Blending Multi-scale Velocity Models - Methods and Validation

Te-Yang Yeh & Kim Bak Olsen
Department of Earth and Environmental Sciences, San Diego State University

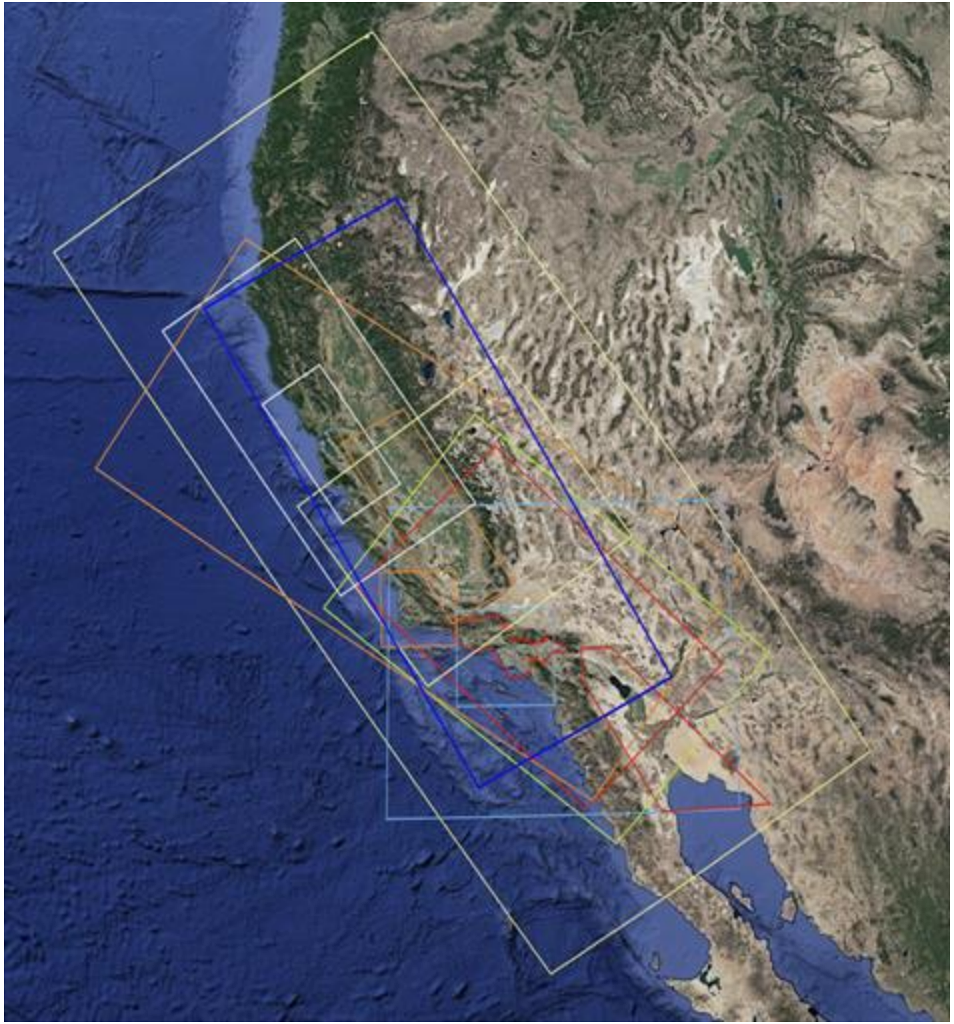
SAN DIEGO STATE UNIVERSITY

Funded by:

SCEC Statewide California Earthquake Center

OAK RIDGE National Laboratory | LEADERSHIP COMPUTING FACILITY

TACC

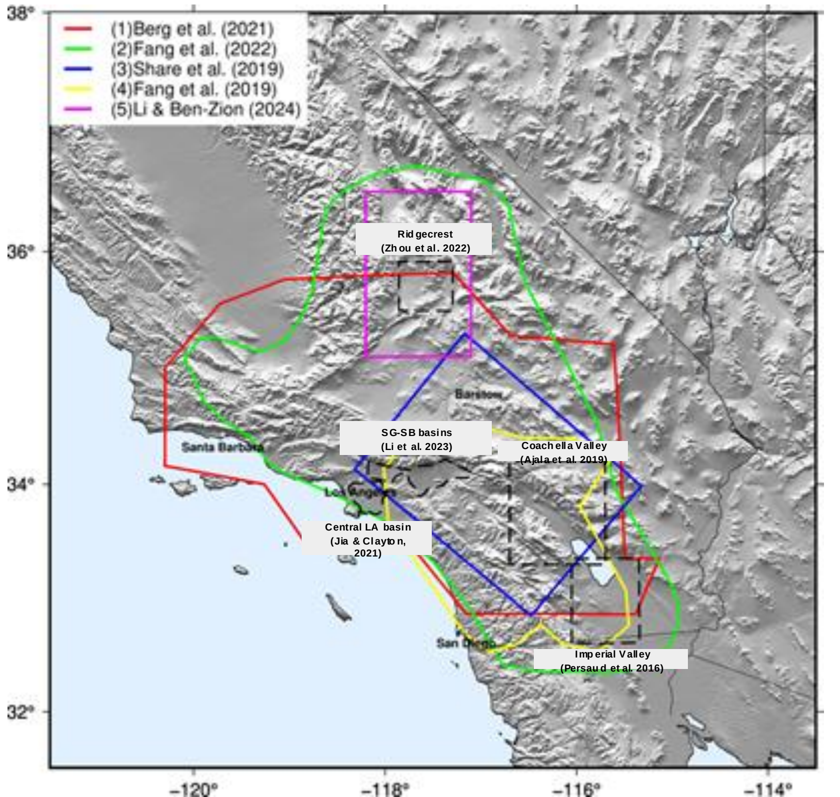


SCEC UCVM

- Many models available in UCVM
- But many are not!
- Need to be collected from individual groups before they are lost!

