Estimating Value of Information in Spatial Decision Making for Reservoir Development

Jo Eidsvik, ***NTNU, Norway***

Debarun Bhattacharjya, ***MS&E, Stanford University***

Tapan Mukerji, ***Stanford University***

Value of Information

- Gathering information is crucial in any decision making process

- Estimating the value of information (VOI) is therefore important for acquiring the right kind of information

VALUE OF INFORMATION IN TIME SAVED, PRODUCTIVITY

Griffiths and King assessed the VOI in terms of time savings. Surveys in eight organizations asked professionals to indicate whether reading journal articles, books, or internal reports saved them any time

Table A-1. Information and Time Savings (%)

Reason for Time Savings	Journal Articles	Books	Internal Reports
Overall time savings	26	42	50
Avoided primary research	49	22	51
Stopped unproductive research	10	21	22
Modified research design	12	13	19
Modified analysis method	16	30	9

Value of Information

Information Entropy approach
versus
Decision theoretic approach

Both well established over many years

Measures of Information – Information Theory

Shannon Entropy:

$$H(x) = -\int p(x)\log[p(x)]dx$$

Mutual Information:

$$MI = \frac{H(x) - \int H(x \mid y)\, p(y)\, dy}{H(x)} \qquad 0 \le MI \le 1$$

reduction in uncertainty of x on observing the outcome y of an experiment

Measures of Information – Decision Theory

Experiment is valuable when

- *material* to the decision

Information from experiment may reduce uncertainty but is not valuable until it can change the decision.

Objective

Formulate a decision-theoretic model to estimate value of information in spatial decision making.

Spatial Decision Making

Decision problems involving:

- Choice of alternatives over space
  (e.g. selecting sites for wells)

- The distinction of interest is spatially correlated
  (e.g. facies, porosity)

Spatial Decision Making

Continuous spatial random field

- porosity, saturation

Categorical spatial random field

- facies

Value of Information: Decision Theoretic Approach

Literature:

Raiffa, H., (1968), Decision analysis, Addison-Wesley.

Matheson, J. E., (1990), Using influence diagrams to value
information and control, [Oliver and Smith (Eds), Influence
diagrams, belief nets and decision analysis, 25-48, Wiley.

Polasky, A., and Solow, A. R., (2001), The value of information in reserve site selection, Biodiversity and Conservation, 10, 1051-1058.

Value of Information

A related problem: Spatial sampling design

Journel,

Zidek, Caselton, Le, & co-workers

Gelfand, Banerjee, et al.

……and others

Value of Information: Decision Theoretic Approach

Literature:

Houck & Pavlov (2006):

VOI for CSEM data at global reservoir level

Bickel et al. (2006):

VOI for seismic attributes at local level

Need to incorporate spatial dependence

Value of information: Decision Theoretic Approach

We build on the concepts presented by earlier workers and present models incorporating *spatial dependence* within a decision-theoretic framework

Values associated with decisions

- Prior Value
- Value with Perfect Information
- Value of Experiment

Example

Simple example: no spatial dependence

Treasure hunt

Revenue = R = \$10000 if treasure!

P(treasure) = p = 0.2.

Cost = C = \$1000 for digging

Prior value =

$PV = \max(0, pR - C)$

$= 0.2 \cdot 10000 - 1000 = 1000.$

Simple Example

Concept of clairvoyance: Perfect information

Value with free clairvoyance

VFC = p(R-C) = 0.2(10000 – 1000) = 1800.

Value of perfect information

VOPI = VFC – PV = 1800 – 1000 = 800.

Simple Example

Concept of experiment: Imperfect information

D = {0, 1} ={Detector displays “no treasure”, Detector displays “treasure”}.

Sensitivity = $P(D = 1|Tr = 1) = P(D = 0|Tr = 0) = 0.9$.

Posterior prob = $P(Tr \mid D)$

Simple Example

Concept of experiment: Imperfect information

$$\text{VFE}= \sum_{d=0,1} \max[0,\ P(Tr = 1|D = d)R - C]P(D = d)$$

Value with free experiment
VFE = 1540.

Simple Example

Prior value: PV = pR –C = 1000

Value with free clairvoyance: VFC = p(R – C)

Value with free experiment: VFE

Value of (imperfect) Information

VOI = VFE – PV = 1540 – 1000 = 540.

Spatial System

- Variable x_i on a spatial lattice n_1 x n_2

- Probability of favorable outcome: $P_i(x_i = 1) = p_i$

- Cost if site i is selected: C_i

  (note: not cost of experiment)

- Revenue: R_i

Values associated with spatial decisions

- Prior Value
- Value with Perfect Information
- Value with Free Experiment
- Value of Information

