



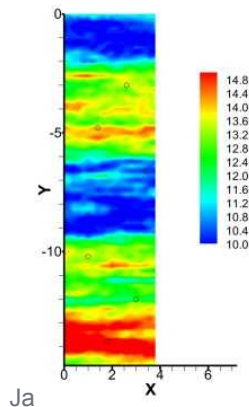
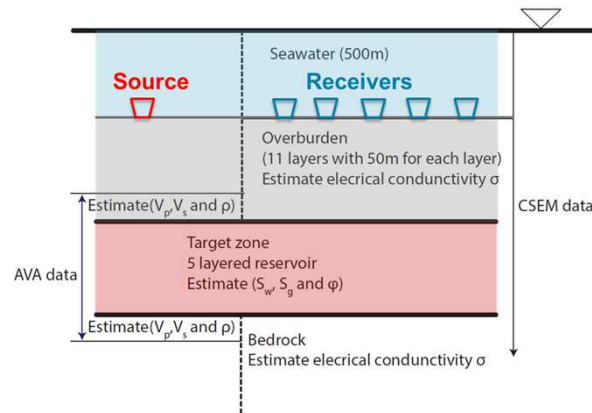
# A Scalable Multi-chain Markov Chain Monte Carlo Method for Inverting Subsurface Hydraulic and Geological Properties

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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

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

Diagram illustrating the Bayesian formulation equation:

- $\pi(\theta | d)$ : Posterior parameter distribution
- $\theta$ : Model parameters
- $d$ : Observed Data
- $\pi(\theta)$ : Prior parameter distribution
- $L(d | \theta)$ : Likelihood function which incorporates the model

# 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  $\sigma^2$ , 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  $\theta_{i+1}$  in the sequence, conditional on  $\theta_i$ .
- ▶ Metropolis-Hastings is a commonly used algorithm
  - Sample a candidate  $Y$  from the proposal density function  $q(Y|\theta_i)$
  - Calculate the acceptance ratio  $\alpha(\theta_i, Y) = \min \left[ 1, \frac{\pi(Y)q(Y|\theta_i)}{\pi(\theta_i)q(\theta_i|Y)} \right]$
  - If  $\alpha(\theta_i, Y) > U$ , set  $\theta_{i+1} = Y$ , else set  $\theta_{i+1} = \theta_i$ .
  - Increment  $i$ .

# Scalable Multi-chain Markov Chain Monte Carlo Method

## Markov Chain Monte Carlo

- ▶ 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)

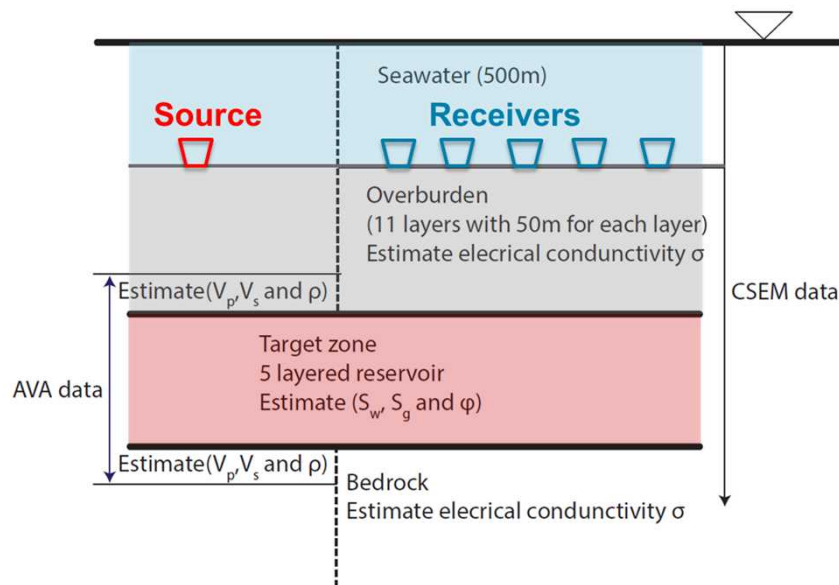
5-layered reservoirs from the upper to bottom with water saturations:

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.

