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Landslide susceptibility and risk analysis in Benighat Rural Municipality, Dhading, Nepal

Ganesh Dhungana [a,b,*], Romi Ghimire [a], Ranjan Poudel [a], Sujan Kumal [a]

[a] Action Nepal, Neelkantha Municipality, Dhading, Nepal
[b] Disaster Preparedness Mitigation and Management, Asian Institute of Technology, Thailand

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ABSTRACT

The complex geology and undulating terrain made Nepal vulnerable to natural disasters like landslides. Benighat-Rorang Rural Municipality (RM), in the Dhading district of Nepal's Bagmati province, has experienced several minor to massive landslides that have harmed both nature and civilization. This study examines the factors influencing landslides in the Benighat-Rorang RM by analyzing soil structure, geology, land cover, geomorphology (primarily slopes and aspects), fault lines, drainage density, weather data, and road density to generate a comprehensive Landslide Susceptibility Mapping (LSM). The LSM will help in identifying landslide-prone zones (high to low), which will, in turn, enable stakeholders to implement appropriate mitigation measures across the landslide-induced rural municipality. The current study intends to create Landslide susceptibility zonation mapping within and around the studied area by applying the AHP method while taking into account the optimal set of geo-environmental parameters to identify regions at risk of future landslides. Elevation, Slope, Aspect, Drainage, Geology, Soil Classes, Fault Line, Lineaments, Land-cover, Road Networks, Population, and climatic parameters (Rainfall, Temperature, Relative Humidity, Surface Pressure, and Wind Speed) are among the fourteen geo-environmental elements used for this research. Using the field verification approach, the results of this procedure have been validated, which can be observed in an estimated success rate curve. Meteorological factors, such as temperature, rainfall, relative humidity, surface pressure, and wind speed, have been examined regarding landslide susceptibility. Thus, an integrated assessment of landslide susceptibility was applied to the area to identify inhabited areas vulnerable to or at risk of landslides. Furthermore, the placement of public amenities throughout the research zone was considered while conducting the social vulnerability risk analysis. Finally, landslide susceptibility zonation, climatic factors influencing landslide susceptibility, and social vulnerability assessment results of the study area have been combined to generate a risk map identifying landslide-prone municipal facilities and vulnerable communities. This study will help in building resilient landslide communities through effective spatial urban planning that incorporates regional risks induced by landslides with infrastructure development and management strategies.

1. Introduction

Natural disasters are affecting more lives and causing economic devastation worldwide (Confuorto et al., 2019). Landslides are among the most common visible natural hazards across mountainous locations, causing human fatalities and infrastructural and economic damage (Pourghasemi and Rahmati, 2018). Long-term records indicate that the risk of landslides is increasing over time, with recent increases related to continuous climate change and rising population (Tehrany et al., 2015). Rapid temperature rise (>0.06 °C), retreating glaciers (>30nullm/year), irregular rainfall, and an increase in the frequency of natural catastrophes such as landslides are all well-documented impacts of climate change (Karki et al., 2017). It is already proved that the landslide issues in Nepal have worsened due to climate change and the increased frequency of catastrophic occurrences (Kayastha et al., 2013; Bijukchhen et al., 2013).

In Nepal, landslides pose severe social and economic damage because of a distinctive combination of dynamic geological settings, rapid weathering, and copious rainfall. Moreover, landslides, though classified as natural phenomena in conception, are also frequently triggered by human endeavors (Lima et al., 2017). Nepal's location in the center of the Himalayan arc already made it vulnerable and target site for the consequences of climate change (Dhungana et al., 2022). This geographic

* Corresponding author. Action Nepal, Neelkantha Municipality, Dhading, Nepal.
E-mail address: gan.dhungana@gmail.com (G. Dhungana).

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Table 1
Year-wise impact from landslides on Nepal's buildings and settlements.

Year	Affected Families	Govt. Residences(Completely Damaged)	Private Residences(Completely Damaged)	Private Residences (Partially Damaged)	Displaced Sheds	Estimated Loss (NPR)
2011	32	0	100	6	8	45,726,800
2012	65	0	65	74	11	20,597,500
2013	174	0	135	60	14	169,127,458
2014	491	0	143	37	14	23,665,979
2015	407	0	121	96	10	642,400
2016	1488	0	358	440	107	810,442,200
2017	334	0	140	40	19	61,543,000
2017	334	0	140	40	19	61,543,000
2018	749	0	188	109	48	130,119,000
2019	3054	0	1132	1590	77	405,186,000
2020	771	3	383	68	93	50,964,900
Total	7565	3	2765	2520	401	1,718,015,237

Source: http://www.drrportal.gov.np/.

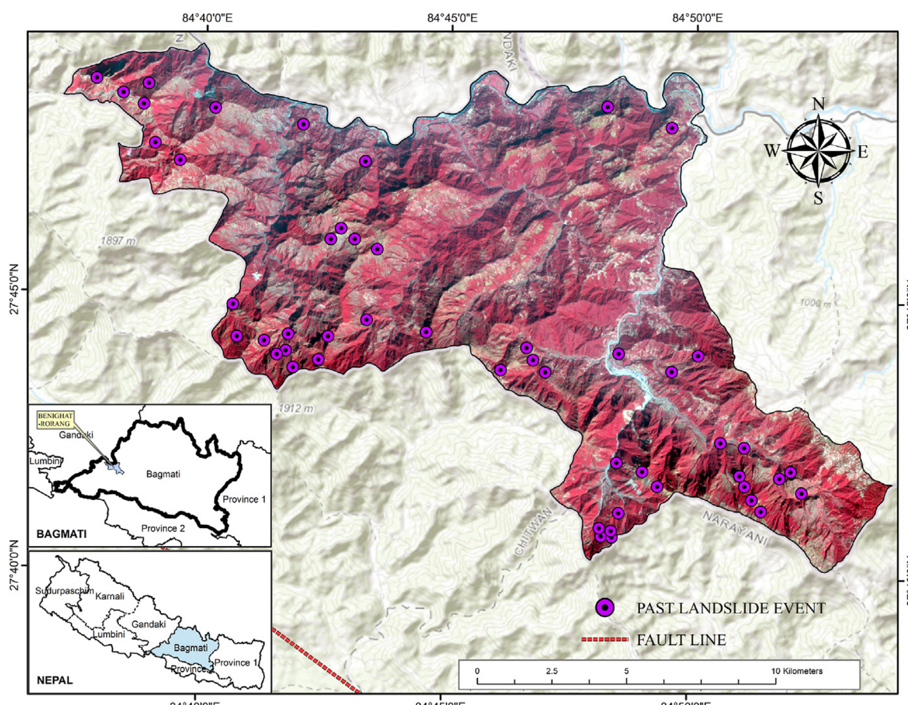

Fig. 1. Area selected for the current study.

disadvantage is further exacerbated by unplanned urbanization, poor development plans, inadequate understanding of landslide hazard risks, and insufficient access to basic public services (Inderberg et al., 2015). All these factors are responsible for making Nepal susceptible to landslide risks, which in turn requires a resilience strategy.

In Nepal, the advent of landslides is directly related to rainfall, and rainfall-induced landslides across the Nepal Himalayas inflict immense damage to lives, properties, infrastructures, and the environment, especially during the monsoons (Dahal and Hasegawa, 2008; Dahal, 2012). According to MoHA (2019) total 28597 disaster incidences (floods, fire events, landslides) were reported across Nepal over a 49-year period (1971–2019). Within this period, Nepal experienced approximately 3729 landslide incidences, claiming 5141 lives, injuring 2053, affecting 7758 families, and destroying 1000 houses (Table 1). Landslides in Nepal account for 35.6% of the total number of fatalities among all disasters (DWIDM, 2015). Therefore, mapping landslide-prone regions in Nepal is critical for efficient land use, disaster management and ultimately building a strong urban resilience plan (Ahmed, 2015). The urban resilience of a place refers to the ability to resist and recover from extreme shocks generated by risks and environmental changes (Pickett et al., 2004). It is possible to effectively build resilience in urban infrastructure by implementing proactive urban development and management strategies that consider and adapt to the various natural hazards and risks.

The first step of building resilience community is to assess the susceptibility of a particular area (Pal et al., 2022), and identify potential landslide risk zones. Susceptibility mapping indicates zones within the study area that are higher or lesser susceptible to subsequent landslides based on relatively greater or lower probabilities or categories of probabilities (Tehrany et al., 2015). On a pixel-by-pixel basis, data-driven or expert-based approaches are typically utilized to generate the LSM. (Nachappa et al., 2019). However, it is possible to achieve LSM through several techniques, including Deterministic Coefficient Model (Li et al., 2022), Statistical Bivariate Models, Frequency Ratios (FRs) (Khosravi et al., 2016), Evidence Belief Functions (EBFs) (Nampak et al., 2014), Multivariate Model of Logistic Regression (LR), and Heuristic Model such as Analytical Hierarchical Processes (AHP) (Ghorbanzadeh et al., 2018). Then the models based on Machine Learning (ML) algorithms like Support Vector Machine (SVM) (Tehrany et al., 2015) and Random Forest (RF) classifier algorithms (Chapi et al., 2017) are also used to assess landslide susceptibility.

Table 2
Preceding landslide incidences occurred across Benighat-Rorang RM, which is used as landslide inventory datasets for the current study.

