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A Case Study on Integrating LiDAR and AHP for Applied Learning in Terrain Stability and Hazard Mapping

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Abstract

This paper presents a case study examining the integration of Light Detection and Ranging (LiDAR)-based geospatial analysis with the Analytical Hierarchy Process (AHP) as an applied instructional approach for teaching terrain stability and hazard mapping in civil engineering education. The study aims to enhance students' capacity to interpret geomorphologic processes, analyze high-resolution geospatial data, and apply structured decision-making methods within a hazard-assessment context relevant to infrastructure resilience and sustainability. Multi-temporal LiDAR-derived Digital Elevation Models (DEMs) from 2014, 2018, and 2020 were processed in ArcGIS Pro to generate geomorphic parameters including slope, aspect, curvature, elevation, Topographic Wetness Index (TWI), and DEM of Difference (DoD) to characterize terrain variability and surface deformation. AHP, following Saaty's methodology, was employed to weigh these parameters through pairwise comparisons and consistency ratio (CR) validation. The weighted overlay analysis produced a landslide susceptibility map classified into five risk zones: very low, low, moderate, high, and very high. A mixed-methods assessment strategy was used to evaluate educational impacts. Quantitative analysis was based on pre- and post-instruction questionnaires measuring students' performance in AHP weighing, CR computation, and weighted overlay implementation, with results indicating measurable gains in technical accuracy and procedural understanding (mean post-instruction CR = 0.02). Qualitative analysis drawn from open-ended responses from post-instruction reflective questionnaires, which revealed improved student confidence in geospatial reasoning, enhanced ability to interpret terrain indicators, and stronger connections between geomorphic parameters and slope-failure risk. The findings suggest that integrating LiDAR analysis with AHP as a curricular case study promotes computational literacy, data-driven decision-making, and geospatial interpretation. Limitations of the study include the single-course implementation, modest sample size, reliance on self-reported qualitative feedback, and the absence of field-based validation within the instructional module. Future work will expand the framework across multiple courses and institutions, incorporate InSAR-based deformation analysis, and integrate field verification to strengthen both predictive capability and educational generalizability.

Keywords: LiDAR, Analytical Hierarchy Process (AHP), Case Study, Engineering Education, Geospatial Analysis, Terrain Stability and Hazard Mapping

1.0. INTRODUCTION

Landslides are among the most pervasive natural hazards affecting both developed and developing regions, posing persistent threats to human safety, transportation infrastructure, and the built environment. Defined as the downslope movement of soil, rock, or debris under the influence of gravity, landslides are commonly triggered by intense or prolonged rainfall, seismic activity, geomorphic instability, and anthropogenic disturbances such as slope excavation and land-use modification [[1], [2]]. Globally, landslides have caused extensive socio-economic losses, with more than 18,000 fatalities and millions of people affected between 1998 and 2017 alone [[3], [4]], while also contributing to environmental degradation through soil erosion, sedimentation of waterways, and ecosystem disruption [[5], [6]]. Projections suggest that climate variability, urban expansion, and infrastructure densification will further increase the frequency and impacts of slope failures, particularly in regions not traditionally classified as mountainous [7].

Accurate detection and mapping of landslide susceptibility are therefore essential for hazard mitigation, resilient infrastructure planning, and risk-informed decision-making. Conventional field-based mapping approaches, while valuable, are labor-intensive, spatially limited, and often impractical for regional-scale assessments [8]. Advances in remote sensing have significantly transformed landside analysis, with airborne Light Detection and Ranging (LiDAR) emerging as a particularly powerful tool due to its ability to generate high-resolution Digital Elevation Models (DEMs) capable of revealing subtle terrain features, even beneath vegetation cover [[9], [10]]. LiDAR-derived DEMs support the extraction of geomorphic parameters (such as slope, aspect, curvature, elevation, and hydrologically derived indices) that are fundamental to understanding terrain processes associated with slope instability [[11], [12], [13], [14], [15]].

Beyond static terrain characterization, multi-temporal LiDAR datasets enable the analysis of surface deformation through DEM of Difference (DoD) techniques, allowing elevation changes between successive time periods to be quantified [[14], [16], [17]]. Such analysis provides critical insight into erosion, deposition, and anthropogenic modification, which are often precursors to shallow landslides and infrastructure-related slope failures. When combined with geomorphic and hydrologic indicators, DoD analysis enhances the interpretability of landslide susceptibility assessments, particularly in low-relief or urbanizing landscapes where landslide signatures may be subtle or spatially localized [18].

To integrate multi conditioning factors influencing landslide occurrence, researchers have widely adopted statistical and empirical modeling approaches, including logistic regression, frequency ratio, weights of evidence, and machine-learning-based techniques [[19], [20], [21], [22], [23], [24], [25], [26], [27]]. While these models can achieve high predictive accuracy (especially in inventory-rich, mountainous environments) their applicability may be constrained by data availability, interpretability, or transferability across regions with differing geomorphic and anthropogenic contexts [[6], [22]]. In contrast, multi-criteria decision analysis (MCDA) approaches, particularly the Analytical Hierarchy Process (AHP), offer a transparent and interpretable framework for synthesizing heterogeneous terrain variables using expert-informed weighing and logical consistency checks [[28], [29], [30]]. AHP has been successfully applied in numerous landslide susceptibility studies, demonstrating its effectiveness in regional-scale assessments where clarity, reproducibility, and decision support are essential [[31], [32], [33]].

Despite the extensive body of research on LiDAR-based landslide susceptibility modeling, relatively limited attention has been given to how these advanced analytical workflows can be meaningfully integrated into civil engineering education. As the profession increasingly demands engineers who are proficient in geospatial analysis, data-driven decision-making, and resilience-oriented design, there is a growing need for instructional approaches that move beyond theoretical exposition and expose students to real-world hazard datasets and analytical frameworks. Teaching slope stability and hazard mapping through authentic case studies allows students to engage directly with diverse terrain processes, computational tools, and decision-analysis methods that mirror professional engineering practice.

