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Structured empirical waveform contamination in moment tensor inversion of shallow mining seismicity: A synthetic diagnostic framework

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SUMMARY

Full moment tensor inversion of shallow mining-induced seismicity is affected by sparse station coverage, near-surface effects, and structured waveform mismatch that is not adequately represented by random-noise assumptions. We present a synthetic diagnostic study using the Jacobina mining district, Brazil, as a realistic reference case for local network geometry, shallow source depths, and empirical waveform contamination. Tests were performed under three contamination regimes: band-limited Gaussian noise, phase-randomised empirical contamination, and structured empirical contamination constructed from small recorded events, thereby preserving source–path–site waveform structure. The phase-randomised case preserves the empirical amplitude spectrum while randomising temporal phase relationships, allowing the effects associated with the empirical amplitude spectrum to be distinguished from those associated with preserved temporal waveform structure. We compare conventional full-waveform inversion with a P–S segmented strategy and examine the effects of prescribed source case, depth, station geometry, and moment tensor constraints. Gaussian contamination produces smooth, variance-dominated degradation. Structured empirical contamination produces stronger mechanism errors and, for the CLVD-like, mixed, and double-couple cases, can inflate spurious non-double-couple components, whereas phase randomisation largely restores Gaussian-like behaviour. The ISO-dominant case remains comparatively stable in orientation but shows persistent decomposition bias. Denser station coverage reduces the amplitude and depth dependence of empirical-contamination errors, although residual degradation can persist at greater depths. P–S segmentation generally reduces sensitivity to structured contamination, especially where P- and S-wave packets are differentially perturbed. Constraint tests show that restrictive source parametrisations can produce solutions that are insensitive to increasing contamination but systematically biased when incompatible with the true mechanism. These results indicate that Gaussian-based thresholds should be treated as comparative stability references and that station geometry and phase-specific waveform treatment should be evaluated jointly when assessing inversion robustness under structured contamination.

Key words: Inverse theory – Numerical modelling – Earthquake source observations – Induced seismicity – Waveform inversion – Wave propagation

1 INTRODUCTION

Seismicity associated with underground mining provides a natural laboratory for studying source processes under strong anthropogenic perturbations. Excavation-driven stress redistribution, combined with pre-existing geological heterogeneity, can produce seismic responses that differ from those of typical tectonic earthquakes, including swarm-like activity, very shallow source depths,

and complex rupture behaviour (Gibowicz & Kijko, 1994). In such environments, reliable characterisation of source mechanisms is important both for understanding the processes governing mining-induced seismicity and for informing hazard mitigation and operational decision-making (Gibowicz & Lasocki, 2001; Barthwal & van der Baan, 2020).

Full moment tensor inversion is widely used in mining set-

tings to distinguish shear slip from tensile opening or collapse-related processes, which may produce considerable non-double-couple components (Lizurek, 2017; Ma et al., 2019). However, source characterisation through moment tensor inversion in shallow mining environments is often challenged by sparse station coverage and waveform distortions associated with near-surface complexity, geological heterogeneity, and path effects that are not adequately represented by simple velocity models or Gaussian-noise assumptions (Duputel et al., 2012; Birnie et al., 2020; Phạm et al., 2024). Understanding and quantifying how these factors affect inversion stability is fundamental for obtaining robust focal solutions and for reliably interpreting and monitoring seismicity in mining districts.

Waveform-based approaches, such as the two-step time-frequency inversion method (Vavryčuk & Kühn, 2012) and the Cut-and-Paste (CAP) technique (Zhao & Helmberger, 1994; Zhu & Helmberger, 1996), improve tolerance to timing mismatches associated with imperfect velocity models. At the same time, it has become increasingly clear that inversion uncertainty reflects not only observational noise but also modelling deficiencies and incomplete physical representations of wave propagation (Duputel et al., 2012).

These concerns have motivated more realistic synthetic assessments. Birnie et al. (2020) showed that benchmarking microseismic imaging and moment tensor inversion methods with white Gaussian noise can yield misleading performance estimates, while more realistic contamination conditions expose instabilities not evident in Gaussian noise tests. Phạm et al. (2024) further demonstrated that full-waveform moment tensor inversion is strongly affected by theory error associated with imperfect three-dimensional Earth structure, especially when structural uncertainties are spatially correlated. In mining settings, Caputa et al. (2021) also showed, through synthetic tests based on the Rudna mine, that realistic station geometry and measured contamination conditions can significantly affect the relative performance of first-motion and waveform-based inversions.

Despite these methodological advances and the growing recognition that realistic noise and forward-model uncertainty can strongly affect moment tensor solutions, an important question remains unresolved: how do systematic waveform distortions that preserve temporal phase structure affect moment tensor stability? Standard synthetic validation commonly relies on random Gaussian noise or incoherent background-noise measures, neither of which presents a structured temporal phase relationship. Although previous studies have shown that realistic noise and correlated theory error can degrade moment tensor inversion more strongly than idealised Gaussian perturbations (Birnie et al., 2020; Phạm et al., 2024), they did not isolate the contribution of temporal phase structure. To our knowledge, no systematic framework has yet explicitly isolated and quantified this contribution under local empirical contamination. This gap is particularly relevant for shallow mining seismicity and for analogous settings such as volcanic and geothermal environments, where coherent scattering, site amplification, near-surface complexity, and structural heterogeneity can introduce systematic waveform distortions across a network.

This study addresses that gap by testing three specific questions: (1) Does structured empirical contamination produce degradation beyond that predicted by Gaussian contamination? (2) Does phase randomisation isolate the contribution of the preserved temporal phase structure? (3) How do station coverage and inversion strategy modulate these effects?

The Jacobina gold mining district, north-eastern Brazil, is used as a realistic reference case to define the local network geometry, shallow source configuration, and empirical waveform-

contamination framework examined in the tests. We evaluate inversion performance under three contamination regimes: band-limited Gaussian noise, phase-randomised empirical contamination, and structured empirical contamination constructed from small recorded events, thereby preserving realistic source–path–site waveform structure. We hypothesise that structured empirical contamination will produce systematic degradation beyond Gaussian predictions and that phase randomisation will restore behaviour closer to the Gaussian baseline by removing temporal phase structure. To assess methodological sensitivity, we compare conventional full-waveform inversion with a P–S segmented inversion strategy adapted from the CAP concept, in which P- and S-wave arrivals are treated as independent waveform segments with separate time shifts and combined misfit contributions. We further examine how station coverage and source depth interact with contamination type to affect solution stability. Because the framework explicitly links source depth, station geometry, contamination type, and inversion strategy, it can also be adapted as a diagnostic tool to compare candidate network configurations in other shallow seismicity settings.

2 METHODS

2.1 Study Area and Temporary Seismic Network

The Jacobina gold mining district is located in the north-eastern São Francisco Craton, Brazil, and comprises underground mines distributed along the Jacobina Ridge (Fig. 1). The district is characterised by shallow mining-induced seismicity and a structurally heterogeneous geological setting that includes metasedimentary rocks of the Jacobina Group, mapped faults, and mafic dyke systems with dominant north–south and secondary east–west trends (Barbosa & Sabaté, 2004; Santos et al., 2019). The geological description is intentionally limited to the information required to define the synthetic diagnostic framework.

The temporary local network consisted of six three-component short-period stations, including GEObit GEOTiny and Raspberry Shake 3-D instruments, sampling at 100 Hz. Two temporary network geometries were deployed: an initial broad configuration operating from February to April 2022 (Network 1), followed by a more compact configuration operating until August 2023 (Network 2; Fig. 1b). These two geometries, together with an idealised 12-station configuration formed by the union of both layouts, are reproduced in the synthetic tests. The network description is retained only to define the station configurations used in the diagnostic experiments.

2.2 Event Detection, Location and Catalogue Use

We constructed a local event catalogue to provide realistic source-depth constraints, representative waveform examples, and empirical contamination waveforms for the synthetic diagnostic tests. Events were detected using the Python Matching Phase Algorithm (PyMPA) of Vuan et al. (2018), a matched-filter method applied to continuous multi-station waveform data. High-quality templates were windowed around P-wave arrivals and filtered between 2 and 20 Hz. The matched-filter search yielded 373 detections, of which 320 events were retained after visual validation, phase picking, and location-quality screening.

Hypocentral locations were obtained with Hypocenter (Lienert & Havskov, 1995), as implemented in SEISAN (Havskov

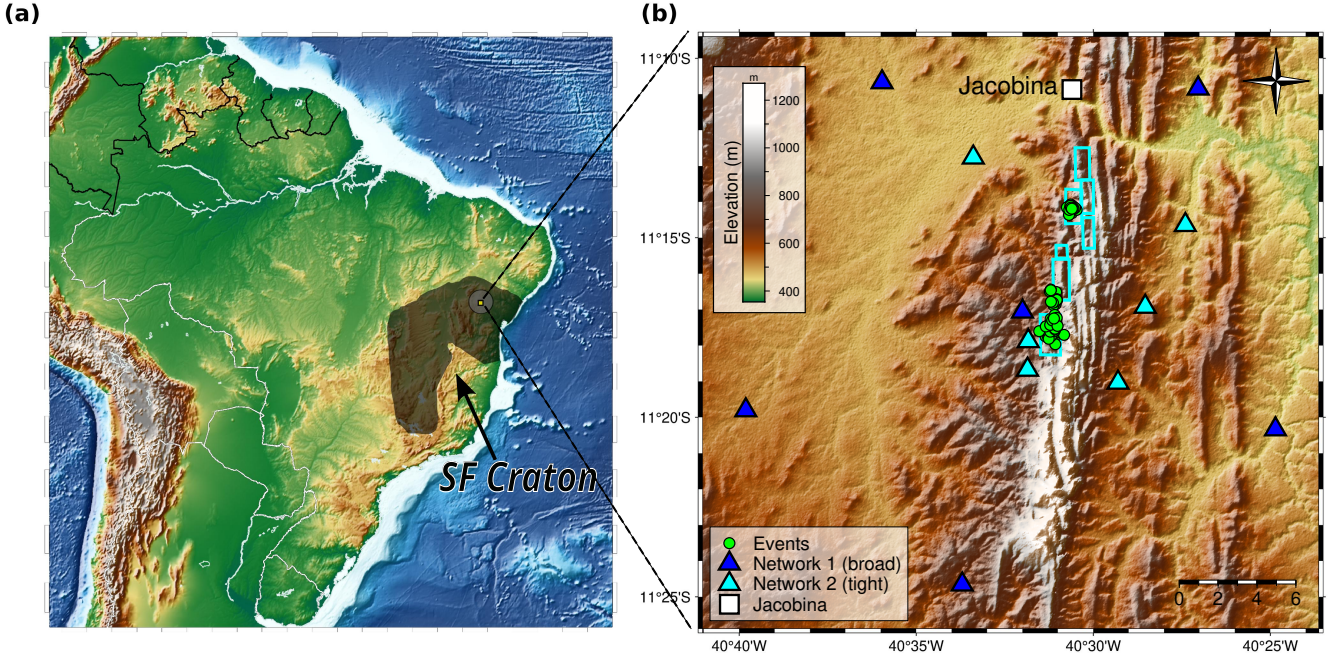


Figure 1. The study area: (a) regional context of the Jacobina mine district (small yellow square), highlighting the main geotectonic unit, the São Francisco Craton (shaded area); and (b) topographic map of study area with triangles denoting the two temporary networks used to study seismicity between 2022 and 2023, with green circles denoting the 191 relocated earthquakes, and open squares delineating mining areas.

