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Bridging traditional and conventional knowledge for soil classification in landslide-prone areas using exploratory factor analysis

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Introduction: Understanding soil movement and landslide susceptibility requires accurate soil classification. Traditional knowledge (TK) from ancient Indian texts describes soil color, texture, smell, and taste as key indicators, yet such qualitative insights remain underutilized in modern geotechnical assessments.

Methods: A questionnaire comprising 32 TK-based soil characteristics (color, texture, smell, taste) was developed and applied by 12 experts across 55 landslide-prone sites in Himachal Pradesh, India. Soil samples were also collected for laboratory-based geotechnical testing. Exploratory Factor Analyses (EFA) were conducted on TK-only, geotechnical-only, and combined datasets to identify latent soil categories and compare their explanatory power.

Results: Three principal soil categories earthy, coarse-grained, and fine-grained were identified. Retained factors explained 65.17%, 68.32%, and 71.46% of total variance for TK, geotechnical, and combined datasets, respectively. Expert discipline and educational background significantly influenced soil categorization, particularly in the fine-grained and coarse-grained groups.

Discussion: Integrating traditional and modern indicators enhances soil classification accuracy and provides a cost-effective framework for assessing landslide susceptibility in Himalayan regions. TK-based soil descriptors, when combined with quantitative geotechnical data, offer a holistic approach to slope stability analysis and risk mitigation.

KEYWORDS

exploratory factor analysis, landslides, soil classification, traditional knowledge, soil color, soil smell, soil texture, soil stability

Introduction

Landslides pose significant global risks, threatening lives, infrastructure, and ecosystems, particularly in geologically unstable regions (Wang et al., 2022). In India, steep slopes, diverse topography, and complex soil composition, especially in the Himalayan region, contribute to frequent landslides (Singh and Pandey, 2024). The region's heavy monsoonal rainfall, tectonic activity, and unstable soil composition necessitate improved risk-management strategies (Singh and Pandey, 2024). Understanding soil properties such as permeability, shear strength, and composition is crucial for assessing slope stability and enhancing landslide prediction models (Petley, 2012). Over the past 2 decades, landslides have resulted in approximately 18,000 fatalities in India, underscoring the urgent need for robust soil-categorization frameworks to improve mitigation strategies (Ramesh et al., 2023). By incorporating region-specific soil properties, such frameworks can provide more precise risk assessments, ultimately reducing the impact of landslides in vulnerable areas (Ren and Ren, 2015).

Conventional geotechnical investigations employ laboratory testing, remote sensing, and machine learning models to assess soil properties and predict landslide risks (Mali et al., 2022). Advances such as LiDAR-based terrain mapping, GIS-based spatial modeling, and satellite imaging have significantly improved landslide prediction accuracy (Casagli et al., 2023). However, while these quantitative approaches provide precise geotechnical insights, they require expensive instrumentation and extensive field surveys, making them impractical for resource-limited regions (Uddin and Hassan, 2022). Additionally, these methods often overlook qualitative soil attributes such as color, texture, and smell, which have been historically used in traditional knowledge (TK) systems to assess soil stability (Arosio et al., 2009).

Despite advancements in geotechnical methodologies, the integration of traditional soil classification frameworks such as TK remains underexplored (Dearing et al., 2015). Existing frameworks lack a comprehensive approach that bridges the quantitative precision of conventional geotechnical methods with the qualitative richness of traditional knowledge, thereby limiting their applicability for cost-effective and rapid assessments in landslide-prone regions (Gupta and Satyam, 2024). This gap is particularly significant for the Himalayan region, where landslide risks result from the complex interplay of climate, topography, and human activity. Vrikshayurveda, an ancient Indian text attributed to Surapala (c. 1000 AD), provides detailed soil classifications based on observable characteristics such as color, moisture retention, fertility, and texture (Mishra, 2019). This text categorizes soils into three primary types: arid, marshy, and ordinary, each associated with specific properties influencing plant growth, water retention, and soil stability (Jallayu et al., 2024). Although Vrikshayurveda has traditionally been applied in agriculture, its principles can offer valuable insights for understanding soil behavior in dynamic landslide-prone environments (Srikanth et al., 2015). Unlike conventional geotechnical approaches that emphasize numerical thresholds for soil cohesion, plasticity, and permeability, Vrikshayurveda provides a qualitative assessment framework based on soil texture, color, and smell, which can serve as a rapid and cost-effective preliminary assessment tool in landslide-prone areas, particularly where terrain inaccessibility limits formal geotechnical testing (Kumar and Jigeesh, 2024; Beniwal et al., 2020). Traditional soil knowledge is deeply embedded in the community practices of agriculture, land use, and slope management (Mishra, 2019). These experiential assessments not only guide cropping and construction choices but also function as early indicators of slope instability in the region (Srikanth et al., 2015). Integrating such community-based understanding with geotechnical analyses enables participatory risk assessment, ensuring that local stakeholders who are most exposed to landslide hazards remain the central beneficiaries of this research. This synthesis aligns with the growing emphasis on the co-production of environmental knowledge for resilient mountain livelihoods.

Previous landslide risk assessment studies have predominantly relied on geotechnical, remote sensing, and GIS-based modeling techniques (Jallayu et al., 2024). While these methods provide high-resolution data for soil stability analysis, they often overlook traditional soil knowledge systems that have been used for centuries to evaluate soil behavior (Smith et al., 2021). By integrating TK-based soil classification with geotechnical parameters, this study developed a holistic soil categorization framework that bridges traditional and conventional knowledge systems to enhance landslide risk assessment methodologies. Studies in the Himalayan region have emphasized the importance of combining geotechnical and geomorphological factors with advanced spatial modeling for landslide risk assessment. GIS-based analyses and susceptibility mapping have been instrumental in identifying high-risk areas and improving hazard management strategies (Hassan et al., 2022). Recent research has advanced slope stability and susceptibility analysis through multi-criteria and machine-learning-based approaches, including slope mass rating (SMR) and GIS-integrated models (Abbasi et al., 2024; Hamedi et al., 2025). For instance, studies in Mandi district demonstrate that integrating spatial models with rainfall and slope data significantly improves risk identification accuracy (Dikshit et al., 2020). Similarly, rainfall-induced landslide studies in the Indian Himalayan region highlight the interactions among climate, soil, and geomorphology, underscoring the need for localized assessments (Dikshit et al., 2020). Similar studies have employed SVM and logistic regression methods to identify critical parameters influencing landslide-prone zones, underscoring the potential of data-driven frameworks that complement traditional knowledge systems (Ahadi and Rosta, 2024).

Advancements in geospatial modeling and soil stabilization techniques have further improved landslide risk management. Interpolation algorithms have provided critical insights into spatial variability in geotechnical properties (Hassan et al., 2023). Additionally, innovative soil stabilization techniques, such as the use of plaster of Paris kiln dust and potassium-rich ions for sodium-rich clays, have been effective in mitigating dispersive soil and internal erosion (Hassan et al., 2023). Similarly, fine marble dust has been explored as a solution for soil dispersion, with statistical evaluations further refining stabilization applications (Ijaz et al., 2023). These geotechnical approaches, when integrated with traditional soil classification systems, can enhance slope management strategies by offering a cost-effective and region-specific framework for landslide risk assessment. These methods, combined with geotechnical soil maps, support better slope management and disaster mitigation strategies (Wang and Nanehkaran, 2024). Prior research has examined how age and experience affect soil classification (Dornik et al., 2016). Combining expert knowledge with geographic object-based image analysis improves soil categorization accuracy (Wang and Nanehkaran, 2024). Specific expertise is also required to analyze soil spectral data (Marques et al., 2019).

However, conventional knowledge may differ from scientific classification in soil mapping (Pereira et al., 2017). Historical studies in Japan highlight the importance of geographical context and size in soil classification (Hirai and Hamazaki, 2004; Grinand et al., 2008; Baruck et al., 2016). Studies show experts' ages did not significantly impact their soil observations, so we hypothesize that soil observations are not affected by age (Slessarev et al., 2019). Integrating this knowledge with geotechnical and traditional attributes can enhance soil classification frameworks for landslide

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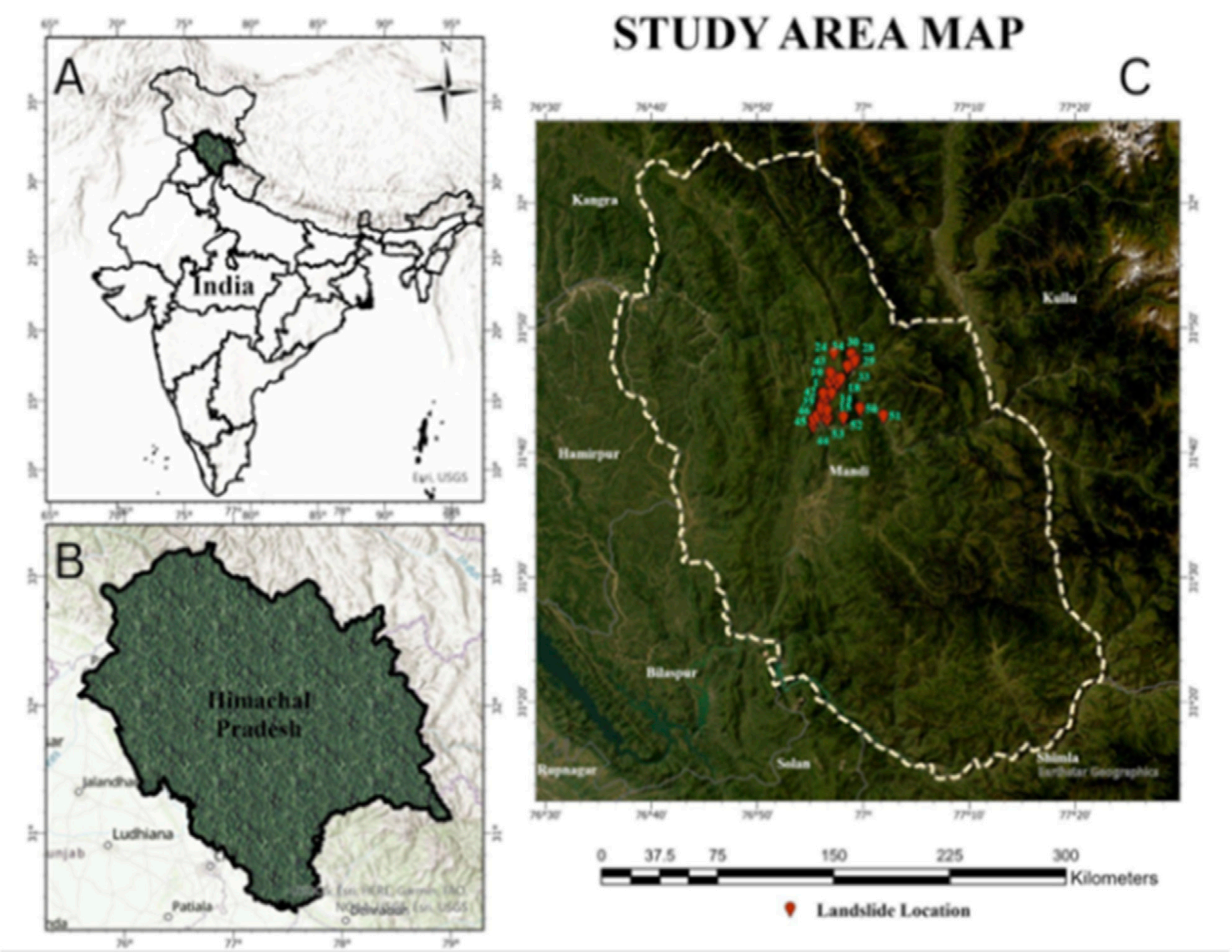

