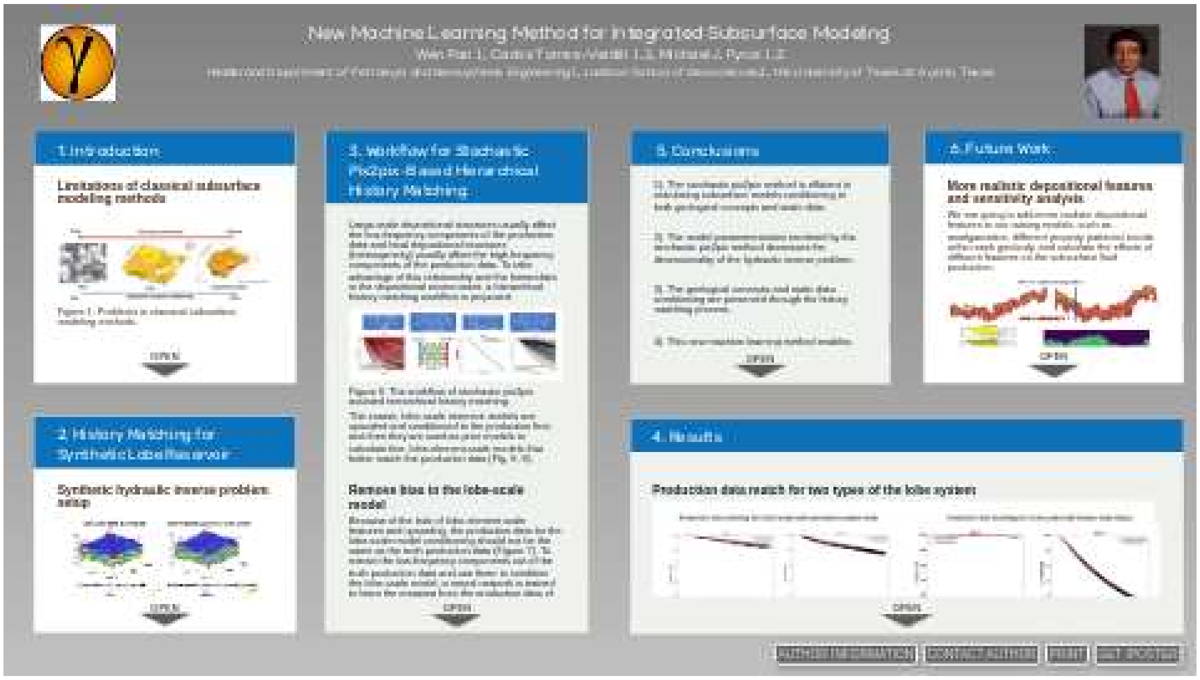
New Machine Learning Method for Integrated Subsurface Modeling



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PRESENTED AT:

1. INTRODUCTION

Limitations of classical subsurface modeling methods

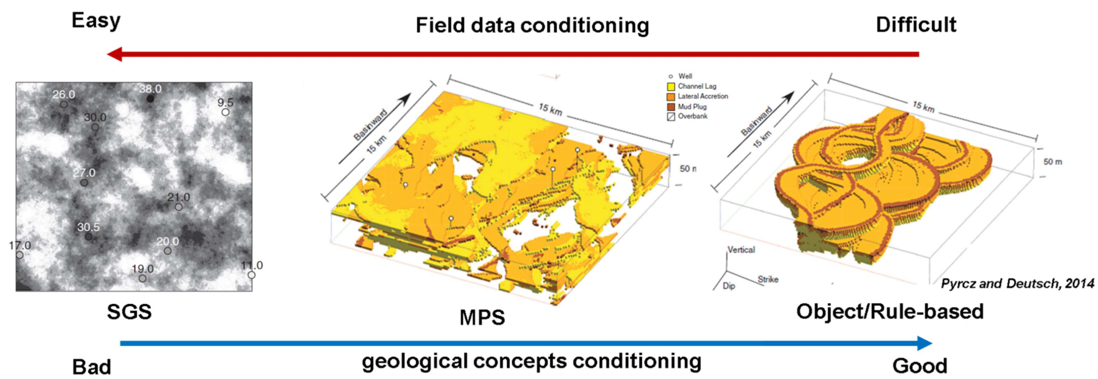


Figure 1. Problems in classical subsurface modeling methods.

