Metrel: Petrel Plug-in for Modeling Uncertainty in Metric Space

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Abstract

Modeling uncertainty for reservoir performance prediction is still a challenging and outstanding problem due to geological complexity of reservoir and CPU demanding flow simulations. Metric space modeling techniques deal with multiple models efficiently and effectively by constructing a metric space where the location of any model is determined exclusively by the mutual differences in responses as defined by a "distance". Once we know the distance between any two (geological) model realizations, any such model (whether a structure or property field) can be represented into a metric space, which is non-dimensional but can be represented through projection into low-dimensional (typically 2D-5D) space through multi-dimensional scaling. Metric space modeling techniques enable model generation (pre-image problem), model selection (kernel k-means clustering), sensitivity analysis and uncertainty assessment. We implemented core technologies (multi-dimensional scaling and kernel k-means clustering) for metric space modeling in the Ocean framework, which is an application development framework that allows to develop applications tightly integrated with the Petrel product family. This paper aims to provide the description and user's guide for developed Petrel plug-in, named Metrel. Additionally, we demonstrate the effectiveness of Metrel to modeling flow uncertainty in a 3D field-scale reservoir..

1 Introduction

Developing a plan to maximize oil production requires constructing reservoir models constrained to all available data. Reservoir modeling is, however, still a vexed question because of various sources and types of data that need to be integrated as well as the possibly existing uncertainty due to lack of data to fully constrain the reservoir model.

From today's oil fields, many types of data are being obtained. One of the most important data is provided by geologists. Geologists produce a geological interpretation

of the reservoir from outcrop or other inspections, resulting in e.g. guesses of channel dimensions, their stacking patterns or where the turbulent flow in the ocean dominated deposition. Additionally, direct observation from a few wells is available as a form of well log, core, or well test data. On the other hand, indirect observation from geophysical survey (esp. seismic survey), often termed "soft" data, provides a lower-resolution constraint. Additionally, production history (bottom hole pressure, oil or water rate) is recorded during the production. Matching the reservoir to the production history is very difficult due to the severe nonlinearity between the reservoir model and the history. Modeling a reservoir requires integration of all available data from varying scales and sources.

In particular at the appraisal stage, where reservoir production data are few and where critical decision need to be made, uncertainty about reservoir volume and prediction performance is still considerable and critical to the decision making process. Such uncertainty is captured and represented by generating several alternative reservoir models by varying key geological, geophysical and reservoir engineering parameters. Hence, a powerful tool for managing multiple reservoir models is required. In order to assess the uncertainty using multiple reservoir models, Monte Carlo simulation or experimental design is widely used. However, Monte Carlo simulation demands a number of flow simulations, which is not feasible practically. Additionally, the experimental design is not applicable to spatial (geological) variables which are often categorical and critical to flow (Caers and Scheidt, 2010).

Metric space modeling means that processes accompanied by modeling a reservoir are reformulated and performed in metric space, where the location of any model is determined exclusively by the mutual differences in responses as defined by a "distance". First step of all metric space modeling techniques is to define a distance to construct a metric space for the initial set of multiple models; Secondly the metric space is represented by its projection to the low-dimensional space by means of multi-dimensional scaling (MDS). MDS generates a map of points with maintaining the distance between any two points. MDS makes it possible to analyze the ensemble of multiple models by simple visual inspection as well as through many statistical analysis techniques. From the constructed metric space, a series of operations for reservoir modeling is available: generating additional models (Caers, 2008; Scheidt et al., 2008), selecting a few representative models by screening and clustering models (Scheidt and Caers, 2009a, 2010), sensitivity analysis and uncertainty assessment for models (Scheidt and Caers, 2008, 2009b), updating models for constraining to nonlinear time-series data (Caers and Park, 2008; Park et al., 2008), and so forth (for a detailed summary, refer to Caers et al. (2010)). While a reservoir model is often represented by millions of parameters (properties at each gridblock), in metric space, a reservoir model is represented by the distance between other models that is correlated with the output of application, which is simple and of critical interest. Also, as long as a distance between any two models is defined, metric space modeling technologies can be applied to any combination of models, such as models of several different structural geometry or models of different geological scenarios.

Ocean is an application development framework that allows to develop applications tightly integrated with the Petrel product family ((Schlumberger, 2008)). Under the Windows.NET environment, Ocean allows developing user-friendly plugins which can be executed in the Petrel using all the Petrel functions and database. Petrel is a reservoir modeling software which makes it possible to generate multiple reservoir models (multiple structures, multiple properties, etc.) given almost all types of geological, geophysical, petrophysical data, and so on. In addition, Petrel has many strong analysis functions for 3D visualization, reservoir flow simulation, uncertainty assessment, and so forth.

In this study, we have developed a Petrel plug-in (*Metrel*) where core technologies for metric space modeling are implemented based on the Ocean framework. First, *Metrel* allows defining any type of distance from the Petrel database. Second, *Metrel* constructs a metric space and map all the initial set of models into low-dimensional space by means of MDS. The results are stored in the Petrel database and each model can be viewed and analyzed in 3D display window as a point. Third, *Metrel* performs kernel k-means clustering (KKM) to divide the set of models into several groups for further analyses. Finally, based on the results from MDS and clustering, sensitivity analysis and uncertainty assessment are available. In **Section** 2, theories for metric space modeling are briefly described. In chapters **Sections** 3 to 5, we explain how the plug-in works and how and where to use *Metrel*, followed by summarizing remarks in **Section** 6.

With *Metrel*, users can choose a few representative model realizations and determine the uncertainty in future prediction (eg. P10, P50, and P90) with the reduced number of model realizations. Additionally, users can analyze the sensitivity of any type of parameters whether continuous (channel width or length) or categorical (type of structural model, multiple geological scenarios). Finally, users can analyze multiple model realizations very easily by means of simple visual inspection.

