

$$D_{ij} = \begin{bmatrix} D_{11} \ldots\ldots\ldots\ldots D_{1n} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ D_{m1} \ldots\ldots\ldots\ldots D_{mn} \end{bmatrix}$$

Where D_{11} is the flood depth due to the discharge “1” at node “1”,

D_{1n} is the flood depth due to the discharge “1” at node “n”,

D_{m1} is the flood depth due to the discharge “m” at node “1”, and

D_{mn} is the flood depth due to the discharge “m” at node “n”.

Step 2: Find the average of each column to get the average flood depth of each node in the road network.

Step 3: Find the logarithmic mean "α" and logarithmic standard deviation "β" of each column to get the flood depth of each node in the road network.

Step 4: Calculate $\phi\left(\frac{\ln x-\alpha}{\beta}\right)$ for each column to get the fragility of each node in the road network. Here, "x" is the damage level.

Influential nodes in the road network based on betweenness centrality

It is required to consider the most important nodes in the road network. Our goal is to find the two-terminal reliability of the road network. To find the two-terminal reliability, the first step is to decide the terminal nodes for which we want to find the reliability. In that scenario, the influential nodes in the road network were found using the betweenness centrality measure[32], and then S-T reliabilities were found from top 1st node to top 2nd node, top 2nd node to top 3rd node, top 3rd node to top 4th node, and so on. Finding the most crucial nodes in the network is the next step after that. Measures of significance of a node are referred to as centrality measures in network analysis. There are numerous methods for calculating centrality because there are numerous approaches to the question, "Which nodes are the most important?" Degree, betweenness centrality, and eigenvector centrality are the three most popular centrality measurements[33,34]. In the present study, we used the betweenness centrality measure to find the critical nodes in the road network.

Betweenness Centrality of any node in the network is defined as the number of times each node appears in all the shortest paths from each node to all other nodes that exist in that network. Betweenness centrality of a node v is given by the expression shown in equation (7)

$$g(v)=\sum_{s\neq v\neq t}\frac{\sigma_{s,t}(v)}{\sigma_{s,t}}, \tag{7}$$

where $g(v)$ is the betweenness centrality of the node v,

$\sigma_{s,t}$ is the total number of shortest paths from node s to node t, and

$\sigma_{s,t}(v)$ is the number of those paths that pass through the node v.

Networkx package provides us with the betweenness module, which we can use to find the betweenness centrality measure of each node in the road network. The inputs required for this algorithm are node and edge names. These inputs were prepared in Excel and used as input for the algorithm.

Connectivity reliability of a road network

The connectivity reliability of the road network shows a probability that there is at least one path to the destination without failure. The disasters, such as floods and earthquakes, can impact elements such as nodes and edges of a road network, leading to connectivity issues and reducing the connectivity reliability of a road network. The present research considers only flood-induced connectivity reliability of a road network.

Table 2. Damage states to roads due to the floods

Damage state	Damage level	Description	Range of flood depth
DS 0	None	Insignificant damage or No damage	Up to 0.15 m
DS 1	Low	Very slight damage to road pavements	0.15 m-0.30 m
DS 2	Medium	Medium pavement damage	0.3 m-0.5 m
DS 3	High	Severe pavement damage	> 0.5 m

The path search algorithm is used to find the connectivity of two nodes in the road network. For this work, there are two graph algorithms available in Python, namely BFS and depth-first search (DFS) algorithms. In the present study, the BFS algorithm was used to check connectivity from the source node to the target node. BFS and DFS in Python are algorithms used to traverse a graph or a tree. They are two of the most important topics in Python. A graph traversal algorithm known as "breadth-first search" begins by exploring all of the neighboring nodes before moving on to the root node. Then it chooses the closest node and investigates every unexplored node. Any node in the graph can serve as the root node when using BFS for traversal.

There are other techniques to navigate the network; however, BFS is the one that is most frequently applied. The process of searching every vertex in a tree or graph data structure is recursive. Every vertex in the graph is divided into two groups by BFS: visited and non-visited. A single node in a network is chosen, and then all of the nodes next to that node are visited.

In the present work, an algorithm was developed to find the reliability of the road network from the source node to the terminal node. A road network consists of elements such as edges and nodes. The failure of nodes is ignored in the present research and only considered the failure of edges to quantify road network reliability.

