



# Application of geostatistics in facies modeling of Reservoir-E, “Hatch Field” offshore Niger Delta Basin, Nigeria

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## Abstract

Lithofacies are very influential in the transmission of fluids within the reservoir. The objective of this study is to use geostatistical techniques of sequential indicator simulation (SISIM) a variogram-based algorithm (VBA), single normal equation simulation (SNESIM) and filter-based simulation (FILTERSIM) of multiple-point geostatistics (MPG) in developing realistic facies model. A reservoir sand package “Reservoir-E” was correlated across five wells in the field. Synthetic seismogram of well HT-1 was generated, and Horizon E picked on seismic section to produce time and depth surfaces of the reservoir. The conditional if statement to generate lithofacies was applied on the extracted volume of shale data within “Reservoir-E,” and the data were inputted in Stanford Geostatistics Modeling Software for facies modeling. The first realization from SISIM was converted to a training image used for MPG. Visually, the MPG algorithm of SNESIM and FILTERSIM produced realization that is substantially better and more realistic than the VBA of SISIM. The magnitude of correlation coefficients of algorithms was carried out using the mean and variance of realizations, the results revealed mean and variance magnitude of correlation coefficients between SISIM and SNESIM with 0.8933 and 0.9637, SISIM and FILTERSIM with 0.8639 and 0.5097 and SNESIM and FILTERSIM with 0.9717 and 0.8603. The results revealed a very good mean and variance magnitude of correlation coefficients between SISIM and SNESIM; good between SISIM and FILTERSIM; and very good mean and variance correlation coefficient between SNESIM and FILTERSIM. The qualitative interpretation of the model built with SNESIM and FILTERSIM clearly detects lithofacies in the field which makes them a better algorithm in facies modeling.

**Keywords** Filter-based simulation · Sequential indicator simulation · Single normal equation simulation · Training image

## Introduction

Facies model is an important part in reservoir characterization (Aliakbar et al. 2016). The connectivity of facies is very influential in the flow of fluids. As the quest for producing reliable facies models in reservoir characterization increases, several facies models have been developed by different authors in reservoir characterization, yet only a few have explicitly characterized these reservoirs in terms of their heterogeneity. Over the past years, different geostatistical approaches have been invented to achieve this goal. Matheron (1973) introduced the basis on an algorithm that is known today as Gaussian simulation. It was after the mid-1980 that several efforts started on the algorithm that

became the foundation of geostatistical modeling, indicator simulation (Journel and Alabert 1989), object-based modeling (Haldorsen and Damsleth 1990). Despite having some shortcomings, variogram-based and object-based algorithms became popular in facies modeling over the years after their inventions (Hashemi et al. 2014). The popular variogram-based methods are called two-point statistics (Liu et al. 2004; Zhang 2008b) or traditional two-point geostatistics (Deutsch and Journel 1998).

Since reservoir properties are tied to facies and since facies are tied to fluid flow, it will be more appropriate to develop a facies model for the middle Miocene Reservoir-E in the Hatch Field before distributing properties; it is based on this note that the researcher is applying sequential indicator simulation (SISIM), single normal equation simulation (SNESIM) and filter-based simulation (FILTERSIM) methods of two-point statistics and multiple-point geostatistics (MPG) in the Hatch Field offshore Niger Delta. The essence of the study is to produce

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a realistic facies model of the field that will be condition to reservoir property distribution. Since variogram only measures linear continuity, variogram algorithms such as SISIM cannot capture curvilinear structures (Hashemi et al. 2014). This is the most critical setback associated with variogram-based algorithm. It is based on this limitation of variogram-based algorithms that the SNESIM and FILTERSIM algorithm methods of MPG will be incorporated in the work to actually capture these curvilinear structures. The MPG algorithms determine geological uncertainty, template scanning and nonstationarity (Eskandaridavand and Srinivasan 2010) in geological scenarios.

## Geology of the study area

The Hatch Field is an oilfield in Nigeria. It was located in License block OPL XXX offshore Niger Delta (Fig. 1). The field covers approximately 154.24 km<sup>2</sup> in an average water depth of 1000 m. The field was discovered in 1996, with government approval for its development given in 2002. The Niger Delta clastic wedge is believed to be formed along a failed arm of the triple junction that originally evolved during the breakup of South American and African plates in the late Jurassic ((Burke et al. 1972) and (Whiteman 1982)). The Niger Delta is a wave and tidal dominated delta (Weber and Daukoru 1975; Doust and Omatsola 1990). The Niger Delta is divided into three formations, namely Benin, Agbada and Akata Formations (Fig. 2), representing prograding