2 Metric space modeling

Let $\mathbf{x}_i$ be a set of parameters that represents a model, which can often be a vector of the property values assigned to each gridblock or to the model itself or the combination of both. If the number of parameters defining a model is N and the number of models L, then a set (or ensemble) of models is represented by the matrix $\mathbf{X}$ (**Equation** 1). Note $N >> L$.

$$\mathbf{X} = \begin{pmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_i & \cdots & \mathbf{x}_L \end{pmatrix}^{\mathsf{T}} \qquad \in \mathbb{R}^{L \times N} \tag{1}$$

Let $\mathbf{g}_i$ be a set of parameters that represents an output of a model $\mathbf{x}_i$ in which we are interested ($\mathbf{g}_i = g(\mathbf{x}_i)$). For example, $\mathbf{g}_i$ is the oil production rate calculated by reservoir simulation of i-th model realization ($g(\mathbf{x}_i)$). Then the distance is defined such that the distance between any two models are reasonably correlated with the difference in the outputs

of the two models (**Equation** 2). We can define any type of function for the distance calculation as long as Equation 2 holds. Note the function $d(\mathbf{x}_i, \mathbf{x}_j)$ should be computationally easy and fast while the evaluation of function $g(\mathbf{x}_i)$ often costs large time and efforts.

$$d_{ij} = d(\mathbf{x}_i, \mathbf{x}_j) \qquad \text{correlates} \quad \text{with} \qquad \sqrt{(\mathbf{g}_i - \mathbf{g}_j)^\intercal (\mathbf{g}_i - \mathbf{g}_j)} \tag{2}$$

In most cases, the size of $\mathbf{g}_i$ is much smaller than that of $\mathbf{x}_i$. In other words, $\mathbf{x}_i$ usually exists in very high-dimensional (10^5D to 10^7D) space and $\mathbf{g}_i$ in low-dimensional (1 to 100) space; if we construct a metric space representing the models exclusively by the distance, the arrangement of models in metric space is much simpler than that in the high-dimensional model space. The fact that what we are actually interested in is not the model itself but the output from the model shows another merit of this application-tailored distance, since we are focusing on the output as well as rendering the problem simple. This is the reason why we can represent the constructed metric space as a projection to low-dimensional (2D to 5D) space through multi-dimensional scaling.

Multi-dimensional scaling (MDS)

MDS is a process that maps the models from metric space into a low-dimensional Cartesian space (MDS space) such that the Euclidean distance between the mapped points in MDS space is as close as possible to the application-tailored distance of Equation 2 (**Equation** 3).

$$\mathbf{X} \mapsto \mathbf{X}_m \qquad \text{s.t.} \qquad d(\mathbf{x}_i, \mathbf{x}_j) \cong \sqrt{(\mathbf{x}_{i,m} - \mathbf{x}_{j,m})^\intercal (\mathbf{x}_{i,m} - \mathbf{x}_{j,m})} \tag{3}$$

where, the subscript *mds* means the point mapped by MDS. MDS is simply done by eigenvalue decomposition and retaining "reasonable" number of eigenvalues as in **Equations** 4 to 6. "Reasonable" means "large enough to capture the variation of models in metric space" and can be determined by the correlation coefficient between the distance in metric space and the distance in MDS space. Equation 4 represents the process of centering the distance matrix.

$$\mathbf{B} = \mathbf{HAH} \tag{4}$$

where, $\mathbf{H}$ represents the centering matrix:

$$\mathbf{H} = \mathbf{I} - \frac{1}{L}\mathbf{1}\mathbf{1}^\intercal \qquad \in \mathbb{R}^{L \times L}$$

with $\mathbf{I}$ of the identity matrix and $\mathbf{1}$ of a column vector of L ones ($\mathbf{1} = [11 \cdots 1]^\intercal \in \mathbb{R}^{L \times 1}$). The element of matrix $\mathbf{A}$ is calculated by

$$a_{ij} = -\frac{1}{2} d_{ij}^2$$

.

Next, the eigenvalue decomposition of $\mathbf{B}$ is

$$\mathbf{B} = \mathbf{V}_\mathbf{B} \mathbf{\Lambda}_\mathbf{B} \mathbf{V}_\mathbf{B}^\mathsf{T} \tag{5}$$

where, $\mathbf{V}_\mathbf{B}$ denotes the collection of eigenvectors of $\mathbf{B}$ and $\mathbf{\Lambda}_\mathbf{B}$ the diagonal matrix of eigenvalues of $\mathbf{B}$. If we retain the M largest eigenvalues and the corresponding eigenvectors to construct a small eigenvalue matrix $\mathbf{\Lambda}_{\mathbf{B},M}$ and eigenvector matrix $\mathbf{V}_{\mathbf{B},M}$, $\mathbf{X}_m$ is finally obtained by

$$\mathbf{X}_m = \mathbf{V}_{\mathbf{B},M} \mathbf{\Lambda}_{\mathbf{B},M}^{1/2} \tag{6}$$

Kernel k-means clustering

Clustering is a useful function for selecting a few representative models, screening out incompatible models, sensitivity analysis, uncertainty assessment, and so on. In *Metrel* clustering is used for model selections and sensitivity analysis on geological/engineering parameters.

Since models in metric space are mapped into a low-dimensional space using MDS, k-means clustering converges easily. More importantly, kernel techniques for clustering, which arrange the models in MDS space linearly in kernel feature space, makes the clustering more reliable and effective.

K-means clustering is an iterative algorithm for finding the locations of cluster centroids so as to minimize the sum of distances between the models and their nearest centroids (**Equations** 7). Once the locations of centroids are determined, the models nearest to each centroid are clustered into a group and assigned its cluster index (**Equations** 8).

$$\mathbf{C}_{opt} = \underset{\mathbf{C}}{\operatorname{argmin}} \sum_{i=1}^{L} \min_j \|\mathbf{c}_j - \mathbf{x}_{i,m}\| \qquad \text{with} \quad j = 1, 2, \cdots, N_c \tag{7}$$

$$u_i = \underset{j}{\operatorname{argmin}} \|\mathbf{c}_{j,opt} - \mathbf{x}_{i,m}\| \tag{8}$$

where, $\mathbf{C}$ represents the collection of cluster centroids of size $M \times N_c$, N_c the number of clusters predefined, and u_i the cluster index for the i-th model $\mathbf{x}_i$. The subscript opt means the optimized cluster centroids.

KKM means k-means clustering in kernel feature space. First, we define a map from MDS space to kernel space (**Equations** 9). In metric space modeling, a Gaussian radial-basis kernel function (k) is often selected since we have already defined a distance and radial-basis kernel function is a function of distance only (**Equation** 10). Then a Euclidean distance between two features in kernel space is represented by **Equations** 11. As seen in Equation 11, the distance in kernel space is calculated from the kernel function, which means $\mathbf{\Phi}$ does not have to be explicitly stated (the kernel trick).

$$\mathbf{X}_m \mapsto \mathbf{\Phi} \quad \text{s.t.} \quad k(\mathbf{x}_{i,m}, \mathbf{x}_{j,m}) = \phi_i^\intercal \phi_j \tag{9}$$

$$k(\mathbf{x}_{i,m}, \mathbf{x}_{j,m}) = exp\left(-\frac{\|\mathbf{x}_{i,m} - \mathbf{x}_{j,m}\|^2}{2\sigma^2}\right) \tag{10}$$

$$\begin{aligned} \|\phi_i - \phi_j\|^2 &= \phi_i^\intercal \phi_i - 2\phi_i^\intercal \phi_j + \phi_j^\intercal \phi_j \\ &= 2 - 2k(\mathbf{x}_{i,m}, \mathbf{x}_{j,m}) \end{aligned} \tag{11}$$

