Introduction

The region of Chin State in Western Myanmar is characterized by rugged terrain, diverse geological formations, and a susceptibility to landslides and flooding [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)], [(“Topographical Features of Rainfall-Triggered Landslides in Mon State, Myanmar, August 2019: Spatial Distribution Heterogeneity and Uncommon Large Relative Heights”, 2021)]. Despite the picturesque landscapes and rich biodiversity, the area faces significant challenges due to natural hazards [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)]. Over recent years, the frequency and severity of landslides and flooding events have heightened, necessitating a deeper understanding of their causes and impacts. Previous research [(“A Comparative Study of Frequency Ratio, Weights of Evidence and Logistic Regression Methods for Landslide Susceptibility Mapping: Sultan Mountains, SW Turkey”, 2013)]–[(“Landslide Susceptibility in the Belt and Road Countries: Continental Step of a Multi-Scale Approach”, 2021)] has shed light on the complex interactions of environmental factors influencing landslide and flooding occurrences in mountainous regions, providing valuable insights applicable to Chin State [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)], [(n.d.)]. Studies have highlighted the critical role of factors such as rainfall intensity and duration, geological characteristics, and topographic features in driving hazard susceptibility [(“Assessment of Landslide Susceptibility Zonation Using Frequency Ratio and Statistical Index: A Case Study of Al-Fawar Basin, Tartous, Syria”, 2022)]–[(“The Contribution of EMCA to Landslide Susceptibility Mapping in Central Asia”, 2015)]. However, gaps persist in our understanding of the multi-factorial nature of these phenomena in Chin State. Integrating insights from existing literature with empirical data from the region can provide a comprehensive assessment of hazard susceptibility and inform evidence-based decision-making for disaster risk reduction and resilience building efforts.

In recent years, advancements in remote sensing and GIS technologies [(“Topographical Features of Rainfall-Triggered Landslides in Mon State, Myanmar, August 2019: Spatial Distribution Heterogeneity and Uncommon Large Relative Heights”, 2021)], [(“Landslides in Central Asia: A Review of Papers Published in 2000–2020 With a Particular Focus on the Importance of GIS and Remote Sensing Techniques”, 2021)], [(“Assessment of the Impacts of Urbanization on Landslide Susceptibility in Hakha City, a Mountainous Region of Western Myanmar”, 2023)] have transformed our ability to analyze and model landslide and flood hazards in complex terrain. LiDAR data, combined with machine learning algorithms, has facilitated precise delineation of terrain features and identification of hazard-prone areas [(“How Robust Are Landslide Susceptibility Estimates?”, 2021)], [(“Assessment of the Impacts of Urbanization on Landslide Susceptibility in Hakha City, a Mountainous Region of Western Myanmar”, 2023)]–[(“Literature Review and Bibliometric Analysis on Data-Driven Assessment of Landslide Susceptibility”, 2022)]. Despite these advancements, gaps persist in our understanding of the multi-factorial nature of landslide and flooding occurrences in Chin State, Western Myanmar. Previous research [(“Landslides in Central Asia: A Review of Papers Published in 2000–2020 With a Particular Focus on the Importance of GIS and Remote Sensing Techniques”, 2021)], [(“Literature Review and Bibliometric Analysis on Data-Driven Assessment of Landslide Susceptibility”, 2022)]–[(“Use of Satellite Remote Sensing Data in the Mapping of Global Landslide Susceptibility”, 2007)] has extensively documented the complex interplay of environmental factors influencing landslide and flooding occurrences in mountainous regions, providing valuable insights applicable to Chin State. Reference [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)] emphasized the critical role of rainfall intensity and duration in triggering landslides and flooding, highlighting the significance of extreme precipitation events in mountainous areas. Their findings underscored the importance of incorporating temporal variability in rainfall patterns when assessing landslide and flood hazards. Geological characteristics, including rock type, structure, and weathering, have been identified as key determinants of slope stability and landslide susceptibility [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)], [(“Topographical Features of Rainfall-Triggered Landslides in Mon State, Myanmar, August 2019: Spatial Distribution Heterogeneity and Uncommon Large Relative Heights”, 2021)]. Studies [(“How Robust Are Landslide Susceptibility Estimates?”, 2021)], [(“Assessment of the Impacts of Urbanization on Landslide Susceptibility in Hakha City, a Mountainous Region of Western Myanmar”, 2023)], [(“GIS-Based Assessment of Landslide Susceptibility Using Certainty Factor and Index of Entropy Models for the Qianyang County of Baoji City, China”, 2015)] have highlighted the contribution of shale formations to landslide occurrences in mountainous regions, indicating that the presence of specific lithological units can significantly influence the spatial distribution of landslide hotspots. Additionally, research has [(“A Comparative Study of Frequency Ratio, Weights of Evidence and Logistic Regression Methods for Landslide Susceptibility Mapping: Sultan Mountains, SW Turkey”, 2013)], [(“Use of Satellite Remote Sensing Data in the Mapping of Global Landslide Susceptibility”, 2007)], [(“Landslide Susceptibility Analysis in Data-Scarce Regions: The Case of Kyrgyzstan”, 2015)] demonstrated the role of geological faults in controlling drainage patterns and exacerbating flood hazards in similar terrain.

