Weights of Evidence Modeling for Landslide Susceptibility Mapping of Kabi-Gebro Locality, Gundomeskel area, Central Ethiopia

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Abstract

Kabi-Gebro area is located within the Abay Basin at Dera District of North Shewa Zone near Gundomeskel town in the Central highland of Ethiopia and it is about 320 Km from Addis Ababa. This is characterized by undulating topography, intense rainfall, active erosion and highly cultivated area. Geologically characterized by weathered sedimentary and volcanic rocks. Currently, landslides are creating serious challenges in road construction, farming practices and affecting people in this area. Active landslides in this area damaged the gravel road, houses and agricultural land. The main objective of this research is to prepare the landslide susceptibility map. To overcome the landslide problem in this area, landslide susceptibility map was prepared using GIS- based Weights of Evidence model. Based on detailed field assessment and Google Earth image interpretation, 514 landslide locations were identified and classified randomly as training landslide (80%) and validation landslide (20%). The training landslide data set include nine landslide causative factors such as lithology, slope angle, aspect, curvature, land use/land cover, distance to stream, distance to lineament, distance to spring and rainfall in order to prepare landslide susceptibility map in this study. The landslide susceptibility maps were prepared by adding the weights of contrast values of the nine causative factors using rater calculator in the spatial analyst tool of ArcGIS. The final landslide susceptibility map was reclassified as very low, low, moderate, high and very high landslide susceptibility classes. This susceptibility map was validated using landslide density index and Area Under the Curve (AUC). The result from this validation showed a success rate and a validation rate accuracies of 82.4% and 83.4% respectively for this model. Finally, this study recommends application of appropriate mitigation or corrective measures in order to lessen the impact of landslide in the area.

Keywords: Landslide susceptibility, GIS, Weights of Evidence, Kabi-Gebro, Gundomeskel, Ethiopia.
**Introduction**

Most natural hazards are frequently related to mountainous regions. From the natural hazards, Landslide is one of the greatest disaster that causes a different level of injuries, life loss as well as damages to built-up and natural environment (Kanungo et al. 2006; Pan et al. 2008; Ghosh 2012, Girma 2015). Landslide is the downslope movement of rock, debris, or earth material (Cruden 1991). Landslides were caused by internal and external factors (Crozier 1986; Siddle et al. 1991). The presence of internal factors makes slope materials susceptible to movement and will be triggered by external factors. Always there is an external factor that contributes to the instability of slope but its influence depends on the degree of internal factors. The landslide generated causalities and economic loss will be greater as compared with other natural hazards in the world (Yilmaz 2009). Proper investigation will help to identify the problem before the event has occurred. This may reduce a minimum of 90 percent of landslide related impacts (Brabb 1993). Therefore, proper investigation on landslide inventory and causative factors is essential inorder to prepare the landslide susceptibility map which may reduce the impact of landslides on property and life.

Landslide hazard is a common problem that causes a considerable damage in the highlands of Ethiopia. In many parts of the Ethiopian highlands, landslide hazards are the most destructive natural phenomena which cause property damages, including failures of engineering structures, human sufferings, environmental degradation and loss of fertile agricultural lands (Ayalew 1999; Ayalew 2000; Ayalew et al. 2004; Ayenew and Barbieri 2005; Woldearegay 2013). From 1960 to 2010 landslide damaged to 388 lives, 24 people injured, cultivated land, environment, infrastructure, and houses (Ayalew 1999; Temesgen et al. 1999; Woldearegay 2008 and Ibrahim 2011). The landslide incidence increase with serious damages on lives and properties in the highland of Ethiopia in recent decades (Meten et al. 2015). Rainfall induced landslides have killed 62 people, injured 30 people, displaced 5091 people from their residence and damage to house and cultivated land in 2018 (Wubalem and Meten 2020). The major intrinsic causes for landslide occurrence in the highland of Ethiopia include geological, geomorphological and hydrogeological factors that are triggered by heavy rainfall (Woldearegay 2013; Ermiyas et al. 2017). Many active landslides exist within the highland of Ethiopia that reactivated by heavy rainfall at the end of August (Ayalew 1999; Woldearegay 2013).

The Kabi-Gebro area is also one of the potential sites where frequent landslides occur in the central highlands of Ethiopia. Currently, in this area, landslide problems are posing serious challenges in road construction, agricultural practices and to the livelihood of local people who settled at the foot and scarp of steep slopes. The active landslide damaged the constructed gravel road, house and the agricultural land. Hence, they were forced to change the road alignment which was constructed without proper study. The frequent damage of this road and other social utilities has considerably increased the maintenance costs and delay in the period of construction. The large landslide that occurred on a gentle slope caused the displacement of local people from their home and damaged their crops. Therefore, identifying landslide location, causative factors and preparation of susceptibility map are very important for the safe construction of infrastructures and the stability of the farmland. Moreover, it is also essential to develop landslide preventive and mitigation measures that contribute to a sustainable infrastructure development and for a safer human livelihood.
The aim of this study is to locate landslides and to prepare the landslide susceptibility map of the Kabi-Gebro area of Dera District in Central Ethiopia. Landslide susceptibility is the likelihood that landslide occurs in a certain area (Mathew et al. 2007). The reliability of the landslide susceptibility map can be determined by the causative factors used, distribution of factors in the area and the model used in landslide susceptibility mapping (Kumar and Anbalagan 2019). Landslide susceptibility maps has the result of spatial association between landslide and influencing factors. It is important in landslide investigation, risk management and landslide hazard preparation. According to van Westen et al. (1997), the landslide susceptibility maps can be prepared through four main steps: (I) the landslide inventory map will be prepared; (II) landslide controlling factor maps will be prepared ; (III) the most appropriate method will be applied to evaluate the weights of each factor and finally (IV) the landslide susceptibility map will be prepared using a GIS procedure. Several approaches have been developed for landslide susceptibility mapping. These approaches can be grouped into qualitative and quantitative methods (Aleotti and Chowdhury 1999; Kanungo et al. 2009; Pardeshi et al. 2013). Qualitative methods are based on expert opinions or entirely on the judgment of the person that conduct the landslide susceptibility or hazard assessment (Anbalagan 1992; Aleotti and Chowdhury 1999; Ayalew and Yamagishi 2005). This method includes field geomorphological analysis and overlaying of index maps with or without a weighting approach (Leroi 1996). Quantitative methods are data driven and based on numerical expressions between landslide controlling factors and landslide events. Quantitative methods can be either statistical or deterministic analysis (Aleotti and Chowdhury 1999). Statistical approaches are based on numerical value driven from relation between landslide distribution and landslide controlling factors (Guzzetti 1999). Statistical approaches can be categorized into bivariate and multivariate (Carrara et al. 2003; Suzen and Doyuran 2004a, Yaclin 2008; Pardeshi et al. 2013). Bivariate statistical methods correlate each data layer of the causative factors with existing landslide events and weighted values based on landslide density (Pardeshi et al. 2013). Susceptibility maps were the result of all causative factors that may be assumed as the main limitation in bivariate statistical methods and these call for the application of multivariate statistical methods (Pardeshi et al. 2013). In multivariate, all relevant factors were evaluated and the relative contributions of each factor was considered (Kanungo et al. 2009). Deterministic method is another numerical approach that can be applied in small to medium-sized areas. For this, detailed slope geometry, stratigraphy and geotechnical result were required (Janevski and Milanovski 2018). In this study, a bivariate statistical model known as weights of evidence model was used to prepare the landslide susceptibility map of the area. Several scholars applied weights of evidence for landslide susceptibility mapping in different parts of the world with a high performance accuracy (Kumar et al. 2008; Ghosh et al. 2009; Blahut et al. 2010; Piacentini et al. 2012; Schicker and Moon 2012; Chen 2014; Sumatra et al. 2015; Bousta and Ait 2018; Mersha and Meten, 2020). Nowadays, weights of evidence model is the most commonly applied method for landslide susceptibility mapping as the model is simple, easy to use and less time consuming (Soeters and Westen 1996; Suzen and Doyuran 2004; Neuhäuser et al. 2012). In this study, weights of evidence model are applied to prepare landslide susceptibility maps and the results obtained from this research might help decision makers, civil engineers and geoscientists to take appropriate mitigation measures in order to prevent the severe impact of the landslide hazard in this area.
Study area

