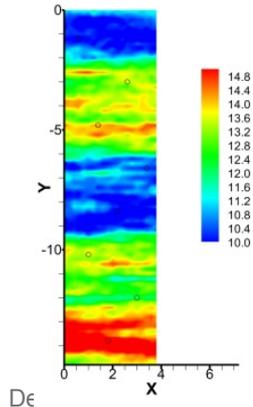
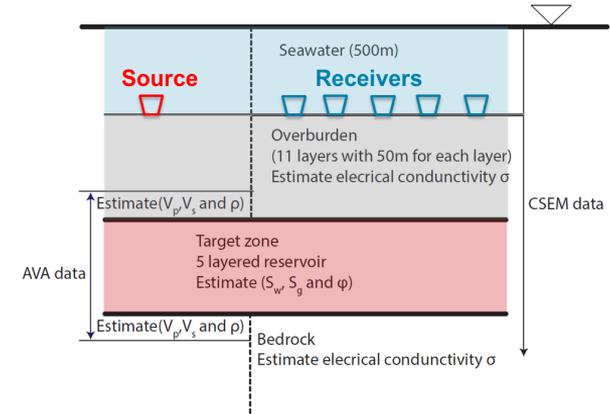


A Scalable Multi-chain Markov Chain Monte Carlo Method for Inverting Subsurface Hydraulic and Geological Properties

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- ▶ Scalable Multi-chain Markov Chain Monte Carlo Method
- ▶ Case 1: **Reservoir porosity and saturation** through invert marine seismic amplitude versus angle (AVA) and controlled-source electro-magnetic (CSEM) data



- ▶ Case 2: **Soil moisture variations** through ground penetrating radar (GPR) travel time data

Scalable Multi-chain Markov Chain Monte Carlo Method

Bayesian Formulation

- ▶ Generate posterior distributions on model parameters, given
 - Experimental data
 - A prior distribution on model parameters
 - A presumed probabilistic relationship between experimental data and model output that can be defined by a likelihood function

$$\pi(\theta | d) \propto \pi(\theta) L(d | \theta)$$

Posterior parameter distribution

Model parameters

Observed Data

Prior parameter distribution

Likelihood function which incorporates the model

The diagram illustrates the Bayesian formulation equation $\pi(\theta | d) \propto \pi(\theta) L(d | \theta)$. Arrows point from descriptive labels to the corresponding terms in the equation: 'Posterior parameter distribution' points to $\pi(\theta | d)$, 'Model parameters' points to θ , 'Observed Data' points to d , 'Prior parameter distribution' points to $\pi(\theta)$, and 'Likelihood function which incorporates the model' points to $L(d | \theta)$.

Scalable Multi-chain Markov Chain Monte Carlo Method

Bayesian Formulation

- ▶ Experimental data = Model output + error

$$d_i = G(\boldsymbol{\theta}_i) + \varepsilon_i$$

- ▶ If we assume error terms are independent, zero mean Gaussian random variables with variance σ^2 , the likelihood is:

$$L(\boldsymbol{\theta}) = \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(d_i - G(\boldsymbol{\theta}_i))^2}{2\sigma^2}\right]$$

- ▶ Markov Chain Monte Carlo (MCMC)
Generating a sampling density that is approximately equal to the posterior.

- ▶ MCMC generates samples that approximate the posterior distribution
- ▶ MCMC requires a “proposal density” which is used for generating θ_{i+1} in the sequence, conditional on θ_i .
- ▶ Metropolis-Hastings is a commonly used algorithm
 - Sample a candidate Y from the proposal density function $q(Y|\theta_i)$
 - Calculate the acceptance ratio $\alpha(\theta_i, Y) = \min \left[1, \frac{\pi(Y)q(\theta_i|Y)}{\pi(\theta_i)q(Y|\theta_i)} \right]$
 - If $\alpha(\theta_i, Y) > U$, set $\theta_{i+1} = Y$, else set $\theta_{i+1} = \theta_i$.
 - Increment i .

