CHAPTER 2

LITERATURE STUDY

2.1 Landslide Occurrence in India

India is well known for its vulnerability to a wide range of natural hazards. Landslide is one of those natural hazards which strike the Indian Territory now and then. Landslide is simply defined as the down slope movement of soil, rock or debris under the influence of gravity. Landslides occur in hilly terrains in response to various conditions and triggering processes like earthquakes, floods, cyclones, cloudbursts, heavy rainstorms and haphazard human activities. Its occurrence poses a considerable threat to life and livelihood, ranging from disruptions of normal activities to widespread loss of property, life and disruption in the supply of essential commodities (Gerrard 1994; Singh 2009). According to the Geological Survey of India (GSI), nineteen states and four union territories out of the entire states and union territories of India are vulnerable to landslide hazards (Fig. 2.1). Major parts of the northern states of India namely Uttarakhand, Himachal Pradesh, Ladakh, Jammu & Kashmir and north-eastern states of the country viz. Tripura, Nagaland, Mizoram, Manipur, Assam, Arunachal Pradesh and Sikkim are vulnerable to landslides due to active tectonics, fragile geology, intense rainfall, critical slopes, high relief as well as increased anthropogenic activities at various locations of these states. Western parts of Kerala, Karnataka, Goa and Maharashtra covering parts of the Western Ghats and eastern parts of Tamil Nadu and Andhra Pradesh in the Eastern Ghats, are also vulnerable to landslides. In India, about 12.6% or 0.42million km^2 of land area, excluding the permafrost regions in the north, spreading over more than 65,000 villages in mountainous/hilly areas, is prone to landslide hazard (https://www.gsi.gov.in).

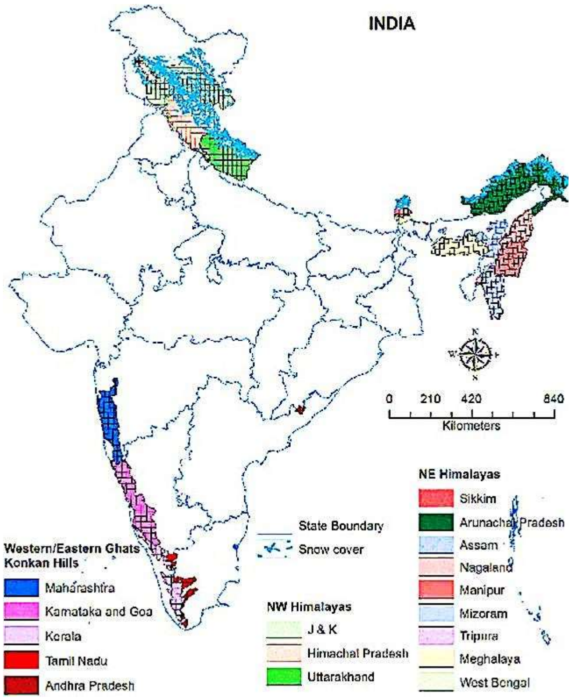

Fig. 2.1. Major landslide prone areas of India (0.42 million km^2)
(Source: https://www.gsi.gov.in)

2.1.1 Impact of Landslide

Landslide is a threat to heritage buildings, tourist spots and pilgrim routes, utility projects (water supply, hydro-electric, transmission line), human settlements and infrastructure, tunnels, open cast mines, vast stretches of border roads and railway lines, farms and fields, aerial ropeways, and holy places (Vasistha et al. 2011). Initial investigations by the Centre for Research on the Epidemiology of Disasters (CRED) indicates 8,658 human casualties due to landslide and avalanches between 1990 and 1999 (McGuire et al. 2004). A recent report indicates close to 11,000 deaths due to the landslide in 12 years. India tops the global list of nearly 56,000 deaths from 4,800 landslides around the globe between 2004 and 2016 (Kalyan 2018; Zhou et al. 2019a). An estimated average annual direct cost of landslide in India is around $1.3billion (Disaster Management in India, MHA, Govt. of India, 2011). Indirect costs may exceed $5 billion (www.imd.gov.in); unfortunately, most indirect costs are often disregarded due to the strenuous nature of its assessment or, when evaluated, are too conservative. India not only accounts for 20% of global landslide deaths but also has the dubious distinction of witnessing the fastest rise in a human-triggered fatal landslide in the world. With the growing population and human interventions in terms of developmental activities over unstable slopes, landslides pose increasing risks to infrastructures, human life and the environment. As individual landslide usually affects limited local areas and residents, the damage resulting from landslide hazards was not recognised as a serious problem and were not given the required attention. Instead, most of the focus includes relief and rehabilitation works post a landslide.

2.1.2 Vulnerability Towards Landslide

Large scale anthropogenic activities and faulty management practices have led to high vulnerability to landslides in hilly regions of the country. Human activities relating to haphazard construction of roads, unscientific mining, expansion on unsafe locations, dams and river training works ignoring natural features contribute to increased landslide intensity. The blockage of the natural flow of water by sediments washed away from civil construction, road construction, and mining sites increase the pore water pressure in the slopes, making it vulnerable to failure (Bhattacharyya et al. 2015; Chaturvedi et al. 2014; Froehlich and Starkel 1993; Raizada and Juyal 2012; Sharma and Ram 2014; Tiwari et al. 2013; Vasistha et al. 2011). Froehlich and Starkel (1993) studied the increased occurrence of landslides around construction and mining sites. They deduced the change in the hydrological regime of the area as the primary cause of reactivation of nearby old landslides. Vasistha et al. (2011) identified the chain reaction between the occurrence of subsequent landslides. Once a landslide occurs, massive amounts of debris containing soil, small and big boulders get generated and deposited. This affects the local ecosystem which in turn trigger more landslide. Tiwari et al. (2013) identified the damage to mountains alongside is more in areas that are weakened due to road construction, and with heavy rains, even dormant landslides are activated. Intensive anthropogenic activities which include the use of heavy machinery, blasting and various constructions and mining activities, induce stresses at the activity site and even distance away from it (Karan 1989; Rawat 1995). The change in stress pattern results in a change in weathering pattern of the area, which in turn change the geotechnical and mechanical properties of the slopes. Frequent blasting at mining sites and along road construction led to open up of cracks and the formation of newer ones which in turn intensifies the physical and chemical weathering process (Chaturvedi et al. 2014; Sharma and Ram 2014; Sumantra and Raghunath 2016). Blasting can weaken the host rock and results in the ingress of water and accelerated weathering of the bedrock resulting in the formation of a deep layer of residual soil. The effect of blasting can be felt far distant apart in hills (Khandelwal and Singh 2007).

The roadway networks are the arteries for the ongoing mining activities and socio-economic development of the region. However, the negative impact of large-scale road constructions needs thorough investigations. Road construction activities have increased the landslide occurrences by 25 to 345 times and are even ranked ahead of surface mining and deforestation as the major anthropogenic factor in initiating new landslides (Joshi et al. 2001). The unscientific constructions of access roads may also lead to stability related issues (Fig. 2.2). The changes in the slope topography can also have a significant effect on the overall stability of the residual soil slopes. As anthropogenic activities lead to change in the slope profile of the hills, the occurrence of landslides will likely increase (Bhattacharyya et al. 2015; Chaturvedi et al. 2014; Raizada and Juyal 2012). The study by Bhambri et al. (2017) on the devastating landslide in Uttarakhand in 2013 revealed that out of the total 2772 mapped landslides, 1434 were new landslides, and the remaining 1338 were reactivated older landslide which suggests that due to change in slope morphology and geology over time, newer landslides can develop in virgin areas.

