Strain accumulation across strike-slip faults : Investigation of the influence of laterally varying lithospheric properties

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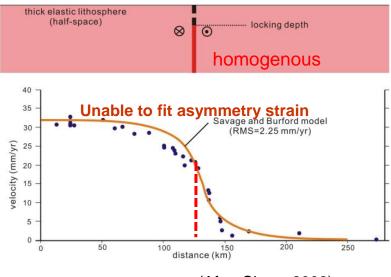
Presenter: Wen-Jeng Huang

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Can we use geodetic data to infer lateral variation in rigidity ?

The Problem





Use gradients in velocity field to identify where active faults are locked and accumulating stress.

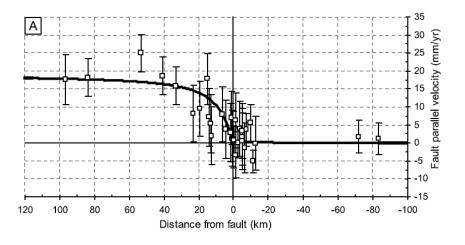
Gradients in velocity field can be attributed to:

 Elastic distortion around locked faults
 Lateral variations in lithospheric rigidity (thickness/stiffness)

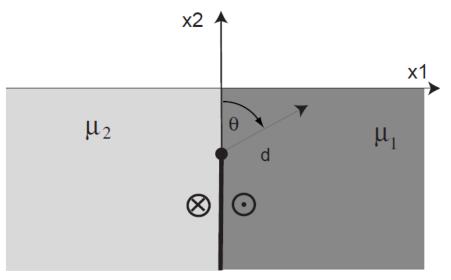
Can we use geodetic data to infer lateral variation in rigidity ?

Inferred Lateral Variations in Crustal Rigidity





Idealized bimaterial fault interface



Elastic Half-Space Models e.g., Le Pichon (2005)

Inferred rigidity ratio (μ_1/μ_2): 30

Inferred Lateral Variations in Crustal Rigidity

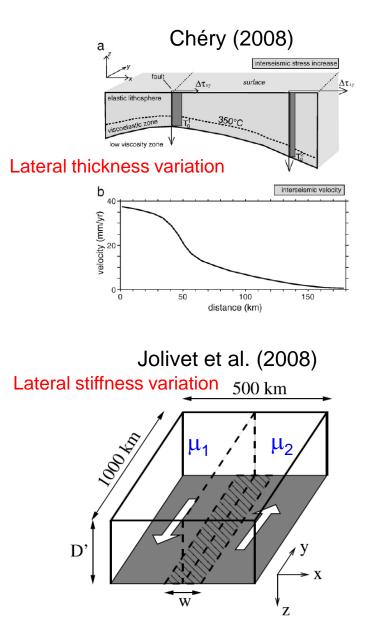
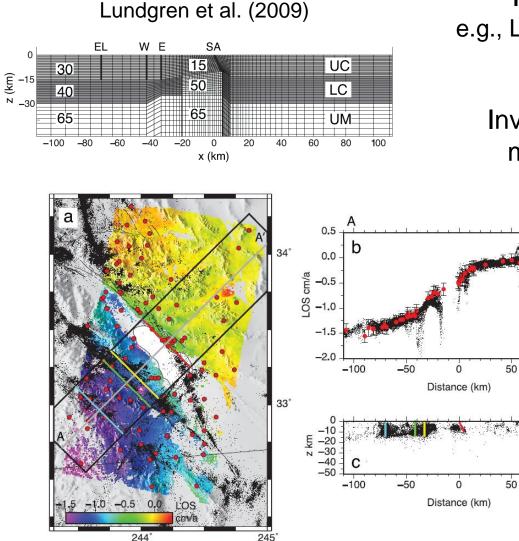


Plate Models e.g., Chéry (2008), Jolivet et al. (2008)

Flow underneath plates is not considered.

Inferred Lateral Variations in Crustal Rigidity



Finite Element Models

e.g., Lundgren et al (2009), Schmalze et al. (2005)

Inversions are difficult because models are computationally expensive.

100

100

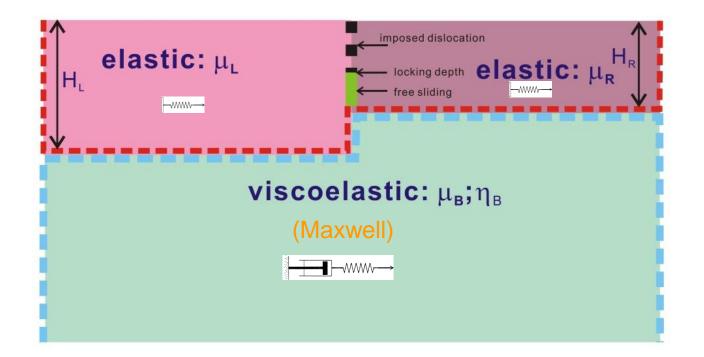
Why revisit this problem?

