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Landslide Inventory, Susceptibility, Hazard and Risk Mapping

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Abstract

Landslide is that the downslope movement of debris, rocks, or earth material under the influence of the force of gravity. Although the causes and mechanisms of landslides are complicated, human action, earthquakes, and severe rainfall can trigger them. It can happen when the driving force surpasses the resisting force due to natural soil or rock slope destabilization. Landslide is one of the foremost destructive and dangerous natural hazards that cause numerous fatalities and economic losses worldwide. Therefore, landslide investigation, susceptibility, hazard, and risk mapping are vital tasks to disaster loss reduction and performance as a suggestion for sustainable land use planning. The determination of the cause variables, identification of existing landslides, and production of a landslide susceptibility, hazard, and risk map are all necessary steps in the mitigation of landslide incidence on the globe. Landslide susceptibility, hazard, and risk maps are the outcome of a statistical relationship between environmental conditions and previously occurring landslides. It provides critical scientific support for the government's reaction to land use practices and the management of landslide threats. The type, concept of landslides, factor, inventories, susceptibility, hazard, and risk, as well as mapping and validation methodologies, have all been examined in this chapter. The distinction between landslide susceptibility and hazard has surely been debated.

Keywords: susceptibility, hazard, risk, inventory

1. Introduction

Landslide inventory, susceptibility, hazard, and risk mapping may be a complex job thanks to a good spectrum of conditioning and triggering factors, lack of record data, and non-uniqueness of mapping methods. As a result, a geologist's participation in landslide inventory, susceptibility, hazard, and risk mapping is critical. In landslide susceptibility, hazard, and risk mapping, mapping and analysis of previous and active landslide incidence are demanding tasks that can be used for landslide prevention and mitigation. Landslide disaster prevention and mitigation will not be effective unless the landslide-prone area is correctly mapped [1]. Landslides can bury animals and persons; demolish houses, farms, and infrastructures in a short amount of time [2] and Wubalem [3]. Hong et al. [2], Wubalem [4] are stated that within a short period, landslides can bury animals and humans, destroy houses, farms, and infrastructures. Landslide is one of the foremost destructive and dangerous natural hazards that cause numerous fatalities and economic losses worldwide [2, 5–7]. Therefore, landslide

inventory, susceptibility, hazard, and risk mapping and assessment are vital to disaster loss reduction and function as a suggestion for sustainable land use planning.

The extenuation actions of landslide incidence within the planet are required determination of the causal factors, identification of prevailing landslides, and generation of landslide susceptibility, hazard, and risk map [8]. Landslide inventory mapping is extremely important to work out landslide type, failure mechanism, spatial distribution, and size in a given region. Landslide inventory is also important for landslide susceptibility, hazard, and risk mapping. Chen and Wang [9] explained that susceptibility, hazard, and risk maps of landslides are the results of the statistical relationship in between landslide governing factors and preexisting landslides. Susceptibility, hazard, and risk map of landslides are imperative for scientific support of the government's response to land use practice and landslide hazards management [9, 10]. The landslide susceptibility or hazard mapping is not only to determine the factors that are most influential to the landslides that occurred within the region but also to appraisal the comparative influence of every landslide governing factors [9]. As stated by Chen and Wang [9], landslide susceptibility or hazard mapping is also significant to inaugurate an association between the factors and landslides to foresee the landslide hazard in the future. As a result, extensive and accurate landslide inventory mapping, as well as the creation of landslide susceptibility, hazard, and risk maps, is critical. Although the reason for landslide incidence and its mechanisms are so complex, human interventions, earthquakes, and heavy rainfall can trigger it. As Kifle [11]; Wubalem and Meten [4] stated that landslide incidence can also occur when the resistance force exceeds by driving force thanks to the destabilization of natural soil or rock slopes. This chapter is provided a summary of the sort of landslide type, factor, landslide inventory, landslide susceptibility, hazard, risk mapping, and validation approaches.

2. Definition and concepts

Landslide is that the movement of the mass of rock, debris, and earth downslope [12–15]. Landslides are also defined as an outsized range of geotechnical phenomena under the influence of gravity. On another hand, a landslide is that the type of mass wasting activity that denotes any outward or downslope movement of soil and rock under the direct influence of gravity when the drive exceeds the resistance force of a slope [13, 14, 16]. These masses may range in size from card to entire mountainsides. Their movements may vary in velocities. Landslide as a geological hazard is caused by earthquake or eruption, rainfall, and act. This is often initiated when an area of a hill slope or sloping section of the seabed is rendered weak to support its weight. It is one of the foremost destructive natural hazards triggered by natural and man-made factors like an earthquake, rainfall [17], and act like an improper/poor quarry, and road construction/inadequate maintenance in mountainous terrain [18].

In geohazard mapping, susceptibility/vulnerability, hazard, and risk mapping are the foremost important activities to understand, mapping, and evaluating the spatiotemporal condition and level of risk because of geo-hazards. These terms have different meanings but some researchers use the terms interchangeably. Susceptibility refers to the probability of occurrence of an event within a selected type during a given location whereas hazard refers to the probability of occurrence of an event within a selected type and magnitude during a given location within a reference period. This means, susceptibility is usually used to predict the spatial occurrence of events, but the hazard is usually used to predict the spatiotemporal occurrence of events during a given terrain. The term risk refers to the expected losses or damage by events during a given region, which are the products of susceptibility, hazard,

and elements in peril. Vulnerability means the degree of loss to a given element of the set of elements in peril resulting from the occurrence of natural phenomena of a given magnitude. It is expressed on a scale from 0 (no damage) to 1 (total damage). Elements at risk is potentially vulnerable of properties, population, and economic activities including public services in peril during a given area.

2.1 Type of landslide or failure mechanism

Landslides are usually classified based on the materials involved (rocks, debris, and soils) and on their mechanism and failure (**Table 1**). Other factors include groundwater content and the rate and dimension of the movement. Classifying and studying this phenomenon is important to manage damages because of the landslide. Classification of the landslide is the primary step to investigate landslides. According to Varnes [13, 19], landslides are classified based on the types of material, mode of movement, landslide activity, the rate of movement, depth, the magnitude of slide and moisture content.

2.1.1 Rotational landslides

Rotational landslides are more common in cohesive, homogeneous soils. The failure, which can be superficial or deep-rooted, occurs along curved surfaces concave upwards, having a shape of a spoon. Successive landslides occur mainly in stiff fissured clays with gradients similar to their angle of equilibrium and in soft very sensitive clays, where the initial landslide causes an accumulation of remolded clay, which as it flows, leaves the material higher up without support, so promoting successive failures. These failures are shallow but can have considerable lateral continuity [20]. Weak rock masses or those with a high degree of fracturing or weathering, where the structural discontinuities do not form preferred surfaces for failure may also suffer this type of successive landslides.

2.1.2 Translational slides

In translational slides, failure takes place along pre-existing planar surfaces or discontinuities (bedding planes, contact between different types of materials,

Movement type		Slope material type		Source	
		Bedrock	Soil mass in failed slope		[13]
			Principal coarse	Principal fine	[13]
Topples		Rock topple	Debris topple	Earth topple	[13]
Fall		Rock fall	Debris fall	Earth fall	[13]
Lateral spread		Rock spread	Debris spread	Earth spread	[13]
Slide	Translational slide	Rockslide	Debris slide	Earth slide	[13]
	Rotational slide				
Flows		Rock flow (Deep creep)	Debris flow	Earth flow	[13]
Composite or complex		Two or more principal types of movement in combination			[13]

Table 1.
Landslide classifications based on material and types of movements [13].

structural surfaces, etc.) and sometimes the failure plane is a fine layer of clay material between more competent strata [20].

The sliding mass can be sometimes rectangular blocks that have been detached from the mass at discontinuities or tension cracks (block landslides). Translational slides generally move faster than rotational ones, because of their simple geometry of failure mechanism.

2.1.3 Flows

As defined by Vallejo and Ferrer [20], flows are mass movements of soil (mud or earth flows), debris (debris flows), or rock blocks (rock fragment flows) often with high water content, where the material behaves as a fluid undergoing continuous deformation but without having well-defined failure surfaces. Water is the main triggering factor because water decreases the strength of materials having low cohesion [20]. Flows mainly affect sensitive clay soils which show considerable loss of strength when mobilized; these movements are not very deep in their extent and develop on slopes $<10^\circ$.

