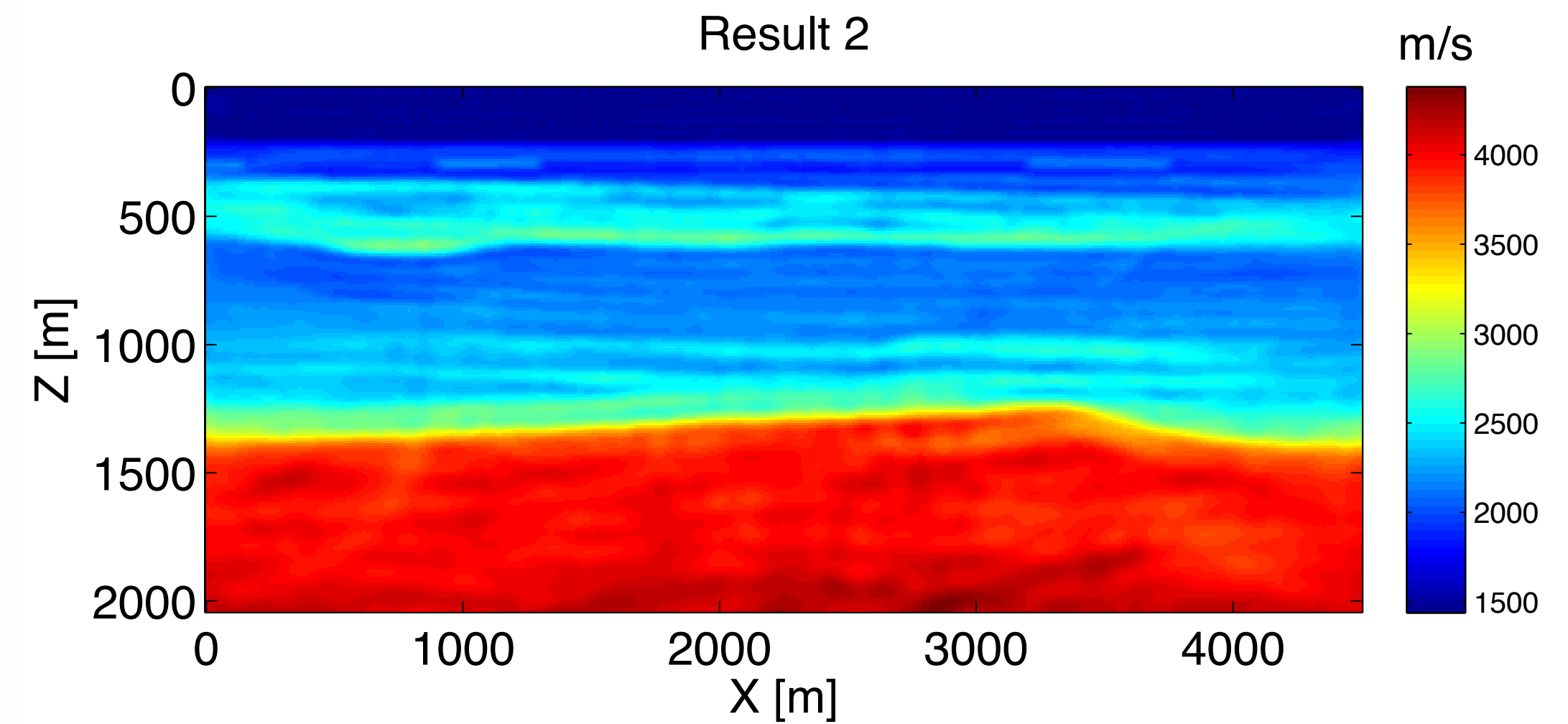
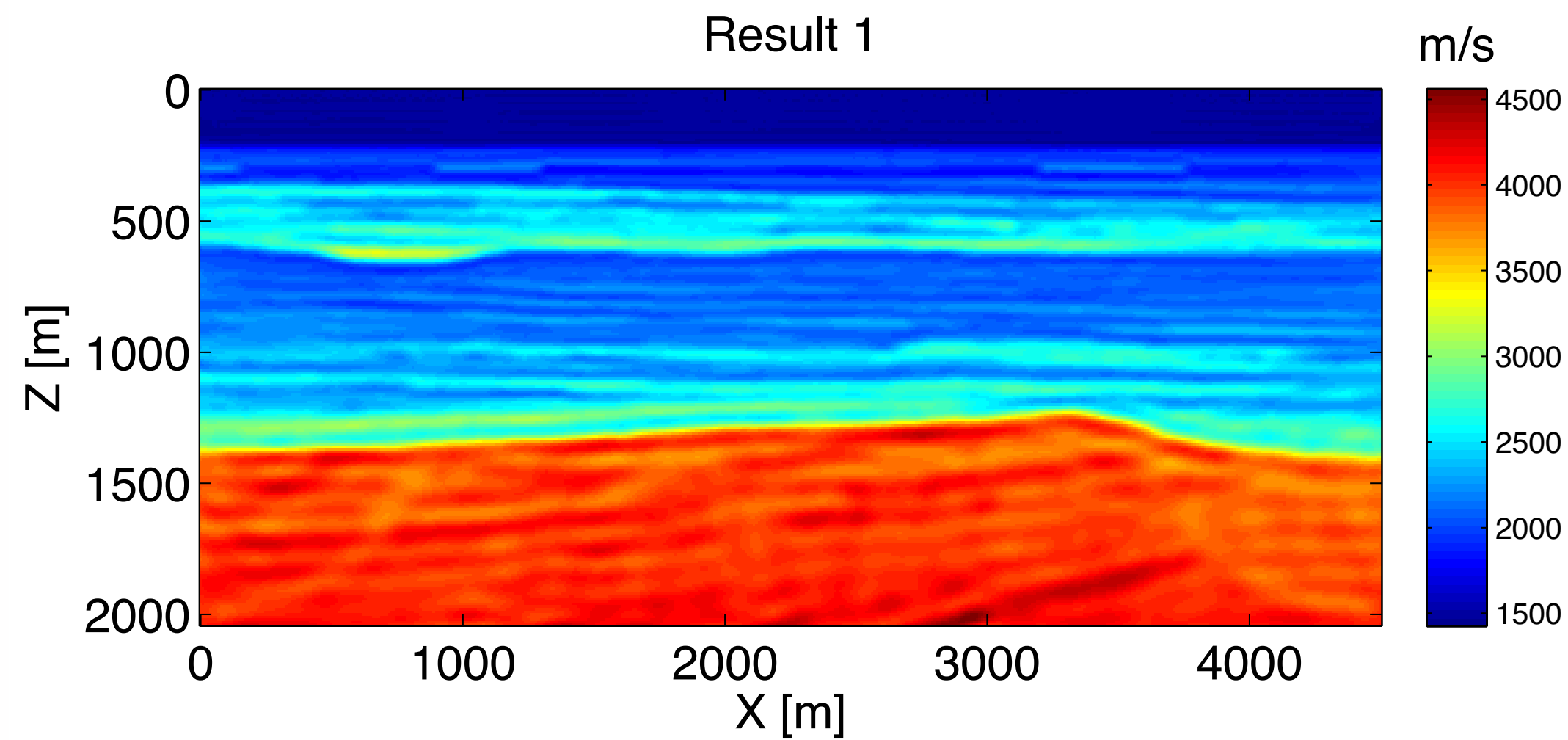


# Uncertainty analysis for full waveform inversion

Zhilong Fang and Felix J. Herrmann  
2013.12.02

# Motivation

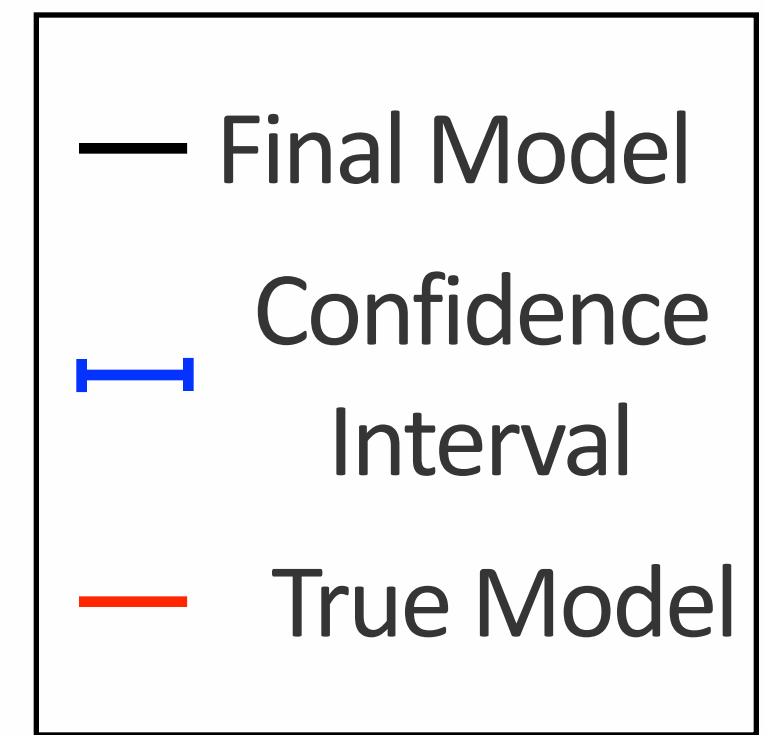
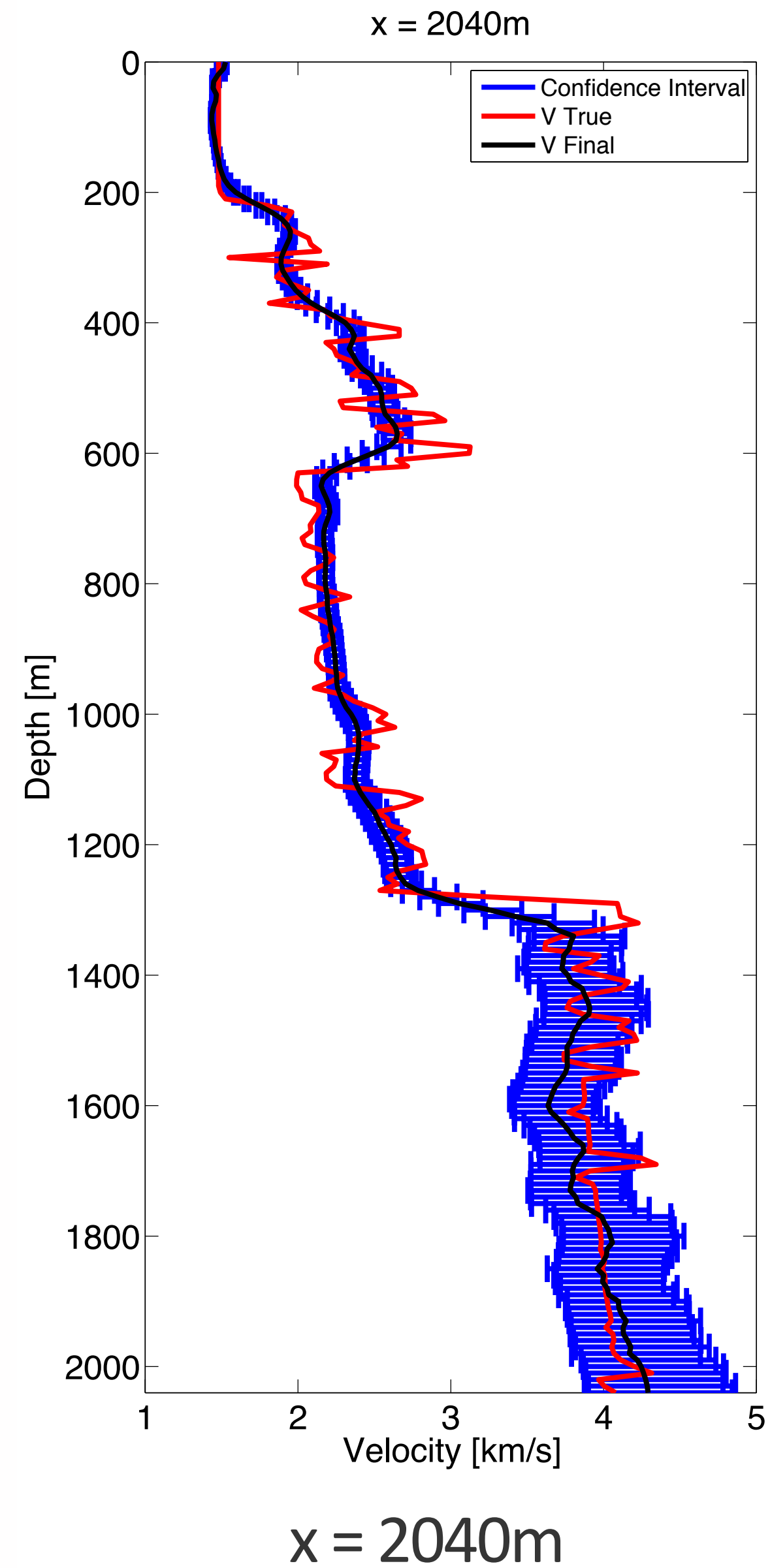


Which one is better?