Kabi-Gebro area is located at Dera District of North Shewa Zone near Gundomeskel town, Oromia Regional State in Central Ethiopia which is about 320 Km from Addis Ababa (Fig. 1). The area is bounded between 38°33'35" E and 38°42'9"E longitudes and 10°21'48" N and 10°14'20" N latitud. This area is part of the Abay (Blue Nile) basin and it is surrounded by tributaries of the Blue Nile (Abay) River. The main river includes Woleka and Shenkora River. It is characterized by different geological processes in the past and active erosional activities upto the present time. As a result, undulating topographic features that contain valleys, very steep slopes to gentle and flat areas are manifested as shown in figure 2. The maximum elevation in the study area is 2524 m at the top of the plateau while the minimum elevation is 1296 m at the river course. The drainage network of the study area shows dendritic and parallel drainage patterns (Fig. 1). The parallel and dendritic drainage patterns were formed following the limestone and basalt cliffs respectively. Based on elevation difference the climate of the study area is categorized under cool and humid in high elevation and warm and semi-arid in low elevation. The heaviest monthly rainfall in July and August is 306.3mm and 332.5mm respectively. The complex geomorphology of the study area was carved out of the Mesozoic sedimentary and Cenozoic volcanic rocks. From bottom to top, Limestone, upper sandstone and moderately to highly weathered basalts constitute the stratigraphy of this area with different geological structures such as lineaments, fault, joint and sedimentary structures.
Figure 1 Location Map of the study area
Methods

In this study, different activities were carried out both in-office and in the field starting from data collection, database generation, model development and validation.

Data collection and Source

For this study, a landslide inventory map and landslide controlling factor maps have been prepared from different sources. Review of relevant literatures such as journals, books and different reports has also been undertaken. The important data like DEM data, landslide inventory of the study area, rainfall data from National Meteorology Agency of Ethiopia, regional geological map and reports from Geological Survey of Ethiopia at a scale of 1: 250,000 and topographic maps at a scale of 1: 50,000 from Ethiopian Geospatial Information Agency were collected. Primarily, potential sites with serious past landslide problems were identified from Google Earth image interpretation in order to prepare the landslide distribution map for landslide susceptibility assessment. In addition, a series of field surveys have been conducted to study the type, activity, extent, damage and cause of landslides. The geological units, geological structures, land use/land cover and spring location was mapped. Moreover, a detail geological characterization has been done based on physical properties.
GIS Database

In this study, a database for all causative factors (slope, aspect, curvature, lithology, land use, rainfall, distance to stream, distance to lineament and distance to spring) and landslide inventory map was prepared in GIS environment of ArcMap 10.4. The data layers were prepared in a raster format with the same projection system (Adindan UTM Zone 37N) and pixel size (30x30m) for data analysis.

Preparation of Landslide Inventory Dataset

This study is based on the assumption that future landslides will occur under similar conditions as past landslides (Lee and Talib 2005). This is to mean that the condition of a past landslide (e.g. location, factors and slope material) where a landslide has occurred is a key for the future. To prepare landslide susceptibility maps, landslide distribution was properly identified and mapped. Landslide inventory map in the study area was prepared from Google Earth image interpretation and field investigation for accessible landslide locations. All the inventory data collected was prepared in polygon or vector format. A total of 514 landslides were identified which were randomly divided into training (80%) and validation (20%) landslides. Finally, the landslide polygons were changed into a raster format in a GIS system with the same coordinate system and pixels size.

Figure 3 Landslide inventory map of the study area
Database Construction of Landslide Controlling Factors

A landslide susceptibility map depends on the complex association of landslide event and their causative factors. The causative factors which were taken into account for the assessment of a landslide susceptibility map have been selected based on literature review and detail field observations. In the case of landslide susceptibility mapping, there is no any standard rule to select which factor to be used or not, rather than deciding on the nature of area and data availability (Ayalew and Yamagishi 2005). Based on this fact, nine causative factors were selected as the main influencing factors for landslide occurrence in this area. The landslide causative factor maps have been prepared from different sources in this study. Topographic parameters such as slope angle, aspect and curvature were extracted from DEM Data of 30x30m resolution. The distance to streams, distance to spring and distance to lineament were extracted from river map, spring location map and geological structure map of the area using GIS buffering. Lithological map was prepared through detail field mapping and Land use/land cover/ map was extracted from Google Earth image interpretation which is supported by field survey. Rainfall map was prepared using GIS buffering of Rainfall stations from National Meteorology Agency of Ethiopia. All these factor maps were stored in raster format with the same coordinate system (Adindan UTM Zone 37N) and pixels size (30x30m resolution). Then, the rasterized training landslide map and all factors maps were used in landslide susceptibility modeling. The weight was calculated for each factor class based on the correlation of landslides with each factor class using the weights of evidence model. Finally, the result was verified by validation landslide dataset.

Weights of evidence (WoE) model

In this study, a bivariate statistical method called weights of evidence model was used for landslide susceptibility mapping. WoE model is data driven model which is based on Bayesian method and uses prior and conditional probability. Initially it was developed for mineral potential evaluation (Bonham-Carter et al. 1988, 1989; Agterberg et al. 1993) and later used for landslide susceptibility assessment (Westen et al. 2003, Lee et al. 2004; Lee and Talib 2005; Lee and Sambath 2006; Pradhan et al. 2010). In this method, the prior probability is determined based on the past landslide without additional information. The prior probability was calculated as number of pixels with landslides is divided by total number of pixels in the map (Bonham-Carter 1994).

\[
P_{\text{prior}} = \frac{\text{Area(landslide)}}{\text{Area (total)}}
\]

(1)

As additional information about the controlling factor is found, the prior probability will be modified to a conditional probability. Bonham-Carter (1994) each factors are conditionally independent and the conditional probability is formulated as follows.

\[
P[S|B] = \frac{N_{\text{pix}}\{S \cap B\}}{N_{\text{pix}}\{B\}}
\]

(2)

Where, $N_{\text{pix}}$ is number of pixel, $S$ and $B$ represent landslide and the factor respectively. By combining landslide with landslide causative factors, the statistical association between classes of a factor map and landslides will be determined.
(Neuhäuser et al. 2012). The weight values can be calculated based on the contribution of causative factors to landslide occurrence. The positive and negative weights (Wi+ and Wi−) values are calculated to know the spatial correlation in the presence or absence of the factor using the formula described by Bonham-Carter (1994) and Bonham-Carter et al. (1989):

\[
W^+ = \ln \left( \frac{N_{pix1}}{N_{pix1} + N_{pix2}} \right) \left( \frac{N_{pix3}}{N_{pix3} + N_{pix4}} \right)
\]

\[
W^- = \ln \left( \frac{N_{pix2}}{N_{pix1} + N_{pix2}} \right) \left( \frac{N_{pix4}}{N_{pix3} + N_{pix4}} \right)
\]

A positive weight (Wi+) shows that the causative factor is present at the landslide locations and the magnitude of this weight is an indication of the positive correlation between them. A negative weight (Wi−) shows the absence of the causative factor and the magnitude of this weight is an indication of the level of negative correlation.

