MAKERERE UNIVERSITY

EFFECT OF SELECTED MECHANICAL PROPERTIES OF AGROFORESTRY TREE ROOTS ON SHALLOW-SEATED LANDSLIDE PRONE AREAS ON MT ELGON, UGANDA

By

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JANUARY, 2023

DECLARATION

I hereby declare that this research is based on my original work except for citations which have been duly acknowledged and that it has never been presented to any institution of learning for a Degree or Diploma or any other award.

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Signature..

Date.....4th - 01 - 2023..........

APPROVAL

This research dissertation has been prepared under our guidance as the academic supervisors to the above-mentioned student and is ready for submission to the Department of Geography, Geo-informatics and Climatic Sciences for the award of Master of Science in Disaster Risk Management.

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DEDICATION

To Zahara-my dear wife, Imran- my son, Bushira- my daughter, my mother Gimono Neumbe and Namataka G. who have stood by me throughout this journey.

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LIST OF ABBREVIATIONS

ALOS-PALSAR	Advanced Land Observing Satellite-Phased Array L-band Synthetic Aperture Radar
ANN	Artificial Neural Network
DBH (bdh)	Diameter at Breast Height
DEM	Digital Elevation Model
FN	False Negatives
FP	False Positives
FR	Frequency Ratio
GIS	Geographical Information System
GPS	Global Positioning System
IoE	Index of Entropy
IRB	Index of Root Binding
Km^2	Square Kilometre
LMT	Logistic Model Tree
LR	Logistic Regression
LSM	Landslide Susceptibility Map
MECDP	Mt. Elgon Conservation and Development Project
Mm	Millimetre
MRC-Mak	Makerere University Mountain Resources Centre
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NGOs	Non-governmental Organisations
ROC	Receiver Operator Characteristics curve
SDG	Sustainable Development Goals
SI	Standard units
SysFor	state-of-the-art artificial intelligence algorithms
TGB	Trees for Global Benefit
TN	True Negatives
TP	True Positives
UNBS	Uganda National Beaurue of Standards
UWA-FACE Project	Uganda Wildlife Authority Face Project

Abstract

Landslides continue to occur in the Elgon region despite interventions such as tree planting initiatives aimed at restraining them. The current study explored the efficacy of landslide model hybridization, tree-landslide relationship and selected mechanical properties of tree roots on slope stability with a keen focus on root tensile strength, soil shear strength, and index of root binding. A hybrid model comprising of frequency ratio, index of entropy and weighted overlay characterized landslide risk and its performance was evaluated using the Receiver Operator Characteristics curve. A standard deviation ellipse method was applied in the spatial distribution patterns of selected agroforestry trees. Tree-landslide relationship was tested using the Pearson correlation method while root tensile and soil shear strength variations were tested with a one-way (ANOVA). Study results indicated that Tsume was characterized as very high 4.70 km² (5.17%) and high 22.62 km² (24.90%) susceptibility with population density and soil type as the highest contributors (12.05%) and (10.86%) consecutively while slope least contributed with (3.40%). Overall model performance was very good with ROC (AUC = 0.91). Species distribution results indicate high dispersion of *Croton macrostachyus* and *Markhamia lutea* across the study area and high concentration of *Albizia coriaria* downstream. A weak negative correlation ($r = -0.20 < 0.01$) was observed between DBH and landslide size. A one way ANOVA test of tensile strength revealed significant difference among species with ($F(5, 573) = [18.161], p < 0.001$), and *Grevillea robusta* (3.02±1.217kg/mm²), *Albizia coriaria* (2.53±1.382kg/mm²), and *Markhamia lutea* (2.28±1.01kg/mm²) as the best performers. *Croton macrostachyus* (1.78±1.167)kg/mm² and *Cordia africana* (1.69±1.153)kg/mm². The best shearing species was *Albizia coriaria* with average shear strength (of 52.46±10.24) kpa followed by *Markhamia lutea* (50.70±15.47) kpa. *Eucalyptus spp*. underperformed with average shear strength (46.75±12.92) kpa. In conclusion, hybridization of single landslide susceptibility models significantly improves landslide mapping and prediction accuracy. The model also showed that population density and soil type are the major drivers of landslide in Tsume micro-catchment. Furthermore, presence of trees reduces landslide risk in an area and DBH is a very important guiding factor. Therefore, mitigation measures should target population control and soil conservation practices such as tree planting specifically *A. coriaria, G. robusta* and *M. lutea which have good slope stability characteristics.*

Key words

Hybrid model, landslide, Mount Elgon, tensile strength, shear strength, Tsume

CHAPTER ONE

INTRODUCTION

1.1 Background

Landslides are a global hazard that lead to dramatic loss of human life, property and soils every year (Chang et al., 2020; Tardío et al., 2016). According to Kavzoglu et al., (2015) landslides are responsible for 17% global fatalities, yet their occurrence is likely to increase due to effects of climate change and land use change (Tardío et al., 2016). In Africa, landslide have been responsible for deaths (3,171 persons), injuries (442 persons) and has affected 221,907 persons between 1910 to 2020 (Thongley and Vansarochana, 2021). This has been specifically reported in countries like Burundi, Kenya, DR. Congo, Tanzania, South Africa, Uganda and Morocco (Nakileza and Nedala, 2020; El Jazouli et al., 2020). In the East Africa 14 million highland people have been affected by landslides and floods combined between 1971 and 2015 (Bahal'Okwibale, 2018).

These enormous impacts have stirred immense studies on landslide causal factors and solutions amongst which include application of trees to restrain landslide risk (Aghda and Razifard, 2017). This use of trees is part of the ideas known as eco-engineering method (Tardío et al., 2016) . By definition Eco-engineering is the planting of trees with good soil stability traits or characteristics that restrain landslides. It was first introduced in 1930s (Mulyono et al., 2018) to stabilize slopes prone to landslides and soil erosion in mountainous areas like Elgon. To date, this method has proven its worth as a hydraulic channel, ground movement barrier and hydraulic pump (Hairiah et al., 2020; Balzano et al., 2019; Ghestem et al., 2011).

In the Mt. Elgon region, studies (e.g. Nakileza & Tushabe, 2018; Nakileza et al., 2017) have however, addressed links of landslides to biodiversity and also recognized the importance of trees on increasing soil shear strength through tensile force provided by plant roots thus reducing landslide risk on scars. Mugagga et al., (2012) on the other hand assessed the role of land use change on landslide occurrence and found that the exponential conversion of forest land to agriculture greatly contributed to the current landslides. Recently Graham, Ihli, & Gassner, (2021) noted that agroforestry could improve community to mitigation and adaptation to climate change.

This current study analysed the mechanical role of tree roots on slope stability towards reducing landslide risks in the Tsume catchment. The key focus is on the dominant agroforestry tree species in the area.

1.2 Problem Statement

The use of plants to restore and protect landslide susceptible areas has been widely accepted as an effective eco-engineering measure (Tardío et al., 2016). This has triggered numerous tree planting initiatives by the local communities, Non-Governmental Organizations (NGOs) and government agencies in Mount Elgon region. For instance, the Face Foundation (UWA-FACE Project) in 1993 (Snoep, 2011; Lang & Byakola, 2006), the Mt. Elgon Conservation and Development project (MECDP) in 2003 (Snoep, 2011), and Trees for Global Benefit (TGB) (Masiga et al., 2012) among others. However, landslides continue to occur even in some of the restored areas (Nakileza & Nedala, 2020) raising debate on whether tree planting is still an effective method for preventing slope failure. Besides, landslide prediction has been dominated by single bivariate statistical models as noted by Mande et al. (2022) and Nakileza & Nedala, (2020) which do not cater for the complex and nonlinear characteristics of landslides thus undermining landslide prediction accuracy. Overall, limited research has been conducted on the efficacy of hybrid models on landslide prediction and the influence of agroforestry tree types particularly soil root reinforcement on slope stability enhancement in the region (Spiekermann et al., 2021; Hairiah et al., 2020).. Therefore, the current study sought to address this information gap by generating a hybrid model, assessing its performance, and quantifying tree roots influence on slope stability in Tsume micro catchment.

1.3 General objective

The study aimed to contribute towards development of an effective Landslide Eco-engineering Mitigation and Resilience plan through availing vital plant information for landslide risk reduction.

1.3.1 Specific objectives

- To identify and characterize landslide susceptible zones in Tsume micro catchment using hybrid model
- To analyse spatial distribution and characteristics of selected tree species with potential to reduce slope failure in high landslide susceptible zones.

To determine selected tree species root reinforcement characteristics as a feature for promoting adoption by farmers and resource managers.

1.3.2 Research Questions

1. Which areas in Tsume micro catchment are prone to landslide hazard?
2. What are the biophysical characteristics of areas in Tsume micro catchment that are prone to landslide hazard?
3. What is the most influential pre-conditioning factor leading to landslide occurrence in Tsume micro-catchment?
4. What relationship exists between tree spatial distribution and landslides?
5. What are the tree-root reinforcement attributes for landslide risk reduction in Tsume micro catchment?

1.4 Justification

The relevance of this study lies in availing vital information on plant root systems to support tree species selection and adoption for slope stabilization in high landslide susceptible zones of Uganda. The research therefore, contributes towards achievement of SDG 13 and 15 which aim at reducing climate change risks and its impacts such as landslides, and conserving and restoration of terrestrial ecosystems including mountains through ending deforestation. The research further contributes to achievement of aspiration 1 goal 7(4) of the agenda 2063 which aims at increasing climate resilience and natural disaster preparedness and prevention (African Union, 2015).

The Office of the Prime Minister, Department of Relief Disaster Preparedness and Management, Ministry of Water and Environment (MoWE); National Forestry Authority (NFA); Uganda Wildlife Authority (UWA); National Environmental Management Authority (NEMA); and Department of Climate Change, Ministry of Water and Environment will use this research as a basis for developing a tree planting policy for combating landslide hazard in high susceptible areas. The NGOs such as Africa 2000 Network (A2N), Tree Adoption etc. will use this information as a guide during resource allocation in particular tree species to community thus avoid planting wrong trees in right places.

The community will make use of the information for informed decision making on which tree species to plant in order to protect and restore their farmlands and increase the safety of their homesteads. Lastly to researchers this research will be a bench mark for further studies in tree-slope stability and landslide management relationships in Uganda.

1.5 Scope of the study

The study was conducted within 93.1 Km² of Tsume micro catchment of the Upper Manafwa Watershed. The study area was selected based on the prior hotspot analysis that revealed high concentration of landslides. Besides, in 2018 a total of 40 people lost their lives as result of landslide in the area. Recently the local media (Daily Monitor, Date July 6, 2022) reported a 3km landslide crack Figure 1 in the catchment which aggravates the risk to the community. This landslide crack was attributed to heavy rainfall that triggered its formation. The tasks in this study entirely focused on: developing a landslide susceptibility map, mapping the distribution of selected tree species while taking measurements of their diameter at breast height (DBH); mapping relationships between landslides and vegetation; analysing root tensile strength, Index of Root Binding (IRB) and soil shear strength in a period of 30 weeks from January 2022 to August 2022. This period was purposely selected to represent both the wet and the dry season. Shear strength analysis was carried in wet season to represent the actual in-situ soil conditions. Only landslides with area (≤450m²) and depth (≤3m), as guided by Collins et al., (2012), were included in the study.

Figure 1: Landslide cracks in Nakhatore village, Tsume micro-catchment

1.6 Conceptual framework

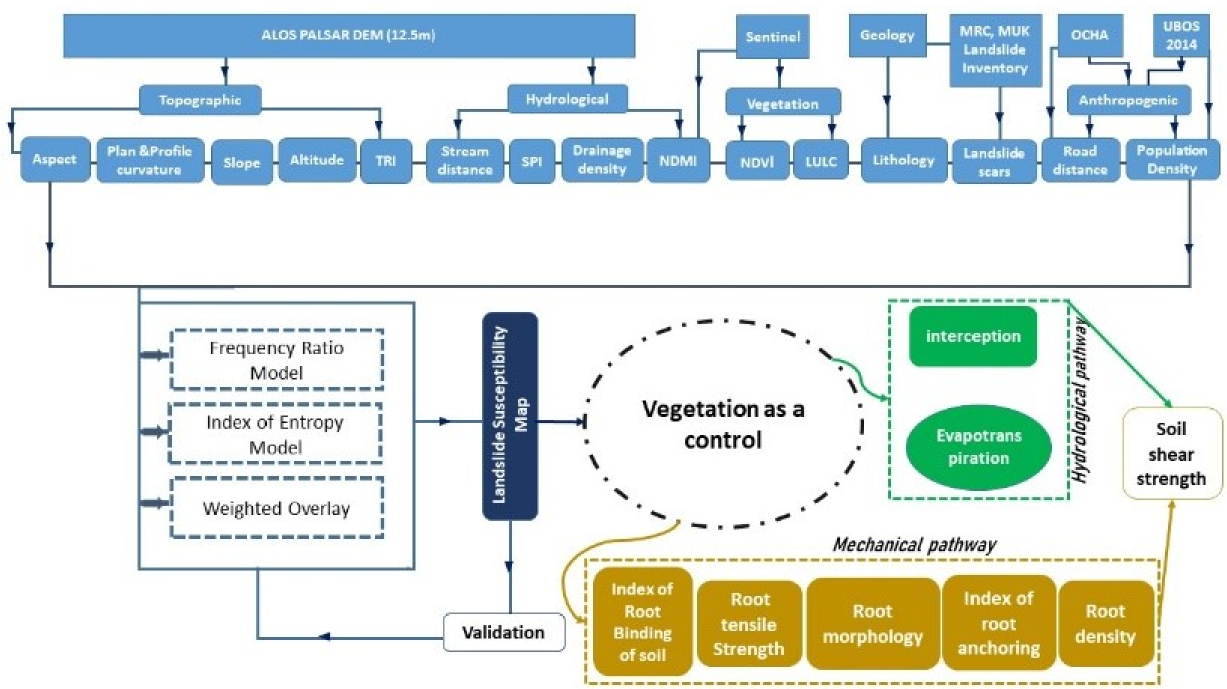
Landslides occur as a result of numerous causative factors (Figure 2) which include; geomorphic, topographic, hydrologic, vegetation, geologic, meteorological, human and pedological factors (Zhao & Chen, 2020). These prepare and operate synergistically to cause landslides, and therefore understanding each factor contribution is a significant milestone towards accurate landslide prediction and management (Devkota et al., 2013). In this particular study however, vegetation as a control through selected mechanical pathways was analysed. Vegetation is the most important landslide causative factor during landslide risk management because it emerges as both a landslide control (Purwaningsih et al., 2020) when well managed and a trigger when mismanaged (Li et al., 2021). This results into a negative feedback or a positive feedback loop respectively.

Vegetation in the negative feedback loop mechanism can be conceptualized as "*Planting a Right Tree in a Right Place"* in this particular study. This concept focuses on only those slope stabilization benefits attained when trees with good characteristics are planted on unstable slope. The good characteristics of trees can be categorized into mechanical and hydrological pathways among others. For instance vegetation facilitates runoff generation compared to infiltration in the process known as interception (Okello et al., 2015). Vegetation also controls soil hydrological properties through increasing suction pressure in a process known as evapotranspiration (Nakileza et al., 2017; Chirico et al., 2013). This enhances the formation of well-drained soil surface horizon (Preti, 2013) and thereby stabilizing a slope. These two processes are categorized as the hydrological pathway of the negative feedback loop.