& Ottemöller, 1999), using a homogeneous velocity model with $V_P = 5.9 \text{ km s}^{-1}$ and $V_P/V_S = 1.69$. These values were derived from Wadati analysis and iterative reduction of RMS residuals and location errors. The catalogue spans local magnitudes from approximately $M_L = -0.5$ to 2.6. Estimated absolute uncertainties are approximately 0.4 km horizontally and 1.3 km vertically; these uncertainties motivated the explicit treatment of source depth as a sensitivity parameter in the synthetic tests.

Relative relocations were performed with HypoDD (Waldhauser & Ellsworth, 2000) using catalogue and cross-correlation differential times. A total of 191 events were relocated in three major mining-sector clusters. These relocations are not interpreted here as a primary seismological result; instead, they define a realistic shallow-source context for the diagnostic experiments and guide the selection of representative recorded events used as empirical waveform contamination.

2.3 Moment Tensor Inversion Framework

Moment tensor inversion was performed using MTUQ, an open-source Python framework for focal mechanism estimation and uncertainty analysis (Thurin et al., 2025). In MTUQ, the full moment tensor is represented as a symmetric 3×3 matrix and decomposed into isotropic and deviatoric components, allowing discrimination between volumetric and complex shear processes. MTUQ implements waveform-based inversion using cross-correlation misfit measures and supports multiple constraint levels, including full moment tensor (FMT), deviatoric (DVT) and pure double-couple (DC) solutions.

Moment tensor space is parametrised using the lune representation (Tape & Tape, 2019), where isotropic and CLVD components are quantified by the parameters δ and γ , respectively. This formulation facilitates systematic exploration of source-type uncertainty

and stability. Given the shallow source depths, sparse station coverage, and velocity-model uncertainty in the Jacobina setting, the focus here is on inversion stability and bias rather than on the interpretation of individual source mechanisms.

2.3.1 Independent P- and S-Wave Inversion (PS-I)

To address the challenges of local body-wave inversion in this shallow mining setting, we implemented a P-S segmented inversion strategy adapted from the Cut-and-Paste method (Zhao & Helmberger, 1994; Zhu & Helmberger, 1996). CAP separates waveform groups and allows independent timing adjustments to reduce sensitivity to travel-time mismatches associated with imperfect velocity models and source locations. For example, Chang et al. (2019) applied CAP to small-to-moderate earthquakes by separating P waves on the vertical and radial components from S waves on the vertical, radial and transverse components, with independent time shifts between the P- and S-wave groups. In the local-distance setting considered here, surface-wave contributions are weak and the usable signal is dominated by body waves. We therefore adopt the same general segmentation principle but formulate the inversion in terms of independent P- and S-wave windows for full moment tensor analysis.

P- and S-wave windows were defined separately (see the values in Table 1), and the two waveform groups were allowed independent time shifts to accommodate differential propagation effects. Individual misfits were computed for the P and S windows using waveform cross-correlation, and the final misfit was calculated as an equally weighted combination:

$$\chi_{PS-I} = \chi_P(\Delta t_P) + \chi_S(\Delta t_S). \quad (1)$$

Here, χ_{PS-I} is the final misfit function for the PS-I inversion method; χ_P and χ_S are the misfits referred to individual P- and S-wave inversions, respectively; Δt_P and Δt_S are independently

194 optimised time shifts whose absolute values are limited to 0.05 s.
 195 This conservative limit was used throughout the synthetic and real-
 196 data inversions to accommodate modest timing errors associated
 197 with location and velocity-model uncertainty.

198 This approach is motivated by three considerations: (1) sep-
 199 arating P and S waves balances their relative contributions and
 200 prevents S-wave amplitude dominance; (2) independent timing ad-
 201 justments partially accommodate phase-dependent travel-time mis-
 202 match without invoking complex 3-D models, including variations
 203 in the V_P/V_S ratio; and (3) segmentation provides separate phase-
 204 specific constraints and prevents P- and S-wave contributions from
 205 being forced into a single coupled waveform fit. The strategy fol-
 206 lows the general CAP principle of fitting P- and S-wave groups with
 207 independent timing adjustments (Zhao & Helmberger, 1994; Zhu
 208 & Helmberger, 1996; Chang et al., 2019), but is implemented here
 209 within a full moment tensor framework tailored to local mining-
 210 induced seismicity. We evaluated PS-I through synthetic compar-
 211 isons with conventional full-waveform inversion (FW-I) under the
 212 contamination regimes described below.

213 2.3.2 Synthetic Waveform Contamination Strategy

214 We implemented a three-stage contamination strategy to assess the
 215 robustness of full moment tensor inversion under progressively
 216 more realistic perturbation conditions. The first stage defines a
 217 Gaussian-contamination baseline in which waveform perturbations
 218 are represented by amplitude-controlled, band-limited (1–5 Hz)
 219 Gaussian noise. This case provides an incoherent reference con-
 220 dition against which the effects of more structured contamination
 221 can be evaluated.

222 The second stage uses empirical contamination derived from
 223 recorded small-magnitude events (M_L 0.5–0.9). These waveforms
 224 preserve realistic source radiation, site effects, scattering, and path-
 225 dependent phase distortions present in the local records. For each
 226 network configuration, three candidate empirical events were tested
 227 and produced qualitatively consistent degradation patterns; the re-
 228 sults shown correspond to a single representative contaminant se-
 229 lected based on signal-to-noise ratio, waveform quality, and net-
 230 work completeness. The selected contaminant was superimposed
 231 on synthetic waveforms for all prescribed source depths. Conse-
 232 quently, the resulting depth-dependent patterns should be inter-
 233 preted as a response to a fixed contaminant waveform, rather than
 234 as a universal function of the source depth. The use of small events
 235 limits waveform complexity associated with longer or more com-
 236 plex ruptures and provides high-quality local records. Thus, we in-
 237 terpret them as structured source–path–site waveform perturbations
 238 rather than as source-free representations of propagation effects.

239 The third stage uses phase-randomised empirical contamina-
 240 tion to isolate the role of preserved temporal phase structure. We
 241 generate random phases independently for each station-component
 242 trace and for each realisation. In this case, the amplitude spectrum
 243 of the empirical waveform is preserved while its phase spectrum is
 244 randomised in the frequency domain according to

$$F_{\text{rand}}(\omega) = |F(\omega)| \exp[i\phi_{\text{rand}}(\omega)]. \quad (2)$$

245 In equation 2, $|F(\omega)|$ is the amplitude spectrum of the original em-
 246 pirical waveform and $\phi_{\text{rand}}(\omega)$ is a random phase drawn indepen-
 247 dently from a uniform distribution over $[0, 2\pi]$ for each frequency.
 248 Randomisation preserved the conjugate symmetry required to re-
 249 cover real-valued time series after inverse transformation. This pro-

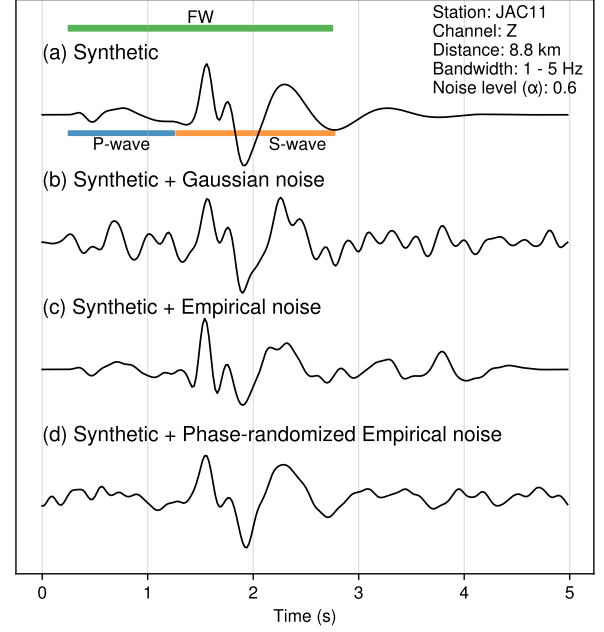


Figure 2. Illustrative waveform effects of the three contamination regimes. (a) Uncontaminated synthetic waveform for an ISO-dominant source case ($M_W = 2$) recorded at station JAC11; thin coloured bands indicate the windows used in the moment tensor inversions. (b)–(d) Synthetic waveform after Gaussian, structured empirical, and phase-randomised empirical contamination, respectively. All examples use $\alpha = 0.6$ and the 1–5 Hz band.

cedure defines an intermediate condition between incoherent Gaussian perturbations and fully phase-structured empirical contamination, allowing the contribution of preserved temporal phase relationships to inversion degradation to be assessed directly.