Subsurface models should match all the static and dynamic field data as well as geological settings, to be able to help optimize the production from a hydraulic or hydrocarbon reservoir. However, It is difficult for classical subsurface modeling methods to satisfy both static data constraints (well log, seismic) and geological concepts (patterns) constraints (Fig. 1). Although recent object/rule-based reservoir modeling methods successfully reproduce the depositional patterns, the hierarchies of the depositional patterns, the model parameterization, and static data conditioning are still unsolved problems.

Stochastic pix2pix for better subsurface modeling

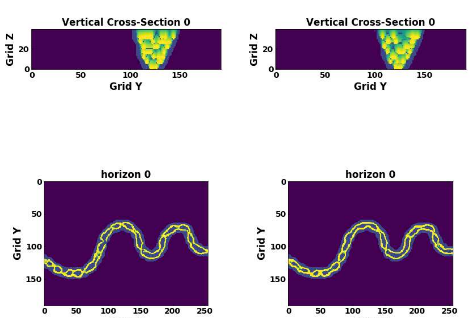


Figure 2. Turbidite channel models calculated with stochastic pix2pix.

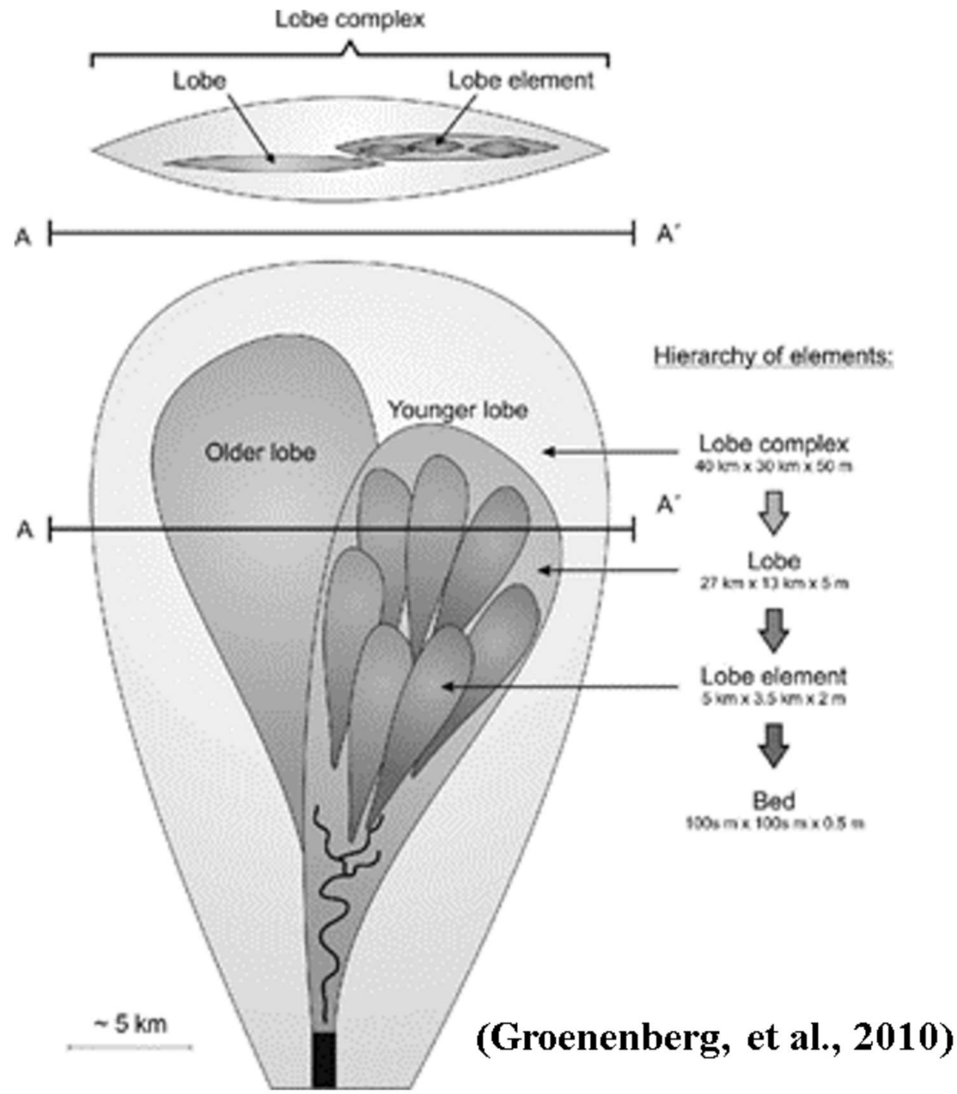
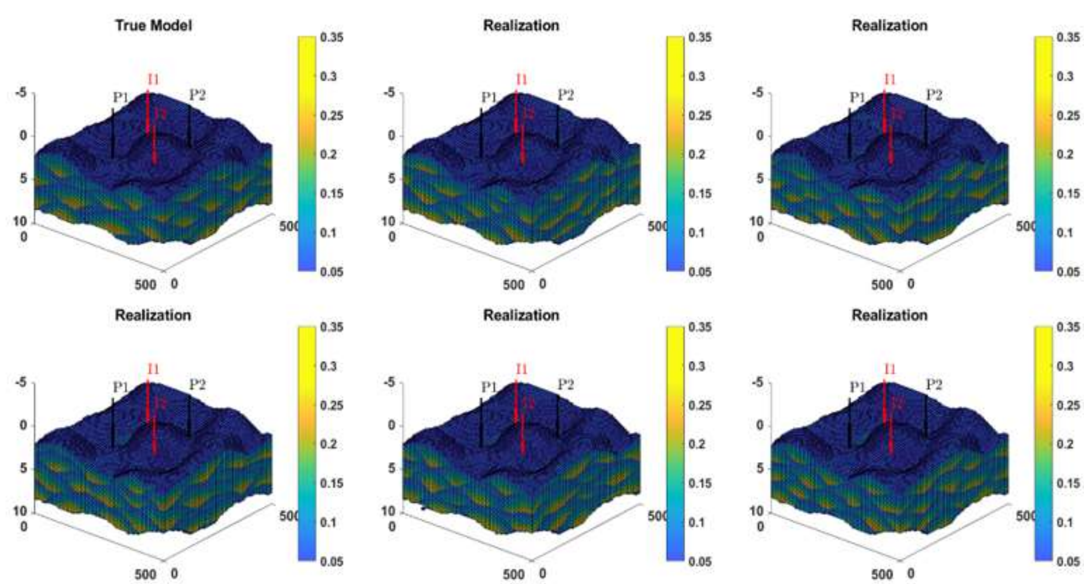