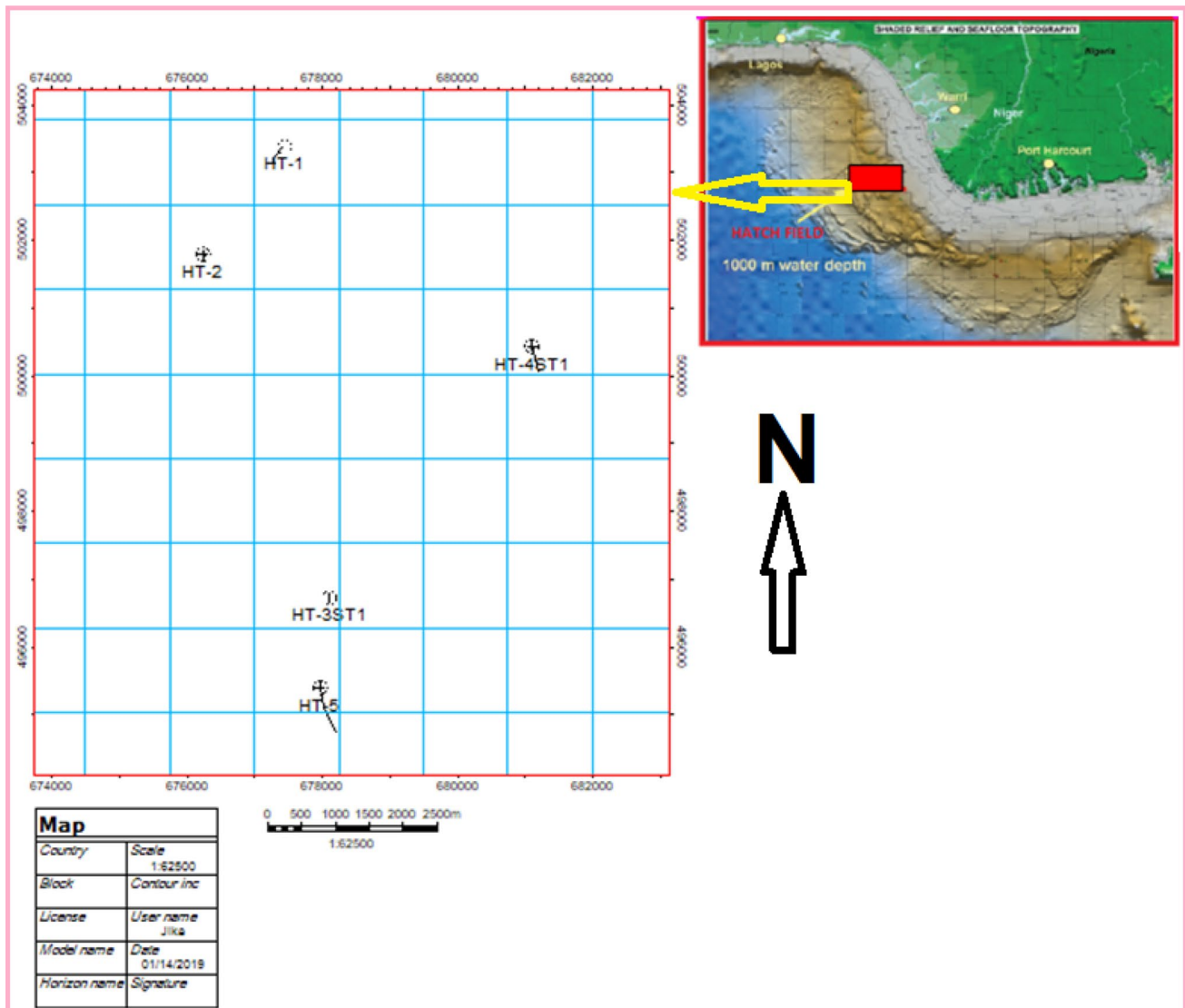
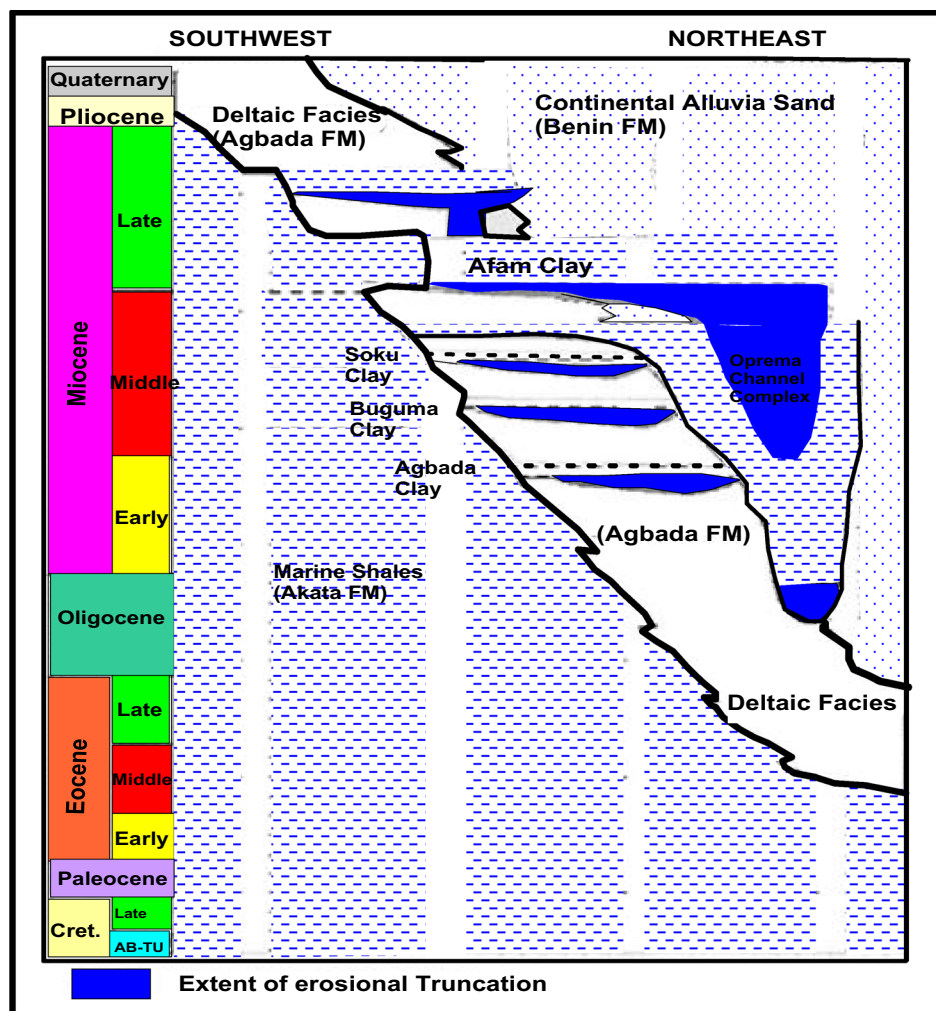


Fig. 1 Map showing location of Hatch Field offshore Niger Delta

**Fig. 2** Stratigraphic column showing formations in the Niger Delta (Modified from Owoyemi 2004)



depositional facies that are distinguished by most authors on the basis of sand/shale ratios. The type sections of these formations are described in (Short and Stauble 1967), and the summary is given in numerous papers (Avbovbo 1978; Doust and Omatsola 1990; Kulke 1995).

**Method of study**

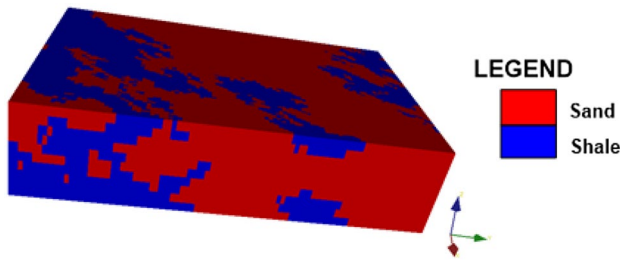
The data used for this study were constrained to well log data for five wells (5) with their log suits, deviation data, check shot, core data and seismic data. The seismic cube is rectangular with inline range of 2650–3809 and crossline range of 2520–3370. A reservoir package named Reservoir-E was delineated and correlated across all the wells in the field. A seismic-to-well tie was performed on the seismic section, and the Reservoir-E top Horizon picked to show the reservoir package on a seismic section. The volume of shale was calculated across all the wells, and conditional if statement was used to calculate the facies in all the wells. In the formulation of the facies model since the plot of brine permeability versus core porosity classified

the environment of deposition into sand and shale the lithofacies were also classified into sand and shale. The conditional if statement used is Facie is equal to if volume of shale is less than 0.05, 0.3, 0.1, 0.4 and 0.2 assign sand else shale for HT-1, HT-2, HT-4ST1, HT-3ST1 and HT-5. A simulation grid of dimension 100\*100\*10 was designed to meet the required resolution need of simulation. The first realization of SISIM was converted to a training image that was used for SNESIM and FILTERSIM using Stanford Geostatistical Modeling Software. Facies models were developed from the computed volume of shale using Eqs. 1 and 2 (Asquith and Krygowski 2004).

$$I_{GR} = \frac{GR_{LOG} - GR_{Min}}{GR_{Max} - GR_{Min}} \tag{1}$$

$$V_{Sh} = \frac{I_{GR}}{3 - 2 * I_{GR}} \tag{2}$$

where  $I_{GR}$  = gamma ray index;  $GR_{log}$  = gamma ray reading from log;  $GR_{min}$  = minimum gamma ray;  $GR_{max}$  = maximum gamma ray; and  $V_{sh}$  = volume of shale.



