

Numerical Simulation Methods in Geophysics, Part 11: Solving problems

1. MGPy+MGIN

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Recap

1. Types of PDEs in geophysics
2. The Finite Difference (FD) method
 - Poisson equation in 1D, look into 2D/3D
 - Heat transfer (diffusion equation) in 1D, time-stepping
3. Solving the hyperbolic (acoustic) wave equation in 1D
4. The Finite Element (FE) method
 - Poisson and diffusion equation in 1D
 - (complex) Helmholtz equation in 2D for EM problems

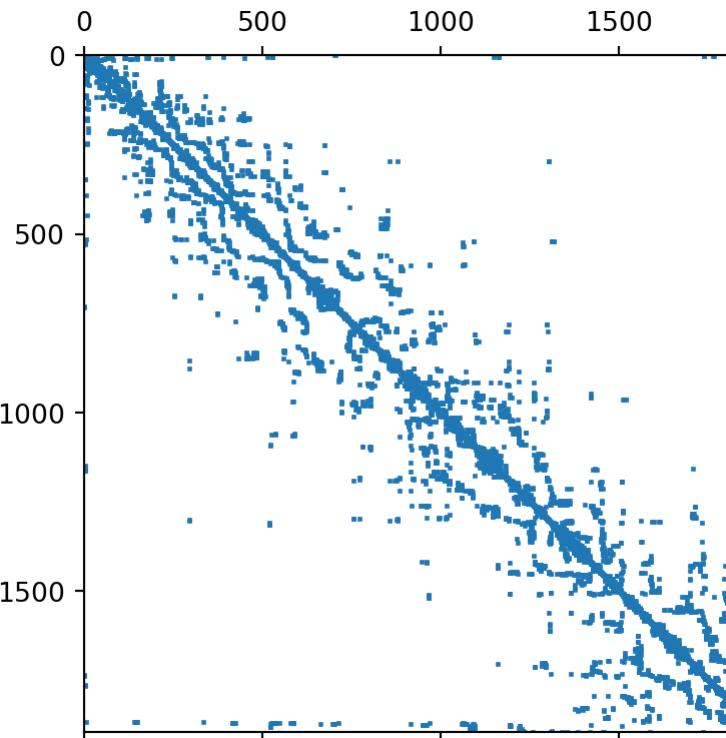
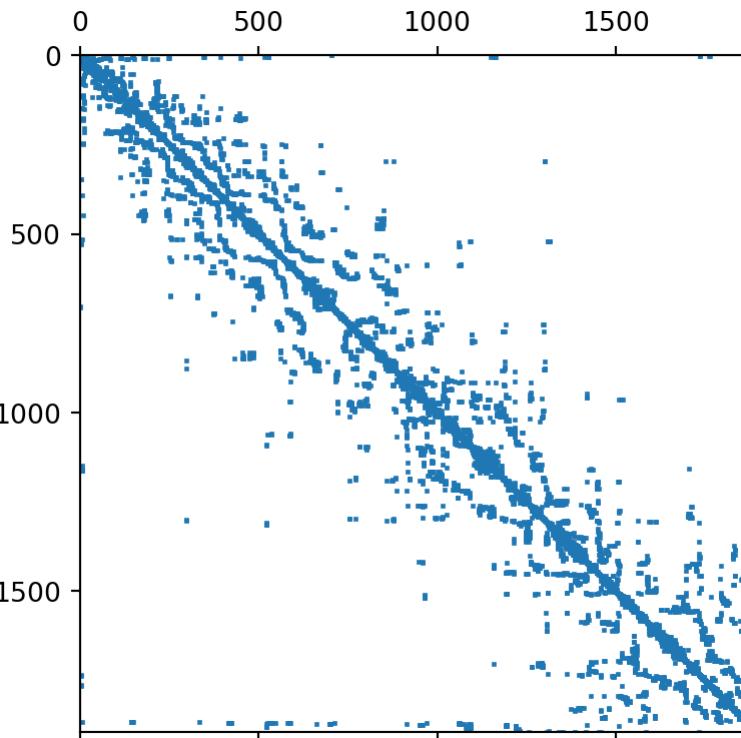
Topics yet to be covered

- solving vectorial EM problems in 2D/3D
 - staggered grid techniques 2D/3D
 - 2.5D solution techniques
 - 3D vector solution using Nedelec elements
- The Finite Volume (FV) method
- solving advection-dispersion problems
- equation solvers and high-performance computing

Three lectures (22/1, 29/1, 5/2) and exercises (23+30/1, 6/2)

The solver module

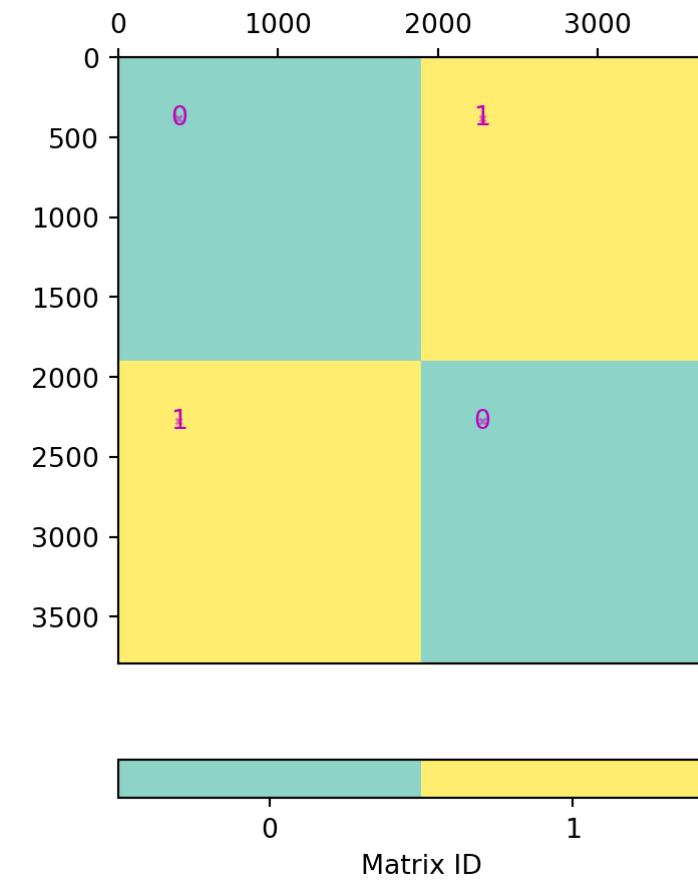
```
1 import pygimli.solver as ps
2 mesh["my"] = 4 * np.pi * 1e-7
3 A = ps.createStiffnessMatrix(mesh, a=1/mesh["my"])
4 M = ps.createMassMatrix(mesh, mesh["sigma"])
5 fig, ax = plt.subplots(ncols=2)
6 ax[0].spy(pg.utils.toCSR(A), markersize=1)
7 ax[1].spy(pg.utils.toCSR(M).todense(), markersize=1)
```



The complex problem matrix

$$\mathbf{B} = \begin{pmatrix} \mathbf{A} & -\omega\mathbf{M} \\ \omega\mathbf{M} & \mathbf{A} \end{pmatrix}$$

```
1 w = 0.1
2 nd = mesh.nodeCount()
3 B = pg.BlockMatrix()
4 B.Aid = B.addMatrix(A)
5 B.Mid = B.addMatrix(M)
6 B.addMatrixEntry(B.Aid, 0, 0)
7 B.addMatrixEntry(B.Aid, nd, nd)
8 B.addMatrixEntry(B.Mid, 0, nd, scale=-w)
9 B.addMatrixEntry(B.Mid, nd, 0, scale=w)
10 pg.show(B)
```



Sparse matrices

Up to now: regular (dense) array: save every element including 0

Save only non-zero components (e.g. using `scipy.sparse`)

- COO - coordinate format
- CSC/CRS - compressed sparse column/row
- BSR - block sparse row format, ...

Equation solvers

Solve systems of equations

direct solvers

- Gauss elimination (expensive and dense)
- Cholesky (or ILU) decomposition

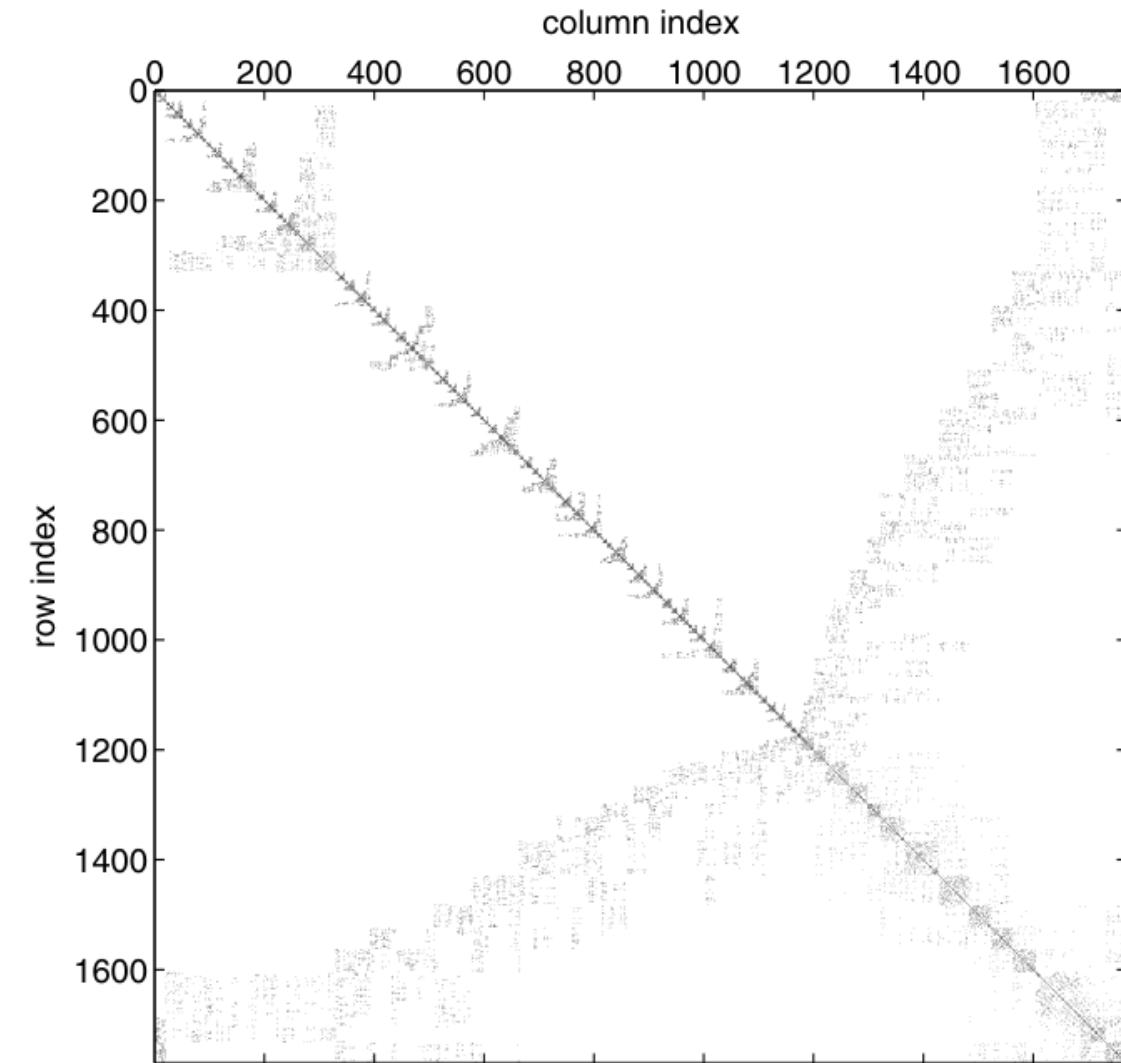
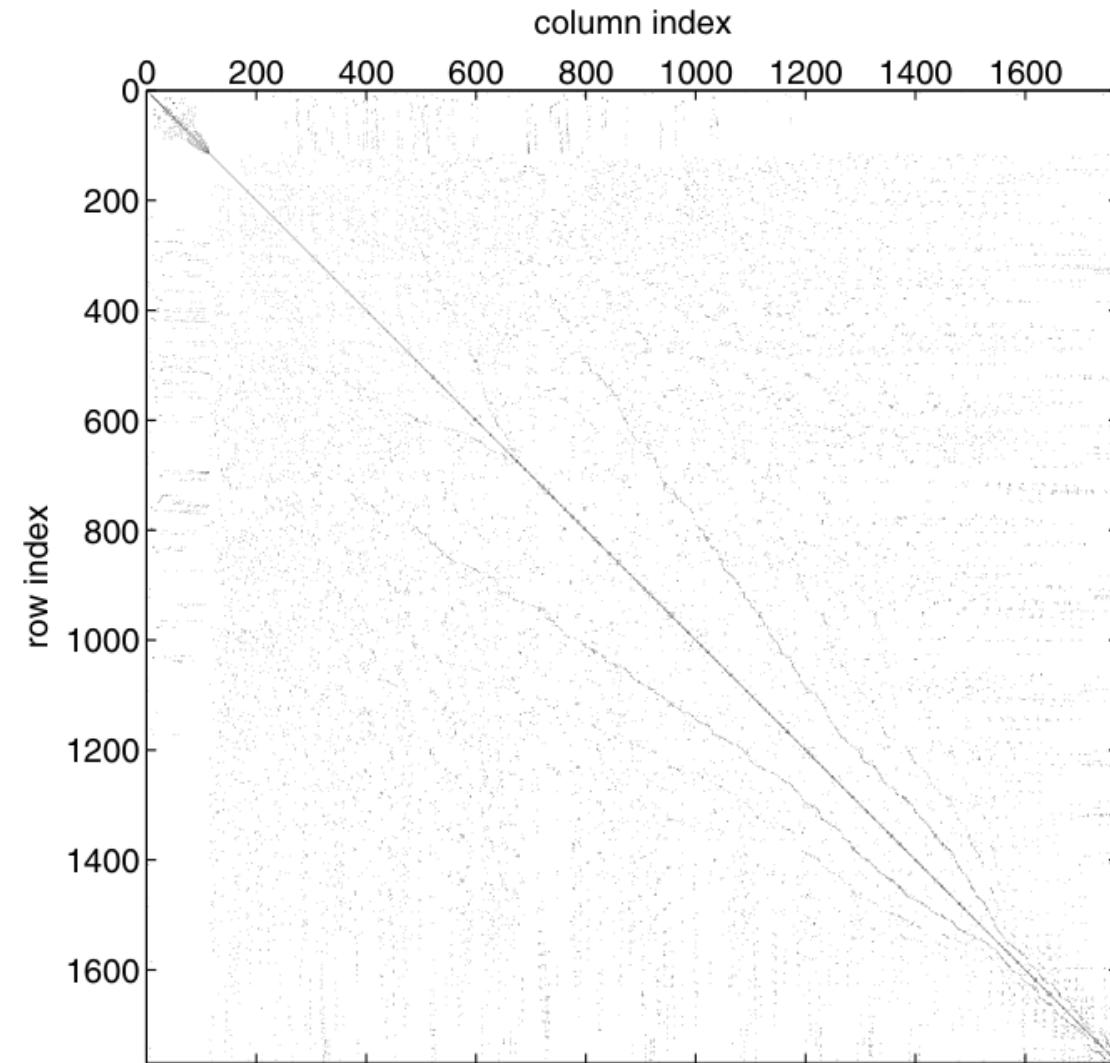
indirect solvers (fixed point iteration)

