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Review article

A review on landslide susceptibility mapping research in Bangladesh

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ABSTRACT

Landslide susceptibility mapping is a common practice for landslide susceptibility assessment across the world. Like many other mountainous areas of the world, Bangladesh is facing frequent catastrophic landslides causing severe damage to the economy and society. As a result, several types of research have been conducted on landslides in Bangladesh. In the current research, a systematic review is conducted on the existing literature related to landslide susceptibility mapping to assess its contemporary trend with global research. The publications analyzed in this research were extracted from a website comprising landslide research of Bangladesh and by manual search. The aspects of the literature considered are year of publication, the journal where published, location/size of the study area, landslide inventory data type, susceptibility assessment/mapping method, thematic variables used, DEM characteristics, accuracy assessment methods and acquired accuracy of the models. The Chi-square test was conducted and correlation was measured to assess relation between selected features and map accuracy but no significant relationship was found. The studies are concentrated into three administrative districts of Chattogram, Rangamati and Cox's Bazar mainly covering the city centre. The publication rate is increasing but not following the global trend. Though various types of models are used and compared, the application of machine and deep learning algorithms are very limited and no evidence of Physically-based methods is found. Most of the cases, landslide inventory is prepared by conducting field survey, but the size is small. The research will help future practitioner in landslide susceptibility mapping research in the area.

1. Introduction

The geographical location of Bangladesh exposed it to frequent natural disasters [1]. Though all types of disasters caused considerable loss to Bangladesh [2], in recent years, landslides caught attention due to their considerable impact on the life and livelihood of the hill community [3]. According to IPCC's special report on "Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation", there is a high potentiality to increase in the frequency of shallow landslides in the near future due to the rise in temperature and rainfall extreme [4].

Due to excessive and prolonged rainfall [5] driven by climate change [6], unplanned development activity, hill cutting, deforestation, urban growth driven by increased population pressure [2,5,7], landslides have become a regular phenomenon in the southeastern hilly areas of Bangladesh [4,5]. There are five administrative districts comprised of small to large hills in the southeastern part

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of the country namely Chattogram, Cox's Bazar, Rangamati, Khagrachhari and Bandarban known as Chattogram Hilly Areas (Fig. 1) [8] where three districts of Rangamati, Khagrachhari and Bandarabn are collectively known as Chattogram Hill Tracts (CHT). The Chattogram Hilly Areas cover 8% of the total land area of Bangladesh [9,10] and have the highest elevated hill ranges in the country [11]. Though all five district faces landslides during monsoon season, due to the growing number of the urban population on the hill slope, Chattogram, Cox's Bazar and Rangamati district have to bear the highest loss of landslides [1]. The southeast hilly areas have two distinct regions: coastal plains and hills ranges. The coastal plains are composed of clay soils affected by tides. The hill ranges are underlain by Tertiary shales and sandstones that are consolidated or unconsolidated and have been strongly folded. Small valleys sharply dissected the steep slopes of this hill range. This hill rages are two types: high hill ranges which are long, narrow, linear ranges with summits up to 1000 m and mainly underlain by consolidated older rocks and low hill ranges which are mainly less than 300 m and consisting primarily of younger, less-consolidated rocks, and include both linear ranges and larger hill regions (Fig. 1) [11]. These low-elevated hills are mainly distributed in Chattograma and Cox's Bazar districts (Fig. 1) [12]. This type of soil structure and bedrock is very unstable and during prolonged rainfall, it becomes more prone to landslides [13–15]. Due to its location in tropical areas, Chattogram hilly area receives a huge annual rainfall of about 3000–5000 mm [11] that significantly triggers landslides during the monsoon season [7].

On June 2017, a series of devastating landslides triggered by prolonged monsoon rainfall [14] occurred in the southeast region of Bangladesh which caused 150–176 deaths [5,12] and damaged 40 thousand houses [14]. In this region, the number of landslide-affected people has increased in recent years (Fig. 2) [16]. The three years with the most landslide fatalities in Bangladesh were 2017, 2007, and 2012, with 176, 127, and 133 deaths in total [5]. Although the total number of deaths related to natural disasters have been decreased in Bangladesh [1], the landslide-related death toll has increased in the southeastern part of the country [5]. Besides the death toll, landslides in the region also damaged roads, houses, telecommunication systems, environmental resources etc. [14]. As a result, landslides cut significant importance in recent times and several research have been carried out, most of them focusing on landslide susceptibility mapping [14].

Landslide susceptibility maps in Bangladesh were prepared using landslide inventory data [6,7,17,18]. Landslide inventory is one of the first steps in landslide susceptibility, hazard and risk assessment [19,20]. Landslide inventory basically illustrates the spatial distribution of landslides, besides; it includes characteristics of previously occurred landslides such as location, size, depth, type,

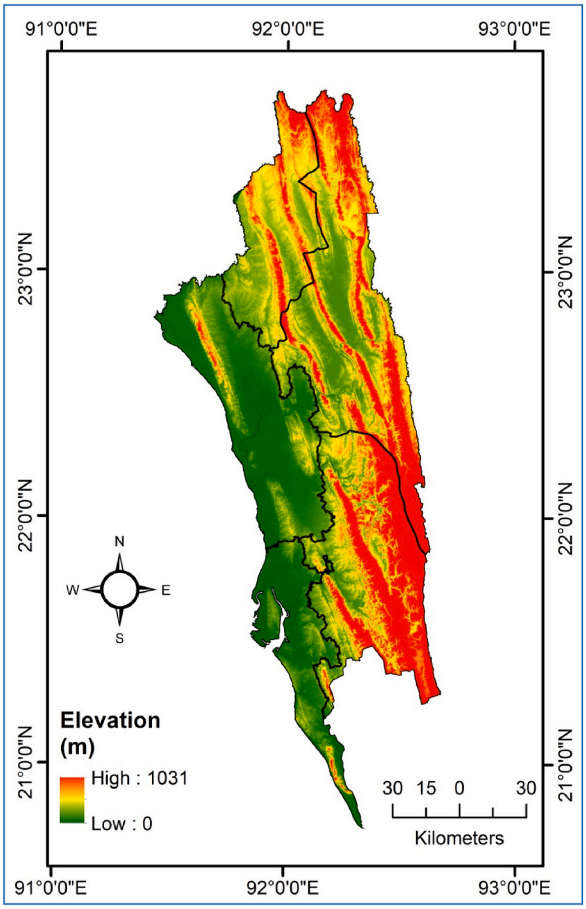

Fig. 1. Elevation of Chattogram hilly areas.

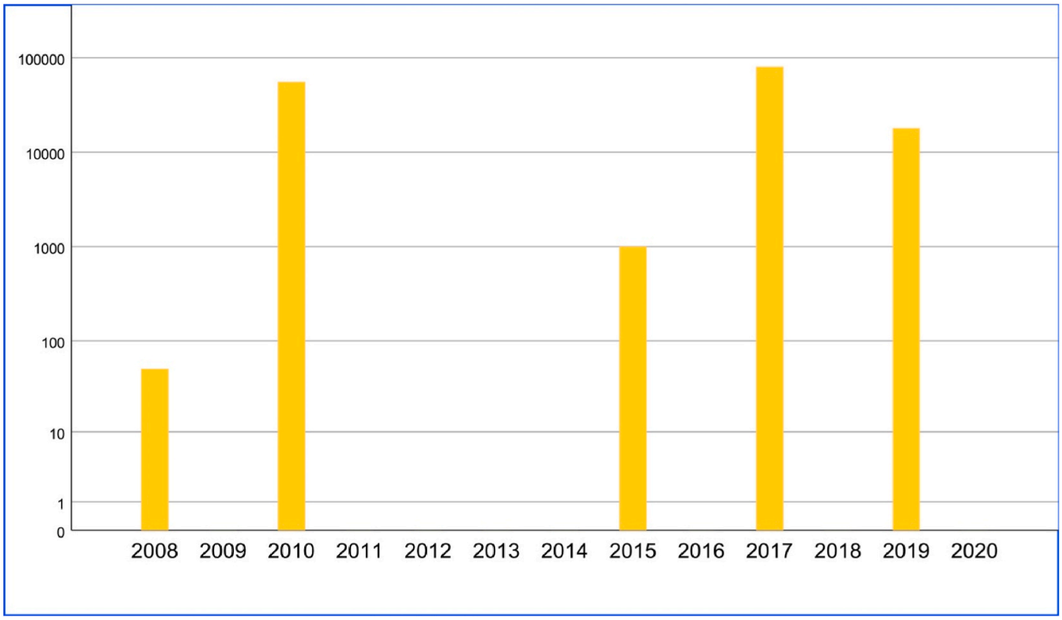

Fig. 2. Landslide affected people from 2008 to 2020 (Source: World Bank, 2020).

casualties etc. [19,21]. According to the scale of the study, a landslide can be mapped as a point or polygon using different techniques such as field mapping, satellite imagery and interpretation of aerial photographs [20–23]. In Bangladesh, landslide inventory is prepared either single method such as SAR offset tracking techniques [18], google image interpretation [6] and field surveys [7,17] or by a combination of methods [20] or open source data was used [24]. Inventory data had been used to measure the weight of conditioning factors by encompassing several types of mathematical models to predict landslide susceptibility in Bangladesh.

According to Brabb (1984) [25], the probability of a landslide happening in a location based on the local topography is known as “landslide susceptibility”. It predicts “where” future landslides are likely to occur [26]. The general assumption behind landslide susceptibility mapping is that landslide potential zones will be in similar environmental conditions to past landslides [17,21,27–29]. Landslide susceptibility assessment techniques can be categorized into three basic types: knowledge-based methods, physically based methods and data-driven methods, where the first one is qualitative and the rest of the two are quantitative methods [30–32]. Each method has both advantages and disadvantages. Details of the methods are discussed in Corominas et al. (2014) [30]. The knowledge-driven approach is more subjective and dependent on expert knowledge about landslides of a particular location. Thus weight to each factor is given according to personal experience. The data-driven methods are more objective and include statistical, machine learning and deep learning methods. This method measures the weights by using geo-environmental conditions of past landslides. Physically-based methods use failure mechanisms and the underlying process of landslides [30–33]. In most cases, physically-based methods are costly, but, now different methods are used in landslide susceptibility mapping with good accuracy at the regional scale and with short analysis time [34–36].

Literature on landslide susceptibility mapping has been increased largely across the world and different techniques have been developed [29]. There are many types of landslide susceptibility mapping methods and the quality of the models also improved over the years but none of them can be determined as suitable one [26,29,37]. The literature review also conducted on landslide susceptibility mapping research across the world [26,28,29,38–41] and also for specific study regions with limited numbers of research papers [42]. A review of the papers on the local scale is also important to identify the research gap in that study area as well as for the scientific community across the globe to understand the landslide characteristics and existing research in different geographical regions. This type of knowledge is important for specific areas and also significant for global-scale landslide susceptibility mapping research.