S.N	Ward No	Place	Year (AD)	Remarks (Source)
1	Benighat Rorang-10	Laitak	2020, July	Ward Office
2	Benighat Rorang-10	Mauwakhola	2020, July	Ward Office
3	Benighat Rorang-10	Kotgau	2020, July	Ward Office
4	Benighat Rorang-10	Jawang	2020, July and 2021, June	Ward Office
5	Benighat Rorang-10	Kosrang	2017, July	Ward Office
6	Benighat Rorang-10	Tigrang Khani	2021, June and 2022, July	News
7	Benighat Rorang-10	Jogimara	2021, August	News
8	Benighat Rorang-9	Panchaling	2021, June	Ward Office
9	Benighat Rorang-9	Bharpang	2020, July	Ward Office
10	Benighat Rorang-9	Besitol	2021, July	Ward Office
11	Benighat Rorang-9	Rowang	2021, June	Ward Office
12	Benighat Rorang-9	Majimtar	2022, May	RM Office
13	Benighat Rorang-8	Dhushatar	2020, June	News
14	Benighat Rorang-7	Krishna Veer Padhero Kholcho	2021, July	Ward Office
15	Benighat Rorang-7	Charaudi dudey	2021, June	Ward Office
16	Benighat Rorang-7	Khanyachaur	2021, July	Ward Office
17	Benighat Rorang-7	Dhusa	2008, July	Ward Office
18	Benighat Rorang-6	Bungrang	2021, June	Ward Office,
19	Benighat Rorang-6	Bungpung	2018, June	Ward Office
20	Benighat Rorang-6	Bhumi Dada	2019, July	Ward Office
21	Benighat Rorang-3	Nayagau	2022, May	RM Office
22	Benighat Rorang-3	Bhantabari	2021, July	Ward Office
23	Benighat Rorang-3	Alegau	2020, July	Ward Office
24	Benighat Rorang-3	Mathillo Orbang	2021, July	Ward Office
25	Benighat Rorang-3	Gomati Gau	2019, June	Ward Office
26	Benighat Rorang-3	Khanikhola	2021, July	Ward Office
27	Benighat Rorang-3	Chisapani Dhap	2021, June	Ward Office
28	Benighat Rorang-3	Laure Dada	2021, June	Ward Office
29	Benighat Rorang-3	Thapa Gau	2020, July	Ward Office
30	Benighat Rorang-3	Orbang School	2021, July	Ward Office
31	Benighat Rorang-2	Hobang	2010, May	Ward Office
32	Benighat Rorang-2	Kafalfedi	2015, April	Ward Office
33	Benighat Rorang-2	Kharkha Laisur	2015, April	Ward Office
34	Benighat Rorang-2	Panchaling	2015, May	Ward Office
35	Benighat Rorang-2	Karkidada	2019, July	Ward Office
36	Benighat Rorang-2	samrang	2015, May	Ward Office
37	Benighat Rorang-2	Kalanga	2015, May	Ward Office
38	Benighat Rorang-2	Gadi, maskharka	2012, July	Ward Office
39	Benighat Rorang-2	Thakpal	2015, April and 2022, June	Ward Office
40	Benighat Rorang-2	Gairang	2022, May	Ward Office
41	Benighat Rorang-2	Dubling	2018, June	Ward Office
42	Benighat Rorang-1	Thimbang-Chitpur	2013, May	Ward Office
43	Benighat Rorang-1	Thimbang-Titekhagi	2013, May	Ward Office
44	Benighat Rorang-1	Baskharkha school	2013, April	Ward Office

The Deterministic method-based Coefficient Model uses historical landslide locations and hazard-inducing variables to determine the susceptibility interval for a particular hazard-inducing factor. Through assessing the susceptibility of various classes to various causes, it is used by Li et al. (2022) to the categorization of data on landslides and non-landslides. FR, a bivariate model, shows how frequently a specific characteristic occurs (Bonham-Carter, 1994). It is utilized to reveal correlations between the occurrence of landslides and the factors influencing them based on the observed relationship (Lee and Talib, 2005). The FR value above 1 indicates that there is a high correlation between the area and landslides and the FR value below 1 indicates a weak correlation (Youssef et al., 2015). EBF is another bivariate model based on the evidence theory of Dempster-Shafer (Dempster, 1967; Shafer, 1976). It has been found to be a viable and efficient method of assessing landslide susceptibility (Achu and Reghunath, 2017; Chen et al., 2018a,b). It can simulate landslide susceptibility by generating values generating values for uncertainty, disbelief, and plausibility, ranging from 0 to 1 (Althuwaynee et al., 2012). The landslide densities are used to rank parameters in this method (Ayalew and Yamagishi, 2005; Chen et al., 2018a,b). LR is a multivariate statistical model that finds the best-fitting curve to characterize the correlation between dependent variable, as the frequency of landslides (0–no landslides, 1–landslides) and a combination of independent variables (slope, angle, drainage network including proximity to rivers or watersheds, etc.). There appear to be no guidelines for identifying variables within logistic regression models used to evaluate landslide risk, and the factors considered in logistic regression analysis vary across published research (Ayalew and Yamagishi, 2005).

The dynamic components were included as explanatory factors in the study and were derived using remote sensing datasets related to dynamic alterations in the surface underneath. Geographic information systems (GIS) play a major role in effective landslide risk management (Aydinoglu and Bilgin, 2015). In general, landslide susceptibility refers to the risk of a specific type of landslide impacting a specific location in the long term (Dilley, 2005). Some primary methods and techniques used and combined to evaluate landslide susceptibility are regression analysis, remote sensing (RS), techniques, and multi-criteria decision-making based on GIS (Pourghasemi et al., 2013; Alam et al., 2019). The efficacy of GIS and RS has improved landslide management (Dou et al., 2014) through landslide susceptibility mapping (LSM), involving the spatially accurate assessment of the risk of potential landslide recurrence based on the impacts of conditioning variables in a specific area (Hong et al., 2015). Furthermore, the heuristic model AHP, based on MCDA ("Multi-criteria decision analysis"), provides qualitative and quantitative paradigms (Li et al., 2022) employed in this study for LSM.

In the current study, the heuristic AHP method was applied to create Landslide susceptibility zonation mapping within and around the studied area while taking into account the optimal set of geo-environmental

Table 3
Datasets used for the current study.

Data Type	Description	Time	Resolution	Source
Elevation Slope Aspect Drainage	Digital Elevation Model (DEM)	2011	30 m	https://srtm.csi.cgiar.org/
Geology	Polygon shape file format		1:5,000,000	https://certmapper.cr.usgs.gov/data/apps/world-maps/
Soil Classes	Digital Soil Map of World (DSMW)	2022	5 km	https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/
Fault Line	Polygon shape file format			https://www.usgs.gov/programs/earthquake-hazards/faults
Land-cover	Multispectral Satellite Imagery (Sentinel-2A)	2022	10 m	https://earthexplorer.usgs.gov/
Roads	Line shape file format	2022	3.2 m	https://openstreetmap.in/#4.37/22.82/82
Lineaments	Multispectral Satellite Imagery (Sentinel-2A)	2015	30 m	https://glovis.usgs.gov/
Rainfall	PERSIANN	2022	0.25 * 0.25	ftp://persiann.eng.uci.edu/CHRSdata/PERSIANN
Temperature	NASA Power	2001–2019	2 m	https://opendatanepal.com/dataset/district-wise-daily
Relative Humidity		2001–2019	2 m	
Surface Pressure		2001–2019	_	
Wind Speed		1981–2019	50 m	
Population	WorldPop Global data	2000–2020	3Arc-Seconds	https://www.worldpop.org/

parameters to identify regions at risk of future landslides. Elevation, Slope, Aspect, Drainage, Geology, Soil Classes, Fault Line, Lineaments, Land-cover, Road Networks, Population, and climatic parameters (Rainfall, Temperature, Relative Humidity, Surface Pressure, and Wind Speed) are among the fourteen geo-environmental elements considered as landslide conditioning factors for this research. Finally, this research investigates the enduring conditioning factors and analyzes them to generate a robust LSM for the study area. Using LSM will facilitate identifying landslide-prone zones (high to low), enabling stakeholders to implement appropriate mitigation measures across the landslide-induced study area and put together strategic resilience frameworks to support the environmentally sustainable development of mountainous communities.

2. Study area

The Benighat-Rorang Rural Municipality (RM) (Fig. 1) in Dhading district of Nepal's Bagmati province has been selected as the study area. Benighat-Rorang RM is split into 10 wards (Dhungana et al., 2022), with Benighat designated as the rural municipality's administrative center (Wikiwand, 2022). As per the digital profile, the rural municipality has approximately 32207 population spanning over 10 municipal wards, covering an area of 206.52 km^2 (Household survey, 2021).

The geology and geomorphology of the region vary significantly, with the former being more or less associated with the region's elevation and gradient (Kayastha and De Smedt, 2009). The geology of this region consists of Precambrian rock formations in the Lesser Himalayan Division, which is characterized by elevated mountainous ranges and river valley networks (Dahal et al., 2014). This study area lies at 2400 m above mean sea level, characterized by the combination of medium to low-graded metamorphic and sedimentary rocks, e.g., quartzite, limestone, dolomite, phyllite, slate, along with granitic outcrops. Here the rock masses are highly layered, faulted, and fractured; an intricate system of fractures and joints on the rocks makes the terrain highly vulnerable to landslides triggered by rain, earthquakes, snow melt, etc. (Kayastha and De Smedt, 2009; Dahal, 2014).