Furthermore vegetation roots contribute to increased shear strength by providing additional reinforcement parametrized as apparent cohesion in slope stability models (Yu et al., 2020; Preti, 2013). These root reinforcement characteristics can be independent of hydrological and chemical properties but rather, dependent on a combination of tensile strength, root density, root depth, and root architecture (Lee et al., 2020). The root density and root architecture can be used to measure horizontal root reinforcement using index of root binding (IRB). These are known as the mechanical pathways of vegetation control.

Planting of *"Wrong Trees in a Right Place"* is the second concept of this research ought to be addressed. This notion falls within the positive feedback loop mechanism of vegetation on landslide. This concept is achieved when accurate prediction of landslide hotspots is performed considering causative factor influence. However, trees with poor slope stability characteristics are planted thus exacerbating landslide formation. Yu et al., (2020) and Nakileza et al., (2017) explored some of the positive feedback mechanisms of trees and vegetation and agreed that mature trees contribute to landslide formation through exerting addition weight on to already unstable slopes. FAO, (2010) added that trees maybe limited especially during windy conditions, on deep landslides, and on very steep slopes but acknowledged that still trees would make a difference.

Therefore, planting trees of negative feedback characteristics in a high landslide susceptible zones after accurate prediction of landslides by considering each causative factor influence would result in an effective landslides control. This is termed as planting "*Right Trees in the Right Place*" as recommended by (Nakileza & Nedala, 2020) as appropriate greening strategy.



Source: Adopted and modified from (Mulyono et al., 2018)

Figure 2: Study Conceptual framework

CHAPTER TWO

LITERATURE REVIEW

2.1 Landslide mapping and characterization

Landslides or landsliding is a well-known subject in Uganda, especially in the Elgon region where their occurrence is abnormally frequent. It is a well-researched subject by numerous scholars (Makabayi et al., 2021; Bamutaze, 2019; Van Eynde et al., 2017; OPM, 2016; Misanya & Øyhus, 2015; Dierickx, 2014; Mugagga et al., 2012a; Knapen et al., 2006). These studies have tried to answer questions as to; why they are common? Where they are common? Landslide implications and solutions among others. In 2014, Dierickx, (2014) studied the socio-economic consequences of landslides in the region considering buildings as one of the major elements at risk. However, most studies have deliberated on deep seated landslides in the region such as the Bukhalasi 2010 landslide and Nametsi 2018 landslide with little attention to shallow seated ones. According to (Balzano et al., 2019) shallow landslides are one of the most important hazards as they have the potential to culminate into highly destructive slides and mudflows. Unfortunately these have not been well studied especially their predictability as stressed by (van Zadelhoff et al., 2021).

2.1.1 Landslide susceptibility mapping

The first critical step in disaster risk management such as landslides in any ecological unit is hazard identification which involves susceptibility mapping (Zhao & Chen, 2020). Landslide susceptibility mapping is defined as the probability of landslide occurrence in certain area under force of action by pre-conditioning factors such as environmental, geological and human activities (Chen et al., 2020). Three distinct approaches for analysing landslide susceptibility have been brought forth and these include statistical modelling, machine learning and hybridization (Chen et al., 2020). However, existing literature has indicated the dominance of statistical models such as logistic regression, frequency ratio, neural networks, overlay, statistical index, evidential belief functions, certainty factor, weight of evidence, index of entropy (Yordanov & Brovelli, 2020) over the others. Nevertheless Roslee et al, (2017), examined the adoption of these approaches and revealed that statistical models are quantitative and can evaluate various effects of each pre-conditioning factors on a case by case basis. In contrary, Kavzoglu et al., (2015) found that statistical approaches draw their conclusions on the assumption that future landslides will be more likely to occur under similar condition to those of the previous landslides which presents some weaknesses.

To counter some of these assumption errors, machine learning models were proposed to fit and predict nonlinear correlations between landslides and conditioning factors (Chang et al., 2020). These include the Random Forest, Artificial Neural Networks (ANN), Kernel machines, Support Vector Machines, Credal Decision Tree, and Radial Basis Function Network (Dung et al., 2021; Lee et al., 2017) among others.

It is of recent that new efficient approaches have emerged to predict landslide risk which, include hybrid models (Dung et al., 2021; MFONDOUM et al., 2020). By definition hybrid models refers to the integration of two or more independent models to solve a single problem. For example (X. Zhao & Chen, 2020) integrated the decision tree model and the logistic regression (LR) model to produce a Logistic Model Tree (LMT). In their research, hybrid model (LMT) was found to be a better predictor of landslides than the single models.

Chen et al., (2020) integrated state-of-the-art artificial intelligence algorithms (SysFor) and two bivariate models, namely the frequency ratio (FR) and index of entropy (IoE), to predict landslides. From their analysis the FR_SysFor model and IoE_SysFor model, which are hybrid models, performed better than the single models under study.

Meanwhile (Dung et al., 2021) explored the effectiveness of Bagging-RS and AdaBoost-RS hybrid models on landslide susceptibility Son La hydropower Reservoir. From their finding the hybrid models performed better than all single models with Bagging-RS being the best predictor. As such (Dung et al., 2021; Zhang et al., 2019) concluded that hybrid models are more fitting to landslide susceptibility mapping than any others because they cater for all complex and nonlinear characteristics of this event.

In Uganda however, landslide susceptibility mapping has followed single statistical models (Nakileza & Nedala, 2020; Broeckx et al., 2019; OPM, 2016; Staudt et al., 2014) that are wanting (Chen et al., 2020) to predict landslide risk. It is in this regard that this study has focused on integrating frequency ratio model, index of entropy and weighted overlay to accurately predict landslide hazard in Tsume micro catchment of Manafwa watershed.

2.1.2 Landslide characterization

In order for one to characterize landslide susceptibility into zones also known as hazard zonation, GIS and remote sensing has been a tool of greater importance because it spatially integrates all the pre-conditioning and trigger factors into one (Roslee et al., 2017). It is from this integration that areas under threat of landslide hazard can be characterized as very high or very low based on statistical and empirical methods in GIS (Cabral et al., 2021). Several parameters have been included in landslide characterization e.g. slope, landuse, distance to streams to mention but a few. For instance, slope is one of the input parameters for landslide characterization which measures the stress distribution inside a slope and effective surface (Zhang et al., 2019). When subjected to snow melting, heavy rainfall, earth quakes, volcanic activities, and land use change that are the major triggering factors (Kavzoglu et al., 2015), then landslides are bound to occur in areas of high slope. Similarly vegetation, aspect and hydrological regimes are equally significant in influencing landslides (Zhang et al., 2019). Lithology on the other hand determines the mechanical strength, weathering resistance, and stress distribution which in turn influences slope stability (Zhang et al., 2019). Therefore, combining lithology with other landslide conditioning factors would produce a more accurate landslide susceptibility map.

Landslide characterization however, suffers from one novel challenge which is selection of the best parameter combinations (Kavzoglu et al., 2015). The parametrization processes is dependent on expert knowledge creating a research gap (Roslee et al., 2017; Kavzoglu et al., 2015). The weight of evidence model is one of the approach that curtails this problem because it is a data driven model (Mande et al., 2022). To produce a logical hazard zonation map, there should be some level of data consistence (Kavzoglu et al., 2015) and parameter standardization which this study intended to address using hybrid model.

2.2 Agro-forestry and slope stability

Vegetation as a landslide control measure has been widely studied by scholars worldwide. Sofia & Afonso, (2019) studied the significance of herbaceous plants, shrubs and trees on slope stability. Their study focused on different pathways in which herbaceous plants, shrubs and tree contribute to slope stability and concluded that trees were more suited for slope stability than herbs. Normaniza et al., (2008) studied the role of leguminous tree *Leucaena leucocephala* on slope stability and concluded that this tree was best suited for slope stability due to high root reinforcement capacity characteristics and high-water absorption capacity. Other studies by state include Kenya (Nyambane & Mwea, 2011); Indonesia and China (Li et al., 2021); USA (Roering et al, 2003); Alaska, Thailand, Canada, New Zealand, Australia; the Mediterranean regions (Hairiah et al, 2020); and Japan (Tsukamoto, 1990) etc., have harnessed tree planting technology by drawing linkages among root strength, landsliding, and forestry tree stands.

In Uganda diminutive attention has been given to agroforestry as landslide control, yet it is the most wide spread initiative adopted by the local community (Mertens et al., 2018). Mertens et al., (2018) studied community perceptions towards landslide hazard controls measures in Kasese district and found that the adoption of tree planting technology was driven by multiple benefits derived from it such as hydrological control, source of energy, source of timber, windbreaker, and source of food among others. Moreover, Buyinza et al, (2020) found that *Cordia africana*, *Albizia coriaria*, *Grevillea robusta* and *Eucalyptus* are the most preferred tree species in Elgon region for landslide risk reduction. Similarly Lunyolo et al., (2021) also found that Eucalyptus species was the dominant tree species utilized for landslide hazard management especially scar recovery because they are fast growing trees. As such Mertens et al., (2018) has described tree planting as the cheapest and within reach control method of landslides by local farmers thus its wide spread.

Nevertheless, there is no systematic scientific research that has been done tailored towards understanding the influence of vegetation on slope stability. That is to say most existing literature focuses on influence of soils (Bamutaze, 2019; Kitutu et al., 2009), shear strength (Mugagga et al., 2012a), land use change (Mugagga et al, 2012b), meteorology (Okello et al., 2015 and Knapen et al., 2006) and topography (Nakileza & Nedala, 2020) creating a research gap.

Most of the existing studies have concluded that vegetation stabilizes slope by strengthening soil structure through hydrological and mechanical means (Ettbeb et al., 2020). The hydrological means of control include suction and interception while mechanical means include increased cohesion as a result of roots and soil particle interaction. Therefore, this study quantified the mechanic influence of selected agroforestry tree species on slope stability in Tsume micro catchment by relating tree species distribution and dbh to landslide slide scar formation.

2.3 Tree root reinforcement for slope stability

Roots are very important structures on plants that provide anchorage to the ground. These root anchorage and reinforcement capabilities are the most important factors of slope stability (Lee et al., 2020). They are characterized by tensile strength which is the measure of force at root rapture to its diameter (Badhon et al., 2021). Roots can respond to shearing force in three ways namely stretching, slipping, and breaking (Tosi, 2007). As such they contribute additional soil strength against horizontal forces during shearing on a plane (Wang et al., 2020). Many scholars have gone an extra mile to evaluate relationships between tensile strength and root diameter (Ettbeb et al., 2020). Their studies have found that root distribution is heterogeneous and the root reinforcement results are controlled by large roots, which hold much more force than small roots (Hairiah et al., 2020).

In summery landslide susceptibility mapping is a critical step in managing landslide risks but the methods of susceptibility modelling are equally important. Eco–engineering was recognized as the most utilized landslide control method by several researchers and community because it is cheaper. Based on the reviewed literature, the most preferred tree species for landslide control were *Cordia africana*, *Albizia coriaria*, *Grevillea robusta* and *Eucalyptus*. However, there was limited information quantifying species by species contribution and roots contribution to slope stabilization. Reviewed literature indicated that susceptibility assessment in Manafwa catchment followed statistical methods such as logistic regression, frequency ratio, and weight of evidence. These do not account for all complex and nonlinear characteristics of landslide events. Thus, calling for improved model versions such as hybridization or use of hybrid models.

CHAPTER THREE

METHODOLOGY

3.1 Description of Study area

Tsume micro catchment is part of the Manafwa watershed located on the upper slopes of Mt. Elgon, stretching to about 93.1Km² (Figure 3). The catchment lies between latitude 0º 59` 0" N to 1º 7` 0" N and longitude 34º 21` 30" E to 34º 32` 0" E with a maximum altitude of 4,226 meters and a minimum of 1,789 meters (a.s.l). River Tsume, Ulukusi and Ukha drain the area pouring their waters in River Manafwa which finally empty's in Lake Kyoga through Mpologoma wetland. The main geology is fenitised basement rocks (Kitutu et al, 2009) and the main soil types are luvisols, feralsols, nitosols and leptosols (Nakileza & Nedala, 2020).

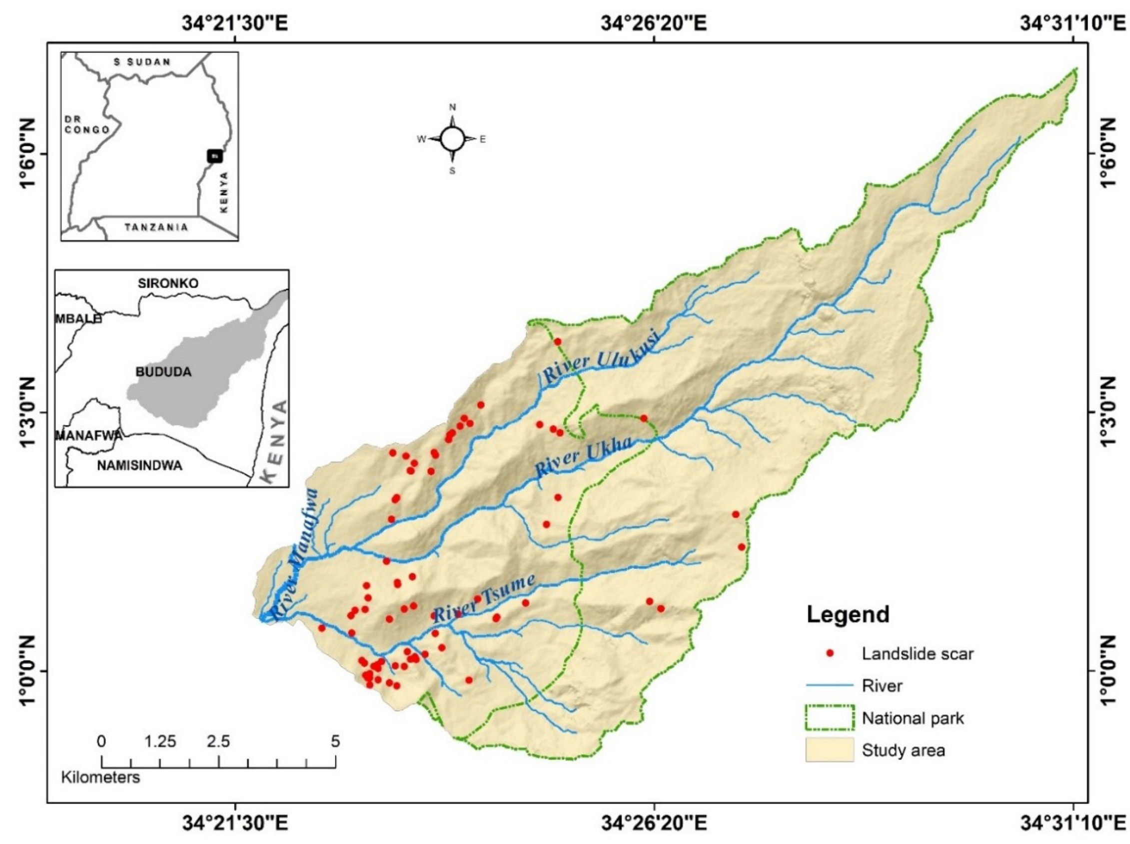


Figure 3: Location of Tsume micro catchment in Uganda

3.1.1 Relief

Tsume comprises of various unique relief features such as the V-shaped valleys, sharp ridges and cliffs (Atuyambe et al., 2011). Specifically the Nusu ridge and Bukhalasi transect are iconic landforms in the micro-catchment characterised by many translational landslides (Makabayi et al., 2021); Claessens et al., 2007). Besides, the slopes of the cliffs and ridges in Tsume appear rectilinear and sharply dissected (Nakileza & Nedala, 2020) due to loss of vegetation and soil type.

