capturing knowledge in code

simpeg and geosci

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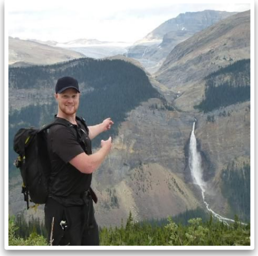

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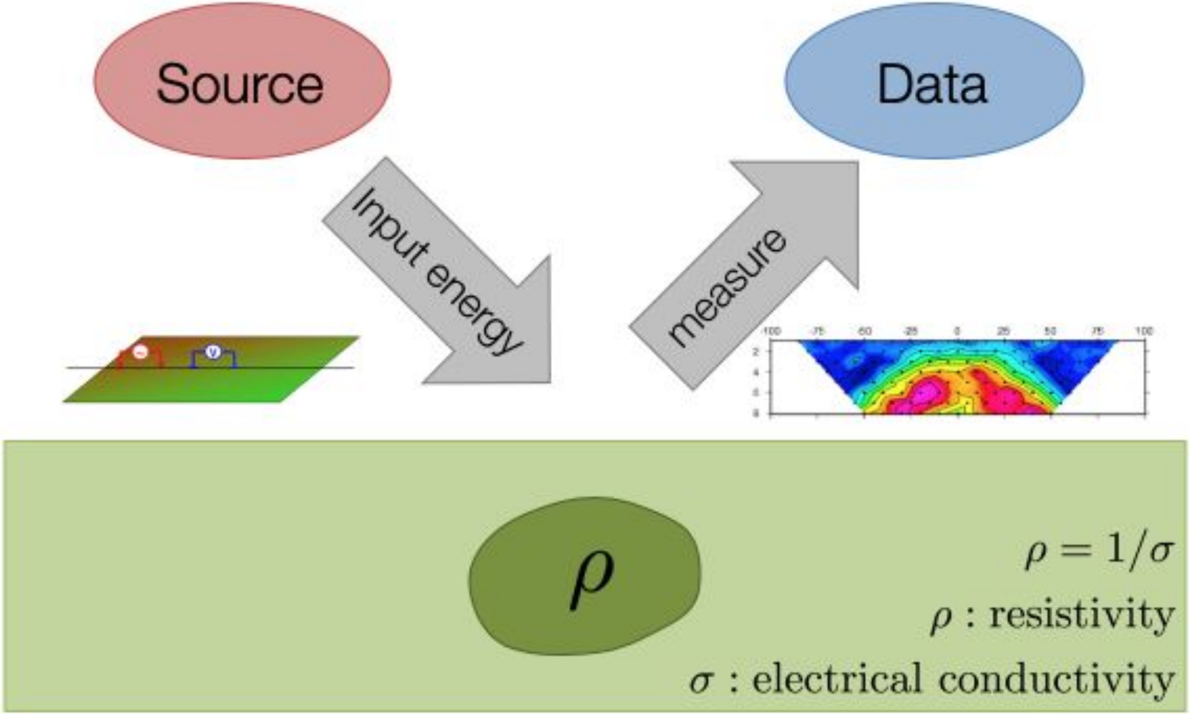
Last week:
Fundamentals of Inversion
Doug Oldenburg

http://www.mtnet.info/EMinars/EMinars.html

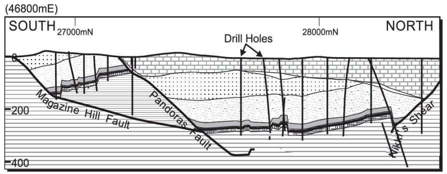
Geophysical experiments & physical properties

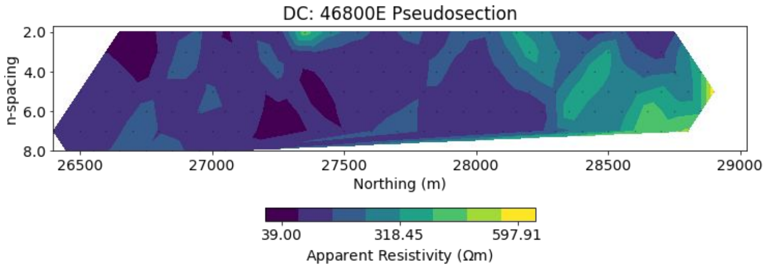


Last week: DC resistivity and IP at century

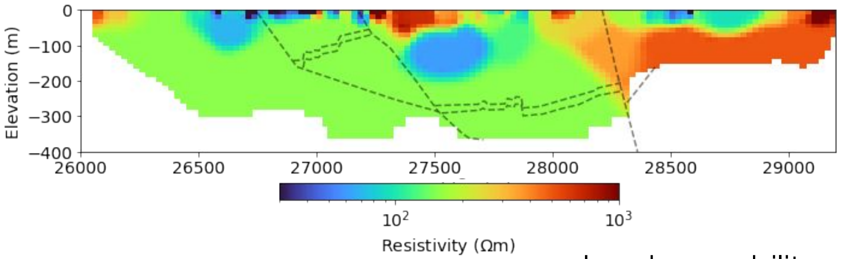
Last week: Century Deposit

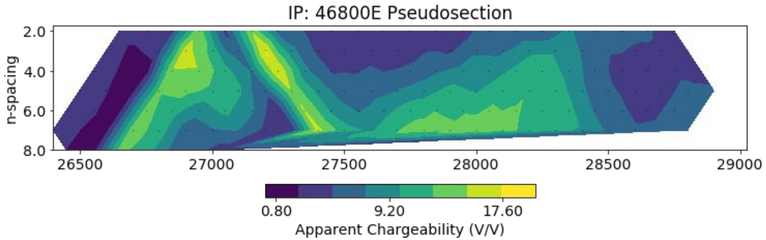
- IP: linear inverse problem
- DC: non-linear inverse problem



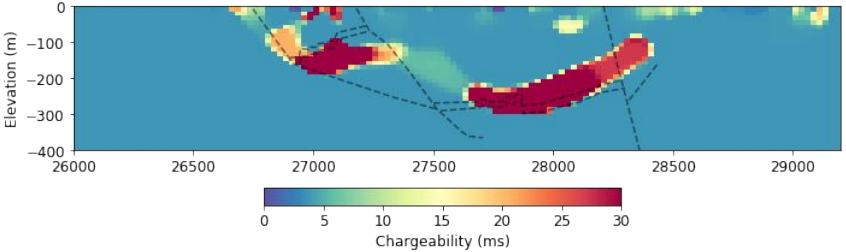


Lp resistivity





Lp chargeability



DC resistivity

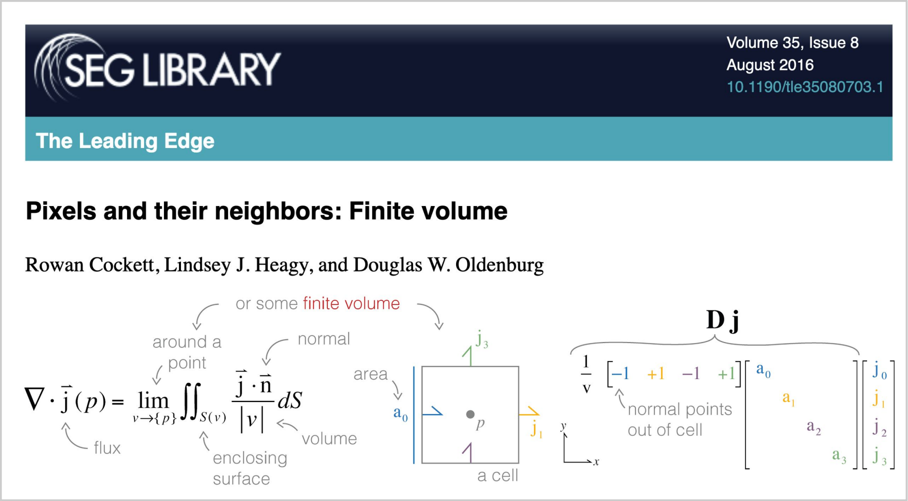
Governing PDE

$$\boxed{\nabla \cdot \frac{1}{\rho} \nabla \phi = -I\delta(r)}$$

DC is an illustrative problem

- foundation for the physics of EM
- poisson equation, starting point: numerical simulations, finite volume
- inverse problem: non-linear, ideal example for showing impacts of: model norm, constraints, …

Finite Volume Tutorial (Cockett et al, 2016)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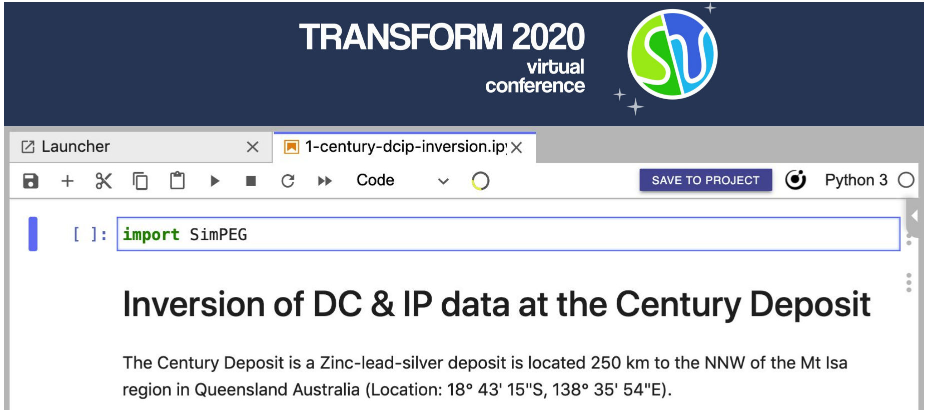
The Leading Edge

Pixels and their neighbors: Finite volume

Rowan Cockett, Lindsey J. Heagy, and Douglas W. Oldenburg

$$\nabla \cdot \vec{j}(p) = \lim_{v \to \{p\}} \iint_{S(v)} \frac{\vec{j} \cdot \vec{n}}{|v|} dS$$

Inversions with SimPEG (Heagy, 2020)




```
[ ]: import SimPEG
```

Inversion of DC & IP data at the Century Deposit

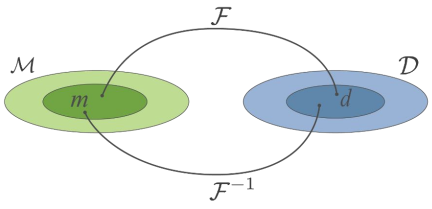
The Century Deposit is a Zinc-lead-silver deposit is located 250 km to the NNW of the Mt Isa region in Queensland Australia (Location: 18° 43' 15"S, 138° 35' 54"E).

Focus for today: electromagnetics

Theory: Maxwell's equations, inversion

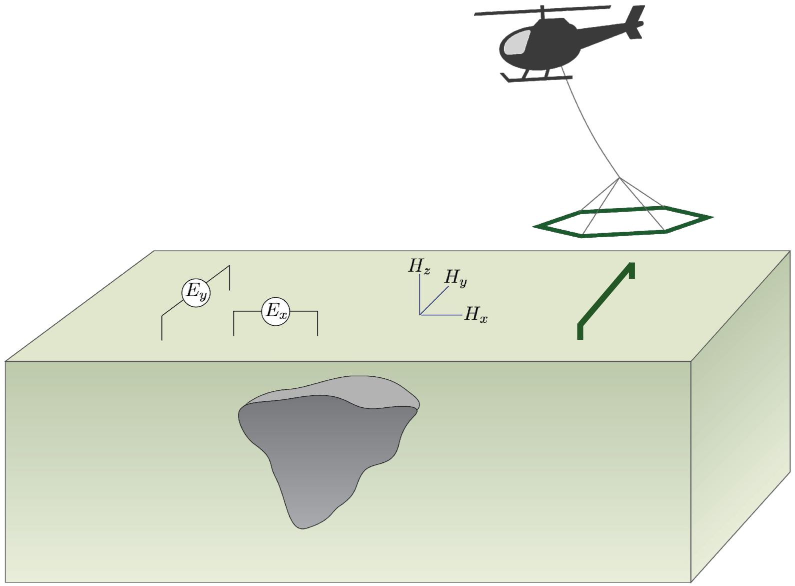
$$\nabla \times \vec{e} = -\frac{\partial \vec{b}}{\partial t}$$

