

Hamiltonian Monte Carlo methods for uncertainty quantification in waveform inversion

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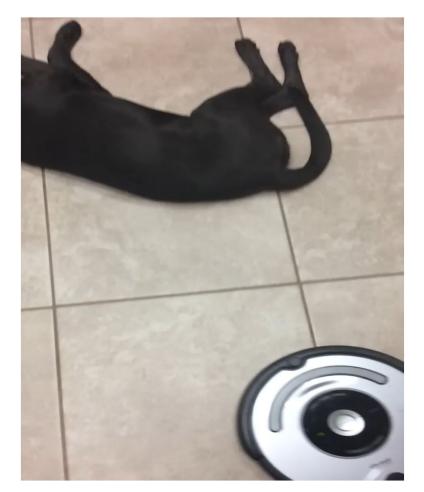
- Motivation
- Hamiltonian dynamics
- Numerical experiments
- Discussion & future work
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- Full waveform inversion (FWI): expensive.
- Uncertainty in FWI?
- Monte Carlo (MC) searches the model space, but...
- HMC: a guided MC variant.

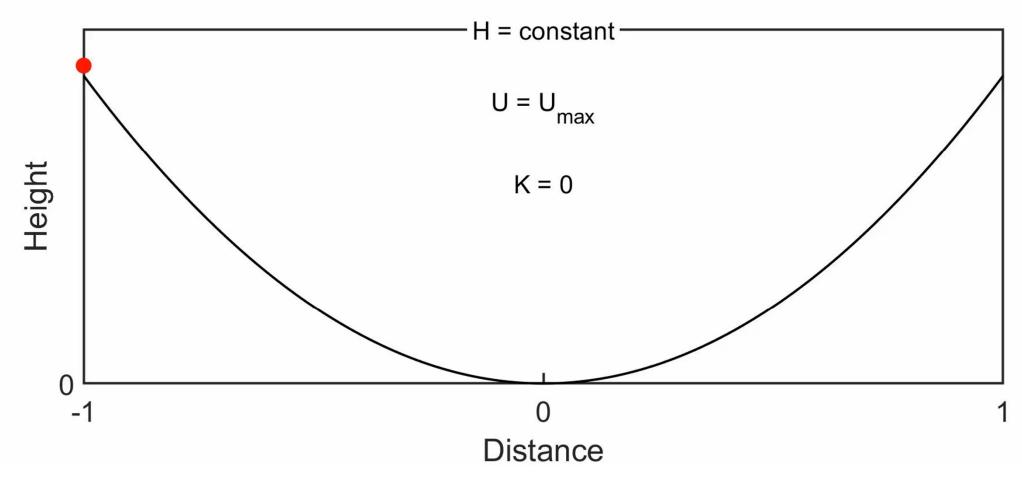


https://www.youtube.com/watch?v=iXLEfsecGNs

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Position and momentum describe the state in Hamiltonian dynamics



U: potential energy

$$U = U(q)$$

K: kinetic energy

$$K = \frac{1}{2} \boldsymbol{p}^T \mathbf{M}^{-1} \boldsymbol{p}$$

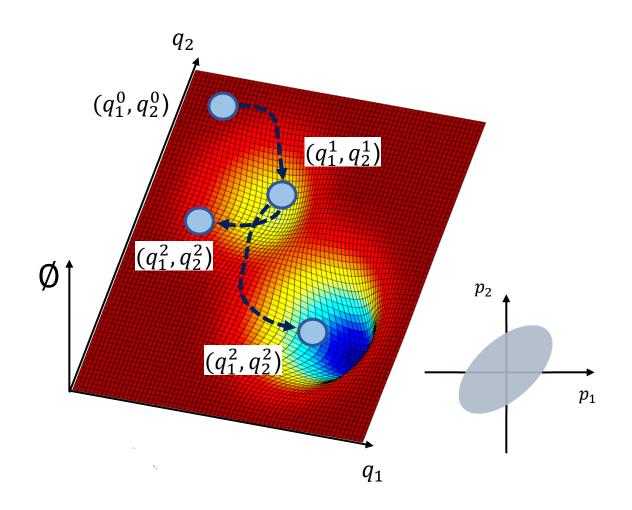
H: total energy

$$H = U + K$$

(Hamilton, 1833)



- V
- a. Start from somewhere q_0 .
- b. Draw $p \sim \mathcal{N}(0, \mathbf{M})$.
- c. Simulate Hamiltonian dynamics for L steps with Δt (leapfrog method, Iserles, 1986).
 - $\Delta t \nabla U \rightarrow \boldsymbol{p}_{new}$
 - $\Delta t \nabla K \rightarrow q_{new}$
- d. Accept or not (energy)
 - Yes -> $q_1 = q_{new}$
 - No -> $q_1 = q_0$
- e. Back to b.



