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Full Length Article

Integrate inter–well connectivity data with static reservoir models based on Bayesian formalism

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ABSTRACT

The inter-well connectivity calculated from reservoir dynamic production data reflects formation heterogeneity quantitatively. Currently, the calculated inter-well connectivity between pair wells is mainly used as a tool for water flood management but not for quantitative reservoir characterization. This study proposes an innovative, dynamic data integration workflow that can integrate inter-well connectivity with a static reservoir model. In the workflow, the first step is calculating the inter-well connectivity vectors from the reservoir pairwise injector and producer wells. The second step covers interpolation in the domain of interest. The third step is to update the permeability model based on the Bayesian updating method. The result of this study shows that integrating the calculated inter-well connectivity with the static models enhances model reliability and it also provides an insight to deeper geological understanding reflected from dynamic data integration in reservoir modeling.

1. Introduction

For reservoir modeling, the static data usually include core analysis results, well logs interpretations, and seismic interpretation. There are also some dynamic data, such as wellhead pressure (WHP) or bottom-hole pressure (BHP), tracer data, fluid level, and fluid production observed data available when doing reservoir modeling, especially for a mature reservoir. Fully integrating dynamic data with static data can enhance the quality of the reservoir models generated and reduce the uncertainties of simulated flow production scenarios. It requires exploring, modeling, and analyzing their discipline-specific data to understand the underground reservoir better (Pyrcz and Deutsch, 2002). The maximum value of these data is only realized when integrated to create a more detailed reservoir model. Only the obtained reservoir can provide the reservoir engineers with a better basis for reservoir simulation and management and allows a more realistic economic evaluation (Cunningham and Begg, 2008; Bratvold et al., 2009).

The current reservoir modeling procedure has many best practices to integrate various static data (Kelkar, 2000; Azim, 2016; Rahimi and Riahi, 2020; Yousefi et al., 2021). Most of them can integrate various sources for data, such as core, open-hole logs, wireline formation tester pretests, vertical interference tests, production logs, and downhole pressure buildup and injection falloff tests are all integrated to infer different scale heterogeneity (Queipo et al., 2002; Ma et al., 2013; Soroush et al., 2014). However, integrating the dynamic data with a static reservoir model is still a challenge in petroleum reservoir modeling.

Integrating dynamic data into the reservoir model is usually solved as an inverse problem. The geological reservoir-related parameters are determined by minimizing an objective function between the observed and calculated dynamic data. Some other efforts also include generating subsurface fracture into the static model. Iterative loops have been used between the static reservoir model and dynamic well–test data to optimize the subsurface fracture generation (Kashib and Srinivasan, 2003, 2006; Zhao et al., 2016).

For various dynamic data, the production and injection rates are the most abundant data available in reservoir development. Injection and production rate data are easily accessible, and using them does not incur the costs of running field tests. Due to the reservoir geology complexity and heterogeneity, quantitative calculation of Inter-well connectivity can be challenging. Various quantitative methods have been proposed to calculate the inter-well

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connectivity, such as Spearman rank correlation (Alizadeh and Salek, 2021), a linear model with coefficients (Yousefi et al., 2021), etc.

Among them, the most widely used inter-well connectivity calculation method is called Capacitance-Resistance Model (CRM) (Sayarpour et al., 2009b; Yousef et al., 2009; Dastgerdi et al., 2020). It integrates flow rate and BHP in a nonlinear signal-processing model to provide a more robust interpretation result of the inter-well connectivity. Several published references show that the CRM method can accurately predict well performances and determine the connectivity distribution between wells (Sayarpour et al., 2009a, 2009b; Mamghaderi and Pourafshary, 2013; Moreno and Lake, 2014; Mamghaderi et al., 2020). Since it was proposed, it has been used in dynamic data integration and analysis to calculate the injection and production fluctuation data analysis. It also has been used to characterize the flow barrier detection through capacitance–resistance calculation of inter-well connectivity (Ogali and Orodu, 2022).

