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Explainable and Uncertainty-Aware Computational Geodetic

Inversion:

A Review and Framework for Multi-Source Earth Observation

Mohit Sheode^{1*} and D. Kishan²

Corresponding author: mhtsht@gmail.com ; 223111001@stu.manit.ac.in

¹ Research Scholar, Department of Civil Engineering, Maulana Azad National Institute of Technology (MANIT),
Bhopal 462003, India

² Associate Professor, Department of Civil Engineering, Maulana Azad National Institute of Technology (MANIT),
Bhopal 462003, India

ORCID ID: Mohit Sheode, <https://orcid.org/0009-0009-5719-5084> ; D. Kishan, <https://orcid.org/0000-0003-1058-3548>

Abstract

Geodetic inversion converts surface and remote sensing data into estimates of concealed Earth system parameters, including fault slip, magma-source geometry, subsurface mass changes, crustal strain, and time-dependent geohazard activities. This review explores geodetic inversion as a computational challenge that involves combining diverse data, optimizing and quantifying uncertainty, and providing explainable decision support. A narrative technical review was compiled using literature records from Scopus and Dimensions on topics such as geodetic inversion, Global Navigation Satellite System (GNSS) measurements, Interferometric Synthetic Aperture Radar (InSAR), gravity and seismic source modeling, Bayesian inversion, sparse regularization, and physics-informed learning. The literature was sorted based on the data types, inverse-problem

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structures, algorithmic groups, uncertainty management, and reporting standards. This review highlights five common computational layers in contemporary geodetic inversion: data harmonization, forward-model encoding, inversion and optimization, uncertainty propagation, and explainable decision support. These layers are synthesized into an explainable artificial intelligence-uncertainty quantification-computational geodetic inversion (XAI-UQ-CGI) framework for multi-source Earth observation. To show that the framework is computationally executable rather than only conceptual, it is demonstrated on a controlled synthetic same-model experiment in which a Mogi volcanic point-pressure source is inverted from synthetic InSAR and GNSS data, yielding empirically assessed least-squares uncertainty intervals and a quantifiable reduction of depth non-uniqueness under sensor fusion. Future geodetic inversion studies should move beyond single best-fit solutions toward reproducible, physics-constrained, uncertainty-preserving, and human-interpretable computational workflows suitable for geohazard monitoring and Digital Earth applications.

Keywords: computational geodetic inversion; multi-source Earth observation; InSAR; GNSS; uncertainty quantification; explainable artificial intelligence

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1. Introduction

Geodetic inversion is a central methodology for converting observations of the Earth surface and gravity field into estimates of hidden geophysical parameters. The term covers a family of inverse problems in which satellite or ground-based measurements are used to infer fault slip, magma chamber pressure, crustal deformation, mass redistribution, density contrast, strain-rate fields, and other physical quantities that cannot be observed directly. In the traditional geophysical literature, this subject is usually discussed through forward modelling, elastic dislocation theory, potential theory, least-squares adjustment, regularization, and Bayesian inference. From a computer science perspective, however, modern geodetic inversion is equally a problem of heterogeneous data representation, optimization under uncertainty, scalable numerical computation, explainable modelling, and decision-oriented geospatial analytics (Aster et al., 2018; Menke, 2018; Parker, 1994; Sjöberg & Bagherbandi, 2017; Tarantola, 2005).

This shift toward a computer-science perspective is closely linked to the changing nature of modern geodetic data. Today, geodetic inversion is no longer based on a single observation type or a limited set of measurements. Interferometric Synthetic Aperture Radar (InSAR) can generate detailed maps of surface deformation, whereas Global Navigation Satellite System (GNSS) networks provide three-dimensional displacement data at specific locations. The Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE Follow-On (GRACE-FO), offer understanding into large-scale mass changes, whereas seismic data help in understanding rupture mechanisms. In addition, Digital Elevation Models (DEMs), geological maps, hydrological datasets, and Geographic Information System (GIS) layers provide essential contextual data for analyzing inversion outcomes. The combined use of these datasets can minimize non uniqueness and enhance the model resolution. However, their integration requires careful consideration of reference frames, spatial and temporal synchronization, data weighting, covariance structure, missing data, uncertainty propagation, and reproducibility (De Novellis et al., 2016; Li et al., 2023a; Liu et al., 2023; Roger et al., 2020; Song et al., 2022; Zhao et al., 2026).

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Inversion is increasingly anticipated to help in decision-making related to hazards. Models of earthquake sources, scenarios of volcanic activity, patterns of subsidence, estimates of hydrological loading, and interpretations of landslide deformation extend beyond academic purposes. They can impact risk communication, infrastructure surveillance, emergency management, and future strategic planning. Thus, relying solely on a single best-fit model is insufficient for this purpose. Users must understand which observations influenced the solution, the sensitivity of the solution to its assumptions, the areas where uncertainty is concentrated, the plausibility of alternative models, and how to interpret the output in terms of physical and societal risks (Bai et al., 2022; Huang et al., 2017; Jiang & González, 2020; Puliero et al., 2026; Tomita et al., 2021; Wald & Graves, 2001).

This article reviews the computational geodetic inversion as a computer science problem. It is not set to replace domain-specific geophysical derivations; rather, it organizes geodetic inversion around algorithmic components that are usual across application areas. These components include data harmonization, forward model encoding, inversion and optimization, uncertainty propagation, and explainable output generation. This study also proposes a layered framework, XAI-UQ-CGI, for explainable and uncertainty-aware computational geodetic inversion. The proposed framework is designed to connect traditional inversion theory with modern artificial intelligence, uncertainty visualization, and traceable geospatial decision support (Fig. 1). The framework is subsequently demonstrated on a controlled synthetic multi-source InSAR–GNSS inversion (Section 8.3).

This review makes four contributions. First, it synthesizes the literature on geodetic inversion from a computational perspective, focusing on algorithms and data structures rather than solely on physical source mechanisms. Second, it maps major inversion methods to data modalities and specific application domains, including co-seismic fault-slip inversion, volcanic deformation-source inversion, hydrological loading inversion, subsidence and reservoir-parameter estimation, and landslide kinematic interpretation. Third, it proposes a practical reporting checklist to improve transparency, reproducibility, and interpretability in future computational geodetic inversion studies. Fourth, it demonstrates the framework end-to-end on a controlled synthetic multi-

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source inversion, providing a reproducible reference implementation (Online Resource 3) that illustrates calibrated uncertainty quantification and the sensor-fusion reduction of non-uniqueness under known ground truth.

Scope note:

This manuscript presents a narrative technical review, a conceptual methodological framework for multi-source geodetic inversion, and a controlled synthetic proof-of-concept that demonstrates the framework end-to-end (*Section 8.3*). The computational formulations, workflow steps, and algorithmic structures are presented as implementation templates. The accompanying synthetic experiment (*Code Availability Section*) is a same-model verification under known ground truth; no field data, real-event inversion, or operational hazard benchmarking was performed, and the demonstration does not establish robustness to structural model error beyond the single mismatch test reported.

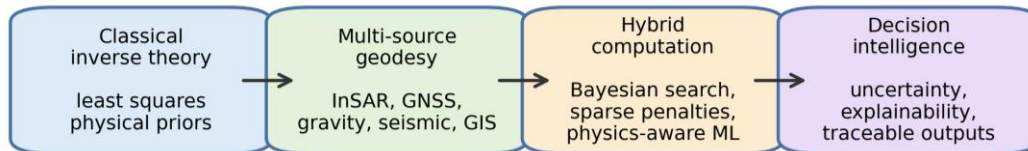


Fig. 1 Evolution of geodetic inversion from classical inverse theory toward explainable computational geodetic intelligence

2. Review Methodology and Literature Base

This article is structured as a narrative technical review supported by database-derived literature mapping. This section describes the literature-mapping methodology only; the design of the synthetic computational experiment used to demonstrate the framework is given separately in *Section 8.3* and *Computer Code Availability Section*. The initial reference pool was assembled from two exported datasets: a Scopus export containing 151 records and a Dimensions export containing 500 records related to geodetic inversion and associated Earth-observation

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inversion topics. DOI-based comparison indicated 95 overlapping records, while combined DOI and title matching produced an approximate unique pool of 556 records. The Scopus pool contained 58 records from 2020 onward and 24 records from 2024 onward, while the Dimensions pool contained 189 records from 2020 onward and 79 records from 2024 onward. Thus, the raw exported datasets contained 247 recent records from 2020 onward. After DOI/title-based deduplication, the combined unique pool contained 211 records from 2020 onward and 89 records from 2024 onward (Table 1).

Table 1 Summary of the literature pool used for the narrative technical review

Record group		Count	Period	Role in review
Scopus export	151		1992-	Focused geodetic inversion and
			2026	source-modelling records
Dimensions export	500		1986-	Broader Earth-observation and
			2026	inversion records
DOI overlap	95		-	Records appearing in both datasets by DOI
Combined unique pool	Approx. 556		1986-	Deduplicated by DOI or normalized
			2026	title
Recent emphasis	247 raw records from 2020 onward; 211 deduplicated unique records from 2020 onward		2020-	Supports current computational and
			2026	AI-oriented framing

The literature search was designed as a focused thematic scan (Table 2) rather than a formal bibliometric ranking. Its main purpose was to identify studies that could support a computer-science-oriented discussion of geodetic inversion. The retrieved records were reviewed using their titles, abstracts, keywords, and publication metadata. Particular attention was given to studies dealing with InSAR and GNSS inversion, gravity inversion, joint inversion, Bayesian approaches, sparse and edge-preserving regularization, source-geometry estimation, uncertainty analysis, machine learning, physics-informed modelling, and ensemble-based inversion. Application studies were retained when they demonstrated computational inversion workflows for earthquakes, volcanic deformation, hydrological loading, land subsidence, reservoir deformation, or landslide-related ground motion.

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A small number of recent studies on physics-aware InSAR change detection, neural-operator-based scientific modelling, dataset-bias analysis, and uncertainty visualization were also considered to strengthen the computer-science framing (Chen et al., 2026; Li et al., 2026a; Li et al., 2026b; Lu et al., 2021; Lundberg & Lee, 2017; Perrot et al., 2026; Wu et al., 2026).

The selected references are used in three ways. Foundational geodesy and inversion references support the mathematical interpretation of inverse problems (Aster et al., 2018; Menke, 2018; Parker, 1994; Sjöberg & Bagherbandi, 2017; Tarantola, 2005). Recent application papers illustrate the diversity of multi-source geodetic inversion across earthquakes, volcanoes, hydrology, subsidence, reservoirs, and landslide deformation (Bai et al., 2022; De Novellis et al., 2016; Huang et al., 2017; Jiang & González, 2020; Li et al., 2023a; Liu et al., 2023; Puliero et al., 2026; Roger et al., 2020; Song et al., 2022; Tomita et al., 2021; Wald & Graves, 2001; Zhao et al., 2026). Computer science and scientific machine learning references support the discussion of physics-informed learning, neural surrogate modelling, explainability, uncertainty visualization, and trustworthy data analysis (Chen et al., 2026; Costa et al., 2025; Fukushima et al., 2025; Li et al., 2021; Li et al., 2026a; Li et al., 2026b; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Perrot et al., 2026; Raissi et al., 2019; Wu et al., 2026).

