A BAYESIAN PERSPECTIVE TO THE STUDY OF EARTHQUAKES

PROBABILISTIC MODELING OF EARTHQUAKES

ZACHARIE DUPUTEL

JOINT INVERSION IN GEOPHYSICS - 2015

OUTLINE

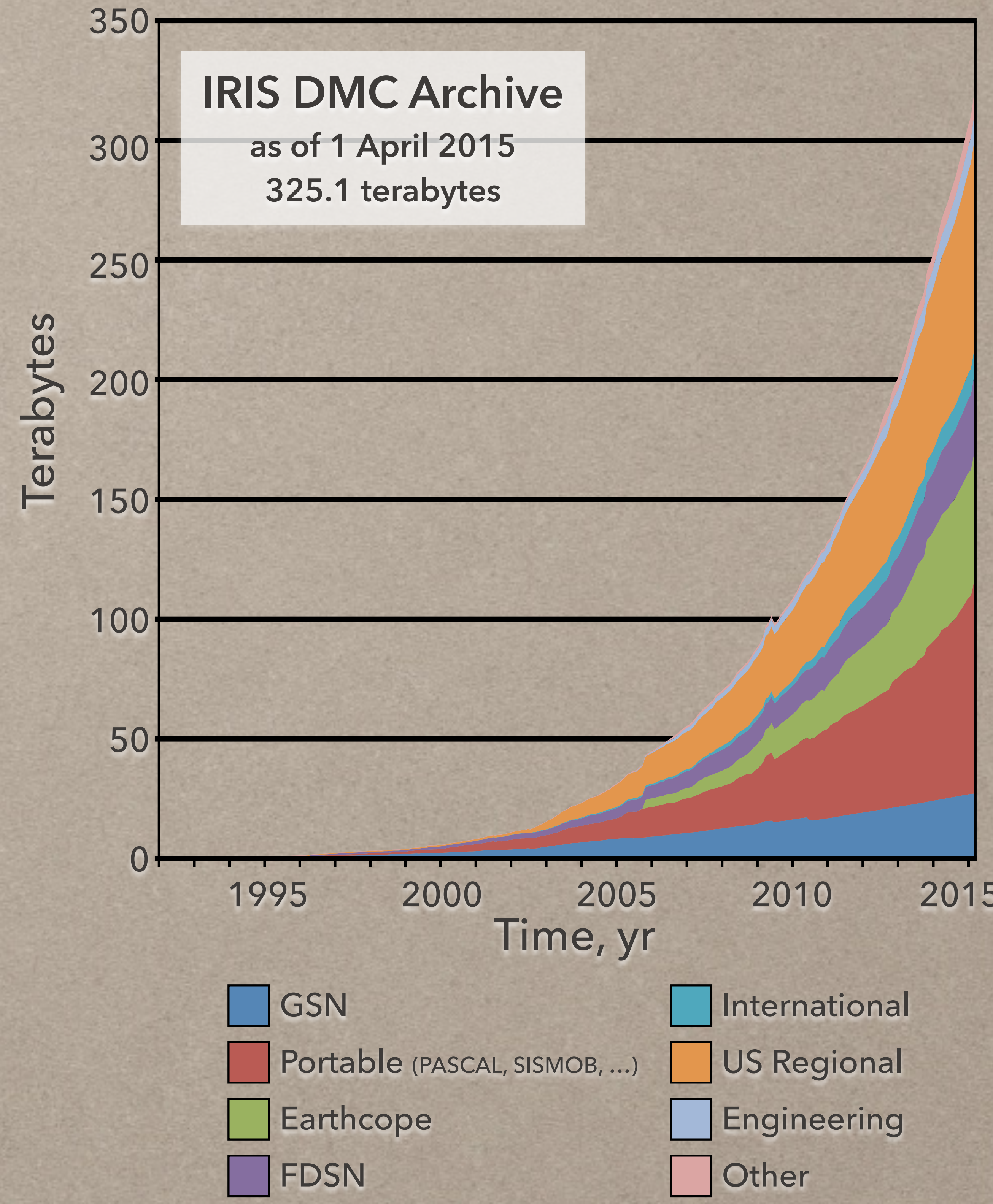
- Introduction & Motivation:
  - Why Bayesian Analysis ?
  - Bayes theorem
  - Monte Carlo
- Hands-on exercice: Toy problem
- Bayesian inference in HD spaces and error model
- Application: Study of earthquakes
  - 2013 Balochistan earthquake (Pakistan)
  - 2014 Pisagua eartquake (Chile)

BIG DATA IN GEOPHYSICS

Explosion of available observations

- Global broad-band seismic network
- Dense seismic networks
- Satellite imagery
- GPS networks
- Tsunami

Higher-dimensional problems



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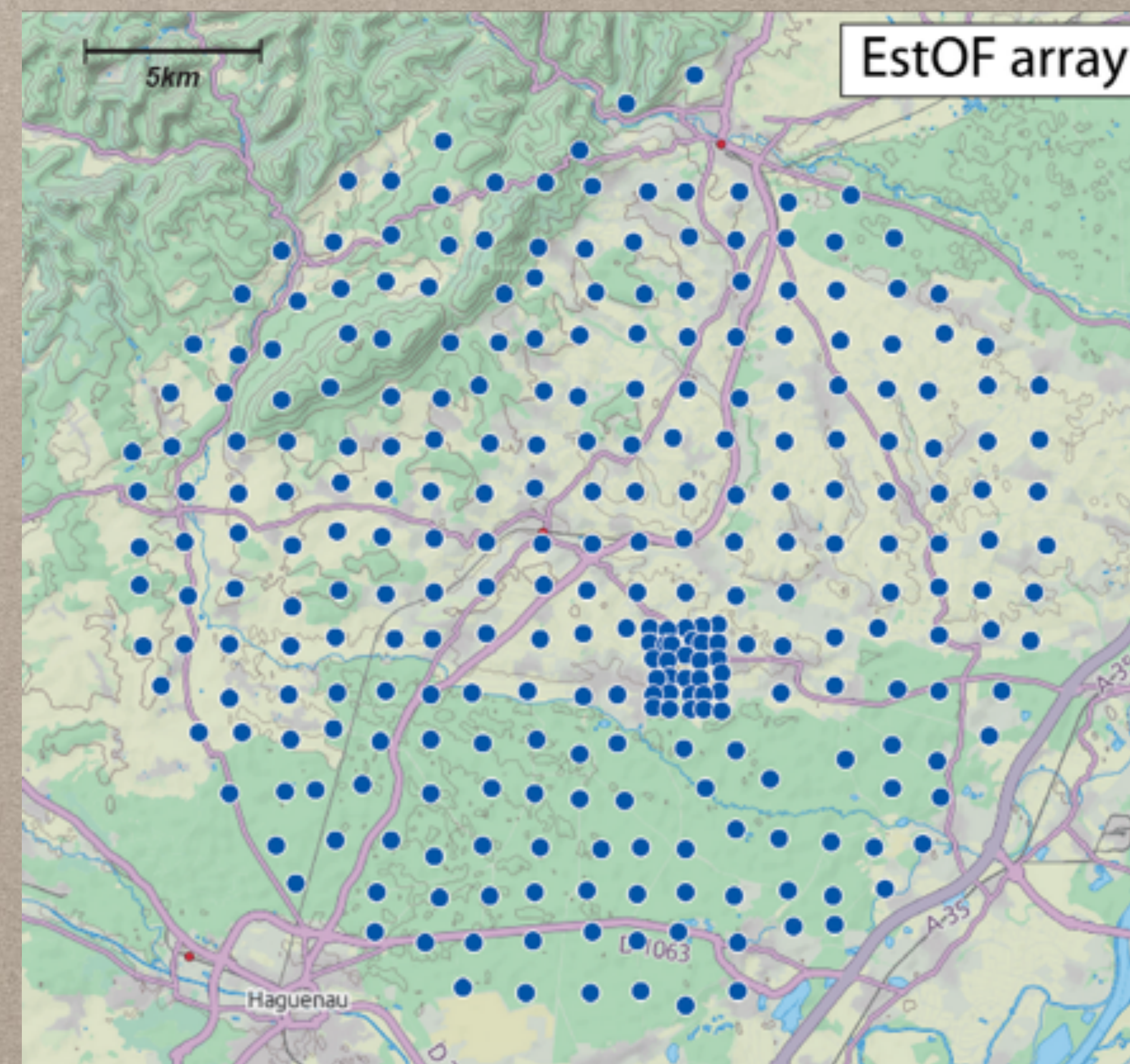
Higher-dimensional problems

EstOF Array

PI: J. Vergne (IPGS)



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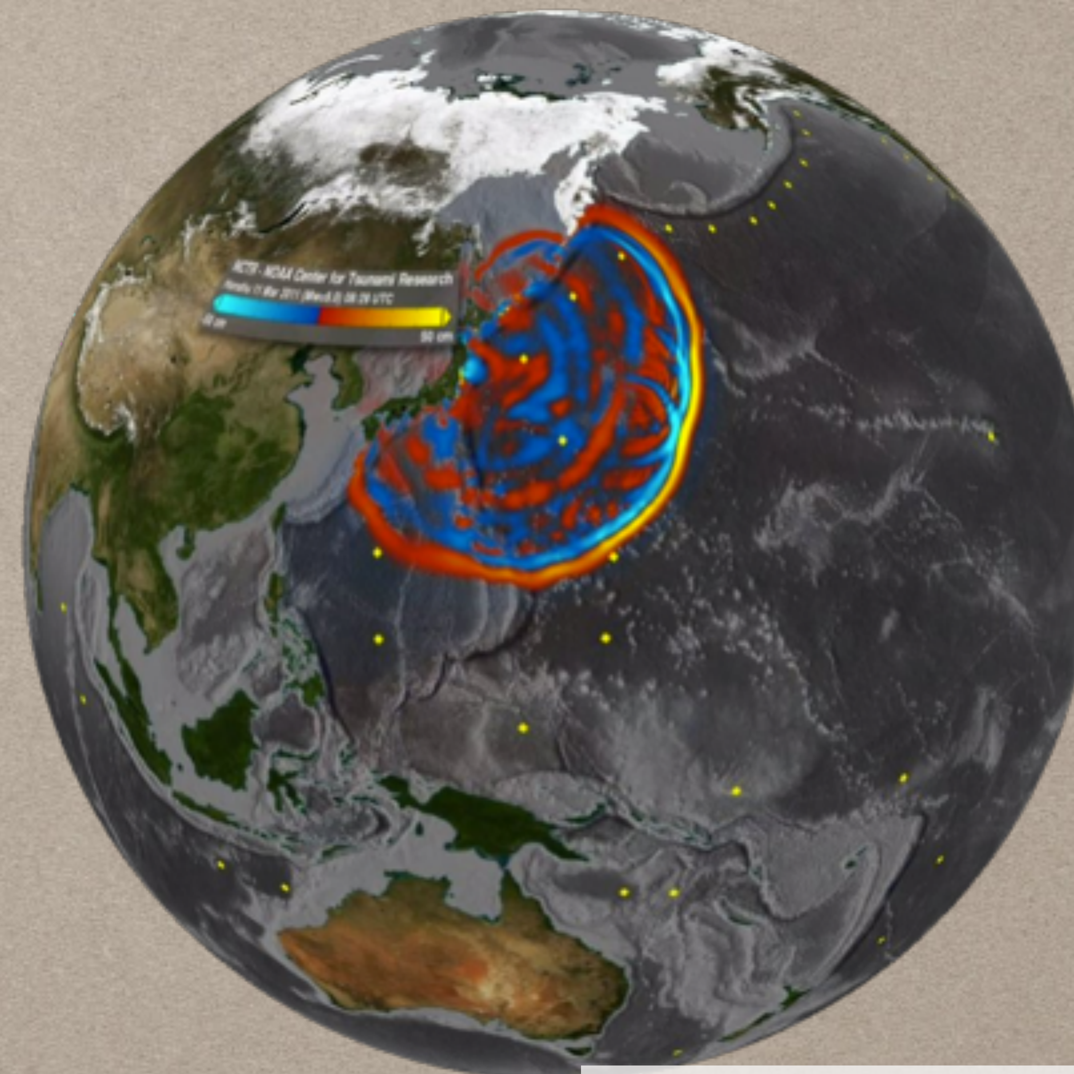

NOAA, USGS
MOST model

BIG DATA IN GEOPHYSICS

Explosion of available observations

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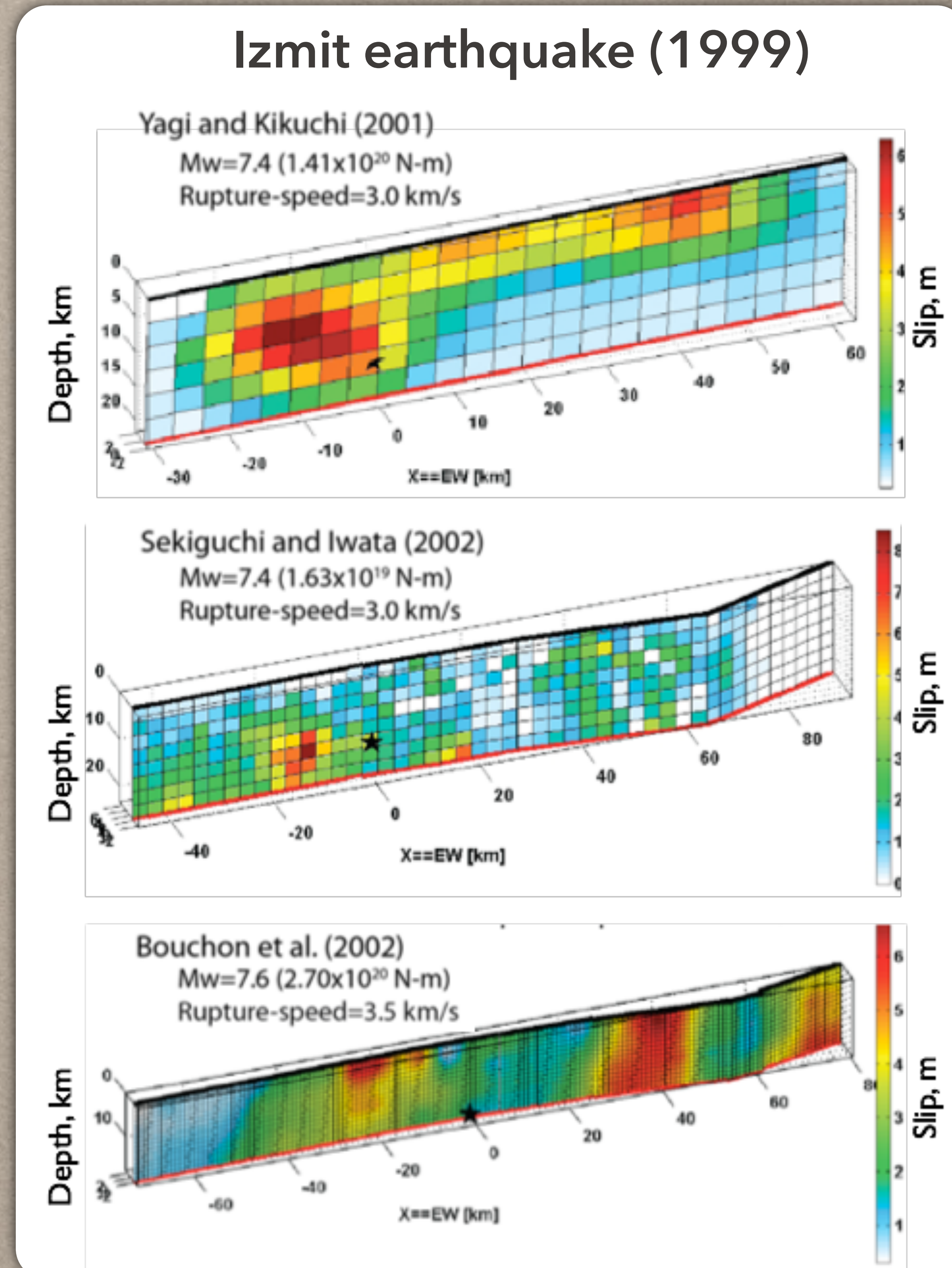
↓

Higher-dimensional problems

WHY BAYESIAN ANALYSIS ?

Geophysics is filled with ill-posed inverse problems

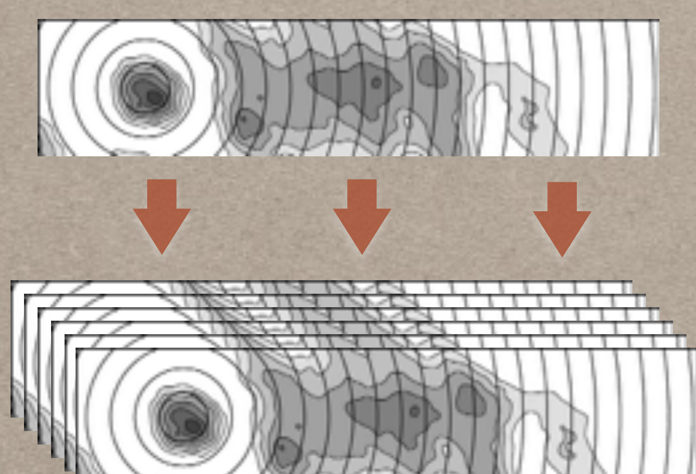
- **<u>Traditional optimization</u>:**
    - Regularized inverse picks one solution which fits data and regularization scheme
    - Choice of regularization is usually based on convenience not physics
    - Choice of regularization can have significant effects on the resulting solution



WHY BAYESIAN ANALYSIS ?

Geophysics is filled with ill-posed inverse problems

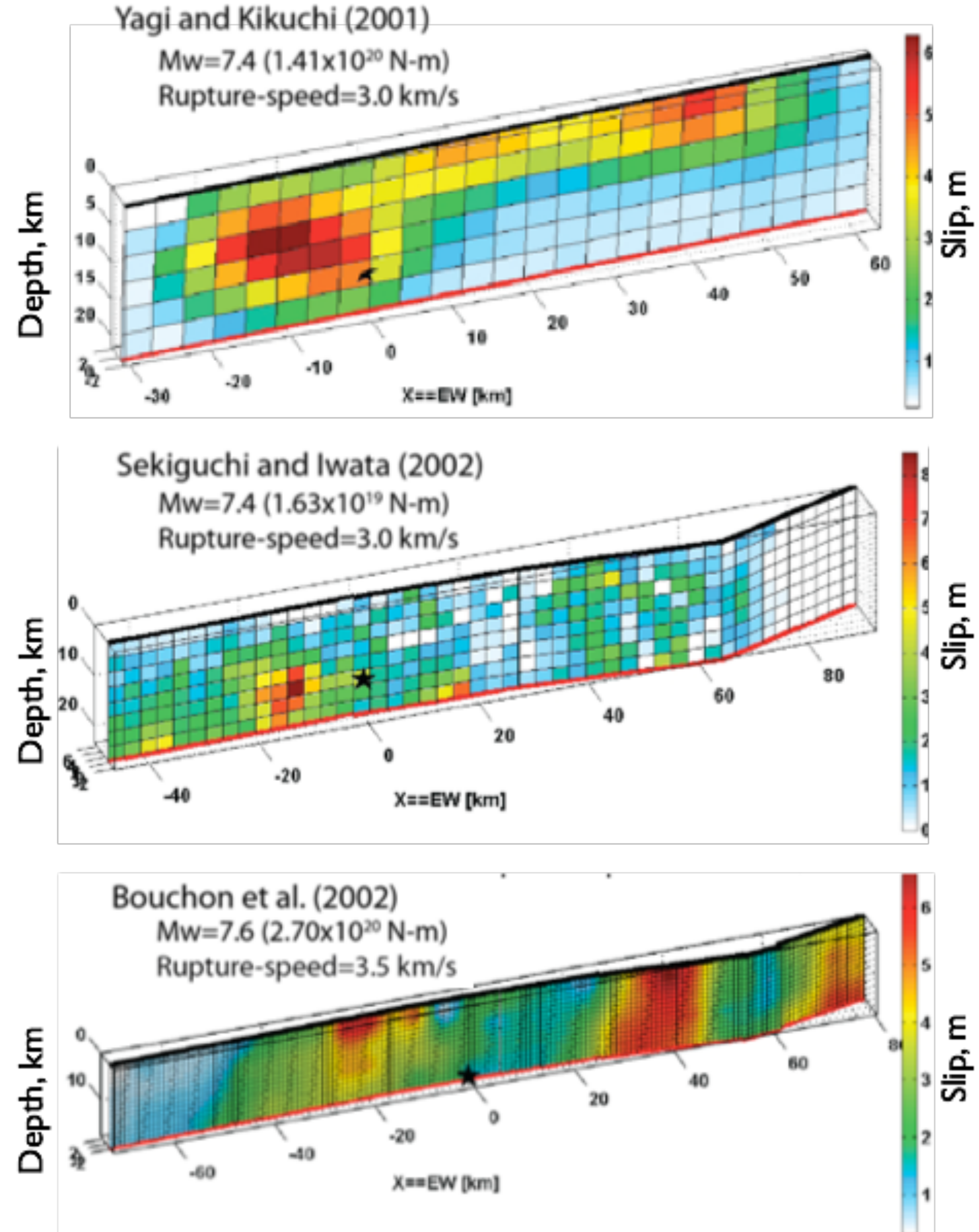
- **Bayesian inference**:
  - Solution includes ensemble of all plausible models
    - ➡ Regularization is not required



Single model

Ensemble of models

Izmit earthquake (1999)



EMBRACE UNCERTAINTY

- When faced with a ill-posed problem, the best answer is to identify the ensemble of all plausible values for your model parameters

