GIS-Based Landslide Susceptibility Mapping in Gorkha Municipality: A Comparison of Frequency Ratio and Logistic Regression Models

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Abstract

Gorkha Municipality, located in the hilly region of Nepal, has been experiencing an increasing number of landslides due to a combination of steep topography, high rainfall, and human activities such as road construction. These landslides damage the infrastructures resulting in economic losses. To address this issue, a landslide susceptibility map was developed to identify areas prone to future landslides. Thirteen causative factors were considered in the analysis, including Slope, Aspect, Curvature, Rock and Soil Types, Topographic Wetness Index, Stream Power Index, Distance to Streams, Normalized Difference Vegetation Index, Rainfall, Distance to Roads, Land Use Land Cover, and Distance to Faults. A total of 347 landslide and 347 non-landslide points were collected through field surveys and Google Earth. Two statistical GIS based models, Frequency Ratio (FR) and Logistic Regression (LR), were applied to assess landslide susceptibility. The results identified distance to roads as the most influential factor contributing to landslides in Gorkha Municipality. Pearson correlation and Variance Inflation Factor analyses and confirmed low multicollinearity among the causative factors. Model performance was evaluated using AUC-ROC, where the FR method achieved an accuracy of 0.819, while the LR method performed better with an accuracy of 0.909. This indicates that the multivariate approach (LR) is more effective than the bivariate method (FR) for this terrain. The results show that 15% of the area falls within the very high susceptibility zone, 19% in high, 19% in moderate, 20% in low, and 28% in very low susceptibility zones. These findings provide valuable insights for disaster risk reduction, land-use planning, and infrastructure development in Gorkha Municipality.

Keywords: *Frequency Ratio, Landslides Causative Factors, Logistic Regression, Multicollinearity*

1. Introduction

Nepal, a mountainous and developing nation, is highly susceptible to landslides due to its geographical location at the convergence of the Indian and Himalayan tectonic plates. These landslides significantly hinder development, causing substantial economic losses and fatalities each year(Petley et al., 2007). The frequency of landslides has increased over the past decade, with 93.26% occurring during the monsoon season, emphasizing the strong correlation between heavy rainfall and slope failures (Kc et al., 2024). The highest landslide impact on individuals is recorded in Gandaki Province, followed by Karnali and Koshi Provinces, whereas Madhesh Province has the lowest risk. A more localized view shows that Gorkha District alone recorded 70 landslides from 2011 to 2025, leading to 70 fatalities, 31 missing persons, and an economic loss of 4,152,000 (Nepal DRR Portal, 2025). Gorkha Municipality, located in the Gandaki Province of Nepal, serves as the administrative center of Gorkha District. It is particularly vulnerable due to rapid urbanization, unplanned development, and deforestation, which increase slope instability and landslide risk.

Landslides are defined as the downward movement of rock, debris, or soil along a slope, driven by gravity (Cruden & Varnes, 1996). They are influenced by a combination of natural and anthropogenic factors. Geological conditions, steep slopes, river induced erosion, and faults increase the likelihood of slope failures (Bathrellos et al., 2024; Thapa, 2023). To effectively assess and predict landslide risk, geospatial models using Geographic information system (GIS) are employed. These models utilize historical landslide and causative factors such as rainfall, land uses, and topography to assess the likelihood of future events (Xiao & Zhang, 2023).

Landslides Susceptibility Mapping (LSM) is a critical tool for disaster risk reduction and sustainable development planning. Various models are used in LSM, including frequency Ratio (FR) and Logistic Regression (LR) approaches. The FR model is a bivariate statistical method that predicts the future landslides occurrence based on historical data. While it is simple and accurate, it assumes factor independence (Lee & Pradhan, 2007; Mersha & Meten, 2020). In contrast, LR is a multivariate approach capable of modeling complex, nonlinear relationships without assuming independence, making it more suitable for diverse terrains (Sun et al., 2018).

This study aims to predict landslide-prone zones in Gorkha Municipality using GIS-based Frequency Ratio and Logistic Regression models. By integrating historical landslide data with causative factors such as slope, roads, land use, geology, faults, vegetation, rainfall, and soil, the study seeks to enhance disaster preparedness and promote resilient infrastructure planning. Given the increasing impact of landslides in Nepal, timely and accurate LSM is crucial. The implementation of GIS-based statistical and machine learning models can significantly improve risk management efforts and reduce both human and economic losses in vulnerable regions.

2. Literature Review

Landslide Trends in Nepal and Gorkha District: Nepal has seen a rising trend in landslides over the past decade, particularly during the monsoon season (June–August), which accounts for 93.26% of total landslides (Kc et al., 2024). The landslide density in Nepal increased from 0.85 per 1,000 km² in 2011 to 3.34 in 2020. In Gorkha District, landslide incidents peaked in 2016 (8 events), 2018 (18 events), 2020 (8 events), 2022 (7 events), and 2024 (8 events). The estimated economic loss from 2011 to 2024 totaled NPR 4.95 million, with the highest costs recorded in 2016, 2018, and 2019 (Nepal DRR Portal, 2025).

Landslide susceptibility mapping (LSM) is crucial for identifying landslide-prone areas and minimizing disaster impacts. It involves assessing terrain attributes such as slope, geology, and land use through various methods, including statistical and GIS-based approaches. For instance, a study in Darjeeling Himalaya applied logistic regression for landslide susceptibility assessment (Das & Lepcha, 2019), while another in Malaysia integrated multiple environmental factors using GIS(Lee & Pradhan, 2007). Landslide susceptibility classifications, such as those used in the 1994 Northridge earthquake (Parise & Jibson, 2000), categorize areas from very high to low risk based on landslide frequency and affected land area. In Gorkha earthquake-affected region, landslide susceptibility was influenced by seismic activity, slope steepness, and precipitation (Roback et al., 2018).

Landslide susceptibility mapping employs qualitative and quantitative methods: Heuristic Approach, Knowledge-driven techniques rely on expert judgment to assign weights to landslide factors. The Analytical Hierarchy Process (AHP) is a widely used heuristic method. Statistical Approach, data-driven methods, such as the Frequency Ratio (FR) model, correlate past landslide occurrences with environmental factors. The FR model provides insights into how terrain features influence landslide likelihood (Lee & Pradhan, 2007; Mersha & Meten, 2020). Machine Learning Approach: Techniques like Random Forest offer data-driven predictions for LSM, improving accuracy in hazard (Rodrigues Neto & Bhandary, 2024).

