COMPARATIVE ANALYSIS OF CERTAINTY FACTOR AND ANALYTIC HIERARCHY PROCESS FOR LANDSLIDE SUSCEPTIBILITY ZONATION IN PARTS OF SOLAN, HIMACHAL PRADESH, INDIA

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Abstract: The state of Himachal Pradesh in India is one of the most important hotspots when it comes to landslides; and Kandaghat, a tehsil in the Solan district of Himachal Pradesh having religious and tourism importance, is substantially affected by frequent landslides causing road blocking. In the present study, the analytic hierarchy process (AHP) and certainty factor (CF) techniques, which form part of the geographic information system (GIS)-based landslide susceptibility models, were used to prepare a landslide susceptibility map for the Kandaghat region, for which, as a preliminary step, an inventory of 214 live landslides was prepared from the Bhukosh data directory. The landslide inventory was cross-verified on the Google Earth platform. About nine landslide causative factors (slope, curvature, aspect, soil, rainfall, land use–land cover, lithology, drainage density and lineament density) were considered for the study area, and against the backdrop of these, the corresponding thematic maps were prepared and used in turn for the preparation of the final landslide susceptibility map. Based on the two mentioned techniques, the thematic maps were assigned weights according to their prominence and dynamic processes in the study area. The model performance for each method was evaluated using the area under the curve (AUC), and the accuracies for the AHP and CF were ascertained as, respectively, 81% and 85.6%. The Himalayan terrains are significantly prone to landslides, and this study outlines the characteristics of one of the important Himalayan towns in terms of vulnerability for landslides, together with providing its classification in terms of slope deformation susceptibility; this procedure can help direct attention towards areas needing to be classified under high to very high landslide susceptibility zones.

Key words: landslide, analytic hierarchy process, certainty factor, landslide susceptibility, area under the curve

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Introduction

Due to the immense growth of population in the low-lying areas, the gradual urbanisation and other construction activities have accelerated in hilly terrains, which have made the slope profiles very unstable and prone to landslides and subsidence. Hence, the movement of the soil in a large amount from its original position towards the downslope is now common in hilly terrains, and this phenomenon is referred to as a landslide (Bahrami et al. 2021). Landslides are considered as one of the most vandalistic and critical natural disasters when it comes to rugged

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topography. The occurrence of landslides is dependent on many factors, such as: geology, lithology, rainfall, climatic conditions, earthquake and the landscape in an area, that is, whether it is flat or hilly. Due to their destructive and often fatal nature, landslides have become one of the hot topics of discussion around the globe, particularly within the wider context of the devastation wrought by undesirable man–nature conflict (Pourghasemi et al. 2013). The loss of resources, economy and human life is very high in the case of landslides. Thus, to minimise this loss, areas having high risk of landslide occurrence can be studied to facilitate early warning and mitigation measures (Devkota et al. 2013). In addressing the need to assess the hazards of a landslide-occurrence and ascertain its causes, use of the landslide susceptibility zonation tool can be one of the best options (Brenning 2005, Xu et al. 2012, Bahrami et al. 2021). Landslide susceptibility mapping (LSM) is highly useful for the planning and mitigation purpose and has been adopted by many municipal bodies (Fell et al. 2008). LSM is proving to be an effective means for initiating an investigation on landslide-prone sites post- and pre-event (Ciampalini et al. 2016). Various landslide modelling methods, encompassing quantitate and qualitative ones, are being used for the preparation of LSM (Kavzoglu et al. 2014, Ramesh, Anbazhagan 2015, Chen et al. 2016, Guo et al. 2021, Sonker et al. 2021, Bahrami et al. 2021, Kamran et al. 2021, Panchal, Shrivastava 2022), and each of these has its own pros and cons (Li et al. 2019). The result from geographic information system (GIS)-based techniques have shown high accuracy, but compared with the machine learning (ML) methods, GIS-based LSM have shown lesser reliability (Zhao, Chen 2020). The GIS is capable of analysing a variety of factor classifications, such as landslide, flood, drought, land use–land cover change, land surface temperature, crop pattern analysis etc. (Tariq, Mumtaz 2022, Tariq et al. 2022, Majeed et al. 2022, Tariq et al. 2023).

Methods that have been used for the preparation of LSM, such as AHP, certainty factor (CF), frequency ratio (FR), fuzzy logic, weight of evidence (WOE), information value (IV), artificial neural network (ANN) etc., have been excellent in preparation of LSM. Analytical hierarchy process (AHP) was proposed by Saaty 1980 and is related to the qualitative comparison of various landslide causal factors (Moragues et al. 2021). It is one of the most-used methods (Shahabi, Hashim 2015, Moragues et al. 2021), and is based on a subjective rating of causal factors carried out by the expert (El Jazouli et al. 2019). It is also important as a tool for multi-criteria decision making (MCDM), which splits complex problems into fragments of differing priority in a hierarchical manner (El Jazouli et al. 2019). CF is also one of the modelling techniques that is employed in the preparation of LSM. CF is a function based on probability that makes analyses of various factors based on the sensitivity of the event and is then finally used for the preparation of LSM (Chen et al. 2016, Zhao, Chen 2020). The FR is based on the values that are acceptable for the analysis of risk and that can later be used for susceptibility mapping (Zhao et al. 2021). It is the ratio of landslide cell frequency upon factor class's cell frequency (Shano et al. 2020). Fuzzy logic is the analysis of the decision models used for the hazard zonation (Ullah, Zhang 2020), and is based upon the mathematic logic (Zhang et al. 2020).