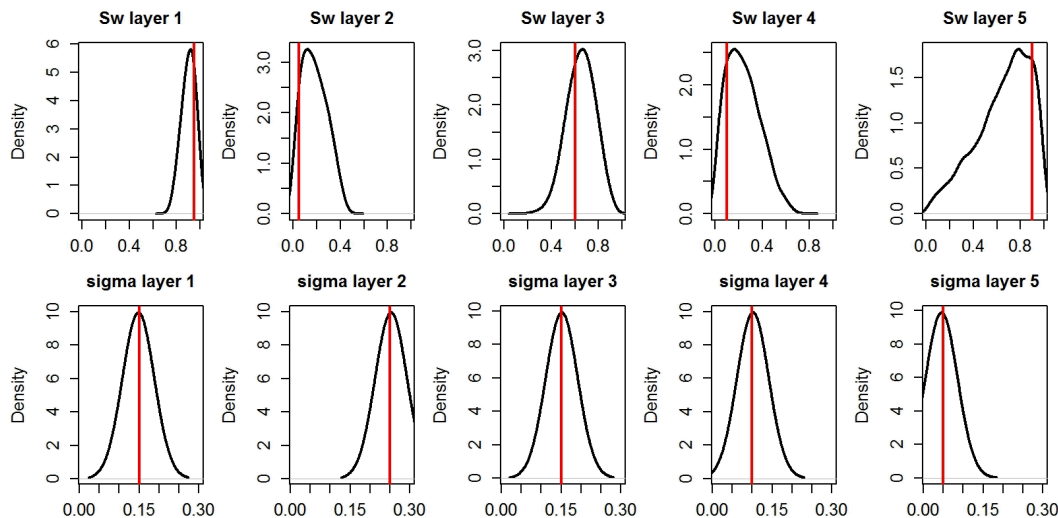




# Case 1: Gas Saturation Estimation

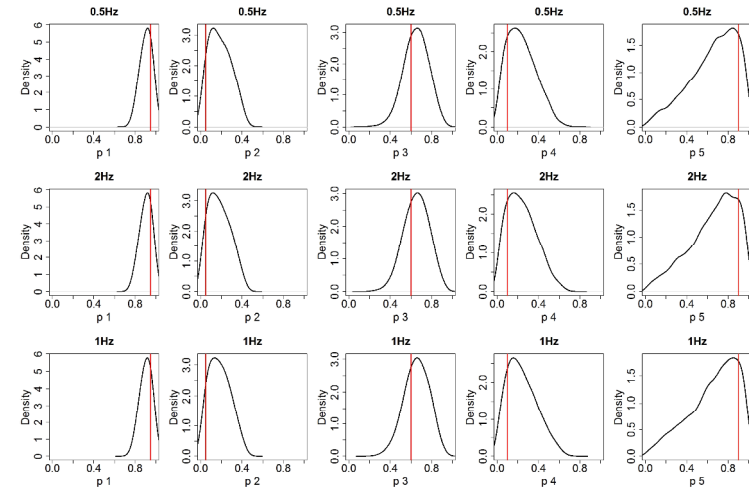
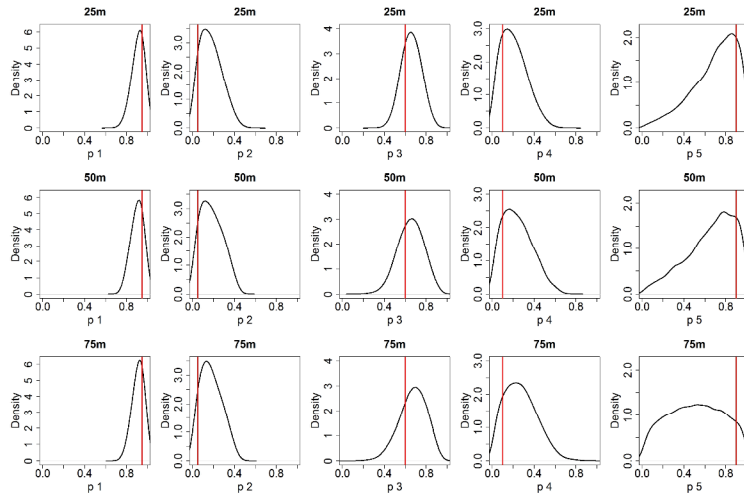
- ▶ Seismic AVA data (80 time steps) was used to estimate porosity and narrow bounds were obtained for each layer, then estimate water saturation.
- ▶ The reservoir thickness is 50m
- ▶ CSEM data were obtained from 2Hz channel

