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Quantifying Efficiency Of Field-Wide Geophysical Surveys For Verifying CO2 Plume Conformance During Storage Operations

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Summary

To manage risks in CO2 storage operations, monitoring systems need to be designed such that the data can inform the operator whether the storage site will continue to behave as expected or not. In order to compare the benefits of different monitoring strategies, we require a measure of 'efficiency' that is based on a balance between monitoring cost on the one hand and reliability of conformance determination on the other. In this work, we present a workflow to quantify, in terms of conformance verification metrics, the contribution of monitoring strategies with various time-lapse geophysical survey configurations (i.e., different survey acquisition times and coverage) in the presence of geological uncertainties. We illustrate the use of the methodology with a simple case study where conformance is associated with regulatory safety bounds for the development of the CO2 plume. The proposed approach can be used to assist operators in the design of monitoring strategies that can ensure compliance with regulation requirements at a reasonable cost.

Introduction

The success of CO_2 storage projects will depend on the operator's capacity to manage operational risks against reasonable cost. Monitoring systems need to be designed such that the data can inform the operator whether the storage site will continue to behave as expected (and in compliance with regulation requirements) or not. In the latter case remediating measures have to be taken. In order to compare the benefits of different monitoring strategies, we require a measure of 'efficiency' that is based on a balance between data quality (cost) on the one hand and reliability of conformance determination (risk) on the other. Important factors influencing cost are data accuracy and coverage, while risk is also additionally affected by uncertainty in the properties of the storage system (e.g. geology) since this will determine the uncertainty in the future development of the CO_2 plume. Here we will present an approach to evaluate the reliability of site conformance verification for different geophysical acquisition configurations.

In this work we consider a notion of conformance associated with regulatory safety bounds for CO_2 storage operations. A virtual boundary is drawn to limit the area where it is safe for the injected CO_2 plume to develop during the storage life-cycle. The compliance with or violation of this virtual boundary determines conformance or non-conformance, respectively (Figure 1).

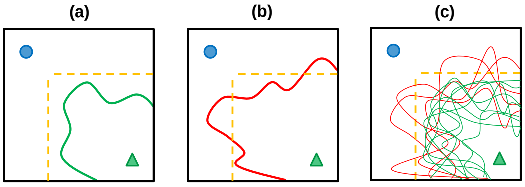

Figure 1 *Schematic illustration of CO_2 plume conformance in a case with a virtual boundary: (a) conformance, (b) non-conformance and (c) scenario-based conformance assessment. The green and red lines indicate the contour of the plume at the end of storage life-cycle in different geological scenarios; green lines correspond to positives (i.e., indication of conformance) and red lines to negatives (i.e., indication of non-conformance).*

Background

The evaluation of the efficiency of monitoring strategies must take place prior to the actual deployment of these strategies in order to be useful for design purposes. When performing an a-priori assessment of future measurements, there are two main categories of approaches: the first one quantifies the impact of future observations on the quality of model predictions[5,6], while the second one (which is not pursued here) incorporates an assessment of the contribution of future observations to the decision making process[1,3,5,8]. In both approaches, typically a Bayesian framework is used to assimilate the (uncertain) information from future simulated measurement scenarios. In the end, the goal is to derive a metric (or score) that quantifies the efficiency of the monitoring strategies, in terms of either the improvements in model predictions or in decision making.

Here we investigate the efficiency associated with the ability to track the position of the CO_2-water front (the extent of the plume) as derived from geophysical monitoring survey data. We estimate uncertain storage system properties from differences between observed and model-simulated front positions[7,10]. In this study, the observed time-lapse front positions are set as known contours without doing the actual synthetic or real geophysical survey acquisition. Uncertainties and limitations of the front positions associated to the geophysical survey properties such as acquisition, resolution and noise are as such not yet taken into account. A future study will include actual geophysical data. Partial (non-perfect) information about the front position would be available if only surveys with limited coverage are conducted. We therefore assess the impact of data coverage on the reliability of conformance determination.

Methodology

The notion of conformance adopted here requires the validation of the expected response (i.e., model predictions) of the storage site against its actual behavior. Monitoring surveys and other measurements constitute means of obtaining partial evidence of the actual behavior of the system after the beginning of CO_2 injection. Because both the monitoring surveys and conformance of interest take place in the future, our a-priori analysis is subject to uncertainty and has to rely on simulated scenarios. Multiple plausible truth scenarios are considered to characterize the inherent geological uncertainty associated with the storage site. We consider these plausible truth scenarios one by one to represent the "actual" behavior. In this way, we can (1) generate a possible (synthetic) realization of the future observations and (2) predict the "actual" conformance (or non-conformance) behavior (illustrated in Figure 1). The model predictions to be verified against the "actual" behavior are also subject to uncertainty, and therefore they are obtained by simulating an ensemble of model realizations. Assimilation of the front positions as derived from synthetic time-lapse survey data is expected to constrain these model realizations closer to the corresponding plausible truth. Therefore, if the plausible truth shows conformance (i.e., plume within the box), the number of realizations showing non-conformance (i.e., plume outside the box) tends to be smaller in the posterior than in the prior ensemble. Ideally, in such a scenario, the number of non-conformant model realizations in the ensembles should be reduced to zero. But, in practice, because of the uncertainties involved, there may be realizations behaving as false negatives (i.e., indicating non-conformance when the plausible truth exhibits conformance) and false positives (i.e., indicating conformance when there is none) using the hypothesis testing terms introduced in Figure 1. Thus, we can calculate the gain in conformance verification quality by comparing the quality of posterior model predictions with respect to predictions prior the assimilation of survey data. By repeating this analysis for all (N = 100) plausible truth scenarios, we are able to assess the contribution of a monitoring strategy given the inherent geological uncertainty. Figure 2 depicts the workflow explained above.