Therefore, the equations for KKM are obtained by slightly modifying Equations 7 and 8 (**Equations** 12 and 13).

$$\mathbf{C}_{opt} = \underset{\mathbf{C}}{\text{argmax}} \sum_{i=1}^{L} \max_j k(\mathbf{c}_j, \mathbf{x}_{i,m}) \qquad \text{with} \quad j = 1, 2, \cdots, N_c \tag{12}$$

$$u_i = \underset{j}{\text{argmax}}\, k(\mathbf{c}_{j,opt}, \mathbf{x}_{i,m}) \tag{13}$$

3 How *Metrel* works

In a Petrel database, three types of tabs exist: `Input`, `Models`, and `Results`. `Input` contains various input parameters, such as well information, fluid petrophysical properties, etc. `Models` contains various models that we generate from the input data. Lastly, `Results` contains simulation or analysis results, such as flow simulation results or sensitivity analysis results.

Since *Metrel* starts from a set of multiple models, the tab `Models` is explained in detail first. In `Models`, there is a pre-defined hierarchy. We can define various structural models in `Models` and each structural model can contain multiple property models (**Figure** 1). For example, if we have 3 structural models: no fault, one-fault, two-fault models, each structural model may be assigned multiple permeability fields or multiple porosity fields (**Figure** 2). Then we can define many combinations of those models and properties for flow simulation or sensitivity analysis; each combination is stored in the Petrel database as a form of the term `Cases` in Petrel.

A `Case` is defined in Petrel for uncertainty analysis as well as for reservoir flow simulation. In order to define a `Case`, we have to assign every input parameter that the reservoir simulation or the uncertainty analysis requires. For instance, we have to assign to a `Case` which structural model to use, which permeability model, which porosity model, which relative permeability curve, which fluid behavior curves, and so on (**Figure** 3). We can define multiple `Cases` from the input and model databases in Petrel. The defined `Cases` are used for the input of *Metrel*.

Using this set of cases defined and chosen for *Metrel*, *Metrel* can perform two core operations for metric space modeling: MDS and KKM.

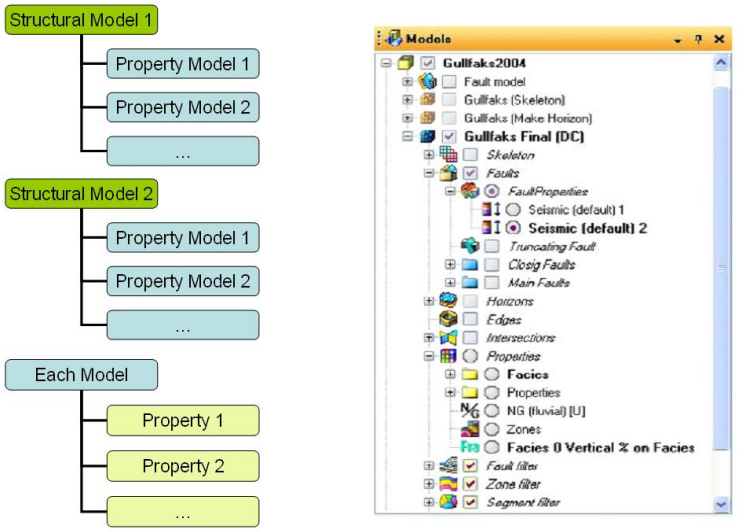


Figure 1: Structure of Petrel database: `Model`.

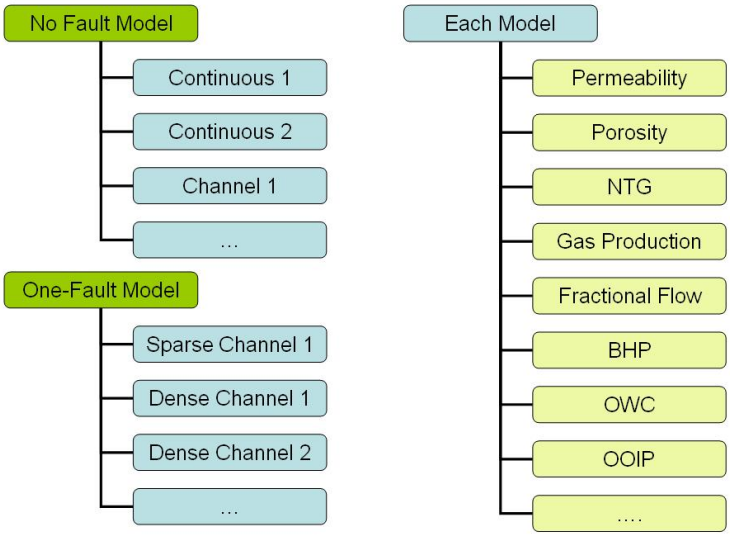


Figure 2: Example of structural models and corresponding property models in Petrel database (`Model`).

Figure 3: Example of `Case` and corresponding properties in Petrel database.

As we discussed in the previous chapter, MDS maps `Cases` into a low-dimensional space preserving the distance between any two `Cases` (**Figure** 4). In *Metrel*, the distance is defined by the difference between properties or simulation results of any two `Cases`. A single property or multiple properties can be chosen to define the distance. For example, the distance can be defined by the difference in oil production and bottom hole pressure obtained through streamline simulation. *Metrel* generates a new `Pointset` for displaying the results of MDS. The `Pointset` can be viewed in the 3D view of Petrel as well as the name of `Case` and parameters used for defining the `Case`.

The second functionality implemented in *Metrel* is KKM (**Figure** 5). *Metrel* makes it possible to apply the clustering to any `Pointset` generated by means of MDS. KKM generates a new `Pointset` which identifies model realizations closest to the cluster centroid and their cluster indices. These model realizations are then selected as representative of the entire set. Additionally KKM generates another new `Pointset` which contains all the model realizations as well as their cluster indices. We can also make use of the statistical analysis tools already implemented in Petrel to analyze e.g. histogram of input parameters or results, sensitivity analysis on input parameters, and so forth.

4 How to use *Metrel*

This section can be regarded as a manual of *Metrel*. The possible use of the plug-in would be as follows.

1. Define multiple `Cases` representing reservoir model uncertainty.
2. Define which property or properties to be used for the distance calculation. If the

Figure 4: Distance and the projection of Cases from metric space by multi-dimensional scaling.

Figure 5: Kernel k-means clustering of Cases in metric space.