Table 2 Thematic reference map for expanded narrative review

Theme	Use cases	Representative studies	Computational contribution
Earthquake source and fault-slip inversion	Main	(Tan et al., 2016; Wald & Graves, 2001; Wei et al., 2025; Xi et al., 2024; Zheng et al., 2023)	Fault geometry, slip distribution, after slip, Green's functions, multi-source weighting
	geodetic inversion backbone		
	Nonlinear source-shape examples	(Guo et al., 2019; Hicks et al., 2026; Jiang & González, 2020; Li et al., 2025; Varugu & Amelung, 2021)	Pressure-source, dike, sill, reservoir, and shape-optimization problems
Volcanic deformation and source geometry			
Hydrology, gravity, and mass redistribution	Mass-change	(Li et al., 2023a; Sjöberg & Bagherbandi, 2017; Tang et al., 2025)	GRACE/GNSS/InSAR fusion, gravity inversion, geoid and mass constraints
	and loading		

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Theme	Use cases	Representative studies	Computational contribution
Subsidence, reservoirs, and anthropogenic deformation	extension	2024; Xu & Rummel, 1994; Zhang et al., 2016)	
	Operational monitoring examples	(Doyle et al., 2001; Liu et al., 2023; Smith et al., 2019; Takada & Fukushima, 2013; Tung & Feigl, 2021)	InSAR time series, compaction, mining, groundwater or reservoir effects
	Primary geohazard use case	(De Novellis et al., 2016; Jiang et al., 2018; Nakata et al., 2017; Qiu et al., 2019; Yin et al., 2022)	Slope kinematics, slow motion, tunnel/slope deformation, terrain uncertainty
Regularization, weighting, and model selection	Core algorithmic layer	(Agata, 2020; Atzori & Antonioli, 2011; Liu et al., 2016; Nozue & Fukahata, 2025; Wang & Xu, 2017)	Covariance components, time-varying smoothing, sparsity, resolution and uncertainty
AI, neural surrogates, visualization, and emerging sensing	Computer-science bridge	(Behr & Bürgmann, 2021; Costa et al., 2025; Li et al., 2021; Li et al., 2026a; Spudich et al., 1995)	Physics-informed learning, neural operators, explainability, uncertainty visualization, DAS/UAV-LiDAR

3. Geodetic Inversion as a Computational Inverse Problem

In common terms, geodetic inversion can be represented by the relationship

$$d = G(m; \theta) + \varepsilon \quad (1)$$

where d is an observation vector, m is a vector of unknown model parameters, G is a forward operator, θ represents governing assumptions such as source geometry or Earth structure, and ε includes observational error, model mismatch, and unmodelled physical processes (Eq. (1)). In a linear problem, G can be represented by a matrix that links the model parameters to the observations. In a nonlinear problem, the forward operator may rely on the source geometry, elastic parameters, boundary conditions, or spatially variable Earth structure. The

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inversion task is to figure out ‘m’ from ‘d’, often under incomplete and noisy observational coverage (Aster et al., 2018; Menke, 2018; Parker, 1994; Sjöberg & Bagherbandi, 2017; Tarantola, 2005).

The key difficulty is non-uniqueness. Various models can replicate identical geodetic observations within the uncertainty bounds. In the context of gravity inversion, it is impossible to uniquely determine the internal mass structures without supplementary data. Similarly, in earthquake slip inversion, identical surface deformation fields can be caused by different fault geometries or slip distributions. In studies of volcanic deformation, different pressure-source configurations can produce comparable InSAR and GNSS signals. Consequently, inversion transcends mere numerical computation and is a problem of constrained computational inference (Bai et al., 2022; Huang et al., 2017; Jiang & González, 2020; Menke, 2018; Mills et al., 2025; Puliero et al., 2026; Sjöberg & Bagherbandi, 2017; Tomita et al., 2021; Wald & Graves, 2001).

Most practical inversion workflows therefore minimize an objective function combining data misfit and model constraints. A common form is

$$J(m) = [d - G(m; \theta)]^T C_d^{-1} [d - G(m; \theta)] + \lambda R(m) \quad (2)$$

where C_d is the data covariance matrix, $R(m)$ is a regularization term, and λ controls the balance between the data fit and model plausibility (Equation (2)). Regularization may impose smoothness, sparsity, boundedness, edge preservation, or physical prior constraints. Choosing these constraints is a computational and epistemic decision; it influences not only the numerical stability but also the scientific meaning of the recovered model (Agata, 2020; Niu et al., 2023; Nozue & Fukahata, 2025; Sun et al., 2025; Wang & Gu, 2020; Xi et al., 2024).

Geodetic inversion is fundamentally connected with computer science. Fundamentally, it deals with optimization and inference in the presence of imperfect conditions: the data input is often noisy, the model space can be extensive, the objective function might be nonlinear or non-convex, and prior assumptions could be uncertain. These features make it an ideal area for computational approaches that focus on modular design, scalability, reproducibility, uncertainty management, and providing explainable results.

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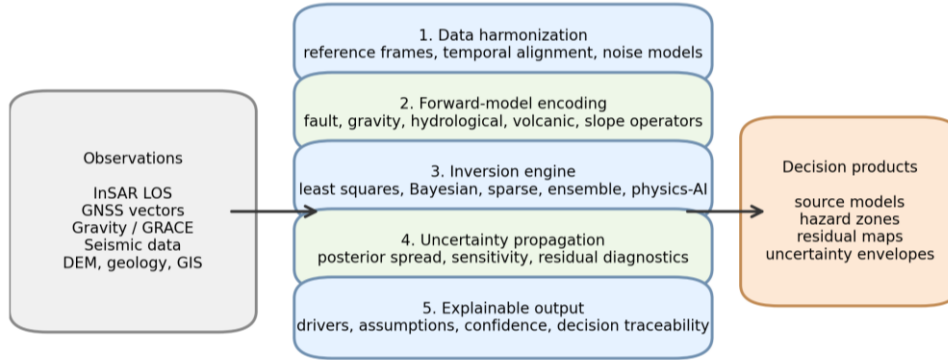


Fig. 2 Proposed XAI-UQ-CGI framework organized into data harmonization, forward-model encoding, inversion, uncertainty propagation, and explainable output layers

4. Data Modalities and Computational Characteristics

One of the main defining features of modern geodetic inversion is the variety of observation types available (Fig. 2). Each type offers a fresh angle on the Earth system process. InSAR delivers dense spatial sampling, although it is limited by line-of-sight sensitivity and decorrelation issues. GNSS captures three-dimensional displacement, but only at widely spaced station locations. Gravity and GRACE/GRACE-FO data are adept at detecting mass redistribution, although at a lower spatial resolution. Seismic data offer understanding of the timing of rupture processes and source dynamics. Digital elevation models (DEMs), geological maps, hydrological products, land-cover layers, and GIS datasets offer contextual constraints and prior information (De Novellis et al., 2016; Li et al., 2023a; Liu et al., 2023; Roger et al., 2020; Song et al., 2022; Zhao et al., 2026).

Addressing the computational challenge involves not just collecting these data but also ensuring their comparability. It is essential to spatially and temporally synchronize data, convert them into consistent reference frames, adjust for recognized biases, and apply suitable uncertainty models. Weighting is especially important in joint inversion. If dense InSAR observations dominate the objective function, sparse but physically important

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GNSS data may be underweighted. If seismic or gravity data have poorly characterized uncertainties, the inversion may overfit one modality while underrepresenting another (Agata, 2020; Jiang & González, 2020; Li et al., 2023a; Puliero et al., 2026; Roger et al., 2020; Xi et al., 2024; Zhao et al., 2026).

The value of multi-source inversion is that independent data types may reduce ambiguity (Table 3). GNSS and InSAR can jointly constrain vertical and horizontal deformation. GNSS and GRACE/GFO can improve terrestrial water storage estimates. InSAR and GNSS can clarify volcanic source geometry. Gravity and geodetic displacement can support mass-change interpretation. However, data fusion also introduces new failure modes: inconsistent temporal sampling, different spatial footprints, mismatched reference systems, correlated errors, and non-Gaussian residuals. These are computer science challenges as much as geodetic ones (Fig. 2).

The same data-fusion logic is likely to expand as new observation systems become more common. Distributed Acoustic Sensing (DAS) can provide dense fiber-optic strain or seismic measurements along infrastructure corridors, while multi-temporal Unmanned Aerial Vehicle (UAV) photogrammetry, UAV Light Detection and Ranging (LiDAR), and optical pixel tracking can add near-field surface-change constraints in landslide, glacier, active-fault, and infrastructure settings. These datasets do not replace satellite geodesy, but they can help where satellite viewing geometry, vegetation, terrain shadowing, or decorrelation limit conventional inversion (Behr & Bürgmann, 2021; Cheng et al., 2024; Guo et al., 2019; Hamling et al., 2017; Pezzo et al., 2023; Puel et al., 2024; Spudich et al., 1995; Yokota et al., 2016).

Table 3 Data modalities commonly used in computational geodetic inversion

Modality	Typical observation		Computational value	Key limitation
InSAR	Dense	line-of-sight	High spatial coverage; sensitive to	Decorrelation, atmospheric delay, phase
	deformation		surface displacement	ambiguity, LOS-only geometry
GNSS	3-D station displacement		High temporal precision; absolute reference frame	Sparse spatial coverage, monument/local effects
Gravity	/	Mass redistribution and	Direct sensitivity to mass change;	Low spatial resolution, leakage, filtering

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Modality	Typical observation	Computational value	Key limitation
GRACE	gravity-field change	regional to global coverage	dependence
Seismic data	Waveform, arrival, finite-	Rupture timing and dynamic source	Requires velocity models and complex
	source constraints	information	source representation
DEM / geology / GIS	Topography, faults,	Physical context and priors	Scale mismatch; uncertain or categorical constraints
	lithology, land use, hydrology		

4.1 Joint Data Weighting and Covariance Treatment

In multi-source inversion, notation and formulae are clearer when separated from the main explanatory text. The observation vector may combine independent but unequal data blocks from Interferometric Synthetic Aperture Radar (InSAR), Global Navigation Satellite System (GNSS), gravity, seismic, and other Earth-observation sources. The combined observation vector can be represented as:

$$\mathbf{d} = [\mathbf{d}_{\text{InSAR}}, \mathbf{d}_{\text{GNSS}}, \mathbf{d}_{\text{grav}}, \mathbf{d}_{\text{seis}}, \dots]^T \quad (3)$$

A common covariance-weighted objective function for the combined inversion is:

$$J(\mathbf{m}) = [\mathbf{d} - \mathbf{G}(\mathbf{m}; \boldsymbol{\theta})]^T \mathbf{C}_d^{-1} [\mathbf{d} - \mathbf{G}(\mathbf{m}; \boldsymbol{\theta})] + \lambda R(\mathbf{m}) \quad (4)$$

When data sources are treated as independent, the covariance matrix is often approximated by a block-diagonal structure:

$$\mathbf{C}_d = \text{blockdiag}(\mathbf{C}_{\text{InSAR}}, \mathbf{C}_{\text{GNSS}}, \mathbf{C}_{\text{grav}}, \mathbf{C}_{\text{seis}}, \dots) \quad (5)$$

While this block-diagonal form serves as a helpful initial approximation, its effectiveness reduces in the presence of factors such as atmospheric noise, GNSS time-correlated noise, gravity leakage, orbit-related effects, and errors in cross-sensor reference frames (Agata, 2020; Atzori & Antonioli, 2011; Fukuda et al., 2008; Hori et al., 2018; Liu et al., 2016; Roger et al., 2020; Wang & Xu, 2017; Williams & Wallace, 2015; Williams & Wallace, 2018; Xi et al., 2024; Xu et al., 2016).

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To achieve practical weighting, it is not enough to simply tally observations. Without employing spatial covariance, quadtree-down sampled observations, empirical semi variograms, or weights based on covariance, dense InSAR pixels may disproportionately influence an objective function. Relative data weights can also be determined using methods such as Variance Component Estimation, Bayesian evidence optimization, residual balancing, or sensitivity tests. While these techniques do not eliminate non-uniqueness, they help balance data sources that are both visible and reproducible (Agata, 2020; Atzori & Antonioli, 2011; Fukuda et al., 2008; Hori et al., 2018; Liu et al., 2016; Roger et al., 2020; Wang & Gu, 2020; Wang & Xu, 2017; Williams & Wallace, 2015; Williams & Wallace, 2018; Xi et al., 2024; Xu et al., 2016).