Landslides result from the interplay of topographical, meteorological, hydrological, and geological parameters. Slope plays a key role in landslide occurrences, as higher slopes correlate with increased gravitational stress (Mersha & Meten, 2020). Curvature influences water drainage and retention, with convex and concave slopes being more susceptible to landslides due to water accumulation (Mersha & Meten, 2020). Rainfall is a dominant triggering factor, with 93.26% of landslides in Nepal occurring during the monsoon season (Kc et al., 2024). The Topographic Wetness Index (TWI) is validated as an essential factor in landslide mapping, representing areas with high soil saturation potential (Sevgen et al., 2019). Similarly, the Stream Power Index (SPI) quantifies erosion potential, with higher values correlating to increased landslide susceptibility in steep terrains (Sevgen et al., 2019a). Proximity to streams is another major factor, as river erosion weakens slope stability, contributing to mass movement events (Akgün & Türk, 2011). Fault proximity and Peak Ground Acceleration (PGA) significantly impact landslide occurrences, with areas closer to active faults exhibiting higher landslide susceptibility, as seen in the Gorkha earthquake study (Pyakurel et al., 2024).

Lithology plays a crucial role, as weak rock layers like flyschoid sequences are prone to structural failures (Upreti, 1999). Soil type also affects landslide risk, with Cambisols exhibiting good water retention properties, influencing slope stability (Grčman et al., 2023). Land Use Land Cover (LULC) changes, such as deforestation and unplanned road construction, contribute significantly to landslides (Basanta Raj Adhikari, 2022). The use of Normalized Difference Vegetation Index (NDVI) is suggested while preparing LSM in dense and tropical vegetation areas (K.C. et al., 2023).

3. Methodology

3.1 Study Area

The study area, Gorkha Municipality, is located in the Gorkha District of Gandaki Province, covering 131.9 square kilometers. The latitude ranging from 27˚54'17" N to 22˚2'22.89" N and longitude from 84˚32'40" E to 84˚32'54" E with elevations from 223m to 1,467m. The region experiences a maximum temperature of 30°C, a minimum of 14°C, and annual precipitation between 190 to 266.5 mm/24nr. Major rivers like Marsyangdi and Daraudi, along with smaller streams, shape the landscape. Geologically, it lies within the Lesser Himalayan Zone, dominated by Kuncha Group formations and alluvial deposit. Fig. 1 shows the study area of the research.

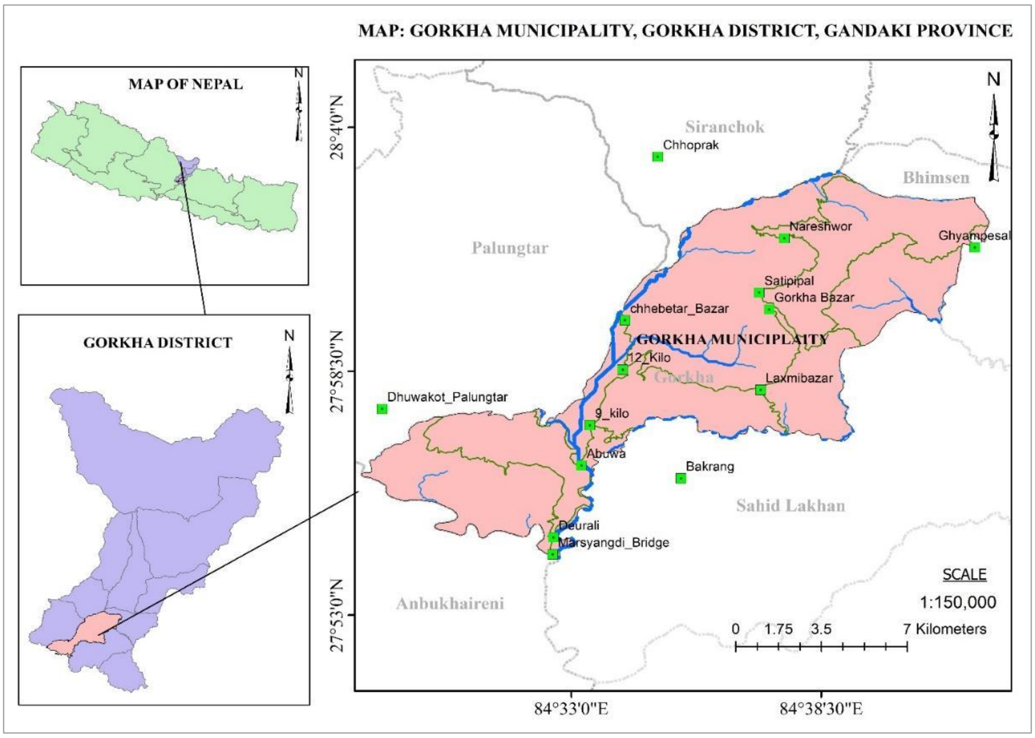


Fig. 1 Study Area (Gorkha Municipality)

3.2 Data Collection

An inventory of past landslides is essential for Landslide Susceptibility Mapping. 347 landslides and 347 non-landslides points were located through field surveys and Google Earth. Digital Elevation Model (DEM) with resolution 12.5m X 12.5m was obtained from the ALOS PASLAR. Landslides Causative factors were collected from multiple sources like Department of Mines and Geology (DMG), Department of Survey, Department of Hydrological and Metrology (DHM), Soil and Terrain (SOTER) Databases. All the sources are mentioned in the Fig. 2.

