A Project report

on

"LANDSLIDE SUSCEPTIBILITY MAPPING OF GUWAHATI CITY USING ANALYTICAL HIERARCHY PROCESS (AHP) IN ArcGIS"

Submitted in partial fulfillment of the requirements for the award of the degree of

MASTER OF TECHNOLOGY

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Under

ASSAM SCIENCE AND TECHNOLOGY UNIVERSITY

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Submitted by:

NILOTPOUL DEKA

M.TECH 4th Semester

Roll No: PG/C/22/12

ASTU Registration No: 003006222 of 2022-2024

Under the guidance of:

DR. ABINASH MAHANTA

Assistant Professor, Assam Engineering College

Department of Civil Engineering

ASSAM ENGINEERING COLLEGE

JALUKBARI, GUWAHATI-13, ASSAM

CANDIDATE DECLARATION

I hereby declare that the work presented in this report entitled **“LANDSLIDE SUSCEPTIBILITY MAPPING OF GUWAHATI CITY USING ANALYTICAL HIERARCHY PROCESS (AHP) IN ArcGIS”,** in the partial fulfillment of the requirement for the award of the degree of Master of Technology in Civil Engineering with specialization in Geotechnical Engineering submitted in the Department of Civil Engineering, Assam Engineering College, Jalukbari, Guwahati-13 under Assam Science and Technology University, is a work carried out in the said college under the supervision of Dr. Abinash Mahanta, Assistant Professor, Department of Civil Engineering, Assam Engineering College, Jalukbari, Guwahati- 13, Assam. Whatever I have presented in this report has not been submitted by me for the award of any other degree or diploma.

Date :

Place : Guwahati

Nilotpoul Deka

M.Tech 4th Semester

Department of Civil Engineering

Assam Engineering College

Jalukbari, Guwahati-781013

CERTIFICATE OF SUPERVISION

This is to certify that the work presented in this report entitled **— "LANDSLIDE SUSCEPTIBILITY MAPPING OF GUWAHATI CITY USING ANALYTICAL HIERARCHY PROCESS (AHP) IN ArcGIS"** is carried out by Nilotpoul Deka, Roll No: PG/C/22/12, a student of M.Tech 4th semester, Department of Civil Engineering, Assam Engineering College, under my guidance and supervision and submitted in the partial fulfillment of the requirement for the award of the Degree of Master of Technology in Civil Engineering with specialization in Geotechnical Engineering under Assam Science and Technology University.

Date:

Place: Guwahati

Dr. Abinash Mahanta

Assistant Professor

Department of Civil Engineering

Assam Engineering College

Guwahati - 781013

CERTIFICATE OF APPROVAL

This is to certify that the following student of M.Tech 4th semester of Civil Engineering Department (Geotechnical Engineering), Assam Engineering College, has submitted his project on **— "LANDSLIDE SUSCEPTIBILITY MAPPING OF GUWAHATI CITY USING ANALYTICAL HIERARCHY PROCESS (AHP) IN ArcGIS"** in partial fulfillment of the requirement for the award of the Degree of Master of Technology in Civil Engineering with specialization in Geotechnical Engineering under Assam Science and Technology University.

Name: NILOTPOUL DEKA

College Roll No: PG/C/22/12

ASTU Roll No: 220620062011

ASTU Registration No: 003006222 of 2022 -2024

Date:

Place: Guwahati

Dr. Abinash Mahanta

Assistant Professor

Department of Civil Engineering

Assam Engineering College

Guwahati - 781013

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Date :

Place : Guwahati

NILOTPOUL DEKA

M.Tech 3rd Semester

Department of Civil Engineering

Assam Engineering College

Jalukbari, Guwahati-781013

ABSTRACT

In light of Guwahati's susceptibility to landslides, which annually impact human lives, there is an urgent necessity for effective risk mitigation strategies. Recognizing the critical importance of mapping landslide susceptibility zones, this study utilizes the Analytical Hierarchy Process (AHP) method within ArcGIS. The research integrates causative factor data sourced from diverse and credible sources to comprehensively map landslide-prone areas in Guwahati. In conjunction with this mapping effort, a slope stability analysis was conducted using SlopeW software. This analysis considered varying slope angles pertinent to Guwahati's terrain, alongside elevated seismic coefficients and adjustments in pore water pressure values.

The combined results underscore the complex interplay of geological, hydrological, and seismic factors influencing slope stability. The study identifies 17 out of Guwahati's 60 municipality wards as highly susceptible to landslides, emphasizing the gravity of the situation and stressing the need for targeted intervention and mitigation measures. By integrating findings from both AHP-based susceptibility mapping and detailed slope stability analyses, this research provides a robust framework for informed decision-making and proactive management of landslide risks in Guwahati.

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INTRODUCTION

1.1 OVERVIEW

Landslides are geological phenomena characterized by the downward movement of rock, soil, and debris along a slope. They are natural hazards that occur when the stability of a slope is compromised, leading to the displacement of materials. Landslides can vary in scale, from small, localized events to large, catastrophic occurrences that can cause significant damage to the environment, infrastructure, and communities.

Fig 1: A mudslide from the hills entirely demolished a house in Boragaon, Guwahati. The house was engulfed in flames, trapping four people inside
Source: https://www.indiatodayne.in/assam/story/assam-landslides-guwahati-atleast-4-dead-388098-2022-06-14

Fig 2: Five people of a family including three child died in landslide incident at Rakhaldubi area in Hailakandi district of Barak Valley.
Source: https://www.thehansindia.com/posts/index/National/2016-05-18/Five-of-a-family-die-in-Assam-landslides/228841

Landslides represent a significant geological hazard in India, affecting diverse landscapes from the Himalayan region to the Western Ghats. This susceptibility is underscored by the country's unique geological setting and climatic conditions. Several studies have delved into understanding the causes, characteristics, and implications of landslides in India, contributing to the body of knowledge on this complex natural phenomenon.

India's geological diversity, notably the collision between the Indian and Eurasian tectonic plates, makes the Himalayan region prone to landslides. Studies by researchers such as Gupta et al. (2018) [1] have emphasized the link between tectonic activity and slope instability in these areas. The monsoon season plays a pivotal role in triggering landslides across the country. The study conducted by Singh and Patel (2019) [2] investigated the relationship between rainfall patterns and landslide occurrences, particularly in the Western Ghats and northeastern states. Anthropogenic activities have increasingly contributed to landslide risks. The work of Sharma et al. (2020) [3] highlighted the impact of deforestation and improper land use planning on landslide occurrences in hilly terrains. Historical landslide events have been extensively documented in literature, shedding light on their consequences and the need for effective mitigation strategies. The analysis by Reddy and Kumar (2015) [4] of the Kedarnath disaster in 2013 provides valuable insights into the complex interplay of geological factors during such catastrophic events.

Landslides pose a significant geohazard in Northeast India, where the combination of complex geological structures, high rainfall, and hilly terrains contributes to the susceptibility of the region. The city of Guwahati, being a prominent urban center in the Northeast, is particularly vulnerable to landslide events. Understanding the causes, patterns, and mitigation strategies specific to this region is crucial for sustainable development and risk reduction. The Northeastern region of India is characterized by intricate geological formations, with tectonic activity playing a significant role. Studies by researchers such as Sen et al. (2017) [5] have highlighted the geological complexities in the region and their influence on slope stability. The monsoon season, with its heavy and prolonged rainfall, exacerbates landslide risks in Northeast India. The work of Baruah and Das (2019) [6] investigated the monsoonal influences on landslide occurrences, emphasizing the need for a thorough understanding of precipitation patterns. Guwahati, as a rapidly growing urban center in the region, faces unique challenges concerning landslides. Studies by Bora et al. (2020) [7] explored the impact of urbanization on landslide susceptibility in the Guwahati region, underscoring the importance of responsible land-use planning. While historical landslide incidents have occurred in various parts of Northeast India, specific events in and around Guwahati have been documented. The analysis by Saikia and Hazarika (2018) [8] of historical landslide incidents in the Guwahati region provides insights into the local dynamics and consequences.

1.2 GIS APPLICATIONS IN LANDSLIDE RESEARCH

Landslides, as dynamic geological events, present complex challenges for research and hazard management. The integration of Geographic Information Systems (GIS) has significantly enhanced our understanding of landslide processes. This literature review explores key studies that highlight the diverse applications of GIS in landslide research, ranging from spatial analysis to decision support systems.

GIS's ability to integrate diverse spatial datasets has been crucial in landslide research.

Researchers such as Lee et al. (2016) [9] emphasized the importance of incorporating topographical, geological, and hydrological data for a comprehensive understanding of landslide susceptibility. Terrain analysis is a cornerstone of GIS applications in landslide research. The work by Van Den Eeckhaut et al. (2012) [10] demonstrated the significance of DEM-based slope analysis in characterizing terrain features influencing landslide occurrence. GIS-based landslide susceptibility mapping has seen significant advancements. Studies by Guzzetti et al. (2006) [11] and Ohlmacher and Davis (2003) [12] utilized GIS to develop susceptibility models, integrating various factors such as land cover, slope, and lithology. The capability of GIS in change detection and monitoring has been underscored by researchers. Brabb and Harrod (2004) [13] highlighted the importance of GIS in detecting changes in land cover and terrain morphology as precursors to landslide events. GIS provides a robust platform for risk assessment and decision support. Recent work by Pourghasemi et al. (2019) [14] emphasized the integration of GIS with multi-criteria decision analysis for a comprehensive landslide risk assessment. GIS facilitates the monitoring of changes in land cover, land use, and terrain over time. By comparing historical and current spatial data, researchers can identify areas susceptible to changes that might trigger landslides. This capability is essential for early warning systems and adaptive management strategie

CHAPTER 2
LITERATURE REVIEW

2.1 INTRODUCTION

The literature work carried out by the researchers related to the field of the present study is in the section. Each of the literature is briefly described with its own outcome to support the undertaking of the present topic of interest

2.2 DEFINITION:

Varnes (1978) [15], proposed a seminal classification system, categorizing landslides into falls, slides, flows, and topples. This classification laid the groundwork for a systematic approach to understanding landslide processes.

Hutchinson (1988) [16], emphasized the significance of slope movement, introducing key factors like shear strength and stress conditions as essential in the geological definition of landslides.

Glade et al. (2000) [17], expanded the definition to include societal activities, land-use changes, and climate influences, reflecting a comprehensive understanding of the interactions shaping landslide occurrences.

Crozier (2010) [18], highlighted the importance of incorporating remote sensing data for detecting, monitoring, and analyzing landslide events, emphasizing the role of technology in refining definitions.

2.3 CLASSIFICATION

Landslides are generally classified based on their movement, the type of material involved, and the specific triggering factors. Here is a general classification

2.3.1 Based on Movement

2.3.1.1 Rockslides:

Involving the sliding or falling of individual rock fragments.

2.3.1.2 Rockfalls:

Sudden, free-fall movement of individual rock blocks.

2.3.1.3 Debris Flows:

Rapid downslope movement of a mixture of soil, rock, water, and organic material.

2.3.1.4 Mudslides:

Movement of fine-grained, wet soil or earth material.

2.3.1.5 Lahars:

Specifically volcanic mudflows, often triggered by volcanic activity.

2.3.2 Based on Material

2.3.2.1 Rock Landslides:

Involving primarily rock material.

2.3.2.2 Earth Landslides:

Involving soil and other unconsolidated materials.

2.3.2.3 Debris Landslides:

Comprising a mixture of rocks, soil, and other materials.

2.3.3 Based on Triggering Factors:

2.3.3.1 Rainfall-Triggered Landslides

Caused by excessive rainfall, leading to saturation of soil.

2.3.3.2 Earthquake-Induced Landslides:

Triggered by seismic activity, often due to ground shaking.

2.3.3.3 Human-Induced Landslides:

Resulting from human activities like excavation, construction, or deforestation.

2.3.3.4 Volcanic Landslides:

Associated with volcanic eruptions, including pyroclastic flows and lahars.

2.4 TRIGGERING FACTORS OF LANDSLIDE:

Kirschbaum et al. (2015) [19], provided an integrated framework considering both precipitation-induced and earthquake-triggered landslides. This approach acknowledges the diverse factors initiating slope failures. Their work highlights the importance of understanding the triggering mechanisms for effective landslide hazard assessment.

Montgomery et al. (2003) [20], Focusing on rainfall-induced landslides, Montgomery et al. examined the role of antecedent soil moisture conditions. Their study emphasized the significance of the initial soil moisture content in influencing the susceptibility of slopes to rainfall-triggered landslides.

Crozier (2010) [21], work delved into the impact of climate change on landslide activity. Changes in precipitation patterns and intensities associated with climate change were identified as potential triggers for increased landslide occurrences. This study underscores the importance of considering long-term climatic trends.

Guzzetti et al. (2008) [22], conducted a comprehensive analysis of landslide-triggering rainfall events. Their study identified critical rainfall thresholds for different regions, emphasizing the importance of rainfall intensity, duration, and cumulative rainfall as triggering factors.

Gariano and Guzzetti (2016) [23], extended the research on rainfall-triggered landslides by proposing an early warning model. Their work incorporates real-time rainfall data to assess the potential for landslide occurrence, contributing to proactive risk management.

Caine (1980) [24], focused on seismic triggers for landslides. The study highlighted the influence of ground shaking, acceleration, and slope angle on earthquake-induced slope failures. Understanding the seismic parameters involved is crucial for assessing landslide susceptibility in seismic-prone regions.

Schuster and Highland (2001) [25], examined the triggering mechanisms of landslides in volcanic terrains. They identified volcanic activity, such as eruptions and lava flow interactions, as significant triggers for slope instability. This research expands our understanding of the diverse factors influencing landslide occurrence.

Crosta and Frattini (2003) [26], investigated the role of human activities in landslide initiation. Their study emphasized the impact of excavation, deforestation, and urbanization on slope stability, highlighting the need for sustainable land-use practices to mitigate landslide risk.

Bovenga et al. (2018) [27], explored the influence of soil moisture variations detected by satellite-based Synthetic Aperture Radar (SAR) on landslide occurrence. Their research showcased the potential of remote sensing technologies in monitoring and understanding the temporal dynamics of landslide-triggering factors.

Hungr et al. (2014) [28], investigated the role of rapid snowmelt in slope failures. Their study underscored how the rapid release of snowpack water content can contribute to increased pore pressures, influencing landslide initiation.

2.5 STUDY APPROACH OF LANDSLIDES:

Hungr et al. (2014) [29], Hungr and co-authors provided a comprehensive update on the Varnes classification of landslide types, presenting an essential framework for understanding and categorizing landslides. The Varnes classification system offers a systematic approach that considers the type and rate of movement, providing a basis for landslide hazard assessment. This classification has been widely accepted and utilized by researchers, geologists, and practitioners globally, serving as a fundamental tool for characterizing landslide events based on their distinctive features.

Sassa (1999) [30], Sassa's work focused on the study approach of landslides from a geotechnical engineering perspective. The research proposed a simplified system based on geotechnical concepts, emphasizing terms like liquefaction and pre-shearing of clays.

This approach facilitates a better understanding of the mechanical behavior of slopes, contributing to the assessment of landslide susceptibility and risk in geotechnically challenging terrains.

Bovenga et al. (2018) [31], Bovenga and colleagues approached landslide studies by leveraging advanced technologies, particularly remote sensing. Their research showcased the potential of Synthetic Aperture Radar (SAR) for monitoring soil moisture variations, offering a valuable tool for understanding the temporal dynamics of landslides. This study highlights the importance of integrating remote sensing techniques into the study approach for enhanced landslide detection and monitoring capabilities.

Montgomery et al. (2003) [32], Montgomery and team contributed to the study approach by investigating rainfall-induced landslides. Their research emphasized the role of antecedent soil moisture conditions as a critical factor influencing landslide susceptibility. This approach enhances our understanding of the hydrological aspects of landslides, particularly the relationship between rainfall patterns and slope stability.

Kirschbaum et al. (2015) [33], Kirschbaum et al. presented an integrated study approach that considers both precipitation-induced and earthquake-triggered landslides. Their research emphasized the need for a holistic understanding of landslide triggers for effective hazard assessment. By combining various triggering mechanisms, this approach provides a more comprehensive view of landslide occurrences, aiding in the development of robust landslide risk management strategies.

Sidle et al. (2017) [34], Sidle and colleagues contributed to the study approach by investigating the impacts of deforestation on landslide occurrence. Their research highlighted the importance of land-use practices in influencing slope stability, emphasizing the need for sustainable land management to mitigate landslide risk.

Crozier (2010) [35], Crozier's work delved into the impact of climate change on landslide activity. Changes in precipitation patterns and intensities associated with climate change were identified as potential triggers for increased landslide occurrences. This study underscores the importance of considering long-term climatic trends.

Gariano and Guzzetti (2016) [36], In a further development, Gariano and Guzzetti extended the research on rainfall-triggered landslides by proposing an early warning model. Their work incorporates real-time rainfall data to assess the potential for landslide occurrence, contributing to proactive risk management.

Guzzetti et al. (2008) [37], Guzzetti and collaborators conducted a comprehensive analysis of landslide-triggering rainfall events. Their study identified critical rainfall thresholds for different regions, emphasizing the importance of rainfall intensity, duration, and cumulative rainfall as triggering factors.

2.6 LANDSLIDE SUSCEPTIBILITY:

Van Westen et al. (2003) [38], Van Westen and colleagues provided a foundational definition of landslide susceptibility, emphasizing the concept as a measure of the likelihood of a location to experience landslides. Their work highlighted the importance of understanding the spatial distribution and interaction of various factors contributing to landslide occurrence.