5. Algorithmic Families in Computational Geodetic Inversion

5.1 Least-squares and nonlinear optimization

Least-squares inversion continues to be a fundamental tool in geodetic modelling because of its ability to clearly relate data discrepancies, model parameters, and residual diagnostics. In numerous studies on earthquakes and deformation, researchers initially investigated nonlinear source parameters such as location, strike, dip, rake, depth, and source size. This is followed by a linear or constrained inversion to determine the slip distribution. Although this two-step approach is computationally efficient, it is susceptible to issues with parameterization and local minima (Bai et al., 2022; Huang et al., 2017; Jiang & González, 2020; Puliero et al., 2026; Tomita et al., 2021; Wald & Graves, 2001).

Nonlinear optimization is essential when the geometry or physical source model is not defined. For instance, volcanic deformation might necessitate ellipsoidal, sill-like, dike-like, or distributed pressure sources; earthquake ruptures could involve several fault segments; hydrological loading might require spatially distributed mass fields; and landslide modelling may require nonlinear material parameters. Various search strategies have been employed, including grid search, evolutionary algorithms, particle swarm optimization, simulated annealing, shape optimization, and hybrid methods (Bai et al., 2022; Jiang & González, 2020; Mills et al., 2025).

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5.2 Regularization, sparsity, and edge preservation

Regularization is crucial because of the frequent ill-posed solutions of geodetic inverse problems. While smoothness penalties help reduce unrealistic fluctuations, they can also blur distinct rupture or boundary features. However, sparse penalties encourage solutions that are compact or easy to interpret, although they might overly simplify distributed deformation. Penalties that preserve edges or use total variation aim to maintain discontinuity while managing noise. Recent advances in sparse modelling and Bayesian regularization indicate that adaptive constraints can represent physical structure more effectively than uniform smoothing (Agata, 2020; Niu et al., 2023; Nozue & Fukahata, 2025; Sun et al., 2025; Wang & Gu, 2020; Xi et al., 2024).

One of the main computational challenges is the selection of parameters. Techniques such as L-curves, cross-validation, information criteria, model resolution analysis, covariance component estimation, and Bayesian evidence can be used to determine the regularization strength. In practical applications, subjective tuning poses issues because it hinders reproducibility. Consequently, the development of explainable methods for parameter selection is an important future focus (Niu et al., 2023; Nozue & Fukahata, 2025; Sun et al., 2025; Wang & Gu, 2020).

5.3 Bayesian and ensemble inversion

Bayesian inversion approaches the solution by considering it as a probability distribution rather than a singular model (Fig. 3). The posterior integrates prior information with the likelihood of the data, allowing it to capture the uncertainty, trade-offs, and non-uniqueness. These Bayesian techniques are particularly advantageous when there is uncertainty in the fault geometry, source parameters, or regularization decisions. Additionally, they offer a systematic method for comparing different source models and transferring observation errors into model uncertainty (Jiang & González, 2020; Niu et al., 2023; Sun et al., 2025; Xi et al., 2024).

One constraint is the computational cost. To sample posterior distributions in high dimensions, techniques such as Markov chain Monte Carlo, ensemble methods, variational approximations, surrogate models, or reduced-

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order representations may be necessary. Recent approaches using ensemble solutions emphasize the importance of not only calculating different solutions but also summarizing and visualizing them in a manner that domain experts can understand (Mills et al., 2025).

5.4 Physics-informed and machine-learning-assisted inversion

Machine learning plays multiple roles in geodetic inversion. It can serve as a rapid substitute for costly forward modelling, generate priors for feasible model spaces, function as a module for denoising or feature extraction, or directly map observations to the model parameters. Physics-informed deep learning seeks to maintain physical consistency by incorporating governing equations, analytical constraints, or forward-operator residuals into the training process (Costa et al., 2025; Fukushima et al., 2025; Li et al., 2021; Lu et al., 2021; Okazaki, 2026; Okazaki et al., 2025; Raissi et al., 2019).

The appeal of physics-informed learning lies in its speed and adaptability (Fig. 3); however, it carries the risk of being opaque and overly confident. A neural network that generates a deformation model without clarifying the data, assumptions, or physical constraints influencing the outcome may not be appropriate for hazard decision-making support. Consequently, AI-assisted inversion should be complemented by uncertainty quantification, residual analysis, sensitivity testing, and the design of explainable outputs. Recent studies on physics-aware InSAR change detection and neural operators have demonstrated how synthetic training, physical signal models, spectral modules, and explainability can bridge data-driven learning with interpretable geoscientific outputs (Chen et al., 2026; Costa et al., 2025; Fukushima et al., 2025; Li et al., 2021; Li et al., 2026a; Li et al., 2026b; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Perrot et al., 2026; Raissi et al., 2019; Wu et al., 2026).

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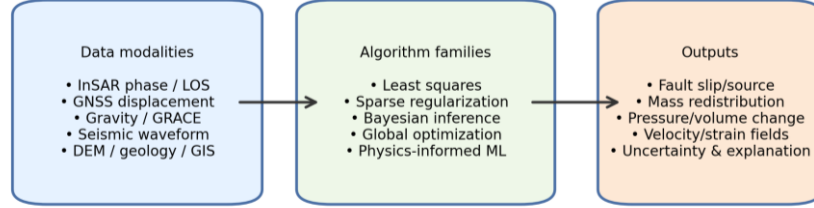


Fig. 3 Computational mapping of multi-source geodetic inversion from observation modalities to algorithmic families and decision-oriented outputs

5.5 Physics-Informed Loss Terms and Assessment Metrics

For AI-assisted inversion, physical consistency should be evaluated alongside prediction error. A generic physics-informed objective can be written as:

$$L_{\text{total}} = L_{\text{data}} + \alpha L_{\text{phys}} + \beta L_{\text{bnd}} + \gamma L_{\text{prior}} + \delta L_{\text{unc}} \quad (6)$$

In Equation (6), the primary components are:

- L_{data} : the loss associated with data misfit, which measures the discrepancy between the predicted and actual deformation, gravity, or other geodetic signals.
- L_{phys} : loss ensuring physical consistency, which penalizes any breaches of governing equations, mechanical equilibrium, mass conservation, or residuals from forward operators.
- L_{bnd} : loss related to boundary conditions or source constraints, such as restrictions on source depth, slip continuity, pressure-source geometry, or permissible deformation gradients.
- L_{prior} : loss derived from prior information based on geological, geodetic, hydrological, or structural constraints.
- L_{unc} : the loss addressing uncertainty or calibration, aimed at reducing overconfidence in predictions and enhancing the reliability of model outputs.

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- α , β , γ , and δ : coefficients that determine the relative impact of the physics, boundary, prior, and uncertainty terms on the overall loss, respectively.

Therefore, the specified loss function should not be viewed as a standard machine-learning detail; it must be connected to the physical assumptions, evaluation context, and anticipated failure modes of the inversion problem (Chen et al., 2026; Costa et al., 2025; Fukushima et al., 2025; Hou et al., 2020; Li et al., 2021; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Raissi et al., 2019; Wang et al., 2022; Yang et al., 2026).

The indicative comparison in Fig. 4 shows that no single algorithmic family is uniformly superior; instead, each method provides a different balance among transparency, scalability, uncertainty representation, nonlinear-search capability, physical fidelity, and decision interpretability.

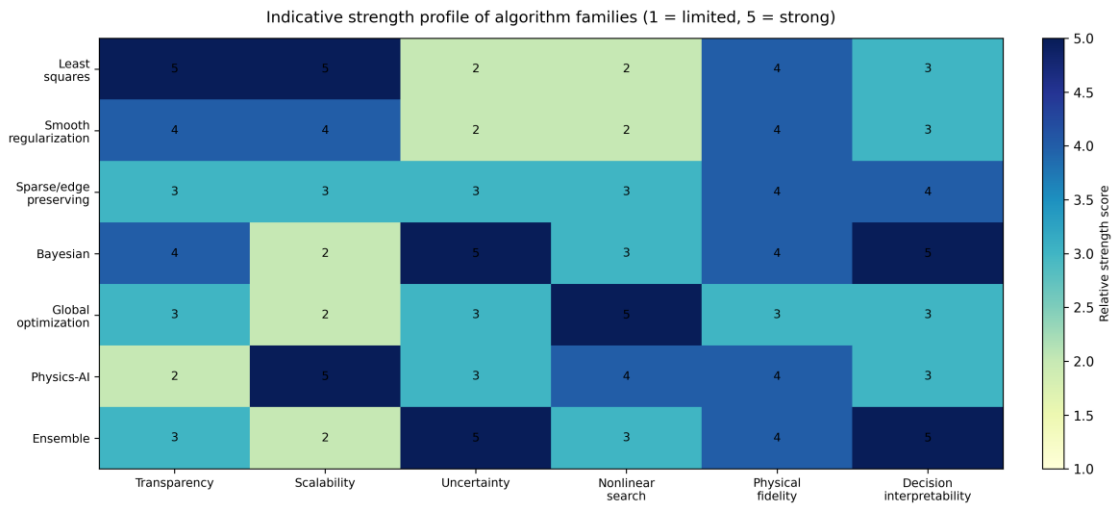


Fig. 4 Indicative strength profile of major algorithmic families used in computational geodetic inversion

The exact physics term must be application-specific and context-dependent. For elastic deformation, it may penalize the violation of mechanical equilibrium or inconsistent displacement gradients. For hydrology and gravity, mass conservation or loading consistency constraints may be included. For volcanic and fault-source inversions, physically implausible source shapes, unrealistic slip gradients, or deformation fields inconsistent

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with the selected forward model may be penalized. Therefore, a useful AI-assisted inversion report should include the training data, loss function components, validation geography, failure cases, and uncertainty behavior (Behr & Bürgmann, 2021; Chen et al., 2026; Cheng et al., 2024; Costa et al., 2025; Fukushima et al., 2025; Hamling et al., 2017; Hou et al., 2020; Li et al., 2021; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Pezzo et al., 2023; Puel et al., 2024; Raissi et al., 2019; Spudich et al., 1995; Wang et al., 2022; Yang et al., 2026; Yokota et al., 2016).

5.6 Comparative Strengths and Practical Limits of Algorithmic Families

There was no rigid ranking among the examined methods. Each group of algorithms plays a unique computational role, offering distinct advantages and disadvantages in geodetic inversion. The effectiveness of these methods is influenced by factors such as the nature of the observations, the way models are parameterized, the structure of uncertainties, computational expenses, and the intended application of the inversion results. Table 4 presents a comparative overview of the major algorithmic families.

Table 4 Major algorithmic families in computational geodetic inversion

Algorithm family	Main role	Strength	Risk or limitation
Least squares / nonlinear optimization	Efficient estimation of source or slip parameters	Transparent and widely used	Sensitive to geometry, weighting, and local minima
Smoothness regularization	Stabilizes ill-posed slip or field inversion	Reduces noise amplification	Can over-smooth sharp boundaries
Sparse / edge-preserving regularization	Compact or discontinuity-aware solutions	Useful for faults and heterogeneous domains	Requires careful parameter selection
Bayesian inversion	Posterior uncertainty and model comparison	Represents non-uniqueness	Computationally demanding
Global optimization	Source geometry and nonlinear search	Can explore complex parameter spaces	Potentially expensive
Physics-informed ML	Surrogate or hybrid inversion	Fast, scalable, adaptable	Needs explainability and physical

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Algorithm family	Main role	Strength	Risk or limitation
Ensemble inversion	Family of plausible solutions	Communicates trade-offs	validation
			Requires summarization and
			visualization

Least-squares and nonlinear optimizations continue to be valuable owing to their clarity, efficiency, and broad comprehension. These methods are particularly effective when the forward model is clearly defined, and the number of unknown variables is limited. However, they can be affected by factors such as source geometry, data weighting, parameterization, and local minima. To stabilize the inversion of noisy or underdetermined slip or deformation fields, smooth regularization is employed, although it may blur distinct rupture boundaries, localized deformation sources, or sudden strain gradients. However, sparse and edge-preserving penalties are beneficial for maintaining compact or discontinuous structures, which is advantageous for faults and heterogeneous domains. However, careful selection of parameters is crucial, as the penalty structure can significantly impact the resulting model (Agata, 2020; Mills et al., 2025; Niu et al., 2023; Nozue & Fukahata, 2025; Perrot et al., 2026; Sun et al., 2025; Wang & Gu, 2020; Xi et al., 2024).

