Finite Volume Method with Inhomogenous Parameters for Realistic Geological Models based on SPE10

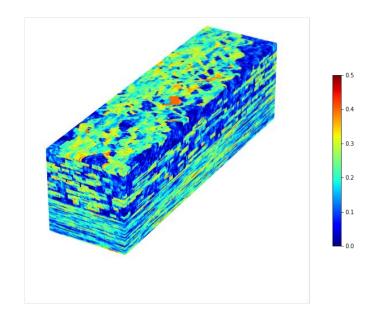
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Tasks

- Write an API for SGeMS
- Implement FVM with inhomogenous parameters

SPE10 model 2 and SGeMS

F/ SGeMS beta File Objects Properties Regions Data Analysis View Scripts Help Algorithms Algorithm Description **Utilities** □ Simulation LU sim Cholesky decomposition SearchTreePartioning IK Integration SNESIM and SISIM cosgsim sequential gaussian co-simulation Sequential indicator co-simulation cosisim dssim Direct sequential simulation Filter-based categorical simulation filtersim cate filtersim cont Filter-based continuous simulation Sequential Gaussian Simulation sgsim sisim Sequential indicator simulation snesim_partition SNESIM with search tree partitionning snesim std Single normal equation simulation **□** Estimation Kriging with secondary attribute cokriging indicator kriging Indicator kriging kriging SK, OK, KT and block kriging kriging_mean Kriging of the mean



• Model: 1200 x 2200 x 170 (ft)

60 x 220 x 85 (cells)

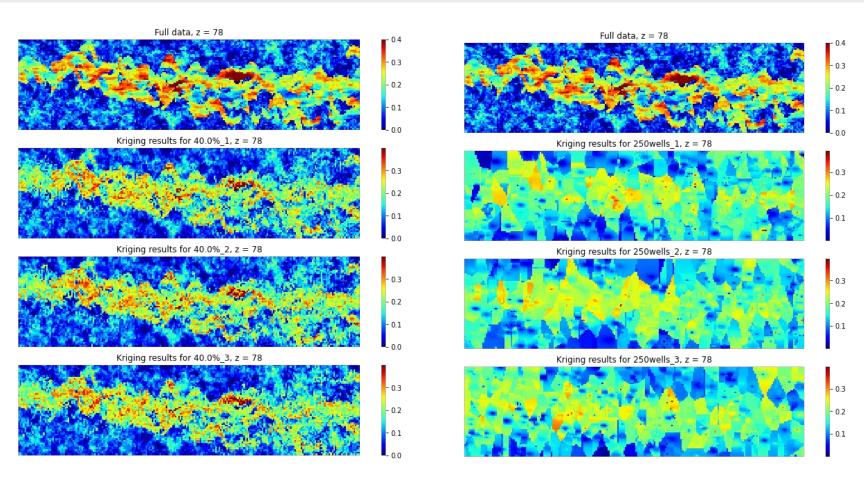
• Cell size: 20 x 10 x 2 (ft)

Kriging and Cokriging

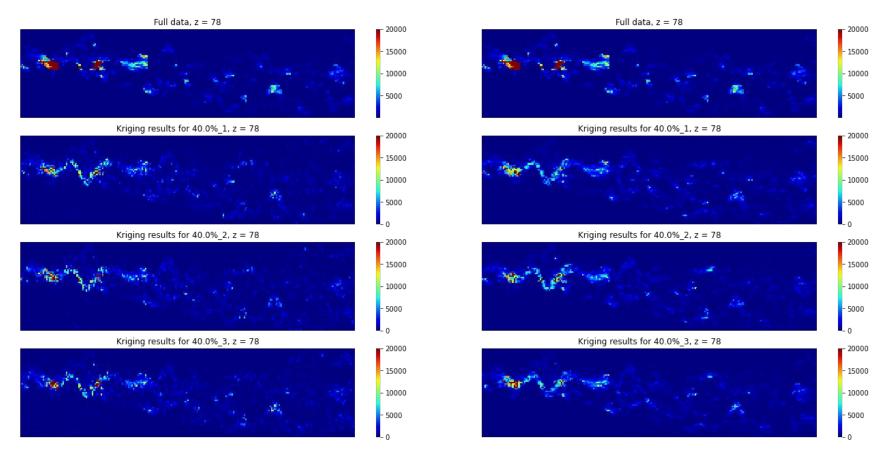
- Weighted interpolation
- Variables are normally distributed
- Prior covariance
- Cross covariance for cokriging