FIGURE 1
Geographical location of the data collection sites in India. **(A)** Map of India, specifically highlighting the geographical location of Himachal Pradesh. **(B)** Map of Himachal Pradesh, highlighting Mandi District. **(C)** Locations within Mandi District from where the data were collected. The red dots represent the data collected from areas where landslides have occurred. The map was created using ArcGIS Pro version 3.2 (https://www.esri.com/arcgis-blog/products/arcgis-pro/announcements/whats-new-in-arcgis-pro-3-2/). In-built satellite and terrain maps were used as base layers, and the study area spans the coordinates 76°55′54′E to 76°59′42′E and 31°42′25′N to 31°46′26′N.

risk assessment. To achieve this, a questionnaire-based survey incorporating 32 TK soil attributes (color, texture, smell, and moisture retention) was developed. These qualitative assessments were then compared against laboratory-tested geotechnical properties, such as cohesion, permeability, and plasticity, across 55 landslide sites in Himachal Pradesh. Using Exploratory Factor Analysis (EFA), distinct soil categories were identified that aligned with both TK classifications and conventional geotechnical findings, providing a statistically validated framework for landslide risk assessment. Additionally, this study investigated how expert background and education influence soil classification accuracy, addressing potential biases in soil assessment methodologies.

This study contributes to the growing discourse on integrating traditional ecological knowledge into contemporary scientific approaches. It provides a replicable model for rapid soil assessment in landslide-prone regions, particularly in areas where conventional laboratory-based methods may not be feasible (Hulathdoowage and Hadiwattage, 2022). These findings offer new perspectives on leveraging ancient wisdom for modern environmental risk management, emphasizing the importance of interdisciplinary approaches in landslide hazard mitigation. By systematically bridging traditional and geotechnical methods, this study enhances the predictive accuracy of landslide susceptibility assessments and offers policymakers practical tools for sustainable land use planning.

We begin by reviewing the literature on TK in soil and plant sciences. We then covered the procedures for gathering information from landslide sites and rating the information using a Likert scale. PCA, one-way analysis of variance (ANOVA), and EFA were used for data analysis. Finally, the factor analysis findings are presented and the component compositions for each type of soil are explained.

Methods

Study area

The study was carried out in the Mandi geographical area, which is situated in Himachal Pradesh, India's mid-Himalayan region (see

Figure 1). Our research specifically concentrated on the region along the route that connects Mandi and Kamand; the coordinates of this area are from 76°55′54′E to 76°59′42′E and from 31°42′25°N to 31°46′26°N. The research area was situated between 850 and 1,250 m above sea level. The frequent landslides in this area were the driving force behind our decision to research in Mandi (Kahlon et al., 2014). These landslide occurrences have sparked worries about the possible impact of precipitation, especially in a region where 1,380 mm of precipitation falls on average annually (Kahlon et al., 2014). We determined that 55 places along the 25-km route in Mandi, Himachal Pradesh, were landslide-prone because they had recently had landslides. Two different kinds of data were gathered from the landslide areas for our investigation. There are two types of soil features: one is based on TK, and the other is geotechnical. Below are the specifics of both data collection methodologies.

Experts

Twelve experts from a reputable university, aged 21–33 years (mean = 29, SD = 2.8), participated in this study. All experts provided informed consent before their participation. Experts included a mix of geotechnical engineers, environmental scientists, and individuals with expertise in traditional soil classification methods such as TK. The experts held either master's or doctoral degrees and specialized in civil engineering, geotechnical engineering, and electronics and communication engineering. Seven experts had extensive research experience in geotechnical engineering and slope-stability analysis, whereas the remaining five had field experience in landslide risk assessment, soil mechanics, geomorphological analysis, and traditional soil classification techniques. Experts were selected based on the following criteria: (1) a minimum master's degree in geotechnical engineering, civil engineering, or other engineering disciplines; (2) research experience in landslide risk assessment and soil characterization; and (3) familiarity with traditional knowledge systems. Their combined academic and field experience facilitated the integration of conventional geotechnical assessments with TK-based soil classification, enabling a comprehensive analysis of soil-environment interactions. The experts conducted field assessments at 55 randomly selected landslide-prone sites and graded soils based on TK principles. The twelve experts evaluated distinct soil properties, including texture, color, and scent, and systematically recorded their observations using a structured questionnaire. To ensure consistency and minimize subjective bias, the assessments were conducted independently by each expert, and inter-rater reliability was analyzed to confirm agreement in soil classifications. This structured approach allowed for direct comparisons between conventional geotechnical features and traditional soil attributes, bridging the gap between conventional engineering assessments and TK soil categorization. Their collective expertise in both traditional and conventional soil characterization methods brought valuable perspectives to the study, allowing for a more comprehensive evaluation of soil properties and their implications for landslide susceptibility. By integrating traditional knowledge with conventional geotechnical assessments, this study highlighted the potential of TK as a complementary tool for rapid soil assessment in landslide-prone areas.

The geotechnical features

The soil samples from 55 locations were collected at a maximum depth of 0.5 m along sloping surfaces for geotechnical analysis. Each sample included *in situ* moisture content, geographical coordinates, and recent landslide locations (Vogel et al., 2023). Soils were extracted by using a stainless-steel sampler (10 cm diameter and 13 cm in height) between 0.3 and 0.5 m depths and with the help of a trowel for rocky strata, weighing approximately 40 kg for each sample. The samples were analyzed in the laboratory for 16 geotechnical features such as *in situ* bulk density, *in situ* water content (wn), plasticity index, liquid and plasticity limits, saturation permeability, and more (ASTM Committee D-18 on Soil and Rock, 2009; American Society for Testing and Materials. Committee D18 on Soil and Rock, 2004; Nhantumbo and Cambule, 2006; Nguyen et al., 2022). In addition, the standard Proctor test was conducted to obtain optimum moisture content and dry density. Relative compaction was estimated by comparing *in situ* and laboratory dry density. The *in situ* density was used to compute the porosity. The geotechnical variables measured include gravel (%), sand (%), clay (%), silt (%), liquid limit, plastic limit, density, fine content (%), natural water content (%), specific gravity, and porosity (refer to Table 1).

We performed a Pearson's correlation analysis to establish the strength of relationships between traditional soil characteristics of color, texture, smell, and taste and geotechnical properties of moisture content, density, and gravel content. Correlations were considered statistically significant using a two-tailed test of significance at $p < 0.05$. Strong correlations, $r \geq 0.5$, were expected to confirm how well the traditional and conventional soil categorizations agreed. For example, we predicted that brown soil would correlate positively with density and moisture content, indicating compactness, while white soils, which are loosely structured, would negatively correlate with gravel content.

To further interpret the contribution of soil to slope instability, we used established literature thresholds and mean values observed in our dataset to qualitatively categorize the landslide susceptibility of each geotechnical feature as low, moderate, and high.

Soils with high porosity of more than 60% have lower particle packing and higher void ratios; hence, they are more susceptible to increase in water infiltration and pore pressure accumulation, which is a critical precursor to slope failure under rainfall conditions. With a mean porosity of 66.6%, these soils thus fall in the category of having high landslide susceptibility (Rahardjo et al., 2007; Sidle and Ochiai, 2006).

Fines content close to 32% represents a transitional soil system of silt and clay that retains water but without the cohesion attributed to high-clay content soil. Consequently, such soils are moderately susceptible to instability, especially under wet-dry cycles and gravitational loading (Thevanayagam, 1998).

A plastic limit of ~16% would indicate that the soil changes from semi-solid to plastic behavior at a moderate level of moisture. These soils have a tendency to show reduced shear strength under

TABLE 1 Geotechnical features and their minimum, maximum, mean values, and corresponding landslide susceptibility levels.

S. No.	Geotechnical feature		Test standard	Minimum value	Maximum value	Mean value	Landslide susceptibility based on mean values
1	Porosity		ASTM 698-12E2	44.8	88	66.6	High
2	Fines content (%)		ASTM-D422-63	5	75	31.9	Moderate
3	Plastic limit (PL) (%)		ASTM D 4318-17e1	4	25	15.9	Moderate
4	Liquid limit (LL) (%)			8	35	24.4	High
5	Plasticity index (PI) (%)			3.70	11.70	8.34	Moderate
6	Saturated water content (%)		ASTM D 2216–19	11.4	16.8	12.5	High
7	Optimum moisture content		ASTM D698	8.5	14.7	10.3	Moderate
8	Sand (%)		ASTM-D422-63	21	88	52.4	Low
9	Saturated unit weight		ASTM D7263	20.6	21.8	15.9	Moderate
10	Specific gravity		ASTM D854	2.5	2.6	2.6	Low
11	Gravel (%)		ASTM-D422-63	0	65	14.8	Low
12	Particle sizes	D10	ASTM-D422-63	0.0	0.7	0.4	Low
13		D30		0.05	2.8	1.6	Moderate
14		D50		0.0	3.2	2.2	Moderate
15		D60		2.5	2.6	2.3	Low

increasing saturation and, therefore, moderate susceptibility (Van Westen et al., 2008).

The liquid limit of 24.4% falls within the range typically associated with soil softening under rainfall and seismic triggers, thus classified as high susceptibility. Clays with LL >20% have been linked to reduced stability during extreme hydrological events (Varnes, 1958).

Plasticity index values of 8%–12% represent transition soils that are neither excessively plastic nor brittle. Accordingly, they are moderately susceptible to deformation by the action of applied external stressors (Skempton, 1953).

An average saturated water content of 12.5% indicates that these soils are capable of developing high moisture retention, with an associated gain in weight and loss of matric suction, which may well increase the potential for slope failure under sustained rainfall. It is considered to be of high susceptibility (Fredlund and Rahardjo, 1993).

While optimum moisture content at 10.3% also indicates moderate risk, it is favorable for compaction in dry conditions, but saturation beyond this point can destabilize the soil matrix and increase landslide risk (Das and Sobhan, 2006).