The calculation of the reliability of the road network involves two stages. They are the state of edge and the state of the network. States of edges are described as a vector, as shown in equation (8)

$$x = \{x_1, x_2, ...x_n\} \quad , \tag{8}$$

where x_i= 1 if edge i works, and x_i = 0 if the edge i fails.

The networks are assumed to be also in two states - UP and DOWN. If there is connectivity from the source node to the target node, then the network is UP; otherwise, the network is DOWN.

Crude monte carlo simulations

The procedure to find the reliability of the road network using Monte Carlo simulations is given briefly in the steps as follows. **Step 1**. Set Y = 0; **Step 2**. For each edge "i" in the road network, simulate its state with fragility p_f and also assign a ϵ (0, 1). If a ≤ p_f, the state of edge is 1 (i.e., edge is working); otherwise, 0 (i.e., edge is failed), **Step 3**. Upgrade the network by deleting the edges with the state 0 and check the connectivity from the source node to the target node, **Step 4**. If there is connectivity, the network state is UP, then Y = Y + 1, **Step 5**. Repeat steps 2, 3, and 4 N times. **Step 6**. Estimate the reliability of the network as follows. R = Y/N. Here R is the reliability of the road network, Y is the number of times the state of the network is UP, and N is the number of simulations.

Table 3. Betweenness centralities of top nodes in the road network

S. No	Node number	Betweenness centrality	Rank
1	335	0.2294	1
2	510	0.2290	2
3	517	0.2250	3
4	549	0.2247	4
5	293	0.2193	5
6	512	0.2151	6
7	524	0.2107	7
8	435	0.2102	8
9	530	0.2062	9
10	409	0.2052	10
11	477	0.2001	11
12	251	0.1958	12
13	307	0.1955	13
14	232	0.1926	14
15	329	0.1899	15
16	212	0.1893	16
17	455	0.1892	17
18	185	0.1861	18
19	172	0.1824	19
20	550	0.1710	20

RESULTS

The calculation of flood depths at nodes, development of fragility curves, identification of influential nodes in the road network, explanation of reliability algorithm, and the required Python modules to perform all these complex calculations were presented reasonably. In the methodology, the preparation of inputs to get results was given. The present research involves the usage of ArcGIS, MS Excel, and Python programming language; however, other relevant working contemporary software may also be used. Python programming language is for performing complex calculations. ArcGIS is for showing the results in jpg format. MS Excel is used to forward the results from the Python console to ArcGIS. The usage of these three applications was clarified properly.

Creation of a road network

The spatial polyline data of a road network are extracted from the OpenStreetMap website, as shown in Figure 7. The obtained spatial polyline data were converted into the network format using the GIS Features to Edges tool (GISF2E tool). The GISF2E tool creates two layers, namely the nodes layer and the edges layer. The nodes layer is shown in Figure 8, and the edges layer is shown in Figure 9. These two layers were merged to get the road network of Silchar town. The road network format is shown in Figure 10.

Flood inundation mapping

In this study, the flood inundation maps were prepared using HEC-RAS open-source software. The obtained flood inundation maps for various assumed discharges are shown below. The flood inundation maps were prepared based on the assumed discharges across the river. The inputs required for preparing flood inundation maps in HEC-RAS are the Digital Elevation Model (DEM), river cross-section details, Manning's coefficient of soil at the right and left banks of the river, and geometric details of the bridge, discharge at the bridge, and flow condition of a flood. Here, the flow is assumed as a steady-state flow to prepare the flood inundation maps for various discharges. Finally, flood inundation maps in raster format

Figure 7. Spatial polyline data of roads shapefile.

