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REVIEW

Remote Sensing-Enhanced Lithological Mapping for Predicting Shallow Landslide Susceptibility in Complex Terrains

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ABSTRACT

Shallow landslides are strongly controlled by near-surface lithological variability, yet conventional geological maps are often too generalized to support accurate susceptibility assessment in complex terrains. This review synthesizes recent advances in remote sensing–based lithological mapping and evaluates their integration into landslide susceptibility modeling. Evidence from the literature indicates that remote sensing-derived lithological products, particularly those incorporating mineralogical information and higher spatial resolution, consistently outperform traditional geological maps in improving model accuracy and spatial detail, especially in heterogeneous environments. However, key challenges remain, including scale mismatches between surface observations and subsurface controls, limited ground validation, uncertainty propagation, and restricted model transferability across regions. The review identifies multi-sensor data fusion and explainable machine learning as the most promising directions for advancing lithological discrimination and model reliability. Future progress depends on integrating remote sensing with process-based understanding, improving validation strategies, and standardizing uncertainty reporting. These developments are essential for enabling more robust, scalable, and operationally relevant landslide susceptibility assessments in complex terrains. Lastly, we describe the directions of research that focus on multi-sensor fusion, explainable machine learning, UAV (Unmanned Aerial Vehicle)-enabled validation, and standardized uncertainty reporting that can help articulate landslide susceptibility assessment, making them

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even more robust and operationally significant.

Keywords: Shallow Landslides; Lithological Mapping; Remote Sensing; Susceptibility Modeling; Complex Terrain

1. Introduction

The most common and destructive geomorphic hazards that occur in mountainous and hilly areas around the world are shallow landslides. Mostly occurring in soil or regolith or highly weathered layers of the underlying rock, which can have failure depths just a few meters, shallow landslides are often caused by heavy or sustained rain, a sudden burst of snow melting, or by seismic shaking. Their relatively small individual volumes notwithstanding, there are often severe effects on infrastructure, ecosystem and human safety due to their large spatial density and rapid development, especially in highly populated or topographically challenging environments. Enhancement of prediction and spatial evaluation of shallow landslide susceptibility is therefore a critical issue in the study of natural hazards and risk reduction [1].

The process of shallow landslides initiation and location is regulated by a large variety of environmental factors, such as topography, hydrology, land cover, soil properties, and geological conditions. Of these, lithology plays one of the fundamental roles since it controls the mechanical strength, the weathering behavior, permeability, and the regolith development of slope materials. Variations in rock type and extent of weathering have a great impact on the soil thickness, the shear strength parameters, and the hydrological pathways in the underworld, all of which directly impact the slope stability during a triggering condition. As a result, lithology is always cited as one of the most significant predictors in landslide susceptibility models in different climatic and tectonic conditions [2–4].

Nevertheless, the lithological variability in complex terrains is a long-standing problem that is difficult to determine. Traditional lithological maps are usually based on field survey and manual interpretation and, therefore, time-consuming, costly, and in many cases limited by access. Consequently, the geological maps available might be old, generalized, or of unequal size and classification, especially in distant or quickly changing topography. These restrictions inject a lot of uncertainty into landslide susceptibility modeling, where the spatial and thematic quality of lithological inputs can have a very strong impact on the final results of the modeling. These issues are also intensified by the intricate landscapes, which are typified by high levels of lithological heterogeneity, steep relief, thick vegetation cover and dynamic processes on the surface [5].

The progress in remote sensing in the last few decades has revolutionized the manner in which lithological data can be obtained, mapped and updated over vast regions [6]. Hyperspectral and multispectral satellite sensors facilitate the identification of surface materials in terms of their spectral reflectance properties and this has been useful in the determination of mineralogical composition and weather conditions. Thermal infrared information can be used to provide further information associated with emissivity and surface temperature differences, whereas radar systems provide sensitivity to surface roughness, structure, and moisture conditions. The growing access to high-resolution satellite imagery, coupled with enhanced radiometric quality and coverage of the entire earth, has increased the potential of remote sensing-based lithological mapping dramatically, especially in areas where conventional field mapping is constrained [7–9].

In addition to the sensor abilities of individuals, multi-source remote sensing images added value to lithological discrimination in heterogeneous settings. Combinations of optical, thermal, and radar data that can be used in data fusion can exploit the physical complementary characteristics of surface materials and enhance the robustness of the classification, as well as minimize the problems of ambiguity due to vegetation cover or illumination conditions. Meanwhile, the recent methodological progress in machine learning and pattern recognition has made it possible to extract more lithological features using high-dimensional remote sensing data. All these changes have brought lithological mapping towards a more automated, quantitative, and reproducible process, rather than a manual and qualitative approach, which was the main approach in the past [10].

A new research direction that has promising research potential is the introduction of remote sensing-obtained lithological data into landslide susceptibility modeling. It has been established in many studies that landslide-prone models that use lithological variables derived from satellite data can be more effective than those that use conventional geological maps. Enhanced lithological products based on remote sensing are frequently of finer spatial resolution, increased thematic consistency, and more flexible to local circumstances, all of which are beneficial to modeling shallow landslides that are very responsive to small-scale changes in the properties of materials. Moreover, remote sensing provides the opportunity to analyze the same area many times, and lithological conditions could be re-evaluated after significant disturbances, like earthquakes, fires, or excessive rains, which can change the surface material properties [3,11].