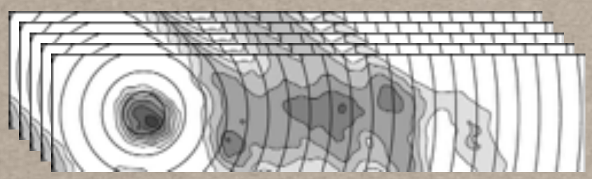
- “Plausible” models are those that satisfy the data and which agree with your prior assumptions about the model parameters

BAYESIAN INFERENCE AND ERROR MODEL

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m})\, p(\mathbf{d}_{\text{obs}}|\mathbf{m})$$

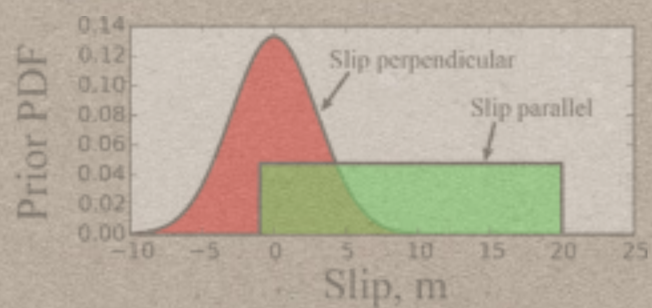
Posterior PDF

ensemble of models



Prior PDF

Constraints (if any)



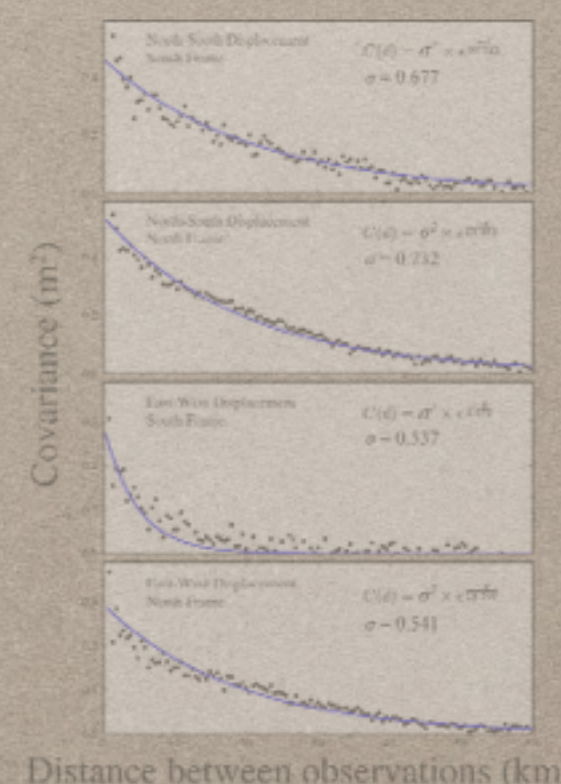
Likelihood

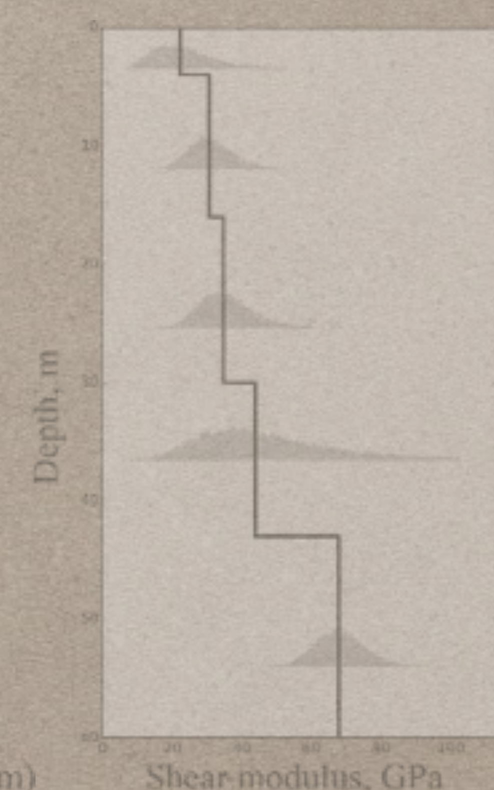
$$\propto \exp\left(-\frac{1}{2}\left(\mathbf{d}_{\text{obs}}-\mathbf{g}(\mathbf{m})\right)^T \mathbf{C}_\chi^{-1}\left(\mathbf{d}_{\text{obs}}-\mathbf{g}(\mathbf{m})\right)\right)$$

2 contributions to the data misfit (

Data uncertainty (e.g. InSAR)

Prediction uncertainty (Elastic structure)





BAYESIAN INFERENCE AND ERROR MODEL

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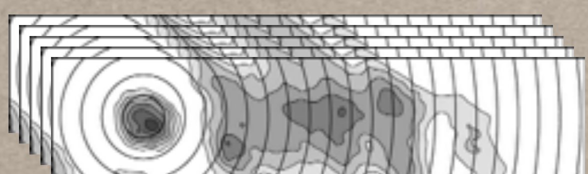

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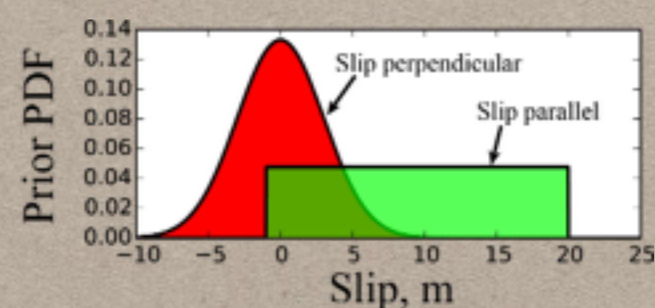

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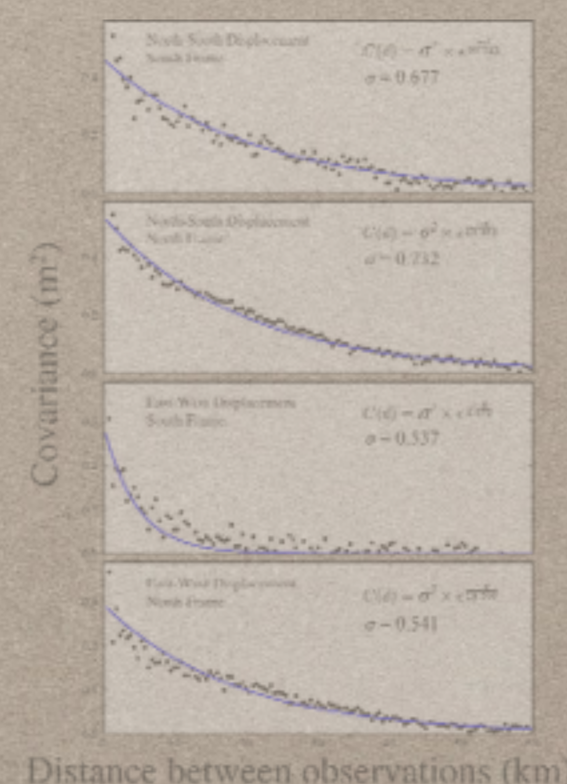
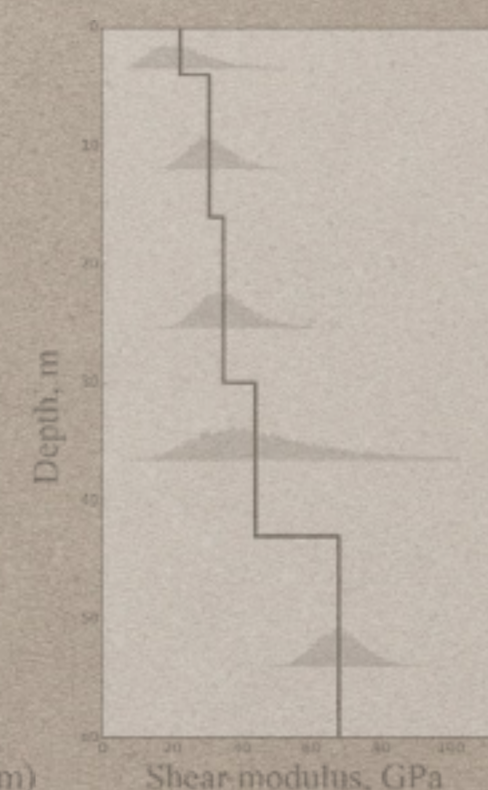




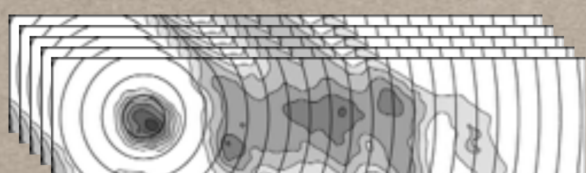
- The "prior" is what you believe the likely values of the model parameters are in the absence of data
  - ➡ Can be used to impose physics-based constraints

BAYESIAN INFERENCE AND ERROR MODEL

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m})\, p(\mathbf{d}_{\text{obs}}|\mathbf{m})$$

Posterior PDF

ensemble of models



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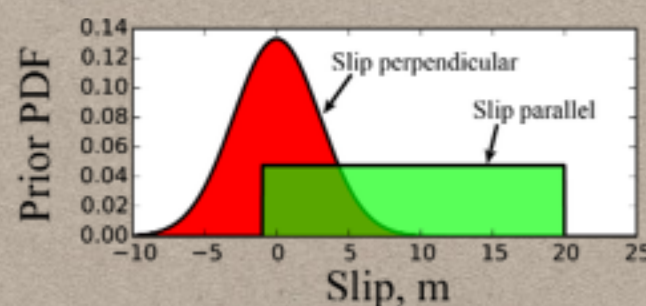


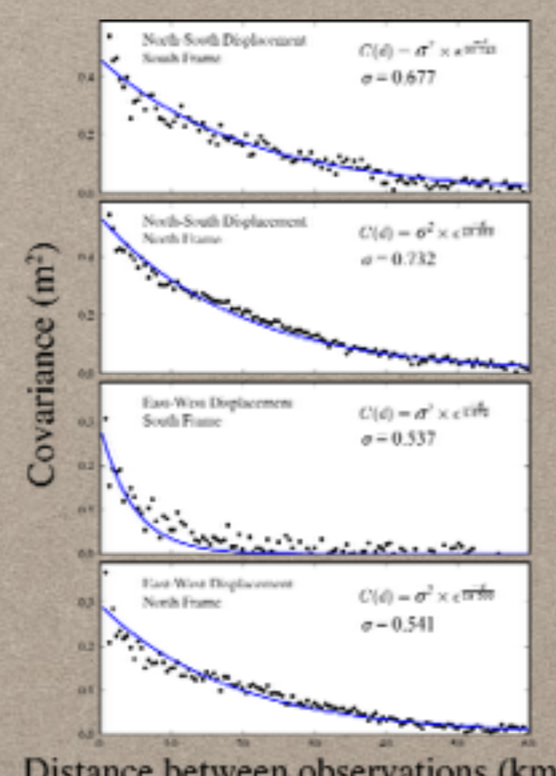
Likelihood

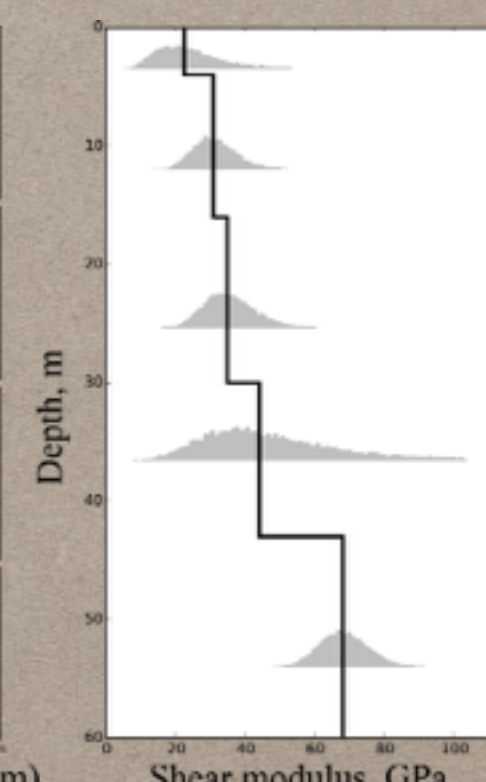
$$\propto \exp\left(-\frac{1}{2}\left(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\right)^T \mathbf{C}_\chi^{-1}\left(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\right)\right)$$

2 contributions to the data misfit ($\mathbf{C}_\chi$):

Data uncertainty (e.g. InSAR)

Prediction uncertainty (Elastic structure)





HOW TO DO BAYESIAN ANALYSIS

- **Two options:**
  1. You can choose whatever priors and data likelihood you want and draw samples of $p(\mathbf{m}|\mathbf{d}_{obs})$ by Monte Carlo simulation
  2. For certain problems, you can get an analytical expression for $p(\mathbf{m}|\mathbf{d}_{obs})$:

     For example:

     $p(\mathbf{m})$ & $p(\mathbf{d}_{obs}|\mathbf{m})$ Gaussian → $p(\mathbf{m}|\mathbf{d}_{obs})$ Gaussian

- **Option 1 may require a lot of computer power**

- **Option 2 requires brain power and possible compromise**

APPROACH 1: MONTE CARLO SIMULATION

- Draw samples from the posterior PDF. The samples will have all the properties of the posterior PDF (mean, variance, etc.).

- There are only a few PDFs (e.g., uniform, Gaussian) that you can simulate directly with a random generator.

- Monte Carlo sampling looks like:

  1. Draw a random realization of your model from a proposal PDF
  2. Decide whether to keep or reject the candidate model (not all samples are accepted… can be very inefficient)
  3. Go back to step 1

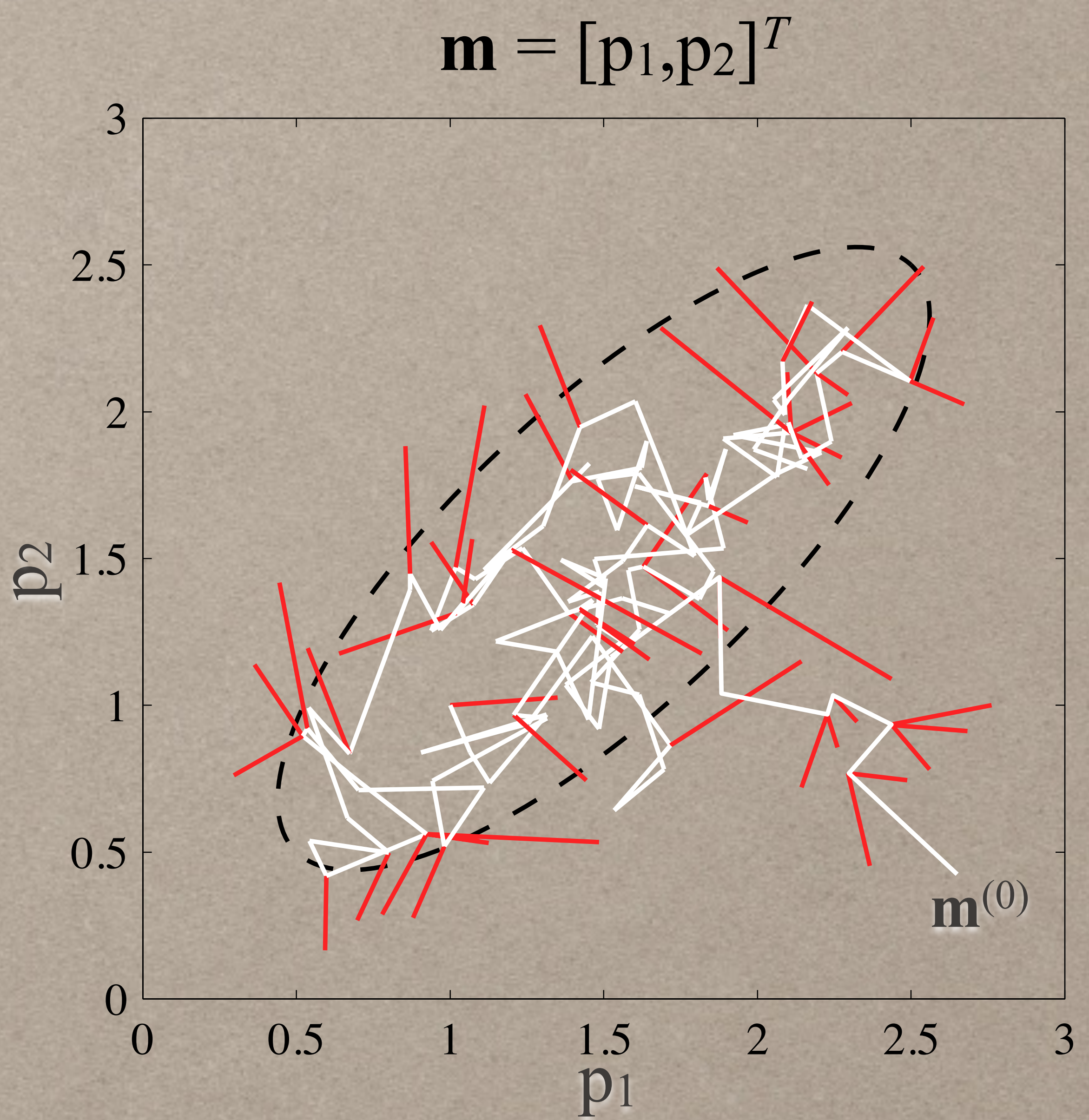
METROPOLIS-HASTINGS

A memoryless random walk through the parameter space

- **Choose:**
  - a starting vector of model parameters ($\mathbf{m}^0$)
  - a proposal PDF ($q(\mathbf{m})$):

    commonly: $q(\mathbf{m}|\mathbf{m}^{(j)}) \sim \mathcal{N}(\mathbf{m}^{(j)},\boldsymbol{\Sigma})$

- **Repeat for j=1,2,…,N**
  - Generate a candidate $\mathbf{m}^*$ from $q(\mathbf{m}|\mathbf{m}^{(j)})$
  - Calculate $r = \min\{1, p(\mathbf{m}^* \mid \mathbf{d}_{obs})/p(\mathbf{m}^{(j)} \mid \mathbf{d}_{obs})\}$
  - Generate u from $\mathcal{U}(0,1)$
  - If $u \leq r$
    - ➡ Set $\mathbf{m}^{(j+1)} = \mathbf{m}^*$
  - Else:
    - ➡ Set $\mathbf{m}^{(j+1)} = \mathbf{m}^{(j)}$



- $\{\mathbf{m}^{(0)}, \mathbf{m}^{(1)},\ldots, \mathbf{m}^{(N)}\}$ **is a set of samples of the posterior PDF** $p(\mathbf{m}|\mathbf{d}_{obs})$

QUESTIONS?