Misfit?  
Eyeball norm?

Uncertainty?  
Standard Deviation?

# Confidence interval



## Bayesian theory

*Deterministic* inverse problem:

$$\mathbf{m}^* = \arg \min \left( \frac{1}{2} \|f(\mathbf{m}) - \mathbf{d}_{obs}\|_W^2 + \frac{1}{2} \|\mathbf{m} - \bar{\mathbf{m}}\|_R^2 \right)$$

*Statistical* inverse problem with Bayesian theory:

$$\pi_{post}(\mathbf{m}) := \pi(\mathbf{m}|\mathbf{d}_{obs}) \propto \pi_{prior}(\mathbf{m})\pi(\mathbf{d}_{obs}|\mathbf{m})$$

where  $\mathbf{m}$  is the model parameter, and  $\mathbf{d}_{obs}$  is the observed data

# Bayesian theory

Assume:

$$\begin{aligned} \text{noise} &\sim \mathcal{N}(0, \Gamma_{noise}) \\ \text{prior model distribution} &\sim \mathcal{N}(\mathbf{m}_{prior}, \Gamma_{prior}). \end{aligned}$$

Negative log-posterior of the posterior pdf:

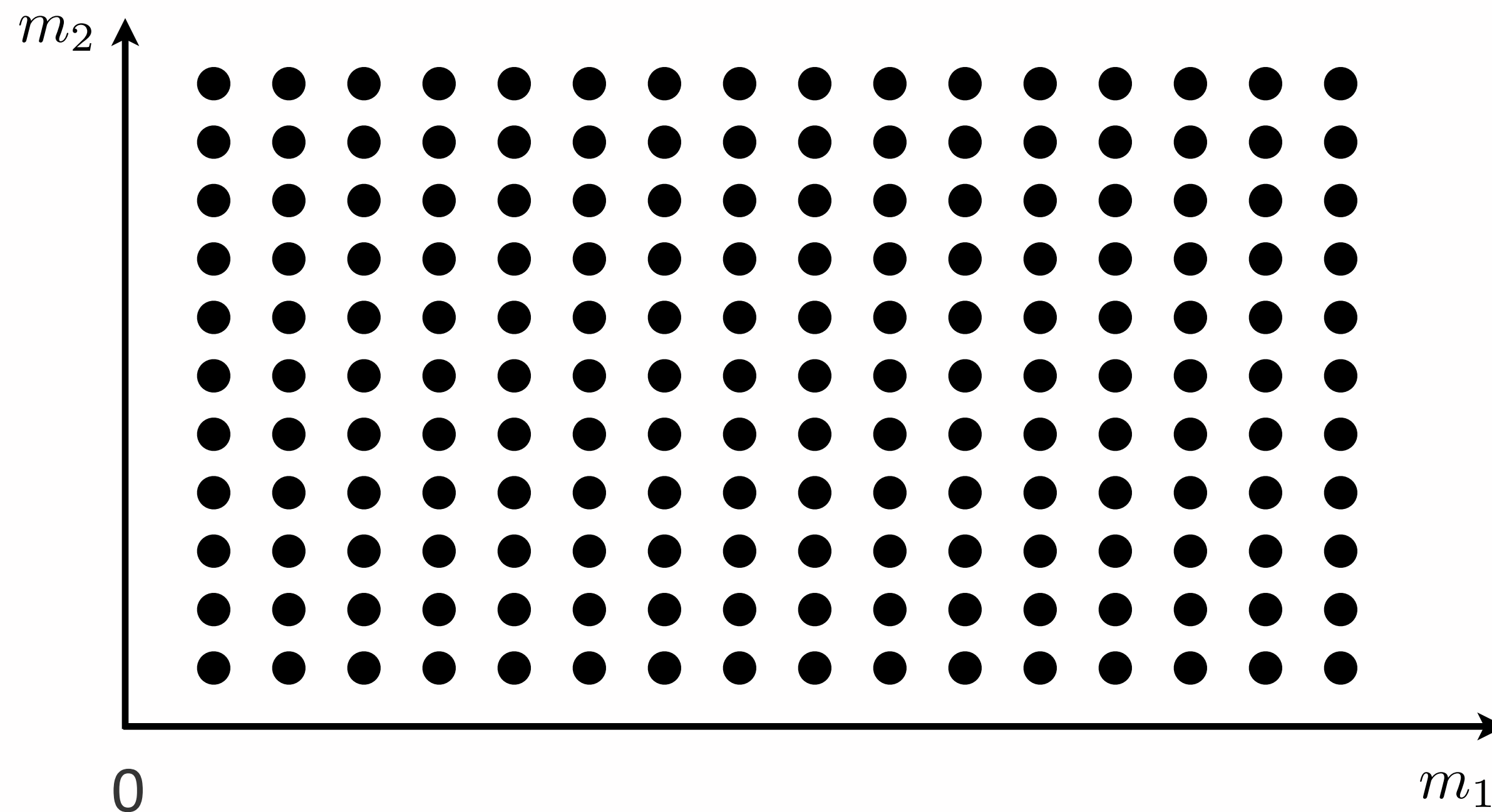
$$\begin{aligned} V(\mathbf{m}) &:= -\log \pi_{post}(\mathbf{m}) := \frac{1}{2} \|f(\mathbf{m}) - \mathbf{d}_{obs}\|_{\Gamma_{noise}^{-1}}^2 + \frac{1}{2} \|\mathbf{m} - \mathbf{m}_{prior}\|_{\Gamma_{prior}^{-1}}^2 \\ \mathbf{m}_{MAP} &= \mathbf{m}^* \end{aligned}$$

$$\|\mathbf{x}\|_{\Gamma_{noise}^{-1}}^2 := \mathbf{x}^T \Gamma_{noise}^{-1} \mathbf{x}$$

## Approximate the pdf

How to obtain the posterior probability density function?

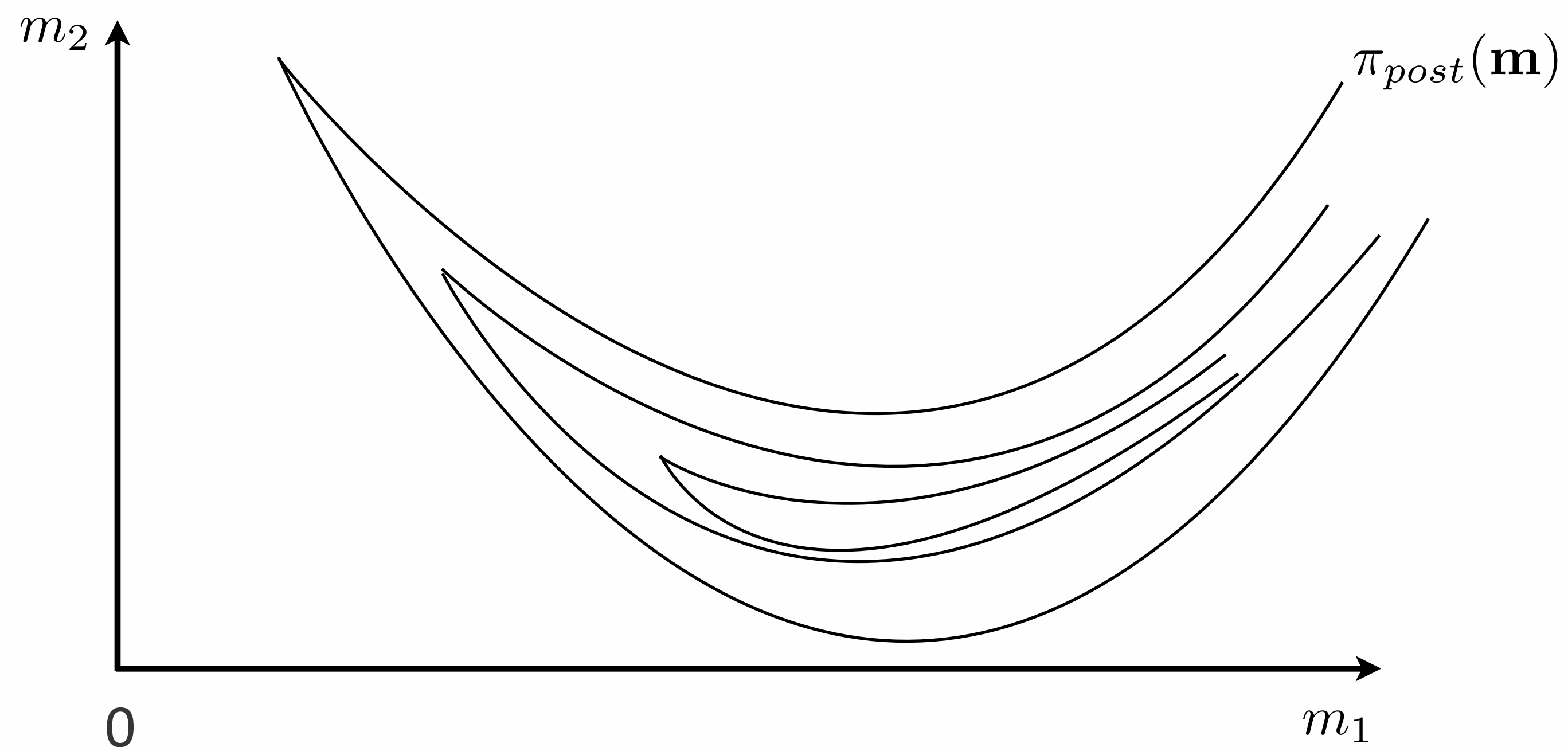
- Uniformly sampling ?



## Approximate the pdf

How to obtain the posterior probability density function?

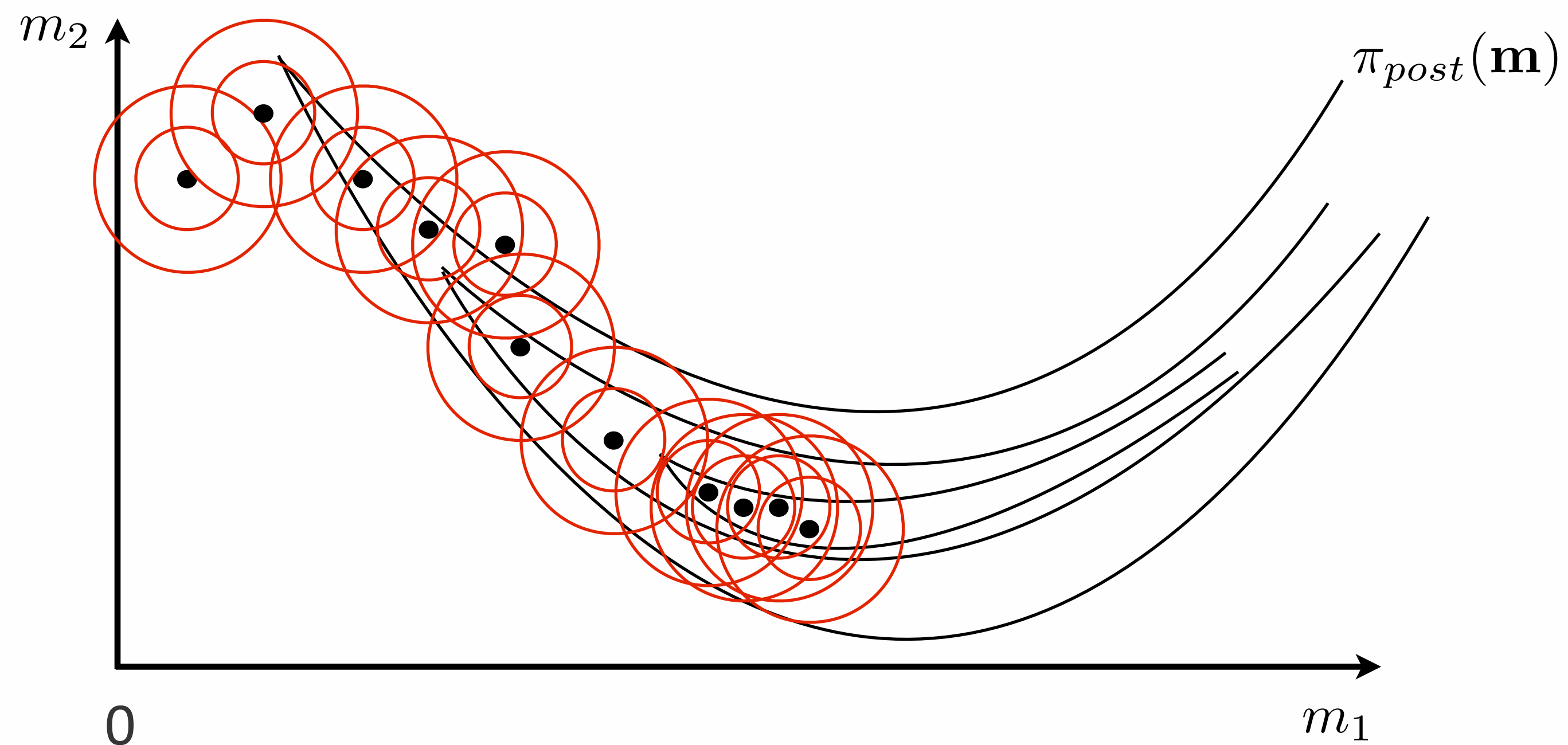
- Uniformly sampling ?
- $N = N_s * N_p$  ;



## Approximate the pdf

How to obtain the posterior probability density function?