In this context, this paper presents a case study that adapts a completed LiDAR and AHP-based landslide susceptibility assessment into an applied instructional module for civil engineering education. Using Prince George's County, Maryland (a low relief, urbanizing region with documented slope failures along transportation corridors) the case study demonstrates how multi-temporal LiDAR analysis and AHP can be employed to teach terrain stability concepts, geospatial reasoning, and structured decision-making within a single coherent framework. Unlike many instructional examples that rely on simplified or synthetic datasets, this case study engages students with research-grade LiDAR DEMs, real geomorphic parameters, and an operational AHP workflow, thereby bridging the gap between academic instruction and professional practice.

The educational significance of this approach lies in its dual contribution: first, it reinforces fundamental geotechnical and geomorphic concepts underpinning slope stability; second, it cultivates computational literacy and decision-analysis skills aligned with contemporary civil engineering competencies. By framing landslide susceptibility analysis as a structured, interpretable, and data-driven process, the case study supports the development of engineers capable of integrating geospatial evidence into resilient infrastructure planning and hazard mitigation strategies. The following sections describe the objectives, theoretical foundation, methodology, and educational outcomes of this LiDAR-AHP case study, highlighting its relevance for teaching terrain stability and hazard mapping in civil engineering curricula.

1.1. Study Objectives

The primary objective of this case study is to demonstrate how an integrated LiDAR-based geospatial analysis and AHP workflow can be effectively used as an instructional tool for teaching terrain stability and landslide hazard mapping in civil engineering education.

The specific objectives of the study are to:

1. Implement a LiDAR-AHP instructional workflow using multi-temporal DEMs to support applied learning in terrain stability and hazard mapping.
2. Enhance students' understanding of geomorphic and hydrologic controls on slope instability.
3. Develop students' geospatial and computational skills through hands-on use of GIS tools for terrain analysis, raster processing, and susceptibility mapping.
4. Introduce structured decision-making concepts by engaging students in AHP weighing, consistency ratio evaluation, and multi-criteria integration.
5. Assess learning outcomes and perceptions using pre- and post-instruction quantitative measures and qualitative student reflections.

2.0. LITERATURE REVIEW AND MOTIVATION

Extensive research has established the effectiveness of LiDAR-derived DEMs and geomorphic analysis for identifying terrain conditions associated with landslide susceptibility [[6], [9], [11],

[13]]. Similarly, MCDA techniques (particularly the AHP) have been widely applied to integrate terrain, hydrologic, and environmental factors within transparent and reproducible susceptibility frameworks [[28], [31], [33], [34]]. Together, these approaches form a mature methodological foundation for landslide hazard assessment in both research and professional practice.

While the technical robustness of LiDAR-based analysis and AHP is well documented, considerably less attention has been given to how these methods are translated into civil engineering education. Existing instructional approaches to slope stability often emphasize analytical formulations or simplified examples, with limited exposure to high-resolution geospatial data, multi-temporal terrain analysis, or structured decision-making workflows reflective of professional practice. As a result, students may acquire theoretical knowledge without developing the applied geospatial and decision-analysis competencies increasingly expected of practicing engineers.

Recent educational efforts have begun to introduce geospatial technologies (such as UAVs Unmanned/Uncrewed Aerial Vehicles, LiDAR, and GIS) into slope stability and hazard related coursework, demonstrating positive impacts on student engagement and conceptual understanding [[35], [36], [37]]. However, many of these implementations focus primarily on data visualization or mapping exercises, without incorporating explicit decision-analysis frameworks that require students to evaluate factor importance, justify weighting schemes, and assess logical consistency. This represents a gap between exposure to advanced geospatial tools and the development of decision-making skills central to engineering judgement.

The motivation for this study is to address this gap through a case study that integrates LiDAR-based terrain analysis with AHP within a structured instructional workflow. By engaging students with real-world datasets and a transparent multi-criteria decision process, the case study emphasizes not only hazard identification but also the reasoning that underpins engineering decisions. This educational focus distinguishes the present work from prior technical studies and positions the LiDAR-AHP workflow as a transferable teaching approach for terrain stability and hazard mapping in civil engineering curricula.

2.1. Study Area

Prince Georges County is located in central Maryland, United States, between approximately 38.5°N and 39.1°N latitude and 76.6°W and 77.1°W longitude Fig. 1. The county spans two major physiographic provinces (the Mid-Atlantic Coastal Plain and the Piedmont Plateau) resulting in pronounced variability in topography, geology, and soil characteristics. This heterogeneity plays a critical role in influencing slope stability and is directly relevant to the spatial distribution and occurrence of landslides.

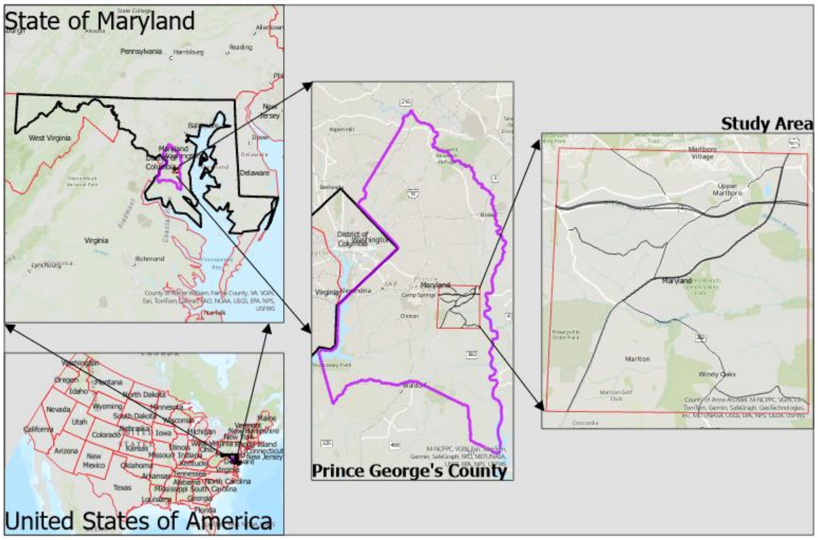


Fig. 1. Study area used for the instructional implementation of the case study

3.0. STUDY FRAMEWORK

The instructional framework used in this case study translates a completed LiDAR-AHP landslide susceptibility analysis into an applied learning sequence for civil engineering education. The framework guides students from interpretation of LiDAR-derived terrain indicators to structured decision-making using AHP, emphasizing transparency, reasoning, and engineering judgment rather than algorithmic optimization. Fig. 2 summarizes this progression, highlighting how geomorphic analysis and decision weighting are integrated within a single instructional workflow suitable for mixed-experience classrooms.