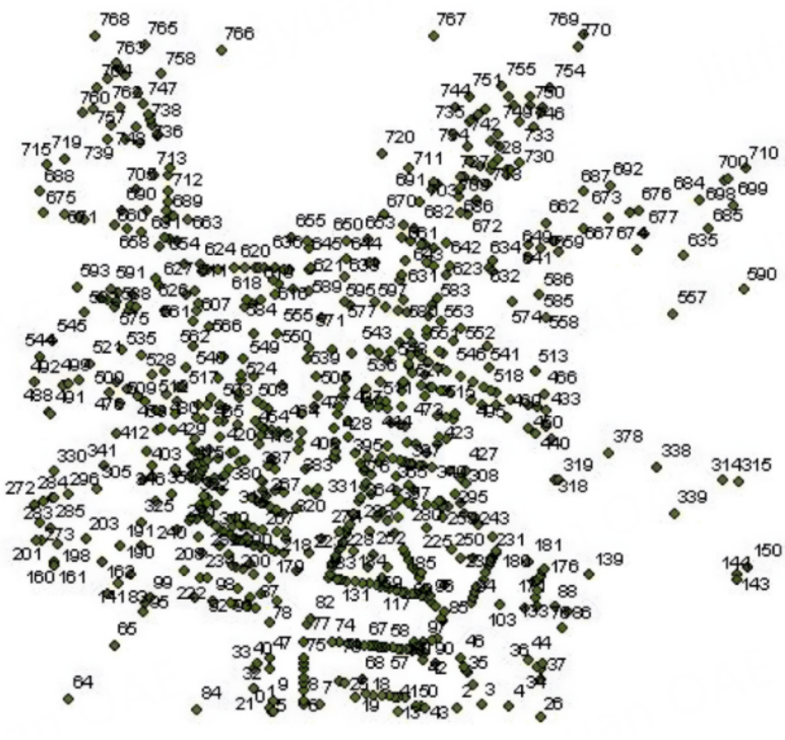

Figure 8. Nodes layer of a road network.

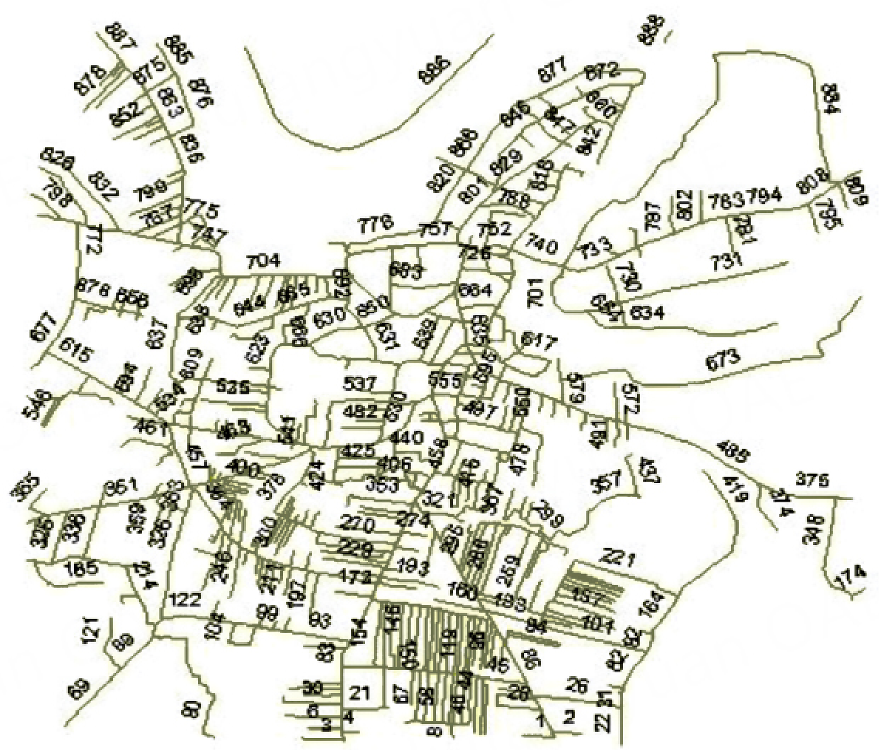

Figure 9. Edges layer of a road network.