40% of initial data

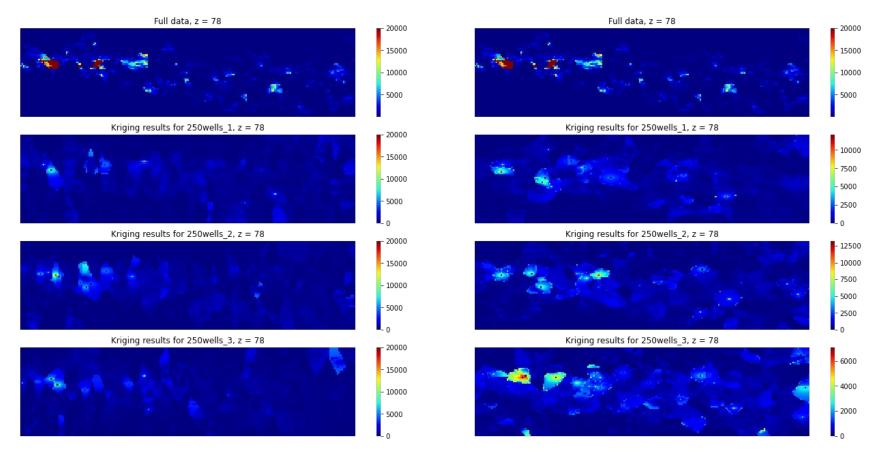
250 wells of initial data



Kriging Cokriging



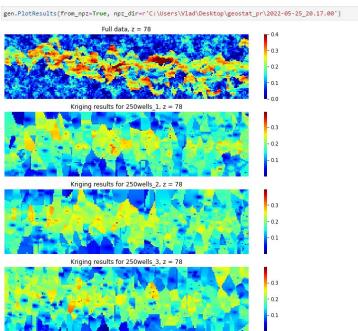
Kriging Cokriging



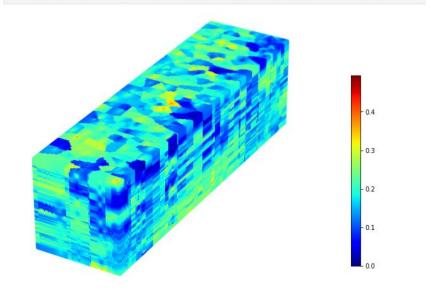
```
from generator import *
input_folder = 'D:/spe10_mod2/input_folder/'
output_folder = 'C:/Users/Vlad/Desktop/geostat_pr/'
gen = Generator(root=input_folder, path_to_save=output_folder, model='spe10m2', alg='ord_kriging')
gen(size=3, alpha=.4, search_ellipsoid='800 700 200 0 90 0')

***
gen(size=3, n_wells=250, search_ellipsoid='800 700 200 0 90 0')

***
```