Objectives & Outlines

- Advancing ground motion prediction by incorporating multi-scale velocity models
- Comparison of fusion methods
  - Windowing x1
  - Machine learning x2
- Model validation against observations
- Improved ground motion prediction
- Conclusions



Blending Method (1) - Windowing

- Option #1: Blending method proposed by Ajala & Persaud (2021, JGR)

  High-resolution (**HR**) model Ω_1 to be merged into a low-resolution (**LR**) model R(x):

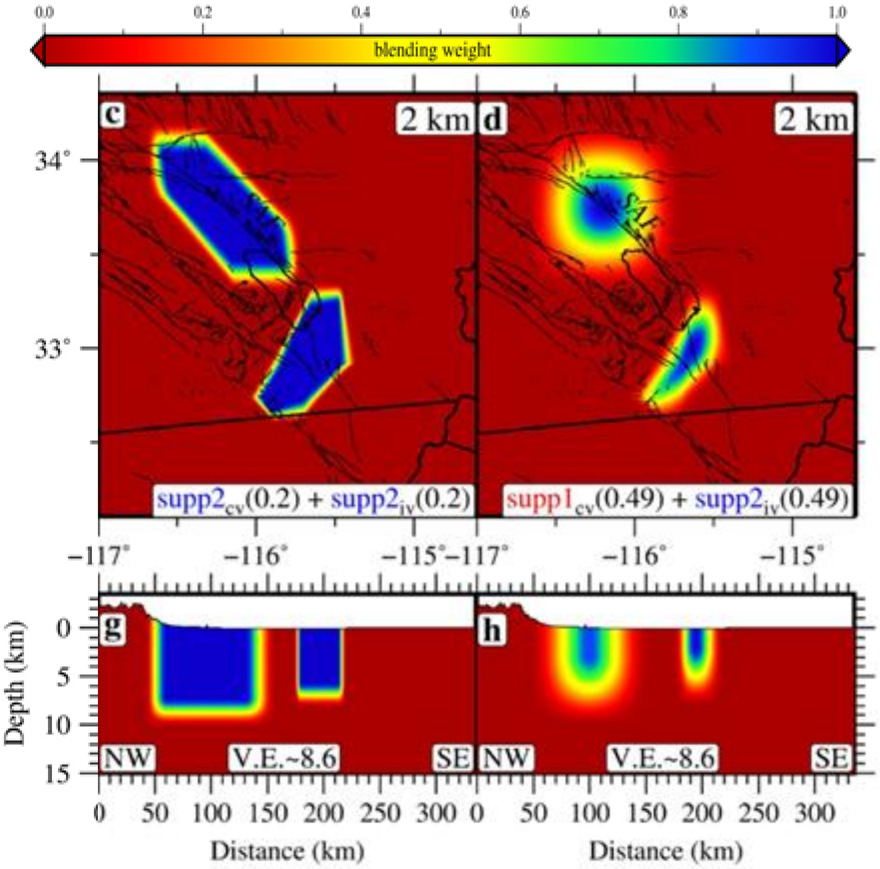
  $$H(\boldsymbol{x}) = \Omega^1(\boldsymbol{x})w(\boldsymbol{x}) + R(\boldsymbol{x})(1 - w(\boldsymbol{x})),$$

  $$w(\boldsymbol{x}) = \begin{cases} 0, & \boldsymbol{x} \in \Omega^1 \backslash \overline{\Omega^2} \\ (0,1], & \boldsymbol{x} \in \overline{\Omega^2} \end{cases}.$$

  H(x): Hybrid model
  w(x): Weight

- Thickness of the transition zone?

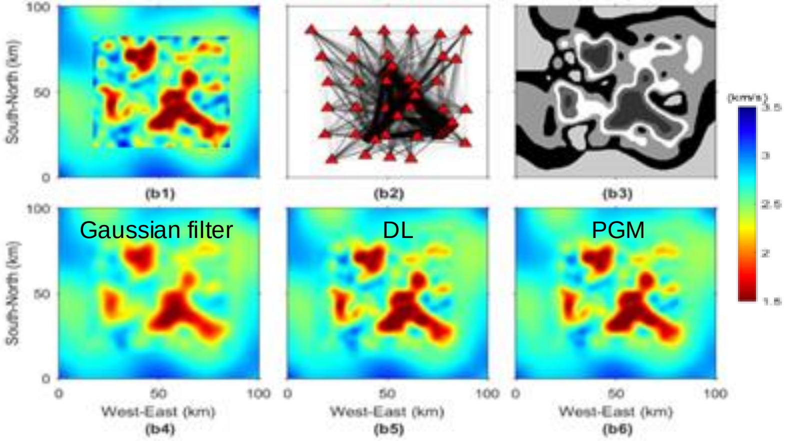
- Starting point of transition zone?

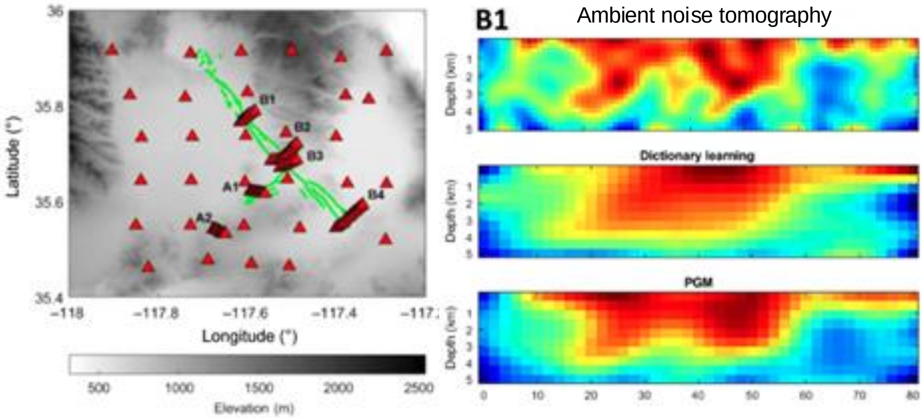


Modified from Ajala and Persaud (2021)

Blending Method (2) - Machine Learning: Probability Graphical Models

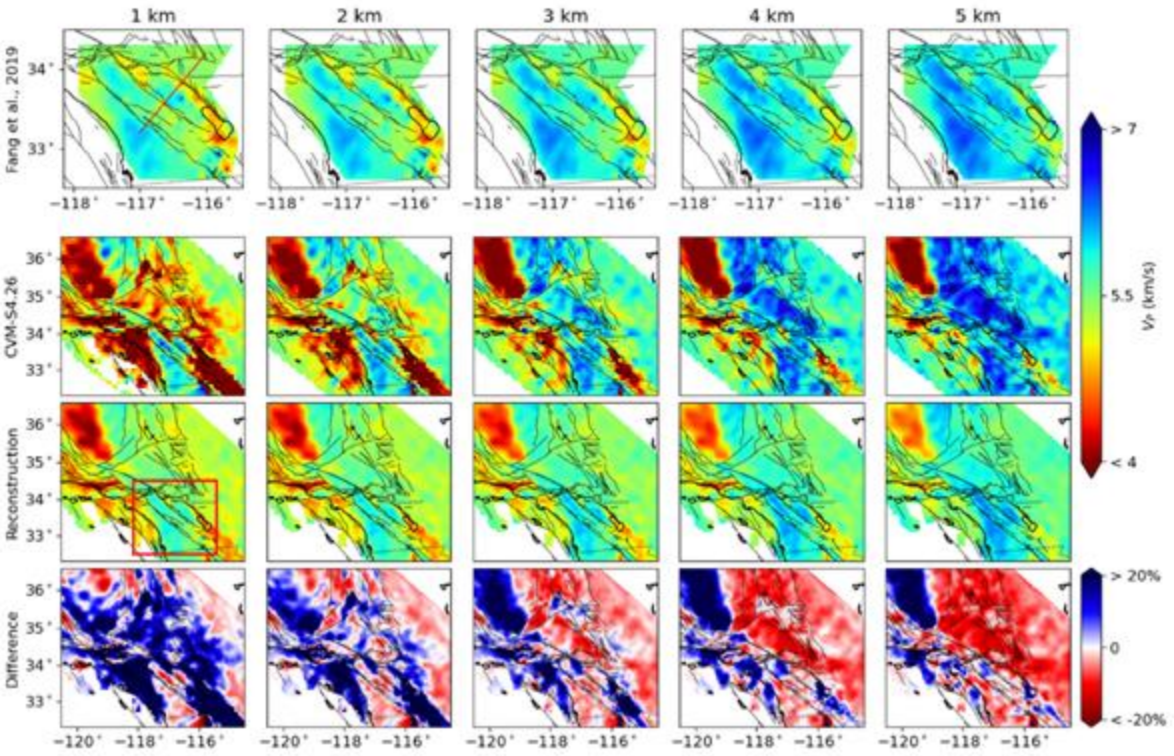
- Using ML-based methods, such as the Probability Graphical Models (PGM) proposed by Zhou et al (2024, BSSA)
- Physics-informed PGM based on level of confidence in the HR model (e.g., ray density)
- PGM can create similar transition zone as the windowing method
- PGM smoothes both LR and HR models
- Higher computational cost for 3D models