Bayesian and ensemble methods are crucial when dealing with interpretations in which uncertainty and nonuniqueness play significant roles. Bayesian inversion captures posterior uncertainty and facilitates the evaluation of different model assumptions in this study. In contrast, ensemble inversion presents a range of plausible solutions rather than a single deterministic best-fit model. The primary challenges of these methods include high computational demands and the necessity for meticulous summarization of the posterior distribution, parameter trade-offs, and alternative interpretations. Global optimization is beneficial when there is uncertainty in the source geometry or model structure, as it can explore complex nonlinear parameter spaces more extensively than local optimization techniques. Nonetheless, it remains computationally intensive and requires physically meaningful constraints to prevent unrealistic outcomes (Agata, 2020; Atzori & Antonioli, 2011; Fukuda et al., 2008; Hori et al., 2018; Jiang & González, 2020; Liu et al., 2016; Mills et al., 2025; Niu et

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al., 2023; Nozue & Fukahata, 2025; Sun et al., 2025; Wang & Gu, 2020; Wang & Xu, 2017; Williams & Wallace, 2015; Williams & Wallace, 2018; Xi et al., 2024; Xu et al., 2016).

Physics-informed machine learning introduces an additional dimension to this methodological framework. It serves as a rapid substitute for costly forward models, acts as a learned prior, or is integrated as a hybrid inversion element, making it appealing for workflows that require scalability and near-instantaneous processing. Nonetheless, its application is justifiable only when physical constraints, checks for physical consistency, uncertainty behaviour, and potential failure scenarios are documented explicitly. In the absence of these precautions, a learned model might seem precise, yet remain physically obscure or unreliable beyond its training scope. In essence, a robust computational geodetic inversion is unlikely to rely solely on a single algorithm. An effective workflow might incorporate transparent optimization, suitable regularization, covariance-aware weighting, Bayesian or ensemble uncertainty estimation, and physics-informed acceleration, contingent on data quality, physical assumptions, computational expense, and decision-making context (Atzori & Antonioli, 2011; Behr & Bürgmann, 2021; Chen et al., 2026; Cheng et al., 2024; Costa et al., 2025; Fukuda et al., 2008; Fukushima et al., 2025; Hamling et al., 2017; Hori et al., 2018; Hou et al., 2020; Li et al., 2021; Liu et al., 2016; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Pezzo et al., 2023; Puel et al., 2024; Raissi et al., 2019; Spudich et al., 1995; Wang et al., 2022; Wang & Xu, 2017; Williams & Wallace, 2015; Williams & Wallace, 2018; Xu et al., 2016; Yang et al., 2026; Yokota et al., 2016).

6. Specific Use Cases of the Proposed Framework

6.1 Landslide kinematic interpretation in mountainous terrain

A use case centered on landslides is particularly pertinent for geohazard monitoring with InSAR in mountainous areas. In these environments, interpreting line-of-sight deformation from InSAR, along with slope geometry from DEMs, geological conditions, rainfall or seismic events, and field data, can help deduce the kinematic state of a slope. Research on slow-moving landslides using DInSAR and finite element modeling, alongside satellite

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radar data on landslides accelerated by earthquakes, indicates that slope deformation cannot be solely understood through displacement magnitude (De Novellis et al., 2016; Song et al., 2022).

In this context, the forward model can connect the observed surface shifts to motion parallel to the slope, deformation influenced by depth, sliding of blocks, groundwater pressure, or a viscoelastic reaction. The inversion challenge is made more complex by factors such as layover, shadow, vegetation loss of coherence, snow, atmospheric distortions, and restricted viewing angles. The suggested framework aids landslide research by mandating detailed reporting of observation geometry, slope adjustments, data uncertainty, regularization, residual deformation patterns, and alternative movement scenarios. Rather than presenting a single deformation value as conclusive, the framework promotes an interpretation that considers uncertainty and assesses whether the slope is stable, moving slowly, accelerating, or reacting to external influences.

6.2 Co-seismic fault-slip inversion

In earthquake research, GNSS and InSAR data are frequently employed to deduce the characteristics of faults, such as their geometry, slip patterns, rupture range, and deformation that varies with depth. The suggested framework facilitates this application by necessitating clear forward model assumptions, balancing data from GNSS and InSAR, defining fault parameters, applying smoothing or sparsity constraints, generating residual maps, and estimating uncertainties. This approach is crucial because different slip distributions can correspond to the same surface deformation pattern, particularly when there is ambiguity in the fault geometry or Earth's structure (Bai et al., 2022; Huang et al., 2017; Jiang & González, 2020; Puliero et al., 2026; Tomita et al., 2021; Wald & Graves, 2001; Xi et al., 2024).

6.3 Volcanic deformation-source inversion

To study volcanic unrest, ground deformation can be analyzed to determine the depth, shape, pressure variation, or expansion of the magma source. This approach promotes clear documentation of the source shape, assumptions about the elastic medium, InSAR viewing angles, GNSS limitations, model discrepancies, and

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uncertainties in the source parameters. This is beneficial because different source shapes, such as spherical, sill-like, dike-like, or irregular, can result in similar patterns of surface deformation (Jiang & González, 2020; Mills et al., 2025).

6.4 Hydrological loading and mass-change inversion

To estimate terrestrial water storage or mass redistribution, hydrological loading inversion employs GNSS, gravity, GRACE/GFO, InSAR, and supplementary hydrological data. This application necessitates meticulous attention to spatial resolution, temporal sampling, reference frames, filtering, leakage, and model uncertainty. The suggested framework can assist in structuring these diverse data sources and convey uncertainty in mass change estimates (Li et al., 2023a; Zhao et al., 2026).

6.5 Land subsidence and reservoir-parameter inversion

In the context of subsidence and reservoir analyses, InSAR time series, groundwater measurements, reservoir production figures, geological strata, and geomechanical assumptions can be employed to deduce compaction, aquifer-system reactions, or reservoir characteristics. This framework facilitates such applications by necessitating precise parameter definitions, a regularization approach, uncertainty assessments, and residual diagnostics. This is crucial because subsidence can result from various processes, such as groundwater extraction, mining, hydrocarbon production, sediment compaction and natural consolidation (Liu et al., 2023).

The relationships between application domains, inferred quantities, typical computational workflows, implementation approaches, and representative studies are consolidated in Table 5.

Table 5 Practical use-case matrix linking domains, workflows, and implementation styles

Use case	Typical inferred quantity		Typical workflow			Implementation style / tools		References
Landslide	Slow	movement,	InSAR	time	series	+	InSAR monitoring,	(De Novellis et al.,

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Use case	Typical inferred quantity	Typical workflow	Implementation style / tools	References
kinematic interpretation	acceleration, slip- surface or material parameters	DEM/slope correction + rainfall/groundwater context + residual diagnostics	slope-stability modelling, UAV/LiDAR-assisted surface change	2016; Puel et al., 2024; Qiu et al., 2019; Spudich et al., 1995; Tian et al., 2018) (Atzori & Antonioli,
Co-seismic fault-slip inversion	Fault geometry, slip distribution, after slip, stress transfer	GNSS/InSAR/seismic fusion + elastic dislocation model + regularized or Bayesian inversion	Finite-fault inversion scripts, Bayesian sampling, sensitivity tests	2011; Gao et al., 2021; Hou et al., 2020; Wald & Graves, 2001; Williamson & Newman, 2018) (Guo et al., 2019; Hicks
Volcanic deformation-source inversion	Pressure source, dike/sill intrusion, reservoir evolution	InSAR/GNSS deformation + source-geometry search + uncertainty envelopes	Geodetic Bayesian inversion, shape optimization, volcanic-source modelling	et al., 2026; Jiang & González, 2020; Li et al., 2025; Varugu & Amelung, 2021) (Li et al., 2023a;
Hydrological loading and mass-change inversion	Terrestrial water storage, gravity anomaly, loading response	GNSS-GRACE/GFO-InSAR fusion + loading model + covariance-aware weighting	Gravity-field analysis, loading inversion, data assimilation	Sjöberg & Bagherbandi, 2017; Tang et al., 2024; Xu & Rummel, 1994; Zhang et al., 2016)
Subsidence and reservoir-parameter estimation	Compaction, pressure change, extraction/injection response	InSAR time-series + reservoir/geo-mechanical priors + parameter inversion	MSBAS/InSAR workflows, reservoir/geo-mechanical inversion	(Doyle et al., 2001; Liu et al., 2023; Smith et al., 2019; Takada & Fukushima, 2013; Tung & Feigl, 2021)

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7. Explainability and Uncertainty as Core Design Requirements

In geodetic inversion, explainability extends beyond the visual representation of the final source model. An inversion that is truly explainable should address five critical questions: which datasets were utilized, what assumptions influenced the solution, which observations dictated the main parameters, where residuals were not accounted for, and the degree of uncertainty in the results. These questions are particularly significant when inversion outcomes are applied to geohazard scenarios.

Uncertainty arises from various sources. Observation-related uncertainty encompasses factors such as phase noise, atmospheric delay, GNSS monument effects, gravity leakage, errors in seismic velocity models, and DEM uncertainty. Model-related uncertainty involves aspects such as source geometry, elastic structure, boundary conditions, and parameterization. Algorithmic uncertainty is linked to issues such as local minima, sampling convergence, regularization choices, and numerical precision. Interpretative uncertainty arises when multiple physical interpretations are feasible. A computational framework should reveal these sources of uncertainty instead of concealing them behind a single favoured model (Agata, 2020; Jiang & González, 2020; Mills et al., 2025; Niu et al., 2023; Nozue & Fukahata, 2025; Sun et al., 2025; Wang & Gu, 2020; Xi et al., 2024).

Visual analytics can help convey uncertainty. Ensemble solutions can be depicted using posterior envelopes, residual maps, parameter trade-off plots, and sensitivity fields. Concepts such as contour boxplots and probabilistic depth, initially developed for visualizing uncertain scalar fields or contour ensembles, offer valuable design principles for illustrating uncertain deformation zones, pressure-source regions, or slip patches (Chen et al., 2026; Li et al., 2026b). Additionally, probing dataset bias is crucial when AI-assisted inversion employs training sets that may inadequately represent certain fault geometries, terrain regimes, land cover conditions, or deformation mechanisms (Wu et al., 2026).

Explainability is essential for AI-assisted inversions. Physics-informed neural networks, neural surrogates, or learned priors should be assessed not only based on prediction errors but also on physical consistency,

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generalization across regions, robustness to noise, and transparency of failure modes. Techniques such as physics-aware synthetic training, feature attribution, residual testing, and human-in-the-loop evaluation can enhance the credibility of AI inversion (Chen et al., 2026; Costa et al., 2025; Fukushima et al., 2025; Li et al., 2021; Li et al., 2026a; Li et al., 2026b; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Perrot et al., 2026; Raissi et al., 2019; Wu et al., 2026).

