

Esript: Open Source Environment For Solving Large-Scale Geophysical Joint Inversion Problems in Python

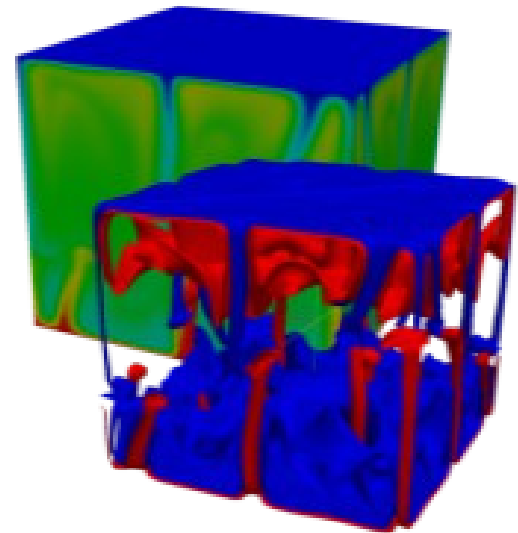
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escript

- Environment for mathematical modelling with partial differential equations (PDEs)
 - Multi-physics modelling
 - python interface
 - uses PDE terminology
 - 2D+3D FEM
 - MPI+OpenMP



see <https://launchpad.net/escript-finley>

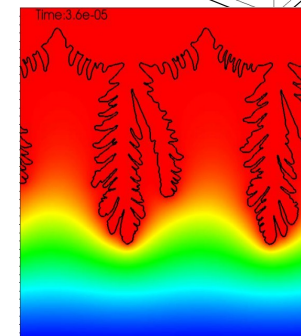
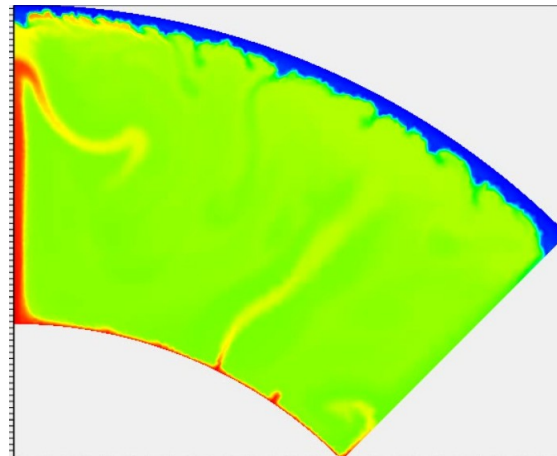
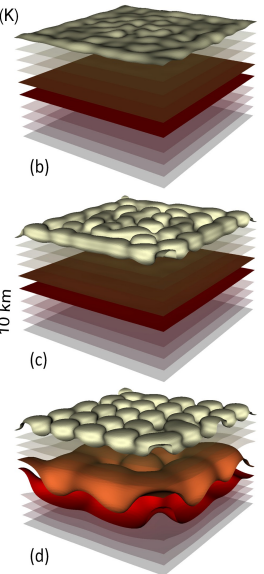
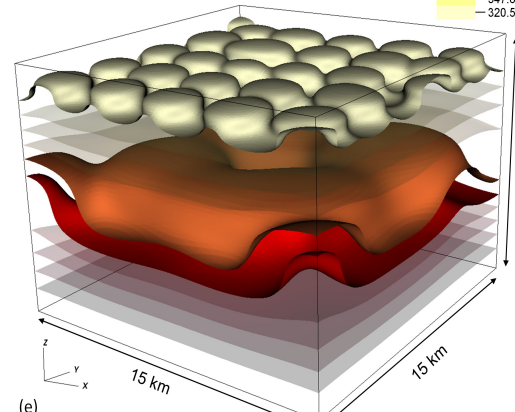
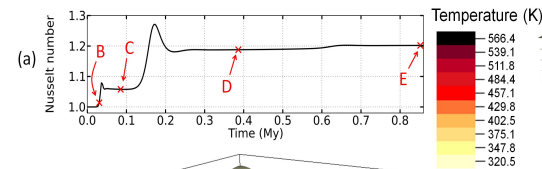
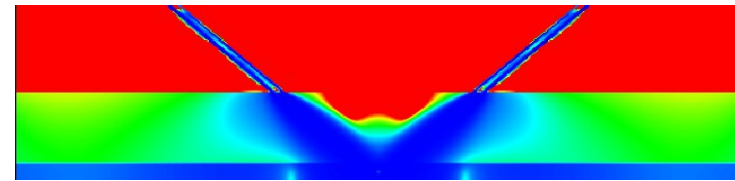
Escript status