Figure 3. Hierarchies in a lobe system.



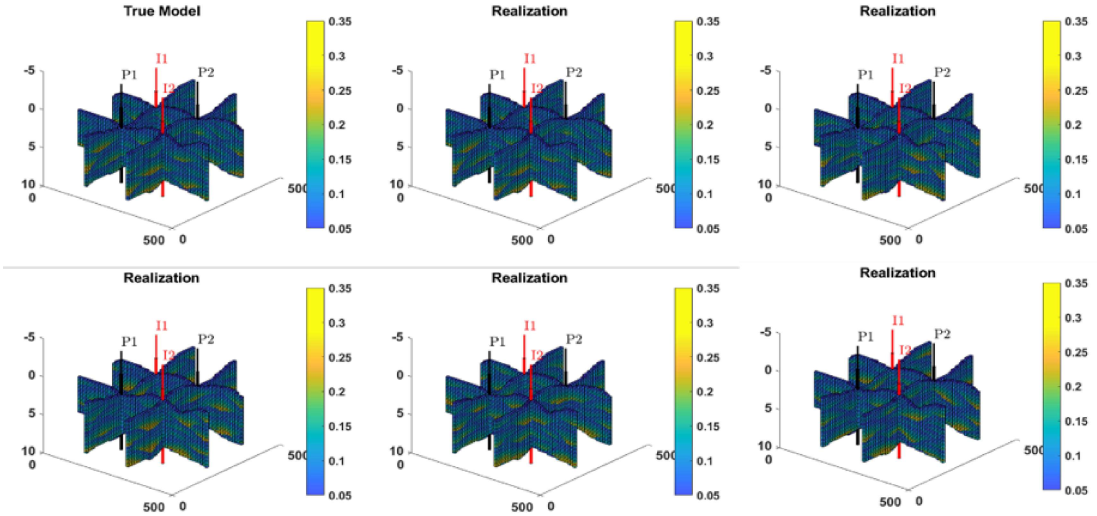


Figure 4. Stochastic reservoir models with good static data and geological concept conditioning calculated with the stochastic pix2pix for a lobe system.

