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Enhancement of Rainfall-Triggered Shallow Landslide Hazard Assessment at Regional and Site Scales Using Remote Sensing and Slope Stability Analysis Coupled with Infiltration Modeling

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Enhancement of Rainfall-Triggered Shallow Landslide Hazard Assessment at Regional and Site Scales Using Remote Sensing and Slope Stability Analysis Coupled with Infiltration Modeling

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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DEDICATION

To My Mother

And

To My Husband
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ABSTRACT

Landslides cause significant damage to property and human lives throughout the world. Rainfall is the most common triggering factor for the occurrence of landslides. This dissertation presents two novel methodologies for assessment of rainfall-triggered shallow landslide hazard. The first method focuses on using remotely sensed soil moisture and soil surface properties in developing a framework for real-time regional scale landslide hazard assessment while the second method is a deterministic approach to landslide hazard assessment of the specific sites identified during first assessment. In the latter approach, landslide inducing transient seepage in soil during rainfall and its effect on slope stability are modeled using numerical analysis.

Traditionally, the prediction of rainfall-triggered landslides has been performed using pre-determined rainfall intensity-duration thresholds. However, it is the infiltration of rainwater into soil slopes which leads to an increase of porewater pressure and destruction of matric suction that causes a reduction in soil shear strength and slope instability. Hence, soil moisture, pore pressure and infiltration properties of soil must be direct inputs to reliable landslide hazard assessment methods. In-situ measurement of pore pressure for real-time landslide hazard assessment is an expensive endeavor and thus, the use of more practical remote sensing of soil moisture is constantly sought. In past studies, a statistical framework for regional scale landslide hazard assessment using remotely sensed soil moisture has not been developed. Thus, the first major objective of this study is to develop a framework for using downscaled remotely sensed soil moisture available on a daily basis to monitor locations that are highly susceptible to rainfall-
triggered shallow landslides, using a well-structured assessment procedure. Downscaled soil moisture, the relevant geotechnical properties of saturated hydraulic conductivity and soil type, and the conditioning factors of elevation, slope, and distance to roads are used to develop an improved logistic regression model to predict the soil slide hazard of soil slopes using data from two geographically different regions. A soil moisture downscaling model with a proven superior prediction accuracy than the downscaling models that have been used in previous landslide studies is employed in this study. Furthermore, this model provides satisfactory classification accuracy and performs better than the alternative water drainage-based indices that are conventionally used to quantify the effect that elevated soil moisture has upon the soil sliding. Furthermore, the downscaling of soil moisture content is shown to improve the prediction accuracy. Finally, a technique that can determine the threshold probability for identifying locations with a high soil slide hazard is proposed.

On the other hand, many deterministic methods based on analytical and numerical methodologies have been developed in the past to model the effects of infiltration and subsequent transient seepage during rainfall on the stability of natural and manmade slopes. However, the effects of continuous interplay between surface and subsurface water flows on slope stability is seldom considered in the above-mentioned numerical and analytical models. Furthermore, the existing seepage models are based on the Richards equation, which is derived using Darcy’s law, under a pseudo-steady state assumption. Thus, the inertial components of flow have not been incorporated typically in modeling the flow of water through the subsurface. Hence, the second objective of this study is to develop a numerical model which has the capability to model surface, subsurface and infiltration water flows based on a unified approach, employing fundamental fluid dynamics, to assess slope stability during rainfall-induced transient seepage conditions. The
developed model is based on the Navier-Stokes equations, which possess the capability to model surface, subsurface and infiltration water flows in a unified manner. The extended Mohr-Coulomb criterion is used in evaluating the shear strength reduction due to infiltration. Finally, the effect of soil hydraulic conductivity on slope stability is examined. The interplay between surface and subsurface water flows is observed to have a significant impact on slope stability, especially at low hydraulic conductivity values. The developed numerical model facilitates site-specific calibration with respect to saturated hydraulic conductivity, remotely sensed soil moisture content and rainfall intensity to predict landslide inducing subsurface pore pressure variations in real time.
CHAPTER 1: INTRODUCTION

1.1 Introduction

Landslides, or downward/outward movements of slope forming material such as earth, debris or rock, are a major natural disaster common to many parts of the world, resulting in extensive property damage and loss of human lives. Landslides are identified as the 5th most frequent natural disaster in the world by United Nations office for the Disaster Risk Reduction, with over 380 landslides been recorded worldwide during the 20 years from 1995 to 2015 [1]. Annual monetary losses and causalities in the United States alone due to landsliding has been estimated between $2 to $4 billion (in 2010 USD)[2] and 25-50 human lives respectively [3]. Thus, early prediction of landslides can prevent extensive losses.

The stability of a naturally existing soil slope is achieved through the balance of forces acting upon it. Slope instability and subsequent sliding occur due to the action of a trigger, which can disrupt this balance. Triggering factors such as rainfall, seismic activity, volcanic eruptions, or wildfire can cause landslides [1]. Of these triggering factors, rainfall is the most common triggering factor [1–4]; hence, this research focuses on rainfall-triggered landslides.

Rainfall-triggered landslides commonly occur in regions consisting of residual soil slopes that are naturally stabilized by negative pore water pressure or matric suction. With the infiltration of rainwater, the soil moisture content increases, thereby destructing the matric suction. This phenomenon results in a decreased effective stress and hence, soil shear strength and increased weight of soil, causing slope instability [6]. Thus, it is realized that if the site soil moisture content
can be used as a direct predictor in assessing landslide hazards, the accuracy of predicting rainfall-triggered landslides can be improved.

1.2 Problem Statement

Historically, the prediction of rainfall-triggered landslides has been performed using designated threshold rainfall intensities and durations at identified landslide locations. However, the fundamental reason behind slope failure is the rise of soil moisture levels and hence, the porewater pressures [7][8]. Past researchers have attempted to use in situ soil moisture measurements as a tool for landslide hazard assessment [9][10][11]. However, measuring in situ soil moisture can be a prohibitive task due to the extensive instrumentation requirements and unreliability of instrument readings. On the other hand, most current landslide prediction methods use indirect means of evaluating the increases in moisture such as the use of hydrological conditioning factors, including distance to drainage, drainage density, and the Topographic Wetness Index or other similar water-drainage based variables [4,10,11] in place of direct ground soil moisture measurements. The use of remotely sensed soil moisture has been suggested as an alternative to in situ soil moisture measurements and alternative water-drainage based variables [7–9]. It is believed that soil moisture records that are acquired from satellites on a regular basis would be particularly effective in such assessments.

On the other hand, physically-based models, including numerical and analytical models that contain the capability to model the subsurface processes that lead to landslides, are employed widely in site-scale landslide hazard assessment as well [15][16][17][18][19][20][21]. These models aim to quantify the pore pressure variation during rainfall by modeling the transient seepage in the unsaturated zone of the soil due to infiltration of rainwater. The transient seepage in soil during rainfall and subsequent loss of matric suction is typically modeled with the Richards
equation. Finally, the slope stability is assessed with a limit equilibrium analysis with soil shear strength reduction due to rainfall typically predicted by the extended Mohr-Coulomb criterion to determine the factor of safety of the slope against failure.

However, the existing numerical and analytical models seldom consider the interplay between surface and subsurface water flows in modeling the infiltration of water into soil due to rainfall. This is often an important component that governs the rate of infiltration of water into the soil, especially during heavy storm events where landslides typically occur. Furthermore, the Richards equation employed in existing models to predict transient seepage due to rainfall is derived using Darcy’s law under a pseudo-steady state assumption. Thus, the inertial components of flow are often ignored in modeling seepage in above mentioned studies.

A physically-based numerical method can be calibrated using remotely sensed surface soil moisture content to obtain pore pressure variations of the subsurface in real time. Thus, the coupling of remote sensing with numerical modeling in this manner will lead to an improved real time landslide hazard assessment methodology.

1.3 Objectives of the Study

Based on the research problems identified in Section 1.2, this research aims to achieve the following objectives:

1. Develop a statistical framework for using remotely sensed soil moisture available on a daily basis to earmark and monitor specific locations that are highly susceptible to rainfall-triggered landslides at a regional scale, with a well-structured assessment procedure. This can be used to evaluate the effect of employing remotely sensed soil moisture along with soil hydraulic conductivity on landslide hazard.
2. Develop a numerical model for slope stability assessment at the earmarked locations during transient seepage conditions which incorporates the effects of continuous interplay between surface and subsurface fluid flows on slope stability by way of fundamental fluid dynamics.

1.4 Description of Study Areas

To achieve the Objective 1, two landslide-prone sites were selected. The first site is in western Oregon, USA (Figure 1a), and the second study site is in northern Kentucky, USA (Figure 1b). Landslide inventories for these two study sites, prepared by the Oregon Geological Survey [22] and Kentucky Geological Survey [23] respectively, were employed in this study.

The selected study area in the state of Oregon ranges from the western coastal range to the Cascade mountains. It has an elevation range of 0–2072 m, a mean elevation of 420 m, and a mean slope of 14.72°. The average primary and secondary road density is 128 m/km². This area generally experiences rainfall from October to May and relatively dry conditions from June to September [24]. The intensity of rainfall in the area ranges from 1,500 mm/year to 5,100 mm/year [25], while the average snowfall can range from 25 mm/year to 380 mm/year. However, the winter precipitation in the area usually occurs in the form of rainfall, although it is subject to occasional heavy snowfall as well [26]. The selected study area in Kentucky, which is situated along the northern mountainous region of Kentucky, has an elevation range of 131 m–892 m, a mean elevation of 341 m, and a slope of 15.22°. This area has an average primary and secondary road density of 338 m/km². The average rainfall of the area is 1,143 mm/year to 1,270 mm/year, with the rainfall being quite evenly distributed throughout the year [27]. However, the snowfall in northern Kentucky has a mean value that is close to 635 mm/year, much higher than that of Oregon [27].
Figure 1: Selected soil slide sites from (a) Oregon, United States (USA) and (b) Kentucky, USA.

1.5 Organization of Chapters

This dissertation is organized into six chapters. Chapter 1 provides an introduction to the study with background information regarding the topic of study, problem statement and objectives of the study. The Chapter 2 of this dissertation documents the literature review. Knowledge gaps identified through the literature review and a re-statement of research objectives are included at the end of Chapter 2. Chapter 3 provides information regarding the research methodology employed to achieve Objective 1 while Chapter 4 provides information regarding the research methodology employed to achieve Objective 2. Chapter 5 contains the results and discussion of the Objectives 1 and 2. Finally, Chapter 6 highlights the conclusions of the study.
2.1 Introduction

The aim of this chapter is to provide an extensive background of the study of landslides. Furthermore, recent literature on the use of remote sensing in landslide hazard assessment is presented. Moreover, existing numerical and analytical methodologies for physically-based modeling of rainfall-triggered landslide occurrence are highlighted. At the end of the chapter, the existing knowledge gaps that will be addressed by this study are stated.

2.2 Types of Landslides

Landslides are primarily classified based on the failure mechanism and the type of material involved in failure [28]. Based on the failure mechanism, landslides can be categorized into six main categories as follows 1) Falls 2) Topples 3) Slides 4) Spreads 5) Flows and 6) Complex landslide movements (Figure 2).

2.2.1 Falls

Falls occur from a slope in a mountainous area due to the separation of material such as rock or earth along a discontinuity such as a joint or a fracture with little to no shear displacement. The material descends mainly by free falling, leaping, bounding or rolling [29][30].

2.2.2 Topples

Toppling slope failures occur due to forward rotation of a soil/rock mass below a point in its center of gravity, under the effect of gravity and forces exerted by adjacent units or fluids in the cracks. This can be observed on occasions where the center of gravity of the failing block overhangs the pivot point [30][28].

2.2.3 Slides

Slope failures that are categorized as slides occur due to the downward movement of slope forming material along the surface of shear failure [28]. Slides can be further categorized as translational slides or rotational slides. In a translational slide, the movement of material occurs along a planar failure surface. This type of failure can occur along geologic discontinuities such as joints, faults or contact surfaces between soil and rock [28]. When the failure surface is curved, the movement of material is rotational. This type of a failure is identified as a rotational slide.

2.2.4 Spreads

Spreads occur in strong upper layers of rock or soil underlain by a weaker, softer layer. Failure of the underlying layer due to liquefaction, saturation, etc. could result in fracturing and spreading of the strong upper layers [28].

2.2.5 Flows

Flow of slope forming material such as earth, debris, mud, etc. can occur due to surface water flow, rapid snow melt, etc. A flow is usually characterized by relatively high material flow velocities [28].

2.2.6 Complex Landslide Movements

A failure is classified as complex when it contains characteristics of multiple types of above failure mechanisms.
Landslides can be further classified based on the type of material that failed such as earth, debris or rock or a combination of the above. The type of material that failed together with the failure mechanism are the most commonly used terminology in landslide classification [31][32][33] (eg: rock fall, debris flow). Other scarcely used methods are the classification of landslides based on the failure rate where a range of classes from extremely rapid to extremely slow are identified [34] and state of activity of the landslides where a range of classes from active to relict are identified [35]. Of the above-mentioned landslide mechanisms, this dissertation focuses on soil slides.

2.3 Causes of Landslide Occurrence

For a landslide to occur, the site should contain favorable conditions for slope failure. However, for a naturally occurring slope with such conditions, typically a trigger is also necessary to cause failure.
2.3.1 Landslide Conditioning Factors

Conditioning factors such as topographical, hydrological, geotechnical, land use, and geological factors create favorable conditions for the occurrence of slope failures, which could then be triggered by a triggering factor [4, 10]. Thus, conditioning factors can be used in predicting slope failures.

2.3.1.1 Topographical Factors

Slope angle is the most widely used topographical factor for the prediction of landslide occurrence. The slope angle plays a major role in slope stability assessment as the movement of surface deposits in a landslide occurs under the effect of gravity. The higher the slope, higher would be the destabilizing force created by gravity, thus creating more favorable conditions for slope failure under the effect of a trigger. Furthermore, the shape of a slope affects the occurrence of landslides. As an example, a terraced slope has been identified to mitigate the landslide potential, compared to a straight slope [13]. Other topographical conditioning factors include (but are not limited to) slope curvature, aspect, sloping length, elevation, and geomorphological units, etc. [10, 13–15].

2.3.1.2 Hydrologic Factors

Since the sustenance of higher levels of soil moisture can create favorable conditions for slope failure, hydrological conditioning factors aim to quantify the effect that rainfall has on landslide hazard. Many water related attributes have been used as indices in landslide studies to quantify this effect. These hydrological factors aim to model the spatial distribution of soil moisture increase in the ground due to rainfall by quantifying the capability of a given site to accumulate and discharge rainwater [8]. Of the hydrological factors that are used as surrogate soil
moisture measurements, distance to drainage accessories, drainage density, and topographic wetness (TWI) are notable [12].

1. Distance to drainage accessories: This factor affects the drainage of rainwater from a basin. A higher distance to drainage accessories (streams or water bodies) would indicate slower drainage of water from a basin and thus, create more favorable conditions for landslides [15-16].

2. Drainage density: The drainage density of a basin is defined as,

\[
\text{Drainage density} = \frac{\text{total length of channels}}{\text{basin area}}
\]  

A lower drainage density would indicate the accumulation of soil moisture on the ground, thereby increasing the landslide hazard.

3. Topographic Wetness Index (TWI): The TWI is defined as,

\[
\text{TWI} = \ln\left(\frac{a}{\tan(b)}\right)
\]

where \(a\) is the upslope contributing area per unit contour length and \(b\) is the slope angle. This indicator measures the effect that topography has on flow accumulation or generation of runoff [16-17]. A location with a higher upslope contribution area would have a greater flow accumulation, greater soil saturation and reduced strength, thus creating favorable conditions for landslides. Furthermore, a lower tangent value of slope would increase prolonged stagnation of rainwater and thus, increase landslide hazard. Hence, by combining the effects of above two variables, it can be said that a location with a higher TWI is expected to be at a greater landslide hazard.

2.3.1.3 Geotechnical Factors

The geotechnical properties of the soil overburden, especially the undrained shear strength, hydraulic conductivity, and bulk density of the soil, can impact the potential for soil slope failures.
A soil with higher shear strength can withstand a greater destabilizing force compared to a soil with a lower shear strength, whereas a higher bulk density increases the destabilizing force. A soil with a higher hydraulic conductivity can drain the increased moisture due to rainfall infiltration faster, and thus create less favorable conditions for slope failure, compared to a soil with a lower hydraulic conductivity [13,14].

2.3.1.4 Land Use

Land use practices can affect the behavior of a slope under the effect of a trigger. Thick vegetation cover improves the shear strength of soil by increasing cohesion and suction through transpiration [39]. Thus, presence of vegetation would indicate conditions unfavorable for landsliding [40]. Conversely, the lack of vegetation cover would create favorable conditions for erosion and slope failure. As an example, deforestation and de-rooting can expose a slope to surface erosion. Moreover, reduction in forested area and the resulting increase of bare area could lead to an increased landsliding potential. [41].

2.3.1.5 Geological Factors

Geological factors such as the lithology, presence of joints, faults, and bedding planes of underlying bedrock, permeability, and strength can impact landslide potential [4,13,14].

2.3.2 Landslide Triggering Factors

In order to destabilize an existing stable slope, a trigger must act upon it. Triggers can be in various forms such as 1) rainfall 2) seismic activity 3) volcanic activity 4) wildfire or 5) human activity [42].

2.3.2.1 Rainfall

The most common triggering factor for landslide occurrence is rainfall [4]. Use of rainfall intensity and duration thresholds developed through empirical or statistical estimations are
commonly used as predictors for rainfall-triggered landslide occurrence [43]. The infiltration of rainwater into soil causes an increase of soil moisture content and the porewater pressure. This leads to a decrease of soil shear strength while the weight of soil is increased. This phenomenon can be further explained by Mohr-Coulomb failure criterion as shown in Equation (3).

$$\tau_f = c + \sigma' \tan \varphi$$  \hspace{1cm} (3)

where $\tau_f$ is the soil shear strength along the failure plane, $c$ is the cohesion, $\sigma'$ is the effective stress of the soil perpendicular to failure plane and $\varphi$ is the angle of internal friction. The effective stress of a soil can be quantified using Equation (4) [44]:

$$\sigma' = \sigma - u_w$$  \hspace{1cm} (4)

where $\sigma$ is the total stress of the soil, and $u_w$ is the pore water pressure. Based on Equation (3), it can be seen that with the increase of porewater pressure, the effective stress decreases, thereby decreasing the shear strength. This can lead to slope instability. The above phenomenon can be further explained in Figure 3.

Figure 3: Sequence of events leading to the occurrence of a landslide.

Thus, the reason behind slope failure due to rainfall is the increase of soil moisture content and pore pressure. Therefore, these factors need to be incorporated in rainfall-triggered landslide
prediction systems. However, measurement of the soil moisture content at the site level can be prohibitive due to high cost and complexity in implementation.

2.3.2.2 Other Triggering Factors

Major earthquakes, which have affected humankind around the world, were usually accompanied by landsliding activity [28]. Vibrations caused by earthquakes can result in soil losing its shear strength (e.g., liquefaction), which leads to landslides. On the other hand, landslides can occur due to volcanic activity as well [28]. Explosive volcanic eruptions as well as the dissolving of gases created by magma in groundwater which weakens the underlying rock could causes landsliding. Furthermore, wildfires can cause damage to flora, which result in de-rooting of slopes exposing them to erosion, thus causing landslides. Moreover, human activities such as deforestation, undercutting of slopes and loading slopes at the crest could trigger landslides [40].

2.4 A Review of Current Methods of Landslide Hazard Assessment

Techniques used in landslide hazard assessment can be classified into the following five broad categories [45]: 1) Stochastic methods [46][47][48][49], 2) Deterministic methods [10][50], 3) Distribution analysis, 4) Qualitative analysis [13] and 5) Frequency analysis [51][52].

2.4.1 Stochastic Methods

Numerous past studies have focused on the use of the stochastic approach to predict landsliding. Stochastic methods operate under the assumption that a landslide can occur at a location under the conditions that led to landsliding in the past [47]. Stochastic approach to landslide hazard assessment can be categorized as follows: 1) Bi-variate statistical analysis and 2) Multi-variate statistical analysis [53]. The bi-variate statistical analysis approach to landslide hazard assessment considers each of the landslide causative factors separately and assigns a weight to each of them statistically, based on the relationship between each causative factor and
lands. Finally, the conditions of causative factors at a given site are combined to arrive at the landslide hazard at that site. Examples of bi-variate statistical methods employed in landslide hazard assessment are frequency ratio analysis, weight of evidence method, fuzzy logic method, etc.

On the other hand, multi-variate statistical analysis considers the effects of several variables simultaneously on landsliding. Logistic regression analysis, probabilistic estimations, discriminant analysis and the use of artificial neural networks are example applications of multi-variate statistical analysis in landslide hazard assessment. Of the above methods, logistic regression is identified as a modeling method that can provide highly accurate results in landslide hazard assessment compared to other statistical methods [10][46]. In addition, logistic regression provides an estimation of the statistical significance of each of the landslide conditioning factors. Hence, it is identified as one of the most preferable methods for landslide hazard assessment [12].

For example, Wang et al. [46] conducted a comparative study to assess landslide hazard in Mizunami City, Japan with logistic regression and several other alternative landslide hazard assessment methods which include decision trees, frequency ratios, weights of evidence, and artificial neural networks. The impact of the conditioning factors on landsliding were investigated to derive landslide hazard predictive relationships of the above alternatives. The logistic regression method was determined to yield the best results in classification. Thus, logistic regression is used in this study for landslide hazard assessment. A stochastic approach is followed to achieve Objective 1 of this study.

2.4.2 Deterministic Method

Deterministic approach to landslide hazard assessment employs mechanistic modeling to model the process leading to a landslide. This method is usually carried out with a slope stability
analysis, accompanied by a seepage analysis. The objective of the seepage analysis is to determine the porewater pressure and soil moisture content variations of the subsurface due to infiltration which shall be incorporated in the slope stability assessment. For a slope subject to rainfall, a transient seepage analysis is required in determining the changes to porewater pressure and soil moisture content at the subsurface due to infiltration of rainwater. In the existing models, the seepage analysis is typically performed using Richards equation [15][54], which is derived using Darcy’s law. The seepage analysis is typically performed with the assumption of an infinite slope [17][20][54]. The shear strength reduction in soil due to seepage is typically estimated using extended Mohr-Coulomb criterion [17][20] proposed by Vanapalli et al. [55]. The slope stability is assessed with a limit equilibrium analysis. The objective of this method is to find the area of the slope which is most susceptible to landsliding. A deterministic approach to slope stability is followed to achieve the Objective 2 of this study and it is discussed further in Section 2.6.