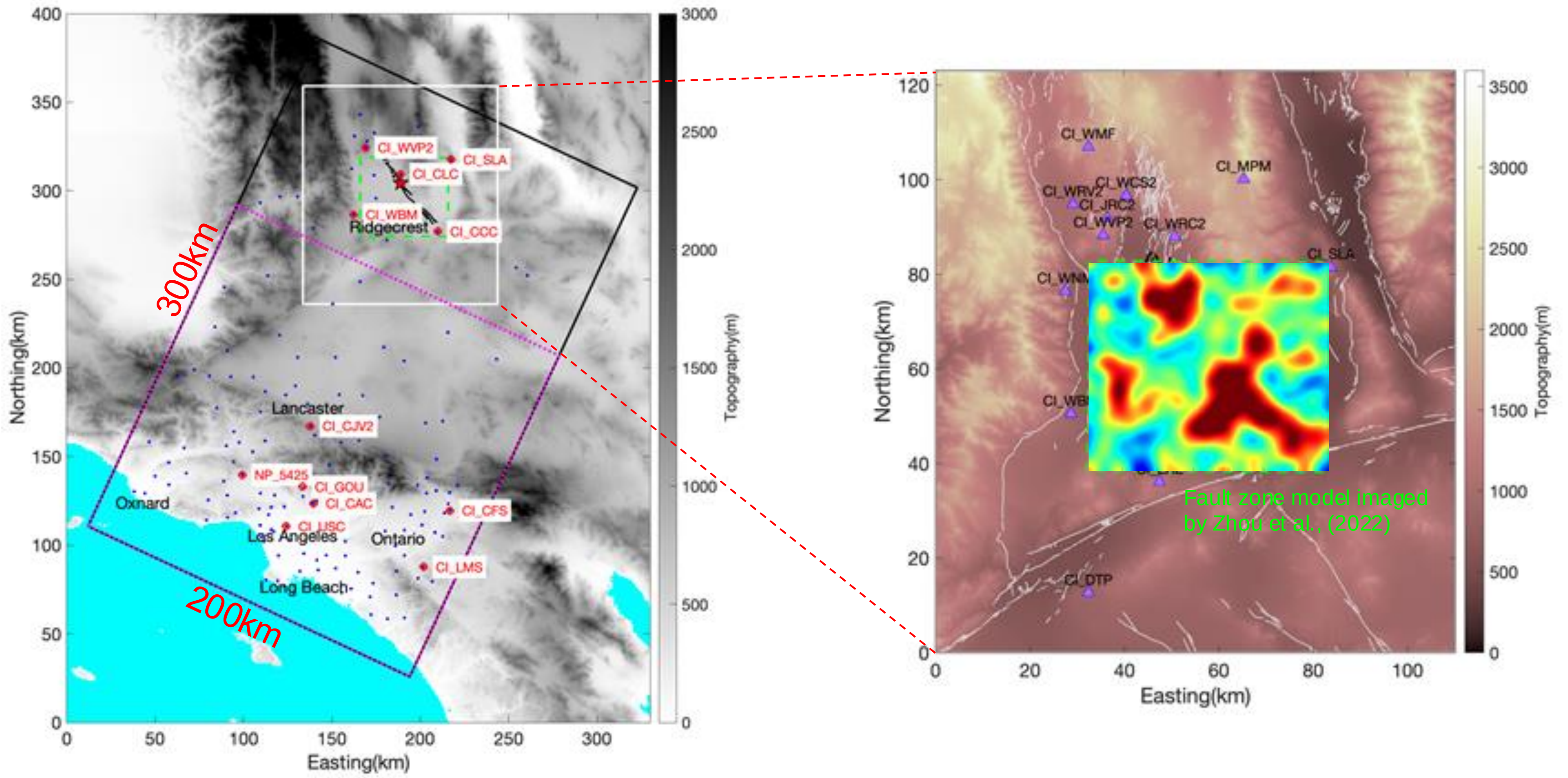


Blending Method (3) - Machine Learning: Sparse Dictionary Learning Model

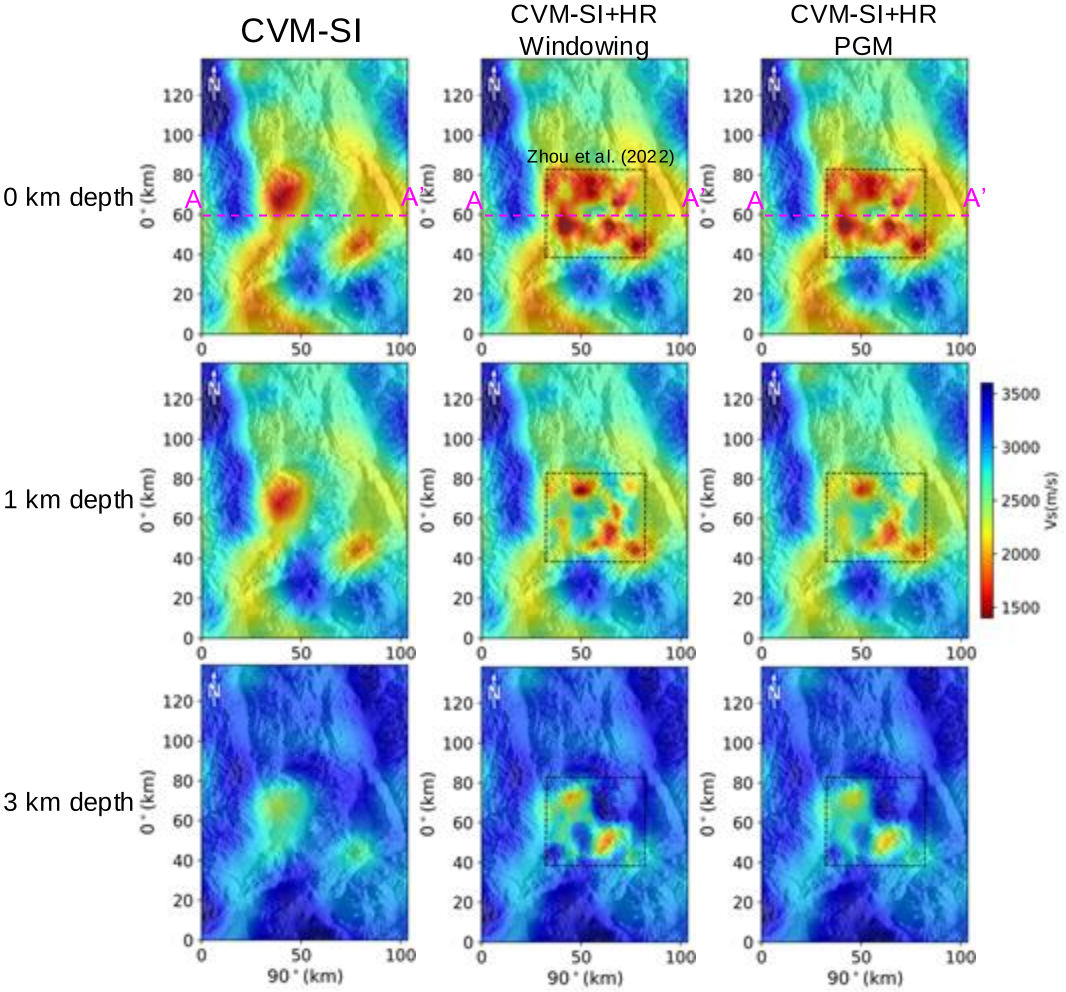
- Sparse Dictionary Learning proposed by Zhang and Ben-Zion, 2024, JGR)
- Both HR and LR models will be modified during reconstruction
- May deviate further from those generated by the other two methods
- Validated with 1 Hz full-waveform modeling



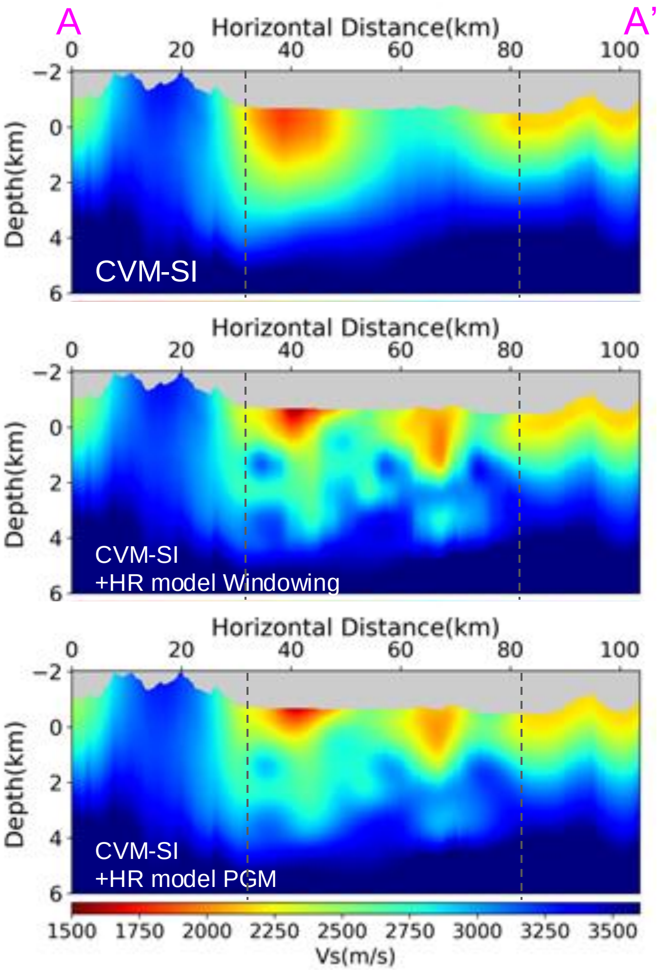
Case Study


300km
200km
CI_WVP2
CI_SLA
CI_CLC
CI_WBM
Ridgecrest
CI_CCC
Lancaster
