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BAYESIAN POSTERIOR EXPLORATION AND PREDICTIVE ANALYSIS OF
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FINITE-FAULT EARTHQUAKE MODELS

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Dedicated to God, my beloved parents, brother and sister

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Abstract

Although earthquake rupture process is inherently complex, recent inversion techniques enable data-constrained physical models that image the spatiotemporal evolution of fault slip. Among these methods, Bayesian inversion framework yields an ensemble of plausible models to reproduce data, in contrast with conventional methods that produce a single best-fit solution. These posterior model ensembles are valuable for exploring relationships among physical parameters, generating downstream physical observables, and quantifying interlinked uncertainty structures. However, large ensembles (from thousands to millions) of high-dimensional models pose computational challenges. Here, we analyze inferred rupture properties and predictive observables of five Bayesian kinematic finite-fault models for large megathrust earthquakes in Japan, Chile, Ecuador and Nepal: 2011 M_w 9.0 Tohoku, 2014 M_w 8.1 Iquique, 2015 M_w 8.3 Illapel, 2016 M_w 7.8 Pedernales, and 2015 M_w 7.8 Gorkha. We compare joint probability distributions of kinematic rupture parameters, including slip, rupture speed, rise time, and average slip rate, and assess relationships locally and fault-wise across events. We use posterior model ensembles to compute static surface deformation and on-fault stress changes, dynamic ground motion, and their spatiotemporal covariances.

We find patch-level correlations are robust between some parameters given expected tradeoffs, but intra-event correlations between most parameters are variable across events. This result conflicts with predicted relations, e.g., between peak slip rate and rupture speed, established by dynamic rupture simulations, suggesting limitations in adopted physics and/or inversion approaches for heterogeneous rupture scenarios. Our

static forward simulations reveal characteristic patterns in the predicted deformation and stress changes across the explored megathrust settings. The predicted surface deformation exhibits spatial variations in amplitude and direction largely inherited from source properties, whereas on-fault static stress is more heterogeneous in space. The variability in uncertainty is influenced by station coverage, source characteristics, and the data-model error structure. Despite source heterogeneity, the event-average static elastic strain drop is tightly constrained within $\sim 100\text{--}300$ microstrain, while static stress drop spans $\sim 5\text{--}25$ MPa. In the dynamic simulations, displacement waveforms stabilize earlier and faster in smaller earthquakes. Predicted peak ground displacements (PGD) exhibit near-field discrepancies with empirical scaling laws due to finite-source and directivity effects. Our findings can inform physics-based earthquake modeling and improve quantification of rupture complexity and hazard impacts.

Chapter 1

Introduction

Characterizing the spatiotemporal complexity of earthquakes relies on inference from surface observations and physical models for the source and Earth’s structure. To understand earthquake dynamics and quantify their hazard impacts, we need robust, fine-scale pictures of where ruptures initiate, how much faults move, how fast ruptures propagate, and how long the ground shaking persists. The past two decades have witnessed the rapid expansion of observation tools from land, space, and ocean to characterize earthquake processes, including the Global Navigation Satellite System (GNSS) (Segall and Davis 1997), Interferometric Synthetic Aperture Radar (InSAR) (Massonnet et al. 1993), and the Deep-ocean Assessment & Reporting of Tsunamis (DART) system (Mungov et al. 2013). This improved observational capability now enables routine studies of major earthquakes globally, generating increasingly detailed models of significant events like the 2004 M_w 9.2 Sumatra (e.g., Bletery et al. 2016; Chlieh et al. 2007; Lorito et al. 2010) and 2011 M_w 9.0 Tohoku-oki (e.g., Koketsu et al. 2011; Ide et al. 2011; Romano et al. 2014; Simons et al. 2011).

These geophysical observations inform two complementary earthquake modeling approaches, kinematic and dynamic rupture models. A kinematic finite-fault model is a simplified representation of earthquake rupture processes, describing the spatiotemporal evolution of slip on a discretized fault interface (Haskell 1964; Kikuchi and Kanamori 1982; Ide 2015; Mai and Thingbaijam 2014). With the computational efficiency for inverse problems, kinematic earthquake models are readily derived to quantitatively

explain observations. In contrast, a dynamic rupture model simulates earthquake slip arising from the governing constitutive equations of fault zones subject to initial and boundary conditions of a computational domain (Andrews 1976; Das and Aki 1977; Day 1982; Harris et al. 2009; Ben-Zion 2001). These models can resolve the physical complexity of earthquake ruptures and event sequences with fine-scale resolutions and timescales in connection to observations (e.g., Tinti et al. 2021; Ma and Beroza 2008; Olsen et al. 1997; Jia et al. 2023; Jiang and Lapusta 2016, 2017; Barbot et al. 2012; Kaneko et al. 2010) while introducing additional physical constraints and dramatically increased computational cost. Based on different levels of assumptions, these models can be constrained by real-world data and used to predict diverse geophysical observables.

Designing realistic kinematic earthquake models requires predicted observables to be consistent with ground-truth observations. The inference of rupture parameters in high-dimensional models based on surface data and knowledge of Earth’s structure is almost always non-unique, entailing the uncertainty and trade-offs of various parameters. Several geophysical inversion schemes have been developed for large-scale inverse problems of earthquake source parameters (Ide 2015). While optimization-based approaches seek the best-fit solutions based on least-squares or other formulations (Aster et al. 2018), the Bayesian inversion approaches for earthquake modeling produce an ensemble of all plausible models subject to data and a priori knowledge (Tarantola 2005). With different model parameterization and physical assumptions, probabilistic inference of kinematic or dynamic rupture properties is now feasible with Markov chain Monte Carlo (MCMC) sampling algorithms (Minson et al. 2013; Dettmer et al. 2014; Gallovič et al. 2019b). In all inversion schemes, accounting for both the observational and model prediction error structures (including covariances) allows a more rigorous treatment for various sources of errors (Tarantola 2005). The combination of diverse

geophysical datasets, increased CPU/GPU computing power, and incorporation of forward modeling errors, e.g., in Earth structure and fault geometry (Hallo and Gallovič 2016; Duputel et al. 2014; Ragon et al. 2018), have led to an increasing inventory of Bayesian finite-fault earthquake models, some containing millions of individual solutions (e.g., Minson et al. 2014; Duputel et al. 2015; Ragon et al. 2019; Hallo and Gallovič 2020; Jolivet et al. 2014; Wei et al. 2023; Tomita et al. 2021).

Several major challenges persist in kinematic earthquake modeling. First, there is a long-standing difficulty in comparisons of quantitative or even some qualitative features of finite-fault models across different studies. The limited efforts in characterizing and documenting uncertainty in the presence of heterogeneous choices in model parameterization, datasets, and inversions hamper consistent interpretation of earthquake source parameters and behavior, even for some of the best-documented major earthquakes like the Tohoku (Wong et al. 2024; Sun et al. 2017). Second, at the expense of significant computational efforts, the full Bayesian posterior model ensembles are often underexplored or incompletely used for comparisons of individual and multiple events in search of empirical relations or underlying physics. Efforts are needed to quantify how diverse observations unlock new information relative to a priori assumptions and clarify the mapping from our assumptions to process inference to model-based predictions and decisions. This requires us to quantify how errors and information propagate in predictive observables in space and time. Third, the connections and synergy between kinematic and dynamic earthquake models should be quantitatively established, given that both modeling frameworks rely on data and physics in complimentary ways. Currently, the limited near-surface observations and simplified parametrization and physics in kinematic models may offer insufficient resolutions or even introduce biases for us to elucidate the plausible physical relations of earthquake parameters or test predictions

from dynamic models (e.g., Schmedes et al. 2010, 2012). Meanwhile, dynamic earthquake source inversions (e.g. Gallovič et al. 2019a; Premus et al. 2022; Schliwa et al. 2024) are feasible and yet especially challenging given the large computational cost, vast null model space, and assumptions and unknowns in constitutive laws. Therefore, a comprehensive understanding of the resolutions, uncertainty, and information gap of kinematic models is an essential step to bridging kinematic and dynamic models and more sophisticated data-model integration.

Furthermore, the increasing use of earthquake rupture models in secondary phenomena and derivative applications hinges on and directly benefits from well-quantified uncertainty in these models. The finite-fault models serve as a major tool for probing earthquake and fault dynamics and predicting broadband ground motion (e.g., Crempien and Archuleta 2014; Goldberg et al. 2022). These source models also feed into investigations of lithosphere processes and other hazards accompanying or following these major earthquakes (e.g., Bürgmann and Dresen 2008; King et al. 1994; Fan et al. 2019). Therefore, quantifying key physical parameters such as deformation and stress associated with earthquakes and their uncertainty is crucial to advancing studies of not only earthquakes but also other related phenomena or processes.

In this study, we address these research gaps by analyzing Bayesian kinematic finite-fault models for five large megathrust earthquakes: 2011 M_w 9.0 Tohoku, 2015 M_w 8.3 Illapel, 2014 M_w 8.1 Iquique, 2016 M_w 7.8 Pedernales, and 2015 M_w 7.8 Gorkha (Minson et al. 2014; Yue et al. 2017; Caballero et al. 2023; Gombert et al. 2018; Duputel et al. 2015) (Chapter 2). The posterior earthquake model ensembles from the selected studies are derived with consistent data processing, source parameterization, and inversion schemes, with minor differences in model prediction errors. Because joint seismic, geodetic, and tsunami observations are used for source inversions without ad

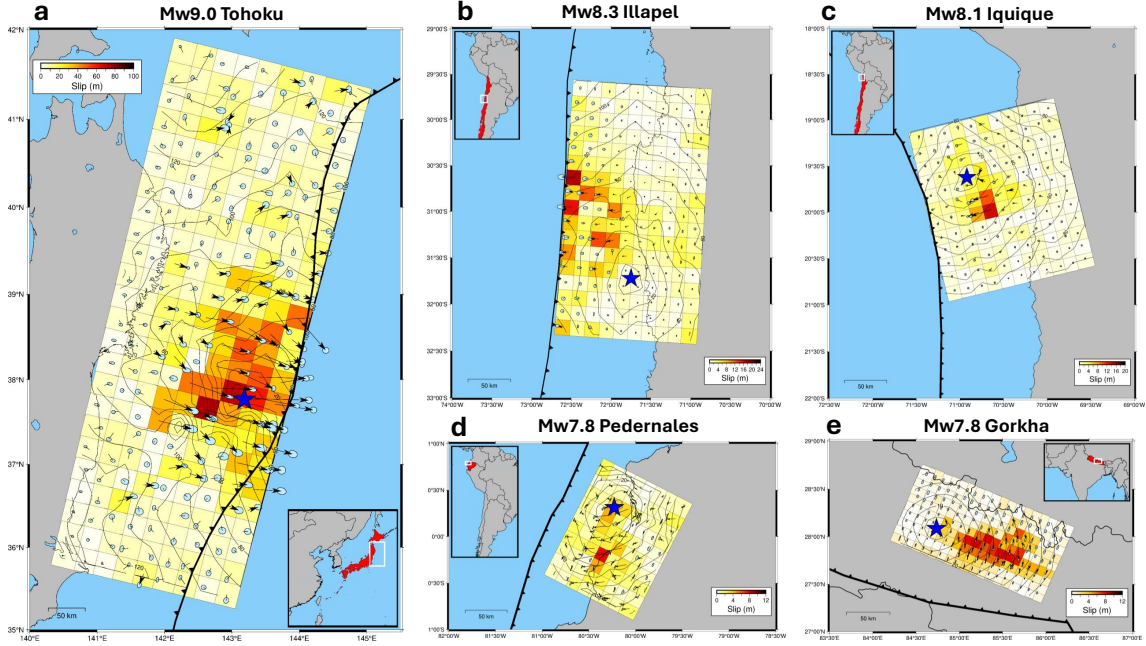


Figure 1.1: **Bayesian finite-fault models of large megathrust earthquakes.** Posterior mean models of total coseismic slip of (a) 2011 M_w 9.0 Tohoku, (b) 2015 M_w 8.3 Illapel, (c) 2014 M_w 8.1 Iquique, (d) 2016 M_w 7.8 Pedernales, and (e) 2015 M_w 7.8 Gorkha earthquakes are shown in color on the surface projection of fault geometry. Arrows represent slip vectors at each patch with 1σ confidence ellipses. Rupture fronts every few seconds are shown as thin overlain contours. Hypocenters are marked by blue stars. Solid black lines show trench lines. Map insets show broader geographic settings with the country (red) and earthquake area (blue).

hoc spatial smoothing, these models represent the highest-resolution, plausible rupture scenarios over the scales of fault parameterization (~ 10 – 30 km), with presumably minimal relative biases due to inversions across studies. Taken together, this small yet diverse set of significant earthquakes in the past 15 years features spatiotemporal variability of megathrust fault slip with global relevance (Figure 1.1). We use the posterior ensembles of these finite-fault earthquake rupture models to quantify the relationships between rupture parameters (Section 3.1) and predict static (permanent) and dynamic (time-dependent) displacements, along with fault stress changes (Sections 3.2 and 3.3). In particular, we compare event-averaged estimates of static stress drop

and elastic strain drop (or potency density). We discuss observed trends and patterns within and between different large earthquakes, along with the associated uncertainty structure (Chapter 4). Our central goal is to establish a quantitative workflow to examine and utilize high-dimensional earthquake models and quantify inferred and derived parameters, with rigorous uncertainty characterization. These efforts can help explore, develop, and test hypotheses about earthquake and fault dynamics and facilitate future applications in engineering and hazard forecasts.

Chapter 2

Data and Methods

We summarize the parameterization, forward, and inverse modeling approaches common for the selected earthquake models (Sections 2.1 and 2.2) and specific information and observations for these events (Section 2.3). Then we adopt a two-component workflow applied to each selected earthquake (Figure 2.1). First, we compare posterior model ensembles at different levels, assessing joint probability distributions and correlation relationships between kinematic parameters from fault patches to events (Section 2.4). Second, by employing ensemble-based forward modeling tools, we compute static fault stress and permanent surface deformation and simulate lower-frequency ground motions (Section 2.5). For both static (time-independent) and dynamic (time-dependent) observables, we perform uncertainty quantification in the form of spatial distributions of standard deviation and relative uncertainty. These efforts aim to explore and test relations between earthquake rupture parameters and establish spatiotemporal trends in predicted observables and associated error structures characteristic of megathrust systems.

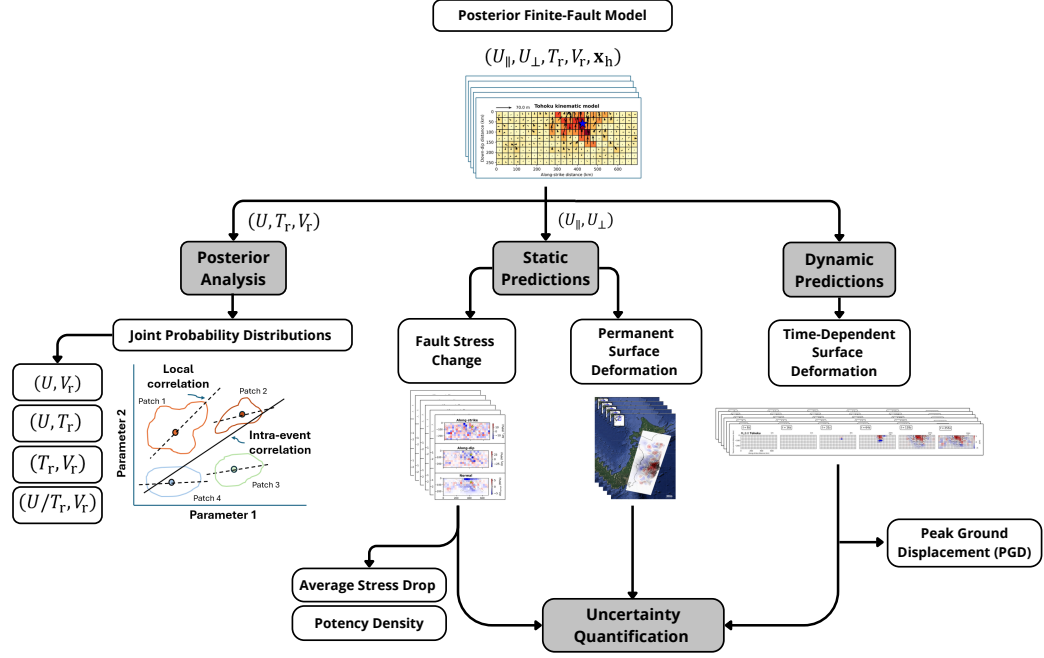


Figure 2.1: **Schematic diagram of our workflow.** The key steps involve the posterior analysis of the inferred model parameters based on joint probability distributions and predictive analysis for ensemble-based calculations of stress and displacement fields used for uncertainty quantification.

2.1 Finite-Fault Earthquake Models

A kinematic finite-fault rupture model idealizes an earthquake as a time-evolving displacement discontinuity (slip or dislocation) over a fault plane (Madariaga 2015). The fault zone is represented as a finite-sized planar or non-planar surface discretized into multiple subfault patches with simplified geometrical parameters (e.g., position, area, strike, and dip). A dislocation source following a rectangular shape or other spatial basis function describes the local movement evolution as the rupture initiates at the hypocenter and propagates outward. The collective behavior of these patches characterizes the spatiotemporal history of coseismic fault slip (e.g., Aki and Richards 2002; Minson et al. 2013).

In a conventional approach, the fault zone is discretized into n_p subfault patches, where the earthquake rupture process is described by local slip vector $\mathbf{U}$, slip duration (or rise time) T_r , and rupture speed V_r on each patch. The slip vector is resolved into two orthogonal components, $U_{\parallel}$ and $U_{\perp}$, in a local Cartesian coordinate system, often corresponding to the along-dip and along-strike directions, or rake-parallel and rake-normal directions, respectively. Capturing the temporal evolution of slip requires knowing the initial rupture time t_0 for each patch. Given a spatially variable rupture speed field and hypocenter $\mathbf{x}_h^0$, the eikonal equation determines how rupture propagation fronts advance in time and space: $|\nabla t_0(x, y)|^2 = 1/V_r^2(x, y)$. Numerical solutions of t_0 for the eikonal equation at all sources can be derived from the fast sweeping method (Zhao 2005). The kinematic rupture model can be completely described by a vector of $4n_p + 2$ dimensions:

$$\mathbf{m} = \left[U_{\parallel}^1, U_{\parallel}^2, \dots, U_{\parallel}^{n_p}, U_{\perp}^1, \dots, U_{\perp}^{n_p}, T_r^1, \dots, T_r^{n_p}, x_{h,\parallel}, x_{h,\perp} \right]^{\top}, \quad (2.1)$$

where the superscript refers to patch index and $x_{h,\parallel}$ and $x_{h,\perp}$ are the along-strike and along-dip local coordinates of the hypocenter, respectively.

Earth's land surface or seafloor undergoes permanent (static) deformation in response to earthquake ruptures. In linear elastic problems, the permanent displacement field results from the linear combination of the total displacements due to all dislocation sources within a homogeneous, layered, or three-dimensional (3D) heterogeneous elastic medium. Mathematically, the static deformation vector, $\mathbf{d}$, which contains displacement in three directions for all surface receivers, is linearly related to $\mathbf{U}$:

$$\mathbf{d} = \mathbf{G}\mathbf{U}, \quad (2.2)$$

where the matrix $\mathbf{G}$ contains the Green's functions that compute all receiver displacements due to unit slip components of all source dislocations corresponding to $\mathbf{U}$. Similarly, the vector field of fault stress change, $\Delta\boldsymbol{\sigma}$, presented in the form of traction change vectors on every subfault follows a linear relation with $\mathbf{U}$:

$$\Delta\boldsymbol{\sigma} = \mathbf{G}'\mathbf{U}, \quad (2.3)$$

where $\mathbf{G}'$ defines a design matrix (different from $\mathbf{G}$) that computes stress changes for unit slip components corresponding to the slip vector $\mathbf{U}$.

Similar to static modeling, time-dependent (termed “dynamic” hereinafter) surface deformation due to kinematic rupture in elastic medium exploits the discrete superposition of all possible source-receiver responses while respecting temporal causality. The dynamic displacement, d_i ($i = x, y, z$), at location $\boldsymbol{\zeta}$ and time t (relative to rupture initiation time) in the i th direction can be formulated as

$$d_i(\boldsymbol{\zeta}, t) = \sum_{j=1}^2 \sum_{k=1}^{n_p} U_j^k g_{i,j}^k(\boldsymbol{\zeta}, t - t_0^k; T_r^k) \quad (2.4a)$$

$$= \sum_{j=1}^2 \sum_{k=1}^{n_p} U_j^k \int_0^{\min(t-t_0^k, T_r^k)} s(\tau; T_r^k) G_{i,j}^k(\boldsymbol{\zeta}, t - \tau) d\tau, \quad (2.4b)$$

where $G_{i,j}^k$ is a Green's function of the displacement waveform in i th direction at observation point $\boldsymbol{\zeta}$ due to a unit slip in the j th direction on the k th subfault without time-offset, and $s(t; T_r)$ represents a source-time function (STF) with rupture duration T_r^k . In the cases we consider here, STF takes a triangular shape, and the local peak unit slip rate is given by $1/2T_r$. The convolution in Equation 2.4 between the impulse response $G_{i,j}^k$ and STF define $g_{i,j}^k$ as a Green's function in terms of delayed time, thus describing the displacement history at $\boldsymbol{\zeta}$ and time t given locally variable rupture duration and initiation times (Minson et al. 2014).