In spite of these developments, there are still some problems with the complete use of lithological mapping of remote sensing to predict shallow landslides. Mapping can be limited by spectral similarity of various rock types, masking of vegetation and soil cover, and scale differences between products of remote sensing and landslides. Propagation of lithological classification to susceptibility models is usually under-quantified, making it difficult to interpret and compare models. In addition, the applicability of remote sensing-based lithological models to other geological and climatic environments is a question to be answered, especially in areas that have minimal ground truth data [2,3].

The need for a synthesis of existing knowledge is timely, considering the fast rate at which technological development takes place and the increasing number of published case studies. Although the role of remote sensing in landslide susceptibility modeling or remote sensing implementation in landslides has been covered in past reviews, a dedicated analysis as to how remote sensing-enhanced lithological mapping plays out in shallow landslide susceptibility assessment in high-terrain complex environments has not been performed hitherto. Such a review is necessary to understand the trends in methodologies, to determine the usual limitations, and to point out the gaps in the research that need to be filled to enable an increase in the predictability of the research studies [12–14].

The aim of the review is thus to critically discuss the role of remote sensing-based lithological mapping in shallow landslide susceptibility prediction in complex terrains [15]. The review adds up-to-date insights on lithological determinants of shallow landslides, weighs significant distant identification methodologies utilized in lithological differentiation, and evaluates the uses of lithological information from remote sensing in the models of susceptibility. The specific focus is placed on the methodological issues, sources of uncertainty, and future research directions, such as high-resolution information, sophisticated machine learning algorithms, and multi-sensor data fusion. This review will attempt to offer directions for future studies and ensure that more powerful and systematic landslide susceptibility evaluations are developed by combining knowledge in different fields [16,17].

2. Lithological Controls on Shallow Landslide Susceptibility

The first-order control exerted by lithology in the initiation and spatially distributed occurrence of shallow landslides is by regulating the properties of slope materials of a physical, mechanical, and hydrological nature. Within complicated terrains, where there is strong relief, coupled with heterogeneous geology and active processes on the surface, lithological variability is usually involved in interaction with topography and climate to create very localized patterns of instability. Lithological factors in the process of shallow landslides are thus critical in the assessment of susceptibility, as well as understanding remotely sensed products [18].

2.1. Influence of Lithology on Mechanical Properties of Slopes

The slope materials are highly influenced by the underlying lithology, as well as the level of weathering, in the determination of their mechanical behavior [19]. The various types of rocks have different strengths, fracture density, and failure modes, and thus they determine the stability of the overlying soils and regolith. Those that are highly fractured, metamorphic, and volcanic formations, which are especially weakly cemented, are highly susceptible to shallow failures, since they tend to form thick regolith beds with low shear strength. Massive and comparatively fresh igneous rocks, conversely, can produce thinner soil mantles and less pronounced forms of landslides, notwithstanding that structural discontinuities may focus failure [20].

The lithology has an effect on the spatial variability of geotechnical parameters, including cohesion, internal friction angle, and bulk density. The parameters are usually supposed to be homogeneous in the mapping units in susceptibility models, but in practice, they can vary considerably inside a single lithological type because of variations in mineral composition, alteration, and weathering intensity. Such variation may lead to high contrasts of slope stability over a limited distance in complex terrains, where lithological boundaries can be sharp and irregular. It is therefore important to capture the mechanical controls on shallow landslide initiation through proper lithological characterization [21].

2.2. Weathering Processes and Regolith Development

Weathering processes give a major connection between lithology and shallow regolith-prone zones by moderating regolith thickness, structure, and material characteristics. Chemical weathering changes mineral structure and weakens rocks, whereas physical weathering encourages fissuring and fracturing. Weathering rate and fashion are highly lithology-dependent, with mafic and volcanic rocks, such as those in quartz-rich lithologies, usually weathering faster than quartz-rich lithologies with similar climatic conditions [22].

The deeper landslides are favored at the contact between less weathered bedrock and the regolith that is undergoing weathering in most mountainous areas. This interface depth and continuity are strongly related to lithology and structural characteristics, e.g., bedding planes, foliation, or sets of joints. Deep and homogenous weathering lithologies are more likely to create thick soil layers, making available more potentially unstable material and making these layers more vulnerable to failures caused by rainfall. On the other hand, more localized and discontinuous landslides can be observed in lithologies with thin or patchy regolith. These associations have demonstrated the significance of lithology in the formation of conditions in the subsurface that cannot be easily seen but are significant to the shallow processes of landslides [20].