• Elastic half-space and plate models neglect viscous flow – we show that this is important

• Finite Element models too slow to fully explore model space

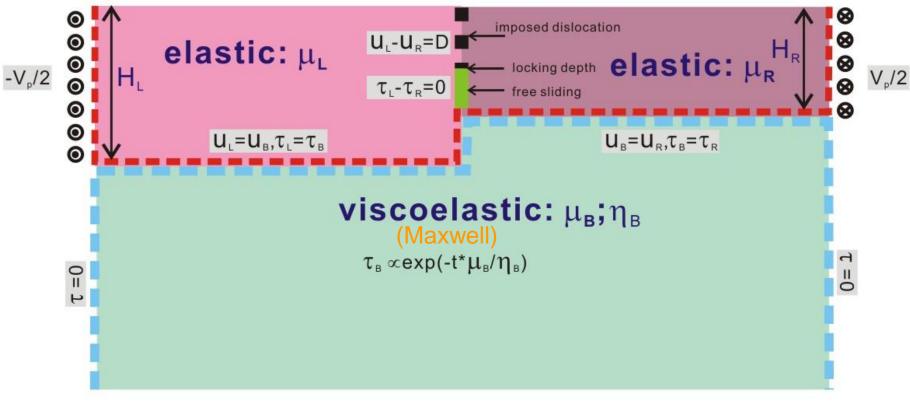
Our Model:

- Displacement-discontinuity Boundary Element Method
- Elastic layers overlying viscoelastic half-space
- Lateral variation of rigidity: e.g. stiffness and thickness
- And Migakeolytion Abap finite-width screw dislocation [e.g. Okada, 1992]





Boundary conditions



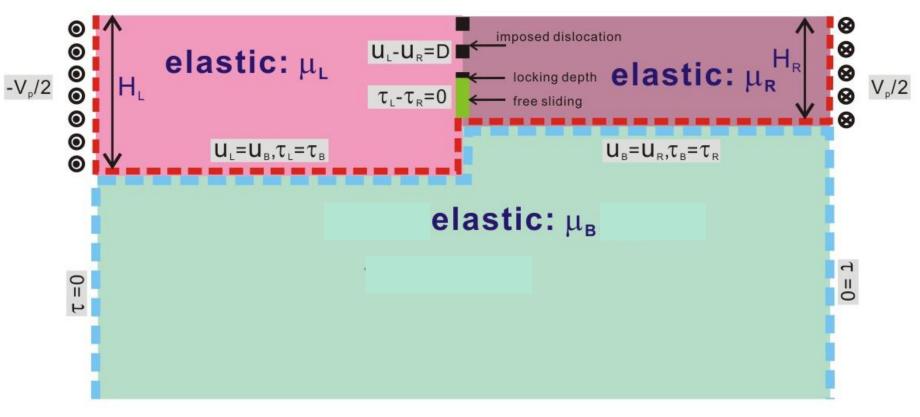
Stress Relaxation time, $t_R=2(\eta_B/\mu_B)$

Our Model:

For a purely elastic problem,

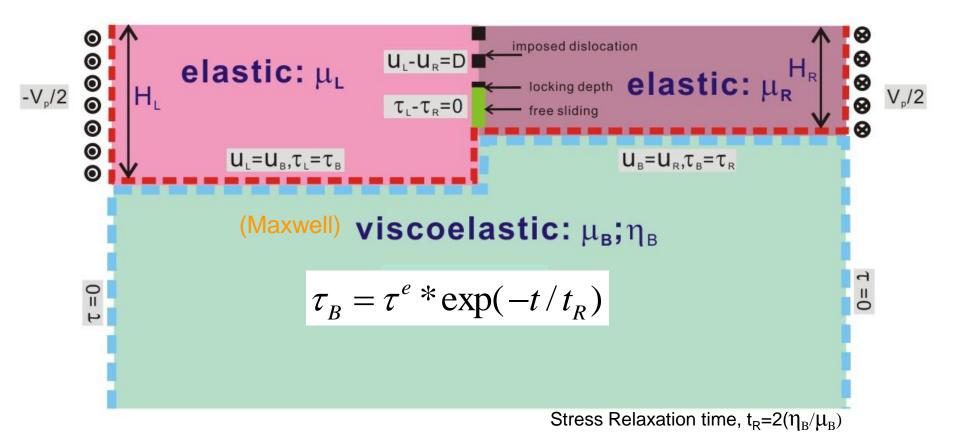
 $b = G^* s$ $= s = G^{-1} b$

- **b** : a vector of boundary conditions
- s: a vector of corresponding displacements
- **G** : a matrix of Green's functions,



Our Model

Stresses vary with time, so do s and b.