3.1.2 Climate

Tsume is situated in a biomodial climate zone with two rainfall season MAM and SOND (Opedes et al., 2022).The annual precipitation of the area ranges from 1000mm to 1600 mm (Nakileza & Nedala, 2020) due to terrain and dense montane forests (Sebatta et al., 2020) of Mt Elgon National Park in the North Eastern part of the micro catchment. The mean average temperature ranges from 15˚C to 23˚C (Opedes et al., 2022; Graham et al., 2021; Mukadasi et al., 2007).

3.1.3 Vegetation cover

Tsume shares similar vegetation characteristics as the entire Elgon region. The vegetation is zoned altitudinally with montane forest types (Sebatta et al., 2020). Afro-Alpine and moorland cover cover areas above 3500m, heath zone (35,000–3000 m), low canopy and mixed bamboo (3000 m to 2500 m), tropical montane forest (2500 m–1800 m), and the farmlands at the foot slopes (Opedes et al., 2022). Common indigenous tree species in the area include *Markhamia lutea*, *Albizia spp*., *Ficus spp*. and *Cordia africana* (Graham et al., 2021). Yushania *alpina* bamboo (Paul et al., 2015) is dominant in high zones.

3.1.4 Socio-economic set up

Agriculture is the major economic activity of the area dominated by subsistence farming (Sebatta et al., 2020). Coffee forms the major cash crop in area grown on an agroforestry system of trees and bananas (Gram et al, 2018). In wet seasons, annual crops such as maize, beans, onions and cabbages are grown (Opedes et al, 2022). Onions are the second-best cash crop after coffee grown within the transboundary management areas of the park. The area is also famously known for eating bamboo shoots of *Yushania alpina* (Paul et al., 2015) locally known as "*Malewa or Maleya*"(Paul et al., 2015).

3.2 Research Approach & Design

A quantitative research approach comprising of mapping surveys and experiments was used to achieve the study objectives. All research activities were concentrated in the very high-risk zones of the landslide susceptibility map and landslide scars. The landslide sampling frame was (*N=171*) scars clustered into two strata namely; landslide in the national park and landslides on community land using the Elgon National Park shapefile, as a classifier regardless of landslide size.

A stratified random sampling technique based on ArcGIS random sampling tool was used to generate sample elements (landslide scars) automatically. A total of (*n=12*) landslide scars was generated where 20 meters buffer was established. The buffer distance was informed by Sofia & Afonso, (2019) who indicated that mature shrubs and trees can extend their roots up to $\geq$16 meter distance or as twice as their canopy. Given the high variations in landslide environmental conditions, size and depth across the study area, scars of area ($\leq$ 450m^3) and depth ($\leq$3m) were considered (Collins et al., 2012) and treated equally as much as possible (Burger et al., 2021). Identification of species, dbh measurements and mapping of agroforestry trees was confined within the 20m buffer.

For root tensile strength analysis, 9 samples Osman et al., (2011) of saplings of each selected agroforestry tree species in the 20m buffer with a dbh $\leq$ 5cm Hairiah et al., (2020) were randomly selected. Only roots with diameter $\leq$ 6mm were considered for tensile strength analysis (Nyambane & Mwea, 2011). This was because the available tensile strength apparatus could only manage small roots of diameter $\leq$ 6mm.

A total of 198 soil shear strength samples were randomly collected at an interval of $\leq$2m from the tree base. Of the total samples (168) were tested *in situ* and 30 were tested in lab for validation. Replicates (28) for *in-situ* and 5 for validation per species were carried out. Direct shear test was done from the lab in accordance with the ASTM D3080 standards (Rasti et al., 2021; Islam et al., 2021). Nevertheless, sampling was limited to only trees that met the tree selection criteria with 5 replicates per species.

3.3 Data Collection Methods

This section presents data types, materials and methods used to achieve the study objectives. It expounds on data types and their sources, roots and soil sampling procedures, sample preparation procedures, spatial analysis tools used, the key methods of data analysis and how they were applied.

3.3.1 Landslide susceptibility modelling

A total of sixteen (16) conditioning and trigger factors were considered for the development of landslide susceptibility map based on the commonly reported factors whose data is readily available (Mande et al., 2022; Opedes et al., 2022; Nakileza & Nedala, 2020) These include; slope angle, altitude, plan curvature, profile curvature, topographic wetness index, slope aspect, stream power index, lithology, drainage density, distance from streams and rivers, distance from road, vegetation cover represented by Normalized Difference Vegetation Index (NDVI), soil moisture represented by Normalized Difference Moisture Index (NDMI) (Fatemi Aghda et al., 2017), land use/cover, topographic roughness index and population density. All conditioning factors were carefully selected to represent topographic, hydrologic and human interactions (Sahana, 2017) unlike most susceptibility models in the study area that entirely focused on biophysical parameters.

High resolution DEM ALOS-PALSAR of 12.5 meter (Ghosh et al., 2020; Alahmadi, 2019; Nitheshnirmal et al., 2019) was acquired from Alaska Satellite Facility (https://search.asf.alaska.edu/#/) and re-projected to Arc1960 UTM 36N to derive topographic and hydrological parameters.

Landslide scars were obtained from Makerere University Mountain Resources Centre database, (MRC-Mak) and the previous study databases by Lunyolo et al., (2021) and Nakileza & Nedala, (2020). These were validated and updated through field visits using a TDC600 GPS and google earth image. About 90% of data from the databases was point data thus suitable for model training and validation.

The NDVI and NDMI were computed from 10- and 20-meter sentinel 2B images to evaluate vegetation influence and soil moisture respectively. Acquired images were downloaded from Copernicus open data hub with <10% cloud cover. Resolution of all datasets was harmonized using bilinear upscaling method and mean downscaling method to 12.5m spectral resolution (Tavares et al., 2019). The Humanitarian Data Exchange portal by OCHA accessed through link (https://data.humdata.org/) was visited for updated road networks data (Payne et al., 2012). These were validated using UNRA road data layer and gaps were filled by digitizing recent Google Earth Pro images

3.3.2 Mapping the spatial distribution of agroforestry tree species

Tree species selection

The criteria for selecting tree species for research included; dominant agroforestry species in the study area, well researched trees (e.g. *Calliandra* and *Cordia africana)* in regard to landslide control (Mulyono et al., 2018), and indigenous tree species such as *Markhamia lutea*. Focused Group Discussions (6) were held in different places (Munyende village, Ibookho, Bundesi primary school, Itimbwa, Nakhatore and Bukhalasi Primary school) to identify commonly planted agroforestry tree species (Figure 4). Details on FGD meetings are provided in Appendix 1. The results from the FGD were then used for the study

(a) FGD with male farmers in Ibookho village, Bukalasi

(b) FGD with female farmers in Ibookho village

Figure 4: Focused Group Discussion with farmers during reconnaissance

Tree mapping

The landslide susceptibility and landslide scar maps were used to determine mapping areas. That is to say, the most susceptible areas and landslide scars were extracted and uploaded to QFIELD Mobile Application on TDC600 GPS to map all tree stands in the 20m buffer and their diameter at breast height (dbh). QFIELD is an open-source mobile application designed for mobile spatial data visualization and capture (Davies et al., 2006). The tool selection was based on Davies et al., (2006) criteria such as ability to run offline, operate on Android operating system, navigate to spatial features using device GPS, display spatial data, store data, capture geographic features among others.

3.3.3 Root sample collection for tensile strength analysis

A detailed sampling framework entailing sample size, design etc. is well articulated in subsection 3.2. above. The digging of the roots was rather dependent on the number of roots available at each particular tree, depth and species and it varied across species and tree. Sampling sites were then tracked using a TDC600 GPS and QFIELD mobile application. Using a hoe, a rake and a sharp knife, roots of selected agroforestry trees were carefully extracted from the soil. These were zipped in a plastic bag and labelled for subsequent analysis in the lab.

Root sample preparation

All roots from the field were cleaned and trimmed to 30cm for easy loading and storage (appendix 2). Defects such as physical damage e.g. breakage due to poor handling and root rot were inspected and removed from all samples. The clean samples were then stored in a deep freezer ≤ 0˚C to control biological processes such as decay and drying of the samples. All frozen samples were kept for only ≤ 36hrs and those beyond were discarded. The assumption was that those beyond the 36hrs had been affected by biological processes and there not fit for use since the study object was to test fresh roots.

Root loading

Root diameter at head and tail was taken using a digital Vernier caliper before loading. The Caliper has a measuring range of 150mm/6in and resolution accuracy of +/-0.01mm (Comino & Marengo, 2010). To reduce root damage by the apparatus clips and increase grip, all samples were wrapped with paper-based sole tape on both ends. The roots were then loaded on the developed tensile machine (apparatus) in the Appendix 3. The apparatus was fabricated in house and it comprised of the digital weighing scale (capacity = 50kg), wedge clips, and a vice that acted as the effort.

3.3.4 Soil sample collection for shear strength analysis

Cylindrical soil cores of 80mm internal diameter and 130mm height were used to collect undisturbed soil samples for shear strength analysis, contrary to Balzano et al., (2019) and Mugagga et al., (2012a) who utilized shear boxes with a square cutter. Cylindrical cores were opted due to the design of the shearing machine. Additionally i*n-situ* shear strength analysis was carried out using a Torvane (Pocket Vane Tester) as described by Avunduk et al., (2021) and Al-Rubaiee & Jajjawi, (2018). The measuring range of the torvane was (0 – 250) kpa and the adapter size for measuring was CL 100 = 1.0936 kg/cm² per complete revolution.

3.4 Data Analysis

3.4.1 Identification & Characterisation of landslide susceptible zones

Landslide susceptibility modelling was performed using hybrid models namely; frequency ratio (FR) equation [1 – 2] (Nakileza & Nedala, 2020), index of entropy equation [3-9] (Perera, et al., 2019) and weighted overlay method (Karimzadeh & Matsuoka, 2018). These are statistical bivariate and probabilistic models which minimize subjectivity in weightage assignment in landslide modelling, producing more objective and reproducible results (Kornejady & Afzali, 2019). The frequency ratio model was adopted to measure factor influence at subclass level while the entropy calculated objective weights of the index system (Jaafari et al., 2014). The two models were integrated by weighted overlay model to produce a landslide susceptibility map. NDVI and NDMI parameters were analysed following Aghda & Razifard, (2017).

$$FR = \frac{({}^{D_i}/_{A_i})}{({}^{\sum D_i}/_{\sum A_i})} \ldots . (1)$$

$$P = \frac{(d^2)u}{e^2} \ldots . (2)$$

Where; D_i represents number of landslides per subclass of a conditioning factor, A_i is the area per subclass of conditioning factor in Km², $\sum D_i$ is the total number of landslides in the study area and $\sum A_i$ is the total area of the study area in Km². Equation 1 was converted into standard units (SI) for easy measurement using equation 2 where d represented the image resolution, u pixel number and e as conversion factor of meters to kilometres which is equivalent to 1000 meters.

The index of entropy was explained as:

$$P_{ij} = \frac{b}{a} \ldots (3)$$

$$(P_{ij}) = \frac{P_{ij}}{\sum_{j=1}^{Sj} P_{ij}} \ldots (4)$$

$$E_j = -K \sum_{i=1}^{Sj} (P_{ij}) log_2(P_{ij}) \;\; j = 1 - n \ldots (5)$$

$$G_j = 1 - E_j, \qquad S_j \text{ is the number of classes} \ldots (6)$$

$$K = \frac{1}{log_2 S_j} \ldots \ldots . (7)$$

$$W_j = \frac{G_j}{\sum_1^n G_j} \quad n = 1,2,3 \ldots \ldots \ldots (8)$$

Where; a and b represent domain and landslide percentages respectively, P_{ij} is the probability density (FR), W_j is the resultant weight value for the factors as a whole. Finally the landslide susceptibility map (LSM) was produced by aggregating all conditioning factors and their influence using equation [9] (Thongley & Vansarochana, 2021) modified to equation [11] to enable operations in weighted overlay tool.

$$LSM = \sum Cx\, W_j \ldots \ldots \ldots (9)$$

$$P_{wj} = \frac{Wj}{\sum Wj} x100 \ldots \ldots .. (10)$$

$$LSM2 = \sum P_{wj}\, C \ldots \ldots \ldots (11)$$

Where; C is the class weight (FR) and W_j is overall conditioning factor weight, P_{wj} is the percentage of overall conditioning factor weights and $LSM2$ is the weighted overlay model.

3.4.2 Tree distribution and slope stability

Spatial distribution and direction of selected agroforestry tree species was analysed using standard deviation ellipse method of ArcGIS (Moore & McGuire, 2019; Zhao et al., 2022). The method is widely used to explore and analyse spatial variation of geographic phenomenon and it provides centre of rotation, distribution, orientation and shape (Guo & Yuan, 2022). In this study species names were used as case file to measure agroforestry tree dispersion and orientation. Standard deviation 1 was used to define ellipse size (Perzia et al., 2022). Finally the relationship between tree distribution and landslide occurrence was achieved through correlation analysis. Collins et al., (2012) has used correlation methods to test relationship between landslide occurrence and several factors such as slope, geology and earthquakes. Similarly in Uganda Bamutaze, (2019) used correlation to test relationship between landslide occurrence and morphometric attributes. In this study landslide size (y-axis) and tree diameter at breast height (x-axis) was correlated.

3. 4.3 Tree species root characteristics for slope stability

Root reinforcement characteristics were determined by analyzing root tensile strength, Index of Root Binding (IRB) of soil and soil shear strength. According to Comino & Marengo (2010) effective root reinforcement can be measured through soil shear strength, root tensile strength and root architecture. Therefore, root tensile strength was expressed as a ratio of resistance and root area [Equation 12] which is measured as the ratio of maximum force applied to a root at the failure surface to its root diameter (Ettbeb et al., 2020; Lee et al., 2020):

$$T_r = {}^{4F}/_{\pi d^2} \ldots (12)$$

Where; T_r is the tensile strength, F is the maximum load at the rupture point (N) and d is the average roots diameter. However, other researchers have expressed the tensile resistance-diameter relationship in terms of force unit using power law equation (Ettbeb et al., 2020; Sofia & Afonso, 2019; Comino & Marengo, 2010) given in equation [13]. The current study focused on tensile strength rather than force as given in equation [12].

$$T_f = \alpha . d^{\beta} \ldots (13)$$

Where; T_f is tensile force (N) and d is the average root diameter (mm).

