

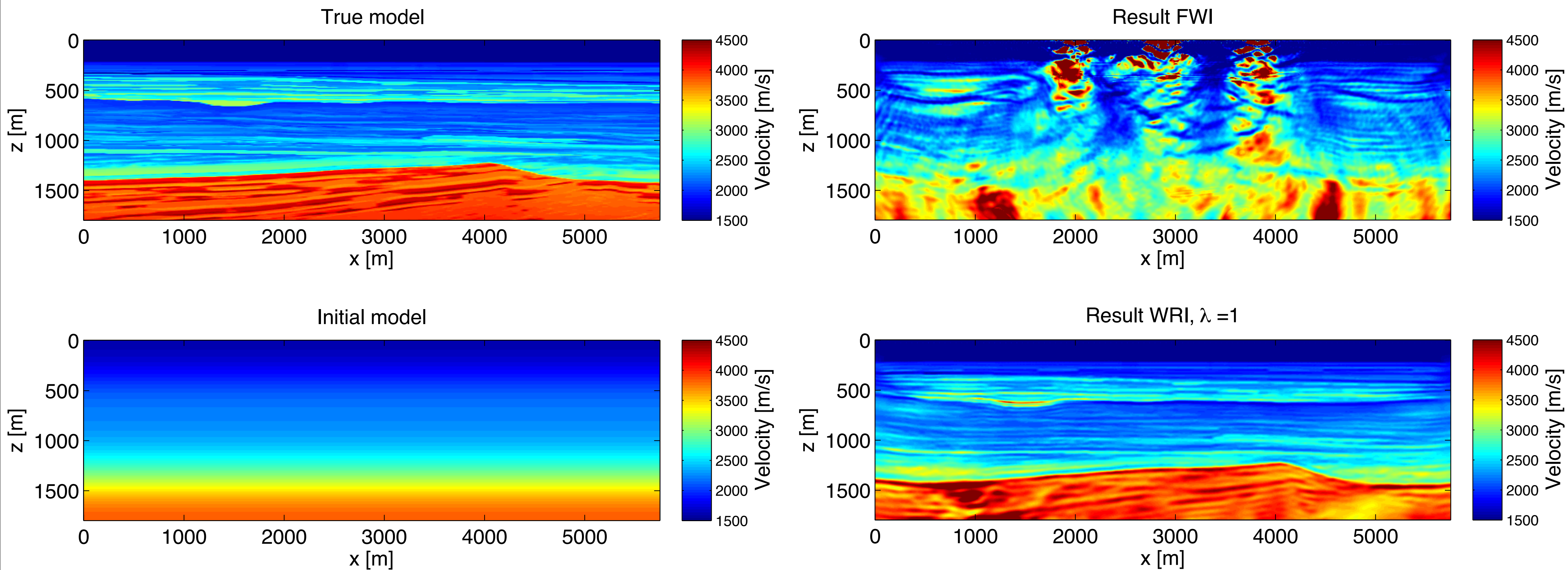
Quadratic-penalty based full-space methods for waveform inversion

Bas Peters
SINBAD Fall Consortium meeting, 2014.
Whistler, BC.

Waveform inversion

Works well if initial model is good

Waveform inversion – poor start model



Example from [Peters et al. 2013]

Wavefield reconstruction inversion

[T. van Leeuwen & F.J. Herrmann, 2013]

Less sensitive to

- starting models compared to FWI
- missing low-frequency data

Avoids cycle-skipping problems by virtue of extending the search space.

But, requires reasonable accurate solve of the augmented wave equation...

Wavefield reconstruction inversion

Still limitations on quality of start models & missing low-frequencies

Can we do better?

Maybe full-space methods?

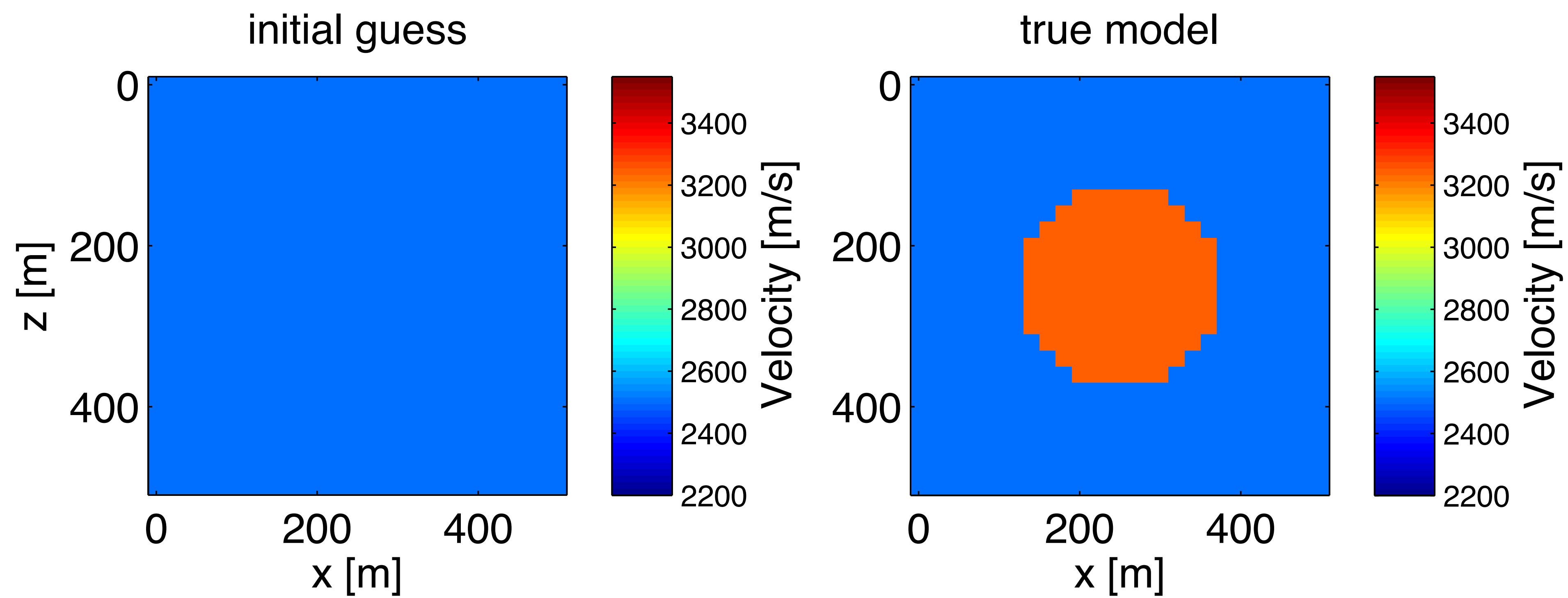
- at the “expense” of storing 2 copies of monochromatic wavefields

But, at the gain of no longer insisting on accurate solves...