3.3 Research Framework

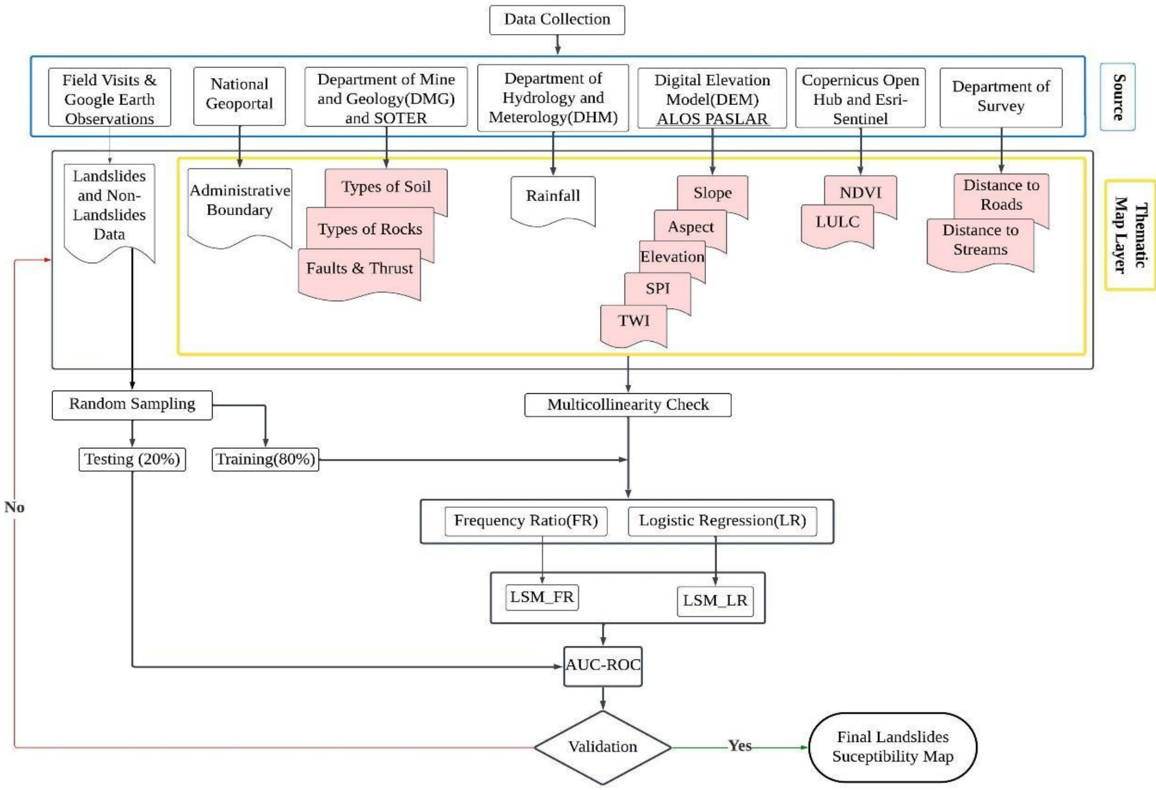


Fig. 2 : Research Framework

The conceptual research framework outlining the methodology and key processes involved in the study is shown in Fig. 2.

3.4 Thematic Map preparation of Landslides Causative Factors using GIS

i. Slope: Slope is a key factor in mass movement. It was derived from the Digital Elevation Model (DEM) in ArcGIS's tool and was classified into five classes. A thematic layer was then created based on this classification in GIS.

ii. Aspect: Aspect identifies the compass direction that the downhill slope faces for each location. It was classified into nine classes (Flat, North(N), North-East(N-E), East, South-East, South, South-West, West, North-West each of range of 22.5° through the automatic natural break classification.

iii. Curvature: Curvature is a terrain parameter derived from a Digital Elevation Model (DEM) that represents the rate of change in slope. It was classified into three types: Concave, Convex and Flat. It represents overall convexity or concavity of the terrain.

iv. The Stream Power Index (SPI) is a parameter that quantifies the erosive potential of flowing water, based on the assumption that discharge is directly proportional to the specific catchment area. SPI was calculated using the Equation 1 (Sevgen et al., 2019b) .

$$SPI = As \times tan\beta \tag{1}$$

Where, As is the specific catchment area (m2m−1) / cite, and β denotes the slope gradient (°).

v. Topographic Wetness Index (TWI): TWI measures the influence of topography on the distribution and extent of saturated source areas that contribute to runoff generation. TWI was calculated using the equation 2 (Sevgen et al., 2019b).

$$TWI = ln(As/tan\beta) \tag{2}$$

vi. Normalized Difference Vegetation Index (NDVI): Sentinel -2 raster data were collected from the. Copernicus Open Hub. Further, For Sentinel-2, to compute NDVI we used equation 3.

$$NDVI = \frac{BAND\ 8 - BAND\ 4}{BAND8 + BAND\ 4} \tag{3}$$

vii. Lithology: Study Area lies in the Kuncha Formation that includes phyllites, sills, quartzites. The Geological maps of 1:25,000 of Gorkha Municipality were collected from DMG and digitized in GIS. The different types of rock are: Fagfog Quartzite, Kuncha Formation, Anpu and Quaternary Alluvium.

viii. Land Use Land Cover (LULC): LULC data with a spatial resolution of 10 m × 10 m was obtained online from the Esri Sentinel-2 source. The LULC raster map was resampled to a resolution of 12.5 m × 12.5 m for consistency with other datasets.

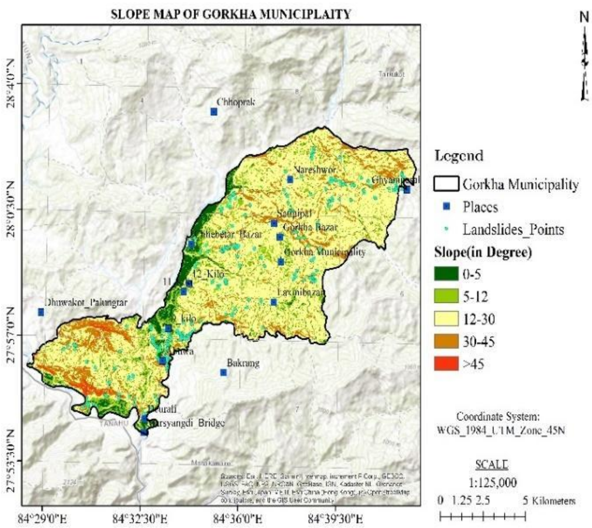
ix. Distance to Roads: The shape file of road was collected from the Department of Survey and using Euclidean distance the thematic layer is prepared in GIS.

x. Rainfall(mm/24hr): The spatial information of meteorological stations was integrated into ArcGIS, and stations relevant to the study area were identified using the Thiessen Polygon method. Finally, rainfall data of 25 years were collected from DHM, and the extreme rainfall thematic layer of resolution 12.5m x 12.5m was created using Inverse Distance Weighting (IDW) interpolation.

