Bayesian Decision Theory in Structural Geological Modeling - How Reducing Uncertainties Affects Reservoir Value Estimations

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1 - Introduction

Structural geological modeling is of central importance for the assessment of uncertain hydrocarbon accumulations in potential reservoirs. Hydrocarbon exploration and production is a high-risk, high-reward sector in which good decision making is indispensable. Actors in this field are faced with numerous uncertainties that have to be considered. We examine respective decision making from a Bayesian perspective.

2.1 - Methods

Construction of a 3D structural geological model:

- Synthetic model of a simple anticline-fault trap in a potential hydrocarbon system (see Figure 1)
- Inclusion of uncertainties by assigning probability distributions to the positions of layer interfaces in depth

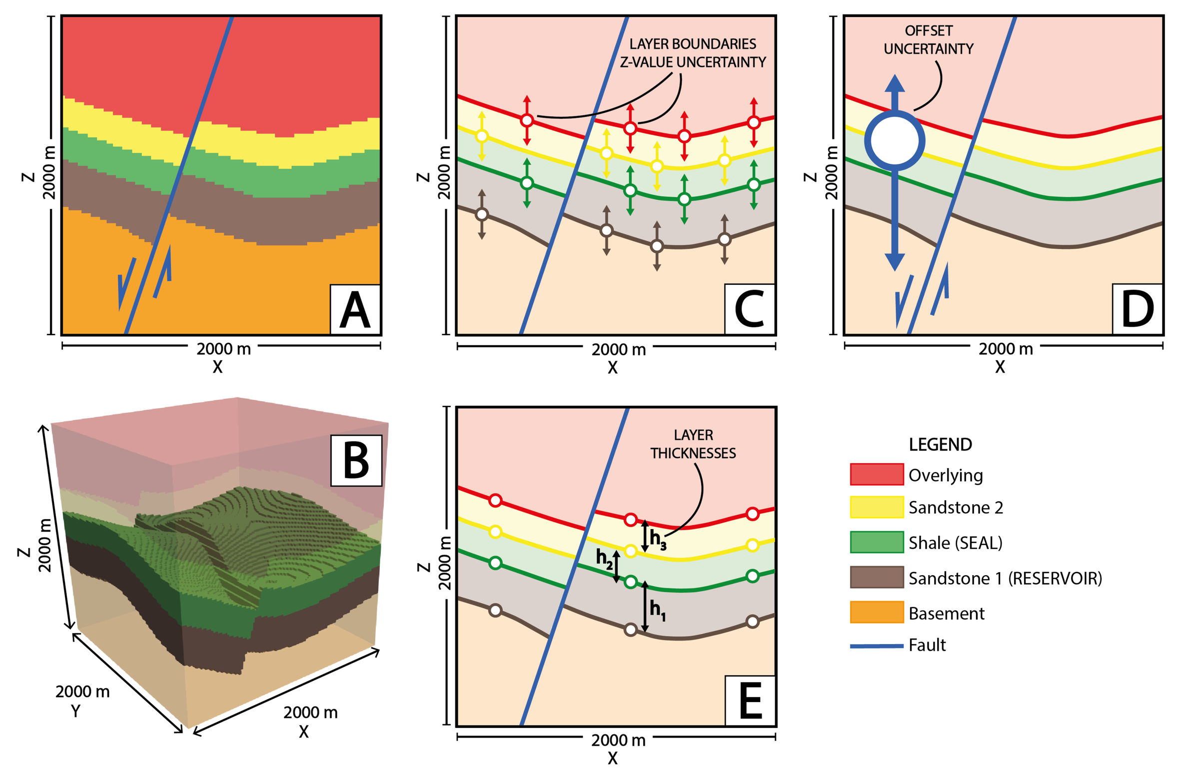

Figure 1: The structural geological model illustrated as a 2D cross section (A) and a 3D voxel representation (B). The inclusion of z-positional uncertainties affecting layer depths and fault offset are depicted in (C) and (D). Thicknesses of the three middle layers are defined by the distances of boundary points (E) and are thus directly dependent on (C).