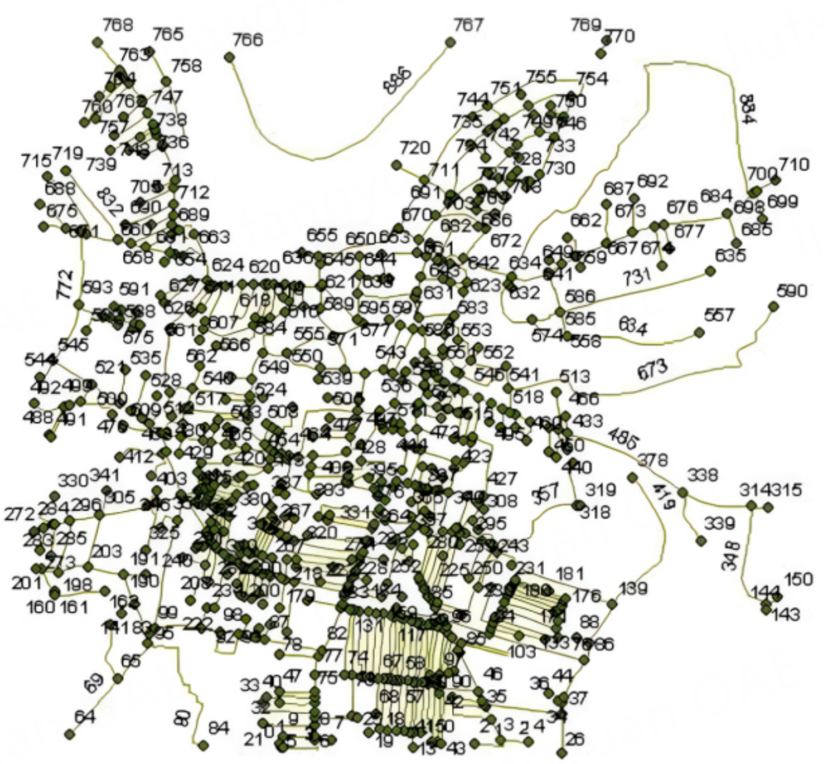

Figure 10. Road network.

in HEC-RAS were obtained. The obtained raster flood inundation maps in HEC-RAS were forwarded to ArcGIS to find flood depth at each node. The flood inundation maps showing flood depth at all nodes in the Silchar road network for the discharge of 14,000 m^3/s and 20,000 m^3/s at the bridge across the river are shown in Figures 11 and 12, respectively.

Assessment of fragilities of elements of the road network

The fragility curve for the road infrastructure was developed using flood depths at nodes from previous years. The average flood depth of each node for the previous years is calculated. Flood level was the damage factor considered for the development of the fragility curve, which was described in Table 2 above. The coordinates of the above fragility curve for DS 3 are used as a reference to interpolate the fragility of each node in the road network according to the average flood depth of each node. The fragility of each edge in the road network is considered as the maximum of the fragilities of the nodes connected to it. The fragilities of each node and edge are shown in Figure 13

Influential nodes in the road network

The important nodes in the road network were found based on the betweenness centrality measure. The betweenness module was available with Networkx package. The road network was given as input to get the betweenness centrality of each node, and found out the top 20 nodes of the road network are shown in Table 3.

The top 20 nodes in the network were calculated with the help of the betweenness module using the Python programming language. The data of the top 20 nodes are forwarded to ArcGIS. The positions of important nodes with their rank are drawn using the ArcGIS application. The top nodes of the road network can be viewed in Figure 14.

S-T reliability

The top 20 nodes in the road network were selected as source and terminal nodes. The S-T reliability of a network was found from the top 1st node to the top 2nd node, the top 2nd node to the top 3rd node, the top 3rd node to the top 4th node, and so on. The S-T reliabilities of a road network are shown in Table 4.

CONCLUSIONS, LIMITATIONS AND FUTURE SCOPE

Conclusions

Our research looked into the network of roads in Silchar town in North-East India for S-T reliability. The road network characteristics of Silchar town are taken into account when proposing the stochastic simulation techniques based on Monte Carlo. Then, a new system was developed that included the suggested methodology. The newly suggested approach is universal and suitable for any road network. The system can be applied as an analysis tool to help the road management departments make decisions. It can be used to assess the S-T reliability of various road network planning schemes, identify the essential elements that require upgrading or improvement, or forecast the increased S-T reliability of a road network when it adds a new edge.

The spatial polyline data (top view) of roads in Silchar town were obtained from the OpenStreetMap website. This spatial polyline data was converted into a road network using the GISF2E (Geographic Information System Features to Edges) tool in ArcGIS. The flood inundation maps were prepared using HEC-RAS open-source software. The flood depth at each node in the road network from flood inundation maps was found using the "Multi values to points" extraction tool in ArcGIS. The fragility curve for road infrastructure against flood hazards was developed using lognormal cumulative distribution functions for flood depths at nodes. Finally, the coordinates of the fragility curve were used to find the probability of

Table 4. S-T reliabilities of the road network

S. No	Source node	Terminal node	S-T reliability
1	335	510	0.046
2	510	517	0.516
3	517	549	0.146
4	549	293	0.04
5	293	512	0.01
6	512	524	0.15
7	524	435	0.05
8	435	530	0.003
9	530	409	0.03
10	409	477	0.01
11	477	251	0.04
12	251	307	0.259
13	307	232	0.117
14	232	329	0.07
15	329	212	0.2
16	212	455	0.36
17	455	185	0.52
18	185	172	0.49
19	172	550	0.21
20	550	335	0.05