These model parameterization and forward models (Equations 2.2, 2.3, and 2.4) form the basis for our characterization and prediction of earthquake source parameters and associated deformation and stress change.

2.2 Bayesian Inversion Approach

To infer earthquake parameters (Equation 2.1) from surface observations, we can formulate a Bayesian inverse problem based on multiple geophysical datasets (e.g., seismic, GNSS, InSAR, tsunami) represented by a vector $\mathbf{d} = \{\mathbf{d}_{\text{gnss}}, \mathbf{d}_{\text{insar}}, \mathbf{d}_{\text{seismic}}, \mathbf{d}_{\text{tsunami}}, \dots\}$ and a set of a priori assumptions on the model parameters (Tarantola 2005). An ensemble of solutions $\{\mathbf{m}_1, \mathbf{m}_2, \dots\}$ is sampled from a high-dimensional posterior probability distribution, $p(\mathbf{m}|\mathbf{d})$, defined by the Bayes theorem (Bayes 1763):

$$p(\mathbf{m}|\mathbf{d}) \propto p(\mathbf{m})p(\mathbf{d}|\mathbf{m}), \quad (2.5)$$

where $p(\mathbf{m})$ is the prior probability distribution and $p(\mathbf{d}|\mathbf{m})$ is the data likelihood. The data likelihood function measures the probability of measuring data $\mathbf{d}$ given the model $\mathbf{m}$.

In earthquake inversion problems, the allowed space of kinematic model parameters is initialized with a set of prior probability density functions (PDFs), e.g., uniform and Gaussian distributions, which are often informed by physical considerations. The data likelihood often takes a Gaussian form:

$$p(\mathbf{d}|\mathbf{m}) \propto \exp\left(-\frac{1}{2}[\mathbf{d} - \mathbf{G}(\mathbf{m})]^\top \mathbf{C}^{-1}[\mathbf{d} - \mathbf{G}(\mathbf{m})]\right), \quad (2.6)$$

where the misfit variance-covariance matrix $\mathbf{C}$ incorporates observation and model prediction uncertainties (Tarantola 2005), e.g., due to errors in subsurface elastic structure (Duputel et al. 2014).

To construct the posterior probability distribution numerically, Minson et al. (2013) developed the Cascading Adaptive Metropolis In Parallel (CATMIP) algorithm. This Markov Chain Monte Carlo implementation enables efficient and tractable sampling in high-dimensional model space. In particular, CATMIP uses a transitioning strategy by which a tempering parameter, β , modulates the convergence to the ultimate posterior distribution via a series of intermediate PDFs. For the events of our analysis, all finite-fault solutions to the Bayesian inversion problem are obtained using the CATMIP algorithm and its later implementation in the AlTar package.

2.3 Large Megathrust Earthquakes

We have selected some of the largest megathrust events in the subduction zone in Japan, South America, and the Himalayan belt over the past 15 years, including the 2011 M_w 9.0 Tohoku (Minson et al. 2014), 2015 M_w 8.3 Illapel (Caballero et al. 2023), 2014 M_w 8.1 Iquique (Duputel et al. 2015), 2016 M_w 7.8 Pedernales (Gombert et al. 2018), and 2015 M_w 7.8 Gorkha (Yue et al. 2017). Kinematic rupture solutions for these earthquakes have been estimated through the similar Bayesian inversion scheme of Minson et al. (2013), with primary differences in the choices of priors and error structures. All these rupture models take advantage of diverse sets of available geophysical datasets, including GNSS (high-rate or daily), InSAR, seismic (teleseismic or strong motion), tide gauges, and/or tsunami waveforms, and incorporate the layered elastic structure (Tables A.1–A.4), thereby offering improved imaging of the rupture process. When InSAR observations are considered, dummy parameters for InSAR orbital ramps

are incorporated in **m**. Details of model parametrization, sampling parameters, and probability distributions are summarized in Tables 2.1 and 2.2, respectively. Below, we briefly summarize these events and associated source models.

Table 2.1: **Parameters for earthquake models and inversions**

Event	Tohoku	Illapel	Iquique	Pedernales	Gorkha
Number of along-dip patches	9	10	11	8	9
Number of along-strike patches	24	17	12	10	18
Patch size (km)	29	18	17	15	10
Number of inverted parameters	866	682	533	331	650
Number of sampled models	1000000	393216	72000	600000	90000
Cooling steps	52	52	56	53	12

2.3.1 2011 M_w 9.0 Tohoku Earthquake

The M_w 9.0 Tohoku-oki earthquake struck the east coast of Japan on March 11, 2011, 05:46:24.120 UTC at 38.19°N, 142.68°E, and 21 km deep (USGS 2024; Chu et al. 2011). The Tohoku event is the best-documented large megathrust event that has generated numerous source studies (Simons et al. 2011; Ide et al. 2011; Uchida and Bürgmann 2021, and references therein). For our selected model (Minson et al. 2014), the design of the megathrust interface over the Pacific Plate consists of a non-planar fault approximated by 9 and 24 square patches (29-km sided) in the along-dip and along-strike directions, respectively, within a five-layer elastic structure (Table A.1). The geophysical dataset for the inversion included static GPS offsets, 1-Hz GPS displacement waveforms, seafloor geodesy, tide gauges, and open-ocean tsunami measurements. The inferred model reveals that the prominent slip region concentrates on a portion

Table 2.2: **Kinematic parameters from earthquake model ensembles**

Event	Parameter ^a	$U_{\perp}$ (m)	$U_{\parallel}$ (m)	T_r (s)	V_r (km/s)
Tohoku	Prior ^b	$\mathcal{N}(0, 10)$	$\mathcal{U}(-10, \infty)$	$\mathcal{U}(12, 42)$	$\mathcal{U}(0, 7.7)$
	Posterior ^c	$[-8.9, 9.9]$	$[-6.1, 40]$	$[19, 35.8]$	$[0.9, 6.1]$
Illapel	Prior	$\mathcal{N}(0, \sim 3)$	$\mathcal{U}(0, 40)$	$\mathcal{U}(\sim 5, 40)$	$\mathcal{U}(0.5, 4)$
	Posterior	$[-3.2, 2.9]$	$[-0.8, 8.7]$	$[8.7, 35.5]$	$[0.7, 3.8]$
Iquique	Prior	$\mathcal{N}(0, \sim 3)$	$\mathcal{U}(-1, 20)$	$\mathcal{U}(\sim 1, 30)$	$\mathcal{U}(0.5, 3.5)$
	Posterior	$[-1.4, 1.5]$	$[-0.7, 3.6]$	$[8.3, 26.4]$	$[0.9, 2.7]$
Pedernales	Prior	$\mathcal{N}(0, 5)$	$\mathcal{U}(-1, 15)$	$\mathcal{U}(1, 16)$	$\mathcal{U}(1, 4)$
	Posterior	$[-1.2, 1.6]$	$[-1, 3.5]$	$[1.6, 10.5]$	$[1.2, 3.9]$
Gorkha	Prior	$\mathcal{N}(0, 1.3)$	$\mathcal{U}(2, 13)$	$\mathcal{U}(4, 16)$	$\mathcal{U}(2.5, 4)$
	Posterior	$[-1.1, 1.4]$	$[-0.8, 7.0]$	$[2.8, 10.8]$	$[2.0, 3.7]$

^a $U_{\perp}$ is the along-strike or rake-perpendicular slip; $U_{\parallel}$ is the along-dip or rake-parallel slip; T_r is slip duration; V_r is rupture speed. ^bPrior probability distribution $p(\mathbf{m})$. ^cPosterior Confidence Interval (CI) for 5–95 percentiles, $[Q_{5\%}, Q_{95\%}]$.

down-dip from the trench, which extends in the along-dip direction for a distance of more than 100 km and reaches a maximum of 74 m at 16 km deep. The rupture propagation evolution (initial rise time contours every 10 s) shows a rapidly expanding pattern with a duration of more than 100 s (Figure 1.1a).

2.3.2 2015 M_w 8.3 Illapel Earthquake

The M_w 8.3 Illapel started off the coast of Northern Chile on September 16, 2015, 22:54:31 UTC at 31.64°S, 71.75°W, and a depth of 23 km (Centro Sismológico Nacional CSN, Li and Liu 2016; Ruiz and Madariaga 2018). In the source model (Caballero et al. 2023), the non-planar fault interface is discretized into 10 and 17 square patches (18-km sided) in the along-dip and along-strike directions within a layered elastic structure (Table A.2). Inversion incorporates continuous and campaign GNSS, ascending and

descending InSAR imagery, tsunami data, high-rate GPS, and displacement data integrated from strong-motion waveforms. The inverted slip distribution is characterized by a 120-s rupture with two shallow large-amplitude domains (up to 16 m) at shallow depth, extending updip to the trench. Slip release activates primarily in the updip direction (Figure 1.1b).

2.3.3 2014 M_w 8.1 Iquique Earthquake

The M_w 8.1 Iquique earthquake occurred in Northern Chile on March 14, 2014, 23:46:45 UTC, with the origin at 19.572°S, 70.908°W, and 25 km deep (Centro Sismológico Nacional, CSN). In the selected model (Duputel et al. 2015), the fault interface between the Nazca and South American plate is modeled as a non-planar fault with 11 and 12 square patches (17-km sided) in the along-dip and along-strike directions within a layered elastic structure (Table A.2). Multiple data sources are used, including InSAR, static GPS, tsunami, tide gauges, high-rate GPS, and strong motion data. The slip inferred for this earthquake mainly concentrates to the south of the hypocenter with a peak amplitude above 10 m. The earthquake propagation is characterized by moderately uneven rupture fronts that travel over 50 seconds (Figure 1.1c).

2.3.4 2016 M_w 7.8 Pedernales Earthquake

Another off-coast event is the M_w 7.8 Pedernales earthquake at the subduction zone between the Nazca plate and the NAS sliver in Ecuador (Nocquet et al. 2014). This earthquake occurred on April 16, 2016, 23:58:36 UTC with a relocated hypocenter at 0.31°N, -80.15°W, depth of 19.6 km (Gombert et al. 2018). In the selected model, the fault is discretized into 8 and 10 patches (15-km sided) in the along-dip and along-strike directions within a layered elastic medium (Table A.3). InSAR, tsunami waveforms,

static and high-rate GPS, and strong-motion data are used in the joint inversions. The inferred earthquake rupture follows a unidirectional trend, leaving two regions of high slip (<8 m) over 40 s after origin time (Figure 1.1d).

2.3.5 2015 M_w 7.8 Gorkha Earthquake

A continental subduction zone event is exemplified by the M_w 7.8 Gorkha in Nepal on May 12, 2015, 07:05:19.730 UTC (USGS 2024). This event started at a hypocenter location at 28.1473°N, 84.7079°E, and 10 km depth (ANSS Comprehensive Catalog). The fault interface is modeled as a single-dip angle surface with 9 and 17 patches (10km-sided) in the along-dip and along-strike directions embedded in a layered elastic structure (Table A.4) (Yue et al. 2017). Data used for inversion consist of InSAR, synthetic aperture radar (SAR) offset imagery, static and high-rate GPS displacements, and teleseismic waveform data. The inversion results reveal a depth-dependent rupture that advances concentrically around the hypocenter for ~ 50 s and peaks at ~ 6 m (Figure 1.1e), consistent with other published models (Galetzka et al. 2015; Avouac et al. 2015).

2.4 Posterior Exploration

For each earthquake, we use the full model ensemble of size N as listed in Table 2.1, which provides N realizations of each kinematic variable for every patch. We use 2D arrays containing N values of slip amplitude $U = \|\mathbf{U}\|$, rupture duration T_r , and rupture speed V_r for all patches to assess the joint probability distributions and correlation relationships. In this analysis, we also consider the average local slip rate U/T_r in comparisons within and across events. For triangular STFs, U/T_r exactly equals half of the peak slip rate, V_{peak} , while STFs in dynamic models could be more complex depending

on the rupture style (Tinti et al. 2005; Gabriel et al. 2012). These kinematic parameters are particularly relevant to dynamic earthquake rupture modeling (Schmedes et al. 2010; Bizzarri 2012; Weng and Ampuero 2022). We focus on four pairs of kinematic parameters: (U, T_r) , (U, V_r) , (T_r, V_r) , and $(U/T_r, V_r)$.

For each earthquake, we compare these parameter pairs at two levels: over the entire event or local patches. We focus on different subsets of patches that host more prominent slip using thresholds of 10%, 20%, and 30% of maximum slip. This is because the kinematic properties of higher-slip ruptured regions are presumably better resolved and likely more informative about the rupture process.

For each parameter pair (X, Y) , we present the joint probability density of every patch considered, with contours containing 68% of the inferred paired parameters and surrounding the respective posterior mean values (x, y) . These mean vectors form a paired array $\{(x_1, y_1), \dots, (x_n, y_n)\}$, from which we can compute the Pearson correlation coefficient:

$$\rho(X, Y) = \frac{\sum_{ij}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i(x_i - \bar{x})^2} \sqrt{\sum_j(y_j - \bar{y})^2}}. \quad (2.7)$$

We call this metric *intra-event correlation*, which allows us to examine whether the two parameters tested exhibit some collective linear interdependency over all fault patches within each event.

In the local analysis, we consider patches individually. For each pair of parameters (X, Y) , we take the inferred values of X and Y of each patch, which make up its corresponding joint probability distribution, to compute the Pearson correlation. This means that each patch has its own correlation coefficient, from which we can assess the spatial pattern of correlation properties for each parametric pair. Through the *local correlations*, we can investigate the differences and tradeoffs between parameters inside and outside the rupture zone. The correlation coefficients for all parameter pairs of five

events for areas with different slip thresholds are listed in Table A.5. We recognize that these correlation coefficients cannot capture nonlinear or even multi-valued physical relations between rupture parameters but can offer a simple quantitative metric for our exploration.

2.5 Predictive Analysis

2.5.1 Static Predictions

To compute static displacement, we use the Okada (Okada 1992, 1985) and EDKS methods (Zhu and Rivera 2002) for a homogeneous (Poisson’s ratio $\nu = 0.25$ and rigidity $G = 30$ GPa) and stratified half space, respectively, available in the Classical Slip Inversion (CSI) package (Jolivet 2024). To be consistent with the original inversions in the published work, the exact or similar 1D layered elastic structures are used (Tables A.1–A.4). We select a suite of $N = 5000$ models randomly sampled from the original ensembles as calculations derived from Okada model using entire ensembles showed negligible difference with respect to those obtained from reduced sample sets. We input the two components of slip ($U_{\parallel}$ and $U_{\perp}$) for each patch into both numerical schemes. We use a refined slip distribution by linearly interpolating the original model into a finer fault surface, which ensures better agreement between both static methods. For each earthquake model, we define the locations of sources and receivers according to a common Cartesian coordinate system with x -, y -, and z -axes oriented in the along-strike, trench-normal (positive toward trench), and vertical (positive up) directions, respectively. We use a grid of receivers at the surface, whose corresponding extent covers at least the projected area of the true dipping fault plane.

We follow similar steps to estimate fault stress changes $\Delta\sigma$ using a set of $N = 5000$ models. We consider the half-space Okada models and assume $G = 30$ GPa. In

this case, no interpolation is carried out and observation points are coincident with the original fault geometry. As Okada produces a stress tensor S_{ij} ($i, j = x, y, z$) at the center of every subfault, we need to resolve it into local normal and shear components using the respective orientation angles, dip δ and strike ϕ . Thus, we multiply the corresponding tensor with the unit vector normal to the subfault patch, namely $\hat{\mathbf{n}} = [\sin(\delta) \cos(\phi), \sin(\delta) \sin(\phi), \cos(\delta)]^\top$, to obtain $\Delta\boldsymbol{\sigma}$ acting on each patch: $\Delta\boldsymbol{\sigma} = \mathbf{S}\hat{\mathbf{n}}$. The stress change vector is further expressed in three components as $\Delta\boldsymbol{\sigma} = [\Delta\sigma_n, \Delta\sigma_\perp, \Delta\sigma_\parallel]^\top$, along the fault-normal, along-strike, and along-dip directions.

To quantify uncertainty in the predicted static observables, the linearity of Equations 2.2 and 2.3 allows us to express corresponding covariance matrices $\mathbf{C}_{\Delta\boldsymbol{\sigma}}$ and $\mathbf{C}_{\mathbf{d}}$ as follows:

$$\mathbf{C}_{\Delta\boldsymbol{\sigma}} = \mathbf{G}'^\top \mathbf{C}_{\mathbf{U}} \mathbf{G}', \quad (2.8a)$$

$$\mathbf{C}_{\mathbf{d}} = \mathbf{G}^\top \mathbf{C}_{\mathbf{U}} \mathbf{G}. \quad (2.8b)$$

The standard deviations of $\Delta\boldsymbol{\sigma}$ and $\mathbf{d}$ at each observation point are estimated from the variances. The relative uncertainty is defined as the ratio between the standard deviation and considered quantity, i.e., s_d/d or $s_{\Delta\sigma}/\Delta\sigma$ at any location.

To facilitate multi-event comparison of stress change distributions, we estimate the average static stress drop of these events, an important physical parameter for ground motion simulations and earthquake scaling laws (e.g., Cotton et al. 2013; Baltay et al. 2019). Here, we focus on the *static stress drop*, which is the difference between the stress levels before and after the event and inferrable from total fault slip. Note that this measure differs from the *dynamic stress drop*, which is influenced by the rupture process and estimated from seismograms (e.g., Brune 1970; Abercrombie 2021). Several approaches can be applied to derive a single measure of static stress drop for

an earthquake (Noda et al. 2013). First, the energy-based (slip-weighted) measure in a 2D rupture problem is formulated as

$$\overline{\Delta\sigma_E} = -\frac{\int_{\Sigma} \mathbf{U}(\mathbf{x}) \cdot \Delta\boldsymbol{\sigma}(\mathbf{x}) d\mathbf{x}}{\int_{\Sigma} \|\mathbf{U}(\mathbf{x})\| d\mathbf{x}}, \quad (2.9)$$

where $\mathbf{U} = [0, U_{\parallel}, U_{\perp}]^T$ in the same coordinate as $\Delta\boldsymbol{\sigma}$ and Σ defines the entire fault surface. The negative sign upfront converts the shear stress change calculations into stress drops. We also derive modified measures $\overline{\Delta\sigma_{E,th}}$ where only patches with slip exceeding a percentage th of the maximum slip are considered in Equation 2.9.

Second, spatially averaged static stress drop measure is estimated as

$$\overline{\Delta\sigma_{A,th}} = \frac{\|\int_{\Sigma_{th}} \Delta\boldsymbol{\sigma}(\mathbf{x}) d\mathbf{x}\|}{\Sigma_{th}}, \quad (2.10)$$

where $\Sigma_{th} = \{\mathbf{x} \in \Sigma : \|\mathbf{U}(\mathbf{x})\| > th\% \cdot U_{\max}\}$ and $U_{\max}$ is the maximum slip during each event.

Since we first calculate the stress changes using a uniform rigidity $G = 30$ GPa, we can account for depth-dependent rigidity, $G(\mathbf{x})$, by multiplying these stress changes in Equations 2.9 and 2.10 by $G(\mathbf{x})/G$.

While stress drop estimates depend on the elastic moduli of the subsurface, geophysical observations better constrain the potency of earthquake sources (Ben-Zion 2001). For this consideration, we use the static stress drops (Equations 2.9 and 2.10) to estimate the static elastic strain drop or potency density (Nanjundiah et al. 2020; Vallée 2013; Ben-Zion 2003) for a homogeneous medium as follows:

$$\bar{\epsilon} = \frac{\overline{\Delta\sigma}}{2G}, \quad (2.11)$$

where $\bar{\epsilon}$ can take the form of $\bar{\epsilon}_E$, $\bar{\epsilon}_{E,th}$, or $\bar{\epsilon}_{A,th}$ similar to stress drop measures.

2.5.2 Dynamic Predictions

To calculate dynamic ground motion at a reasonable computational cost, we use a smaller subset of $N = 100$ models from each earthquake including all kinematic variables, i.e., $U_{\parallel}$, $U_{\perp}$, T_r , V_r , and $\mathbf{x}_h$. We adopt the forward modeling routines in MudPy package (Melgar et al. 2016), which is compatible with kinematic rupture model inputs and integrates frequency-wavenumber code (FK) (Zhu and Rivera 2002). We set sampling frequency f , number of STF points N_t , and wavenumber interval dk to be 1 Hz, 256, and 1 km^{-1} , respectively, and use the original or adapted 1D layered Earth's structures. We do not apply any filter or tapering to the results. For each earthquake, we pre-compute Green's functions only once, as these do not depend on specific kinematic parameters.