This paper's inter-well connectivity calculation is not the main focus point. The main contribution is to propose a method to raster it to the spatial static model domain. And also, the current study provides an innovative way to integrate it into a static reservoir model to get a more reliable reservoir model based on the weighted Bayesian updated methodology. All of the works are based on the understanding that the inter-well connectivity, inferred from dynamic production data, can be looked at as a reflection of the underground reservoir heterogeneity. Indeed, this, in turn, will significantly reduce the static model uncertainty, improve the history matching and even help to discover more geological features that might be unlikely to be characterized by static data.

2. Theory background

2.1. Well pair connectivity calculation

This study implements the most widely used capacitance model in the inter-well connectivity calculation. Here is a short introduction, and the following references can give more details (; Sayarpour et al., 2009a, Sayarpour et al., 2009a, 2009b; Liang, 2010; Kim et al., 2012; Mamghaderi and Pourafshary, 2013; Kaviani et al., 2014). Based on the capacitance model, it is proved that with one injector/producer well paired in a drainage volume, the estimated total production rate $q(t)$ of producer j is written as:

$$\widehat{q}(t)=\lambda_{ij}q_j(t_0)e^{\frac{-(t-t_0)}{\tau_{ij}}}$$

$$+\sum_{i=1}^{N_w}\lambda_{ij}w'_{ij}(t)+\sum_{k=1}^{k=K}\vartheta_{ij}\left\{p_{wf_k}(t_0)e^{\frac{-(t-t_0)}{\tau_{kj}}}-p_{wf_k}(t)+p'_{wf_{kj}}(t)\right\} \quad (1)$$

where $\widehat{q}(t)$ is the estimated total production rate, $w'_{ij}(t)$ and $p'_{wf_{kj}}(t)$ can be calculated as:

$$w'_{ij}(n)=\sum_{m=1}^{n}\left\{e^{\frac{-(t_m-t)}{\tau_{ij}}}-e^{\frac{-(t_m-t)^{-t}}{\tau_{ij}}}\right\}w_i(t_m) \quad (2)$$

and

$$p'_{wf_{kj}}(t)=\sum_{m=1}^{n}\left\{e^{\frac{-(t_m-t)}{\tau_{ij}}}-e^{\frac{-(t_m-t)^{-t}}{\tau_{ij}}}\right\}p_{wf_k}(t_m) \quad (3)$$

The weight factor λ_{ij} indicates the connectivity for the ij well pair, τ_{ij} is the time constant for the medium between injector i and producer j, w' is the filtered injector rate of injector i on producer j, $p'_{wf_{kj}}(t)$ is the convolved BHP of producer k on producer j, ϑ_{ij} is a coefficient that determines the effect of the changing BHP of producer k on producer j, $q_j(t_0)$ is the initial total production rate of producer j, τ_{ij} is the resultant item constant of the primary production component, and τ_{kj} is the time constant between producer k on producer j. The time constants in the BHP term (and the definitions for convolved BHP) have been changed from τ_j to τ_{kj} to account for additional interactions.

Usually, an iterative, nonlinear optimization procedure is required to determine the optimum values of the above parameter, such as τ and λ. More details of the optimization procedure can be found in the literature (Al-Yousef, 2006; Holanda et al., 2018). At the end of the optimization procedure, the obtained optimum λ_{ij}, τ_{ij} and other parameters allow us to use the error estimates of the weights based on MLR.

In this study, the quantitative inter-well connectivity, λ_{ij} will be used to update the permeability model in static model updating as the two are highly correlated. While variable τ_{ij} is a reflection of porosity between the pair wells. During static updating, the porosity model will not update as it is more related to oil in place, which is well built-in static modeling with less uncertainty. So in this study, λ_{ij}, inferred from dynamic production injection data is explicated and used to update the static permeability model to achieve production data integration in the geo–modeling procedure.