CI_CJV2
NP_5425
CI_GOU
CI_CAC
CI_CFS
Oxnard
CI_USC
Los Angeles
Ontario
CI_LMS
Long Beach
Northing(km)
Easting(km)
Topography(m)
CI_WMF
CI_MPM
CI_WRV2
CI_WCS2
CI_JRC2
CI_WVP2
CI_WRC2
CI_SLA
CI_DTP
Fault zone model imaged
by Zhou et al., (2022)

Surface Vs

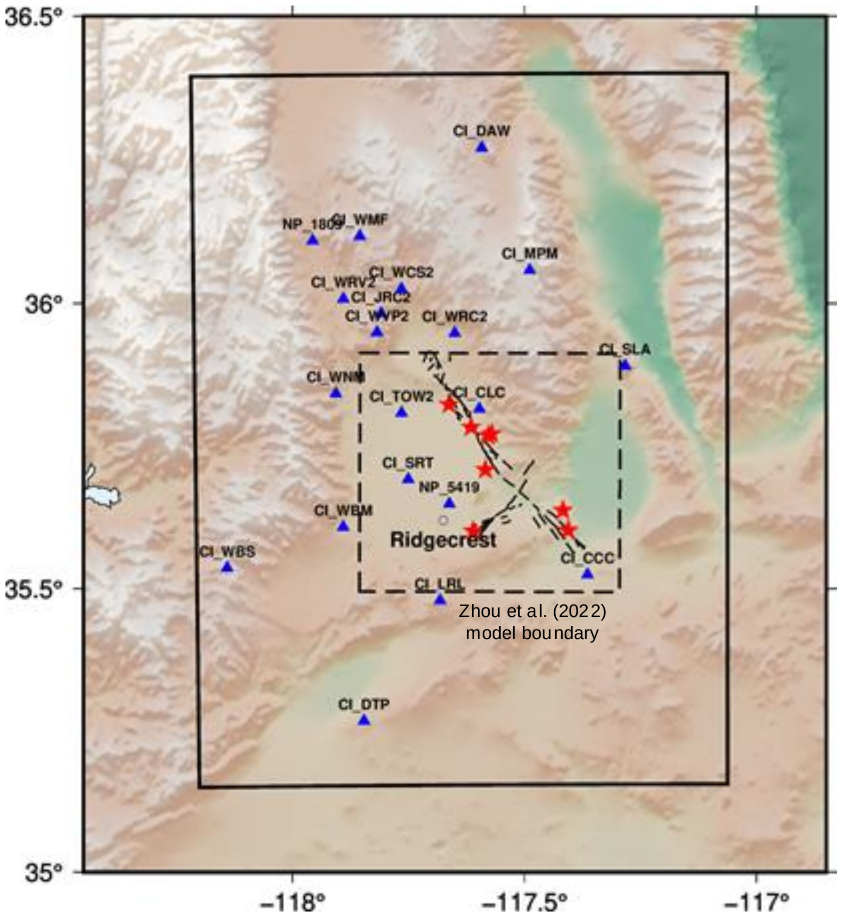


Vs Transect



Model Validation

- Focus on commonly-used ground motion metrics
- Simulating 8 Mw 4.0 - 4.6 events
- SCEDC data (CI and NP networks)
- 20 stations recording 2+ events
- High S/N ratio
- SCEDC moment tensor solutions

