

Non-peer reviewed paper submitted to *Progress in Earth and Planetary Science* (PEPS)

Stabilizing seismic source inversion by accounting for P-wave picking uncertainty: A waveform-shift covariance approach

Yuji Yagi

Institute of Life and Environmental Sciences, University of Tsukuba, Tennodai 1-1-1, Tsukuba, Ibaraki, 305–8572, Japan

e-mail: yagi-y@geol.tsukuba.ac.jp

Abstract

In seismic source inversion using teleseismic P waves, P-wave arrival times are picked from observed waveforms and used to adjust their timing relative to the predicted arrivals. However, uncertainty in the picked arrival times remains after this correction. Picking errors shift the entire waveform and produce temporally correlated waveform errors. If these errors are not properly accounted for, small differences in arrival-time picks may substantially alter the inferred source models and contribute to discrepancies among analysts. In this study, I propose a waveform-shift covariance approach that approximately constructs the component of the data covariance matrix associated with P-wave picking uncertainty from observed waveforms and a probability distribution of time shifts. I incorporate this approach into potency density tensor inversion (PDTI) and compare it with a conventional approach that neglects picking uncertainty, using 125 synthetic waveform datasets that differ only in picking errors. Relative to the conventional approach, the proposed method reduces the normalized model root mean square error (RMSE) by approximately 0.09 and reduces the variability among inferred source models across datasets to less than 40% of that for the conventional approach. Although the normalized data RMSE is comparable between the two approaches, the normalized model RMSE for individual datasets is concentrated within 0.32–0.36 for the proposed method, whereas it spans 0.35–0.50 for the conventional approach. These results show that incorporating P-wave picking uncertainty into the data covariance matrix yields more accurate and stable source models, even though the proposed and conventional approaches fit the observed waveforms similarly well. Application to real earthquake data with uncertain P-wave picks suggests that neglecting the data error structure may lead to overfitting in the conventional approach. Accounting for picking uncertainty changes how waveform discrepancies are weighted in the inversion, reducing the tendency to interpret waveform-shift errors as source complexity. These findings underscore the importance of returning to a basic principle for reliable estimation of earthquake rupture processes: interpreting source signals in observed data requires an understanding of not only the signal structure but also the error structure.

Keywords: Seismic source inversion; P-wave picking uncertainty; Data covariance

1 Introduction

An earthquake involves rupture propagation along faults. Stable estimation of the rupture process, including fault geometry, is important not only for understanding earthquake phenomena but also for predicting strong ground motion and tsunamis from future large earthquakes (e.g., Geist, 2002; Klinger et al., 2018; Taufiqurrahman et al., 2023).

However, as multiple source models have been published for individual large earthquakes, substantial differences among models obtained by different researchers have become an issue in seismic source studies (e.g., Beresnev, 2003; Vallée and Bouchon, 2004; Gallovič and Ampuero, 2015; Mai et al., 2016). In general, observational and modeling errors can introduce correlations among data, making it important to account for their error structure. In geodetic data analysis, methods have been developed to account for temporal and spatial correlations in observational errors (e.g., Langbein and Johnson, 1997; Fukahata and Wright, 2008). In seismic waveform inversion for source processes, studies have mainly focused on correlations in modeling errors, including errors associated with discretization of the source process (Yagi and Fukahata, 2008) and uncertainty in Green's functions (Yagi and Fukahata, 2011). Subsequent studies have also shown the importance of properly accounting for error correlations in source inversions (e.g., Minson et al., 2013; Dettmer et al., 2014; Duputel et al., 2014; Ragon et al., 2018).

In particular, accounting for Green's-function uncertainty opened a path toward stable estimation of seismic source processes without imposing the non-negativity constraints commonly used in source inversions (Yagi and Fukahata, 2011). This development led to potency density tensor inversion (PDTI), which estimates the source process together with information on fault geometry (Shimizu et al., 2020). PDTI relaxes assumptions about fault orientation and estimates the spatiotemporal distribution of potency density tensors. The underlying idea is to extract information on fault geometry from waveform discrepancies that were previously treated as modeling errors. Methods for estimating fault geometry from observed data have also been proposed from this perspective (e.g., Shimizu et al., 2021; Dutta et al., 2021; Sato et al., 2026).

In source inversion using teleseismic P waves, P-wave arrival times calculated from assumed source parameters and Earth structure do not necessarily agree with actual arrival times because of three-dimensional

structural heterogeneity. To reduce the effects of these travel-time errors, P-wave arrival times are picked from observed waveforms and used to correct their time alignment (e.g., Ohara et al., 2023). The importance of arrival-time corrections for source estimation has also been noted (e.g., Ji et al., 2004; Shao et al., 2011). Back-projection (BP) studies likewise use time corrections based on cross-correlation among observed waveforms to reduce the effects of travel-time errors (e.g., Ishii et al., 2007). However, compared with BP analyses using waveforms recorded within an array, seismic source inversions require stations spanning a broad azimuthal range to limit uneven station coverage. Waveforms may differ considerably because of the azimuthal dependence of radiation patterns and differences in propagation paths, so time corrections based on cross-correlation among observed waveforms require careful assessment. Moreover, accurate P-wave picking is difficult at stations with high background noise, such as those on oceanic islands (e.g., Okuwaki et al., 2016). Completely eliminating picking uncertainty is not practical. Picking errors shift the entire waveform and thus produce waveform errors that are correlated across time. Therefore, accounting for picking errors requires incorporating the uncertainty remaining after arrival-time correction into the inversion through the waveform-error covariance.

In this study, I represent P-wave picking errors as waveform time shifts and derive an approximate expression for the covariance of the resulting waveform errors. I propose a waveform-shift covariance approach that can be incorporated into existing seismic source inversion methods, including PDTI, and evaluate its effectiveness through synthetic tests using PDTI. I also discuss its applicability to other waveform analyses.

2 Mathematical Formulation

I represent the teleseismic P waveform $u_j(t)$ from an earthquake observed at station j as a superposition of potency-rate density functions for five basis double-couple components (Kikuchi and Kanamori, 1991) distributed over a model plane (Shimizu et al., 2020):

$$u_j(t) = \sum_{q=1}^5 \int_S \dot{D}_q(t, \xi) * [G_{qj}(t, \xi) + \delta G_{qj}(t, \xi)] d\xi + e_{bj}(t) + e_{pj}(t). \quad (1)$$

Here, $\dot{D}_q$ is the potency-rate density function for the q th basis double-couple component, G_{qj} is the calculated Green's function for unit potency, and δG_{qj} is the difference between the true and calculated Green's functions. The terms e_{bj} and e_{pj} represent background noise and waveform errors caused by P-wave picking errors, respectively. The variable ξ denotes a position on the model plane S , and $*$ denotes convolution in time.

I define δt as the picked P-wave arrival time minus the true arrival time and approximate its probability density function $p_j(\delta t)$ by a Gaussian distribution with zero mean and variance σ_{pj}^2 . When the picked arrival time is taken as the time origin, a pick later than the true arrival shifts the waveform toward earlier times. I approximate the waveform error associated with this time shift by the difference between the shifted and unshifted observed waveforms:

$$e_{pj}(t; \delta t) \approx u_j(t + \delta t) - u_j(t). \quad (2)$$

In constructing the data covariance function below, I treat the observed waveform $u_j(t)$ as a fixed reference waveform.

Even when the time shift has zero mean, the waveform-shift error in eq. (2) does not necessarily have zero mean. To simplify the error model in the observation equation, I approximate $e_{pj}(t)$ by a Gaussian

process with zero mean and covariance function $C_{pj}(t, t')$. I use the second moment of the waveform-shift error as the covariance of this Gaussian approximation:

$$C_{pj}(t, t') = \int e_{pj}(t; \delta t) e_{pj}(t'; \delta t) p_j(\delta t) d\delta t. \quad (3)$$

Because the mean waveform-shift error is not subtracted, this definition accounts for the magnitude of the error, including its nonzero mean.

If the time shift is sufficiently small compared with the timescale of waveform variation, a first-order Taylor expansion of eq. (2) gives

$$e_{pj}(t; \delta t) \approx \dot{u}_j(t) \delta t, \quad (4)$$

where $\dot{u}_j$ is the time derivative of the observed waveform. Under this linear approximation, the waveform-shift error has zero mean, and eq. (3) becomes

$$C_{pj}(t, t') = \sigma_{pj}^2 \dot{u}_j(t) \dot{u}_j(t'). \quad (5)$$

I refer to the covariance constructed using this linear approximation as LinearCov.

Even when the linear approximation is not valid, eq. (3) can be evaluated directly by applying finite time shifts to the observed waveform. Let Δt_j be the sampling interval of the observed waveform and define discrete time shifts as

$$\delta t_{mj} = m \Delta t_j \quad \{m = -M_j \cdots M_j\}. \quad (6)$$

Discretizing eq. (3) gives

$$C_{pj}(t, t') = \sum_{m=-M_j}^{M_j} w_{jm} e_{pj}(t; \delta t_{mj}) e_{pj}(t'; \delta t_{mj}), \quad (7)$$

where the weights are normalized over the finite shift interval:

$$w_{jm} = \frac{p_j(\delta t_{mj}) \Delta t_j}{\sum_{n=-M_j}^{M_j} p_j(\delta t_{nj}) \Delta t_j}. \quad (8)$$

The range of time shifts used in the calculation is chosen based on the standard deviation of the picking error σ_{pj} to limit numerical approximation errors. I refer to the covariance constructed from finite waveform shifts as ShiftCov.