8. Proposed Framework: XAI-UQ-CGI

The XAI-UQ-CGI framework is structured to organize computational geodetic inversion into five distinct layers (Table 6), serving as a conceptual model applicable through traditional inversion techniques, Bayesian methods, or hybrid systems integrating physics and AI.

Layer 1 emphasizes data harmonization, involving the conversion of inputs from sources such as InSAR, GNSS, gravity, seismic data, DEM, geology, hydrology, and GIS into compatible formats concerning space, time, and reference frames, while maintaining metadata integrity. Prior to inversion, uncertainties in the observations, missing data, and potential biases were documented.

Layer 2 pertains to forward model encoding, where physical models are articulated as computational operators. These encompass elastic dislocation models, gravity kernels, hydrological loading functions, volcanic pressure-source models, finite element models, and learned surrogate operators. This layer is essential for differentiating physical assumptions from the inversion algorithm, ensuring that the assumptions are explicit and reusable.

Layer 3 is devoted to the inversion and optimization of the engine. Depending on the specific problem, this layer may utilize methods such as least squares, constrained optimization, Bayesian sampling, sparse regularization, ensemble inversion, global search or physics-informed learning. The framework does not prescribe a specific method but requires that the selected method be documented, parameterized, and linked with uncertainty diagnostics.

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Layer 4 focuses on uncertainty propagation, transforming uncertainties from observations, models, and algorithms into comprehensible outputs, such as posterior distributions, ensemble spreads, residual maps, model resolution indicators, sensitivity maps, and confidence flags.

Layer 5 constitutes an explainable decision layer that translates the outputs into user-relevant statements. It identifies reliable source parameters, locates model uncertainties, assesses the significance of assumptions, determines the data that most influences the solution, evaluates the plausibility of alternative models, and relates the results to hazard interpretation.

Table 6 XAI-UQ-CGI framework layers

Layer	Purpose	Examples
1.Data harmonization	Align observations in space, time, reference frame, and uncertainty structure	InSAR stacks, GNSS, GRACE, seismic, DEM, geology
2.Forward-model encoding	Represent physical assumptions as operators	Fault dislocation, gravity kernels, hydrological loading, volcanic sources
3. Inversion engine	Estimate model parameters under constraints	Least squares, Bayesian, sparse, global search, physics-informed ML
4.Uncertainty propagation	Quantify non-uniqueness and sensitivity	Posterior spread, residual fields, ensemble summaries
5. Explainable decision layer	Translate model results into traceable interpretation	Driver attribution, confidence flags, limitation statements

8.1 Programmatic View and Layer Interfaces

To enhance the reproducibility of XAI-UQ-CGI, the five layers should be regarded as computational interfaces, rather than merely conceptual components. Each interface must specify the necessary inputs, anticipated outputs and diagnostic evaluations. This approach establishes a pipeline that can be executed using classical inversion, Bayesian sampling, sparse modelling or hybrid physics-AI methods. The resulting programmatic sequence and

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diagnostic checkpoints are illustrated in Fig. 5, while the required inputs, principal outputs, and diagnostic checks associated with each layer interface are summarized in Table 7.

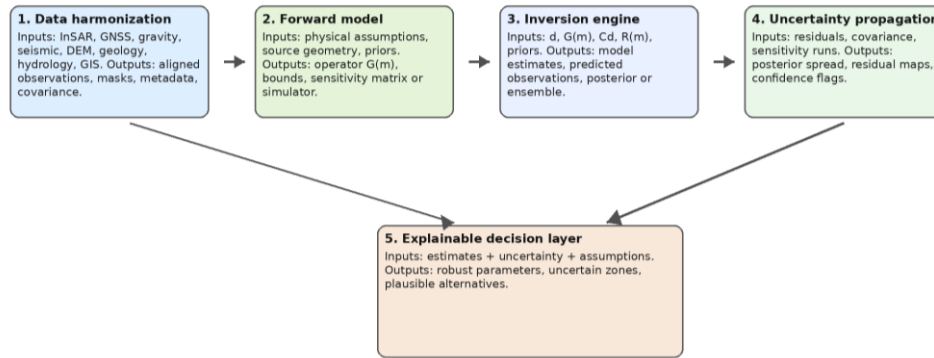


Fig. 5 Programmatic view of the XAI-UQ-CGI pipeline with layer interfaces and diagnostic checkpoints

Table 7 Programmatic layer interfaces and diagnostic checkpoints of the XAI-UQ-CGI framework

Layer interface	Required inputs			Main outputs			Diagnostic checks	
Data harmonization	InSAR, seismic, hydrology, GIS	GNSS, DEM, geology	gravity, geology	Aligned observations, metadata, uncertainty model	masks,	Reference-frame consistency, missing data, noise screening		
Forward-model encoding	Source geometry, assumptions, conditions	physical, priors, boundary		Forward operator G(m), parameter vector, bounds, sensitivity matrix/simulator		Assumption audit, dimensional consistency, parameter identifiability		
Inversion engine	d, G(m), Cd, R(m), bounds	priors,		Best estimates, posterior samples, ensembles, predicted observations		Convergence, local minima, residual behavior, regularization sensitivity		
Uncertainty propagation	Covariance, residuals, samples, alternative geometries			Posterior ranges, ensemble spread, residual maps, confidence flags		Non-uniqueness, resolution, robustness to data removal		
Explainable decision layer	Model estimates, residuals, data diagnostics	uncertainty, data influence		Traceable statements about robust parameters and plausible alternatives		Assumption disclosure, dominant data drivers, decision limits		

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8.2 Algorithmic Workflow and Supplementary Implementation Template

The computational workflow is presented first as an abstract, method-agnostic template (*Algorithm 1, Code Availability Section*) and then instantiated as a concrete, reproducible experiment in *Section 8.3 (Code Availability Section)*. The following algorithm outlines the implementation that *Section 8.3* realizes for a synthetic multi-source InSAR–GNSS case.

Algorithm 1. Unified XAI-UQ-CGI workflow for review and future implementation.

Input: observation blocks $D = \{\text{InSAR, GNSS, gravity, seismic, DEM/geology/GIS}\}$; forward-model assumptions θ ; priors and bounds; uncertainty assumptions.

Output: documented model estimates, predicted observations, residual diagnostics, uncertainty summaries, and an explainable decision statement.

- i. Import observation blocks, metadata, acquisition geometry, and quality masks.
- ii. Harmonize coordinate systems, temporal windows, reference frames, and observation units.
- iii. Estimate or declare sensor-wise uncertainty and covariance structures, including correlated-error assumptions.
- iv. Assemble the observation vector d , forward operator $G(m; \theta)$, covariance matrix C_d , regularization $R(m)$, priors, and parameter bounds.
- v. Select an inversion engine appropriate to the problem: least squares, constrained optimization, Bayesian sampling, sparse or edge-preserving inversion, ensemble search, or physics-informed surrogate modelling.
- vi. Estimate candidate model parameters and compute predicted observations $G(m; \theta)$.
- vii. Compute residuals and evaluate weighting sensitivity, data-source influence, assumption dependence, and possible local-minimum behavior.

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- viii. Propagate uncertainty using covariance analysis, posterior or ensemble spread, model-resolution tests, or sensitivity experiments.
- ix. Produce an explainable decision summary stating robust parameters, uncertain zones, dominant data drivers, plausible alternatives, and limits of interpretation.
- x. Archive configuration choices, equations, parameter bounds, diagnostic checks, and software/code notes for reproducibility.

8.3 Synthetic proof-of-concept: end-to-end demonstration of the five layers

This subsection provides a controlled synthetic proof-of-concept showing how the five XAI-UQ-CGI layers can be executed as a single reproducible computational pipeline. It is not a validation against a geophysical event or an operational hazard test. Synthetic InSAR and GNSS observations are generated and then inverted with a Mogi point-pressure model (Mogi, 1958; Segall, 2010), so that data harmonization, parameter estimation, posterior non-uniqueness, sensor-fusion effects, residual diagnostics, and explainable output can all be examined under a known ground truth. Because the data-generating and inversion operators are deliberately matched, the experiment verifies pipeline behavior under correct model specification; the effect of structural model error is treated separately as a dedicated mismatch test at the end of the subsection. The Mogi source was chosen because it is analytically compact yet exhibits a canonical form of non-uniqueness—the depth–volume trade-off—that gives the uncertainty and explainability layers visible work to do. The five-layer architecture carries over to distributed fault-slip or loading problems, although the priors, regularization, covariance structure, parameter dimensionality, resolution analysis, and solver may all differ; only the architecture, not the specific layer contents, is claimed to be general. Every quantity below is produced by the script released as Resource 3 under a fixed random seed.

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Layer 1 — Data harmonization

Two heterogeneous observation blocks were synthesized from a common ground-truth source ($x_0 = 1000$ m, $y_0 = -500$ m, $d = 3500$ m, $\Delta V = 3.0 \times 10^6$ m³) and expressed in a shared east–north–up (ENU) frame. The InSAR block emulates a single descending track: a regular grid spanning -4000 to 4000 m in both horizontal axes at 200 m spacing (41×41 nodes) is decimated by a fixed Bernoulli mask (retention probability 0.25 , fixed seed), yielding exactly 427 line-of-sight (LOS) samples that are identical in every run reported here. The modelled ENU displacement is projected onto the normalized descending look vector $\ell = (0.621, -0.112, 0.776)$ in ENU order, with the sign convention that positive LOS denotes motion toward the satellite (range decrease). The GNSS block comprises nine three-component stations at the fixed coordinates listed in the Online Resource 3 configuration file. Independent zero-mean Gaussian noise was added with standard deviations of 15 mm for InSAR LOS and 2 mm (horizontal) and 5 mm (vertical) for GNSS.

The InSAR block additionally contains a deterministic planar term standing in for an atmospheric or orbital ramp, $g(x, y) = c_0 + c_x x + c_y y$, with true coefficients $c_0 = 2.0$ mm, $c_x = 1.2$ mm km⁻¹, and $c_y = -0.8$ mm km⁻¹. Rather than being removed by preprocessing, this ramp is **estimated jointly as three nuisance parameters** during inversion, so that its interaction with the source signal is propagated into the reported uncertainty. The two blocks are combined through a block-diagonal data covariance: cross-sensor error correlation is neglected by assumption in this illustrative experiment because the principal InSAR and GNSS error-generating processes are treated as distinct. A fuller treatment would replace the InSAR block with a distance-dependent covariance to capture spatially correlated atmospheric noise; this is noted as a limitation rather than implemented here (Fig. 6).

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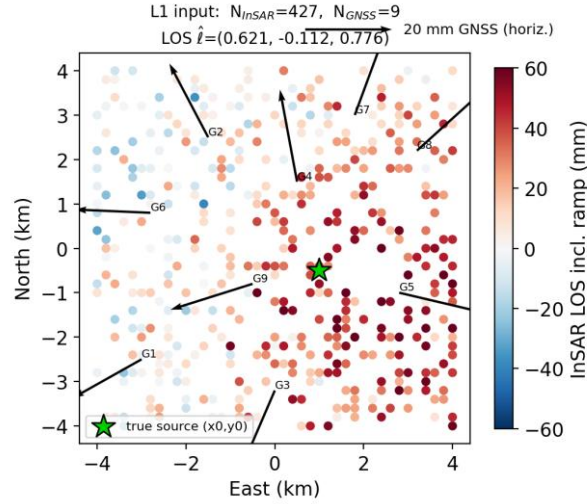


Fig. 6 Layer 1 input. Decimated InSAR LOS field (color, ramp included; $N = 427$) and nine three-component GNSS stations (arrows, labelled G1–G9) synthesized from the same Mogi source. Arrows show the horizontal GNSS components for display only; the vertical component is also included in the inversion. The star marks the true horizontal source position; the normalized ENU look vector is annotated. Both blocks are harmonized in a common ENU frame with declared per-sensor uncertainty

Layer 2 — Forward-model encoding

The forward operator encodes the surface response of a point pressure source in a homogeneous, isotropic elastic half-space with a flat free surface. For a source at depth $d > 0$ (positive downward) and horizontal position (x_0, y_0) , the ENU surface displacement at station (x, y) is

$$\mathbf{u}(x, y) = [(1-\nu)/\pi] \cdot \Delta V \cdot (x-x_0, y-y_0, d)^T / R^3, \quad R = \sqrt{(x-x_0)^2 + (y-y_0)^2 + d^2} \quad (7)$$

where $\mathbf{u} = (u_E, u_N, u_U)^T$ is the displacement vector (m), $\nu = 0.25$ is the Poisson ratio, ΔV is the source volume change (m^3), d and R are in meters, and station and source coordinates share the ENU origin at the grid centre.

