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. Utilizing a Bayesian approach, we examine the influence of model uncertainties and respective uncertainty changes on the decision making of actors in this field.

2 - 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

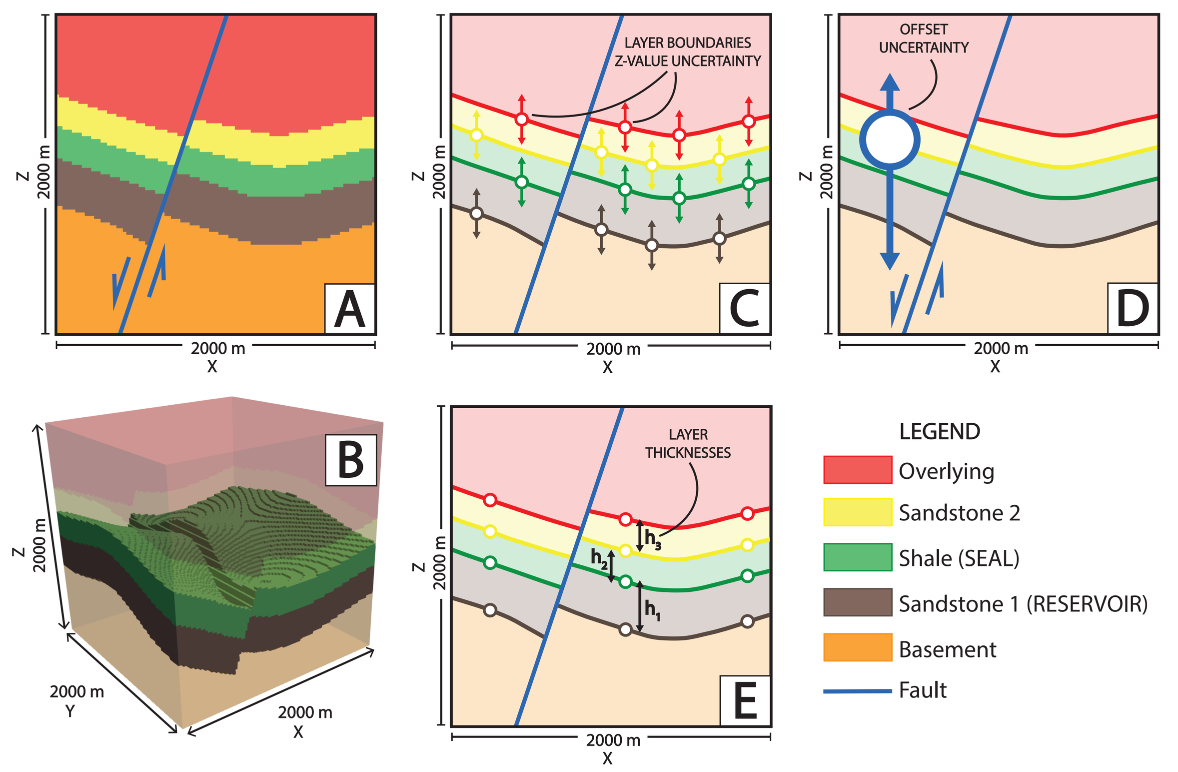

Figure 1: The structural geological model illustrated as a 2D cross section (A) and a 3D voxel representation (B). The inclusion of z-positional uncertainties affecting layer depths and fault offset are depicted in (C) and (D). Thicknesses of the three middle layers are defined by the distances of interface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

Integration in a probabilistic modeling framework for Bayesian analysis:

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

Evaluation of modeling results:

- Shannon entropy for uncertainty visualization (after Wellmann and Regenauer-Lieb (2012))
- Implementation of customized 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 loss function that is employed to estimate the ROV as the crucial reservoir value

2 - Methods (continued)

Custom loss function design:

We regard decision making as the process of estimating the posterior ROV by optimizing a customized loss function that considers the preferences of differently risk-affine actors. A decision that minimizes expected loss, according to such a function, is referred to as Bayes action (Davidson-Pilon, 2015). We extend the standard absolute-error loss function with a risk factor r and several other weighting factors to express the expected loss relative to the nature and magnitude of deviation of the estimate $\hat{\theta}$ from the true value θ:

$$L(\theta,\hat{\theta}) = \begin{cases} |\theta-\hat{\theta}| * r^{-0.5}, & \text{for } 0 < \hat{\theta} < \theta \\ |\theta-\hat{\theta}| * a * r, & \text{for } 0 < \theta < \hat{\theta} \\ |\theta-\hat{\theta}| * b * r, & \text{for } \theta \leq 0 < \hat{\theta} \\ |\theta-\hat{\theta}| * c * r^{-0.5}, & \text{for } \hat{\theta} \leq 0 < \theta \end{cases}, \text{ with } a,b,c,r \in \mathbb{Q}.$$