**Fig. 3** Training image from first realization of SISIM for Reservoir-E in Hatch Field

The magnitude of correlation coefficient (Zayed 2017) between realization of two different algorithms *A* and *E* is given by

$$|\gamma| = \left| \frac{\sum_m \sum_n (A_{mn} - \bar{A})(E_{mn} - \bar{E})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (E_{mn} - \bar{E})^2)}} \right| \quad (3)$$

where  $\bar{A} = \text{mean } 2(A)$ , and  $\bar{E} = \text{mean } 2(E)$ .

**Sequential indicator simulation (SISIM)**

The work flow for SISIM involves picking a pixel where a lithology type is unknown, identifies a neighboring pixel with known lithology type, assigns weights to the neighboring points, constructs a local cumulative distribution function (CDF) for the lithology type probability from the neighboring lithology type, extracts from the CDF of single

lithology type to occupy the empty pixel point, proceeding to step one and repeating the process until the entire simulation grid is simulated (Zhang 2008a; Yu and Li 2012). The SISIM is not memory demanding like the multiple-point geostatistics methods and takes less time for simulation as compared to multiple-point geostatistics methods (Manchuk et al. 2011). The SISIM generates models that the highs are maximally disconnected from the lows, thus producing maximum entropy in their generated model (Caers and Zhang 2004).

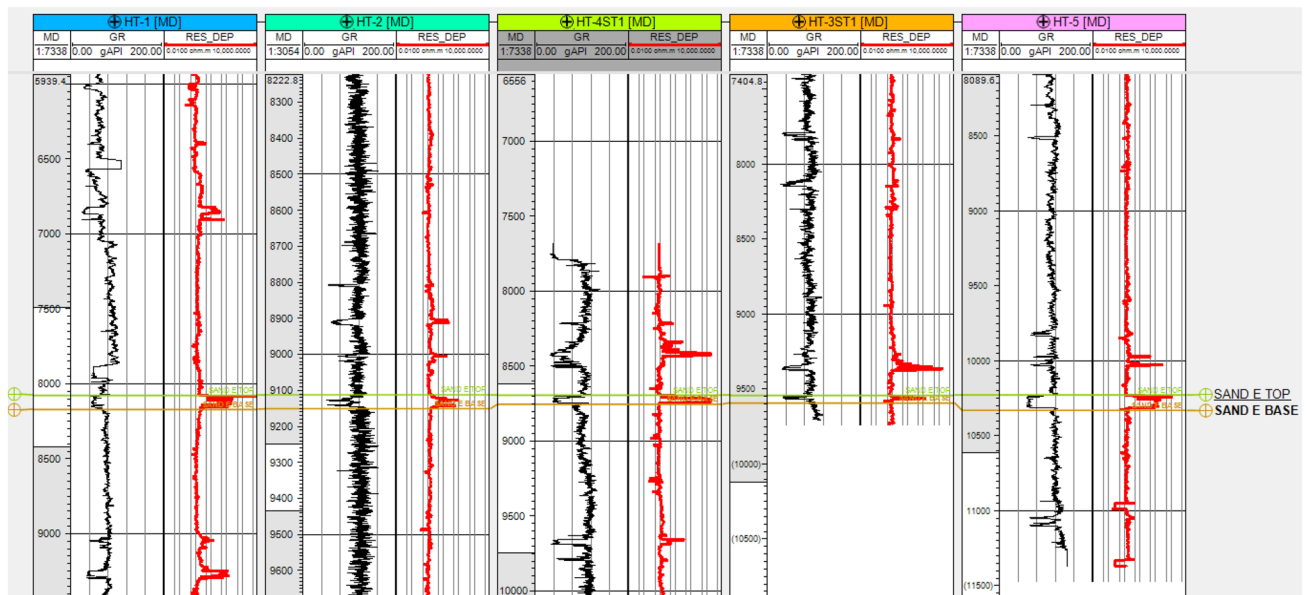
**Single normal equation simulation (SNESIM)**

The single normal equation simulation algorithm (SNESIM) developed by Strebelle (2000, 2002) is a multiple-point geostatistics method, from the use of training images. It is an efficient pixel-based sequential simulation algorithm. The training image exported can be conditioned to hard or soft data or both.

For every location  $K = (x, y)$  along a random path, spatial configuration of the local data values termed data event is recorded. Replicate that matches this event is done by scanning the training image. The replicates corresponding to the central node values are used to calculate the

**Table 1** Top and base of Reservoir-E in all the wells in Hatch Field

Well name	HT-1	HT-2	HT-3ST1	HT-4ST1	HT-5
Top (ft)	8076.39	9112.08	9541.75	8692.93	10,226.50
Base (ft)	8170.55	9150.50	9593.18	8754.08	10,329.50