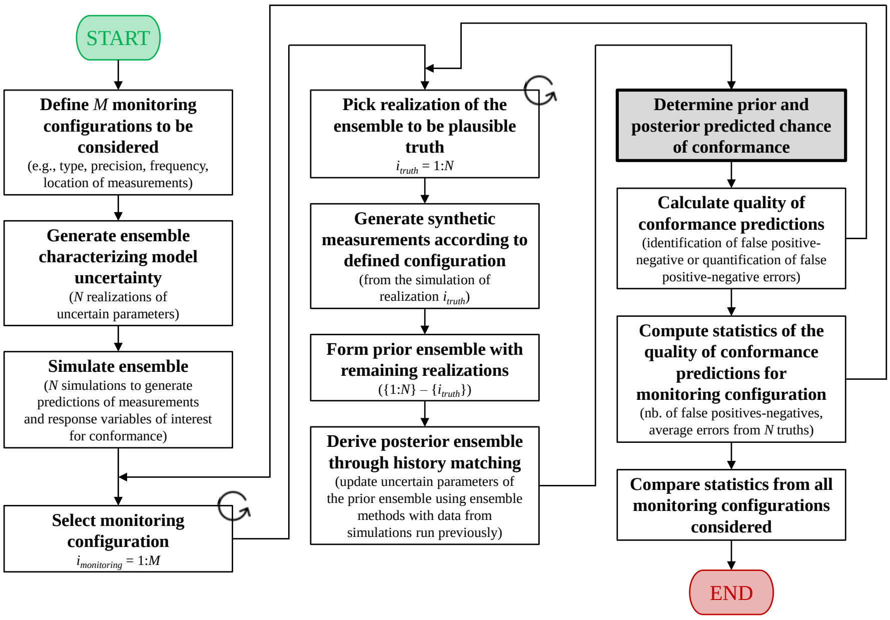

Figure 2 *Workflow for quantification of conformance verification efficiency of different monitoring configurations.*

Examples

We consider a 2D reservoir example with uncertainty in spatial permeability and porosity distributions characterized by an ensemble of N = 100 model realizations (Figure 3). The heterogeneities in the permeability and porosity fields have a direct impact on the propagation of the CO_2 plume. The conformance quantity of interest is the position of the plume after T = 1,800 days of injection (Figure 3). The ES-MDA[4] history matching method is used to incorporate the information from the plume tracking measurements (e.g., time-lapse surveys) into the models and improve their predictions. The survey observation is assumed to have a measurement precision of σ_{survey} = 0.5 (grid-block units) in the identification of the front position. The reservoir is initially at p_{res} = 83 bar and fully saturated with water. CO_2 is injected at $q_{\text{inj}} = 1.0\times10^5$ m³/day with a maximum injection pressure of $p_{\max}$ = 200 bar. A discharge well operated at p_{dis} = 80 bar starts producing water after t_{dis} = 360 days to relieve the pressure in the reservoir. The reservoir simulations are performed with OPM Flow[9] under the assumption that CO_2 is immiscible in water. The model predictions are then used to determine the probability of conformance (non-conformance) by identifying the fraction of model realizations for which the CO_2 plume remains inside (extends outside) of the virtual boundary (Figure 3, yellow box).

Impact of acquisition time

We quantify the efficiency of M = 5 monitoring strategies consisting of a single survey. The candidate survey acquisition times considered are t_{survey} = {300, 600, …, 1,500} days. Figure 4 shows the results obtained in terms of the fraction of false positives and negatives before and after assimilating the surveys from different times. Later surveys are more effective in reducing the number of wrong predictions. This is an expected result given the fact that the later the surveys are acquired the closer they are to the time of interest for conformance verification purposes (T = 1,800 days). From a decision-making point of view, later surveys imply less flexibility available for the operators to react to the new information. Therefore, depending on the type of actions being considered and on the impact of prediction reliability on the decision making process, earlier surveys may be more valuable.