Guzzetti et al. (2006) [39], Guzzetti and co-authors contributed to the definition by considering landslide susceptibility as a spatial probability assessment based on the presence of conditioning factors. Their study emphasized the need for quantitative models to express susceptibility, incorporating factors such as slope, lithology, and land use.

Ayalew and Yamagishi (2005) [40], Ayalew and Yamagishi defined landslide susceptibility as the inherent predisposition of an area to landslides based on geological, geomorphological, and environmental factors. Their research emphasized the use of GIS and statistical models to quantify and map susceptibility for effective hazard assessment.

Van Den Eeckhaut et al. (2006) [41], Van Den Eeckhaut and colleagues extended the definition by incorporating dynamic factors such as climate and land-use changes into the assessment of landslide susceptibility. Their work highlighted the evolving nature of susceptibility over time and the importance of considering temporal aspects in susceptibility definitions.

Ohlmacher and Davis (2003) [42], Ohlmacher and Davis contributed to the definition by introducing the Weight of Evidence method for landslide susceptibility assessment. They emphasized the concept of evidence weightings based on the spatial relationships between conditioning factors and landslide occurrences.

Carrara et al. (1999) [43], Carrara and collaborators defined landslide susceptibility as a measure of the likelihood of slope failure based on the spatial distribution of factors that influence slope stability. Their work underscored the integration of various data types, including remote sensing and GIS, to enhance the accuracy of susceptibility assessments.

Chung and Fabbri (2000) [44], Chung and Fabbri's work added a fuzzy set theory perspective to the definition of landslide susceptibility. They defined susceptibility as a degree of membership in a fuzzy set representing the potential for landslides, acknowledging the uncertainty and imprecision inherent in susceptibility assessments.

Pradhan (2010) [45], Pradhan extended the definition by introducing machine learning approaches, such as Artificial Neural Networks (ANNs), for landslide susceptibility assessment. The definition emphasized the ability of these models to capture complex relationships among conditioning factors.

2.7 ADVANCEMENTS IN LANDSLIDE SUSCEPTIBILITY MAPPING:

Lee et al. (2004) [46], Lee and co-authors conducted a pioneering study on landslide susceptibility mapping using a GIS-based approach. Their research focused on the integration of various factors, including slope, lithology, land use, and precipitation, to assess and map landslide susceptibility. This work laid the foundation for subsequent studies in the field of landslide susceptibility mapping.

Van Westen et al. (2008) [47], Van Westen and colleagues contributed significantly to the advancement of landslide susceptibility assessment by introducing the Analytical Hierarchy Process (AHP) method. Their research emphasized the importance of integrating expert knowledge to assign weights to different susceptibility factors, providing a more accurate and robust landslide susceptibility mapping approach.

Guzzetti et al. (1999) [48], Guzzetti and team explored the use of statistical models, particularly logistic regression, for landslide susceptibility mapping. Their study demonstrated the effectiveness of incorporating conditioning factors such as land cover, lithology, and slope angle to develop a quantitative model for assessing landslide susceptibility.

Ohlmacher and Davis (2003) [49], Ohlmacher and Davis contributed to the field by introducing a statistical index known as the Weight of Evidence (WoE) method for landslide susceptibility assessment. Their study emphasized the significance of considering the spatial distribution of conditioning factors and their relationships with landslide occurrences.

Ayalew and Yamagishi (2005) [50], Ayalew and Yamagishi conducted research on landslide susceptibility mapping in the Upper Blue Nile River basin, Ethiopia, using a combination of GIS and remote sensing techniques. Their study highlighted the potential of satellite imagery and GIS-based approaches in delineating susceptible areas and assessing landslide susceptibility.

Pradhan (2013) [51], Pradhan's work focused on the application of machine learning algorithms, particularly the Artificial Neural Network (ANN), for landslide susceptibility mapping. This research demonstrated the capability of ANN models in capturing complex relationships among landslide-related factors, leading to improved accuracy in susceptibility assessments.

Hong et al. (2004) [52], Hong and co-authors explored the integration of rainfall-induced landslides and susceptibility mapping. Their study emphasized the temporal dynamics of landslide susceptibility, particularly during heavy rainfall events, providing insights into the importance of considering dynamic factors in susceptibility assessments.

Chung and Fabbri (1999) [53], Chung and Fabbri's research laid the groundwork for fuzzy logic-based approaches in landslide susceptibility mapping. Their study introduced the Fuzzy Algebraic Sum Model, showcasing the potential of fuzzy set theory in handling uncertainties and incorporating expert knowledge for more realistic susceptibility assessments.

2.8 GIS FOR LANDSLIDE ANALYSIS

Carrara et al. (1991) [54], laid the foundation for the application of Geographic Information Systems (GIS) in mapping landslide hazard. The study emphasized the significance of GIS technology in integrating various spatial data, including terrain parameters, geological information, and land cover, to assess and map areas prone to landslides. This work marked a pivotal moment in utilizing GIS for landslide analysis.

Guzzetti et al. (1999) [55], provided a comprehensive review of landslide hazard evaluation techniques, focusing on a multi-scale study in Central Italy. The research emphasized the role of GIS in analyzing and synthesizing diverse spatial data for landslide susceptibility assessment. The study underscored the importance of GIS in understanding landslide processes at different scales.

Lee and Talib (2005) [56], contributed to the literature by exploring probabilistic methods for landslide susceptibility mapping using GIS. The study incorporated factor effect analysis, highlighting the role of GIS in handling spatial data and assessing the influence of various factors on landslide occurrence. Probabilistic approaches within GIS provide a valuable framework for quantifying landslide susceptibility.

Van Westen et al. (2003) [57], focused on the integration of geomorphological information in indirect landslide susceptibility assessment through GIS. The study emphasized the importance of utilizing GIS for processing and analyzing geomorphic data to enhance the accuracy of landslide susceptibility assessments. GIS played a crucial role in incorporating landscape characteristics into the analysis.

Ohlmacher and Davis (2003) [58], demonstrated the effectiveness of multiple logistic regression and GIS technology in predicting landslide hazard. The study, conducted in northeast Kansas, USA, showcased the integration of GIS for spatial analysis and modeling, incorporating factors such as slope, land use, and soil properties in landslide susceptibility assessments.

2.9 APPLICATIONS OF GIS SOFTWARE IN SPATIAL DATA ANALYSIS AND MAPPING:

Geographic Information System (GIS) software, essential for spatial data analysis and mapping, encompasses a variety of applications, including proprietary solutions like ArcGIS by ESRI, open-source alternatives such as QGIS and GRASS GIS, cloud-based platforms like Google Earth Engine, statistical computing with R, and collaborative mapping through OpenStreetMap.

2.10 ARC GIS:

ArcGIS by ESRI is a widely recognized GIS software known for its comprehensive functionalities. Researchers leverage its capabilities for landslide susceptibility mapping, integrating various factors such as terrain, geology, and land use to produce accurate and informative susceptibility models.

Lee et al. (2003) [59], employed ArcGIS in their study, utilizing likelihood ratio and logistic regression models for landslide susceptibility mapping in Janghung, Korea. The research demonstrated the effectiveness of ArcGIS in handling complex spatial analyses for susceptibility assessments. Pradhan et al. (2010) [60], utilized ArcGIS for GIS-based landslide susceptibility mapping, incorporating probabilistic likelihood ratio and spatial autocorrelation weight methods. The study showcased the usability of ArcGIS in integrating diverse modeling techniques for accurate susceptibility assessments. Yilmaz (2009) [61], applied ArcGIS alongside various methods such as frequency ratio, logistic regression, and artificial neural networks for landslide susceptibility mapping in Tokat, Turkey. The research highlighted ArcGIS's compatibility with different modeling approaches in landslide studies. Hong et al. (2007) [62], incorporated ArcGIS in their global landslide susceptibility mapping, emphasizing the integration of satellite remote sensing data. The study underscored the significance of ArcGIS in handling large-scale data for comprehensive susceptibility assessments. Ayalew and Yamagishi (2005) [63], employed ArcGIS in their study, utilizing logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. The research illustrated the usability of ArcGIS in logistic regression modeling for localized susceptibility assessments.

2.11 ANALYTICAL HIERARCHY PROCESS (AHP):

The Analytical Hierarchy Process (AHP) is a multi-criteria decision-making method that helps in dealing with complex decisions involving multiple criteria and alternatives. It was introduced by Thomas L. Saaty in the 1970s.

Thomas L. Saaty's (1980) [64] foundational work provides the fundamental principles and methodologies of the AHP. This book introduces the AHP as a decision-making tool for complex problems, emphasizing its application in planning, priority setting, and resource allocation. Saaty, T. L. (1990) [65], delves into the detailed process of utilizing AHP for decision-making. The paper provides insights into the step-by-step methodology, emphasizing its practical application in real-world scenarios. Saaty, T. L. (2008) [66], explores decision-making applications of the AHP in various service sectors. The article discusses the flexibility and adaptability of the AHP across different domains, showcasing its versatility as a decision support tool. Ishizaka, A., & Labib, A. (2009) [67], critically examine the benefits and limitations of the AHP in their paper. This contribution provides a comprehensive understanding of the method's strengths and challenges, contributing to the ongoing discourse on AHP. Opricovic, S., & Tzeng, G. H. (2004) [68], extends the discussion to comparative analyses of AHP with other Multiple Criteria Decision Making (MCDM) methods, shedding light on its relative effectiveness in decision-making processes.

2.12 WEIGHT OVERLAY METHOD:

The Weight Overlay Method is a GIS technique used for combining and analyzing multiple spatial datasets by assigning different weights to each layer based on their relative importance.

Ishizaka, A., & Labib, A. (2009) [69], critically examines the benefits and limitations of the Weight Overlay Method. The paper provides insights into the method's practical applications in decision-making scenarios, offering a comprehensive understanding of its strengths and challenges. Opricovic, S., & Tzeng, G. H. (2004) [70], contribute to the discourse by presenting a comparative analysis of compromise solutions using Multiple Criteria Decision Making (MCDM) methods, including the Weight Overlay Method. The analysis sheds light on the method's effectiveness in providing compromise solutions. Saaty, T. L. (1980) [71], work on the Analytic Hierarchy Process (AHP) also discusses the Weight Overlay Method as part of a broader decision-making framework. Saaty's contribution provides a foundational understanding of the method's integration within the AHP. Saaty, T. L. (1990) [72], delves into the detailed process of utilizing the Weight Overlay Method for decision-making. The paper emphasizes the step-by-step methodology, offering practical insights into its application in various real-world scenarios. Saaty, T. L. (2008) [73], explores decision-making applications of the Weight Overlay Method in various service sectors. The article discusses the method's flexibility and adaptability across different domains, showcasing its versatility as a decision support tool.

2.13 INDIAN STANDARD CODE PROVISIONS

The Bureau of Indian Standards (BIS) has outlined guidelines for the macro-level landslide hazard zonation in India, specifically detailed in IS 14496 Part 2: 1998 (Reaffirmed 2002). This standard adopts a heuristic approach for landslide hazard assessment, employing a factor rating scheme to evaluate susceptibility in a 1:50,000 scale. The framework incorporates six key causative factors essential for hazard zonation, namely lithology, geological structure, slope characteristics, land morphology, land use patterns, land cover attributes, and hydrological conditions.

2.14 Slope Stability Analysis

Slope stability analysis is a critical area of geotechnical engineering aimed at assessing the stability of natural and engineered slopes under various conditions. Understanding factors influencing slope stability is crucial for infrastructure development, environmental management, and hazard mitigation.

2.15 OBJECTIVE

The primary objective of this study is to generate a landslide susceptibility map for Guwahati city. To achieve the primary objective, the study encompasses the following key aspects:

a.Undertake a thorough investigation into the causative factors influencing landslides, including geological, topographical, and anthropogenic elements. Explore and analyze data extraction techniques from diverse authentic sources to ensure the acquisition of accurate and reliable information for landslide susceptibility mapping.

b. Develop a comprehensive understanding of the ArcGIS application, emphasing functionalities, tools, and capabilities relevant to landslide susceptibility mapping.

c.Apply the acquired knowledge to perform landslide analysis within the ArcGIS software, utilizing appropriate methodologies and tools for accurate susceptibility assessment.

d. Validate the generated landslide susceptibility map by comparing it with the existing landslide inventory data specific to Guwahati city, ensuring the accuracy and reliability of the developed map.

e. Conduct a slope stability analysis using SlopeW software to evaluate various slope angles relevant to Guwahati City, considering elevated seismic coefficients and varying pore water pressure values.

CHAPTER 3

STUDY AREA AND METHODOLOGY

3.2. AREA OF INTEREST

Guwahati, the largest city in Assam, India, is situated at approximately (26°4’45’’ - 26°14’) N latitude and (91°33’ - 91°52’6”) E longitude along the southern bank of the Brahmaputra River. Administered through a total of 60 municipal wards, covering an expansive area of about 328 square kilometers, Guwahati is characterized by its undulating terrain, surrounded by prominent hills like Jalukbari/Lankeswar, Fatasil, Gotanagar, Kharguli, Navagraha, Noon mati, Kamakhya/Nilachal, Kalapahar, Narangi, Hangrabari, Sarania, Narakashur, Sunsali, Kainadhara, Khanapara, and Garbhanga. The city's topography, coupled with a monsoon climate, exposes it to landslide risks, particularly in areas with steep slopes and loose soil. Notably, Nilachal Hill hosts the Kamakhya Temple, a cultural and spiritual landmark. Guwahati's unique geographical features and susceptibility to landslides underscore the importance of comprehensive mapping and risk mitigation strategies for sustainable urban development.

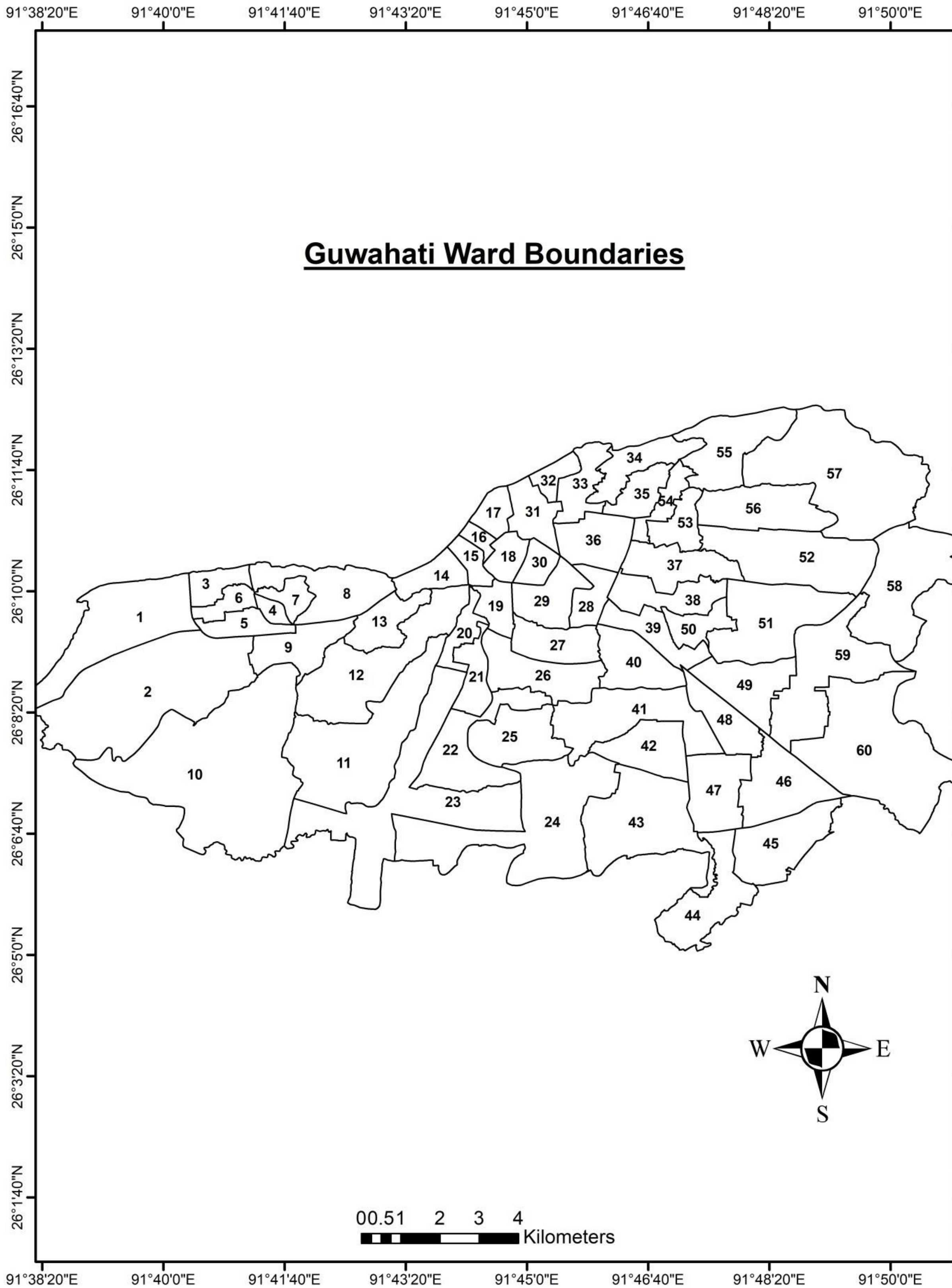


Fig 3: Guwahati Municipality Ward Map of 2022

(Source: Guwahati Municipal Corporation)

3.3 HISTORY OF LANDSLIDE OCCURANCE

Situated amidst the scenic landscapes of northeastern India, Guwahati has been shaped by its unique topography, featuring lush hills, intermontane valleys, and the mighty Brahmaputra River. In the backdrop of this dynamic terrain, landslides have become a recurrent natural event, leaving a significant imprint on the city's history. Examining the historical record of landslides is essential for understanding the city's vulnerability and formulating effective strategies for risk mitigation.