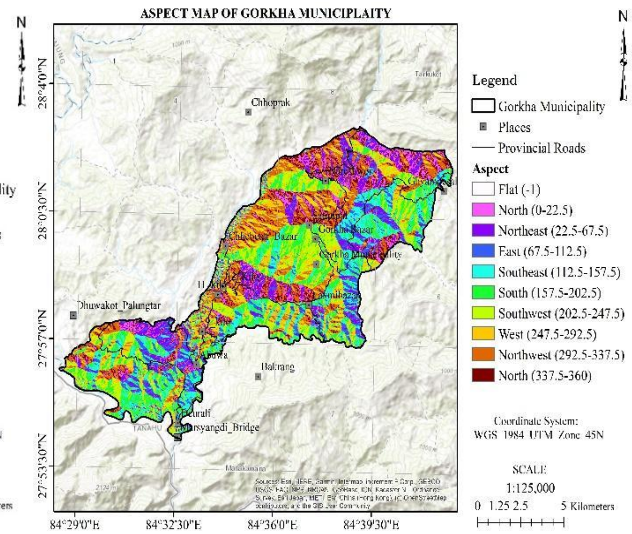
xi. Distance to Stream(m): The shape file of road was collected from the Department of Survey and using Euclidean distance the thematic layer was prepared in GIS.

xii. Distance to Fault (m) data were sourced from the DMG (2025), regional map of Gorkha District (1:25,000). The presence of numerous faults in this area was digitized and its proximity was calculated using Euclidean Distance in GIS.

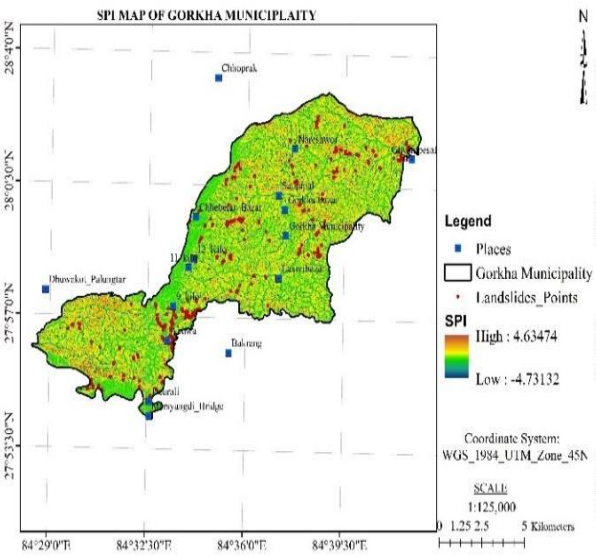
xiii. Types of Soil: Types of Soil influence landslide occurrences due to variations in shear strength., soil data were obtained from Soil and Terrain Database (SOTER) for analysis. Three types of soil of cambisols family were identified in the study area with different saturation levels and water retention capacity. Cambisols represent the mixture of sand, clay, pebbles and gravel.



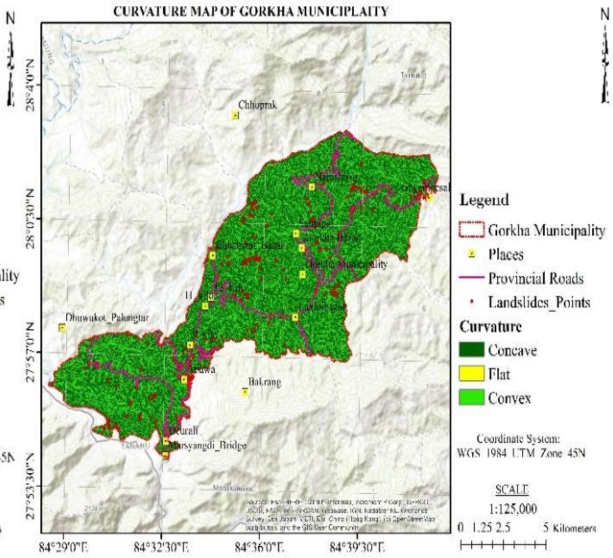
(a)



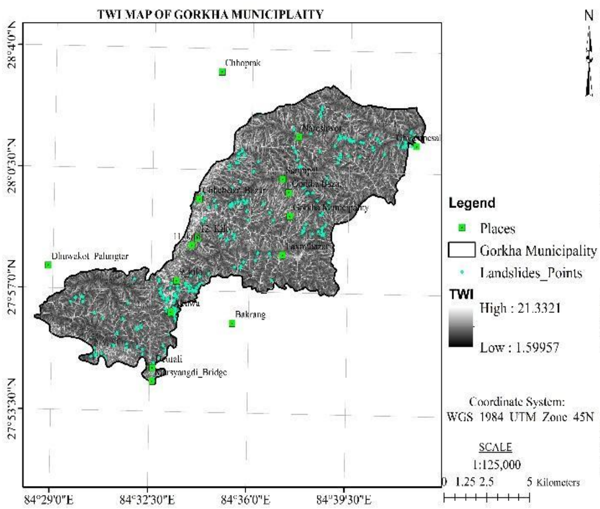
(b)


SPI MAP OF GORKHA MUNICIPLAITY
Chhoprak
Dhuwakot_Palungtar
Bakrang
Legend
Places
Gorkha Municipality
Landslides_Points
SPI
High : 4.63474
Low : -4.73132
Coordinate System:
WGS_1984_UTM_Zone_45N
SCALE
1:125,000
0 1.25 2.5 5 Kilometers
84°29'0"E
84°32'30"E
84°36'0"E
84°39'30"E
28°4'0"N
28°0'30"N
27°57'0"N
27°53'30"N

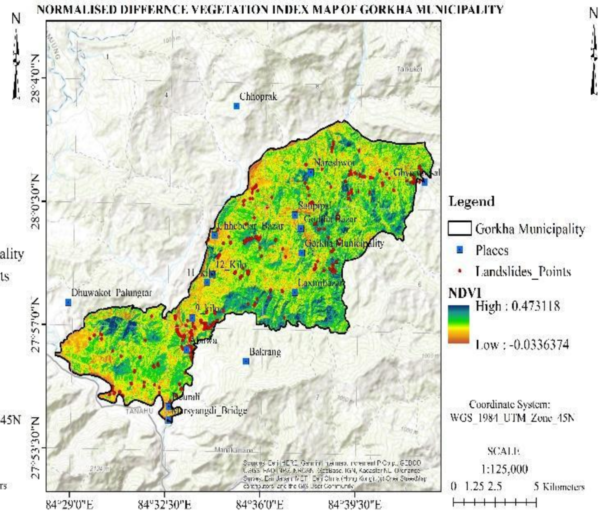
(c)