Toy problem

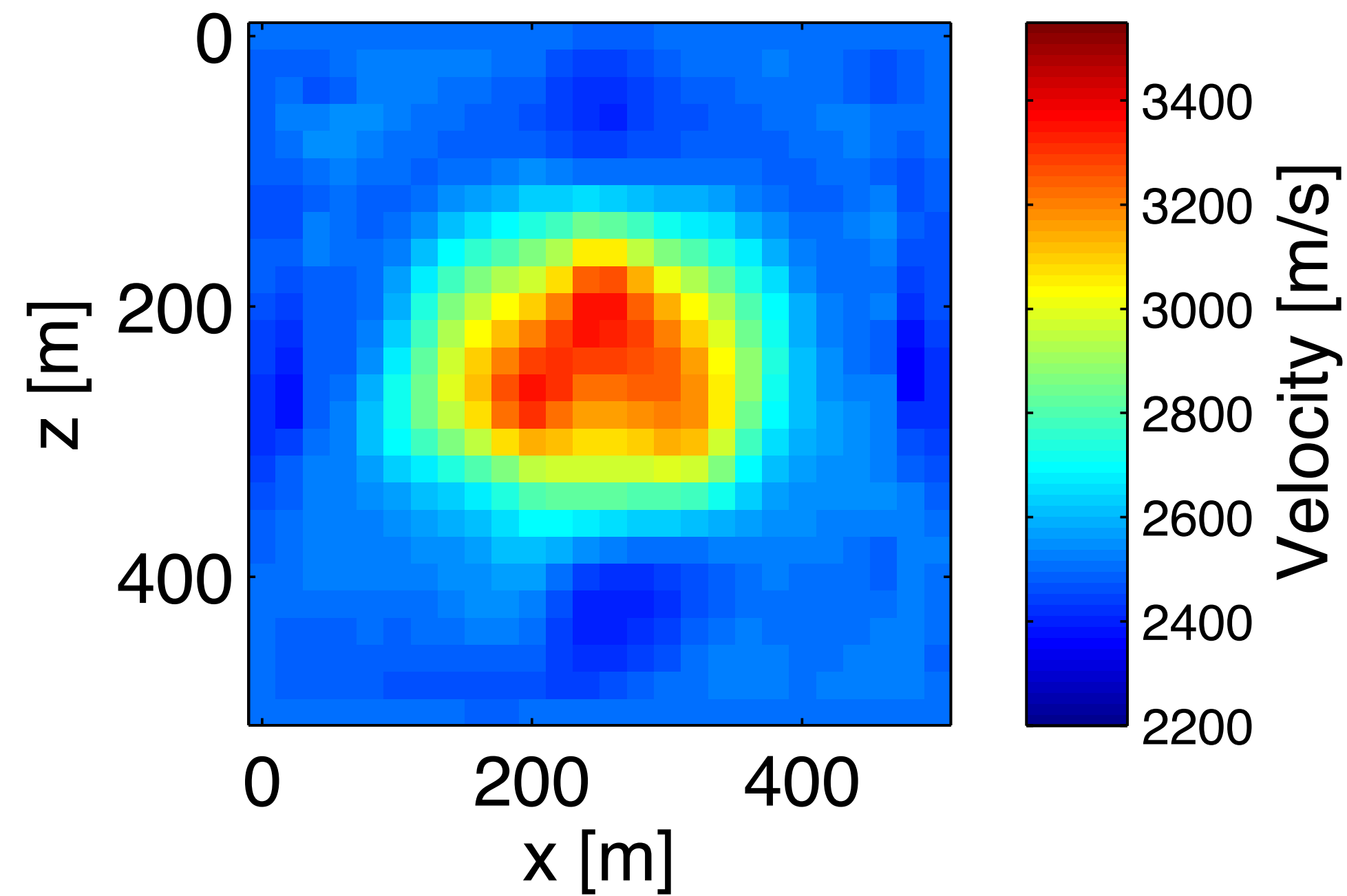
- cross-well setting
- 4 frequencies [6-10] Hz
- 5 simultaneous sources
- 5 receivers