Values associated with decisions

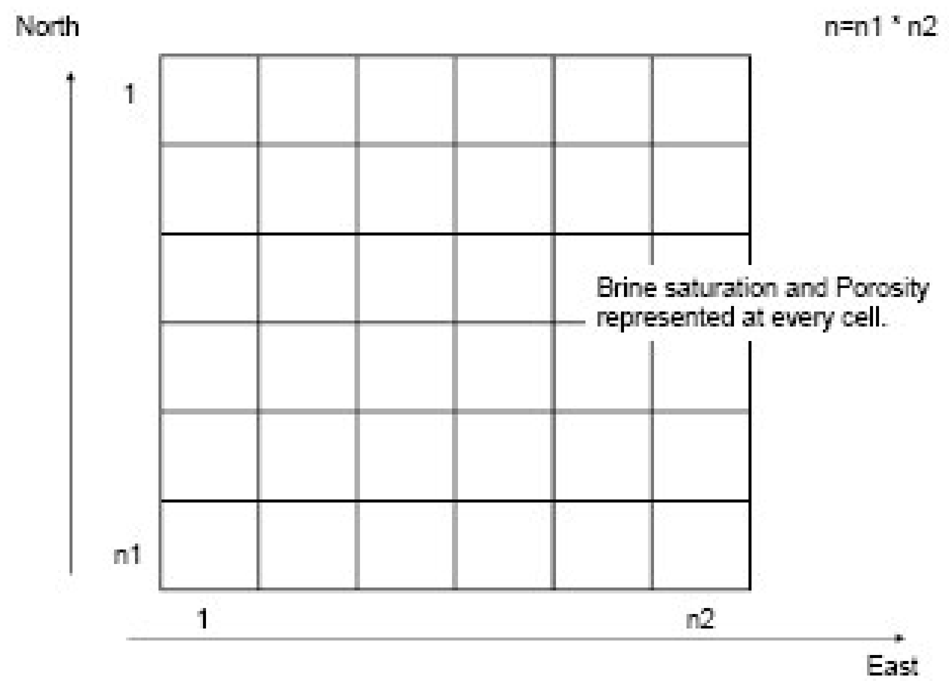
- All calculations assume, for the sake of clarity, that the decision maker is risk-neutral.

- Model can incorporate risk aversion or risk seeking behavior.

Spatial Lattice Model

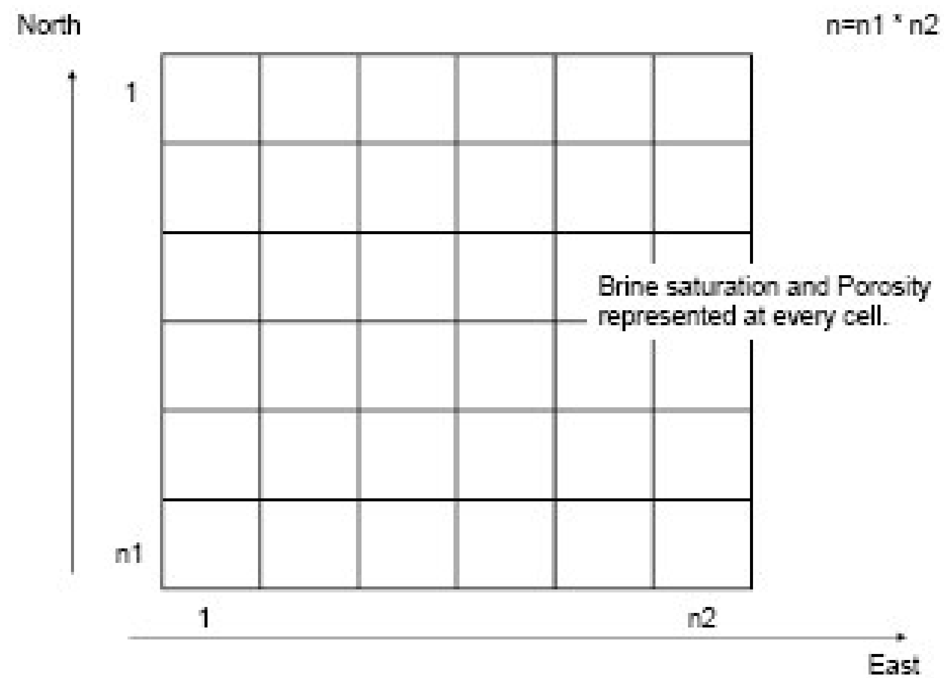
- Brine saturation s = (s1, . . . , sn) on a lateral grid.
- Porosity = (ϕ1, . . . , ϕn) on a lateral grid.

$$\phi_i \sim \{\phi_i, s_i\}$$



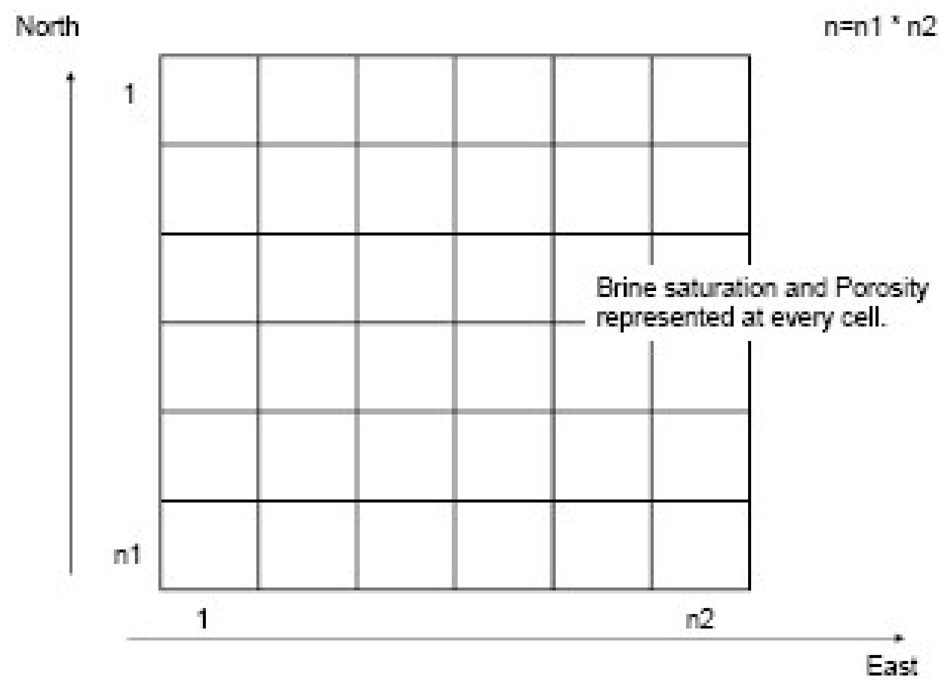
Spatial Lattice Model

- Gaussian Markov Random field (GMRF) for logistic transforms of porosity and saturation
- Exponential Spatial Covariance Σ



Spatial Lattice Model

- Each node is a possible selection site.