In terms of landslide susceptibility, Benighat-Rorang RM ranks high in the MoFE (2021) climate-induced hazards exposure ranking (0.435–0.578) among RMs. According to the IPCC RCP ("Representative Concentration Pathway"), Benighat-Rorang's climate risk rank is very high (>5.2) by 2030 (RCP 4.5), and 2050. (RCP 4.5; 8.5) (Ministry of Forests and Environment, 2021). Fig. 1 also shows the past landslide events occurred in the rural municipality under current study. These indices and future scenarios show that there will be a significant rise in risk for the Benighat-Rorang RM as a result of the increasing probability of severe events like landslides.

3. Materials and methods

3.1. Landslide inventory

A detailed landslide inventory strategy can assist studies in better understanding the relationship between chronological landslide occurrence and landslide trigger factors (Yu et al., 2022). However, the Department of Survey, the Government of Nepal, and the MoFE have produced a landslide inventory dataset of historical data, an archive of documented landslide episodes, with the allocation of location, type, borders, materials, and deformation aspects ("Ministry of Forests and Environment") is not regularly updated, nor does it cover all landslide-prone areas in minute detail. The inventory points in the current study have been randomly allocated into two clusters: 70% (152 points) in training and 30% (46 points) in validation. Validating all chronological landslides in the study area from April 2020 to July 2020 (Table 2), a handheld GPS device has been employed to verify and reorganize the borders and positions of all landslides. The ability of GPS technology to track these ground movements' sub-centimeter deformations has been demonstrated. The primary benefit of GPS sensors is that there is no need for a direct line of sight among the locations. This makes it possible for GPS to keep track of the landslide in real time even when the weather is unfavorable (Rawat and Joshi, 2011). Thus for the current study handheld GPS has been used to monitor and recognize the borders and positions of the recent landslide events occurred in the study area.

3.2. Relevant data

A landslide, according to Westen et al., (2008), is the movement of materials over the slope. This term accurately depicts the system's intricacy and the range of conditioning factors that influence it. The most common variables, according to the literature review, are the hydrographic parameters such as drainage density, distance from rivers, morphometric parameters such as slope, aspect, elevation, land use, proximity to fractures, and related elements (van Westen et al., 2008). In this study, elevation has been considered an essential factor influencing landslide susceptibility because the elevation of a region influences landslide susceptibility since different elevation ranges comprise

Table 4
Classified table with weights and vulnerability classes allocated to the causative factors.

$$\boldsymbol{LSM} = (Slope*3) + (rainfall*2) + (elevation) + (Aspect) + (Drainage) + (Geology) + (Fault\ Line) + (Land\ Cover) + (Road) + (Proximity\ to\ Road) + (Proximity\ to\ Lineaments) \quad \text{Eq.(1)}$$

Data Type	Class	Susceptibility classes	Weights
Elevation	>2050 m	Very high	**1**
	1550–2050 m	High	
	1050–1550 m	Moderate	
	650–1150 m	Low	
	<650 m	Very Low	
Slope	>60°	Very high	**3**
	45°–60°	High	
	30°–45°	Moderate	
	15°–30°	Low	
	<15°	Very low	
Aspect	>288°	Very high	**1**
	216°–288°	High	
	144°–216°	Moderate	
	72°–144°	Low	
	<72°	Very low	
Geology	Igneous (Granitic Outcrop)	High	**1**
	Sedimentary (limestone, dolomite)	Low	
	Metamorphic (Quartzite Phyllite, Slate)	Moderate	
Soil	Dystric Cambisols	Moderate	**1**
Fault Line	>2050 m	Very high	**1**
	1350–1950 m	High	
	750–1350 m	Moderate	
	100–750 m	Low	
	<100 m	Very Low	
Land Cover	Built-up Area	Very high	**1**
	Open Land	High	
	Water Body	Moderate	
	Crop Land	Low	
	Forest	Very low	
Rainfall	>1350 mm/year	Very high	**2**
	1050–1350 mm/year	High	
	700–1050 mm/year	Moderate	
	350–700 mm/year	Low	
	<350 mm/year	Very low	
Drainage Density	3.152–3.94 km^{-1}	Very high	**1**
	2.364–3.152 km^{-1}	High	
	1.576–2.364 km^{-1}	Moderate	
	0.788–1.578 km^{-1}	Low	
	0.788 km^{-1}	Very low	
Proximity to Roads	<200 m	Very high	**1**
	200–400 m	High	
	400–600 m	Moderate	
	600–800 m	Low	
	>800 m	Very low	
Proximity to Lineaments	<200 m	Very high	**1**
	200–400 m	High	
	400–600 m	Moderate	
	600–800 m	Low	

LSM has been used in the current study using the following equation (1) (Michael and Samanta, 2016).

different soil layers, vegetation types, and rainfall patterns, along with human activities (Costanzo et al., 2012; Dai & Lee, 2002). As standard deviation of elevation is directly linked to relative relief and could be used to determine the potential energy for erosion and mass wasting (Günther et al., 2013; Oguchi, 1997; Sabatakakis et al., 2013). Usually, landslides tend to be more common at higher elevations. As a result, elevation is regarded as a significant driving component inducing landslides (Vojteková and Vojtek, 2020a). Aside from that, elevation is the most commonly used factor in determining landslide vulnerability (Guo et al., 2021; Ngo et al., 2021).In terms of physical predispositions to landslides, the slope is considered a component influencing landslide susceptibility in the current study. The slope as a landslide conditioning factor has been prioritized in recent studies (Bera et al., 2019; A. Kumar et al., 2018; Nicu, 2018). It is chosen as one of the main factors for landslide susceptibility mapping because it is closely linked to the slope stress region, which influences the collapse mechanism and dynamic properties of landslides (Hong et al., 2019). Following the work of Demek (1972), the slopes have been reclassified into five classes (>60°, 45°–60°, 30°–45°, 15°–30°, <15°) in this study.The aspect factor plays a vital role in this study of landslide susceptibility mapping because it affects microclimatic parameters such as solar radiation, soil moisture, slope exposure, rainfall, and wind intensity, which influence plant growth and soil humidity. Then these have an indirect influence on landslides (Guzzetti et al., 1999; Dai & Lee, 2002; Demir et al., 2013; Dou et al., 2015.; Wang et al., 2019). Previous studies have revealed that aspect value is crucial when landslides occur following the development of tension cracks. Thus following Abraham et al. (2021), the aspect value of the study area, which ranges from 0° to 360°, was applied as a categorical variable after reclassifying the angular values into five classes based on its facing orientation.Geology is considered an essential landslide-conditioning component for this study since it is linked to the resistance to landslides, which varies due to the composition of

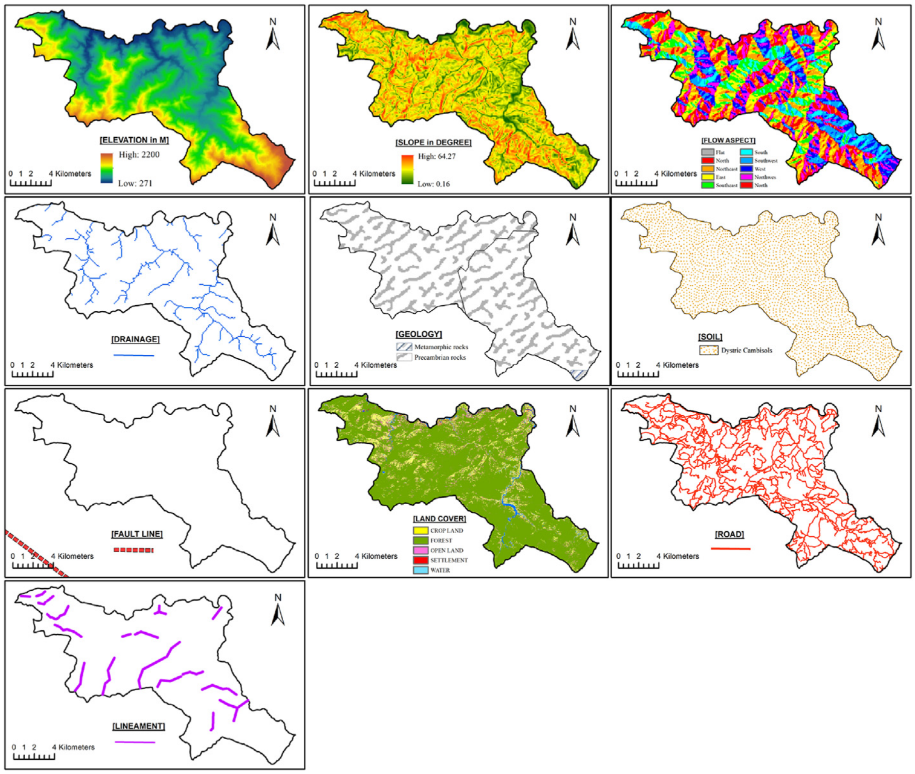

Fig. 2. The thematic layers of the input parameters required for the current study: a) Elevation, b) Slope, c) Aspect, d) Drainage, e) Geology, f) Soil, g) Fault Line, h) Land Cover i) Road, j) Lineaments.