The number of pixels in each class can be calculated as:

I. \[N_{pix1} = N_{sclass}\]

ii. \[N_{pix2} = N_{slide} - N_{sclass}\]

iii. \[N_{pix3} = N_{class} - N_{sclass}\]

iv. \[N_{pix4} = N_{map} - N_{slide} - N_{class} + N_{sclass}\]

The above variables represent \(N_{slide}\) = Number of pixels with landslides in the map, \(N_{class}\) = Number of pixels in the class, \(N_{sclass}\) = Number of pixels with landslides in the class and \(N_{map}\) = Total number of pixels in the map.

Weights of contrast is the difference between positive and negative weights. The magnitude of these contrast values reflects the overall spatial association between each causative factor class and the landslides. The positive contrast value indicates positive spatial associations while the negative ones for a negative spatial association.

\[C = W^+ - W^-\]

\[W_{map} = \sum C\]

Finally, the landslide susceptibility index (LSI) is produced by combining the weighted map (\(W_{map}\)) of each factor through summation process using equation 7 below. The final landslide susceptibility map is verified based on landslide validation.

\[LSI = \sum W_{map}\]
Landslide Inventory

It is becoming universal that landslide susceptibility mapping starts with landslide inventory mapping (Ayalew et al. 2004). Landslide inventory map is the simplest form of landslide distribution map Hansen (1984). Landslide inventory maps can be prepared by different techniques, depending on their purpose, the extent of the study area, the scales of base maps and aerial photographs and the resources available to carry out the work (Guzzetti et al. 2000). It is the distribution of the past landslide which indicates landslide event in terms of space (location) and time. Identifying landslides from field studies only are expensive and time-consuming. In this study, landslide inventory was mapped by interpreting google earth images and detail field assessment. A series of field surveys have been conducted to study the type, activity and extent of landslides. Landslide locations in the study area were verified during the fieldwork. In this
study, 15.1km$^2$ (16774 pixels) of landslide area was identified out of 199.5Km$^2$ (221755 pixels) total area. From a total area of 15.1km$^2$ (16774 pixels), 12.08 Km$^2$ (13405 pixels) was used for training and the remaining 3.02 Km$^2$ (3369 pixels) was used for validation. Both can be stored as a polygon data. The characterization and landslide distribution mapping in the study area were done through intensive fieldwork with the help of Google Earth image. Generally, areas with flat to gentle slopes were considered to have low or no landslide occurrence. A high density of landslides was found in the central, northeastern, northwestern, southeastern and southwestern parts of the study area. Landslides in this area are predominantly distributed following basalt and limestone ridges/cliffs. The most common types of landslides that are found in the study area include earth slide (rotational and translational slide), debris slide, debris flow, rock fall, topple, rock slide lateral spread, creep and complex as show in figure 5. The common landslide types, their causes and effects will be described in the following sections.

The southeastern parts include Kabi Derami, Golelcha and Dada Gimbel Villages are highly affected by different types of landslides. This area is characterized by undulating physiography and covered by moderate to highly weathered basalt, colluvial deposit (basalt origin) and residual soil deposit. Mostly, landslides in this area are caused by road undercutting, steep slope, high degree of weathering, geological structures (faults and joints), groundwater and active erosion. A crack on the failed slope and new crack out of the failed slope followed by spring discharge are also indicators of a future landslide in this area. Menelego, Were Cheri and Were Bu’i localities in the southwestern part of the study area were affected by landslide incidences. Mostly the study area is covered by limestone, residual soil and colluvial deposit. Earth slide (rotational and translational slide), rock fall, rock slide and wedge failure are common types of landslides in this area. The northwestern Parts of the study area includes Gebro Beresa, Gebro Asmare and Gorba Villages which is an area of high spring discharge and affected by large earth and rock slides. Concavity, presence of geological structures (lineaments), groundwater and man-made activity were the main landslide controlling factors. The northeastern part of the study area including Birje Golelcha, Dembi Birje and Ambisa Villages are characterized by a cliff forming limestone and black soil on top of the cliff covering the flat area. The main causes of landslide occurrence in this specific area are stream and river undercutting, lineaments in the limestone and spring water. The most common types of landslides that were observed in this area are earth slide, rockslide, rock fall and topples. As a result, crops were damaged by an active landslide and most of the farmland areas became unworkable. Giranyi Mukecha, Mestawet and Sekeyo villages, which are found in the central parts of the study area, are mainly affected by road cutting. Weathered basalt, colluvial and residual soil deposits are the dominant lithologic units covering the area. In addition to road cutting, this area is characterized by high degree of weathering and steep slope angle with a high elevated area. As a result, rock fall, rock topples, debris flow and slide, lateral spread and creep were the common landslides in this area.
Figure 5 Field photos illustrating different landslide types. Yellow dotted lines indicate the main scarp of a landslide and, black dotted line indicate direction of the slide. (a) Debris slide (b) Lateral spread (c) Earth slide (d) Debris flow (e) Rock slide (f) Rockfall and Topple and (g) Creep.
Landslide Causative Factors

According to Ayalew (1999) landslides occur as a result of adverse natural and/or artificial conditions. The Ethiopian highland is characterized by a steep slope, concave segments as well as the presence of highly jointed and weathered rocks and the action of both rivers and man. Most landslides occurred and reactivated in every rainfall season in the study area, especially along stream banks and were thick black soil are encountered. This implies most of the highlands of Ethiopia are vulnerable to slope instability. For this study, nine landslide controlling factors such as slope, aspect, curvature, lithology, rainfall, land use/land cover, distance to spring, distance to lineaments and distance to stream were selected.

Slope

The slope gradient is considered as a key factor for GIS-based landslide susceptibility mapping (Guzzetti et al. 1999; Dai and Lee 2002). It’s one of the most controlling factors of a landslide that affects the concentration of moisture and the level of pore pressure at a local scale and it controls regional hydraulic continuity at larger scales (Ayalew and Yamagishi 2005). The slope gradient was derived from DEM data of 30 by 30m spatial resolution. The slope data was reclassified into six classes with 10º intervals i.e. <5º, 5-15º, 15-25º, 25-35º, 35-45º and >45º as shown in figure 5A. It was reclassified in this way to evaluate the effect of the slope with optimum class intervals. Landslide inventory data showed an increasing trend of past landslide occurrences as the slope angle increases (Fig. 6). From past landslide distribution data, 61.7% of the landslides occurred in the slope class > 45º. The past landslide revealed that most susceptible slopes in the study area fall under steep slopes and these have been shown from limestone and basalt cliffs. More than 84% of landslide in the study area fall in slopes greater than 25º.