CURVATURE MAP OF GORKHA MUNICIPLAITY
N
Chhoprak
Dhuwakot_Palungtar
Bakrang
Legend
Gorkha Municipality
Places
Provincial Roads
Landslides_Points
Curvature
Concave
Flat
Convex
Coordinate System:
WGS 1984 UTM Zone 45N
SCALE
1:125,000
0 1.25 2.5 5 Kilometers
84°29'0"E
84°32'30"E
84°36'0"E
84°39'30"E

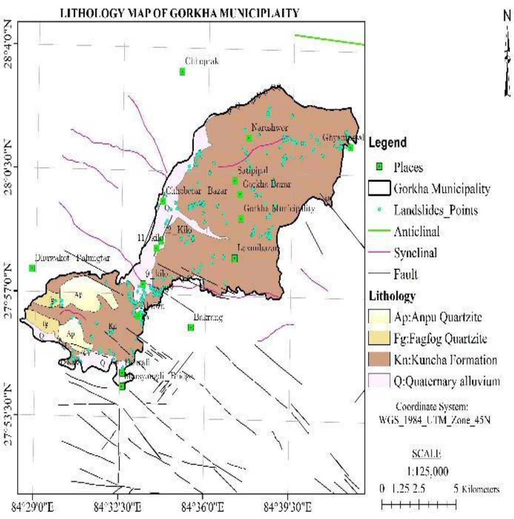
(d)


TWI MAP OF GORKHA MUNICIPLAITY
Chhoprak
Dhuwakot_Palungtar
Bakrang
Legend
Places
Gorkha Municipality
Landslides_Points
TWI
High : 21.3321
Low : 1.59957
Coordinate System:
WGS 1984 UTM Zone 45N
SCALE
1:125,000
0 1.25 2.5 5 Kilometers
84°29'0"E
84°32'30"E
84°36'0"E
84°39'30"E

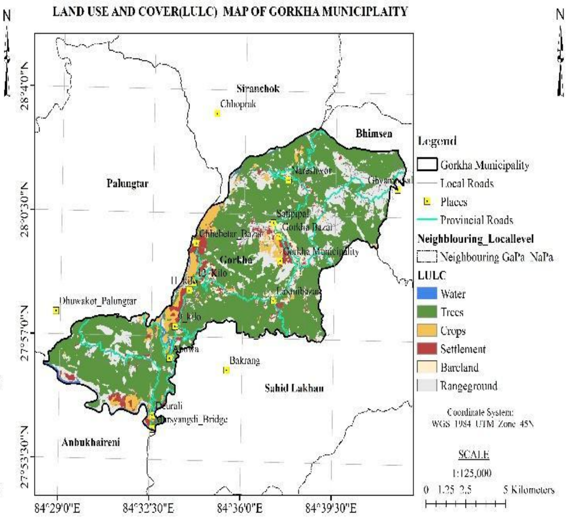
(e)


NORMALISED DIFFERNCE VEGETATION INDEX MAP OF GORKHA MUNICIPALITY
N
Chhoprak
Dhuwakot_Palungtar
Bakrang
Legend
Gorkha Municipality
Places
Landslides_Points
NDVI
High : 0.473118
Low : -0.0336374
Coordinate System:
WGS_1984_UTM_Zone_45N
SCALE
1:125,000
0 1.25 2.5 5 Kilometers
84°29'0"E
84°32'30"E
84°36'0"E
84°39'30"E

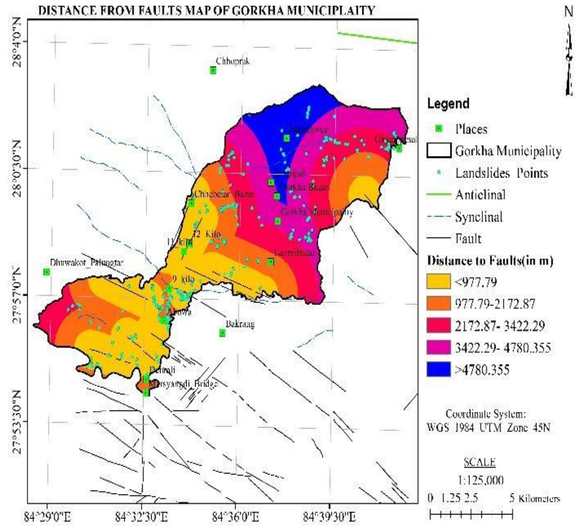
(f)


LITHOLOGY MAP OF GORKHA MUNICIPLAITY
Legend
Places
Gorkha Municipality
Landslides_Points
Anticlinal
Synclinal
Fault
Lithology
Ap:Anpu Quartzite
Fg:Fagfog Quartzite
Kn:Kuncha Formation
Q:Quaternary alluvium
Coordinate System:
WGS_1984_UTM_Zone_45N
SCALE
1:125,000
0 1.25 2.5 5 Kilometers
84°29'0"E
84°32'30"E
84°36'0"E
84°39'30"E

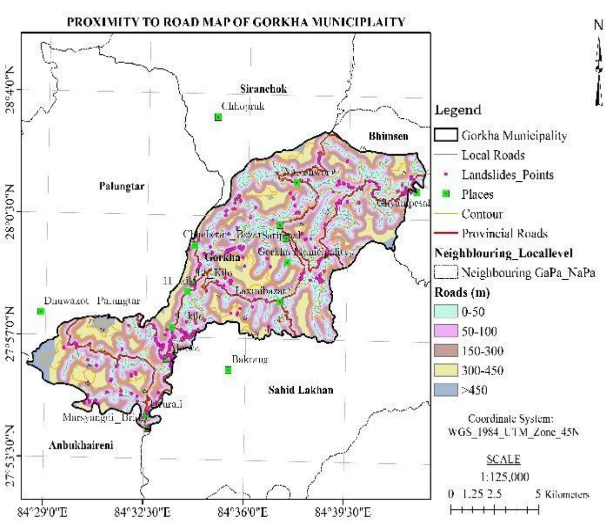
(g)