Fig. 2.2. Several localised slope failures are observed along the hill roads

Moderate to steep slopes are the critical features of the Himalayan geomorphology (Rupke 1974). The hillslopes lie at an average angle of 45^0, steepening locally to 60^0 and sometimes can be of nearly vertical rock slope (Bartarya and Valdiya 1989; Gupta et al. 1999; Mahanta et al. 2016; Mehrotra et al. 1996). Change in slope gradient caused by natural processes (like erosion and weathering, glacier movement and rising of mountains due to tectonic forces) and anthropogenic activities (like excavation, cultivation, blasting and construction) are the principal factors triggering landslides. Any disturbances in the slope gradient, whether natural or anthropogenic, disturb the equilibrium condition of the mountain system by changing the internal stress of the soil or rock mass and can lead to the formation of cracks along the weak zones that might get saturated with water, thereby initiating the failure (Miščević and Vlastelica 2014). The prevalence of subtropical climate, along with the most characteristic feature of the southwest monsoon, expedite the chemical weathering and assist in triggering landslides in the Himalayas (Bartarya and Valdiya 1989; Vyshnavi et al. 2015). Due to the presence of favourable climatic conditions, extensive chemical weathering extends to enormous depth resulted in the formation of thick columns of residual soil over the bedrocks.

2.2 Slope Failure in Residual Soil Slope

Weathering is the process of breakdown and alteration of rock at or near the Earth's surface by physical disintegration and chemical decomposition, which ultimately lead to soil formation (Regmi et al. 2013; Regmi et al. 2014; Yalcin 2007). The final product of the physical and chemical weathering is residual soil. The warm temperate and subtropical climatic zones of the Himalayan Region have ensured deep weathering of the rock mass, thus producing thick deposits of laterites and saprolites, also known as residual soils (Regmi et al. 2013; Vyshnavi et al. 2015). Blight (1977) described residual soil as ‘a soil-like material obtained from weathering and decomposition of in situ rock, which has not been relocated from its original location’ (Fig. 2.3). The progressive weathering of slope materials by slow natural processes is the key factor responsible for increasing the likelihood of landslide in residual soil (Regmi et al. 2014; Sajinkumar et al. 2011). Several studies were carried out over time to manifest the relationship between residual soil and the occurrence of landslide (Anbalagan et al. 2008; Bhasin et al. 2002; Chaudhary et al. 2010; Das and Saikia 2010; Huat et al. 2006; Kanungo et al. 2013; Koo 1982; Kumar et al. 2018; Lim et al. 1996; Rahardjo et al. 2004; Sharma 2007; Talib et al. 2016).

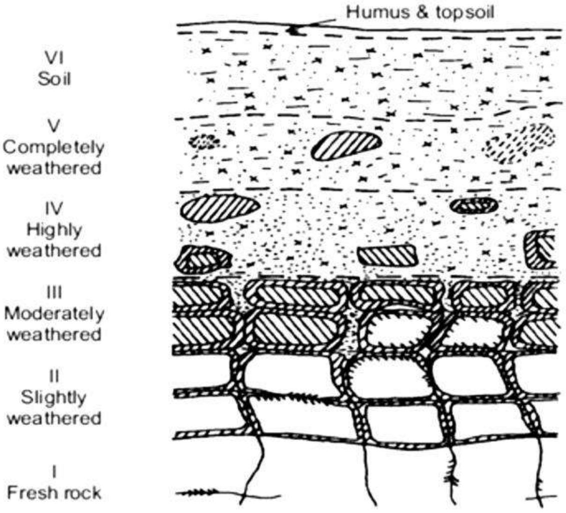

Fig. 2.3. Typical weathering profile in rocks (Little 1969)

2.2.1 Characteristics of Residual Soil

The engineering properties of residual soil vary considerably with depth and horizontally because of differential weathering patterns, thereby inducing heterogeneity in the slope profile (Babu and Mukesh 2003; Talib et al. 2016). Che et al. (2012) and El-Ramly et al. (2005a) studied the heterogeneity in the residual soil profile and concluded that it is due to the redistribution, mobilisation, and accumulation of minerals and clay horizons during differential weathering. A significant disparity exists between the physical and mechanical properties of parent rock and formed residual soil. These variations are not homogeneous along with the soil profile and are mainly governed by the extent of chemical weathering (Rahardjo et al. 2004). The chemical weathering rate decreases with depth from the ground surface owing to the decrease in leaching action due to percolating surface water. This results in a gradual reduction in the formation of residual soil with depth until the unaltered bedrock is found. These characteristics are further validated by measurements of the penetrative hardness of rocks by (Yokota and Iwamatsu 2000), where a gradual increase in hardness from the slope surface to the interior was recognised. The hardness change was almost concordant with changes in other weathering indices, such as clay minerals, rock colour, and apparent grain size. Weathering and landslide are not individual phenomena; instead, they act in tandem. Apart from natural factors like lithology, mineralogy, slope morphology, hydrology, and climate, anthropogenic factors like change in stress, slope topography and hydrology are some of the essential physio-chemical factors which govern weathering patterns and in turn, the occurrence of landslides (Ghimire 2011).

2.2.2 Residual Soil in Himalayan Region

The Himalayan Mountain slopes generally comprise of several stratigraphic layers (Anbalagan et al. 2008; Chaudhary et al. 2010; Gupta et al. 2016a; Kanungo et al. 2013; Kumar et al. 2017). A residual soil layer at the top, which is underlain by a highly weathered layer of rock and, finally, the parent bedrock (Fig. 2.3). Ietto et al. (2016) proved it through seismic refraction surveys coupled with field borehole tests. The depth of all three layers varies considerably from region to region, but overall, the stratigraphy remains the same up to moderate slope inclinations (40^0-60^0). Steep slopes (>60^0) are mostly devoid of the residual soil cover and have a rocky nature having the inner two-layer, i.e., weathered layer and the bedrock (Bartarya and Valdiya 1989; Mehrotra et al. 1996; Sati and Sundiyal 2007). Usually, slope movement is initiated by the sliding of the residual soil mass, which lies in contact with the low-friction bedding planes. Bhasin et al. (2002) noted that during the landslide process, the overlying residual soil and the discrete joint surfaces of the weathered/fractured rock mass have relocated.

Slope morphology influences the depth of failure surface in two significant ways, reflecting whether the failure zone passes within the bedrock itself or from the surface layer of weathered material (Regmi et al. 2013). The slopes having residual soil cover, rock influences are more subtle, and failure surface generally passes through the weathered material. The properties of the residual soil would influence the overall stability of the slope (Gerrard 1994). The depth of weathering also varies from place to place, as reported by many researchers. However, most engineers and geologists fail to judge the deep depths that weathering can reach. Ollier (2010), while studying deep weathering profiles, deduced the reach of weathering depths of hundreds of meters and often in a very irregular manner. Also, the transformation profile of bedrock into residual soil is not gradual. Instead, there is a knife-sharp contact between weathered and fresh rock called the weathering front. Singh (2009) performed in situ tests in the Himalayan region and concluded that shallow landslides are prominent in weathered slopes having gentle to moderate slope stiffness (up to 40^0-60^0) followed by the steep slope (>60^0). Geotechnical investigations carried out at different locations in the Himalayas revealed that the Himalayan slopes are highly weathered. The textural composition of the residual soil ranges from medium-grained sandy soil mixed with weathered boulders and bedrock to silty sand mixed with clayey material (Bhasin et al. 2002; Chaudhary et al. 2010; Kanungo et al. 2013; Sengupta et al. 2010; Sharma et al. 2015). The slide materials in the landslide site are mainly debris consisting of assorted fragments ranging from clay to big boulders (Anbalagan et al. 2008).