- Markov chain Monte Carlo method ? ● N is still large and needs burn-in period;

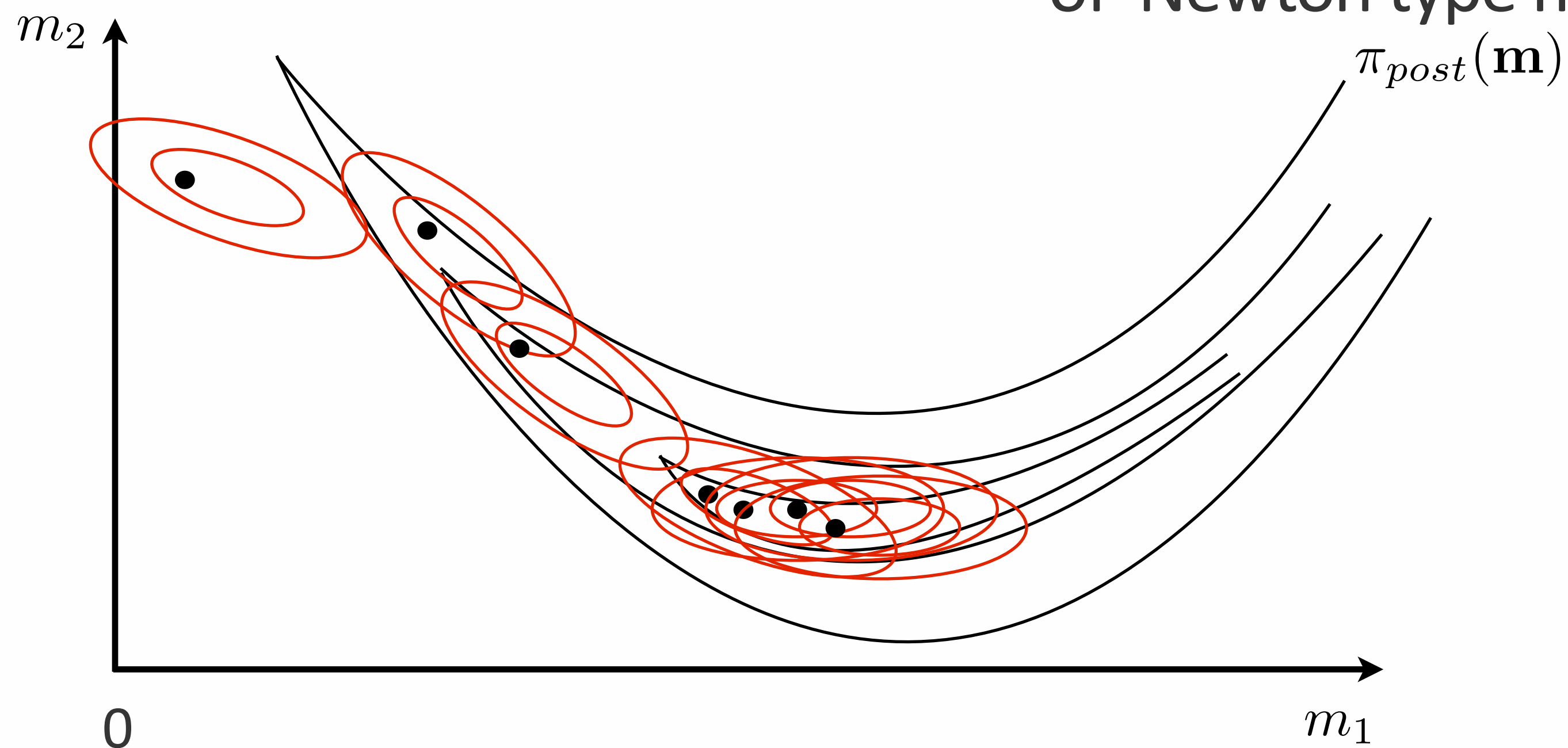




## Approximate the pdf

How to obtain the posterior probability density function?

- Stochastic Newton MCMC ?  
(James Martin *et al*, 2012)
- Generating a sample equals to one iteration of Newton type method.



# Approximate the posterior pdf

**Possible Solution** — use the *approximated* Gaussian distribution at the point of *optimal* solution as the *approximated* pdf.

Let  $\mathbf{m}_{opt}$  be the optimal solution of the deterministic problem.

$$V(\mathbf{m}) \approx \tilde{V}(\mathbf{m}) := \frac{1}{2}(\mathbf{m} - \mathbf{m}_{opt})^T \mathbf{H}(\mathbf{m} - \mathbf{m}_{opt}) + \mathbf{g}^T (\mathbf{m} - \mathbf{m}_{opt}) + V(\mathbf{m}_{opt})$$

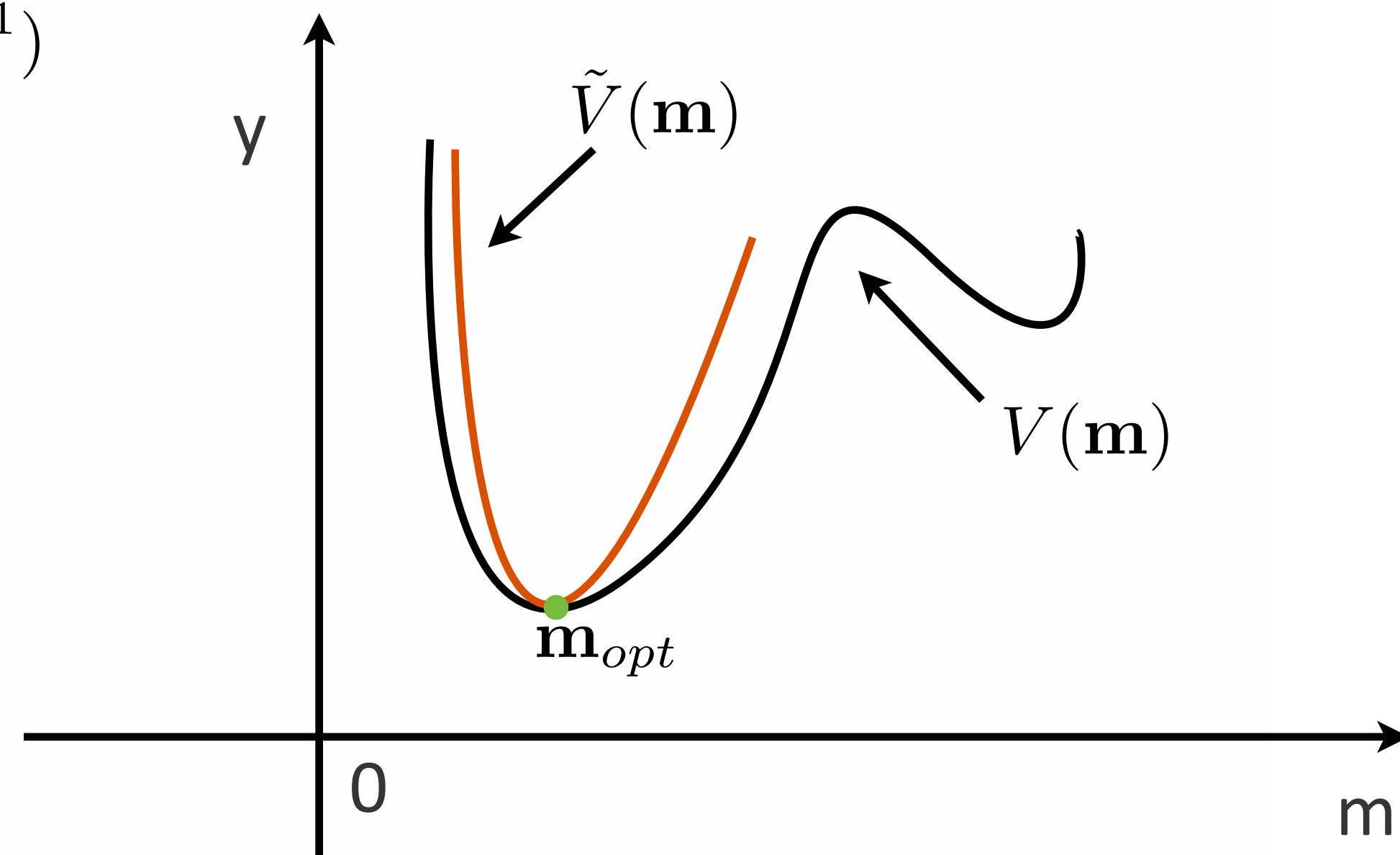
$$\tilde{V}(\mathbf{m}) = \frac{1}{2}(\mathbf{m} - \mathbf{m}_{opt} + \mathbf{H}^{-1}\mathbf{g})^T \mathbf{H}(\mathbf{m} - \mathbf{m}_{opt} + \mathbf{H}^{-1}\mathbf{g}) + \text{const}$$

$$\pi_{post}(\mathbf{m}) \approx \tilde{\pi}(\mathbf{m}) \sim \exp(-\tilde{V}(\mathbf{m})) : \mathcal{N}(\mathbf{m}^*, \mathbf{H}^{-1})$$

where  $\mathbf{m}^* = \mathbf{m}_{opt} - \mathbf{H}^{-1}\mathbf{g}$ .

**H is a linear operator!**

**Forming H explicitly is impossible!**



## Approximate the pdf

Possible solution: low-rank approximation

$$\mathbf{H} = \mathbf{H}_{\text{misfit}} + \mathbf{\Gamma}_{\text{prior}}^{-1} = \mathbf{L}^{-T} (\mathbf{L}^T \mathbf{H}_{\text{misfit}} \mathbf{L} + \mathbf{I}) \mathbf{L}^{-1}$$

where  $\mathbf{L} = \mathbf{\Gamma}_{\text{prior}}^{\frac{1}{2}}$ .