- gradient methods: steepest descent, conjugate gradients
- preconditioning: incomplete factorizations (of submatrices)

Cholesky decomposition

$$\mathbf{A} = \mathbf{LL}^T \quad \text{or} \quad \mathbf{A} = \mathbf{LDL}^T$$

Reordering



original (left) & reordered (right) matrix (Rücker et al. 2006)

Iterative solvers - Fixpunktverfahren

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

decompose $\mathbf{A} = \mathbf{M} - \mathbf{N}$ and solve

$$\mathbf{M}\mathbf{x} = \mathbf{N}\mathbf{x} + \mathbf{b}$$

iteratively by $\mathbf{x}^{k+1} = \mathbf{M}^{-1} (\mathbf{N}\mathbf{x}^k + \mathbf{b})$

e.g. $\mathbf{M} = \text{diag}(\mathbf{A})$ (Jacobi method) or
 $\mathbf{M} = \text{tril}(\mathbf{A})$ (Gauss-Seidel method)

Gradient methods

minimize residual $\mathbf{r} = \mathbf{b} - \mathbf{Ax}$

Steepest descent method

$$\mathbf{r}_0 = \mathbf{b} - \mathbf{A}\mathbf{x}_0$$

go towards \mathbf{r}_0 and minimize step length α

$$\mathbf{r}_1^T \mathbf{r}_0 = 0 = \mathbf{b} - \mathbf{A}(\mathbf{x}_0 + \alpha \mathbf{r}_0)$$

$$\Rightarrow \alpha = \frac{\mathbf{r}_0^T \mathbf{r}_0}{\mathbf{r}_0^T \mathbf{A} \mathbf{r}_0}$$

Steepest descent algorithm

for $i = 0, 1, \dots$

$$\mathbf{r}_i = \mathbf{b} - \mathbf{A}\mathbf{x}_i$$

$$\Rightarrow \alpha_i = \frac{\mathbf{r}_i^T \mathbf{r}_i}{\mathbf{r}_i^T \mathbf{A} \mathbf{r}_i}$$

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \alpha_i \mathbf{r}_i$$

Conjugate directions

Set of orthogonalen directions \mathbf{d} with

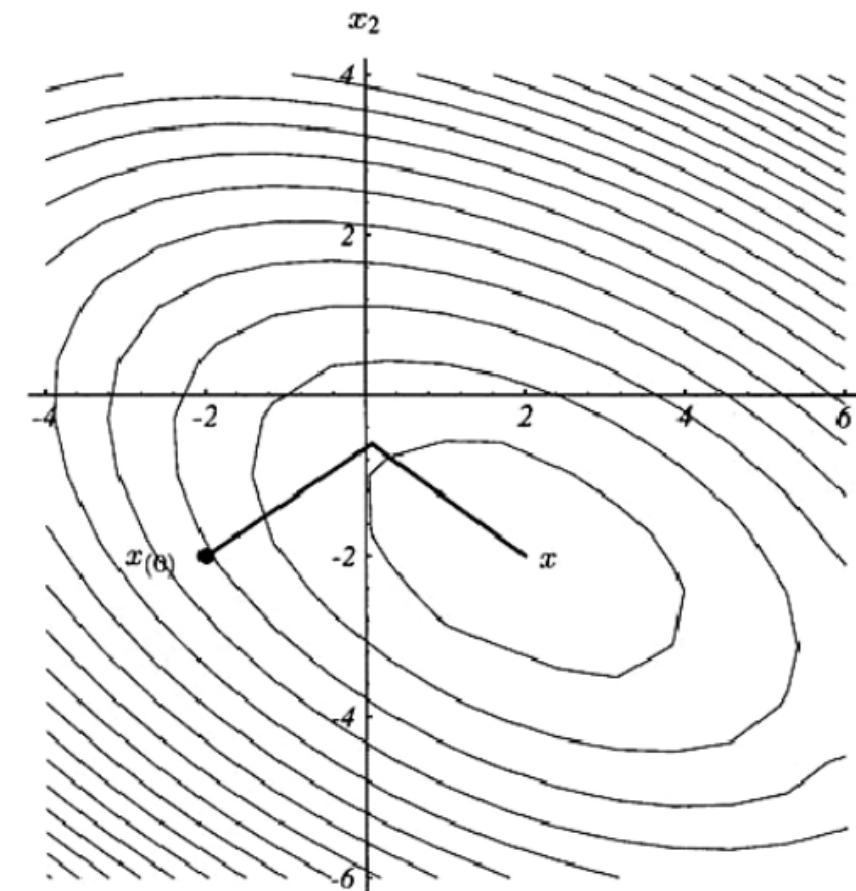
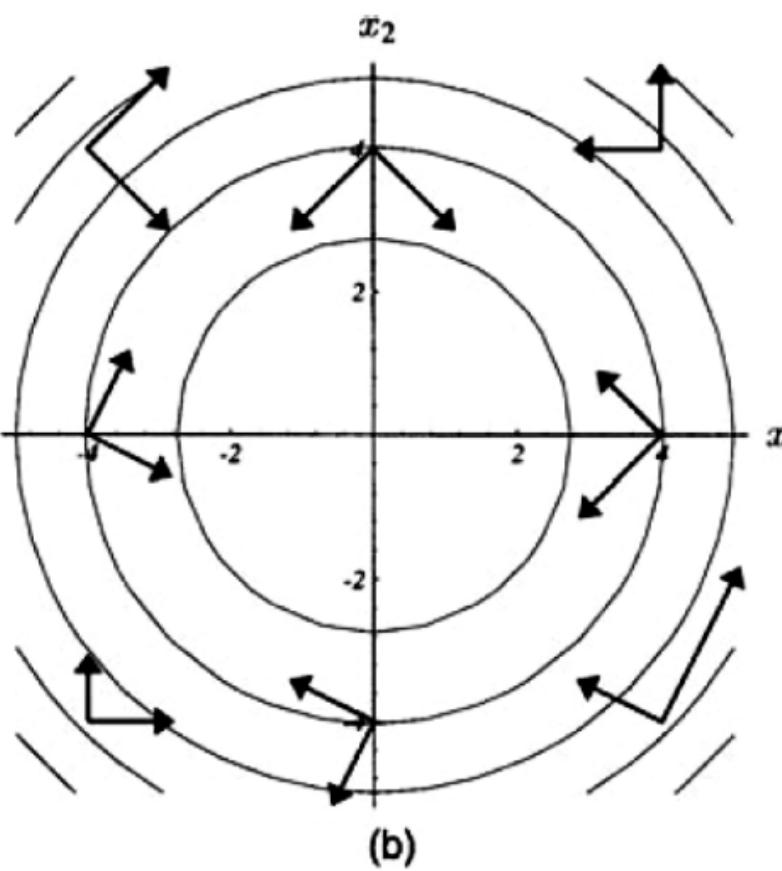
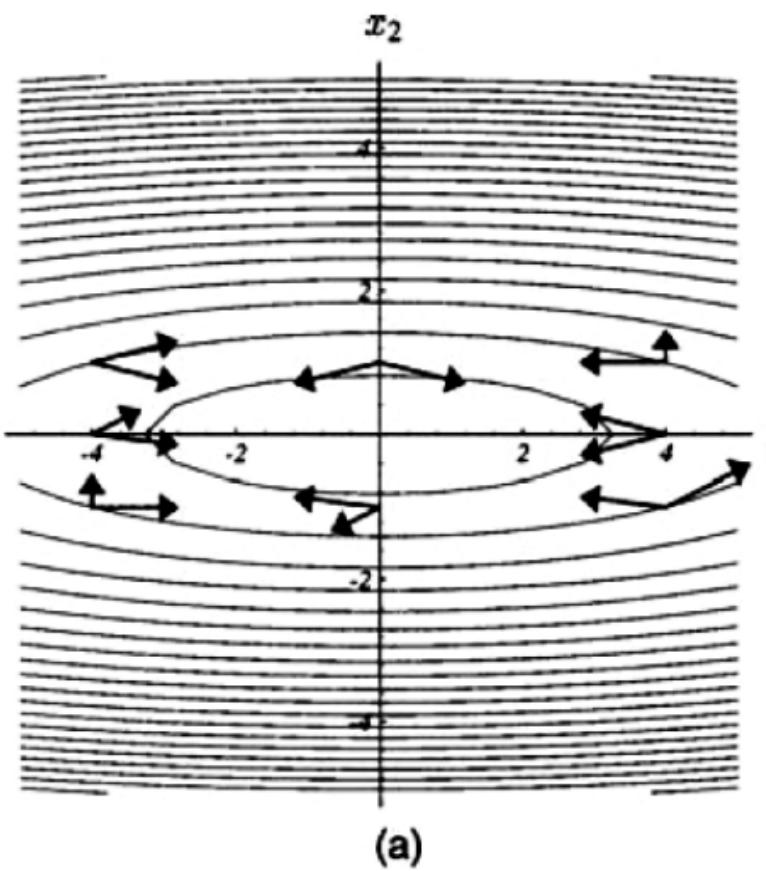
$$\mathbf{d}_i^T \mathbf{A} \mathbf{d}_j = 0 \quad \forall i \neq j$$

