Constraining On- and Off-Fault Nonlinear Dynamic Rupture Parameters

SCRIPPS INSTITUTION OF OCEANOGRAPHY UC San Diego



via Hierarchical Bayesian Inversion of GNSS and Satellite Data for the 2019 Mw 7.1 Ridgecrest Earthquake

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Delayed dynamic triggering and

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enhanced high-frequency seismic

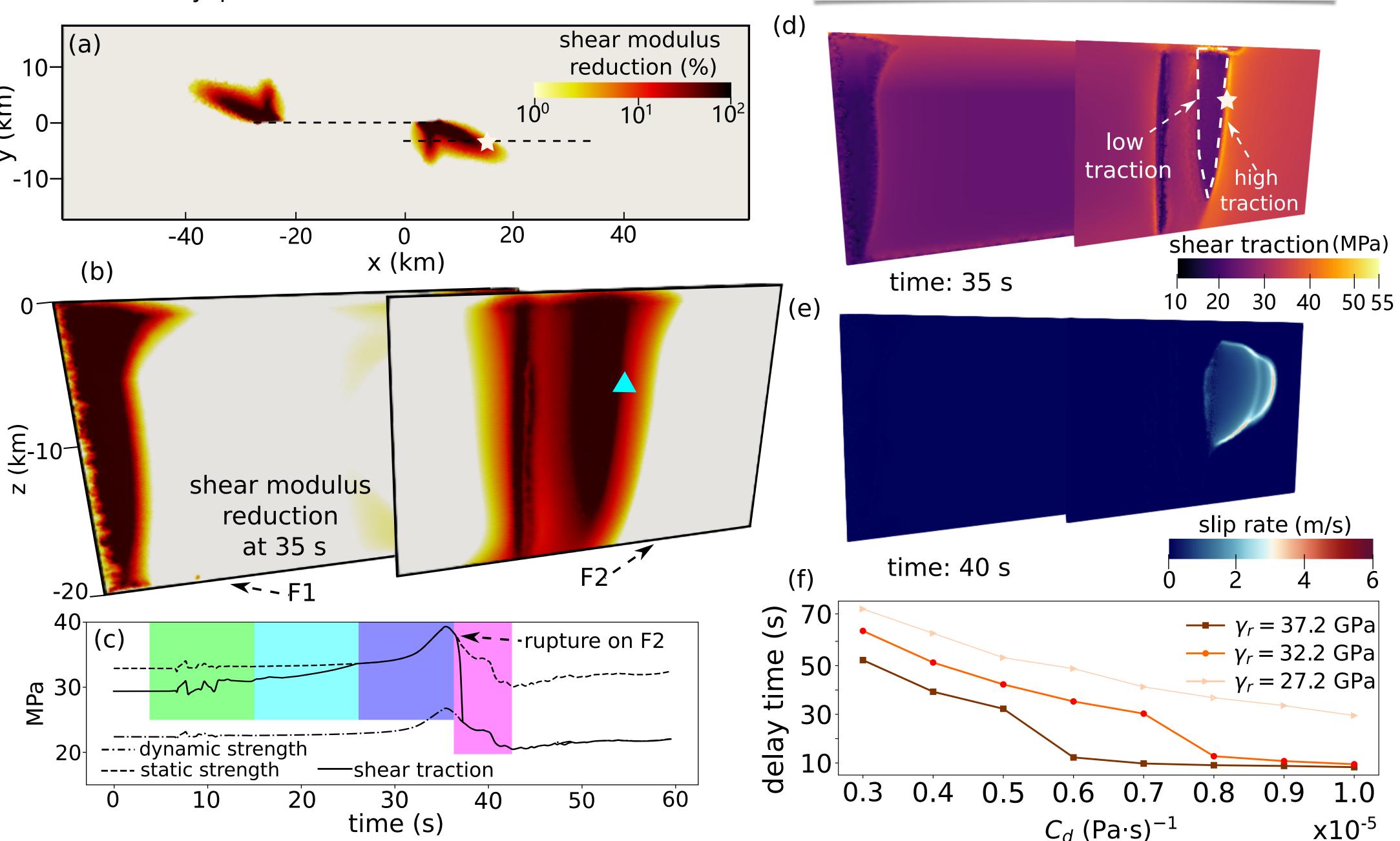
3D multi-fault rupture simulations

radiation due to brittle rock damage in

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• Dynamic rupture simulations link fault friction, off-fault damage, and seismic radiation