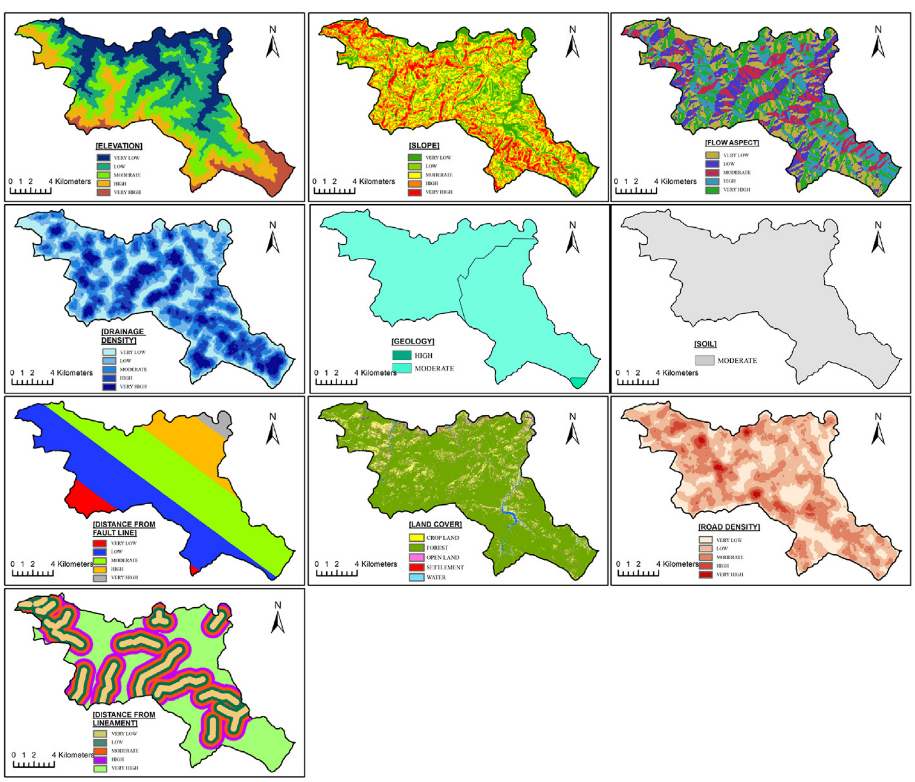

Fig. 3. Landslide conditioning parameters: The thematic layers of the input parameters required for the current study: a) Elevation, b) Slope, c) Aspect, d) Drainage, e) Geology, f) Soil, g) Fault Line, h) Land Cover, i) Proximity to Road, j) Lineaments.

underlying different rock types (Gemitzi et al., 2011; Vojteková and Vojtek, 2020b). As the geology of the area under study (Table 4) consists of igneous granitic outcrops; sedimentary limestone and dolomites; metamorphic quartzite, phyllite, and slate, it possesses differential

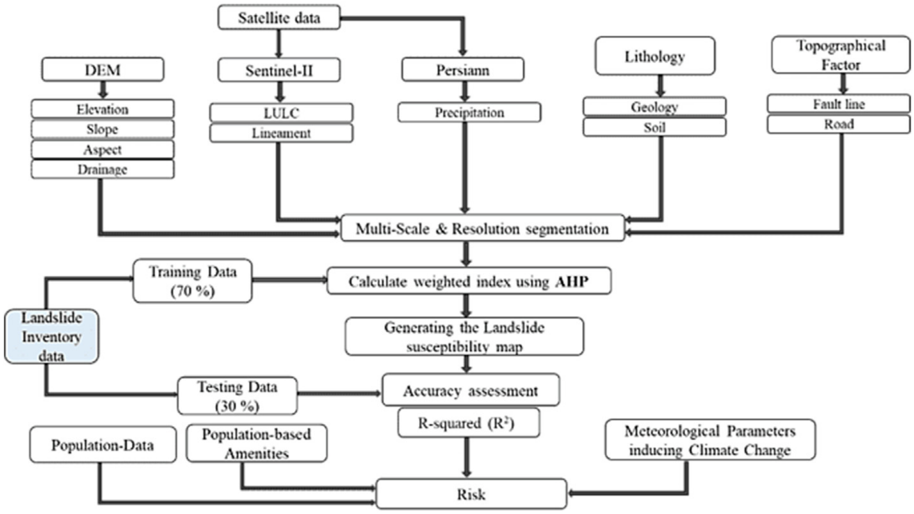

Fig. 4. Workflow of the methodology applied in the current study.

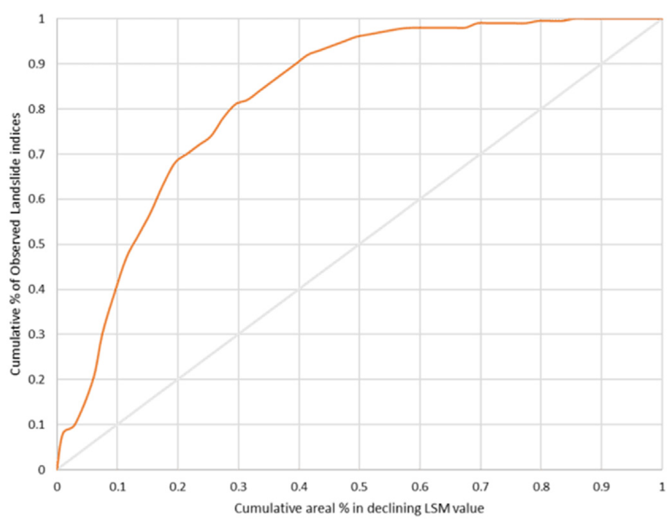

Fig. 5. The cumulative proportion of reported landslide events vs the cumulative percentage of declining landslide susceptibility index score is depicted by a success rate curve.

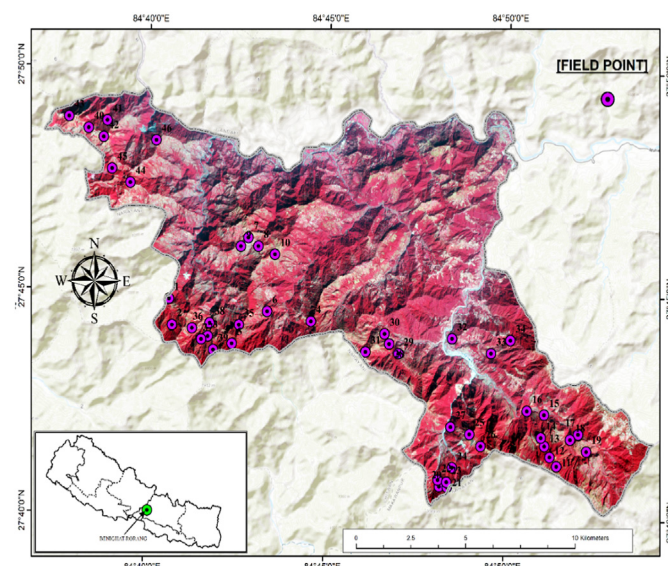

Fig. 6. Field verification points.

resistance to landslides. Since most of the region's geology is composed of granitic outcrops, which are more brittle under dynamic stress and are subject to primary erosion following a landslide, thus they are highly vulnerable to the same (Schramm et al., 1998). The sedimentary limestones and dolomites make up a minor fraction of the geology of the study area and are assigned less susceptible to landslides compared to granites (Table 4) and regarded to be resistant to landsliding formations. However, this is exceedingly reliant on a variety of elements, including erosion intensity and structural integrity, all of which can change the basic nature of a geological formation (Gemitzi et al., 2011). Then the study area's dolomite composition termed “Dhading Dolomite”, is less susceptible to landslides due to its relatively rough surface and dearth of clay minerals (Khanal, 2013). The metamorphic rocks (quartzite, phyllite, and slate) that make up the last portion of the geology of the study area are then classified as moderately susceptible to landslides since they are weakly deformed low-grade metamorphic rocks (Budha et al., 2016).The soil component has been included in the current study on Landslide susceptibility mapping since this method reflects the propensity of soil to induce landslides, and the complex character of landslides is dependent on the soil condition of the area under study (Liu et al., 2019).The distance from faults is recognized as a standard landslide-conditioning element since it is considered in several studies on landslide susceptibility (van Westen et al., 2008; Vojteková and Vojtek, 2020b). In the current work on landslide susceptibility mapping, the factor, distance to faults has been taken into consideration since, along with other landslide causative factors (slope, aspect, drainage density), it has been found to have a positive correlation with the incidence of landslides (Dou et al., 2015). All faults in tectonically active regions are considered vital in triggering landslides (Bui et al., 2011). As a result, the distance to faults has been included in this study to assess the relationship between lineaments and the occurrence of landslides.Land use was selected as a landslide-conditioning factor in the current study as it is one of the preliminary characteristics indicating an area's predisposition for landslide incidence (Vojteková and Vojtek, 2020b). Land use is among the top five factors utilized in landslide susceptibility evaluations (Pourghasemi et al., 2012). Land use patterns are frequently observed to significantly affect the occurrence of landslides because they are primarily associated with anthropogenic intervention on hill slopes, which contributes to landslide incidences (Pradhan and Lee, 2010; Zhu et al., 2010). According to the possible contributions to landslide susceptibility, five land use classes (Built-up Area, Open Land Water Body, Crop Land, and Forest) were analyzed and categorized using remote sensing data. As

Fig. 7. Pictures of the landslides sites in Benighat-Rorang RM a) Laitag (b) Baangti Khola (c) Bungaira, (d) Nayagau.

