Earthquake Dynamics from Graph Neural Networks

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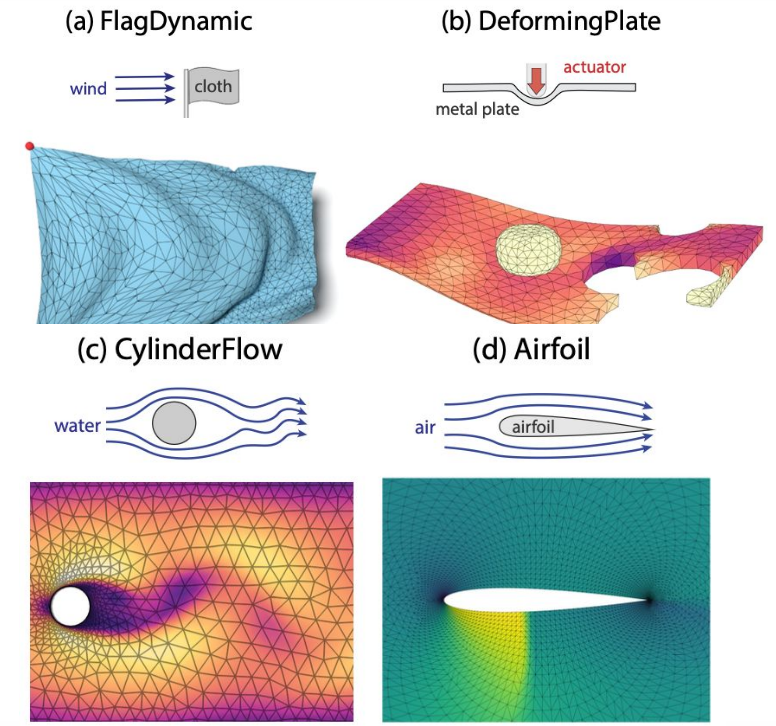
TEXAS Geosciences
The University of Texas at Austin
Jackson School of Geosciences

NSF

SCEC Statewide California Earthquake Center

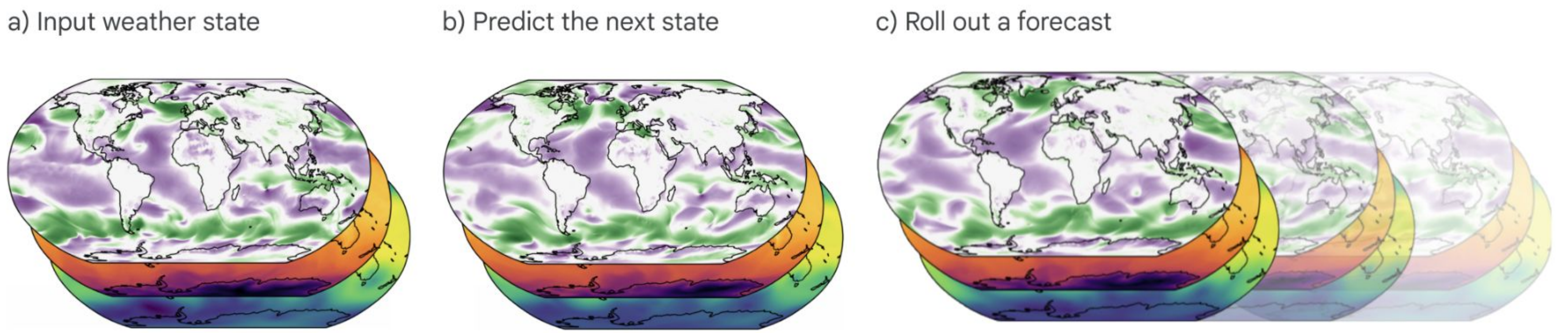
UTIG

Emerging Graph Network Simulators (GNSs) to Rapidly Emulate Physical Systems

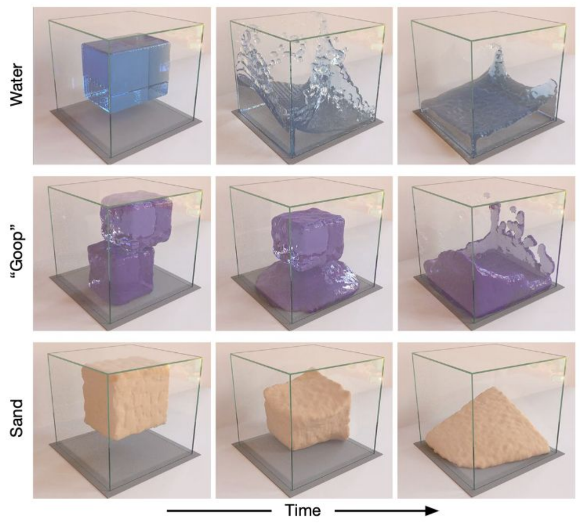


Fluid, solid, deformables (Pfaff et al., 2020)

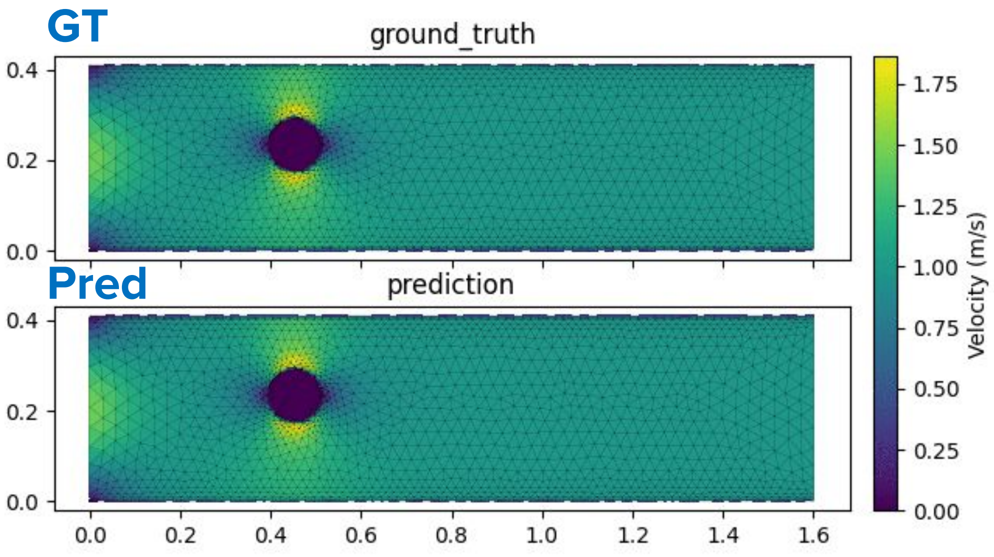
Granular flow
(Vantassel and Kumar, 2022; Kumar and Choi, 2023; Choi and Kumar, 2024)



Weather, GraphCast (Lam et al., 2023)

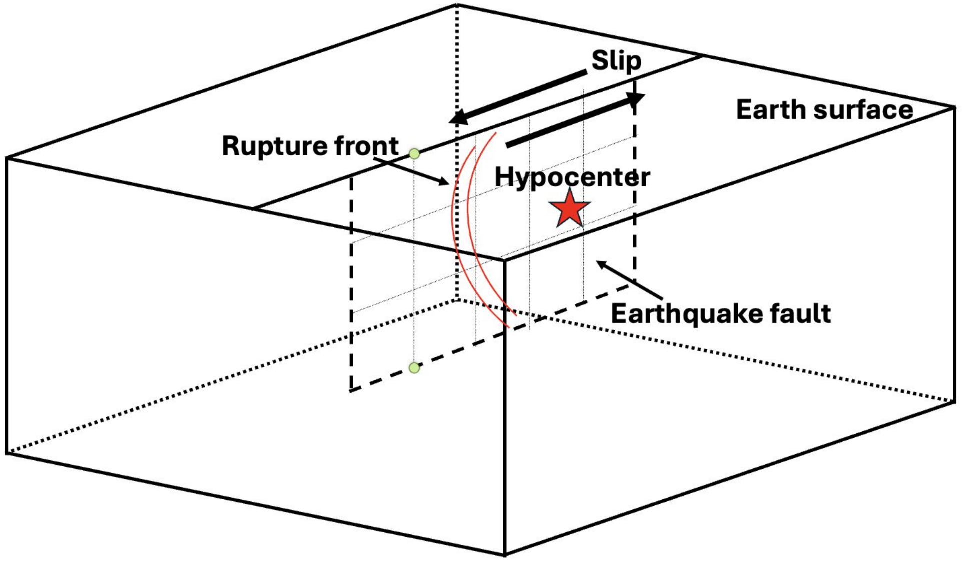


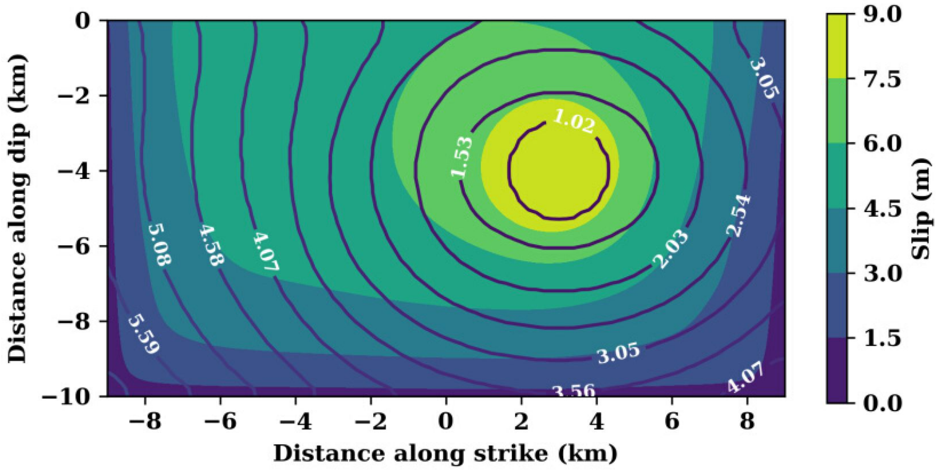
Goop, sand, and water
(Sanchez-Gonzales et al., 2020)

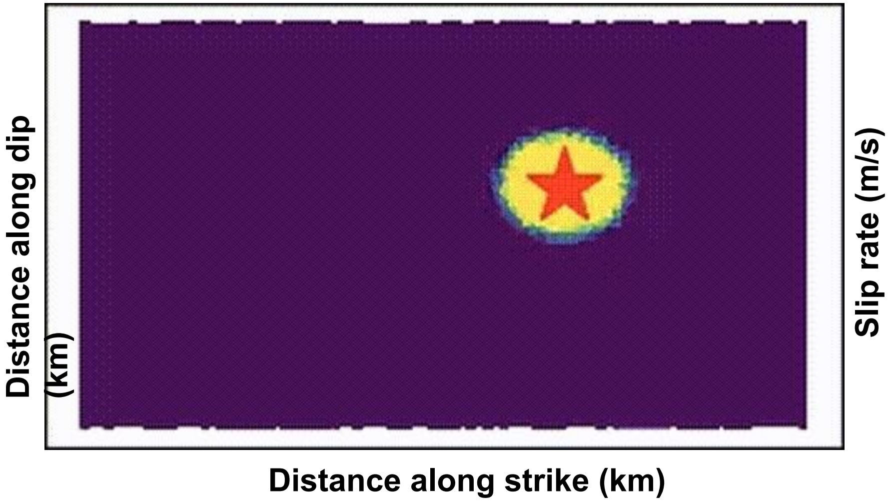


Fluid flow
(Vantassel and Kumar, 2022; Kumar and Choi, 2023; Choi and Kumar, 2024)
https://github.com/geoelements/gns.git

Earthquake Rupture Dynamics







Rupture dynamics:
- ***Rupture arrivals;***
- ***Final slips;***
- ***Slip rate evolutions;***
- ***Stress & friction evolutions (not shown).***

Statewide California Earthquake Center (SCEC) Benchmark problem TPV104
- ***High spatiotemporal resolutions: 200 m & 0.016 s;***
- ***Highly nonlinear friction evolutions with rate- and state- friction plus strong rate weakening;***
- ***Localized high slip rate at rupture fronts;***
- ***Elastodynamic + friction.***

Can GNS learn non-linear rupture dynamics and predict it?