The Poisson ratio is **fixed and not inferred**; holding it constant deliberately suppresses one source of model

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uncertainty, which should be kept in mind when interpreting the posterior widths. For the InSAR block the prediction is projected onto the line of sight and combined with the planar ramp,

$$d_{\text{LOS}} = \ell^T \mathbf{u} + (\mathbf{c}_0 + \mathbf{c}_{xx} + \mathbf{c}_{yy}) = \ell_E u_E + \ell_N u_N + \ell_U u_U + g(x, y), \|\ell\|_2 = 1 \quad (8)$$

while the GNSS block retains all three components of $\mathbf{u}$. The governing assumptions—homogeneous isotropic half-space, single point source, static snapshot, and flat surface—are recorded in a machine-readable configuration file (Online Resource 3) so that they remain explicit and reusable, consistent with the reporting requirement of Section 9.1.

Layer 3 — Inversion engine

Two engines are applied to identical harmonized inputs to separate the point estimate from its uncertainty. The point estimate is obtained with the trust-region-reflective least-squares solver of SciPy (`scipy.optimize.least_squares`, method “trf”), using Jacobian-based variable scaling, a two-point finite-difference Jacobian, step and cost tolerances of 10^{-12} , and physical bounds on all parameters; the reported run terminated at a first-order-optimality stopping condition. Residuals are weighted by the reciprocal of each block’s standard deviation. The reduced chi-square is defined as $\chi^2_v = \sum r_i^2 / (N_{\text{obs}} - N_{\text{par}})$, with r_i the weighted residuals, $N_{\text{obs}} = 454$ observations (427 InSAR + 27 GNSS), and $N_{\text{par}} = 7$ fitted parameters (four source parameters plus three ramp nuisance parameters); the solution gives $\chi^2_v = 0.98$, consistent with the assigned noise. The parameter covariance is taken from $(J^T J)^{-1}$ scaled by χ^2_v and is a local linearized approximation valid near the optimum.

The full posterior is characterized with an affine-invariant ensemble sampler (Foreman-Mackey et al., 2013; Goodman & Weare, 2010) under uniform priors bounded by the physical search ranges. Four overdispersed, independently seeded ensembles of 40 walkers were run for 9000 steps each; each ensemble centre was drawn from a broad distribution around the least-squares solution (about 3.5 times the posterior width) so that the chains begin in genuinely separated regions of parameter space. After discarding 2250 steps as burn-in and thinning by five, the ensembles provide 216 000 posterior samples. Convergence was assessed with the rank-

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normalized split- $\hat{R}$ and bulk effective sample size computed with ArviZ (Kumar et al., 2019) over the 160 walker-chains, preserving ensemble and time structure rather than flattening: the rank-normalized split- $\hat{R}$ is ≤ 1.01 for every source parameter (maximum 1.013) and the bulk effective sample size exceeds 12 000, with a mean acceptance fraction of 0.49 and an integrated autocorrelation time of about 73 steps (Gelman & Rubin, 1992). Trace plots and the full diagnostic summary are provided in Online Resource 3. The observed, modelled, and residual LOS fields show small, spatially unstructured residuals for the reference realization (mean ≈ 0 , RMSE ≈ 14.5 mm; exploratory Moran's $I = -0.03$ against a null expectation of -0.002 , and nearest-neighbour correlation ≈ 0), confirming that the residual map—rather than a single global misfit number—is the more informative diagnostic advocated in Section 9.6 (Fig. 7).

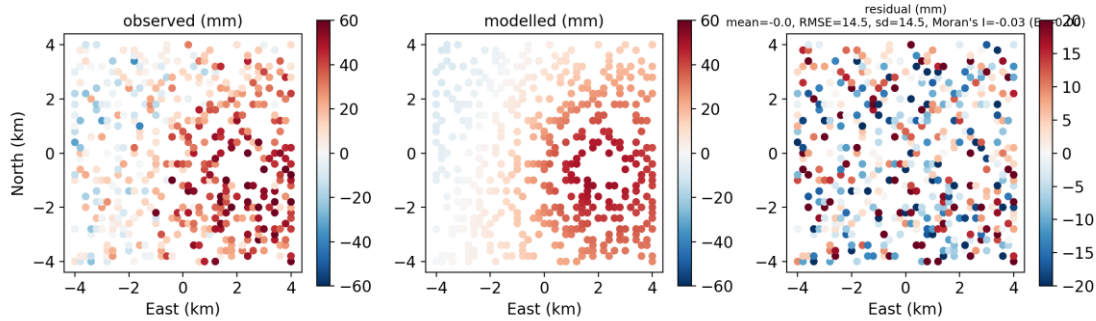


Fig. 7 Layer 3/4 fit diagnostics. Observed (left) and modelled (centre) InSAR LOS fields are shown on an identical scale; the residual (right) uses a separate symmetric scale and is annotated with its mean, RMSE, standard deviation, and an exploratory Moran's I spatial-autocorrelation statistic (null expectation ≈ -0.002). Residuals are small and spatially unstructured at the assigned noise level

Layer 4 — Uncertainty propagation

All credible intervals reported here are equal-tailed central 68% intervals (16th–84th posterior percentiles), and the quoted correlation is the Pearson coefficient computed from all retained posterior samples. The posterior confirms that horizontal position is tightly constrained (68% half-widths ≈ 85 m) while depth and volume change

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are not independently resolved: their marginals are broad and strongly correlated ($r = +0.95$), tracing the shallow-small versus deep-large ridge that a single best-fit model would conceal (Figs. 8, 9; Table 8).

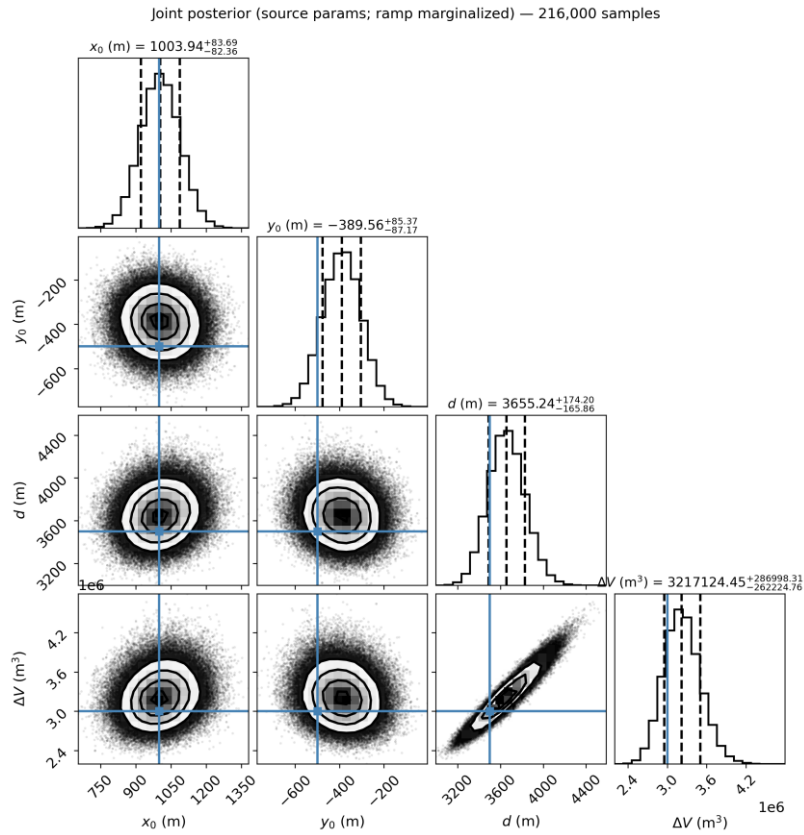


Fig. 8 Layer 4 joint posterior over the four source parameters (ramp nuisance parameters marginalized). Blue lines and squares mark the ground truth; dashed lines mark the 16th, 50th, and 84th percentiles. The depth– ΔV panel shows the correlated ridge that encodes the source non-uniqueness

To quantify which modality controls which parameter, the inversion was repeated with each block removed in turn (Table 9). Depth is the decisive case: once the ramp is estimated jointly, the InSAR block alone leaves depth almost unconstrained (68% width ≈ 2160 m), because the long-wavelength signal that carries depth information is partly absorbed by the ramp nuisance terms; the GNSS block alone constrains it well (≈ 380 m), and the joint inversion reaches ≈ 340 m. Relative to the single-modality inversions, the joint depth interval is about 84%

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narrower than InSAR-only and 11% narrower than GNSS-only for this reference realization. The term “single-modality” is used here in preference to “single-look”: the depth ambiguity is ultimately a property of the single descending look direction, but the comparison in Table 9 is between data modalities.

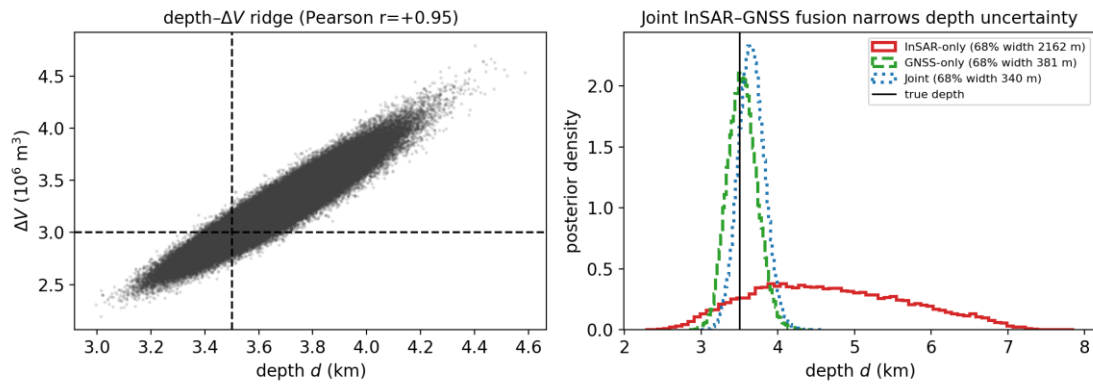


Fig. 9 Layer 4 uncertainty structure and fusion benefit. Left: the depth– ΔV posterior ridge ($r = +0.95$); dashed lines mark the truth. Right: depth marginals for InSAR-only, GNSS-only, and joint inversions—joint InSAR–GNSS fusion produces the narrowest, best-centered depth estimate

Table 8 Recovered source parameters: ground truth, weighted least-squares estimate, and Bayesian posterior summary from the joint InSAR + GNSS inversion. $\pm 1\sigma$ values are the local linearized least-squares standard deviations; the 68% CI is the equal-tailed central credible interval. “Trade-off dominated” marks parameters that are correlated in the posterior (depth– ΔV , $r = +0.95$) and are not independently resolved by the single descending look direction. Fit: reduced $\chi^2 = 0.98$ (dof = 447; 7 parameters including 3 ramp nuisance terms); convergence: rank-normalized split- $\hat{R} \leq 1.01$ (bulk-ESS > 12 000)