We define that normal overestimation is 25% ($a = 1.25$), fatal overestimation 100% ($b = 2$) and fatal underestimation 50% ($c = 1.5$) worse than normal underestimation. A risk factor $r = 1$ represents risk neutrality, while $r < 1$ expresses risk-friendly, and $r > 1$ risk-averse behavior.

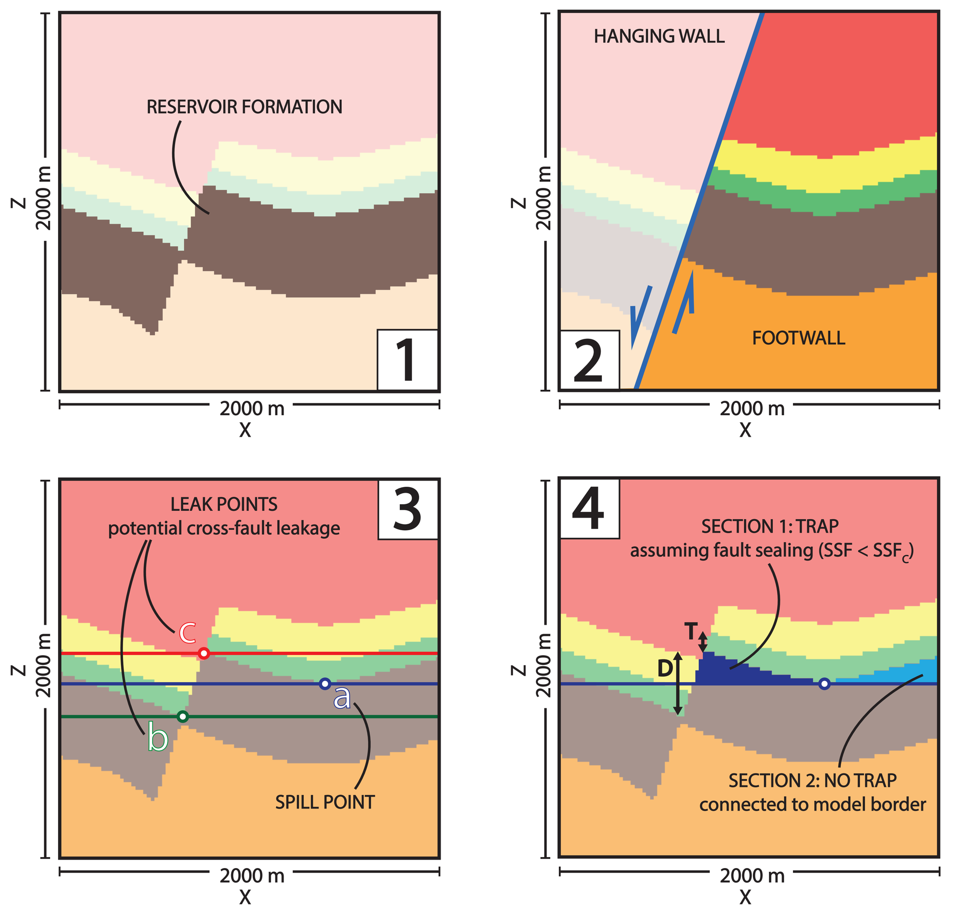

Figure 2: To be recognized as part of a trap, a reservoir voxel (1) has to be positioned in the footwall (2). The maximum trap fill is defined by either the anticlinal spill point (3;a) or a point of leakage across the fault, depending on juxtapositions with layers underlying (3;b) or overlying the seal (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). Voxels connected to the model border are discarded.