A sand content over 50% improves permeability normally and enables good drainage, hence a minimal development of pore pressure. Since the mean sand content is 52.4%, these soils are to be classified as having low susceptibility (Bishop, 1955).

Saturated unit weight of 15.9 kN/m^3 indicates moderately dense soils, which, when saturated, may develop considerable driving forces downslope and justify a moderate risk classification (Das and Sobhan, 2006).

A specific gravity of 2.6 corresponds to a stable silicate mineralogy with coarse fractions, which indicates structural resistance and effective drainage. This corresponds to low susceptibility according to (Das and Sobhan, 2006).

Gravel content contributes to macro-porosity and facilitates drainage, lowering water retention and pore pressure accumulation, with a mean of 14.8%. Consequently, these soils are rated as low susceptibility (Macciotta and Hendry, 2021). Particle size parameters: D10 = 0.4 mm and D60 = 2.3 mm indicate that the well-graded soil allows for good compaction, reducing the risks of internal erosion, hence supporting low susceptibility. On the other hand, D30 = 1.6 mm and D50 = 2.2 mm indicate intermediate grading, which may show some sensitivity under stress and hence are rated as moderate susceptibility according to USDA Soil Survey (Garc and Frankenstein, 2015). Hence, the susceptibility classification in Table 1 integrates these parameter thresholds and their known geomaterial behaviors to qualitatively indicate the relative potential for landslide initiation in the study area. This context strengthens the engineering geological relevance of the dataset by relating lab-measured soil properties to field-observed landslide patterns in a Himalayan terrain dominated by colluvial and weathered metamorphic formations.

Survey questionnaire

A structured questionnaire was developed based on the principles of traditional soil classification to gather expert

TABLE 2 Traditional features and their minimum, maximum, and mean values.

Traditional features	Minimum value	Maximum value	Mean value
Color of the soil 1. Red 2. Brown 3. Black 4. White 5. Green 6. Yellow	1	5	 1. 3.6 2. 1.8 3. 2.7 4. 2.1 5. 1.7 6. 2.3
Content 1. Sand 2. Silt 3. Gravel 4. Clay 5. Rocks & debris 6. Coarseness	1	5	 1. 3.6 2. 2.9 3. 3.2 4. 2.4 5. 3.4 6. 3.3
Related to water 1. Retention 2. Drainage 3. Moisture 4. Dryness 5. Hardness 6. Smoothness 7. Density	1	5	 1. 3.3 2. 3.4 3. 3.3 4. 2.7 5. 2.9 6. 2.8 7. 3.1
Smell 1. Earthy 2. Musty 3. Faul	1	5	 1. 3.6 2. 2.6 3. 1.8
Taste 1. Sweetness 2. Saltness	1	5	 1. 3.1 2. 2.9
Fertility 1. Fertile 2. Plant health 3. Deforestation 4. Vegetation cover	1	5	 1. 3.8 2. 3.9 3. 2.5 4. 3.9
Field test 1. Stickiness 2. Crumbling 3. Clump	1	5	 1. 2.9 2. 3.3 3. 3.4

evaluations and quantifiable data (see Table 2). As shown in Table 2, the questionnaire assessed soil properties, including soil color (e.g., red, white, yellow), smell (e.g., earthy and musty), texture (e.g., stickiness, smoothness), and taste (e.g., sweetness and saltiness), using a 5-point Likert scale (+2 = significant agreement, +1 = agreement, 0 = neutrality, −1 = disagreement, −2 = significant disagreement) for standardized expert responses (Alabi and Jelili, 2023; South et al., 2022; Kumar and Brijesh, 2023). The 32 questions included in the questionnaire were carefully selected following a comprehensive review of the traditional texts and contemporary literature on soil properties. Experts in geotechnical engineering and environmental science evaluated the relevance of each question to ensure alignment with both the traditional and conventional soil classification methods. For more details on the questionnaire, refer to the Supplementary Material.

Before the main data collection, a calibration session was conducted with all the participating experts to standardize the interpretation of qualitative descriptors, such as color, smell, taste, and texture. Experts were trained on how to assign ratings using the five-point Likert scale (−2 to +2) and were shown representative soil samples (black, white, and brown) to achieve a consensus on interpretation. This session ensured that the qualitative evaluations were harmonized across experts. To validate the questionnaire, two geotechnical experts independently reviewed the 32 questions for clarity, relevance, and comprehensiveness before full implementation. Each question was rated for validity and consistency using a 5-point Likert scale, and the inter-rater reliability was assessed using Cronbach's alpha, which was computed as 0.86, indicating a high level of agreement among experts. Additionally, Cronbach's alpha for the full dataset of 660 responses across 32 items was 0.77, further confirming the reliability of the questionnaire. This validation process ensured that the questionnaire effectively captured the intended soil characteristics while maintaining consistency in the expert assessments.

Experts administered the questionnaire at randomly selected landslide-prone sites to evaluate soil fertility, moisture content, water retention, drainage capacity, stickiness, hardness, and disturbance response. The effects of vegetation cover on soil stability were also analyzed. Soil color was noted to assess both organic and mineral components, providing insight into soil composition. These expert evaluations, guided by structured criteria, ensure consistency across assessments and enable objective comparisons between soil samples.

The structured questionnaire provided a standardized framework for evaluating soil characteristics, enabling comparisons across diverse landslide-prone sites, while minimizing variability in expert assessments. Given the challenges of conducting direct measurements in remote locations, the questionnaire facilitates an efficient and field-adaptable method for soil classification. This approach also incorporates diverse disciplinary perspectives, as experts from geotechnical, and civil engineering backgrounds apply a consistent evaluation framework to the same soil samples.

Data analyses

All statistical analyses were performed using SPSS software (IBM Corp, 2016). To determine the suitability of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were employed (Gupta and Shukla, 2018). The KMO measure assesses the proportion of variance among variables that might be a common variance, indicating the appropriateness of factor analysis. A KMO value above 0.5 was considered acceptable for proceeding with Exploratory factor analysis (EFA) (Rahardjo et al., 2007). Bartlett's Test of Sphericity tests the null hypothesis that the correlation matrix is an identity matrix, which would indicate that variables are unrelated and unsuitable for structure detection. A significant result ($p < 0.05$) from Bartlett's test suggests that there are adequate relationships among variables for factor analysis (Gupta and Shukla, 2018). All traditional knowledge (TK) descriptors were transformed into numeric values using a five-point Likert scale (−2 to +2), representing the ordered intensity of each sensory attribute. These ordinal scores were treated as quasi-interval data, suitable for multivariate analysis. Significant correlations ($r \geq 0.3$, $p < 0.05$) confirmed that the Likert scale transformations captured meaningful gradations in soil properties. The suitability of the transformed three datasets for factor analysis was further verified using KMO (>0.7) and Bartlett's test ($p < 0.01$).

To minimize inter-rater bias among experts with different disciplinary and educational backgrounds, individual questionnaire scores were recorded independently and later aggregated using the mean Likert value for each descriptor. This approach reduces individual influence while preserving the collective trend. Before data collection, a calibration session was held with all experts to standardize the rating criteria and align the interpretation of qualitative descriptors, functioning similarly to the Delphi-style consensus process.

The EFA was executed using Principal Component Analysis (PCA) for factor extraction, followed by varimax rotation to achieve a clearer factor structure (Dziuban and Shirkey, 1974). EFA was executed using Principal Component Analysis (PCA) for factor extraction, followed by varimax rotation to achieve a clearer factor structure. The stability of the extracted factors was evaluated by comparing the loading patterns obtained from the traditional, geotechnical, and combined datasets. The factors consistently aligned with the same soil categories (fine-grained, coarse-grained, and earthy), confirming the stable structural relationships. The internal consistency of each factor was verified using Cronbach's alpha, which ranged from 0.75 to 0.86. Given the moderate sample size, confirmatory factor analysis (CFA) was deferred to future studies with larger datasets. The EFA was chosen for its ability to identify latent constructs and relationships within the dataset, which included both traditional and geotechnical soil properties (Gupta and Shukla, 2018). This method is particularly suitable for datasets in which multiple variables are expected to be grouped into distinct underlying factors, such as fine-grained, coarse-grained, and earthy soil categories (Gupta and Shukla, 2018). The traditional feature-based dataset consists of 660 data points derived from expert evaluations across 55 landslide sites (with twelev experts assessing each site). The geotechnical features dataset, on the other hand, comprised 55 laboratory analyzed soil samples collected from these same sites. In addition, the sample size met the recommended thresholds for EFA, ensuring the reliability of the extracted factors. By uncovering the underlying structure of soil properties, EFA allows for the development of a robust soil categorization framework that effectively integrates traditional and geotechnical characteristics.

The eigenvalues represent the amount of variance explained by each factor (Shrestha, 2021). Following the Kaiser Criterion, factors with eigenvalues greater than 1.0 were considered significant, as these factors explain more variance than an individual variable (Yong and Pearce, 2013). However, the ultimate threshold for retention was the cumulative variance explained by these factors. For each dataset, only the factors that collectively explained greater than 55% of the total variance were retained. Scree plots were also used to visually confirm the number of retained factors (Howard, 2016). This combined approach ensures that the retained factors meaningfully contribute to the overall explanatory power of the analysis, while minimizing noise.

Next, one-way ANOVA was used to explore the potential impacts of soil factors identified by EFA and to investigate the differences in factor scores among the demographic and expert groups, focusing on age and expertise level (education level and discipline) (Belkhiri and Narany, 2015).

Results

Correlation analyses

The results revealed several significant correlations, highlighting the interdependencies among soil color, composition, water retention, and geotechnical properties. Brown soil showed a significant positive correlation with rocks and debris (r (658) = 0.112, $p < 0.05$) and density (r (658) = 0.351, $p < 0.01$), suggesting that denser soils with rock fragments tended to exhibit brown coloration, which may indicate higher compaction levels. In contrast, white soils were positively correlated with silt content (r (658) = 0.267, $p < 0.01$) and negatively correlated with gravel content (r (658) = −0.202, $p < 0.01$), indicating that soils with high silt proportions and fewer coarse particles appear lighter in color. Soil water retention exhibited a strong positive correlation with earthy soil smell (r (658) = 0.483, $p < 0.01$) and moisture content (r (658) = 0.617, $p < 0.01$) but was negatively correlated with sand content (r (658) = −0.417, $p < 0.01$). These results suggest that soils with high organic content and finer particles tend to retain more water, whereas sandy soils drain moisture more rapidly. The specific gravity was significantly correlated with cohesion (r (658) = 0.521, $p < 0.01$), supporting the notion that denser soils tend to have stronger particle bonding and higher shear resistance. Stickiness was positively correlated with silt content (r (658) = 0.352, $p < 0.01$), suggesting that fine-grained soils exhibited greater plasticity and cohesion, reinforcing their vulnerability to landslides under wet conditions. Additionally, silt content was strongly correlated with the plasticity index (r (658) = 0.239, $p < 0.01$), reinforcing the importance of fine-grained soils in determining soil deformation characteristics. Soil drainage exhibited a strong positive correlation with soil density (r (658) = 0.432, $p < 0.01$), indicating that denser soils may exhibit better compaction and structural stability, and reduce permeability. Smoothness was significantly positively correlated with the sweet taste of soil (r (658) = 0.137, $p < 0.01$), which aligns with the presence of certain mineral compositions possibly linked to organic-rich soils. Additionally, vegetation cover was negatively correlated with soil thickness (r (658) = −0.276, $p < 0.01$), implying that thicker soil layers may have lower vegetation cover owing to potential instability or poor nutrient retention. Soil clumping was positively associated with the average internal friction (r (658) = 0.256, $p < 0.01$), indicating that well-aggregated soils may resist shear forces more effectively.