2.3 Slope Stability Analysis Using Numerical Simulation

The Factor of Safety (FOS) values, which represents the ratio of shear strength of the slope to shear stress on the slope, is generally used to determine how close or far slopes are from failure (Lin and Cao 2014; Singh et al. 2008). Various techniques are available, including analytical (Limit Equilibrium) and numerical (Finite Difference and Finite Element) methods which can be used to obtain the FOS of a slope under investigation. Analytical methods, which include the Limit Equilibrium Method (LEM), utilise the slope displacement model for locating the possible sliding surface and the corresponding FOS. Although analytical methods are computationally efficient, due to their inherent drawbacks, such as utilisation of predefined failure surface and simplifications of the whole study region, they fail to provide a complete understanding of the slope behaviour. This restricts the use of analytical methods to simple slope geometries in a limited area. In order to overcome the drawbacks of analytical methods, numerical simulation was developed as a theoretically more realistic and rigorous technique for slope stability analysis (Verma et al. 2016). The major disadvantage of numerical simulation is the prolonged solution time required to set up the computer model and perform the analysis (Abdalla et al. 2015). With the development in computation and data analysis, numerical simulation can now be executed within a reasonable period and with higher accuracy. Non-linear modelling using numerical simulation offers several advantages over LEM, including the capability to model progressive failure, the elimination of assumptions regarding the locations and inclinations of interslice forces, the incorporation of displacement-controlled ground-structure interaction, the calculation of deformations and the elimination of a priori assumptions on the location and shape of failure surfaces (Griffiths and Lane 1999). The general approach is valid for a wide range of applications. Griffiths and Lane (1999) highlighted some key differences between traditional LEM and numerical methods and elaborated on the advantage of numerical methods over LEM. Numerical methods like Finite Difference Method (FDM) and Finite Element Method (FEM) can model complex behaviours, such as problems that consist of non-linear material behaviour, several stages, unstable systems (even cases of total collapse or failure/yield over large areas) and large strains and displacements.

The FOS calculations using FEM and FDM uses the Shear Strength Reduction (SSR) technique (Dawson et al. 1999; Duncan 1996; Griffiths and Lane 1999; Hammah et al. 2005). In the SSR method, shear strength parameters (friction angle and cohesion) of slope forming material are reduced until failure occurs, and critical Strength Reduction Factor (SRF) is calculated, which is equivalent to the FOS (Gover and Hammah 2013; Sharma et al. 2017). The SSR technique involves using factored strength parameters in a non-linear numerical method. The shear strength properties of the model material are scaled until the stability limit is reached (Dawson et al. 1999; Griffiths and Lane 1999; Hammah et al. 2004). In this technique, simulation of the slope model is performed in a series of increasing F_{trial}, and the actual shear strength properties (cohesion (c) and friction angle (φ)) are decreased with each trial as per the equation shown below:

$$\mathrm{C_{trial}} = \frac{1}{\mathrm{F_{trial}}}\mathrm{C} \tag{2.1}$$

$$\varphi_{\mathrm{trial}} = \tan^{-1}\left(\frac{1}{\mathrm{F_{trial}}}\tan\varphi\right) \tag{2.2}$$

$$\tau_{\mathrm{trial\ strength}} = \mathrm{C_{trial}} + \sigma_{\mathrm{n}}\tan\varphi_{\mathrm{trial}} \tag{2.3}$$

$$\mathrm{F_{trial}} = \frac{\tau_{\text{trial strength}}}{\tau_{\text{stress}}} \tag{2.4}$$

where C_{trial}, φ_{trial} and $\tau_{trial\ strength}$ are the reduced value of friction angle, cohesion and shear strength on each trial, respectively. The F_{trial} at which the slope model fails is the FOS of the model. The continuum approach to SSR considers a discretised zone in a finite difference or finite element continuum model and uses model convergence or predefined displacement limits at points of interest as an indicator of equilibrium. For similar element shape functions, the set of algebraic equations solved in the finite difference method is identical to finite element analysis (Dawson et al. 1999). This factoring of strength parameters allows reinforcement and other external effects to be modelled without modification to determine stability. The approach allows for the reinforcement and the rock and soil mass (if heterogeneous) to develop modified internal loads and stresses as a function of pre-yield displacements and strains. Most importantly, the critical failure surface develops naturally during the non-linear solution and does not need to be predefined or determined through optimisation algorithms. Dilation effects and strain-softening or brittle behaviour are also accommodated.

2.4 Heterogeneity Associated with Residual Soil

Soils are geological materials derived from weathering of bedrock. They have been subject to various stresses, pore fluids, and physical and chemical changes over time. Thus, the physical properties of soils vary from place to place within the same deposits. Geotechnical variability is a complex attribute that results from many disparate sources of uncertainties. Many sources of uncertainty exist in geotechnical analysis ranging from the material parameters to the sampling and testing techniques. The primary sources of geotechnical uncertainties are inherent variability and measurement error while testing (Jiang et al. 2015; Kumar and Anbalagan 2016; Park et al. 2005). Spatial heterogeneity of geomaterial can result from various processes associated with depositional effects, chemical alterations and mechanical actions. In contrast, errors due to testing are associated with sampling, specimen collection, laboratory testing and others related to jobs ranging from specimen collection to testing. Uncertainty in material properties is considered one of the significant factors affecting the accuracy of stability analysis.

2.4.1 Probabilistic Slope Stability Analysis

In a traditional slope stability analysis, it is assumed that the values of all model input parameters are precisely known. For a given slip surface, a single factor of safety value is calculated. This type of analysis can be referred to as a deterministic analysis (Hammah et al. 2009). The prime demerit in the application of deterministic FOS lies in the fact that it uses a particular value for all material parameters ignoring the fact that geomaterials by nature are fundamentally heterogeneous, and so-called homogenous geomaterials also display a certain amount of inconsistent in their physio-mechanical properties (Ersöz and Topal 2018; Pathak and Nilsen 2004; Ray et al. 2019a). The slopes designed based on the deterministic analysis sometimes fail even when the calculated FOS is more than unity (El-Ramly et al. 2002). Christian (1996) presented cases studies of slopes showing that the ones with the highest safety factors are not necessarily the safest. He concluded that a simple prescription of a FOS is not realistic and may lead to too conservative or not conservative enough designs. Therefore, the presence and significance of uncertainties hold a key factor in slope stability analysis.

For most real-world slope stability problems, the values of many input parameters are not very well known; therefore, a probabilistic approach to slope stability analysis can be helpful (El-Ramly et al. 2002; Lari et al. 2014). In a probabilistic slope stability analysis, the model input parameters, such as loads, material properties, water table location, support properties, etc. are assigned particular statistical distributions (El-Ramly et al. 2005b; Pathak et al. 2006). By assigning a statistical distribution to one or more model input parameters, the degree of uncertainty in the value of the parameters can be accounted. Input data samples are randomly generated based on the user-defined statistical distributions. A given slip surface may then have many different values of safety factors calculated. This results in a distribution of safety factors, from which a Probability of Failure for the slope can be calculated. The probabilistic analyses can provide the designer with insight into the inherent risk level of a design (Hammah et al. 2009).