2.1.3.1 Mud or earth flows

Mud or Earth flows occur in predominantly fine and homogeneous materials and may move at a speed of the many meters per second; the loss of strength is typically caused by water saturation. They are classified consistent with the sort of fabric, its strength, and its water content. Mudflows are generally small-scale and slow but sometimes especially in-saturated conditions, they are extensive and fast, with catastrophic consequences once they reach populated areas. Fine volcanic materials are particularly vulnerable to this sort of process.

2.1.3.2 Debris flows

Debris flows are complex movements, which include rock fragments, blocks, cobbles, and gravel in a fine-grained matrix of sands, silts, and clays. They occur on slopes covered with loose or non-consolidated material, especially where there is no vegetation cover.

2.1.4 Creep

Creep may be a very slow, almost imperceptible superficial movement (a few decimeters deep), which affects soils and weathered materials, causing continuous deformations that becomes progressively noticeable on slopes over time. This causes fences, walls, or posts to lean or offset and trees to be bent. Creep may be a time-dependent deformation and defines the deformational behavior of the fabric instead of the sort of movement.

2.1.5 Solifluction

Solifluction affects the saturated surface layer of slopes. This is often a slow movement produced by the freeze–thaw process because the daily or seasonal temperature variations change the water phase and water content of fine-grained soils in cold regions.

2.1.6 Rock falls

Rock falls are very quick free falls of rocks, which are dislodged from pre-existing discontinuity planes (tectonic, bedding surfaces, and tension cracks). The movement could also be by a vertical fall, by a series of bounces, or by rolling down the slope surface. They are common on steep slopes in mountainous areas, on cliffs, and generally, on rock walls and therefore the blocks are bounded by different sets of discontinuities often forming wedge-shaped blocks. The factors that cause rock falls include erosion and loss of support for previously loosened blocks in steep slopes, water pressures in discontinuities, and tension cracks and seismic shakes. Although the fallen blocks could also be relatively small in terms of volume, rock falls are sudden processes that pose a big risk to communication routes and buildings in mountainous zones and at the foot of steep slopes. Masses of soil can also fall from vertical natural and excavated slopes, thanks to the existence of tension cracks generated by tensional stresses or shrinkage cracks within the ground that has dried.

2.1.7 Toppling

The toppling of strata or blocks of rock may be included in rock falls. Toppling occurs when the strata dip in the opposite direction to the slope and form naturally inclined blocks, which are free to rotate because of failure at the foot of the slope. Toppling tends to occur mainly on rocky slope faces, which intersect steeply dipping strata [20].

2.1.8 Rock avalanches

Rock avalanches are rapidly falling masses of rock and debris that detach themselves from steep slopes, sometimes amid ice or snow. The rock masses disintegrate during their fall and form deposits of very different block sizes and form deposits of very different block sizes, with no rounding from abrasion and chaotic distribution [20]. Rock avalanche deposits are unstructured and have great porosity [20]. Avalanches are generally the results of large-scale landslides or rock falls during which due to the steep gradient and therefore the lack of both structure and cohesion in their materials, travel down over steep slopes at great speed (up to 100 Km/h).

2.1.9 Debris avalanches

Debris avalanches are formed from rock material containing an excellent sort of sizes and should include large blocks and abundant fines [20]. Loose deposits and loose materials resulting from volcanic eruptions are susceptible to this process. The most difference with debris flows, aside from water content (which is not necessary for debris avalanches), is that the rate and speed of movement of the avalanche in areas of a steep gradient.

2.1.10 Lateral displacements

This sort of movement (also called lateral spreading) refers to the movement of rock blocks or coherent, cemented soil masses that rest on soft & deformable slopes. These movements are thanks to the loss of strength of the underlying material, which either flows or deformed under the load of the rigid blocks. Lateral spreading can also cause by liquefaction of the underlying material or by lateral extrusion of

sentimental, wet clays under the load of the masses above them [20]. These movements occur on gentle slopes and should be very extensive.

2.2 States and distribution of landslide

Determining the states and distribution of landslides is extremely important to repair the consequences of landslides on infrastructures, lives, farmlands, and environments. The landslide are going to be found within the following different states of condition. Active landslide is currently moving. A suspended landslide has moved within the last twelve months but is not active at the present. A reactivated landslide is a lively landslide that has been inactive. An inactive landslide is a landslide, which did not moved at most for year.

Inactive landslides are often subdivided into these states:

- A dormant landslide is an inactive landslide, which will be reactivated by its original causes or other causes.
- An abandoned landslide is an inactive landslide that is not suffering from its original causes.
- A stabilized landslide is an inactive landslide that has been shielded from its original causes by artificial remedial measures.
- A relict landslide is an inactive landslide that developed under geomorphological or climate considerably different from those at the present.

2.3 Recognition of landslides

Potential and existed landslides can be identified or recognized using different techniques considering various features that existed on the earth's surface. Different features indicate landslide signs like

- Depression at top (water ponding)
- Bulging at toe Tension cracks
- Water seepage (generally at toe)
- Tilted and crooked trees
- Change in vegetation
- Change in topography
- Change in drainage pattern

2.4 Landslide factors

2.4.1 Introduction

In hazard minimization, the evaluation of landslide conditioning and triggering factors is a very important task. Geodynamic processes affecting the earth's surface cause mass movements of different types, sizes, and speeds [20]. Landslide

movement is that the most frequent and widespread sort of mass movement generated by the gravitational downslope displacement of soil and rock masses [20]. The force of gravity and therefore the progressive weakening of geological materials, mainly thanks to weathering, alongside the action of other natural and environmental phenomena, make mass movements relatively common on the earth's surface [20]. These processes create potential geological risks, as they will cause economic loss and social damage if they affect human activities, buildings, and infrastructure [20]. How to avoid these adverse effects is the subject of research including mass movements, their characteristics, instability mechanisms, controlling factors, and causes. To carry out this research, it is necessary to understand the characteristics and therefore the geological, geotechnical, and hydrogeological properties of the soil and rock materials involved and their mechanical behavior also because the factors that condition and trigger such movements [20]. Studies during this field should specialize in the investigation of [20]

- Particular processes for the design of stabilizing measures to either mitigate or reduce damage.
- Analysis of the factors, which control and trigger processes at particular locations, to stop possible movements.
- Mapping either unstable or potentially unstable zones, in order that the hazardous areas are often delimited and preventive measures are often applied.

As usual, landslides might transpire when shear stress exceeds the shear strength of slope material. The factors that cause landslide have been classified as factors that contribute to an increase of the shear stress and factors that contribute to the decrease of shear strength; however, water is another factor contributing to both increasing and decreasing shear stress and shear strength of slope material respectively. Factors these increase shear stresses are included removal of lateral support; surcharge/ overloading, transitory earth stress, regional tilting, removal of underline support, and increase in lateral pressure. The factors that contribute to the decrease of shear strength of slope material include factors like initial state or inherent characteristics of materials and the changing or variable factors that tend to lower the shear strength of a material. On other hand, factors that control landslides are classified into two such as intrinsic/inherent/static and external/dynamic landslide factors [21–23].

2.4.2 Intrinsic controlling factors

According to Anbalagan [21], and Raghuvashi et al. [24], intrinsic parameters are the inherent controlling factors that outline the favorable or unfavorable condition within the slope. These include slope material, slope geometry, structural discontinuity, land use/cover, and groundwater. These factors have an excellent influence to decrease the strength of the slope material. Hence, mapping and perception of their impression are crucial for slope stability analysis.

2.4.2.1 Lithology

The kind of fabric during a slope is closely associated with the sort of instability. Different lithology are going to be showed different degrees of susceptibility to potential slippage or failure. The stress–strain behavior of materials is governed by their

strength properties, which also depend upon the presence of water. Sorts of failure and therefore the location of failure surfaces depend upon factors like alternating materials of various lithology, the extent of weathering, and therefore the presence of layers of sedimentary material or hard strata. Soils, which are considered homogeneous materials, compared to rock masses, instability could also be generated by differences within the degree of compaction, cementation, and grain size, which can make some areas more vulnerable to weakness and water flow. In rock masses, characterization and analysis of slope behavior are further complicated by the presence of layers of strata with differing strengths and properties [20].