(Liu and Becker, 2025)

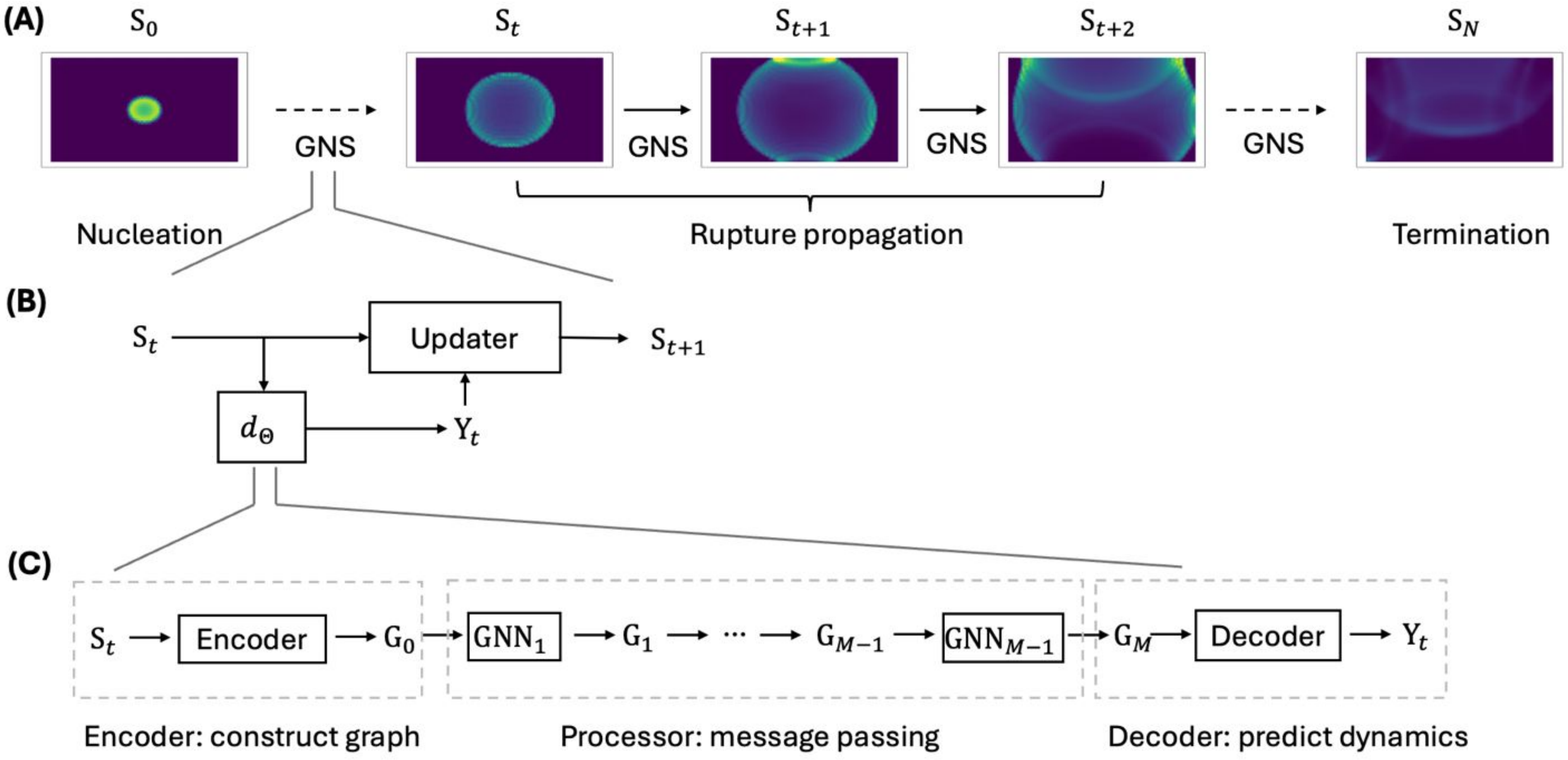
EQdyna: Physics-based Simulations

- ***EQdyna***: Parallel finite-element solution to earthquake dynamic rupture and wave propagation **(e.g., Duan and Oglesby, 2006, 2007; Liu and Duan, 2018; Liu et al., 2021, 2022)**. (https://github.com/EQDYNA/EQdyna.git).
- Extensively verified in SCEC code verification **(e.g., Harris et al., 2018)**.
- Earthquake physics:
  - Heterogeneous stresses: past earthquakes, loading dynamics, interactions with structures, etc.
  - Rock friction: slip weakening / rate-state-friction, etc.
  - Heterogenous frictional parameters.
  - Fault geometric complexity: dips, bends, stepovers, roughness, etc.
  - 3-D velocity structure and attenuation.
  - Rheology: elasticity and off-fault plasticity.
  - Other physical processes: solid-fluid interaction, thermal pressurization, poroelasticity, etc.
  - Multiscale.
- High dimensional parameter space.

The GNS Architecture

$$State_t \rightarrow State_{t+1}$$

Meshnet from https://github.com/geoelements/gns.git
(Vantassel and Kumar, 2022; Kumar and Choi, 2023; Choi and Kumar, 2024)
EQGNS: https://github.com/dunyuliu/EQGNS.git



- Graph Network;
- Message Passing;
- Inertial framework + Updater;
- Encoder-Processor-Decoder.

(Choi and Kumar, 2024)

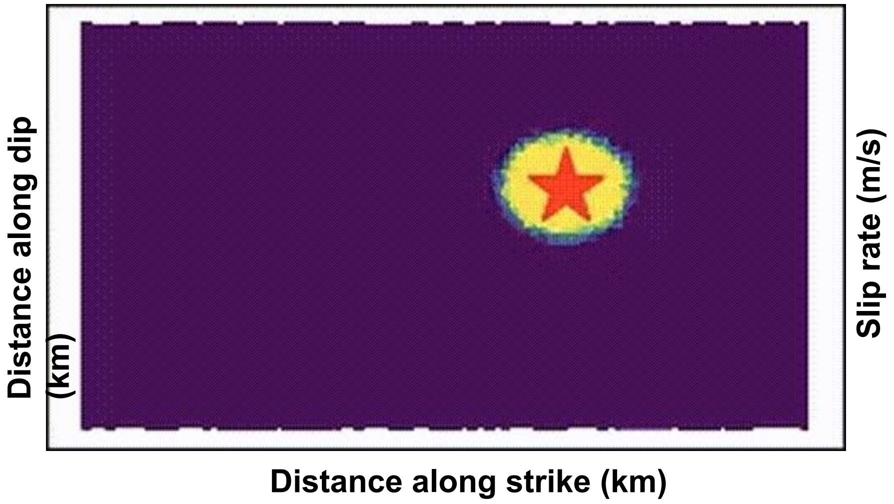
(Liu and Becker, 2025)

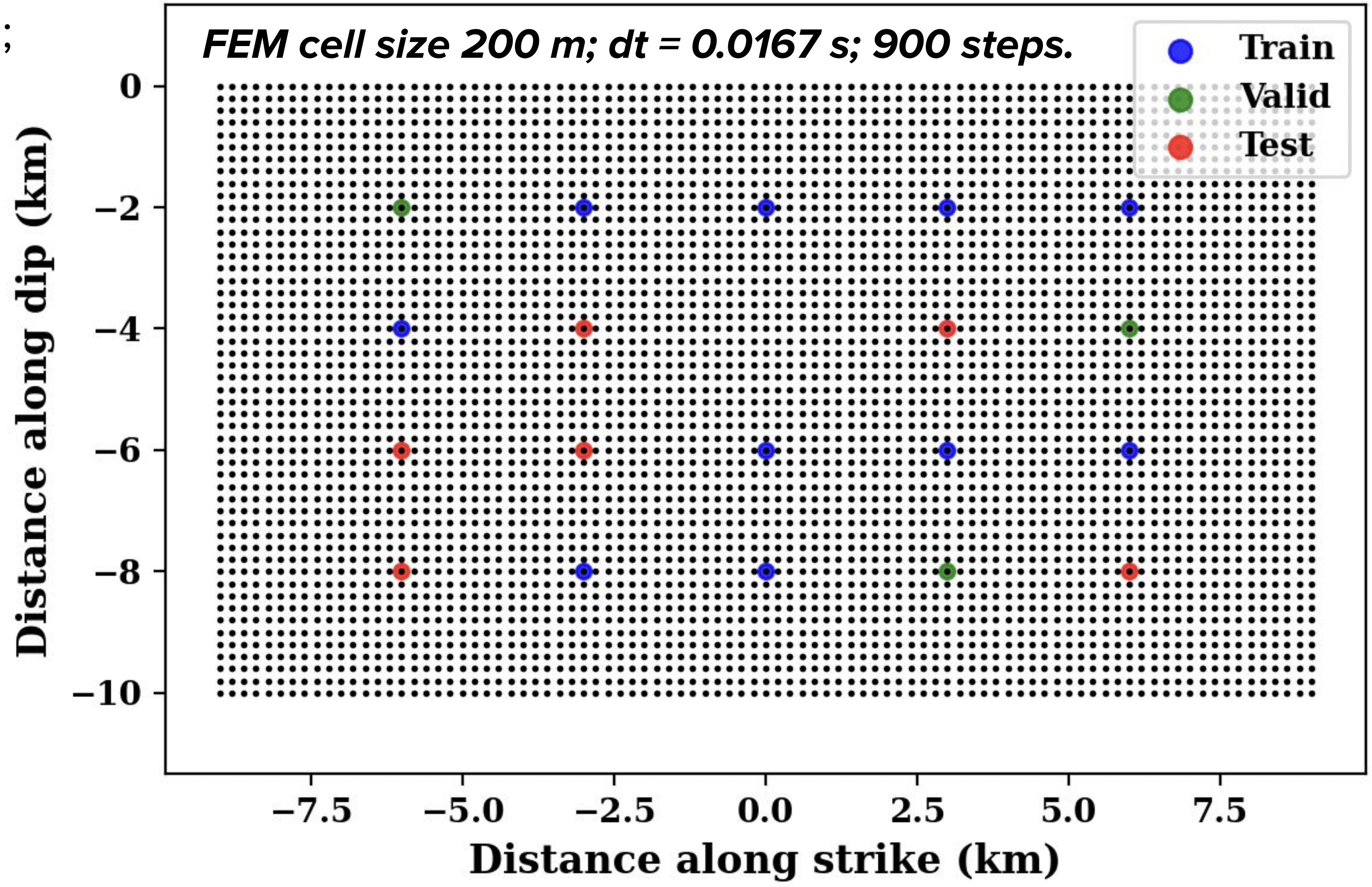
D1: Generalization to Unseen Hypocenters

- We cannot yet predict with high fidelity where a next earthquake will begin in a fault system.