COMING UP: TOY PROBLEM

TOY PROBLEM: LOCKED FAULT MODEL

- **Infinite strike-slip fault in a half-space**
  - Vertical fault
  - Locked from the surface to depth H
  - Deep dislocation: $H \rightarrow \infty$ (constant slip)

- **Forward problem:**

$$v(x) = S \cdot \tan^{-1}(x/H) / \pi$$

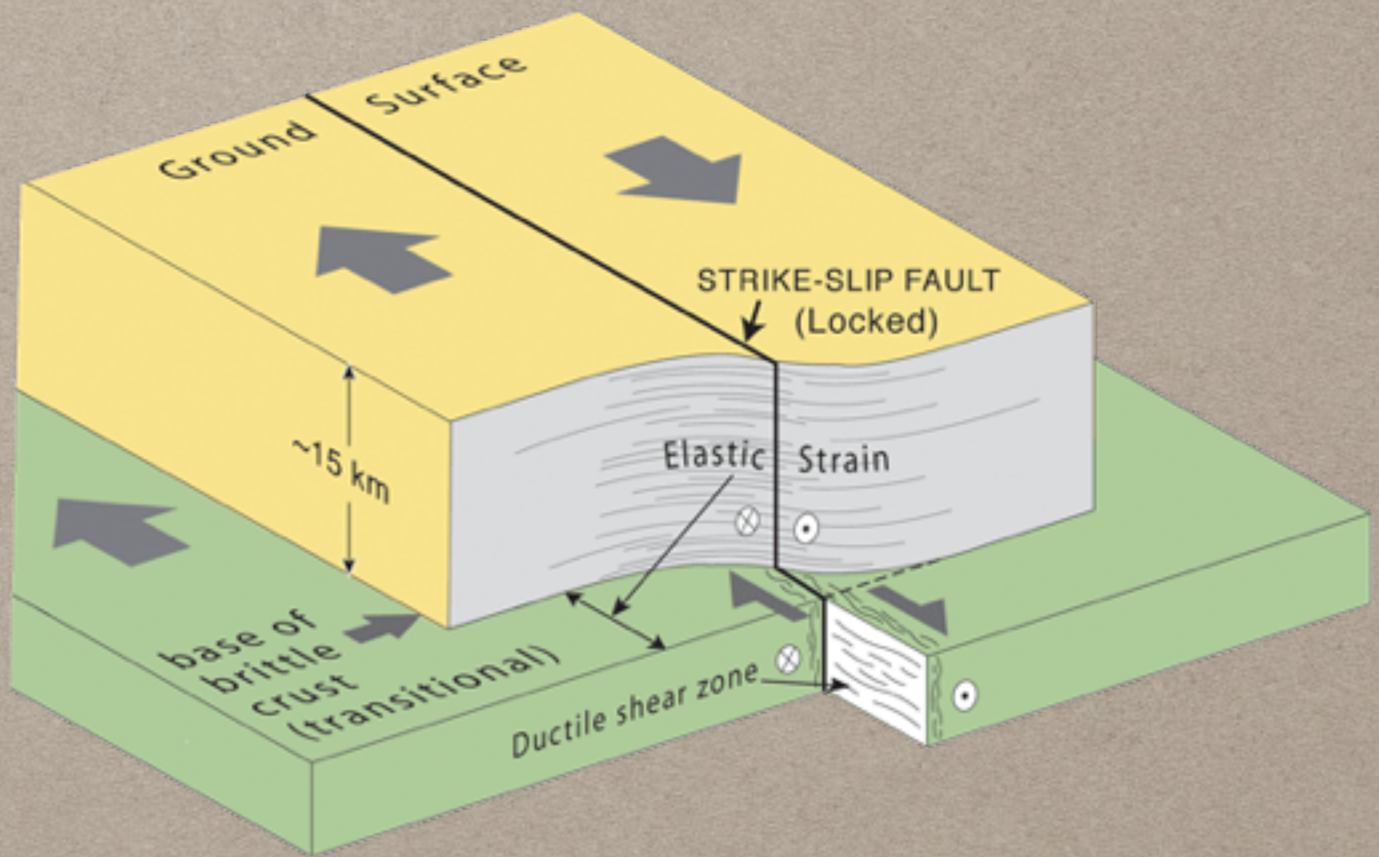
  - Velocity: v
  - Slip rate: S
  - Locking depth: H
  - Distance from the fault: x
  - Inverted parameters: $\mathbf{m} = [S\ ,\ H]^T$

- **Posterior distribution:**

$$p(\mathbf{m} \mid \mathbf{d}_{\text{obs}}) \propto p(\mathbf{d}_{\text{obs}} \mid \mathbf{m})\, p(\mathbf{m})$$

  - Likelihood: Gaussian, Uncorrelated errors
  - Prior: Uniform PDF
  - Bayesian sampling using metropolis

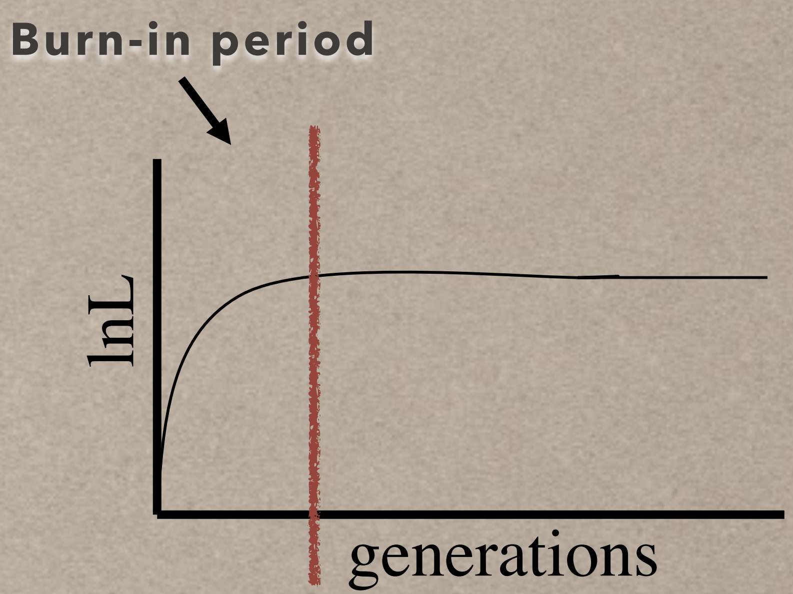
Interseismic deformation

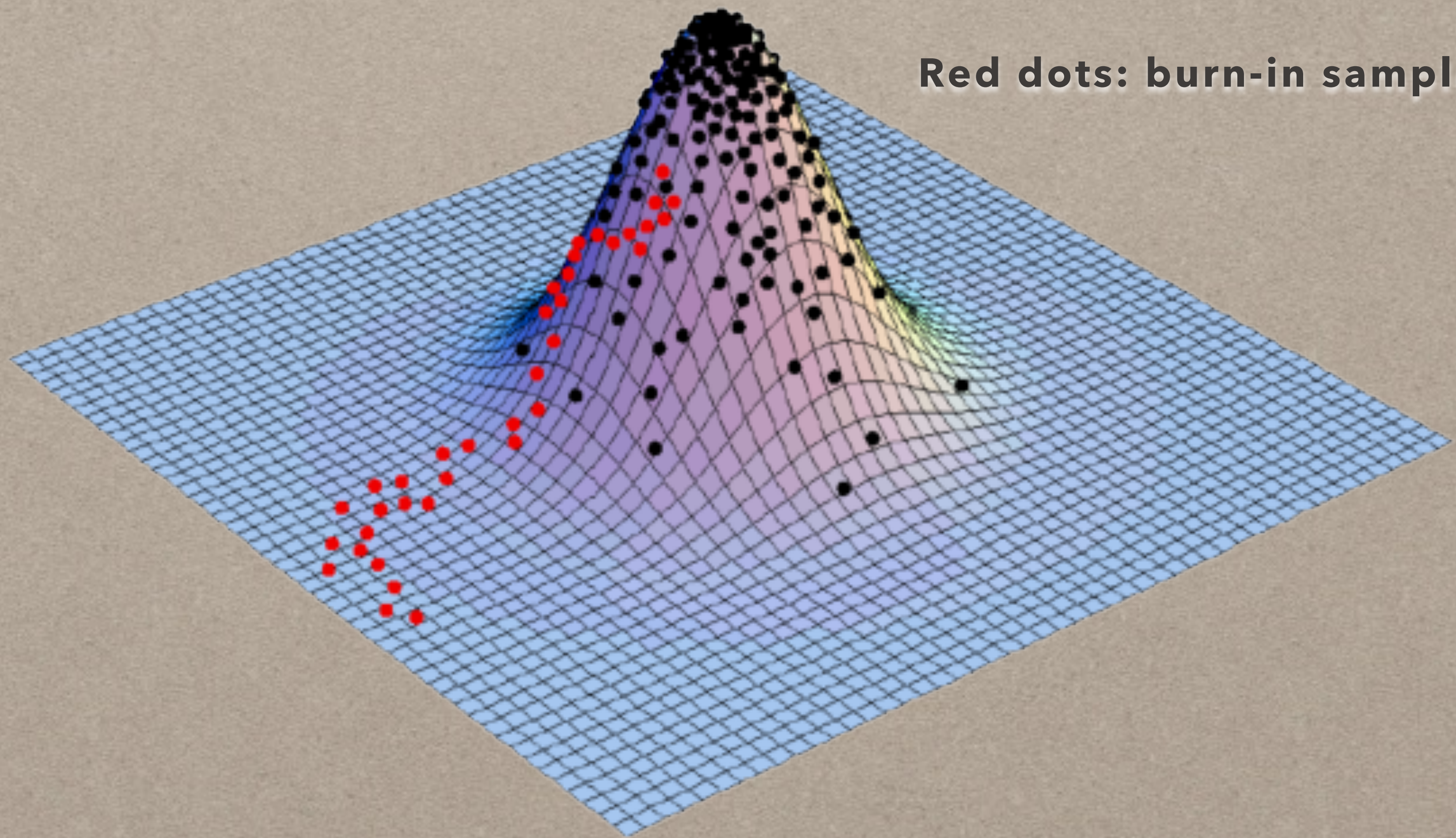


http://funnel.sfsu.edu

BURN-IN PERIOD

- **Burn-in**
  - Refers to the practice of discarding an initial portion the samples so that the effect of initial values on the posterior is minimized





https://faculty.washington.edu/wjs18/Lecture%20PDFs/MCMC.pdf

TOY PROBLEM: LOCKED FAULT MODEL

"Hierarchical" Bayesian inversion

- **Forward problem:**

  $v(x) = S \cdot \tan^{-1}(x/H) / \pi$

  - Slip rate: S
  - Locking depth: H
  - Distance from the fault: x
  - Inverted parameters: $\mathbf{m} = [S , H]^T$
  - Hyper-parameter : σ_d

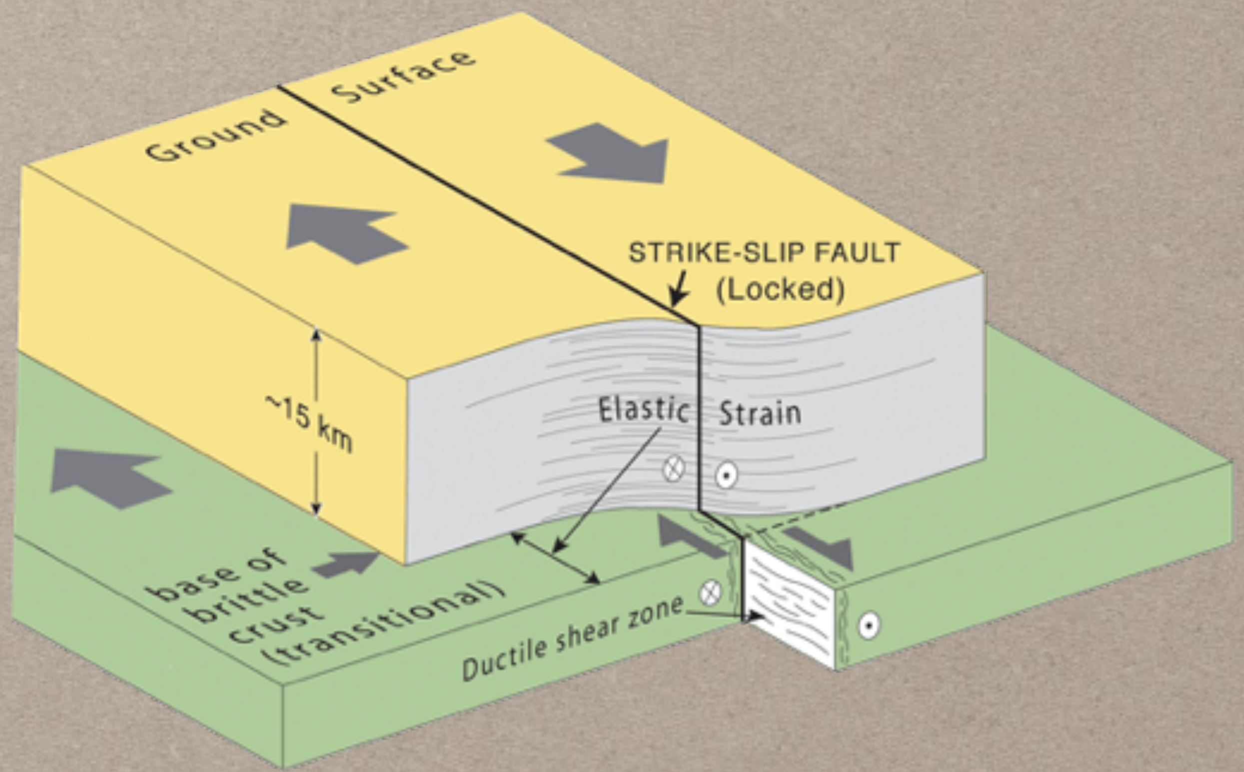
    (control the shape of $p(\mathbf{d}_{obs} \mid \mathbf{m})$)

- **Uncertain data noise:**
  - Posterior PDF:

    $p(\mathbf{m}, \sigma_d \mid \mathbf{d}_{obs}) \propto p(\mathbf{d}_{obs} \mid \mathbf{m}, \sigma_d)\, p(\mathbf{m})\, p(\sigma_d)$
  - Priors ($p(\mathbf{m})$, $p(\sigma_d)$): Uniform PDF
  - Likelihood:

    $p(\mathbf{d}_{obs} \mid \mathbf{m}, \sigma_d) = [(2\pi)^{N/2}\, \sigma_d{}^N]^{-1} \exp\, [-\|\mathbf{d}_{obs} - \mathbf{g}(\mathbf{m})\| / 2\, \sigma_d\,]^2$

Interseismic deformation



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TOY PROBLEM: LOCKED FAULT MODEL

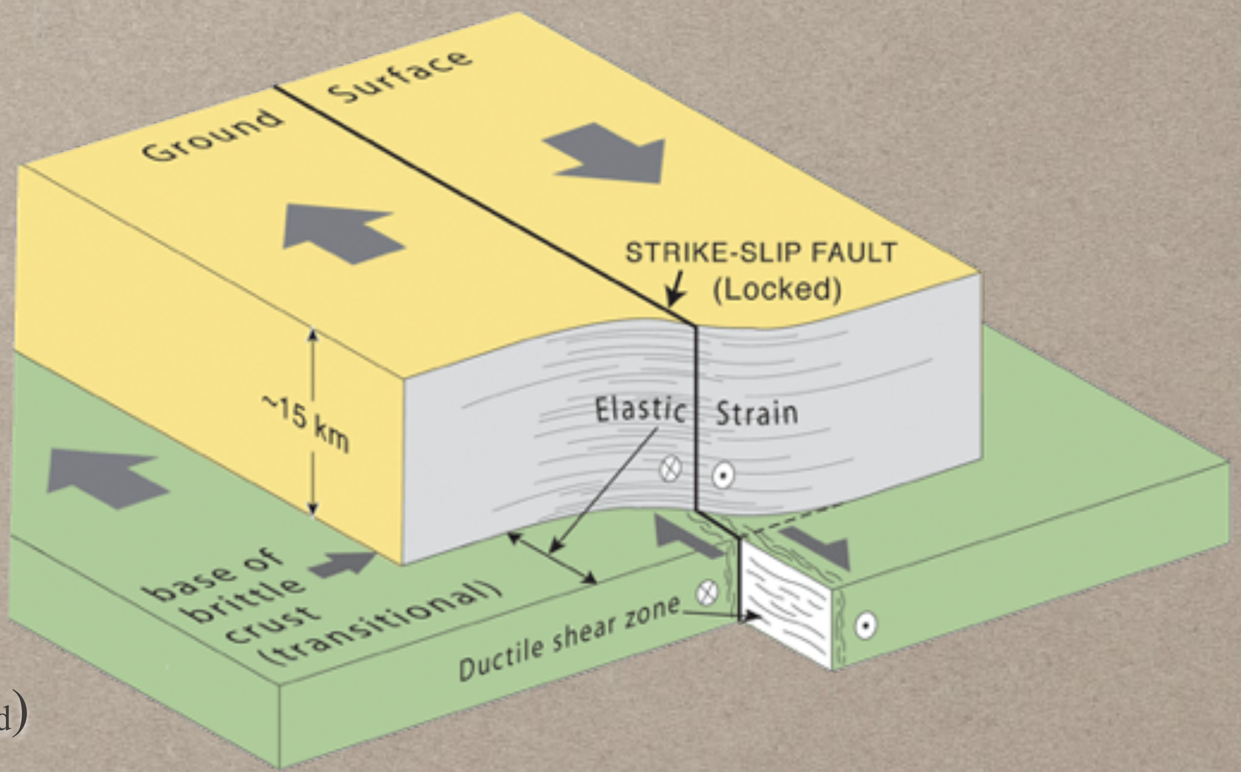
"Hierarchical" Bayesian inversion, bias in data/predictions

- **Forward problem:**

  $$v(x) = S \cdot \tan^{-1}(x/H) / \pi$$

  - Slip rate: S
  - Locking depth: H
  - Distance from the fault: x
  - Inverted parameters: $\mathbf{m} = [S , H]^T$
  - Hyper-parameters : σ_d, $\boldsymbol{\mu}_d$
    (control the shape of $p(\mathbf{d}_{obs} \mid \mathbf{m})$)

Interseismic deformation



- **Uncertain data noise:**
  - Posterior PDF:

    $$p(\mathbf{m}, \sigma_d, \boldsymbol{\mu}_d \mid \mathbf{d}_{obs}) \propto p(\mathbf{d}_{obs} \mid \mathbf{m}, \sigma_d, \boldsymbol{\mu}_d)\, p(\mathbf{m})\, p(\sigma_d)\, p(\boldsymbol{\mu}_d)$$

  - Priors: $p(\mathbf{m})$, $p(\sigma_d)$, $p(\boldsymbol{\mu}_d)$
  - Likelihood:

    $$p(\mathbf{d}_{obs} \mid \mathbf{m}, \sigma_d, \boldsymbol{\mu}_d) = [(2\pi)^{N/2}\, \sigma_d^N]^{-1} \exp\, [-||\mathbf{d}_{obs} - \mathbf{g}(\mathbf{m}) - \boldsymbol{\mu}_d|| / 2\, \sigma_d\,]^2$$

e.g., 2nd order polynomial functions to remove SAR offsets due to possible orbital errors

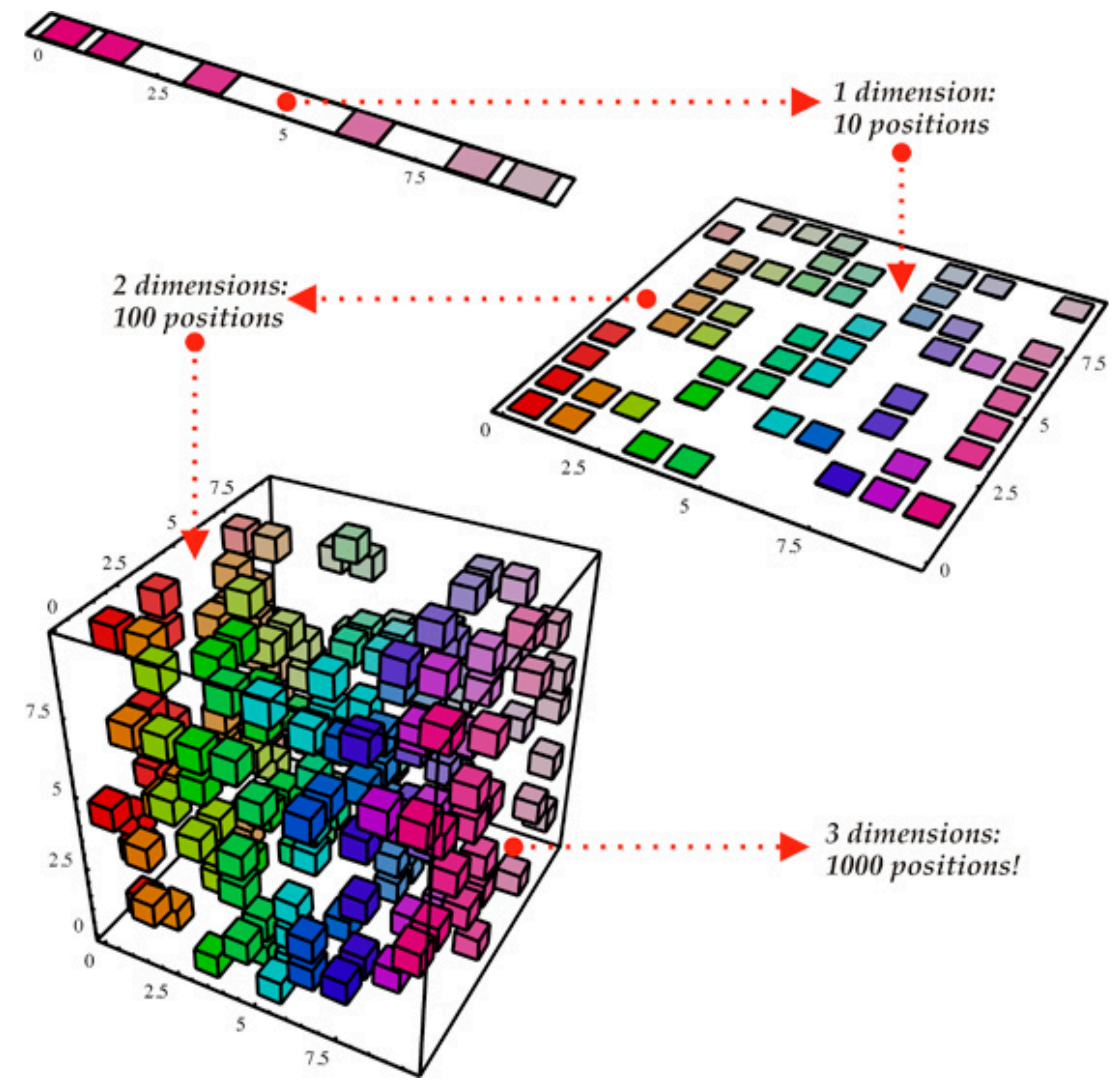
http://funnel.sfsu.edu

QUESTIONS?

