

Review

Advances in Deep Learning Applications for Slow Earthquake Research

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Abstract

Slow earthquakes represent an important mode of fault slip transitional between stable creep and dynamic rupture. Their occurrence is jointly controlled by mineral composition, pore-fluid pressure, effective normal stress, system stiffness, and microstructural evolution. Because the internal state of natural faults cannot be directly observed, studies of slow slip, tectonic tremor, and low-frequency earthquakes have long been challenged by weak signals, complex noise, and discrepancies in observational scales. Building on the physical foundations of rock friction and slip stability, this review summarizes recent applications of deep learning to laboratory friction and acoustic data, natural seismic waveforms, Global Navigation Satellite System (GNSS) observations, and strain measurements, with particular emphasis on event detection, fault-state estimation, rate-and-state friction parameter inversion, and forecasting of slip evolution. Existing studies have progressed from event identification to the reconstruction of shear stress, estimation of frictional parameters, and prediction of future fault states. Nevertheless, applications to natural faults remain dominated by event detection and catalog construction, whereas parameter inversion and forecasting still rely largely on laboratory experiments or synthetic data. Physics-informed neural networks, transfer learning, reduced-order modeling, and data assimilation provide promising pathways for integrating laboratory experiments, numerical simulations, and natural observations; however, their reliability remains limited by constitutive-model dependence, parameter non-uniqueness, domain shift, and insufficient independent validation. Future work should strengthen multi-observation integration, cross-region validation, and uncertainty quantification, while developing a bidirectional framework linking laboratory experiments, numerical simulations, and natural fault observations. At present, deep learning is better suited to fault-state characterization and probabilistic assessment of slip trends than to deterministic prediction of the exact timing of slow earthquakes.



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1. Introduction

Slow earthquakes are a class of fault-slip phenomena characterized by relatively long durations, low rupture velocities, and weak high-frequency seismic radiation. They mainly include slow slip events (SSEs), tectonic tremor, low-frequency earthquakes (LFEs), and very-low-frequency earthquakes (VLFs). These phenomena occur in shallow portions of

subduction zones, near the downdip limits of seismogenic zones, and at depth along active continental faults, and are commonly located adjacent to or partially overlapping the source regions of large earthquakes. Slow earthquakes contribute to strain release along plate boundaries and may modify the stress state of neighboring locked regions, making them important for understanding the continuum of fault-slip behaviors and the earthquake cycle [1–3].

Slow earthquakes cannot be attributed to a single mineralogical component or frictional parameter. Mineral composition establishes the material basis of fault friction, whereas temperature, pore-fluid pressure, effective normal stress, slip velocity, and system stiffness collectively regulate the stability boundary. Laboratory experiments have demonstrated that stable sliding, slow instability, and rapid stick-slip can transition continuously as frictional properties and loading conditions vary, and that clay-rich or serpentinite-rich materials may also enter regimes of slow instability under specific conditions [4–6]. Slow earthquakes are therefore more likely to arise within transitional regimes in which frictional weakening competes with dilatant strengthening, velocity strengthening, pressure-resolution processes, or viscoplastic dissipation, rather than being uniquely associated with a particular lithology.

The mineralogical structure, stress state, and frictional parameters of natural faults cannot be continuously measured in situ and must instead be inferred indirectly from seismic waveforms, GNSS displacements, strain observations, and laboratory acoustic signals. Slow-slip deformation is also commonly superimposed on seasonal signals, groundwater-related deformation, instrumental drift, and background noise, while tectonic tremor and LFEs cannot be regarded as direct equivalents of the total aseismic slip occurring on a fault. As illustrated in Figure 1, deep learning provides a means of linking observable signals to hidden fault states and can therefore be applied to event detection, state estimation, parameter inversion, and assessment of future slip trends. Its scientific value lies not merely in increasing detection rates, but in determining whether model outputs correspond to physically meaningful fault states that can be independently validated.

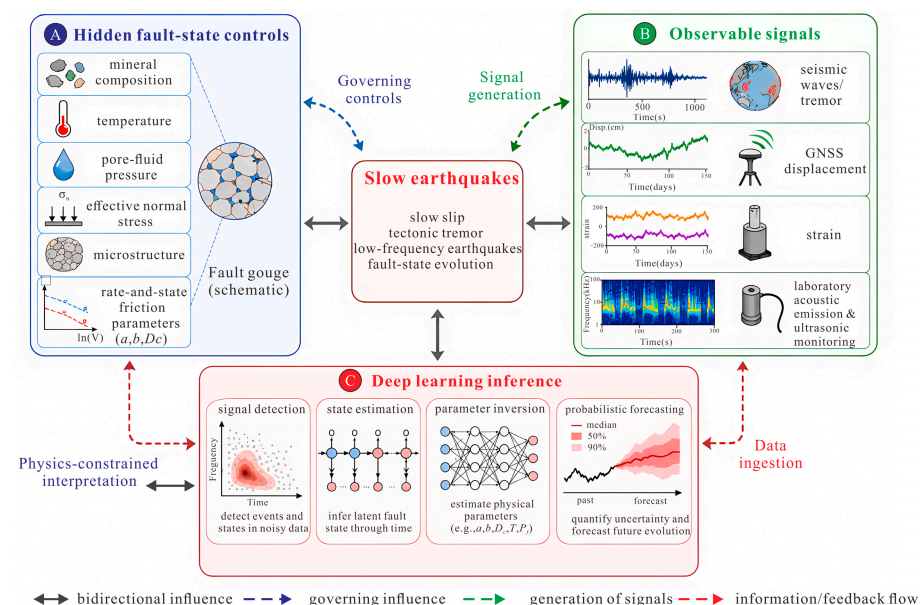


Figure 1. Conceptual framework linking observable signals, data-driven inference, and hidden fault states in slow-earthquake research.

In recent years, deep learning has been applied to the detection of tectonic tremor and LFEs, slow-slip catalog construction, reconstruction of frictional states, and analysis of future slip evolution [7–10]. Physics-informed neural networks, transfer learning, reduced-

order modeling, and data assimilation have further incorporated rate-and-state friction laws and fault dynamics into data-driven frameworks, allowing research to progress from signal classification toward the estimation of state variables and frictional parameters [11–15]. Nevertheless, a model may learn recurrence patterns, instrumental responses, or region-specific noise rather than fault physics, and the inclusion of physical equations does not automatically guarantee physically correct solutions. Model credibility therefore depends on whether the adopted constitutive relationships are appropriate, whether the parameters are sufficiently constrained by observations, and whether the results can be reproduced across independent experiments, time periods, and tectonic regions.

Against this background, this review begins with the mineralogical controls on rock friction and the physical basis of fault-slip stability. It then examines the characteristics of laboratory friction and acoustic data, as well as natural seismic, GNSS, and strain observations, before reviewing recent advances in slow-earthquake detection, fault-state estimation, friction-parameter inversion, and slip-trend forecasting. Finally, the roles and limitations of physics-constrained modeling, cross-domain transfer, reduced-order modeling, data assimilation, and cross-scale integration are discussed. Particular attention is given to the distinction between laboratory, synthetic, and natural-fault evidence, as well as to model validation, physical consistency, and the extent to which inferred fault states can be independently constrained.

2. Review Methodology and Literature Selection

The literature reviewed in this study was identified through searches of Web of Science, Scopus, ScienceDirect, and Google Scholar, supplemented by backward and forward citation tracking of key publications. The final literature search was conducted on 10 July 2026. Search terms related to slow fault slip, including “slow earthquake”, “slow slip event”, “tectonic tremor”, “low-frequency earthquake”, “very-low-frequency earthquake”, “fault slip”, and “laboratory earthquake”, were combined with methodological terms such as “machine learning”, “deep learning”, “neural network”, “Transformer”, “autoencoder”, “physics-informed neural network”, “transfer learning”, “reduced-order model”, “data assimilation”, “fault-state estimation”, and “friction parameter inversion”. Additional literature on rate-and-state friction, critical stiffness, fault gouge, frictional stability, pore-fluid effects, frictional healing, mineralogy, and microstructural evolution was examined where necessary to establish the physical basis for interpreting data-driven results. Classical studies were retained when they remained fundamental to frictional theory or slow-slip mechanics, whereas recent studies were emphasized when assessing developments in learning methods, observational datasets, model validation, and cross-domain applications.

Studies were included when they contributed directly to the detection of slow-earthquake-related signals, estimation of fault-state variables, inversion or constraint of frictional parameters, forecasting of slip evolution, or the physical interpretation of these processes. Studies with no direct relevance to slow fault slip or without transferable methodological or mechanistic information were excluded from the main synthesis. Because the reliability of inference differs substantially among laboratory experiments, numerical or synthetic models, and natural observations, evidence from these three domains was evaluated separately rather than treated as directly equivalent. Particular attention was given to the physical quantity being inferred, the source and quality of reference labels, the independence of training and validation data, uncertainty treatment, and consistency with fault mechanics. Detection, state estimation, parameter inversion, and forecasting were also distinguished because they represent progressively different levels of inference and therefore require different degrees of observational constraint and independent validation. The literature-selection process therefore followed three sequential stages: identification

through database and citation searches, screening for direct relevance to slow-earthquake research, and final inclusion based on methodological or mechanistic relevance to the objectives of this review.

3. Frictional Physics Underlying Slow Earthquakes

3.1. Rock and Mineral Composition and Fault Frictional Properties

Slow earthquakes generally occur under conditions transitional between stable creep and dynamic rupture, and the composition of fault materials defines the fundamental range of their frictional behavior. Differences in crystal structure, grain morphology, surface chemistry, and water–rock reactivity among minerals can modify grain contacts, frictional healing, compaction–dilatancy behavior, and velocity dependence. However, mineral type does not correspond uniquely to a specific slip mode. Clay-rich and serpentinite-rich faults commonly exhibit relatively low frictional strength but are not necessarily stable, whereas quartz-, feldspar-, and gabbro-rich materials generally have higher frictional strength but do not inevitably undergo rapid instability. The resulting slip behavior is ultimately governed by the combined effects of temperature, fluids, effective normal stress, slip velocity, and shear fabric [1,3,16].

Clay minerals are widespread in shallow subduction-zone sediments and fault gouges. Their layered crystal structures, adsorbed water, and interlayer water generally reduce shear resistance along crystallographic planes, resulting in relatively low friction coefficients in clay-rich materials. Their frictional stability, however, varies with clay content, grain interlocking, dilatancy, and healing capacity. Ikari et al. [16,17] and Saffer and Marone [18] showed that clay-rich fault gouges can remain velocity strengthening or undergo condition-dependent changes in frictional stability despite their relatively low frictional strength. Ashman et al. [19], Seyler et al. [20], and Shreedharan et al. [21] further demonstrated that increasing clay content and reduced frictional healing can modify interseismic strength recovery. The low-velocity, long-duration instabilities observed by Volpe et al. [5] further indicate that clay-rich faults are not restricted to stable creep. Rather, clay minerals tend to reduce fault strength and healing rates while broadening the range of conditions under which slow instability may occur.

