MULTISCALE RESERVOIR MODELING FOR CO_2 STORAGE AND ENHANCED OIL RECOVERY USING MULTIPLE POINT STATISTICS

Extended Abstract

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Introduction

New applications are being developed in the field of reservoir modeling to answer questions about CO_2 storage and CO_2 enhanced oil recovery (EOR). The Energy & Environmental Research Center (EERC) and Plains CO_2 Reduction Partnership Program, in collaboration with the U.S. Department of Energy, have been constructing 3-D geocellular models for the purposes of studying CO_2 storage and change mitigation and greenhouse gas reduction.

Targets for potential geologic storage of CO_2 may consist of a variety of reservoir types, comprising heterogeneous lithologies from numerous depositional environments. Each depositional environment contains its own reservoir and nonreservoir rock based on 1) the presence of economically viable petrophysical properties (porosity and permeability), 2) the existence of temperature and pressure conditions effective in keeping injected CO_2 in the supercritical phase, and 3) the presence of a competent cap rock or seal to limit vertical mobility of sequestered CO_2. An understanding of reservoir hydrodynamics (where injected fluids may migrate or accumulate) is necessary to accurately model and monitor CO_2 injection. An additional consideration for realistic scenarios is the proximity to CO_2 sources for economic viability of CO_2 storage.

The characterization and assessment of geologic targets for potential CO_2 storage is achieved through the construction and simulation of a reservoir model. The geologic modeling workflow includes 1) data acquisition, 2) structural modeling, 3) data upscaling and property modeling utilizing advanced geostatistical methods, 4) uncertainty analysis and history matching, and 5) predictive simulations of CO_2 injection, pressure response, and fluid saturation and migration.

There are several geostatistical approaches to assist in reducing uncertainty with various data sets. If the depositional environment is well understood, an optimized facies model can be constructed by using a unique method called multiple-point statistics (MPS). Unlike Gaussian and object-based algorithms, MPS uses a training image instead of a variogram to determine facies associations between control points in the 3-D grid (Strebelle and Journel, 2002; Caers and Zhang, 2004). The training image is an idealized reservoir volume, providing stratigraphic principles such as facies proportions, facies stacking, and lateral facies associations. The ability to apply geologic understanding of a depositional model to estimate conditions in unsampled locations is a strength not available in variogram-based methods and may result in more realistic results (an example being the knowledge that fluvial facies are likely to exhibit high connectivity rather than a widely scattered distribution of fluvial facies; see **Figure 1**). Variogram-based statistical methods are perhaps better suited for the distribution of petrophysical properties within each facies, needing only to apply a general understanding of anisotropic trends.

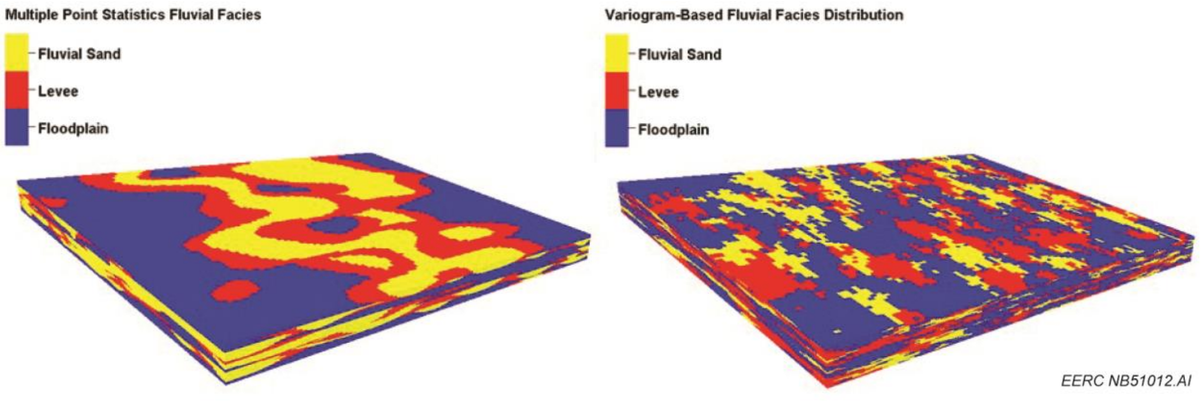

Figure 1. *Comparison of fluvial facies distributions using the multiple-point statistical method (left) and the more conventional variogram-based indicator simulation (right).*

Facies Modeling Workflow Using MPS

The MPS method has a particular usefulness in the facies modeling process, producing model realizations which may be used to constrain other variogram-based geostatistical property distributions (such as porosity and permeability). Well log and core data may be utilized to develop depositional/diagenetic facies characteristics in known locations (control points) and interpreted pattern of distribution (training image).