Parameter	True	LS estimate ($\pm 1\sigma$)	Posterior median (68% CI)	Identifiability
East position x_0 (m)	1000	1002 $\pm$ 83	1004 (–82 / +84)	robust
North position y_0 (m)	–500	–388 $\pm$ 84	–390 (–87 / +85)	robust
Source depth d (m)	3500	3627 $\pm$ 170	3655 (–166 / +174)	trade-off dominated
Volume change ΔV (m ³)	3.0 $\times 10^6$	3.18 $\times 10^6 \pm 2.7 \times 10^5$	3.22 $\times 10^6$ (–2.6 / +2.9 $\times 10^5$)	trade-off dominated

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Table 9 Per-parameter sensor-removal ablation. Posterior medians and equal-tailed 68% widths for each data configuration, with the reduced χ^2 and the depth– ΔV correlation. Depth is essentially unconstrained by InSAR alone (once the ramp is estimated) and well constrained once GNSS is added

Quantity	InSAR-only	GNSS-only	Joint
x_0 median (68% width, m)	1316 (529)	916 (187)	1004 (166)
y_0 median (68% width, m)	−622 (431)	−330 (194)	−390 (173)
d median (68% width, m)	4615 (2162)	3536 (381)	3655 (340)
ΔV median (68% width, 10^6 m^3)	5.52 (8.30)	3.08 (0.57)	3.22 (0.55)
Reduced χ^2	0.94	1.63	0.98
$r(d, \Delta V)$	+0.95	+0.95	+0.95

Because a narrow posterior is useful only if it is also accurate, the estimator was checked over 300 independent noise realizations (Fig. 10). This study evaluates the empirical coverage of the local **linearized least-squares** intervals, not the Bayesian posterior credible intervals; the result therefore validates the least-squares covariance approximation under the matched synthetic model and should not be read as a posterior-coverage validation. The mean parameter biases are negligible relative to their uncertainties (for example, ≈ -11 m in depth against a ≈ 340 m width), and the empirical coverage is close to nominal (68% intervals: 0.66–0.68; 95% intervals: 0.94–0.96). The joint-versus-InSAR depth-width reduction is stable across realizations, with a median of 73% and a 16th–84th-percentile range of 66–80%, confirming that the fusion benefit seen in the single reference realization is representative rather than fortuitous.

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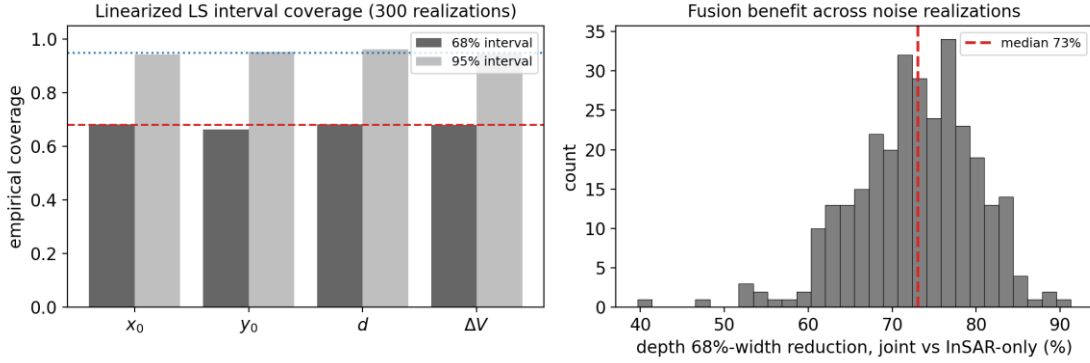


Fig. 10 Layer 4 calibration over 300 noise realizations. Left: empirical coverage of the linearized least-squares 68% and 95% intervals per parameter; dashed lines mark the nominal levels. Right: distribution of the joint-versus-InSAR-only depth 68%-width reduction; the dashed line marks the median (73%)

Finally, to make explicit that same-model verification does not establish robustness to structural error, the pipeline was run on data generated from *two* point sources but inverted with a single source, using a separate common noise realization created specifically for this test. The evidence of structural error is carried by several diagnostics together rather than by any single scalar: the reduced χ^2 rises only modestly, from 0.96 (matched control) to 1.19, but the residuals develop clear spatial organization—the exploratory Moran’s I increases from ≈ 0 (matched) to +0.12—and the single recovered source is a biased compromise, its depth shifted by $\approx +320$ m and its volume change inflated by $\approx 1.8 \times 10^6$ m³ as it absorbs the second source. Because this test uses its own noise realization, the matched-control reduced χ^2 (0.96) differs slightly from that of the principal joint inversion (0.98). This confirms that real applications require the model-selection and robustness checks of Sections 9.7 and 9.8 (Fig. 11).

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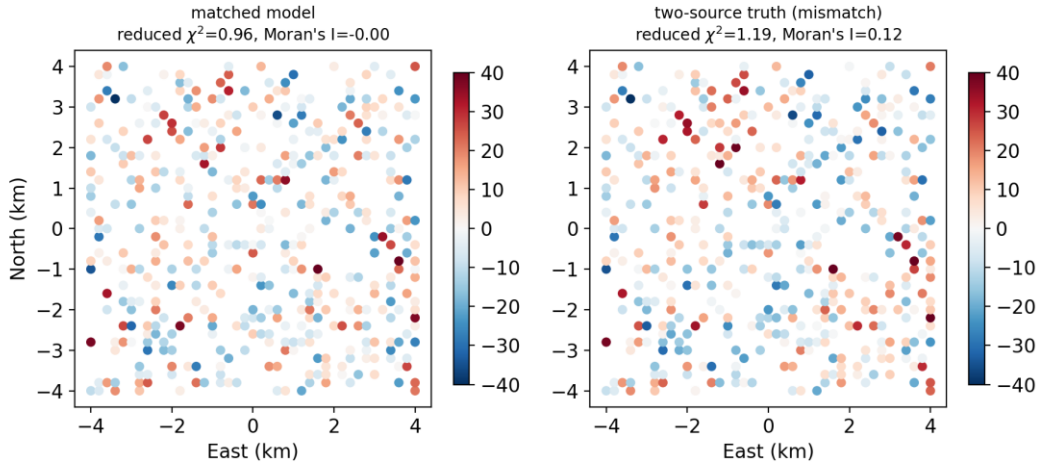


Fig. 11 Model-mismatch test. LOS residuals when a single-source model is fitted to matched single-source data (left) versus data generated from two sources (right); both panels use a separate common noise realization generated specifically for this test. Structural model error raises the reduced χ^2 and, more tellingly, organizes the residuals spatially, with the exploratory Moran's I rising from ≈ 0 to +0.12

Layer 5 — Explainable decision layer

The final layer converts the numerical posterior into a compact, traceable statement rather than a lone map. For this experiment it records: (i) robust parameters—the horizontal source position, constrained to about ± 85 m; (ii) trade-off-dominated parameters—depth and volume change, resolvable only jointly along a correlated ridge ($r = +0.95$); (iii) the dominant data driver—GNSS three-component displacement, which reduces the depth 68% width from ≈ 2160 m (InSAR-only) to ≈ 340 m (joint), while InSAR constrains horizontal position and the deformation pattern, each claim being supported by the full ablation of Table 9 rather than asserted; (iv) plausible alternatives—shallower-smaller and deeper-larger sources along the ridge that fit the data comparably; and (v) the limits of interpretation—a homogeneous isotropic half-space, single point source, static snapshot, and fixed Poisson ratio, valid here only as a same-model synthetic proof-of-concept and explicitly not a hazard decision product. This record is emitted in both human-readable and machine-readable (JSON) form against a

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documented schema, and the exact generated record is included in Online Resource 3, satisfying the interpretability requirement of Section 9.10.

Taken together, the experiment demonstrates the five-layer architecture in a controlled same-model synthetic setting: heterogeneous observations are harmonized (L1), physical assumptions are encoded explicitly (L2), complementary point-estimation and posterior engines are applied (L3), uncertainty and non-uniqueness are quantified, calibrated, and shown to shrink under fusion (L4), and an auditable interpretation record is produced (L5). All *applicable* reporting items of Section 9 are generated as pipeline outputs; the AI-specific reporting items of Section 9.9 do not apply to this non-learning demonstration. The code, fixed configuration, random seed, synthetic observations, diagnostics, and decision-record JSON are provided in Online Resource 3. The demonstration verifies reproducible execution under the declared assumptions; real-data performance and robustness to structural model error require separate, case-specific validation.

9. Reporting Requirements for Explainable and Uncertainty-Aware Geodetic Inversion

A recurring theme across recent geodetic inversion literature is that inversion outputs are strongly controlled by the forward model, data geometry, weighting strategy, regularization, parameterization, and treatment of uncertainty. A computational geodetic inversion study should therefore report not only the final inferred model but also the assumptions, data constraints, alternative solutions, and uncertainty structure that led to that model. Based on the reviewed Scopus and Dimensions corpus, the following ten reporting requirements are proposed for explainable and uncertainty-aware geodetic inversion (Fig. 12). Section 8.3 provides a worked example in which all applicable items below are produced as pipeline outputs; the AI-specific item (Section 9.9) does not apply there.

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9.1 State the forward model and its governing assumptions

A geodetic inversion result is only as meaningful as the forward operator that generated it. Authors should report the equation or computational operator used to connect observations with unknown parameters, together with source geometry, rheology, boundary conditions, dimensionality, and simplifications of Earth structure. Fault-geometry inversion, trans-dimensional slip modelling, and joint tsunami-geodesy rupture studies all show that changes in operator design can alter the inferred source model (Bai et al., 2022; Huang et al., 2017; Tomita et al., 2021; Wald & Graves, 2001).

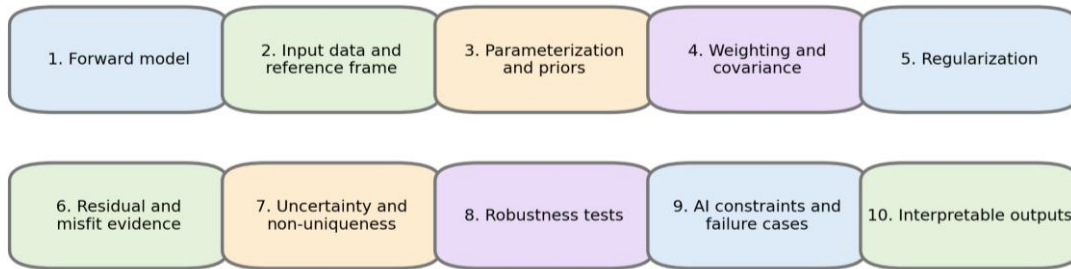


Fig. 12 Minimum reporting checklist for transparent computational geodetic inversion

9.2 Describe input datasets, acquisition geometry, reference frame, preprocessing, and uncertainty

Multi-sensor inversion works best when observational bookkeeping is treated as part of the method. For GNSS data, station distribution, displacement components, reference frame, and time window should be stated. For InSAR, acquisition mode, orbit direction, viewing geometry, line-of-sight sensitivity, phase treatment, masking, and atmospheric correction should be described. For gravity and hydrological applications, spatial resolution,

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temporal aggregation, filtering, and reference models should be reported (De Novellis et al., 2016; Li et al., 2023a; Liu et al., 2023; Roger et al., 2020; Song et al., 2022; Zhao et al., 2026).

