

# Disaster & Development

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- Climate and Urban Fire Disaster in Mountain Environment of Aizawl Municipal Corporation Area, Mizoram, India
- A Five-Tier Framework for Scalable Public Health Emergency and Disaster Management: Enhancing Pandemic and Climate Resilience
- Landslide hazard Zonation Mapping using Binary Logistic Regression and its Validation in Mandakini Valley, Garhwal Himalaya
- Exploring the Relationship Between Disasters and Tourism in India: A Quantitative Approach
- Scenario of Geo-Hydrological Disasters and their Perception among People in a Himalayan Town: A Case Study from Almora Town
- Landscape Dynamics and Its Impact on Landslide Susceptibility: A Case Study of Idukki District, Kerala

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## Disaster & Development

Journal of the National Institute of Disaster Management, Delhi

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# Editor-in-Chief

It gives me great pleasure to present this issue of the Disaster and Development Journal, which brings together cutting-edge research addressing critical challenges in disaster risk reduction, climate resilience, and hazard management across diverse geographic and socio-economic settings.

This edition features two noteworthy contributions. The first, 'Climate and Urban Fire Disaster in the Mountain Environment of Aizawl Municipal Corporation Area, Mizoram, India', provides a comprehensive analysis of the climatic, environmental, and socio-economic factors influencing urban fire hazards in a densely populated mountain city. By integrating meteorological data, fire service records, and statistical modelling, the study offers actionable recommendations for fire risk mitigation, spatial planning, and community awareness particularly significant for rapidly urbanizing hill regions.

The third paper, 'Landslide Hazard Zonation Mapping Using Binary Logistic Regression and its Validation in Mandakini Valley, Garhwal Himalaya', applies advanced geospatial analysis and statistical techniques to assess landslide susceptibility in a disaster-prone Himalayan watershed. The research highlights the efficacy of Binary Logistic Regression combined with high-resolution spatial datasets in delineating hazard-prone areas, thereby enabling informed planning, robust mitigation strategies, and safer infrastructure development in fragile mountain ecosystems.

Both studies underscore the value of interdisciplinary approaches that blend scientific rigour, technological innovation, and community engagement. They also reaffirm the Journal's mission to disseminate research that not only deepens our understanding of hazards but also guides practical policies and strategies for building resilience.

I extend my sincere appreciation to the authors for their scholarship, the reviewers for their thoughtful feedback, and the editorial team for their dedicated efforts in bringing this issue to fruition. I hope the knowledge shared here will inspire further research, foster collaboration, and advance effective disaster risk governance at local, national, and global levels.

A handwritten signature in blue ink, consisting of stylized, overlapping loops and a long horizontal stroke extending to the right.

**Safi Ahsan Rizvi, IPS**  
**Executive Director, NIDM**

# Editorial Note

The latter half of 2025 was marked by a succession of impactful disasters worldwide, reaffirming the pressing need for strengthened resilience, adaptive governance, and the integration of disaster risk reduction (DRR) within development agendas. In India, the monsoon season triggered widespread floods, flash floods, and landslides particularly across the Himalayan belt where the combined effects of climate change and unplanned land use magnified vulnerabilities. These events reinforced the urgency of robust early warning systems, effective preparedness measures, and sustainable land management in hazard-prone regions.

The Himalayan states witnessed heightened landslide activities, affecting Himachal Pradesh, Uttarakhand, Jammu-Kashmir, Sikkim etc. The resulting loss of lives, damage to infrastructure and disruption of livelihoods. While these displayed significant losses, they also revealed ongoing challenges in ensuring long-term rehabilitation and climate-adaptive rebuilding. Globally, other disasters such as fires, extreme heat waves and geo-hydro-meteorological disasters demonstrated the interconnected nature of risk, calling for stronger international cooperation and comprehensive disaster governance frameworks.

This issue of the *Disaster and Development Journal* presents a diverse range of scholarly contributions addressing such multifaceted challenges. Studies on landslide hazard mapping including binary logistic regression in Mandakini Valley of Garhwal Himalaya and landscape dynamics and its impact on landslide in Idukki-Kerala are given. Study on urban fire disaster in Aizawl Municipal Corporation Area showcases the risk of fire in Aizawl city of Mizoram. The public health emergencies and disaster management with five-tier framework is focused in the journal. In addition, studies on

relationship between disaster and tourism in India and geo-hydrological disaster in Almora town underline the importance of sustainable land use.

Together, these contributions demonstrate the value of inter-disciplinary research, technological innovation, and policy integration in building disaster resilience. I extend my sincere appreciation to all authors, reviewers, and the publication team especially Dr. Ravinder Singh, Senior Consultant, Shri S. K. Tiwari, Librarian and Ms. Karanpreet Kaur Sodhi, Junior Consultant for their dedication, and to our readers for their continued trust in this UGC-CARE listed open-access journal. We look forward to your sustained engagement as we strive toward a safer and more resilient future.

A handwritten signature in black ink, appearing to read 'S.P. Parkash'.

**Surya Parkash, Ph.D.**

# Climate and Urban Fire Disaster in Mountain Environment of Aizawl Municipal Corporation Area, Mizoram, India

R. Lalrinchhana, R. Zonunsanga\*<sup>1</sup>,  
Rintei Renthlei<sup>1</sup>, Zothansanga Hmar<sup>1</sup> and, Ankita Mishra<sup>1</sup>

## Abstract

*Fire is known as the earliest element which roots human civilization. It serves as an excellent servant but also sometimes exhibits its characters as a terrible master. Fire-induced disasters are amongst the most destructive hazards in urban environment as they imposed massive threats to loss of properties and lives especially to the weaker sections in the society such as youngsters, old-aged and female. Fire disasters can be however mitigated through awareness and analysis of atmospheric weather condition to comprehend its risk and vulnerability. Mizoram is one of the most vulnerable states of fire hazards due to frequent delay in the onset of the monsoon and prevalence of long dry spell season. The urban environment having high density of buildings poses threats to occurrences of fire from house to house. This paper attempts to analyze the various climatic and weather elements with environmental scenarios and correlate the same with the occurrences of house fire within the jurisdiction of the Aizawl Municipal Corporation Area (AMC). Data procured from the Fire and Emergency Services Department, Government of Mizoram and the Meteorological Centre, Aizawl have been analyzed including other secondary data collected from reliable sources. The study reveals that low rainfall, low humidity and low temperature are the factors imposing threats to urban fire in the study area.*

**Keywords:** *Climate, Hazards, Disasters, Environment, Urbanization, Season*

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## 1. Introduction

The history of humanity starts with the discovery of fire which is the earliest source of power. Fire is known as the earliest element which roots human civilization. The four fundamental and basic requirements of human civilization have been food, clothing, shelter, and security since the beginning of time. Perhaps man first came into contact with fire to fulfil his primal craving (Jain 2007).

Disasters caused by fire are extremely dangerous for people, property, and the environment. These terrible occurrences can happen anywhere, at any moment, and leave destruction and hopelessness in their wake. It is essential to comprehend the origins, effects, determinant factors, anthropogenic activities and mitigation strategies for fire disasters in order to lessen their negative social effects.

Fire hazard, either natural or man-made has dominated the field of disasters (Cavallini et al. 2007). Fire serves as an excellent servant, but also as a terrible master. Fire and fire-related accidents cause the biggest concern and carry the highest risk of all hazards. The presence of a well-equipped public fire service and their correct servicing and maintenance; proper in-build fire safety measures in the building/premises as per specifications lower the fire risk to a large extent. The majority of fire disasters are caused by human error, inadequate maintenance, or sabotage. Almost everywhere, including houses, offices, hospitals, or public spaces, one can expect to encounter fire disaster (Vidyadharan et al. 2018). Mitigating or eliminating the adverse effects of such fires on the service functions of urban ecosystems, while enhancing the resilience of urban greening systems in disaster prevention and risk reduction, has become a pivotal challenge in modern urban development and management (Zhang et al. 2025).

The number of fire accident has significantly increased, putting lives in danger and harming the economy and the environment (Felix et al. 2015). Uncontrolled fire is one of the main of building collapses, causing damage, probable injury and loss among other factors (Wong and Jan 2003). The subject of fire safety management has become a source of concern for the Indian situation because, on average, about 21 (33.5%) men and 42 (66.5%) women passed away each day from such fire and related reasons (Vidyadharan et al. 2018). According to the National Crime Records Bureau, fire causes

the death of roughly 60 persons each day in India with approximately 25,000 people perishing annually as a result of fires and other associated cause. Urbanization and its consequent population pressure increase the number of high-rise buildings and hence the implementation fire safety has become significantly difficult (Kodur et al. 2019). Yao et al. (2024) mentioned that temperature variability is one of the primary factors of urban fire in China and that the fire-temperature relationship is seasonally and regionally explicit.

Apart from other disasters, Mizoram is one of the most vulnerable states of fire hazards in India. As per the record (2012 - 2021) of the Department of Fire and Emergency Services, Government of Mizoram, there were 728 house fire causing 30 fatalities and 71 injuries. In most cases, these recorded fire disasters were the resultants of malfunctioning and leakage of electricity and negligence and, hence the need of systematic and effective fire hazard management is crucial for the state. Many of these incidents are reported to have started from the places where foods are cooked at the basement of houses for domesticated animals which are reared for commercial purposes at the suburb of the city.

## **2. Background of the Study Area**

The present study is mainly confined in the AMC area which is the capital of Mizoram, one of the northeastern states of India. It is located within the grids of 23° 39'36" - 23° 48' 00" N latitude and 92° 40' 48" - 92°45'00" E longitude in the northern part of the state, covering 176 km<sup>2</sup> (Figure 1). The city is densely populated with several high-rise building constructed mostly along steep slopes and hill-top which makes the buildings highly vulnerable from catching fire from one building to the other. Further, its geographical features impose certain restrictions for traffic movement of concerned personnel during fire disaster and emergency.

Aizawl District has the highest district-wise population and highest urban population in Mizoram. The average sex ratio of Aizawl urban area (2011 Census) was 1,024 female per 1000 males showing the high vulnerability of casualties and fatalities arising from the dominant female population. Further, the city is prone to fire disaster due to lack

of spatial planning. Due to rapid urbanization and population pressure, the organized areas with growing population are gradually converting into unorganized area causing greater problems (Sharma 2020).

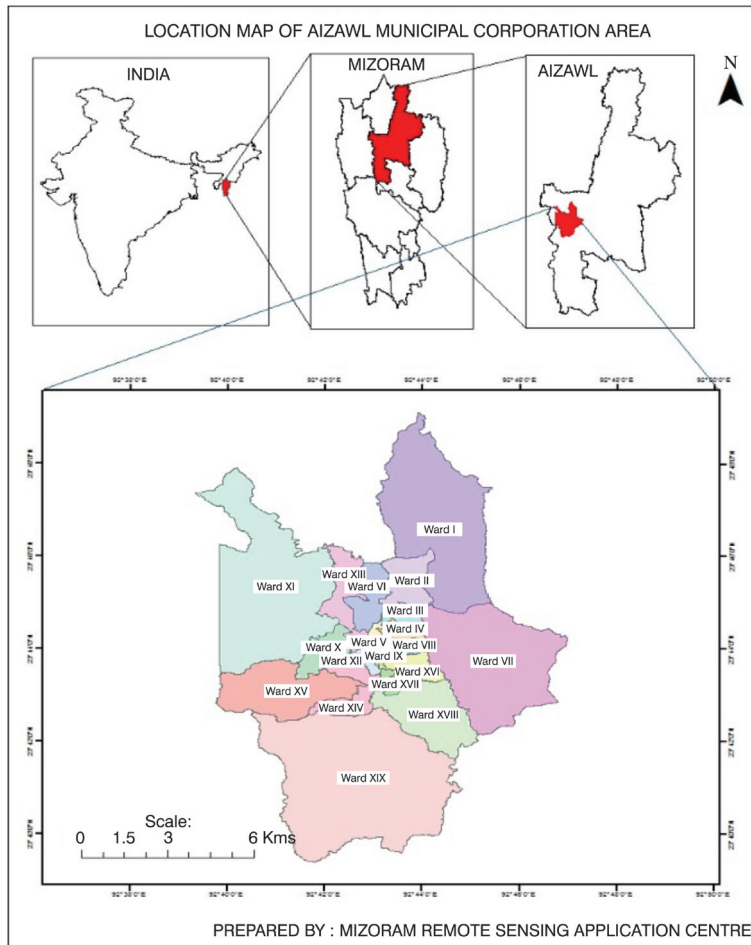


Figure 1 : Map of AMC Area

The AMC, formed in the year 2010, is divided into 19 Wards and represented by 19 elected members and others, officially appointed by the Governor of Mizoram. There are 85 Local Councils comprising of several elected members under these 19 Wards.

### 3. Data Collection and Methodology

This paper is based on a time-dimensional analysis of past fire disaster extracted and gathered from the official records of the Fire and Emergency Services Department, Mizoram and the daily weather data including temperature, humidity and rainfall were collected from the Meteorological Centre, Aizawl covering the period during 2012 – 2022.

The two main metrics used to assess the severity of a fire disaster during a certain time period were the quantity and value of property loss and the number of fire disaster incidents. The two primary climatic seasons classified as ‘dry’ and ‘wet’ seasons are used to determine the occurrences of fire in the area. The months of January to April and November to December are considered as Dry seasons and the other remaining six (06) months are classified as Wet season. Calculation of the average temperature is based on the lowest and highest daily temperatures to acquire the average temperature for a month and similarly for the course of the eleven (11) years. Descriptive statistics such as mean, percentage etc. are used in this research to simplify the analyzed data. Besides, a multiple regression is utilized to predict and explain the expected and actual data.

**Multiple Regression Analysis** (Factors Affecting House Fire Cases in AMC Area)  
In this study a multiple regression was employed to predict and explain the house fire cases in the AMC area. A regression equation is a statistical tool that helps to determine the value of the dependent variable using the independent variable.

$$y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \mu_i$$

Where  $y_i$  the dependent variable,  $X_1, X_2, \dots, X_n$  are independent variables which help to predict the value of  $y_i$ ,  $\beta_1, \beta_2, \dots, \beta_n$  are coefficients.

In this study, the dependent variable is house fire cases and independent variables are humidity, temperature, and rainfall. The analysis of multiple regression are discussed as follows:

Dependent variable : House fire cases ( $y_i$ )

Independent variables :  $X_1$ = Temperature (Degree Centigrade)

$X_2$ = Humidity (Percentage)

$X_3$ =Rainfall (mm)

$$\text{Fire Cases} = \beta_0 + \beta_1 (\text{Temperature}) + \beta_2 (\text{Humidity}) + \beta_3 (\text{Rainfall}) + \mu_i$$

**Table 1 : Coefficient of Determination**

R	R Square <sup>b</sup>	Adjusted R Square	Sig.	Std. Error of the Estimate
.915 <sup>a</sup>	0.837	0.776	.002 <sup>b</sup>	5.289

**a. Predictors:** Temperature, Humidity, Rainfall.

**c. Dependent Variable:** House fire cases.

From the table above  $R^2 = 0.837$  which indicate that 83.7 percent changes or variation in house fire cases was explained by humidity, temperature, and rainfall, while the remaining 16.3 per cent were unexplained by Random error which may results from other factor not considered in this research.

**Table 2 : Multiple Regression Analysis of Fire Cases in Relation to Humidity, Temperature, and Rainfall**

Variable	Unstandardized Coefficients	SE of B	Standardized Coefficients	T value	P value
Temperature	-1.827	1.112	-0.369	-1.643	0.139
Humidity	-0.656	0.346	-0.472	-1.894	0.095
Rainfall	-0.456	0.753	-0.197	-0.605	0.562

**Note:** \* denotes significant at 5 per cent level.

\*One regression equations was found out to predict the value of dependent variable.

## 4. Results and Discussion

According to historical fire statistics, over 90% of the known fires are human-caused (Guo et al. 2016) and human activities are the main causes of fires especially where population density is high (Zong et al. 2021) that weather conditions alone have the least responsibility towards fire outbreak and weather factors are the only influencing factors and such environmental factors cannot be generalized. The research findings of Guo et al. (2023) however reveal that the hysteresis effect of temperature is very important in driving fire occurrence.

According to Table 1, the multiple regression coefficient of 0.915 reflects the strength of the association between the actual and expected fire cases. Since the projected values are generated as a linear combination of humidity, temperature, and rainfall, the coefficient value of 0.915 suggests a strong and positive association between house fire cases and the three independent variables. The R-square ( $R^2$ ) that is Coefficient of Determination assesses the goodness of fit of the estimated Sample Regression Plane (SRP) in terms of the percentage of the variation of the response variables that is described by the sample regression equation. Hence, the value of  $R^2$  is 0.837, which indicates that about 83.7 per cent of the variation in house fire cases is explained by the estimated SRP that employs humidity, temperature, and rainfall as independent variables, and the value of  $R^2$  is significant at the 5 per cent level.

Holding all other variables fixed the coefficient temperature of -1.827 shows the partial influence on house fire. The calculated negative sign indicates that this impact is negative, with a -1.827 decrease in house fire for every increase in temperature, and the value of this coefficient is statistically insignificant. The coefficient of humidity is -0.656, which shows the partial influence of humidity on house fire when all other variables are held constant. The calculated negative sign indicates that the impact is positive, with the fire case decreasing by -0.656 for every unit increase in humidity and the coefficient value is significant. The coefficient of rainfall is -0.456, which shows the influence of rainfall on house fire, with other variables being held constant. The estimated negative sign indicates that this impact is negative, with house fire decreasing by -0.456 for every unit increase in rainfall, and the value of this coefficient is statistically significant at 5 percent level. In accordance with the standardized coefficient, rainfall (-0.197) is the

most significant element in determining house fire, followed by temperature (-0.369) and humidity (-0.472).

## 5. Chronology of Fire Disaster

The frequency of house-fire occurrences in the study area during the 11 years (Table 3) shows that there were 212 registered cases with 234 numbers of actual houses on fire.

The highest recorded number of registered house-fire staggering to 26 incidents with actual number of 30 house-fire incidents took place in the year 2012 which was followed by the year 2013 and 2021 as the second and third highest respectively. The year 2022 recorded the lowest number of annual house-fire cases with 14 registered house-fire cases and actual 17 houses burnt and one (01) fatality. This decreased in the number of house fire incident is attributed to the increasing attention towards the concept of disaster resilience gained over the past years (Gernay et al. 2016).

Table 3 : Year-wise Fire Occurrence in the Study Area (2012 – 2022)

Sl. No	Year	Number of House Fire		Number of Casualty		Property Damage Value (INR)
		Case Registered	Actual Number	Loss of lives	Persons Injured	
1	2012	26	30	3	5	8,60,15,110.00
2	2013	25	25	1	4	1,40,88,180.00
3	2014	20	23	0	0	2,35,21,000.00
4	2015	17	21	1	0	1,63,42,500.00
5	2016	19	19	0	0	1,97,09,900.00
6	2017	18	20	0	0	8,66,47,000.00
7	2018	15	16	0	0	3,28,18,000.00
8	2019	16	16	0	0	1,21,05,730.00

9	2020	19	19	0	0	4,08,06,680.00
10	2021	23	28	0	0	9,20,40,000.00
11	2022	14	17	1	0	4,57,92,220.00
<b>TOTAL</b>		<b>212</b>	<b>234</b>	<b>6</b>	<b>9</b>	<b>46,98,86,320.00</b>

The second and third lowest of fire cases were recorded in the year 2018 and 2019 respectively. Throughout this (11) eleven years, the average number of house-fire was 19.27. It means that about 20 houses are burnt every year and the highest value of property damage and loss was witnessed in the year 2021.

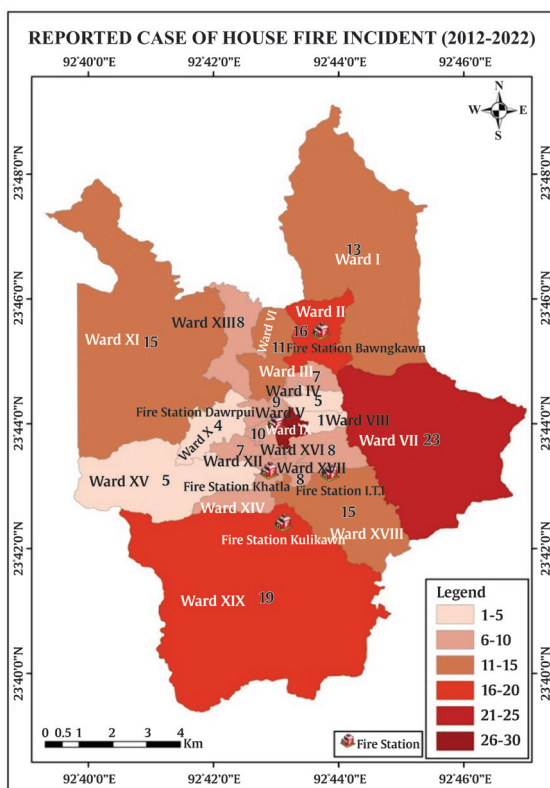


Figure 2 : Location of Fire Stations and No. of reported house fire incident

According to the Meteorological Department, the state of Mizoram typically receives sufficient amount of rainfall from the South-West Monsoon. Owing to its tropical-monsoon location, the region exhibits one of the World's most precipitous zones (Zonunsanga & Magner 2017). The summer monsoon, often known as the rainy season, officially begins in April and lasts until late October. From May through September witnesses heavy rainfall whereas November through February, known as the winter season is often dry and receives relatively low rainfall. Analysis of house-fire frequency reveals that majority of house-fire disaster in the course of the study period occurred during dry season from November to April with a record of 171 houses burnt accounting for almost three-fourth of the total house-fire, and 63 houses burnt during wet season between May to October.

Figure 2 and Table 4 represent the month-wise occurrences of house fire in AMC area during 2012 – 2022 by numbers as well as calculated average. The month of January is observed as having the highest frequency of house fire recorded as 38 houses burnt during the period, followed by March (35), December (32), February (28) and April (23) which all fall under the realms of dry season. The figures apparently show that fire flames spread easily to its other adjacent houses during the dry season. On the other hand, during the wet season the number of house fire incident and the actual number of house on fire were the same, clearly showing that during the wet season, despite the occurrences of fire incident, the flames do not spread to other buildings within its neighborhood. In this regard, not only the climatic conditions, i.e. the dry-rainless season but also the urban environment such as topography and density of houses also determine the risk and vulnerability. During dry season, a single fire incident often caused multiple number of houses on fire which implies that a house on fire imposes high vulnerability to the adjacent house at the higher ground to catch fire owing to both topographic and dryness conditions.

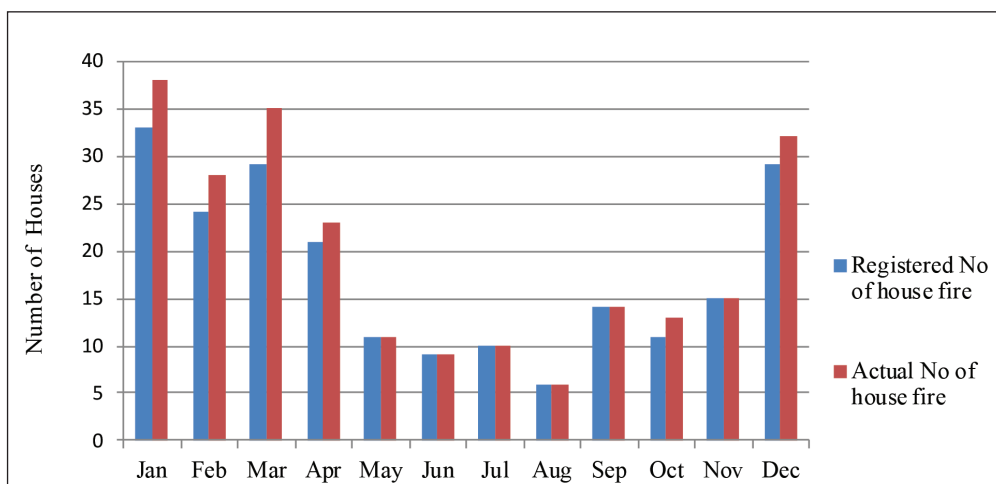


Figure 3 : Month-wise house-fire in the Study area

Table 4 shows that the average weather/climatic parameters of the AMC environment such as temperature, humidity and rainfall of every month during the years from 2012 to 2022 along with the average house fire case as well as the average number of house fire during each respective month. According to the table, during the dry season (January, February, March, April, November and December) the average rainfalls of each month were comparatively less and that the average number of house fire was greater than rest of the remaining wet months.

Additionally, a considerable direct variation was found between the average monthly rainfall and the numbers of monthly house fire case according to the Pearson correlation result.

Table 4 : Year-wise Fire Occurrence in the Study Area (2012 – 2022)

Month	Average Weather/Climatic Conditions (2012 – 2022)			Total Number of House Fire (2012 – 2022)		Average Number of House Fire (Monthly)		Property Loss and Damage Value (in INR)
	Temperature (°C)	Humidity (%)	Rainfall (mm)	Cases Registered	Actual Number	Cases Registered	Actual Number	
Jan	17.00	71.20	0.34	33	38	3.00	3.45	9,96,35,100. 00
Feb	19.20	60.30	0.44	24	28	2.18	2.54	3,74,54,000. 00
Mar	21.89	62.98	1.41	29	35	2.63	3.18	3,79,83,720. 00
Apr	22.78	70.30	4.17	21	23	1.90	2.09	7,24,11,900. 00
May	22.76	76.81	8.05	11	11	1.00	1.00	65,38,000. 00
Jun	22.72	82.87	12.83	09	09	0.81	0.81	98,65,500. 00
Jul	22.72	84.50	11.39	10	10	0.90	0.90	1,39,07,000. 00
Aug	22.84	84.05	11.24	06	06	0.54	0.54	38,62,000. 00
Sep	22.71	75.42	9.14	14	14	1.27	1.27	52,87,180. 00
Oct	22.88	82.92	6.23	11	13	1.00	1.18	6,51,44,910. 00
Nov	20.51	75.36	1.23	15	15	1.36	1.36	1,41,15,710. 00
Dec	17.20	71.30	0.41	29	32	2.64	2.90	10,36,81,300. 00
Total Value of Property Loss and Damage (in Rs.)								46,98,86,320. 00
Dry Season			2012 – 2022 Data Analysis Record				Wet Season	

Considering the property damage, the estimated property loss by the concerned authorities during dry period reached more than three quarter, i.e. 78% of the total property loss during the years 2012 to 2022. The total value of property damage/loss during the wet season accounts for only about 22% of the total loss from house fire. To be more precise, the property damage value during the dry season was Rs. 36,52,81,730/- (INR) and during the wet season was Rs. 10,46,04,590/- (INR). This scenario of property loss clearly shows that seasonal variations i.e. either dry or wet seasons exert major influence on the extent of property loss and damage caused by fire where house fire during dry season is more devastating as the fire grows and burns more rapidly before arrival of professional fire fighters.

The monetary value of property damaged by house fire has been calculated by the concerned authority based on the type of houses which are classified as RCC building, Semi-RCC building, Assam type building and Kutcha houses.

**Table 5 : AMC Ward-wise House Fire occurrences**

AMC Ward No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
No of Fire Incident	13	16	7	5	9	11	23	1	28	4	15	10	8	7	5	8	8	15	19
No of House Fire	13	16	7	5	10	15	26	1	28	4	16	10	10	7	10	9	8	19	20



Figure 4 (Plate) : Location of Aizawl City on steep mountainous slope

#### **4. Conclusion and Recommendation**

The study revealed that house fire hazard can happen at any climatic seasons but variation in house fire cases is greatly influence by the humidity, temperature, and rainfall in the study area during the study period. Fire events occurred more frequently during the dry season when humidity and air temperature are low.

The results have implications for the Fire and Emergency Services Department, Mizoram and other relevant stakeholders in terms of preventing and reducing fire hazards during times of high fire risk. The services of fire fighters have been recently enhanced through modern equipment and also the installation of fire hydrants attached to domestic water supply pipelines at various stations which have been made in collaboration with the Public Health Engineering Department of the state Government.

Spatial planning of the AMC area is a must to combat fire disasters through augmentation of groundwater recharge by means of afforestation to enhance groundwater infiltration and interception by vegetative canopies. Water availability lowers the risk of fire disaster. House fire at the foothill can cause devastating impact to the adjacent building constructed at the higher slope as flames are subject to rise which could easily transfer the heat and flame upward.

The semi-slums and the marginal are generally residing at the outskirts foothill of the city. Owing to their low economy, burning of fuel-wood for domestic cooking is sometimes necessary, which are further kept unattended and neglected while cooking due to lack of awareness. Electricity supplies are often directly connected from the main lines mostly for use as heater during dry-cold winter season which often cause short circuit and leakages and resulted house fire. Such situations impose serious threats to loss of their lives and properties and also put their neighborhoods at high risks. Accessibility of houses on fire amidst the rugged and narrow terrain without proper roads also hinders the emergency services to quickly respond which can be tackled through induction of highly maneuver light motor vehicles as fire engines to ply through narrow-congested roads.



Figure 5 (Plate) : Panoramic view of the Eastern flank of middle hill ridge, Aizawl

## 5. Declaration and Statements

The author(s) declare that the research article entitled '*Climate and Urban Fire Disaster in Mountain Environment of Aizawl Municipal Corporation Area, Mizoram, India*' is neither published nor sent for publication elsewhere other than the NIDM's journal 'Disaster and Development'.

Further, the authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article and that the author(s) received no financial support for the research, authorship, and/or publication of this article.

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# A Five-Tier Framework for Scalable Public Health Emergency and Disaster Management: Enhancing Pandemic and Climate Resilience

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## Abstract

*Escalating public health emergencies and disasters driven by climate change, urbanization, and globalization highlight the need for integrated, multisectoral preparedness frameworks. Current approaches often lack comprehensive strategies, resulting in significant human and financial losses. This study introduces a five-tier Public Health Emergency and Disaster Management (PHEDM) framework designed to strengthen resilience from community action to national policy. Using a mixed-methods approach including literature review, stakeholder consultations, and pilot testing in Uttarakhand, the PHEDM framework was developed and evaluated. Training packages, structured by Bloom's taxonomy and expert review, were implemented across Tiers I–III, targeting community volunteers, frontline workers, and subnational managers. Community Threat and Hazard Identification and Risk Assessment (THIRA) tools guided the development of Village and District Disaster Management Plans. A standardized mentor-mentee system was integrated across all tiers. Results from the Uttarakhand pilot and subsequent scale-up in Rajasthan and five additional states demonstrated significant knowledge gains (18–25%,  $p < 0.001$ ), high satisfaction, and*

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*improved community preparedness. The PHEDM framework aligns with national and international policies, integrating climate resilience and public health. Enhanced by its mentorship system, PHEDM offers a scalable, adaptable model for strengthening health systems and community preparedness, contributing to global health security and sustainable development.*

**Keywords:** *Public Health Emergency Management, Public Health Emergency and Disaster Management, International Health Regulation, Bloom's Taxonomy, Whole-of-Society Approach, Nature-Based Solutions, Pandemic Preparedness, Climate Resilience, Health Emergency and Disaster Risk Management*

## 1. Introduction

The escalating frequency and severity of public health emergencies driven by infectious disease outbreaks, natural and human-induced disasters, and climate-driven impacts pose significant threats to global health. The COVID-19 pandemic alone incurred indirect costs exceeding 10% of the global GDP, disrupting supply chains and livelihoods [1, 2]. Climate change exacerbates these challenges, with rising temperatures, extreme weather events, and environmental degradation amplifying the public health risks. The Conference of the Parties (COP) agreements under the United Nations Framework Convention on Climate Change (UNFCCC), including COP21, COP25, COP26, and COP29, emphasise integrated adaptation, health-focused climate resilience, and support for loss and damage in vulnerable communities [3]. Frameworks such as the World Health Organization's Health Emergency and Disaster Risk Management (WHO-Health EDRM) and its guidance on preparing for national responses to health emergencies and disasters advocate risk-based, all-hazard approaches and multisectoral collaboration to strengthen health system preparedness [4, 5]. However, a scoping review by Sasie et al. (2024) highlighted persistent gaps in public health emergency management frameworks, including fragmented coordination, limited community engagement, and inadequate integration of climate-related risks, underscoring the need for comprehensive, scalable models that bridge grassroots actions with policy [6]. Successful examples, such as Mumbai's Dharavi model for COVID-19 containment and Odisha's cyclone response, demonstrate the value of community-driven strategies [7, 8]. Field Epidemiology Training Programs (FETPs), implemented in over

80 countries, are a cornerstone of global health security, equipping public health professionals with advanced skills in disease surveillance, outbreak investigation, and data analysis to effectively manage health threats such as Ebola, Zika, and COVID-19 [9]. For instance, FETP-trained epidemiologists have strengthened national surveillance systems and led rapid response teams, contributing to timely outbreak containment and improved global health outcomes [10]. However, as noted by Sasie et al. (2024), FETPs primarily focus on individual- and institutional-level training, with less emphasis on community empowerment, climate resilience, cross-sectoral policy integration, and policies.