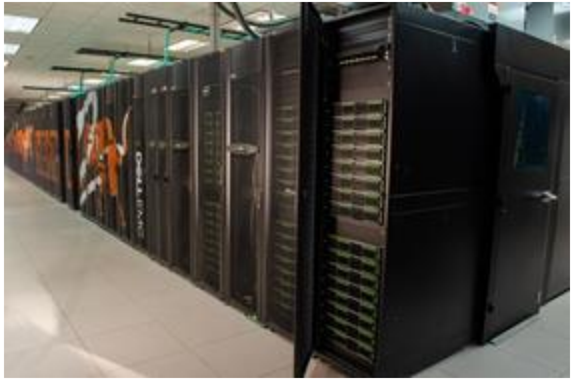


0-1 Hz simulations using AWP-ODC

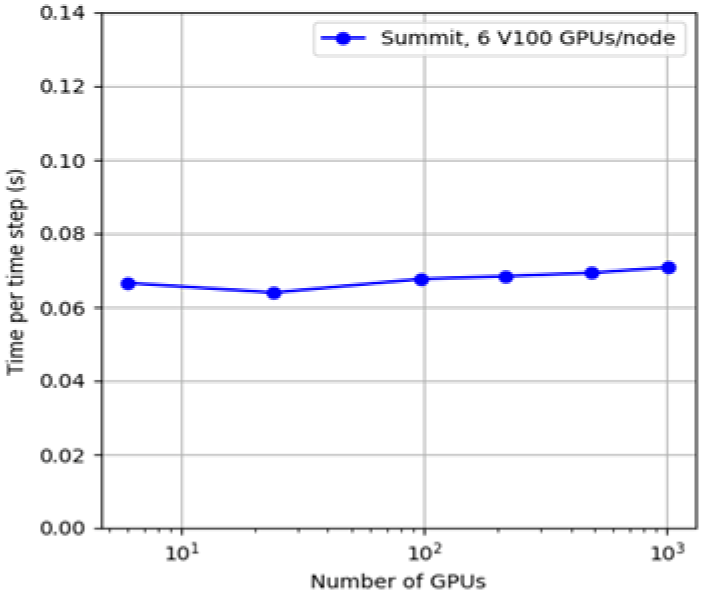
4th-order Scalable Finite Difference Method with Support for Topography, Discontinuous Mesh, and Q(f)

Frontier supercomputer at OLCF

Vista supercomputer at TACC



O'Reilly, O., T.-Y. Yeh, K.B. Olsen, Z. Hu, A. Breuer, D. Roten, and C. Goulet (**2022**). A high-order finite difference method on staggered curvilinear grids for seismic wave propagation applications with topography, *Bull. Seis. Soc. Am.*, **112 (1)**, 3-22.



Goodness-of-fit Metrics

FAS bias (for component j): $$\epsilon^j_{FAS} = \frac{1}{N_f}\Sigma_{i=1}^{N_f} log_{10}\frac{FAS^j_{syn}(i)}{FAS^j_{obs}(i)}$$

CAV bias (for component j): $$\epsilon^j_{CAV} = log_{10}\frac{\Sigma_{i=1}^{N_t}|v^j_{syn}(i)|}{\Sigma_{i=1}^{N_t}|v^j_{obs}(i)|}$$

PGV bias (for component j): $$\epsilon^j_{PGV} = log_{10}\frac{PGV^j_{syn}}{PGV^j_{obs}}$$

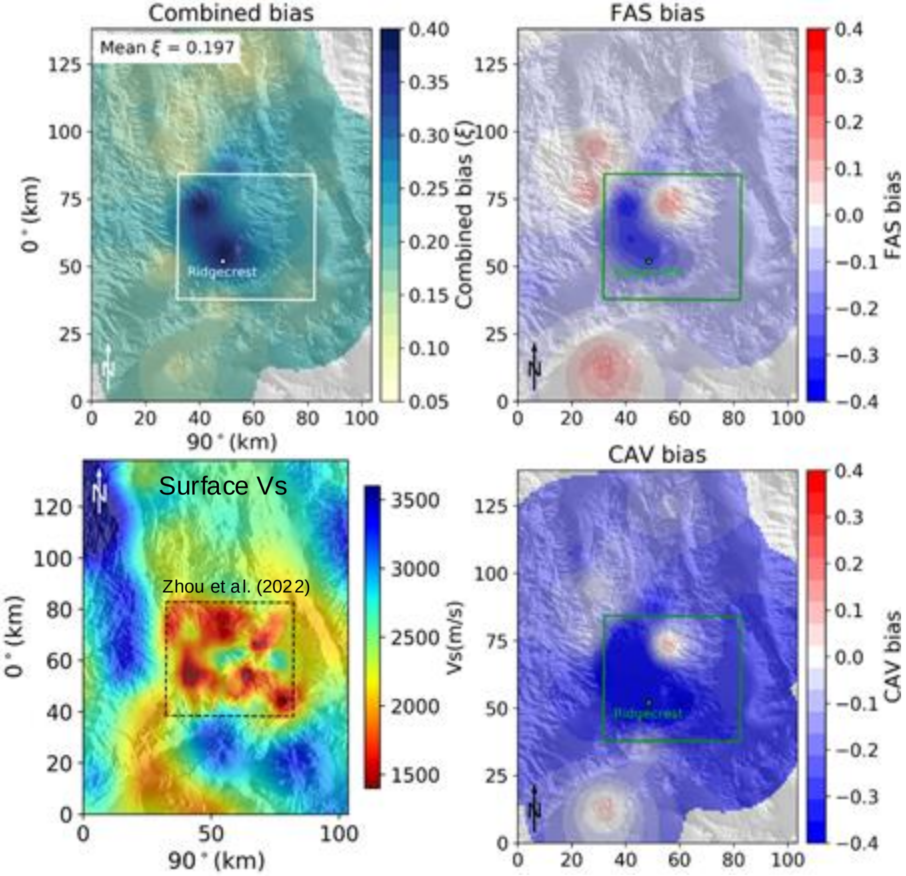
PGA bias (for component j): $$\epsilon^j_{PGA} = log_{10}\frac{PGA^j_{syn}}{PGA^j_{obs}}$$