Training dataset:

- 10 trajectories with varied hypocenters;
- Each trajectory lasts 15 *s* including:
    - rupture nucleation,
    - propagation,
    - and termination.

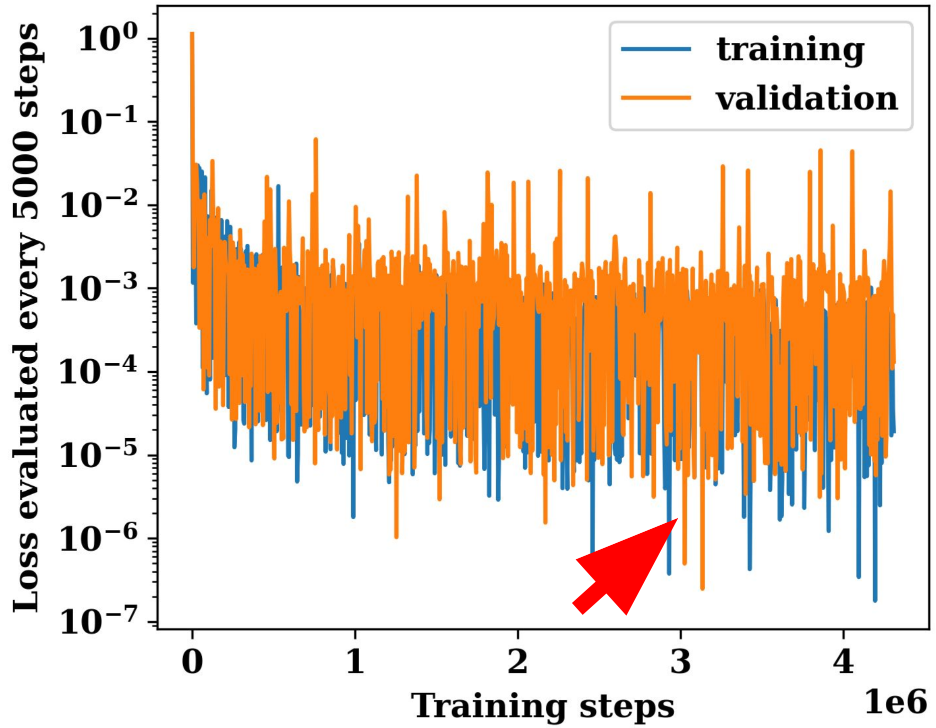


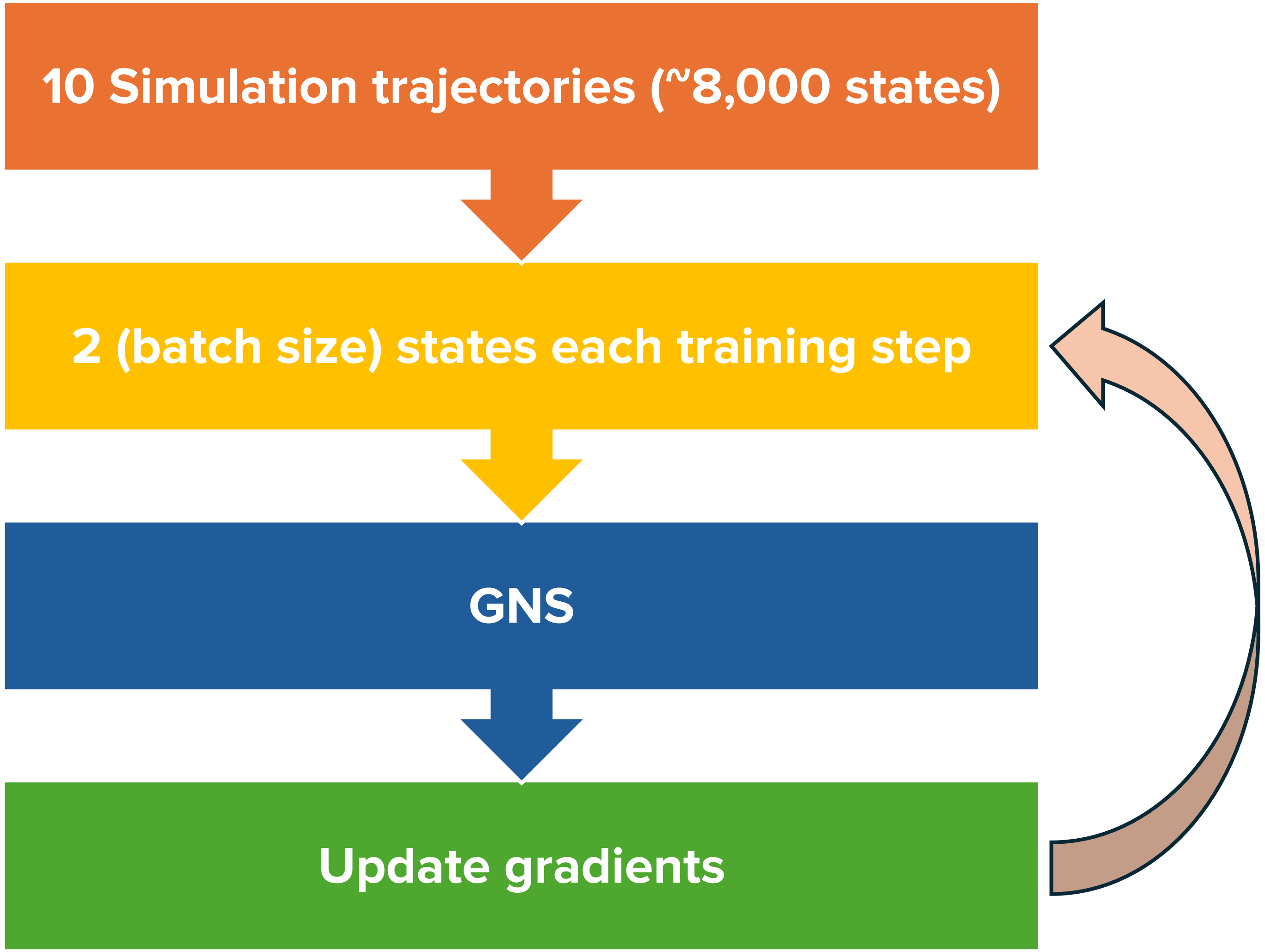


M1: Generalization to Unseen Hypocenters

We train GNS parameters by minimizing MSE between predicted slip-acceleration proxy and ground-truth acceleration (from slip-rate derivatives), across all fault vertices, using the *Adam* optimizer **(Kingma & Ba, 2014)** over trajectory time steps and epochs **(Choi and Kumar, 2024)**.

Model	M1/M2
Learning rate	10^{-4}
Batch number	2
Number of message passing steps	5/10/15
Gaussian noise level	0.02/0.005
Number of hidden layers in multi-layer perceptron	2
Dimension of hidden layers in multi-layer perceptron	128





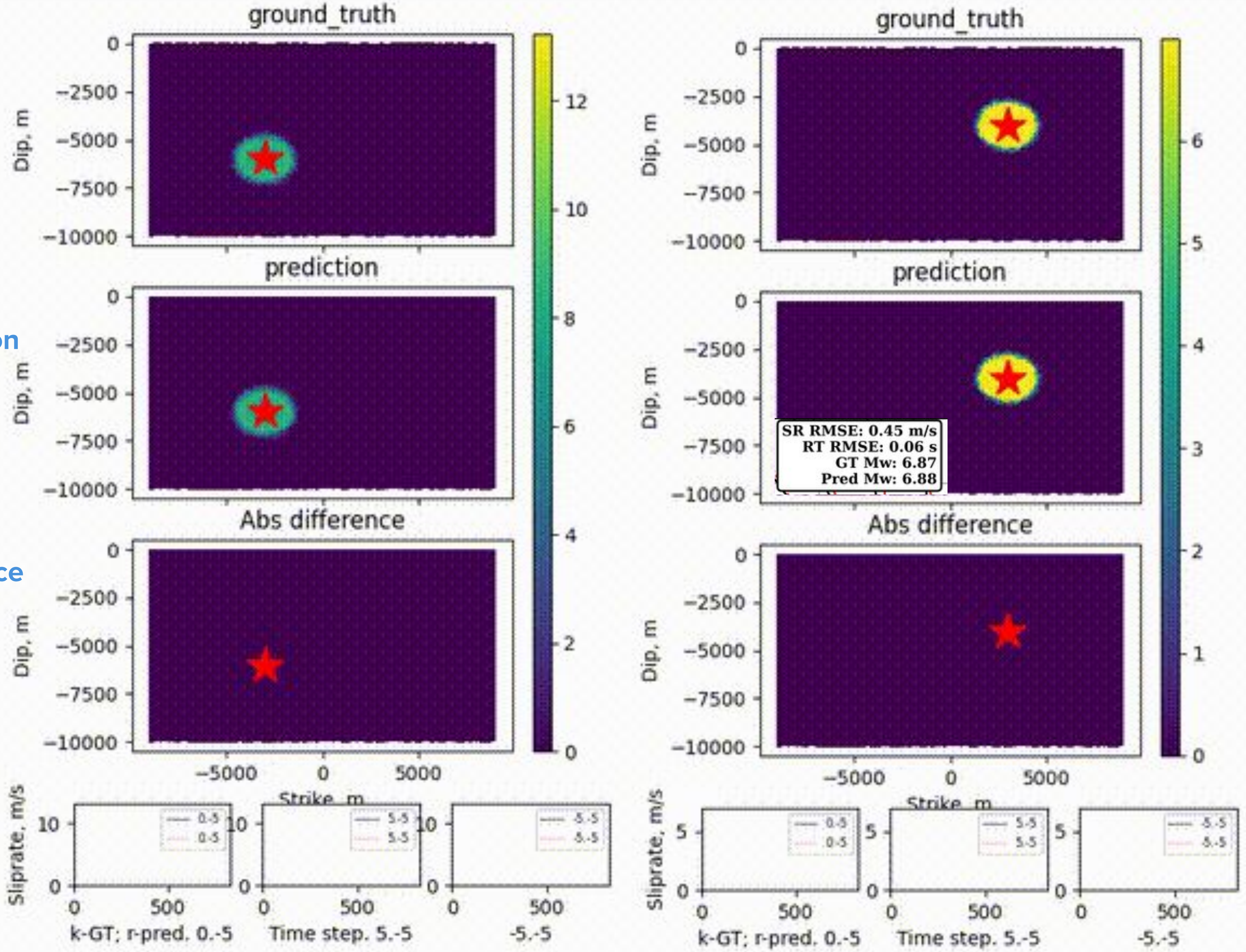
M1: Generalization to Unseen Hypocenters