For all three contamination strategies, the contaminant windows were filtered and aligned with the corresponding synthetic windows using the P-wave arrival for the segmented P-wave and full-waveform inversions, and the S-wave arrival as the reference for the corresponding S-wave inversion. The contaminant was then scaled independently for each trace according to eq. (3).

$$u_{\text{noisy}}(t) = u_{\text{syn}}(t) + \alpha \frac{\text{RMS}_{\text{syn}}}{\text{RMS}_{\text{cont}}} u_{\text{cont}}(t), \quad (3)$$

where u_{syn} and u_{cont} denote the uncontaminated synthetic waveform and the contaminant waveform, respectively; u_{noisy} is the contaminated waveform; α is the scaling factor; and RMS_{syn} and RMS_{cont} are the root-mean-square amplitudes of the synthetic and contaminant waveforms measured over the same analysis window. This normalisation provides direct control over the virtual signal-to-noise ratio, such that $\text{SNR} = 1/\alpha$, where $\text{SNR} = \text{RMS}_{\text{syn}}/\text{RMS}_{\text{scaled}}$. The tested contamination levels ranged from $\alpha = 0.2$ to 1.0, corresponding to SNR values of 5.0 to 1.0 and ranging from moderate to severe contamination. The non-zero rotation angles at $\alpha = 0$ in Section 3.1 reflect the finite sampling of the moment-tensor search grid and therefore define the numerical baseline of the inversion rather than contamination-induced error.

We selected the 1–5 Hz band as a compromise between maintaining a sufficient signal-to-noise ratio and limiting the high-frequency waveform complexity of empirical contaminants. Fig. 2 illustrates the effect of the three contamination regimes on a representative synthetic trace.

2.3.3 Synthetic Tests and Constraints

Synthetic waveforms were generated by convolving prescribed moment tensors with precomputed Green's functions calculated using Computer Programs in Seismology (Herrmann, 2013). Source depths ranged from 0.1 to 5 km, and source–receiver epicentral geometries matched those represented by the empirical contaminants. Green's functions and uncontaminated synthetic waveforms were generated using the same homogeneous 1-D model adopted for hypocentral location, with $V_P = 5.9 \text{ km s}^{-1}$ and $V_S \simeq 3.49 \text{ km s}^{-1}$. Synthetic traces were sampled at 0.02 s with 512 samples, and a Dirac delta source-time function was used.

The baseline synthetic tests contain no intentional forward-model mismatch; structured waveform mismatch is introduced through the empirical contamination. A concise summary of the Green's-function and waveform-generation settings is provided in Table S2; the complete CPS model accompanies the processing scripts described in the Data Availability section.

The synthetic test suite considered three network configurations: two 6-station geometries reproducing the real deployments (Fig. 1b) and an idealised 12-station configuration that includes all available stations, that is, the union of the two 6-station layouts. For each configuration, we evaluated four prescribed source cases: ISO-dominant (ISO), CLVD-like (CLVD), mixed (MIX), and double-couple (DC), together with three representative orientations corresponding to normal, reverse, and strike-slip faulting styles. The ISO and CLVD abbreviations are shorthand labels for prescribed lunge locations and do not denote mathematically pure end members; the DC case is the only pure end member. The corresponding lunge parameters and component decompositions are provided in Table S1. For Gaussian and phase-randomised contamination, 15 independent realisations were generated for each combination of network geometry, source case, source orientation, source depth, contamination level, and inversion method, whereas structured empirical contamination used a single representative contaminant for each network. For all the tests, the final synthetic waveforms simulated an event with a prescribed magnitude of $M_W = 2$.

Inversion performance was quantified primarily by the rotation angle ω between the true and recovered moment tensors. This parameter was defined in Tape & Tape (2012) as an alternative to the usual Kagan angle and provides a compact measure of mechanism error.

In the PS-I method, P- and S-window misfits were optimised independently, each with a maximum allowed shift of 0.05 s. Component-level shifts followed the implementation of the MTUQ cross-correlation, while the final misfit was computed from the P- and S-window contributions. For the transverse components, the time shifts were allowed to be independent of the corresponding vertical and radial components. Table 1 summarises the principal network, waveform-window, contamination, and inversion settings used in the synthetic tests.

2.3.4 Real-Data Diagnostic Inversion

A representative M_L 1.2 event recorded by Network 2 (stations JAC7–JAC12) was analysed to determine whether the synthetic diagnostics were consistent with the observed sparse-network data. Waveforms were processed in the same 1–5 Hz band and inverted with the same Green's functions, component weighting, window lengths, and maximum time shifts used in the corresponding Network 2 synthetic tests.

Full moment tensor solutions were searched over source

depths from 0.1 to 2.5 km at 0.2 km intervals and moment magnitudes from M_W 1.0 to 1.4 at 0.1-unit intervals. Both FW-I and PS-I were applied. The real-data example is used only to illustrate method- and depth-dependent non-uniqueness and is not interpreted as evidence for a preferred source mechanism.

3 RESULTS

3.1 Synthetic Validation

3.1.1 Gaussian Noise Baseline

We first examine Gaussian-noise experiments to determine how random waveform perturbations affect the stability of moment tensor inversion. These experiments define a reference regime in which waveform contamination is governed by random amplitude perturbations without imposed phase structure.

For the CLVD-like, mixed, and DC source cases, both full-waveform inversion (FW-I) and P–S segmented inversion (PS-I) showed progressive and approximately monotonic degradation in mechanism recovery. Fig. 3a shows the ω distribution across contamination levels for FW-I, with ω increasing systematically with α for both networks. By contrast, the ISO-dominant case exhibited comparatively stable mechanism recovery, with ω remaining near 5° across the full range of contamination levels. This pattern was consistent across both network geometries, indicating that the predominantly isotropic radiation pattern of this prescribed case is less sensitive to random waveform perturbations than the more strongly deviatoric cases. The results for the 12-station configuration are shown in Fig. S1(a) of the Supplementary Material and exhibit the same overall behaviour, with only a modest reduction in rotation-angle dispersion relative to the 6-station networks.

We next examine the depth dependence of the Gaussian-noise response to determine whether source depth systematically modulates inversion stability. As shown in Fig. 3b, FW-I results exhibited no systematic variation in mechanism degradation with source depth. PS-I results indicated slightly elevated ω values for shallow sources, particularly at higher contamination levels and most clearly in Network 2, although the increase remained modest and lacked a systematic depth dependence. The corresponding 12-station results in Fig. S1(b) likewise showed limited depth dependence, consistent with the weak sensitivity of the Gaussian-contamination case to network geometry.

We then examine the influence of Gaussian contamination on the recovery of non-double-couple (NDC) components to assess how source decomposition is affected. To quantify this, we measured the difference in NDC component contribution between the true and recovered moment tensors ΔNDC . For example, for DC sources, the true NDC contribution was defined as $\text{NDC}_{\text{TRUE}} = \text{ISO}_{\text{TRUE}} + \text{CLVD}_{\text{TRUE}} = 0\%$, while the recovered contribution was $\text{NDC}_{\text{REC}} = \text{ISO}_{\text{REC}} + \text{CLVD}_{\text{REC}}$. Consequently, $\Delta\text{NDC} = |\text{NDC}_{\text{TRUE}} - \text{NDC}_{\text{REC}}|$. Fig. 3c shows the mean and standard deviation of ΔNDC for the prescribed source cases at two representative contamination levels ($\alpha = 0.2$ and 0.8). Across all prescribed source cases and both inversion methods, increasing α values led to larger spurious NDC contributions and greater variability in ΔNDC . For the ISO-dominant case, however, this increase was less pronounced because decomposition errors were already comparatively elevated at the lower contamination level. Fig. S1(c) shows that the 12-station network exhibited the same variance-dominated behaviour, with slightly reduced spread of the recovered solutions.

Table 1. Inversion parameters used in this study. Full source-type and orientation combinations are listed in Table S1.

Parameter	Setting
Green's functions	CPS wavenumber integration
Velocity model	Homogeneous 1-D model
Frequency band	1–5 Hz
Inversion methods	FW-I; PS-I
Constraint levels	FMT (all tests); DVT and DC (Section 3.1.5 only)
Synthetic depth grid	0.1–5.0 km, with denser sampling at shallow depths and coarser sampling at greater depths
Network configurations	Broad 6-station (Network 1); compact 6-station (Network 2); full 12-station network
Contamination models	Gaussian (15 realisations); structured empirical (one realisation); phase-randomised empirical (15 realisations)
Contamination scaling	$\alpha = 0.0, 0.2, 0.4, 0.6, 0.8, \text{ and } 1.0$
Time windows (Network 1 and 12-station)	P: 1.5 s; S: 2.0 s; FW: 3.5 s
Time windows (Network 2)	P: 1.0 s; S: 1.5 s; FW: 2.5 s
Maximum time shift	0.05 s
Time-shift strategy	Independent P and S shifts; common shift for vertical/radial components and independent shift for transverse components
Diagnostic metric	Rotation angle ω