Spatial Decision Making

- Prior: Lattice model for brine saturation and porosity in reservoir - with spatial correlation.

- Experiment:
  - Seismic data (Amplitude Versus Offset)
  - Electromagnetic data (CSEM)

Expected Prior Value (PV)

Expected profit = p_iRi - C_i

Choose site only if expected profit > 0

$$V_i = \max\{0, [p_i R_i - C_i]\}$$

$$PV = \sum_i V_i$$

Value with Free Clairvoyance (VFC)

Decision maker has perfect information about latent variable

$$VFC = \sum_i p_i \max\{0, (R_i - C_i)\}$$

$$VFC = \sum_i p_i (R_i - C_i)$$

For R > C

Value of Perfect Information (VOPI)

$$VOPI = VFC - PV$$

Value of Perfect Information is an upper bound on the Value of Information

Value with Free Experiment (VFE)

Experiment performed and data y_i is observed

Conditional probability of
favorable outcome: $P_i(1|y_i)$

Expected Posterior Value

Prior:

$$V_i = \max\{0,[p_i R_i - C_i]\}$$

Posterior:

$$V_i^{post} = \int \max\{0,[p_i(1 \mid y_i)R_i - C_i]\}P(y)dy$$

$$VFE = \sum_i V_i^{post}$$

Value with free experiment

Expected Posterior Value: Continuous variable

Prior:

$$V_i = \max\{0, [E(\phi_i)R_i - C_i]\}$$

Posterior:

$$V_i^{post} = \int \max\{0, [E(\phi_i \mid y_i)R_i - C_i]\}P(y)dy$$

$$VFE = \sum_i V_i^{post}$$

Value with free experiment

Value of Information

VOI = VFE - PV

Value of Information =
Value with Free Experiment – Prior Value

Geology and Physics Relations

Spatial random field

Prior:

$$V_i = \max\{0, [E(\phi_i)R_i - C_i]\}$$

Posterior:

$$V_i^{post} = \int \max\{0, [E(\phi_i \mid y_i)R_i - C_i]\} P(y) dy$$

Related by physics and wave propagation forward models

Likelihood of experiment

- Seismic data y = (y1, . . . , yn) at all grid cells.
- y_i =(Zero-offset reflectivity , AVO gradient), or similar.

Gassmann's relations (s_i, ϕ_i) → (μ_i, K_i, ρ_i)

Aki–Richards approximations (μ_i, K_i, ρ_i) → (Ro, G)

Likelihood of experiment

- EM data y = (r1, . . . , rn) along a sail line.
- r_i = inverted resistivity

Archie's relations $(s_i, \phi_i) \Rightarrow r_i$

- Averaging over mutiple cells to simulate lower resolution

Likelihood

Local geology and deposition sets the expected rock physics model and geophysical response for different porosity and saturation.

Computations

Computations of expectations and conditional expectations by Monte Carlo simulations of

- spatial random fields
- forward modeled datasets over the simulated fields.
- posterior conditional expectation by iterated linear approximation

Spatial Models and Rock Physics Relations

Posterior:

$$V_i^{post} = \int \max\{0, [E(\phi_i \mid y_i)R_i - C_i]\} P(y)dy$$

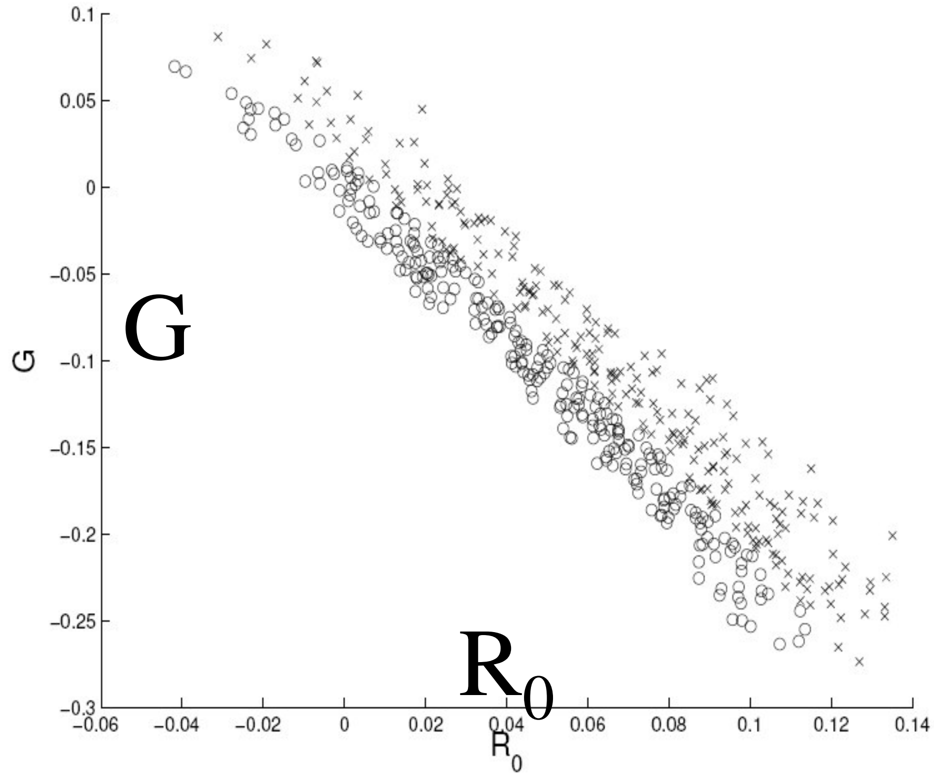
Iterated linear approx

Monte Carlo Integration

AVO Example

Spatial random field: porosity, saturation

Data: AVO intercept & gradient, R_0 & G

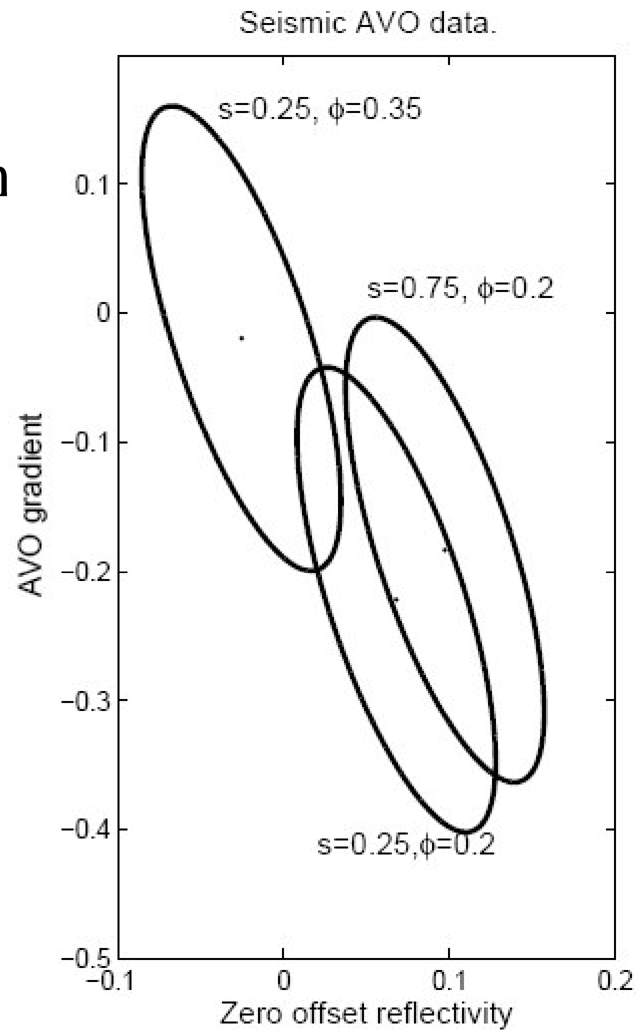