For sampling times t_i and $t_{i'}$ used in the inversion, the elements of the covariance matrix $\mathbf{C}_{jp}$ are given by

$$[\mathbf{C}_{pj}]_{ii'} = C_{pj}(t_i, t_{i'}). \quad (9)$$

Following Yagi and Fukahata (2011), I discretize eq. (1) and express it in vector form as

$$\mathbf{d}_j = \mathbf{H}_j \mathbf{a} + \mathbf{e}_{gj}(\mathbf{a}) + \mathbf{e}_{bj} + \mathbf{e}_{pj}. \quad (10)$$

Here, $\mathbf{d}_j$ is the data vector at station j , $\mathbf{H}_j$ is the kernel matrix constructed from the calculated Green's functions and the spatial and temporal basis functions, and $\mathbf{a}$ is the vector of expansion coefficients for the discretized potency-rate density functions. The vectors $\mathbf{e}_{gj}$, $\mathbf{e}_{bj}$ and $\mathbf{e}_{pj}$ represent errors arising from Green's-function uncertainty, background noise, and P-wave picking errors, respectively.

Neglecting cross-covariances among these error terms, the error covariance matrix is expressed as

$$\mathbf{C}_{dj}(\sigma_g^2, \sigma_{bj}^2, \sigma_{pj}^2, \mathbf{a}) = \sigma_g^2 \mathbf{C}_{gj}(\mathbf{a}) + \sigma_{bj}^2 \mathbf{C}_{bj} + \mathbf{C}_{pj}(\sigma_{pj}^2). \quad (11)$$

Here, σ_g^2 is a hyperparameter controlling the scale of Green's-function errors, $\mathbf{C}_{gj}(\mathbf{a})$ describes their model-dependent covariance structure, and $\mathbf{C}_{bj}$ describes the correlation structure of background noise.

In general, uncertainty in P-wave arrival-time picks increases with the background-noise variance σ_{bj}^2 . Conversely, a steeper slope v_j at the P-wave onset reduces the effect of a given noise amplitude on the picked arrival time. Based on these properties, I use the following empirical relation to convert amplitude uncertainty into timing uncertainty:

$$\sigma_{pj}^2 = \varepsilon \sigma_{bj}^2 / v_j^2, \quad (12)$$

where ε is a dimensionless tuning parameter specified empirically. For LinearCov, $\mathbf{C}_{pj}$ is proportional to the background-noise variance. For ShiftCov, changing the background-noise variance also changes the width of the time-shift distribution, so $\mathbf{C}_{pj}$ is not simply proportional to that variance.

To incorporate the proposed covariance into the framework of Yagi and Fukahata (2011), I adopt an approximation that fixes the structure of the picking-error covariance constructed from the observed waveform and applies a common scale factor to the background-noise and picking-error covariances. First, I estimate the background-noise variance λ_{bj}^2 from the 10 s of observed waveform preceding the P-wave arrival. Taking the sampling interval as an assumed lower bound on the standard deviation of the picking error, I define

$$\hat{\sigma}_{pj}^2 = \max(\Delta t_j^2, \varepsilon \lambda_{bj}^2 / v_j^2), \quad (13)$$

and construct a reference picking-error covariance matrix $\hat{\mathbf{C}}_{pj}$. I then introduce a dimensionless scale factor $\hat{\sigma}_b^2$, common to all stations, and approximate the error covariance matrix as

$$\mathbf{C}_{dj}(\sigma_g^2, \hat{\sigma}_b^2, \mathbf{a}) \approx \sigma_g^2 \mathbf{C}_{gj}(\mathbf{a}) + \hat{\sigma}_b^2 [\lambda_{bj}^2 \mathbf{C}_{bj} + \hat{\mathbf{C}}_{pj}]. \quad (14)$$

For ShiftCov, this approximation scales the entire covariance matrix while keeping the width of the time-shift distribution fixed. For LinearCov without a lower bound on the picking-error variance, this operation is equivalent to scaling the background-noise variance according to eq. (12). With the lower bound introduced in eq. (13), however, it is also an approximation for LinearCov.

Using this covariance model, I estimate the hyperparameter $\gamma^2 (= \sigma_g^2 / \hat{\sigma}_b^2)$, which controls the relative scales of Green's-function and observational errors, together with the smoothing hyperparameters based on Akaike's Bayesian Information Criterion (ABIC; Akaike, 1980; Yabuki and Matsu'ura, 1992; Sato et al., 2022), following the framework of Yagi and Fukahata (2011). This allows the error structure associated with P-wave picking uncertainty to be incorporated into PDTI.

3 Synthetic Tests

I conducted synthetic tests to evaluate the effectiveness of ShiftCov and LinearCov. In general, background-noise levels vary among stations, and stations with high noise levels, such as those on oceanic islands, may be concentrated within particular azimuths. To incorporate these observational conditions, I used waveforms recorded during the 2008 Wenchuan earthquake. Broadband vertical-component records from 66 stations were obtained through the Seismological Facility for the Advancement of Geoscience (SAGE) using Wilber 3 (Fig. 1a). After removing the instrument responses and converting the records to velocity waveforms, I estimated the background-noise variance λ_{bj}^2 from the 10 s preceding the P-wave arrival and used these estimates to generate the synthetic input data.

To keep the computational cost manageable, I constructed an input source model representing a moderate-sized, thrust earthquake (Fig. 1b). The model plane had a strike of 225° , a dip of 30° , and dimensions of $34 \text{ km} \times 22 \text{ km}$, with a spatial grid interval of 2 km. The temporal knot interval was 0.4 s, and the time function at each spatial knot ended at 8.4 s after the origin time. To reduce the number of model parameters, I introduced a hypothetical front propagation velocity of 3.5 km/s and set the starting time of the temporal knots at each spatial knot to the arrival time of this hypothetical front.

Within this model setting, I constructed an input source model in which the main rupture propagated from the hypocenter toward shallower parts of the fault, while a smaller rupture propagated southwestward along strike. Local strike angles varied spatially so that the fault trace formed a gentle curve.

Green's functions were calculated using a modified version of the program of Kikuchi and Kanamori (1991). I adopted the ak135 reference velocity model (Kennett et al., 1995), calculated ray parameters and related quantities using TauP (Crotwell et al., 1999), and set the teleseismic anelastic attenuation parameter t^* to 1 s. To generate synthetic waveforms, I added zero-mean Gaussian errors to the Green's functions, with a standard deviation of 2.5% of their maximum amplitude, and convolved the perturbed Green's functions with the potency-rate density functions of the input model. Zero-mean Gaussian background noise with variance λ_{bj}^2 was then added to the resulting waveforms.

Picking-error variances were specified using eq. (13) (Fig. 2a), with the dimensionless tuning parameter ε set to 1. I generated 125 input datasets by applying station-specific time shifts drawn from zero-mean Gaussian distributions with these variances. The Green's-function errors and background noise were identical across all datasets; only the time shifts varied. The datasets were resampled at an interval of 0.4 s. Exploiting the characteristics of teleseismic body waves, I used the low-pass effect of anelastic attenuation for anti-aliasing, allowing the background-noise correlation matrix $\mathbf{C}_{bj}$ to be approximated by the identity matrix (e.g., Yamashita et al., 2022; Tadapansawut et al., 2022).

Each dataset was inverted using the same model plane, spatial grid interval, temporal knot interval, and hypothetical front propagation velocity as those used for the input model. I adopted time-adaptive smoothing (Yamashita et al., 2022) and set one of the basis double-couple components to represent pure reverse slip with the strike and dip of the model plane. I performed PDTI with ShiftCov and LinearCov, as well as conventional PDTI that neglects picking uncertainty. I refer to the conventional approach as FixedPick.

I evaluated the estimated models using the root mean square error (RMSE), which measures deviations from the true model; the root mean square (RMS) of the differences between the ensemble mean model and the true model (bias-RMS); and the RMS of the differences between individual estimated models and their ensemble mean (spread-RMS), which quantifies variability across datasets. Each measure was normalized by the RMS of the true model. Let L be the number of datasets, $\mathbf{a}_l$ the model vector estimated from dataset l , $\mathbf{a}^{true}$ the true model vector, and $\bar{\mathbf{a}}$ the mean model vector for each approach. The measures are defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{l=1}^L \|\mathbf{a}_l - \mathbf{a}^{true}\|_2^2}{L \|\mathbf{a}^{true}\|_2^2}}, \quad (15)$$

$$\text{bias-RMS} = \sqrt{\frac{\|\bar{\mathbf{a}} - \mathbf{a}^{true}\|_2^2}{\|\mathbf{a}^{true}\|_2^2}}, \quad (16)$$

$$\text{spread-RMS} = \sqrt{\frac{\sum_{l=1}^L \|\mathbf{a}_l - \bar{\mathbf{a}}\|_2^2}{L \|\mathbf{a}^{true}\|_2^2}}, \quad (17)$$

where $\|\cdot\|_2^2$ denotes the squared L2 norm. The normalized RMSE, bias-RMS, and spread-RMS can also be calculated for each dataset individually. Corresponding measures for the moment-rate function and potency density distribution can be obtained by replacing the model coefficient vectors in these equations with vectors representing these quantities. For simplicity, I hereafter refer to the potency density distribution as slip and the potency-rate density as slip rate.