- ▶ MCMC requires more than 10,000 evaluations of forward simulation model
- ▶ We want to avoid surrogates

COMPUTATIONALLY VERY EXPENSIVE

- ▶ Parallel MCMC

MCMC is inherently sequential

SaChES: Scalable Adaptive Chain-Ensemble Sampling

Scalable Multi-chain Markov Chain Monte Carlo Method

SaChES: Scalable Adaptive Chain-Ensemble Sampling

- ▶ Hybrid method that incorporates:
 - **DREAM (DiffeRential Evolution Adaptive Metropolis)** to utilize multiple chains to obtain high-quality proposal densities
 - **DRAM (Delayed Rejection Adaptive Metropolis)** to obtain posterior distributions efficiently
 - Parallel chains to accelerate computations

More details about the method is available on the poster

Bayesian calibration of the Community Land Model using a multi-chain Markov chain Monte Carlo method

Jaideep Ray, Laura Swiler, Maoyi Huang, Zhangshuan Hou

Thursday, 17 December, 13:40 – 18:00

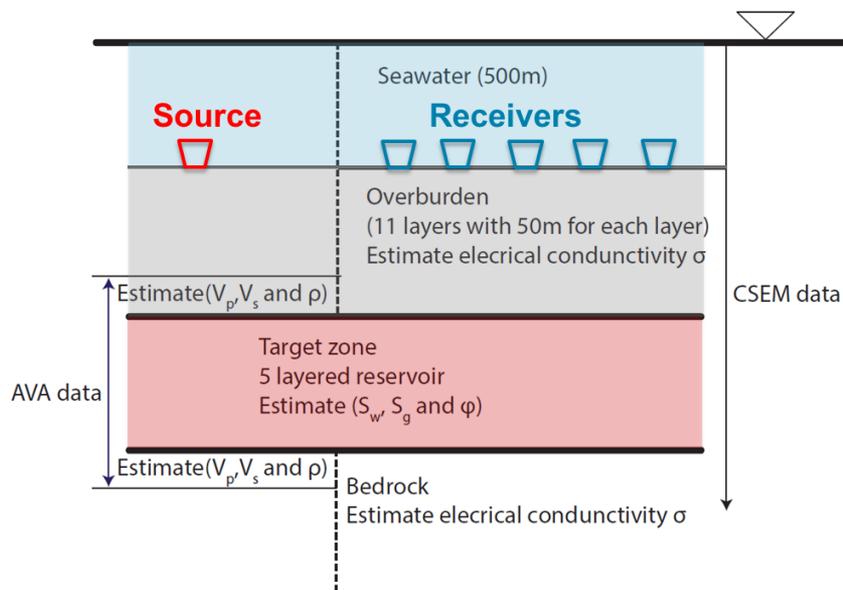
Moscone South – Poster Hall

Case 1: Gas Saturation Estimation

► Inversion domain

Seismic amplitude versus angle(AVA)

Controlled-source electro-magnetic(CSEM)



5-layered reservoirs from the upper to bottom with water saturations:

0.95, 0.05, 0.6, 0.9 and 0.1

and the porosity:

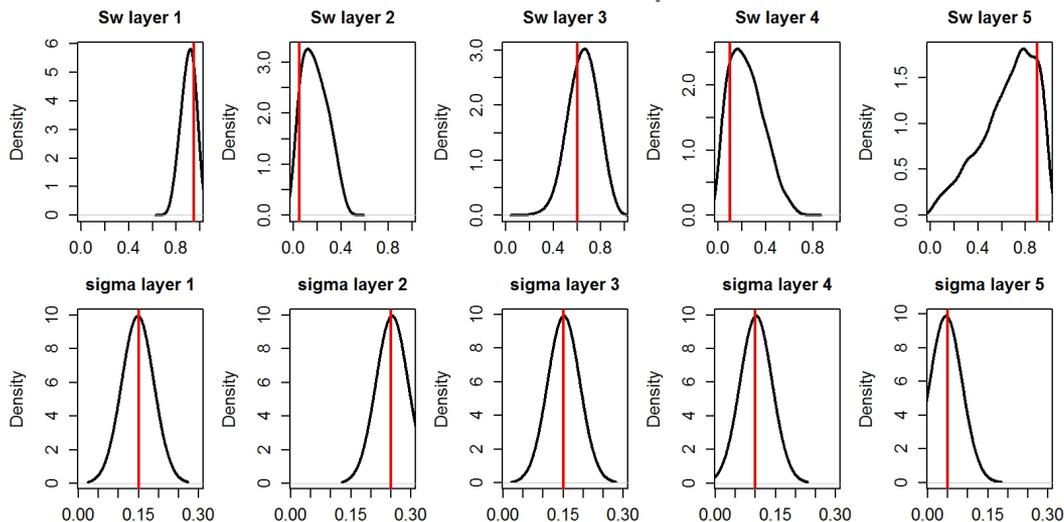
0.15, 0.25, 0.15, 0.1 and 0.05

The source and receivers were both located 50m above the seafloor. 21 receivers were away from electrodes from 500m to 5000m.

Case 1: Gas Saturation Estimation

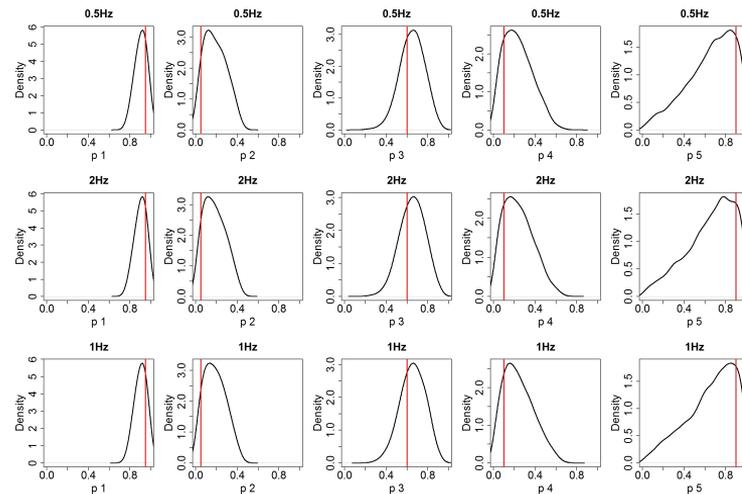
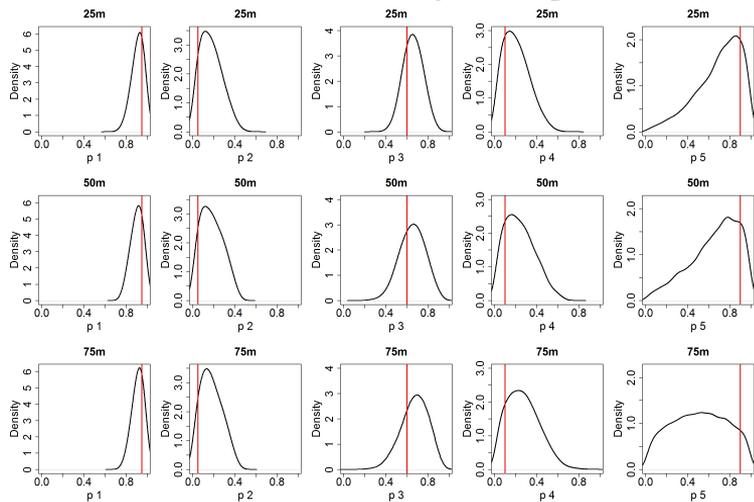
- ▶ Seismic AVA data (80 time steps) was used to estimate porosity and narrow bounds were obtained for each layer, then estimate water saturation.
- ▶ The reservoir thickness is 50m
- ▶ CSEM data were obtained from 2Hz channel