- Since 2003 with about two software engineers at any time
 - AuScope NCRIS, CRIS, NCRIS2
 - AGOS EIF
 - Total Funding \$A ~ 2.6 Million (until July'15)
- Open Source under OSF 3.0
- Using best best practice
 - SVN
 - Nightly testing
 - >60000 functional tests
 - On ~10 platforms
 - Source and binary distribution via <https://launchpad.net/escript-finley>
 - Bug tracking



escript applications

- Geophysical inversion
- Mantel Convection
- Pores Media Flow
- Earthquakes
- Reactive Transport
- Volcanoes
- Tsunamis



escript.LinearPDE

Interface to a general linear PDE in variational form:

find $u_k : \Omega \rightarrow \mathbb{R}, u_k = r_k$ where $q_k > 0$

for all $v_i : \Omega \rightarrow \mathbb{R}, v_i = 0$ where $q_i > 0$

$$\int_{\Omega} A_{ijkl} v_{i,j} u_{k,l} + B_{ijk} v_{i,j} u_k + C_{ikl} v_i u_{k,l} + D_{ik} v_i u_k \, dx \\ = \int_{\Omega} X_{ij} v_{i,j} + Y_i v_i \, dx$$

with PDE coefficients $A_{ijkl}, B_{ijk}, C_{ikl}, D_{ik}, X_{ij}, Y_i, q_k, r_k$

Example

Gravitational field anomaly g_i due
to density variation ρ

$$-u_{,ii} = 4\pi \cdot \rho$$

$$g_i = -u_{,i}$$

$$-\Delta u = 4\pi \cdot \rho$$

$$\mathbf{g} = -\nabla u$$

Example (cont.)

Variational Formulation of the PDE:

for all $v : \Omega \rightarrow \mathbb{R}$

$$\int_{\Omega} \underbrace{\delta_{jl}}_{A_{jl}} v_{,j} u_{,l} dx = \int_{\Omega} \underbrace{4\pi \cdot \rho \cdot v}_Y dx$$

for all $v : \Omega \rightarrow \mathbb{R}$

$$\int_{\Omega} \nabla^t v \nabla u dx = \int_{\Omega} 4\pi \cdot \rho \cdot v dx$$

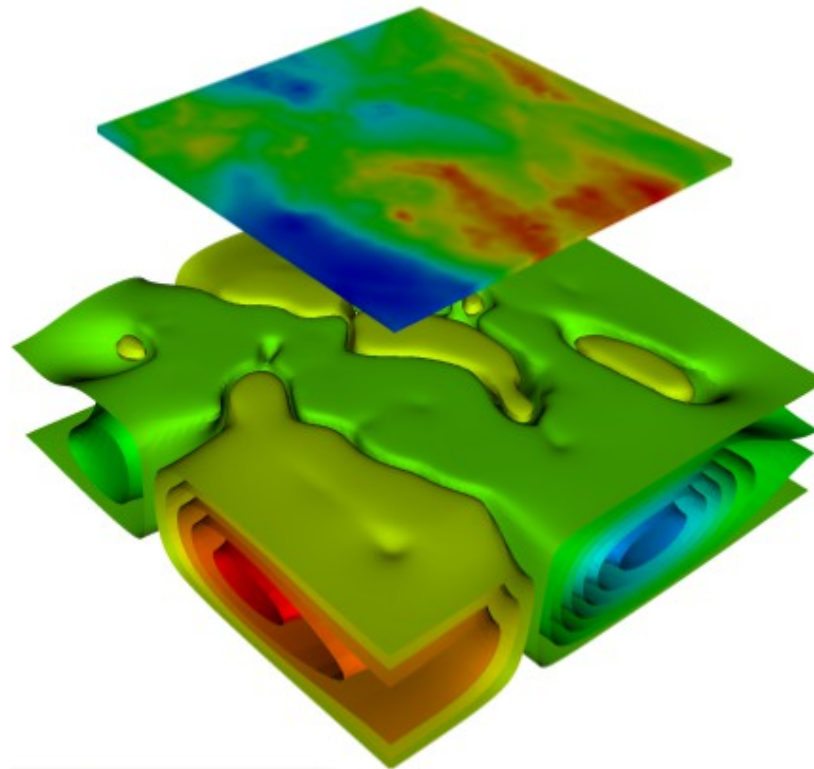
Implementation in python

```
from esys.escript import *
import esys.escript.unitSI as U
rho=200*U.kg/U.m**3
# 100x100x10km with 200m resolution
domain=Brick(500,500,50,100*U.km,100*U.km,10*U.km)
# solve the PDE:
myPDE=LinearPDE(domain)
z=domain.getX()[2] # get z coordinates
mypde.setValue(A=kronecker(3), Y=4*pi*rho, \
               q=whereZero(z-sup(z)) # fix potential @ top
u=myPDE.getSolution()
g=-grad(u)
# calculate misfit to vertical gravity data
d=getMyGravityData(...)
D=0.5*integrate((g[2]-d)**2)
```

