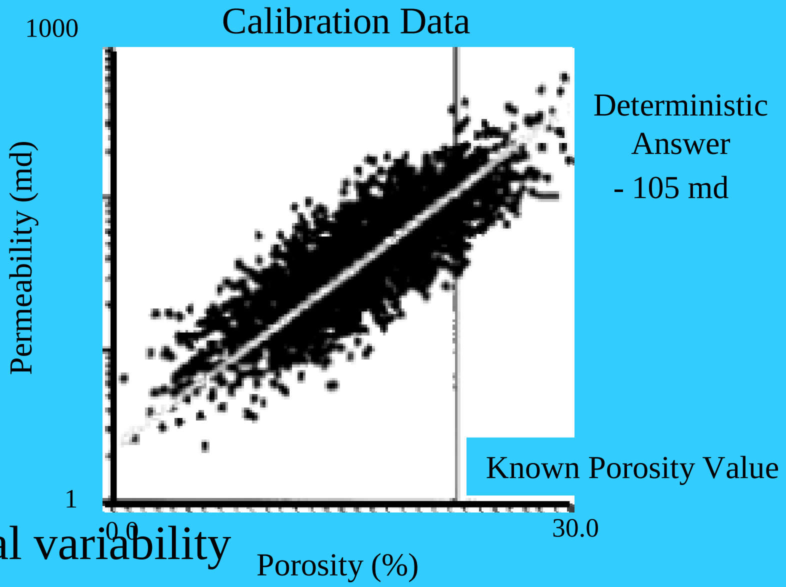
Annealing Techniques for Data Integration

- Discuss the Problem of Permeability Prediction
- Present Annealing Cosimulation
- More Details on Simulated Annealing
- Examples
- SASIM program

Regression-Type Deterministic Approaches



Approaches:

- linear regression
- quadratic, cubic, ... regression
- porosity class average or conditional averages

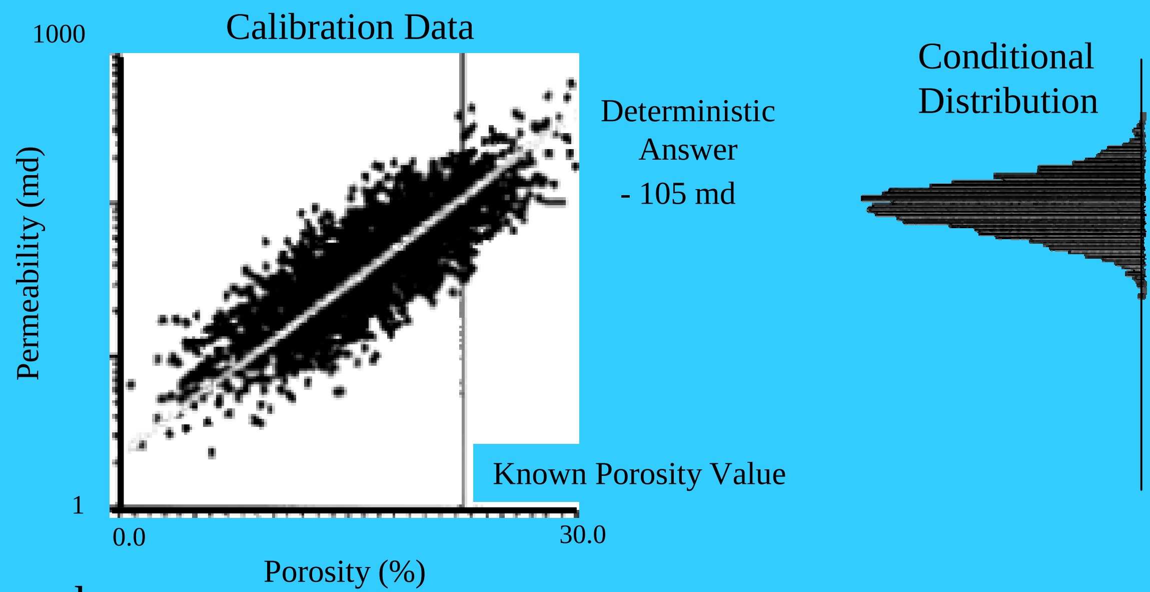
Characteristics:

- smooth out low and high values
- does not capture uncertainty
- transformed permeability have incorrect spatial variability

Considerations:

- extreme high and low values have the most impact on fluid flow
- spatial correlation (connectivity) is very important fewer “hard” permeability *K* data than porosity ϕ
- *K* is correlated with porosity ϕ
- build ϕ model first then *K* model (exhaustive secondary variable)

Stochastic Approaches



Approaches:

- stochastic simulation from porosity classes
- Markov-Bayes (implemented as a sequential simulation algorithm)
- collocated cosimulation (Gaussian)

Characteristics:

- can extract a single expected value (for looking at trends)
- calculate probability intervals (90% interval: 44-210 md)
- ⇒ DRAW SIMULATED VALUES

Annealing Techniques to Account for a Secondary Variable

What is Annealing?

Annealing, or more properly simulated annealing, is an optimization algorithm based on an

analogy with the physical process of annealing.

- Treat *O* as an *energy* function
- Cool an initial realization:
  - perturb system to simulate thermal agitation
  - always accept swaps that lower *O*
  - sometimes accept swaps that increase *O*
  - cool slowly $\Rightarrow$ find a minimum energy solution

What is Cosimulation?

Cosimulation is the act of generating a numerical model of one variable that is conditional to

the results of another variable, for example,

- model permeability conditional to porosity
- model porosity conditional to log data
- simulate multiple variables sequentially

Simulated Annealing

- Simulated annealing is a solution method in the field of combinatorial optimization based on an analogy with the physical process of annealing.

  Solving a combinatorial optimization problem amounts to finding the ‘best’ or ‘optimal’ solution among a finite or countable infinite number of alternative solutions.
- Introduced in the early 1980's by Kirkpatrick, Gelatt & Vecchi [1992;1983] and independently Cerny [1985]
- “Simulating the annealing process” dates back to 1953 and the work of Metropolis, Rosenbluth, Rosenbluth, Teller & Teller
- Applications in Spatial Statistics:
  - Geman and Geman, 1984
  - Farmer, 1989
  - Others, 1990-present
- In the application of annealing there is no explicit random function model, rather, the creation of a simulated realization is formulated as an optimization problem to be solved with a stochastic relaxation or “annealing” technique.