$$\nabla \times \vec{h} = \vec{j} + \frac{\partial \vec{d}}{\partial t}$$

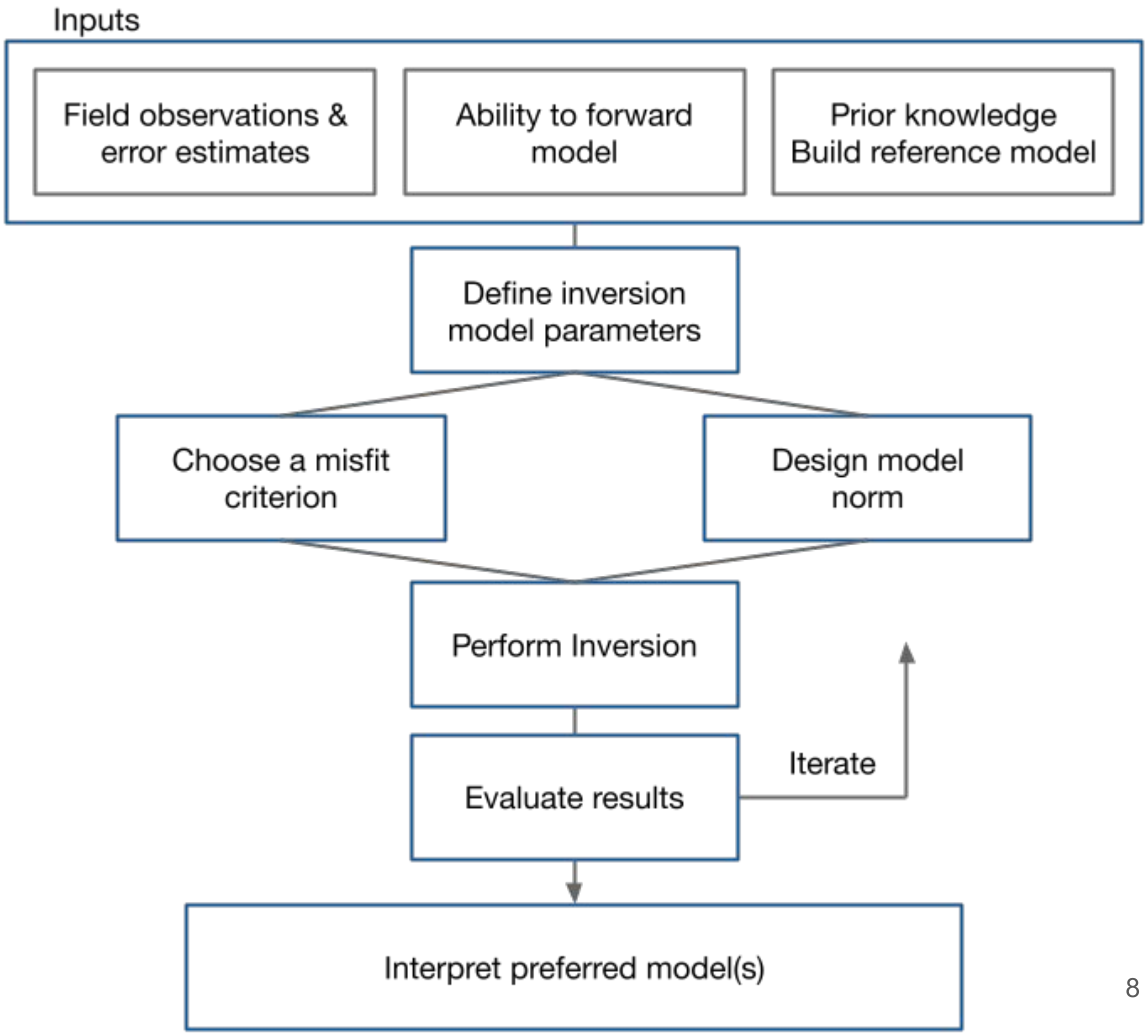


Captured in code

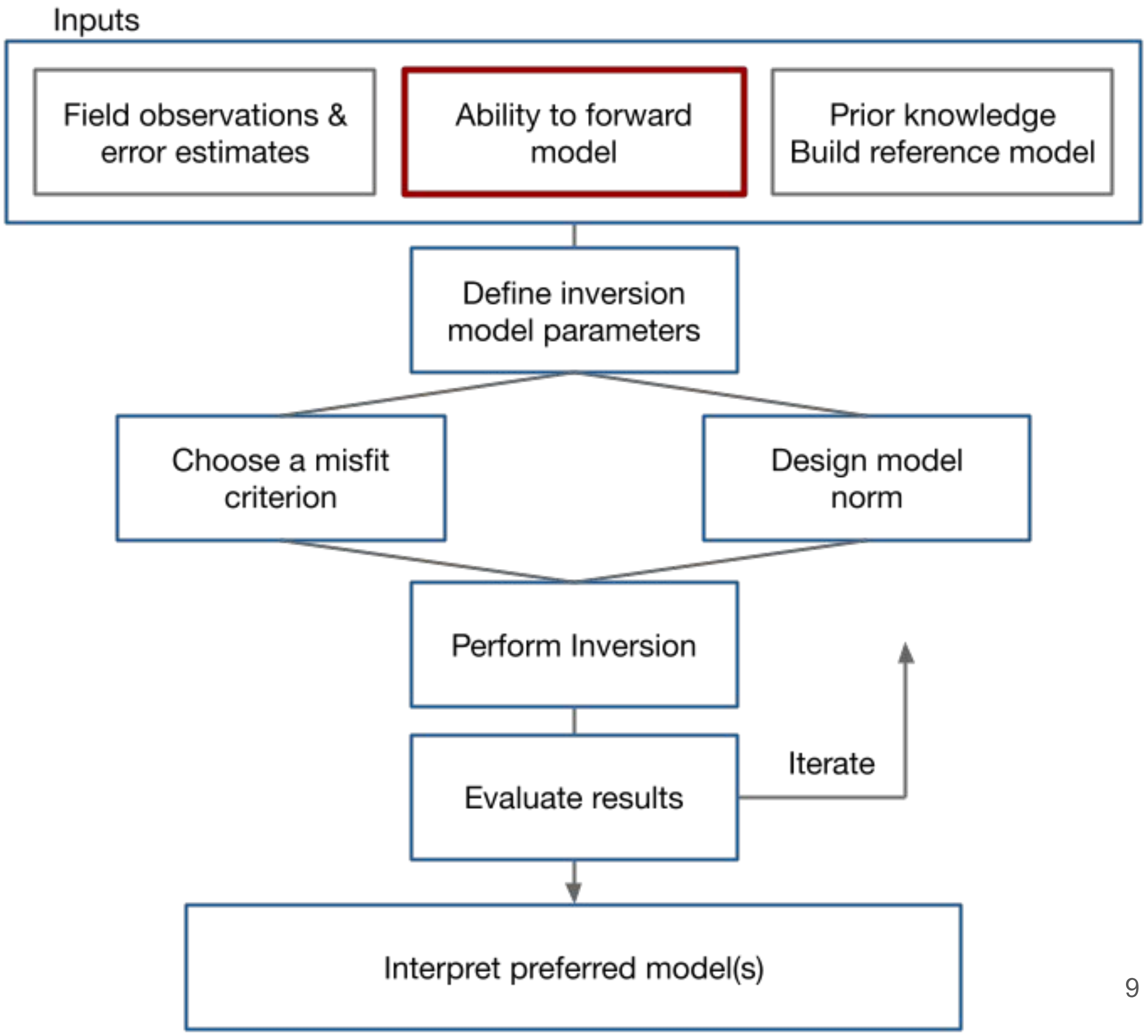
```
from SimPEG import electromagnetics
```



inversion flowchart



inversion flowchart



Electromagnetics: basic equations (quasi-static)

	Time	Frequency
Faraday's Law	$\nabla \times \vec{e} = -\frac{\partial \vec{b}}{\partial t}$	$\nabla \times \vec{E} = -i\omega \vec{B}$
Ampere's Law	$\nabla \times \vec{h} = \vec{j} + \frac{\partial \vec{d}}{\partial t}$	$\nabla \times \vec{H} = \vec{J} + i\omega \vec{D}$
No Magnetic Monopoles	$\nabla \cdot \vec{b} = 0$	$\nabla \cdot \vec{B} = 0$
Constitutive Relationships (non-dispersive)	$\vec{j} = \sigma \vec{e}$ $\vec{b} = \mu \vec{h}$ $\vec{d} = \varepsilon \vec{e}$	$\vec{J} = \sigma \vec{E}$ $\vec{B} = \mu \vec{H}$ $\vec{D} = \varepsilon \vec{E}$

* Solve with sources and boundary conditions

Electromagnetics: frequency domain equations

Use constitutive relations, reduce to two equations, one field, one flux

$$\nabla \times \vec{E} + i\omega\vec{B} = 0$$

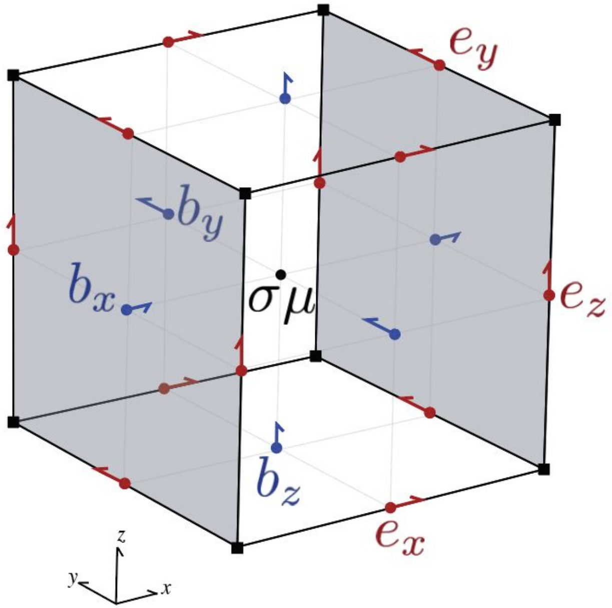
$$\nabla \times \mu^{-1}\vec{B} - \sigma\vec{E} = \vec{J}_s$$

Boundary conditions

$$\hat{n} \times \vec{B}|_{\partial\Omega} = 0$$

Staggered grid discretization

- Physical properties: cell centers
- Fields: edges
- Fluxes: faces



Electromagnetics: frequency domain equations

Continuous equations

$$\nabla \times \vec{E} + i\omega \vec{B} = 0$$

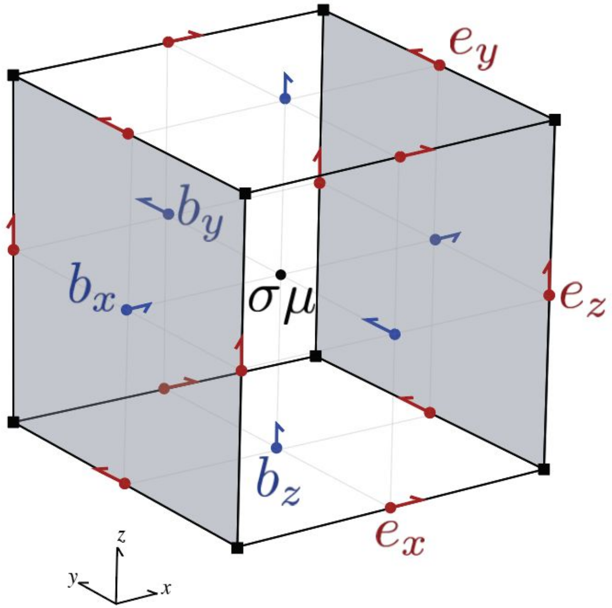
$$\nabla \times \mu^{-1} \vec{B} - \sigma \vec{E} = \vec{J}_s$$

$$\hat{n} \times \vec{B}|_{\partial \Omega} = 0$$

Finite volume discretization (see: Haber, 2014; Cockett et al., 2016)

$$\mathbf{C}\mathbf{e} + i\omega \mathbf{b} = 0$$

$$\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}} \mathbf{b} - \mathbf{M}^e_\sigma \mathbf{e} = \mathbf{M}^e \mathbf{j}_s$$



Electromagnetics: frequency domain equations

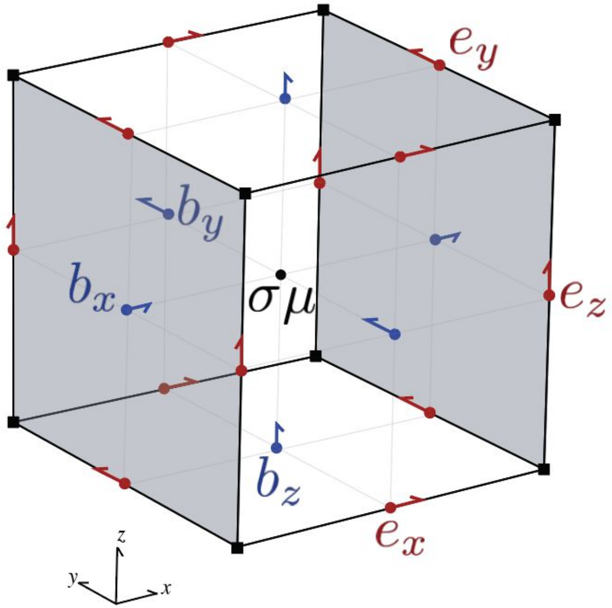
Discrete equations

$$\mathbf{C}\mathbf{e} + i\omega\mathbf{b} = 0$$

$$\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}}\mathbf{b} - \mathbf{M}^e_{\sigma}\mathbf{e} = \mathbf{M}^e\mathbf{j}_s$$

Eliminate **b** to obtain a second-order system in **e**

$$\underbrace{(\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}}\mathbf{C} + i\omega\mathbf{M}^e_{\sigma})}_{\mathbf{A}(\sigma,\omega)} \underbrace{\mathbf{e}}_{\mathbf{u}} = \underbrace{-i\omega\mathbf{M}^e\mathbf{j}_\mathbf{s}}_{\mathbf{q}(\omega)}$$



Solving an FDEM problem

$$\underbrace{(\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}} \mathbf{C} + i\omega \mathbf{M}^e_\sigma)}_{\mathbf{A}(\sigma,\omega)} \underbrace{\mathbf{e}}_{\mathbf{u}} = \underbrace{-i\omega \mathbf{M}^e \mathbf{j_s}}_{\mathbf{q}(\omega)}$$

$\mathbf{A}(\sigma,\omega)$

- Complex
- Symmetric
- Factor once for each frequency (solve for multiple sources)
- Need to refactor on each model update
- Separable over frequencies

Solving an FDEM problem

$$\underbrace{(\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}} \mathbf{C} + i\omega \mathbf{M}^e_\sigma)}_{\mathbf{A}(\sigma,\omega)} \underbrace{\mathbf{e}}_{\mathbf{u}}$$

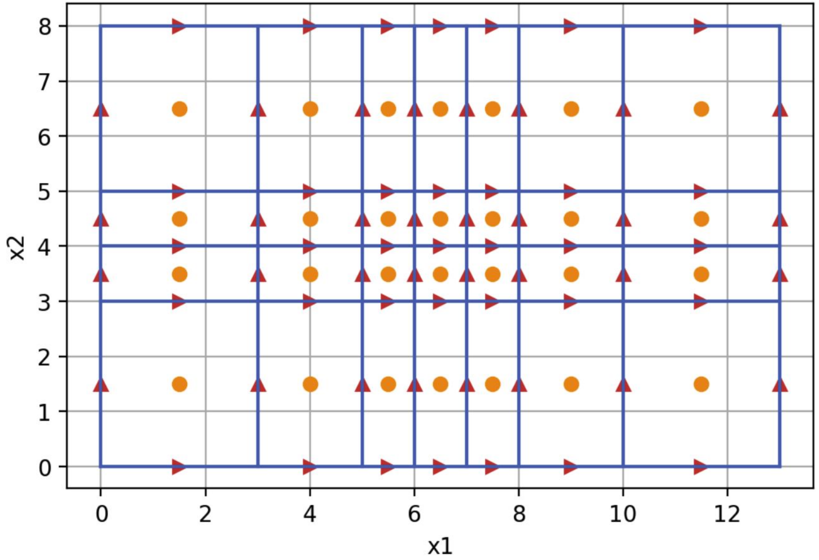
$$= \underbrace{-i\omega \mathbf{M}^e \mathbf{j_s}}_{\mathbf{q}(\omega)}$$

```
ω = 2 * pi * frequency

C = mesh.edge_curl
Mfμi = mesh.get_face_inner_product(1/mu_0)
Meσ = mesh.get_edge_inner_product(sigma)

A = C.T * Mfμi * C + i * ω * Meσ
Ainv = Solver(A)  # acts like A inverse

Me = mesh.get_edge_inner_product()
q = -i * ω * Me * js

u = Ainv * q
```

Create a mesh: the discretize package

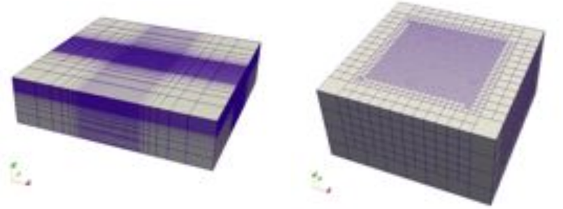
```python
import discretize
```

```python
hx = [3, 2, 1, 1, 1, 2, 3]
hy = [3, 1, 1, 3]
mesh = discretize.TensorMesh([hx, hy])
mesh.plot_grid(edges=True, centers=True);
```

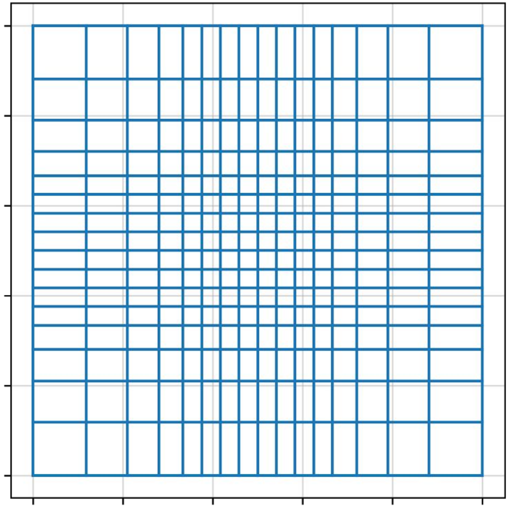


Properties or Methods
`dim, origin`
`n_cells, n_nodes, n_faces, n_edges`
`cell_volumes, face_areas, edge_lengths`
`cell_centers, nodes, edges, faces`
`nodal_gradient, face_divergence, edge_curl`
`average_edge_to_cell,` `average_node_to_cell, ...`
`get_edge_inner_product()`
`get_interpolation_matrix(location)`