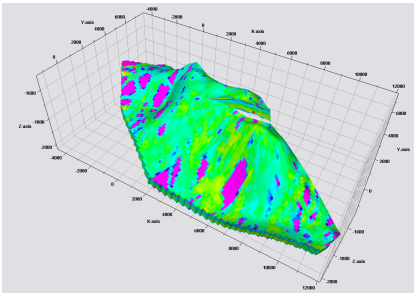


Figure 10: Permeability based on facies information.

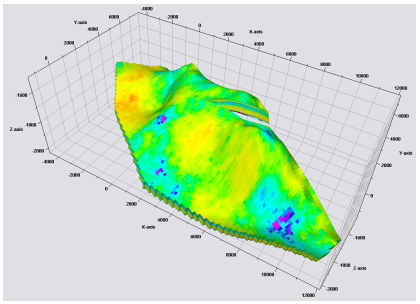


Figure 11: Permeability without using facies information.

2. Run Frontsim for the 104 `Cases`. **Figure** 12 shows the streamlines that are used in one of the Frontsim simulations.

3. Start the plugin (*Metrel*).

4. Define a distance as the difference in oil and water production over 10 years resulting from frontsim simulations and choose all 104 `Cases`.

5. Perform MDS by clicking the button: `Map multiple models into metric space`. **Figure** 13 depicts the result of MDS. Each point represents each `Case`. The `Cases` are arranged in the 3D space (projection of the metric space) such that similar `Cases` in terms of their oil and water flow characteristics are located close to each other.

6. Perform KKM by clicking the button: `Kernel k-means clustering`. **Figure** 14 shows the result of KKM (6 clusters). Each point has been assigned the cluster index to which it belongs. All the `Cases` are clustered based on their flow characteristics. Figure 14 also displays the `Cases` closest to centroids, which are the representative `Cases` amongst 104 `Cases`: BRUGGE33, 48, 68, 78, 88, 93.

7. Run full reservoir simulations for the chosen `Cases` (Eclipse) and analyze the `Pointsets` generated in the `Input` tab for the uncertainty assessment and sensitivity analysis as presented in the following subsections.

5.1 Uncertainty assessment

Original work on the uncertainty assessment through metric space modeling techniques is published in Scheidt and Caers (2008, 2009a). In this example, the objective of uncertainty assessment is to determine the uncertainty in 10-year prediction of oil and water production by Eclipse flow simulations. The uncertainty in future prediction is usually represented by p10, p50, and p90 curves of oil and water production curves by reservoir

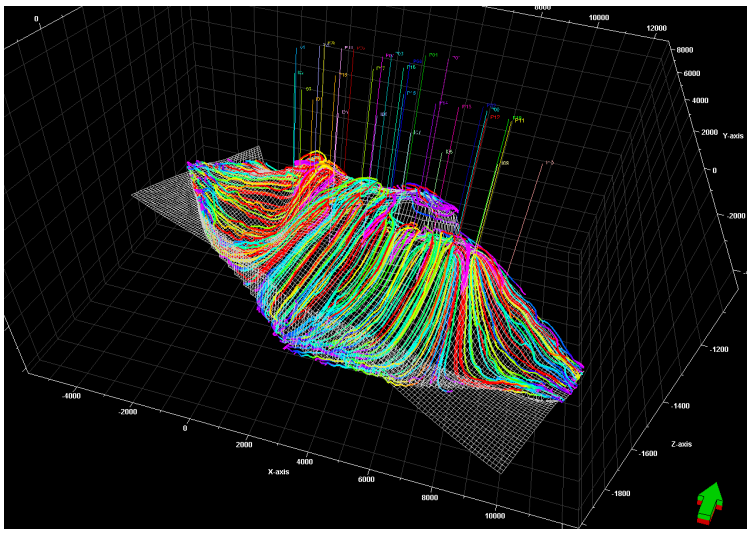


Figure 12: Streamlines traced by one of the Frontsim simulations.

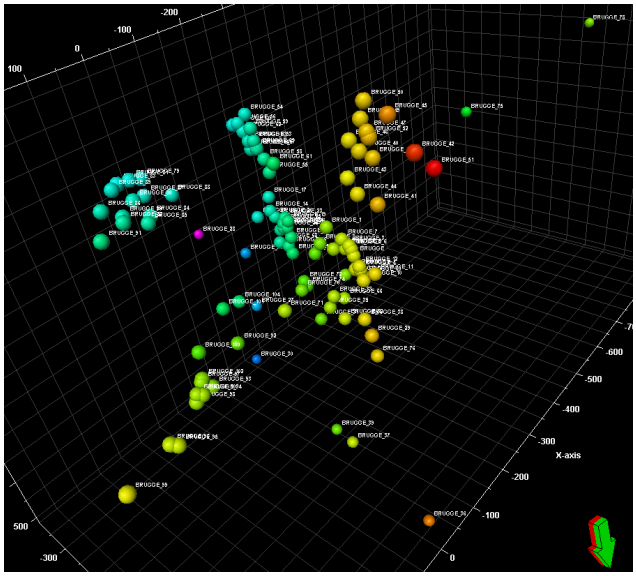


Figure 13: Projection of metric space by MDS. Each dot represents a reservoir model realization (`Case`). The color means z-dir location of each `Case`

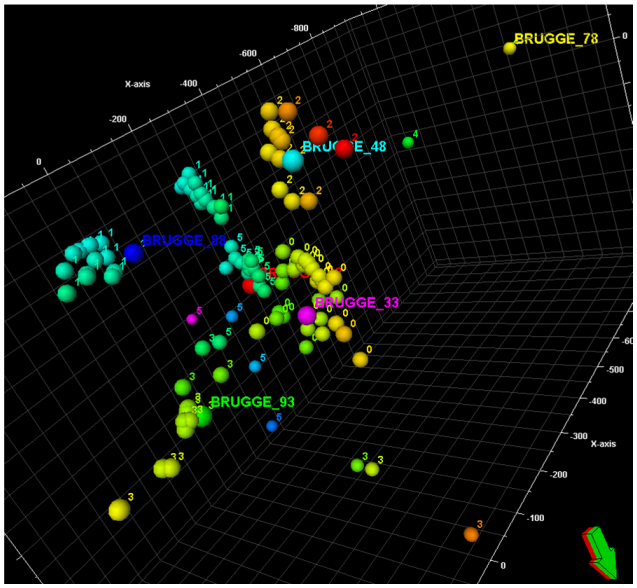


Figure 14: Clustering results and a few representative `Cases` chosen by KKM. Chosen `Cases` are represented by large circles which labeled `BRUGGE_33`, `BRUGGE_48`, `BRUGGE_68`, `BRUGGE_78`, `BRUGGE_88`, and `BRUGGE_93`.