Application of Simulated Annealing

Prerequisites to apply simulated annealing as a numerical optimization technique:

- description of the system
- quantitative objective (energy) function
- random generator of moves or rearrangements
- an annealing schedule of the temperatures and the lengths of time to let the system evolve at each temperature

Some example applications:

- studying the behavior of materials such as crystals, magnetic alloys, and spin glasses
- travelling salesman-type problems
- routing of garbage collection trucks
- wiring layout of computers and circuit layout on computer chips
- assisting with seismic inversion
- geostatistics

Steps in Annealing-Based Simulation

1. Establish an initial guess that honors the well data

   Assign a *K* value to each cell by drawing from the conditional distribution of *K* given the cell's ϕ

2. Calculate the initial objective function

   Numerical measure of mismatch between the desired variogram and the one of the initial guess

3. Consider a change to a cell's permeability

   Randomly choose a non-data cell and then consider a new *K* from the conditional distribution of *K* given the cell's ϕ

4. Evaluate new objective function

- better? - accept change
- worse? - reject change

5. Is objective function close enough to zero?

- yes - done
- no - go to 3

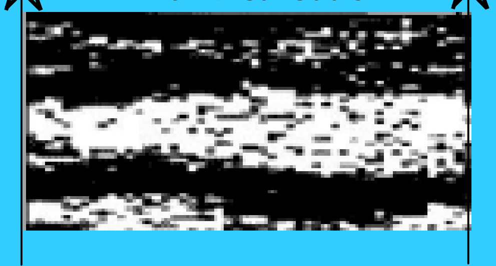
An Example

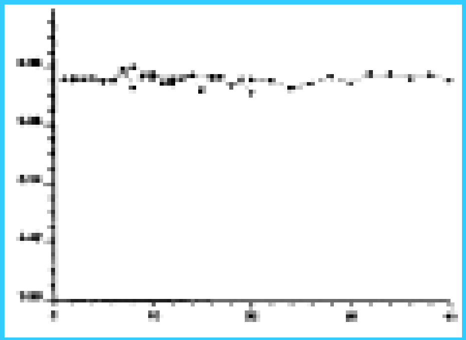
$$O = \sum_{i=1}^{n_h} [\gamma_Z^*(h_i) - \gamma_Z(h_i)]^2$$

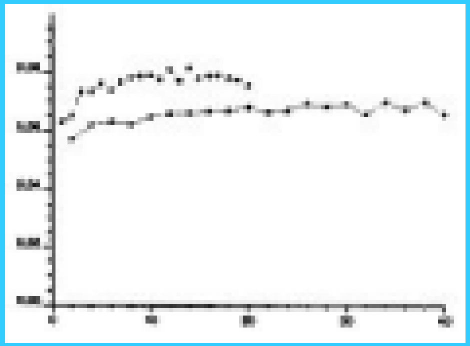
Starting Image

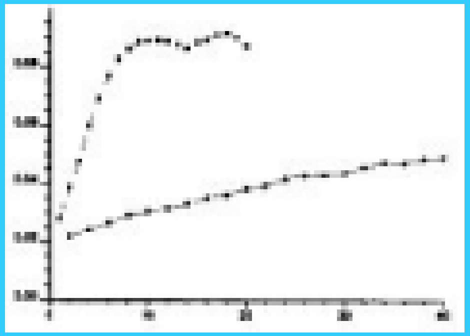
Half Way

Final Distribution





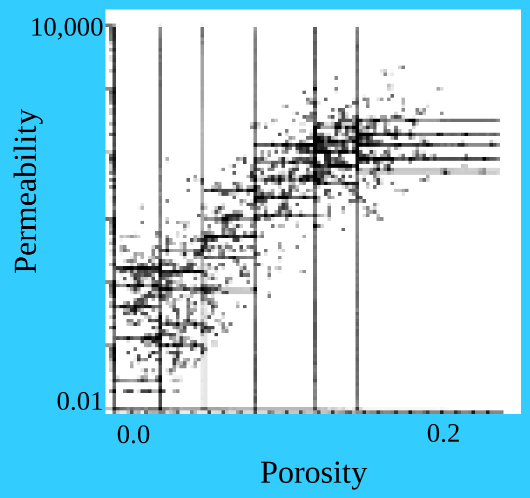




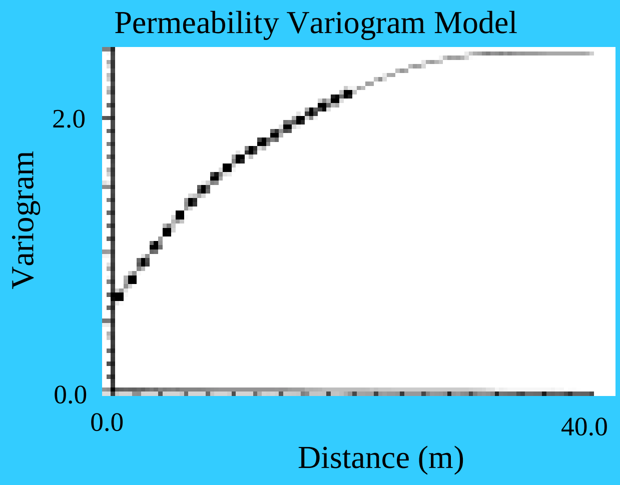
The Objective Function

Honor the Porosity/Permeability Cross-plot:

$$O_c = \sum_{i=0}^{n_\phi}\sum_{j=0}^{n_k}[f(\phi_i,K_j)_{calibration} - f(\phi_i,K_j)_{realization}]^2$$

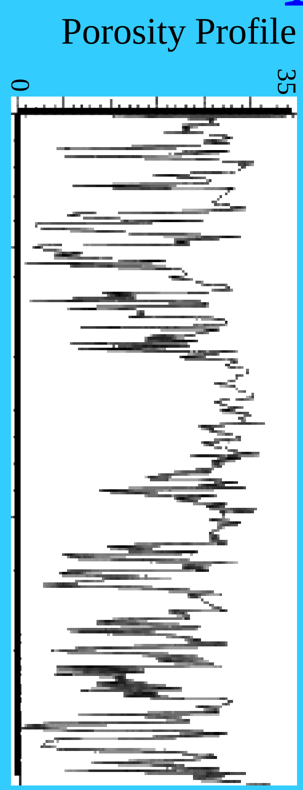


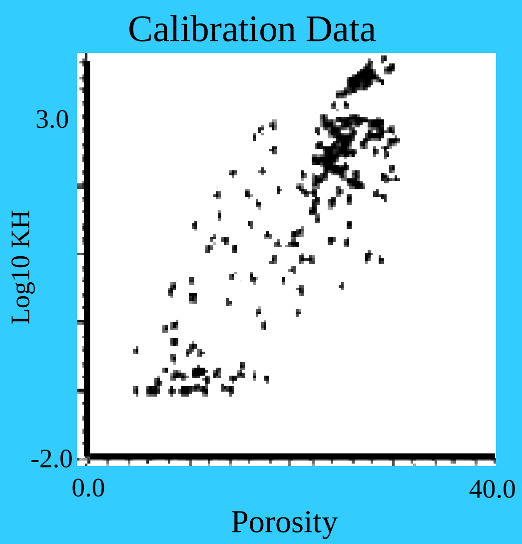
Honor the Variogram:

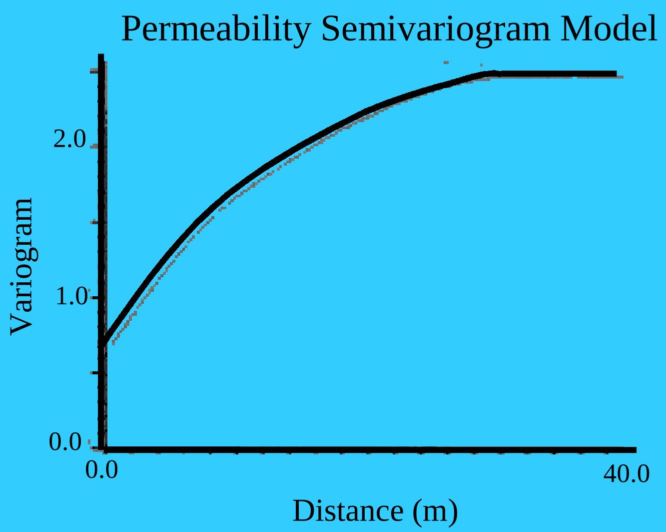


$$O_c = \sum_{i=1}^{n}[\gamma_i^{model} - \gamma_i^{realization}]^2$$

A Simple Example



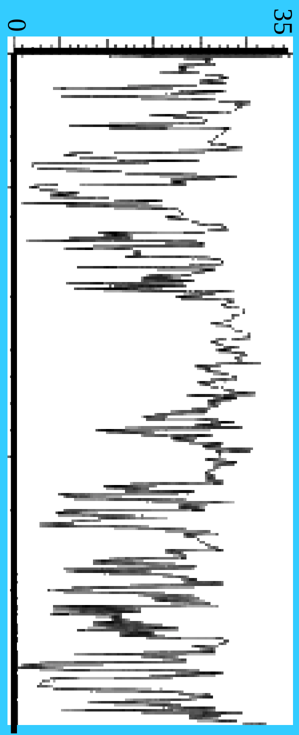




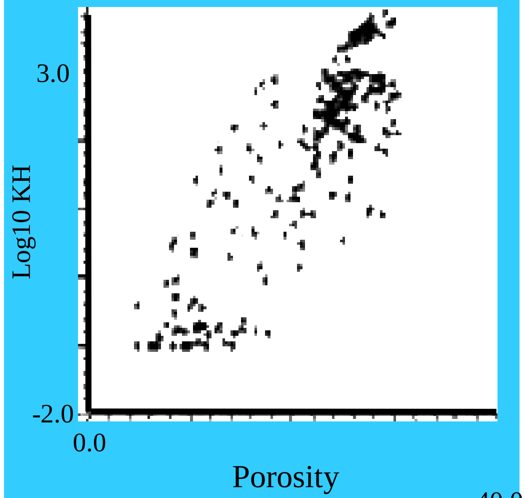
- Generate corresponding permeability values
- Need an objective function for ACS

A Simple Example: Results

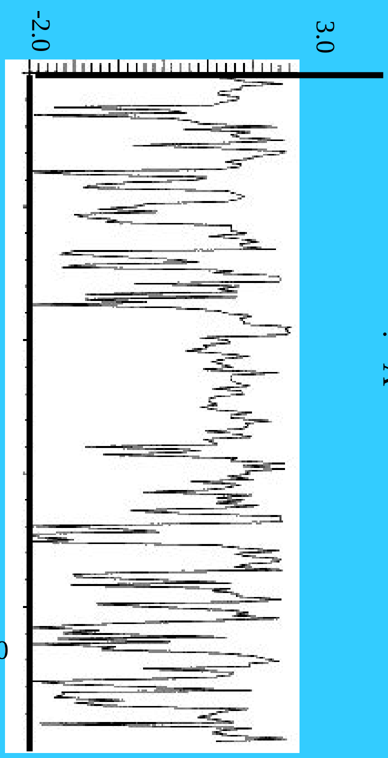
Porosity Profile



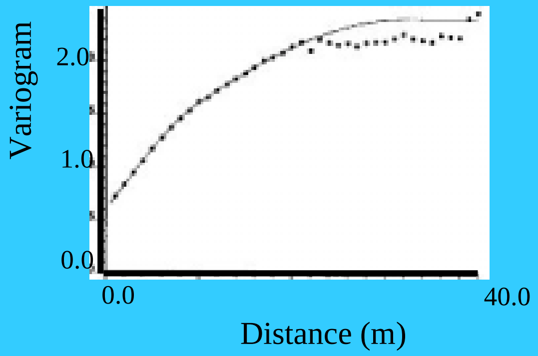
Calibration Data



Permeability Profile



Down Well Semivariogram:
model and simulated



Weighting Different Constraints

- The weights ν_c allow equalizing the contributions of each component in the global objective function $O = \sum_{c=1}^{n} \nu_c \cdot O_c$
- Each weight ν_c is made inversely proportional to the average change in absolute value of its component objective function:

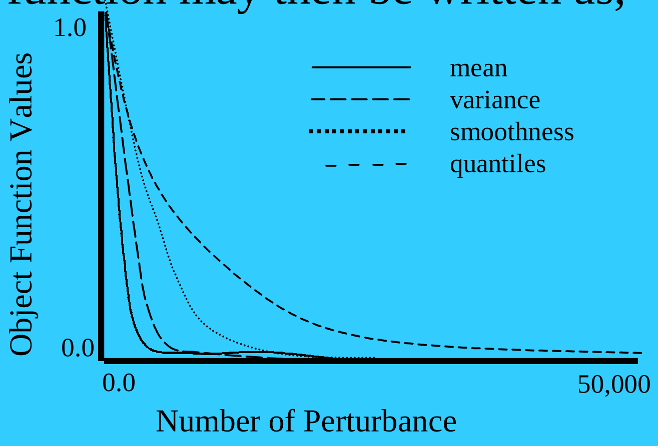
$$\nu_c = \frac{1}{\overline{|\Delta O_c|}}, \quad c = 1,\dots,C$$

- $\overline{|\Delta O_c|}$ is numerically approximated by:

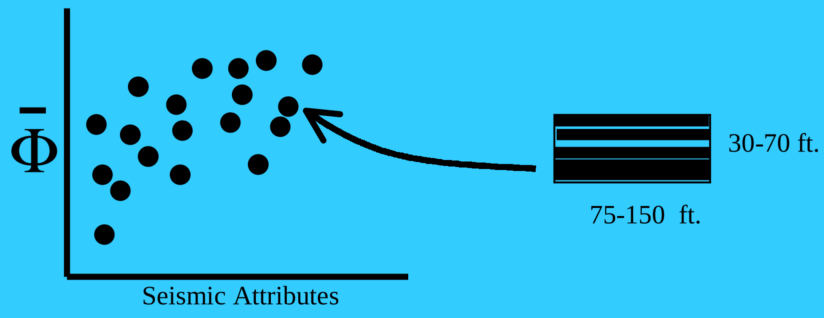
$$\overline{|\Delta O_c|} = \frac{1}{M} \sum_{m=1}^{M} |O_c^{(m)} - O_c|, \quad c = 1,\dots,C$$

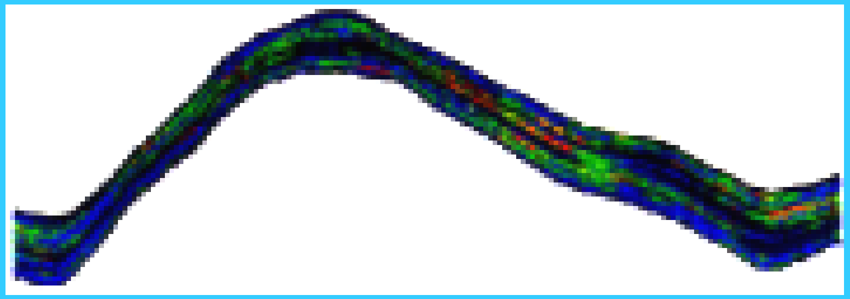
- The overall objective function may then be written as,

$$O = \frac{1}{O^{(0)}} \cdot \sum_{c=1}^{C} \nu_c \cdot O_c$$



Scale and Precision of Seismic Data





- Geological models have greater vertical resolution than that provided by seismic data (areal resolution is comparable)
- Seismic attribute (impedance, integrated energy, **...**) does not precisely inform the vertical average of porosity
- May also imprecisely inform the relative proportion of specific rock types
- Very valuable information due to the near exhaustive coverage

Annealing Approach

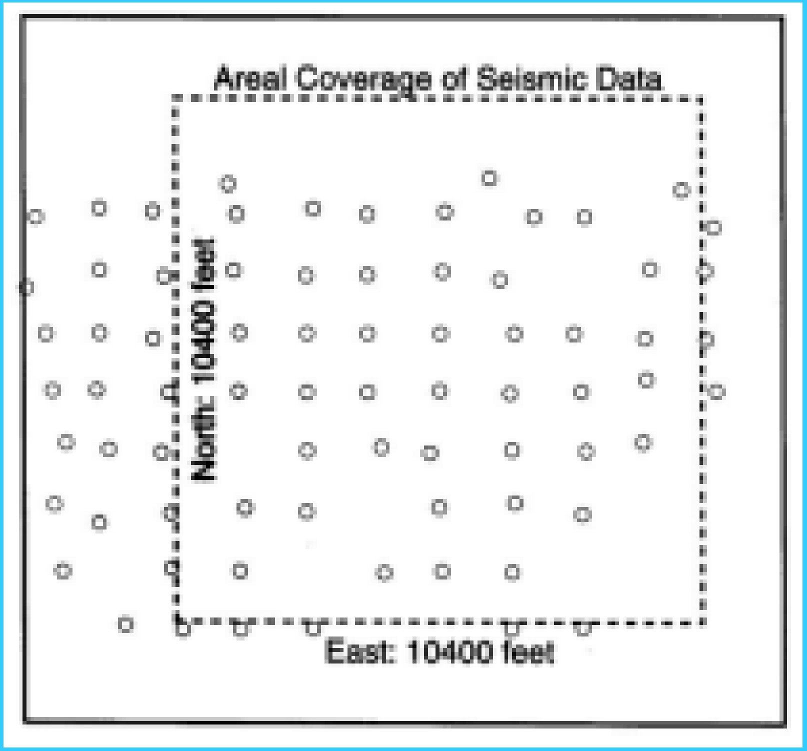
- Consider the annealing procedure:
  1. Establish an initial realization that honors the well data
  2. Calculate the initial objective function
  3. Consider a change to a cell's permeability
  4. Evaluate new objective function (better? - accept change; worse? - reject change)
  5. Is objective function close enough to zero? (yes - done; no - go to 3)
- Add component objective function(s) that capture the correlation with between vertical averages of the porosity (rock type proportion) and the seismic attribute

$$O_c = \sum_{i=0}^{n_\phi} \sum_{j=0}^{n_k} [\, f(\phi_i, K_j)_{calibration} - f(\phi_i, K_j)_{realization}\,]^2$$

$$O_c = [\rho_{calibration} - \rho_{realization}]^2$$

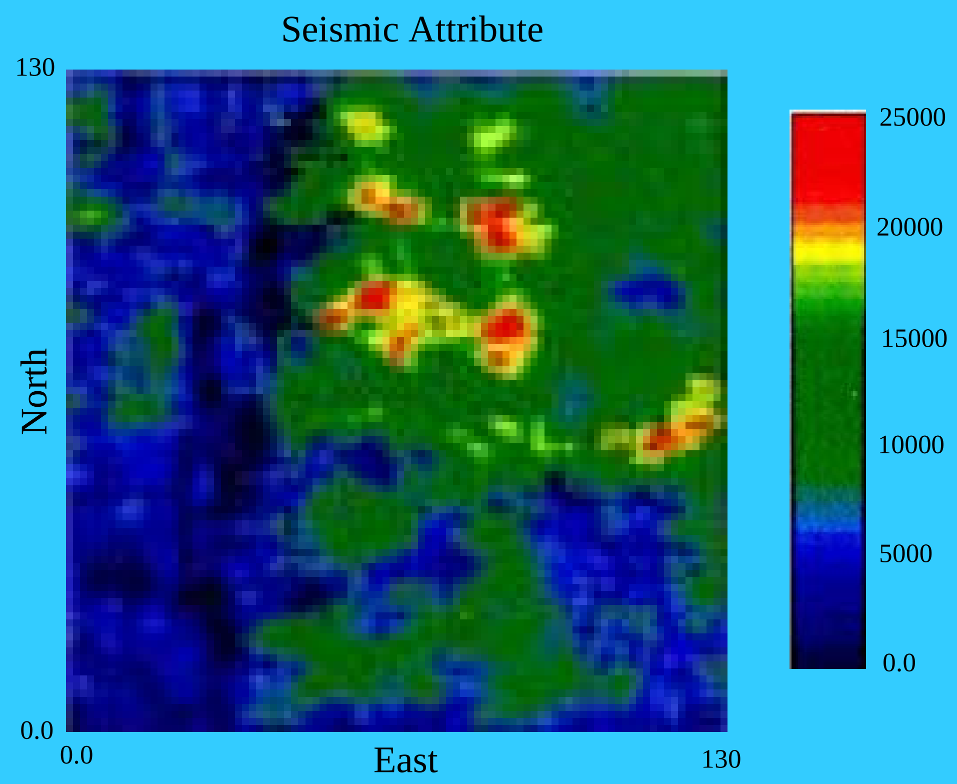
- Where ρ is defined between the vertically averaged porosity and the seismic attribute, *S* is the seismic average, and *P* is the vertically averaged porosity