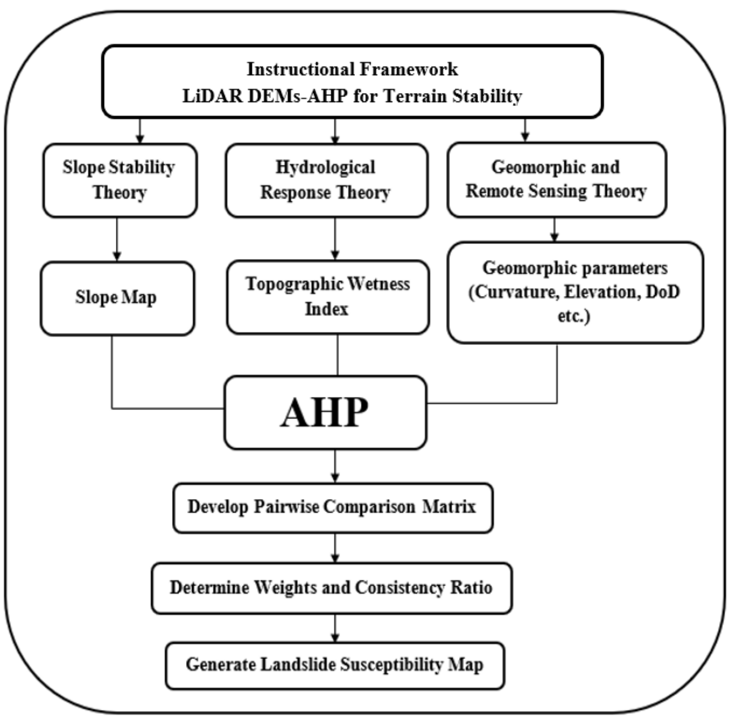
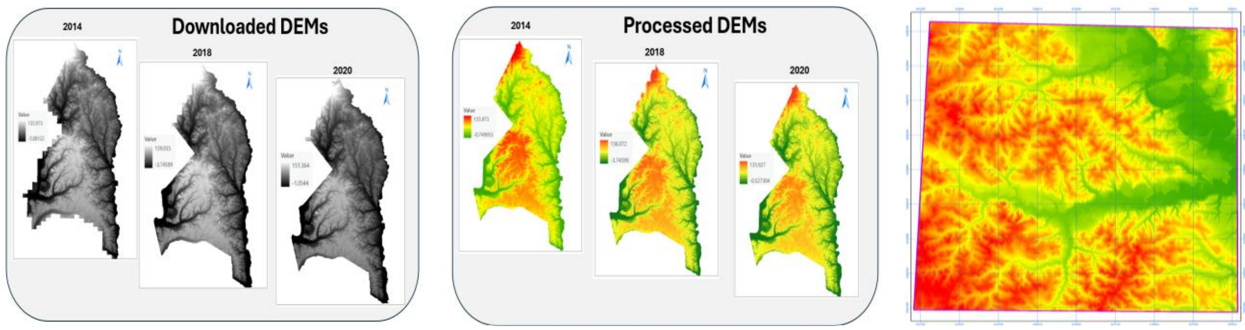


Fig. 2. Conceptual instructional framework

The framework is organized as a sequential workflow that mirrors professional hazard-assessment practice while remaining accessible to students with varied levels of prior geospatial experience. It begins with exposure to high-resolution LiDAR-derived DEMs, which serve as the primary data source for terrain analysis Fig. 3. Students are guided through the derivation and interpretation of key geomorphic and hydrologic parameters (such as slope, aspect, curvature, elevation, TWI, and DoD) to establish a conceptual link between terrain characteristics and slope instability mechanisms [[11], [14], [15]].



(a.) **(b.)** **(c.)**

Fig. 3. (a) DEMs **(b)** Processed DEMs **(c)** Processed DEM clipped to study area's extent

Following terrain parameterization, the framework introduces multi-criteria decision analysis through the AHP. Students define susceptibility criteria based on the derived terrain layers and perform pairwise comparisons to assign relative importance to each factor. Emphasis is placed on the logical structure of AHP, including the interpretation of weighting decisions and the evaluation of consistency using the consistency ratio (CR), rather than on mathematical formalism alone [[28], [30], [38]]. This step is intentionally iterative, encouraging students to reflect on and revise judgements to achieve acceptable consistency levels.

The final stage of the framework integrates the weighted criteria within a GIS environment (ArcGIS Pro) using raster reclassification and weighted overlay operations to produce a landslide susceptibility map classified into relative risk zones. This synthesis stage reinforces spatial reasoning by requiring students to evaluate how individual terrain factors interact across space and how decision weights influence the resulting hazard patterns. The susceptibility map serves both as a technical output and as a basis for discussion on engineering judgement, uncertainty, and the implications of hazard mapping for infrastructure planning and risk mitigation. Throughout the framework, instructional emphasis is placed on transparency, reproducibility, and interpretability of results. Students are encouraged to document assumptions, justify weight decisions, and reflect on the limitations of the analysis. By structuring the case study around a complete LiDAR-AHP workflow, the framework supports the development of geospatial literacy, analytical reasoning, and decision-making skills that are directly transferable to professional civil engineering practice.