Toy problem

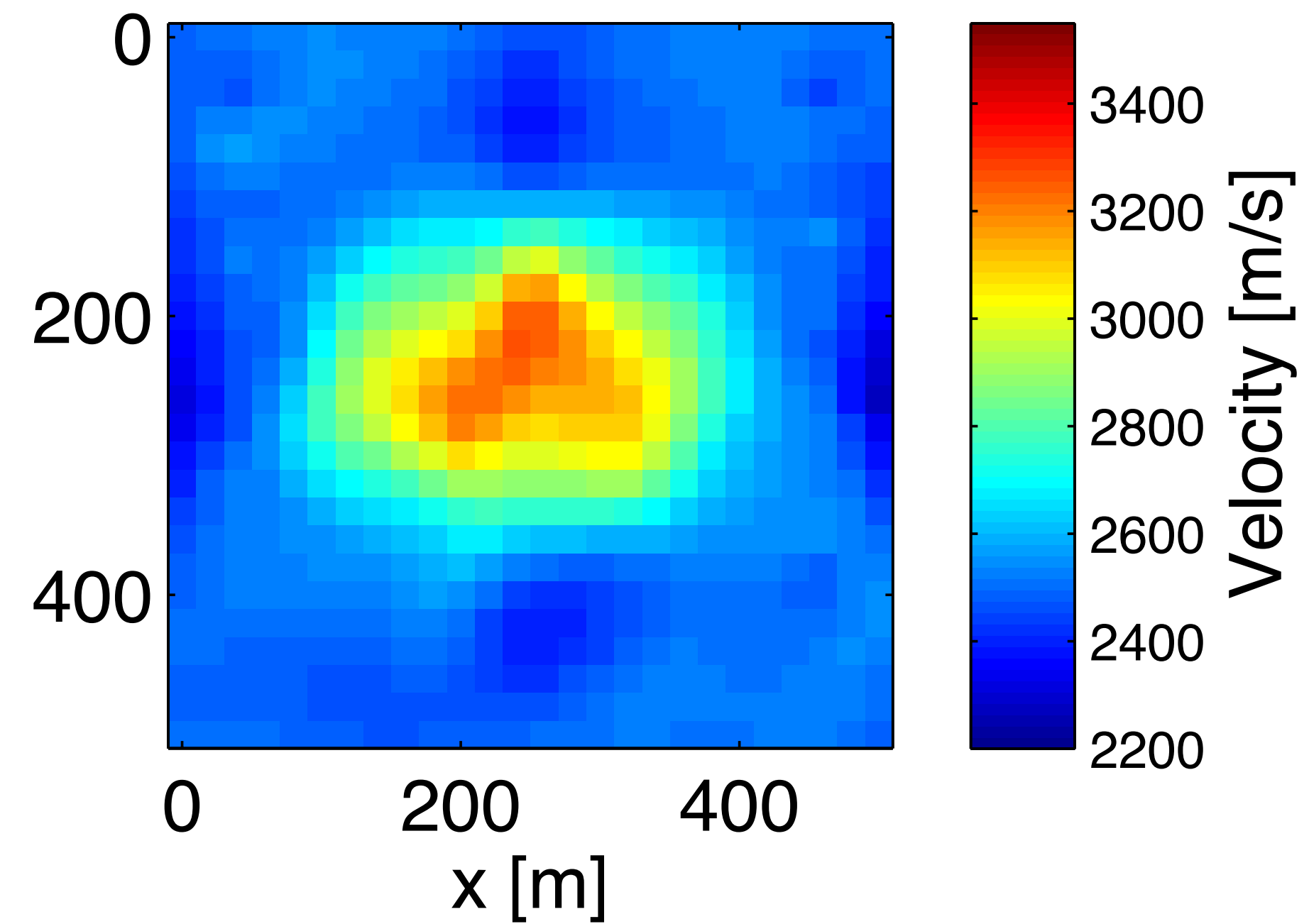


Toy problem

direct solve, full space, $\lambda=1000$



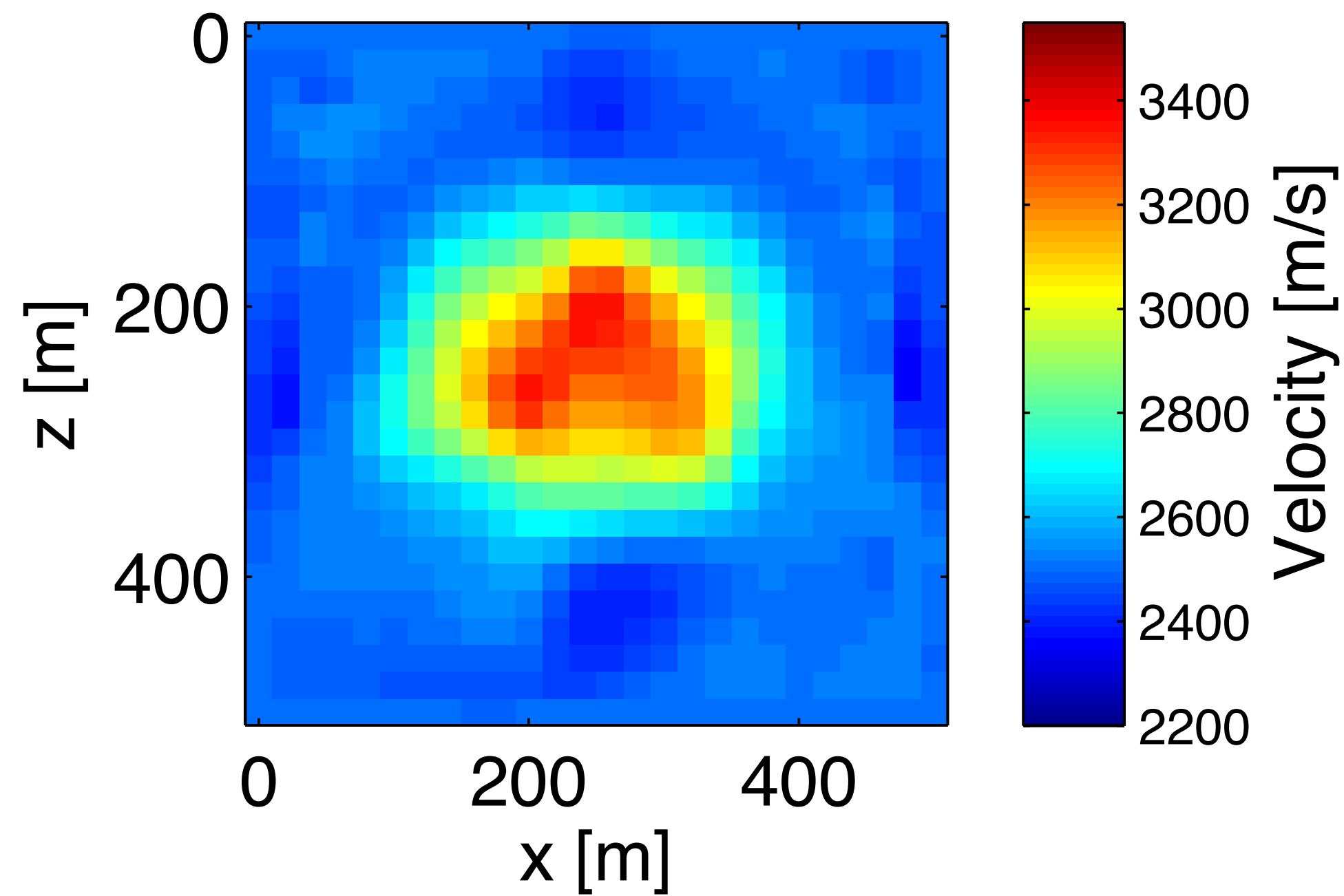
direct solve, reduced space, $\lambda=1000$



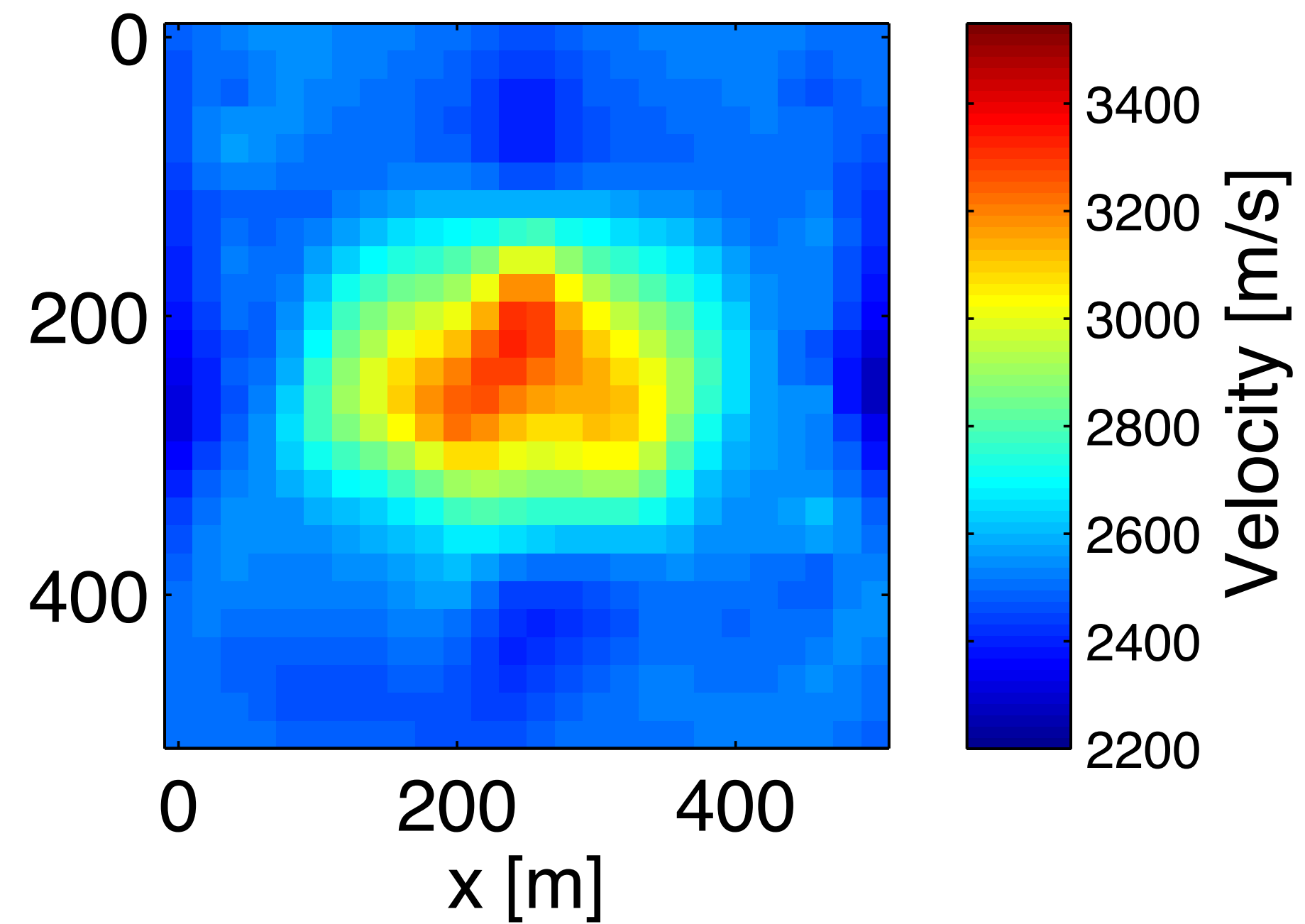
direct solution for least-squares problems