Aspect

Slope aspect is referred to as the direction of maximum slope of the terrain surface (Dai et al. 2002; Kumar et al. 2008). Exposure of the terrain aspect to sunlight, wind, rainfall and wave controls the moisture content of soils, degree of weathering and rainfall intensity (Huang et al. 2015). For this study, the slope aspect was derived from DEM data with a spatial resolution of 30m. It was generated in ArcGIS using the spatial analyst tools of “slope” function and reclassified into 9 classes: Flat (<1º), North (337.5-360º and 0-22.5º), Northeast (22.5-67.5º), East (67.5-112.5º), Southeast (112.5-157.5º), South (157.5-202.5º), Southwest (202.5-247.5º), West (247.5-292.5º) and Northwest (292.5-337.5º) (Fig. 6B). The highest landslide density in the study area falls in the west (15.2%) and northwest (14.4%) aspect classes followed by southwest (14.1%) and north (11.2%). These may be due to favorable orientation of lineaments and the occurrence of high discharge springs in these aspect classes.

Curvature

The shape of the slope can play a great role in causing landslide as it has a strong influence on creating slope instability (Gadtaula and Dhakal 2019). Concave and convex curvatures influence the stability of slopes covering 71% of the study area. The curvature map of the study area was prepared from DEM data with a spatial resolution of 30m. It was classified into three classes; concave or negative curvature (-5.45 - - 0.01), flat (-0.01 - 0.01) and convex or positive
curvature (0.01- 4.78) as shown in the figure 6C. The distribution of past landslide indicates that high percentage of landslides occurred in the concave curvature classes accounted for 39.2%. The distribution of landslides is high in concave class as compared to other classes. This is due to concentration of water in concave slopes which increase the degree of saturation in a slope.

**Lithology**

The geological formation has a great influence on landslide occurrence (Ayalew and Yamagishi 2005). According to these authors, lithological and structural variations often lead to a difference in strength and permeability of rocks and soils. The study area contains seven lithological units including limestone, sandstone, highly weathered basalt, moderately weathered basalt, residual soil deposit, alluvial deposit and colluvial deposit (Fig. 6D). Basalt was highly weathered and affected by different geological structures that make it susceptible to slope movement by reducing the shear strength of slope materials. Moreover, this unit was also grouped under high productive aquifer which is the source for most springs. About 35.4% of the past landslides were distributed within moderately weathered basalt and 27.3% in alluvial deposits as shown in figure 7. These landslide distributions were followed by colluvial deposit (14.8%) and limestone (13.7%). The occurrence of high landslide density in the moderately weathered basalt may be due to steep slope, high degree of weathering and presence of springs. The low concentration of landslide within highly weathered basalt is due to the presence of flat topography in this rock unit.

**Land Use/land Cover**

Land use is also one of the key factors that initiate landslides and from land use classes, barren land is highly prone to landslide occurrence. The presence of vegetation is important in slope stability due to its adherence and bonding of slope materials (Mathew et al. 2007). The vegetated area is less affected by landslide problems as it prevents erosion by the natural anchorage of plant roots (Kumar et al. 2008). Land use/land cover map of the area was prepared from Google Earth image analysis supported with field study. It can be grouped into eight classes including moderate forest, sparse forest, bush land, bare land, grass land, agricultural land, riverbed and settlement. The distribution of landslides within the land use types of river bed (course) and barren land showed 22.2% and 20.9% of the total landslides in the study area respectively. The lower distribution of landslides was recorded in the land use classes of settlement (1.2%) (Fig. 7).

**Rainfall**

The main triggering factor of slope failures is heavy rainfall (Ayalew 1999; Abebe 2010). Variable topographical, geological, hydrological and land use conditions can affect the slope instability of the Ethiopian highland but most of the landslides were triggered by heavy rainfall (Woldearegay 2013). Landslide occurs when the shear stress is greater than the shear strength of slope materials. Intense rainfall leads to saturation of the slope materials which is the primary cause of landslides. The shear strength of saturated slope materials decreases due to changes in effective inter-granular cohesion and friction. In addition, the shear stress of saturated slope materials increases due to the added weight and the development of pore water pressure. Most of the landslides occurred at the end of August and September. This indicates
that landslide occurrence is directly related to slope saturation due to intense and accumulated rainfall during the months of June, July and August (Meten et al. 2015). The rainfall map of the study area was prepared using kriging method in GIS. Kriging method was important when rain gauge stations are far from each other. The continuous rainfall map was reclassified into seven classes with 10mm/year interval i.e. 927-947mm/year, 947-967mm/year, 967-987mm/year, 987-1007mm/year, 1007-1027mm/year, 1027-1047mm/year, 1047-1064mm/year (Fig. 6F). High density of landslides is associated with the high annual rainfall classes. The landslide distribution within the rainfall class of 1047-1064mm accounted for 23.6% of the landslides in the study area. The remaining percentages of landslides are distributed in the remaining rainfall classes (Fig. 7)

**Distance to Spring**

To evaluate groundwater contribution in landslide susceptibility mapping, springs which are indirect surface manifestations of groundwater were considered (Anbalagan 1992). Raghuvanshi et al. (2015) spring location and landslides showed a direct relationship. The study area falls into three aquifer zone. These are very low, low to moderate and very high productive aquifer classes. The low to a moderate productive aquifer and very high productive aquifers belong to the limestone and weathered basalt units respectively. It was realized that most of the springs emerge from weathered basalt unit and basaltic origin colluvial and residual soil deposits. Most of the springs, which were identified in the field, emerged from the failed slope sections. Spring locations were directly related to landslide locations. From the interview of local people, most springs emanated after the slope failures and the number of springs increases as landslide is reactivated. This showed that spring locations that indicate the relative depth of groundwater will affect the degree of saturation for the slope mass. Abrupt changes in the water level cause the pore water pressure on slopes to increase and mechanical strength of a soil to decrease by washing out soluble cementing substances that lead to slope instability. The distance to spring was reclassified into seven classes with 100m interval i.e. 0 - 100m, 100 - 200m, 200 - 300m, 300 - 400m, 400 - 500m, 500 - 600m and > 600m (Fig. 6G). In this study, as the distance to spring decreases, the percentage landslides increases. The distance to spring classes of 0 - 100m and 100 - 200m accounted for 21.1% and 18.5% of landslides respectively.

**Distance to Lineament**

Lineaments include tectonic structures and a linear arrangement of geomorphological features that may be continuous or interrupted without any clear evidence of displacement such as topographic break (Ayalew and Yamagishi 2005). The Ethiopian highland is characterized by high relief and rugged topography (deep valleys and gorges with steep slope) which was induced by large scale Pliocene-quaternary uplift (Mohr 1986). As a result, Ethiopian highland was crossed by different structures that give horst, tectonic depression and fault scarp (Korme et al. 2004). The present study has located in the northwestern part of Ethiopian highland which is affected by different structures. Generally, as distance to any structure/lineament decreases, the potential for slope failure increases. This is a very important controlling factor to evaluate landslide susceptibility (Yilmaz 2009; Conforti et al. 2014) as geological structures increases the degree of weathering and fracturing which implies a reduction in the strength of slope materials. These structures can be used as a slip/failure surface and conduit for water movement (Conforti et al. 2014). In the present
study, distance to lineament was considered as the main influencing factor and it was extracted from the regional geological map, Google Earth image and field study which was further subjected to GIS buffering analysis. Lineaments were buffered by a distance of 50 m which was then classified into seven classes: 0 - 50m, 50 - 100m, 100 - 150m, 150 - 200m, 200 - 250m, 250 - 300m and > 300m. The past landslide density showed an increasing trend as distance to lineament decreases. For instance, 28.1% of the landslides in the study area fall in the distance to lineament class of 0 - 50m.