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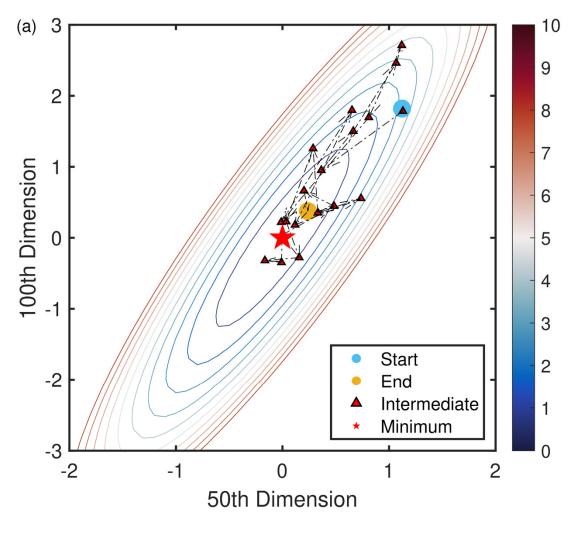


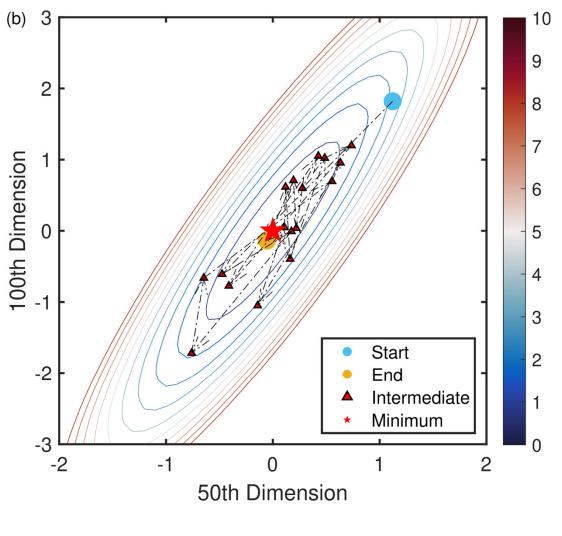
$$U(\mathbf{m}) = \frac{1}{2} \mathbf{m}^T C_M^{-1} \mathbf{m} \qquad C_M = \begin{bmatrix} 0.01^2 & 0 & \cdots & 0 \\ 0 & 0.02^2 & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & 1^2 \end{bmatrix}$$

- 0.45 correlation in the 50th and 100th dimensions
- MCMC: 1.5e+5
- HMC: 1e+3 samples, with L = 150, and $\Delta t \sim \mathcal{U}(0.0104, 0.0156)$ (Brooks et al., 2011)
- Not a fair game!