- Damage rheology governs rupture cascades and triggering delay times (Niu et al., JGR in press)
- Requires integrated 3D modeling, inversion and uncertainty quantification



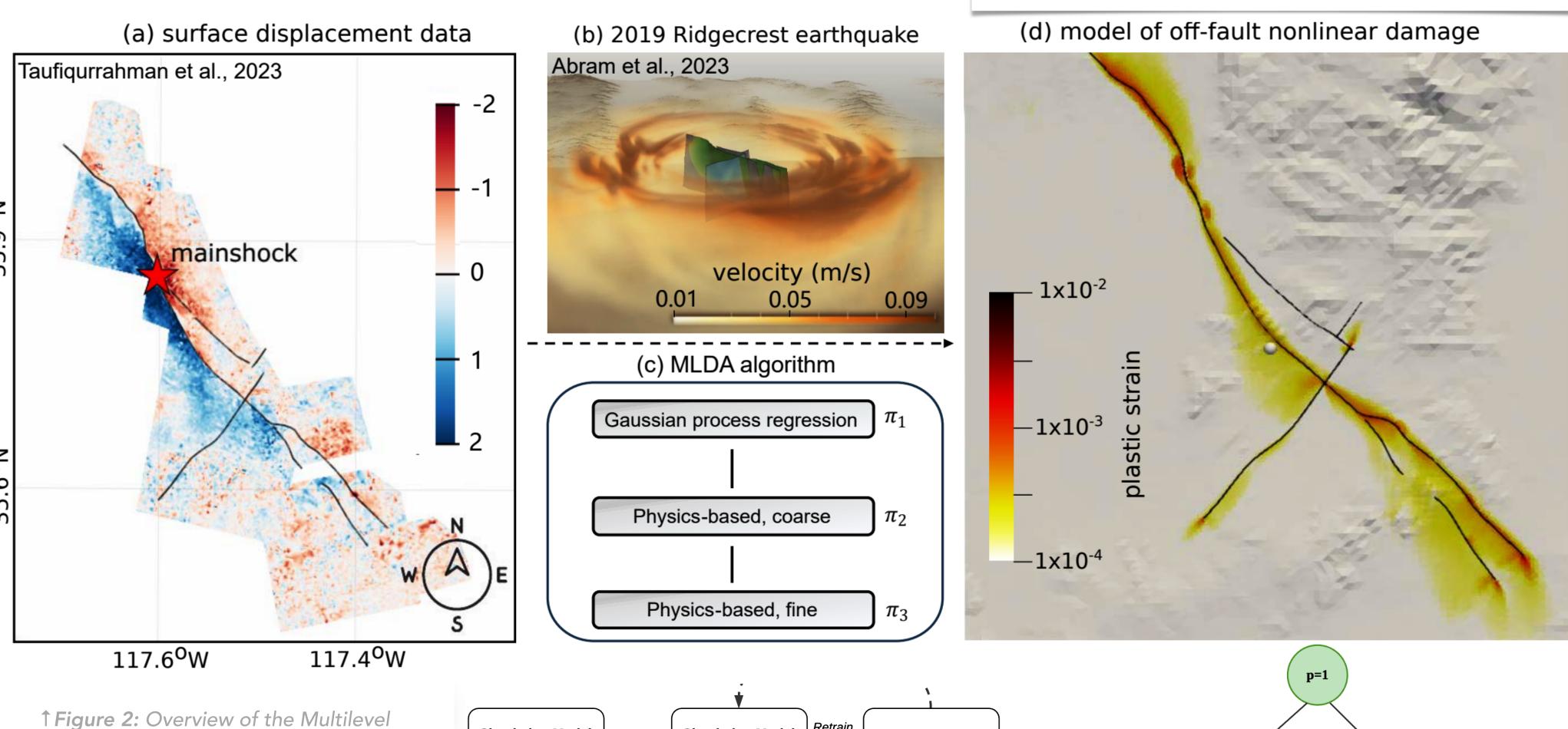
Motivation

Figure 1: Delayed dynamic triggering across fault segments due to off-fault damage. (a) Shear modulus reduction distribution at 7.5 km depth, 35 s after rupture initiation, showing localized off-fault damage extending between faults F1 and F2. The white star shows the hypocenter of delayed triggered rupture on F2. (b) Close-up view of shear modulus distribution near the two faults, indicating the location of a receiver (cyan triangle) at (12.5, -3.0, -7.5) km. (c) Time series comparing shear traction (solid curve), static (dashed curve) and dynamic (dash-dotted curve) frictional shear strength at the receiver location indicated in (b) The black-dashed arrow marks the initiation of spontaneous rupture on fault F2. (d) Spatial distribution of shear traction on both faults at 35 s, with the hypocenter on F2 marked by a white star. (e) Slip rate distribution at 40 s while fault F2 is dynamically delayedtriggered. (f) Variation in delay time between rupture initiation on fault F1 complete rupture of fault F1 and the initiation on fault