Over the past few decades, principles and fundamentals of Probabilistic Slope Stability Analysis (PSSA) have been developed, established, and documented in the literature (El-Ramly et al. 2002; Vanmarcke 1980). The earliest papers appeared in the 1970s (Alonso 1976; Matsuo and Kuroda 1974; Tang et al. 1976; Vanmarcke 1977) and have continued steadily (Chowdhury et al. 1987; Christian 1996; Christian et al. 1994; D'Andrea and Sangrey 1982; El-Ramly et al. 2005a; Hassan and Wolff 2000; Johari and Lari 2017; Lari et al. 2014; Singh et al. 2013). While statistical techniques provide a convenient way to describe what is known about spatial variation in geomaterial properties, sufficient data is required to develop the probability density function for each variable which significantly affect the overall safety of the slope. The application of SSR, in combination with the probabilistic analysis tool (like Monte Carlo Simulation), has been used by many researchers to evaluate the FOS and other deformation parameters for soil and rock slope (Dawson et al. 1999; Griffiths and Lane 1999). It is required that the statistical distribution of all the input parameters is either known or assumed to determine the probability of failure and FOS (El-Ramly et al. 2005a; Vanmarcke 1980).

In order to carry out a PSSA (Fig. 2.4), at least one input parameter, which may include material property, joint property or field stress, need to be defined as a random variable. The next step includes identifying the probable statistical distribution function that best fits the selected random variable. From the best fit statistical distribution function, the distribution parameters are obtained. Finally, using the distribution parameters, sampling is performed to get the distribution of FOS (El-Ramly et al. 2002). The ultimate goal of a probabilistic slope stability analysis is to obtain the complete distribution of FOS values given a set of random (uncertain) input variables with specified statistical properties. From the distribution of FOS values, the probability of failure can be determined.

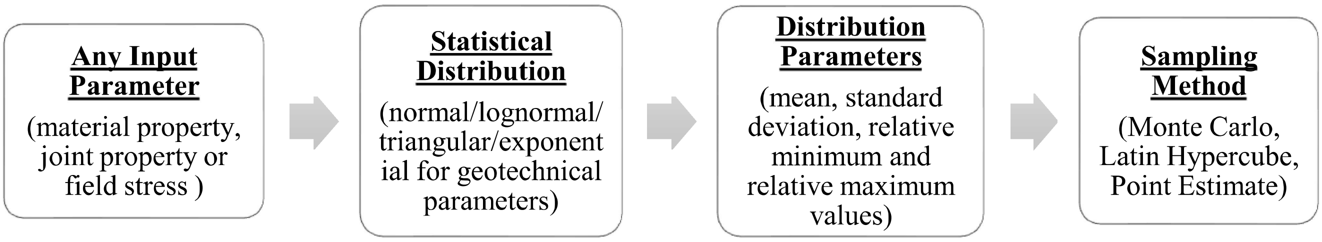

Fig. 2.4. Steps in Probabilistic Analysis

2.4.2 Sampling by Monte Carlo Sampling Method

After selecting the random variable and identifying its statistical distribution function and statistical properties, the probabilistic analysis is performed using various sampling methods like Monte Carlo, Latin Hypercube, or the Point Estimate method. Among all these sampling methods, the Monte Carlo Sampling Method (MCSM) is the most widely used. MCSM allows the user to define the number of samples directly, and there is flexibility in choosing from a wide variety of statistical distributions for each variable. For MCSM, each input parameter that is defined as a random variable is sampled according to the statistical distribution that was selected for that particular variable, the sampling method and the number of samples (El-Ramly et al. 2002). This generates '*N*' values of each random variable (where *N* is the number of samples). As shown in Fig. 2.5, each iteration of the Probabilistic Analysis is carried out by loading a new set of random variable samples and re-running the analysis. This is repeated ‘*N*’ times where ‘*N*’ is the number of samples.

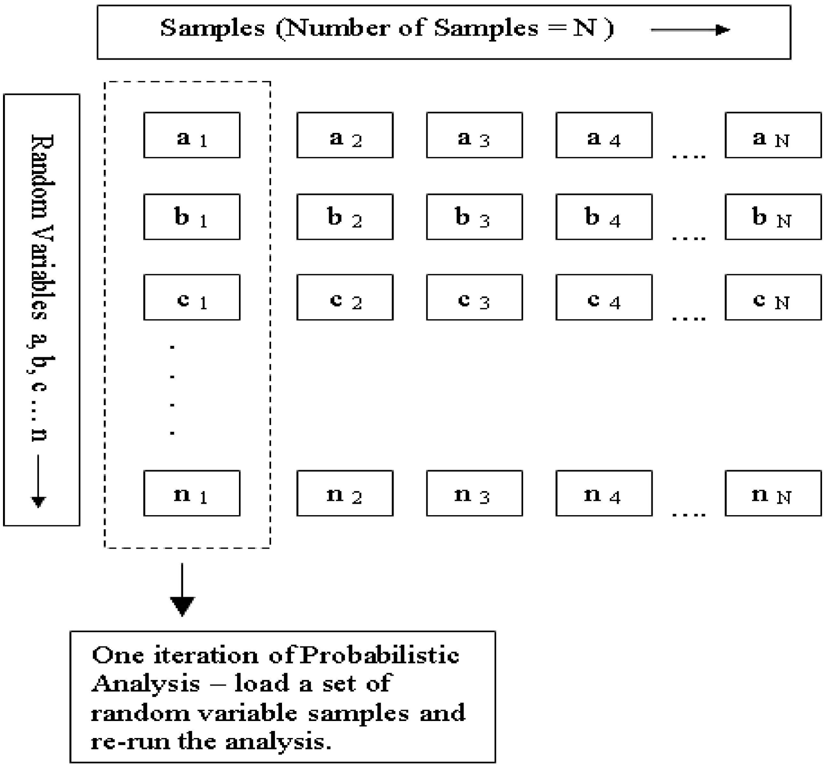

Fig. 2.5. Random Variable Samples used for Monte Carlo Probabilistic Analysis
(Source: www.rocscience.com/probabilisticanalyses)

In the MCSM, samples of probabilistic input variables are generated, and their random combinations are used to perform several deterministic computations. For the MCSM, the number of samples must be defined. This will determine the number of samples generated for each random variable for the probabilistic analysis. For example, if the Number of Samples = 1000, then 1000 values of each random variable (for example, Cohesion of Material 1) will be generated, according to the sampling method and statistical distribution for each random variable (Cohesion of Material 1 in this case). The analysis will run 1000 times, creating 1000 sets of results from which the statistical output data will be derived. The accuracy of MCSM increases with the increase in the number of samples generated (Basahel and Mitri 2019), whereas computation time also increases with the increase in the number of samples. Therefore, selecting the number of samples depends on the level of accuracy required for a particular problem.

2.5 Identification of Landslide Hazard

Identifying landslide-prone areas is essential for safer strategic planning of future developmental activities. Several different methods and techniques have been proposed to identify and map slope failures (Rib and Liang 1978), evaluate landslide hazards (Guzzetti et al. 2002) and ascertain landslide risk (Cruden 2018; Fell 2018). Several authors have worked in this regard and developed several Landslide Susceptibility Zonation (LSZ)/Landslide Hazard Zonation (LHZ) maps (Deshpande et al. 2009; Gupta et al. 1999; Mathew et al. 2007; Sarkar et al. 1995). Both developmental planning and landslide disaster management requires landslide hazard zonation maps. Only then it would be possible to carry out safer construction practices for the future and to project damage scenarios and carry out reliable risk analysis for present infrastructure and human settlements.