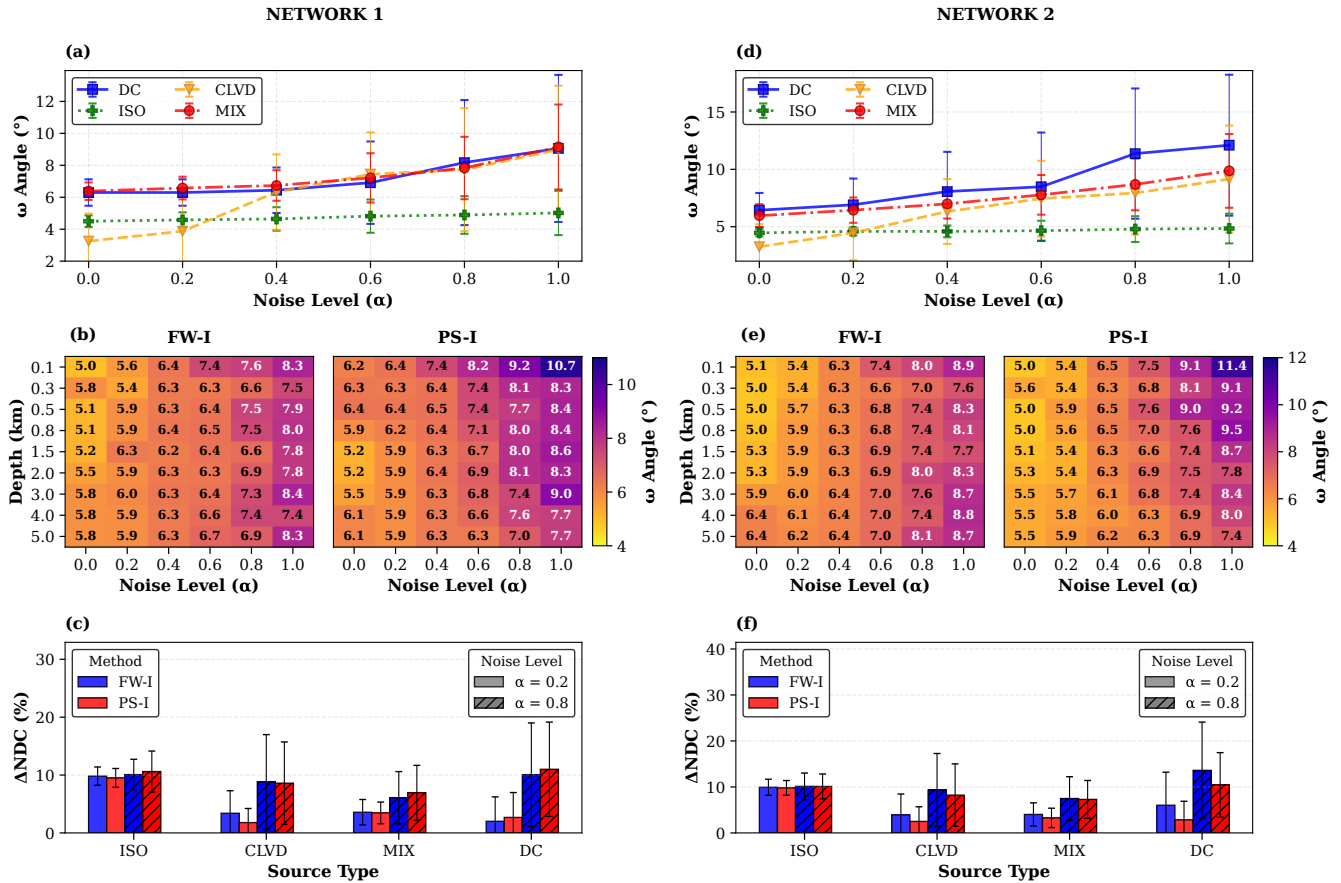


Figure 3. Gaussian contamination effects on MTI for Network 1 and Network 2. (a), (d) FW-I rotation angle ω across contamination levels for the prescribed source cases: ISO-dominant (ISO), CLVD-like (CLVD), mixed (MIX), and double-couple (DC). Values and error bars denote the median and median absolute deviation across source orientations, depths, and independent realisations. (b), (e) Median ω across selected source depths and contamination level for FW-I and PS-I. (c), (f) NDC-component errors (ΔNDC) at $\alpha = 0.2$ and 0.8 for the prescribed source cases and both inversion methods.

3.1.2 Effects of Structured Empirical Contamination

We now examine empirical-contamination experiments to determine how structured waveform distortion affects the stability of moment tensor inversion. Unlike the Gaussian-contamination tests, the empirical-contamination experiments used a single representative waveform realisation for each network. As a result, the observed variability reflects sensitivity to source case, fault orientation, and depth rather than stochastic variance. Structured empirical contamination produced stronger degradation than Gaussian contamination at equivalent scaling factors, although the magnitude of this additional degradation varied with source case and network configuration (Fig. 4). Following a similar framework adopted in Section 3.1.1, we evaluate this behaviour by examining the variation of ω with empirical contamination level for the classical FW-I approach (Fig. 4a); the depth dependence of the additional degradation caused by empirical contamination in relation to Gaussian contamination, $\Delta\omega$, for FW-I and PS-I (Fig. 4b); and the comparison of the generation of spurious NDC components (ΔNDC) between empirical and Gaussian contamination (Fig. 4c). The corresponding full empirical-contamination results are shown in Figs S2 and S3, and the 12-station empirical-versus-Gaussian comparison is shown in Fig. S4.

For CLVD-like, mixed, and DC source cases, FW-I solutions generally exhibit larger rotation angles under structured empirical contamination than under Gaussian contamination, particularly at higher contamination levels. This effect is clear for both 6-station networks, although its magnitude differs between the broad and compact geometries. By contrast, the ISO-dominant case remains comparatively stable in orientation, with low ω values even at high empirical-contamination levels. The 12-station network preserves this source-case hierarchy but substantially reduces the absolute ω values, indicating that improved station coverage mitigates much of the orientation instability associated with structured empirical contamination (Fig. S4(a)).

The depth-dependent response confirms that empirical contamination does not act as a simple amplitude-controlled perturbation. To quantify this effect, we measured the difference between ω values obtained under empirical and Gaussian contamination, $\Delta\omega$. For Network 1, the additional FW-I degradation is concentrated mainly at shallow to intermediate depths, with smaller residual effects also occurring at other depths. For Network 2, FW-I degradation is more pronounced at greater depths, with the strongest positive $\Delta\omega$ values occurring between approximately 3 and 5 km. PS-I reduces the strongest empirical-contamination effect, especially in Network 2, but does not eliminate all shallow or intermediate-depth sensitivity. For the 12-station network, the additional degradation is strongly attenuated across most depths, with residual FW-I sensitivity concentrated mainly at 4–5 km and largely suppressed by PS-I (Fig. S4(b)). These patterns indicate that the specific empirical contaminants used here interact with source depth and station geometry in a manner distinct from Gaussian contamination, with the detailed depth dependence varying between network configurations.

Empirical contamination also affects NDC recovery, although this effect is source- and network-dependent rather than uniform. Compared with Gaussian contamination, empirical contamination generally increases spurious NDC contributions for the more strongly deviatoric cases, particularly the CLVD-like and DC cases in the compact network. However, the magnitude of this increase varies across source case, method, and network geometry, and the associated variability remains substantial. Generally, PS-

I method slightly reduces the empirical contamination effect on NDC component recovery (Fig. 4c). In the 12-station configuration, empirical-contamination-induced NDC errors are reduced but not completely removed (Fig. S4(c)). These results suggest that structured empirical contamination introduces systematic source-decomposition bias, but the strength of this bias depends on the network geometry, on the prescribed source case and on the inversion method used.

3.1.3 Role of Preserved Temporal Phase Structure

We now examine phase-randomisation experiments. This contamination strategy aims to isolate the effects of the temporal phase structure on moment tensor inversion. In these experiments, the empirical amplitude spectrum was preserved while temporal phase relationships were randomised. This design allows the effects of amplitude content to be separated from those of coherent temporal waveform structure. Fig. 5 compares structured empirical contamination with phase-randomised empirical contamination for the two 6-station networks, while the corresponding 12-station results are shown in Fig. S5.

The mechanism-rotation response shows that phase randomisation substantially reduces the additional degradation associated with empirical contamination. For the CLVD-like, mixed, and DC source cases, the phase-randomised empirical results more closely approximate Gaussian-contamination behaviour than the structured empirical results, indicating that the additional degradation cannot be explained by spectral amplitude alone. The ISO-dominant case remains comparatively insensitive to contamination type, consistent with its predominantly isotropic radiation pattern. In the 12-station configuration, the absolute ω values are reduced, and the structured and phase-randomised empirical curves become more closely aligned, indicating that denser station coverage suppresses much of the phase-structured contribution to mechanism rotation (Fig. S5(a)).

The depth-dependent comparison reinforces this interpretation. We measured the difference between the ω values obtained under structured empirical contamination and those under phase-randomised empirical contamination, $\Delta\omega$. For the 6-station networks, the resulting $\Delta\omega$ patterns closely resemble the empirical-versus-Gaussian depth dependence, showing that preserved temporal phase structure accounts for much of the additional empirical-contamination degradation. FW-I is generally more sensitive to this effect, whereas PS-I reduces the depth-dependent differences. In the 12-station network, the phase-structure effect is strongly attenuated across most depths, with the clearest residual FW-I degradation concentrated at the greatest tested depths (Fig. S5(b)).

The same tendency appears in the recovery of NDC components. Structured empirical contamination generally produces larger spurious NDC contributions than the phase-randomised empirical case, whereas phase randomisation yields NDC levels closer to those obtained under Gaussian contamination. The difference is clearest for the CLVD-like, mixed, and DC cases and is reduced in the 12-station configuration (Fig. S5(c)). These results indicate that preserved temporal waveform structure is a major contributor to systematic moment tensor bias, although its expression is modulated by prescribed source case, station geometry, and inversion strategy.