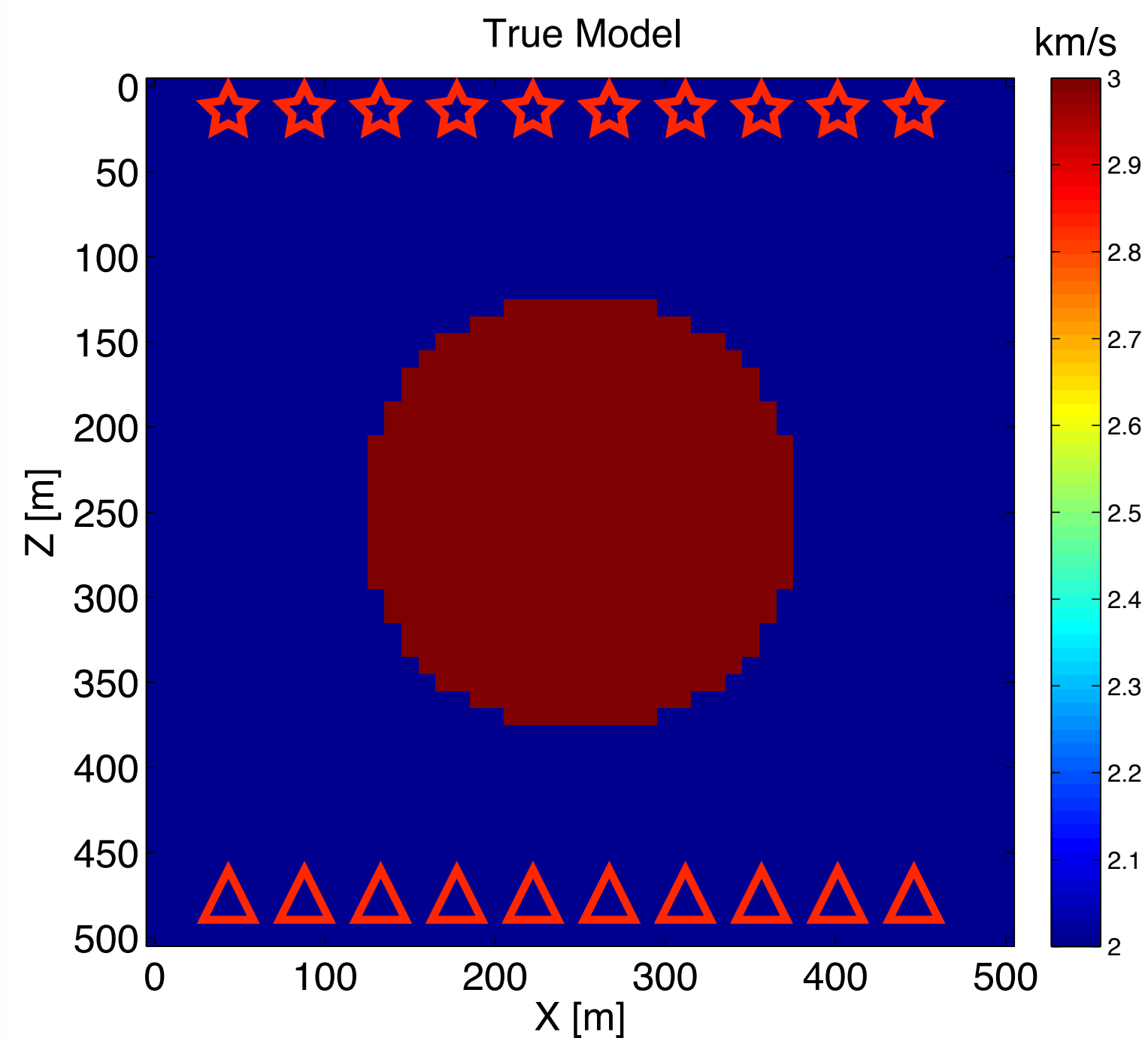
$r$ -rank approximation of  $\mathbf{L}^T \mathbf{H}_{\text{misfit}} \mathbf{L}$ :

$$\mathbf{L}^T \mathbf{H}_{\text{misfit}} \mathbf{L} \approx \mathbf{V}_r \mathbf{D}_r \mathbf{V}_r^T$$

$$\begin{array}{c} \left[ \begin{array}{c} \mathbf{L}^T \\ \hline \end{array} \right] \left[ \begin{array}{c} \mathbf{H}_{\text{misfit}} \\ \hline \end{array} \right] \left[ \begin{array}{c} \mathbf{L} \\ \hline \end{array} \right] \approx \left[ \begin{array}{c} \mathbf{V}_r \\ \hline \end{array} \right] \left[ \begin{array}{c} \mathbf{D}_r \\ \hline \end{array} \right] \left[ \begin{array}{c} \mathbf{V}_r^T \\ \hline \end{array} \right] \\ n \times n \quad n \times n \quad n \times n \quad n \times r \quad r \times r \quad r \times n \\ r \ll n \end{array}$$

# Numerical Experiments

## Camambert model



- ☆ - source
- △ - receiver

Statistical parameter to be inverted:

Standard deviation :  $\sigma$

Confidence :  $W = P((1 - \lambda)\mathbf{m} \leq \mathbf{m} \leq (1 + \lambda)\mathbf{m})$

Confidence interval:  $P(\mathbf{m} \in I_{ci}) \geq \alpha$

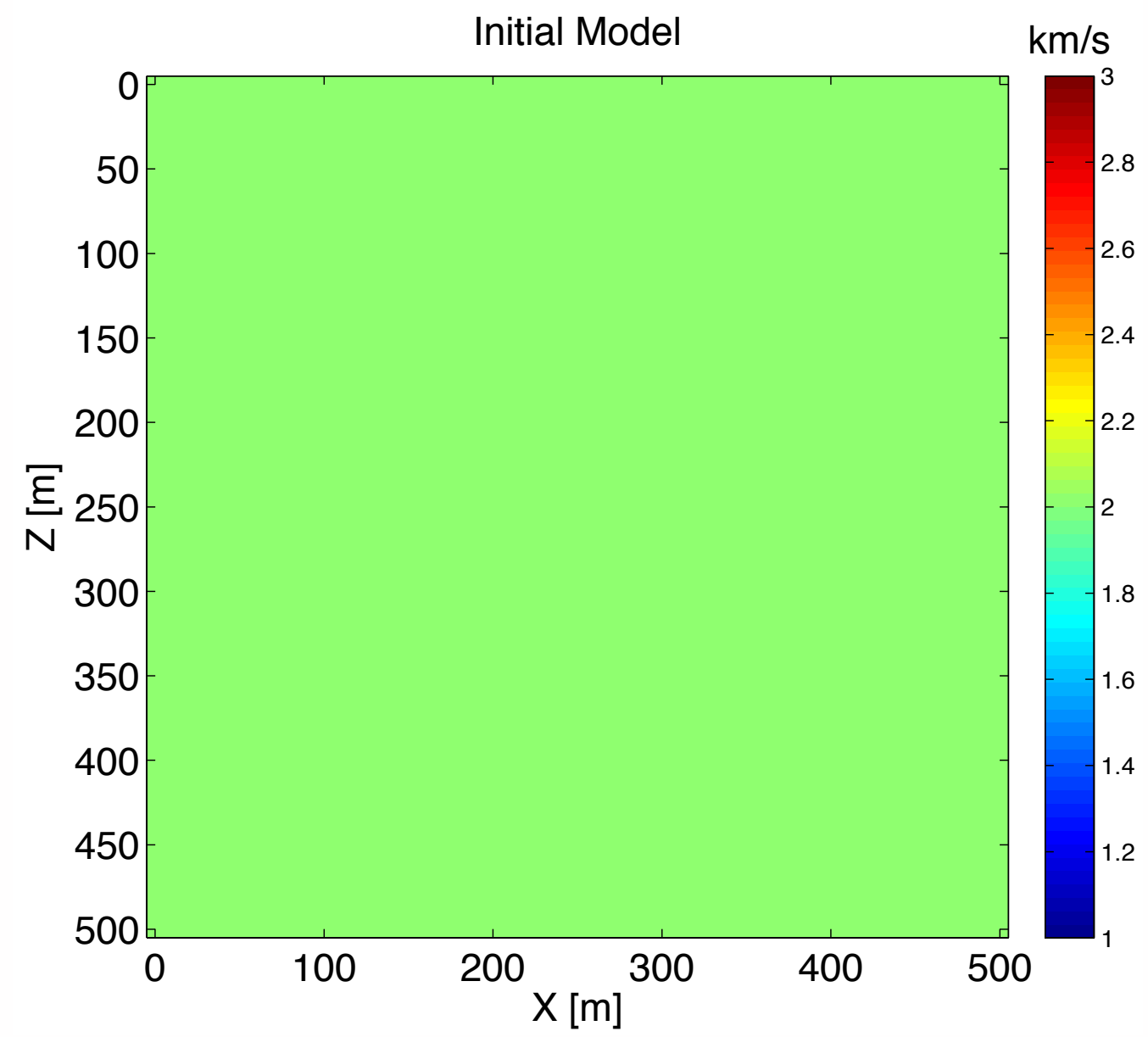
Acquisition Geometry:

26 shots

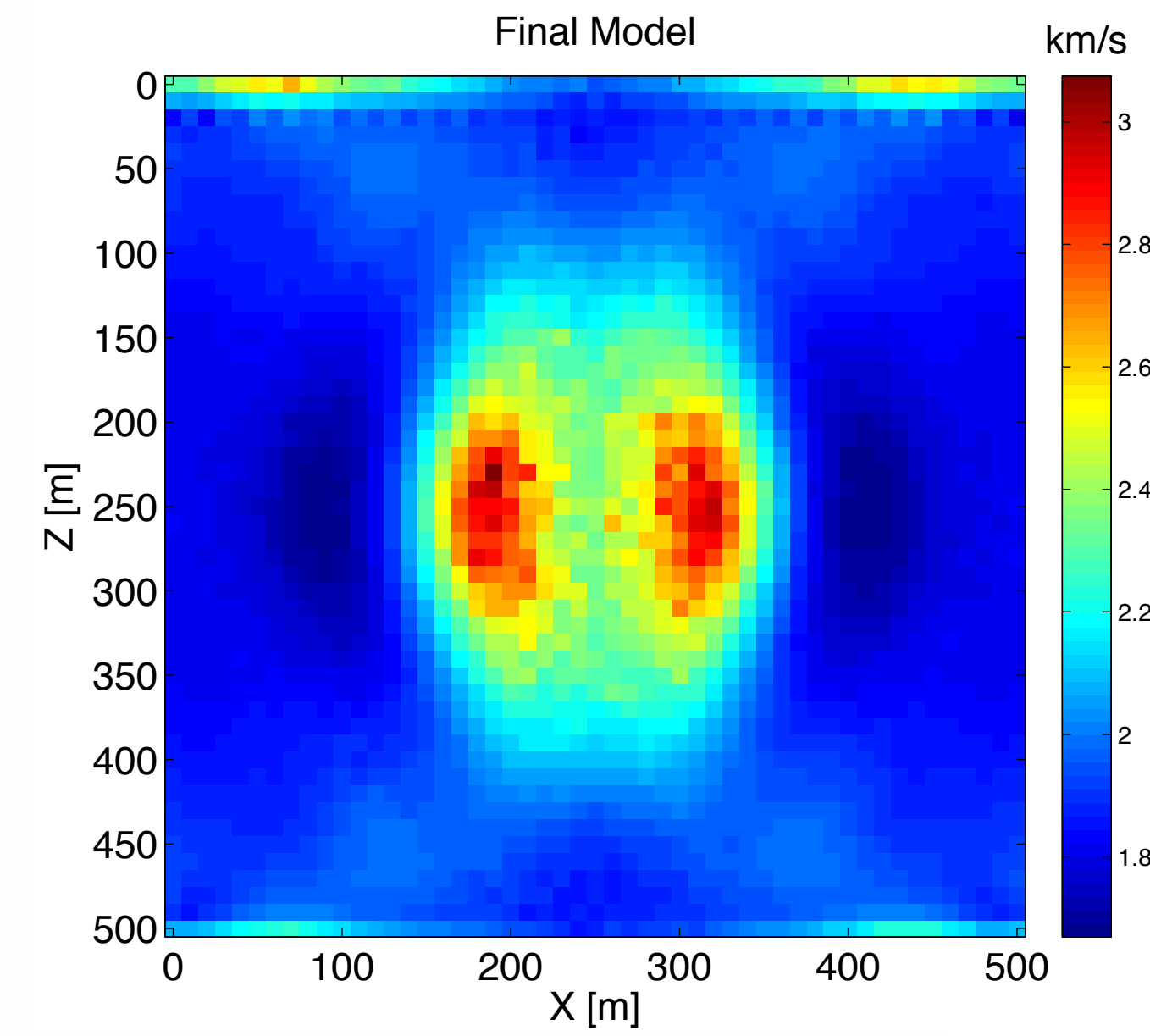
51 receivers

10 frequencies

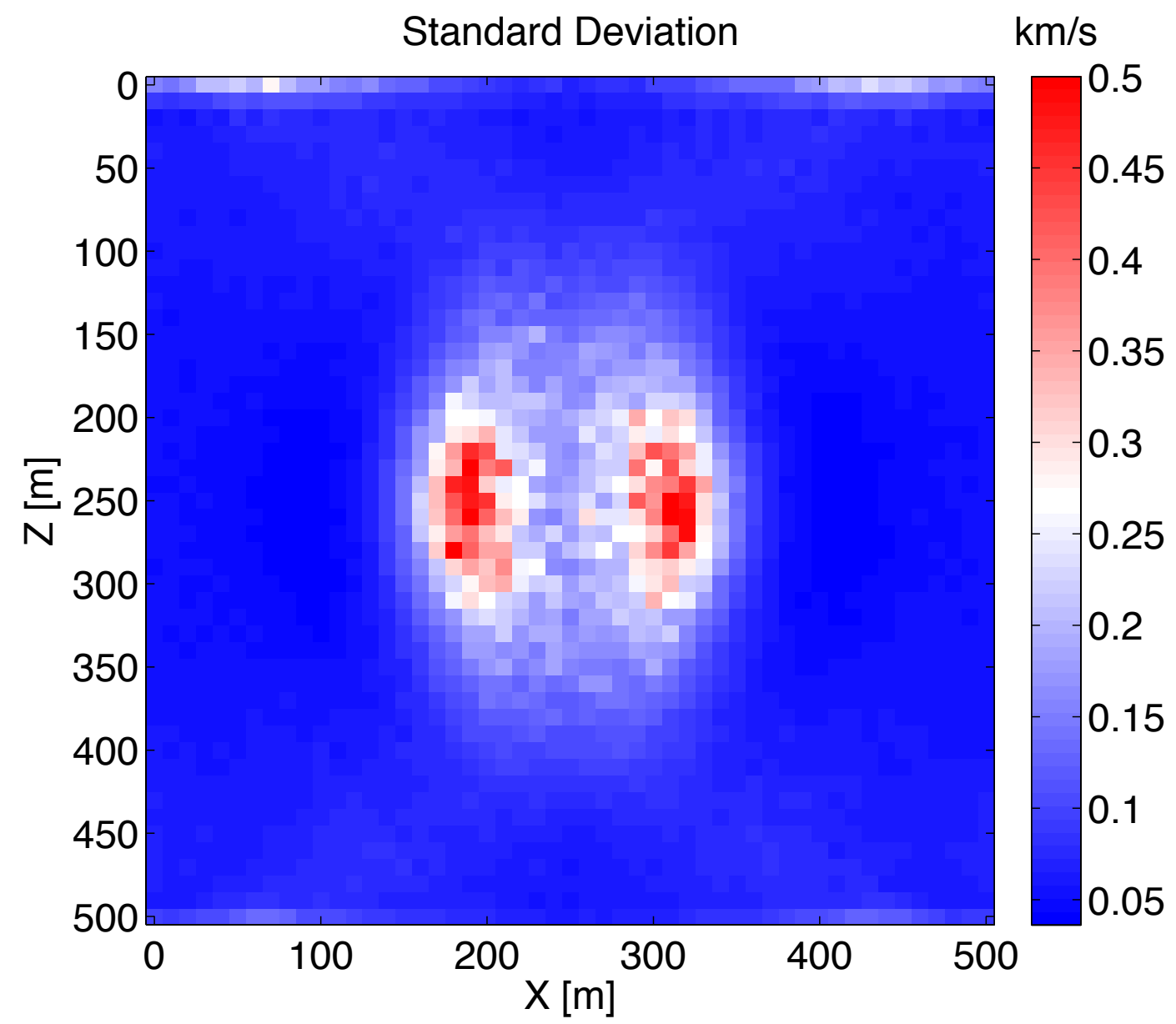
Initial model



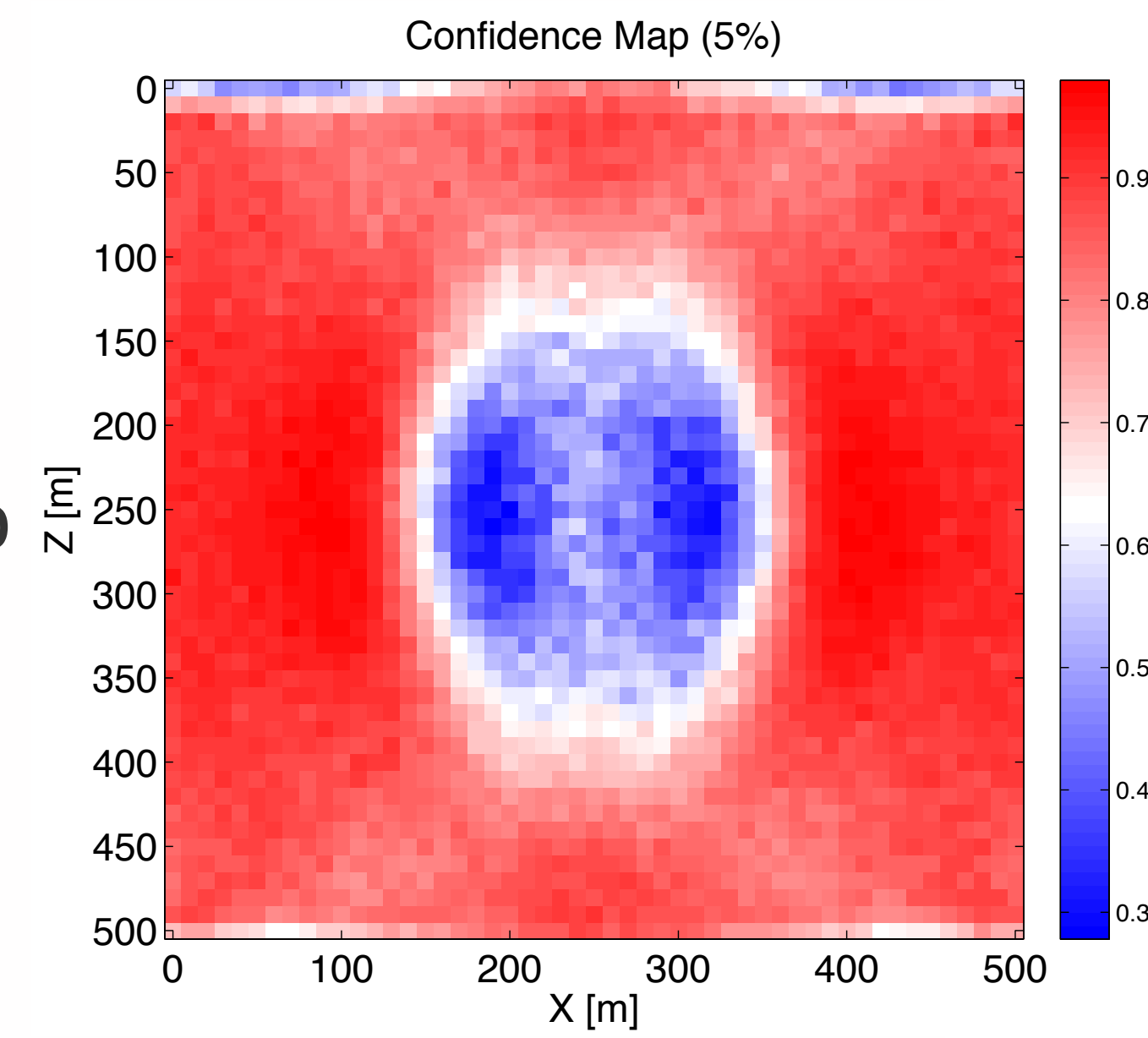
Final model



Standard deviation

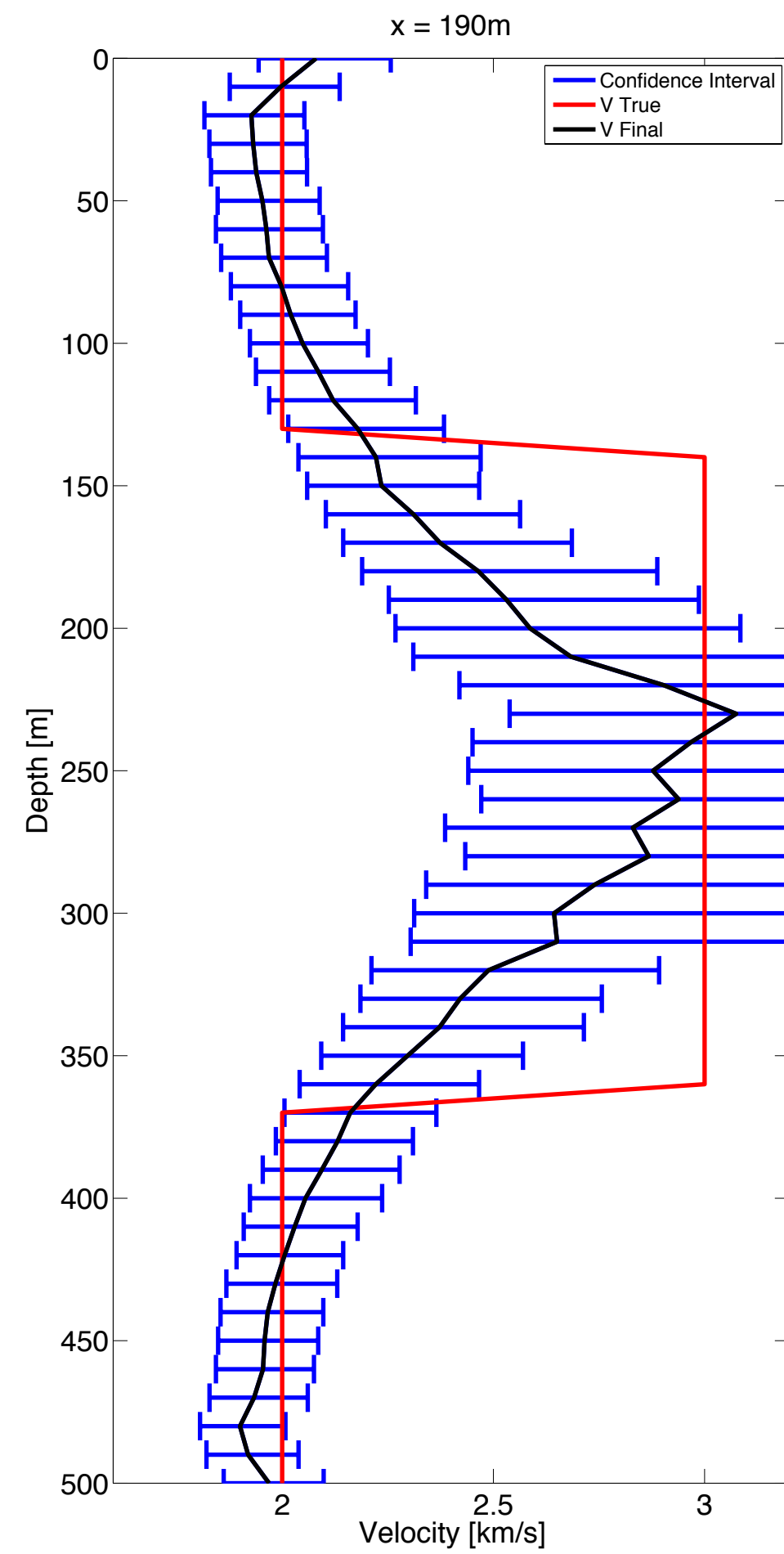


