"VISVESVARAYA TECHNOLOGICAL UNIVERSITY"

JNANA SANGAMA, BELAGAVI – 590 018

Project Work Phase-I Report On

"Landslide Zone Mapping using Logistic Regression"

Submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF ENGINEERING

In

ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

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GOVERNMENT ENGINEERING COLLEGE, KARWAR
MAJALI – 581 345, UTTARA KANNADA, KARNATAKA
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DEPT. OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

Certified that the Project Work Phase-I entitled "Landslide Zone Mapping using Logistic Regression" carried out **by Mr. Charan A Bijapur USN: 2GP20EC006** and **Miss. Sahana AS USN: 2GP20EC014** are bonafide students of Government Engineering College, Karwar in partial fulfillment for the award of **Bachelor of Engineering** in **Electronics and Communication Engineering** of the Visvesvaraya Technological University, Belagavi during the year 2023-2024. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report. The Project Work Phase-I Report has been approved as it satisfies the academic requirements in respect of the Project Work prescribed for the Bachelor of Engineering Degree.

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DECLARATION

We, the members of the Project Work Phase-I, studying in the 7th semester of Electronics and Communication Engineering, Government Engineering College, Karwar, Majali, hereby declare that the entire project entitled **"Landslide Zone Mapping using Logistic Regression"** has been carried out under the guidance of **Dr. Choodarathnakara A. L.**, Associate Professor and Head of the Department of Electronics and Communication Engineering, Government Engineering College, Karwar, Majali. This Project Work is submitted to the Visvesvaraya Technological University, Belagavi in partial fulfillment of the requirement for the award of the degree of **Bachelor of Engineering in Electronics and Communication Engineering** during the academic year 2023-2024. This Project Work has not been submitted previously for the award of any other degree or diploma to any other institution or university.

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ABSTRACT

Landslides arise as a result of interactions between various geoenvironmental elements, human activity, climatic change, and rapid urbanization. Landslides pose challenges to the development of any region due to the economic losses they entail. This paper introduces a landslide zone mapping approach to address the mitigation of this issue within a region of Kodagu. Kodagu district in Karnataka state lies in the southern part of Western Ghats with high range hills. The district has a mountainous configuration, which presents a grand panorama ofverdant valleys, ravines, fast flowing streams, lofty peaks, and awe-inspiring spurs. The topography of the region is sensitive and any changes in the land use causes landslide or slope failures affecting the population. More than 150 landslide-prone locations have been identified by the Geological Survey of India in Kodagu alone. Landslide zone map analysis is an essentialtool for landslide hazard management. Landslide zone map analysis involves assessing the likelihood of landslides occurring in a particular area based on various factors and data. Statistical methods are often employed in landslide zone map modeling to analyze and quantifythe relationships between landslide occurrences and the influencing factor. Seven landslide causing factors (i.e., slope, SPI, aspect, TWI, elevation, curvature, and distance to roads) wereselected for the susceptibility assessment. A logistic regression (LR) coupled with the frequency ratio (FR) has been used in conjunction with geographical information system (GIS)to make a susceptibility map of the potential landslides in Kodagu. Using the LR and FR, the historical landslides were linked to the causing factors to compute their importance on landslidesusceptibility. A susceptibility map was extracted from each method and validated by utilizingthe area under curve (AUC) and ROC.

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Chapter 1

Introduction

1.1 Preamble

Landslides are one of the major geological processes and they become hazards when they have a direct effect on the human life and their properties [1]. The term ‘landslide’ is defined as “the movement of a mass of rock, debris, or earth down a slope” (Cruden, 1991) under the influence of gravity. The movement of the mass may be slow or rapid. Some mass movement processes, such as soil creep, are almost imperceptibly slow and diffuse while other, such as landslides, are capable of moving at high velocity, discrete, and have clearly identifiable boundaries, often in the form of shear surfaces (Crozier, 1989). Landslide susceptibility assessment is the globally approved procedure to prepare geohazard maps of landslide-prone areas, which are highly used in urban management and minimizing the possible disasters due to landslides [2]. The Coorg district in Karnataka state with distinctive geomorphological, geological, hydrological and meteorological characteristics has long been known for landslides in selected areas during certain months of a year [3] These events failed to attract the attention of the researchers due to various reasons including insignificant damage caused, thick vegetation, wild life, lack of exposures, high hillocks, accessibility, thick soil cover. Of late, the number of events increased in proportion to the human activity and also the amount of damage caused has also increased. Several factors although have a bearing on slope failures or landslides, topography, climate, slope angle and anthropogenic activities play a significant role [4].