2.2. Inter–well connectivity spatial rasterization

Usually, a static model is built using various cell-based modeling approaches (Isaaks and Srivastava, 1988; Desbarats and Srivastava, 1991; Deutsch and Journel, 1998; Syed et al., 2022). Each cell will get a porosity, permeability, and oil saturation values for flow simulation in the model. The inter-well connectivity coefficient is an overall reflection of the reservoir heterogeneity between the well pairs and is expressed as a vector. In order to use the connectivity coefficient to update the static model, it must be projected into all the cells between each producer and injector pair. The connectivity coefficient also must be rasterized into the model spatial area first.

Given a homogeneous reservoir, the streamlined shape of the controlled region between injection-production wells will follow an ellipse shape theoretically (Whitaker 1986; Feng and Yu, 2015; Song, 2018; Barletta, 2019). Therefore, in this study, the connectivity between injection-producer will be assumed to have an ellipse effluence region, as shown in the right Fig. of Fig. 1. The major axis of the ellipse is the distance between injection-production wells L_{ij}. The minor axis of the ellipse B_{ij} determines the controlled region of the connectivity coefficient. Out of the region, it is believed that the connectivity coefficient can be neglected and not affect the property between injector and producer.

Based on the above reasonable assumption, we can define a region between each producer and injector pair, as shown in Fig. 2. Within each controlled region, one connectivity coefficient value will be given to the cells within the region. From Fig. 2, it can be seen that there is an overlap between different injection and production wells on the ellipse influence region. In the rasterization process, the maximum connectivity value is taken at the overlapping grid as the value of the grid connectivity. One example of the obtained spatial connectivity coefficient field is shown in Fig. 3.

Also, it should be noted that we have to do normalization in the whole spatial domain to reflect the distance of each effluence region. Based on the definition of connectivity coefficient:

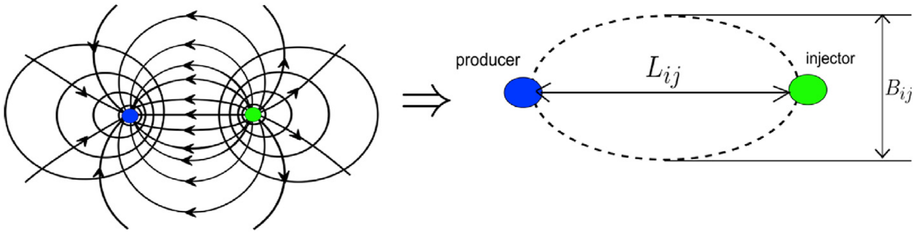

Fig. 1. Theoretical inter-well connectivity shape

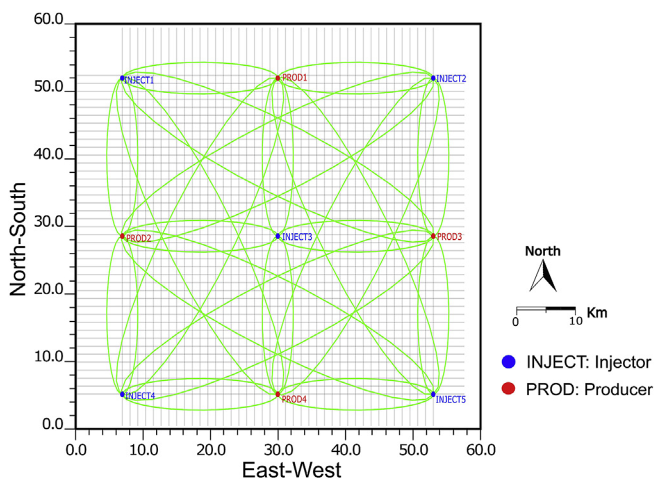

Fig. 2. An inter-well connectivity shape calculation example for a 9–point well group.

