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Review

Multi-Source Remote Sensing for Dynamic Landslide Susceptibility Assessment: From Static Mapping to Spatiotemporal Inference and Updating

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Highlights

What are the main findings?

- Dynamic landslide susceptibility reflects evolving slope predisposition rather than fixed spatial conditions.
- Multi-source remote sensing supports dynamic assessment through forcing, state, regulation, and memory signals.

What are the implications of the main findings?

- Dynamic susceptibility assessment should move beyond repeated static mapping toward process-consistent spatiotemporal inference and map updating.
- Future research should prioritize event-resolved inventories, uncertainty-aware multimodal fusion, and validation designs that test temporal extrapolation, spatial transferability, and update rationality.

Abstract

Multi-source remote sensing is transforming landslide susceptibility assessment from static terrain-based zonation toward observation-driven spatiotemporal inference and dynamic map updating. Satellite precipitation products, interferometric synthetic aperture radar (InSAR) deformation time series, optical image sequences, land-cover products, and multi-temporal terrain observations provide complementary evidence of hydrometeorological forcing, slope kinematics, land-system regulation, and geomorphic reorganization. However, these observation streams differ substantially in spatial support, temporal resolution, physical meaning, and uncertainty structure and therefore cannot be reliably integrated as generic predictors without process-aware interpretation. This review synthesizes recent progress in remote sensing-enabled dynamic landslide susceptibility assessment by linking four key components: dynamic factor construction from Earth observation data, spatiotemporal representation and learning, susceptibility map updating, and validation under temporal and spatial independence. The reviewed literature is organized around four process roles: rainfall- and soil moisture-related forcing, kinematic state and response captured by InSAR, land-system and ecological regulation derived from optical time series, and geomorphic memory represented by multi-temporal digital elevation models

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(DEMs). We further examine how these signals are encoded and integrated through temporal models, graph-based representations, attention mechanisms, and hybrid frameworks, with particular emphasis on consistency among process role, data structure, mapping unit, inference target, and validation design. Current progress remains constrained by temporally coarse landslide inventories, cross-scale incompatibility among remote sensing products, uneven and insufficiently process-aware multimodal fusion, and limited physical interpretability. Future advances require event-resolved inventories, uncertainty-aware multimodal fusion, process-consistent spatiotemporal learning, and validation designs that explicitly test whether susceptibility maps can be updated in a scientifically defensible manner as new Earth observation data become available.

Keywords: landslide susceptibility; dynamic; multi-source remote sensing; spatiotemporal learning; validation

1. Introduction

Landslides are recognized as among the most destructive natural hazards worldwide, causing thousands of deaths and billions of dollars in economic losses each year [1,2]. According to statistics reported by the United Nations Office for Disaster Risk Reduction [3], landslides account for 17.3% of all deaths associated with geological hazards worldwide during 2000–2020, and an even higher proportion is observed in mountainous countries. As a cornerstone of disaster risk management, landslide susceptibility assessment provides critical support for land-use planning, hazard early warning, and emergency response by identifying the spatial probability distribution of potentially unstable slopes.

The concept of landslide susceptibility was introduced by Brabb [4] to describe the likelihood of landslide occurrence within a region under given local terrain conditions. Fell et al. [5] further noted that conventional landslide susceptibility assessment has, for decades, relied primarily on static conditioning factors such as topography, geology, and land-use to determine where landslides are likely to occur, thereby producing spatial probability maps of susceptibility. Since then, static susceptibility maps have been widely adopted and have played an important role in landslide hazard zonation. However, static landslide susceptibility assessment is fundamentally built on a critical assumption: susceptibility is treated as a time-invariant spatial property of slopes. Although this assumption remains acceptable in relatively stable environmental settings, it becomes increasingly inadequate under contemporary conditions of climate change and broader global environmental change. Extreme weather events are becoming more frequent at large scales [6,7], the human footprint continues to expand [8–10], and pressures from mining activities [11] and land-use change are intensifying [12]. As a result, landslide activity increasingly exhibits new characteristics, including higher frequency, reactivation, and cascading evolution, giving rise to emerging susceptibility patterns that cannot be adequately captured by static frameworks.

In recent years, the rapid development of multi-source remote sensing has provided an essential observational foundation for the transition of landslide susceptibility assessment from static mapping to dynamic analysis. In particular, the expansion of high-revisit satellite constellations, represented by Sentinel-1, Sentinel-2, and Planet, markedly enhances the capacity for continuous observation of surface environmental change [13,14]. Sentinel-1 synthetic aperture radar data, when combined with InSAR, enable millimeter-scale monitoring of ground deformation [15]. Meanwhile, Sentinel-2 and Planet optical imagery support high-frequency detection of vegetation condition, land-cover change, and geomorphic disturbance [16,17]. Consequently, remote sensing no longer serves merely to

update static conditioning layers; it increasingly delivers temporally explicit observations of precipitation forcing, surface kinematics, land-cover transitions, infrastructure expansion, and terrain reorganization. These observation streams make it possible to ask a different scientific question: not only where failures are likely to occur, but how slope predisposition is reorganized as forcing, state, regulation, and response evolve through time.

In fact, the temporal dimension of landslide susceptibility is not an entirely new research question. Earlier studies had already attempted to examine the evolution of landslide susceptibility from the perspective of environmental change [18]. Hufschmidt et al. [19] further formalized the incorporation of time into the natural hazard research framework, emphasizing that landslide susceptibility is not a fixed property, but one that continuously evolves over time under nonstationary conditions. Operationally, landslide susceptibility asks where slopes are predisposed to failure under given environmental conditions. Static susceptibility mainly represents the spatial distribution of potential landslide occurrence under comparatively stable background conditions and is commonly used for long-term land-use planning and regional hazard zonation. Dynamic susceptibility, by contrast, asks how and where slope predisposition is reorganized as hydrometeorological forcing, kinematic state, land-system regulation, and geomorphic memory evolve through time. Its target is not the immediate occurrence of a specific landslide, but the spatiotemporal updating of slope predisposition at event, seasonal, annual, or multi-year scales. Landslide hazard further moves from predisposition to the probability of landslide occurrence within a specified area and time window under given triggering conditions. Landslide early warning differs from both susceptibility and hazard assessment because it focuses on whether immediate action is warranted based on near-real-time thresholds, monitoring signals, or forecasted triggering conditions. Therefore, dynamic susceptibility occupies an intermediate conceptual position between static susceptibility and operational early warning: it preserves a focus on predisposition but allows that predisposition to change as environmental forcing and slope state conditions evolve.

Several review studies in recent years have examined the application of remote sensing to landslide research from different perspectives. Wasowski et al. [15] systematically reviewed the application of InSAR in landslide hazards. Cheng et al. [20] further summarized recent progress in satellite-based InSAR for landslide susceptibility assessment and pointed out the insufficient integration of dynamic deformation information into conventional static susceptibility models. Xu et al. [21] provided a comprehensive overview of remote sensing technologies for landslide detection, monitoring, and prediction. Huang et al. [22] and Pawar and Sharma [23], in turn, reviewed methodological advances in landslide susceptibility assessment from the perspectives of machine learning and deep learning, respectively. Nevertheless, most existing reviews remain organized around a single sensor family, a single methodological branch, or a broad remote sensing toolbox. A synthesis is still needed that explicitly asks how remote sensing observations should be transformed into dynamic susceptibility factors, how their distinct process roles should be represented in spatiotemporal inference frameworks, and how dynamically updated susceptibility maps should be validated under temporal extrapolation and spatial independence constraints.

This need for synthesis is also linked to the conceptual evolution of landslide susceptibility assessment. The current dynamic susceptibility paradigm did not emerge de novo from deep learning or satellite constellations but builds on earlier concerns about temporal change in hazard and risk under nonstationary conditions [19]. Traditional susceptibility assessment mainly focused on spatial probability under relatively stable environmental conditions [5], whereas probabilistic hazard frameworks had already distinguished spatial susceptibility from temporal probability and landslide intensity [5,24]. Earlier scenario-based studies considering land-use or climate change provided important foundations but

lacked continuous observations for operational map updating [25,26]. Since approximately 2015, high-revisit satellite observations, including InSAR, precipitation and soil moisture products, optical image sequences, and multi-temporal terrain observations, have made this transition increasingly operational [15,27,28]. Thus, the novelty of current dynamic susceptibility assessment lies in the ability to represent and update changing slope predisposition using multi-source Earth observation data.

Against this background, a review explicitly centered on the shift from static to dynamic assessment is timely. Rather than organizing the field as a catalogue of sensors or algorithms, this review asks how different observation streams, model structures, and validation schemes contribute to the process-consistent representation of nonstationary slope systems. The objective is not only to summarize what has been done, but also to clarify what dynamic susceptibility should mean, how it should be represented, and how its updating logic should be evaluated. Figure 1 summarizes the revised conceptual framework.