COMING UP: MONTE CARLO IN H.D. SPACES

MONTE CARLO - CURSE OF DIMENSIONALITY

- **Monte Carlo simulation requires drawing enough samples to fill the model space**
  - Huge numbers of samples required for high-dimensional problems
  - One sample = One forward model evaluation
- **Total numeric cost is:**
  - Nsamples x Time(forward model)
  - For large number of model parameters, we need very fast forward model
- **A few of the many sampling algorithms in existence:**
  - **Reject method:** parallel but inefficient
  - **Metropolis algorithm:** more efficient, but MCMC (e.g., a random walk) is serial
  - **Gibbs sampling:** certain restrictions on types of PDFs that can be simulated
  - Tempering and transitioning algorithms (e.g., **Parallel tempering**)



http://www.iro.umontreal.ca/~bengioy/yoshua_en/research.html

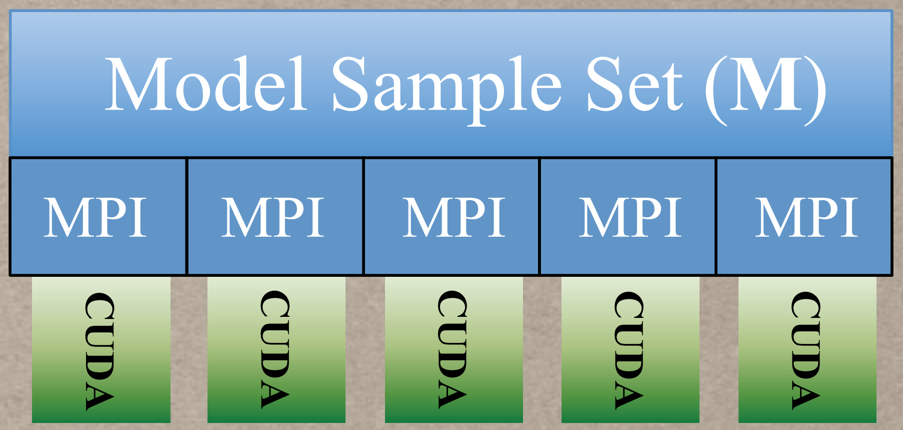
Good reference for parallel tempering: Sambridge, M., 2013. A Parallel Tempering algorithm for probabilistic sampling and multimodal optimization. Geophys. J. R. astr. Soc. 196, 357–374. doi:10.1093/gji/ggt342

MONTE CARLO - ALTAR

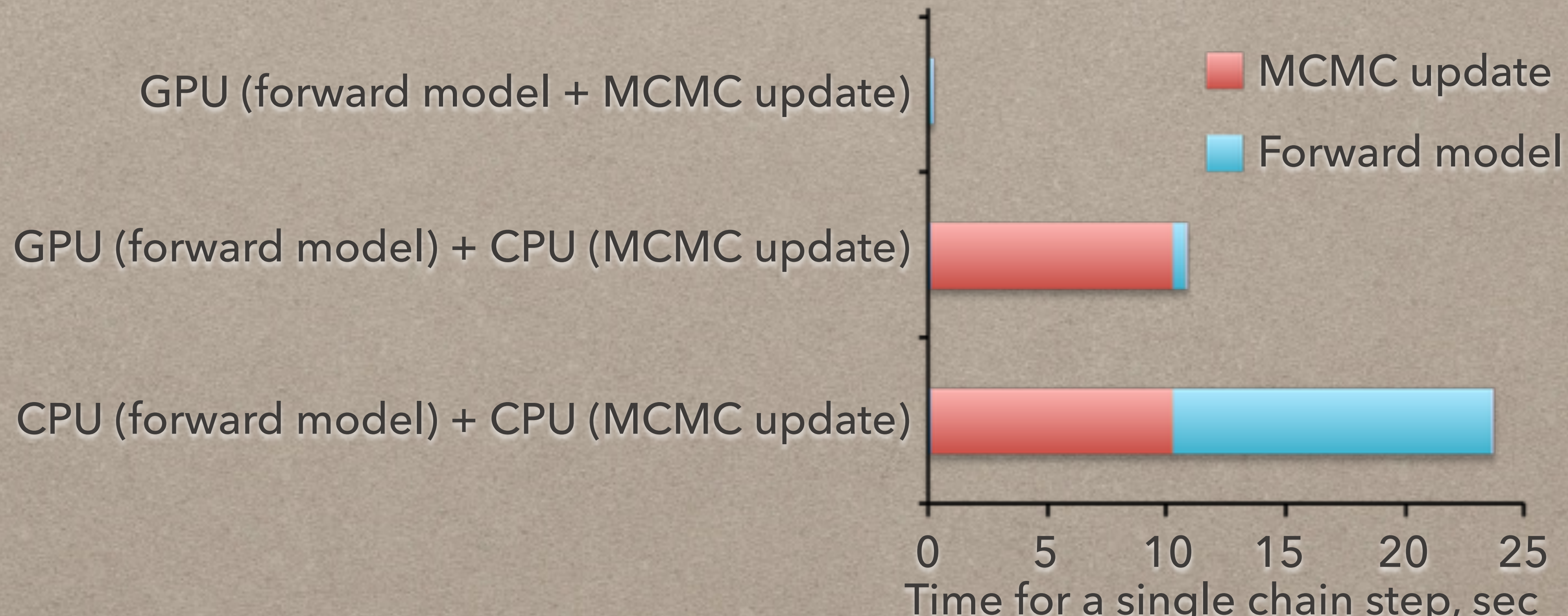
- Based on the CATMIP algorithm (Minson et al., 2013)
  - Developed in collaboration with Caltech, IPGS, Géoazur
  - A parallel tempered MCMC algorithm
  - Embarrassingly parallel

- GPU parallelization
  - IDEX project BAYES
  - ANR project BEBOP (JCJC)

Parallelization scheme



ALTAR benchmark for 288 model parameters



PREDICTION UNCERTAINTY

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m})\, p(\mathbf{d}_{\text{obs}}|\mathbf{m})$$

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m}) \int_D p(\mathbf{d}_{\text{obs}}|\mathbf{d})\, p(\mathbf{d}|\mathbf{m})\, d\mathbf{d}$$

Stochastic model for the measurement process

- $p(\mathbf{d}^*|\mathbf{d})$ is the probability (density) for getting the measured value $\mathbf{d}^*$ when the uncertain physical quantity being measured has the value $\mathbf{d}$
- $p(\mathbf{d}_{\text{obs}} \mid \mathbf{d})$ comes from substituting $\mathbf{d}^* = \mathbf{d}_{\text{obs}}$ in the probability model $p(\mathbf{d}^*|\mathbf{d})$. It describes the likelihood of having observed $\mathbf{d}_{\text{obs}}$ if the actual displacement was $\mathbf{d}$

Stochastic forward model for the predictions

- Uncertainties in the forward modeling
- Uncertainties of the theory
- Model discrepancy

Jolivet et al. (2013) https://profile.usgs.gov/mcnamara

PREDICTION UNCERTAINTY

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m}) \int_D p(\mathbf{d}_{\text{obs}}|\mathbf{d})\, p(\mathbf{d}|\mathbf{m})\, d\mathbf{d}$$

Measurement uncertainty

$$p(\mathbf{d}^*|\mathbf{d}) = \mathcal{N}(\mathbf{d}^*|\mathbf{d}, \mathbf{C}_{\text{d}})$$

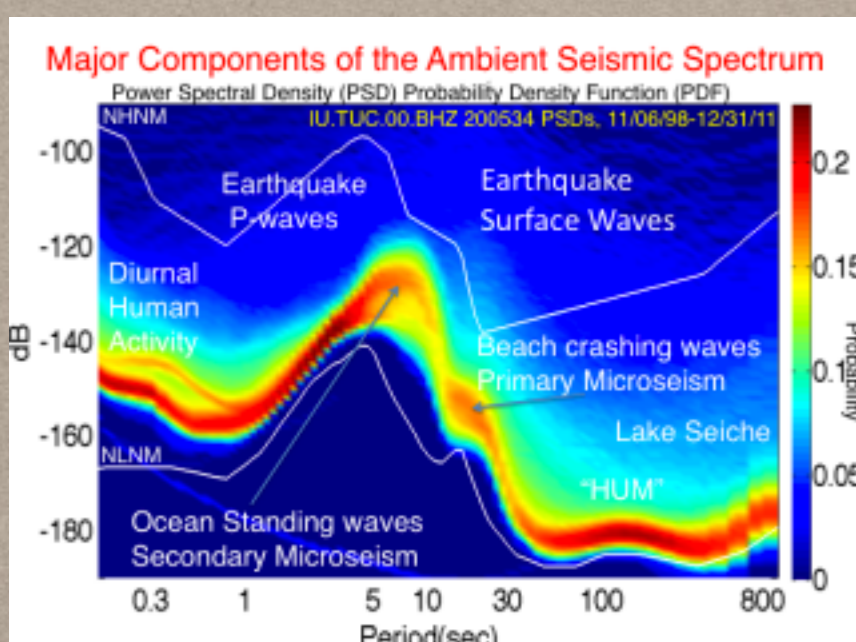
Prediction or model uncertainty

$$p(\mathbf{d}|\mathbf{m}) = \mathcal{N}\left(\mathbf{d}\,|\,\mathbf{g}(\mathbf{m}), \mathbf{C}_{\text{p}}\right)$$

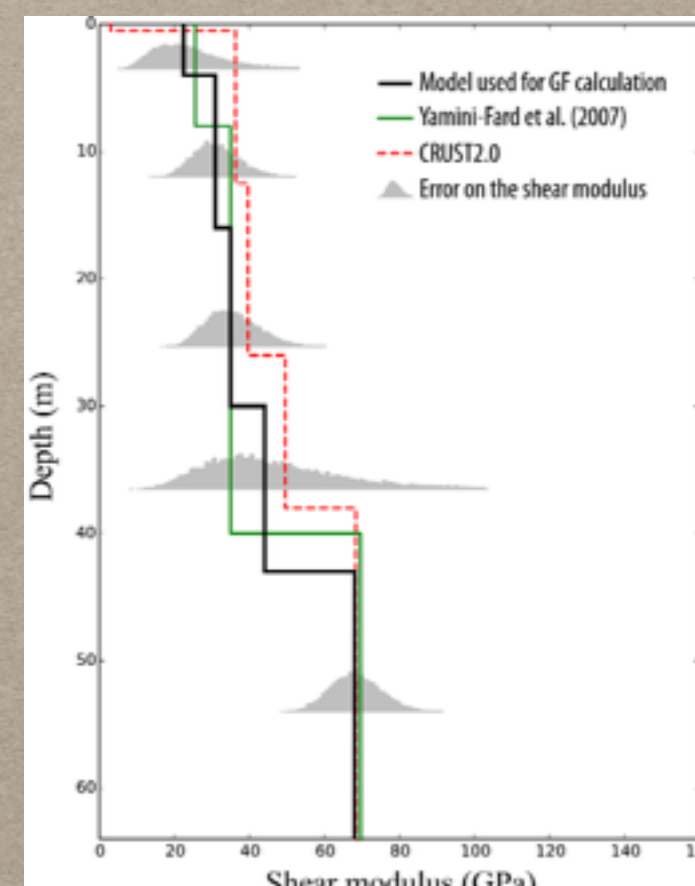
- Likelihood $p(\mathbf{d}_{\text{obs}}|\mathbf{m}) \propto \exp\left(-\frac{1}{2}\left(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\right)^T \mathbf{C}_\chi^{-1}\left(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\right)\right)$

2 contributions to the data misfit ($\mathbf{C}_\chi = \mathbf{C}_{\text{d}} + \mathbf{C}_{\text{p}}$):

Measurement uncertainty ($\mathbf{C}_{\text{d}}$)
(e.g. ambient noise)



Prediction uncertainty ($\mathbf{C}_{\text{p}}$)
(Elastic structure)



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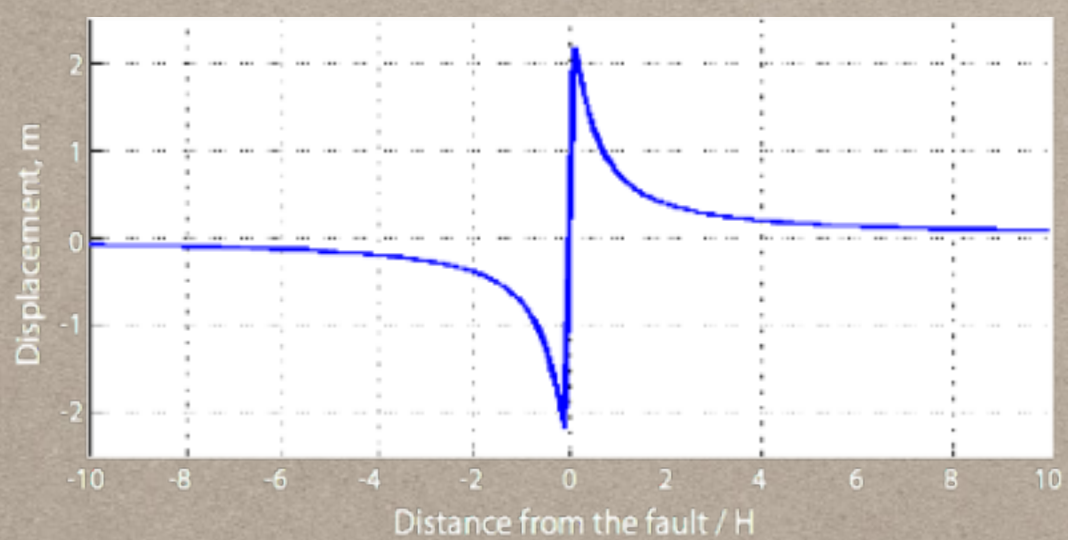
PREDICTION UNCERTAINTY

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m})\, p(\mathbf{d}_{\text{obs}}|\mathbf{m})$$

- Likelihood $\propto \exp\left(-\frac{1}{2}\left(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\right)^T \mathbf{C}_\chi^{-1}\left(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\right)\right)$ with $\mathbf{C}_\chi = \mathbf{C}_\text{d} + \mathbf{C}_\text{p}$

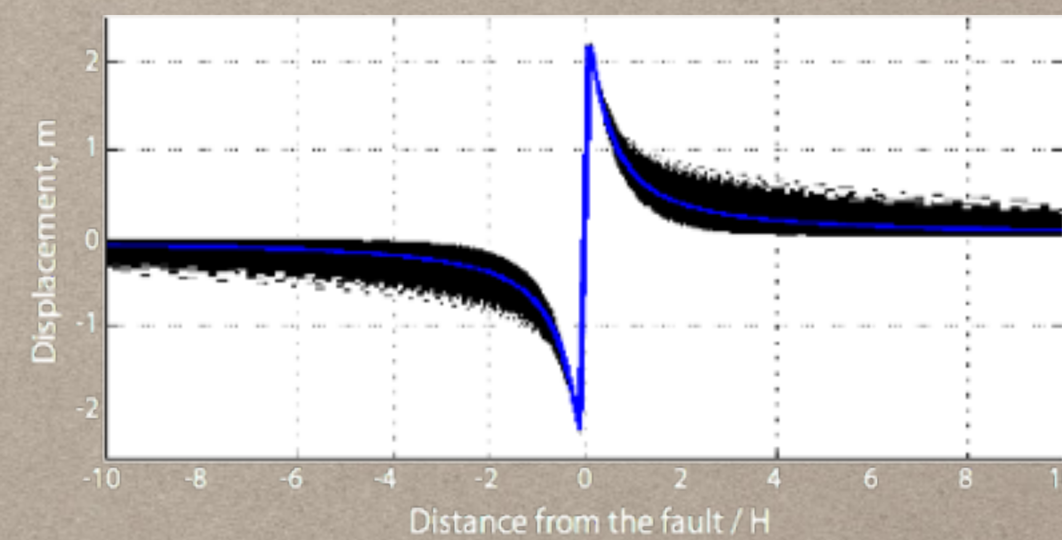
Exact theory

$p(\mathbf{d}|\mathbf{m}) = \delta(\mathbf{d} - \mathbf{g}(\tilde{\Omega},\mathbf{m}))$



Stochastic (non-deterministic) theory

$p(\mathbf{d}|\mathbf{m}) = N(\mathbf{d} \mid \mathbf{g}(\tilde{\Omega},\mathbf{m}), \mathbf{C}_\text{p})$



- Calculation of Cp based on the physics of the problem: a perturbation approach

$$\boldsymbol{\delta}\mathbf{p} = \mathbf{K}_\mu \cdot \boldsymbol{\delta}\mathbf{ln}\boldsymbol{\mu} \quad \Rightarrow \quad \mathbf{C}_\text{p} = \mathbf{K}_\mu \cdot \mathbf{C}_\mu \cdot \mathbf{K}_\mu^T$$

$\mathbf{K}_\mu$: Partial derivatives w.r.t. the elastic parameters (sensitivity kernel)

$\mathbf{C}_\mu$: Covariance matrix describing uncertainty in the Earth model parameters