The documented history of landslides in Guwahati offers valuable insights into the patterns, frequencies, and spatial distribution of these events. Drawing on data from NASA's comprehensive landslide inventory, which meticulously catalogues instances of landslides, our exploration aims to uncover the historical nuances that have influenced the city's susceptibility to such geological phenomena.

This retrospective analysis not only illuminates the natural processes contributing to landslides but also underscores the human factors that may intensify the risk. As we embark on this journey, a thorough understanding of Guwahati's historical landslide occurrences becomes the cornerstone for our contemporary endeavors in landslide susceptibility mapping. This knowledge forms the basis for developing proactive measures to protect the city's residents and infrastructure from the ongoing challenges posed by landslides.

Table 1: Landslide inventory of Guwahati City occurred during 2007 to 2017 (Source: NASA)

Sl. No	Date	Source	Place	Trig Factor
1	7/19/2007	Saharas Samay	Guwahati	Rain
2	9/13/2007	Saharas Samay	Guwahati	Rain
3	4/20/2010	Assam Tribune	Raj Bhavan Guwahati, Assam	Downpour
4	4/20/2010	Assam Tribune	Kharghuli, Guwahati, Assam	Downpour
5	9/23/2011	Nbtvlive	Maighuli, Guwahati, Meghalaya	Downpour
6	6/2/2012	Ibnlive.in	Guwahati , Assam	Downpour
7	6/20/2012	twocircles.net	Lalunggaon,	Downpour

			Guwahati, Assam	
8	6/22/2012	thesop.org	Gorchuk area	Downpour
9	5/11/2013	articles.timesofindia.indiatimes.com	Sarania Hills, North Guwahati , Guwahati	Rain
10	5/11/2013	articles.timesofindia.indiatimes.com	Nursery, North Guwahati, Guwahati, Assam	Rain
11	10/6/2013	articles.timesofindia.indiatimes.com	Nilachal Hill, Guwahati, Assam	Downpour
12	10/6/2013	articles.timesofindia.indiatimes.com	Batahguli, Guwahati, Assam	Downpour
13	6/26/2014	Two Circles	Narakasur	Continuous _ rain
14	6/26/2014	Two Circles	Bamunimaidam	Continuous _rain
15	6/27/2014	Assam Times	Bhangagarh, Assam	Rain
16	6/28/2014	Assam Times	Kharghuli Hills, Assam	Rain
17	9/22/2014	Assam Tribune	VIP Road	Rain
18	9/22/2014	Assam Tribune	Dakhingaon	Rain
19	9/22/2014	Assam Tribune	Noonmati	Rain
20	9/22/2014	Assam Tribune	Dhirenpara	Rain
21	9/22/2014	Assam Tribune	Batahghuli	Rain
22	9/22/2014	Assam Tribune	Lalmati	Rain
23	2/14/2015	Telegraph	Kailashpur Hill	Mining
24	9/23/2015	Assam Times	Kamakhya Temple	Continuous_rain
25	6/22/2016	NYOOOZ	Piyali Phukan Nagar	Downpour
26	7/14/2016	Indian Express	Pub sarania hill, South Sarania, Guwahati, Assam, India	Monsoon
27	7/14/2016	Indian Express	Noonmati Nijarapar area of the city, Guwahati, Assam, India	Monsoon
28	7/20/2016	Times of India	Noonmati, Guwahati, Assam,India	Rain
29	12/15/2016	NBC Daily	Landslide at Pub Sarania Hill	Unknown
30	12/15/2016	NBC Daily	Landslide at Noonmati Nijarapar	Unknown
31	7/6/2017	DY365	Landslide crushes house	Continuous_rain
32	7/10/2017	The Assam Tribune	Landslide damages house	Continuous_rain
33	7/10/2017	The Assam Tribune	Landslide in Chandmari	Continuous _rain

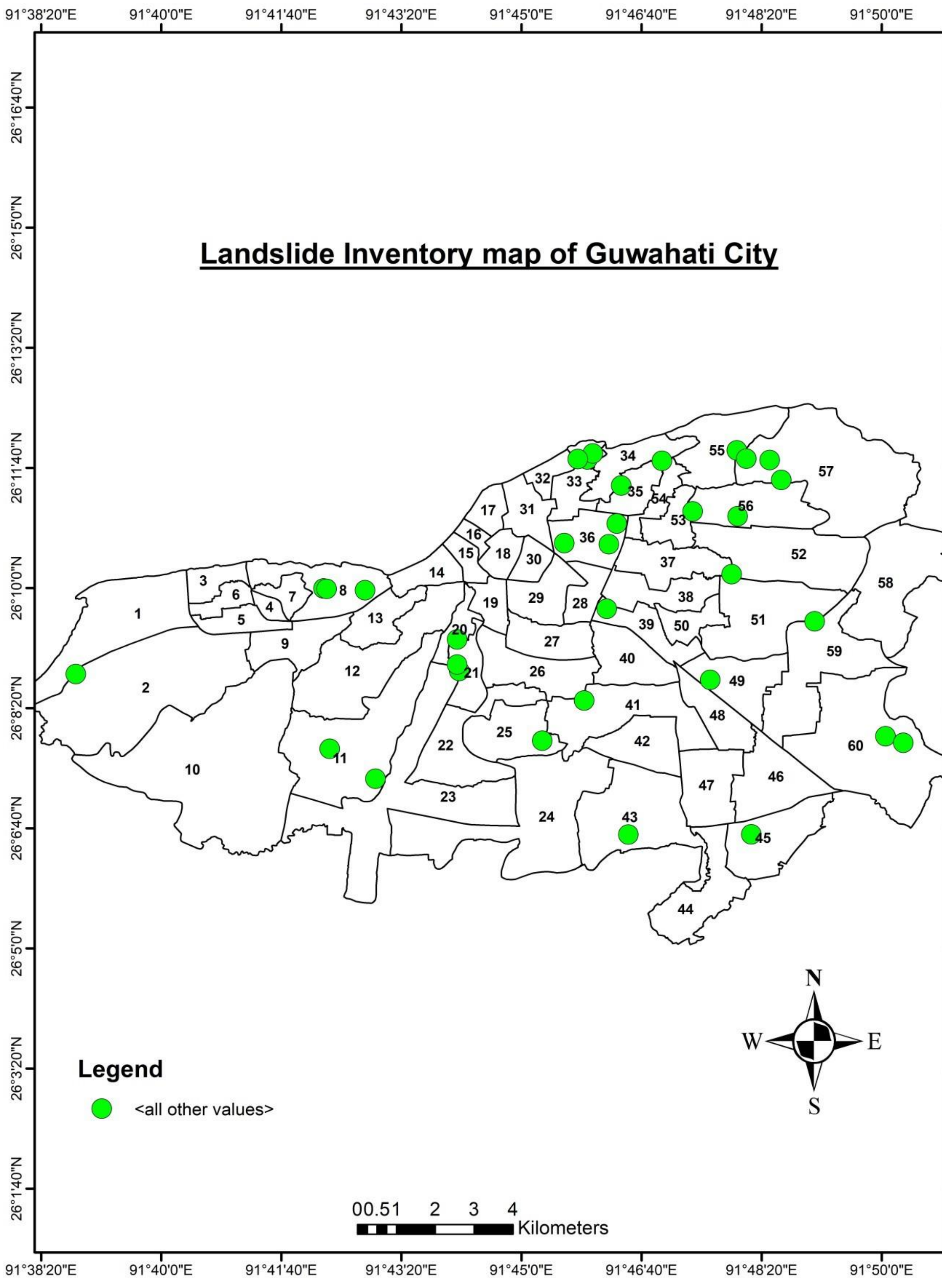


Fig 4: Landslide inventory of Guwahati City occurred during 2007 to 2017

(Source: NASA)

3.3 CAUSATIVE FACTORS CONSIDERED FOR THE LANDSLIDE SUSCEPTIBILITY MAPPING

3.3.1 Slope

Slope steepness is a critical factor influencing landslides. Steeper slopes are generally more prone to instability, as gravitational forces act more strongly on inclined surfaces, leading to increased potential for slope failure. Ishizaka, A., & Labib, A. (2009) [74], conducted a comprehensive study on the influence of slope on landslide occurrence. Their research highlighted the correlation between slope steepness and the likelihood of landslides.

3.3.2 Aspect

Aspect, or the orientation of slopes, plays a role in landslide susceptibility. Certain aspects receive more sunlight and precipitation, affecting soil moisture and erosion rates, thus influencing landslide occurrence. Van Den Eeckhaut et al. (2007) [75], explored the impact of aspect on landslide susceptibility. Their study emphasized how the orientation of slopes contributes to variations in landslide occurrence

3.3.3 Roughness

Surface roughness refers to the irregularity of terrain. Rougher terrains may provide more opportunities for water retention and soil entrapment, influencing landslide initiation and movement. Xie et al. (2011) [76], investigated the role of surface roughness in landslide initiation. Their research demonstrated how variations in terrain roughness influence slope stability.

3.3.4 Hill Shade

Hill shade represents the shading effect on terrain features due to sunlight. It influences the distribution of solar radiation, affecting soil moisture, temperature, and vegetation, thereby impacting landslide susceptibility. Sun, Wu, and Su (2013) [77], focused on the significance of hill shade in landslide susceptibility mapping. Their study highlighted the shading effects on terrain features and their relation to landslide-prone areas.

3.3.5 Average Rainfall

Precipitation, especially in the form of heavy rainfall, can saturate soils and increase pore water pressure, reducing soil cohesion. High average rainfall is a key trigger for landslides. Chen et al. (2015) [78], delved into the influence of average rainfall on landslide occurrence. Their research emphasized the role of precipitation patterns and intensity in triggering landslides.

3.3.6 Land Use and Land Cover

Human activities, land development, and changes in land cover can alter the stability of slopes. Deforestation, urbanization, and agricultural practices contribute to increased landslide susceptibility. Pan et al. (2015) [79], investigated the impact of land use and land cover on landslide susceptibility. Their study highlighted the role of human activities and vegetation in slope stability.

3.3.7 Lithology

Geological characteristics, such as rock type and composition, influence landslide susceptibility. Weaker lithologies are more prone to slope failures, and different rock types respond differently to external forces. Ayalew, Yamagishi, and Ugawa (2004) [80] explored the influence of lithology on landslide susceptibility. Their research emphasized how geological characteristics contribute to slope instability.

3.3.8 Geomorphology

Landforms and geomorphic features can indicate past and potential landslide areas. Certain landforms, such as steep cliffs or concave slopes, are more predisposed to landslides. Günther and Reichenbach (2003) [81], studied the relationship between geomorphology and landslides. Their research highlighted how specific landforms contribute to landslide occurrence.

3.3.9 Distance from Road

Roads can alter the natural drainage patterns and stability of slopes. Excavations during road construction, as well as increased water runoff, can contribute to landslide susceptibility near roads. Chen, Lee, and Chang(2016) [82], investigated the impact of distance from road on landslide susceptibility. Their study emphasized the influence of road construction and maintenance on slope stability.

3.3.10 Distance from Railway

Similar to roads, railways can impact slope stability. Cut-and-fill operations during railway construction, as well as changes in drainage patterns, can influence landslide occurrence near railway tracks. Tien Bui et al. (2016) [83], explored the influence of distance from railway on landslide susceptibility. Their research highlighted how railway infrastructures can affect slope stability.

3.4 BASICS OF ARCGIS

ArcGIS, developed by Esri, is a powerful Geographic Information System (GIS) software widely utilized for spatial analysis, mapping, and geospatial data management. Understanding the basics of ArcGIS is foundational for integrating geospatial technology into landslide susceptibility mapping.

3.4.1 Introduction to Key Terms

3.4.1.1 Vector Data

In the realm of ArcGIS, spatial data is categorized into two main types: vector and raster. Vector data represents geographic features using points, lines, and polygons. Points denote specific locations, lines represent linear features, and polygons enclose areas. This format is highly suitable for representing discrete features, such as roads, rivers, or administrative boundaries. Vector data maintains precision in representing the spatial relationships between features.

3.4.1.2 Raster Data

Contrasting with vector data, raster data employs a grid of cells to represent geographic features. Each cell in the grid contains a value, creating a pixelated representation of the landscape. This format is ideal for continuous data, such as elevation or temperature, where values change gradually across space. Raster data is efficient for large-scale mapping and spatial analysis, providing a different perspective on geographic phenomena.

3.4.1.3 Shapefile

A fundamental concept in ArcGIS is the shapefile, a common geospatial vector data format. A shapefile comprises multiple files that collectively store geometric and attribute information. Geometric data includes points, lines, or polygons defining spatial features, while attribute data provides additional information related to these features. Shapefiles are versatile and widely used for storing and sharing geographic information due to their simplicity and compatibility with various GIS applications.

3.4.1.4 Thematic Maps

Thematic maps are graphical representations of spatial data that highlight and illustrate a specific theme, variable, or attribute across a geographic area. The primary purpose of thematic maps is to visually communicate spatial patterns and relationships of a chosen theme, facilitating a better understanding of geographic phenomena.

3.5 ANALYTICAL HIERARCHY PROCESS

The Analytical Hierarchy Process (AHP) stands as a robust and versatile decision- making tool, rooted in the realm of multi-criteria analysis. Introduced by mathematician and operations researcher Thomas L. Saaty in the late 1970s, AHP has since found widespread application across various disciplines, from business to environmental management.

3.5.1 Key Components of AHP:

3.5.1.1 Hierarchical Structure:

AHP organizes decision problems into a hierarchical structure, breaking down complex issues into a series of interconnected criteria and alternatives. This structured approach provides a systematic framework for decision-makers to evaluate and prioritize elements.

3.5.1.2 Pairwise Comparisons:

Central to AHP is the concept of pairwise comparisons. Decision-makers assess the relative importance of criteria and alternatives by comparing them in pairs. This process establishes a set of numerical values that quantify the preferences and priorities within the hierarchy. The goal is to establish a hierarchy of criteria or alternatives based on their relative importance. Decision-makers compare each criterion or alternative against every other one, indicating which is more important or preferable. A scale is used to express the preference or importance of one element over another. The scale is typically a numerical scale, often ranging from 1 to 9, with 1 representing equal importance and 9 indicating extremely more important. The comparisons are organized into a matrix known as the Pairwise Comparison Matrix. If there are 'n' criteria or alternatives, the matrix is an 'n x n' matrix. Each cell in the matrix corresponds to the comparison between two elements. If comparing criterion i with criterion j, the decision-maker assigns a value that represents the importance of i relative to j.

3.5.1.3 Consistency Check

To ensure the reliability of judgments, a consistency check is performed. Inconsistencies arise when, for example, A is considered more important than B, and B is considered more important than C, but A is considered less important than C. Consistent judgments contribute to the reliability of the final results.

3.5.1.4 Calculating Weight Vectors

Once the matrix is filled, mathematical processes, often involving eigenvectors and eigenvalues, are applied to derive weight vectors. These weight vectors represent the relative importance or priority of each criterion or alternative.

3.5.1.5 Normalization

The derived weights are normalized to ensure they sum up to 1, providing a meaningful comparison.

3.5.1.6 Aggregation of Criteria

The final step involves aggregating these weights in a hierarchical structure to determine the overall priorities.

3.5.1.7 Decision Matrix

The priorities obtained from the AHP process can be used in decision-making, such as evaluating alternatives or ranking criteria.

3.6 WEIGHT OVERLAY METHOD

The Weight Overlay Method is a geospatial analysis technique widely used in Geographic Information System (GIS) applications for combining and synthesizing different thematic maps to create a composite map. The primary objective is to integrate multiple thematic maps, each representing a specific criterion or factor, into a single composite map. It is often employed in decision-making processes, such as in determining the suitability or vulnerability of an area based on various factors. Each thematic map is assigned a weight based on its perceived importance or influence on the overall analysis. Weights are assigned to each thematic map to reflect the significance of the factor it represents in the decision-making process. These weights are usually assigned subjectively or through a more objective process, such as the Analytical Hierarchy Process (AHP). Thematic maps are overlaid, pixel by pixel, to create a composite map. Each pixel in the resulting map is a combination of the values from corresponding pixels in the individual thematic maps, weighted according to their assigned importance. The Weight Overlay Method commonly uses a weighted sum approach. The value of each pixel in the composite map is calculated as the sum of the products of the values in each thematic map and their corresponding weights. To ensure that the composite map values are within a meaningful range, normalization may be applied. Normalization adjusts the values to a standard scale, often ranging from 0 to 1. The final output is a composite map that represents the integrated information from multiple thematic maps, reflecting the combined influence of various factors. This map is useful for decision-making, such as identifying suitable locations for a particular land use, assessing environmental vulnerability, or other spatial analyses.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 INTRODUCTION

The Results and Discussion chapter presents the culmination of extensive research and analysis, unraveling the intricate spatial patterns of various factors contributing to landslide susceptibility in Guwahati City. Each thematic map represents a critical aspect of the city's landscape, and their collective synthesis through the Analytical Hierarchy Process (AHP) forms the foundation for a comprehensive understanding of landslide susceptibility.