2.5.1 Landslide Hazard Zonation Maps

The LHZ map generally divides the landslide-prone hilly terrain into different zones according to the relative degree of susceptibility to landslides. This requires the identification of those areas that are or could be affected by the landslide and assessing the probability of such landslides occurring within a specific period. LHZ mapping serves as one of the many components in landslide risk assessment. LHZ is a safe and very quick mitigation measure for strategic planning and to identify the most vulnerable areas and channelise most of the protective measures and techniques to a more focused area (Marrapu and Jakka 2014). The ultimate aim of all the zoning activities is to comprehensively manage the landslide risk in fragile mountainous and hilly areas so that losses due to landslide hazards are substantially reduced. Therefore, landslide zoning is always construed and viewed as an integral part of the broader landslide risk management framework (Picarelli et al. 2005). Various researchers propose several different methods for landslide hazard assessment due to the complexity involved in the landslide triggering mechanisms. LHZ can be grouped into three parts: qualitative, quantitative and geotechnical based approaches (Fig. 2.6). The advantages or disadvantages of different LHZ mapping approaches have been discussed in detail by Kanungo et al. (2009).

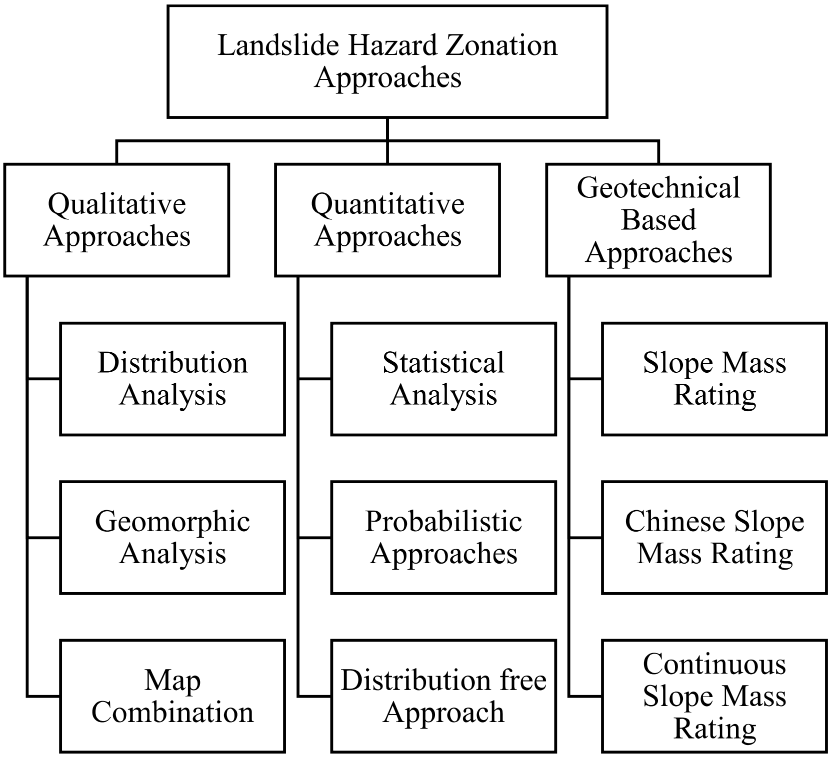

Fig. 2.6. Flow chart showing taxonomy of LHZ approaches (Kanungo et al. 2009)

The qualitative approaches rely on expert knowledge or experience, which dictates the selection, the weighting and the combination function of the factors and, therefore, can be considered conventional or subjective (Aleotti and Chowdhury 1999). The qualitative approaches, such as distribution analysis, geomorphic analysis and map combination methods, were very popular in the late 1970s among engineering geologists and geomorphologists (Guzzetti et al.

1999; Soeters and Van Westen 1996; Wieczorek 1984; Wright et al. 1974). In these methods, a lot of subjectivity is introduced in the form of assignment of weights based on the experience of the experts on the subject and about the study area in preparation of various thematic data layers contributing to landslide occurrences, which are integrated into the generation of LHZ map of the area. The weights may vary from expert to expert and also from region to region. Also, there is a difficulty in extrapolating a model developed for a particular area to other areas.

However, in the case of quantitative approaches, to minimise subjectivity in the weight assignment process, objective ways of quantifying the relative importance of various causative factors can be deployed to produce an LHZ map (Kanungo et al. 2009). The various quantitative approaches like statistical analysis, probabilistic analysis and distribution-free analysis became quite popular in the last decades depending on the advancements in remote sensing and GIS technologies (Clerici et al. 2002; Ercanoglu and Gokceoglu 2004; Gorsevski et al. 2003; Marrapu and Jakka 2014). The quantitative models use mathematics and statistics to express the relationships between the existing landslide distribution and the categories of factors. Therefore, these can be considered more objective than conventional approaches because the data-dependent character and less experience are needed (Aleotti and Chowdhury 1999). However, the success of these approaches is highly affected by the quantity, quality and reliability of data.

Qualitative and quantitative methods are used to develop an LHZ map for regional scale and are primarily based on past landslide occurrences and remote sensing data. However, both this method lacks an in-depth assessment of the slope, which include slope geotechnical parameters, topology and hydrology. In order to take into account the detailed geomechanical properties of the slope, a Geotechnical investigation-based approach (or slope classification methods) is introduced. These methods are more extensive in identifying the geo-mechanical properties of the slope under study, including the execution of various in-situ and laboratory tests. Thus is limited to a local scale or a particular type of slope/lithologies. In this method, the accuracy for identifying the current stable state is high. However, this accuracy depends on the number of stabilising factors considered for investigation and the extent of in-situ and laboratory testing. The choice of the work scale and the accuracy of the output results affect the selection of the approach. Thus, qualitative and quantitative approaches may suit a larger area covering the entire Himalayan range. In contrast, a geotechnical engineering approach based on the safety factor calculations or associated failure probability would suit the regional scale or any particular lithologies. The qualitative and quantitative approaches are quicker to perform than the geotechnical engineering approach which include lots of in-situ and laboratory testing. The results obtained through qualitative and quantitative LHZ are satisfactory; however, the results obtained from the geotechnical engineering approach have more reliability.

2.5.2 Geotechnical Investigation-Based Landslide Hazard Identification

The geotechnical investigation-based approach is generally conducted in two phases. In the first phase, the data on various factors that affect the overall stability of the slope under investigation is obtained through field investigation, in-situ testing and laboratory testing. In the second phase, the data is used to develop slope stability models using well-known techniques like limit equilibrium to numerical simulation using FEM and FDM. Based on the analysis, the landslide hazard zonation or slope classification systems are proposed. Some of the widely used geotechnical investigation-based approaches for slope classification include Slope Mass Rating (SMR) (Romana 1991), Chinese Slope Mass Rating (CSMR) (Chen 1995) and Continuous Slope Mass Rating (CoSMR) (Tomás et al. 2007). All three slope classification systems are developed for rock slopes. SMR was developed by Romana (1985) as the extension of one of the early engineering classifications of rock masses, i.e., Rock Mass Rating (RMR) developed by Bieniawski (1973).