2.4.2.2 Discontinuities

Geological structures or discontinuities play a definitive role in conditioning the slope stability in rock masses. A mixture of structural elements and geometric slope parameters, like height, gradient, and orientation, defines problems, which will occur. The spatial distribution of discontinuities is that the structure of the rock mass [20]. The presence of those surfaces of weakness (bedding surfaces, joints, and faults) dipping towards the slope face implies the existence of potential failure planes on which sliding can readily occur.

The orientation and spatial distribution of discontinuities will condition the sort and mechanism of the instability. A specific system of fracturing will condition both the direction of movement and therefore the size of blocks susceptible to slide or the presence of a fault dipping towards a slope face will limit the unstable area. Structural changes and singularities within the rock mass, like Tectonized or shear areas, or abrupt changes within the dip of the strata, indicate heterogeneities from which failure might originate. Slope stability could also be suffering from changes to the initial conditions during excavation; for instance, the existence of tectonic in place stress related to compressive or extensional structures like folds and faults.

2.4.2.3 Hydrogeological conditions

Most failures are caused by the effects of water in the ground, including pore pressures and erosion of the slope materials. Water is considered the worst enemy of slope stability, together with human actions where excavations are carried out without adequate geotechnical care. The presence of water in a slope reduces stability by decreasing ground strength and increasing forces, which favor instability. The main effects of water are a reduction in the shear strength of failure surfaces as effective normal stress, σ'_n , decreases. $\tau = c + (\sigma'_n - u) \tan \phi$. Increase in the downslope shear forces as water pressure is exerted in tension cracks. Increase in weight of the material due to saturation: $\gamma = \gamma_d + S n \gamma_w$ where γ_d = dry apparent unit weight; S = degree of saturation; n = porosity and γ_w = unit weight of water. Softening of soils associated with an increase in their water content. Internal erosion or piping caused by surface or underground flow. The shape of the water table on a slope depends on such factors as the permeability of materials and the geometry or shape of the slope. In rock masses, the configuration of the water table is greatly influenced by the geological structure and the alternation of permeable and impermeable materials, which in turn affect the distribution of pore water pressures on any potential slip surfaces. The influence of water on the properties of materials depends on their hydrogeological behavior. The greatest effect is produced by the pressure exerted defined by the piezo metric head [20].

The following aspects should be known to understand the effects of water in a slope [20]: 1) Hydrogeological behavior of the materials 2) Presence of water table and piezo metric heads 3) Water flow in the slope 4) Relevant hydrogeological parameters:

permeability coefficient or hydraulic conductivity, hydraulic gradient, transmissivity, and storage coefficient. One way of obtaining an approximate assessment of the entire force exerted by water on discontinuity surfaces or tension cracks is to assume the triangular distribution of hydrostatic pressure on these surfaces.

2.4.2.4 Properties of soil and rock masses

The possible failure of a slope along a surface depends on the strength, which depends on cohesion and therefore the interior angle of friction. The influence of geological history (e.g. consolidation, erosion, diagenetic processes, in situ stresses, and weathering) on the mechanical (shear strength) properties of soils must be determined considering the geological characteristics. In rock masses, mechanical behavior is decided by the strength properties of the discontinuities and therefore the intact rock counting on its degree of fracturing and the nature of the materials and discontinuities within it. The behavior of a tough rock mass generally depends on the characteristics of its discontinuities, although the lithology and its geological evolution can also play a crucial role. The shear strength of surfaces of weakness depends on their nature and origin, persistence, spacing, roughness, type and thickness of infill, and thus the presence of water.

Slope stability is highly control by in situ stresses [20]. The strain relief from decompression when the slope is excavated may transform its material properties [20]. In rock slopes, the weakest areas are often degraded and begin to behave like soft rock or granular soil. This effect is common in mudstone or mud-shale slopes subjected to high in place stresses; the rock formation is weakened into a granular material with cement-sized fragments several meters thick inside the slope, resulting in disintegration and collapse of the slope.

2.4.2.5 Geomorphological factors (slope, aspect, and curvature)

Slope morphometry refers to the steepness of the slope, which controls not only the strain distribution inside the slope mass but also affects weathering layer depth and surface runoff [25]. As reported by Lai [25], the degree and height of the slope influence the quantity of runoff and thus the extent of erosion. The steeper the slope, the upper velocity of water flowing down a slope and have higher erosive power. Thus, the slope material that supports the slope are getting to be removed and heighten the slope instability problem.

Aspect is that the orientation of the slope. Different slope direction has different weather, land cover, and radiation intensity that affects the exposure of the slope to radiation, wind impact, and rainfall [26, 27].

Curvature is that the measure of the roughness of a given terrain. The curvature may ask the concaveness, concaveness, and flatness of a slope. According to Pradhan [28, 29]; Alkhasawneh et al. [30], as cited in Meten et al. [26] the negative value refers to the valley, the positive value refers to Capitol Hill slope, and zero/ approaches zero value refers to flat acreage. The curvature condition controls the hydraulic condition and thus the consequences of gravity for slope stability.

2.4.3 External triggering factors

External triggering factors are dynamic factors, which may trigger slope movement by increasing driving force. These triggering factors include rainfall, seismic and act. Static and dynamic loads exerted on slopes modify the force distribution and may produce instability. Static loads include the load of structures or buildings on a slope or loads derived from fills, waste dumps, or heavy vehicles, and when

these loads are exerted on the slope head, they create a further weight, which will contribute to the destabilizing forces. Dynamic loads are mainly thanks to natural or induced seismicity and vibrations caused by nearby blasting. These mainly affect jointed rock masses by opening up pre-existing discontinuities, reducing their shear strength, and displacing rock blocks, which can then fall. Dynamic forces produced by an action earthquake can be given as a function of the maximum horizontal acceleration. Precipitation and climate regime influence slope stability by modifying groundwater content. The strength of the soil mass becomes loss due to changes in soil structure by alternating periods of rainfall and drought.

Man Made Factors: Abebe et al. [31]; Kifle [11, 32] is explained that the demand for new land for infrastructure, settlement, and agriculture are primary means in which humans can contribute to slope instability condition through the excavation of slope toe or slope faces, loading of slope crest, drawdown (or reservoirs), irrigation, mining, artificial vibration, deforestation, and water leakage from utilities.

2.5 Landslide inventory mapping

Landslide inventory is that the simplest sort of landslide map [33]. The landslide inventory map portrays the spatial distribution, frequency, activity, size, time, type, displace material, the intensity of injury, and density of landslide. It is often used because the base for future landslide susceptibility, hazard, and risk prediction by evaluating the connection between the prevailing landslide event and landslide driving factors [34]. Besides, landslide inventory is often used to evaluate the accuracy and performance of the landslide susceptibility, hazard, and risk maps. Landslide inventory map shows the past and current landslide incidences, which may be prepared using various techniques like the aerial photograph, Google Earth