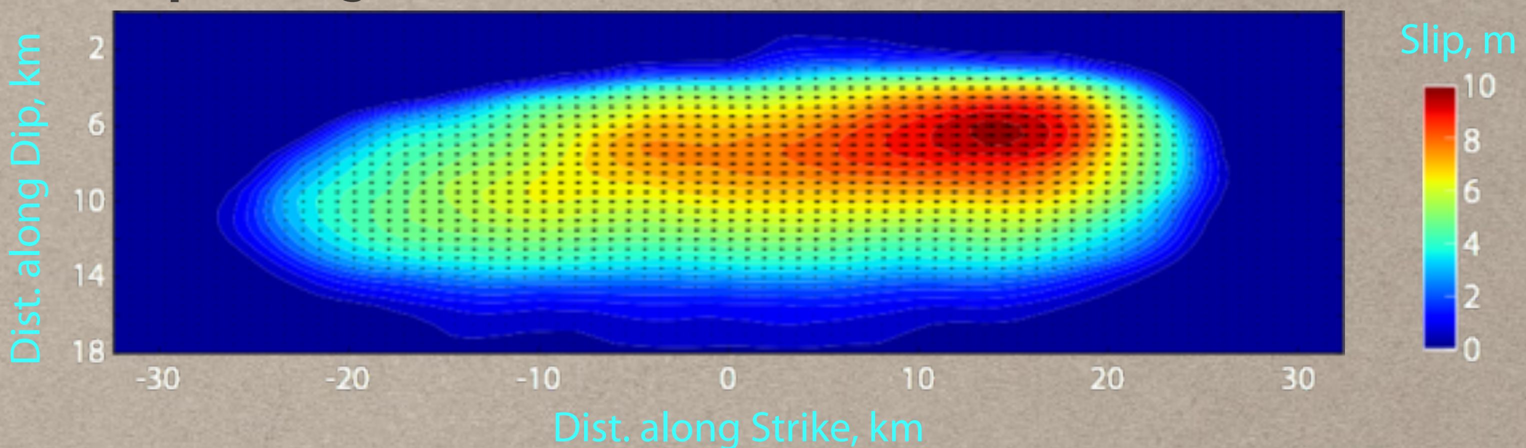
Duputel et al., 2014

PREDICTION UNCERTAINTY: TOY MODEL

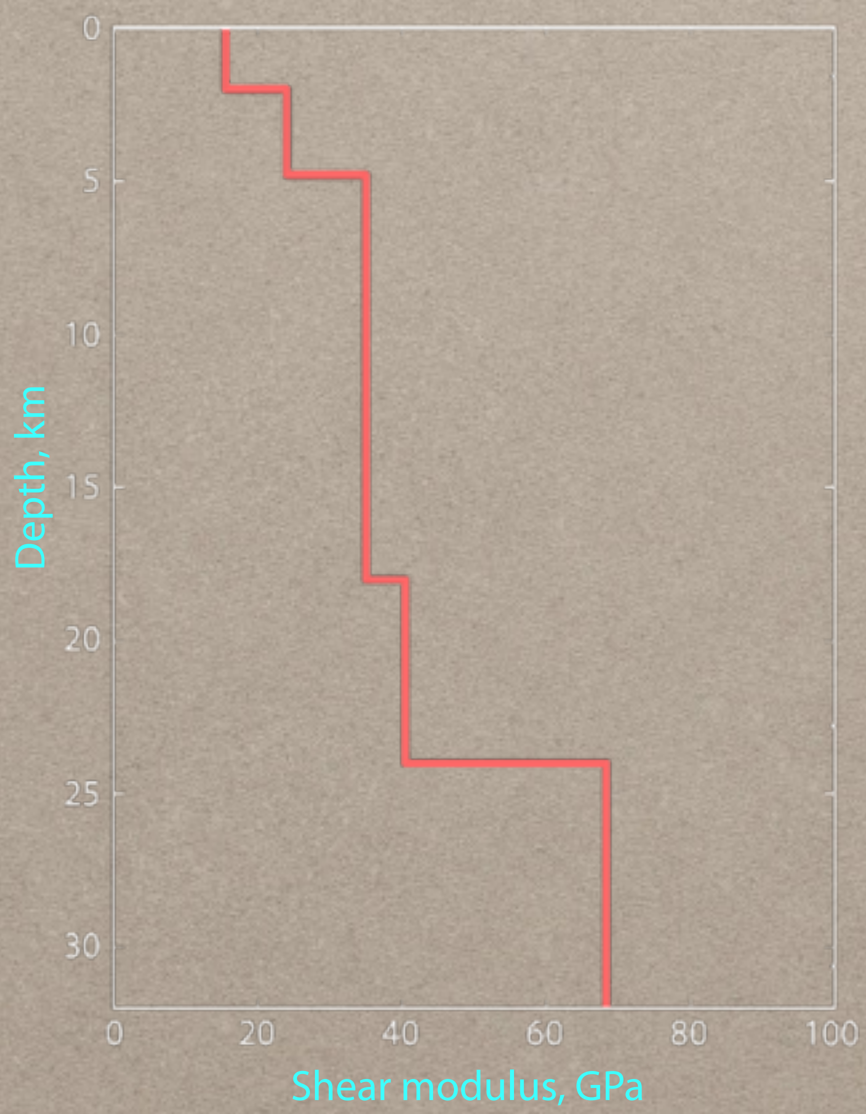
Finite strike-slip fault

- Top of the fault at 0 km
- South-dipping = 80°
- Data for a layered half-space

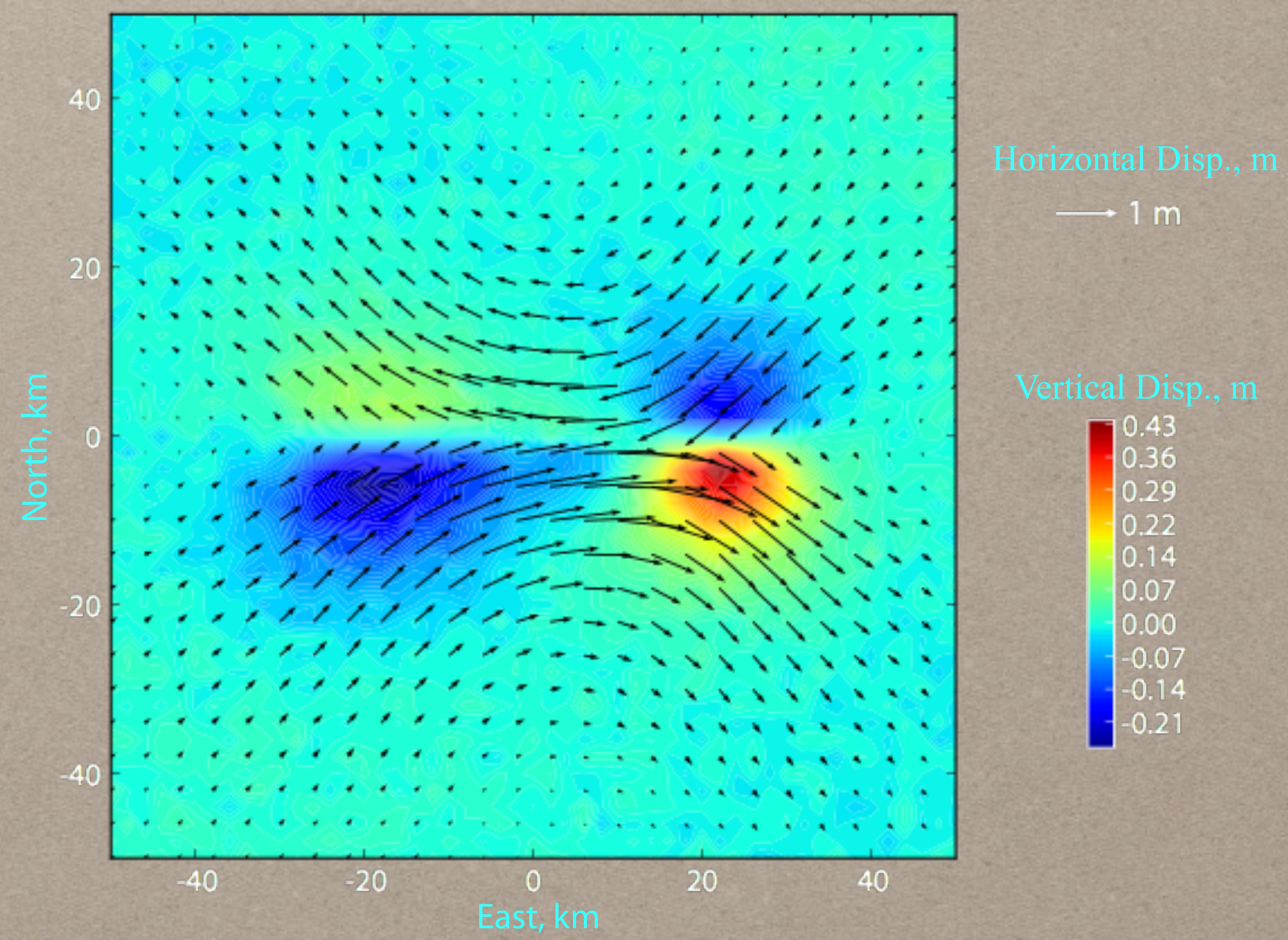
Input (target) model



Earth model



Data

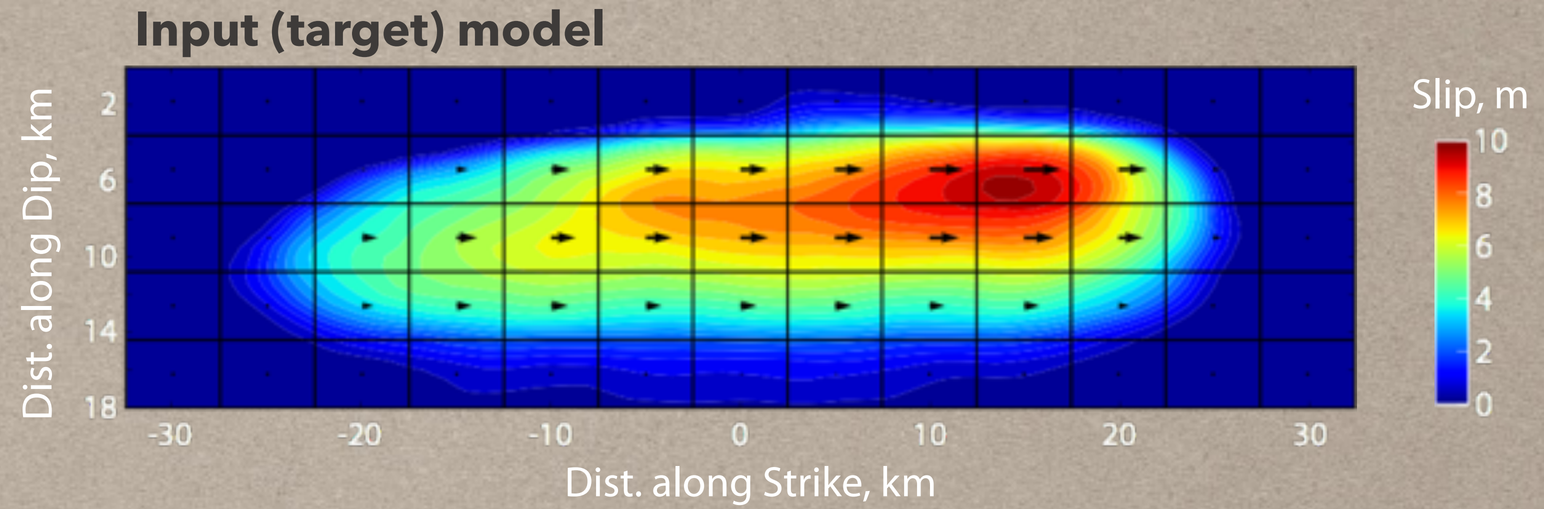


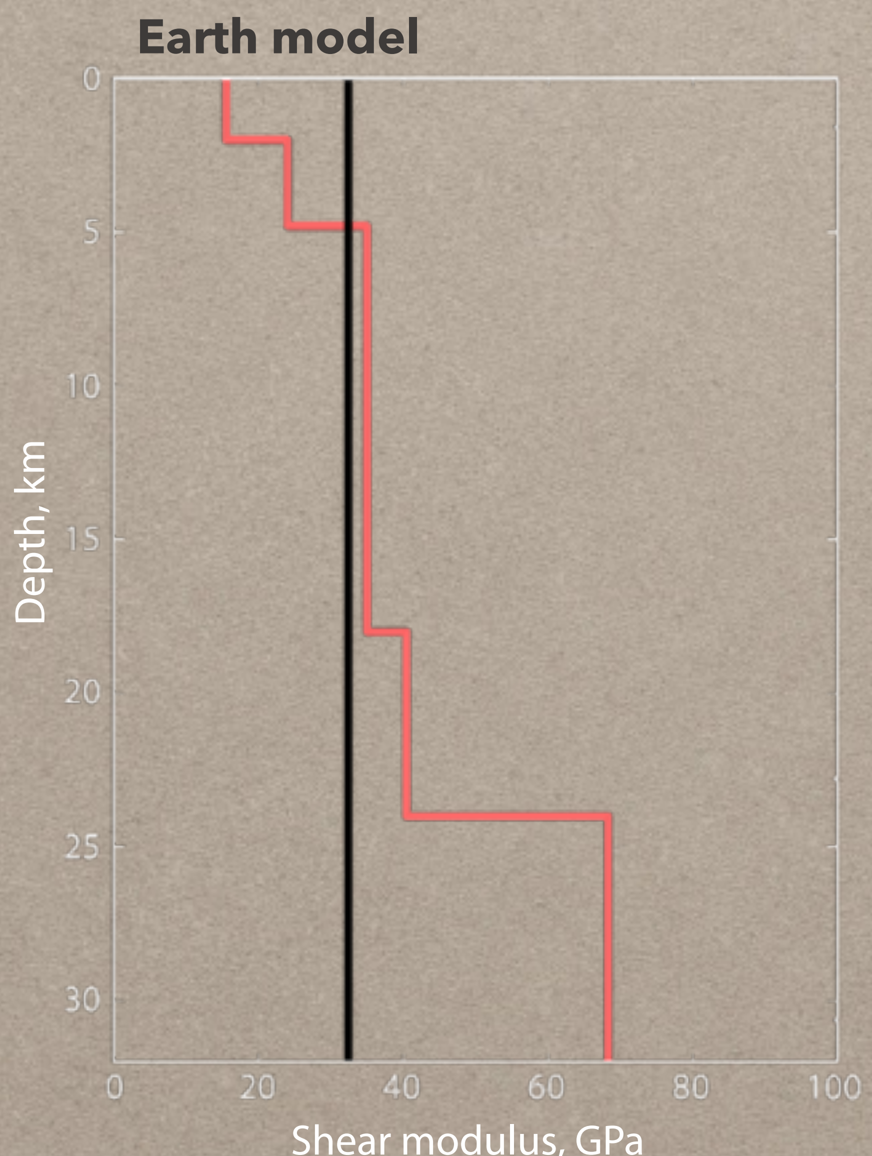
Duputel et al., 2014

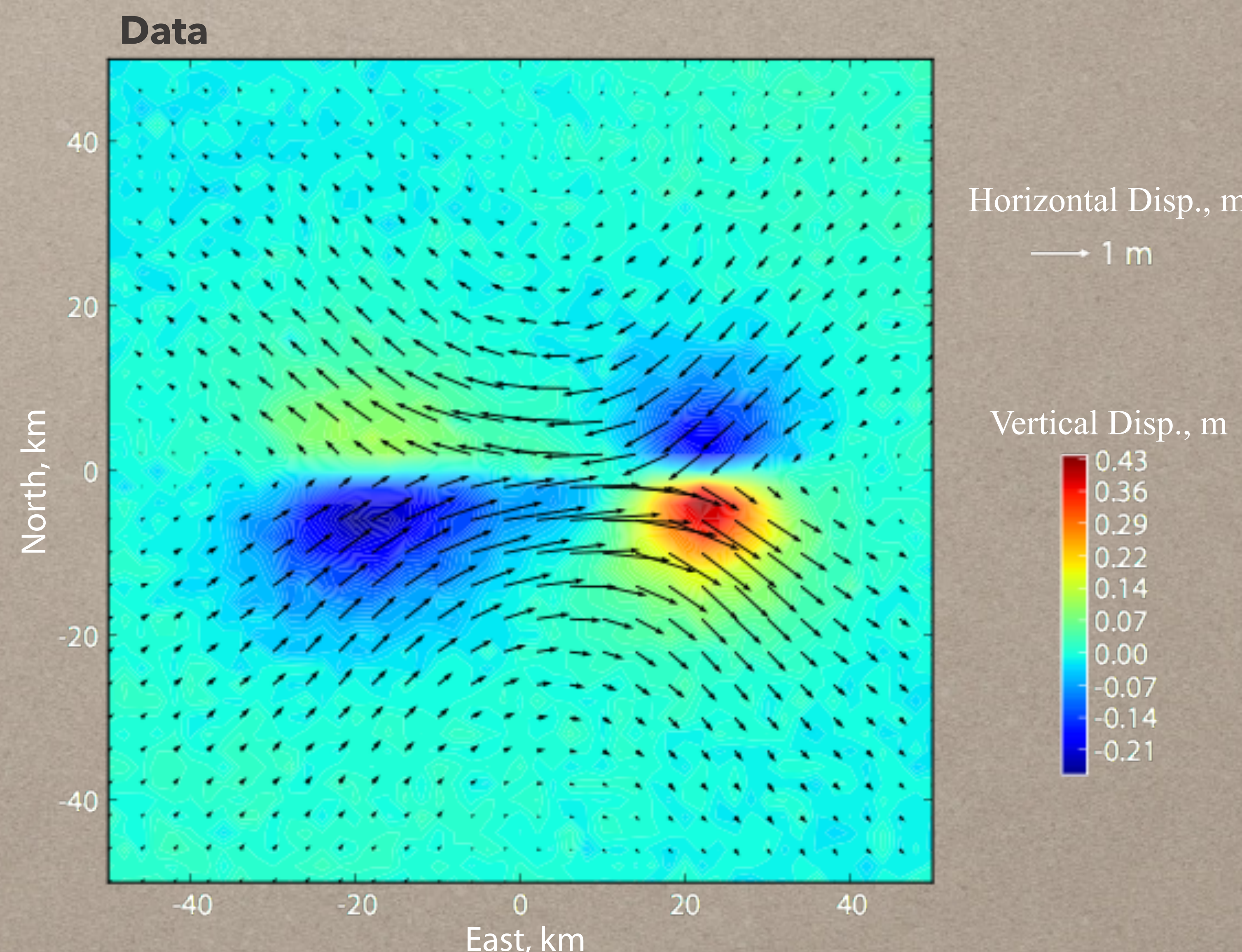
PREDICTION UNCERTAINTY: TOY MODEL

Finite strike-slip fault

- 65 patches, 2 slip components
- 5mm uncorrelated noise ($\rightarrow \mathbf{C_d}$)
- GFs - half-space ($\rightarrow \mathbf{C_p}$)







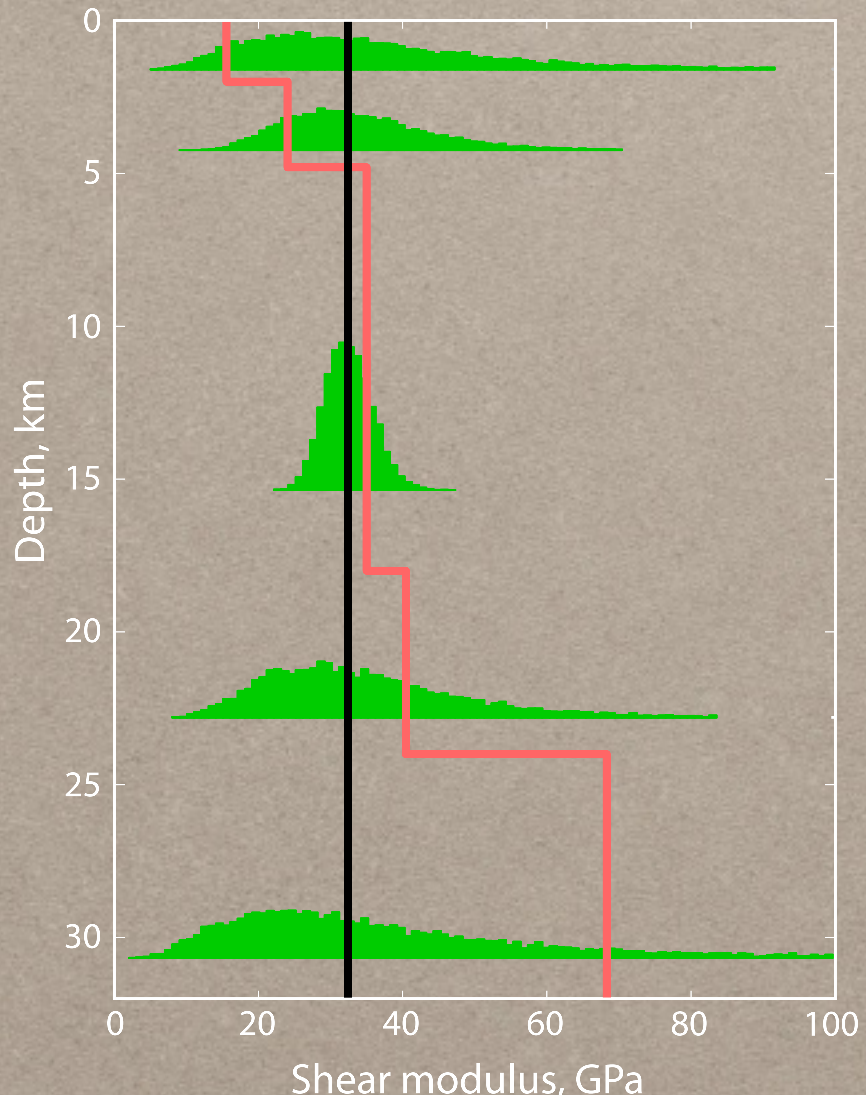
Duputel et al., 2014

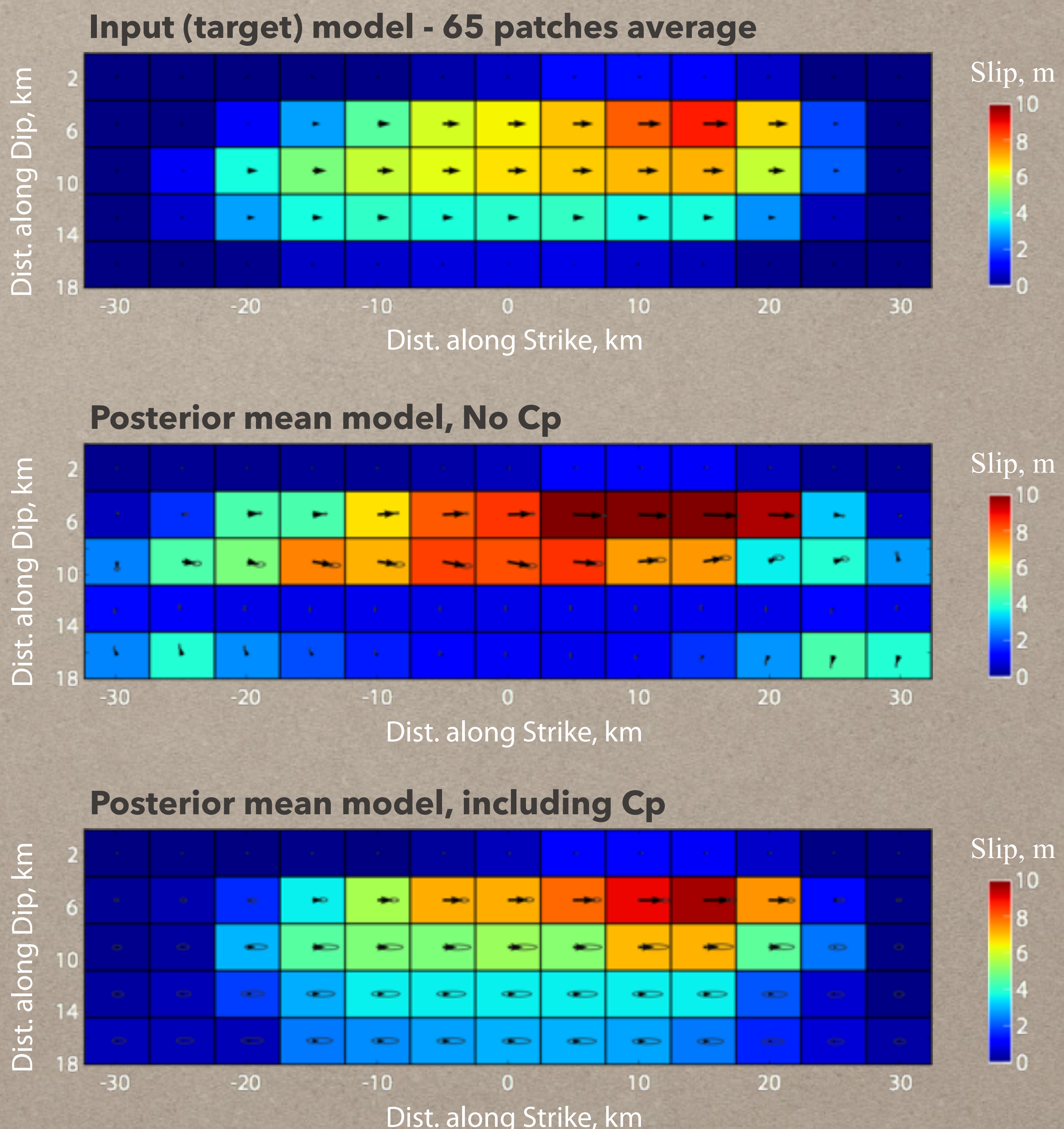
PREDICTION UNCERTAINTY: TOY MODEL

Finite strike-slip fault

- Top of the fault at 0 km
- South-dipping = 80°
- Data for a layered half-space

Earth model





Duputel et al., 2014

QUESTIONS?