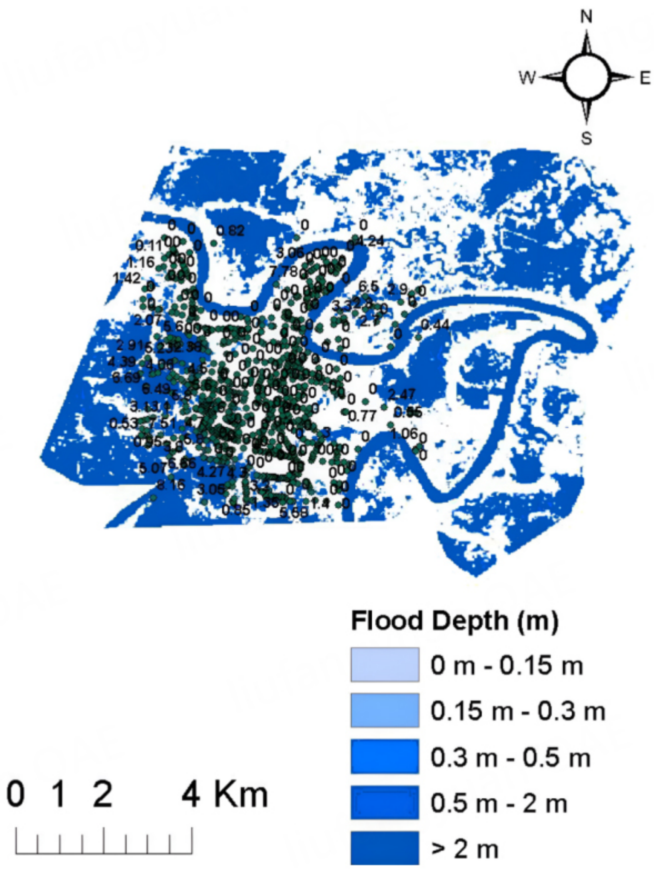

Figure 11. Flood inundation map of an area for the discharge of 14,000 m^3/s.

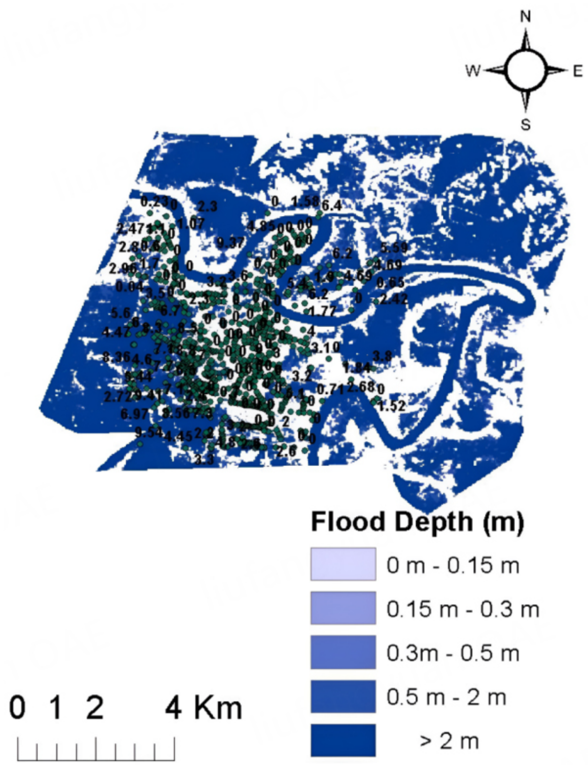

Figure 12. Flood inundation map of an area for the discharge of 20,000 m^3/s.