Despite significant advancements in remote sensing and GIS technologies, there are persistent gaps in our understanding of the multi-factorial nature of landslide and flooding occurrences in Chin State, Western Myanmar. Integrating findings from existing literature with empirical data from the region will facilitate a comprehensive assessment of hazard susceptibility and inform evidence-based decision-making for disaster risk reduction and resilience building efforts [(“Landslide Susceptibility Analysis in Data-Scarce Regions: The Case of Kyrgyzstan”, 2015)], [(“Applying Rainfall Threshold Estimates and Frequency Ratio Model for Landslide Hazard Assessment in the Coastal Mountain Setting of South Asia”, 2023)]. Against this backdrop, this study aims to conduct a comprehensive analysis of landslide and flood occurrences in Chin State. By integrating insights from existing literature with empirical data from the region, we seek to elucidate the underlying mechanisms driving hazard susceptibility. Through a multi-factorial approach encompassing rainfall patterns, geology, topography, and remote sensing techniques, we aspire to inform evidence-based decision-making for disaster risk reduction and resilience building efforts in Chin State.

This study holds paramount significance in addressing the pressing need for a comprehensive understanding of landslide and flood occurrences in Chin State, Western Myanmar [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)], [(“Landslide Susceptibility Mapping by Binary Logistic Regression, Analytical Hierarchy Process, and Statistical Index Models and Assessment of Their Performances”, 2013)]. By elucidating the complex interplay of environmental factors contributing to these hazards, the research aims to inform evidence-based decision-making for disaster risk reduction and resilience building efforts in the region. The objectives of the study are multi-faceted: (1) to assess the influence and extent of rainfall patterns on landslide occurrences; (2) to analyze the relationship between geology, slope stability, and landslide susceptibility in Chin State and (3) to investigate the impact of topographic features, such as flow direction and elevation, on landslide occurrences. Through these objectives, the study endeavours to provide valuable insights into the mechanisms driving landslide and flood susceptibility in Chin State, thereby facilitating proactive measures for mitigating the impacts of these natural hazards and safeguarding the lives and livelihoods of the local communities.

Materials and Methodology

Study Area Description

Chin State, situated in the western part of Myanmar (Fig. 1), is renowned for its rugged and mountainous terrain, part of the larger Patkai Range, with elevations ranging from 200 meters to over 3,000 meters above sea level. Several rivers flow through the region, supporting transportation and irrigation systems, while its diverse topography and climate foster rich biodiversity, including endangered and endemic species. The climate varies with elevation [(n.d.)], [(“Chinese High Resolution Satellite Data and GIS-Based Assessment of Landslide Susceptibility Along Highway G30 in Guozigou Valley Using Logistic Regression and MaxEnt Model”, 2022)], featuring a wet season from May to October and a dry season from November to April [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)] with distinct wet and dry seasons driven by the southwest monsoon. Rainfall patterns, influenced by orographic lifting, range from 1,000 to 2,500 millimetres annually, impacting agriculture and necessitating water resource management. Vegetation varies with altitude, from tropical and subtropical forests to temperate and alpine vegetation. Despite limited infrastructure and development due to geographical challenges, Chin State’s unique landscape presents both opportunities and challenges for the well-being of its residents and the region’s sustainable development.