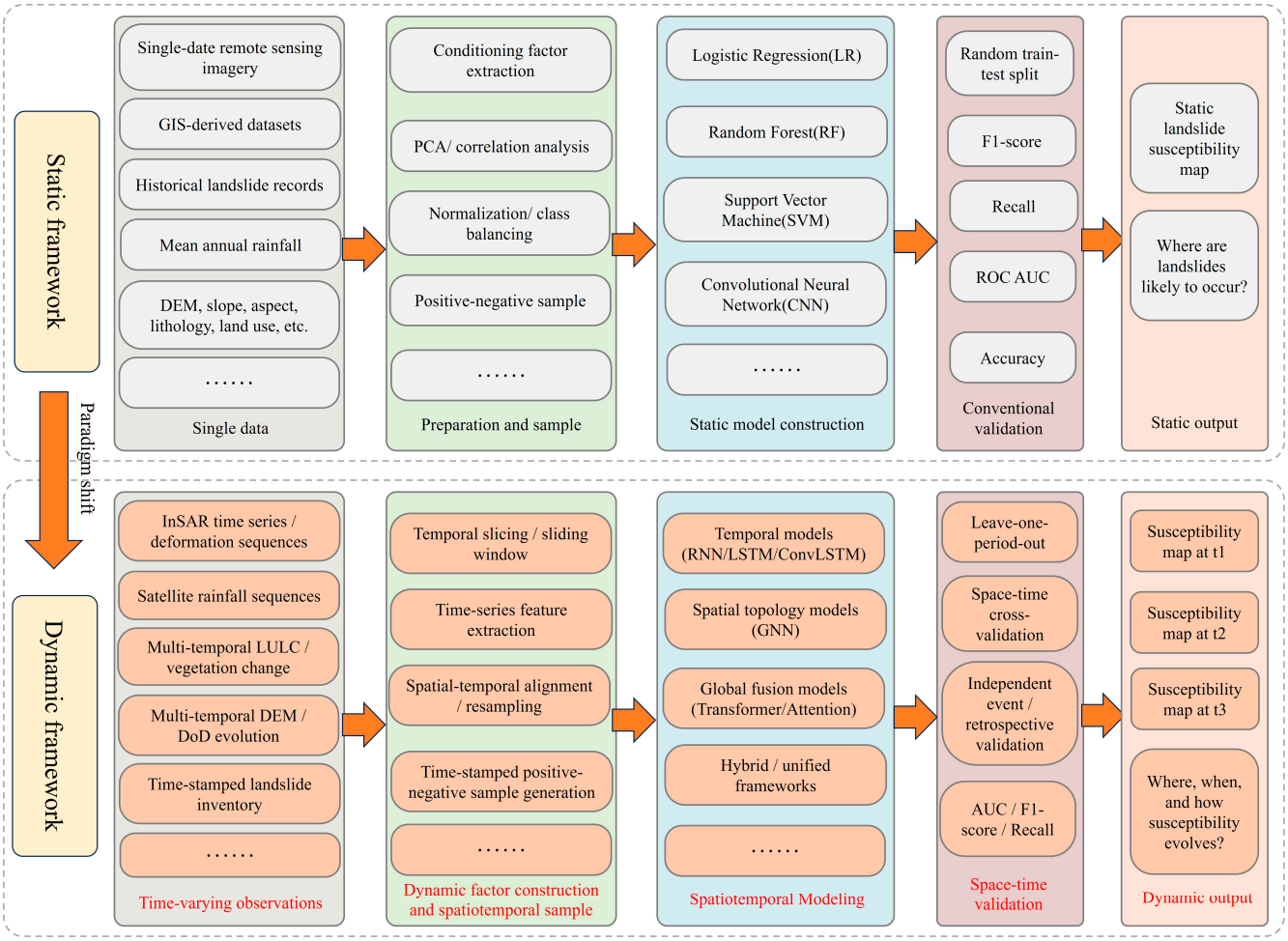


Figure 1. Conceptual framework of remote sensing-enabled dynamic landslide susceptibility assessment.

The innovative contribution of this review is threefold. First, it reframes dynamic landslide susceptibility as the spatiotemporal reorganization of slope predisposition rather than as a simple repetition of static susceptibility mapping. Second, it organizes multi-source remote sensing observations according to their process roles, including hydrometeorological forcing, kinematic state and response, land-system regulation, and geomorphic memory, thereby avoiding the indiscriminate stacking of heterogeneous predictors. Third, it proposes a process-consistent logic for dynamic susceptibility map updating, in which new Earth observation data are used not only to refresh input layers but also to revise

susceptibility patterns in a temporally plausible, observationally supported, and scientifically defensible manner. This updating logic is operationalized in Section 3.4 through the update rationality indicators and the multi-dimensional validation framework, which jointly examine temporal plausibility, spatial independence, event-level transferability, and consistency with subsequent landslide occurrence or independent instability evidence.

2. Materials and Methods

2.1. Review Design and Literature Corpus

This review was designed as a structured conceptual review rather than a full bibliometric or PRISMA-style systematic review. Its aim is not to provide an exhaustive scientometric mapping of landslide-related publications but to establish a transparent literature basis for examining how dynamic landslide susceptibility is currently conceptualized, observed, represented, and validated. This review therefore emphasizes process roles, multi-source remote sensing observations, spatiotemporal inference strategies, map updating logic, and validation designs.

The literature was surveyed from the Web of Science Core Collection over the period 2005–2025. The search strategy combined three groups of terms: landslide susceptibility terms, dynamic or temporal assessment terms, and remote sensing-related terms. These included expressions related to landslide susceptibility mapping and slope predisposition; dynamic, temporal, spatiotemporal, time-varying, updating, and multi-temporal assessment; and remote sensing, InSAR, precipitation, soil moisture, land-cover, land-use, and DEM.

A broader corpus was first assembled from studies concerned with landslide susceptibility assessment to frame the general development of the field. A narrower focused corpus was then constructed from studies that moved beyond static susceptibility mapping toward temporally explicit assessment, dynamic factor construction, remote sensing-based updating, or spatiotemporal validation. The overall search, screening, and corpus construction workflow is shown in Figure 2, while the operational details of corpus construction are summarized in Table S1.

It should be noted that the literature search was restricted to English-language records indexed in the Web of Science Core Collection. This choice was made to ensure consistency, traceability, and reproducibility of the structured corpus, but it also introduces a language-related limitation. This limitation is particularly important because many studies on dynamic susceptibility, InSAR-based landslide monitoring, reservoir-bank slope instability, and regional landslide updating have been conducted in Chinese mountainous and reservoir areas. Because no separate multilingual search of CNKI, Wanfang, or VIP was conducted, we do not provide a numerical estimate of excluded Chinese-language studies. The potential under-representation is most likely to affect Chinese mountainous and reservoir-bank studies, especially MT-InSAR deformation monitoring, Three Gorges reservoir-bank slope research, rainfall–reservoir water level interactions, and regional susceptibility updating in Southwestern China. Consequently, the focused corpus should be interpreted as an English-language representation of the field rather than a fully exhaustive global corpus. Future reviews could reduce this bias by integrating multilingual databases and comparing English- and Chinese-language evidence bases.

2.2. Screening Criteria and Conceptual Coding

The screening process was selective but not arbitrary. Studies were retained as core literature when they contributed to the conceptual, observational, methodological, or validation-related development of dynamic landslide susceptibility assessment. Particular attention was given to studies addressing time-varying forcing, slope state evolution,

land-system or ecological regulation, geomorphic reorganization, spatiotemporal learning, dynamic map updating, or validation under temporal and spatial independence.

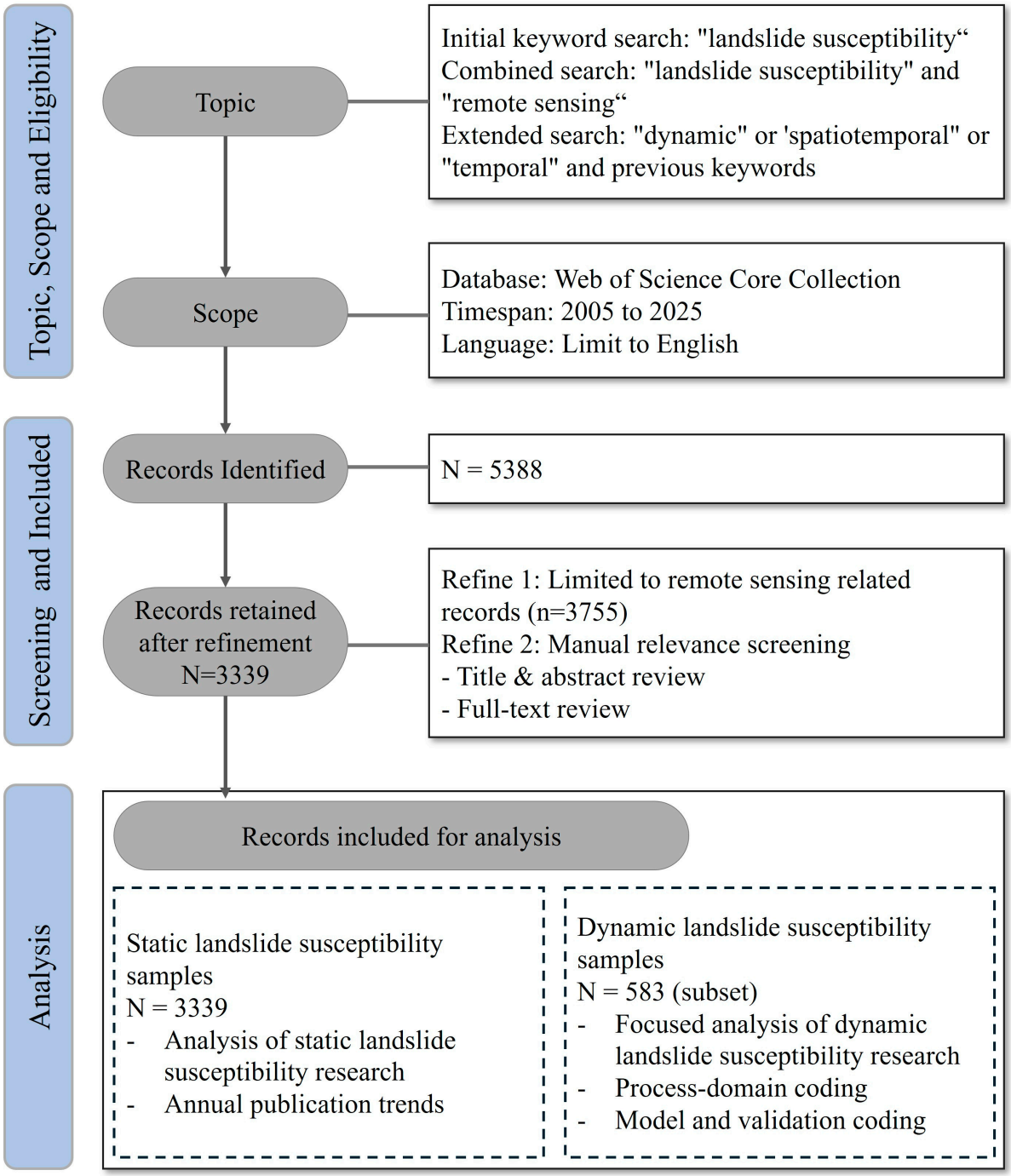


Figure 2. Literature screening and corpus construction workflow.