Beginning with the past few decades, the Himalayan region has been witnessing a number of slope disturbances, and in particular the foothill areas that are highly populated have seen massive destructions, especially in the extreme rainfall seasons. The increasing anthropogenic interference caused by the rising population number in the hilly terrains has not only disturbed the natural topography but also impacted the inherent lithology and its structural parameters. The present study aimed at generating information regarding the relative importance of triggering factors responsible for the landslide hazard at Kandaghat (Chandigarh–Shimla Highway NH-5) by employing the AHP and CF methods. The significance of the area chosen for study lies in its importance in terms of tourism and religious purposes. At many of the places in this area, the slopes are highly unstable and the roads are badly damaged because of the frequent landslides Therefore, the presence of roads that are cut into the sides of highly unstable slopes, in conjunction with dense populations in the surroundings, prompts us to undertake the present landslide susceptibility study.

Study area

Kandaghat is a sub-district located in the state of Himachal Pradesh, India (latitude: 30.9702°N and longitude: 77.1054°E), and having a rich natural source of vegetation and forest cover of 9681 ha (Fig. 1). Mostly this is a mountainous area, with an average altitude of 1410 m. Quartzitic rock exposures constitute most of the geology in the study area. Various types of trees and plants are present in the area, including *Abies pindrow* (tosh), *Acacia catechu* (khair), *Acer caesium* (maple), *Aesculus indica* (khanor – horse chestnut), *Ailanthus excelsa* (ailanthus), *Albizzia stipulata* A. (lebbek dic, siris) etc. The climatic conditions of Kandaghat are warm and temperate, where the winters receive little amount of rainfall as compared to the summer season. The annual temperature of the Kandaghat region ranges up to 16.0°C, with an annual precipitation of 1262 mm.

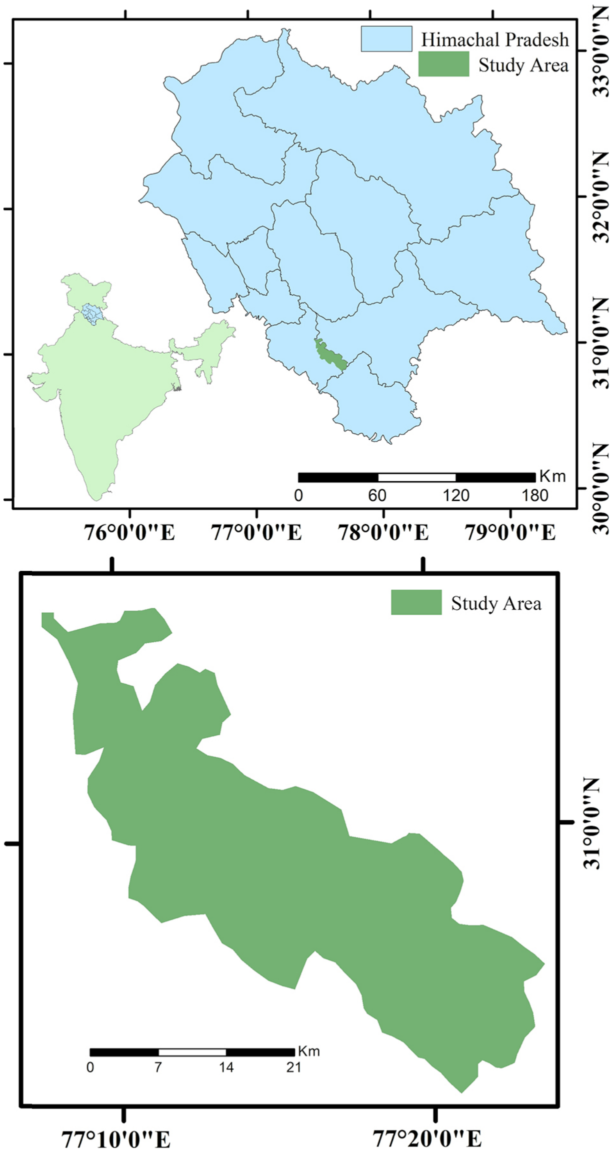

Fig. 1. Study area in Himachal Pradesh, India.

Methodology

For the present study, data have been downloaded from various platforms, such as United States Geological Survey (USGS) for rainfall and Bhukosh for soil distribution; other data needed to arrive at the final susceptibility map were also obtained. Data were also downloaded from the Geological Survey of India (GSI) platform, particularly to obtain the map of landslide inventory; the data downloaded from GSI were verified against Goggle Earth. All the thematic layer maps were prepared using ArcGIS software version 10.8.1 by ESRI. The digital elevation model (DEM) file was downloaded from the platform of Bhuvan and the maps were prepared. In the map preparation, the cell size of every map was taken as 30 m of resolution. For the preparation of land use land cover (LULC), first the requisite data were downloaded from the USGS, and all the downloaded slides were checked according to the dates because the downloaded slides must have a cloud-count <10%. Later, the mosaicking process was done in ArcGIS software and further clipped according to the shape of the study area. For the preparation of lithology map, first the data were downloaded from GSI, and then imported into ArcGIS software, where clipping, as well as classification based on the required shape and number of classes, was performed. For the preparation of rainfall map, points were drawn around the study area on the Google Earth application, and then the shape file was uploaded on the USGS; the downloaded data were in the excel sheet form, and the data were calculated month- and year-wise. The remainder of the thematic layers were made from the DEM file according to the commands used in ArcGIS. It is very difficult to identify exactly which factors are majorly responsible as the causative ones underlying landslides' occurrence (Singh, Kumar 2018). So, after the study of previous published inventories and documents, the following factors – namely, slope, curvature, aspect, soil, rainfall, LULC), lithology, drainage density and lineament density – were chosen for landslide susceptibility study.

Landslide inventory map

The landslide inventory map provides an exact idea of event location and frequency of landslides in a particular area. The landslide inventory map can be made from the data that are already available for any area in the environment of ArcGIS. The data of landslides were downloaded from Bhukosh, and the same were verified on Google Earth. A total of 214 landslides were found according to the data.