Initial 20 walks show that HMC takes larger steps



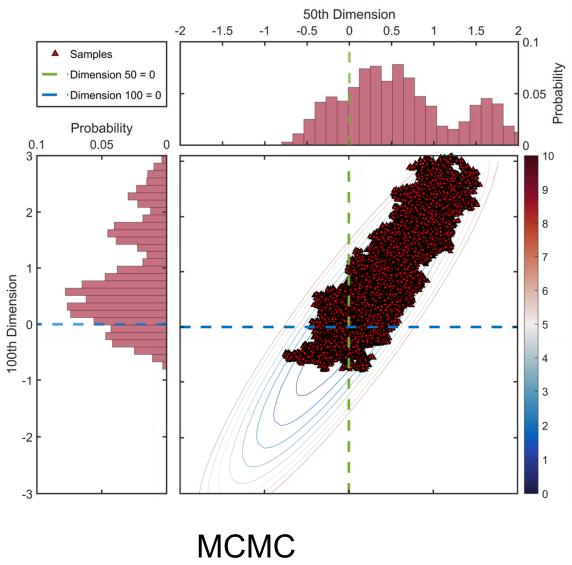


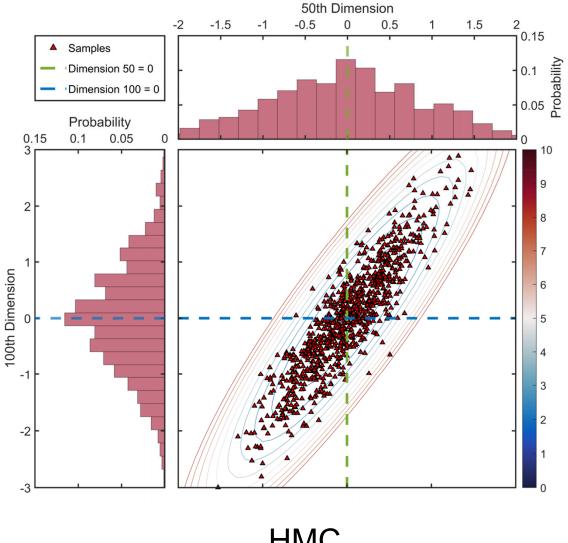
MCMC

HMC



HMC gives more plausible marginal distributions



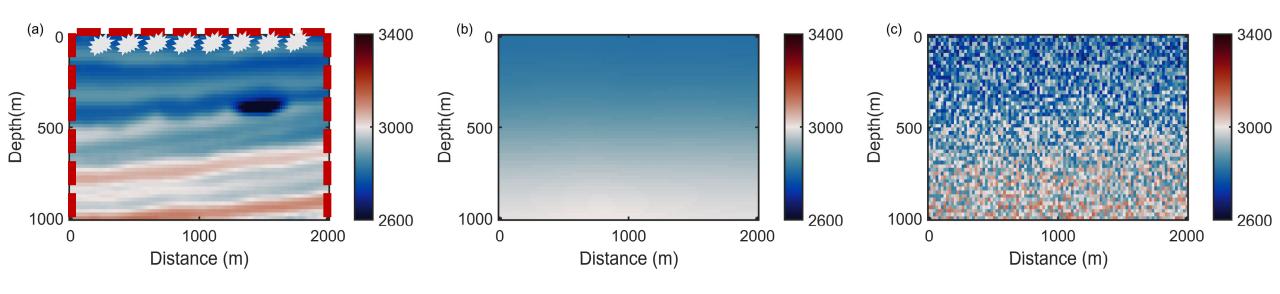




$$U(\boldsymbol{m}) = \frac{1}{2} (\boldsymbol{d}_{syn} - \boldsymbol{d}_{obs})^T C_D^{-1} (\boldsymbol{d}_{syn} - \boldsymbol{d}_{obs})$$

N samples: 30,000

Adaptive tuning: Li and Innanen (2023)