Drawing on lessons from the COVID-19 pandemic, Mumbai's Dharavi model, Odisha's cyclone response, the growing threat of climate change, and established systems such as the Field Epidemiology Training Program (FETP), WHO-Health Emergency and Disaster Risk Management (Health EDRM), UNFCCC, and International Health Regulations (IHR), the need to address persistent gaps in community engagement, climate resilience, and policy integration is evident. In response, an innovative five-tier Public Health Emergency and Disaster Management (PHEDM) framework was designed and developed. This innovative framework is a joint initiative of the National Institute of Disaster Management (NIDM), the National Centre for Disease Control (NCDC), and CDC India. This framework is the outcome of a systematic approach, comprehensive literature review, and multiple expert consultations aimed at bridging these gaps and enhancing preparedness for future pandemics and climate-related emergencies in the country. The PHEDM framework builds on the strengths of FETPs by integrating a five-tier model that actively engages community volunteers, frontline workers, subnational managers, national and state leaders, and policy makers. It incorporates community-led hazard, vulnerability, and risk assessment processes; climate-related health risk management; and the development of community preparedness and response plans and protocols, thereby strengthening the capacity for effective public health emergency and disaster management at all levels.

The PHEDM framework is closely aligned with India's National Health Policy (NHP) 2017, which emphasises robust emergency response systems, training community health workers, such as Accredited Social Health Activists (ASHAs), and integrating mental health initiatives, such as yoga [11]. PHEDM's Tier I empowers community

volunteers, including ASHAs and Gram Panchayat members, with skills in first aid, cardiopulmonary resuscitation (CPR), and outbreak reporting, fostering community-driven preparedness, as seen in Dharavi's COVID-19 response, which reduced case growth from 12% to 1% [7]. Tier II trains frontline workers in triage, community infection control, rapid testing, and enhancement of local response capacity. Tiers III and IV strengthen a country's emergency management capacity and coordination through emergency operations centres (EOCs/PHEOCs) and hospital preparedness. Tier V engages policymakers to integrate community lessons into national frameworks. These elements align with the NHP's goals of building resilient health systems and ensuring multisectoral coordination to address pandemics and climate-related disasters.

The PHEDM framework is further aligned with India's National Disaster Management Plan (NDMP), NITI Aayog's report on future pandemic preparedness, and global benchmarks, including IHR 2005, Sustainable Development Goals (SDGs), particularly those related to health system strengthening and resilience, and COP agreements [12, 13, 14, 15]. COP25 urged countries to boost adaptation and capacity building, with India emphasising a collective journey towards a clean, green, and healthy planet. [16]. By incorporating nature-based solutions, such as afforestation and mangrove restoration, the PHEDM supports India's NDC commitments and COP25/COP29's emphasis on ecosystem-based adaptation. Unlike FETPs, which excel in epidemiological training but are less focused on climate adaptation or community engagement, the PHEDM integrates adult learning principles from Bloom's taxonomy, Incident Management/Response Systems, and well-being activities to create a continuous adaptive preparedness process [17, 18, 19].

The PHEDM framework operates within the context of global and national disaster risk reduction and public health priorities, aligned with the WHO Health EDRM, Sendai Framework for Disaster Risk Reduction (SFDRR), and UNFCCC COP agreements [4, 3, 20].

India's diverse socioeconomic and environmental landscapes require a scalable and participatory model that leverages local traditions and knowledge and integrates them into national policies. By extending FETPs' epidemiological expertise to include community action, climate resilience, and policy engagement, PHEDM addresses the need for a cohesive, evidence-based approach to mitigate and manage public health and climate-related crises [6, 9, 10].

A summary of the key research questions and their corresponding descriptions are provided below to guide the focus and objectives of this study (Table 1).

**Table 1: Overview of the PHEDM Framework: Key Questions and Contributions**

Key Question	Description
What is already known?	Frameworks like WHO’s EDRM use risk-based, all-hazard approaches but focus on isolated phases (e.g., preparedness, response). FETP, gaps remain in linking community action to policy, addressing climate threats and workforce well-being.
What is the new approach and how does it differ?	PHEDM offers a five-tier model: community empowerment, frontline training, emergency coordination, institutional preparedness, and policy leadership. Integrates adult learning, nature-based solutions, digital monitoring, and well-being activities. Connects grassroots to national policy via Incident Response/Management Systems for real-time, scalable coordination.
What are the implications for public health preparedness?	PHEDM improved participant knowledge by 25%, well-being by 94% and mentor-mentee system during training. Modular design adapts to pandemics and climate disasters, integrating community innovations into national strategies. Fosters resilient health systems

## 2. Objectives

### Primary Objective:

1. To develop, implement, and evaluate a structured, tiered adult learning training

package for public health emergency and disaster management (PHEDM) across communities, frontlines, and professional responders.

### **Secondary Objectives:**

1. To evaluate the effectiveness of a tiered adult learning training package (Tiers I-III) in enhancing participants' knowledge, skills, and engagement.
2. To assess the impact of integrated well-being activities, such as yoga sessions, on participants' health and workforce fitness.
3. To explore participants' perceptions of improvements in collaboration, information sharing, and emergency response following the training.
4. To examine the integration of the PHEDM framework into national policy and emergency management systems (Tier V) and its influence on policy adoption and emergency response outcomes.

## **3. Methods**

### **Overview**

A mixed-methods approach was employed to develop and evaluate the Public Health Emergency and Disaster Management (PHEDM) framework. The framework was developed through a narrative literature review synthesising evidence from peer-reviewed studies, policy documents, and reports on public health emergencies and climate resilience, including lessons from the COVID-19 pandemic and successful models such as Mumbai's Dharavi containment strategy [6, 7]. Multi-stakeholder expert consultations involve national and state health officials, disaster management authorities, climate experts, and community leaders to identify gaps in existing frameworks, such as working in silos, fragmented coordination, and limited community

engagement, as highlighted by Sasie et al. (2024) [6]. The methodology drew on established frameworks, including the FETP model [10], World’s Health Emergency and Disaster Risk Management (WHO-Health EDRM) [4], Sendai Framework for Disaster Risk Reduction (SFDRR) [20], WHO International Health Regulations (IHR) 2005 core capacities [14], WHO Joint External Evaluation (JEE) Monitoring and Evaluation Framework [21], India’s National Health Policy (NHP) 2017 [11], and UNFCCC COP agreements [3]. The process targeted the cognitive, psychomotor, and affective learning domains using Bloom’s taxonomy [17] to ensure comprehensive capacity building across community volunteers, frontline workers, subnational managers, national/state leaders, and policymakers. The consultations informed the design of a five-tier model, with each tier tailored to a specific role (Figure 1).

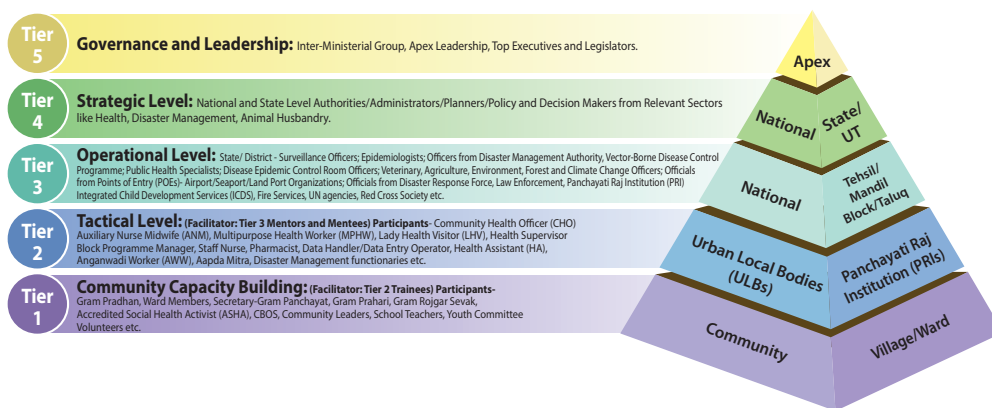


Figure 1 : Hierarchical PHEDM Framework: A Five-Tiered Approach to Public Health Emergency and Disaster Management in India

## PHEDM Training Package Development and Implementation

The PHEDM training package for Tiers I–III was systematically developed through a series of expert stakeholder workshops to ensure input from a diverse range of professionals in public health, disaster management and emergency response. This development process was further strengthened by rigorous external expert reviews,

which provided critical evaluations and validations of the training content. Bloom's taxonomy was deliberately applied throughout the design and review phases to ensure that the curriculum comprehensively addressed the cognitive (knowledge-based), psychomotor (skills-based), and affective (attitude- and value-based) domains of learning [17]. This approach facilitated the creation of a robust and multidimensional training package capable of meeting the diverse learning needs of participants at different levels. Following the initial development, the Tier III training package underwent an additional layer of scrutiny through an external review, ensuring alignment with national and international standards and best practices. Subsequently, the package was submitted to the NIDM for formal approval of the training programme. Upon receiving NIDM approval, the Tier III training package as a participant and facilitator guide was officially published and made available for implementation [25].

Uttarakhand State was strategically selected as the site for pilot testing of the PHEDM training package, providing an opportunity to evaluate the program's effectiveness and contextual relevance in a real-world setting. The outcomes of this pilot implementation are expected to inform the further refinement and scaling of the training program across other regions.

### **PHEDM Tier III Training**

The Tier III pilot was conducted in two cohorts in Uttarakhand (Garhwal and Kumaon Mandals), covering all 13 districts, with 32 participants and 13 mentors in Garhwal, and 31 participants and 4 mentors in Kumaon, with a total of 80 participants. A standard cohort size of 35–40 participants was maintained throughout the Tier III training program to ensure an interactive learning environment and a manageable span of control for the facilitators.

The program was conducted over five consecutive days and was strategically structured to maximise knowledge acquisition and practical skill development in emergency response and incident management. Training commenced with a faculty preoperative workshop designed to establish foundational knowledge and align instructional objectives, followed immediately by a dedicated mentor workshop aimed

at building mentoring capacity and ensuring effective knowledge transfer through evidence-based adult learning methods. Over the next three to four days, participants engaged in a balanced mix of instructor-led didactic sessions (comprising 20–30% of each day) that provided theoretical grounding in incident response principles and protocols and active learning methods (70–80%), such as case studies, scenario-based exercises, and tabletop exercises utilising Incident Response System (IRS) protocols to reinforce decision-making, problem-solving, and collaborative planning. A key feature of the program was the development and group discussion of state-specific public health threats and disaster case scenarios, which allowed participants to contextualize their learning and collaboratively address regionally relevant challenges. Specialised hands-on training was delivered by expert teams from the National Disaster Response Force (NDRF), focusing on the practical application of emergency protocols and operational procedures during crises, and included state-specific presentations to assess and enhance the understanding of existing capacities in personnel, resources and systems. Finally, emphasis was placed on sharing best practices, enhancing inter-agency collaboration, and aligning district disaster management plans (DDMP) with national disaster management plans (NDMP) and frameworks. The evaluation tools included pre and post-tests, interactive quizzes (Kahoot App), Likert scale ratings, and qualitative feedback. Integrated yoga sessions were conducted to enhance the resilience of the workforce. Post-training “hotwash” debriefings and detailed training reports provided continuous improvement [26]. Following the successful pilot implementation in Uttarakhand, the PHEDM training package was further refined and modernized based on pilot feedback and evaluation. This enabled its subsequent launch in Rajasthan and facilitated the scale-up of the program across five additional states, ensuring a broader regional impact and integration of best practices identified during the pilot phase.

### **Tier I and II Training: Risk Assessment Approach and Process**

For the pilot implementation of Tiers I and II in Uttarakhand, Udham Singh Nagar District was chosen under the guidance of State Health, Disaster Management, and Panchayati Raj leadership. Nausar Village Panchayat (VP) in the Khatima Block was selected based on hazard and vulnerability assessments. Stakeholders recommended conducting a comprehensive risk assessment prior to training to establish a resilient

community model. An adapted Community Threat and Hazard Identification and Risk Assessment (THIRA) tool was developed and applied by a multidisciplinary team comprising members of the Integrated Disease Surveillance Program (IDSP), Disaster Management, Panchayati Raj, local authorities, community leaders, and frontline workers. This multidisciplinary team worked under the guidance of experts from the NCDC, the NIDM, and CDC India.

The assessment process involved systematic identification and evaluation of local threats and hazards using the Community THIRA tool, with risks assessed for their scale, likelihood, and potential impacts. Guided by the trained team, the community analyzed existing capabilities, identified critical gaps, and developed targeted plans for resource allocation and capacity building. This structured assessment provided a robust evidence base for tailoring training modules, developing a Village Disaster Management Plan (VDMP), and establishing relevant protocols, ensuring that preparedness strategies were aligned with the specific needs and vulnerabilities of the community.

The risk assessment also guided the refinement of Tier I and II training packages before pilot testing, which involved 41 and 35 participants for Tier I and II, respectively, at Nausar Village. The methodology was participatory and multisectoral, engaging local volunteers, leaders, and frontline workers through flip chart instructions, group discussions, practical exercises, and disaster simulations. The training emphasised community risk assessment, VDMP, protocol development, and the application of adult learning principles. Each Tier I and II training session was delivered over three half-day sessions to facilitate active participation and accommodate community schedules. Monitoring and evaluation included pre- and post-training assessments and participant feedback to measure improvements in knowledge, skills, and community preparedness.

### **Scaling and Policy Integration**

Following pilot testing and refinement based on participant feedback and emerging evidence, the Tier I and II curricula were launched in Alwar District, Rajasthan. Tier III is similarly scaled to the additional states. Tier IV was not advanced, pending the review of Tier III outcomes. For Tier V, policymakers engaged in workshops, leadership summits, and policy briefs to align the PHEDM framework with broader emergency preparedness strategies [27].

## Data Collection and Evaluation

Quantitative and qualitative data were collected to assess PHEDM's feasibility, impact, and policy integration of the PHEDM. Pre- and post-training assessments measured knowledge and skill gains, while interactive tools, such as Kahoot App quizzes and Likert-scale ratings, evaluated participant engagement [26]. Qualitative feedback from focus groups, including participants, faculty members, stakeholders, and "hotwash" debriefings, provided insights into adaptability to infectious diseases and climate-related hazards. Policy integration was evaluated through stakeholder consensus at the Leadership Summit and adoption of PHEDM-aligned policies [27]. Data were analysed to ensure alignment with the IHR 2005, JEE, NHP 2017, and COP priorities, with continuous refinement based on the findings of the analysis.

## 4. Results

The pilot implementation and evaluation of the PHEDM framework in Uttarakhand demonstrated significant improvements in participants' knowledge, practical skills, and overall community preparedness for public health emergencies and disasters. These positive outcomes informed the program's successful launch in Rajasthan and supported its subsequent scale-up to include five additional states. Utilising a mixed-methods approach that integrated Bloom's taxonomy and the Community THIRA tool, the training was effectively tailored across Tiers I–III. The evaluation findings indicate that this approach enabled scalable capacity building for both pandemic preparedness and climate-related hazards, highlighting the adaptability and effectiveness of the PHEDM framework in diverse settings.

### PHEDM Tier III Training Outcomes

The Tier III pilot in Uttarakhand's Garhwal and Kumaon Mandals engaged 80 participants, including 17 mentors from the health, disaster management, animal health, climate, and law enforcement sectors [25]. Pre- and post-training assessments

showed a significant increase in mean knowledge scores from 55% to 78% (23% absolute gain,  $p < 0.001$ ), reflecting enhanced operational coordination and resource management skills (Table 2). Participants rated the sessions highly (mean 4.3/5 on a Likert scale), with 85% reporting improved well-being from integrated yoga sessions, supporting the NHP 2017’s holistic health focus [11]. Real-time evaluation via interactive tools, such as the Kahoot App, was well received (99% positive feedback), aligning with the method’s emphasis on immediate assessment. The mentor-mentee system, with mentors matched to two to four mentees, achieved 95% completion, ensuring effective knowledge transfer [24].

**Table 2 : Uttarakhand Pilot Test-Pre and post-training evaluation of knowledge and skills**

Metrics	Pre-Training	Post-Training	Change/Outcomes
Mean Knowledge Score	55%	78%	+23% ( $p < 0.001$ )
Mean Session Rating (Likert)	-	4.3/5	Good satisfaction
Yoga Session Positive Feedback	-	85%	Improved well-being
Feedback on Real Time assessment	-	99%	High acceptance of immediate evaluation

Scaling to Rajasthan formally launched further improved outcomes, with knowledge scores rising from 59% to 84% (25% gain,  $p < 0.001$ ), session ratings of 4.6/5, and 91% positive yoga feedback, demonstrating the framework’s adaptability (Table 3). [26].

## PHEDM Tier III Launch in Rajasthan

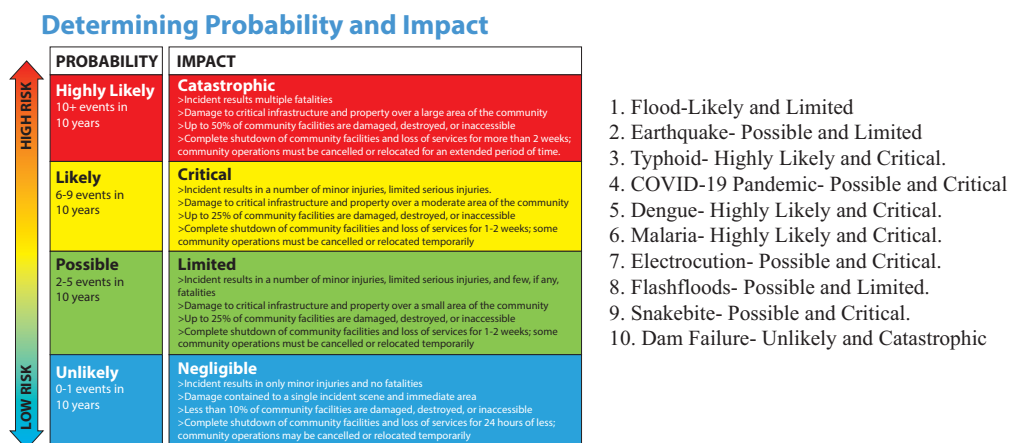
**Table 3 : PHEDM Tier III Launch in Rajasthan- Pre and post-training evaluation of knowledge and skill**

Metrics	Pre-Training	Post-Training	Change/ Outcomes
Mean Knowledge Score	59%	84%	+25% (p <0.001)
Mean Session Rating (Likert)	-	4.6/5	High satisfaction
Yoga Session Positive Feedback	-	91%	Improved well-being
Top 3 Scorers Facilitated	-	3 per cohort	Boosted motivation

## PHEDM Tier I and II: Community-Level Outcomes

In Nausar Village, Uttarakhand (population: 4,896; area: 686.8 hectares), the Community THIRA tool identified key hazards, including frequent health threats (Typhoid, Dengue, Malaria: highly likely, critical impact) and environmental risks (floods: 2010, 2013, 2019; earthquakes: November 2022; potential dam failure: unlikely, catastrophic) [23]. Existing capabilities, such as the functional Panchayati Raj Institution (PRI) system, Village Health Sanitation and Nutrition Committee, one health sub-centre, one wellness centre, five Anganwadi Kendras, and active community organisations (Mahila & Yuva Mangal Dal), supported preparedness, although gaps in healthcare capacity and historical data were noted (Table 4)

Table 4 : Nausar Village Hazard and Risk Assessment



**PHEDM Tier I**

Tier I training (41 participants) increased the knowledge scores from 56% to 74% (18% gain, p < 0.001), with high satisfaction (4.8/5) and 94% yoga positive feedback (Table 5).

Table 5 : Pre and post-training evaluation of knowledge and skills

Metrics	Pre-Training	Post-Training	Change/Outcomes
Mean Knowledge Score	56%	74%	+18% (p <0.001)
Mean Session Rating (Likert)	-	4.8/5	Very High satisfaction
Yoga Session Positive Feedback	-	94%	Strong positive impact
Top 3 Scorers Facilitated	-	3 per cohort	Boosted motivation

## PHEDM Tier II

Tier II training (35 participants) improved knowledge from 58% to 83% (25% gain,  $p < 0.001$ ), with a 4.6/5 session rating and 90% positive yoga feedback (Table 6). The top scorers (three per cohort) were motivated.

**Table 6 : Pre and post-training evaluation of knowledge and skills**

Metrics	Pre-Training	Post-Training	Change/Outcomes
Mean Knowledge Score	58%	83%	+25% ( $p < 0.001$ )
Mean Session Rating (Likert)	-	4.6/5	High satisfaction
Yoga Session Positive Feedback	-	90%	Improved well-being
Top 3 Scorers Facilitated	-	3 per cohort	Boosted motivation

The training facilitated the establishment of Community Emergency Management Teams (CEMTs) and Community Emergency Response Teams (CERTs) in Nausar Village, comprising the Gram Pradhan, ward members, Accredited Social Health Activists (ASHAs), community leaders, and school teachers. CEMTs adopted the Incident Management/Response System (IMS/IRS) model to coordinate management functions, while CERTs were responsible for immediate response activities, aligning with the National Health Policy (NHP) 2017's emphasis on community participation. This collaborative approach led to the development of a comprehensive Village Disaster Management Plan (VDMP) and associated protocols, thereby strengthening community resilience to the identified hazards (Figure 2). When scaled to Alwar and Rajasthan, the model demonstrated sustained improvement, with Tier I and II training further reinforcing VDMP development and promoting community-driven preparedness.

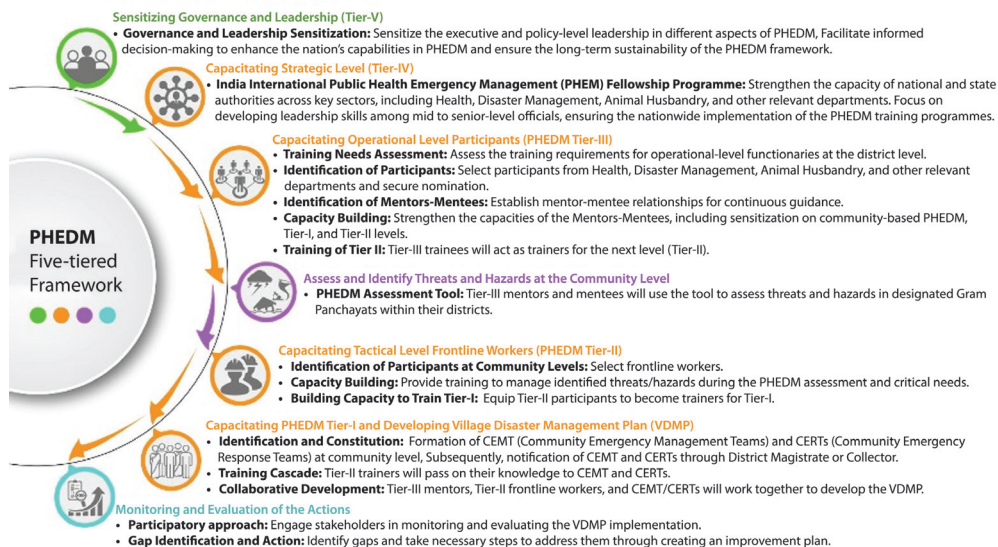


Figure 2 : PHEDM Five-Tiered Framework: Strengthening Public Health Emergency and Disaster Management in India

## 5. Discussion

The Public Health Emergency and Disaster Management (PHEDM) framework demonstrated significant improvements in knowledge, skills, and community preparedness across Tiers I–III, addressing the critical gaps in public health emergency management identified by Sasie et al. (2024), such as fragmented coordination and limited community engagement [6]. The mixed-methods approach, integrating a narrative literature review, multi-stakeholder consultations, and pilot testing in Uttarakhand and launched in Rajasthan, facilitated the development of a scalable five-tier model that aligns with India’s National Health Policy (NHP) 2017 [11], WHO International Health Regulations (IHR) 2005 [14], and UNFCCC COP priorities for climate-resilient health systems [3]. The significant knowledge score gains (18% for Tier I, 25% for Tier II, and 23–25% for Tier III,  $p < 0.001$ ) reflect the effectiveness of training packages designed to engage experts, community leaders, volunteers, and

stakeholders using Bloom's taxonomy, which targets the cognitive, psychomotor, and affective domains [17]. These outcomes compare favourably with Field Epidemiology Training Programs (FETPs), which typically achieve 15–20% knowledge gains in epidemiological training but lack PHEDM's focus on community empowerment and climate adaptation [9, 10].

The application of the Community THIRA tool in Nausar Village identified critical health (Typhoid, Dengue, Malaria) and environmental (floods, earthquakes) hazards, enabling tailored training and the development of Village Disaster Management Plans (VDMs). This community-driven approach, supported by the formation of Community Emergency Management Teams (CEMTs) and Community Emergency Response Teams (CERTs), aligns with the NHP 2017's emphasis on community participation and strengthens local resilience, mirroring successful models such as Mumbai's Dharavi containment strategy [11, 7]. The high satisfaction ratings (4.3–4.8/5) and positive yoga feedback (85–94%) underscore the framework's holistic approach, addressing workforce well-being as prioritized by the NHP 2017 [11]. The mentor-mentee system, with 95% completion, facilitated effective knowledge transfer and cascade training, and enhanced scalability across tiers [24].

Tier III's success in Uttarakhand (80 participants) and Rajasthan (knowledge gain from 59% to 84%) demonstrates the PHEDM's adaptability to subnational coordination needs, aligning with the IHR 2005 core capacities for surveillance and response [14]. The integration of emergency operations centres (EOCs/PHEOCs) and climate risk assessments supports the Sendai Framework for Disaster Risk Reduction (SFDRR) and the WHO Health EDRM priorities for multisectoral collaboration [3, 4]. The leadership summit's stakeholder consensus highlights the PHEDM's potential for policy integration, aligning with NITI Aayog's pandemic preparedness recommendations and UNFCCC COP25/COP29's focus on health resilience [13, 3]. However, the deferred implementation of Tier IV limits insights into national-level outcomes, and the framework's reliance on pilot settings (Uttarakhand) and launch in (Rajasthan) may constrain generalisability to diverse contexts [26].

The inclusion of nature-based solutions, such as afforestation, in Tier I training aligns with India's Nationally Determined Contributions (NDCs) and COP25/COP29

ecosystem-based adaptation goals, addressing climate-driven hazards, such as floods and heat waves [3, 11, 16]. Unlike traditional frameworks, PHEDM's integration of climate resilience and community engagement in PHEDM positions it as a comprehensive model for addressing the dual challenges of pandemics and climate change, as highlighted by Sasie et al. [6]. The high acceptance of real-time evaluation tools (99% for Tier III) suggests that interactive methods, such as the Kahoot App, enhance engagement, supporting the method's emphasis on robust evaluation [26]. These findings underscore PHEDM's potential of PHEDM to bridge the gaps in global health security and disaster risk reduction, offering a scalable model for India and beyond.

## **6. Conclusion**

The PHEDM framework effectively enhanced knowledge, skills, and community preparedness across Tiers I–III, as evidenced by significant knowledge gains (18–25%,  $p < 0.001$ ), high satisfaction (4.3–4.8/5), and positive well-being outcomes from yoga sessions (85–94%) in the Uttarakhand pilot and Rajasthan launch [26]. The Community THIRA tool and mentor-mentee system (95% completion) enabled tailored VDMPs and scalable capacity building, addressing gaps in community engagement and climate resilience, as identified by Sasie et al. [6]. The framework's alignment with the NHP 2017, IHR 2005, SFDRR, and UNFCCC COP agreements positions it as a robust model for integrating public health and climate adaptation [11, 14, 16]. The stakeholder consensus of the leadership summit underscores its potential for national policy integration [27]. The PHEDM offers a scalable, evidence-based approach to strengthen health systems and community resilience, contributing to global health security and sustainable development.

## **7. Recommendations**

1. **Scale PHEDM Implementation:** Expand Tiers I–III to additional states, leveraging digital platforms to sustain training and cascade knowledge transfer, and build on the mentor-mentee system's 95% completion rate [25].

2. **Advance Tier IV and V:** Implement and evaluate Tier IV to strengthen national-level preparedness and engage policymakers through regular summits to ensure sustained policy integration [27].
3. **Enhance Climate Integration:** Incorporate advanced climate risk assessments into all tiers, aligning with COP25/COP29 priorities and India's NDCs to address escalating climate-driven hazards [3, 16].
4. **Strengthening Community Networks:** Supporting CEMTs and CERTs with ongoing training and resources to maintain VDMPs and ensure long-term community resilience [25].
5. **Leverage Technology:** Integrate real-time evaluation tools, such as the Kahoot App and digital learning platforms, to enhance engagement and monitor outcomes across diverse settings [26].

## 8. Limitations

The limitations of this study are typical of pilot studies and do not undermine the robust outcomes achieved. The deferred implementation of Tier IV, planned for a future phase, limits current insights into national-level preparedness but does not affect the success of Tiers I–III. Pilot testing for Tiers I and II was conducted in Nausar Village, Uttarakhand, and launched in Alwar, in Rajasthan. Tier III was piloted in 13 districts in Uttarakhand and launched in Rajasthan, further expanded to five additional states, successfully producing Village and District Disaster Management Plans (VDMPs/DDMPs), and establishing Community Emergency Management and Response Teams (CEMTs/CERTs). However, broader applications across India's diverse contexts are required to confirm their scalability. Self-reported feedback, including Likert-scale ratings (4.3–4.8/5) and yoga session feedback (85–94%), was consistent with standard evaluation methods but may benefit from objective validation in future studies [26]. The lack of long-term follow-up data, typical for initial pilots, limits insights into sustained outcomes, which can be addressed through extended monitoring [25]. These limitations highlight opportunities for further research to enhance the scalability and impact of the PHEDM frameworks.

## **9. Data Access Statement**

Research data supporting this publication are available from NIDM training and provided by Integrated Disease Surveillance Programme, Department of Medical Health and Family Welfare, Dehradun, Government of Uttarakhand.

Link1: <https://nidm.gov.in/modules.asp>

Link 2: <https://doi.org/10.18231/j.ijfcm.2023.010>

## **10. Ethical Considerations**

Administrative permission from the participants in the training and individual informed consent were obtained. Responses were anonymous, and average scores were analysed while keeping all records confidential.

## **11. Funding**

No funding was obtained for the manuscript development.

## **12. Competing Interests**

The authors declare no competing interests.