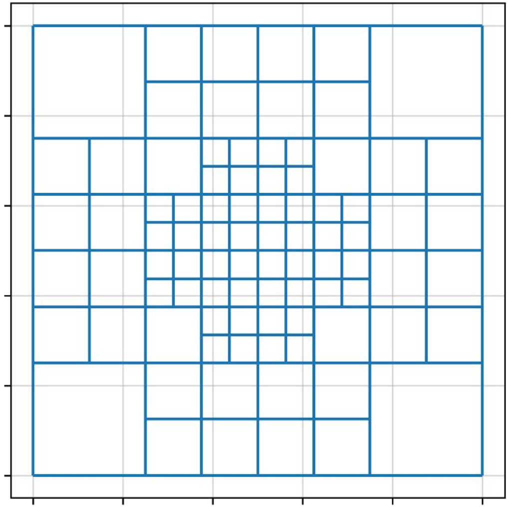
mesh types in simpeg



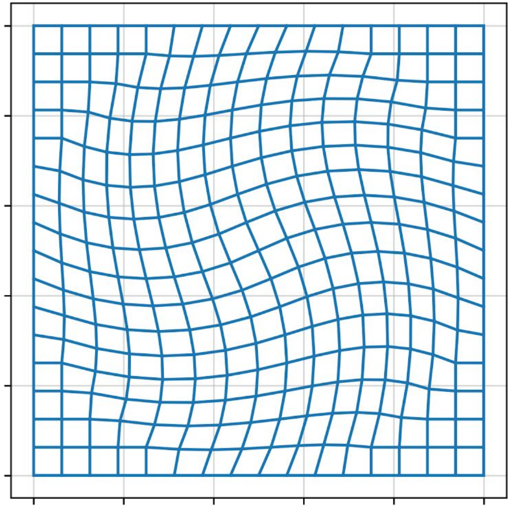
Tensor / Cylindrical



QuadTree / OcTree



Curvilinear



Joe
Capriotti

Survey: sources and receivers

Sources

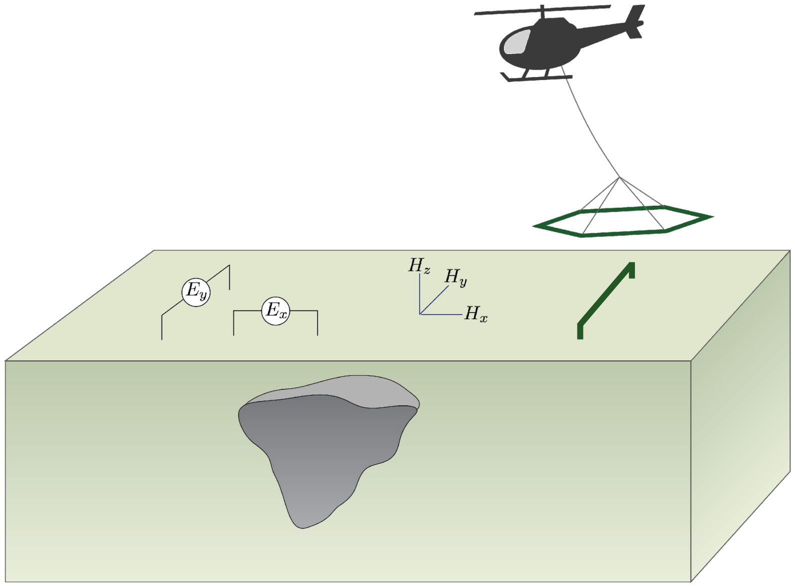
$$\underbrace{(\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}} \mathbf{C} + i\omega \mathbf{M}^e_\sigma)}_{\mathbf{A}(\sigma,\omega)} \underbrace{\mathbf{e}}_{\mathbf{u}} = \underbrace{-i\omega \mathbf{M}^e \mathbf{j_s}}_{\mathbf{q}(\omega)}$$

- inductive
- grounded

Receivers

- electric
- magnetic
- interpolate to locations

$$\mathbf{d}^{\text{pred}} = \mathbf{P}(\mathbf{u}, \omega)$$




```
source_list = [
    fdem.sources.MagDipole(receiver_list, f, location)
    for f in frequencies
]
survey = fdem.survey(source_list)
```

Bring it all together: simulation

```
from SimPEG.electromagnetics import frequency_domain as fdem
```

```
simulation = fdem.Simulation3DElectricField(
    mesh=mesh, survey=survey, solver=Pardiso,
    sigmaMap=maps.IdentityMap()
)
```

For each frequency, solve

$$\mathbf{A}(\sigma, \omega)\mathbf{u} = \mathbf{q}(\omega)$$

```
u = simulation.fields(model)
```

Project to receiver locations

$$\mathbf{d}^{\text{pred}} = \mathbf{P}(\mathbf{u}, \omega)$$

```
dpred = simulation.dpred(model, fields=u)
```

Sensitivities (we will need them later!)

For inverse problem, also need sensitivities (and adjoint)

$$\mathbf{J} = \frac{\partial \mathbf{d}^{\text{pred}}}{\partial \mathbf{m}}$$

$$= \frac{\partial \mathbf{P}(\mathbf{u}, \omega)}{\partial \mathbf{u}} \frac{\partial \mathbf{u}}{\partial \mathbf{m}}$$

where the derivative of the fields (**u**) is computed implicitly (requires a solve)

$$\frac{\partial \mathbf{A}(\sigma, \omega)\mathbf{u}^{\text{fixed}}}{\partial \mathbf{m}} + \mathbf{A}(\sigma, \omega)\frac{\partial \mathbf{u}}{\partial \mathbf{m}} = 0$$

J is a large, dense matrix → compute products with a vector if memory-limited

Demo

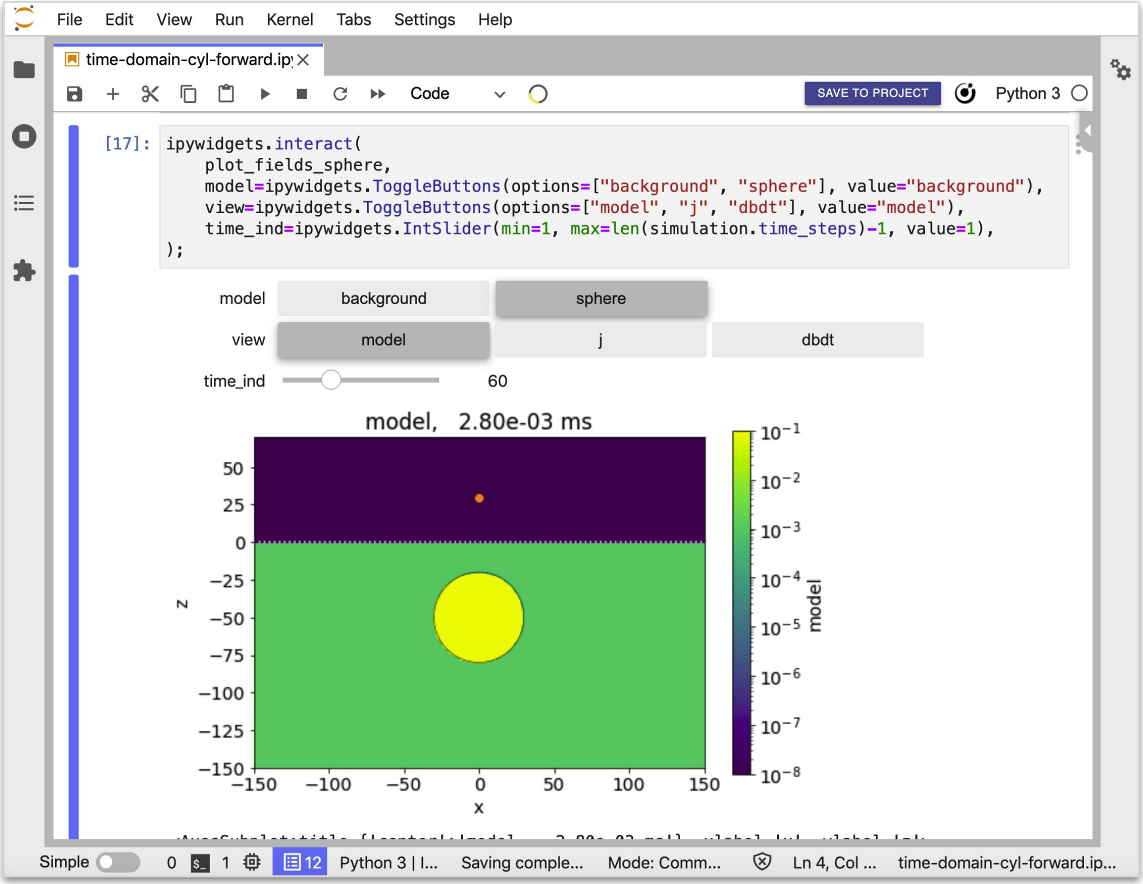
conductive sphere in a halfspace

cylindrical mesh

time-domain

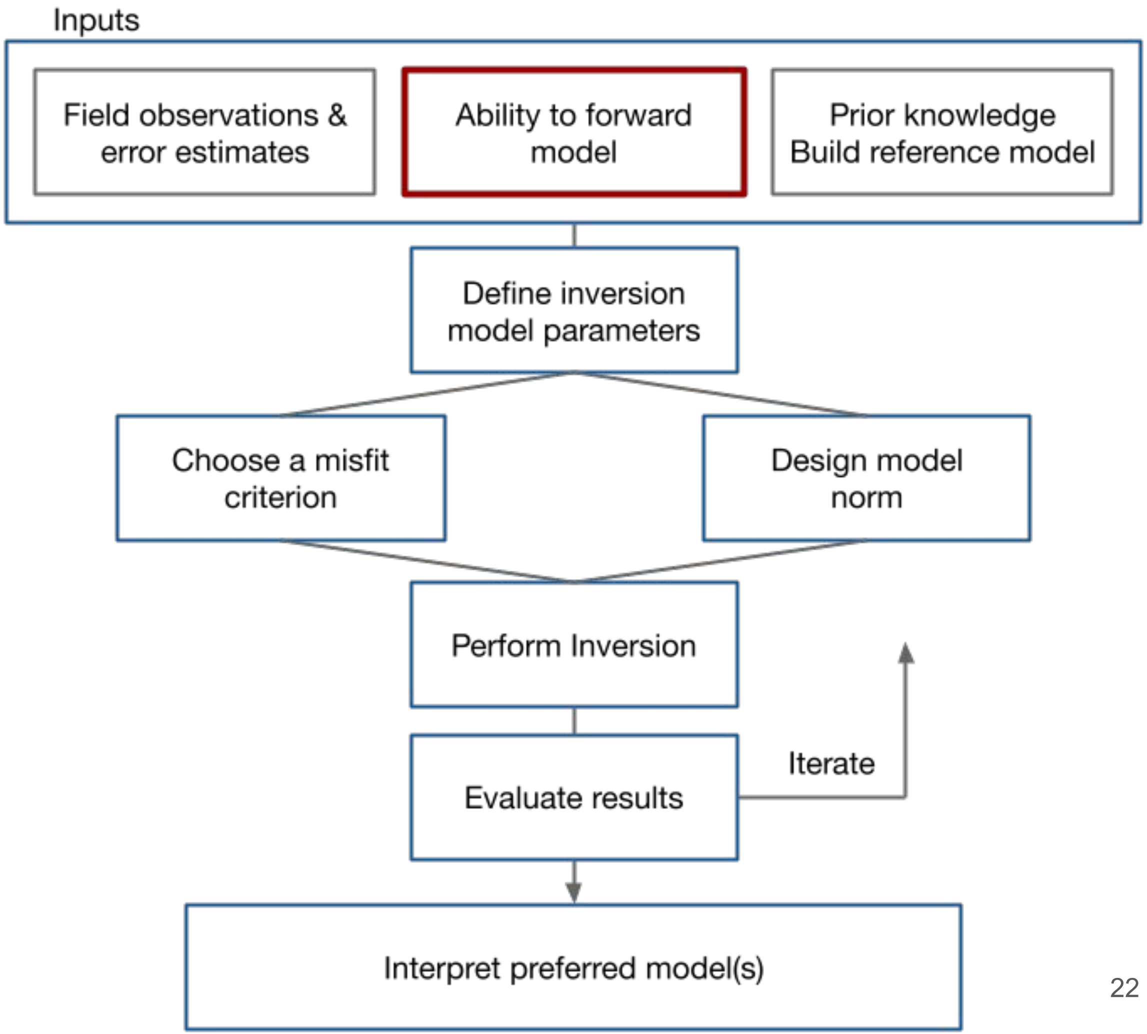
$$\nabla \times \vec{e} = -\frac{\partial \vec{b}}{\partial t}$$