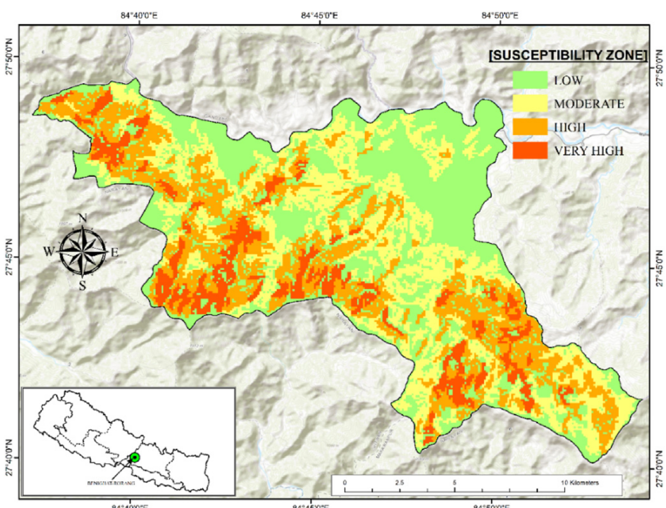

Fig. 8. Landslide susceptibility map of the Benighat-Rorang RM.

Table 5
Areal extent of the landslide susceptible zones of the Benighat-Rorang RM.

Landslide Susceptibility Zones	Area Susceptible to Landslide	
	km^2	%
Very High	21.95	10.77
High	53.1	26.05
Moderate	54.97	26.97
Low	34.94	17.14
Very Low	38.84	19.06

per Kumar et al., 2018, agricultural activities (moderate susceptibility to landslides), built-up areas involving the construction of buildings and roads in the region (very high susceptibility to landslides), deforestation leading to the formation of open lands (high susceptibility to landslides), and landslides are the anthropogenic factors responsible for reducing the stability of the hill slope.Many studies indicate that various variables, including the construction of new communities and infrastructure in landslide-prone regions, variations in land use patterns, and the impacts of climate change on the onset of severe rainfall events, are accountable for the genesis of landslides (Zare et al., 2013; Guzzetti, 2016; Reichenbach et al., 2018). Thus, rainfall intensity is selected as a main landslide-triggering factor for this study on Landslide susceptibility mapping. Rainfall is a critical triggering factor of landslides in Nepal, as evidenced by the fact that most landslides occur during the rainy season. When rain falls, infiltration occurs, and pore water pressure develops on soils and rock mass, which reduces the shear strength of the rocks and soil, inducing landslides (Khanal, 2013). As per Table 4, areas with high rainfall (1350–2050nullmm/year) are thus more susceptible to landslides than areas with less rainfall, and the current study's findings validate this assumption. Drainage density is selected as a factor conditioning landslides since Dou et al. (2015) stated that increasing density in the drainage network increases the frequency of landslides. Thus, in this study, the distance to drainage networks and the incidence of landslides were most significant at 3.152–3.94 km^{-1}, followed by 2.364–3.152 km^{-1}. It is linked to the fact that topographical change produced by gully erosion may influence landslide initiation (Dou et al., 2015). Therefore, the drainage network plays a significant part in the crucial role in the recurrence of the landslides in the study area due to the application of the Analytical Hierarchical Process (AHP) technique in the current study.-Following the work of Jebur et al. (2014), proximity to the river and road buffer was chosen for our current study on landslide susceptibility mapping based on the frequency of failures along the river and the road's proximity. Construction of roads across steep slopes and hilly terrain fractures the rock mass, reducing its strength and increasing the risk of landslide occurrence (Donati and Turrini, 2002). Therefore, this component is considered one of the most important in landslide susceptibility analysis.Lineaments known as tectonic faults create optimum conditions for the occurrence of landslides. According to Tien Bui et al. (2012) (2013), the lineament-proximity factor was utilized in specific research to estimate the effect on landslides. Therefore, in the current study for measuring landslide vulnerability, closeness to lineaments is regarded as a landslide-conditioning factor.In this study, every afore-mentioned factor (Elevation, Slope, Aspect, Geology, Soil, Fault Line, Land Cover, Rainfall, Drainage Density, Proximity to Roads, and Proximity to Lineaments) played a critical role since the study area is located in Nepal, where landslides are prevalent. The current analysis of Landslide susceptibility is in itself a summary that requires careful consideration and analysis of each factor for accurate estimation.

The current analysis is based on currently obtainable remotely sensed datasets, including satellite data (Sentinel-2 imagery), and elevation data (SRTM DEM). The datasets given in Table 3 provide insights into the 10 input parameters (Fig. 2) utilized to achieve the objectives of the current study, which is to designate the landslide-prone zones in the study region.

Among the 15 factors listed in Tables 3 and 9 of them (Geology, Fault line, Land-cover, Elevation, Slope, Aspect, Drainage, and Roads) are

Table 6
Civic Amenities Present in the study area.

SL. NO.	Hotel and Restaurants	TYPE
1	Hill Top Restaurant ""Gol Ghar""	restaurant
2	Blue Heaven Restaurant	restaurant
3	Trishuli River Side Resort	restaurant
4	Anmol Food Land	restaurant
5	Pokhara Hotel and Lodge	restaurant
6	Chandra Hotel and Lodge	restaurant
7	Kritan Bhojanalaya	restaurant
8	Chitwan Taas Ghar	restaurant
9	Ever Green Restaurant and Resort	hotel
10	Sangam Hotel	hotel
11	Stay Different Resort	hotel
SL. NO.	Banks	TYPE
1	Deva Development Bank	bank
2	ndep development bank	bank
3	Rastriya Banijya Bank	bank
SL. NO.	Hospitals, Clinics & Pharmacies	TYPE
1	Benighat Health Cllinic	clinic
2	Malekhu Petrol Pump	fuel
3	Rajmarga Samudayak Hospital	hospital
4	Bihani Pharmacy	pharmacy
5	Area Police Office	police
SL. NO.	**Educatioal Institutes**	**TYPE**
1	Shree Shankha Higher Secondary School	school
2	Shree Jogimara Pra Vi	school
3	Shri Rastriya Ni Ma Vi	school
4	Shri Janajyoti Pra V	school
5	Shri Rastriya Pra Vi	school
6	Shri Mahakali Pra V	school
7	Shri Panchakanya Pra V	school
8	Shri Panchayat Pra V	school
9	Shri Basanta Pra Vi	school
10	Shri Chandrodaya Ma Vi	school
11	Shri Janagaun Pra Vi	school
12	Shri Janachetana Pra V	school
13	Shri Jhagaredanda Pra V	school
14	Shree Dhusa Pra V	school
15	Shree Jalkanya Pra Vi	school
16	Shree Bhangeri Pra V	school
17	Shree Janaprabhat Pra V	school
18	Shri Bagh Bachala Pra V	school
19	Shree Adarsha Pra V	school
20	Shree Sidhha kali Pra Vi	school
21	Shree Praja Pra V	school
22	Shree Mahadevsthan Pra V	school
23	Shree Lawang Pra Vi	school
24	Sahara Bal Bikas Chandra	school
25	Shree Baskharka Ni Ma V	school
26	Shree Gaurishankar Pra V	school
27	Shree Bhumisthan Pra V	school
28	Shree Deurali Pra V	school
29	Shree Ghairang Pra V	school
30	Shri Buddhi Bikash Pra V	school
31	Shri Bhumisthan Pra Vi	school
32	Shree Mahakali Pra V	school
33	Shri Tinkanya Pra V	school
34	Shree Sitamai Pra V	school
35	Shree Bageshwori Pra V	school
36	Shree Malika Pra Vi	school
37	Shree Harkpur Secondary School	school
38	Shree Janjagriti Siddha Pra V	school
39	Shree Beldanda kalika Pra V	school
40	Shri Orbang Pra V	school
41	Shree kunchurung Pra Vi	school
42	Shree Netrajoti Pra vi	school
43	Jeeban joti aadarbhut	school
44	Shree Chandrodaya Uccha Ma V	college

thematic layers extracted from the standard datasets and were computed in a GIS environment, as shown in Fig. 2. Aside from that, only rainfall data were utilized in the AHP approaches for the LSM output, and additional climatic datasets (Temperature, Relative Humidity, Surface Pressure, Wind Speed, and Wind Direction) were employed to assess the influence of climate change on landslides.

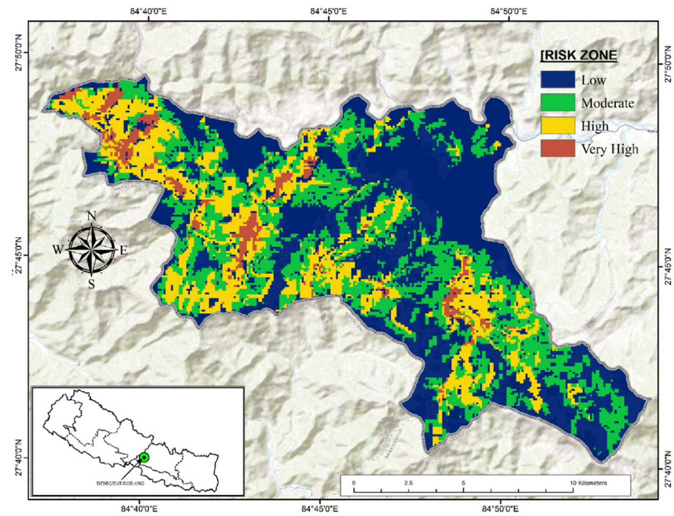

Fig. 9. Spatial integrated output of the current study risk zone susceptible to climate change and topographical dynamism induced landslides in Benighat-Rorang RM.