Experiment with a search ellipsoid

```
from generator import *
input folder = 'D:/spe10 mod2/input folder/'
output folder = 'C:/Users/Vlad/Desktop/geostat pr/'
gen = Generator(root=input folder, path to save=output folder, model='spe10m2', alg='ord kriging')
size, number = 1, 1
alpha = .3
prop name = 'poro'
gen.search ellipsoid = '450 300 100 0 90 0'
gen.run name = 'choose ellip 1'
gen._set_generation_mode(size, alpha)
gen. upload data()
gen._match_coord()
gen.work dir = abs join path(gen.size dir, str(alpha*100)+'% '+str(number))
gen. take points()
os.mkdir(gen.work dir)
print('Saving GSLIB files to: ' + gen.work dir)
gen._save_gslib_all(number)
gen.est results = {}
gen.property name = prop name
gen. set algorithm()
```

```
: # Can change parameters of the chosen algorithm
  gen. print alg tree()
  2022-05-26 12:50:17.617 | INFO
                                      pysgems.algo.sgalgo:show tree:70 - algorithm
  2022-05-26 12:50:17.618 | INFO
                                      pysgems.algo.sgalgo:show_tree:71 - {'name': 'kriging'}
 2022-05-26 12:50:17.619 | INFO
                                      pysgems.algo.sgalgo:show tree:70 - Variogram
 2022-05-26 12:50:17.620 | INFO
                                      pysgems.algo.sgalgo:show_tree:71 - {'nugget': '0', 'structures_count': '1'}
  2022-05-26 12:50:17.621 | INFO
                                      pysgems.algo.sgalgo:show tree:78 - Variogram//structure 1
 2022-05-26 12:50:17.622 | INFO
                                      pysgems.algo.sgalgo:show tree:79 - {'contribution': '0.0087', 'type': 'Exponential'}
 2022-05-26 12:50:17.623 | INFO
                                      pysgems.algo.sgalgo:show_tree:78 - Variogram//structure_1//ranges
 2022-05-26 12:50:17.624 | INFO
                                      pysgems.algo.sgalgo:show_tree:79 - {'max': '486', 'medium': '417', 'min': '125'}
                                      pysgems.algo.sgalgo:show_tree:78 - Variogram//structure_1//angles
 2022-05-26 12:50:17.624 | INFO
                                      pysgems.algo.sgalgo:show_tree:79 - {'x': '60', 'y': '0', 'z': '0'}
 2022-05-26 12:50:17.625 | INFO
  2022-05-26 12:50:17.626 | INFO
                                      pysgems.algo.sgalgo:show tree:70 - Grid Name
 2022-05-26 12:50:17.627 | INFO
                                      pysgems.algo.sgalgo:show tree:71 - {'value': 'computation grid', 'region': ''}
 2022-05-26 12:50:17.629 | INFO
                                      pysgems.algo.sgalgo:show_tree:70 - Property_Name
 2022-05-26 12:50:17.632 | INFO
                                      pysgems.algo.sgalgo:show_tree:71 - {'value': 'kriging'}
 2022-05-26 12:50:17.634 | INFO
                                      pysgems.algo.sgalgo:show tree:70 - Kriging Type
 2022-05-26 12:50:17.635
                                      pysgems.algo.sgalgo:show tree:71 - {'type': 'Ordinary Kriging (OK)'}
 2022-05-26 12:50:17.636 | INFO
                                      pysgems.algo.sgalgo:show tree:78 - Kriging Type//parameters
 2022-05-26 12:50:17.636 | INFO
                                      pysgems.algo.sgalgo:show_tree:79 - {}
 2022-05-26 12:50:17.637 | INFO
                                      pysgems.algo.sgalgo:show_tree:70 - Hard_Data
 2022-05-26 12:50:17.638 | INFO
                                      pysgems.algo.sgalgo:show_tree:71 - {'grid': 'poro_grid', 'property': 'poro'}
                                      pysgems.algo.sgalgo:show_tree:70 - Min_Conditioning Data
 2022-05-26 12:50:17.639 | INFO
 2022-05-26 12:50:17.642 | INFO
                                      pysgems.algo.sgalgo:show tree:71 - {'value': '0'}
 2022-05-26 12:50:17.644 | INFO
                                      pysgems.algo.sgalgo:show tree:70 - Max Conditioning Data
 2022-05-26 12:50:17.644 | INFO
                                      pysgems.algo.sgalgo:show_tree:71 - {'value': '12'}
 2022-05-26 12:50:17.646 | INFO
                                      pysgems.algo.sgalgo:show_tree:70 - Search_Ellipsoid
                                      pysgems.algo.sgalgo:show_tree:71 - {'value': '450 300 100 0 90 0'}
 2022-05-26 12:50:17.647 | INFO
 2022-05-26 12:50:17.648 | INFO
                                      pysgems.algo.sgalgo:show tree:70 - AdvancedSearch
                                     pysgems.algo.sgalgo:show tree:71 - {'use advanced search': '0'}
 2022-05-26 12:50:17.650 | INFO
 search_ellipsoid = '800 700 200 0 90 0'
 gen. change alg params(search ellipsoid)
  2022-05-26 12:50:21.866 | INFO
                                      pysgems.algo.sgalgo:xml update:115 - Updated
 2022-05-26 12:50:21.867 | INFO
                                      pysgems.algo.sgalgo:xml_update:116 - Search_Ellipsoid
```

pysgems.algo.sgalgo:xml update:117 - {'value': '800 700 200 0 90 0'}

2022-05-26 12:50:21.868 | INFO

Consider, initially, a one-dimensional problem expressible as a conservation law in vector form: $u_t + f(u)_x = 0$