Toy problem

iterative solve, full space, $\lambda=1000$



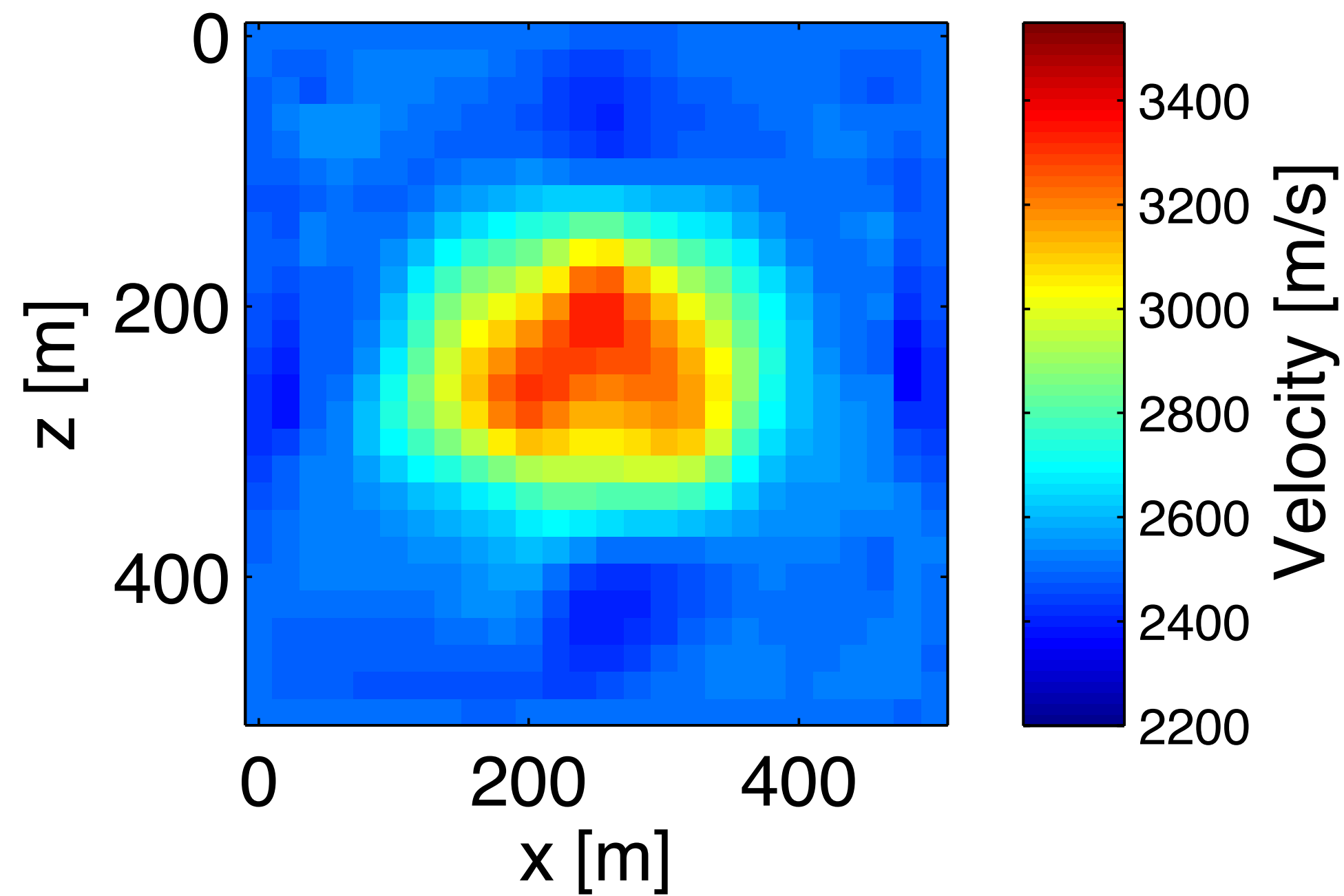
iterative solve, reduced space, $\lambda=1000$