Then the Index of Root Binding of soil (IRB) was calculated using equation [14] as proposed by Hairiah et al., (2020) expressed as:

$$IRB = \frac{\sum(DHR)^2}{DBH^2} \ldots . (14)$$

Where; DBH is tree diameter at breast height (1.3m height) and DHR is the diameter of the horizontal roots. However, this method was modified to mean diameter of horizontal roots and mean DBH. Finally the overall root reinforcement was determined using the soil shear strength calculated from equation [12] below (Yu et al., 2020; Ettbeb et al., 2020; Sofia & Afonso, 2019; Comino & Marengo, 2010).

$$IRB = \frac{\sum(Mean\ Diameter\ of\ horizontal\ roots)^2}{Mean\ DBH^2} \ldots . (15)$$

$$S = \c{C} + C\varepsilon + \c{\sigma} tan\c{\delta} \ldots (15)$$

Where, S denotes the effective soil shear strength (KPa), $\c{C}$ is the soil cohesion (KPa), $C\varepsilon$ is the root reinforcement calculated from equation [16] (Fata et al., 2021), $\c{\sigma}$ is normal load (pa), and $\c{\delta}$ is the angle of internal friction in degrees.

$$C\varepsilon = T_r\left(\frac{A_r}{A}\right)(\sin\theta + \cos\theta\tan\emptyset) \ldots (16)$$

Where T_r is the tensile strength per unit area of roots, θ is the relative vertical deviation angle of roots subjected to shear deformation in degrees, A_r is the total cross-sectional area of all roots and A is the area of soil in the sample.

3.5. Validation of susceptibility map

Accuracy assessment of a landslide model is a fundamental step towards managing landslide hazards (Pourghasemi et al., 2012). The process starts by defining training data samples and validation samples. Training data is 70% of total landslide inventory and is used to train the model while 30% is the validation data (Dung et al., 2021; Chen et al., 2016). In this research 120 (70%) was used to train the model while 51(30%) to validate the model. Receiver Operator Characteristics curve (ROC) method constructed on true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) (Thongley & Vansarochana, 2021) was used to achieve this exercise. The performance of the landslide susceptibility map was automatically evaluated based on the area under the curve (AUC) values from ArcSDM extension of ArcGIS (Wang et al., 2020; Ma et al., 2018) model performance are generated automatically.

3.6. Environmental and Ethical consideration

Tensile strength assessment required one to uproot the entire plant to expose available roots, thus making this method destructive. To minimize such effects, only three roots were extracted from each sample element after careful observation of the plant health. Plants exhibiting poor health or stunted growth were excluded from the study. Farmers consent prior to root extraction was pursued verbally after informing them about the likely risks of giving out their trees for the study. Then using a hoe and a sharp knife, roots were carefully dug out about 30cm away from the stem base.

A no plastic bag policy was also strictly adhered to by the researcher and his helpers to avoid or minimize plastic pollution of the ecosystem. Only reusable materials were utilized including metallic cans for carrying drinking water and sisal sacs for carrying soil samples. Root tensile strength were carried out in the field to avoid littering.

3. 7. Limitations

Testing tensile strength of big roots would be impeccable for this study however, there was shortage of equipment to cover big roots. As such a small apparatus comprising of a digital spring weighing scale, clump and a Vernier calipers was developed from scratch to test small roots (<6mm) diameter. The study assumed that a tree species with good characteristics at young age such as high tensile strength, IRB and shear strength would maintain or even improve its characteristics with maturity. However, Ettbeb et al., (2020) noted that there is an inverse relationship between root diameter and tensile strength and small roots have higher tensile strength compared to larger roots. Unfortunately, their study did not provide the most ideal diameter (upper limit) thus leaving a gap for doubt. Basing on this literature and limitation by the tensile machine, (<6mm) diameter threshold was selected depending on the easy of loading. Calibration of the system particularly the weighing scale was undertaken following Uganda National Beaurue of Standards (UNBS) guidelines to improve precision and accuracy of the machine. The calibration certificate is provided as evidence in Appendix 4. Additionally, tree age influence on shear strength and slope was not integrated in the model due to shortage of equipment and failure to identify tree species age *in situ*. Digging of roots especially *Markhamia lutea and Cordia africana* was very challenging. *Markhamia lutea* was characterized by fewer roots and *Cordia african* with a deep root system which increase sample extraction time. Finally, the soil shear strength testing was very expensive with limited laboratories that can perform the analysis. To reduce the cost and also increase on the sample size, a handheld shear Torvane was used to measure 168 shear samples in-situ and only 30 lab as validation data.

CHAPTER FOUR

PRESENTATION OF RESULTS

4.1 Characterization of Tsume catchment landslide susceptibility using a hybrid model

Detailed characterization of Tsume landslide susceptibility is presented in table 1 and individual maps in Figure 6. The NDVI frequency ratio (FR) indicated that class 0.51 - 0.6 and 0.41 - 0.5 were the most problematic in terms of landslide occurrence with a FR (2.64) and FR (1.29) respectively. The highest FR (2.37) and FR (1.44) of the NDMI was recorded in class 0.11 - 0.21 and -0.04 - 0.1 indicating that increase in soil moisture directly increases the risk to landslide. Distance from streams network analysis revealed that the highest FR (1.29) was in the range of 50.1 – 100. Moreover, an analysis of altitude and landslide occurrence revealed that most landslides were bound to occur in class 1,288 - 1,500 with highest FR (3.67) thus it is very problematic.

Similarly, the Stream Power Index (SPI) also indicated that class 1.36 - 2.04 was the most problematic with FR (2.58) while class 0.92 - 3.48 of the plan curvature and class 0.433 - 1.29 of the profile curvature emerged as the most challenging classes with FR (1.36) and (2.19) consecutively. In terms of aspect the Northeast facing slopes presented more proneness to landslides with high FR (8.57). This was further exacerbated by slope angle of 25.1 – 30 degrees with a FR (2.21).

In terms of LULC, the Built-up area and the Agriculture classes had the highest FR (2.47) and FR (2.43) indicating the importance of human activity on landslide occurrence. The results were in agreement with population density and distance from road data. Their frequency ratios were recorded as (4.73) in class 1,001 - 1,500 persons per square kilometer of the population density and (2.50) and (2.09) of class distance 0.06 - 0.18 and < 0.05 km consecutively.

The relationship of soil type with landslide occurrence indicated that the Yellowish-brown sandy clay loams Figure 5 were the most prone to landslide with FR score of (3.92). The drainage density class 15.01 - 20.00 also indicated high proneness to landslides with FR (3.67) signifying the hydrological impact on landslide scars. Finally, class -1.282 - -0.425 of the Topographic Roughness Index (TRI) revealed high susceptibility to landslides.

Table 1: Frequency Ratio Model results for all conditioning factors under study

S/N	Conditioning factor	Class	No. pixel	No. Landslides (Di)	Area class km/sq (Ai)	FR
1	Normalized Difference Vegetation Index (NDVI)	0.11 - 0.4	67968	8	10.62	0.58
		0.41 - 0.5	91544	24	14.30	1.29
		0.51 - 0.6	106288	57	16.61	2.64
		0.61 - 0.69	126260	28	19.73	1.09
		0.7 - 0.81	197917	3	30.92	0.07
		Total	**589977**	**120**	**92.18**	
2	Normalized Difference Moisture Index (NDMI)	-0.37 - -0.05	49988	2	7.81	0.20
		-0.04 - 0.1	78779	23	12.31	1.44
		0.11 - 0.21	139259	67	21.76	**2.37**
		0.22 - 0.3	156533	20	24.46	0.63
		0.31 - 0.61	165418	8	25.85	0.24
		Total	**589977**	**120**	**92.18**	
3	Distance from streams (meters)	< 25	235513	43	36.80	0.90
		25.1 – 50	141507	24	22.11	0.83
		50.1 – 100	152528	40	23.83	**1.29**
		100.1 – 150	47324	11	7.39	1.14
		150.1 – 200	11044	2	1.73	0.89
		200.1 – 250	1877	0	0.29	0.00
		250.1 >	185	0	0.03	0.00
		Total	**589977**	**120**	**92.18**	
4	Altitude in meters (a.s.l)	1,288 - 1,500	60311	45	9.42	**3.67**
		1,501 - 2,000	179852	69	28.10	1.89
		2,001 - 2,500	126039	2	19.69	0.08
		2,501 - 3,000	118082	3	18.45	0.12
		3,001 - 3,500	50068	1	7.82	0.10
		3,501 - 4,000	50628	0	7.91	0.00
		4,001 >	4997	0	0.78	0.00
		Total	**589977**	**120**	**92.18**	
5	Stream Power Index (SPI)	-32.1 - -0.94	68328	10	10.68	0.72
		-0.93 - -0.26	18647	0	2.91	0.00
		-0.25 - -0.03	1481	0	0.23	0.00
		-0.02 - 0.43	169063	24	26.42	0.70
		0.44 - 0.89	128404	20	20.06	0.77
		0.9 - 1.35	87985	19	13.75	1.06
		1.36 - 2.04	70430	37	11.00	**2.58**
		2.05 - 26.32	45640	10	7.13	1.08
		Total	**589977**	**120**	**92.18**	
6	Plan curvature	-32.14 - -1.67	10715	1	1.67	0.46
		-1.66 - -0.38	165134	44	25.80	1.31
		-0.37 - 0.26	215723	39	33.71	0.89
		0.27 - 0.91	142843	21	22.32	0.72

S/N	Conditioning factor	Class	No. pixel	No. Landslides (Di)	Area class km/sq (Ai)	FR
		0.92 - 3.48	54403	15	8.50	**1.36**
		3.49 - 22.58	1160	0	0.18	0.00
		Total	**589977**	**120**	**92.18**	
7	Profile curvature	-21.175 - -2.14	4585	0	0.72	0.00
		-2.139 - -1.283	149887	17	23.42	0.56
		-1.282 - -0.425	225381	44	35.22	0.96
		-0.424 - 0.432	158544	37	24.77	1.15
		0.433 - 1.29	49319	22	7.71	**2.19**
		1.291 - 26.757	2262	0	0.35	0.00
		Total	**589978**	**120**	**92.18**	
8	Aspect	Northeast	14922	26	2.33	**8.57**
		East	12035	3	1.88	1.23
		Southeast	47282	14	7.39	1.46
		South	87974	24	13.75	1.34
		Southwest	102282	15	15.98	0.72
		West	116642	8	18.23	0.34
		Northwest	137774	16	21.53	0.57
		North	71066	14	11.10	0.97
		Total	**589977**	**120**	**92.18**	
9	Slope gradient	< 5	28402	2	4.44	0.35
		5.1 – 10	69999	6	10.94	0.42
		10.1 – 15	90094	11	14.08	0.60
		15.1 – 20	95885	10	14.98	0.51
		20.1 – 25	87328	16	13.65	0.90
		25.1 – 30	82408	37	12.88	**2.21**
		30.1 – 35	60549	24	9.46	1.95
		35.1 >	75312	14	11.77	0.91
		Total	**589977**	**120**	**92.18**	
10	LULC 2020	Shrub	4019	1	0.63	1.22
		Agriculture	151710	75	23.70	**2.43**
		Bushland	22704	0	3.55	0.00
		Planted forest	50786	14	7.94	1.36
		Built up	15914	8	2.49	**2.47**
		Grassland	56888	17	8.89	1.47
		Tropical Forest High stocked	139349	2	21.77	0.07
		Bare Surfaces and Impediment	49602	0	7.75	0.00
		Topical forest Low stocked	99005	3	15.47	0.15
		Total	**589977**	**120**	**92.18**	
	Soil type	Humose red sandy clay loams	304489	8	47.58	0.13

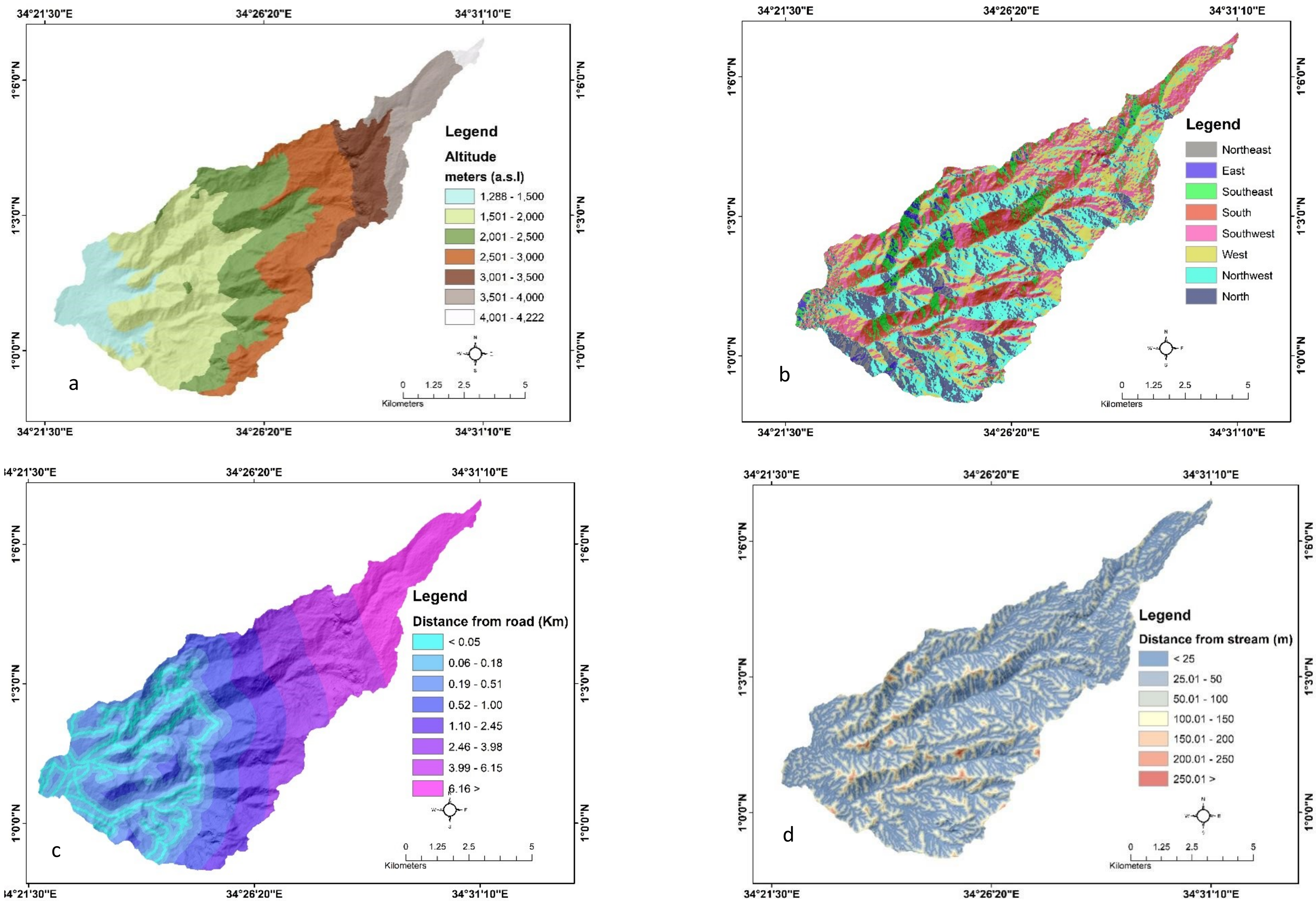
S/N	Conditioning factor	Class	No. pixel	No. Landslides (Di)	Area class km/sq (Ai)	FR
11		Black humose sandy clay loam	113424	0	17.72	0.00
		Yellowish brown sandy clay loams	135367	108	21.15	**3.92**
		Red clay loams and sandy clay loams	36697	4	5.73	0.54
		Total	**589977**	**120**	**92.18**	
12	Drainage Density	<10	426308	59	66.61	0.68
		10.01 - 15.00	100873	28	15.76	1.36
		15.01 - 20.00	44188	33	6.90	**3.67**
		20.01 - 25.00	12601	0	1.97	0.00
		25.01 >	6007	0	0.94	0.00
		Total	**589977**	**120**	**92.18**	
13	Topographic Roughness Index (TRI)	-21.175 - -2.14	11382	2	1.78	0.86
		-2.139 - -1.283	16387	0	2.56	0.00
		-1.282 - -0.425	103686	27	16.20	**1.28**
		-0.424 - 0.432	318840	81	49.82	1.25
		0.433 - 1.29	112121	9	17.52	0.39
		1.291 - 26.757	27562	1	4.31	0.18
		Total	**589977**	**120**	**92.18**	
14	Distance from the road (km)	< 0.05	49480	21	7.73	2.09
		0.06 - 0.18	100150	51	15.65	**2.50**
		0.19 - 0.51	83876	28	13.11	1.64
		0.52 - 1.00	76626	15	11.97	0.96
		1.10 - 2.45	72647	3	11.35	0.20
		2.46 - 3.98	70185	2	10.97	0.14
		3.99 - 6.15	68384	0	10.69	0.00
		6.16 >	68629	0	10.72	0.00
		Total	**589977**	**120**	**92.18**	
15	Population Density (sq. km)	22 – 250	233529	9	36.49	0.19
		251 - 1,000	201114	11	31.42	0.27
		1,001 - 1,500	102850	99	16.07	**4.73**
		1,501 - 2,500	52369	1	8.18	0.09
		2,501 - 3,529	115	0	0.02	0.00
		Total	**589977**	**120**	**92.18**	