There has been a discernible rise in the frequency of natural disasters globally, resulting in significant human casualties and property damage. These disasters tend to have a more pronounced impact in areas characterized by rugged terrain and isolated human settlements [5] Therefore, the mitigation of landslide hazards has become a vital tool in land use planning and management. Multiple approaches to providing susceptibility maps for landslides have one specification. Logistic regression is a statistical-based model that investigates the probabilities of the events which is received extensive success in landslide susceptibility assessment. LR is a valuable tool for landslide susceptibility analysis due to several key reasons. Firstly, landslide susceptibility analysis often involves binary classification, where areas are categorized as either susceptible or not susceptible to landslides [6] LR is specifically designed for binary classification problems, making it well-suited. Secondly, LR provides estimates of the probability that an area belongs to a specific class, which is particularly useful in landslide susceptibility analysis. By estimating the probability of an area being susceptible to landslides based on various input factors, LR enables a more nuanced understanding of the likelihood of landslides occurring in different areas [7].

1.2 Study Area

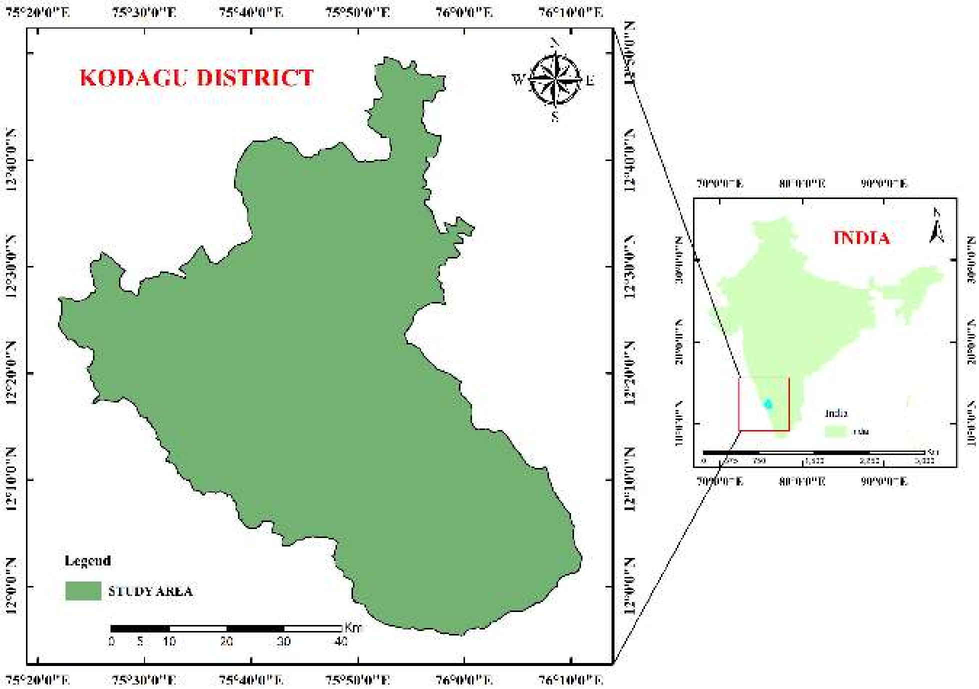

Figure 1: Map of Study Area

Kodagu district experienced hefty rainfall during the southwest monsoon of 2018. The cumulative rainfall in the Kodagu district was 3464 mm from January 1 to August 31, 2018. It was 32 per cent more than the average annual rainfall over the last 20 years. Between 10 and 17 August 2018, the heavy rainfall 2018 caused several landslides and

There are no sources in the current document**.** killed 20 people, damaged 4056 homes, and 18,000 people were evacuated. This was the first colossal tragedy experienced by the district and the first significant episode of the landslide observed by Karnataka State.

More than 150 landslide-prone locations have been identified by the Geological Survey of India in Kodagu alone. Hence there is a necessity of creating landslide susceptibility mapping for the mitigation purpose which is huge essential research to find the future arising same spots landslides.

1.3 Relevance

The second most hazardous geo-hazard phenomenon in the worldwide is Landslides which cause countless damages to infrastructures and loss of lives. Geologically, the wide variety of mass movements on the Earth surface that triggered by certain influence factors which are immersively detailed in the ongoing project.

1.4 Organization of the Report

This project report is organized into 4 chapters

Chapter 1: A brief introduction about landslides and necessity of landslide mapping of Kodagu district using satellite images and also this chapter brief about the motivation and relevance of the project work.

Chapter 2: It explains the existing literature of landslide mapping of various places, satellite data used, techniques used to formulate the problem.

Chapter 3: We clearly determines the objectives of the project work

Chapter 4: Elucidates the methodology proposed along with objectives of the project work.

Chapter 5: We predict the excepted outcome of the project

Chapter 2

Literature Survey

2.1 Introduction

Landslide susceptibility analysis considers multiple input factors, such as predisposing factors and historical landslide records. LR can handle continuous and categorical variables, accommodating a wide range of data types and allowing for a comprehensive analysis [8]. Landslides are induced by a combination of numerous inter-related landslide conditioning factors (LCFs) and sometimes one can be more dominating than others .Therefore, the selection and preparation of these LCFs to be considered as independent variables for the modelling is a vital procedure for the accuracy of the LSA model in determining landslide-susceptible regions [9]