F2 as a function of the nonlinear modulus yr and damage evolution coefficient Cd in the CDB model. Each marker represents delay times from an independent simulation. We show simulations with varying \mathbf{\gamma}r and Cd in (f).

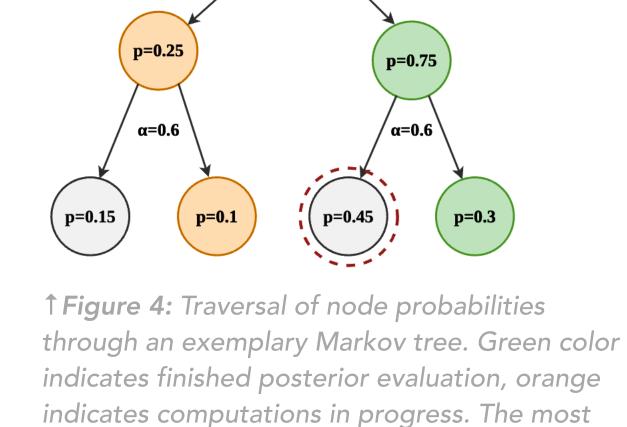
Scalable Bayesian Inference via Asynchronous Prefetching Multilevel Delayed Acceptance (MLDA)

• Multilevel delayed acceptance (MLDA) Bayesian inversion (Kruse et al., PASC 2025), reducing the number of costly simulations needed for uncertainty quantification by combining fast approximate coarse models with fewer fully resolved simulations





Simulation Model **Simulation Model** Delayed Acceptance MCMC (MLDA) Level K algorithm and its target application, the 2019 Ridgecrest earthquake. (a) Surface displacement data during the earthquake. (b) Visualization of the simulated earthquake source and the generated seismic wave field. ←Figure 3: (c) Structure of the proposed MLDA model **Load Balancer** Computational setup hierarchy. (d) Modeled plastic deformation, consisting of UQ client, which is controlled by physical parameters, cluster-side load the target of the inference in this work. Parallel Requests balancer, adaptive surrogate model and parallel simulation **MCMC Client** instances.