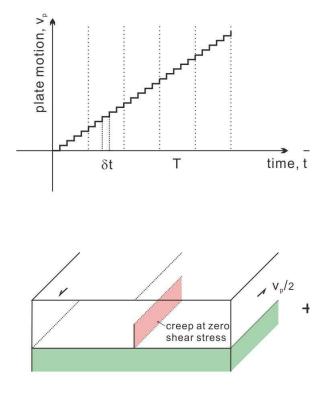


Our Model:

Stresses vary with time, so do s and b.

At the *jth* increment, the displacement discontinuity distribution is j^{-}

$$\mathbf{s}_{j} = \sum_{j=1}^{J-1} \mathbf{G}(t, t_{R}, s_{1}, s_{2}, \dots, s_{j-1})^{-1} \mathbf{b}$$

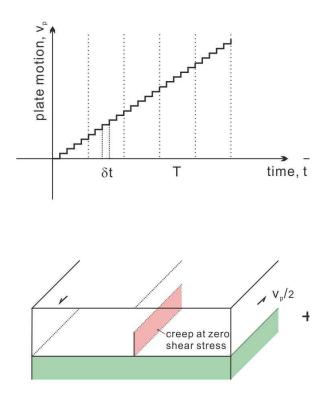


steady plate motion

Our Model: EQ cycle model

Scheme for computing an earthquake cycle-invariant velocity profile

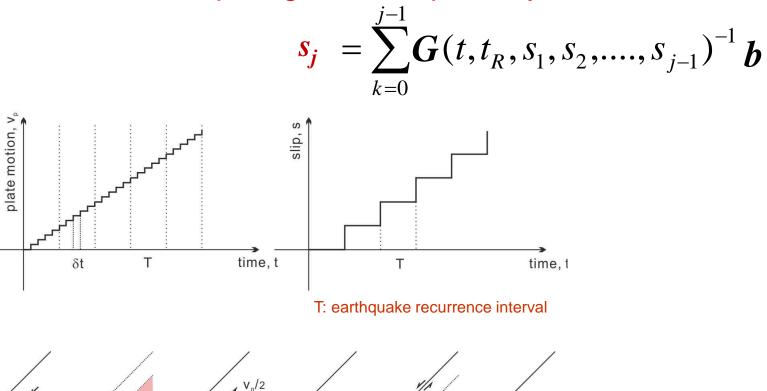
$$\mathbf{s}_{j} = \sum_{k=0}^{j-1} \mathbf{G}(t, t_{R}, s_{1}, s_{2}, \dots, s_{j-1})^{-1} \mathbf{b}$$