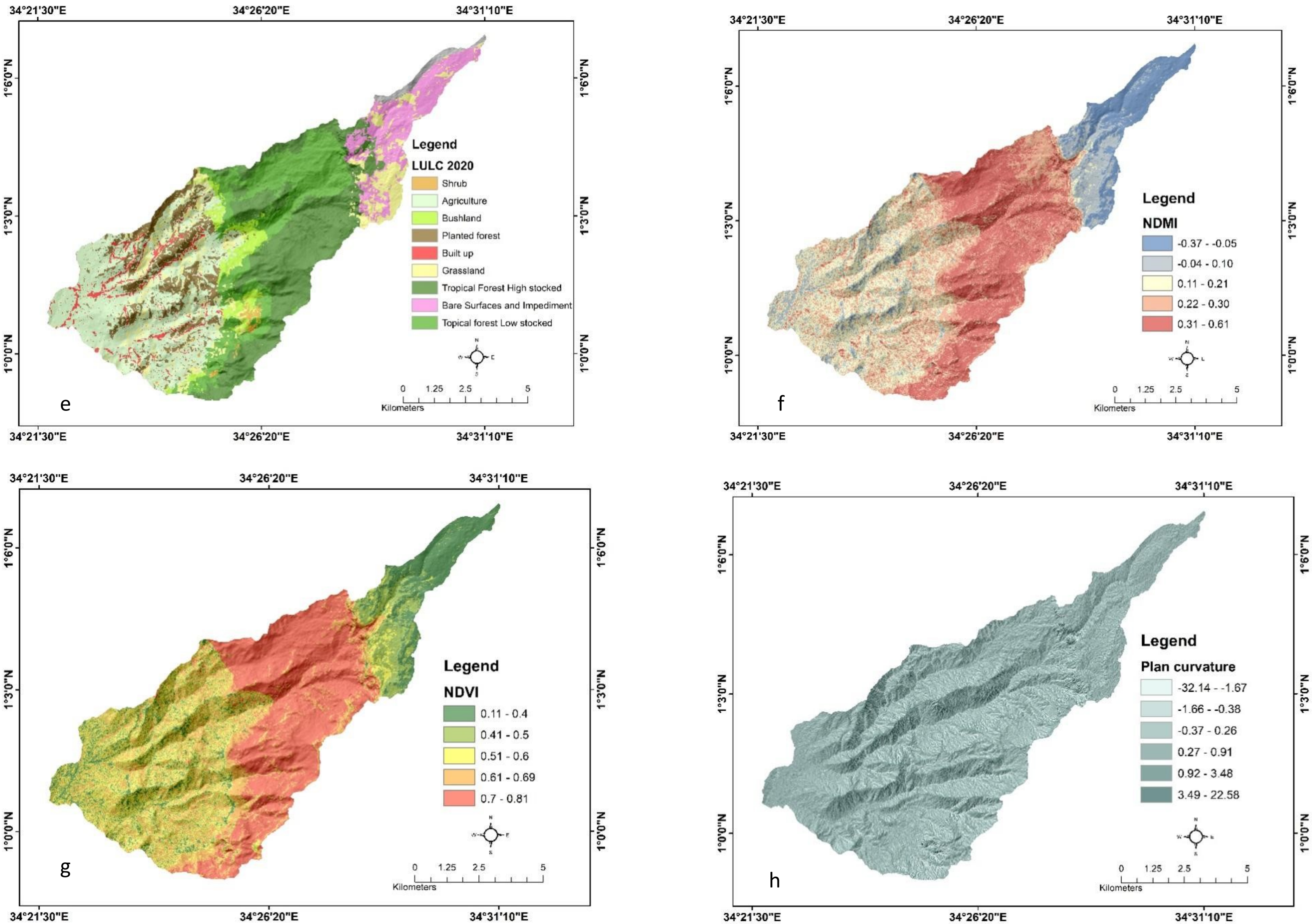
(a) Shallow landslide in a banana garden, Bukalasi

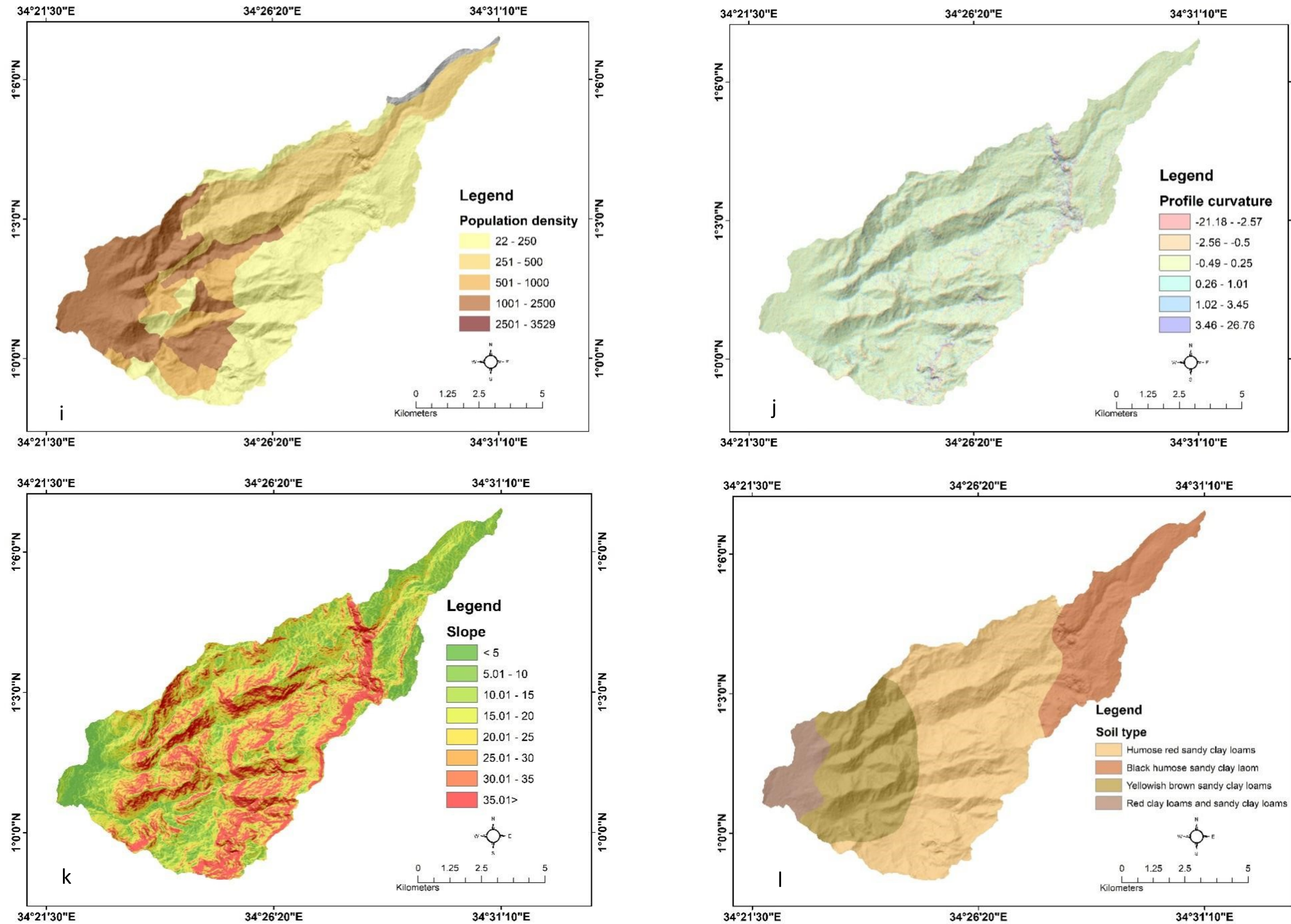
(b) Shallow landslide in Eucalyptus woodlot Bukalasi

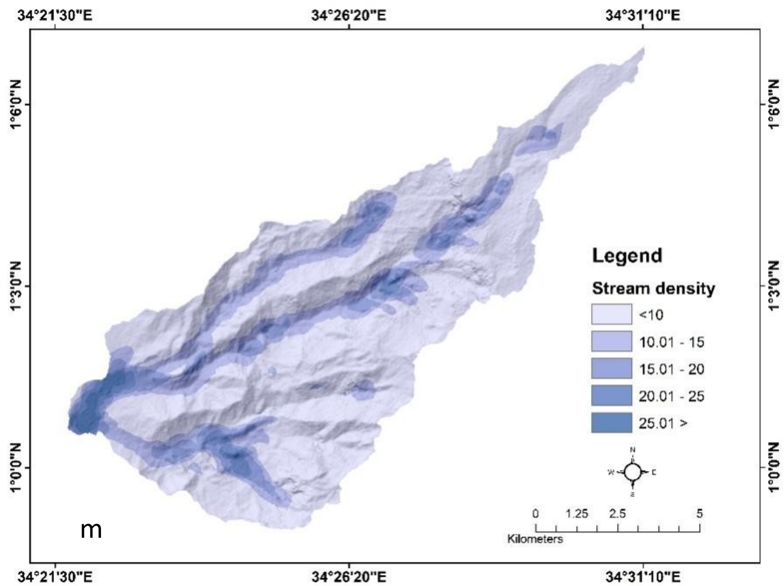
Figure 5: shows exposed Yellowish-brown sandy clay loams of 2 shallow landslides in Tsume micro-catchment

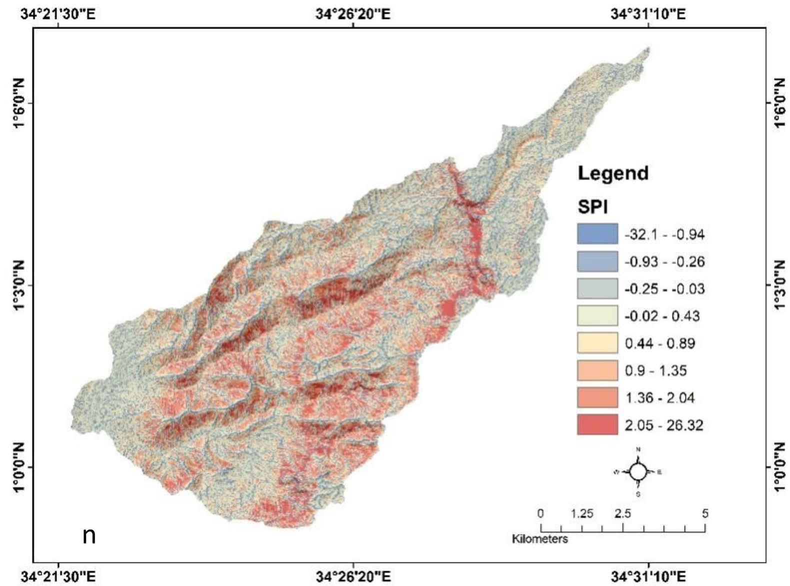
Figure 6: Selected conditioning factor maps for landslide susceptibility maps

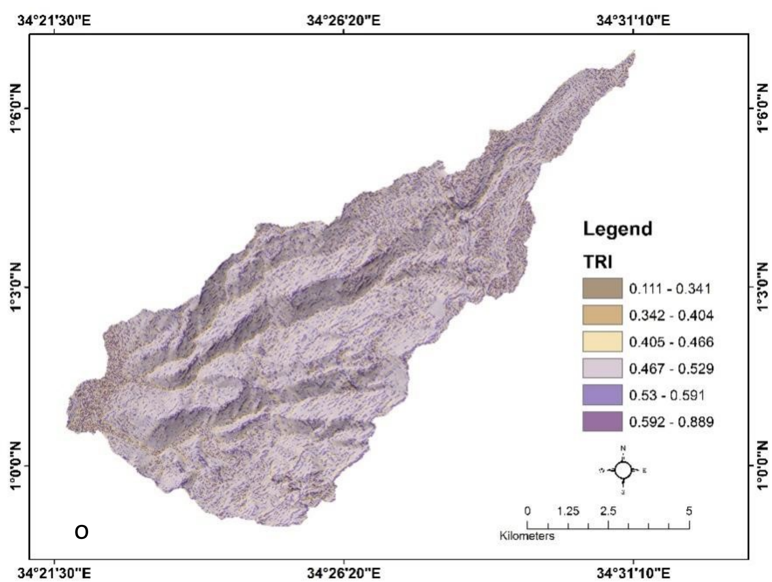



34°21'30"E
34°26'20"E
34°31'10"E
1°6'0"N
1°3'0"N
1°0'0"N
Legend
LULC 2020
Shrub
Agriculture
Bushland
Planted forest
Built up
Grassland
Tropical Forest High stocked
Bare Surfaces and Impediment
Topical forest Low stocked
0 1.25 2.5 5
Kilometers
e
Legend
NDMI
-0.37 - -0.05
-0.04 - 0.10
0.11 - 0.21
0.22 - 0.30
0.31 - 0.61
f
Legend
NDVI
0.11 - 0.4
0.41 - 0.5
0.51 - 0.6
0.61 - 0.69
0.7 - 0.81
g
Legend
Plan curvature
-32.14 - -1.67
-1.66 - -0.38
-0.37 - 0.26
0.27 - 0.91
0.92 - 3.48
3.49 - 22.58
h