**Fig. 4** Reservoir-E correlation across wells in Hatch Field



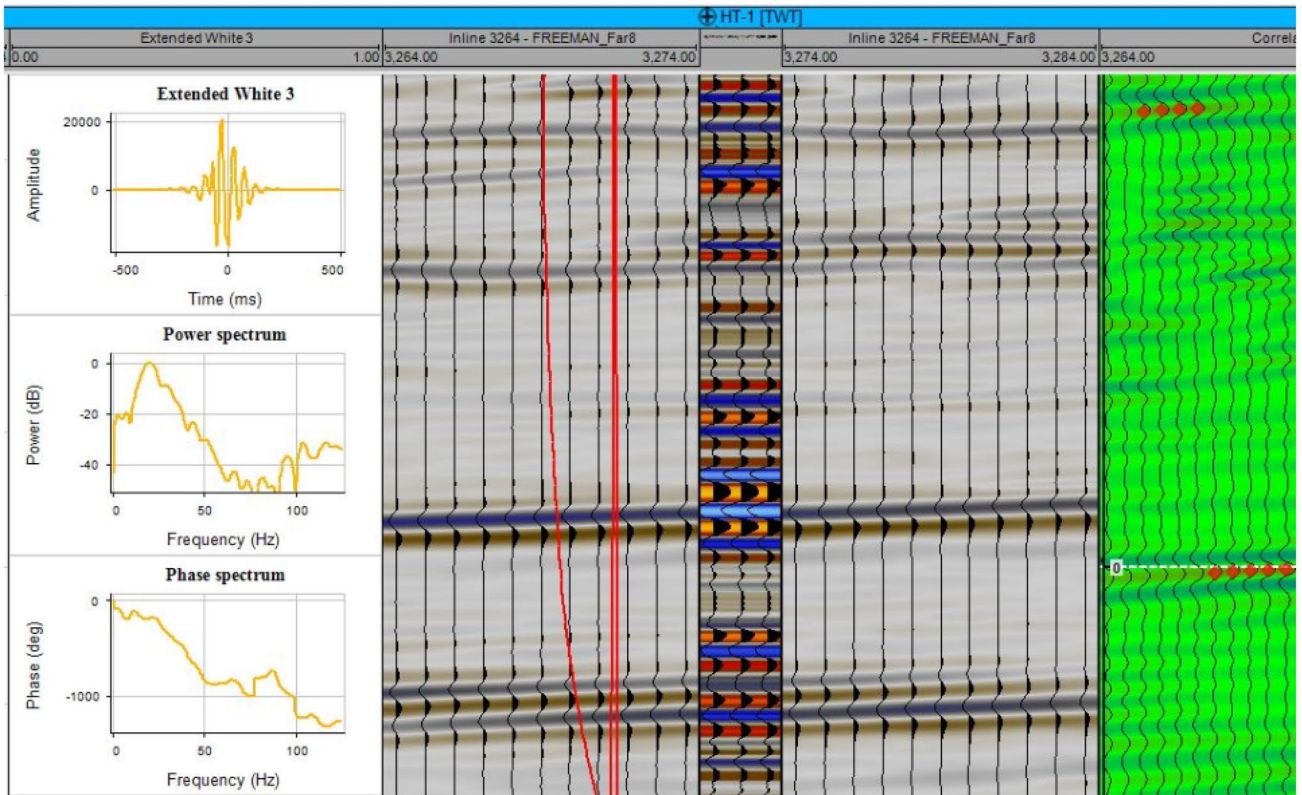


Fig. 5 Seismic-to-well tie using checkshot of HT-1 Hatch Field

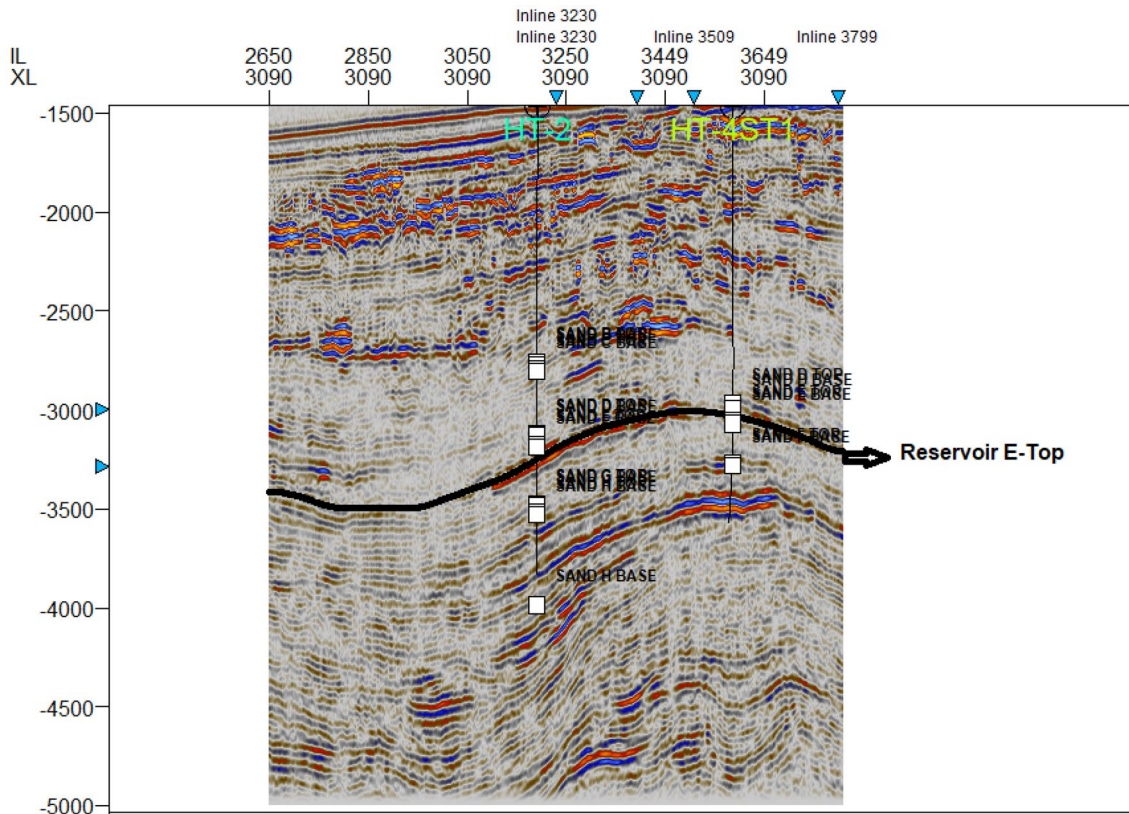


Fig. 6 Reservoir-E top picked on a 3D seismic volume of Hatch Field

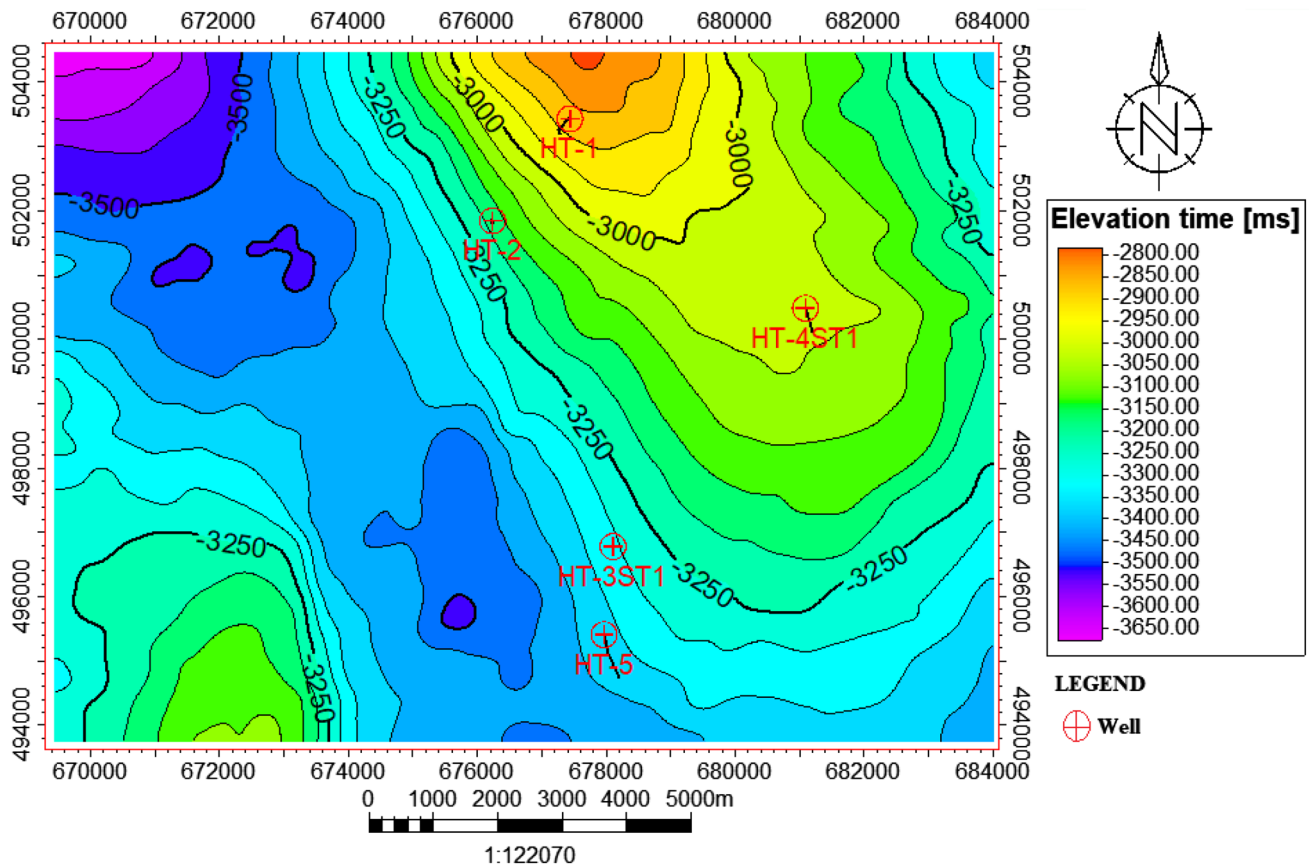


Fig. 7 Horizon E time surface map for Hatch Field

conditional probability of the central value, given the data event. The implementation of SNESIM requires significant CPU efficiency by performing this scanning before simulation and saving the conditional probabilities in a dynamic data structure that is referred to as search tree. The method is used successfully in facies model (Park et al. 2013). The issue of memory is one among the limitations of SNESIM algorithm. In complex 3D, multi-facies cases, where large training images with strong data connectivity, the RAM demand may exceed the current hardware system, thus preventing the algorithm from running. This limitation can be overcome eventually by the continuously increasing computer memory (Strebelle and Cavelius 2014).

### Filter-based simulation (FILTERSIM)

FILTERSIM is an MPS algorithm called filter-based simulation (Zhang et al. 2006), the algorithm was proposed to solve the challenges posed by SNESIM which handles only categorical variable in simulation, and it is memory demanding when the training image is large with a large variety of different pattern. The FILTERSIM algorithm