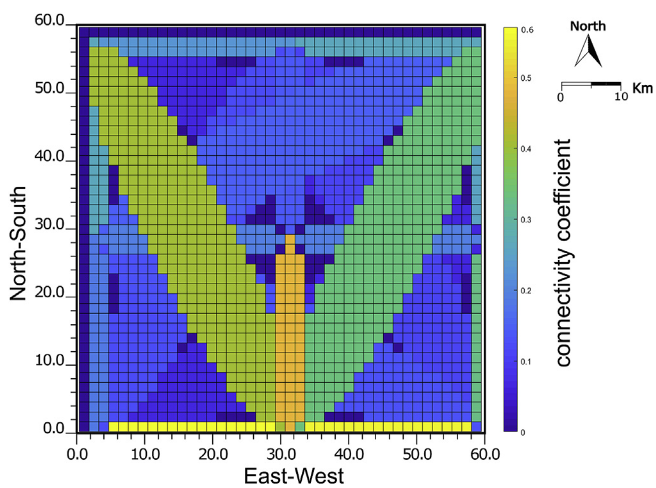

Fig. 3. Inter–well connectivity coefficient field rasterization illustration.

$$\lambda_{ij} = \frac{T_{ij}}{\sum\limits_{j=1}^{N_0} T_{ij}} \tag{4}$$

where the conductivity T_{ij} is defined as:

$$T_{ij} = \frac{\overline{k_{ij}} A_{ij}}{\mu L_{ij}} \tag{5}$$

The conductivity is the result of the combined effect of the viscosity of crude oil μ, the cross-section area of injection-production well $A_{i\ j}$, injector-producer distance L_{ij} and the average permeability between injection and production wells $\overline{k}_{ij}$. It is reasonable to assume that the viscosity of crude oil μ and the cross-section area of the injection-production well $\overline{A}_{ij}$ are the same between any pair of injection-production wells from a static model. Then, the difference in the inter-well connectivity coefficient is mainly determined by the injector-producer distance L_{ij} and the average permeability between injection and production wells $\overline{k}_{ij}$. Then, a normalized connectivity coefficient $\widehat{\lambda}_{ij}$ can be calculated as:

$$\widehat{\lambda}_{ij} = \frac{\lambda_{ij} L_{ij}}{\sum\limits_{j=1}^{N_0} \lambda_{ij} L_{ij}} \tag{6}$$

One example of normalized rasterized inter-well connectivity is shown in Fig. 4. The spatial rasterized inter-well connectivity is now sampled in the spatial modeling domain and could be used as a posterior message to update the static model.

2.3. Bayesian formalism

Bayesian formalism has been shown as a powerful tool for integrating geological static models with dynamic data (Cunha, 2004; De Luca et al., 2022). Following Bayesian formalism, the given static model will be considered a prior distribution. The heterogeneity characterized by the connectivity coefficient will be looked at as likelihood information to the permeability distribution. The Bayesian updating to the prior static model will obtain a

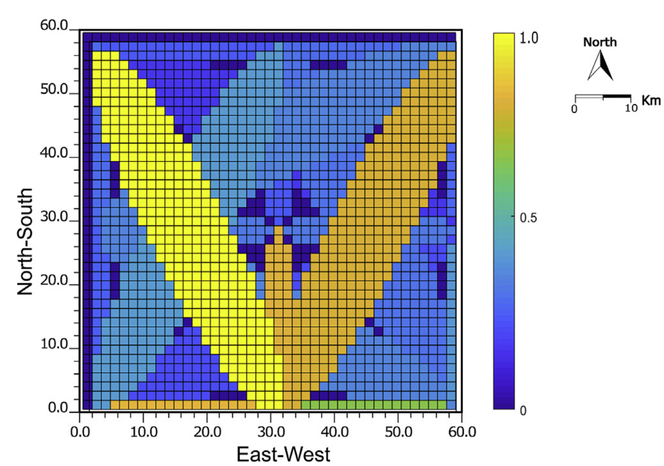

Fig. 4. Normalized Inter–well connectivity coefficient.

posterior distribution.