- constant
- tagging
- PDE solution

Inversion

Recover physical properties in the subsurface from measurements near/above surface.



PDE constraint Optimisation

Find $\arg \min_{\rho} J(\rho) := D(u) + \mu \cdot R(\rho)$

$$\text{data misfit : } D(u) = \frac{1}{2} \int_{\Omega} (u_{,2} - \hat{g})^2 dx$$

PDE constraint : $u = Q[\rho]$ defined by
for all $v : \int_{\Omega} v_{,l} u_{,l} dx = \int_{\Omega} 4\pi \cdot \rho \cdot v dx$

$$\text{regularization: } R(\rho) = \frac{1}{2} \int_{\Omega} \rho_{,l} \rho_{,l} dx$$

escript.downunder

find property functions : $\mathbf{m} = (\text{density}, \text{susceptibility}, \dots)$

cost function $J(\mathbf{m}) := R(\mathbf{m}) + \sum_f D^f(u^f)$

data misfit for forward model f : $D^f(u^f) = \frac{1}{2} \int_{\Omega} (w_i^f \cdot u_{,i}^f - \hat{g}^f)^2$

PDE constraints : $u^f = Q^f[\mathbf{m}]$

Regularization Term

$$R(\mathbf{m}) = \sum_k \int_{\Omega} \mu_k S(m_k) + \sum_{i < k} \int_{\Omega} \mu_{ik} C(m_k, m_i)$$

$$\text{smoothing : } S(m) = \frac{1}{2} (w_1 \cdot m_{,l} m_{,l} + w_0 \cdot m^2)$$

$$\text{cross-gradient : } C(m, n) = \frac{1}{2} \left((m_{,l} m_{,l}) \cdot (n_{,l} n_{,l}) - (m_{,l} \cdot n_{,l})^2 \right)$$

Gradient

find $\mathbf{m} : \langle \nabla J(\mathbf{m}), \mathbf{p} \rangle = 0$ for all increments $\mathbf{p}$ to $\mathbf{m}$

$$\langle \nabla J(\mathbf{m}), \mathbf{p} \rangle = \int_{\Omega} X_{ij} p_{i,j} + Y_i p_i \, dx$$

- with suitable functions X_{ij} and Y_i of $\mathbf{m}$
- calculate via superposition
- extra adjoint PDE per forward problem

Quasi-Newton Method

iteration count $v=0$; initial guess $\mathbf{m}^{(0)}$

$$\mathbf{g}^{(v)} = \nabla J(\mathbf{m}^{(v)})$$

find $\mathbf{p}^{(v)}$ with: for all $\mathbf{q} : \langle \mathbf{H}^{(v)} \mathbf{p}^{(v)}, \mathbf{q} \rangle = \langle \mathbf{g}^{(v)}, \mathbf{q} \rangle$