## Posterior distribution of the parameters



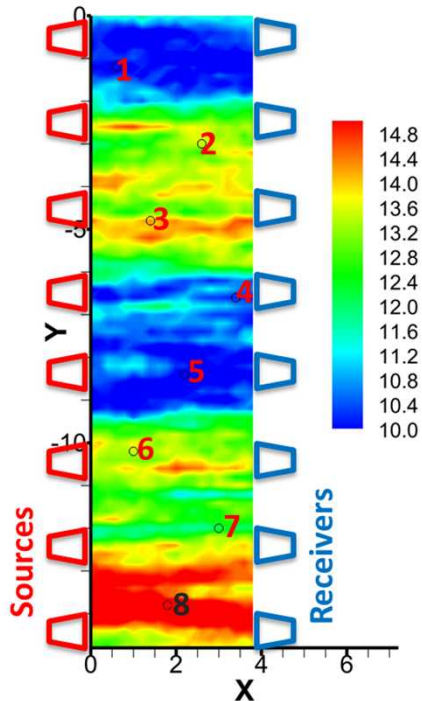
# Case 1: Gas Saturation Estimation

- ▶ 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

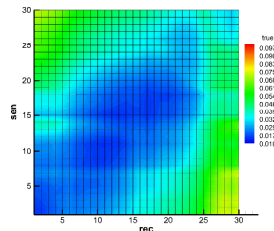
8 pilot points, and range (correlation length)

Generate a random dielectric field in SGSIM

## ► Ground penetrating radar (GPR) travel time simulation

Velocity:  $v = \frac{v_l}{\sqrt{\epsilon}}$

Calculate the radar signal travel time between each source and receiver

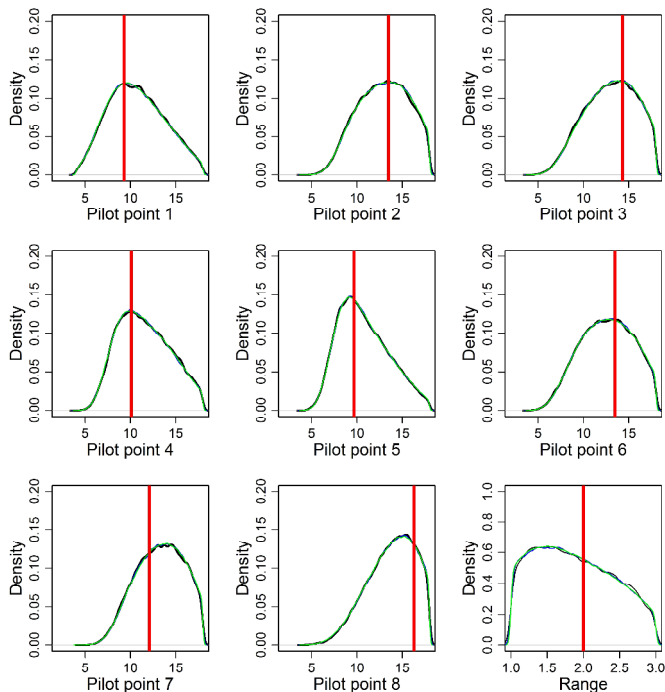


“Observations”