Studies focused primarily on landslide detection, inventory compilation, post-event mapping, or operational early warning were not treated as core dynamic susceptibility studies unless they also contributed directly to susceptibility meaning, representation, modeling, or validation. This distinction is necessary because the present review focuses on slope predisposition under environmental nonstationarity rather than on landslide observation, monitoring, or forecasting in a broader sense.

To support comparative synthesis, the focused literature was coded according to five conceptual dimensions: dominant observation domain, temporal scale of analysis, spa-

tial mapping unit, model or inference family, and validation design. These dimensions correspond to the main analytical structure of the review. Observation domain coding supports the synthesis of dynamic factor construction; temporal-scale and mapping unit coding clarify spatiotemporal support; model family coding informs the comparison of spatiotemporal learning frameworks; and validation design coding supports the discussion of temporal extrapolation, spatial transferability, event-level usefulness, and update rationality. Detailed coding definitions are provided in Table S2, while descriptive publication trends and domain-specific distributions are provided in Figures S1–S4.

3. Results

3.1. Corpus-Level Coding Results and Conceptual Synthesis

The coding results provide a quantitative basis for the subsequent synthesis. Table 1 summarizes the dominant coding frequencies in the 583-paper focused corpus across observation domain, temporal scale, model family, and validation design. Because some studies addressed more than one process signal or methodological category, the table reports the dominant category assigned during coding, while more detailed temporal and domain-specific distributions are retained in the Supplementary Materials.

Table 1. Condensed synthesis of coding frequencies in the 583-paper focused corpus.

Coding Dimension	Main Result	Number
Observation domain	Hydrometeorological forcing	245
	Land-system	152
	InSAR	89
	Terrain	78
Temporal scale	Multi-year/Decadal/Scenario horizon	275
	Short-term sequence	179
	Event-scale	75
	Seasonal	54
Model	Conventional statistical	130
	Sequential deep models	18
	Graph/Attention/Transformer models	26
Validation	Conventional accuracy-based validation	171
	Update rationality evaluation	54

The coding frequencies indicate that dynamic landslide susceptibility research remains unevenly developed across process domains. Hydrometeorological forcing accounts for the largest share of the focused corpus, whereas InSAR-based kinematic studies and terrain/geomorphic change studies remain less frequent. Methodologically, conventional statistical or machine learning models are still more common than sequential deep models and graph-, attention-, or Transformer-based models. Validation practices are also weakly aligned with the requirements of dynamic map updating: many studies still rely on conventional accuracy-based validation, whereas explicit evaluation of susceptibility change, temporal consistency, and update rationality remains limited. These results provide the empirical basis for the following synthesis of remote sensing observations, spatiotemporal learning frameworks, and validation logic.

3.2. Remote Sensing Observations for Dynamic Factor Construction

Static susceptibility became influential because it offered a tractable way to organize complex terrain information into spatially explicit predisposition patterns. However, the deeper assumption behind that success was that the conditioning environment changes

slowly enough that a single map can stand in for predisposition over an extended period. That assumption weakens when rainfall regimes intensify, urban and transport corridors reconfigure slope hydrology, vegetation cover fluctuates after disturbance, and post-failure terrain evolves over years to decades. Under those conditions, susceptibility can no longer be treated as a stable background field.

A more useful conceptual reformulation is to regard dynamic susceptibility as the evolving organization of slope predisposition generated by at least four process domains. Rainfall primarily represents transient forcing; InSAR deformation time series often act as state- or response-sensitive observations; land-use and land-cover (LULC) change reflects medium- to long-term human–ecological regulation; and topographic or geomorphic evolution records the memory of cumulative reorganization, threshold migration, and sediment redistribution. Dynamic susceptibility becomes meaningful only when these observation streams are interpreted according to their process roles and characteristic timescales rather than stacked indiscriminately as generic predictors (Figure 3).

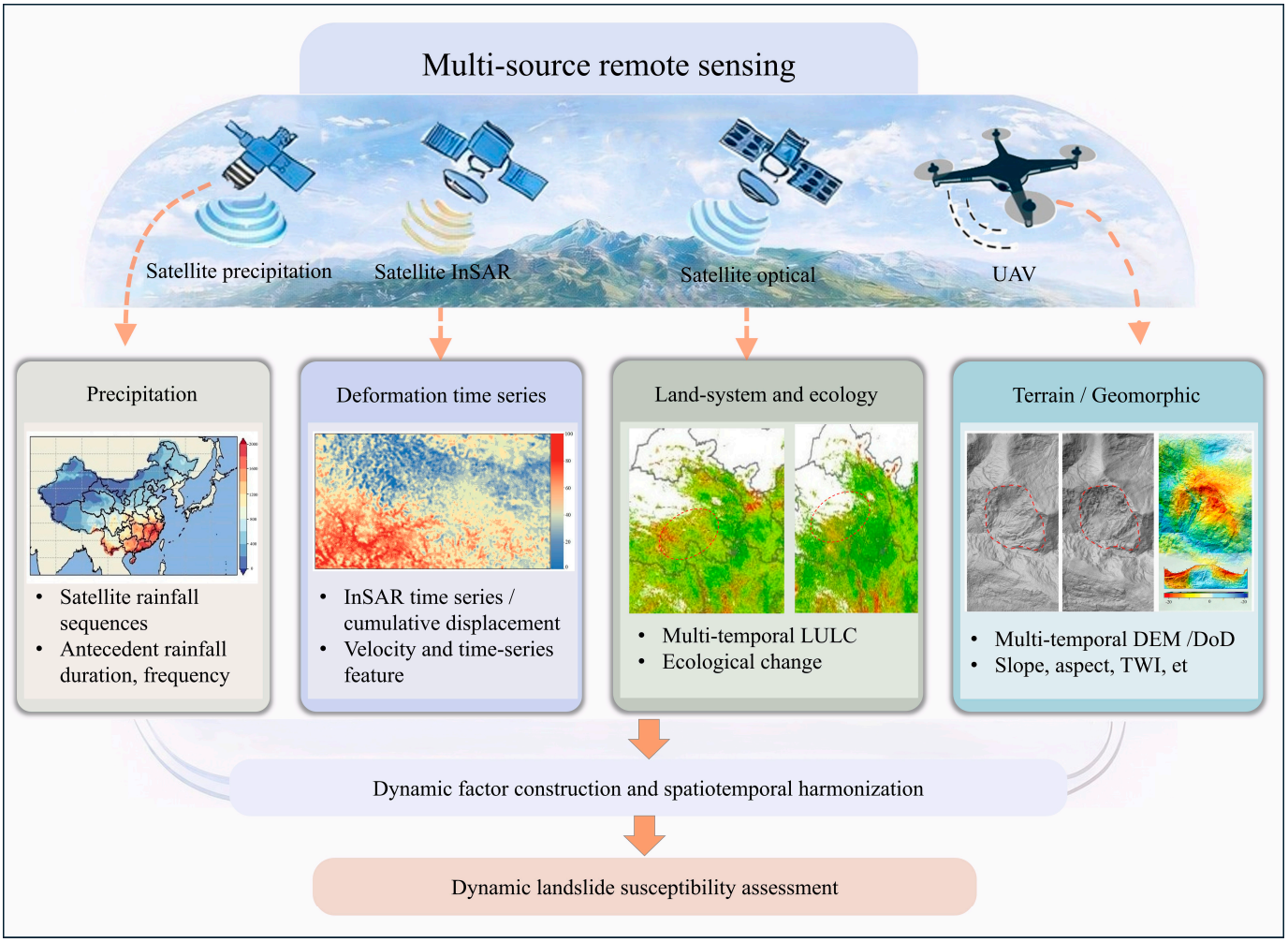


Figure 3. Multi-source remote sensing observations for dynamic factor construction and spatiotemporal harmonization.

3.2.1. Satellite Precipitation and Soil Moisture-Related Forcing

Among the various types of landslides, rainfall-induced shallow landslides are the most common, and their spatiotemporal variability directly influences both the frequency and spatial distribution of landslide occurrence [27]. In earlier studies, annual precipitation was often introduced into landslide susceptibility assessment as a static conditioning

factor and incorporated into conventional static models [29–31], while some studies used daily rainfall records to explore the relationship between landslides and precipitation [32]. Nevertheless, such approaches not only overlook the short-term pulse-like nature of rainfall triggering but also fail to capture the progressive hydrological evolution through which antecedent rainfall accumulation increases soil moisture and gradually reduces slope stability. However, the scientific role of rainfall changes substantially when susceptibility is viewed dynamically.

Multi-satellite retrieval has become fundamental to this transition [33]. Since the launch of the Tropical Rainfall Measuring Mission (TRMM) in 1997 [34], remote sensing-based precipitation retrieval systems have been continuously improved, leading to the development of increasingly mature and widely used products, including TRMM Multi-satellite Precipitation Analysis (TMPA) [34], the Climate Prediction Center morphing technique (CMORPH) [35], and Integrated Multi-Satellite Retrievals for Global Precipitation Measurement (GPM-IMERG) [36]. These products have substantially enhanced the capacity to capture rainfall events across space and time.

Beyond precipitation, satellite and reanalysis soil moisture products provide a more direct representation of the slope's hydrological state and thus of the antecedent wetness that modulates landslide susceptibility [37,38]. Operational products such as the Soil Moisture Active Passive (SMAP) mission [39], the Soil Moisture and Ocean Salinity (SMOS) mission [40], and reanalysis such as ERA5-Land [41] offer temporally explicit observations of surface and root-zone soil moisture at daily to sub-daily intervals. In dynamic landslide susceptibility assessment, these observations are valuable because they capture the legacy of antecedent rainfall—how precipitation forcing is stored and transformed into pore water pressure—rather than treating each rainfall event as an independent trigger.