9.3 Define model parameters, bounds, priors, and parameterization choices

Parameterization quietly shapes the answer. Whether the unknowns are slip patches, strain-rate cells, fault nodes, pressure sources, frictional parameters, or water-storage loads, readers need to know how the model was discretized, what was fixed, what was free, and what prior ranges or structural priors were imposed. Trans-dimensional and sparse inversion studies show that model complexity and localization are themselves part of the inference problem (Fukushima et al., 2025; Huang et al., 2017; Nozue & Fukahata, 2025; Wang & Gu, 2020).

9.4 Explain data weighting, covariance assumptions, and correlated errors

In joint inversion, weighting is part of the scientific argument rather than a housekeeping choice. Relative sensor influence can change materially when InSAR density, GNSS sparsity, non-uniform station coverage, or spatial correlation are handled differently. Authors should state whether diagonal, empirical, distance-dependent, or full covariance structures are used, and should explain how cross-sensor weights are assigned (Agata, 2020; Jiang & González, 2020; Puliero et al., 2026; Roger et al., 2020; Xi et al., 2024).

9.5 Report the regularization strategy and how parameters were selected

Regularization is where numerical conditioning meets geological or geophysical style. Smoothness, sparsity, Bayesian priors, and edge-preserving terms each favor different model structures. The regularizer should be stated along with the rule used to select its strength, such as L-curve analysis, cross-validation, model-resolution analysis, covariance component estimation, Bayesian evidence, or sensitivity testing (Agata, 2020; Niu et al., 2023; Nozue & Fukahata, 2025; Sun et al., 2025; Wang & Gu, 2020).

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9.6 Provide residual maps, residual statistics, and evidence of model misfit

Residuals should be treated as data products in their own right. A convincing inversion should show where the model fails spatially, not only how well it scores globally. Localized residual patterns can reveal geometry errors, missing physics, atmospheric artefacts, or insufficient parameterization. Residual maps, variance reduction, normalized misfit, and geographically structured error summaries are therefore more informative than a single final root-mean-square number (Bai et al., 2022; De Novellis et al., 2016; Huang et al., 2017; Jiang & González, 2020; Liu et al., 2023; Puliero et al., 2026; Tomita et al., 2021; Wald & Graves, 2001).

9.7 Quantify uncertainty, non-uniqueness, and sensitivity to assumptions

Inversion outputs are better understood as constrained families of models than as singular discoveries. Bayesian weighting studies, ensemble summarization, trans-dimensional inversion, and wrapped-phase Bayesian inversion point to the need to report posterior spread, alternative geometries, parameter trade-offs, and model-resolution effects alongside the preferred estimate (Huang et al., 2017; Jiang & González, 2020; Mills et al., 2025; Niu et al., 2023; Xi et al., 2024).

9.8 Test robustness to data removal, alternative weighting, and geometry changes where feasible

Robustness tests help distinguish stable structure from interpretation that depends heavily on one modelling choice. Useful checks include removing one sensor, changing the weighting family, perturbing source geometry, varying regularization strength, or repeating the inversion over alternative time windows. Joint weighting, rupture optimization, and landslide-recovery studies show the value of such perturbation tests (Bai et al., 2022; Huang et al., 2017; Roger et al., 2020; Song et al., 2022; Tomita et al., 2021; Wald & Graves, 2001).

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9.9 For AI-assisted inversion, report training design, physical constraints, validation strategy, and failure cases

AI-assisted inversion should be reported with additional transparency. Authors should describe the training data, synthetic-to-real transfer logic, input features, physical constraints, loss functions, validation split, uncertainty treatment, domain-transfer tests, and recognizable failure modes. Physics-informed crustal deformation, slow-slip frictional parameter estimation, and physics-aware InSAR change-detection studies all show that learned models should be evaluated for physical consistency rather than prediction error alone (Costa et al., 2025; Fukushima et al., 2025; Li et al., 2021; Okazaki, 2026; Okazaki et al., 2025; Perrot et al., 2026; Raissi et al., 2019).

9.10 Provide interpretable outputs and avoid falsely unique best-fit models

The final inversion product is most useful when it communicates why the model looks the way it does and how much confidence should be attached to it. Ensemble summaries, posterior distributions, residual maps, sensitivity plots, uncertainty maps, and explainable AI diagnostics can help communicate data influence, uncertainty concentration, and alternative plausible explanations (Chen et al., 2026; Li et al., 2026a; Li et al., 2026b; Lundberg & Lee, 2017; Mills et al., 2025; Sun et al., 2025; Wu et al., 2026).

Together, these requirements emphasize a common computational pattern: observation modelling, uncertainty-aware optimization, robustness analysis, and explainable output design. They are not intended to impose a single inversion method. Rather, they provide a transparency framework that can be adapted to classical, Bayesian, hybrid, and AI-assisted geodetic inversion workflows. The principal contribution and reporting requirement associated with each computational method family are summarized in Table 10.

Table 10 Reporting implications of common computational inversion methods

Method family	Typical formulation	What it contributes	What should be reported
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Method family	Typical formulation	What it contributes	What should be reported
Smoothness / Tikhonov	$R(m) = \ Lm\ _2^2$	Stable recovery of distributed fields and slip models	Smoothing operator, selection rule for λ , effect on sharp boundaries
Sparse / edge-aware	$R(m) = \ m\ _1$ or TV-type penalty	Compact or discontinuity-preserving structure	Sparsity prior, thresholding logic, localization effect
Bayesian inversion	$p(m d) \propto p(d m) p(m)$	Uncertainty intervals and non-uniqueness	Prior choice, likelihood, covariance, sampler or approximation
Ensemble / trans-dimensional	Multiple plausible models	Model-family summaries and sensitivity	Ensemble size, convergence logic, summary statistics
Physics-informed ML	$L = L_{\text{data}} + \alpha L_{\text{phys}} + \beta L_{\text{reg}}$	Fast surrogate or hybrid inference	Training data, physics terms, transfer tests, failure cases
Multi-sensor weighting	C_d^{-1} or block-weighted misfit	Prevents one sensor from dominating	Noise model, cross-sensor scaling, spatial correlation

10. Discussion

The literature review indicates that geodetic inversion is transitioning from a specialized geophysical modelling practice to a broader computational discipline. Fundamental mathematical challenges, such as ill-posedness, non-uniqueness, noise, and prior dependence, persist. However, there have been changes in the scale and diversity of data, availability of computational resources, and expectation that inversion outputs should inform operational and policy-relevant decisions. This evolution presents opportunities for computer science research. Data engineering and GIS methods can enhance the harmonization of heterogeneous observations in the following ways. Optimization theory and high-performance computing can improve the scalability. Bayesian computation and ensemble methods can represent non-uniqueness more accurately (demonstrated quantitatively in Section 8.3, where joint inversion narrows the depth interval by a median of about 73% across noise realizations relative to InSAR alone). Scientific machine learning can expedite forward modelling, learn priors, or facilitate rapid approximation. XAI and visual analytics can render inversion outputs more interpretable to geoscientists, engineers, and decision-makers. However, the integration of AI must be approached with caution. Purely data-

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driven inversion may fail outside the domain represented by the training data. The learned models may generate plausible but physically inconsistent results. Dataset bias, scale mismatches, and hidden spurious correlations pose significant risks. Therefore, the most defensible approach is hybrid physics-AI inversion, which strengthens rather than discards physical forward models, uncertainty propagation, and explainability (Chen et al., 2026; Costa et al., 2025; Fukushima et al., 2025; Li et al., 2021; Li et al., 2026a; Li et al., 2026b; Lu et al., 2021; Lundberg & Lee, 2017; Okazaki, 2026; Okazaki et al., 2025; Perrot et al., 2026; Raissi et al., 2019; Wu et al., 2026). For geohazard monitoring, future systems are likely to be more effective if they are modular rather than monolithic. A modular inversion system can incorporate new InSAR, GNSS, gravity, or seismic data; update uncertainties; test alternative source models; and produce an explainable summary of changes and the reliability of the results. This system aligns with Digital Earth thinking, where geospatial intelligence relies on traceable connections between observations, models, uncertainties, and decisions.

11. Limitations of This Review

This article is best understood as a narrative technical review, not as a systematic review or meta-analysis. The database exports were used mainly to trace recurring themes and select representative studies for discussion. Citation counts, journal frequency, and database occurrence were therefore not used as measures of methodological quality. It is also possible that some relevant work is not captured in the review, particularly studies that discuss inversion without using the exact term "geodetic inversion," or papers located in closely related areas such as seismic tomography, hydrogeology, geomechanics, and geo-statistics. The proposed Explainable Artificial Intelligence-Uncertainty Quantification-Computational Geodetic Inversion (XAI-UQ-CGI) framework is presented as a conceptual structure and will need to be tested through future case-specific implementations. A few artificial-intelligence-oriented references are included not because they are direct geodetic inversion methods, but because they offer useful computational ideas that may be transferred to future inversion workflows.

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The synthetic demonstration of Section 8.3 is a same-model verification: the data-generating and inversion operators are matched, so it tests correct-specification behavior rather than robustness to structural model error. It further assumes independent Gaussian noise with a block-diagonal covariance, a homogeneous isotropic elastic half-space, a single static point source, and a fixed Poisson ratio, and uses no field data. These simplifications make the experiment reproducible and interpretable but limit generalization; realistic applications require spatially correlated noise models, alternative source geometries, and case-specific validation against independent observations.

12. Conclusion

Geodetic inversion is entering a stage in which computational design is as important as physical formulation. Multi-source Earth observation provides unprecedented information about earthquakes, volcanoes, hydrology, subsidence, reservoirs, and slope deformation, but it also increases the complexity of data fusion, uncertainty modelling, and interpretation. Classical inversion methods remain essential, yet they must increasingly be embedded within transparent, scalable, and explainable computational workflows.

This review proposed a computer-science framing of geodetic inversion, introduced the XAI-UQ-CGI framework, and demonstrated it on a controlled synthetic multi-source InSAR–GNSS inversion that verifies reproducible end-to-end execution under known ground truth, leaving operational field-data validation to future work. The framework emphasizes five layers: data harmonization, forward-model encoding, inversion and optimization, uncertainty propagation, and explainable decision support. Its purpose is to move inversion studies beyond isolated best-fit models toward reproducible, interpretable, uncertainty-aware systems that can support scientific understanding and geohazard decision-making.

Future research should prioritize hybrid physics-AI inversion, scalable Bayesian and ensemble computation, sparse and edge-preserving regularization, standardized reporting, open benchmark datasets, and visual analytics

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for uncertainty communication. Such developments can help transform geodetic inversion from a specialized modelling procedure into an explainable computational geospatial intelligence workflow.

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Note: the least-squares solver (SciPy (Virtanen et al., 2020)) and the array/plotting libraries (Harris et al., 2020; Hunter, 2007), and the diagnostics library ArviZ (Kumar et al., 2019) are software-implementation references distinct from the method references (Foreman-Mackey et al., 2013; Gelman & Rubin, 1992; Goodman & Weare, 2010; Mogi, 1958; Segall, 2010); for package versions details refer Code Availability Section.

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Code Availability

The source code and reproducibility materials developed for this study are openly available in a public GitHub repository at https://github.com/mhtsht-cyber/XAI-UQ-CGI_CAGEO_GitHub_Repository and can be downloaded anonymously. The repository contains three documented components: (1) the XAI-UQ-CGI workflow template and Python scaffold corresponding to Algorithm 1; (2) the derived bibliographic-audit materials supporting Tables 1 and 2; and (3) the complete reproducibility package for the synthetic InSAR-

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GNSS experiment, including the source code, fixed configuration and random seed, synthetic observations, posterior and convergence diagnostics, trace plots, figure and table source data, sensor-removal ablation results, and machine-readable decision record. A top-level README provides installation and execution instructions and a lightweight quick-test example. The version corresponding to this manuscript is archived as *Release v1.0.0*. Source code is released under the *MIT License*; synthetic data, derived audit files, figures, and documentation are released under CC BY 4.0.