$$SMR = RMR_{Basic} + (F1 \times F2 \times F3) + F4 \tag{2.5}$$

where RMR_{Basic} is the RMR index resulting from Bieniawski's Rock Mass Classification and taking into consideration the first five parameters only

$$RMR_{Basic} = R(UCS) + R(SD) + R(CD) + R(GD) + R(RQD) \tag{2.6}$$

F1, *F2* and *F3* are adjustment factors related to joint orientation with respect to slope orientation. While F_4 is a correction factor that depends on the excavation method used. *RQD* is Rock Quality Designation, *UCS* is Uniaxial Compressive Strength, *SD* is Spacing of Discontinuities, *CD* is Condition of Discontinuities, and *GD* is Groundwater Condition. A comprehensive definition of these adjustment factors can be found in Pastor et al. (2019). Based on SMR, Romana (1985) proposed five different classes for rock slope stability. CSMR system was developed by Chen (1995) to adopt SMR system to rock slope condition in China. They introduce two coefficients, ξ and λ and modify SMR.

$$CSMR = (\xi * RMR) + [\lambda * F1*F2*F3 + F4] \tag{2.7}$$

Here ξ represents the slope height factor, and λ represents the discontinuity factor. These factors are included in the system because several failures had occurred, but SMR indicates these are stable slopes. So, to improve the classification system, these two factors are included. Here,

$$\xi = 0.57+0.43*80/H \tag{2.8}$$

where H is the height of slope in meters

and, λ = 1 for faults, long weak seams filled with clay

= 0.8 to 0.9 for bedding planes, large scale joints with gauge

= 0.7 for joints, tightly interlocked bedding planes

Furthermore, *F1*, *F2*, *F3* and *F4* are the adjustment factors from SMR.

The factor ξ is applicable only for heights greater than 40 m. However, this is an accepted classification system in Chinese conditions only and needs several corrections and modifications before using at any other place. CoSMR is a modification of the discrete SMR technique of Romana (1985), which is based on Bieniawski (1973) RMR technique. The factors *F1*, *F2*, *F3* and *F4* in SMR are discrete and relies more on the judgment of the explorer and investigator Since it requires a lot of experience in assigning the rating based on one's experience. Tomás et al. (2007) proposed a continuous function for *F1*, *F2*, *F3* and *F4,* which best suited the discrete values and developed the CoSMR. Following are the equations for the continuous functions:

$$F_1 = \left(\frac{16}{25}\right) - \left(\frac{3}{500}\right)\tan^{-1}\left(\frac{1}{10}|A| - 17\right) \tag{2.9}$$

$$F_2 = \left(\frac{9}{16}\right) + \left(\frac{1}{195}\right)\tan^{-1}\left(\frac{17}{100}B - 5\right) \tag{2.10}$$

$$F_3 = -30 + \frac{1}{3}\tan^{-1}(C) \quad \text{(for planar and wedge failure)} \tag{2.11}$$

$$F_3 = -13 + \frac{1}{7}\tan^{-1}(C - 120) \quad \text{(for topple failure)} \tag{2.12}$$

where *A* is the difference between slope strike and plunge direction of the angle of intersection for wedge failure and parallelism between slope strike and joint strike for planar and toppling failures (Fig. 2.7). *B* is the plunge of the angle of intersection in wedge failure and dip of joint in planar failure. *C* is the difference between the angle of slope and dip of joint for planar failure, in case of toppling failure, the difference between the angle of slope and plunge of the line of intersection, for wedge failure, the addition of slope angle and dip of joint.

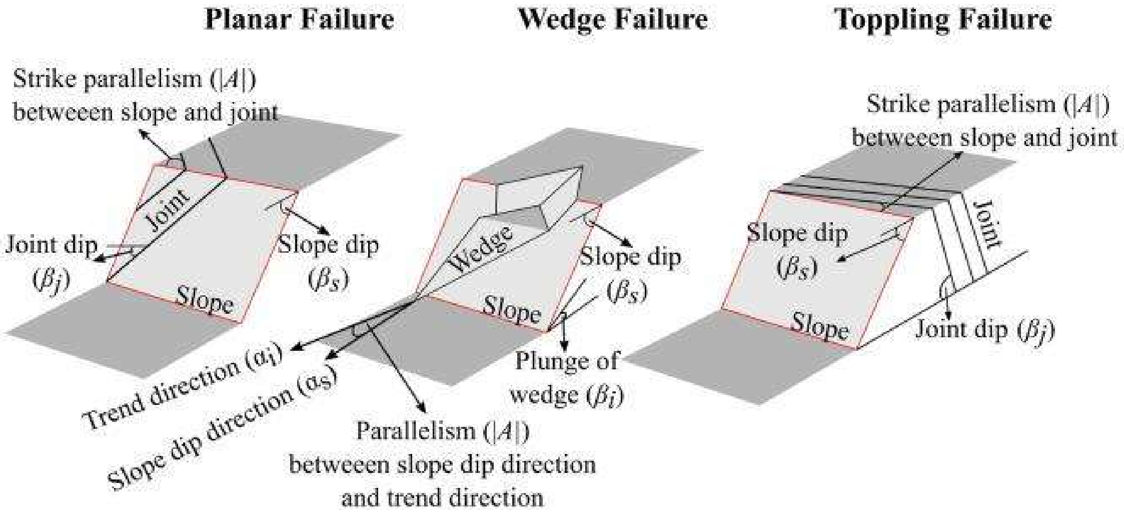

Fig. 2.7. Depicts various parameters used to obtain CoSMR (Dhiman and Thakur 2022)

The adjustment factor *F4* has been fixed empirically as follows:

Natural Slope: F4=+15	Presplitting: F4=+10	Smooth Blasting: F4=+8
Normal Blasting: F4=0	Deficient Blasting: F4=-8	Mechanical Excavation: F4=0

The stability classes of SMR values, rock mass description, stability and probability of failure given by Romana (1985) is also applicable for CSMR classification.

2.6 Machine Learning for Identification of Landslide Hazard

Establishing a technique for residual soil slope stability prediction is very strenuous as a precise evaluation involves many geometric and mechanical variables (Pham et al. 2018; Qi and Tang 2018; Ray et al. 2019b; Trigila et al. 2015). Such a prediction technique must have a high level of accuracy and adaptability. Furthermore, due to the demanding nature of engineering assignments, the prediction should be made in a short computational time. These requirements have aggravated the complication in evolving a precise prediction technique for slope stability analysis. The overall performance of a slope and precise prediction of its FOS is not a simple task. This is primarily due to the complexity in the precise estimation of mechanical properties of the influencing parameters, their magnitude of impact, and the intricacy of their relationships.

Therefore, various sources of uncertainties govern the evaluation of slope stability (Cho 2009). The overall performance and the corresponding FOS of a slope have been probed analytically, numerically and latest by using Machine Learning (ML) by researchers (Abdalla et al. 2015; Rukhaiyar et al. 2018).

Analytical methods have inherent drawbacks, such as simplifications of the whole study region and utilisation of predefined failure surfaces; they fail to provide a complete understanding of the slope behaviour. Thus, analytical methods are mostly restricted to a limited area having simple slope geometries. In order to overcome the drawbacks of analytical methods, numerical simulation was developed as a theoretically more realistic and rigorous technique for slope stability analysis (Verma et al. 2016). However, the major disadvantage of numerical simulation is the prolonged solution time required to set up the computer model and perform the analysis (Abdalla et al. 2015). With the development in computation and data analysis, numerical simulation can now be executed within a reasonable period and with higher accuracy. Other drawbacks of the numerical simulation include defining the boundary conditions that simulate the field, selection of parameters and the choice of an appropriate constitutive model, which is not available in many cases (Erzin and Cetin 2013; Sakellariou and Ferentinou 2005). As a result, there is a demand for a technique with higher precision and quick response that can substitute the analytical and numerical simulation methods**.** In recent years, ML techniques have been an attractive research topic for solving geotechnical problems. Currently, ML techniques are considered one of the most sorted analytical techniques for instability prediction (Das et al. 2011; Khandelwal et al. 2015a; Kim et al. 2018; Lu and Rosenbaum 2003; Paudel et al. 2016; Verma et al. 2016).