The quality of landslide susceptibility mapping methods is still improving by applying existing methods in a different way, hybridizing the methods or introducing new methods, with no exception in Bangladesh. The increased landslide frequency and damage in Bangladesh and the ever-growing landslide susceptibility assessment methods across the world as well as in Bangladesh pose significant importance to evaluate the existing research papers related to landslide susceptibility mapping in Bangladesh. The current research aims to conduct a systematic review of the published research papers on landslide susceptibility in Bangladesh by considering the following specific aspects: year of publication, the journal where published, location/size of the study area, landslide inventory type, method of susceptibility assessment/mapping, thematic variables, DEM characteristics, accuracy assessment methods and acquired accuracy of the models. This research will help to identify the existing research on landslide susceptibility mapping in Bangladesh, characteristics of the inventory data and thematic variables and validation methods used in the research. The findings of the research will help to identify the research gap by examining existing landslide susceptibility mapping methods which will be beneficial in future research on landslide susceptibility mapping in Bangladesh.

2. Materials and methods

The published papers about landslide susceptibility mapping in Bangladesh are collected by a systematic search using different journal domains and Google Scholar. Besides, a web page (https://www.landslidebd.com/publications/) containing most of the landslide-related research papers of Bangladesh is also used. The articles directly related to landslide susceptibility mapping are then selected manually. Papers published till December 2022 are considered in this research. Full-length peer-reviewed research papers are considered for this research. Keywords used for the literature search were “Bangladesh”, “Landslide”, “Susceptibility”, and “Landslide Susceptibility Mapping”. The papers considered are written only in English. The literature survey method is shown in Fig. 3.

From the selected research papers, the aspects considered for analysis are: (1) Year of publication-the year paper published, (2) Journal where published-name of the journal in which paper was published, (3) Location of study area-the study area covering the administrative unit was identified, (4) Size of the study area-the area considered for preparing landslide susceptibility map, (5) Landslide inventory data source-the source of landslide database used for analysis, (6) Method of susceptibility assessment/mapping-methods applied for landslide susceptibility mapping was identified, (7) Thematic variables-the thematic variables used for susceptibility mapping was collected and organized, (8) DEM characteristics-source and spatial resolution of DEM used in research, (9) Accuracy assessment methods-methods used for accuracy assessment of the landslide susceptibility map was identified, (10) Acquired accuracy of the models-the accuracy of the prepared landslide susceptibility maps was identified [28,29,42,43]. The impact of the selected aspects of on the accuracy of the landslide susceptibility maps was measured by Chi-square test and pearson’s, knedall and spearman’s correlation.

3. Results and discussion

After filtering manually, 21 papers were found that are directly related to landslide susceptibility mapping. All the papers are published in English and most of them are published in Springer, MDPI and Taylor and Francies journal domain. In this research, only full-length peer-reviewed papers are considered for analysis according to the selected criteria. Landslide has become a common hazard in the southeastern hilly areas of Bangladesh. Though the whole hilly areas are somehow vulnerable to landslides, the research focused on landslide susceptibility mapping is limited in regards to the number and specific study area. The study area did not always cover the whole hill tracts.

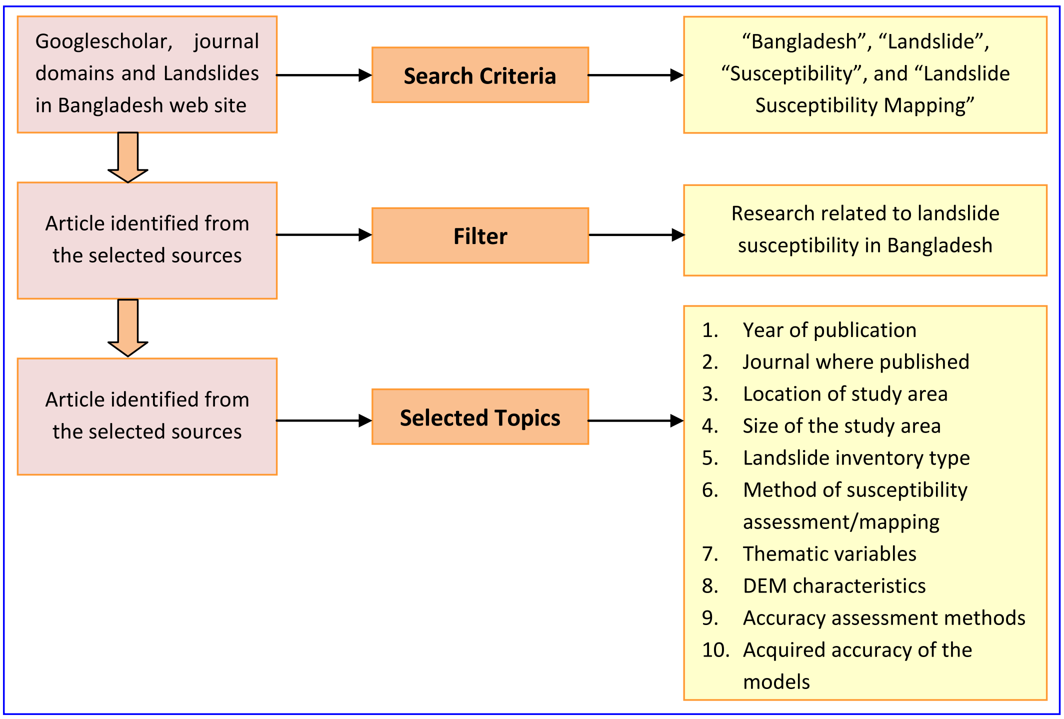

Fig. 3. Steps of systematic analysis process of the research.

3.1. Year of publication

Research papers related to landslide susceptibility mapping in Bangladesh increased between 2015 and 2022 (Fig. 4), but there is no gradual increasing trend during these eight years. The first three publications were from 2015 [13,17,44]. 36% of the papers were published in 2020, followed by 27% in 2022, 14% in 2015 and 2017 and 5% in 2021 (Fig. 4). No published paper was found in the year 2016 and 2019. During the first half (2015–2018) of the eight years, 32% of the total papers were published and during the second half (2019–2022), 68% of papers were published. Reichenbach et al. (2018) [26] counted two papers related to landslide susceptibility mapping in Bangladesh till 2016 and Lee (2019) [28] counted five papers till 2018. But in this research, three papers found till 2016 and seven papers found till 2018. It is because of the difference between the searching methods and publishing time of the papers.

3.2. Publishing journals of the research paper

The papers were published in 18 different journals focusing on geosciences, environmental engineering, hazards, remote sensing and landslides. The highest number of publications in Bangladesh are found in the Remote Sensing journal (14%) followed by the International Journal of Geoinformatics and Geocarto International (both have 9% of papers) (Fig. 5). The rest of the journals has 5% publications in each. The publication pattern of Bangladesh is focused on remote sensing and geoinformatics because remote sensing data and geographic information systems are extensively used in the research. There is extensive use of morphological, hydrological and land cover factors that are derived from remote sensing images of SRTM DEM, ASTER GDEM and Landsat images (Fig. 14) and processed by geographic information systems.

3.3. Location of the study area

The location of the study area is categorized according to the administrative district and then into a specific study location. All these research papers are focused on Chattogram, Cox's Bazar and Rangamati District (Fig. 6a) and only two papers considered the whole Chattogram Hilly Area (Fig. 7). All three districts have seven papers.

When considering the specific study area, most of them found focusing only on the metropolitan area or the area under the City Corporation of the districts (Fig. 6 b,c,d and e and Fig. 8). The highest number of publications were found for Rangamati City (Fig. 6d and 8) followed by Chittagong Metropolitan Area (Fig. 6b and 8), Chittagong City Corporation (Figs. 6c and 8), and Rohingya Refugee Camp (Fig. 6e and 8). Due to severe landslides in 2017, Rangamati metropolitan area got attention for studying landslide susceptibility [6,18,45–47]. Two papers were found studying the whole Rangamati district [6,48] and one paper was found studying the whole Chattogram district [49] for preparing the landslide susceptibility map (Fig. 7).

Rohingya Refugee Camp though established in 2017 due to the forced migration of the Rohingya community from Myanmar [3,50], it got paramount importance in landslide susceptibility mapping research [50–52]. Beside landslide susceptibility mapping, there are some other research also evident considering geotechnical process mechanisms regarding landslides in Rohingya refugee camps [53]. As the Rohingya Refugee Camp is the largest refugee camp in the world and they are facing severe crisis due to landslides the region has got importance within a short time.

The other study areas covered administrative units of Rangamati city, Rangamati municipality, Chattogram metropolitan area and Chattogram City Corporation because of the high concentration of landslide events and corresponding damage in these specific areas. Because of the high exposure of the population, road connection and economic resources in the city hub, these administrative areas got the paramount importance during landslide susceptibility mapping. Accessibility to landslide locations is also a factor for the highest concentration of research work in those areas. Besides, most of the information on landslides is also found in the city areas or along the road connection. The information on landslide occurrence in inaccessible areas did not cover and sometimes ignorable loss also restricts landslide information though it is a large landslide. This indicates, in Bangladesh, casualties and economic loss get the highest

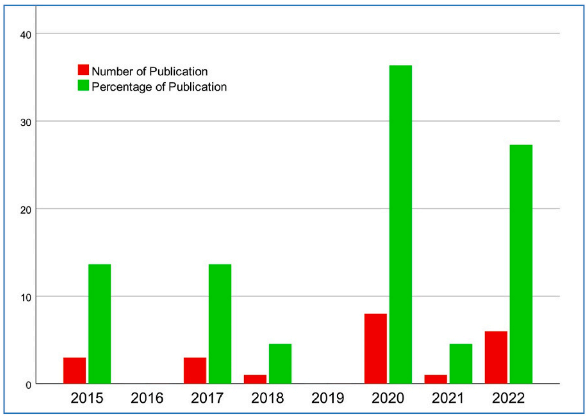

Fig. 4. Year of publication on landslide susceptibility mapping in Bangladesh from 2015 to 2022.

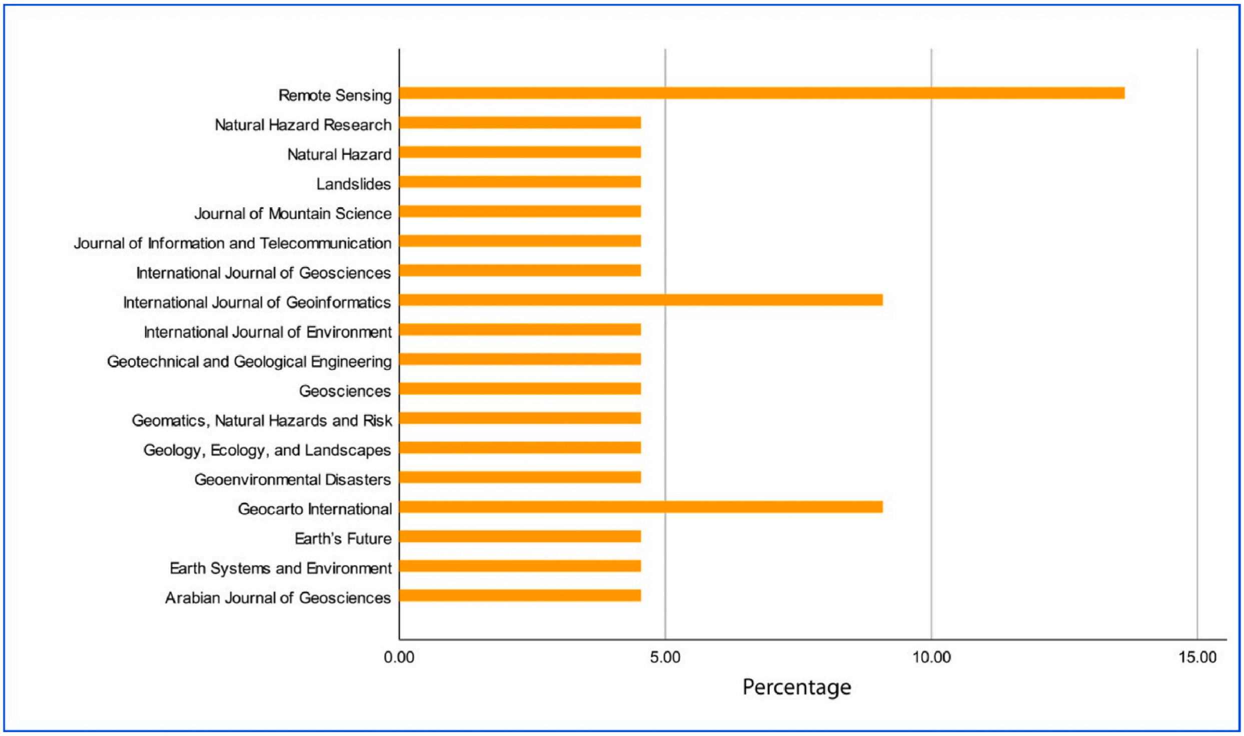

Fig. 5. Journal with landslide susceptibly mapping publications in Bangladesh.

importance considering landslide event as a disasters over natural resources loss.