Note

every search direction is only used once

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \alpha_i \mathbf{d}_i$$

Conjugate directions



Conjugate gradient (Hestenes&Stiefel, 1952)

$$\mathbf{d}_0 = \mathbf{r}_0 = \mathbf{b} - \mathbf{A}\mathbf{x}_0$$

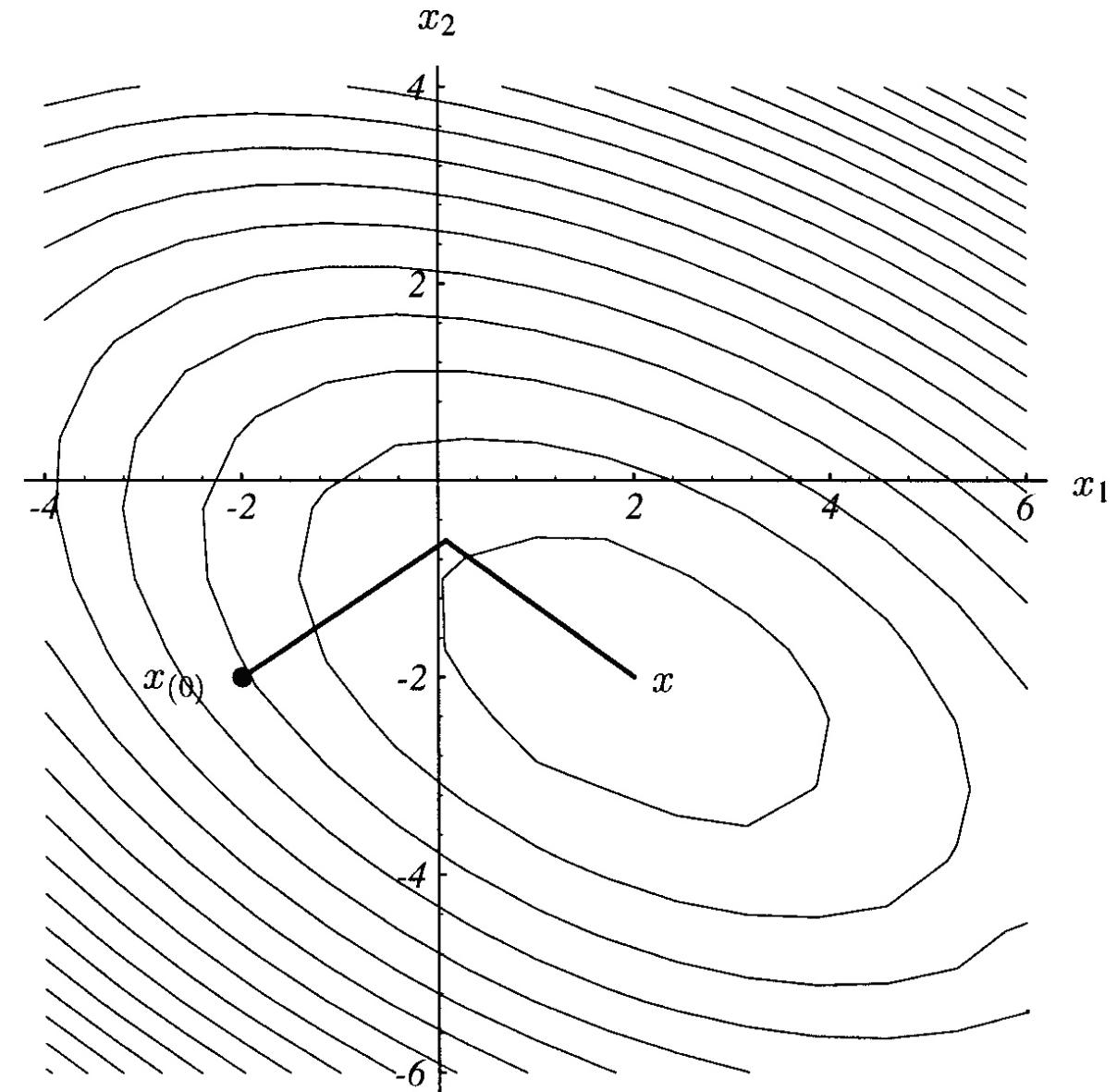
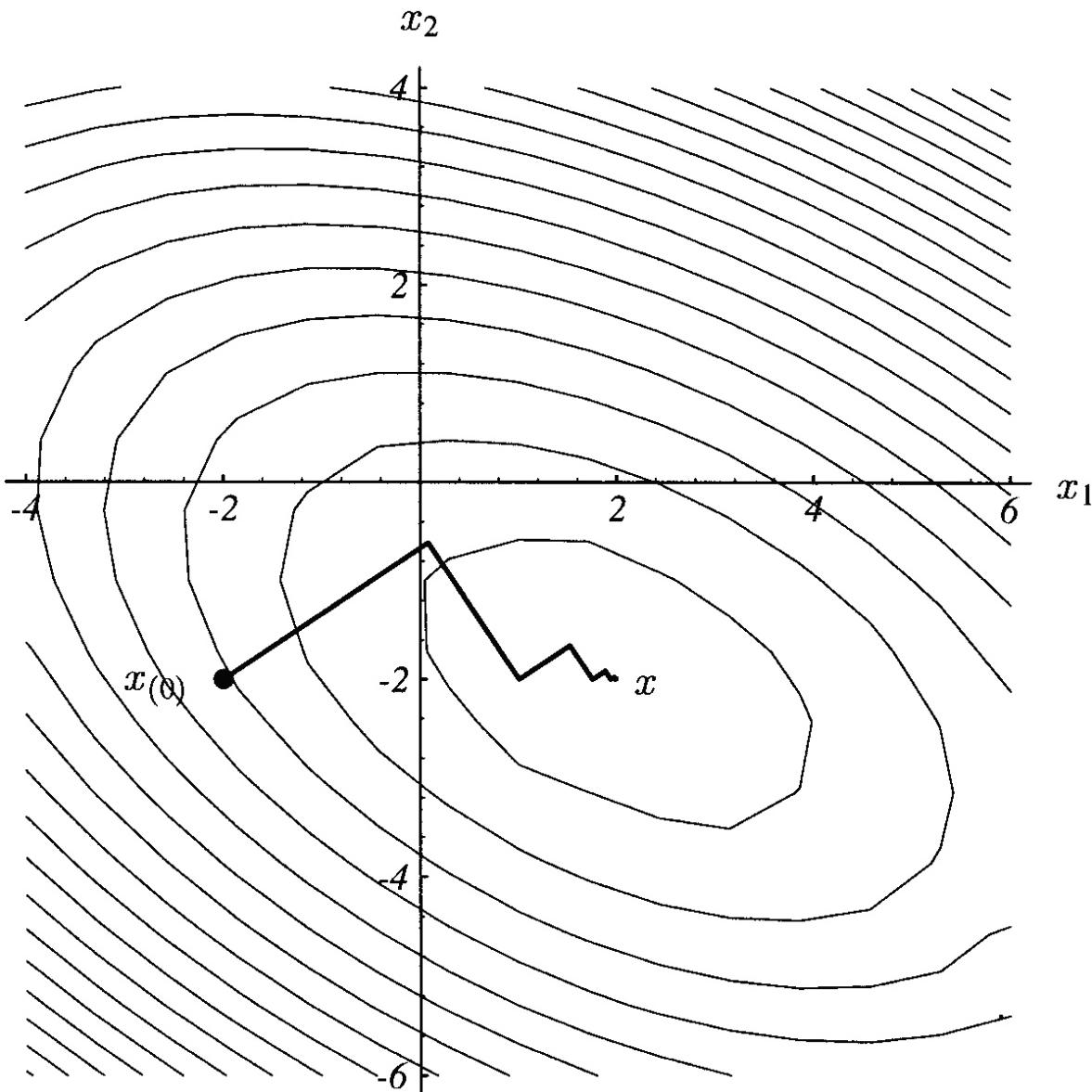
$$\alpha_i = \frac{\mathbf{r}_i^T \mathbf{r}_i}{\mathbf{d}_i^T \mathbf{A} \mathbf{d}_i}$$

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \alpha_i \mathbf{d}_i$$

$$\mathbf{r}_{i+1} = \mathbf{r}_i - \alpha_i \mathbf{A} \mathbf{d}_i$$

$$d_{i+1} = \mathbf{r}_{i+1} + \mathbf{d}_{i+1} \frac{\mathbf{r}_{i+1}^T \mathbf{r}_{i+1}}{\mathbf{r}_i^T \mathbf{r}_i}$$

Steepest descent vs. conjugate gradient



Preconditioning

$\mathbf{Ax} = \mathbf{b}$ often badly conditioned (elongated) \Rightarrow slow convergence

Idea: transform (precondition) equation system by preconditioner \mathbf{K}

$$\mathbf{K}^{-1}\mathbf{Ax} = \mathbf{K}^{-1}\mathbf{b}$$

Extreme cases: 1. $\mathbf{K} = \mathbf{I}$, cheap PC but no gain

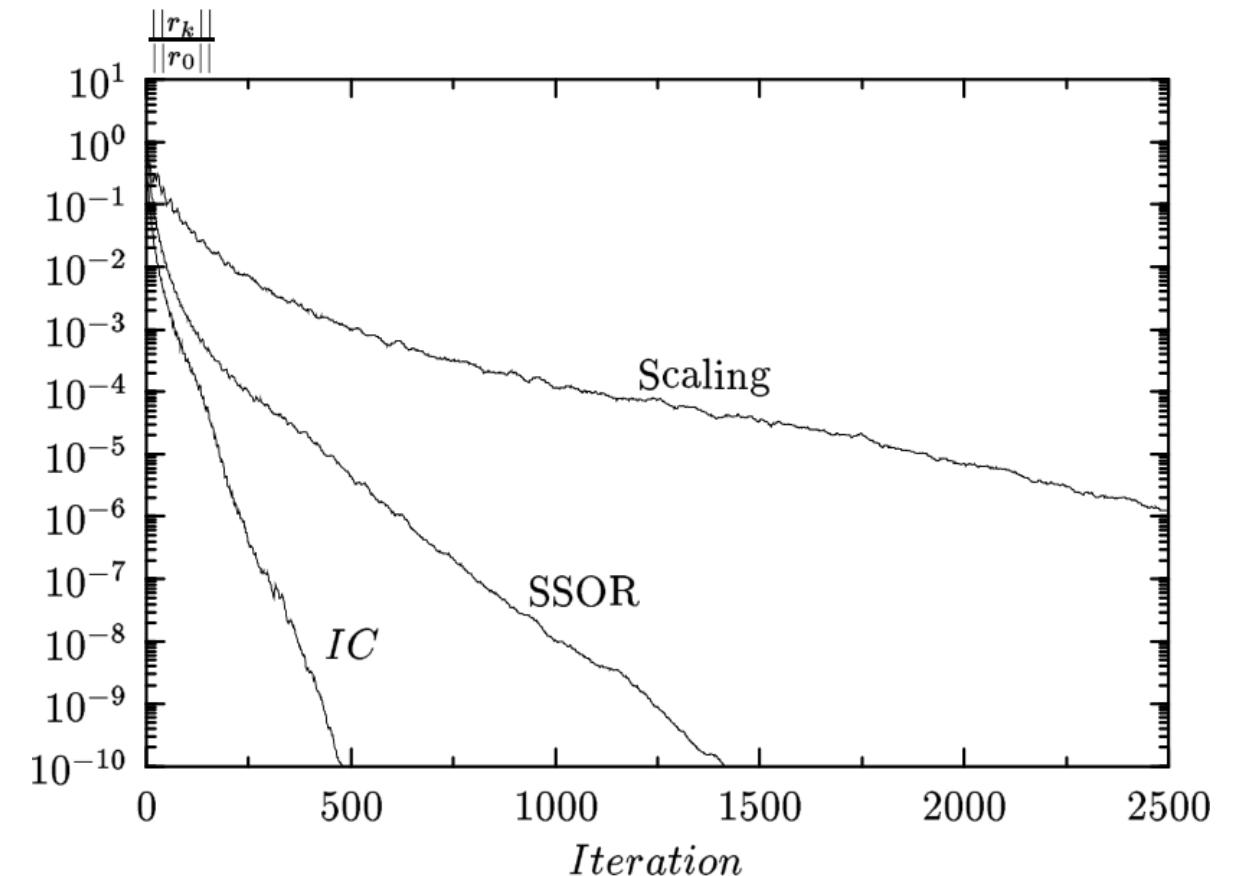
2. $\mathbf{K} = \mathbf{A}$, perfect conditioning but expensive PC

e.g. $\mathbf{K} = \text{diag} A$ or $\mathbf{K} = \epsilon \text{tril} A$

Incomplete Cholesky decomposition

$$\mathbf{A} \approx \mathbf{LL}^T$$

with certain accuracy or sparsity



Preconditioning

EM problem

$$\mathbf{B} = \begin{pmatrix} \mathbf{A} & -\omega\mathbf{M} \\ \omega\mathbf{M} & \mathbf{A} \end{pmatrix}$$

