U31A-001: Integration of Multiresolution Data using Geostatistics, Stratigraphy, and Seismic Inversions to Build Realistic Flow Simulation Models

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Abstract

Flow models commonly require high-resolution (~1 m vertical) grids of properties. Seismic data are areally dense, but their vertical resolution (~10 m) may be too coarse for flow models. We propose a method to downscale seismic inversions to flow models. The method combines Bayesian seismic inversion for coarse-scale effective properties (e.g. thickness, porosity), with rock physics models to couple elastic and flow properties, and geostatistics for spatial correlations and well data. These downscaling constraints propagate correlated inter-property and inter-layer information from seismic into the flow model. Possible pinchouts make the seismic constraint only piecewise linear, which complicates sampling. A subspace projection technique addresses this difficult configurational problem.

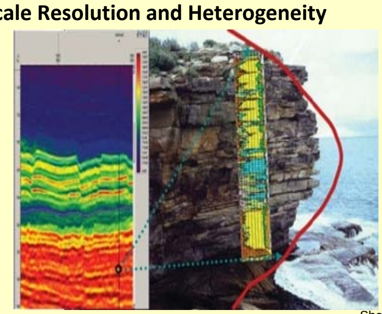
The uncertainty is developed in a hierarchical or cascading workflow. Each realization from a stochastic seismic inversion is used as an exact constraint in generating a sub-ensemble of models. Because the cascading workflow is combinatoric, it may generate many plausible prior models. There may be far too many models to examine using full-field, multiphase simulation. Nonetheless, the widest possible range of models should be examined with the full simulation method if uncertainty is to be assessed.

To make uncertainty assessment feasible, we propose a method to select a particularly relevant subset of the prior models. The approach uses a simple, fast simulation method (single phase tracer flow) to screen the large set of models. Although the screening simulation does not include all of the physics or operational constraints of the full-field model, it does incorporate many important effects of heterogeneity; and it is being used to select models, not to approximate them. Many responses (here, 24) can be computed from the set of tracer simulations. The responses are transformed to principal components, allowing a reduction in dimensionality for sampling. We then use a quasi-Monte Carlo method to sample in the principal components space.

In addition to the PC sampling method, preliminary factorial studies can provide guidance on important factors. In this study, the sand thickness range appeared unimportant, and that dimension (and contribution to combinatorics) can be removed from the stochastic model sampling process.

These methods appear to be first steps toward a fully stocastic seismic-to-simulation workflow.

Scale Resolution and Heterogeneity



Shanor, 2006

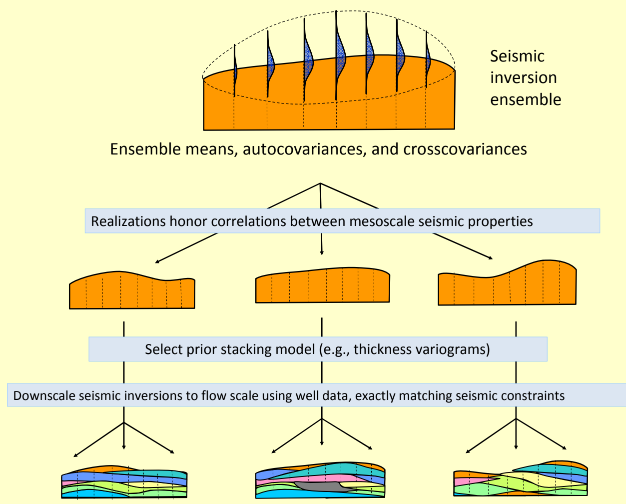
- Seismic data acquisition and processing provide excellent spatial coverage of the reservoir
- A welltie/wavelet extraction step calibrates the log data to the seismic data. The seismic inversion step produces rock properties and geometry direct from seismic amplitudes, using the extracted wavelet.
- Seismic resolution (~10 m) is still coarser than for flow models
- Well log data and their derived interpretations provide excellent vertical resolution and insight into the distribution of the log-derived petrophysical properties at the well locations
- Geostatistical methods can improve flow behaviour predictions by using sparse conditioning data and dense low resolution seismic data