To calculate synthetic waveforms, we use the fault geographical coordinates to set up the receiver grid, which is coarser than in EDKS, to save computational costs. At each patch, the initial rupture time t_0 is computed using the Fast Sweeping algorithm implemented in the CSI package; we utilize a triangular source time function with rise time equal to the inferred rupture duration T_r , which is then properly shifted by corresponding onset time t_0 through MudPy. For each rupture model, we derive the final 3D displacement waveforms at every receiver due to all sources and construct time-dependent deformation fields. We iterate these steps over the ensemble of models.

Different from the static case, to quantify spatiotemporal uncertainty in the displacement field, we compute 1- σ standard deviation $s_{d_i}(\mathbf{x}, t)$ ($i = x, y, z$) from the ensemble of predicted displacement history Equation 2.4. At time t_k , a single sample prediction for the receiver grid with n_p points takes the column-vector form:

$$\mathbf{d}(t_k) = [d_x(\mathbf{x}_1, t_k), \dots, d_x(\mathbf{x}_{n_p}, t_k), d_y(\mathbf{x}_1, t_k), \dots, d_z(\mathbf{x}_{n_p}, t_k)]^{\top}. \quad (2.12)$$

Altogether, we have a set of N such predictions. This means N observations for $3n_p$ variables at time t_k , yielding a covariance matrix of size $3n_p \times 3n_p$. Then, we take the square root of variances to derive $s_{d_i}(\mathbf{x}_n, t_k)$ for $1 \leq n \leq n_p$ and $1 \leq k \leq N_t$.

Using deformation fields for each source model, we extract the peak ground displacement (PGD) values at each fault patch $\mathbf{x}_n$:

$$\text{PGD}(\mathbf{x}_n) = \max_t \left(\sqrt{d_x(\mathbf{x}_n, t)^2 + d_y(\mathbf{x}_n, t)^2 + d_z(\mathbf{x}_n, t)^2} \right). \quad (2.13)$$

We analyze the change in PGD values in terms of hypocentral distance (or distance to the W-phase centroid) and azimuth angle (measured from the fault strike line) across different earthquake scenarios. These predictions are compared with the empirical scaling law derived from GNSS observations (Melgar et al. 2015):

$$\log_{10}(\text{PGD}) = -4.434 + 1.047M_w - 0.138M_w \log_{10}(R), \quad (2.14)$$

where R is the hypocentral distance in m.

Chapter 3

Results

3.1 Posterior Analysis

We first focus on the posterior exploration of the Tohoku rupture model (Figure 3.1). Overall, the intra-event correlations between all parameter pairs appear weak in larger-slip areas ($|\rho| < 0.17$), whereas the correlations of (U, V_r) and $(U/T_r, V_r)$ becomes more negative (~ -0.2 to -0.4) when smaller-slip areas are included (Figure 3.1a–d and Table A.5). Within the ruptured regions, fault patches tend to exhibit consistent spatial patterns of low-to-moderate local correlations (Figure 3.1e–h). For the (U, V_r) pair (Figure 3.1a), the clustering of parameter values appears to depend on total slip U , where smaller-slip patches have more variable rupture velocity V_r , with apparently higher posterior mean values, than larger-slip patches. This is partly because of the lower observational resolutions of these patches resulting in broader posterior PDFs (Table 2.2). We do not find a coherent spatial pattern of significant local correlation between U and V_r (Figure 3.1e). For the (U, T_r) pair (Figure 3.1b,f), we notice that rupture duration T_r is more tightly constrained with increased slip, yielding weak intra-event correlations ($|\rho| < 0.17$); local correlations tend to be mostly positive yet small. For the (T_r, V_r) pair, parameter values are generally more distributed for different thresholds, resulting in intra-event correlations less than 0.20; some probability densities feature local positive-slope trends (Figure 3.1c). This behavior is better

captured in the spatial local correlation distribution, where coefficients tend to low-to-moderate positive values (Figure 3.1g). This is partly explained by the expected trade-off between T_r and t_0 (decrease with V_r) in reproducing the waveform data (e.g., Gombert et al. 2018). For the $(U/T_r, V_r)$ pair, we observe similar pattern as (U, T_r) , with intra-event correlations ranging from -0.36 to 0.007 (Figure 3.1d). Also, most patches exhibit a slightly more pronounced negative correlation, particularly within the ruptured domain (Figure 3.1h). This pattern is attributable to the combined effect of positive local correlations of (T_r, V_r) and non-correlation of (U, V_r) .

Illapel, Iquique, and Pedernales models exhibit largely similar correlation patterns as Tohoku (Figures 3.2, A.1, A.2). In general, intra-event correlation coefficients for all kinematic pairs stay below 0.3, suggesting a weak linear dependence between paired parameters. Furthermore, the joint probability densities of (U, V_r) , (U, T_r) and $(U/T_r, V_r)$, corresponding to fault areas with slip exceeding 30% of maximum slip, appear sparser and slightly better constrained than those associated with lower slip values. These features again reflect the better resolutions in higher-slip patches. The slip-dependent patterns of (T_r, V_r) overlap more frequently such that a given pair of rupture speed and duration can equally occur in patches with low and high slip. On average, spatial distributions of local correlations show consistent patterns of positive values for (T_r, V_r) and negative values for $(U/T_r, V_r)$, as expected based on the considerations of parameter trade-offs. Within high-slip areas, the positive local correlation of (U, T_r) and negative correlations for (U, V_r) appear more prominent in these three cases than the Tohoku.

The patterns for the Gorkha model are rather different: the strengths of the intra-event correlations for paired parameters exceed 0.3 over the different slip-based clusters (Figure A.3). Moreover, (U, V_r) and $(U/T_r, V_r)$ feature positive intra-event correlations

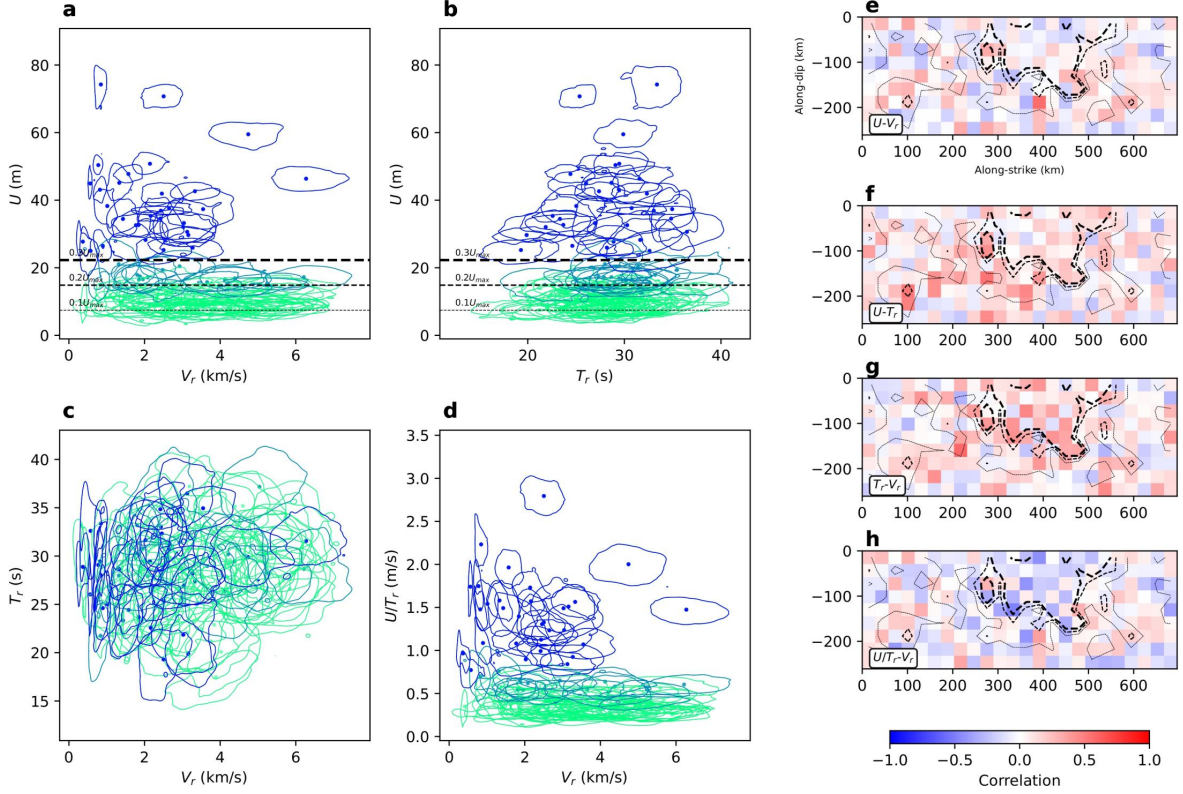


Figure 3.1: **Exploration of posterior parameters for the Tohoku rupture mode.** (a–d) Joint probability distributions of (a) slip and rupture speed (U, V_r), (b) slip and rupture duration (U, T_r), (c) rupture duration and speed (T_r, V_r), and (d) average slip rate and rupture speed ($U/T_r, V_r$). Solid contours represent 68% of posterior probability density and enclose posterior mean values of a parameter pair for each fault patch. *Intra-event correlation* is computed over all fault patches for each parametric pair. Patches with slip exceeding different thresholds (10%, 20%, and 30%; dashed lines) of maximum slip amplitude are shown in different colors. (e–h) Spatial distributions of *local correlation* at each patch between (e) (U, V_r) , (f) (U, T_r) , (g) (T_r, V_r) and (h) $(U/T_r, V_r)$. Dashed lines mark contours of 10%, 20%, and 30% of peak slip.

while (T_r, V_r) and (U, T_r) are negative (Figure A.3a–d). For each subfault, pairs of inferred parameters do not exhibit local correlation, consistent with the shapes of the probability densities (Figure A.3e–h).

Figure 3.3 shows the posterior parameter space of the four kinematic pairs evaluated across different earthquakes using a reduced ensemble size of $N = 10000$. In the (U, T_r)

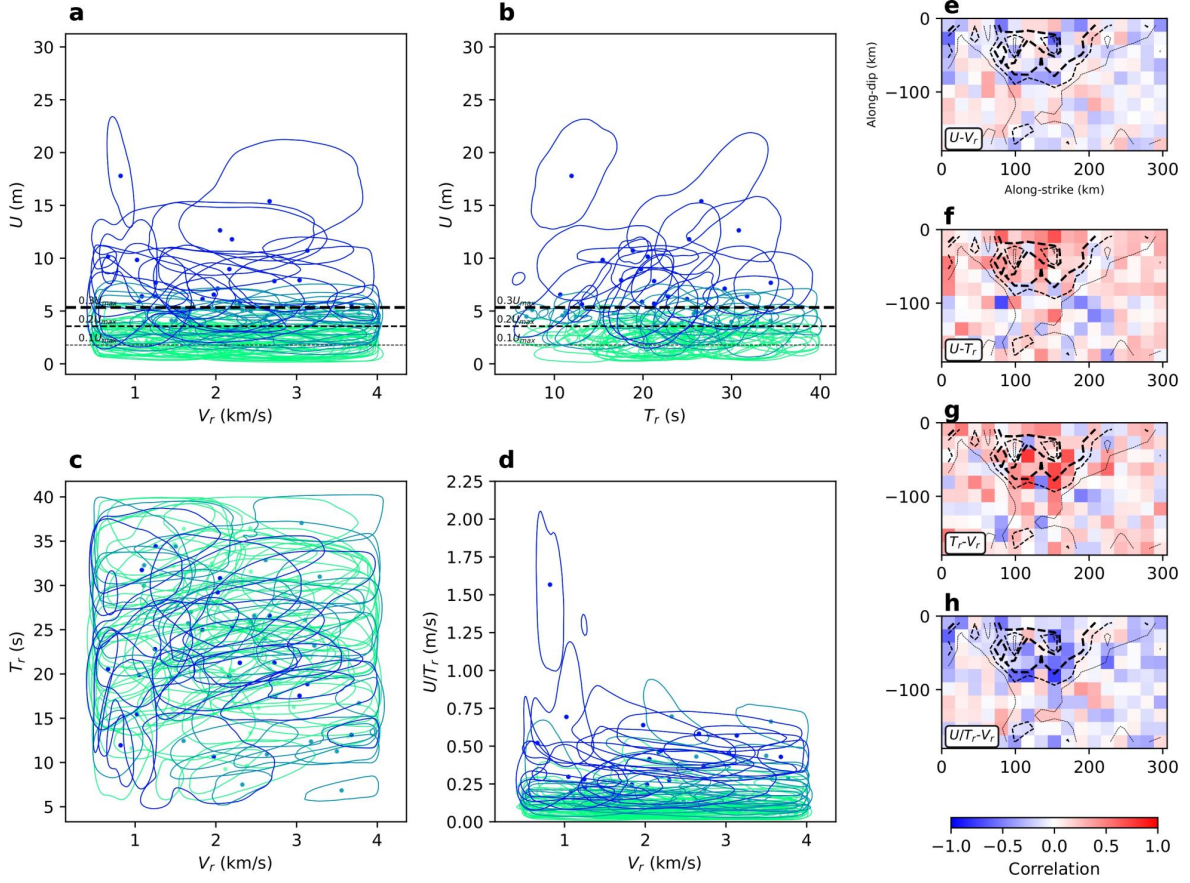


Figure 3.2: **Exploration of posterior parameters for the Illapel rupture model.** Plotting conventions are the same as in Figure 3.1.

space, the parameter clustering shows their dependence on the event size: the majority of fault patches in Tohoku, Illapel, and Iquique models ruptured for a longer duration of 30–40 s than those in Gorkha and Pedernales with less than 12 s (Figure 3.3b). For all earthquake models except Tohoku, mean rupture speeds reach 4 km/s in areas slipping less than 20 m. In contrast, the Tohoku has large-slip and rapidly-ruptured fault areas (Figure 3.3a). We notice similar behavior when comparing (T_r, V_r) space, where large (Tohoku, Illapel) and smaller (Gorkha and Pedernales) earthquakes cluster together to some extent according to T_r values (Figure 3.3c). Figure 3.3d corresponding to the domain of $(U/T_r, V_r)$ does not show a significant differential grouping based

on earthquake size. Instead, the average slip rates across all patches and events lie below 3 m/s. Interestingly, some fault patches in Gorkha and Pedernales slipped at comparable or even larger rates than in Tohoku. Iquique and Illapel are confined to slip rates that, on average, do not exceed 1 m/s.

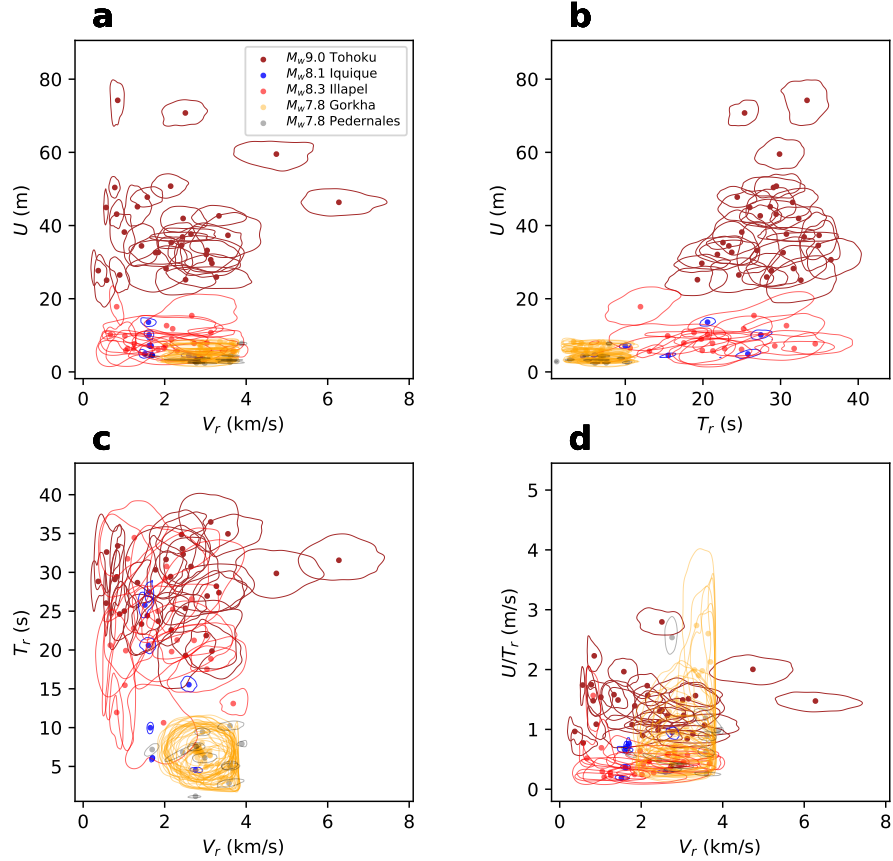


Figure 3.3: Multi-event comparison of kinematic parameters within the rupture zone. Joint probability distributions of (a) slip and rupture speed (U, V_r), (b) slip and rupture duration (U, T_r), (c) rupture duration and speed (T_r, V_r), and (d) average slip rate and rupture speed ($U/T_r, V_r$) for all patches with at least 20% of peak slip. Colored solid contours enclose 68% of posterior probability density on each fault patch. Earthquakes are represented by different colors.

3.2 Static Predictions

3.2.1 Static Surface Deformation

We present mean static deformation for both Tohoku and Gorkha earthquakes using an ensemble of posterior models (Figures 3.4a, 3.5a; Figures A.7a and A.7e). Results for other earthquakes are in supplementary materials (Figures A.4–A.7). Across all five events, the predicted vertical surface deformation features compact areas of uplift closer to the trench and landward subsidence. Moreover, horizontal motion is predominantly controlled by the along-dip fault slip, with maximum displacements in the trench-normal direction. We notice that displacement over 10s of cm rarely extends beyond the surface projection of the fault plane, indicating that the chosen fault plane is adequately large to contain fault slip. These features are consistent with expectations for linear elastic earthquake deformation.

The Tohoku models produce smaller regions of seafloor uplift away from the trench, with minor subsidence occurring in inland zones (Figures 3.4a and A.7a). Along-strike surface displacement in Tohoku is more variable in magnitude and direction. The Japanese coast at 37–40°N undergoes subsidence of up to 2 m (Onawaga region) and displacements of a few meters in the trench-normal direction. Above the large-slip zone, the horizontal displacement field mostly points trenchward. Some local variations in orientation exist in the northern and southernmost areas of the main rupture zone. In the case of Gorkha (Figures 3.5a and A.7e), the surface above the fault plane is mostly displaced southward by up to 3 m, coinciding with uplift. Vertical predictions feature two distinct regions of uplift (south) and subsidence (north) with similar magnitudes (<2 m). Kathmandu lies to the south of the transition zone (white gap), experiencing uplift and movement to the southwest.

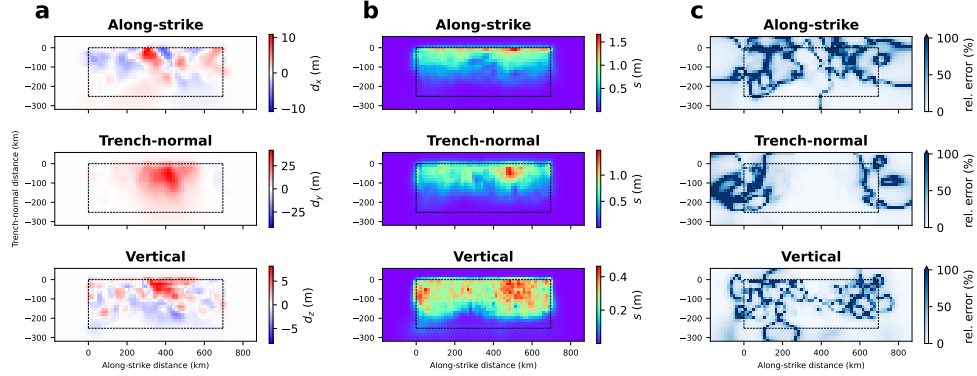


Figure 3.4: **Static surface deformation and associated uncertainty for the M_w 9.0 Tohoku event.** (a) 3D permanent surface deformation field, (b) uncertainty (1σ) distribution, and (c) relative error distribution. The along-strike, trench-normal, and vertical components of variables are shown in the top, middle, and top panels, respectively. The dashed lines indicate the surface projection of the fault geometry in all panels.