**Distance to Stream**

Landslide occurrence was also controlled by proximity to drainage and drainage density (Kumar and Anbalagan 2019). Active river or stream incision has greatly influenced slope stability by toe erosion and by saturating the slope materials thereby causing further slope steepening and instability (Mathew et al. 2007; Abebe 2010). The stream map has been extracted from DEM and the distance to stream map was prepared by Euclidean distance buffering which was then classified into seven groups with a 50m buffer distance into seven classes of 0 - 50m, 50 - 100m, 100 - 150m, 150 - 200m, 200 - 250m, 250 - 300m and > 300m (Fig. 6I). The last class comprises of high percentage of landslides and the distance to stream in this class didn’t show a direct relation with landslides. The reason for the high density of landslides in a distance to stream class of > 300m may be due to the combined effect of other factors (Ayalew et al. 2004; Raghuvanshi et al. 2014).
Figure 6 Landslide causative factor maps: (a) Slope  (b) Aspect  (c) Curvature  (d) Lithology  (e) Land use/Land cover  (f) Rainfall  (g) Distance to spring  (h) Distance to lineament  (i) Distance to stream
| Causative Factor Class          | Percentage of Landslide |
|--------------------------------|-------------------------|
| **Land use/Landcover**         |                         |
| Agricultural Land              | 6.6%                    |
| Sparse Forest                  | 18.3%                   |
| Bare Land                      | 20.9%                   |
| Settlement                     | 1.2%                    |
| River                          | 22.2%                   |
| Grazing Land                   | 6.4%                    |
| Moderate Forest                | 5.7%                    |
| Bush land                      | 18.5%                   |
| **Lithology**                  |                         |
| HW Basalt                      | 1.1%                    |
| Colluvial Deposit              | 14.8%                   |
| MW Basalt                      | 35.4%                   |
| Alluvial Deposit               | 27.3%                   |
| Limestone                      | 13.7%                   |
| Sandstone                      | 3.5%                    |
| Residual Soil Deposit          | 4.2%                    |
| **Curvature**                  |                         |
| Convex                         | 31.6%                   |
| Flat                           | 22.6%                   |
| Concave                        | 39.2%                   |
| **Aspect**                     |                         |
| North West                     | 14.4%                   |
| West                           | 15.2%                   |
| South West                     | 14.1%                   |
| South                          | 8.9%                    |
| South East                     | 6.2%                    |
| East                           | 8.2%                    |
| North East                     | 10.1%                   |
| North                          | 11.2%                   |
| Flat                           | 4.9%                    |
| **Slope (degree)**             |                         |
| >45                            | 61.7%                   |
| 35-45                          | 46.1%                   |
| 25-35                          | 23.6%                   |
| 15-25                          | 10.6%                   |
| 5-15                           | 3.7%                    |
| <5                             | 1.6%                    |
| **Rainfall (mm/year)**         |                         |
| 1047 - 1064                    | 23.6%                   |
| 1027 - 1047                    | 15.9%                   |
| 1007 - 1027                    | 7.7%                    |
| 987 - 1007                     | 17.2%                   |
| 967 - 987                      | 17.4%                   |
| 947 - 967                      | 8.8%                    |
| 927 - 947                      | 9.5%                    |
| **Distance to spring (m)**    |                         |
| >600                           | 8.7%                    |
| 500-600                        | 10.2%                   |
| 400-500                        | 11.8%                   |
| 300-400                        | 13.8%                   |
| 200-300                        | 15.9%                   |
| 100-200                        | 18.5%                   |
| 0-100                          | 21.1%                   |
| **Distance to Stream (m)**    |                         |
| >300                           | 20.4%                   |
| 250-300                        | 14.6%                   |
| 200-250                        | 15.4%                   |
| 150-200                        | 11.2%                   |
| 100-150                        | 10.5%                   |
| 50-100                         | 12.4%                   |
| 0-50                           | 15.5%                   |
| **Distance to Lineament (m)** |                         |
| >300                           | 3.2%                    |
| 250-300                        | 9.7%                    |
| 200-250                        | 11.3%                   |
| 150-200                        | 13.2%                   |
| 100-150                        | 15.1%                   |
| 50-100                         | 19.5%                   |
| 0-50                           | 28.1%                   |

Figure 7 Percentage of landslide occurrence in each factor class of the landslide causative factors.
**Result and Discussion**

**Relationship Between Landslide and Causative Factors**

The present study also depends on the relationship between landslides in the study area and each causative factor. The significance of each causative factor class can be determined based on the weights of evidence model. According to Bonham-Carter et al. (1989), the landslide susceptibility assessment weights between 0.1 and 0.5 have middle predictive, 0.5 and 1 are moderately predictive, 1 and 2 are strongly predictive and greater than 2 are extremely predictive. The extremely predictive classes of the slope are > 45° (W⁺ = 2.572) and 35 - 45° (W⁺ = 2.085). The strongly predictive classes of the slope are 25 - 35° (W⁺ = 1.191). From the lithologic map of the area, the moderately weathered basalt and alluvial deposit are in a moderately predictive classes with W⁺ of 0.927 and 0.631 respectively. From land use/land cover factor map, the bare land, river and bushland fall in a moderately predictive class of landslide susceptibility with W⁺ values of 0.898, 0.837 and 0.708 respectively. For the distance to lineament the strongly predictive class is 0 - 50m with W⁺ = 1.344 followed by moderately predictive classes of 50 - 100m, 100 - 150m and 150 - 200m with W⁺ = 0.906, 0.610 and 0.462 respectively. For the factor map of distance to spring, the moderately predictive classes are 0 - 100m, 100 - 200m and 200 - 300m with W⁺ = 0.818, 0.666 and 0.498 respectively. The moderate predictive class of rainfall includes 1047 - 1064mm/year with W⁺ = 0.593. In general, many of the factor classes fall in the middle predictive classes of Bonham-Carter et al. (1989) (Table 1).

**Relationship Between Landslide and Topographic Parameters**

The slope of the study area is classified into six classes and the contribution of the class was determined. As the steepness of the slope increases, the probability of landslide occurrence also increases (Lee and Min 2001). Generally, as the slope angle increase, the driving force of the landmass increases while the resistive force decreases (Mahdadi et al. 2018). The result obtained from this study also verified this concept. As discussed previously, the slope class > 45 contains 61.7% of the landslides which indicates a high probability of landslide occurrence. This class reveals high significance (C = 2.585) followed by slope classes 35 - 45° and 25 - 35° (C =1.439 and 2.209, respectively). The slope class above 15° indicated positive C values and positive correlation between landslide and factor classes. The remaining classes below 15° showed negative weights and a negative correlation.

In the case of aspect classes, the W, NW and SW slope faces have shown a positive correlation between landslide and each factor class with C = 0.355, 0.294 and 0.251 respectively. This indicate that most of the slopes facing towards the west direction have high probability of landslide occurrences. The slope facing to this direction is mainly affected by stream erosion, geological structures (lineaments) and high discharge springs. This is due to the fact that most of streams and springs are flowing in this direction. The remaining classes showed a negative correlation (Table 1).