Exploratory factor analysis of traditional features

Using the questionnaire, twelve experts assessed each of the 55 locations, generating a total of 660 responses. An EFA was performed on these 660 responses, and the results are presented in Table 3 (Mvududu and Sink, 2013). Before conducting EFA, the suitability of the data was assessed. The KMO measure of sampling adequacy was 0.897, which confirmed that the sample size was appropriate. Bartlett's Test of Sphericity was significant (χ^2 = 2,137.6, $p < 0.01$), suggesting that the dataset exhibited sufficient intercorrelations for factor extraction. PCA was employed for factor extraction, initially identifying four factors. However, factors that explained less than 55% of the total variance were excluded, resulting in three retained factors. KVN rotation was applied to optimize factor separation. Figure 2 shows the scree plot, where the eigenvalues dropped sharply after the third factor, confirming the retention of the three dominant factors. The final model retained three factors, which explained 65.17% of the total variance. The eigenvalues were 4.8, 4.7, and 3.8, corresponding to fine-grained soil (Factor 1), coarse-grained soil (Factor 2), and earthy soil (Factor 3), respectively, as detailed in Table 3. The factor loadings ranged from 0.504 to 0.838, while communalities varied between 0.294 and 0.926 (Table 4), indicating strong associations among the extracted variables. To interpret the retained factors, factor loadings were analyzed to identify the dominant soil characteristics. Factor 1, representing fine-grained soil, showed high loadings for variables such as clay content, black color, and water retention, which aligns with traditional classification of moisture-retentive and fertile soils. Factor 2, associated with coarse-grained soils, included high loadings for sand content, gravel, and coarseness, confirming the alignment with well-drained, low-cohesion traditional soil descriptions. Factor 3, representing earthy soils, exhibited high loadings for brown color and earthy smell, reinforcing its classification as an organic-rich soil with moderate cohesion.

Traditional knowledge-based soil classification and correlations

Fine-grained soils included clay, silt, black color, high water retention, moisture content, high fertility, and a musty smell (Table 5). These attributes align with TK descriptions of fertile and moisture-retentive soils that support plant growth, but may experience stability issues under saturation. Coarse-grained soils comprised sand, gravel, rocks, debris, yellow and white colors, coarseness, easy crumbling, stickiness, healthy plants, and high-water drainage (Table 3). The presence of yellow and white coloration in conjunction with coarse particles suggests that these soils are well drained and prone to surface erosion rather than deep-seated movement. Earthy soils are characterized by a brown color, earthy smell, and moderate water retention. The significant correlation between earthy smell and water retention (r (658) = 0.483, $p < 0.01$) applies specifically to earthy soils, reinforcing their classification as moderately moisture-retentive with respect to organic content (Table 5). This classification aligns with TK description of ordinary soils that exhibit moderate stability but require external reinforcement for sustained fertility and structure. These findings validate the alignment between traditional soil classifications and conventional geotechnical assessments, demonstrating that qualitative attributes, such as color, smell, and texture, are strongly associated with measurable soil properties.

Exploratory factor analysis of geotechnical features

The geotechnical characteristics of the soil samples were analyzed using EFA on 55 laboratory test results to identify the significant underlying factors (Mvududu and Sink, 2013). The extraction results are summarized in Table 6. PCA was employed for factor extraction, with a KMO measure of sampling adequacy of 0.506, confirming that the sample size was acceptable for the factor analysis. Bartlett's Test of Sphericity was significant (χ^2 = 462.3, $p <$

TABLE 3 Extraction of three factors from EFA traditional features.

Factor	Eigenvalue (rotated)	% of variance (rotated)	Cumulative % of variance (rotated)
1	4.8	22.14	22.14
2	4.7	20.14	43.01
3	3.8	16.91	65.17

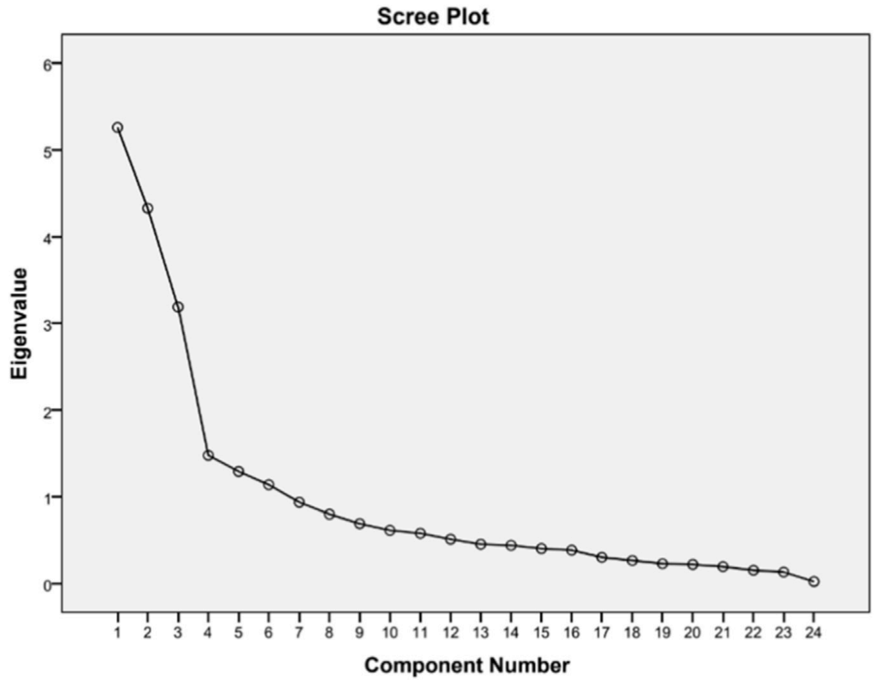

FIGURE 2
Scree plot for the traditional dataset.

0.01), indicating that the correlation matrix was not an identity matrix and that factor analysis was appropriate. Factors that explained greater than 55% of the total variance were retained. The EFA of the geotechnical dataset identified three factors that explained a cumulative variance of 68.32%. KVN rotation was applied to improve factor interpretability (Table 6). Figure 3 illustrates the scree plot, which demonstrates a significant decline in eigenvalues after the third factor, thus supporting the three-factor solution. The three extracted factors were classified as fine-grained, coarse-grained, and earthy, based on the dominant geotechnical properties loading onto each factor. A factor loading threshold of 0.5 was applied, ensuring that each item loaded uniquely onto one factor without cross-loading (Table 7). The factor loadings ranged from 0.573 to 0.943, with communality values between 0.415 and 0.848, indicating a strong variable association with the respective factors. The interpretation of these factors was guided by factor loadings, with higher loading values indicating stronger contributions from specific geotechnical properties. Factor 1 (fine-grained soil) included cohesion, plasticity index, and specific gravity, confirming its classification as highly cohesive soil with high water retention. Factor 2 (coarse-grained soil) had high loadings for sand content and friction, reinforcing its characterization as a well-drained, granular soil. Factor 3 (earthy soil) was associated with water content and moderate cohesion, aligning with the traditional descriptions of soils with organic content and moderate stability.

Geotechnical-based soil classification and correlations

Fine-grained soils were characterized by cohesiveness, specific gravity, and plastic limits (Table 8). The correlation between specific gravity and cohesion (r (658) = 0.591, $p < 0.01$) reinforces the geotechnical properties of fine-grained soils, highlighting their compact nature and resistance to structural failure under dry conditions. However, their high plasticity index and low permeability render them prone to reduced shear strength under saturation conditions. Coarse-grained soils comprised silt and the plasticity index, indicating their role in the soil deformability and drainage properties. The strong correlation between silt content and plasticity index (r (658) = 0.573, $p < 0.01$) suggests that fine material within coarse-grained soils contributes to their cohesion and water retention capacity, thereby affecting slope stability. Earthy soils

TABLE 4 Factors and communality loadings of traditional features.

Item	Factor 1	Factor 2	Factor 3	Communalities
Clay content	0.926			0.691
Silt content	0.789			0.660
Black color	0.773			0.653
Water retention	0.740			0.550
Moisture	0.725			0.539
High fertility	0.659			0.473
Musty smell	0.653			0.519
Stickiness		0.797		0.759
Sand content		0.728		0.689
Gravel content		0.684		0.527
Rocks & debris		0.651		0.650
Yellow color		0.608		0.411
White color		0.602		0.392
Coarseness		0.588		0.390
Easy to crumble		0.552		0.354
Healthy plants		0.527		0.540
High-water drainage		0.504		0.294
Earthy smell			0.853	0.735
Brown color			0.838	0.814
Low water retention			0.596	0.405

TABLE 5 Composition of the extracted factors of traditional features.

Factor name	Composition of factor	Significant correlations
Fine-grained soil	Clay, silt, black color, high water retention, moisture content, high fertility, and musty smell	
Coarse-grained soil	Sand, gravel, rocks and debris, yellow color, white color, coarseness, easy to crumble Stickiness, healthy plants and high-water drainage	
Earthy soil	Earthy smell, Brown color, and water retention	Earthy smell with water retention (r (658) = 0.483, $p < 0.01$)

TABLE 6 Extraction of three factors from EFA of geotechnical features.

Factor	Eigenvalue (rotated)	% of variance (rotated)	Cumulative % of variance (rotated)
1	4.1	25.49	28.49
2	2.4	20.27	51.23
3	1.8	20.21	68.32

exhibit sand, friction, and water content, confirming their role in soil drainage and surface erosion. These findings confirm that fine-grained soils, owing to their high cohesion and plasticity, require targeted stabilization strategies to mitigate landslide risks. Similarly, coarse-grained soils retain silt, which contributes to instability under fluctuating moisture conditions, despite their high drainage capacity.