34°21'30"E
34°26'20"E
34°31'10"E
1°6'0"N
1°3'0"N
1°0'0"N
Legend
Population density
22 - 250
251 - 500
501 - 1000
1001 - 2500
2501 - 3529
0 1.25 2.5 5
Kilometers
i
Legend
Profile curvature
-21.18 - -2.57
-2.56 - -0.5
-0.49 - 0.25
0.26 - 1.01
1.02 - 3.45
3.46 - 26.76
0 1.25 2.5 5
Kilometers
j
Legend
Slope
< 5
5.01 - 10
10.01 - 15
15.01 - 20
20.01 - 25
25.01 - 30
30.01 - 35
35.01>
0 1.25 2.5 5
Kilometers
k
Legend
Soil type
Humose red sandy clay loams
Black humose sandy clay laom
Yellowish brown sandy clay loams
Red clay loams and sandy clay loams
0 1.25 2.5 5
Kilometers
l


34°21'30"E
34°26'20"E
34°31'10"E
1°6'0"N
1°3'0"N
1°0'0"N
Legend
Stream density
<10
10.01 - 15
15.01 - 20
20.01 - 25
25.01 >
0 1.25 2.5 5
Kilometers
m


34°21'30"E
34°26'20"E
34°31'10"E
1°6'0"N
1°3'0"N
1°0'0"N
Legend
SPI
-32.1 - -0.94
-0.93 - -0.26
-0.25 - -0.03
-0.02 - 0.43
0.44 - 0.89
0.9 - 1.35
1.36 - 2.04
2.05 - 26.32
0 1.25 2.5 5
Kilometers
n


34°21'30"E
34°26'20"E
34°31'10"E
1°6'0"N
1°3'0"N
1°0'0"N
Legend
TRI
0.111 - 0.341
0.342 - 0.404
0.405 - 0.466
0.467 - 0.529
0.53 - 0.591
0.592 - 0.889
0 1.25 2.5 5
Kilometers
o

4.1.1 Factor importance and contribution to landslide occurrence

The overall importance of each pre-conditioning factor to landslide occurrence was assessed and presented using the calculated entropy weight and entropy percentage weights. The results are summarised in Table 2. From the analysis population density emerged as the highest influencing factor contributing 0.12 (12.05%) entropy percentage weight followed by soil type (10.86%), topographic randomness index (8.91%) and Altitude (8.58%). Surprisingly slope (3.40%) was found to be the least contributor to landslide occurrence.

Table 2: Entropy score of landslide conditioning factors

Conditioning factor	Category	Calculated Entropy Weight (Wj)	Percentage weight/contribution
Population density 2014	Anthropogenic	0.12	12.05
Soil type	Soil	0.11	10.86
Topographic Roughness Index (TRI)	Topographic	0.09	8.91
Altitude	Topographic	0.09	8.58
Stream Density	Hydrological	0.09	8.57
Distance from road	Anthropogenic	0.07	7.33
Profile curvature	Topographic	0.07	6.76
NDMI	Hydrological	0.06	6.32
NDVI	Vegetation	0.06	5.89
Aspect	Topographic	0.05	4.83
Plan curvature	Topographic	0.05	4.55
Distance from stream	Hydrological	0.04	4.23
LULC 2020	Anthropogenic	0.04	3.87
Stream Power Index	Hydrological	0.04	3.86
Slope degrees	Topographic	0.03	3.40
Total		**1.00**	**100.00**

4.1.2 Tsume landslide characterization

Figure 7 illustrates the spatial landslide susceptibility of Tsume micro catchment. Landslide susceptibility in Tsume micro catchment was characterized as very low 1.79 km² (1.93%), low 30.68 km² (32.96%), moderate 32.63 km² (35.05%), high 23.18 km² (24.90%) and very high 4.82 km² (5.17%). The accuracy of the LSM map was tested using ROC method and the hybrid model prevailed as a better predictor with (AUC = 0.914) than single bivariate statistical models. The receive operating curve (ROC) is presented in Figure 8.

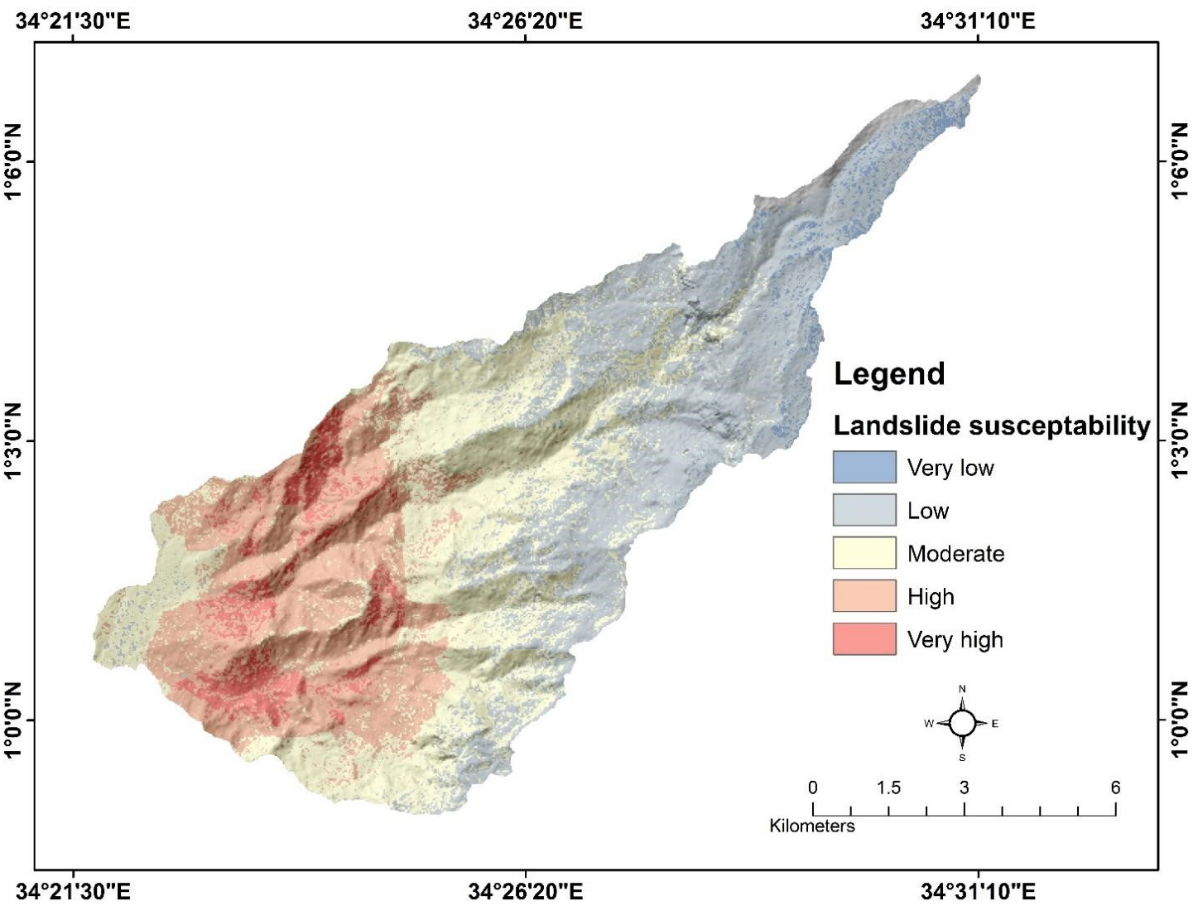


Figure 7: Landslide susceptibility map from the hybrid model

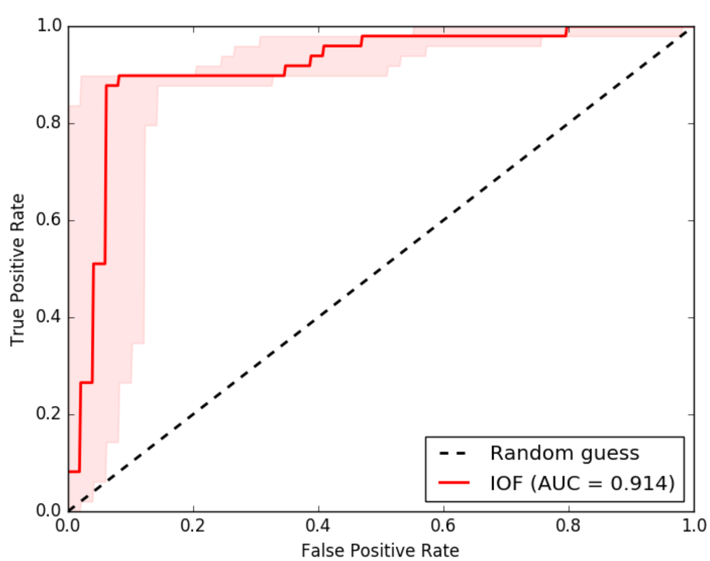


Figure 8: ROC for model validation

4.2 Tree distribution analysis

A total of 129 trees were mapped from 12 selected landslide scars and their distribution per site is presented in Figure 9. Of the total trees mapped, *Eucalyptus Spp* (28%) was the most abundant, followed by *Markhamia lutea* (23%), *Cordia africana* 19 (15%), *Grevillea robusta* (14%), *Albizia coriaria* (12%) and *Croton macrostachyus* (8%). Species dispersion and direction was analyzed using standard deviation ellipse method and results are presented in Figure 10. From the analysis, *Croton macrostachyus* and *Markhamia lutea* were highly dispersed than any other species in the study area. *Albizia coriaria* was the most localized in the downstream. *Croton macrostachyus* was more dispersed to the western direction while *Markhamia lutea* was at the centre of the axis. *Albizia coriaria* and *Eucalyptus Spp* was dispersed towards the Southwestern direction while *Grevillea robusta* and *Cordia africana* to Northwest. The Pearson's correlation method was undertaken to study relationship between landslide size and tree diameter at breast height (DBH). A weak negative correlation (r = -0.20 < 0.01) was observed between DBH and landslide size.

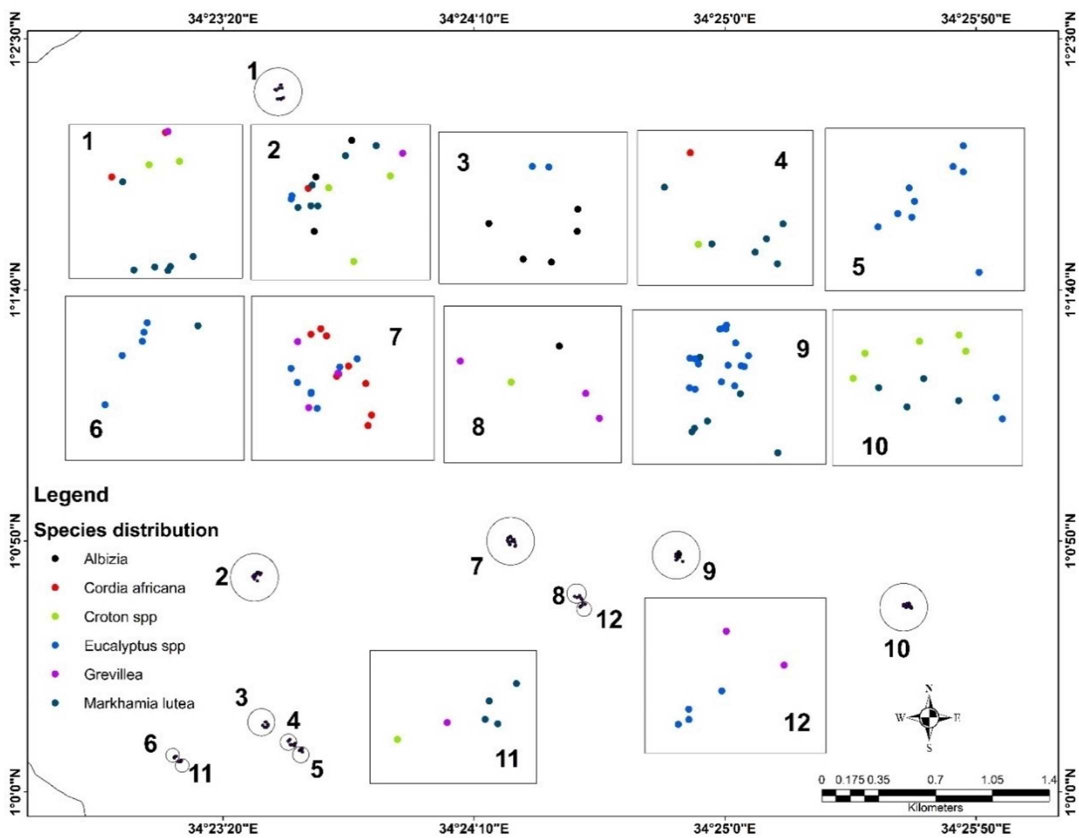


Figure 9: Tree distribution in 12 sites

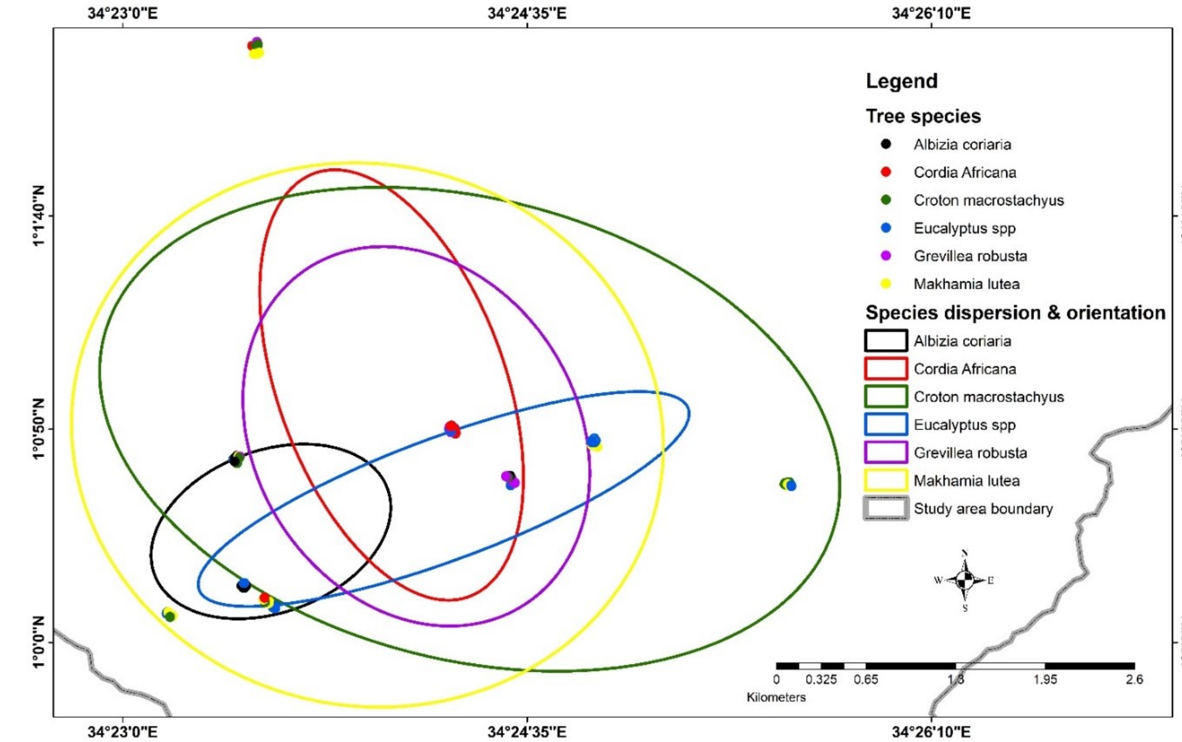


Figure 10: Standard deviation Ellipse showing dispersion and direction of selected tree species