2.2 Review Based on Techniques and Approaches for different Study Area

The Table 1 shows the comparison of various landslide mapping techniques and its results obtained in various locations. Here different authors have produced the Landslide susceptibility mapping using different techniques such as ANN, SVM,LOR,CNN,RF,KNN, LR, etc., which produced different accuracy depending on the influencing factor as per the survey. The Table shows approaches, techniques and results obtained by different authors

Table 1 Review Based on Techniques and Approaches for different Study Area

Reference	Location	No of causative factors And causative factors	Approaches	Assessment techniques	Result
[10]	Abottabad (Pakistan)	14 LCCS, Soil type, NDWI, Slope, Lithology, NDVI, Elevation, Fault Density, Road Density, Profile Curvature, Plan Curvature, Total Curvature, Aspect, TRI	LiR(Linear Regression) LoR(Logistic Regression) SVM	ROC, AUC	LiR=85% LoR=79% SVM=83%
[11]	Muzaffarabad (Pakistan)	17 Aspect, Curvature, Earthquake, Elevation, Flow, Lithology, NDVI, NDWI, Plane Curvature Precipitation, Profile Curvature, Slope, Faults, Roads, Waterways	Logistic Regression (LGR), Linear Regression (LR), Support Vector Machine (SVM), Multi-Criteria Decision Making (MCDM) techniques,		SVM model-produced map was Somewhat higher (85%), followed by LR (83%), AHP (80%), LGR (79%), and TOPSIS (78%)

			namely Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS		
[8]	Maragheh County (Iran)	11 Elevation, Slope aspect, Slope angle, Rainfall, Land use, Lithology, Weathering, distance from faults, distance from river, distance from road, distance from cities	Logistic Regression	ROC , AUC	Closer the numerical value of AUC is to 1, the higher the overall accuracy and the closer to 0, which indicates low accuracy
[9]	National Highway G30 in the Guozigou Valley, (China)	7 Elevation, slope, aspect, gully density(Stream density), lithology, fault density, and normalized difference vegetation index (NDVI)	Logistic Regression, MaxEnt Model (Maximum Entropy model)	ROC , AUC	Compared with the conventional statistical model (LR), MaxEnt produced more reliable and robust results
[12]	Hanyin County (China)	9 Altitude, Slope angle, Aspect, MAP(mean annual precipitation), Lithology, Distance to rivers, Distance to faults, Distance to roads, NDVI	landslide net (LSNet), support vector machine model (SVM), kernel logistic regression model (KLR)	Area Under Receiver Operating Characteristics Curve (AUROC)	SVM = 0.825 KLR = 0.900 LSNet = 0.950
[13]	Chitral district (Pakistan)	13 Aspect, Curvature Earthquake activity, Elevation, Flow accumulation, Lithology, NDVI, NDWI, Plane Curvature, Precipitation, Profile Curvature, Slope, Faults, Roads, Soil, Land use	logistic regression (LGR), linear regression (LR), and support vector machines (SVM),	multi-criteria decision-making (MCDM) techniques, namely analytical hierarchy process (AHP) and the technique for order of preference by similarity to ideal solution (TOPSIS)	LGR=78% LR=84% SVM=88% AHP=81% TOPSIS=79%
[5]	Dongchuan district (China)	11 lithology, distance to a river, profile curvature, plane curvature, NDVI index, distance to road, aspect, slope, elevation, and fluctuation	Logistic regression (LR), and support vector machines (SVM),	AUC	LR=0.84 SVM=0.91
[2]	Qinghai-Tibetan Plateau (QTP)	13 annual rainfall, distance to drainage, distance to faults , drainage density, elevation , fault density , lithology, normalized difference vegetation index , plan curvature , profile curvature , slope , stream power index, and topographic wetness index	deep neural network (DNN), logistic regression (LR), Naïve Bayes (NB), random forest (RF), and support vector machine (SVM)	AUC,ROC	DNN=0.9556 LR=0.947 RF=0.980 NB=0.930 SVM=0.947

[1]	city of Laibin (China)	9 Elevation, slope ,aspect height difference, Plain curve, profile curve, precipitation, TWI, vegetation coverage.	FR, FR-AHP, FR-LR, FR-BPNN and FR-SVM	AUC	FR, FR-AHP, FR-LR, FR-BPNN and FR-SVM models were 0.783, 0.786, 0.804, 0.792 and 0.798, respectively.
[7]	Sichuan Province (China)	7 Ht, PGA, distance to roads, distance to rivers, distance to faults, NDVI, and lithology	Method Kernel density estimation (KDE) LR algorithm.		KDE-MLR=71% LR=72%

In Abbottabad, Pakistan [10], 14 causative factors were considered, including LCCS, soil type, NDWI, slope, lithology, NDVI, elevation, fault density, road density, profile curvature, plan curvature, total curvature, aspect, and TRI. The approaches employed were Linear Regression (LiR), Logistic Regression (LoR), and Support Vector Machine (SVM), with corresponding ROC and AUC evaluations. LiR achieved 85%, LoR 79%, and SVM 83% accuracy.