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# Landslide Hazard Zonation Mapping Using Binary Logistic Regression and its Validation in Mandakini Valley, Garhwal Himalaya

Suman Das<sup>1</sup> and Ashish Kumar Saha<sup>2</sup>

## Abstract

*Landslides frequently occur in mountainous regions globally, posing risks to human settlements, lives, livelihoods, and infrastructure. The monsoon season in June 2013 began two weeks ahead of its typical schedule in Uttarakhand. Between June 15 and June 17, 2013, intense rainfall and cloud bursts affected numerous areas in the upper Himalayan region. Landslides are complex phenomena that are influenced by a variety of factors, including rock composition, strength of the rock mass, and other physical characteristics. In the Himalayan region, landslides occur in different types and dimensions and have generic variations. The present study focused on Landslide Hazard Zonation (LHZ) in the Mandakini watershed, which is part of the Garhwal Himalaya region. The dataset for this study comprises 18 landslide conditioning factors along with the landslide inventory map of the region. Training data (70%) and testing data (30%) were then separated from the landslide inventory data. The Binary Logistic Regression (BLR) of Maximum likelihood estimation is used with the logit variable (derived from the dependent variable) to assess the probability of landslides in the area. The model was validated based on the ROC curve. It was observed that the binary logistic regression model selected 82 out of 102 initial independent variables. The BLR model attained a prediction accuracy of 89.6%, effectively classifying binary training data. In the accuracy assessment through ROC, 91.4% were achieved using testing data. The LHZ map provide valuable insight to understand the landslide hazard in the Mandakini valley especially after 2013 Kedarnath disaster. The research will further help in effective planning and landslide mitigation strategies for comprehensive landslide disaster management over the study area.*

**Keywords:** *Landslide, LHZ, BLR, ROC, Mandakini Valley, Himalaya*

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## 1. Introduction

Landslides frequently occur in mountainous regions globally, posing risks to human settlements, lives, livelihoods, and infrastructure. The monsoon season in June 2013 began two weeks ahead of its typical schedule in Uttarakhand. Between June 15 and June 17, 2013, intense rainfall and cloud bursts affected numerous areas in the upper Himalayan region. Landslides are intricate phenomena influenced by various factors, including rock composition, strength of the rock mass, and other physical characteristics. In the Himalayan region, landslides occur in different types and dimensions and have generic variations. The present study focused on Landslide Hazard Zonation (LHZ) in the Mandakini watershed. The Himalaya are vulnerable to numerous natural hazards owing to their geo-dynamically active characteristics and distinct weather patterns. An initiative for mapping landslide hazards would aim to pinpoint regions susceptible to landslides based on geological and topographical factors as well as the current landslide situation (Mathew et al., 2007). The likelihood of landslide hazards, which is characterized as the chance of potentially destructive events occurring in a specific location, depends on various environmental factors that influence this risk. A landslide hazard zonation (LHZ) map offers advanced insight into potential landslide zones based on a set of geo-environmental elements conducive to landslides. It also helps in implementing mitigation techniques following any landslide threat. The premise of LHZ relies on the belief that future landslides are likely to occur in areas that share similar geo-environmental conditions to those found at present and historical landslide sites. (van Beek, 2002; Kanungo et al., 2012). Landslide Hazard zonation,' (LHZ) refers to the likelihood of landslide occurrences within a geographical area, determined by various geo-environmental factors. (Kayastha et al., 2013 Kundu et al., 2013; Bisht et al., 2018). The primary objective of landslide hazard mapping is to reduce the losses of human life and economic assets. A landslide hazard map provides crucial information about locations where landslides may happen in the future by highlighting regions with previous landslide events and areas that share similar physical features (van Westen et al., 2006). A landslide hazard zonation (LHZ) map can significantly mitigate the risk associated with possible landslides through the implementation of suitable management strategies and in the course of planning forthcoming

development projects. The dependability of these landslide hazard maps is influenced by the data quality and the methods or models employed in their creation (Ayalew and Yamagishi, 2005).

The selection of factors that influence landslides relies on the availability of data, the expertise of professionals, and comprehensive field investigations. The advantage of the machine learning technique is that it is a fast computation package, easy data availability, and Geographical Information systems (GIS) have given new thrust into landslide hazard research (Hadmoko et al., 2010; Pradhan & Lee, 2010; Tien Bui et al., 2012; Li et al., 2013; Qiu et al., 2017). The precision of a hazard map relies significantly on the effective integration of environmental elements that lead to landslides. Consequently, it is essential to comprehend how each factor contributes to landslide events and to examine the relationships between these factors in order to assess the likelihood of landslides occurring in a specific region.

Numerous approaches and techniques have been suggested to evaluate landslide hazards. Regardless of the variations, all the methods and processes rely on a limited number of assumptions (Pardeshi et al., 2013). First, landslides leave sensible signs, such signs can be recognized, categorized, and mapped through the analysis of satellite imagery or in the field (Mondini et al., 2011; Thanh and De, 2012; Guzzetti et al., 2012). Second, landslides and their circumstances are governed by physical properties that can be examined empirically, deterministically or statistically. Conditions that activate landslides, directly or indirectly related to slope failures, can be used to frame predictive models for the spatial occurrence of landslides (Dietrich et al., 1995). Third, for landslide studies, "the past and present are keys to the future" (Carrara & Guzzetti, 1995). This assumption indicate that future landslides are more probable under analogous conditions, so facilitating an understanding of both history and present instability (Furlani & Ninno, 2015). Lastly, the spatial occurrence of landslides can be analyzed through heuristic investigation, calculated through physical models or through the analysis of environmental information. Hence, a territory can be classified based on various susceptibility classes ranked based on different probabilities (Carrara et al.,

1995; Glade & Crozier, 1996). Approaches and techniques for assigning landslide hazards can be qualitative or quantitative. Qualitative methods are inherently subjective, evaluate vulnerability through heuristic techniques, and express risk levels with descriptive language. In contrast, quantitative approaches yield numerical estimates, or in other terms, probabilities related to landslide occurrences within specific hazard zones (Guzzetti et al., 1999).

Quantitative methods in Statistical approaches analyze the functional relationships between known factors of slope instability and the distribution of landslides, both historical and current (Huabin et al., 2005; Van Westen et al., 2008). An examination of the literature database indicates that methods grounded in statistics and those based on physical principles are favoured for determining landslide susceptibility in quantitative terms. Reichenbach et al. (2014) examine statistically-based modelling methods and terrain zonation. They use the words "susceptibility modeling" and "modeling" to refer to landslide susceptibility modelling. With the development of geospatial technologies and improved computational resources, research on landslides has evolved significantly. The integration of GIS and remote sensing has demonstrated its effectiveness as a valuable tool for conducting landslide hazard assessments (van Westen et al., 2003). The Geographical Information System (GIS) has played a role in structuring the database and performing mathematical modelling. Over the past forty years, researchers worldwide have conducted numerous studies on landslide hazard assessment utilizing both quantitative and qualitative models enhanced by remote sensing and GIS methodologies. (Pradhan and Lee, 2010; Tien Bui et al., 2011; Li et al., 2013; Qiu et al., 2017). The thematic layers related to the causes of landslide events have been developed using remote sensing techniques, along with ancillary data.

## 2. Study Area

The present study focused on the Mandakini watershed (Figure 1), which is fall in Rudraprayag district of Uttarakhand. Mandakini valley spans approximately 1,646 sq. kms. It consists of the Lesser and Higher Himalayan terrain of Garhwal Himalaya. Mandakini watershed stretches from Kedarnath in the north to Rudraprayag in the south, situated between 30°15'N to 30°45'N and 78°45'E to 79°30'E. It falls within Survey of India Toposheet numbers - 53J /14, 53J/15, 53N/1, 53N/2, 53N/3, 53N/4, and 53N/6.

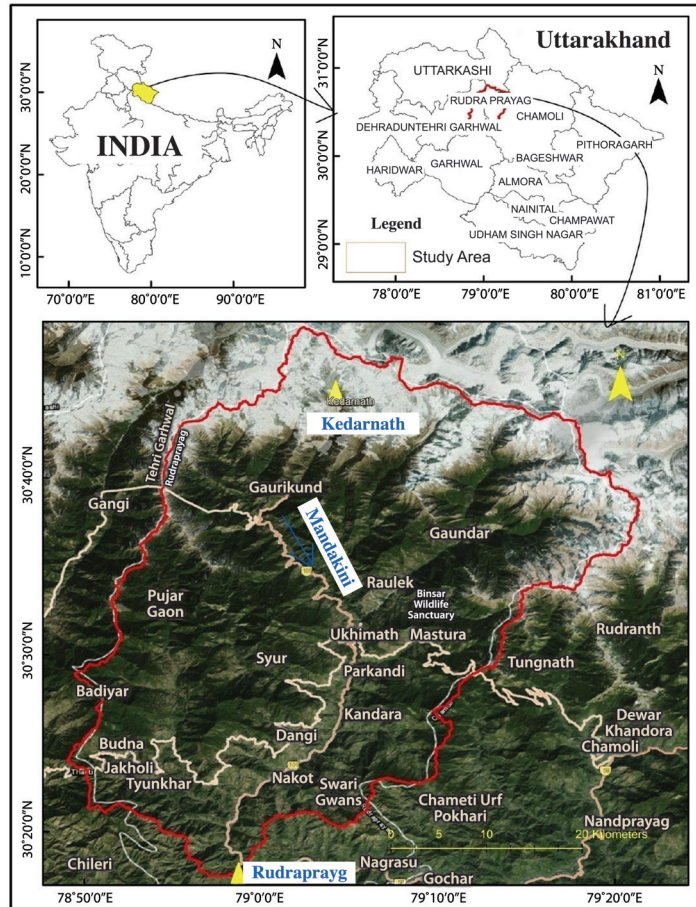


Figure 1 : Study area, Mandakini Valley

Source : Das & Saha., 2020.

Rudraprayag town is located at the confluence of Mandakini and Alaknanda rivers. The Mandakini River traverses the Main Central Thrust (MCT), which delineates the boundary between the Higher Himalaya and the Lesser Himalaya. The MCT zone is characterized by numerous faults and consists of fractured and weathered rock formations. The primary roadway within this watershed provides connectivity from Sonprayag in the north to Rudraprayag in the south. Beyond Sonprayag, individuals undertake a trek of approximately 17 kilometres to reach Kedarnath town, renowned

for its historical and cultural significance, as it is home to the esteemed Kedarnath Temple (Naithani et al., 2011; Sati et al., 2011; Sati & Gahalaut, 2013). The catchment exhibits a diverse array of rock types, with geological ages spanning from the Palaeoproterozoic to the Mesoproterozoic period. The rock succession exposed in the study area is categorised into two groups, the rock sequences between Main Central Thrust (MCT) and Main Boundary Fault (MBF), which constitute the Lesser Himalaya, and the rock sequences located north of Main Central Thrust (MCT), which comprise the Higher Himalaya.

### **3. Materials and Methods**

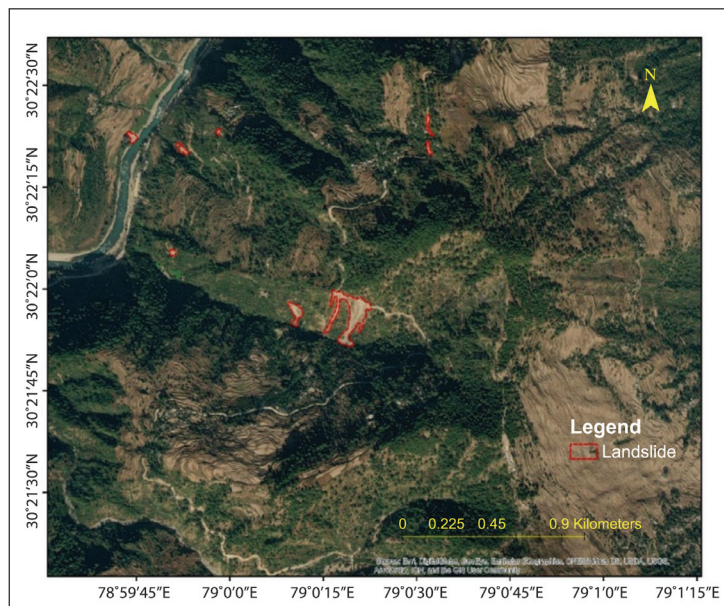
To create a landslide susceptibility map, it is crucial to develop a spatial database that includes several factors related to landslides. Data from satellite sensor IRS-1D LISS IV multispectral digital data with spatial resolution of 5m and IRS Cartosat-1 Pandigital stereo data with spatial resolution of 2.5m were used for this study. The topographic parameters including slope, slope length, elevation, curvature and convergence index, were from Cartosat DEM, while environmental factors, including Normalised Difference Vegetation Index (NDVI), and land use land cover (LULC) extracted through LISS IV multispectral digital data. The spatial data pertinent to landslide hazard zonation can be divided into three principal categories: landslide inventory data, environmental factors, and triggering factors (van Westen et al., 2006).

#### **3.1. Landslide Inventory**

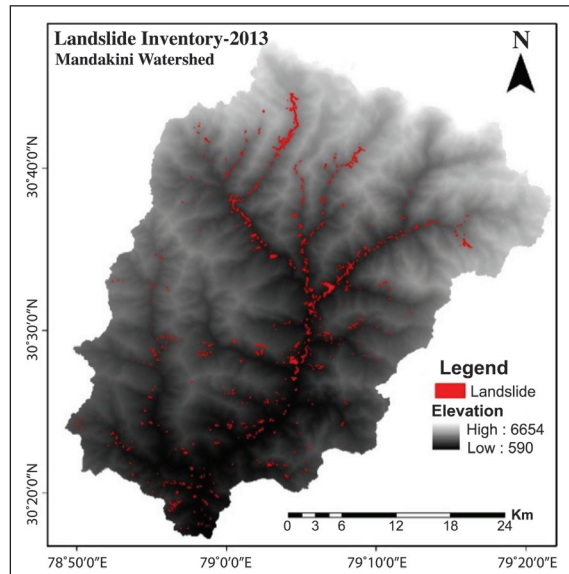
The landslide inventory map is the backbone of the landslide study. The initial critical step in conducting landslide hazard assessments involves gathering data on prior landslide events. This information is essential for informing and improving future spatial predictions (Ercanoglu & Gokceoglu, 2004). In this study, an image interpretation technique was used to obtain a multi-temporal landslide inventory map. Landslides exhibit distinctive characteristics in remote sensing images and aerial photographs, including aspects like colour, shape, shadow, and variations compared to the surrounding terrain (Yang et al., 2010; Guzzetti et al., 2012; Sun et al., 2018). High-resolution Google Earth data of the Kedarnath disaster time, along with SRTM DEM data, were used as the primary data product for generating the multi-temporal

landslide inventory. The following steps were used to map a landslide polygon in ArcGIS and build its inventory attribute. In total, 5.30 sq. km. of landslides were identified in the post-disaster landslide inventory (Figure 2b) and mapped from the digitally enhanced Google Earth satellite images based on the tone, texture, and size of the landslide (Figure 2a). The landslides were field-checked along NH 109, Kalimath Road, Okhimath Road, and the foot track to Kedarnath.

Most of the landslides occur within a distance of less than 30 m on either side of the road and might have resulted from the removal of the toe or the cutting of roads. Riverbank failures due to toe erosion by drainages/nalas are also common in the study area, especially along the Mandakini River and its tributaries passing through the area. Most of the landslides are shallow translational debris/rock slides, with a depth of slip plane being less than 5 m. The landslide inventory has been separated into training and testing/validation datasets, with 70% assigned for training and 30% allocated for testing and validation. This division was conducted through random splitting, as the temporal data regarding landslide occurrences was not available.



(a)



(b)

Figure 2 : Landslide Inventory using Google Earth Image (a) & Landslide Inventory Map of the Study Area (b).

### 3.2. Elevation

While elevation does not directly cause landslides, it interacts with various other factors such as tectonic activities, weathering processes, erosion and precipitation. Consequently, elevation plays a significant role in landslide occurrence and affects the overall system (Rozos et al., 2011). The elevation map was generated using the CARTOSAT DEM in Arc GIS software. The classification of the DEM was done using natural break methods (Li et al., 2013; Arabameri et al., 2020). The elevation varies from 590 m to 6654 m in the study area (Figure 2b). For the present study, the elevation was subdivided into five classes: < 1725 m, 1725–2511 m, 2511–3400 m, 3400–4404 m, and > 4404 m, respectively (Figure. 3a).

### 3.3. Slope

The degree of slope is a significant factor that impacts slope stability (Pourghasemiet al., 2012b; Lee & Min, 2001). This conditioning factor is commonly utilized in the

preparation of landslide hazard maps (Pourghasemi et al., 2012a & b). The slope for the present study area was derived from the digital elevation model (DEM) and classified into five distinct categories using the natural break method (Figure 3b), i.e.,  $<15.71^\circ$ ,  $15.71^\circ - 25.03^\circ$ ,  $25.03^\circ - 33.47^\circ$ ,  $33.47^\circ - 42.78^\circ$  and  $> 42.78^\circ$ . In the slope angle, the highest area covered by class three covers 28.80% of the total geographical area, followed by class two, four one, and five, which cover an area of 26.08%, 21.70%, 19.99%, and 9.43%, respectively.

### **3.4. Slope Aspect**

The slope aspect has been identified as a significant contributing factor to the occurrence of landslides (Lee et al., 2004; Pourghasemi et al., 2012a). The characteristics of slope aspect within the study area were obtained using the Digital Elevation Model (DEM), using Arc GIS, and it was categorized into nine classes; i.e., north, northeast, east, southeast, south, southwest, west, northwest and flat, to illustrate the correlations between aspect and landslides (Figure 3c).

### **3.5. Curvature**

The curvature function as a marker of the erosional susceptibility of the slopes as well as the existing slope morphology (Sharma & Mahajan, 2018). In this study, a plan curvature map was generated using ArcGIS GIS software and classified into three categories: concave, planar, and convex. This classification was based on specific criteria: a profile curvature of less than -0.1 indicates convex slope morphology; a profile curvature between -0.1 and 0.1 denotes linear slope morphology; and a profile curvature greater than 0.1 signifies concave slope morphology (Zhang et al., 2012), which are illustrated in the accompanying curvature thematic map (Figure 3d).

### **3.6. Slope Length**

Slope length is considered one of the topographical factors that influence the occurrence of landslides. Many researchers (i.e., van der Knijff et al., 2000; Kumar & Anbalagan, 2015; Arabameri et al., 2020) consider slope length as a landslide

conditioning factor in their studies. The slope length of the terrain is classified into five different classes, i.e., < 14.82 m, which cover an area of 72.95%, 14.82 m – 45.82 m, 45.82 m – 83.57 m, 83.57 m – 133.44 m and > 133.44 m (Figure 3e).

### 3.7. Relative Relief

Relative relief refers to the variation between the minimum and maximum altitudes within a defined area or facet, and it is determined through spatial analysis (Pandey et al., 2008). The relative relief is calculated in the Arc-GIS environment using the DEM data. The range of relative relief (Figure. 3f) was found to be 915.83–3117.21 m. Further, it is classified into five classes, i.e., < 1433.80 m, 1433.80-1684.15 m, 1684.15-1977.67 m, 1977.67-2374.78 m, and >2374.78 m.

### 3.8. Convergence index (CI)

The convergence index is a critical topographic factor that significantly influences landslide occurrences within a particular region. The convergence index (CI) provides a metric for assessing whether flow within a cell diverges (convergence index < 0) or converges (convergence index > 0), (Claps et al., 1996). CI map prepared using a tool in SAGA-GIS (Figure. 4a).

$$CI = \left( \frac{1}{8} \sum_{i=1}^8 \theta_i \right) - 90^\circ \quad \text{Eq. 1}$$

Where  $\theta$  denotes the mean angle created between the aspects of neighboring cells and the orientation towards the central cell.

### 3.9. Lithology

Distinct lithological units exhibit varying landslide hazard values, making them a critical component in landslide hazard assessments (Pourghasemi *et al.*, 2012b; Yalcin & Bulut, 2007). The lithological mapping of the region (Figure. 4b) indicates the presence of the Vaikrita Formation in the northern area, characterized primarily by coarse mica-garnet-kyanite and sillimanite-bearing psammitic metamorphics. This formation constitutes a

significant portion of the Greater/Higher Himalaya in Garhwal. These rocks contribute to a highly rugged topography, featuring deep gorges and high peaks, with the higher altitudes predominantly snow-covered, resulting in the formation of U-shaped broad valleys characteristic of a glacial landscape. This geological group is intruded by Tertiary pegmatites and granites, specifically the Badrinath Granite, which facilitates the development of migmatites, biotite-rich schists, and calc-schists. The mineral assemblages observed suggest a medium to high-grade metamorphism, comparable to the amphibolite facies found in the rocks of the Vaikrita Group (Valdiya, 1980). The Munsiri Formation, located to the south of this geological feature, is found within the Lesser Himalaya. This formation comprises a range of rock types, including meso- to epi-grade para- and ortho-gneisses, schists, calc-silicate rocks, marbles, granites, and their corresponding mylonitic equivalents (Choubey *et al.*, 1999). South of the Munsiri Formation, the Ramgarh Group is Present. The primary rock formations consist of dark green chloritic and greenish-brown schist, finely layered biotite-rich coarse-grained schist, interbedded sericite-chlorite-quartz schist, and porphyroid (Chahal *et al.*, 2017). The high landslide hazard in the Mandakini watershed is due to complicated geological settings, changing slopes and relief, substantial rainfall, and ever-increasing human intervention in the ecosystem (Kumar & Anbalagan, 2019). Extreme climatic events contribute to the instability of the terrain, as exemplified by the Kedarnath disaster (Dubey *et al.*, 2013).

### 3.10. Thrust

A map illustrating the significant thrusts traversing the study area (Figure 2.1) has been prepared upon the work of Valdiya (1980) and Khanduri *et al.* (2018). The Main Central Thrust (MCT) represents the primary geological feature, forming an extensive area between Rambara and Kund (Valdiya, 2014; Sundriyal *et al.*, 2015) characterized by rocks that have been significantly sheared, fractured, and crushed due to tectonic processes (Chahal *et al.*, 2017). Apart from the MCT, VT and Banswara Thrust are the significant structures found in the study area. The following buffer zones were designated around these thrusts: < 500, 500–1000, 1000–1500, 1500–2000, and >2000 m. in Arc-GIS (Figure. 4c) using the Euclidean distance tool. The presence of the Main Central Thrust zone contributes to significant shearing and fracturing within the region, resulting in rock instability and an increased susceptibility to landslides and other natural hazards.

### 3.11. Distance from Faults

Faults represent a weak line or zone distinguished by intensely fractured geological formations (Fell *et al.*, 2000). Alaknanda Fault, Mandakini Fault, Rawan Ganga Fault, Madhyamaheshwar Fault, Laster fault and Kyunja Fault are among the tectonic interactions found in the region. These significant faults are aligned along the main channel course of the valleys. The distance from faults was divided into five categories with an interval of 500 m (Sahana and Sajjad., 2017) in Arc-GIS using the Euclidean distance tool (Figure. 4d).

### 3.12. Lineament

The study area's photo-lineament (buffer) map was extracted from the LISS - IV satellite image as polyline features. A lineament is a linear feature of the surface, whether simple or composite, that can be mapped and has components that are aligned either straight or slightly curved. These features are distinctly different from the pattern of surrounding elements and indicate a subsurface phenomenon (van & Seijmonsbergen, 2006; Hamza & Raghuvanshi, 2017). Near the lineaments, the likelihood of landslide occurrences is deemed greater compared to regions located farther from the lineaments. The distance to lineament was calculated using the Euclidean distance tool with an interval of 500 m in Arc-GIS and categorized into five buffer zones of < 500, 500–1000, 1000–1500, 1500-2000, and >2000 m (Figure. 4e).

### 3.13. Distance to Drainage

Drainage networks have the potential to negatively impact slope stability through mechanisms such as toe undercutting or by saturating the material that forms the slope. Consequently, the distance to drainage layers has been analyzed using GIS (Saha et al., 2005). Based on the extracted drainage, a map of proximity to the drainage network was generated using the Arc-GIS Euclidean distance tool (Arabameri et al., 2020). In this study, five distinct buffer zones were produced in the study area, e.g., 0–100, 100–200, 200–300, 300-400, and more than 500 m (Figure 4f).

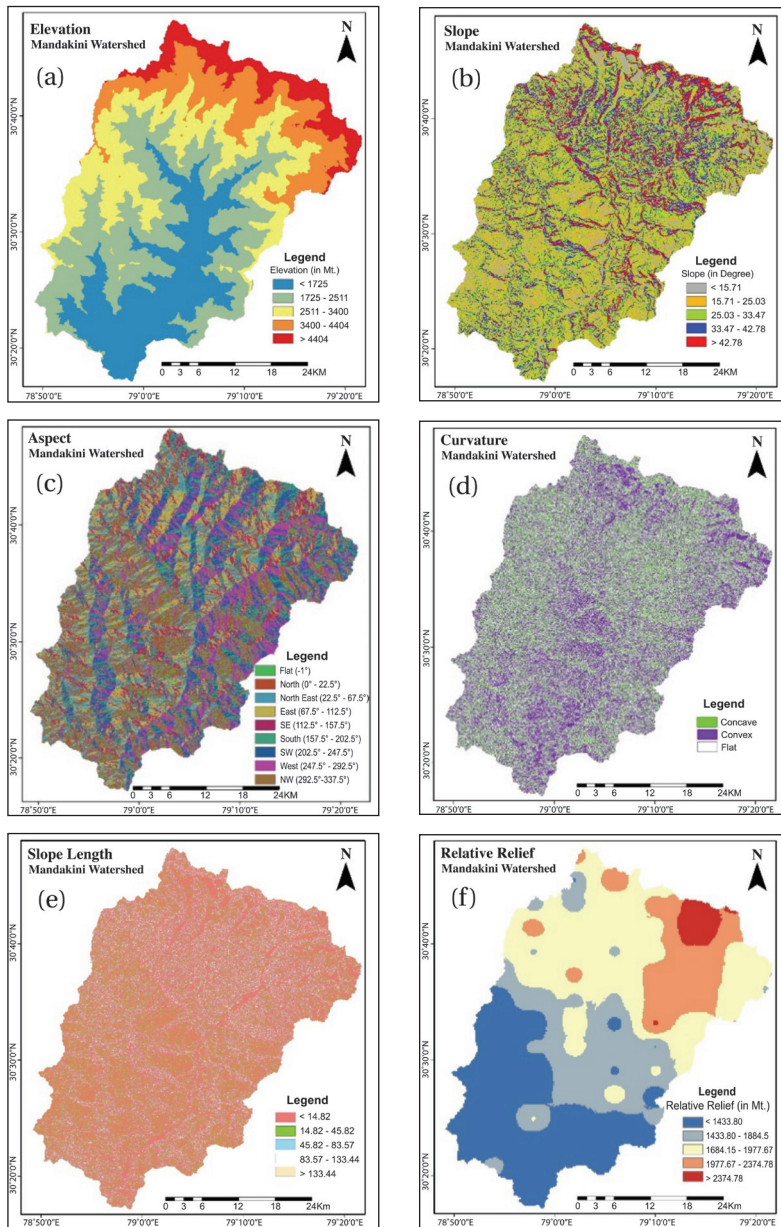
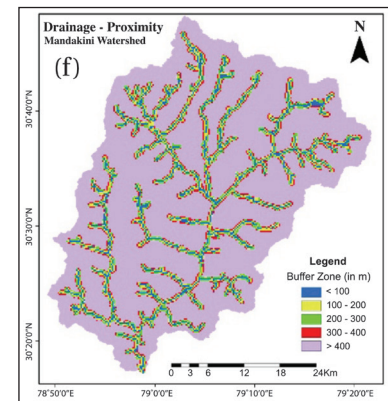
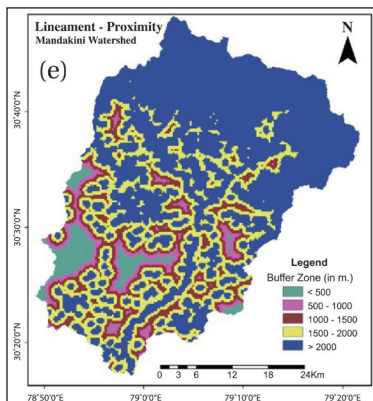
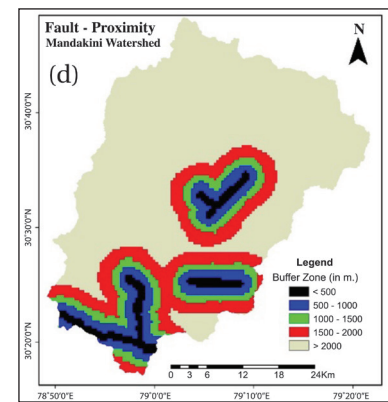
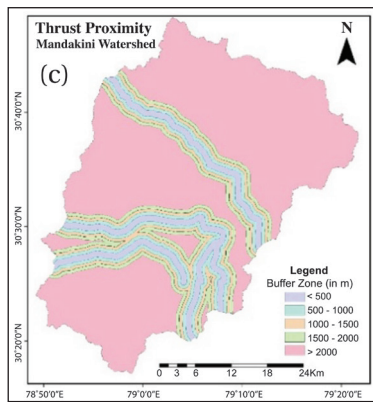
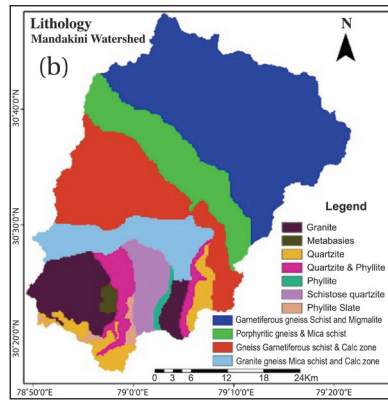
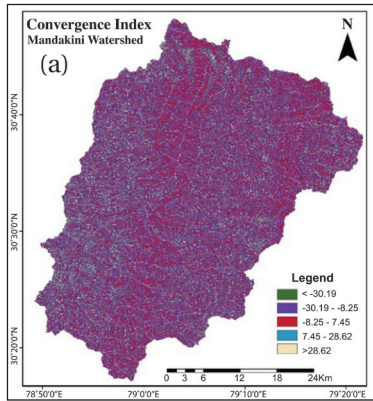


Figure 3 : Landslide Causative Factors – Elevation (a), Slope (b), Aspect (c), Curvature (d), Slope Length (e) & Relative Relief (f).



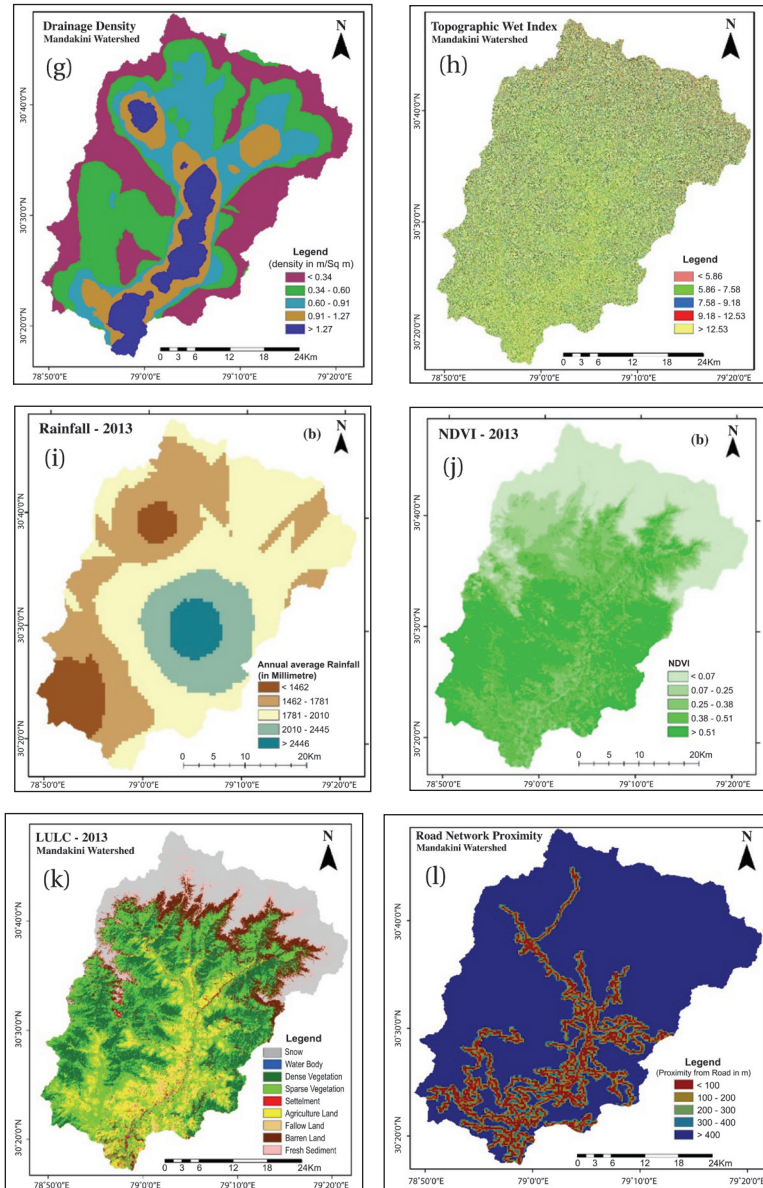


Figure 4 : Landslide Causative Factors – Convergence Index (a), Lithology (b), Thrust (c), Fault (d), Lineament (e) Drainage (f), drainage Density (g), TWI (h), Rainfall (i), NDVI (j), LULC (k) & Road Network (l).