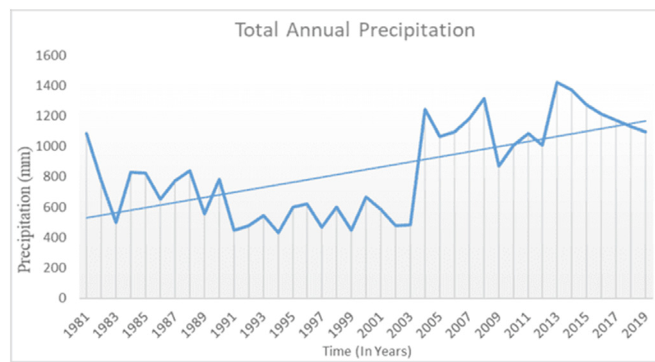

Fig. 10. Total annual precipitation of the study area.

The DEM ("Digital Elevation Model") data was built utilising open data from the SRTM DEM and the layers of slope and aspect were extracted from it. Land cover data were extracted from multispectral Sentinel 2 imageries applying Object-Oriented (OO) classification using GLCM ("Gray-Level Co-Occurrence Matrix"). The geology and fault line datasets mentioned in Table 3 were acquired from the USGS. The drainage network was derived using morphometric analysis of DEM data, whilst the road network was derived from OSM ("Open Street Map"). The rainfall dataset has been acquired from CHRS ("Center for Hydrometeorology and Remote Sensing") Data Portal. All of the aforementioned datasets were processed and estimated in Arc GIS 10.7 (https://desktop.arcgis.com/en/arcmap) to develop the landslide conditioning factors for LSM.

3.3. Landslide conditioning factors

Generally, there is no set criterion for determining landslide susceptibility conditioning factors, and the factors chosen must be operational, measurable, non-homogeneous, and non-redundant (Ayalew and Yamagishi, 2005). Eleven conditioning parameters were chosen for this LSM based on area geomorphological features and previous research. The relevant datasets in Fig. 2, were analyzed and converted into the factors conditioning landslides, which were chosen for the current study. These factors (Fig. 3) include soil, geology, land cover, fault lines, elevation, slope, aspect, rainfall, drainage, proximity to lineaments, and roadways.

The conditioning factors considered for landslide in this study could be divided into three major categories: geological, climatological and social. Geomorphological factors include morphology, elevation, slope, aspect, soil, fault line, drainage density and land cover. Whereas climatic factor is the rainfall and social factors are, road proximity, and lineament proximity. Geology and geomorphology have major roles in landslide activities and susceptibility since various geological and geomorphological strata have varied strengths and vulnerabilities to landslide incidents (Roering et al., 2005). Elevation is a crucial conditioning factor for landslides, and two of the eleven conditioning variables (slope and aspect) are direct measurements or are directly impacted by elevation (Meena et al., 2019). As a result of taking the LSM into account, the elevation of the region has been segmented into five groups in this study, classified in the range of very low to very high: <650 m (very low), 650–1150 m (low), 1050–1550 m (moderate), 1550–2050 m (high), and >2050 m (very high) above MSL (Fig. 3). Similarly, the slope angle conditioning factor has been estimated from the SRTM DEM and divided into five classes ranging from very low to extremely high: 15° (very low), 15°–30° (low), 30°–45° (moderate), 45°–60° (high), and >60° (very high) and aspect wise the study area was divided into nine categories based on slope direction: 0° (flat), 0°–22.5° (N), 67.5°–112.5° (E), 157.5°–202.5° (S), 202.5°–247.5° (SW), 247.5°–292.5° (W), 292.5°–337.5° (NW), 337.5°–360° (N). These were then classed into five classes of susceptibility ranging from very low to very high, as shown in Fig. 3. As the origin of earthquakes, active faults perform a significant function in inducing landslides (Chen et al., 2018a,b), and active faults have crucial roles in stone cracking, and triggering instability. This unconnected geological structure in the study area decreases the rock's shear strength, resulting in landslides. The proximity to faults has been calculated considering the extent of landslides from the fault and grouped into five classers depending on the range of landslide susceptibility from very low to very high: <100 m (very low) 100–750 m (low) 750–1350 m (moderate), 1350–1950 m (high), >2050 m (very high), illustrated in Fig. 3. Land cover is also a critical precondition for LSM (Persichillo et al., 2017) as it often accounts for highly complex patterns of landslides in the subsequent LSM.

Climatic factor rainfall has a prominent impact on the landslides in Nepal (Dahal and Hasegawa, 2008). Rainfall characteristics can change depending on meteorological conditions and topographical elements, resulting in significant temporal and geographical variations during a rainfall event. Landslide onset in Nepal is highly associated with rainfall (Dahal and Hasegawa, 2008). The total annual rainfall obtained from Nepal's District-Level Climate Data (NASA LaRC POWER Project, 2019) from 1981 to 2019, divided into five classes: <350 mm/year (very low), 350–700 mm/year (low), 700–1050 mm/year (moderate), 1050–1350 mm/year (high), and >1350 mm/year (very high) for LSM.

The social factors like proximity to road or lineament are controlling components for slope stability. The distance from roadways is a significant anthropogenic element in the frequency of landslides (Dang et al., 2019). In addition to greater road access, communities have seen an increase in uncontrolled tree cutting. As a result, a road proximity map has been developed created based on the idea that slope collapse occurs more frequently on surrounding streets. The road network map has been rasterized and the proximity to the road was measured in meters to create the map illustrating road proximity. After then, the map was divided into five categories based on the susceptibility range: >800 m (very low), 600–800 m (low), 400–600 m (moderate), 200–400 m (high), and <200 m (very high) (Fig. 3). Apart from these, geological features such as faults, bends, junctions, strata, and lineament zones have a higher impact on slope stability. This interdependence can be worsened by rainfall or tremors, which trigger collapse across these fragile zones (Kanungo et al., 2012). The vicinity of the slope to such features has a tremendous impact on its stability, heightening the risk of landslide occurrences (Michael and Samanta, 2016). Thus, in the current study, the lineaments were extracted from the Sentinel 2A imagery taking into consideration that the risk of landslide reduces with increasing proximity from the lineament structures.

3.4. Methodology

The flow diagram for the present study's methodology, which summarises all the metrics and datasets utilized to get the study results, is shown in Fig. 4. In the current work, geographical and remote sensing datasets were analyzed using a GIS environment, and spreadsheets were used for quantitative analysis and data processing to generate the LSM.

AHP method has been adopted for the current study for mapping landslide susceptibility and hazards due to its application flexibility and knowledge-dependent usage. AHP is widely used in site selection, site-suitability analysis, and assessing landslide risk (Ayalew et al., 2005). The AHP comprises important steps of breaking down a decision question into component factors, organizing those factors in a hierarchical sequence, and finally assigning numerical weightage values to evaluate the relative significance of each item based on their subjective relevance (Saaty, 1994). The benefits of implementing AHP, being an expert-based approach in landslide susceptibility assessment, are that almost all sorts of landslide evidence can be incorporated in the discussion phase; judgment is framed in such a way so that all input gets properly considered, and discussion guidelines are centered on expert knowledge and experiences (Thanh and De Smedt, 2012). In the current study, AHP has been used to assign weighted factors to the causative factors (Table 4).

3.4.1. Landslide susceptibility modeling

Eleven of the previously specified factors (elevation, slope, aspect, drainage, geology, soil, fault line, land cover, road, closeness to lineaments, and roadways) were chosen for the current study, and each parameter was classified and ranked (Table 4). These are then weighted based on their level of influence regarding the other parameters. The values allocated to the distinct parameters are shown in Table 4. The susceptibility rankings are very high, high, moderate, low, and very low, with a total weight of 14 for the specified parameters ranging from very low to very high.

3.4.2. Social vulnerability analysis

Landslide susceptibility modeling has been carried out using geospatial techniques to identify landslide-prone areas. WorldPop data were collected at the VDC level for Nepal at five-year intervals over 2000, 2005, 2010, 2015, and 2020 to determine whether more significant or lower patch populations became sensitive to landslides. Aside from that, the location of public amenities throughout the research region was taken into account when conducting the social vulnerability risk analysis.

3.5. Validation

Validation is a key element of a study since it offers information about the models' predicted accuracy (Ghorbanzadeh et al., 2019). The accuracy scores show whether the model applied can accurately anticipate landslide-prone areas (Pourghasemi and Rahmati, 2018). This study region's landslide inventory database contains 70% (152) of cumulative landslide data points for training and 30% (46) for validation which was done in field visit (Figs. 7 and 8). The LSM output can be confirmed using scientific and analytical methodologies such as landslide density calculation, success rate curve, or chi-square testing. An LSM's overall value is determined by the landslide density per class, which is a proportion of observed landslides (Sarkar and Kanungo, 2004). Table 5 illustrates the findings of LSM, and as per the validation graph (Fig. 6), the computed and categorized susceptibility sections correspond strongly with the occurrences of last landslides. The assessment by success rate curve aids in the validation of the LSM (Van Westen et al., 2003).