Combined metric:

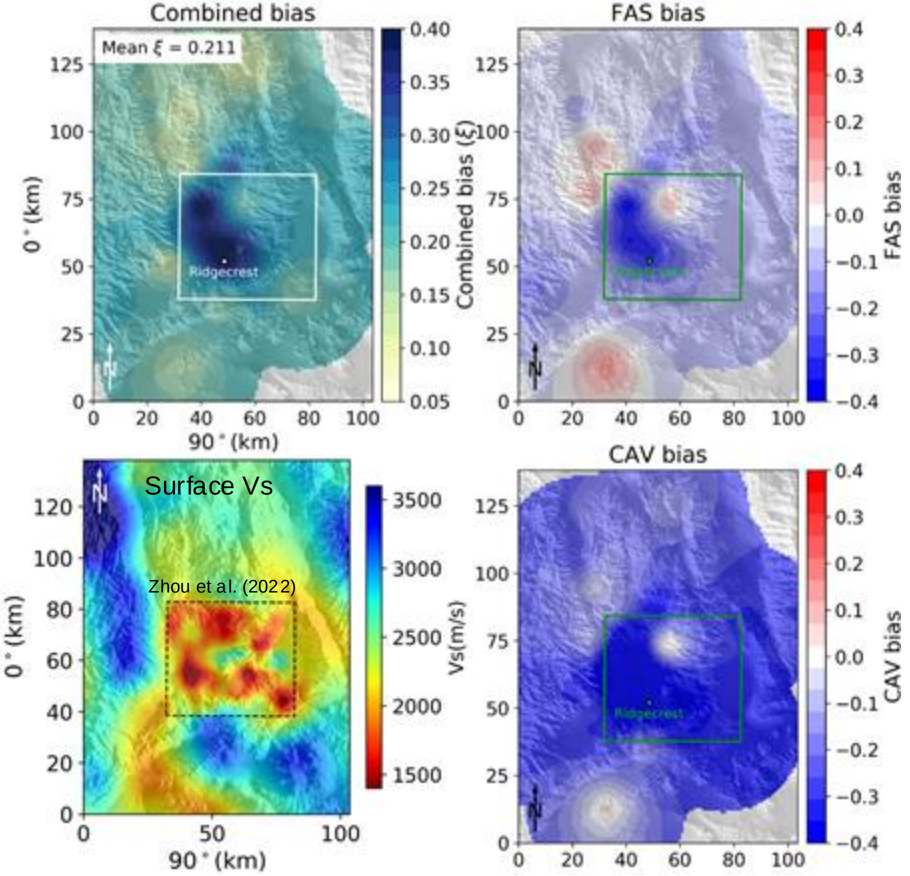
$$\xi = \frac{\Sigma_{j=1}^{3}(|\epsilon^j_{FAS}|+|\epsilon^j_{CAV}|+|\epsilon^j_{PGV}|+|\epsilon^j_{PGA}|)}{12}$$

Windowing vs PGM

CVM-SI (LR)+HR **Windowing**

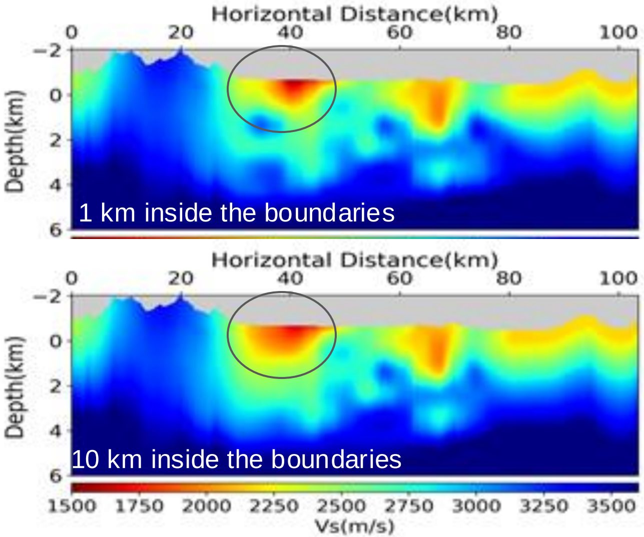


CVM-SI (LR)+HR **PGM**

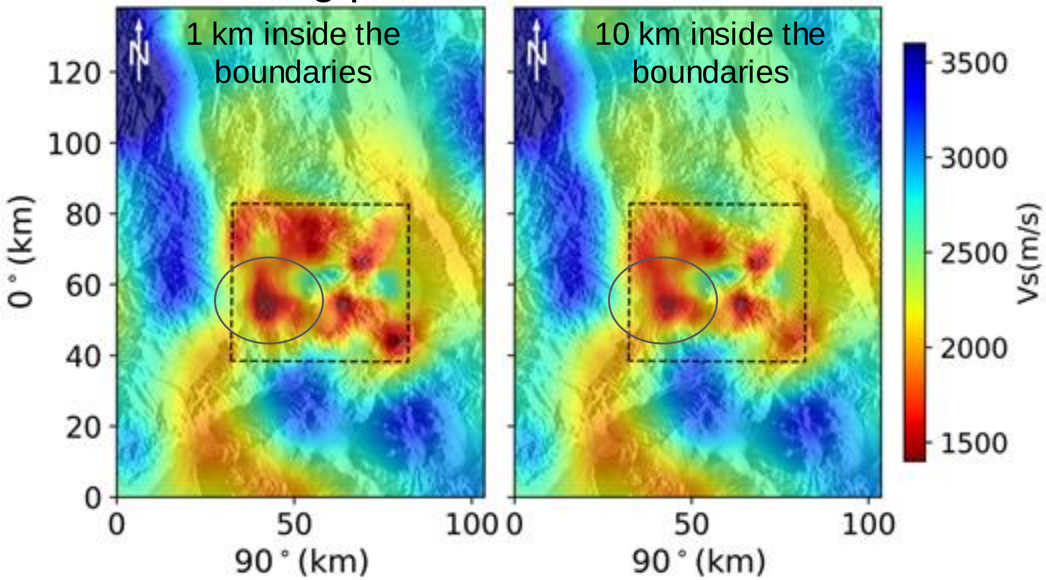


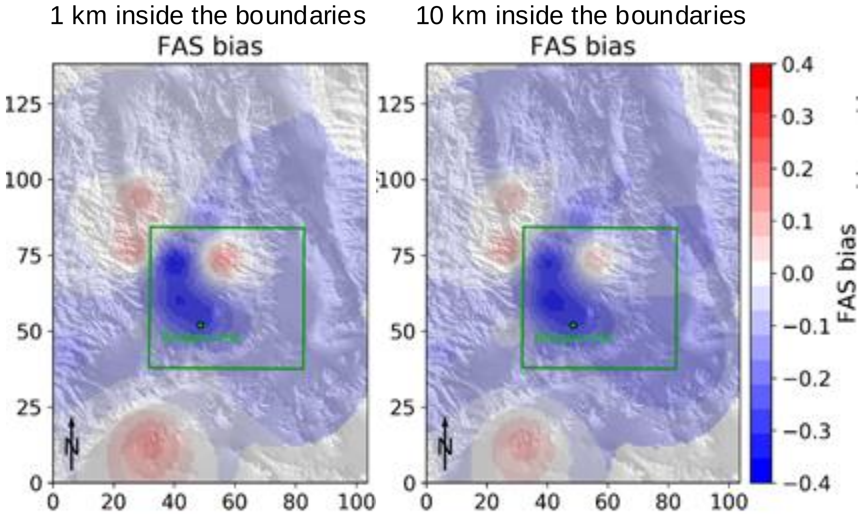
Does Transition Zone Matter?