### 3.14. Drainage Density

The total length of drainage channels within a unit area of a river basin is known as the Drainage Density (Horton, 1945). The study by Dahal et al. (2008b) shows that the areas with higher drainage density are typically more vulnerable to shallow-seated landslides during heavy rainfall, whereas the large-scale landslide is frequent in areas with lesser drainage density. Drainage density was calculated using line density tools in Arc GIS (Saha et al., 2002, 2005) and divided into five classes: 0–14.80, 14.80–40.29, 40.29–68.24, 68.24–108.53, and > 108.53m/sq m (Figure. 4g).

### 3.15. Topographical Wet Index (TWI)

It is another topographic factor within the runoff model (Pradhan and Kim, 2014; Wang et al., 2015). TWI is calculated as:

$$TWI = \ln \left( \frac{S}{\tan \alpha} \right) \quad \text{Eq. 2}$$

Where S denotes the specific catchment area for each cell, and  $\beta$  signifies the slope gradient (measured in degrees) of the topographical elevations (Moore *et al.*, 1991; Saadatkhah et al., 2015). In the present study, the TWI was calculated using the tool in SAGA-GIS, and values were arranged in five classes through the natural break method (NBM) of Jenk's in Arc GIS: 0 to 5.86, 5.86 – 7.58, 7.58–9.18, 9.18- 12.53 and > 12.53 as shown in the Figure 4h.

### 3.16. Rainfall

Rainfall is an important triggering factor in landslide occurrence in Himalaya from the beginning of June to the end of September; thus, it is another significant parameter in landslide hazard zonation. In this study, an annual rainfall map was generated by using the weather data of fifteen stations of the Indian Meteorological Department (IMD) in the area and its elevation of surrounding localities by applying the Co-kriging (Eq. 3) interpolation method (Goovaerts, 2000),

$$z_{CK}^*(u) = \sum_{a=1}^{n(u)} \lambda_{\alpha}^{CK}(u) Z(u_{\alpha}) + \lambda^{CK}(u) [y(u) - m_y + m_z], \quad \text{Eq. 3}$$

The interpolation was done using Arc-GIS environment, classified into five classes through natural break method (NBM) of Jenk's in GIS (Figure. 4i), where the minimum rainfall was 1033 mm/year and maximum rain was 3217 mm/year in 2013.

### 3.17. Normalized Difference Vegetation Index (NDVI)

A high vegetation density can reduce the probability of landside occurrence and also defer soil transmission and erosion, while a high probability of landslide occurrence can be found in the low vegetation area (Arabameri et al., 2020). The NDVI values varied from -0.12 to +0.68 (Figure. 4j). The NDVI is further categorized into five sub-layers for using the natural break method.

### 3.18. Land Use and Land Cover (LULC)

The distribution of land cover plays a critical role in influencing slope conditions related to landslide occurrences (Lee et al., 2013). The present study used IRS-1D and LISS-IV remote sensing data to map land cover. In order to improve the result and achieve higher accuracy than using spectral data from a remote sensing sensor alone, the LISS-IV, multispectral image with spatial resolution of 5m was used as the primary data for creating the LULC map of the study area. Additionally, ancillary data, such as the DEM from Cartosat 1 and NDVI (Figure 4k) extracted from the LISS-IV image also incorporated into the sensing classification process in this study. In this study, the supervised classification of the Maximum Likelihood classifier (MLC) was used on the Erdas Imagine platform. The LULC is classified into nine categories, namely – Snow, Water Body, Dense Vegetation, Sparse Vegetation, Agricultural Land, Fallow Land, Barren Land, Fresh Sediment and Settlement (Figure 4k). Various LULC classes over the Mandakini watershed indicate the significant impact of 2013 Kedarnath disaster on LULC (Das & Saha., 2020). The study shows that dense and sparse vegetation classes cover 22.05% and 27.03%, respectively. At the same time, the agricultural land covers

an area of about 12.08% and fallow land of 3.22%. In the category of Barren, land and fresh sediment cover 9.17% and 3.95%, respectively.

### **3.19. Proximity to the Road**

In, Himalaya most of the landslides were observed along the road. Distance from the road has been produced through proximity analysis. (Mathew et al., 2009). Using Google Earth Image and Survey of India toposheets as a reference map, a polyline feature of the NH-109, Kalimath-Okhimath road and other PWD roads were prepared. The distance to roads was determined using the Euclidean distance tool in the ArcGIS program (Arabamer et al., 2020). Furthermore it reclassified them into five classes: 0–100, 100–200, 200–300, 300–400 and >400 m, and >4000 m (Figure.4l).

## **4. Methodology**

As, discussed earlier As discussed earlier, elevation, slope, aspect, curvature, slope length, relative relief, convergence index, lithology, thrust, fault, lineament, drainage density, drainage network, topographical wet index, rainfall, land use land cover (LULC), NDVI, road network along with landslide Inventory has been used for hazard mapping. All datasets were generated within a GIS environment at a pixel resolution of  $5 \times 5$  m. The vector layers (i.e., landslide inventory, drainages, thrusts, and lithology/fault) corresponding to point, linear, and polygonal features were converted to raster format alongside other raster datasets such as elevation, slope, aspect and other parameters. All these raster datasets were converted to ASCII format using tools available in Erdas Imagine software. Thus, it can be read in SPSS for using Binary Logistic Regression (BLR) to predict landslide hazards. The database was further recoded in SPSS software for analysis purposes.

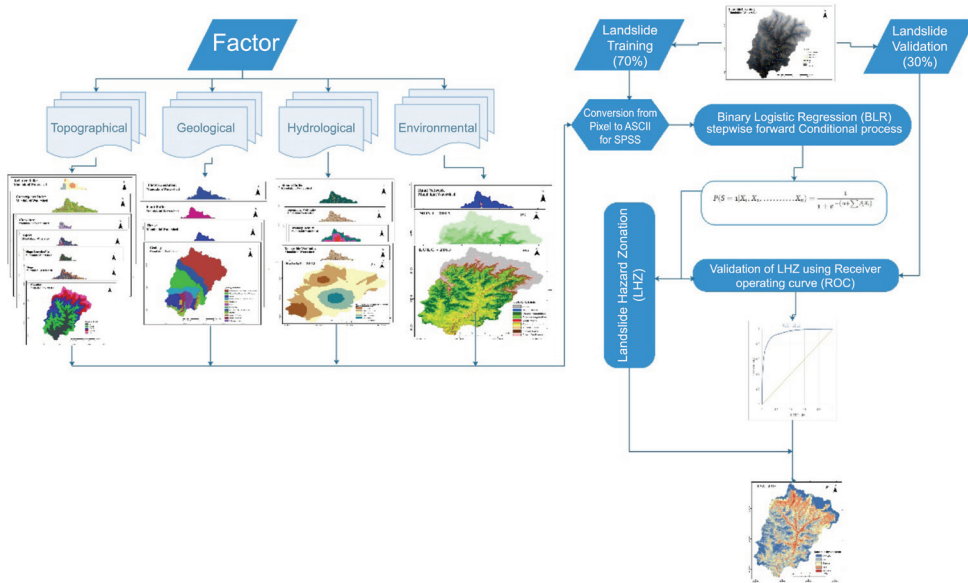


Figure 5 : Methodology Flow Diagram of Landslide Hazard Mapping over Study Area.

#### 4.1 Binary Logistic Regression (BLR) Analysis

To determine the probability, BLR uses maximum likelihood estimation based on the logit variable, which is transformed from the dependent variable. The BLR framework is a type of generalized linear regression model where relevant independent variables influence the positive outcomes of dependent variables. For LHZ, a considerable benefit of the BLR model, in comparison to other multivariate statistical methods, is that it has probability values that range from 0 to 1 (Kleianbum, 1991; Kumar & Anbalagan, 2015). BLR can be expressed as –

$$P = \frac{1}{1 + e^{-z}} \quad \text{Eq. 4}$$

In this context, the estimated probability of landslide occurring is denoted by p, which is influenced by various causative factors. The probability is characterized by an

S-shaped curve, as described by Kleianbum (1991), and the linear combination denoted by  $z$  (as shown in Eq. 5) can range from  $-\infty$  to  $+\infty$ . This unique aspect of the logistic function allows the logistic model to effectively assess the probability of slope failure risk for any specific grid. (Mathew et al., 2007a).  $z$  can be expressed as

$$Z = (\alpha + \sum_{i=1}^n \beta_i X_i) \tag{Eq. 5}$$

Where,

$\alpha$  is the constant,

$X_i$  is the independent variable, and

$\beta_i$  is the corresponding coefficient

Thus,  $z$  is an index that combines the independent variables. By substituting Eq. 4.2 in 4.1, then it would be:

$$f(z) = \frac{1}{1 + e^{-(\alpha + \sum_{i=1}^n \beta_i X_i)}} \tag{Eq. 6}$$

Thus, the logistic model for slope failure can be expressed as:

$$P(S=1|X_1, X_2, \dots, X_n) = \frac{1}{1 + e^{-(\alpha + \sum_{i=1}^n \beta_i X_i)}} \tag{Eq. 7}$$

where,  $P(S=1|X_1; X_2; \dots X_n)$  is the probability of a land unit–cell undergoing slope failure, given the presence of independent variables  $X_1$  to  $X_n$ .  $X_1, X_2, \dots, X_n$

A constant ( $\alpha$ ) and the coefficients of the independent variables ( $\beta_i$ ) are among the regression parameters that are estimated by the model. Using a maximum likelihood approach, this estimation is based on the dependent variable’s status inside the sample cells and the values of the independent variables (Mathew *et al.*, 2009). The value of

independent variables associated with causative factors is included in the database to estimate the BLR coefficients and the condition of the dependent variable, which indicates whether landslides are present or absent of each pixel has been carefully assessed. It is assumed that the predictor variables are mutually independent. Every input parameter was acquired in raster format with a grid size of 5m x 5m. In the Mandakini watershed, 211233 (5 m×5 m) pixels were identified as landslide affected. Using a random sampling selection, 70% of landslide pixels, i.e.,147863, have been selected for the regression analysis, and the remaining 30% of landslide pixels (i.e., 63,370) have been retained for accuracy assessment. Similarly, an equal percentage (i.e.,70%) of the non-landslide pixels about 459,56890 (5 m×5 m) has been randomly selected from the study area, and the rest is used for accuracy assessment purposes.

## 4.2. Validation of the Model

The validation is crucial for landslide hazard mapping. The landslide hazard model will lack significance without validation. The assessment of model validity can be performed by juxtaposing the computed probability values for different cells with their actual states. This procedure is enabled through receiver operating characteristic (ROC) curve analysis (Zweig & Campbell, 1993). In this study, the ROC curve has been used (Kundu et al., 2013; Kumar & Anbalagan, 2015; Sun et al., 2018) to estimate the accuracy of the binary logistic regression model for landslide prediction, which is used as a quantitative measurement. The ROC curve illustrates the relationship between the probability of correctly identifying actual positive landslides and the probability of incorrectly identifying false positives, as the cut-off probability varies (Gorsevski et al., 2000). This curve effectively represents the trade-off between sensitivity ( $S_n$ ) and specificity ( $S_p$ ). Sensitivity, defined as the probability that a landslide cell is accurately classified, is represented on the y-axis of the ROC curve; conversely, one minus sensitivity reflects the false-negative rate. Specificity indicates the probability that a non-slide cell is correctly classified; similarly, one minus specificity corresponds to the false positive rate and is plotted along the x-axis of the curve (Hanley & McNeil, 1982). The area under the curve assesses the test's effectiveness in accurately

classifying pixels associated with landslide risk, both with and without it. The shape of the curve reflects the model's performance. A ROC plot that is positioned closer to the upper left corner indicates a higher overall accuracy of the test.

## 5. Results

### 5.1. Logistic Regression Coefficient

As discussed earlier, the forward stepwise BLR approach commenced with no variables out of 102 excluded in the first Step and terminated at the eighty-three steps, retaining 82 variables out of 102 variables. The BLR model attained a prediction accuracy of 89.6% (Table. 1), by classifying binary training data. The area under the curve assesses the test's effectiveness in accurately classifying pixels associated with landslide risk versus those without. The shape of the curve indicates the performance of the model. Table 2 presents the comprehensive model statistics from the regression analysis performed in this study utilizing SPSS. A critical component for the conventional analysis of the test is the model chi-square value, which provides a standard significance test for logistic regression, as referenced by Ayalew and Yamagishi (2005). In this study, the model chi-square value is notably high, suggesting that the independent factors significantly influence the occurrence of landslides. The elevated chi-square value indicates that landslides are less likely in the presence of the influencing parameters when compared to the complete regression model that includes all parameters. If the ROC plot approaches the upper left corner, it signifies higher overall accuracy for the test.

**Table 1 : Classification Summary of the BLR Model at 83<sup>rd</sup> Step in 2013 (Post-disaster)**

Observed		Landslide in 2013			Percentage Correct
		0 (No Landslide)	1 (Landslide)		
		Step	Landslide in 2013	0 (No Landslide)	1 (Landslide)
83 <sup>rd</sup>		0 (No Landslide)	187364	23869	88.7
		1 (Landslide)	20278	190955	90.4
	Overall Percentage				89.6

*Note: The cut value is .500*

The Cox and Snell  $R^2$  (1989) and Nagelkerke  $R^2$  (1991) values always indicate how the model fits the data. According to Ayalew and Yamagishi (2005), an  $R^2$  value of 1 indicates a perfect fit, while an  $R^2$  value of 0 signifies no correlation with the data. Additionally, when the pseudo  $R^2$  exceeds 0.2, it demonstrates relative goodness of fit (Clark and Hosking, 1986; Akgun, 2012). The statistical values computed for Cox and Snell  $R^2$  (1989) and Nagelkerke  $R^2$  (1991) in the 75<sup>th</sup> Step observed as 0.341 and 0.814 respectively, at 85<sup>th</sup> Step which indicates a good fit to the data.

**Table 2 : The Overall Statistics of the BLR Model at 83<sup>rd</sup> Steps**

Hosmer and Lemeshow Test			-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Chi-square	df	Sig.			
726.060	8	.000	943538.141	0.341	0.814

*Note: Estimation terminated at iteration number 56 because parameter estimates changed by less than .001.*

The BLR analysis has produced estimates for the constant and the coefficients of the independent variables. A positive logistic coefficient signifies that the independent variable enhances the likelihood of a landslide, while negative values imply an inverse association with landslide incidence (Vanwalleghem et al., 2008; Kundu. et al., 2013; Kumar & Anbalagan, 2015). The predictors retained in the final model and their estimated coefficients are given in Table. 3. The corresponding predicted probability value was represented by numbers falling between 0 and 1. The pixel value around 0 signifies a low likelihood of landslide, whereas the value near 1 denote a higher probability of landslide. The likelihood map of LHZ has been reclassified into five hazard zones viz. Very high hazard (VHH), High hazard (HH), Moderate hazard (MH), Low hazard (LH), and very low hazard (VLH) zone (Figure 7).

**Table 3 : The Predictor Variables Retained in the BLR Model after 83<sup>rd</sup> Steps and their Coefficient**

Category	Class	B	S.E.	Wald	df	Sig.	Exp(B)
Elevation	Elevation <sup>2</sup>	.200	.014	191.446	1	.000	.819
	Elevation <sup>3</sup>	.738	.020	1365.365	1	.000	.478
	Elevation <sup>4</sup>	1.795	.025	5147.586	1	0.000	.166
	Elevation <sup>5</sup>	-6.971	.448	241.686	1	.000	.001
Slope	Slope <sup>1</sup>	-.391	.011	1163.212	1	.000	.676
	Slope <sup>2</sup>	.119	.010	131.524	1	.000	.888
	Slope <sup>3</sup>	.032	.009	11.937	1	.001	.969
Aspect	N	-.577	.022	704.284	1	.000	.562
	NE	-.040	.019	4.340	1	.037	.961
	E	.104	.019	31.339	1	.000	1.109
	SE	.048	.019	6.526	1	.011	1.049
	S	.184	.019	91.526	1	.000	.832
	SW	-.526	.020	697.800	1	.000	.591
	W	-.981	.023	1788.434	1	0.000	.375
	NW	-.453	.027	272.301	1	.000	.636
Curvature	Concave	-.054	.015	13.547	1	.000	.947
	Flat	.024	.007	11.247	1	.001	1.024
	Convex	-.089	.016	32.092	1	.000	.915

Category	Class	B	S.E.	Wald	df	Sig.	Exp(B)
Slope Length	SL <sup>2</sup>	-.176	.014	165.609	1	.000	.839
	SL <sup>4</sup>	.038	.018	4.407	1	.036	1.039
	SL <sup>5</sup>	-.161	.033	23.806	1	.000	.851
Convergence Index	CI <sup>1</sup>	.331	.014	587.783	1	.000	.718
	CI <sup>4</sup>	-.163	.008	407.671	1	.000	.850
	CI <sup>5</sup>	-.160	.017	89.305	1	.000	.852
Relative Relief	RR <sup>1</sup>	.503	.023	480.374	1	.000	.604
	RR <sup>3</sup>	.432	.015	844.264	1	.000	.649
	RR <sup>4</sup>	-.883	.018	2407.819	1	0.000	.414
Lithology	Qp	2.409	.037	4268.100	1	0.000	11.124
	Ggsm	1.410	.034	1735.814	1	0.000	4.095
	PgMs	.400	.037	118.747	1	.000	1.492
	GgsCz	.804	.036	493.482	1	.000	2.236
	GgmsCz	.883	.035	651.925	1	.000	2.419
	Gr	1.311	.064	420.953	1	.000	3.710
	Me	-.170	.041	16.770	1	.000	.844
	Sq	.635	.064	98.184	1	.000	1.886
	Ps	-.564	.041	187.545	1	.000	.569
	Ph	.828	.056	215.400	1	.000	2.288

Category	Class	B	S.E.	Wald	df	Sig.	Exp(B)
Proximity to Fault	Fault <sup>1</sup>	.770	.018	1825.589	1	0.000	.463
	Fault <sup>2</sup>	.870	.021	1647.243	1	0.000	.419
	Fault <sup>4</sup>	-.061	.020	9.565	1	.002	.940
	Fault <sup>5</sup>	-.440	.021	453.755	1	.000	1.552
Proximity to Thrust	Thrust <sup>2</sup>	.059	.015	14.840	1	.000	.943
	Thrust <sup>3</sup>	.705	.014	2456.714	1	0.000	2.024
	Thrust <sup>4</sup>	.367	.016	516.093	1	.000	1.444
	Thrust <sup>5</sup>	-.539	.013	1715.239	1	0.000	1.714
Proximity to Lineament	PL <sup>1</sup>	.392	.060	43.297	1	.000	1.480
	PL <sup>2</sup>	.356	.055	42.347	1	.000	.701
	PL <sup>4</sup>	-.083	.031	7.312	1	.007	.921
	PL <sup>5</sup>	-1.280	.027	2166.872	1	0.000	3.596
Proximity to Stream Network	Stream <sup>1</sup>	.130	.008	257.120	1	.000	.878
	Stream <sup>3</sup>	-.809	.012	4631.871	1	0.000	.445
	Stream <sup>4</sup>	-1.084	.014	5892.538	1	0.000	.338
	Stream <sup>5</sup>	-1.872	.011	30603.150	1	0.000	.154
Drainage Density	DDensity <sup>1</sup>	-1.223	.020	3733.136	1	0.000	.294
	DDensity <sup>2</sup>	.032	.011	9.209	1	.002	1.033
	DDensity <sup>3</sup>	.037	.014	6.895	1	.009	.964
	DDensity <sup>4</sup>	-.232	.015	237.939	1	.000	.793

Category	Class	B	S.E.	Wald	df	Sig.	Exp(B)
Topographic Wet Index	TWI <sup>1</sup>	.099	.015	43.656	1	.000	1.104
	TWI <sup>3</sup>	-.053	.011	24.151	1	.000	.948
	TWI <sup>4</sup>	.055	.015	14.030	1	.000	1.056
	TWI <sup>5</sup>	-.020	.009	4.824	1	.028	.981
Relative Relief	RF2013 <sup>1</sup>	-1.393	.022	4143.277	1	0.000	.248
	RF2013 <sup>2</sup>	-.259	.011	530.505	1	.000	.772
	RF2013 <sup>4</sup>	.437	.009	2377.798	1	0.000	1.548
	RF2013 <sup>5</sup>	.883	.013	4941.515	1	0.000	2.417
Land Use Land Cover	Lulc2013 <sup>1</sup>	2.066	.040	2611.439	1	0.000	7.894
	Lulc2013 <sup>2</sup>	.615	.026	10008.199	1	0.000	13.668
	Lulc2013 <sup>3</sup>	-1.717	.042	1676.225	1	0.000	.180
	Lulc2013 <sup>5</sup>	1.511	.015	9775.722	1	0.000	4.530
	Lulc2013 <sup>6</sup>	1.820	.014	16945.041	1	0.000	6.169
	Lulc2013 <sup>7</sup>	2.830	.018	24762.329	1	0.000	16.937
	Lulc2013 <sup>8</sup>	3.742	.015	59924.282	1	0.000	42.181
	Lulc2013 <sup>9</sup>	3.892	.015	67963.527	1	0.000	48.987
Normalized Difference Vegetation Index	NDVI2013 <sup>1</sup>	-.450	.016	765.200	1	.000	.638
	NDVI2013 <sup>2</sup>	.072	.011	45.224	1	.000	.931
	NDVI2013 <sup>4</sup>	.411	.018	550.464	1	.000	1.509
	NDVI2013 <sup>5</sup>	-.161	.023	48.078	1	.000	1.174

Category	Class	B	S.E.	Wald	df	Sig.	Exp(B)
Distance from Road Network	DR <sup>1</sup>	.109	.010	116.160	1	.000	1.115
	DR <sup>3</sup>	-.653	.015	1930.250	1	0.000	.520
	DR <sup>4</sup>	-.974	.018	2903.520	1	0.000	.377
	DR <sup>5</sup>	-1.342	.012	13430.802	1	0.000	.261
	Constant	-7.430	.051	20926.029	1	0.000	.001

SE: Standard Error of estimate, Wald: Wald chi-square value, df: Degree of freedom, Sig: Significance, Exp(B): Exponentiated coefficient

## 5.2. Validation & Accuracy of the Model

LHZ was validated based on the ROC curve for the present study. The ROC curve analysis was done using the remaining 30% dataset of the presence of landslide pixels (i.e., 63,370) and absence of landslide pixels (i.e., 196,95,810). The area under the curve quantifies the test's effectiveness in accurately classifying pixels associated with landslide risk, both present and absent. The configuration of the curve reflects the model's performance. A curve that approaches the upper left corner of the ROC plot indicates a higher overall accuracy of the test. The area beneath the ROC curve reaches a maximum of 1 for flawless prediction, while a number approaching 0.5 indicates the model's inadequacy. The ROC curve for the present study is presented in Figures 6. The area under the curve was 0.914 (Table 4), indicating an accuracy of 91.4% for the model constructed by binary logistic regression. The standard error (0.006) and asymptotic signature value are found to be < 0.05, which indicates the validity of the ROC curve. The landslide hazard map generated by this model demonstrates effectiveness in predicting both known and previously unrecognized landslide occurrences.

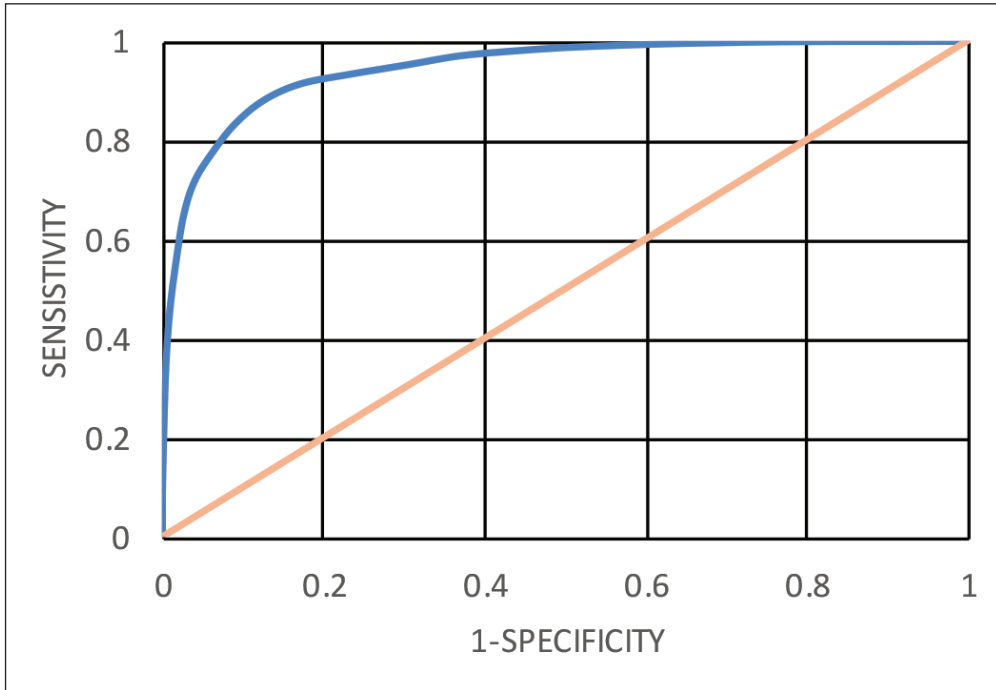


Figure 6 : ROC Curve of 2013 Showing Prediction Accuracy of LHZ Map.

Table 4 : Area under ROC Curve in 2013.

Area	Std. Error	Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
0.914	.006	0.000	0.905	0.926

Note: Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

## 6. Discussion

### 6.1. Analysis of BLR Result

Hazard Coefficients values ( $\beta_i$ ) in Table 4.7 suggest the significance of independent variables in determining the degree of landslide hazard in the study area. As mentioned earlier, positive and negative  $\beta_i$  values influence the probability of a landslide. A positive  $\beta_i$  value indicates that the corresponding classes contribute positively to the likelihood of landslide occurrence. In contrast, a negative  $\beta_i$  value suggests a negative influence on landslide occurrence. In contrast, insignificant independent values do not result in  $\beta_i$  values.

The binary logistic regression model selected 82 out of 102 initial independent variables in post-disaster Landslide Hazard Zonation (Table 4.7). The topographic factors Elevation class two, three, and four show positive  $\beta_i$  value influence, whereas slope and slope length also have a positive  $\beta_i$  value. Amongst the topographic attributes, the class two ( $15.71^\circ - 25.03^\circ$ ) and class three ( $25.03^\circ - 33.47^\circ$ ) slope categories, while sloping length class four has positive  $\beta_i$  value and class two and five resulted in a negative influence on slope failure. The Southeast, South, and East slope aspects show greater influence, creating slope instability than other aspect classes due to the higher solar insolation that these aspects receive in the Himalayan terrain. Flat curvature has also found positive  $\beta_i$  value while concave and convex resulted in a negative impact on slope failure. Within the convergence Index class, one has a positive  $\beta_i$  value for landslide conditioning. In the relative relief classes, a very high positive  $\beta_i$  value is observed relief for the very low to medium comparative class (e.g., Class one and three). In contrast, negative  $\beta_i$  is observed for the high relief class.

The next factor retained in the model is lithological units contributing towards slope instability. Within the lithological unit, higher  $\beta_i$  found in Quartzite & Phyllite (Qp) and Granite (Gr) of the Garhwal Group flowed by Garnetiferous Gneiss Schist & Migmalite (Ggsm) of the Vaikrita group. In contrast, high  $\beta_i$  observed in the Granitic Genesis Mica schist & Calc zone (GgmsCz) and Gneiss Garnetifarous Schist & Calc zone (GgsCz)

of Jutogh group flowed by phyllite (Ph) and Schistose Quartzite (Sq) of Garhwal and Vaikrita group respectively. Negative  $\beta_i$  value found in Metabasies (Me) and Phyllite Slate (Ps) of the Garhwal group. The proximity of geological structures exhibits a relatively high estimated coefficient value, suggesting an increased likelihood of slope failure in regions with elevated values for this parameter. This phenomenon can be attributed to the diminished strength of the rock mass in areas characterized by a high density of geological discontinuities. Conversely, both the distance to confirmed thrusts and faults, as well as the distance to lineaments, demonstrate an inverse relationship; as the distance increases, their influence on slope destabilization correspondingly diminishes. Positive  $\beta_i$  values are observed up to the distance of 1000 m in the case of the fault line and photo lineament, whereas in thrust, the Positive  $\beta_i$  value is reflected for classes two, three, and from 500 m to 2000 m.

Within the study area, the Hydrology factor drainage density shows a high positive  $\beta_i$  value in classes two and three, while high  $\beta_i$  values are observed for the stream distance up to 100 m. In the topographic wet index class, one and four have positive  $\beta_i$  values. Rainfall has found a strong relation with land sliding within the hydrological parameter. The High  $\beta_i$  value has been found in classes three, four, and five of the rainfall zones. The fresh sediment, settlement, and barren land, under the land use land cover parameter, exhibits a significantly high value of Exp ( $\beta_i$ ), which indicates its susceptibility to slope failure. This phenomenon may be attributed to the absence of root-induced cohesion in the material, thereby increasing the likelihood of shallow landslides. Additionally, agricultural lands and water bodies also contribute to the potential for slope failure, as evidenced by the findings of this analysis. A very high  $\beta_i$  value is also observed for distances up to 100 m of road, reflecting the contribution of fragile cut slopes left intact after the road construction.

## 6.2. Landslide Hazard Zonation

A landslide probability map has been created based on the statistical analysis and the output probabilities generated from the logistic regression model. The map has been categorized into various hazard classes utilizing natural break methods (NBM).

Worldwide, various literature shows that many methods are available to realize this necessity (Ayalew & Yamagishi, 2005; Lee, 2005).