simulations of 104 models generated. **Figure** 15 shows 104 field oil and water production curves of 104 models. However, running all 104 full flow simulations (Eclipse) is not feasible in most practical studies, since it would take more than three days of CPU. In order to assess performance of our method, we did execute all 104 flow simulations with Eclipse. On the other hand, **Figure** 16 depicts 6 oil and water production curves of 6 representative models chosen by metric space modeling techniques: MDS and KKM. **Figures** 17 and 18 show the comparison of P10, P50, P90 curves of field oil and water production rates of the exhaustive set of 104 model realizations and the selected 6 representative model realizations. As seen in Figures 17 and 21, 6 representative curves are reproducing the statistics of 104 representative curves reasonably well. **Figures** 19 and 20 display the oil and water production rates of individual well (p17) of 104 model realizations and 6 representative model realizations. **Figures** 21 and 22 show the comparison of P10, P50, P90 curves of oil and water production rates of individual well (p17) of 104 model realizations and 6 representative model realizations. The uncertainty of production curves for individual well are also represented well by the chosen 6 models, although not as well as the field production: this is to be expected since well production is more varying; selecting more models will give a better approximation (as shown in Scheidt and Caers (2009a)). In this example, the number of clusters are set to 6 through the visual inspection of the cloud of 104 `Cases` in metric space.

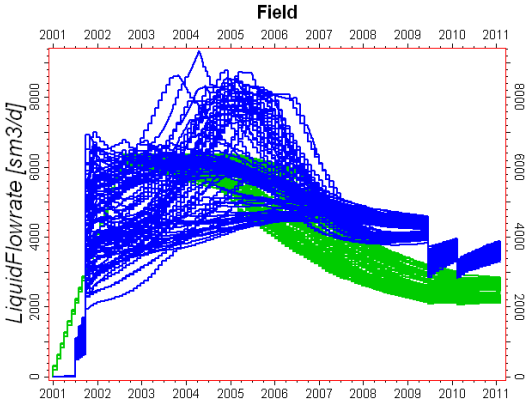


Figure 15: Field oil and water production curves of 104 models by exhaustive simulations, which cannot be applied in the field.

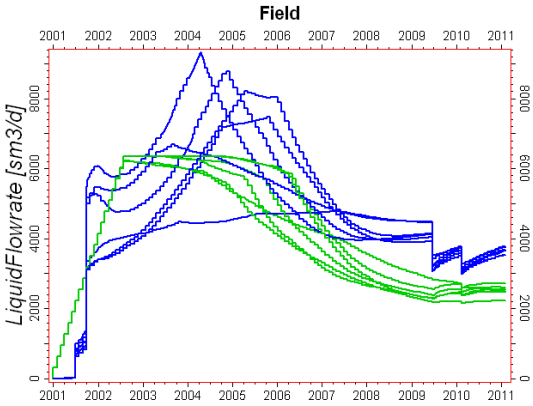


Figure 16: Field oil and water production curves of 6 representative models chosen by KKM.

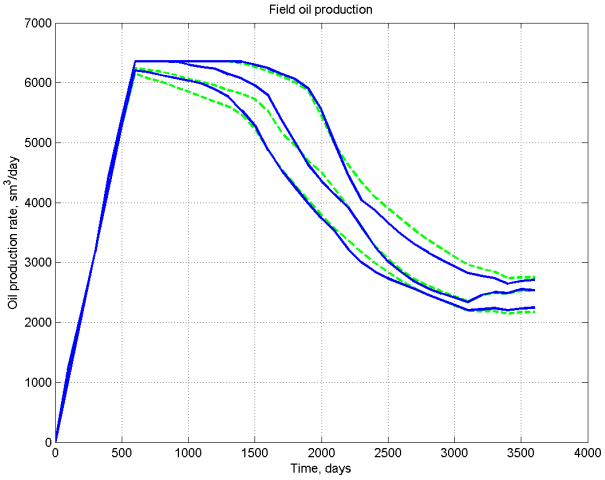


Figure 17: P10, P50, P90 of field oil production curves of 104 models (green dashed lines) and 6 representative models chosen by KKM (blue solid lines).

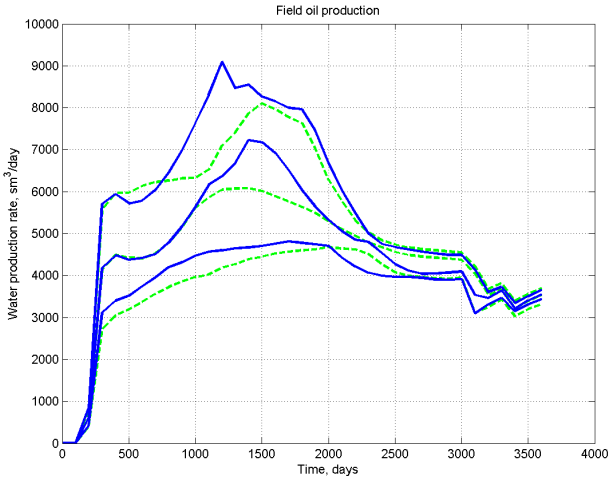


Figure 18: P10, P50, P90 of field water production curves of 104 models (green dashed lines) and 6 representative models chosen by KKM (blue solid lines).

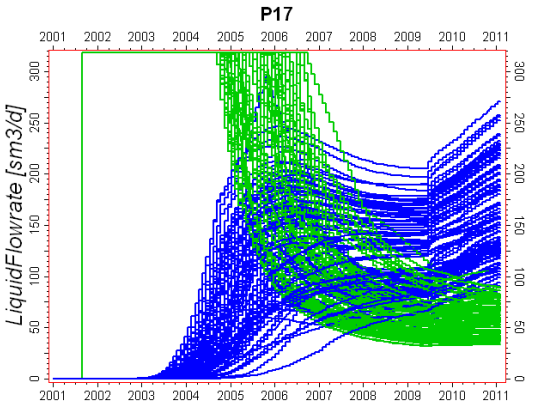


Figure 19: Well (p17) oil and water production curves of 104 models by exhaustive simulations, which cannot be applied in the field.

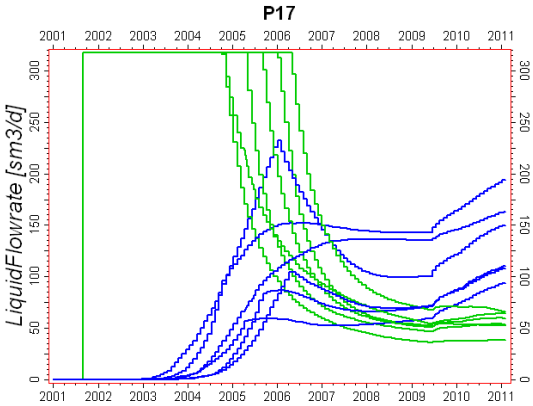


Figure 20: Well (p17) oil and water production curves of 6 representative models chosen by KKM.