is far much less memory demanding, and it can handle both categorical and continuous variables during simulation. FILTERSIM uses linear filters to classify training patterns in a filter score space of reduced dimensions. The algorithm reduces pattern dimensions by applying special designed filters and lowering the dimensional space of the patterns. Coded patterns are then clustered, and a prototype is chosen for each grid node. This speeds up the search process and reduces the run time of the algorithm (Wu et al. 2008).

The proposed FILTERSIM algorithm is actualized in three major steps (Wu et al. 2008): filter score calculation, pattern classification and pattern simulation. The process works by applying a set of filters to the template data obtained from scanning the training image. This produces a set of filter score maps, with each training pattern represented by a vector of score values. This is done to actually reduce the pattern data dimension from the template size to a smaller number of filter scores. The similar training patterns are clustered into a so-called prototype class, each of this class is being identified by a point-wise average pattern. In the course of sequential simulation process, the conditioning data event is retrieved with a search template of same size

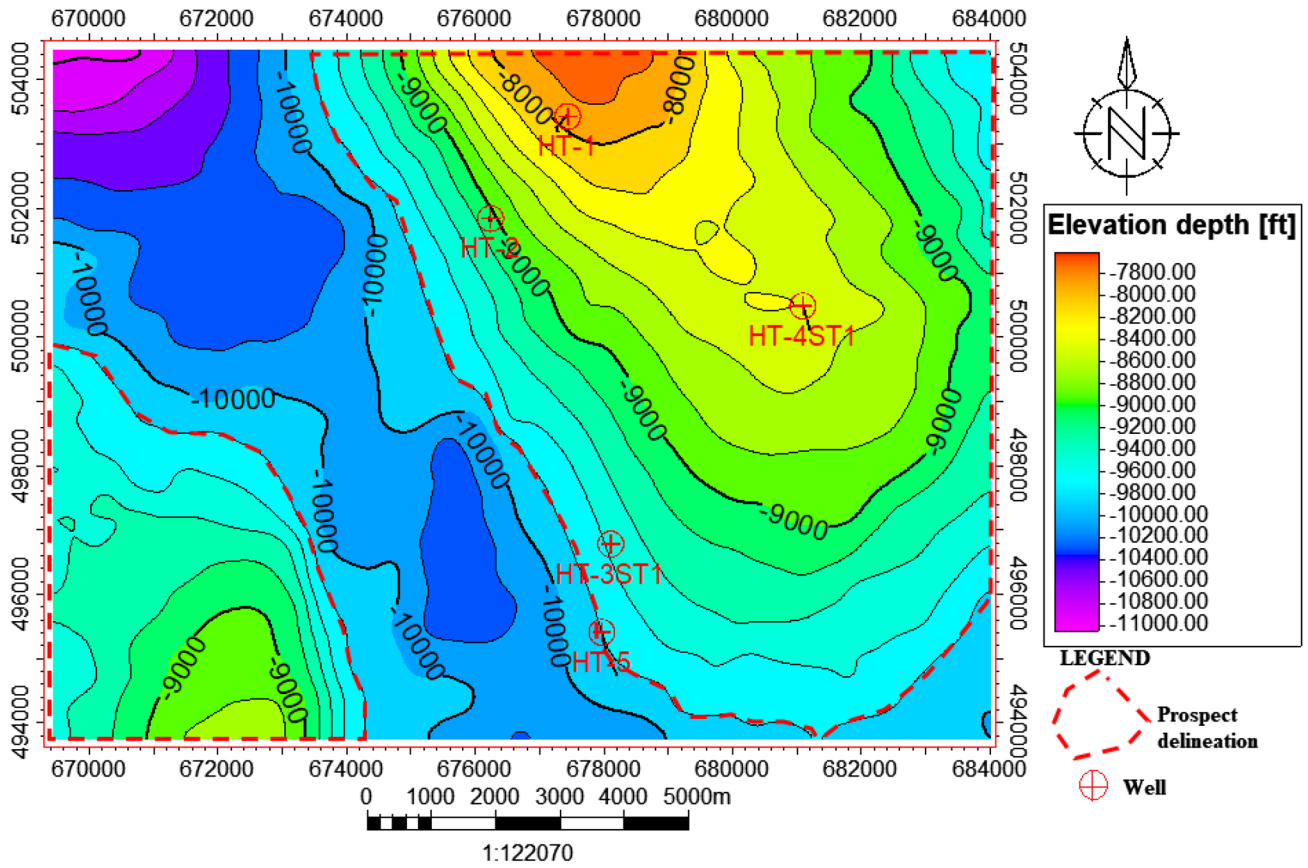


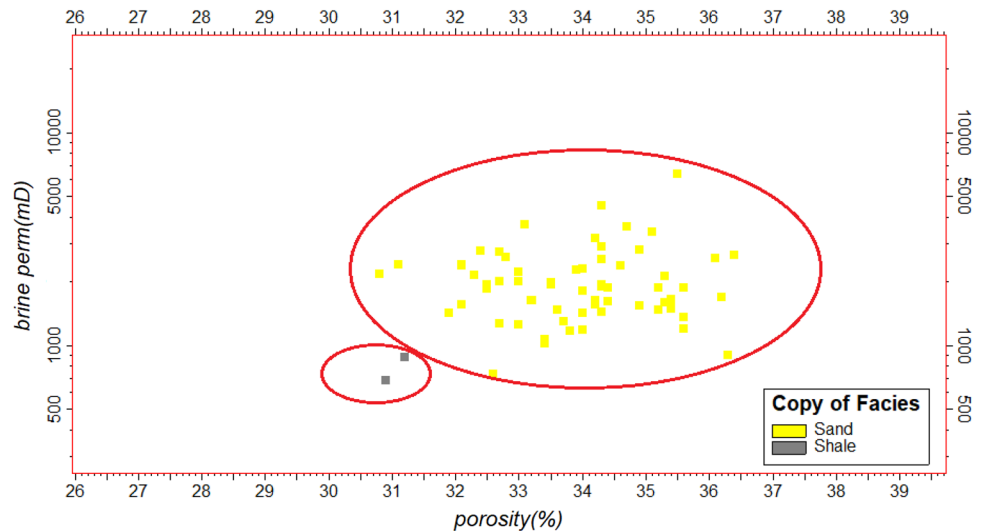
Fig. 8 Horizon E depth surface map for Hatch Field