4.3 Root characteristics for slope stability

4.3.1 Tensile strength analysis

A one-way analysis of variance (ANOVA) was performed to compare root tensile strength of six (6) selected agroforestry tree species as a characteristic for consideration in adoption for slope stability. The results indicated that all species means were significantly different from each other with ($F(5, 573) = [18.161]$, $p < 0.001$). However, *Grevillea robusta, Albizia coriaria,* and *Markhama lutea* had the highest tensile strength with average weight of 3.02±1.217kg/mm², 2.53±1.382kg/mm², and 2.28±1.01kg/mm² consecutively (Table 3). On the other hand, *Croton macrostachyus* (1.78±1.167)kg/mm² and *Cordia africana* (1.69±1.153)kg/mm² had the least tensile strength. A scheffe post hoc criterion for significance confirmed variability within species as follows. The root tensile strength of *Albizia coriaria* (2.206±0.832) was significantly different from *Grevillea robusta* ($p < 0.001$) and *Markhamia lutea* ($p < 0.001$). Similarly, *Cordia africana* (3.065±0.872) was significantly different from *Markhamia lutea* (5.096±0.358; $p < 0.001$). A same pairwise comparison also revealed that *Croton macrostachyus* (2.143±0.683) was significantly different from *Eucalyptus spp* ($p = 0.049$), *Grevillea robusta* ($p < 0.001$), and *Markhamia lutea* (p

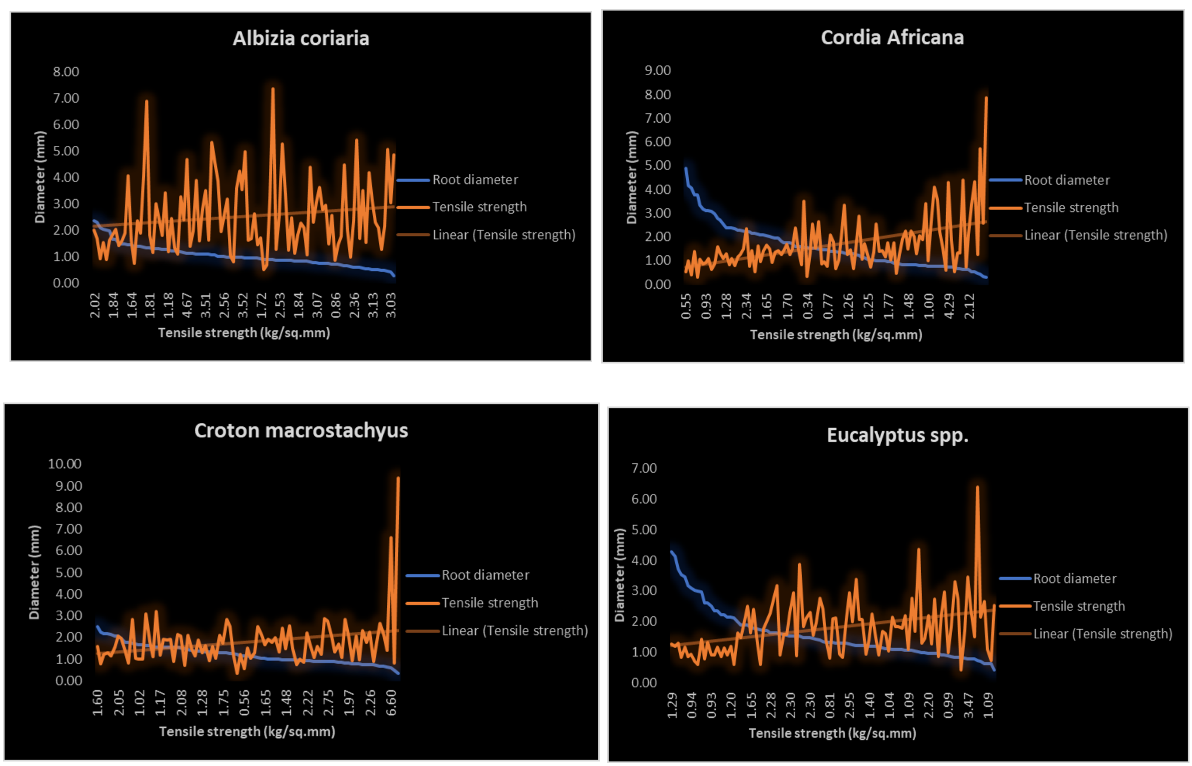
< 0.001). Finally, *Eucalyptus spp* (3.457±0.144) significantly (p = 0.002) differed from *Markhamia lutea*. The index of root binding was highest for *Albizia coriaria* (81.31), and lowest for *Markhamia lutea* (47.84) as presented in Table 3.

Table 3: Mean and standard deviation rapture weight (kg) of selected agroforestry tree species

Species	**N**	**Mean weight (kg)**	**Std**	Mean T_r(kg/sq.mm)	**Std**	***IRB***
Albizia coriaria	98	2.21	0.832	2.53	1.382	81.31
Cordia africana	105	3.10	0.872	1.69	1.153	69.90
Croton macrostachyus	87	2.14	0.683	1.78	1.167	51.69
Eucalyptus spp	99	3.50	0.144	1.80	0.926	58.87
Grevillea robusta	85	4.22	0.500	3.02	1.217	57.44
Markhamia lutea	105	5.10	0.358	2.28	1.013	47.84

4.3.2 Root diameter verses tensile strength

As shown in Figure 11, all species indicated an inverse relationship between tensile strength and root diameter. Sharp slopes were observed among *Cordia africana, Grevillea robusta, Eucalyptus* Spp. and *Markhamia lutea*.



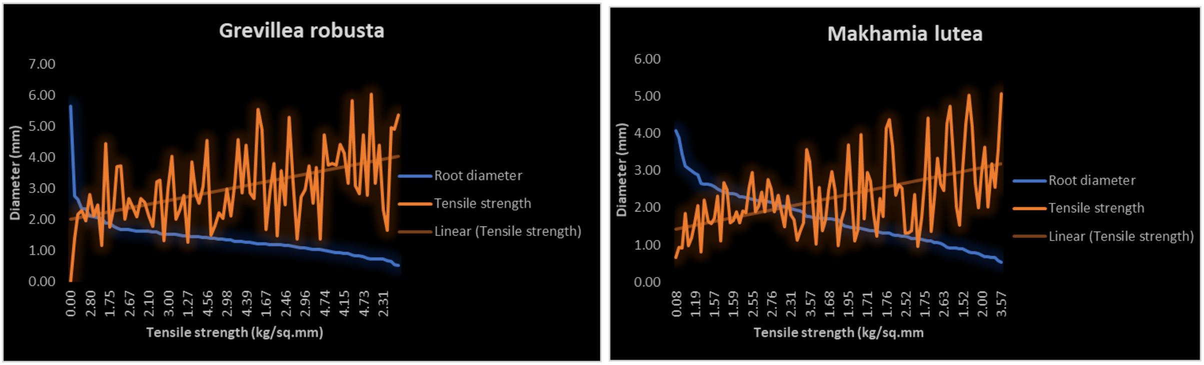


Figure 11: Root tensile strength-diameter relationship

4.3.3 Shear strength of selected agroforestry

Figure 12 presents average shear strength of selected agroforestry tree species under study. The best performing species in terms of shear strength was *Albizia coriaria* with average shear strength (52.46±10.24) kpa followed by *Markhamia lutea* (50.70±15.47) kpa. The worst performing species in shear strength was *Eucalyptus spp*. with average shear (46.75±12.92) kpa. However, the results did not differ significantly.

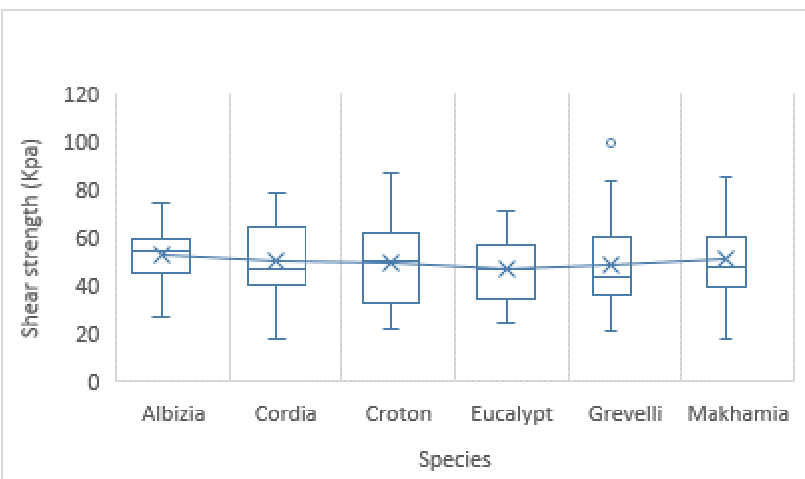


Figure 12: Box plot showing average shear strength of selected agroforestry tree species

4.3.4 Soil texture analysis for selected trees

Soil texture results as presented in figure 13 indicate average highest clay content (27.8%) in soil samples picked near *Markhamia lutea*, sand (33.6%) in *Eucalyptus Spp* and silt (54.0%) in *Albizia coriaria* soil samples.

Figure 13: Percentage soil texture

CHAPTER FIVE

DISCUSSION OF RESULTS

5.1 Landslide risk characterization of Tsume micro-catchment

Landslides occur as a result of several conditioning and trigger factors. However, choosing the best for an event presents a challenge of its own. Moreover, several arguments have been raised on the use of single models to predict landslide susceptibility. The augments originate from the predictive capacity and reliability of each model given the complex nature of landslides. For example frequency ratio models have gained high reliability status because of their high predictive capacity as stressed by Chen et al., (2020). In the current study a hybrid model comprising of frequency ratio (FR), index of entropy (IOE) and weighted overlay (WO) was used to predict landslides in Tsume micro catchment. The influence of 15 selected conditioning factors to landslide formation was assessed.

From the hybrid model, NDVI explained 5.89% of Tsume landslide susceptibility Map. The FR results indicated that a decline in NDVI resulted in increase of landslide frequency in an area while a NDVI of <5 presented more problems. An increase in NDVI implied an increase in vegetation cover and health conditions and arguably the vegetation cover control by roots and canopy. These results coincided with the land use/cover findings where low FR (0.07) was recorded in Tropical Forest High stocked unlike in Built up area and the Agriculture where the highest FR were observed. Overall contribution of LULC to landslide susceptibility was 3.87%. High forest cover negatively affected landslide formation, which is in agreement with Preti, (2013) and FAO (2010). This is explained by the root system that cause a negative feedback. Whereas, high FR in agriculture and built area signified the positive human interactions with the biophysical environment resulting into positive feedback. Similar findings have been reported by Mugagga et al. (2012) where LULC was considered as a trigger factor. In their study high prevalence of landslides was observed in degraded areas as well. Singh et al., (2021) also found landslide concentration (95%) in degraded fields characterized by agriculture and built up. Recently, Mande et al., (2022) revealed that most landslides are concentrated in agricultural fields and attributed the phenomenon to over cultivation and modification of the environment.

The TRI and NDMI also greatly contributed to the landslide susceptibility of Tsume micro-catchment while slope gradient least contributed. The FR results of the above three (3) parameters showed similar trend where a unit increase in a parameter value would increase the prevalence of landslides up to a certain peak and then decreases (Razifard et al., 2019). TRI results were in line with Nakileza & Nedala (2020) findings who reported high landslide concentration from class 0.15 - 0.31 to 0.40 - 0.5 map units. Suyeda & Setiawan, (2022) have used NDMI as an alternative method for analyzing ground water content of a soil. Marino et al., (2020) stressed the importance of soil moisture especially the antecedent soil moisture to landslide occurrence and concluded that this is ideal for improving prediction. In 2019 (Razifard et al., 2019) reported a strong relationship between soil moisture and landslide occurrence in Khaje, East Azerbaijan. In regards to slope gradient, studies by Nakileza & Nedala, (2020) and Kornejady et al., (2019) depicted similar findings that landslide concentration is high on slopes between (15˚ – 25˚). However, on contrary slope gradient was the major influencing factor for (Nakileza & Nedala, 2020) unlike in this study where it is the least influential. The scale of analysis could be one of the reasons for the low contribution of slope gradient to landslide formation in this particular catchment. Moreover, it should also be noted that earlier researchers on the subject (e.g. Mande et al. 2022; Nakileza & Nedala, 2020; Broeckx et al., 2019; OPM, 2016; Staudt et al., 2014) used low spatial resolution data (30 and 90) meters which presents some level of generalization during prediction. Also, dominance of relatively gentle to moderately gentle slopes in the study area could account for the observed differences. However, these arguments are subject to further analysis in different sub catchments and catchments.

Distance from streams and road networks contributed 4.23% and 7.33% consecutively to the overall LSM. Both parameters presented an inverse relationship similar to other findings (Devkota et al., 2013). As distance increased, landslide occurrence decreased signifying the importance of proximity to streams and roads. This implies that opening of more roads on steep slopes would obviously increase the risk of landslides in the micro catchment. McAdoo et al., (2018) studied similar events and found a strong correlation between landslide occurrence and road network in Nepal. In regard to stream distance, studies by Kavzoglu et al., (2015) have found that distance from streams is very important factor of consideration because it highly contributes to landsliding. This is attributed to the river erosion activities Devkota et al., (2013) that affect slope stability and increase soil moisture at points of contact Jaafari et al., (2014). The process is worsened when the area is characterized by high drainage density greater than 15. In this study however, landslide concentration was observed in drainage class 15.01 to 20.00 with limited landslides above it. Its overall importance was 8.57% thus, making it the 5th most important influencing parameter. Gentle slopes (<5˚) in the low lands could account for high drainage density.

Altitude revealed that most landslides were common between altitudinal heights above 1,200 and 1,500 meters above sea level. The overall contribution of altitude to landslide susceptibility was siginificant thus assuming the 4th position. These results can be explained by high rainfall (Nakileza & Nedala, 2020) that attracts intensive cultivation in these areas thus undermining slope stability. Stream power index (SPI) is a measure of erosive power of water flow based on the assumption that discharge is proportional to a particular catchment (Thongley & Vansarochana, 2021; Duman et al., 2006). In this study statistical results of SPI indicated a low overall influence. FR results revealed that landslide concentration increased with increase in erosive power of the stream. Moreover, a comparison between SPI and slope maps indicate a positive relationship between the two. Thongley & Vansarochana, (2021) reported similar trends in their study and concluded that SPI significantly influence landslides.