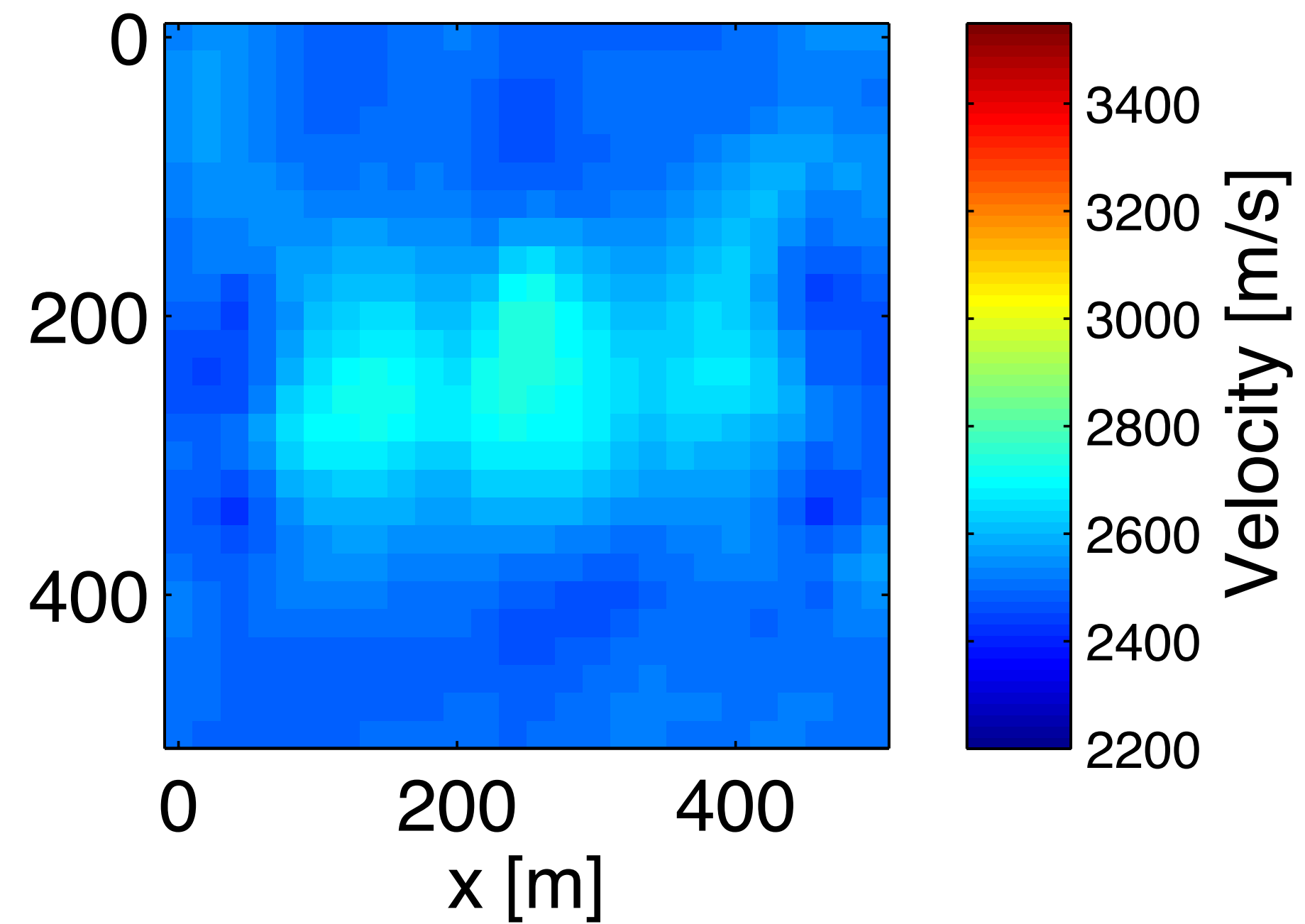
accurate iterative solution for least-squares problems

Toy problem

iterative solve, full space, $\lambda=1000$



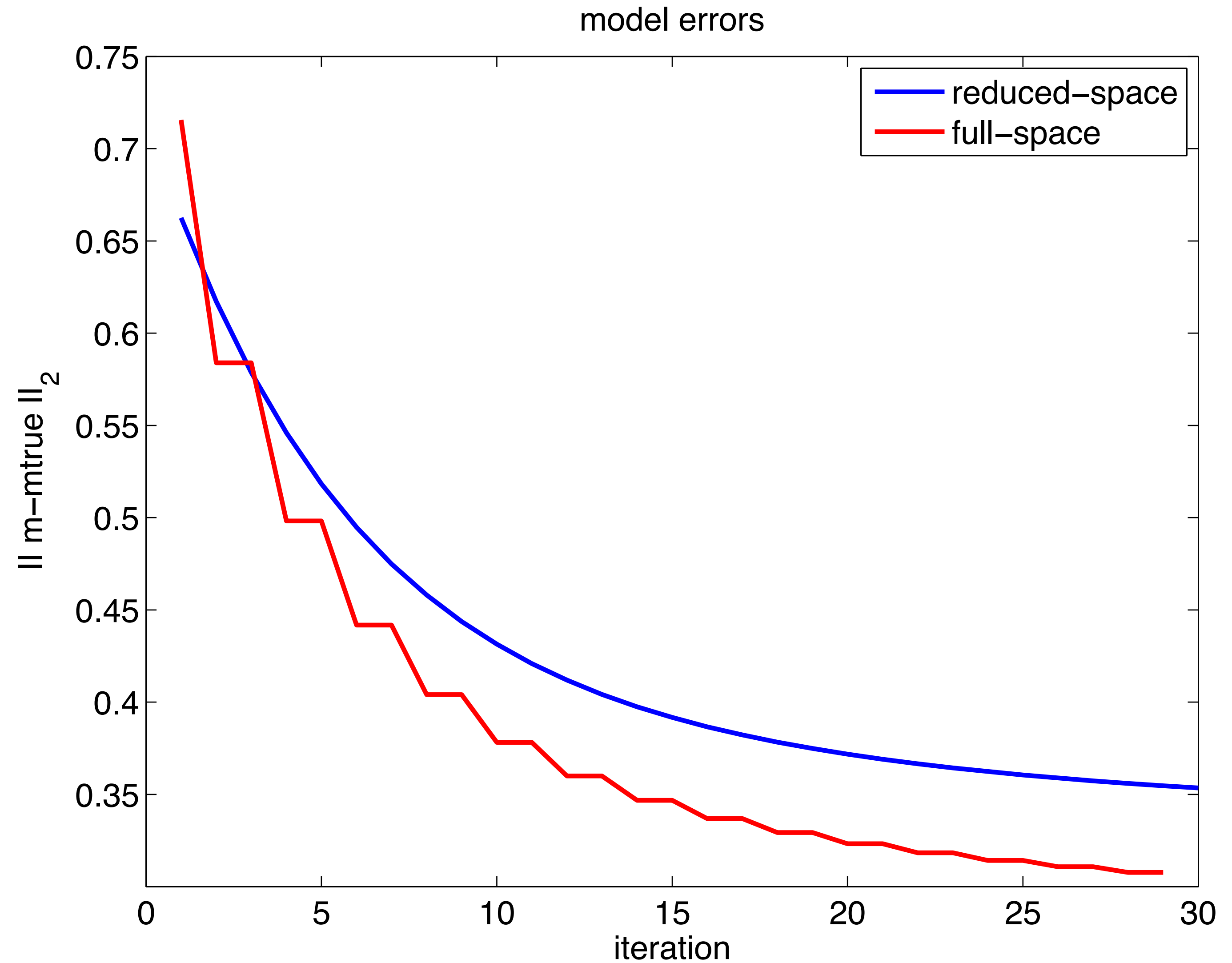
iterative solve, reduced space, $\lambda=1000$