Goals

The multiple goals of this work include

- Downscale seismic data to flow models
- Integrate the precision of different data consistently
- Understand the effects of priors using tracer flooding
- Choose realizations using Principle Component Analysis (PCA)

Working on Exact and Inexact Constraints



Model Parameterization

- Fine scale layer thickness h
- Seismic scale thickness H
- Fine scale porosity ϕ
- Seismic scale porosity Φ

Constraints

- Shale thickness $\sum_{k=1}^{K_s} h_{s,k} = H_s$
- Sand thickness $\sum_{k=1}^{K_{sh}} h_{sh,k} = H_{sh}$
- Sand porosity $\sum_{k=1}^{K_s} \phi_k h_{s,k} = \Phi H_s$

Exact Constraints

- Using seismic inversion realization
- Constraints preserve rock physics covariances
- Prior distribution P(t,ϕ) is a spatially correlated multi-Gaussian distribution for sublayer thicknesses, porosity etc, conditioned on well data
- Likelihood enforces exact constraints:
    - Zero if constraints not satisfied
    - One if constraint satisfied

A Cascading Workflow

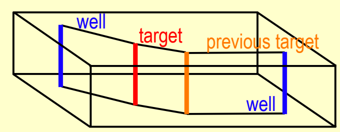
- The proposed workflow uses a hierarchy of models and methods, ranging from seismic inversion to the final downscaled model. Each level in the hierarchy introduces variability appropriate to the level of uncertainty in that modeling process or measurement.
- The cascading workflow has several benefits:
    - Using inversion realizations as exact constraints preserves desired multivariate correlations in the rock physics model
    - Each modeling component is simplified -- the downscaler doesn't have to 'know' any rock physics
    - The programs for inversion, imposing seismic constraints, and modeling stratal styles are separate, simplifying development and modification (and re-using code effectively)
- On the other hand, cascade can lead to a combinatoric explosion in the number of models to be explored. This motivates the use of screening methods, which select a subsample of especially informative models (see Selecting the Most Relevant Realizations: Screening).
- This requires computing the conditional probability $P(m_f|m_c, m_\eta)$ by kriging, and specifying prior distributions for the fine-scale metaparameters, $P(m_\eta)$. The prior for the coarse models, $P(m_c)$, is obtained from the stochastic inversion.

Problem Formulation

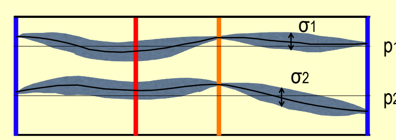
$$P(m_f) \sim P(m_f|m_c, m_\eta)P(m_\eta)P(m_c)$$

- $P(m_f)$ is the fine, downscaled model
- $P(m_c)$ is the course, seismically resolved model
- $P(m_\eta)$ is drawn from the distribution of fine-scale meta parameters such as sill, ranges etc.

Sequential Algorithm



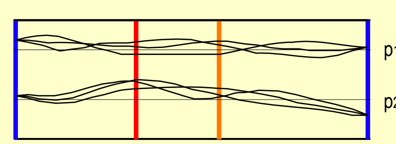
Demonstration of algorithm on arbitrary cross section through two wells, previous target location and new target.



p = layer property such as thickness or porosity

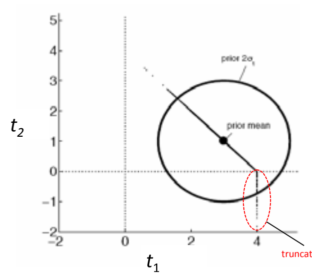
σ = standard deviation

1. Krig using well data and previously simulated points to get prior at target location
2. Do this in subspace projection to satisfy exact constraints
3. Use MCMC to generate realization that satisfy all constraints, prior, and truncations