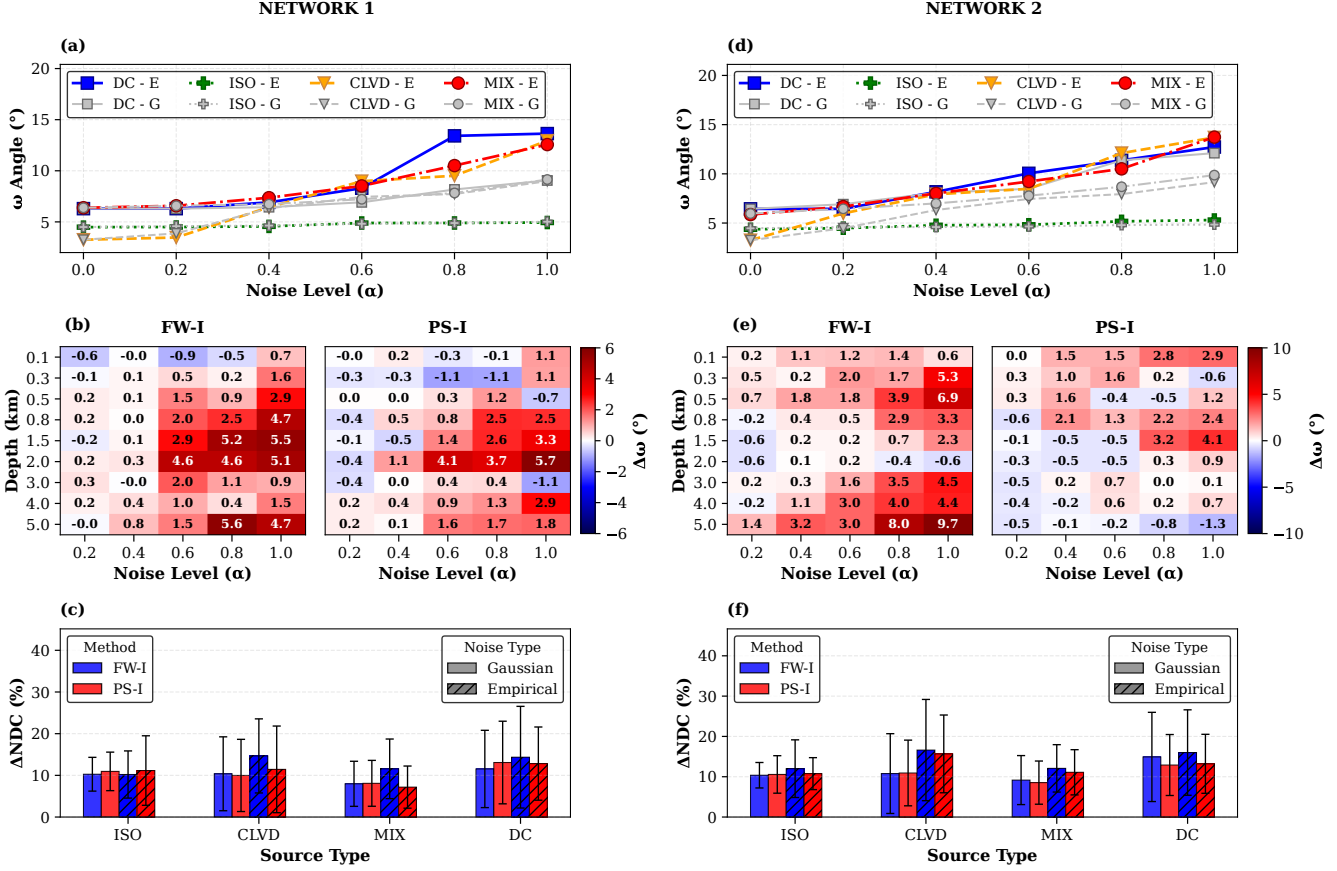


Figure 4. Structured empirical versus Gaussian contamination for Network 1 and Network 2. (a), (d) Median FW-I rotation angle ω across contamination levels for the ISO-dominant (ISO), CLVD-like (CLVD), mixed (MIX), and double-couple (DC) source cases under structured empirical (E) and Gaussian (G) contamination. (b), (e) Difference between median rotation angles under structured empirical and Gaussian contamination across selected source depths and contamination level, $\Delta\omega = \omega_{\text{empirical}} - \omega_{\text{gaussian}}$. (c), (f) NDC-component errors (ΔNDC) under Gaussian and structured empirical contamination. Bars and error bars denote the mean and standard deviation, respectively.

3.1.4 Role of Network Geometry

We finally examine in more detail how network geometry affects the robustness of moment tensor inversion.

Under Gaussian contamination, differences among network configurations are relatively small. Increasing the station count mainly results in a modest reduction in rotation-angle dispersion, consistent with the 12-station Gaussian results shown in Fig. S1. In contrast, under structured empirical contamination, network geometry exerts a stronger control on the depth-dependent degradation pattern (Fig. 6). Because the empirical contaminant is fixed for each network, the depth of maximum degradation should be interpreted as contaminant-specific rather than as a universal function of source depth.

In the broad 6-station configuration (Network 1), FW-I solutions show the greatest degradation at shallow to intermediate depths, particularly around 1–2 km, where ω reaches its highest values at the highest contamination levels (Fig. 6a). At greater depths, the degradation decreases but remains above the Gaussian baseline in some cases. PS-I does not remove this depth dependence; instead, it produces values that are broadly comparable to FW-I at several depths and redistributes the degradation pattern. Thus, for Network 1, the main effect of PS-I is not a uniform reduction of ω , but a modification of how empirical contamination is mapped into the recovered mechanism.

For the compact 6-station configuration (Network 2), the empirical-contamination response differs markedly. FW-I degradation increases strongly at depth, with the largest ω values occurring between approximately 3 and 5 km (Fig. 6b). PS-I substantially suppresses this deep degradation and produces lower values at the greatest depths, although elevated ω values remain at shallow to intermediate depths for high contamination levels. This indicates that P–S segmentation is particularly effective where structured contamination produces depth-dependent full-waveform inconsistency, but it does not eliminate all sensitivity to empirical contamination.

The 12-station configuration provides the clearest evidence for the stabilising effect of increased station coverage. For this geometry, empirical-contamination effects are strongly reduced across most depths for both inversion strategies. At high contamination levels, FW-I remains close to the Gaussian reference through most of the shallow to intermediate depth range, but residual degradation persists at 4–5 km. PS-I further suppresses this residual deep effect and remains comparatively stable across the tested depths (Fig. 6c). The supplementary full-network comparisons in Figs S3–S5 confirm that denser station coverage reduces both the overall amplitude and depth dependence of the errors. However, it does not completely remove the effect of structured empirical contamination.

Together, these results show that station geometry strongly

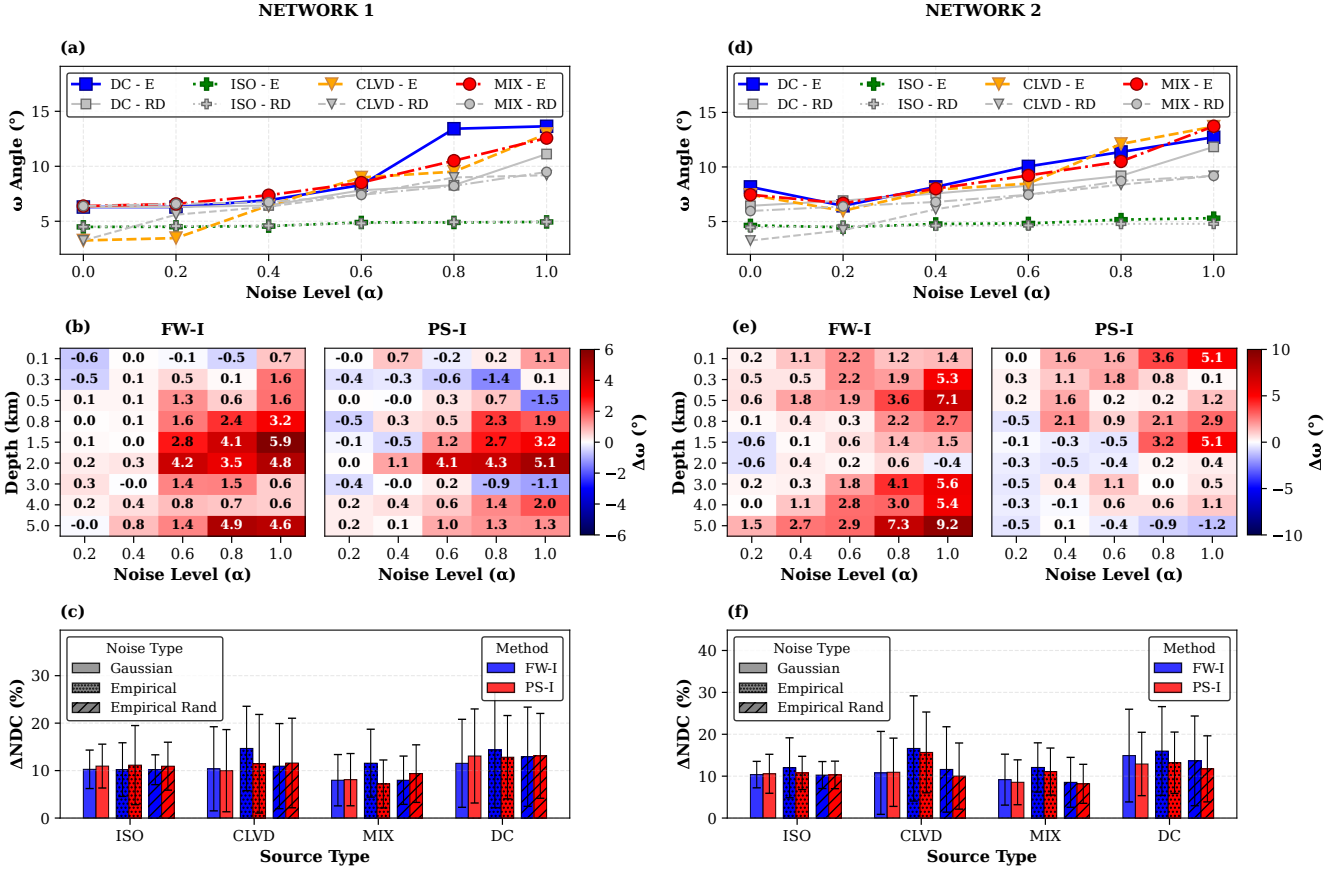


Figure 5. Structured empirical versus phase-randomised empirical contamination for Networks 1 and 2. (a), (d) Median FW-I rotation angle ω across contamination levels for the ISO-dominant (ISO), CLVD-like (CLVD), mixed (MIX), and double-couple (DC) source cases under structured empirical (E) and phase-randomised empirical (RD) contamination. (b), (e) Difference between median rotation angles under structured and phase-randomised empirical contamination across selected source depths and contamination level, $\Delta\omega = \omega_{\text{empirical}} - \omega_{\text{randomised}}$. (c), (f) NDC-component errors (ΔNDC) under Gaussian, structured empirical, and phase-randomised empirical contamination. Bars and error bars denote the mean and standard deviation, respectively.

modulates the impact of structured empirical contamination. Denser coverage reduces overall instability, but the depth at which degradation becomes most pronounced depends on the interaction among source depth, station distribution, and the specific empirical contaminant waveform used in each network.