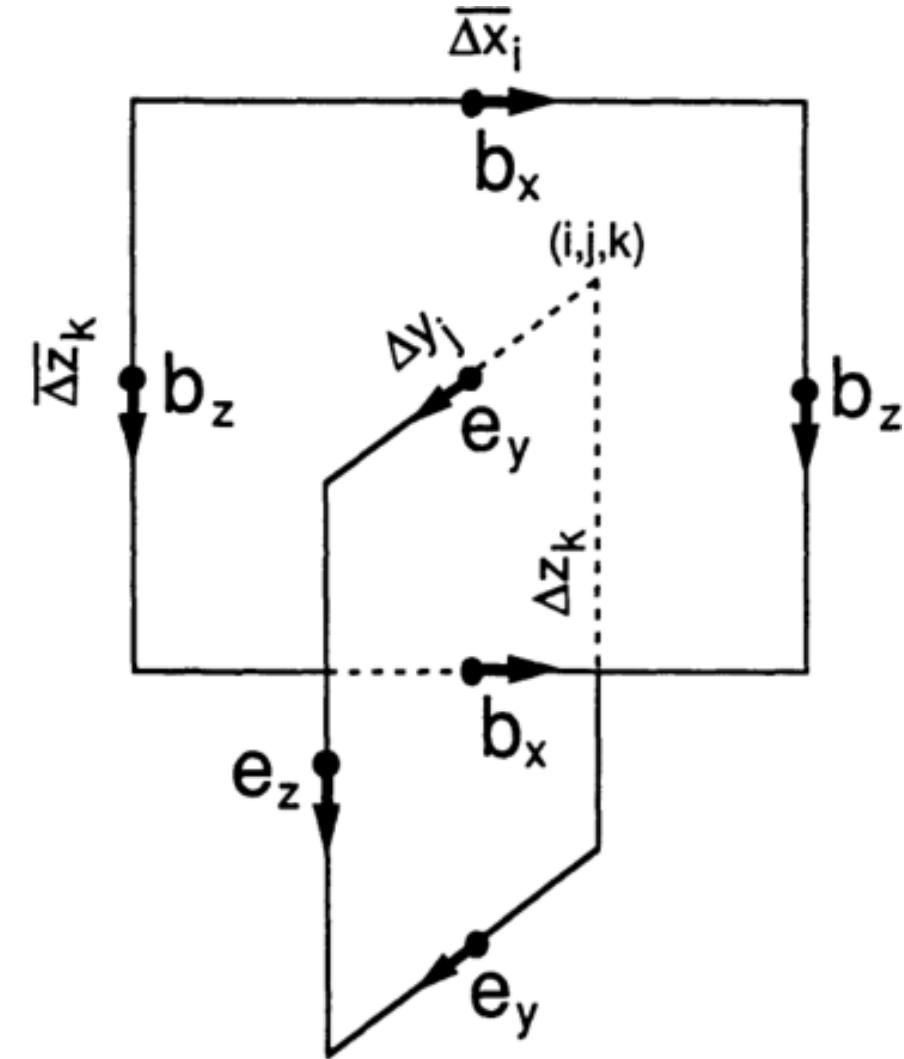
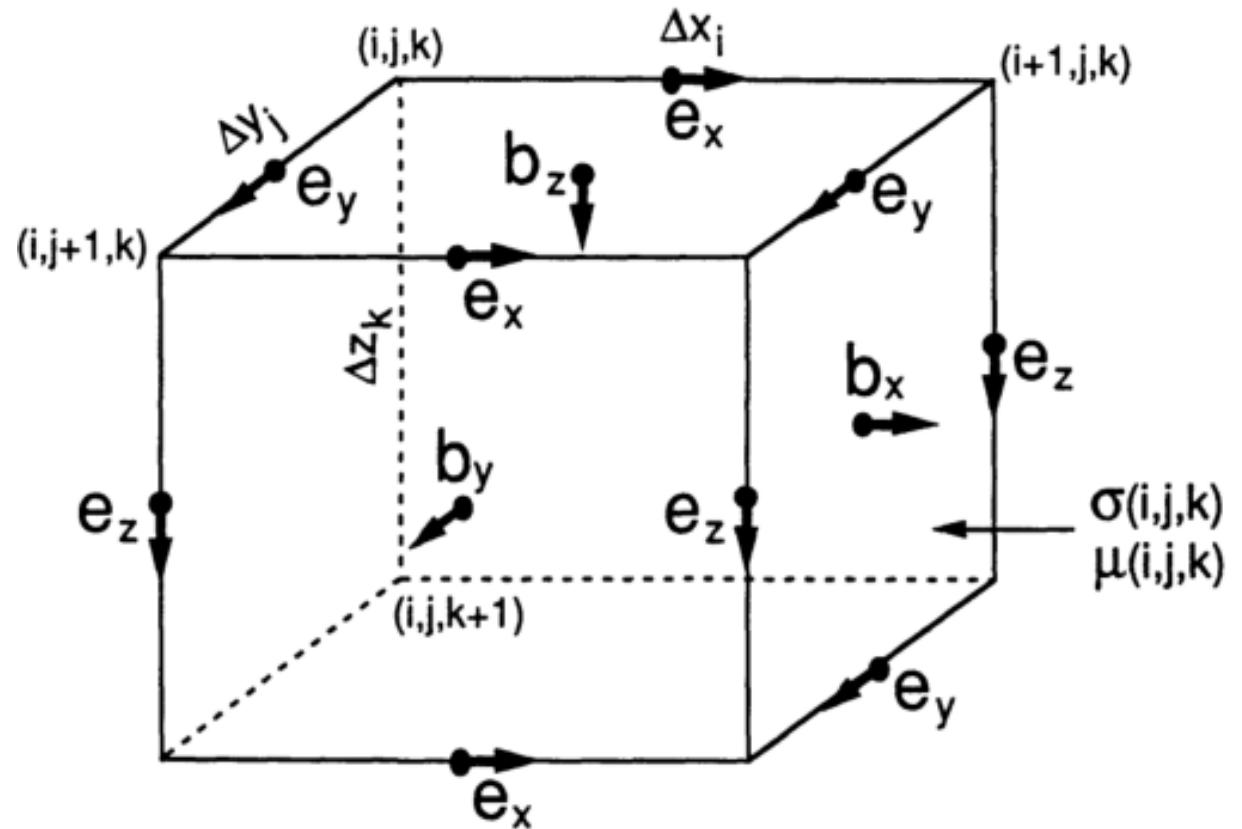
$$\mathbf{K} = \begin{pmatrix} \mathbf{A} + \omega\mathbf{M} & 0 \\ 0 & \mathbf{A} + \omega\mathbf{M} \end{pmatrix}$$

or Schur complement. E.g., hold factorization of \mathbf{A} and \mathbf{M} in memory

Development of EM modelling

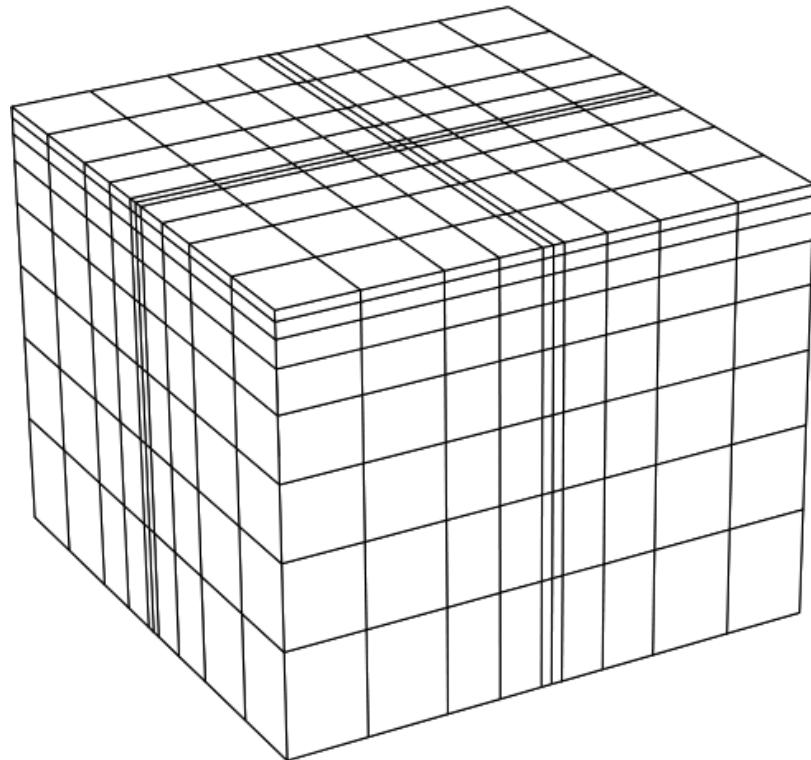
- approaches: integral equations (IE), finite differences (FD) and elements (FE)
- decompose 3D source (2D inverse) problems in wavenumber domains
- improvement of equation solvers and preconditioners
-

Solving EM problems with staggered grid

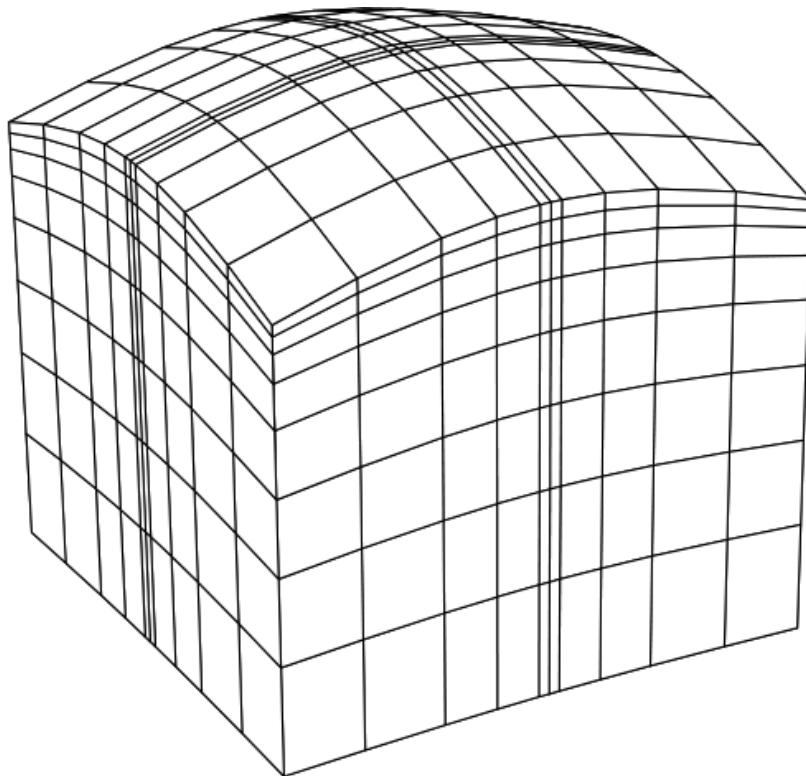


Staggered grid cell after Yee (1966)

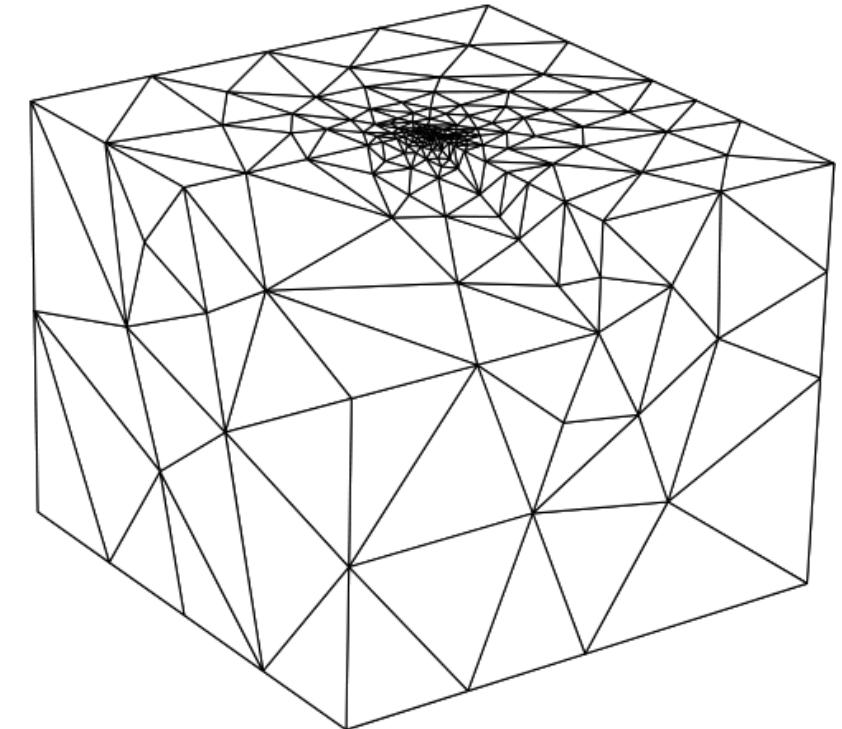
The way from FD to FE



(a)



(b)



(c)