steady plate motion

Our Model: EQ cycle model

Scheme for computing an earthquake cycle-invariant velocity profile



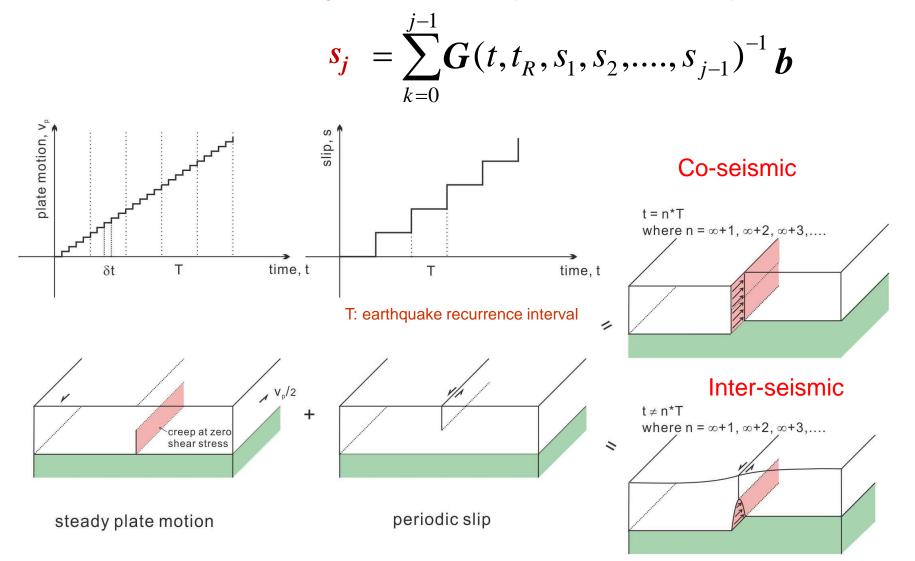


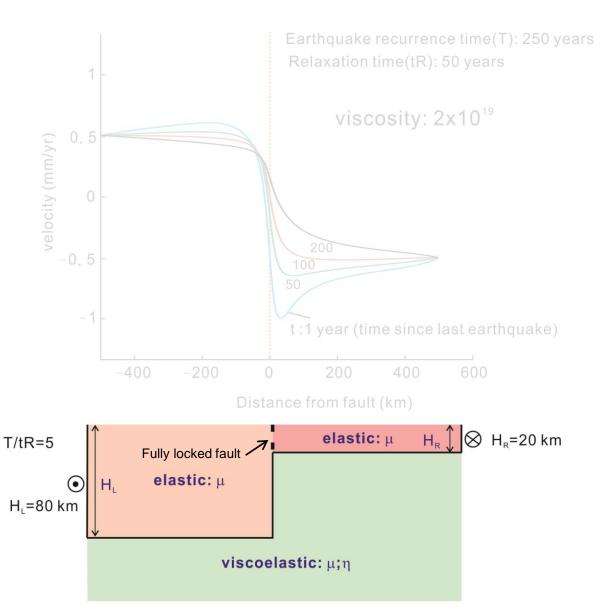
creep at zero shear stress

periodic slip

Our Model: EQ cycle model

Scheme for computing an earthquake cycle-invariant velocity profile

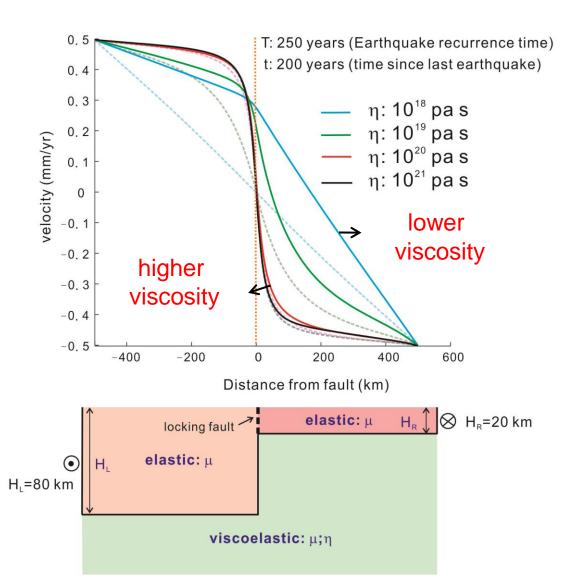




Contrast in Elastic Thickness

Asymmetry varies with the time since last earthquake (t)

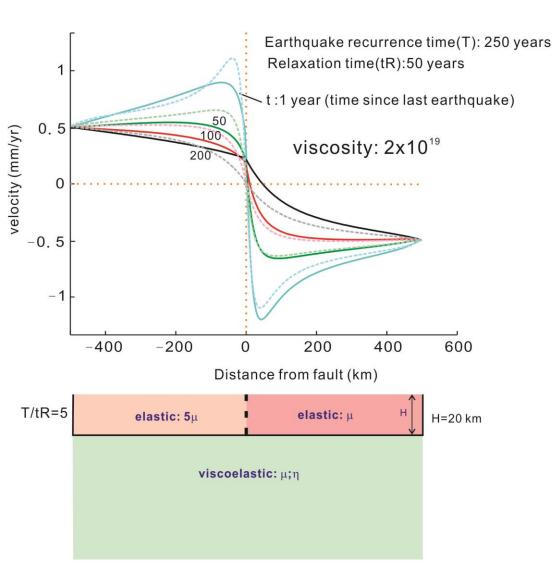
Asymmetry is more pronounced at early times



Contrast in Elastic Thickness

Asthenosphere viscosity is important:

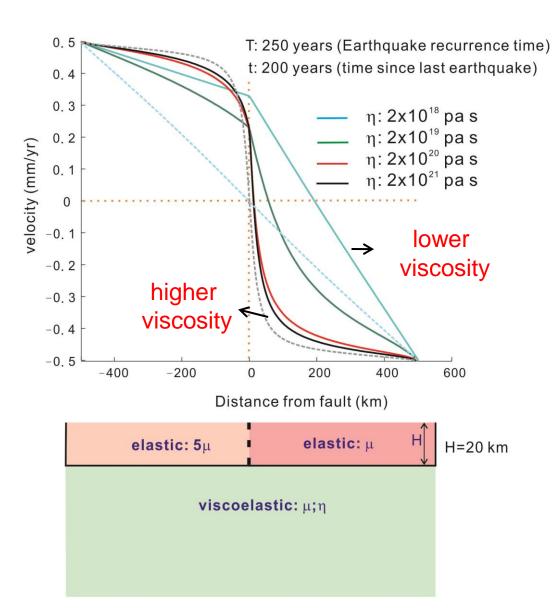
Asymmetry is more pronounced for lower viscosities



Contrast in Elastic stiffness

Asymmetry varies with the time since last earthquake (t)