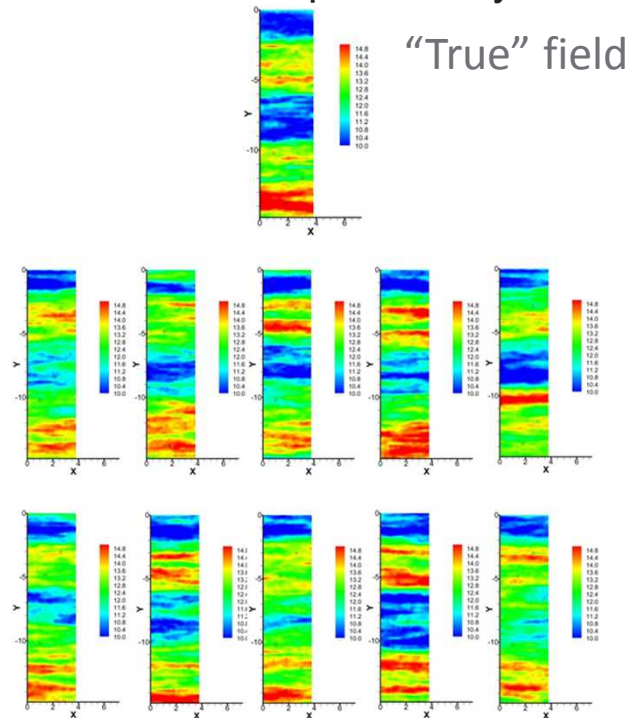
Travel time between 30 sources and 30 receivers

# Case 2: Soil Moisture Variations

## ► Posterior distribution of the parameters



## ► Inversed dielectric permittivity field

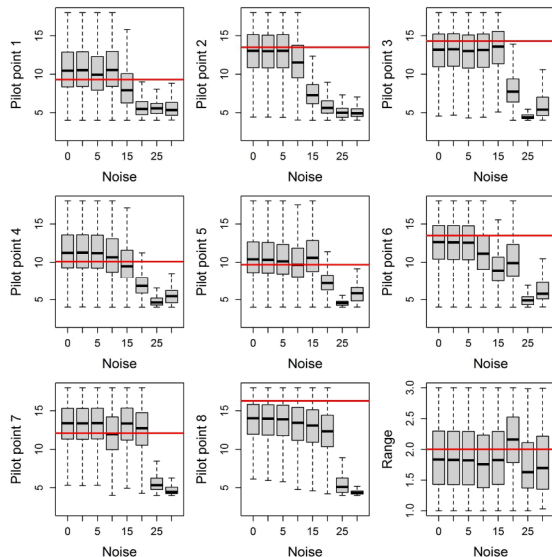


10 best inversed fields

# Case 2: Soil Moisture Variations

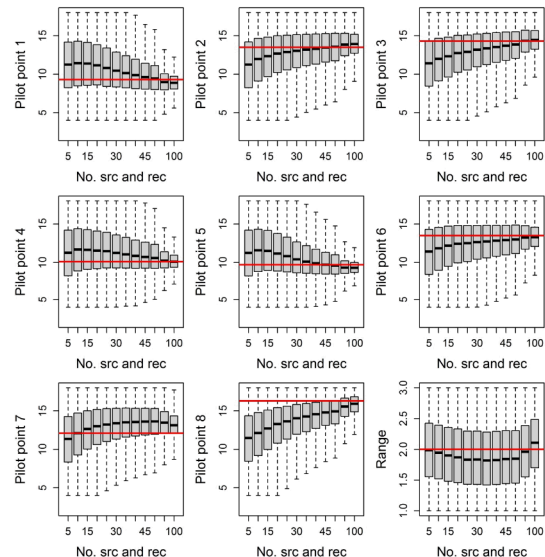
## ► Noise on observation

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?