4. 0. METHODOLOGY

This study adopts a case study methodology to examine the educational effectiveness of integrating LiDAR-based geospatial analysis and the AHP into instruction on terrain stability and hazard mapping. The methodology focuses on instructional implementation, student engagement with the analytical workflow, and assessment of learning outcomes rather than on the development of new hazard modeling techniques.

4.1. Participants and Course Context

The case study was implemented within an upper-level civil engineering course enrolling 35 students at the beginning of the module, with 32 completing the module and participating in the post assessment due to course drop. Participants included senior undergraduates and graduate students from civil engineering and related infrastructure-focused programs. The instructional design intentionally accommodated varied levels of prior geospatial experience, reflecting typical civil engineering classroom conditions. The study is explicitly framed as a single-course instructional case study.

4.2. Instructional Implementation and Case Study Design

The instructional case study was structured as shown in Fig. 4. Students engaged with multi-temporal LiDAR-derived DEMs and derived geomorphic and hydrologic parameters, including slope, aspect, curvature, elevation, TWI, and DoD as shown in Fig. 5 using ArcGIS Pro software. Instruction emphasized interpretation of these parameters in the context of slope instability rather than automated model execution.

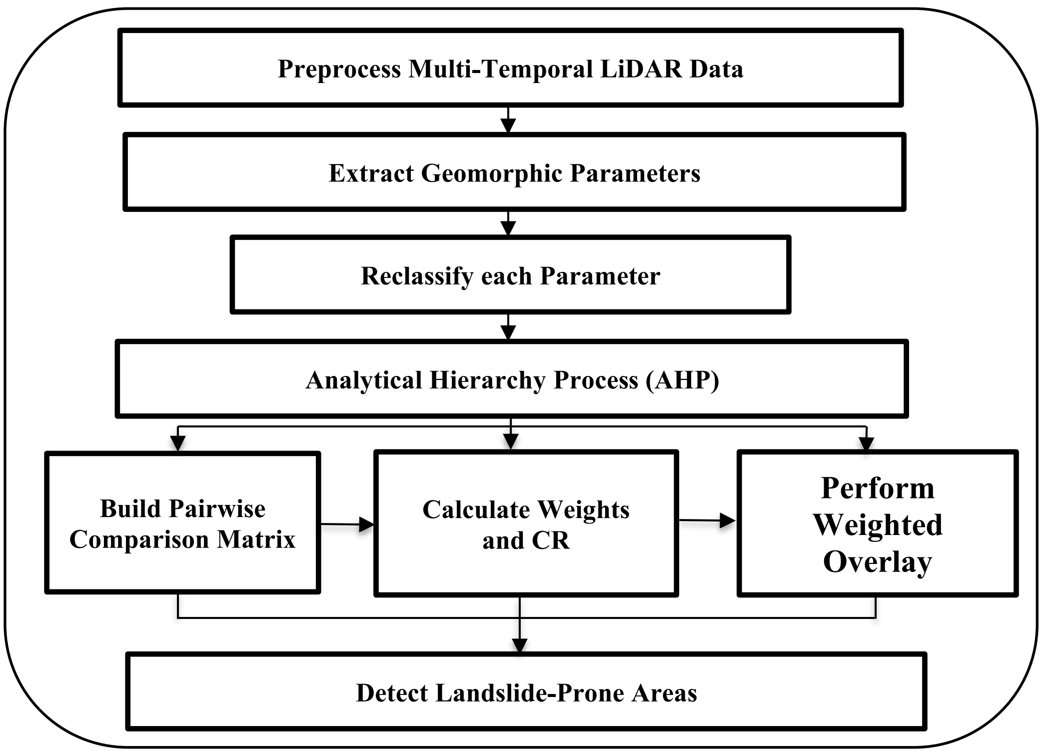


Fig. 4. Instructional methodology workflow

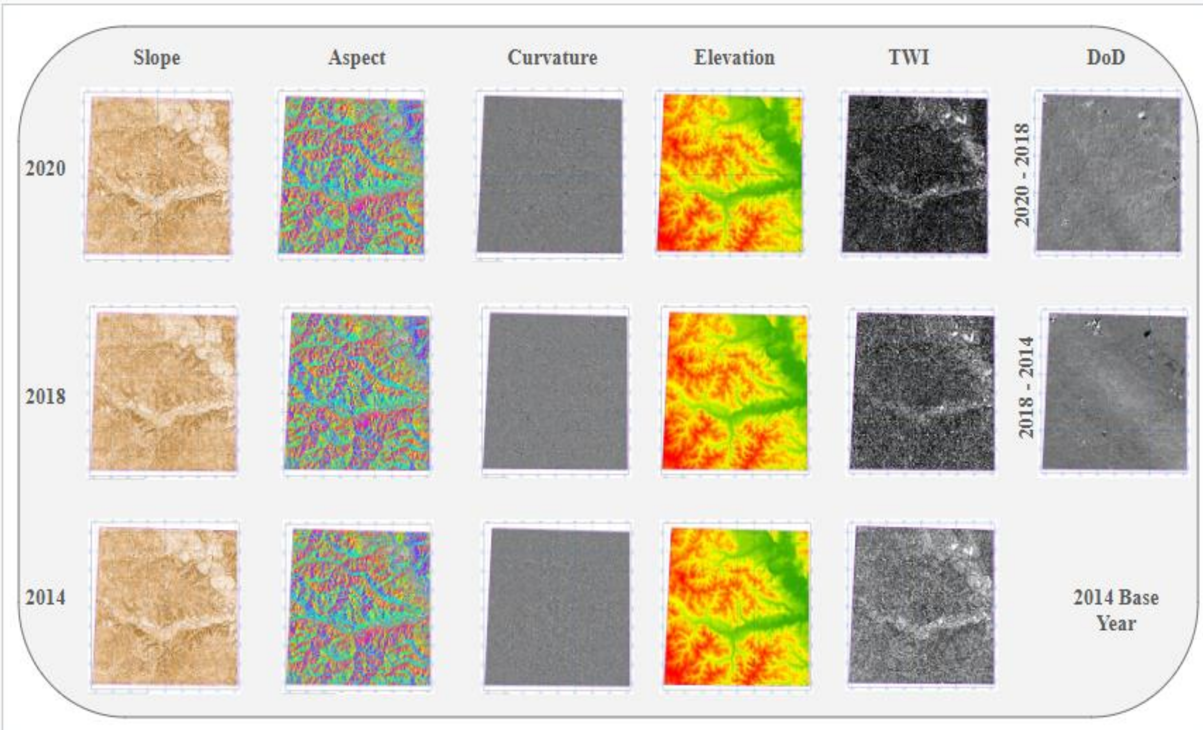


Fig. 5. Sample geomorphic parameters generated during the instructional lab