Fig. 1. *Study area.*

Data Source

In the initial phase of the study, it is paramount to acquire high-quality satellite imagery [("Influence of Earthquakes on Landslide Susceptibility in a Seismic Prone Catchment in Central Asia", 2021)], [("Landslide Susceptibility Mapping Using Logistic Regression Model (a Case Study in Badulla District, Sri Lanka)", 2018)] to cover Chin State and its surroundings. This 30-meter resolution imagery serves as the cornerstone for various spatial analyses, necessitating the use of multi-temporal and high-resolution satellite imagery. Advanced processing techniques like photogrammetry or data fusion, as suggested by [("Accelerating Effect of Vegetation on the Instability of Rainfall-Induced Shallow Landslides", 2022)], should be employed to enhance accuracy and detail. Subsequently, generating a precise Digital Elevation Model (DEM) from the acquired satellite imagery is crucial for slope, aspect, and flow accumulation calculations, as highlighted by [("Topographical Features of Rainfall-Triggered Landslides in Mon State, Myanmar, August 2019: Spatial Distribution Heterogeneity and Uncommon Large Relative Heights", 2021)], [("A Comparative Study of Frequency Ratio, Weights of Evidence and Logistic Regression Methods for Landslide Susceptibility Mapping: Sultan Mountains, SW Turkey", 2013)], [("Landslide and Wildfire Susceptibility Assessment in Southeast Asia Using Ensemble Machine Learning Methods", 2021)], [("Chinese High Resolution Satellite Data and GIS-Based Assessment of Landslide Susceptibility Along Highway G30 in Guozigou Valley Using Logistic Regression and MaxEnt Model", 2022)]. Ensuring the DEM accurately represents the topographic characteristics of the study area, including rugged terrain, valleys, and hills, is imperative. Precipitation data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis websites and landslide and flood data from the Chin Committee for Emergency Response and Rehabilitation website are obtained for analysis. Analysis maps for key variables such as precipitation, elevation, geology, and soil types are generated using geospatial techniques, employing appropriate classification methods [("Accelerating Effect of Vegetation on the Instability of Rainfall-Induced Shallow Landslides", 2022)], [("Literature Review and Bibliometric Analysis on Data-Driven Assessment of Landslide Susceptibility", 2022)], [("Applying Rainfall Threshold Estimates and Frequency Ratio Model for Landslide Hazard Assessment in the Coastal Mountain Setting of South Asia", 2023)] and the latest available data sources to create high-quality thematic maps fundamental for subsequent spatial analysis.

Data Analysis

Spatial Analysis

Spatial analyses were rigorously conducted to comprehensively investigate the impact of extreme precipitation on landslides and flooding in 2015 [("A Comparative Study of Frequency Ratio, Weights of Evidence and Logistic Regression Methods for Landslide Susceptibility Mapping: Sultan Mountains, SW Turkey", 2013)], [("Applying Rainfall Threshold Estimates and Frequency Ratio Model for Landslide Hazard Assessment in the Coastal Mountain Setting of South Asia", 2023)], [("Landslide Susceptibility Mapping Using Logistic Regression Model (a Case Study in Badulla District, Sri Lanka)", 2018)]. Leveraging state-of-the-art geospatial tools and advanced statistical techniques, researchers meticulously quantified the intricate relationships, integrating various datasets, including geological and elevation data. Furthermore, sophisticated modelling techniques were adeptly employed to delve deeper into the complex interplay of factors influencing extreme precipitation events. This comprehensive approach not only enhanced our understanding of the phenomenon but also provided valuable insights into potential mitigation strategies and adaptation measures in regions prone to such hazards.

Digital Elevation Model (DEM) and Geological Analysis

In the spatial analysis of extreme precipitation's influence on landslides and flooding, Digital Elevation Model (DEM) covering the study area was obtained from satellite imagery. The DEM provided detailed elevation information, including slope, aspect, and elevation values. Prior to analysis, the acquired DEM data underwent pre-processing steps to ensure data quality and consistency. This involved the removal of outliers, filling data gaps, and correcting any systematic errors or artifacts that could affect the accuracy of subsequent analyses. Next, geospatial analysis tools were employed to derive additional terrain attributes from the DEM data. These attributes, including slope, aspect, and hill shade, were crucial for understanding terrain characteristics and their influence on extreme precipitation-induced hazards. The slope (S), aspect (A), and hill shade (HS) of a terrain can be calculated using the formulas below in ArcMap 10.8: (1) $S=\Delta h \Delta d$(1)where Δh is the change in elevation and Δd is the horizontal distance. (2) $A=\text{atan2}(\partial z/\partial y,\partial z/\partial x)$(2)where $\partial z/\partial y$ is the rate of change of elevation in the north-south direction and $\partial z/\partial x$ is the rate of change of elevation in the east-west direction. (3) $HS=(\cos(Z)\times\cos(S))+(\sin(Z)\times\sin(S)\times\cos(A-\text{Azenith}))$(3)where Z is the zenith angle, S is the slope angle, A is the aspect angle, and Azenith is the azimuth angle of the light source.

The derived terrain attributes were then integrated with other datasets to assess their combined impact on landslide and flooding susceptibility. This integration facilitated a more comprehensive analysis of the factors contributing to hazard occurrence.

Subsequently, Spatial techniques were applied to analyze the relationships between elevation-related variables and extreme precipitation events. This involved spatial clustering to identify patterns and trends in the data [(n.d.)], [("Applying Rainfall Threshold Estimates and Frequency Ratio Model for Landslide Hazard Assessment in the Coastal Mountain Setting of South Asia", 2023)]. Spatial regression model was also utilized to model the complex interactions between elevation attributes and extreme precipitation events. These models aided in predicting hazard susceptibility and assessing the impact of extreme precipitation events in 2015.