Factor analysis of traditional and geotechnical features

The EFA was conducted on 660 questionnaire responses and 55 laboratory test results to identify the shared structural components across the traditional soil classifications and

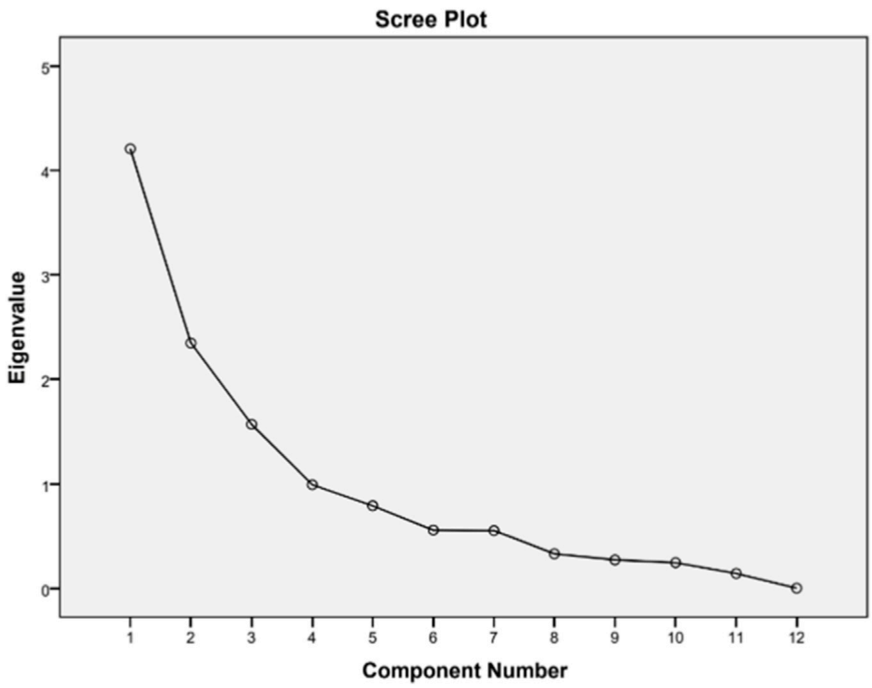

FIGURE 3
Scree plot for the geotechnical dataset.

TABLE 7 Factors and communality loadings of geotechnical features.

Item	Factor 1	Factor 2	Factor 3	Communalities
Specific gravity	0.943			0.842
Cohesion	0.715			0.519
Plastic limit	0.618			0.740
Silt content		0.774		0.623
Plasticity index		0.672		0.649
Sand content			0.712	0.515
Friction			0.636	0.621
Water content			0.623	0.456

TABLE 8 Composition of the extracted factors of geotechnical features.

Factor name	Composition of factor	Significant correlations
Fine-grained soil	Specific gravity, cohesion, and plastic limit	Specific gravity with cohesion (r (658) = 0.521, $p < 0.01$)
Coarse-grained soil	Silt and plasticity index	Silt with plasticity index (r (658) = 0.573, $p < 0.01$)
Earthy soil	Sand, friction and water content	

geotechnical properties (Mvududu and Sink, 2013). The extraction results including eigenvalues are presented in Table 9. The KMO measure of sampling adequacy was 0.788, confirming that the combined dataset was suitable for the factor analysis. Bartlett's Test of Sphericity was significant (χ^2 = 1685.4, $p < 0.01$), ensuring that inter-variable correlations justified factor extraction.

TABLE 9 Extraction of three factors from EFA of traditional and geotechnical features.

Factor	Eigenvalue (rotated)	% of variance (rotated)	Cumulative % of variance (rotated)
1	4.8	24.86	24.86
2	4.1	18.55	43.42
3	1.9	14.32	71.46

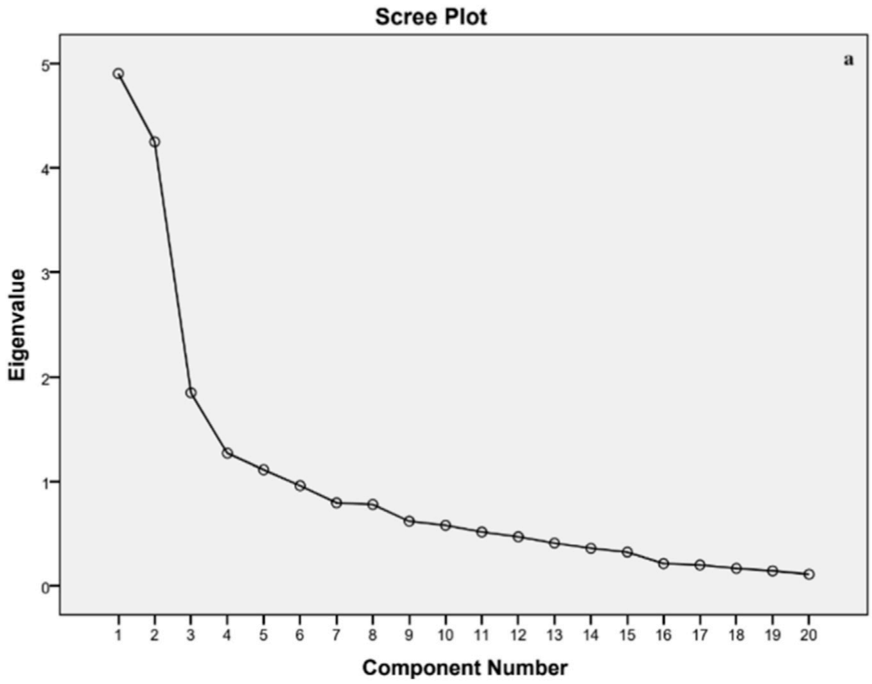

FIGURE 4
Scree plot for the combined dataset.

PCA was applied for factor extraction, initially identifying four factors. However, based on the scree plot and total variance contribution, factors explaining less than 55% of the total variance were excluded. Figure 4 illustrates the scree plot, which shows a sharp eigenvalue drop beyond the third factor, justifying the retention of the three dominant factors. The final EFA model retained three factors that collectively explained 71.46% of the total variance (Table 9). The factor-loading analysis followed the same procedure as in the previous sections, with items loaded onto a given factor if they exhibited a factor loading ≥0.5 and did not cross-load onto other factors (Table 10). The retained factors were classified as fine-grained, coarse-grained, and earthy soil types, aligned with both the traditional and geotechnical soil categorizations. The combined EFA dataset demonstrated a strong alignment between the traditional attributes and conventional geotechnical properties. For instance, factor loadings for soil color and moisture retention in the traditional dataset were strongly associated with geotechnical properties, such as water content and cohesion, confirming the validity of integrating traditional and quantitative methods. The correlation between earthy smell and water retention (r (658) = 0.332, $p < 0.01$) further supports the reliability of qualitative assessments for landslide-prone soil classification.

Traditional and geotechnical features with significant correlations

The composition of each extracted factor is listed in Table 11. Fine-grained soil (Factor 1) accounted for the highest variance (24.86%), followed by coarse-grained soil (18.55%), and earthy soil (14.32%). Fine-grained soil exhibits properties such as water retention, stickiness, smoothness, hardness, soil clumping tendency, and silt content. A significant correlation was observed between stickiness and silt content (r (658) = 0.450, $p < 0.01$), thereby reinforcing the role of fine particles in soil cohesion and permeability. This supports the traditional classification of fertile moisture-retentive soils, which exhibit high plasticity under saturation, making them susceptible to landslides in wet conditions. Earthy soil includes density, earthy smell, musty smell, plastic limit, and high moisture content. A significant correlation was found between the earthy smell and plastic limit

TABLE 10 Factors and communality loadings of traditional and geotechnical features.

Item	Factor 1	Factor 2	Factor 3	Communalities
Water retention	0.832			0.719
Stickiness	0.795			0.660
Smoothness	0.789			0.657
Hardness	0.724			0.524
Soil clump easily	0.717			0.528
Silt content	0.676	0.794		0.480
Rocks and debris		0.742		0.777
Sand content		0.741		0.739
White color		0.734		0.737
Black color		0.655		0.544
Density		0.794		0.461
Earthy smell			0.814	0.669
Musty smell			0.761	0.707
Plastic limit			0.628	0.439
High moisture			0.609	0.428

TABLE 11 Composition of the extracted factors of traditional and geotechnical features.

Factor name	Composition of factor	Significant correlations
Fine-grained soil	Transitional: Stickiness, smoothness, hardness, soil clump together easily; geotechnical: Water retention, silt content	Stickiness with silt content (r (658) = 0.450, $p < 0.01$)
Coarse-grained soil	Transitional: Rocks and debris, white color, and black color Geotechnical: Density, sand content	
Earthy soil	Transitional: Earthy smell, musty smell, geotechnical: Plastic limit, and high moisture	Earthy smell with plastic limit (r (658) = 0.312, $p < 0.01$)

(r (658) = 0.312, $p < 0.01$), suggesting that organic-rich soils retain moderate plasticity, water content, and balance stability with permeability. This aligns with traditional description of transitional soils that exhibit mixed characteristics of moisture retention and structural variability under wet-dry cycles. Unlike fine-grained and earthy soils, no statistically significant correlations were observed for coarse-grained soils. This suggests that coarse-grained soils, which include components such as sand, gravel, and rocks, behave more independently of finer geotechnical and traditional soil attributes. Their properties are largely governed by the granular structure rather than cohesive interactions, reinforcing their high permeability and low susceptibility to plasticity-related instabilities. These findings demonstrate that transitional qualitative soil classifications closely align with measurable geotechnical parameters in fine-grained and earthy soils, reinforcing the importance of integrating traditional ecological knowledge into conventional landslide risk assessments.

Analysis of variance

A one-way ANOVA was conducted to examine the impact of the demographic variables (age, discipline, and education level) on the three soil types (fine-grained, coarse-grained, and earthy soils) (see Table 12).

Effect of age

Age did not significantly affect soil classification across fine-grained (F (2, 657) = 0.761, $p = 0.51$, $\eta^2 = 0.01$), coarse-grained (F (2, 657) = 0.761, $p = 0.41$, $\eta^2 = 0.01$), or earthy soils (F (2,657) = 0.500, $p = 0.61$, $\eta^2 = 0.01$). This suggests that soil categorization was not influenced by age differences among the experts, which is consistent with previous findings that expertise-based assessments remain consistent across age groups.

TABLE 12 Statistical results of ANOVA for the influence of demographic variables.