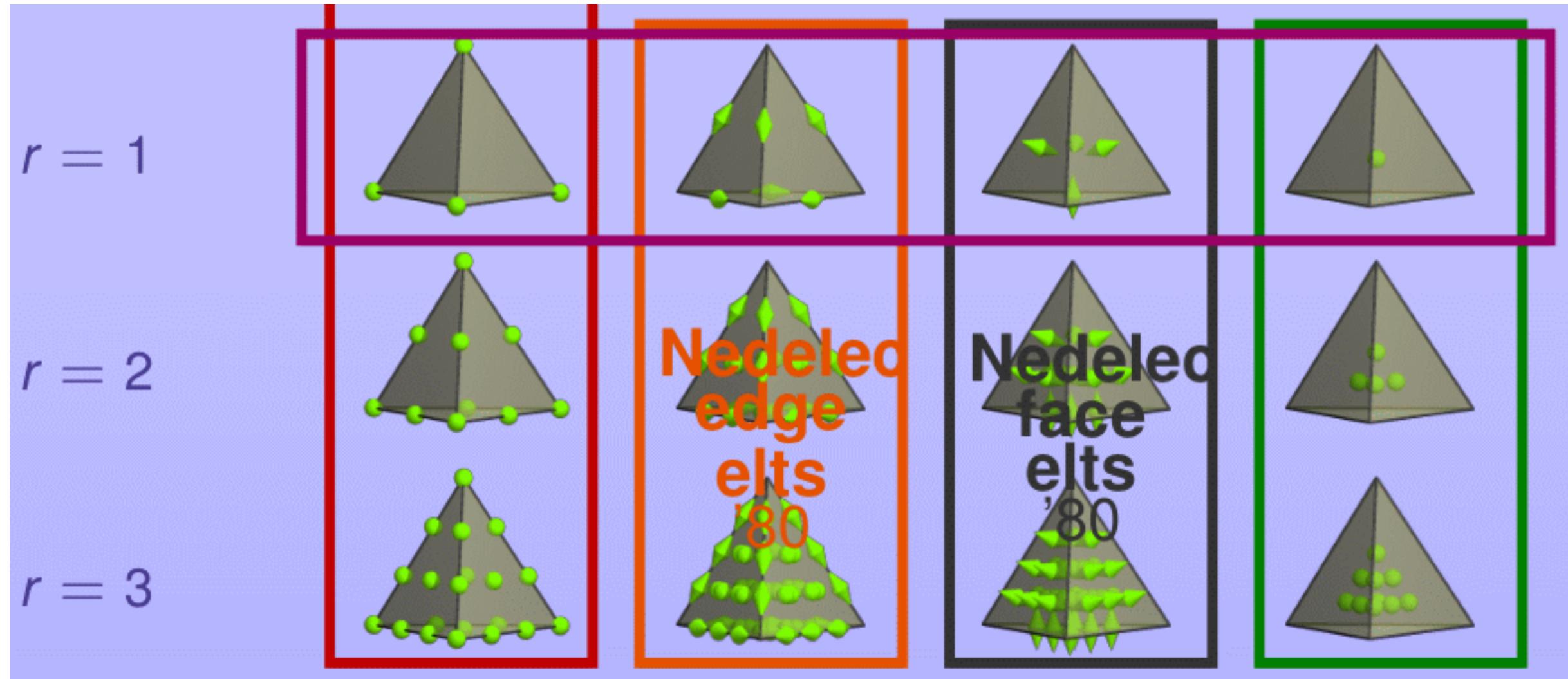
Figure 1. Different grid types: Orthogonal cuboid (a), non-orthogonal hexahedral (b) and unstructured tetrahedral (c) grid.

Orthogonal, non-orthogonal and irregular grids (Rücker et al., 2006)

The Finite Element zoo (1D & 2D)

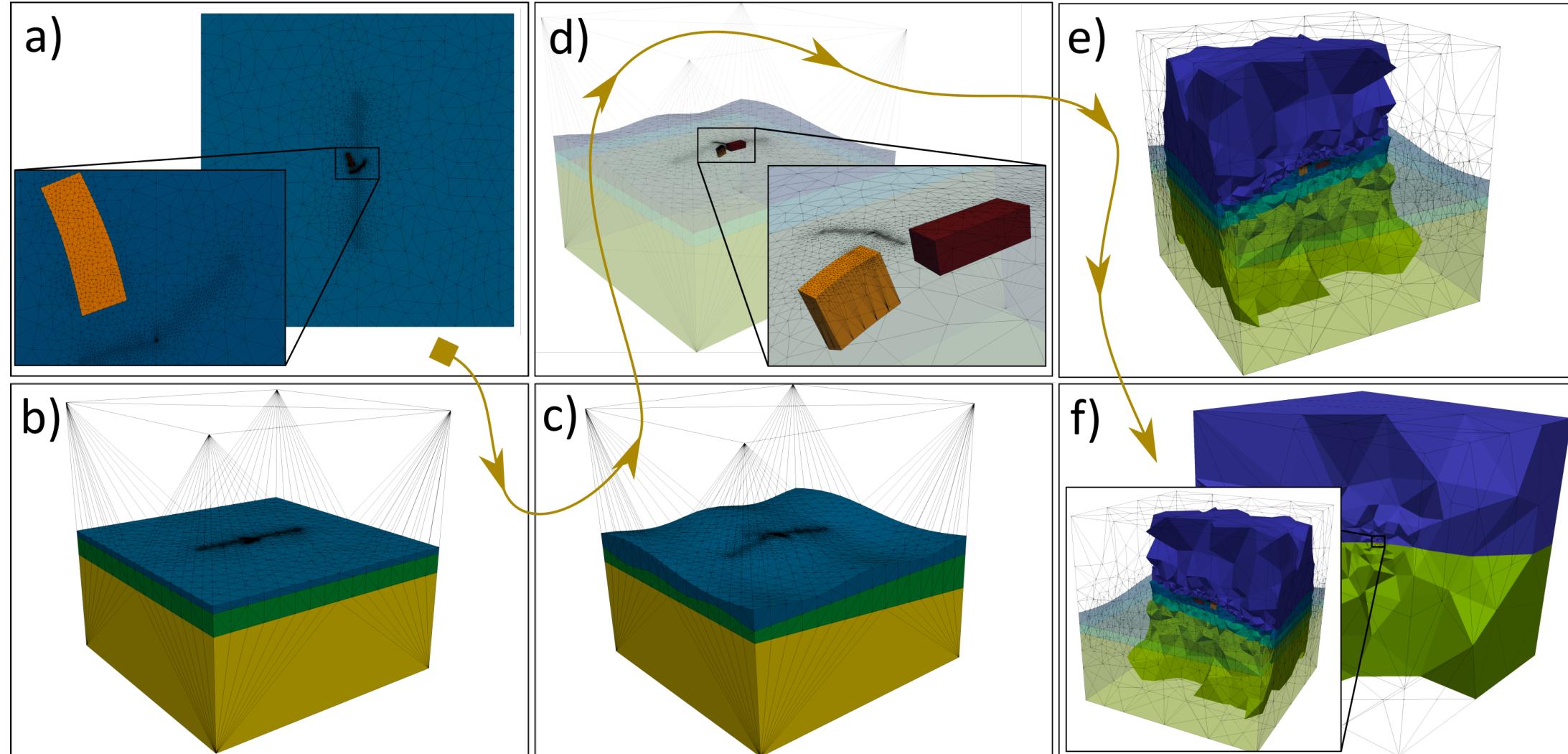
	$k = 0$	$k = 1$	$k = 2$	$k = 3$
$r = 1$				$\sum_i (-)^i \lambda_i d\lambda_0 \wedge \cdots \wedge d\lambda_{k-1}$
$r = 2$				
$r = 3$				
Lagrange				

The Finite Element zoo (3D)



Arnold, Periodic table of elements

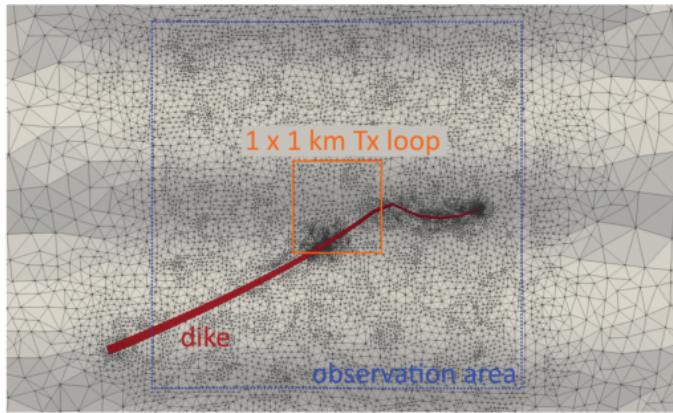
Meshing complicated geometries



Mesher workflow in custEM (Rochlitz et al., 2019)

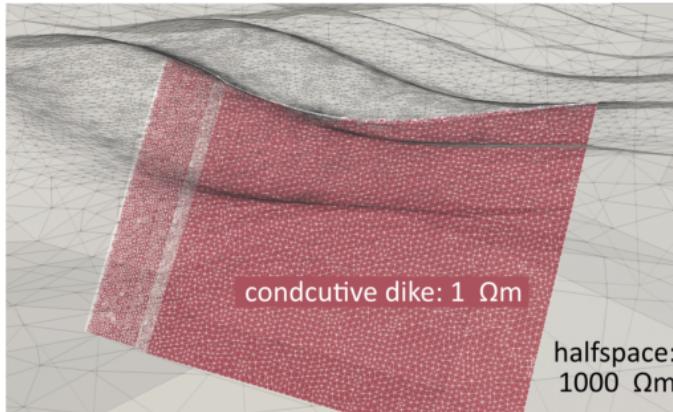
Modelling example

a) surface view (bird perspective)

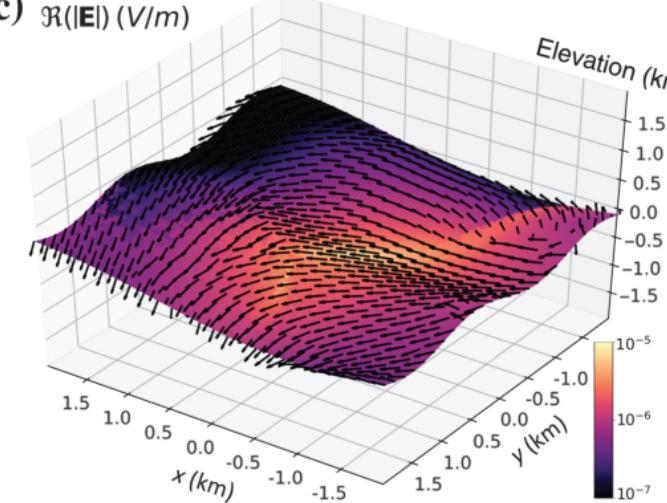


b) horizontal view

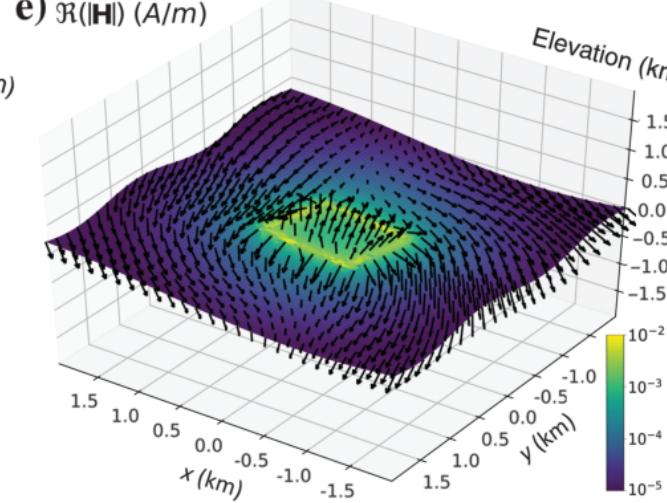
varying sinusoidal topography in x- and y-directions



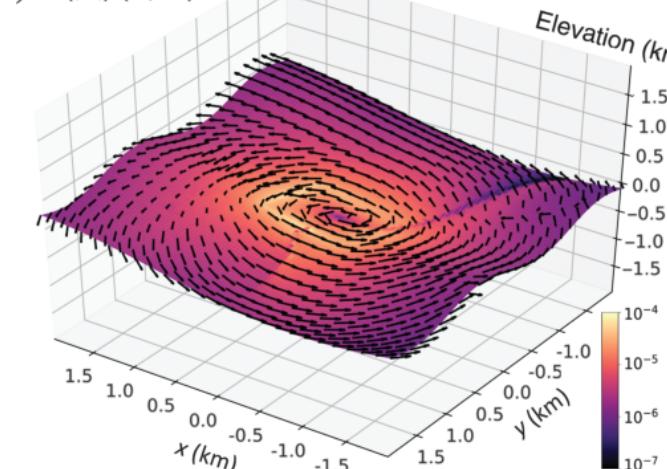
c) $\Re(|\mathbf{E}|)$ (V/m)



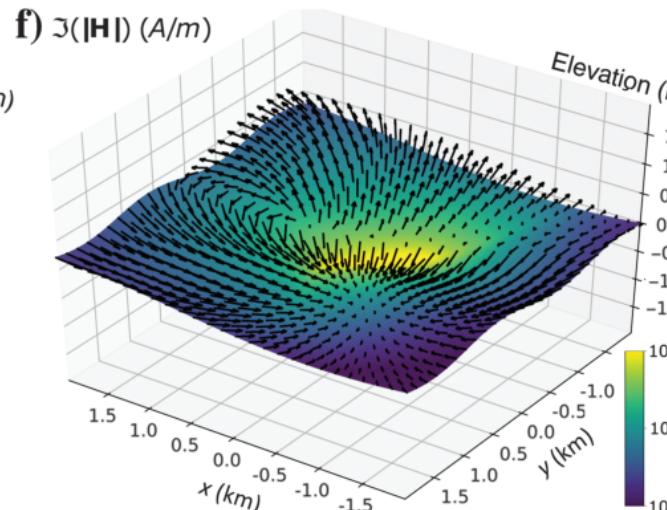
e) $\Re(|\mathbf{H}|)$ (A/m)



d) $\Im(|\mathbf{E}|)$ (V/m)



f) $\Im(|\mathbf{H}|)$ (A/m)



Modelling example of a conductive dike (Rochlitz et al., 2019)