Serpentine-bearing materials are also characterized by relatively low friction and complex velocity dependence, but their behavior is strongly controlled by mineral phase and environmental conditions. Antigorite, lizardite, and chrysotile differ substantially in crystal structure, grain morphology, and deformation behavior and therefore cannot be treated as mechanically equivalent forms of “serpentine” [22,23]. Laboratory experiments further indicate that serpentinite-rich faults may exhibit relatively low frictional healing and large slip-weakening distances, which can prolong the transition from peak to steady-state friction [24]. At greater temperatures and depths, deformation of antigorite-rich serpentinite may additionally involve semi-brittle or viscoplastic processes that increase fault stability and suppress rapid rupture acceleration [25].

The contrasting stability observed among serpentinite experiments largely reflects differences in pressure–temperature conditions and deformation pathways. Under some high-temperature hydrothermal conditions, dehydration, grain-size reduction, and shear localization can promote slow stick-slip or pronounced instability [26,27]. Earlier hydrothermal experiments likewise showed that the strength and velocity dependence of serpentinite gouges can change substantially with temperature and serpentinite mineralogy [28,29]. In contrast, Liu et al. [6] found that serpentinite gouge subjected to high pore-fluid pressure and low effective normal stress remained velocity strengthening under most experimental conditions, with only slight velocity weakening and quasi-static oscillations occurring at the lowest loading rate; velocity strengthening was restored as slip velocity increased.

Lower pore pressure may favor dehydration and localization, whereas higher pore pressure may suppress dehydration while enhancing pressure solution and diffusive deformation. Serpentine-bearing faults may therefore limit rupture through weak healing and viscoplastic dissipation, or generate self-limiting slip through a transition from velocity weakening at low slip rates to velocity strengthening at higher rates.

Quartz-, feldspar-, pyroxene-, and gabbro-rich materials generally exhibit higher frictional strength and more pronounced grain interlocking and fragmentation [30]. Nevertheless, increasing the proportion of mechanically strong minerals does not necessarily increase the tendency toward instability. Their effect depends on whether the grains form a continuous load-bearing framework and whether shear localizes within the strong granular framework or along interconnected weak phases. When quartz–feldspar grains carry most of the load, grain fragmentation and shear localization may become more pronounced. Conversely, when clay or another weak phase forms a continuous shear surface, slip may preferentially localize along that weak phase. Consequently, fault gouges with similar bulk mineral proportions can exhibit markedly different frictional behavior depending on weak-phase connectivity, spatial grain distribution, and the structure of the principal slip zone. Microphysical modeling of phyllosilicate–quartz gouges likewise predicts strong condition dependence as frictional sliding and thermally activated deformation compete under different pressure–temperature and slip-rate conditions [31].

The representative settings, frictional behavior, dominant deformation processes, and relevance to slow slip of different fault materials are summarized in Table 1. Two general features emerge from these comparisons. First, neither frictional strength nor mineral composition alone determines the resulting slip mode; weak clay- and serpentine-rich materials may exhibit stable or unstable behavior, while stronger crystalline materials can also approach instability under appropriate conditions. Second, transitions in frictional stability depend strongly on velocity dependence, temperature, fluid conditions, and the evolving structure of the fault zone. The characteristics summarized in Table 1 should therefore be interpreted as condition-dependent trends rather than fixed relationships between individual materials and specific slip modes.

Table 1. Representative frictional characteristics of fault materials relevant to slow-slip behavior.

Material System	Representative Setting	Frictional Behavior	Dominant Processes	Relevance to Slow Slip
Clay minerals	Shallow, fluid-rich subduction gouges	Low friction; mainly velocity strengthening	Platelet sliding, pressure solution, water-film lubrication	Stable creep to slow instability
Serpentine-bearing materials	Deeper, water-rich subduction settings; 100–500 °C	Low friction; strengthening–weakening transitions	Dehydration, localization, grain fragmentation	Stable, slow, or self-limiting slip
Gabbro and mafic rocks	Oceanic basement; high stress–temperature conditions	High friction; commonly velocity weakening	Grain crushing, localization, plastic deformation	Slow instability possible near critical conditions
Subduction sediments	Shallow plate interfaces; high pore pressure	Weak; mainly velocity strengthening	Compaction, fluid migration, clay transformation	Shallow slow slip and transient instability
Quartz–feldspar mixed gouge	Shallow–intermediate crust; variable fluids	Intermediate friction; condition-dependent $a - b$	Fragmentation, localization, pressure solution	Stable-to-unstable transitions
Mixed gouge	Heterogeneous natural faults; broad P–T–fluid range	Highly variable friction and $a - b$	Multimineral interaction, shear-zone evolution	Multiple slip modes; strong spatial heterogeneity

Natural faults generally consist of multiple minerals and lithological units, and their spatial heterogeneity may be more important than their average mineral composition. Sediments sampled from the shallow slow-slip region of the Hikurangi margin exhibit

distinct frictional strength, velocity dependence, and healing behavior. Such contrasts may produce zones of stable sliding, regions capable of limited stress accumulation, slow-slip nucleation sites, and barriers to slip propagation [32]. Arts et al. [33] further demonstrated that spatially segmented clay-rich and sand-rich fault gouges cannot be adequately represented by uniformly mixed materials. As shear accumulates, clay smearing, increasing foliation continuity, and localization within a principal slip zone can continuously modify the bulk frictional response.

Mineral composition itself is also not static during fault evolution. Dissolution, precipitation, dehydration, carbonation, grain-size reduction, and shear localization continuously reorganize grain contacts and the connectivity of weak phases. Elevated temperatures can reduce the frictional stability of quartz–kaolinite fault gouges, while chemical reactions in serpentinite–carbonate systems may produce reaction-induced weakening [34,35]. Consequently, the central question has shifted from whether a particular mineral is intrinsically “stable” to identifying the structural, fluid, and thermal conditions under which specific mineral assemblages promote transitions in frictional stability.

Overall, mineral composition constrains the range of possible frictional behaviors but does not independently determine slow-slip occurrence. More important are the ways in which mineral phase, grain size, hydration state, weak-phase connectivity, shear fabric, and reaction history collectively control frictional parameters and their evolution. For subsequent deep-learning applications, lithological labels should therefore not be used directly as proxies for stable or unstable behavior. More physically meaningful model inputs should include mineral proportions, grain size, fabric, temperature, pore-fluid pressure, effective normal stress, slip velocity, and cumulative displacement. Such variables would allow models to learn conditional relationships among mineralogy, environmental conditions, and frictional behavior rather than superficial correlations between sample names and slip modes.

3.2. Rate-and-State Friction and Slip Stability

Mineral composition defines the material basis of fault friction, but the magnitude of the friction coefficient alone cannot determine whether a fault will undergo stable creep, slow slip, or rapid rupture. Slip stability is instead governed by how frictional resistance responds to perturbations in slip velocity and sliding history, together with whether the elastic stiffness of the surrounding medium or loading system is sufficient to suppress frictional weakening. Rate-and-state friction (RSF) laws therefore provide a fundamental theoretical framework linking laboratory friction experiments, stability analysis, and numerical modeling of slow earthquakes [36–38].

$$\mu = \mu_0 + a \cdot \ln(V/V_0) + b \cdot \ln(V_0 \cdot \theta / D_c) \quad (1)$$

where μ is the friction coefficient, μ_0 is the reference friction coefficient at the reference slip velocity V_0 , V is the instantaneous slip velocity, and θ is the state variable describing the evolving contact state of the fault. The dimensionless parameters a and b characterize the direct velocity response and state-dependent frictional evolution, respectively, where D_c is the characteristic slip distance over which the state variable evolves following a perturbation. These parameters provide an effective description of changes in frictional resistance and contact renewal during sliding, but they should not be interpreted as unique representations of individual grain-scale deformation mechanisms.

For illustration, the aging law is adopted as the representative state-evolution relation:

$$\frac{d\theta}{dt} = 1 - \frac{V \cdot \theta}{D_c} \quad (2)$$

where t denotes time. Under this formulation, the state variable increases during stationary contact and evolves toward its steady-state value during sliding. Other state-evolution formulations, particularly the slip law, can reproduce the same steady-state velocity dependence while yielding different transient responses, nucleation behavior, and inferred values of D_c . The state-evolution law should therefore be specified whenever RSF parameters are estimated or compared across studies.

At steady state, $\theta_{SS} = D_c/V$, and Equation (1) reduces to:

$$\mu_{ss} = \mu_0 + (a - b) \cdot \ln\left(\frac{V}{V_0}\right) \quad (3)$$

The sign of $a - b$ describes the steady-state velocity dependence of friction. When $a - b > 0$, friction increases with slip velocity and the fault is velocity strengthening; velocity perturbations are therefore generally damped. When $a - b < 0$, friction decreases with increasing slip velocity and the fault is velocity weakening, providing a necessary—but not sufficient—condition for frictional instability. The magnitude and sign of $a - b$ are condition dependent and may vary with temperature, mineral phase, effective normal stress, pore-fluid pressure, slip velocity, and deformation history. As illustrated in Figure 2, even the same material may span velocity-strengthening, near-neutral, and velocity-weakening regimes under different experimental conditions.

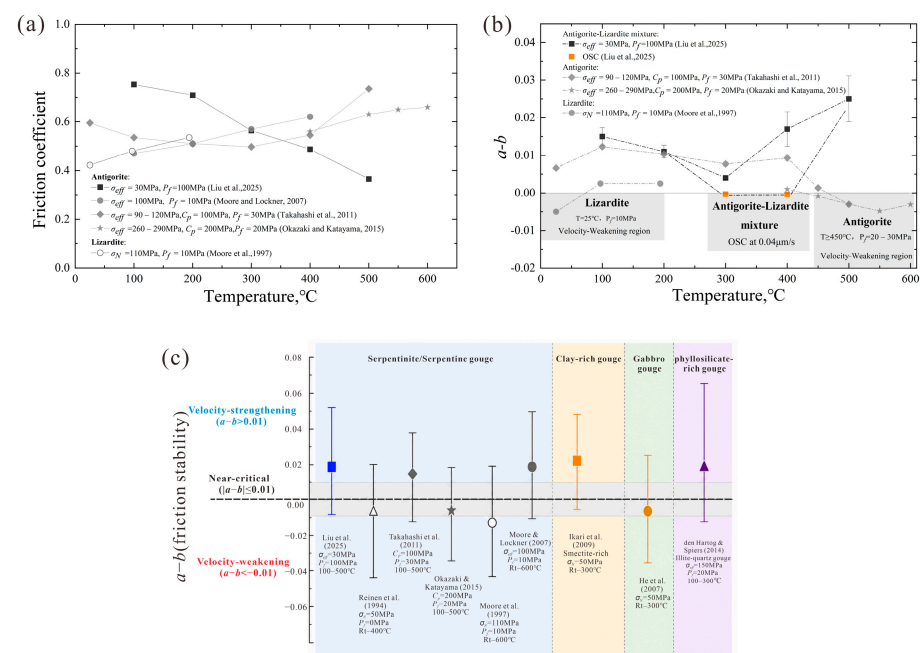


Figure 2. Representative frictional properties and stability characteristics of fault materials under different experimental conditions. (a) Variation in friction coefficient with temperature for representative serpentine-bearing materials. (b) Temperature dependence of the rate-and-state friction parameter $a - b$, showing transitions among velocity-strengthening, near-neutral, and velocity-weakening behavior. (c) Comparison of representative $a - b$ values and frictional-stability tendencies among different fault-material systems. Symbols identify the datasets indicated in the legends; background colors distinguish material groups and frictional regimes, and vertical bars show reported ranges. Data were compiled from Refs. [6,17,23,24,26–31] and replotted for comparison.