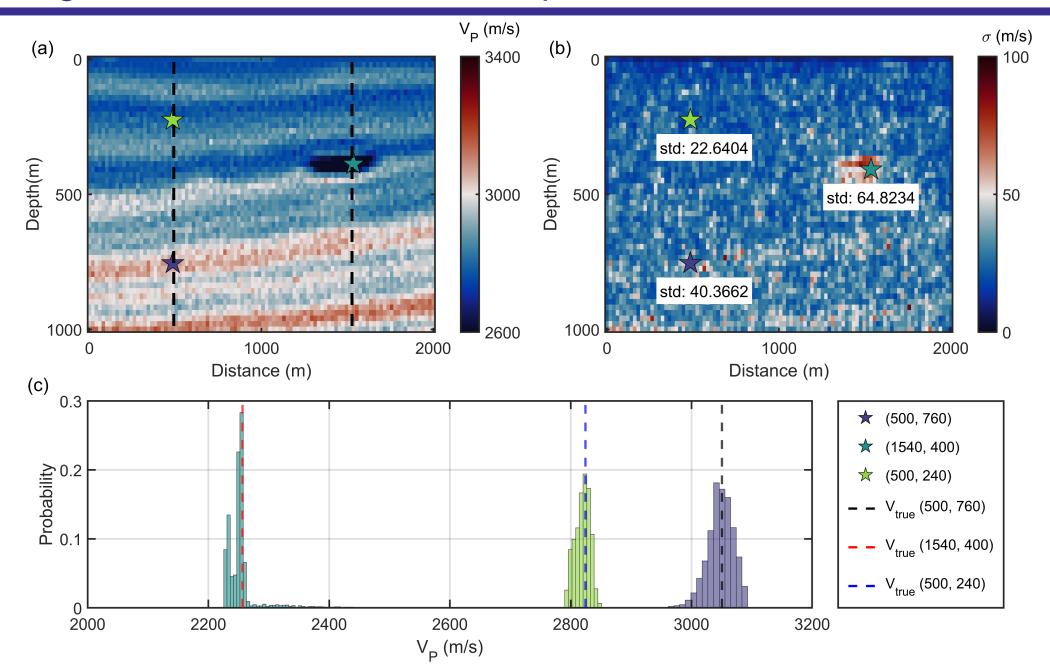
True model

Smoothed model

Actual initial model $U(\mathbf{m}_{smooth} \pm 150)$

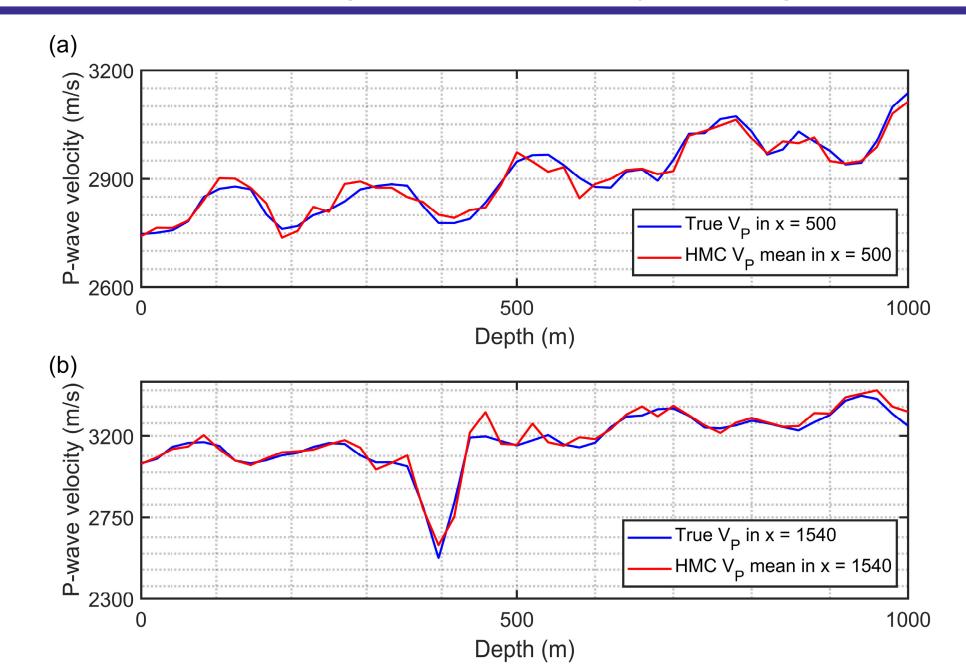


HMC gives descent results, and depicts uncertainties of FWI



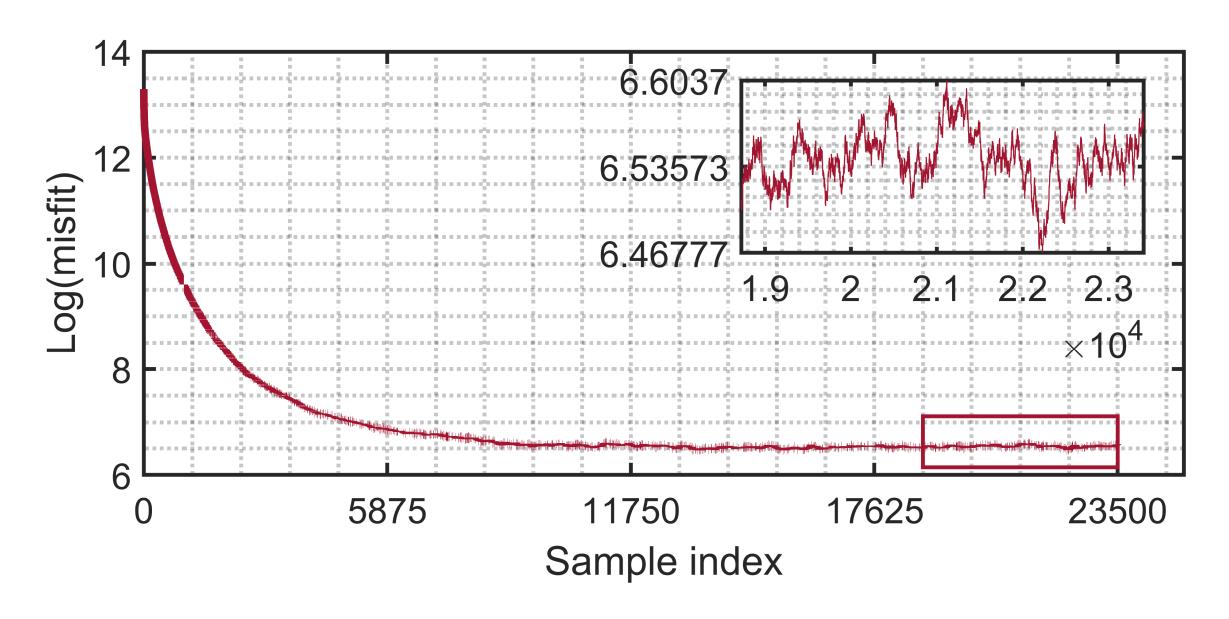


Profiles are close, although HMC is not fully converged



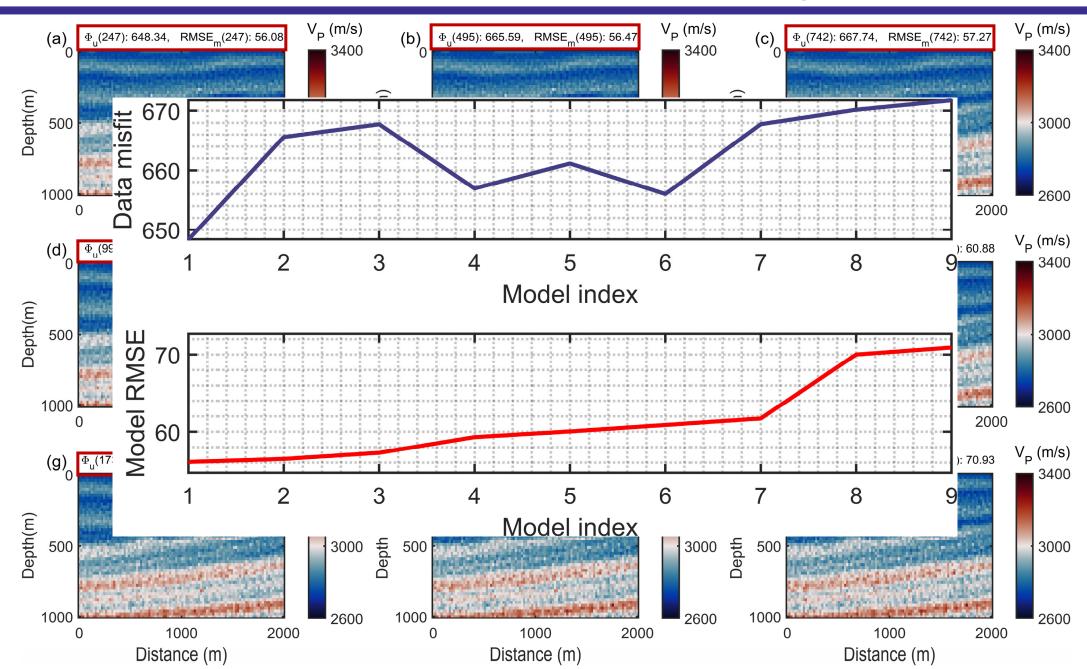








9 models in the "inversion nullspace" when setting tolerance to 0.11%



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- Ensemble chain adaptation (ECA).
- Quantum-inspired HMC.
- Accessing inversion nullspace (Fichtner et al., 2021)?
- Tunable parameters $(L, \Delta t, \mathbf{M})$ need more comprehension (Li and Innanen, 2023).
- Time-lapse.