Integration in a probabilistic modeling framework for Bayesian analysis (see Figure 3):

- Setting up a full probability model taking into account all parameter probability distributions
- Bayesian updating: Conditioning of parameters on additionally observed data via likelihood functions
- Approximation of posterior distributions through the use of MCMC sampling

2.2 - Methods (continued)

Evaluation of modeling results:

- Shannon entropy for uncertainty visualization (after Wellmann and Regenauer-Lieb (2012).
- Implementation of algorithms for structural analysis, trap recognition (see Figure 2) and calculation of recoverable oil volumes (ROV)
- Decision making based on the optimization of a case-specific custom loss function that considers differently risk-affine actors

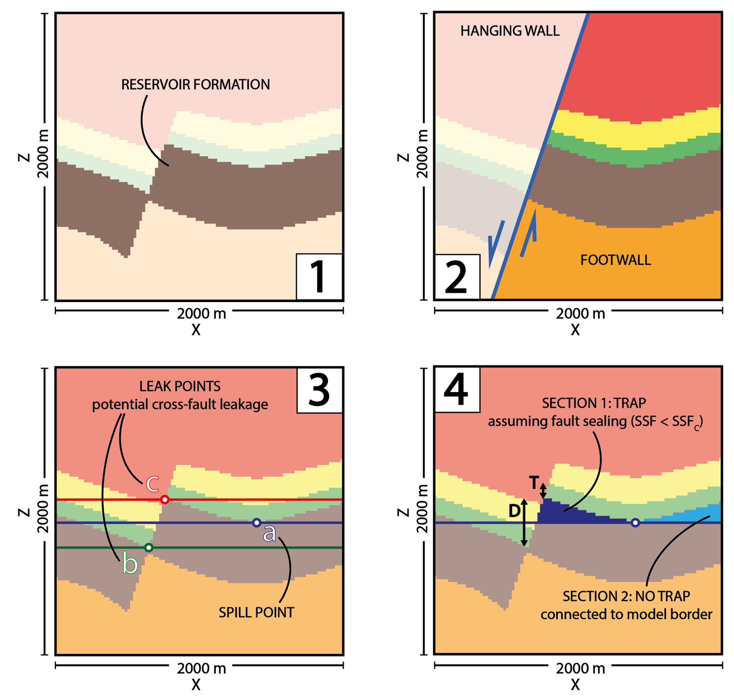

Figure 2: To be recognized as part of a trap, a reservoir voxel (1) has to be positioned in the footwall (2). The maximum trap fill is defined by either the anticlinal spill point (3;a) or a point of leakage across the fault, depending on juxtapositions with layers underlying (3;b) or overlying the seal (3;c). The latter is only relevant if the critical Shale Smear Factor (SSF_c) is exceeded, as determined over D and T in (4).

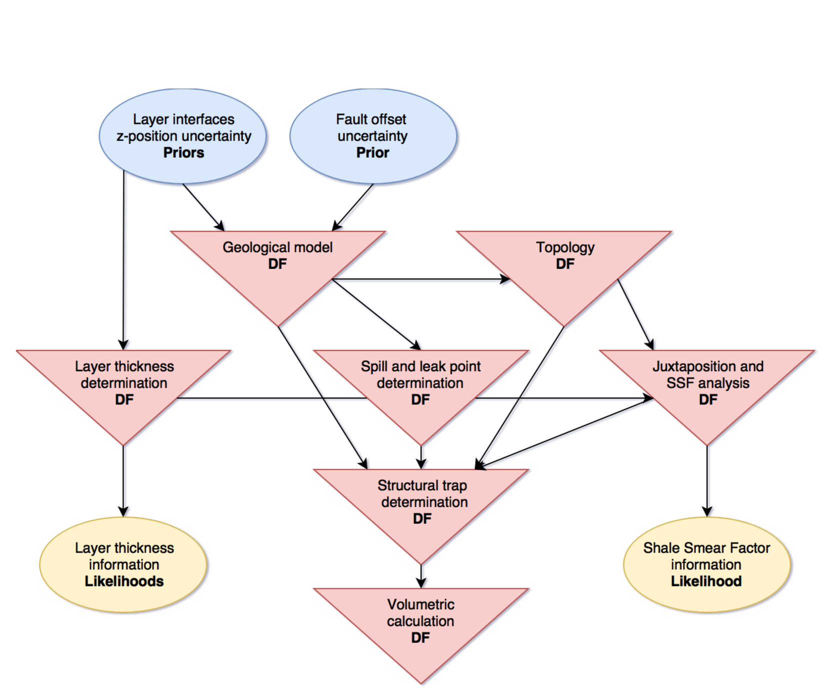

Figure 3: Illustration of the probabilistic model as a hierarchical Bayesian network after Koller and Friedman (2009). Stochastic nodes are represented by ellipses (blue for priors, yellow for likelihoods). Deterministic functions are depicted as triangles in red. Arrows indicate direct connections from parent to child nodes.

3 - Results

Posterior ROV probability distributions are realized depending on the nature of likelihoods implemented in the Bayesian inference step. Applying the custom loss function shows that the various Bayes estimators shift according to the characteristics of this underlying value distribution. While bimodality and overall uncertainty lead to separation, risk-averse and risk-friendly decisions converge and decrease in expected loss given narrower unimodal distributions. A decisive factor in our model is the reliability of the sealing across the fault, as it defines the probability of complete trap failure. Two examples are summarized in Figures 4 and 5.