4.2 INDIVIDUAL THEMATIC MAPS

4.2.1 Slope

The Slope thematic map delineates the topographical variations, indicating areas prone to steep gradients, a key factor influencing landslide susceptibility.

Table 2: Reclassified values of Slope generated in ArcGIS

Classification	Angle of slope (in degrees)
1	0 – 4.3
2	4.4 – 9.8
3	9.9 - 16
4	17 - 24
5	25 - 45

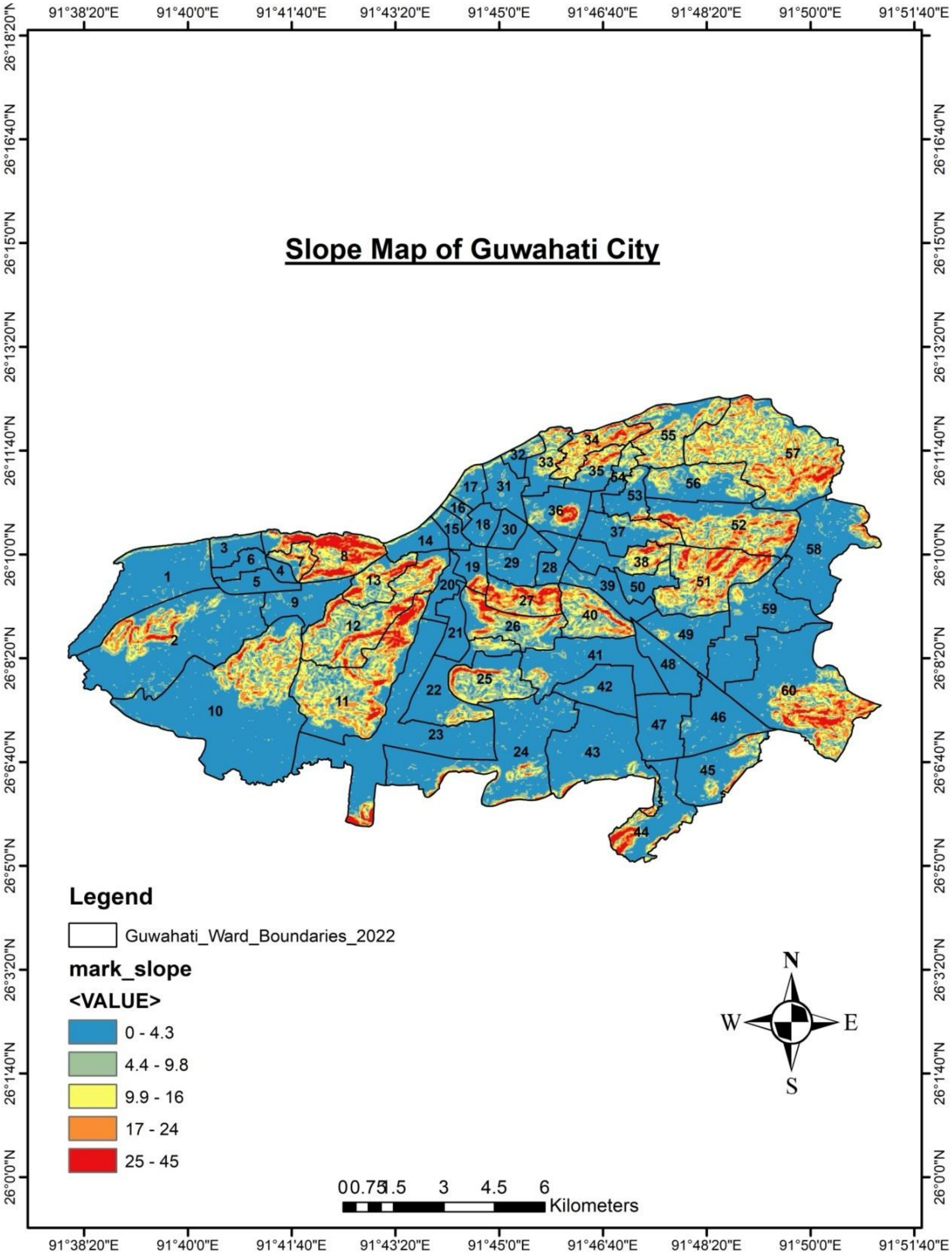


Fig 5: Thematic map of Slope of Guwahati City generated in ArcGIS

4.2.2 Aspect

Aspect mapping reveals the directional orientation of slopes, shedding light on how different slopes may be exposed to varying sunlight and moisture conditions.

Table 3: Reclassified values of Aspect generated in ArcGIS

Classification	Aspect (in degrees)
1	0 – 72
2	72 – 150
3	160 - 210
4	220 - 290
5	300 - 360

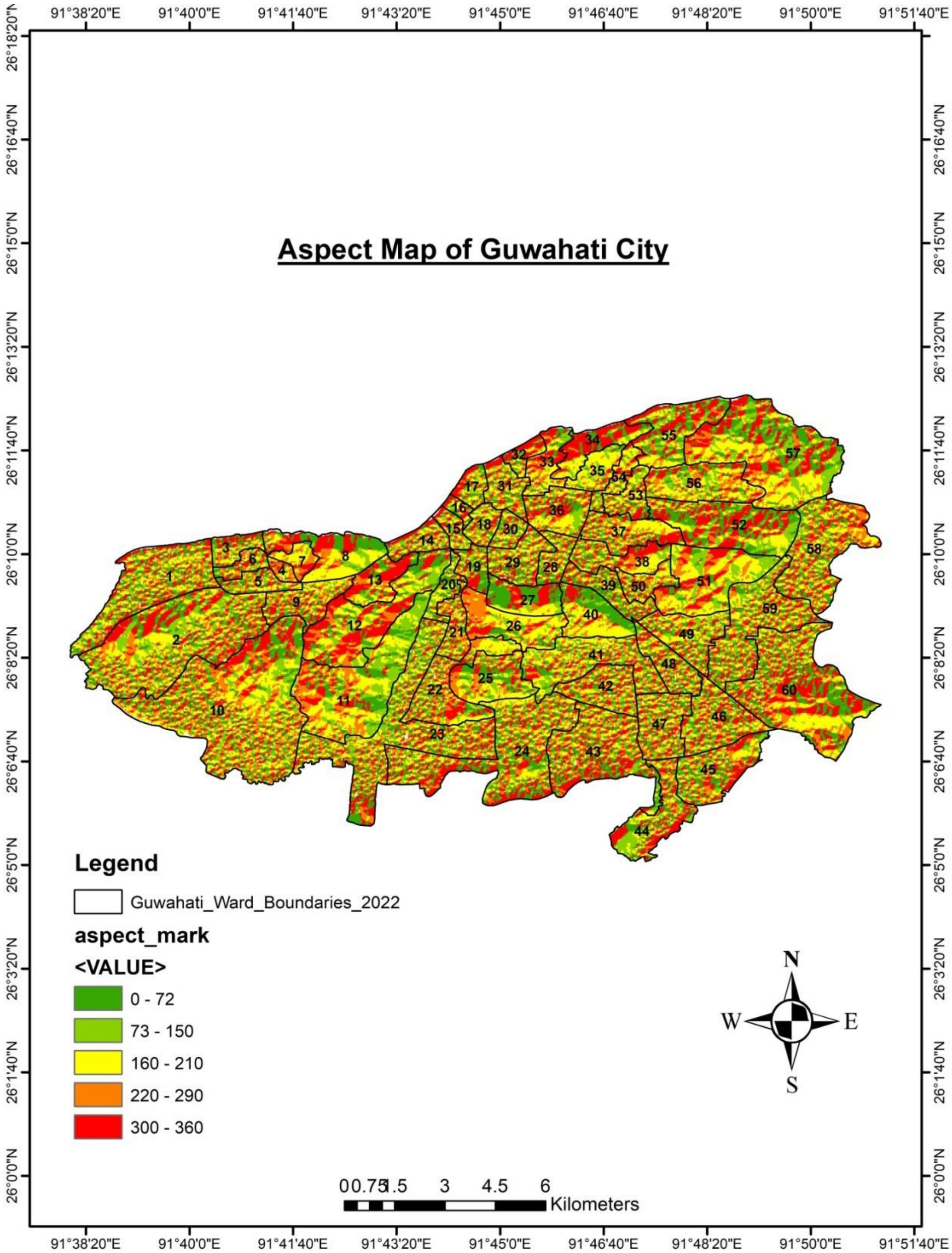


Fig 6: Thematic map of Aspect of Guwahati City generated in ArcGIS

4.2.3 Roughness

The Roughness map illustrates the surface irregularities, crucial in identifying areas with heightened susceptibility due to complex terrain features.

Table 4: Reclassified values of Roughness generated in ArcGIS

Classification	Roughness (unitless)	Physical meaning
1	0 – 6.8	Flat or Smooth terrain
2	6.9 - 16	Gentle Slope
3	17 - 26	Hilly or uneven landscape
4	27 - 39	Mountaneous terrain
5	40 - 82	Mountaneous landscapes

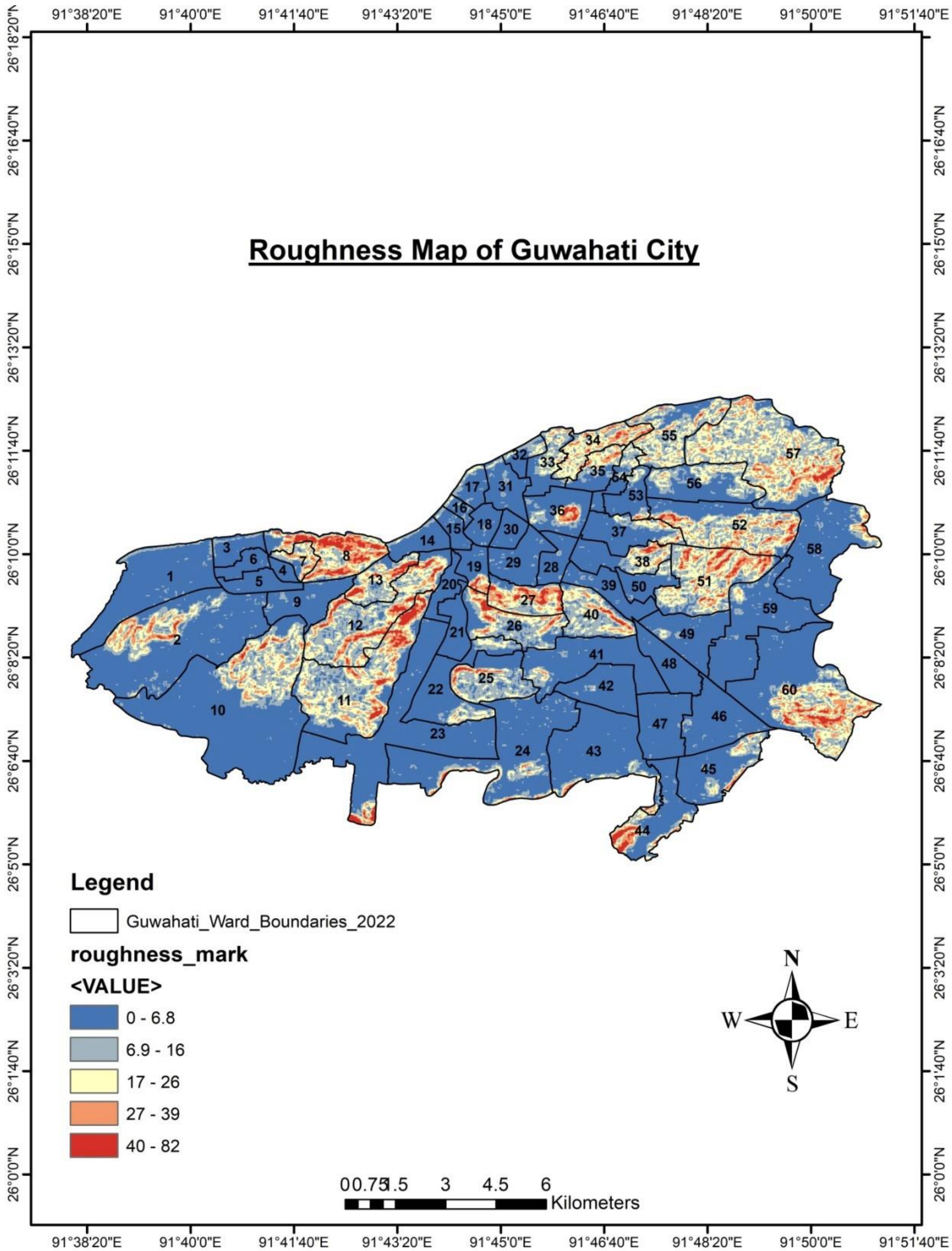


Fig 7: Thematic map of Roughness of Guwahati City generated in ArcGIS

4.2.4 Hill shade

Hill shade mapping provides a nuanced representation of the terrain, considering illumination angles, aiding in identifying shadowed and illuminated areas.

Table 5: Reclassified values of Hillshade generated in ArcGIS

Classification	Rating	Physical Meaning
1	1 - 42	Low Hillshade Intensity
2	43 - 110	Moderate to Low Hillshade intensity
3	120 - 180	Moderate Hillshade Intensity
4	170 - 200	Moderate to High Hillshade intensity
5	210 - 260	High Hillshade Intensity

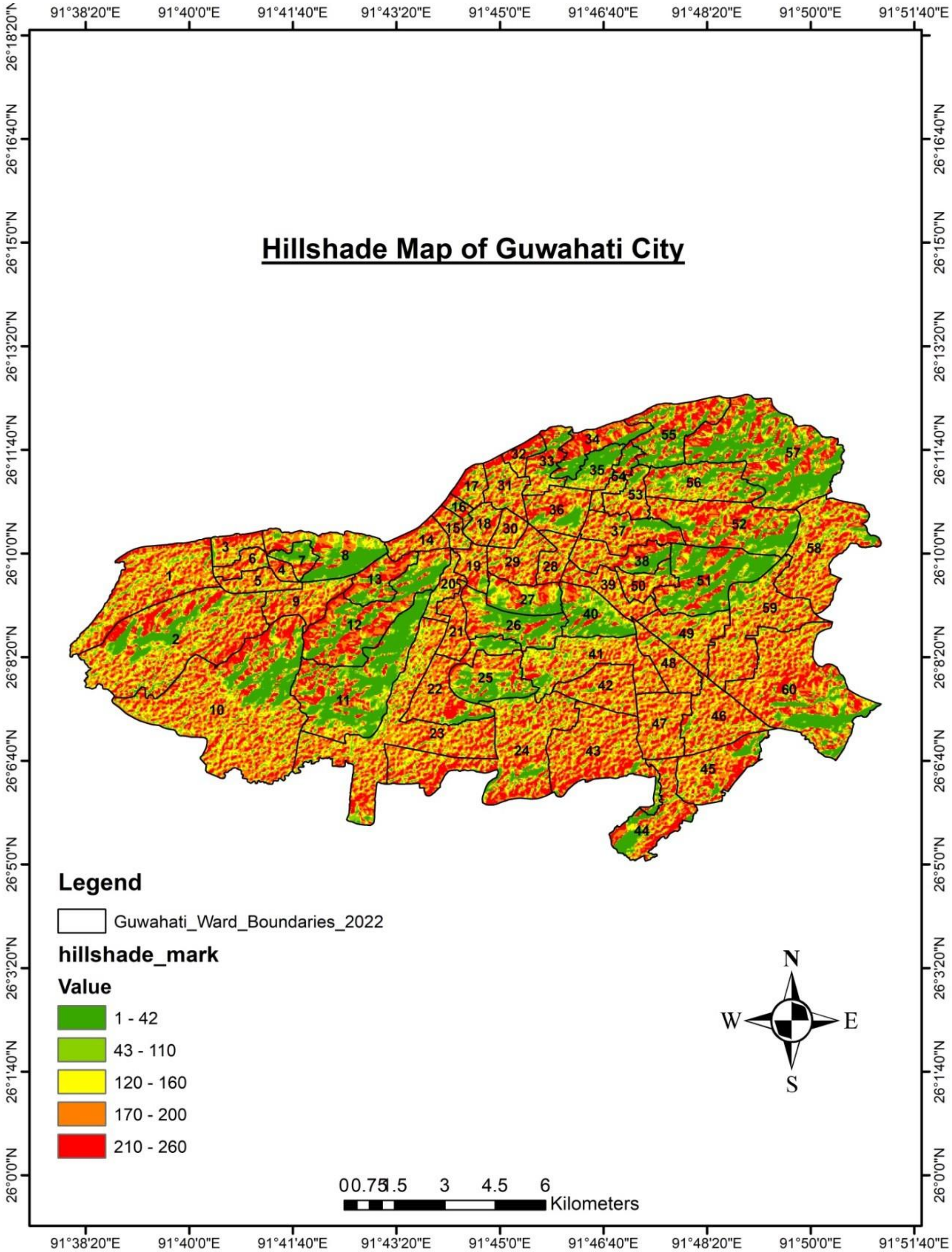


Fig 8: Thematic map of Hillshade of Guwahati City generated in ArcGIS

4.2.5 Average Rainfall

This map incorporates rainfall data, a pivotal factor in landslide initiation, highlighting areas with consistently high precipitation.