Within dynamic landslide susceptibility assessment, the significance of satellite-derived rainfall information extends beyond the provision of temporally refined precipitation input. More fundamentally, it reshapes the conceptual treatment of rainfall within susceptibility analysis [42]. Under dynamic perspectives, rainfall is not merely a background environmental descriptor but a transient forcing sequence whose effects emerge through the joint influence of timing, accumulation, intensity, duration, and antecedent wetness conditions [28,43,44]. Soil moisture observations, in turn, encode how this forcing is integrated into slope hydrology over time, bridging the gap between meteorological inputs and geotechnical response. What this implies is a broader epistemic shift: susceptibility modeling is moving away from static characterization of rainfall background toward process-oriented representation of short-term hydrometeorological forcing and its coupling with evolving slope instability [45,46].

At the same time, the utility of these hydrometeorological products is constrained by mountainous retrieval bias, coarse grid support relative to hillslope-scale failures, shallow sensing depth, vegetation and surface roughness effects, and uncertain alignment with the actual timing of failure. These limitations matter because forcing information that is temporally explicit but physically or spatially misaligned can still degrade inference. Dynamic susceptibility therefore benefits not from rainfall or soil moisture data alone, but from forcing and preconditioning data whose timing, spatial support, and physical meaning are sufficiently consistent with slope-scale triggering processes.

3.2.2. Deformation Time Series

InSAR observations provide one of the clearest remote sensing pathways for representing evolving slope state [47,48]. Although conventional differential InSAR was widely applied in early studies, its performance in long-term dynamic monitoring is strongly constrained by temporal and spatial decorrelation, as well as atmospheric delay effects [49,50].

To overcome these limitations, multi-temporal InSAR (MT-InSAR) techniques were subsequently developed [51]. Representative approaches include small baseline subset InSAR (SBAS-InSAR) [52], persistent scatterer InSAR (PS-InSAR) [53], and distributed scatterer InSAR (DS-InSAR) [54].

In early applications, InSAR observations are often reduced to lower-dimensional representations, most commonly by using the annual mean deformation rate as a single supplementary factor combined with static variables such as topography and geology in conventional machine learning models [55,56]. In practice, coupling strategies such as conditional matrices [57–59] and modified matrices [60] are widely adopted. For instance, Miao et al. [61] spatially overlay a susceptibility map derived from conventional conditioning factors with an InSAR deformation rate map to refine susceptibility zonation boundaries, whereas Zhou et al. [62] show that the incorporation of InSAR-derived surface deformation can effectively reduce false-positive errors in susceptibility classification. Yet, these approaches generally assume that areas with higher deformation rates are associated with higher landslide probability. In essence, deformation information is still treated in a static manner, and its temporal evolutionary signal is largely lost.

Within dynamic landslide susceptibility assessment, InSAR is particularly valuable because it resolves the temporal trajectory of slope instability rather than merely providing a static deformation rate proxy [63–65]. The methodological transition is therefore not simply a shift from one deformation metric to another, but from the extraction of summary rates to the construction of temporally explicit dynamic features. Instead of relying on a single annual mean deformation value, recent studies have segmented deformation time series into monthly or seasonal windows using sliding temporal strategies [66] or have directly derived physically meaningful temporal descriptors for input into deep learning models [67]. In this way, time series deformation data can capture persistence, acceleration, seasonality, recovery, and pre-failure movement trajectories that static deformation proxies tend to obscure.

At the same time, deformation evidence must be interpreted cautiously. Line-of-sight geometry, shadowing, layover, coherence loss, vegetation cover, snow, atmospheric delay, and phase unwrapping uncertainty can all distort deformation estimates. Moreover, deformation is not equivalent to failure probability: some slopes deform persistently without catastrophic collapse, while others fail rapidly with limited pre-failure motion. Dynamic susceptibility models should therefore combine InSAR with rainfall, terrain, lithology, and land-system information rather than treating deformation as susceptibility itself.

3.2.3. Optical Image Time Series and Land-System Regulation

Land-use and land-cover (LULC) are among the most widely used environmental factors in landslide susceptibility assessment because they reflect both surface cover conditions and human land development activities, both of which exert important controls on slope stability [68]. It should be noted, however, that land-cover and land-use are not identical concepts. The former refers to the biophysical characteristics of the Earth's surface, such as vegetation, bare soil, water bodies, and built-up areas, whereas the latter describes the ways in which land is used by humans, including agriculture, urban expansion, infrastructure construction, and mining activities. This distinction is particularly important in dynamic susceptibility assessment because land-cover change and land-use change may influence slope instability through different mechanisms and timescales. In conventional static landslide susceptibility assessment, LULC is commonly represented by a single-date classification map or by a derived spectral index, such as the normalized difference vegetation index, and is implicitly assumed to remain unchanged during the assessment period [69–72]. Such simplification is increasingly inadequate under rapidly changing environmental conditions. Substantial LULC change may occur within only

a few years [73], potentially leading to pronounced variations in both the intensity and spatial pattern of landslide susceptibility. With advances in remote sensing and machine learning, increasing attention is therefore being given to the role of dynamic LULC change in landslide development [74,75].

Optical image time series provide an important observational basis for representing such changes. Medium- to high-resolution satellite imagery from Landsat [76], Moderate Resolution Imaging Spectroradiometer (MODIS) [77], and other optical platforms enables repeated observation of vegetation dynamics, surface disturbance, bare-soil exposure, built-up expansion, and land-cover transitions. In dynamic landslide susceptibility assessment, these observations are valuable not merely because they update surface information, but because they allow land-system regulation to be represented as a temporally evolving process. For example, time series vegetation indices such as NDVI can be used to describe vegetation degradation, seasonal fluctuation, and post-disturbance recovery, whereas multi-temporal land-cover maps can reveal the expansion of roads, settlements, cultivated land, or engineering activities that modify local hydrological and mechanical slope conditions [78].

The influence of LULC change on landslide susceptibility can be understood through two main pathways. One relates to urban expansion and engineering construction, which are commonly accompanied by vegetation removal, slope cutting, and increased road infrastructure; together, these processes intensify anthropogenic disturbance and may directly reshape local instability patterns [79–81]. The other relates to vegetation change, as shifts in forest, grassland, and shrub cover can modify root reinforcement, soil structure, and runoff regulation, thereby indirectly influencing slope stability [82–84].

From this perspective, the significance of optical remote sensing time series lies not simply in replacing outdated LULC layers, but in revealing how slope predisposition is reorganized by evolving human–environment interactions. Dynamic LULC information helps bridge the gap between static environmental characterization and temporally evolving landscape processes. However, the use of optical image time series also introduces several methodological challenges. Cloud contamination, seasonal phenological variation, spectral confusion among land-cover classes, and classification uncertainty may all affect the reliability of dynamic factors.

3.2.4. Multi-Temporal Terrain Observations and Geomorphic Memory

Topography is widely regarded as a fundamental controlling factor in landslide susceptibility, and conventional studies generally rely on the static assumption that terrain remains unchanged during the assessment period. Under this assumption, a DEM and its derived variables, such as slope and curvature, are typically treated as fixed inputs to susceptibility models [85–87]. However, growing evidence suggests that geomorphic reconfiguration, erosion–deposition transitions, large-scale material redistribution triggered by strong earthquakes, and human engineering disturbance may all introduce a pronounced temporal dimension to the terrain itself [88]. Li et al. [89] demonstrated, using multi-temporal DEMs, that terrain differences across time periods can substantially alter landslide susceptibility zonation results and recommended that DEM data be matched as closely as possible to the study period. Liu et al. [90] further suggested that static models relying only on present-day topographic conditions may overlook the cumulative effects of historical terrain evolution, thereby leading to overestimation or underestimation of susceptibility. Within dynamic assessment frameworks, topographic evolution therefore represents not merely an update of background data, but a key expression of long-term instability accumulation, geomorphic threshold migration, and trajectories of environmental recovery or degradation.

In terms of data sources, information on topographic evolution is derived primarily from multi-temporal DEMs, digital surface models (DSMs), and their differencing products, commonly referred to as DEMs of difference (DoD). Frequently used sources include airborne light detection and ranging (LiDAR), structure-from-motion and multi-view stereo reconstructions based on unmanned aerial vehicle imagery or historical aerial photographs, and other multi-temporal photogrammetric products. Fernández et al. [91] used multi-temporal aerial photographs and LiDAR data from 1984 to 2016 to construct DSM and DoD products, through which landslide activity was identified over a 32-year period and its type, morphology, and activity state were characterized. Azmoon et al. [92] further showed that, after rigorous co-registration and threshold filtering, multi-temporal high-resolution LiDAR DEMs can effectively extract vertical displacement and surface deformation information and noted that annual-scale terrain acquisition is more suitable for capturing actual post-landslide topographic change.

At present, the role of topographic evolution in dynamic landslide susceptibility assessment is mainly reflected at two levels. First, it allows derived variables such as slope and curvature to be updated so that susceptibility models can reflect the actual geomorphic state of different periods. Second, change metrics, including DoD, surface uplift or incision, and local erosion–deposition intensity, can be introduced directly as time-varying explanatory variables into dynamic models to characterize slope evolution trajectories [93,94]. It should be noted, however, that most existing studies still use topographic evolution primarily for landslide detection, inventory updating, and activity analysis, whereas its systematic integration into dynamic landslide susceptibility prediction frameworks remains relatively limited. Future studies could address this gap by transforming geomorphic change products into explicit dynamic predictors. For example, DoD-derived erosion and deposition rates can be encoded as time-varying node or edge attributes in graph-based models to represent terrain reorganization and sediment connectivity. Multi-temporal LiDAR or UAV-derived displacement and incision metrics can also be coupled with physically based shallow slope stability models to update local stability conditions. Such pathways would allow geomorphic memory to contribute directly to susceptibility updating rather than remaining limited to landslide detection, activity analysis, or inventory refinement.