2.3. Hydrological Behavior and Lithological Controls

The hydrological processes are key in the initiation of shallow landslides, especially in humid and monsoon-dominated areas, and lithology is very important in controlling water movement beneath the soil. The permeability, porosity, and connectivity of the fractures are diverse across lithological units, which influence the degree of infiltration, storage of groundwater, and formation of pore pressure during rainfall events. Low-permeability lithologies or where the layers have a high textural contrast allow positive pore water pressure to accumulate rapidly, reducing effective stress and slope stability [23].

Lithological heterogeneity in complex terrains will tend to favor preferential flow paths and localized zones of saturation, which will serve as a source of shallow failures. The existence of impervious bedrock under permeable soils is also an efficient arrangement in most weathered landscapes, which increases the chances of landsliding due to poor vertical drainage. The hydrological impacts in most cases are not consistent at the traditional geological map scales, and thus lithological data with enough spatial character are needed to be able to undertake the susceptibility modeling [24].

2.4. Interaction with Topography and Other Environmental Factors

Lithology does not work on its own but it interacts with topography, land cover, as well as external triggering factors in controlling shallow landslide susceptibility. In the steep slopes that occur on weak or highly weathered lithologies, failures tend to occur more and in the same case, steep slopes that occur on competent rock may be subject to similar conditions. The vegetation is capable of reducing lithological weaknesses through strengthening the soils and increasing evapotranspiration but with less effect on the lithologies that can tolerate rapid saturation or shallow soil failure. As demonstrated in **Table 1**, lithological characteristics, such as rock type, weathering degree, and permeability, play critical roles in shaping the stability of slopes and the susceptibility to shallow landslides [25,26].

Landslide patterns are also complicated in tectonically active areas, where structural controls related to lithology, e.g., faults and shear zones, induce areas of high fracturing and non-uniform material properties. Such interactions lead to the high spatial variability of the shallow landslides in complex terrains and create serious challenges to assessing the susceptibility on a regional scale. Lithological control captures at relevant spatial and thematic resolutions are thus necessary to enhance predictive performance, especially when susceptibility models are used outside of local areas of intense study. **Figure 1** illustrates the complex interactions between lithology and surface processes in driving shallow landslide susceptibility. As the figure shows, lithology directly influences soil strength, weathering rates, and pore pressure dynamics, all of which are essential in determining landslide occurrence[27,28].

Table 1. Relationships between lithological characteristics and shallow landslide controlling factors.

Lithological Characteristic	Dominant Physical Property	Influence on Slope Stability	Relevance to Shallow Landslides
Rock type and mineral composition	Strength and weathering resistance	Controls regolith formation and shear strength	Determines susceptibility to rainfall-induced failure
Degree of weathering	Material cohesion and friction angle	Weakens near-surface layers	Promotes shallow slip surfaces
Structural features (bedding, joints, foliation)	Discontinuity density	Localizes stress and failure planes	Governs landslide geometry and depth
Permeability and porosity	Hydrological response	Regulates infiltration and pore pressure buildup	Critical for triggering during intense precipitation
Soil–bedrock interface	Mechanical contrast	Acts as preferential failure horizon	Common location of shallow landslide initiation

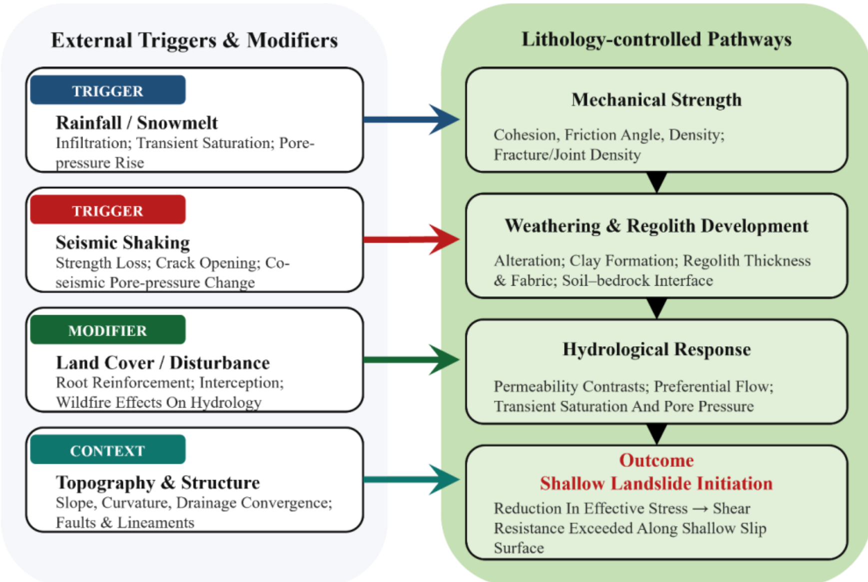

Figure 1. Conceptual framework illustrating how lithology influences shallow landslide susceptibility through interactions with surface processes and external triggers.

3. Remote Sensing Techniques for Lithological Mapping

Remote sensing has been a very useful instrument in mapping, especially the lithological mapping in complex terrain areas, where field-related studies have been restricted in terms of accessibility, scale, and cost. Remote sensing data can give indirect, spatially continuous, lithological variability information primarily through the capture of surface properties of mineral composition, texture, structure, and moisture conditions. The success of the remote sensing in the lithological mapping process is a result of the sensor properties, the data processing policies, and the extent to which surface manifestations depict the underlying geology[29,30].