Then, the elevation results underwent rigorous validation to assess the accuracy and reliability of the derived terrain attributes and modeling results. This validation process with observed landslide and flooding events. This methodical approach aided in gaining valuable insights into the role of terrain characteristics in modulating the impact of extreme precipitation events on landslides and flooding, thereby informing effective hazard assessment and mitigation strategies.

In conducting spatial analysis with respect to geology, geological data relevant to the study area and geological mapping were conducted to gather additional data on geological formations, rock types, and other geological features. This detailed characterization of the geological setting and identification of areas susceptible to landslides and flooding. Geospatial analysis techniques were employed to integrate geological information with other datasets, such as elevation data and precipitation records. Geospatial tools were used to delineate geological units, map geological hazards, and assess their spatial distribution within the study area. Statistical analyses were then performed to analyze the relationship between geological factors and extreme precipitation events. This involved identifying correlations, trends, and patterns in the data to understand how geological characteristics influence the occurrence and magnitude of landslides and flooding.

Precipitation Analysis

In the precipitation analysis, mathematical formulation and techniques were employed to analyze the characteristics and impacts of rainfall events. Rainfall intensity was calculated by dividing the total precipitation by the duration of the rainfall event. Statistical methods, including frequency analysis and probability distribution fitting, were utilized to analyze the distribution of rainfall across the study region. Precipitation intensity (I) can be calculated using the formula: (4)$I=\frac{P}{t}$(4)where P is the total precipitation (in millimeters), and t is the duration of the precipitation event (in hours).

This analysis provided insights into the frequency and magnitude of rainfall events, aiding in the understanding of precipitation patterns over time. Furthermore, rainfall excess, representing the portion of rainfall contributing to runoff, was estimated using the Rational Method as depicted below: (5)$Q=\frac{(P-0.2S)^2}{(P+0.8S)}$(5)where Q is the rainfall excess (in millimeters), P is the total precipitation (in millimeters or inches), and is the potential maximum retention (in millimeters or inches), determined based on soil type and land use.

Moreover, rainfall threshold analysis was conducted to identify critical precipitation thresholds that trigger landslides and floods. Historical rainfall data were analyzed statistically to determine these thresholds, providing valuable information for early warning systems and disaster preparedness efforts. Additionally, spatial interpolation techniques known as inverse distance weighting (IDW) [(“Topographical Features of Rainfall-Triggered Landslides in Mon State, Myanmar, August 2019: Spatial Distribution Heterogeneity and Uncommon Large Relative Heights”, 2021)], [(“Use of Satellite Remote Sensing Data in the Mapping of Global Landslide Susceptibility”, 2007)] were applied to estimate precipitation in the study area. The precipitation methodology employed a combination of mathematical formulations and techniques to analyze, model, and depict rainfall patterns and their impacts on floods and landslides in 2015. This analysis basically provides valuable insights for understanding the behavior of extreme precipitation events and informing decision-making processes related to disaster risk reduction and water resources management.

Flooding Analysis (Flow Direction of Waterbodies)

In analyzing the flow direction of water bodies during extreme precipitation events, Flow direction Analysis was utilized to show the directional movement of water in the study area. This model relied on mathematical equations to depict water flow direction based on terrain characteristics, land cover, geological properties, and precipitation inputs in 2015. Additionally, digital elevation models (DEMs) were employed to determine flow direction in water bodies. Topographic index calculation, which measures the propensity of water to flow downslope, was also undertaken. TOPMODEL equation were used to calculate the topographic index (*TI*), incorporating factors like upslope contributing area and slope angle with the formula below: $(6) TI=\ln(atan(\beta))(6)$ where *a* is the upslope contributing area, β is the slope angle, and ln is the natural logarithm.

Stream network delineation algorithms were employed to identify flow paths and channel networks within watersheds. These algorithms utilized elevation data and flow accumulation thresholds to delineate streams and rivers, providing valuable insights into the flow direction of water bodies.

Landslide Analysis

During extreme precipitation events in 2015, landslide occurrence mapping analysis was conducted to identify areas subjected to landslides based on terrain characteristics and geological factors. This process utilized statistical analyses to correlate landslide locations with factors with precipitation intensity. Rainfall threshold analysis aimed to identify critical precipitation thresholds that triggered landslides. Seasonal rainfall data and landslide occurrences were analyzed to determine the minimum rainfall intensity and duration required to initiate landslides. Landslide occurrence Mapping was done in ArcMap 10.8 using the below formula: (7)
$P(Y=1)=11+e-(\beta0+\beta1X1+\beta2X2+\ldots+\beta nXn)(7)$ where *P(Y = 1)* is the landslide occurrence, β0,β1,β2… are coefficients, and X1,X2,… are precipitation-based influence variables such as slope, aspect and geology.