Curvature is the key factor that controls the flow of groundwater and surface water. Concave classes showed a positive correlation with C = 0.303. This may be due to the high groundwater discharge and erosion activity in this area. The weight of this class also indicated a high probability of landslide occurrence. The remaining classes showed a negative correlation as shown in table 1.
Relationship between Landslide and Lithology, Land use and Rainfall

The higher percentages of the landslides have occurred within moderately weathered basalt, alluvial deposit, colluvial deposit and limestone as shown in figure 6. As a result, the higher probability of landslide occurrence will be expected in these factor classes. Moderately weathered basalt showed the highest values of $C = 1.246$ followed by alluvial deposit ($C = 0.645$). The remaining classes i.e. residual soil, limestone, colluvial deposit, highly weathered basalt and sandstone have shown negative weights of contrast values with a negative association.

In case of land use/land cover, a high probability of landslides will occur in the bushland ($C = 1.009$), river ($C = 0.866$), bare land ($C = 0.826$) and sparse forest ($C = 0.644$) classes with a decreasing order of weights contrast. The remaining classes characterized by negative $C$ with negative correlation. This is because bare land and bushland are occupying the steep slopes of highly weathered basalt and limestone. In addition to the bare land, the sparsely forested area is favorable for water saturation and active erosion that make it susceptible to landslides. The river bed has an area of active erosional activity.

The landslide incidence increase as rainfall intensity increases (Anis et al. 2019). The current study also confirmed this scenario with some exceptions. The rainfall classes 1047 - 1067 mm and 1027 - 1047 mm revealed high landslide occurrence with high contrast values of $C = 0.619$ and 0.181 respectively. The last four rainfall classes showed progressive increases in the probability of landslide occurrence except for the interruption of one class i.e. 1007 – 1027mm with a negative weights of contrast value.

Relationship between Landslide and Distances to Lineament, Stream and Spring

The distances to lineaments and springs showed an increasing probability of landslide occurrence as distances to lineaments and springs decrease. Both factor classes also showed a positive association with high weights of contrast values except in the last classes which have $C$ values of 1.561 and 0.833 respectively.

The distance to stream classes didn’t show a good correlation with landslides as distance to stream decreases. The occurrence of landslides was higher in the last class with distance to stream class > 300m followed by the first distance to stream class of 0 - 50m. These indicates that the landslide occurrence was the result of different causative factors.

Table 1 The input data used in the analyses and results obtained from the Weights of Evidence model.

| Factors | Class | Nclass | Npix1 = Nclass | Npix2 | Npix3 | Npix4 | W+ | W- | C   |
|---------|-------|--------|---------------|-------|-------|-------|-----|-----|-----|
| slope (degree) | <5     | 29863  | 361           | 13043 | 29502 | 178848| -1.660 | 0.125 | -1.785 |
|          | 5-15   | 111669 | 3096          | 10308 | 108573| 99777 | -0.814 | 0.474 | -1.287 |
|          | 15-25  | 52516  | 4131          | 9273  | 48385 | 159965| 0.283  | -0.104 | 0.387  |
|          | 25-35  | 22125  | 3864          | 9540  | 18261 | 190089| 1.191  | -0.248 | 1.439  |
|          | 35-45  | 5161   | 1760          | 11644 | 3401  | 204949| 2.085  | -0.124 | 2.209  |
|          | >45    | 420    | 192           | 13212 | 228   | 208122| 2.572  | -0.013 | 2.585  |
| aspect  | flat (-1) | 77    | 2             | 13404 | 76    | 208274| -0.894 | 0.000 | -0.894 |
| Land use/land cover | N (0-22.5 & 337.5-360) | NE (22.5-67.5) | E (67.5-102.5) | SE (112.5-157.5) | S (157.5-202.5) | SW (202.5-247.5) | W (247.5-292.5) | NW (292.5-337.5) |
|---------------------|-------------------------|----------------|----------------|-----------------|----------------|-----------------|----------------|-----------------|
| Residual soil deposit | 4418 | 74 | 13331 | 4344 | 204003 | -1.329 | 0.016 | -1.344 |
| Sandstone | 3068 | 42 | 13363 | 3026 | 205321 | -1.534 | 0.011 | -1.545 |
| Limestone | 108975 | 5877 | 7528 | 103098 | 105249 | -0.121 | 0.106 | -0.227 |
| Alluvial deposit | 3568 | 385 | 13020 | 3183 | 205164 | 0.631 | -0.014 | 0.645 |
| MW Basalt | 36834 | 5149 | 8256 | 31685 | 176662 | 0.927 | -0.320 | 1.246 |
| Colluvial deposit | 29493 | 1728 | 11677 | 27765 | 180582 | -0.033 | 0.005 | -0.038 |
| HW Basalt | 35396 | 150 | 13255 | 35246 | 173101 | -2.716 | 0.174 | -2.890 |
| Bush Land | 46816 | 5408 | 7997 | 41408 | 166942 | 0.708 | -0.295 | 1.003 |
| Modestly Vegetated Forest | 5739 | 119 | 13286 | 5620 | 202730 | -1.111 | 0.018 | -1.130 |
| Grazing Land | 35835 | 1725 | 11680 | 34110 | 174240 | -0.241 | 0.041 | -0.282 |
| River | 3123 | 404 | 13001 | 2719 | 205631 | 0.837 | -0.017 | 0.854 |
| Settlement | 12646 | 74 | 13331 | 12572 | 195778 | -2.392 | 0.057 | -2.448 |
| Bare Land | 11970 | 1632 | 11773 | 10338 | 198012 | 0.898 | -0.079 | 0.976 |
| Agricultural Land | 105626 | 4043 | 9362 | 101583 | 106767 | -0.480 | 0.310 | -0.790 |

| Distance to lineament (m) | 0-50 | 50-100 | 100-150 | 150-200 | 200-250 | 250-300 | >300 |
|--------------------------|------|--------|--------|--------|--------|--------|------|
| 0-50 | 16723 | 3309 | 10096 | 13414 | 194936 | 1.344 | -0.217 | 1.561 |
| 50-100 | 16381 | 2249 | 11156 | 14132 | 194218 | 0.906 | -0.113 | 1.019 |
| 100-150 | 16100 | 1705 | 11700 | 14395 | 193955 | 0.610 | -0.064 | 0.675 |
| 150-200 | 12332 | 1143 | 12262 | 11189 | 197161 | 0.462 | -0.034 | 0.496 |
| 200-250 | 14409 | 1143 | 12262 | 13266 | 195084 | 0.292 | -0.023 | 0.315 |
| 250-300 | 12849 | 877 | 12528 | 11972 | 196378 | 0.130 | -0.008 | 0.138 |
| >300 | 132961 | 2979 | 10426 | 129982 | 78368 | -1.032 | 0.726 | -1.759 |

| Distance to stream (m) | 0-50 | 50-100 | 100-150 | 150-200 | 200-250 | 250-300 | >300 |
|-----------------------|------|--------|--------|--------|--------|--------|------|
| 0-50 | 44548 | 2890 | 10515 | 41658 | 166691 | 0.075 | -0.020 | 0.095 |
| 50-100 | 36022 | 1876 | 11529 | 34146 | 174203 | -0.158 | 0.028 | -0.186 |
| 100-150 | 35312 | 1554 | 11851 | 33758 | 174591 | -0.335 | 0.054 | -0.388 |
| 150-200 | 26348 | 1234 | 12171 | 25114 | 183235 | -0.270 | 0.032 | -0.301 |
| 200-250 | 24021 | 1546 | 11859 | 22475 | 185874 | 0.067 | -0.008 | 0.075 |
| 250-300 | 18460 | 1132 | 12273 | 17328 | 191021 | 0.015 | -0.001 | 0.017 |
| >300 | 37043 | 3173 | 10232 | 33870 | 174479 | 0.376 | -0.093 | 0.468 |

| Distance to spring (m) | 0-100 | 100-200 | 200-300 |
|-----------------------|-------|--------|--------|
| 0-100 | 2774 | 353 | 13052 | 2421 | 205928 | 0.818 | -0.015 | 0.833 |
| 100-200 | 6755 | 752 | 12653 | 6003 | 202346 | 0.666 | -0.028 | 0.695 |
| 200-300 | 10341 | 990 | 12415 | 9351 | 198998 | 0.498 | -0.031 | 0.529 |
Landslide Susceptibility Mapping Using Weights of Evidence Model