3 - Results

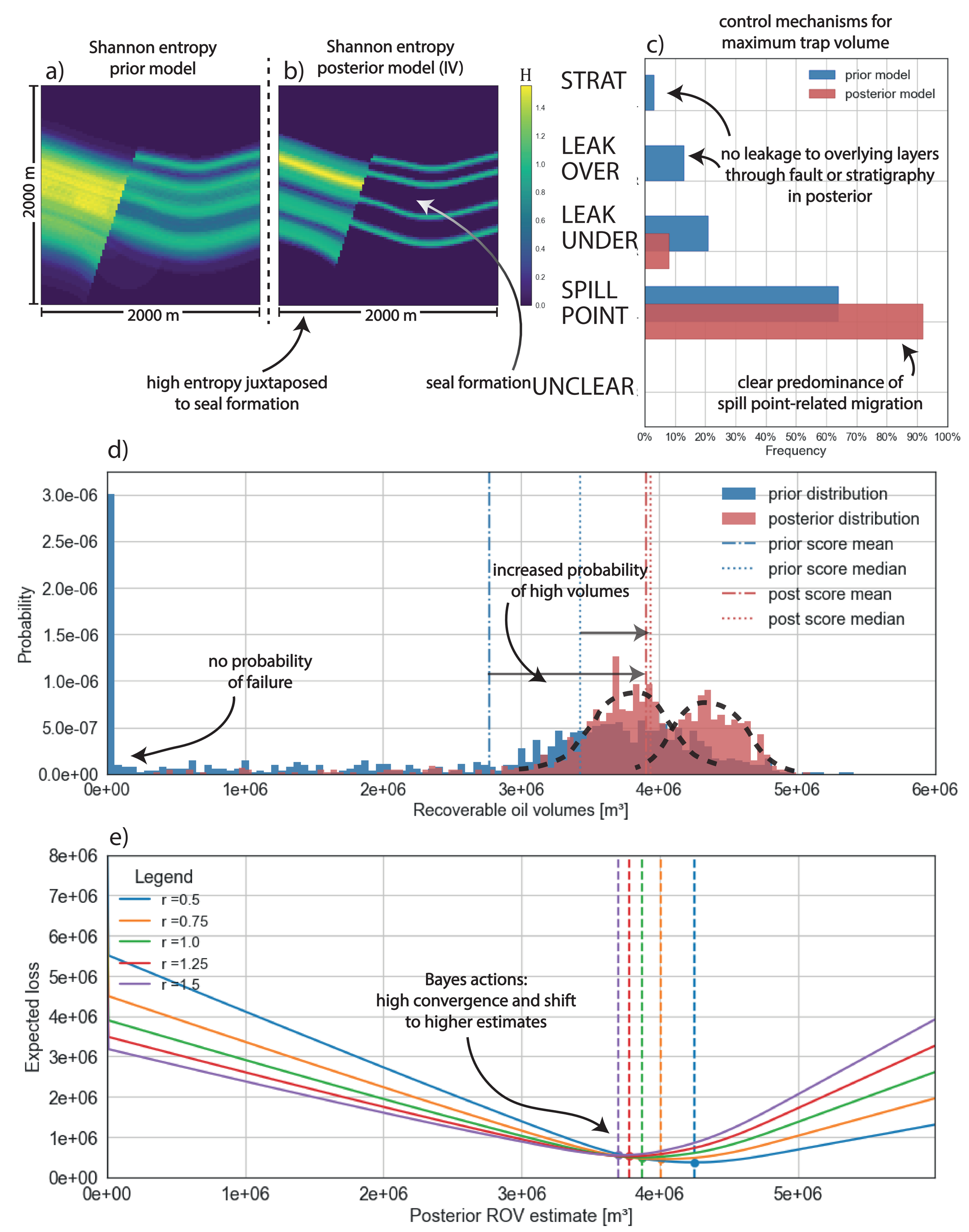

Figure 3: Evaluation of a model conditioned on thickness and SSF likelihoods which assure a reliable trap closure and reinforce the probability of a high ROV. Shannon entropy is significantly reduced in the posterior model (b). Cross-fault leakage to overlying layers is eliminated as a trap control mechanism (c) and coincides with the disappearance of the probability of failure in the posterior ROV distribution (d). The respective loss functions are plotted in (e), showing high decision convergence.