Slope

The slope is considered as one of the most important elements for the occurrence of landslides (Panchal, Shrivastava 2022). It is the changing rate of elevation in the downward or falling direction. The angle of the slope is directly proportional to the stability of the slope (Guo et al. 2021). The slope map for the study area was prepared using the DEM, having a resolution of 30 m (Fig. 2).

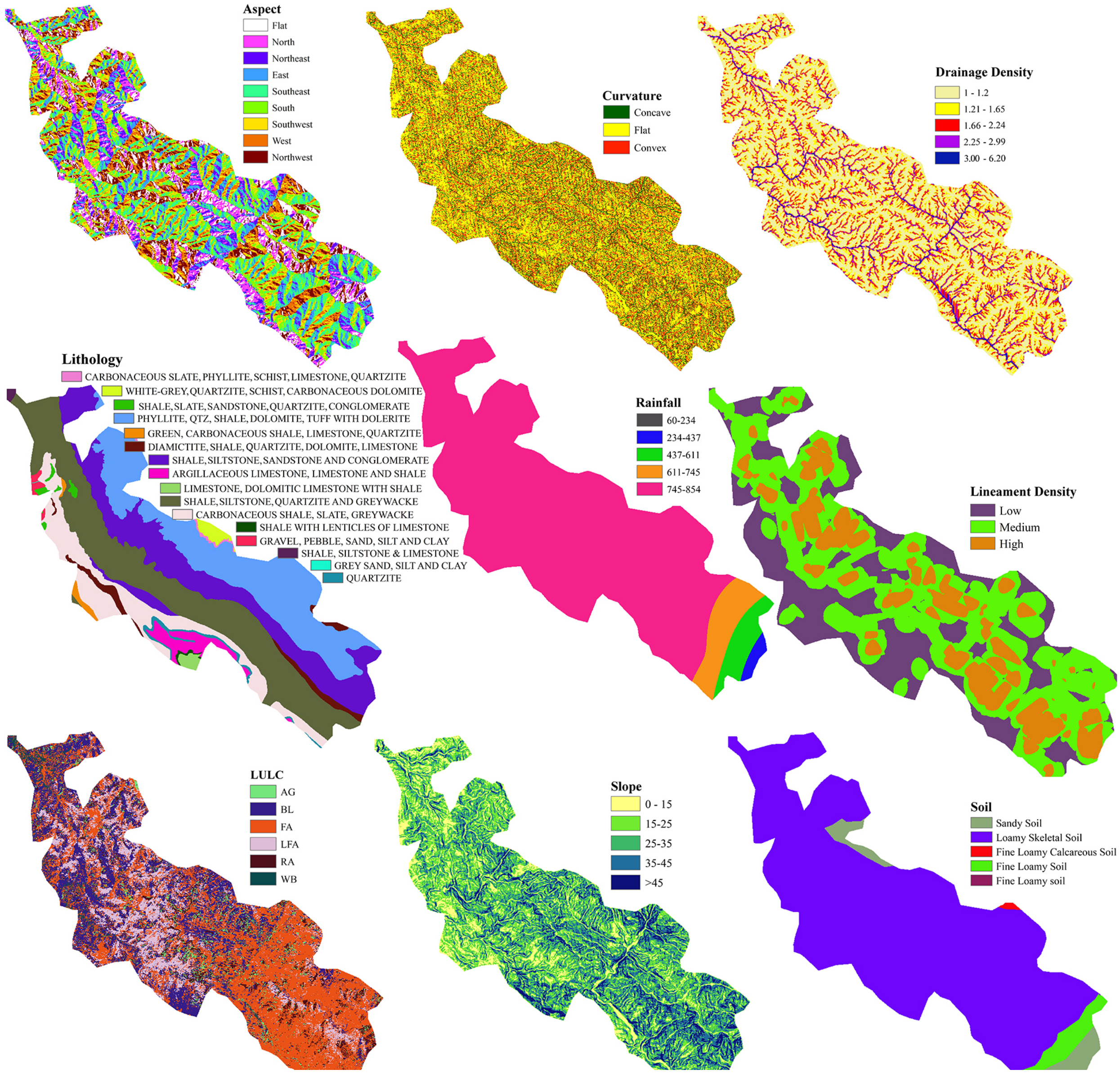

Fig. 2. Thematic layers of causative factors: aspect, curvature, drainage density, lithology, rainfall, lineament density, LULC, slope and soil.

Curvature

Curvature refers to the joining of various planes with the surface (Ramesh, Anbazhagan 2015). It is a very essential and important perimeter in the study of the driving and opposing stresses that are contained within the landslide body (Sonker et al. 2021). The classified curvature map is shown in Figure 2.

Aspect

Aspect defines the direction of a slope with respect to the north direction (Panchal, Shrivastava 2022). The temperature and moisture content are related with the aspect of a slope (Singh, Kumar 2018). An aspect map was also derived from the DEM and was classified (Fig. 2).

Land use and land cover

Any change in land use and land cover can bring the area under the threat of landslide (Chen et al. 2016). Several studies in the literature have suggested that the role of LULC in bringing about landslides is strong (Singh, Kumar 2018). Toposheets, LISS-III satellite imagery and Google Earth were used to prepare the LULC map (Fig. 2). It is found that the study area has barren land, forest area, agriculture land and populated flat cover in the maximum extent.

Lithology

Lithology defines the types of rocks present in the area. The resistance to erosion, weathering and slope stability are also dependent on lithology (Bahrami et al. 2021). The datasets required for the lithology map were downloaded from Bhukosh (GSI) and then clipped in ArcGIS software for the particular area that was identified through Google Earth. The map was then prepared and classified (Fig. 2).