2.4.3 Distribution Analysis

Distribution analysis involves direct mapping of historic landslides and thus, it provides information regarding landslide hazard only at the locations of previous failures. This is the simplest form of landslide hazard mapping. It involves the preparation of landslide inventories based on field observations, aerial or LIDAR imagery. The prepared hazard maps would provide an indication of landslide hazard immediately after the occurrence of a landsliding event [45]. The landslide inventories developed for the states of Oregon and Kentucky, which are used in this study, are example applications of this method [22]. However, this method has major shortcomings as it fails to predict the occurrence of future landslides on locations where past landslides have not occurred. Nor does it provide a quantification regarding future landslide susceptibility.
2.4.4 Qualitative Analysis

The qualitative approach to landslide hazard assessment provides an improvement to the above-mentioned distribution analysis by incorporating the experts’ judgement to assess landslide susceptibility. It is defined by Mantovani et al. [56] as follows “direct or semi-direct methods in which the geomorphological map is renumbered to a hazard map or in which several maps are combined into one using subjective decision rules based on the experience of the earth scientist”.

The current method of landslide susceptibility analysis used in Sri Lanka is an example application of this method [57]. This method involves first identifying potential landslide causative factors and then assigning ratings (R) to each site based on the condition of each causative factor, based on experts’ judgment. Furthermore, a weight (W) is assigned to each causative factor, again based on experts’ judgment. The final landslide susceptibility is obtained by combining weights and ratings under one rule (summation), using Equation 5.

\[ S_j = \sum_{i=1}^{N} W_i R_{ij} \]  

where \( S_j \) represents landslide susceptibility at location \( j \), \( W_i \) represents the weight assigned to causative factor \( i \), \( R_{ij} \) represent the rating assigned to location \( j \) based on factor \( i \) and \( N \) is the number of causative factors considered. Moreover, the method for “macro level hazard zonation” proposed in Bureau of Indian Standards [58] follows a similar methodology for landslide susceptibility assessment.

However, the incorporation of experts’ judgement to determine weights and ratings introduce subjectivity to the methodology. Each causative factor is considered separately and thus, the interrelationships between causative factors, such as geology and soil type, are not been accounted for. Furthermore, combining of all the factors, irrespective of their contribution to landsliding at the given location, could lead to under/over prediction of hazard since adverse
conditions of all factors are not necessary for landslide occurrence. Moreover, the effect caused by a landslide trigger is not considered in this approach.

2.4.5 Frequency Analysis

Frequency analysis focuses on identification of thresholds in triggering factors leading to landsliding, based on observed past relationships. Rainfall intensity thresholds, rainfall intensity-duration thresholds, antecedent rainfall and cumulative rainfall are the known thresholds employed in assessing rainfall-triggered landslide hazard [53]. The most common thresholds are rainfall intensity-duration thresholds [51]. This method was first proposed by Caine [52] to predict debris flow occurrences. After studying numerous past landslide studies, the following threshold (Equation 6) was obtained by plotting rainfall intensity which caused landslides on these occasions against duration:

$$I = 14.82D^{-0.39}$$

where $I$ (mm/hr) is the rainfall intensity and $D$ (hr) is the duration.

In a recent study, Zezere et al. [51] proposed another empirical method to identify critical rainfall thresholds causing landslides in Portugal for five identified landslide prone areas. In this study, cumulative rainfall-duration thresholds as well as rainfall intensity-duration thresholds were developed. Due to the difference in topography, geology, etc. in the five study areas, the above-mentioned researchers decided to develop area specific thresholds. Hence, it might be difficult to be implemented at a regional scale as it requires several area specific thresholds. Furthermore, since this is an empirical method, it lacks the flexibility to be adjusted according to changes which can occur in the conditions of landslide causative factors at a given location.

In addition, when considering the process leading to rainfall-triggered landsliding as described in Section 2.3.2.1, it is evident that the real reason behind slope failure is the rise of soil
moisture conditions leading to slope instability. Hence, use of the increased soil moisture as a
predictor variable could be more representative of any impending instability. In addition, past
research has emphasized the potential use of soil moisture content in place of rainfall thresholds
in the prediction of landslide occurrence [59].

2.5 A Review of Applications of Remote Sensing in Landslide Investigations

In the past, landslide investigations have been performed predominantly with field surveys.
The advancement of remote sensing technology has provided an opportunity to improve the
effectiveness of landslide studies by curtailing the need for field surveys. Hence, remote sensing
is widely applied in landslide investigations today. Based on a review performed by Scaioni et al.
[60] applications of remote sensing in landslide investigations can be found under the following
three broad categories: 1) Landslide detection and mapping, 2) Landslide monitoring and 3) Landslide hazard assessment.

2.5.1 Applications of Remote Sensing in Landslide Detection and Mapping

Optical, microwave and laser remote sensing techniques are widely employed in detecting
and mapping past landslides. In landslide detection using optical imagery, manual, semi-automated
and automated mapping techniques are being employed. The optical imagery used in this process
come in the form of either aerial imagery or high resolution (HR), very high resolution (VHR),
multispectral, hyperspectral and stereo satellite imagery. These methods focus on identification of
visible signatures left by landsliding activity such as loss of vegetation and ground displacements
and then mapping them. Semi-automated and automated approaches use change detection
techniques in identifying landsliding locations by comparing images obtained before and after a landslide [60].
On the other hand, microwave based Interferometric Synthetic Aperture Radar (InSAR) is the most popular method of landslide mapping. This method involves comparison of the phase difference between two InSAR images, obtained prior to and after a landslide, in order to obtain the relative displacement due to a landslide. In addition, ground or air borne laser scanners are employed widely in landslide mapping (eg: LiDAR- Light Detection and Ranging). High resolution digital elevation models developed by laser scanning is being used in the identification of landslide locations either heuristically or via semi-automated processes [60].

2.5.2 Applications of Remote Sensing in Landslide Monitoring

Monitoring the changes which occur in existing landslides over time, in order to identify possible future slope movements [45], has been achieved through optical, microwave remote sensing and laser scanning. Monitoring of ground deformations, land cover changes, crack propagation over time could provide a reliable indication of a looming slope failure. Optical remote sensing techniques such as aerial imagery, as well as high resolution, very high resolution and stereo satellite imagery can be employed in this regard. Additionally, InSAR and laser scanning can be employed in landslide monitoring due to their ability to monitor fine displacements. It should be noted that only slow moving landslides can be effectively monitored by satellite remote sensing due to the coarse temporal resolutions of these images [60].

2.5.3 Applications of Remote Sensing in Landslide Hazard Assessment

A landslide occurs as a result of favorable conditions in causative factors, accompanied by a triggering factor. Hence, applications of remote sensing in landslide hazard assessment essentially refers to the use of remote sensing in identification of the magnitude of these causative and triggering factors [60], which can be employed in assessing the landslide hazard, at a given location.
Landslide causative factors such as topography and land cover can be obtained from digital elevation models and land cover maps developed via satellite imagery respectively. On the other hand, important hydrological factors such as distance to streams, rainfall and soil moisture content, can be obtained from various remote sensing platforms. This study focuses on the use of remotely sensed soil moisture together with landslide causative factors in landslide hazard assessment.

2.5.4 A Review of the Applications of Remotely Sensed Soil Moisture in Landslide Hazard Assessment

Some recent research effort has been spent on using remotely sensed soil moisture in the study of landslides. One of the early research in this area has been performed by Ray et al. [9] The above-mentioned researchers worked toward establishing a qualitative relationship between remotely sensed soil moisture, precipitation and landslide events. The objective of the above study was two-fold: 1) Remotely sensed soil moisture measurements are affected by factors such as surface roughness, topography and soil texture. Since landslides occur in steep terrain, there could be pronounced effect from the above factors on remote sensing signals obtained at these locations. Therefore, the first objective of the above researchers was to explore whether microwave remotely sensing can be employed to extract useful information regarding soil moisture in such terrains. 2) To determine whether a qualitative relationship exists between remotely sensed soil moisture and landsliding events.

AMSR-E (Advanced Microwave Scanning Radiometer - Earth Observing System) derived surface (< top 5cm depth) soil moisture and TRMM (Tropical Rainfall Measuring Mission) derived rainfall were employed in the above authors’ study conducted in landslide prone areas of California USA, Leyte, Philippines and Dhading, Nepal. The temporal variation of remotely sensed soil moisture, precipitation and landslide events for these three locations were plotted for a period from
January 2005 – May 2006. A weekly moving average soil moisture was employed in the above study since daily soil moisture levels were found to be highly variable. Seasonal trends in soil moisture displayed agreement with trends in precipitation. The increased periods of soil moisture were observed to correspond to periods of intense rainfall with the events of intense rainfall preceding events of high soil moisture. In the study site in California, all the slope movements coincided with periods of high soil moisture, however interestingly, they did not exactly match the dates of high rainfall. At the Leyte, Philippines study site a single landslide event was observed. However, on the day of landslide disaster (February 17th, 2006), the top soil was not as wet as it was before (in January 2006), where no landslides occurred. The above researchers suspect the possible subsurface saturation due to prolonged rainfall events in December 2005, which was not captured by the surface soil moisture, as the probable reason for the slope failure. Finally, in the study site in Nepal, the soil moisture did not appear to correspond to rainfall for a period from September to February, possibly indicating a measurement problem due to increase in vegetation density as a result of late August plantations, as pointed out by the researchers. However, the landsliding event in early August appear to coincide with monsoonal (June to September) rainfall.

Through this study, the researchers were able to demonstrate that remotely sensed soil moisture can be employed to extract useful information in landslide prone regions and the existence of a qualitative relationship between remotely sensed soil moisture and landslide events. Furthermore, the Ray et al. [9] observed that events of landslides do not necessarily coincide with events of high precipitation, thereby raising questions regarding the use of rainfall intensity duration thresholds as a method of landslide prediction. Moreover, a quantification of the estimates of soil moisture levels that would lead to slope instability under different site conditions has not been achieved in the above research.
The above-mentioned researchers have used AMSR-E derived soil moisture at 25km x 25km spatial resolution and TRMM measurements at 27.5km x 27.5km spatial resolution, which is much coarser than the influence area of a landslide. Moreover, as indicated above, the authors have studied only the soil moisture levels at the top surface. However, deep seated landslides can occur due to adverse conditions in soil subsurface such as the presence of a weak soil layer or a low permeable clay layer. Saturation of such layers can result in the layer losing its existing shear strength and becoming unstable. The methodology proposed by Ray et al. [9] does not capture this effect, which is a limitation of this research.

In another study, Brocca et al. [11] investigated the relationship between remotely sensed soil moisture derived from ASCAT (Advanced Scatterometer) satellite, rainfall and the activation of Torgiovanetta rock slide in Italy. This rock slide site is equipped with extensometers and the current method of predicting the slope movement is based on the rate of crack width propagation. The above researchers aimed to use an Antecedent Precipitation Index (API), which is the cumulative precipitation in the past 20 days and Soil Water Index (SWI), an indicator of root zone soil moisture, derived semi-empirically from ASCAT soil moisture, [61] as alternatives to landslide prediction based on the rate of crack width propagation. Brocca et al. [11] explored the subsurface conditions of the rock mass and concluded that the presence of weak thin clay layers between hard calcareous layers on a steep slope as the possible reason for marginal safety conditions.

Furthermore, a stepwise regression approach has been followed in the study to determine the relationship between the above variables for the period 2007-2009. The crack aperture has been correlated separately with 1) rainfall, 2) rainfall +API, 3) rainfall +SWI and 4) rainfall +API +SWI. The highest correlation coefficient of 0.87 was observed when all three variables were used.
together. However, the use of precipitation + SWI demonstrated a better accuracy than precipitation +API. Hence, the improvement in reliability of predictions when soil moisture is used in place of rainfall is demonstrated.

In the above study, the Brocca et al. [11] used ASCAT derived soil moisture at a 25km x 25km spatial resolution. Although they achieved a reasonable accuracy, the coarse spatial resolution could present an hindrance to reliable prediction of a landslide occurrence. Furthermore, the study was based strictly on the prediction of a rockslide.

Ray et al. [10], [62] conducted another study where a deterministic approach was followed to in employing remotely sensed soil moisture for landslide hazard assessment. A numerical model to determine slope stability was developed first [62] and then it was modified to incorporate remotely sensed soil moisture and was applied to a landslide prone area in order to determine landslide susceptibility [10].

The above numerical is model based on limit equilibrium approach to slope stability with a one-dimensional infinite slope (Figure 4), where the slope length is considered far greater than the soil mantle thickness. In this model, the soil was considered to consist of 2 layers: 1) The layer above the groundwater table and 2) The layer below the groundwater table, of the same soil type. Another assumption in the model is that soil fails in sliding, at the bedrock-soil interface along a planar failure surface. Based on the above assumptions, Ray et al. [62] derived a factor of safety for the slope as a function of unsaturated zone soil moisture content, effective cohesion, root cohesion and angle of internal friction of the soil, saturated and dry unit weights of the soil, thicknesses of the soil layer and the unsaturated zone, surcharge on the soil, slope angle and voids ratio of the soil. Stability of soil slopes against sliding is determined based on the factor of safety (FoS). In this study, Ray et al. [62] considered areas corresponding to FoS≤1, 1<FoS<1.25,
1.25<\text{FoS}<1.5 \text{ and } \text{FoS}\geq1.5 \text{ to be highly susceptible, moderately susceptible, slightly susceptible and not susceptible to landsliding, respectively.}

Figure 4: Illustration of the infinite slope model employed in the study. $H<<L$ (adapted and modified from Ray et. al, 2010).

In a second study, microwave remote sensing was applied to derive the dynamically varying unsaturated zone soil moisture contents [10]. Downscaled AMSR-E derived soil moisture at 1km x 1km spatial resolution, downscaled using the model developed by Chauhan et al. [63], was employed to represent soil moisture content of the entire unsaturated zone, which is a variable in the safety factor model discussed above. The factor of safety model modified with remotely sensed soil moisture content was employed in estimating the landslide susceptibility in Cleveland Corral region, CA, USA. Furthermore, the results were compared with those obtained with the use of unsaturated zone soil moisture content derived with a land surface model (VIC-3L model) and AMSR-E derived soil moisture at 25km x 25km spatial resolution. The VIC-3L, or the Variable Infiltration Capacity – 3 Layer, is a macroscale land surface hydrological model which employs water balance and energy balance to quantify surface and subsurface hydrological processes [64]. This model is applied in this study to determine the variation of soil moisture content in the surface.
and subsurface layers of soil in order to compare with the results obtained via the factor of safety model developed by the above-mentioned authors.

In this study, the landslide susceptibility was analyzed under three scenarios: 1) Full saturation, where the groundwater table (GWT) was assumed to be at the top of the soil surface 2) Half saturation, where the GWT was assumed to be at the middle of the soil mantle and 3) Maximum modeled saturation, which corresponds to the maximum moisture content observed at the study area for the three year period that was considered for this study. It should be noted that under full saturation, the soil moisture of the unsaturated layers is the same under all three modeling methods. It was observed that only a little difference in prediction was observed between the two AMSR-E based methods (1km x 1km and 25km x 25km spatial resolutions). Nevertheless, the researchers suggest the use of higher resolution dataset in slope stability analysis as higher resolution datasets are consistently recommended for landslide mapping. Furthermore, the three modeling methods identified these areas susceptible to different hazard categories fairly consistently. However, the percentage of susceptible areas identified by AMSR-E derived methods were slightly lower than those of the VIC-3L based method. As an example, under the maximum model saturation scenario, the VIC-3L model-based method identified 0.49% of the area to be highly susceptible to landsliding while AMSR-E (1km x 1km spatial resolution) based method identified only 0.42% of the area to be highly susceptible. On the other hand, the AMSR-E (25km x 25km spatial resolution) based method identified 0.41% of the area to be highly susceptible under above conditions.

Finally, the model results were compared with ten observed past and present landslides of the study region. It was observed that under the maximum modeled saturation, six out of the above ten locations were identified as highly susceptible while the remaining four locations were
identified as moderately susceptible under all three modeling methods. Through this study, the authors were able to demonstrate that remotely sensed soil moisture does provide an efficient means to develop landslide susceptibility maps.

However, following shortcomings can be identified in the research methodology followed by the above researchers. The study was based on an infinite slope model which is different to a realistic slope of a finite length, consisting of upstream and downstream flat land. Furthermore, the model assumes that slope failure only occurs in a planar failure surface. Moreover, the soil mantle is assumed to consist of a single soil type and the failure plane is restricted to bedrock-soil interface. Thus, the applicability of the model is limited by the above assumptions. In addition, the effect of soil hydraulic conductivity on slope stability was not considered.

Furthermore, soil moisture downscaling models that have the capability to model the spatial distribution of soil moisture more accurately compared to the model developed by Chauhan et al. [63], which was employed by Ray et al. [10] in the above study have been developed recently. This will be discussed further in Section 2.5.6.

2.5.5 A Review of Remote Sensing Methods Employed in Detecting Soil Moisture

Following three remote sensing techniques are currently being employed in the detection of soil moisture:

1. Microwave
2. Visible infrared
3. Thermal

2.5.5.1 Microwave Remote Sensing of Soil Moisture

Microwave remote sensing is the most widely used remote sensing technique for the detection of soil moisture. The ability of microwave to penetrate cloud cover and precipitation has
resulted in making microwave remote sensing the most popular technique for the remote sensing of soil moisture. In addition, microwaves possess the advantage of night time coverage and high temporal resolutions. Furthermore, the physical basis for the detection of soil moisture via microwave remote sensing is well established [65].

Microwaves belong to the 300MHz to 300GHz frequency range in the electromagnetic spectrum. When microwave radiation comes into contact with an object on earth, different portions of the radiation are reflected, scattered, absorbed and transmitted by the object as illustrated in Figure 5. The absorbed radiation is later emitted by the object.

![Figure 5: Behavior of a microwave pulse in contact with an object on earth.](image)

Microwave remote sensing can be categorized into two basic categories;

1. Active microwave remote sensing - In active microwave remote sensing, a microwave pulse is sent to the object of interest by the satellite and the portion of scattering returned is measured by the receiver. The level of scatter depends on several characteristics of the object on which microwave radiation is incident upon and the properties of the incident wave itself. Some of the characteristics related to the current study are the soil moisture content, soil surface roughness, vegetation cover, incidence angle and frequency. Hence, the scattering of microwave radiation offers important information which could be used to remotely sense the properties of land surface. Scattering is quantified using a parameter known as the “backscatter coefficient”. The backscatter coefficient is defined as the differential scattering cross section per unit volume for a scattering angle of 180° [66]. This
quantifies the amount of differential scattering, w.r.t. scattering angle, scattered back to the receiver antenna at an 180° angle, per unit volume.

2. Passive microwave remote sensing [65] - Passive microwave remote sensing quantifies the earth’s emission of the microwave radiation which it has absorbed from solar radiation. The emission is quantified using the ‘brightness temperature’ which is the temperature of a black body in thermal equilibrium with its surrounding, which would emit the same intensity of radiation of the measured frequency as the considered gray body. A black body absorbs all the incident electromagnetic radiation, irrespective of the frequency. A black body in thermal equilibrium is an ideal emitter, i.e., it emits more energy than any other body at the same temperature, irrespective of the frequency. Moreover, the energy is emitted isotopically in every direction.

2.5.5.1.1 Theoretical Background of the Derivation of Soil Moisture from Microwave Remote Sensing

2.5.5.1.1.1 Active Microwave Remote Sensing

Theoretical models have been developed to relate the backscatter coefficient to the properties of land surface as well as the properties of the wave. One such model is the small perturbation surface backscattering model [65].

The small perturbation surface backscattering model is used to calculate the backscatter coefficient (σ) when the surface roughness is low. The backscatter coefficient is defined in terms of the wave number of the incident microwave (k), the incident angle (θ), surface height standard deviation (σ), surface correlation length (L), magnetic permeability (μr) and effective permittivity (dielectric constant) of the surface material (εr), which is a function of the soil moisture content. The wave number of the incident wave is defined in Equation 7.
where $\lambda$ is the incident wavelength. In order to apply this model, the surface roughness should conform to the following constraints:

$$k \sigma < 0.3, \left(\frac{\sigma}{\lambda}\right) < 0.3, kL < 3$$

The surface roughness is defined in terms of its surface height standard deviation and correlation length. Finally, the backscatter coefficient is quantified using Equation 9.

$$\sigma = \left(\frac{4k^4\sigma^4\cos^4 \theta}{\pi^2 \epsilon_r - \sin^2 \theta} \left(\mu_r \epsilon_r - \sin^2 \theta \right)^2 W(2\sin \theta, 0)\right)^{\frac{1}{2}}$$

where $W$ is the surface spectra evaluated at different spectral values, which can be expressed as the surface height autocorrelation function defined in the wavelength domain using a two dimensional Fourier Transform [65].

### 2.5.5.1.1.2 Passive Microwave Remote Sensing

The theoretical background of determining soil moisture content from brightness temperature derived from passive microwave remote sensing has been widely studied [65]. The intensity of radiation from a black body, according to Plank’s law is given in Equation 10.

$$I_{\nu B} = \frac{2h\nu^2}{c^2} \frac{1}{e^{\frac{h\nu}{kT}} - 1}$$

where $\nu$ is the frequency of radiation, $h$ is the Plank’s constant, $c$ is the speed of light, $T$ is the temperature of the blackbody and $k$ is the Boltzmann’s constant. Furthermore, the intensity of radiation from a gray body is a $E^{th}$ fraction of the intensity of radiation of a blackbody where $E$ is the emissivity of soil. Thus, the intensity if radiation from a gray body can be defined in Equation 11.

$$I_{\nu} = EI_{\nu B}$$
Therefore, the intensity of radiation from a gray body at the same temperature T can be expressed using Equation 12.

\[ I_\nu = \frac{E}{c^2} \frac{1}{\frac{\nu}{e^{kT} - 1}} = \frac{2h\nu^2}{c^2} \frac{1}{e^{\frac{\nu}{kT_b} - 1}} \]  

(12)

where \( T_b \) is the brightness temperature of the object. Thus, the brightness temperature of an object can be expressed using Equation 13.

\[ T_b^{-1} = \frac{k}{h\nu} \ln \left( 1 + \frac{\nu}{e^{kT_b} - 1} \right) \]  

(13)

Neglecting the scattering component, the emissivity \( E \) can be expressed using Equation 14.

\[ E = 1 - R \]  

(14)

where \( R \) is the reflectance. The specular reflectance of \( h \) (horizontal) and \( v \) (vertical) polarized waves can be expressed by Fresnel’s equations (Equations 15-16).

\[ R_v = \frac{\cos \theta - \sqrt{\varepsilon_r - \sin^2 \theta}}{\cos \theta - \sqrt{\varepsilon_r + \sin^2 \theta}} \]  

(15)

\[ R_h = \frac{\varepsilon_r \cos \theta - \sqrt{\varepsilon_r - \sin^2 \theta}}{\varepsilon_r \cos \theta - \sqrt{\varepsilon_r + \sin^2 \theta}} \]  

(16)

where \( \varepsilon_r \) refers to the effective permittivity of soil and \( \theta \) is the incidence angle.