3.4. Size of the study area

The size of the study area mentioned in the research is categorized in Fig. 9. Except for Sifa et al. (2020) [18], the size of the study area is found in all the other research papers. The highest number of research papers covers 501-100 and 1001–2000 square kilometres of area and both have a frequency of 4. Three papers have study areas of less than 100 square kilometres and another three papers have study areas between 1001 and 2000 square kilometres. The size of the study area was always determined by the administrative unit. There was no research conducted considering natural boundaries like hill range units or basin units. This may alter the susceptibility zones and visualize more accurate areas of landslide susceptibility.

3.5. Landslide inventory type

In Bangladesh, most of the landslide susceptibility map is prepared using field survey data. Twelve literatures have used field survey data for preparing landslide susceptibility maps and three used secondary data which is also somehow related to the field surveys (Fig. 10). The combined use of field survey and google images is found in two literatures (Fig. 7). Ahmed et al. (2020a) [51] did not mention the inventory data source. Sifa et al. (2020) [18] used SAR offset tracking technique, Khatun et al. (2022) [6] used Google Earth images with sphere identification and authentication and Hafsa et al. (2022) [48] used both google image interpretation and field survey. Rabby and Li (2019) [20] prepared a landslide inventory database for the whole hilly areas using used both google image interpretation and field survey. Ahmed et al. (2020a) [51] did not mention the source of the inventory data. Adnan et al. (2020) [54], Rabby et al. (2020a) [45] and Chowdhury and Hafsa (2022) [49] used secondary data but the inventory was prepared based on field survey, first, one used the inventory data of Ahmed et al. (2020b) [52] and the rest of the two used inventory data of Rabby and Li (2020) [8], respectively. Islam et al. (2017) [24] also used secondary data but they directly relied on secondary data sources from different web portals.

3.5.1. Characteristics of inventory database

Some remarkable characteristics of inventory data are shown in Table 1. It is found that 19 literature used landslide inventory data either by conducting field surveys or collected from other sources. In Bangladesh, 12 literatures used training and testing data during landslide susceptibility mapping which is almost 60% of all literature. Eight of the literature used all the inventory data for training purpose. Maybe the limited number of inventory data is the cause of using all data for training purposes. Besides, the use of knowledge driven and bivariate models methods also encourages using all data for training purpose. Among the literature, only six used non-

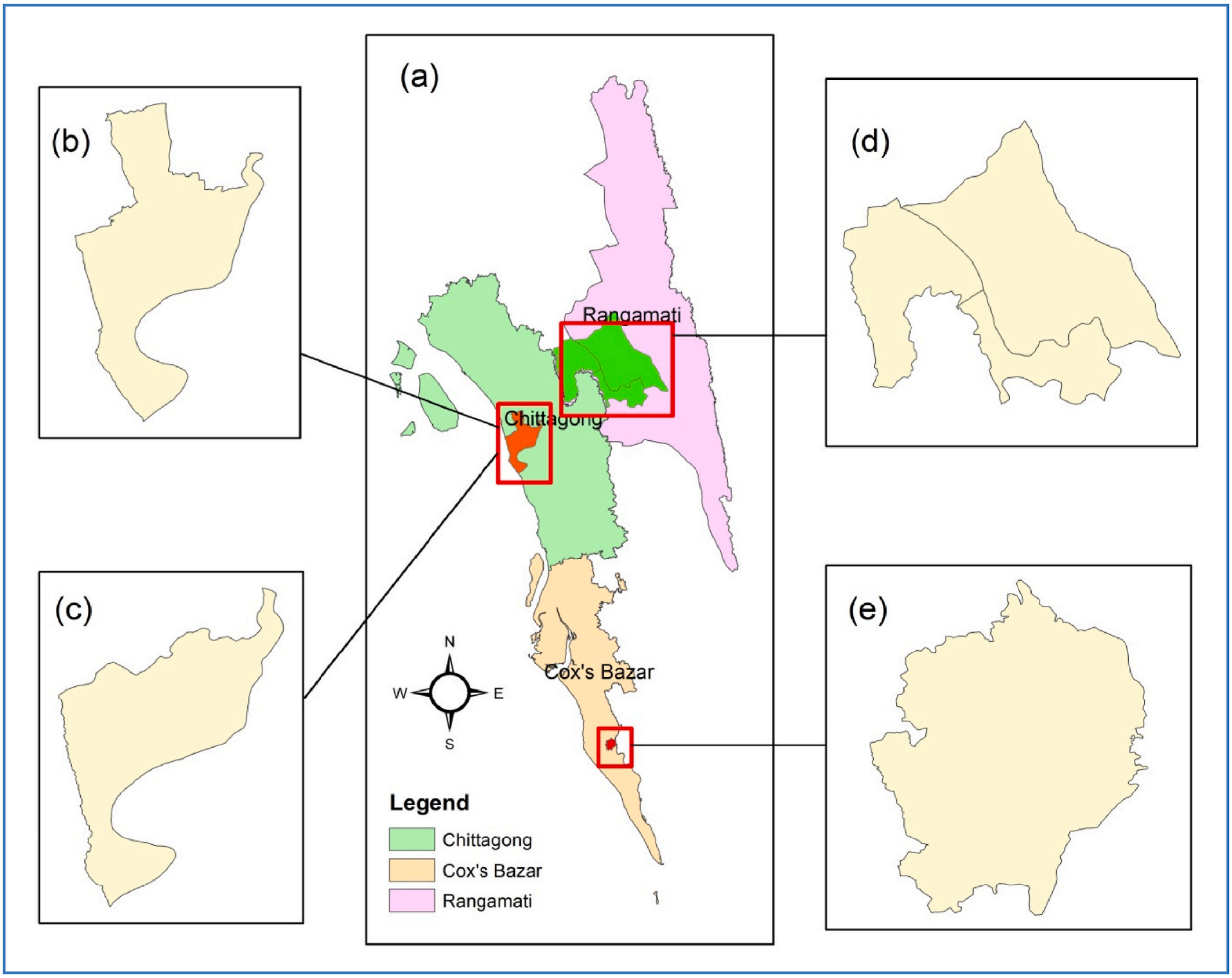

Fig. 6. Areas covered by landslide susceptibility research. a) three hill districts studied in research, b) Chattogram metropolitan area, c) Chattogram city corporation area, d) Rangamati municipality and e) Kutupalong Rohingya refugee camp.

landslide data in the inventory database. The use of non-landslide location is very common practice in multivariate, machine learning and deep learning methods because the use of non-landslide location reduces the bias of the result. There are different ranges of dividing testing and training data in Bangladesh. There is no strict rule followed during dividing the dataset into testing and training.

The frequency of the size of the landslide inventory dataset is also measured (Fig. 11). Most of the landslide inventory data had sample sizes between 50 and 500 and the frequency is 13 (Fig. 11). Three papers were found with a landslide inventory size of less than 20 samples and one research was found with an inventory size greater than 1000. The largest-sized inventory data was used by Emberson et al. (2021) [55] contains more than 2300 samples. This database was collected from UNDP and the database was developed at Rohingya Refugee Camp.

Lee (2019) [28] found that almost 27.1% of the articles that he reviewed studied less than 100 landslides. Comparing to other region, landslide inventory is more clear and detailed in Bangladesh. But it needs improvement in respect to area covered and event occurred.

3.6. Landslide susceptibility mapping methods used in Bangladesh

In Bangladesh, a total of 27 types of methods were applied to prepare landslide susceptibility maps. In this case, all the methods used in each of the publications are considered. The most frequently used methods are Logistic regression (six times), Random forest (six times), Frequency ratio (six times), Analytical hierarchy process (five times), Weight of evidence (four times) and Multiple regression (three times) (Fig. 12). In some papers, instances of model integration was found such as frequency ratio integrated with logistic regression [8,48] and analytical hierarchy process [8] and Dempster-Shafer method integrated with the weight of evidence method [7].

Logistic regression is the most common method used for landslide susceptibility mapping globally followed by frequency ratio,

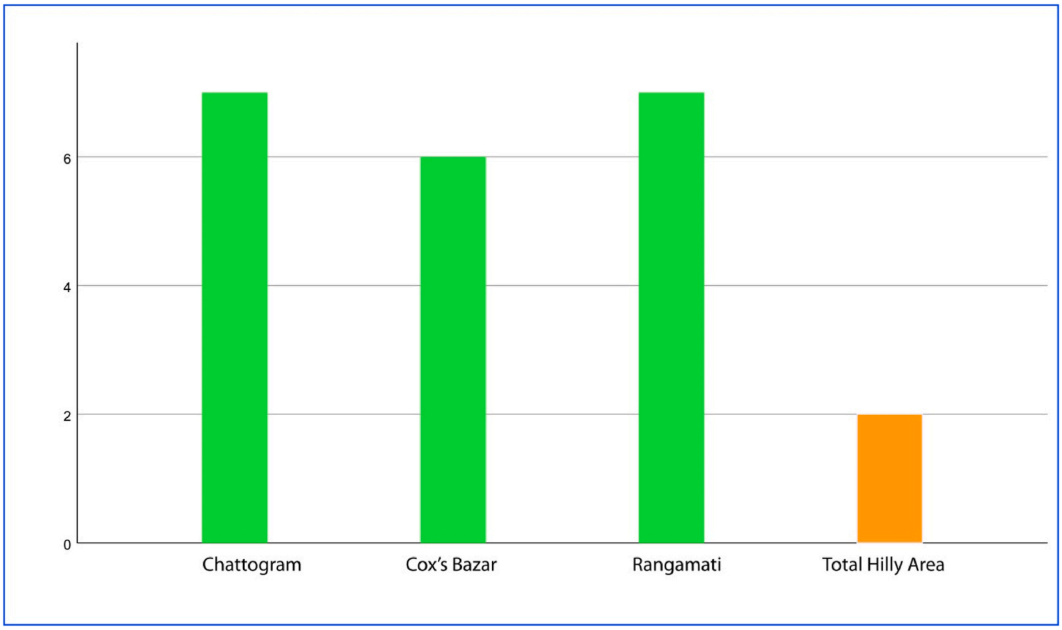

Fig. 7. Number of research paper according to district.