3.1. Optical Multispectral Remote Sensing

The extended temporal history, expansive spatial scale, and comparatively simplified process of processing Multispectral optical remote sensing have been extensively applied in lithological mapping. Visual, near-infrared and shortwave infrared sensors monitor the difference in surface reflectance that is directly associated with mineralogical composition and weathering conditions. These diagnostic absorption properties in the shortwave infrared region can be used to differentiate between lithological units of many rock-forming minerals in the case of adequate surface exposure conditions [8].

Multispectral data are also especially applicable in complex terrains for regional-scale lithological characterization, where regional contrasts between major rock types can be determined. The small number of spectral bands, however, restricts the success of the spectral bands in resolving subtle mineralogical variations, particularly where lithological units are compositionally analogous. Steeper topography also creates effects of light; also, vegetation cover and soil formation add more complexity to spectral interpretation. Consequently, closely preselected multispectral methods can, in general, be understood as demanding topographical correction and vegetation masking to enhance lithological discrimination [31].

3.2. Hyperspectral Remote Sensing for Mineralogical Discrimination

Hyperspectral remote sensing is a significant improvement in lithological mapping in that hundreds of adjacent spectral bands are available, allowing a more detailed description of the surface mineralogy. The spectral resolution of the high resolution enables the recognition of specific absorption characteristics related to the clay minerals, carbonates, iron oxides, and alteration products that are normally important indicators of the weathering and mechanical weakness when it comes to shallow landslides.

Hyperspectral data find specific use in complex terrain environments to differentiate between lithologies that cannot be easily differentiated through the use of multispectral imagery. They also allow mapping of weathering zones and the modified materials that might not necessarily reflect the traditional lithological boundaries. In spite of these benefits, the use of hyperspectral data is still limited due to the availability of data, the cost of data acquisition, and sensitivity to weather. Moreover, hyperspectral data is highly dimensional and therefore, involves complex processing and high validation, which may be difficult in regions where ground reference data is scarce [9].

3.3. Thermal Infrared Remote Sensing

Complementary information to lithological mapping is provided by thermal infrared remote sensing, which takes advantage of the variations in surface emissivity and thermal inertia. Mineral composition, grain size, and roughness on the surface of these properties are known to affect them, and this enables some lithological units to be identified in terms of their thermal behavior. The thermal data are also applicable in the mapping of silicate and carbonate rocks, and in determining the surface materials that have dissimilar heat retention properties.

In the complicated terrains, thermal infrared products can be used to complement the optical data in lithological interpretation, particularly in areas that have low vegetation density. Nevertheless, the thermal signals are highly influenced by the variations of the day temperatures, moisture on the surface, and atmospheric conditions, and thus may create uncertainty during lithological classification. This means that thermal infrared data should be applied as an integrated and multi-sensor solution compared to an isolated solution [32].

3.4. Radar Remote Sensing and Structural Information

Synthetic aperture radar, which is part of radar remote sensing, provides special lithological mapping opportunities because it is sensitive to the surface roughness, structure, and moisture content, and can even be used without daylight or cloud cover. The radar backscatter behaviors may indicate the differences between the lithological units that have various surface textures or cracks that are frequently associated with the geological structure below. The diverse range of remote sensing techniques available for lithological mapping is summarized in **Table 2**, highlighting the strengths and limitations of each sensor type in complex terrains [7,33].

Radar data would be of great use in intricate terrain to detect lineaments, faults, and areas of heavy fracturing that would otherwise be hard to detect with optical imagery. Such structural features often tend to overlap with lithological boundaries or mechanically weak areas, which affect shallow landslides. The interpretation of radar, however, is indirect and usually ambiguous due to the effects of sensor geometry, surface moisture, and vegetation structure. As a result, radar-based lithological mapping is normally based on the combination with optical or thermal data in order to enhance interpretability.

Table 2. Summary of remote sensing techniques used for lithological mapping in complex terrains.

Remote Sensing Type	Key Spectral or Physical Sensitivity	Typical Spatial Scale	Main Advantages	Key Limitations
Multispectral optical	Broad mineralogical contrasts	Regional to local	Long-term data availability; wide coverage	Limited spectral resolution; vegetation masking
Hyperspectral	Diagnostic mineral absorption features	Local to regional	Detailed mineralogical discrimination	Data availability; atmospheric sensitivity
Thermal infrared	Emissivity and thermal inertia	Regional	Complementary lithological information	Influenced by moisture and diurnal effects
Synthetic Aperture Radar (SAR)	Surface roughness and structure	Local to regional	Cloud- and illumination-independent	Indirect lithological interpretation
Multi-sensor fusion	Combined surface properties	Flexible	Improved classification robustness	Increased processing complexity

3.5. Multi-Sensor Data Integration and Advanced Classification Methods

Multi-sensor data combining strategies to map lithology have been motivated by the constraints of the lithological information of the individual remote sensing sensors. The optical, hyperspectral, thermal, and radar data, frequently used together by researchers, allow them to leverage complementary surface characteristics and minimize the ambiguities that the single-sensor methods have. This kind of integration is useful, especially in complicated terrains, where the expression of lithology is different based on the slope orientation, vegetation cover, and the degree of weathering experienced [7].