The stochastic pix2pix method proposed by Pan et al.(2020). This new machine learning method learns depositional patterns and data conditioning from training images calculated based rule-based models to calculate new subsurface model realizations. It successfully calculates subsurface models with good reproduction of the depositional patterns and hierarchies and good static data conditioning (Fig. 2,3,4). It also maps the conditional models to a small Gaussian latent space, rendering a good model parameterization.

A synthetic case study is used to demonstrate the advantages and the workflow of using the stochastic pix2pix method for solving hydraulic inverse problems

2. HISTORY MATCHING FOR SYNTHETIC LOBE RESERVOIR

Synthetic hydraulic inverse problem setup

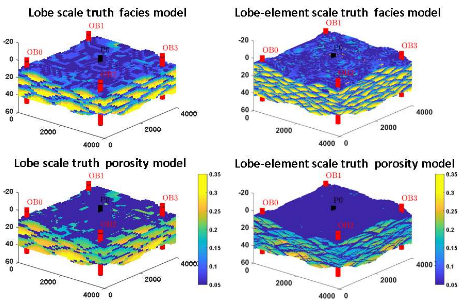


Figure 5. Truth facies and porosity model at lobe scale and lobe-element scale.

1). A lobe reservoir with 4 observation wells(OB) and one production well(P0), the production well is producing at a constant 300 psi bottom hole pressure (BHP), and the initial pressure of the reservoir is 1000 psi (Fig. 5).

2). The BHPs of the four observation wells are used to calculate the facies and property distribution of the reservoir.

3). Unknown parameters: lobe and lobe-element distribution (latent variables in the stochastic pix2pix), porosity/ permeability multipliers of each lobe, and lobe element.

4). The depositional patterns and static data conditioning should not be distorted during solving the hydraulic inverse problem.

3. WORKFLOW FOR STOCHASTIC PIX2PIX-BASED HIERARCHICAL HISTORY MATCHING

Large-scale depositional structures usually affect the low-frequency components of the production data and local depositional structures (heterogeneity) usually affect the high-frequency components of the production data. To take advantage of this relationship and the hierarchies in the depositional environment, a hierarchical history matching workflow is proposed.

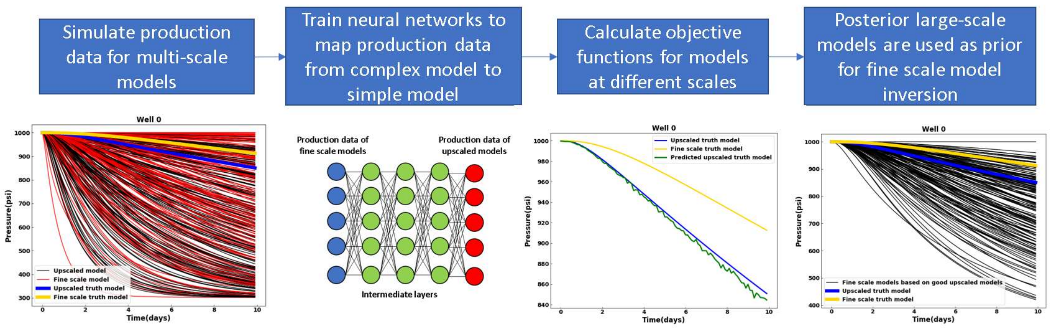


Figure 6. The workflow of stochastic pix2pix assisted hierarchical history matching.

The coarse, lobe-scale reservoir models are upscaled and conditioned to the production first, and then they are used as prior models to calculate fine, lobe-element-scale models that better match the production data (FIg. 6, 9).