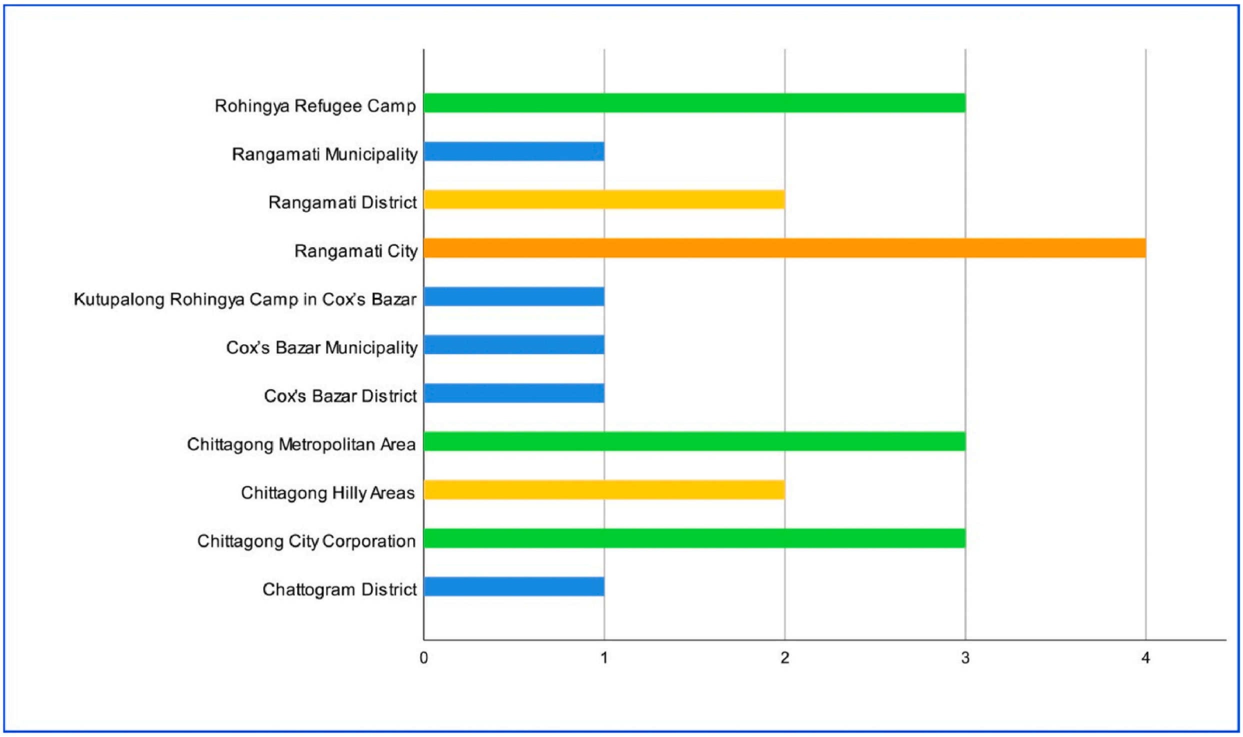

Fig. 8. Number of research paper according to specific study area.

artificial neural network, fuzzy logic, support vector machine, analytical hierarchy process and weight of evidence [38]. In recent times, the use of machine learning algorithms has become extensive in landslide susceptibility mapping research across the globe [40]. But the instances of the use of these models are very limited in Bangladesh. The only use of use logistic regression (6 times), random forest (6 times), support vector machines (2 times) and artificial neural networks (1 time) are found (Fig. 12).

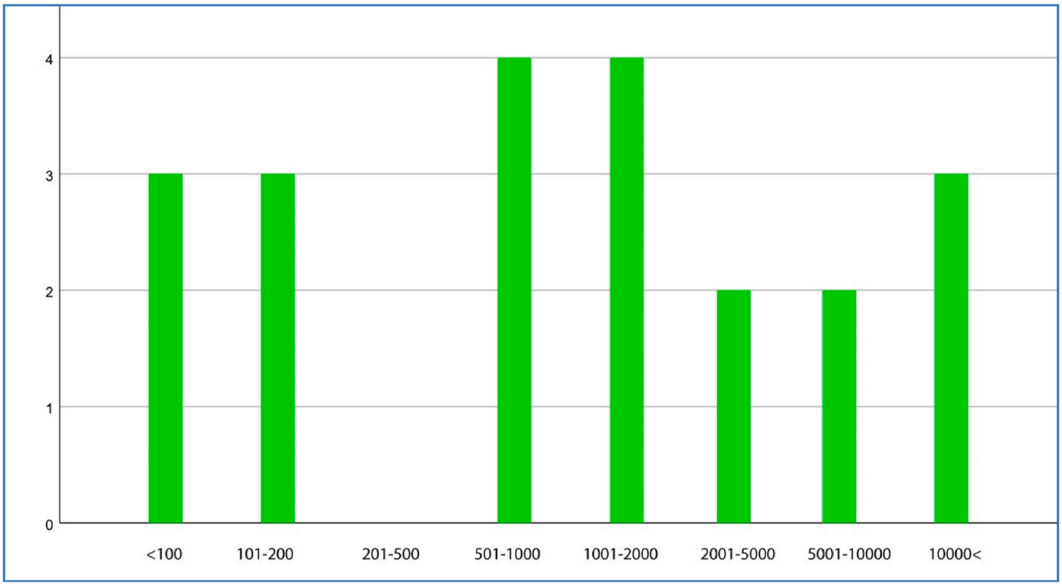

Fig. 9. Size of the study area in square kilometers.

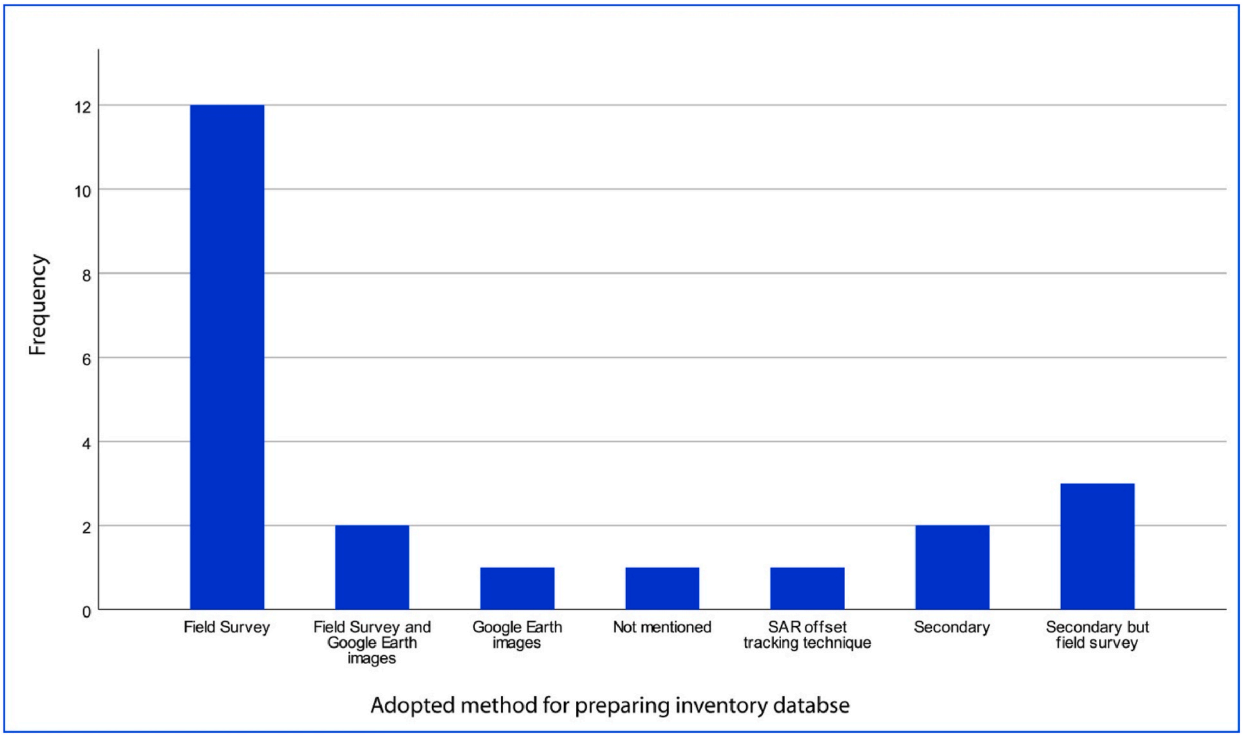

Fig. 10. Inventory data source for LSM of all publications.

3.6.1. Categorization of LSM methods in Bangladesh

Sixty instances of landslide susceptibility maps are found in literatures are categorized into knowledge-driven, bivariate, multivariate and machine learning (Fig. 13) following the classification scheme of Corominas et al. (2014) [30]. In Bangladesh, Bivariate (37%) and knowledge driven (23%) methods were used most frequently followed by multivariate method (22%) to prepare LSM (Fig. 13). But the number of LSMs prepared using machine learning algorithms is very limited. Only 18% of maps were prepared using the machine learning method (Fig. 13). In Bangladesh, the use of machine learning and multivariate methods is very limited compared to knowledge-driven and bivariate methods (Fig. 13). The small number of landslide samples in inventory (Fig. 11) may encourage

Table 1
Main characteristics of inventory database.

Characteristics	Frequency	Ratio of Testing and Training Data	Frequency
Use of Inventory	20	Training 50% and Testing 50%	1
No Information of Inventory	2	Training 60% and Testing 40%	1
All data used for Training Purpose	8	Training 70% and Testing 30%	3
Use of Training and Testing Data	12	Training 75% and Testing 25%	4
Use of Non Landslide Data	6	Training 80% and Testing 20%	3

The most frequently used ratio is 75% training and 25% testing data [18,45,46,48] followed by 80% training and 20% testing data [8,47,51] and 70% training and 30% testing data [55–57]. Adnan et al. (2020) [54] used 60%/40% and Rahman et al. (2017) [58] used 60%/40% data for training and testing purposes, respectively (Table 1).

