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Joint Assimilation of Electromagnetic and Seismic Data - a Stochastic Approach

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Summary

The complementary nature of seismic and electromagnetic (EM) data asks for joint inversion of these data sets for reservoir characterisation and monitoring. EM data contain valuable information on the reservoir lithologies and have the ability to discriminate between hydrocarbon- and brine-filled rock. As the EM signal is diffusive, the resolution of the data is generally low, and is best combined with seismic data and appropriate prior models that help constrain the solution space.

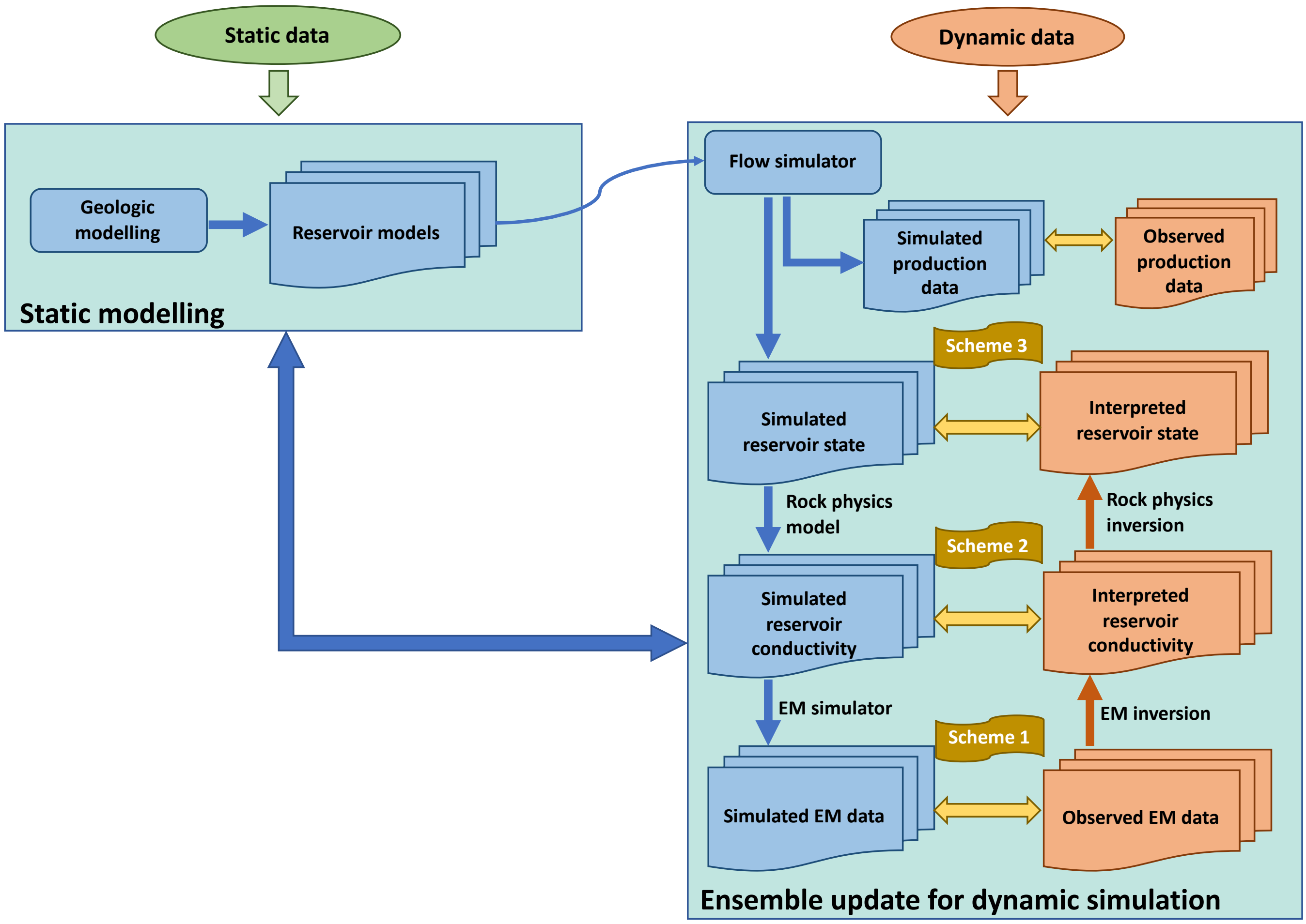
To account for uncertainties in the data in a statistically robust manner, we propose to make use of data assimilation techniques. This approach is especially attractive in monitoring applications where dynamic models provide a physically consistent prior estimate of the reservoir characteristics and its state evolution. After providing an overview of the possibilities for joint assimilation of EM and seismic data, a number of data-assimilation examples will illustrate the advantages and disadvantages of the various approaches.