$$\nabla \times \vec{h} = \vec{j}$$

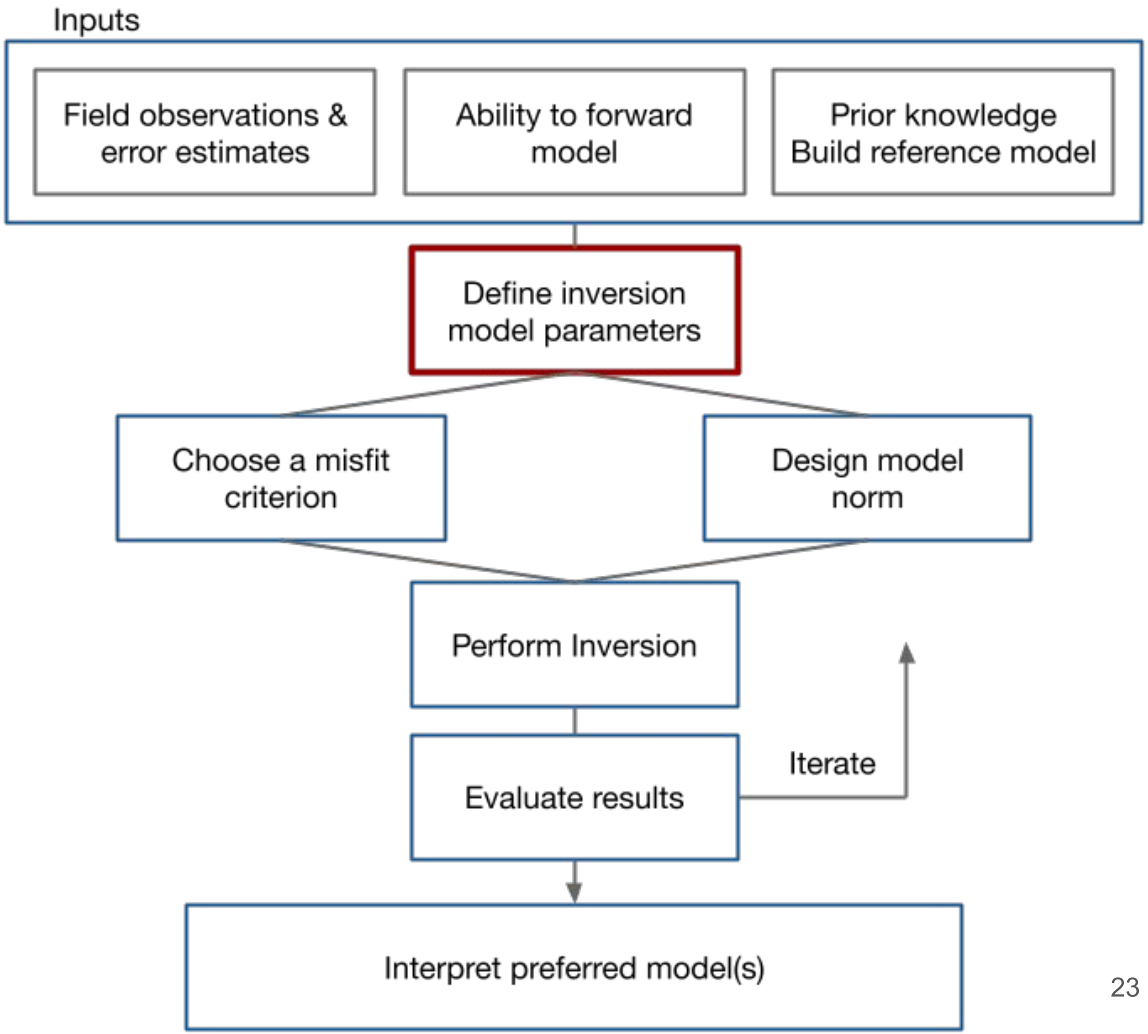


curvenote.com/@geosci/inversion-module

inversion flowchart

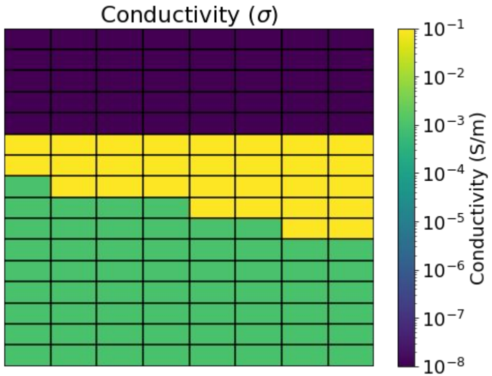


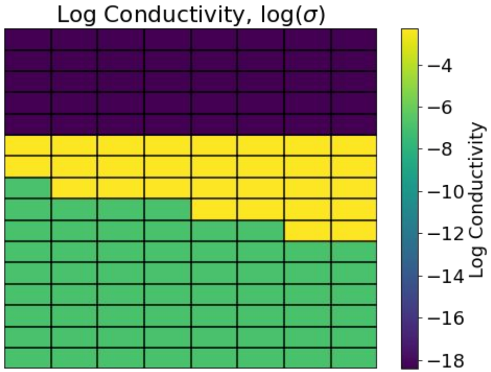
inversion flowchart

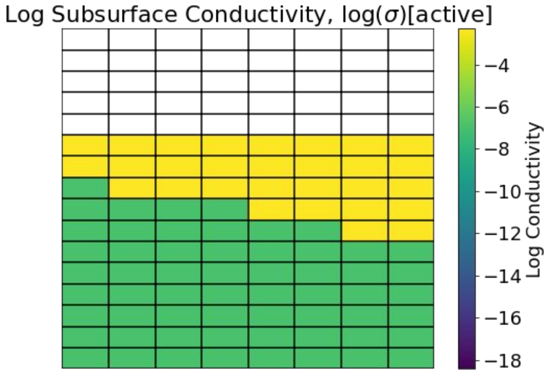


Inversion model parameters & mappings

What parameters are we inverting for?

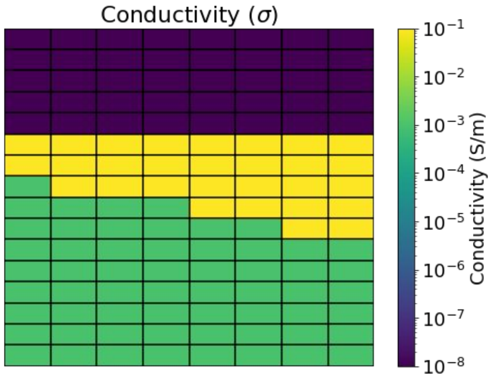


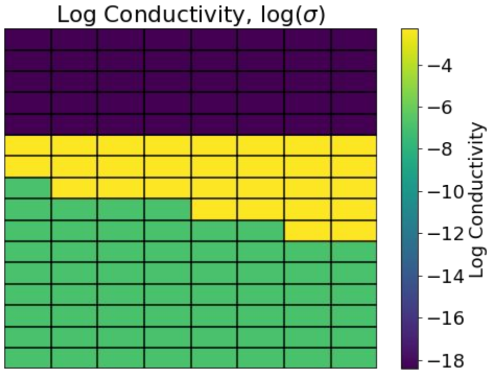


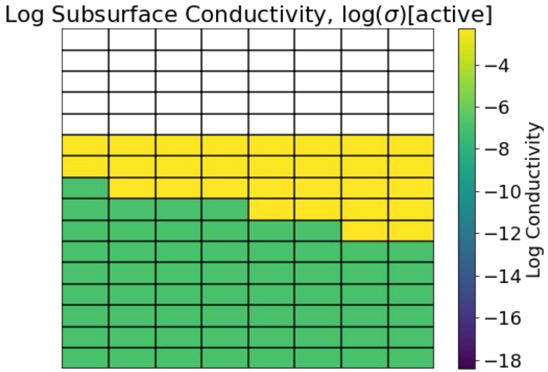


Inversion model parameters & mappings

What parameters are we inverting for?







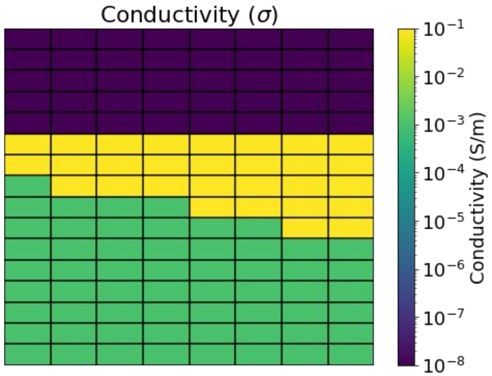
σ $\mathbf{m}$

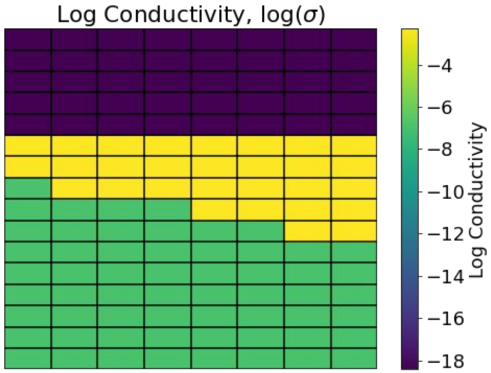
a mapping translates model parameters to physical properties on simulation mesh

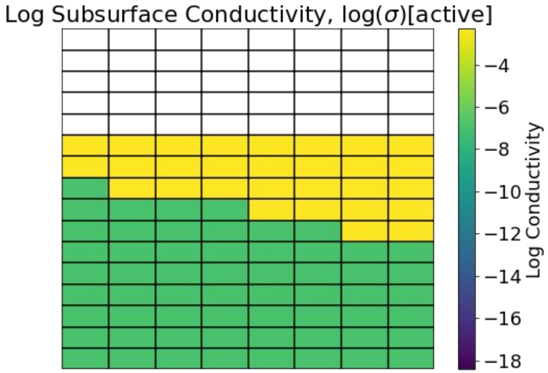
$$\sigma = \mathcal{M}(\mathbf{m})$$

Inversion model parameters & mappings

What parameters are we inverting for?





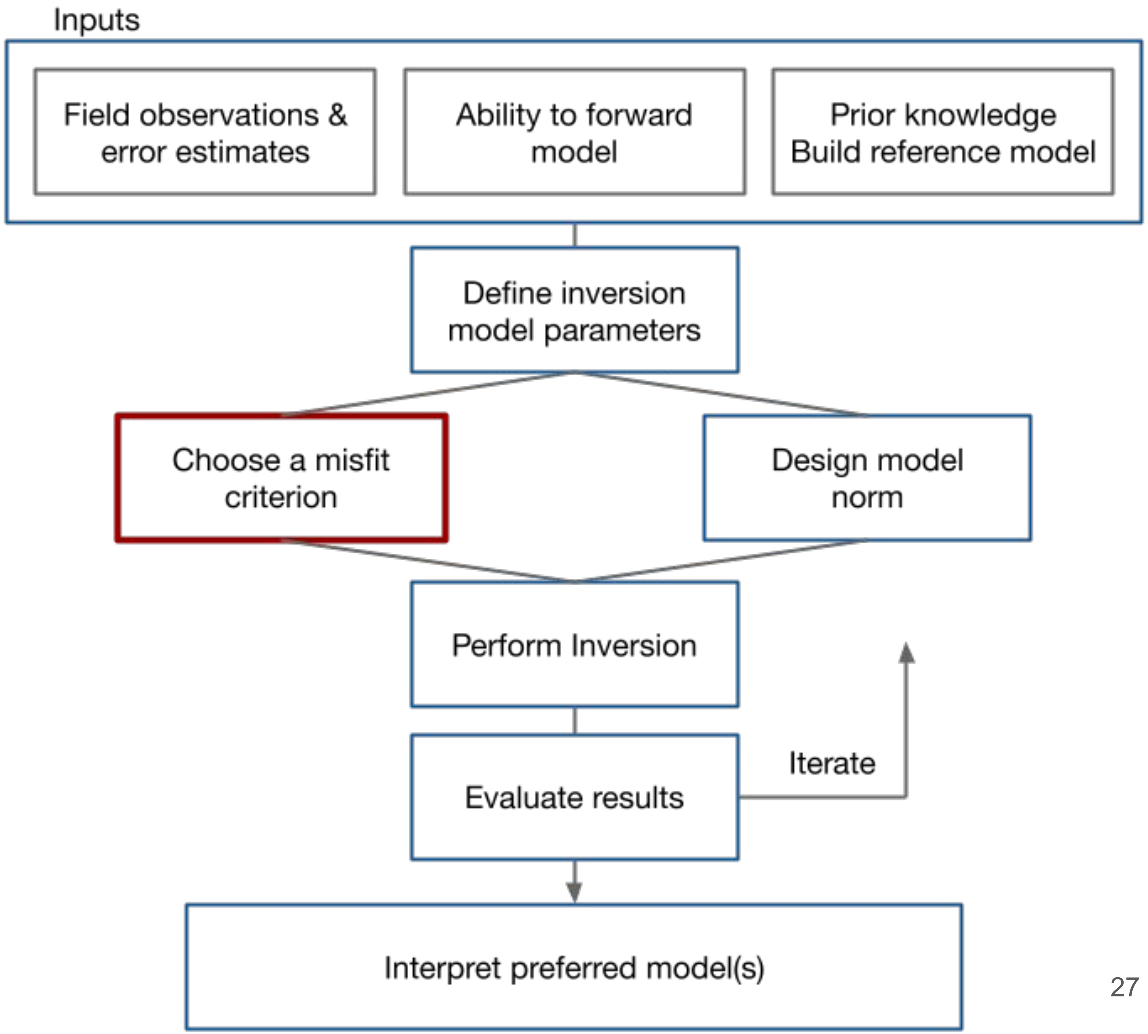


σ ← `maps.ExpMap` ← `maps.InjectActiveCells` ← $\mathbf{m}$

$$\sigma = \mathcal{M}(\mathbf{m})$$

- Mappings can be composed
- Includes parametric models
- Keep track of derivatives (for sensitivities)

inversion flowchart



observed data, uncertainties, and data misfit

Data misfit term

$$\phi_d = \|\mathbf{W}_d(\mathcal{F}(\mathbf{m}) - \mathbf{d}^{\text{obs}})\|^2$$

uncertainties captured in W matrix

$$\mathbf{W}_d = \text{diag}\left(\frac{1}{\boldsymbol{\epsilon}}\right)$$

$$\epsilon_j = \%|d_j^{\text{obs}}| + \text{floor}$$

observed data, uncertainties, and data misfit

Data misfit term

$$\phi_d = \|\mathbf{W}_d(\mathcal{F}(\mathbf{m}) - \mathbf{d}^{\text{obs}})\|^2$$

uncertainties captured in W matrix

$$\mathbf{W}_d = \text{diag}\left(\frac{1}{\epsilon}\right)$$

$$\epsilon_j = \%|d_j^{\text{obs}}| + \text{floor}$$

Data class: survey geometry, observed data, assigned uncertainties

```
from SimPEG import Data
data = Data(survey, dobs, relative_error, floor)
```

Data misfit instantiated with

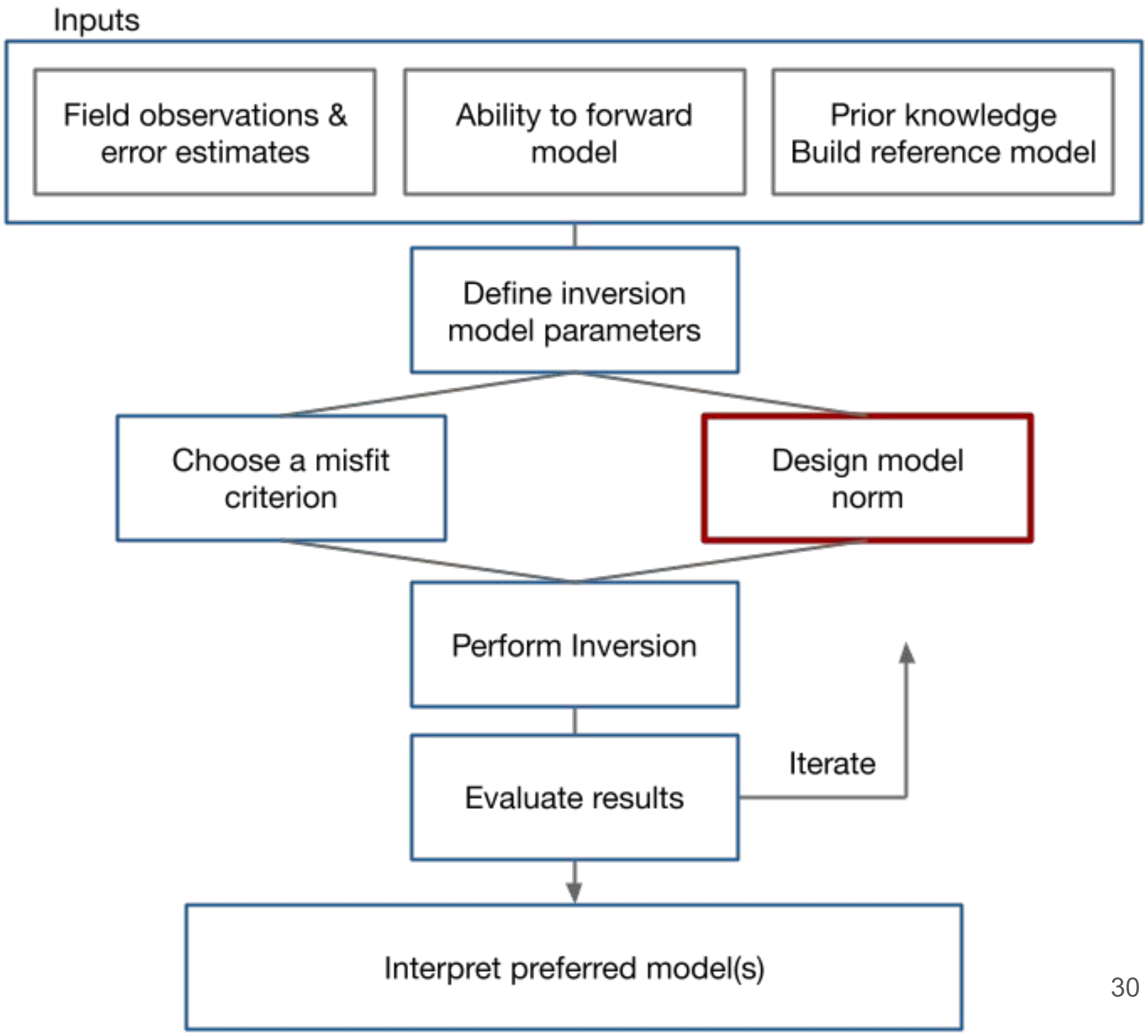
- simulation: to compute $\mathcal{F}(\mathbf{m})$
- data: defines $\mathbf{W}_d$, $\mathbf{d}^{\text{obs}}$

```
from SimPEG import data_misfit
phi_d = data_misfit.L2DataMisfit(data, simulation)
```

can now evaluate data misfit + derivatives

```
phi_d(m), phi_d.deriv(m), phi_d.deriv2(m, v)
```

inversion flowchart



Designing a model norm: regularization class

Basic Tikhonov regularization

$$\phi_m = \underbrace{\alpha_s \int_V w_s (m - m_{\text{ref}})^2 dV}_{\text{smallness}} + \underbrace{\alpha_x \int_V w_x \left(\frac{d(m - m_{\text{ref}})}{dx}\right)^2 dV}_{\text{smoothness}}$$

discretize

$$\phi_m = \alpha_s \|\mathbf{W}_s(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2 + \alpha_x \|\mathbf{W}_x(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2$$