Application from West Texas



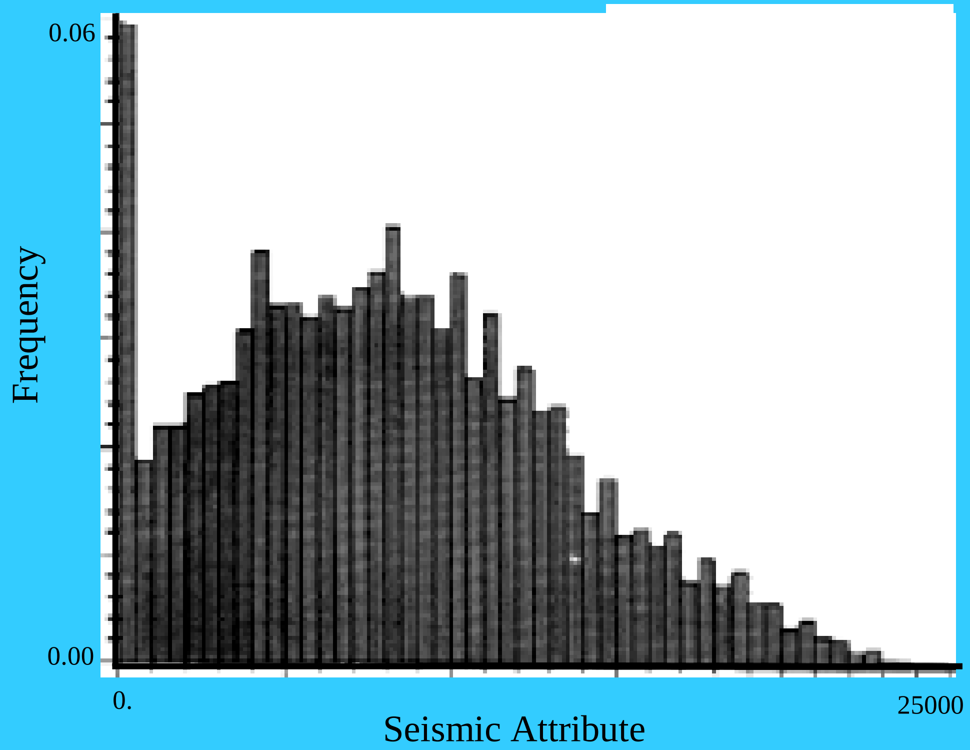
- West Texas Permian Basin (data provided to SCRF for technique development)
- 74 wells in the area (50 within the area covered by the 3-D seismic survey)

Seismic Attribute Data



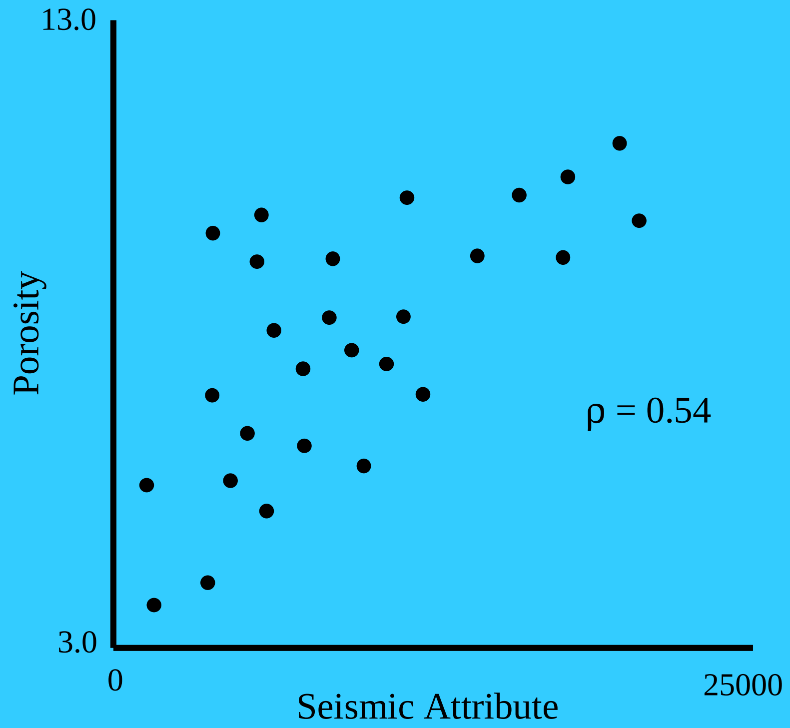
- 130 by 130 - 80 foot square areal pixels
- Significant areal variation

Seismic Attribute Data



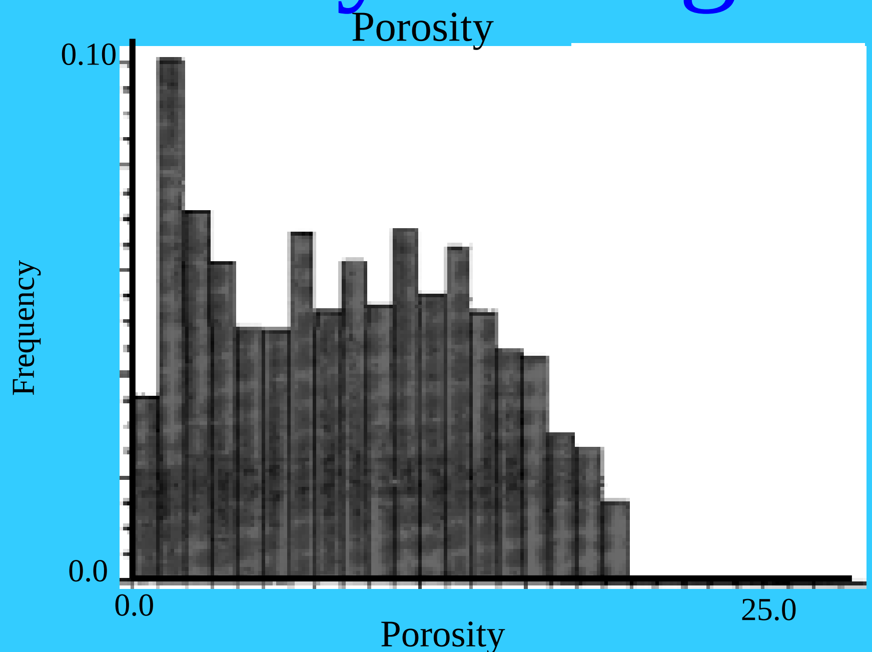
- spike of zero values
- relatively low coefficient of variation