- Yes! Both **starting point** and **thickness** matter
- Starting early -> losing more HR model
- Too thin -> artificial velocity contrast
- Losing low Vs in the HR -> more underprediction



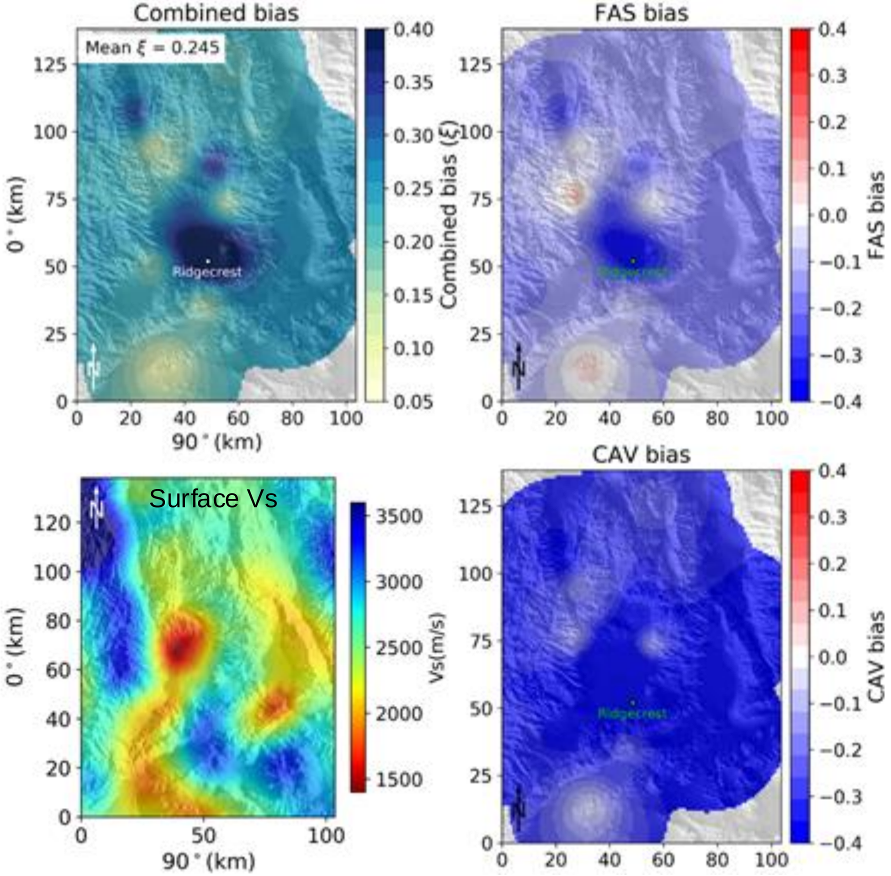
Starting point of transition zone



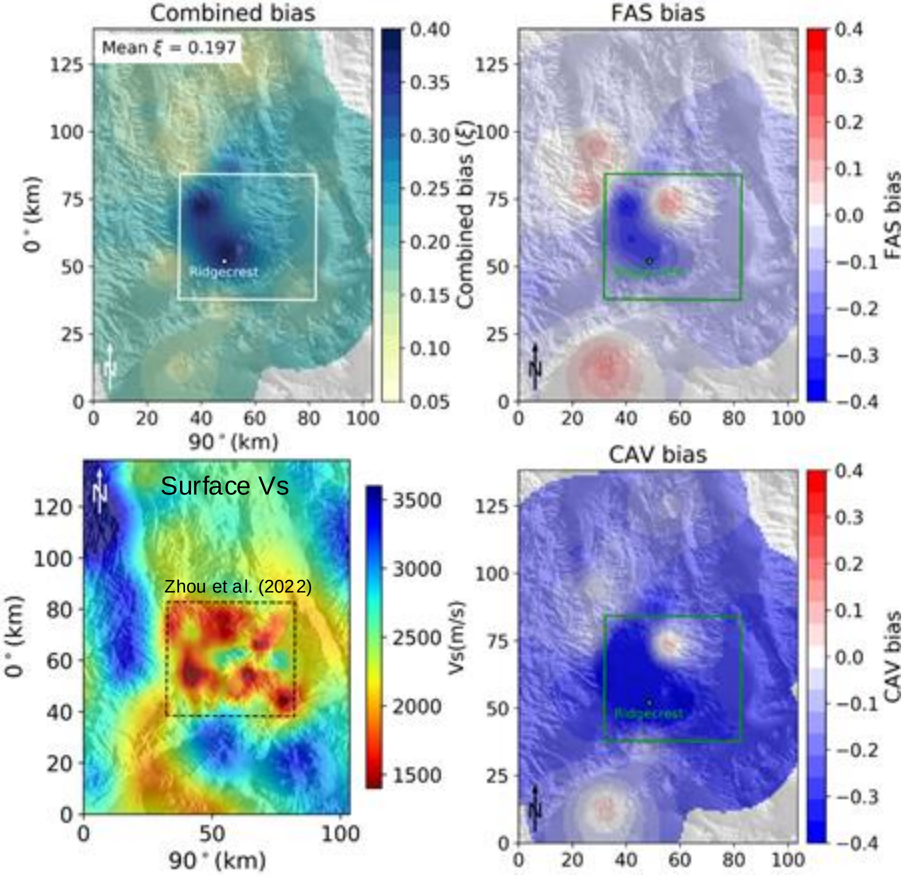


Effects of Including HR Model

CVM-SI (LR)