Asymmetry is more pronounced at later times



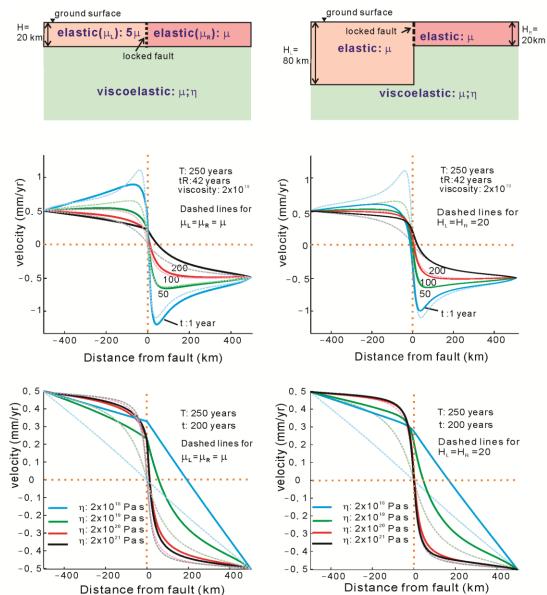
Contrast in Elastic stiffness

Asthenosphere viscosity is important:

Asymmetry is more pronounced for lower viscosities

Contrast in Elastic stiffness

Contrast in Elastic Thickness



Monte Carlo Inversion -- Metropolis method

To sample the posterior distribution, we initiate a random walk through the model space that samples the a priori distribution.

$$\underline{\mathbf{m}}_{j} = \underline{\mathbf{m}}_{i} + \sum_{k=1}^{d} \alpha_{k} \gamma_{k} e_{k}$$
, where $\underline{\mathbf{m}} = [m^{1} \ m^{2} \ m^{3} \ m^{4} \ \dots \ m^{d}]$

 α_k : scale factor

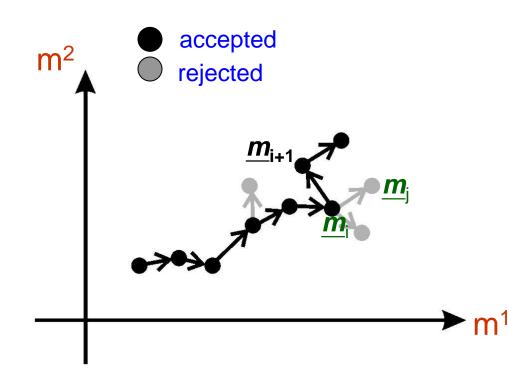
 γ_k : (-1, 1) uniform random deviate

 e_k : the unit vector along the *k*th axis in parameter space

Markov Chain random walk An example: samples projected to 2D

 $\underline{\mathbf{m}} = [\underline{\mathbf{m}}^1 \ \underline{\mathbf{m}}^2 \ \underline{\mathbf{m}}^3 \ \underline{\mathbf{m}}^4 \ \dots \ \underline{\mathbf{m}}^d]$

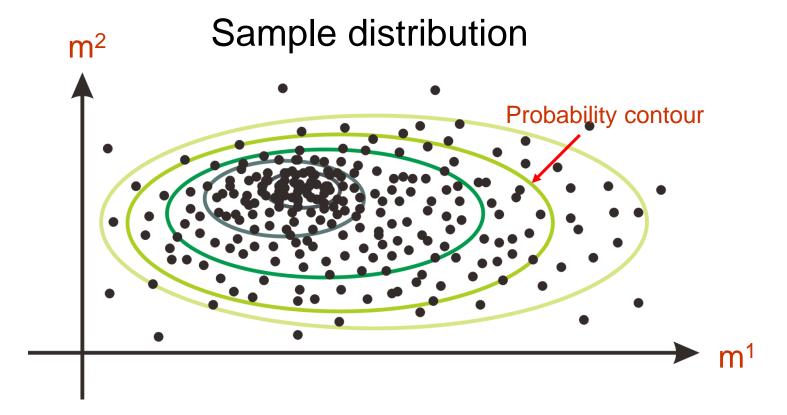
The walk moves to the next model with probability



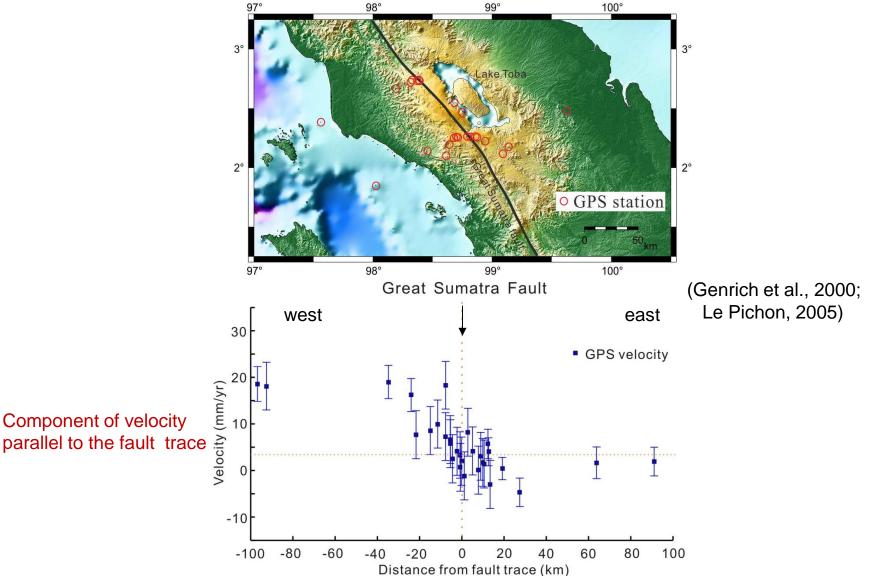
$$P_{ij} = \min\left(1, \frac{\rho_D(g(\underline{m}_j))}{\rho_D(g(\underline{m}_j))}\right)$$