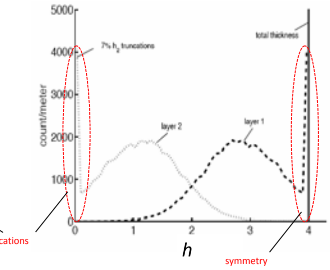


multiple realizations that satisfy:
(1) exact seismic constraints
(2) truncations
(3) well constraints

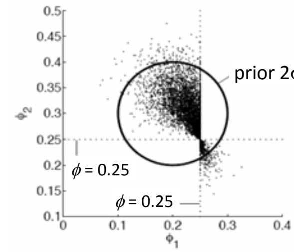
2D and 3D Examples for Exact Constraints



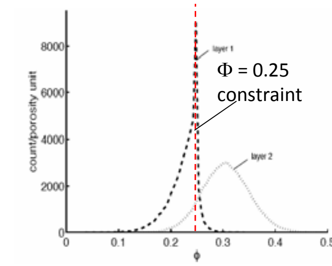
(a) Scattergram, N = 5000



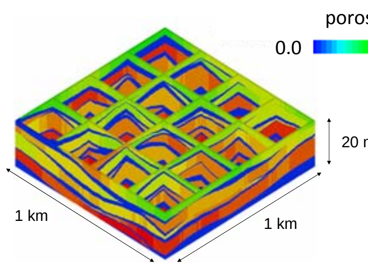
(b) Histogram of h (m)



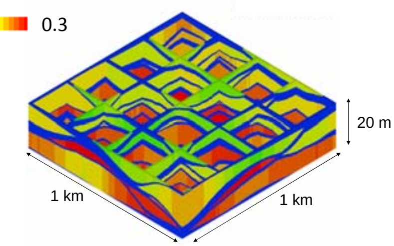
(c) Scattergram, N = 5000



(d) Histogram of ϕ



(e) Medium Sand Variance (4 m²)



(f) High Sand Variance (36 m²)

2D Example (a, b, c, d)

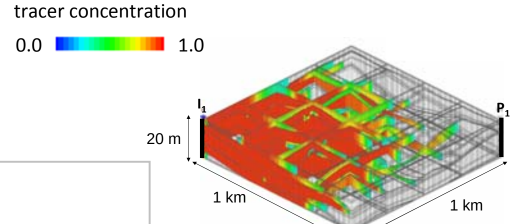
- Fig. a and Fig. b are thickness results for a two layer case with $\bar{H} = 4$ $\bar{\mathbf{t}} = (3,1)^T$ $\sigma_t = 1$
- In Fig. a all the realizations are on the constraint surface
- In Fig. b priors and constraints on thickness are such that 7 percent of the realizations have $h_2 = 0$ which creates a spike for layer 1 at $h_1 = 4$ m
- Fig. c and Fig. d are porosity results for two layers with priors $\bar{\phi} = (0.2, 0.3)$ $\sigma_\phi = 0.05$.
- In Fig. c because of the constraints the porosity of both the layers cannot be greater or less than 0.25 simultaneously
- In Fig. d porosity distributions of both the layers is shown. The constraints are such that $\phi_2 > 0.25$ are not very probable and this skews the curve steeper on the right side.

3D Example (e, f)

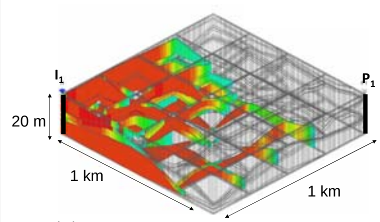
- Simulation on a 100 x 100 x 10 cornerpoint grids, areal extent is X = Y = 1000m, and 4 conditioning traces are used.
- Both realizations use Gaussian variogram with range 500 m
- Constraints used are $H = 20$ m, $H_s = 14$ m, and $\Phi H_s = 3.5$ m; $\Phi = 0.25$.
- Blue lines are shales and all constraints are satisfied