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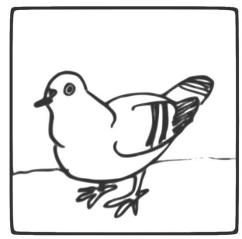
- HMC better explores the model space in MC variants.
- Needs to be tailored and tuned.
- Uncertainty quantification in FWI with HMC is feasible.
- Potential to extend to various topics.

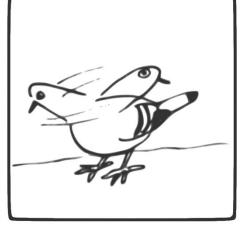


- CREWES sponsors & colleagues
- NSERC
- CSEGF



When your program is a complete mess, but it does its job

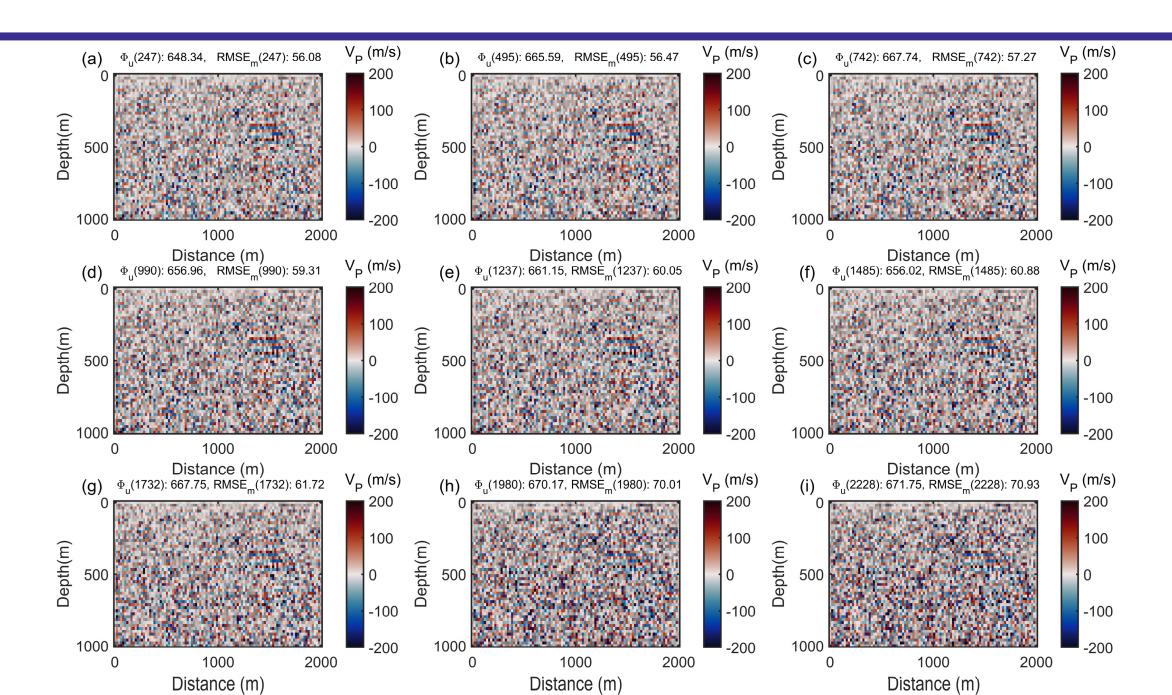






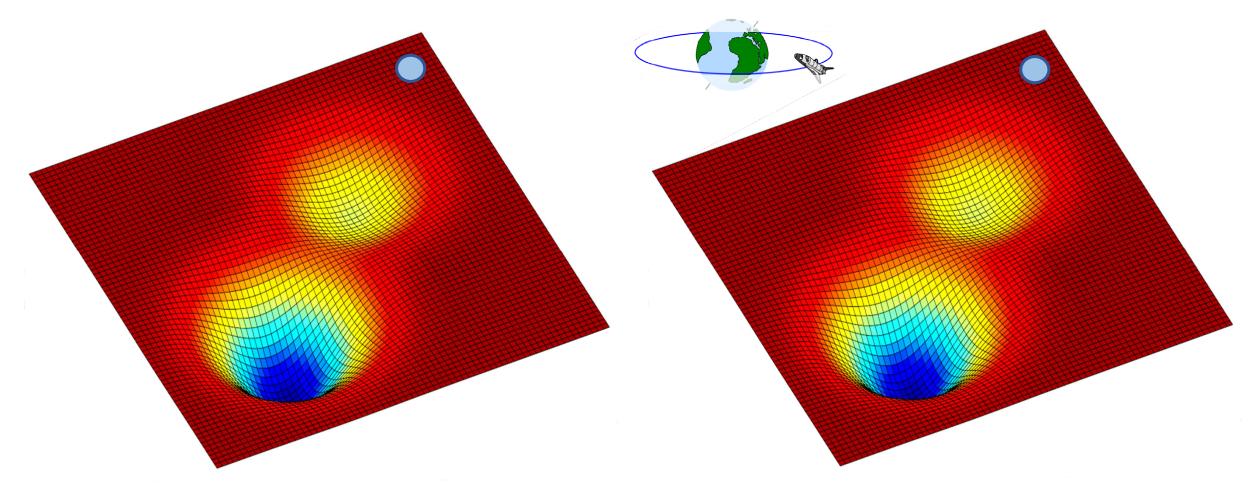










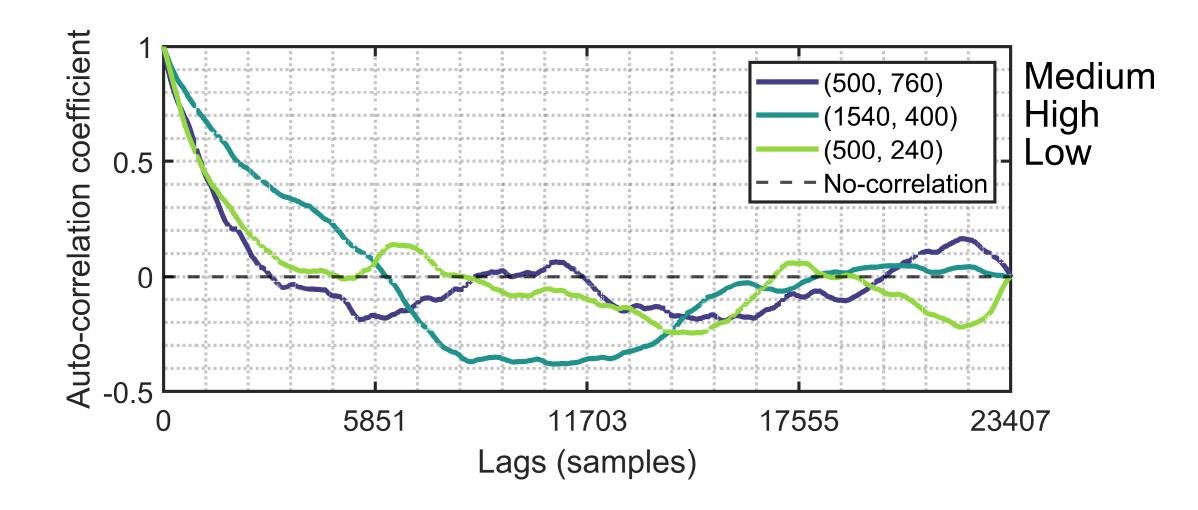


Random walk: Not allowable searches cause a waste of resources.

Guided path: certain trajectories, fewer dependent proposals.