Posterior distribution of the parameters



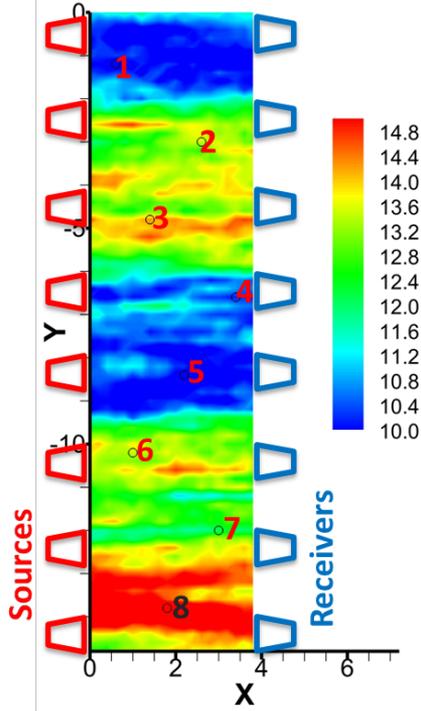
Case 1: Gas Saturation Estimation

- ▶ The effect of thickness for each reservoir layer
 - Each layer thickness: 25m, 50m and 75m
- ▶ The effect of CSEM data frequency
 - CSEM data frequency: 0.5Hz, 1Hz and 2Hz



Case 2: Soil Moisture Variations

- ▶ “True” dielectric permittivity field



- ▶ Synthetic test case

3.8 X 15 m; 20 X 75 points

8 pilot points, and range (correlation length)

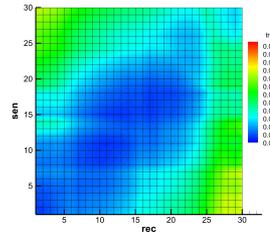
Generate a random dielectric field in SGSIM

- ▶ Ground penetrating radar (GPR) travel time simulation

Velocity: $v = v_{ll} / \sqrt{\epsilon}$

Calculate the radar signal travel time

between each source and receiver

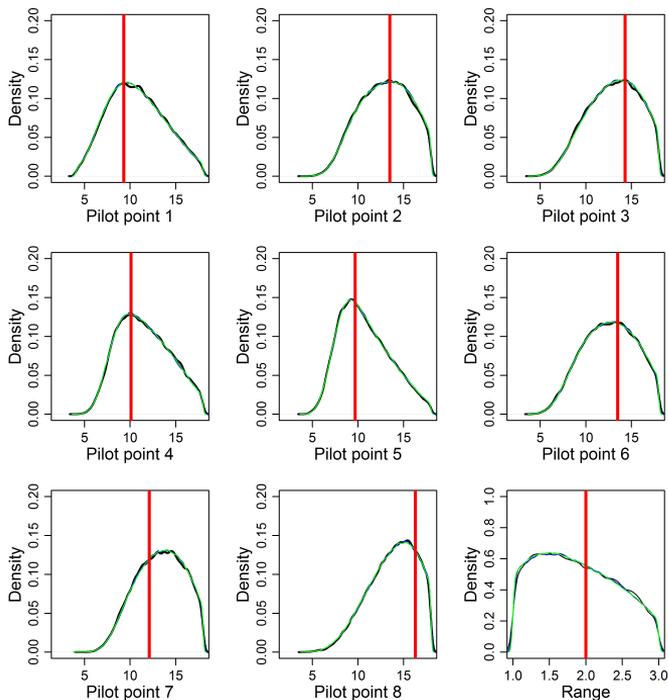


“Observations”