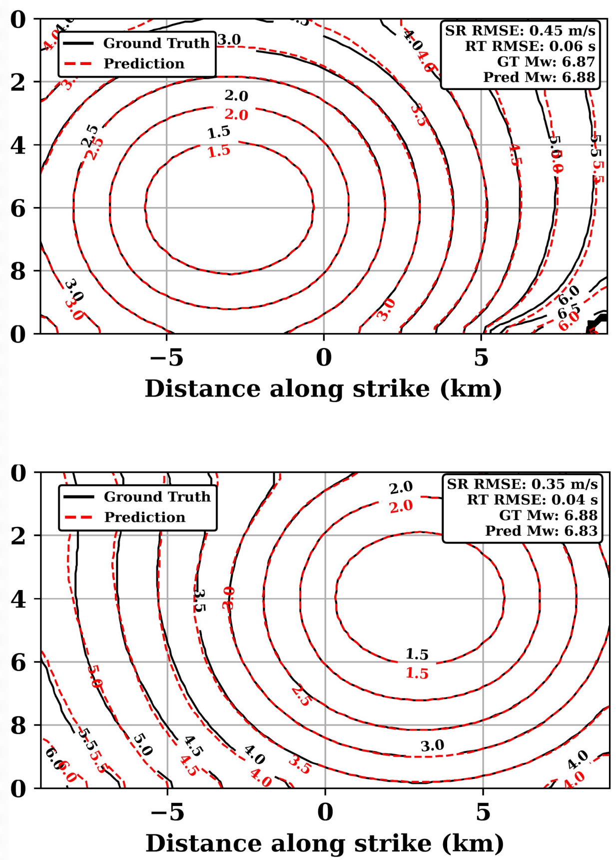
Ground truth

GNN prediction

Difference

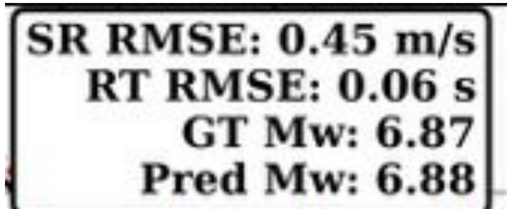
Slip rate time series





Quantitative metrics:

- RMSE rupture arrival times
- RMSE slip rate states
- Earthquake magnitude error.



M1: Generalization to Unseen Fault Size

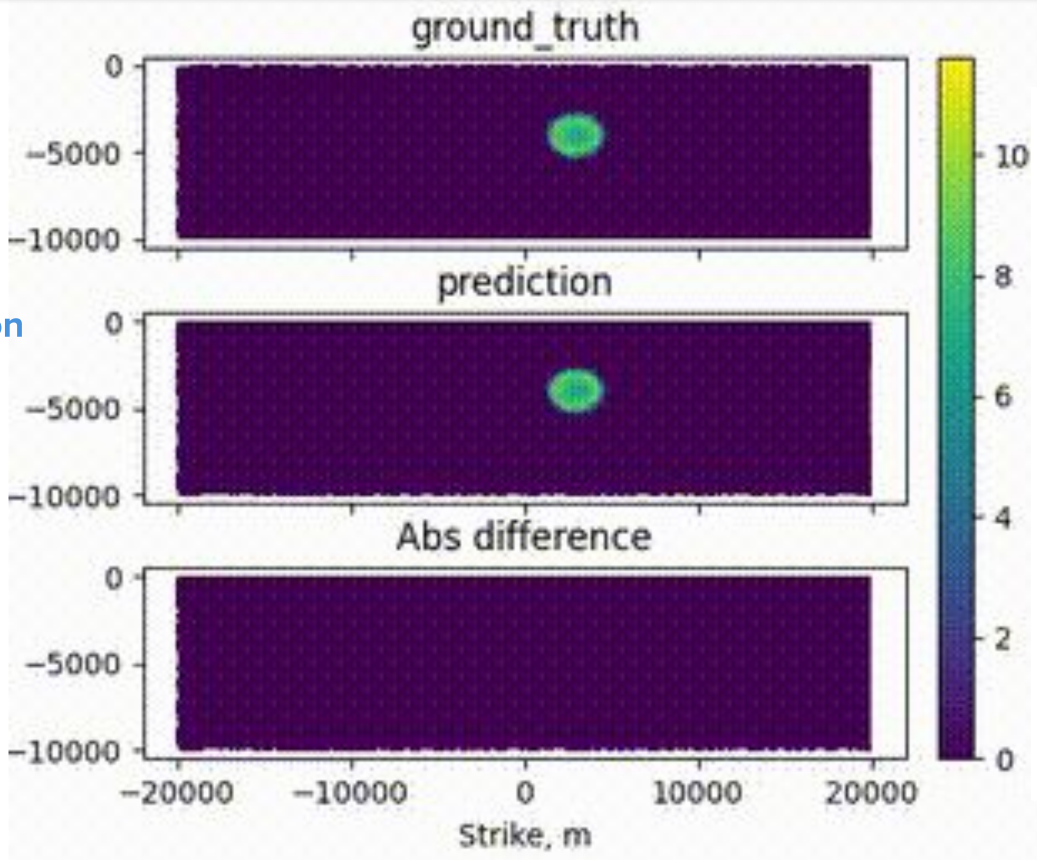
Ground truth

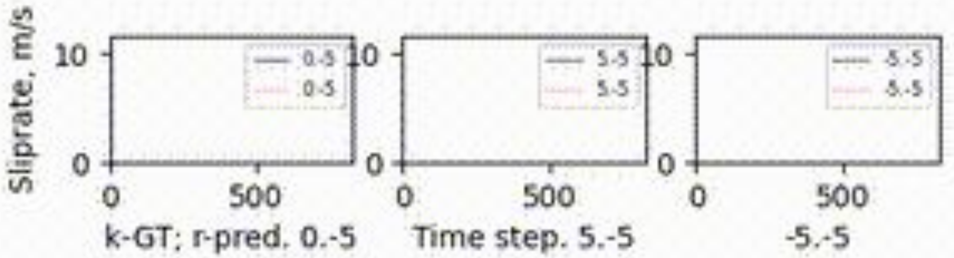
GNN prediction

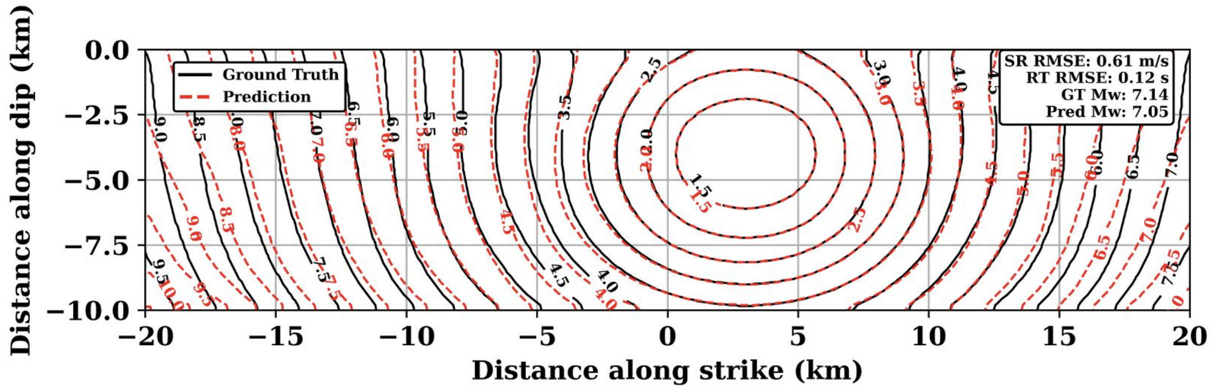
Diff

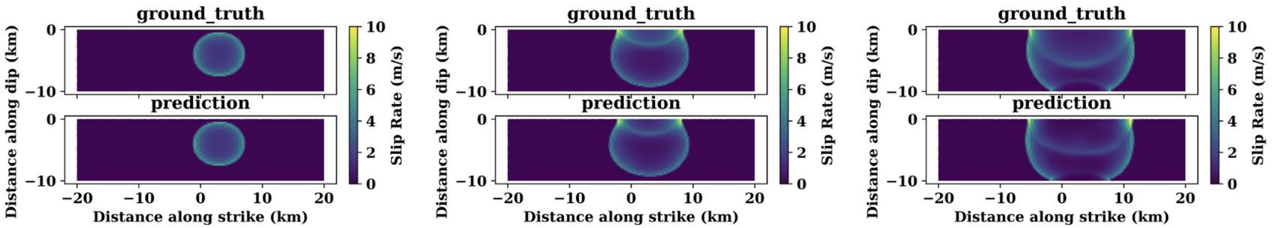
Slip rate time series

Rupture time contours









- Prediction on an unseen larger fault;
- GNS learns a coarse-grained local interaction “stencil” that allows it to generalize to larger model domains.