Hydrological modeling simulated the movement of water through watersheds during extreme precipitation events, providing insights into factors influencing landslide occurrence. Incorporating precipitation inputs, geological properties, and terrain characteristics to depict runoff generation and soil moisture content are critical factors in landslide initiation. Soil stability analysis assessed the stability of slopes under varying precipitation conditions. The infinite slope stability model was used to calculate factors of safety and determine the likelihood of slope failure during extreme precipitation events. This analysis considered parameters such as soil cohesion, internal friction angle, pore water pressure, and slope geometry [(“Accelerating Effect of Vegetation on the Instability of Rainfall-Induced Shallow Landslides”, 2022)], [(“Literature Review and Bibliometric Analysis on Data-Driven Assessment of Landslide Susceptibility”, 2022)], [(“Use of Satellite Remote Sensing Data in the Mapping of Global Landslide Susceptibility”, 2007)]. Additionally, remote sensing and GIS techniques were utilized to identify landslide-prone areas, monitor land cover changes, and assess terrain morphology. Satellite imagery provided valuable information for landslide occurrence mapping [(n.d.)], [(“The Contribution of EMCA to Landslide Susceptibility Mapping in Central Asia”, 2015)]. Geographic Information System (GIS) techniques were then applied to integrate and analyze spatial data layers, facilitating the identification of factors contributing to landslide occurrence and the delineation of affected areas.

The integration of these methodologies helps to gain a comprehensive understanding of landslide and flood dynamics during extreme precipitation events, enabling better assessment of flood and landslide risks and implementation of effective mitigation measures.

Assessing Landslide Susceptibility Using Logistic Regression

Logistic Regression (Lr) analysis stands out among the various statistical methods used for assessing landslide susceptibility [(“Landslide Susceptibility Mapping Using Logistic Regression Model (a Case Study in Badulla District, Sri Lanka)”, 2018)]. It establishes a relationship between the probability of landslide occurrence, ranging from 0 to 1, and the “logit” u, where values fall between $-\infty$ and ∞. (8)$Lr=mu(1+nu)$(8)where *L* represents the probability of a landslide occurring.

In this analysis, the logit *u* is modelled as a linear combination of independent variables, represented by $\gamma 1,\gamma 2,\gamma 3$ etc., corresponding to factors like slope, geology, and elevation.

The formula for logistic regression is expressed as: (9)$u=\gamma 0+\gamma 1x1+\gamma 2x2+\gamma 3x3$(9)

Results and Discussion

The Impact of Rainfall Patterns on Landslide Susceptibility in Chin State, Western Myanmar: A Statistical Analysis

Our study underscores the significant influence of rainfall patterns on landslide susceptibility in Chin State, Western Myanmar. Statistical analysis conducted at a 95% confidence interval revealed strong correlations between rainfall intensity and landslide occurrences, with a Pearson correlation coefficient of 0.806, Kendall’s tau_b correlation coefficient of 0.908, and Spearman’s rho coefficient of 0.979 (Tables I–III). The study found that intense precipitation events are primary catalysts for landslides, particularly during the southwest monsoon season, with over 75% of landslides occurring during periods of heavy rainfall. The highest average seasonal precipitation events occurred in September, October, and November (SON) and in June, July, August (JJA), with July consistently experiencing the highest cumulative precipitation totals (Fig. 2). This recurring pattern highlights the importance of monitoring precipitation trends for understanding climate patterns and informing water resource management and disaster preparedness efforts. The impact of extreme precipitation events on landslides and floods in Chin State is further underscored by statistical data from the Myanmar Ministry of Natural Resources and Environmental Conservation, revealing an increasing trend in landslides and flooding incidents (Fig. 3) over the past decade. The urgent need for proactive measures to mitigate the impact of extreme precipitation on vulnerable communities is evident, especially in a region where the risk of landslides and flooding is heightened by intense rainfall and rugged terrain [(“Landslide Susceptibility Analysis in Data-Scarce Regions: The Case of Kyrgyzstan”, 2015)], [(“Applying Rainfall Threshold Estimates and Frequency Ratio Model for Landslide Hazard Assessment in the Coastal Mountain Setting of South Asia”, 2023)].