Following terrain analysis, students were introduced to multi-criteria decision analysis using the Analytical Hierarchy Process adapted from Saaty's methodology. Guided exercises led students through criteria definition for conditioning landslide parameters, pairwise comparison, weight derivation, and consistency ratio evaluation. Emphasis was placed on understanding the logic of decision weighting, the implications of inconsistency, and the iterative refinement of judgements.

At the end of the lab instruction a mean CR value of 0.02 was obtained by finding the average of the consistency ratio computed by all participants.

The final instructional activity involved integrating weighted terrain layers within a GIS environment using raster reclassification and weighted overlay analysis to generate a landslide susceptibility map classified into relative risk zones Fig. 6. Students were encouraged to reflect on how analytical choices influenced spatial outcomes and to consider implications for infrastructure planning and hazard mitigation.

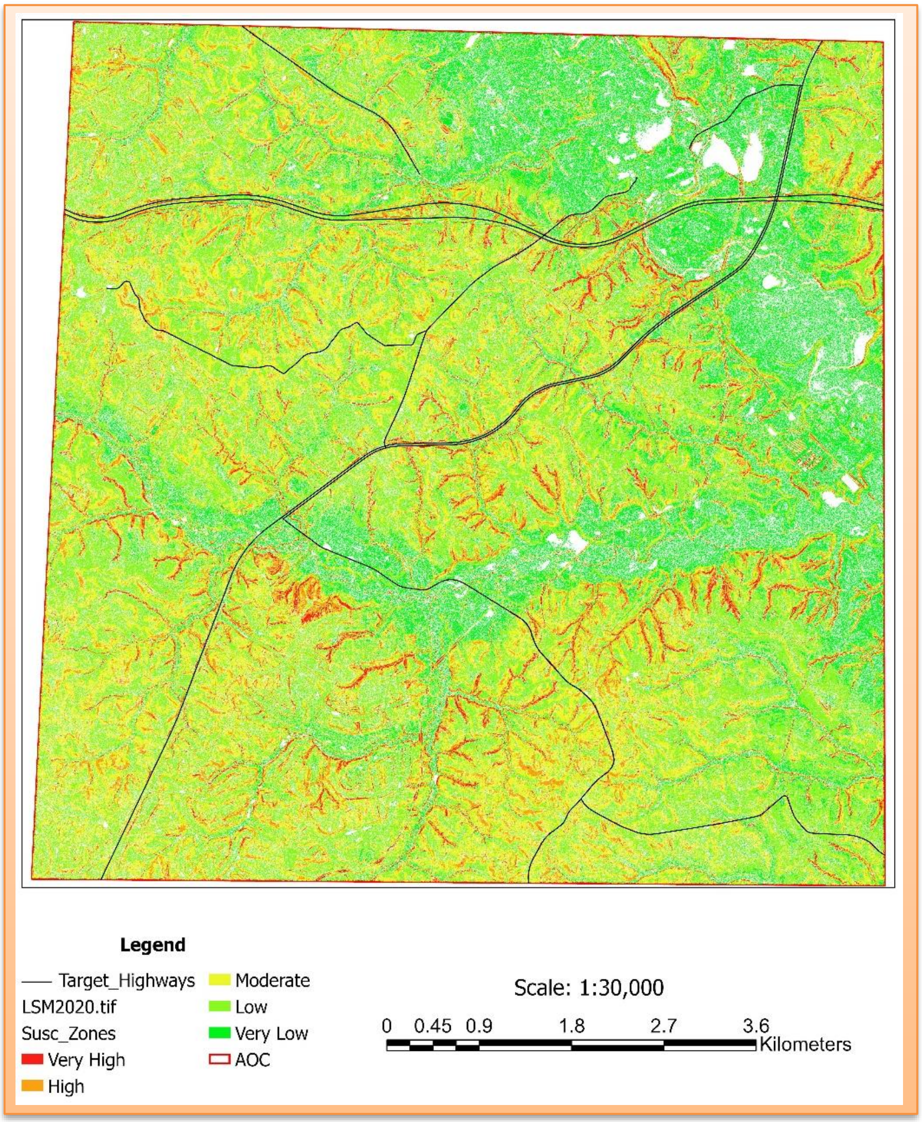


Fig. 6. A sample Landslide Susceptibility Map generated during the instructional lab for hazard mapping of the case study (part of Prince George's County, Maryland)

4.3. Quantitative Data Collection

Quantitative assessment data were collected using structured pre-instruction and post-instruction questionnaires. The instruments measured student self-reported knowledge and confidence across four domains: baseline geospatial knowledge, analytical and computational skills, understanding of terrain stability and hazard mapping, and perceptions of the instructional framework. Responses were recorded using ordered categorical scales ranging from low to high levels of understanding or confidence. The pre-instruction questionnaire established baseline conditions, while the post-instruction questionnaire captured changes following completion of the instructional module. Descriptive statistics were used to summarize shifts in response distributions between pre- and post-instruction measurements.