Choices:

- α - parameter values
- reference model
- mref in the smoothness terms
- norm applied on each term

Designing a model norm: regularization class

Basic Tikhonov regularization

$$\phi_m = \underbrace{\alpha_s \int_V w_s (m - m_{\text{ref}})^2 dV}_{\text{smallness}} + \underbrace{\alpha_x \int_V w_x \left(\frac{d(m - m_{\text{ref}})}{dx}\right)^2 dV}_{\text{smoothness}}$$

discretize

$$\phi_m = \alpha_s \|\mathbf{W}_s(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2 + \alpha_x \|\mathbf{W}_x(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2$$

Choices:

- α - parameter values
- reference model
- mref in the smoothness terms
- norm applied on each term

Regularization instantiated with

- mesh: to evaluate spatial derivs
- alphas, mref have default values, can be replaced with user values

```
from SimPEG import regularization
```

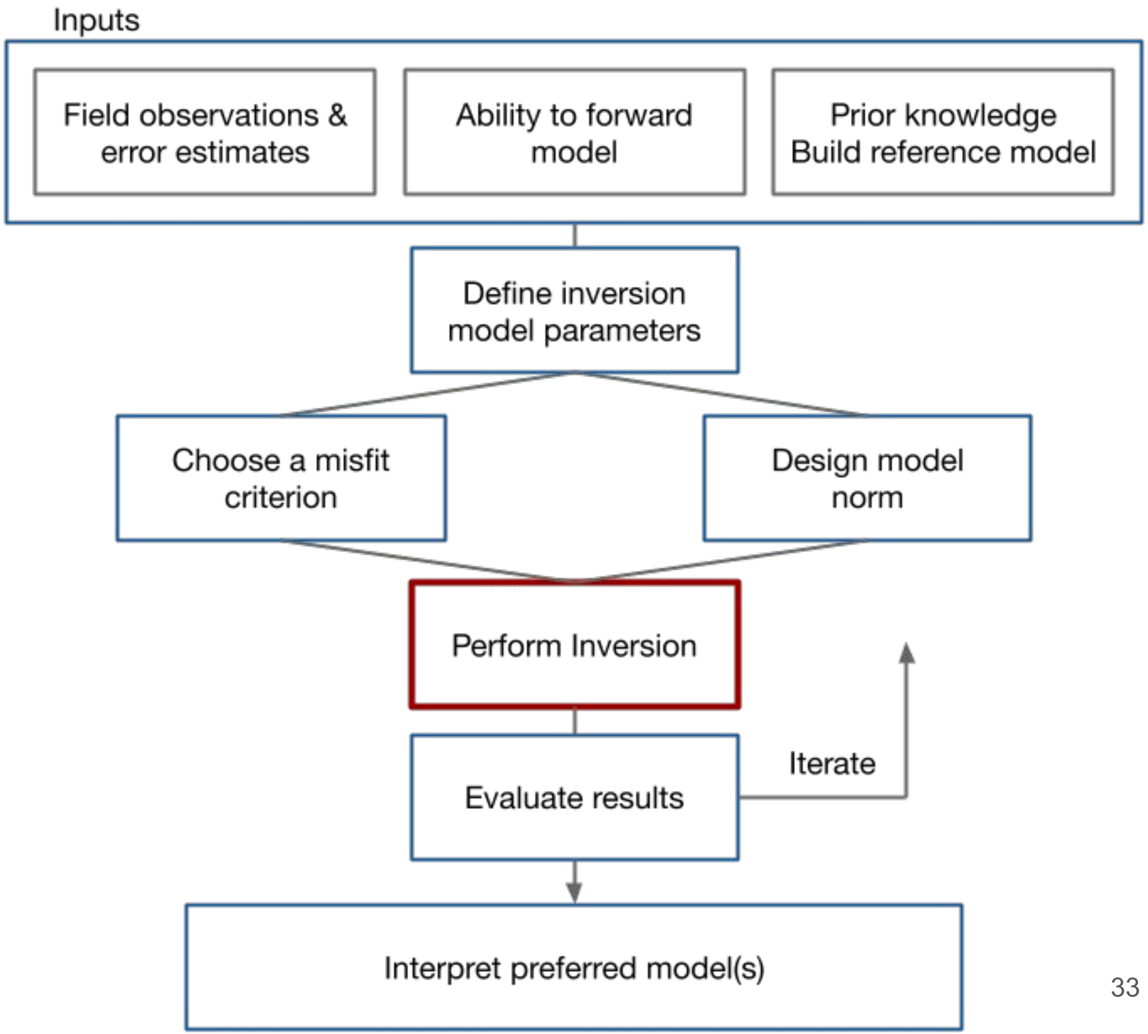
```
phi_m = regularization.Tikhonov(
    mesh, mref=mref, alpha_s=alpha_s, alpha_x=alpha_x
)
```

```
phi_m_sparse = regularization.Sparse(
    mesh, mref=mref, norms=[1, 1]
)
```

can now evaluate phi_m + derivatives

```
phi_m(m), phi_m.deriv(m), phi_m.deriv2(m, v)
```

inversion flowchart



Perform the inversion: stating the objective function

Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\underline{\mathbf{m}}) = \underline{\phi_d}(\mathbf{m}) + \beta \underline{\phi_m}(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

At this stage, we have specified

- parameters we are inverting for
- data misfit
- model norm

Perform the inversion: stating the objective function

Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

Still to define

- optimization method
- upper and lower bounds
- choice of initial beta
- choice of beta-cooling schedule
- target misfit and stopping the inversion

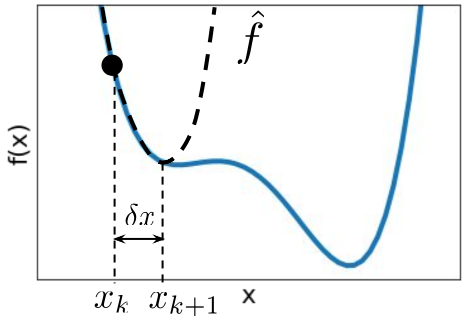
Perform the inversion: optimization approach

Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

Second-order methods




```
from SimPEG import optimization
```

```
opt = optimization.InexactGaussNewton(maxIter=20, maxIterCG=20)
```

```
opt_with_bounds = optimization.ProjectedGNCG(lower=0)
```

Perform the inversion: inversion directives

Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \underline{\beta}\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \underline{\phi_d^*} \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

We use **directives** to make parameter updates and orchestrate the inversion, e.g.

- estimating initial beta
- defining a beta-cooling schedule
- stopping the inversion when target misfit reached

Perform the inversion: inversion directives

Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \underline{\beta}\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

Initial beta

- estimate "size" of data misfit and model norm by approximating eigenvalues of

$$\mathbf{J}^\top \mathbf{W}_d^\top \mathbf{W}_d \mathbf{J}, \ \mathbf{W}_m^\top \mathbf{W}_m$$

- take ratio, weight by a parameter controlling relative importance of each

```
from SimPEG import directives
beta0 = directives.BetaEstimate_ByEig(beta0_ratio=100)
```

Perform the inversion: inversion directives

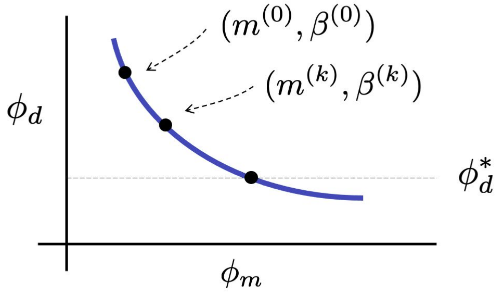
Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \underline{\beta}\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \le \phi_d^* \quad \mathbf{m}_L \le \mathbf{m} \le \mathbf{m}_U$$

Beta-cooling

- Define how often beta is reduced (every N iterations)
- Define how much beta is reduced by




```
beta_cooling = directives.BetaSchedule(coolingRate=2, coolingFactor=4)
```

Perform the inversion: inversion directives

Inversion as an optimization problem (deterministic approach)

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \underline{\phi_d^*} \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

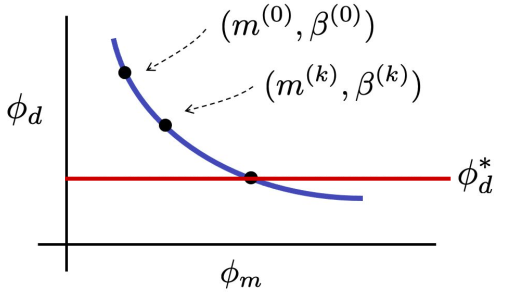
Target misfit

- Expected value of data misfit

$$E[\phi_d] \simeq N$$

- Define target misfit as (default χ= 1)

$$\phi_d^* = \chi N$$




```
target_misfit = directives.TargetMisfit(chifact=1)
```

Perform the inversion: inversion directives

Inversion as an optimization problem (deterministic approach)

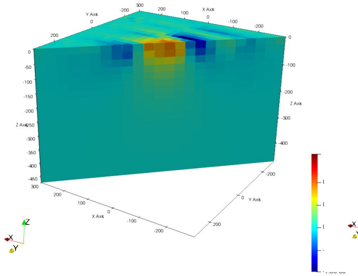
$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta \phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

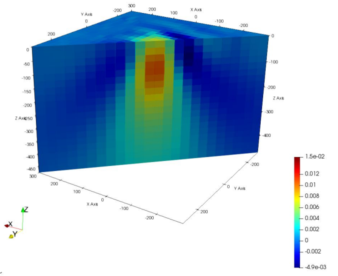
Other uses for directives

- saving inversion model at each iteration
- saving inversion progress (beta, data misfit, ...)
- including / updating sensitivity weighting
- updating values for norms (L2 → Lp)

Recovered susceptibility



Sensitivity weighted susceptibility



Perform the inversion: bringing it all together

Inversion as an optimization problem (deterministic approach)

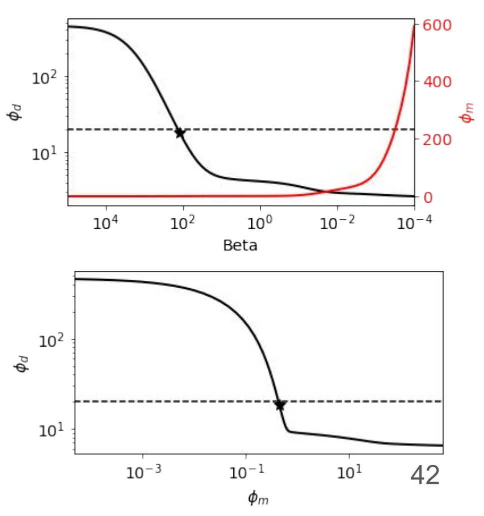
$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$

```python
from SimPEG import inverse_problem, inversion
```

```python
inv_prob = inverse_problem.BaseInvProblem(phi_d, phi_m, opt)
inv = inversion.BaseInversion(inv_prob, [beta0, beta_cooling, target_misfit])
```

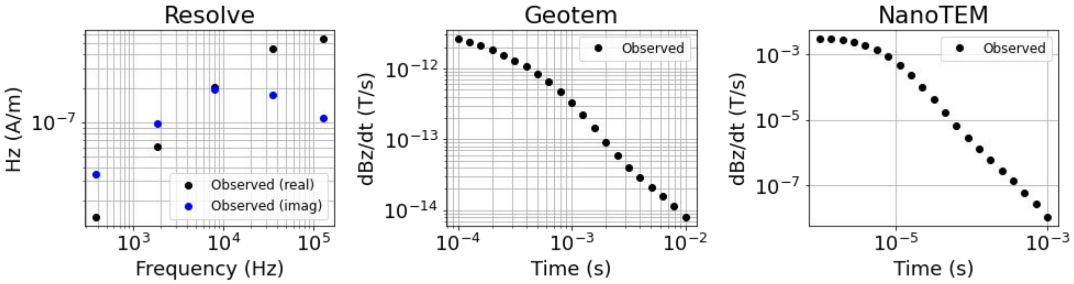
```python
inv.run(m0)
```

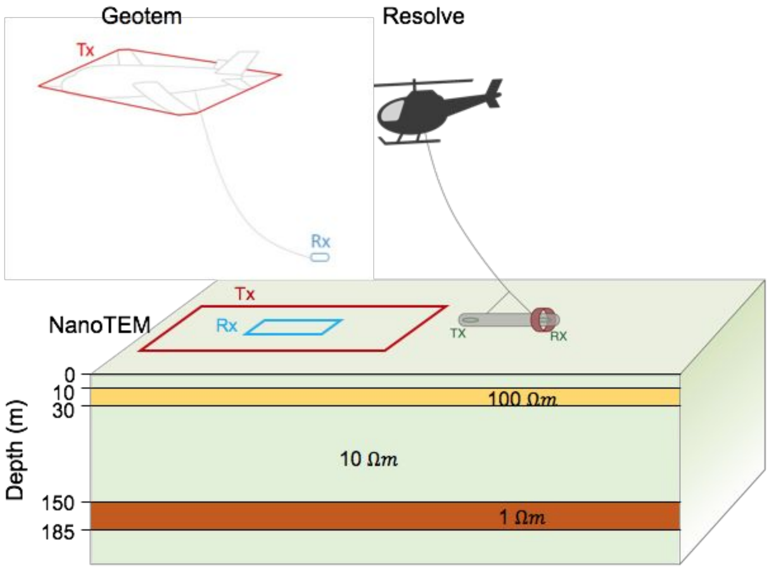


An example: 1D inversions

Layered earth, 3 different EM systems

- Resolve (airborne, frequency)
- Geotem (airborne, time-domain)
- NanoTEM (ground, time-domain)



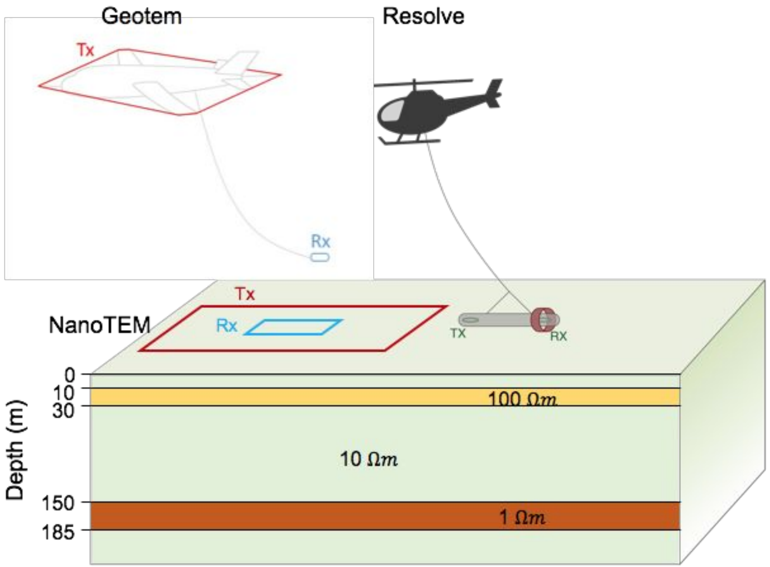


(Oldenburg et al, 2020)