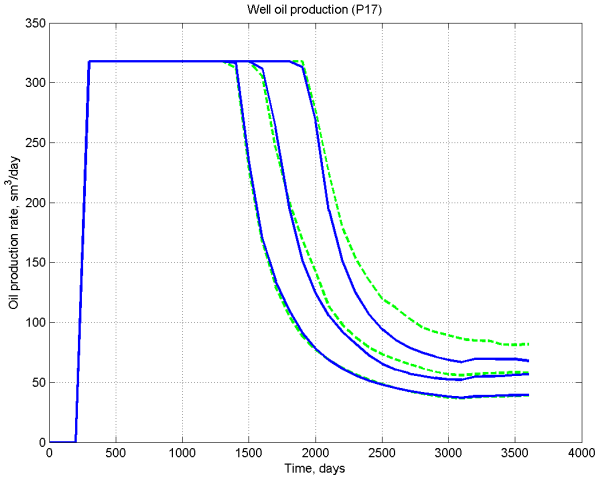


Figure 21: P10, P50, P90 of well (p17) oil production curves of 104 models (green dashed lines) and 6 representative models chosen by KKM (blue solid lines).

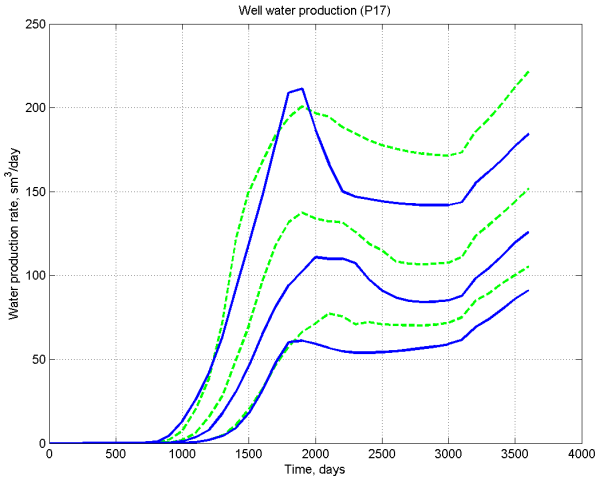


Figure 22: P10, P50, P90 of well (p17) water production curves of 104 models (green dashed lines) and 6 representative models chosen by KKM (blue solid lines).

5.2 Sensitivity analysis

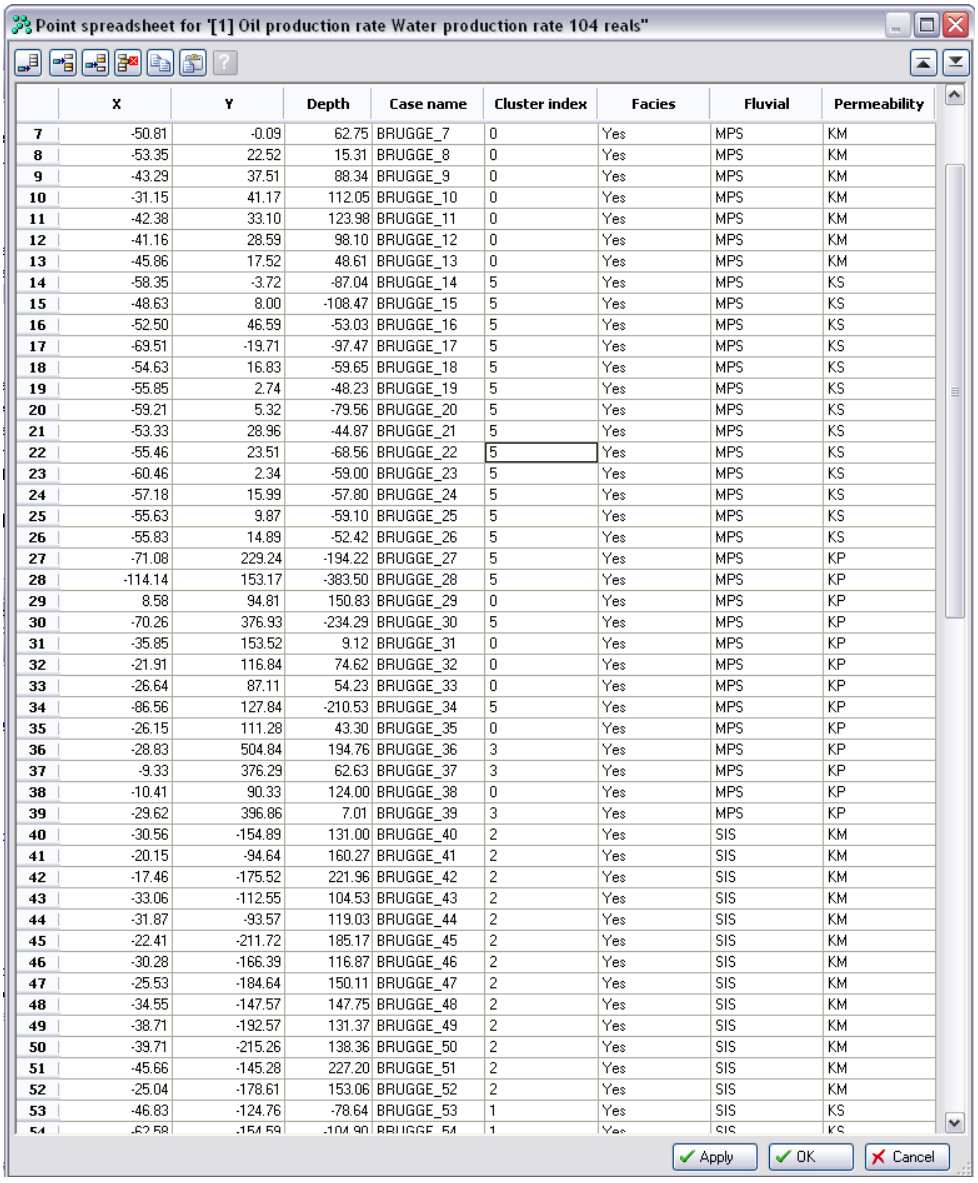
In this example, the 104 porosity and permeability models are generated by different techniques: facies-based or not, porosity by MPS or SIS, and permeability by single poroperm regression or poroperm regression per facies or coKriging on porosity. Hence, a possible objective of sensitivity analysis would be to determine which parameter is the most critical for future prediction of oil and water production or how influential the parameter is. This can also be achieved from the results of *Metrel* run.