3.1.5 Sensitivity to Moment Tensor Constraint Strategy

We performed a limited sensitivity analysis to examine how commonly used moment tensor constraints affect solution bias and contamination sensitivity under structured empirical contamination. Here, the term “constraint” refers to the degree of restriction imposed on the source parametrisation, namely, full moment tensor, deviatoric, or double-couple inversion. Because the empirical-contamination tests were performed using a single representative realisation for each configuration, variability across results should not be interpreted as stochastic repeatability in the same sense as in the Gaussian and phase-randomised experiments. Instead, the comparison is designed to assess how each constraint modifies the inversion’s response to increasing structured contamination.

To separate absolute bias from contamination sensitivity, we summarised the results using two quantities. The first is the mean rotation angle across contamination levels, $\bar{\omega}$, which is used as a proxy for overall mechanism bias. The second is the increase in

rotation angle between the uncontaminated and most contaminated cases, $\Delta\omega = \omega_{\alpha=1} - \omega_{\alpha=0}$, which measures the sensitivity to increasing empirical contamination. Fig. 7 compares these quantities for representative source cases, constraint levels, inversion strategies, and network geometries.

The results show a clear bias–sensitivity trade-off. When the imposed constraint is compatible with the prescribed source case, the solutions generally remain with a relatively low mean $\bar{\omega}$. However, they may still exhibit non-negligible $\Delta\omega$, especially for the more strongly deviatoric cases under full moment tensor inversion. In contrast, when the imposed constraint is incompatible with the true mechanism, the solutions commonly shift toward a much larger $\bar{\omega}$, while $\Delta\omega$ becomes small. This pattern is particularly evident for the ISO-dominant case inverted under deviatoric or double-couple constraints, and for the mixed case inverted under more restrictive parametrisations. These cases are, therefore, contamination-insensitive but strongly biased.

The comparison between FW-I and PS-I further indicates that P–S segmentation can reduce the contamination sensitivity in several cases. Still, it does not remove the bias introduced by an inappropriate constraint. In both networks, PS-I tends to reduce $\Delta\omega$ for some compatible or weakly constrained cases. At the same time, the high-bias solutions produced by incompatible constraints remain displaced toward large $\bar{\omega}$. Thus, the main effect of constraint

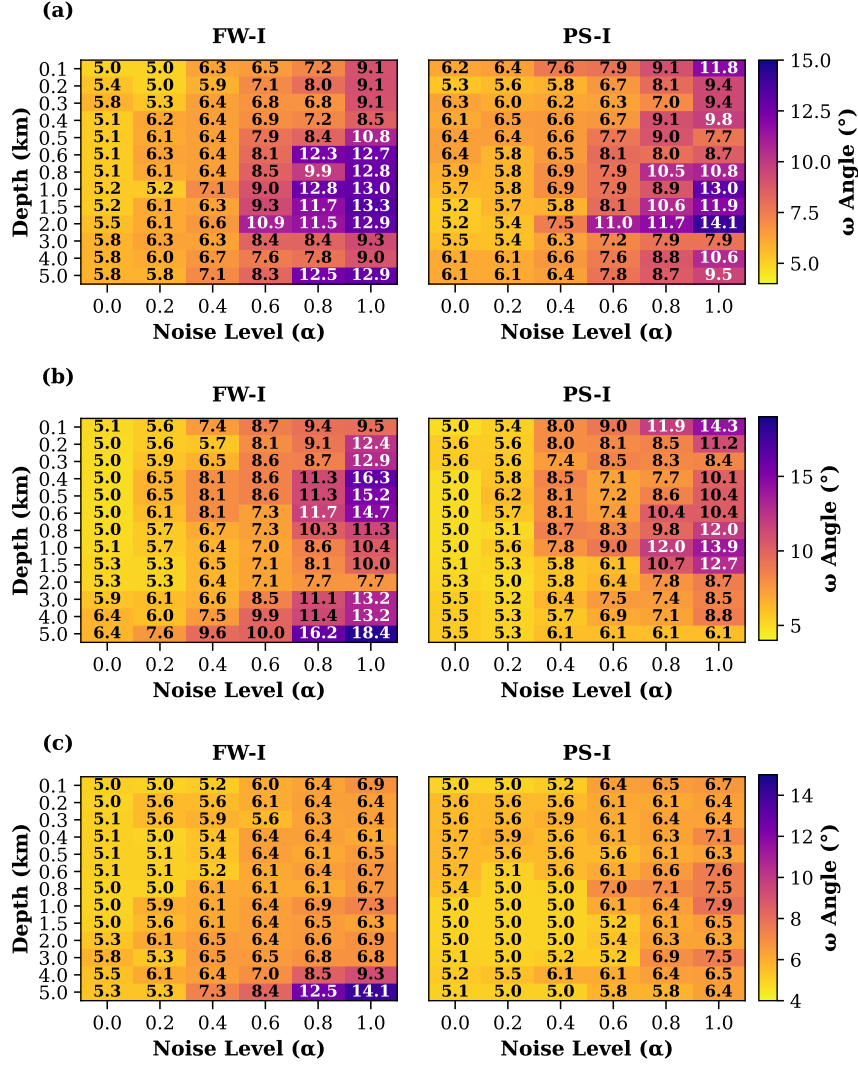


Figure 6. Depth dependence of structured empirical contamination for the three network configurations: (a) and (b) show median ω value across depths for Network 1 and Network 2, respectively. (c) The same for the 12-station network. Results for each network uses its own colour scale.

choice is not simply to improve or degrade stability, but to redistribute the error between sensitivity to contamination growth and persistent mechanism bias.

3.2 Real-Data Illustration of Method-Dependent Depth Trade-off

To assess whether synthetic diagnostics are relevant to the observed mining-induced seismicity, we analysed one representative event recorded by the local six-station Network 2 using the procedure described in Section 2.3.4. Because the objective is diagnostic rather than descriptive, the event is used only to illustrate the method-dependent depth trade-off under realistic sparse-network conditions.

Fig. 8 shows the depth-dependent misfit and corresponding preferred full moment tensor solutions for the M_L 1.2 event obtained with FW-I and PS-I. In both cases, the minimum misfit occurs at approximately 0.5–0.8 km depth. The methods therefore do not select fundamentally different depth regimes, but they differ in the shape of the misfit curve and in the evolution of the preferred

mechanism with depth. FW-I shows larger changes in source character away from the shallow minimum, whereas PS-I preserves a more coherent mechanism family across a broader part of the tested interval.

The moment magnitude selected within the search also varies with depth, but the main diagnostic information is the joint depth dependence of misfit and mechanism. This example is not used to infer a preferred physical mechanism or structural interpretation for the event.

4 DISCUSSION

The sensitivity of moment tensor inversion to noise and modelling uncertainties has long been recognised, particularly for shallow and low-magnitude events, where limited bandwidth, source-depth trade-offs, and structural complexity can exacerbate solution instability (Vavryčuk, 2007; Duputel et al., 2012; Pham et al., 2024). By systematically comparing Gaussian contamination, structured empirical contamination, and phase-randomised empirical contamination, we aimed to isolate the respective roles of random variance,

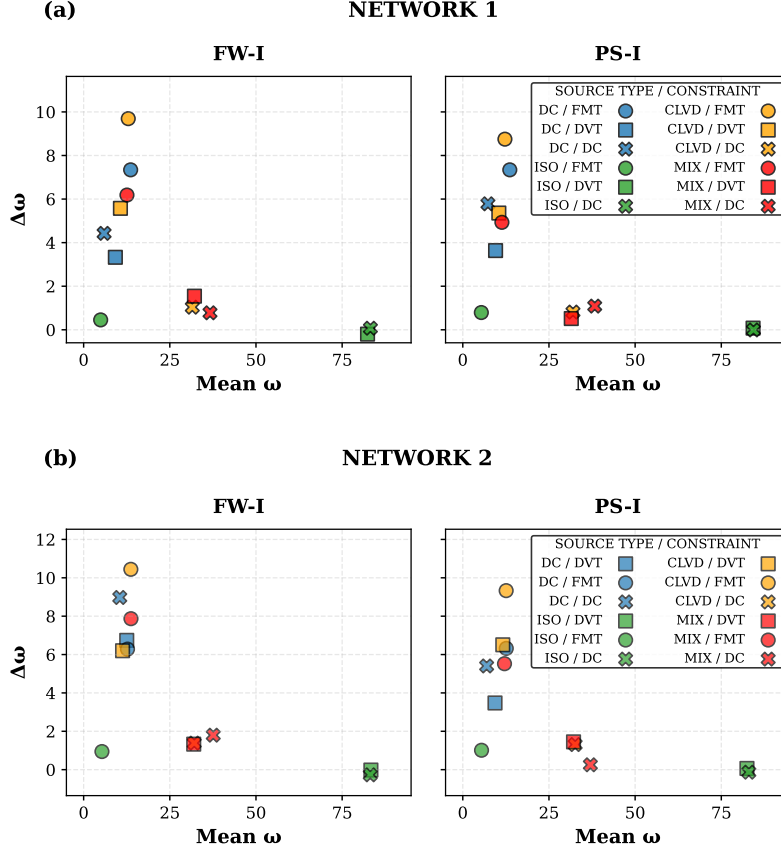


Figure 7. Bias-sensitivity trade-off for representative constraint strategies under structured empirical contamination for Network 1 (a) and Network 2 (b). Each point denotes the mean rotation angle across contamination levels and the increase in rotation angle between $\alpha = 0$ and $\alpha = 1$ ($\Delta\omega$) for the ISO-dominant (ISO), CLVD-like (CLVD), mixed (MIX), and double-couple (DC) source cases under full moment tensor, deviatoric, and double-couple constraints.

systematic bias, and temporal phase coherence in shaping inversion outcomes.

Within this framework, Gaussian contamination defines a baseline regime in which inversion degradation is driven primarily by random amplitude perturbations. Under these conditions, both full-waveform inversion and P-S segmented inversion exhibited smooth and approximately monotonic degradation of mechanism recovery for the CLVD-like, mixed, and DC source cases. By contrast, the ISO-dominant case remained comparatively stable even at high contamination levels. The results presented in Sections 3.1.1–3.1.3 indicate that random contamination mainly increases solution variance without introducing a clear systematic mechanism rotation or coherent non-double-couple artefacts. Gaussian-noise tests, therefore, provide a useful reference for variance-dominated behaviour, but they are insufficient for assessing systematic bias under realistic waveform contamination.