### 2.5.5.1.1.3 Relationship between the Effective Permittivity and Soil Moisture Content

As discussed previously, the backscatter coefficient (\( \sigma \)) and brightness temperature (\( T_B \)) are properties of soil dielectric constant or the effective permittivity (\( \varepsilon_r \)). The effective permittivity of the soil is dependent upon its constituents such as soil particles, water and air voids. The large difference between dielectric constant of water and dry soil (eg: 80 for water and 3-6 for dry sand) facilitate the detection of soil moisture content via backscatter coefficient or brightness temperature [67].
Dielectric mixing models have been developed for the extraction of soil moisture content from effective permittivity [68]. One such model is Rayleigh mixing formula. According to this model, the effective permittivity of a mixture with homogeneous, spherical inclusions can be defined using Equation 17.

\[
\frac{\varepsilon_r - \varepsilon_0}{\varepsilon_r + 2\varepsilon_0 + \nu(\varepsilon_r - \varepsilon_0)} = \sum f_i \frac{\varepsilon_i - \varepsilon_0}{\varepsilon_i + 2\varepsilon_0 + \nu(\varepsilon_r - \varepsilon_0)}
\]  

(17)

where \(\varepsilon_r\) is the effective permittivity of the mixture, \(\varepsilon_0\) is the permittivity of the base material, \(\varepsilon_i\) is the permittivity of the \(i^{th}\) constituent of the mixture, \(f_i\) is the volume fraction of the \(i^{th}\) constituent and \(\nu\) is a free parameter which accounts for the effect of the polarization of a particle from its neighboring particles. \(N\) can be quantified using the volume percentages of sand, silt, clay, moisture and the microwave frequency using Equation 18 [69].

\[
\nu = -0.00525.Sand + 0.021627.Silt - 0.02642.Clay + 0.1095.Moisture + 0.007001.Frequency + 3.976294
\]  

(18)

2.5.5.2 VIR Remote Sensing of Soil Moisture

VIR remote sensing utilizes the visible and near infrared frequency ranges of the electromagnetic spectrum, to sense soil moisture. The effect of soil moisture on the reflectance of visible range of electromagnetic spectrum has been studied since 1925 [70]. The main advantage of using VIR remote sensing in this regard lies in the fact that it has a relatively finer spatial resolution. Utilization of VIR remote sensing for the determination of soil moisture can be studied under two broad categories: 1) single spectral analysis and 2) vegetation index method [71].

2.5.5.2.1 Single Spectral Analysis

Single spectral analysis operates under the observation that soil surface reflectance decreases with the increase of soil moisture content. Research effort has been focused on developing empirical relationships between soil moisture content and surface reflectance through
laboratory experiments [71]. The response of soils to VIR signals were found to be greatly dependent upon soil type [72]. Therefore, the use of these relationships is largely limited to the soils with similar characteristics to those for which the experiments were carried out. Lobell et al. [73] provided an improvement to the above models by incorporating reflectance characteristics of four different soil orders, namely aridisol, andisol, mollisol and entisol in a single model. An exponential relationship between reflectance and soil moisture content was observed and it was empirically quantified using Equation 19 [73].

\[
s = -\frac{\ln\left(\frac{R-fR_{dry}}{(1-f)R_{dry}}\right)}{c} \times 100
\] (19)

where \( s \) is the volumetric soil moisture content (%), \( R \) is the reflectance (ratio of reflected radiation to the total incident radiation), \( c \) is a constant that corresponds to the rate of change in reflectance due to soil moisture, \( R_{dry} \) is the dry soil reflectance and \( f \) is the ratio between saturated and dry soil reflectance. All of the above parameters are specific to the soil type and measured wavelength. Furthermore, additional research has been performed to incorporate more soil types by Liu et al. [74]. However, it should be noted that these methods are essentially empirical and therefore, lack a physical basis. Furthermore, since these models are developed through laboratory experiments, the effects from atmospheric interaction as well as vegetation are not considered. Moreover, remote sensing measurements obtained via VIR remote sensing can be hampered by cloud cover and precipitation.

2.5.5.2.2 Vegetation Index Method

The sensitivity of vegetation to drought conditions is utilized under this method. The presence or absence of vegetation at a location is considered as indicative of drought conditions and hence, soil moisture conditions [71]. Such models have been expressed in terms of vegetation indices which can be easily derived via remote sensing. Vegetation Condition Index (VCI) is one
such index. VCI is estimated based on time series Normalized Difference Vegetation Index (NDVI) data. Normalized difference vegetation index (NDVI) can be defined using Equation 20.

\[
NDVI = \frac{NIR - R}{NIR + R}
\]  

(20)

where \(NIR\) represents the near infra-red band’s reflectance and \(R\) represents the red band’s reflectance in a satellite image. Based on the NDVI, VCI can be expressed using Equation 21

\[
VCI = \frac{100(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})}
\]  

(21)

where \(NDVI\) represents the weekly average normalized difference vegetation index, \(NDVI_{min}\) and \(NDVI_{max}\) are the multi-year minimum and maximum weekly-average NDVI observations.

However, such a vegetation index does not quantify the exact soil moisture content at a location. Furthermore, there is a time lag between soil moisture and corresponding vegetation index measurements. Hence, the vegetation index-based soil moisture detection would not be suitable for landslide hazard mitigation. Moreover, vegetation is not only dependent upon drought conditions, but it is also affected by deforestation, crop plantation, urbanization as well as phenological changes, which are not considered under this method.

2.5.5.3 TIR Remote Sensing of Soil Moisture

Thermal Infrared (TIR) remote sensing of soil moisture utilizes the relationship between Land Surface Temperature (LST) and soil moisture content. The main advantage of using thermal remote sensing to detect soil moisture lies in its high spatial resolution. With the increase of soil moisture levels, the latent energy for evaporation and transpiration increases, thereby reducing LST. Methods for deriving soil moisture from LST can be categorized into two, namely 1) thermal inertia method and 2) temperature index method [71].
2.5.5.3.1 Thermal Inertia Method

Thermal inertia is the resistance to change of temperature of a body, due to external temperature variations. Thus, with the increase of soil moisture content, the latent energy required for evapotranspiration increases, thereby increasing thermal inertia. Many remote sensing models have been developed for the derivation of thermal inertia, with either theoretical modeling or experimentation. Thermal inertia obtained in this manner can be employed for the derivation of soil moisture.

An example in this regard would be the model developed by Lu et al. [76]. The two-step approach followed by these authors consist of Equations 22-23.

\[
P = P_{\text{dry}} + (P_{\text{sat}} - P_{\text{dry}})K_p
\]  
(22)

\[
K_p = \exp[\gamma(1 - S_r^{\gamma - \delta})]
\]  
(23)

where \( P \) is the soil thermal inertia, \( P_{\text{sat}} \) and \( P_{\text{dry}} \) are saturated and dry soil thermal inertia values, \( K_p \) is the Kersten correction function, \( \gamma, \delta \) are soil texture dependent parameters and \( S_r \) is the degree of saturation of soil. The above model has been derived empirically by studying twelve soils over a wide range of moisture contents.

However, the application of such a model in deriving soil moisture requires soil physical parameters such as \( P_{\text{sat}} \) and \( P_{\text{dry}} \) which could be difficult to obtain. Furthermore, its applicability would be limited to areas of bare to sparse vegetation. Moreover, the application of thermal inertia method requires clear day and night thermal images which could be difficult to obtain during cloud cover and nightly conditions.

2.5.5.3.2 Temperature Index Method

This is an indirect method for the estimation of soil moisture content based on remotely sensed temperature indices. For bare ground, LST represents actual soil temperature, which is
indicative of soil moisture content. However, for a densely vegetated area, LST readings obtained by a sensor would be representative of the canopy temperature. Vegetation subject to high water stress results in low transpiration and thus high canopy temperature. Thus, high canopy temperature indirectly indicates a low soil moisture level whereas a low canopy temperature indicates a relatively higher soil moisture level.

Examples of temperature indices used in representing soil moisture are Normalized Difference Temperature Index (NDTI) and Crop Water Stress Index (CWSI). NDTI is defined using Equation 24.

\[
\text{NDTI} = \frac{\text{LST}_\infty - \text{LST}}{\text{LST}_\infty - \text{LST}_0}
\]

(24)

where \(\text{LST}_\infty\) and \(\text{LST}_0\) are upper and lower boundaries for LST at specific atmospheric forcing conditions. LST is found to be highly correlated with soil moisture [71].

On the other hand, the CWSI defined in Equation 25.

\[
\text{CWSI} = \frac{(T_c - T_a) - (T_c - T_a)_{\text{min}}}{(T_c - T_a)_{\text{max}} - (T_c - T_a)_{\text{min}}}
\]

(25)

where \(T_c\) is the vegetation canopy temperature and \(T_a\) is the air temperature. CWSI is indicative of the ratio between actual and potential evapotranspiration, which is indicative of the water stress or the moisture condition.

2.5.5.3.3 Combination of VIR and TIR Remote Sensing to Derive Soil Moisture

Although LST demonstrates a definitive relationship with soil moisture, it can be affected by the presence of vegetation. Thus, in order to mitigate this effect by vegetation, the universal relationship between soil moisture, land surface temperature and vegetation (usually represented by Normalized Difference Vegetation Index, NDVI) is utilized. This relationship represents the LST-NDVI space as either a triangle or a trapezoid (Figure 6) with a high soil moisture and low
LST bottom “wet edge” and an upper decreasing “dry edge” which denotes the highest surface temperatures [77].

Figure 6: Triangular relationship between LST and NDVI.

The x-axis of Figure 6 represents the normalized NDVI (NDVI*) defined in Equation 26.

$$NDVI^* = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$$

where $NDVI_{max}$ and $NDVI_{min}$ represent the maximum and minimum NDVI values in the LST-NDVI space (Figure 6) respectively.

The y-axis of Figure 6 represents the normalized LST (LST*) defined using Equation 27.

$$LST^* = \frac{LST - LST_{min}}{LST_{max} - LST_{min}}$$

where $LST_{max}$ and $LST_{min}$ represent the maximum and minimum LST values in the LST-NDVI space respectively.

The relationship between soil moisture and LST-NDVI space is expressed with the following polynomial regression formula (Equation 28) [77]:

$$M = \sum_{i=0}^{n} \sum_{j=0}^{n} a_{ij} NDVI^{*i}LST^{*j}$$

where $a_{i,j}$ represent the regression coefficient.
The results obtained by this model would also be site specific and hence it needs to be calibrated according to site conditions. Furthermore, in order to apply the above model, the complete LST-vegetation space has to be known. Also, it ignores the variations in soil moisture due to surface roughness, different soil types, atmospheric effects, etc.

Through the VIR and NIR remote sensing-based soil moisture retrieval methods examined up to now, it can be seen that the main advantages of using these methods lie in the high spatial resolutions and availability of multiple satellites to derive such imagery. However, the readings from these satellites can be hampered by cloud cover, precipitation, vegetation, night time and atmospheric conditions. Furthermore, the temporal resolution of these satellites is relatively low. Although there are strong physical bases for employing these parameters (LST and reflectance) for soil moisture detection, they have not been explored very well. Hence, many available relationships for the derivation of soil moisture are derived empirically and are site specific. Moreover, no quantitative relationship has been widely accepted by all the experts [71].

Of the above discussed remote sensing methods of soil moisture, microwave remote sensing have the following advantages: 1) The effects from cloud cover and precipitation is minimal 2) Both the active and passive soil moisture retrieval algorithms can account for the effects from vegetation 3) Global soil moisture maps have been developed for a temporal resolution of 1 day (where the images are available) 4) Strong physical basis for soil moisture retrieval has been established 5) The temporal coverage is old enough (ESA CCI project has temporal coverage since 1978) and 6) Soil moisture content derived through various satellites have been merged and are available online. However, on the downside, these images have coarse horizontal and vertical spatial resolutions.
On the other hand, VIR and TIR products have a finer horizontal spatial resolution. However, these images have a coarser temporal resolution and can be hampered by cloud cover and precipitation. Furthermore, in VIR and TIR models, a strong physical basis for soil moisture retrieval is not well established.

Thus, the properties of microwave, VIR and TIR remote sensing are complimentary, i.e. the disadvantages of one product is negated by the advantages of the other. Therefore, a better soil moisture product could be obtained by combining the products obtained by microwave, VIR and TIR remote sensing. This can be performed effectively by employing VIR and TIR remote sensing products in downscaling microwave derived soil moisture, to improve its spatial resolution.

### 2.5.6 Downscaling of Microwave Derived Soil Moisture

Remotely sensed soil moisture developed by microwave remote sensing is typically obtained at coarse spatial resolution. Hence, the microwave remotely sensed soil moisture must be downscaled to improve the spatial representation. Significant past research effort has been spent on the exercise of downscaling or disaggregation of microwave derived soil moisture data with visible/thermal remotely sensed products. Chauhan et al. [72] developed one of the earliest and widely used models in this regard. This model utilizes the triangular relationship which exists between LST, NDVI and soil moisture. In addition, surface albedo was employed in this model as well. The above researchers employed AVHRR (Advanced Very High Resolution Radiometer) derived NDVI, LST and surface albedo at a 1km x 1km spatial resolution to downscale via a regression based approach, the soil moisture data obtained at 25km x 25km spatial resolution by SSM/I (Special Sensor Microwave Imager).

Researchers have first aggregated the NDVI, LST and albedo to microwave image resolution (25km x 25km). The relationship between LST, NDVI and soil moisture in the LST-
NDVI space was modified to include the albedo and following relationship was developed (Equation 29):

$$M = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=0}^{n} a_{ijk} \text{NDVI}^{*}(i)T^{*}(j)A^{*}(k)$$  

(29)

where $M$ represents soil moisture and $T^{*}$, $\text{NDVI}^{*}$ and $A^{*}$ represents normalized LST, NDVI and albedo respectively. $a_{i,j,k}$ represent the regression coefficient.

The surface albedo is normalized using Equation 30.

$$A^{*} = \frac{A-A_{\text{min}}}{A_{\text{max}}-A_{\text{min}}}$$

(30)

where $A_{\text{min}}$ and $A_{\text{max}}$ represent the minimum and maximum albedo values, respectively.

The above relationship was expanded to obtain a second order polynomial in Equation 31:

$$M = a_{000} + a_{001}A^{*} + a_{100}T^{*} + a_{001}\text{NDVI}^{*} + a_{002}A^{*2} + a_{020}T^{*2} + a_{200}\text{NDVI}^{*2} + a_{011}T^{*}A^{*} + a_{011}\text{NDVI}^{*}A^{*} + a_{110}\text{NDVI}^{*2}T^{*}$$

(31)

The above regression model developed at a 25km x 25km spatial resolution is used backwards to derive soil moisture content at 1km x 1km spatial resolution by substituting NDVI, LST and surface albedo values known at 1km x 1km spatial resolution.

Another downscaling model, popularly known as UCLA method, has been developed by Kim and Hogue [78]. This model is based on a trapezoidal LST-VI space, but rather than using the above polynomial approach, a downscaling factor derived using a Soil Wetness (SW) is employed for downscaling. Furthermore, Enhanced Vegetation Index (EVI) was employed in place of NDVI, since EVI is a more sensitive indicator of the water status, compared to NDVI. The downscaling equation developed in this model can be expressed as using Equation 32.

$$M_{H} = M_{L} \left( \frac{\text{SW}_{H}}{\text{SW}_{L}} \right)$$  

(32)
where $M_H$ and $M_L$ represent the soil moisture at high and low resolutions respectively while $SW_H$ and $SW_L$ represent the soil water index at high and low resolutions. The SW is defined in Equation 33.

$$SW = 1 - \frac{(1-\beta EVI)\Delta T}{(1-EVI)\Delta T_{\text{max}} + EVI\Delta T_e}$$  \hspace{1cm} (33)

where $EVI$ represents the Enhanced Vegetation Index, defined in Equation 34.

$$EVI = G \frac{NIR - Red}{NIR + C_1 \cdot Red - C_2 \cdot Blue + L} (1 + L)$$  \hspace{1cm} (34)

In this equation $NIR$, $Red$ and $Blue$ represent Near Infrared, Red and Blue band reflectance respectively, $C_1$ and $C_2$ are coefficients of aerosol resistance, $L$ is a soil adjustment factor and $G$ is a gain factor. These factors ($C_1$, $C_2$, $L$ and $G$) are constants for the satellite engaged in collecting the above information.

$\Delta T$ is the difference between observed LST and minimum LST, $\Delta T_{\text{max}}$ is the difference between maximum and minimum LST values observed in LST-VI space, $\Delta T_e$ is the difference between maximum LST observed with full vegetation cover (because $EVI=1$) and minimum LST. $\beta$ is a water stress parameter defined in Equation 35.

$$\beta = 1 - \frac{\Delta T_e}{\Delta T_{\text{max}}}$$  \hspace{1cm} (35)

Recently, Wang et al. [79] developed a downscaling model, based on triangular approach to mapping LST-VI space, with soil moisture products obtained by the European Space Agency’s Climate Change Initiative (ESA CCI) project (Section 3.2.3). This method is commonly known as PKU method. The soil moisture product at a low spatial resolution was downscaled with a downscaling factor derived from LST and EVI derived from MODIS (Moderate resolution Imaging Spectroradiometer) satellite. The downscaling factor, defined as Temperature-vegetation-drought index (TVDI) is defined in Equation 36.
\[
\text{TVDI} = \frac{T - T_{\text{min}}}{a + b \cdot \text{EVI} - T_{\text{min}}} \tag{36}
\]

where \(T\) represents the observed LST, \(T_{\text{min}}\) represents the minimum LST observed on the LST-EVI space, \(a\) and \(b\) are the parameters representing the dry edge of LST-EVI space. The resolution of soil moisture can be improved with the TVDI using Equation 37.

\[
M_H = M_L \left(\frac{1 - \text{TVDI}_H}{1 - \text{TVDI}_L}\right) \tag{37}
\]

where \(M_H, M_L, \text{TVDI}_H\) and \(\text{TVDI}_L\) represent soil moisture at high resolution, soil moisture at low resolution, TVDI at high resolution and TVDI at low resolution respectively. The researchers (Wang et al. [79]) compared the classification accuracy of the results observed with this method to those of the first two methods. Then, the performance of these three methods were compared with in-situ measurements and PKU method was determined to produce lowest RMSE (Root Mean Square Error).

The above-mentioned three downscaling methods utilize the triangular/trapezoidal relationship of the LST-VI space. These methods account for sub-pixel variation of soil moisture by considering sub-pixel variation of vegetation and LST. In addition to the above, the surface soil moisture depends on root zone soil moisture, soil type, surface roughness, precipitation, etc. However, the sub-pixel variation in some of the above parameters is considered indirectly through LST, VI and, in the model developed by Chauhan et al. [72], the surface albedo. However, since these models are derived empirically, they lack any physical basis.

To address this deficiency, Merlin et al. [80] developed a downscaling model which is based on physical parameters. In this, downscaling is performed via a downscaling factor, which is based on Soil Moisture Indices (SMI). The downscaled soil moisture can be determined using Equation 38.

\[
M_H = M_L + f_{1,L}(\text{SMI}_H - \text{SMI}_L) \tag{38}
\]
where $M_H$ and $M_L$ refer to volumetric soil moisture at high resolution and low resolution, respectively. $f_{L,H}$ is a scaling parameter which is used to convert SMI to volumetric soil moisture content and $SMI_H$ and $SMI_L$ are the SMI’s observed at high and low resolutions respectively. The two soil moisture indices proposed by the above authors are: 1) Evaporative Fraction (EF) defined as the ratio of evapotranspiration to total energy available at the surface 2) Actual EF (AEF) defined as the ratio of actual to potential evapotranspiration. Although these are good indicators of available moisture content at the surface, they need to be derived via biophysical modeling, which could be a rigorous task. Furthermore, $f_{L,H}$ can be obtained by calibrating the model

Wang et al [79]. compared the results obtained using the Merlin method [80], which is the most commonly used physical parameter based approach to downscaling, with those obtained by the PKU method. The PKU method was determined to produce a better accuracy. Hence, it can be observed that PKU method produces a better downscaling accuracy, compared to other popular methods. Furthermore, the former provides a practical and efficient method for downscaling. Moreover, it has been tested on ESA CCI project dataset, which is the soil moisture content dataset that is expected to be used in the current project and proven to produce fairly accurate results. Thus, PKU method for downscaling the soil moisture products in the current project.

2.6 A Review of Numerical and Analytical Methods of Landslide Hazard Assessment

Many analytical [15][16] and numerical [17][18][19][20][21] methodologies have been developed in the past to model the effect of infiltration and subsequent transient seepage during rainfall on the stability of natural slopes. These models consist of a seepage analysis where pore pressure and water content changes of soil due to infiltration is estimated followed by a slope stability analysis where the stability of slope against sliding is assessed.
2.6.1 Slope Stability Analysis

Limit equilibrium analysis is employed to determine the stability of slope against sliding. In this method, potential for failure blocks or wedges to slide under the gravity is identified based on their factor of safety (FoS) with FoS less than 1 indicating slope failure. FoS of a slope against sliding is defined in in Equation 39.

\[ FoS = \frac{\tau_f}{\tau_d} \]  

(39)

where \( \tau_f \) is the average shear strength of the soil and \( \tau_d \) is the average developed shear stress along the failure surface. The shear strength of a saturated soil constitutes of two terms, cohesion (c) and angle of shearing resistance of a saturated soil (\( \varphi \)). The shear strength of a saturated soil can be expressed using Mohr-Coulomb failure criterion, with Equation 3 (Section 2.3.2.1).

\[ \tau_f = c + \sigma' \tan \varphi \]  

(3)

where \( \sigma' \) is the effective stress of the soil normal to the failure plane, defined in Equation 4.

\[ \sigma' = \sigma - u_w \]  

(4)

where \( \sigma \) is the total stress of the soil and \( u_w \) is the pore water pressure.