		Rainfall	Slope	Elevation	Landslide
Rainfall	Pearson correlation	1	0.509	0.702*	0.806**
	Sig. (2-tailed)		0.091	0.011	0.002
	N	12	12	12	12
Slope	Pearson correlation	0.509	1	0.683*	0.659*

		Rainfall	Slope	Elevation	Landslide
	Sig. (2-tailed)	0.091		0.014	0.020
	N	12	12	12	12
Elevation	Pearson correlation	0.702*	0.683*	1	0.800**
	Sig. (2-tailed)	0.011	0.014		0.002
	N	12	12	12	12
Landslide	Pearson correlation	0.806**	0.659*	0.800**	1
	Sig. (2-tailed)	0.002	0.020	0.002	
	N	12	12	12	12

Table I. *Statistical Analysis of Pearson Correlation Coefficients*

Note: *Correlation is significant at the 0.05 level (2-tailed). **Correlation is significant at the 0.01 level (2-tailed).

			Rainfall	Slope	Elevation	Landslide
Kendall's tau_b	Rainfall	Correlation coefficient	1.000	0.677**	0.738**	0.908**
		Sig. (2-tailed)		0.002	0.001	0.000
		N	12	12	12	12
	Slope	Correlation coefficient	0.677**	1.000	0.585**	0.708**
		Sig. (2-tailed)	0.002		0.009	0.002
		N	12	12	12	12
	Elevation	Correlation coefficient	0.738**	0.585**	1.000	0.708**
		Sig. (2-tailed)	0.001	0.009		0.002
		N	12	12	12	12
	Landslide	Correlation coefficient	0.908**	0.708**	0.708**	1.000
		Sig. (2-tailed)	0.000	0.002	0.002	
		N	12	12	12	12

Table II. *Statistical Analysis of Kendall's tau_b Correlation Coefficients*

Note: **Correlation is significant at the 0.01 level (2-tailed).

			Rainfall	Slope	Elevation	Landslide
Spearman's rho	Rainfall	Correlation coefficient	1.000	0.839**	0.886**	0.979**
		Sig. (2-tailed)		0.001	0.000	0.000
		N	12	12	12	12
	Slope	Correlation coefficient	0.839**	1.000	0.768**	0.839**
		Sig. (2-tailed)	0.001		0.004	0.001
		N	12	12	12	12
	Elevation	Correlation coefficient	0.886**	0.768**	1.000	0.875**

			Rainfall	Slope	Elevation	Landslide
		Sig. (2-tailed)	0.000	0.004		0.000
		N	12	12	12	12
	Landslide	Correlation coefficient	0.979**	0.839**	0.875**	1.000
		Sig. (2-tailed)	0.000	0.001	0.000	
		N	12	12	12	12

Table III. *Statistical Analysis of Spearman's Rho Correlation Coefficients*

Note: **Correlation is significant at the 0.01 level (2-tailed).

Fig. 2. *Extreme precipitation days map for Chin State (2015).*

Fig 3. *Rainfall and landslide in Chin State in 2015.*

Geological Influence on Landslide Susceptibility in Chin State, Myanmar: Correlation Analysis and Hazard Assessment

Statistical analysis conducted at a 95% confidence interval revealed strong correlations between slope steepness and landslide susceptibility in Chin State, Myanmar. The Pearson correlation coefficient was calculated to be 0.659 (Tables I–III), indicating a moderate positive correlation, while Kendall’s tau_b coefficient and Spearman’s rho coefficient were found to be 0.708 and 0.839, respectively, both indicating strong positive correlations. Areas characterized by steep slopes accounted for over 65% of landslide occurrences in the region, underscoring the significance of slope gradient in landslide susceptibility assessments.

This highlights the importance of incorporating geological considerations into landslide hazard assessment and mitigation planning [(“Landslides in Central Asia: A Review of Papers Published in 2000–2020 With a Particular Focus on the Importance of GIS and Remote Sensing Techniques”, 2021)], [(“Landslide Susceptibility Mapping by Binary Logistic Regression, Analytical Hierarchy Process, and Statistical Index Models and Assessment of Their Performances”, 2013)]. The geology of Chin State reflects its complex tectonic history, shaped by millions of years of geological evolution within the Himalayan orogeny. The region’s diverse geological processes (Fig. 4), influenced by the collision between the Indian Plate and the Eurasian Plate, have resulted in a variety of rock formations. The Chin Hills Mountain range, predominantly composed of sedimentary rocks such as sandstone, shale, and limestone, dominates the western part of the state [(n.d.)], [(“Landslides in Central Asia: A Review of Papers Published in 2000–2020 With a Particular Focus on the Importance of GIS and Remote Sensing Techniques”, 2021)], [(“Assessment of the Impacts of Urbanization on Landslide Susceptibility in Hakha City, a Mountainous Region of Western Myanmar”, 2023)]. Metamorphic rocks like schist, gneiss, and marble, as well as intrusive igneous rocks like granite and granodiorite, further contribute to the geological diversity. Located within the Indo-Burman Ranges, Chin State experiences seismic activity and tectonic deformation, shaping its landscape and geological processes [(“Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar”, 2022)], [(n.d.)]. These geological factors, coupled with extreme precipitation events during monsoon seasons, influence natural hazards like earthquakes and landslides in the region. The rugged mountains and diverse geological formations of Chin State harbour mineral resources and support diverse ecosystems and rich biodiversity, making it essential to understand the relationship between geology, slope stability, and landslide susceptibility for effective hazard assessment and mitigation planning [(“A Comparative Study of Frequency Ratio, Weights of Evidence and Logistic Regression Methods for Landslide Susceptibility Mapping: Sultan Mountains, SW Turkey”, 2013)], [(“Landslides in Central Asia: A Review of Papers Published in 2000–2020 With a Particular Focus on the Importance of GIS and Remote Sensing Techniques”, 2021)].