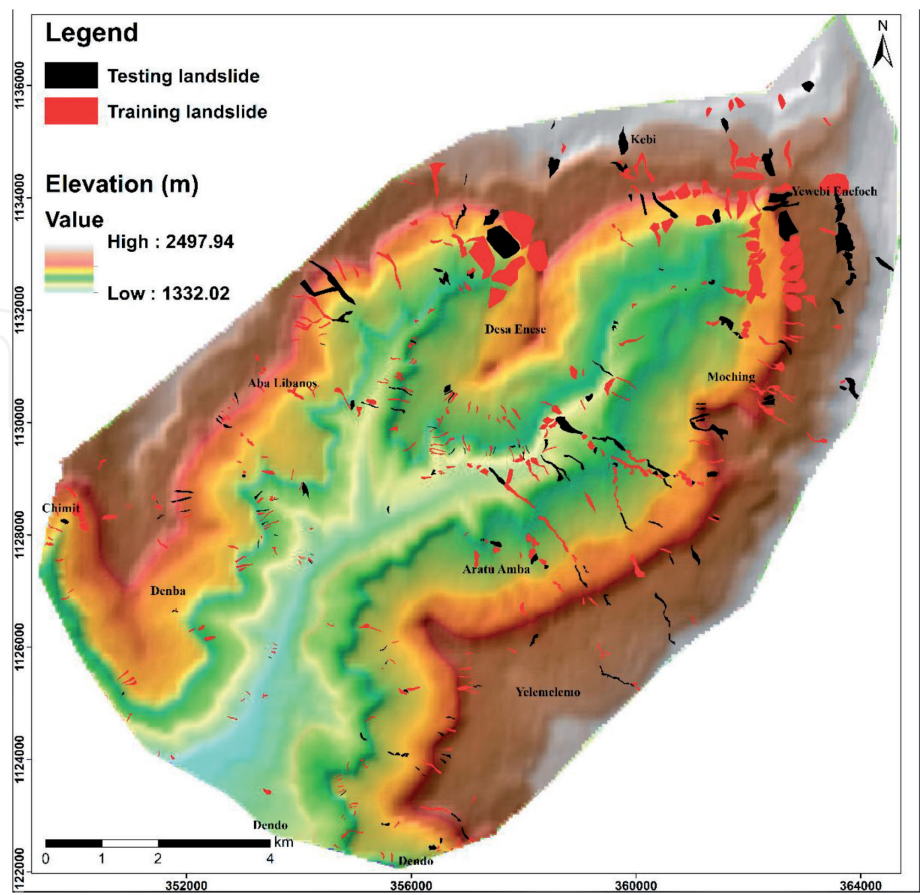


Figure 1. Landslide inventory map of the study area [36].

imagery, field investigation, and evaluation of archive data including GIS tools. Depend upon the aim, the size of the base map or aerial photograph, the extent of the study area, and therefore the availability of resources, a landslide inventory map are often prepared using different techniques as expressed above [35]. For instance, a small-scale landslide inventory map (1:25,000) landslide inventory maps are often prepared for a selected area using aerial photographs at the size of >1:20,000, Google Earth Imagery analysis, and extensive fieldwork [3, 4, 36, 37]. The Google Earth Imagery may be a free tool that helps not only to spot statistic landslide boundary but also want to determine the area coverage, perimeter, and distance of slope material movement compared to other techniques, however, it needs field for verification purpose. As a result, currently, from the active and old landslide scarps, researchers intended to spot historical landslides using statistic Google Earth Imagery analysis instead of an aerial photograph. Depend upon the dimensions of

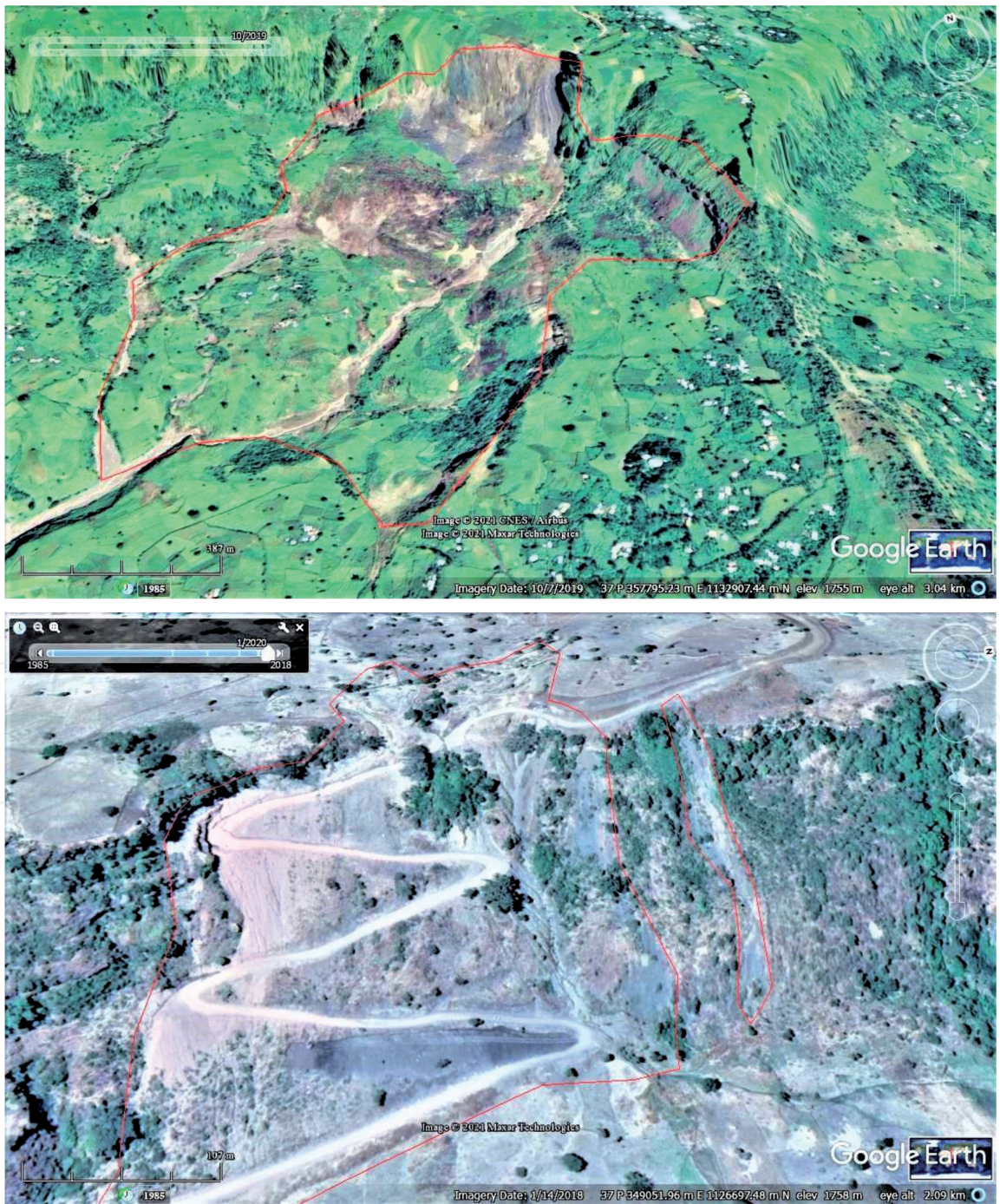


Figure 2.
Landslide in Chemoga catchment, northwestern Ethiopia.

the landslide and therefore the mapping scale, active and old landslide boundaries are often digitized into polygons employing a GIS tool with the assistance of Google Earth Imagery, and eventually, a landslide inventory map are often produced. The landslide inventory is going to be classified as training data sets and testing landslide data sets (**Figure 1**). Most of the researchers classified landslides into 70% for training data sets and 30% for testing landslide data sets [26, 38–40]. As shown in **Figures 2–4**, Google Earth Imagery analysis is so effective for landslide inventory mapping. Landslide investigation is an important task in landslide disaster reduction strategies. It can be conducted to determine and predict old, active, and future landslide incidence by examining land features. For example, field survey is used to evaluate slope gradient, geomorphology, geology, drainage, nature of soil, land use land cover, surface and subsurface water, geodynamic process, old and active landslide conditions. Generally, the methods or techniques that used to investigate landslides are summarized in **Table 2**.