Drainage density

Drainage density is defined as the ratio between stream length and the total basin area. Drainage density plays an important role in determining the slope's groundwater level (Kavzoglu et al. 2014). It has been documented that there is a catastrophic relationship between the drainage density and the ground water conditions. Drainage density is directly proportional to the susceptibility for landslides. The drainage density map was prepared from the DEM of a resolution of 30 m and classified (Fig. 2).

Soil

There were four types of soil found in the study area, namely sandy soil, loamy skeletal soil, fine loamy calcareous soil and fine loamy soil. In the area of Kandaghat, it has been found that the soil of the area still retains several minerals that are naturally present in it, among these being phosphorus, zinc, calcium, copper, iron, potassium, magnesium, manganese, nitrogen and organic carbon. The data used for the preparation of soil map were downloaded from Buhkosh (GSI), analysed and prepared using ArcGIS software (Fig. 2).

Rainfall

For this study, rainfall data were downloaded from the CHRS portal (chrsdata.eng.uci.edu/) considering the annual average of 5 years, from 2015 to 2021. Many studies have suggested that rainfall is considered as one of the main triggering factors, acting as the initial trigger point responsible for setting off the landslide event (Kim et al. 2021). As India receives a good amount of rainfall in the monsoon season, Kandaghat, which is situated in the Western Indian Himalayan region, is easily affected by heavy and prolonged rainfall events, which typically result in rock blockages, loss of life and property etc. Thus, rainfall was analysed based on the rainfall map, which was prepared and classified (Fig. 2).

Lineament density

Geological structures such as faults, fractures and rock cleavages play a major role in building the pore pressure. Due to the intense shearing evident from faults in the Himalayan region, there is a threat of landslide hazards (Leir et al. 2004). The lineament density map has been created from the DEM of a resolution of 30 m with the help of ArcGIS software and presented on the classified map (Fig. 2).

Landslide hazard zonation results

Analytical hierarchy process (AHP) and CF processing methods were adopted for the preparation of landslide susceptibility hazard zonation (LSHZ) maps using ArcGIS software in the present study. In 1980, Saaty put forward a decision-making process known as AHP. The capability and the results obtained from the AHP technique were used for LSM. It is used with the application of GIS and remotely sensed data to create a susceptibility map for landslides. CF is a function of probability that is used for the preparation of susceptibility map.

Analytical hierarchy process (AHP)

Principally applied in adding-up the value outcomes of complex decisions, AHP is considered one of the key tools that can be used in the assessment of the hazards of landslides' occurrence; it also finds application in relating various phenomena considered potential causative factors for landslides with their actual occurrence (Singh, Kumar 2018). The study and applications of this method have proved to be highly successful in the decision-making process. This method is framed upon three principles, namely: breaking down the complex problem, judgement based on compression and union of respective importance. In the very first step of the AHP method, the causative factors are first systematised to slow hierarchy. The systematised data are then placed in contrast with the matrix as per their possibility of compression, and then the appropriate weights are assigned to each causative factor so that it becomes feasible to compute the consistency ratio (CR) (Singh, Kumar 2018). The weights were assigned inside a comparison matrix to different factors in between the ranges of 1–9 on the basis of their importance. In this process, each given weight undergoes a comparison vis-à-vis the factors that are responsible for causing landslides. Based on the relative significances of the various factors responsible for bringing about landslides, weights were assigned in the compression matrix, using values that lie between 1 and 9, as shown in Table 1. For the purpose of inverse compression, the values of weights ranged in the form of reciprocals of the dominant causative factors. CR can be calculated by the formulae that were given by Saaty (1990):

$$\mathrm{CR} = \frac{\textit{Consistency Index}}{\textit{Random Index}}$$

where:

$$\text{consistency index} = \frac{\lambda\text{max} - \text{n}}{n - 1}$$

where:
- λmax = principle Eigen value,
- n is the order of matrix.

Table 1 shows the link between the landslide causative factors and landslide locations using AHP model. The slope angle >45° has a high CF value of 0.48, followed by 35°–45° (0.23), while the remainder among the classes show comparatively low AHP values. Thus, slope angles >45° have high triggering factors and are indicative of greater vulnerability to landslides. The AHP values for the northern part of Kandaghat area show the higher range, followed by the southeast class. The higher the class values of the curvature, the greater the possibilities of landslides. From the present study, we observe that the AHP value of the concave class is demonstrated to be higher at 0.67, followed by those corresponding to the flat and convex ones. Generally, excessive soil moisture levels are associated with an unstable slope and therefore its stability decreases. With the increase in the drainage density, the possibilities of landslides are higher. From the present study, it is observed that the low class shows an AHP value of 0.56, followed by the medium and high ones. Lithology being an internal factor plays a crucial role in governing landslides. The lithology of the present study shows a number of classes in which greywacke and quartzite show higher AHP values of 0.069 and 0.066, respectively. Soil and landslides are inter-linked with each other as any kind of movement in the soil mass can cause a landslide. From the present study, it is observed that loamy soil and loamy sand show the higher values of 0.52 and 0.25, respectively, which indicates that these types of soils have a higher landslide triggering capacity (Table 1).

Results of AHP model

It has been found that the steepness of a slope is inversely proportional to its stability. Slopes with a steepness of >45° account for approximately 8.92% of the total study area and have the highest AHP weightage of 0.48, with a 35.64% occurrence of landslides. Slopes with angles of 35°–45° cover 26.34% of the Kandaghat region, and

Table 1. Numerical weights of AHP (CR – consistency ratio).