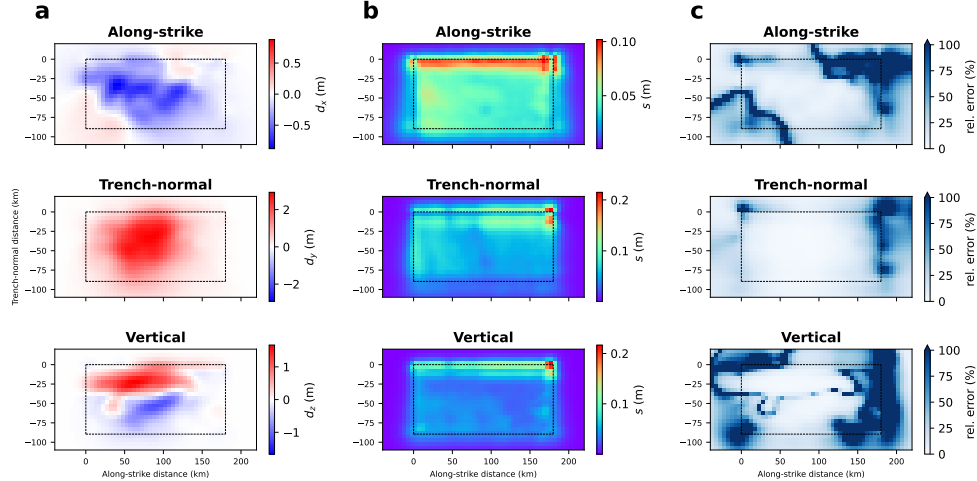


Figure 3.5: **Static surface deformation and associated uncertainty for the M_w 7.8 Gorkha event.** Plotting conventions are the same as in Figure 3.4.

The 3D deformation fields for Illapel and Iquique are qualitatively similar (Figures A.4, A.5, A.7b, and A.7c). In both cases, Chilean regions onshore immediately close

to the rupture zone undergo subsidence by 10s of cm. The horizontal displacement field is mainly directed toward the trench, with minor variations to the north and south of the large displacement region. Pedernales earthquake differs from other offshore earthquakes in terms of directivity and magnitude (Figures A.6 and A.7d). Uplift occurs in coastal lands with up to ~ 1 m. An extended region landward in the northwest is affected by subsidence of several cm. We notice that both seafloor uplift and subsidence equally arise near the trench. Although the horizontal deformation field mainly displaces the surface southwestward, near-trench deformation points to the northwest.

Across all events, the larger uncertainty in predicted surface displacements concentrates near the trench (or the upper edge of the fault plane in Gorkha) and extends along the strike direction (Figure 3.4b). Observation points closer to the trench (or upper fault boundary in Gorkha) tend to exhibit higher uncertainty magnitude in all displacement components, with relatively higher values in the vertical and trench-normal directions. This higher uncertainty appears on both sides of the trench line or surface projection of the upper fault boundary, suggesting that near-source seafloor/ground deformation is more sensitive to source models. The spatial extent of larger uncertainty mostly coincides with the surface area above the fault plane. We note that large errors do not necessarily coincide with large amplitudes (e.g., Gorkha; Figure 3.5b). For offshore earthquakes, large uncertainty in predictions does not protrude the coastline except for Pedernales.

The relative uncertainty shows different patterns from the absolute uncertainty across events (Figures 3.4c, 3.5c, and A.4–A.6). High anomalies exceeding 100% tend to demarcate the boundaries between regions with compact displacements, often due to the combination of smaller displacements and moderate standard deviations. Predictions in areas with prominent deformation accumulate less than 25% relative errors, some of which extend outside the observation grid.

3.2.2 Static Fault Stress Change

For all earthquakes, we find that the maximum stress changes at most patches have the larger amplitudes in the along-dip component (positive up-dip), followed by the along-strike and then normal (positive upward) components. While large stress changes broadly occur around the rupture zone, the stress changes are highly heterogeneous in space (Panel a in Figures 3.6, 3.7, and A.8–A.10). As expected for these primarily dip-slip events, the along-dip component of stress change is more coherent and higher-amplitude than the along-strike component, while the normal stress exhibits coherent patterns with the lowest amplitude and different signs. Iquique, Illapel, and Gorkha fault surface experience notable negative and positive $\Delta\sigma_n$ in the shallower and deeper depths, respectively.

The uncertainty in stress changes exhibits more complex patterns compared to deformation (Panel b in Figures 3.6, 3.7, and A.8–A.10). However, non-zero error for normal stress changes tends to concentrate near the shallower edge of the fault plane. Like displacement, relative error shows very large levels of uncertainty, often in areas with lower stress changes (Panel c in Figures 3.6, 3.7, and A.8–A.10).

3.2.3 Trench-to-Coast Features

Spatial profiles of fault slip and predicted surface displacements and stress changes through the peak slip region showcase characteristics of megathrust earthquakes (Figure 3.8). Although stress change curves exhibit fluctuations around zero, peak slip tends to align with the maximum amplitude of negative along-dip stress changes. Trench-normal displacements increase from distant areas and peak at locations immediately above the peak slip and decrease near the trench (except for Illapel). We notice

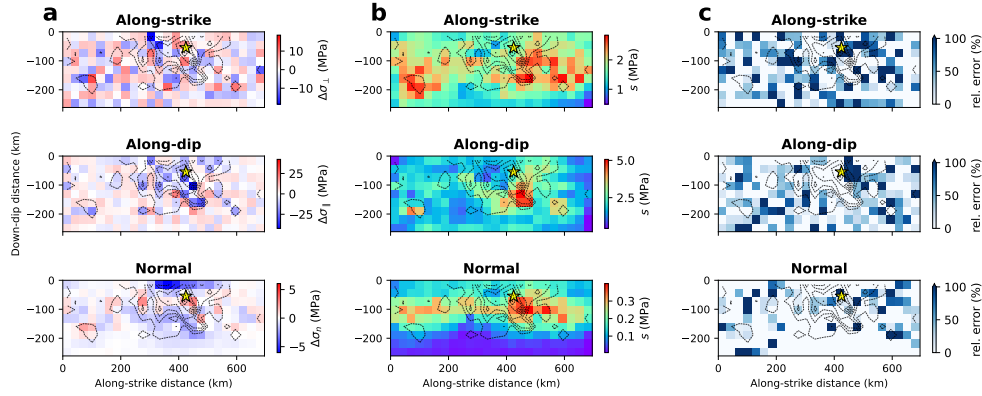


Figure 3.6: **Static fault stress change and associated uncertainty for the $M_w 9.0$ Tohoku event.** (a) 3D stress change on fault surface, (b) uncertainty (1σ) distribution, and (c) relative error distribution assuming a uniform rigidity of 30 GPa. The along-strike, along-dip, and fault-normal components of on-fault traction vectors are shown in the top, middle, and top panels, respectively. Thin dashed lines indicate contours of coseismic slip. The hypocenter is marked by a yellow star.

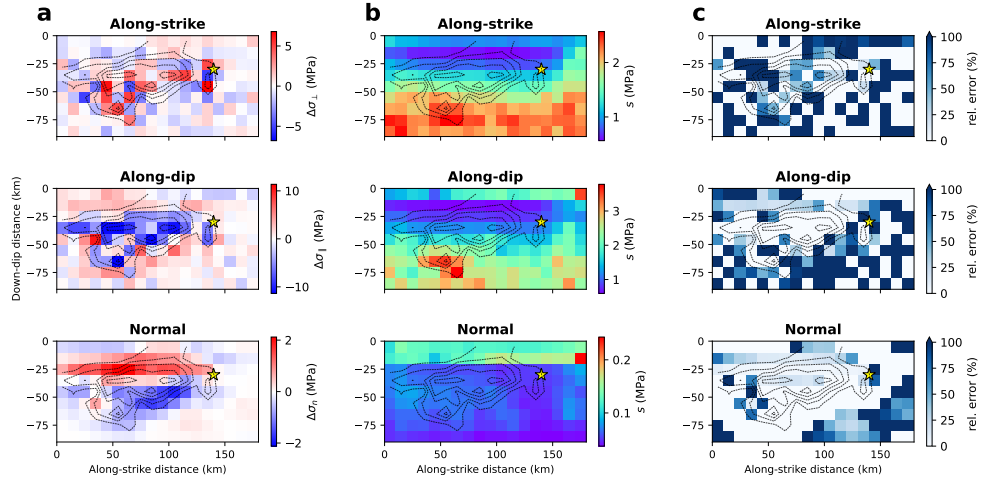


Figure 3.7: **Static fault stress change and associated uncertainty for $M_w 7.8$ Gorkha event.** Plotting conventions are the same as in Figure 3.6.

that spatial overlap between maximum fault slip and trench-normal displacement is greater than stress changes. Vertical displacements shift from negative (subsidence) to

positive (uplift) as they pass through the peak-slip region towards the trench, albeit with differing amplitudes across events. While the trench-normal amplitudes dominate for most events, the vertical displacements for Iquique and Pedernales earthquakes are even larger than trench-normal displacements around the peak-slip locations.

The error bars (1σ) of fault slip profiles show that large-slip areas tend to have higher absolute uncertainty (yet lower relative uncertainty), whereas the near-trench fault patches (all but Gorkha) have either higher (Illapel) or comparable uncertainty relative to downdip patches, depending on the resolutions of tsunami data incorporated in the inversions. Gorkha case shows more different pattern in fault slip uncertainty, with lower values around large-slip regions, likely due to the dense, full-azimuthal coverage of the surface data. Overall, the different levels of uncertainty across the five events arise from the combination of data coverage and resolutions, the adopted error structure in source inversions, and specific source features, which we discuss in Section 4.2.

For predicted observables, the uncertainties are more apparent in stress changes than those in displacement curves, implying stress calculations are more sensitive to earthquake source models. Moreover, larger absolute errors in displacements and particularly stress do not necessarily occur at only peak locations but approximately track larger errors in fault slip. For example, slip and displacement errors in Illapel increase with their mean values toward the trench, corresponding to the less resolved shallow slip (Figure 3.8a).

3.2.4 Stress Drop and Potency Density

Different average static stress drop and potency density estimates vary within an order of magnitude across events, ranging from 0.7 to 25 MPa and 25 to 300 μ strain,

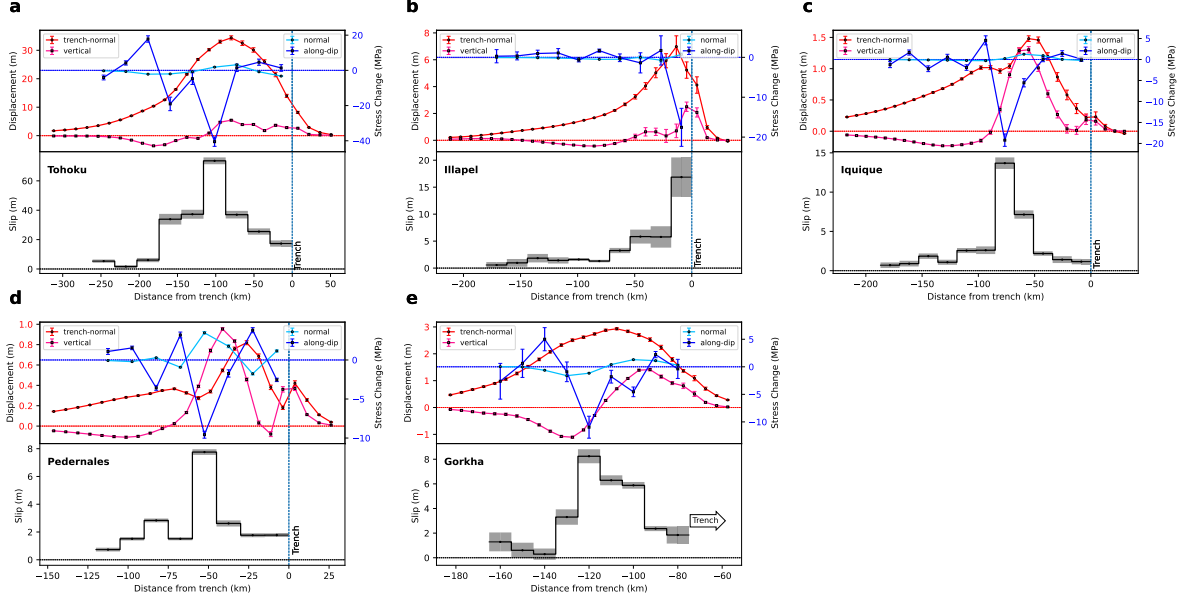


Figure 3.8: **Variations of inferred slip and derived observables with distance from the trench.** Profiles of mean dip-slip (black), on-fault stress change (blue and cyan), and surface displacement (orange and purple) are shown along trench-normal cross-sections through the peak-slip patch for (a) Tohoku, (b) Illapel, (c) Iquique, (d) Pedernales, and (e) Gorkha. Error bars and filled bands define 1σ -credible levels. Vertical dotted lines indicate the trench location.

respectively (Figure 3.9 and Table A.6). The energy-based stress drop estimates, $\overline{\Delta\sigma_E}$, are 23.1 ± 0.7 MPa (Tohoku), 13.0 ± 0.9 MPa (Illapel), 12.2 ± 0.6 MPa (Iquique), 9.7 ± 0.3 MPa (Pedernales) and 6.2 ± 0.3 MPa (Gorkha). For each earthquake, $\overline{\Delta\sigma_E}$ is larger than $\overline{\Delta\sigma_{A,th}}$ for all slip thresholds tested, as found in Noda et al. (2013). The energy-based potency density estimates, $\bar{\epsilon}_E$, are 275.6 ± 7.3 (Tohoku), 161.1 ± 13.3 (Illapel), 125.3 ± 5.7 (Iquique), 124.7 ± 3.0 (Pedernales), and 112.3 ± 5.0 (Gorkha) in μ strains.

For both stress drops and potency density, the broader probability distributions correspond to Tohoku, Illapel and Iquique compared to Pedernales and Gorkha, suggesting these observables of the larger events are less well resolved than smaller events. Introducing the depth-dependent rigidities in static stress drop estimates makes the probability distributions for all events more separate and distinguishable. These comparisons indicate that these megathrust events have more similar potency density,

especially the three events with large slip confined at the seismogenic depths (110–130 μ strains), while their stress drops are more different because of different layered rigidity structures.

We include other modified measures, such as $\overline{\Delta\sigma}_{E,10\%}$, $\overline{\Delta\sigma}_{E,20\%}$, $\bar{\epsilon}_{E,20\%}$, and $\bar{\epsilon}_{E,10\%}$, in Table A.6 for completeness. The larger differences between $\overline{\Delta\sigma}_E$, $\overline{\Delta\sigma}_{E,10\%}$, and $\overline{\Delta\sigma}_{E,20\%}$ for the Tohoku case may be due to the resolved spatial heterogeneity in slip distribution and stress changes.

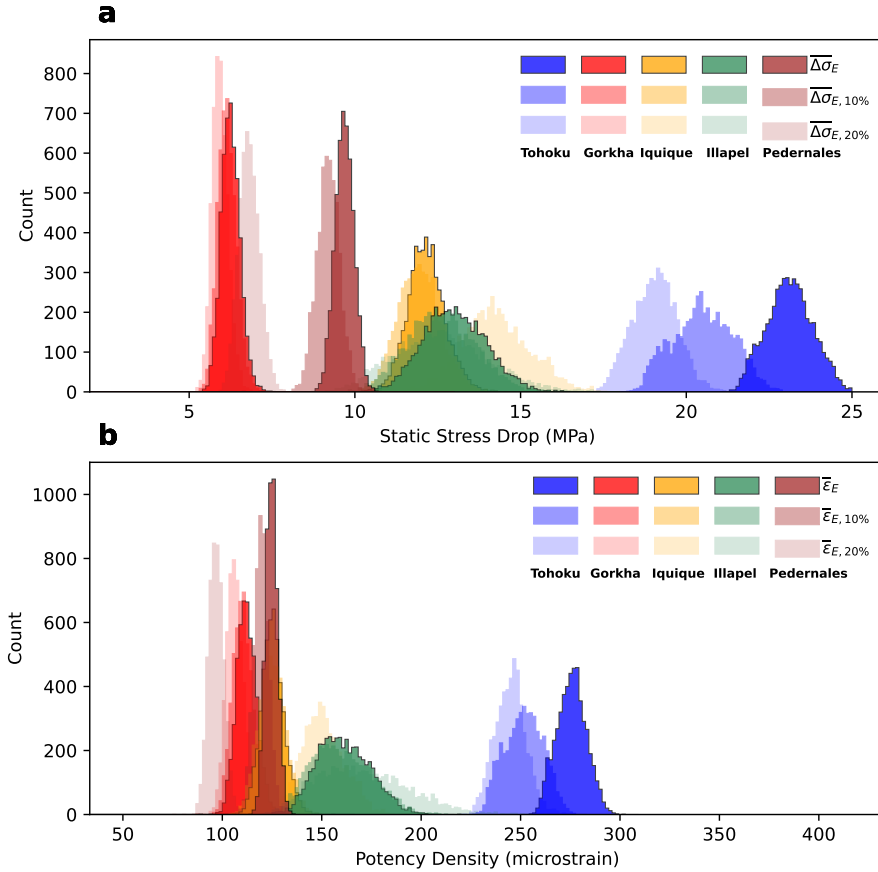


Figure 3.9: **Average static stress drop and potency density across events.** Probability distributions of (a) average static stress drop and (b) potency density estimates for M_w 9.0 Tohoku (blue), M_w 8.3 Illapel (red), M_w 8.1 Iquique (yellow), M_w 7.8 Pedernales (brown), and M_w 7.8 Gorkha (red). Histograms with high, medium, and low transparency represent (a) $\overline{\Delta\sigma}_E$, $\overline{\Delta\sigma}_{E,10\%}$, and $\overline{\Delta\sigma}_{E,20\%}$, and (b) $\bar{\epsilon}_E$, $\bar{\epsilon}_{E,10\%}$, and $\bar{\epsilon}_{E,20\%}$, respectively. Note that the horizontal ranges in two panels are proportional by $2G$, facilitating a comparison between scenarios with uniform and layered structures.

3.3 Dynamic Predictions

3.3.1 Dynamic Surface Deformation

For each earthquake, the evolution of the surface deformation field is shown as snapshots at logarithmically equal time intervals since the event initiation (Figure 3.10). Over a 256-s period, the final state of deformation largely agrees with static predictions. While the qualitative patterns in static cases are recovered, how this convergence occurs in time and space is different across events. We note that the convergence time from dynamic to permanent deformation above the fault surface varies according to earthquake size. For Pedernales and Gorkha, static deformation is resolved rapidly within ~ 60 s. Deformation for Iquique reaches its stable pattern within ~ 90 s. The convergence time for Illapel, with a slightly larger magnitude than Iquique, is longer by ~ 30 s. For the Tohoku, it takes ~ 165 s for the surface to reach a steady pattern. Beyond these periods, we resolve the permanent deformation fields.

The displacement field at the surface begins with two quasi-symmetric areas of uplift and subsidence centered above the hypocenter. Over time, these areas expand differently. Surface deformation in Gorkha and Pedernales tends to grow unevenly, while for Tohoku, Illapel, and Iquique, deformation fronts advance more radially. The dominant direction of horizontal motion is established from the outset. For Tohoku, Illapel, and Iquique, surface displacement primarily occurs in the trench-normal direction. In contrast, for the Gorkha and Pedernales regions, the horizontal displacement vectors trend obliquely.