Upon transferring to integer-centered cell averages in the spatial direction, obtain for a characteristic time step: $\bar{u}(x,t+\Delta t) = \bar{u}(x,t) - \frac{1}{\Delta x} \int_{-\Delta t}^{t+\Delta t} \left[f\left(u\left(x+\frac{\Delta x}{2},\tau\right)\right) - f\left(u\left(x-\frac{\Delta x}{2},\tau\right)\right) \right] d\tau$

Assuming that the solution is expressible as a certain polynomial supported on the integer-centered cells (of piecewise order n-1 for n-th order of convergence), sample on the staggered centres (i.e. cell breakpoints) to obtain our final expression:

$$\bar{w}_{j+\frac{1}{2}}^{n+1} = \frac{1}{\Delta x} \int_{I_{j+\frac{1}{2}}} w(x, t^n) \, dx - \frac{1}{\Delta x} \left[\int_{t^n}^{t^{n+1}} f(w(x_{j+1}, t)) \, dt - \int_{t^n}^{t^{n+1}} f(w(x_j, t)) \, dt \right]$$

The rest of the method consists in finding the quadraturae employed above.

We state for the sake of completeness the second-order piecewise linear polynomial's constituent term and note that higher order is trivially obtainable by considering an appropriate Taylor expansion: $p_j(x) = \bar{w}_j^n + w_j' \left(\frac{x - x_j}{\Delta x}\right)$

The principal demand we place upon the reconstruction of point values and derivatives of w in the above is (aside from, naturally, preservation of cell averages) the demand of non-oscillatory nature. A natural and intuitive demand of such kind is the non-increasing behavior of the function's supremum, which naturally translates into the satisfaction by our polynomial the condition imposed by the Weierstrass theorem, thereby eliminating the spurious oscillation: $\sup_x |\sum_i p_j(x) \chi_j(x)| \leq \sup_x |\sum_i \bar{w}_i^n \chi_j(x)|$

A second-degree accurate method, proposed by the source paper, employs the van Leer MinMod limiter:

$$w'_{j} = \operatorname{MinMod}(\alpha \Delta_{+} \bar{w}_{j}, \Delta_{0} \bar{w}_{j}, \alpha \Delta_{-} \bar{w}_{j}), \quad 1 \leqslant \alpha < 4.$$

With
$$\Delta_{\pm}w_j = \pm (w_{j\pm 1} - w_j)$$
, and $\Delta_0 = \frac{1}{2}(\Delta_+ + \Delta_-)$ and $\Delta_0 = \frac{1}{2}(\Delta_+ + \Delta_-)$

It ought to be noted that the MinMod assumes a zero value wherever the signs are distinct and that this particular reconstruction enjoys an additional TVD (total-variation diminishing) property, meaning that it preserves the monotonicity of functions, which is an upgrade if we were to consider shocks and rarefaction waves (spoiler: we don't)

It is also noted that we are at liberty to choose the parameter alpha, which we mostly keep at 1.4-1.5 as is customary.

Having produced the reconstruction outlined above (implicitly, since we never write the polynomials down explicitly: we evaluate only specific parts of them), we obtained the following for the first integral in the evolution equation:

$$\frac{1}{\Delta x} \int_{I_{j+\frac{1}{2}}} w(x, t^n) dx = \frac{1}{\Delta x} \left[\int_{x_j}^{x_j + \frac{1}{2}} p_j(x) dx + \int_{x_{j+\frac{1}{2}}}^{x_{j+1}} p_{j+1}(x) dx \right] = \frac{1}{2} [\bar{w}_j^n + \bar{w}_{j+1}^n] + \frac{1}{8} [w_j' - w_{j+1}'].$$