Factors comparison	–1	–2	–3	–4	–5	–6	–7	–8	–9	–10	Normalised Eigen weight Wk
Slope	1										0.2109
Aspect	0.5	1									0.0672
Curvature	0.33	7	1								0.0996
Land use and land cover	0.2	0.11	0.14	1							0.0368
Lithology	0.14	0.33	0.11	0.17	1						0.0187
Soil	0.11	7	3	9	9	1					0.1631
Drainage density	1	5	5	3	4	3	1				0.1889
Lineament density	0.33	1	7	5	9	0.14	0.2	1			0.1038
Rainfall	0.22	0.14	0.22	3	7	0.33	0.11	0.17	1		0.1065
CR = 0.76											
Comparison of factor classes											*Wik*
Slope (°)											
(1) 0–<15	1										0.0405
(2) 15–<25	3	1									0.0887
(3) 25–<35	3	3	1								0.1483
(4) 35–<45	5	3	3	1							0.2393
(5) >45	7	5	5	7	1						0.4829
CR = 0.079											
Aspect											
(1) Flat	1										0.0423
(2) North	2	1									0.0615
(3) Northeast	0.32	0.2	1								0.0189
(4) East	0.15	0.5	0.33	1							0.0256
(5) Southeast	1	3	5	5	1						0.0852
(6) South	3	5	7	3	5	1					0.2469
(7) Southwest	5	2	7	5	7	0.15	1				0.1552
(8) West	0.2	0.13	1	0.33	0	0.5	0.11	1			0.0145
(9) Northwest	1	0.5	9	5	1	0.11	0.33	3	1		0.0642
(10) North	7	5	7	7	3	1	5	7	9	1	0.2623
CR = 0.89											
LULC											
(1) Thickly vegetated forest area	1										0.0681
(2) Populated flat land	2	1									0.0864
(3) Less vegetated area	2	2	1								0.1116
(4) Moderately vegetated area	3	3	4	1							0.2131
(5) Barren land	2	4	2	2	1						0.2081
(6) Water body	3	3	3	3	3	1					0.3187
CR = 0.87											
Curvature											
(1) Concave	1										0.6763
(2) Flat	0.13	1									0.0728
(3) Convex	0.34	4	1								0.2507
CR = 0.032											
Drainage density											
(1) Low	1										0.5644
(2) Medium	0.5	1									0.549
(3) High	0.33	0.33	1								0.3011
CR = 0.05											
Soil											
(1) Coarse loamy	1										0.0854
(2) Fine loamy	1	1									0.1357
(3) Loamy sand	3	3	1								0.2568
(4) Loamy soil	9	2	3	1							0.5219

Factors comparison	–1	–2	–3	–4	–5	–6	–7	–8	–9	–10	Normalised Eigen weight Wk
CR = 0.07											
Lithology											
(1) Quartzite	1										0.0137
(2) Shale	3	1									0.0284
(3) Siltstone, sandstone	0.5	0.33	1								0.0254
(4) Greywacke	0.2	0.14	0.2	1							0.0692
(5) Limestone	0.33	0.13	0.12	1	1						0.0403
(6) Lenticles of limestone	0.33	0.13	0.33	2	1	1					0.0327
(7) Quartzite	2	7	9	7	3	7	1				0.0668
(8) Shale, dolomite, tuff with dolerite	0.12	0.33	0.5	7	3	3	0.14	1	7		0.0471
CR = 0.097											
Rainfall (mm)											
(1) 60–234	1										0.0129
(2) 234–437	3	1									0.0156
(3) 437–611	0.33	0.5	1								0.0453
(4) 611–745	0.12	0.14	0.5	1							0.0529
(5) 745–854	0.5	9	0.14	7	1						0.0987
CR = 0.073											
Lineament density											
(1) Low	1										0.0399
(2) Medium	2	1									0.0632
(3) High	3	3	1								0.0746

the AHP weightage of landslides that in aggregate occur in such regions is 39.53%. This is followed by slopes having angles ranging from 25° to 35°, which cover 30.11% of the study area and have a weightage of 0.14, with a 20.5% chance of landslide occurrence. If the angle of the slope is <25°, there are fewer instances of landslides. The research area contains slopes with an inclination angle of 35° in 40.10% of the total area, with an 8.94% chance of landslide occurrence. The aspect of a slope refers to the direction it faces in relation to magnetic north. It has been revealed that aspects with a north, northwest, west and southwest orientation have a greater effect on the occurrence of landslides, indicated by the AHP weightage of 0.40, 0.08, 0.14 and 0.23, respectively. Landslides are more likely to occur as a result of water action on surfaces with concave curvature, followed by surfaces with convex curvature. Along the flat curve, the possibility of landslides is eliminated or reduced. The frequency of landslides increased in direct proportion to the density of drainage. Landslides have higher association with areas having more drainage density. Landslides occurring in regions characterised by a high drainage density account for 24.2% of the aggregate landslides occurring in the total study area for the time period under consideration; but despite this fact, areas characterised by a high drainage density amount to only 4% of the total land area. In areas with medium drainage densities, which covered 36.02% of the land, 59.07% of the total landslides occurred. In the 23.62% of the total area characterised by low drainage density, only 25.11% of the total landslides occurred. The density of the lineament had a huge impact on the number of landslides that occurred. The upper class accounts for only 18.82% of the land area, but it is responsible for 59.93% of all landslides. The soil in the present study area has been classified into four categories, namely coarse loamy soil, fine loamy soil, loamy soil and loamy sandy soil; out of these four categories, loamy sandy soil is present mostly on steep slopes, covering an area of 89.92% and being responsible for approximately 93.8% of landslides. On the other hand, fine loamy, loamy soil and coarse loamy soils cover a lesser area and thus their contribution in the occurrence of landslides is lesser. A rainfall of 437–611 mm per year fell on 29.54% of the studied region, resulting in landslides in 27.14% of the area subject to this rainfall. Landslides affected 20.25% of the area with rainfall in the range of 234–437 mm per year. Approximately 23.44% of the area with a rainfall of 745–854 mm per year experienced 57.93% of the landslides. Thus, the