The latest developments in machine learning have also promoted the possibilities of lithological mapping based on remote sensing. Multi-source datasets, classifying lithological units using algorithms that can process nonlinear relationships and high-dimensional data, have been increasingly used to classify the lithological units. These methods have been revealed to have better classification and strength, particularly in comparison to conventional pixel-based methods or rule-based methods. However, their functioning is largely dependent on the quality and representativeness of training data, and the interpretation of their results might not easily be made geologically. It is a significant problem to ensure that the classification products are geologically useful and can be used across regions [34].

Comprehensively, remote sensing methods are potent instruments of lithological mapping in complex topographies, which provide depth in space and coverage that can scarcely be accomplished by the use of traditional techniques. The benefits and constraints of various sensors and integration plans must be known in order to effectively consider remote sensing-based lithological data in the process of shallow landslide susceptibility modeling. **Figure 2** presents a typical workflow for processing remote sensing data into lithological maps, demonstrating how multi-sensor integration and machine learning techniques enhance lithological classification accuracy [35].

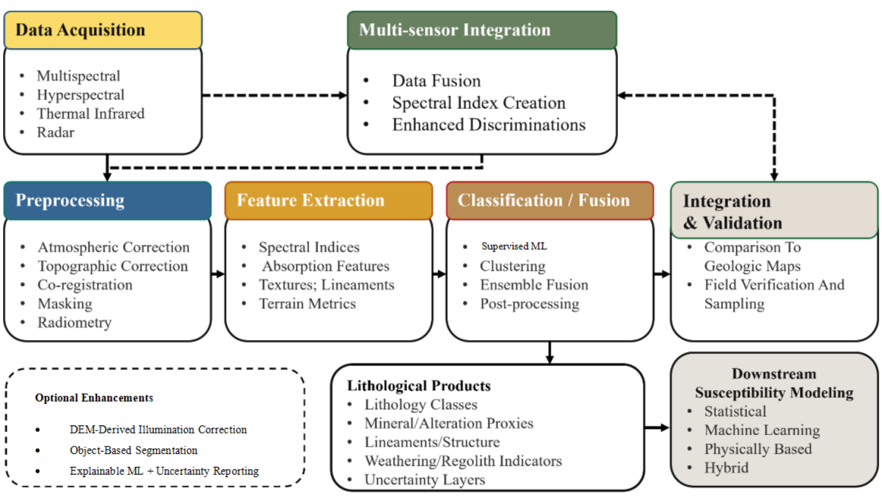

Figure 2. Generalized workflow for generating remote sensing-based lithological maps.

4. Integration of Remote Sensing-Derived Lithology in Landslide Susceptibility Modeling

Incorporation of lithological information derived by remote sensing into landslide susceptibility models has become more popular with the development of sensor technology and data processing, as the quality and accessibility of lithological products have become better. In complex terrains with shallow landslides, where failure processes are extremely dependent on near-surface material properties, how lithological information is modeled and how this is included in susceptibility models can have a powerful impact on predictive behavior. The use of remote sensing to improve the lithology has the potential to address some of the limitations that are present with the typical geological maps, and also gives rise to new methodological issues that should be handled with caution. As summarized in **Table 3**, several integration strategies exist for incorporating remote sensing–derived lithology into landslide susceptibility models, ranging from statistical methods to more complex hybrid approaches. Each method offers distinct advantages and challenges, depending on the modeling framework and the quality of lithological data [4,36].

Table 3. Approaches for incorporating remote sensing-derived lithological information into landslide susceptibility modeling.

Modeling Framework	Lithological Input Type	Typical Integration Strategy	Strengths	Limitations
Statistical models	Categorical lithology classes	Predictor variable encoding	Simplicity; interpretability	Sensitive to map accuracy
Machine learning models	Classes or spectral proxies	Nonlinear feature learning	High predictive power	Reduced transparency
Physically based models	Parameter constraints	Material property assignment	Process realism	High data demand
Hybrid models	Combined proxies and parameters	Data–process integration	Balanced performance	Calibration complexity

4.1. Representation of Lithological Information in Susceptibility Frameworks

Landslide susceptibility models are usually based on a combination of conditioning factors explaining terrain conditions, environmental conditions, and geological conditions. Lithology is normally presented as a categorical variable when describing discrete units of rock or as a collection of continuous variables based on the material properties. Lithological mapping. Remote sensing is an expansion of these representations by giving them spatially detailed classifications, mineralogical indices, or proxy variables pertaining to weathering or surface composition.