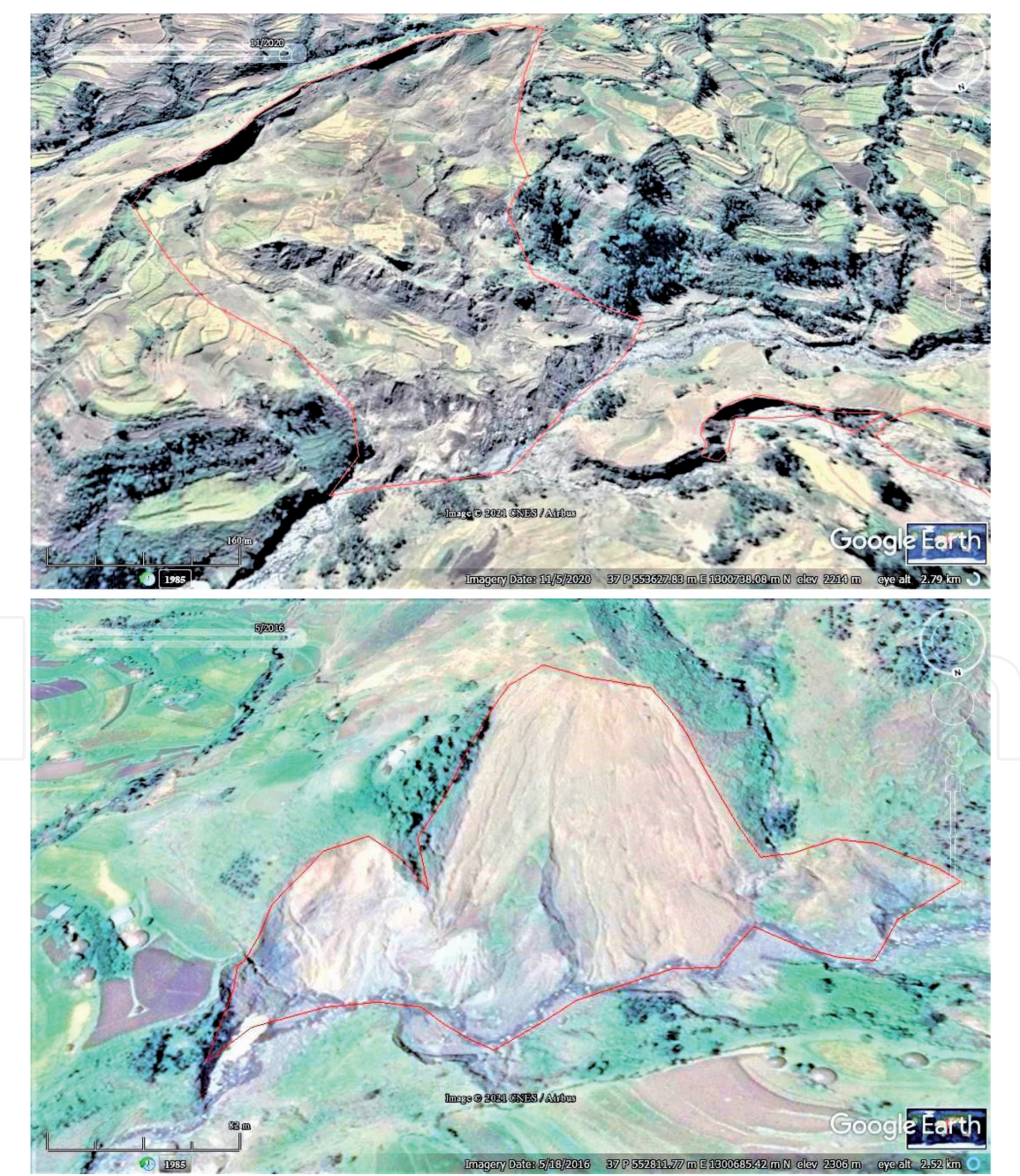


Figure 3.
Landslide in Woldia area, northwestern Ethiopia.



Figure 4.
Landslide in Dessie town, Ethiopia.

Scop	Phase of study	Methods or thetechniques	Objectives
Regional landslide study	Preliminary	Review of existing information and existing maps. Google Earth Imagery analysis, Interpretation of aerial photos and remote sensing.	Identify processes and type of movements. Identify conditioning factors. General evaluation of stability of the area. Indentify location and boundary of landslide.
	General study	Field observations. Processes mapping. Factors mapping.	
Conducted to investigate landslides or slope failure for specific area	Study of process and causal factors	Field surveys. Preliminary underground investigation: geophysical methods.	Describe and classify processes and materials. Susceptibility analysis based on the existing processes and concurrence of conditioning factors. Record landslide type, location, magnitude, frequency, dimation, damage, and element at risk.
	Detail investigation	Boreholes, geophysical methods, in situ tests, sampling, Laboratory tests.	Describe and classify movements. Collect morphological, geological, hydrogeological and geomechanical data.
	Monitoring	Inclinometers, extensometers, tiltometers, piezometers.	Collect data on speed, direction, stability analysis using Limit equilibrium methods and Stress–strain numerical models. Determine situation of failure planes, water pressures.
	Stability analysis	Limit equilibrium methods. Stress–strain numerical models.	Define failure models and failure mechanisms. Evaluate stability. Design corrective measures.

Table 2.
Summary of landslide investigation techniques [20].

2.6 Landslide susceptibility, hazard and risk mapping

Landslide susceptibility may be a quantitative or qualitative evaluation of landslide occurrence of a specific type in a given location that is used to predict spatial distribution, classification, and area of existed or potentially prone area [12, 37]. However, a landslide hazard map is employed to predict future spatial and temporal landslide occurrence with a specific type and magnitude. Although both landslide susceptibility and hazard map are different concepts, many researchers are used the terms as interchangeable. The researchers consider their susceptibility map as a hazard map during which magnitude and frequency did not consider in their model generation. The landslide risk map is employed to predict the expected spatial and temporal losses or damage by landslide incidences during a given region, which are the products of susceptibility or vulnerability, hazard, and elements in danger. Although landslide susceptibility, hazard, and risk maps are the results of the connection between landslide events and sets of landslide factors supported expert judgment or statistical analysis, hazard and risk maps become differ by some input parameters. For instance, a landslide hazard map will have additional landslide frequency, and magnitude input parameters whereas for a risk map, both susceptibility and hazard map become input parameters besides, the element in danger. As stated by Wubalem [3], landslide susceptibility and hazard map results from the sum of all weighted landslide factors employing a raster calculator or weighted overlay method in ArcGIS. Compare to landslide susceptibility mapping, landslide hazard mapping required excellent landslide inventories that contain magnitude, date of occurrence, and frequency. The shortage of frequency, date of occurrence, and magnitude of landslide, landslide hazard mapping become a difficult task. Thus, landslide research trends are shifted to landslide susceptibility mapping for the last twenty century. Now a day, thanks to technological advancement, landslide hazard mapping becomes a simple task for that area frequently suffering from landslide incidence. Lithological, geomorphological, geological structure, hydrological, climatological, anthropological, seismic, and land use/cover parameters and detailed landslide inventories are the foremost important input variables in GIS-based landslide susceptibility mapping. However, landslide frequency and magnitude are additional parameters in landslide hazard mapping. The susceptibility, hazard, and risk map produced from the expert judgment have a subjective problem for weight rating of the consequences of sets of parameters; however, the statistical analysis helps to develop maps supported the statistical relationship between sets of parameters and past or current landslide inventory data. Detailed landslide susceptibility, hazard, and risk map are often also developed for selected purpose at large scales using physical-based approaches. During this case, geotechnical properties of soil or rock slope material, angle of slope, and pore water pressure are the foremost important parameters to get a landslide susceptibility map supported the extent of an element of safety. Then, the hazard map are often produced by considering the factor of safety, landslide frequency, and magnitude. The danger map also can produce on large scale. Finally, the accuracy of the small-scale and detailed models are often validated using landslide inventory data using different techniques.

2.7 Landslide susceptibility and hazard mapping approaches

Landslide susceptibility or hazard zonation is a technique used to classify the slope into zones based on the level of actual or potential landslide susceptibility and hazard. Landslide susceptibility and hazard zonation are important for a rapid assessment of slope stability over a large area [21]. Landslide susceptibility map can forecast/provide important information about the spatial future landslide occurrence [3]. However, a landslide hazard map can forecast the spatial and temporal future landslide occurrence. In landslide susceptibility and hazard mapping, several

approaches are developed, which may be categorized into qualitative, semi-quantitative, and quantitative methods [41–45].

2.7.1 Qualitative (expert evaluation) method

The expert evaluation method is a widely used technique, but a relatively subjective approach that explains the level of landslide condition in a descriptive expression based on the decision of the expert. Qualitative methods are an expert-driven approach, which required field experience specialists [41, 43, 45–49]. Field geomorphological analysis, landslide inventory analysis, and parameter assignment superimposition are the main activities for qualitative landslide susceptibility, and hazard mapping. Relying on the experience and professional background knowledge of experts and subjectivity is the drawback of these methods [41, 43, 45–47, 49]. This method has included heuristic, landslide inventory mapping, landslide hazard evaluation factor and slope stability evaluation parameter.