like the one used for scanning the training image. The prototype class similar to the conditioning data event is selected using some distance function. A training pattern sampled from that pattern class and pasted on the simulation grid. This simulation is actually based on pattern similarity.

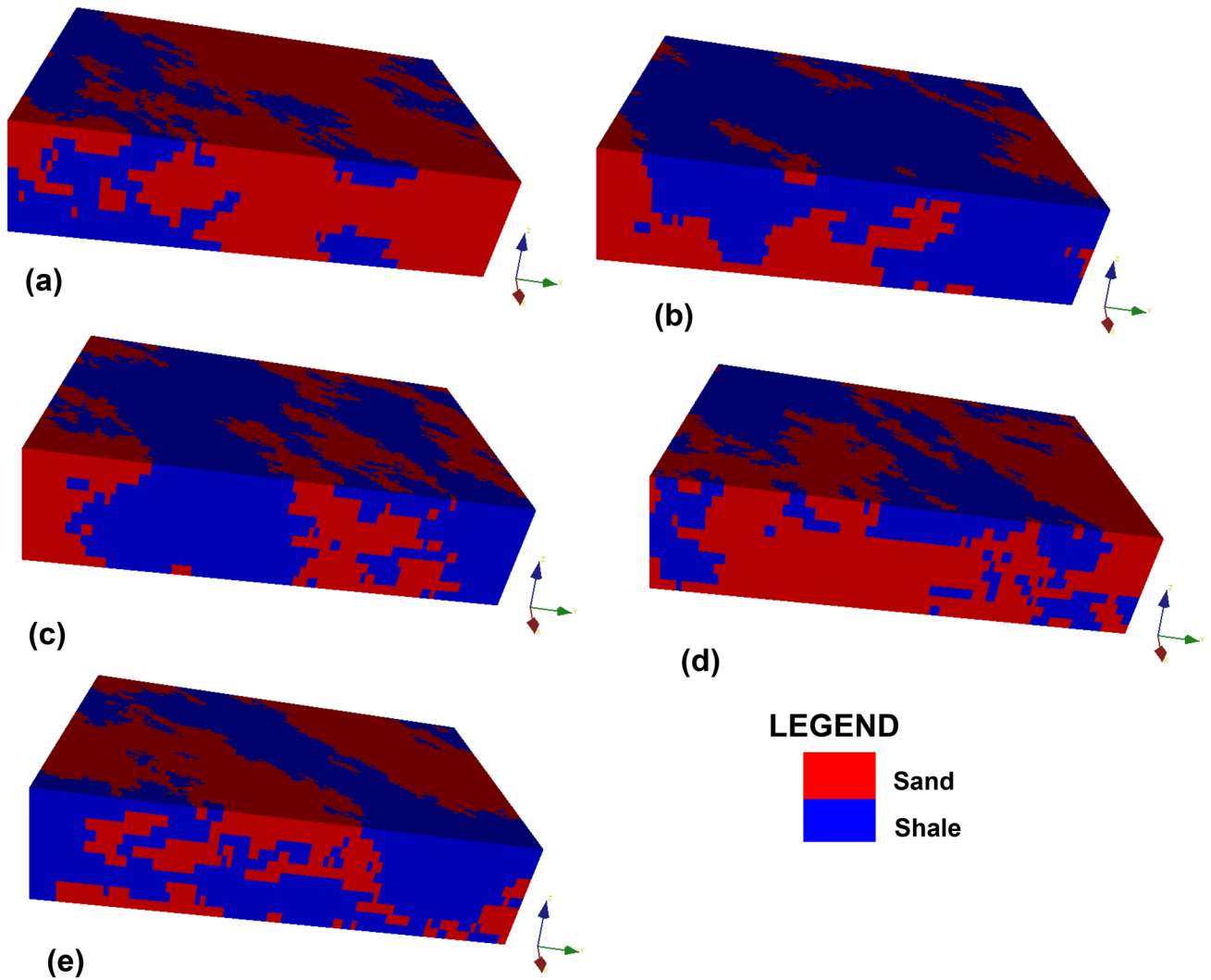
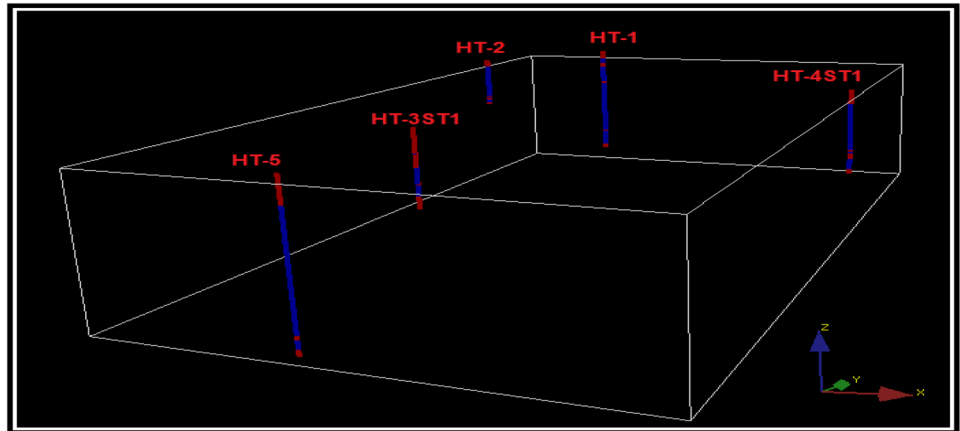
### Training image

Construction of 3D training image is challenging since most geological pattern is either in 1D or 2D; nevertheless, a code in MATLAB was used in the conversion of our training image from jpeg format to SGeMS format that will be