Effect of Priors on Reservoir Responses

	Sand Variance (m²)	Shale Variance (m²)	Sand Range (m)	Shale Range (m)
Low	2.25	0.25	250	250
Medium	16	1	500	500
High	36	4	1000	1000



(a)Medium sand thickness variance

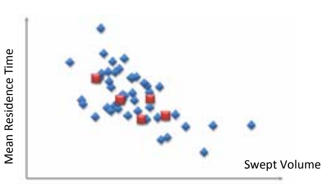


(b) High sand thickness variance

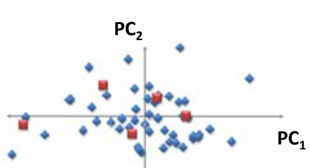
Tracer Flooding Results (a, b)

- A two-level full factorial design examines the above four factors
  - Recovery factor varies between 0.30 to 0.65
  - Stochastic fluctuations are comparable to prior variations
  - Sand sill (variance of thickness) is the dominant factor
  - Note: shale thickness and porosity priors were not varied in this design.
- Focus on fluctuation with six-fold replicates
  - Mean responses are different (p = 0.09243, Welch two-sample t-test)
  - Prior specifications significantly affect recovery
- Examining flow models (Figs. a,b) indicates lower recovery in high sill case may be caused by
  - Variability in thickness leading to velocity fluctuations
  - More frequent terminations increasing tortuosity
- Implications
  - A range of plausible priors should be considered
  - Some components of prior may dominate (e.g., sand sill), simplifying modeling
  - Caveat: $P(m_\eta)$ for the variogram parameters has not been specified. This will be required to do a full hirerarchial MCMC simulation. The factorial design simply examines sensitivities.

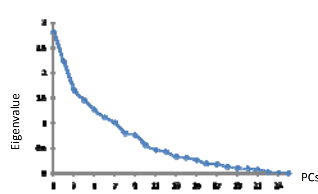
Selecting the Most Relevant Realizations: Screening



(a) Two correlated responses form tracer flooding



(b) Loading parameters for first two significant PCs



(c) Variance captured by each PC

Selecting Realizations using PCA and Hammersley Sampling

- Used tracer simulation as fast screening device
  - purely local problem, >100X faster than multiphase flow
- 24 different responses were considered (Fig. a)
  - diverse types, e.g., injectivity, residence time
  - in several directions, because of 9-spot geometry (simulation model, below)
- Use Principal Components (PC) for dimensionality reduction (Fig. b)
  - Here, the first 7 components capture 90 percent of the variance (Fig. c)
  - We can sample in 7 rather than 24 dimensions
- Sample the low-dimensional space to select models for detailed simulation
  - Here, use Hammersley sequences
  - Select nearest model to each Hammersley point
- The components of the method could be adapted to other responses and sampling methods. The essential components are
  - A fast screening simulation that indicates model flow variability at a fraction of full simulation cost
  - Dimensionality reduction
  - Sampling in reduced space for model selection

Summary

1. Stochastic seismic inversion models can be integrated with a truncated Gaussian geostatistical model for fine–scale layer thicknesses and porosity using a Markov chain Monte Carlo algorithm.
2. Mesoscale seismic inversion realizations (which act as exact constraints) of net-sand, gross sand, and porosity are "stochastically downscaled," using a Metropolis Hastings sampler exploiting dimensionality reduction and projection to the constraint surface.
3. Synthetic three–dimensional cases demonstrate that the proposed data integration procedure is acceptably efficient for exact (5000 samples at each trace < 8 min on laptop) and is capable of producing models consistent with seismic data and exhibiting diverse flow behavior.
4. Prior model specification has a statistically significant effect on response, and prior variability and stochastic fluctuations may both make substantial contributions to overall response variability.
5. A smaller but still diverse subsample of plausible models can be selected by performing a PCA on flow responses computed with a fast, approximate method, and then applying Hammersley sampling in PCA space.

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