Collectively, geomorphic change products contribute something that many other observation domains cannot: a record of geomorphic memory. They capture how past disturbances reorganize terrain and thereby condition the future spatial pattern of slope predisposition. However, transforming multi-source, multi-temporal DEM data into reliable dynamic factors remains constrained by substantial remote sensing-related challenges. The foremost difficulty lies in the accurate co-registration of multi-temporal terrain data: even centimeter-scale horizontal or vertical alignment errors may be amplified in DoD calculations into pseudo-deformation noise comparable in magnitude with actual topographic change, thereby seriously interfering with feature learning in dynamic models. Additional uncertainty may also arise from differences in point-cloud filtering and interpolation algorithms among sensors such as optical photogrammetry and LiDAR.

As summarized in Table 2, the major observation domains used in dynamic landslide susceptibility differ not only in what they measure, but also in the process roles they represent and the risks they introduce when misinterpreted. Dynamic susceptibility therefore depends not simply on adding more temporally explicit variables, but on transforming heterogeneous observations into process-consistent representations.

Table 2. Remote sensing data streams for dynamic landslide susceptibility assessment.

Remote Sensing Data Stream	Typical Products or Sensors	Temporal Resolution or Update Frequency	Dynamic Factors	Process Role	Main Limitations
Satellite precipitation and soil moisture proxies	TRMM, GPM-IMERG, CMORPH, SMAP, SMOS, ERA5-Land	Sub-daily to daily; several days for some soil moisture products	Rainfall intensity, duration, antecedent accumulation, wetness proxies	Transient hydrometeorological forcing	Retrieval bias in mountains; coarse spatial support; shallow sensing depth; mismatch with failure timing
SAR/InSAR time series	Sentinel-1, ALOS/PALSAR; SBAS, PS, DS InSAR	Days to weeks; often aggregated monthly or seasonally	Velocity, acceleration, persistence, seasonal deformation, recovery	Kinematic state and response	LOS limitation; layover/shadowing; decorrelation; atmospheric delay; deformation–failure ambiguity
Optical image time series	Landsat, Sentinel-2, Planet and related products	5–16 days; seasonal or annual for land-cover products	NDVI/EVI, LULC transition, disturbance frequency, road/urban expansion	Land-system and ecological regulation	Cloud contamination; phenological effects; classification uncertainty; causal ambiguity
Terrain observations	Multi-temporal DEM, LiDAR, DSM, DoD	Event-based, annual, or multi-year	Slope/curvature updates, erosion, deposition, terrain displacement	Geomorphic memory and reorganization	Low revisit frequency; co-registration error; vertical uncertainty; differencing noise

3.3. Spatiotemporal Learning for Remote Sensing-Driven Dynamic Susceptibility

The scientific difficulty of dynamic landslide susceptibility assessment does not lie only in acquiring multi-source remote sensing observations but also in representing them in a way that preserves temporal order, spatial connectivity, global dependency, and process meaning. Hydrometeorological forcing, slope deformation, land-cover change, and terrain reorganization are observed at different spatial resolutions, temporal frequencies, and physical supports. If these heterogeneous signals are simply resampled and stacked as generic predictors, the resulting model may appear dynamic in terms of input variables but remain static in its inferential logic. Mapping unit choice directly affects dynamic inference. Pixel-based frameworks are suitable for raster time series inputs, such as precipitation grids, optical sequences, and InSAR deformation stacks, and allow susceptibility to be updated as a continuous surface. In contrast, slope unit-based frameworks are more geomorphically interpretable and can aggregate rainfall, deformation, land-cover change, and terrain evolution metrics within terrain process units. They also provide natural nodes for graph-based models, where edges can represent adjacency, hydrological connectivity, lithological similarity, or deformation correlation. Therefore, mapping unit selection should be consistent with temporal feature construction, graph topology, and the intended logic of susceptibility updating.

Accordingly, spatiotemporal learning for remote sensing-driven dynamic susceptibility should not be understood merely as the replacement of conventional models by more complex algorithms. Rather, it requires representational frameworks capable of encoding ordered forcing–state–response sequences, capturing topological relationships among slope units or terrain elements, modeling nonlocal dependencies and multimodal interactions, and integrating these complementary capacities into unified inference frameworks. In this review,

these methods are grouped into three major representational directions: temporal encoding, topological representation, and global dependency modeling, which can be further integrated through hybrid or unified frameworks for dynamic susceptibility inference (Figure 4).

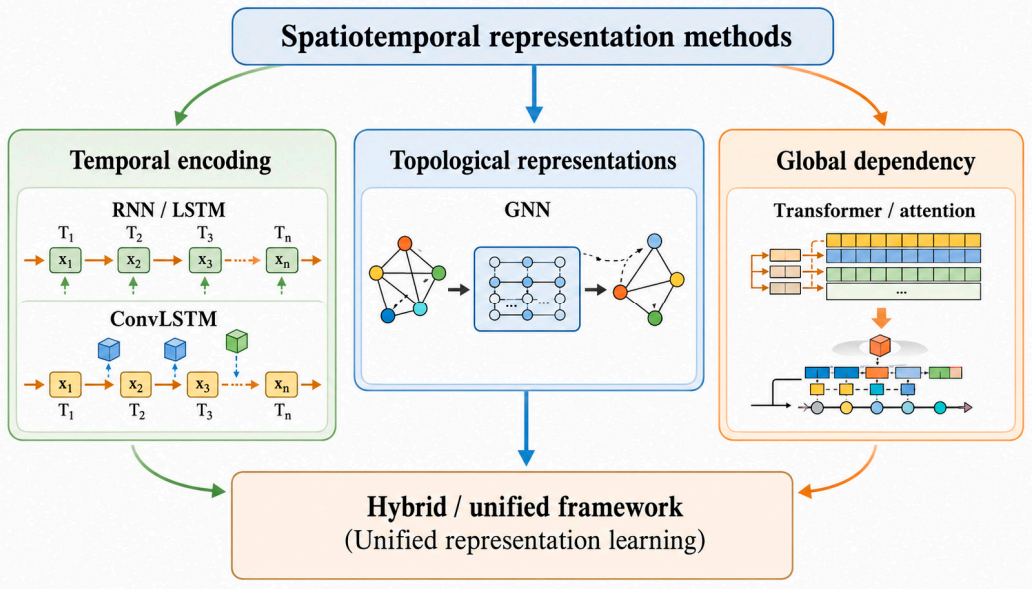


Figure 4. Spatiotemporal learning architectures for remote sensing-driven dynamic landslide susceptibility.

3.3.1. Conventional Models as Static and Semi-Dynamic Baselines

The core objective of landslide susceptibility assessment is to establish the relationship between environmental factors and landslide occurrence. According to their underlying modeling principles, existing approaches are generally classified into three categories: knowledge-driven, physically based, and data-driven models [95]. Knowledge-driven models [96] rely primarily on expert judgment and combine conditioning factors through approaches such as weighted overlay or fuzzy logic. These models are suitable for rapid assessment in data-scarce regions and offer a certain degree of interpretability, although they remain strongly subjective. Physically based models [97] simulate slope behavior on the basis of engineering geological and mechanical principles. While they provide explicit mechanical meaning and enable detailed interpretation of landslide processes, they require extensive geotechnical parameters, whose uncertainty is often substantial at the regional scale. Data-driven models have become the dominant paradigm in landslide susceptibility mapping because of their ability to capture nonlinear relationships between landslide occurrence and multiple environmental factors [98]. Representative methods include random forest (RF) [99], logistic regression (LR) [100], support vector machine (SVM) [101], convolutional neural networks (CNNs) [102], and artificial neural networks (ANNs) [103]. These models have substantially improved the flexibility and predictive performance of susceptibility assessment, especially when combined with remote sensing-derived topographic, spectral, deformation, and land-cover variables.

However, most conventional models do not inherently represent temporal order or spatial dependence. When time-varying remote sensing variables are reduced to summary statistics and stacked as ordinary predictors, dynamic information may be lost. Such models can be described as semi-dynamic when they use updated factors, but they do not fully infer the evolution of susceptibility through ordered observations.

3.3.2. Temporal Encoding of Forcing, State, and Lagged Response

The first requirement of dynamic landslide susceptibility assessment is temporal encoding. Landslide occurrence commonly exhibits cumulative and lagged effects, as reflected

in antecedent rainfall accumulation, variations in soil moisture, vegetation degradation or recovery, and the progressive evolution of surface deformation. The central task is therefore not merely to input time series observations, but to encode them in a way that allows the model to infer persistence, accumulation, recovery, acceleration, and pre-failure evolution.

From this perspective, recurrent sequence models are important not simply because they constitute a class of high-performance algorithms, but because they provide a formal mechanism for representing temporal dependence. Recurrent neural networks (RNNs) [104], through recurrent connections, provide a basic architecture for sequence representation and are therefore useful for learning short-range temporal dependencies in landslide-related signals [105,106]. Long short-term memory (LSTM) networks [107] extend this capability by introducing memory cells and gating mechanisms, making them better suited to representing long-range dependencies, cumulative forcing, and delayed slope response, including antecedent rainfall effects, slow deformation, soil moisture variation, and persistent vegetation change [108,109]. Convolutional long short-term memory (ConvLSTM) [110] further generalizes this temporal encoding framework to regularly gridded remote sensing data by incorporating convolutional operations into recurrent units. This design allows spatial neighborhood structure to be preserved during temporal recursion. ConvLSTM is therefore particularly suitable for satellite precipitation grids, optical image sequences, InSAR deformation map stacks, and other raster-based observations in which temporal evolution and local spatial organization need to be represented simultaneously [111–113].

The methodological significance of these temporal models lies not simply in improved predictive accuracy, but in their ability to transform evolving environmental observations into inferable process trajectories. In other words, their main contribution is to move dynamic susceptibility beyond repeated static mapping at separate time slices and toward explicit inference over ordered sequences of forcing, state, and lagged response. For remote sensing-driven dynamic susceptibility, this means that rainfall, deformation, vegetation, and land-surface observations are no longer treated only as isolated predictors, but as temporally structured evidence of changing slope predisposition. However, LSTM and ConvLSTM models may overfit when multi-temporal landslide inventories are sparse or temporally coarse. This risk can be reduced through geomorphically informed transfer learning, physics-guided sample augmentation, and lightweight sequential architectures. Transfer learning can fine-tune models from data-richer source regions to target areas with similar terrain, lithology, triggering regimes, and environmental conditions [114]. Physics-guided augmentation can generate plausible rainfall–soil moisture–deformation sequences rather than relying only on unconstrained resampling [115,116]. Lightweight recurrent units, shallow ConvLSTM variants, or temporal convolutional modules can further reduce parameter demand and improve generalization in inventory-sparse regions.