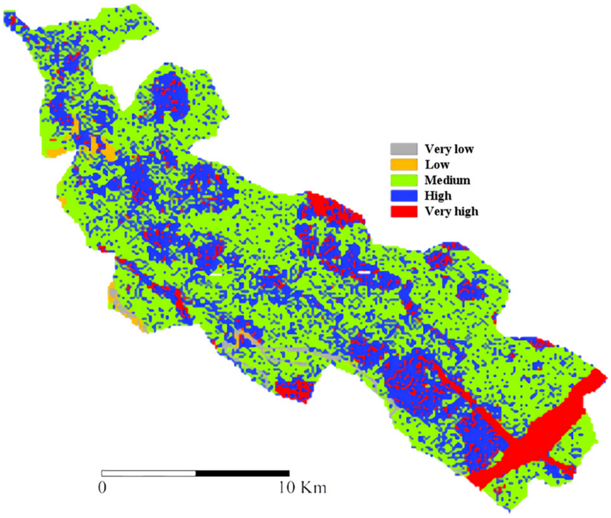

Fig. 3. AHP model based Landslide Hazard Zonation map.

higher the rainfall, more likely it is that a landslide will occur. On the other hand, the rest of the classes have comparatively less rainfall and have few chances of landslides. High and medium forests covered approximately 45.2% of the study area and were found responsible for approximately 60.23% of landslide events. Landslides affected 4.97% of barren and agricultural land. Landslides affected 49.8% of the lightly forested and populated area, accounting for 24.35% of the total study area (Fig. 3).

Certainty factor

This is an indicator used to express or determine the CF (hazard). It is an approach that can be used for the reconciliation of the differences and uncertainties observed in the given (input) values, and also for resolving any issues that might arise pursuant to adding up all the different layers of data (Devkota et al. 2013). The formula for the calculation of CF is defined below:

$$CF = Ppa - Pps / Ppa\ (1 - Pps) \text{ if } Ppa \geq Pps$$

now, if

$$Ppa \leq Pps, \text{ then } CF = Ppa - Pps / Pps\ (1 - Ppa)$$

where Ppa and Pps are the ratio between cell count and landslide count, and ratio of the total cell count to the total landslide count, respectively.

Table 2 defines the calculation of CF for the study area. The CF ranges between −1 and +1, in which the positive values show high certainty and the negative values show low certainty (i.e. an indication that the geological environment is characterised by good conditions). And if the value reaches 0, it then shows that the CF cannot be defined or determined. Table 2 shows the link between the landslide causative factors and landslide location using the CF model. The slope angle >45° has a high CF value of 0.38, followed by 35°–45°, while the remainder of the classes show comparatively low CF values. Thus, the slope angle >45° is responsible for the largest number of potential causal factors, and accordingly, when this angle is prevalent, the vulnerability to landslides is the greatest. The CF values for the southern side show the higher range, followed by the east and western east classes. The higher the class values of the curvature, the greater the possibilities of landslides. From the present study, we observe that the CF value of the convex class is demonstrated to be higher at 0.20, followed by the flat and concave curvature classes. Generally, excessive soil moisture levels are associated with an unstable slope of the curvature zones; the explanation for the association is that when the moisture content of the soil increases, this results in a decrease in its stability. With the increase in the drainage density, the possibilities of landslides are higher. From the present study, we observe that the high class shows a CF value of 0.37, which indicates that there is a high risk of landslides in this class of drainage density. Lithology being an internal factor plays a crucial role in governing landslide activity. The lithology of the present study shows a number of classes in which shale and white-grey quartzite demonstrate the higher CF values of 0.97 and 0.52, respectively.

Soil and landslides are also inter-linked with each other as any kind of movement in the soil mass can cause a landslide. From the present study, it is observed that coarse loamy soil and loamy sand soil show the higher values of 0.9 and 0.5, respectively, which indicates that these types of soils are characterised by a higher landslide triggering capacity (Table 2).

Results of CF model

A total of nine landslide causal factors were analysed using the CF method, as shown in

Table 2. Numerical weights of certainty factor (CF).