In complex terrains, due to the increased spatial resolution of lithology derived by remote sensing, susceptibility models are able to resolve fine-scale heterogeneity that is commonly diffused in conventional maps. This is especially applicable to shallow landslides, which often occur in very thin areas of weak or modified material. The categorical nature of most lithological products, however, makes statistical modeling difficult, either where the boundaries of the classes are unclear or where there are rare lithological units underrepresented. Lithological variables should be carefully coded, and scale effects must be taken into account, to make sure that the information derived by remote sensing has a contribution to make in the susceptibility assessment [37].

4.2. Statistical and Machine Learning Approaches

The most popular techniques to model landslide susceptibility are statistical and machine learning because they can account for numerous conditioning variables and nonlinear and complicated relationships. Lithological variables obtained using remote sensing are also being integrated into these models directly as the form of classified lithological units or indirectly using spectral or textural characteristics. Many studies have indicated that remote sensing lithology should be incorporated so as to enhance the performance metrics of the models, including prediction accuracy and spatial consistency, as opposed to models using only the traditional geological data.

Machine learning methods work especially well in complicated landscapes to make use of the highly spatialized information that is offered by remote sensing. Algorithms that are able to learn hierarchical or nonlinear patterns can encompass subtle interactions between lithology, topography, and hydrology factors that hold such significance in shallow landslides initiation. However, these models are also prone to the quality of training data and can overfit lithological peculiarities of the region, which restricts their transferability. The relative significance of lithological variables in complex models is also difficult to interpret, as certain modeling strategies require explanation and transparency [38–40].

4.3. Physically Based and Hybrid Modeling Approaches

Physical-based models provide a different paradigm of integrating lithological information in which explicit representation is given of the processes that determine slope stability, e.g., soil strength, hydrology, and pore pressure. The lithology plays a role in the susceptibility of these models based on the depth of the soil, its hydraulic conductivity, and shear strength, among which can be estimated or constrained based on remote sensing-derived lithological and mineralogical data. Remote sensing can complement field measurements to provide spatially continuous inputs that cannot be easily obtained by field measurements alone, especially in inaccessible or heterogeneous terrain [41].

A promising direction has also been in the Hybrid approaches that combine the concepts of physical basis with data-driven approaches. When this is implemented, lithology is determined by remote sensing and used to parameterize the model or place restrictions on model structure; statistical or machine learning elements are used to take into consideration uncertainties and intricate interactions. These methods can be better interpreted physically, but would need strict calibration and validation of the sensor, which in turn validates that remote sensing proxies would be true representatives of the conditions in the subsurface that are important to shallow landslides [42].

4.4. Comparison with Conventional Geological Mapping

The recurrent similarity in the literature is that susceptibility models that use traditional geological maps are compared with the susceptibility models that use remote sensing to derive lithological information. In most instances, the models with remote sensing prove to be better in spatial resolution and predictability, especially in areas where the current geological maps are crude or old-fashioned. The possibility of updating lithological data after significant disturbances in the environment only helps to increase the importance of remote sensing in terms of dynamic susceptibility.

Nevertheless, lithological products based on remote sensing do not always substitute the traditional geological maps, but can also be used as an extension of them. Geological maps are useful in giving contextual information on stratigraphy, structure, and underground relationships, which might not be easily observed with the remote sensing data. A combination of the two sources of data can thus be able to give a stronger susceptibility model as long as the differences in scale, classification, and uncertainty are controlled [43].

4.5. Uncertainty and Model Performance Evaluation

Lithological inputs are a sensitive yet frequently under-researched factor of landslide susceptibility modeling due to the levels of uncertainty involved. The lithological classification by remote sensing is prone to error, which can be transmitted in the susceptibility models, which alters the predictions and interpretation of the models. The quantification and communication of these uncertainties are especially hard in complex terrains where ground truth data are only sparse [44,45].

Performance evaluation of models should therefore be done on a basis that not only is the performance of the model in question accurate but sensitive to the lithological input of susceptibility. Multiple lithological datasets can also be used to provide comparative analyses that can give useful information on the robustness of the models and these can also be validated in various temporal and spatial settings. Uncertainty in remote sensing-based lithology integration is a critical issue to be considered in order to promote the validity and real-world implementation of shallow landslide susceptibility models.

5. Current Challenges and Future Research Directions

Although much has been done so far towards remote sensing-enhanced lithological mapping and its use with regard to shallow landslide susceptibility prediction, various issues still restrain its wider and dependable application in intricate landscapes. These problems are caused by the constraints on the data, uncertainty in the methodology and the fundamental complexity of geological and geomorphological processes. These are critical problems to be addressed in order to improve the scientific knowledge and the practical application of remote sensing-based methods [46].

5.1. Scale, Resolution, and Terrain Complexity

The disconnect between the available data and the appropriate scale at which landslide processes occur is one of the key problems of transferring the lithological information obtained with the help of remote sensing to shallow landslide susceptibility modelling. Small-scale changes in the material properties and the ground conditions usually control shallow landslides, and most of the products of remote sensing and geological datasets are created at regional or national scales. Difficult terrains, steep slopes, changing illumination, and patchy land cover also make the extraction of credible lithological information at the fine spatial scales even more complicated [2].