3.3.3. Graph-Based Topological Representation and Slope Connectivity

Temporal encoding alone is insufficient because landslide predisposition is organized not only through time, but also through space. Slope instability is shaped by geomorphic position, hydrological pathways, lithological boundaries, slope unit adjacency, road disturbance, and engineering modification. These conditions generate spatial autocorrelation and topological dependence that cannot be fully represented by models assuming independent grid cells or isolated terrain units. Dynamic susceptibility assessment must therefore explicitly incorporate relational structure into the inference process.

Graph-based methods provide a formal representation of irregular spatial units and their interconnections. Slope units, grid cells, catchments, monitoring points, or road-influenced terrain segments can be encoded as nodes, while edges can be defined by spatial

adjacency, hydrological connectivity, terrain similarity, lithological continuity, deformation correlation, or anthropogenic disturbance pathways. Graph neural networks (GNNs) [117] allow susceptibility to be inferred not only from local attributes, but also from relational structure among connected terrain elements. When satellite precipitation, soil moisture, InSAR deformation, optical land-cover change, vegetation dynamics, or geomorphic change indicators are introduced as dynamic node or edge attributes, the graph can be extended into a dynamic relational framework capable of representing how instability propagates, clusters, or reorganizes across connected slope systems [118–120].

The scientific value of GNNs depends critically on graph construction. The choice of nodes determines the spatial support of inference, whereas edge definition determines which forms of connectivity become learnable. A graph based only on geometric adjacency may overlook downslope hydrological routing, road-induced disturbance, or deformation coherence. However, while this theoretical sensitivity is well established, rigorous empirical comparisons—such as ablation studies quantifying the differences in dynamic susceptibility outputs across alternative edge definitions (e.g., geometric versus hydrological versus deformation-based)—remain largely unaddressed in the current literature. Although recent static susceptibility studies have begun comparing topological strategies [115], the empirical validation of how different graph topologies shape dynamic updating represents a significant, unaddressed gap. Accordingly, GNNs should not be regarded merely as another model family to be benchmarked against alternatives, but as an inference framework where explicit testing of topological designs represents a critical frontier for future research.

3.3.4. Global Dependency Modeling and Multimodal Fusion

The dependencies involved in dynamic landslide susceptibility assessment are not always local in either time or space. Regional rainfall organization, broad geomorphic setting, vegetation change, deformation anomalies, land-cover transitions, and human disturbance may interact across locations, scales, and observation modalities. Such interactions cannot always be represented adequately through short temporal windows, local convolutional operations, or neighborhood-based graph structures alone. This creates a further requirement for dynamic susceptibility assessment: the ability to represent global dependence and fuse heterogeneous remote sensing observations within a coherent feature space.

Transformers and attention-based mechanisms are especially relevant in this context because they provide flexible means of modeling nonlocal interactions and cross-source relationships [121]. Self-attention can establish dependencies among distant terrain units, different variables, and different temporal slices at relatively early stages of representation learning. Spatial, temporal, and channel attention can also help identify which locations, time windows, or observation streams are most informative for evolving landslide predisposition [122,123]. This is particularly useful when integrating satellite precipitation, InSAR deformation, optical land-cover information, vegetation dynamics, and terrain change indicators, because these data differ substantially in spatial resolution, temporal frequency, physical meaning, and uncertainty structure.

Nevertheless, attention-based models should not be interpreted as automatic solutions to multimodal fusion. Attention weights do not necessarily provide causal explanations, and high model complexity may increase the risk of overfitting when landslide inventories are sparse or temporally coarse. In addition, optical cloud contamination, InSAR decorrelation, precipitation retrieval bias, and DEM co-registration uncertainty may all propagate into the fused representation. Therefore, Transformers and attention mechanisms are best understood not as isolated alternatives in a model comparison exercise, but as tools for scale-bridging, global dependency modeling, and cross-modal inference. Their value is greatest when the

aim is to infer how large-scale environmental organization and heterogeneous remote sensing signals jointly shape the temporal reconfiguration of slope predisposition.

3.3.5. Hybrid/Unified Frameworks

As shown in Table 3, the models discussed above are not mutually substitutive; rather, each addresses a distinct representational problem in dynamic landslide susceptibility assessment. Temporal models are effective for encoding sequential dependence, cumulative forcing, and lagged response. Graph-based approaches are well suited to representing topology, adjacency, and slope connectivity. Transformers and attention-based mechanisms are particularly useful for capturing global dependence and multimodal interaction. The central issue is therefore no longer which individual model performs best in isolation, but how these different representational capacities can be integrated into a coherent spatiotemporal inference framework.

Table 3. Comparative suitability of representative model families for different data structures.

Model	Best Suited Problem	Strength	Main Caveat
RNN/LSTM/ConvLSTM	Sequential forcing or state evolution	Captures temporal order, cumulative effects, and lagged response	Weak explicit handling of irregular spatial connectivity; high overfitting risk and data demand in inventory-sparse regions
GNN	Slope unit or connectivity-aware systems	Represents topology and irregular spatial interaction	Strongly dependent on node and edge construction
Transformer/Attention	Heterogeneous multimodal inputs and nonlocal dependencies	Models global dependency and cross-modal feature weighting	High data demand; attention weights are not necessarily causal explanations
Hybrid/Unified framework	Integrated dynamic inference and map updating	Combines temporal encoding, topology, multimodal fusion, and updating capacity	Requires careful scale alignment, uncertainty handling, and physical consistency

This shift toward integration is already evident in existing studies. He et al. [124], for example, incorporated pixel-level temporal features and neighborhood information in parallel within a single network, thereby accounting simultaneously for temporal dependence and local spatial structure. Huang et al. [125], through a hybrid Conv-SE-LSTM architecture, combined convolution, recurrent modeling, and attention-based feature reweighting to jointly represent local spatial patterns, temporal evolution, and variable importance. More recent hybrid studies further suggest that architectures integrating temporal encoding with topological or global dependency modeling may outperform individual component models because they are better able to reconcile multiple process dimensions within a unified framework [126–129].

For remote sensing-driven dynamic susceptibility assessment, however, hybridization should not be understood as the simple stacking of multiple model modules. A meaningful unified framework should organize different observation streams according to their process roles: rainfall and soil moisture as transient forcing, InSAR deformation as state or response evidence, optical land-cover and vegetation dynamics as medium-term regulation, and multi-temporal terrain products as geomorphic memory. Looking ahead, effective unified frameworks should accommodate asynchronous updating, heterogeneous spatial and temporal resolutions, uncertainty propagation, and continuous revision of susceptibility patterns as new Earth observation data become available. More broadly, the field is shifting

away from competition among individual architectures and toward process-consistent, uncertainty-aware, and physically interpretable spatiotemporal learning.

3.4. Spatiotemporal Generalization and Validation Logic

Validation should not be treated as a routine post-modeling step in dynamic landslide susceptibility assessment but as a direct test of whether inferred susceptibility patterns possess genuine spatiotemporal generalization capability. Unlike conventional static studies, which often rely on random training–testing splits and emphasize classification accuracy at a single time slice, dynamic assessment must evaluate whether a model can extrapolate across time, remain robust under spatial separation, and update susceptibility patterns in a physically and observationally consistent manner. The central issue is therefore no longer accuracy alone, but the credibility of dynamic inference.

This distinction is important because random partitioning can substantially overestimate model performance when spatial autocorrelation and temporal dependence are not controlled [130]. If training and testing samples are located in close spatial proximity, or if samples collected before and after the same landslide event are simultaneously involved in model development and validation, the model may benefit from shared local context or temporal leakage rather than genuine predictive skill. As a result, commonly reported metrics such as area under curve (AUC), receiver operating characteristic (ROC)-based indices, F1-score, and recall may appear favorable while masking limited transferability to new times, new locations, or new environmental conditions. Validation must therefore be designed to test independence, extrapolation, and update reliability rather than merely sample-level discrimination.

From this perspective, a credible validation framework should address at least three complementary dimensions of model generalization (Figure 5). The first is leave-one-period-out validation [131,132], in which a model is trained on earlier multi-temporal data and tested on subsequent periods or independent events in order to evaluate its temporal extrapolation capability. The second is spatiotemporal cross-validation [133], in which both spatial proximity and temporal leakage are controlled so that inflated accuracy caused by locally similar samples can be avoided. The third is event-level transferability [134,135], which assesses whether an existing susceptibility model can meaningfully anticipate newly occurred landslides, post-event inventories, or subsequently observed instability signals. Retrospective validation and independent-event validation are particularly valuable because they test model performance against real future events rather than re-partitioned historical samples [136]. Operationally, spatial buffers should be selected according to mapping resolution, landslide size, and spatial autocorrelation, with sensitivity tests across several pixels, landslide lengths, or slope unit widths. Temporal separation should exceed the longest lag or aggregation window used to construct dynamic predictors. In event-level transferability tests, spatial overlap between historical and newly compiled inventories should be removed, buffered, or treated as reactivated known instability rather than independent new test samples.