Table 6: Reclassified values of Average Rainfall generated in ArcGIS

Classification	Average Rainfall Intensity (in mm)
1	950 - 970
2	980 - 990
3	1000
4	1100 - 1000
5	1100

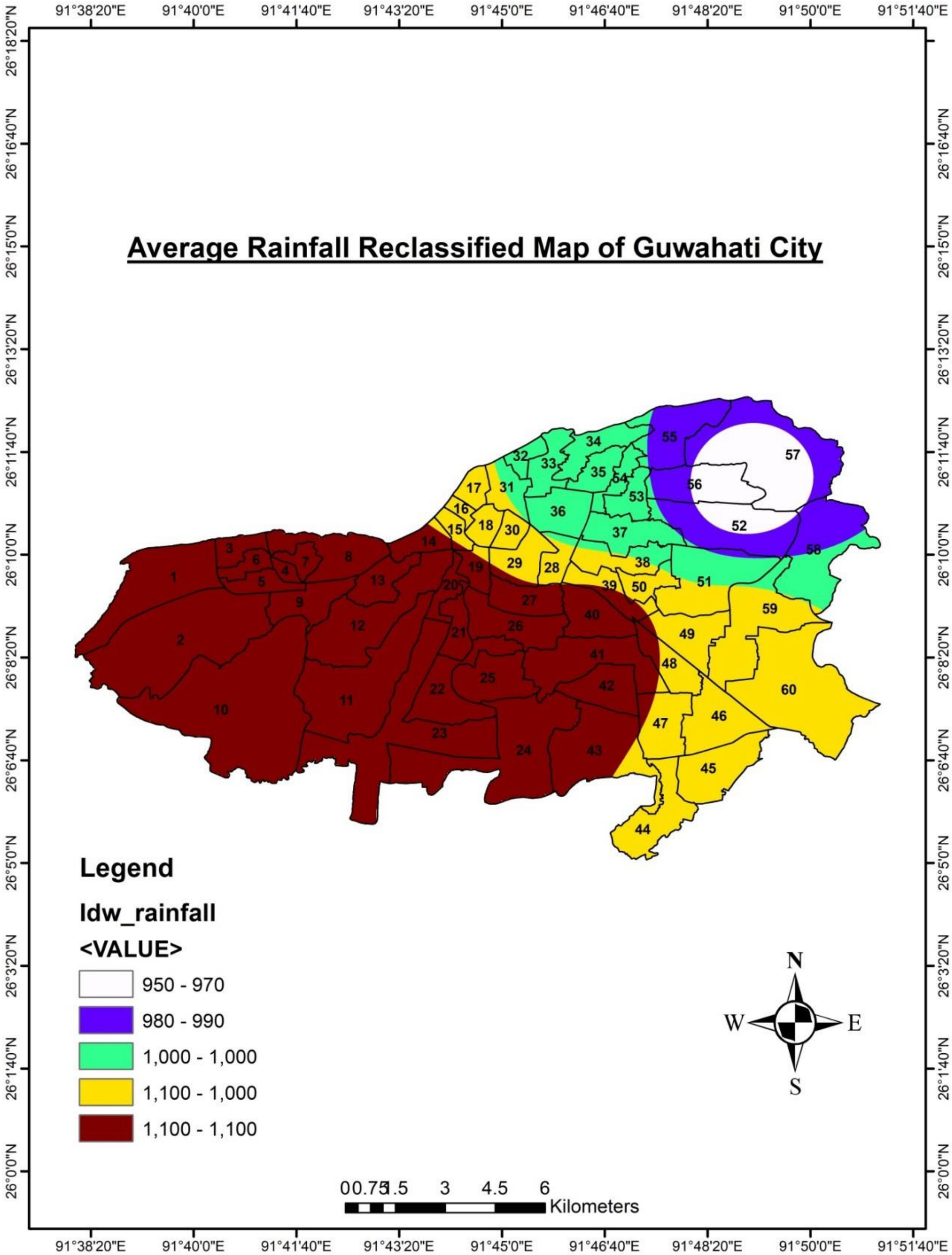


Fig 9: Thematic map of Average Rainfall of Guwahati City generated in ArcGIS

4.2.6 Land Use and Land Cover (LULC)

The Land Use and Land Cover map classifies urban, agricultural, and forested regions, contributing to a holistic understanding of human-induced changes in susceptibility.

Table 7: Reclassified values of LULC generated in ArcGIS

Classification	Rating	Physical Meaning
1	1	Natural or Undisturbed
2	1.1 - 2	Low Intensity Urban
3	2.1 - 5	Moderate Intensity Urban
4	5.1 - 8	High Intensity Urban
5	8.1 - 11	Intensely Developed or Built- Up

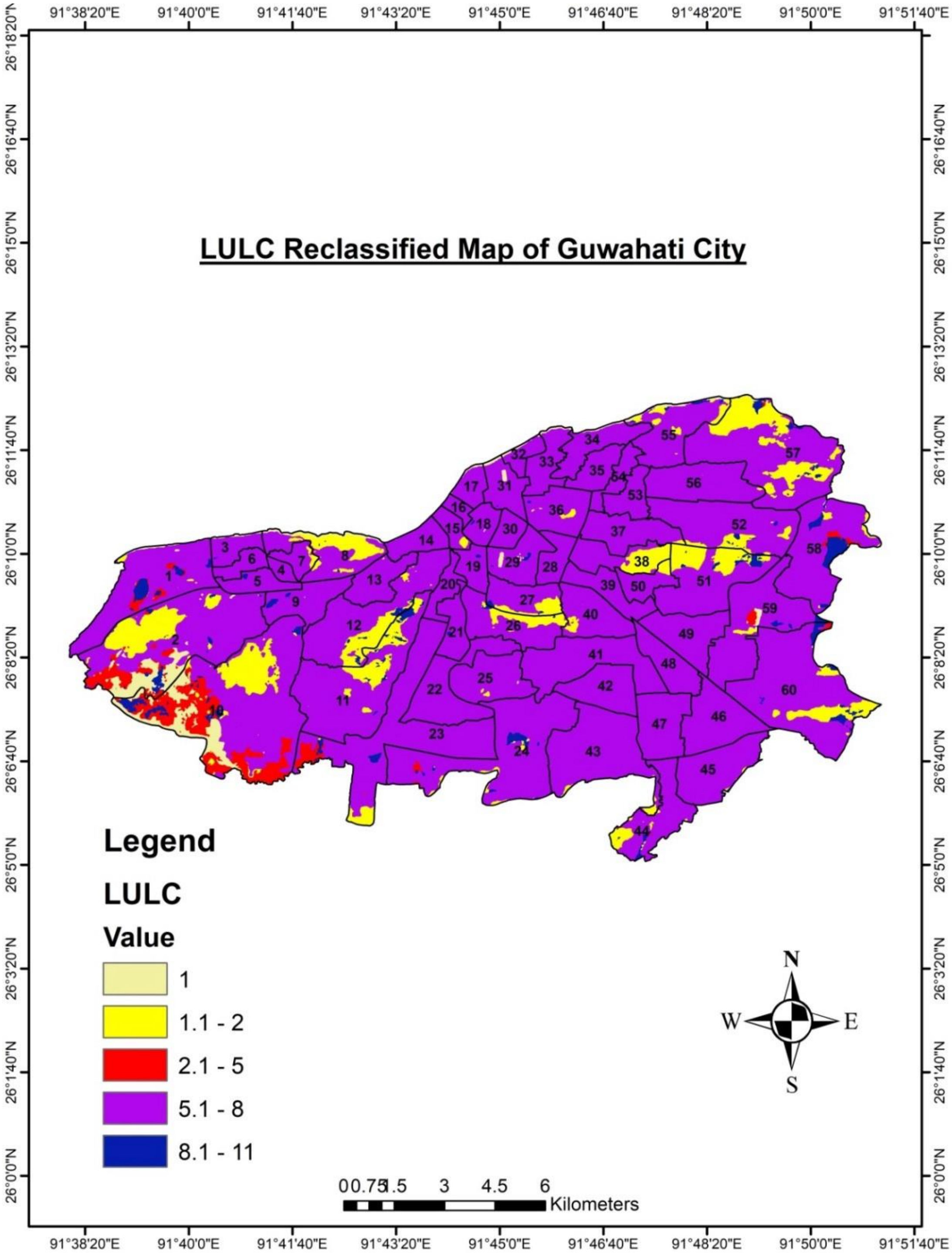


Fig 10: Thematic map of Land Use and Land Cover of Guwahati City generated in ArcGIS

4.2.7 Lithology

Lithology mapping captures the geological composition, crucial in identifying areas with specific rock types prone to instability.

Table 8: Reclassified values of Lithology generated in ArcGIS

Classification	Rating	Physical Meaning
1	1 - 8	Basic Rock Types
2	8.1 - 19	Specific Sedimentary Rocks
3	20 -29	Specific Igneous Rocks
4	30 - 36	Metamorphic Rock and Complex Formations
5	37 - 45	Highly Specific Lithological Units

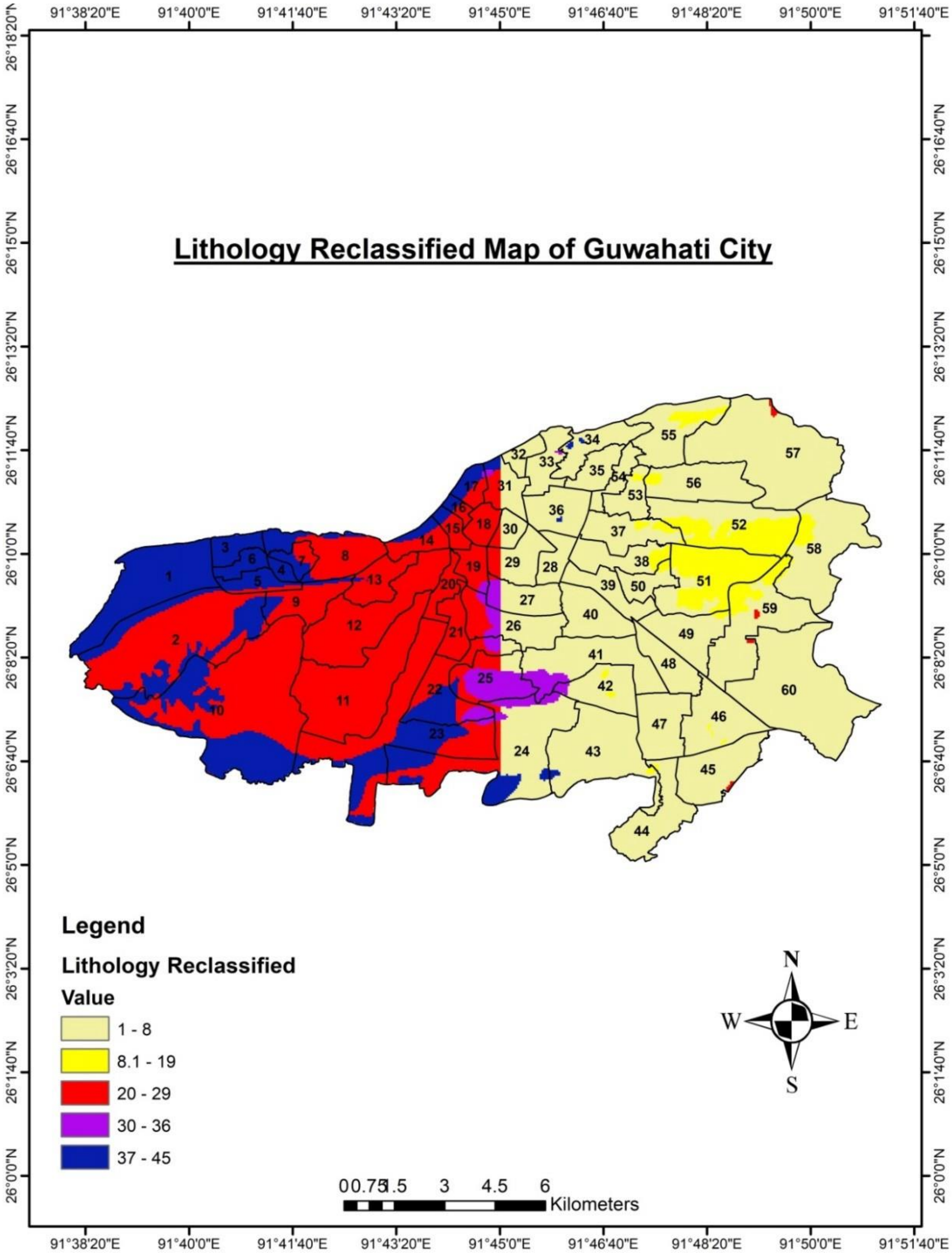


Fig 11: Thematic map of Lithology of Guwahati City generated in ArcGIS

4.2.8 Geomorphology

Geomorphological features are highlighted, delineating landforms that significantly influence landslide susceptibility.

Table 9: Reclassified values of Geomorphology generated in ArcGIS

Classification	Rating	Physical Meaning
1	1 - 4	Minimal Topographic Variation
2	4 - 8	Moderate Slopes or Landform
3	8 - 13	Mix of Landforms
4	13 - 17	Rugged Terrain, Steeper Slopes
5	17 - 21	Steep Cliffs, Deep Valeys

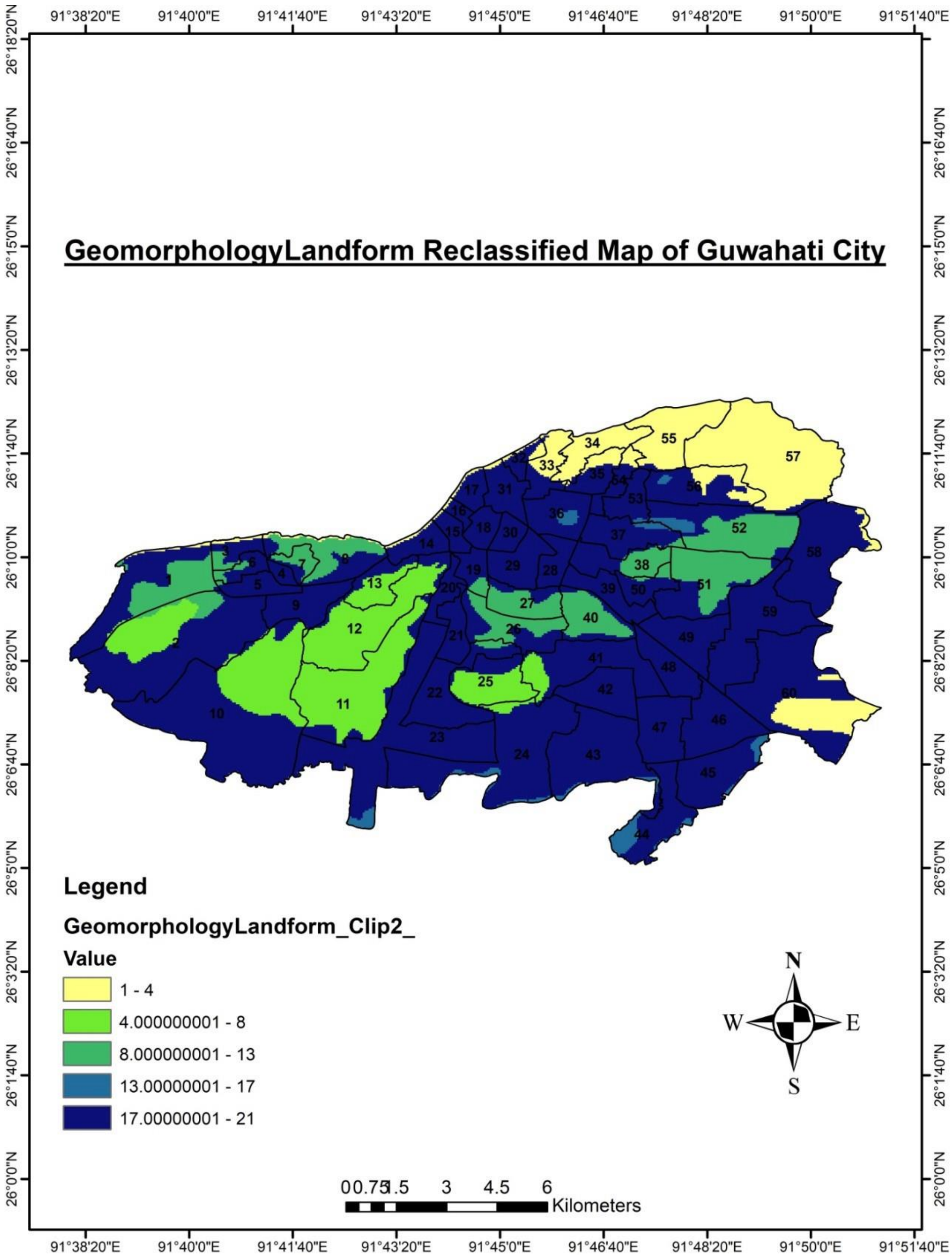


Fig 12: Thematic map of Geomorphology of Guwahati City generated in ArcGIS

4.2.9 Distance from Railway

Maps depicting proximity to transportation infrastructure pinpoint areas where human activities and engineering structures may elevate susceptibility.