Table 1 summarizes the results for ShiftCov, LinearCov, and FixedPick. ShiftCov yielded the smallest RMSE, reducing it by approximately 0.09 relative to FixedPick. The reduction for LinearCov was only approximately 0.02. The bias-RMS values differed little among the approaches, indicating similar magnitudes of deviation between the mean and true models. In contrast, the spread-RMS for ShiftCov was 0.097, less than 40% of the values for LinearCov and FixedPick. This result indicates that the improvement in RMSE achieved with ShiftCov was mainly due to reduced variability among datasets. The limited improvement obtained with LinearCov suggests that the picking errors in these tests were not sufficiently small relative to the timescales of waveform variation for the linear approximation to be adequate.

The slip-rate evolution broadly reproduced both the main rupture propagating from the deeper part of the fault toward shallower regions and the smaller rupture propagating along strike in the deeper part after 2 s, for all approaches and datasets (Fig. 3). Consistent with the spread-RMS results, variations among datasets were small for ShiftCov but larger for LinearCov and FixedPick.

The moment-rate functions broadly reproduced the peaks near 1.6, 4, and 7 s for all approaches and datasets (Fig. 4). These main features were common to all approaches, but variations among datasets were smaller for ShiftCov than for LinearCov and FixedPick. The spread-RMS of the moment-rate function was 0.014 for ShiftCov, less than 40% of the values for the other approaches (Table 2). Differences among approaches therefore remained evident in the moment-rate functions derived from spatial integration of the potency-rate density tensor components.

The final slip distributions broadly reproduced the peak near the hypocenter and the peak approximately 10 km from the hypocenter in the dip direction for all approaches and datasets (Fig. 5). Variations among datasets were small for ShiftCov but larger for LinearCov and FixedPick. The spread-RMS of the final slip distribution was 0.055 for ShiftCov, less than 40% of the values for the other approaches (Table 2). Thus, differences among approaches also remained evident in the final slip distributions derived from time integration of the potency-rate density tensor components.

For all approaches, the normalized RMSE of the final slip distribution was approximately half that of the model coefficient vector, while the normalized RMSE of the moment-rate function was less than 15% of that of the model coefficient vector. In these synthetic tests, quantities obtained by temporal or spatial integration therefore had smaller relative estimation errors than the model coefficients. Furthermore, the spread-RMS values in Table 2 also show that moment-rate functions varied less among datasets and were estimated more stably than final slip distributions.

The spatial strike distributions broadly reproduced the curved strike pattern for all approaches and datasets (Fig. 6), although the estimated variations were smoother than those in the input model. ShiftCov yielded consistent strike distributions across datasets, whereas the strike directions inferred using the other approaches varied to some extent among datasets.

4 Discussion

4.1 Time correction using cross-correlation

Methods have been proposed to reduce the effects of uncertainty in phase arrival times by correcting waveform alignment through cross-correlation between observed waveforms and synthetics obtained from an initial inversion, followed by reinversion (e.g., Fan et al., 2014). Source inversion software with cross-correlation-based time-correction capabilities is also available (e.g., Goldberg et al., 2026). To evaluate the improvement obtained from a single time correction and reinversion, I calculated synthetic waveforms from the FixedPick models and determined the time corrections that maximized their cross-correlation with the observed waveforms. I then shifted the observed waveforms using these corrections and repeated the conventional inversion. I refer to this approach as CorrPick.

Figure 2b shows the frequency distribution of differences between the estimated and true time corrections. The differences were concentrated between -0.05 and 0.05 s, although residual timing errors remained after cross-correlation-based correction. Relative to FixedPick, CorrPick reduced the normalized RMSE by 0.050 and the spread-RMS by 0.070 , but both reductions were smaller than those obtained with ShiftCov. Consistent with the spread-RMS results, CorrPick yielded less variability across datasets than FixedPick and LinearCov, but more than ShiftCov, in the spatiotemporal potency-rate density distributions, moment-rate functions, final slip distributions, and spatial strike distributions (Figs. 3–6). The normalized RMSE of the moment-rate function was comparable for CorrPick and ShiftCov (0.041 and 0.044 , respectively), whereas the spread-RMS for ShiftCov was less than half that for CorrPick (Table 2).

In these synthetic tests, time correction based on cross-correlation between observed and synthetic waveforms reduced variations in the inferred models caused by picking errors. However, variability across datasets remained despite the concentration of residual timing errors between -0.05 and 0.05 s, and the reduction was smaller than that achieved with ShiftCov. This correction requires careful assessment for earthquakes with complex rupture processes, for which multiple peaks in the cross-correlation function may make the appropriate time shift difficult to identify.

4.2 Data RMSE and model RMSE

Waveform fit is evaluated using the squared L2 norm of the difference between observed and synthetic waveforms or a normalized residual. The residual mean square divided by the mean square of the observed data is equal to the square of the data RMSE normalized by the RMS of the observed data. I therefore used this normalized data RMSE to examine the relationship between waveform fit and model RMSE.

Figure 7 shows the relationship between model RMSE and data RMSE for individual datasets. The horizontal axis represents the deviation of the estimated model from the true model, while the vertical axis represents the discrepancy between observed and synthetic waveforms. The horizontal spread indicates the variation in model estimation accuracy among datasets. The normalized data RMSE values for ShiftCov, LinearCov, and FixedPick were mostly within the range of 0.19–0.23. In contrast, the normalized model RMSE values were concentrated within 0.32–0.36 for ShiftCov but were more broadly distributed within 0.35–0.50 for LinearCov and FixedPick. Thus, models with comparable waveform fits can differ substantially in estimation accuracy and stability. Waveform residuals that do not account for the error correlation structure are therefore insufficient to assess the quality of inferred models.

For CorrPick, the normalized data RMSE evaluated against the time-corrected observed waveforms fell approximately within 0.15–0.19 and was smaller than for the other approaches. However, although the normalized model RMSE improved relative to FixedPick before correction, it remained broadly distributed within 0.32–0.46. Improving waveform fit through time correction therefore does not consistently improve model estimation accuracy. These results show the limitations of assessing source-model reliability solely from the L2 norm of waveform differences or normalized residuals based on its square, consistent with the discussion of Fan et al. (2014). These results highlight the need to evaluate waveform fit using measures that account for the data covariance matrix, rather than relying solely on waveform residuals.

4.3 Application to a real earthquake

To examine the practical applicability of the proposed approach, I applied it to teleseismic P waves from the 2008 Wenchuan earthquake. I used the broadband waveform records from the same 66 stations used in the synthetic tests. P-wave arrivals were picked only once, without the repeated reassessment of picks normally performed during source analysis. The observed velocity waveforms used to estimate background noise for

the synthetic tests were resampled at an interval of 0.8 s. Exploiting the characteristics of teleseismic body waves, I used the low-pass effect of anelastic attenuation for anti-aliasing (e.g., Yamashita et al., 2022; Tadapansawut et al., 2022).

Following Yamashita et al. (2022), I adopted a model plane with a strike of 225° , a dip of 32° , and dimensions of $350 \text{ km} \times 70 \text{ km}$, with spatial knots spaced at 10 km intervals. The hypothetical front propagation velocity was set to 3.5 km/s. Slip was allowed at each spatial knot for up to 60 s after passage of the hypothetical front, but all rupture was required to end by 130 s after the origin time. The temporal knot interval of the potency-rate density functions was 0.8 s. Green's functions were calculated using a modified version of the program of Kikuchi and Kanamori (1991). Ray parameters and related quantities were calculated using TauP (Crotwell et al., 1999) with the ak135 global reference velocity model (Kennett et al., 1995). The teleseismic anelastic attenuation parameter t^* was set to 1 s. For the velocity structure near the source, I adopted the model used by Yamashita et al. (2022), which was slightly modified from CRUST1.0 (Laske et al., 2013). I adopted time-adaptive smoothing and set one of the basis double-couple components to correspond to the best-fitting double-couple component of the global centroid moment tensor solution (Dziewonski et al., 1981; Ekström et al., 2012). The dimensionless tuning parameter ε was set to 1. The resulting standard deviations of picking errors, σ_{pj} , had a mean of 0.41 s and a median of 0.22 s.

Figure 8 shows the results obtained with ShiftCov and FixedPick. Although the ShiftCov moment-rate function contained a sharp peak, it was generally smoother and had less high-frequency content than the FixedPick function. Both approaches yielded reverse slip with a strike-slip component. Both models also showed large final slip near the epicenter, although the slip distribution obtained with ShiftCov was smoother than that obtained with FixedPick, as also observed for the moment-rate functions. For ShiftCov, final slip peaked near the epicenter and approximately 140 km northeast of the epicenter, with peak slip values of approximately 8.6 and 3.8 m, respectively. This slip pattern was broadly consistent with those reported in previous studies (Shen et al., 2009; Feng et al., 2010; Fielding et al., 2013; Hartzell et al., 2013). In contrast, FixedPick yielded slip peaks near the epicenter and approximately 80 km northeast of the epicenter.

The normalized residual mean square was 0.298 (normalized data RMSE = 0.546) for ShiftCov and 0.176 (normalized data RMSE = 0.419) for FixedPick, indicating a better waveform fit for FixedPick. However, as shown by the synthetic tests, a better waveform fit does not necessarily imply more accurate source estimation. Comparison of observed and synthetic waveforms showed small differences in peak times at station KDAK, where the P-wave arrival was easy to identify. At station PAF, where picking was difficult, the synthetic waveform peaks obtained with ShiftCov were consistently delayed relative to the observed peaks. For FixedPick, the synthetic peaks corresponding to the initial rupture were also delayed, whereas differences in peak times were smaller after 20 s. The systematic delay observed for ShiftCov is consistent with the possibility that the P-wave arrival at PAF was picked later than its true arrival time, because picking the arrival later than the true onset shifts the aligned observed waveform toward earlier times.