For an idealized one-degree-of-freedom spring–slider system governed by velocity-weakening RSF behavior, the critical stiffness can be written as:

$$k_c = \frac{\sigma'_n \cdot (b - a)}{D_c} \quad (4)$$

where k_c is the critical stiffness, k is the actual elastic loading stiffness, and σ'_n is the effective normal stress. When $k > k_c$, elastic unloading can suppress frictional weakening and the fault tends toward stable sliding. When $k < k_c$, velocity perturbations may continue to amplify. When k approaches k_c , the system lies near the transition between stable and unstable behavior and is more likely to exhibit slow stick-slip or quasi-static oscillations. Laboratory experiments by Leeman et al. [4,39] demonstrated that variations in the velocity dependence of friction, effective normal stress, or system stiffness can drive the same experimental fault continuously among stable sliding, slow slip, and rapid stick-slip. These observations support the interpretation of slow earthquakes as transitional behavior within a continuum of fault-slip modes rather than as phenomena fundamentally distinct from ordinary earthquakes.

The critical-stiffness criterion, however, remains dependent on how frictional parameters are determined and on the constitutive assumptions adopted. D_c controls the evolution of frictional state and influences the nucleation scale, but its fitted value can be strongly affected by apparatus stiffness, sampling frequency, the range of velocity steps, detrending procedures, and the selected state-evolution law. Under near-critical sliding or quasi-static oscillatory conditions, fitted D_c values are therefore more appropriately regarded as effective parameters under specific experimental conditions rather than as fixed geometric length scales intrinsic to natural faults [39,40].

Similarly, identical values of $a - b$ do not necessarily imply identical transient frictional behavior. The absolute values of a , b , and D_c continue to influence instantaneous strengthening, subsequent weakening, and slip acceleration during non-steady-state evolution. The aging law and slip law may yield the same steady-state velocity dependence while predicting different nucleation scales and acceleration pathways. Frictional parameters should therefore be reported together with the adopted state-evolution law, boundary conditions, and parameter-estimation procedure.

Slow slip may arise through several pathways involving proximity to a critical stability boundary. Rate-and-state simulations show that aseismic transients can emerge spontaneously on faults operating close to the transition between stable and unstable sliding [41,42]. In one scenario, a fault exhibits relatively weak velocity weakening while the system stiffness remains close to k_c , allowing perturbations to grow without rapidly developing into dynamic rupture. Slow transients can also occur within velocity-strengthening regions when they are driven by stress changes from neighboring fault segments [43]. In another scenario, the velocity dependence itself changes with slip rate: velocity weakening at low slip rates promotes slip initiation, whereas velocity strengthening after acceleration limits rupture velocity and propagation distance [44]. The serpentine-gouge behavior illustrated in Figure 2b provides experimental support for the latter self-limiting pathway. Nevertheless, its applicability depends on mineral composition, pressure–temperature conditions, loading history, and uncertainty in friction-parameter estimation, and it should not be regarded as the sole mechanism responsible for slow slip in natural faults.

When RSF behavior is extended from an idealized single-degree-of-freedom system to a spatially distributed fault, slip stability is further controlled by fault dimensions, elastic interactions, and the spatial heterogeneity of frictional properties [45]. Even when a local velocity-weakening region satisfies the conditions for instability, perturbations may be dissipated by adjacent velocity-strengthening regions if the unstable patch is smaller than the critical nucleation dimension. Laboratory experiments by Song and McLaskey [46] showed that velocity-strengthening patches can arrest rupture propagation. Slip behavior within slow-earthquake source regions therefore depends not only on local frictional parameters but also on the size, connectivity, and spatial arrangement of velocity-strengthening and velocity-weakening regions.

Effective normal stress and pore-fluid pressure can likewise shift the stability boundary, but their effects are dynamic rather than purely static. Changes in pore pressure can reduce fault strength, while slip-induced dilatancy and drainage may generate stabilizing feedbacks. Consequently, $a - b > 0$ does not completely preclude transient slow slip, whereas $a - b < 0$ does not guarantee rapid dynamic rupture. The coupled effects of pore pressure, drainage conditions, and microstructural evolution are discussed in detail in the following section.

Overall, the value of RSF theory lies not in using any single parameter to determine whether a slow earthquake will occur, but in providing a quantitative framework for describing how close a fault is to a stability boundary. The slow-slip state can be represented by a multidimensional state space involving the friction parameters a , b , and D_c , effective normal stress σ'_n , system stiffness k , slip velocity V , state variable θ , and pore-fluid pressure P_f . Within this framework, $a - b$ characterizes steady-state velocity dependence, D_c controls state renewal and influences the nucleation scale, σ'_n and k regulate the stability boundary, and V , θ , and P_f describe the evolving mechanical and hydrological state of the fault. The position and trajectory of a fault within this state space determine whether a perturbation decays, grows slowly, becomes self-limiting, or develops into dynamic rupture. For deep-learning applications, model outputs should therefore extend beyond discrete labels such as “stable” or “unstable” to include the fault’s proximity to critical stability, plausible parameter ranges, and associated uncertainties.

3.3. Effects of Temperature, Fluids, and Microstructural Deformation

Rate-and-state friction parameters are not fixed material constants independent of environmental conditions. Temperature alters deformation mechanisms at grain contacts and the rates of mineral reactions; fluids not only regulate effective normal stress through pore pressure but also participate in dissolution, precipitation, hydration, and dehydration reactions; and grain fragmentation, compaction, dilatancy, and shear localization can in turn modify pore structure, permeability, and pore-pressure evolution. Slow slip is therefore more likely to emerge in transitional regimes where frictional weakening, fluid transport, and time-dependent deformation compete with one another, rather than as a direct consequence of a single temperature or pore-pressure condition.

The influence of temperature on frictional stability is strongly dependent on mineralogy and fluid conditions. Increasing temperature may promote contact creep, diffusion, and pressure solution, thereby favoring stable deformation, but it may also induce desorption of bound water, mineral decomposition, grain-size reduction, and strain localization, all of which can enhance weakening. Ashman et al. [34] showed that elevated temperature reduced the frictional stability of quartz–kaolinite fault gouges, demonstrating that higher temperature does not necessarily promote stable viscous deformation. Serpentine experiments further illustrate that different frictional pathways may occur under similar thermal conditions. At relatively low pore-fluid pressures, antigorite dehydration and shear localization may promote instability [26,27], while high-temperature devolatilization reactions in carbonated serpentinite may also produce reaction-induced weakening [35]. In contrast, Liu et al. [6] observed enhanced pressure solution and diffusive deformation under high pore-fluid pressure, while the samples remained predominantly velocity strengthening. These observations indicate that temperature primarily modifies the relative rates of competing microphysical processes, whereas mineral composition and fluid conditions determine which processes become dominant.

Fluid effects likewise cannot be reduced to the simple assumption that increasing pore pressure necessarily promotes instability. Higher pore-fluid pressure reduces effective normal stress and fault strength, but slip-induced dilatancy may temporarily lower local

pore pressure, increase effective normal stress, and generate a stabilizing feedback that limits acceleration. Segall and Rice [47] established a coupled rate-and-state framework in which dilatancy, compaction, and pore-fluid evolution modify slip stability. Segall et al. [48] subsequently showed that dilatant strengthening can allow a velocity-weakening fault to release stress through slow slip rather than dynamic rupture. Whether this stabilizing feedback persists depends on drainage conditions, permeability, and the characteristic timescale of pore-pressure diffusion. Experiments by Affinito et al. [49] further showed that transitions among stable sliding, slow slip, and rapid instability do not necessarily require persistently anomalous pore pressure. Scuderi et al. [50] demonstrated that the connectivity of clay-rich fabrics can simultaneously reduce frictional strength and permeability, thereby modifying dilatancy-induced pressure drops under transiently undrained conditions. Fluid effects therefore depend not only on the magnitude of pore pressure but also on how fault structure controls fluid transport. Natural observations also suggest that pore-fluid conditions may evolve together with slow-slip activity; Frank et al. [51] inferred along-fault pore-pressure changes during a large slow-slip event in Guerrero.

The physical state and chemical activity of fluids can also alter frictional mechanisms. Feng et al. [52] showed that gabbro-built faults exhibit different slip-weakening behavior and velocity sensitivity under liquid, vapor, and supercritical water conditions. This indicates that even under comparable effective normal stresses, variations in water–rock reactions, interfacial chemistry, and grain-scale lubrication can lead to different frictional responses. Fluids should therefore be regarded not only as mechanical variables, but also as chemically active agents that participate in mineral reactions and interfacial restructuring.

Microstructure provides an important link between temperature, fluids, and macroscopic frictional parameters. Grain fragmentation increases the abundance of fine particles and reactive surface area, compaction reduces pore space, dilatancy modifies pore pressure, and pressure solution and precipitation continuously alter contact strength and pore structure. Microphysical models developed by Niemeijer and Spiers [53] and den Hartog and Spiers [31] demonstrate how competition among frictional sliding, dilatation, pressure solution, and thermally activated deformation can generate pronounced velocity dependence in phyllosilicate-bearing fault gouges. This implies that $a-b$ does not uniquely represent a single grain-contact friction mechanism, but may instead reflect the macroscopic outcome of competition between relatively rapid shear deformation and slower structural recovery.

Shear localization further enhances this condition dependence. Once deformation becomes concentrated within a narrow principal slip zone, bulk frictional behavior increasingly becomes controlled by local fine-grained material, mineral alignment, and chemical reactions. Localization may promote sustained weakening, but pressure solution, precipitation, or grain bonding may also lead to healing and restrengthening. Similar bulk mineral compositions and pressure–temperature conditions therefore do not necessarily produce similar slip behavior, because the spatial distribution of shear strain may be more important than the average properties of the sample.

Frictional healing reflects the continued evolution of fault structure with time. During hold periods, the real area of contact and intergranular bonding generally increase, leading to higher restrengthening upon reloading, although this process remains sensitive to mineralogy and fluid conditions. Shreedharan et al. [21] found that some materials associated with shallow slow-slip environments exhibit very low healing rates, which may correspond to smaller stress drops and shorter recurrence intervals. Feng et al. [54] further showed that the healing rate of some feldspar-rich materials under hydrothermal conditions can even shift from positive to negative values. Frictional healing should therefore not be treated as

a fixed parameter determined solely by hold time, but rather as a dynamic property jointly controlled by temperature, fluids, and contact structure.

These processes can be summarized as a bidirectional feedback chain: pressure–temperature and fluid conditions → grain-scale deformation and mineral reactions → evolution of fabric, porosity, and permeability → changes in pore pressure and frictional parameters → transitions in slip stability.