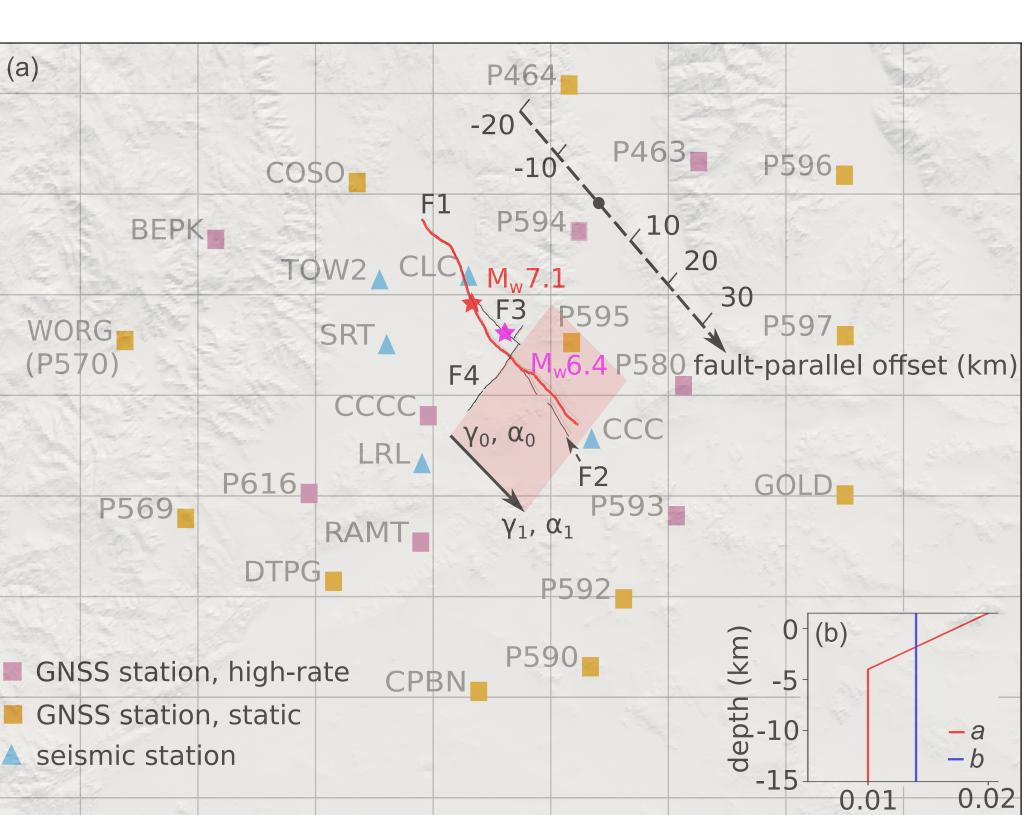


likely candidate, selected for the next posterior

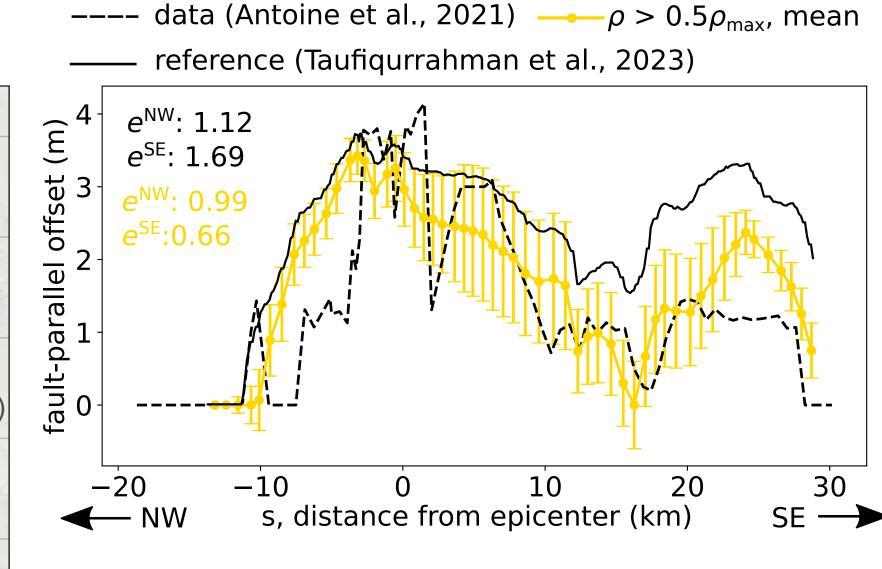
evaluation, is encircled in red.

First Bayesian inversion using complex 3D dynamic rupture simulations with off-fault plasticity

- Joint inversion of on- and off-fault nonlinear dynamic rupture parameters
- Using fault-parallel surface offsets from satellite imagery, high-rate GNSS time series, static GNSS displacements
- Quantify uncertainties and correlations among on- and off-fault dynamic rupture parameters
- Using 4 million CPU hours



† Figure 4: Data and model setup for the 3D dynamic rupture inversion. (a) Map view of the GNSS and seismic stations used to constrain the inversion, located within 100 km of the Mw 7.1 Ridgecrest mainshock epicenter (red star). The fault trace (F1) of the main fault segment that ruptured during the 2019 Mw 7.1 Ridgecrest mainshock is shown as a solid red line, thinner black lines mark the secondary segment ruptured during the mainshock (F2), the subparallel fault (F3) where the Mw 6.4 foreshock nucleates (pink star), and the conjugate fault (F4) that hosted the foreshock and reruptured during the mainshock. The 3D fault structure is shown in Fig. S2. Pink squares indicate GNSS stations with high-rate displacement time series, and orange squares mark GNSS stations used for static co-seismic displacements. Blue triangles denote locations of strong-motion seismic stations used to validate the inversion.