Neglecting error correlations or uncertainty in model predictions can lead to overfitting of error-contaminated observations and distort inferred source models (e.g., Yagi and Fukahata, 2008; Duputel et al., 2014; Agata et al., 2022). The data covariance matrix determines how waveform discrepancies are weighted in the inversion. Accounting for picking uncertainty reduces the penalty for discrepancies that can be explained by waveform time shifts. The smaller timing discrepancies after 20 s for FixedPick suggest that some of the mismatch associated with picking errors was instead accommodated through changes in the source model. Together with the synthetic-test results, these findings support the interpretation that accounting for P-wave picking uncertainty helps reduce overfitting and obtain more stable source models from real earthquake data.

4.4 Applicability to other inversion methods

I have proposed an approach that incorporates waveform errors caused by P-wave picking uncertainty into seismic source inversion through a covariance matrix. The synthetic tests show that even small picking errors can affect inferred models if waveform-shift errors are not properly accounted for. In tsunami waveform inversion, temporally correlated errors have been addressed using covariance matrices (Dettmer et al., 2016), and phase corrections have been shown to affect inferred tsunami source distributions (Takagawa et al., 2025). The proposed approach may be applicable to tsunami waveform analyses involving arrival-time uncertainty. Moreover, unlike the covariance of Green's-function errors, which depends on model parameters (Yagi and

Fukahata, 2011), the proposed covariance can be constructed from observed waveforms and a probability distribution of time shifts.

Although application to and validation with other inversion methods are beyond the scope of this study, I describe how the proposed covariance can be incorporated into existing algorithms such as nonnegative least squares (NNLS; Lawson and Hanson, 1974), which is used in many seismic source inversions. Let $\mathbf{C}_{cj}$ be the diagonal covariance matrix conventionally used at station j , and $\mathbf{C}_{pj}$ the covariance matrix associated with picking errors. I assume that cross-covariances between the two error terms can be neglected. If the data covariance matrix $\mathbf{C}_{cj} + \mathbf{C}_{pj}$ is positive definite, its Cholesky decomposition is

$$\mathbf{C}_{cj} + \mathbf{C}_{pj} = \mathbf{L}_j \mathbf{L}_j^T, \quad (18)$$

where $\mathbf{L}_j$ is a lower triangular matrix. Neglecting error correlations among stations, the objective function to be minimized is the sum of squared Mahalanobis distances:

$$\sum_j (\mathbf{d}_j - \mathbf{H}_j \mathbf{a})^T (\mathbf{L}_j \mathbf{L}_j^T)^{-1} (\mathbf{d}_j - \mathbf{H}_j \mathbf{a}). \quad (19)$$

This can be rewritten in the standard least-squares form:

$$\sum_j \|\mathbf{L}_j^{-1} \mathbf{d}_j - \mathbf{L}_j^{-1} \mathbf{H}_j \mathbf{a}\|_2^2. \quad (20)$$

Thus, for a fixed covariance matrix, existing NNLS and other least-squares algorithms can be used after transforming the data vector and kernel matrix by $\mathbf{L}_j^{-1}$. The covariance matrices can be constructed and decomposed separately for each station, without constructing a large covariance matrix containing data from all stations.

5 Conclusions

I proposed a waveform-shift covariance approach (ShiftCov) that represents P-wave picking errors as time shifts common to the entire waveform and incorporates the resulting temporal error correlations into seismic source inversion. The covariance matrix is constructed from observed waveforms and a probability distribution of time shifts. I incorporated this covariance matrix into the PDTI framework.

Synthetic tests using 125 datasets that differed only in time shifts showed that ShiftCov reduced model RMSE and variability among datasets compared with FixedPick, which neglects picking uncertainty, and LinearCov, which uses a linear approximation. A single cross-correlation-based time correction followed by reinversion also improved the estimated models, but its effect was smaller than that of ShiftCov. Models with comparable waveform fits differed in estimation accuracy, highlighting the need to account for the data error covariance when evaluating waveform fit and source-model reliability. Application to the 2008 Wenchuan earthquake suggests that ShiftCov helps reduce overfitting by accounting for picking errors that might otherwise be interpreted as features of the rupture process.

In addition to efforts to improve arrival-time picks, accounting for the waveform error correlations associated with the remaining picking uncertainty reduces the sensitivity of inferred source models to the picked arrival times. The proposed covariance matrix can also be incorporated into existing least-squares methods, including NNLS, through a Cholesky-based transformation of the data and kernel matrices.

List of abbreviations

ABIC: Akaike's Bayesian Information Criterion

CorrPick: Conventional inversion with cross-correlation-based time correction

FixedPick: Conventional inversion without accounting for picking uncertainty

GCMT: Global Centroid Moment Tensor

GMT: Generic Mapping Tools

LinearCov: Linear approximation of waveform-shift covariance

NNLS: Non-negative least squares

PDTI: Potency density tensor inversion

RMSE: Root mean square error

RMS: Root mean square

SAGE: Seismological Facility for the Advancement of Geoscience

ShiftCov: Waveform-shift covariance approach

References

- Agata R, Nakata R, Kasahara A, Yagi Y, Seshimo Y, Yoshioka S, Inuma T (2022) Bayesian multi-model estimation of fault slip distribution for slow slip events in Southwest Japan: effects of prior constraints and uncertain underground structure. *J Geophys Res Solid Earth* 127:e2021JB023712.
<https://doi.org/10.1029/2021JB023712>
- Akaike H (1980) Likelihood and the Bayes procedure. *Trab Estad Investig Oper* 31:143–166.
<https://doi.org/10.1007/BF02888350>
- Beresnev IA (2003) Uncertainties in finite-fault slip inversions: to what extent to believe? *Bull Seismol Soc Am* 93:2445–2458. <https://doi.org/10.1785/0120020225>
- Crotwell HP, Owens TJ, Ritsema J (1999) The TauP Toolkit: flexible seismic travel-time and ray-path utilities. *Seismol Res Lett* 70:154–160. <https://doi.org/10.1785/gssrl.70.2.154>
- Dettmer J, Benavente R, Cummins PR, Sambridge M (2014) Trans-dimensional finite-fault inversion. *Geophys J Int* 199:735–751. <https://doi.org/10.1093/gji/ggu280>
- Dettmer J, Hawkins R, Cummins PR, Hossen J, Sambridge M, Hino R, Inazu D (2016) Tsunami source uncertainty estimation: the 2011 Japan tsunami. *J Geophys Res Solid Earth* 121:4483–4505.
<https://doi.org/10.1002/2015JB012764>
- Duputel Z, Agram PS, Simons M, Minson SE, Beck JL (2014) Accounting for prediction uncertainty when inferring subsurface fault slip. *Geophys J Int* 197:464–482. <https://doi.org/10.1093/gji/ggt517>
- Dutta R, Jónsson S, Vasyura-Bathke H (2021) Simultaneous Bayesian estimation of non-planar fault geometry and spatially variable slip. *J Geophys Res Solid Earth* 126:e2020JB020441.
<https://doi.org/10.1029/2020JB020441>
- Dziewonski AM, Chou TA, Woodhouse JH (1981) Determination of earthquake source parameters from waveform data for studies of global and regional seismicity. *J Geophys Res* 86:2825–2852.
<https://doi.org/10.1029/JB086iB04p02825>
- Ekström G, Nettles M, Dziewoński AM (2012) The global CMT project 2004–2010: centroid-moment tensors for 13,017 earthquakes. *Phys Earth Planet Inter* 200–201:1–9. <https://doi.org/10.1016/j.pepi.2012.04.002>

- Fan W, Shearer PM, Gerstoft P (2014) Kinematic earthquake rupture inversion in the frequency domain. *Geophys J Int* 199:1138–1160. <https://doi.org/10.1093/gji/ggu319>
- Feng G, Hetland EA, Ding X, Li Z, Zhang L (2010) Coseismic fault slip of the 2008 Mw 7.9 Wenchuan earthquake estimated from InSAR and GPS measurements. *Geophys Res Lett* 37:L01302. <https://doi.org/10.1029/2009GL041213>
- Fielding EJ, Sladen A, Li Z, Avouac JP, Bürgmann R, Ryder I (2013) Kinematic fault slip evolution source models of the 2008 M7.9 Wenchuan earthquake in China from SAR interferometry, GPS and teleseismic analysis and implications for Longmen Shan tectonics. *Geophys J Int* 194:1138–1166. <https://doi.org/10.1093/gji/ggt155>
- Fukahata Y, Wright TJ (2008) A non-linear geodetic data inversion using ABIC for slip distribution on a fault with an unknown dip angle. *Geophys J Int* 173:353–364. <https://doi.org/10.1111/j.1365-246X.2007.03713.x>
- Gallovič F, Ampuero JP (2015) A new strategy to compare inverted rupture models exploiting the eigenstructure of the inverse problem. *Seismol Res Lett* 86:1679–1689. <https://doi.org/10.1785/0220150096>
- Geist EL (2002) Complex earthquake rupture and local tsunamis. *J Geophys Res* 107:2086. <https://doi.org/10.1029/2000JB000139>
- Goldberg DE, Hunsinger H, Koch P, Haynie KL, Melgar D, Riquelme S (2026) Wavelet Inversion for Slip (WISP): open-source earthquake slip modeling software. *Seismol Res Lett* 97:2747–2763. <https://doi.org/10.1785/0220250055>
- Hartzell S, Mendoza C, Ramírez-Guzmán L, Zeng Y, Mooney W (2013) Rupture history of the 2008 Mw 7.9 Wenchuan, China, earthquake: evaluation of separate and joint inversions of geodetic, teleseismic, and strong-motion data. *Bull Seismol Soc Am* 103:353–370. <https://doi.org/10.1785/0120120108>
- Ishii M, Shearer PM, Houston H, Vidale JE (2007) Teleseismic P wave imaging of the 26 December 2004 Sumatra-Andaman and 28 March 2005 Sumatra earthquake ruptures using the Hi-net array. *J Geophys Res* 112:B11307. <https://doi.org/10.1029/2006JB004700>