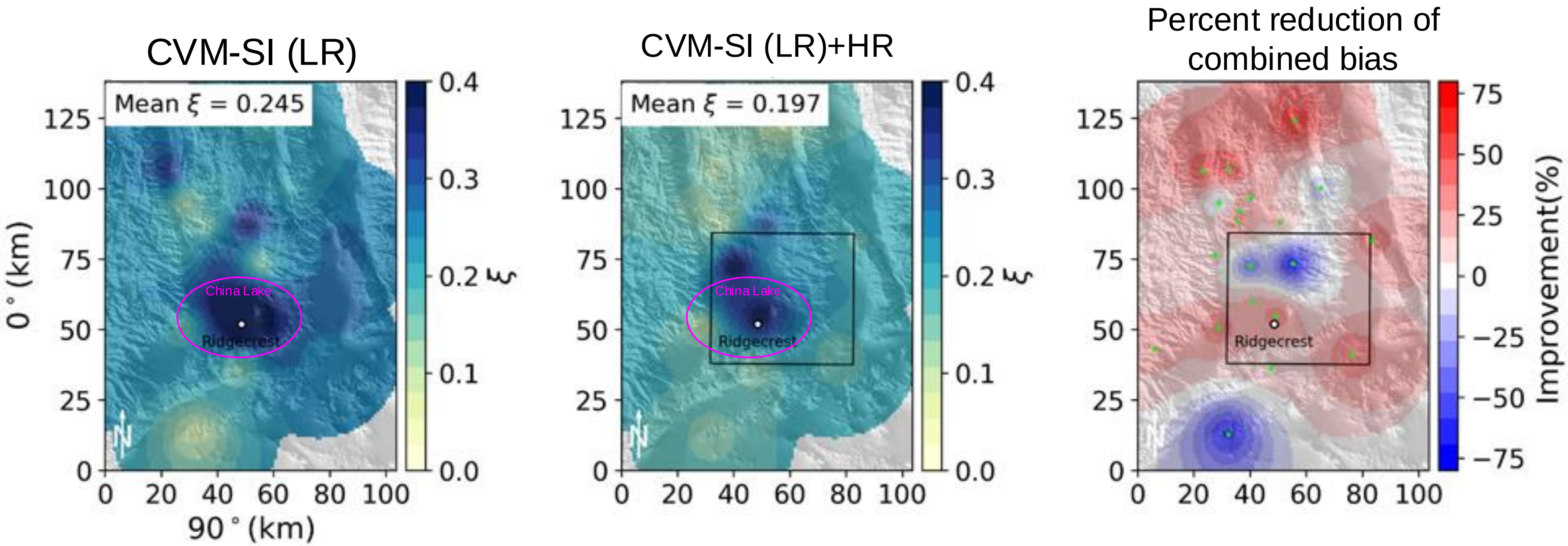


CVM-SI (LR)+HR Windowing

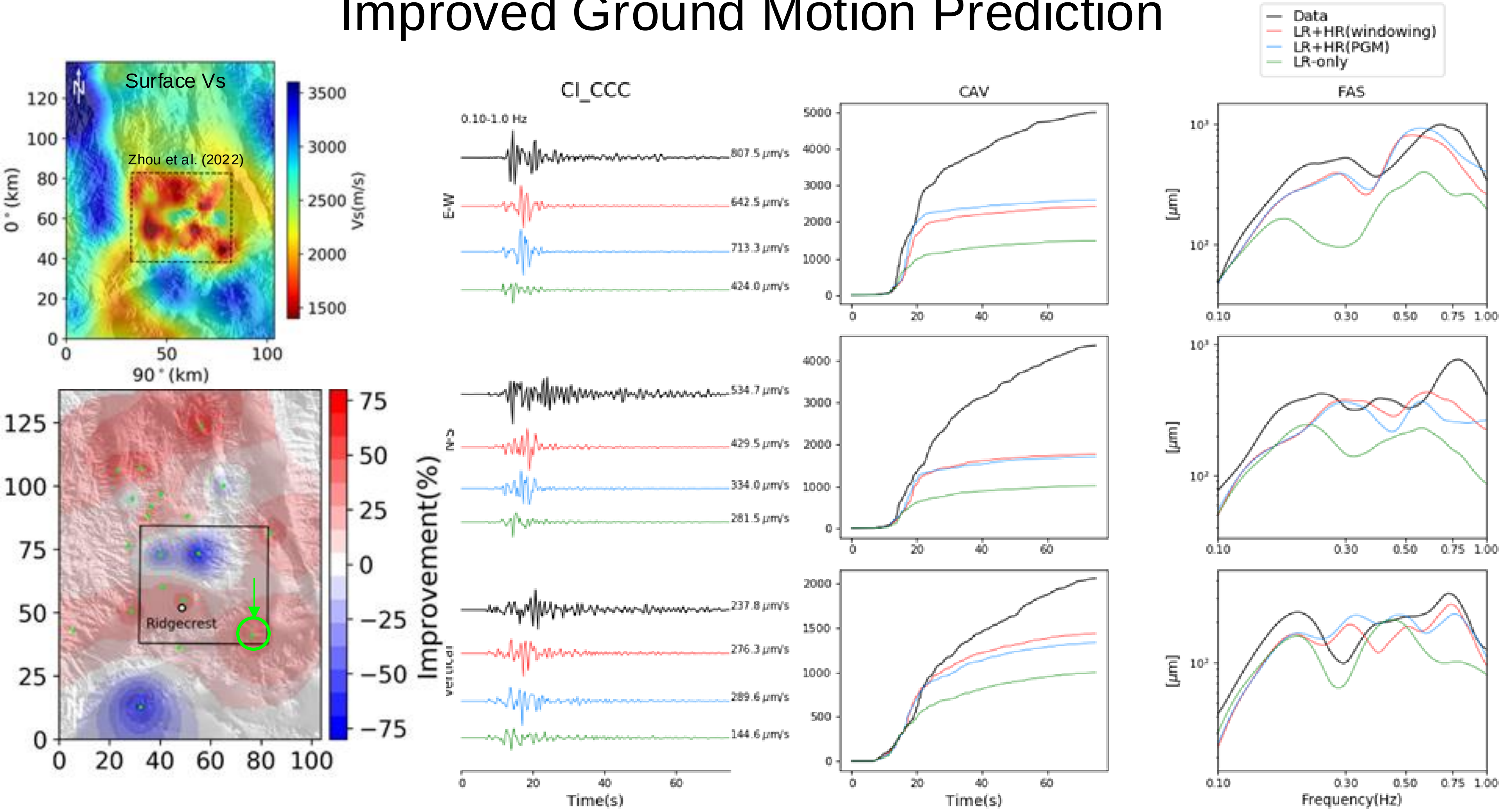


Improved Ground Motion Prediction

- ~20% reduction on mean combined bias
- Improvement both inside and outside the HR domain
- China Lake area still underpredicted



Improved Ground Motion Prediction



Conclusions

- We demonstrate fusion models (LR+HR) using windowing & PGM methods and validate them with numerical simulations
- Windowing method preserves features in LR and HR models, except for the transition zone
- Machine-learning methods modify both LR and HR models
- PGM produces smoother version of models blended using windowing method
- Design of transition zone matters
- Windowing method results in slightly lower mean bias than PGM in this particular case