LAND USE AND COVER(LULC) MAP OF GORKHA MUNICIPLAITY
N
Siranchok
Chhoprak
Bhimsen
Palungtar
Dhuwakot_Palungtar
Bakrang
Sahid Lakhan
Anbukhaireni
Legend
Gorkha Municipality
Local Roads
Places
Provincial Roads
Neighbouring_Locallevel
Neighbouring GaPa_NaPa
LULC
Water
Trees
Crops
Settlement
Bareland
Rangeground
Coordinate System:
WGS 1984 UTM Zone 45N
SCALE
1:125,000
0 1.25 2.5 5 Kilometers
84°29'0"E
84°32'30"E
84°36'0"E
84°39'30"E

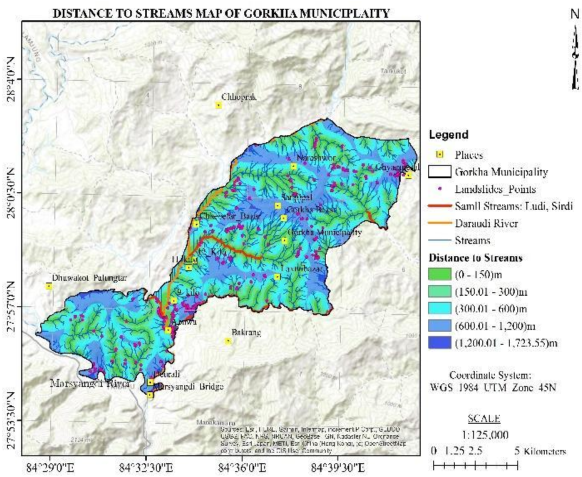
(h)



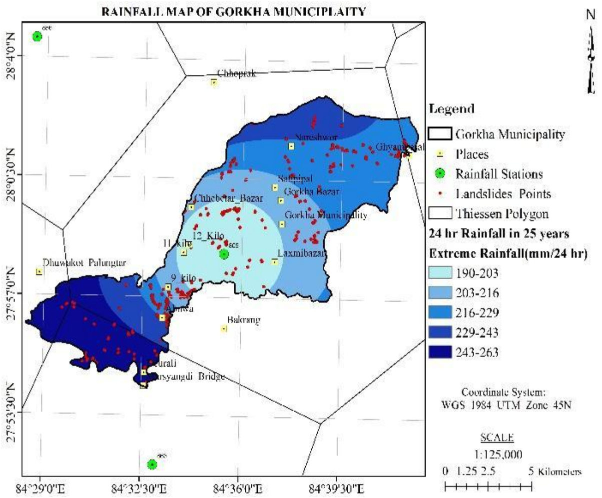
(i)



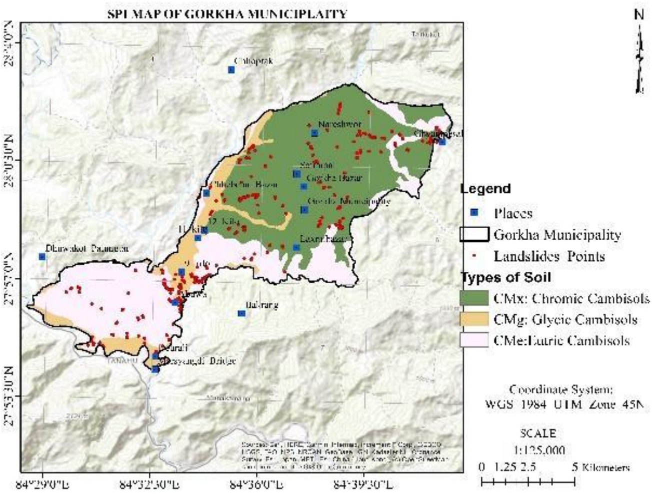
(j)



(k)



(l)



(m)

Fig. 3 Landslide Causative Factors Map for Gorkha Municipality, (a) Slope Map, (b) Aspect Map, (c) SPI Map, (d)Curvature Map, (e) TWI Map, (f) NDVI Map, (g) Lithology Map, (h) LULC Map, (i) Distance From Fault Map, (j)Proximity to Roads Map, (k) Distance to Streams Map, (l) Rainfall Map, (m) Soil Map:

3.5 Methods used for Landslides Susceptibility Mapping

Frequency Ratio Method: The frequency ratio for each factor classes were calculated by dividing the percentage of landslide pixels by the percentage of area pixels for each factor class (Equation 5)(Mersha & Meten, 2020).

$$FR\ i,j = \frac{Npix(Si,j)/\ \Sigma jNpix(Si,j)}{Npix(Ni,j)/\Sigma jNpix(Ni,j)} \tag{5}$$

Where: Npix(Si,j) is the number of pixels with landslides in class j of factor i.

Npix(Ni,j) is the number of pixels in class j of factor i.

ΣjNpix(Si,j) is the total number of pixels with landslides in the study area.

ΣjNpix(Ni,j) is the total number of pixels in the study area.