SimPEG EM1D

Seogi Kang

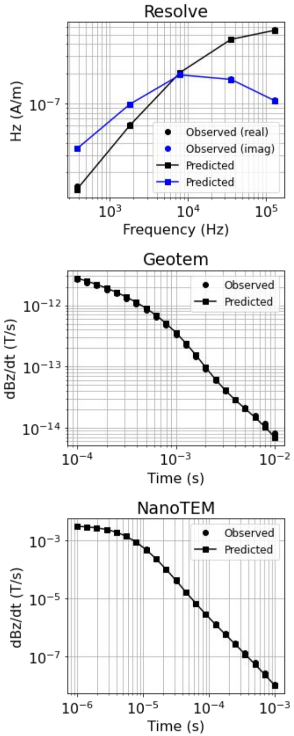
- Efficient forward simulation, sensitivity calculation using digital filters
    - relies on empymod (Werthmüller, 2017)
- Parallelized over soundings
- Common FDEM, TDEM system parameters implemented

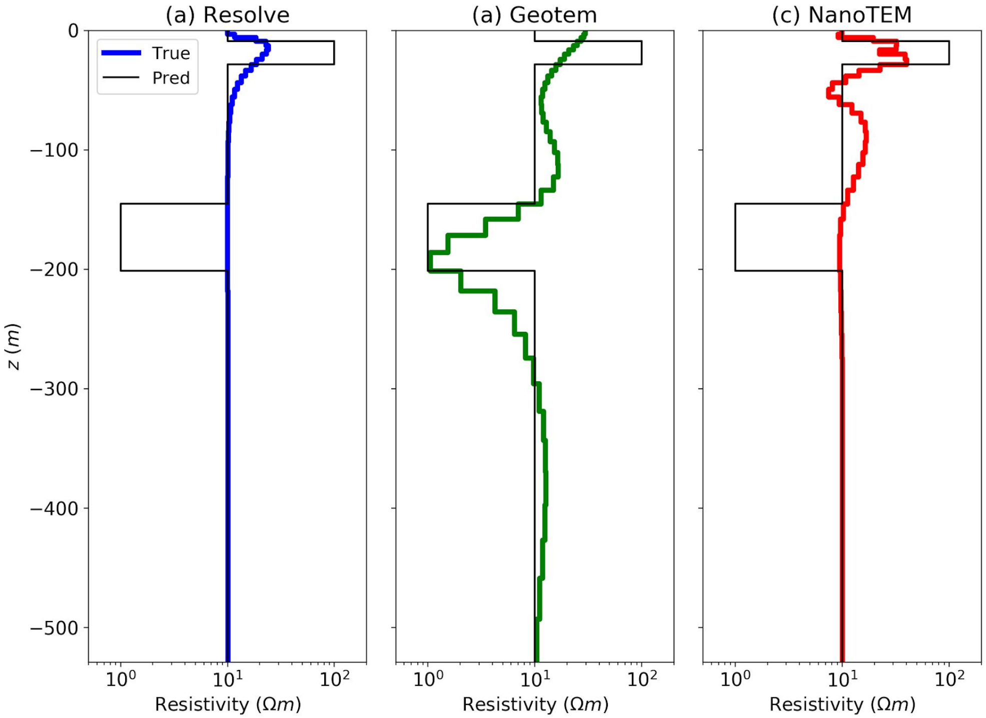


(Kang et al, 2018)

Individual inversions

L2 regularization



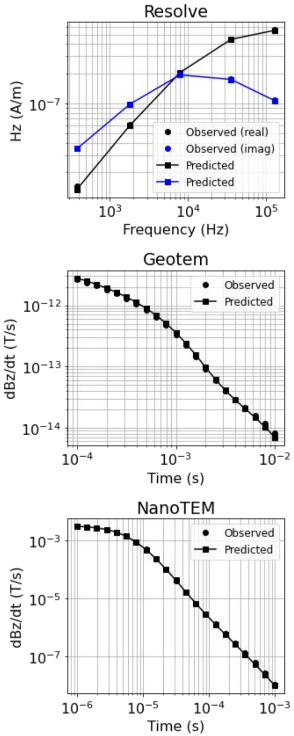


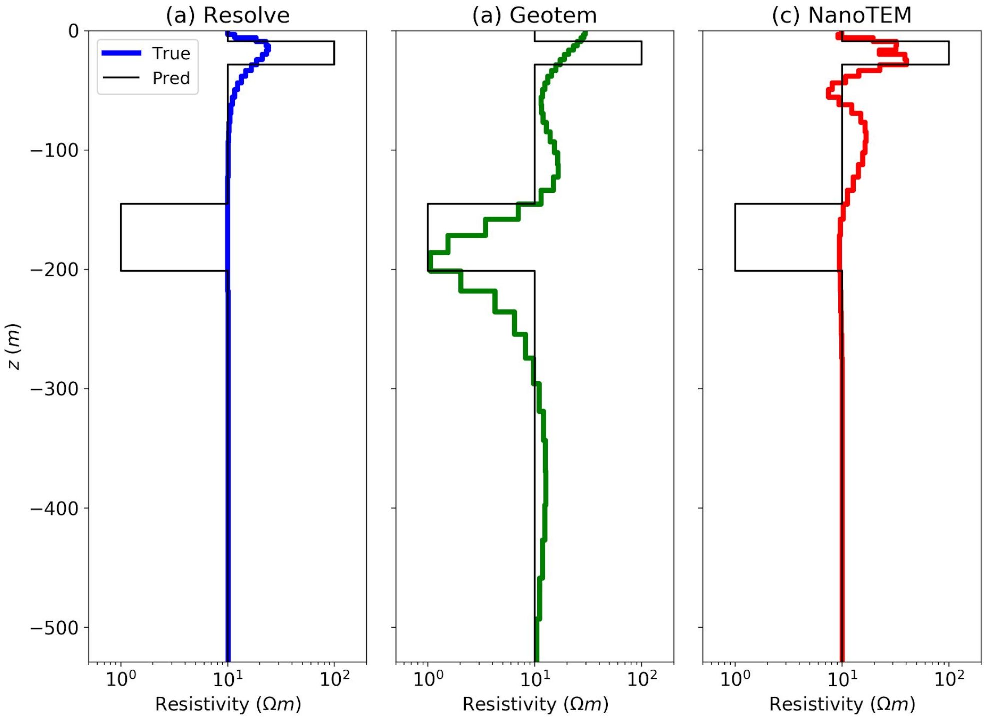
Joint Inversion

$$\phi(\mathbf{m}) = \underbrace{\phi_d^{\text{Resolve}} + \phi_d^{\text{Geotem}} + \phi_d^{\text{NanoTEM}}}_{\phi_d(\mathbf{m})} + \beta\phi_m(\mathbf{m})$$

L2 regularization

```
phi_d = phi_d_resolve + phi_d_geotem + phi_d_nanotem
```



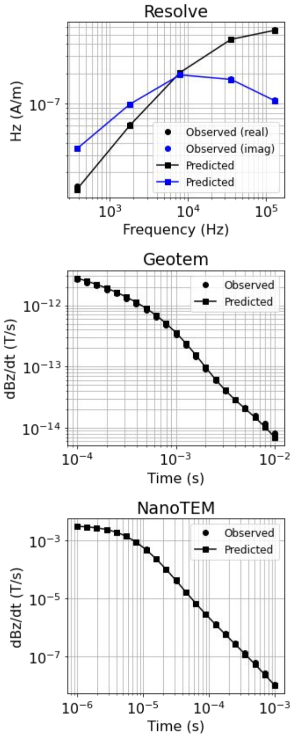


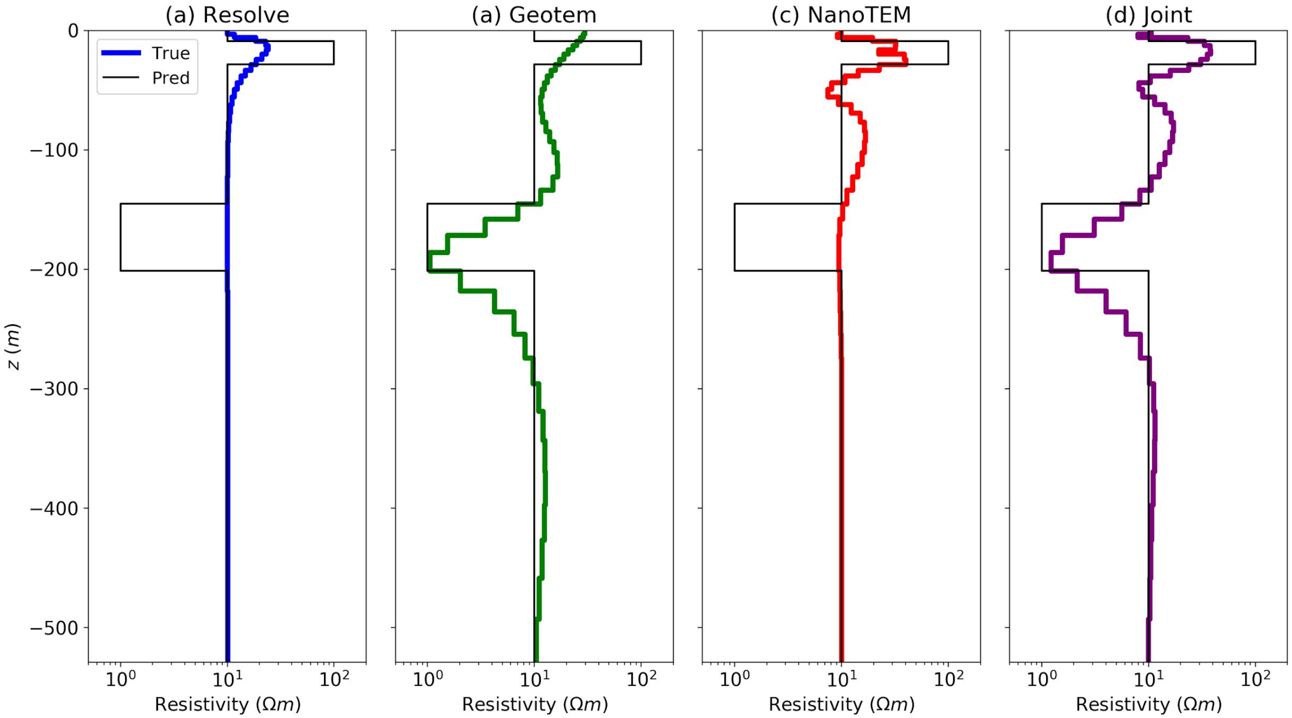
Joint Inversion

$$\phi(\mathbf{m}) = \underbrace{\phi_d^{\text{Resolve}} + \phi_d^{\text{Geotem}} + \phi_d^{\text{NanoTEM}}}_{\phi_d(\mathbf{m})} + \beta\phi_m(\mathbf{m})$$

L2 regularization

```
phi_d = phi_d_resolve + phi_d_geotem + phi_d_nanotem
```



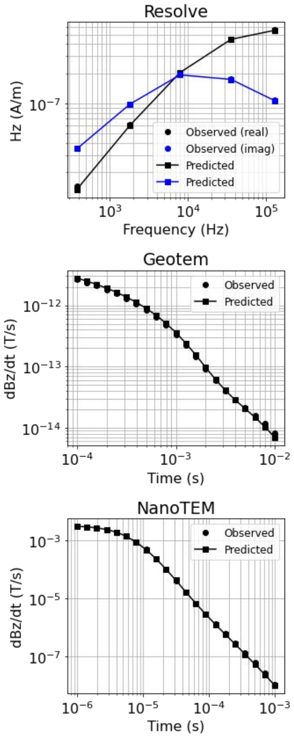


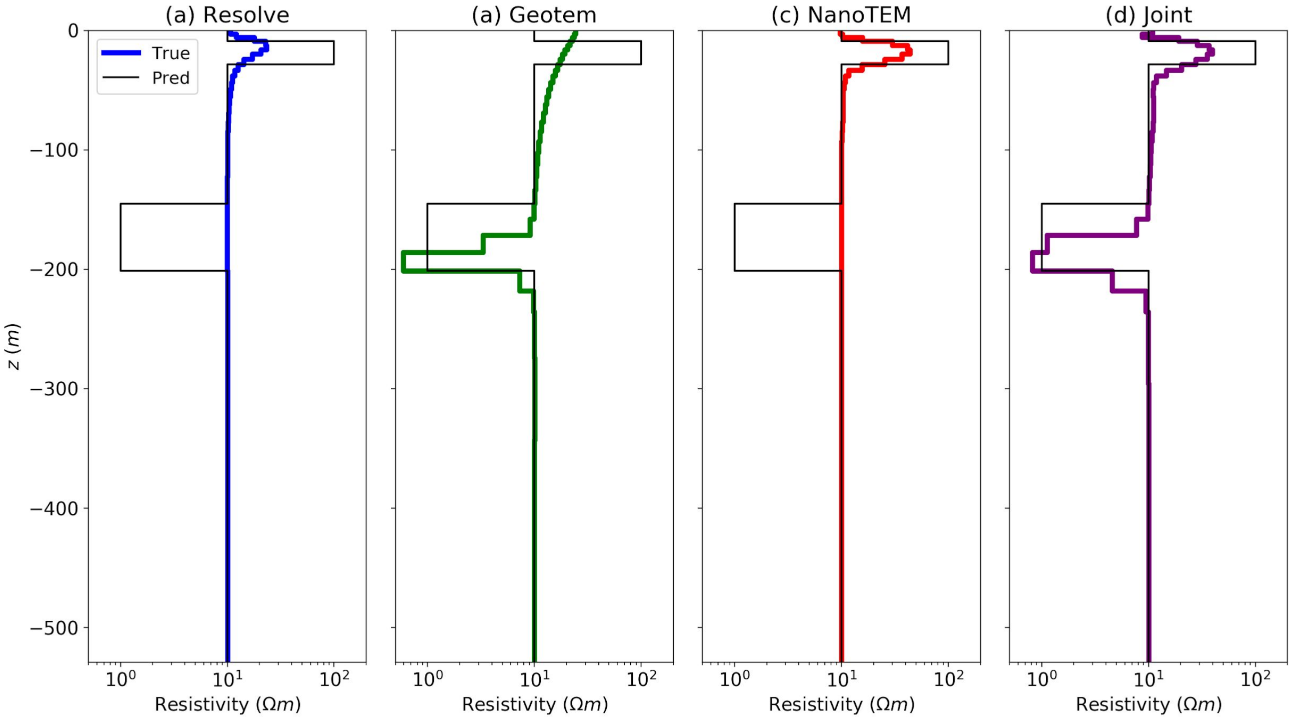
Joint Inversion

$$\phi(\mathbf{m}) = \underbrace{\phi_d^{\text{Resolve}} + \phi_d^{\text{Geotem}} + \phi_d^{\text{NanoTEM}}}_{\phi_d(\mathbf{m})} + \beta\phi_m(\mathbf{m})$$