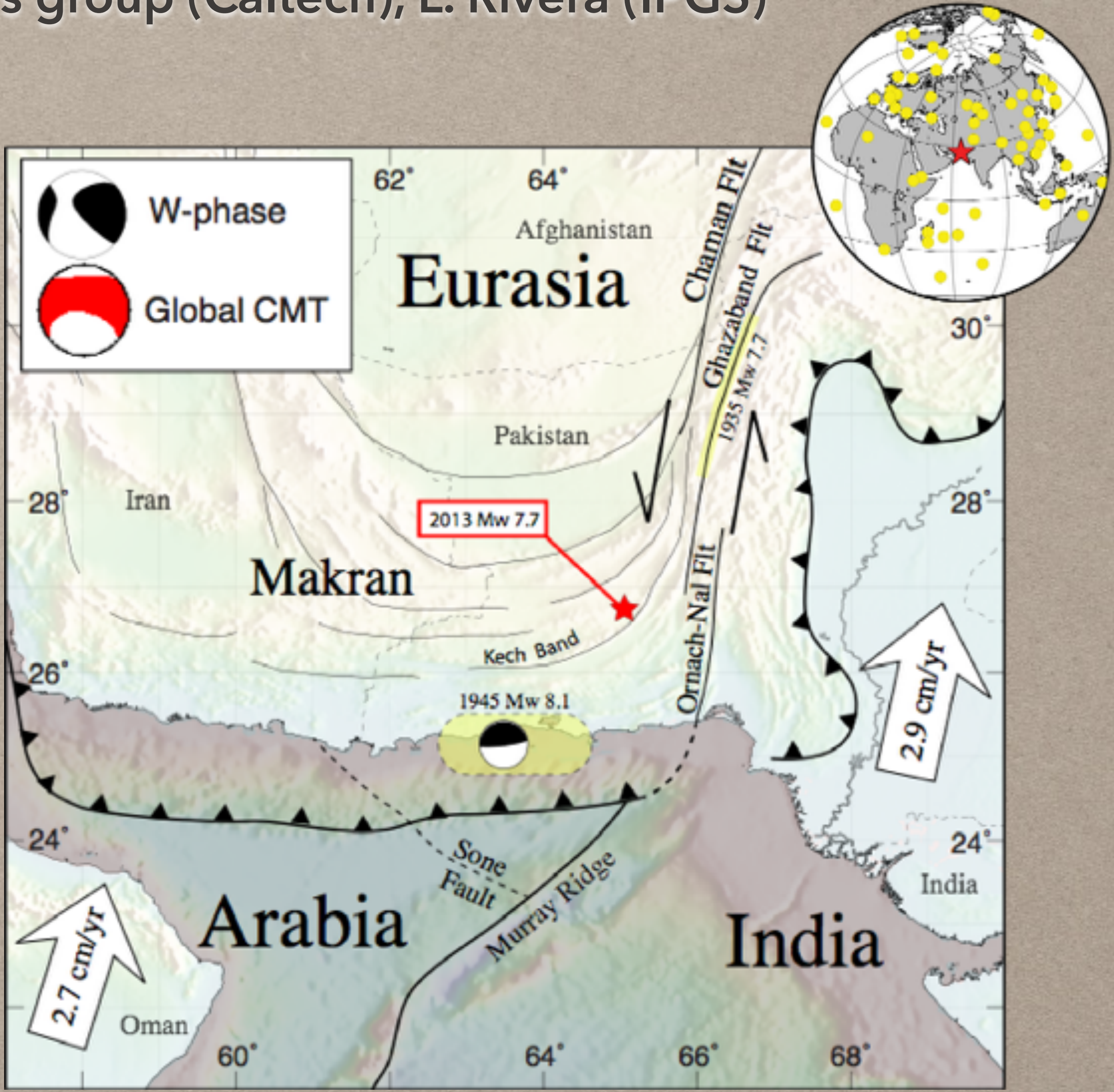
COMING UP: APPLICATION EXAMPLES

BALOCHISTAN EARTHQUAKE (2013, M7.7)

Collaborations: R. Jolivet, M. Simons group (Caltech), L. Rivera (IPGS)

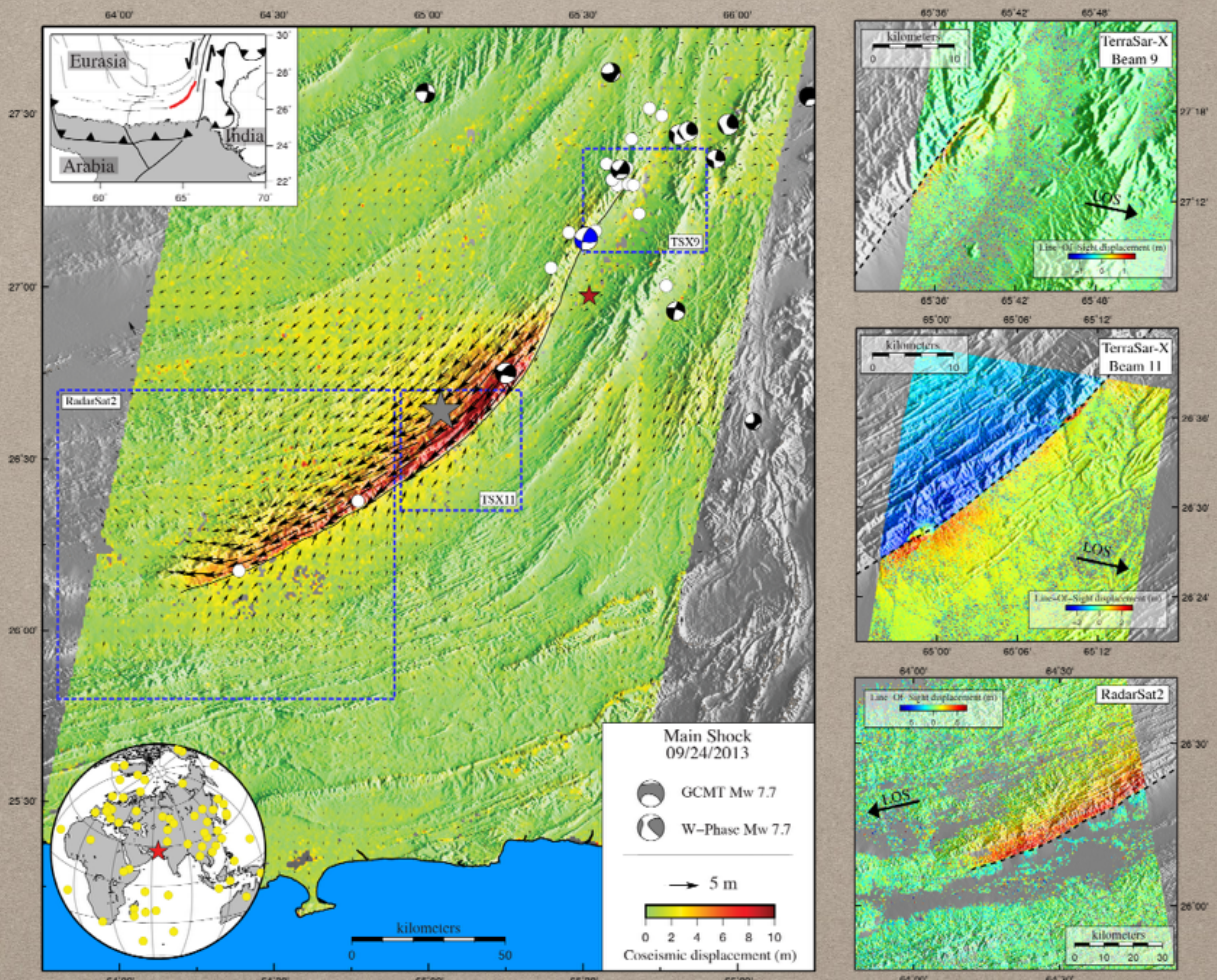
- Large earthquakes rarely occur within accretionary prisms
  - aseismic deformation
  - partitioning of deformation
  - high pore pressures - weak unconsolidated sediments
- Low seismicity:
  - Séisme de Quetta (1935, Mw~7.5)
  - Séisme de Makran (1945, Mw~8.1)
- Shallow locking depths:
  - Szeliga et al. (2012)
  - smaller than 5km on several faults

➡ Low likelihood for a large earthquake in this region



Jolivet et al., 2013

BALOCHISTAN EARTHQUAKE (2013, M7.7)



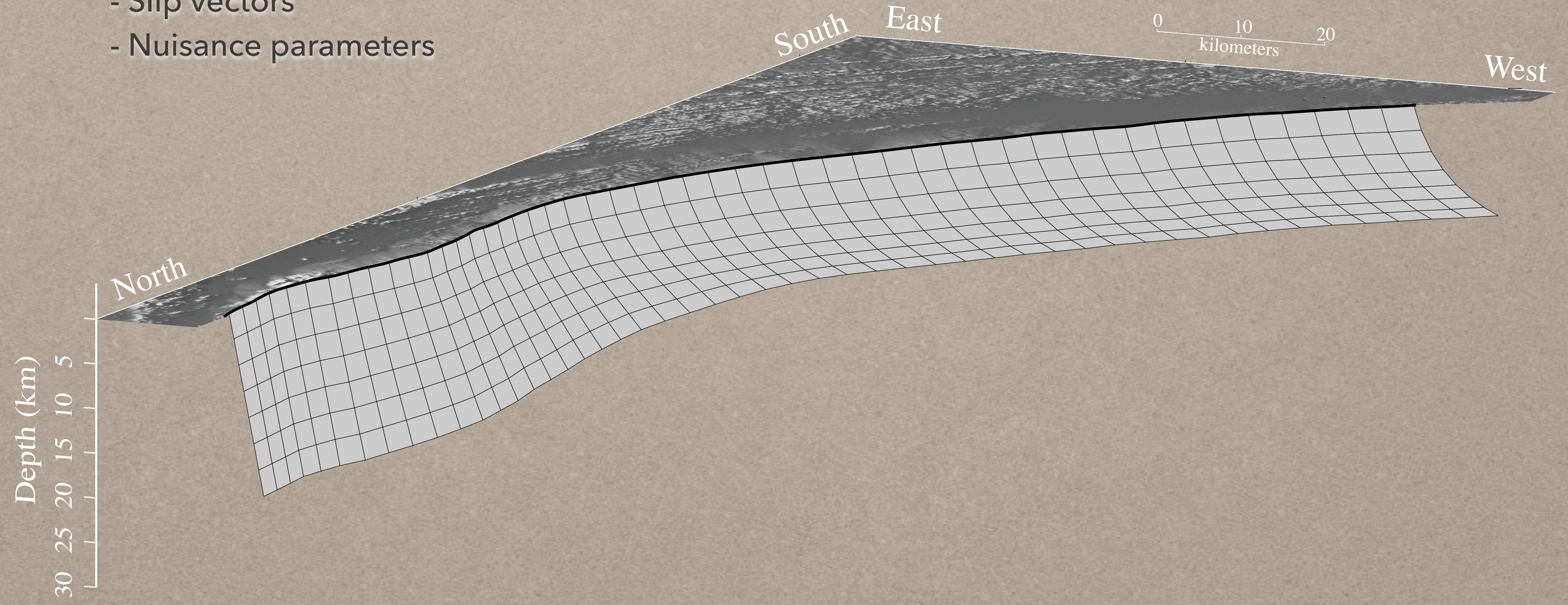
BALOCHISTAN EARTHQUAKE (2013, M7.7)

Listric fault geometry

- Based on W-phase dip angles (δ=70° in the north, δ=50° in the south)
- Structural studies: décollement at 10km depth (e.g., Ellouz-Zimmermann et al., 2007)
- Depth dependent dip angle

Static Parameters:

- Slip vectors
- Nuisance parameters

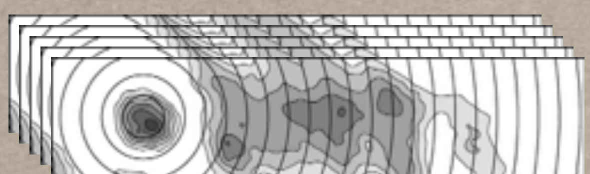


BALOCHISTAN EARTHQUAKE (2013, M7.7)

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m})\, p(\mathbf{d}_{\text{obs}}|\mathbf{m})$$

Posterior PDF

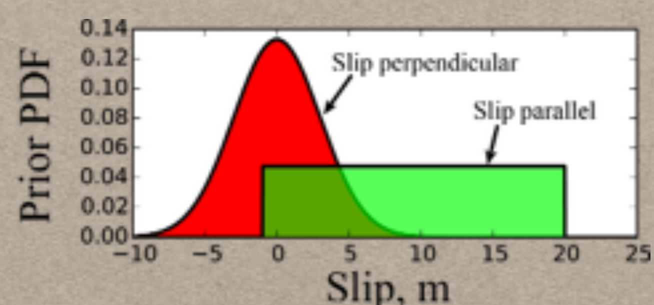
ensemble of models



Prior PDF

Constraints (if any)

- Strike-slip: $\mathcal{U}(-1,20)$
- Dip-slip: $\mathcal{N}(0,3)$



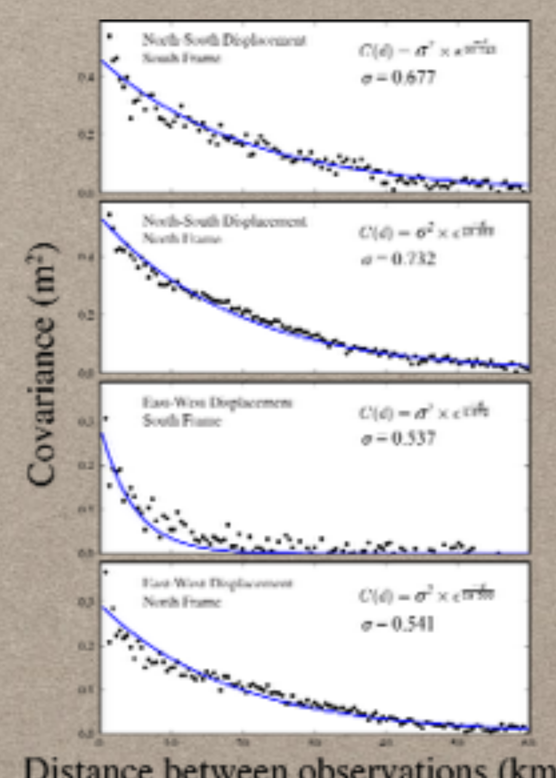
Likelihood

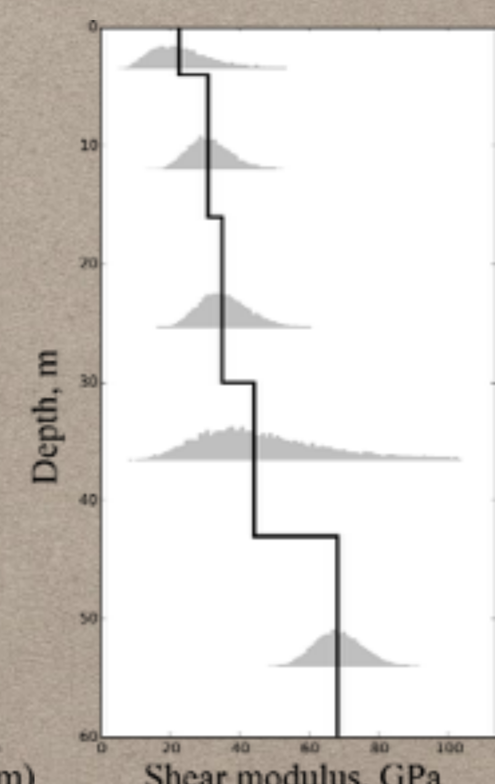
$$\propto \exp\left(-\frac{1}{2}\Big(\mathbf{d}_{\text{obs}}-\mathbf{g}(\mathbf{m})\Big)^T \mathbf{C}_\chi^{-1}\Big(\mathbf{d}_{\text{obs}}-\mathbf{g}(\mathbf{m})\Big)\right)$$

2 contributions to the data misfit ($\mathbf{C}_\chi$):

Data uncertainty (e.g. InSAR)

Prediction uncertainty (Elastic structure)

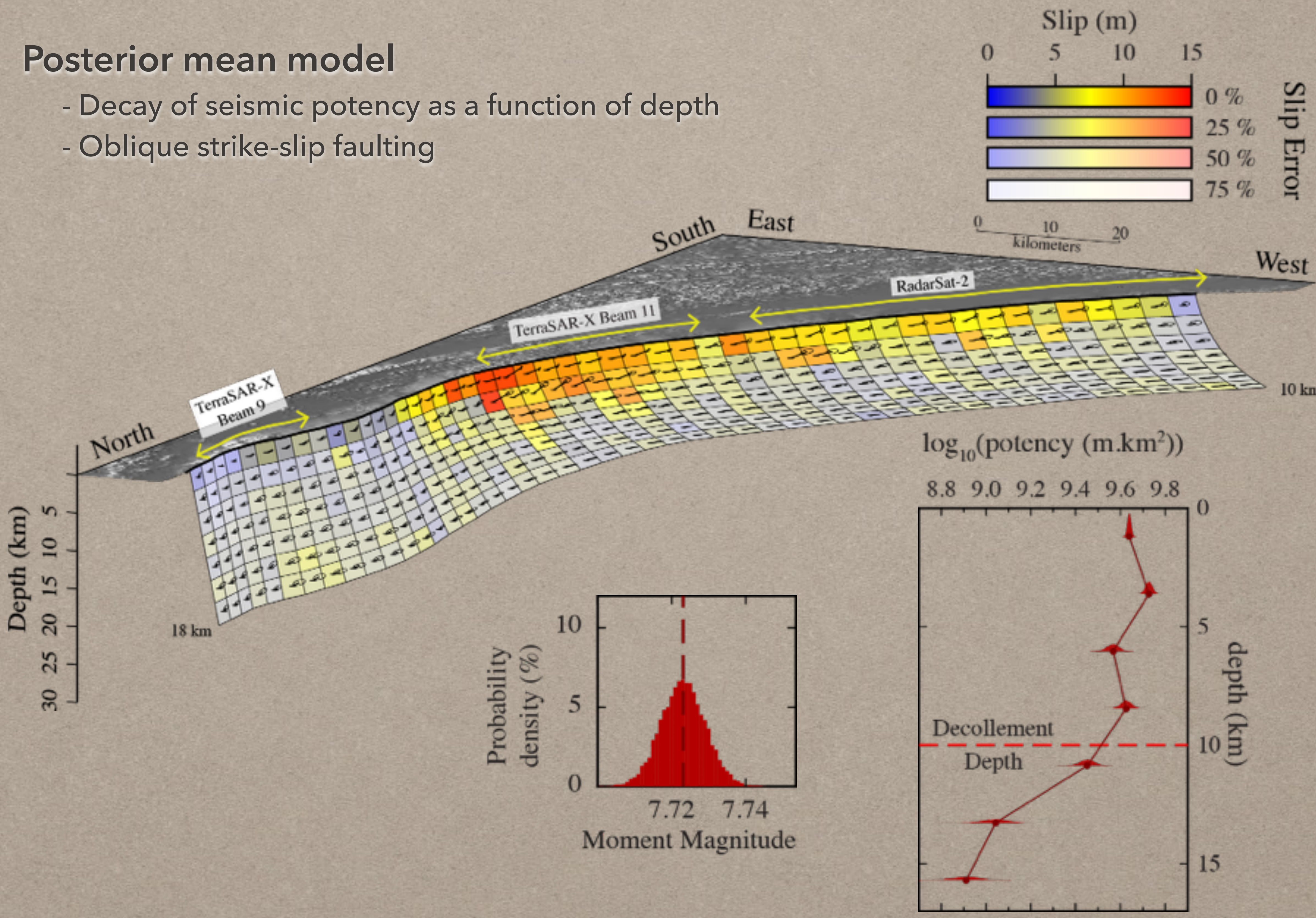




BALOCHISTAN EARTHQUAKE (2013, M7.7)

Posterior mean model

- Decay of seismic potency as a function of depth
- Oblique strike-slip faulting



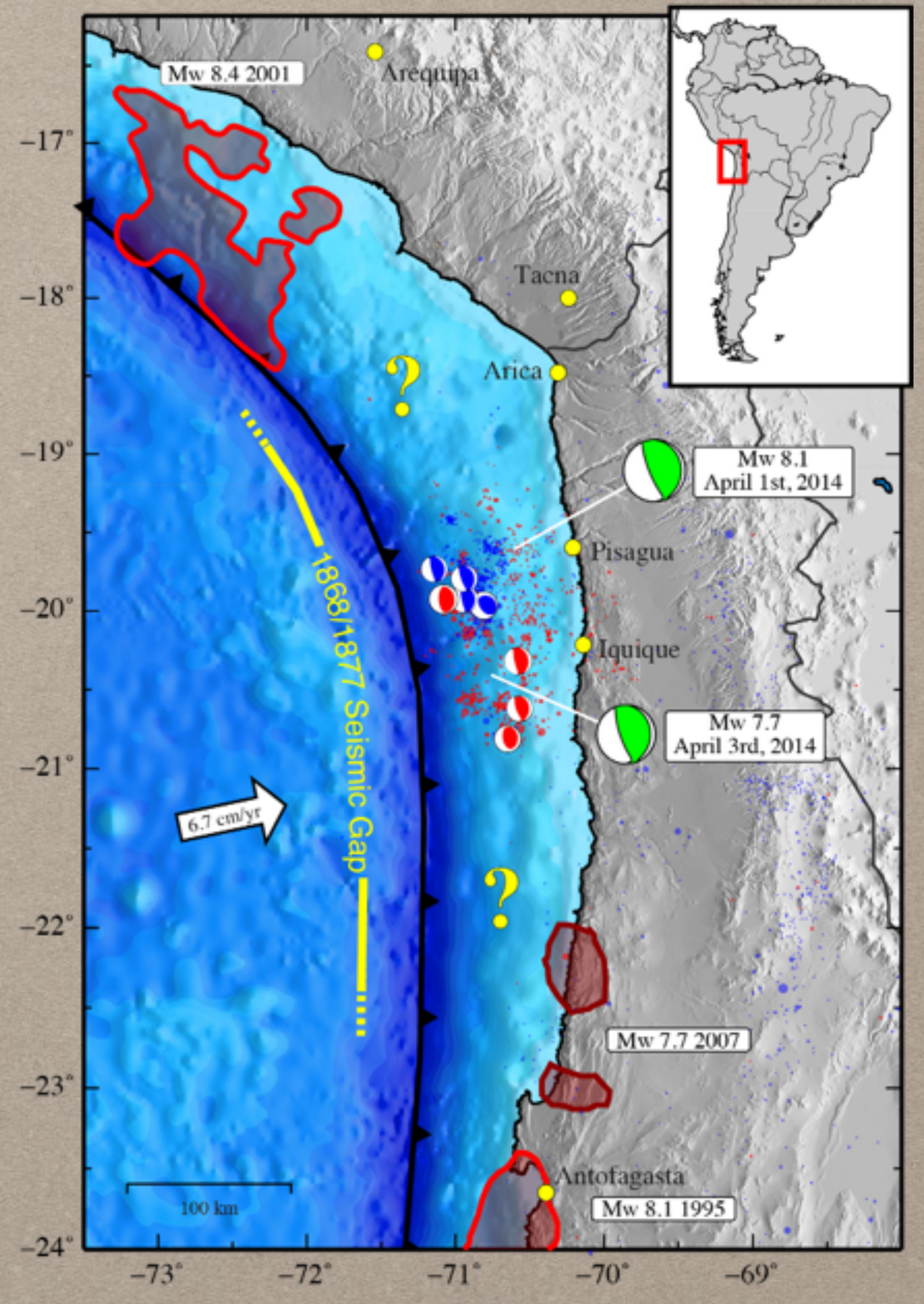
Jolivet et al., 2013

PISAGUA EARTHQUAKE (2014, M8.1)