Now considering the integral with flux terms, we can see that it is integrable in numerical quadraturae to arbitrary accuracy provided the insides of cells have no discontinuities of the target fields. For simplicity, take the midpoint rule $\int_{a}^{r+1} f(w(x_j,\tau)) \, d\tau \approx \Delta t f(w_j^{n+\frac{1}{2}}),$

And obtain the following predictor with lambda a mesh ratio: $w_j^{n+\frac{1}{2}} = \bar{w}_j^n - \frac{\lambda}{2} f_j', \quad f_j = f(w_j^n)$

In this case we are well able to avoid evaluation of the Jacobian: $f'_j = \mathbf{MinMod}(\alpha \Delta_+ f_j, \Delta_0 f_j, \alpha \Delta_- f_j), \quad f_j = f(w_j^n)$

Then:

$$\int_{t^n}^{t^{n+1}} f(w(x_j,\tau)) d\tau \approx \Delta t f(w_j^{n+\frac{1}{2}}) =: \Delta t f_j^{n+\frac{1}{2}},$$

And we also have corrector:

$$\bar{w}_{j+\frac{1}{2}}^{n+1} = \frac{1}{2} [\bar{w}_{j}^{n} + \bar{w}_{j+1}^{n}] + \frac{1}{8} [w_{j}' - w_{j+1}'] - \lambda \left[f_{j+1}^{n+\frac{1}{2}} - f_{j}^{n+\frac{1}{2}} \right]$$

Now consider a two-dimensional problem of same kind: $u_t + f(u)_x + g(u)_z = 0$.

Similarly, take cell averages:

$$\begin{split} \bar{u}_t(x,z,t) + \frac{1}{\Delta x \Delta z} \int_{z-\frac{\Delta z}{2}}^{z+\frac{\Delta z}{2}} \left[f\left(u\left(x + \frac{\Delta x}{2}, \eta, t\right)\right) - f\left(u\left(x - \frac{\Delta x}{2}, \eta, t\right)\right) \right] d\eta \\ + \frac{1}{\Delta x \Delta z} \int_{x-\frac{\Delta z}{2}}^{x+\frac{\Delta z}{2}} \left[g\left(u\left(\xi, z + \frac{\Delta z}{2}, t\right)\right) - g\left(u\left(\xi, z - \frac{\Delta z}{2}, t\right)\right) \right] d\xi = 0. \end{split}$$

Proceeding analogously to what we did before except with upscaling of everything in dimension, we obtain the following general evolution relation which we now set to evaluate:

$$\bar{w}_{j+\frac{1}{2}k+\frac{1}{2}}^{n+1} = \bar{w}_{j+\frac{1}{2}k+\frac{1}{2}}^{n} - \frac{1}{\Delta x \Delta z} \int_{t^{n}}^{t^{n+1}} \int_{z_{k}}^{z_{k+1}} [f(w(x_{j+1}, z, t)) - f(w(x_{j}, z, t))] dz dt$$
$$- \frac{1}{\Delta x \Delta z} \int_{t^{n}}^{t^{n+1}} \int_{x_{j}}^{x_{j+1}} [g(w(x, z_{k+1}, t)) - g(w(x, z_{k}, t))] dx dt.$$

How do we approximate with polynomials in 2D? We elect to follow the multilinear approach (in our case bilinear): we simply interpolate in 1D along each spatial axis: $p_{jk}(x,z) = \bar{w}_{jk}^n + w'_{jk}(\frac{x-x_j}{\Delta x}) + w_{jk}(\frac{z-z_k}{\Delta z})$

The right-slanted primes are a feature and not a bug: they denote z-derivative as opposed to x-derivative:

$$w'_{jk} = MinMod(\alpha \Delta_{+x} \bar{w}_{jk}^n, \Delta_{0x} \bar{w}_{jk}^n, \alpha \Delta_{-x} \bar{w}_{jk}^n).$$

$$\overrightarrow{w}_{ik} = \operatorname{MinMod}(\alpha \Delta_{+z} \overline{w}_{ik}^n, \Delta_{0z} \overline{w}_{ik}^n, \alpha \Delta_{-z} \overline{w}_{ik}^n).$$