For remote sensing-driven dynamic susceptibility assessment, validation should also examine the rationality of map updating. Metrics such as AUC, F1-score, recall, and precision remain useful [130], but they are insufficient on their own. A dynamically updated susceptibility map should evolve in a temporally plausible way, and high-susceptibility zones should migrate consistently with newly observed rainfall anomalies, InSAR deformation, land-cover disturbance, vegetation degradation or recovery, and terrain reorganization. More importantly, such changes should correspond to subsequent landslide occurrence, newly mapped post-event inventories, or independently observed instability signals. In frameworks enhanced by InSAR or multi-source Earth observation, the focus is gradu-

ally shifting from whether a model correctly classifies samples at one moment in time to whether it can revise earlier misjudgments and progressively reduce false negatives and false positives as new observations become available [137]. Our supplementary audit of the 583-paper focused corpus indicates that this validation dimension remains rarely evaluated. Only 54 studies (9.3%) explicitly assessed whether updated susceptibility patterns were consistent with subsequent landslide occurrence, independent instability evidence, or process-relevant remote sensing signals. In contrast, most studies continued to rely primarily on random splits or conventional accuracy metrics, confirming that update rationality remains an under-addressed validation gap in the current literature. To make the evaluation of update rationality more operational, future studies should combine conventional accuracy metrics with indicators that directly describe map revision [98,138,139]. Predictive improvement can be assessed using changes in AUC, F1-score, precision–recall AUC, Brier score, or calibration error [140–142]. Event correspondence can be evaluated by testing whether newly mapped landslides or independent instability signals are concentrated in areas where susceptibility increases, using landslide density ratios, success rate curves, enrichment factors, permutation tests, or chi-square tests [25,138,139]. Process consistency can be further examined by correlating susceptibility changes with dynamic explanatory signals, such as rainfall anomalies, InSAR-derived acceleration, vegetation degradation, land-cover disturbance, or DEM-of-difference metrics, using Spearman/Kendall correlation or spatial regression [132,143,144]. In addition, the reduction of false negatives and false positives after updating can be used to quantify error revision. These indicators provide a more explicit basis for judging whether map updating is statistically improved, observationally supported, and process-consistent.

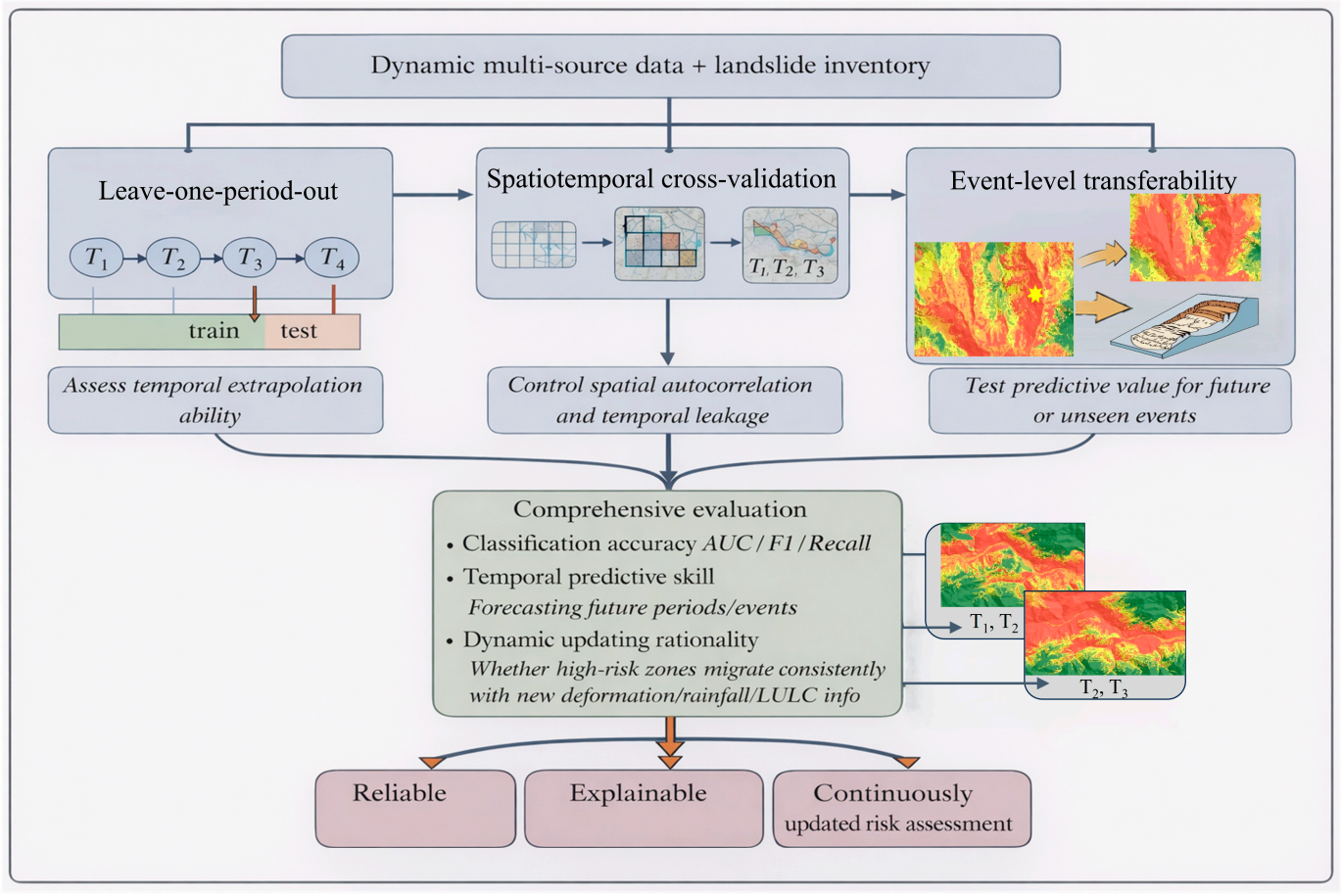


Figure 5. Spatiotemporal generalization and validation framework.

More broadly, validation is evolving from random accuracy testing toward a logic centered on spatiotemporal generalization and update rationality. What must ultimately be demonstrated is not simply that a model fits historical samples well, but that it preserves predictive credibility under temporal extrapolation, spatial separation, independent-event testing, and continuous data updating. In this sense, validation is inseparable from the broader representational and inferential framework of dynamic susceptibility: only when a model can generalize across space and time and update its outputs in a process-consistent way can its inferred susceptibility patterns be considered scientifically meaningful.

4. Discussion

Remote sensing-enabled dynamic susceptibility assessment is advancing rapidly, but the field remains methodologically immature. The major bottlenecks are no longer simply the lack of data or algorithms. They concern the fidelity of landslide evidence, the compatibility of heterogeneous remote sensing observations, the depth of multimodal fusion, and the physical credibility of dynamic map updating.

4.1. Inventory Fidelity and Uncertainty in the Evidence Base

Landslide inventories constitute the primary evidence base for landslide susceptibility modeling [145,146]. They may contain a unique identifier for each landslide, together with information on landslide type, movement status, occurrence time, geometry, and associated material properties [147,148]. In dynamic landslide susceptibility assessment, however, inventories are required to do more than indicate where landslides have occurred. They must also provide sufficiently reliable information on when landslides occurred and whether their spatial distribution can be aligned with the temporal evolution of remote sensing observations. This requirement makes inventory uncertainty more consequential under dynamic conditions than in conventional static assessment [149,150].

Inventory incompleteness and spatiotemporal mismatch are among the most important sources of uncertainty. Many inventories remain cumulative rather than event-resolved, and occurrence times are often recorded only coarsely or not at all. This makes it difficult to align landslide occurrence with short-term triggering signals such as rainfall, seismic shaking, rapid deformation change, or abrupt land-cover disturbance [151]. As a result, the central difficulty is not simply sample scarcity, but the lack of temporally faithful supervision for dynamic inference. This problem is further compounded by spatial incompleteness. In densely vegetated, remote, or high-relief terrain, landslides may be under-recorded or sparsely labeled, producing spatial bias in the evidence base [152]. Such bias affects not only static susceptibility patterns, but also the model's ability to learn how slope predisposition evolves across different geomorphic and environmental settings [153].

For remote sensing-driven dynamic susceptibility assessment, inventory compilation strategy is also critical. Multi-temporal optical imagery, SAR/InSAR observations, UAV surveys, and post-event interpretation can improve landslide detection and temporal attribution, but they may also introduce sensor-specific uncertainties related to cloud contamination, vegetation concealment, image resolution, deformation detectability, and interpretation consistency. The issue is therefore not only whether inventories are complete [154], but whether they are temporally, spatially, and process-wise compatible with the dynamic phenomena that the model is expected to represent.

A related source of uncertainty concerns negative-sample construction. In dynamic settings, the historical absence of a mapped landslide at a given location cannot be equated with stability under changing forcing or disturbance conditions [155]. Random or heuristic negative-sample selection may therefore contaminate the training set with potentially unstable sites, particularly under extreme rainfall, progressive deformation, vegetation degradation, or

evolving anthropogenic disturbance [156]. This issue is especially important when susceptibility maps are updated through time, because locations treated as non-landslide samples in one period may become unstable in a later period. To address this issue, future studies should explore dynamic negative sampling strategies in which candidate non-landslide samples are re-evaluated or excluded at time steps when new landslides are mapped or when dynamic predictors, such as rainfall anomalies, InSAR-derived acceleration, or land-cover disturbance, indicate increasing instability. In addition, temporal weighting schemes can be adopted to assign lower confidence weights to older negative samples or to samples located in environmentally transitioning zones. In this way, the model's definition of "non-landslide" can adapt to evolving slope conditions rather than implicitly assuming permanent stability. Table 4 summarizes the major sources of inventory-related uncertainty and their implications for dynamic landslide susceptibility assessment.

Table 4. Uncertainty in landslide samples.