Remove bias in the lobe-scale model

Because of the lack of lobe-element scale features and upscaling, the production data for the lobe-scale model conditioning should not be the same as the truth production data (Figure 7). To extract the low-frequency components out of the truth production data and use them to condition the lobe-scale model, a neural network is trained to learn the mapping from the production data of unconditional lobe-element-scale models to their corresponding lobe-scale models (Figure 8).

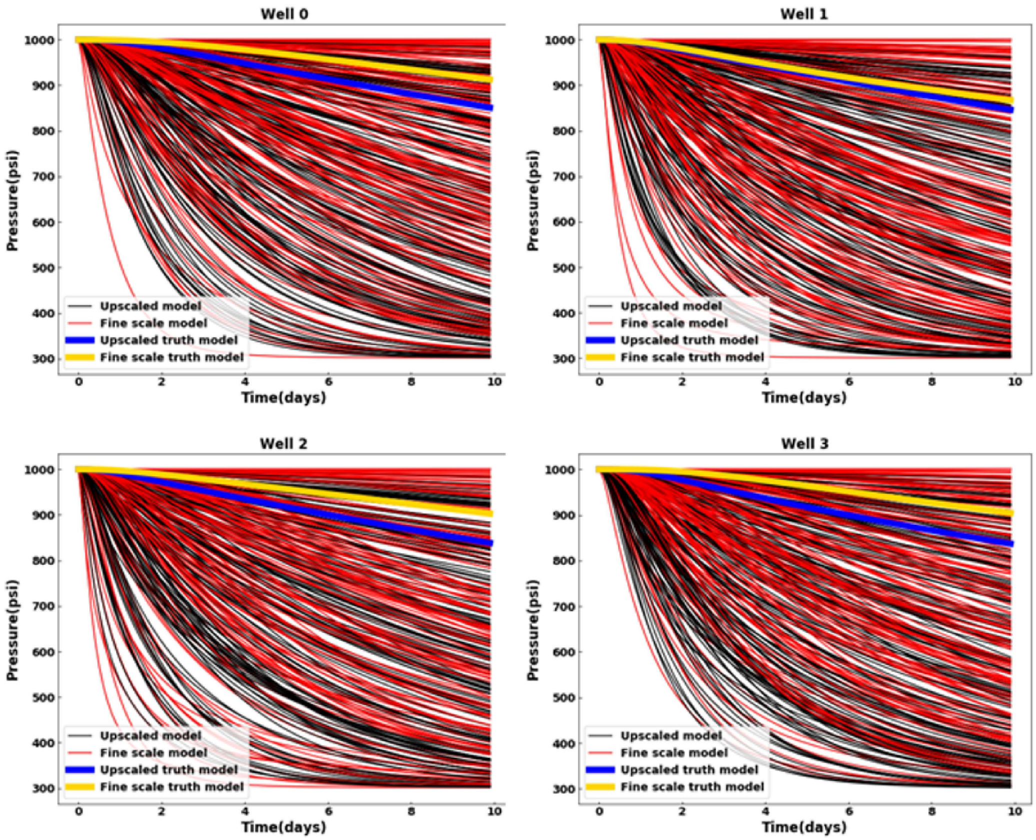


Figure 7. Different production data from lobe-element-scale models and their corresponding lobe-scale models.