Muzaffarabad, Pakistan [11], assessed 17 factors, such as aspect, curvature, earthquake activity, elevation, flow, lithology, NDVI, NDWI, plane curvature, precipitation, profile curvature, slope, faults, roads, and waterways. Logistic Regression (LGR), Linear Regression (LR), Support Vector Machine (SVM), and Multi-Criteria Decision Making (MCDM) techniques were employed. SVM demonstrated the highest accuracy at 85%, followed by LR (83%), AHP (80%), LGR (79%), and TOPSIS (78%).

Maragheh County, Iran [8], considered 11 factors, including elevation, slope aspect, slope angle, rainfall, land use, lithology, weathering, distance from faults, distance from rivers, distance from roads, and distance from cities. Logistic Regression was the chosen approach, evaluated using ROC and AUC, where a higher AUC value indicates higher overall accuracy.

National Highway G30 in the Guozigou Valley, China [9], evaluated seven factors: elevation, slope, aspect, gully density (stream density), lithology, fault density, and normalized difference vegetation index (NDVI). Logistic Regression and MaxEnt Model were used, with ROC and AUC assessments. MaxEnt produced more reliable results compared to the conventional statistical model (LR).

Hanyin County, China [12], assessed nine factors, including altitude, slope angle, aspect, mean annual precipitation (MAP), lithology, distance to rivers, distance to faults, distance to roads, and NDVI. Different models like landslide net (LSNet), support vector machine (SVM), and kernel logistic regression model (KLR) were evaluated using Area Under Receiver Operating Characteristics Curve (AUROC). SVM achieved 0.825, KLR 0.900, and LSNet 0.950 AUROC.

Chitral district, Pakistan [13], considered 13 factors and employed logistic regression (LGR), linear regression (LR), support vector machines (SVM), and multi-criteria decision-making (MCDM) techniques. AHP and TOPSIS were also used. SVM demonstrated the highest accuracy at 88%, followed by LR (84%), AHP (81%), LGR (78%), and TOPSIS (79%).

Dongchuan district, China [5], assessed 11 factors using logistic regression (LR) and support vector machines (SVM). AUC values were 0.84 for LR and 0.91 for SVM.

Qinghai-Tibetan Plateau (QTP) [2], considered 13 factors and employed deep neural network (DNN), logistic regression (LR), Naïve Bayes (NB), random forest (RF), and support vector machine (SVM). AUC and ROC were used for evaluation, where RF demonstrated the highest accuracy at 0.980.

City of Laibin, China [1], evaluated nine factors using different models such as FR, FR-AHP, FR-LR, FR-BPNN, and FR-SVM, with AUC assessment. FR-LR exhibited the highest accuracy at 0.804.

Sichuan Province, China [7] , assessed seven factors using Kernel density estimation (KDE) and LR algorithm. KDE-MLR achieved 71%, while LR achieved 72% accuracy.

2.3 Review Based on Influencing Factors selected for different Study Area

The Table 2 shows the influencing factor of the study area that caused landslides as referred by different authors. In this project, the landslide affecting factor is selected based on local conditions of the affected area, changes in environment. Major influencing factor were selected by using different selection methods and correlation techniques.

Table 2 Review Based on Influencing Factors selected for different Study Area

Ref No Author and Year	Study Area and Type of region	Number of Landslide	Number of Factors	Influencing Factors	Key/Conditional Factors Susceptibility Selection Method Or Correlation Method	Major Influencing Factors	Most common IF for different type of regions
[10]	Abottabad (Pakistan) Metamorphic and Sedimentary Region	116	14	LCCS, Soil type, NDWI, Slope, Lithology, NDVI, Elevation, Fault Density, Road Density, Profile Curvature, Plan Curvature, Total Curvature, Aspect, TRI	LiR(Linear Regression) LoR(Logistic Regression) SVM	Lithology, NDWI, slope, and LCCS.	
[11]	Muzaffarabad (Pakistan) Hilly Terrain Region	606	15	Aspect, Curvature, Earthquake, Elevation, Flow, Lithology, NDVI, NDWI, Plane Curvature Precipitation, Profile Curvature, Slope, Faults, Roads, Waterways	Logistic Regression (LGR), Linear Regression (LR), Support Vector Machine (SVM), and two Multi-Criteria Decision Making (MCDM) techniques, namely Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)		
[8]	Maragheh County (Iran)	20	11	Elevation, Slope aspect, Slope angle, Rainfall, Land use, Lithology, Weathering, distance from faults, distance from river, distance from road, distance from cities	VIF	Elevation, Slope aspect, Slope angle, Rainfall, Land use, Lithology, Weathering, distance from faults, distance from river, distance from road, distance from cities	