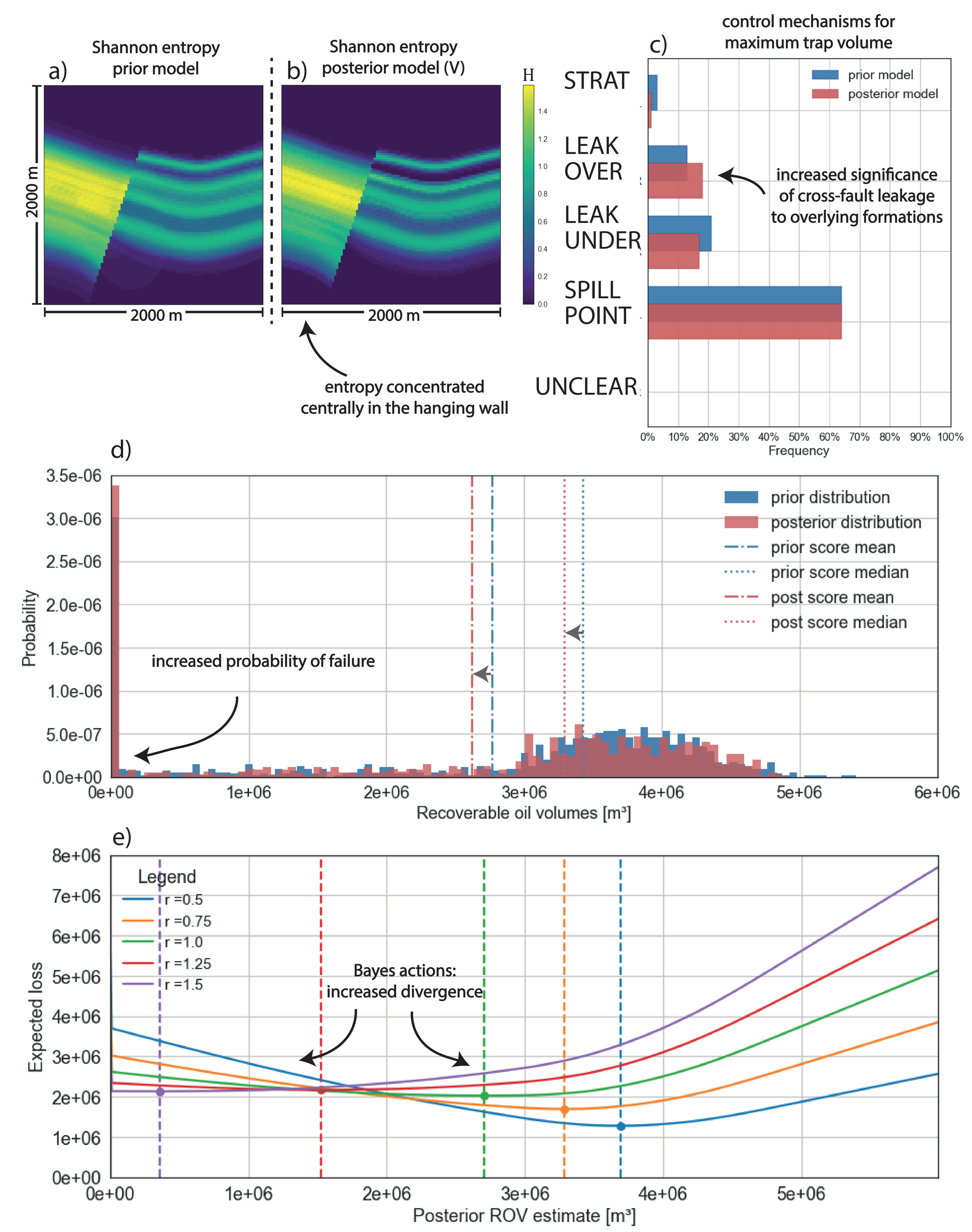

Figure 4: Evaluation of a model conditioned on a SSF likelihood which narrows around the critical SSF_c and thus amplifies the duality in the posterior ROV distribution (d). Shannon entropy is only slightly diminished (a,b). general cross-fault leakage remains a significant trap control mechanism (c). The resulting loss function realizations show a high divergence of differently risk-affine decisions.

3 - Results (continued)

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 actions 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 seal reliability, as it defines the probability of complete trap failure. Two examples are summarized in Figures 3 and 4.

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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6 - Further information

Geological models were created in a Python environment using GemPy (de la Varga et al., 2018) and integrated into a probabilistic framework via PyMC (Salvatier et al., 2016).

This research poster is based on a master thesis submitted to the Institute of Computational Geoscience and Reservoir Engineering (CGRE) at the RWTH Aachen University in 2017 (see Stamm (2017)).