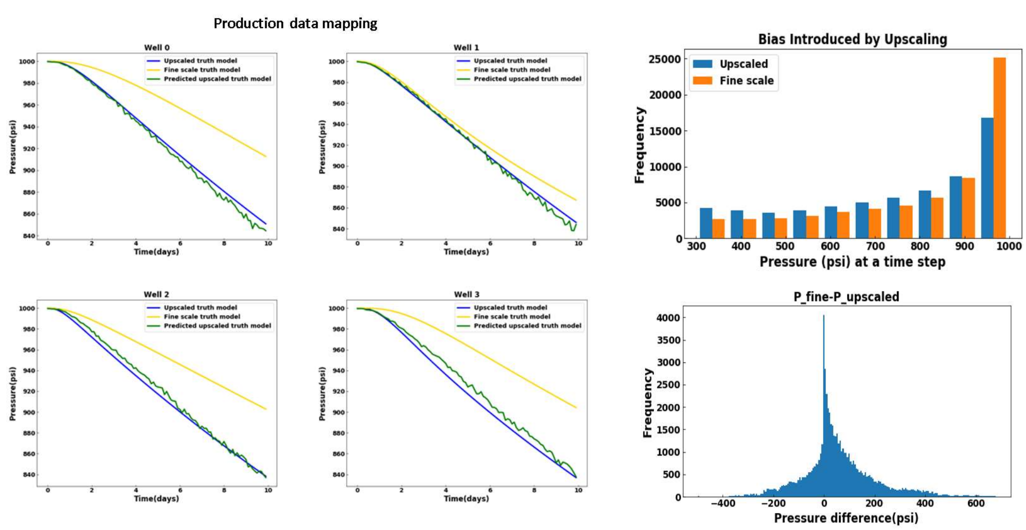


Figure 8. The mapping of production data learned by the NN.

Conditional lobe-scale models are used as prior models for lobe-element-scale model history matching

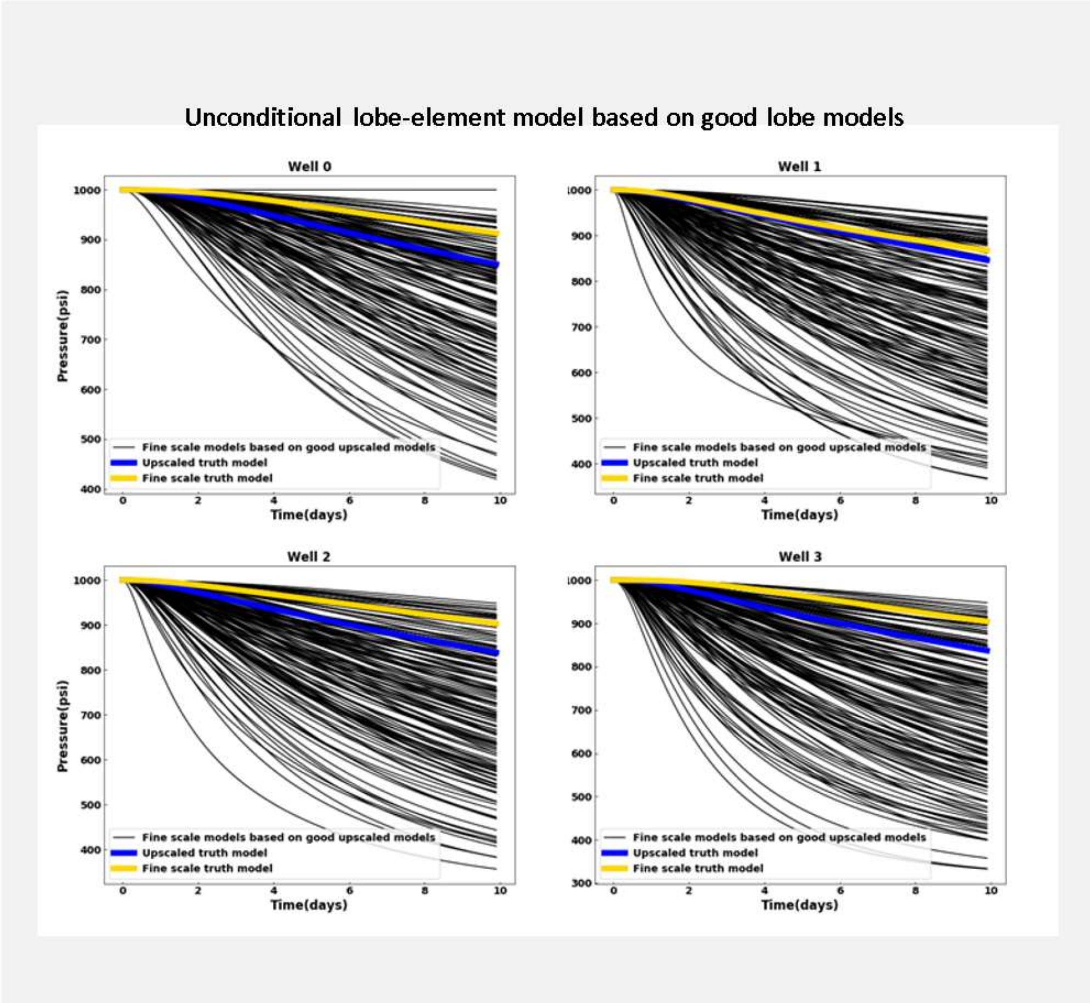


Figure 9. Conditional lobe-scale models are used as prior models for lobe-element-scale model history matching.