[9]	National Highway G30 in the Guozigou Valley, (China)	35	7	Elevation, slope, aspect, gully density(Stream density), lithology, fault density, and normalized difference vegetation index (NDVI)		Elevation, slope, aspect, gully density(Stream density), lithology, fault density, and normalized difference vegetation index (NDVI)	
[12]	Hanyin County (China)	259	9	Altitude, Slope angle, Aspect, MAP(mean annual precipitation), Lithology, Distance to rivers, Distance to faults, Distance to roads, NDVI	VIF and TOI	Altitude, Slope angle, Aspect, MAP(mean annual precipitation), Lithology, Distance to rivers, Distance to faults, Distance to roads, NDVI	
[13]	Chitral district (Pakistan)	193	16	Aspect, Curvature Earthquake activity, Elevation, Flow accumulation, Lithology, NDVI, NDWI, Plane Curvature, Precipitation, Profile Curvature, Slope, Faults, Roads, Soil, Land use		Aspect, Curvature Earthquake activity, Elevation, Flow accumulation, Lithology, NDVI, NDWI, Plane Curvature, Precipitation, Profile Curvature, Slope, Faults, Roads, Soil, Land use	
[5]	Dongchuan district (China)	12	11	Lithology, distance to a river, profile curvature, plane curvature, NDVI index, distance to road, aspect, slope, elevation, and fluctuation		Lithology, distance to a river, profile curvature, plane curvature, NDVI index, distance to road, aspect, slope, elevation, and fluctuation	
[2]	Qinghai-Tibetan Plateau (QTP)		13	annual rainfall, distance to drainage, distance to faults , drainage density, elevation , fault density , lithology, normalized difference vegetation index , plan curvature , profile		annual rainfall, distance to drainage, distance to faults , drainage density, elevation , fault density , lithology, normalized difference vegetation index , plan curvature , profile	

				curvature , slope , stream power index, and topographic wetness index		curvature , slope , stream power index, and topographic wetness index	
[1]	City of Laibin (China)		9	Elevation, slope ,aspect height difference, Plain curve, profile curve, precipitation, TWI, vegetation coverage.		Elevation, slope ,aspect height difference, Plain curve, profile curve, precipitation, TWI, vegetation coverage.	
[7]	Sichuan Province (China)		7	Ht, PGA, distance to roads, distance to rivers, distance to faults, NDVI, and lithology		Ht, PGA, distance to roads, distance to rivers, distance to faults, NDVI, and lithology	

The table summarizes key differences among several landslide susceptibility mapping studies conducted in distinct regions. In Abottabad, Pakistan [10] , the study area lies in a Metamorphic and Sedimentary Region, considering 116 landslides and 14 influencing factors, including LCCS, soil type, NDWI, slope, lithology, NDVI, and others. The susceptibility selection methods involve Linear Regression (LiR), Logistic Regression (LoR), and Support Vector Machine (SVM), focusing on key factors like lithology, NDWI, slope, and LCCS. In contrast, Muzaffarabad, Pakistan [11], a Hilly Terrain Region, examines 606 landslides and 15 factors, utilizing Logistic Regression (LGR), Linear Regression (LR), SVM, and Multi-Criteria Decision Making (MCDM) techniques, such as Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Maragheh County, Iran [8], explores 20 landslides with 11 factors, employing the Variance Inflation Factor (VIF) and emphasizing factors like elevation, slope aspect, and rainfall. National Highway G30 in the Guozigou Valley, China [9], focuses on 35 landslides and 7 factors, lacking a specified susceptibility selection method but emphasizing factors like elevation and slope. Hanyin County, China [12], examines 259 landslides and 9 factors, utilizing VIF and Transferability of Information (TOI), with emphasis on altitude, slope, and lithology. Chitral district, Pakistan [13], assesses 193 landslides and 16 factors, emphasizing aspects, curvature, and earthquake activity, utilizing unspecified methods. Dongchuan district, China [5], considers 12 landslides and 11 factors, with a focus on lithology, distance to a river, and aspect, lacking explicit susceptibility selection methods. Qinghai-Tibetan Plateau (QTP) [2] involves 13 landslides and various factors, utilizing unspecified methods, while City of Laibin, China [1], studies 9 landslides with diverse factors, employing the Frequency Ratio (FR) method and highlighting elevation, slope, and precipitation. Lastly, Sichuan Province, China [7], evaluates 7 landslides, employing Kernel Density Estimation (KDE) and Linear Regression (LR), emphasizing factors like height (Ht), peak ground acceleration (PGA), and lithology. These studies exhibit variations in study areas, the number of landslides, influencing factors, susceptibility selection methods, and major factors across different regions.

2.4 Review based on Remote Sensing Data Source used for Landslide Susceptibility Mapping

Spatial resolution refers to focuses on measuring image quality and distance represented by a pixel in an image by a satellite used for accessing data. In a different region of the world and its measure of the smallest object in the ground area resolved by the sensor and usually 30m is the best spatial resolution available today for remote sensing using high resolution commercial satellite, it is the important factors to decide the quality of the remote sensing image. Resolution can be divided into three types such as low resolution, moderate resolution, high resolution. Temporal resolution means time interval or the number of days needed to revisit and obtain data from the same location and the ability of a satellite sensor to measure specific wavelengths of the electromagnetic spectrum is referred as spatial resolution, it can determine the quality of an image and describe how detailed. The capability for satellite to provide images of the same geographical area more frequently has increased dramatically since the dawn of the space age. Landsat TM, Landsat 8 OLI and Sentinel are some of the satellites with different bands represented by name and range of electromagnetic spectrum are used by different Authors based on their requirement. As per Table 1, Sentinel-2 gives best spatial resolution which can be used in our study