Fredlund et al. [81] extended the Mohr-Coulomb failure criterion to unsaturated soil using the Equation 40.

\[ \tau_f = c + (\sigma - u_a)\tan \varphi + (u_a - u_w)\tan \varphi^b \]  

(40)

where \( u_a \) is the pore air pressure and \( \varphi^b \) is the angle of shearing resistance with respect to matric suction. Vanapalli et al. [55] proposed the determination of angle of shearing resistance w.r.t. matric suction based on soil water characteristics, as defined in Equation 41.

\[ \tan \varphi^b = \tan \varphi \left( \frac{\varnothing - \varnothing_r}{\varnothing_s - \varnothing_r} \right) \]  

(41)

where \( \varnothing \) is the volumetric water content of soil, \( \varnothing_r \) is the residual water content of soil and \( \varnothing_s \) is the saturated water content of soil. The extended Mohr-Coulomb criteria, widely employed in past
landslide research [21][82][83], is employed in this study to determine the shear strength of soil in the unsaturated zone.

 Typically, soil is assumed to slide along a weak seam or in the absence of a weak layer, a circular failure surface [44]. In the conventional analysis of failure, the potential of wedge is assumed to consist of a number of slices (Figure 7). Then the FoS is obtained by considering the force equilibrium of every slice and the moment equilibrium of the entire wedge. The derivation of FoS is discussed further in Section 4.1.4.

![Figure 7: A circular failure surface employed in the method of slices.](image)

### 2.6.2 Transient Seepage Analysis

In existing numerical and analytical models, the transient seepage conditions that prevail during rainfall is typically modeled using Richards equation [15][17][20][54]. Richards equation is a parabolic partial differential equation (PDE), defined in Equation 42.

\[
\frac{\partial \theta}{\partial t} = - \frac{\partial}{\partial y} \left[ K(\theta) \left( \frac{\partial h}{\partial y} + 1 \right) \right] + S
\]

where \( \theta \) is the volumetric water content, \( t \) is time, \( y \) is the direction of water flow, \( K \) is the hydraulic conductivity of soil in the \( y \) direction, \( h \) is the pressure head and \( S \) is the rate of gain (or loss) of volumetric water content due to a source (or a sink).
Richards equation (Equation 42) combines water balance and the Darcy’s law. Since Darcy’s law, defined in Equation 43, is a semi-empirical relationship accurate only under steady state conditions. Since Richards equation employs Darcy’s law to model fluid flow velocities under transient conditions, it can be said that Richards equation follows a pseudo-steady state approach to model transient seepage.

\[ v = Ki \]  

(43)

where \( v \) is the fluid flow velocity, and \( i \) is the hydraulic gradient.

On the other hand, Navier-Stokes equations, which are derived using fundamental fluid dynamics, have the capability to model the dynamically varying fluid flow velocities, without any pseudo-steady state assumptions. Jeyisanker and Gunaratne [84] employed the Navier-Stokes equations for modeling seepage through both saturated and unsaturated zones.

The general form of the Navier-Stokes equation for the conservation of mass is given in Equation 44.

\[
\frac{\partial \phi}{\partial t} + \nabla \cdot (\phi \vec{U}) - Q = 0
\]  

(44)

The general form of the Navier-Stokes equation for the conservation of momentum is given in Equation 45.

\[
\left( \frac{\partial \phi \vec{U}}{\partial t} + \vec{U} \cdot \nabla \phi \vec{U} \right) = \frac{\phi}{\rho} (-\nabla P + \mu \nabla^2 \vec{U}) + F
\]  

(45)

where \( \rho \) is the fluid density, \( Q \) is the rate of water loss/gain from a sink/source, \( P \) is the fluid pressure, \( \mu \) is the fluid viscosity and \( F \) is any external force acting on the fluid.

Furthermore, NS equations contain the inertial components of the flow, namely diffusive acceleration \( \frac{\partial \phi \vec{U}}{\partial t} \) and convective acceleration \( (\vec{U} \cdot \nabla \phi \vec{U}) \) terms, while the Richards equation does not contain the inertial components. This is another advantage of using, NS equations in place of Richards equation to model transient seepage.
Moreover, NS equations have the capability to model both surface, subsurface and infiltration flows with a single set of equations and without employing extraneous boundary conditions. In existing coupled surface and subsurface flow models, fluid dynamics and the Richards equation are employed for modeling surface and subsurface flows respectively with matching boundary conditions and water routing at the surface [18][85][86]. Weill et al. [87] modified the above approach and used a single set of equations to model surface and subsurface water flows by using a modified form of the surface flow equations to achieve compatibility with the Richards equation. In the above approach, the diffusive wave equations used to model the surface flow were simplified by neglecting the inertial component of the surface flow so that they can mathematically be in the form of the Richards equation. However, in the proposed approach, the authors model transient seepage using Navier-Stokes equations to retain the inertial components of the flow.

2.6.3 A Review of Existing Numerical and Analytical Methods of Modeling Slope Stability During Transient Seepage

An analytical model for transient seepage and vertical infiltration during uniform rainfall through a homogeneous soil and a soil with two layers has been developed by Srivastava and Yeh [15]. In the above model, the Richards equation was employed to model the transient seepage. An exponential hydraulic conductivity function was assumed to model the hydraulic conductivity of the unsaturated zone [15]. However, it is identified that an exponential hydraulic conductivity function does not accurately reproduced soil behavior near saturation [15]. In contrast, the approach for modeling hydraulic conductivity function proposed by Fredlund et al. [88], based on a soil water characteristic curve proposed by Fredlund and Xing [89] (discussed in Section 4.1.2) is valid for a broader suction range. Furthermore, the Richards equation is employed to model
transient seepage, which has several drawbacks over fluid dynamics based Navier-Stokes equations, as discussed in Section 2.6.2. Another analytical model for the prediction of landslide hazard due to infiltration of rainwater was developed by Iverson [16] who studied the effect of physical processes that operate on different time scales on landsliding. Iverson [16] used an infinite slope and a constant rainfall intensity with a known duration and characteristic hydraulic diffusivity. The Richards equation was used to quantify the effects of rainfall infiltration as well. It was concluded that slope failures are typically triggered by storms occurring in a relatively shorter period of time, due to transient pore pressure dissipation during or after the rainfall although no direct evidence of consideration of the loss of matric suction in unsaturated ground was provided.

Furthermore, many researchers including Chen et al., [17], Collins and Znidarcic [19] and Tsai et al. [20] have developed physically based shallow landslide hazard assessment models based on numerical schemes considering seepage through unsaturated zones of soil using the Richards equation and limit equilibrium analysis. In one study, Chen et al. [17] evaluated threshold rainfall intensity-duration relationships for landslide occurrence, considering the lateral flow. A two-dimensional numerical model based on the Richards equation was developed to assess the seepage and stability of an infinite slope while the infiltration into the soil was considered to occur at the rate of rainfall. Furthermore, all the rainfall is assumed to infiltrate into the soil, and the surface flow generation and continuous interplay between surface and subsurface hydrological processes was not modeled.

In another study, Wu and Selvadurai [54] developed a coupled numerical model for modeling the infiltration during rainfall and deformation of soil. The above study examines the stability of an infinite slope using an infiltration equation based on conservation of mass and
Darcy’s law. In addition, the deformation of soil medium is expressed using an incremental elastic stress-strain relationship to incorporate hydro-mechanical coupling. However, the water film and surface flow generation due to rainfall were not considered in the above study. It was concluded that the hydro-mechanical coupling is an important aspect of unsaturated ground response to rainfall.

As highlighted above, all the above models disregard the continuous interaction between surface and subsurface water flows that prevail during high intensity rainfalls. Thus, there exists a gap in the literature for a slope stability assessment that considers the effect of continuous interplay between surface and subsurface fluid flows during transient seepage on slope stability. Furthermore, all the existing models employ the Richards equation to model transient seepage which is based on a pseudo-steady state assumption and does not incorporate the inertial components of flow. Thus, there exists a gap in literature for a slope stability modeling approach which uses fundamental fluid dynamics to model transient seepage.

**2.7 Identified Gaps in Literature and Re-statement of Research Objectives**

The following two research gaps were identified based on the literature review:

1. In the existing studies, the feasibility of using downscaled remotely sensed soil moisture in landslide hazard assessment has not been evaluated statistically. Furthermore, the effects of remotely sensed soil moisture and the important soil drainage property of hydraulic conductivity on landslide hazard have not been evaluated.

2. Existing numerical and analytical methods that assess slope stability during transient seepage seldom consider the continuous interplay between surface and subsurface water flows that prevail during landslide inducing high intensity storms. Furthermore, all the existing models employ the Richards equation to model transient seepage which is derived
based on Darcy’s law assuming a pseudo-steady state. Hence, the seepage analysis modules of existing numerical models do not incorporate the inertial component of flow.

This research aims to address the above research gaps. Thus, the objectives of this research can be re-stated as follows:

1. Develop a statistical framework for using remotely sensed soil moisture available on a daily basis to monitor specific locations that are highly susceptible to rainfall-triggered landslides at a regional scale, with a well-structured assessment procedure and evaluate the effect of employing remotely sensed soil moisture together with soil hydraulic conductivity on landslide hazard.

2. Develop a numerical model for site-specific slope stability assessment during transient seepage conditions which incorporates the effects of continuous interplay between surface and subsurface fluid flows on slope stability by way of fundamental fluid dynamics.
CHAPTER 3: DEVELOPMENT OF A REGIONAL SCALE LANDSLIDE HAZARD ASSESSMENT MODEL BASED ON REMOTE SENSING

The purpose of this chapter is to describe in detail the methodology followed to achieve the objective 1 of this dissertation.

As discussed in Chapter 2, a gap exists in literature for a statistical methodology which can evaluate the landslide hazard using remotely sensed soil moisture content and landslide conditioning factors. Thus, in order to address this gap, a statistical framework was developed using remotely sensed soil moisture and landslide conditioning factors such as soil hydraulic conductivity, slope, elevation, proximity to roads and soil type.

3.1 Description of Data

Two landslide-prone sites were selected for this part of the study. The first site is in western Oregon, USA (Figure 1a), and the second study site is in northern Kentucky, USA (Figure 1b). Landslide inventories for these two study sites were prepared by the Oregon Geological Survey [22] and Kentucky Geological Survey [23], respectively. The sources of the Oregon landslide inventory were aerial photos, photogrammetric elevation data, light detection and ranging (LiDAR) elevation data, and geologic and hazard maps, whereas the sources of the Kentucky landslide inventory were the findings of the research and field work performed by the Kentucky

Geological Survey, published geologic maps, state and local government agencies, media reports, and the information provided by the public [24][25]. The landslide data used in this study were which are available as point features. Furthermore, all of the landslides were dated, and the satellite-based soil moisture images were obtained on the day of the landslide. On instances where the soil moisture images were not available on the day of the landslide, soil moisture images on the day before the landslide or the day after were used in the stated order.

At these sites, several different slope failure types, namely soil slides, rockslides, rock falls, debris slides, mudslides, earth flows, debris flows, topples, and complex slope failures have been observed. Since different landslide types occur because of different combinations of geotechnical, topographical, geological, and hydrological conditions, it is important to group them into different landslide types to perform a meaningful analysis. However, Budimir et al. [15] observed that most of the existing landslide studies do not differentiate between landslide types, especially at the large scale. To address this shortcoming, in this study, a rigorous vetting procedure was employed to select only the soil slides. Furthermore, all of the soil slope failures considered in this study were rainfall-triggered soil slides. Hence, the vetting procedure was specifically aimed at selecting only the rainfall-triggered soil slides.

Furthermore, the frequency distributions of slope, elevation, primary and secondary road density, and land cover are included in Figure 8a–d. It should be noted that the plotted road density (Figure 8c) corresponds only to pixels where a primary or a secondary road was present.

3.2 Methodology Used for Model Development

3.2.1 Development of the Soil Slide Database

As discussed in Section 1.4, two landslide-prone sites from western Oregon, USA and northern Kentucky, USA were selected for this study. Of the available slope failures at these two
sites, the rainfall-triggered slope failures were selected by eliminating any slide that could have been caused by seismic activity or snowfall. The effect of snowfall was eliminated by removing

Figure 8: Frequency distributions of (a) elevation, (b) slope angle, (c) road density and (d) land cover in the two study areas.
any landslides occurring during the months between November and April, at altitudes above 200m, where snowfall was expected. Possible earthquake-triggered landslides were excluded by discarding any landslide that had occurred immediately following a recorded earthquake. Furthermore, rainfall records on the dates of landslides as well as personal communications with the staff of the respective State Geological Surveys further confirmed that the slope failures selected for this study were triggered by rainfall.

The study was limited to ‘slides’ where the failure material given in the database was ‘soil’. Furthermore, by observing the images of failed locations, any further locations that contained evidence of possible rock failures such as exposed rock and sliding grooves were excluded from the study. Images of two such locations that were excluded from the study due to the presence of exposed rock and sliding grooves are included in Figure 9a,b.

![Figure 9: (a)-(b) Images of two sample locations that were excluded from the study due to the presence of exposed rock (Google Earth, 2018).](image_url)

Figure 10a,b contains current images of two selected soil slide locations from the landslide database. These locations are identified as soil failures (and not rock failures) since the color of the exposed slope, presence of vegetation in the vicinity, shallow depth of failure, and lack of sliding grooves indicate so. Finally, it was further observed that there are several soil slides in the database that had occurred on a single day. In these situations, some soil slides may have been
triggered by a precursor soil slide. Thus, in such cases, the successor soil slides cannot be considered as independent events and must be excluded from the analysis. To do so, any soil slide with small dimensions occurring within a distance of two times or less than the larger dimension of a larger soil slide occurring on the same day were excluded from the study.

Figure 10: (a)-(b) May 2018 images of two selected soil slide sites (Google Earth, 2018).

Furthermore, the exact sliding location with respect to the depth was not available for many of the soil slides. Thus, the soil properties of the failed soil layer cannot be included in the analysis. To address this shortcoming, only the soil slides with a homogeneous soil profile were considered for the analysis, so that the soil type and hydraulic conductivity properties were fairly uniform across the depth. The soil type and hydraulic conductivity were derived at every slide location, and the soil profile is considered uniform if the soil type is uniform across the depth, and the coefficient of variation of the saturated hydraulic conductivity is less than or equal to 2.5. Ultimately, a total of 33 soil slides that matched the vetting criteria were earmarked in both geographical areas (in the states of Oregon and Kentucky). Of the 33 soil slides that matched the vetting criteria, 22 were from Oregon, USA, and 11 were from Kentucky, USA. A schematic diagram of the vetting procedure used for soil slide selection is given in Figure 11.
3.2.2 Development of the Non-Soil Slide Database

The statistical model developed in this study is used to differentiate locations with a high soil slide potential from those with a low soil slide potential. Thus, non-soil sliding locations need to be used in developing the model as well. These locations were selected randomly from areas where no previous slope failures have been recorded. To do so, the two study areas were divided...
into grids, with each grid cell being 1 km in size. All of the observed failure locations were plotted on the grid, and the soil type and hydraulic conductivity of each grid cell were derived. Grid cells with no previous slope failures that contained homogeneous subsurface soil conditions were selected for the non-soil slide database. Out of the above empty grid cells, 100 locations were selected randomly to be included in the study. Of the selected non-soil slides, 70 were from Oregon, while 30 were from Kentucky. The non-soil slides were distributed among the study areas roughly in the same ratio as the soil slides.

Furthermore, images of all of the selected non-soil slide locations were observed to ensure that the non-soil slide locations contained a soil surface, and not an impervious surface. The conditioning factors of slope, elevation, saturated hydraulic conductivity, the Enhanced Vegetation Index (EVI), soil type, and distance to roads were also obtained at these locations. Furthermore, the downscaled remotely sensed soil moisture content, which was obtained on a randomly selected date, was assigned to the non-soil slide locations as well. Figure 12a,b contains images of two such randomly selected non-soil slide locations, whereas Figure 13a,b demonstrates the distribution of all of the non-soil slide locations within the states of Oregon and Kentucky.

![Figure 12: (a)-(b) Two randomly selected non-soil slide locations used in the study (Google Earth, 2018).](image)
Figure 13: Selected non-soil slides from (a) Oregon, USA, and (b) Kentucky, USA.

3.2.3 Acquisition of Remotely Sensed Soil Moisture - ESA CCI Soil Moisture

Soil moisture Climate Change Initiative (CCI) is part of the European Space Agency’s (ESA) program on global monitoring of Essential Climate Variables (ECV). This project currently provides the most consistent and complete active and passive microwave derived soil moisture data at the global scale. Soil moisture products derived from the following active microwave sensors: 1) AMI-WS (Active Microwave Instrument Wind Scatterometer) on board ERS-1 (European Remote Sensing-1) and ERS-2 (European Remote Sensing-2) satellites and 2) ASCAT (Advanced SCATerrometer), as well as following passive microwave sensors: 1) SMMR (Scanning Multi-channel Microwave Radiometer), 2) SSM/I (Special Sensor Microwave Imager), 3) TMI (Tropical rainfall measuring mission Microwave Imager), 4) AMSR-E (Advanced Microwave Scanning Radiometer), WindSat, and 5) AMSR2 (Advanced Microwave Scanning Radiometer 2), are available through this project. In addition, a combined product where active
and passive products are merged, is also available. These products are available at a 0.25° x 0.25° spatial resolution and a daily temporal resolution. In the passive and combined product, the volumetric soil moisture content (m³/m³) is produced while in the active product, the degree of saturation (%) is produced [90]. These satellites measure only the surface soil moisture content, which is indicative of the moisture content only on the top few centimeters of the soil. Typically, the sensing depth of such sensor ranges between 1/10th to 1/4th of the wavelength [72].

The algorithm employed for the derivation of soil moisture content from the backscatter coefficients derived from AMI-WS and ASCAT sensors is based on a statistical approach. This algorithm operates under following assumptions: 1) The backscatter coefficient and soil moisture content follow a linear relationship. 2) The backscatter coefficient (σ) depends strongly on incidence angle (θ). However, the σ-θ relationship depends only on land cover and it is not affected by soil moisture. σ at any day of the year (d) can be expressed as a second order polynomial of θ. 3) Surface roughness and land cover are stationary in time, i.e. they would be the same on the same day of every year. 4) The backscatter coefficient varies with vegetation. The relationship between σ and vegetation would depend on θ. However, there exist a θ where σ, for completely wet or dry soil, would not depend on vegetation (2 different θ values for wet and dry conditions, named wet crossover angle and dry cross over angle). These cross over angles are employed to correct the impact of vegetation on σ. 5) Phenological changes affect σ only on a seasonal scale and short term fluctuations are suppressed at the scale of measurement [91].

The algorithm involves first resampling data into a grid of 0.25° x 0.25° and correction of noise due to instrument errors, speckle (noise caused by interference to the returning microwave by the transducer aperture), etc. The relationship between σ and θ given by the following second order polynomial (Equation 46) is developed next.
\[
\sigma^0(\theta, d) = \sigma^0(\theta_{\text{ref}}, d) + \sigma^0(\theta_{\text{ref}}, d)(\theta - \theta_{\text{ref}}) + \frac{1}{2}\sigma^0(\theta_{\text{ref}}, d)(\theta - \theta_{\text{ref}})^2
\]

where \(\sigma^0(\theta, d)\) is the measured backscatter coefficient at angle \(\theta\) on the day \(d\), \(\sigma^0(\theta_{\text{ref}}, d)\) is the normalized backscatter coefficient at reference angle \(\theta_{\text{ref}}\), \(\sigma'^0(\theta_{\text{ref}}, d)\) refers to the first derivative (slope) and \(\sigma''^0(\theta_{\text{ref}}, d)\) refers to the second derivative (curvature). The slope and curvature are obtained through time series data. Thus, this relationship can be utilized to obtain \(\sigma\) values normalized to a reference angle of 40\(^0\).  

Once the \(\sigma\) is normalized at 40\(^0\), the historically driest and wettest states of normalized \(\sigma\) for that particular day (\(\sigma^{\text{dry}}(\theta_{\text{ref}}, d)\) and \(\sigma^{\text{wet}}(\theta_{\text{ref}}, d)\)), are determined statistically. In order to determine the driest \(\sigma\), irrespective of vegetation, normalized backscatter measurements are shifted to dry cross over angle of 25\(^0\). Once the driest \(\sigma\) is obtained, that measurement is normalized back to 40\(^0\). It must be noted that this step is not necessary for wet conditions as the wet crossover angle is determined to be 40\(^0\). Furthermore, another correction is applied to account for instances where the wet reference does not represent full saturation.

Finally, the degree of saturation of the soil is expressed using Equation 47.

\[
S\% = \frac{\sigma^0(\theta_{\text{ref}}, d) - \sigma^{\text{dry}}(\theta_{\text{ref}}, d)}{\sigma^{\text{wet}}(\theta_{\text{ref}}, d) - \sigma^{\text{dry}}(\theta_{\text{ref}}, d)} \times 100
\]

where \(S\) is the degree of saturation, \(\sigma^0(\theta_{\text{ref}}, d)\) is the normalized backscatter coefficient for the day \(d\), \(\sigma^{\text{dry}}(\theta_{\text{ref}}, d)\) is the dry reference for day \(d\) and \(\sigma^{\text{wet}}(\theta_{\text{ref}}, d)\) is the wet reference for day \(d\).