In Petrel, those generation methods (YES or NO, MPS or SIS, and KS or KM or KP; see Table 1) can be added as a new `Attribute` to the `Pointset` generated by MDS or KKM. **Figure** 23 shows how those input parameters are introduced into the Petrel database and can be edited by the users. (Note that the current version of Ocean (version 2009.2) does not allow the users to access those input parameters from `Cases` but the new version of Ocean (version 2010.1, however not available at the time of plugin development) would allow the access. So with Ocean 2010.1 the input parameters can also be automatically displayed.) **Figure** 24 shows the input parameters of the 6 representative `Cases` selected by KKM of *Metrel*. Then, the user can display the metric space with the input parameters as in **Figures** 25 to 27.

Figure 25 shows the `Cases` on the left-hand side as indicated by `NO`, which means those are generated without considering facies information, while the `Cases` on the right-hand side are all `YES`. Likewise, the porosity generation method (MPS or SIS) divides the `Cases` horizontally. The `Cases` located at the upper side of map are generated by SIS, and the `Cases` in the lower side of map by MPS (Figure 26). More importantly, the `Cases` are clustered by themselves based on the permeability generation technique (KS or KM or KP) (Figure 27). Therefore, facies information and porosity generation method have a sensitivity to the future prediction oil and water production to some extent but the permeability generation technique is more important in prediction of future flow performance.

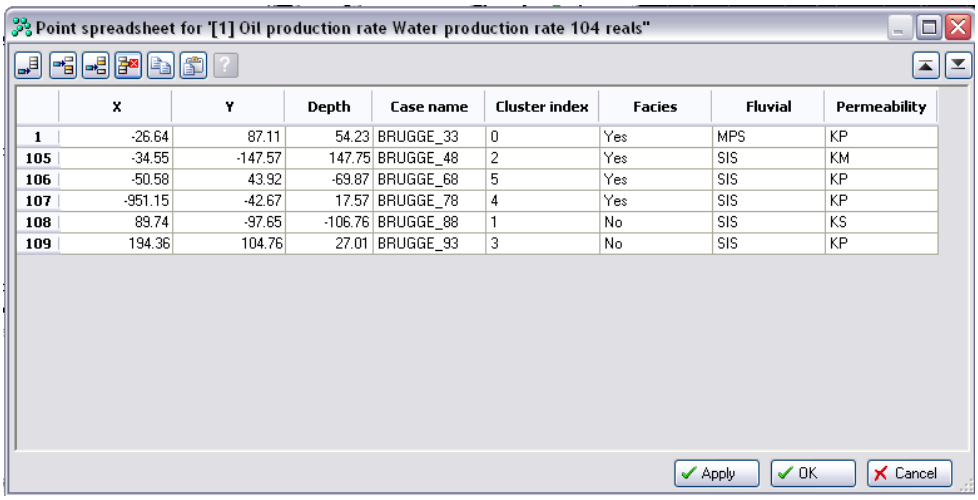
6 Summary

We have developed a petrel plug-in (*Metrel*) using Ocean development framework. *Metrel* enables core technologies of metric space modeling (MDS and KKM) in Petrel. *Metrel* allows us to analyze multiple models in 2D or 3D view of Petrel or other Petrel analysis functions. *Metrel* can choose a few representative models amongst a set of multiple models, which would help the efficient further analyses, such as calculating P10, P50, and P90 of prediction from reservoir flow simulations. *Metrel* helps to analyze the sensitivity of the input parameters or methods to the results interested. An example run of *Metrel* with the Brugge field-scale data set exhibits that 6 representative models chosen by *Metrel* and 6 full flow simulations are enough to assess the uncertainty and analyze the sensitivity.



	X	Y	Depth	Case name	Cluster index	Facies	Fluvial	Permeability
7	-50.81	-0.09	62.75	BRUGGE_7	0	Yes	MPS	KM
8	-53.35	22.52	15.31	BRUGGE_8	0	Yes	MPS	KM
9	-43.29	37.51	88.34	BRUGGE_9	0	Yes	MPS	KM
10	-31.15	41.17	112.05	BRUGGE_10	0	Yes	MPS	KM
11	-42.38	33.10	123.98	BRUGGE_11	0	Yes	MPS	KM
12	-41.16	28.59	98.10	BRUGGE_12	0	Yes	MPS	KM
13	-45.86	17.52	48.61	BRUGGE_13	0	Yes	MPS	KM
14	-58.35	-3.72	-87.04	BRUGGE_14	5	Yes	MPS	KS
15	-48.63	8.00	-108.47	BRUGGE_15	5	Yes	MPS	KS
16	-52.50	46.59	-53.03	BRUGGE_16	5	Yes	MPS	KS
17	-69.51	-19.71	-97.47	BRUGGE_17	5	Yes	MPS	KS
18	-54.63	16.83	-59.65	BRUGGE_18	5	Yes	MPS	KS
19	-55.85	2.74	-48.23	BRUGGE_19	5	Yes	MPS	KS
20	-59.21	5.32	-79.56	BRUGGE_20	5	Yes	MPS	KS
21	-53.33	28.96	-44.87	BRUGGE_21	5	Yes	MPS	KS
22	-55.46	23.51	-68.56	BRUGGE_22	5	Yes	MPS	KS
23	-60.46	2.34	-59.00	BRUGGE_23	5	Yes	MPS	KS
24	-57.18	15.99	-57.80	BRUGGE_24	5	Yes	MPS	KS
25	-55.63	9.87	-59.10	BRUGGE_25	5	Yes	MPS	KS
26	-55.83	14.89	-52.42	BRUGGE_26	5	Yes	MPS	KS
27	-71.08	229.24	-194.22	BRUGGE_27	5	Yes	MPS	KP
28	-114.14	153.17	-383.50	BRUGGE_28	5	Yes	MPS	KP
29	8.58	94.81	150.83	BRUGGE_29	0	Yes	MPS	KP
30	-70.26	376.93	-234.29	BRUGGE_30	5	Yes	MPS	KP
31	-35.85	153.52	9.12	BRUGGE_31	0	Yes	MPS	KP
32	-21.91	116.84	74.62	BRUGGE_32	0	Yes	MPS	KP
33	-26.64	87.11	54.23	BRUGGE_33	0	Yes	MPS	KP
34	-86.56	127.84	-210.53	BRUGGE_34	5	Yes	MPS	KP
35	-26.15	111.28	43.30	BRUGGE_35	0	Yes	MPS	KP
36	-28.83	504.84	194.76	BRUGGE_36	3	Yes	MPS	KP
37	-9.33	376.29	62.63	BRUGGE_37	3	Yes	MPS	KP
38	-10.41	90.33	124.00	BRUGGE_38	0	Yes	MPS	KP
39	-29.62	396.86	7.01	BRUGGE_39	3	Yes	MPS	KP
40	-30.56	-154.89	131.00	BRUGGE_40	2	Yes	SIS	KM
41	-20.15	-94.64	160.27	BRUGGE_41	2	Yes	SIS	KM
42	-17.46	-175.52	221.96	BRUGGE_42	2	Yes	SIS	KM
43	-33.06	-112.55	104.53	BRUGGE_43	2	Yes	SIS	KM
44	-31.87	-93.57	119.03	BRUGGE_44	2	Yes	SIS	KM
45	-22.41	-211.72	185.17	BRUGGE_45	2	Yes	SIS	KM
46	-30.28	-166.39	116.87	BRUGGE_46	2	Yes	SIS	KM
47	-25.53	-184.64	150.11	BRUGGE_47	2	Yes	SIS	KM
48	-34.55	-147.57	147.75	BRUGGE_48	2	Yes	SIS	KM
49	-38.71	-192.57	131.37	BRUGGE_49	2	Yes	SIS	KM
50	-39.71	-215.26	138.36	BRUGGE_50	2	Yes	SIS	KM
51	-45.66	-145.28	227.20	BRUGGE_51	2	Yes	SIS	KM
52	-25.04	-178.61	153.06	BRUGGE_52	2	Yes	SIS	KM
53	-46.83	-124.76	-78.64	BRUGGE_53	1	Yes	SIS	KS
54	-62.58	-154.59	-104.90	BRUGGE_54	1	Yes	SIS	KS