Table 3 Review based on Remote Sensing Data Source used for Landslide Susceptibility Mapping

Ref No Author and Year	Remote Sensing Satellite/Mission	Study Area and Type of region	Influence Factors	Non -Remote Sensing Source and Remote Sensing Bands / Spatial data (SAR,MSS DEM)	Scale/Spatial Resolutio	Band s used for Feature
[8]	Landsat TM, ETM+	Maragheh County (Iran)	Elevation, Slope aspect, Slope angle, Rainfall, Land use, Lithology, Weathering, distance from faults, distance from river, distance from road, distance from cities	DEM	30 m (60 m – thermal, 15-m pan)	Band 1 (0.45-0.515) Band 2 (0.525-0.605) Band 3 (0.63-0.69)

						Band 4 (0.775-0.90) Band 5 (1.55-1.75) Band 6 (10.4-12.5) Band 7 (2.08-2.35) Band 8 (0.52-0.9)
[9]	ALOS Palsar **EO** (Gaofen-1)	National Highway G30 in the Guozigou Valley, (China)	Elevation, slope, aspect, gully density(Stream density), lithology, fault density, and normalized difference vegetation index (NDVI)		Polarmetric :30 m Fine Resolution: 10m, 20m ScanSAR: 100m Pan: 2 m; MS: 8 m(nadir) MS 16 m(nadir)	L-Band (1.27 GHz) B1/blue: 0.45-0.52 µm B2/green: 0.52-0.59 µm B3/red: 0.63-0.69 µm B4/NIR: 0.77-0.89 µm
[12]	GF-2 (Gaofen-2)	Hanyin County (China)	Altitude, Slope angle, Aspect, MAP(mean annual precipitation), Lithology, Distance to rivers, Distance to faults, Distance to roads, NDVI	DEM	Panchromatic = 0.8m Multispectral = 3.2m	B01 - 0.45~0.52 µm B02 - 0.52~0.59 µm B03 - 0.62~0.69 µm B04 - 0.77~0.89 µm

[13]	Landsat-8	Chitral district (Pakistan)	Aspect, Curvature Earthquake activity, Elevation, Flow accumulation, Lithology, NDVI, NDWI, Plane Curvature, Precipitation, Profile Curvature, Slope, Faults, Roads, Soil, Land use		30m	Band 1 Coastal Aerosol (0.43 - 0.45 µm) 30 m Band 2 Blue (0.450 - 0.51 µm) 30 m Band 3 Green (0.53 - 0.59 µm) 30 m Band 4 Red (0.64 - 0.67 µm) 30 m Band 5 Near-Infrared (0.85 - 0.88 µm) 30 m Band 6 SWIR 1(1.57 - 1.65 µm) 30 m Band 7 SWIR 2 (2.11 - 2.29 µm) 30 m Band 8 Panchromatic (PAN) (0.50 - 0.68 µm) 15 m Band 9 Cirrus (1.36 - 1.38 µm) 30 m
[10]	Landsat-8	Abottabad (Pakistan) Metamorphic and Sedimentary Region	LCCS, Soil type, NDWI, Slope, Lithology, NDVI, Elevation, Fault Density, Road Density, Profile Curvature, Plan Curvature, Total Curvature, Aspect, TRI	SRTM DEM	30m*30 m	Band 1 Coastal Aerosol (0.43 - 0.45 µm) 30 m. Band 2 Blue (0.450 - 0.51 µm) 30 m. Band 3 Green (0.53 - 0.59 µm) 30 m. Band 4 Red (0.64 - 0.67 µm) 30 m. Band 5 Near-Infrared (0.85 - 0.88 µm) 30 m. Band 6 SWIR 1(1.57 - 1.65 µm) 30 m. Band 7 SWIR 2 (2.11 - 2.29 µm) 30 m
[11]	Landsat-8	Muzaffarabad (Pakistan) Hilly Terrain Region	Aspect, Curvature, Earthquake, Elevation, Flow, Lithology, NDVI, NDWI, Plane Curvature Precipitation, Profile Curvature, Slope, Faults,	ASTER DEM	30m*30 m	Band 1 Coastal Aerosol (0.43 - 0.45 µm) 30 m. Band 2 Blue (0.450 - 0.51 µm) 30 m. Band 3 Green (0.53 - 0.59 µm) 30 m. Band 4 Red (0.64 - 0.67 µm) 30 m. Band 5 Near-Infrared (0.85 - 0.88 µm) 30 m.