Slip, in turn, modifies fluid pathways and reaction rates through grain fragmentation, dilatancy, compaction, and localization. Slow earthquakes may preferentially occur when the characteristic timescales of these processes become comparable: frictional weakening is sufficient to initiate slip, whereas dilatant strengthening, pressure solution, viscoplastic dissipation, or velocity strengthening acts to limit further acceleration.

For deep-learning applications, temperature, pore-fluid pressure, and microstructure should not be treated merely as static background variables. In addition to temperature and pore pressure, model inputs should, where possible, include drainage state, permeability, changes in porosity, frictional healing, cumulative displacement, and the degree of shear localization. Model outputs should likewise move beyond fixed estimates of a , b , and D_c , and instead characterize how these parameters evolve with environmental and structural conditions, together with their associated uncertainties. Only in this way can deep-learning models distinguish different physical processes that may produce similar observable signals and provide reliable constraints for fault-state inversion and the assessment of slow-slip trends.

4. Data and Methodological Foundations for Deep Learning Research

4.1. Laboratory Friction and Acoustic Data

Laboratory friction experiments allow stress, displacement, slip velocity, and acoustic responses to be recorded simultaneously while mineral composition, temperature, pore-fluid pressure, effective normal stress, and loading stiffness are precisely controlled. Compared with natural observations, their principal advantage is not simply the availability of a larger number of repeated events, but the ability to establish relatively well-defined relationships among observable signals, the physical state of the fault, and the resulting slip behavior. Existing deep-learning studies have primarily relied on three types of laboratory data: mechanical measurements, passive acoustic emissions, and active ultrasonic monitoring.

Mechanical measurements typically include shear stress, friction coefficient, displacement, slip velocity, normal stress, and pore-fluid pressure, and they provide the primary labels for model training and validation. Shear stress, friction coefficient, slip phase, and time remaining before the next instability can all be formulated as supervised-learning targets. Compared with natural-event catalogs, these labels generally have better-defined boundaries. However, mechanical sensors predominantly record the bulk response of the sample and cannot directly resolve internal grain rearrangement, localized slip, or the evolution of contact networks within the fault gouge. Mechanical data are therefore well suited to characterizing macroscopic frictional states but are insufficient on their own to explain the internal processes responsible for state evolution.

Passive acoustic emission records elastic waves generated spontaneously within the fault during loading and sliding. Grain fragmentation, contact-scale slip, and activity within localized shear bands can all produce signatures in continuous acoustic waveforms, making passive acoustic emissions particularly sensitive to subtle internal changes preceding macroscopic instability. Previous studies have demonstrated that such signals contain information related to frictional state and fault instability [55,56]. Complementary analyses have shown that acoustic-energy evolution varies systematically through the laboratory

seismic cycle and that related machine-learning features can illuminate similarities between slow and fast laboratory failure modes [57,58]. However, their amplitudes and spectral characteristics are also influenced by sensor location, coupling conditions, sample dimensions, apparatus configuration, and instrumental response. Consequently, the patterns learned by a model may reflect not only the evolving fault state but also persistent characteristics of the experimental apparatus.

Active ultrasonic monitoring repeatedly transmits controlled waveforms through the fault using transducers and characterizes the elastic properties of the fault zone through changes in transmitted-wave velocity, amplitude, and spectral content. In contrast to passive acoustic emissions, which record internally generated energy release, active monitoring measures the fault's response to an imposed perturbation and is therefore more sensitive to changes in real contact area, crack state, and bulk stiffness [59,60]. Independent ultrasonic experiments have likewise documented precursory changes in seismic velocity across a spectrum of laboratory failure modes [61]. Its main advantage is that both the source waveform and emission time can be controlled. Its limitations include sensitivity to transducer coupling, propagation paths, repeated-source intervals, and the mechanical boundary conditions of the apparatus.

These three data types represent different aspects of the same fault-slip process. As illustrated in Figure 3, mechanical measurements describe the macroscopic sequence of loading, instability, and recovery; passive acoustic emissions primarily respond to microfracturing and localized slip; and active ultrasonic measurements reflect changes in the contact network and bulk elastic structure. Although all three signals may change as instability approaches, they differ in response timescale, noise characteristics, and physical sensitivity. No single acoustic indicator should therefore be interpreted as a complete representation of fault state. The principal value of multi-source observations lies in their ability to provide complementary constraints on macroscopic mechanics, localized damage, and contact-network evolution.

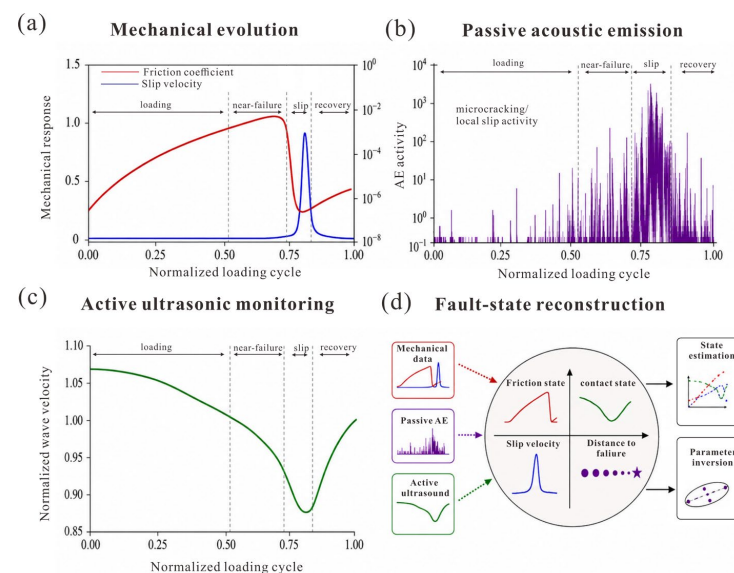


Figure 3. Conceptual framework linking multi-source laboratory observations to the reconstruction of evolving fault states. (a) Mechanical evolution during loading, instability, and recovery. (b) Passive acoustic emissions associated with microcracking and localized slip. (c) Active ultrasonic responses reflecting changes in fault-contact stiffness and elastic structure. (d) Integration of mechanical, passive-acoustic, and active-ultrasonic observations for fault-state and parameter reconstruction. Colors distinguish the three observation types, arrows indicate information flow, and the circles and star represent progression toward failure. The curves are conceptual syntheses based on previously reported experimental behaviors and are not direct reproductions of a single synchronized dataset.

The organization of experimental data strongly affects whether reported model performance is credible. If adjacent time windows from the same slip cycle are randomly divided between training and test sets, the model may exploit temporal correlations and cycle-to-cycle repetition, resulting in artificially inflated performance. More rigorous data partitioning should therefore be conducted at the level of complete slip cycles, entire experiments, or independent loading conditions. Validation across normal stress, slip velocity, material type, and experimental apparatus should be prioritized. Sampling frequency, window length, sensor location, filtering procedures, and label construction should also be fully reported; otherwise, meaningful comparison among different studies becomes difficult. Recent studies further illustrate that forecast horizon and feature construction can materially influence apparent prediction skill and its physical interpretation [62,63].

Laboratory datasets also have inherent limitations in scale and representativeness. Regular stick-slip experiments often exhibit pronounced periodicity, whereas natural slow-slip events occur under much more complex recurrence patterns, fault geometries, fluid conditions, and loading configurations. A model that successfully reconstructs frictional state within a single apparatus does not necessarily contain acoustic features that can be transferred directly to another apparatus or to a natural fault. Laboratory data are therefore better suited to identifying physically meaningful state representations, testing whether model outputs are consistent with frictional behavior, and providing reference constraints for subsequent numerical modeling and interpretation of natural observations, rather than to training a universal predictor that can be applied to all faults without recalibration.

Overall, the primary value of laboratory friction and acoustic datasets lies in their ability to provide independently testable physical labels. Mechanical measurements define and validate the macroscopic fault state, passive acoustic emissions reveal localized damage activity, and active ultrasonic measurements constrain the evolution of the contact network. Simultaneous acquisition of these observations, together with complete experimental meta-data, provides a robust foundation for fault-state estimation, friction-parameter inversion, and forecasting of future slip evolution.

4.2. Natural Seismic, GNSS, and Strain Observations

Compared with laboratory friction data, natural observations record real fault activity but do not provide simultaneous measurements of friction coefficient, stress state, or proximity to a stability boundary. Slow-slip signals are generally weak and long lasting and are commonly superimposed on seasonal deformation, groundwater-related variations, instrumental drift, and background seismic activity. The main challenge posed by natural datasets is therefore not simply a lack of observations, but determining which aspect of fault activity is represented by each type of measurement. Existing studies primarily use continuous seismic waveforms, GNSS displacement time series, and strain or tilt records, which respectively reflect seismic radiation, surface displacement, and localized deformation. Slow slip is also strongly transient and intermittent across multiple timescales, which further complicates the construction of complete and unambiguous observational labels [64].

Continuous seismic records provide high temporal resolution and are well suited to detecting tectonic tremor and low-frequency earthquakes and to tracking temporal changes in their activity rates [65,66]. However, tremor and low-frequency earthquakes mainly represent radiation from localized brittle patches embedded within a broader slow-slip region, and neither their number nor amplitude maintains a fixed relationship with the total amount of aseismic slip. Seismic waveforms are also influenced by source mechanisms, propagation paths, site effects, and instrumental response. Seismic observations can

therefore provide sensitive indicators of localized fault activity, but they cannot, on their own, demonstrate that aseismic slip of a particular magnitude has occurred [7,9].

GNSS observations provide a more direct record of surface displacement generated by slow slip and are therefore among the principal datasets used to constrain event duration, spatial extent, and slip magnitude [67]. Daily GNSS time series, however, commonly contain seasonal components, common-mode errors, data gaps, and millimeter-scale noise, limiting their ability to resolve short-duration or low-amplitude events. Models based on single stations may incorrectly interpret local anomalies as tectonic deformation, whereas multi-station analyses can exploit the spatial coherence of genuine fault slip to suppress station-specific noise.

Synthetic datasets can broaden the range of event magnitudes, locations, and durations represented during model development, but they inevitably inherit assumptions about fault geometry and noise characteristics. Real observations better reflect the actual data distribution but are constrained by limited sample sizes and incomplete labels. A more reliable strategy is therefore to use synthetic data for pretraining or expansion of the parameter space and then calibrate and independently validate the resulting models using real events [8,68–70]. Comparable network-based machine-learning detection has also been explored in northern Chile [71], providing an additional regional test case beyond Cascadia and southwest Japan.

Strainmeters and tiltmeters help bridge the observational gap between high-frequency seismic records and daily GNSS measurements. They are particularly sensitive to small deformation transients on timescales ranging from minutes to several days and are therefore well suited to detecting short-duration slow-slip events. These records are, however, highly sensitive to tides, atmospheric pressure, rainfall, and groundwater variations, while limited station coverage makes it difficult to independently constrain source location and slip magnitude. Spatial consistency among multiple stations, together with synchronous responses observed in nearby creepmeters, GNSS stations, or seismic activity, provides important evidence for determining whether a candidate transient has a tectonic origin [10,72].