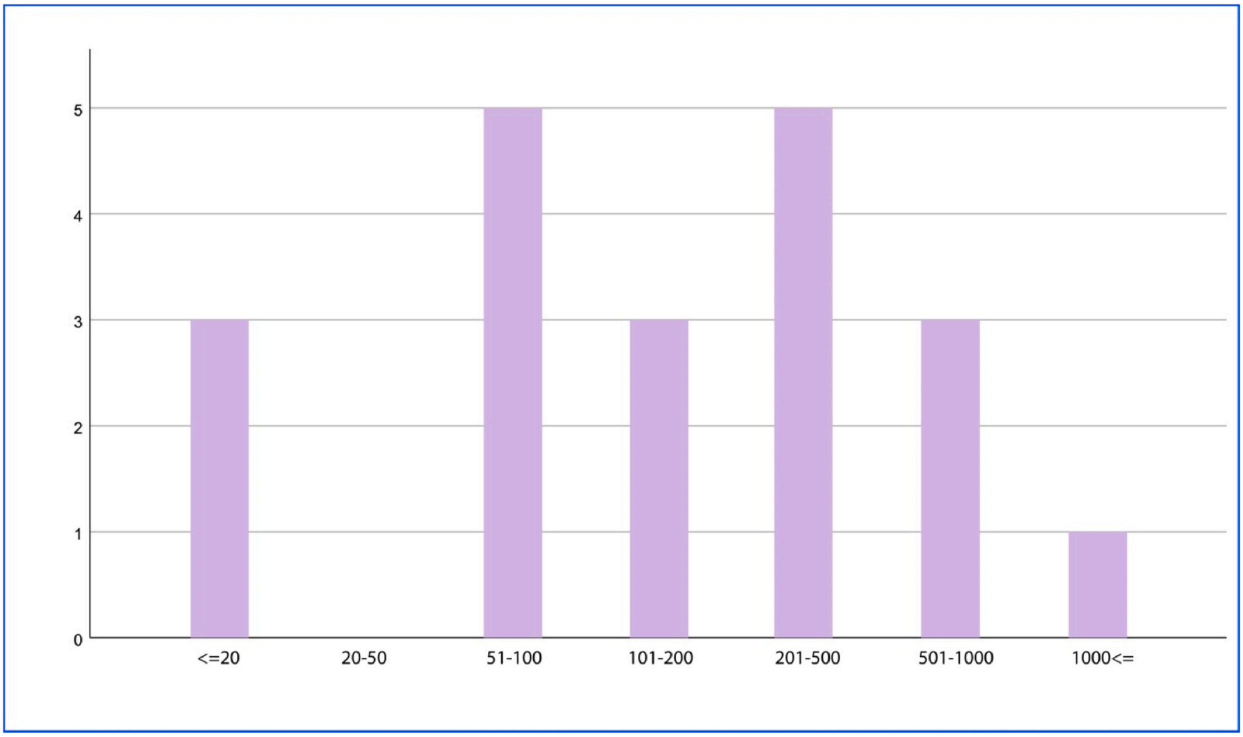

Fig. 11. Number of landslide location in inventory database.

researchers to use the bivariate and knowledge-driven approach [7,13,17]. Machine learning methods can produce good results using a small number of samples such as support vector machines [39] but the larger the sample size the more accurate will be the result [59].

3.6.2. Methods used in administrative district

The classification scheme of Corominas et al. (2014) [30] is also applied to the individual districts. The use of bivariate, multivariate and machine learning methods is found for all three studied districts (Fig. 14). Knowledge driven approach was not found for the Rangamati district.

Though machine learning and deep learning methods are popularly and extensively being used across the world but their use is very limited in Bangladesh. There is no specific method had been developed that can be considered the best method for landslide susceptibility mapping, so, there is a need to apply different types of machine and deep learning methods in Bangladesh.

3.7. Thematic variables used in literature

45 types of landslide conditioning factors were used in the literature. The most frequently used conditioning factors are Slope angle (21), Land use and land cover (17), Aspect (17), Elevation (16), Geology (16), NDVI (16), Distance from road (14), Rainfall (12) and Distance from stream (11) (Fig. 15). Only mathematical methods are used to produce LSM in Bangladesh, so, suitable conditioning factors are used. In most cases, easily producible conditioning factors from DEM data were used more frequently. The easily available and producible data source was also in the first propriety such as almost all the morphological and hydrological variables can be

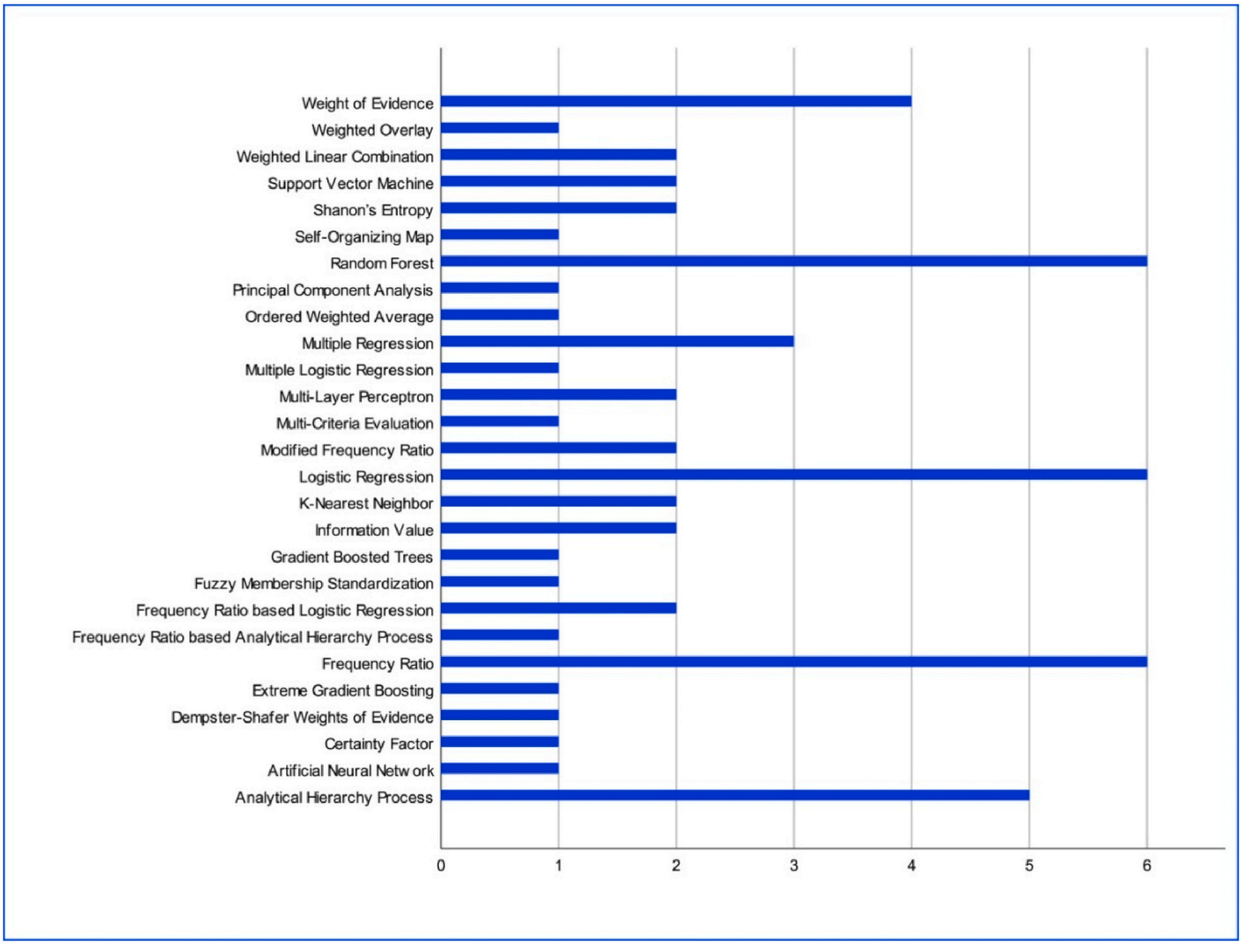

Fig. 12. Number of methods used in Bangladesh.

produced by processing DEM (Digital Elevation Model) and both of the variables comprise 50% of the total variables used (Figs. 15 and 16). In the case of climatic variables, only rainfall is used. In Brazil, according to Dias et al. (2021) [42], wind force is considered as a thematic variable in landslide susceptibility mapping. During prolonged rainfall landslide occurs and during that time wind speed also remains high enough due to the tropical climatic condition, so, it can be considered as a landslide conditioning factor in Bangladesh.

Slope, lithology, aspect, land use/land cover, elevation, distance from river and distance from faults had been popularly used across the globe for landslide susceptibility mapping. The use of distance from road, precipitation, topographic wetness index, curvature and drainage density has increased in recent times [38]. Pourghasemi et al. (2018) [38] compared the use of these factors between two time periods 2005–2012 and 2013–2016. Lee (2019) [28] divided the use of conditioning factors into the three-time intervals and found slope, geology, soil, aspect, land, forest, and curvature are extensively used between 1999 and 2008 and slope, geology, river or stream, aspect, land use, curvature and fault used between 2009 and 2013 and slope, curvature, geology, river or stream, aspect, elevation and land use had been used between 2014 and 2018.

Slope, geology, aspect and curvature have got the first preference in landslide susceptibility mapping across the world and river or stream, land use and fault are getting importance in recent times [26,28,38]. One very important parameter significantly assessed in Bangladesh is land use and land cover change. As the hilly areas had undergone extensive land cover change due to the increased population, except for land use and land cover, land use and land cover change have a significant impact on landslides in respect of Bangladesh.

In Bangladesh Slope angle (21), Aspect (17), Land use and land cover (17), Elevation (16), Geology (16), NDVI (16), Distance from the road (14), Rainfall (12) and Distance from Stream (11) has been given the highest importance in landslide susceptibility mapping. To get a more realistic susceptibility map, geological and lithological factors that are directly affected by rainfall can be considered in Bangladesh.

3.7.1. Categorization of conditioning factors in Bangladesh

In Bangladesh, morphological factors (33%) are more frequently used in literature followed by hydrological (17%), land cover (15%) and geological (13%) factors (Fig. 16). Human footprint over specific morphological features is a significant triggering factor

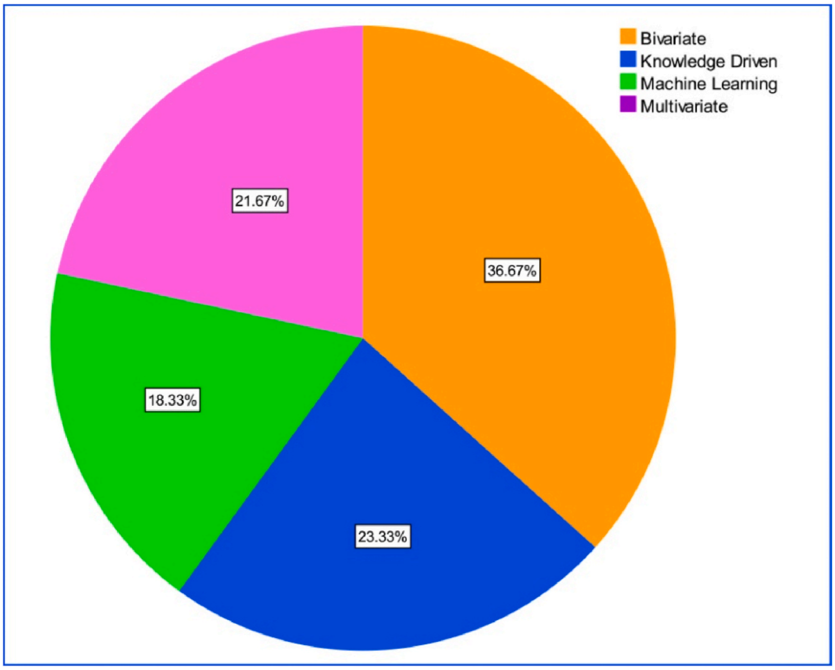

Fig. 13. Percentage of methods used for landslide susceptibility mapping in Bangladesh.