The prior distribution expresses our uncertainty about the spatial distribution value of the underground reservoir. It is assumed that the distribution would follow any statistics distribution. However, it can be transformed into a normal distribution. Thus, it can be characterized by a mean and variance. This study assumed that permeability is log-normal with ln(K). Usually, given a specified variogram model, the log-permeability field will follow multivariate Gaussian distribution.

The probability density function (pdf) of a normal distribution (Gaussian distribution) is:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(\mu-x)^2}{2\sigma^2}} \quad (7)$$

Given the inter-well connectivity information from dynamic production data is inferred, it is defined as new information in Bayesian formalism (Banerjee et al., 2009). Based on Bayesian statistics, the sample information from the same process can be used to obtain a posterior normal distribution.

In this study, it is believed that the sample of observations within the inter-well connectivity effluence region can be represented with a new normal distribution with sample mean m' and a sample variance σ'. Then, a posterior or updated mean and variance will be a weighted combination of the mean and variance from the prior and the sample. The larger the sample and the smaller the sample variance, the higher the weight the sample information receives.

In the case of an initial permeability, the new information are those observations within the effluence area confined by the well connection area. It will be local area around the prospect to be evaluated. A new property means will be proposed to fit the objective inter-well connectivity. The prior distribution will be updated according to the new information. The posterior mean (m'') and variance (m''^2) under the above assumptions are calculated as:

$$m'' = \frac{\sigma' m' + n\sigma'^2 m}{n\sigma'^2} \quad (8)$$

and

$$\sigma''^2 = \frac{\sigma^2 \sigma'^2}{n\sigma'^2 + \sigma^2} \quad (9)$$

Where n is the reservoir model cell number within the target inter-well connectivity effluence region. Given the posterior mean and variance, adopting a Monte Carlo procedure to update all the permeability values within the connectivity inter-well region is accessible.

As a quick summary, the updating procedure based on Bayesian will follow these four steps.

(1) Calculation of the prior distribution using kriging;
(2) Calculate the mean of likelihood distribution based on the inter-well connection based on dynamic data of each well affect region;
(3) Updating the prior distribution with the likelihood distribution to get the updated distribution;
(4) Performing the back transformation using the posterior distribution and Monte-Carlo simulation using the updated mean and variance.

3. Workflow and implementation example

3.1. Workflow

The above inter-well connectivity analysis and Bayesian formalism are the theoretical basis for the current proposed static model and dynamic data assimilation. The overall workflow is shown in Fig. 5.

The core part is an iteration procedure to match the target inter-well connectivity calculated from actual production well data. Before iteration begins, the target inter-well connectivity is based on the theory given in section 2.1. It is rasterized following the principle given in section 2.2. For each iteration, the model will be locally updated according to the comparison between current inter-well connectivity (λ^{model}) calculated from the current model and the target inter-well connectivity (λ^{target}). The updating to get a renewed model is based on the Bayesian updating given in section 2.3. The above workflow will be illustrated with a case study in the coming sections.

3.2. Geological model and basic dynamic production background

The geological studies show the facies feature of the research area is a fluvial channelized reservoir formation, as shown in Fig. 6. The permeability distribution is heterogeneous, whereas the porosity distribution is uniform. There is no capillary pressure, rocks are incompressible, and dead oil and water PVT properties are defined using superficial relationships. It is produced under water flooding conditions with eight water injectors and four producers. The producers operate under constant bottom–hole pressure (395 bar) and eight water injectors with a given injection rate (60–120 m^3/day). A five–spot layout is used for the well's location.

The heterogeneous permeability distribution affects the time of water appearance in the production wells. This information is collected in the first ten years (120 months) of production time. The purpose of this study will show that it can provide valuable information for static model building.