The three observation types should be regarded as complementary rather than interchangeable. The observed space–time correlation between geodetically inferred slip and tectonic tremor in Cascadia illustrates the value of combining independent seismic and deformation observations [73]. Seismic waveforms provide high-temporal-resolution information on localized fault activity, GNSS constrains the overall displacement field and spatial extent of slip, and strain measurements capture localized deformation over shorter timescales. Tectonic tremor, GNSS displacement transients, and strain anomalies should therefore not be treated as equivalent labels. More reliable analyses should combine multiple independent observations and assess whether candidate events can be reproduced across separate stations, different data types, and time periods not used for model training. Only under these conditions are model outputs more likely to represent genuine fault slip rather than instrument-specific or region-specific noise.

4.3. Deep-Learning Models, Task Definition, and Evaluation Methods

In slow-earthquake research, model architecture is important, but the first priority is to define precisely what problem the model is intended to solve. The same neural-network architecture may be used to determine whether slow slip occurs within a given time window, estimate the current frictional state, or predict future fault evolution. These tasks differ substantially in label construction, physical interpretation, and evaluation criteria. If event detection, state estimation, and forecasting are treated as equivalent problems, even high predictive accuracy provides limited insight into whether the model has genuinely improved our understanding of fault processes.

From the perspective of research objectives, existing applications can be grouped into four levels. The first is detection and classification, which aims to determine whether slow slip, tectonic tremor, or low-frequency earthquakes are present. The second is state estimation, in which acoustic or geophysical observations are used to recover continuous variables such as shear stress, friction coefficient, or slip velocity. The third is trend forecasting, which uses present and historical observations to infer future events or the subsequent evolution of frictional behavior. The fourth is parameter inversion, in which observations are used to constrain frictional parameters such as a , b , and D_c , together with their possible spatial distributions. As these tasks move progressively closer to the internal physical state of the fault, they become increasingly dependent on label quality, observational coverage, and model assumptions. A particularly important distinction is that identifying an event that has already begun constitutes detection, whereas forecasting requires inference of slip that has not yet occurred.

Model selection should therefore be driven by the physical task rather than treated as the primary criterion for evaluating a study. Convolutional neural networks are well suited to extracting local patterns from waveforms and spatiotemporal sequences, whereas recurrent neural networks and Transformer architectures are better suited to representing loading history and longer-range temporal dependencies. Encoders and other low-dimensional representations can be used for high-dimensional data compression and unsupervised anomaly detection. Transfer learning is not a distinct network architecture but rather a training strategy for adapting knowledge learned in a source domain to a new experiment or tectonic region. Similarly, physics-informed neural networks constrain the solution space by incorporating governing equations and boundary conditions into the learning process. These approaches can be combined, but increasing model complexity does not necessarily lead to more reliable physical interpretation. Network architecture, time-window length, sampling rate, and preprocessing choices can all influence performance, and the critical question is whether these choices are appropriate for the physical process and observational scale of interest [8,9,11,12,74,75]. These distinctions also highlight substantial differences in the evidential basis of existing studies. Representative applications are compared in Table 2 in terms of data source, inference task, model type, validation strategy, uncertainty treatment, and physical consistency. The comparison is intended to distinguish improvements in statistical prediction from evidence that a learned relationship remains valid across independent data or is consistent with the underlying fault mechanics.

Table 2. Comparison of representative data-driven studies relevant to slow-earthquake and fault-slip research.

Study	Data and Task	Model	Validation and Uncertainty	Physical Consistency/Limitation
Rouet-Leduc et al. [55]	Lab AE; time-to-failure	Random forest	Within laboratory records; ensemble variability	Fault-state-sensitive AE; laboratory recurrence
Rouet-Leduc et al. [56]	Lab AE; friction estimation	ML regression	Laboratory validation; limited uncertainty analysis	Compared with measured friction; laboratory scale
Shreedharan et al. [59]	Active seismic; stress and failure timing	ML regression	Multiple laboratory slip cycles	Linked to fault-zone evolution; controlled conditions
Laurenti et al. [62]	Lab AE; stress forecasting	DL/autoregressive	Multiple forecast horizons	Laboratory recurrence; horizon dependence
Tanaka et al. [70]	Natural GNSS; SSE detection	ML classifier	Real GNSS testing; observational noise considered	Direct deformation signal; incomplete event labels

Table 2. *Cont.*

Study	Data and Task	Model	Validation and Uncertainty	Physical Consistency/Limitation
Donoso et al. [71]	Natural GNSS; SSE detection	ML classifier	GNSS-network evaluation	Direct deformation; regional dependence
Wang et al. [74]	Simulation + lab AE; friction estimation	Transfer learning	Cross-domain transfer; target-domain calibration	Compared with measured friction; recalibration required
Wang et al. [75]	Lab AE; future friction	CNN–Transformer	Multiple forecast horizons; forecast error reported	Direct friction target; laboratory only
Thomas et al. [76]	Natural seismic data; LFE detection	Deep learning	Multi-station seismic observations	Seismic validation; no direct aseismic-slip constraint
Lin et al. [77]	Continuous seismic data; LFE detection	Deep learning	Long-term continuous observations	Catalog consistency; detection rather than state inference
Hulbert et al. [78]	Cascadia seismic data; slip evolution	Machine learning	Multiple slow-slip cycles; limited uncertainty	State-related seismic energy; recurrence influence possible
Fukushima et al. [79]	Synthetic SSEs; inversion and forecasting	PINN	Synthetic forward/inverse tests	RSF constraints; idealized spring–slider system

Table 2 highlights a clear distinction between predictive performance and evidential strength. Laboratory studies provide direct mechanical reference variables but remain constrained by apparatus and loading conditions, whereas natural-data studies capture real fault behavior but rarely provide direct observations of internal frictional states. Transfer-learning and physics-informed approaches improve the connection between data and fault mechanics, but their validation remains largely dependent on laboratory or synthetic systems. Model performance should therefore be interpreted together with validation independence, uncertainty, and the physical observability of the inferred target.

Evaluation metrics must be matched to the task being addressed. For slow-earthquake and low-frequency-signal detection, non-event samples commonly outnumber event samples by a large margin, meaning that overall accuracy alone can obscure substantial false-negative rates. Precision, recall, F1 score, and precision–recall relationships should therefore be reported together with event-level measures such as errors in onset and termination time, missed detections, and duplicate detections. For regression tasks involving frictional state, stress, or slip velocity, commonly used metrics include mean absolute error, root-mean-square error, and correlation coefficients. These metrics should, however, be evaluated separately during loading, nucleation, and slip phases so that overall performance is not dominated by long intervals of relatively steady behavior. Forecasting studies should additionally report both forecast lead time and prediction error, because an accurate estimate obtained immediately before an event carries a fundamentally different scientific meaning from a stable forecast made substantially earlier.

The way data are partitioned can be even more important than the choice of evaluation metric. If adjacent time windows from the same slip cycle or continuous record are randomly divided between training and test sets, the model may exploit temporal correlation, event periodicity, or fixed instrumental characteristics, resulting in artificially inflated performance. More rigorous validation should therefore use complete events, entire experiments, or continuous time intervals as independent units. Validation should then progressively extend across stress conditions, experimental apparatuses, material types, and tectonic regions. Performance obtained after target-domain fine-tuning should also be clearly distinguished from true out-of-domain generalization without recalibration. Only when test data are drawn from genuinely unseen data distributions can model

performance be interpreted as evidence that the learned relationship extends beyond the statistical structure of a specific experiment or region [15].

Uncertainty in the labels must also be incorporated into model evaluation. Natural slow-slip catalogs are incomplete, and estimates of event onset, termination, and slip magnitude are commonly derived from inversions that themselves depend on prior assumptions. Disagreement between model output and an existing catalog may therefore represent either a false positive or a genuine event that was omitted from the catalog. A single catalog should consequently not be treated as an absolute ground truth. Candidate detections should instead be evaluated using consistency across stations, independent observation types, and subsequent physical analysis. Likewise, parameter-inversion and probabilistic-forecasting studies should not report only a single optimum value; they should quantify plausible parameter ranges, forecast uncertainty, and the sensitivity of these uncertainties to noise level and observational coverage.

Overall, deep-learning studies of slow earthquakes should not be evaluated primarily on the basis of network depth, model name, or a single accuracy metric. A more appropriate evaluation framework should incorporate three complementary dimensions: statistical performance, which measures consistency between predictions and reference labels; cross-dataset validation, which determines whether model performance is maintained across different experiments or tectonic regions; and physical consistency, which evaluates whether the inferred results are compatible with frictional stability and fault-slip dynamics. Only when all three criteria are satisfied can data-driven studies progress from statistical fitting within a specific dataset toward reproducible and testable interpretations of slow-earthquake processes.

5. Deep Learning Applications in Slow-Earthquake Research

5.1. Detection of Slow Earthquakes and Low-Frequency Signals

The objective of slow-earthquake detection is to identify genuine fault activity within continuous observations characterized by weak amplitudes, long signal durations, and complex noise. Compared with ordinary earthquakes, slow-slip events often lack clear phase onsets and strong high-frequency radiation. Tectonic tremor, low-frequency earthquakes, and subtle surface deformation therefore provide important observational proxies. The contribution of deep learning extends beyond simply increasing the number of detected events; it has also promoted a transition from repeated searches for known event families toward the discovery of previously unidentified events, reconstruction of continuous fault activity, and joint validation using multiple observation types.

Early detection of low-frequency earthquakes relied primarily on template matching, in which waveforms from previously identified events were used to search continuous records for similar signals. This approach is effective for detecting known event families but may miss events with different source locations or waveform characteristics. Thomas et al. [76] demonstrated that neural networks can identify low-frequency earthquakes with weak signal-to-noise ratios and poorly defined phase arrivals. Lin et al. [77] subsequently applied deep learning to 14 years of continuous seismic records from southern Vancouver Island and constructed an expanded catalog containing more than one million events. These methods substantially improve detection sensitivity, but they remain dependent on existing catalogs for training labels and may therefore continue to overlook event types that are absent from the original catalog.

Münchmeyer et al. [9] further decomposed low-frequency-earthquake monitoring into phase picking, event association, and source localization. Their framework recovered known sources and identified previously uncataloged events across several regions of slow-earthquake activity, while also exhibiting a degree of cross-regional generalization.

This progression indicates that deep learning is evolving from classifiers designed for specific event families toward more complete monitoring systems for low-frequency seismicity. Nevertheless, detecting a larger number of low-frequency earthquakes does not necessarily imply that a greater amount of slow slip has been detected, because localized brittle seismic radiation and the total aseismic slip on a fault do not maintain a fixed relationship.

Continuous seismic records may also contain information related to the evolution of slow slip. Rouet-Leduc et al. [7] showed that statistical characteristics of tremor-frequency seismic signals in Cascadia could track variations in slow-slip rate. Hulbert et al. [78] further observed a progressive increase in seismic energy before major slow-slip events. These results suggest that natural faults may undergo a gradually evolving preparatory process that can, in principle, be detected from continuous seismic observations. However, the strongest evidence currently comes from Cascadia, where slow-slip recurrence is relatively quasi-periodic. Variations in propagation path, tremor radiation efficiency, and background noise could produce similar statistical patterns, meaning that independent confirmation using GNSS or strain observations remains necessary.