4. RESULTS

Production data match for two types of the lobe system

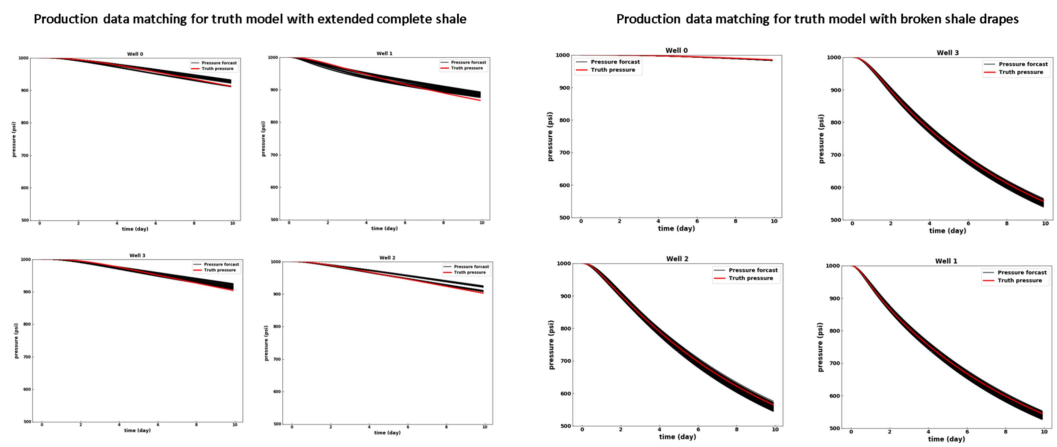


Figure 10. BHP data match at four observation wells.

Based on 5-day BHP data of 4 observation wells, the pressure forecast based on the posterior models are satisfactory.

Posterior reservoir porosity models

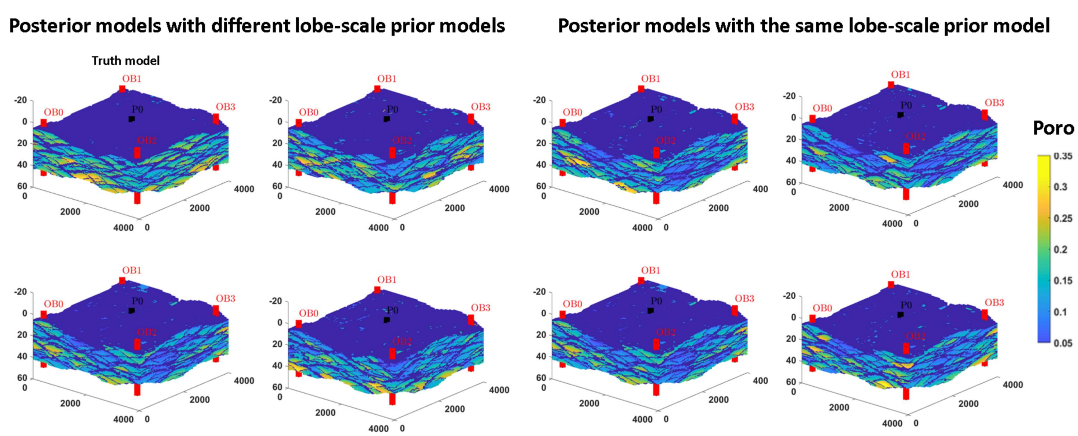


Figure 11. Posterior lobe-element-scale models conditional to static, dynamic data as well as geological concepts.

The depositional patterns, hierarchies and static data conditioning are preserved during history matching.

5. CONCLUSIONS

1). The stochastic pix2pix method is efficient in calculating subsurface models conditioning to both geological concepts and static data.

2). The model parameterization rendered by the stochastic pix2pix method decreases the dimensionality of the hydraulic inverse problem.

3). The geological concepts and static data conditioning are preserved through the history matching process.

4). This new machine learning method enables efficient, geologically hierarchical history matching, making reservoir models more realistic.