In deriving the soil moisture content with passive microwave sensors, a physically based approach is followed. The Land Parameter Retrieval Model (LPRM) is employed in this regard. According to this model, the brightness temperature of an area consisting of soil and vegetation can be expressed using Equation 48 [92].
$T_{b,p1} = \Gamma_a \left( T_{b,s,p1} + (1 - e_{r,p1}) \left( T_{b,d,p1} + T_{b,extra,p1} \Gamma_a \right) \Gamma_v^2 \right) + T_{b,u,p1}$

(48)

where $T_{b,p1}$ is the brightness temperature observed by a radiometer, $\Gamma_a$ and $\Gamma_v$ are atmosphere and vegetation transmissivity respectively, $T_{b,s,p1}$ is the surface brightness temperature, $e_{r,p1}$ is the rough surface emissivity, $T_{b,d,p1}$ and $T_{b,u,p1}$ are the upwelling and downwelling brightness temperatures respectively, $T_{b,extra,p1}$ is the extraterrestrial brightness temperature and “p1” represents the direction of polarization of the microwave signal, which could be either vertical or horizontal. The vegetation atmosphere transmissivity can be expressed using Equation 49.

$\Gamma_v/a = e^{-\tau_v/a \cos(u)}$

(49)

where $u$ is the incidence angle and $\tau_v/a$ is the vegetation optical depth. The upwelling brightness temperature from atmosphere can be expressed using Equation 50.

$T_{b,u,p1} = 70.2 + 0.72T_a(1 - \Gamma_a)$

(50)

Furthermore, the upwelling and downwelling temperatures are assumed to be equal and extraterrestrial brightness temperature is set to 2.7 K. The brightness temperature from the surface can be expressed using Equation 51.

$T_{b,s,p1} = T_s e_{r,p1} \Gamma_v + (1 - \omega)T_v (1 - \Gamma_v) + (1 - e_{r,p1})(1 - \omega)T_v (1 - \Gamma_v) \Gamma_v$

(51)

where $T_s$ and $T_v$ are surface and vegetation temperatures respectively and $\omega$ is the single scattering albedo. Furthermore, following relationship (Equation 52) is used in quantifying the emissivity of the surface.

$e_{r,p1} = 1 - Q(r_{s,p2} + (1 - Q)r_{s,p1}) e^{-h \cos(u)}$

(52)

where $Q$ is the polarization mixing factor, $h$ is the roughness height, $r_s$ is the surface reflectivity and $p_1$ and $p_2$ are the polarization directions. The surface reflectivity can be obtained with Fresnel’s equations.
The vegetation optical depth can be obtained from equation 53.

\[
\tau_v = \cos(u) \ln(ad + \sqrt{(ad)^2 + a + 1})
\]  

(53)

where,

\[
a = \frac{1}{2} \left[ e_{r,p1} - e_{r,p2} \right]_{MPDI} - e_{r,p1} - e_{r,p2}
\]  

(54)

\[
d = \frac{1}{2} \frac{\omega}{(1-\omega)}
\]  

(55)

where MPDI is the Microwave Polarization Difference Index defined as in Equation 56.

\[
MPDI = \frac{T_{b,s,p1} - T_{b,s,p2}}{T_{b,s,p1} + T_{b,s,p2}}
\]  

(56)

Equations 46-56, together with a dielectric mixing model (Section 2.5.5.1), can be solved to obtain soil moisture content when the knowledge of following parameters are available: atmospheric, vegetation and soil temperatures, optical depth of the atmosphere, roughness parameters Q and h and single scattering albedo.

The surface temperatures at day and night times are determined from the brightness temperature derived from 37GHz band, using the relationship shown in Equations 57 and 58.

Day time:

\[
T_s = 0.898T_{b,37v} + 44.2
\]  

(57)

Night time:

\[
T_s = 0.893T_{b,37v} + 44.8
\]  

(58)

where “v” represents vertically polarization.

In order to derive the merged active and passive soil moisture product, the active and passive soil moisture measurements obtained through different sensors are merged spatially and temporally at 0.25° x 0.25° spatial resolution. The merged active and passive microwave soil moisture products derived through the CCI project contain a reasonable spatial and temporal
coverage and hence, would provide a convenient dataset for the current research. Thus, this product was employed in this study.

The soil moisture images were downscaled from 0.25\(^0\times0.25\(^0\) to 1km x 1km using PKU method discussed in Section 2.5.6. [79]. Furthermore, since the study area of this research is relatively large, the use of a single downscaling model will not produce significantly accurate results. Yu et al. [93] performed a downscaling of North America’s soil moisture data, and found that a moving window method performs better compared to a single window, with the regression coefficient improving from 0.19 to 0.70. Hence, a moving window method, with different downscaling models for different geographic regions, was developed in this study for downscaling soil moisture. Three windows were used for the study area in western Oregon, while two windows were used for the study area in northern Kentucky. The three windows in Oregon were selected at the top, bottom, and middle of the study area in Figure 1a, while the two windows of Kentucky were selected at the top and bottom parts of the study area in Figure 1b.

3.2.4 Determination of Landslide Conditioning Factors

Geotechnical properties of the overburdened soil were obtained from the United States Natural Resources Conservation Services SSURGO (Soil Survey Geographic Database) database [94]. This database provides the values of saturated hydraulic conductivity and soil type along with the soil profile. The soil types observed at the sites were high plasticity clay (CH), low plasticity clay (CL), high plasticity silt (MH), low plasticity silt (ML), clayey gravel (GC) and silty gravel (GM).

Digital elevation models (DEM) developed for the states of Oregon and Kentucky at a resolution of 10 m × 10 m were used to obtain the elevation. The slope angles were evaluated from the tangents of the digital elevation models. Furthermore, the cutting of slopes for road
construction increases the soil slide hazard [7][95]. Hence, proximity to roads was found to be related to the soil slide potential of a given mountainous area. Thus, the distance to roads, namely primary and secondary roads, is used as an explanatory variable in the developed model.

Moreover, the Enhanced Vegetation Index (EVI), which was defined in Equation (34), was found to be an appropriate indicator of land cover, and particularly of the vegetation cover in a given location [96]. Moreover, EVI is sensitive to the canopy structure, and does not tend to saturate at high leaf area indices [97]. Due to this advantage over other remote sensing-based vegetation indices such as the Normalized Difference Vegetation Index (NDVI), the EVI is recognized as a superior remote sensing-based indicator of vegetation cover [97]. Thus, the EVI is used in this study to represent the vegetation cover. Locations with lower EVI values are expected to be prone to erosion, and hence, they are subject to elevated soil slide hazard compared to locations with higher EVI values.

### 3.2.5 Correlation Coefficients Among Explanatory Variables

The correlation coefficients of the explanatory variables were calculated (Table 1) and checked for multicollinearity. Silt and clay soil types, gravel, hydraulic conductivity, and downscaled and undownscaled soil moisture contents are highly correlated variables (with correlation coefficients $>0.7$), which indicate multicollinearity. Of the above highly correlated variables, only one was included in the model at any given time. Of the dummy variables for the three soil types (gravel, silt, and clay), only two (clay and silt) were included in the model to avoid multicollinearity.
Table 1: Correlation matrix of the explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Elevati on (m)</th>
<th>Slope</th>
<th>Presence of Clay Soil Type (Categorical Variable)</th>
<th>Presence of Silt Soil Type (Categorical Variable)</th>
<th>Presence of Gravel Soil Type (Categorical Variable)</th>
<th>EVI</th>
<th>Downscal ed Soil Moisture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation (m)</td>
<td>-</td>
<td>0.17</td>
<td>-0.37</td>
<td>0.03</td>
<td>0.46</td>
<td>-0.002</td>
<td>-0.03</td>
</tr>
<tr>
<td>Slope</td>
<td>0.17</td>
<td>-</td>
<td>-0.28</td>
<td>-0.03</td>
<td>0.41</td>
<td>-0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>Presence of clay soil type (categorical variable)</td>
<td>-0.37</td>
<td>-0.28</td>
<td>-</td>
<td>-0.70</td>
<td>-0.50</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>Presence of silt soil type (categorical variable)</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.70</td>
<td>-</td>
<td>-0.28</td>
<td>-0.03</td>
<td>-0.04</td>
</tr>
<tr>
<td>Presence of gravel soil type (categorical variable)</td>
<td>0.46</td>
<td>0.41</td>
<td>-0.50</td>
<td>-0.28</td>
<td>-</td>
<td>0</td>
<td>-0.02</td>
</tr>
<tr>
<td>EVI</td>
<td>-0.002</td>
<td>-0.04</td>
<td>0.03</td>
<td>-0.03</td>
<td>0</td>
<td>-</td>
<td>-0.23</td>
</tr>
<tr>
<td>Downscaled soil moisture</td>
<td>-0.03</td>
<td>0.07</td>
<td>0.05</td>
<td>-0.04</td>
<td>-0.02</td>
<td>-0.23</td>
<td>-</td>
</tr>
<tr>
<td>Undownscal ed soil moisture</td>
<td>-0.02</td>
<td>0.04</td>
<td>0.07</td>
<td>0</td>
<td>-0.11</td>
<td>-0.16</td>
<td>0.83</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>0.42</td>
<td>0.42</td>
<td>-0.44</td>
<td>-0.15</td>
<td>0.77</td>
<td>0.02</td>
<td>-0.09</td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>0.67</td>
<td>0.19</td>
<td>-0.44</td>
<td>0.06</td>
<td>0.52</td>
<td>-0.02</td>
<td>-0.19</td>
</tr>
<tr>
<td>Proximity to drainage (m)</td>
<td>-0.05</td>
<td>-0.14</td>
<td>0.18</td>
<td>-0.08</td>
<td>-0.14</td>
<td>0.26</td>
<td>0.01</td>
</tr>
<tr>
<td>Drainage density (m^{-1})</td>
<td>0.32</td>
<td>0.36</td>
<td>-0.31</td>
<td>0.12</td>
<td>0.27</td>
<td>-0.17</td>
<td>-0.02</td>
</tr>
<tr>
<td>TWI</td>
<td>-0.19</td>
<td>-0.60</td>
<td>0.09</td>
<td>0.08</td>
<td>-0.21</td>
<td>0.04</td>
<td>-0.06</td>
</tr>
</tbody>
</table>
Table 1: (Continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Un-Downscaled Soil Moisture</th>
<th>Saturated Surface Hydraulic Conductivity (microns per second)</th>
<th>Distance from Roads (m)</th>
<th>Distance to Drainage (m)</th>
<th>Drainage Density (m(^{-1}))</th>
<th>Topographic Wetness Index (TWI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation (m)</td>
<td>−0.02</td>
<td>0.42</td>
<td>0.67</td>
<td>−0.05</td>
<td>0.32</td>
<td>−0.19</td>
</tr>
<tr>
<td>Slope</td>
<td>0.04</td>
<td>0.42</td>
<td>0.19</td>
<td>−0.14</td>
<td>0.36</td>
<td>−0.60</td>
</tr>
<tr>
<td>Presence of clay soil type (categorical variable)</td>
<td>0.07</td>
<td>−0.44</td>
<td>−0.44</td>
<td>0.18</td>
<td>−0.31</td>
<td>0.09</td>
</tr>
<tr>
<td>Presence of silt soil type (categorical variable)</td>
<td>0</td>
<td>−0.15</td>
<td>0.06</td>
<td>−0.08</td>
<td>0.12</td>
<td>0.08</td>
</tr>
<tr>
<td>Presence of gravel soil type (categorical variable)</td>
<td>−0.11</td>
<td>0.77</td>
<td>0.52</td>
<td>−0.14</td>
<td>0.27</td>
<td>−0.21</td>
</tr>
<tr>
<td>EVI</td>
<td>−0.16</td>
<td>0.02</td>
<td>−0.02</td>
<td>0.26</td>
<td>−0.17</td>
<td>0.04</td>
</tr>
<tr>
<td>Downscaled soil moisture</td>
<td>0.83</td>
<td>−0.09</td>
<td>−0.19</td>
<td>0.01</td>
<td>−0.02</td>
<td>−0.06</td>
</tr>
<tr>
<td>Undownscaled soil moisture</td>
<td>-</td>
<td>−0.16</td>
<td>−0.21</td>
<td>−0.05</td>
<td>0</td>
<td>−0.05</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>−0.16</td>
<td>-</td>
<td>0.57</td>
<td>−0.09</td>
<td>−0.19</td>
<td>−0.20</td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>−0.21</td>
<td>0.57</td>
<td>-</td>
<td>−0.18</td>
<td>−0.16</td>
<td>−0.10</td>
</tr>
<tr>
<td>Proximity to drainage (m)</td>
<td>−0.05</td>
<td>−0.09</td>
<td>−0.18</td>
<td>-</td>
<td>−0.06</td>
<td>−0.07</td>
</tr>
<tr>
<td>Drainage density (km(^{-1}))</td>
<td>0</td>
<td>−0.19</td>
<td>−0.16</td>
<td>−0.06</td>
<td>1</td>
<td>−0.21</td>
</tr>
<tr>
<td>TWI</td>
<td>−0.05</td>
<td>−0.20</td>
<td>−0.10</td>
<td>−0.07</td>
<td>−0.21</td>
<td>-</td>
</tr>
</tbody>
</table>
3.2.6 Statistical Approach Used in Model Development

As discussed in Section 2.4.1, logistic regression was used in this study for soil slide hazard assessment. Based on the triggering factors such as downscaled remotely sensed soil moisture content and location-based conditioning factors of saturated hydraulic conductivity, slope, elevation, distance to roads, EVI, and soil type, the likelihood of a soil slide can be predicted at a given location with a logistic regression model. The maximum likelihood estimation was used to determine the parameter estimates for each predictor variable. The resulting probability of failure can be considered as a ‘hazard index’ for soil slide occurrence. In a logistic regression model, the probability of occurrence of a slope failure can be expressed using Equation 59.

\[
P(f) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + \cdots)]}
\]  

(59)

where \(P(f)\) is the probability of failure, \(X_i\) represents continuous variables, \(X_k\) represents categorical variables, \(\beta_0\) is the constant, and \(\beta_1\) and \(\beta_k\) are the corresponding parameter estimates of the above variables. In predicting soil slides, the independent variables are the soil slide conditioning and triggering factors. For the categorical variable \(X_k\), if category ‘k’ is observed at the soil slide location, the value of \(X_k\) would be equal to 1, rendering the contribution to Equation 59 from category ‘k’ to be \(\beta_k\). If the category ‘k’ is not observed at the soil slide location, the value of \(X_k\) would be equal to zero, rendering the contribution to Equation 59 from category ‘k’ to be zero.

The goodness of fit of a logistic regression model is assessed by the log likelihood. The likelihood function is the joint probability density function of the data sample if it was observed from a statistical distribution with a parameter vector \(\theta\), which is given in Equation 60 [98][99]:

\[
L(\theta | X) = \prod_{i=1}^{n} f(x_i, \theta)
\]

(60)

where \(L\) is the likelihood function and \(f\) is the probability density function. Typically, the goodness of fit, and thus the log likelihood of a model improves as the number of variables used in the model
increases. To compare models with different numbers of variables, the log likelihood values must be penalized for the number of variables used in the model. Akaike information criterion (AIC) and Bayesian information criterion (BIC) are two such penalizing methods that can be used in comparing models with different numbers of variables [100]. AIC and BIC are defined in Equations 61 and 62, respectively:

\[ \text{AIC} = 2K - 2\text{LL} \]  
\[ \text{BIC} = K \cdot \ln(n) - 2\ln(\text{LL}) \]

where \( K \) is the number of parameter estimates, \( n \) is the number of observed data, and \( \text{LL} \) is the log likelihood. Lower AIC and BIC values would typically indicate better model performance. Generally, the BIC method applies a larger penalty compared to the AIC method.

In the developed model, only the explanatory variables that are statistically significant at a level of 0.1 or higher were used. The best performing model was selected considering the goodness of fit, model complexity, statistical significance of the variables, and interpretability of the parameter estimates. Furthermore, as clay and silt soil types are highly correlated, only the silt soil type was used in the analysis. Moreover, the interaction effect of different explanatory variables is also considered in developing this model to improve the model prediction accuracy.

### 3.2.7 Soil Slide Hazard Estimation Model with Alternative Water Drainage-based Explanatory Variables

Additional logistic regression models for soil slide hazard assessment were developed with alternative water drainage-based variables in the place of downscaled soil moisture content, and the performance of these models was compared with the model based on downscaled soil moisture content. In this regard, three alternative water drainage-based variables that are commonly used in landslide studies in order to capture the effect of increased soil moisture content on landslide
hazard (Section 2.3.1.2), namely distance to drainage accessories, drainage density and the Topographic Wetness Index (TWI), were considered in this study as substitutes for the downscaled soil moisture content.

3.2.8 Methodology of Soil Slide Hazard Assessment with the Developed Model

It must be noted that the probability of failure defined by the logistic regression model is merely a hazard index, and it does not provide a threshold for the occurrence of a soil slide. Hence, as the final step of the process, a threshold probability of failure was determined by maximizing the classification accuracy between soil slide and non-soil slide locations. Classification accuracy is defined in Equation 63:

\[ A = \frac{\text{Number of locations correctly classified}}{\text{Total number of locations}} \times 100 \]  

(63)
CHAPTER 4: DEVELOPMENT OF A SITE-SPECIFIC LANDSLIDE HAZARD ASSESSMENT MODEL

This chapter discusses the methodology followed to achieve Objective 2 of this dissertation.

As discussed in Chapter 2, a gap exists in literature for a deterministic landslide hazard estimation model that considers the effect of continuous interplay between surface and subsurface water flows during transient seepage and is developed based on fundamental fluid dynamics. Thus, in order to address this gap, a numerical model which computes transient seepage using Navier-Stokes equations and has the capability to model the continuous interplay between surface and subsurface water flows during infiltration was developed. Furthermore, the pore pressure variations obtained from this model was employed to assess slope stability during and after a rainfall event.

4.1 Analytical Methodology

4.1.1 Modeling of the Fluid Flow

As discussed in Section 2.6.2, Navier-Stokes equations that are employed in modeling surface, subsurface and infiltration water flows consist of two equations: 1) continuity equation and 2) conservation of momentum. A coupled approach was followed in solving the Navier-Stokes equations in two-dimensions to obtain the changes in pore pressure of soil due to infiltration of rainwater.
The general forms of the Navier-Stokes equation for the conservation of mass is given in equation 44.

\[
\frac{\partial \phi}{\partial t} + \nabla \cdot (\phi \vec{U}) - Q = 0
\]  

(44)

The general forms of the Navier-Stokes equation for the conservation of momentum is given in equation 44.

\[
\left(\frac{\partial \phi \vec{U}}{\partial t} + \vec{U} \cdot \nabla \phi \vec{U}\right) = \frac{\phi}{\rho}(-\nabla P + \mu \nabla^2 \vec{U}) + F
\]  

where \(\rho\) is the fluid density, \(Q\) is the rate of water loss/gain from a sink/source, \(P\) is the fluid pressure, \(\mu\) is the fluid viscosity and \(F\) is any external force acting on the fluid.

4.1.1.1 Infiltration Flow

The infiltration excess runoff model, which typically governs the runoff generation during heavy rainfall events [101][102] is employed to model the surface runoff generated due to rainfall. In the developed model, the infiltration occurs at the rate of rainfall as long as the rainfall does not exceed the infiltration capacity \(I\) of the soil. Once the infiltration capacity of the soil is exceeded, ponding and subsequent surface runoff of water begins, and the infiltration rate is decreased asymptotically. The governing equation for modeling the infiltration, Equation 64, was developed by applying Navier-Stokes momentum conservation equation normal to the flow at the interface.

\[
\frac{\partial (Snv)}{\partial t} + u \frac{\partial (Snv)}{\partial x} + v \frac{\partial (Snv)}{\partial y} = - \frac{Sn \partial P}{\rho_w \partial y} + \frac{D}{\rho_w} + gSn(\cos \theta)
\]  

(64)

where \(v\) is the infiltration velocity which is equal to the rate of infiltration \(I\), \(u\) is the flow velocity parallel to the surface (assumed to be uniform across the Z plane), \(S\) is the degree of saturation of soil, \(n\) is the soil porosity, \(P\) is the pore water pressure, \(\rho_w\) is the density of water, \(D\) is the near-surface drag force acting between soil particles and infiltrating water, \(\theta\) is the slope angle of the soil embankment and \(t\) is time. A point at mid-depth of the water layer (point A in Figure 14(a))
and that in the vicinity of the ground surface (point B in Figure 14(a)) were considered in calculating the pressure gradient in Equation 64.

4.1.1.2 Surface Flow

The governing equations for modeling of surface flow are derived from Navier-Stokes equations employing the widely used shallow wave assumptions. When the vertical scale is much smaller compared to the horizontal scale, it can be assumed that the vertical velocity in the surface water is negligible compared to the horizontal velocity. Thus, Equation 65 can be derived from Equation 44 for continuity of flow:

$$\frac{\partial H}{\partial t} + \frac{\partial (uH)}{\partial x} - r(cos\theta) + l = 0$$

(65)

where $H$ is the water film thickness, and $r$ is the rainfall, as seen in Figure 14(a).

Furthermore, if viscous forces in water are neglected compared to surface friction, the equation for the conservation of momentum, Equation 45, can be simplified to the following form (Equation 66):

$$\frac{\partial (Hu)}{\partial t} + u \frac{\partial (uH)}{\partial x} = -gH \left[ \frac{\partial Hcos(\theta)}{\partial x} + S_{fx} - \sin \theta \right]$$

(66)

where $g$ is the gravitational acceleration and $S_{fx}$ is the friction slope given in Equation 67.

$$S_{fx} = \frac{M^2 u^2}{R_h^3}$$

(67)

where $M$ is the Manning’s roughness coefficient of the surface and $R_h$ is the hydraulic radius of the channel. Equations 66 and 67 were employed in modeling surface water flow in this study.
Figure 14: (a) The modeled hillslope and (b) flow of water through a surficial water element.

4.1.1.3 Subsurface Flow

Jeyisanker et al. [84] employed the Navier-Stokes equations for modeling seepage through both saturated and unsaturated zones. In this study, consideration of water flow was limited to the unsaturated zone since the objective was to predict the gradual loss of matric suction in the unsaturated zone (Figure 14).

For incompressible water flow through unsaturated soil, Navier-Stokes continuity equations along the X and Y axes (Figure 16) can be expressed using equation 68.

\[
\frac{\partial S_n}{\partial t} + \frac{\partial (S_n u)}{\partial x} + \frac{\partial (S_n v)}{\partial y} = 0
\]  

(68)

where \( u \) and \( v \) correspond to the x-directional and y-directional water velocity components respectively.