Demographic variable	Soil type	ANOVA result	Post-hoc analysis
Age	Fine-grained soil	F (2, 657) = 0.761, p = 0.51, η^2 = 0.01	—
	Coarse-grained soil	F (2, 657) = 0.761, p = 0.41, η^2 = 0.01	—
	Earthy soil	F (2,657) = 0.500, p = 0.61, η^2 = 0.01	—
Discipline	Fine-grained soil	**F (2, 657) = 2.9, p < 0.05, η^2 = 0.01**	CE > ECE (p < 0.05). CE ~ CSE (p = 0.56); CSE ~ ECE (p = 0.15)
	Coarse-grained soil	F (2, 657) = 1.567, p = 0.25, η^2 = 0.01	—
	Earthy soil	**F (2, 657) = 3.9, p < 0.05, η^2 = 0.03**	ECE > CE (p < 0.05); ECE > CSE (p < 0.05). CE ~ CSE (p = 0.99)
Education level	Fine-grained soil	F (2, 657) = 1.662, p = 0.23, η^2 = 0.01	—
	Coarse-grained soil	F (2, 657) = 0.267, p = 0.92, η^2 = 0.01	—
	Earthy soil	**F (2, 657) = 2.892, p < 0.05, η^2 = 0.04**	PG > G (p < 0.05); PG > Ph.D. (p < 0.05). Ph.D. ~ G (p = 0.89)

Bolded text indicates significant results with p < .05., *CE: civil engineering, *CSE: computer science engineering, *ECE: electronics and communication engineering, *PG: postgraduate, *G: graduate, *Ph.D.: doctor of philosophy.

Effect of discipline

Discipline (civil engineering (CE), computer science engineering (CSE), and electronics and communication engineering (ECE)) significantly influenced fine-grained soil categorization (F (2, 657) = 2.9, p < 0.05, η^2 = 0.01). Tukey's post hoc test (see Table 10) indicated that CE participants assigned significantly higher scores to fine-grained soils than ECE participants (CE (M = 16.1, SD = 2.3) > ECE (M = 14.3, SD = 2.1), p < 0.05). However, no significant differences were observed between CE and CSE (p = 0.56) or between CSE and ECE (p = 0.15). These findings highlight that CE participants, trained in geotechnical principles, prioritized fine-grained soils more than ECE participants, who may have placed less emphasis on soil cohesive properties. Similarly, discipline significantly influenced the classification of earthy soils (F (2, 657) = 3.9, p < 0.05, η^2 = 0.03). ECE participants rated earthy soils significantly higher than CE (ECE (M = 9.2, SD = 0.6) > CE (M = 7.3, SD = 1.3), p < 0.05) and CSE (ECE (M = 9.2, SD = 0.5) > CSE (M = 7.2, SD = 1.4), p < 0.05), whereas CE and CSE did not differ significantly (p = 0.99). These results suggest that ECE experts may have been more inclined to consider traditional qualitative attributes, such as smell and texture, leading to a stronger emphasis on earthy soil classifications. For coarse-grained soil, no significant effect of discipline was found (F (2, 657) = 1.567, p = 0.25, η^2 = 0.01), indicating that disciplinary training did not influence classification. This may be attributed to the straightforward nature of coarse-grained soils, which exhibit clear geotechnical properties, such as high permeability and low cohesion, reducing the likelihood of subjective interpretation.

Effect of education level

Education level (Ph.D., postgraduate (PG), or graduate (G)) did not significantly influence the classification of fine-grained soils (F (2, 657) = 1.662, p = 0.23, η^2 = 0.01) or coarse-grained soils (F (2, 657) = 0.267, p = 0.92, η^2 = 0.01), suggesting that expertise across these levels resulted in similar assessments for these soil types. However, education level significantly affected the earthy soil classification (F (2, 657) = 2.892, p < 0.05, η^2 = 0.04). Post-hoc analysis (Table 10) showed that PG participants rated earthy soils significantly higher than both G (PG (M = 9.1, SD = 0.8) > G (M = 8.1, SD = 1.3), p < 0.05) and Ph.D. participants (PG (M = 9.3, SD = 0.9) > Ph.D. (M = 7.5, SD = 1.3), p < 0.05). No significant difference was found between PhD and G participants (p = 0.89). This suggests that PG participants who are at an intermediate level of specialization may have been more open to integrating both traditional and geotechnical attributes in their assessment of earthy soils.

Discussion

The integration of conventional geotechnical assessments with transitional principles presents a novel framework for evaluating landslide susceptibility by bridging the gap between traditional knowledge and contemporary engineering methods. This study establishes how qualitative soil classifications based on color, texture, and smell align with quantitative geotechnical parameters, such as cohesion, permeability, and moisture content. The identified soil categories fine-grained, coarse-grained, and earthy soils demonstrate a strong convergence between the transitional principles and geotechnical findings. Fine-grained soils, described in TK as fertile and highly water-retentive, exhibit high plasticity and cohesion, but experience a significant reduction in shear strength under saturation, making them particularly prone to landslides. These characteristics align with geotechnical assessments, which consistently identify water retention and reduced permeability as the major risk factors for slope failure. The strong correlation between specific gravity and cohesion supports this relationship, highlighting that fine-grained soils exhibit higher stability when dry but are vulnerable to structural failure under wet conditions.

To validate the mechanical relevance of the TK-derived soil categories, factor-based classifications were compared with laboratory-measured geotechnical parameters, including cohesion, internal friction angle, plasticity index, and saturated unit weight. Fine-grained soils exhibit higher cohesion and plasticity, coarse-grained soils exhibit higher permeability and lower shear strength, and earthy soils exhibit intermediate characteristics. Field observations further confirmed that the mapped landslide zones corresponded primarily with fine-grained soil areas, supporting the mechanical validity of the TK-based classification framework.

In contrast, coarse-grained soils, which are categorized as arid and loosely structured in TK, exhibit high permeability and low cohesion, making them more susceptible to surface erosion than deep-seated movement. Although coarse-grained soils have been widely studied in geotechnical engineering, this study reinforces their instability under heavy rainfall conditions by correlating silt content with plasticity index. This finding supports previous studies, such as those by Roslee, which highlighted the role of particle size distribution in landslide susceptibility, particularly in tropical environments (Roslee, 2019). Earthy soils, classified as ordinary in TK, display instability under fluctuating moisture conditions because of their low water retention capacity, a finding that closely aligns with the geotechnical assessments of moderate cohesion and increased porosity. The significant correlation between earthy smell and water retention validated the role of smell-based soil assessments in identifying moisture-sensitive soils, thereby providing an effective preliminary indicator of landslide risk. In addition to mechanical parameters, significant correlations were observed between traditional knowledge (TK) indicators and geotechnical properties. For instance, soils with an earthy smell were positively correlated with the plastic limit (r = 0.312, $p < 0.01$), suggesting a potential link between olfactory perception and clay behavior under moisture. Musty-smelling soils were significantly associated with water retention (r = 0.483, $p < 0.01$) and moisture content (r = 0.617, $p < 0.01$), indicating that these descriptors may reflect organic-rich or fine-grained conditions that favor a high water-holding capacity. In contrast, white soils were positively correlated with silt content (r = 0.267, $p < 0.01$) and negatively correlated with gravel content (r = −0.202, $p < 0.01$), reinforcing that color perceptions are related to soil texture. These statistically supported correlations illustrate that traditional sensory-based assessments, such as smell and color, are not merely anecdotal but are associated with measurable soil properties relevant to landslide susceptibility. These findings parallel the observations of Pardede, who demonstrated that alternating wet and dry cycles significantly affect soil cohesion and shear strength (Pardede, 2023).

By adopting the TK-based soil categorization, landslide-prone regions can benefit from a rapid, low-cost, and accessible assessment method that does not require specialized laboratory testing or expensive geotechnical equipment. The reliance on qualitative indicators such as color, texture, and smell makes this approach particularly useful for preliminary evaluations in remote or resource-limited areas. In addition, this method can serve as a first-level screening tool for identifying high-risk soil types before deploying more detailed geotechnical investigations.

By correlating qualitative insights from TK, such as smell, color, and texture, with measurable geotechnical parameters, such as density and moisture content, this study bridges traditional and conventional knowledge systems. The findings emphasize the value of ecological traditions in contemporary soil assessments, offering practical insights for slope management and disaster mitigation in landslide-prone regions, such as the Himalayas. Importantly, the integrated TK and geotechnical framework is not restricted to the Himalayas alone but can be adapted to other mountainous, tropical, or arid environments where soil-landscape interactions drive slope stability. This generalizability underscores its contribution to broader landscape evolution studies and enhances its relevance to global soil geomorphology research. Unlike conventional geotechnical studies, which primarily emphasize numerical thresholds for properties such as cohesion and permeability, this research demonstrates that traditional qualitative descriptors such as soil color, smell, and texture provide comparable insights into landslide susceptibility. This integration of local ecological knowledge with conventional geotechnical assessments aligns with Mali's findings on the importance of plasticity index and cohesion in determining landslide risk (Mali et al., 2022). Furthermore, although Casagli demonstrated the advantages of remote sensing for landslide detection, this study provides a complementary approach that relies on direct soil evaluation, making it more accessible in resource-limited areas (Casagli et al., 2023).

The factor analysis results further support the alignment of geotechnical attributes with traditional soil classifications. Fine-grained soils are strongly associated with high water retention, smoothness, and stickiness, corresponding to higher cohesion and plasticity index values. Coarse-grained soils, composed primarily of sand, gravel, and rocks, exhibit high permeability and low cohesion, reinforcing their propensity to surface erosion. Earthy soils, identified by their characteristic earthy smell and brown color, displayed moderate cohesion and increased porosity. The significant correlations between the traditional and geotechnical properties validate the scientific relevance of the transitional soil classification (Table 3). Dearing et al. emphasized the value of integrating local ecological knowledge into environmental management, but their study lacked quantitative validation (Liu et al., 2018). This study overcomes this limitation by employing statistical techniques to confirm the alignment between the traditional soil properties and conventional geotechnical parameters. Comparable advances have been reported in recent studies that employed hybrid laboratory and modelling frameworks for landslide evaluations (Danesh et al., 2025; Ab et al., 2025). For example, recent studies have examined the creep behavior in high-plasticity soils under constant shear and demonstrated GIS-based susceptibility mapping using ANN, SVM, and RF models (Danesh et al., 2025; Ab et al., 2025). These efforts align with the objective of the present study, which is to integrate diverse datasets to derive interpretable soil behavior patterns. The influence of discipline and education level on soil categorization highlights the potential biases in expert assessments. Civil engineering experts emphasize geotechnical properties, particularly for fine-grained soils, whereas experts from other engineering disciplines place greater emphasis on traditional qualitative attributes. Similarly, postgraduate participants demonstrated a greater ability to integrate both perspectives, whereas graduate and Ph.D. participants showed a tendency toward specialization, which may hinder the holistic integration of traditional and conventional frameworks. These findings align with Liu's work, which underscores the impact of disciplinary backgrounds on risk assessment approaches (Liu et al., 2018). However, this study extends these findings by demonstrating that the educational level also influences the ability to synthesize diverse classification frameworks.