- Ji C, Helmberger DV, Wald DJ (2004) A teleseismic study of the 2002 Denali fault, Alaska, earthquake and implications for rapid strong-motion estimation. *Earthq Spectra* 20:617–637.
<https://doi.org/10.1193/1.1778388>
- Kennett BLN, Engdahl ER, Buland R (1995) Constraints on seismic velocities in the Earth from traveltimes. *Geophys J Int* 122:108–124. <https://doi.org/10.1111/j.1365-246X.1995.tb03540.x>
- Kikuchi M, Kanamori H (1991) Inversion of complex body waves—III. *Bull Seismol Soc Am* 81:2335–2350.
<https://doi.org/10.1785/BSSA0810062335>
- Klinger Y, Okubo K, Vallage A, Champenois J, Delorme A, Rougier E, Lei Z, Knight EE, Munjiza A, Satriano C, Baize S, Langridge R, Bhat HS (2018) Earthquake damage patterns resolve complex rupture processes. *Geophys Res Lett* 45:10279–10287. <https://doi.org/10.1029/2018GL078842>
- Langbein J, Johnson H (1997) Correlated errors in geodetic time series: implications for time-dependent deformation. *J Geophys Res* 102:591–603. <https://doi.org/10.1029/96JB02945>
- Laske G, Masters G, Ma Z, Pasyanos M (2013) Update on CRUST1.0—a 1-degree global model of Earth's crust. *Geophys Res Abstr* 15:EGU2013-2658
- Lawson CL, Hanson RJ (1974) Solving least squares problems. Prentice-Hall, Englewood Cliffs
- Mai PM, Schorlemmer D, Page M, Ampuero JP, Asano K, Causse M, Custódio S, Fan W, Festa G, Galis M, Gallovič F, Imperatori W, Käser M, Malyskyy D, Okuwaki R, Pollitz F, Passone L, Razafindrakoto HNT, Sekiguchi H, Song SG, Somala SN, Thingbaijam KKS, Twardzik C, van Driel M, Vyas JC, Wang R, Yagi Y, Zielke O (2016) The Earthquake-Source Inversion Validation (SIV) Project. *Seismol Res Lett* 87:690–708. <https://doi.org/10.1785/0220150231>
- Minson SE, Simons M, Beck JL (2013) Bayesian inversion for finite fault earthquake source models I—theory and algorithm. *Geophys J Int* 194:1701–1726. <https://doi.org/10.1093/gji/ggt180>
- Ohara K, Yagi Y, Yamashita S, Okuwaki R, Hirano S, Fukahata Y (2023) Complex evolution of the 2016 Kaikoura earthquake revealed by teleseismic body waves. *Prog Earth Planet Sci* 10:35.
<https://doi.org/10.1186/s40645-023-00565-z>

- Okuwaki R, Yagi Y, Aránguiz R, González J, González G (2016) Rupture process during the 2015 Illapel, Chile earthquake: zigzag-along-dip rupture episodes. *Pure Appl Geophys* 173:1011–1020.
<https://doi.org/10.1007/s00024-016-1271-6>
- Ragon T, Sladen A, Simons M (2018) Accounting for uncertain fault geometry in earthquake source inversions—I: theory and simplified application. *Geophys J Int* 214:1174–1190.
<https://doi.org/10.1093/gji/ggy187>
- Sato DSK, Fukahata Y, Nozue Y (2022) Appropriate reduction of the posterior distribution in fully Bayesian inversions. *Geophys J Int* 231:950–981. <https://doi.org/10.1093/gji/ggac231>
- Sato DSK, Yagi Y, Okuwaki R, Fukahata Y (2026) Smooth surface reconstruction of earthquake faults from distributed moment-potency-tensor solutions. *Geophys J Int* 245:ggag116.
<https://doi.org/10.1093/gji/ggag116>
- Shao G, Li X, Ji C, Maeda T (2011) Focal mechanism and slip history of the 2011 Mw 9.1 off the Pacific coast of Tohoku Earthquake, constrained with teleseismic body and surface waves. *Earth Planets Space* 63:559–564. <https://doi.org/10.5047/eps.2011.06.028>
- Shen ZK, Sun J, Zhang P, Wan Y, Wang M, Bürgmann R, Zeng Y, Gan W, Liao H, Wang Q (2009) Slip maxima at fault junctions and rupturing of barriers during the 2008 Wenchuan earthquake. *Nat Geosci* 2:718–724. <https://doi.org/10.1038/ngeo636>
- Shimizu K, Yagi Y, Okuwaki R, Fukahata Y (2020) Development of an inversion method to extract information on fault geometry from teleseismic data. *Geophys J Int* 220:1055–1065.
<https://doi.org/10.1093/gji/ggz496>
- Shimizu K, Yagi Y, Okuwaki R, Fukahata Y (2021) Construction of fault geometry by finite-fault inversion of teleseismic data. *Geophys J Int* 224:1003–1014. <https://doi.org/10.1093/gji/ggaa501>
- Tadapansawut T, Yagi Y, Okuwaki R, Yamashita S, Shimizu K (2022) Complex rupture process on the conjugate fault system of the 2014 Mw 6.2 Thailand earthquake. *Prog Earth Planet Sci* 9:26.
<https://doi.org/10.1186/s40645-022-00484-5>

- Takagawa T, Chida Y, Fujiki T, Kawaguchi K (2025) High-resolution source inversion of 2024 Noto Peninsula earthquake tsunami with modeling error corrections. *Sci Rep* 15:24889. <https://doi.org/10.1038/s41598-025-08978-0>
- Taufiqurrahman T, Gabriel AA, Li D, Ulrich T, Li B, Carena S, Verdecchia A, Gallovič F (2023) Dynamics, interactions and delays of the 2019 Ridgecrest rupture sequence. *Nature* 618:308–315. <https://doi.org/10.1038/s41586-023-05985-x>
- Vallée M, Bouchon M (2004) Imaging coseismic rupture in far field by slip patches. *Geophys J Int* 156:615–630. <https://doi.org/10.1111/j.1365-246X.2004.02158.x>
- Wessel P, Luis JF, Uieda L, Scharroo R, Wobbe F, Smith WHF, Tian D (2019) The Generic Mapping Tools version 6. *Geochem Geophys Geosyst* 20:5556–5564. <https://doi.org/10.1029/2019GC008515>
- Yabuki T, Matsu'ura M (1992) Geodetic data inversion using a Bayesian information criterion for spatial distribution of fault slip. *Geophys J Int* 109:363–375. <https://doi.org/10.1111/j.1365-246X.1992.tb00102.x>
- Yagi Y, Fukahata Y (2008) Importance of covariance components in inversion analyses of densely sampled observed data: an application to waveform data inversion for seismic source processes. *Geophys J Int* 175:215–221. <https://doi.org/10.1111/j.1365-246X.2008.03884.x>
- Yagi Y, Fukahata Y (2011) Introduction of uncertainty of Green's function into waveform inversion for seismic source processes. *Geophys J Int* 186:711–720. <https://doi.org/10.1111/j.1365-246X.2011.05043.x>
- Yamashita S, Yagi Y, Okuwaki R, Shimizu K, Agata R, Fukahata Y (2022) Potency density tensor inversion of complex body waveforms with time-adaptive smoothing constraint. *Geophys J Int* 231:91–107. <https://doi.org/10.1093/gji/ggac181>

Availability of data and materials

All seismic waveforms used in this study were downloaded from the Seismological Facility for the Advancement of Geoscience (SAGE) using Wilber 3 (https://ds.iris.edu/wilber3/find_event). The data were obtained from seismic networks AU (<https://doi.org/10.26186/144675>); CN (<https://doi.org/10.7914/SN/CN>); G (<https://doi.org/10.18715/GEOSCOPE.G>); GE (<https://doi.org/10.14470/TR560404>); II (<https://doi.org/10.7914/SN/II>); IM (<https://doi.org/10.7914/vefq-vh75>); IU (<https://doi.org/10.7914/SN/IU>); MN (<https://doi.org/10.13127/SD/FBBBTDTD6Q>); NL (<https://doi.org/10.21944/e970fd34-23b9-3411-b366-e4f72877d2c5>).

Competing interests

Y.Y. serves as Chief Editor of the Solid Earth Sciences section of *Progress in Earth and Planetary Science* and will not be involved in the editorial handling or peer review of this manuscript. The author declares no other competing interests.

Funding

This work was supported by JSPS KAKENHI Grant Number 25K01075.

Authors' Contributions

Y.Y. designed the study, developed the method, performed the analyses, and wrote the manuscript.