Cumulative displacement curves reveal that convergence occurs earlier and faster in small earthquakes than in larger ones (Figure 3.11). In this respect, the transient portions of the displacement waveforms for Pedernales and Gorkha are closer in time

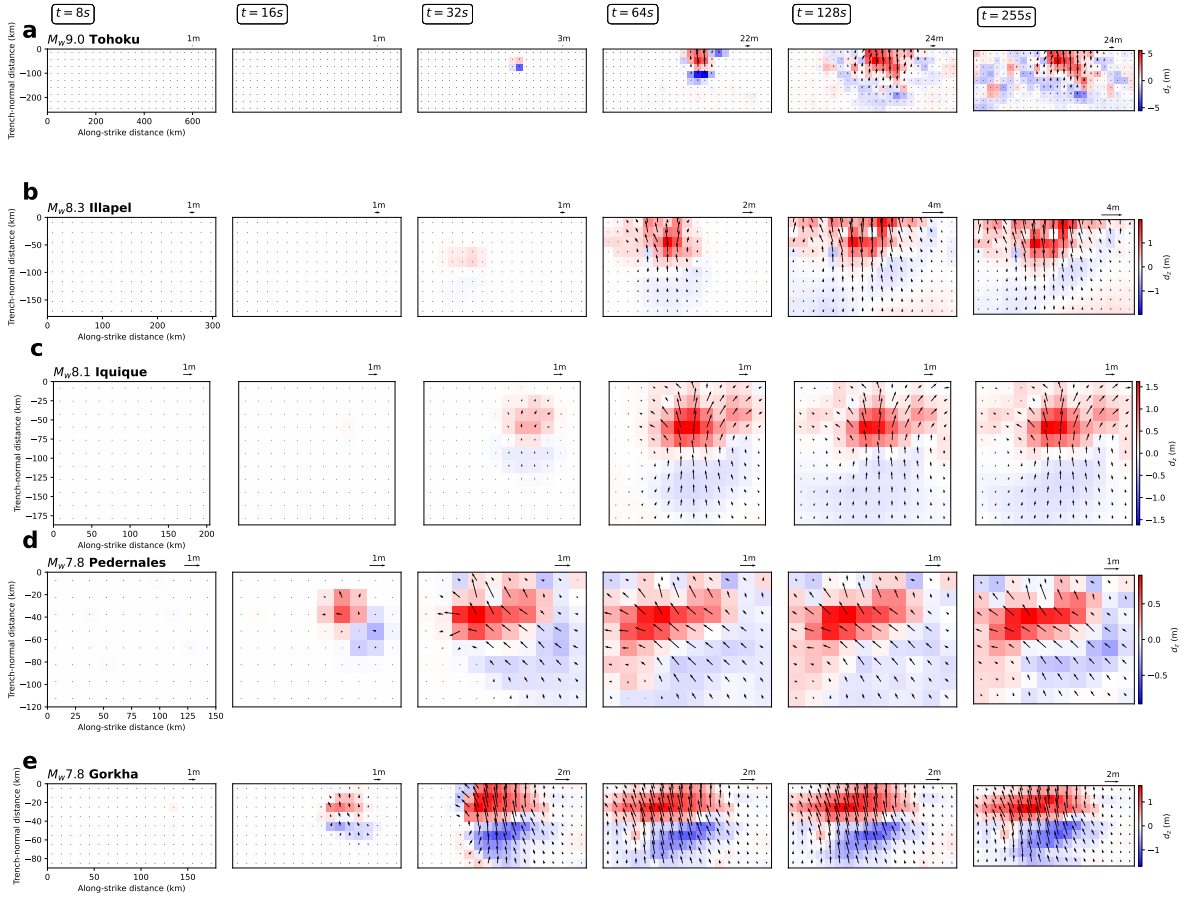


Figure 3.10: **Multi-event comparison of dynamic ground deformation.** Snapshots of surface displacement field over time for (a) M_w 9.0 Tohoku, (b) M_w 8.3 Illapel, (c) M_w 8.1 Iquique, (d) M_w 7.8 Pedernales, and (e) M_w 7.8 Gorkha for the first 256 s of the event. Horizontal movement is represented as a vector field with vertical deformation in color.

and steeper. For events above M_w 8, error and predictions have higher amplitudes at locations near the trench that gradually decrease away from it at longer transient periods (Figures 3.11 and A.11–A.15). Vertical displacement curves for far-field observation points remain near zero.

Similarly, distributions of absolute and relative uncertainties in the three static displacement components are also largely recovered from dynamic counterparts after a 256-s period (Figures A.11–A.15). As seismic waves arrive at the surface immediately

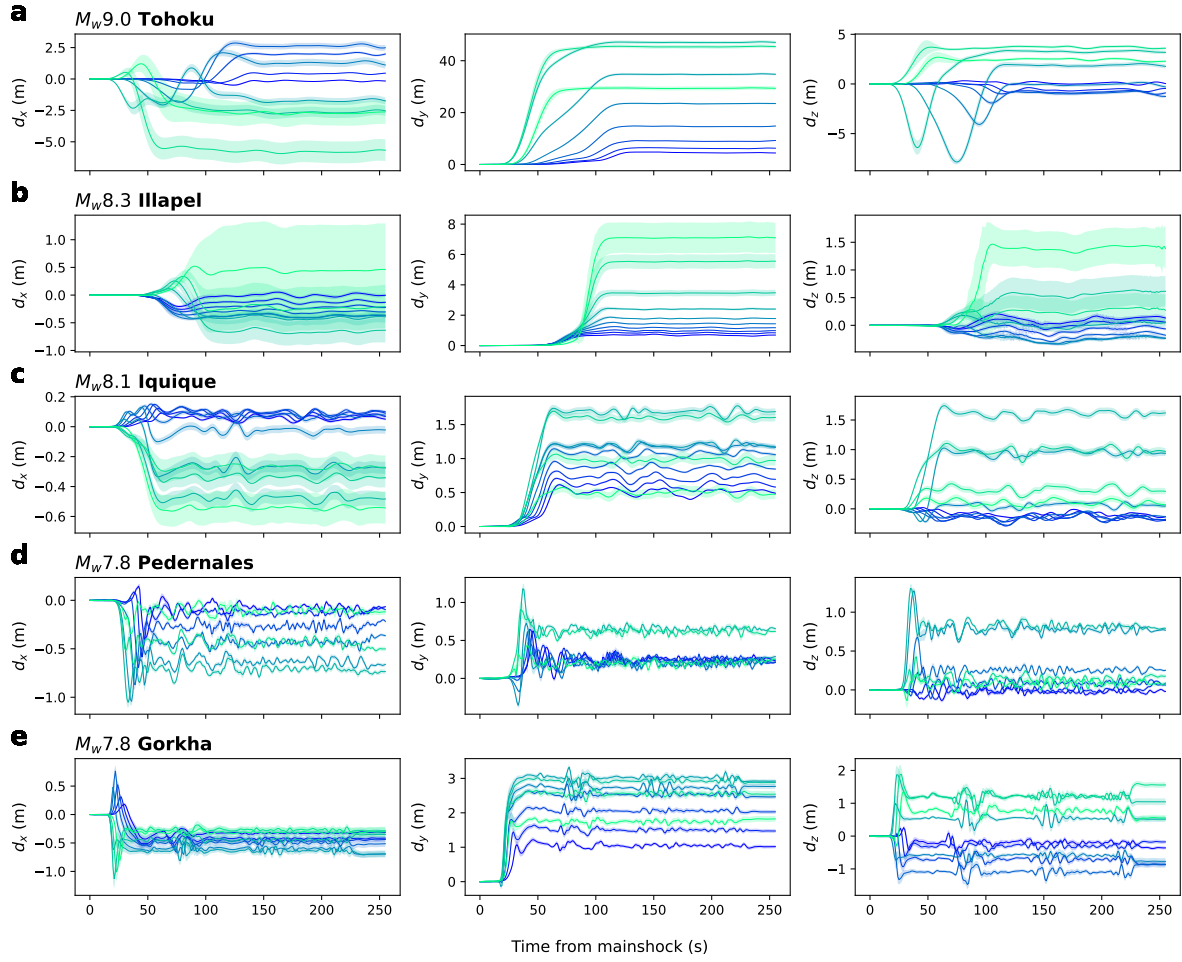


Figure 3.11: **Multi-event comparison of dynamic surface displacement waveforms and their variability with distance from the trench.** Mean displacement (colored lines) and 1- σ standard deviation (filled bands) time-series at points located along a trench-normal cross-section through the absolute peak displacement point within the first 256 s of (a) $M_w 9.0$ Tohoku, (b) $M_w 8.3$ Illapel, (c) $M_w 8.1$ Iquique, (d) $M_w 7.8$ Pedernales, and (e) $M_w 7.8$ Gorkha. Trench-parallel, trench-normal, and vertical components of displacements are shown in the left, center, and right columns, respectively. The colors indicate distance from the trench, with dark green and blue representing the location closest to and farthest from the trench, respectively.

above the rupture zone, non-zero errors emerge and spread out in different manners. At later times, for Tohoku, Illapel, and Iquique, prominent uncertainty builds up close to the trench, while for Pedernales and Gorkha, it extends more widely. Regarding relative errors, we find that very large values delineate boundaries similar to those in

the static case. Relative errors are large and widespread during the early stages, but this behavior diminishes over time. By comparing deformation components, we observe that large relative uncertainty in along-strike and vertical components cover a broader surface than in the trench-normal direction.

3.3.2 PGD Distribution and Scaling

We find that the spatial distribution of PGD agrees with the permanent displacement field qualitatively, with minor differences in amplitudes. We plot synthetic PGD values against hypocentral distance and angle from the strike line (positive clockwise) (Figure 3.12). Our PGD distributions versus hypocentral distance are broadly consistent with GNSS-based empirical scaling laws relating PGD, earthquake magnitude, and hypocentral distance (Melgar et al. 2015). However, discrepancies between predictions from our models and empirical laws become larger for smaller hypocentral distances (down to ~ 20 km, approximately equal to the depth of the event hypocenter), where near-source observations are often lacking. This is partly explained by the effect of finite earthquake size not adequately captured by field observations.

While the largest PGD amplitudes for Tohoku occur at near-source locations, this pattern does not hold for other events, where peak PGDs occur at intermediate hypocentral distances (~ 100 km for Gorkha and Illapel). The PGD variations over azimuthal angles measured from the strike line (Figure 3.12b) reveal the earthquake rupture directivity as the cause of complex multi-valued PGD estimates at the same hypocentral distance. While Tohoku exhibits a more uniform azimuthal distribution of PGD, Illapel and Gorkha events feature opposite trench-parallel propagation directions, giving rise to higher PGDs at -45° and 180° azimuthal angles, respectively. The PGD errors are minimal near the source and visibly large at distant locations, indicating that PGD is a robust measure of earthquake ground motion.

Furthermore, we examine how the maximum displacements of the horizontal and vertical components of displacement change with the distance to the hypocenter or W-phase centroid (Figure A.17). The results demonstrate that vertical displacement primarily contributes to PGD. It is also evident that the linear log-log scaling relation between PGD and distance is better retained in the near-source distances if we consider the W-phase centroid as the origin point. This reflects the effect of large earthquake rupture where deformation is controlled by the event centroid and less by the initiation point.

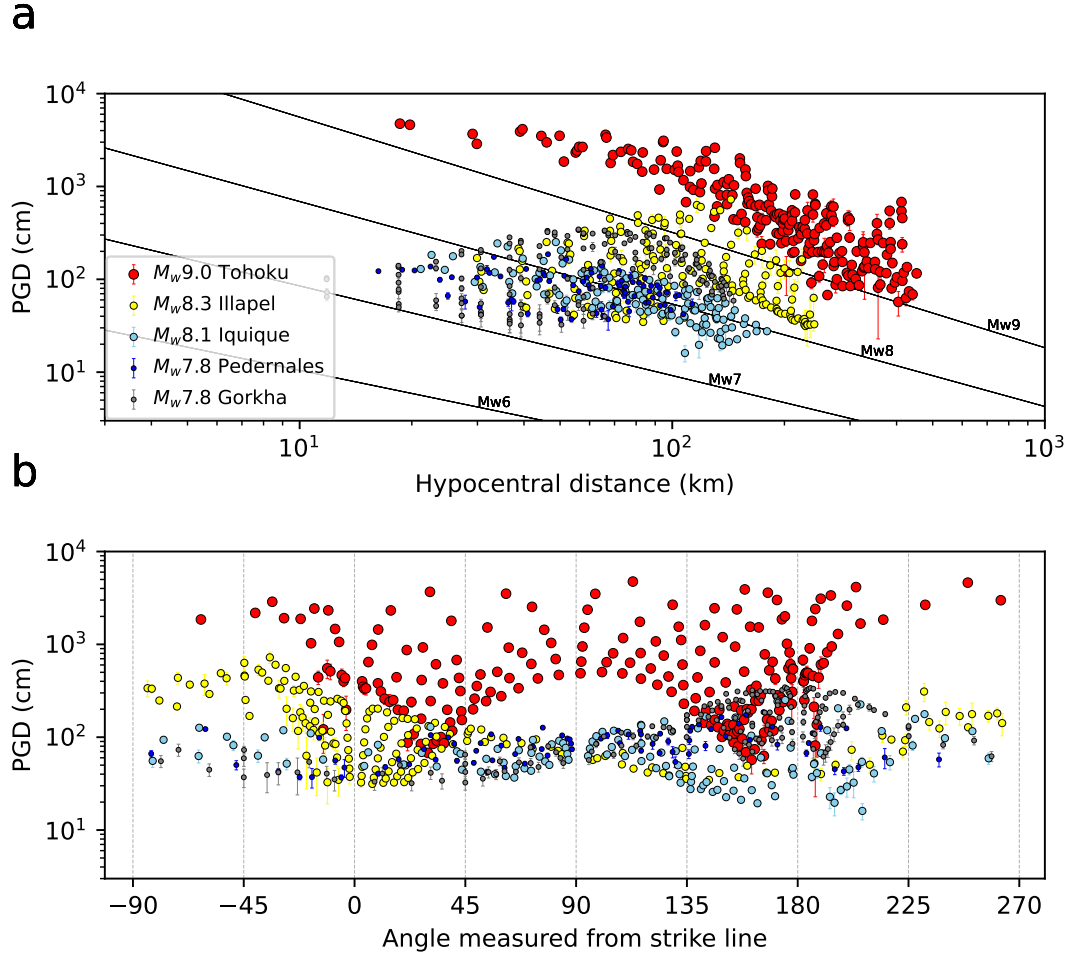


Figure 3.12: **Multi-event peak ground displacement (PGD) distributions as a function of hypocentral distance and angle from strike line.** PGD variations with (a) hypocentral distance and (b) angle measured from strike line (positive clockwise) for $M_w 9.0$ Tohoku (red), $M_w 8.3$ Illapel (yellow), $M_w 8.1$ Iquique (light blue), $M_w 7.8$ Pedernales (blue), and $M_w 7.8$ Gorkha (grey). Solid slanted lines define empirical scaling laws for $M_w 6-9$ (Melgar et al. 2016). Error bars represent 1σ credible intervals of calculated PGD values.

Chapter 4

Discussion

4.1 Interpretation of Rupture Parameter Relationship

The comparisons between kinematic rupture parameters show highly variable patterns in local correlation and intra-event correlation. A robust relationship common in most earthquakes is the locally positive correlation of (T_r, V_r) and negative correlation of $(U/T_r, V_r)$ in large-slip areas (panels g and h in Figures 3.1 and 3.2). This feature is intuitively expected because a faster rupture arrival time will trade-off with a longer rupture duration to produce similar timings of local moment release. In comparison, the pairs of (U, V_r) and (U, T_r) yield weaker correlations, with potentially negative and positive values, respectively. Such relationships are interesting, given that no a priori constraints have been applied to these parameters.

Interpreting intra-event correlations is more challenging because these measures are calculated from the posterior mean values over different fault areas without incorporating the associated uncertainty. In large-slip areas of most earthquakes, the posterior uncertainty of parameters at each patch is relatively small (except for Gorkha), which, in principle, allows the inference of a potential correlation relationship or lack thereof. For $(U/T_r, V_r)$, the correlation is more positive for Iquique (0.26) and Gorkha (0.6), slightly negative for Illapel (-0.18), and near zeros for others. For (U, V_r) , the correlation is positive for Gorkha (0.34) and Pedernales (0.28), negative for Iquique (-0.5), and near zeros for others. In addition, given adopted triangular STF, any relations

involving U/T_r holds true for the corresponding peak slip rate V_{peak} in these models. Overall, we conclude that there is a lack of strong intra-event correlation between kinematic parameters in general and no common simple relationship for all five earthquakes based on the analysis of these rupture models.

These empirical findings appear to contradict some predictions from dynamic earthquake rupture models. Simulations of subshear dynamic rupture scenarios suggest that peak fault slip rate increases with rupture speed (Schmedes et al. 2010; Bizzarri 2012; Gabriel et al. 2013) and that cumulative slip amplitude positively correlates with rise time (Schmedes et al. 2010). The positive correlation of V_{peak} and V_r is also observed in dynamic inversions of the 2004 M 6.0 Parkfield earthquake (Schliwa et al. 2024), but not in models incorporating thermal pressurization (Vyas et al. 2023). These discrepancies may arise from limitations in physical models, observational inferences, or both. From the physical perspective, the highly variable and sometimes different relationships between rupture parameters may result from the interplay of spatially heterogeneous pre-rupture stress and fault strengths, with the latter also dependent prior slip history and rupture process via complex fault constitutive relations. The essential physics or heterogeneity may be insufficiently accounted for in current dynamic models. From the observational perspective, temporal resolutions of the filtered time series data or STF parameterization adopted in kinematic inversions may fail to resolve the higher-frequency aspects of the rupture propagation (Schmedes et al. 2012). For example, the spatial distribution of inferred average fault slip rates U/T_r and V_r may be unrepresentative of true peak fault slip rates and rupture front speed, introducing spatially incoherent biases in large-slip areas that manifest in skewed parametric relations. Alternatively, choices in the source inversions, in particular the model prediction errors, might influence the posterior results and hamper our comparisons, which we further

discuss in Section 4.3. Future research are needed to explain and reconcile the discrepancies among our results and other physical models.

When analyzing all five events, the posterior space of rupture speed and average slip rate are less sensitive to earthquake magnitude than any other kinematic pair (Figure 3.3), because these variables appear to be confined to a more reduced subdomain across all events. This result suggests that fault slip rates during these large earthquakes are similarly large with over ~ 1 m/s. The finding is also consistent with field, laboratory, and theoretical studies (e.g., Gao et al. 2012; Chen et al. 2021; Weng and Ampuero 2022) that report similar earthquake rupture velocity across a wide range of earthquake sizes.

4.2 Evaluating Predictions and Uncertainty Quantification

The predictions of static deformation and stress changes follow the expected behavior of linear elastic problems. The most prominent permanently deformed regions are concentrated immediately above the fault plane, reflecting the rupture size and earthquake magnitude. The largest amplitudes of surface displacement and fault stress change occur in the trench-normal directions. The uncertainty in the displacement exhibits a different pattern, with the largest errors near the upper fault edge (or trench) and broadly decaying away. In comparison, the stress change fields and associated uncertainty are more heterogeneous in space.

Using different measures, we estimate average static stress drops for heterogeneous slip and stress changes for each event, yielding higher $\overline{\Delta\sigma_E}$ than $\overline{\Delta\sigma_{A,th}}$, as theoretically predicted by Noda et al. (2013). While global estimates of stress drop and potency density show large variability over several orders of magnitudes (Allmann and

Shearer 2009; Nanjundiah et al. 2020), our estimates of these parameters are comparatively tighter within one order of magnitude, with relative uncertainty well within 8% for all events. All earthquakes except for Tohoku have an average potency density of $\sim 100\text{--}130\ \mu\text{strains}$ and stress drops of $\sim 6\text{--}7.8\ \text{MPa}$ if assuming uniform G of $30\ \text{MPa}$ or $\sim 6\text{--}14\ \text{MPa}$ if accounting for depth-dependent rigidity. Interestingly, the three events (Pedernales, Iquique, Gorkha) with similar potency density values feature slip confined at seismogenic depths, whereas other models (Illapel and Tohoku) have tsunamigenic shallow fault slip, intimating a potential link between this quantity and rupture style. While the overall narrow range of potency density or elastic strain drop is consistent with a magnitude-invariant strain drop model (Vallée 2013), the decrease of this quantity with earthquake centroid depths is also consistent with those in a global compilations (Nanjundiah et al. 2020). Improved estimates from these and additional cases would be valuable for testing these suggested patterns and related models in the future.

For the Tohoku case, our stress drop estimates, $\overline{\Delta\sigma}_E$ of $23.1\pm 0.7\ \text{MPa}$, is on the higher end of published estimates. This estimate predominantly stems from localized fault patches with high slip and stress decreases in the heterogeneous model (Figure 3.6). While other Tohoku studies (e.g., Hasegawa et al. 2011; Hooper et al. 2013) also suggest overall or locally higher stress drops of over $10\ \text{MPa}$, compilations of finite-fault slip models yield averaged estimates on the order of $1\text{--}3\ \text{MPa}$ (Brown et al. 2015). This discrepancy can be partly explained by the different stress drop measures ($\overline{\Delta\sigma}_E$ always larger than $\overline{\Delta\sigma}_{A,\text{th}}$; Noda et al. 2013) and spatial smoothing of fault slip typically applied to regularize the otherwise under-determined inversions. While the selected Tohoku model can likely be improved with better error models and forward models (Section 4.3), the notable discrepancy between our estimate and other studies

demonstrate that even some first-order source parameter estimates are sensitive to the complexity of model inversions and source heterogeneity.

We test the static predictions of alternative Tohoku model ensembles from different cooling steps of the CATMIP algorithms (Appendix; A.18 and A.19), corresponding to effectively inflated amplitudes of $\mathbf{C}_\chi$. The comparison of these model results indicates that static predictions and their uncertainty structure are robustly captured by static model parameters, even before the full posterior of kinematic models are derived.

In our dynamic predictions, close agreement is attained between the static prediction and final displacements in dynamic predictions. The predictions reveal characteristics of ground motion and PGD in the data-sparse near field ($\sim 10\text{--}100\text{ km}$) (Figure 3.12). Predicted ground displacements feature temporally coherent relative uncertainty that are largest near the trench and source and decays to the far field (Figure 3.11). Notably, the larger near-field predictive uncertainty is partly inherited from slip uncertainty due to the lack of observations near the rupture zone and poor azimuthal data coverage, particularly in offshore rupture scenarios. Nonetheless, PGD estimates appear to be better resolved in the near field while their uncertainty increase with hypocentral distance.

4.3 Limitations and Implications

Our comparative analysis focuses on finite-fault rupture models of major earthquakes derived from a similar scheme of source inversion and uncertainty quantification. These models incorporate a diverse range of available geophysical datasets for each event. With this strategy, we can minimize the sources of bias arising from heterogeneous choices of model parameterization and inversions, which often challenge comparisons

of different finite-fault models. Hence, we expect that the relative differences in earthquake characteristics, especially first-order features, e.g., static stress drops and potency density, should be better resolved in our comparison.