Confidence map

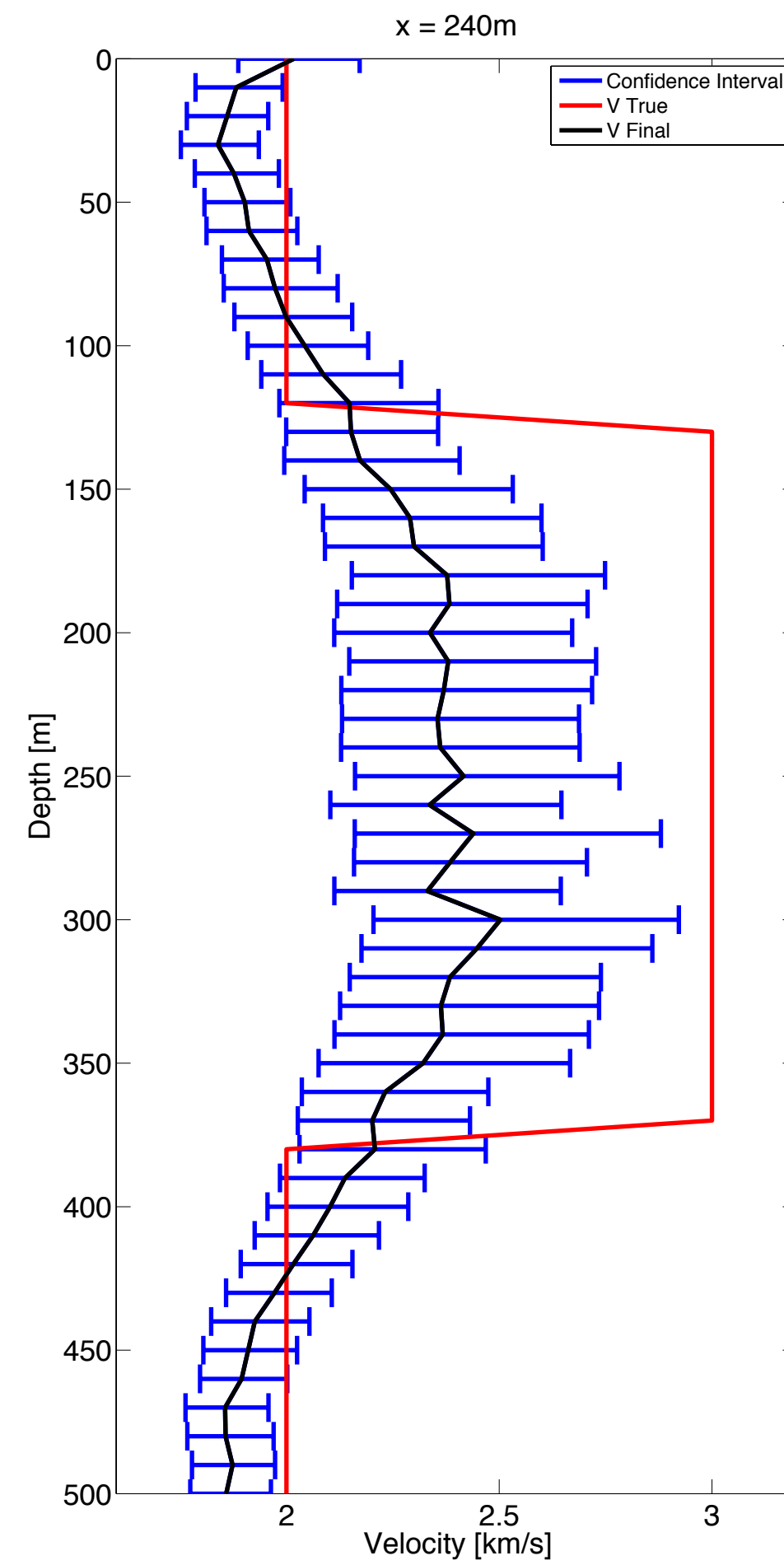


# Confidence Interval

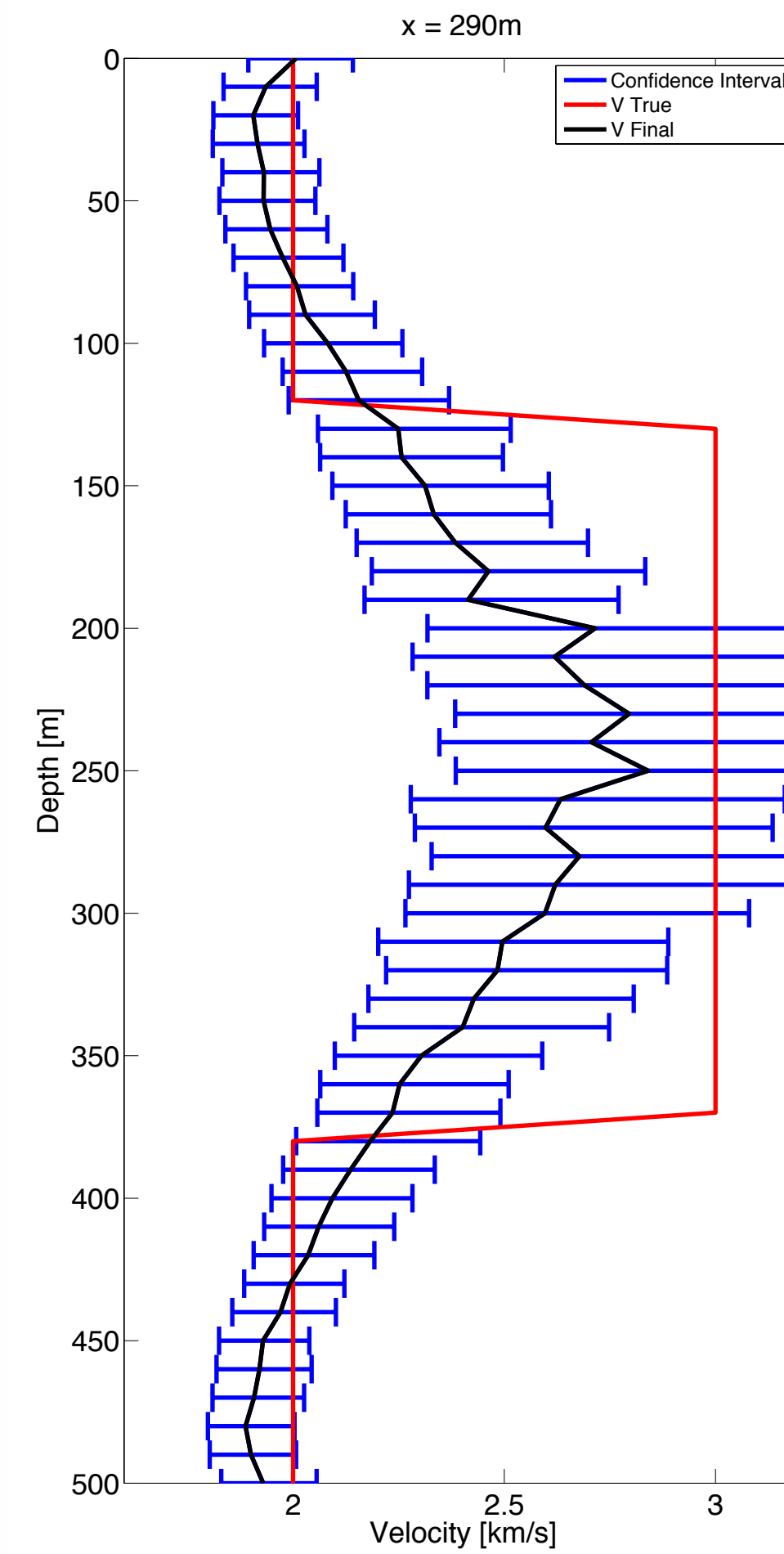
$$\alpha = 0.9$$



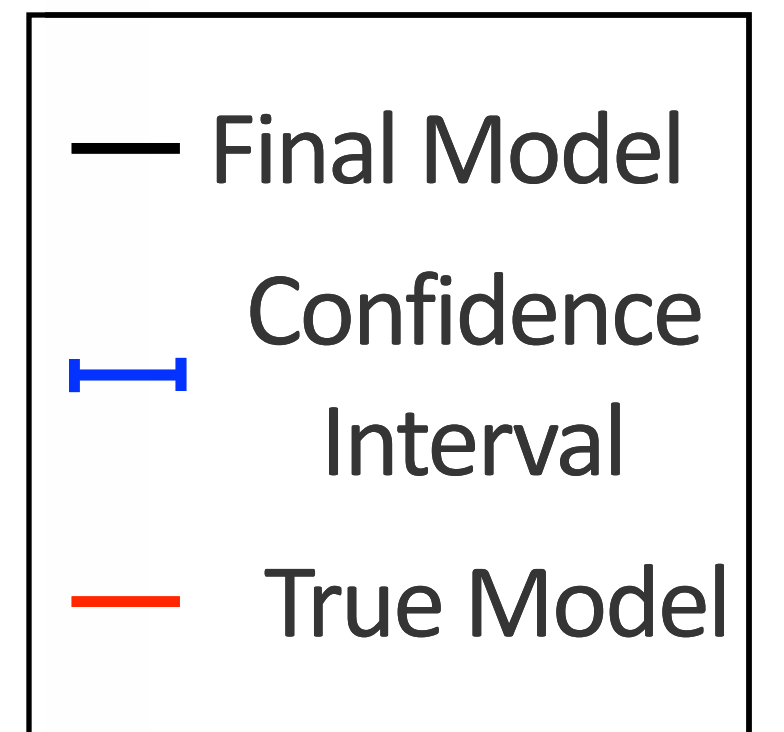
x = 190m



x = 240m