4.4. Qualitative Data Collection

Qualitative data was obtained from open-ended questions included in the post-instruction questionnaire. These questions invited students to reflect on: (1) which aspects of the LiDAR-based analysis most enhanced their understanding of terrain stability and hazard mapping; (2) challenges encountered during AHP weighting and consistency ratio computation; and (3) perceived applications of LiDAR and decision-analysis tools in future engineering practice. All responses were anonymized prior to analysis. The qualitative data provided contextual insight into student learning experiences, complimenting the quantitative results by capturing perceptions, reasoning processes, and experiential challenges associated with the instructional workflow.

5.0. DATA ANALYSES AND RESULTS

This section presents the results of the study, beginning with quantitative analysis of pre- and post-instruction survey responses, followed by thematic qualitative analysis of post-instruction open-ended reflections. Together, these results provide evidence of learning gains and instructional effectiveness associated with the LiDAR-AHP case study.

5.1. Quantitative Analysis

Quantitative results are based on responses from 35 participants who started the course module (pre-instruction) and 32 participants who completed the module (post-instruction). Analysis focuses on descriptive statistics and distributional shifts across survey items.

5.1.1. Participant Background (Q1 – Q3)

Table 1 summarizes participant academic level, disciplinary background, and prior exposure to geospatial technologies.

Table 1. Participant Background (Pre/Post Instruction)

Category	***Pre***	***Post***
Academic Level		
Senior	20	17
Graduate	15	15
Prior GIS/RS/LiDAR Experience		
Yes	14	16
No	21	16

The cohort included a mix of senior undergraduate and graduate students, with over 60% reporting no prior geospatial experience at pre-instruction underscoring the instructional relevance of the case study for mixed-experience classrooms. Fig. 7 shows that over 60% of responders are from the civil engineering program, thereby displaying the largest participation in the case study.

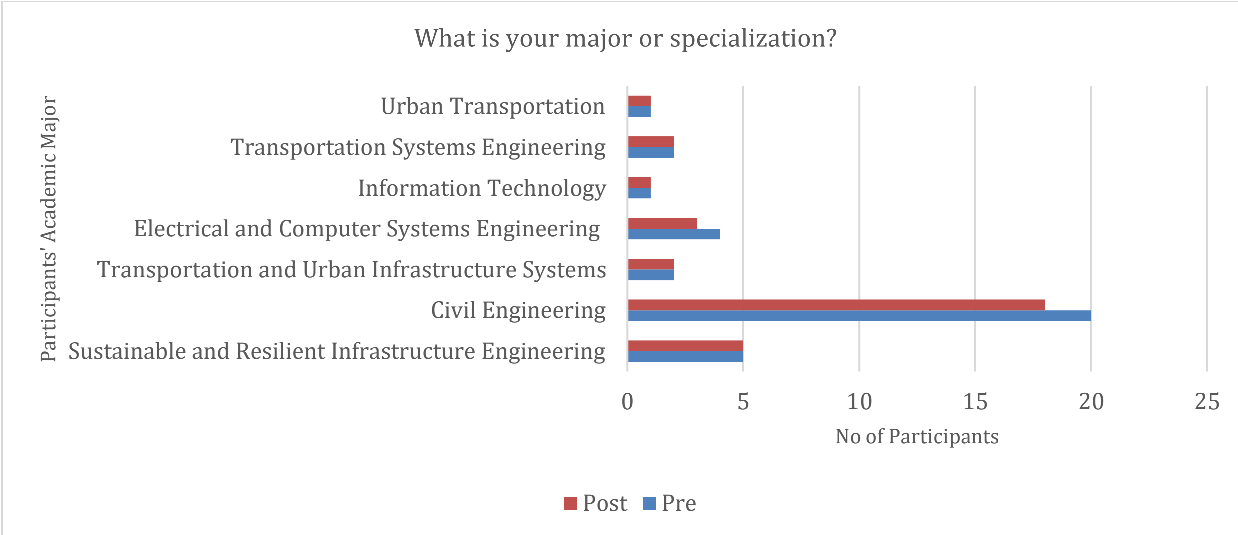
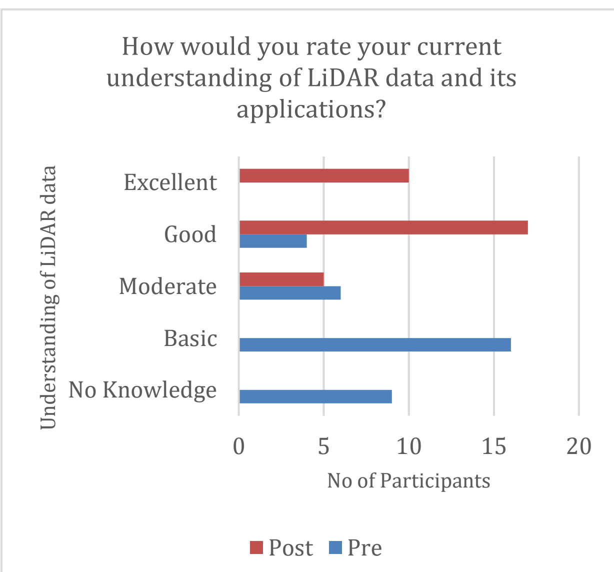


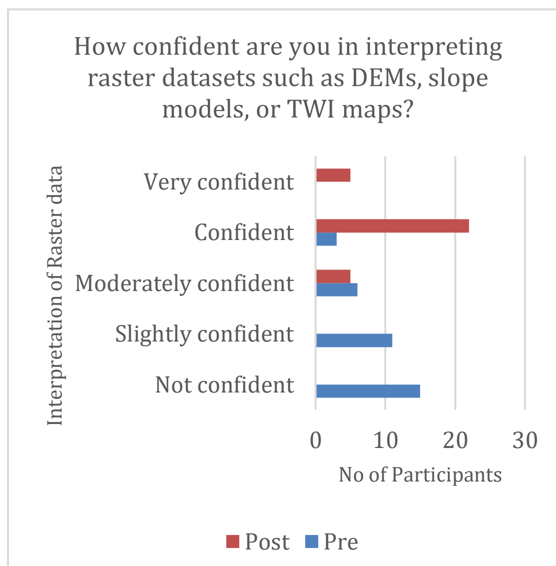
Fig. 7. Participants' Demography

5.1.2. Baseline Geospatial Knowledge (Q4 – Q5)

Substantial gains were observed in students' understanding of LiDAR data and confidence in interpreting raster-based terrain products Fig. 8.