2.6.1 Artificial Neural Network Models for Slope Stability Assessment

ML algorithms are powerful and flexible statistical modelling tools used for formulating complex geotechnical problems, owing to their fruitful conduct in simulating non-linear multivariate problems (Chen et al. 2019; Das et al. 2011; Erzin and Cetin 2013; Kim et al. 2018; Paudel et al. 2016). One of the most commonly used ML techniques is Artificial Neutral Networks (ANN) which is comparatively new in slope stability analysis. An ANN is a modern computing technique used to simulate data in a manner the human brain analyses and processes any information (Verma et al. 2016; Yilmaz 2010). It comprises an interconnected assembly of artificial neurons that pass on the information through the tendons, which exist in the neuron. Due to its robust computational structure, ANN can be trained to model complex physical phenomenon (Pradhan and Lee 2010b). Several ANN architectures have been used in geotechnical engineering applications (Qian et al. 2019; Siddiqui et al. 2015) and particular slope stability assessment (Chakraborty and Goswami 2017; Choobbasti et al. 2009; Oh and Lee 2017; Zare et al. 2013). Some of the key benefits of using ANN include:

i. Organic Learning

   Neural networks can learn organically. This means an ANN outputs are not limited entirely by inputs and results given to them initially by an expert system. ANNs can generalise their inputs. This ability is valuable for robotics and pattern recognition systems.

ii. Nonlinear Data Processing

   ANNs are efficient data-driven modelling tools widely used for dynamic nonlinear systems and identification due to their universal approximation capabilities and flexible structure that capture complex nonlinear behaviours observed in slope stability analysis.

iii. Fault Tolerance

ANN have the potential for high fault tolerance. The output generation is not affected by the corruption of one or more cells of an artificial neural network.

iv. Self-Repair

ANN can do more than routing around parts of the network that no longer operate. If they are asked for finding out specific data that is no longer communicating, these ANNs can regenerate large amounts of data by inference and help in determining the node that is not working. This trait is useful for networks that require informing their users about the current state of the network and effectively result in a self-debugging.

v. The ability to work with insufficient knowledge

After the training of ANN, the output produced by the data can be incomplete or insufficient. The importance of that missing information determines the lack of performance.

vi. The ability of parallel processing

These networks have numerical strength, which makes them capable of performing more than one function at a time.

The ANN model comprises hundreds of single units, neurons, and respective weights combinedly formed neural structures. Since it processes the information, it is also called processing elements. The processing element is an equation that forms a relationship between independent and dependent variables (Agatonovic-Kustrin and Beresford 2000; Monjezi et al. 2013). Each neural network is formulated in three layers, viz. the input layer, one or more hidden layers, and an output layer (Fig. 2.8). The intermediate layer(s) do not interact directly with the external environment and are called hidden layers. All the neurons are positioned into hidden and output layers, while the input layer remains free of neurons (Pradhan and Lee 2010a; Pradhan and Lee 2010b).

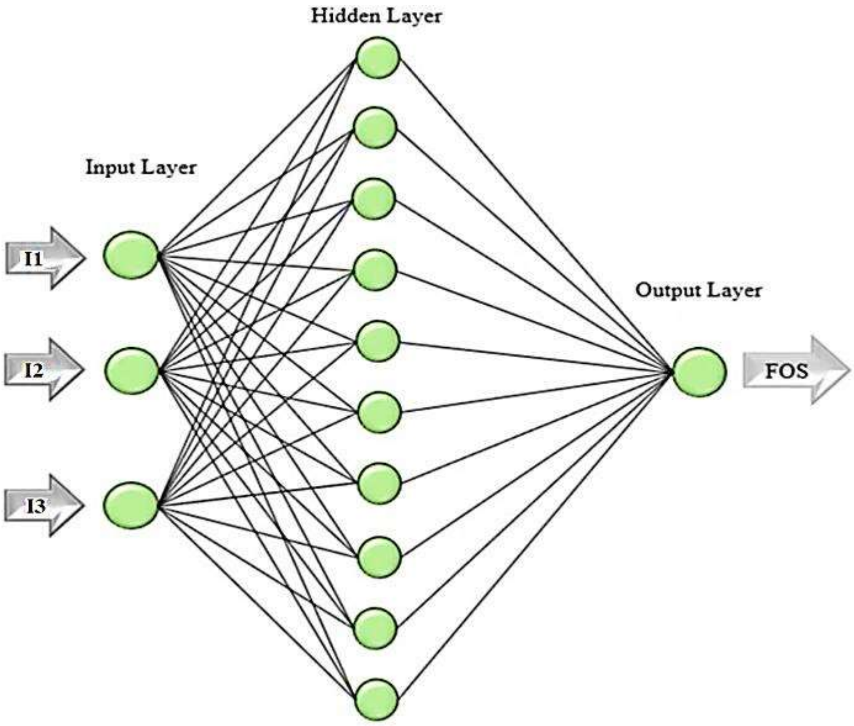

Fig. 2.8. Basic Architecture of an ANN network

ANN is a powerful tool for data simulation used primarily when the relationship between the independent and dependent variables is unknown. It can quickly identify and learn the existing correlation between the dependent and independent variables from recorded data. In the last few decades, there have been several successful applications of ANN that investigated slope stability and evaluated slope failure characteristics. In recent years, various ANN models were developed and proposed to predict the FOS, and they were successful with different levels of accuracy (Cho 2009; Das et al. 2011; Ferentinou and Sakellariou 2007; Sakellariou and Ferentinou 2005; Ural and Tolon 2008; Verma et al. 2016). These ANN methods were based on training data resulting from experimental data or generated by some specific analysis method. It was observed that the neural network models predict slip surfaces better than the limit equilibrium slip surface search using the most conservative criteria (Kaunda et al. 2010).

2.7 Landslide Generated Debris Flow Analysis

Slope failure results in dislodge of a specific quantity of earth material, also known as debris, from its original position on the slope, which moves downslope owing to gravity. Debris flows are dangerous landslide-related hazards due to their fast flow velocity, long-runout, and large impact force, in association with low predictability (Choi et al. 2020; Vagnon 2020; Zhou et al. 2019b). The worldwide diffusion and the colonisation of virgin areas, coupled with rapid industrial and population growth, increased the probability for a debris flow to cause disasters (Skilodimou et al. 2018; Surya 2012; Vagnon 2020; Zhou et al. 2019a). Several cases of debris flow resulting in severe damage to infrastructure and even engulfing entire towns have been reported in the past (Fig. 2.9) (Guthrie et al. 2009; Li et al. 2019; Martha et al. 2015; Nagarajan and Khire 1998; Phien-Wej et al. 1993; Zhou et al. 2019b).