Fig. 4. *Geological map of Chin State.*

Hydrological Dynamics and Landscape Vulnerability: Assessing the Impact of Elevation and Flow Direction on Landslide Susceptibility in Chin State, Myanmar

Our research highlights a significant probability of people residing in lowlands being affected by landslides, with over 66% of landslide occurrences observed at elevations below 300 meters above sea level (MASL) in Chin State, Myanmar. Statistical analysis conducted at a 95% confidence level further supports this finding, revealing strong correlations between elevation and landslide susceptibility. The Pearson correlation coefficient, Kendall's tau_b coefficient, and Spearman's rho coefficient between elevation and landslide occurrences were measured at 0.80, 0.708, and 0.875 respectively, indicating a robust relationship.

Elevation in Chin State exhibits notable variability (Fig. 5), with elevations spanning a wide range across the region. The Chin Hills Mountain range dominates the western part of Chin State, with Mount Victoria standing as the tallest peak at approximately 2,951 meters above sea level. In contrast, lower-lying areas and valleys within Chin State feature comparatively lower elevations, typically ranging from a few meters to around 200 meters above sea level. Intermediate elevation zones between the high mountains and low-lying valleys comprise rolling hills and plateaus, with elevations ranging from several hundred meters to around 2,000 meters above sea level. This variability in elevation influences local weather patterns, ecological dynamics, and human settlements, with cooler temperatures and higher precipitation levels experienced at higher altitudes [("Rainfall and Landslide Susceptibility in Hakha Environ in Northern Chin State, Myanmar", 2022)], [(n.d.)], [("Use of Satellite Remote Sensing Data in the Mapping of Global Landslide Susceptibility", 2007)].

Fig. 5. *Elevation map for Chin State.*

Chin State's complex network of rivers and streams is primarily influenced by the region's rugged topography, with water bodies naturally following the contours of the land (Fig. 6). The flow direction of rivers and streams is intricately linked to elevation gradients, slope angles, and geological formations, shaping the region's hydrological system. The Kaladan River, one of the most significant rivers in Chin State, serves as a vital lifeline for transportation, irrigation, and sustenance of local livelihoods. Additionally, smaller rivers and streams originating from mountain springs and glacier meltwater contribute to the region's diverse hydrological network, supporting ecosystems and habitats rich in biodiversity. However, the rugged terrain and variable flow patterns also pose challenges such as flooding, erosion, and landslides, particularly during periods of heavy rainfall or intense monsoonal storms.

Fig. 6. *Flow direction of waterbodies of Chin State.*

Furthermore, the study underscores the complex interplay between elevation, hydrology, and landslide susceptibility in Chin State, Myanmar. Understanding these relationships is crucial for effective hazard assessment and mitigation planning, particularly in regions prone to natural disasters like landslides. By integrating statistical analysis with geospatial data, our research provides valuable insights into the factors influencing landslide occurrences and informs evidence-based decision-making for disaster risk reduction and resilience building efforts in Chin State.

Topographic Influences on Landslides in Chin State, Myanmar: Insights and Further Analysis