			Roads, Waterways			Band 6 SWIR 1(1.57 - 1.65 µm) 30 m. Band 7 SWIR 2 (2.11 - 2.29 µm) 30 m
[5]	sentinel-1A	Dongchuan district (China)	Lithology, distance to a river, profile curvature, plane curvature, NDVI index, distance to road, aspect, slope, elevation, and fluctuation	NASA SRTM	5*5m	C-band (central frequency of 5.404 GHz). Other space borne SAR's operate at L-band (1.3 GZ) or X-band (9.6 GHz).
[2]		Qinghai-Tibetan Plateau (QTP)	annual rainfall, distance to drainage, distance to faults , drainage density, elevation , fault density , lithology, normalized difference vegetation index , plan curvature , profile curvature , slope , stream power index, and topographic wetness index			
[1]	Institute of Geographical Sciences and Resources, Chinese Academy of Sciences National Meteorological Science Data Center	City of Laibin (China)	Elevation, slope ,aspect height difference, Plain curve, profile curve, precipitation, TWI, vegetation coverage.	SRTM DEM	60m	

[7]	Landsat-8 Landsat-7	Sichuan Province (China)	Ht, PGA, distance to roads, distance to rivers, distance to faults, NDVI, and lithology	The topographic information entropy was Calculated using 1:35 0000 DEM -data30. The distance to the fault was derived from the 1:500,000 regional geo-logical -map38. The distance to the river was obtained from 1:3 million National Hydrogeological Atlas (https:// www. osgeo. cn/ map/ m04dd). Statistical yearbook and historical data were obtained through remote sensing interpretation. Lithology data were retrieved from 1:500,000 regional geological -map38, 39.	30m 30m	Band 1 Coastal Aerosol (0.43 - 0.45 µm) 30 m. Band 2 Blue (0.450 - 0.51 µm) 30 m. Band 3 Green (0.53 - 0.59 µm) 30 m. Band 4 Red (0.64 - 0.67 µm) 30 m. Band 5 Near-Infrared (0.85 - 0.88 µm) 30 m. Band 6 SWIR 1(1.57 - 1.65 µm) 30 m. Band 7 SWIR 2 (2.11 - 2.29 µm) 30 m Landsat 7 Band 1 - Blue 0.45-0.52 30m Band 2 - Green 0.52-0.60 30m Band 3 - Red 0.63-0.69 30m Band 4 - Near Infrared (NIR) 0.77-0.90 30m

The provided table summarizes the remote sensing characteristics of various studies focusing on landslide susceptibility mapping in different regions. In Maragheh County, Iran [8], Landsat TM and ETM+ satellites are employed, with influencing factors such as elevation, slope, and lithology. The DEM data at a spatial resolution of 30 m is used, and various spectral bands (1 to 8) are utilized for feature extraction. For National Highway G30 in the Guozigou Valley, China [9], ALOS Palsar and Gaofen-1 EO satellites are used for polar metric and fine resolution scans, emphasizing factors like elevation, slope, and gully density. Bands in the L-Band spectrum are applied for feature extraction. In Hanyin County, China [12], Gaofen-2 (GF-2) satellite is used, focusing on altitude, lithology, and distance-related factors. The Panchromatic and Multispectral bands with varying spatial resolutions are employed for feature extraction. Landsat-8 is used in Chitral district, Pakistan [13], and Abottabad, Pakistan [10], both employing DEM data at a spatial resolution of 30 m. The Landsat-8 bands are applied for feature extraction, with specific emphasis on coastal aerosol, blue, green, red, and near-infrared bands. In Dongchuan district, China [6], Sentinel-1A is utilized for lithology-related factors, with NASA SRTM DEM data at a spatial resolution of 5*5 m. The C-band is used for feature extraction. For the City of Laibin, China [1], SRTM DEM data at 60 m spatial resolution is employed for elevation and vegetation-related factors. In Sichuan Province, China [7], Landsat-8 and Landsat-7 satellites are used, with various bands and a spatial resolution of 30 m for factors related to topography, distance, and lithology. The table provides insights into the diverse remote sensing techniques and data sources used in landslide susceptibility mapping studies across different geographic regions.

2.5 Problem Identification

The second most hazardous geo-hazard phenomenon in the worldwide is Landslides which cause countless damages to infrastructures and loss of lives. Geologically, the wide variety of mass movements on the Earth surface that triggered by certain influence factors which are immersive detailed in the ongoing project.

Kodagu district experienced hefty rainfall during the southwest monsoon of 2018. The cumulative rainfall in the Kodagu district was 3464 mm from January 1 to August 31, 2018. It was 32per cent more than the average annual rainfall over the last 20 years. Between 10 and 17 August 2018,the heavy rainfall 2018 caused several landslides and killed 20 people, damaged 4056 homes, and 18,000 people were evacuated. This was the first colossal tragedy experienced by the district and the first significant episode of the landslide observed by Karnataka State. More than 150 landslide-prone locations have been identified by the Geological Survey of India in Kodagu alone. Hence there is a necessity of creating landslide susceptibility mapping for the mitigation purpose which is huge essential research to find the future arising same spots landslides.

2.5 Summary

In this chapter is all about review of different literatures, which includes number of landslides in different region from past years technique used to access the data by suitable satellite and digital elevation model which depending on location and the technique suitable for particular dataset and software used and study area

Chapter 3

Objectives

3.1 Objectives

1. Generation of geo-spatial dataset of Kodagu district.
2. Prepare dataset on Considered Influencing factors
3. To develop the Logistic Regression Model for landslide susceptibility analysis.
4. To develop Frequency Ratio Model for landslide susceptibility analysis.
5. To validate and compare the performance of two technique.
6. To generate the Landslide Susceptibility Mapping for the study area.