 ho_D : probability density function of the model parameters

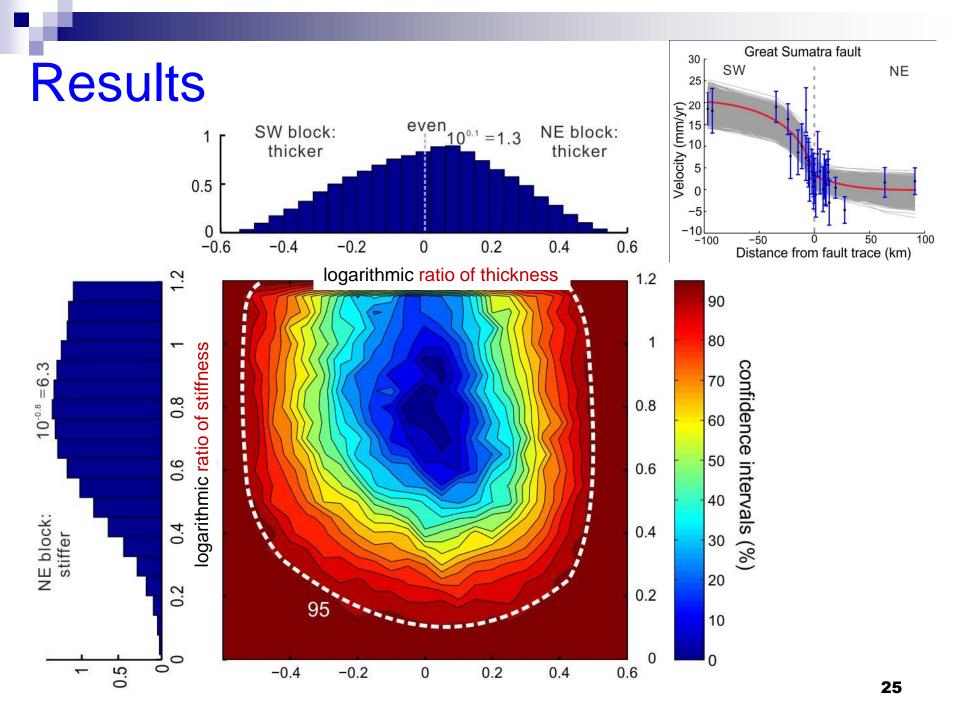
Markov Chain random walk



Great Sumatra Fault, Indonesia



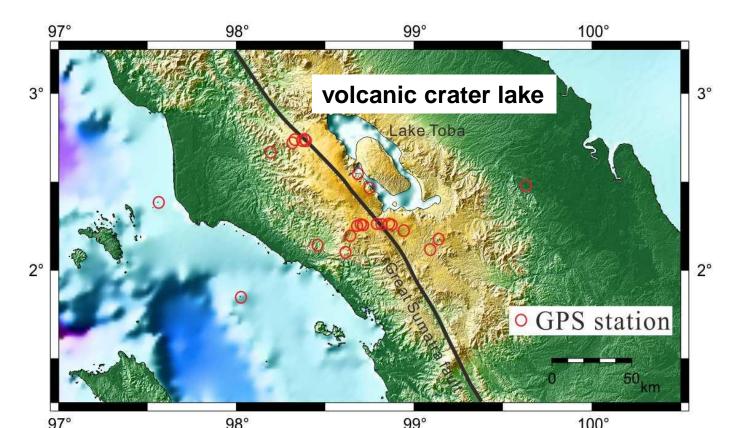
24



Results

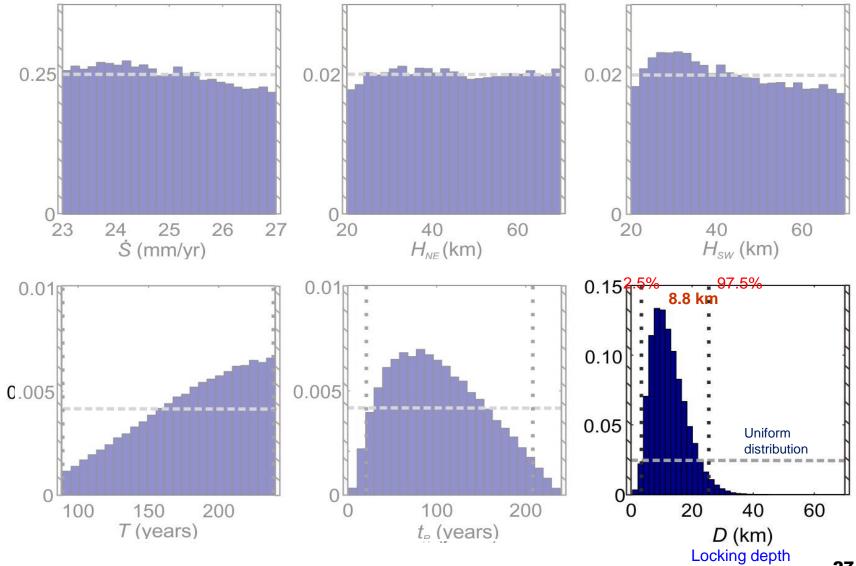
■ For Great Sumatra fault, the inversion result shows eastern elastic layer must be stiffer than western one but there is no resolved a contrast in elastic thickness.