4.1 Empirical Contamination and Structured Waveform Bias

In contrast to the Gaussian baseline, empirical contamination produced stronger degradation at equivalent contamination levels, particularly for the CLVD-like, mixed, and DC source cases. Elevated rotation angles and inflated non-double-couple components indicate that empirical contamination acts as a structured waveform perturbation rather than as a random fluctuation. These effects are consistent with unmodelled path- and site-dependent propagation phenomena, including near-surface scattering, attenuation, and site

amplification (Gibowicz & Kijko, 1994; Duputel et al., 2012; Phạm et al., 2024).

Because the empirical contaminant is itself a recorded seismic event, it should be interpreted as a structured source-path-site waveform perturbation rather than as a source-free representation of propagation effects alone. This distinction is important: the empirical-contamination tests do not isolate pure path effects, but instead evaluate how inversion results respond to realistic, phase-structured waveform interference that contains source radiation, propagation, and site contributions. In mining-induced and other shallow seismic environments, such structured waveform distortions cannot be adequately represented by random-noise models alone (Gibowicz & Kijko, 1994; Birnie et al., 2020).

Phase-randomisation experiments provide the key diagnostic for separating amplitude-spectrum effects from preserved temporal waveform structure. When the phase structure of empirical contamination was randomised while its amplitude spectrum was preserved, inversion performance shifted towards the Gaussian baseline. The additional degradation under structured empirical contamination is, therefore, not controlled by the amplitude content alone. Previous studies have shown that real-data waveform mismatch often reflects modelling and propagation effects rather than random uncertainty (Duputel et al., 2012; Phạm et al., 2024); the present results further show that the preserved temporal phase relationships account for most of the additional moment tensor bias in this experiment. Phase randomisation nevertheless modifies several time-domain waveform attributes simultaneously, so the com-

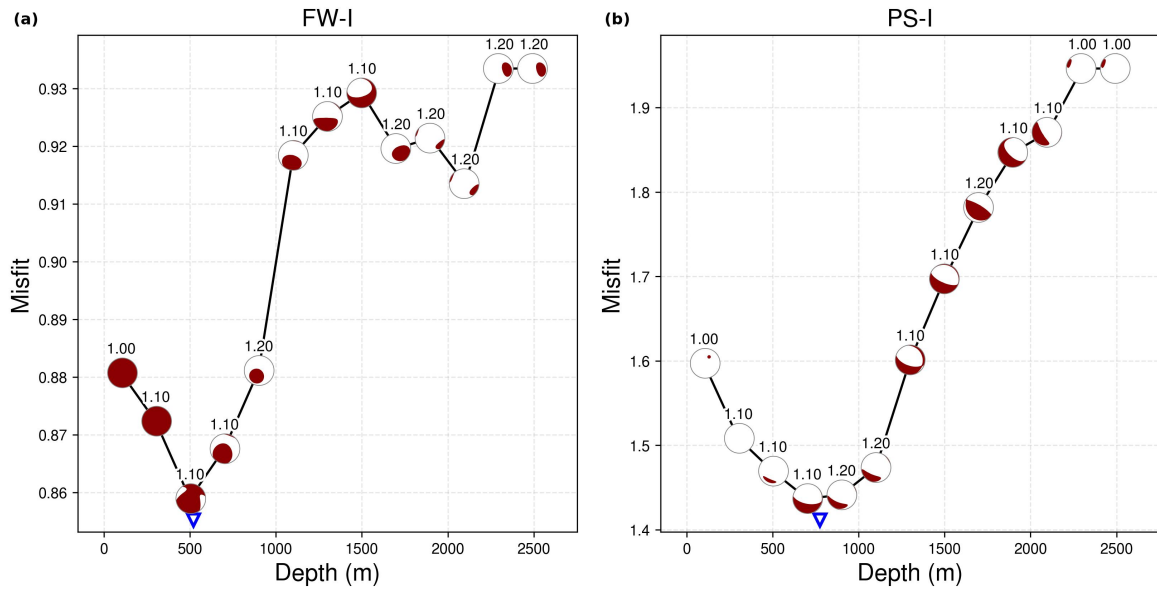


Figure 8. Real-data depth trade-off illustration for a representative event using (a) full-waveform inversion (FW-I) and (b) P-S segmented inversion (PS-I). The black curve shows the misfit as a function of tested source depth, and the blue inverted triangle marks the minimum-misfit depth in each inversion. Beachballs denote the preferred full moment tensor solution obtained at each tested depth, and the numbers above the beachballs indicate the moment magnitude selected within the search scheme at that depth. The search range of moment magnitude was 1.0 to 1.4 M_W . The figure is presented for diagnostic purposes only and is not used to infer a preferred physical mechanism for the event.

parison should be interpreted as isolating the contribution of preserved phase structure broadly rather than a single travel-time parameter. In practical terms, timing and phase misalignment of the waveform packets provide the most immediate expression of this bias, whereas waveform broadening, amplitude redistribution, and late-coda complexity are more complex manifestations of the same mismatch.

4.2 Source-Type Dependence and the Apparent Orientation Stability of the ISO-Dominant Case

The ISO-dominant source case exhibited a distinct response to waveform contamination compared to the more strongly deviatoric cases. Across both Gaussian and structured empirical contamination, its mechanism orientation changed little with increasing contamination. This behaviour is consistent with its predominantly isotropic radiation pattern, which has a weak nodal structure and is therefore less sensitive to phase- and polarity-dependent perturbations. However, this apparent orientation stability does not necessarily imply high-fidelity recovery of moment tensor decomposition.

The near invariability of the source-decomposition error across increasing contamination levels (see Figs 3c and 3f for Gaussian contamination and Figs S2(c) and S2(f) for structured empirical contamination) indicates that the dominant error for the ISO-dominant case is largely independent of contamination amplitude. Deviations in recovered decomposition reflect both limited resolution of its predominantly isotropic contribution and leakage among isotropic, CLVD, and double-couple components. The persistence of this error under both Gaussian and structured empirical contamination suggests a bias floor controlled by limited resolvability

and parameter trade-offs, including restricted take-off-angle diversity, bandwidth limitations, and depth or model uncertainty, rather than by stochastic variance or contamination strength alone. This interpretation is consistent with the known difficulty of resolving isotropic and related non-double-couple components for shallow sources (Kawakatsu, 1996).

This behaviour contrasts with the CLVD-like, mixed, and DC cases, for which structured empirical contamination perturbs the phase and polarity information required to resolve the deviatoric radiation pattern, producing contamination-dependent mechanism rotation and spurious component inflation. Consequently, the ISO-dominant case may appear stable in orientation while still exhibiting a persistent, largely contamination-insensitive decomposition bias. This distinction should be considered when interpreting collapse-like or volume-change sources in shallow, structurally complex environments.

4.3 Effect of Station Coverage Under Structured Empirical Contamination

The synthetic tests show that increased station coverage substantially improves inversion stability under structured empirical contamination. For the geometries considered here, the 12-station configuration largely suppresses the additional degradation observed under empirical contamination relative to the Gaussian baseline across shallow to intermediate depths. This behaviour indicates that dense spatial sampling can reduce the impact of station-specific coherent distortions when they are not consistently aligned across the network. A similar general conclusion has been reached in mining-oriented synthetic studies, where realistic station geometry strongly influences inversion performance (Caputa et al., 2021).

This stabilising effect, however, is not complete. At greater depths, full-waveform inversion solutions in the 12-station network still exhibit residual empirical-contamination degradation beyond the Gaussian baseline, indicating that increased station count alone does not fully eliminate systematic bias. This suggests that, where depth sensitivity is reduced or coherent propagation effects remain sufficiently consistent across stations, spatial redundancy can reduce but not remove the influence of structured waveform mismatch.

In general, these results refine the role of station coverage. Denser networks can strongly reduce empirical-contamination-induced degradation over much of the tested depth range, but residual bias can persist where source depth, station distribution, and coherent waveform structure jointly limit full-waveform consistency.

4.4 Method Dependence and the Role of P–S Segmentation

Waveform-segmentation strategies derived from the CAP framework improve tolerance to moderate timing mismatch by allowing distinct waveform groups to be aligned independently rather than forcing the entire seismogram to share a single timing correction (Zhao & Helmberger, 1994; Zhu & Helmberger, 1996). This principle has been applied in practical focal-mechanism studies of small-to-moderate earthquakes. For example, Chang et al. (2019) separated P waves on the vertical and radial components from S waves on the vertical, radial, and transverse components, allowing independent time shifts between the P- and S-wave groups when fitting regional body-wave observations.

The P–S segmented inversion used here follows the same general principle but extends it to full moment tensor analysis of shallow, local mining-induced seismicity. In PS-I, the P- and S-wave windows contribute independently to the total misfit and are permitted separate timing adjustments. This formulation is intended to reduce the extent to which differential travel-time and phase mismatch between the two wavefields is mapped into mechanism rotation or artificial source complexity.

Across the tested network configurations, PS-I generally showed a lower sensitivity to structured empirical contamination than fully coupled full-waveform inversion, although the improvement was not uniform across all source depths or geometries. The clearest benefit of PS-I occurred where the structured contamination produced different timing or phase perturbations in the P- and S-wave packets. In these cases, FW-I was required to reconcile incompatible waveform segments simultaneously, whereas PS-I could accommodate part of the phase-dependent mismatch through independent alignment. This behaviour was particularly evident for the deeper FW-I degradation in the compact 6-station and 12-station configurations, where P–S segmentation substantially reduced the residual empirical-contamination effect.

For the broad 6-station geometry, however, PS-I did not uniformly reduce rotation angles across all depths. Instead, it modified the depth-dependent expression of the degradation and produced results comparable to FW-I in some configurations. The advantage of segmentation should therefore not be interpreted as a universal superiority over full-waveform inversion. Rather, its effectiveness depends on the degree to which the dominant waveform mismatch differs between the P- and S-wave windows.