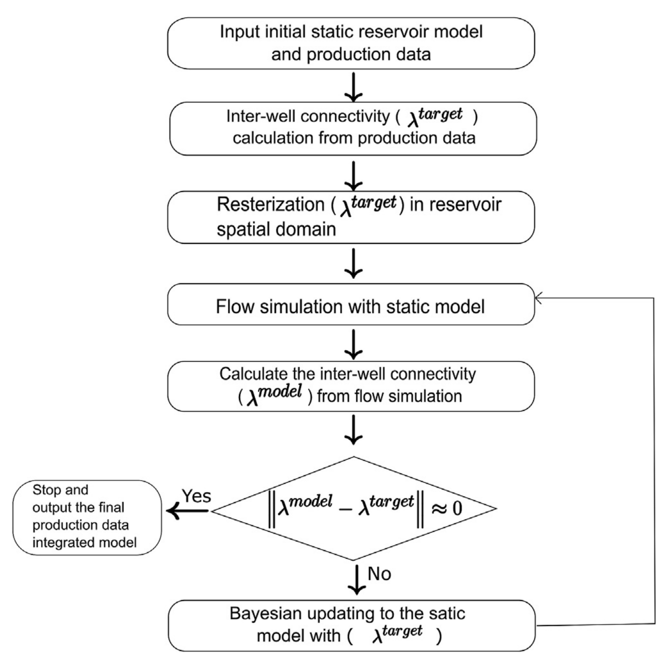

Fig. 5. Workflow based on Bayesian formalism

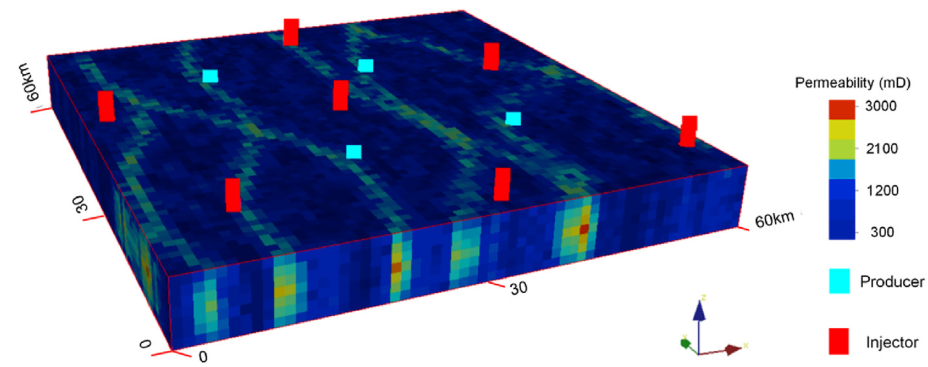

Fig. 6. Initial permeability model of the research area from a target reservoir model