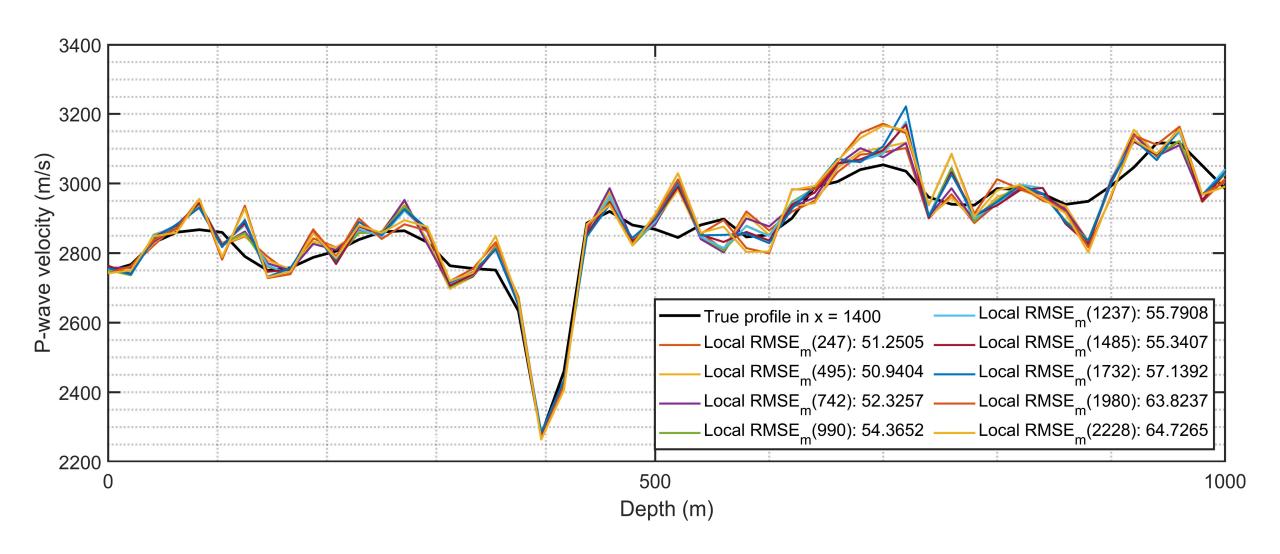






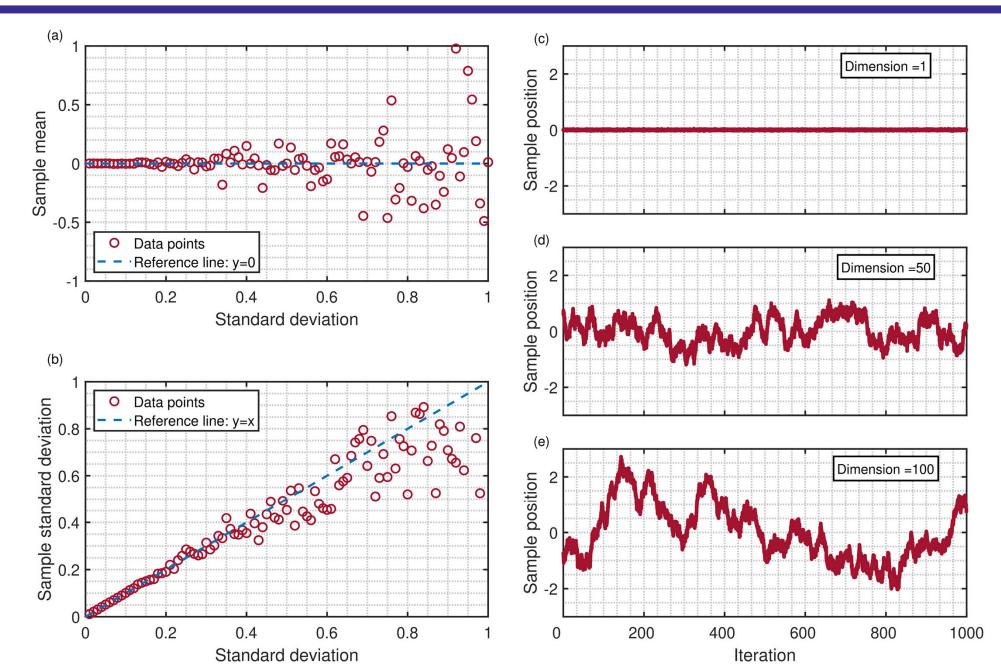


Essential features are captured by all the models in the subset





100D-MCMC: strong correlation while searching (25% acceptance)





100D-HMC: relatively independent samples (87% acceptance)