2.7.1.1 Heuristic method

This method is opinion based that is used to classify landslide susceptibility and hazard maps by mapping all landslide factors, and landslide through proper rating each factor classes to prepare a landslide susceptibility and hazard map. The demerits of this method are its subjectivity.

2.7.1.2 Landslide inventory method

Inventory is a simple method, which records the location and dimension of events occurred in the given area [50]. Landslide inventory is the way that used to record landslide location, size, occurrence time, displace material and types of slope failure. This method has used as the base for landslide susceptibility, hazard, and risk assessments; however, it does not provide the spatial relationship between landslide and sets of landslide factors rather than it only shows the location and volume of a landslide [51]. In this approach, landslide data can obtain through field mapping, historical record, satellite image or Google Earth Imagery analysis, and aerial photograph interpretation [36, 52].

2.7.1.3 Landslide Hazard evaluation factors (LHEF)

According to Anbalagan [21] this method is used for landslide susceptibility and hazard zonation /mapping with consideration of the inherent controlling factors only. It is simple and cost-effective over a large area. Nevertheless, this method has the following limitations.

- i. Has a rating of low value for groundwater effect on slope instability.
- ii. It does not account the triggering factors.
- iii. The condition of the rock mass with structural discontinuity and characteristics of the structural discontinuity (roughness, aperture, etc.) are not considered.
- iv. It is Subjective
- v. Give the same rating for lithology and structural discontinuity but discontinuities have great influence than lithology.

2.7.1.4 Slope stability evaluation parameters (SSEP)

Slope stability evaluation parameters (SSEP) is a landslide hazard zonation technique that is used to evaluate both inherent (slope material, slope geometry, structural discontinuity, land use and land cover, groundwater) and external factors (rainfall, seismicity, and human activity) to prepare landslide susceptibility map. Raghuvashi et al. [24], develop this method considering the dynamic and static landslide causative parameters. This technique is simple and supported by much field data but it is subjective for weighting assignment.

2.7.2 Semi quantitative method

Semi-quantitative methods are the combination of qualitative and quantitative methods, which introduce grading and weighting of the effects of landslide factors on landslide incidence [42, 53, 54]. In this method, both qualitative and quantitative methods can be applied to evaluate the effects of landslide governing factors on landslide occurrence [55]. Analytical hierarchy process, weighted linear combination, and expert knowledge/heuristic [42, 48, 56–59] are examples of semi-quantitative methods. Although some statistical concepts are introduced in this method, it depends on the expert's experience and the background of professional knowledge and some subjectivity remains [42, 60].

2.7.3 Quantitative (statistical) method

According to Canoglu [61]; Chen et al. [62], the quantitative methods are grouped into three categories such as machine learning/data mining, physical-based, and statistical methods. The statistical methods are indirect methods which is extensively or routinely used to assess the association between landslide governing factors and landslides based on mathematical [9, 41]. They are classified into multivariate and bivariate statistical methods [3]. The statistical methods are provided reliable results [4, 26, 42, 63–69]. The numerical methods rely on the mathematical model, expression, and less expert judgments, which provides comparatively reliable results, unlike the qualitative method. Among quantitative methods, the statistical method is the one, which used to evaluate the spatial slope instability based on the relationship between the past/active landslide and landslide factors [70]. A statistical method is an indirect method used to prepare a landslide hazard/susceptibility map, which is considered as objective and worked by integrated GIS tool with statistical analysis based on the landslide and sets of landslide factors spatial relationship. However, in this method, the most difficult thing that we have to consider is accurate database construction, model calibration, and model validation iteration procedures [71]. In this method, each factor has mapped and overlaid over past/active landslides to carry out the contribution of each factor and subclass on the instability of the slope [24, 52, 72]. The limitation of the statistical method is its requirement for detailed and quality landslide and landslide factor data, and it is time-consuming to acquire them over a large area Raghuvashi et al. [24]. The statistical method cannot apply to the area where a landslide has not occurred. This is one of the limitations of statistical methods in landslide susceptibility, hazard, and risk mapping.

2.7.3.1 Bivariate statistical analysis

The bivariate statistical procedure is straightforward to use and update, which is capable to differentiate the consequences of every sub factor class for landslide

occurrence. Within the bivariate statistical procedure, the presence of landslide has been considered because the variable and therefore the parameters that enhanced the occurrence of the landslide has been considered as the independent variable [73]. In this technique, each determinant map has been classified into sub-classes to work out the response of individual factor classes to landslide occurrence. The landslide factor classes are often combined with a landslide distribution map and weighting values supported the landslide densities of every determinant class. After weight value calculation, the weighted raster map is carefully sum up employing a raster calculator in Math algebra under the GIS tool to urge the landslide susceptibility index map. The landslide susceptibility or hazard index map are often reclassified using various methods like natural break under the GIS tool to urge the ultimate landslide susceptibility map. The benefits of bivariate statistical methods are they will cover an outsized area with effective cost; it is simple to apply; it can provide spatially distributed landslide information and its relationship with landslide factors. However, the bivariate statistical methods have the subsequent limitation 1. It cannot distinguish which factor is more influential and non-influential. 2. It cannot provides the knowledge about the inherent condition of the slope material like geotechnical method 3. It can predict the landslide susceptibility regions but it cannot be predicted when this landslide will occur and it needs landslide occurrence during a certain region to predict the opposite region which has some environmental factor. The load of evidence, information value, certainty factor, and frequency ratio is that the commonest techniques in bivariate statistical analysis.

2.7.3.2 Multivariate statistical analysis

This method will provide more realistic and accurate results. It also considers the mutual relationship among landslide factors, unlike bivariate statistical methods. The weight of causal factors indicates the relative contribution of every factor to the degree of hazard in a given land unit. The multivariate statistical procedure helps to perform multivariate statistical analysis unlike the bivariate statistical procedure. One among the merits of the multivariate method is capable to work out the influential power of individual landslide factors on landslide occurrence. Logistic regression, discriminant analysis, and cluster analysis are the foremost commonly applied techniques in this method.

2.7.3.3 Data mining method

In recent times, advanced data mining methods have been widely used in landslide susceptibility modeling., including random forest [56–58], boosted regression tree [74], classification and regression tree [74], Naïve Bayes [53, 75], support vector machines [32, 76], kernel LR [77], logistic model tree [56–58, 77], index of entropy [39], and artificial neural networks [56–58, 78, 79]. Data mining methods are incapable to work out the consequences of every landslide factor class, need high computing capacity, time-consuming, and therefore the internal calculation process of those methods is intensive and cannot easily be understood. Although both statistical and data mining methods have a bit little difference in the degree of predictive accuracy, they can provide reliable predictive accuracy landslide susceptibility map in landslide susceptibility or hazard mapping [78, 80].

2.7.3.4 Physical based approach

The physical-based approach includes limit equilibrium and finite element numerical models. These methods can be applied for both soil and rock slope

stability analysis. This method can provide hazard in absolute value /factor of safety or probability/quantitative results that can directly use for design purposes [52] and Raghuvashi et al. [24]. Physical-based methods are used to calculate the quantitative value of the inherent slope materials of the factor of safety over a defined area [81]. These methods can be applied when landslide types are simple (shallow landslides) and the intrinsic properties of slope material are homogeneous [81]. It requires detailed ground data such as unit weight of soil, soil strength, soil layer thickness, slope angle, pore water pressure, depth below the terrain surface, and slope height. The physical-based method has been employed over a small area, and oversimplification, data availability to acquire frequently is impossible are the drawback of these methods [81]. These methods can be focused on an on-site investigation to assess the geotechnical properties of soil/rock, soil depth, surface and subsurface water condition, the geometry of the slope, landslide location, failure mechanism, depth, and distance of landslide. These methods are used to analyze slope conditions by calculating factors of safety using different software like PLAXIS and Slope/w in GeoStudio software package as two or three-dimensional models. The oversimplification of geological, geotechnical model and the difficulty to predict pore water pressure and its relationship with rainfall /snowmelt are the main problems that challenge use the of geotechnical approaches [82].