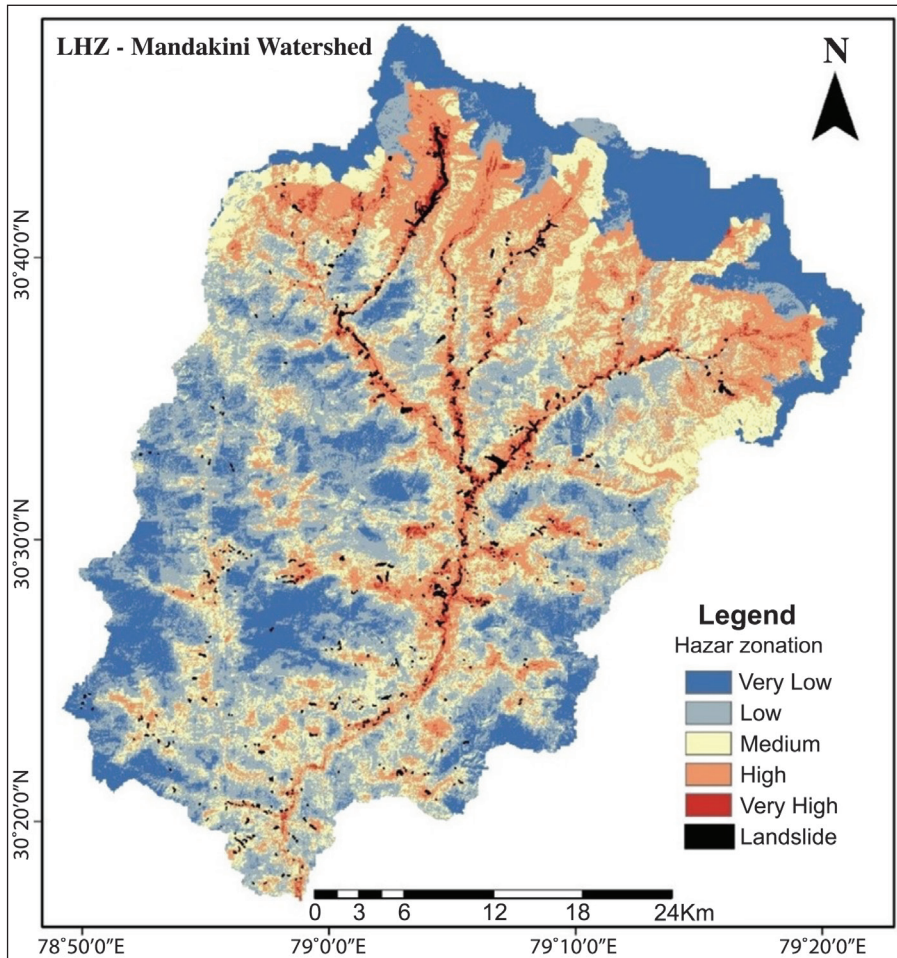
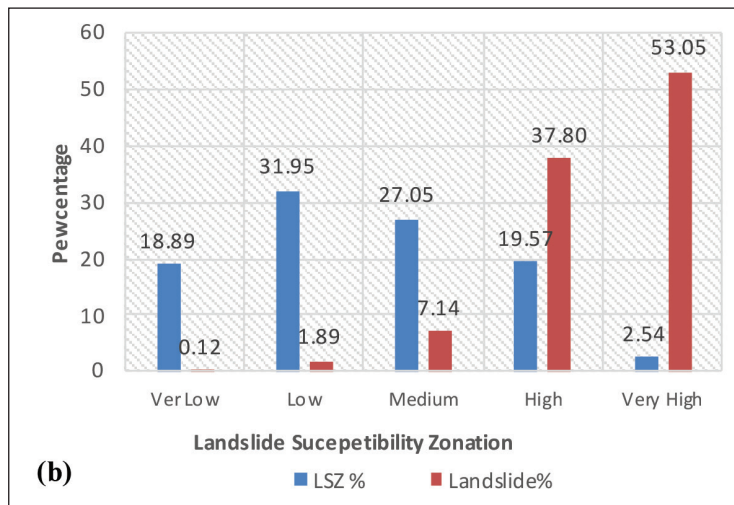


Figure 7 : Landslide Hazard Zonation Map of Mandakini Watershed in 2013

The natural breaks classification method segments the data to determine the best value arrangement in different classes. The NBM classification approach aims to minimise the average deviation from the mean class value while concurrently maximising the deviation from the means of other classes. Moreover, the NBM optimises

inter-class variance while minimising the intra-class variance (Arabamer et al., 2020). Therefore, five landslide hazard zones are identified for visual interpretation using the natural break methods, e.g., very low, low, medium, high, and very high zones. Figure 7 shows the landslide hazard zonation map with an overlay of observed landslides.

The landslide hazard zonation map shows that the very low hazard zone covers 18.89% of the entire study area, whereas low, medium, high, and very high hazard zones cover 31.95%, 27.05%, 19.57%, 2.54% of the total area, respectively. The landslide hazard zone map, developed through a logistic regression model, has been compared with the current landslide distribution layer. Figure 8 presents the percentage of the predicted hazard zones alongside the corresponding percentage of observed landslides within each zone. The 'very high hazard zone' encompasses about 2.54% of the overall area yet accounts for a significant 53.05% of landslide occurrences. Moreover, the landslide percentages in the 'high hazard zone' are significantly elevated at 37.80% in contrast to the area, which stands at merely 19.57%. The medium hazard zone encompasses 27.05% of the area and comprise merely 7.14% landslides. The low and very low hazard zones collectively comprise 50.84% of the territory with a landslide occurrence of 2.01% only.



**Figure 8 : Percentage Area of Predicted Landslide Hazard Zones and the Percentage of the Observed Landslides in each Zone of Mandakini Watershed.**

## 7. Conclusion

The development of a landslide hazard map represents a crucial advancement in the pursuit of effective hazard management. In recent years, these maps have been generated using GIS-based qualitative and quantitative methodologies. This study is carried out in the Mandakini watershed of Garhwal Himalaya, which was vastly affected by the 2013 glacier lake outburst flood known as the Kedarnath Disaster. Many landslides were activated and newly emerged around Kedarnath, along the Mandakini River channel and NH 107 in 2013 nature fury. Binary logistic regression is a robust method for evaluating the likelihood of occurrence of a dichotomous dependent variable, such as a landslide, particularly in landslide-prone regions like the Himalayas. This method proves beneficial even when a significant number of the independent variables are categorical. The BLR model was terminated at the eighty-three steps, retaining 82 variables out of 102 independent variables. The BLR model achieved 89.6% prediction accuracy for Landslide Hazard Zonation over the study area by classifying binary training data. In the accuracy assessment through ROC, 91.4% accuracy was achieved using testing data. The findings demonstrate that the BLR model is both suitable and effective for the scale utilized in this study.

Analysis of Landslide hazard zonation revealed that the very low hazard zone covers 18.89% of the entire study area, whereas low, medium, high, and very high hazard zones cover 31.95%, 27.05%, 19.57%, 2.54% of the total area, respectively. Most of the high-hazard zones in Mandakini Valley fall along with human habitation and affect the connectivity network as well as the livelihood of the people. Therefore, it can be concluded that the 2013 disaster had a massive impact on the region's topography and resulted in increased vulnerability of the region. The increasing pattern of landslide events in very high and high-hazard zones needs to be monitored, and suitable management systems should be developed to reduce the further impact of landslide hazards.

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# Exploring the Relationship Between Disasters and Tourism in India: A Quantitative Approach

R. Rajesh<sup>1</sup> and M. Praveen<sup>2</sup>

## Abstract

*This study examines the impact of natural disasters on India's tourism industry, leveraging secondary data from Indian Tourism Statistics 2022, National Disaster Management, and other reputable sources covering 2020-2021. Utilizing growth analysis, Karl Pearson's Correlation Coefficient, and regression analysis, the research reveals a significant relationship between disasters and tourism. Notably, domestic tourist growth increased by 10% from 2020 to 2021, while foreign tourist arrivals declined by 5%. Meghalaya and Jammu & Kashmir emerged as exceptions, with 85% and 74% increases in domestic tourist arrivals, respectively, indicating minimal disaster impact. The findings underscore the vulnerability of tourism to natural disasters, emphasizing the need for resilient and sustainable tourism strategies.*

**Keywords:** *Natural Disaster, Tourism Industries, India, Disaster resilience, Domestic & International Tourism*

## 1. Introduction

### Exploring How Disasters Affect Tourism in India

Disasters are events which happen without warning, a natural disaster will reduce the development of the place and also create fear among the people, natural disasters have a major impact on tourism industries, due to fear people will reschedule their tourism

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plans. Due to natural disasters, the roots of the tourism destination are blocked. Many tourist places in India are vulnerable to natural disasters in Uttar Pradesh Varanasi is a spiritual place which attracted 4 million tourists (2020 to 2021) but it is susceptible to floods most the flood happen because of the Ganga river, the Kerala Backwaters are a beautiful river which attracts more than 6 lack tourist between 2020 to 2021 this place is also vulnerable for natural disaster, in Kerala Backwaters the flood happened every year due to monsoon (Balakrishnan Nair & M R, 2020) they stated that the flood in 2018 as a major impact on tourism sectors, the house Botes are used for recuse peoples hotels are transformed into disaster shelter this flood affected the medical tourism of Kerala, backwater tourism and ecotourism. In Himachal Pradesh Shimla & Manali are beautiful places which attracted more than 10 million (2020 to 2021) tourists they are vulnerable to Earthquake, Andaman and Nicobar Islands are places have Radhanagar Beach, Laxmanpur Beach, Ross Island, Limestone Cave, Mud Volcano, Coral Reefs which attract more than 4,40,000 (2020 to 2021) tourist which is Vulnerable for Cyclone this place face average of two cyclone a year. In 2020 Cyclone Amphan & Cyclone Nivar affected the place in 2021 Cyclone Yaas affected the place, the Darjeeling hills of west Bengal is also know has eastern Himalayan jewel this place has varies destination like tiger hills, Kanchenjunga view point, Darjeeling Himalayan Railway, Japanese Peace Pagoda, Rock claiming, white water rafting, where more than 5,50,000 tourist use to visit the places between 2020 to 2021 but still it is vulnerable to landslides 14 landslide happen between 2020 to 2021 (Rosselló, Becken, & Santana-Gallego, 2020) he study stated due to natural disaster like Earthquake, tsunamis, flood, Wildfire, Strom led to reduce the tourism arrivals for some destinations which is found by Correlation coefficient (Mark, 2020) the report show the Direct and Indirect Impact on tourism sector due to natural disaster, the study covers Direct Impact as building damages, infrastructure damages, assets and cultural damages and Indirect damages covers delay in supply chain management, financial damages affected the Good will of the firm. The study gives the data which show food, beverage, and Tabacco have a high impact on the tourism industries

### **The Vulnerability of India's Tourism Industry to Disasters**

As we discussed above many tourist places in India are affected by natural disasters the reasons for vulnerability are most of the tourism destinations are located in coastal areas, hills, and floodplains. The climate conditions also led to natural disaster in India, there is lack of planning in tourism infrastructure development the communication and evacuation is slow during and after disaster, following are the states which affected mostly by disaster, Goa, Odisha, Rajasthan, Darjeeling, Uttarakhand Himachal Pradesh are the states mostly affected by the natural disaster (Meher, 2024) the study stated in Odisha three cyclone is recorded in 2021 has Yass, Gulab, Jawad, in 2013 more than 2,200 crore damages where recorded during Cyclone Gulan, also 1.35 million people are affected by the disaster (Lamba & Jat, 2022) the study show most vulnerable Place in Rajasthan, the high risk area of Rajasthan are Barma, Jalore, Jaisalmer, Bikaner, Jalore, Alwar and Bhagalpur (Pal, Biswas, Mondal, & Pramanik, 2016) the research explain the history of flood in Darjeeling, the biggest landslide was happened in the year 1968, Darjeeling use to face many earthquakes from the year 1885 till now, due to this many tourism destination in Darjeeling are affected by continuous flood.

### **Tourism and Disasters:**

A Growing Concern in India: Tourism is a service industry classified into many types like Eco tourism, Adventure tourism, Educational Tourism, Health Tourism, Domestic tourism, heritage tourism, Inbound tourism, and Outbound tourism, the activity during adventure tourism is Hiking where the tourist travels by walk to admire the new places, trekking is nothing but going inside the forest, mountain climbing, Zip lines, cycling, Caving is travelling inside the cave to explore new findings. Nowadays education Tourism increased in India many students from Sri Lanka, Nepal, Afghanistan, and Africa visit India for education. The development of hospitals in India led to improvement in health tourism in India 5,00,000 people visited India for health care in 2020. The major cities in India have separate hospitals for Cardiology, Neurology, organ transplants, genetic testing, and wellness treatment which developed health tourism in India (Praveenadevi, et al., 2024) the study stated that health tourism

in India has the following advantages as online treatment, documentation preparing, convenient foreign exchange services, infrastructure facilities are the leading factors which develop the health tourism in India, The people travel inside their countries are known as Domestic tourist, in India majority of the people are interested in domestic tourism following are the famous tourism destination in India Alappuzha, Andaman, Munnar, Srinagar, Beach in goa, Thrissur waterfalls, Kanjira, Rajasthan Desert. (Kumar & Sharma, 2023) The study stated that increasing the value of the destination heritage is the most important factor. For improving the heritage of the place, the local people are willing to work for the growth of heritage tourism in India. If the people of India visit other countries it is known as outbound Tourism, if foreign travellers visit India is known as Inbound tourism (Sharma, Mohapatra, & Giri, 2022) the study stated ICT Play a significant role in improving Inbound Tourism in India, the researcher put forward the infrastructure development in technology are the government steps to improve the Inbound tourism in India

There are two types of disasters they are Natural disasters & Man-made disasters. In India, more tourist places are affected by natural disasters than Man-made Disaster, natural disasters like Earthquake, Flood, Landslide, Cyclone, Clod waves & Heat waves happen usually, tourism sectors in India as disaster management which cover pre-disaster plans, during disasters & after disasters. Before disaster the disaster management was used to frame the plans such as investing in Insurance policy, document safety, Guest Safety, and analysing the previous disaster to know the impact of the disaster. During a disaster, the important factors are acting fast, communicating fast, organising quickly, gathering information from the government, and replacing the guests in a safe place. After the disaster the sectors mainly focused on how to restart the business, recover from the financial issues, make an Insurance claim, getting government help are some of the disaster management practises in India (Albattat, Mat Som, & Alaa, 2014) The study stated that some of the high-class hotels have implemented disaster management in their hotels but small hotels in Malaysia have not had any disaster prevision plans, the government has taken steps to promote

the Hotels industries after the disaster the hotels use to provide a discount for the guest, increasing the quality of the services, organising some events, are the development steps in the hotels to bring back the business from the disaster.

### **Disaster Resilience in India's Tourism Industry:**

Tourism is the sectors which depend on the travellers, the purpose of the travel differs according to the needs of the people, Some people may use their holiday to enjoy themselves with their families, some may be interested in exploring new places, many people visit the place which is popular for the tourist, some peoples travelling purpose may be business too, peoples use to travel to the historical place to learn and gain knowledge, the people may go for a regional place for relaxation, but there is some factor which influences the decision of the travellers, in this scenario, media is always spreading the negative news about the tourism destination after any natural or man-made disaster, by putting up the names & Numbers of the Death, affected & places created fear among the travellers, and many travellers use to changed their tourism destination due to negative news about the destination. There are many indirect Impacts happen due to Natural & man-made disasters such as the destruction of buildings, and roads, flooding in airports, damage in hotels, shortage in drinking water, effect on the transportation network of the state and lack of natural resources, this is some other reasons which are considered an as difficult time for the tourist during their stay, its factors also create a negative impact on the word of mouth (Barbhuiya & Chatterjee, 2019) The study put forward that natural disasters have influenced foreign tourists to visit India after any natural or man-made disaster, on the other hand, domestic tourism is not affected by natural disasters but this tourism is impacted by political interruptions. (Bharadwaj & Athulya, 2022) stated that tourism is a growing sectors in the world which provide employment opportunities but still tourism destinations are vulnerable to natural disasters. (Sharma, Dogra, & Sonia, 2024) They explain that various methods such as Technology, digitalisation, business model innovation partnership and coordination tourism behaviours are the factors which help to rebuild the tourism destination after any natural or man-made disaster.

## 2. Literature Review

(Barbhuiya & Chatterjee, 2020) The disaster has different types of Impact on the places there are varies types of natural disaster happing in this world the research analysed the impact of Natural & Man Made disaster of all the states of India, for the study they used many different destination like Beaches, Hill Stations, Important monuments of India, the study stated that Domestic tourism arrivals in Tamil Nadu was 15.36 crores from 2008 to 2014 and in Andhra Pradesh Domestic tourism arrivals was 14.89 crores between 2008 to 2014 they stated after the natural disaster the Domestic tourism is not had any major Impact, the recovering process also not taken many days while comparing to Foreign tourism arrivals the foreign tourism has a huge Impact due to natural disaster, after the disaster to increase the number of foreign tourist has taken many days to recovery from the damages, the Maharashtra received 31,72,976 foreign tourist in between 2008-2004 followed by Tamil Nadu received 27,43,214 foreign tourist between 2008-2004, the researcher used Multi Regression for finding the framed hypothesis.

(Sadikhova, 2021) The study stated pull and push factors towards the tourism destination they explain the tourism has a direct Impact because of natural disaster, this reduce the inflow of tourist to certain destination, due to natural disaster the pull factor are affected by unexpected events, for example the Doubt about the safety & security measures of the places. They pointed out there is a negative impact among the travellers in choosing the destination after the natural disaster news, the study stated the Impact of Yogyakarta earthquake (2006), Flood in Jakarta (2013), Tsunami (2004) in Thailand, Hurricane Katrina (2005) in USA, Volcano eruption (2010) in Iceland, the study also show the short term and long term Impact of natural disaster, after the disaster the tourism sectors are slowly recover from the damages, by building the effective communication system the negative impact of the natural disaster can be reduced.

(Balakrishnan Nair & M R, 2020) The paper explains the impact of the natural disasters, the study focused on the important in recovering management after disaster the researcher used Faulkner's crisis management model, this research paper covered

Kerala flood 2018 to study the recovery process such as rescue operations, effective communication, government support, marketing strategies, after the natural disaster to restore the tourism sector. (Liu, Pahrudin, Tsai, & Hao, 2024) The study explains the importance of disaster management it was stated after the bombing in Bali the tourism sectors was very badly affected, this happened because of lack of pre-disaster plans, for the growth of tourism the sectors must have better disaster management for sustainable growth, this study explains the challenges and opportunities in the disaster management & tourism sectors, after recovering from the disaster. The Bali tourism place is developed slowly after implementing various actions by government & industries (Genc, 2018). The study mainly focused on four models such as Destination Image, Community Activity, Total revenue & Impact of Natural disaster on tourism sectors, they explain the poor crisis management has a long-lasting effect on the disaster this paper stated the continuously checking over the security & safety measures, natural events studying the past disaster will reduce the impact of the natural disaster.

### 3. Methodology and Data

#### 3.1 Tools

From the following multiple regression equation the impact faced by Domestic Tourism and Foreign tourism by the natural & man-made disaster are measured:

$$DO = \beta_0 + \beta_1 AF + \beta_2 DE$$

$$FO = \beta_0 + \beta_1 AF + \beta_2 DE$$

DO is Domestic tourist, AF is Affected by natural disaster, DE is No of Death by Natural Disaster, FO is foreign tourism this equation is performed to find the relationship between Disaster Affected & Death with Domestic & Foreign tourist this tool was calculated manually using excel page this one is previously used by (Barbhuiya & Chatterjee, 2020) in their research they used multiple Regression analysis to find Domestic tourism & Foreign tourism relationship between fatalities, Internal conflict.

The Karl Pearson's Correlation Coefficient was analysed to find the relationship with all the data's this calculation is performed by SPSS Software. The Growth Percentage is used to find the difference between 2020 and 2021 this was calculated manually, for this study the Reliability test is calculated and Cronbach's Alpha value is given for Affected, Death, Domestic Tourism, & Foreign Tourism.

### **3.2 Data**

For this study secondary data was collected these data are collected from Indian Tourism Statistics 2022, National Disaster Management, and other reputable sources covering 2020-2021, the tourism data are collected from various transportation sectors like Airports Harbour, Railway authority, disaster related data's were gathered from National disaster Management, State Disaster Management & District Disaster Management Departments.

### **3.3 Area**

The study area for this research is India, this research try to cover all the states of the country, totally 35 places are covered by this research paper has we see India is called as subcontinua of the world by analysing this data it will enable us to understand various types of people and culture, previses researcher (Gantait , Mathew, Chatterjee, & Singh, 2024) as stated from 2005 to 2018 total of Rs 13,43,97,381 fund was raised from the ecotourism in India.

### **3.4 Hypothesis**

To find the disaster impact on tourism sectors the following alternative hypotheses are framed:

H1: There is a close relationship between the number of people Affected by Natural disasters with Domestic tourism

H2: There is a close relationship between the number of people deaths by Natural disasters with Domestic tourism

H3: There is a close relationship between the number of people Affected by Natural disasters with foreign tourism

H4: There is a close relationship between the number of people deaths by Natural disasters with foreign tourism

### **3.5 Limitations**

The study has several limitations that impact its accuracy and reliability. One major concern is its heavy reliance on secondary data, which may compromise accuracy and reliability. Additionally, the analysis has a narrow focus on disaster deaths and affected, overlooking other crucial factors that might influence tourism, such as economic indicators, infrastructure development, and government policies. The study's geographic scope is also limited to India, which restricts its generalizability to other regions and potentially neglects unique external factors. Furthermore, the analysis only considers data from two years, restricting insights into long-term impacts and trends. Another limitation is the study's reliance on annual data, which may mask seasonal or quarterly fluctuations in tourism demand. Lastly, the analysis may benefit from alternative model specifications or estimation techniques to provide more comprehensive insights. Overall, addressing these limitations is crucial to enhancing the study's validity and applicability.

## **4. Result and Discussions**

The data's which was collected from varies sources was put for the reliability test by using Cronbach's Alpha and the following table show the reliability of the data.

**Table 1 : Result of Reliability test for number of people affected, death during 2020 and 2021 & Number of Domestic, Foreign Tourism activities inside India for 2020 and 2021**

S:No	Variables		Cronbach's Alpha	Cronbach's Alpha
1.	Affected	2020	.999	.956
		2021	.999	
2.	Death	2020	.927	.937
		2021	.927	
3.	Domestic	2020	.969	.984
		2021	.969	
4.	Foreign	2020	.536	.321
		2021	.536	

The above table show reliability test for the number of people affected by natural disaster during 2020 and 2021 the Cronbach's Alpha 0.956 is closer to 1 which show the dates had high reliability the data can put for several test. The number of people died in natural disaster across India during 2020 and 2021 data had high reliability value of 0.937. the number of domestic tourist visited varies places across India data had a high reliability with Cronbach's Alpha value 0.984. for Foreign tourism the Cronbach's Alpha value is lesser than .75 which show less reliability value of 0.321.

**Table 2 : Number of Affected and Death across states of India, Domestic tourist and foreign tourist arrivals across the states of India**

Years	2020 <sup>a</sup>		2021 <sup>a</sup>		2020 <sup>b</sup>		2021 <sup>b</sup>		Domestic		Foreign	
	Affected	Death	Affected	Death	Domestic	Foreign	Domestic	Foreign	Growth	Growth	Growth	Growth
Andhra Pradesh	77,000	95	1,10,500	155	7,08,28,590	67,591	9,32,77,569	27,551	24%	-1.45%		
Assam	56,000	140	79,500	215	12,66,898	7,285	14,09,161	536	10%	-12.59%		
Bihar	48,000	125	65,000	175	56,38,024	3,08,080	25,01,193	1,046	-125%	-293.53%		
Gujarat	25,000	60	48,000	110	1,94,64,517	2,10,047	2,45,25,210	11,319	21%	-17.55%		
Karnataka	45,500	95	62,500	155	7,74,53,339	1,65,325	8,13,33,659	72,487	5%	-1.28%		
Kerala	25,000	75	37,500	115	49,88,972	3,40,755	75,37,617	60,487	34%	-4.63%		
Maharashtra	52,500	160	80,000	280	3,92,34,591	12,62,409	4,35,69,238	1,85,643	10%	-5.80%		
Odisha	89,000	130	1,25,000	215	46,22,273	10,206	37,42,221	2,269	-24%	-3.49%		
Tamil Nadu	99,000	120	1,45,000	185	14,06,51,241	12,28,323	11,53,36,719	57,622	-22%	-20.31%		
Uttar Pradesh	86,000	190	1,22,000	285	8,61,22,293	8,90,932	10,97,08,435	44,737	21%	-18.91%		
West Bengal	78,000	200	1,11,000	150	2,88,41,732	4,63,285	2,43,25,984	34,828	-19%	-12.30%		
Arunachal Pradesh	21,235	27	26,000	65	42,871	961	1,02,915	182	58%	-4.28%		

Years	2020 <sup>a</sup>		2021 <sup>a</sup>		2020 <sup>b</sup>		2021 <sup>b</sup>		Domestic		Foreign	
	Affected	Death	Affected	Death	Domestic	Foreign	Domestic	Foreign	Growth	Growth	Growth	Growth
Chhattisgarh	23,000	60	45,000	120	28,10,227	2,322	47,47,417	8	41%	-289.25%		
Dadra & Nagar	2,500	12	6,000	25	1,04,959	222	1,97,802	80	47%	-1.77%		
Daman & Diu	4,000	20	9,000	40	2,97,436	1,382	4,63,420	105	36%	-12.16%		
Goa	13,000	0	28,000	0	32,58,715	3,02,751	33,08,089	22,128	1%	-12.68%		
Haryana	8,000	30	16,000	55	21,14,731	17,474	20,25,450	4,578	-4%	-2.81%		
Himachal Pradesh	13,500	45	26,000	70	31,70,714	42,665	56,32,270	4,932	44%	-7.65%		
Jammu & Kashmir	10,500	30	19,500	55	25,19,524	5317	1,13,14,920	1,650	78%	-2.22%		
Jharkhand	16,500	40	27,000	65	25,74,704	490	33,83,642	1,637	24%	0.70%		
Lakshadweep	6,000	15	12,500	30	3,462	413	13,500	4	74%	-102.25%		
Manipur	13,500	40	25,500	65	49,669	3,139	49,371	648	-1%	-3.84414%		
Meghalaya	11,500	40	21,000	65	24,734	2,311	1,54,409	411	84%	-4.62287%		
Mizoram	7,500	25	14,500	50	30,890	265	87,232	234	65%	-0.13248		
Nagaland	4,500	12	11,500	12	10,979	518	23,968	325	54%	-0.59385		

Years	2020 <sup>a</sup>		2021 <sup>a</sup>		2020 <sup>b</sup>		2021 <sup>b</sup>		Domestic		Foreign	
	Affected	Death	Affected	Death	Domestic	Foreign	Domestic	Foreign	Growth	Growth	Growth	Growth
Puduchery	8,000	20	17,000	40	11,14,942	92,080	12,53,213	321	11%	-285.854		
Punjab	15,000	45	28,000	75	1,66,92,197	3,59,114	2,66,40,429	3,08,135	37%	-0.16544		
Rajasthan	61,000	55	1,20,000	90	1,51,17,239	4,46,457	2,19,88,734	34,806	31%	-11.827		
Sikkim	8,000	30	15,000	55	3,16,408	19,935	5,11,669	11,508	38%	-0.73227		
Telangana	29,000	75	29,000	75	3,99,97,001	46,694	3,20,00,620	5,917	-25%	-6.8915		
Tripura	13,500	40	25,500	65	1,27,815	31,877	1,77,816	5	28%	-6374.4		
Uttarakhand	20,000	65	37,500	105	70,05,264	41,339	1,94,34,475	8,532	64%	-3.84517		
Madhya Pradesh	44,000	130	60,000	180	2,35,19,632	99,819	2,55,54,067	41,601	8%	-1.39944		
	11,15,235	2,333	17,04,500	3562	60,50,56,809	64,94,207	67,03,03,464	9,53,992	10%	-5.8074		

<sup>a</sup>National Disaster Management report 2020 to 2021 (<https://ndma.gov.in/index.php/Resources/AnnualReports>)

<sup>b</sup>ReliefWeb (<https://reliefweb.int/disasters?list=India%20Disasters&advanced-search=%28C119%29>)

<sup>c</sup>Indian Tourism Statistics 2022 (<https://tourism.gov.in/sites/default/files/202209/India%20Tourism%20Statistics%202022%20%28English%29.pdf>)

The above table show the number of disaster and Death in the states of India, and the study stated total number of Domestic & Foreign tourist visited the states across India here we discussion top 3 states which was most affected & Least affected by the natural disaster.

Tamil Nadu was affected by many natural disasters such as Cyclone Nivar which killed 14 people. This disaster has had an impact on tourist places (Vilvijayan & Lalitha, 2021) like Marina Beach, Mahabalipuram, Puducherry Beach, Aurobindo Ashram, Nagapattinam Beach, Port Town, Cuddalore Beach, Devanampattinam Beach, Viluppuram Temple followed by the state was affected by Cyclone Burevi in December 2020 which affect the following tourism places Vivekananda Rock Memorial, Thiruvalluvar Statue, Kanyakumari Beach, Muthu Nagar Beach, Tiruchendur Murugan Temple, Ramanathaswamy Temple, Dhanuskodi, Meenakshi Amman Temple, Courtallam Falls. In the year 2021 Cyclone Yaas had some impact on tourism places like Marina Beach, Elliot Beach, Fort St. George, Silver Beach, Pichavaram Mangrove Forest, Velankanni Church, Nagapattinam Beach, Promenade Beach, Serenity Beach, Shore Temple, Mahabalipuram Beach followed by in the year 2021 November Monsoon Flood affected (Rinisha & Lakshmanan, 2022) the tourism places like Marina Beach, Kapaleeshwarar Temple, San Thome Basilica, Elliot's Beach, Short Temple, Mahabalipuram Beach, Kanchi Kailasanathar Temple, Kamakshi Amman Temple, Ooty Lake, Botanical garden's, Doddabetta Peak, Rock Memorial, Thiruvalluvar Statue, Kanyakumari Beach, Silver Beach, Annamalayar Temple, Courtallam falls, Brihadeewarar Temple the total affected people was 2,44,000 in 2020 & 2021.

The second most affected state was Odisha which faced many natural disasters like Cyclone Amphan in May 2020 (Gupta, Bhattacharya, Thapa, & Kaur, 2021) affected tourist places such as Puri, Chilika Lake, Sun Temple, Bhitarkanika National Park, Gopalpur. Followed by in the year 2021 Cyclone Yaas (Mandal , Mandal, Das , Payra, & Bhanja, 2023) affected major tourist places like Puri Beach, Jagannath Temple, Chandipur Beach, Digha, Sun Temple and in September 2022 Cyclone Gulab as left the Impact in Gopalpur beach, Taptapani, Chandragiri Monastery, Berhampur, during December 2021 another cyclone Jawad affected the following tourism destination

Jagannath Temple, Chilika lake, Konark Beach as per the above table total of 2,14,000 people are affected by natural disaster in Odisha.

The third most affected state in India was Uttar Pradesh where a total of 2,08,000 people were affected by the natural disaster. The following are the major tourist places affected by natural disasters in the years 2020 to 2021 (Arya & Singh, 2021) this state mostly affected by flood the places are Kashi Varansi temple, Ghats of Varanasi, Sangam, Allahabad fort, Ram Janmabhoomi Temple, Krishna Janmabhoomi Temple, Yamuna River Ghat, Taj Mahal, Agar Fort, due to Heat wave some of the tourism destination in Uttar Pradesh are affected those place are Taj mahal, agar fort which affected by 40°C in summer season, Kashi Vishwanath Temple, Allahabad fort, Sangam, Bara imambara, Rumi Darwaza, Chota Imambara, Yuman River, ISKCON Temple.

Dadra & Nagar Haveli is a union territory that is less affected by natural disasters, with a total of approximately 8,500 people affected during the years 2020 and 2021. It is a small region with an area of 603 square kilometres. This territory is covered with mountains, lies outside the earthquake-prone zones, and is located near the Arabian Sea, which is relatively less affected by cyclonic events. The union territory has effective disaster preparedness plans that help minimize the impact of natural calamities. However, some tourism destinations were impacted during Cyclone Tauktae in May 2021, including Jampore Beach, Devka Beach, St. Jerome Fort, Vanganga Lake Garden, Tribal Cultural Museum, Dudhni Lake, Hirwa Van Garden, and the Lion Safari Wildlife Park, as noted in a study conducted by Sarkar (2024).