Several sources of uncertainty still remain, for example, the observational and/or modeling errors encapsulated in the data-model misfit variance-covariance matrix $\mathbf{C}_\chi$. For example, the Tohoku model (Minson et al. 2014) adopts a simplified diagonal matrix of $\mathbf{C}_\chi$ with ad hoc modeling errors based on peak data amplitudes, whereas Iquique, Pedernales, and Illapel models account for errors in $\mathbf{C}_\chi$ due to imperfect elastic structures (Duputel et al. 2015; Gombert et al. 2018; Caballero et al. 2023). The simplified error model and potential data overfitting may partly explain the small uncertainty of Tohoku model parameters. Furthermore, the three-dimensional structure and topography (e.g., Masterlark et al. 2001; Hsu et al. 2011; Langer et al. 2020) are ignored in these rupture models, potentially comprising a source of biases in results if not fully accounted for in the model prediction errors. Consequently, the characterization of error structures and other modeling ingredients and their impacts on the relationships of posterior parameters and derivatives should be further investigated in the future.

We take advantage of kinematic finite-fault earthquake models to quantify relationships of physical parameters and simulate megathrust behavior with well-quantified uncertainty. The inferred kinematic characteristics can directly inform the development of physics-based models of earthquake rupture and sequences (e.g., Harris et al. 2009; Jiang et al. 2022; Erickson et al. 2020). The results complement the understanding of phenomena following megathrust earthquakes and motivate the incorporation of error analysis in published models simulating these processes, including aftershocks (e.g., King et al. 1994; Cattania et al. 2014), postseismic deformation (e.g., Liu et al. 2022; Jiang et al. 2021; Wang and Day 2017; Sun et al. 2014), tsunamis (e.g., Fujii et al.

2011; Melgar and Bock 2015; Jiang and Simons 2016), landslides (e.g., Kargel et al. 2016; Dunham et al. 2022), flooding (e.g., McEwan et al. 2023), and other geohazards (e.g., Fan et al. 2019). Well-quantified uncertainty in earthquake source models also has direct implications for structural and earthquake engineering (e.g., Kalkan and Kunnath 2006; Kamai et al. 2014; Burks and Baker 2016). Furthermore, as data assimilation and inversion methodologies become more sophisticated, it is essential to report derived results and their uncertainty to identify limitations in our inference and interpretation and facilitate continued improvements. In this sense, our work can be instructive for future research efforts in the application and refinement of Bayesian inversion techniques for earthquake modeling.

Chapter 5

Summary and Conclusions

To understand earthquake behavior and impacts, we analyze the Bayesian finite-fault models of five large (M_w 7.8–9.0) megathrust earthquakes spanning 2011–2016 to quantify the relationships of kinematic rupture parameters and predict static and dynamic observables and associated uncertainty. The incorporation of joint geophysical observations, consistent probabilistic inversion schemes, and no ad hoc regularization in these models facilitates cross-event comparisons at high spatial resolutions and with minimized relative biases.

For posterior exploration, we compare joint probability distributions between key kinematic rupture parameters and derive correlations over local fault patches and for the whole event. Even though many kinematic parameters appear locally well resolved, the local and intra-event correlations between most parameter pairs are weak and variable across events. The relationships between rupture speed, average/peak slip rate, and slip appear to contradict some simple theoretical predictions obtained from single-event dynamic earthquake rupture models. These discrepancies could be attributed to the different high-frequency information in data-based inversions and these models, real-world complexity and heterogeneity not yet incorporated in these physical models, or model parameterization and prediction errors unaccounted for in these source inversions. Future efforts are needed to identify the causes of these discrepancies and mitigate uncertainty and biases.

For predictive analysis, we derive spatial distributions of static and dynamic displacements, static fault stress changes, and their associated absolute and relative uncertainties. Besides identifying salient spatial patterns expected for the linear elastic problem, we assess characteristics of fault slip, displacements, and stress changes for these megathrust events from the trench to the coast and examine how the uncertainty of predicted observables depend on source feature and uncertainty, data coverage, and error models adopted in the inversions.

In particular, we perform comparative analyses of event-averaged static stress drop and elastic strain drop (potency density), as well as PGD scaling, for the five earthquakes. We find very close agreement of potency density for all events ($\sim 250\text{--}300\ \mu\text{strain}$ for Tohoku and $\sim 100\text{--}200\ \mu\text{strain}$ for others), while stress drop estimates considering depth-dependent rigidity structure are characterized by slightly more variable values, albeit still within an order of magnitude ($\sim 21\text{--}25\ \text{MPa}$ for Tohoku and $\sim 5\text{--}15\ \text{MPa}$ for others). The predicted PGD exhibits similar scaling with hypocentral distance as empirical observations but illustrates the near-source effects of finite rupture dimensions and directivity. Although covering a small sample set of events with a narrow magnitude range, these results serve as the first step to quantitatively explore the nature of event or magnitude (in)dependence of earthquake source parameters.

Our workflow for Bayesian posterior and predictive analysis is applicable to other finite-fault models. While selected Bayesian earthquake source models can be improved with more accurate error models and elastic structural models, our comparative analysis reduces potential common errors and helps reveal relative differences between these significant events with well-quantified uncertainties and posterior predictive errors. These results can provide quantitative measures to compare and validate models of earthquake ruptures and derivative phenomena.

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Appendix

1 Alternative Posterior Model Ensembles

Choices of different model prediction errors, $\mathbf{C}_\chi$, influence the estimates and uncertainty of inferred model parameters (Tarantola 2005). In the CATMIP algorithm, the posterior is sampled through a series of M cooling steps with different β_m , involving intermediate model ensembles, $p(\mathbf{m}|\mathbf{d}, \beta_m)$, as follows:

$$\begin{aligned} p(\mathbf{m}|\mathbf{d}, \beta_m) &\propto p(\mathbf{m})p(\mathbf{d}|\mathbf{m})^{\beta_m}, \\ m &= 0, 1, \dots, M, \\ 0 = \beta_0 &< \beta_1 < \dots < \beta_M = 1. \end{aligned}$$

For example, the Tohoku model from Minson et al. (2014) corresponds to the final (52nd) cooling step ($\beta = 1$) in the convergence simulation, which yields the posterior distribution defined by the Bayes' theorem. We test the differences of alternative posterior models for the Tohoku earthquake from cooling steps 37 and 44 (β of 0.253 and 0.505, respectively) in predictions of 3D static surface deformation and uncertainty (Figures Figure A.18– A.19). Based on the expression of $p(\mathbf{d}|\mathbf{m})$ (Equation 2.6), these models are equivalent to the posteriors with misfit covariance of approximately $4\mathbf{C}_\chi$ and $2\mathbf{C}_\chi$, essentially with 2 and 1.412 times the adopted standard deviations. Compared to outcomes from the final posterior ensemble, we notice negligible differences in the mean predictions of static variables. However, uncertainty reveals some small discrepancies in large-deformation areas, with errors changing from slightly broader to more localized and less amplified. This test demonstrates that intermediate posterior models with different effective errors (same covariance structure) has a largely proportional influence

on the uncertainty of static predictions, but the consequences for kinematic observables are likely more significant.

2 Supplementary Tables

Tables A.1– A.4 show layered elastic structures used for simulating static and dynamic surface deformation. For the dynamic simulations, we use the same p- and s-wave quality factors for all earthquakes: $Q_p = 1000$ and $Q_s = 500$ as employed in Minson et al. (2014).

Table A.1: **Layered elastic structure for Tohoku**

Thickness (km)	V_p (km/s)	V_s (km/s)	ρ (g/cm ³)	μ (GPa)
2.8	5.0	2.7	2.5	18.2
5.0	5.7	3.3	2.7	29.4
8.2	6.0	3.4	2.75	31.8
16.0	6.7	3.9	2.9	44.1
∞	7.7	4.5	3.3	66.8

Taken from Minson et al. (2014)

Table A.2: **Layered elastic structure for Iquique and Illapel**

Thickness (km)	V_p (km/s)	V_s (km/s)	ρ (g/cm ³)	μ (GPa)
2.5	5.37	3.09	2.10	20.0
2.0	5.55	3.19	2.60	26.5
2.0	5.72	3.29	2.60	28.1
2.0	5.89	3.39	2.60	30.0
2.0	5.98	3.44	2.60	30.8
4.5	6.80	3.75	2.60	36.6
5.0	6.81	3.88	2.90	43.7
5.0	6.95	3.94	2.90	45.0
5.0	6.98	4.05	2.90	47.6
5.0	7.11	4.11	3.10	52.4
5.0	7.41	4.18	3.10	54.2
5.0	7.69	4.30	3.10	57.3
5.0	8.05	4.39	3.10	59.7
10.0	8.48	4.73	3.10	69.4
∞	8.48	4.78	3.10	70.8

Modified from Husen et al. (1999) and Duputel et al. (2015)

Table A.3: **Layered elastic structure for Pedernales**

Thickness (km)	V_p (km/s)	V_s (km/s)	ρ (g/cm ³)	μ (GPa)
4.2	3.39	1.96	1.686	6.48
23.3	5.86	3.39	2.553	29.3
∞	8.07	4.66	3.325	72.2

Taken from Nocquet et al. (2016)

Table A.4: **Layered elastic structure for Gorkha**

Thickness (km)	V_p (km/s)	V_s (km/s)	ρ (g/cm ³)	μ (GPa)
4.0	5.50	3.20	2.11	21.6
20.0	5.70	3.20	2.72	27.8
22.0	6.30	3.70	2.79	38.2
∞	8.21	4.55	3.38	70.0

Taken from Yue et al. (2017)

Table A.5: **Intra-event correlation coefficients between kinematic parameters**

Earthquake	Slip Threshold ^a	(U, V_r)	(U, T_r)	(T_r, V_r)	$(U/T_r, V_r)$
Tohoku	10%	−0.3305	0.0477	0.1601	−0.3562
	20%	−0.2073	−0.0153	0.192	−0.2468
	30%	0.0567	0.1659	0.1165	0.007
Illapel	10%	−0.1164	−0.1189	−0.1609	−0.0456
	20%	−0.2605	−0.0675	−0.2462	−0.1217
	30%	−0.1053	−0.0588	−0.162	−0.1812
Iquique	10%	−0.1038	0.1105	−0.1426	0.0917
	20%	−0.1653	0.096	−0.0898	0.1184
	30%	−0.5013	0.5078	−0.5154	0.2644
Pedernales	10%	0.1793	0.101	−0.2424	0.207
	20%	0.2944	0.1969	0.2428	0.3128
	30%	0.2771	0.1714	−0.0221	0.0366
Gorkha	10%	0.4699	−0.5074	−0.6009	0.5978
	20%	0.3133	−0.4498	−0.6496	0.5358
	30%	0.3384	−0.4601	−0.6899	0.5988

^a Correlation is estimated for fault patches with slip exceeding a threshold percentage (th%) of the maximum slip.

Table A.6: **Event-averaged static stress drop and potency density**

Event	$\overline{\Delta\sigma_E}$ (MPa)	$\overline{\Delta\sigma_{E,10\%}}$	$\overline{\Delta\sigma_{E,20\%}}$	$\overline{\Delta\sigma_{A,10\%}}$	$\overline{\Delta\sigma_{A,20\%}}$
Tohoku	23.1 ± 0.7	20.5 ± 0.9	19.0 ± 0.7	5.6 ± 0.6	13.4 ± 0.9
Illapel	13.0 ± 0.9	12.6 ± 1.0	12.6 ± 1.4	2.3 ± 0.5	4.9 ± 1.2
Iquique	12.2 ± 0.6	11.9 ± 0.6	14.3 ± 1.0	3.2 ± 0.4	7.0 ± 0.8
Pedernales	9.7 ± 0.3	9.2 ± 0.3	6.0 ± 0.3	0.8 ± 0.1	3.2 ± 0.3
Gorkha	6.2 ± 0.3	6.1 ± 0.3	5.9 ± 0.2	1.5 ± 0.2	3.6 ± 0.3
	$\bar{\epsilon}_E$ (μ strain)	$\bar{\epsilon}_{E,10\%}$	$\bar{\epsilon}_{E,20\%}$	$\bar{\epsilon}_{A,10\%}$	$\bar{\epsilon}_{A,20\%}$
Tohoku	275.6 ± 7.3	251.7 ± 9.4	244.9 ± 7.7	68.1 ± 6.3	164.5 ± 9.2
Illapel	161.1 ± 13.3	159.5 ± 15.1	171.0 ± 22.5	32.7 ± 6.7	70.9 ± 17.9
Iquique	125.3 ± 5.7	125.1 ± 6.7	150.5 ± 10.8	32.1 ± 3.8	73.6 ± 8.0
Pedernales	124.7 ± 3.0	119.5 ± 3.7	97.0 ± 3.7	10.8 ± 1.1	39.7 ± 3.4
Gorkha	112.3 ± 5.0	110.2 ± 5.0	106.4 ± 4.3	26.8 ± 3.4	64.3 ± 4.8

3 Supplementary Figures

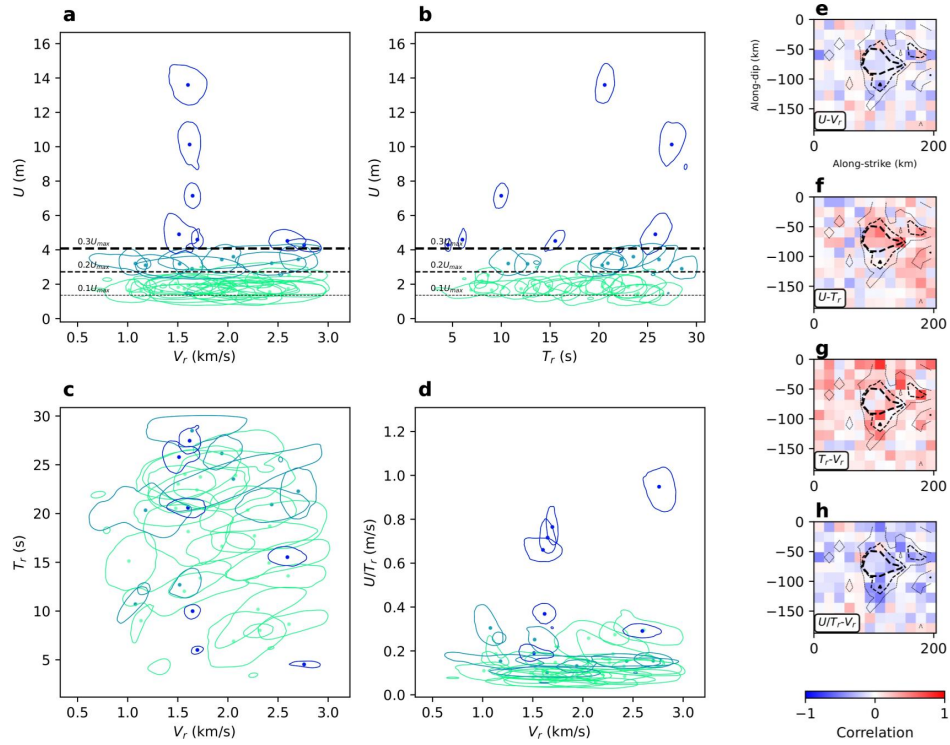


Figure A.1: **Exploration of posterior parameters for the Iquique rupture model** (a–d) Joint probability distributions of (a) slip and rupture speed (U, V_r), (b) slip and rupture duration (U, T_r), (c) rupture duration and speed (T_r, V_r), and (d) average slip rate and rupture speed ($U/T_r, V_r$). Solid contours represent 68% of posterior probability density and enclose posterior mean values of a parameter pair for each fault patch. *Intra-event correlation* is computed over all fault patches for each parametric pair. Patches with slip exceeding different thresholds (10%, 20%, and 30%; dashed lines) of maximum slip amplitude are shown in different colors. (e–h) Spatial distributions of *local correlation* at each patch between (e) (U, V_r), (f) (U, T_r), (g) (T_r, V_r) and (h) ($U/T_r, V_r$). Dashed lines mark contours of 10%, 20%, and 30% of peak slip.

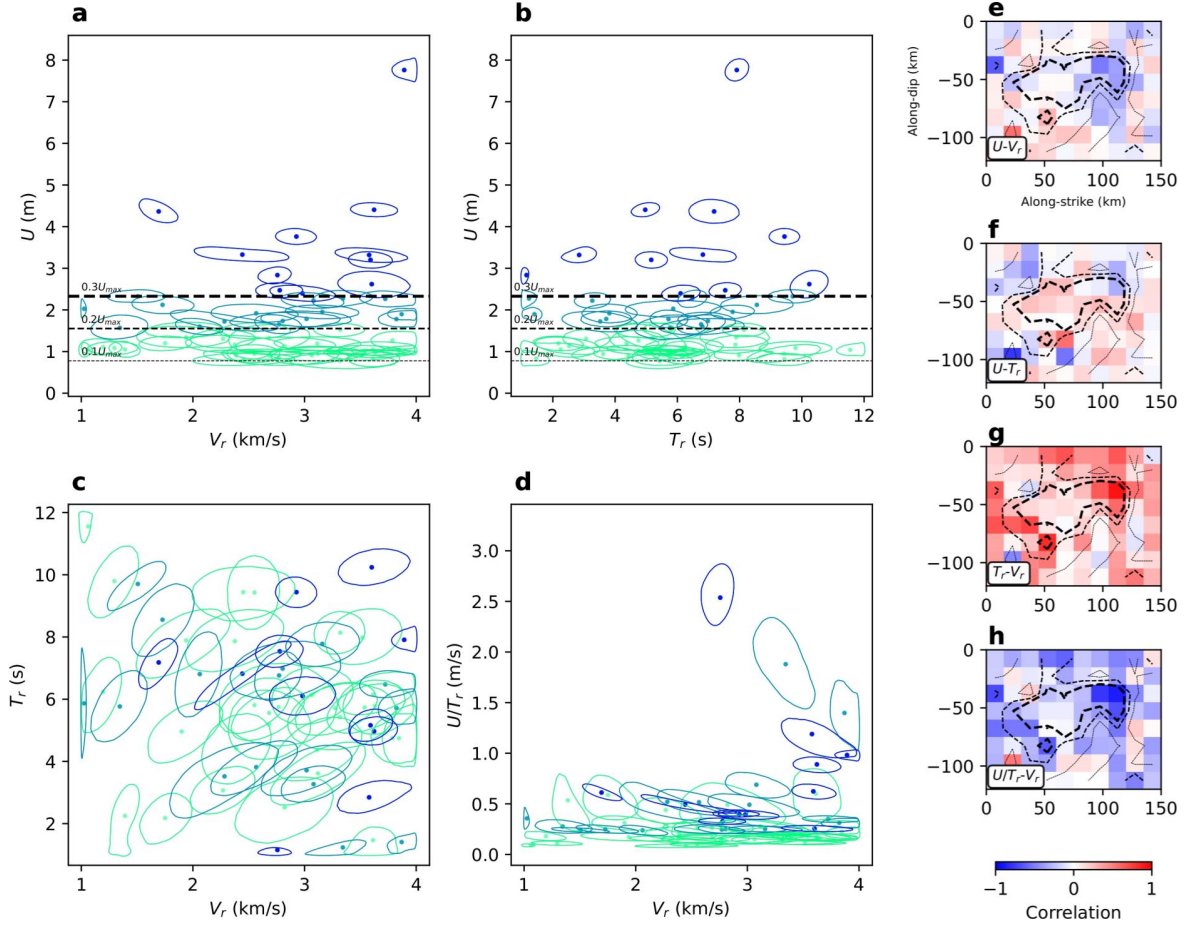


Figure A.2: **Exploration of posterior parameters for the Pedernales rupture model.** Plotting conventions are the same as in Figure A.1

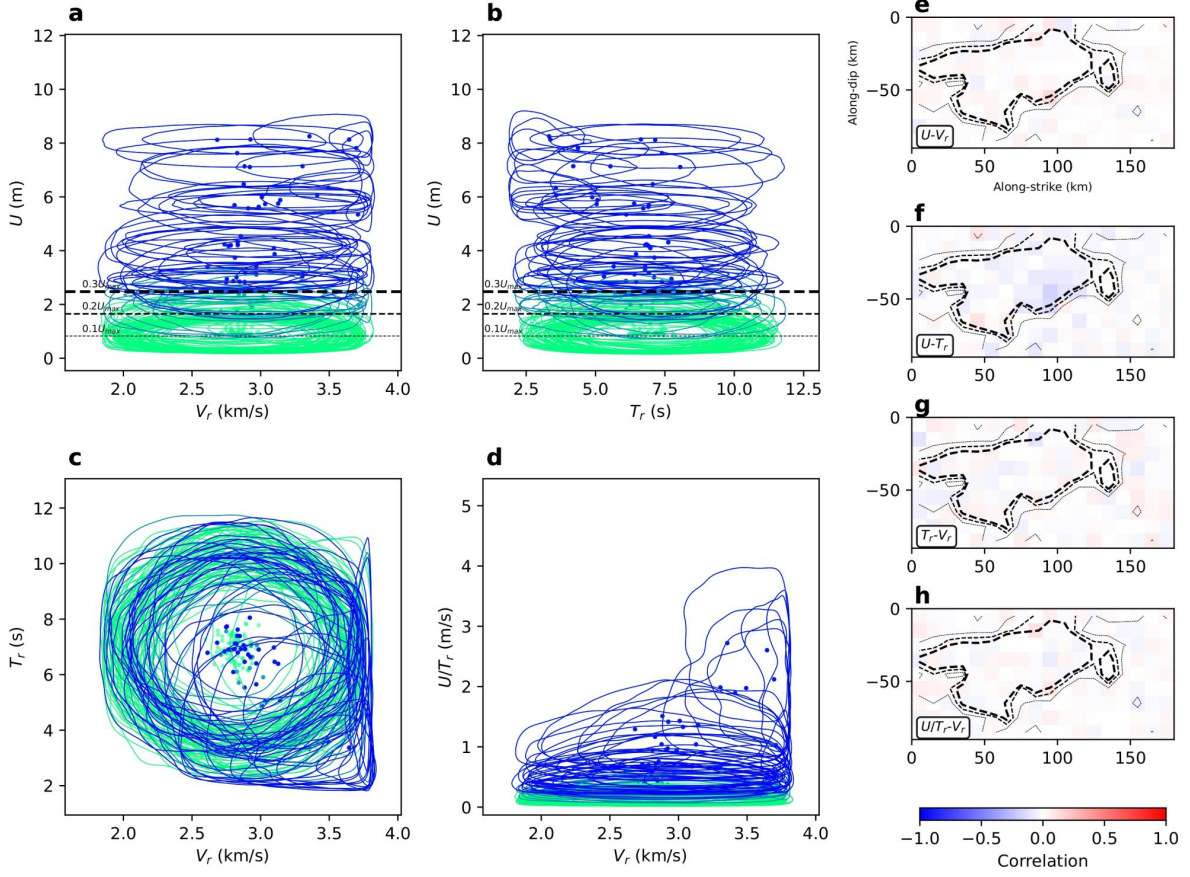


Figure A.3: **Exploration of posterior parameters for the Gorkha rupture model.** Plotting conventions are the same as in Figure A.1.