The practical implications of this study extend to landslide risk management, in which soil classification provides key mitigation strategies. Fine-grained soils, which are prone to water saturation and reduced shear strength, require drainage systems, slope grading, and retaining walls. Coarse-grained soils, characterized by high permeability and low cohesion, require stabilization techniques such as geotextiles, vegetation cover, and terracing to mitigate surface erosion. Earthy soils, affected by wet-dry cycles, benefit from bioengineering approaches, such as vegetation-based stabilization. The findings of Machado, who demonstrated the effectiveness of vegetation cover in landslide mitigation, support this study's results on TK emphasis on soil fertility and stability (Machado et al., 2019).

The integrated framework developed in this study is directly applicable to local Himalayan communities, where conventional laboratory testing is often inaccessible. By translating traditional qualitative soil cues, such as color, smell, and texture, into standardized risk indicators, community members can perform rapid, low-cost evaluations of slope stability. These assessments can guide agricultural planning, construction siting, and early warning awareness. Furthermore, training local residents in the use of these descriptors for preliminary slope checks can complement institutional monitoring efforts, promoting participatory and sustainable landslide risk management.

This study provides a valuable framework for policymakers and practitioners involved in land-use planning and disaster mitigation. The integrated soil categorization model enables targeted interventions such as prioritizing high-risk zones for early warning systems and designing context-specific stabilization techniques (Froude and Petley, 2018). By incorporating traditional knowledge with conventional geotechnical assessments, policymakers can implement cost-effective strategies tailored to regional soil characteristics. For instance, fine-grained soils with high water retention can benefit from improved drainage systems, whereas coarse-grained soils require surface stabilization techniques, such as terracing and vegetation reinforcement (Petley, 2012; Huang and Fan, 2013). This hybrid approach enhances decision making, particularly in resource-limited regions, by reducing dependence on laboratory-based soil testing while offering scalable field-based assessments (Dearing et al., 2016). By integrating the TK soil categorization with conventional geotechnical techniques, policymakers and practitioners can develop a hybrid approach that enhances landslide risk assessment and mitigation strategies. The ability to classify soil types using traditional qualitative markers makes this framework especially valuable for disaster-prone regions, where rapid assessments are crucial. Moreover, the use of TK-based categorization in combination with early warning systems can strengthen community-based landslide preparedness and response strategies.

Future research should extend the TK-inspired soil categorization framework to diverse geological settings beyond the Himalayas, including arid, tropical, and coastal environments, where soil properties and landslide risks vary significantly. Longitudinal studies monitoring soil stability under changing climatic conditions will further enhance the predictive models for landslide susceptibility. Integrating modern technologies, such as machine learning and IoT-based sensors, presents exciting possibilities for refining this framework. Machine learning models trained on larger datasets can identify complex correlations between transitional soil features and geotechnical properties. Similarly, IoT-enabled sensors and remote sensing tools, such as LiDAR, can provide real-time data for landslide risk prediction and monitoring. In addition, the study did not include geochemical or mineralogical testing (e.g., clay mineralogy, ionic composition, pore structure), which are likely to underpin several of the TK indicators, such as salty or sweet taste. Future studies should integrate mineralogical and geochemical analyses to evaluate whether these sensory-based traditional descriptors reflect the deeper compositional attributes that affect slope stability.

Despite its contributions, this study has some limitations. For example, this study is conducted within the context of the Himalayan region, which has unique geological and environmental characteristics. While the findings offer valuable insights for similar mountainous terrains, further studies in different geographic and climatic regions are necessary to assess the broader applicability of the results. Although qualitative assessments, such as soil smell and texture, provided useful preliminary information, incorporating objective methods like laboratory analyses and IoT-based soil sensors in future research could enhance measurement accuracy. In addition, expert calibration and reliability testing may have a certain level of subjective bias in sensory interpretation, which represents an inherent limitation of expert-based traditional knowledge assessments.

Overall, by bridging traditional and conventional knowledge, this study lays the foundation for a holistic and adaptive soil-categorization framework with significant implications for sustainable environmental management and disaster mitigation.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by Institutional Ethics Committee of the Indian Institute of Technology Mandi. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

SS: Formal Analysis, Resources, Writing – review and editing, Project administration, Software, Writing – original draft, Methodology, Investigation, Validation, Conceptualization, Data curation, Supervision. KU: Funding acquisition, Resources, Project administration, Supervision, Writing – review and editing, Validation. VD: Methodology, Validation, Software, Resources, Writing – review and editing, Project administration, Supervision.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Supplementary material

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References

Abgrami, A., Zhang, W., Mao, H., and Wang, L. (2025). GIS-Based comparative landslide susceptibility mapping for kelardasht county with ANN, SVM, and RF models. *Civ. Geoengin. Lett.* 2 (1), e100028. doi:10.22034/CGEL.2.1.e100028

Abbasi, N., Fakor, E., and Nikbakht, M. (2024). Slope mass rating (SMR) application for rock slope stability analysis in azarshahr, NW of Iran. *Civ. Geoengin. Lett.* 1 (1), e100008. doi:10.22034/CGEL.1.1.e100008

Ahadi, E., and Rosta, D. A. (2024). Landslide susceptibility analysis for azershahr region using SVM and logistic regression methods. *Civ. Geoengin. Lett.* 1 (2), e100022. doi:10.22034/CGEL.1.2.e100022

Alabi, A. T., and Jelili, M. O. (2023). Clarifying likert scale misconceptions for improved application in urban studies. *Qual. and Quantity* 57 (2), 1337–1350. doi:10.1007/s11135-022-01415-8

American Society for Testing and Materials. Committee D18 on Soil and Rock (2004). *Standard test methods for particle-size distribution (gradation) of soils using sieve analysis*. West Conshohocken, PA: ASTM International.

Arosio, D., Longoni, L., Papini, M., Scaioni, M., Zanzi, L., and Alba, M. (2009). Towards rockfall forecasting through observing deformations and listening to microseismic emissions. *Nat. Hazards Earth Syst. Sci.* 9 (4), 1119–1131. doi:10.5194/nhess-9-1119-2009

ASTM Committee D-18 on Soil and Rock (2009). *Standard test methods for particle-size distribution (gradation) of soils using sieve analysis*. West Conshohocken, PA: ASTM international.

Baruck, J., Nestroy, O., Sartori, G., Baize, D., Traidl, R., Vrščaj, B., et al. (2016). Soil classification and mapping in the alps: the current state and future challenges. *Geoderma* 264, 312–331. doi:10.1016/j.geoderma.2015.08.005

Belkhiri, L., and Narany, T. S. (2015). Using multivariate statistical analysis, geostatistical techniques and structural equation modeling to identify spatial variability of groundwater quality. *Water Resour. Manag.* 29, 2073–2089. doi:10.1007/s11269-015-0929-7

Beniwal, S. P. S., Nene, L. Y., and Pandey, S. T. (2020). Relevance of vrikshayurveda and traditional knowledge for ecofriendly sustainable agriculture to meet SDGs in India. *Asian Agri-History* 24 (1).

Bishop, A. W. (1955). The use of the slip circle in the stability analysis of slopes. *Geotechnique* 5 (1), 7–17. doi:10.1680/geot.1955.5.1.7

Casagli, N., Intrieri, E., Tofani, V., Gigli, G., and Raspini, F. (2023). Landslide detection, monitoring and prediction with remote-sensing techniques. *Nat. Rev. Earth and Environ.* 4 (1), 51–64. doi:10.1038/s43017-022-00373-x

Danesh, N., Taghizadeh, A., Valinejad, M., and Kouhdaragh, M. (2025). Laboratory investigation of creep behavior in high-plasticity loose soils under constant shear stress. *Civ. Geoengin. Lett.* 2 (1), e100025. doi:10.22034/CGEL.2.1.e100025

Das, B. M., and Sobhan, K. (2006). Principles of geotechnical engineering.

Dearing, J. A., Acma, B. Ü. L. E. N. T., Bub, S., Chambers, F. M., Chen, X., Cooper, J., et al. (2015). Social-ecological systems in the anthropocene: the need for integrating social and biophysical records at regional scales. *Anthropocene Rev.* 2 (3), 220–246. doi:10.1177/2053019615579128

Dearing, J. A., Acma, B., Bub, S., Chambers, F. M., Chen, X., and Cooper, J. (2016). Social-ecological systems in the anthropocene: the need for interating social and biophysical records at regional scales. *Nat. Geosci.* 9 (8), 594–600. doi:10.5751/ES-03645-150421

Dikshit, A., Sarkar, R., Pradhan, B., Segoni, S., and Alamri, A. M. (2020). Rainfall induced landslide studies in Indian himalayan region: a critical review. *Appl. Sci.* 10 (7), 2466. doi:10.3390/app10072466

Dornik, A., Drăguţ, L., and Urdea, P. (2016). Knowledge-based soil type classification using terrain segmentation. *Soil Res.* 54 (7), 809–823. doi:10.1071/sr15210

Dziuban, C. D., and Shirkey, E. C. (1974). When is a correlation matrix appropriate for factor analysis? Some decision rules. *Psychol. Bull.* 81, 358–361. doi:10.1037/h0036316

Fatima, B., Alshameri, B., Hassan, W., Maqsood, Z., Jamil, S. M., and Madun, A. (2023). Sustainable incorporation of plaster of paris kiln dust for stabilization of dispersive soil: a potential solution for construction industry. *Constr. Build. Mater.* 397, 132459. doi:10.1016/j.conbuildmat.2023.132459

Fredlund, D. G., and Rahardjo, H. (1993). *Soil mechanics for unsaturated soils*. John Wiley and Sons.

Froude, M. J., and Petley, D. N. (2018). Global fatal landslide occurrence from 2004 to 2016. *Nat. Rev. Earth and Environ.* 2 (3), 187–196. doi:10.5194/nhess-18-2161-2018

Garc, A., and Frankenstein, S. (2015). USCS and the USDA soil classification system: development of a mapping scheme (No. ERDCCRRELTR154).