Calibration Data



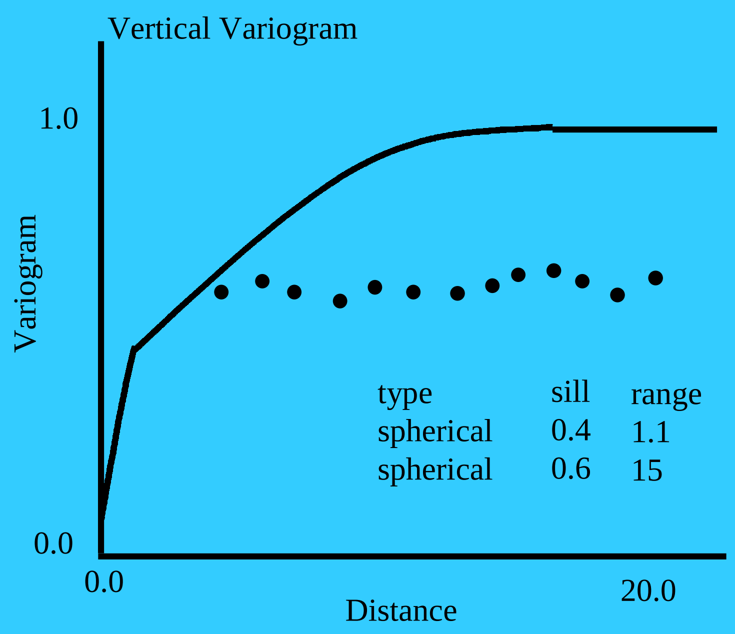
- Positive correlation between the vertically averaged porosity and seismic attribute
- Linear correlation coefficient of 0.54 is typical
- Calibration covers the range of seismic values (this can be a significant problem when there are few wells)

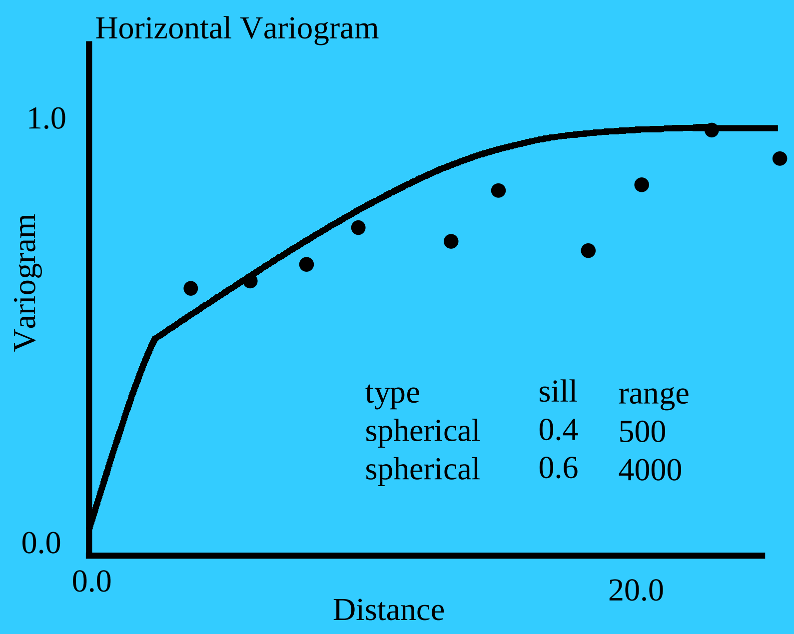
Porosity Histogram



- Greater variance than 2-D vertical average (as expected)
- Declustering and perhaps smoothing should be considered to get representative histogram
- 3-D models will, within ergodic fluctuations, replicate this histogram. Consider a resampling procedure to assess uncertainty in porosity histogram