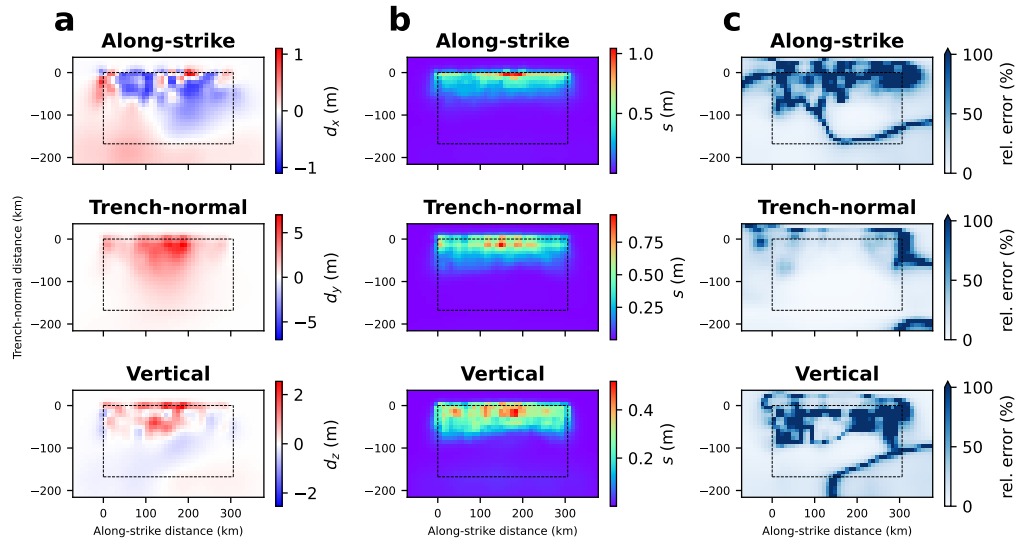


Figure A.4: **Static surface deformation and associated uncertainty for the M_w 8.3 Illapel event.** (a) 3D permanent surface deformation field, (b) uncertainty (1σ) distribution, and (c) relative error distribution. The along-strike, trench-normal, and vertical components of variables are shown in the top, middle, and top panels, respectively. The dashed lines indicate the surface projection of the fault geometry in all panels.

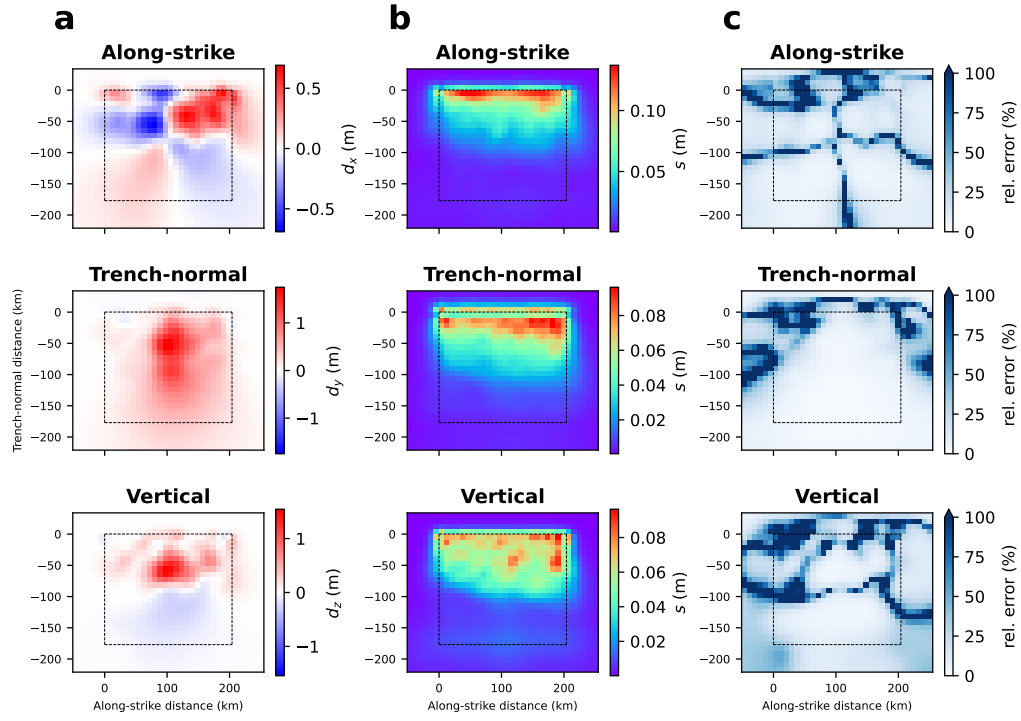


Figure A.5: **Static surface deformation and associated error for the $M_w 8.1$ Iquique event.** Plotting conventions are the same as in Figure A.4.

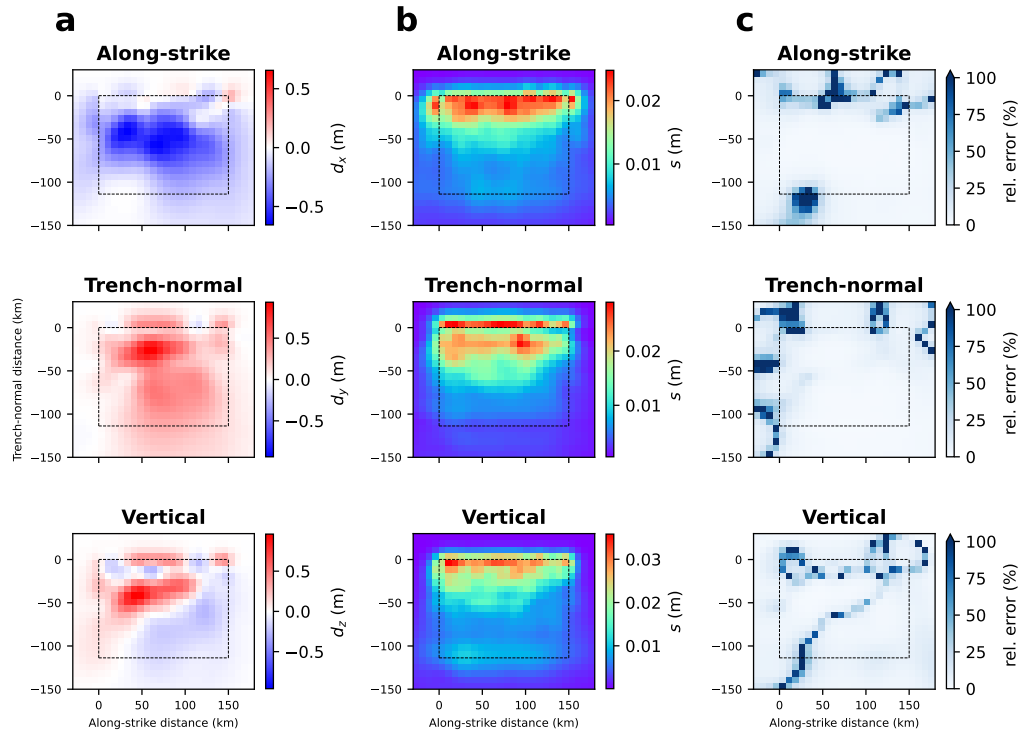


Figure A.6: **Static surface deformation and associated error for the $M_w 7.8$ Pedernales event.** Plotting conventions are the same as in Figure A.4.

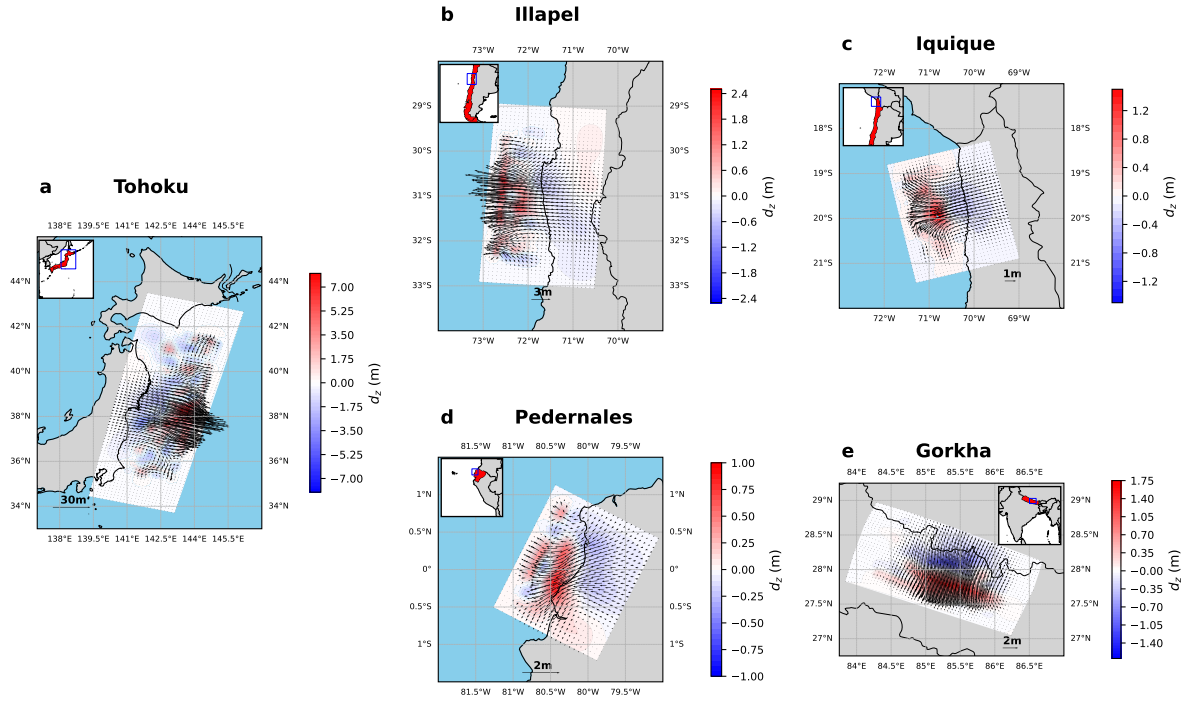


Figure A.7: **3D static deformation field across all earthquakes.** Permanent deformation in (a) Japan, (b) Central Chile, (c) Northern Chile, (d) Ecuador, and (e) Nepal due to the Tohoku, Illapel, Iquique, Pedernales, and Gorkha earthquakes, respectively.

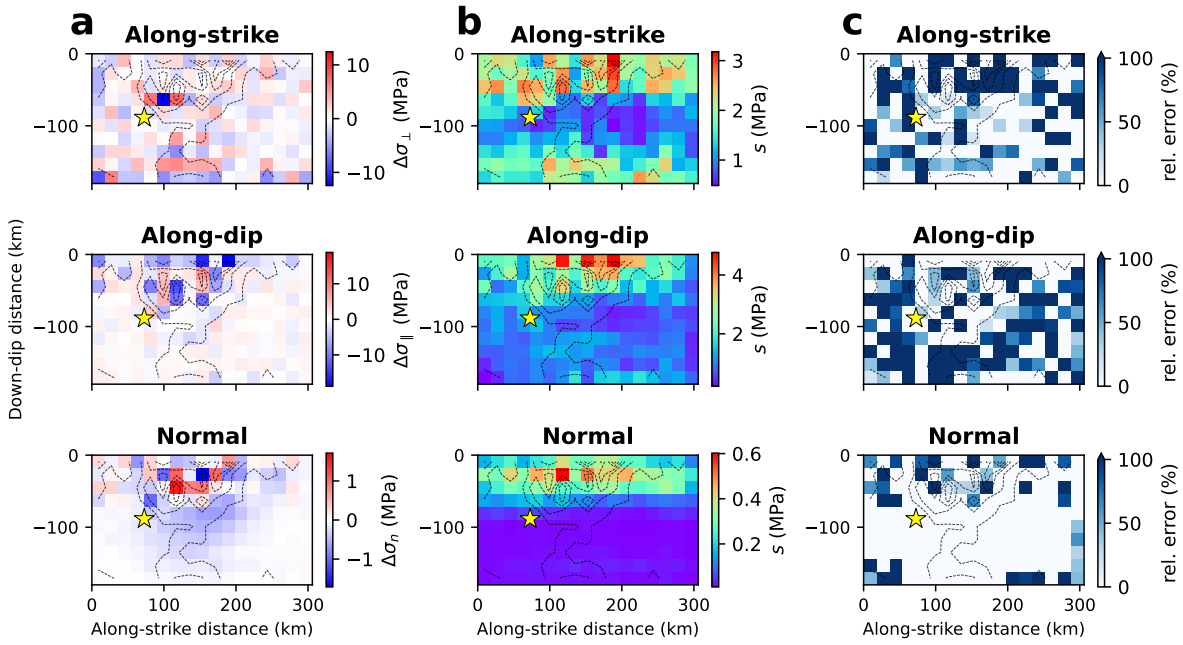


Figure A.8: **Static fault stress change and associated uncertainty for the M_w 8.3 Illapel event.** (a) 3D stress change on fault surface, (b) uncertainty (1σ) distribution, and (c) relative error distribution. The along-strike, along-dip, and fault-normal components of on-fault traction vectors are shown in the top, middle, and top panels, respectively. Thin dashed lines indicate contours of coseismic slip. The hypocenter is marked by a yellow star.

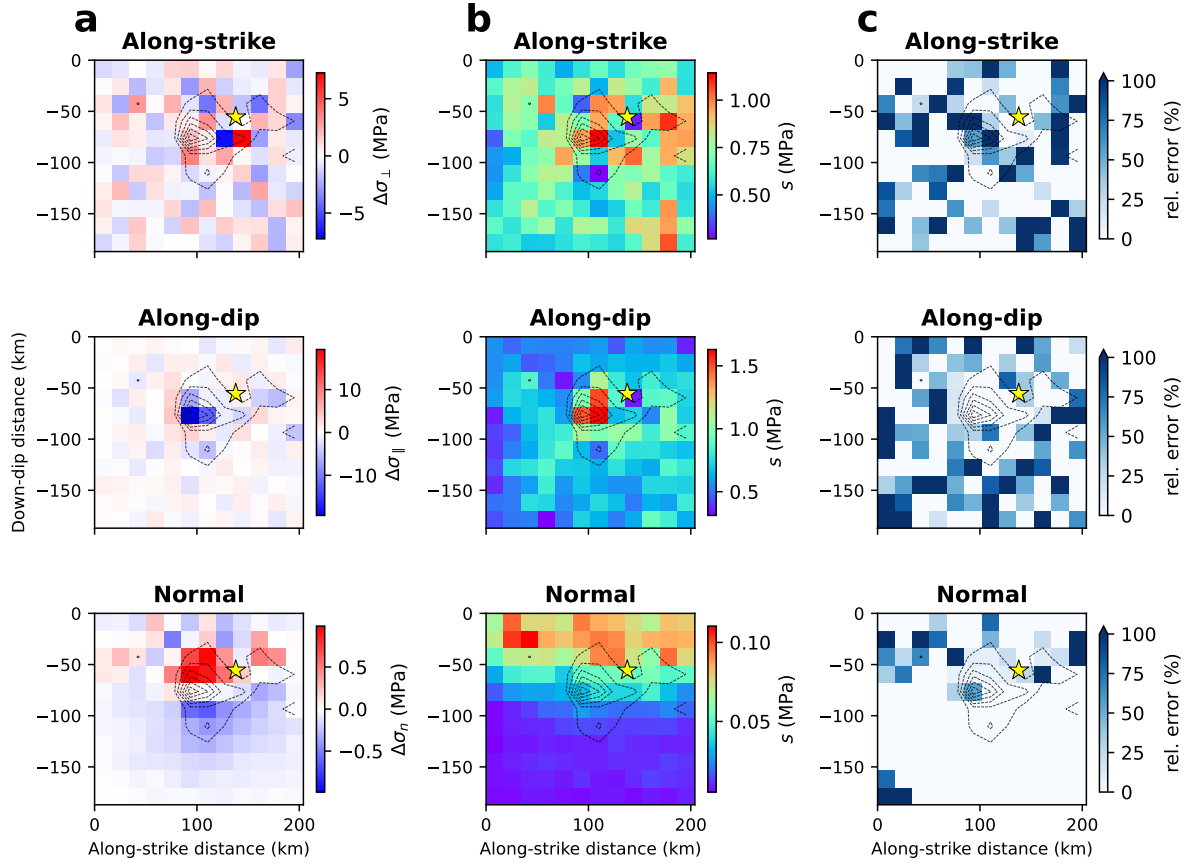


Figure A.9: Static fault stress change and associated uncertainty for the $M_w 8.1$ Iquique event. Plotting conventions are the same as in Figure A.8.

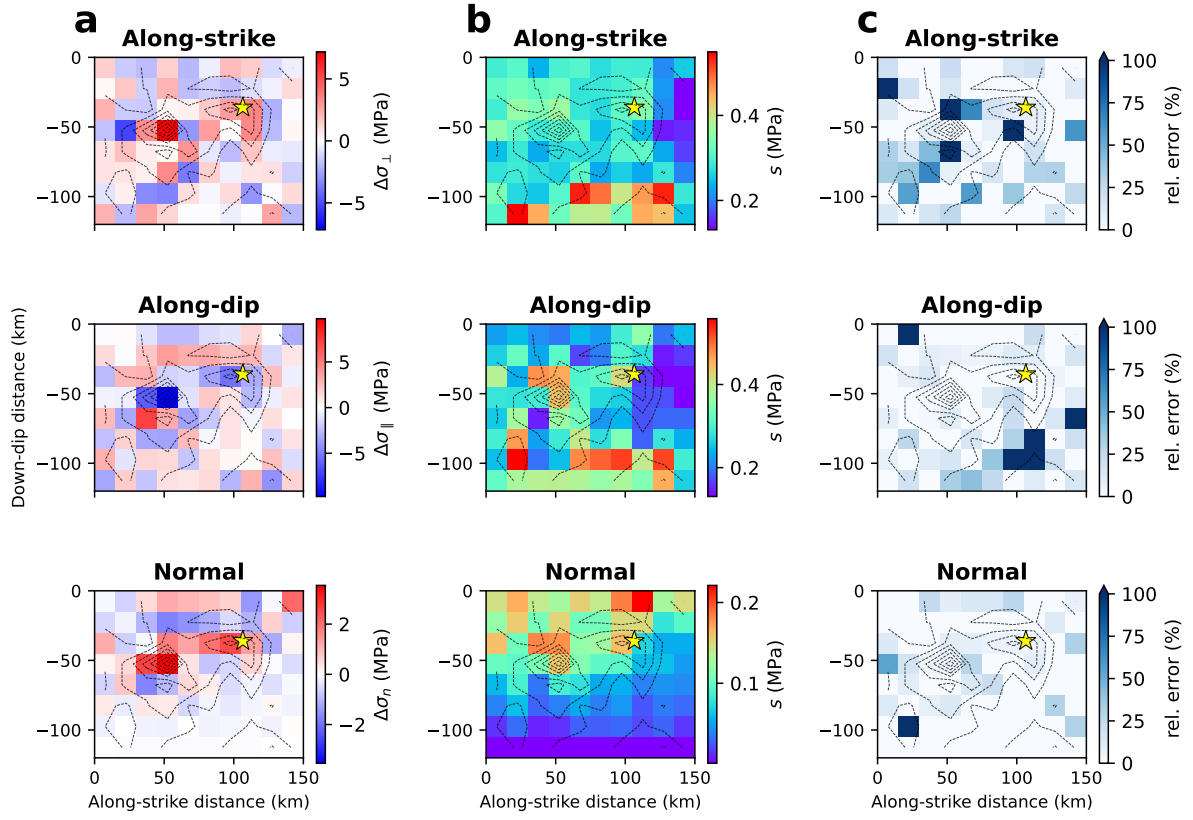


Figure A.10: **Static fault stress change and associated uncertainty for the $M_w 7.8$ Pedernales event.** Plotting conventions are the same as in Figure A.8.