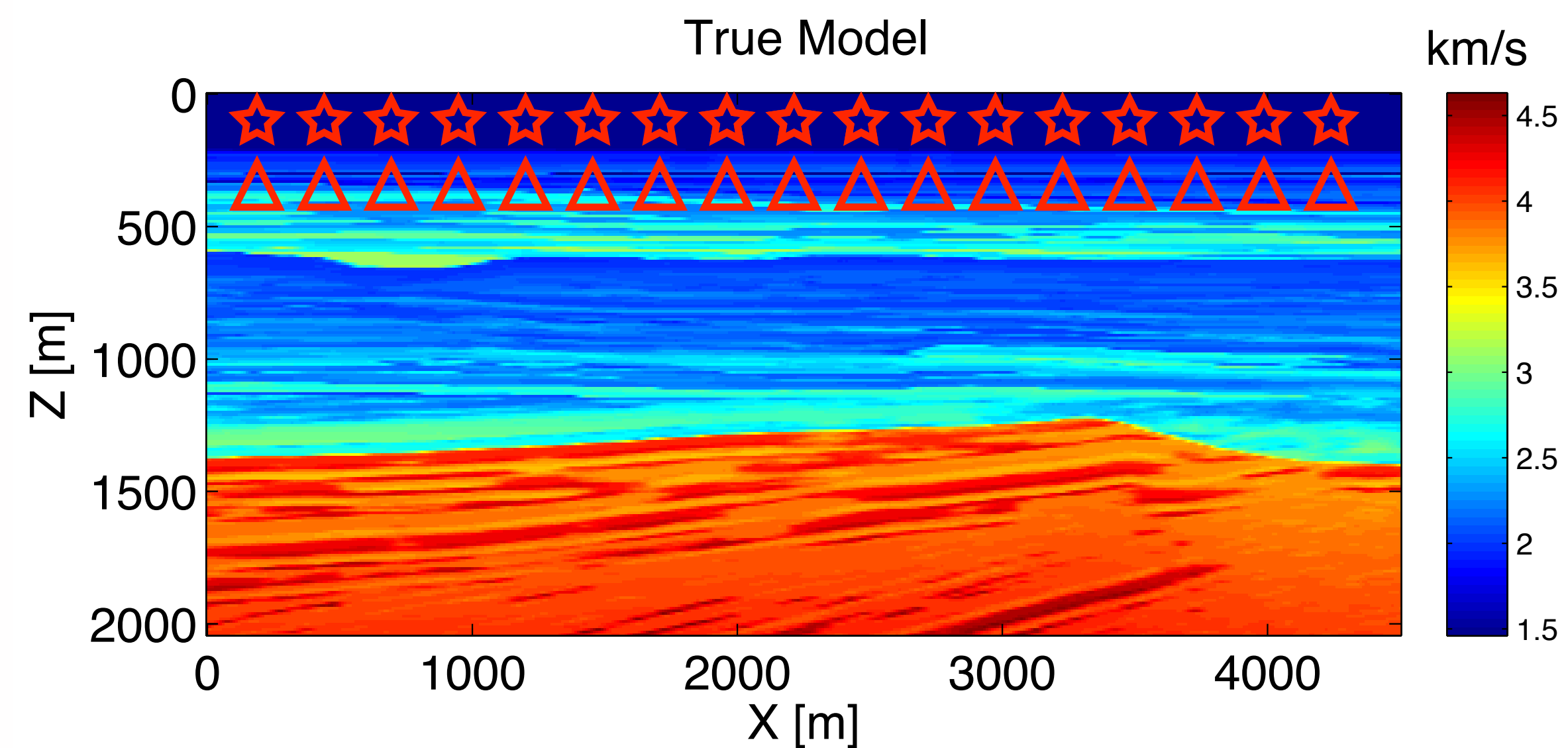


x = 290m



# Numerical Experiments

## BG model

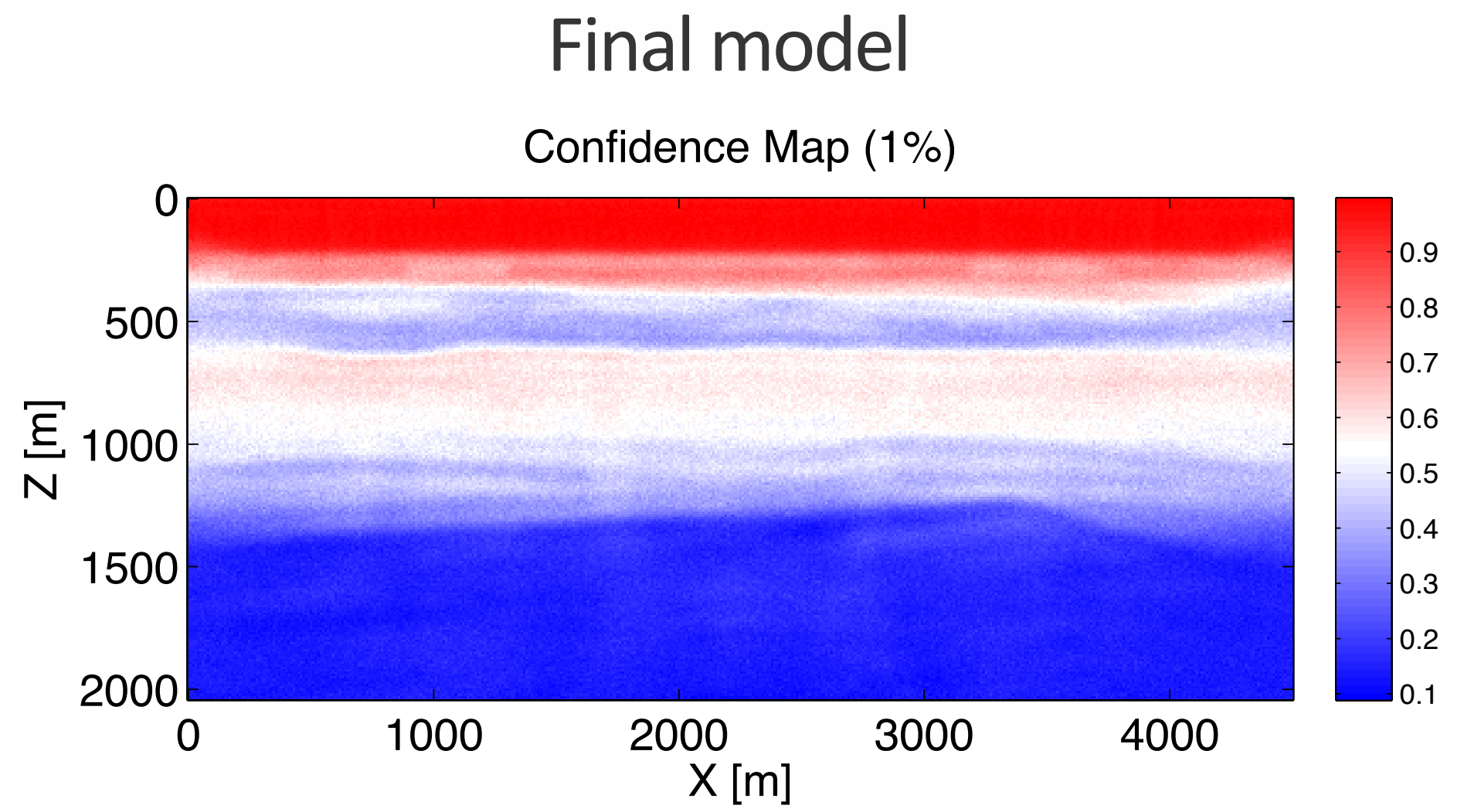
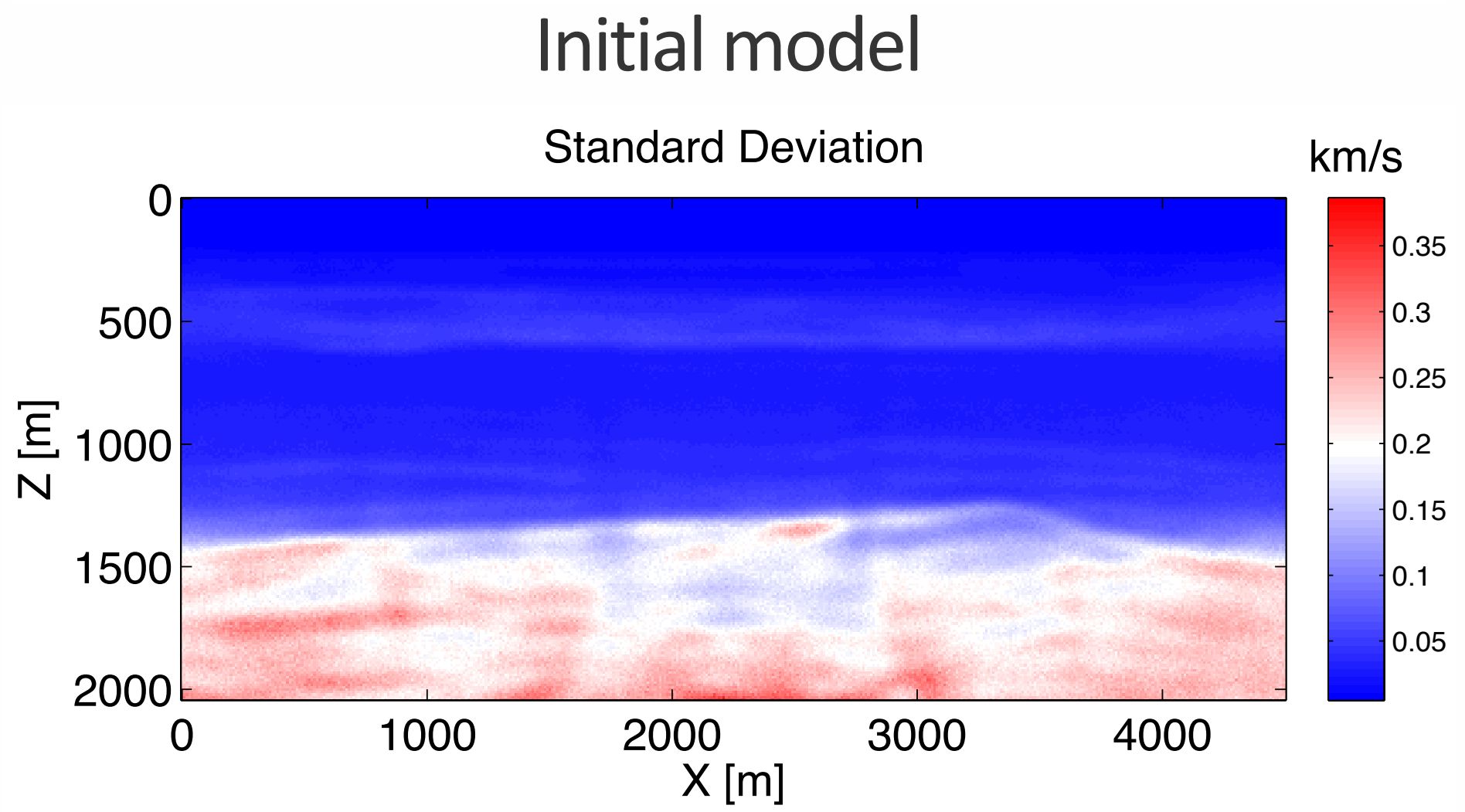
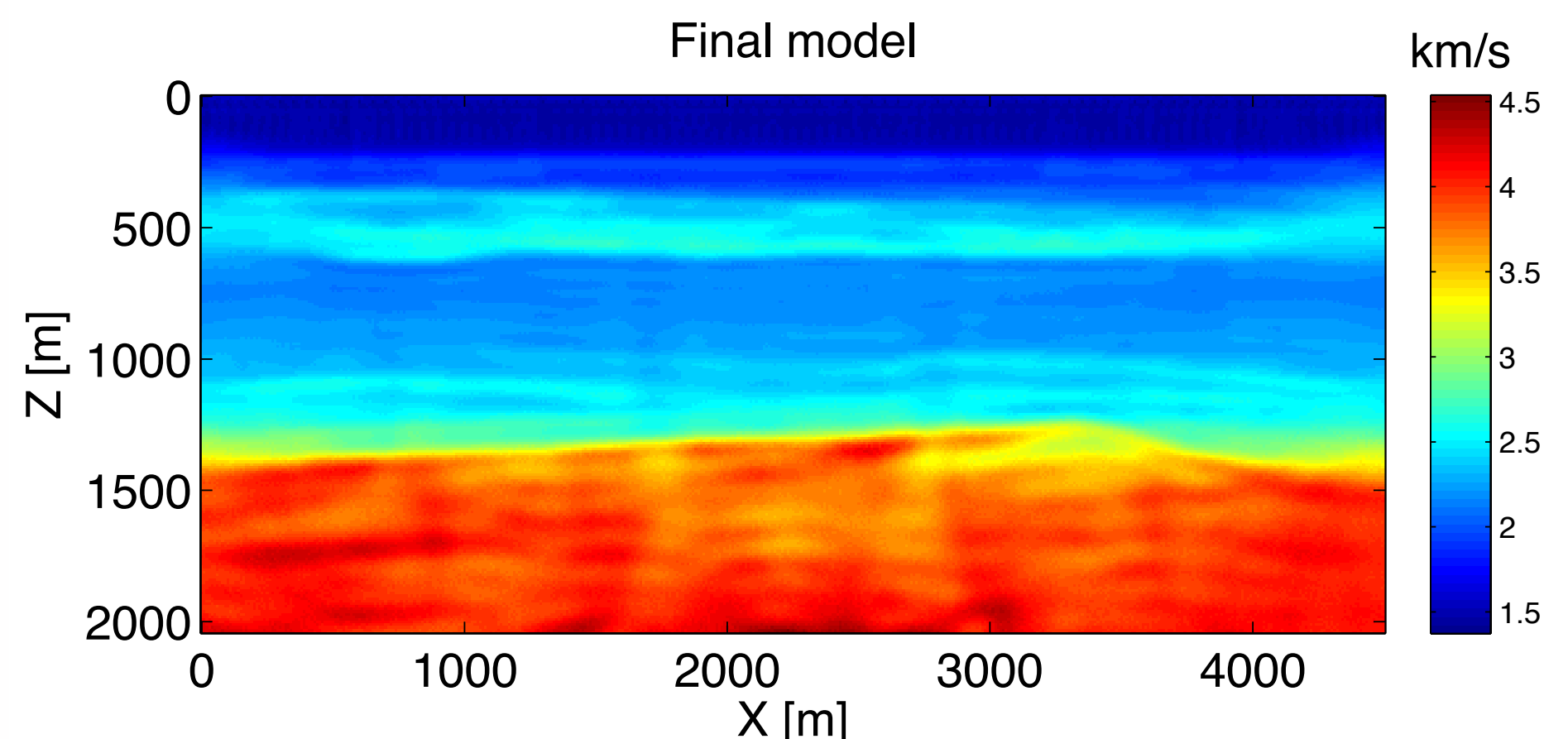
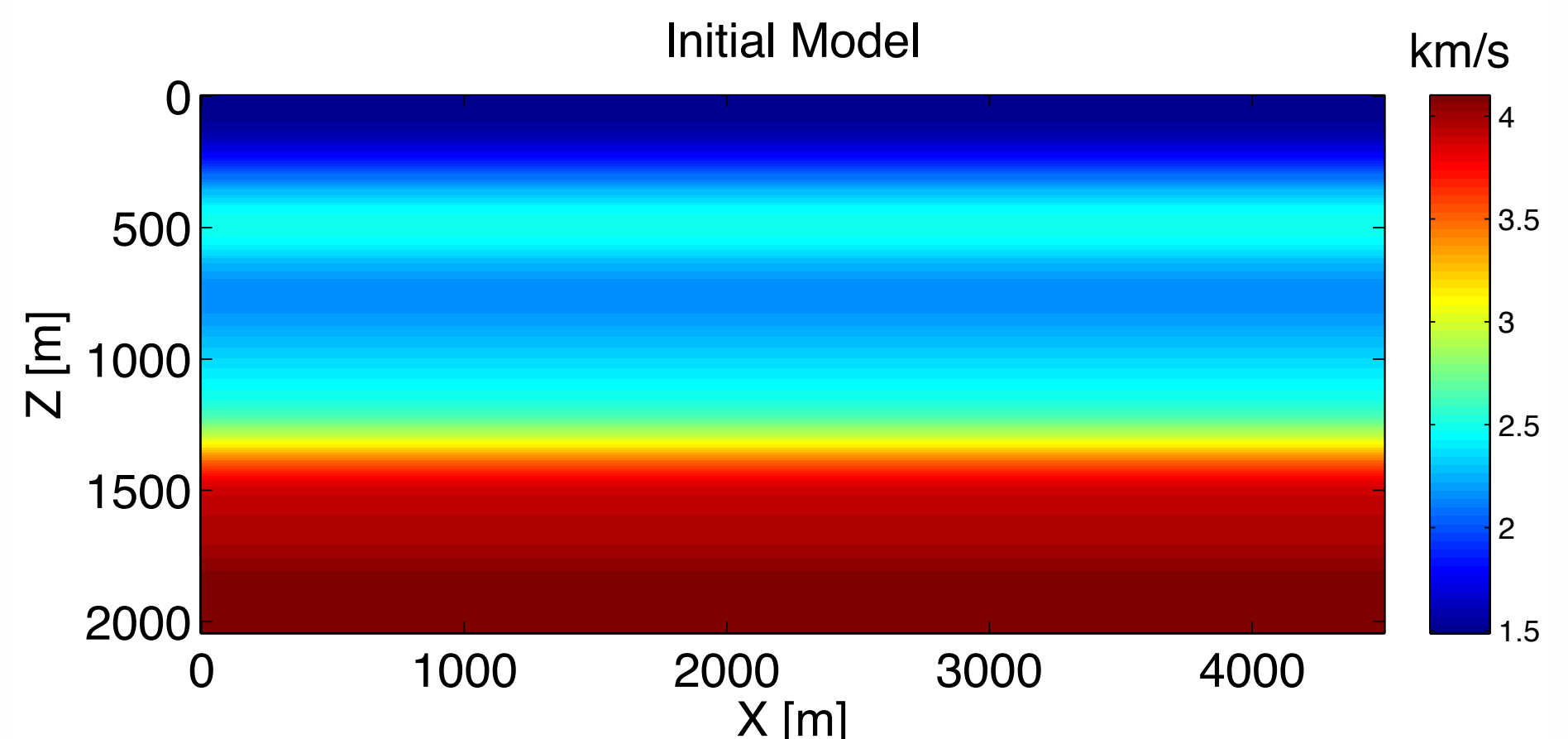