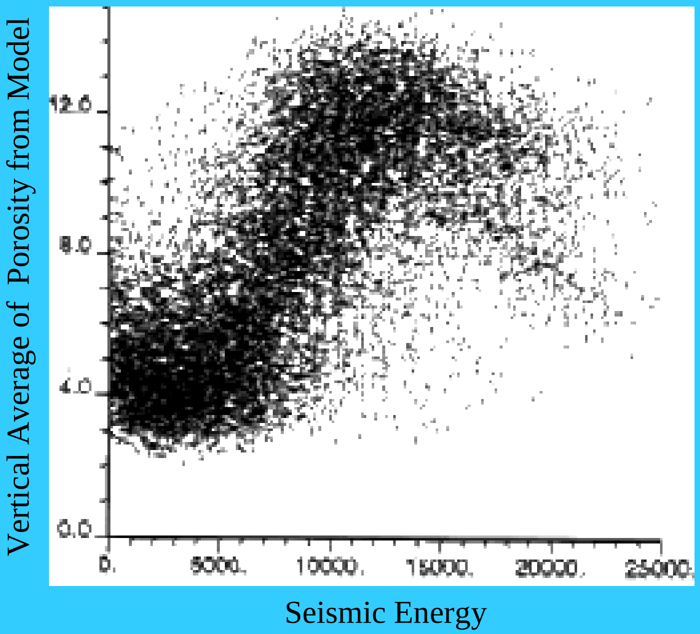
Porosity Variogram



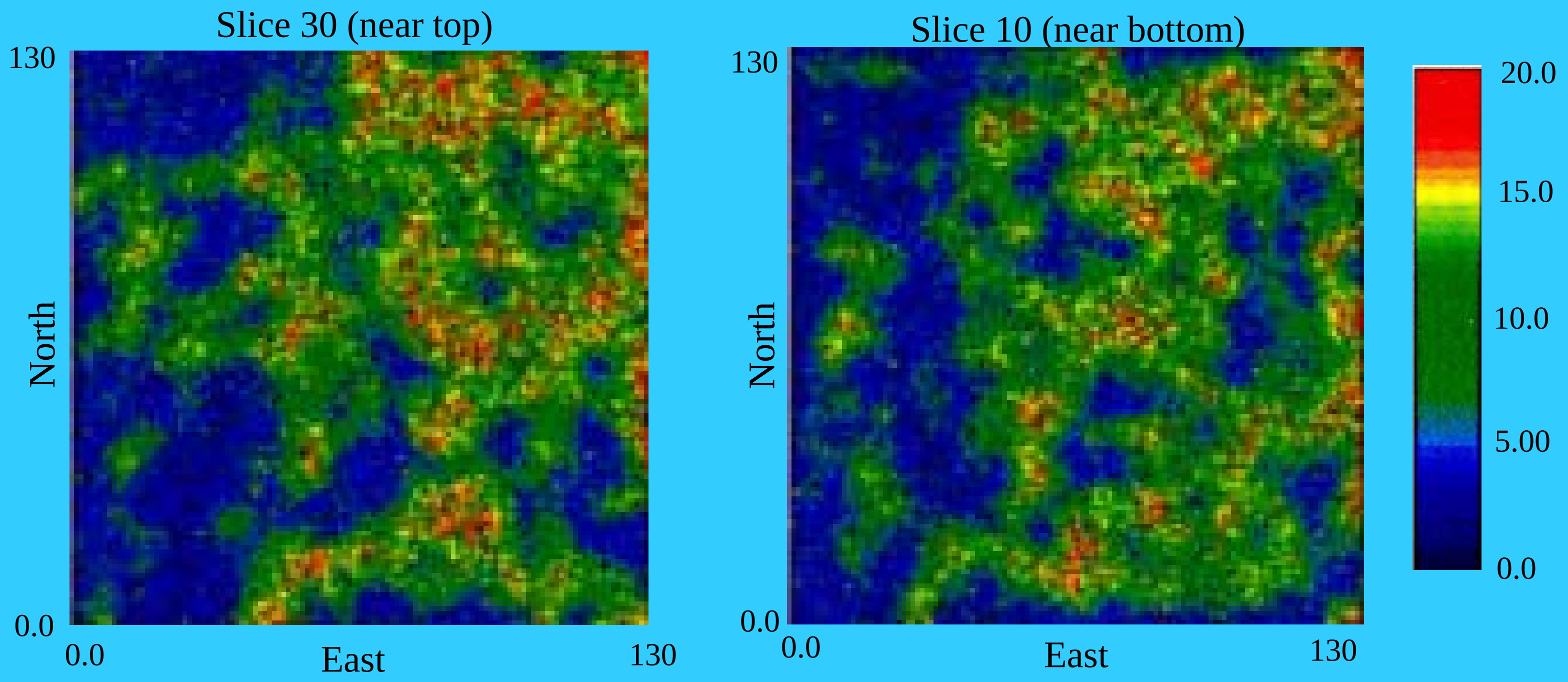


3-D Porosity Modeling

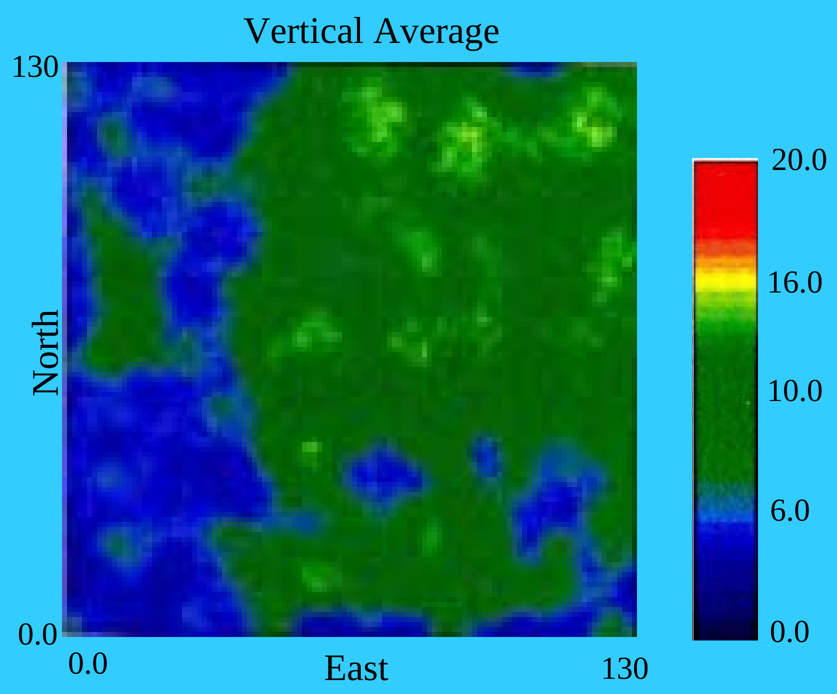
- Annealing-based simulation constrained to:
  - local well data
  - 99 evenly spaced quantiles of the porosity histogram
  - 50 variogram lags
  - correlation coefficient of 0.54 between the vertically averaged porosity and the seismic attribute
- Can create multiple realizations
- Show one for illustration
- Cross plot from model