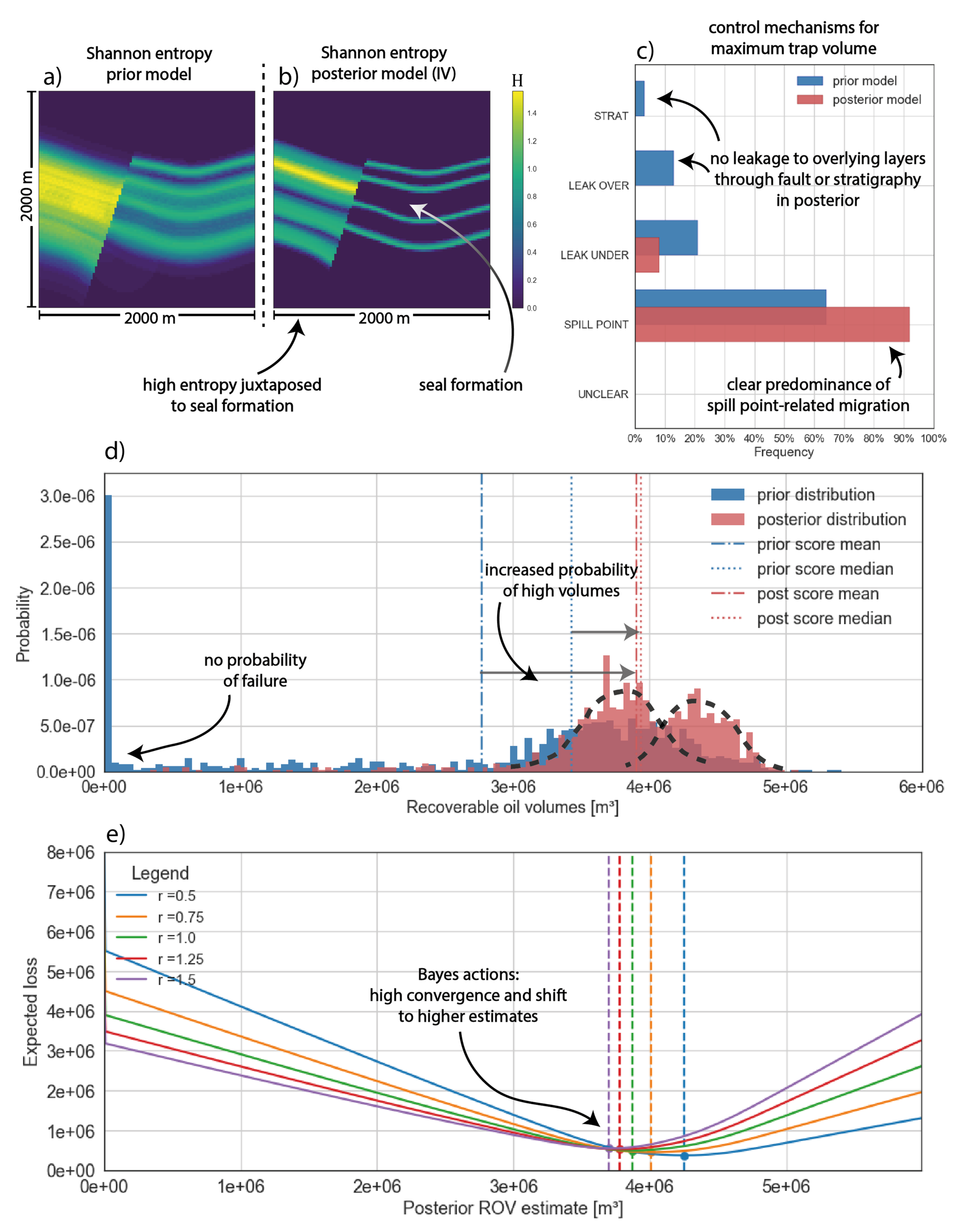

Figure 4: Evaluation of a model conditioned on thickness and SSF likelihoods which reinforce the probability of a high ROV and reliable trap closure. Posterior Shannon entropy was reduced (b). Cross-fault leakage to overlying layers was eliminated as a trap control mechanism (c) and coincides with the disappearance of failure probability in the posterior ROV distribution (d). Respective loss functions visualize high decision convergence (e).