Geodetic observations allow deep-learning methods to identify aseismic slip more directly. Costantino et al. [8] trained a deep-learning model using multi-station GNSS time series, with synthetic training samples incorporating data gaps, common-mode errors, and spatially correlated noise, enabling candidate slow-slip events to be identified directly from the time series. Wang et al. [69] similarly exploited spatiotemporal information from multiple GNSS stations to identify candidate events not included in existing catalogs. Tanaka et al. [70], in contrast, trained a detector using real GNSS observations in order to reduce the discrepancy between synthetic noise assumptions and actual observational data. These two strategies are constrained, respectively, by assumptions embedded in synthetic models and by the limited number of real labeled events. A more robust approach is therefore to use synthetic data to expand the range of possible event parameters, followed by calibration and independent validation using real observations.

High-sensitivity strain measurements further extend the range of detectable event timescales. Zali et al. [10] analyzed borehole strain observations from Parkfield using wavelet representations, autoencoders, and unsupervised clustering, identifying short-duration slip signals that are difficult to resolve in daily GNSS data. Candidate events were further evaluated through coherent responses recorded by multiple strainmeters and a nearby creepmeter. This example demonstrates the potential of unsupervised learning for identifying previously unknown transients when complete event catalogs are unavailable. However, limited station coverage still constrains the ability to determine source geometry and total slip magnitude.

Overall, slow-earthquake detection is undergoing three major transitions: from template-dependent searches to the discovery of previously unidentified events, from single-station classification to spatially coordinated detection, and from single-signal identification to validation using multiple independent observations. Model evaluation should therefore extend beyond the number of detected events and assess whether candidate signals exhibit temporal and spatial coherence, whether they are supported by independent observations, and whether the model remains effective in regions or time periods not included in the training data. Only under these conditions can deep learning progress from a technical tool for increasing detection sensitivity to a method for characterizing the spatiotemporal evolution of fault slip. Determining what frictional states these signals represent, however, requires the further development of fault-state estimation and parameter inversion.

5.2. Fault Frictional-State Identification and Parameter Inversion

Slow-earthquake detection addresses the question of whether anomalous slip has occurred, whereas fault-state estimation seeks to determine the stress level currently sustained by the fault, its frictional stage, and its proximity to a stability boundary. Because the friction coefficient, state variables, and rate-and-state friction parameters of natural faults cannot be continuously measured directly, existing studies have generally first established mappings between acoustic observations and mechanical states in laboratory experiments and then extended state estimation toward parameter inversion through friction laws. These two tasks represent successive levels of inference: the former reconstructs continuous variables such as shear stress, friction coefficient, and slip velocity, whereas the latter further estimates parameters such as a , b , and D_c , together with their spatial distributions.

Laboratory acoustic studies first demonstrated that faults are not completely unobservable during the intervals between macroscopic instabilities. Rouet-Leduc et al. [56] used passive acoustic emissions to estimate the instantaneous frictional state of an experimental fault and showed that weak acoustic activity contains information about stress evolution and the evolution of grain-contact conditions during loading. Shreedharan et al. [59], using active ultrasonic measurements, reconstructed shear-stress evolution from variations in wave velocity and amplitude and also estimated the timing of the next instability. Passive acoustic emissions are particularly sensitive to grain-scale fracturing and localized microslip, whereas active ultrasonic signals more directly reflect changes in the bulk contact stiffness and elastic structure of the fault zone. Combining these signals with mechanical measurements can therefore improve the observability of hidden frictional states.

However, the relationship between acoustic signals and frictional state is not unique. Sensor coupling, apparatus geometry, sample dimensions, and grain fabric can all alter the recorded waveforms. High state-estimation accuracy therefore demonstrates that a stable observation-to-state relationship has been recovered under a particular set of experimental conditions, but it does not prove that a given acoustic feature uniquely represents a specific physical variable. The main advance achieved by laboratory studies is thus the transition from identifying fault state only at the time of macroscopic instability to estimating it continuously throughout the entire slip cycle.

Physics-constrained models further extend fault-state estimation toward friction-parameter inversion. Fukushima et al. [79] incorporated rate-and-state friction laws into a spring–slider framework and used synthetic observations to simultaneously reconstruct state variables, estimate frictional parameters, and predict subsequent slip evolution. Borate et al. [12] combined passive acoustic emissions, active ultrasonic monitoring, and mechanical measurements to infer a , b , and D_c directly from stick-slip cycles, thereby reducing reliance on separate velocity-step experiments. These studies indicate that when observations are limited or slip cycles are irregular, physical constraints can eliminate at least some solutions that are inconsistent with the governing friction law.

The scope of parameter inversion has subsequently expanded from single-degree-of-freedom systems to spatially distributed faults. Rucker and Erickson [13] simultaneously solved one- and two-dimensional fault-dynamics forward problems while inferring depth-dependent frictional parameters. Fukushima et al. [14] further used synthetic GNSS observations to estimate both the spatial extent of slow-slip regions and the distribution of frictional parameters. These studies show that combining deep learning with physical models can extend inversion from single-point parameter estimation to spatially distributed fields. However, the resulting resolution remains strongly constrained by station coverage, noise level, and assumptions embedded in the fault model. Because current spatial inversions still rely predominantly on synthetic data, they primarily demonstrate methodological

feasibility within prescribed model settings rather than unique recovery of frictional parameters on natural faults.

Overall, fault-state research is progressing from continuous estimation of mechanical quantities to the reconstruction of state variables and ultimately to inversion of constitutive parameters and their spatial distributions. As the inference task moves closer to the underlying physical mechanism, the results become increasingly dependent on the adopted friction law, boundary conditions, and observational coverage. Fault-state estimation and parameter inversion should therefore not be treated as independent problems. Multi-source observations provide constraints on the evolving state, friction laws organize those states into constitutive parameters, and independent experiments and natural observations are needed to test whether the inferred parameters are physically meaningful. Ideally, model outputs should include not only a single best-fitting parameter set, but also plausible parameter ranges, spatial resolution, and an estimate of how close the fault is to a critical stability state.

5.3. Slow-Slip Evolution and Forecasting of Occurrence Trends

Compared with event detection and fault-state estimation, slow-slip forecasting requires models to use current and historical observations to infer slip processes that have not yet occurred. Relevant targets include the time remaining until the next event, future slip velocity or frictional evolution, the likely location of future activity, and the associated uncertainty. A clear distinction must therefore be made between genuine state forecasting and simple recurrence-based extrapolation. If a model primarily estimates the timing of the next event from approximately repeating recurrence intervals, even a small prediction error does not necessarily indicate that the model has identified the physical preparation process of the fault. Physically meaningful forecasting should instead rely on observations that evolve with fault state and should provide additional information before conventional methods have already recognized the event.

Forecasting approaches considered here can be broadly distinguished as classical machine learning, deep learning, and physics-informed or hybrid methods. Classical machine learning generally relies on predefined statistical or signal features, whereas deep learning learns hierarchical representations directly from high-dimensional observations through neural-network architectures. Physics-informed and hybrid approaches additionally introduce governing equations, numerical models, reduced-order representations, or data assimilation to constrain or update the learned state. These categories are not strictly mutually exclusive, but distinguishing them is important because their predictive skill and physical interpretability arise from different sources.

Laboratory studies first demonstrated that continuous acoustic signals contain information related to future instability. Using a classical machine-learning approach based on statistical characteristics of acoustic emissions, Rouet-Leduc et al. [55] estimated the time remaining before the next stick-slip event. Subsequent studies extended this problem from prediction of a single event time toward reconstruction of future frictional trajectories. Using a deep-learning approach, Wang et al. [75] combined a convolutional encoder with a Transformer architecture to predict subsequent frictional evolution from historical acoustic-emission data. Laurenti et al. [62] further evaluated autoregressive deep-learning models for forecasting future laboratory fault stress over multiple horizons, showing that predictive performance becomes increasingly difficult to maintain as the forecast horizon extends. Such models generally perform well over short forecast horizons and in the period immediately preceding instability, but prediction errors increase as the forecast window becomes longer. This suggests that acoustic signals can constrain near-term fault evolution

but remain insufficient for robust reconstruction of the long-term dynamics of an entire slip cycle.

Representative evidence for machine-learning-based forecasting of natural slow-slip events has come primarily from Cascadia. Hulbert et al. [78] found that continuous seismic energy within the tremor-frequency band varied systematically over an approximately 14-month slow-slip cycle and increased progressively from several weeks to several months before major slow-slip events. Models could use preceding seismic observations to estimate the time remaining until the next slow-slip event, providing evidence that natural faults may contain an observable preparatory phase. However, slow slip in Cascadia is relatively quasi-periodic, and seismic-energy variations may also be influenced by changes in the spatial extent of tremor activity, wave-propagation effects, and background noise. Current results therefore do not demonstrate that the same forecasting pattern applies to regions characterized by irregular recurrence, weak tremor activity, or shorter observational records.

A third category comprises physics-informed and hybrid forecasting approaches, which differ from purely data-driven prediction by explicitly incorporating physical evolution models or dynamical constraints. Fukushima et al. [79] used a physics-informed framework combining rate-and-state friction laws with spring-slider equations to estimate the current fault state and predict subsequent slip under synthetic observational conditions. Reduced-order modeling and data assimilation represent related hybrid strategies rather than standalone deep-learning architectures. Magen et al. [80] used low-dimensional representations to reduce the computational cost of long-term slow-slip-cycle simulations and parameter exploration, whereas Kaveh et al. [81] integrated reduced-order models with data assimilation, allowing forecasts to be continuously updated as new observations became available. These studies demonstrate the feasibility of a framework combining physical evolution models, computationally efficient surrogates, and observational correction. Nevertheless, most supporting evidence still comes from idealized or synthetic fault sequences and should not be interpreted as evidence that natural slow-slip events can already be forecast reliably in real time.

Forecasting studies have thus progressed from event-time estimation toward reconstruction of future states, physics-based prediction, and dynamic data assimilation. However, the strength of the supporting evidence has not advanced equally across laboratory and natural-fault scales. Laboratory events are highly repeatable, and both mechanical states and instability times can be measured directly. Natural faults, in contrast, must be characterized indirectly using seismic, GNSS, and strain observations; the number of well-observed events is limited, and recurrence patterns may evolve over time. High short-term forecast accuracy therefore does not automatically imply long-term generalization, and retrospective reconstruction cannot substitute for prospective evaluation on future unseen events.

At the current stage, a more rigorous objective is to forecast slow-slip occurrence trends and probabilities rather than to provide a single deterministic event time. Models should, at a minimum, report forecast lead time, event probability, uncertainty intervals, and performance relative to baselines that explicitly test the contributions of recurrence and temporal structure. Suitable controls include mean- or distribution-based recurrence models, persistence forecasts, and conventional statistical time-series models. Phase-randomized surrogate data provide an additional test by preserving the amplitude spectrum and linear autocorrelation of the original record while disrupting its phase relationships [82]; performance that cannot exceed such a surrogate baseline would provide limited evidence that the model has learned fault-state-dependent temporal structure beyond simple autocorrelation. Forecast skill should therefore be evaluated on chronologically held-out events or future observational intervals rather than randomly partitioned neighboring windows.