Satellite and airborne data have high spatial resolution; however, they have restricted coverage or availability in order to conduct large area assessments. Furthermore, the enhancement of spatial resolution does not always correspond to the enhancement of lithological accuracy in the case of weak or covered by vegetation and soil surface expressions. The next step in research should thus be to determine the most effective scales for lithological mapping to strike the right balance between the spatial and the thematic reliability, especially when using the scales in susceptibility modeling [2].

5.2. Surface–Subsurface Decoupling and Validation Constraints

Surface features are mostly recorded in remote sensing, but shallow landslide origin is more often governed by the conditions in the lower layers, including the thickness of the regolith, the weathering of the bedrock, and the boundaries between the soil and the bedrock. This type of surface–subsurface decoupling is a fundamental constraint of lithological mapping with remote sensing data only. Surface materials used in most landscapes can be misleading about the mechanical or hydrological properties of deeper materials used in the mechanism of failure.

Even though field validation is still necessary to determine the reliability of remote sensing-produced lithological products, the field data are rather sparse or distributed unevenly over complex landscapes. This can impact the accuracy of lithological classification as well as calibration of susceptibility models. The emergence of ways to combine field observations that are limited with remote sensing and the study of indirect means to understand the state of the underground will be a significant avenue in future studies [36].

5.3. Uncertainty Propagation and Model Transferability

The uncertainty in the lithological mapping and the susceptibility modelling is a natural feature of hazard assessment, which is rarely quantified or reported. The susceptibility models can spread the errors of remote sensing-based lithological classification in both nonlinear and spatially inhomogeneous manner, especially where the lithology has a strong impact on the model. These uncertainties can be enhanced by topographic, hydrologic, and land cover interactions in complex terrains [47–49].

The other important issue is the applicability of the models based on the lithological information obtained by remote sensing. Models that are tuned in one geological or climatic environment can be ineffective in a different location, despite the fact that similar remote sensing information is employed. Such a limitation is an expression of the variations in lithological expression and weathering regimes, and landslide processes, which cannot be adequately described by surface measurements. Future research must place more focus on cross-regional validation and come up with more generalized modeling frameworks [6,50].

5.4. Emerging Technologies and Methodological Advances

The emergence of high-speed technological advancements provides an opportunity to overcome some of the weaknesses that come along with remote sensing-based lithological mapping. Ultra-high-resolution imaging Unmanned Aerial Vehicles offer very fine-scale lithological and structural details, especially in small study regions. The subsequent development of hyperspectral sensor technology and the availability of data will only enhance the mineralogical discrimination, even in the problematic setting [51].

Deep learning methods have already demonstrated potential at the methodological level in deriving multi-source remote sensing datasets with complex patterns. The methods are potentially useful in increasing the accuracy of lithological classification and making the extraction of features automated; however, their use must be very attentive to training data, interpretability, and computational requirements. Cloud-based processing platforms are also useful in the processing of large datasets to provide a more consistent and reproducible lithological mapping at the regional to global scale. **Table 4** outlines the key challenges in remote sensing–enhanced lithological mapping and proposes potential research avenues to overcome them, particularly in the context of scale mismatches, classification uncertainty, and model transferability [2,3,52].

Table 4. Challenges and research priorities for remote sensing-enhanced lithological mapping in shallow landslide susceptibility assessment.

Challenge	Underlying Cause	Implications for Modeling	Future Research Direction
Scale mismatch	Process vs. data resolution	Reduced predictive reliability	Multi-scale analysis frameworks
Surface–subsurface decoupling	Limited subsurface observability	Parameter uncertainty	Proxy-based subsurface inference
Classification uncertainty	Sensor and algorithm limits	Error propagation	Explicit uncertainty quantification
Limited transferability	Geological and climatic variability	Poor model generalization	Cross-regional validation
Data and validation gaps	Sparse field observations	Reduced confidence	UAV and targeted field integration

5.5. Toward Integrated and Interdisciplinary Frameworks

A stronger interconnection between remote sensing, geology, geomorphology, and geotechnical engineering will be required in the future to make predictions of shallow landslides in complex terrains. The information obtained by remote sensing to determine lithology must be considered as a part of a more complex framework of a model, which encompasses the field observations, process knowledge, and analysis of uncertainties. Interdisciplinary cooperation is especially necessary in the process of making sure that remote sensing products are geologically significant and applicable to the slope stability processes [36].

Standardization of methods of lithological mapping, model integration, and performance evaluation would further improve the inter-study comparability and facilitate the operations. In future scenarios with the further development of remote sensing data and analytical tools, their successful application in landslide potential assessment has great promise, considering the better prediction of hazards and risk management, as long as the existing challenges are addressed in a systematic way. **Figure 3** provides a visual summary of the key challenges and future research priorities for improving remote sensing-enhanced lithological mapping in landslide susceptibility assessments. These priorities highlight the need for multi-scale approaches and integration with emerging technologies [2–4,53–56].