Fig. 9 Cross-plot of depositional facies in Hatch Field



**Fig. 10** Upscale facies for Reservoir-E for the five wells in Hatch field



**Fig. 11** SISIM realization for Reservoir-E Hatch Field Niger Delta



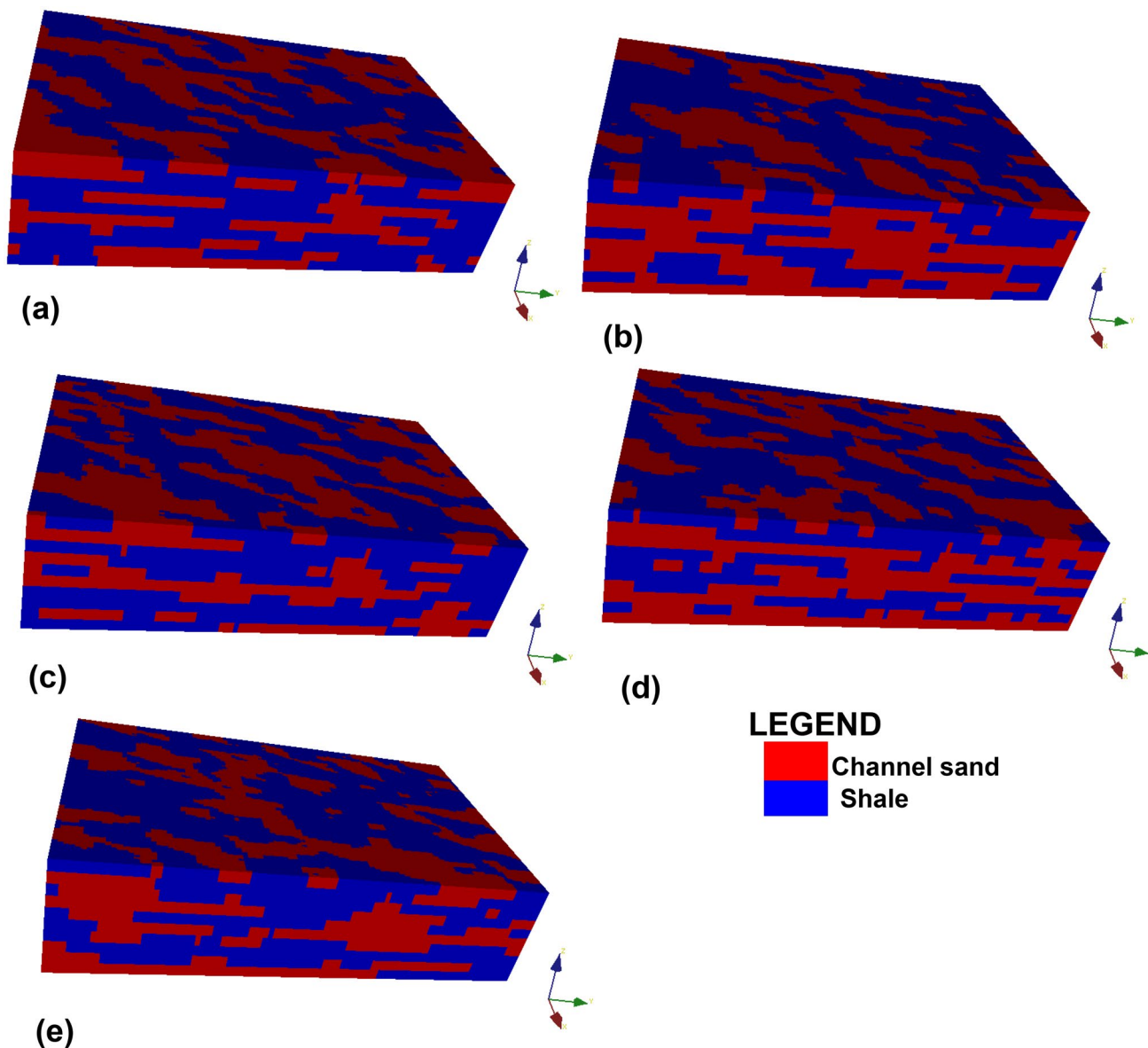


Fig. 12 SNESIM realization for Reservoir-E Hatch Field Niger Delta

acceptable by the Stanford Geostatistical Modeling software in our modeling. In this study, the first realization of SISIM was converted from jpg format to SGeMS format and was used as a training image (Fig. 3).

**Hard data conditioning**

Primary data are direct measurement of targeted reservoir properties; for example, well log data are typical example of a primary data sets. The training image used in this study was conditioned to these hard data using Stanford Geostatistical Modeling Software.

**Results and discussion**

**Well correlation**

The five wells HT-1, HT-2, HT-3ST1, HT-4ST1 and HT-5 were loaded in Petrel environment displaying measured depth, gamma ray (black) and resistivity (red) logs, respectively. The gamma ray log was used for our lithofacies, and the resistivity log was used to identify the presence of hydrocarbons to confirm it as a reservoir. Reservoir-E was delineated and correlated across all the wells (Fig. 4) to enable us produce a realistic facies model of the Hatch Field. The Reservoir-E tops and base in all the wells are presented in Table 1.