Landslide susceptibility index can be calculated based on the overall spatial association between the nine causative factors and training landslides. In this study, the total number of landslide pixels is 16,774 and the total number of pixels within the entire area or map is 221,754. These landslide and area pixels were classified into different factor classes to develop and validate the landslide susceptibility map. Weight of each factor class was calculated based on the density of landslides within each factor class. The positive and negative weights of each factor class were calculated based on equations 3 and 4. The weight of contrast values of all factors including slope, curvature, aspect, lithology, land use/land cover, rainfall, distance to stream, distance to spring and distance to lineament were calculated. Weight of contrast is the difference between positive and negative weight values. Raster maps of all the nine causative factors were prepared using weights of contrast values. The rater maps of all the nine causative factors were integrated using a raster calculator of the spatial analyst tool in ArcGIS to produce the landslide susceptibility index (LSI) map. The final landslide susceptibility index map was prepared based on equation 8 as follows.

\[ LSI = C_{\text{slope}} + C_{\text{aspect}} + C_{\text{curvature}} + C_{\text{lithology}} + C_{\text{landuse}} + C_{\text{rainfall}} + C_{\text{dlineament}} + C_{\text{spring}} + C_{\text{stream}} \]  

(8)

Where \( C_{\text{slope}} \) = weights of contrast value of slope, \( C_{\text{aspect}} \) = weights of contrast value of aspect, \( C_{\text{curvature}} \) = weights of contrast value of curvature, \( C_{\text{lithology}} \) = weights of contrast value of lithology, \( C_{\text{landuse}} \) = weights of contrast value of land use, \( C_{\text{rainfall}} \) = weights of contrast value of rainfall, \( C_{\text{dlineament}} \) = weights of contrast value of distance to lineament, \( C_{\text{spring}} \) = weights of contrast value of distance to spring and \( C_{\text{stream}} \) = weights of contrast value of distance to stream.

The LSI value ranges from -11.308 to 7.520. These values were reclassified into five landslide susceptibility classes of Very Low (-11.308 - - 6.106), Low (-6.106 - - 3.580), Moderate (-3.580 - - 1.117), High (-1.117 - 1.600) and Very High (1.600 - 7.520) using the natural breaks classification method (Fig. 7). The study area covered 199.5 Km\(^2\) out of which 80.32 Km\(^2\) falls to the very low and low landslide susceptibility classes that comprised 2.49% of the landslide density. Landslide density data indicated that 85% (69.49 Km\(^2\)) of the past landslides occurred in the high and very high
landslide susceptibility classes. The remaining 12.48% (49.69 Km²) of landslides occurred in a moderate landslide susceptibility class (Table 2).

Figure 8 Landslide susceptibility map of the study area
Table 2 The relation between landslide susceptibility classes and training landslides

| Landslide Susceptibility Class (LSI) | NPLSM | %PLSM | NTLSP | %TLSP | Area (km²) |
|-------------------------------------|-------|-------|-------|-------|------------|
| Very Low (-11.308 - - 6.106)        | 33611 | 15.16 | 75    | 0.56  | 30.24      |
| Low (-6.106 - - 3.580)              | 55665 | 25.10 | 259   | 1.93  | 50.08      |
| Moderate (-3.580 - - 1.117)         | 55230 | 24.91 | 1673  | 12.48 | 49.69      |
| High (-1.117 - 1.600)               | 49709 | 22.42 | 4929  | 36.77 | 44.72      |
| Very High (1.600 - 7.520)           | 27532 | 12.42 | 6468  | 48.25 | 24.77      |

Note: LSI = Landslide Susceptibility Index, NPLSM = Number of Pixel in a Landslide Susceptibility Map, %PLSM = Percent of Pixels in a Landslide Susceptibility Map, NTLSP = Number of Training Landslide Pixels, %TLSP = Percent of Training Landslide Pixels

Validation of the Landslide Susceptibility Model

Validation of the model is an important procedure to know how the model predicts well. Several approaches were used in the validation of landslide susceptibility maps. The most commonly used ones include the success rate curve, predictive rate curve, landslide percent comparison, landslide density, relative error, relative landslide density index and Receiver operating characteristics curve. For this study, landslide density index, success rate and predictive rate curves were used to check the accuracy of model.

Area Under the Curve (AUC)

Validation of the LSM using AUC is divided into success rate and prediction rate curves (Sumatra et al. 2015). The success rate describes how well the model fits with past events and prediction rate describes how well the model predicts the occurrence of landslide occurrence in the future. The success rate curve was prepared by crossing LSI with landslide training and the prediction rate curve was prepared by overlaying validation landslides with landslide susceptibility index. The LSI values were reclassified into hundred classes and sorted in a descending order. Then the percentage of landslide susceptibility index value is plotted against the percentage of cumulative landslide occurrence to produce the success and predictive rate curves (Fig. 8). The area under the curves was estimated from rate graphs (Lee and Talib 2005; Lee and Sambath 2006). The area under the curve values showed 0.824 and 0.834 for success rate and predictive rates respectively. This showed an accuracy of 82.4% and 83.4% for the training and validation models respectively of the landslide susceptibility map indicating that the model has a very good performance.
Landslide Density Index (LDI)

Based on landslide density index, the model is considered valid when the landslide density value increases from very low to very high landslide susceptibility classes (Pradhan and Lee 2010). LDI is calculated as the ratio of the percentage of pixels with landslides in landslide susceptibility class to the percentage of pixels within the landslide susceptibility class. The landslide density index of the area indicated that the density of landslides increases from very low to very high landslide susceptibility classes (Table 3). This verifies that the resulting landslide susceptibility map is valid. The plotted landslide density graph is used to show the distribution of landslide density in each susceptibility class (Fig. 10). The statistical analysis results obtained from overlay analysis of the training landslides over the landslide susceptibility class indicated that maximum area of landslide distribution was observed in the very high and high susceptibility classes i.e. 48.3% and 36.8% respectively followed by moderate landslide susceptibility class (12.5%), low (1.9%) and very low classes (0.6%). Likewise, the validating landslides showed the maximum landslide distribution in the very high(50.5%) and high (34.8%) susceptibility classes followed by moderate (12.9%), low (1.5%) and very low (0.2%) landslide susceptibility classes.