(a)



(b)

Fig. 8. (a) Understanding of LiDAR Data **(b)** Confidence in Raster Data Interpretation

These results indicate a clear shift from novice-level familiarity to confident application, supporting gains in foundational geospatial literacy.

5.1.3. Analytical and Computational Skills (Q6 – Q7)

Marked improvements were observed in confidence performing GIS geoprocessing tasks and familiarity with AHP Table 2.

Table 2. Analytical and Computational Skill Development

Response Level	*GIS Geoprocessing (Pre)*	*GIS Geoprocessing (Post)*
Not / Slightly Confident	26	0
Moderately Confident	6	19
Confident / Very Confident	3	13

Response Level	*AHP Familiarity (Pre)*	*AHP Familiarity (Post)*
Not / Slightly Confident	29	0
Moderately Confident	4	2
Confident / Very Confident	2	30

Following instruction, 94% of participants reported being familiar or very familiar with AHP, indicating successful introduction of structured decision-making concepts.

5.1.4. Understanding of Terrain Instability and Hazard Mapping (Q8 – Q9)

Students demonstrated substantial gains in conceptual understanding and applied confidence related to landslide hazard identification and contributing factors Fig. 9 – Fig. 10.

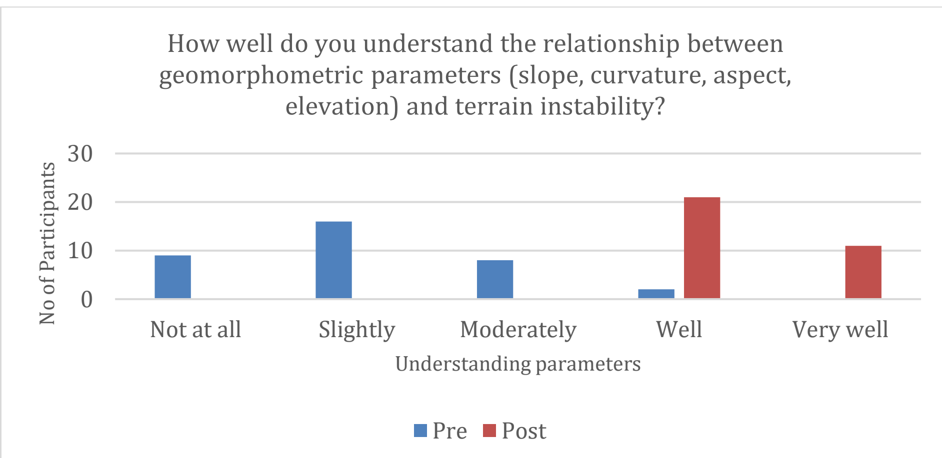


Fig. 9. Understanding of Terrain-Instability

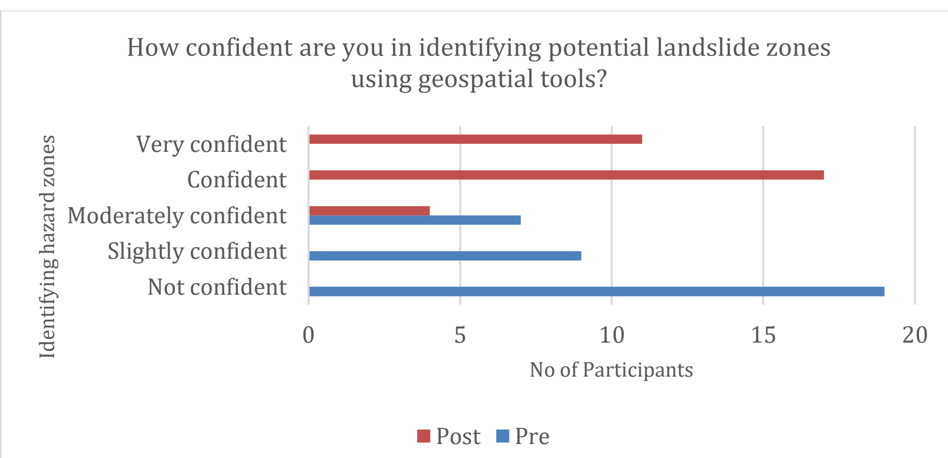


Fig. 10. Hazard Zone Identification Confidence

These shifts indicate strong learning gains in connecting geomorphometric indicators to slope instability and hazard mapping.

5.1.5. Perceived Instructional Effectiveness (Q10 – Q11)

Post-instruction responses indicate strong perceived educational value of the LiDAR-AHP framework. All respondents reported that the workflow improved their understanding of terrain stability analysis, with the majority indicating *significant* or *extreme* improvement. Similarly, all students rated the hands-on laboratory as *useful* or *very useful* in connecting geospatial analysis to engineering decision-making. These findings reflect perceived instructional effectiveness rather than statistically tested learning gains.

5.2. Qualitative Analysis

Qualitative analysis was conducted using inductive thematic coding of the post-instruction open-ended responses (32 participants per question). Four dominant themes emerged across the three reflection prompts.