M2: Generalization to Unseen Prestress

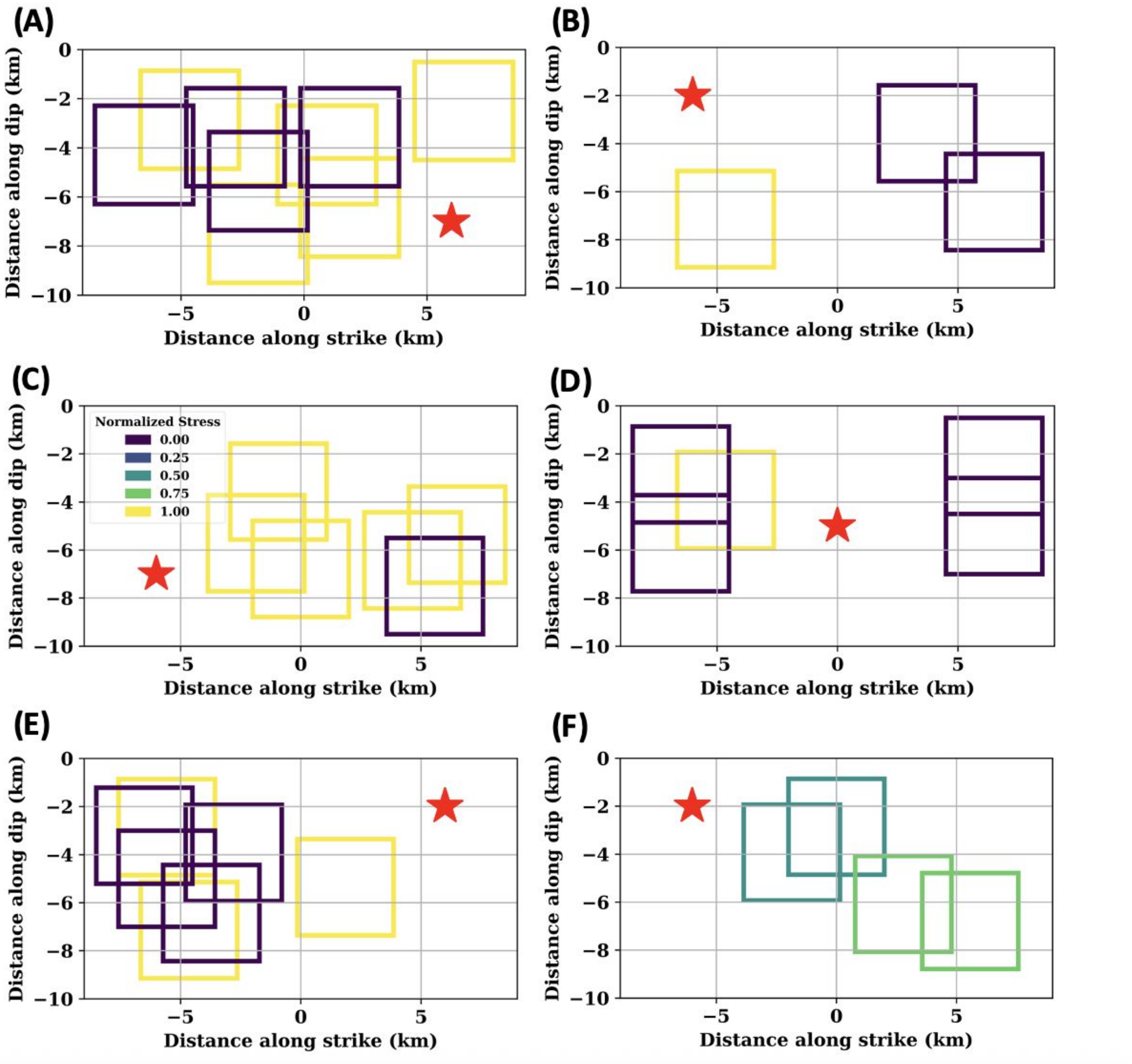
- Initial stresses are poorly constrained.
- Can GNS, trained on limited stress levels and complexities, generalize to the full spectrum?

Training dataset:

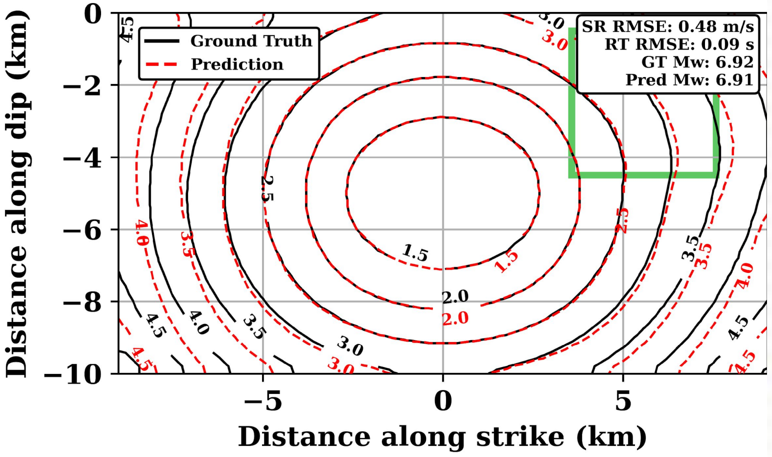
- **30** scenarios with square stress asperity (35/55MPa; 40MPa outside).
- ~10% heterogeneity.

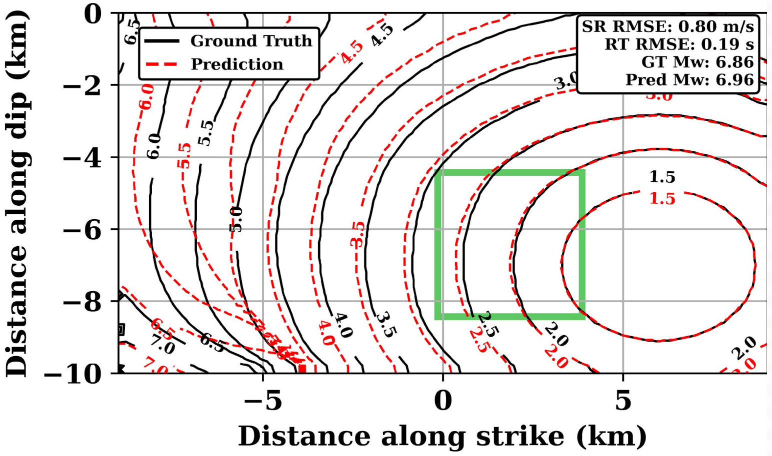
Prediction:

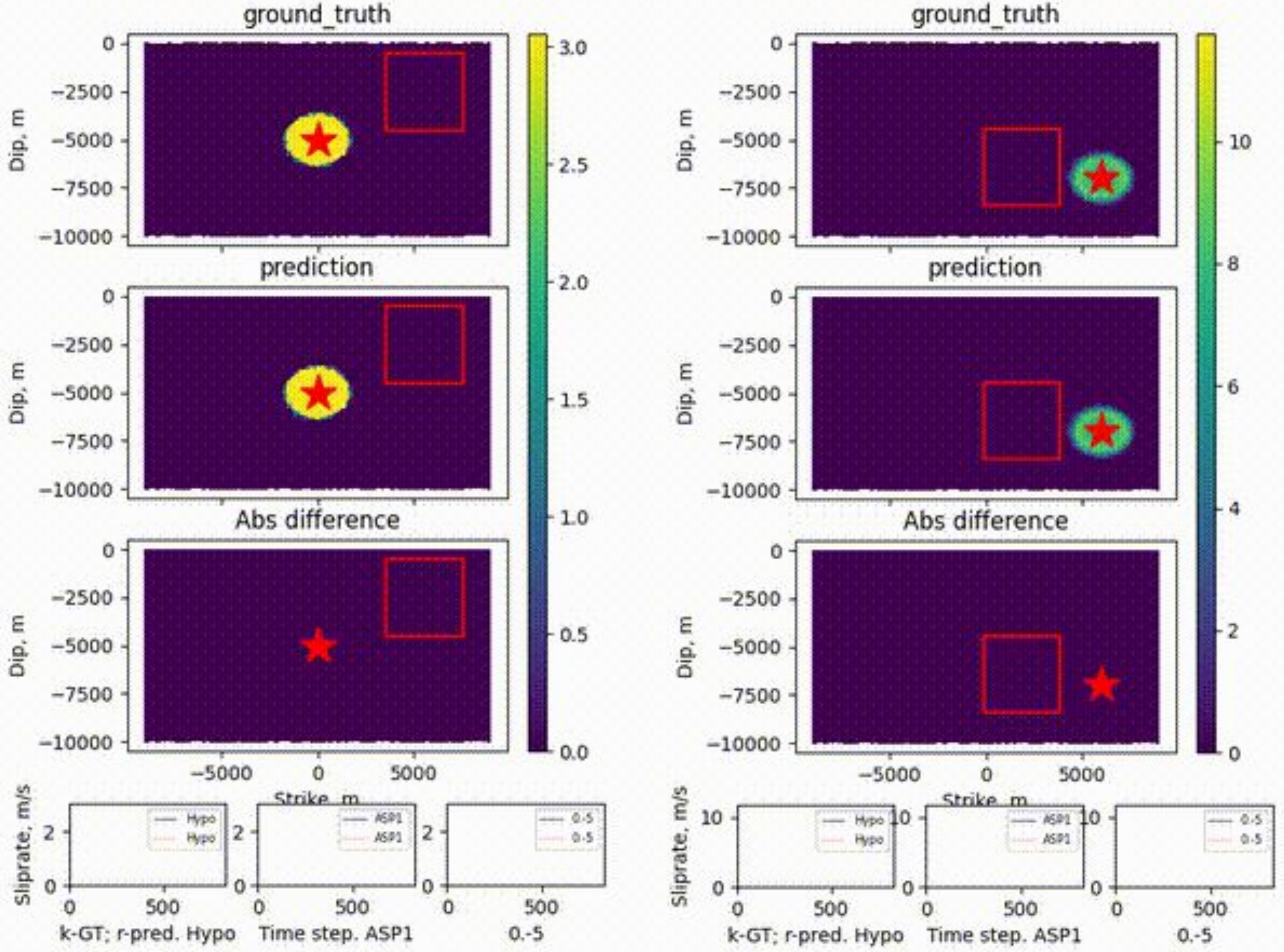
- New asperity locations +
- New stress levels (40/45MPa) +
- new hypocenters.