Collaborations: M. Simons group (Caltech), L. Rivera (IPGS)

- Occurred in the north chilean seismic gap
  - Last ruptured in 1877 (Mw~8.8)
  - Before 1877: unclear if the region failed in huge single ruptures or in sequences of smaller ruptures
- Foreshock activity:
  - Started on 16 March with a Mw=6.7 thrust event
  - Followed by thrust faulting aftershocks
- Aftershock activity
  - Mw=7.7 aftershock on 3 April 2014

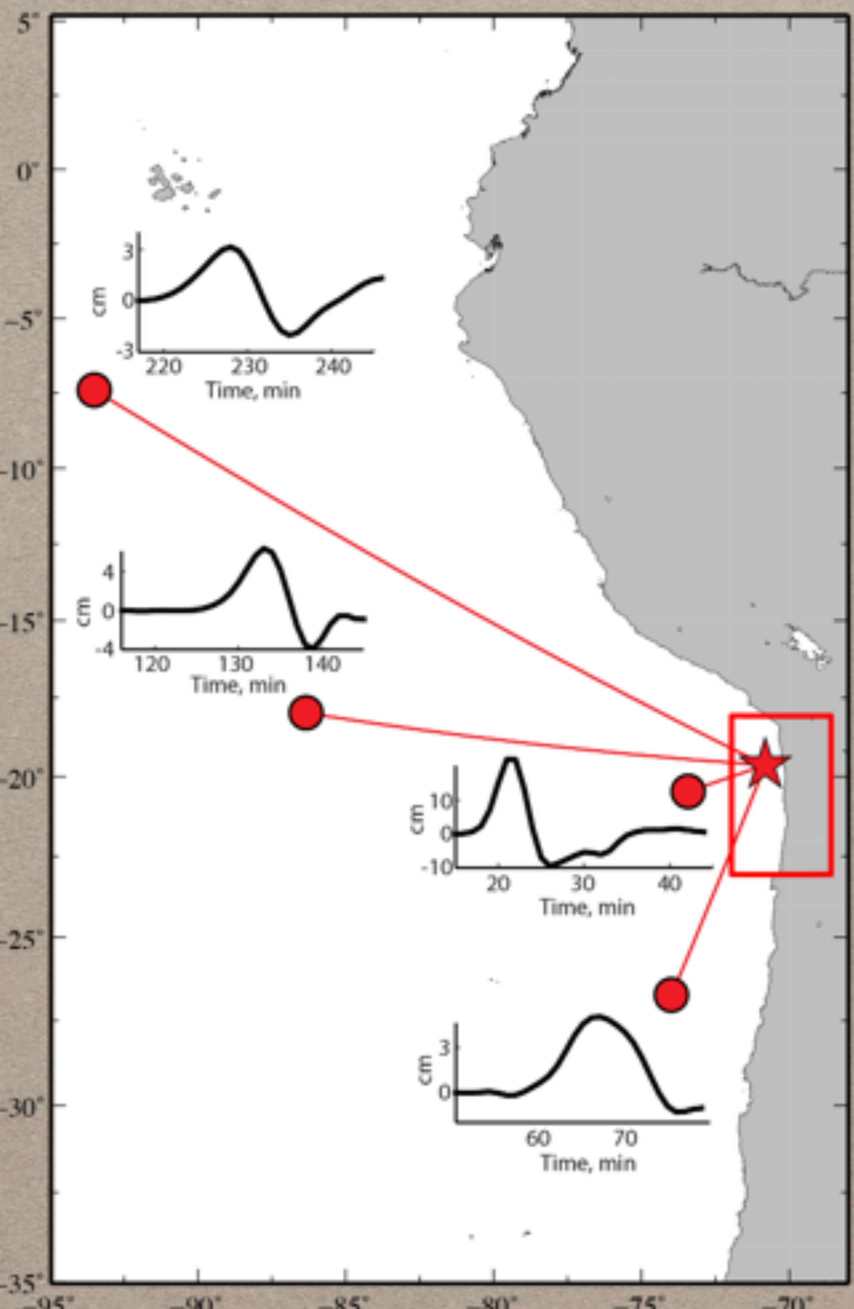
<u>Goal</u>: Provide a reliable description of the mainshock source attributes



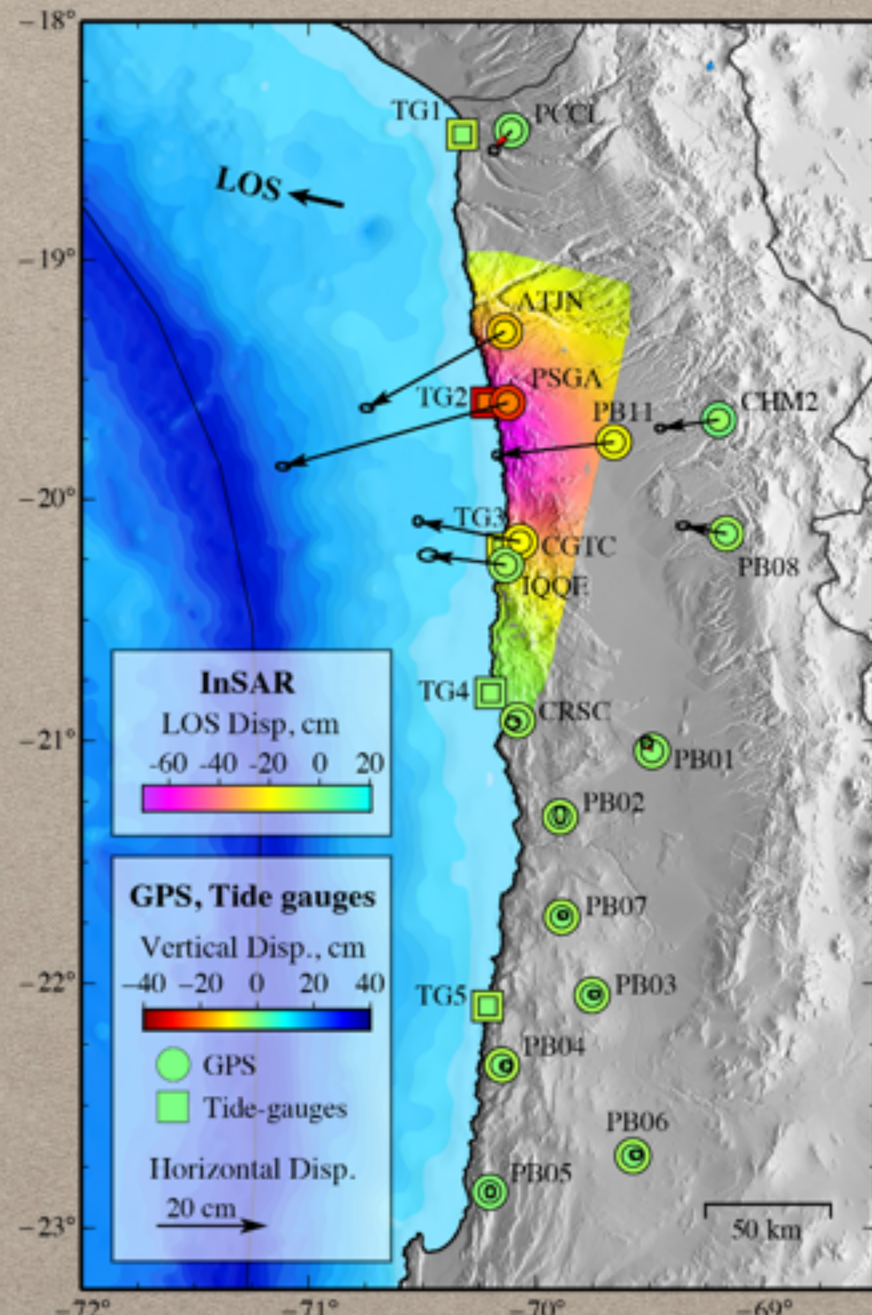
PISAGUA EARTHQUAKE (2014, M8.1)

Observations

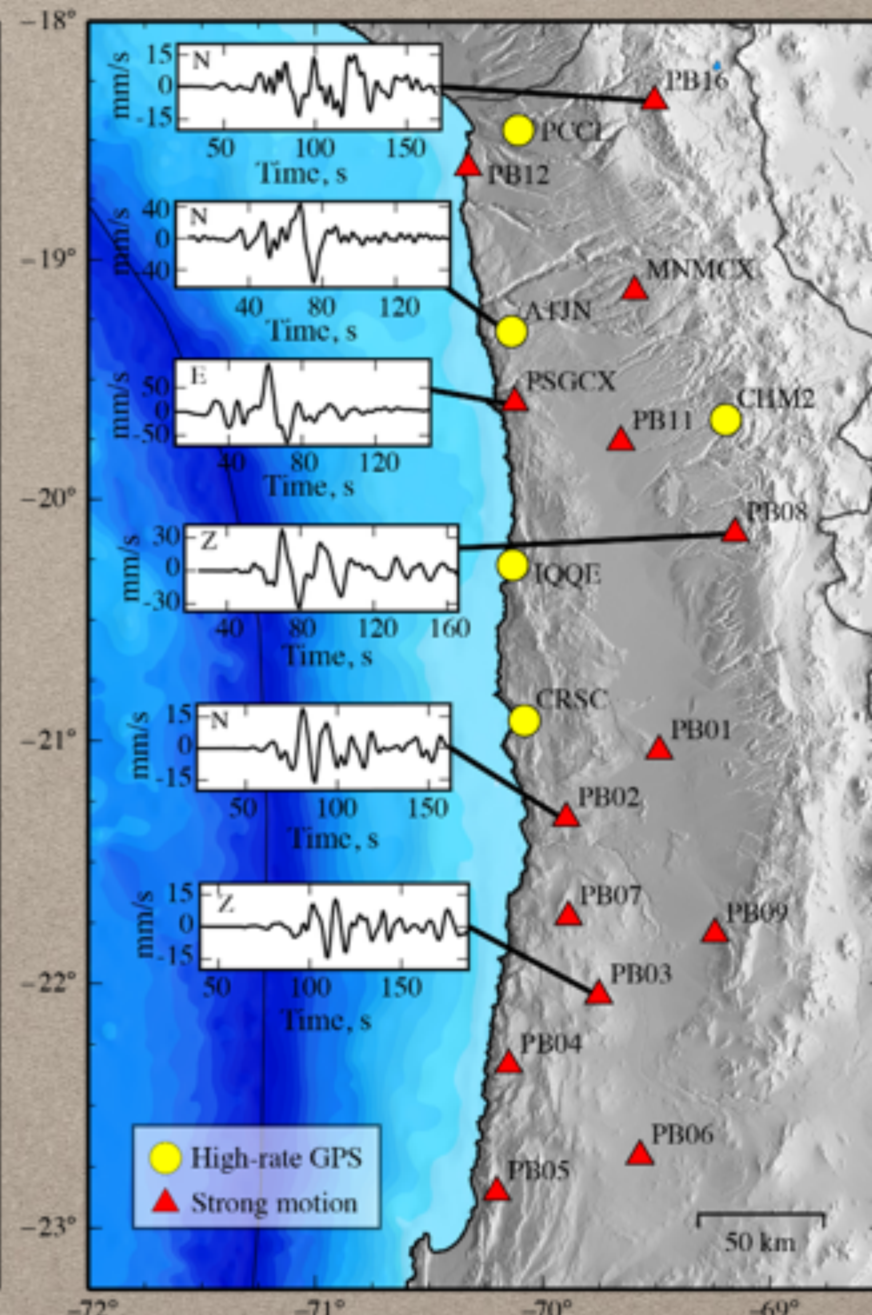
Tsunami (DART)



InSAR+GPS(●)+Tide gauges(■)



HR GPS(●)+Strong motion(▲)



Duputel et al., in prep.

PISAGUA EARTHQUAKE (2014, M8.1)

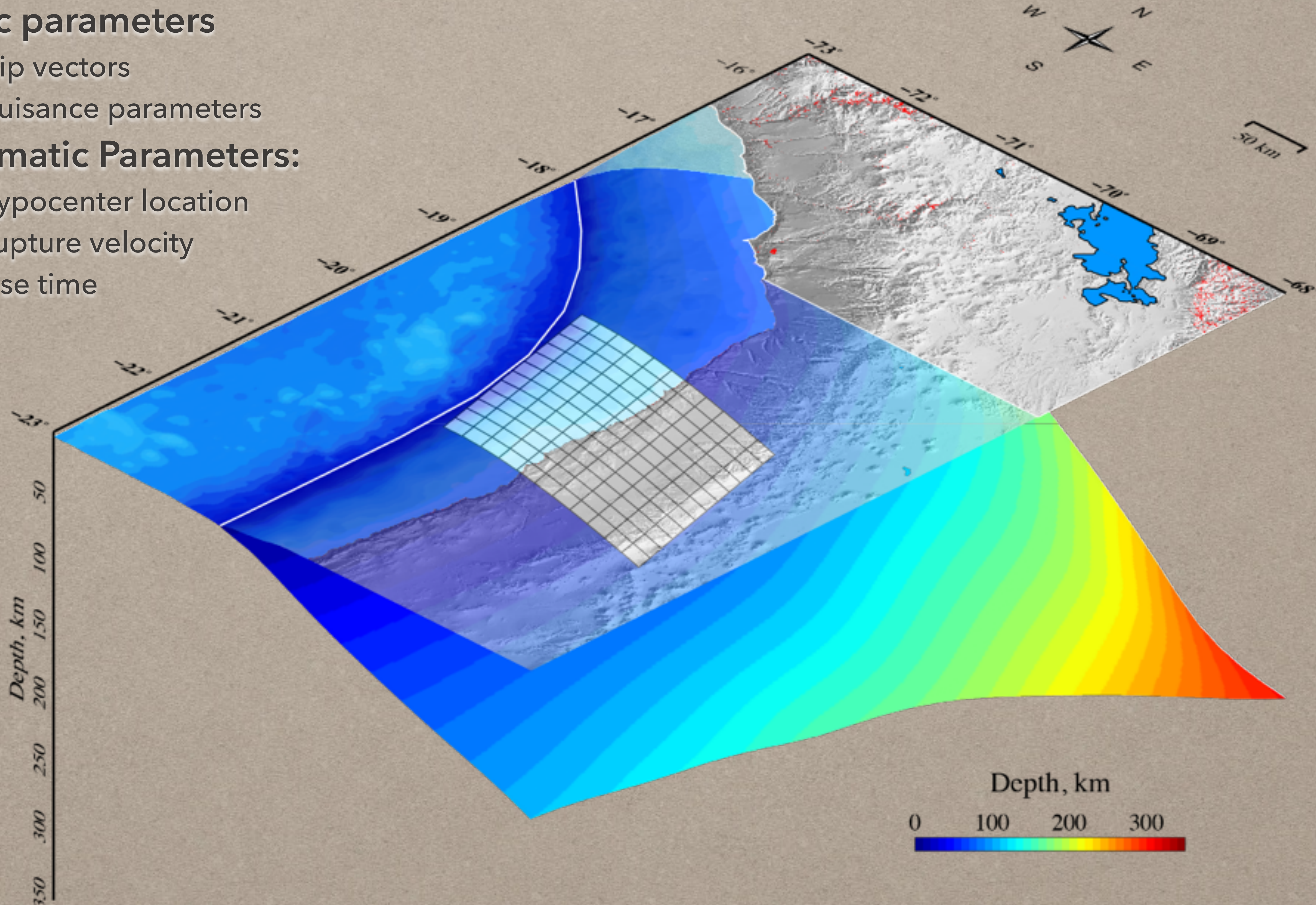
Curved fault geometry, 132 subfaults

Static parameters

- Slip vectors
- Nuisance parameters

Kinematic Parameters:

- Hypocenter location
- Rupture velocity
- Rise time

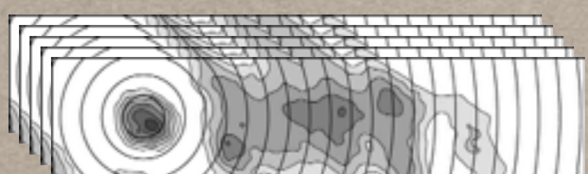


PISAGUA EARTHQUAKE (2014, M8.1)

$$p(\mathbf{m}|\mathbf{d}_{\text{obs}}) \propto p(\mathbf{m})\, p(\mathbf{d}_{\text{obs}}|\mathbf{m})$$

Posterior PDF

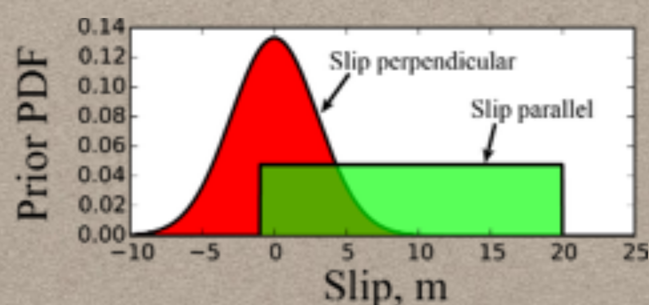
ensemble of models



Prior PDF

Constraints (if any)

- Dip-slip: $\mathcal{U}$(-1,20)
- Strike-slip: $\mathcal{N}$(0,3)
- Vr: $\mathcal{U}$(0.5, 4)
- Tr: $\mathcal{U}$(2, 30)



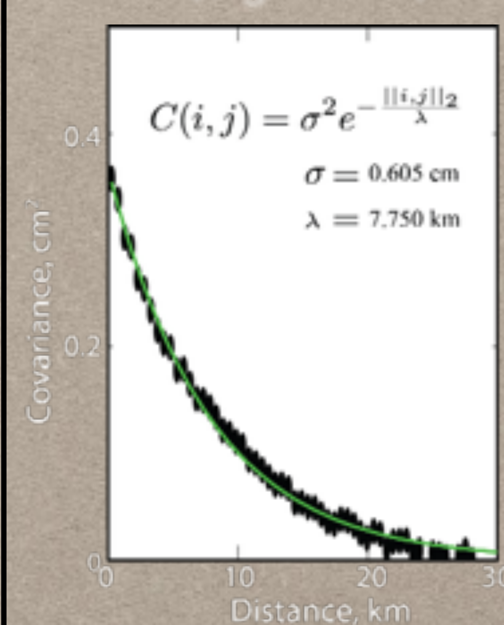
Likelihood

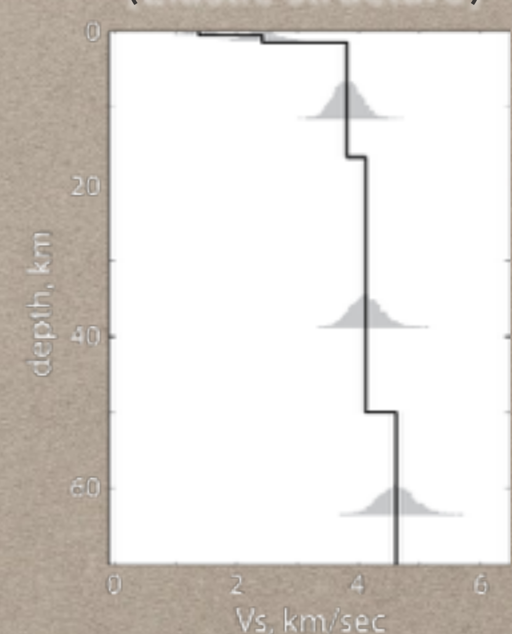
$$\propto \exp\left(-\frac{1}{2}\Big(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\Big)^T \mathbf{C}_\chi^{-1}\Big(\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})\Big)\right)$$

2 contributions to the data misfit ($\mathbf{C}_\chi$):

Data uncertainty (e.g. InSAR)

Prediction uncertainty (Elastic structure)





PISAGUA EARTHQUAKE (2014, M8.1)

Information integration using a cascading approach

1 **Static inversion:** $p(\mathbf{m}_\mathrm{s}|\mathbf{d}_\mathrm{s}) \propto p(\mathbf{m}_\mathrm{s})\, p(\mathbf{d}_\mathrm{s}|\mathbf{m}_\mathrm{s})$

- Data (d_s): GPS, InSAR, Tide gauges, Tsunami
- Parameters (m_s): Slip vectors

↓

2 **Kinematic inversion:** $p(\mathbf{m}_\mathrm{s}, \mathbf{m}_\mathrm{k}|\mathbf{d}_\mathrm{s}, \mathbf{d}_\mathrm{k}) \propto p(\mathbf{m}_\mathrm{s})\, p(\mathbf{d}_\mathrm{s}|\mathbf{m}_\mathrm{s})\, p(\mathbf{m}_\mathrm{k})\, p(\mathbf{d}_\mathrm{k}|\mathbf{m}_\mathrm{s}, \mathbf{m}_\mathrm{k})$