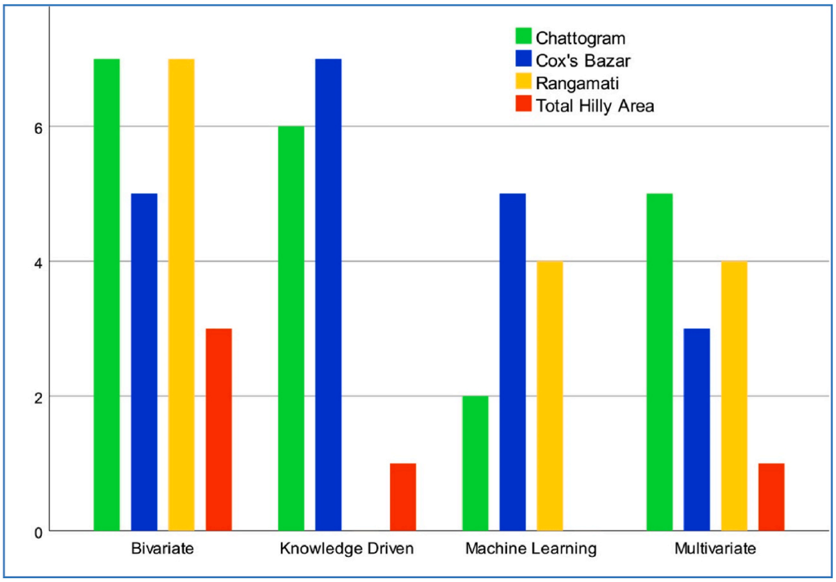

Fig. 14. Method used to prepare LSM according to district.

followed by rainfall.

3.8. DEM characteristics

In Bangladesh, ASTER GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model) is used to prepare 48% of the landslide susceptibility map. In some papers more than one DEM was used to check the accuracy of the maps according to different resolutions and different sources of DEM [46]. As different models were also tested in one paper, all the maps found in each paper are aggregated for this analysis. Use of SRTM (Shuttle Radar Topography Mission) DEM constitutes the second highest portion (28%) in landslide susceptibility mapping (Fig. 17a). Other types of DEM had been used are ALOS (Advanced

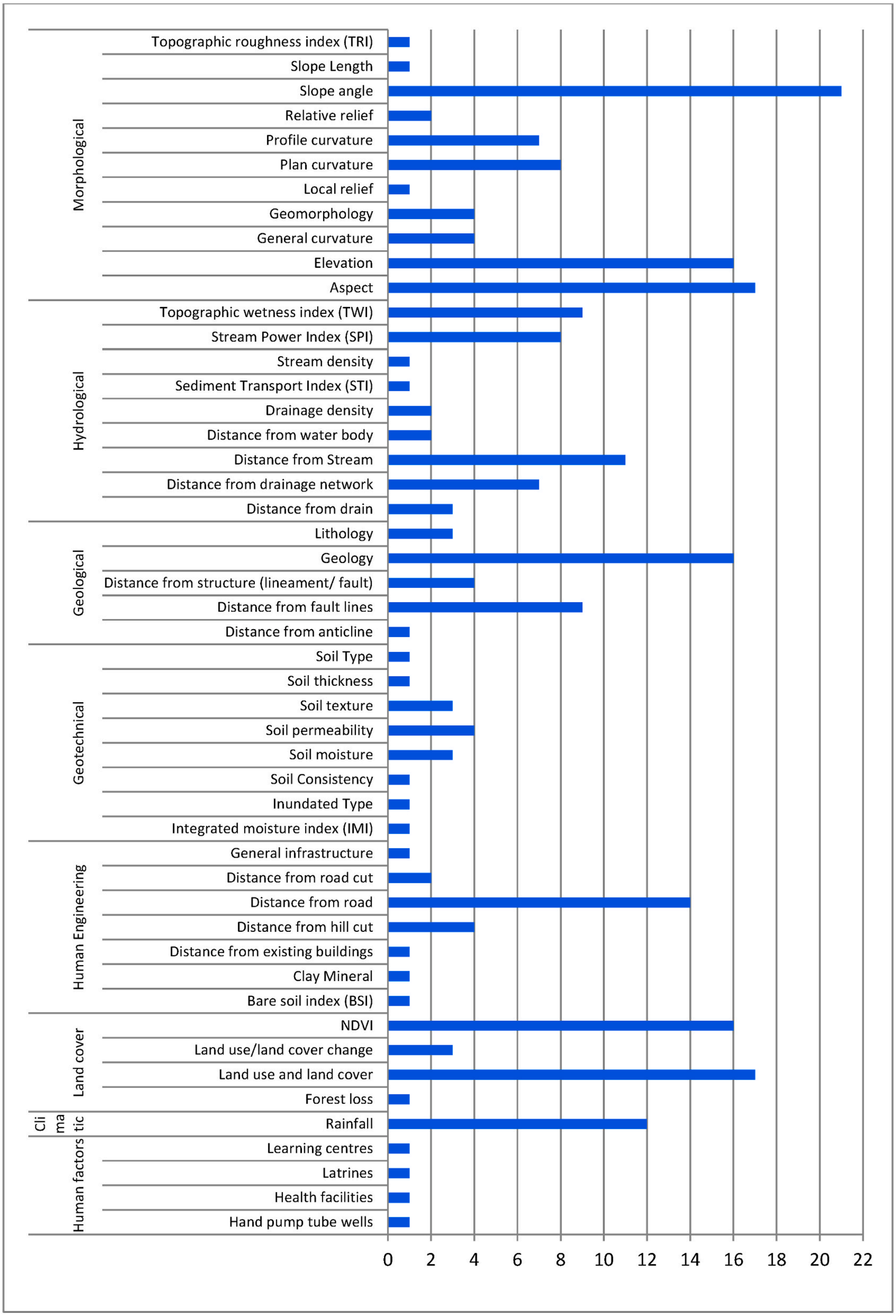

Fig. 15. Categorization and Frequency of Conditioning Factors used in Bangladesh.

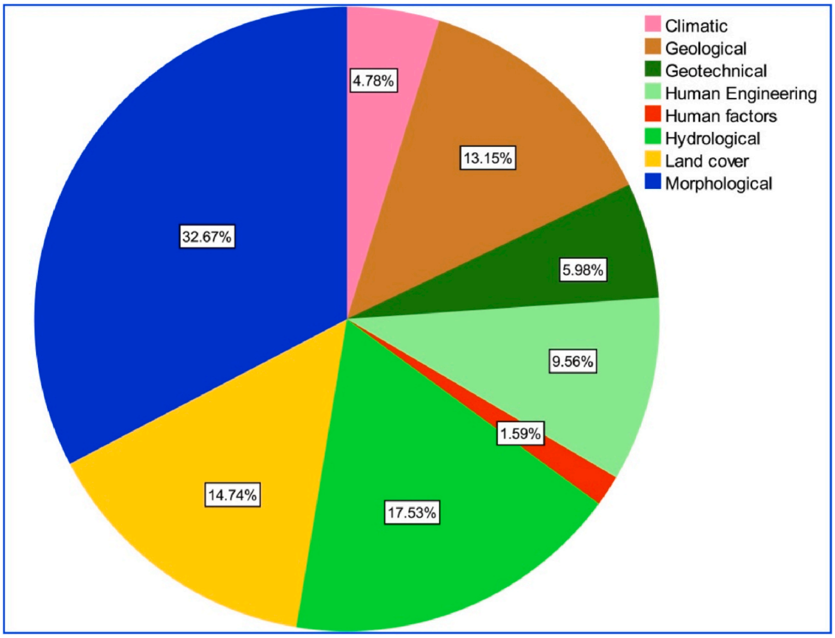

Fig. 16. Percentage of conditioning Factor used in Bangladesh.

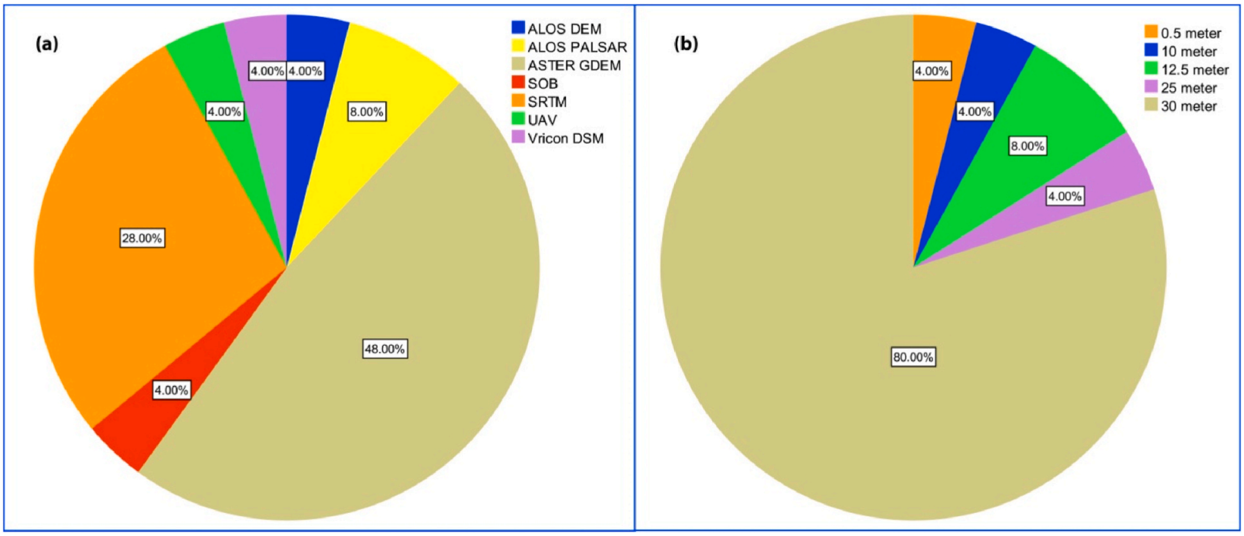

Fig. 17. Source of DEM

Land Observing Satellite) PALSER (8%), ALOS DEM (4%), SOB (Survey of Bangladesh) (4%), UAV (Unmanned Aerial Vehicle) (4%) and Vricon DSM (4%).

A variety of spatial resolution of DEMs was also found, but 30 × 30-m DEMs are used more frequently in the research and it is used to prepare 80% of the landslide susceptibility maps (Fig. 17b). The rest of the DEMs were used 4% times each. SRTM DEM and ASTER GDEM have a 30-m spatial resolution. DEM of SOB is 25-m spatial resolution, ALOS PALSER is 12.5-m resolution, Vricon DSM is 10-m resolution and UAV DEM is 0.5-m resolution. DEM of SRTM, ASTER and ALOS PALSER are freely available across the world. SOB is the government authority in Bangladesh which prepares DEM for Bangladesh. Vricon DSM is a commercial DEM that can be brought using API. UAV DEM is prepared for the Rohingya Refugee Camp in Bangladesh and it is also not accessible for all.

3.8.1. Mapping units

Landslide susceptibility maps or susceptibility terrain zonation significantly affected by the selection of mapping units. So that it is considered as a fundamental step in landslide susceptibility mapping [26]. Guzzetti (2006) [22] discussed the advantages and limitations of different mapping units in landslide susceptibility mapping research. Reichenbach et al. (2018) [26] reviewed the mapping units used in landslide susceptibility mapping across the world and found 86.4% of the studied papers used “pixel” as mapping unit. The other types of mapping units used are slope units and unique conditions units found in literatures are 5.1% and 4.6% respectively. The other types or combinations of the above three types are found in 3.9% across the world. In Bangladesh, only “pixel” is used as mapping units for landslide susceptibility mapping.