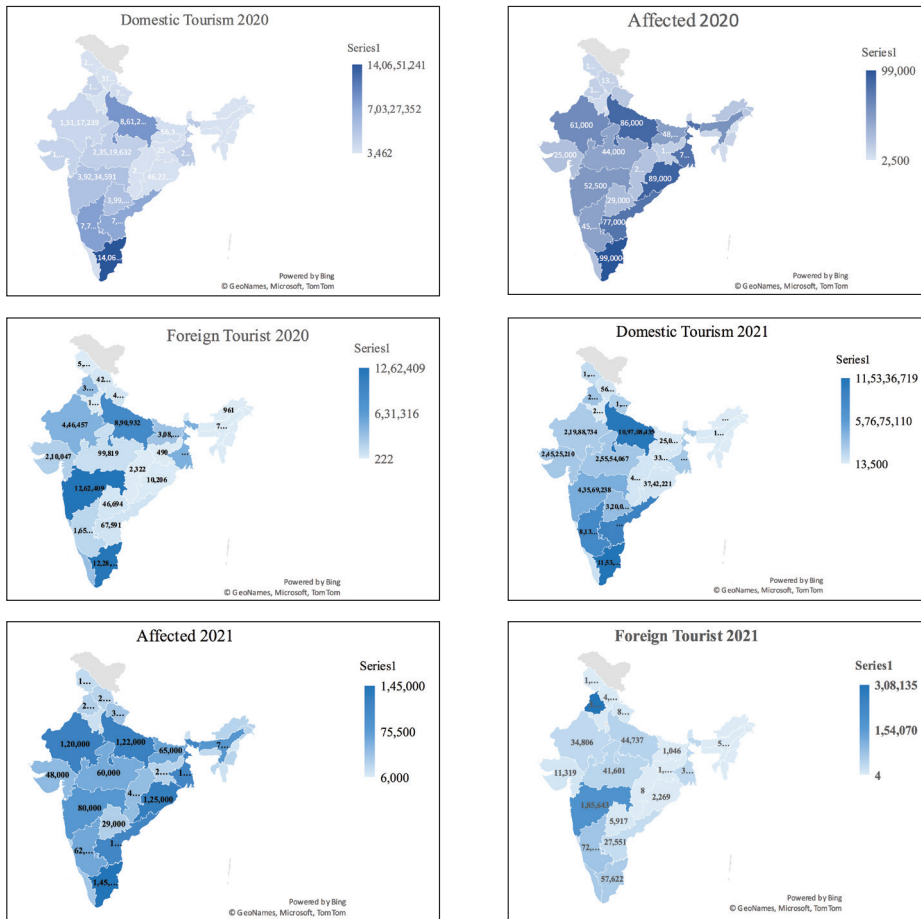
The second less affected place was Daman & Diu, a union territory of India. The reason behind the lesser impact is its relatively low population; the smaller number of people residing there reduces the overall impact of natural disasters. Another reason for the lower impact is the proactive measures taken by the central government, including advanced warning systems, disaster management plans, and evacuation strategies, which have helped minimize disaster risks in the coastal areas. Additionally, this territory is located near the Arabian Sea, which experiences fewer natural disasters compared to the Bay of Bengal. The main tourism places affected by heavy rain include

Jampore Beach, Devka Beach, and Daman Fort. The data shows that during 2020 and 2021, approximately 13,000 people were affected by natural disasters in this region.

The third less affected place is Nagaland, the 16th state of India, where around 16,000 people were affected by natural disasters in 2020 and 2021. The lower impact is attributed to the absence of large rivers, which minimizes flooding risks. Moreover, no significant earthquakes were recorded in those years. Another contributing factor is its relatively small population of about 2.2 million, which is low compared to other Indian states.

Now let us discuss about the growth of tourism in both Domestic and Foreign here the growth percentage is calculated and we discuss the Top three states which have High growth percentages and Lowest growth percentages in Domestic and Foreign Tourism.

Even though there are many factors which had a negative influence on domestic tourism still this sector has a very fast growth in India from the above table it is found that Meghalaya has the highest growth percentage of 84% in the year 2020 the state received 24,734 Domestic tourists but was increased to 1,54,409 in 2021 the reason for this growth is after lockdown many people are eager to visit different places which lead to growth in domestic tourism, and also the government of Indian has continuously promoting the tourism destination in North India, which is also the reason for the growth of domestic tourism in Meghalaya, this places is one the beautiful places which has lakes, waterfalls, natural, caves, hill stations. The top tourist destinations in Meghalaya are Shillong the capital of Meghalaya which receives 50% of Domestic tourists to Wards Lake, Elephant Falls, Shillong Park, Don Bosco Museum and other popular places are Nohkalikai Falls, Mawsmai Cave, Double-Decker Living Root Bridge, Dainthlen Falls, Mawjynbuin Cave, Umngot River, Laitlum Canyons, Umiam Lake, Krang Suri Falls, Nartiang Monoliths, Nongkhnun Island, Balpakram National park, Siju Cave. (Peinlang, 2019) The study shows the Meghalaya received 1,61,701 tourists in the year 1999 was increased to 7,26,453 in the year 2014 this place has Adventure tourism, Cultural tourism, Agri tourism, and Educational tourism.



These observations are supported by studies focused on disaster vulnerability and management across Indian states and union territories, including their impact on coastal tourism and resilience planning (Magotra, 2021; NIDM Annual Report, 2021–22).

The second highest growth percentage was in Jammu & Kashmir this state received 25,19,524 tourist in the year 2020 and it was increased to 1,13,14,920 tourist in 2021, the reason for growth is this is one of the places with a wonderful natural beauty in it after the Covid-19 lock down there where some restriction for the foreign travellers to visit India, this is also an reason for domestic tourism development, the Jamu and

Kashmir is the vast places which reduce the crowd which lead to safety after Covid-19, the important reason behind the development was the government improved the securities measures after the Article 370 during 2019 which improved the safety and security of the tourism destination, government also taken steps to develop the tourism in jamu & Kashmir by having campaigns conducting events, promoting in digital media marketing, gives the boost to the domestic tourism, the Infrastructure development such has development of air road & air ports, infrastructure development in railway which lead easy access to the tourism destination, the popular tourism destination in Jamu & Kashmir (Lone & E.Ravi, 2023) which attract more tourist are Dal lake averagely receive 40% tourist, Nigeen Lake receive 15% of tourist, Mughal Gardens receive 40% of tourist, Shankaracharya Temple receive 20% of visitors, Hazratbal Shrine received 30% visitor to the state there more than 30 tourism destination are there in Jammu & Kashmir following are some of the tourism destination Skiing and winter Sports, Golf Course, Lidder River, Betaab Valley, Aru Valley, Thajiwas Glacier, Vaishno Devi Temple, Amar Mahal Palace, Pangong Lake, Magnetic Hill, Hemis Monastery, Yusmarg, Kupwara, Dachigam National Park, Bhaderwan valley etc.

Lakshadweep recorded the third highest growth rate in domestic tourist arrivals, showing a remarkable 74% increase compared to the previous year. In 2020, the union territory received only 3,462 tourists, which rose significantly to 13,500 in 2021. This growth can be attributed to several key factors: special promotional travel packages were offered, room rates were discounted, and both water and air connectivity were enhanced to make travel more convenient. Additionally, many parts of Lakshadweep remain unexplored, adding to its appeal. The territory's focus on eco-tourism also attracted visitors seeking sustainable and serene travel experiences. The sparse population made it a preferred choice for travelers post-Covid, as people opted for less crowded destinations. Some of the most visited tourist spots include Agatti Island, Bangaram Island, Kavaratti Island, Kadmat Island, Minicoy Island, Kalpeni Island, and Thinnakara Island. These factors collectively contributed to the significant rise in tourism (Lakshadweep Tourism Development Authority, 2022; Kokkranikal et al. 2003).

Bihar is the state which received 56,38,024 domestic tourist in the year 2020 which was reduced in the year 2021 has 25,01,193 the Table 1 show the growth percentage as -185% it is too low compare to the previous year the major reason for downfall in domestic tourism was Second Covid-19 wave which lead to made many restriction on the people who visit Bihar, like people has to get permission to enter the state the person who are get inside the states must produce proper medical report before entering the state, Bihar is will know for religious and spiritual tourism during 2021 this places locked and no visitors are allow to vest the major religion places which lead to reduce the domestic tourism in Bihar the popular religion and spiritual places are Bodhi Gaya is the place where Buddha got enlightenment, Mahabodhi Temple, Bodhi Tree, Nalanda, Nalanda Archaeological Museum, Rajgir, Vishwa Shanti stupa, Griddhakuta, Saptaparni Cave, Jain Temple, Ashoka Pillar, Relic Stupa, Takht Sri Harmandir sahib, Vishnupad temple, Phalgu River, Mangla Gauri Temple, Sitamarhi, Vikramshila etc. As noted by Patro et al. (2024), Bihar's tourism sector—especially its spiritual and heritage tourism—faced major disruptions during the pandemic, and understanding these patterns is crucial for future tourism planning, sustainability, and economic revival in emerging states like Bihar.

The second most dropped state is Chandigarh which received 4,17,953 Domestic tourists in the year 2020 and dropped to 2,28,809 Table 1 Shows the growth percentage as -84% the major downfall happened because of lockdown and government restrictions, most of the tourism destinations are affected mostly by second Covid-19 waves the destination is Sukhna lake, Rock Garden, Rose Garden, Elate Mall, Chandigarh Capitol Complex, Pinjore Gardens are the famous tourism destination which are badly affected by Covid-19 Pandemic. The paper highlights the city's rich tourism potential—especially in eco, cultural, and heritage tourism—while also pointing out key challenges like poor infrastructure, lack of policy, and weak planning. These issues, combined with the COVID-19 pandemic, severely impacted popular sites like Sukhna Lake and Rock Garden, leading to a major drop in tourist arrivals Sarkar, S. (2025). Telangana is the state which is in third place which dropped domestic tourism up to -25% compared to the previous year. In 2020 the state received 3,99,97,001 domestic tourists which

dropped to 3,20,00,620 tourists in the year 2021 the reason for the drop may be many people avoided crowded places the long-distance travel during 2021 which caused the state downfall in domestic tourism in the year 2021. Sarkar (2024) finds that Telangana's domestic tourism plummeted from approximately 3.99 crore in 2020 to 3.20 crore in 2021, marking a 25 % decline largely due to COVID 19 restrictions and public reluctance to travel. While the state boasts rich attractions like Charminar, Ramappa Temple, eco-tourism and tribal circuits, infrastructure gaps and pandemic era movement restrictions hindered recovery.

When we see the foreign travellers all states are very badly affected compared to the previous year all the states' growth percentages went negative Bihar received 1,046 foreign tourists to Bihar in the year 2021 but in 2020 the state received 3,08,080 Foreign travellers, This 3 lack foreign visitors visit Bodh Gaya, Nalanda, Rajgir, Vaishali, Patna, Kesaria stupa this place where locked due to second covid-19 wave in 2020 which lead to reducing the foreign travellers followed by the foreign tourist visit Chhattisgarh in 2021 was only 8 but in 2020 the state received 2,322 the reason was Covid-19 which affected the International tourism badly. If we see the Figure 1 all the states are noted in light blue which denotes there are fewer foreign travellers visiting the states of India during 2021 following are the states which as less impact on foreign tourist arrival Andhra Pradesh received more the 27,000 foreign tourists, Karnataka received more the 72,000 foreign tourists in 2021, Haryana received 4,000 foreign tourist in 2021 Jharkhand is the only state which has the positive value compared to 2020 in this year the state received 490 foreign tourists but it was increased to 1,637 foreign tourists in the year 2021 the Important reason for the growth is relaxing the restriction and open it for tourist which leads to improving the number of foreign tourists also the promotions steps taken by the government like promoting through digital media provide safe and hygiene tourism destination help to improve the tourism destination image in International market. "According to Singh & Shukla (2023), India saw a substantial decline in foreign tourist arrivals during the pandemic period particularly from 2019 through 2021 with the most severe drops in 2020 and 2021 following strict international travel restrictions and heritage site closures.

**H1: There is a signification between Natural disaster and Tourism (2020AND- 2020 Affected By Natural Disaster, 2020NDND- 2020 Number of Death by Natural Disaster, 2021AND- 2021 Affected By Natural Disaster, 2021NDND- 2021 Number of Death by Natural Disaster, 2020DT- 2020 Domestic Travel, 2020FTVI- 2020 Foreign Travellers Visited India, 2021DT- 2021 Domestic Travel, 2021FTVI- 2021 Foreign Travellers Visited India)**

**Table 3 : Natural disaster and Tourism-Correlations**

Karl Pearson's Correlation Coefficient		2020 AND	2020 NDND	2021 AND	2021 NDND	2020 DT	2020 FTVI	2021 DT	2021 FTVI
2020 AND	Pearson's Correlation	1	.832**	.980**	.795**	.677**	.569**	.666**	.149
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)		.000	.000	.000	.000	.000	.000	.394
	N	35	35	35	35	35	35	35	35
2020 NDND	Pearson's Correlation	.832**	1	.800**	.927**	.554**	.592**	.566**	.250
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.000		.000	.000	.001	.000	.000	.147
	N	35	35	35	35	35	35	35	35
2021 AND	Pearson's Correlation	.980**	.800**	1	.781**	.671**	.611**	.669**	.171
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.000	.000		.000	.000	.000	.000	.326
	N	35	35	35	35	35	35	35	35

Karl Pearson's Correlation Coefficient		2020 AND	2020 NDND	2021 AND	2021 NDND	2020 DT	2020 FTVI	2021 DT	2021 FTVI
2021 NDND	Pearson's Correlation	.795**	.927**	.781**	1	.574**	.627**	.610**	.303
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.000	.000	.000		.000	.000	.000	.077
	N	35	35	35	35	35	35	35	35
2020 DT	Pearson's Correlation	.677**	.554**	.671**	.574**	1	.700**	.969**	.295
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.000	.001	.000	.000		.000	.000	.086
	N	35	35	35	35	35	35	35	35
2020 FTVI	Pearson's Correlation	.569**	.592**	.611**	.627**	.700**	1	.665**	.536**
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.000	.000	.000	.000	.000		.000	.001
	N	35	35	35	35	35	35	35	35
2021 DT	Pearson's Correlation	.666**	.566**	.669**	.610**	.969**	.665**	1	.337*
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.000	.000	.000	.000	.000	.000		.048
	N	35	35	35	35	35	35	35	35

Karl Pearson's Correlation Coefficient		2020 AND	2020 NDND	2021 AND	2021 NDND	2020 DT	2020 FTVI	2021 DT	2021 FTVI
2021 FTVI	Pearson's Correlation	.149	.250	.171	.303	.295	.536**	.337'	1
	Remark	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted	Accepted
	Sig (2-tailed)	.394	.147	.326	.077	.086	.001	.048	
	N	35	35	35	35	35	35	35	35

\*\* Correlation is significant at the 0.01 level (2-tailed)

\* Correlation is significant at the 0.05 level (2-tailed)

Source: National Disaster Management report 2020 to 2021, Indian Tourism Statistics 2022

The above table shows the relationship between disaster Death & Effects by domestic Foreign tourists when two data were put in for Karl Pearson's Correlation Coefficient test it was found that they all have a positive relationship with each other the above table does not show any negative relationship among the variables it leads to accepted all four Alternative hypotheses of the study.

But there is a little gap between the variables which are discussed below several people affected by natural disasters (AND) During 2020 with Total Number of Domestic Tourist visiting India Shows a Correlation Value of 0.677, the year 2020 shows there was a positive relationship but the affected peoples are 11,15,235 and Domestic tourist arrivals are 60 million there was a positive growth between this two variables the reason behind this issue was the domestic travellers will know about the climatic conditions of the regions they may avoid the disaster happening month and visited in the different month which leads to increase the domestic tourism, another reason may the travels are interested to see the place which is affected by a natural disaster, many people may go to the tourism places see their relatives who lived in the disaster zone, well prepared plan by the government to overcome the disaster event, the advertisement campaigns, events, and Continuous promotion in digital marketing advertisements this is also another positive reason for the development of Domestic tourism after being affected by a natural disaster.

The positive correlation value of 0.677 between the number of individuals affected by disasters and the development of domestic tourism in 2020 can be leads to several factors. Natural disasters, particularly cyclones, typically occur during specific months and primarily impact coastal areas. Consequently, regions such as Chennai, Mahabalipuram, Nilgiris, and Thanjavur experienced a decline in tourist inflow due to Cyclone Nivar in November 2020. In Tamil Nadu, which welcomed a remarkable 14,06,51,241 domestic tourists in 2020, the average monthly tourist arrivals across major destinations-Chennai, Madurai, Rameswaram, Kanyakumari, Nilgiris, Mahabalipuram, and Thanjavur amounted to approximately 11,72,093 visitors. However, these factors vary significantly due to seasonal influences. For instance, from April to June, the Nilgiris typically attracts more than 18,75,350 tourists per month during its peak season. The impact of Cyclone Nivar in November led to an estimated reduction of 17,58,139 tourists across affected areas. Specifically, Chennai's tourist arrivals dropped by approximately 5,86,046 visitors, and in the Nilgiris, tourism was halved due to the cyclone's effects. Conversely, during this time, other tourist destinations such as Madurai, Rameswaram, Thanjavur, Kodaikanal, and Kanyakumari continued to attract a higher number of visitors, as they were not significantly impacted by the cyclone. This phenomenon illustrates the positive correlation: as tourism in affected coastal areas declines, other destinations benefit from the reallocation of tourist traffic, ultimately contributing to overall tourism development in the state. Therefore, understanding these dynamics can help stakeholders in the tourism industry plan and adapt to changing conditions, ensuring sustainable growth even in the face of natural disasters.

The Foreign tourist decline in India is explained using multi regression values in following table:

Table 4 : Natural Disaster Affected, Death and Domestic, Foreign Tourism Multi Regression Analysis

S:No	States	$\beta_0$	$\beta_1$	$\beta_2$	Domestic (DO)	Equation	Foreign (FO)
1.	Andhra Pradesh	-27539262	670	37,4150	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
2.	Assam	126008.3751	-0.836663337	-0.001498501	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
3.	Bihar	10,97,188.63	6	1,897	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
4.	Gujarat	239817.7918	-3.481997333	-0.011112757	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
5.	Karnataka	23905452	-185	-6273.66	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
6.	Kerala	157691.3425	-0.055368461	-0.000162848	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
7.	Maharashtra	14,863,375.81	220	101214	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
8.	Odisha	114907.3884	-0.115736081	-0.0002516	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
9.	Tamil Nadu	58983777	228	64672	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
10.	Uttar Pradesh	128794.2731	-0.183114673	-0.000646287	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
11.	West Bengal	-6161350	204	63716	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
12.	Arunachal Pradesh	202014.7688	-0.044600168	-0.000142721	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
13.	Chandigarh	23012503	158	36122	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		725718.0124	-0.025539439	-0.000111445	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
		85,83,945	-24	-10,354	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		4,91,561.3	-4.53572	-0.01071	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
		2,54,52,4258	-550	-3,89,454	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		6,47,766.2175	-0.039292	-5.552	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
		-2,91,87,735	655	2,48,275	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		4,72,259.0387	-0.042543385	-0.000112267	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
		2,37,10,200	-137	90,315	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		2,56,334.9229	-0.077020564	0.000116698	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
		-297397	13	1580	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		145037.656	-6.116816431	-0.048780488	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$
		855086	-25	-10508	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		20194.84698	-1.108319787	-0.002659967	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$

S:No	States	$\beta_0$	$\beta_1$	$\beta_2$	Domestic (DO)	Equation	Foreign (FO)
14.	Chhattisgarh	-2120802	88	32287	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		324417.1175	-9.507346586	-0.025929127	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
15.	Dadra & Nagar Have	-93480	27	7142	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		104906.2148	-24.64788732	-0.091549296	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
16.	Daman & Diu	-84327	33	8299	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		26194.24393	-3.915426782	-0.015661707	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
17.	Goa	-	-	-	-	-	-
		163535.2762	-0.053452497	0	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
18.	Haryana	2355790	-11	-3571	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		18470.25112	-0.620347395	-0.001938586	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
19.	Himachal Pradesh	11607138	-448	98462	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		19607.9092	0.455761005	-0.00066255	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
20.	Jamm & Kash- mir	-22693945	977	351816	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		40298.62476	-2.454322334	-0.006817562	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
21.	Jharkhand	-395254	77	32358	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		-198044.0087	9.154315606	0.02179599	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
22.	Lakshadweep	-20861	2	669	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		147214.2152	-15.89242054	-0.036674817	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
23.	Manipur	50630	0	-12	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		95832.20434	-4.817342433	-0.01003613	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
24.	Meghalaya	-404559	14	5187	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		82611.69079	-5	-0.013157895	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
25.	Mizoram	-113989	8	2254	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		2484150.71	-225.8064516	-0.806451613	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
26.	Nagaland	-15590666	2	1298900	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$	-	-
		290577.0052	-36.26943005	-5.18135	-	$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	

S:No	States	$\beta_0$	$\beta_1$	$\beta_2$	Domestic (DO)	Equation	Foreign (FO)
27.	Odisha	15089558	-80	-58670	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		116417.8153	-1.385914073	-0.001889883		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
28.	Puducherry	784628	15	6914	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		47426.54431	-0.098083022	-0.000217962		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
29.	Punjab	-14682996	765	331608	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		339107.185	-0.255006964	-0.000588478		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
30.	Rajasthan	-6220999	116	196328	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		253602.4451	-0.143325293	-8.50235		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
31.	Sikkim	-238691	28	7810	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		25274.25454	-0.830663344	-0.002966655		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
32.	Telangana	2324952175	-799638100	-799638100	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		26305.50713	-2.45236	-2.45236		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
33.	Tripura	-33438	4	2000	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		23282.90865	-0.376506024	-0.000784388		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
34.	Uttarakhand	-33611622	710	310730	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		40271.50756	-0.533422745	-0.001219252		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
35.	Madhya Pradesh	11618187	127	40689	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		85001.24	-0.274829091	-0.000858841		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	
36.	INDIA	325091384	111	53089	$DO = \beta_0 + \beta_1 AF + \beta_2 DE$		-
		3874055.629	-0.106361396	-0.000221833		$FO = \beta_0 + \beta_1 AF + \beta_2 DE$	

DO is Domestic tourist, AF is Affected by Natural Disaster, DE is No of Death by Natural Disaster, FO is Foreign Tourist

Source: National Disaster Management report 2020 to 2021, Indian Tourism Statistics 2022

Calculation: <https://1drv.ms/x/c/d8d90f2b26b583fc/EUSZCKi0PedMvdOOcemWJYAB0nXfmbT8vUkrf36XmDe4UA?e=2BjL>

This Table 4 helps us understand the relationship between the inflow of domestic and foreign tourists and the impact of natural disasters, particularly the number of people affected and those who died. The table clearly illustrates the effects of the coefficients.

- $\beta_1$  represents how the inflow of both domestic and foreign tourists increases or decreases based on the number of people affected by natural disasters.
- $\beta_2$  reflects how the number of tourists, both domestic and foreign, changes in response to the number of deaths caused by natural disasters.

These coefficients indicate whether tourism rises or falls about the scale of the disaster's impact. As we discussed earlier, domestic tourism in India shows a positive correlation with natural disasters which indicates people are not afraid of natural disasters so they are not cancelling their plans the people choose other tourism destinations which are unaffected by natural disasters. There is flexibility in choosing the destination to reduce the Impact of catastrophe, there are 3,500 tourist destinations spread across India which gives vast options for the people to select the destination, this leads to sustainability of tourism industries in India as the people are easily changing the plans to other tourism destination ensuring the continued inflow of tourism in a destination which minimizing the Impact of natural disaster.

When there is no natural disaster or zero disaster the inflow of domestic tourism in India is expected to reach 325.03 million, every 1 unit increase in death due to a natural disaster will lead to an increase the domestic tourism by 111 units, also every 1 unite increase in disaster affected will lead to increase 53,089 unites in domestic tourism in India, the reason for rise may be happened because of a shift in tourism destination within India due to natural disaster when we see the overall growth this may be the reason behind, apart from the impact the sector contributing to the overall development of tourism.

The disaster management systems in Indian states have implemented proactive strategies to minimize risks and ensure quick recovery from natural calamities, making tourism destinations safer. For instance, Odisha's effective evacuation plans during Cyclone Fani in 2019 helped over 1.1 million people evacuate, showcasing strong preparedness. Gujarat's State Disaster Management Authority has become a model for earthquake response, developing training and infrastructure improvements after the 2001 earthquake. Kerala has emphasized community engagement and rapid recovery processes post-2018 floods, while Tamil Nadu's preparedness for cyclones includes preemptive evacuations and public awareness campaigns. Key factors in reducing disaster risks include effective early warning systems, community involvement, regular training, infrastructure enhancements, and inter-agency collaboration, which collectively contribute to the resilience and sustainability of India's tourism sector. (P J, V.G., Chatterjee, & Singh, 2024) The study put forward the development of Domestic tourism after the Covid-19 Impact they explain the interest of the people and vast population led to the development of Domestic tourism in India, the short tripe is increased vastly the people use the weekend for the tour and in the month of May-June all the domestic tourism destination where received many tourists has it is the summary holiday. (Nair & Ramachandran, 2016) The study stated that growing competition in Domestic tourism made the tourism destination have an innovative idea as the Internet has been a source of advisement following the Internet is an important factor which has the positive and Negative Image of the destinations the study gives the positive relationship with Climate Marketing & destination with development of domestic tourism with  $Y = 1.9998E-016 + 0.108 X1 + 0.611 X3$ .

When we see foreign tourism the  $\beta_2$  value is going negative which shows that every unit increase in death and affected by natural disasters will reduce the foreign tourist arrival to India. As we see in Table 4 value for India shows the  $\beta_1$  Value is -0.106 and  $\beta_2$  Value -0.00022 which shows maximum of the states are affected by natural disasters and had a great Impact on the tourism sector. This Mizoram is a state which is affected

mostly by natural disasters and has the  $\beta_1$  Value of -225.8064516 which shows that every one-unit increase in death will reduce the Foreign tourism arrival by 225 units for example for one unit death 1000 Foreign tourism arrivals will reduce in Mizoram (Mishra1, Puhan, & Mishra, 2021) they stated that the Mizoram received 4000mm rainfall between 2011 to 2012 it is told there was a heavy rainfall during the year this types of heavy rainfall lead to many landslides in Mizoram. Nagaland the state of India which second most affected by the  $\beta_1$  Value at -36.26943005 which shows that every one-unit increase in death will reduce 36% of Foreign tourism arrivals for Nagaland (Nagaland, 2019) the report stated that various earthquakes and landslides happened in Nagaland it show during the month of April to June many landslides are reported but this states is vulnerable for earthquake which has the recorded report that every month in year the earthquake happened. The third most affected union territory is Dadra & Nagar with the  $\beta_1$  Value of -24.64788732 which determined that every one-unit increase in death will reduce 24% in Foreign tourism arrivals to Dadra & Nagar.

The minimum impacted three states due to natural disaster are explained. The first least affected state was Maharashtra with the  $\beta_1$  Value of -0.025539439 which shows that every unit increases in death will reduce the Foreign tourism arrivals by 2.5% to Maharashtra (Joseph, Srivastava, Kunte, Singh, & Vaidya, 2004) the study gives us the steps taken by the states to prevent the business from natural disaster the following are some of the steps the state organise six International workshops and Seminars, public awareness Campaigns in Law College, Tata Institute, Mumbai Commerce Centre, etc. formed search and rescue task force, Response Strategy, Emergency operation centres, tie up with International Cooperative. Followed by Tamil Nadu is second less affected by natural disasters with the  $\beta_1$  Value of -0.039292 which shows that every one-unit increase in death will lead to reduce 3.9% of Foreign tourism arrivals to Tamil Nadu (National Disaster Management Authority, n.d) the following are the steps taken by the Tamil Nadu government to reduce the disaster Impact Disaster Management Policy, Disaster Management Plan, Strengthening of

emergency Operations Centres in the States & Districts, Strengthening of emergency Responses at Hospitals, State Disaster Response force, State level Resource Database, Capacity Building programmes etc. The third less affected state was Uttar Pradesh with the  $\beta_1$  Value of -0.042543385 Which determined that every unit increases in death will reduce 4.2% Foreign tourism arrivals to Uttar Pradesh (Mishra & Uniyal , 2010) the following are the steps taken by Uttar Pradesh Forecasting warning and alert system, Access to Information, strategy for Prevention, awareness programs, Building guidelines, Disaster risk Assessment map, earthquake resistant construction, Government buildings, Upgrading of Seismic resistance plans for basic risk etc.

Rajasthan is the state which has the maximum number of affected people with the  $\beta_2$  Value of -8.50235 Established for every one unit increase in affected people will reduce 8.5% Foreign tourism arrivals to Rajasthan (Kumar, Prakash, & Mishra, 2015) the study stated Jaipur fire Accident in 2009, Fire accident in 2012, Flash flood in 1968, Desert flood in 2006, earthquake with high magnitude are the major natural disaster the poor technology lead to more impact in the state. Followed by the second most affected state is Tamil Nadu with the  $\beta_2$  Value of -5.552 Which determined that every unit increases in affected people in Tamil Nadu will reduce Foreign tourism arrivals by 5% to the State (Gokhale, 2005) the study stated that following villages are affected by natural disaster Akkalpettai, Keechankuppam Poompuhar, Sonankuppam, Tiruvankudu, roypuram, Singarathope, Vailankanni srinivasapuram they climb the addition disaster Shelters for fishermen the third most affected state was Nagaland with the  $\beta_2$  Value of -5.18135 which show for every one unit increase in affected people in Nagaland will reduce 5% of Foreign tourism arrivals for the state.

The less affected three states are exemplified. This is the state which has no Impact because of Natural disasters the  $\beta_2$  Value of 0 shows that forever one unit increases there is no Increase or decrease in foreign tourism arrivals it may be the constant value of  $\beta_0$  Value of 163535.2762, Followed by West Bengal is the state in second place which

has the positive  $\beta_2$  Value of 0.000116698 which show for every one unit increase in affected peoples will increase 0.1% foreign tourism arrivals, Which the  $\beta_2$  Value of 0.02179599 in Jharkhand show for every one unit increases in affected people in the state will increase 1% growth in Foreign tourism in the state of Jharkhand.

## 5. Suggestion

The following states and Union Territory need to enhance their disaster management efforts: Bihar, which experienced a decline in growth rates of -125% and -293%, and Chandigarh, which saw decreases of -83% and -1.24%. Telangana also recorded a drop in domestic tourism, with growth rates falling by -25% and -6.89%. To attract a larger number of tourists, promotional strategies must be strengthened. India has faced a significant decline in foreign tourist inflow, which needs to be addressed as a serious issue. The tourism sector should aim to provide optimal services to boost international travel. Additionally, some states, like Tamil Nadu, witnessed a drop in domestic tourism in 2021, which could negatively impact the nation's revenue.

## 6. Conclusion

The study highlights a negative relationship between natural disasters and the inflow of foreign tourists. However, by enhancing safety and security measures, the influx of international visitors can be improved. The research indicates that after the COVID-19 lockdown, there has been a strong desire among people to travel to various destinations, which has contributed significantly to the growth of domestic tourism in India. The improved commutation systems and transportation infrastructure have also played a key role in this development.

India, being prone to natural disasters such as cyclones, floods, and earthquakes, requires an effective disaster management system to mitigate the impact of these events, especially in tourism-rich regions. Implementing efficient disaster preparedness

plans can help create safer environments for tourists, which in turn, would encourage both domestic and international travel to a wider variety of destinations across the country.

From 2020 to 2021, most states and Union Territories in India saw a rise in domestic tourism, driven by the increasing interest in local travel after international travel restrictions were imposed during the pandemic. The ease of movement within the country, combined with an increased awareness of the diverse travel experiences India offers, boosted domestic tourism in regions like Kerala, Himachal Pradesh, and Uttarakhand.