Control points are actual or synthetic wells which penetrate the 3-D model and represent the known reservoir conditions at a particular location and depth. Vertical facies associations can be inferred from well log analysis to develop a facies log, which can be used in the initial guidance of a multiple-point statistical facies distribution.

A training image is a 3-D template containing geostatistical information in a digital format which software processes for measurement and calculation spatial probabilities. Creation of an accurate training image requires knowledge and confidence in the reservoir geologic characterization and may be assisted by applying known relationships measured from historical geologic cross-sectional interpretations, maps, photographs, or modern analogs (for instance, characterizing a fluvial system in a training image may be assisted by measuring a modern fluvial system for channel width, depth, sinuosity, migration, etc.). A proper training image is created at a resolution (cell size) similar to that of the reservoir model itself and contains the present geologic constituents, the relationship of the constituents in space (both laterally and vertically), and proportions of the geologic constituents. Care should be taken to keep the training image as simple as possible (small cell count, small number of constituents). There may be a tendency to create a very complex training image, but the multiple-point distribution can be computationally intensive. Increased complexity may mean much longer computational duration.

The actual facies distribution process is well discussed by Caers and Zhang (2004) and is achieved by 1) specification of a seed value (starting point within the 3-D grid) and definition of a random path, 2) searching for the nearest control points or previously simulated cells, 3) construction of a probability model based upon proximal control points and the relationships measured from the training image, 4) assignment of the most probable value to the unknown cell, and 5) moving to the next unknown cell, following the predefined random path, to repeat the process until all cells have been visited.

Additional information may be supplied to guide the MPS distribution in the form of soft data (probabilities, seismic data), but it should be noted that even with a valid training image, the results will likely not be geologically sound without accurate control points to guide the distribution. Without using control points, the resulting facies distribution will be statistically viable in comparison with the training image, but it is unlikely that you will achieve a realistic result.

Training Image Characterization and MPS Applications

There is a large amount of freedom in the application of the MPS method. The method excels in the capturing and replication of very complex facies associations, with the only requirements being accurate control points and training images. For clastic modeling, it is possible to create training images and resulting MPS facies distributions representing fluvial systems (simple, braided, anastomosing, etc.), deltaic progradation, barrier bar and bay-mouth bar complexes, eolian deposits, turbidites, and others. In the modeling of carbonate reservoirs, there is the capability of employing the MPS method to characterize reefs (pinnacle, barrier, patch, atoll; see pinnacle reef training image example and resulting distribution in **Figure 2**), mounds, karsting, or carbonate shallow shelf deposits.

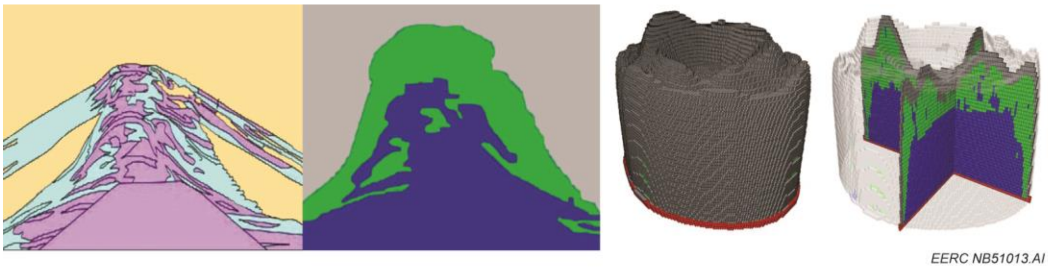

Figure 2. *Pinnacle reef facies model development; from left to right:1) illustration of interpreted pinnacle reef facies associations, 2) pinnacle reef training image developed from interpreted facies associations, 3) resulting pinnacle reef facies distribution, and 4) facies property cross sections illustrating the pinnacle reef's internal structure.*

CASE STUDIES

The EERC has developed several facies models using MPS methods representing various depositional environments with varying degrees of input data, reservoir complexity, and resulting model uncertainty. Relatively small models (2–30 km in diameter) of pinnacle reefs, multiple reef complexes, and carbonate mound accumulations have been developed to assess CO_2 storage resource in recent research efforts at the EERC. Similarly, oil field-scale to basin-scale clastic and carbonate models have also been constructed using the MPS facies distribution workflow.