M2: Generalization to Unseen Prestress

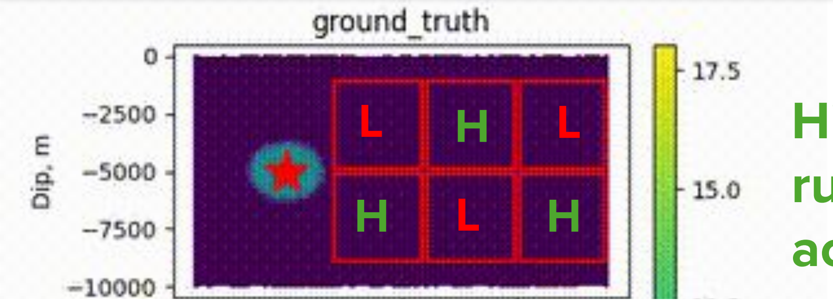




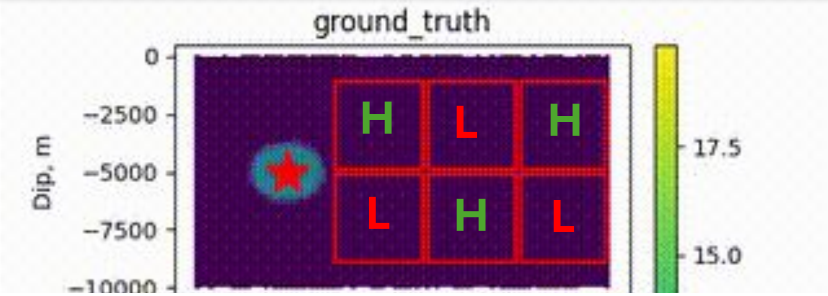


Prediction on rupture acceleration at unseen higher prestress asperity

M2: More Complexity? Checkerboard-style Heterogeneity



High stress:
rupture
acceleration



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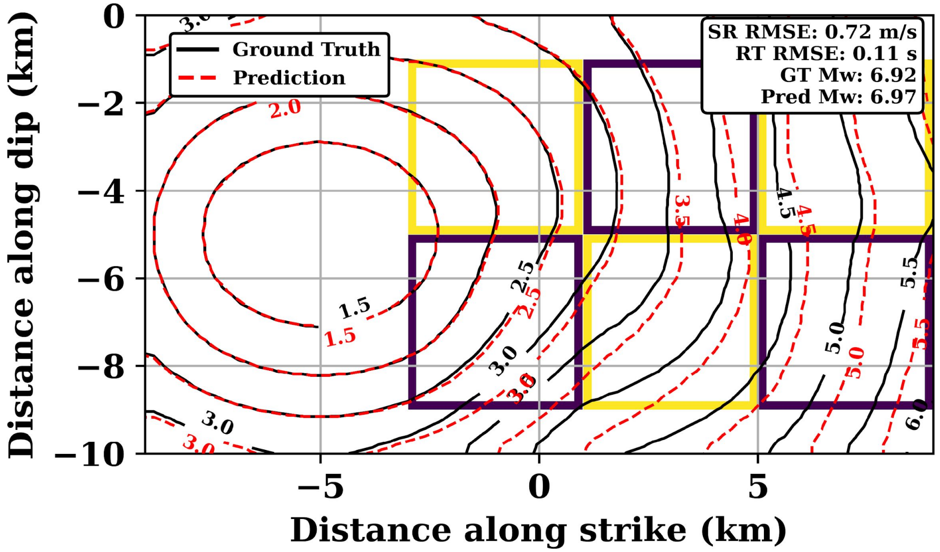
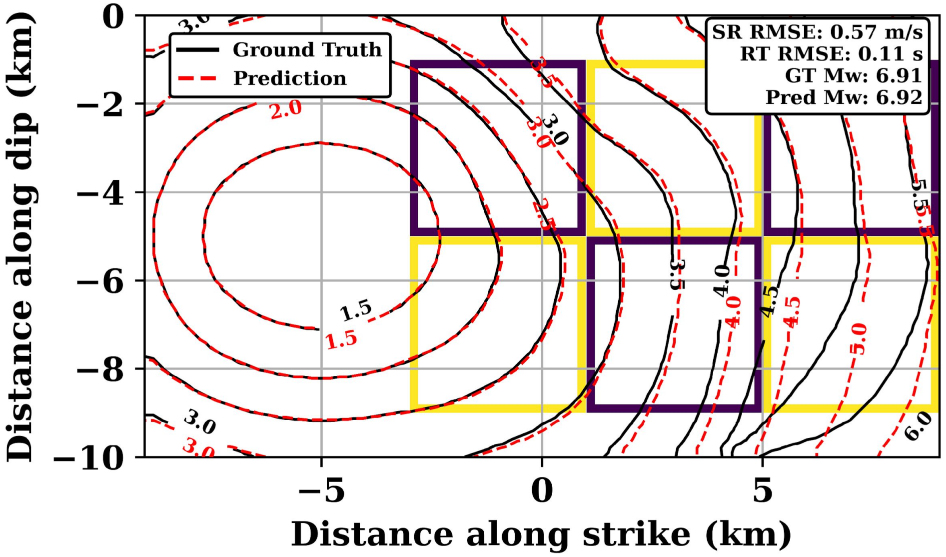
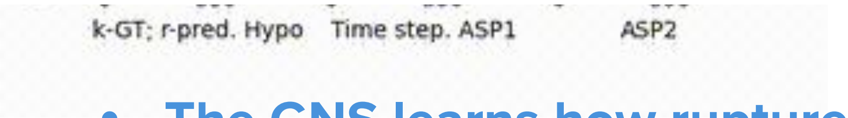
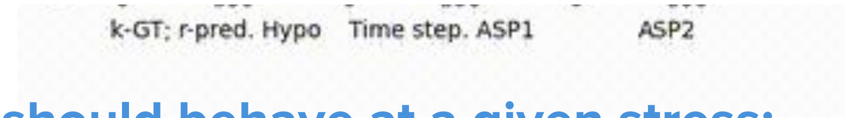
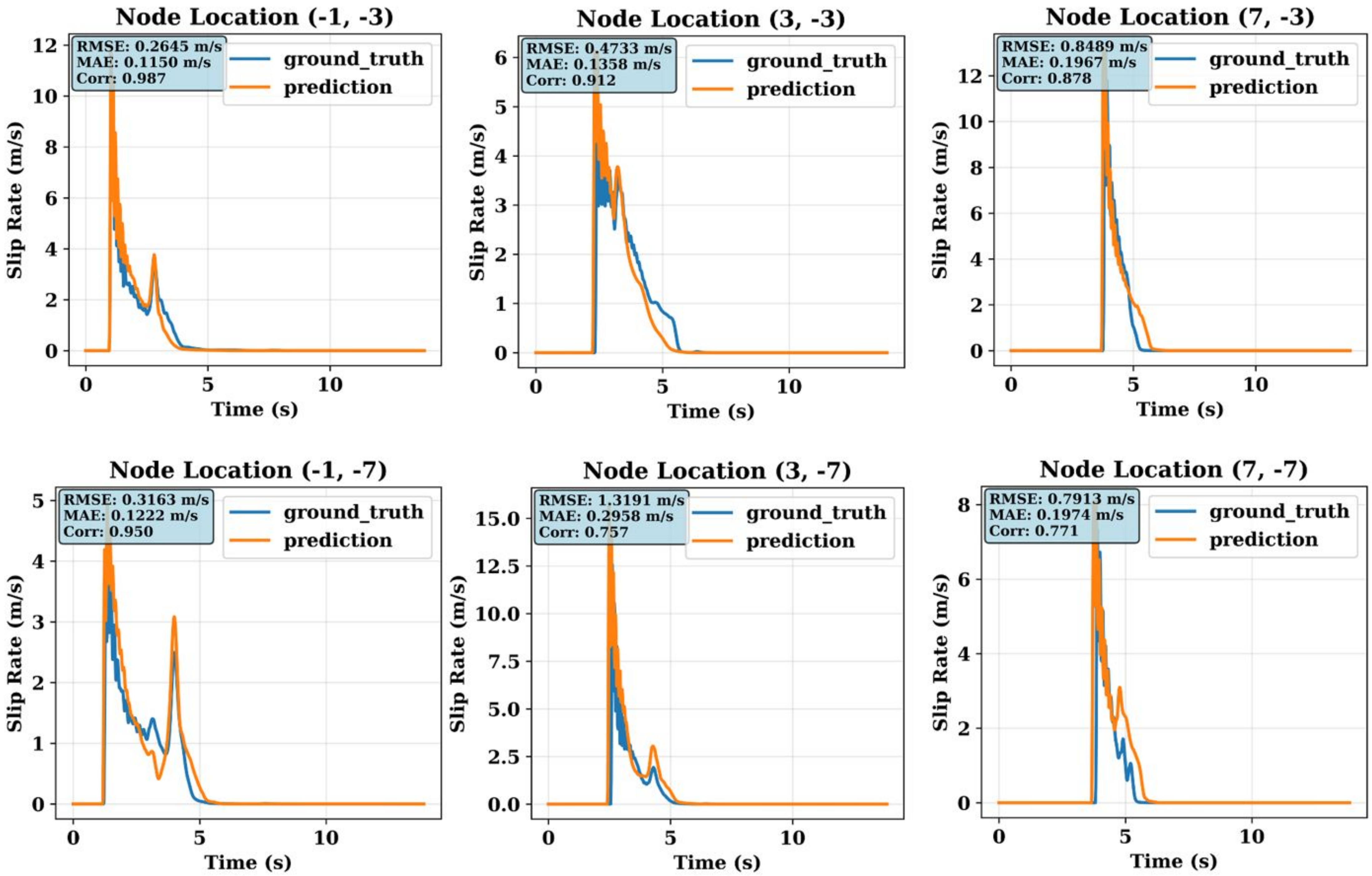








- The GNS learns how rupture dynamics should behave at a given stress;
- With limited sampling, it generalizes the behavior to all fault vertices.


Node Location (-1, -3)
RMSE: 0.2645 m/s
MAE: 0.1150 m/s
Corr: 0.987
Node Location (3, -3)
RMSE: 0.4733 m/s
MAE: 0.1358 m/s
Corr: 0.912
Node Location (7, -3)
RMSE: 0.8489 m/s
MAE: 0.1967 m/s
Corr: 0.878
Node Location (-1, -7)
RMSE: 0.3163 m/s
MAE: 0.1222 m/s
Corr: 0.950
Node Location (3, -7)
RMSE: 1.3191 m/s
MAE: 0.2958 m/s
Corr: 0.757
Node Location (7, -7)
RMSE: 0.7913 m/s
MAE: 0.1974 m/s
Corr: 0.771
ground_truth
prediction
Slip Rate (m/s)
Time (s)

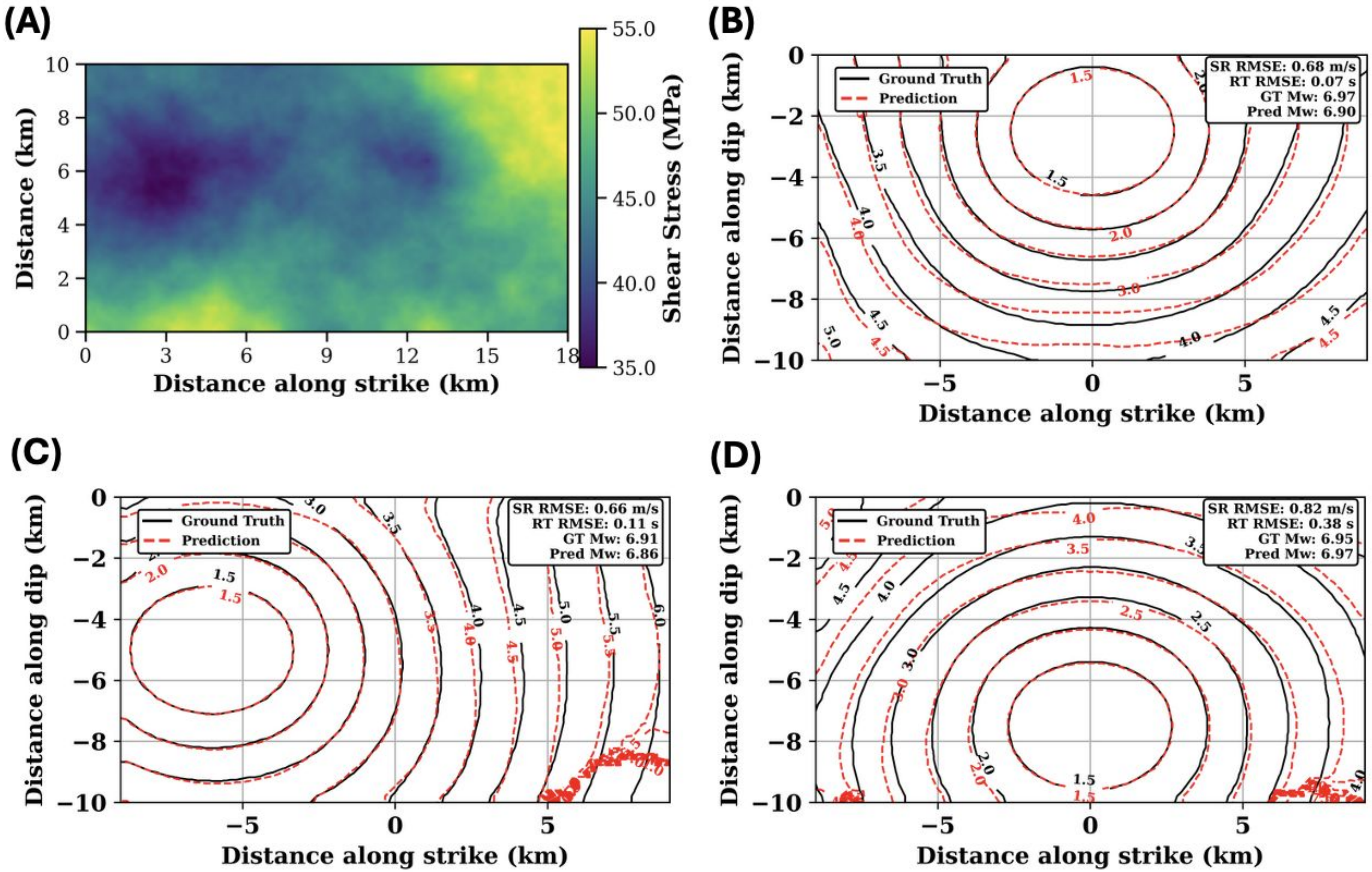
M2: Even More Complexity? Low Fractal Stresses

Good performance; SR RMSE ~0.6m/s; SR RMSE ~0.15 s; Mag error<0.1.