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# Scenario of Geo-Hydrological Disasters and their Perception Among People in a Himalayan Town: A Case Study from Almora Town

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## Abstract

*Disasters, whether natural or human-made, often have a profound impact on people's perceptions and responses. The perception of disasters among people is complex and multifaceted, influenced by a combination of factual information, media portrayal, personal experience, cultural background, and societal responses. Understanding these perceptions is crucial for effective disaster preparedness, response, and recovery efforts. Public perception influences policy decisions related to land use planning, infrastructure development, building codes, and environmental conservation. Accurate perceptions of disaster risks inform policies that promote resilience and reduce vulnerabilities over the long term. Decision makers rely on public support and understanding implement effective policies that mitigate disaster risks. The Himalayas are highly prone to earthquakes, landslides, flashfloods, snow avalanches etc. Today likewise other towns, Himalayan towns are expanding. Population pressure and other urban problems are very common there. The present paper discusses the people's perception on disasters and their management in Almora town.*

**Keywords:** Disaster Management, Perception, Himalaya, Earthquake, Landslides

## 1. Introduction

A Disaster is an event, natural or human-made, that has a significant impact which affects society or the environment in a destructive manner. Disaster management is

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the process of preparing for, responding to, and recovering from disasters, whether natural or human-made. It is a continuous cycle that includes activities from planning and mitigation before a disaster occurs, to response and relief during the disaster, and finally to reconstruction and recovery, aiming to minimize the impact of disasters on lives and property.

The Kumaon Himalayan region is highly vulnerable to natural disasters. Various natural calamities strike the study area almost every year, causing loss of life and property, agricultural land, forests, settlements, and assets worth millions of rupees. In the study area, natural disasters such as landslides, cloudbursts, earthquakes, large-scale devastation, storms, etc., occur naturally. Himalayan towns present a distinct framework of settlement. Over time, these towns have been increasingly burdened by population pressure. Unplanned development has raised questions about their future existence. The geographical structure, tectonic activities, changing climate, and human interventions have made these towns more vulnerable to disasters. Almora town is primarily sensitive to natural disasters. This region is particularly vulnerable to natural calamities such as earthquakes and landslides. Before managing any disaster, it is essential to understand what people know about that disaster, what their level of understanding is, and what their perceptions are. By knowing these aspects, disaster management can be implemented more effectively for that region.

## **2. Methodology**

The study employs a mixed-methods approach, combining quantitative and qualitative research methods. This design allows for a comprehensive understanding of the subject matter by integrating numerical data with in-depth insights. A primary survey has been done to know the perception of people about disasters and disaster management. Male and female respondents are chosen equally for the survey. A 25-60 years age group has been taken to complete the questioner because this age group has greater responsibility regarding disaster-related training, ongoing construction work in the city, and the changes taking place. 65 male and 65 female respondents are taken because male and female are equally important for a society and their representation should be equally. The number of respondents is selected randomly.

There are 10 questions in the questionnaire. The questionnaire is divided into two parts. The first part is related to the general perception of disasters and the second part is related to the perception about geo-hydrological disasters.

Field photography is important to know the real ground situation. Authors have tried to take pictures of disaster-prone areas in the study area.

This methodology provides a robust framework for exploring the perceptions and management of disasters across different communities. By combining quantitative and qualitative approaches, the research aims to yield comprehensive insights that can inform more effective disaster management strategies for a mid-Himalayan town.

### **3. Objectives**

1. To understand the reason of hazards in the study area.
2. To understand people perception on disasters in Almora town.

### **4. Literature Review**

Disasters, whether natural or man-made, have significant impacts on societies globally. The perception of these disasters and their subsequent management are critical in mitigating their effects. This literature review explores various aspects of disaster perception and management, examining key themes, theoretical frameworks, and practical applications. Slovic (1987) highlights that people tend to overestimate rare, catastrophic events while underestimating common, less dramatic risks. Protection motivation theory (Rogers, 1975) explains how people are motivated to protect themselves based on their perception of the severity and likelihood of a threat, their perceived ability to perform protective actions, and the efficacy of those actions. Individual perceptions of disasters are shaped by personal experiences, media influence, and social networks. Studies (e.g., Wachinger et al., 2013) have shown that those who have experienced a disaster firsthand are more likely to perceive future risks as significant and take precautionary measures. Research by Gaillard and Mercer

(2013) indicates that traditional knowledge and practices play a vital role in shaping how communities perceive and respond to disasters. In 2014, Salvati et al. studied perception of flood and landslide risk in Italy.

## 5. Study Area

The study area is located between 29°37' to 29°62' North latitude and 79°40' to 79°67' east longitude (fig.1). The study area is situated on a ridge in the Central Himalayas. The average altitude of this ridge above sea level is 1600 meters. The eastern part of this ridge is known as Tail Faat (sunny) and the western part is known as Sail Faat (shady). Currently, the study area covers an area of 7.54 square kilometers in Almora. Almora municipality was established in the year 1864. At present, the entire Almora municipality consists of 13 wards. Almora town is surrounded on three sides by hills known respectively as Syahi Devi, Kasar Devi, and Banari Devi, which also have temples of the goddesses. The Kosi and Suyal rivers flow to its west and southeast, respectively.



**Tail Faat (sunny)**



Sail Faat (shady)

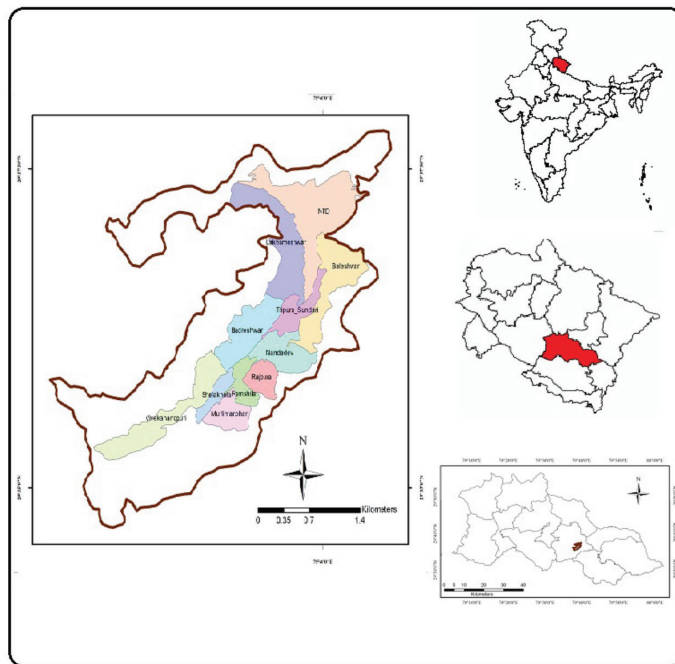


Figure 1 : Location Map of the Study Area

## 6. Result & Discussion

### 6.1 Geology & Geo-hydrological Hazards

Landslide and Earthquake are the main geo-hydrological hazards in the study area. The area of investigation is impacted by active faults and other geological movements. The study area is bounded by two thrust, North Almora Thrust and South Almora thrust. The entire area comes under Almora Crystalline. Tectonic activities are still going on, so the area of investigation is unstable. Many mountainous regions prone to landslides have also experienced moderate to significant earthquake activity throughout recorded history. Earthquakes in these steep, landslide-vulnerable areas significantly heighten the risk of landslides, either through ground shaking or the shaking-induced loosening of soil, which facilitates rapid water infiltration. The Lesser Himalaya, in particular, is highly susceptible to seismic activity. According to the seismic zonation map, the study area comes under the 4-5 zone.

### 6.2 Climatic Conditions & Hazards in the area of investigation

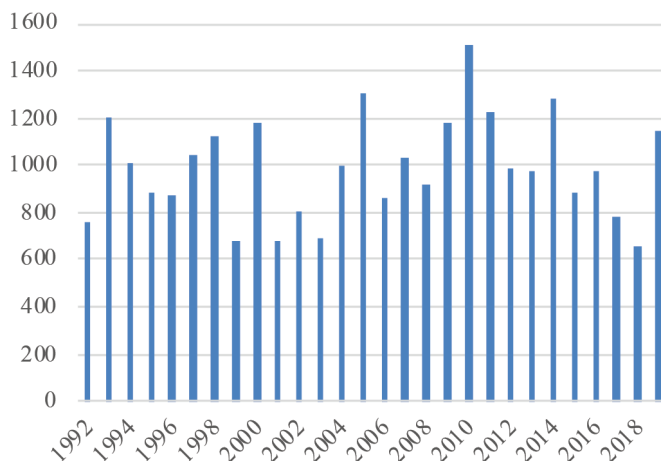
The climate plays a crucial role in the occurrence of disasters. The area of investigation consists warm and temperate type of climate which gets maximum rain in the monsoon. Rainfall is a basic indicator of hydrological disasters. The study area witnessed flash flood and landslides in the recent past.

**Table 1 : Rainfall Data of Almora Region 1992 to 2019**

Year	Rainfall in mm
1992	764
1993	1205
1994	1008
1995	889
1996	874

Year	Rainfall in mm
1997	1042
1998	1127
1999	683
2000	1185
2001	679
2002	803
2003	690
2004	996
2005	1307
2006	865
2007	1033
2008	920
2009	1178
2010	1505
2011	1230
2012	982
2013	972
2014	1282
2015	883
2016	974
2017	779
2018	654
2019	1140

Source: NRDMS Centre Almora



**Figure 2 : Rainfall in mm**

Table number 1 shows the rainfall data for the Almora region. 1998, 2010, 2014 and 2019 are the years in which the area got high rainfall as well as experienced cloud burst and landslide disasters.

**Demography in the study area**

Demography plays an important role in disaster management. In areas with high population density, the impact of disasters is greater because more people are affected. This also influences people's perceptions. In densely populated areas, people may have more information and resources, which can lead to better perceptions and responses to disasters.

**Table 2 : Ward-Wise Population of the Study Area (2011)**

S.N.	Ward	Male	Female	Total Population
1.	Tripur Sundari	1160	1299	2459
2.	Ramshila	1127	1132	2259
3.	Badreshwar	1764	1705	3469
4.	Dugalkhola	1122	1060	2182

S.N.	Ward	Male	Female	Total Population
5.	Selakhola	737	700	1437
6.	Lakshmeshwar	1673	1634	3307
7.	Murlimanohar	1485	1464	2949
8.	Baleshwar	2374	2245	4619
9.	Railapali	1253	810	2063
10.	Rajpura	2054	1850	3904
11.	Nandadevi	2014	1825	3839
12.	Vivekanand Puri	1128	1274	2402
13.	NTD	1839	1636	3475
	<b>Total Population</b>	<b>19730</b>	<b>18634</b>	<b>38364</b>

Source: Municipal Board Almora

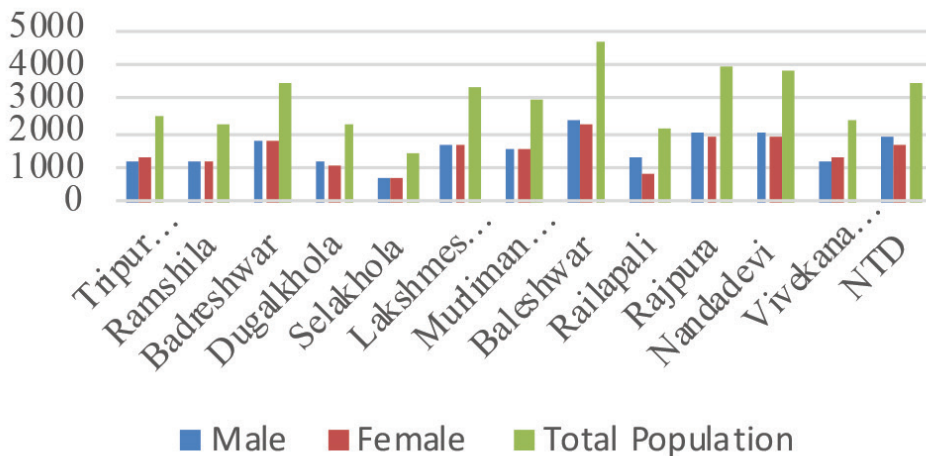


Figure 3 : Ward-Wise Population (Reviewer Comment: Fig. Included)

Rajpura, Vivekannadpuri, Dugalkhola & Railapali wards are more vulnerable to landslides. Small landslides in every monsoon take place. In these areas, construction activities are also progressing rapidly, but they are not being carried out in accordance with regulations.



**Construction on Steep slopes (Field Photographs)**

The photographs taken during the field visit indicate that construction work is being carried out on the slopes in Almora, which is not appropriate from a disaster management perspective. This has been observed more prominently in Dugalakholi, Railapali and Rajpura.

### **People Perception**

A questionnaire was developed to understand people's thoughts and perceptions about disasters, and it was administered to 130 individuals from 13 wards of Almora. This group included men and women aged between 25 and 60 years.

### General Perceptions about Disasters

#### 1. Do you know about Disaster?

**Table 3**

SN	Respondents	Yes	No	Total
1	Male	46	19	65
2	Female	51	14	65
	<b>Total</b>	<b>97</b>	<b>33</b>	<b>130</b>

Source: Primary Data

According to the table number 3, 74% of total respondents know about disasters. Percentage of female is more, which is interesting as well as good because female spent more time in their homes and more vulnerable to the disasters.

#### 2. Do you know the difference between Hazard & Disaster?

**Table 4**

SN	Respondents	Yes	%	No	%	Total
1	Male	4	6	61	94	65
2	Female	3	4	62	96	65
	<b>Total</b>	<b>05</b>	<b>11</b>	<b>123</b>	<b>95</b>	<b>130</b>

Source: Primary Data

A vast 95% of respondents do not understand the difference between a hazard and a disaster. This reflects a critical weakness in disaster literacy, which could negatively impact both individual preparedness and community resilience.

3. What are the types of disaster in Almora?

Table 5

SN	Type of Disaster	Number of Respondents	%
1	Natural	86	66
2	Man Made	14	11
3	Both	23	23
	<b>Total</b>	<b>130</b>	<b>100</b>

Source: Primary Data

4. Do you know about disaster management?

Table 6

SN	Disaster Management	Number of Respondents	%
1	Don not Know	25	19
2	During & Post-Disaster Management	83	64
3	Pre, During & N114 Post Disaster Management	22	17
	<b>Total</b>	<b>130</b>	<b>100</b>

Source: Primary Data

The data reveals a significant gap in knowledge of pre-disaster planning, which is a critical component of disaster risk reduction. People tend to associate disaster management mostly with response and recovery, rather than preparedness and mitigation. This mindset can limit community resilience, as prevention and

preparedness efforts (e.g., hazard mapping, early warning systems, community drills) are neglected or underprioritized.

5. Have taken any training related to disaster management?

**Table 7**

SN	Respondents	Yes	%	No	%	Total
1	Male	09	14	56	86	65
2	Female	05	08	60	92	65
	Total	14	11	116	89	130

Source: Primary Data

Above tables shows the perception and understanding reading to disaster and its management. Most of the respondents does not have much understanding regarding to disaster management. Table number 4 shows 95 % of total respondents do not know the difference between hazard and disaster. In table number 5, 89 % of total respondents have not trained in disaster management. The fact that 89 % of the total respondents have not received any kind of training indicates that there is no prior preparedness among people to deal with disasters.

### **Perceptions about Geo-hydrological disaster**

1. What do you know about earthquake?

Respondent have less understanding about earthquakes. They say that the sudden shaking of earth is called an earthquake. Only 22% of total respondent know the reason behind it, rest 78% do not know the reason behind an earthquake.

2. Do you know which earthquake zone Almora falls?

**Table 8**

SN	Respondents	Yes	%	No	%	Total
1	Male	20	31	45	69	65
2	Female	15	23	50	77	65
	<b>Total</b>	<b>35</b>	<b>27</b>	<b>95</b>	<b>73</b>	<b>130</b>

Source: Primary Data

Out of 130 respondents, only 27% (35 individuals) were aware of the earthquake zone in which Almora falls. A significant 73% (95 individuals) were not aware. This reflects a very low level of seismic risk awareness among the population.

3. What could be consequences of this?

**Responses:**

- A large number of people may die.
- Many people may get injured.
- Buildings, bridges, roads, and other structures may be destroyed.
- Electricity, water, and gas supply may be disrupted.

4. Do you know about earthquake resistant buildings?

**Table 9**

SN	Respondents	Yes	%	No	%	Total
1	Male	25	39	40	61	65
2	Female	10	15	55	85	65
	<b>Total</b>	<b>35</b>	<b>27</b>	<b>95</b>	<b>73</b>	<b>130</b>

Source: Primary Data

In table number 9, only 27% of total respondents know about earthquake resistant buildings. Most of the people knows about the consequences of earthquake.

5. Do you know about landslide?

All the respondents have minimum understanding about landslide hazard. They said 'sliding of land is called a landslide. The main causes of landslides are heavy rainfall, slope erosion, and the reduction of vegetation.

6. Do you know the landslide prone areas in Almora?

According to the respondents Dugalkhola, Railapali, Near Rghunath City Mall, Ranidhara are the major landslide prone areas in Almora town.

**Table 10**

SN	Respondents	Yes	%	No	%	Total
1	Male	21	32	44	68	65
2	Female	25	38	40	62	65
	<b>Total</b>	<b>46</b>	<b>35</b>	<b>84</b>	<b>65</b>	<b>130</b>

Source: Primary Data

Respondents have identified Dugalkhola, Railapali, Near Raghunath City Mall, and Ranidhara as the major landslide-prone areas in Almora town. Out of 130 respondents, only 35% (46 individuals) were aware of the landslide-prone areas. A significant 65% (84 individuals) were not aware of such zones. This indicates a low level of awareness among the general population about the local disaster-prone regions. The results reflect a general lack of public awareness, which could worsen the impact of landslides if early warnings or evacuations are ignored.

## 7. Conclusion

In conclusion, the perception of geo-hydrological disasters among people in Almora town is shaped by many complexities. People have less understanding of disaster management. Today, towns are expanding in the Himalaya. As a result, problems are also increasing.

This study reveals that Almora town is vulnerable to the perspective of geo-hydrological disasters, and the perceptions of the people regarding disasters indicate that there is a need for disaster-related information and training. Most of the individuals included in the study have only very limited general knowledge about disasters.

Enhancing disaster education programs, advancing early warning systems, and combining local knowledge with scientific insights can significantly improve resilience in these vulnerable regions. Future studies should explore the shifting impact of climate change on disaster risks and examine how various communities adapt to these evolving challenges. By integrating traditional wisdom with modern disaster management practices, we can develop more effective, community-centered strategies for disaster preparedness in the Himalayas. By fostering a collaborative approach that bridges traditional insights with modern disaster risk-reduction methods, policymakers and communities can work together to build a more resilient and informed society in the Himalayas.

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# Landscape Dynamics and Its Impact on Landslide Susceptibility: A Case Study of Idukki District, Kerala

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## Abstract

*Hazard is an event which may cause danger by natural, and human made activities. The hazard will become a disaster when it leads to life property and environment. Among the Natural hazard the Landslide are particularly devastating, especially in steep region, intense rainfall and uncontrolled or unregulated land use practices. The study Area Idukki district is reportedly the most prominent landslide susceptibility zone in Kerala. For this study the Multi Influencing Factor (MIF) method integrated with Geographic Information System (GIS) to assess the Landslide vulnerability zones of Idukki. The eleven parameters were selected for the analysis, which is Rainfall, Slope, Geology, Geomorphology, Land use land cover, Drainage density, Road density, soil, Normalized Difference Vegetation Index (NDVI), Topographic Wetness Index (TWI), Curvature and Elevation. These parameters are taken and converted into individual spatial layers then overlay these layers and find final output for the study. From this output the study provides detailed landslide susceptibility maps and categorises the study area into various susceptibility zones such as very low (0.33), low (5.42), moderate (31.10), high (63.12) and very high (3.59) susceptibility regions. The findings reveal that the area with steep slope, High rainfall, LULC especially unplanned human activities like deforestation, unregulated construction this will also exacerbate the risk of landslide. Understanding the dynamics of landscape and its impact in landslide susceptibility clearly indicates why the study area is demarcated as the intense zone of landslide vulnerability in Kerala and it will help to showcase through maps and can generate future developmental activities according to this fact.*

**Keywords:** Landslide, Western Ghats, MIF, GIS, Idukki

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## 1. Introduction

Landslides are one of the most destructive natural hazards, endangering lives, property, and disrupting infrastructure in vulnerable regions across the globe. These events involve the rapid down slope movement of earth, rock, or debris, often initiated by a mix of geological, environmental, and climatic triggers. Natural catastrophic agents such as heavy rainfall, earthquake, and anthropogenic activities such as deforestation and construction are frequently cited as catalysts (Guzzetti et al., 1999). In India, the Western Ghats recognised by UNESCO as biodiversity hotspot and spreading mountain range, are particularly more susceptible to landslides. This mass wasting process accelerating especially in the topographic steepness and intensive monsoon rainfall areas (Kuriakose et al., 2010). These are all the main factor in the Idukki District of Western Ghats range in Kerala emerges as a focal point for landslide risk. Many studies indicate that Idukki is the most severely impacted region in Kerala when it comes to disaster distribution (Kumar, 2020). Even though the region faces the wrath of most of the hazards, Landslides are identified as the major one. Thus, the key objective of this research is to undertake a comprehensive and detailed investigation specifically centered on Idukki District. The increased vulnerability of Idukki district to landslides can be understand from its different geographical features. Due to the influence of Western Ghats, Idukki is categorised by rugged terrain, steep slopes, and dense forest cover (Sajinkumar et al., 2014). These physical features significantly increase the Idukki's landslide risk, especially during the monsoon season when torrential rains are very common. Globally, these mass wasting landslides in the mountain areas have caused devastating losses for both human lives and assets. From the historical data, it reveals that the most catastrophic landslides have resulted in as many as 100,000 fatalities (Li and Wang, 1992).

The studies related to landslides in the mountainous terrain of Idukki district point out that the interactions of steep slopes and heavy precipitation create a risky environment (Thennavan & Pattukandan, 2021). From this understanding, this research tries to investigate the causes, consequences, and possible mitigation strategies to reduce landslide risks in the district. This research also aims to provide

application-oriented strategies by thoroughly examining 11 parameters related to the physiographic and climatic characteristics of the area. These parameters include slope, soil, elevation, curvature, drainage pattern, rainfall, NDVI, TWI, geology, land use and land cover, and road density. The goal of the study is to strengthen preparedness and resilience against future landslide events in Idukki. This study will help us to estimate the loss of landslides including loss of agriculture and damage in infrastructure in similar contexts (Petley, 2012).

It is evident from an understanding of landscape dynamics and how they affect landslide susceptibility why the study area has been designated as Kerala's high-risk landslide zone. This knowledge can be used to illustrate the area on maps and to inform future development initiatives. Understanding these impacts in Idukki can inform policy decisions and resource allocation.

The land based development is always been a question in our country. How can a region which is prone to multiple hazards can intervene in developmental activities and is it even possible for the region and its people to engage themselves in a quality of life as enjoyed by the other people. The answer remains, only if the development is done based on a proper planning and management that is suitable for the vulnerable location, then only the successful implementation of future building through infrastructure can happen and as to happen the same it is very much evident to understand the landscape dynamics. Especially in Idukki district of Kerala, comparatively, the varied topography with hilly and mountain terrain always falls behind such development.

Moreover, the study builds on prior research that shows the role of anthropogenic factors, such as land-use changes, in exacerbating landslide risks (Wasowski et al., 2011). By synthesizing these findings, this investigation aims to contribute to a broader framework for disaster risk reduction. Ultimately, the focus on Idukki District highlights the need for tailored strategies to address this pressing challenge. Through a detailed assessment of local conditions, this study aspires to pave the way for enhanced safety and sustainability in one of India's most landslide-prone regions.

## 2. Geographical Profile of the Study Area

In the state of Kerala Idukki was the worst hit district of landslide. Idukki District lies in the Western Ghats of Kerala, India, between 9°15' and 10°21' North latitude and 76°37' to 77°25' East longitude. Covering 4,612 square kilometers, it is Kerala's largest district, making up 12.9% of the state's area (Figure 1). It borders Kottayam, Pathanamthitta, Thrissur, Ernakulam, and Tamil Nadu's Dindigul, Coimbatore, and Theni districts. Its elevation spans from 130 meters above sea level to 2,695 meters at Anamudi, South India's highest peak. The average elevation is about 900 meters, supporting diverse flora and fauna. This range shapes the district's climate, agriculture, and ecological richness. Research shows an average annual rainfall of 377 centimeters (3,770 millimeters), key for plantation crops. Rainfall varies from 250 to 425 centimeters, with some areas like Peermedu reaching 500 centimeters. Lower rainfall, around 150 centimeters, occurs in rain shadow zones like Marayur. Temperatures fluctuate between 16°C and 32°C, influenced by elevation and the Western Ghats. The hot season (March to May) peaks above 87°F, while the cool season (June to September) dips below 80°F. High elevations like Munnar can near freezing, with mist above 1,300 meters. The 2011 census records a population of 1,108,974, with a density of 217 per square kilometer. This low density reflects a landscape over 50% forested and mountainous. The sex ratio is 1,006 females per 1,000 males, showing gender balance. The literacy rate is 92.18%, surpassing the national average, driven by urban centers. Kattappana and Thodupuzha are denser, while rural villages remain sparse. The district has 8 blocks and 52 grama panchayats for administration. Idukki generates 66% of Kerala's hydroelectric power, notably via the Idukki Dam. It's a tourist draw with Munnar hill station and Periyar National Park. Agriculture, including tea, coffee, and spices, thrives due to elevation and rainfall. Tribal communities and regional influences enrich their cultural heritage. Sustainable development is vital for its ecological and economic future. This analysis highlights Idukki's role as an agricultural and ecological hub.

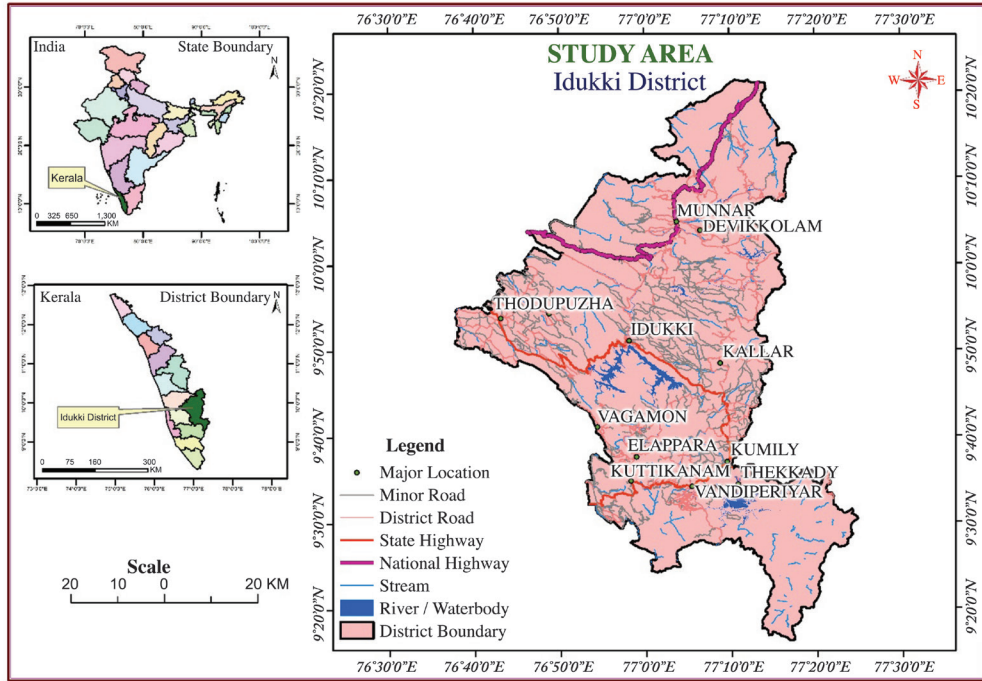


Figure 1 : Study Area

### 3. History of Landslides in Idukki District

Idukki district has a long history of landslides, with numerous significant events recorded over the years. News reports and historical data highlight major landslides along with their fatalities, revealing the severity of these incidents. The area's vulnerability to landslides is largely undulating steep slope and hilly terrain. Periyar river floods are recorded as the massive ones caused due to slope failure in history dates to 1341 AD (Sekhar L. Kuriakose et al., 2008). In recent decades, landslides become a more frequent and destructive agent. One of the earliest major tragedies was the Kumpanpara debris flow on 26 June 1985, which claimed 9 lives in Thodupuzha taluk. This was followed by the Bison Valley landslide on 14 July 1994, killing 7 people in Udumbanchola taluk. Deadly series of landslides struck Devikulam taluk between 21-25 July 1997, resulting in 13 deaths in Pazhampallichal, Ozhuvathadam,

Cheeyappara, and Valara regions. The Kattapana-Thodupuzha corridor experienced around 70 landslides between 20-25 August 2000. Some of the other notable landslides are Chinikuzhi slide (9 July 2001, 3 deaths) and the Venniyani Mala landslide (9 July 2002), which killed a photojournalist. In July 2005 multiple disasters affecting Idukki district including the Anthoniar Colony slide (25 July, 4 deaths) and collapses at Kozhippalli, Velliyani Mala, and Methotti Mala (31 July). The 2007 monsoon triggered several landslides, including those at Edamuttam, Churuli, Dyemuttam-Vandiperiyar, and Chelachuvadu (22 June), as well as Periyar Valley, Kudikayathil, Rajapuram, Konnathadi, and Muthanmudi (1 July). The Mankulam rotational slump was also linked to replantation activities. In 2018, multiple landslides in Adimali, Korangatti, and other areas caused at least 11 deaths. The 2020 Pettimudi disaster was especially devastating, with 66 fatalities, highlighting the persistent landslide threat. The 2021 Koottickal and Kokkayar landslides along the Meenachil River killed 13 people, while the 2022 Kudayathoor landslide near Thodupuzha resulted in 5 deaths. While these major events are well-documented, many smaller landslides without casualties likely go unreported, suggesting the actual number of incidents is much higher.

#### **4. Data Source**

The present study employed a range of thematic layers from credible data sources to assess landslide susceptibility. The rainfall data was collected from NASA's earth data portal, while the topographic parameters such as slope, curvature and TWI were extracted from the advanced land observing satellite ALOS and Dem with a spatial resolution of 12.5 meters. Vegetation cover was represented using the Normalized Difference Vegetation Index (NDVI), derived from Landsat 8 OLI/TIRS Level 1 imagery (Path 144, Row 053) dated 2 March 2021, accessed via the USGS Earth Explorer platform. Geological data were obtained from the Idukki District Mineral Resource Map at a scale of 1:250,000. Drainage density was calculated using both ALOS DEM and Survey of India (SOI) topographical maps at a 1:50,000 scale. Land use and land cover information was sourced from the Kerala State Land Use Board (2015), and road density was mapped using data from OpenStreet Map. Soil characteristics were incorporated from the Idukki Soil Map provided by the Kerala State Soil Survey Department. Data sources and their detailed metadata are given in Table 1.