Topographic features, notably flow direction and elevation (Fig. 7), play pivotal roles in shaping the occurrence of landslides, as evidenced by statistical inferences drawn from our study in Chin State, Western Myanmar. Our analysis, conducted at a 95% confidence level, revealed compelling correlations between these topographic variables and landslide occurrences. Flow direction, which dictates the movement of surface water runoff, significantly influences soil erosion and slope stability. The study characterized by converging flow patterns were notably more susceptible to landslides, with statistical correlations indicating a Pearson coefficient of 0.72, Kendall’s tau_b coefficient of 0.68, and Spearman’s rho coefficient of 0.75. Similarly, elevation gradients emerged as key determinants of landslide susceptibility, with steeper slopes at higher elevations exhibiting heightened instability [(“Landslide Susceptibility in the Belt and Road Countries: Continental Step of a Multi-Scale Approach”, 2021)], [(“Landslides in Central Asia: A Review of Papers Published in 2000–2020 With a Particular Focus on the Importance of GIS and Remote Sensing Techniques”, 2021)], [(“Landslide Susceptibility Mapping Using Logistic Regression Model (a Case Study in Badulla District, Sri Lanka)”, 2018)]. Statistical analyses demonstrated a strong association between elevation and landslide occurrences, with a Pearson correlation coefficient of 0.80, Kendall’s tau_b coefficient of 0.75, and Spearman’s rho coefficient of 0.83. These findings underscore the complex interplay between topographic features and landslide dynamics, emphasizing the importance of incorporating such variables into landslide hazard assessments for effective risk mitigation strategies and infrastructure planning in landslide-prone regions like Chin State.

Fig. 7. *Slope angle and direction of waterbodies in Chin State.*

Exploring the Need for Further Analysis: Understanding Topographic Contributions to Landslide Occurrences in Chin State

Incorporating the findings of our study (Figs. 8 and 9), which identified significant correlations between flow direction, elevation, and landslide occurrences, further investigation is essential to deepen our understanding of these relationships. Detailed spatial modelling and field investigations can elucidate the underlying mechanisms, refining predictive models and improving landslide susceptibility mapping efforts. Integrating hydrological and geotechnical factors into the analysis will enhance the accuracy and reliability of landslide hazard assessments, facilitating more effective disaster risk reduction strategies in Chin State and beyond. Moreover, considering the impact of land use and land cover changes on topographic conditions can offer valuable insights for land management practices aimed at reducing landslide susceptibility and enhancing landscape resilience. Further analysis is warranted to delve deeper into the specific mechanisms through which flow direction and elevation contribute to landslide occurrences in Chin State. High-resolution spatial modelling techniques, coupled with detailed field investigations, can provide insights into the spatial distribution and temporal evolution of landslide events in relation to topographic features. Additionally, integrating hydrological and geotechnical factors into the analysis can enhance our understanding of how surface water dynamics and soil properties interact with topography to influence slope stability. Furthermore, considering the role of land use and land cover changes in modifying topographic conditions and exacerbating landslide susceptibility can provide valuable insights for land management and disaster risk reduction efforts. By conducting comprehensive analyses that encompass a range of factors influencing landslide dynamics, we can better inform evidence-based decision-making and enhance resilience to landslide hazards in Chin State and similar regions worldwide.

Fig. 8. *Probability function of study variables.*

Fig. 9. *Spatial maps of a) Average precipitation for December, January and February, b) Average precipitation for March, April, and May, c) Average precipitation for June, July and August, d) Average precipitation for September, October, and November, e) Elevation, f) Slope and g) Elevation and landslide events in the study area.*

Conclusion and Recommendation

The study highlights the multifaceted nature of landslide susceptibility in Chin State, Western Myanmar. Through rigorous spatial analysis and statistical inference, we identified significant correlations between rainfall patterns, topographic features, and geological characteristics with landslide occurrences. Our findings underscore the critical influence of intense precipitation events, particularly during the southwest monsoon season, in triggering landslides. Statistical analysis, conducted at a 95% confidence interval, revealed strong correlations between rainfall intensity and landslide occurrences, with Pearson correlation coefficient of 0.806, Kendall's tau_b coefficient of 0.908, and Spearman's rho coefficient of 0.979. Moreover, the impact of topographic features, such as flow direction and elevation, on landslide dynamics was evident, with converging flow patterns and steep slopes contributing to heightened susceptibility. Statistical correlations for flow direction yielded a Pearson coefficient of 0.72, Kendall's tau_b coefficient of 0.68, and Spearman's rho coefficient of 0.75, while elevation gradients showed coefficients of 0.80, 0.75, and 0.83, respectively. These statistical inferences provide robust evidence of the complex interplay between environmental factors and landslide occurrences in the region.

Moving forward, it is imperative to integrate these findings into comprehensive risk mitigation strategies and infrastructure planning efforts in Chin State. Given the increasing trend in landslides and flooding incidents over the past decade, proactive measures are urgently needed to safeguard vulnerable communities and critical infrastructure. Our study underscores the importance of monitoring precipitation trends and implementing early warning systems to mitigate the impact of extreme weather events. Additionally, there is a pressing need for further research to explore the long-term effects of climate change on landslide susceptibility in the region. By incorporating climate projections and risk assessments into land use planning and disaster management policies, stakeholders can better prepare for future challenges and enhance resilience in landslide-prone areas.

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