Table 10: Reclassified values of Distance from Railway generated in ArcGIS

Classification	Rating	Physical Meaning
1	0 – 0.0032	Very Close Proximity
2	0.0033 – 0.0076	Close Proximity
3	0.0077 - 0012	Moderate Proximity
4	0.013 – 0.018	Farther Proximity
5	0.019 – 0.029	Distant Proximity

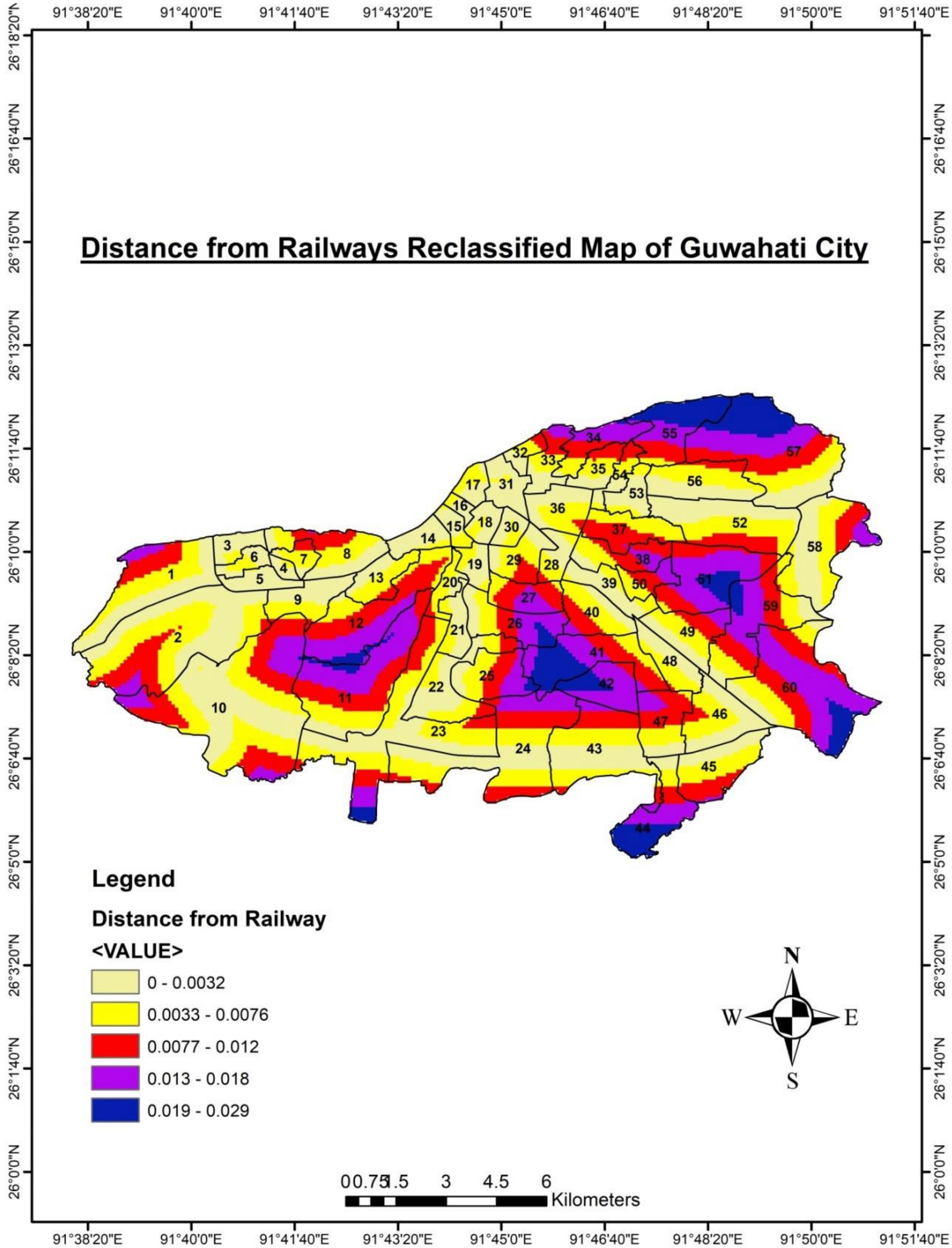


Fig 13: Thematic map of Distance from Railway of Guwahati City generated in ArcGIS

4.2.10 Distance from Road

The distance from roads thematic map is crucial in identifying areas influenced by the presence of road networks. Additionally, road construction activities and associated cut-and-fill processes may destabilize slopes, making proximity to roads a significant factor in landslide assessment.

Table 11: Reclassified values of Distance from Road generated in ArcGIS

Classification	Rating	Physical Meaning
1	2 - 2200	Very Close Proximity
2	2300 - 8000	Close Proximity
3	5200 - 8000	Moderate Proximity
4	8000 - 11000	Farther Proximity
5	12000 - 15000	Distant Proximity

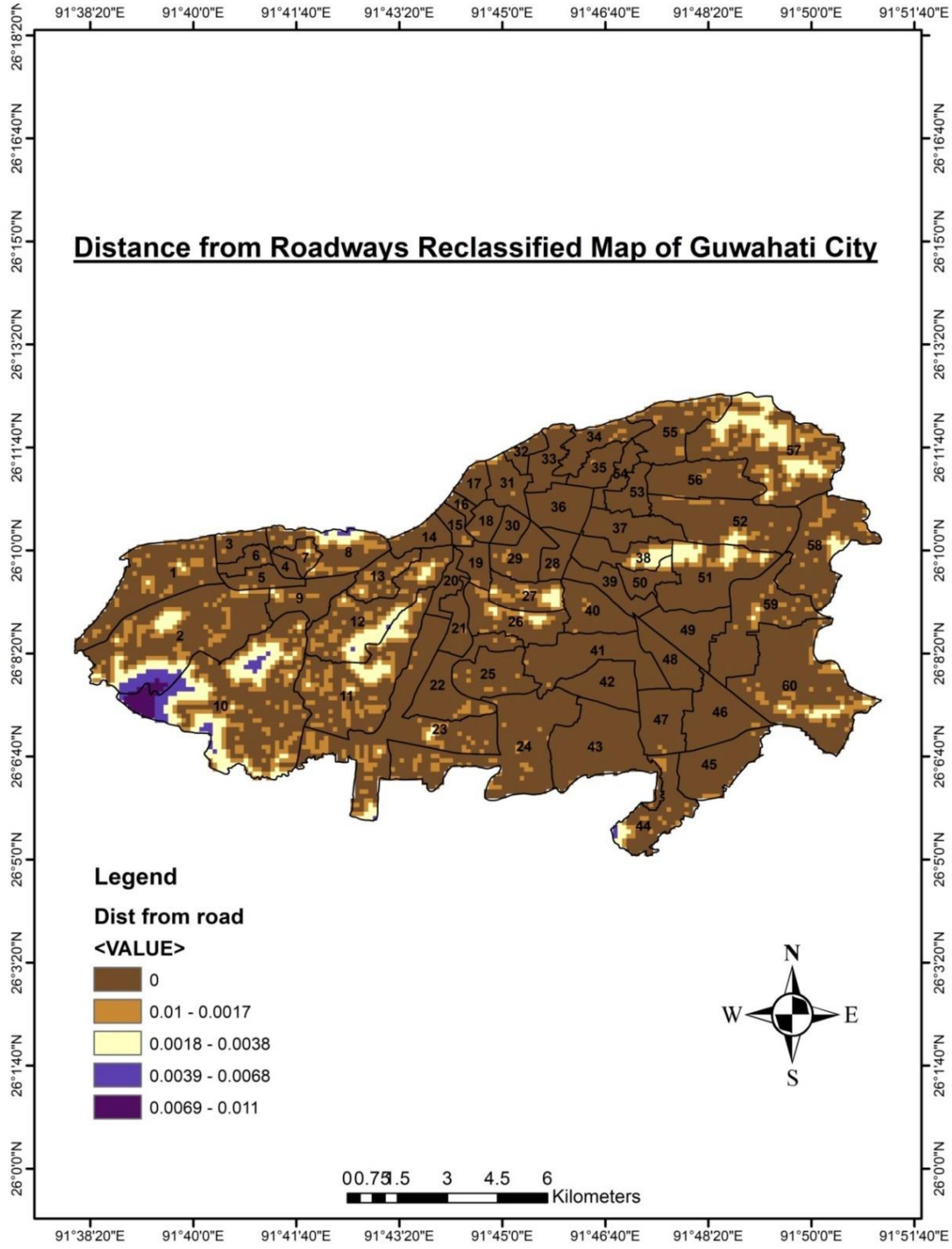


Fig 14: Thematic map of Distance from Road of Guwahati City generated in ArcGIS

4.3 COMPARISON MATRIX AND WEIGHTS

The pairwise comparison matrix and calculated weights for each thematic map unveil the relative significance assigned through the AHP, providing a quantitative understanding of their contributions.

4.3.1 Scoring Scale

The comparison is being done using Saaty's scale, which assigns numerical values to the strength of preference. The scale looks like this:

1: Equal importance

3: Moderate importance of one over another

5: Strong importance

7: Very strong or demonstrated importance

9: Extreme importance

2, 4, 6, 8: Intermediate values for judgments that fall between the two adjacent judgments.

4.3.2 Comparision Matrix

The presented comparison matrix in this report is derived from expert opinions and references a range of literature sources. This matrix systematically captures the relative importance of different causative factors in the context of landslide susceptibility. It serves as a critical foundation for the Analytic Hierarchy Process (AHP), enabling the assignment of pairwise values that contribute to the generation of a comprehensive and accurate landslide susceptibility map.

Table 12: 10 x 10 Comparision Matrix

		Slope	Aspect	Roughness	Hillshade	Average Rainfall	LULC	Lithology	Geomorphology	Distance from Road	Distance from railway
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Slope	**1**	1	3	2	3	3	3	3	3	1	1
Aspect	**2**	1/3	1	1	1	3	3	1	3	1	1
Roughness	**3**	1/2	1	1	1	3	3	3	3	1	1
Hillshade	**4**	1/3	1	1	1	1	3	1	1	1	1
Average Rainfall	**5**	1/3	1/3	1/3	1	1	3	3	3	1	1
LULC	**6**	1/3	1/3	1/3	1/3	1/3	1	3	3	1	1
Lithology	**7**	1/3	1	1/3	1	1/3	1/3	1	3	1	1
Geomorphology	**8**	1/3	1/3	1/3	1	1/3	1/3	1/3	1	1	1
Distance from Road	**9**	1	1	1	1	1	1	1	1	1	1
Distance from railway	**10**	1	1	1	1	1	1	1	1	1	1

The pairwise values are formulated into a 10 x 10 matrix, and the normal principal eigenvector of this matrix provides the weights of each causative factor. The matrix was solved using the numpy library in Python, ensuring precise computation and consistency in the determination of these weights. This methodological approach enhances the robustness and reliability of the landslide susceptibility analysis presented in this report.

Programiz Python Online Compiler

main.py Save Run

```python
import numpy as np

# Function to input matrix from the user
def input_matrix():
    print("Enter the elements of the 10x10 matrix row-wise (separate values with commas):")
    matrix = []
    for i in range(10):
        row = input(f"Row {i + 1}: ").strip().split(',')
        row = [eval(num.strip()) if '/' in num else float(num.strip()) for num in row]
        matrix.append(row)
    return np.array(matrix)

# Calculate normalized principal eigenvector in percentage
def calculate_normalized_principal_eigenvector(matrix):
    eigenvalues, eigenvectors = np.linalg.eig(matrix)
    principal_eigenvector = np.real_if_close(eigenvectors[:, 0])
```

Fig 15: Python Code for Inputting a 10x10 Matrix and Calculating the Normalized Principal Eigenvector

Programiz Python Online Compiler

main.py

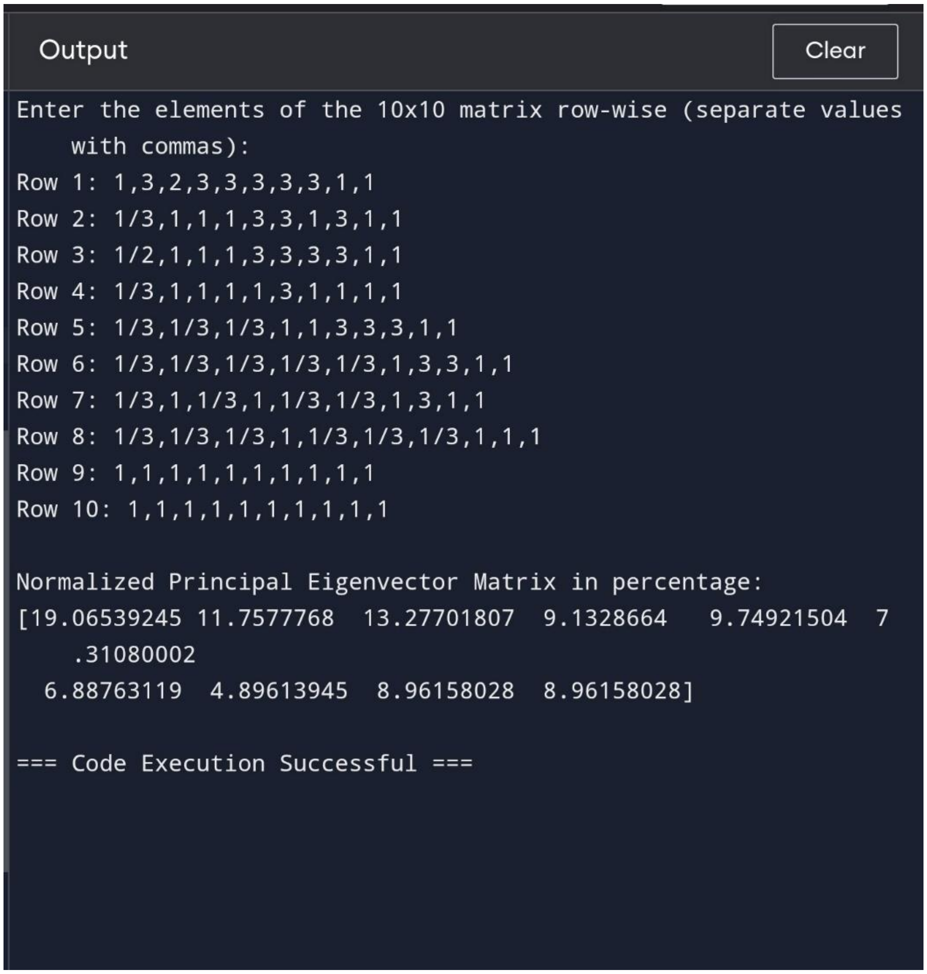
```
    principal_eigenvector = np.real_if_close
        (eigenvectors[:, 0])
    normalized_eigenvector_percentage =
        (principal_eigenvector / np.sum
        (principal_eigenvector)) * 100
    return normalized_eigenvector_percentage

# Main program
if __name__ == "__main__":
    # Input matrix from the user
    matrix = input_matrix()

    # Calculate normalized principal eigenvector in
        percentage
    normalized_eigenvector_percentage =
        calculate_normalized_principal_eigenvector
        (matrix)

    # Print the result
    print("\nNormalized Principal Eigenvector Matrix in
        percentage:")
    print(normalized_eigenvector_percentage)
```

Fig 16: Python Code for Inputting a 10x10 Matrix and Calculating the Normalized Principal Eigenvector



```
Output                                                      Clear
Enter the elements of the 10x10 matrix row-wise (separate values
    with commas):
Row 1: 1,3,2,3,3,3,3,3,1,1
Row 2: 1/3,1,1,1,3,3,1,3,1,1
Row 3: 1/2,1,1,1,3,3,3,3,1,1
Row 4: 1/3,1,1,1,1,3,1,1,1,1
Row 5: 1/3,1/3,1/3,1,1,3,3,3,1,1
Row 6: 1/3,1/3,1/3,1/3,1/3,1,3,3,1,1
Row 7: 1/3,1,1/3,1,1/3,1/3,1,3,1,1
Row 8: 1/3,1/3,1/3,1,1/3,1/3,1/3,1,1,1
Row 9: 1,1,1,1,1,1,1,1,1,1
Row 10: 1,1,1,1,1,1,1,1,1,1

Normalized Principal Eigenvector Matrix in percentage:
[19.06539245 11.7577768  13.27701807  9.1328664   9.74921504  7
    .31080002
  6.88763119  4.89613945  8.96158028  8.96158028]

=== Code Execution Successful ===
```

Fig 17:

Output Display of the 10x10 Matrix Input and Normalized Principal Eigenvector Calculation

4.3.3 Weight Ovelay

The subsequent section presents the weight overlay table, a critical output derived from the Analytic Hierarchy Process (AHP). This table serves as a pivotal input into the ArcGIS software, playing a decisive role in the creation of the final thematic map. The values within the weight overlay table signify the relative importance and contribution of each causative factor, offering a nuanced understanding of their influence on landslide susceptibility. This integration of expert opinions and systematic weights is instrumental in producing a robust and informed thematic map.