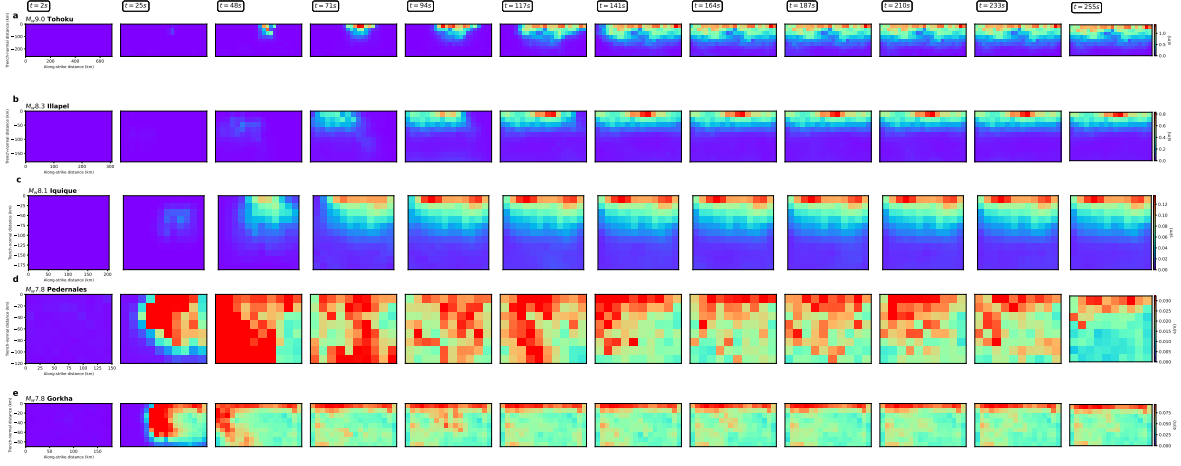


Figure A.11: **Multi-event evolution of uncertainty in along-strike surface displacement.** Snapshots of along-strike surface displacement error for (a) M_w 9.0 Tohoku, (b) M_w 8.3 Illapel, (c) M_w 8.1 Iquique, (d) M_w 7.8 Pedernales, and (e) M_w 7.8 Gorkha over common times for the first 256 s after the main shocks.

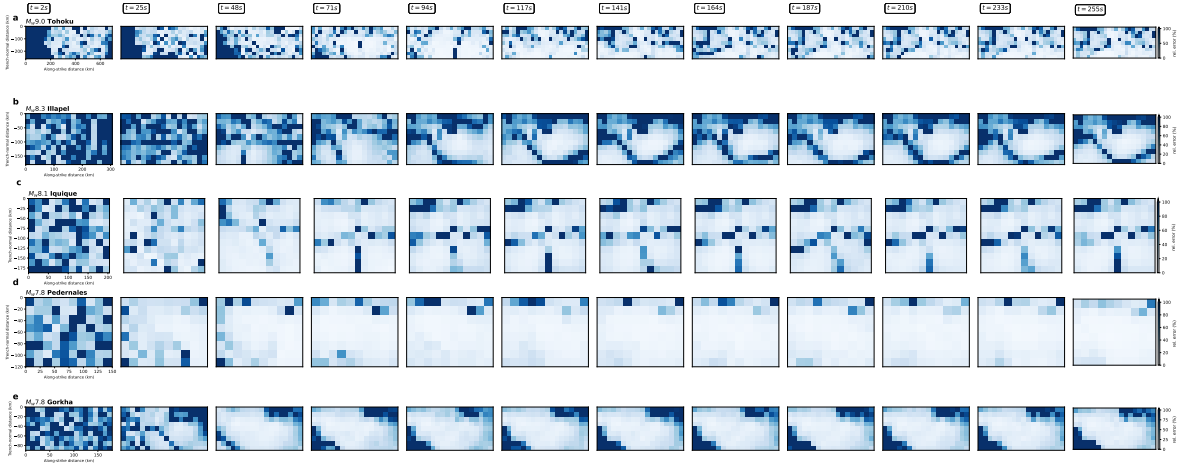


Figure A.12: **Multi-event evolution of relative uncertainty in along-strike surface displacement.** Plotting conventions are the same as in Figure A.11.

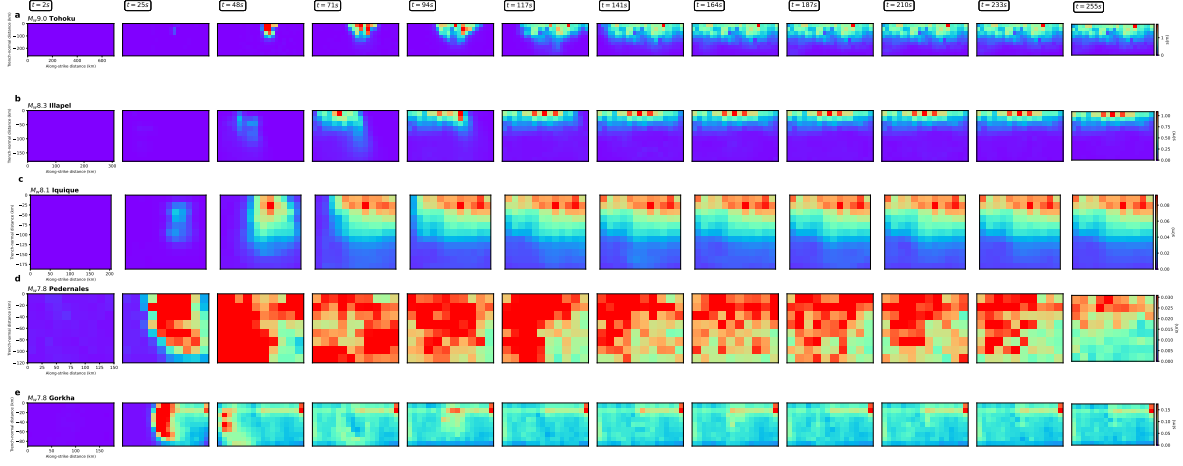


Figure A.13: **Multi-event evolution of uncertainty in trench-normal surface displacement.** Plotting conventions are the same as in Figure A.11.

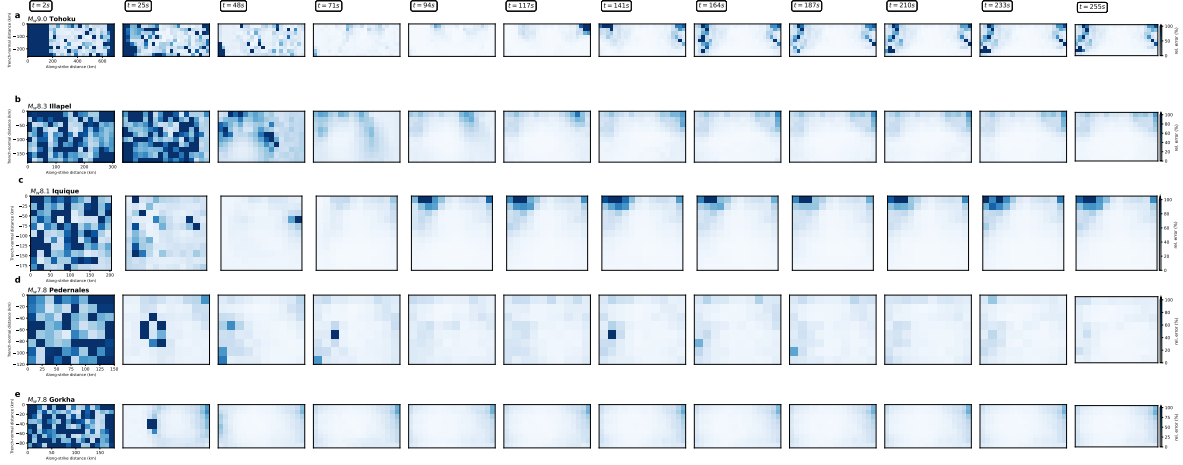


Figure A.14: **Multi-event evolution of relative uncertainty in trench-normal surface displacement.** Plotting conventions are the same as in Figure A.11.

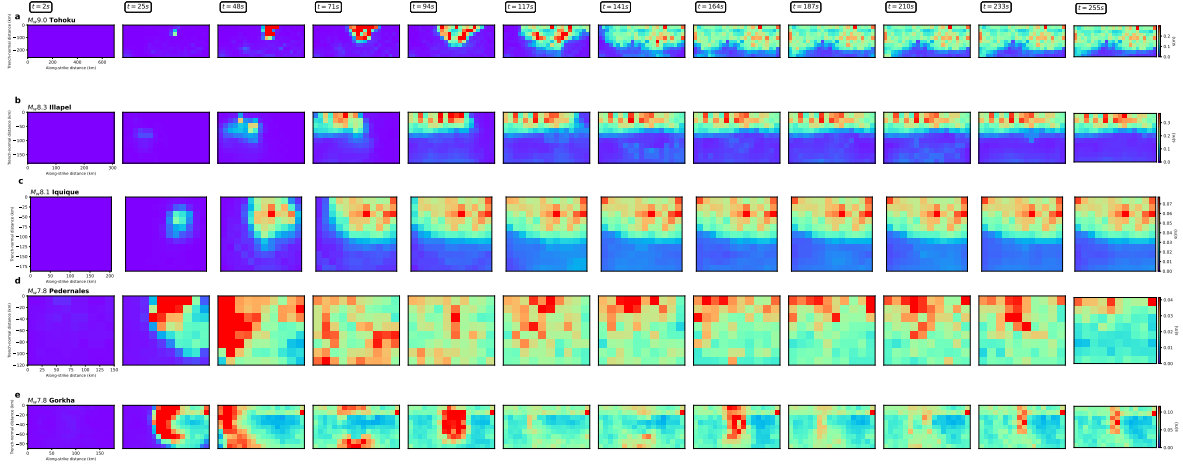


Figure A.15: **Multi-event evolution of uncertainty in vertical surface displacement.** Plotting conventions are the same as in Figure A.11.

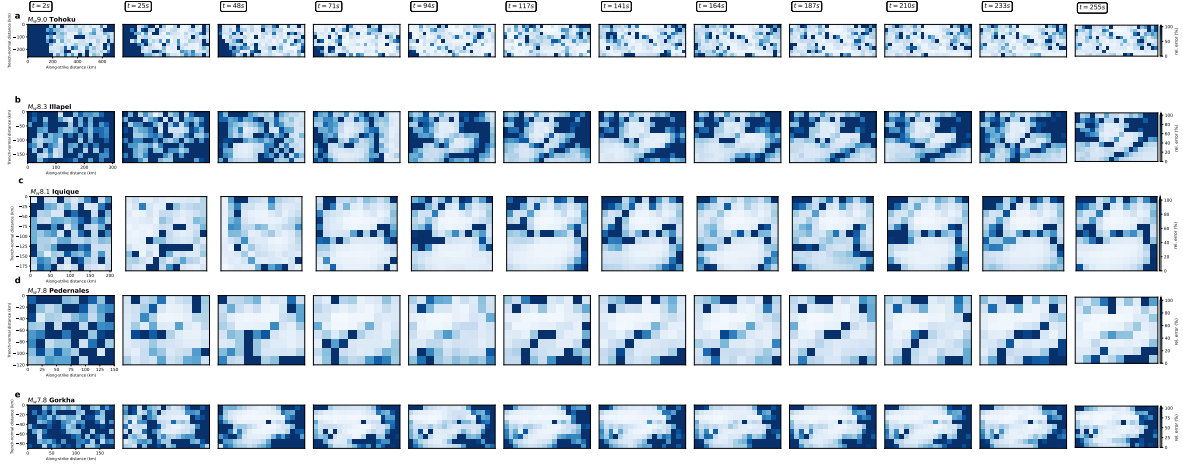


Figure A.16: **Multi-event evolution of relative uncertainty in vertical surface displacement.** Plotting conventions are the same as in Figure A.11.

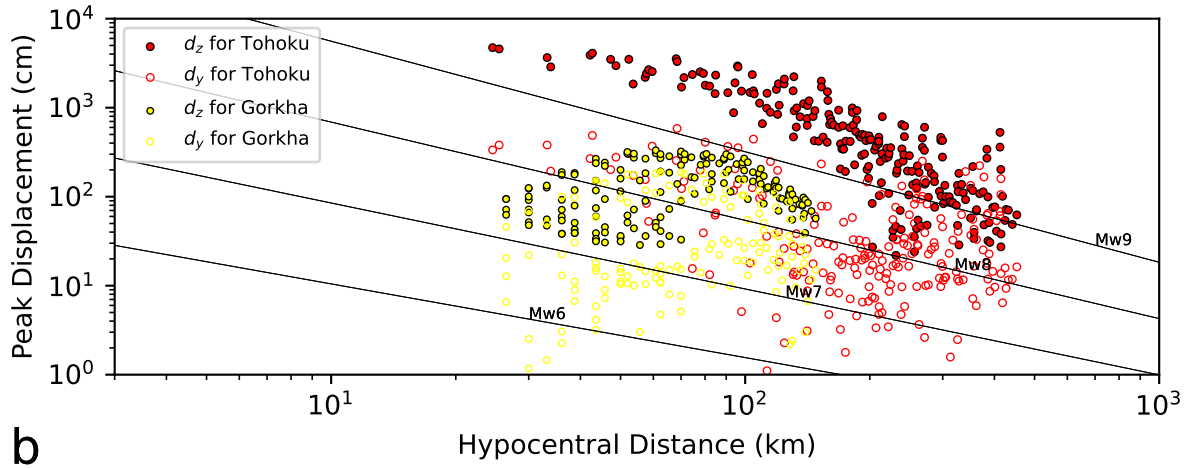
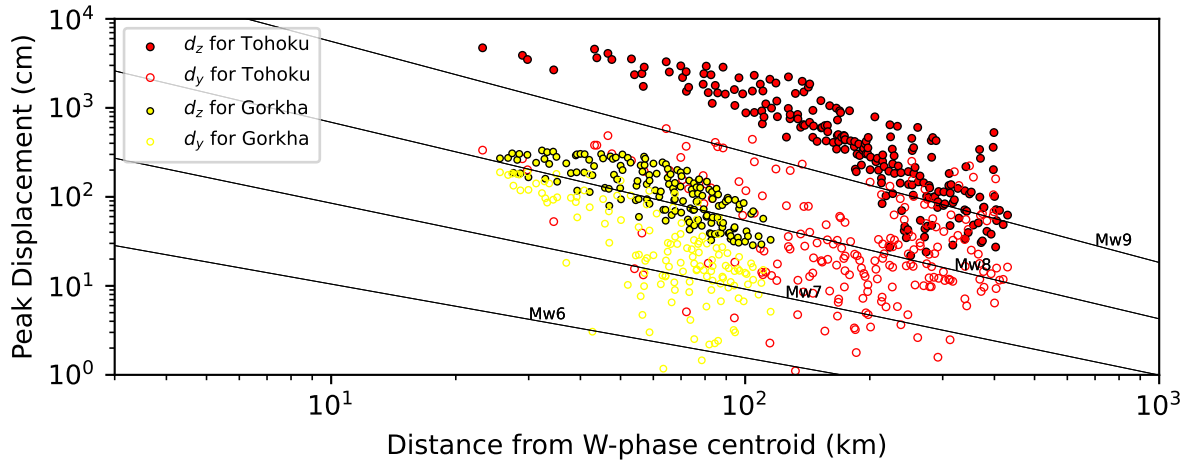
a**b**

Figure A.17: **Scaling of peak ground displacement components with distance.** Maximum trench-normal (d_y) and vertical (d_z) ground displacements for the Tohoku and Gorkha earthquakes are plotted as a function of (a) hypocentral distance and (b) distance from the W-phase centroid.

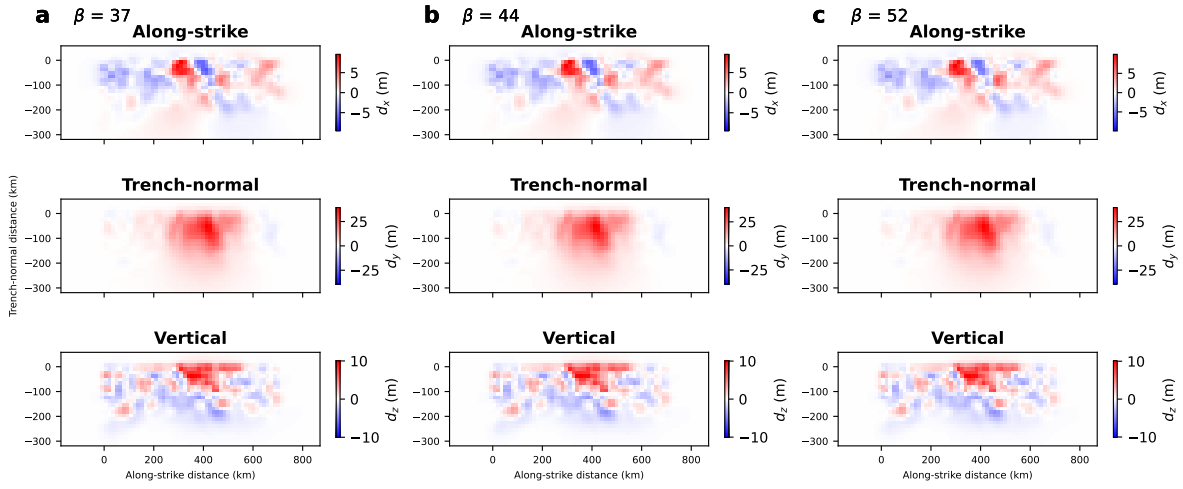


Figure A.18: **Predicted mean deformation of Tohoku slip models from different β steps.** Models in (a–c) correspond to 37th, 44th, and 52nd cooling steps in Minson et al. (2014), respectively.

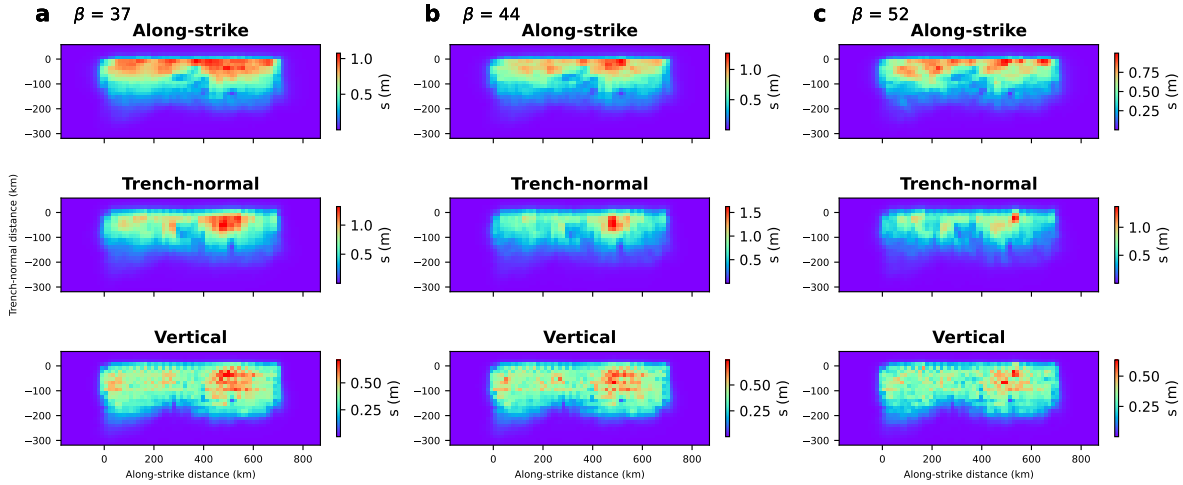


Figure A.19: **Predicted uncertainty in deformation of Tohoku slip models from different β steps.** Plotting conventions are the same as in Figure A.18.