Acknowledgments

I thank Hiroo Kanamori for raising the question that motivated this study and encouraging me to address it. Discussions with Akinori Moteki and Ryo Okuwaki were helpful in developing this work. All figures were prepared using the Generic Mapping Tools (GMT; Wessel et al., 2019). ChatGPT (OpenAI) and Gemini (Google) were used to assist with English translation, manuscript revision, and the development of analysis

code and shell scripts for figure preparation. The author reviewed and verified the resulting text and code and takes full responsibility for the final manuscript.

Author information

Authors and Affiliations

Institute of Life and Environmental Sciences, University of Tsukuba, Tennodai 1-1-1, Tsukuba, Ibaraki, 305–8572, Japan

Yuji Yagi

Corresponding author

Correspondence to Yuji Yagi (yagi-y@geol.tsukuba.ac.jp)

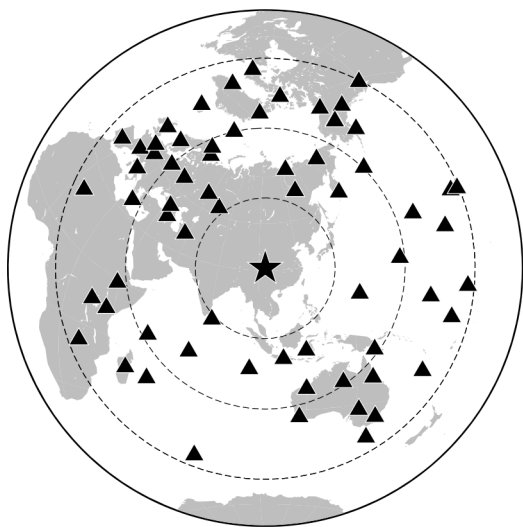
Table 1. Normalized RMSE, bias-RMS, and spread-RMS calculated using the full model coefficient vector for each method.

	RMSE	bias-RMS	spread-RMS
ShiftCov	0.338	0.324	0.097
LinearCov	0.409	0.327	0.246
FixedPick	0.427	0.342	0.256
CorrPick	0.377	0.327	0.186

Table 2. Normalized RMSE and spread-RMS for the moment-rate function and final slip distribution obtained with each method.

	Moment-rate function		Final slip distribution	
	RMSE	spread-RMS	RMSE	spread-RMS
ShiftCov	0.044	0.014	0.152	0.055
LinearCov	0.051	0.036	0.207	0.151
FixedPick	0.057	0.039	0.216	0.150
CorrPick	0.041	0.028	0.178	0.117

(a) Station distribution



(b) Input source model

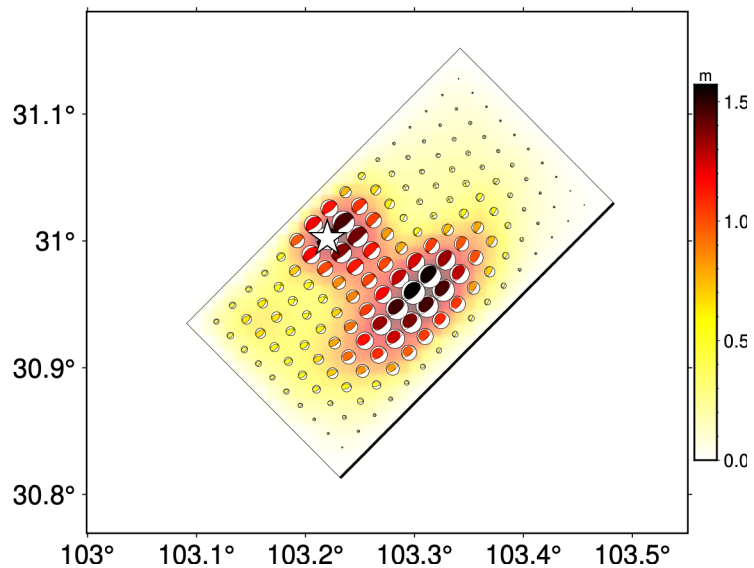


Figure 1. Station distribution and input source model. (a) Distribution of seismic stations. The black star and triangles indicate the epicenter and stations, respectively. (b) Input potency density tensor distribution. Beach balls represent the final potency tensors, and the open star indicates the epicenter.

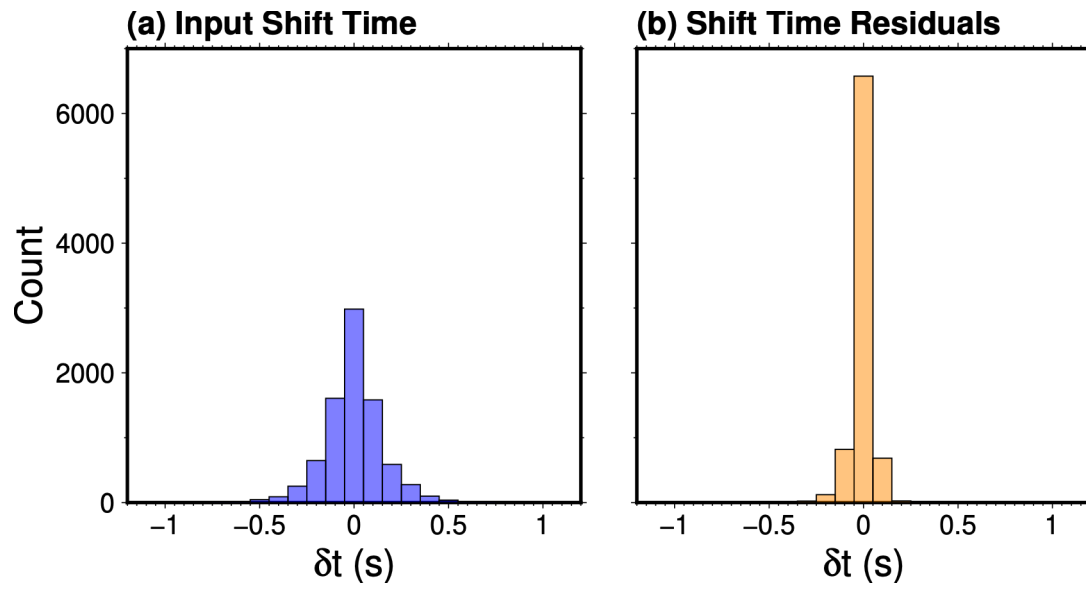


Figure 2. Distributions of picking errors and residual timing errors. (a) Frequency distribution of the imposed P-wave picking errors. (b) Frequency distribution of the differences between the time corrections estimated by cross-correlation and the true corrections.

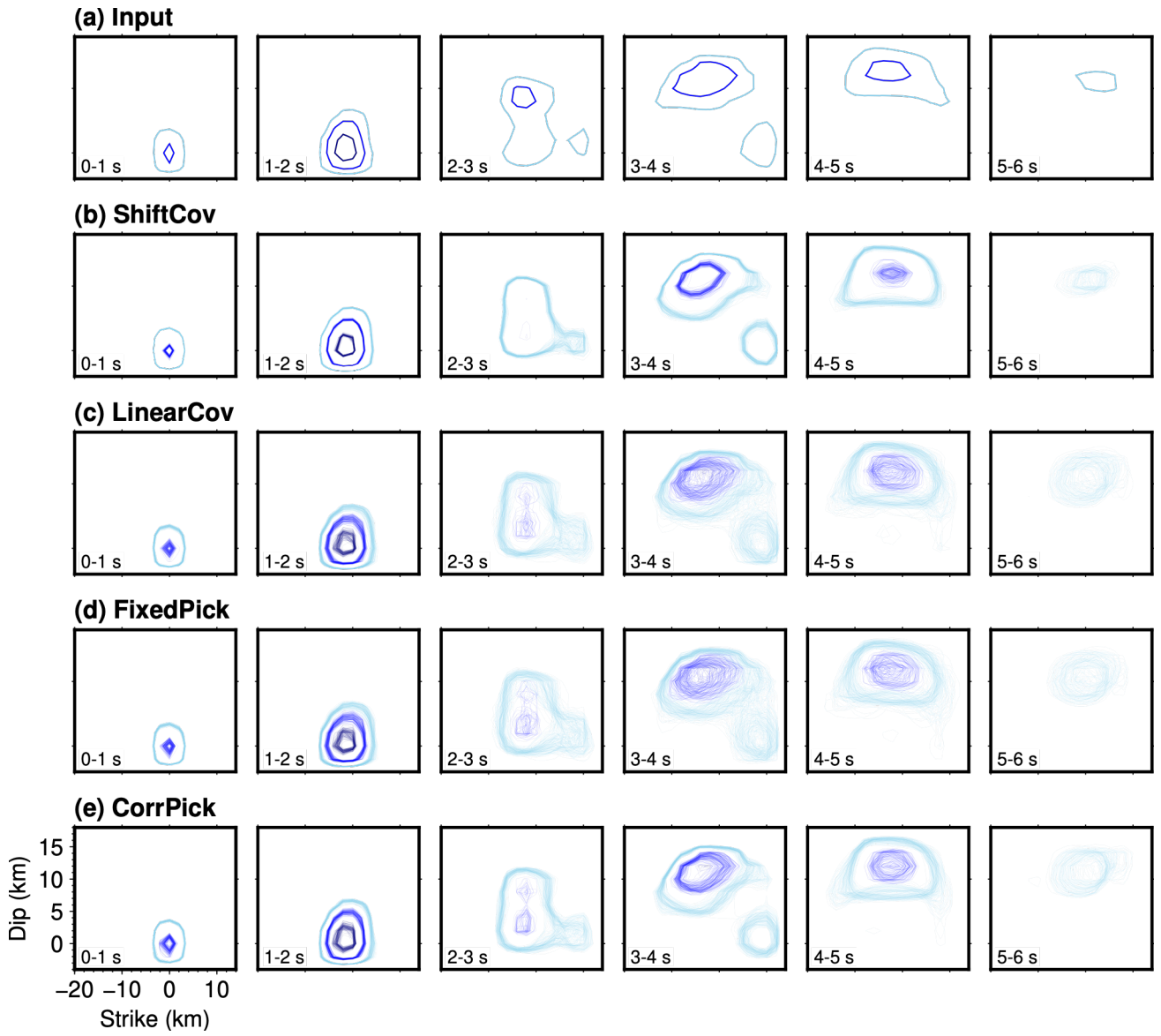


Figure 3. Temporal evolution of slip-rate distributions. Sky-blue, blue, and navy contours indicate slip rates of 0.2, 0.4, and 0.6 m/s, respectively. (a) Input model. (b–e) Results for the 125 datasets obtained using (b) the waveform-shift covariance approach (ShiftCov), (c) the linear approximation to the picking-error covariance (LinearCov), (d) the conventional method that neglects picking uncertainty (FixedPick), and (e) the conventional method following cross-correlation-based time correction (CorrPick).