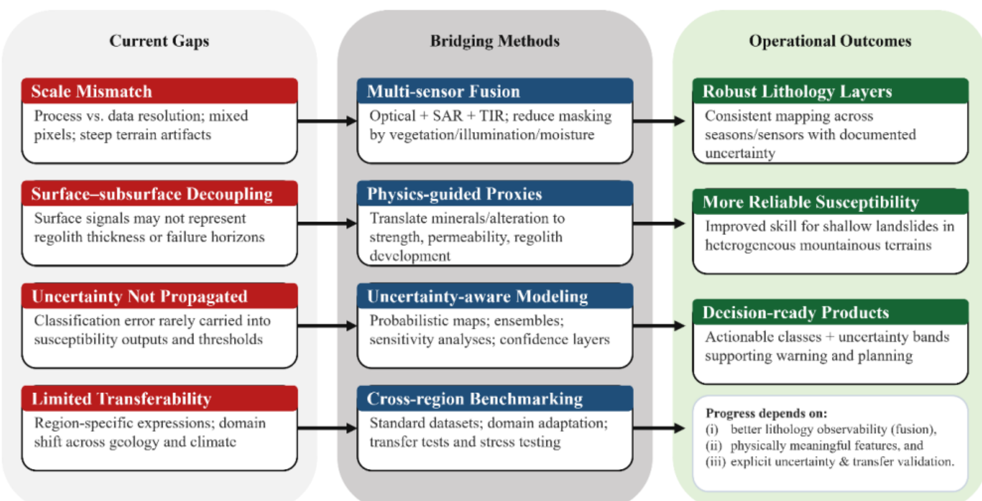

Figure 3. Summary of current research gaps and future research directions in remote sensing–based lithological mapping for shallow landslide susceptibility.

6. Conclusion

This review has considered the use of remote sensing-enhanced lithological mapping to predict shallow landslide susceptibility in complicated landscapes, and how the lithology contributes to slope instability, and how methodological developments are helping to demonstrate the lithology to work in susceptibility models. Lithology, in essence, dominates the mechanical, hydrological and weathering nature of materials in the near-surface region and, through this, is at the core of determining the spatial distribution and occurrence of shallow landslides. To support a sound susceptibility outlook, the desire to capture this lithological variability at the correct spatial and thematic resolutions is an important need in heterogeneous, topographically complex landscapes.

The recent developments in remote sensing technologies have increased the possibilities of mapping the lithological conditions of large and frequently inaccessible environments significantly. Multispectral, hyperspectral, thermal infrared, and radar data give complementary data on surface composition, structure, and moisture-related properties, whereas data integration by multisensors and sophisticated classification methods has enhanced lithological discrimination in harsh conditions. Remote sensing-based lithological products can be more spatially detailed, more consistent, and updated in response to environmental change than are conventional geological maps. They are especially useful in shallow landslide research.

The inclusion of remote sensing-derived lithological data in landslide susceptibility models has been shown to have apparent potential to improve predictive capability in diverse statistical, machine learning, and physically-based models. These models provide a more effective representation of the circumstances contributing to shallow slope failures because of improved representation of the fine-scale material heterogeneity and lithology-related processes. Simultaneously, the review points out that the lithology obtained with the use of remote sensing is to be considered as a supplement to conventional knowledge in geology, in particular, in the context in which it is necessary to be aware of the conditions inherent in the subsurface and the structural controls.

In light of these developments, there are still many challenges that restrict the use of the remote sensing-improved lithological mapping in determining the level of susceptibility of the landslides. Among the important challenges are scale anomalies between the data and the process, the indirect correlation between the surface observations and the mechanisms behind the subsurface failures, the uncertainty of the data that is propagated in the model about lithological classification, and the inability of the models to transfer across various geological and climate environments. To overcome these challenges, there is a need to enhance validation schemes, clear representation of uncertainty, and closer unification between remote sensing measurements and process insight.

Utilize multispectral satellite data combined with statistical or conventional machine learning models to generate broad lithological classifications and susceptibility maps, suitable for large-area screening and hazard zoning. Integrate high-resolution multisource data, including hyperspectral imagery, UAV observations, and radar products, with advanced machine learning or hybrid models to capture fine-scale lithological heterogeneity, supported by targeted field validation. Couple remote sensing-derived lithological proxies with physically based or hybrid models to explicitly represent subsurface processes, uncertainty propagation, and hydromechanical controls on slope stability. Across all tiers, standardized uncertainty quantification, cross-regional validation, and integration with geological knowledge are essential. This tiered approach provides a scalable pathway for improving the robustness, transferability, and operational applicability of shallow landslide susceptibility assessments in complex terrains.

In the future, a variety of new technologies, including high-resolution airborne platforms, enhanced hyperspectral sensors, deep learning approaches, and cloud-based analysis environments, will become available and enhance the ability of lithological mapping. These tools will require interdisciplinary cooperation and the creation of transparent and standardized methodologies to make sure that they have relevance and reproducibility in geology. This review can be used to support further research on remote sensing-based lithology mapping as an effective part of shallow landslide susceptibility mapping in complex landscapes by synthesizing existing knowledge and highlighting the main research directions, which in turn will result in more valid hazard prediction and risk management.

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Conflicts of Interest

The author declares no conflict of interest.

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