3.9. LSM verification methods used in Bangladesh

Out of 22 literatures, 4 of them did not measure the accuracy (Fig. 18) of the landslide susceptibility map [14,18,24,44]. Sifa et al. (2020) [18] prepared the AUC curve to show the success rate of the landslide susceptibility map but no specific value of AUC was mentioned rather indicating the percentage of landslides covered by the susceptibility zones. Ahmed et al. (2020a) [51] mainly relied on the AUC of ROC for validation, besides they also measured the confusion matrix for all the models applied. Along with AUC, Rabby and Li (2020) [8] used true positive and false negative rates and overall accuracy of the landslide susceptibility map. Rabby et al. (2020a) [45] measured statistical indices of true positive and false negative rates, overall accuracy and kappa index of landslide susceptibility map along with AUC. The rest of the literature used either AUC or AUC of ROC for validation purposes.

3.10. Accuracy of the LSMs in Bangladesh

Literature used AUC, Area under ROC, ROC, confusion matrix and kappa indices for validating LSM. But all the methods did not use testing data for assessing the prediction performance of LSM. Fig. 19 shows the accuracy assessment results of landslide susceptibility maps in Bangladesh where both the success rate and prediction rate are considered. Most of the maps have accuracy between 70% and 80%. In the case of the AUC of ROC accuracy is found between 80 and 100%. A very small portion of the maps is found that have accuracy below 70%. AUC value between 70 and 80% represents a good performance of the model.

AUC value between 50 and 60% or less than 50% indicates a very poor performance of the model and if it is less than 50% the model cannot be applied in landslide susceptibility analysis. AUC value between 60 and 70% indicates the average performance of the model, between 70 and 80% indicates a good performance, and between 80% and 90% indicates a very good performance of the model and 90–100% indicates an excellent performance of the model [60]. In Bangladesh, AUC of ROC indicates excellent performance and AUC indicates a good performance of the models. So there is a need to check some other models to get a higher accuracy model for Bangladesh. This need can be met using machine and deep learning models for landslide susceptibility mapping. Machine and deep learning and also model hybridization have produced comparatively higher accuracy in landslide prediction across the world [61–63].

The accuracy of the maps is also demarcated into success rate and prediction rate. The prediction rate is not measured for all the models. The success rate curve is prepared by comparing the prediction map and the landslide data used in the model [64]. The prediction rate curve compares the prediction map with testing data that have not been used in the model [64]. Among this two, the prediction rate is more reliable for understanding the performance of the landslide susceptibility map.

Both the success rate and prediction rate are demarcated and their accuracy ranges are shown in Fig. 19. The highest success rate of AUC was found between 70 and 80% and the highest AUC of ROC is distributed between rage of 80–90% and 90–100% (Fig. 19)

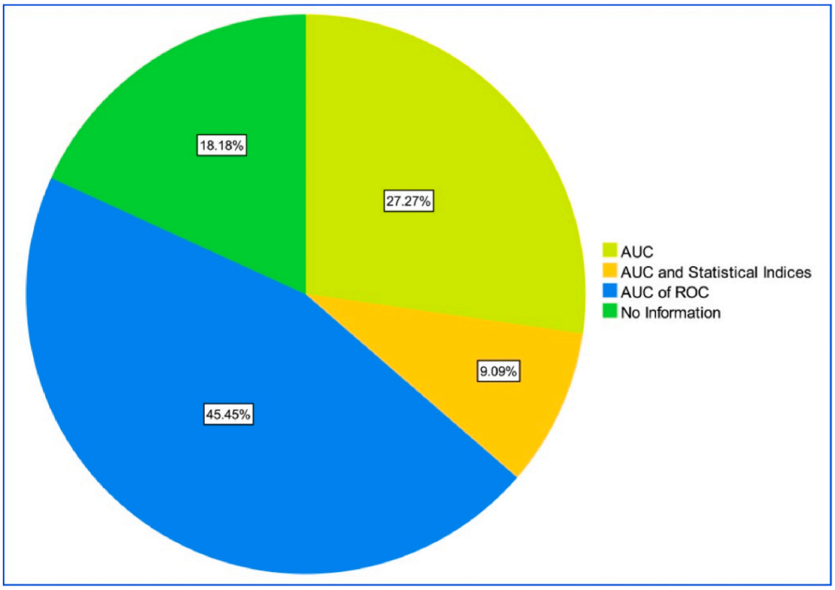

Fig. 18. Accuracy assessment methods used in Bangladesh.

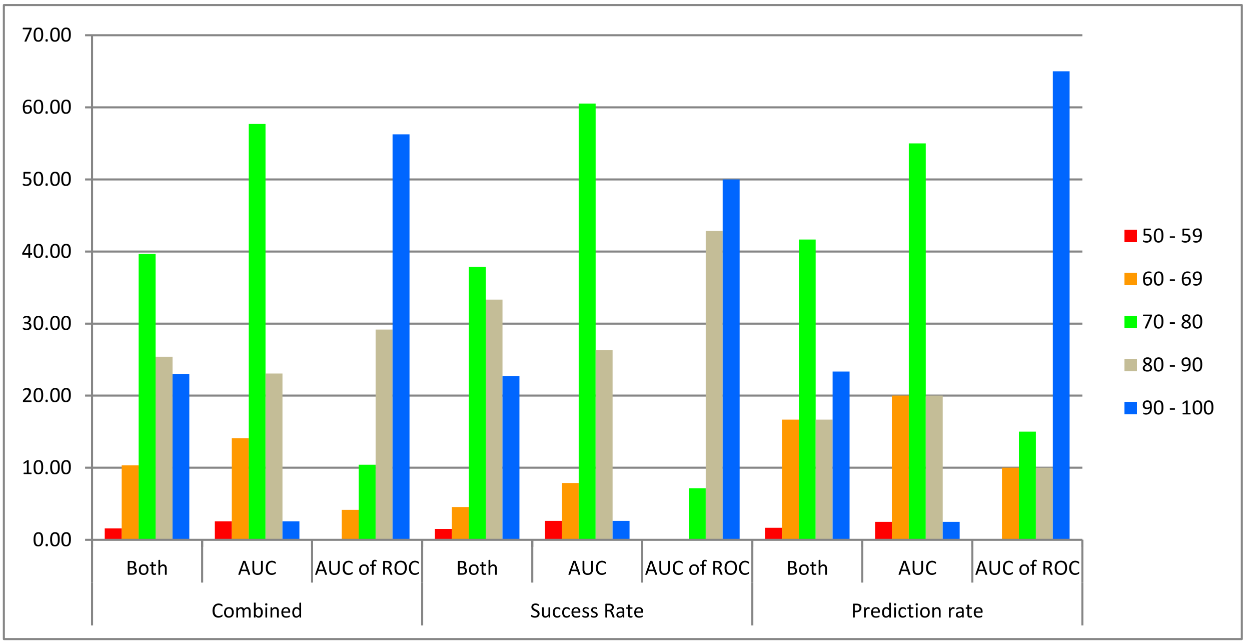

Fig. 19. Accuracy assessment results of landslide susceptibility maps in Bangladesh.

indicating a good agreement of the landslide susceptibility map.

In the case of prediction rate, the highest AUC distributed in the accuracy range between 70 and 80% indicating a good prediction rate of future landslide and the highest AUC of ROC was found between accuracy ranges between 90 and 100% indicating an excellent prediction power of future landslide of the landslide susceptibility maps.

In most cases AUC values are distributed between the accuracy range between 70 and 80% and AUC of ROC is distributed above 80% and in most cases, they are found between 90 and 100%.

3.11. Significance and correlation of selected features with accuracy

The Chi-square test was performed between the accuracy of the maps and Success and Prediction Rate, Mapping Method, DEM Type, Accuracy Assessment Method, DEM Resolution, Size of Study Area, Size of Inventory, Number of Factors and Use of Non-Landslide Point (Table 2) at 95% significance level. There is no significance found between the accuracy of maps and the corresponding factors. Though different resolutions of DEM have different effects on landslide susceptibility maps [46,65,66], in Bangladesh no significance was found. Rabby et al. (2020b) [46] found significant improvement in accuracy after increasing the number of conditioning factors. But when all the maps of the published papers are considered an insignificant relationship was found. It is not certain that increasing the number of conditioning factors will increase the accuracy of the landslide susceptibility map. The size of inventory data also showed no effect on the accuracy of landslide susceptibility map.

Because of the presence of some categorical variables, Chi-square was tested first and then the correlation of some factors was tested as they have numeric values. Correlation between accuracy and Size of the study area, Size of Inventory, DEM resolution and Number of Conditioning Factors were measured (Figs. 20 and 21 and Table 3) at 95% significance level.

Pearson's (Fig. 20), kendall (Fig. 21) and spearman's (Fig. 21) correlation coefficients were measured for the selected variables at 95% significance level. But there was no significant correlation was found between them. But in all cases, DEM resolution showed a comparatively high correlation with map accuracy.

Table 3 shows the correlation value and it is found that only DEM resolution has a comparatively better correlation with accuracy at 95% significance level. In spearman's test, it showed a 0.438 correlation value.

3.12. Direction to the future research

The result section shows that there are limited numbers of publications and are also many limitations in landslide susceptibility mapping research in Bangladesh. The use of machine learning algorithms in landslide susceptibility mapping is very limited in Bangladesh and no evidence was found for deep learning algorithms and physically-based methods [29]. Deep learning algorithm and their hybridization and ensembles are producing a very good results across the world [61–63,67–69]. In many tropical regions where rainfall is very dominant and shallow landslides are more common, different physically-based methods such as SHALSTAB, SINMAP, TRIGRS, SLIP etc. are successfully used for landslide susceptibility mapping [29,70]. Marin et al. (2021) [71] found very good accuracy of physically-based models in a data-scarce region. Physically-based methods can also be used for regional-scale landslide

Table 2
Significance (95%) of considered factors on the accuracy of landslide susceptibility maps.

Features	X-squared	df	p-value
Success and Prediction Rate	212.74	228	0.758
Mapping Model	2775	2736	0.297
DEM Type	844.76	798	0.122
Accuracy Assessment Method (AUC or AUC of ROC)	121.76	114	0.292
DEM Resolution	484.84	456	0.1692
Size of Study Area	1781.2	1710	0.113
Size of Landslide Inventory	1538.7	1482	0.149
Number of Conditioning Factors	1075.5	1026	0.138
Use of Non Landslide Data in Inventory	119.96	110	0.243

susceptibility mapping and analysis can be done within a short time. Some "plugins" of physically-based models are also available in different GIS software such as QGIS [34–36].

Like other areas of the world, the geographical bias in landslide susceptibility mapping [29] is also evident in Bangladesh. The administrative units are considered during landslide susceptibility mapping, where only three landslide-affected districts were studied and the rest of the two districts Khagrachhari and Bandarban are un-served. Landslides of the other areas should also need to asses to better understand the slope failure mechanism over the hilly areas. Sylhet region of Bangladesh is also facing landslides in recent times and casualties are also considerable [12] but not studied yet.