inaccurate iterative solution for least-squares problems

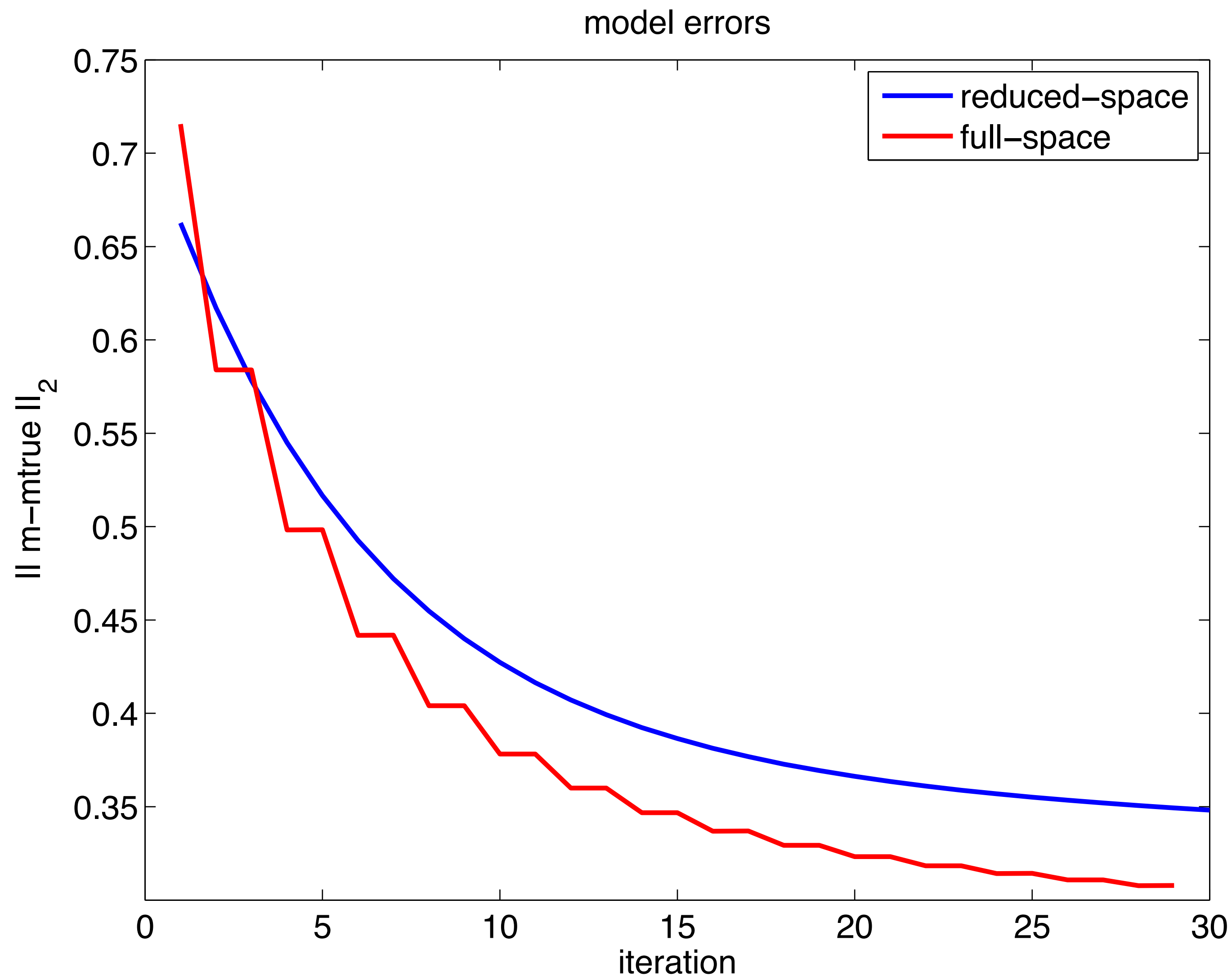
Toy problem

model errors,
direct solver



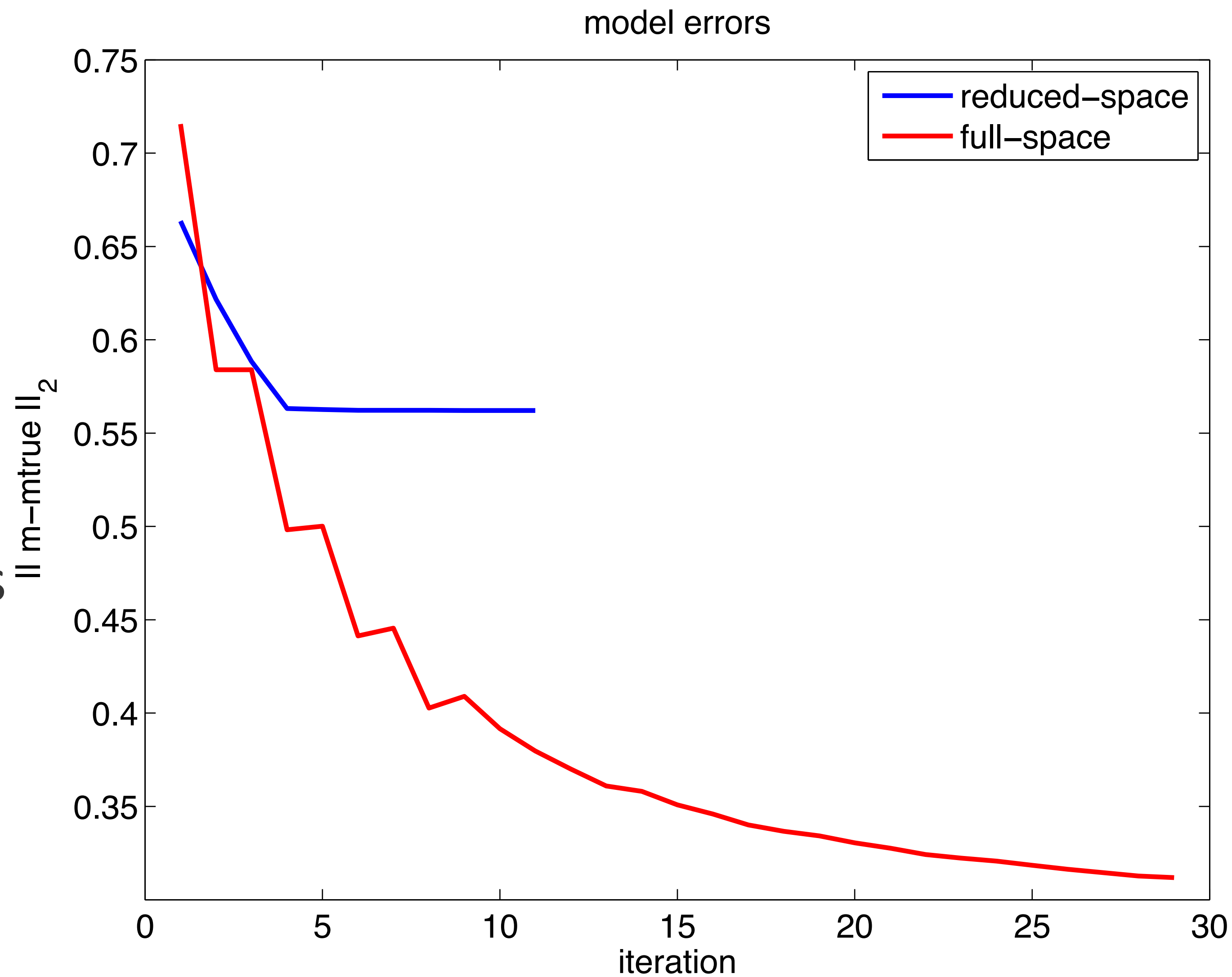
Toy problem

model errors,
accurate iterative solutions



Toy problem

model errors,
inaccurate iterative solutions



Toy problem

Inexact iterative linear system solves:

- full-space method not very sensitive
- WRI & FWI quite sensitive

Full-space vs reduced-space methods

Bottom line

reduced-space: solve for the fields
 update the medium parameters

full-space: update fields & medium parameters

Full-space vs reduced-space methods

Bottom line

reduced-space: solve for the fields
 update the medium parameters

← alternating strategy

full-space: update fields & medium parameters

Full-space vs reduced-space methods

Bottom line

reduced-space: solve for the fields
 update the medium parameters

← alternating strategy

full-space: update fields & medium parameters

← joint updating

Full-space vs reduced-space methods

FWI & WRI are in the reduced-space class –i.e., wave-equations are solved

Full-space is commonly used in a Lagrangian setting.

Because of memory requirements, rarely used in (academic) geophysics. [EM: E. Haber et al., 2004 ; Seismic: M. J. Grothe et al., 2011]

Short derivation

Problem formulation:

$$\min_{\mathbf{m}, \mathbf{u}} \frac{1}{2} \|\mathbf{P}\mathbf{u} - \mathbf{d}\|_2^2 \quad \text{s.t.} \quad \mathbf{H}(\mathbf{m})\mathbf{u} = \mathbf{q}$$

Short derivation

Quadratic penalty form (WRI):

$$\phi(\mathbf{m}, \mathbf{u}, \lambda) = \frac{1}{2} \|\mathbf{P}\mathbf{u} - \mathbf{d}\|_2^2 + \frac{\lambda^2}{2} \|\mathbf{H}(\mathbf{m})\mathbf{u} - \mathbf{q}\|_2^2$$

Short derivation

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$$\phi(\mathbf{m}, \mathbf{u}, \lambda) = \frac{1}{2} \|\mathbf{P}\mathbf{u} - \mathbf{d}\|_2^2 + \frac{\lambda^2}{2} \|\mathbf{H}(\mathbf{m})\mathbf{u} - \mathbf{q}\|_2^2$$

$$\begin{array}{ccc} \begin{array}{c} \left(\begin{array}{c} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \dots \\ \mathbf{P}_k \end{array} \right) \begin{array}{c} \left(\begin{array}{c} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_k \end{array} \right) - \left(\begin{array}{c} \mathbf{d}_1 \\ \mathbf{d}_2 \\ \vdots \\ \mathbf{d}_k \end{array} \right) \end{array} & & \begin{array}{c} \left(\begin{array}{c} \mathbf{H}_1 \\ \mathbf{H}_2 \\ \dots \\ \mathbf{H}_k \end{array} \right) \begin{array}{c} \left(\begin{array}{c} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_k \end{array} \right) - \left(\begin{array}{c} \mathbf{q}_1 \\ \mathbf{q}_2 \\ \vdots \\ \mathbf{q}_k \end{array} \right) \end{array} \end{array} \\ \swarrow & & \downarrow \end{array}$$

Short derivation

$$\begin{array}{ccc}
 \text{Hessian} & \text{Newton's method} & \text{gradient} \\
 \uparrow & & \uparrow \\
 \hline
 \begin{pmatrix} \mathbf{P}^* \mathbf{P} + \lambda^2 \mathbf{H}^* \mathbf{H} & \nabla_{\mathbf{u}, \mathbf{m}}^2 \phi \\ \nabla_{\mathbf{m}, \mathbf{u}}^2 \phi & \lambda^2 \mathbf{G}_{\mathbf{m}}^* \mathbf{G}_{\mathbf{m}} \end{pmatrix} & \begin{pmatrix} \delta_{\mathbf{u}} \\ \delta_{\mathbf{m}} \end{pmatrix} & = - \begin{pmatrix} \mathbf{P}^* (\mathbf{P} \mathbf{u} - \mathbf{d}) + \lambda^2 \mathbf{H}^* (\mathbf{H} \mathbf{u} - \mathbf{q}) \\ \lambda^2 \mathbf{G}_{\mathbf{m}}^* (\mathbf{H} \mathbf{u} - \mathbf{q}) \end{pmatrix} \\
 \hline
 & \downarrow & \\
 & \text{updates for medium parameters} & \\
 & \text{updates for all fields} &
 \end{array}$$

Short derivation

Newton's method:

$$\begin{pmatrix} \mathbf{P}^* \mathbf{P} + \lambda^2 \mathbf{H}^* \mathbf{H} & \nabla_{\mathbf{u}, \mathbf{m}} \phi \\ \nabla_{\mathbf{m}, \mathbf{u}} \phi & \lambda^2 \mathbf{G}_m^* \mathbf{G}_m \end{pmatrix} \begin{pmatrix} \delta_{\mathbf{u}} \\ \delta_{\mathbf{m}} \end{pmatrix} = - \begin{pmatrix} \mathbf{P}^* (\mathbf{P} \mathbf{u} - \mathbf{d}) + \lambda^2 \mathbf{H}^* (\mathbf{H} \mathbf{u} - \mathbf{q}) \\ \lambda^2 \mathbf{G}_m^* (\mathbf{H} \mathbf{u} - \mathbf{q}) \end{pmatrix}$$

Short derivation

Approximate Hessian:

$$\begin{pmatrix} \mathbf{P}^* \mathbf{P} + \lambda^2 \mathbf{H}^* \mathbf{H} & 0 \\ 0 & \lambda^2 \mathbf{G}_m^* \mathbf{G}_m \end{pmatrix} \begin{pmatrix} \delta_u \\ \delta_m \end{pmatrix} = - \begin{pmatrix} \mathbf{P}^* (\mathbf{P} \mathbf{u} - \mathbf{d}) + \lambda^2 \mathbf{H}^* (\mathbf{H} \mathbf{u} - \mathbf{q}) \\ \lambda^2 \mathbf{G}_m^* (\mathbf{H} \mathbf{u} - \mathbf{q}) \end{pmatrix}$$

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Can be solved inexactly (cheap)!