The success rate curve, used to validate the LSM output, is generated by graphing the accumulated percentage of reported landslide incidence against the accumulated percentage in declining LSM values. The area beneath the curve could be employed to measure the forecast accuracy subjectively. The area beneath a curve equals 0.7269, indicating that the total rate of success of the LSM is 72.69% (Fig. 6). It means that in the LSM, if 20% of the classes possess a high landslide susceptibility rating for forthcoming landslides, 68% of the subsequent landslides would accurately fit. Because of this degree of precision, the LSM was deemed a better landslide susceptibility mapping for the studied area with a 1–100% (lesser to greater susceptibility) class of LSM.

4. Results and discussion

4.1. Landslide susceptibility analysis

The current study indicates that if AHP could be employed to analyze landslide activity in each predisposing factor, and the results indicate an intriguing correlation between the exacerbating causative variables and landslide incidence. Fig. 5 depicts the results of merging multiple weighted parameters inside the ArcGIS weighted summation framework using the AHP method. The resultant LSM output is divided into low, medium, high, and highly vulnerable landslide-prone zones. According to Table 5, the extraordinarily high landslide susceptible zone accounts for 10.77% (21.95 km^2) of the research area, while the high, moderate, and low susceptible zones account for 26.05% (53.1 km^2), 26.97% (54.97 km^2), 17.14% (34.94 km^2), and 19.06% (38.84 km^2), respectively. Thus, the estimated findings indicate that the zones crossing steep slopes are located along the North West, South West, and South East. As a result, infrastructures, culture, and subsistence activities are extremely susceptible to landslides, debris slides, and mudflows caused by these steep elevated slopes.

5. Risk analysis

Analyzing land slide risk requires zoning, which is founded on hazard mapping data, considering the probable impact to humans and properties (annual value of damages incurred) for those aspects under risk, as well as their frequency and susceptibility across temporal and spatial scales (Flentje et al., 2007).Thus, based on analyses of the landslide susceptibility zones, climatic factors increasing landslide susceptibility, and social vulnerability parameters including landslide-prone civic amenities and vulnerable population zones, Fig. 6 depicts a final risk zone map of landslide-prone areas based on the results of these analyses. The steep hills areas in the southeast and northwest have a very high risk of landslides, according to the risk zonation map. As a result of steep slopes close to rivers, steep slopes in the same area are prone to landslides. Additionally, the surrounding areas, particularly those in the northeast, northwestern, southeast, and southern regions, provide a moderate to low risk of landslides.

6. Discussion

Nepal is vulnerable to natural disasters due to a number of factors, including its rough and fragile geophysical structure, high relief, steep slopes, extremely complicated geology, varying climatic factors, and active tectonic processes still going on in the Himalayan region. The human interference and subsequently uncontrolled and unplanned settlement for the growing population, poor economic situation, and low literacy rate further exacerbated the situation. Therefore, in this study, AHP-based landslide susceptibility mapping was performed to identify the potential landslide zones in Benighat-Rorang Rural Municipality of Dhading in Nepal. As previously stated, in the current study's resulting AHP, considering the geospatial formats of the factors mentioned above, taking into account 26.05% (53.1 km^2) of the study area falls under the zone of high susceptibility to landslide, 17.14% (34.94 km^2) of the area falls under moderate exposure to landslide, and 19.06% (38.84 km^2) of the area falls under lower susceptibility to landslide. (Meena et al. (2019) also conducted the susceptibility zonation in Central Nepal, where they discovered that 13.17% of the region is extremely vulnerable to landslides based on the AHP map that has been generated.

The LSM of the current study (Fig. 5) indicates that the study area's southern places are very highly susceptible to landslides, and the probability gradually decreases towards the north. The internal validation based on field observations and inventory data (70% or 152 points in training and 30% or 46 points in validation) further supports the results as well as other model derived products for Dhading and surroundings (Ray et al., 2020; Regmi et al., 2016; Ray and Jacobs, 2008). In the current study, 70% of the landslide sites (152 points) were chosen at random from the landslide inventory map to generate the training dataset. These landslides have been then translated into 30 * 30 m pixels. Finally, the training data has been generated by randomly choosing these landslide and non-landslide pixels with the 14 landslide conditioning variables. 30% of the other landslide locations (46 points) were also transformed into 30 * 30 m pixels for the testing dataset. To construct the testing dataset, these landslide and non-landslide pixels have been sampled given the 14 landslide conditioning factors. The training dataset has been then utilized to develop the landslide model, whereas the testing dataset was utilized to validate and compare the landslide models' performance. The factors responsible for the vulnerability of the region towards landslide have been identified and categorized into three broad factors namely geological, climatic and socio-economic factors.

Since different geological units in the study area are more or less prone to active geomorphological processes, geology is an important component in assessing landslide susceptibility and risk (Dai et al., 2001; Pachauri et al., 1998). Geological parameters like elevation, slope, morphology, soil, land cover and position of the fault line were analyzed and added as input in the AHP model. The Central Nepal, especially Dhading area falls under highly unstable zone with regional slope instability (Kayastha and De Smedt, 2009; Ray, and De Smedt, 2009) with folded and fragmented rock types. Moreover, the study area is covered with Dystric Cambisols soil, which is considered as young soil and highly prone to landslides. Added to the highly unstable geology, high precipitation rates during monsoon further worsen the condition. The increasing trend of observed precipitation in Nepal (Fig. 7) is well documented in literature (Baidya et al., 2008; Pokharel et al., 2020; Muñoz-Torrero Manchado et al., 2021). With the extreme rainfall events likely to increase in future (Karki et al., 2017; Shrestha et al., 2021; Bohlinger and Sorteberg, 2018) as a result of climate change, the landslide vulnerable zones are likely to increase. Furthermore, the poor socio-economic condition of the local communities pose them in immediate danger from natural hazards like landslides. The population residing along the northern boundary of the study area are highly vulnerable according to the analysis. The risk map of Benighat-Rorang (Fig. 6) generated by integrating all three factors (including geological, climatic and socio-economic) further illustrates the places currently at high risk from the landslides.

Increasing opportunities for local people involve building infrastructures like road network, building and other amenities in order to improve access for large number of growing population. The informal constructions along the roadways or famous spots frequently cause landslides by undercutting slopes, allowing water to infiltrate into hazardous slide planes, and generating debris that is quickly mobilized during heavy rain (Kjekstad and Highland, 2009). Therefore, a general perception that the number of landslide events are increasing, might be due to increased vulnerability (greater population exposure to risk) than an actual growth in intensity or frequency. This perception was tried to establish via analyzing social vulnerability of the study area. As previously mentioned, a growing population needs civic amenities like bus stop, hospitals, police stations, banks, hotels and resturants to function properly. Since the study area is located in the mountainous terrain, unplanned constructions might cause the structures vulnerable. Therefore, vulnerability assessment of the social infrastuctures were also performed in this study. At the same time, population density was also calculated in the study area to identify the places where landslide events could have a more devastating effect in the lives and livelihoods of the community.

6.1. Social vulnerability

6.1.1. Analysis of landslide-prone civic amenities

The study area (Benighat-Rorang RM) is in Nepal's Hill Region, which is surrounded by the country's most populated districts (Pokhara Valley, Kathmandu). Due to the steep slopes of the hills, this region is prone to avalanches during the winter, and moreover, landslides along with mudflow occurring during the monsoon, once the slopes get saturated and weakened by rain. Thus, landslides induced by climate change and dynamic geophysical settings have wreaked havoc on the area's existing civic amenities. This sort of hindrance is common throughout Nepal's monsoon season, but the frequency and severity of such incidents and problems have grown compared to previous years. Individuals have often been forced to shift their belongings on their backs, and others have been unable to access hospitals, educational institutions (schools and colleges), banks, hotels, administrative offices, and other facilities. Thus, the important civic amenities susceptible to landslides' wrath have been listed in Table 6 and plotted in Fig. 8.