Grinand, C., Arrouays, D., Laroche, B., and Martin, M. P. (2008). Extrapolating regional soil landscapes from an existing soil map: sampling intensity, validation procedures, and integration of spatial context. *Geoderma* 143 (1-2), 180–190. doi:10.1016/j.geoderma.2007.11.004

Gupta, K., and Satyam, N. (2024). Integrating real-time sensor data for improved hydrogeotechnical modelling in landslide early warning in Western himalaya. *Eng. Geol.* 338, 107630. doi:10.1016/j.enggeo.2024.107630

Gupta, S. K., and Shukla, D. P. (2018). Application of drone for landslide mapping, dimension estimation, and its 3D reconstruction. *J. Indian Soc. Remote Sens.* 46, 903–914. doi:10.1007/s12524-017-0727-1

Hamedi, A., Nejhad, S. M., and Mofrad, H. H. (2025). AHP-Based susceptibility analysis for landslides in fuman county, northwestern Iran. *Civ. Geoengin. Lett.* 2 (1), e100030. doi:10.22034/CGEL.2.1.e100030

Hassan, W., Alshameri, B., Nawaz, M. N., Ijaz, Z., and Qasim, M. (2022). Geospatial and statistical interpolation of geotechnical data for modeling zonation maps of islamabad, Pakistan. *Environ. Earth Sci.* 81 (24), 547. doi:10.1007/s12665-022-10669-2

Hassan, W., Alshameri, B., Haider, A., Maqsood, Z., Jamil, S. M., and Shahzad, A. (2023). A novel technique for the construction industry to mitigate dispersibility and internal erosion problems of sodium rich clays by using water-soluble potassium rich ions material. *Constr. Build. Mater.* 400, 132780. doi:10.1016/j.conbuildmat.2023.132780

Hirai, H., and Hamazaki, T. (2004). Historical aspects of soil classification in Japan. *Soil Science Plant Nutrition* 50 (5), 611–622. doi:10.1080/00380768.2004.10408519

Howard, M. C. (2016). A review of exploratory factor analysis decisions and overview of current practices: what we are doing and how can we improve? *Int. Journal Human-Computer Interaction* 32 (1), 51–62. doi:10.1080/10447318.2015.1087664

Huang, R., and Fan, X. (2013). The landslide story. *Nat. Geoscience* 6 (5), 325–326. doi:10.1038/ngeo1806

Hulathdoowage, N. D., and Hadiwattage, C. (2022). Applicability of drywall technologies for disaster-induced housing reconstruction. *Int. J. Disaster Resil. Built Environ.* 13 (4), 498–515. doi:10.1108/ijdrbe-01-2021-0001

IBM Corp (2016). *SPSS for windows*. Armonk, NY: IBM Corp.

Ijaz, Z., Zhao, C., Ijaz, N., Rehman, Z. U., and Ijaz, A. (2023). Statistical evaluation of multiple interpolation techniques for spatial mapping of highly variable geotechnical facets of soil in natural deposition. *Earth Sci. Inf.* 16 (1), 105–129. doi:10.1007/s12145-022-00924-2

Jallayu, P. T., Sharma, A., and Singh, K. (2024). Vulnerability of highways to landslide using landslide susceptibility zonation in GIS: mandi district, India. *Innov. Infrastruct. Solutions* 9 (9), 354. doi:10.1007/s41062-024-01653-9

Kahlon, S., Chandel, V. B. S., and Brar, K. K. (2014). Landslides in himalayan Mountains: a study of Himachal Pradesh, India. *Int. J. IT Eng. Appl. Sci. Res.* 3 (9), 2319–4413.

Kumar, K. K., and Brijesh, K. (2023). Vrikshayurveda-A capital for conservative agronomy. *J. Ayurveda Integr. Med. Sci.* 8 (7), 121–123. doi:10.21760/jaims.8.7.22

Kumar, M. S., and Jigeesh, P. P. (2024). A book review on vrkshaayurveda. *Int. Res. J. Ayurveda Yoga* 7 (4), 77–79. doi:10.48165/irjay.2024.70415

Liu, T., Bruins, R. J., and Heberling, M. T. (2018). Factors influencing farmers' adoption of best management practices: a review and synthesis. *Sustainability* 10 (2), 432. doi:10.3390/su10020432

Macciotta, R., and Hendry, M. T. (2021). Remote sensing applications for landslide monitoring and investigation in Western Canada. *Remote Sens.* 13 (3), 366. doi:10.3390/rs13030366

Machado, R. A., Oliveira, A. G., and Lois-González, R. C. (2019). Urban ecological infrastructure: the importance of vegetation cover in the control of floods and landslides in salvador/Bahia, Brazil. *Land Use Policy* 89, 104180. doi:10.1016/j.landusepol.2019.104180

Mali, N., Shukla, D. P., and Kala, V. U. (2022). Identifying geotechnical characteristics for landslide hazard indication: a case study in mandi, Himachal Pradesh, India. *Arabian J. Geosciences* 15 (2), 144. doi:10.1007/s12517-022-09475-8

Marques, K. P., Rizzo, R., Carnieletto Dotto, A., Souza, A. B. E., Mello, F. A., Neto, L. G., et al. (2019). How qualitative spectral information can improve soil profile classification? *J. Near Infrared Spectrosc.* 27 (2), 156–174. doi:10.1177/0967033518821965

Mishra, S. (2019). "Principles of plant taxonomy: a fresh insight into the ancient Indian methodology and philosophy of naming and classifying medicinal plants," in *New perspectives in Indian science and civilization* (New Delhi, India: PHI Learning Pvt. Ltd.), 122–134.

Mvududu, N. H., and Sink, C. A. (2013). Factor analysis in counseling research and practice. *Couns. Outcome Res. Eval.* 4 (2), 75–98. doi:10.1177/2150137813494766

Nguyen, B. T., Ishikawa, T., Zhu, Y., Subramanian, S. S., and Nguyen, T. T. (2022). New simplified transient method for determining the coefficient of permeability of unsaturated soil. *Eng. Geol.* 300, 106564. doi:10.1016/j.enggeo.2022.106564

Nhantumbo, A. B., and Cambule, A. H. (2006). Bulk density by proctor test as a function of texture for agricultural soils in Maputo province of Mozambique. *Soil Tillage Research* 87 (2), 231–239. doi:10.1016/j.still.2005.04.001

Pardede, E. J. P. (2023). Analisis geoteknik ditinjau dari karakteristik kuat geser material longsoran. *Syntax. Idea* 5 (9), 1554–1573. doi:10.46799/syntax-idea.v5i9.2595

Pereira, P., Brevik, E. C., Oliva, M., Estebaranz, F., Depellegrin, D., and Novara, A. (2017). "Goal oriented soil mapping: applying modern methods supported by local knowledge," in *Soil mapping and process modeling for sustainable land use management* (Elsevier), 61–83.

Petley, D. (2012). Global patterns of loss of life from landslides. *Geology* 40 (10), 927–930. doi:10.1130/g33217.1

Rahardjo, H., Ong, T. H., Rezaur, R. B., and Leong, E. C. (2007). Factors controlling instability of homogeneous soil slopes under rainfall. *J. Geotechnical Geoenvironmental Engineering* 133 (12), 1532–1543. doi:10.1061/(asce)1090-0241(2007)133:12(1532)

Ramesh, M. V., Thirugnanam, H., Singh, B., Nitin Kumar, M., and Pullarkatt, D. (2023). "Landslide early warning systems: requirements and solutions for disaster risk reduction—India," *Prog. Landslide Res. Technol.* 1(2)259–286. doi:10.1007/978-3-031-18471-0_21

Ren, D., and Ren, D. (2015). SEGMENT-landslide and applications to various climatic zones. *Storm-Triggered Landslides Warmer Clim.*, 81–153. doi:10.1007/978-3-319-08518-0_6

Roslee, R. (2019). Engineering geological investigation on karambunai-lok bunuq landslides, kota kinabalu, Sabah. *Malays. J. Geosciences (MJG)* 3 (2), 1–6. doi:10.26480/mjg.02.2019.01.06

Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *Am. Journal Appl. Math. Statistics* 9 (1), 4–11. doi:10.12691/ajams-9-1-2

Sidle, R., and Ochiai, H. (2006). Processes, prediction, and land use. *Water Resources Monograph. Am. Geophys. Union* 525, 870. doi:10.1029/WM018

Singh, G., and Pandey, A. (2024). Climate change induced disasters and highly vulnerable infrastructure in Uttarakhand, India: current status and way forward towards resilience and long-term sustainability. *Sustain. Resilient Infrastructure* 9 (2), 145–167. doi:10.1080/23789689.2023.2253409

Skempton, A. W. (1953). The colloidal activity of clays. *Sel. Papers Soil Mechanics* 1, 57–61.

Slessarev, E. W., Feng, X., Bingham, N. L., and Chadwick, O. A. (2019). Landscape age as a major control on the geography of soil weathering. *Glob. Biogeochem. Cycles* 33 (12), 1513–1531. doi:10.1029/2019gb006266

Smith, L., Quincey, D. J., Dixon, T., and Bingham, E. (2021). Integrating AI and satellite technologies to enhance monitoring and predictive modeling of landslides. *Nat. Commun.* 12 (1), 3455.

South, L., Saffo, D., Vitek, O., Dunne, C., and Borkin, M. A. (2022). Effective use of likert scales in visualization evaluations: a systematic review. *Comput. Graph. Forum* 41 (3), 43–55. doi:10.1111/cgf.14521

Srikanth, N., Tewari, D., and Mangal, A. K. (2015). The science of plant life (vrikshaayurveda) in archaic literature: an insight on botanical, agricultural and horticultural aspects of ancient India. *World J. Pharm. Pharm. Sci.* 4 (6), 388.

Thevanayagam, S. (1998). Effect of fines and confining stress on undrained shear strength of silty sands. *J. Geotechnical Geoenvironmental Engineering* 124 (6), 479–491. doi:10.1061/(asce)1090-0241(1998)124:6(479)

Uddin, M., and Hassan, M. R. (2022). A novel feature based algorithm for soil type classification. *Complex and Intelligent Syst.* 8 (4), 3377–3393. doi:10.1007/s40747-022-00682-0

Van Westen, C. J., Castellanos, E., and Kuriakose, S. L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: an overview. *Eng. Geology* 102 (3-4), 112–131. doi:10.1016/j.enggeo.2008.03.010

Varnes, D. J. (1958). Landslide types and processes. *Landslides Engineering Practice* 24, 20–47.

Vogel, S., Emmerich, K., Schröter, I., Bönecke, E., Schwanghart, W., and Rühlmann, J. (2023). *The effect of soil moisture content and soil texture on fast* in situ *pH measurements with two types of robust ion-selective electrodes*, 2023. Munich, Germany: Springer, 1–20.

Wang, Y., and Nanehkaran, Y. A. (2024). GIS-based fuzzy logic technique for mapping landslide susceptibility analyzing in a coastal soft rock zone. *Nat. Hazards* 120, 1–33. doi:10.1007/s11069-024-06649-3

Wang, H., Ji, F., Zhan, X., Tan, C., and Feng, C. (2022). WITHDRAWN: sensitivity evaluation of landslide geological hazards based on Multi-source remote sensing data. *Opt. (Stuttg).*, 170481. doi:10.1016/j.ijleo.2022.170481

Yong, A. G., and Pearce, S. (2013). A beginner's guide to factor analysis: focusing on exploratory factor analysis. *Tutorials Quantitative Methods Psychology* 9 (2), 79–94. doi:10.20982/tqmp.09.2.p079