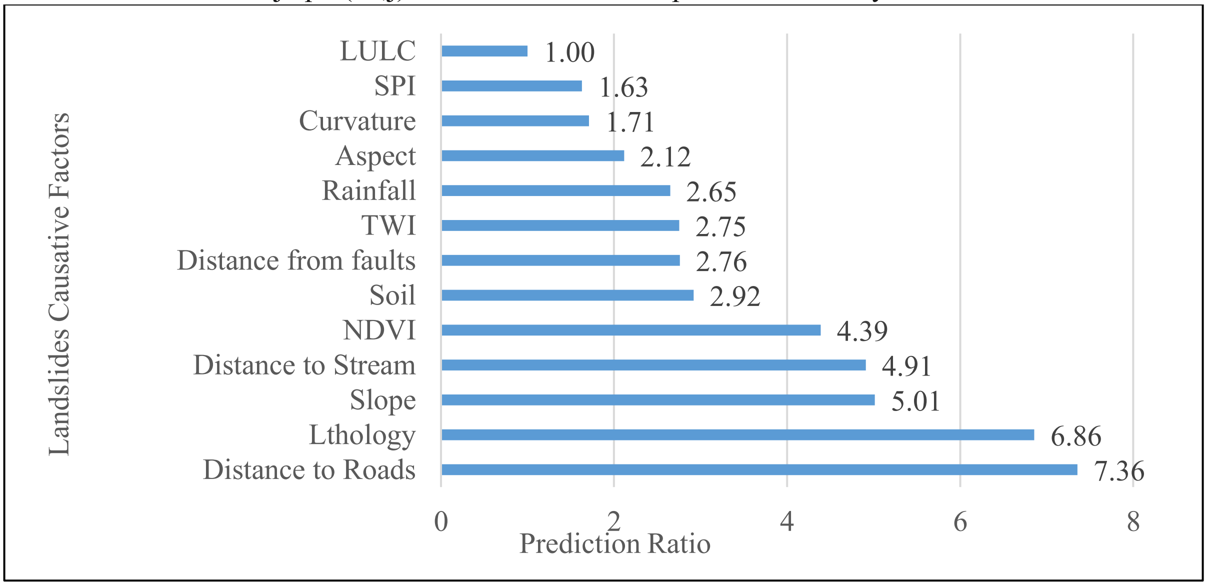


Fig. 4 Landslides Causative Factors Versus Predictive Ratio using Frequency Ratio

Fig. 4 shows that the roads are the most influential factor governing landslide occurrences in the study area. The graph highlights that proximity to roads significantly increases landslide susceptibility emphasizing the need for careful planning and risk assessment in vulnerable regions.

3.6 Multicollinearity Check and Variance Inflation Factor

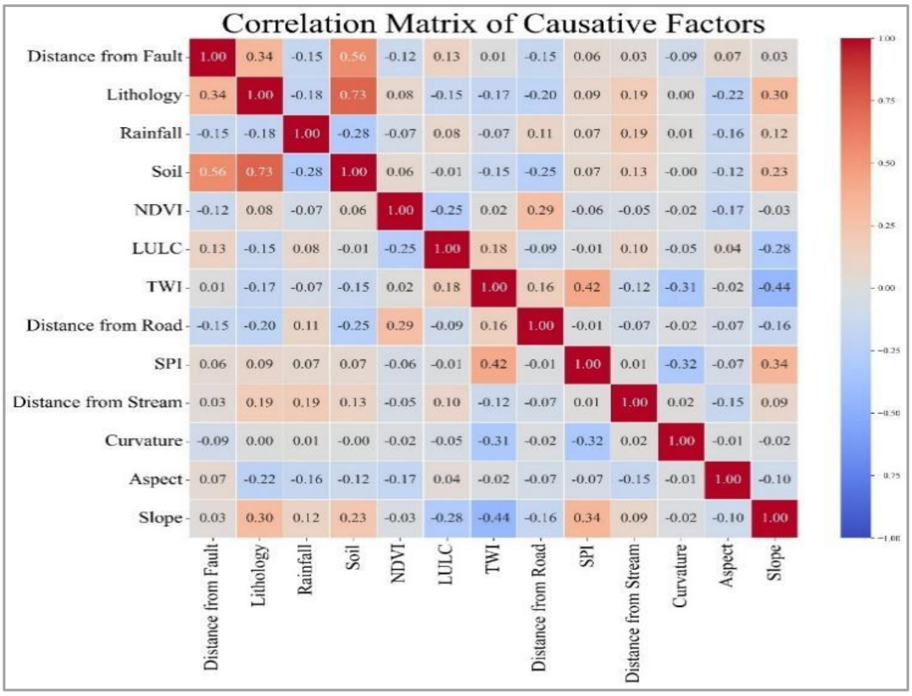


Fig. 5: Co-relation Heat Map

The correlation between various individual causative factors were calculated using the Python environment and heat map was developed. Correlation heat matrix shown on Fig. 5 shows the presence of high correlation values (for example, Soil & Lithology). This suggests potential multicollinearity concerns in regression models.

Further, Variance Inflation Factor (VIF) analysis was used to evaluate redundancy among predictors using equation 6.

$$VIF = \frac{1}{1-R^2} \tag{6}$$

Where, R^2 is the coefficient of determination obtained by regressing the independent variable Xi on all the other independent variables in the model. None of the variables exhibit VIF values exceeding 5, implying that severe multicollinearity is not present. Similarly, tolerance less than 0.2 indicates low collinearity.

Logistic Regression: The logistic regression model is formulated as equation 7:

$$P = \frac{1}{1+e\verb|^|(-logit)} \tag{7}$$

where: logit = β0 + β1X1 + β2X2 + ... + βn Xn

P is the probability of a landslide occurring,

β0 is the intercept.

β1, β2, ..., βn are regression coefficients.

X1, X2, ..., Xn are predictor variables such as slope, aspect, soil type, and precipitation

Table 1 Significant Landslides Causative Factors

Causative Factors	p-value
constant	0.15781
Distance from Faults (m)	0.03837
Lithology	0.56048
Rainfall (mm/24 hr)	0.02225
Soil	0.20871
NDVI	0.20073
LULC	0.17959
TWI	0.56757
Distance from Roads (m)	0
SPI	0.97248
Distance from Streams(m)	0.67234
Curvature	0.83247
Aspect (Degree)	0.84148
Slope (Degree)	0

The analysis (table 1) shows several statistically significant relationships. A negative coefficient for distance from the fault suggests that as distance increases, the response variable decreases ($p < 0.05$). Higher rainfall is associated with a decrease in the response variable ($p < 0.05$). Distance from the road also has a strong negative association with the response variable (p is very small). A positive coefficient for slope indicates that as slope increases, the response variable also increases ($p \approx 0$), making it a highly significant positive relationship.