It has become clear through the development of these differing models that the approach and workflow in facies modeling is quite variable and dependent upon the scale and the amount of available data. There are certain cases with very high uncertainty (see **Figure 3**; lowest tier in pyramid), having very few available data or large expanses of unsampled areas between data points. These cases may require the insertion of artificial wells within the model to control facies distribution, and most rely heavily on the geologic interpretations of modern analogues in training image construction. There are other cases with lower uncertainty (uppermost tier in **Figure 3** below**)**, having many sampled locations, little distance between sampled locations, interpretations and data available in literature, available seismic data, etc., which have many control points and an informed understanding of the spatial relations and proportions of facies with which to construct a more specific training image for MPS facies modeling.

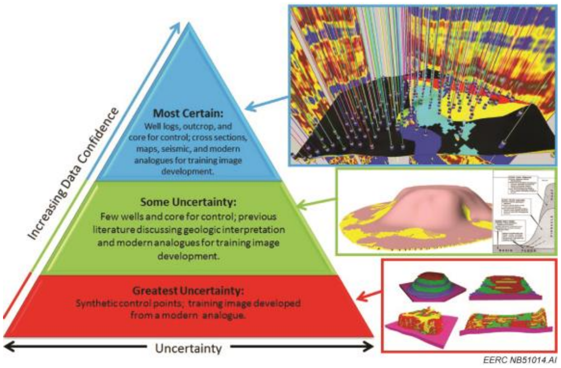

Figure 3. *Illustration of uncertainty in facies modeling stemming from data availability with EERC model examples (from bottom to top: Leduc pinnacle reef, Winnipegosis pinnacle reef, Cretaceous sandstone reservoir).*

In some complex reservoirs, there may not be a "one size fits all" training image and MPS facies distribution. For example, an interpreted marginal marine-deposited sequence consisting of multiple mythologies appearing to have influences of deltaic progradation, fluvial channel incision barrier bar and lagoon deposition, longshore drift processes, and tidal channel incision, was broken into multiple geobody regions with each region having a unique training image and facies distribution (see **Figure 4**).

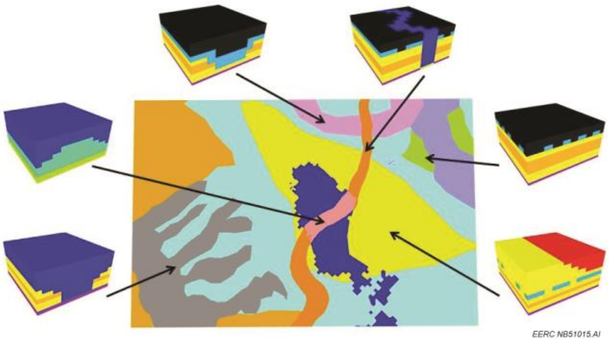

Figure 4. *Example of a reservoir model divided into multiple geobody regions, each having a unique training image and resulting MPS facies distribution.*

Conclusions

MSP is a tool incorporated within high-performance reservoir modeling software capable of 3-D geocellular model construction, such as Schlumberger's Petrel software, and is proving effective in estimating reservoir facies in unsampled locations. The MPS method allows the user to incorporate a preexisting knowledge of the spatial relations and proportions of geologic constituents in the creation of a more realistic facies model. The more conventional variogram-based statistical methods do not allow the user to apply such knowledge of reservoir facies and may produce questionable results in some scenarios. Variogram-based statistical methods are better suited for the distribution of petrophysical properties within each facies, needing only to apply a general understanding of porosity and permeability anisotropic trends.

The requirements in utilizing the MPS method include a training image and control points to be used as "hard data" in guiding the distribution. The training image may be constructed from multiple data sources, but it must depict an accurate relation in both lateral and vertical facies and contain similar proportions of the constituents. A good training image will satisfy these requirements while also being simple enough to avoid unnecessary computational expense. The MPS method may be used to more accurately capture and model reservoir heterogeneity in different lithologies, scales, and with varying degrees of uncertainty, resulting in more accurate prediction when taken into simulation, whether for CO_2 storage or resource exploitation.

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