Table 3 Validation of the model using landslide density index

| Landslide Susceptibility Class (with LSI) | NPLSM | %PLSM (c) | NTLSP | %TLSP (a) | LDI = a/c | NVLSP | %VLSM (b) | LDI = b/c |
|----------------------------------------|-------|-----------|-------|-----------|-----------|-------|-----------|-----------|
| Very Low (-11.308 - - 6.106)           | 33611 | 15.16     | 75    | 0.56      | 0.04      | 6     | 0.18      | 0.01      |
| Low (-6.106 - - 3.580)                 | 55665 | 25.10     | 259   | 1.93      | 0.08      | 52    | 1.54      | 0.06      |
| Class       | NPLSM | %PLSM | NTLSM | %TLSP | NVLSP | %VLSP |
|------------|-------|-------|-------|-------|-------|-------|
| Moderate   | 55230 | 24.91 | 1673  | 12.48 | 436   | 0.50  |
| High       | 49709 | 22.42 | 4929  | 36.77 | 1173  | 1.64  |
| Very High  | 27532 | 12.42 | 6468  | 48.25 | 1702  | 3.89  |

Note: LSI = Landslide Susceptibility Index, NPLSM = Number of pixels in a landslide susceptibility map, %PLSM = Percent of pixels in a landslide susceptibility map, NTLSM = Number of training landslide pixels, %TLSP = Percent of training landslide pixels, NVLSP = Number of landslide pixels, %VLSP = Percent of landslide validation pixels, and LDI = Landslide density index

Figure 10 The relation between landslide susceptibility class and landslide density (Note: TLS = Training landslide; VLS = Validating landslide)

Figure 11 Bar graph showing validation of the model using landslide density index
Conclusion

Kabi-Gebro area is an area where active erosion, rugged and undulating topography, and cultivated land is prevailing. This area is highly affected by a landslide problem which is caused by natural phenomena and man-made activities. The most common types of landslide in the study include rock slide, earth slide, rock fall, topple, earth flow, rock flow, debris flow, debris slide, lateral spread and creep. Landslides affected the agricultural land, crop, human lives, road and settlement in the study area. Therefore, preparing the landslide susceptibility map is very important to manage the effect of this hazard. In this study, landslide susceptibility mapping has been carried out using weights of evidence model. For this study, 514 landslide locations were identified and classified into training (80%) and validation landslides (20%). Landslide susceptibility map was prepared based on the spatial association between the training landslides and the nine causative factors such as slope, curvature, aspect, lithology, rainfall, land use, distance to stream, distance to lineament and distance to spring. The percentage of landslides was calculated in each factor class to evaluate which of landslide factor class is mostly influencing the landslide occurrence. The landslide distribution data showed that the highest percentages of landslides occurred in the factor classes of slope > 45º (61.7%), concave curvature (39.2%), moderately weathered basalt (35.4%), distance to lineament (0 - 50m) (28.1%), rainfall (1047-1064mm/year) (23.6%), distance to spring (0 - 50m) (21.1%), bare land (20.9%), distance to stream (>300m) (20.4%) and west facing aspect (15.2%). The weights of contrast values of each factor class was calculated during landslide susceptibility modeling. The slope class > 45º has an extremely highest effect on landslide occurrence with $C = 2.583$. The slope classes (25º - 35º, 35º- 45º and > 45º), lithology class (moderately weathered basalt), land use class (bush land) and distance to lineament classes (0 - 50m and 50 - 100m) have shown high and a positive weights of contrast values ($C \geq 1$). These factor classes have a relatively very high impact on landslide occurrence. The other factor classes like lithology (alluvial deposit), land use (bare land, sparse forest and river), distance to lineament (100 - 150m and 150 - 200m), distance to spring (0 - 100m, 100 - 200m and 200 -300m), distance to stream (> 300m) and rainfall (1035 - 1063mm/year) have also a high weights of contrast values ($C = 0.5 – 1$). There are many factor classes which have weights of contrast values ($C$) in between 0 and 0.5. Finally, a landslide susceptibility map was prepared using a raster calculator of the spatial analyst tool in ArcGIS by adding all weights of contrast values of the nine landslide causative factors. Then, the landslide susceptibility map was reclassified into very low, low, moderate, high and very high landslide susceptibility classes based on natural breaks method. The key issue in any landslide susceptibility mapping is validating the model. The performance of the model used and the accuracy of the landslide susceptibility map was evaluated using landslide density index and area under the curve (AUC). AUC of the model showed the success rate accuracy 82.4% and the predictive rate accuracy 83.4%. This confirms that the weights of evidence model has a very good performance. The landslide density index showed that the percentage of landslides progressively increases from very low to very high landslide susceptibility classes proving the validity of the landslide susceptibility map. Finally, the weights of evidence model, which was applied in this study, was found to be simple, reliable and effective in assessment of numerous causative factors with landslides. Hence, the final landslide susceptibility map from weights of evidence model in this study area can provide a first-hand information for decision makers in infrastructure development and land use planning at district, zonal, regional and federal levels.
Recommendation

The result obtained from this research was important to take proper mitigation measures to prevent the impact of landslide hazard. Providing adequate training for local people on ‘how’ and ‘where’ the landslide occurs is very important before any preventive or corrective measures are taken. The main aggravating factors should be minimized by reducing steep slopes along the road section, dewatering high groundwater and managing poor agricultural practices. Beside, detail geotechnical investigation is also important to make a thorough investigation for designing sophisticated landslide mitigation measures. To reduce the effect of a landslide on human lives and engineering structures, the high and very high susceptibility classes should be provided with the necessary mitigation measures. Areas of new cracks which indicate the future landslide occurrences can be avoided by restricting or prohibiting settlement in such areas. Additionally, relocating local people who are living in these hazardous zones and minimizing any development activities can help to reduce the impact of landslides in the study area in particular and the Blue Nile (Abay) Basin in general.

Abbreviations

Geophys J Roy Astron Soc: Geophysical Journal Roy Astron Society, Stat Appl in Earth Sci: Statistical Applied in Earth Sciences, Eng Geol: Engineering Geology, Science and Eng: Science and Engineering, J Geom: Journal of Geomorphology, J South Asia Disaster Stud: Journal of South Asia Disaster Studies, Gondwana Res: Gondwana Research, J Remote Sens: Journal of Remote Sensing, Env Geol: Environmental Geology, J Jpn Landslide Soc.: Journal of Japan Landslide Society, Geophys J Roy Astron Soc: Geophysical Journal Roy Astron Society, Environ Model Softw: Environmental Model Softwares, Nat Hazards Risk: Natural Hazards Risk, J. Afri. Earth Sci.: Journal of Africa Earth Sciences, Ethiop J Sci: Ethiopia Journal Sciences, Nat Hazard: Natural Hazard, Earth Surf Proc Landforms: Earth Surface Process and Landforms, Geophys Res Abstr: Geophysical Research Abstracts, J Comput Geosci: Journal of Computer and Geosciences.

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Availability of data and materials

The available data sources were described in the main body of manuscript.
Authors’ contributions

NG as a first author participated in different phases of the research work starting from literature review, secondary data collection in different offices and primary data collection in the field, landslide inventory mapping and landslide susceptibility map preparation. MM as an advisor also participated in this research by giving critical comments for improvement in each phase of the research and supervised the first author by checking the validity of the data and results and further enriched the research by adding his inputs. This helped to improve the quality of the research significantly. Finally, both authors approved the manuscript submission.

Competing interests

The authors confirm that they have no competing interests with any individual or organization.

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