Convective acceleration terms (eg: \( u \frac{\partial (S_n u)}{\partial x} + v \frac{\partial (S_n u)}{\partial y} \)) were assumed to be negligible compared to the local acceleration term since the former ones are significantly smaller than the latter for flow velocities in soil. Furthermore, viscous drag forces were assumed negligible compared to the drag force generated due to soil-water interaction (herein, referred to as the drag force). The simplified X and Y-directional momentum conservation equations are given in Equations 69 and 70 respectively.
\[
\frac{\partial (S_n u)}{\partial t} = - \frac{S_n \partial p}{\rho_w \partial x} + \frac{D}{\rho_w} + Sng (\sin \theta) \quad (69)
\]

\[
\frac{\partial (S_n v)}{\partial t} = - \frac{S_n \partial p}{\rho_w \partial y} + \frac{D}{\rho_w} + Sng (\cos \theta) \quad (70)
\]

Numerous empirical and semi-empirical relationships have been developed for the quantification of drag forces between soil and water \((D)\) based on soil properties such as particle size diameter, porosity and properties of water such as viscosity and density [84]. However, in the case of fine-grained material such as silt and clay which exhibit properties of continua, it is unrealistic to visualize the interaction between discrete soil particles and the seeping fluid. Hence, the authors formulated the following scheme to express the drag forces acting in fine grained soils in terms of the traditional hydraulic conductivity measured easily in the laboratory, by comparing the momentum equation, reduced under steady state conditions, to the widely used Darcy’s equation. This is quite logical since the hydraulic conductivity of a medium is determined by the drag forces encountered by water flow.

Under steady state conditions where the laboratory hydraulic conductivity values are measured, Equation 70 simplifies to Equation 71.

\[
0 = - \frac{S_n \partial p}{\rho_w \partial y} + \frac{D}{\rho_w} + Sng \quad (71)
\]

The Equation 71 can be re-arranged which results in Equation 72.

\[
\frac{D}{\rho_w} = \frac{Sny_w}{\rho_w} \cdot \frac{\partial}{\partial y} \left( \frac{p}{\gamma_w} - y \right) \quad (72)
\]

where \(\gamma_w\) is the unit weight of water. \(\frac{\partial}{\partial y} \left( \frac{p}{\gamma_w} - y \right)\) term in Equation 71 represents the hydraulic gradient \(i\). Thus, under steady state flow, Equation 72 can be expressed in Equation 73.

\[
D = Sny_w i \quad (73)
\]

On the other hand, Darcy’s law for the flow of water through a soil is strictly applicable under steady state conditions is expressed in Equation 74.
\[ v' = - Ki \]  
(74)

where \( v' \) is the Darcy’s discharge velocity which is related to the flow velocity \( v \) which is expressed in Equation 75.

\[ v' = n v \]  
(75)

Hence, the drag force can be expressed using Darcy’s hydraulic conductivity \( K \) and the velocity of water as shown in Equations 76a-76b.

\[ D = - Y_w S_n K v' \]  
(76a)

\[ D = - Y_w S_n^2 K v \]  
(76b)

Thus, drag force and be expressed in terms of soil properties of porosity, degree of saturation and the steady-state hydraulic conductivity at the transient water velocity.

4.1.2 Water Retention and Permeability Characteristics of the Unsaturated Zone

The relationship between suction \( (P) \) and the volumetric water content \( (\Theta) \) in unsaturated soil is expressed by the soil water characteristic curve (SWCC). The SWCC developed by Fredlund and Xing [89] is employed in this study (Equation 77). Jeyisanker et al. [84] has successfully applied the SWCC equation developed by Fredlund and Xing [89] along with NS equations in modeling the flow of water through the unsaturated zone.

\[ \Theta = \left\{ \left[ - \ln \left( \frac{1 + \frac{P}{P_r}}{1 + 10^6} \right) + 1 \right] \right\} \left\{ \Theta_s \left( \ln \left( \frac{\Theta_s}{\alpha^q} \right) \right)^m \right\} \]  
(77)

where \( P_r \) is the residual suction (kPa) corresponding to the residual water content \( \Theta_r \), \( \Theta_s \) is the volumetric water content at saturation and \( \alpha, m, q \) are three parameters defining the shape of the SWCC. Parameter \( \alpha \) represents the air entry value of soil while parameters \( m \) and \( q \) control the slope of the SWCC.
4.1.3 Unsaturated Hydraulic Conductivity

Several theoretical models are available to express the variation of hydraulic conductivity in the unsaturated zone. The authors chose the one developed by Fredlund et al. [88] for this study since it is compatible with the soil water characteristic curve (SWCC). It must be noted that the hysteresis effects of the SWCC have been neglected in this study as has been the case with similar studies [15][54][103]. In the above model, the unsaturated hydraulic conductivity can be expressed by Equation 78.

\[ K_r(P) = \frac{\int_{\Phi}^{P_a} \frac{\Phi(y) - \Phi(P)}{\Phi'(y)} dy}{\int_{P_{aev}}^{P_a} \frac{\Phi(y) - \Phi(P)}{y} \Phi'(y) dy} \]  

(78)

where \( K_r \) is the coefficient of hydraulic conductivity, \( P_{aev} \) is the suction at air entry value, \( \Phi \) is the volumetric water content, \( \Phi'(y) \) is the first derivative of the SWCC w.r.t. suction and \( y \) is the dummy (suction) variable that facilitates integration w.r.t. suction. Thus, the unsaturated hydraulic conductivity of a given soil can be determined from its SWCC.

4.1.4 Slope Stability Assessment

A model for slope stability assessment was developed considering two failure circles (one shallow and one deep) through the unsaturated zone. Bishop’s method considering the moment equilibrium of slices was used in developing the slope stability model (Figure 15). The slices were considered perpendicular to the slope and the interslice shear forces were assumed to balance. The factor of safety (FoS) based on the shear strength of an unsaturated soil [55] is expressed in Equation 79.
Figure 15: A failure circle used in computing FoS.

\[
FoS = \frac{\sum_{i=1}^{N} b_i \left[ C \frac{\gamma_i h_i \cos \theta \tan \varphi}{\cos (\alpha_i - \theta)} P_i \tan \varphi b \right]}{\sum_{i=1}^{N} \gamma_i h_i b \left[ \sin \alpha_i - \frac{h_i \sin \theta}{2R} \right]}
\]  

where \( b_i \) is the width of a slice, \( C \) is cohesion of soil, \( \varphi \) is the angle of internal friction of soil, \( \gamma_i \) is the unit weight of soil, \( h_i \) is the height of a slice, \( \alpha_i \) is the angle each slice makes with the horizontal, \( N \) is the number of slices and \( R \) is the radius of the failure circle. The weight of each slice is defined in Equation 80.

\[
\gamma_i = \frac{\sum_{j=1}^{m} [n S_i j \gamma_w + (1-n) \gamma_w G_s]}{H_i} \Delta y
\]  

where \( j \) is the number of elements in a slice, \( n \) is the soil porosity, \( \gamma_w \) is the unit weight of water, \( \Delta y \) is the distance between 2 nodes in the y direction, and \( G_s \) is the specific gravity of soil. \( \varphi_b \) is the angle of shearing resistance with respect to matric suction, which can be expressed in Equation 81.

\[
tan \varphi_b = tan \varphi \left( \frac{\theta - \theta_r}{\theta_s - \theta_r} \right)
\]
4.2 Computational Methodology

Since the theoretical formulation consisted of flow and momentum equations which can be coupled conveniently with the unsaturated soil characteristics in Equations 77 and 78, theoretical equations introduced in Section 4.1 were solved using the finite difference (FD) method in this study. Furthermore, the geometric transitions of the problem can be handled effectively with the FD approach as described in Section 4.2.1

4.2.1 Finite Difference Grid Used in the Numerical Model

Forward difference equations were used to model the flow of water on the surface and in the subsurface of the hillslope. The FD grids used for different sections of the slope are shown in Figures 16(a-c). The fineness of spatial and temporal discretization was optimized by two criteria: 1) significant changes in results, and 2) minimization of computational time. In applying Equations 68-70, X and Y axes were chosen to be vertical or horizontal respectively in upstream and downstream flat areas while along the slope, X and Y axes were parallel and normal to the slope respectively. The abrupt changes in the flow direction due to sudden changes of the slope angle at upstream and downstream were smoothened to provide a gradual transition. This was achieved by dividing the transition zone into a number of smaller segments with gradually changing slopes.

Figure 16: Finite difference grid in the (a) upstream flat area, (b) along the sloping ground and (c) downstream flat area.
4.2.2 Finite Difference Form of the Governing Equations

The FD forms of the governing equations for surface and subsurface flow are given in Equations (82)-(87). A staggered grid was used where variables $S$, $P$ and $H$ are defined at the middle node of an element while the velocities $u$, $v$ and $I$ are computed on corner nodes. The use of staggered grid facilitates the computation of the mass flow rates across elements, or the
application of continuity equation, without any interpolation of the velocity fields [84]. The subscript i refers to time step and subscripts j and k refer to x and y-directional coordinates of each node in the grid, respectively.

Finite difference form of the equation to model infiltration of water into soil (Equation 64) is given in Equation 82.

\[
\frac{S_{i,j,k}}{\Delta t} + u_{i,j+1,2} \frac{S_{i,j+2,k}}{2\Delta x} + I_{i,j} \frac{S_{i,j+2,k}}{2\Delta y} = - \frac{S_{i,j,k}}{\rho_w} \frac{H_{i,j} \cos \theta}{\Delta y} - \\
g \frac{S_{i,j,k}}{K_y} I_{i+1,j} + S_{i,j,k} \eta (\cos \theta)
\]  

(82)

Finite difference form of the equation to model continuity of surface flow (Equation 65) is given in Equation 83.

\[
\frac{(H_{i+1,j} - H_{i,j})}{\Delta t} + \frac{(u_{i,j+1,2} H_{i,j} - u_{i,j-1,2} H_{i,j-2})}{2\Delta x} - r_{i+1} (\cos \theta) + I_{i,j} = 0
\]  

(83)

Finite difference form of the equation to model conservation of momentum of surface flow (Equations 66 and 67) is given in Equation 84.

\[
\frac{(H_{i+1,j} u_{i,j+1,2} H_{i,j} - u_{i,j-1,2} H_{i,j-2})}{\Delta t} + u_{i,j+1,2} \frac{(u_{i,j+1,2} H_{i,j} - u_{i,j-1,2} H_{i,j-2})}{2\Delta x} = - g H_{i,j} \left(\frac{H_{i,j+2} \cos \theta - H_{i,j} \cos \theta}{2\Delta x}\right) + \\
\frac{n^2 u_{i+1,j+1,2}}{R^2} - \sin \theta
\]  

(84)

where \(\Delta y\) is the y-directional spatial increment.

Finite difference form of the equation to model continuity of subsurface flow (Equation 68) is given in Equation 85.

\[
\frac{(S_{i+1,j,k} - S_{i,j,k})}{\Delta t} = \frac{S_{i,j,k} (v_{i,j,k+1} - v_{i,j,k-1})}{2\Delta y} + \frac{S_{i,j,k} (u_{i,j,k+1} - u_{i,j,k-1})}{2\Delta x}
\]  

(85)

Finite difference form of the equations to model X and Y-directional conservation of momentum of subsurface flow (Equations 69 and 70) are given in Equations 86 and 87 respectively.
\[
\frac{S_{i,j,k}(u_{i+1,j+1,k} - u_{i+1,k})}{\Delta t} = - \frac{S_{i,j,k}(p_{i,j+2,k} - p_{i,j,k})}{2 \Delta x \rho_w} - \frac{gS_{i,j,k} n^2}{K_x} u_{i+1,j+1,k} + S_{i,j,k} n g (\sin \theta)
\] (86)

\[
\frac{S_{i,j,k}(v_{i+1,j,k+1} - v_{i,j,k})}{\Delta t} = - \frac{S_{i,j,k}(p_{i,j+2,k} - p_{i,j,k})}{2 \Delta y \rho_w} - \frac{gS_{i,j,k} n^2}{K_y} v_{i+1,j,k+1} + S_{i,j,k} n g (\cos \theta)
\] (87)

**4.2.3 Boundary Conditions**

The criteria defined in Equations (88) and (89) are employed to model the infiltration at the water-soil interface. Hence:

if Infiltration capacity \((I_{i,j}) \geq r_i \text{ and } H_{i,t} = 0\), then \(I_{i,j} = r_i\) (88)

otherwise; \(I_{i,j} = I_{i,j}\) (89)

The infiltration capacity \(I_{i,j}\), which is the \(v\) defined in Equations 64 at a node \(i,j\), is calculated using the momentum equation at the water-soil interface. The phreatic line is formed at the bottom boundary which facilitates interaction between the saturated zone, which is considered as a water reservoir, and the unsaturated zone. Thus:

\(S_{i,j,e} = 1\) (90)

\(P_{i,j,e} = \gamma_w \Delta y\) (91)

where \(e\) is the last node in the y-direction (first node in the saturated zone in Figure 16a).

Far field boundary conditions (Equations 92-97) were assumed for the upstream boundary.

Water film thickness \(H_{i,2} = H_{i,4}\) (92)

Surface water flow velocity \(U_{i,3,2} = U_{i,5,2}\) (93)

Infiltration \(V_{i,2,3} = V_{i,4,3}\) (94)

Degree of saturation \(S_{i,2,k} = S_{i,4,k}\) (95)

x-directional water flow velocity \(U_{i,3,k} = U_{i,5,k}\) (96)

y-directional water flow velocity \(V_{i,2,k+1} = V_{i,4,k+1}\) (97)

where 4 is the first element in the x direction for which the above variables are evaluated.
Water was assumed to discharge into a stream and in order to generate an exit hydraulic gradient that induces discharge into the stream, a negative pressure profile, equivalent to the initial pressure profile in the unsaturated zone, was assumed at the downstream boundary.

**4.2.4 Iterative Procedure**

Equations 82-87 were solved in an iterative manner to obtain the variation of surface flow velocity, water film thickness, rate of infiltration, degree of saturation and subsurface water flow velocities with time (Figure 17). Computations related to surface water flow are performed first, followed by those of the interface and subsurface flow. At a given time step i and a soil column j (Figures 16 (a)-(c)), the infiltration triggered by rainfall was calculated using the results obtained from the previous time step. Next, the conservation of momentum along the surface and continuity of the surface flow equations were solved to obtain surface flow velocity and water film thickness at the above time step. Thereafter, the subsurface continuity equation was solved to obtain the degree of saturation and the corresponding water pressure was calculated using the relevant SWCC. Then, the x and y-directional momentum conservation equations were applied to determine the x and y-directional water flow velocities. The above procedure was followed to obtain degree of saturation and x and y-directional subsurface flow velocities in the soil column j at the i\textsuperscript{th} time step, thus completing the first iteration at the given time step i. The same procedure was repeated in the subsequent iterations, using updated results of the latest iteration, instead of results of the previous time step, until convergence of the variables is achieved based on Equation (98) and a maximum error of 5%.

\[
\text{Error} = \frac{\text{Result of iteration (n+1)} - \text{Result of iteration (n)}}{\text{Result of iteration (n)}} \times 100
\]  

(98)
Figure 17: Flow chart for the iterative procedure for solving the surface and subsurface flows for a single time step and a soil column.

Once convergence was achieved for a given column, the above iterative process was extended to the adjacent soil column at the same time step. When the process was accomplished for the entire spatial domain for a given time step, it was extended to the following time step and continued until the entire duration of rainfall is covered and then up to 14 hours after the end of the rainfall.
CHAPTER 5: RESULTS AND DISCUSSION

The purpose of this chapter is to describe and discuss the results obtained from this study. The first part of this chapter describes and discusses the results obtained from the effort to achieve Objective 1, whereas the second part of this chapter describes and discusses the results obtained from work performed to achieve Objective 2.

5.1 Statistical Model for Regional Scale Landslide Hazard Assessment

5.1.1 Results of the Dry Edge Parameters of the LST–EVI Space

The LST–EVI dry edge parameters that were developed for the three downscaling windows of the Oregon study area and two downscaling windows of the Kentucky (Section 3.2.3). study area using linear regression are given in Figure 18a–e. For the three windows of Oregon, the LST and EVI values produced good correlation coefficients along the dry edge whereas for the two windows of Kentucky, the correlations were lower, especially at lower EVI values.

5.1.2 Statistics of Explanatory Variables

The frequency distributions of downscaled and undownscaled soil moisture are given in figures 19a and 19b, respectively. Furthermore, the means and standard deviations of downscaled and undownscaled soil moisture are given in Table 2. The mean and standard deviation of

Figure 18: Dry edge parameters of (a) the top window of Oregon, (b) the middle window of Oregon, (c) the bottom window of Oregon, (d) the top window of Kentucky and (e) the bottom window of Kentucky.

downscaled soil moisture at the soil slide locations were 0.2787 and 0.075, respectively, while those of the non-soil slide locations were 0.2523 and 0.0585 respectively. On the other hand, the mean and standard deviation of the undownscaled soil moisture content at the soil slide locations
were 0.2682 and 0.0519, respectively, while those at non-soil slide locations were 0.2503 and 0.0478, respectively. It could be observed that the mean soil moisture content at the soil slide locations was higher than those at the non-soil slide locations for both downscaled and undownscaled soil moisture contents. However, downscaling increased the mean soil moisture at the soil slide locations, thereby leading to a larger difference between the means of the soil slide and non-soil slide locations. Moreover, downscaling increased the standard deviation of soil moisture content at both the soil slide and non-soil slide locations.

Figure 19c contains the frequency distribution of saturated hydraulic conductivity at the soil slide and non-soil slide locations. It could be observed that the soil slide locations had lower hydraulic conductivity values (mean 7.84 microns per second) compared to the non-soil slide locations (mean 10.04 microns per second). In addition, the variability of the hydraulic conductivity (of the surface) of the soil slide locations (standard deviation is 4.15 microns per second) was much lower than the non-soil slide locations (standard deviation is 7.39 microns per second). Furthermore, the distribution of soil types in the study areas is given in Table 3. It could be observed that of the soil slide locations, 70% was on clayey soil, while 27% and 3% were on silty and gravelly soils, respectively. Moreover, of the non-soil slide locations, 51% was on clayey soil, 28% was on silty soil, and 21% was on gravelly soil.

The frequency distributions of elevation and slope are given in Figure 19d,e respectively. The mean elevation of the soil slide locations (189 m) was much lower than that of the non-soil slide locations (335 m). This is because the majority of the slope failures in this study occurred in close proximity to primary and secondary roads. Since primary and secondary roads are built on lower elevations, the mean elevation of soil slide locations is expected to be much lower than that of non-soil slide locations. Furthermore, it can be observed from Table 2 that the mean slope angle
of the soil slide locations (20.93) was much higher than that of the non-soil slide locations (13.34), indicating that a higher slope angle leads to an elevated soil slide hazard.

Furthermore, the frequency distributions of EVI at the soil slide locations on the day of the soil slide, and the non-soil slide locations on the day that the moisture was evaluated, are given in Figure 19f. The mean EVI at the soil slide locations was 0.402, whereas the mean EVI at the non-soil slide locations was 0.4403. The lower mean EVI at the soil slide locations indicates that the lack of land cover exposes a slope to a higher soil slide hazard. Moreover, the frequency distribution of the distance from roads is given in Figure 19g. For soil slide locations, the mean distance from roads is 257 m, whereas that of non-soil slide locations is 6676 m. However, it should be noted that of 33 total soil slides, 27 occurred at a distance less than 20 m from a road. Hence, the majority of selected soil slides can be classified as failures due to road-cut slopes. In addition, it could be observed that most variables in Figure 19 that although most of the variables follow a normal distribution, variables of slope at non-landslide locations, hydraulic conductivity, and distance to roads follow a normal distribution. This could be attribute to the small size of the database.

Table 2: Statistics of the explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Soil Slide Locations</th>
<th>Non-Soil Slide Locations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Downscaled soil moisture (m³/m³)</td>
<td>0.2787</td>
<td>0.0750</td>
</tr>
<tr>
<td>Undownscaled soil moisture (m³/m³)</td>
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<td>0.0519</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>7.84</td>
<td>4.15</td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>20.93</td>
<td>12.29</td>
</tr>
<tr>
<td>Elevation (m)</td>
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<td>100</td>
</tr>
<tr>
<td>EVI</td>
<td>0.4020</td>
<td>0.1568</td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>257</td>
<td>637</td>
</tr>
</tbody>
</table>
Table 3: The distribution of soil types at soil slide and non-soil slide locations

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>% Soil Slide Locations</th>
<th>% Non-Soil Slide Locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>GM (silty gravel)</td>
<td>3.03</td>
<td>5</td>
</tr>
<tr>
<td>GC (clayey gravel)</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>ML (low plasticity silt)</td>
<td>27.27</td>
<td>14</td>
</tr>
<tr>
<td>MH (high plasticity silt)</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>CL (low plasticity clay)</td>
<td>27.27</td>
<td>29</td>
</tr>
<tr>
<td>CH (high plasticity clay)</td>
<td>42.42</td>
<td>22</td>
</tr>
</tbody>
</table>

5.1.3 Results of the Soil Slide Hazard Estimation Models

5.1.3.1 Model with Downscaled Remotely Sensed Soil Moisture Content

A logistic regression model for the prediction of soil slide hazard was developed using the explanatory variables discussed in Sections 3.2.3 and 3.2.4 such as downscaled soil moisture, elevation, slope, saturated surface hydraulic conductivity, soil type, EVI, and distance to roads. The resulting parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the developed model are given in Table 4. Of the explanatory variables, downscaled soil moisture content, elevation, slope angle, saturated hydraulic conductivity (of the surface soil), distance to roads, and silt soil type are identified as statistically significant based on a significance level of 0.1.

However, EVI and clay soil type were found to be statistically insignificant, although the negative parameter estimate of EVI shows a reduction in the soil slide hazard as the vegetation cover increases, and the parameter estimate of clay shows an increase of soil slide hazard as the presence of clayey soil increases, which are both intuitive findings. Furthermore, the clay soil type was identified to be highly correlated with the silt soil type (Table 1). Thus, EVI and clay soil type were excluded from the analysis, and an improved logistic regression model was developed using only the statistically significant variables such as downscaled soil moisture content, elevation, slope angle, saturated hydraulic conductivity, silt soil type, and distance to roads. The parameter
estimates, standardized parameter estimates, \( t \)-statistics, and \( p \)-values of the resulting best performing logistic regression model are given in Table 5.