Causative factors	Categories	Value	Cell count	Landslide count	PPA	PPS	CF
Aspect	Flat	1	22,655	17	0.001	0.0008	–0.11
	North	2	22,368	9	0.000	0.0008	–0.52
	Northeast	3	18,085	23	0.001	0.0008	0.34
	East	4	22,260	32	0.001	0.0008	0.42
	Southeast	5	26,489	12	0.000	0.0008	–0.46
	South	6	29,490	56	0.002	0.0008	0.56
	Southwest	7	31,371	33	0.001	0.0008	0.20
	West	8	28,629	4	0.000	0.0008	–0.83
	Northwest	9	26,444	20	0.001	0.0008	–0.10
	North	10	27,083	8	0.000	0.0008	–0.65
Curva-ture	Concave	1	43,901	27	0.001	0.0008	–0.27
	Flat	2	149,442	125	0.001	0.0008	0.00
	Convex	3	61,531	62	0.001	0.0008	0.20
Drainage density	Low	1	39,566	53	0.001	0.0008	0.37
	Medium	2	141,605	116	0.001	0.0008	–0.02
	High	3	73,682	45	0.001	0.0008	–0.27
Line density	Low	1	78,363	43	0.001	0.0008	0.35
	Medium	2	121,167	113	0.001	0.0008	0.10
	High	3	54,470	57	0.001	0.0008	0.00
Lithology	White-grey quartzite, schist and carbonaceous dolomite	1	76,929	136	0.002	0.0008	0.53
	Shale, slate, sandstone, quartzite and conglomerate	2	55,002	14	0.000	0.0008	–0.69
	Shale, siltstone, sandstone and conglomerate	3	1090	42	0.039	0.0008	0.98
	Shale, siltstone, quartzite and greywacke	4	1451	17	0.012	0.0008	0.93
	Shale, siltstone and limestone	5	66,064	3	0.000	0.0008	
	Shale with lenticles of limestone	6	25	0	0.000	0.0008	–1.00
	Quartzite	7	499	0	0.000	0.0008	–1.00
	Phyllite, quartzite, shale, dolomite and tuff with dolerite	8	1456	0	0.000	0.0008	–1.00
	Limestone and dolomitic limestone with shale	9	31,718	0	0.000	0.0008	–1.00
	Grey sand, silt and clay	10	6376	0	0.000	0.0008	–1.00
	Green, carbonaceous shale, limestone and quartzite	11	816	0	0.000	0.0008	–1.00
	Diamictite, shale, quartzite, dolomite	12	2200	0	0.000	0.0008	–1.00
	Carbonaceous slate, phyllite, schist, lst. and quartzite	13	437	0	0.000	0.0008	–1.00
	Carbonaceous shale, slate and greywacke	14	6464	0	0.000	0.0008	–1.00
	Argillaceous limestone, limestone and shale	15	4186	0	0.000	0.0008	–1.00
Soil	Coarse loamy	1	13,074	138	0.011	0.0008	0.92
	Fine loamy	2	232,569	75	0.000	0.0008	–0.62
	Loamy sand	3	506	1	0.002	0.0008	0.58
	Loamy	4	8706	0	0.000	0.0000	
Slope	0–15°	1	39,010	9	0.000	0.0008	–0.73
	15–25°	2	63,822	30	0.000	0.0008	–0.44
	25–35°	3	71,048	51	0.001	0.0008	–0.15
	35–45°	4	57,153	62	0.001	0.0008	0.23
	>45°	5	23,841	62	0.003	0.0008	
Rainfall	60–234 mm	1	32,135	138	0.004	0.0002	0.96
	234–437 mm	2	25,246	38	0.002	0.0002	0.87
	437–611 mm	3	32,912	34	0.001	0.0002	0.81
	611–745 mm	4	137,645	3	0.000	0.0002	–7.84
	745–854 mm	5	878,021	0	0.000	0.0002	–1.00

Causative factors	Categories	Value	Cell count	Landslide count	PPA	PPS	CF
LULC	Ag	1	10,952	152	0.014	0.0008	0.94
	BL	2	66,546	16	0.000	0.0008	–0.71
	FA	3	116,814	11	0.000	0.0008	–7.88
	LFA	4	38,384	13	0.000	0.0008	–0.59
	RA	5	17,666	2	0.000	0.0008	–0.86
	WB	6	4534	19	0.004	0.0008	0.80

Table 2. Slope angle >45° has the highest CF value (0.23), followed by classes of 35–45° (0.32) and 25–35° (0.22), while the remainder of the classes show comparatively low CF, indicating that slope classes having low values are less susceptible and slope classes with higher values are more exposed to the landslide event in the region of Kandaghat. In the case of aspect, south (0.55) shows the highest CF value followed by east and northeast with the CF values of 0.41 and 0.20, respectively. Additionally, it is demonstrated that north, southwest, flat, west, northwest and southeast are characterised by low CF values, which indicates that these classes are less susceptible to landslides. In the case of curvature, the category of convex has the maximum CF value of 0.25; and since the concave and flat classes exhibit negative values, this may be taken as an indication that the occurrence of landslides in these particular classes is low, thereby rendering the concerned regions less prone to landslides. Three classes of lineament density, namely high, medium and low, were considered. The high class has a positive CF value (0.27) and thus is more prone to landslides; and medium and lower classes having the CF values of 0.10 and 0.08, respectively, suggests that there are enough chances of landslides in the medium class as well, but that there is a low possibility of landslides in the low class. With the increase in the drainage density, the possibilities of landslides are higher. Based on scrutiny of the CF for the three classes of drainage density, it is clear that the higher class is having the CF value of 0.34, which demonstrates a significant chance for the occurrence of landslides concerning this class; and as for the other two classes, namely medium and low, having the CF values of 0.10 and –0.1, respectively, it may be inferred that the possibility of landslides is considerably lesser. As mentioned previously, four classified classes of soil are found in the study area; among these, coarse loamy soil has a CF value of 0.92, which indicates that it is imbibed with the highest shearing among these classes, in turn implying the attendant high possibility of landslides; on the other hand, skeletal soil, fine loamy calcareous soil and fine loamy soil have the CF values of 0.52, 0.12 and 0.31, respectively, which suggests a lesser possibility of landslides. The lithology map shows that white quartzite having the high CF value of 0.97 indicates a high possibility of triggering factors for the occurrence of landslide, while white-grey quartzite having the CF value of 0.52, as well as pinkish-grey dolomite shale, cherty dolomite, quartzite, limestone oxidised silt, micaceous sandstone, mudstone, brown sandstone, red clay, purple chocolate shale, shale, slate, quartzite, cherty dolomite clay and purple sandstone having comparatively low values of CF, indicates an absence of landslide.