Fig. 2.9. A severe debris flow affecting downslope settlements (Haugen and Kaynia 2008)

Debris flow hazard analysis is a crucial step for preserving lives, mitigating disasters, and determining layouts for safer economic construction (Wang et al. 2018). Jeong (2015) identified the high risk the local communities near a mine often face by extreme precipitation events coupled with debris flow from the mine sites. The author examined the geotechnical and rheological characteristics of mine deposits to delimit the hazardous areas near mines. With the increase in various anthropogenic activities in the hills coupled with changing climatic conditions, the landslide occurrence has increased in recent years. The study of the post-failure landslide debris flow will help avoid or contain any significant losses to human life and vegetation in downslope areas. The movement of landslide generated debris is a very complex phenomenon, with many parameters associated which are sometimes hard to assess. Delimiting the extent of endangered areas is fundamental to landslide risk assessment. These require accurate prediction of the runout behaviour of a landslide, such as how far and how fast landslides travel once mobilised. Generally, runout behaviour is a set of quantitative or qualitative spatially distributed parameters that define the destructive potential of a landslide. These parameters for landslide risk assessment mainly includes depth of the moving mass, runout distance, velocity, energy, depth of deposits, and damage corridor width (Hungr et al. 1999; Wong et al. 1997). A realistic estimate of the runout behaviour of a landslide depends on an adequate understanding of the generic factors that control the flow. Relevant parameters to consider include slope morphology, downhill path, residual strength behaviour of sheared zones, debris composition, mechanisms of failure and modes of debris movement.

The material which flows in a landslide consists of a mixture of two extreme ends of earthen material, i.e., rock and soil. The direct application of established theories of rock or soil mechanics does not give accurate results due to the mixture of these two extreme states of geological media. Furthermore, a considerable variation is observed in the composition of such material. With the addition of water, it becomes challenging to develop a generalised theory for the soil-rock mix. Iverson (1997) pointed out the similarity between dry granular material and landslide debris by their frictional contacts and their rapid flow with high numbers of inelastic collisions. The only difference was the fluid medium which is water with suspended silt and clay in case of landslide debris. This fluid media in debris cause viscous flow with lesser friction and fast transfer of momentum compared to dry angular particle flow (Zhou et al. 2019a). Its high speed and a large number of particles, whose size may range from a few micron diameter clay particles to boulders with a size ranging up to a few meters, is hazardous for infrastructures in the valley. Usually, such flow originates from a highly fractured and weathered zone with a steep slope, but sufficiently high pore pressure may result in failure at an unexpected site (Iverson 2014; Ray et al. 2020a).

Several authors have successfully studied the morphology of debris flow by analysing the distribution characteristics, formation conditions, depositional mechanisms and starting mode (Cheung et al. 2018; Fan et al. 2017; Gao and Sang 2017; Prochaska et al. 2008; Song et al. 2019). Huayong et al. (2014) and Chang et al. (2020) developed a hazard assessment map of Hou Gully, China-based on the occurrence probability and intensity of mine waste debris flow that can provide a scientific basis for reconstruction and mitigation projects in the future. In all the study it was observed that debris flow was strongly influenced by the physical properties of the slope and geotechnical properties of the geomaterial.

2.8 Discussion

India is vulnerable to different types of geohazards. The Himalayan and other hilly regions of India are affected by landslide and landmass movement activities. Each year, landslides cause significant destruction in terms of loss of lives and property. In recent years, landslide incidences have increased due to extreme weather events, environmental degradation due to human interference and other anthropogenic activities resulting in heavy losses of human lives, livestock and property. One of the prominent observations associated with performing anthropogenic activities in hills is the change in hydrological regime and weathering patter in and around the activity area. Due to a continuous outflow of sediments forms civil, mining and road construction sites, the natural water flow channels get blocked. This results in a complete change in the hydrology of the area. As water is one of the major factors for triggering a landslide, disturbed hydrology results in the frequent occurrence of landslides. Change in stress is another significant outcome of various anthropogenic activities. Activities that include the use of heavy machinery blasting and various constructions activities induces stresses at the working site and even distance away from it. The change in stress pattern results in a change in weathering pattern of the area, which in turn change the geotechnical and mechanical properties of the residual soil slopes. Also, the induced vibrations increase the compaction of the loose residual soil thereby decreasing its permeability. This, in turn, can affect the water movement and landslide occurrence. Also, the change in slope profile due to various anthropogenic and natural activities led to increased vulnerability of the slopes to failure. Thus, it is observed that the stability condition of the slopes is constantly changing over time due to various natural and anthropogenic conditions. This requires developing a landslide hazard identification system that will incorporate the change in slope physical, geotechnical and hydrological aspects. It will help not only help in identifying the present stability condition of the slopes but will also help in identifying the stability condition with time.

The change in weathering and hydrological pattern due to various anthropogenic activities has a marked influence on the formation and overall properties of the residual soil. This not only affects the geotechnical properties of the residual soil but also bring heterogeneity into account. The study of slopes, especially the residual soil slopes, needs to consider the change in the geotechnical properties, hydrological variations and slope topography/profile along with inherent heterogeneity of the geomaterial properties. Thus, the use of a large number of parameters that affect the stability of the slope, along with the use of probabilistic analysis, can give a more reliable result compared to the use of deterministic analysis using a limited number of parameters. The application of probabilistic analysis in terms of Monte Carlo Simulation in conjugation with Numerical Simulation is the best available method for analysing the stability of residual soil slope. Some of the benefits of using the Monte Carlo method includes flexibility in incorporating a wide variety of probability distributions without much approximation, the ability to readily model correlations among variables, and can be used to capture the influence of joint network uncertainty.

Several techniques have been developed for landslide hazard identification. This includes qualitative, quantitative and geotechnical based approaches. Each has its applicability and limitations. The obtained LHZ maps based on qualitative and quantitative techniques have less reliability as compared to the geotechnical based approaches. This is because two slopes having the same gradient and height, resembling each other externally, were seen to behave very differently in terms of slope stability. However, they can be seen identical through LHZ maps developed using qualitative and quantitative techniques. In some cases, the reason was the difference in their geological and presence of minor geotechnical details. In other cases, it was the difference in hydrological exposure, and so on. In case when a detailed vulnerability assessment is not required, the qualitative and quantitative-based LHZ maps can provide sufficiently reliable and faster results. While the geotechnical based approaches are testing intensive hence require extended time and are limited to a particular area/lithology. The choice for a particular type of

LHZ map depends on the intended usage. However, the literature study indicates the non-availability of detailed LHZ maps or charts, particularly for residual soil slopes.

With the advance in computation power and development of artificial intelligence, several works have been performed to incorporate artificial intelligence in the field of geotechnical engineering and particularly in slope stability analysis. Artificial intelligence-based machine learning tool like ANN has proved to be a versatile, adaptive, progressive and supportive option for identifying the slope stability behaviour. Previous works on ML concluded that computational intelligence tools are encouraging and should be further implemented in addressing complex geotechnical problems. However, the use of ANN for slope stability analysis related to residual soil is not explored to a large extent.

In order to undertake sustainable anthropogenic activities in the highly fragile Himalayan geology, efforts must not only be given to avoid or identify the landslide hazard but care must be taken to develop knowledge regarding post-failure debris flow behaviour. This will help increase the resilience of the entire human-nature ecosystem by limiting the adverse impact of landslides. The literature review indicates a highly variable nature of the debris flow behaviour. Much work has been done to identify the cause of slope failure and predict the type of failure and location of failure plane but investigation on flow pattern and prediction of damage due to post-failure debris flow are still in the nascent stage. The effect of topography (slope angle, slope profile, and slope height), particle size distribution, and water content on debris flow patterns need a thorough study. Since the debris flows analysis requires the study of flow behaviour, including displacement, velocity and kinetic energy, the traditional continuum-based numerical methods like FDM and FEM cannot be applied. In this case, a Distinct Element based method with proper calibration, validation and testing needs to be developed.