Equipped with this, we can now evaluate the first (average) term in our formula:

$$\begin{split} \bar{w}_{j+\frac{1}{2}k+\frac{1}{2}}^{n} &= \frac{1}{\Delta x \Delta z} \int_{x_{j}}^{x_{j+\frac{1}{2}}} \int_{z_{k}}^{z_{k+\frac{1}{2}}} p_{jk}(x,z) \; \mathrm{d}z \; \mathrm{d}x + \int_{x_{j+\frac{1}{2}}}^{x_{j+1}} \int_{z_{k}}^{z_{k+\frac{1}{2}}} p_{j+1,k}(x,z) \; \mathrm{d}z \; \mathrm{d}x \\ &+ \frac{1}{\Delta x \Delta z} \int_{x_{j}}^{x_{j+\frac{1}{2}}} \int_{z_{k+\frac{1}{2}}}^{z_{k+1}} p_{j,k+1}(x,z) \; \mathrm{d}z \; \mathrm{d}x + \int_{x_{j+\frac{1}{2}}}^{x_{j+1}} \int_{z_{k+\frac{1}{2}}}^{z_{k+1}} p_{j+1,k+1}(x,z) \; \mathrm{d}z \; \mathrm{d}x \\ &= \frac{1}{4} (\bar{w}_{jk}^{n} + \bar{w}_{j+1,k}^{n} + \bar{w}_{j,k+1}^{n} + \bar{w}_{j+1,k+1}^{n}) \\ &+ \frac{1}{16} \Big[(w_{jk}' - w_{j+1,k}') + (w_{j,k+1}' - w_{j+1,k+1}') + (w_{jk}' - w_{j,k+1}') + (w_{j+1,k}' - w_{j+1,k+1}') \Big] \end{split}$$

Then, like before, we do the predictor step with lambda and mu being mesh ratios (of temporal to spatial step): $n+\frac{1}{2}$ -n λ μ

step):
$$w_{jk}^{n+\frac{1}{2}} = \bar{w}_{jk}^n - \frac{\lambda}{2} f_{jk}' - \frac{\mu}{2} g_{jk}'$$

Employ a direct Jacobian-free approximation:

$$f'_{jk} = \operatorname{MinMod}(\alpha \Delta_{+x} f_{jk}, \Delta_{0x} f_{jk}, \alpha \Delta_{-x} f_{jk}),$$

$$g'_{jk} = \operatorname{MinMod}(\alpha \Delta_{+z} g_{jk}, \Delta_{0z} g_{jk}, \alpha \Delta_{-z} g_{jk}).$$

And approximate the flux integrals:

$$\int_{t^n}^{t^{n+1}} \int_{z_k}^{z_{k+1}} f(w(x_{j+1}, z, t)) dz dt \sim \frac{\Delta z \Delta t}{2} \left[f(w_{j+1, k}^{n+\frac{1}{2}}) + f(w_{j+1, k+1}^{n+\frac{1}{2}}) \right]$$

$$\int_{t^n}^{t^{n+1}} \int_{x_t}^{x_{j+1}} g(w(x, z_{k+1}, t)) dx dt \sim \frac{\Delta x \Delta t}{2} \left[g(w_{j+1, k+1}^{n+\frac{1}{2}}) + g(w_{j, k+1}^{n+\frac{1}{2}}) \right].$$

In the end, an evolution formula is obtained!

$$\begin{split} \bar{w}_{j+\frac{1}{2}k+\frac{1}{2}}^{n+1} &= \frac{1}{4} \big(\bar{w}_{jk}^n + \bar{w}_{j+1,k}^n + \bar{w}_{j,k+1}^n + \bar{w}_{j+1,k+1}^n \big) + \frac{1}{16} \big(w_{jk}' - w_{j+1,k}' \big) - \frac{\lambda}{2} \left[f \big(w_{j+1,k}^{n+\frac{1}{2}} \big) - f \big(w_{jk}^{n+\frac{1}{2}} \big) \right] \\ &+ \frac{1}{16} \big(w_{j,k+1}' - w_{j+1,k+1}' \big) - \frac{\lambda}{2} \left[f \big(w_{j+1,k+1}^{n+\frac{1}{2}} \big) - f \big(w_{j,k+1}^{n+\frac{1}{2}} \big) \right] + \frac{1}{16} \big(w_{jk}' - w_{j,k+1}' \big) \\ &- \frac{\mu}{2} \left[g \big(w_{j,k+1}^{n+\frac{1}{2}} \big) - g \big(w_{jk}^{n+\frac{1}{2}} \big) \right] + \frac{1}{16} \big(w_{j+1,k}' - w_{j+1,k+1}' \big) - \frac{\mu}{2} \left[g \big(w_{j+1,k+1}^{n+\frac{1}{2}} \big) - g \big(w_{j+1,k}^{n+\frac{1}{2}} \big) \right]. \end{split}$$