L0 regularization

```
phi_d = phi_d_resolve + phi_d_geotem + phi_d_nanotem
```



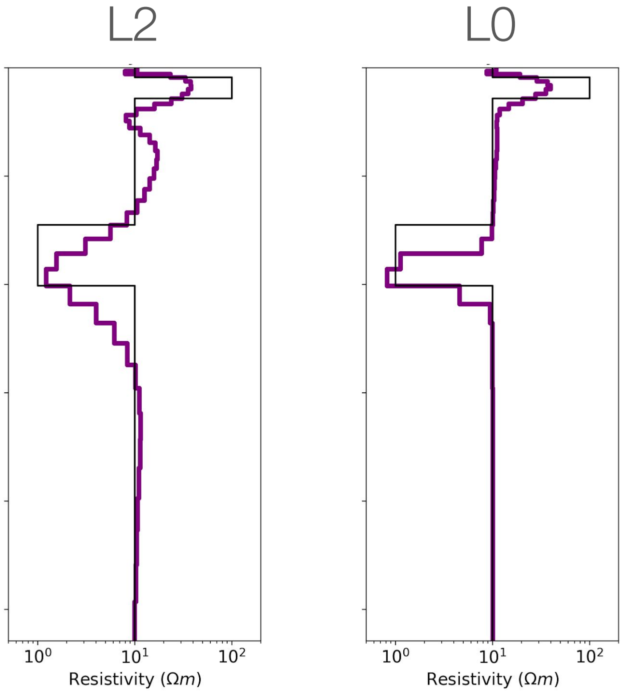


Joint Inversion

Flexibility to handle:

- multiple surveys / physics
- different model parameterizations
- different simulation mesh for each datum
- separate forward simulation and inversion meshes

```
phi_d = phi_d_resolve + phi_d_geotem + phi_d_nanotem
```



Example: Bookpurnong

Murray River Floodplain

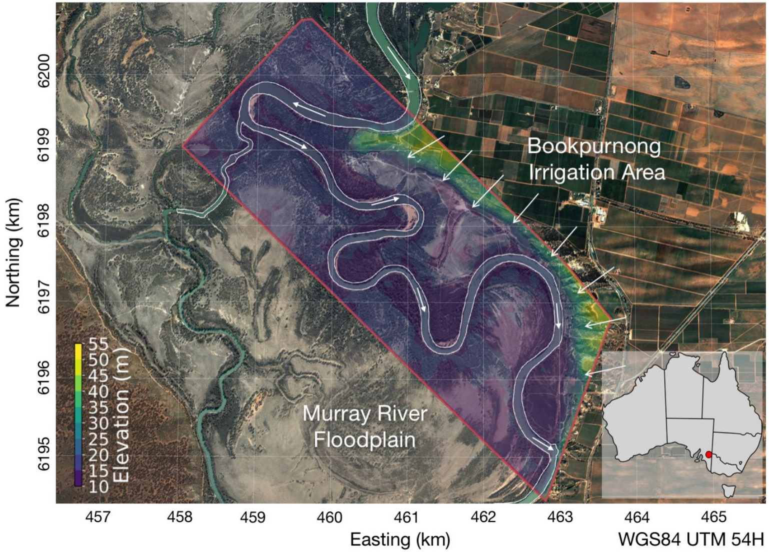
- over-irrigation and drought
- saline water recharges river
- floodplain salinization

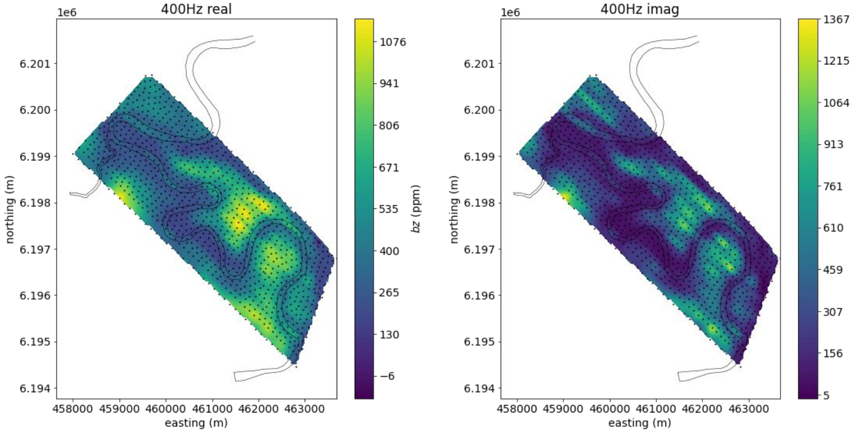
Data

- 2006: SkyTEM (time-domain)
- 2008: RESOLVE (frequency-domain)

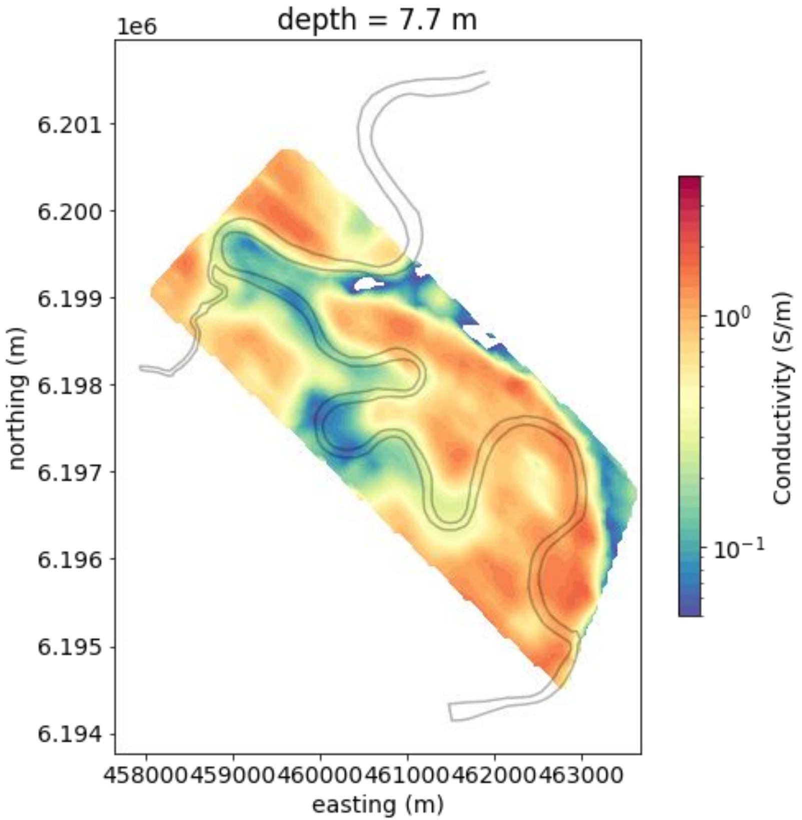
Inversion

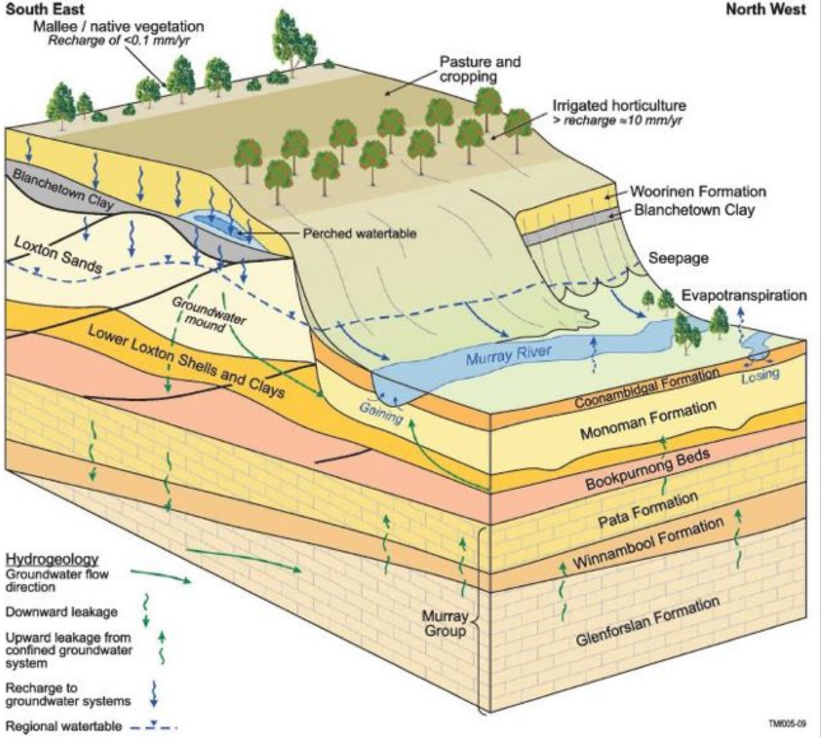
- Spatially constrained 1D





Example: Bookpurnong

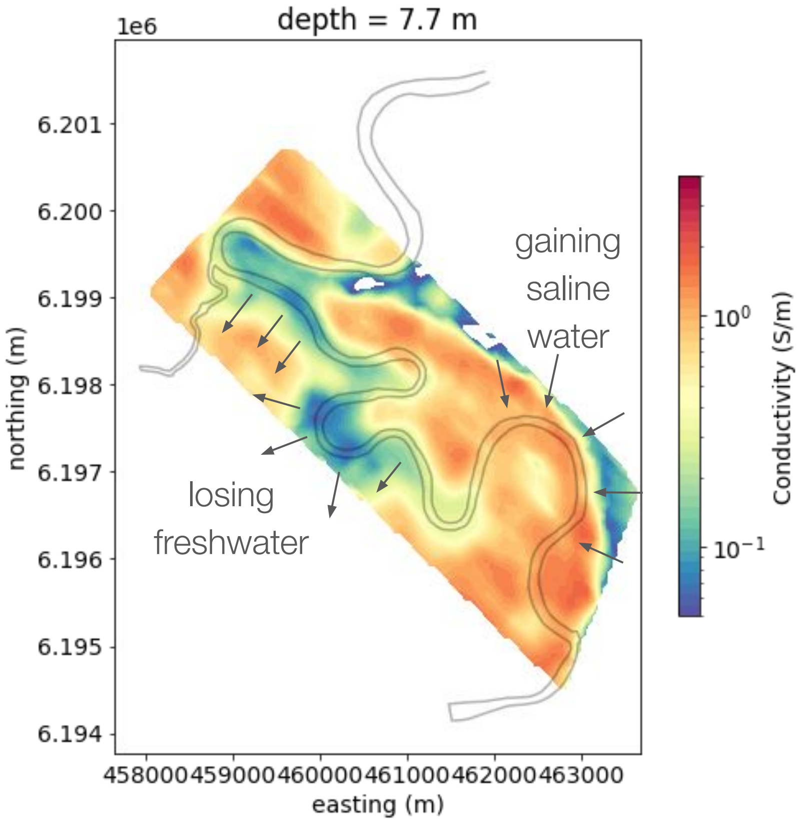




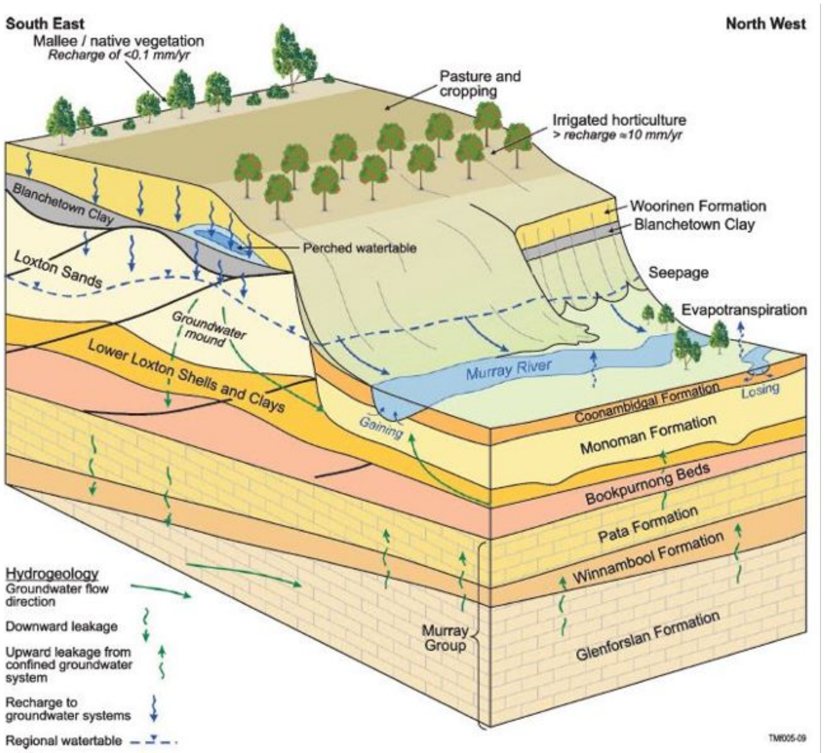
coming to the docs soon!

(Viezzoli et al., 2009)

Example: Bookpurnong



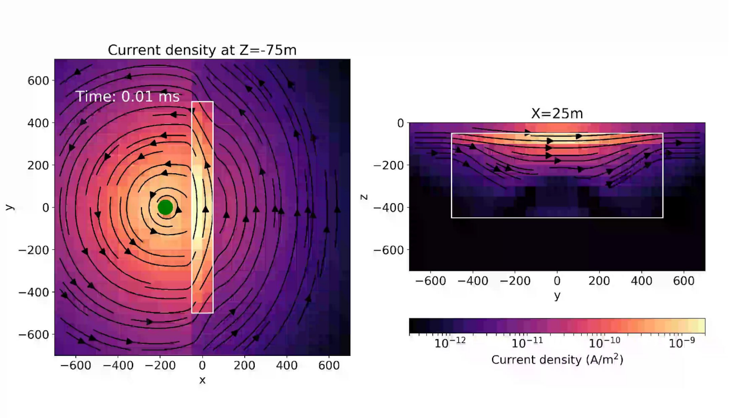
coming to the docs soon!