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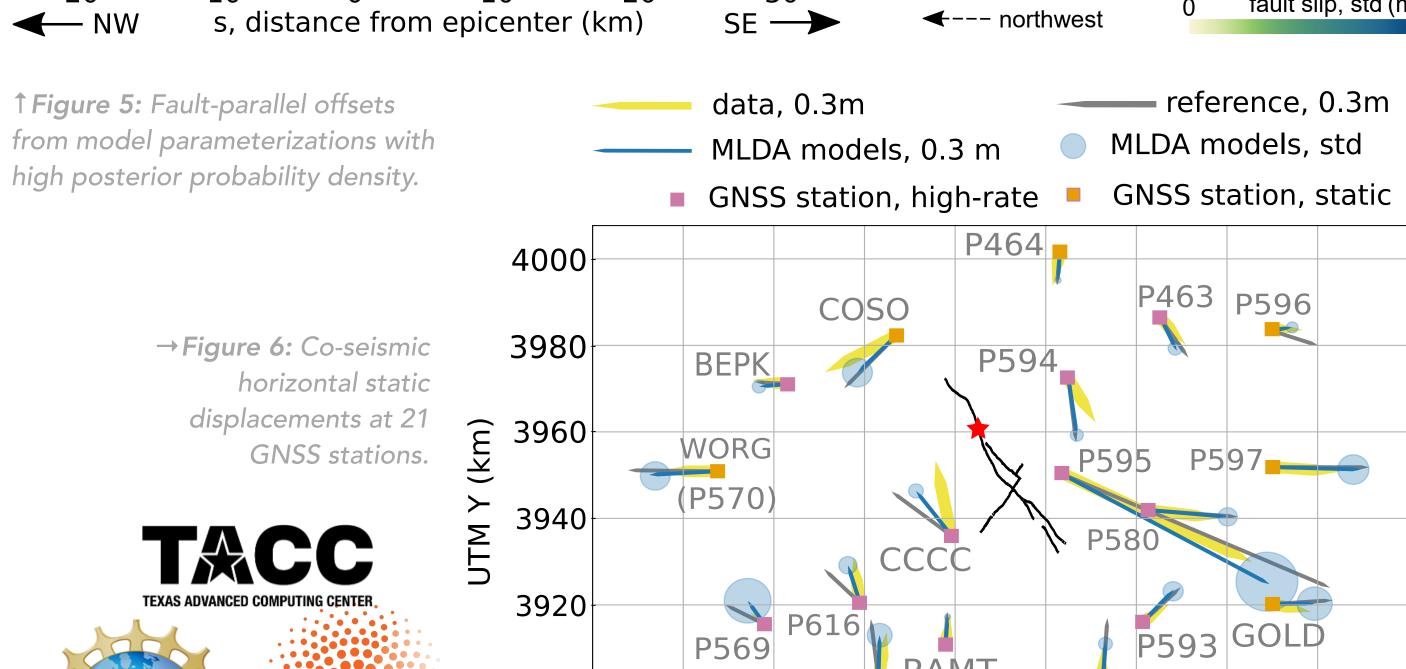
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European Research Council

Established by the European Commission



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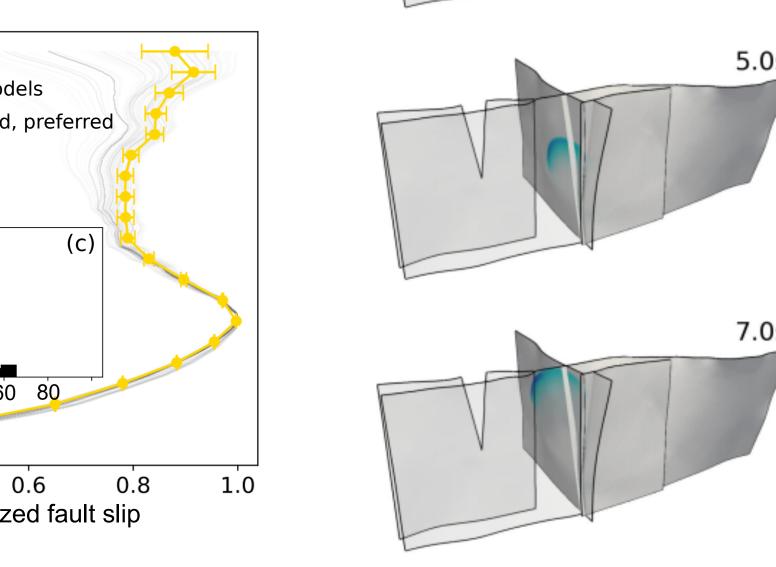
across all models. (d) Variation of fault slip with depth. ^(a) depth (km) all MLDA models mean and std, preferred o fault slip, mean (m) 4.0 ^(b) depth (km) fault slip, std (m) 1.30 normalized fault slip