Figure 19: Frequency distribution of (a) downscaled soil moisture, (b) undownscaled soil moisture, (c) saturated surface hydraulic conductivity, (d) elevation, (e) slope angle, (f) EVI and (g) distance from roads.
Table 4: Parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the logistic regression model with all of the explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standardized Parameter Estimate</th>
<th>$t$-Statistic</th>
<th>$p$-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$-2.54$</td>
<td>$-0.42$</td>
<td>$0.67$</td>
<td></td>
</tr>
<tr>
<td>Downscaled soil moisture</td>
<td>$17.47$</td>
<td>$1.05$</td>
<td>$0.01$</td>
<td></td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>$-0.01$</td>
<td>$-1.92$</td>
<td>$0.04$</td>
<td></td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>$0.18$</td>
<td>$1.92$</td>
<td>$0.01$</td>
<td></td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>$-0.003$</td>
<td>$-19.86$</td>
<td>$0.001$</td>
<td></td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>$-0.38$</td>
<td>$-2.55$</td>
<td>$0.09$</td>
<td></td>
</tr>
<tr>
<td>Presence of silt soil type (ML and MH)</td>
<td>$5.80$</td>
<td>$2.55$</td>
<td>$0.13$</td>
<td></td>
</tr>
<tr>
<td>Presence of clay soil type (CL and CH)</td>
<td>$3.35$</td>
<td>$1.65$</td>
<td>$0.37$</td>
<td></td>
</tr>
<tr>
<td>EVI</td>
<td>$-2.42$</td>
<td>$-0.59$</td>
<td>$0.56$</td>
<td></td>
</tr>
</tbody>
</table>
Table 5: Parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the best performing logistic regression model with downscaled soil moisture content

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standardized Parameter Estimate</th>
<th>t-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.38</td>
<td>-</td>
<td>1.03</td>
<td>0.30</td>
</tr>
<tr>
<td>Downscaled soil moisture</td>
<td>12.48</td>
<td>0.72</td>
<td>1.71</td>
<td>0.09</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>-0.01</td>
<td>-2.03</td>
<td>-2.32</td>
<td>0.02</td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>0.17</td>
<td>1.79</td>
<td>2.98</td>
<td>0.003</td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>-0.009</td>
<td>-65.37</td>
<td>-2.44</td>
<td>0.01</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>-0.52</td>
<td>-3.43</td>
<td>-2.61</td>
<td>0.009</td>
</tr>
<tr>
<td>Presence of silt soil type (ML and MH)</td>
<td>3.32</td>
<td>1.44</td>
<td>1.97</td>
<td>0.05</td>
</tr>
<tr>
<td>Downscaled soil moisture $\times$ Distance to roads</td>
<td>0.02</td>
<td>35.67</td>
<td>1.96</td>
<td>0.05</td>
</tr>
</tbody>
</table>

5.1.3.2 Model with Undownscaled Remotely Sensed Soil Moisture Content

An additional model for soil slide hazard assessment with undownscaled soil moisture content in place of downscaled soil moisture content was also developed, and the performance of this model was compared with that of the previously developed downscaled soil moisture-based model. The parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the best performing model with undownscaled soil moisture content are given in Table 6. Soil slide hazard increases with the increase of undownscaled soil moisture content as well. However, the undownscaled soil moisture is determined to be statistically less significant in soil slide hazard assessment than downscaled soil moisture. It is seen in Table 6 that among the conditioning factors, elevation, slope angle, distance to roads, saturated hydraulic conductivity, and silt soil type are statistically significant.

5.1.3.3 Model with Alternative Water Drainage-based Explanatory Variables

As discussed in Section 3.2.6, logistic regression models for soil slide hazard assessment were developed with alternative water drainage-based variables, namely distance to drainage,
drainage density, and the Topographic Wetness Index (TWI). The best performing model with
distance to drainage is given in Table 7. The soil slide hazard was predicted to increase with an
increasing distance to drainage. The explanatory variables of elevation, slope, distance to roads,
saturated hydraulic conductivity, and the interaction of distance to drainage accessories and
elevation were statistically significant. However, the hydrological variable of distance to drainage
accessories was statistically less significant compared to downscaled soil moisture content.

Secondly, the best performing model with drainage density is given in Table 8. The
negative parameter estimate of drainage density indicates an increasing soil slide hazard with the
decrease of drainage density. Of the conditioning factors, only the slope and elevation were
determined to be statistically significant.

Finally, in the prediction model developed with TWI as the explanatory hydrological
variable (Table 9), although an increase in TWI was seen to increase the soil slide hazard, TWI
was found to be statistically less significant compared to downscaled soil moisture content. Of the
explanatory variables, elevation, slope angle, distance to roads, saturated hydraulic conductivity,
and the presence of the silt soil type were found to be statistically significant.

Table 6: Parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the
best performing logistic regression model with undownscaled soil moisture content

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standardized Parameter Estimate</th>
<th>$t$-Statistic</th>
<th>$p$-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.54</td>
<td>-</td>
<td>0.20</td>
<td>0.84</td>
</tr>
<tr>
<td>Undownscaled soil moisture</td>
<td>12.15</td>
<td>0.57</td>
<td>1.48</td>
<td>0.14</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>$-0.007$</td>
<td>$-1.48$</td>
<td>$-1.98$</td>
<td>0.05</td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>0.14</td>
<td>1.47</td>
<td>2.99</td>
<td>0.003</td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>$-0.002$</td>
<td>$-16.24$</td>
<td>$-3.64$</td>
<td>0.0003</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>$-0.36$</td>
<td>$-2.46$</td>
<td>$-2.35$</td>
<td>0.02</td>
</tr>
<tr>
<td>Presence of silt soil type (ML and MH)</td>
<td>2.12</td>
<td>0.94</td>
<td>1.77</td>
<td>0.08</td>
</tr>
</tbody>
</table>
Table 7: Parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the best performing logistic regression model with proximity to drainage accessories

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standardized Parameter Estimate</th>
<th>$t$-Statistic</th>
<th>$p$-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>6.85</td>
<td>-</td>
<td>2.27</td>
<td>0.02</td>
</tr>
<tr>
<td>Distance to drainage accessories (m)</td>
<td>$-0.009$</td>
<td>$-1.52$</td>
<td>$-1.39$</td>
<td>0.16</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>$-0.026$</td>
<td>$-5.21$</td>
<td>$-2.62$</td>
<td>0.01</td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>0.16</td>
<td>1.69</td>
<td>3.06</td>
<td>0.002</td>
</tr>
<tr>
<td>Distance from roads (m)</td>
<td>$-0.002$</td>
<td>$-13.41$</td>
<td>$-3.49$</td>
<td>0.0005</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>$-0.37$</td>
<td>$-2.49$</td>
<td>$-1.81$</td>
<td>0.07</td>
</tr>
<tr>
<td>Distance to drainage $\times$ Elevation</td>
<td>$1.68 \times 10^{-5}$</td>
<td>3.16</td>
<td>1.81</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Table 8: Parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the best performing logistic regression model with drainage density

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standardized Parameter Estimate</th>
<th>$t$-Statistic</th>
<th>$p$-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.81</td>
<td>-</td>
<td>1.00</td>
<td>0.32</td>
</tr>
<tr>
<td>Drainage density (km$^{-1}$)</td>
<td>$-0.48$</td>
<td>$-0.60$</td>
<td>$-1.90$</td>
<td>0.06</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>$-0.013$</td>
<td>$-2.46$</td>
<td>$-3.86$</td>
<td>0.0001</td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>0.15</td>
<td>1.67</td>
<td>4.08</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 9: Parameter estimates, standardized parameter estimates, $t$-statistics, and $p$-values of the best performing logistic regression model with Topographic Wetness Index (TWI)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter Estimate</th>
<th>Standardized Parameter Estimate</th>
<th>$t$-Statistic</th>
<th>$p$-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$-0.75$</td>
<td>-</td>
<td>$-0.24$</td>
<td>0.81</td>
</tr>
<tr>
<td>Topographic Wetness Index</td>
<td>0.44</td>
<td>0.81</td>
<td>1.64</td>
<td>0.1</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>$-0.007$</td>
<td>$-1.35$</td>
<td>$-1.85$</td>
<td>0.06</td>
</tr>
<tr>
<td>Slope angle (degrees)</td>
<td>0.18</td>
<td>2.01</td>
<td>2.99</td>
<td>0.003</td>
</tr>
<tr>
<td>Distance to roads (m)</td>
<td>$-0.002$</td>
<td>$-15.62$</td>
<td>$-3.77$</td>
<td>0.0002</td>
</tr>
<tr>
<td>Saturated surface hydraulic conductivity (microns per second)</td>
<td>$-0.39$</td>
<td>$-2.63$</td>
<td>$-2.60$</td>
<td>0.01</td>
</tr>
<tr>
<td>Presence of silt soil type (ML and MH)</td>
<td>1.70</td>
<td>0.76</td>
<td>1.48</td>
<td>1.40</td>
</tr>
</tbody>
</table>
5.1.3.4 Comparison of the Performance of Developed Logistic Regression Models

The performance comparison of the above models is given in Table 10. It is seen that the model with downscaled soil moisture has the lowest AIC and BIC values, indicating that this model performs best among the developed logistic regression models. Thus, it can be concluded that remotely sensed soil moisture content is a more relevant explanatory variable in soil slide hazard assessment compared to currently used water drainage-based alternative variables.

Table 10: Comparison of the performance of logistic regression models

<table>
<thead>
<tr>
<th>Hydrological Variable in the Model</th>
<th>Log Likelihood</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downscaled soil moisture content</td>
<td>−17.90</td>
<td>51.8</td>
<td>74.92</td>
</tr>
<tr>
<td>Undownscaled soil moisture content</td>
<td>−23.33</td>
<td>60.6</td>
<td>80.89</td>
</tr>
<tr>
<td>Distance to drainage accessories (m)</td>
<td>−22.30</td>
<td>58.6</td>
<td>78.89</td>
</tr>
<tr>
<td>Drainage density (m$^{-1}$)</td>
<td>−49.71</td>
<td>107.4</td>
<td>118.98</td>
</tr>
<tr>
<td>Topographic Wetness Index</td>
<td>−23.28</td>
<td>60.6</td>
<td>80.79</td>
</tr>
</tbody>
</table>

Furthermore, the best performing model with downscaled soil moisture performs better than the model with undownscaled soil moisture, indicating that downscaling does improve the soil slide prediction capability of remotely sensed soil moisture.

5.1.4 Discussion of the Parameter Estimates of the Best Fit Logistic Regression Model with Downscaled Soil Moisture

The lone effect of downscaled soil moisture content (excluding its interaction effects with other factors) of the best fit model with downscaled soil moisture (Table 5) is statistically highly significant at a significance level of 0.09. Furthermore, the positive parameter estimate of 12.48 of the downscaled soil moisture content indicates an increase of soil slide hazard with the increase of soil moisture content. The elevated moisture levels cause a greater reduction in effective stress and matric suction that leads to decreased soil shear strength and slope instability. Moreover, the elevation of the location is significant at a 0.02 significance level, while the lone effect of distance
from roads is significant at a 0.01 level. The parameter estimates of distance from roads and elevation indicate an increasing soil slide hazard the distance from roads and the elevation decrease. This relationship is intuitive, as this indicates that locations that are closer to roads, which are typically at lower elevations, have a higher soil slide hazard. This is because the cutting of natural slopes for road construction reduces the confining pressure of the soil, thereby decreasing the soil shear strength, and thus the safety factor. Thus, locations that are closer to roads in a mountainous area that were employed in the study have a higher soil slide hazard.

The slope angle is also highly significant at a significance level of 0.003. The positive parameter estimate of slope shows that as the slope angle increases, the destabilizing force acting on the slope increases, thereby creating more favorable conditions for soil sliding. The saturated hydraulic conductivity of the surface soil is statistically significant at a significance level of 0.009. Furthermore, its parameter estimate of −0.52 indicates an increasing soil slide hazard with the decrease of soil hydraulic conductivity. When the hydraulic conductivity of soil is low, water takes a longer duration to drain from the soil, and thus the reduced shear strengths persist for a longer period of time. Hence, the soil slide hazard remains elevated for a longer period of time compared to a soil with a higher hydraulic conductivity. Moreover, the presence of silty soil is statistically significant at a level of 0.05, and the positive parameter estimate of silty soil indicates an increasing soil slide hazard with the presence of silty soil. The undrained shear strength of fine-grained soil is relatively low, and as a result slopes with such soils are subject to higher soil slide hazards due to the undrained conditions created during heavy rainfall.

In the developed logistic regression model, interactions between explanatory variables were considered, since the interaction effects aim to capture the synergistic or antagonistic effects between variables, and thus improve the model’s performance. According to the effect hierarchy
principle, the effects with a higher order such as those involving multiple factors are usually of lesser importance in a model compared to those due to the main factors and the interaction between two given factors [104]. Furthermore, the sparsity of effects principle states that usually, the main effects and low-order effects govern a system [105]. Thus, of the interaction effects, only the interactions between two given factors were considered as the governing interactions in this study. Moreover, according to the effect heredity principle, main factors with small effects typically show no significant interactions [106]. Thus, only the interaction between variables that demonstrated significant main effects such as downscaled soil moisture content, elevation, slope, distance to roads, saturated hydraulic conductivity, and silt soil type were considered.

The interaction between downscaled soil moisture content and distance to roads was the only interaction variable that was determined to be statistically significant, and it was significant at a 0.05 significance level with a coefficient of 0.02, as seen in Table 5. A parametric study was performed to observe the interaction effect of downscaled soil moisture and distance to roads on the probability of failure by eliminating the other variables. Equation 99 represents the effects that these two variables alone have on the probability of failure.

\[
P(f) = \frac{1}{1 + \exp[-(12.48 \times SM - 0.009 \times \text{Distance to roads} + 0.02 \times SM \times \text{Distance to roads})]} \tag{99}
\]

The soil moisture content was kept constant at a low value (0.05) and a high value (0.41) respectively, and the variation of soil slide hazard with the distance to roads was observed (Figure 20a). As expected, the probability of failure decreased with the increase of distance from roads. However, the probability of failure is higher at the high moisture level. In fact, at the higher moisture level, the reduction of soil slide hazard with the increase of distance from roads is minimal. Similarly, the distance from roads was kept constant at a low value (10 m) and a high value (2000 m), respectively, and the variation of the probability of failure was observed (Figure
It can be observed that the location at a shorter distance from roads displays an elevated soil slide hazard at the same moisture content, compared to the farther location from a road. The above results indicate that locations with elevated moisture levels that are located closer to roads will experience the highest soil slide hazard compared to locations with the same moisture levels but that are located farther away from roads, or locations that are closer to roads but with lower moisture levels.

Figure 20: Variation of probability of failure with distance to roads (a) under low and high soil moisture contents and (b) at low and high distances from roads.

5.1.5 Assessment of Fitness of the Developed Logistic Regression Model with Downscaled Soil Moisture Content

The logistic regression model developed with downscaled soil moisture content was employed to assess the probability of failure of all of the soil slide and non-soil slide locations that were used in this study, using Equation 59. Figure 21 is a plot of the predicted probability of failure for the selected soil slide and non-soil slide locations, whereas Figure 22 shows how a threshold
probability for the classification as failure/non-failure was determined by maximizing the classification accuracy.

Based on the model developed in this study, the classification accuracy can be expressed as a function of the threshold probability of failure, using Equation 100.

\[
A = -24.0657^2 + 26.4927T + 85.916
\]  

(100)

where \( A \) is the classification accuracy, and \( T \) is the threshold probability for classification as a soil slide. The optimum threshold probability of 0.55 was identified to provide the maximum classification accuracy for these data sets based on Equation 100, and it has also been plotted in Figure 22 to show the degree of its effectiveness.

Based on the above threshold, the model has an overall classification accuracy of 93.2%, with classification accuracies of 95.7% and 80.5% for Oregon and Kentucky, respectively (Table 11). Thus, it can be observed that the model performs fairly well in differentiating soil slide locations from non-soil slide locations on both geographical locations. Furthermore, in terms of the classification accuracies within the classes of soil slides and non-soil slides, the model performed fairly consistently as well. Nearly all (95.5%) of the soil slides in Oregon and 81.8% of the soil slides in Kentucky were classified correctly, while 95.7% of the non-soil slides in Oregon and 90% of the non-soil slides in Kentucky were classified accurately (Table 12). Hence, it can be envisioned that this soil slide hazard assessment model has broader geographical applicability for soil slides caused by conditions similar to those that were considered in this study. Moreover, the classification of soil slide locations in Oregon and Kentucky are mapped in Figure 23a,b respectively.
Figure 21: Distribution of the predicted probability of failure at the soil slide and non-soil slide locations.

Figure 22: Selection of the failure probability threshold by maximizing the classification accuracy.
Figure 23: Classification of soil slides in (a) Oregon and (b) Kentucky.

Table 11: Classification accuracies of Oregon and Kentucky

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Classification Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>All data</td>
<td>93.2</td>
</tr>
<tr>
<td>Oregon data</td>
<td>95.7</td>
</tr>
<tr>
<td>Kentucky data</td>
<td>80.5</td>
</tr>
</tbody>
</table>

Table 12: Classification accuracies of soil slide and non-soil slides for Oregon and Kentucky

<table>
<thead>
<tr>
<th></th>
<th>Oregon %</th>
<th>Kentucky %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil slides</td>
<td>81.8</td>
<td>95.5</td>
</tr>
<tr>
<td>Non-soil slides</td>
<td>90</td>
<td>95.7</td>
</tr>
</tbody>
</table>

The confusion matrix for the soil slide classification model with downscaled soil moisture is given in Table 13. This provides the comparison between true class versus class predicted by the model. The confusion matrix shows that six of the 100 non-soil slides were classified as soil slides, resulting in false positives. Furthermore, three of 33 soil slides were classified as non-soil slides, resulting in false negatives.
Furthermore, the frequency of soil moisture values at a 20-m distance from roads as well as the soil moisture thresholds for soil slide occurrence with distance from roads within an influence zone of 20 m were observed. Figure 24a shows the frequency distribution of soil moisture values within a 20-m distance from roads, while Figure 24b shows the soil moisture thresholds for soil slide occurrence within a 20-m distance from roads. The oscillation seen in Figure 24b can be attributed to gaps in a database corresponding to specific distance intervals to roads. In such cases, it is difficult to expect a smooth relationship between the threshold moisture and distance to roads. However, Figure 24b shows an increasing trend of the soil moisture threshold for soil slide occurrence with distance from roads, which indicates that locations that are at a closer distance from roads experience a greater threat of failure.

![Graph a: Frequency distribution of soil moisture at a 20-m distance from roads](image1)

![Graph b: Variation of soil moisture thresholds for soil slide occurrence with distance from roads](image2)

Figure 24: (a) Frequency distribution of soil moisture at a 20-m distance from roads and (b) the variation of soil moisture thresholds for soil slide occurrence with distance from roads within a 20-m influence zone.

Moreover, the variation of probability of failure with slope angle within a distance of 20m from a road, while the remaining variables were set constant at the average values observed in landslide and non-landslide locations, was plotted (Figure 25). It could be observed that when the
slope angle exceeds 14.5°, the probability of failure exceeds the threshold of 0.55, leading to slope failure, which can be used as a guideline in designing road cut slopes.

![Graph showing the variation of probability of failure with slope angle.](image)

**Figure 25**: Variation of probability of failure with slope angle.

**Table 13**: Confusion matrix for the results obtained with the soil slide classification model

<table>
<thead>
<tr>
<th>True class</th>
<th>Soil Slides</th>
<th>Non-Soil Slides</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil slides</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>Non-soil slides</td>
<td>6</td>
<td>94</td>
</tr>
</tbody>
</table>

**5.2 Analytical Model for Site-Specific Landslide Hazard Assessment**

**5.2.1 Verification of the Model**

An experimental study conducted by Abdul and Gillham [107], was used to verify the developed model. In the above study, a laboratory experiment was conducted using a plexiglass box of length 140cm, height 120cm and width 8 cm. The box was filled with medium-fine sand at a top slope of 12°. The sand used in the study was found to have a saturated hydraulic conductivity of 9x10^{-5} m/s and a total porosity of 0.34. Manning’s coefficient (M) of sand was assumed to be 0.0185 sm^{-1/3} in the numerical simulation [107]. The water accumulated at the downstream edge was discharged using a pipe into a stream. In the above experiment, the water table was located at the toe of the slope and the system was subject to a uniform rainfall of 4.3 cm/hour intensity.
bottom boundary and the side vertical boundaries were considered as no-flow boundaries. The wetting curve of this sand, obtained experimentally and published in the original publication [107], was employed as well in the authors’ numerical simulation.

The comparison of results obtained from the numerical simulation with those of Abdul and Gillham [107] is given in Figure 26(a), which represents the stream response variation with time. It must be noted that the stream response has been normalized with respect to the rainfall [108]. Figure 26(a) shows that the model results are in reasonable agreement with the Abdul and Gillham [107] experimental results.

Furthermore, the developed model was verified with respect to the analytical model developed by Srivastava and Yeh [15]. The comparison of pressure profile predictions from authors’ model to those of Srivastava and Yeh [15] for homogeneous ground conditions and uniform rainfall conditions is shown in Figures 26(b). A reasonable agreement can be observed between the predictions of authors model and the predictions from Srivastava and Yeh [15] analytical model.

Figure 26: Model verification (a) w.r.t. Abdul and Gillham [107] and (b) w.r.t. Srivastava and Yeh [15].
5.2.2 Case Study

The developed methodology was applied to a site with a homogeneous and isotropic colluvial silty soil with grid dimensions of \( X_1 = 11 \text{m}, X_2 = 13 \text{m}, X_3 = 31 \text{m} \), a slope angle of 30° and \( W=3\text{m} \) in Figure 16. However, it should be noted that this model is valid for a variety of slope geometries, boundary conditions, soil geotechnical properties and rainfall conditions. A saturated hydraulic conductivity of \( 5 \times 10^{-6} \text{ m/s} \) and average particle diameter of 0.05mm were assumed for this case. The corresponding SWCC parameters are \( a= 4.7, q=2.5, m=0.2 \) and \( P_r=3000 \text{ kPa} \), total porosity = 0.5 [109] and cohesion = 1.0 kPa and angle of internal friction = 21° [110]. The surface flow was modeled with Manning’s coefficient \((M)= 0.04\), representing a mountainous stream with no vegetation in the bed [111]. The slope was subject to a rainfall represented by a \( \pi \)-distribution with a cumulative value of 125mm and a duration of 10 hours (Figure 27).