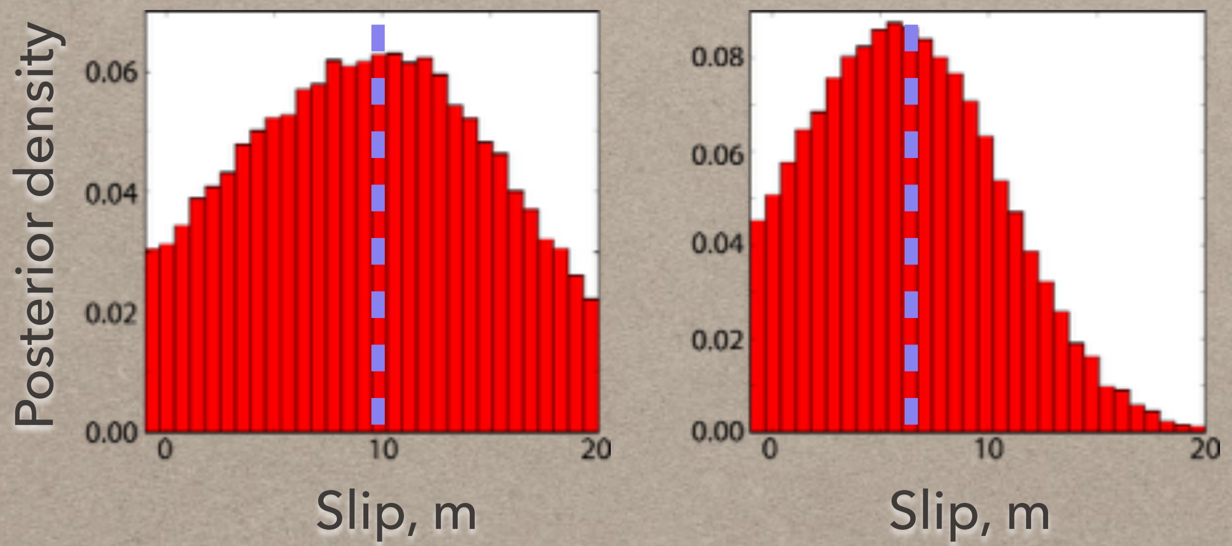
- Data (d_s, d_k): GPS, InSAR, Tide gauges, Tsunami, High-Rate GPS, Strong motion
- Parameters (m_s, m_k): Slip vectors, Hypocenter loc., Rupture velocity, Rise-Time

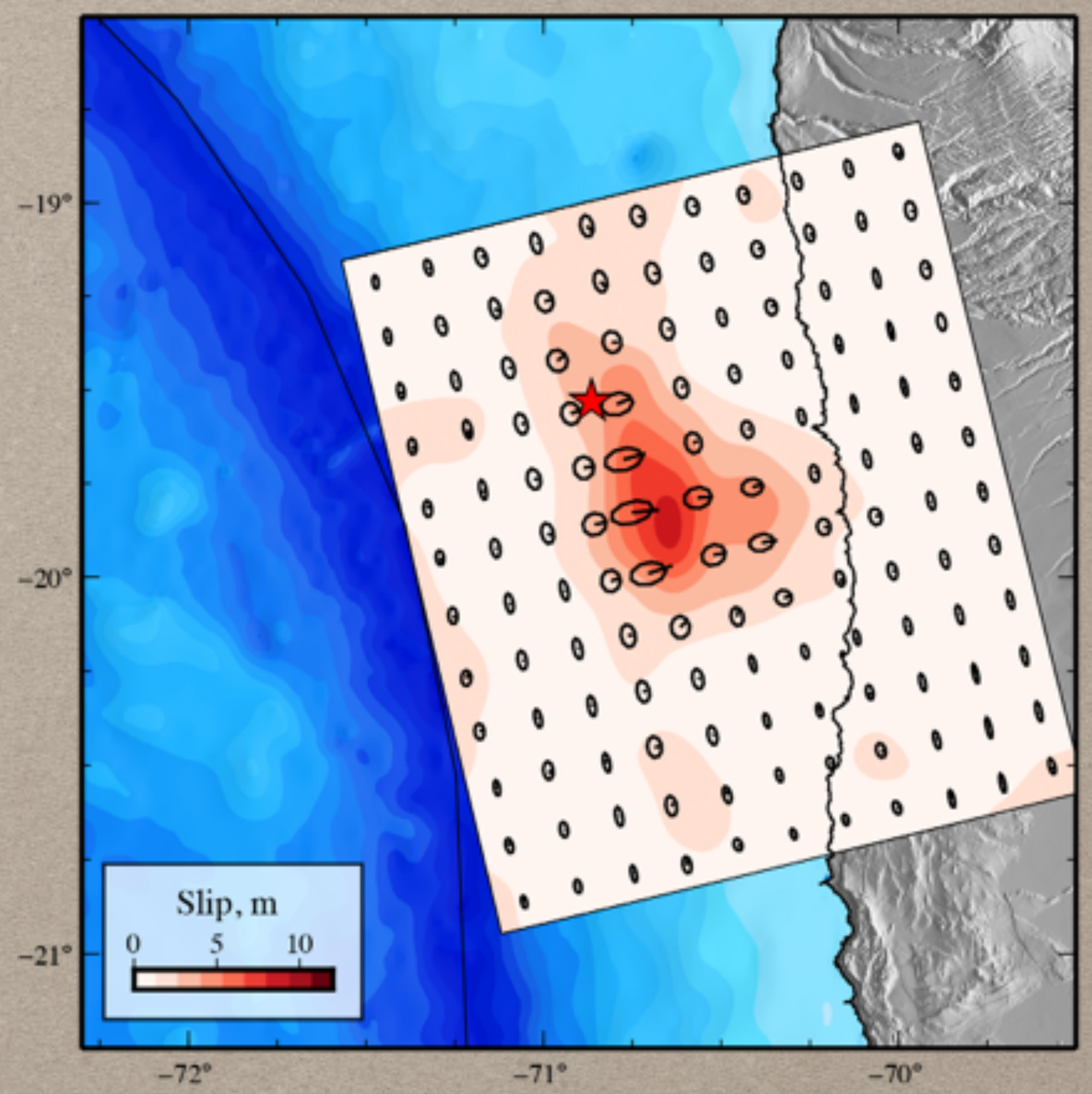
Minson et al., 2013

PISAGUA EARTHQUAKE (2014, M8.1)

1 Static slip inversion (GPS, InSAR, Tide gauges, Tsunami)

- Posterior Mean Model
- 95% Probability Error-ellipses
- PDF for patches with large slip:



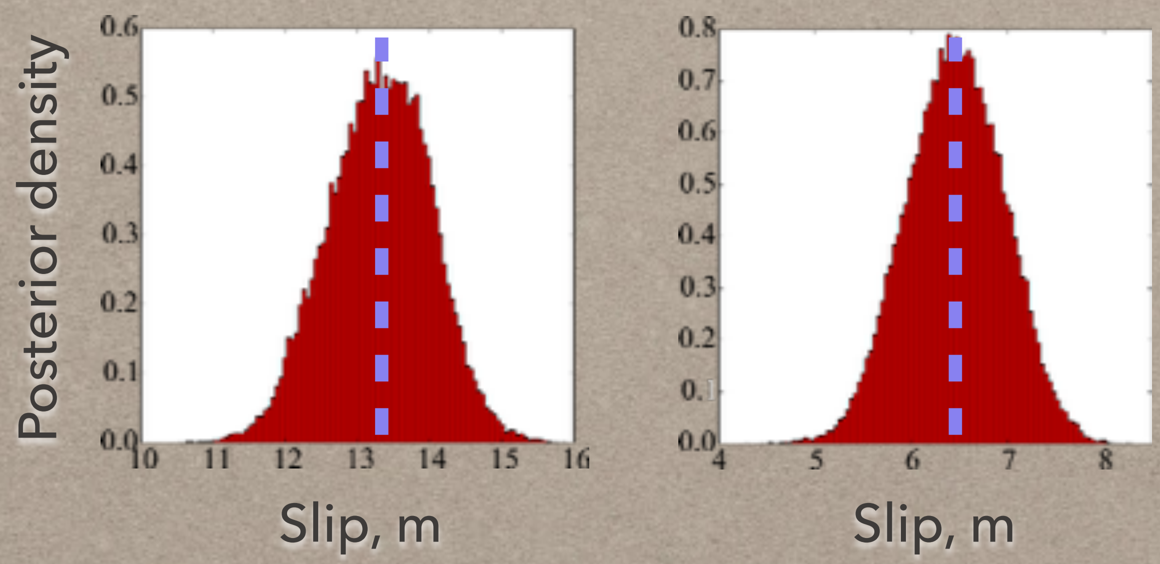


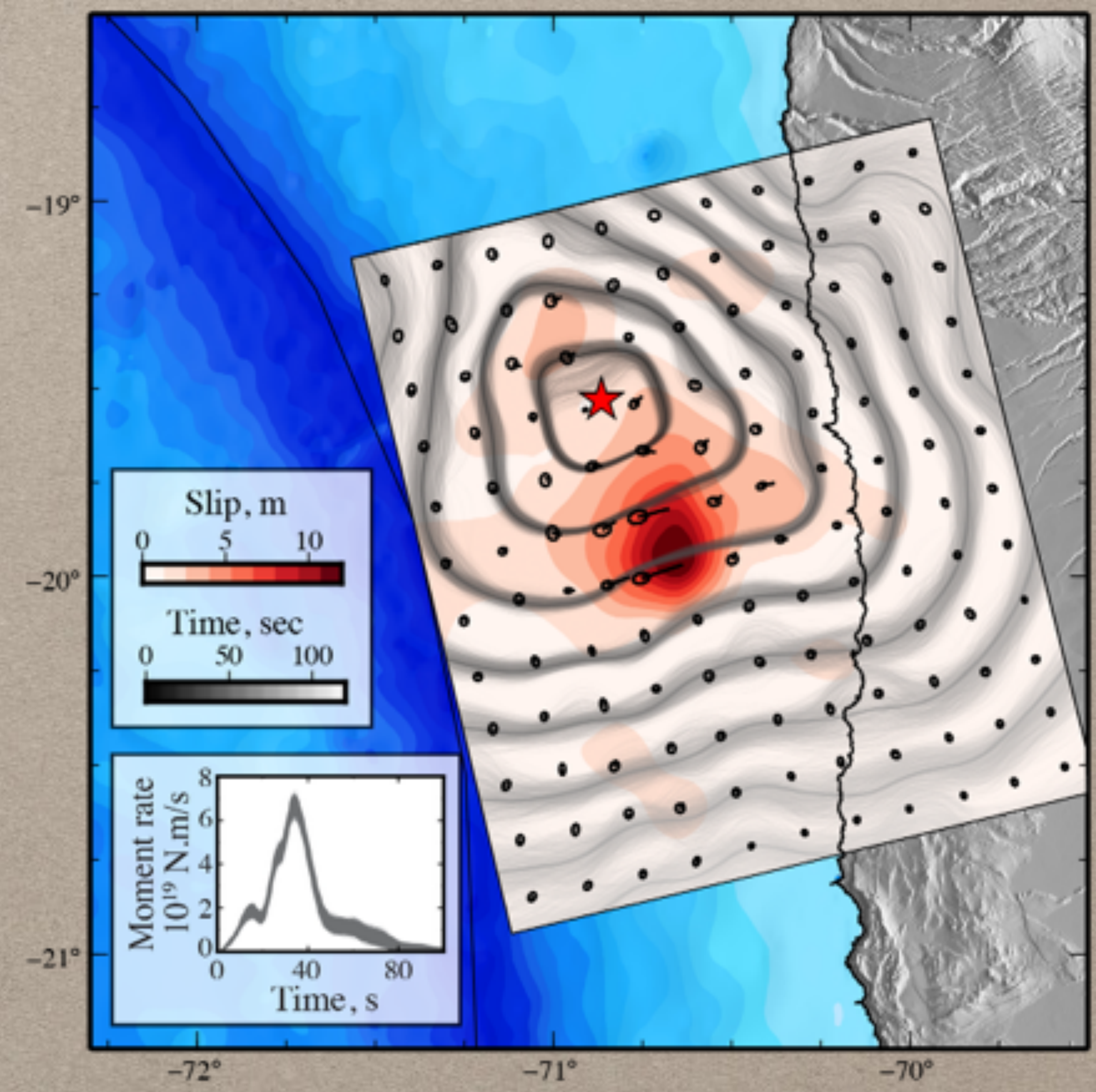
2 Kinematic slip inversion (+High-Rate GPS, Strong motion)

PISAGUA EARTHQUAKE (2014, M8.1)

1. Static slip inversion (GPS, InSAR, Tide gauges, Tsunami)

2. Kinematic slip inversion (+High-Rate GPS, Strong motion)
   - Posterior Mean Model
   - 95% Probability Error-ellipses
   - Rupture front uncertainty
   - PDF for patches with large slip:

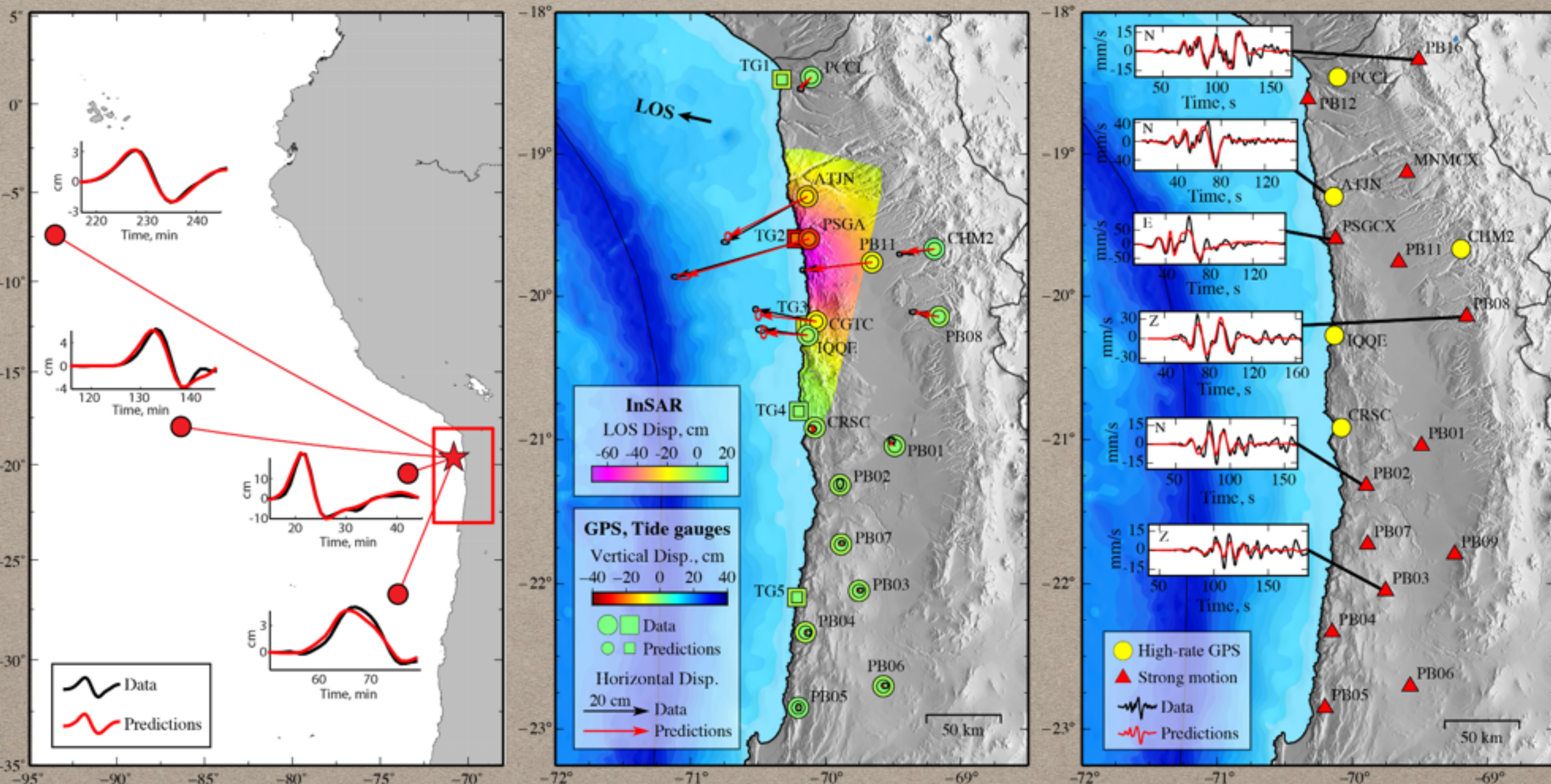




PISAGUA EARTHQUAKE (2014, M8.1)

Predictions

Tsunami (DART) | InSAR+GPS(●)+Tide gauges(■) | HR GPS(●)+Strong motion(▲)

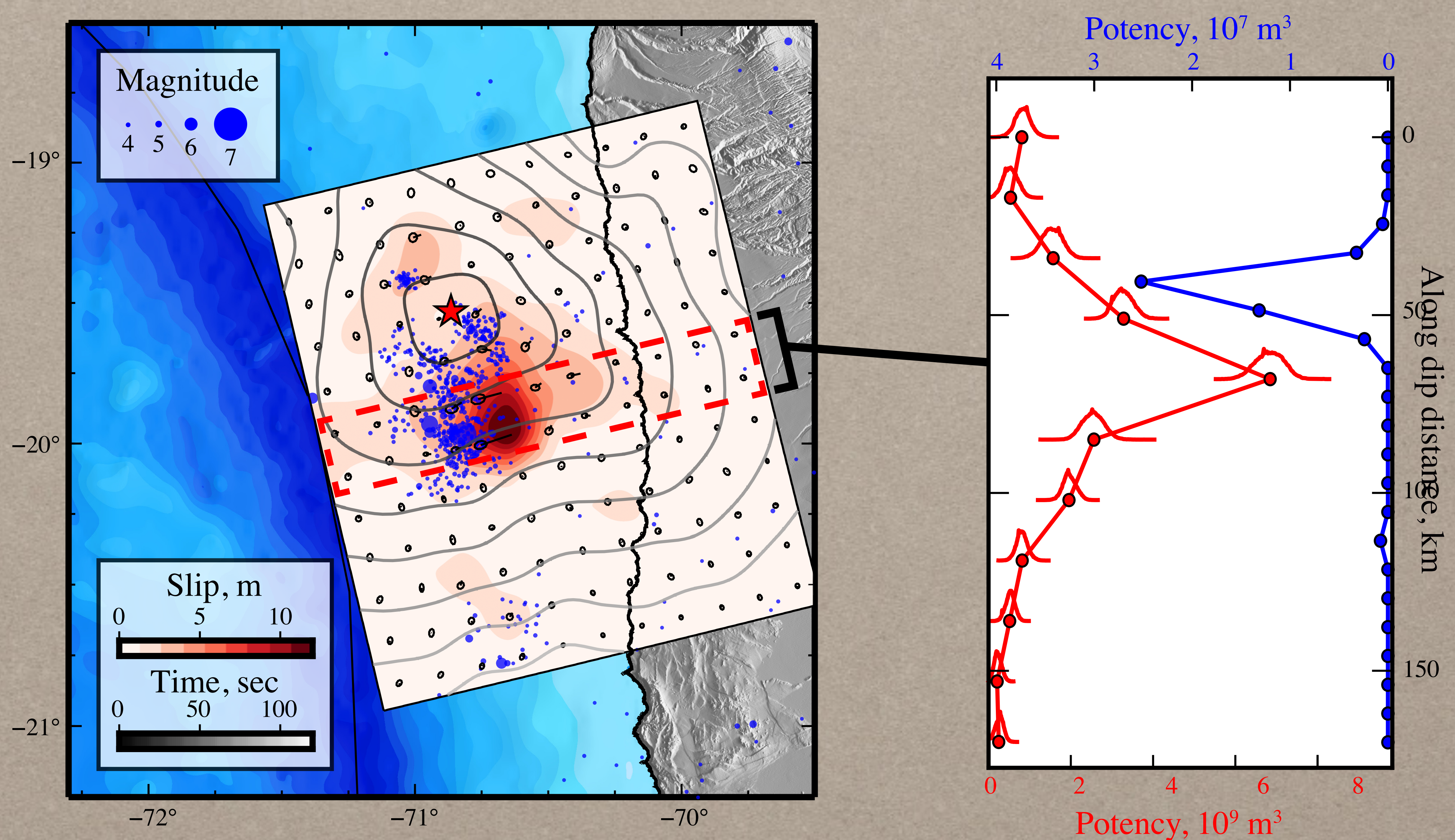


Duputel et al., in prep.

PISAGUA EARTHQUAKE (2014, M8.1)

Joint static-kinematic model

- Localized slip that did not rupture up to the trench
- Foreshocks located up-dip of the main slip area



Duputel et al., in prep.

WHAT WE DISCUSSED

- **Motivation**
  - Big data
  - Build new models for inter-, co- and post-seismic deformation
  - e.g., Earthquakes, Slow-slip events

- **Issues and opportunities**
  - The Bayesian approach has many advantages over traditional optimisation solutions
    - Solve ill-posed problems without smoothing
    - Produce the ensemble of acceptable models
  - Given sufficient computational ressources, Bayesian solution can be formed by Monte Carlo simulation