Rare feature: early termination

M2: Even More? Intermediate Fractal Stresses

Still good; SR RMSE ~ 0.6m/s; RT RMSE ~0.07-0.38 s; Mag error < 0.1.

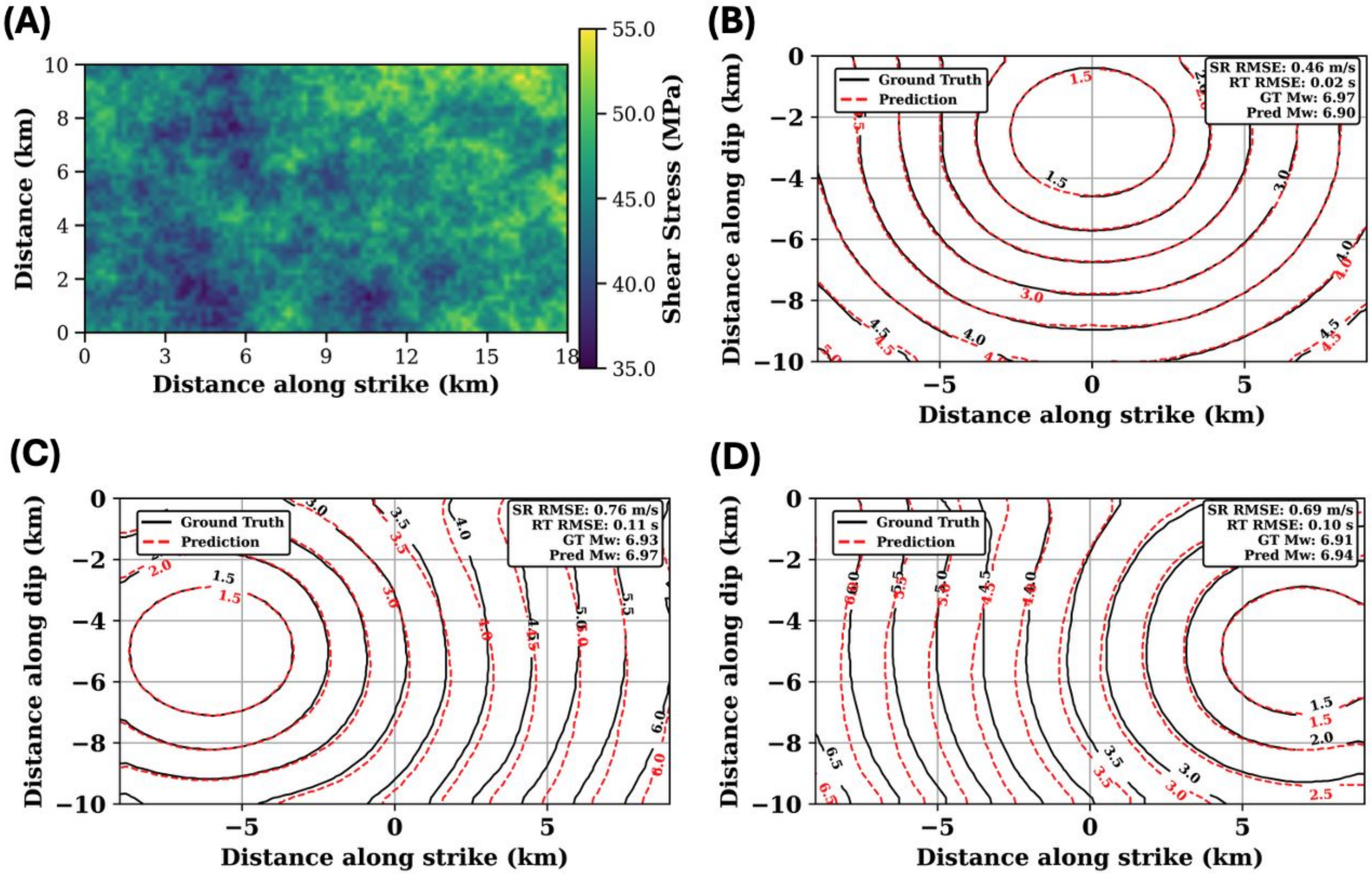


High Fractal Stresses? Calling for a Larger Model M3 (148)

Model	M2			M3			Better model
Metrics	SR RMSE (m/s)	RT RMSE (s)	M_w error	SR RMSE (m/s)	RT RMSE (s)	M_w error	
Low stress roughness R = 0.1							
D3.T0	0.57	0.11	0.03	0.35	0.04	0.01	**M3**
D3.T1	0.58	0.16	0.01	0.71	0.27	0.08	M2
D3.T3	0.92	0.95	0.04	0.82	0.88	0.05	**M3**
D3.T4	0.53	0.08	0.01	0.73	0.15	0.05	M2
Intermediate stress roughness R = 0.5							
D3.T5	0.68	0.07	0.07	0.46	0.03	0.07	**M3**
D3.T6	0.66	0.11	0.05	0.63	0.09	0.02	**M3**
D3.T7	1.08	0.37	0.01	0.88	0.13	0.07	**M3**
D3.T8	0.82	0.38	0.02	0.88	0.12	0.06	**M3**
D3.T9	0.9	0.21	0.07	0.93	0.33	0.03	**M3**
High stress roughness R = 0.9							
D3.T10	0.65	0.06	0.1	0.46	0.02	0.07	**M3**
D3.T11	0.93	0.17	0.02	0.76	0.11	0.04	**M3**
D3.T12	3.2	0.28	0.19	0.69	0.1	0.03	**M3**
D3.T13	0.99	0.13	0.09	0.82	0.11	0.02	**M3**
D3.T14	0.94	0.16	0.07	0.66	0.24	0	**M3**

M3: Most complexity? High Fractal Stresses

Good; SR RMSE ~0.47-0.76 m/s; RT RMSE <0.11 s; Mag error <= 0.07.



Backward Compatibility: Phased Introduction of New Features?

- Yes!
- M2 vs M1 on D1.
- New opportunity to add other heterogeneity such as friction, geometry and more.

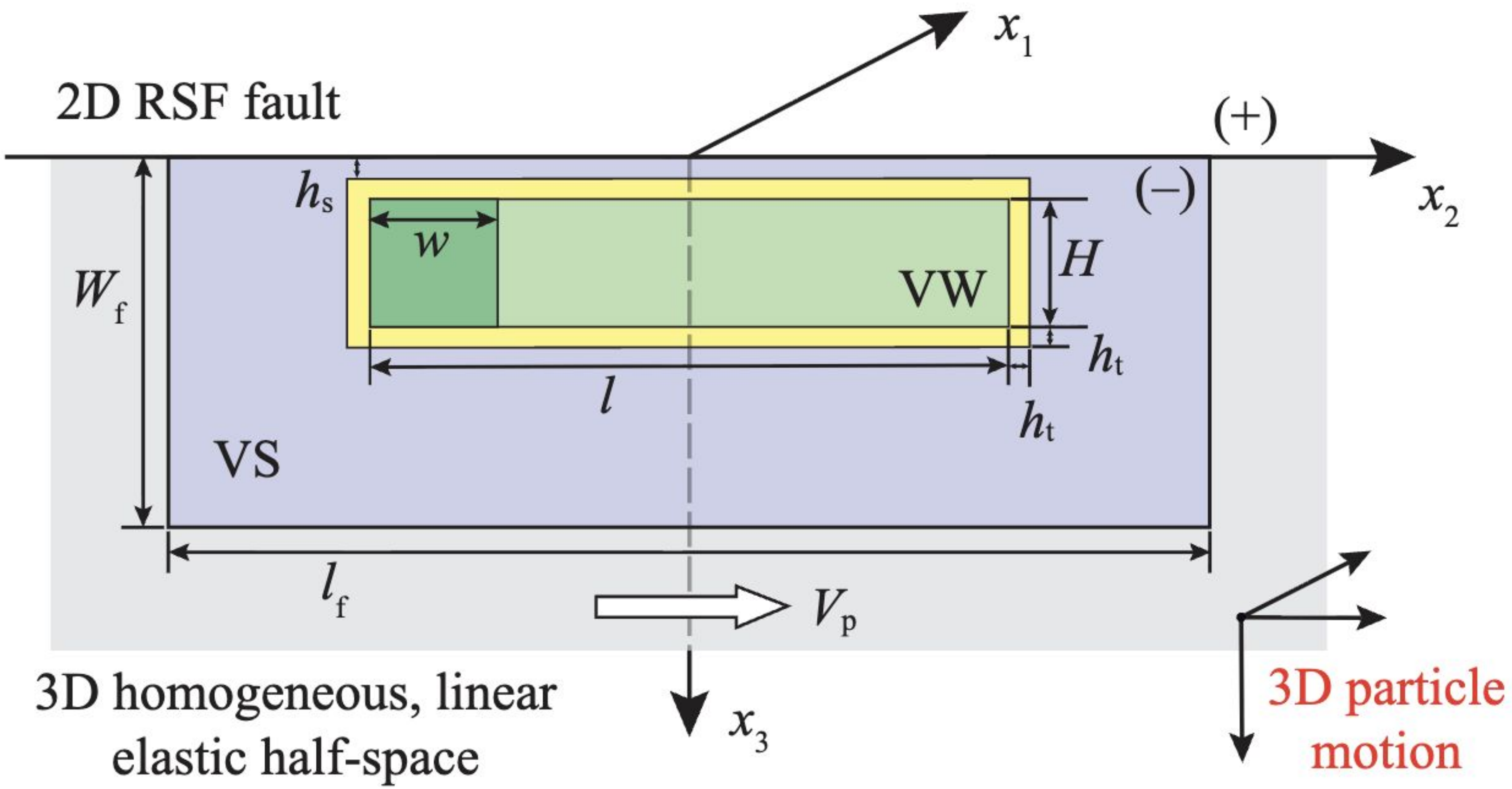
Model	M1			M2		
Metrics	SR RMSE (m/s)	RT RMSE (s)	M_w error	SR RMSE (m/s)	RT RMSE (s)	M_w error
D1.T0	0.35	0.04	0.05	0.39	0.05	0.0
D1.T1	0.45	0.06	0.01	0.49	0.17	0.01
D1.T2	0.81	0.47	0.07	0.93	0.79	0.09
D1.T3	0.33	0.04	0.03	0.41	0.05	0.01
D1.T_large	0.61	0.12	0.09	0.51	0.07	0.05

Computational Performance

Per-time-step speed up			
Grid size	**1 Nvidia A100 GPU GNS (ms/step)**	**8 AMD EPYC 7543 CPU *EQdyna* (ms/step)**	**Speedup**
200m	20	~322	**~29.3**
100m	67	~1449	**~41.4**

- GNS generates full evolution of system states, in contrast to end-to-end ML approaches.
- Different ways to compute speedup. Gong et al. (2025) and Tainpakdipat et al. (2025) predicts final state or subsampled states.
- While physics-based simulations have been optimized over decades, opportunities remain to enhance GNS performance by leveraging advances in data encoding, neural architecture engineering, optimization strategies and on-going GPU-based cyberinfrastructure investments.