Figure 23: Checking the type of porosity and permeability model generation method in the spreadsheet of `Pointset`. **x**, **y**, **Depth** represent the location of each model realization in the space projected by MDS. The case name, cluster index, and generation methods of permeability and porosity are listed in the table.



	X	Y	Depth	Case name	Cluster index	Facies	Fluvial	Permeability
1	-26.64	87.11	54.23	BRUGGE_33	0	Yes	MPS	KP
105	-34.55	-147.57	147.75	BRUGGE_48	2	Yes	SIS	KM
106	-50.58	43.92	-69.87	BRUGGE_68	5	Yes	SIS	KP
107	-951.15	-42.67	17.57	BRUGGE_78	4	Yes	SIS	KP
108	89.74	-97.65	-106.76	BRUGGE_88	1	No	SIS	KS
109	194.36	104.76	27.01	BRUGGE_93	3	No	SIS	KP

Figure 24: Checking the type of porosity and permeability model generation method for 6 representative models only in the spreadsheet of `Pointset`.

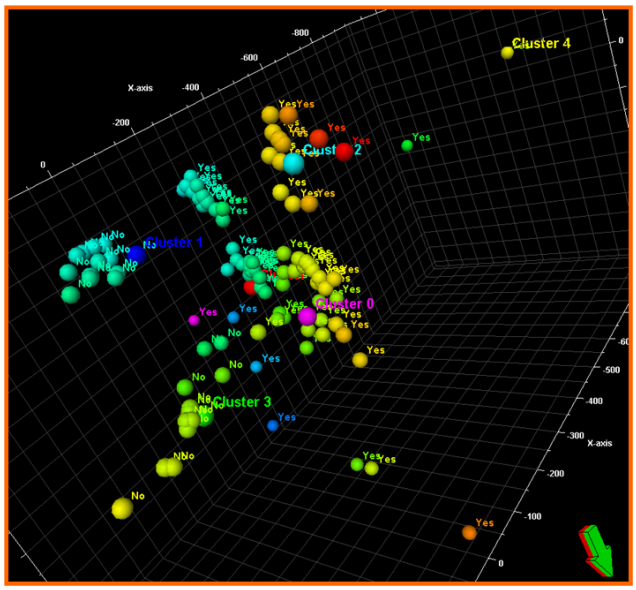


Figure 25: Projection of metric space with displaying the usage of facies information for the generation of porosity model (YES: facies considered; NO: facies ignored).

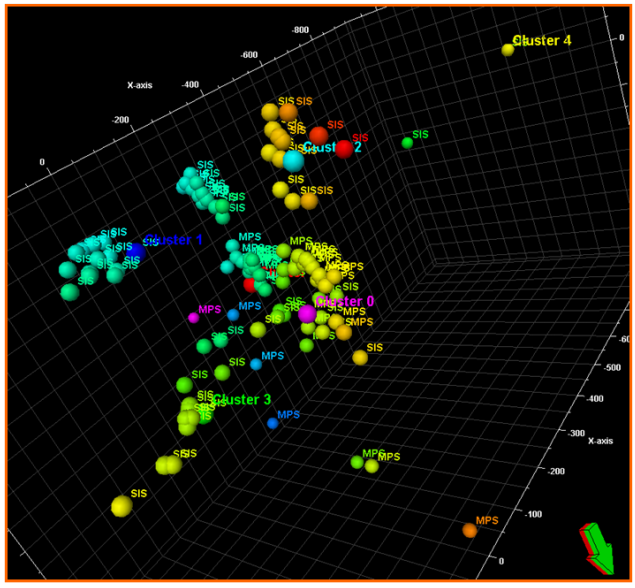


Figure 26: Projection of metric space with displaying the type of simulation method to generate porosity model (MPS: multiple-point geostatistical method; SIS: sequential indicator simulation).

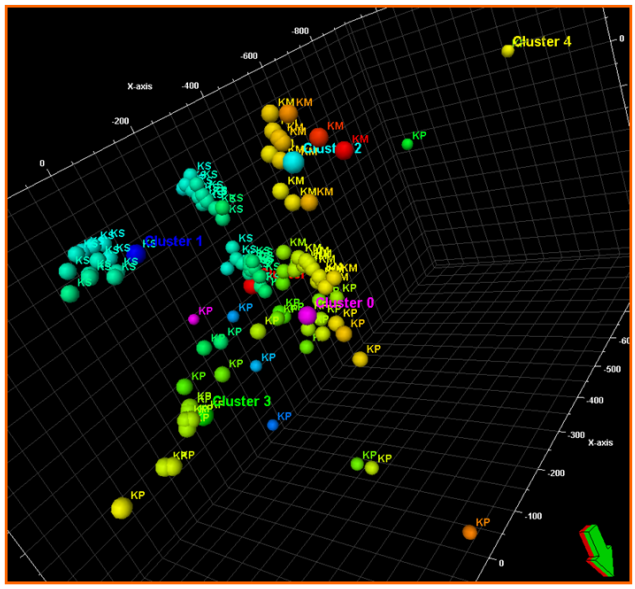


Figure 27: Projection of metric space with displaying the type of method to generate permeability model (KS: single poroperm regression; KP: poroperm regression per facies; KM: coKriging on porosity).

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