↓ Figure 7: Uncertainties in fault slip distribution among

all models in the MLDA chains. Panels (a) and (b) show,

respectively, the mean and the standard deviation of

fault slip. (c) Histogram of shallow slip deficits (SSDs)



foreshock

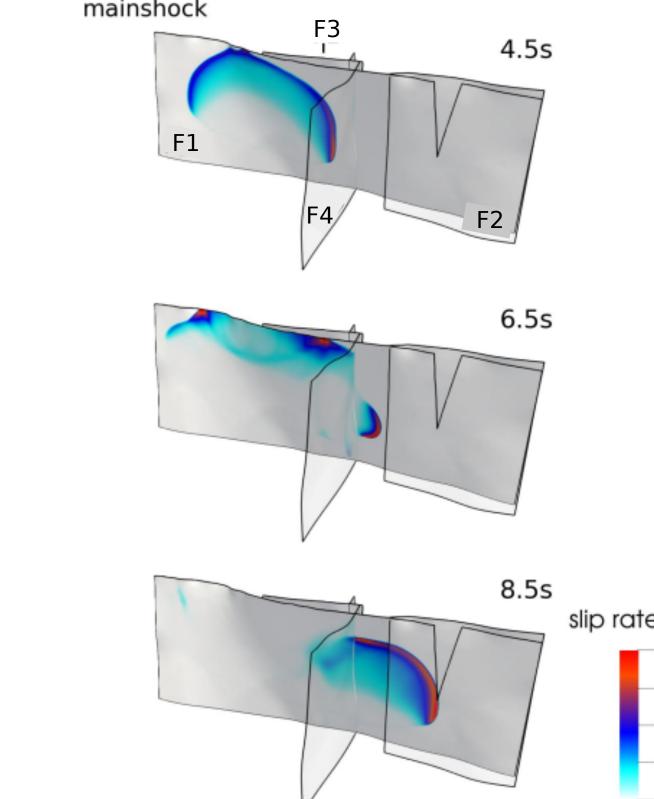


Figure 8: Snapshots of fault slip rate distribution during the Searles Valley foreshock and the Ridgecrest mainshock in the reference dynamic rupture model from Taufiqurrahman et al. (2023), Schliwa et al. (2025).

Conclusions

- Strong correlation between on-fault frictional weakening and off-fault plasticity
- Increased inelastic deformation trades off with stronger velocity-weakening frictional behavior
- Along-strike changes in fault maturity: Preferred rupture models have increasing (a-b) from northwest to southeast, reducing velocity-weakening effects
- Shallow damage zone: lower off-fault plastic cohesion enhances the match to observed surface deformation; shallow slip deficit (SSD) of $13.1\% \pm 5.1\%$,
- Integrating 3D dynamic rupture simulations and multilevel Bayesian inversion is feasible to rigorously characterize on- and off-fault earthquake physics and quantify uncertainties in dynamic parameters

Kruse et al., (2025), "Scalable Bayesian Inference of Large Simulations via Asynchronous Prefetching Multilevel Delayed Acceptance", In Platform for Advanced Scientific Computing Conference (PASC '25), June 16–18, 2025, Brugg-Windisch, Switzerland. ACM, doi:10.1145/3732775.3733581 Z. Niu, A.-A. Gabriel, Y. Ben-Zion (2025), "Delayed dynamic triggering and enhanced high-frequency seismic radiation due to brittle rock damage in 3D multi-fault rupture simulations", Journal of Geophysical Research: Solid Earth, in press, preprint: ArXiv arXiv:2503.21260. Zihua Niu, L. Seelinger, N. Schliwa, H. Igel, A.-A, Gabriel, "Constraining On- and Off-Fault Nonlinear Dynamic Rupture Parameters via Hierarchical

Bayesian Inversion for the 2019 Mw 7.1 Ridgecrest Earthquake", in prep.