Consistent with the manifestion of geology

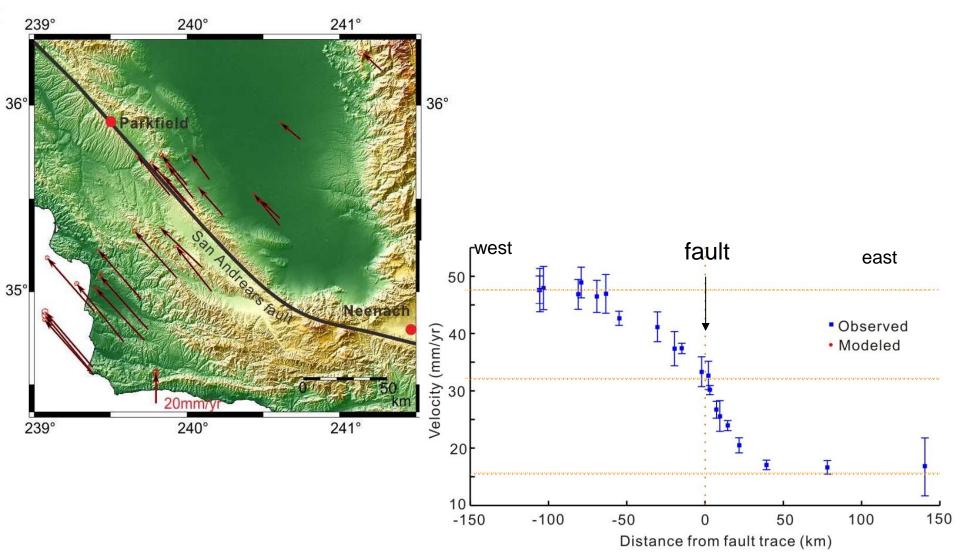


26

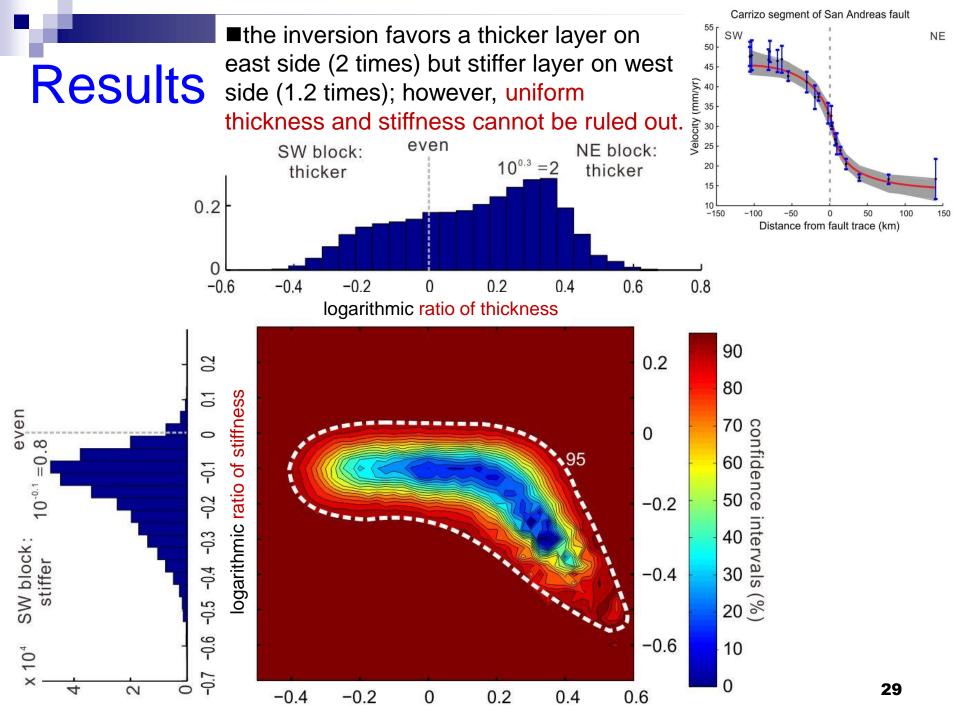
Results



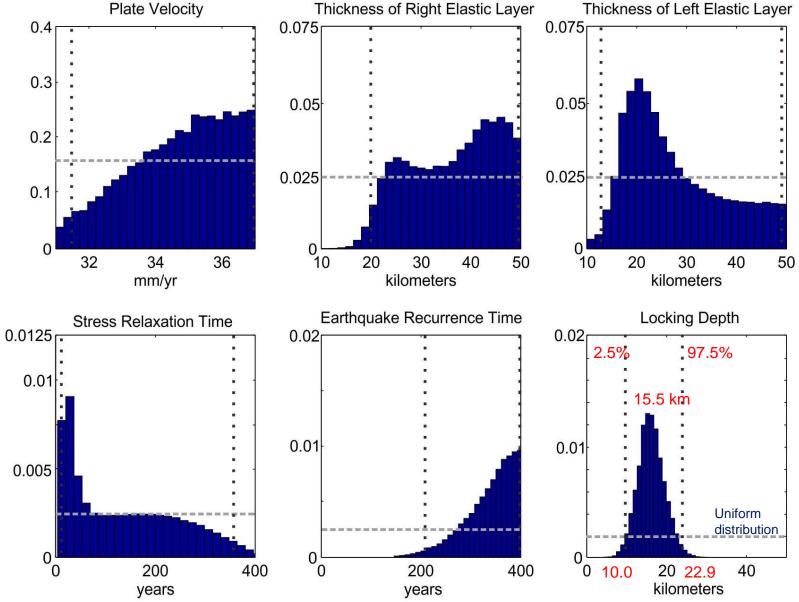
Carrizo segment of San Andreas Fault, USA



28



Results



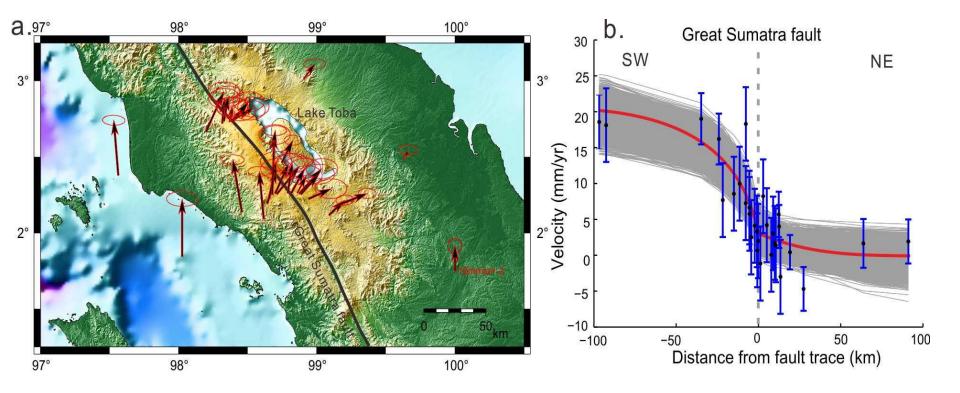
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Conclusions