$P(R_0, G)$ from forward model

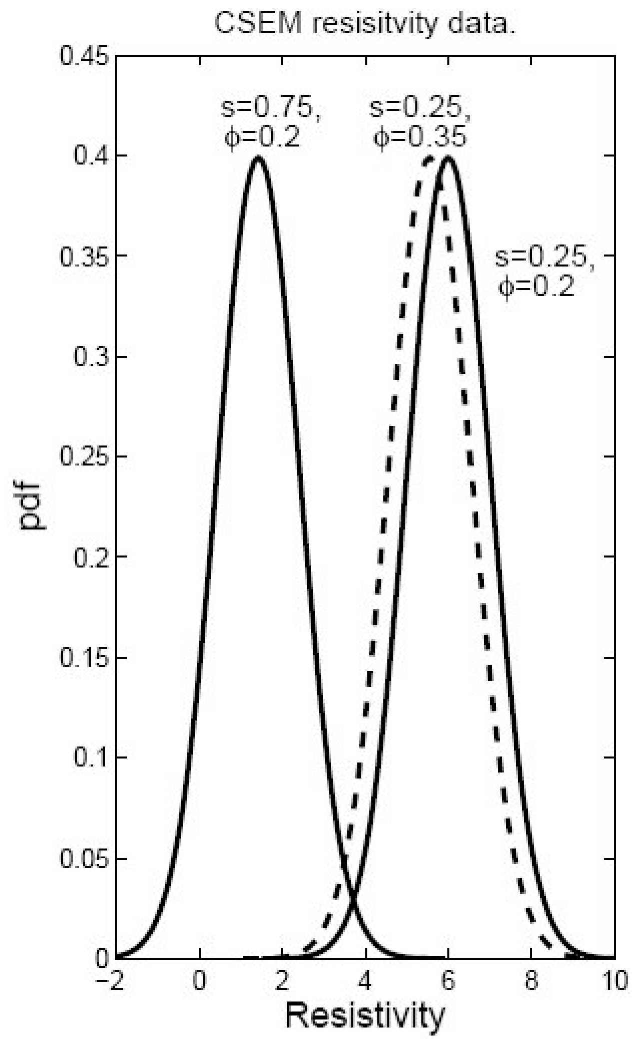
AVO and CSEM Example

P(R_0 ,G|m) from forward model

G



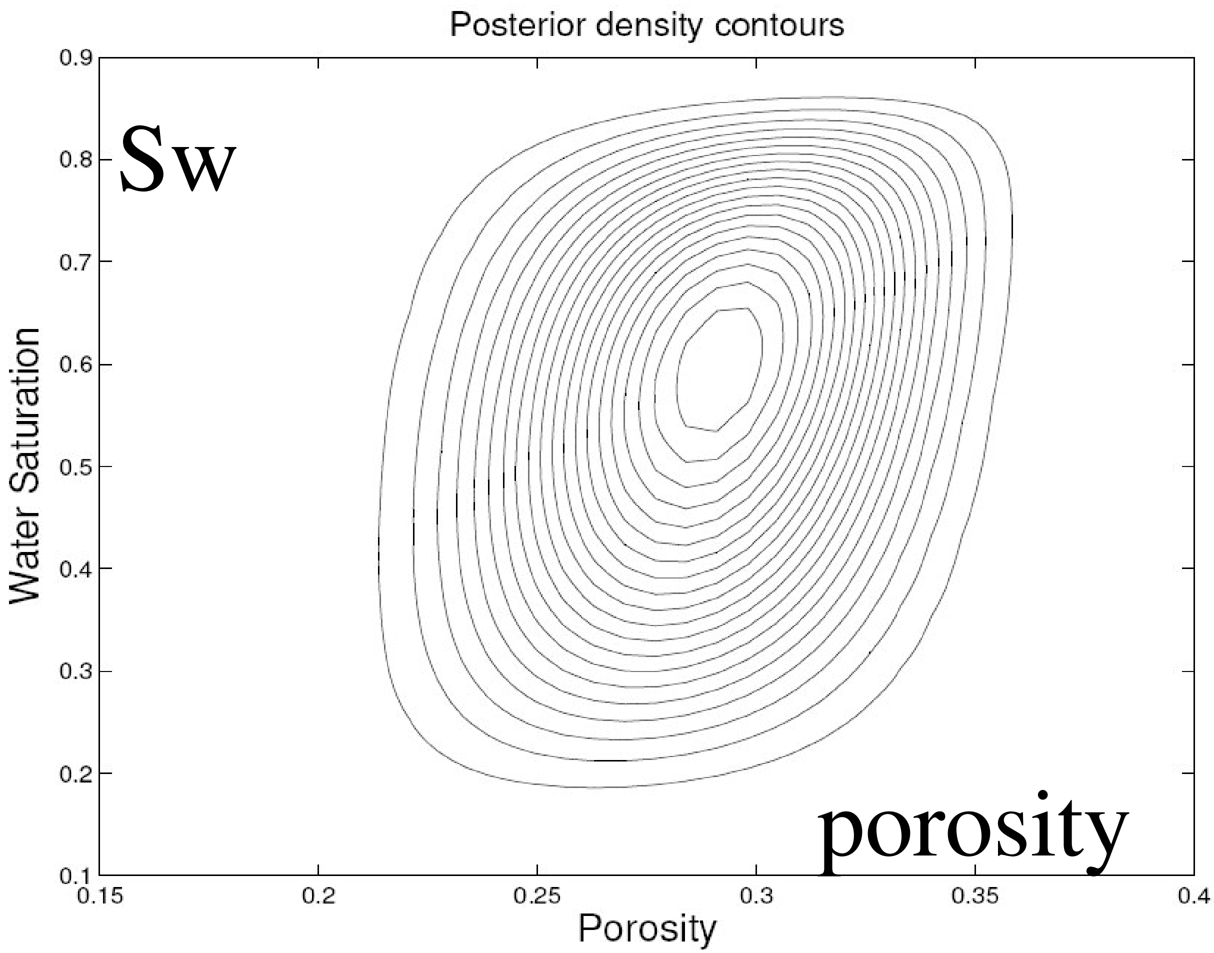
R_0



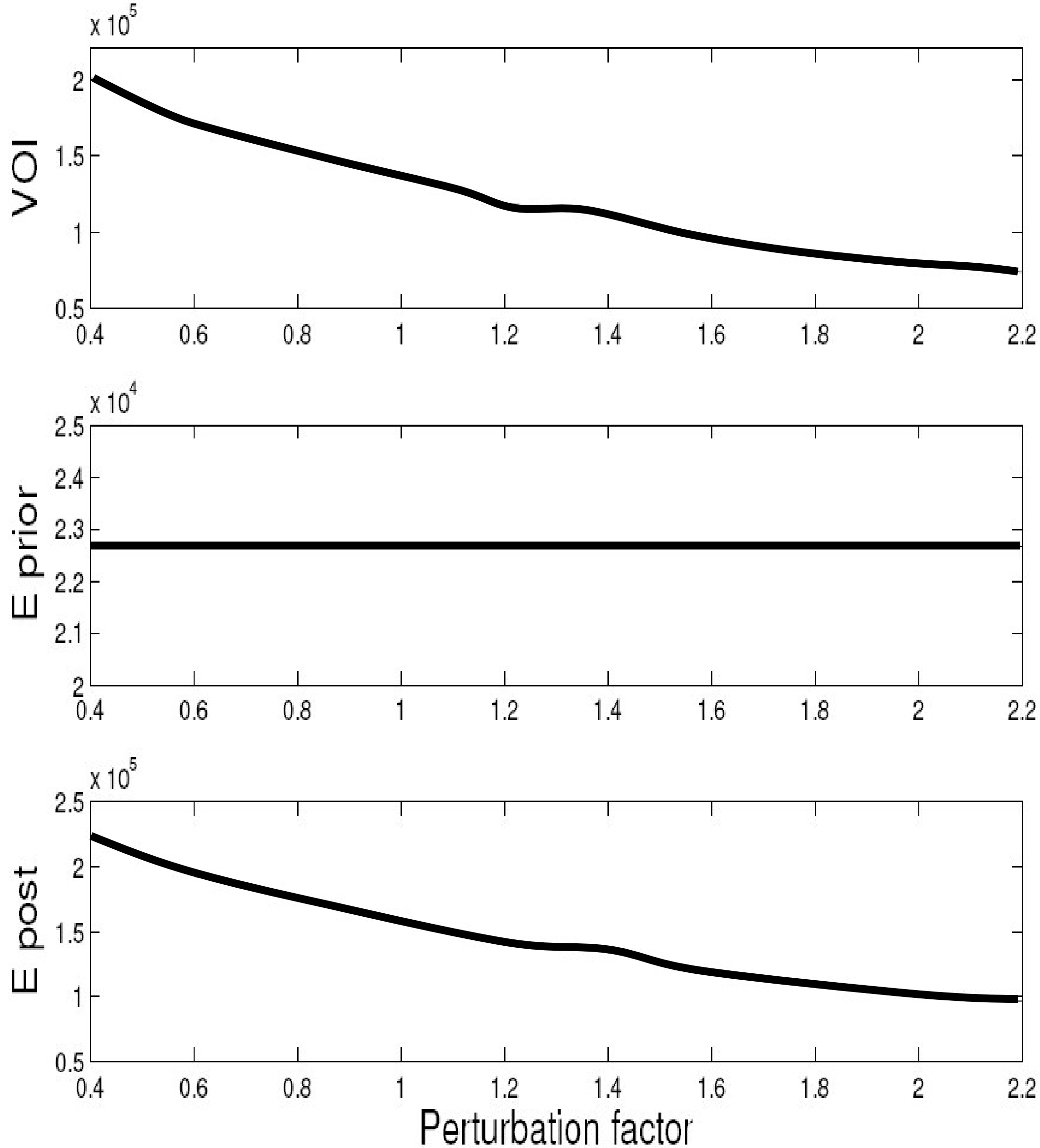
P(r|m) from forward model

AVO Example

P(porosity, saturation | R_0 = 0.05, G = -0.05)