3.2 Summary

The study involves the generation of a geo-spatial dataset for Kodagu district, focusing on influencing factors. A dataset is prepared for these factors to facilitate the development of a Logistic Regression Model and a Frequency Ratio Model for landslide susceptibility analysis. The research aims to validate and compare the performance of these two techniques, ultimately leading to the generation of Landslide Susceptibility Mapping for the study area.

Chapter 4

Proposed Methodology

4.1 Methodology

Phases I: In the first phase the datasets are created utilizing factors such as slope, SPI (Standardized Precipitation Index), aspect, TWI (Topographic Wetness Index), elevation, curvature, and distance toroads from the study area. Subsequently, these datasets will be employed to create the landslide inventory map.

Phase II: Employing a machine learning approach, a logistic regression model is developed based on the previously generated datasets. Simultaneously, a frequency ratio model is formed using statisticalmethods with the same dataset.

Phase III: In this phase, both the logistic regression and frequency ratio models are evaluated using AUC (Area under the Curve) and ROC (Receiver Operating Characteristic) analyses to assess their performance.

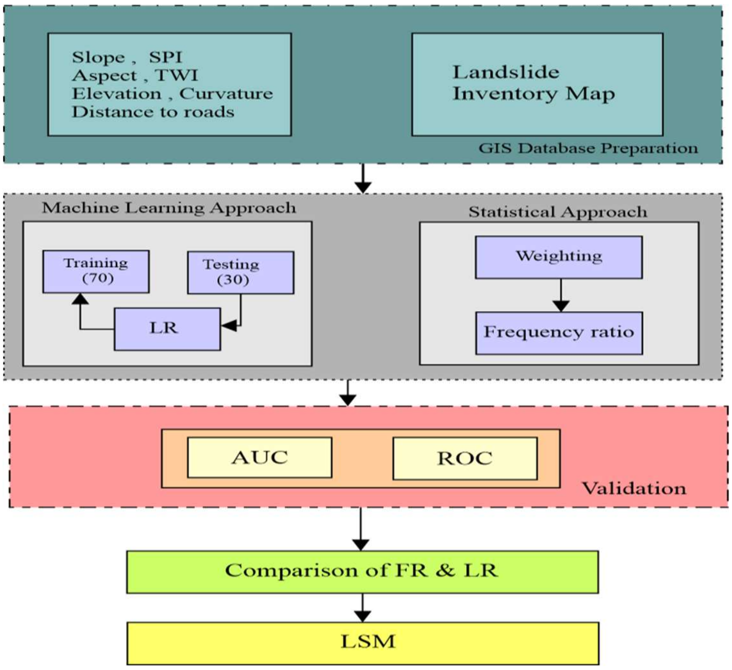

Fig 2 Proposed Methodology

Phase IV: During phase four, a comparison and evaluation of both the LR (Logistic Regression) and FR (Frequency Ratio) models are conducted to determine which one is more efficient.

Phase V: In the final phase, the most effective method will be implemented and employed for the purpose of landslide susceptibility mapping in the study area.

4.1 Summary

The methodology comprises five distinct phases. In Phase I, datasets are created by considering various factors, including slope, aspect, NDVI, elevation, curvature, and distance to roads within the study area. These datasets are then utilized to generate a comprehensive landslide inventory map. Moving on to Phase II, a machine learning approach is employed to develop a logistic regression model using the previously generated datasets. Simultaneously, a frequency ratio model is constructed using statistical methods with the same dataset. Phase III involves the evaluation of both models using AUC (Area under the Curve) and ROC (Receiver Operating Characteristic) analyses to gauge their performance. In Phase IV, a detailed comparison and evaluation of the logistic regression and frequency ratio models are conducted to identify the more efficient model. Finally, in Phase V, the most effective method is selected and implemented for the purpose of landslide susceptibility mapping in the study area.

Chapter 5

Excepted Outcome

1. The collection creation of the geo-spatial database will be undertaken at the end of phase 1.
2. By the end of phase 2, Logistic Regression and Frequency Ratio models will be developed forlandslide zone mapping.
3. With the use of AUC and ROC the performance of both models is observed, analyzed andcompared.
4. The Landslide Zone Mapping Model for the study area will be generated

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SCI Journal List

SL.NO	Journals	Impact Factor	ISSN .NO
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2	REMOTE SENSING	1.02	2072-4292
3	FORESTS	1.05	1999-4907
4	SUSTAINABILITY	0.67	2071-1050
5	FRONTIERS IN ENVIRONMENTAL SCIENCE	0.68	2296-665X
6	SCIENTIFIC REPORTES	1.06	2045-2322
7	NATURAL HAZARDS AND EARTH SYSTEM SCIENCES	0.95	1561-8633
8	SENSORS	0.69	1424-8220
9	GEOSCIENCE LETTERS	0.89	2196-4092

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