The rainfall class of 745–854 mm is having the highest CF value at 0.93, which suggests the maximal possibility for landslides; on the other hand, there are comparatively lesser chances for landslides in the range of 611–745 mm that has

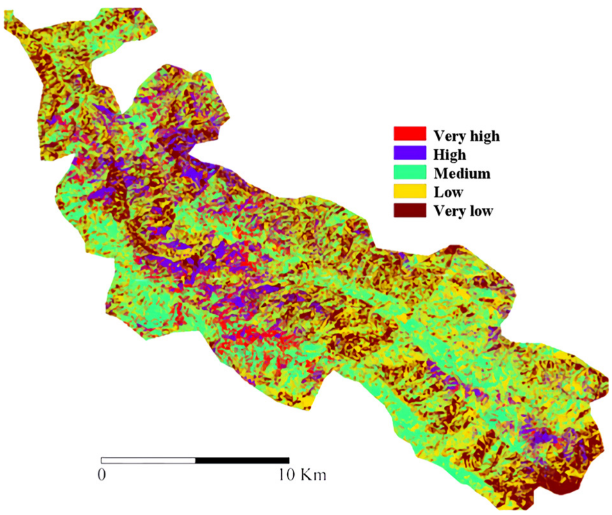

Fig. 4. Certainty Factor Model based Landslide Hazard Zonation map.

the CF value of 0.81; further, in the remainder of the ranges, the possibility of landslides' occurrence is even more sparse. The prepared LULC map is classified into six classes, namely forest area, populated land, less vegetated area, moderately vegetated area, barren land and water bodies; the CF value of 0.80 is the highest sheared by the water bodies, which suggests that the areas near water bodies are highly prone to landslides while other classes are less prone to landslides (Fig. 4).

Discussion

The results of the present study and our discussion thereon have been categorised into three parts, namely the performance of the models, the final susceptibility map and the causative factors. In this study, the landslide susceptibility zonation map/models have been prepared using the AHP and CF methods. Concerning the performance of the models, we can say that the two prepared models (AHP and CF) had an almost good accuracy, the accuracy values amounting to 81.1% and 85%, respectively.

The final susceptibility maps were divided into five categories, namely very low, low, medium, high and very high classes, to show the overall landslide susceptibility distribution in the study area. The final map layers and the final landslide susceptibility maps, namely those based on the framework of the AHP, CF and LR methods, were prepared in the environment of ArcGIS software. The amounts of cell count in different susceptibility zones/classes were calculated and determined. The values associated with all final maps and their weights are recorded in the tables forming part of the paper. Causal factor map layers were defined as the governing layers of the landslides. Nine causative factors were considered, and their maps prepared using ArcGIS software. All the parameters were considered and the final LSZ map layers were classified into the required susceptibility classes.

Validation

For the validation purpose, various techniques such as receiver operating characteristic (ROC) curve, area under the curve (AUC) etc. are typically used in the literature. In this study, AUC has been used for validation and the accuracy percentage was calculated, as shown in Figure 5. Based on the values obtained, it was concluded that the CF and AHP methods demonstrate the accuracy values of 85.6% and 81%, respectively.

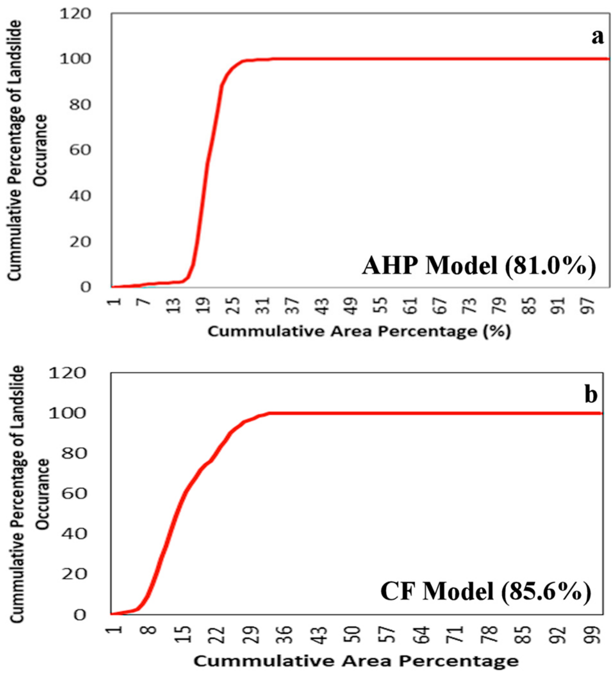

Fig. 5. Area under curve validation graphs for AHP (a) and CF (b) models.

Conclusion

In the present study, the AHP and CF models were used to prepare the susceptibility map for the study area. Based on the results obtained using the AHP and CF methods, all the landslide factors were determined and classified into the required classes. Since the final landslide susceptibility map would be needed separately for each model, the causative factor maps needed to be prepared first, before preparation of the susceptibility maps; and to prepare the final map with the help of the thematic layer maps, the raster calculator commands were used in the environment of ArcGIS software. The final maps were classified using natural breaks into five classes, namely very low, low, medium, high and very high. It was found that the area that is at the hilly slope side has greater chances of landslides' occurrence, and falls into the very high class; and the remainder of the majority area falls into the high and medium classes. The susceptibility maps that were obtained can only show the regions of vulnerability with their respective classes according to classification based on the zone of occurrence. However, since they make available a classification of the Kandaghat area into regions with varying levels of susceptibility to landslides, these maps can be used as a future reference and can also be utilised as an effective guide to decision-making by civil engineers, geology and mining department etc. To curb the havoc of landslides, the governing bodies should take the necessary steps needed to mitigate this problem, and accordingly devise acceptable solutions, in particular by way of ensuring that regular checks are carried out on the prone areas, dams, slopes and other sensitive zones.

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Author's contribution

Adil Ahmad Magray: conceptualisation, investigation, visualisation and writing (draft and review). Kanwarpreet Singh: conceptualisation, methodology, visualisation, figure design and elaboration and writing (draft and review). Swati Sharma: visualisation, figure design and elaboration and writing (draft).

Conflict of interest

Authors have no conflict of interest.

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