Acquisition Geometry:

91 shots

451 receivers

15 frequencies from 3Hz to 17Hz



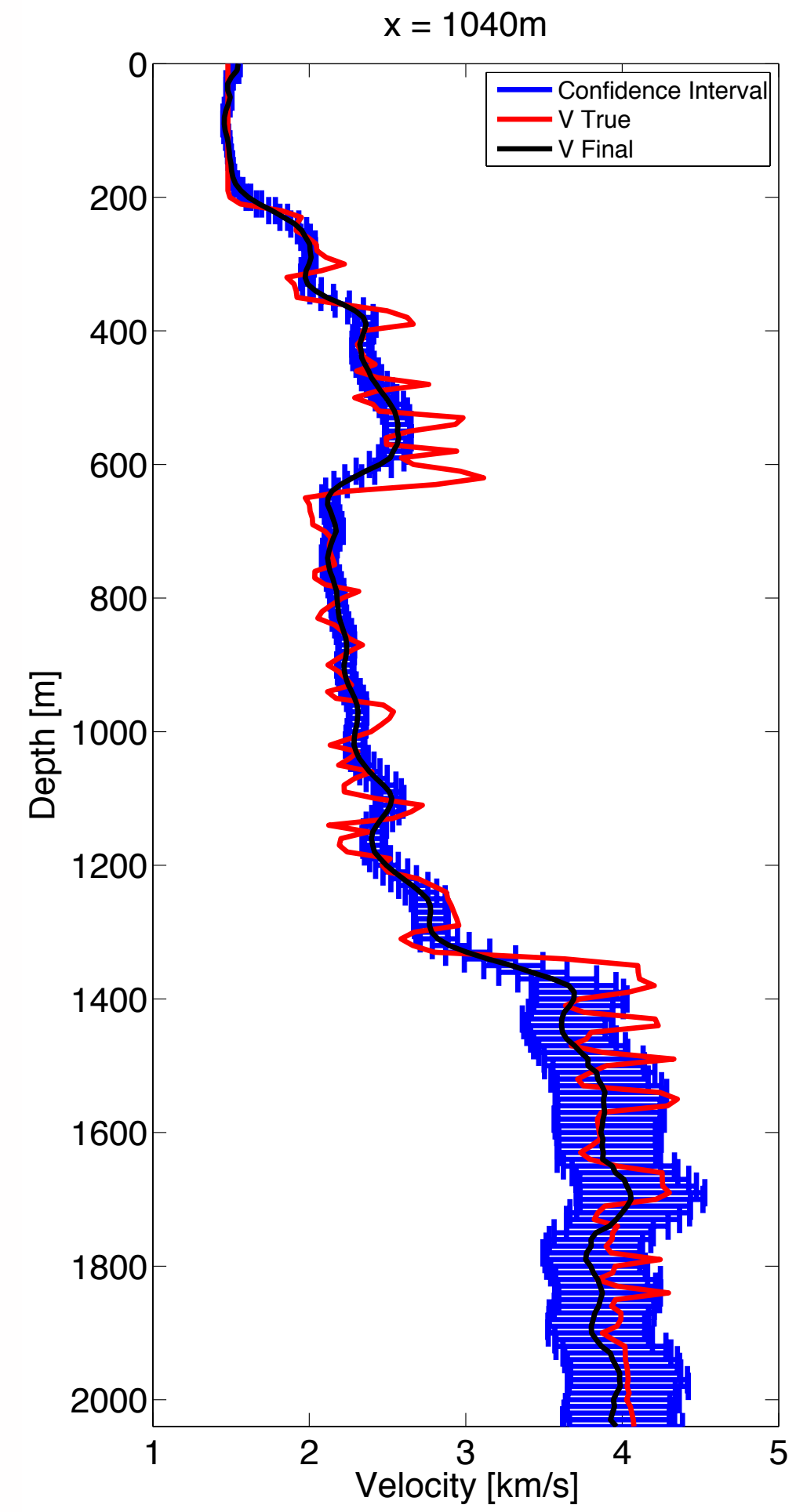
Standard deviation

Confidence map

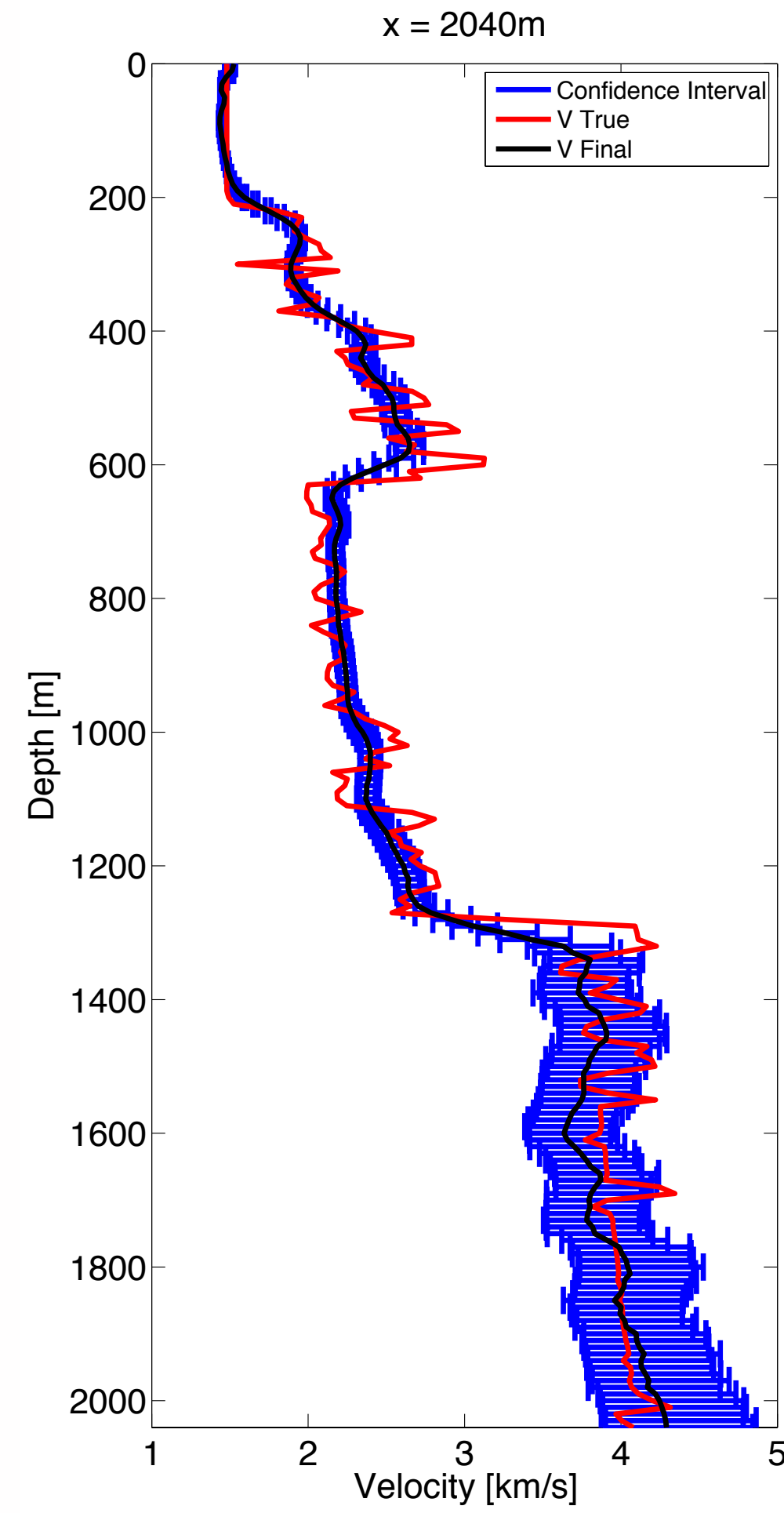


# Confidence Interval

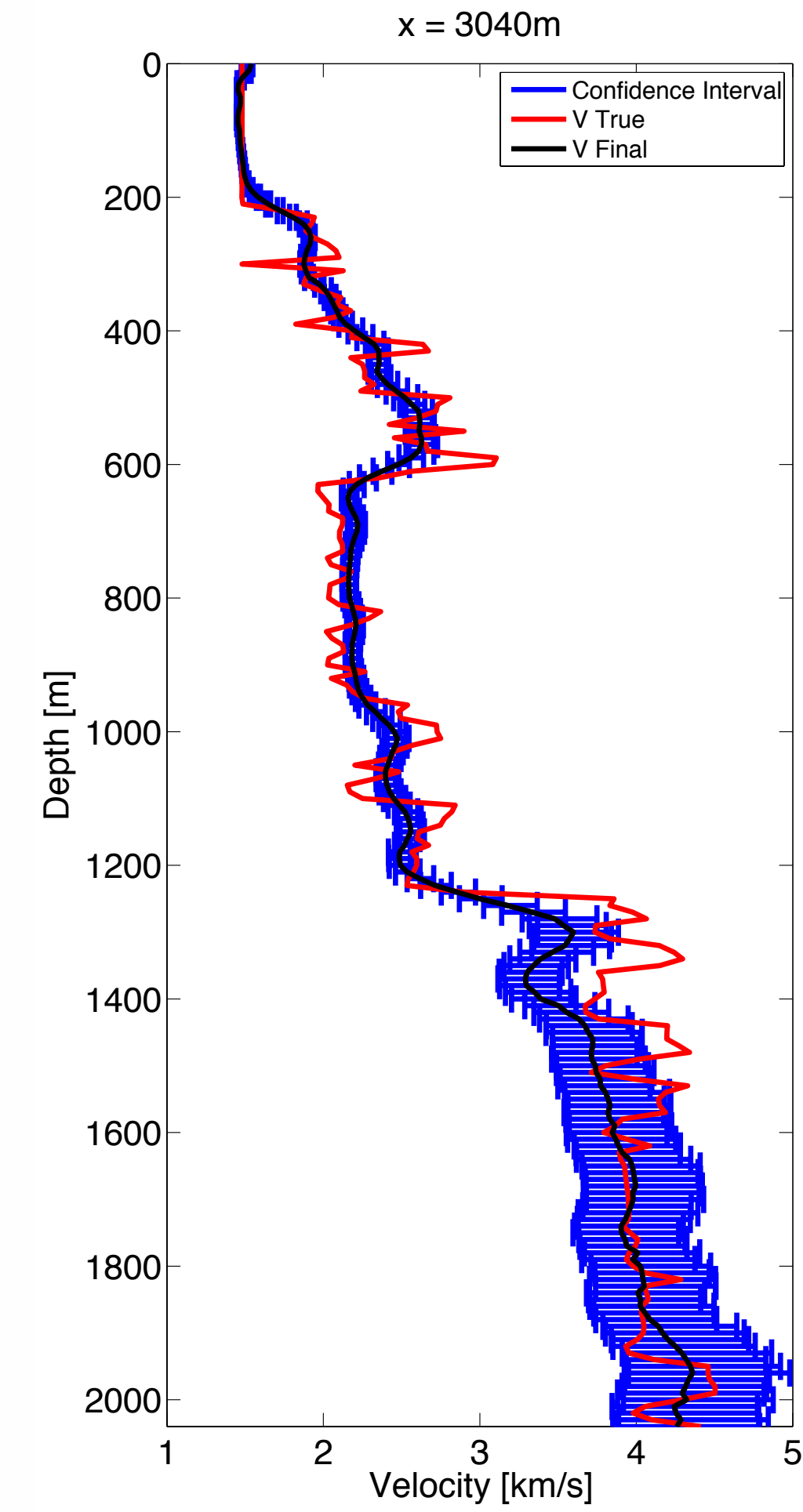
$\alpha = 0.9$






x = 1040m



x = 2040m



x = 3040m

-  Final Model
-  Confidence Interval
-  True Model

## Conclusions

- With *low-rank* approximation, the *evaluation of Hessian* becomes *tractable*.
- Problem is that the wave-equation Hessian is often NOT low-rank in exploration seismolog
- We only need to solve one Newton type method and evaluate Hessian once when using the *approximated* Gaussian distribution at the point of *optimal* solution.

## Future Work

- Use (randomized) probing techniques to represent the Hessian
  - ▶ parametric high-frequency approximation of WE Hessian by Demanet
  - ▶ Hessian approximation by HSS matrices
- Use simultaneous shots to reduce the computational cost;
- Use LBFGS Hessian instead of Gauss-Newton Hessian to reduce the computational cost.
- Uncertainty analysis based on different assumption of the likelihood part and prior information;
- Uncertainty analysis based on the stochastic PDE constraint optimization problems

## Acknowledgements

Thank you for your attention !

<https://www.slim.eos.ubc.ca/>



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