The station coverage and waveform segmentation consequently play complementary roles. While increasing station count reduces the influence of station-specific structured distortions

through spatial redundancy, the P–S segmentation reduces sensitivity to phase-dependent inconsistency that can remain even when network coverage is improved. The present results extend the practical CAP precedent illustrated by Chang et al. (2019) by showing, through controlled synthetic tests, how independent P- and S-wave treatment affects full moment tensor stability under structured empirical contamination. They also indicate that station- and phase-specific timing distortions may represent a practical target for future calibration, although the effectiveness of such corrections must be evaluated for each network and propagation setting.

4.5 Depth Dependence of Structured Empirical-Contamination Effects

The depth dependence of structured empirical-contamination effects varied systematically with network geometry, indicating that inversion stability is controlled by the interaction among source depth, station configuration, and a network's ability to decorrelate coherent waveform perturbations. At the same time, because the empirical contamination for each network was derived from a single recorded event and superimposed on synthetic waveforms over the full set of prescribed depths, the detailed depth-dependent patterns should be interpreted as the response to a fixed empirical contaminant waveform rather than as a universal function of source depth alone.

Within that framework, the broad and compact 6-station networks exhibit contrasting depth-dependent responses. In the broad geometry, the strongest degradation is concentrated at shallow to intermediate depths, whereas in the compact geometry, full-waveform degradation becomes more pronounced at greater depths. The 12-station configuration suppresses much of this depth-dependent instability, but residual degradation persists at the deepest tested depths, especially in fully coupled full-waveform inversion. P–S segmentation reduces this residual deep-seated degradation, indicating that wavefield-dependent phase inconsistency remains important even with improved station coverage.

Together, these results indicate that the observed depth dependence reflects the combined influence of station geometry, source depth, wavefield-dependent propagation effects, and the specific empirical contaminant used for each network. The principal conclusion is therefore not that structured empirical contamination produces a universal depth of maximum degradation, but that it introduces depth-variable bias, the detailed expression of which depends on the interaction between network geometry and the contaminant waveform.

4.6 Sensitivity to Moment Tensor Constraint Strategy

The constraint analysis provides a complementary perspective on how inversion choices redistribute error between persistent mechanism bias and sensitivity to increasing structured empirical contamination. Because the empirical-contamination tests were based on a single representative realisation for each network, the comparison is best interpreted through the two quantities shown in Fig. 7: the mean rotation angle across contamination levels, used as a proxy for persistent mechanism bias, and the increase in rotation angle, $\Delta\omega$, from $\alpha = 0$ to $\alpha = 1$, used as a measure of contamination sensitivity.

When the imposed constraint is compatible with the prescribed source case, restricting the model space can reduce the in-

crease in rotation angle with contamination level while maintaining a relatively low mean misorientation. In such cases, the constraint helps limit the response to increasing contamination without introducing substantial additional bias. By contrast, when the imposed constraint is inconsistent with the true mechanism, the inversion can become less responsive to contamination growth while remaining systematically shifted away from the true solution. Such cases produce solutions that are contamination-insensitive but biased in an absolute sense.

The practical implication is that a low contamination sensitivity does not necessarily indicate a reliable inversion when the corresponding mean rotation angle is large. More restrictive inversions can therefore appear more robust without actually improving mechanism recovery. Constraint strategies do not eliminate structured empirical effects; instead, they redistribute their expression between persistent mechanism bias and sensitivity to increasing contamination. Constraint choice should therefore be interpreted cautiously in shallow, structurally complex environments where coherent waveform perturbations are expected to influence moment tensor inversion.

4.7 Real-Data Illustration and Diagnostic Consistency

The real-data example is best interpreted as a practical extension of synthetic diagnostics. In the synthetic tests, source depth was prescribed, and the results showed that the inversion bias and degradation varied systematically with depth, method, and contamination type. In the real-data case, depth is itself uncertain, so this sensitivity appears as a depth trade-off: different tested depths can yield comparably acceptable fits, and the inferred mechanism depends on the inversion strategy.

Within this framework, the contrast between full-waveform inversion and P-S segmented inversion is informative. Both methods favour a similar shallow depth range for the representative event. Still, full-waveform inversion shows stronger mechanism variability as depth increases, whereas P-S segmented inversion preserves a more coherent mechanism family across the same interval. This behaviour is consistent with the synthetic results, which indicate that inversion performance is strongly depth- and method-dependent under realistic perturbations.

The field example is therefore not used to infer a preferred physical mechanism, but to show that the type of non-uniqueness diagnosed synthetically is relevant in practice. Under sparse-network, shallow-source conditions, full moment tensor inversion outcomes remain sensitive to both inversion strategy and unresolved depth uncertainty.

4.8 Implications for Synthetic Thresholds, Calibration and Network Design

Previous studies have shown that performance thresholds derived from synthetic tests under idealised assumptions should not be transferred directly to real data, where realistic waveform contamination can generate behaviour that is not reproduced by Gaussian-noise benchmarks (Birmie et al., 2020). The present results reinforce this point and suggest that Gaussian-based thresholds are best treated as relative stability references, useful for comparing inversion strategies, network geometries, and processing choices, rather than as fixed quantitative criteria for screening real events.

The close correspondence observed here between Gaussian

contamination and phase-randomised empirical contamination indicates that perturbations without preserved empirical phase structure mainly produce variance-dominated behaviour. By contrast, structured empirical contamination resembles correlated source-path-site waveform mismatch. This interpretation is consistent with studies showing that structural and path-related uncertainty contributes a theory-error component to waveform misfit and can materially affect moment tensor inference (Duputel et al., 2012; Pham et al., 2024). Improving inversion performance under realistic conditions, therefore, requires addressing structured waveform bias rather than simply increasing signal-to-noise ratio, because denser station coverage and methodological adjustments may reduce, but not necessarily eliminate systematic effects.

Within this context, the empirical-contamination strategy should be viewed as a diagnostic representation of structured source-path-site waveform contamination rather than as a direct model of pure path effects. The additive empirical perturbation superimposes an external structured wavefield on the primary signal, emulating coherent interference and correlated waveform mismatch that may be encountered in mining settings. It does not modify the Earth's transfer function; instead, it competes with the target source signal in a way that the inversion may misinterpret as source complexity. The approach therefore complements Gaussian-noise tests by evaluating sensitivity to structured waveform contamination.

Although the present study is framed around the Jacobina mining district, the synthetic framework is not, in principle, site-specific. By replacing the local velocity model, candidate station geometries, source-depth range, expected source mechanisms, and representative empirical contamination waveforms, the same workflow can be adapted to other local seismicity settings. In particular, the comparison between the two real 6-station layouts and the idealised 12-station configuration illustrates how such tests can be used as a pre-deployment diagnostic tool for evaluating candidate network geometries. This use should be understood as a stability-screening exercise rather than as a substitute for site-specific calibration with real data.

These results motivate future calibration strategies that target structured waveform mismatch directly. Possible approaches include empirical Green's functions, which incorporate propagation effects through convolution (Hartzell, 1978; Mueller, 1985), and simpler station- and phase-specific timing corrections applied to P- and S-wave packets. Testing such corrections lies beyond the scope of this diagnostic study, but the present results identify the type of mismatch that future calibration strategies should address.

5 CONCLUSIONS

This study provides a diagnostic evaluation of moment tensor inversion stability under increasingly realistic contamination regimes in shallow mining-induced seismic settings. The results show that inversion degradation is controlled not only by the amplitude of the contaminant waveforms, but also by their temporal phase structure. Gaussian and phase-randomised perturbations produce mainly variance-dominated behaviour, whereas structured empirical contamination introduces systematic mechanism bias, can inflate spurious non-double-couple components, and weakens the transferability of synthetic stability thresholds to real-data applications.

The tests also show that the expression of this bias depends on prescribed source case, station geometry, and inversion strategy. Because structured empirical contamination was represented by a

single recorded event per network, the detailed depth-dependent degradation patterns should be interpreted as contaminant-specific rather than as universal functions of source depth. The ISO-dominant case remains comparatively stable in orientation but exhibits persistent decomposition bias, whereas the CLVD-like, mixed, and DC cases are more strongly affected by mechanism rotation and spurious component inflation. Denser station coverage reduces the amplitude and depth dependence of empirical-contamination errors, although residual bias can persist at greater depths, suggesting that station coverage alone does not fully eliminate the influence of structured waveform mismatch under the tested configurations. P–S segmented inversion generally reduces sensitivity to structured empirical contamination, with the clearest benefit where differential perturbations of P- and S-wave packets affect fully coupled waveform alignment.

The constraint analysis further shows that apparent robustness does not necessarily imply reliable mechanism recovery. Incompatible moment tensor constraints can produce solutions that are relatively insensitive to increasing contamination while remaining systematically biased. This bias–sensitivity trade-off indicates that constraint choice should be interpreted cautiously in shallow, structurally complex environments where structured waveform perturbations are expected to affect moment tensor inversion.

Taken together, these findings indicate that Gaussian-noise thresholds should be used primarily as comparative stability references rather than as fixed screening criteria for real events. They also motivate calibration strategies that explicitly address structured waveform bias, including empirical Green’s function approaches or simpler station- and phase-specific timing corrections. More generally, the synthetic workflow developed here can be adapted to other shallow seismicity settings as a pre-deployment diagnostic tool for comparing candidate network geometries, provided that local velocity structure, source-depth ranges, expected source mechanisms, and representative empirical contamination are incorporated.

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During preparation of this manuscript, the authors used OpenAI ChatGPT and SciSpace AI to assist with language editing, manuscript organisation and document formatting. These tools were not used to generate the underlying seismic data, inversion results or figures. All AI-assisted text was reviewed and edited by the authors, who take full responsibility for the manuscript.

Conflicts of interest: The authors declare no conflicts of interest.

DATA AVAILABILITY

The numerical results underlying the main and supplementary figures, the machine-readable parameter tables, the synthetic-test configuration files, and the scripts used for waveform contamination, phase randomisation, inversion processing, data summarization, and figure generation are archived in Zenodo at <https://doi.org/10.5281/zenodo.21651740> ([dataset] Gomes et al., 2026).

The raw continuous waveform data and detailed station and mining-site metadata are not publicly available because they are subject to ongoing-study and data-use restrictions. Access is administered by LabSis/UFRN and requires prior written authorisation from the relevant data owner. These restrictions do not apply to the synthetic results, scripts, and derived numerical products deposited in Zenodo.

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