Can we use geodetic data to infer lateral variation in rigidity ? Yes, we can (up to some degree).

Thank you for your attention!

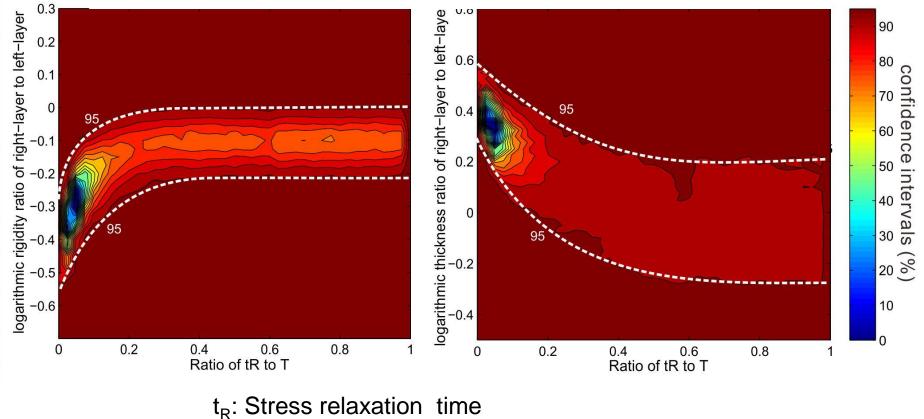
Great Sumatra Fault



Results

ratio of t_R to T vs. rigidity ratio

ratio of t_R to T vs. thickness ratio



T: earthquake recurrence time