Algorithm

0. construct initial guess \mathbf{m} for medium and \mathbf{u}_i for each field
 - while** not converged **do**
 1. form Hessian and gradient // form (~free)
 2. ignore the $\nabla_{\mathbf{u},\mathbf{m}}^2 \phi$, $\nabla_{\mathbf{m},\mathbf{u}}^2 \phi$ blocks // approximate
 3. find $\delta\mathbf{m}$ & each $\delta\mathbf{u}_i$ in parallel // solve
 4. find steplength α using linesearch // evaluate (~free)
 5. $\mathbf{m} = \mathbf{m} + \alpha\delta\mathbf{m}$ & $\mathbf{u} = \mathbf{u} + \alpha\delta\mathbf{u}$ // update model and fields
 - end**
-

Algorithm

-
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 - end**
-

medium and field updates
are independent

Algorithm

0. construct initial guess \mathbf{m} for medium and \mathbf{u}_i for each field

while not converged **do** depend on the updated model and updated fields

1. form Hessian and gradient // form (~free)

2. ignore the $\nabla_{\mathbf{u},\mathbf{m}}^2 \phi$, $\nabla_{\mathbf{m},\mathbf{u}}^2 \phi$ blocks // approximate

3. find $\delta\mathbf{m}$ & each $\delta\mathbf{u}_i$ in parallel // solve

4. find steplength α using linesearch // evaluate (~free)

5. $\mathbf{m} = \mathbf{m} + \alpha\delta\mathbf{m}$ & $\mathbf{u} = \mathbf{u} + \alpha\delta\mathbf{u}$ // update model and fields

end

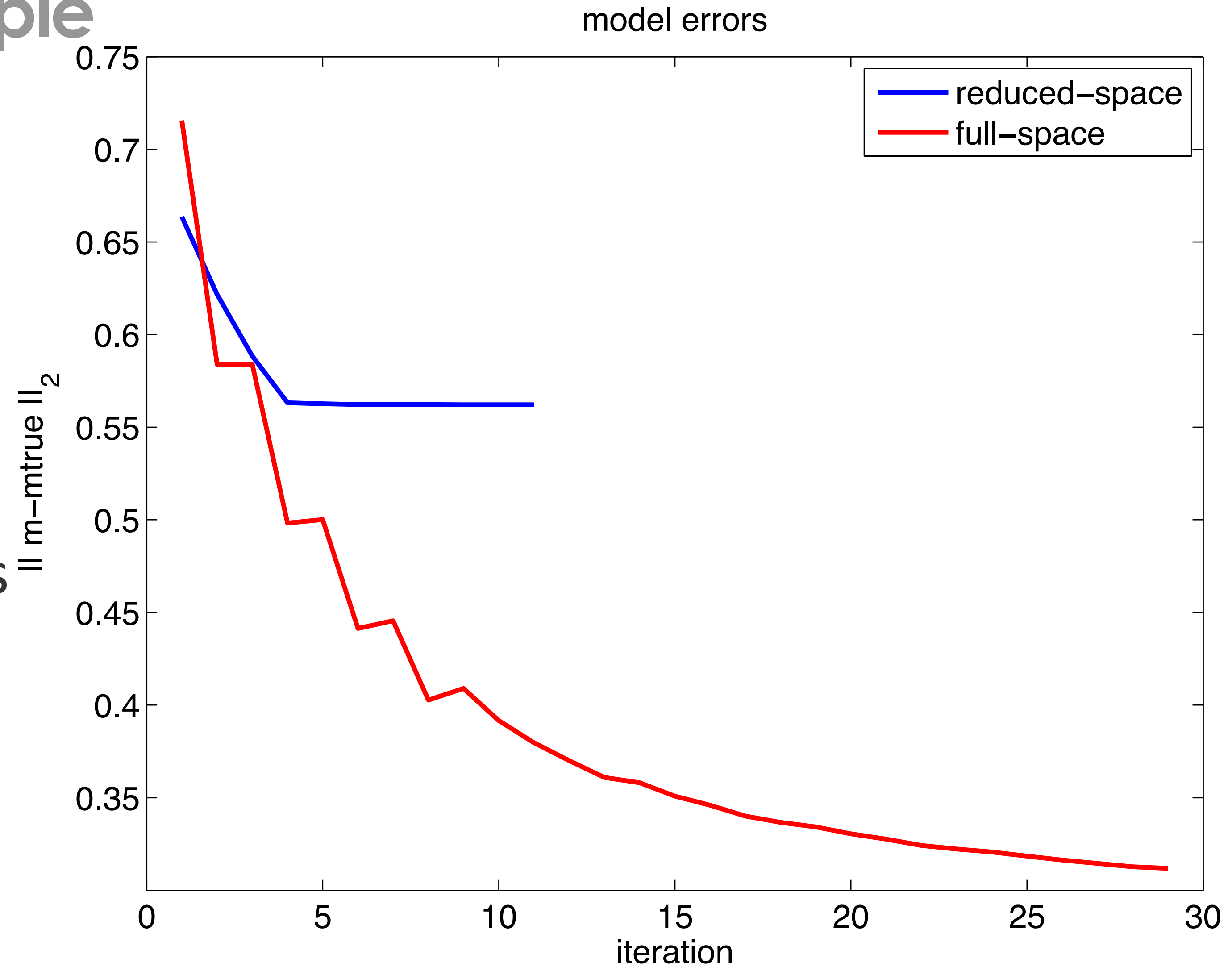
Full-space vs reduced-space methods

	FWI & WRI	full
Hessian	dense	sparse
Hessian	solve "PDE's"	~free
gradient	solve "PDE's"	~free
memory	2 fields per parallel process	all fields in memory (can be distributed over nodes)
function evaluation	solve "PDE's"	~free

~free = sparse matrix-vector products

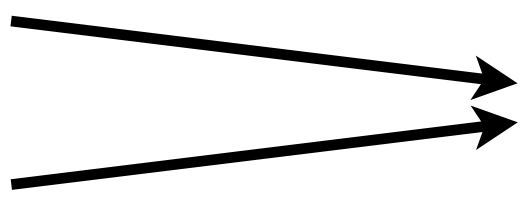
Previous example

model errors,
inaccurate iterative solutions



Inexact full-space vs inexact reduced-space

FWI & WRI:

- error in objective function value
 - error in gradient
 - error in Hessian
- error in medium parameter update
- 

Inexact full-space vs inexact reduced-space

FWI & WRI:

- error in objective function value
 - error in gradient
 - error in Hessian
- error in medium parameter update

Full-space from WRI:

- objective function value always exact
 - gradient always exact
 - Hessian always exact
- 0 iterations → gradient descent
many iterations → Newton's method

Toy examples

Using a direct solver:

- similar reconstruction quality compared to WRI+diagonal Hessian approximation
- need to test on more realistic models.

Memory requirements

save all fields for all frequencies & sources

can be distributed over multiple nodes

Feasible? Need

- parallel computing
- simultaneous sources
- small frequency batches

Computational cost

Independent update computation

No communication between compute nodes to compute updates

1 iteration of WRI \approx 1 iteration of full-space Newton type quadratic penalty

Conclusions

Constructed a full-space method which:

- updates fields & medium parameters simultaneously
- computational cost \approx reduced-space methods
- similar parallelism as in FWI & WRI
- many properties are different from FWI & WRI
- promising results with iterative solvers

- con: need to store all fields
- but, less storage needed compared to Lagrangian full-space methods

Current & future work

Test on more realistic examples.

Evaluate reconstruction quality compared to WRI.

Maximize benefit from inexact update computation.

Acknowledgements



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