Abstract

The complementary nature of seismic and electromagnetic (EM) data asks for joint inversion of these data sets for reservoir characterisation and monitoring. EM data contain valuable information on the reservoir lithologies and have the ability to discriminate between hydrocarbon- and brine-filled rock. As the EM signal is diffusive, the resolution of the data is generally low, and is best combined with seismic data and appropriate prior models that help constrain the solution space.
To account for uncertainties in the data in a statistically robust manner, we propose to make use of data assimilation techniques. This approach is especially attractive in monitoring applications where dynamic models provide a physically consistent prior estimate of the reservoir characteristics and its state evolution.
Data assimilation techniques are traditionally applied in meteorology and oceanography, where they combine prior probabilistic estimates with observations and their likelihood to obtain the most likely estimate of the state and parameters of the ocean or atmosphere. While variational data assimilation methods make use of the tangent-linear and adjoint models for a deterministic estimate of the optimal state, ensemble-based methods do so by making use of stochastic perturbations in a set of dynamic model representations to represent the probability distribution and error covariances of the prior estimate.
In subsurface applications, the most commonly used data-assimilation method, Ensemble Kalman Filtering, is an ensemble-based method that assumes Gaussian distributions for the prior uncertainties to represent the prior error covariance with an ensemble of model realisations. For more non-linear processes, sequential Monte Carlo methods such as particle filtering may be more appropriate as the full propagation of distributions in these methods allow for non-Gaussian distributions. With ever-increasing computing resources, sequential Monte Carlo methods are becoming more attractive. For the particular application of joint EM-seismic data assimilation, it is presently not clear whether the methods can best be used to directly incorporate electromagnetic and seismic data, or whether these data first need to inverted separately before they are assimilated. In this presentation, I will present the different possibilities for joint assimilation of seismic and electromagnetic data and highlight how ensemble-based data assimilation methods can combine all sources of information in a dynamically consistent manner.
As an example, Figure 1 illustrates three levels at which electromagnetic data can be assimilated into a dynamic reservoir model. While the first level compares the observed EM responses directly to their model equivalent, the second level assimilates the conductivity estimates derived from the EM data to the conductivity as estimated from the model variables. A third level requires inversion of the EM data to obtain the reservoir state (i.e., saturation) from the EM data, that can be directly compared to the model variables. The third level has the advantage that the inversion can take place outside of the assimilation procedure, which makes the method computationally more feasible, but this also implies that the prior information of the dynamic model is not being used to solve for the reservoir saturation in the EM data inversion.

After providing an overview of the possibilities for joint assimilation of EM and seismic data, a number of data-assimilation examples will illustrate the advantages and disadvantages of the various approaches.

Figure 1 *Ensemble-based data-assimilation workflow with different assimilation schemes of EM data. Three integration schemes of EM data are indicated with numbers 1, 2 and 3. Simulation and inversion steps (after dynamic reservoir simulation), partly shared between the different schemes, are indicated by the blue and red arrows, respectively. (Figure taken from Zhang, Hoteit and Vossepoel, submitted to SPE Journal, 2019)*



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