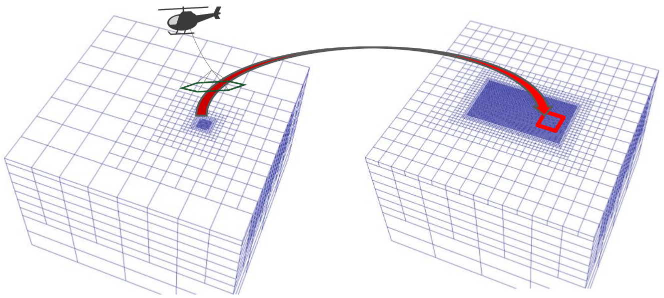


(Viezzoli et al., 2009)

geophysical methods in SimPEG

- Gravity
- Magnetics
- Direct current resistivity
- Induced polarization
- Electromagnetics
  - Frequency Domain
  - Time Domain
  - Controlled + natural sources
- Fluid Flow
  - Richards Equation

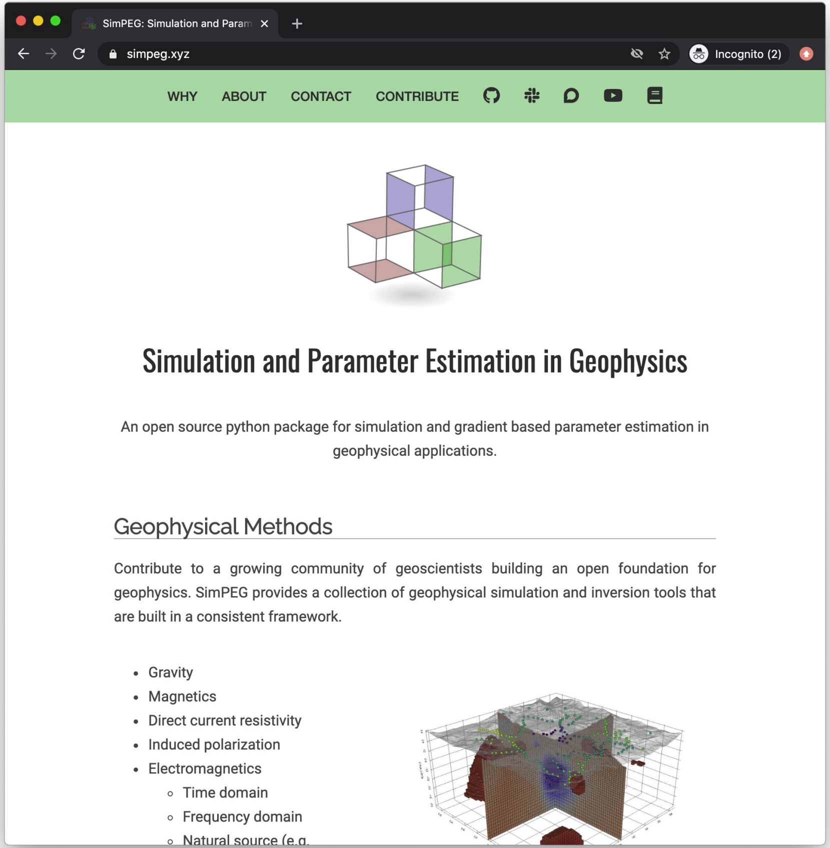


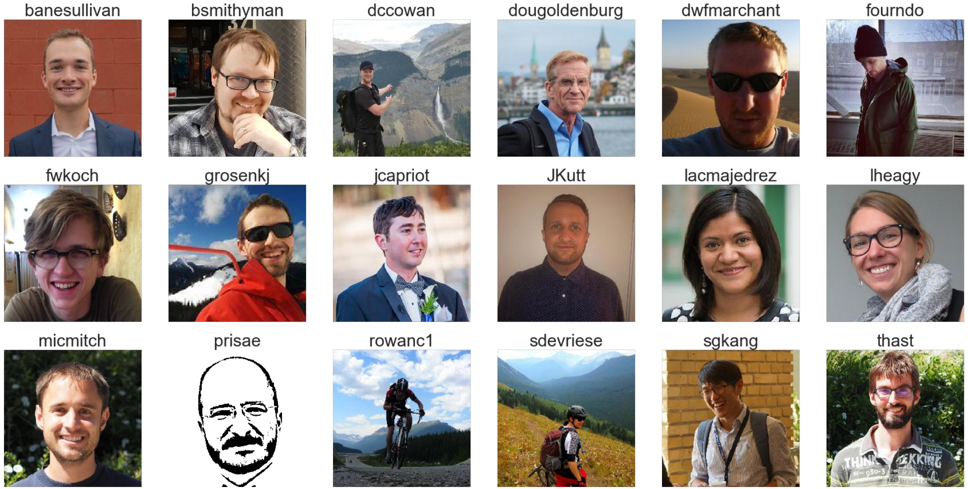


Tiled, parallelized inversions in progress

Dom Fournier

what is simpeg?





https://simpeg.xyz

code + community

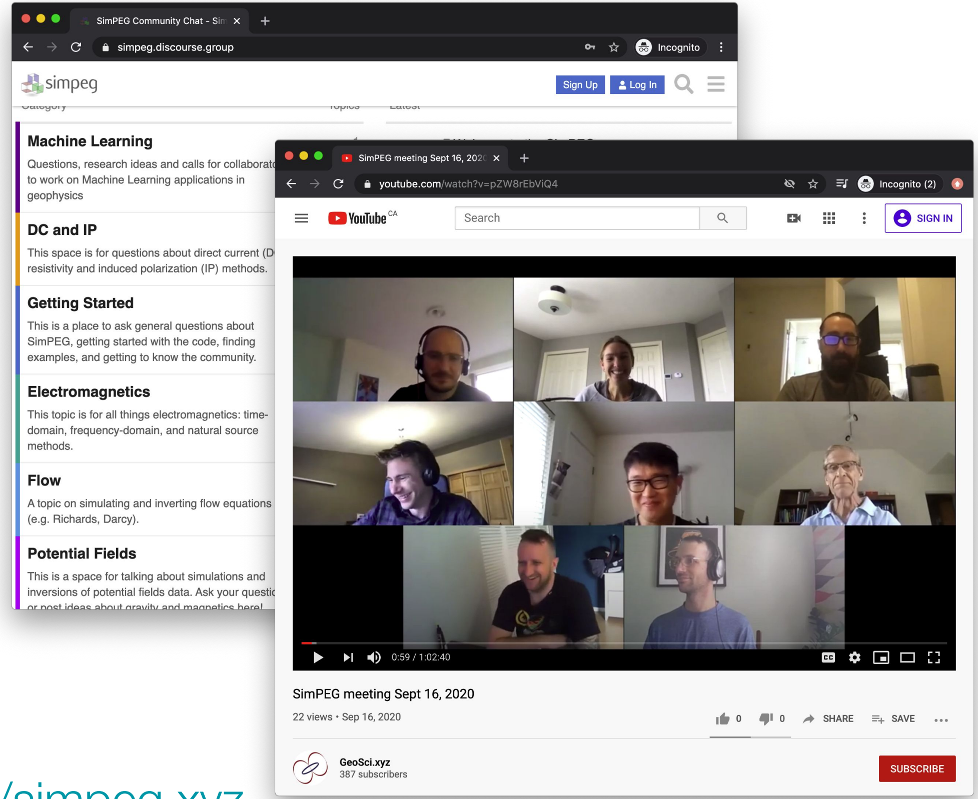
simpeg

Software practices

- Versioning code
- Tracking issues
- Testing code
- Suggesting changes
- Peer-reviewing changes

Communication

- Weekly meetings (recorded)
- Discourse forum for Q&A
- Chat with slack



https://simpeg.xyz

testing

mathematical properties

analytic solutions

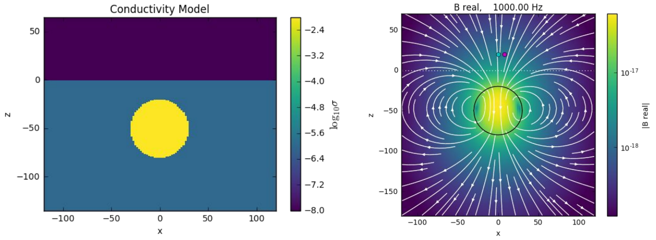
code comparisons

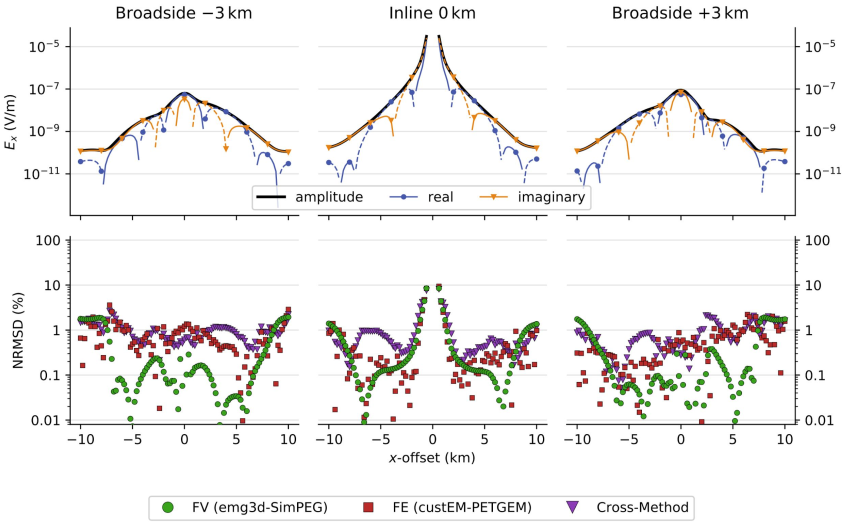
?

confidence

vector identity: $\nabla \cdot \nabla \times \vec{v} = 0$

```
[2]: v = np.random.rand(mesh.nE)
     np.all(mesh.faceDiv * mesh.edgeCurl * v == 0)

[2]: True
```

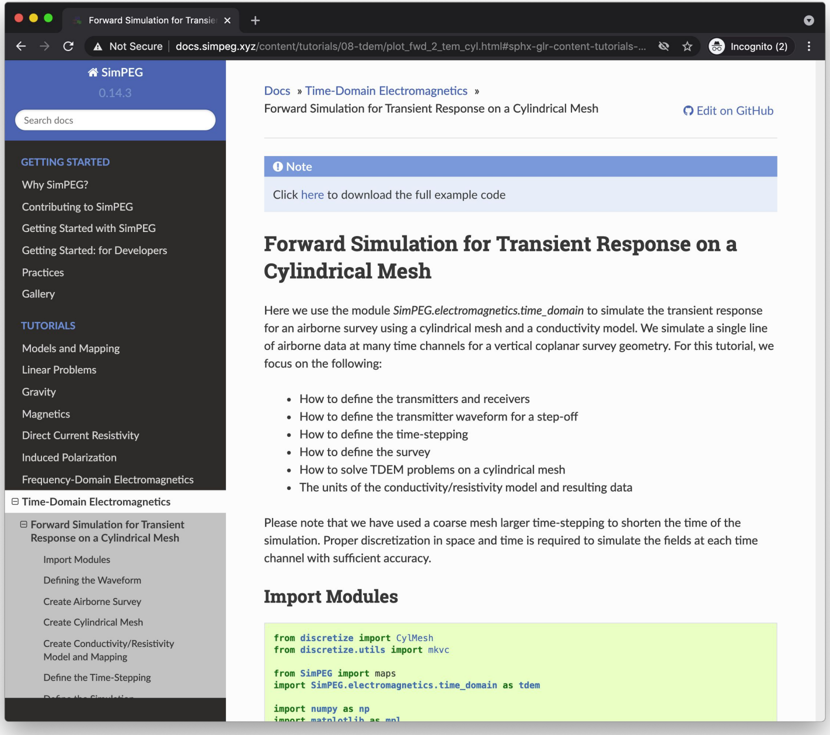




(Werthmüller et al., 2020)

community: connecting + resources

- documentation:
  docs.simpeg.xyz
- community forum:
  simpeg.discourse.group
- chat:
  slack.simpeg.xyz
- meeting notes + recordings:
  curvenote.com/@simpeg/meeting-notes



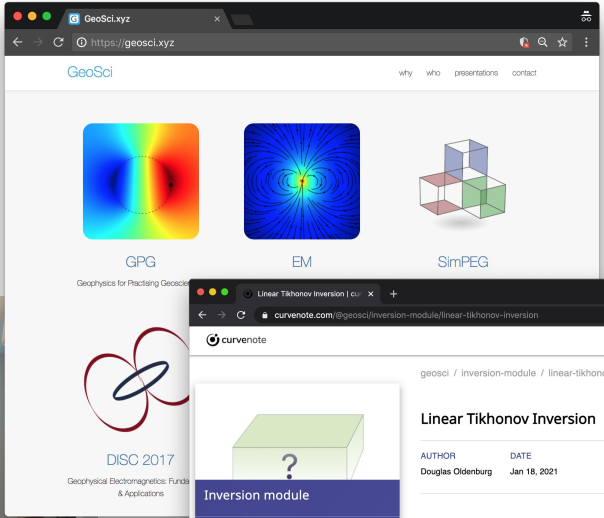
Devin Cowan

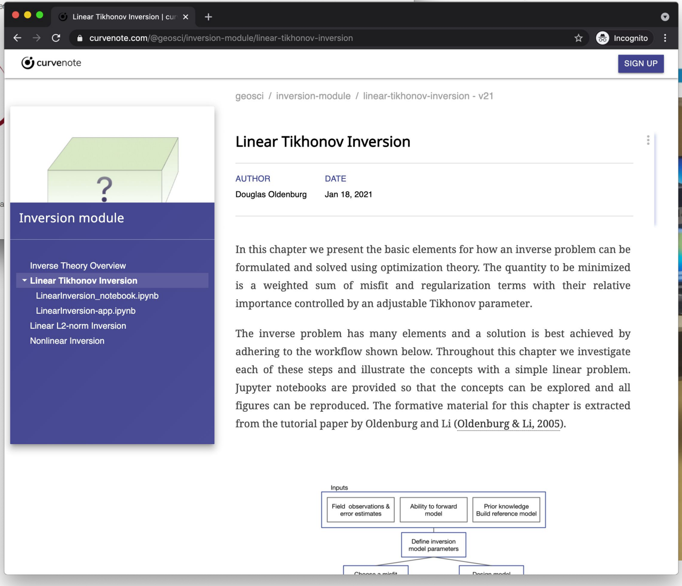
GeoSci.xyz

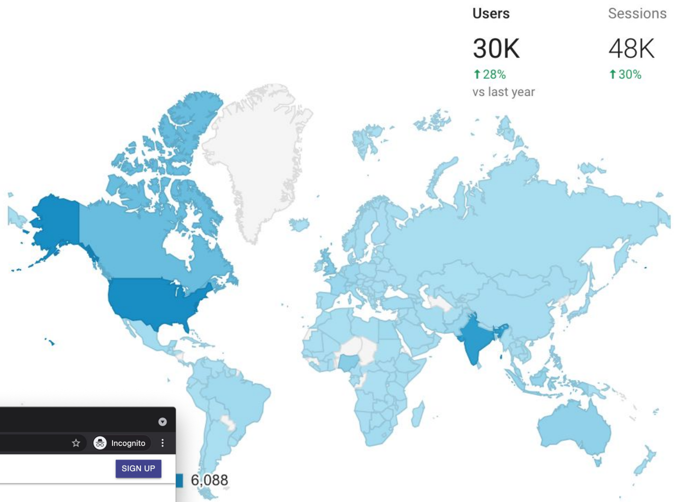
https://geosci.xyz

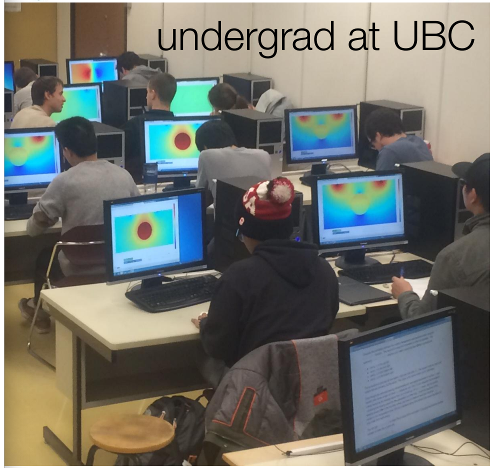
DISC 2017
Electromagnetics Fundamentals and Applications

26 locations worldwide









curvenote.com/@geosci/inversion-module

thank you!

simpeg

banesullivan

bsmithyman

dccowan

dougoldenburg

dwfmarchant

fourndo


fwkoch

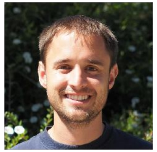
grosenkj

jcapriot

JKutt

lacmajedrez

lheagy


micmitch

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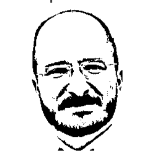
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Alan Jones


Max Moorkamp

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