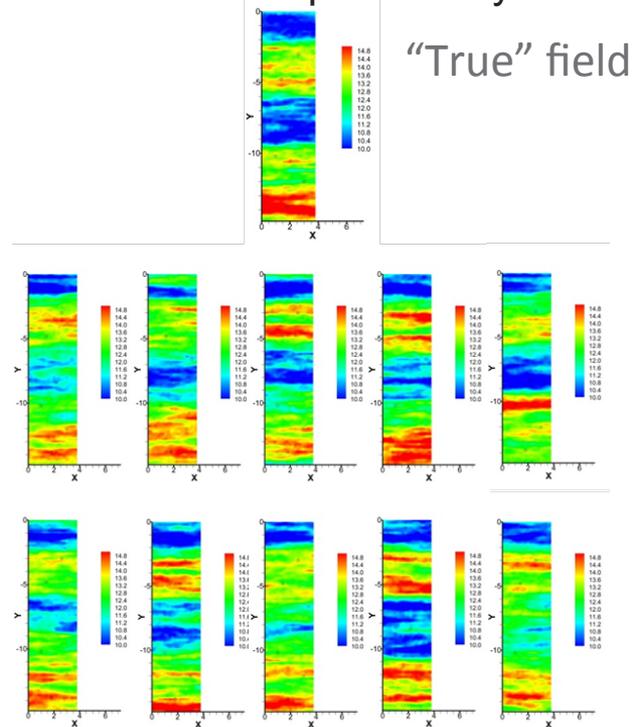
Travel time between 30 sources and 30 receivers

Case 2: Soil Moisture Variations

► Posterior distribution of the parameters



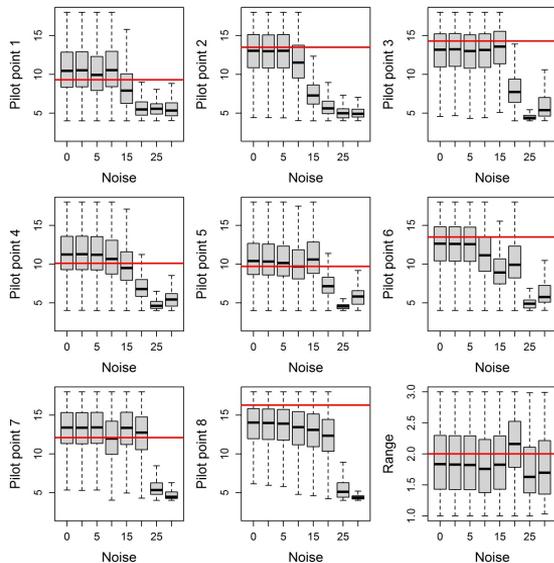
► Inversed dielectric permittivity field



Case 2: Soil Moisture Variations

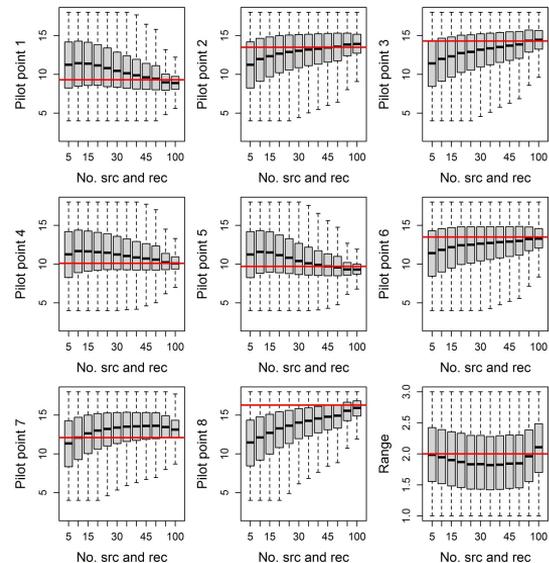
► Noise on observation

Noise's standard deviation is defined as the percentage of the mean of the true observation



► Number of sources and receivers

5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 75, and 100 sources and receivers



Questions?