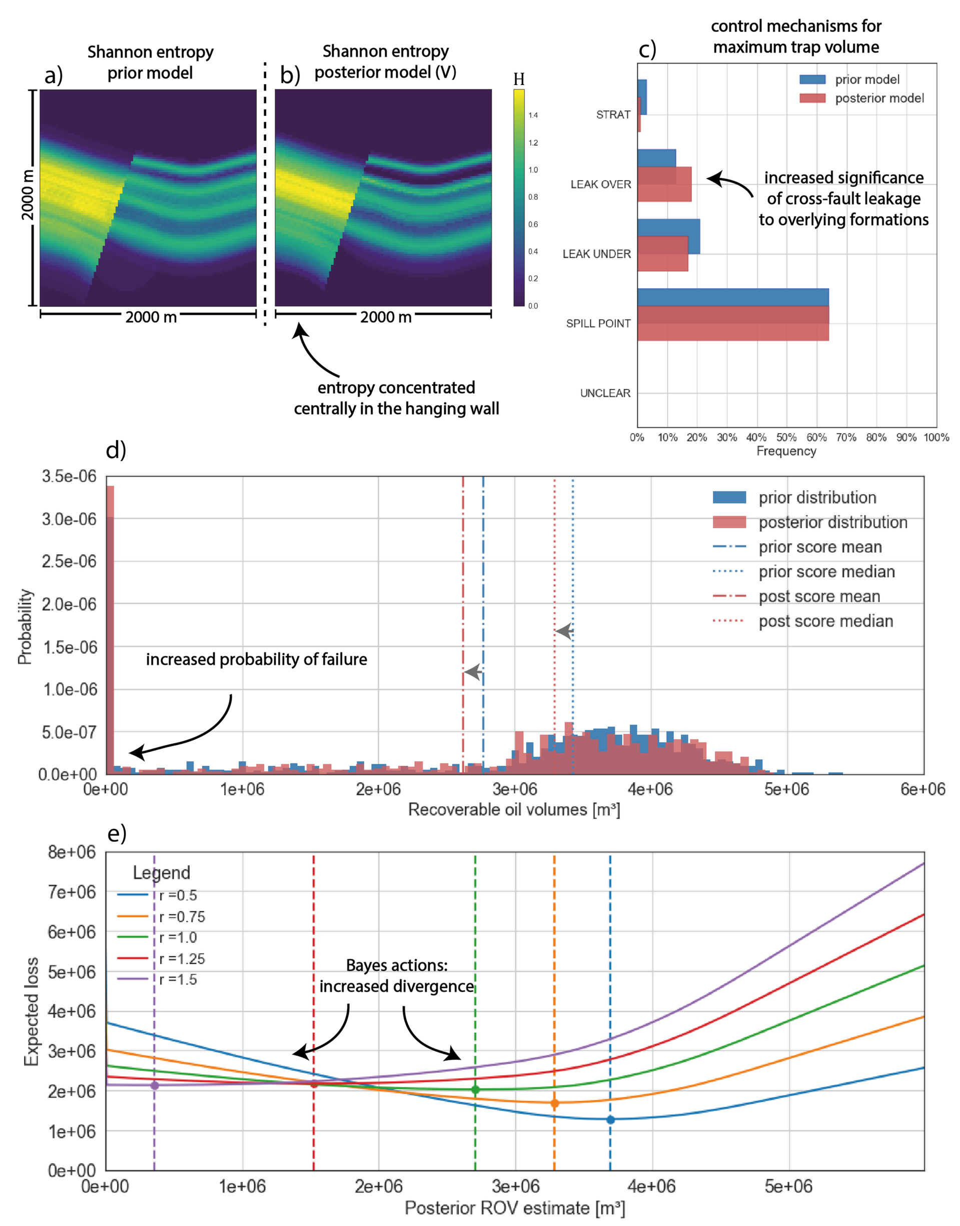

Figure 5: Evaluation of a model conditioned on a SSF likelihood which narrows around the critical SSF_c and thus amplifies the duality in the posterior ROV distribution (d). Shannon entropy was only slightly diminished (a,b), general cross-fault leakage remains a significant trap control mechanism (c). The resulting loss function realizations illustrate high divergence of differently risk-affine decisions (e).

4 - Conclusions

- The degree of decision convergence can be considered a measure for the state of knowledge and its inherent uncertainty at the moment of decision making.
- This decisive uncertainty does not change in alignment with model uncertainty but depends on alterations of critical parameters and respective interdependencies.
- Actors are affected differently by one set of information, depending on their risk affinity.
- It is important to identify the model parameters which are most influential for the final decision in order to optimize the decision-making process.

These results and conclusions refer to a generic hydrocarbon system case study but are transferable to other fields where decisions are based on uncertain geological models, for example in hydrogeological or geothermal exploration.

5 - References

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