![Rainfall modeled in this study.](image)

The contour plots of pore pressure on the slope at different times are given in Figures 28 (a-d). It can be observed that there is a rapid loss of matric suction near the surface of the soil at peak rainfall. With time, as rainwater infiltrates further into the soil, significant loss of matric suction is observed at the subsurface of the soil while the suction at the surface of the soil increases slightly due to deeper infiltration. After rainfall ceases, the suction of the soil is gradually restored.
Two toe failure circles, one shallow failure circle (Figure 30a) and one deep failure circle (Figure 30b) were considered in the stability analysis. The variation of FoS with time for the two failure circles is shown in Figure 31. With the shallow failure circle, the FoS decreases with the infiltration of rainfall into the soil, reaching a minimum around 2 hours after the rainfall peaks and then, the FoS increases gradually. With the deep failure circle, the variation of FoS with time is more gradual, as less rainwater infiltrates into the deep subsurface. Furthermore, the response to rainfall is delayed with the minimum FoS reached 3 hours after the end of the rainfall.

Figure 28: Pore pressure contours along the slope (a) prior to the beginning of rainfall, (b) at peak rainfall, (c) at the end of rainfall and (d) 14 hours after the cessation of rainfall (all the pore pressures are in kPa).
Figure 29: Pressure profiles for the slope at downstream.

(a)  
(b)  

Figure 30: (a) The relatively shallow failure circle and (b) the relatively deep failure circle considered in the study.

Figure 31: FoS variation with time for colluvial soil with $K_s = 5 \times 10^{-6} \text{ m/s}$ with shallow and deep failure circles.
5.2.3 Effect of the Interaction between Surface and Subsurface Flows

The variation of water film thickness, infiltration rate and surface flow velocity at upslope, mid slope and downslope locations are shown in Figure 32. The water film and surface flow begin to develop 2.5 hours after the beginning of rainfall. However, water film and the surface flow diminish soon after the rainfall peak. Furthermore, due to the development of surface water film and surface flow, it can be observed that the infiltration rate close to the peak rainfall exceeds the rainfall intensity. After the water film disappears, as expected, the infiltration occurs at the rate of rainfall. Furthermore, fairly similar variations of water film thickness, surface flow velocity and infiltration rates were observed at upslope, midslope and downslope locations.

Figure 32: Upslope, midslope and downslope variation of (a) water film thickness, (b) infiltration rate and (c) surface flow velocity for $K_s = 5 \times 10^{-6}$ m/s.

Next, the surface flow, water film thickness and infiltration variation were obtained for a higher $K_s$ of $5 \times 10^{-5}$ m/s. In this case, more infiltration of rainfall occurs into the soil and thus, no
surface flow or water film develops and the infiltration into the soil occurs at the rate of rainfall. Furthermore, the results in Figure 31 were compared to those observed at a lower hydraulic conductivity of $5 \times 10^{-6}$ m/s (Figure 32). Since less infiltration occurs into the soil initially, larger

![Figure 33: Upslope, midslope and downslope variation of (a) water film thickness, (b) infiltration rate and (c) surface flow velocity with $K_s = 2.5 \times 10^{-6}$ m/s.](image)

5.2.4 Sensitivity Analysis of Hydraulic Conductivity on FoS

A study was performed to evaluate the sensitivity of soil hydraulic conductivity ($K_s$) on the factor of safety. The variation of FoS with time with five $K_s$ values was observed (Figure 34a-b) for the two failure circles discussed in Section 4.7. Although the SWCC generally changes with the soil structure that causes changes in $K_s$ and hence $K_r$, the SWCC was kept constant in order to observe the sensitivity of $K_s$ on FoS.
The sensitivity of Ks on FoS for the shallow failure circle discussed in Section 4.7 is shown in Figure 34a while that of the deep failure circle discussed in Section 4.7 is shown in Figure 34b. From Figure 34a, it can be seen that the FoS decrease is more prominent as the Ks decreases. This is to be expected as lower Ks values lead to higher accumulation of water at the surface, thereby leading to higher loss of matric suction. The lowest FoS was observed for a Ks of 1x10^-5 m/s. The lower hydraulic conductivity of 5x10^-6 m/s demonstrate similarly low FoS values, however, the response is delayed due to the interplay between surface and subsurface flows, as discussed in Section 4.8. With Ks values of 2.5x10^-4 m/s, 1x10^-4 m/s and 5x10^-5 m/s, the rain water infiltrates faster into the soil without stagnating in the vicinity of the surface. This leads to lower reductions in matric suction and subsequently, higher FoS values.

Furthermore, according to Figure 34b, for a deeper toe failure circle, the FoS reduction is lower. However, the largest FoS reduction is still observed for a Ks of 1x10^-5 m/s while the lowest FoS reduction is observed for a Ks of 1x10^-4 m/s. It is also noted that there is a significant time lag between the occurrence of minimum FoS values between the 2 failure circles. The above time lag becomes more prominent as Ks decreases. For the lowest Ks of 2.5x10^-6 m/s, FoS is shown to be still decreasing after the 24-hour period for which the pore pressure variation was observed in this study.
Figure 34: Variation of the FoS for a (a) shallow failure circle and (b) deep failure circle with time for different hydraulic conductivity values.

5.2.5 Comparison of Navier-Stokes and Richards Equation-based Approaches

In this section, the advantages of using Navier-Stokes equations, in place of the Richards equation, in modeling transient seepage in soil is highlighted. It was shown in Section 3.3.1.3 that Navier-Stokes equation for conservation of momentum (y-direction) can be expressed as:

$$\frac{\partial (SnV)}{\partial t} = -\frac{\partial (SnP)}{\rho w \partial y} - \frac{\gamma wn^2 S}{K_y \rho w} V + \text{Sng}(\cos \theta)$$  

(101)
Assuming the porosity and degree of saturation of soil are constant, Equation 101 results in Equation 102.

\[
\frac{\partial V}{\partial t} = -\left(\frac{\gamma_w n}{K_y \rho_w}\right)V + \left(g \cos \theta - \frac{\partial p}{\rho_w \partial y}\right) \tag{102}
\]

where \(g \cos \theta - \frac{\partial p}{\rho_w \partial y}\) is the hydraulic gradient of soil. Assuming a typical site of a slope angle of 30\(^\circ\) modeled in this study consisting of a soil with a hydraulic conductivity of \(1 \times 10^{-5}\) m/s and a porosity of 0.5, which is subjected to a pressure gradient of 8kPa/m, observed typically at the beginning of the rainfall, Equation 102 becomes,

\[
\frac{\partial V}{\partial t} = -490500V + 0.496 \tag{103}
\]

Strictly, the Darcy's law is valid only under the steady-state conditions, i.e., when the term \(\frac{\partial V}{\partial t}\) is zero, i.e. when V is equal to \(1.01 \times 10^{-6}\) m/s based on the Equation 103. The velocities observed at initial stages of the rainfall are lower than the above and thus, the Darcy's law-based Richards equation would not be as accurate as Navier-Stokes equations in modeling transient seepage that prevails during short-duration high-intensity rainfall.

Furthermore, the results obtained using the Richards equation were compared to that of NS equations. For this comparison, seepage analysis was performed with the current model by setting the inertial term in Equation 45 to zero which simulates the condition applicable to the Richards equation. Figure 35 displays the % difference in outflow rates obtained by NS and Richards equation-based approaches, obtained using Equation 104:

\[
% \text{difference between outflow rates predicted by NS and Richards equations} = \frac{\text{Outflow rate predicted by Richards} - \text{Outflow rate predicted by NS}}{\text{Outflow rate predicted by NS}} \times 100 \tag{104}
\]
It can be observed from Figure 35 that the Richards equation generally tends to slightly overpredict the outflow rate compared to NS equations. This is particularly the case during infiltration when the degree of saturation of the soil is increases. However, once the infiltration ceases and subsequently the degree of saturation of the soil decreases, oscillations can be observed in the difference between the outflow rates predicted by the two models. The above oscillations reduce in magnitude with time but the slight overprediction continues.
CHAPTER 6: CONCLUSIONS

The objective of this section is to summarize the conclusions reached through the results obtained from this study. The first section provides a review of identified research gaps and how the research gaps were addressed by this study. The second section discusses the limitations of the developed approach and avenues for future research.

6.1 Contributions of the Study

The general objective of this dissertation was to develop improved methodologies for rainfall triggered landslide hazard assessment. This dissertation aimed to addresses the following two knowledge gaps:

1. The prediction of rainfall-triggered landslides in real-time is a difficult task, as regular and uninterrupted evaluation of the in-situ soil moisture conditions can be prohibitive due to the high cost and complexity of instrumentation involved. Thus, satellite-based remotely sensed soil moisture can be employed as an alternative. The feasibility of using downscaled remotely sensed soil moisture in soil slide hazard had not been evaluated statistically in previously existing models. Furthermore, the effect of remotely sensed soil moisture and soil hydraulic conductivity on landslide hazard had not been evaluated.
2. In the existing deterministic studies that assess slope stability during transient seepage using numerical and analytical methods, the continuous interplay between surface and subsurface water flows that prevail during landslide inducing high intensity storms has been seldom considered. Furthermore, all the existing models employ the Richards
equation to model transient seepage which is derived based on the Darcy’s law and hence, inherits the assumption of a pseudo-steady state. Hence, the seepage component of existing numerical models does not incorporate the inertial component.

Therefore, the objectives of this dissertation can be re-stated as follows:

1. Develop a statistical framework for using remotely sensed soil moisture available on a daily basis to monitor locations that are highly susceptible to rainfall-triggered soil slides at a regional scale, with a well-structured assessment procedure and evaluate the effect of employing remotely sensed soil moisture together with the soil hydraulic conductivity on the landslide hazard.

2. Develop a numerical model for slope stability assessment during transient seepage conditions which incorporates the effects of continuous interplay between surface and subsurface fluid flows on slope stability and employs fundamental fluid dynamics.

To achieve the first objective, two landslide prone sites from western Oregon and northern Kentucky were selected. A thorough vetting procedure was followed to pick only the soil slope failures from a vast database that contains historic landslides with different types of slope failures, including earth slides, rockslides, rock falls, mudflows, debris flows, etc. Thus, only the slope failures that were classified as ‘soil slides’ were selected for this study. The above demarcation enables this study to address a major deficiency in current statistical studies that blend different types of failure mechanisms in developing a single model, as identified by Budimir et al. (2015) [12]. Furthermore, the triggering mechanism of all of the selected slides was rainfall, and any landslide that was initiated by a precursory landslide was excluded from the study.

The remotely sensed soil moisture is available at a $0.25° \times 0.25°$ spatial resolution. Hence, the remotely sensed soil moisture images are downscaled to improve the spatial resolution. Soil
moisture is downscaled based on the downscaling model suggested by Wang et al. [79]. The above model has been determined to provide a better accuracy in downscaling soil moisture compared to alternative models used in previous studies [63]. The modification achieved by downscaling soil moisture was shown to be statistically significant for the prediction of soil slides, with the predicted soil slide hazard increasing with higher soil moisture contents. Furthermore, downscaled soil moisture was found to improve the prediction accuracy of the model compared to undownscaled soil moisture content.

Moreover, the best performing model with downscaled soil moisture was compared with that associated with alternative water-based factors that are commonly used in other such studies, namely: distance to drainage accessories, drainage density, and the Topographic Wetness Index. The downscaled soil moisture performs better than all of the physical-based factors in soil slide hazard assessment, and thus it can be concluded that the direct use of downscaled remotely sensed soil moisture content certainly improves the predictive capability of the model compared to alternative water-based factors.

Finally, a technique for determining a threshold probability of failure based on maximizing the classification accuracy is introduced to identify locations that are subject to high soil slide hazards from those with low soil slide hazards. For the dataset used in this study, this threshold was determined to be 0.55. The model provides a satisfactory overall classification accuracy of 93%, with 95% of the locations in Oregon, and 80.5% of the locations in Kentucky having been classified accurately. Furthermore, by comparing the classification accuracies of the soil slide and non-soil slide locations separately, it can be concluded that the developed model is capable of differentiating soil slide locations in both states of OR and KY with more or less similar accuracies. Thus, it can be concluded that the model performs equally well in both geographical regions,
promising a wide spatial applicability. Indeed, this is a significant advancement in the prediction capability of such models, since past studies have used remotely sensed soil moisture contents for soil slide hazard assessment primarily at a site-specific level [7,9]. Thus, this study demonstrates that with remotely sensed soil moisture available at a daily temporal resolution, and a well-structured assessment approach, it is feasible to implement a real-time process for the continuous monitoring of locations that are highly susceptible to soil slides in different geographical regions.

On the other hand, to achieve the second objective of this dissertation, a unified approach for modeling surface and subsurface transient fluid flow in unsaturated ground during rainfall has been proposed using fundamental fluid dynamic equations, namely the Navier-Stokes equations. The above approach enables the consideration of continuous interplay between surface water flow and subsurface hydrological processes which governs the rate of infiltration and is shown to have a significant bearing on slope safety assessment. Another advantage of using the Navier-Stokes equations over the widely used Richards equation to model transient seepage is that the inertial components of the flow can be considered in Navier-Stokes equations. Water retention and permeability characteristics of unsaturated ground have been incorporated using the soil water characteristic curve proposed by Fredlund and Xing [89]. Furthermore, a realistic landslide site containing a hillslope often surrounded by upstream and downstream flat land with an embedded non-horizontal phreatic line has been considered in this study in contrast to the commonly modeled infinite slopes. With a shear strength model based on effective shear strength parameters and matric suction incorporated in it, this model can be used to assess the slope stability with respect to time as the rainfall infiltration and the accompanied loss of soil matric suction take place.

Corresponding predictions from the developed model were compared with the experimental results obtained by Abdul and Gillham [107] and a good agreement was
demonstrated. The numerical prediction of the pore pressure variations were also compared with Srivastava and Yeh [15] analytical model. Furthermore, the surface flow was shown to impact the subsurface flow significantly, especially at low hydraulic conductivities. At low soil hydraulic conductivity values, a delayed response in critical FoS w.r.t. rainfall was observed. Due to the low infiltration capacity of such soils more water accumulates on the surface, leading to infiltration of rainwater to continue even after the rainfall terminates, thereby causing a delayed response in the critical FoS.

The developed model, which is applicable to unsteady state flow conditions, conveniently uses a parameter, namely the soil hydraulic conductivity that can be evaluated from laboratory tests and the variation in flow velocity to express the drag force. The sensitivity of soil hydraulic conductivity on slope stability, w.r.t. shallow and deep toe circles were assessed. It was concluded that, for both failure circles, slope instability is more prominent when the soil hydraulic conductivity is low as it leads to the stagnation of water at the surface for a longer period of time, leading to a greater reduction of matric suction. However, the response to infiltration is more delayed with a deep failure circle compared to a shallow failure circle, as expected.

The developed numerical model can be calibrated for a given hazardous site using the time variation of remotely sensed soil moisture content measurements to infer the representative in-situ saturated hydraulic conductivity of the site soil. Such a calibrated model would be capable of predicting landslide inducing pore pressure variations of the subsurface in real time.

6.2 Discussion of Limitations of the Study

Data from two study areas, namely western Oregon and northern Kentucky, were used in the first part of this study to improve the size of the database and extend the applicability of one model to many somewhat similar databases. As discussed in Section 1.5, the two study areas
contain similarities in terms of the many conditioning factors such as the mean and distribution of the slope angle, the distribution of land cover, and the distribution of road density. Only 33 soil slides that met the vetting criteria (Figure 10) were available and were thus used in developing the model for regional scale landslide hazard assessment. Although selected soil slides are representative of the type of soil slides in the study area, the use of a relatively low number of soil slides could have impact the predictive capability of the model. Furthermore, only the slides in areas with the same rock types were used in the study from the two study areas, thus eliminating any impact on the results due to differences in the geological conditions of the two study areas. Moreover, all of the selected slides had similar subsurface soil profiles as well. Thus, similarity in many conditioning factors between the two study areas was observed. However, some of the differences between the study areas are: (1) Kentucky receives higher average annual snowfall than Oregon. However, all of the possible soil slides due to snow melting were removed from the database, and thus, this factor could not have an impact on the model performance; (2) distribution and mean of the elevation; (3) mean road density; and (4) differences in any other unconsidered conditioning factor. Thus, the above dissimilarities between the two study areas could affect the model performance. However, the satisfactory and intuitive results obtained from model prediction support the implementation of such models on a wider scale, i.e., not restricting that to one study area.

On the other hand, the distance to roads is a highly statistically significant variable in the developed model. Naturally, the majority of soil slides that are conspicuous are at distances less than 100 m from roads. Since the soil slide data were collected from historical landslide databases, it is possible that the locations that are closer to human settlements and thus are more impactful to human lives are recorded more often than those occurring in sparsely populated areas, as discussed
by Carrara et al. [112], whereas non-soil slide locations are distributed randomly, leading to a bias in the dataset. This is reflected in the fact that many recorded false negatives and false positives are at distances greater than 100 m from the roads. Thus, the model can underestimate the soil slide hazard in sparsely populated areas. However, the model does highlight the conditions causing soil slide hazards in populated areas, the prediction of which are more critical to human lives. With the collection of better distributed soil slide data at a wide distribution of distances from roads and subsequent image interpretation, this bias in the model can be overcome, and the soil slide hazard at greater distances from roads can be assessed more reliably.

The resolution of downscaled soil moisture is larger than the mean size of the observed soil slides. The soil moisture content provided by satellite images will be the average soil moisture content in an area of 1 km$^2$ containing the soil slide, rather than the specific soil moisture content at the exact location of the soil slide. This is a limitation associated with the proposed model. Since the shear strength of a soil plays a major role in slope stability, the direct inclusion of available soil shear strength parameters at failed locations would obviously improve the prediction accuracy of the model. Hence, it is important to identify the potential failure planes and the corresponding shear strengths. Furthermore, the possible use of the alternative parameter of percentage increase in soil moisture content on the day of the soil slides due to rainfall with respect to the initial dry state, is expected to improve the predictive capability of the model further. As frontiers of technology expands, satellite-based continuous soil moisture evaluation would be upgraded, thus facilitating the soil moisture increases to be included in rainfall-triggered soil slide monitoring programs.

In the second part of this dissertation, the soil structure deformations due to infiltration of rainwater were assumed to be negligible. The deformation of soil structure leads to changes in soil
porosity, which influences the seepage [54][113][114]. The hydromechanical coupling which incorporates the above deformations helps to better understand the natural process of infiltration of water into unsaturated soil.

Moreover, the effect of hydraulic hysteresis of the soil water characteristic curve arising from wetting and drying cycles was not considered in this study. Past research has suggested that hydraulic hysteresis may have a significant contribution to the occurrence of landslides [114]. Thus, the developed model can be improved further by incorporating hydraulic hysteresis.

The developed slope stability assessment model uses the Bishops method, which is developed based on the assumption that the interslice shear forces balance. Thus, this method does not satisfy the overall equilibrium with respect to forces. The developed method can be improved by employing the Spencer [115] method, which satisfies the force equilibrium of each slice as inter-slice shear forces are considered. Furthermore, the soil was assumed to fail on a circular failure surface, whereas more general slip surfaces can be considered by employing the Morgenstern and Price [116] method.

6.3 Avenues for Future Research

With the advancement of technology, as remotely sensed soil moisture products with improved resolutions become available, the regional scale landslide hazard assessment model can be improved. As an example, the soil moisture images produced via SMAP (Soil Moisture Active Passive) mission provides remotely sensed soil moisture at 1-3km spatial resolution, which can be used to improve the developed model. Furthermore, the European Space Agency (ESA) is currently developing a root zone soil moisture product, which can be used to improve the model performance as well.
On the other hand, the site specific scale can be improved further by incorporating the hydro-mechanical coupling (as proposed by Wu and Selvadurai [54]) in the unsaturated zone, with the inclusion of the volumetric deformation of the soil skeleton to further upgrade the soil porosity term \((n)\) in Equations 68-70.

Finally, it is expected to calibrate the developed numerical model for in-situ saturated hydraulic conductivity, using remotely sensed surface soil moisture measurements (employed in Objective 1). This provides the capability to obtain subsurface soil moisture variation in real time, leading to a more reliable landslide hazard assessment method.
REFERENCES


APPENDIX A: MODELING NON-UNIFORM RAINFALL

This appendix discusses the derivation of the rainfall intensity-duration curve used in this study. As seen in Figure A, the time variation of intensity of a rainfall spanning T-hours can be represented in terms of a symmetric π-curve expressed in terms of Equations 4-1 and 4-2.

\[ 0 < t \leq t_s ; \quad r(t) = \frac{2I_0t^2}{Tt_s} \]  \hspace{1cm} \text{(A)}

\[ t_s < t \leq \frac{T}{2} ; \quad r(t) = \frac{-I_0}{\left(\frac{T}{2}-t_s\right)} \left[\frac{2t^2}{T} - 2t + t_s\right] \]  \hspace{1cm} \text{(B)}

where \( t \) is time, \( I_0 \) is the peak rainfall intensity. When the cumulative T-hour rainfall \( C \) is known, \( t_s \) can be obtained as follows:

\[ C = 2 \left[ \int_0^{t_s} \frac{2I_0t^2}{Tt_s} \, dt + \int_{t_s}^{T/2} \frac{-I_0}{\left(\frac{T}{2}-t_s\right)} \left(\frac{2t^2}{T} - 2t + t_s\right) \, dt \right] \]  \hspace{1cm} \text{(C)}

\[ C = 2 \left[ \frac{2I_0t^3}{3Tt_s} \bigg|_0^{t_s} - 2 \frac{I_0}{\left(\frac{T}{2}-t_s\right)} \left(\frac{2t^3}{3T} - t^2 + t_s\right) \bigg|_{t_s}^{T/2} \right] \]  \hspace{1cm} \text{(D)}

Thus, when the cumulative T-hour rainfall and maximum rainfall intensity are known, \( t_s \) can be found as;

\[ t_s = T - \frac{3C}{2I_0} \]  \hspace{1cm} \text{(E)}
Figure A: Variation of rainfall intensity with time for a rainfall with a $T=24$ hours.
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**An Improved Data-Driven Approach for the Prediction of Rainfall-Triggered Soil Slides Using Downscaled Remotely Sensed Soil Moisture**

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