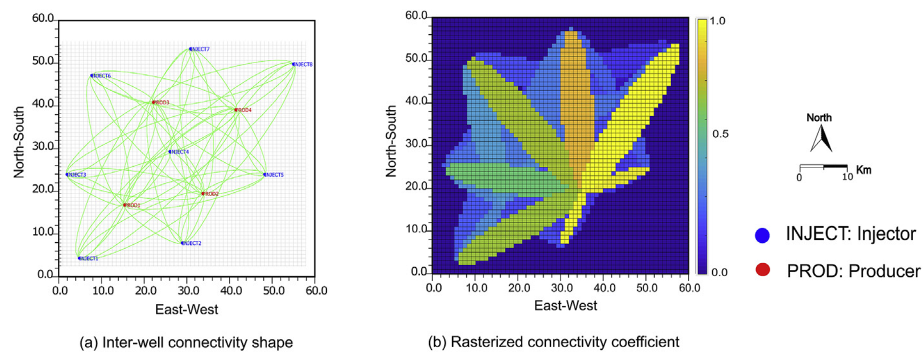

Fig. 7. Inter-well connectivity and rasterization from the well production data

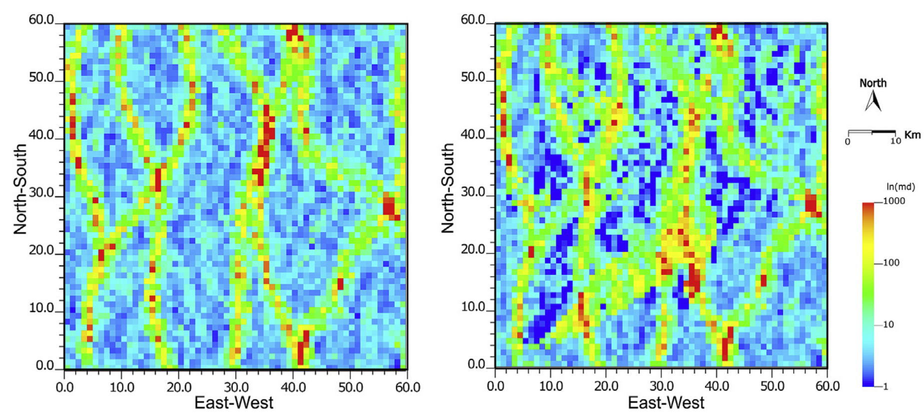

Fig. 8. One updated permeability model during iteration.

3.3. Inter-well connectivity calculation and spatial rasterization

Based on the inter-well connection theory introduced in section 2.1, a Matlab program is developed for current case study. Feeding the collected production data into the program with other essential information such as location and production data, a 2D spatial rasterized inter-well connectivity coefficient between injection and production wells can be calculated as shown in Fig. 7.

3.4. Model updating

For illustration, only one step of the updated permeability model is shown in Fig. 8, compared to the initial permeability model. From those two geological models, one can observe that inter-well connectivity information is reflected in certain areas of the updated model, such as between well pair of INJ1 and PROD2.

After iteration is converged, the calculated inter-well connectivity can be very close to the production data. Based on the updated permeability model, geological understanding could also be updated. Fig. 9 shows that the fluvial channel shape is adjusted according to this reservoir's message obtained from dynamic data.

4. Conclusions

In this study, the CRM model calculates the connectivity between wells, and the connectivity coefficient can reflect the geological information. Thus, based on the dynamic production data, we can calculate the inter-well connectivity between wells,

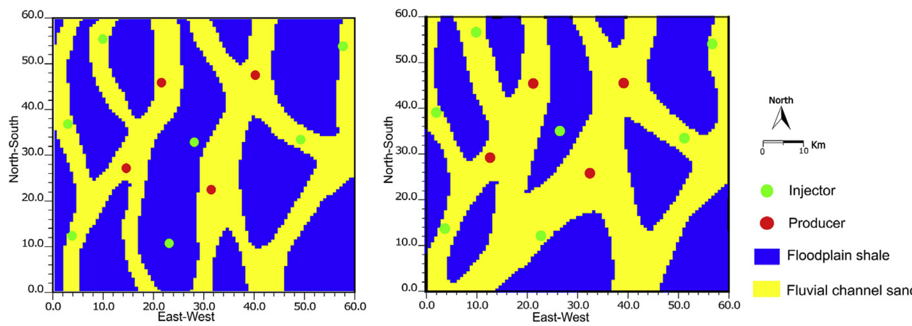

Fig. 9. The updated static facies model after dynamic data are integrated.

which can be used to guide the updating of the geological model and also gain deeper geological understanding as well.

The novel inter-well connectivity rasterization approach provides a way for other similar quantitative vector data integration in reservoir characterization and flow simulation.

In this study, the Bayesian updating method combines well connectivity information with a permeability model updating. The reservoir heterogeneity reflected from the dynamic data is integrated into the static model. The coupling of dynamic data integration and static model updating provides a way of automatic assisted history matching.

It could also be used as quantitative criterion to check the static model quality when multiple models are available. And it provides a kind of clear clue of how we should update those static models to fit the truth of underground heterogeneity.

Declaration of competing interest

The authors declare that they have no competing interests.

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