Where recurrence-aware or surrogate baselines are unavailable, high retrospective accuracy should be interpreted cautiously as predictive association rather than definitive evidence of a learned preparatory process. Ultimately, forecasting research should address not only when the next event may occur, but also which observable changes indicate that the fault is approaching a critical state and how reliably those changes generalize beyond the recurrence pattern represented in the training data.

6. Physics-Constrained Deep Learning and Cross-Scale Research

6.1. Physics Constraints and Identifiability of Frictional Parameters

Purely data-driven models can learn statistical relationships from acoustic signals, seismic waveforms, and GNSS time series, but they do not guarantee that the resulting solutions satisfy stress equilibrium, frictional constitutive laws, or state-evolution dynamics. Physics-informed neural networks (PINNs) address this limitation by incorporating observational errors, governing equations, initial conditions, and boundary conditions into a unified learning framework [83,84], thereby constraining the admissible solution space:

$$L = \lambda_d \cdot \tilde{L}_{data} + \lambda_p \cdot \tilde{L}_{physics} + \lambda_i \cdot \tilde{L}_{initial} + \lambda_b \cdot \tilde{L}_{boundary} \quad (5)$$

where $\tilde{L}_{data}$, $\tilde{L}_{physics}$, $\tilde{L}_{initial}$ and $\tilde{L}_{boundary}$ denote the normalized data, physics, initial-condition, and boundary-condition losses, respectively, and λ_d , λ_p , λ_i and λ_b are their weighting coefficients. Because the corresponding residuals may differ substantially in physical units and numerical magnitude, they should be nondimensionalized or normalized before weighting. For mean-square-error-type losses, this can be achieved by scaling each residual by an appropriate characteristic magnitude, such as the standard deviation, representative range, or physically defined reference scale of the corresponding variable, before the loss is evaluated. The weighting coefficients then regulate the relative importance of the normalized constraints rather than compensating directly for differences in units or numerical scale. Rate-and-state friction laws, spring–slider equations, and continuum fault-dynamics models can all be incorporated into slow-slip studies, while unknown frictional parameters can be treated as trainable variables. Previous studies have demonstrated the feasibility of this approach in low-dimensional models, laboratory acoustic datasets, and spatially distributed fault systems [11–14,79]. However, the ability to obtain a set of frictional parameters does not imply that those parameters have been uniquely identified.

A fundamental limitation of physics-constrained inversion arises from its dependence on the assumed constitutive framework. The parameters inferred by a neural network are not model-independent “true parameters”; rather, they represent the parameter combinations that best reconcile the observations with a prescribed friction law, state-evolution formulation, and set of boundary conditions. Natural faults may additionally involve pore-pressure evolution, mineral reactions, viscoplastic deformation, temporally varying frictional properties, or nonlocal damage processes, such that classical rate-and-state friction captures only part of the underlying dynamics. Under these circumstances, a small physics residual does not necessarily demonstrate that the inferred solution closely represents the actual fault system; it may instead indicate that the solution has been confined to an overly idealized dynamical space. Governing equations should therefore be treated as testable physical priors rather than as immutable representations of reality.

This constitutive dependence is compounded by the non-uniqueness of friction-parameter inversion. Different combinations of a , b , D_c , effective normal stress, and system stiffness may generate similar histories of slip velocity, stress, or surface displacement, particularly when observations are sparse and trade-offs among parameters cannot be independently resolved. Consequently, accurate reconstruction of an observed time series

does not by itself demonstrate that the underlying parameters have been uniquely recovered. Establishing parameter identifiability requires examining the stability of the inversion across multiple initializations, quantifying parameter sensitivities and correlations, and estimating posterior distributions rather than reporting only a single optimum solution. Combining mechanical measurements with active ultrasonic monitoring, passive acoustic emissions, and geodetic observations can provide complementary constraints and thereby reduce the range of observationally equivalent parameter combinations.

Even after normalization, the balance between observational information and physical constraints introduces an additional source of uncertainty. Excessive emphasis on the data term may cause the model to fit observational noise while departing from the governing equations, whereas an overly strong physics constraint may force discrepancies that cannot be explained by the assumed constitutive framework to be absorbed artificially into the inferred parameters. This issue becomes particularly important because loading, nucleation, and slip occur over different amplitudes and characteristic timescales, making a single fixed weighting scheme unlikely to be equally appropriate throughout the entire fault cycle. Adaptive loss weighting, stage-dependent training, and explicit representation of model discrepancy may therefore provide a more robust means of distinguishing observational noise and genuine parameter evolution from limitations of the constitutive model [85].

Observational geometry further determines the extent to which frictional parameters can be resolved. Spatial inversion deteriorates rapidly when stations are sparse, observations are located far from the principal slip region, or only a single data type is available. Model outputs should therefore not be limited to a single optimal parameter set or a smoothly varying spatial field. They should also quantify plausible parameter ranges, spatial resolution, and sensitivity to observational noise, station density, and assumptions regarding fault geometry.

Physics-constrained inversion should, at minimum, be subjected to three types of validation. First, the model should reproduce complete slip sequences that were not included during training. Second, inferred parameters should be cross-validated against independent friction experiments, conventional inversion methods, or alternative observation types. Third, uncertainty should increase in a physically reasonable manner as observational noise increases, station coverage decreases, or model assumptions are altered. The primary advantage of physics constraints is therefore not that they necessarily guarantee higher predictive accuracy than conventional neural networks, but that they can exclude dynamically implausible solutions when observations are limited and the inverse problem is ill posed. Only when model applicability, parameter identifiability, and uncertainty are evaluated jointly can the inferred parameters be assigned reliable physical meaning.

6.2. Transfer Learning, Reduced-Order Models, and Data Assimilation

Beyond the incorporation of physical constraints, slow-earthquake modeling faces several practical challenges. Laboratory experiments, numerical simulations, and natural observations differ substantially in their data distributions; high-resolution fault-dynamics models are computationally expensive; and models calibrated under fixed conditions cannot readily adapt as new observations become available. Transfer learning, reduced-order modeling, and data assimilation address these challenges from complementary perspectives by enabling cross-domain knowledge reuse, dynamical compression, and continuous state updating.

Transfer learning seeks to exploit information learned in a data-rich source domain and adapt it to a target domain in which observations are more limited. Wang et al. [74], for example, used numerical simulations to pretrain mappings between acoustic observations and frictional states before refining the latent representation using experimental

data. Wang et al. [15] further examined transfer across different experimental apparatuses, stress conditions, slip velocities, and fault materials. These studies show that a limited amount of target-domain data can substantially improve model performance, while direct application across conditions without recalibration remains difficult. Transferability is also inherently asymmetric: as the source and target domains diverge in slip-cycle characteristics, acoustic response, and loading configuration, the amount of reusable information progressively decreases.

The challenge becomes even greater when models are transferred from laboratory systems to natural faults. Domain differences then extend beyond loading conditions to include spatial scale, mineralogical composition, wave-propagation effects, sensor response, noise structure, and event recurrence behavior. The presence of similar periodic patterns in two datasets does not necessarily indicate that the model has learned a scale-invariant frictional mechanism. Transfer performance should therefore not be evaluated solely from the reduction in prediction error after fine-tuning. It is equally important to determine whether the transferred latent representation retains physically meaningful relationships with stress, slip velocity, state variables, or proximity to frictional instability. A more defensible strategy is to proceed progressively from numerical simulations to laboratory experiments, from one set of experimental conditions to another, and ultimately to natural observations, with independent validation performed at each stage.

Reduced-order models provide a different solution to the difficulty of exploring high-dimensional fault dynamics. By representing the system within a low-dimensional latent space, through modal decomposition, or by constructing machine-learning surrogates, reduced-order approaches can lower the computational cost of long-term slow-slip simulations, parameter searches, and ensemble forecasting. Studies by Kaveh et al. [86] and Magen et al. [80] suggest that much of the dominant evolution in complex slow-slip sequences may be represented within a state space of substantially lower dimensionality, providing a basis for rapid scenario exploration and inverse modeling.

Dimensional reduction, however, is not lossless. Low-dimensional representations tend to preserve energetic and large-scale modes, whereas localized nucleation, small frictional patches, and short-duration transients may be attenuated or omitted. The performance of a reduced-order model should therefore not be assessed solely from its ability to reproduce average recurrence intervals or total slip. More physically informative evaluation should examine nucleation locations, event-size distributions, propagation distances, and state errors during critical phases of the slip cycle. For long-term forecasting, it is also necessary to determine whether neglected modes introduce systematic errors that accumulate with time.

Data assimilation complements these approaches by repeatedly updating slip velocity, stress, state variables, or frictional parameters as new observations become available and then allowing the dynamical model to evolve forward from the corrected state. Kano et al. [87] and van Dinther et al. [88] showed that limited observations can constrain unmeasured fault states through covariance relationships among model variables. Kaveh et al. [81] further combined reduced-order modeling with ensemble Kalman filtering, updating the system state in a low-dimensional space while generating forecasts of event timing and location together with associated uncertainty.

Although data assimilation can reduce errors in the initial state, it cannot automatically compensate for incorrect fault geometry or an inadequate constitutive model. When systematic structural errors are present, repeated assimilation may continuously pull the simulated state toward observations without correcting the underlying physical deficiency. Observational error, parameter uncertainty, and structural model error should therefore be distinguished explicitly. Persistent disagreement between model predictions and obser-

vations should be treated as evidence that the governing equations, parameter-evolution laws, or fault geometry may require revision rather than merely stronger state correction.

Taken together, transfer learning, reduced-order modeling, and data assimilation can form a continuous modeling framework. Transfer learning adapts previously acquired knowledge to new observational domains, reduced-order models provide computationally efficient representations of fault dynamics, and data assimilation updates the evolving state and its uncertainty as new observations become available. The effectiveness of this framework ultimately depends on whether the reduced state preserves information relevant to nucleation and rupture propagation, whether transferred features retain their physical meaning across domains, and whether uncertainty estimates respond appropriately to changes in observational quality and model error.

6.3. Cross-Scale Integration of Experiments, Simulations, and Natural Observations

Laboratory experiments, numerical simulations, and natural observations provide complementary constraints on the mechanisms, states, and real-world behavior of slow earthquakes. Laboratory experiments allow mineral composition, temperature, pore-fluid pressure, effective normal stress, and loading stiffness to be controlled while frictional and acoustic responses are recorded simultaneously. Numerical simulations extend the accessible fault scale and parameter space and provide a means of testing nucleation, propagation, and arrest processes. Natural seismic waveforms, GNSS measurements, and strain observations, in turn, record the behavior of real faults. Each domain nevertheless has intrinsic limitations: experiments are constrained by sample size and apparatus conditions, simulations depend on simplified geometries and constitutive assumptions, and natural observations cannot directly measure subsurface frictional state. The key challenge in cross-scale research is therefore not to transfer raw signals or fitted parameters directly across these domains, but to identify physical quantities whose definitions remain meaningful across scales and whose relation to the available observations can be explicitly tested.