A detailed national landslide inventory database is required containing all types of information about landslides in Bangladesh. In some countries national level initiatives had been taken such as the UK has a national landslide database [72], India had taken the initiative to produce a national level micro-scale landslide susceptibility map [73], Denmark [74] and Ireland [75] has national landslide susceptibility maps and related database. CDEMA (Caribbean disaster emergency management agency) has a national database for Caribbean nations and they have specific guidelines for landslide inventory database creation [76]. Similar guidelines are also found in India [73].

In Bangladesh use of non-landslide locations for training purposes is limited. But it is well established that non-landslide sampling reduces the bias of the probabilistic model. There are several methods used for non-landslide sampling such as random choice [77], buffer analysis [78], Mahalanobis distances [79] etc. In Bangladesh non-landslide sampling is always produced arbitrarily (random choice) considering all the areas out of landslide are non-landslide locations. During non-landslide sampling buffer analysis [78], Mahalanobis distances [79] should be considered because the distance of non-landslide location has a significant impact on the accuracy of landslide susceptibility map [77,78]. Non-landslide sampling in environmental and lithological heterogeneous and homogeneous areas also affects the accuracy of statistical models [80]. So these should be considered during landslide susceptibility mapping in Bangladesh because these are not tested yet.

The proportion of training and testing data significantly affects the prediction of landslide susceptibility models especially machine learning models [32]. With increased training samples accuracy also increases [81]. This should be considered in two aspects such as dividing samples during training machine learning models and during the selection of input data [82].

In GIS-based landslide susceptibility mapping, inventory data is divided into two parts one for model training and another for map validation. There is no strict rule followed during the data split, roughly 70–90% was used for modelling and 30-10% was kept for map validation. During modelling again 70% data is divided into training and testing the model performance. It should be addressed during research how much data was used for training purposes and how they are applied. Because additional data in the model changes the prediction of the model and also affects map accuracy during map validation.

It is also required to produce landslide susceptibility according to the different characteristics of landslides. Because this type of susceptibility mapping also provides the environmental characteristics of different landslides in different areas. Superimposing these types of maps may produce more accurate and realistic landslide susceptibility maps.

In different areas of the world, landslide susceptibility maps were produced according to the natural boundary or specific characteristic areas such as road corridors, and urban areas. This type of mapping is more important because landslide not follows the administrative boundary but rather a natural boundary as it is a natural phenomenon [62,69,83–86].

Nowadays UAV is successfully applied in landslide susceptibility mapping in different areas of the world and producing very good maps. Freely available DEMs are not upgraded and they are almost 10–20 years old. So, to produce a real-time and up-to-date landslide susceptibility map, UAV can be a great solution [87,88].

Landslide susceptibility maps of Bangladesh were produced on pixel-based assessment. Slope unit-based mapping sometimes produced more accurate results compared to pixel-based mapping. Bivariate, machine learning and deep learning algorithm can be used in slope unit-based assessment. In Bangladesh, this type of analysis has still not been conducted and it needs to implement such kind of analysis [89,90].

4. Conclusion

This literature review and meta-analysis revealed different aspects of landslide susceptibility mapping research in Bangladesh, especially, the commonly used input data and methods, acquired map accuracy and the relationship between map accuracy and input data characteristics. Results depicted that there is a variety of methods used in literature but the application of machine learning and

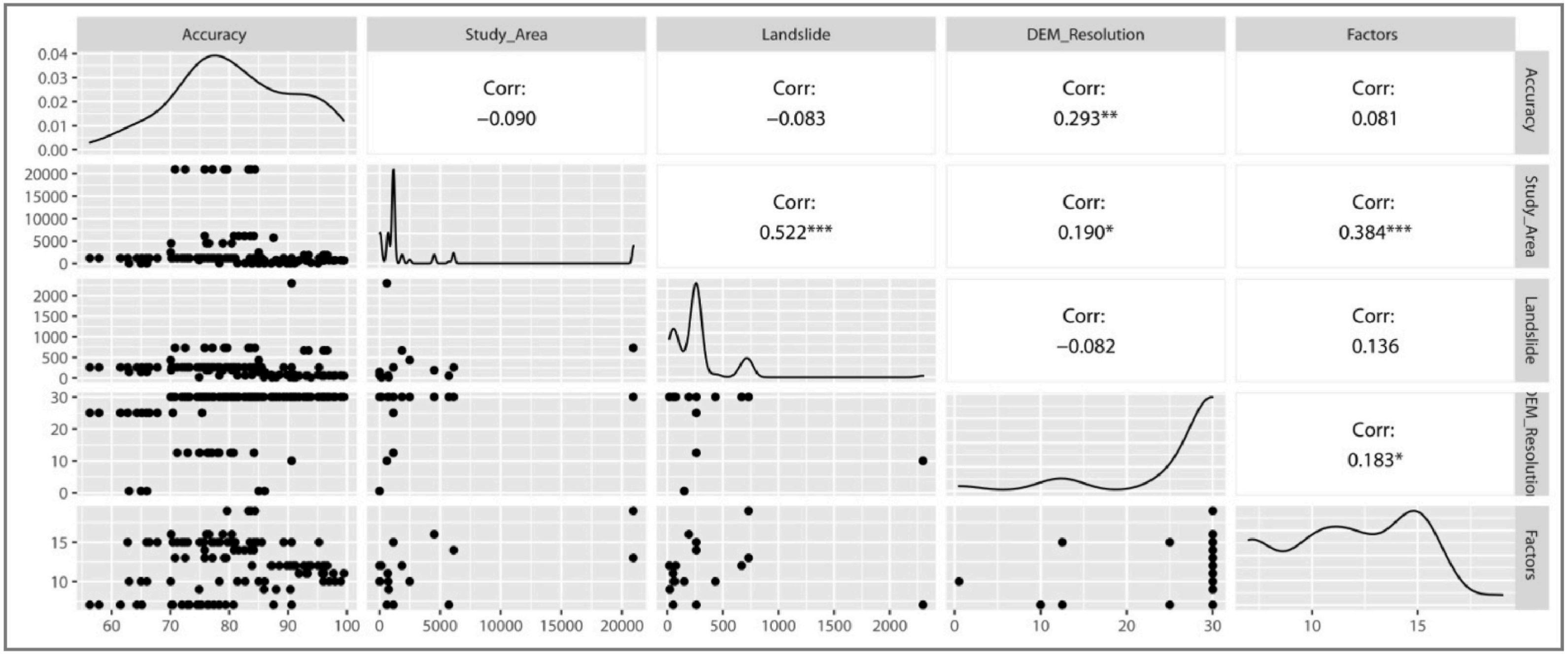

Fig. 20. Pearson's correlation test (95%) and the distribution of the data.

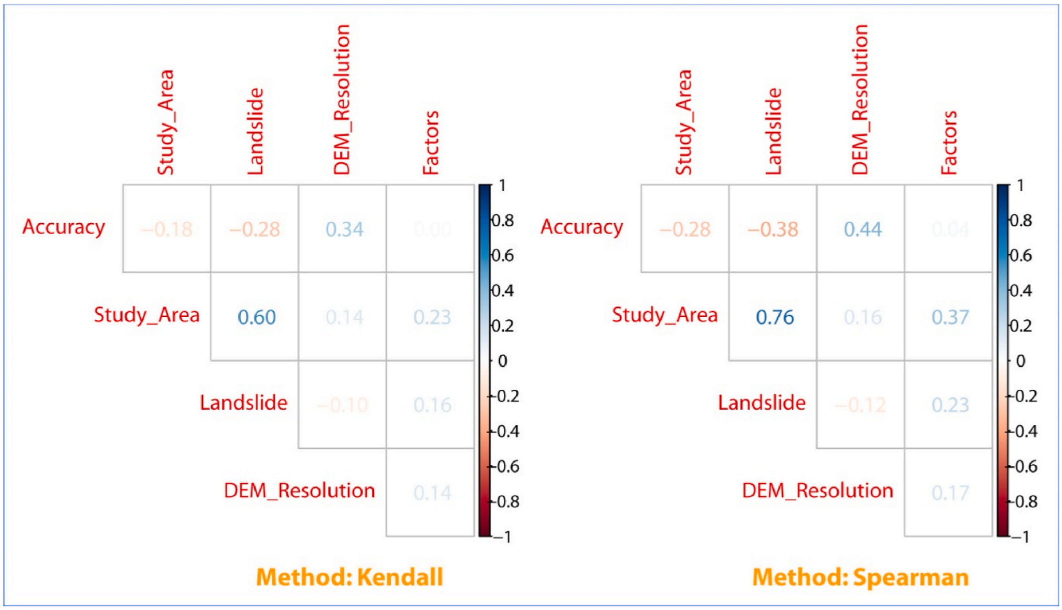

Fig. 21. Kendall and Spearman's correlation test.

Table 3
Kendall, pearson and spearman's correlation (95%) between accuracy and Study Area, Landslide, DEM Resolution and Conditioning Factors.

Feature	kendall	pearson	spearman
Size of the Study Area	−0.177	−0.090	−0.284
Size of Landslide Inventory	−0.276	−0.083	−0.382
DEM Resolution	0.337	0.293	0.438
Number of Conditioning Factors	−0.001	0.081	0.036

deep learning algorithms is limited. Though landslide susceptibility mapping research has an increasing trend in Bangladesh it is not following the global trend.

The landslide susceptibility mapping is also limited to some specific areas especially the metropolitan areas of Chattogram, Rangamati and Cox's Bazar district though the whole southeastern hilly region faces landslides during monsoon season. This is because the death toll and economic loss are confined to these regions. But there is a need to assess the landslide characteristics of the other areas because the excluded areas may face serious landslides in future because of climate change-induced extreme rainfall.

In Bangladesh, morphological factors are most commonly used followed by hydrological and land cover factors. Emphasis should also be given to geological and geotechnical factors as the region are composed of complex geological formations and landslides are rainfall induced. For landslide susceptibility mapping, random forest, logistic regression, frequency ratio and analytical hierarchy process are more frequently used methods in Bangladesh. Following the global landslide analysis methods, emphasis should be given to machine and deep learning algorithms to get a more accurate and realistic result. In most cases, the reliability of the landslide susceptibility map is measured using only the success rate curve (AUC curve) but it needs to use testing data to get more reliable and realistic maps. Though some statistical indices are also measured beside AUC and AUC of ROC to test map accuracy, it should be implemented in more cases.

Comparing the accuracy of the map and other metadata related to the accuracy, it is found that the accuracy of the map is not dependent to these factors. Only a negligible correlation was found for DEM resolution, but there is a high chance of biases because most of the maps were prepared using 30-m DEMs. Though the number of conditioning factors has an impact on landslide susceptibility mapping, the analysis showed there is no relation exist between them.

Some specific recommendations from this research are as follows:

- Using machine and deep learning algorithm and physically-based methods for landslide susceptibility mapping.
- Assessing landslide susceptibility for the whole region (all the five districts).
- Producing a national landslide inventory database and updating it regularly.
- Trying to produce national micro scale landslide susceptibility map.
- Developing guidelines for inventory mapping and landslide susceptibility mapping.
- Dividing training and testing data following some rules and mentioning them specifically in the paper.

- Using slope unit in landslide susceptibility mapping.
- Introducing UAVs in landslide susceptibility mapping.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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