6.2. Population vulnerability analysis

Although many regions around the world are vulnerable to climate hazards, climate vulnerability is determined by the nature and severity of

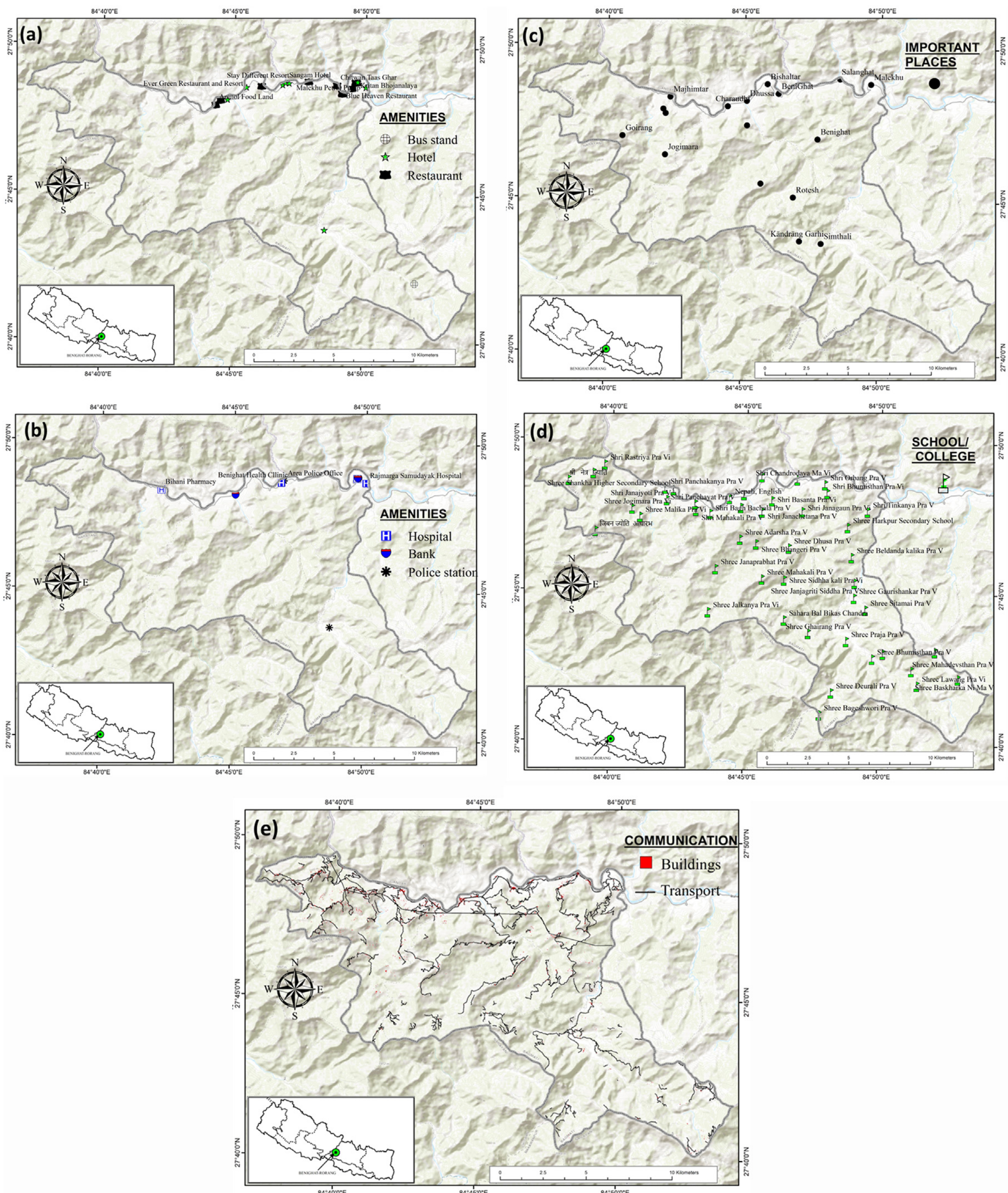

Fig. 11. Important civic amenities present across the landslide susceptible zones in Benighat-Rorang RM.

the hazard, the sensitivity of the environment, the quantity of impacted people, and the capability to recover. The current study indicated significant regional disparities in population susceptibility to climate change throughout the study area, Nepal, with the high mountain zones showing the most sensitivity, followed by the lower elevations. According to a recent examination by Aryal (2012) on historical catastrophe data, the frequency and intensity of disaster occurrences are increasing in Nepal coinciding with continuous population growth.

In the current study, as per the results of our analysis, Fig. 9 shows the population vulnerability has increased from time to time during 2000–2020. It can be observed that specifically the Northeastern section of the Benighat-Rorang RM has become more vulnerable to landslide incidence from the year 2000–2020. The resultant spatial distribution of population vulnerability (Fig. 10) towards climate-induced landslides as a consequence of exposure, susceptibility, and lack of adaptation capacity revealed that the majority of the study area's high mountainous regions, the northeast region, and sections of the riverside regions accrossed-hill zones are the most sensitive to climatic calamities (see Figs. 11–13).

7. Conclusion

According to the study findings, climate change-related risks have affected the study region in several areas. Examining climate data and studying perceptions, consequences, mitigation plans, and adaptation tactics at the community level have been beneficial. The current study highlights the condition of the local community by looking at civic facilities, perception, and observed climatic datasets by observing increased temperatures and irregular rainfall patterns. The results of the current study indicate that landslide susceptibility is highest along the southern border of the study area and the probability of landslides gradually decrease towards north which is understandable as the active fault line is situated at the south of the study area. The landslide risk assessment produced similar kind of results with higher risk in the south and lower in the northern part of the study area. The effect of probable landslides on the community was also evaluated through the vulnerability assessment of important social infrastructure and population density across the study area. Although the southern part of the study area is more prone to landslides, the social vulnerability is higher towards the

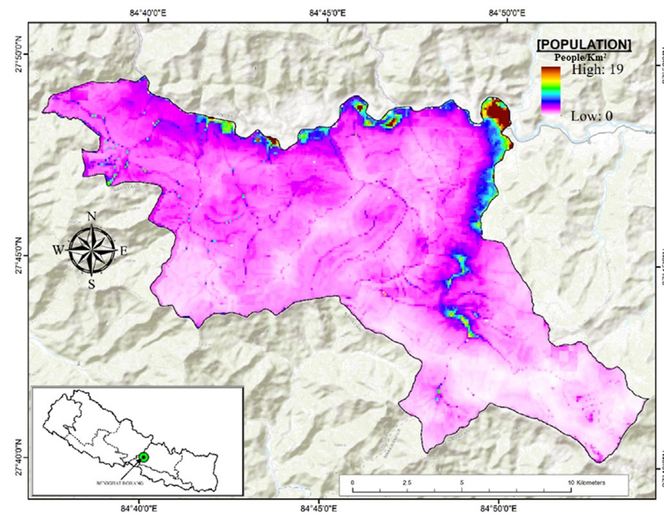

Fig. 13. Spatio-temporal vulnerability map displaying population exposed to landslides, 2020.

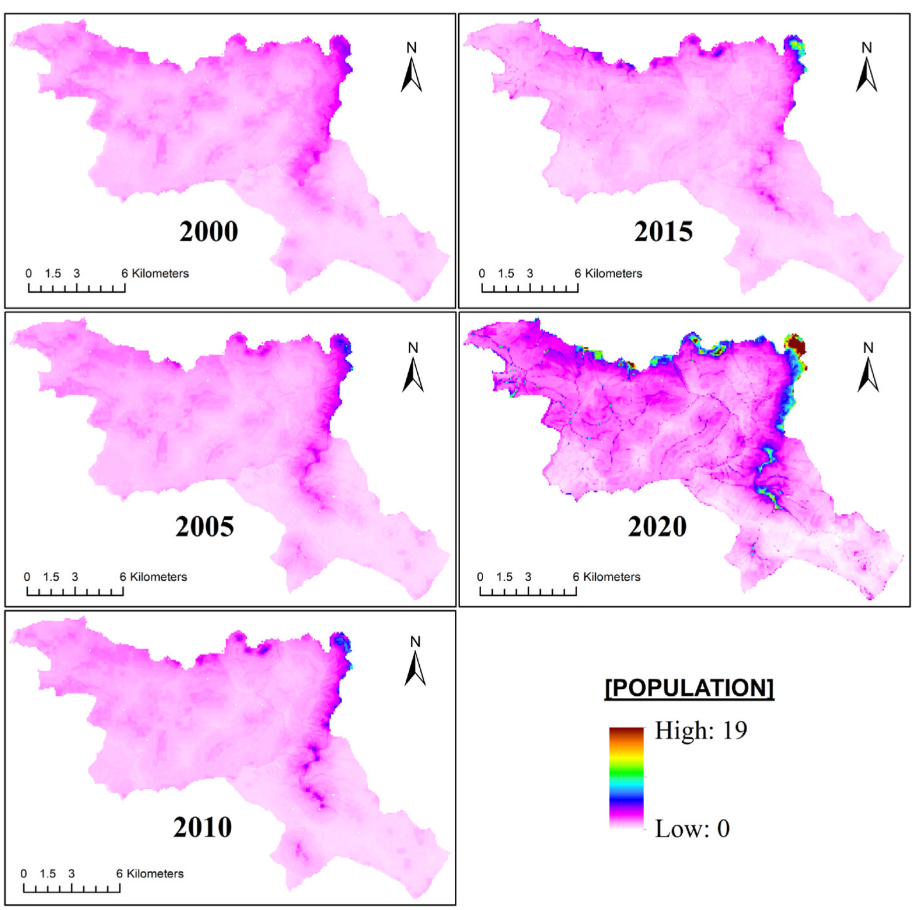

Fig. 12. Spatio-temporal vulnerability map displaying population exposed to landslides (2000–2020).

north and north-eastern border of the study area. This might be due to the fact that along the southern border, the population is very low which contributes of the low vulnerability and vice-versa.

Landslides in Dhading have affected the community in several ways, including the socioeconomic issues residents face, the productivity of the agricultural sector, and the frequency of natural disasters like landslides. The effects of various municipal facilities on the local economy impact people's daily lives. As a result of environmental issues, many people turn to alternative sources of income, such as wage and non-resident employment. The community should already begin to undertake several tactics to protect itself against the current and future consequences of climate change and adapt to changing environmental circumstances. With this in mind, policymakers should build infrastructure to help communities implement new sustainable measures in response to hazards induced by climate changes and regional dynamic tectonic settings.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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