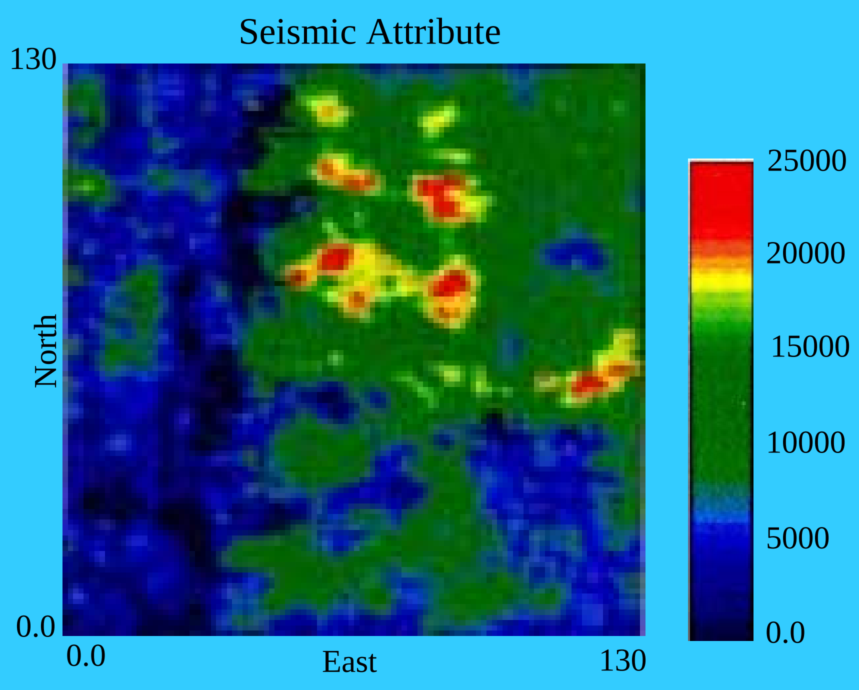


Horizontal Slices

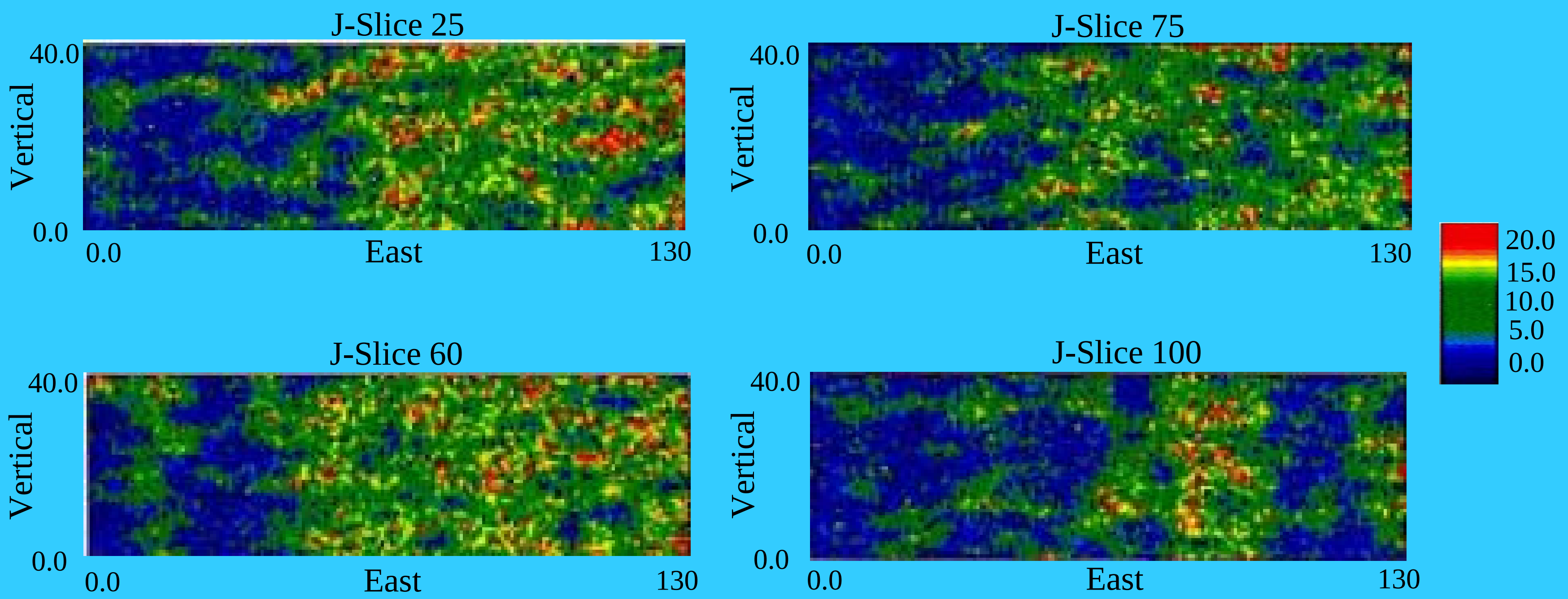


Vertical Average





Cross Sections



Permeability Modeling / Annealing

- Simulated annealing:
  - honors local data
  - accounts for histogram, variogram, and cross plot
  - allows the integration of other types of data, e.g., seismic, welltests, production history, **...**
  - solves problems that are intractable with alternative better
  - understood methodologies
  - easy to explain
  - not multiGaussian
  - requires some tradecraft in its implementation to achieve acceptable CPU times and to avoid artifacts
  - not as *elegant* as other methodologies
- SASIM program in GSLIB 2.0
- Covariate, continuity of extremes, non-linear averaging, **...**

GSLIB
Geostatistical Software LIBrary
Available at www.GLSIB.com

Parameter File (1)

Simulated Annealing Based Simulation
****

```
START OF PARAMETERS:
1  1  1  0  0          \ components: hist,varg,ivar,corr,cpdf
1  1  1  1  1          \ weight:     hist,varg,ivar,corr,cpdf
1                      \ 0=no transform, 1=log transform
1                      \ number of realizations
50    0.5   1.0        \ grid definition: nx,xmn,xsiz
50    0.5   1.0        \                  ny,ymn,ysiz
 1    0.5   1.0        \                  nz,zmn,zsiz
69069                  \ random number seed
4                      \ debugging level
sasim.dbg              \ file for debugging output
sasim.out              \ file for simulation output
1                      \ schedule (0=automatic,1=set below)
```

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Parameter File (2)

```
0.0   0.05  10   3  5  0.001        \      schedule: t0,redfac,ka,k,num,Omin
10.0                                \      maximum number of perturbations
 0.1                                \      reporting interval
0                                   \ conditioning data:(0=no, 1=yes)
../data/cluster.dat                 \      file with data
1   2   0   3                       \      columns: x,y,z,attribute
-1.0e21    1.0e21                   \      trimming limits
1                                   \ file with histogram:(0=no, 1=yes)
../data/cluster.dat                 \      file with histogram
3   5                               \      column for value and weight
99                                  \      number of quantiles for obj. func.
1                                   \ number of indicator variograms
2.78                                \      indicator thresholds
../data/seisdat.dat                 \ file with gridded secondary data
1                                   \      column number
```

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Parameter File (3)

```
1                      \            vertical average (0=no, 1=yes)
0.60                   \ correlation coefficient
../data/cal.dat        \ file with paired data
2  1  0                \            columns for primary, secondary, wt
-0.5  100.0            \            minimum and maximum
5                      \            number of primary thresholds
5                      \            number of secondary thresholds
51                     \ Variograms: number of lags
1                      \            standardize sill (0=no,1=yes)
1  0.1                 \            nst, nugget effect
1  0.9  0.0  0.0  0.0  \            it,cc,ang1,ang2,ang3
   10.0  10.0  10.0    \            a_hmax, a_hmin, a_vert
1  0.1                 \            nst, nugget effect
1  0.9  0.0  0.0  0.0  \            it,cc,ang1,ang2,ang3
   10.0  10.0  10.0    \            a_hmax, a_hmin, a_vert
```