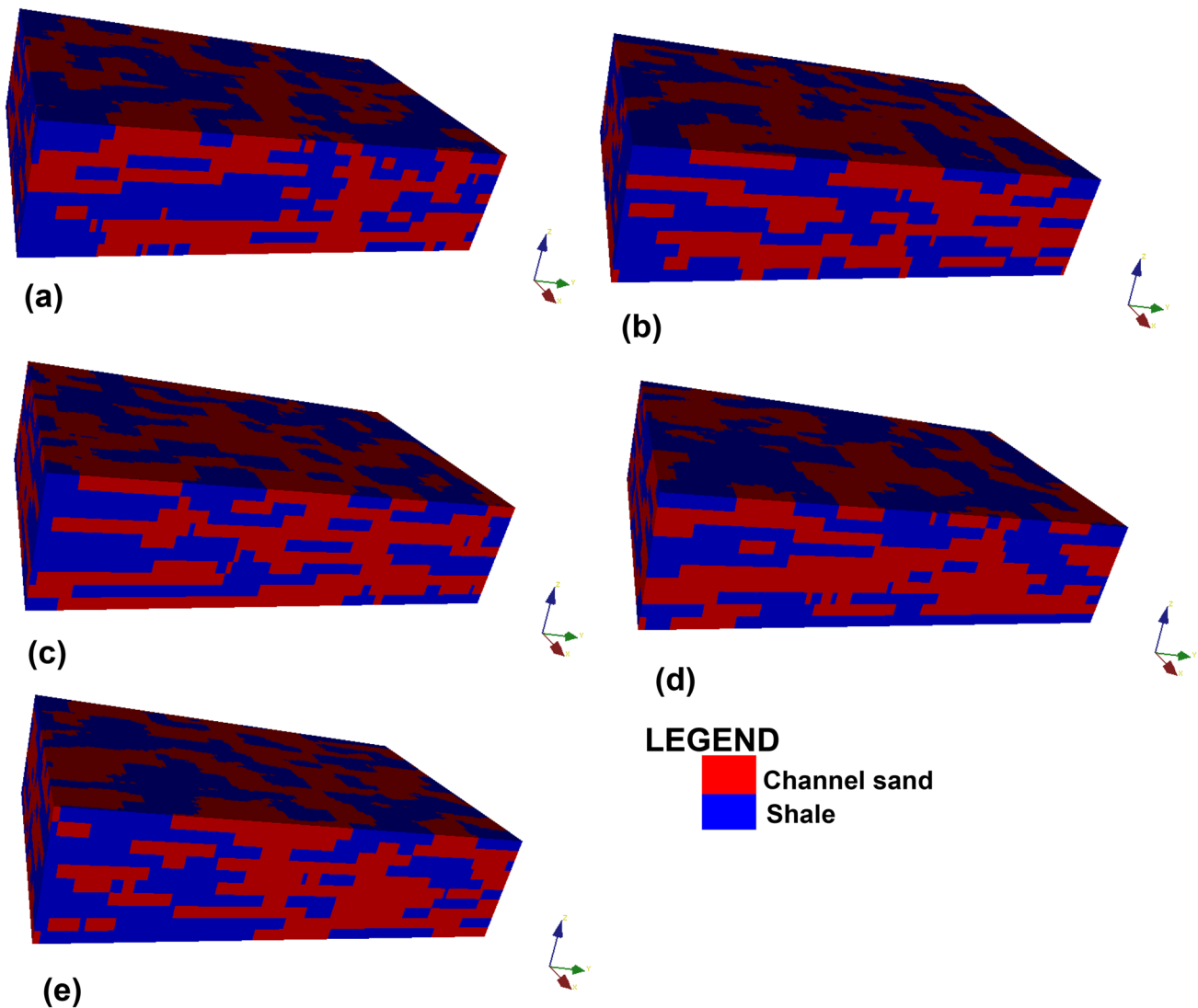


Fig. 13 FILTERSIM realization for Reservoir-E Hatch Field Niger Delta

### Seismic horizon interpretation

A seismic-to-well tie was generated (Fig. 5) with a good tie and Horizon E picked as Reservoir-E top (Fig. 6). The horizons picked were used to create time and depth surfaces for Reservoir-E (Figs. 7, 8). The surface map revealed a ridge like structure (anticline) in the North-east and South-west that is separated by a syncline that trends North-west to South-east that divides the anticlinal structures (Fig. 8). The anticlinal structures are areas of interest for hydrocarbon exploitation.

### Volume of shale analysis

The plot of brine permeability versus core porosity reveals two facies in the depositional environment (Fig. 9). The areas with lower permeability values are classified as shale,

while those with high permeability are classified as sand. The plot reveals that the reservoir is dominated by sand facies with smaller fractions of shale. This was the basis for our interpretation of classifying the lithofacies into sand and shale.

The volume of shale calculated gave a proportion of sand to shale as 0.7232:0.2768. The result clearly shows that Reservoir-E is composed of 72.32% of sand and 27.68% of shale. These percentages reaffirm Reservoir-E as a potential reservoir in Hatch Field Niger Delta.

### SISIM, SNESIM and FILTERSIM algorithm interpretations

The data loaded in Stanford Geostatistics Modeling Software were up-scaled (Fig. 10), and the facies properties

**Table 2** Mean and variance realization statistics for SISIM algorithm

SISIM algorithm statistics	Realization 000	Realization 001	Realization 002	Realization 003	Realization 004
Mean	0.28999	0.56274	0.56501	0.23354	0.36771
Variance	0.205898	0.246066	0.245776	0.179001	0.232502

**Table 3** Mean and variance realization statistics for SNESIM algorithm

SNESIM algorithm statistics	Realization 000	Realization 001	Realization 002	Realization 003	Realization 004
Mean	0.55366	0.52457	0.54341	0.49417	0.53387
Variance	0.247123	0.249399	0.248118	0.249969	0.248855

**Table 4** Mean and variance realization statistics for FILTERSIM algorithm

FILTERSIM algorithm statistics	Realization 000	Realization 001	Realization 002	Realization 003	Realization 004
Mean	0.49685	0.5334	0.48363	0.49358	0.47783
Variance	0.249993	0.248887	0.249735	0.249961	0.249511

**Table 5** Variance magnitude of correlation coefficient between SISIM and SNESIM, SISIM and FILTERSIM, and SNESIM and FILTERSIM

Realization	SISIM	SNESIM	SISIM	FILTERSIM	SNESIM	FILTERSIM
0	0.205898	0.247123	0.205898	0.249993	0.247123	0.249993
1	0.246066	0.249399	0.246066	0.248887	0.249399	0.248887
2	0.245776	0.248118	0.245776	0.249735	0.248118	0.249735
3	0.179001	0.249969	0.179001	0.249961	0.249969	0.249961
4	0.232502	0.248855	0.232502	0.249511	0.248855	0.249511
	Corrcoef(SISIM, SNESIM) =0.9637		Corrcoef(SISIM, FILTERSIM) =0.5097		Corrcoef(SNESIM, FILTERSIM) =0.8603	

distributed using SISIM, SNESIM and FILTERSIM. The SISIM realization revealed poor connectivity in the lithofacies distribution as compared to SNESIM and FILTERSIM (Fig. 11a–e). Qualitatively, the visual interpretation of the MPG algorithm of SNESIM and FILTERSIM produces realizations that are distinctly better than the popular variogram-based model (two-point statistics) ((Fig. 12a–e) and (Fig. 13a–e)). The five realizations for SNESIM and FILTERSIM clearly show good connectivity in lithofacies distribution within Reservoir-E of the Hatch Field. The mean and variance realization of the algorithms are presented in Tables 2, 3 and 4. The magnitude of correlation coefficient of algorithms was calculated using variance and mean of their realization as shown in Tables 5 and 6. The magnitude of correlation coefficient between SISIM and SNESIM

yielded a value of 0.9637 for mean and 0.8933 for variance, 0.5097 and 0.8639 for SISIM and FILTERSIM, and 0.8603 and 0.9717 for SNESIM and FILTERSIM.

## Conclusion

The study shows that Reservoir-E is characterized by channel sand with the presence of shale as seen from the realization of SNESIM and FILTERSIM. These sands will allow transmission of fluid from one point to another. The SNESIM and FILTERSIM algorithm show good continuity in lithofacies distribution when compared to the SISIM algorithm which considers X and Y direction neglecting the Z direction. MPG simulations produce explicit facies models

**Table 6** Mean magnitude of correlation coefficient between SISIM and SNESIM, SISIM and FILTERSIM, and SNESIM and FILTERSIM

Realization	SISIM	SNESIM	SISIM	FILTERSIM	SNESIM	FILTERSIM
0	0.28999	0.55366	0.28999	0.49685	0.55366	0.49685
1	0.56274	0.52457	0.56274	0.5334	0.52457	0.5334
2	0.56501	0.54341	0.56501	0.48363	0.54341	0.48363
3	0.23354	0.49417	0.23354	0.49358	0.49417	0.49358
4	0.36771	0.53387	0.36771	0.47783	0.53387	0.47783
	Corrcoef(SISIM, SNESIM) =0.8933		Corrcoef(SISIM, FILTERSIM) =0.8639		Corrcoef(SNESIM, FILTERSIM) =0.9717	

with sharp display of realistic geological constraints that are honored by sampling training image TI that was generated using SISIM. The multiple-point geostatistics is able to capture the X, Y and Z direction of Reservoir-E, thus giving more realistic geologic images than the mostly used SISIM algorithm.

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