Table 1 : Data Sources

Sl No	Parameter	Data source	Year	Band/Toposheet Number
1	Rainfall	<a href="https://dsp.imdpune.gov.in/">https://dsp.imdpune.gov.in/</a>	1951-2023	-
2	Elevation, Slope, TWI, Relief	ALOS DEM (12.5 Meter Resolution)	2024	-
3	Land use land cover	<a href="https://earthexplorer.usgs.gov/r-Landsat-8-OLI/TIRS-C1-Level-1-Path-144-Row-052">https://earthexplorer.usgs.gov/r-Landsat 8 OLI/TIRS C1 Level-1, Path 144, Row: 052</a>	2023	Band 2, Band 3, Band 4, Band 5, Band 10, Band 11
4	NDVI	Landsat-8 from Google Earth Engine.		Band 4, Band 5
5	Road Density	<a href="http://www.openstreetmap.com">www.openstreetmap.com</a>	2023	
6	Drainage Density	Survey of India (1: 50,000) toposheet)	1970	58A08, 58A12, 58A16, 58 B09
7	Geomorphology	Kerala State Land Use Board	2005	-
8	Geology	Idukki District Geology and Mineral Resource Map (1: 2,50,000) prepared by Geological Survey of India	-	-
9	Soil Texture	<a href="https://www.keralasoils.gov.in">https://www.keralasoils.gov.in</a>	2020	

## 5. Materials and Methods

The multi-criteria analysis approach is assessing more than one criterion together, which have different measurement units and are incoherent among each other and which are weighed to determine and group more than one alternative and to determine priority choices (Yoon, K., Hwang, C. 1995). There are different methods that are used to conduct multi-criteria analysis within the environment of GIS. These methods are mainly based on Boolean operator principles of AND and OR. When degree of significance is considered among the criteria in addition to that, the weighting process among criteria has been made (Malczewski, J. 1999).

Delineating landslide vulnerable area is done through the Multi-Influencing Factor (MIF) technique. MIF methods have been widely accepted by academics

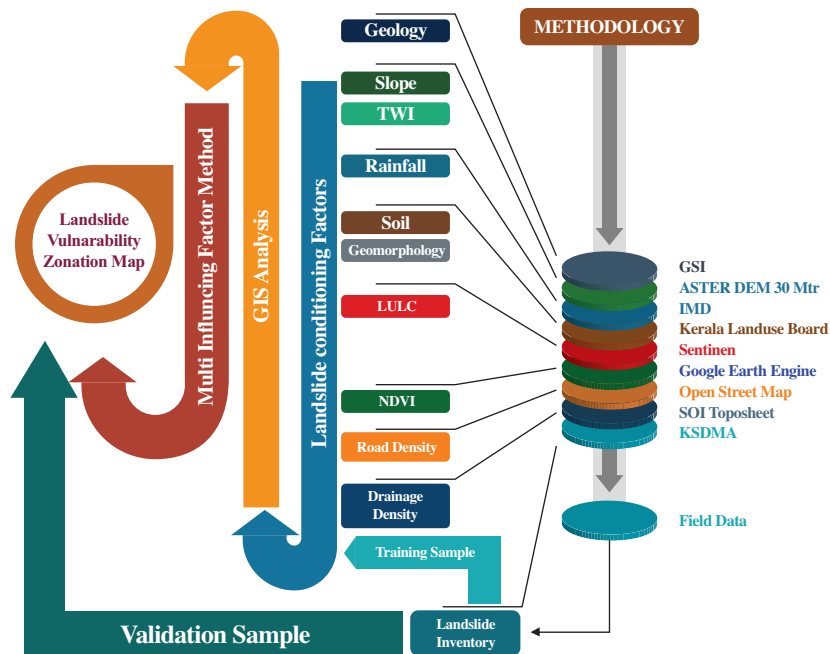


Figure 2 : Methodology Chart

since the 1990s for the spatial decision-making process (Roy, S. et al., 2023); in addition, with the integration of GIS and remotely sensed data it is possible to solve

critical problems regarding spatial distribution and choosing desirable locations (Alkaradaghi et al., 2019; and Hussein et al., 2018). Therefore, several researchers have found that geographic information systems (GIS) and remotely sensed data in combination with the MIF method have a great potential for enhancing land related applications (Pramanik, 2016; Orhan et al. 2021; Everest et al., 2021; Mendas et al., 2021). FAO (1976) provided a logical method to evaluate land suitability ranges from highly suitable to unsuitable based on climatic data, topographical features, and factors related to soil parameters. Additionally, a weighted aggregation method based on equations was proposed by Bandyopadhyay et al. (2009) for assessing agricultural land suitability potentials using remote sensing and GIS. However, when it comes to spatial mapping, the interplay between different thematic layers is critical (Thomas & Duraisamy, 2018). Therefore, despite several methods, it is always appropriate to integrate remote sensing and GIS with MIF technique for critical evaluation of landslide and land degradation assessment, as it benefits planners and managers, as well as helps to determine the most appropriate spatial pattern for sustainable management (Kumar et al., 2021).

Rainfall, Slope, Soil, Drainage Density, Land Use Land Cover, TWI, Road Density, Geology, Vegetation Cover, and Curvature are the major parameters considered for the delineation of landslide assessment (Figure 3). Each parameter is interdependent on other parameters viz. Each parameter has a major effect (A) and minor effect (B) upon other parameters. For each major and minor inter-related factor, a weightage of 1 and 0.5 is assigned respectively. A relative rate is calculated for each factor by cumulating all the weights of major and minor interrelated factors (A+B). A factor with a higher relative rate shows a larger impact on the landslide and vice versa. This relative rate is further used to calculate the score by each influencing factor by using the following formula (equation 1).

$$= \left\{ \frac{(A+B)}{(\sum A+B)} \right\} \times 100 \dots \dots \dots \text{Equation 1}$$

Where A is the major inter-relationship between two factors B is the minor inter-relationship between two factors A+B is the relative weight of each factor (Table 2 & 3).

**Table 2 : Influencing Factors with major and minor effect**

Influencing Factors	Major Effect A	Minor Effect B
Rainfall	Soil, Drainage Density, TWI, Vegetation Cover, Land Use Land Cover	Slope, Road Density, Geology, Curvature
Slope	Soil, drainage density, land use land cover, TWI, Road Density, Vegetation Cover, Curvature	Rainfall, Geology
Soil	Rainfall, Slope, LULC, Geology, Vegetation Cover	TWI, Road Density, Drainage Density, curvature
Drainage Density	Slope, Rainfall, TWI, Vegetation Cover	Soil, LULC, Road Density, Geology, Curvature
Land Use Land Cover	Rainfall, Soil, Road Density, Vegetation Cover, Slope	TWI, Geology, Curvature, drainage density
TWI	Geology, Rainfall, curvature, Vegetation Cover, slope, Drainage Density	Soil, LULC, Road Density,
Road Density	Slope, LULC	Rainfall, Soil, Drainage Density, TWI, Geology, curvature
Geology	Soil, Curvature, TWI	Rainfall, Slope, Drainage Density, Road Density, Vegetation Cover, LULC
Vegetation Cover	Rainfall, Soil, Slope, TWI, Drainage Density	Curvature, Road Density, LULC, Geology
Geomorphology	Slope, TWI, Geology, Drainage Density	Vegetation Cover, Rainfall, Soil, LULC, Road Density

Here, the Table 2 indicates that the influencing factors taken for the study is directly or indirectly related with other potential factors. Through this table, it is more relevant in understanding how each parameter is influencing the other potential factors in causing both major and minor effects.

**Table 3 : Influencing Factors: Their Impact, Relative Rates and Scores**

Influencing Factors	Major Effect A	Minor Effect B	Proposed Relative Rates (A+B)	Proposed Score for Each Influencing Factors
Rainfall	1+1+1+1+1	0.5+0.5+0.5+0.5	7	10
Slope	1+1+1+1+1+1+1	0.5+0.5	8	12
Soil	1+1+1+1+1	0.5+0.5+0.5+0.5	7	10
Drainage Density	1+1+1+1	0.5+0.5+0.5+0.5+0.5	6.5	9
Land Use Land Cover	1+1+1+1+1	0.5+0.5+0.5+0.5	8	12
TWI	1+1+1+1+1+1	0.5+0.5+0.5	7.5	11
Road Density	1+1	0.5+0.5+0.5+0.5+0.5+0.5+0.5	5.5	8
Geology	1+1+1	0.5+0.5+0.5+0.5+0.5+0.5	6.5	9
Vegetation Cover	1+1+1+1+1	0.5+0.5+0.5+0.5	7	10
Geomorphology	1+1+1+1	0.5+0.5+0.5+0.5+0.5	6.5	9
<b>SUM</b>			<b>68.05</b>	<b>100</b>

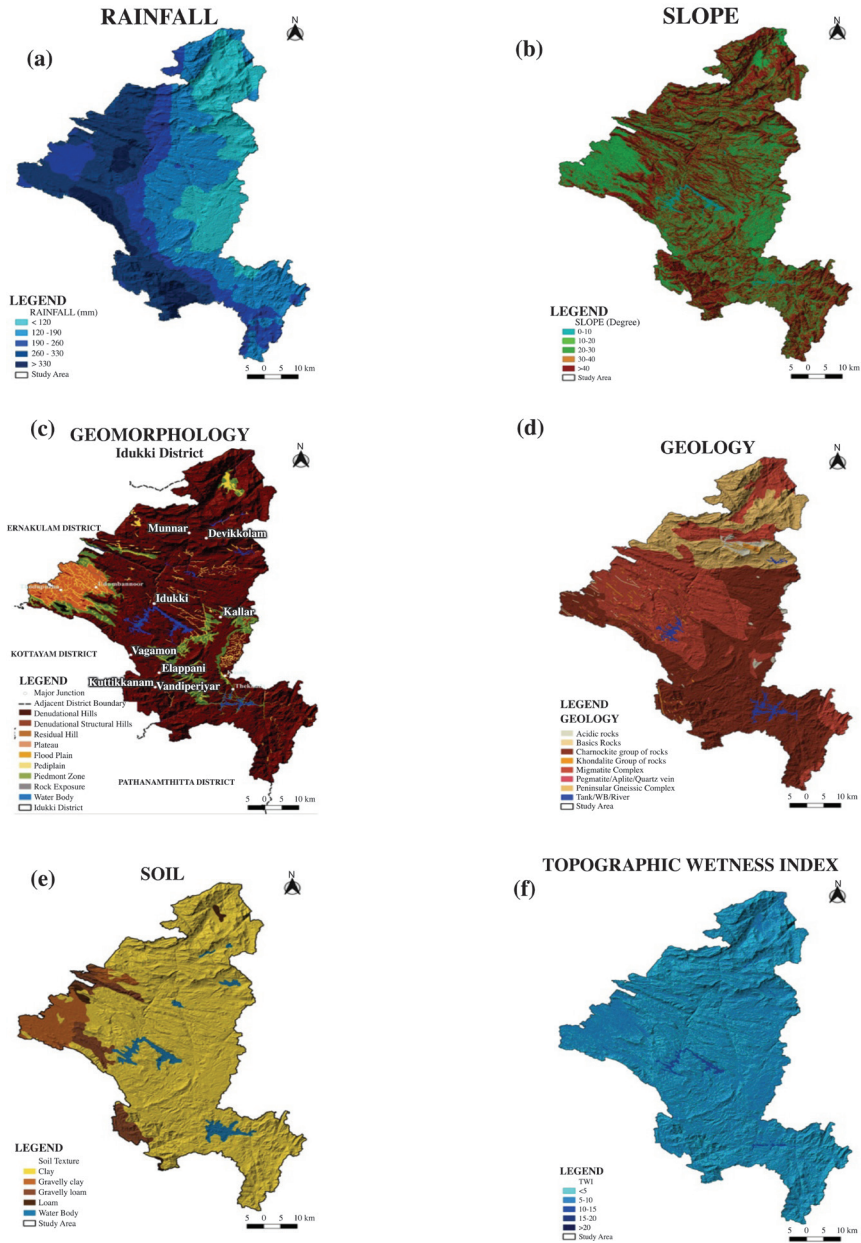


Figure 3 : Landslide Influencing Factors

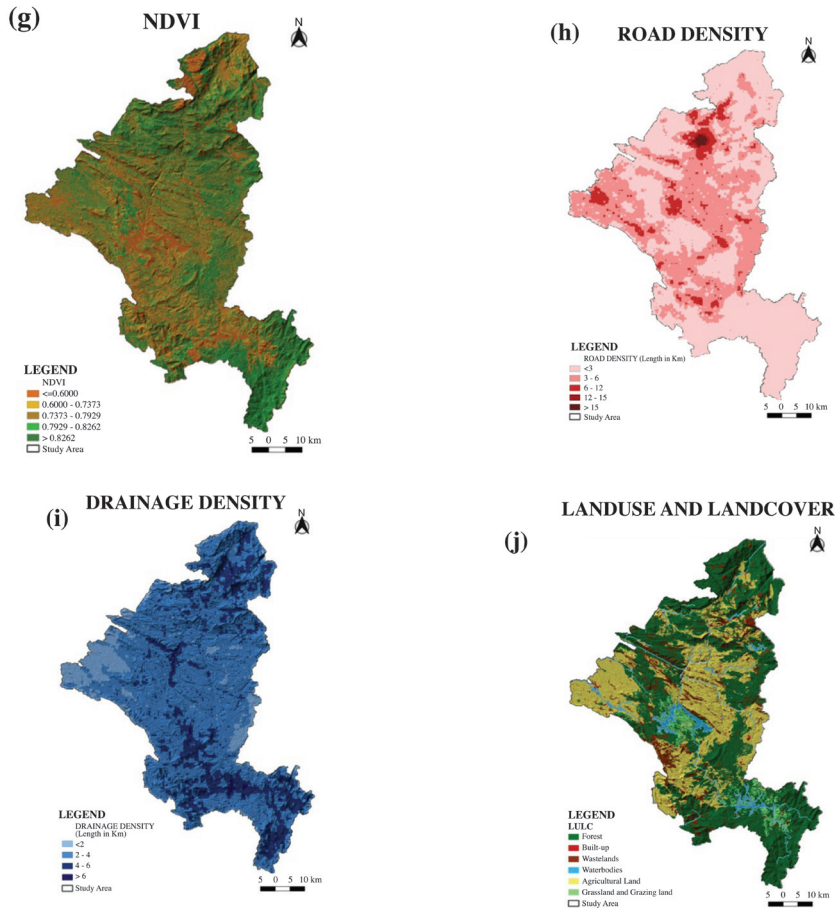


Figure 3 : Landslide Influencing Factors

## 5.1 Rainfall

The relationship between rainfall and landslides in the Idukki district is a critical area of study due to the region's susceptibility to landslides, particularly during the monsoon season. Heavy rainfall acts as a primary trigger for landslides, triggered by the district's unique topography and soil conditions. Factors such as slope, elevation, and rainfall, along with anthropogenic factors like land use, significantly influence landslide susceptibility (Jones et al., 2021). The scarp of the Western Ghats receives an annual rainfall high as 5000mm as a southwest monsoon, northeast monsoon and the

pre-monsoon (Kuriakose, S.L et al., 2009). The high intensity of rainfall leads to pore water pressure within the soil mass, which eventually decreases the shear strength of the soil (Figure 3a). This will be considered as the primary triggering factor of landslides in the Western Ghats (Jaiswal, P and van Westen, C.J., 2009). For the purpose of infrastructure like road developmental activity and tourism related constructions this will lead to large scale hill toe modification which leads to hill slope becoming steeper without any lateral support. The terraced slopes, modified for monoculture plantations with no sufficient drainage provisions, aggravated the scenario (Abraham et al., 2019). Due to the drainage blockage the water from the intense rainfall accumulates in the top soil layer leads to landslide activity. The landslide types vary from creep and subsidence to debris flows, along the district's road corridors the earth or debris slide will commonly become monsoon period (Sajeev, R et al., 2014). Continuing rainfall and the subsequent pore pressure increase adversely affect the steep slopes and leads to landslides. Here the impact caused by Rainfall in the study area is major. The regions that receive a higher rate of rainfall is more susceptible to landslide risk zones.

## 5.2 Geology

Geologically the study area consists of charnokite, khondolite and migmatite group of rocks contribute the formation of a part of a part of south Indian Precambrian metamorphic shield (Sulal, N et al., 2019). The geology of Idukki District, characterized by Precambrian crystalline rocks of the Southern Granulite Terrain, significantly influences its landslide susceptibility patterns, with major lithologies including charnockites, khondalites, migmatites, gneisses, lateritic cappings, and alluvial deposits (Figure 3d). Charnockites, while generally resistant, represent jointed and fractured structures that facilitate water infiltration, particularly along shear zones, whereas khondalites, rich in garnet and sillimanite, weather into clay-rich soils that reduce slope stability. Migmatites and gneisses, with their foliated structures, are prone to differential erosion, creating tension cracks and overhang that lead to rock fall and debris slides, while lateritic deposits, though porous, are vulnerable to piping erosion during heavy rainfall. Structural weaknesses such as the NNE-SSW trending Periyar Shear Zone act as groundwater conduits, elevating pore pressure, and deep weathering profiles in khondalites further diminish shear strength, correlating with moderate to high landslide risk zones.

### 5.3 Geomorphology

Idukki District in Kerala is characterized by a diverse geomorphology, dominated by the rugged Western Ghats, deep river valleys, and rolling hills. The Periyar and Thodupuzha rivers shape its terrain, while the Idukki Arch Dam sits amidst steep slopes. Anamudi (2,695 m), India's highest peak, lies here, along with dense forests, plateaus, and waterfalls. Geomorphic classification of the terrain divided the district into four. They are rugged hills, ridges and valleys, fringe slopes and plateau (Sulal, N et al., 2019). Scarps of the Idukki district consist of frictional soil with less cohesion, thus being stable in dry conditions and losing their strength when the moisture content increases (Figure 3c). Plateau regions have a thick layer of topsoil which is rich in clay content, due to their morphology and tropical climate (Sajeev, R.; Sajinkumar, K.S. (2013).

### 5.4 NDVI

The relationship between vegetation condition and landslides in Idukki district is critical, as changes in land use and vegetation cover significantly influence landslide susceptibility (Figure 3g). The decline in dense vegetation, coupled with increased built-up areas, has heightened the region's vulnerability to landslides over the past eight years (Sankar et al., 2023). This is boosted up by heavy rainfall, which is a primary trigger for landslides in the area, as evidenced by the establishment of rainfall thresholds for future predictions (Abraham et al., 2019). When vegetation cover decreases landslide risk will increase and more areas become highly prone to landslides (Sankar et al., 2023). Vegetation plays an important role in keeping soil cohesion, as plant roots hold the soil in place and help to prevent soil erosion, which reduces the intensity of landslide occurrences. (Lalitha et al., 2021).

### 5.5 Drainage Density

Drainage density and landslides in Idukki district are correlated as drainage density impacts slope stability and hydrological conditions. As a result, in the recurring events landslides are more frequent in the more drainage density regions. When drainage density increases, the runoff and soil saturation also increase, which are the crucial factors in landslide occurrence. The undulating terrain and steep slopes of Idukki

leads to high drainage density (Figure 3i), which increase landslide risks (Raveendran et al., 2015). The increasing drainage density leads to rapid runoff, increasing soil moisture and initiating pore water pressure, which are critical in triggering landslides (Kuriakose, 2024). The landslide hazard zoning analysis in Idukki reveals that the highly vulnerable zones can be linked to areas of high drainage density (Raveendran et al., 2015). Deforestation and other human activities like urban expansion, unplanned infrastructure activities etc. that lead to the drainage density further destabilizing the slope and thereby ramp up the landslide frequency (Aparna et al., 2023).

### **5.6 Topographic Wetness Index (TWI)**

Landslide susceptibility studies required Topographic Wetness Index (TWI) data, especially the hilly terrain of Idukki district. Because TWI directly helps to landslide vulnerability due to its mountainous topography and abundant rainfall. TWI is a metric that evaluates possible soil saturation, a major landslide trigger, by combining slope and upstream contributing area. Because regions with high TWI values are more likely to have soil saturation and subsequent slope failures, there is a considerable correlation between TWI and landslides in Idukki. Soil saturation levels can be predicted using TWI values and it is important for determining the risk of landslides. The high TWI values indicate places where water collection is expected more, increasing the risk of landslides (Montgomery & Dietrich, 1994). The integration of TWI with other factors such as slope angle and soil properties enhances the landslide susceptibility models using GIS based methods (Thomas et al., 2021). In Idukki, rainfall is the primary means of landslides, and empirical models reveal that antecedent rainfall conditions have a substantial effect on landslide occurrences (Abraham et al., 2019). The correlation between the high TWI area and the actual positions of landslides has now been confirmed with SAR interferometry and other remote sensing methods in studies performed to determine the suitability of TWI in landslide prediction (Kalaranjini & Ramakrishnan, 2020). Topographically based models that consider TWI and other topographic and hydrological factors have been found to be consistent with observed patterns of landslides and so could be used in regional landslide risk analysis (Montgomery & Dietrich, 1994). The huge number of water bodies like streams, rivers and the reservoirs are the main factors that contribute to the water accumulation of the whole district.

## 5.7 Road Density

The relationship between road density and mass wasting in the Idukki hilly region is combined by both natural and human induced factors. Roads can aggravate landslide risks by altering natural drainage patterns and destabilizing slopes, while also providing access for mitigation efforts. In Idukki, the interaction between road networks and landslide occurrences is significant, as evidenced by various studies focusing on the region's geospatial and geotechnical characteristics (Figure 3h). Geospatial techniques have been employed to map landslide-prone areas along the Thodupuzha-Idukki-Munnar road, identifying highly fragile zones that require immediate attention (Abraham & Shaji, 2013). To make it possible to classify areas depending to their fragility—a critical component of road design and maintenance GIS platforms incorporate topography data as slope, land use, and drainage density (Abraham & Shaji, 2013). Roads can increase landslide susceptibility by disturbing the natural stability of slopes, as seen in the Adimali-Munnar road study, which identified unstable slope profiles due to both natural and man-made factors (Ishack & Abraham, 2011). A spatial statistical analysis across various regions indicates that landslide density is often higher near roads, suggesting a potential mapping bias or a genuine increase in susceptibility due to road proximity.

## 5.8 Land Use and Land Cover (LULC)

Land Use and Land Cover (LULC) changes and landslides in Idukki district is significant. Over the past years, urbanization has increased while dense vegetation has decreased, and this situation leads to increased landslide susceptibility. Studies indicate that both natural and man-made factors contribute to this phenomenon. Increased built up areas have been observed in the district, which disrupts natural drainage and increases runoff (Sankar et al., 2023). The decline in dense vegetation of the district reduced soil stability, making the slope more susceptible to landslides occurrence (Sankar et al., 2023). The expansion of agriculture in the early period, land and deforestation have made worse to the situation, that contribute to increased landslide frequency and while the focus on LULC changes highlight the increasing risk of landslides, it is also essential to consider the role of climate change and extreme weather events, which further complicate the landscape and increase vulnerability in Idukki district (Aparna et al.,

2023). Due to the plantation activities and restructure in the agricultural activities became one of the important reason among Wasteland, Built up area, Forest, etc.

## 5.9 Soil

The soil characteristics of the district, particularly the Atterberg limits play a crucial role in landslide occurrences. The stability of the soil in various moisture conditions is controlled by these limits, which are altered by elements including weathering and soil composition. The Atterberg limits, which include the soil convert to plastic stage to liquid stage and flow like thick liquid (liquid limit), the soil changing to semi solid to the (plastic stage), lowest moisture content at which the moisture content of the soil rolled into thin threads without crumbling (plastic limit) and the range of moisture content in the soil stay in moldable and help to assess its stability and potential for swelling (plasticity index) are critical in assessing soil stability. Idukki is vulnerable to deep landslides and possesses regolith thicknesses that vary from 0.25 to 5 m (Kuriakose, S.L et al., 2009) (Government of Kerala, 2018). In Idukki, the highly weathered lateritic soils exhibit low cation exchange capacity and variable charge minerals, making them prone to landslides during heavy rainfall and the soil profile morphometry, with specific plastic limit values, is associated with landslide occurrences, particularly in steep sloping areas (Lalitha et al., 2021). The natural factors such as slope, elevation and rainfall significantly influence landslide occurrences and the topography and high rainfall during monsoons exacerbate the risk (Jones et al., 2021). Human activities, including land use changes, road density, increased quarry density and deforestation lead to an increase in landslide susceptibility. The increase in built up areas and decrease in dense vegetation over recent years have heightened the risk of making landslide scenario (Sankar et al., 2023). The increasing frequency and intensity of landslides is mainly due to climate change and human activities.

## 5.10 Slope

The Western Ghats' peculiar geography renders the region more vulnerable; several landslides have been reported there, especially during the monsoon seasons when the area suffers steep slopes with substantial rainfall. The geography of the region consists of a slope as steep as 80° and elevation ranges up to 2695m. About 97% of the major roads

in the district cut through this rugged mountain and hills which are often blocked due to landslide in the monsoons (Sajeev, R et al., 2014). Idukki district has a high incidence of landslides, with 2,219 occurrences reported, making it the most affected area in Kerala during the 2018 disaster (Jones et al., 2021). Landslides are predominantly found on steep slopes, with studies indicating that 22 out of 27 observed slides occurred in steep terrain (Kalaranjini and Ramakrishnan, 2020). The heavy rainfall (61.6 cm) and steep slope in Pettimudi during august 2020 give a way to worse landslide in the district (Achu et al., 2021). The combination of natural factors like slope, geology and anthropogenic influences land use, road density significantly increases landslide susceptibility (Jones et al., 2021). So here we can understand that the slope, especially deep slope region will very vulgarly be converted into more risk region during monsoon.

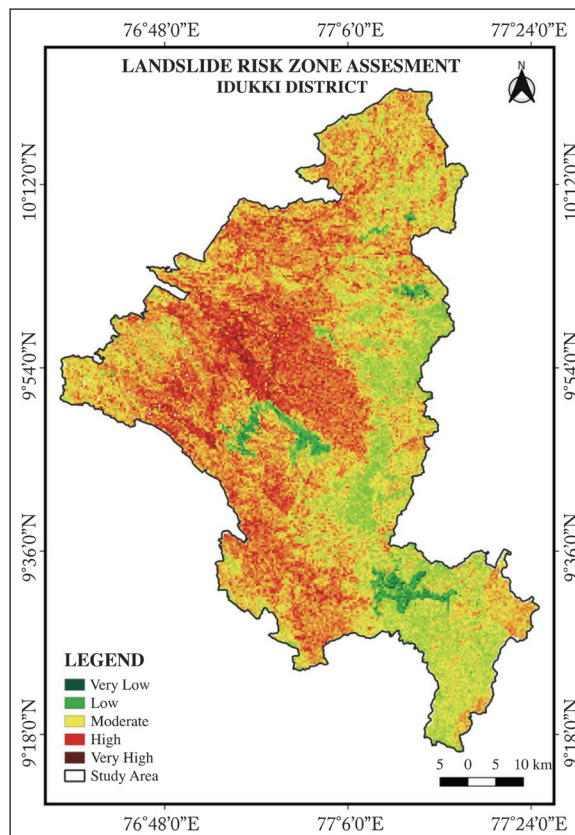


Figure 4 : Landslide risk zone assessment

Table 3 : Landslide risk area

Sl.No	Land Slide Risk Area	Area in Km <sup>2</sup>	Area in %
1	Very Low	14.44	0.33
2	Low	47.01	1.86
3	Moderate	1349.62	31.10
4	High	2739.56	63.12
5	Very High	155.72	3.59
	<b>Total</b>	<b>4361.40</b>	<b>100</b>

## 6. Results and Discussion

The landslide susceptibility zonation for Idukki District, generated using the Multi-Influencing Factor (MIF) technique, reveals a spatially revealed risk distribution influenced by geomorphological, hydrological, and anthropogenic factors. The analysis classified the region into five risk categories: Very Low (0.33%), Low (1.86%), Moderate (31.10%), High (63.12%), and Very High (3.59%), covering a total area of about 4,361 km<sup>2</sup>.

The Very Low and Low risk zones, encompassing only about 2.19%, moderate covers and high risk zones covers 94.22% of the district, correlate with stable geological formations, gentle slopes (<10°), and dense vegetation cover, which mitigate slope instability (Figure 3b). These areas are predominantly underlain by less weathered rocks and show low drainage density, reducing water-induced shear stress. In contrast, the Moderate risk zones (25.28%) coincide with intermediate slope angles (10°–20°), mixed land use (e.g., agriculture), and moderate rainfall (2,600–3,300 mm/year). Here, the interplay between soil saturation (TWI >5) and periodic anthropogenic disturbances (e.g., road cuts) elevates susceptibility.

The High and Very High risk zones (66.71% combined) are localized in steep slopes (>30°), fractured lithologies (e.g., migmatites), and areas with high drainage density

(>4 km/km<sup>2</sup>). These regions are further aggravated by intense monsoon rainfall (>3300 mm/year), which amplifies pore pressure, and deforestation, which reduces root cohesion. Notably, the Very High risk pockets (0.03%) align with concave slope profiles and proximity to road networks, where cut-and-fill activities destabilize slopes.

The MIF-based susceptibility map demonstrates strong agreement with observed landslide occurrences, particularly in the High and Very High risk zones of Devikulam and Udumbanchola taluks. The slope gradient emerged as the dominant vulnerable factor, with steeper slopes revealing higher displacement potential due to gravitational stress. Rainfall acts as a primary triggering mechanism, with prolonged precipitation increasing hydraulic pressure in permeable soils (e.g., laterites), leading to reduced shear strength.

Soil type and geology further modulate susceptibility; for instance, clay-rich soils in the Western Ghats exhibit low permeability, promoting rapid runoff and surface erosion, while weathered granulites are prone to deep-seated failures (Fig. 3e). Drainage density exacerbates risk in high-order streams, where concentrated flow undercuts slopes. Land use changes, such as tea plantations replacing natural forests, diminishing evapotranspiration and increasing infiltration, elevating groundwater-induced instability.

Topographic Wetness Index (TWI) highlights convergence zones where water accumulation lowers soil cohesion, particularly in hollows and valleys (Fig. 3f). Road density introduces anthropogenic triggers by altering natural drainage and creating artificial fill slopes. The study also highlights the interaction of contributing factors, where slope characteristics and rainfall patterns form the primary physical basis for landslides, while human interventions such as road construction significantly increase the inherent instability of these slopes.

From table no. we can identify that the very low landslide risk zone addressed only seven landslides, then in the low landslide occurrence zone have about 120 landslide incidents it records 5.42 percentage of the total landslide in the district. Moderate landslide risk zone reports 457 landslides that record 20.63 percent of the total landslide occurrence. The high landslide risk zone has 857 landslides and that was

38.69 percent of the total landslide and in very high 774 incidents occurred that was about 34.94 percent of the total landslide occurrence. From the table we can understand that most of the landslides occurred in high and very high landslide risk zone of the study area that was 73.63 percent.

## 7. Conclusion

This study assessed landslide susceptibility in Idukki District, Kerala, using the Multi-Influencing Factor (MIF) method integrated with GIS. The analysis incorporated 10 parameters—Rainfall, Slope, Geology, Geomorphology, LULC, Drainage Density, Road Density, Soil, NDVI and TWI to classify the region into five risk zones. Results revealed that 73% of the area falls under very low to low risk, characterized by stable slopes and dense vegetation, while 1.72% (high to very high risk) comprised steep slopes ( $>30^\circ$ ), fractured lithologies, and intense rainfall zones. The majority (85%) of fatal landslide events occurred between June-August during the monsoon season, with Devikulam followed by Thodupuzha taluks being the most active landslide-prone areas. The MIF technique effectively highlighted the interplay of natural and anthropogenic factors, with slope and rainfall emerging as dominant triggers, while road construction and deforestation exacerbated instability. The susceptibility map aligned with historical landslide occurrences, particularly in these high-risk taluks. This study reveals the need for monsoon-specific early warning systems and sustainable land-use planning, especially in Devikulam and Thodupuzha, to enhance resilience against future landslides. The findings provide a scientific basis for policymakers to implement targeted mitigation measures in this ecologically sensitive Western Ghats region. Landslide vulnerability is addressed as a notable risk on a global scale, especially in India's varied topography with mountains and hilly terrains. By giving an empirical approach in understanding variables like slope, rainfall, and geology, the study may create more accuracy in susceptibility maps using quantitative models like FR and MIF. These results empower hazard preparedness throughout susceptible zones by covering large areas with high precision. The significance of these data-driven evaluations will only increase on a regional and global scale as landslides become more frequent.

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