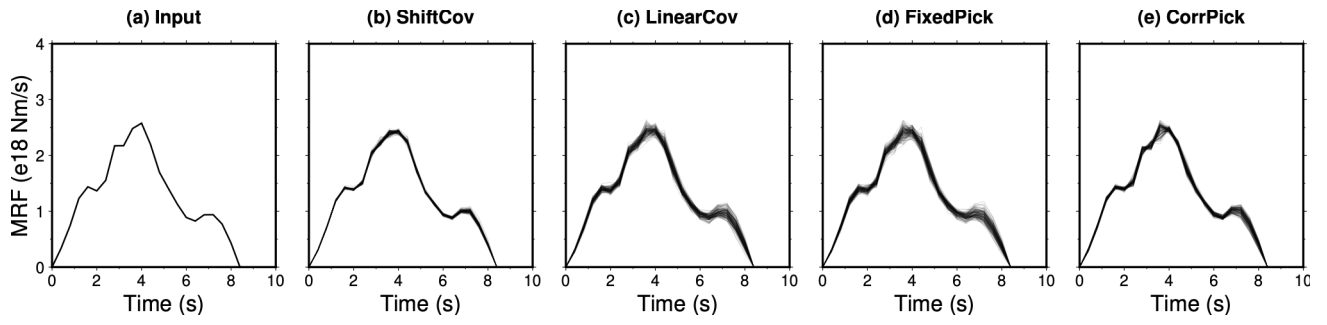


Figure 4. Moment-rate functions. (a) Input model. (b–e) Moment-rate functions for the 125 datasets obtained using (b) ShiftCov, (c) LinearCov, (d) FixedPick, and (e) CorrPick.

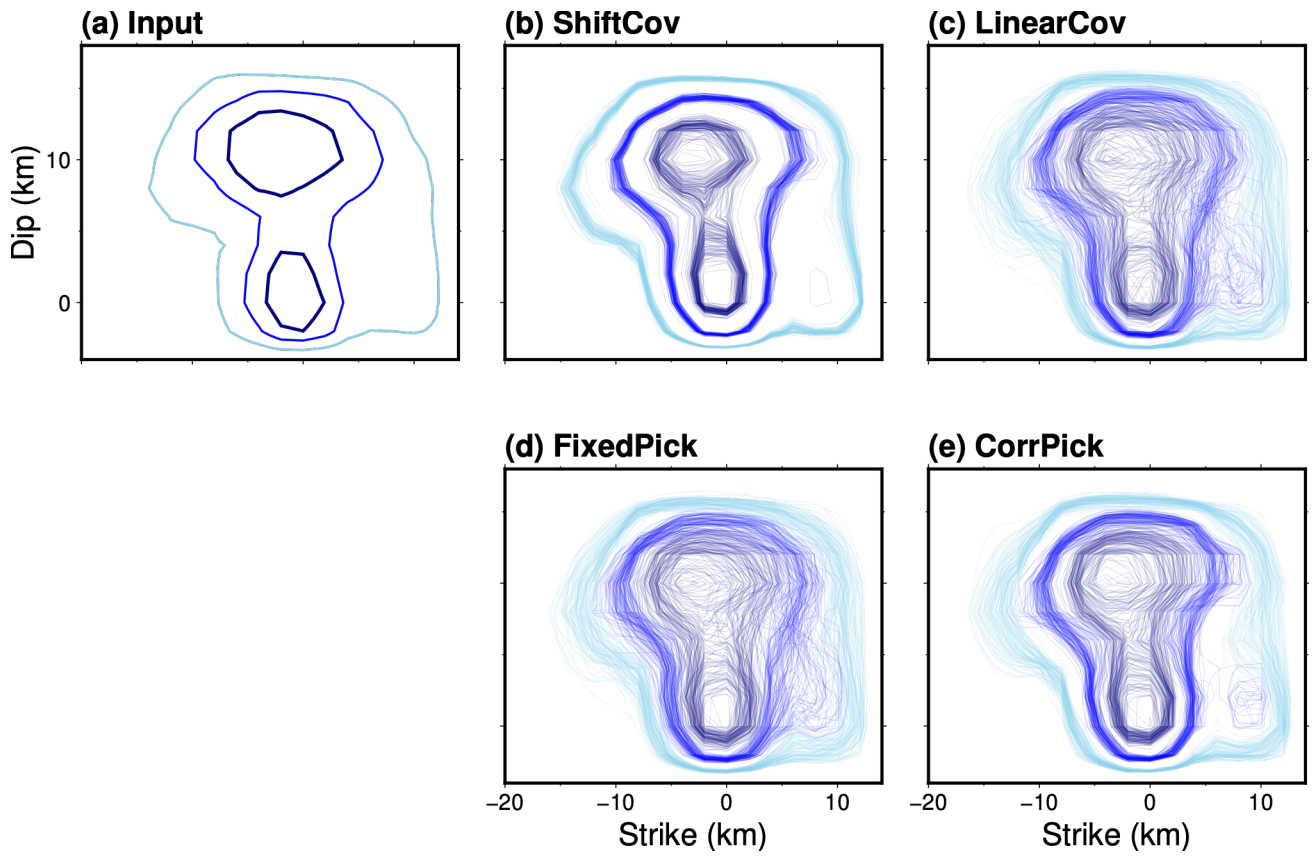


Figure 5. Final slip distributions. Sky-blue, blue, and navy contours indicate slip amplitudes of 0.4, 0.8, and 1.2 m, respectively. (a) Input model. (b–e) Results for the 125 datasets obtained using (b) ShiftCov, (c) LinearCov, (d) FixedPick, and (e) CorrPick.