3.7 Validation

The landslide inventory data was randomly divided into two subsets using an 80:20 ratio, where 80% of the data was allocated for model training and the remaining 20% was used for testing. (Singh et al., 2022). The testing data can be validated from F1 Score, Kappa and Area Under Curve (AUC) and it was found out that highest accurate value obtained using AUC (Singh et al., 2023)

4. Results and Discussion

1. To assess landslide susceptibility, two statistical models, Frequency Ratio (FR) and Logistic Regression (LR) were applied and evaluated. Both models analyzed the relationship between landslide occurrences and various environmental factors, but they differ in their methodological approaches. The Frequency Ratio model is a bivariate statistical method that calculates the probability of landslides based on observed frequencies, while Logistic Regression is a multivariate statistical approach that assesses the combined effect of multiple independent variable.
2. While analyzing multicollinearity among the causative factors, it is found to be within acceptable limits (VIF < 5), the p-values from the logistic regression analysis indicate that some variables, such as Lithology and Stream Power Index (SPI), are not statistically significant contributors to the model. This is due to regional geological homogeneity or the scale of analysis.
3. To compare the models, their accuracy was assessed using statistical performance metrics, Area Under the Receiver Operating Characteristic (ROC) Curve (AUC). The AUC of Logistic Regression is 0.909 demonstrating higher accuracy than the Frequency Ratio of AUC is 0.819. This indicates that the LR model provides a better fit for predicting landslide susceptibility in the study area and has a stronger ability to distinguish between landslide-prone and non-landslide-prone areas. Logistic Regression model outperformed the Frequency Ratio model, the final Landslide Susceptibility Map (LSM) was developed using the LR as shown in the Fig. 6. This LR performance is notably superior when compared to several similar studies conducted in other regions. For instance, (Sun et al., 2018) reported an AUC of 0.834 using Logistic Regression for landslide susceptibility mapping along the Jinsha River, China.

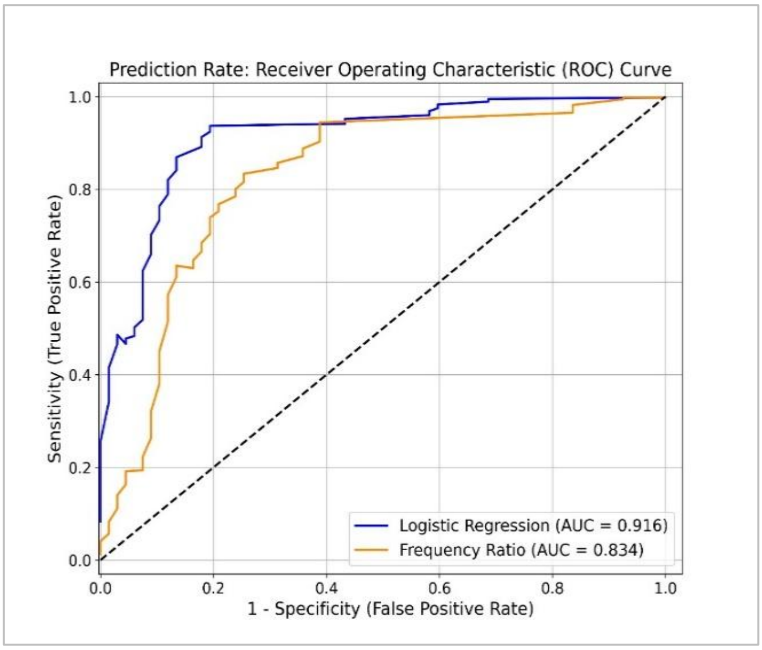


Fig. 6: Area Under Curve -Receiver Operating Characteristics (AUC-ROC) Curve

4. GIS-based modeling revealed that in Gorkha Municipality, around 28% of the area is classified as having very low landslide susceptibility, while 20% falls into the low susceptibility category. Additionally, 19% of the region is moderately susceptible, another 19% is highly susceptible, and the remaining 15% is at very high risk of landslides.

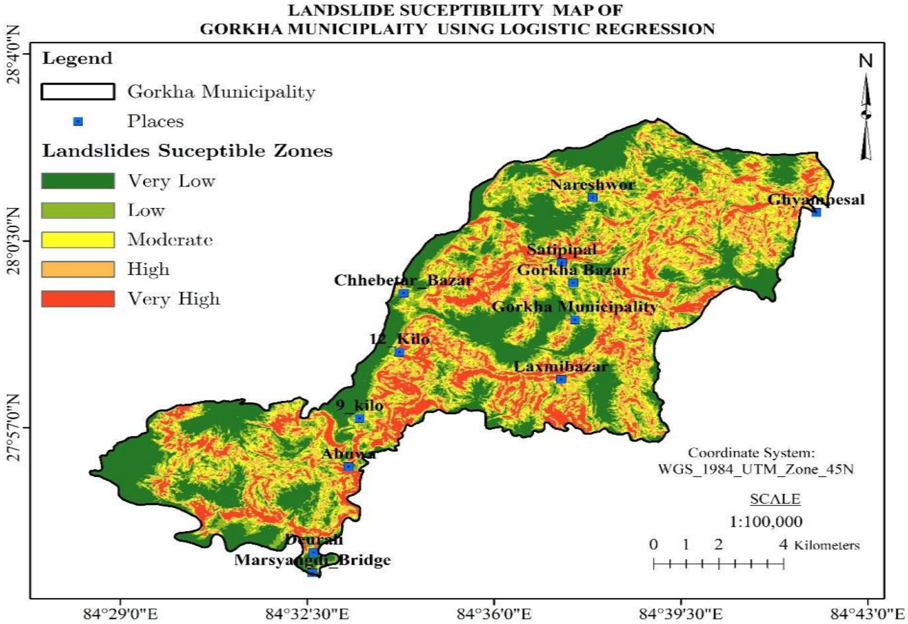


Fig. 7: Landslide Susceptibility Map using Logistic Regression of Gorkha Municipality

5. Conclusion and Recommendations

The study compared Frequency Ratio and Logistic Regression models for landslide susceptibility mapping in Gorkha Municipality. Logistic Regression is found to be more accurate than FR in the study area. 28% of the study area has very low landslides susceptibility, while 15% is at very high risk. Road proximity significantly influences landslides . While road construction cannot be avoided, detailed slope analysis and geotechnical studies must be conducted to prevent hazards. Poorly planned roads should be avoided, and alignments should prioritize less landslide-prone areas for safer development.

Landslide Susceptibility Mapping (LSM) is crucial for risk reduction, disaster preparedness, and sustainable development. These results provide valuable input for hazard mitigation and land-use planning in the region. By identifying high-risk areas, LSM aids in development of early warning systems, evacuation planning, and mitigation strategies, making it more cost-effective than post-disaster recovery. It also informs regional planner to ensure safer infrastructure construction while guiding policymakers in enforcing zoning regulations.

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