2.8 Landslide risk mapping approaches

Landslide risk is the expected loss or damage due to landslide Incidences, which include fatalities, damage to properties, infrastructure, farmland, environment, interruption of services, and economic activities. As compare to landslide susceptibility, and hazard mapping, landslide risk mapping is not common so far due to it requires complex input parameters. It is a complex task due to the lack of necessary information to produce input parameters including vulnerability/susceptibility, hazard, and element at risk [33]. In addition to landslide susceptibility/vulnerability, and hazard maps, landslide risk map is very important in the regulation of land use, landslide risk management, and mitigation strategies. One has a plan to prepare a landslide risk map, it is necessary to estimate landslide susceptibility, hazard, and element at risk.

In landslide risk mapping, qualitative and quantitative techniques are commonly practiced methods. The qualitative (heuristic) method is used to estimate the level of risk in an area qualitatively, when the numerical estimation of hazard, vulnerability, and element at risk is difficult due to lack of landslide frequency, date of occurrence, and magnitude data [33, 83]. The landslide risk map can be produced based on the knowledge of experts about landslide vulnerability, hazard, and element at risk. In a quantitative approach, landslide risk can be estimated numerically using a mathematical equation developed by Varnes and IAEG Commission on landslides and other mass movements on slopes (1984). $\text{Risk} = \text{hazard} * \text{vulnerability} * \text{element at risk}$. Where the hazard is the probability of landslide occurrence in a particular type and magnitude in a given location within a referenced period. Vulnerability is the expected degree of loss due to landslides. Element at risk is potentially affected elements in landslide-affected areas.

2.9 Landslide susceptibility, hazard, and risk model validation

In the case of model validation, landslide area has been classified based on time, space, and random partition [26, 84, 85]. The model can be validated by applied various validation techniques like predictive rate curve, success rate curve, simple

overlay, a landslide percent comparison column chart, relative error, relative landslide density index (R – index), receiver operating characteristics (ROC), and landslide density.

2.9.1 Success and predictive rate curve

As indicated in [26], the success rate curve can be plotted using training landslide against the landslide susceptibility or hazard or risk map area. Success rate and a predicted rate curve can be plotted using a cumulative percentage of training/testing landslide area against the cumulative percentage of the landslide susceptibility/hazard/risk map area [86]. For this purpose, the landslide susceptibility or hazard or risk index has to be reclassified into 100 classes by descending order of the value. Then landslide raster can be combined with these classes to obtain landslide pixels. Both landslide and map area pixels have converted into a cumulative percentage to plot the success and predicted rate curve. The success rate curve can be plotted using the cumulative percentage of training landslide vs. a cumulative percentage of map area while the predicted rate curve can be plotted using a cumulative percentage of testing or validation landslide area vs. map area. The success rate explains how well the model and how landslide susceptibility, hazard, and risk mapping results are classified the study area using training landslide data. The predict rate curve explains the predictive capability of the conditioning factor for the model. If the curve deflects and closes to the top left of the reference line along the diagonal, the model has higher accuracy.

2.9.2 Landslide density

As states by Pham et al., [87] and Fayez et al., [88], the landslide density has calculated using the equation of landslide density (LD). $LD = \frac{\text{percent of observed landslide}}{\text{percent of predicted landslide}}$. The higher landslide density on the high, and very high landslide susceptibility, hazard, and risk region confirms that the model is reliable and accurate [87].

2.9.3 Relative landslide density index (R: Index)

Landslide susceptibility, hazard, and risk models can also be validated using the relative landslide density index, which is calculated using the following

equation. $R - Index = \frac{\frac{ni}{Ni}}{\sum \frac{ni}{NI} * 100}$. Where ni is the number of landslide in a landslide

susceptibility classes while Ni is the number of landslide susceptibility/hazard/risk class pixel within that class. The relative density can calculate using an equation through a comparison of landslide susceptibility with landslide inventory data set [73, 89]. As the R- index value increases from the very low to very high landslide susceptibility/hazard/risk classes confirms that the model is accurate and reliable.

2.9.4 Relative error

The other model validation technique relative error calculation is one of the techniques that help us to evaluate and determine the quality of the model and the number of landslides in the higher landslide susceptibility, hazard/risk classes.

The higher the relative error value the poorer the model accuracy. When the relative error greater than 0.5, the model is not acceptable [90]. However when the relative error less than or equal to 0.5 and the number of landslide in the high landslide susceptibility/hazard/risk class more than half, the given model is accurate and reliable. $Relative\ error(\xi) = \frac{\sum TNLS - \sum NLS}{\sum TNLS}$. Where TNLS is the total number of landslide in a region and NLS is a number of landslide in the high and very high landslide susceptibility/hazard/risk classes.

2.9.5 Receiver operating characteristics (ROC)

The ROC is the curve used to evaluate the performance of the landslide susceptibility, hazard, and risk models. ROC curve is the graphical representation of true positive rate (TPR) as y-axis and false positive rate (FPR) as x-axis. In the ROC curve, the area under the curve (AUC) is the most important diagnostic feature that helps to evaluate whether the model performance is accurate or not accurate. As stated by Yesilnacar and Topal [91], the value of AUC is usually found in between 0.5–1. The model has excellent performance when the AUC value is in between 0.9–1; the model has very good performance when the AUC value is in between 0.8–0.9. The model has good performance when the AUC value is between 0.7–0.8. When the value of AUC is between 0.6–0.7, the model has average performance however if the AUC value is between the range of 0.5–0.6 and equal to 0.5 or less than 0.5, the model has poor and useless results.

2.10 Case study on landslide susceptibility mapping

2.10.1 Landslide susceptibility mapping using statistical methods in Uatzau catchment area, Northwestern Ethiopia

Recent unconsolidated soil deposits, rugged topography, active gully, riverbank erosion, and improper land use practice characterize the study area (Uatzau), making it vulnerable to a variety of landslides, including earth fall, soil creep, weathered rockslide, soil slide, earth flow, and debris flow. Landslide susceptibility zones of the study area were determine using Frequency ratio (FR), certainty factor (CF), and information value (IV) models. These maps also depict the spatial distribution of projected landslides and the locations where they are expected to occur. The maps, on the other hand, may not be able to predict the amount of material that will be displaced, as well as the time and frequency with which the landslide will occur. The landslide susceptibility models can also helpful for preventative and mitigation measure of landslide hazard in regional land use planning [81, 82, 92–96]. The success rate curve and predictive rate curve were used to validate the maps using training and testing/validation landslide data sets. The success rate curve was used to assess how successfully the models identified the location and supported the landslide events that were occurring at the time [26, 96]. The prediction rate curve was created to assess how effectively the models can forecast future landslide events that are unknown [94, 96]. Within the region, steep slopes covered by very loose shallow soil deposits, closer to the stream, agricultural land on a steep slope, active gully erosion, and concave slope shapes resulted in the high and very high susceptibility classes, while the moderate susceptibility class is found in high-land landscapes. Low plain landscapes and areas covered by vast weathering-resistant rock masses are into the realm of very low and low susceptibility of a region.