Source	Specific Manifestation	Implications
Missing or coarse temporal labels	Only the year of occurrence is known, or no occurrence time is recorded	Landslide occurrence cannot be reliably aligned with rainfall, deformation, land-cover disturbance, or other time-varying observations
Spatial sampling bias	Landslides are concentrated along roads, settlements, or easily accessible areas	Model performance may be overestimated in well-mapped areas but remain weak in remote, vegetated, or high-relief terrain
Inventory incompleteness	Small, shallow, or vegetation-covered landslides are under-recorded	Susceptibility patterns may be biased toward easily detectable landslide types or sensor-favorable environments
Negative-sample contamination	Potentially unstable locations are labeled as non-landslide samples	Discriminative ability is weakened, especially where susceptibility changes under later forcing or disturbance

4.2. Heterogeneity in Multi-Source Remote Sensing Data

Dynamic landslide susceptibility assessment relies on the continuous observation of an evolving surface environment, and multi-source remote sensing provides the essential basis for this objective. However, the main challenge is not simply that different sensors have different strengths and weaknesses, but that they observe the landscape through fundamentally different spatial, temporal, and physical lenses. Optical imagery records surface reflectance and land-cover information at relatively high spatial resolution but is vulnerable to cloud cover and seasonal data gaps [157]. SAR supports all-weather observation and is uniquely valuable for deformation monitoring, yet its products may degrade in steep or densely vegetated terrain [13]. LiDAR offers highly accurate terrain information, but its revisit frequency and acquisition cost often limit its use in routine dynamic monitoring [158].

The key issue, therefore, is representational incompatibility across scales and modalities. Dynamic susceptibility models increasingly attempt to combine sub-meter imagery, daily or sub-daily meteorological information, monthly deformation observations, and longer-term terrain or land-cover changes within a single framework [159]. Yet these observations do not share a common temporal support, spatial footprint, or process meaning. Rainfall provides the clearest example: information relevant at hourly or daily scales for triggering processes may not be equivalent to the monthly [160] or seasonal summaries more appropriate for broader environmental characterization [161]. Without explicit mechanisms for temporal alignment, scale reconciliation, and role-sensitive encoding, such data

fusion risks collapsing fundamentally different kinds of evidence into a nominally unified but conceptually unstable feature space.

Multimodal fusion in dynamic susceptibility assessment is therefore better understood as an unevenly developed frontier rather than as a uniformly shallow practice. Earlier studies often relied on feature stacking, weighted overlay, conditional matrices, or post hoc map combination, which can incorporate multiple data sources but cannot fully model cross-source interactions [162]. More recent studies have begun to explore deeper fusion architectures, including sliding-window deformation features, CNN–LSTM or ConvLSTM-based spatiotemporal encoding, attention-based feature reweighting, graph-based integration, and hybrid frameworks that jointly represent temporal evolution and spatial structure [65,124–129]. These approaches show that the field is moving beyond simple feature stacking. However, they remain comparatively limited relative to the wider corpus and are not yet routinely coupled with explicit scale alignment, process role separation, uncertainty propagation, or update rationality validation. Future research should therefore focus less on adding more data streams and more on developing representation-learning frameworks that can adaptively align heterogeneous inputs across spatial supports, temporal frequencies, physical meanings, and uncertainty structures.

Uncertainty in remote sensing-driven dynamic susceptibility assessment should therefore be understood as a propagation chain rather than as isolated sensor error [99,156,163,164]. At the remote sensing inversion stage, precipitation retrieval bias, InSAR atmospheric delay, optical classification uncertainty, and DEM co-registration error may affect the reliability of primary observations. Although atmospheric correction products such as ERA5 can reduce InSAR atmospheric delay, residual errors may persist in steep mountainous terrain because of DEM errors and unresolved local microclimatic effects. During feature extraction, these uncertainties can be transferred or amplified through temporal aggregation, spatial resampling, normalization, thresholding, and lag window construction. For example, InSAR coherence threshold selection involves a direct trade-off between spatial coverage and phase noise, while the choice between PS and DS processors critically determines time series reliability in sparsely vegetated landslide-prone regions; similarly, the threshold for optical cloud masking or the lag window for antecedent rainfall can dictate the quality and physical consistency of dynamic features. At the model training stage, inventory incompleteness, temporally coarse landslide labels, negative-sample contamination, class imbalance, and temporal leakage may further distort the learned relationship between dynamic predictors and landslide occurrence. During dynamic updating, the accumulated uncertainty may finally influence the direction, magnitude, and spatial coherence of susceptibility changes. Future frameworks should therefore report uncertainty at each stage, propagate it through the modeling workflow where possible, and express updated susceptibility maps together with uncertainty layers or sensitivity analyses. In practice, this can be implemented through Bayesian uncertainty propagation, Monte Carlo dropout or Bayesian neural networks for estimating model uncertainty, and ensemble-based variance analysis for identifying whether uncertainty mainly arises from precipitation, InSAR, optical, terrain, or model structure choices [165–167]. In this way, dynamic susceptibility maps can be presented not only as probability surfaces, but also as probability–uncertainty products.

4.3. Physical Consistency and Interpretability in Dynamic Updating

Even when data-driven models achieve high predictive accuracy, their scientific and practical value in dynamic susceptibility assessment remains limited if their outputs cannot be interpreted in physically credible terms. The fundamental concern is not only that deep learning models are often regarded as black boxes, but that purely statistical associations

may diverge from the actual processes governing slope failure. A model may identify strong correlations among rainfall, topography, vegetation, and landslide occurrence while failing to represent pore pressure evolution, effective stress change, subsurface flow concentration, or strength degradation [168]. Under unfamiliar climatic extremes or novel geomorphic settings, such models may therefore generate predictions that are numerically plausible but physically ungrounded.

This issue is especially consequential for dynamic landslide susceptibility assessment, because the goal is not simply to classify a slope as "stable" or "unstable" at a given moment but to infer how predisposition is progressively reorganized under continuously evolving forcing, slope state, and environmental regulation. Interpretability, therefore, should not be treated as an optional add-on to high-performing models, but as a fundamental requirement for credible dynamic inference. The growing importance of physics-informed machine learning stems from its capacity to embed physical knowledge—such as limit equilibrium theory [100,169], hydrological processes [170,171], and seepage mechanisms [172,173]—into learning architectures through loss function constraints, prior parameters, or mechanism-guided formulations, thereby reducing the risk that model outputs diverge from known laws of slope behavior. Physics-informed dynamic susceptibility can be strengthened through physical constraints with different data demands and regional applicability. Limit equilibrium or infinite slope models can provide factor-of-safety-related features or soft constraints and are relatively scalable for regional assessment, although soil strength and pore pressure parameters remain uncertain. Hydrological infiltration, pore pressure response, or rainfall threshold models are useful for rainfall-driven temporal updating but require temporally consistent hydrometeorological data. In contrast, seepage- or PDE-based constraints offer stronger process fidelity but usually require detailed hydraulic parameters and boundary conditions, making them more suitable for local slope studies or reduced-order regional applications. InSAR-derived deformation indicators can further serve as observational state constraints for checking whether susceptibility updates are consistent with evolving slope kinematics.

Explainable artificial intelligence provides a complementary means of evaluating whether model decisions are consistent with process understanding. Methods such as SHapley Additive exPlanations (SHAP) [174,175], Local Interpretable Model-agnostic Explanations (LIME) [176,177], and partial dependence plots (PDPs) [178] can help examine feature importance, local decision pathways, and variable–response relationships. For remote sensing-driven dynamic susceptibility, these tools are particularly useful for assessing whether updated predictions respond reasonably to rainfall anomalies, InSAR deformation, vegetation degradation or recovery, land-cover disturbance, and terrain reorganization. However, interpretability tools should not be equated with physical explanation; they can indicate whether model behavior is plausible, but they cannot by themselves prove causality.

Future progress will depend on tighter integration among multi-source remote sensing observations, physically based constraints, and interpretable learning strategies. The goal is not merely to produce more accurate models, but to develop dynamic susceptibility frameworks whose updates are traceable, process-consistent, and defensible under real-world decision-making conditions. In other words, the field should move toward models that are not only predictive, but also physically credible, interpretable, and scientifically auditable.

5. Conclusions

This review highlights that dynamic landslide susceptibility assessment should be understood not as a simple temporal extension of static mapping, but as a reframing of slope predisposition under environmental nonstationarity. Three main conclusions can be drawn. First, susceptibility is not a fixed spatial property; it evolves as hydrometeorological

forcing, slope state, land-system regulation, and geomorphic memory change through time. Second, multi-source remote sensing has made this reframing increasingly feasible by providing temporally explicit observations of rainfall forcing, InSAR deformation, optical land-cover dynamics, vegetation change, and terrain reorganization. Third, the scientific challenge is no longer only to add dynamic variables to existing models, but to transform heterogeneous Earth observation data into process-consistent spatiotemporal inference.

The reviewed literature demonstrates the promise of this transition but also reveals that the field remains structurally uneven. Dynamic variables are often incorporated without sufficient consideration of their process roles, temporal scales, spatial supports, or uncertainty structures. Similarly, model performance is still frequently evaluated through random accuracy testing, whereas dynamic susceptibility requires validation designs that explicitly test temporal extrapolation, spatial independence, event-level transferability, and update rationality. These limitations indicate that the next phase of progress will depend less on methodological novelty alone than on a tighter synthesis of multi-source Earth observation, geomorphic reasoning, inventory design, role-consistent multimodal encoding, physically interpretable learning, and scientifically credible validation.

If this synthesis is achieved, dynamic landslide susceptibility assessment can become more than a methodological extension of conventional susceptibility mapping. It can provide a process-oriented framework for understanding how unstable terrain reorganizes under climate extremes, human disturbance, and continuing geomorphic change, and for updating susceptibility patterns in a scientifically defensible manner as new remote sensing observations become available.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs18132153/s1, Table S1: Corpus construction logic used in the review; Table S2: Coding framework and category definitions used in the review; Figure S1: Annual publication output in the broader landslide susceptibility literature (2005–2025). The bars indicate the number of articles per year, and the line indicates the cumulative total; Figure S2: Global distribution of publication output in the broader landslide susceptibility literature; Figure S3: Annual publication output in dynamic landslide susceptibility research (2005–2025). The bars indicate the number of articles per year, and the red line indicates the cumulative total; Figure S4: Annual domain-specific distributions across the coded dynamic landslide susceptibility corpus, grouped into precipitation, land-system regulation, InSAR, and terrain/geomorphic change.

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Conflicts of Interest: Author Yu Zhao was employed by the company Xizang No.3 Geological Team Mineral Resources Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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