Table 13: Weight overlay values obtained from AHP method

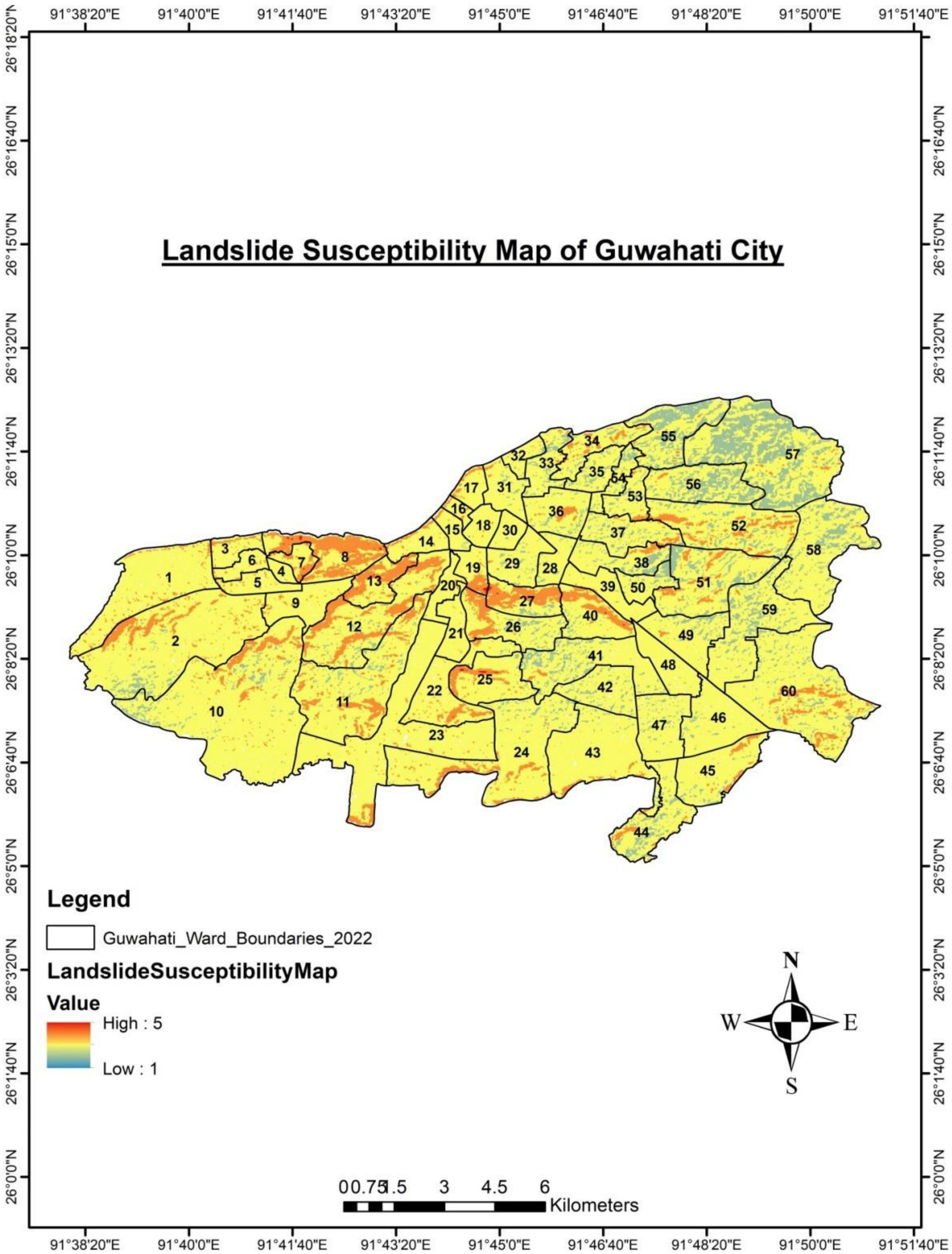
Sl. No.	Causative Factor	Weights
1	Slope	19%
2	Aspect	12%
3	Roughness	13%
4	Hillshade	9%
5	Average Rainfall	10%
6	LULC	7%
7	Lithology	7%
8	Geomorphology	5%
9	Distance from road	9%
10	Distance from railway	9%

4.4 FINAL LANDSLIDE SUSCEPTIBILITY MAP

The synthesis of individual thematic maps, considering their weighted contributions, culminates in the development of the final Landslide Susceptibility Map for Guwahati City. Out of the total 60 municipality wards analyzed, 17 have been identified as falling within the high susceptibility zone for landslide, underscoring the significance of targeted mitigation efforts in these specific areas.

Table 14: Table representing the High Susceptible wards of GMC for Landslide

GMC WARD NOS.	GMC WARD NAME	LANDSLIDE SUSCEPTIBILITY ZONE (AS PER FINDINGS)
2	Gotanagar	High
8	Kamakhya	High
10	Jalukbari	High
11	Garchuk	High
12	Maligaon	High
13	Bharalumukh	High
19	Bishnupur	High
25	Jyotikuchi	High
26	Kahilipara	High
27	Rupnagar	High
34	Kharghuli	High
36	Gandhi Basti	High
38	Christian Basti	High
40	Ganeshguri	High
51	Hengerabari	High
52	Bamunimaidam	High
60	Khanapara	High



. **Fig 18:** Thematic map of Final Landslide Susceptibility Map of Guwahati City generated in ArcGIS

4.5 Slope Stability Analysis using SlopeW

Given that slope emerged as the most critical factor among all the causative factors in our landslide susceptibility analysis, we aimed to further investigate its influence by incorporating seismic and pore water conditions of the soil. To achieve this, we employed the SlopeW software to conduct a detailed slope stability analysis. This analysis involved determining the Factor of Safety (FoS) under various conditions, where the FoS serves as an indicator of slope stability—values less than one suggest potential failure, while values greater than one indicate stability. By integrating seismic activity and pore water pressure into our analysis, we sought to gain a comprehensive understanding of the slope's stability and its susceptibility to landslides under these critical conditions.

4.5.1 Slope Stability Analysis Parameters:

To accurately assess the stability of slopes in Guwahati under the influence of slope angle, including seismic activity and pore water conditions, we employed several constant parameters and specific analysis types in the SlopeW software. The following constant parameters were used in our analysis:

Table 15: The list of constant parameters

Analysis Type	Morgenstern-Price method
Staged Pseudo-static Analysis Option	Effective stress strengths
Direction of Movement	Right to left
Material Model	Mohr-Coulomb
Seismic Coefficient: Horizontal	0.36
Seismic Coefficient, Vertical	0.18
Cohesion of Soil	15 KPa
Angle of Internal Friction	28
Unit Weight of Soil	18 KN/m2

4.5.2 Integration of Variable Parameters in Slope Stability Analysis: Impact of Slope and Pore Water Ratio (Ru):

In addition to the constant parameters, the analysis also incorporated several variable parameters to examine their effects on slope stability. The variable parameters considered were the slope angle and the pore water pressure ratio (Ru value). The analysis was conducted for different combinations of these variable parameters to understand their impact on the Factor of Safety (FoS). The specific combinations analyzed are detailed below:

4.5.2.1 Slope Angle 20°

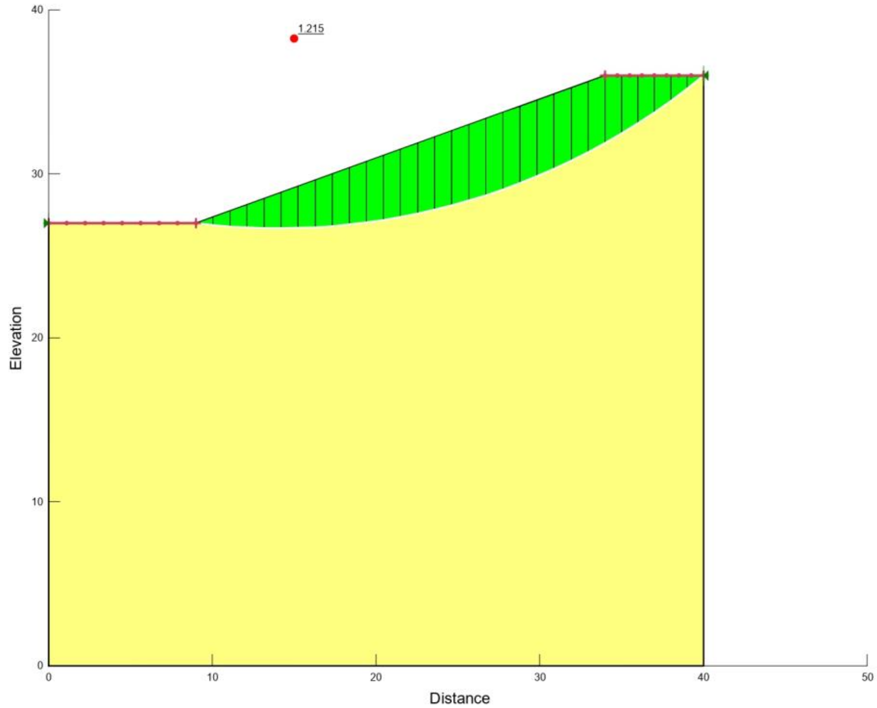


Fig 19: SlopeW analysis for Ru = 0

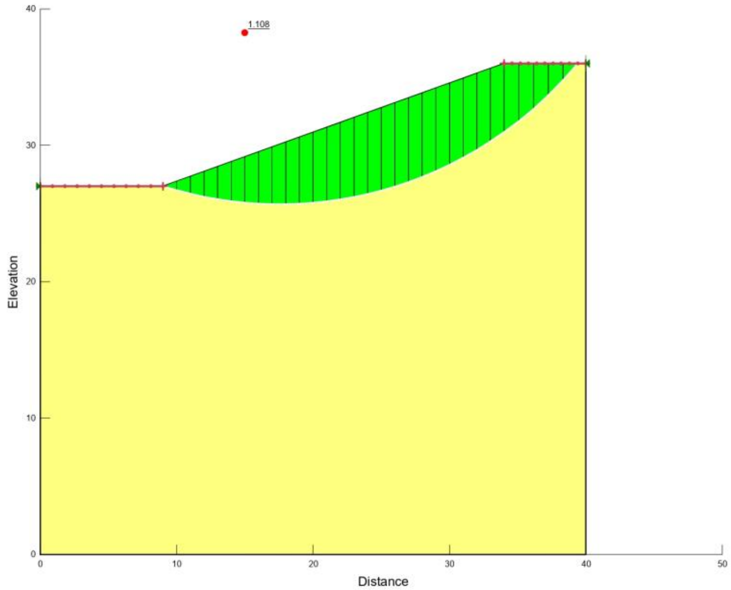


Fig 20: SlopeW analysis for Ru = 0.1

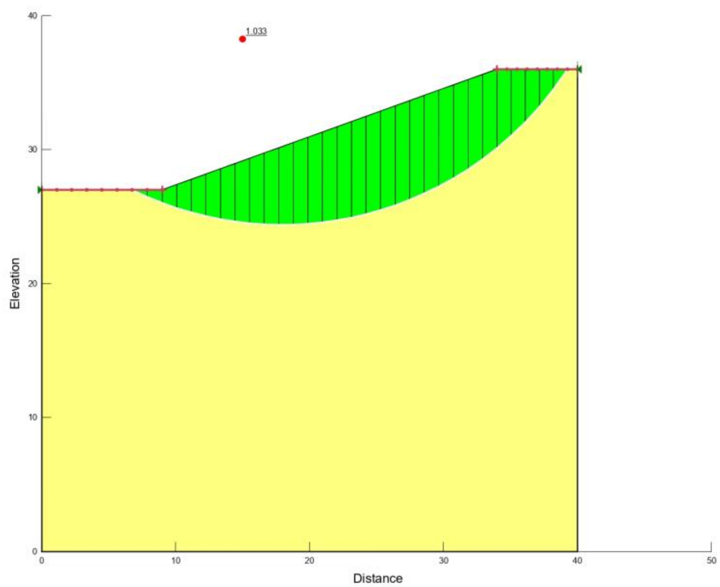


Fig 21: SlopeW analysis for Ru = 0.2

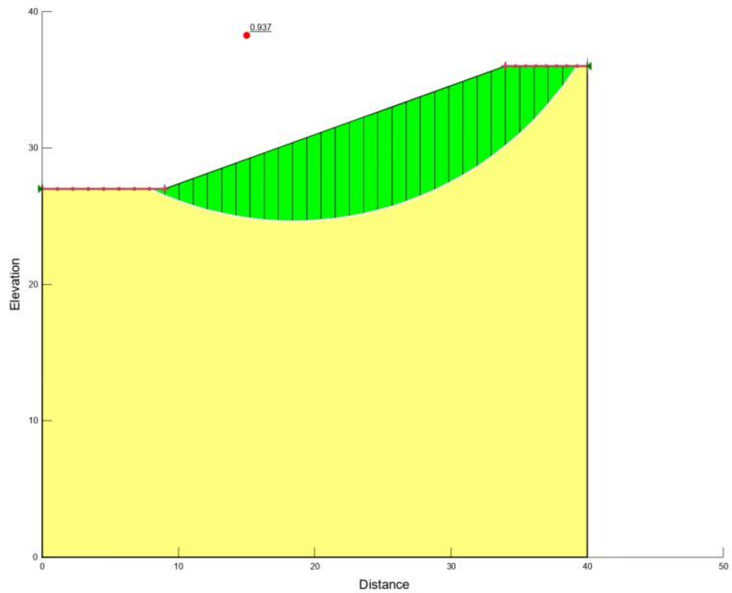


Fig 22: SlopeW analysis for Ru = 0.3

4.5.2.2 Slope Angle 30°

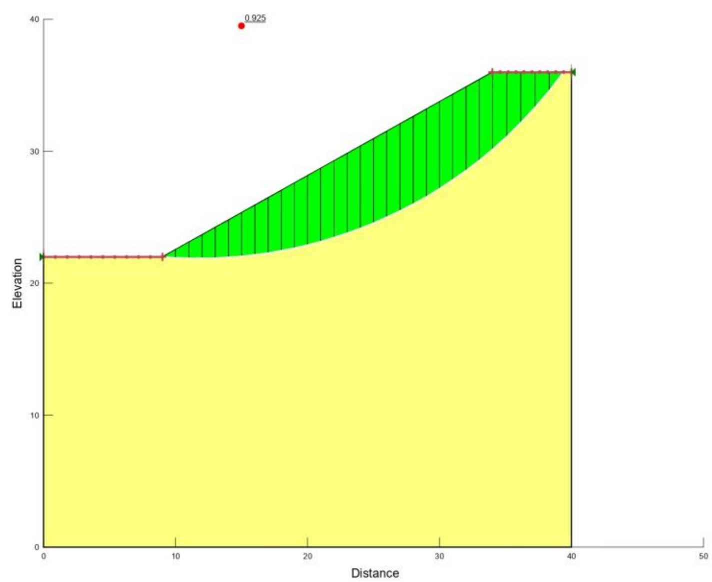


Fig 23: SlopeW analysis for Ru = 0

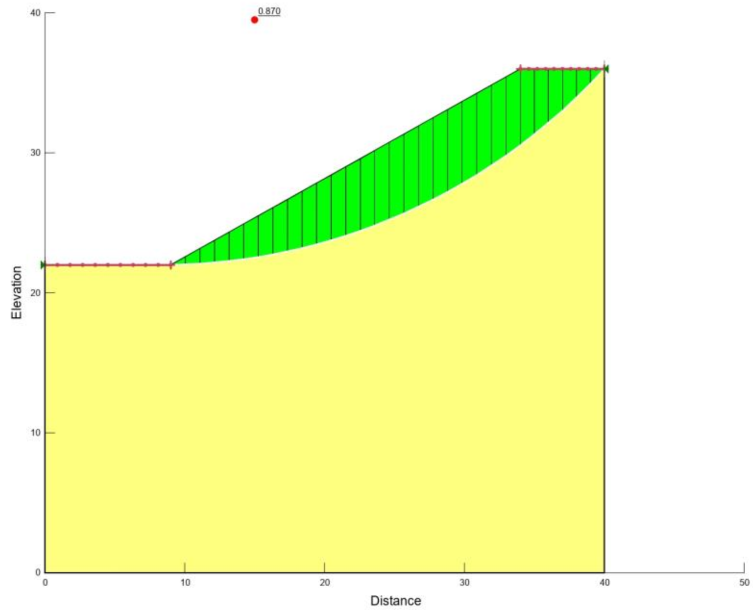


Fig 24: SlopeW analysis for Ru = 0.1

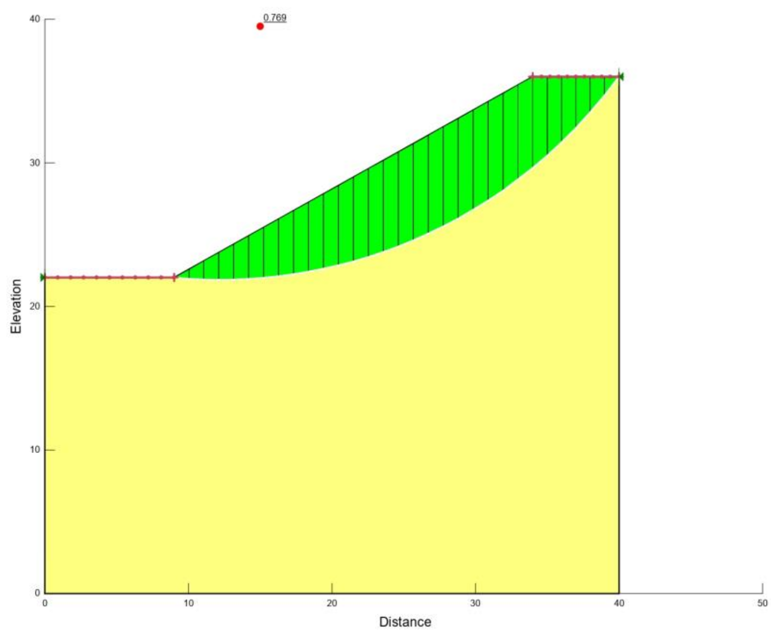


Fig 25: SlopeW analysis for Ru = 0.2

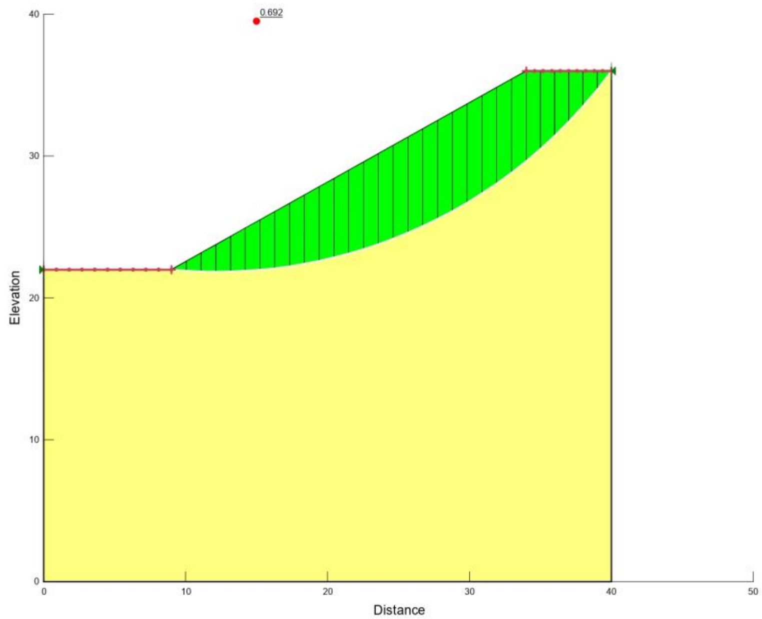


Fig 26: SlopeW analysis for Ru = 0.3

4.5.2.2 Slope Angle 40°

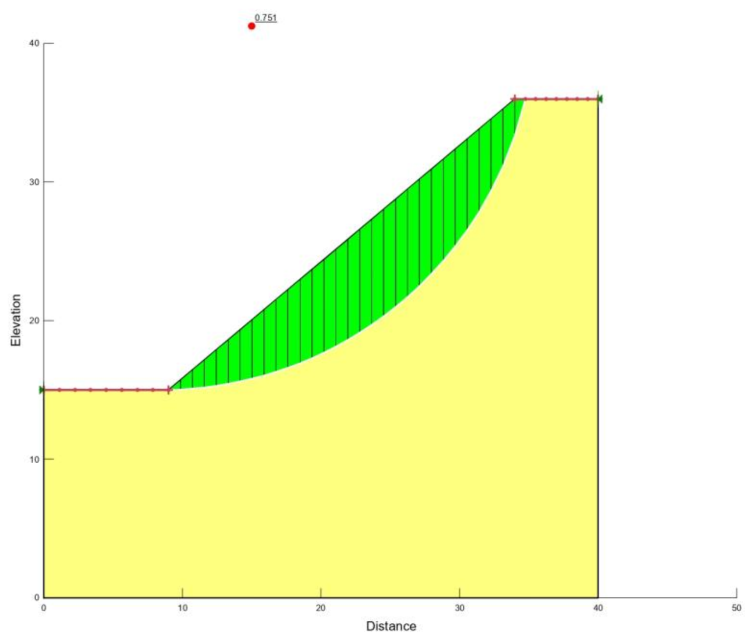


Fig 27: SlopeW analysis for Ru = 0

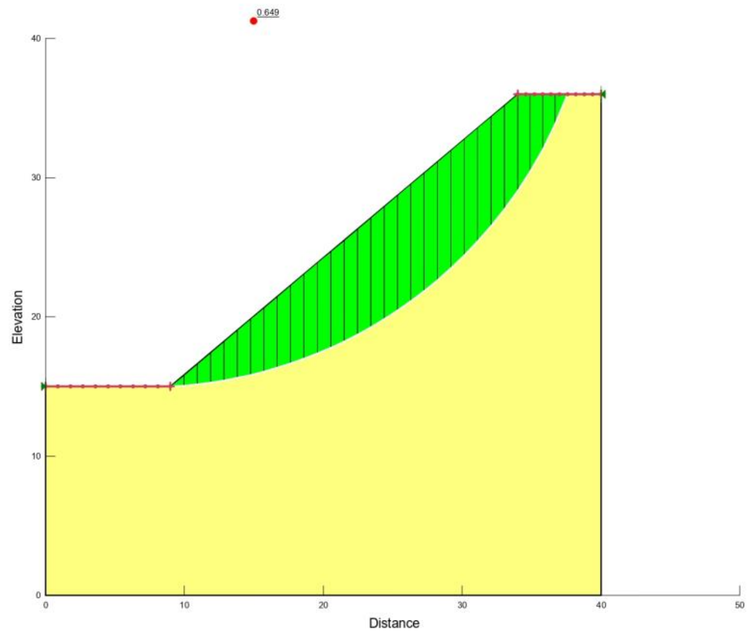


Fig 28: SlopeW analysis for Ru = 0.1

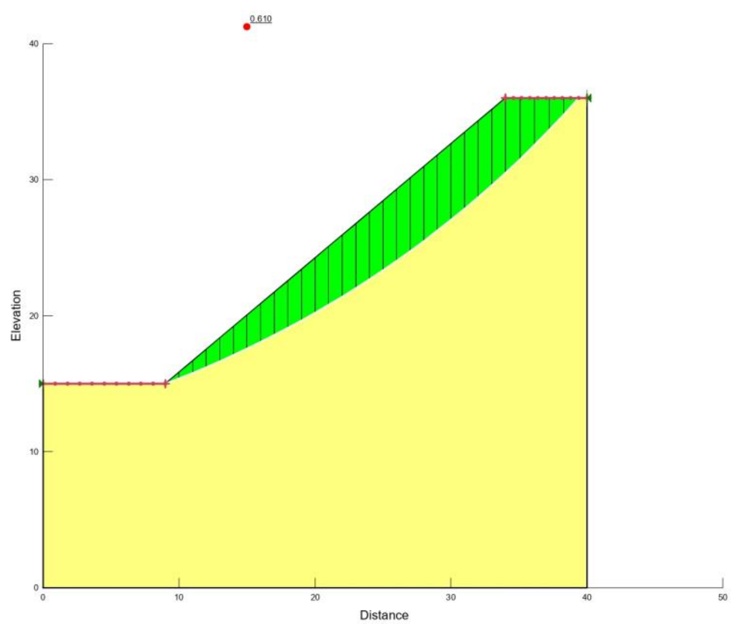


Fig 29: SlopeW analysis for Ru = 0.2

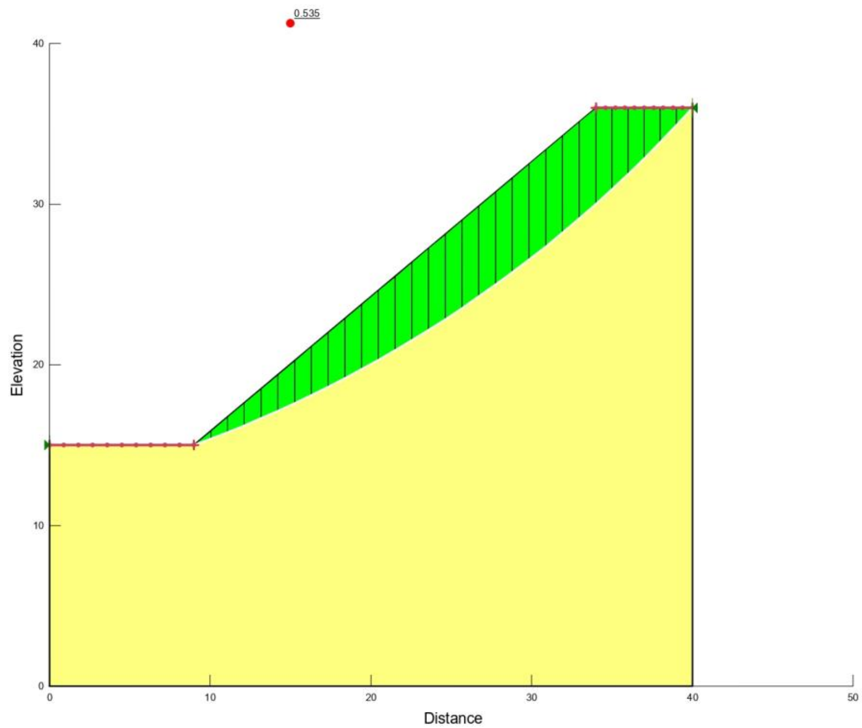


Fig 30: SlopeW analysis for Ru = 0.3

4.5.3 Impact of Pore Water Pressure Ratio (Ru) on Factor of Safety

The analysis of slope stability included a detailed examination of how varying pore water pressure ratios (Ru values) affect the Factor of Safety (FoS), while maintaining a constant slope angle. The results, depicted graphically below, illustrate the significant influence of Ru vlues on the stability of slopes in Guiwahati City.

4.5.3.1 Slope angle 20°

Table 16: Ru vs FoS values generated for a slope of 20°

Slope angle		20°		
Ru	0	0.1	0.2	0.3
FoS	1.215	1.108	1.033	0.937

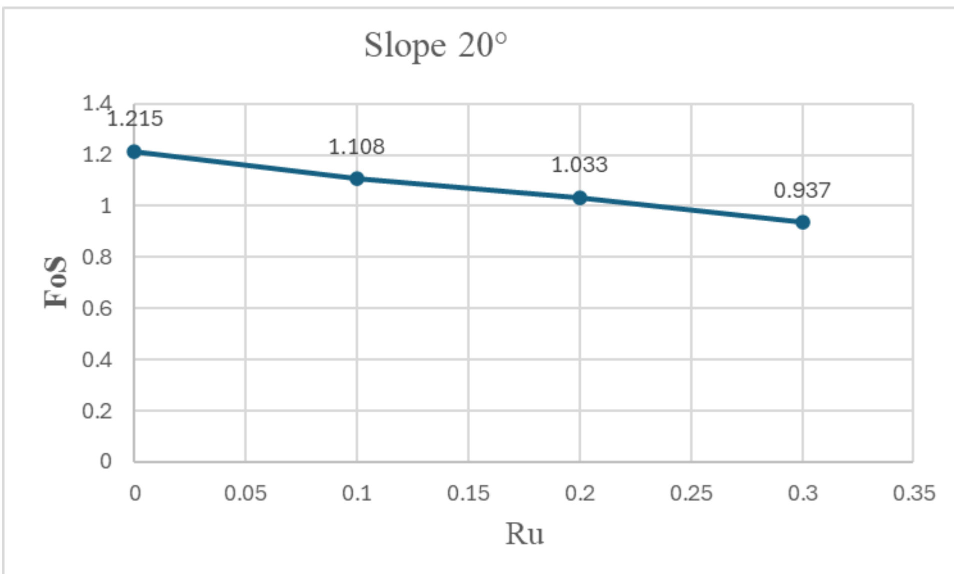


Fig 31: Ru vs FoS graph for a slope of 20°

4.5.3.2 Slope angle 30°

Table 17: Ru vs FoS values generated for a slope of 30°

Slope angle		30°		
Ru	0	0.1	0.2	0.3
FoS	0.925	0.87	0.769	0.692

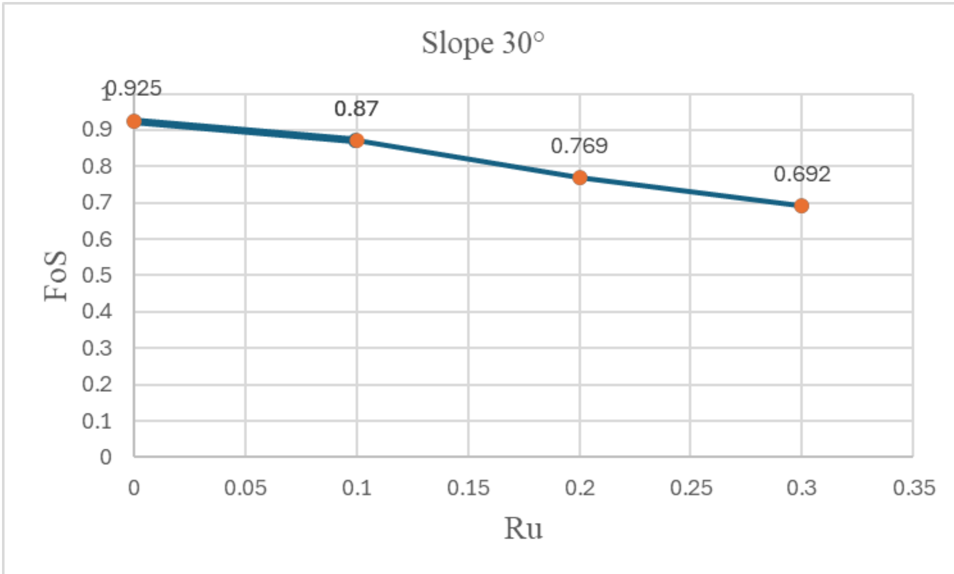


Fig 32: Ru vs FoS graph for a slope of 30°

4.5.3.3 Slope angle 40°

Table 18: Ru vs FoS values generated for a slope of 40°

Slope angle		40°		
Ru	0	0.1	0.2	0.3
FoS	0.711	0.649	0.61	0.535

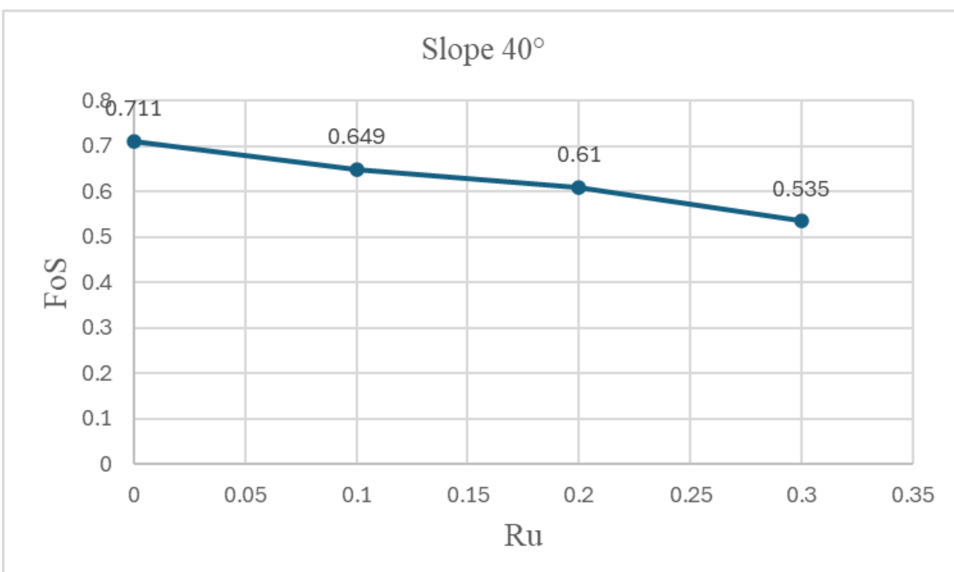


Fig 33: Ru vs FoS graph for a slope of 40°

4.5.4 Analysis:

The Factor of Safety (FoS) decreases as the Ru value (pore water pressure ratio) increases for all the slope angles. This trend suggests that higher pore water pressures (represented by higher Ru values) reduce the stability of the slope.

4.5.4.1 Key Observations

4.5.4.1.1 Decreasing Factor of Safety

As Ru increases from 0 to 0.3, the FoS decreases. This indicates that higher pore water pressures lead to a lower margin of safety against slope failure.

4.5.4.1.2 Significance of Ru

Pore water pressure in a high seismic zone such as Guwahati city plays a critical role in slope stability. Elevated Ru values signify increased water content or pressure within the slope material, which can decrease the effective stress and shear strength of the soil mass, thereby reducing stability.

4.5.4.1.3 Implications for Slope Management

Understanding the sensitivity of slope stability to changes in pore water pressure is essential for effective slope management and risk mitigation strategies. Monitoring and controlling water infiltration or drainage in slopes can help maintain or improve slope stability under varying environmental conditions.

CHAPTER 5

CONCLUSION

5.1 INTRODUCTION

The integration of various thematic maps, each contributing weighted insights, has culminated in the development of the final Landslide Susceptibility Map for Guwahati City. This comprehensive analysis has identified 17 out of 60 municipality wards as falling within high susceptibility zones for landslides. This underscores the urgent necessity for targeted mitigation efforts in these specific areas to protect lives and property.

To address the heightened susceptibility to landslides, a multifaceted approach is required, which includes:

1. Development of Standard Guidelines: It is crucial to formulate and disseminate comprehensive guidelines for landslide management and mitigation, ensuring accessibility to all stakeholders, including local communities, in their native language.
2. Regulation of Construction in High-Risk Zones: Strict regulation and avoidance of construction activities in identified high-risk areas are essential to prevent exacerbation of slope destabilization.
3. Retrofitting of Existing Structures: Enhancing the resilience of vulnerable structures through retrofitting measures can mitigate the impact of landslides.
4. Enhancement of Drainage Systems: Implementing scientifically designed drainage networks is vital for effective management of surface runoff and erosion control, thereby reducing landslide risks.
5. Implementation of Afforestation and Vegetative Measures: Promoting afforestation and ecological management practices to increase vegetation cover can stabilize slopes and minimize erosion risks.
6. Community Awareness and Engagement: Educating local communities about landslide causes and prevention measures is critical. Community participation in monitoring and reporting unauthorized constructions and other risk factors can significantly bolster mitigation efforts.

In addition to these measures, incorporating findings from slope stability analyses is crucial. The analyses have revealed that higher pore water pressures (Ru values) and seismic conditions significantly reduce the Factor of Safety of slopes, thereby increasing landslide susceptibility. Understanding these dynamics informs targeted interventions and reinforces the importance of comprehensive risk management strategies.

By implementing these concerted efforts, Guwahati City can effectively mitigate landslide risks, safeguard its residents, and promote a resilient urban environment.

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