Packages

Mesh generation: [TetGen](#) (3D), [GMsh](#) (2D/3D)

FE packages: [FEniCS](#), [NETGEN/NGsolve](#)

Equation solvers: [SuiteSparse](#), [MUMPS](#), [SciPy](#)

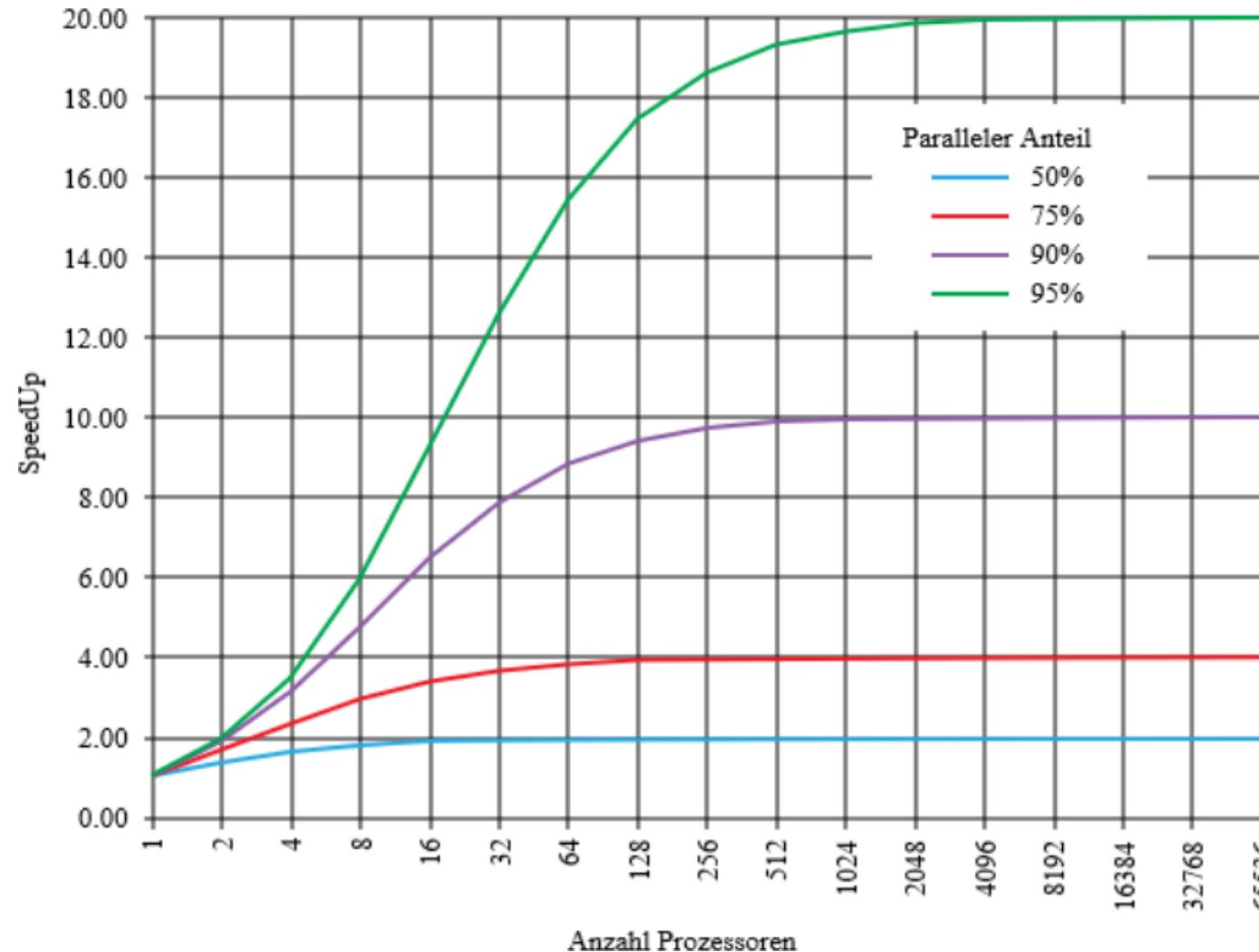
Computational frameworks: [PetSc](#), [MPI](#)

EM modelling (and inversion) packages: [Mare2DEM](#), [emg3d](#), [GoFEM](#),
[PETGEM](#), [custEM](#), [SimPEG](#), [ModEM](#), [FEMTIC](#)

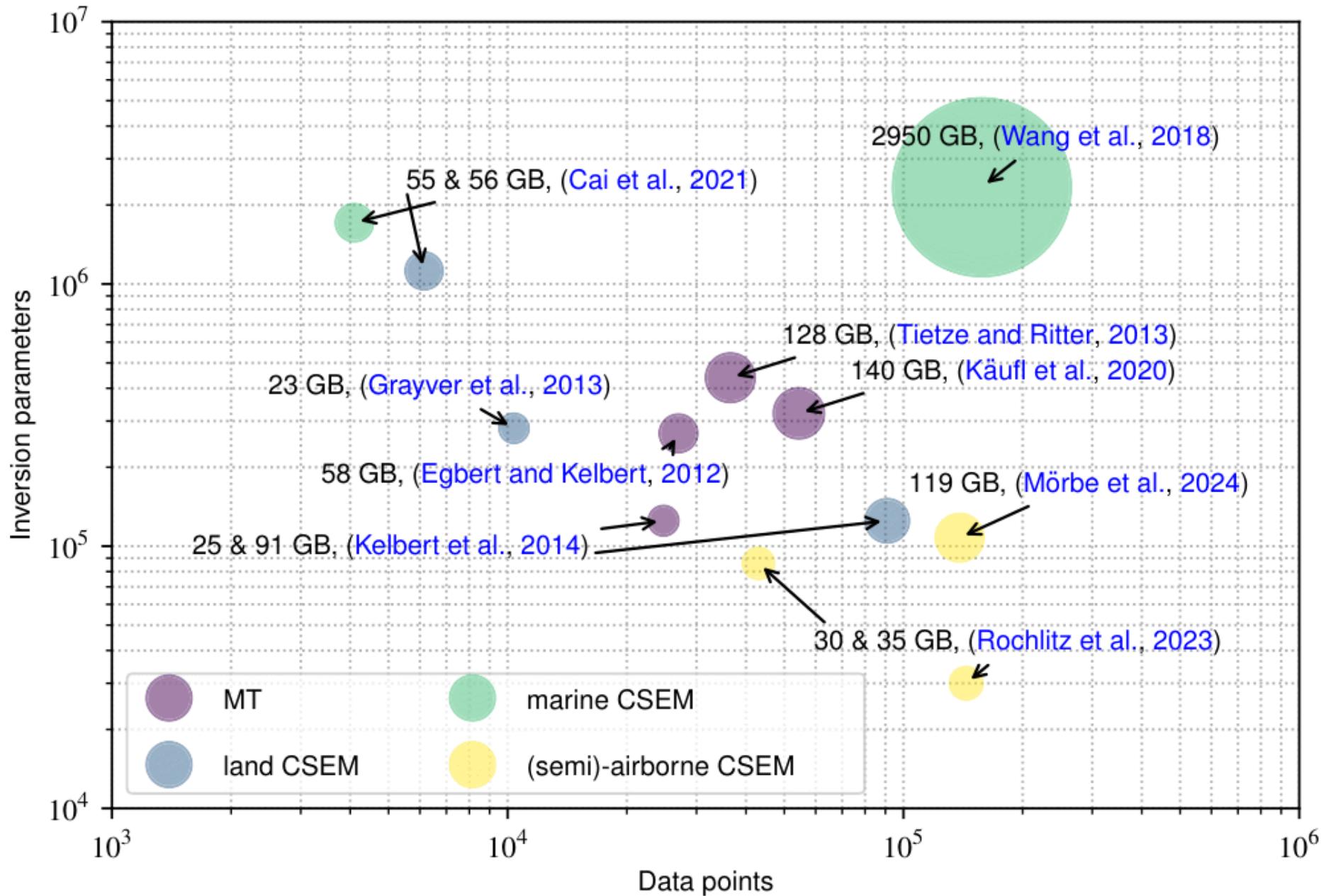
Performance on Parallel machines

Amdahlsches Gesetz

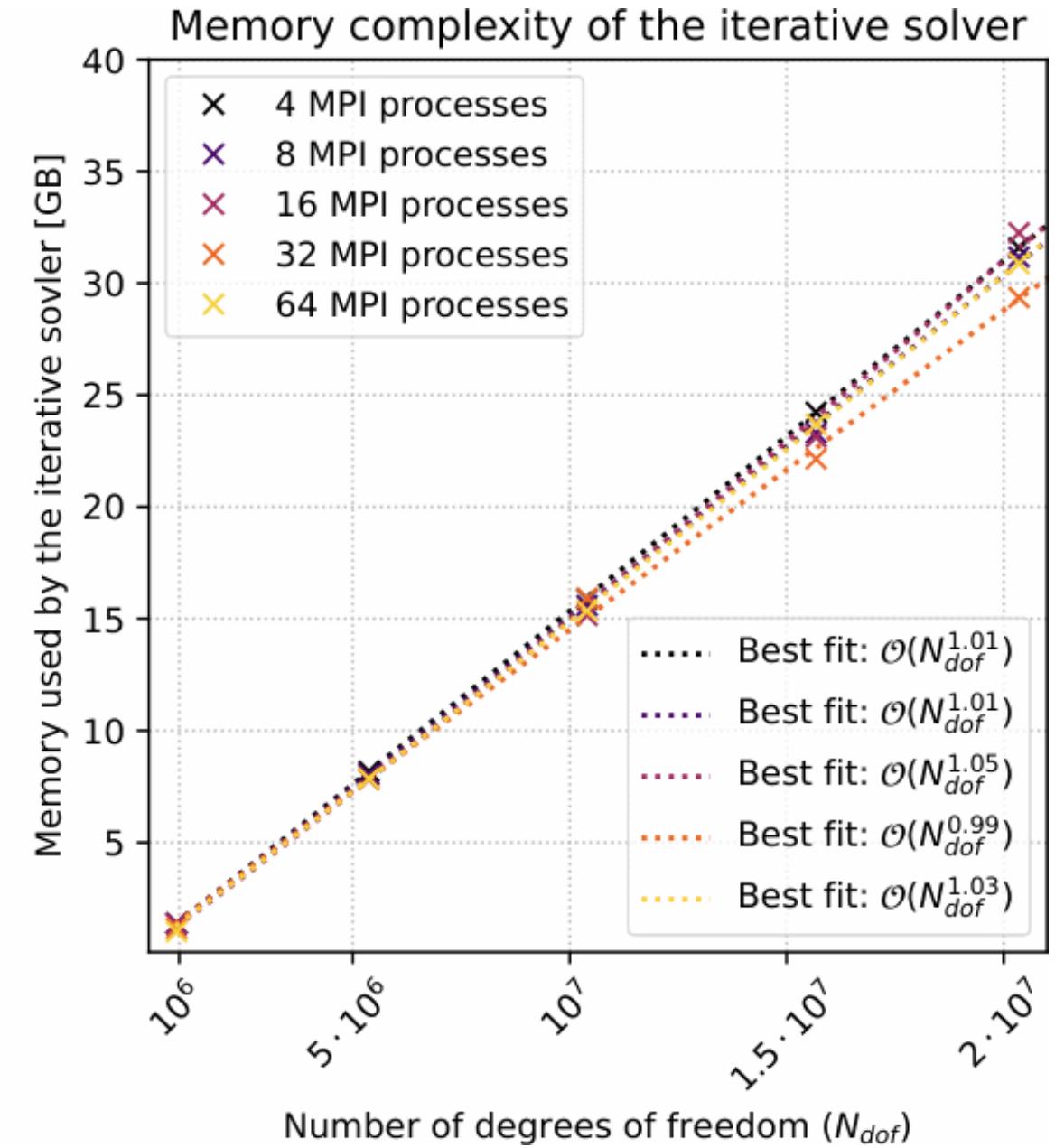
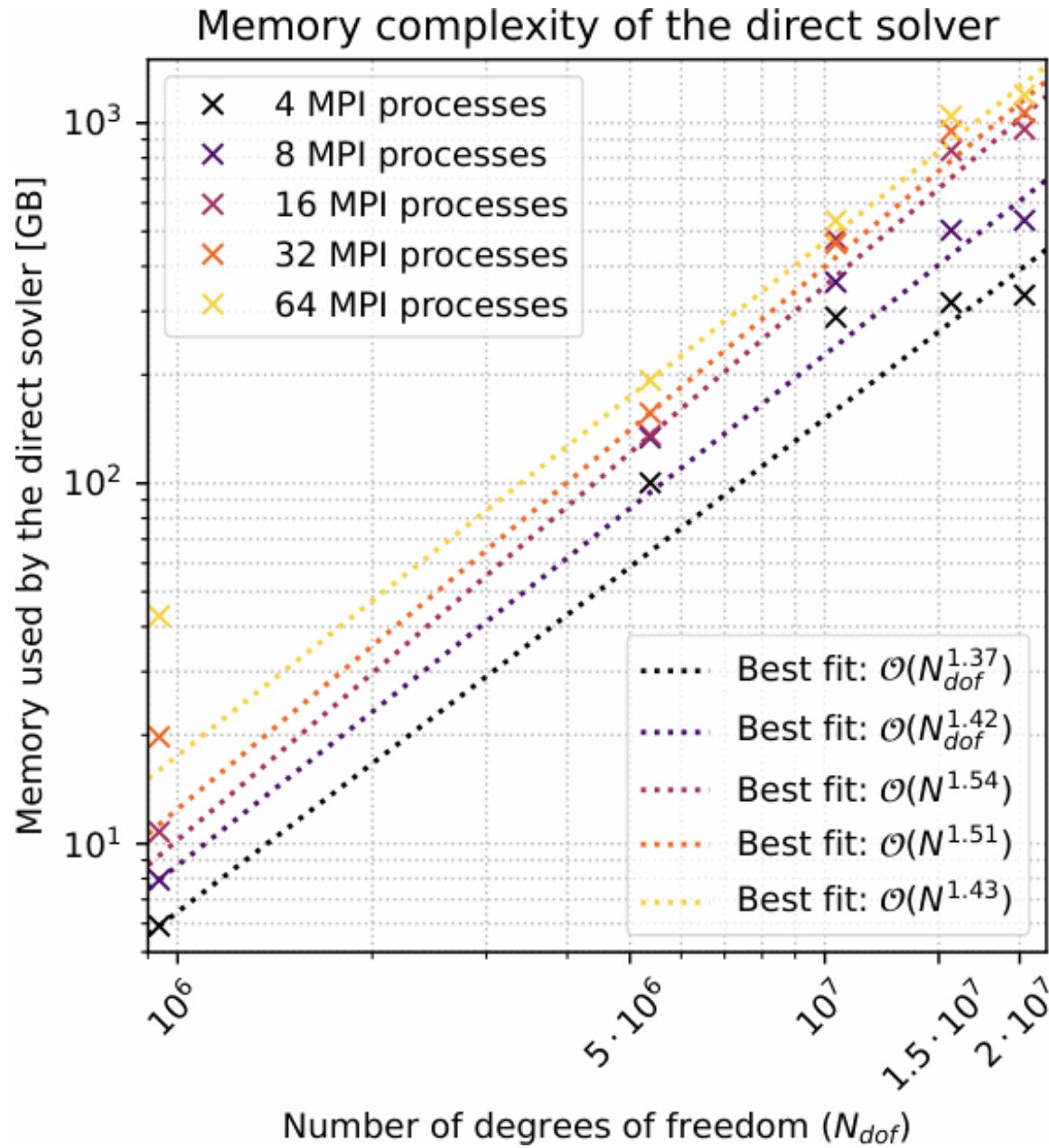
Zerlegung in seriellen und parallelen Anteil $t = t_s + t_p/N(+t_c(N))$