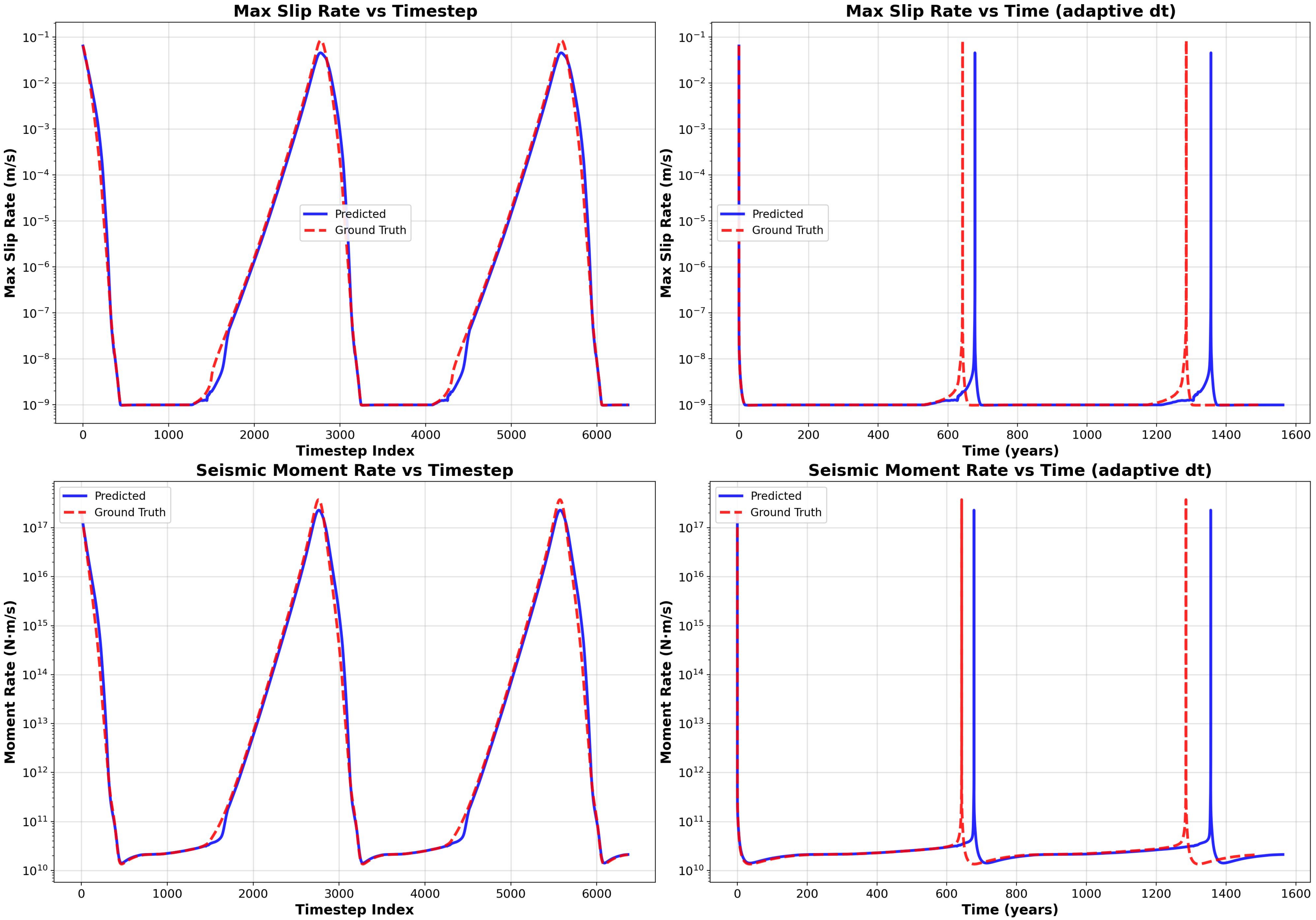
A More Challenging System: Earthquake Cycle Dynamics



(Jiang et al., 2022)

- Earthquake cycle dynamics governed by the nonlinear rate- and state- friction with elastodynamics.
- Slip rates range from 10^{-12} m/s to 10^{1} m/s, over tens of order of magnitude.
- Varying time steps from a fraction of a second to years.
- Long and never-ending autoregressive rollout.

Graph Transformer-based Simulator (GTS)



(Liu, Sun, Becker, and Jia, 2026, in preparation)

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Graph Transformer-based Simulator (GTS)

(Liu, Sun, Becker, and Jia, 2026, in preparation)

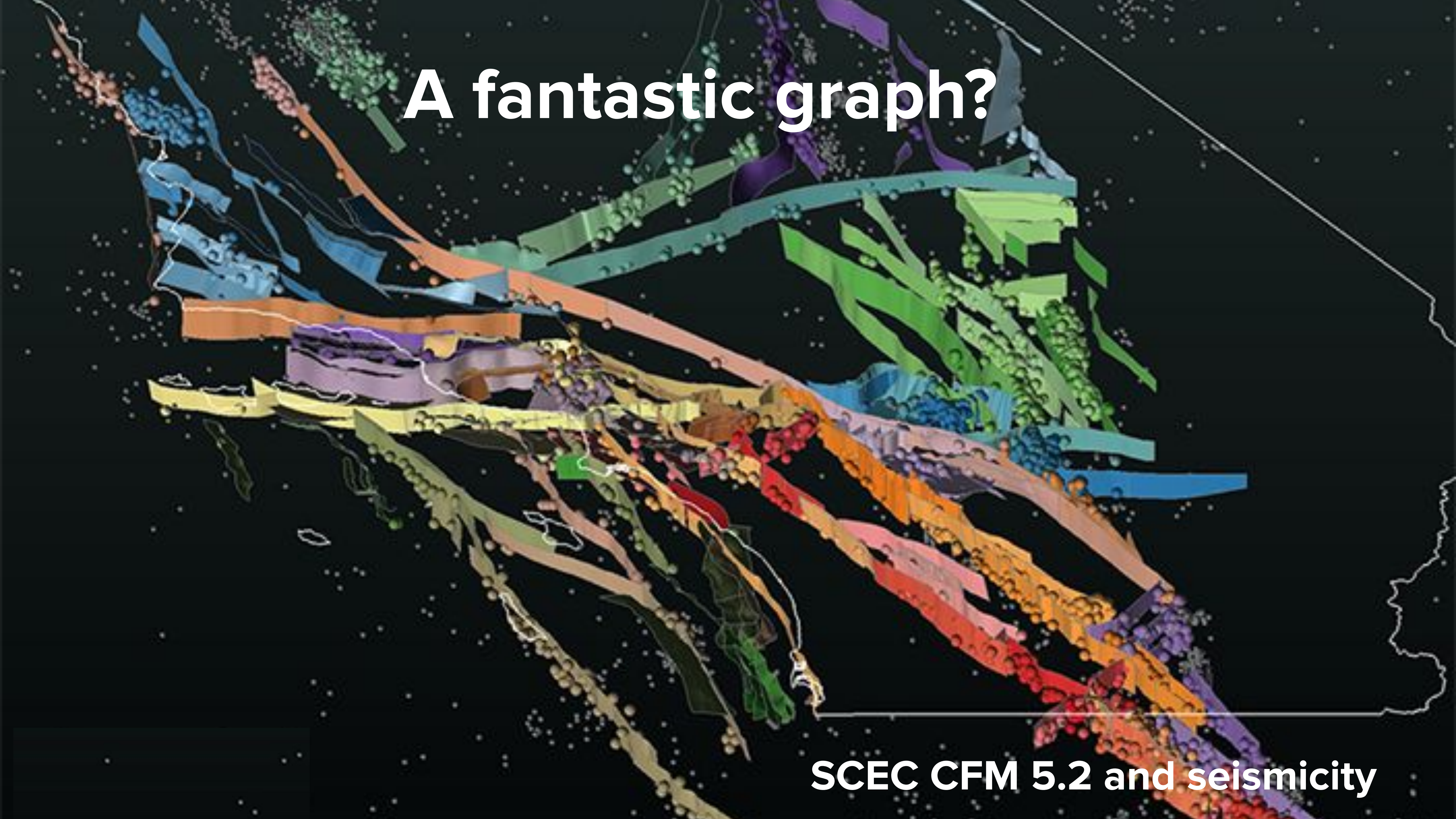
Concluding Remarks

- The Graph Network Simulator (GNS) and Graph Transformer Simulator (GTS) learn an interaction ***"stencil"***—a coarse-grained, local abstraction of the governing physics.
- This stencil appears central to GNS' ability to generalize. *What exactly is this stencil? Can we interpret, refine, and leverage it for improved performance?*
- GNS frameworks can gradually broaden its scope by training on selected parameter levels and scenarios.
- Efficiency gain from GNS may benefit Bayesian inference, uncertainty quantification, and ensemble analysis.

Next Steps:

- Expand system state to explicitly include ground shaking and earthquake cycles,
- Incorporate friction parameters, multiple friction laws, geometric complexities, and rheological effects
- Accelerate GNS computations (New optimization gains another 2X speedup.)
- Extend to complex fault networks

A fantastic graph?



SCEC CFM 5.2 and seismicity

Acknowledgement

- ***EQGNS*** *is inspired by* ***Google's GraphCast*** (Lam et al., 2023) *and developed from* ***Meshnet*** from **https://github.com/geoelements/gns.git** (Vantassel and Kumar, 2022; Kumar and Choi, 2023; Choi and Kumar, 2024)

- **Thank you for your attentions! Questions?**

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