On preservation of dimensionality and stagger recovery

It is observed readily that upon transition to cells from endpoints the vector dimensionality diminishes by 1. Additionally, the evolution step yields the forward-staggered by a halfstep values. They need to be brought under control. One option is to explicitly reconstruct the polynomials and evaluate them at endpoints of staggered cells, incurring further computational costs. However, it is more attractive to alternative forward- and backstaggering by means of alternating padding from the right and the left endpoints. In our code the alternating padding is employed implicitly by using modified formulae for each of the cases.

On solenoidal projection

The density field obtained by staggered evolution is not necessarily solenoidal, which may be undesirable if we e.g. deal with incompressible fluids. Additionally, if we wish to make our solver capable of treating magnetic fields, this problem is to be solved.

A so-called Leray projection is then in order at the end of each step. It can be done, of course, by projecting onto a basis of solenoidal functions, e.g. solenoidal RBFs (Daniel A. Cervantes Cabrera, Pedro Gonzalez-Casanova, Christian Gout, L. Juárez Héctor, Rafael Resendiz. Vector field approximation using radial basis functions). However, I employed a different idea.

My idea (formulated for B)

Let $B = B_s + B_i$, with B_s solenoidal and B_i irrotational (permissible by Helmholtz theorem). Then:

$$\nabla \cdot B = \cdot B_i = \nabla \cdot \nabla \Phi$$

$$\nabla \cdot B = \Delta \Phi$$

Therefore, upon subtracting $\nabla \Phi$, found from above, from B, we get a solenoidal projection.

Kelvin-Helmholtz instability w/ an external magnetic field

To make points denser @ region of greater influence of

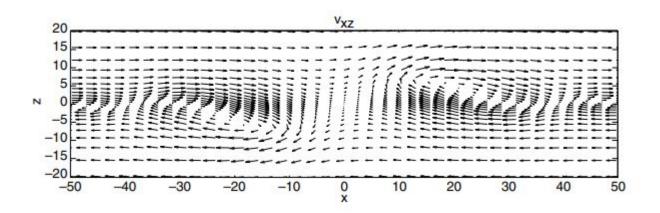
small perturbation, employ Roberts transform:

$$z \leftarrow \frac{H \sinh(\tau z/2H)}{\sinh(\tau/2)}, \quad \tau = 6$$

(stole the idea from G.-S. Jiang, C.C. Wu,

A high-order WENO finite difference scheme for the equations of ideal magnetohydrodynamics)

```
1 7=1056
 2 K=192
 3 \text{ cfl} = 0.4
 4 \text{ alpha} = 1.4
 6 x_init=-27.5*np.pi
 7 x final=27.5*np.pi
 8 z init=-20.0
 9 z final=20.0
10 t init=0
11 t final=145
12 dx=(x final - x init)/(J-1)
13 dz_eq=(z_final-z_init)/(K-1)
14 x = np.arange(x_init, x_final+dx, dx)
15 z = np.zeros([1, K]).reshape(-1)
16 z[0] = z init
17 z_beg=z[0]-dz_eq
18 for k in range(1,K):
19 z[k] = dz_eq+z[k-1]
20 \text{ z end} = \text{z}[-1]+\text{dz eq}
21 z_beg=20*np.sinh(z_beg*3/20)/np.sinh(3)
22 for k in range(K):
23 z[k]=20*np.sinh(z[k]*3/20)/np.sinh(3)
24 z_end=20*np.sinh(z_end*3/20)/np.sinh(3)
25 dz = np.zeros_like(z)
26 for k in range(1,K-1):
    dz[k]=.5*(z[k+1]-z[k-1])
28 dz[0]=.5*(z[1]-z_beg)
29 dz[-1]=.5*(z_end-z[-2])
30 v_init = np.zeros([J, K, 8])
31 for j in range(J):
32 for k in range(K):
       vx_init=np.tanh(z[k])
       v_init[j,k,0]=1.0
       v_init[j,k,1]=vx_init
       v_init[j,k,2]=0
       v_init[j,k,3]=0
       v_init[j,k,4]=0
       v_init[j,k,5]=1.0
       v_init[j,k,6]=0
41 j1=int(np.ceil(25*np.pi/dx)+1)
42 j2=int(np.ceil(30*np.pi/dx)+1)
43 for j in range(j1,j2):
    for k in range(K):
       v init[j,k,2]=v init[j,k,2] - .008*(np.sin(.4*x[j]))*(1.0/(1.0+z[k]**2))
46 for j in range(J):
     for k in range(K):
       v init[j,k,7]=1.0+.5*v init[j,k,2]**2
```