AVO Example: VOI



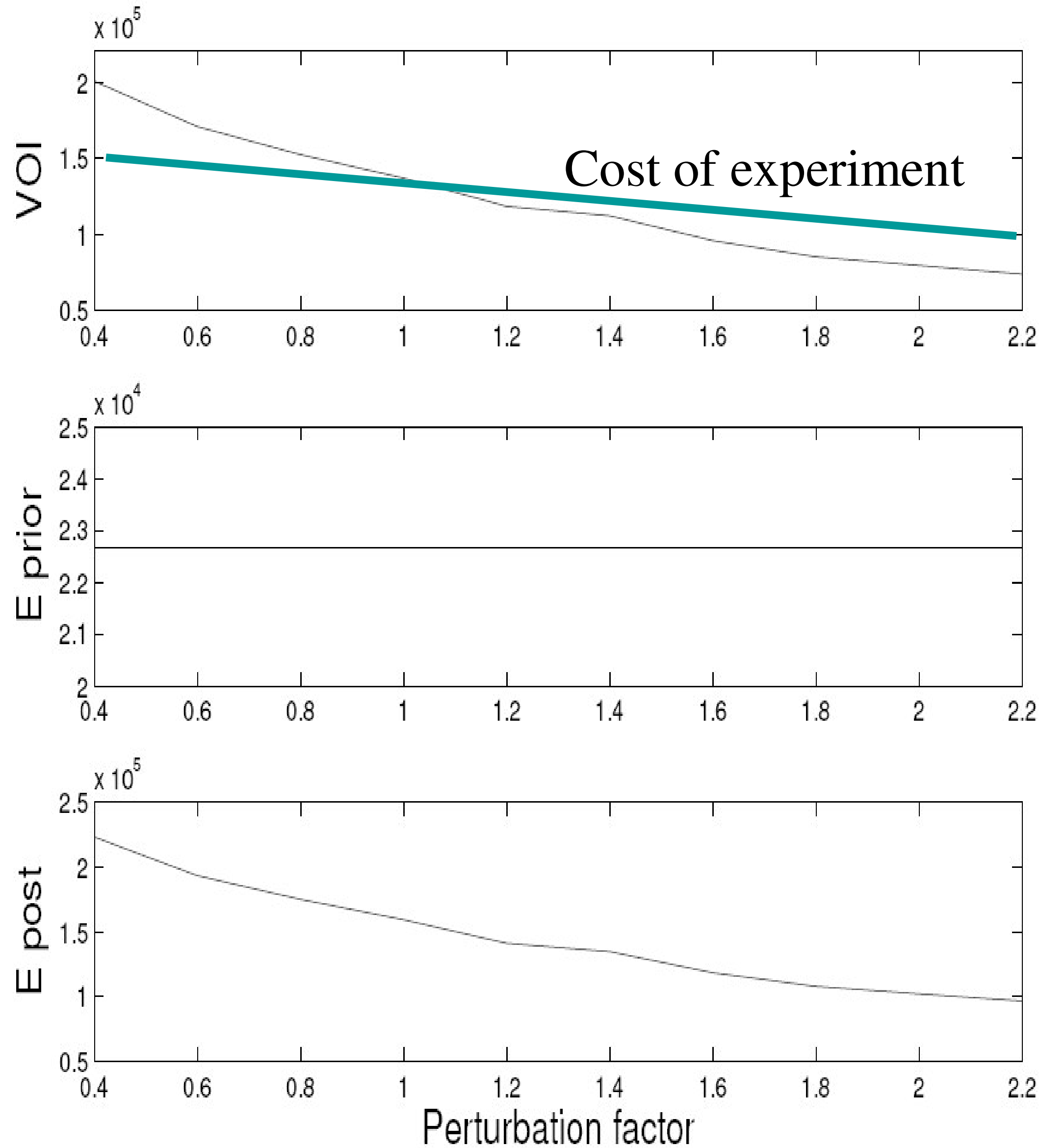
VOI

Prior Value

Posterior

Better data quality

AVO Example: VOI



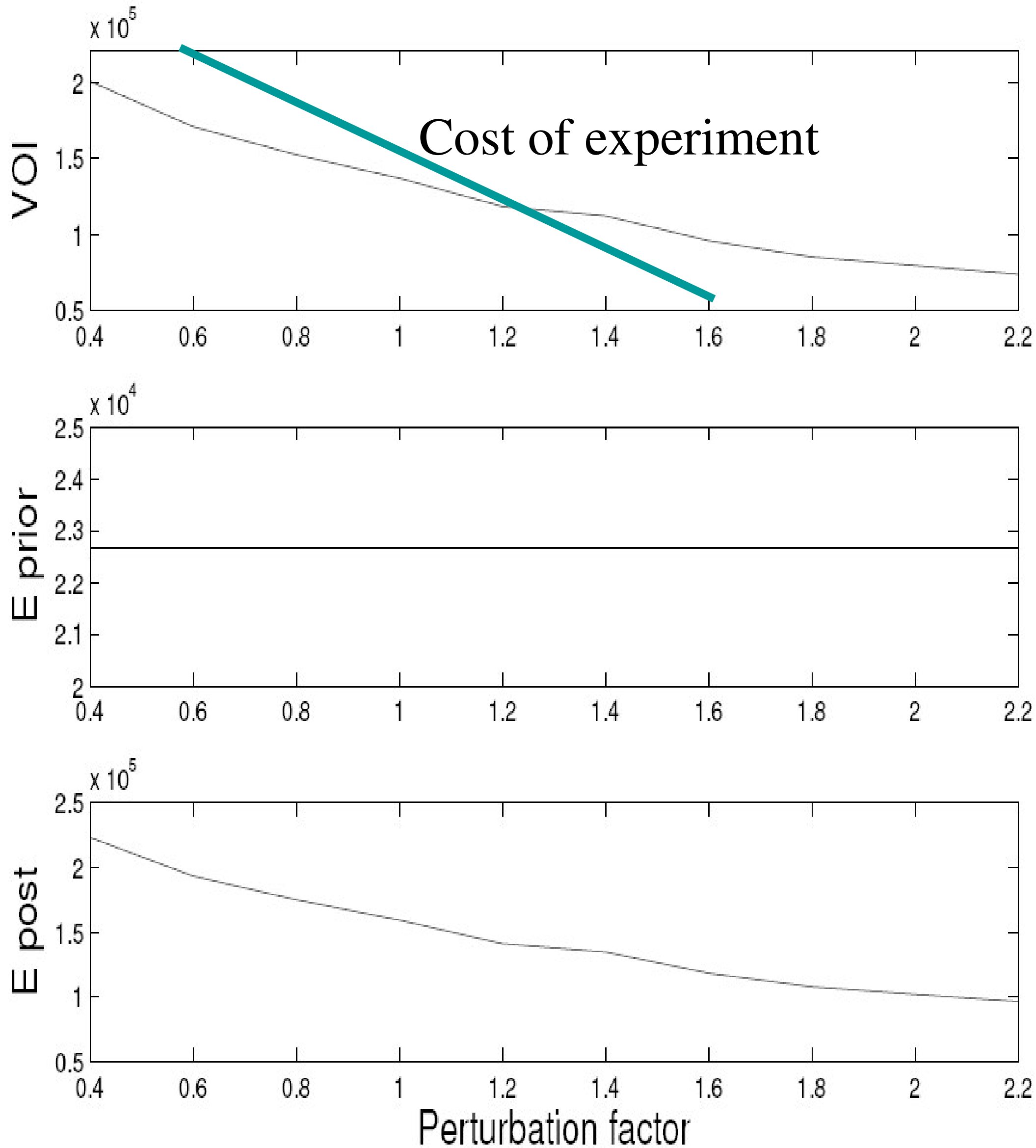
VOI

Prior Value

Posterior

← Better data quality

AVO Example: VOI



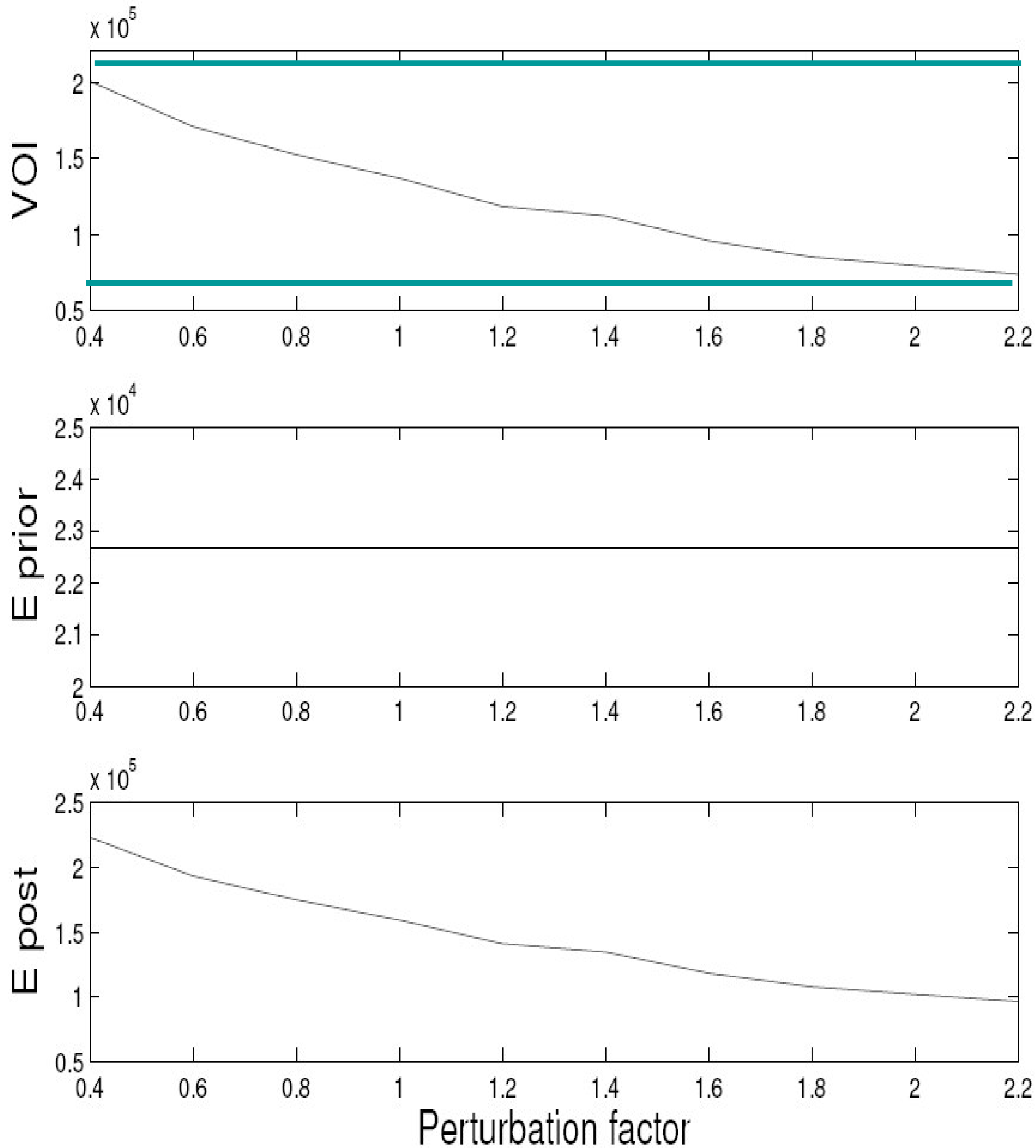
VOI

Prior Value

Posterior

← Better data quality

AVO Example: VOI



VOI

Prior Value

Posterior

← Better data quality

Chance of Knowing

CK = VOI/VOPI

$$0 \leq CK \leq 1$$

Rates worth of an experiment and compares different experiments on the variable of interest

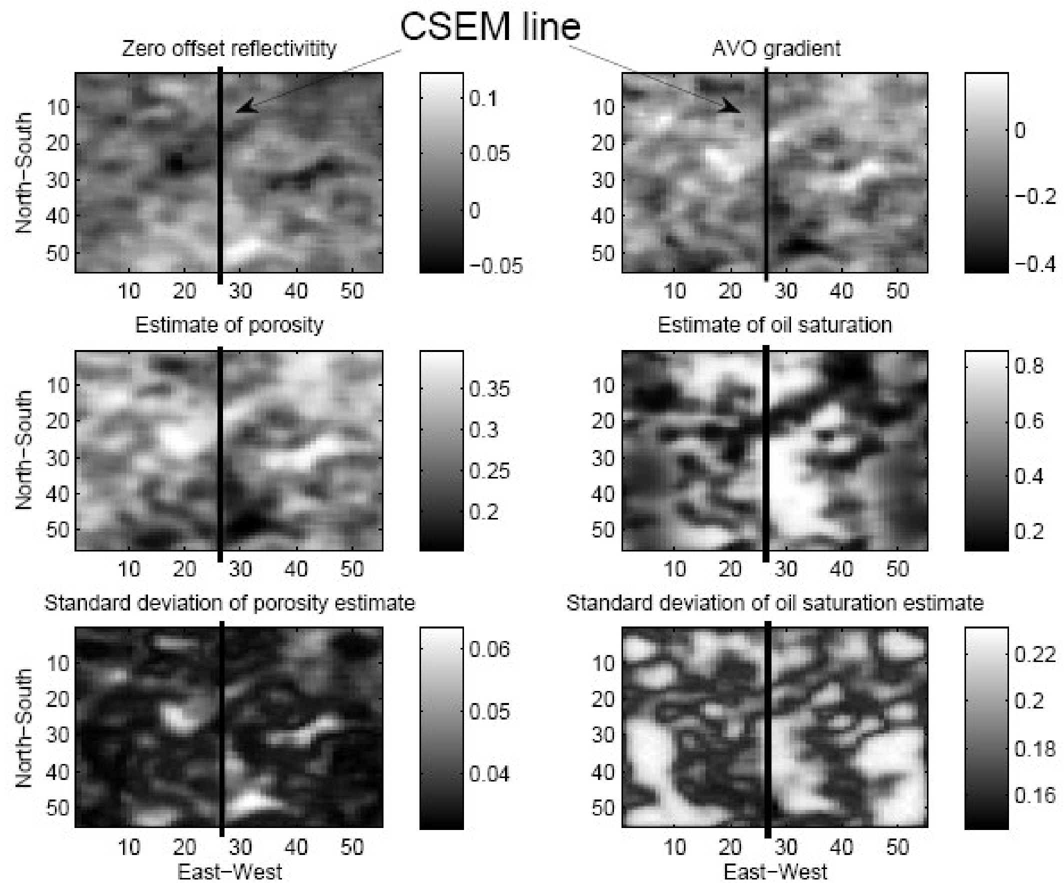
e.g. Seismic and CSEM

Value of Information

Rates worth of an experiment and compares different experiments

e.g. Seismic and CSEM

(VFE – PV)/PV



Measures of Information

MI: Information theoretic

VOI: Decision theoretic

MI:

- -how much uncertainty can be reduced by an experiment
- -not linked to decision

VOI:

- -how much decision maker should pay for the experiment
- -linked to decision
- -more complete for valuing information
- -more difficult to estimate

Measures of Information

Experiment is valuable when

- *relevant* to the distinction of interest
- *material* to the decision

Information from experiment may reduce uncertainty but is not valuable until it can change the decision.

Entropy based measures address relevancy alone.
VOI addresses relevancy and materialness of experiment.

Summary and Conclusions

Demonstrated a method for computing the Value of Information (VOI) for a spatial decision making – correlated variables

Information theoretic vs. Decision theoretic

VOI in a spatial setting involves complex interplay between the reliability of the experiment, spatial uncertainty and the nature of decision and values.