5.2.1. Theme 1: Enhanced Spatial Reasoning and Terrain Interpretation

Students consistently identified LiDAR-derived slope, curvature, TWI, and DoD analyses as critical to understanding terrain instability, particularly through visualization of spatial patterns and temporal change. When asked the question (what part of the LiDAR-based analysis was most helpful in improving your understanding of terrain stability or hazard mapping?), a representative insight from the participant's response stated *"multi-temporal LiDAR and DoD analysis clarified subtle deformation processes and the dynamic nature of slope instability.",* another said, *"multi-temporal LiDAR analysis strengthened my understanding of terrain dynamics."*, another participant also said, *"generating and interpreting curvature and TWI layers improved my understanding of how water concentration affects slope failure."* Finally, a participant said, *"combining multiple LiDAR-derived layers in the weighted overlay improved my spatial reasoning."*

5.2.2. Theme 2: Value of Integrated, multi-Factor Analysis

Responses highlighted the importance of combining multiple geomorphic indicators through weighted overlay, enabling students to synthesize complex spatial information into a coherent hazard assessment. For example, students reported improved ability to *"see how multiple factors interact,"* strengthening holistic understanding of landslide susceptibility. One participant said, *"slope and aspect analysis helped explain why certain areas are more prone to failure.",* and another one says, *"slope classification was most impactful because it directly linked terrain steepness to landslide susceptibility.",* while another participant said, *"the TWI layer clarified the role of moisture accumulation in slope instability."* In addition, a participant said, *"the weighted overlay process helped me synthesize multiple factors into a single hazard map."*

5.2.3. Development of Structured Decision-Making Skills

When the question was asked (how do you think LiDAR and decision-analysis tools like AHP can be integrated into future engineering practice?). Participants noted that AHP introduced a transparent and logical framework for assigning importance to terrain factors, reinforcing analytical reasoning and justification of engineering decisions. Students described AHP as helping them *"justify decisions with data"* and understand the impact of weighting assumptions on outcomes. One response reads, *"in practice, LiDAR and AHP can help engineers justify design decisions to stakeholders using data-driven evidence."*, another, *"these methods can improve* *transparency in engineering decisions.",* and another participant also responded that, *"LiDAR and AHP can be integrated into professional practice to support hazard screening and prioritization during early stage infrastructure planning."*

5.2.4. Challenges with Consistency and Quantification of Judgement

While students valued AHP, many reported initial difficulty with pairwise comparisons, eigenvalue-based computations, and achieving acceptable consistency ratios, highlighting the cognitive demand of translating judgement into numerical form. Students emphasized the iterative nature of achieving logical consistency as both challenging and educationally valuable. For example, when asked (what challenges did you encounter during the AHP weighting or consistency ratio computation?), one participant said, *"the main challenge was maintaining consistency during pairwise comparisons, especially when differentiating closely related parameters."* And another said, *"maintaining logical consistency across all pairwise comparisons were difficult."*

5.3. Summary of Results

Overall, the results indicate that the LiDAR-AHP case study supported substantial perceived improvements in geospatial understanding, confidence with analytical workflows, and appreciation of structured decision-making. Qualitative reflections further suggest enhanced spatial reasoning and clearer connections between terrain indicators and slope instability. These outcomes support the instructional relevance of the approach while acknowledging that measured improvements are perception-based.

6.0. DISCUSSION

The results of this case study demonstrate that integrating LiDAR-based terrain analysis with the AHP can serve as an effective instructional approach for teaching terrain stability and hazard mapping in civil engineering education. The observed learning gains across geospatial knowledge, analytical skills, and hazard interpretation suggest that students benefited not only from exposure to advanced datasets, but also from the structured integration of decision-making logic within the instructional workflow.

Students perceived gains in spatial reasoning and interpretive capacity highlight the pedagogical value of using high-resolution, real world geospatial data rather than simplified instructional examples. Consistent with prior studies, engagement with authentic LiDAR-derived terrain products appears to enhance conceptual understanding of hazard-related processes and their spatial manifestation [[35], [36], [37]]. In particular, the inclusion of multi-temporal analysis through DoD helped students recognize terrain instability as a dynamic phenomenon, aligning with broader research on the importance of temporal terrain analysis in landslide assessment [[16], [17], [18]].

The AHP component played a central role in fostering structured engineering judgement. While data-driven and machine learning approaches are increasingly common in landslide susceptibility analysis [[20], [26]], their limited transparency can reduce instructional value. In contrast, AHP required students to explicitly evaluate factor importance, assess logical consistency, and reflect on how weighting assumptions influence hazard outcomes. Although students reported challenges with pairwise comparisons and consistency ratio computation, these difficulties contributed to deeper engagement with decision logic and judgement quantification, reflecting practices common in professional engineering contexts [[28], [30], [38]].

Uniformly positive perceptions of the hands-on laboratory activities further reinforce the instructional effectiveness of the integrated LiDAR-AHP approach. Students reported that the case-study helped bridge geospatial analysis and engineering decision-making, supporting its relevance to infrastructure planning, hazard mitigation, and resilience-oriented design. Such perceived relevance is known to influence student motivation and engagement, particularly in interdisciplinary instructional settings.

From an educational standpoint, this case study contributes to an effort to modernize civil engineering curricula by embedding data-driven, geospatially informed decision-making within terrain stability instruction. The LiDAR-AHP workflow offers a transferable instructional model that emphasizes transparency, interpretability, and conceptual understanding without overwhelming students with technical detail. While limited to a single-course implementation, the study illustrates the potential of this approach when thoughtfully integrated into civil engineering education, particularly for developing competencies in spatial reasoning, hazard awareness, and engineering judgement.

7.0. CONCLUSION

This case study demonstrates how an integrated LiDAR-AHP workflow can be repurposed effectively for civil engineering education, emphasizing applied learning, interpretability, and engineering judgement. By engaging students with real-world terrain data and transparent decision-analysis processes, the instructional module supports development of geospatial reasoning and decision-making competencies aligned with contemporary civil engineering practice. While limited to a single course and relying partly on self-reported measures, the case study provides a transferable instructional model for incorporating hazard-informed, data-driven learning into terrain stability curricula.

STUDY LIMITATIONS

This case study was implemented within a single course and involved modest sample size of 35 participants who attended the pre-survey but only 32 finished the post-survey due to course drop before the end of the course, these limits broader generalization of the findings. Quantitative results are based on self-reported measures of knowledge and confidence rather than direct performance assessments. In addition, the assessment instrument was custom designed for this study and has not undergone formal validation. Finally, the instructional module did not include field-based validation or comparison with alternative teaching approaches. These limitations define the scope of the study and suggest directions for future instructional refinement.

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