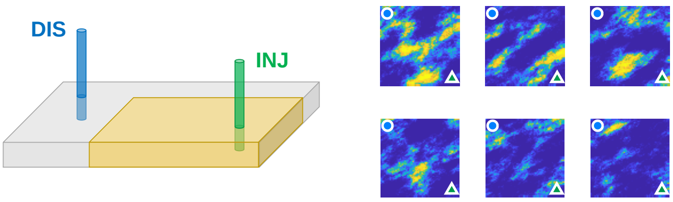

Figure 3 *Synthetic test case study with one CO_2 injection well and one brine discharge well (left). The yellow box indicates the region within the virtual conformance boundary. 6 randomly selected realizations of the permeability field (right).*

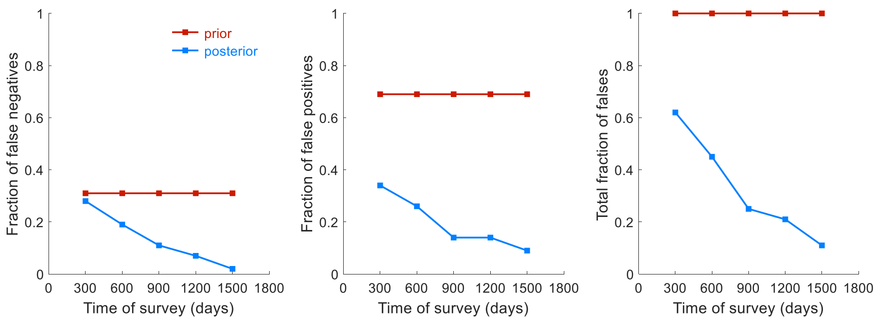

Figure 4 *Fraction of erroneous conformance predictions for different survey times, without (prior) and with (posterior) information from the survey: false negative (left), false positive (middle) and both (right).*

Impact of spatial coverage

Next, we quantify the efficiency of M = 4 monitoring strategies consisting of a single survey acquired at t_{survey} = 1,500 days. The survey designs considered have different spatial coverages (Figure 5), ranging from full reservoir coverage to sparse two-dimensional lines.

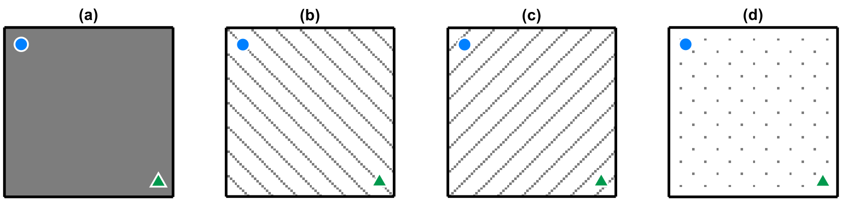

Figure 5 *The four survey configurations with different reservoir coverages. The grey pixels indicate the locations (grid blocks) in the reservoir where the CO_2 plume can be tracked. The positions of the CO_2 injection and brine production wells are indicated by the green triangle and blue circle, respectively.*

Figure 6 compares the 4 configurations in terms of false positives and negatives (like in Figure 4). The very low number of false negatives indicates that, with the acquisition of the full coverage survey (a), our models will be very reliable when predicting scenarios where conformance takes place. On the other hand, even with the acquisition of a very informative survey reporting conformance at t_{survey} = 1,500 days, the updated models are not able to rule out the risk of non-conformance at T = 1,800 days entirely. Due to the nature of the physical processes involved, tracking the CO_2 plume provides more information about the areas of reservoir situated behind the propagation front than the areas ahead of it. The configurations with partial coverage of the reservoir are not able to reduce the conformance prediction errors as much as the survey with full coverage. Despite having the same degree of sparsity, configuration (c) results in lower errors than configuration (b) in terms of false negatives, indicating a better orientation of the two-dimensional lines. The sparsest configuration (d) is not as effective as the others but is still useful (better than prior).

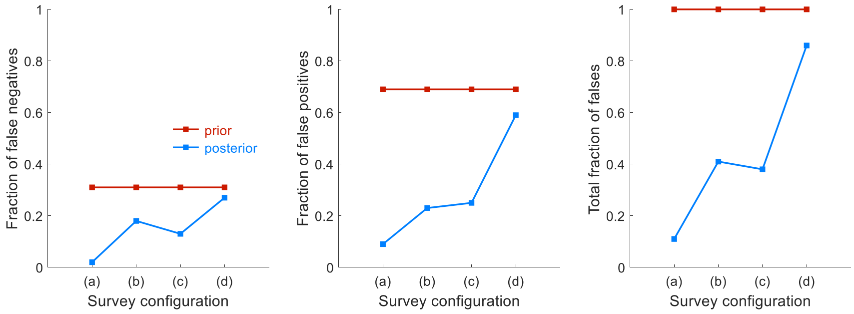

Figure 6 *Fraction of erroneous conformance predictions for different survey times, without (prior) and with (posterior) information from the survey: false negative (left), false positive (middle) and both (right). All surveys are acquired at* t_{survey} *= 1,500 days.*

Conclusions

We developed a methodology to quantify, in terms of conformance verification, the contribution of monitoring strategies with various time-lapse survey configurations in the presence of geological uncertainties. The proposed approach can be used to assist operators in the design of monitoring strategies that can ensure compliance with regulation requirements at a reasonable cost. We illustrated the approach with an example where time-lapse surveys may be acquired in different configurations. The effect of actual time-lapse geophysical imaging in terms of acquisition, resolution and noise needs additional investigation. This work is a first step towards the development of a workflow where surface acquisition configurations of geophysical surveys and more realistic geophysical modeling can be included.

Acknowledgements

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