Given an initial density distribution as an exponential function of a scaled sum of X,Y and arrays of K, phi, compute the evolution.

Consider the equation of Darcy single-phase flow.

$$\nabla \cdot \left[\frac{\alpha \rho K}{\mu} (\nabla p + \rho g \nabla D) \right] + \alpha q = \alpha \frac{\partial (\phi \rho)}{\partial t}$$

We use the following simplifications: thickness is uniform, depth is uniform, fluid viscosity and compressibility are unity (induces a simple multiplicative scaling factor that is not very important qualitatively)

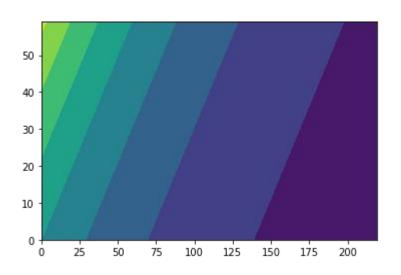
We get (in absence of wells):
$$\nabla \cdot \left[\frac{K}{\mu c} \nabla \rho \right] = \frac{\partial \phi \rho}{\partial t}$$

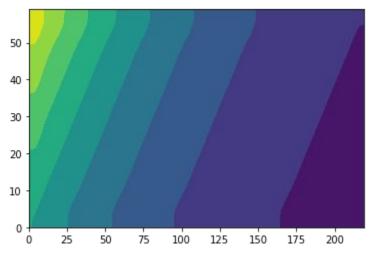
And transform into a conservation law:
$$u+f(u)_x+g(u)_y=0$$

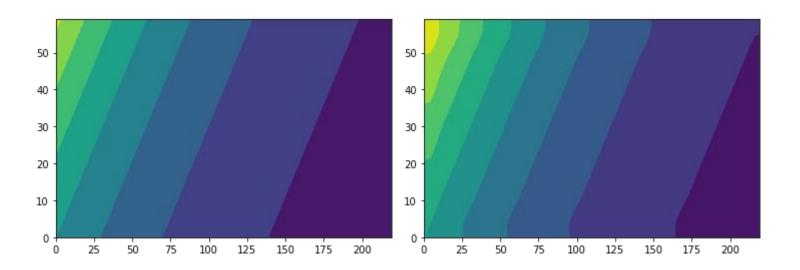
$$u=(\rho,r,p)$$

$$-f=(\frac{K_{xx}r}{\phi},\rho,0)$$

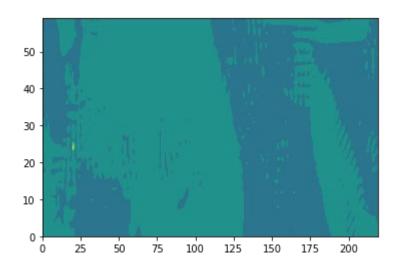
$$-g=(\frac{K_{yy}r}{\phi},0,\rho)$$







At much greater permeabilities we get



On adding wells

Adding wells is a nontrivial task because they do not easily conform to the conservation law form. In order to add them, one may well introduce such a field Q that the sink-source term q is given as a divergence of Q. This is the only way I see.