$\mathbf{H}^{(v)} \approx$ Hessian Operator at $\mathbf{m}^{(v)}$

$$\mathbf{m}^{(v+1)} = \mathbf{m}^{(v)} + \alpha \cdot \mathbf{p}^{(v)} \text{ with}$$

$\min_{\alpha} J(\mathbf{m}^{(v)} + \alpha \cdot \mathbf{p}^{(v)})$ via line search

$$v \leftarrow v+1$$

Hessian Operator

- Ignore forward models
- If no cross gradient term

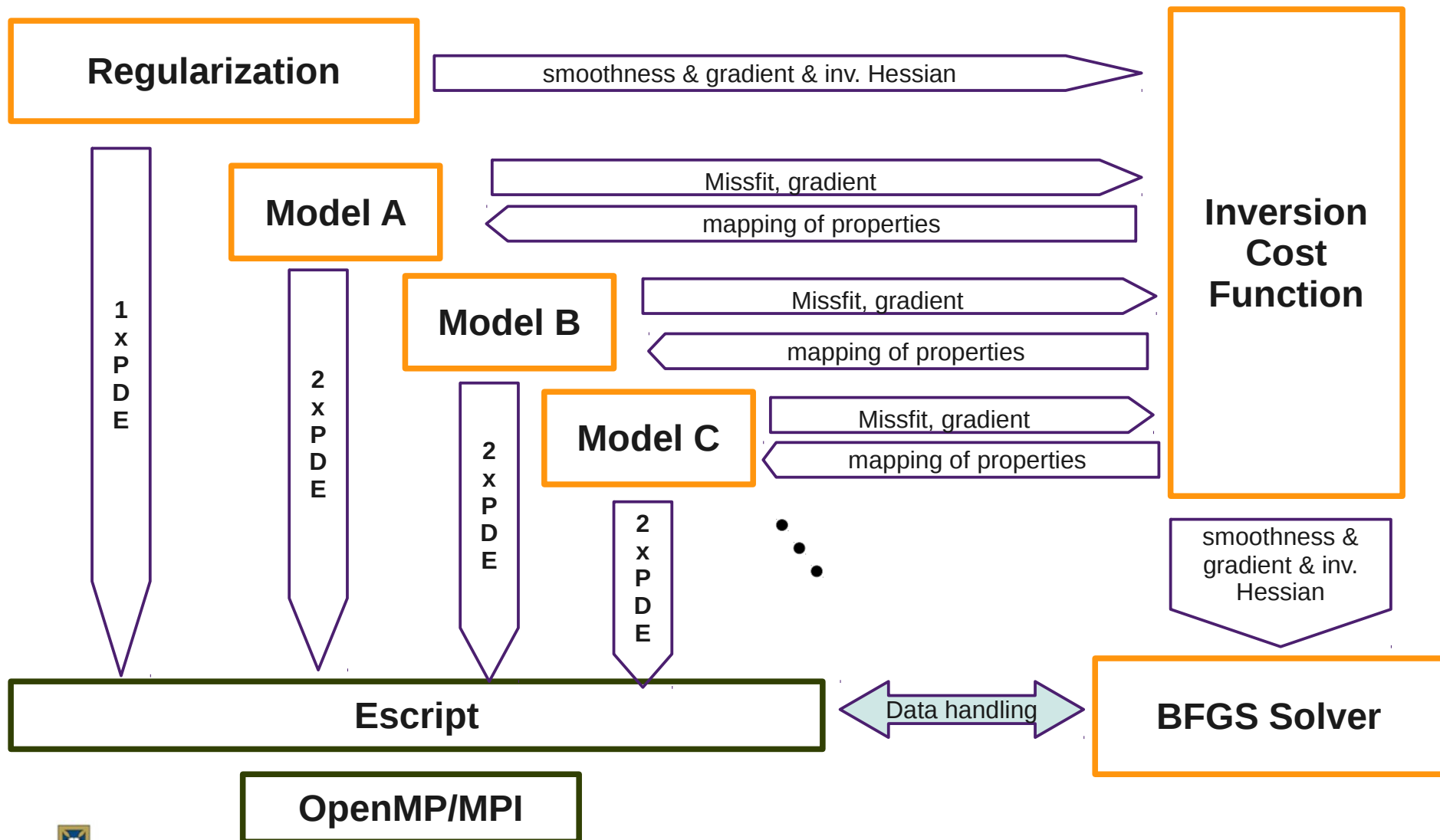
$$\langle \mathbf{H}^{(\mathbf{v})} \mathbf{p}^{(\mathbf{v})}, \mathbf{q} \rangle = \langle \mathbf{g}^{(\mathbf{v})}, \mathbf{q} \rangle$$