5). An efficient workflow about hierarchical modeling and hierarchical history matching is provided for integrated subsurface modeling.

6. FUTURE WORK

More realistic depositional features and sensitivity analysis

We are going to add more realistic depositional features to our taining models, such as amalgamation, different property patterns/ trends within each geobody, and calculate the effects of different features on the subsurface fluid production.

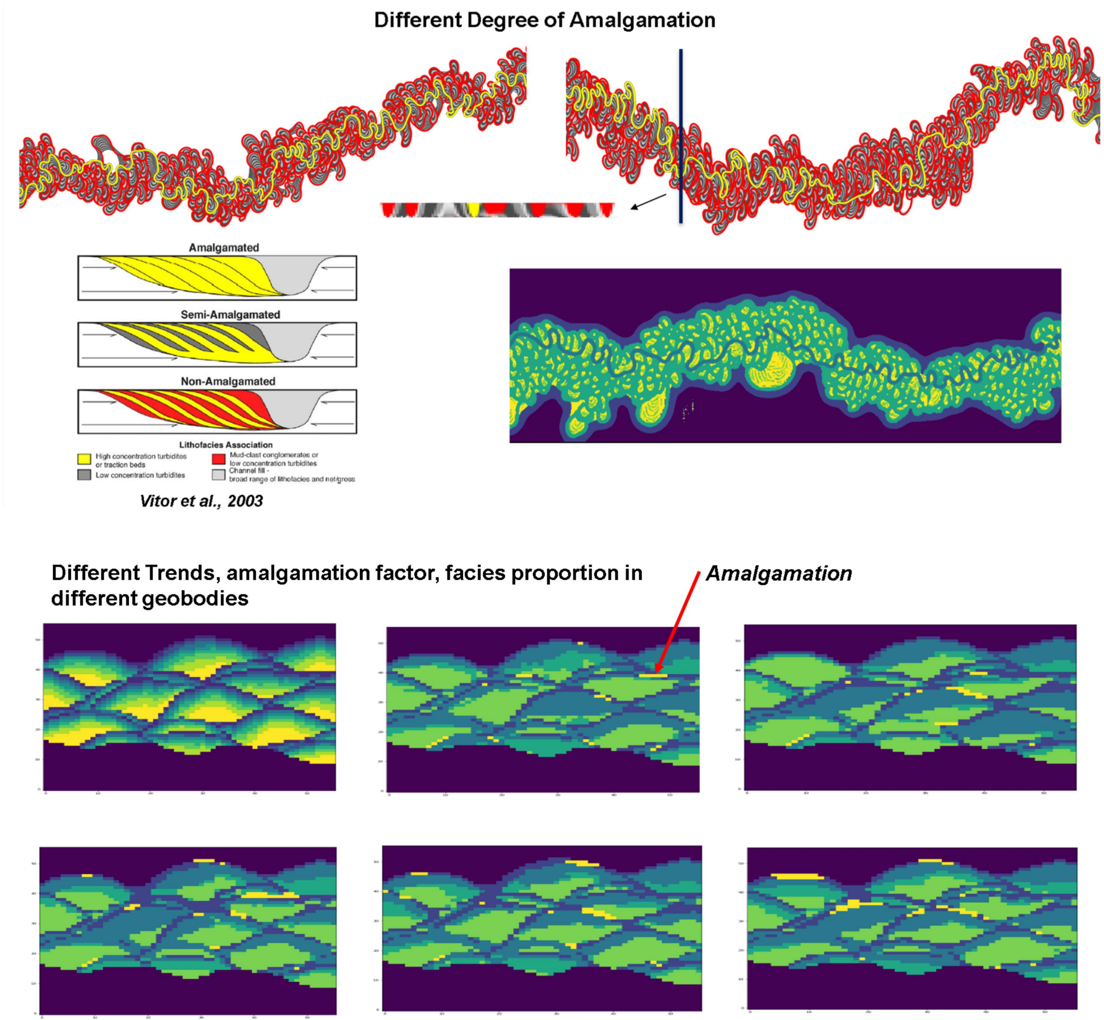


Figure 12. Adding amalgamation to the training models and adding more heterogeneity by calculating different property trends within different geobodies.

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