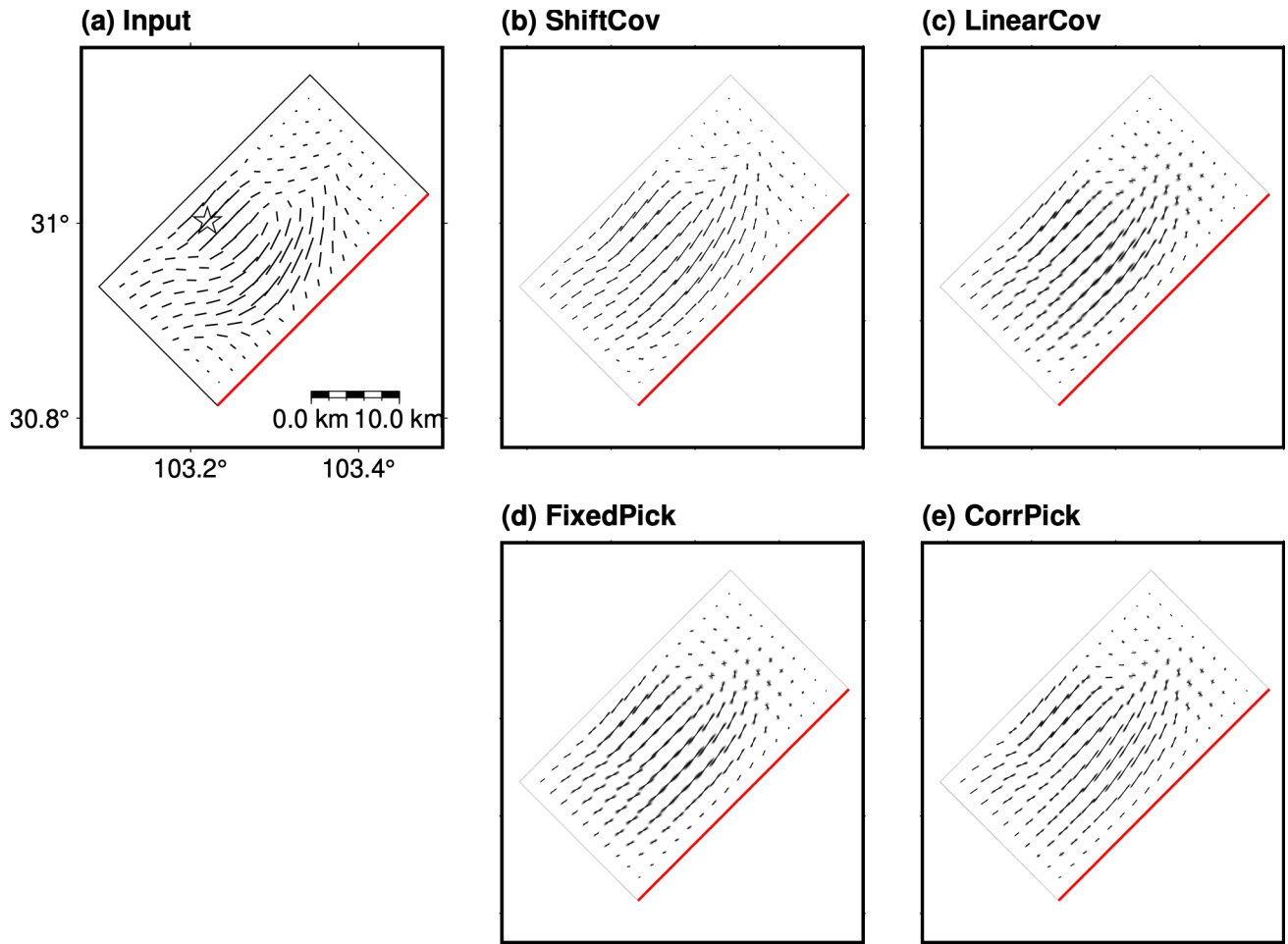


Figure 6. Spatial distributions of fault strike. (a) Input model. The star indicates the epicenter. (b–e) Results for the 125 datasets obtained using (b) ShiftCov, (c) LinearCov, (d) FixedPick, and (e) CorrPick.

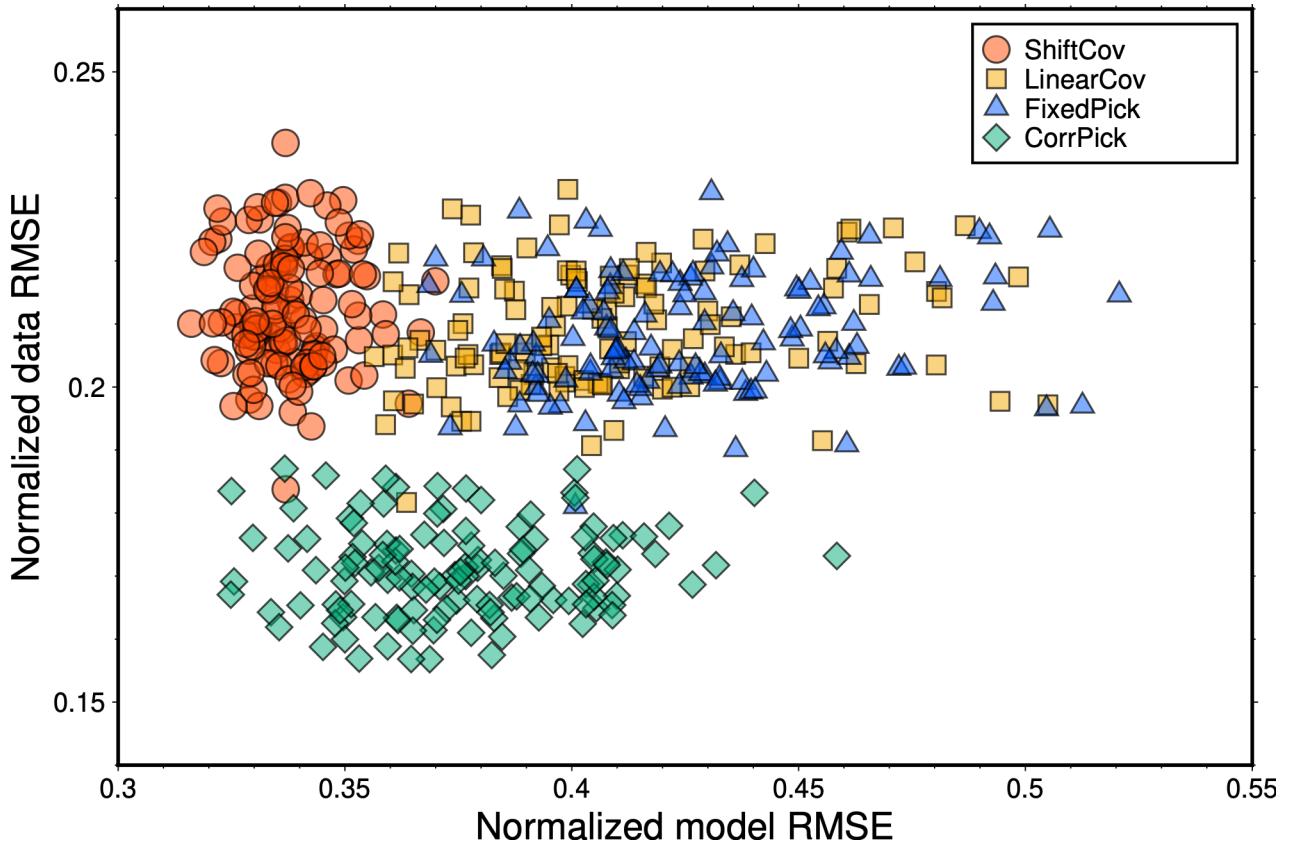


Figure 7. Relationship between normalized model RMSE and normalized data RMSE. Each symbol represents the result for one dataset. Pink circles, yellow squares, blue triangles, and green diamonds indicate ShiftCov, LinearCov, FixedPick, and CorrPick, respectively.

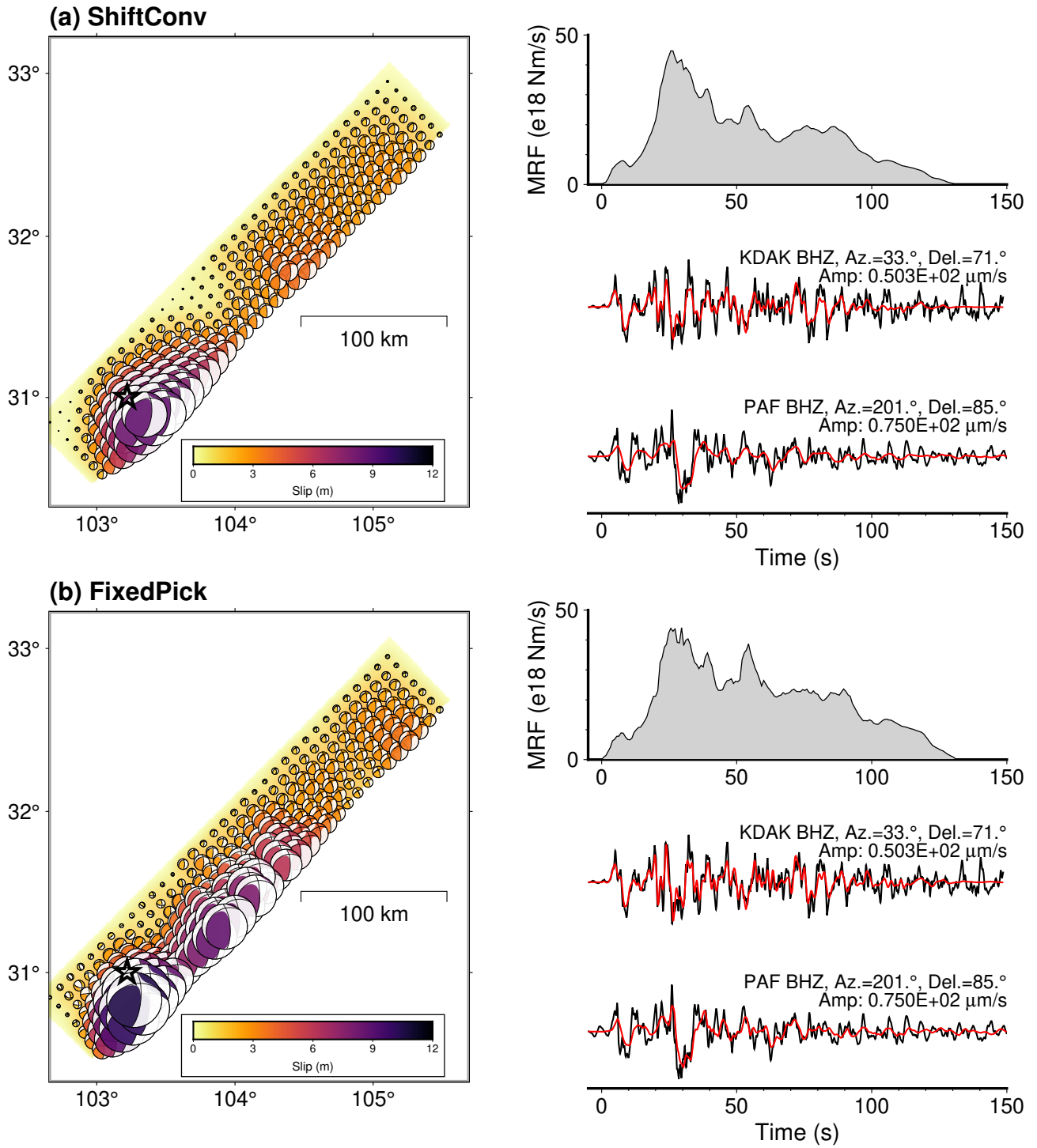


Figure 8. Source models and waveform fits for the 2008 Wenchuan earthquake. Results obtained using (a) ShiftCov and (b) FixedPick. The panels show the potency density tensor distribution (left), moment-rate function (upper right), and observed and synthetic waveforms (lower right).