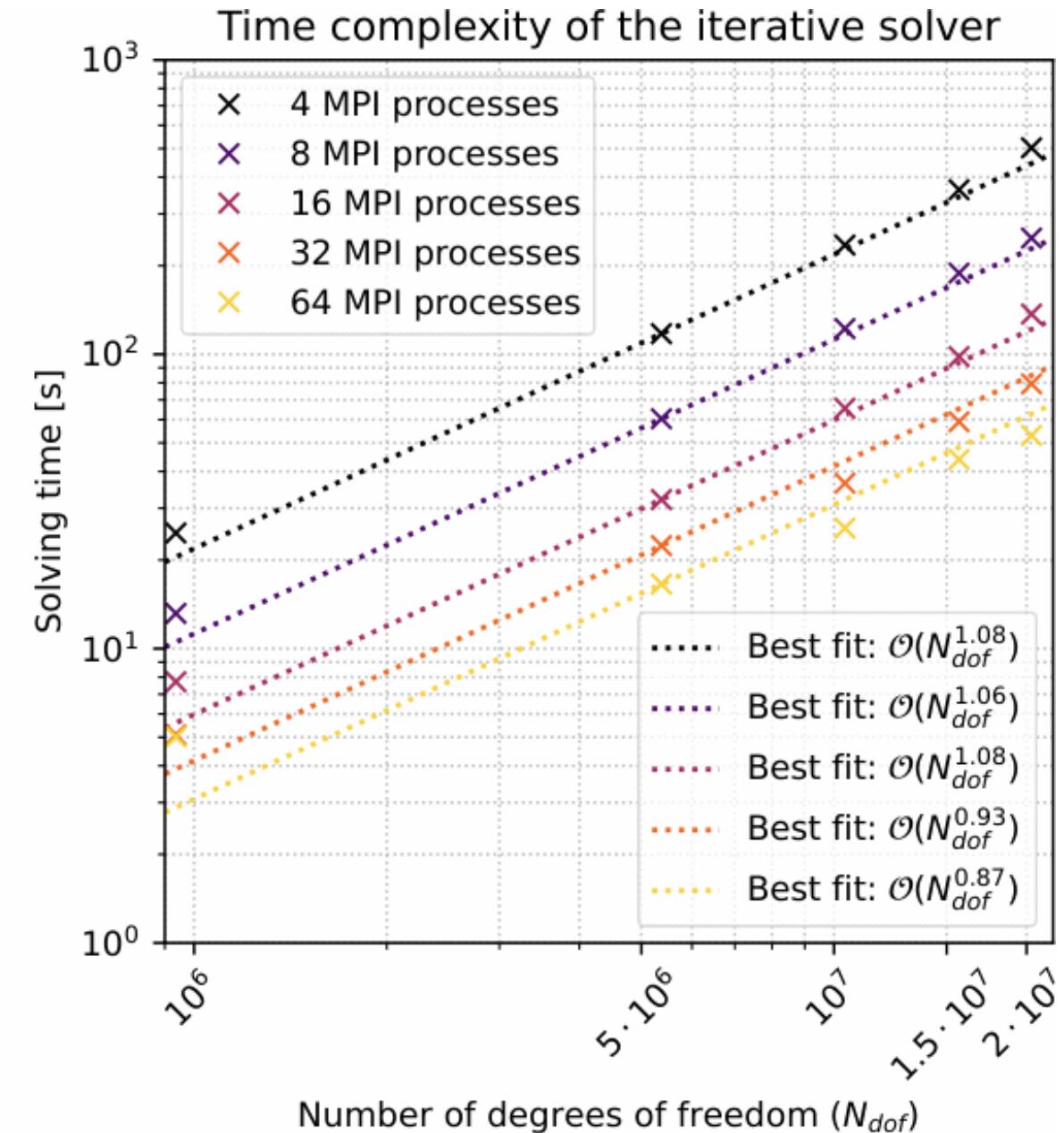
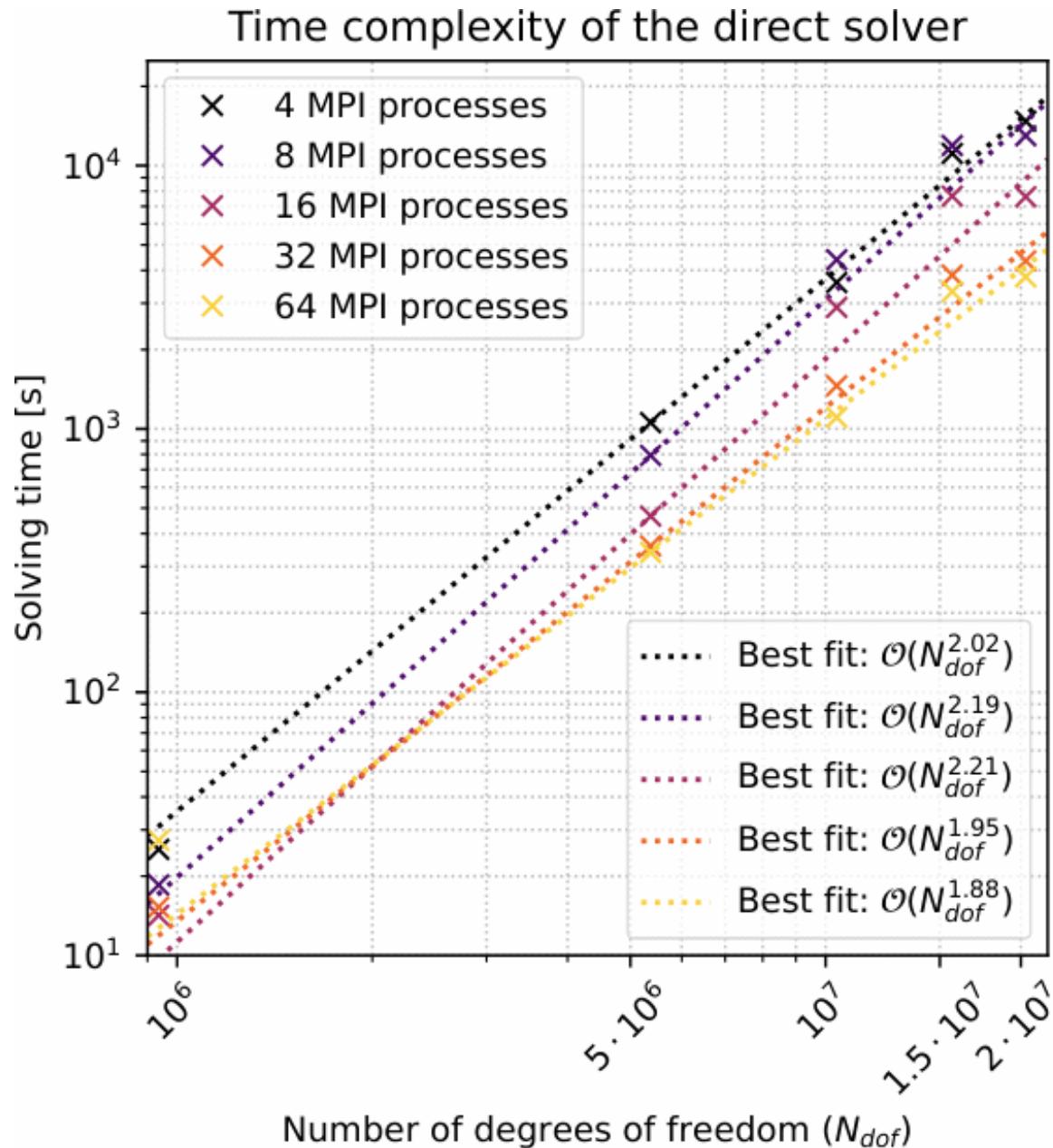
Computational size