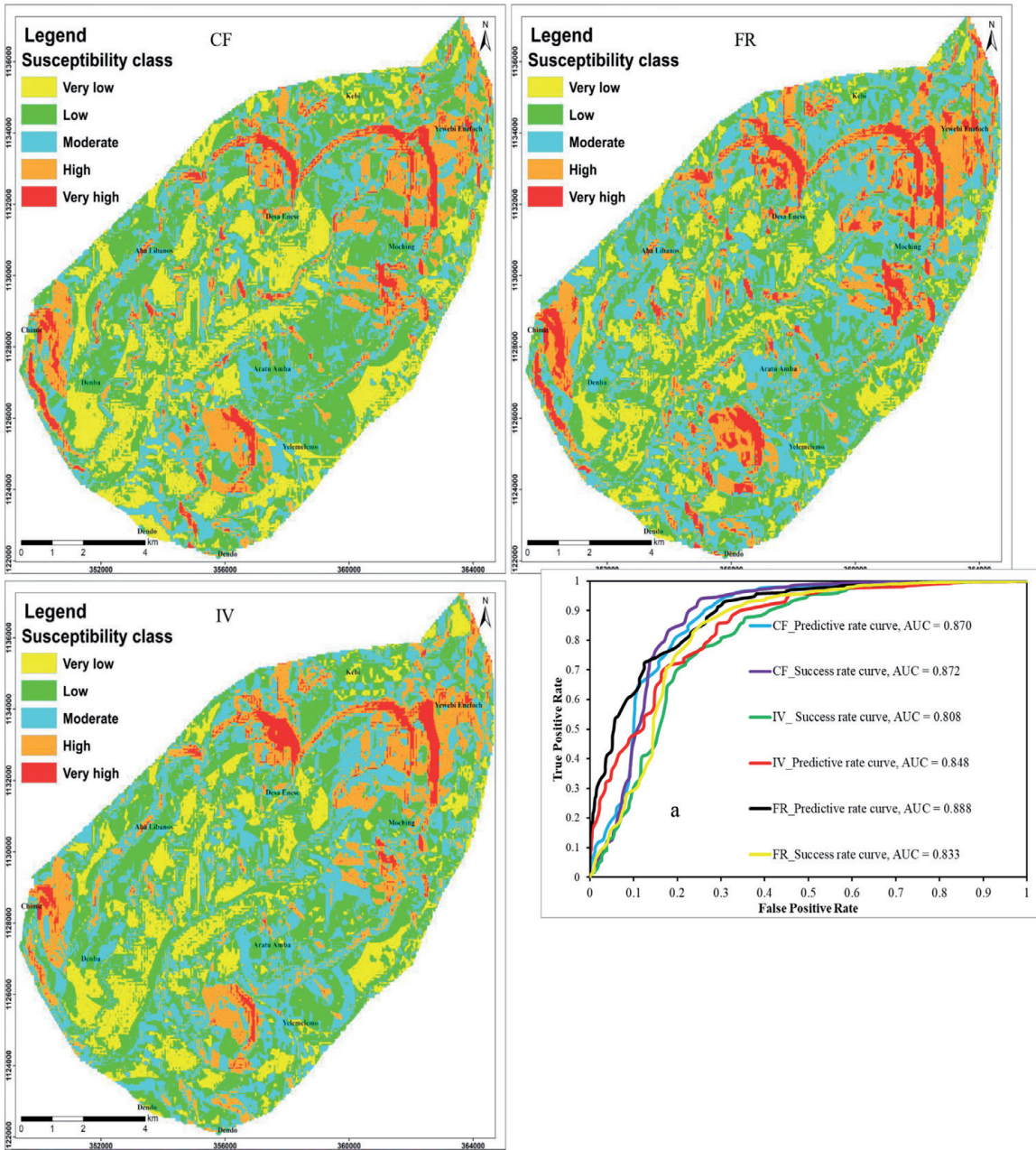


Figure 5. Landslide susceptibility maps of frequency ratio (FR), certainty factor (CF), information value (IV) methods [36] and a) receiver operating characteristics curve (ROC) [36].

Zine et al. [97] stated that higher prediction accuracy (AUC = 89.05%) and AUC = 85.57%) was received using the information value and frequency ratio methods. Similarly, the frequency ratio approach outperformed the information value methods for both success rates (AUC = 83.27%) and prediction rate curve (AUC = 88.8%) in this investigation. The accuracy of the two models falls within the same ranges, which may be a good performance. The frequency ratio model revealed a slight difference in the AUC value. Qiqing et al. [40] stated that a high predictive accuracy of AUC value of 75 was received using a certainty factor model when compared to the prediction rate curve value (AUC = 64.08%) of information value model. However, their accuracy values were within the same ranges, suggesting that they performed well. Similarly, in the current model, the certainty factor model had a greater prediction rate value (AUC = 87.03%) than the information value model, which had a lower prediction rate value (AUC = 84.8%), but they both required an equivalent accuracy range, which may be a good performance. The work of Haoyuan et al. [98] supported the predictive rate value of the area

Information value method	LSI Value	LSI	Factor class area (%)	Validation data set (%)	Training data set (%)	AUC for validation landslide	AUC for training landslide
	−0.5-0.9	VLS	15.5	3.9	6.3	0.848323	0.808265
	0.9-1.5	LS	24.3	7.9	11.8		
	1.5-2	MS	31.5	20.1	23.8		
	2.0-2.6	HS	21.1	40.8	31.8		
	2.6-4.1	VHS	7.6	27.3	26.3		
Certainty Factor (CF)	−2.2- −0.97	VLS	17.8	4.7	6.0	0.870348	0.871933
	−0.97- −0.47	LS	31.0	12.3	16.4		
	−0.47-0.04	MS	28.8	17.5	24.8		
	0.04-0.74	HS	19.0	34.8	33.0		
	0.74-2.61	VHS	3.4	30.7	19.7		
Frequency Ratio (FR)	3.1-4.3	VLS	22.7	5.4	9.3	0.888337	0.832718
	4.3-4.8	LS	30.8	14.7	17.8		
	4.8-5.3	MS	22.4	19.5	20.0		
	5.3-6	HS	19.3	43.7	35.0		
	6-7.7	VHS	4.8	16.7	17.8		

VLS is for very low susceptibility, LS stands for low susceptibility, MS stands for moderate susceptibility, HS stands for high susceptibility, VHS stands for very high susceptibility, LSI stands for landslide susceptibility index and AUC stands for area under the curve.

Table 3.
Statistical summary of information value, certainty factor, and frequency ratio methods [36].

under the receiver operating characteristic curve (AUC), showing that the frequency ratio and certainty factor models have the more or less similar predictive capacity, with the certainty factor model having 81.18% and the frequency ratio model having 80.14%, respectively. The Frequency ratio model, on the other hand, performed worse than the CF model. The two models in this study had essentially identical AUC values for the prediction rate curve (87.03% for the certainty factor model and 88.8% for the frequency ratio model) (**Figure 5**). The closer prediction capacity with AUC > 64% and AUC > 80%, respectively, fall within the range of good and extremely good performance, according to the three bivariate statistical methods in the literature and this work [91]. High and extremely high susceptibility classes encompassed nearly 20% of the research area in this study (**Table 3**). The landslide validation findings for the three models are more similar than they are dissimilar, and they are all in the same region of outstanding performance. Aside from that, the percentages of landslides that fall into the high and highly susceptible classes are nearly the same (60.4%, 65.5% & 68.1% for FR, CF, and IV, respectively). Because of these findings, the research effort concludes that in landslide susceptibility mapping, the three models have similar potential for identifying landslide-prone locations, although factor selection should take precedence over methodologies. However, when compared to the FR and CF approaches, the IV models’ moderate, high, and very high susceptibility area coverage exhibited minor differences in a single example. This is frequently due to flaws discovered in IV during weight rating for each factor class, i.e. when there is no landslide in a certain component class the IV results become zero. This gives a good indication of the model’s overall accuracy. FR and CF models are better for regional land use

planning, landslide hazard mitigation, and prevention based on the prediction accuracy of AUC value. Although the generated maps cannot predict when and how often landslides will occur, they do show the spatial distribution of landslide risk.

2.11 Conclusion

This chapter introduces and overview the concepts of landslide, type, factors, inventories, susceptibility, hazard, and risk. Moreover, different mapping and validation approaches were introduced. The confusing between the term susceptibility and hazard is clearly discussed. Detail and quality data should tend emphasis in getting quality landslide susceptibility, hazard, and risk maps. Field landslide investigation integrated with Google Earth Imagery analysis is vital to work out and record, the relative occurrence date, magnitude, dimension, type, and state of landslide. GIS-based landslide susceptibility, hazard, and risk mapping is suitable for regional scale where as physical based mapping is recommendable for detail landslide study where geotechnical investigation is require.

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Contributions of the authors

I was responsible for all aspects of the project, including the conception and design of the work, model development, statistical analysis, and interpretation of the results.

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Data and materials are readily available.
The corresponding author can provide all of the datasets that were utilized and analyzed during the current investigation.

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