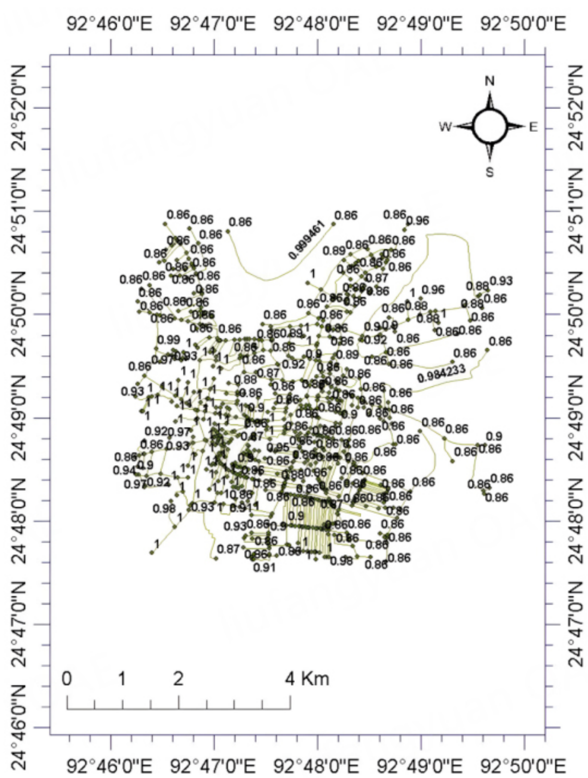

Figure 13. Road network showing fragilities of nodes and edges.

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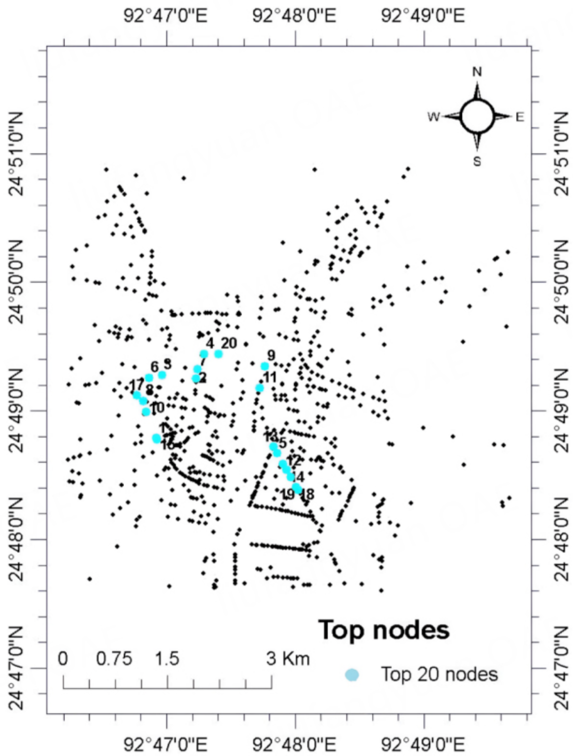

Figure 14. Top 20 nodes of the road network.

failure of each node in the road network. The fragility of each link in the road network is assumed as the maximum of the fragilities of the nodes connected to it. Finally, a program was developed using Python programming language to find road network reliability with the help of Monte Carlo simulations.

Limitations

The flood inundation maps were prepared based on the discharge at the bridge across the river. But in a real case, the sources of the flood are the intensity of rainfall, water levels of lakes and ponds, drainage facilities, and porosity of the soil. The Manning's coefficient of the soil at the left and right banks of the river is assumed as 0.06, and across the river is assumed as 0.035. The flood depth values of flood inundation maps at each node are assumed to follow a lognormal distribution. But it is necessary to find the flood depth values distribution to develop a realistic fragility curve and to get the realistic failure probabilities of every node and edge in the road network. The flood data contains zeros. The lognormal distribution does not take zeros. So, the nodes with non-zero flood depths were selected, and the flood fragility curve was developed. The S-T reliabilities in the present work are very few due to the assumption that flood data follows a lognormal distribution. So, there is a need to find which distribution the flood depths at each node follows.

Future scope

This proposed method does not work due to parallel edges in the road network. The present algorithm should be upgraded to find the reliability of road networks with parallel edges. Bridges also exist in the road network. The present work is valid for road networks with no bridges. To find the reliability of a road network with bridges, we have to develop the fragility curves for the types of bridges that exist in that specific road network against flood hazards.

In this work, flood depth is the only parameter considered that damages the edges of the road network. There are other parameters, such as flood duration, flood velocity, *etc.*, that damage the edges in the road network. The present method is to be upgraded in the future such that it covers all the disadvantages of the present method. The proposed work deals only with the two-terminal reliability of a road network. In the future, we can develop the algorithm to find the k-terminal reliability and all terminal reliability of road networks against flood hazards.

DECLARATIONS

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Authors' contributions

Made substantial contributions to the conception and design of the study and performed data analysis and interpretation: Laskar JI, Dutta S

Performed data acquisition and provided administrative, technical, and material support: Laskar JI, Dutta S

Availability of data and materials

Some data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Financial support and sponsorship

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Conflicts of interest

Both authors declare that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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