Cross-scale integration requires a distinction between directly observed quantities and model-dependent hidden variables. Seismic waveforms, GNSS displacements, strain, laboratory stress, slip, and acoustic measurements are observables, whereas slip velocity at depth, stress state, pore-fluid pressure, frictional state variables, and constitutive parameters such as a , b , and D_c are generally inferred quantities in natural faults. As illustrated in Figure 4, laboratory experiments, numerical simulations, and natural observations are therefore linked not through a set of equally observable state variables, but through physically defined relationships between measurable signals, inferred fault states, and model constraints. Laboratory experiments provide controlled measurements and mechanistic constraints, numerical models connect these constraints to evolving fault states, and natural observations provide the measurable quantities against which simulated or inferred states can ultimately be tested. The recoverability of hidden variables depends on the governing model, observation type, station geometry, noise level, and correlations among unknown parameters; they should therefore not be treated as equally observable or uniquely identifiable across laboratory, numerical, and natural systems.

A physically meaningful cross-scale inference should therefore be accompanied by sensitivity and identifiability tests. At minimum, the stability of inferred states or parameters should be examined against changes in observational noise, station density and geometry, initial parameter values, and plausible constitutive assumptions. Synthetic-recovery tests with known reference states can determine whether the inversion can recover the imposed quantities under realistic observational limitations, while multiple initializations, parameter-correlation analysis, and posterior or ensemble distributions can reveal non-uniqueness. Confidence is strengthened further when the same inferred state is consistent

with independent observation types, such as seismic, GNSS, and strain data, rather than with a single data stream alone.

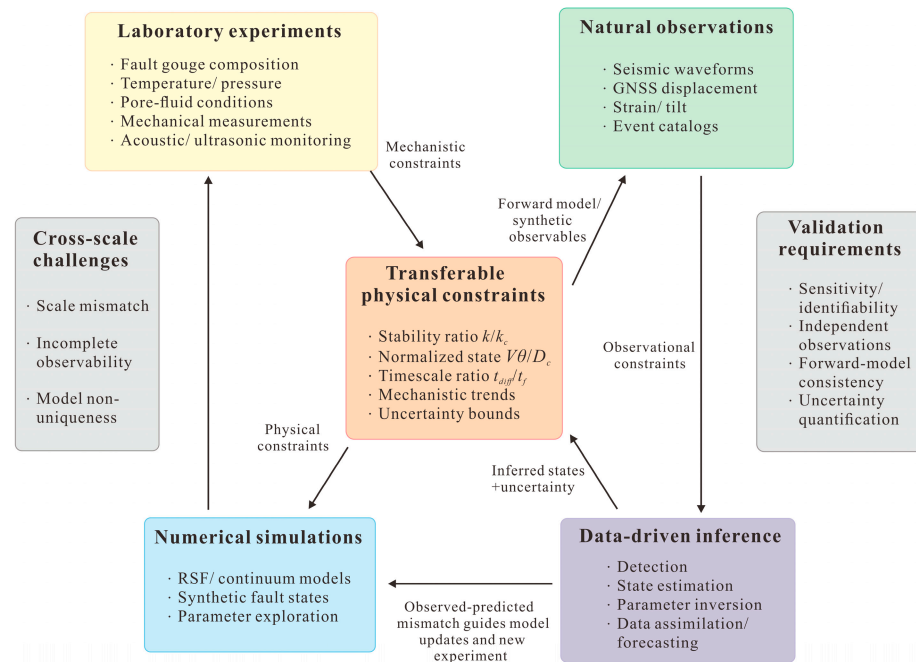


Figure 4. Cross-scale framework linking laboratory experiments, numerical simulations, data-driven inference, and natural observations through transferable physical constraints. Laboratory experiments provide mechanistic constraints, while numerical models and data-driven approaches bridge observations across scales. Cross-scale transfer relies on dimensionless stability indicators, characteristic timescale ratios, mechanistic trends, and uncertainty assessment rather than directly equivalent fault-state variables.

Cross-scale transfer should therefore focus primarily on dimensionless stability relationships, normalized state measures, characteristic timescale ratios, and mechanistic trends rather than on direct extrapolation of dimensional values of a , b , or D_c . For example, the stiffness ratio k/k_c provides a scale-independent measure of proximity to the frictional stability boundary [39,40], whereas the ratio $V\theta/D_c$ describes the state-evolution condition relative to steady sliding [36,37]. Competition between hydraulic and frictional evolution can similarly be expressed through a timescale ratio such as t_{diff}/t_f , where t_{diff} is a characteristic hydraulic-diffusion timescale and $t_f \sim D_c/V$ represents a frictional state-evolution timescale [47,48]. These dimensionless relationships do not eliminate differences in geometry, constitutive behavior, or boundary conditions, but they provide a more defensible basis for comparing whether similar stability regimes and competing physical processes operate across laboratory, numerical, and natural-fault scales.

Linking simulations to natural observations additionally requires forward models that translate fault states into measurable seismic waveforms, surface displacements, and strain signals. Synthetic datasets are particularly useful because they provide complete state labels over broad parameter ranges and can support model pretraining, sensitivity analysis, and scenario exploration. However, assumptions regarding fault geometry, constitutive behavior, and noise structure are inevitably embedded within such synthetic data and may therefore propagate into the trained model. Synthetic datasets should consequently support, rather than replace, independent validation using real observations.

Natural observations should also provide feedback to laboratory interpretations and numerical assumptions. If a particular parameter set or constitutive formulation cannot simultaneously account for seismic, GNSS, and strain observations, the appropriate response

is to reconsider the assumed fault structure, parameter ranges, or governing equations rather than simply increase model complexity. Data assimilation can continuously update state estimates and parameter distributions as new observations become available, but persistent discrepancies should also trigger reevaluation of the underlying model structure.

Most existing studies currently connect only adjacent components of this framework, whereas fully bidirectional integration among experiments, simulations, and natural observations remains limited. The main difficulty is not simply the absence of more sophisticated learning architectures, but the fact that these three research domains rely on different observables, spatial and temporal scales, and validation criteria. A robust cross-scale framework should therefore ensure that laboratory results enter simulations as mechanistic constraints, dimensionless stability relationships, and uncertainty-bounded parameter information; that simulated states are converted through forward models into observable quantities and tested against independent natural data; and that natural observations feed back to update both parameter uncertainty and model structure when persistent discrepancies arise. Only through such bidirectional correction can deep learning meaningfully connect experimentally accessible fault processes with slow slip on natural faults.

7. Research Gaps, Future Directions, and Practical Implications

Despite rapid methodological progress, the principal limitation of current data-driven slow-earthquake research is the uneven strength of evidence across different inference tasks. Natural observations now support increasingly robust detection of tremor, low-frequency earthquakes, and geodetic transients, whereas continuous fault-state estimation remains much better constrained in laboratory experiments, and friction-parameter inversion and long-term forecasting are still dominated by synthetic or idealized systems. A major research priority is therefore not simply to develop more complex network architectures, but to determine whether inferred states remain reproducible when models are tested on complete unseen events, independent experiments, different tectonic regions, and future observations. Prospective validation, explicit comparison with recurrence and statistical baselines, and uncertainty estimates that remain reliable under domain shift will be essential for distinguishing physically informative forecasting from retrospective pattern recognition.

A second unresolved problem concerns the physical meaning and cross-scale identifiability of learned fault states. Variables such as frictional state, stress, pore-fluid pressure, and rate-and-state parameters are only indirectly constrained on natural faults, and different constitutive assumptions may reproduce similar observable signals. Future studies should therefore combine sensitivity analysis, synthetic-recovery experiments, parameter-uncertainty estimation, and joint inversion of complementary seismic, geodetic, and strain observations. Cross-scale comparisons should emphasize dimensionless stability relationships, characteristic timescale ratios, and mechanistic transitions rather than direct extrapolation of laboratory-derived parameter values. Equally important is the development of forward models that convert simulated fault states into measurable observables, allowing laboratory and numerical hypotheses to be rejected or refined through independent natural data. Such bidirectional testing is more important for physical generalization than achieving incremental improvements in prediction accuracy within a single dataset.

The reviewed evidence also has implications for fault-related site characterization and geotechnical investigation, although its present role is primarily to support characterization and model selection rather than to provide deterministic design criteria. Site investigations in tectonically active settings should prioritize variables that control frictional stability, including mineralogical composition, fault-zone fabric, pore-fluid conditions, stress state, and evidence of spatial heterogeneity [89], while monitoring strategies should combine

seismic and deformation observations where feasible. Laboratory characterization can then reproduce representative pressure, temperature, fluid, and loading conditions to constrain frictional strength, velocity dependence, healing behavior, and transitions in slip stability. These measurements provide a physical basis for selecting and calibrating constitutive models and for defining plausible parameter ranges in numerical analyses. Deep learning can assist by identifying weak signals, integrating heterogeneous observations, and estimating latent states, but current model dependence, observational sparsity, domain shift, and scale differences prevent such outputs from being used directly as universal failure thresholds or deterministic engineering design parameters. For practical decision-making, their more defensible role is to support monitoring design, scenario evaluation, model updating, and probabilistic assessment together with conventional geological, geophysical, laboratory, and mechanical evidence.

8. Conclusions

This study shows that deep learning has substantially expanded the ability to extract and interpret weak signals associated with slow earthquakes, but its reliability varies markedly among different research tasks and data environments. Applications to natural faults are currently most mature in the detection of tectonic tremor, low-frequency earthquakes, and slow-slip-related deformation, where seismic, GNSS, and strain observations provide direct constraints on observable signals. In contrast, continuous estimation of frictional state, stress, and slip evolution is supported more strongly by laboratory experiments, where mechanical and acoustic variables can be measured simultaneously. Friction-parameter inversion and long-term forecasting remain more dependent on synthetic data, idealized physical models, and controlled experimental systems. Deep-learning applications should therefore be interpreted according to the physical quantity being inferred and the strength of the observations available to constrain it, rather than solely according to predictive accuracy.

The integration of frictional physics with data-driven methods is essential for extending deep learning from signal recognition toward physically meaningful fault-state inference. Slow-slip behavior reflects the combined effects of frictional constitutive properties, effective normal stress, pore-fluid pressure, loading stiffness, microstructural evolution, and their interactions across spatial and temporal scales. Physics-informed learning, transfer learning, reduced-order modeling, and data assimilation provide useful approaches for incorporating these processes, but physical constraints do not eliminate constitutive-model dependence, parameter non-uniqueness, observational uncertainty, or domain shift. Reliable inference therefore requires independent validation, uncertainty quantification, and consistency with fault mechanics. Cross-scale comparison should likewise emphasize stability relationships, characteristic timescales, and mechanistic trends rather than direct extrapolation of laboratory-derived values of a , b , and D_c .

Overall, the present evidence supports deep learning primarily as a tool for improving slow-earthquake detection, integrating heterogeneous observations, characterizing evolving fault states, and assessing slip trends probabilistically. Its value lies in linking laboratory experiments, numerical simulations, and natural observations so that fault processes that cannot be measured directly can be progressively constrained and tested against observable signals. However, the current evidence is insufficient to support deterministic prediction of the exact timing of natural slow earthquakes or the direct transfer of laboratory-derived frictional parameters to natural faults. A physically credible application of deep learning therefore depends not on increasing model complexity alone, but on combining data-driven inference with frictional mechanics, independent observations, and explicit treatment of uncertainty.

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