The plan and profile curvatures revealed a moderate influence o on landslide susceptibility thus assuming the 11th and 7th positions consecutively. Positive values of the plan curvature indicated that the sideward convex slopes are more prone to landslides than concave slopes. Likewise, the upward concave slopes of the profile curvature were more problematic than to the convex slopes. Similar finding have been reported by Mande et al. (2022) in the same catchment. However, in contrary Nakileza & Nedala (2020) found the negative curvature slopes as the most prone in the upper catchment that includes Tsume. Such differences depict unique and complex characteristics of landslides and therefore call for micro catchment level analysis for a better understanding. Aspect is another important pre-conditioning factor of landslide assessment in this research put under consideration. The FR results indicated proneness of Northeast, East and South east facing slopes to landslides with low overall importance putting this parameter in the 10th position. These results are in agreement with researchers such as (Thongley & Vansarochana, 2021; Nakileza & Nedala, 2020) who attributed it to high rainfall received on those slopes.

High population density (1st position) emerged as the most influential factor of Tsume landslide susceptibility with areas above 1000 people/km² being the most problematic. High population density is highly correlated to land use change and system conversion. Studies (e.g. Van Eynde et al., 2017; Dierickx, 2014; Knapen et al., 2006) have indicated that a high population density of 400 to 1300 people /km^2 existed in Bududa district as of 2002 and 2011. Galabuzi et al., (2021) estimated about 1.5million people in entire Elgon region with a population density of 400 to 800 people/km^2. Recently UBOS (2017) in a National Housing and Population Census (NHPC) report indicated a total population of 210,173 people with youth (<17 years) making up the majority. This high population density reveals the future risk of land scarcity and over cultivation for subsistence on vulnerable slopes.

The relationship of soil type with landslide occurrence indicated that the Yellowish-brown sandy clay loams are the most prone to landslides. The overall contribution of soil to landslide susceptibility like population density was very significant thus assuming the second place of importance. A study by Knapen et al. (2006) reported high silt clay soil (52% clay, B2t) content predisposition on coarser sandy silt loam (6% clay, A3/E3) as a factor of concern impairing water movement in Manafwa watershed thus landslide. A later study by Claessens et al, (2007) confirmed that Bukhalasi suffered several shallow landslides as a result of a distinct boundary between the soil and the underlying bed rock. This abrupt transition between the bedrock and the soil acted as a shear plane during heavy rainfall. Similar results were noted by Kitutu et al. (2009) who further concluded that soil type had no influence on landslides but rather texture of which kaolinite and illite clay were significant. Nakileza et al., (2017) observed and concluded that high clay rich soils have a high potential of shearing in wet season. Their findings were similar to (Makabayi et al., 2021) who reported a 30% clay content in the Bududa soils. However contrary to this study, (Makabayi et al., 2021) reported insignificant influence by soil type and rather attributed the latter to soil texture.

The accuracy of the LSM map revealed very good prediction rate of the proposed hybrid model with (AUC = 0.91). Thongley & Vansarochana, (2021) noted that for success rate of any model that falls under AUC (0.7 to 0.8) is a good predictor and above (>0.8) is very good predictor. In the current study the very good success rate of the proposed hybrid model was a leverage from two models FR and IoE recommended by (Jaafari et al., 2014) as good models for landslide modelling.

5.2 Landslides and tree distribution

The analysis of the relationship between landslides and tree distribution revealed an inverse relationship between landslide scar size and DBH. The results imply that presence of trees reduce landslide risk in an area and DBH is a very important factor. A study by Nelson et al., (2015) indicated that DBH (< 25 and > 60 cm) do not guarantee slope stability due to low factor of safety (< 1) while those within do. Yang et al., (2017) concluded that large trees (DBH > 20cm) reduce landslide risk for as far as 10m distance from the tree base. They further pointed out that much as large DBH may increase surcharge pressure downslope to weight of trunks, the net effect of large trees on slope stability is positive. The latter is true for lower landslide susceptibility in the Southwest direction of the LSM (high rather than very high) where *Albizia coriaria* was highly concentrated. The high concentration was due to high adoption by farmers in their coffee and banana systems as a result of promotion by Shunya Yettana CBO (Nakileza et al., 2017) and other players.

5.3 Root characteristics for landslide control

The study considered root characteristics as a feature for tree adoption to control landslides. A one-way ANOVA indicated high variability of tensile strength among species. The variability is as a result of environmental condition, species and age (Nyambane & Kinyua , 2011; Schmidt et al., 2001). Results also showed that *Grevillea robusta, Albizia coriaria,* and *Markhamia lutea* were the best performing trees with highest tensile strength. Strikingly *Cordia africana* was among the worst performers yet it had been widely promoted to farmers among the indigenous species for landslide control. According to Mugagga et al. (2015) *C. africana* is among good carbon sequesters thus the reason for its promotion. Nakileza & Tushabe, (2018) associated their adoption to tap root system that penetrate into deeper layers of the soil. Galabuzi et al., (2021) on the other side found that *Cordia africana* adoption was highly linked to good shed, firewood and timber. However, in contrary Graham et al., (2021) reported a low adoption of indigenous trees particularly *Cordia africana* and *ficus spp.* against exotic tree species such as *Eucalyptus* and *Grevilia spp.* among community.

Comparison among species indicated a significant difference between *Albizia coriaria* and *Grevillea robusta* ($p < 0.001$), *Albizia coriaria* and *Markhamia lutea* ($p < 0.001$); *Cordia africana* and *Markhamia lutea* ($p < 0.001$); *Croton macrostachyus* and *Eucalyptus spp* ($p = 0.049$); *Grevillea robusta* ($p < 0.001$) and *Markhamia lutea* ($p < 0.001$); and *Eucalyptus spp* and

Markhamia lutea with (p = 0.002). A study by Hairiah et al., (2020) and Comino & Marengo, (2010) suggested that fibre and lignin content are factors that can explain tensile strength variations among species. For instance, Hairiah et al., (2020) found that lignin explained 70% of variations among species. A study by Senthamaraikannan et al., (2019) reported a high cellulose content (64.54 wt%) and low microfibrile angle in *Albizia amara* barks which offers high tensile strength (640±13.4 Mpa). They further reported low fibre density, a feature which could reduce surcharge weight on slope direction. However, an in-depth study is required to confirm this factor. Similarly Gopinath et al., (2021) studied *Albizia saman* cellulosic fibre content and tensile strength. Their results reported a 60.76 wt% cellulose, slightly lower than *A. amara* and a high tensile strength (381 – 1092 *Mpa*). Recently Madhu et al., (2022) reported (55.83 wt%) cellulose and tensile strength (483.40±18 Mpa) for *Albizia julibrissin*. The tensile strength results by Madhu et al., (2022); Gopinath et al., (2021); and Senthamaraikannan et al., (2019) were significantly higher than the current study because their test were conducted on dry samples. Also, the machine used for testing their tensile strength were highly developed compared to the current study. Of recent Hairiah et al., (2020) found a positive relationship between plant root nitrogen and tensile strength. These research findings further suggested that *Albizia coriaria* and *Cordia africana* had more advantage of holding soil unlike *Markhamia lutea*. According to Harahap et al., (2018) and Mulyono et al., (2018) trees with high IRB are well suited for slope stability than those with low IRB. During root extraction in the field, it was observed that *Markhamia lutea* had fewer roots compared to any other species and this could contribute to low IRB. Also, trunk volume was lowest compared to other trees which could have contributed to the observed results.

Finally shear strength results suggests *Albizia coriaria* as the best tree for slope stability followed by *Markhamia lutea* although the results were not significant. On the contrary *Eucalyptus Spp.* was the worst performing tree with lowest mean shear strength yet the most preferred and abundant tree due to its fast growing characteristics (Buyinza et al., 2021) and economic value Graham et al., (2021) and Nakileza et al., (2017). High silt and clay content recorded in soil samples collected near *Albizia coriaria* and *Markhamia lutea* would somehow account for the observed high shear strength in the two species while high sand content would explain the low shear strength in soil samples near *Eucalyptus spp*. This therefore suggests that not only roots affect shear strength but also other factors. According to (Hairiah et al., 2020) soil shear strength is also highly dependent on soil texture.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Conclusion

The current study aimed at improving landslide prediction using hybrid model and investigating how the knowledge of plant characteristics (DBH, tensile strength, index of root binding and soil shear strength) could be harnessed to control landslide risk in Tsume micro catchment. The research process started by proposing a hybrid model which evaluated the importance of each landslide causative factor. Then finally evaluation of the selected tree root characteristics as key features of tree adoption. The following is a summary of the conclusions emerging from this study:

a. Hybridization of independent/single landslide susceptibility models significantly improves landslide mapping and prediction accuracy. The current study integrated three models of low accuracy (frequency ratio, Index of entropy and weighted overlay) and gained very high predictive accuracy ROC (AUC =0.91). The model also revealed that population density (12.05%) and soil type (10.86%) were the most important factors which was contrary to other researcher findings.
b. The presence of trees reduces landslide risk in an area and DBH is a very important guiding factor. The relationship revealed that as DBH increase the landslide risk reduces and vice versa.
c. The tree species in this study namely *Grevillea robusta, Albizia coriaria,* and *Markhamia lutea* emerged as best performers in terms of root tensile strength and soil shear strength hence their suitability for enhancing slope stability. Additionally, *Albizia coriaria* and *Cordia africana* have more associated benefits of holding soil particles together unlike *Markhamia lutea* that has low index of root binding. On the contrary *Eucalyptus Spp*., which is widely favoured in the region for its rapid growth was the worst performer with very low shear strength. Therefore, careful consideration of the tree characteristics is essential during promotion campaigns for slope stability in fragile environments.

6.2 Recommendations

The recommendations below are based on the study findings;

a) The hybrid model emerged as a very good landslide predictor in Tsume micro-catchment thus highly recommended for micro scale analysis. However, to reduce any reasonable doubts and increase its applicability in landslide predication across the country, more studies at different scale of analysis in different catchments are required. The model's high precision in landslide risk mapping demonstrates support to any policy action through population exposure control such as family planning, relocation and slope soil stability by tree planting.

b) The tree planting programs and campaigns need to prioritize mixed planting of *Albizia coriria., Grevellia robusta* and *Markhamia lutea* on farm plots due to their high tensile strength, IRB and shear strength characteristics as observed in this research. The trees need to be allowed to grow up to a certain size (DBH $\geq$ 20cm) for full realization of the slope stability characteristics before harvest. However, for sustainability of this policy recommendation, a Regulatory Impact Assessment (RIA) towards establishment of an Effective Landslide Mitigation and Resilience Plan as part of DRR strategy aimed at promoting the above tree species by OPM to reduce disaster risk in mountainous areas is required.

6.3 suggestion for future research

- An in-depth tensile strength analysis using a modern tensile machine of higher capacity is highly recommended to test bigger roots for proper comparison of the results so as to increase confidence in the findings. This is because the current study utilized a simple rudimentary tensile machine which was limited to root diameter ($\leq$ 6mm).
- Also, a similar investigation on other indigenous tree species, fruit trees, shrubs and grasses would be beneficial for widening the scope of other species variates with good slope stabilization characteristics to farmers.
- Finally, further research is required to test interactions of tree species age on shear strength and slope to identify best tree combinations and age with optimum slope stability characteristics on different slope angles. This kind of sensitivity analysis was not possible in this study due to limitation by equipment and failure to identify tree age in situ.

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APPENDICES

Appendix 1: Reconnaissance study

a) Field visit in Bundesi village with Prof. Mugagga (left), and Dr Nakileza (middle)

b) Inspection of exposed *Eucalyptus spp.* tree roots in Ibookho village

c) FGD with teachers and parents at Bundesi Primary School (In attendance was Prof. Mugagga in white T-shirt

Appendix 2: Root sample cleaning and trimming

Trimming of washed *Markhamia lutea* root samples to 30cm for easy storage and loading

Appendix 3: Tensile machine

Appendix 4: Calibration certificate

UGANDA NATIONAL BUREAU OF STANDARDS

Headquarters
Plot 2 - 12, Bypass Link,
Bweyogerere Industrial &
Business Park,
P.O. Box 6329 Kampala
Web: www.unbs.go.ug

Telephone: +256 417 333250
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+256 417 333252
Helpline: 0800 133133

UGANDA NATIONAL BUREAU OF STANDARDS
17 JUN 2022
SIGN:..................................
MBALE REGIONAL OFFICE

VERIFICATION CERTIFICATE

CERTIFICATE NO: 151280/MRO/2022 **DATE TESTED:** June-2022
SUBMITTER/USER: NEDALA SHAFIQ **DUE DATE:** June-2023
ADDRESS: MBALE CITY **S/NO:** -
DESCRIPTION: Digital Spring balance **MODEL:** -
CAPACITY: 50 kg **DIVISION SIZE:** 0.005 kg
TRACEABILITY THROUGH CERTIFICATE NO: MET/0108679

ACCURACY TEST **C=Correct within tolerance** **I= Out of Tolerance**

Applicable Tolerances: From 0.00 g to 200.00 g. MPE 0.001 g			**Test Load**	**Run up error**		**Run down error**	
From: 0.00 g **to** 50.00 kg. **MPE** 0.05 kg				C	I	C	I
			5.00	✓		✓	
No.	**Serial No.**	**Sticker No.**	10.00	✓		✓	
1	-	SB000060010	15.00	✓		✓	
			20.00	✓		✓	
			30.00	✓		✓	
			50.00	✓		✓	
Additional Tests							
Repeatability		30.00 kg					
Over Range Blank		N/A					
Tare		N/A					

CERTIFICATE

This is to certify that the above instrument meets the requirements of the Weights and Measures Act (CAP 103) and may be used in trade.

Gideon Mutabazi 17/06/2022.

Inspector of Weights and Measures **Date**

Nakawa
Plot M217 Nakawa
Industrial Area
P.O. Box 6329, Kampala

Katwe
Plot 64/65, 3rd Floor Quality
Chemicals House
Katwe Road

Jinja City
Plot 51/53, Luba Road,
Trans Africa Plaza. PO
Box 1630

Mbale City
Bugwere Road
Plot 1-3
Po Box 356 Mbale

Lira City
Plot 26/28, Amulam
Complex
P.O. Box 804 Lira

Mbarara City
Plot 31, Constantine Robo
Road
P.O. Box 279 Mbarara

Gulu City
Plot 3B Ogwok Ayaru Road
Upper Gulu Town
Tel: 0417333274

Appendix 5: Tree root extraction

Extracted root from *Cordia africana*

Digging of *Cordia africana roots*

Back filling of soil

Root extraction from *Albiza coriaria*

Appendix 6: Tree distribution mapping

Appendix 7: Soil sampling for laboratory shear strength analysis

Composite samples for soil texture analysis

Soil samples for shear strength analysis

Field soil sample collection