Performance analysis - Memory

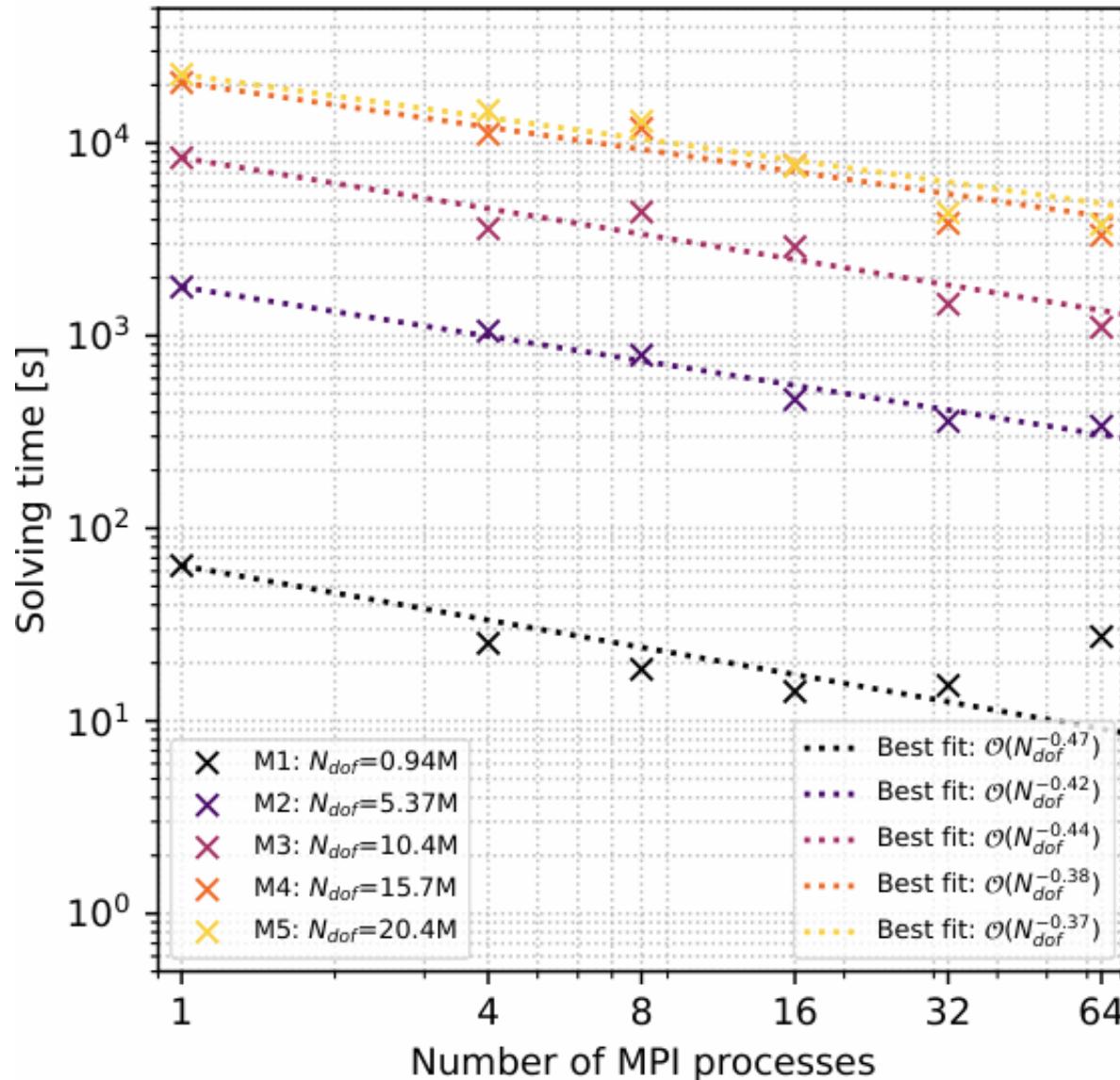


Performance analysis - Time

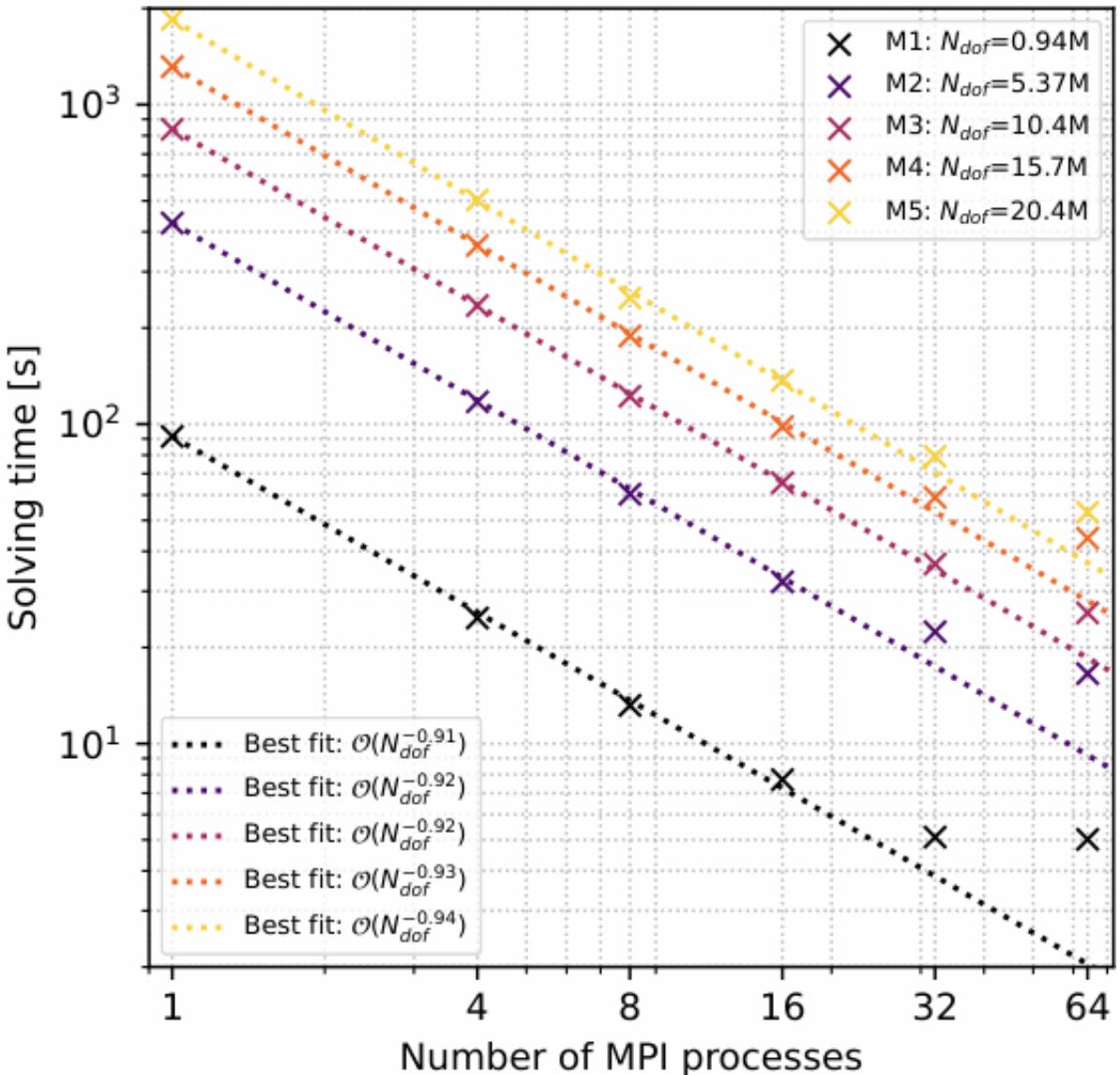


Performance analysis - MPI scaling

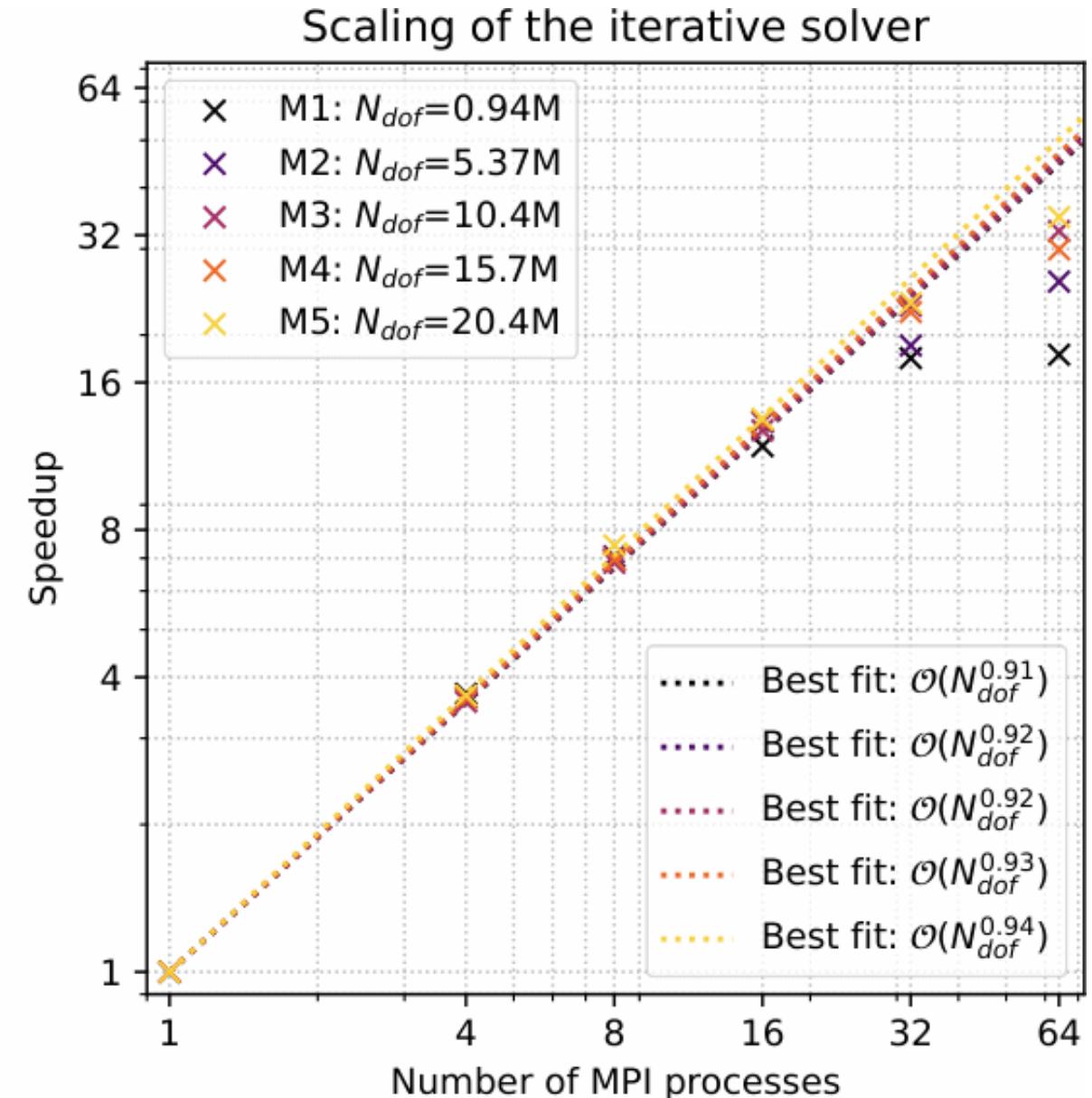
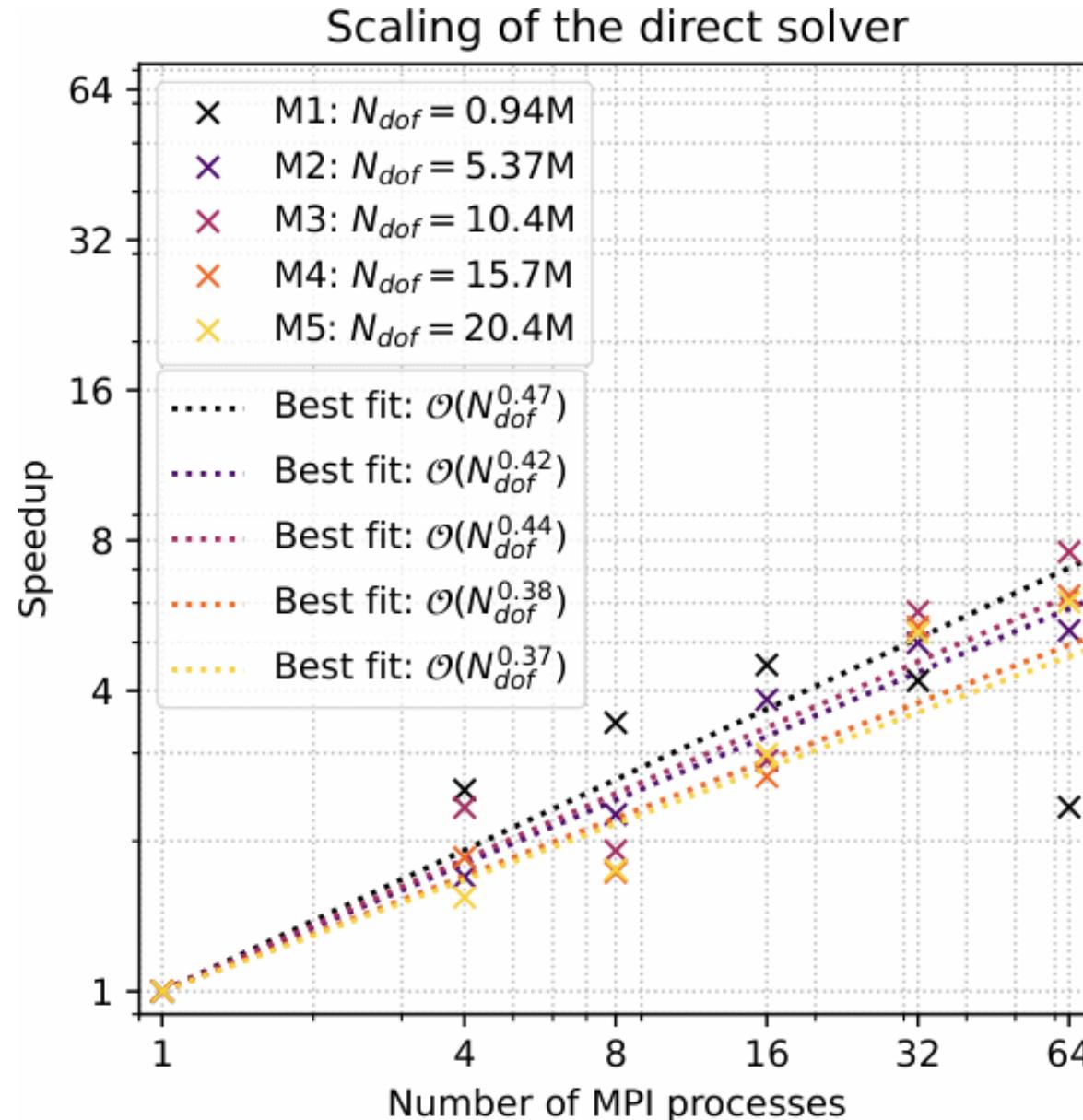
Parallel performance of the direct solver



Parallel performance of the iterative solver



Performance analysis - MPI scaling



Multiple right-hand sides