$$\int_{\Omega} w_{1k} p_{k,l} q_{k,l} + w_{0k} \cdot p_k q_k \, dx = \int_{\Omega} X_{ij} q_{i,j} + Y_i q_i \, dx$$

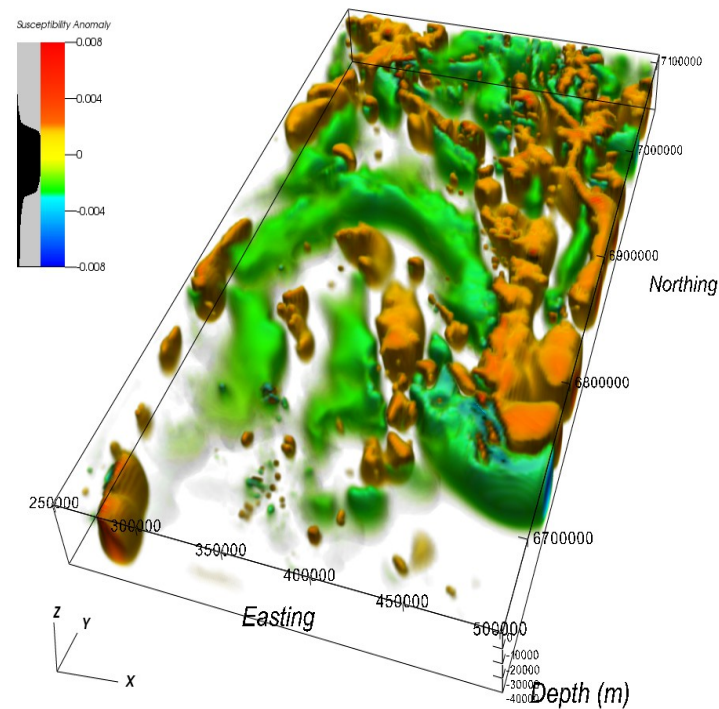
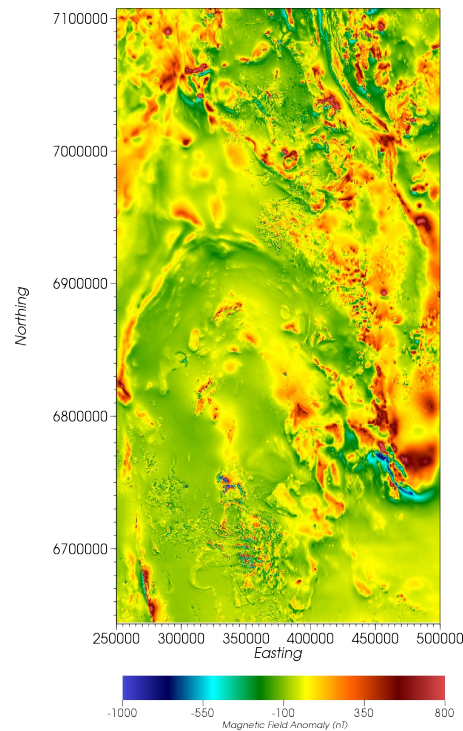
→ PDE solved by escript

Inversion Framework in Python



Example: Clarence-Moreton Basin

- Magnetic data from vgl.auscope.org.au, resolution <100m
- 500 Million cells on 8000 cores in < 1.5 hours



Summary

- Inversion as PDE constraint optimization
 - “First optimize then discretize”
 - Adaptive meshing
 - Computational scalability
- Escript based inversion framework
- Visit <https://launchpad.net/escript-finley>