

# Ensemble Histogram a tool for Geostatistical Realization Validation: Hatch Field Niger Delta Basin, Nigeria

By

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## Abstract

*Seismic data, Well log data and 3D object generated training image were made available for the study. Visual inspection of the seismic data revealed channel fills in Hatch field Offshore Niger Delta Basin. Two continuous reservoirs named reservoir-D and reservoir-E were penetrated by four and five wells and their lithofacies correlated across the field. The reservoirs in the field were investigated for their lithofacies and channel sand distribution using Multiple Point Geostatistics algorithm of Single Normal Equation Simulation (SNESIM) and Filter-based Simulation (FILTERSIM). The results from the simulations revealed that the training image mean, and variance is 0.60083 and 0.239835. The mean and variance ensemble histogram for reservoir-D using SNESIM algorithm is 0.598 and 0.240, and that for reservoir-E is 0.599 and 0.240. The mean of means and the mean of the variance ensemble histogram for reservoir-D using FILTERSIM algorithm is 0.681 and 0.217, and that for reservoir-E is 0.683 and 0.216. The results shows that the SNESIM algorithm shows greater similarity to the training image mean and variance than the FILTERSIM algorithm and thus would be preferred in Hatch field.*

**Keywords:** Training image, ensemble histogram, mean, variance, simulation

## Introduction:

Geostatistics has grown over years as a suitable tool for estimation and simulation. Model validation of the estimated or simulated reservoir properties is key in decision making for acceptance of the given model. The goal of any regional ensemble is the generation of a reliable stochastic forecasts<sup>1</sup>. Several approaches for the representation of a given model error have been tested for optimum model<sup>1</sup>. From geostatistical perspective, model validation is the process of determining whether a given variable of interest for a physical system is within some tolerance determined by the intended use of the geostatistical model. The major setback in previous geostatistical model developed is the inability of the developer to validate the model if it is within the tolerance limit. The Oil and gas industries are interested in studies with minimal risk and model validation within the tolerance limit. The validation of these geostatistical model is often done outside the software used in developing the model which has turn geostatistics into a black box, thus allowing for inferior model<sup>2</sup>. The tool required for validation of these models and are not often provided as part of the software used in developing the model<sup>3</sup>. The validation of a given model

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<sup>1</sup>Li, CH, Berner J, Hong JS, Fong CT, Kuo, YH (2019). The Taiwan WRF Ensemble Prediction System: Scientific Description, Model-Error Representation and Performance Results. Asia-Pacific Journal of Atmospheric Sciences. doi:10.1007/s13143-019-00127-8

<sup>2</sup> Srivastava M (1995). "An Overview of Stochastic Methods for Reservoir Characterization, in Yarus J, and Chambers R., Eds., Stochastic Modeling and Geostatistics: Principles, Methods, and Case Studies," *Computer Applications in Geology, AAPG*, 3, 3-16.

establishes the veracity of the model<sup>3</sup>. The international Atomic Energy Agency has defined a validated model as the one that provides a good representation of the actual processes occurring in a real system. Leutbecher and others<sup>4</sup> studied the impact of two stochastic schemes in the global model framework and the results revealed that Stochastic Perturbed Physics Tendency scheme was more significant to additional spread in the ensemble than Stochastic Kinetic Energy Backscatter scheme, irrespective of region, thereby minimizing ensemble mean error. In the classical sequential optimal filtering theory and in the Kalman filtering Model errors are assumed to be the white (in time) noise<sup>5,6</sup>. Reservoir characterization is an important process in the petroleum industry for estimating and simulating various properties of the petroleum reservoirs and needs the ensemble histogram method to validate the model to determine its tolerance limit. The ensemble methodology was originally applied on classification and clustering problems, which include bio-information<sup>7</sup>, detection of objects<sup>8,9</sup>, gene expressions<sup>10</sup>, protein synthesis<sup>11</sup> and later its application extended to time series prediction problems<sup>12</sup>. With the ensemble histogram method, the selection of the overall best hypothesis reduces the likelihood of an unfortunate selection of a poor model.

The ensemble methodology has the ability to handle cases of big data and sparse data<sup>13,14</sup>. The ensemble methodology can handle and combine different expert opinion to optimize the predictions of various petroleum reservoir properties of interest<sup>15,16</sup>. The rank histogram for model

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<sup>3</sup>Oreskes N, Shrader-Frechette K and Belitz K (1994). Verification, validation, and confirmation of numerical models in the earth sciences. *Science*, 263:641–646

<sup>4</sup>Leutbecher M, Lock SJ, Ollinaho P, Lang STK, Balsamo G, Bechtold P, Bonavita M, Christensen HM, Diamantakis M, Dutra E, English S, Fisher M, Forbes RM, Goddard J, Haiden T, Hogan RJ, Juricke S, Lawrence H, MacLeod D, Magnusson L, Malardel S, Massart S, Sandu I, Smolarkiewicz PK, Subramanian A, Vitart F, Wedi N, Weisheimer A (2017). Stochastic representations of model uncertainties at ECMWF: state of the art and future vision. *Q. J. R. Meteorol. Soc.* **143**, 2315–2339

<sup>5</sup>Jazwinski AH (1970). Stochastic processes and filtering theory. Academic Press, New York and London

<sup>6</sup>Pugachev VS, Sinitsin IN (1987). Stochastic differential systems. Analysis and filtering. John Wiley, New York, USA

<sup>7</sup>Caragea C, Sinapov J, Silvescu A, Dobbs D, Honavar V (2007). Glycosylation site prediction using ensembles of Support Vector Machine classifiers. *BMC Bioinformatics*, 8(1), 438. doi:10.1186/1471-2105-8-438

<sup>8</sup>Chen S, Wang W, Zuylen H (2009). Construct support vector machine ensemble to detect traffic incident, *Exp. Syst. Appl.* 36:10976–10986

<sup>9</sup>Wu J, and Rehg JM (2012). Object detection in: Zhang C and Ma Y (Eds.), *Ensemble Machine Learning: Methods and Applications*, Springer Science + Business Media, LLC, 2012 <http://dx.doi.org/10.1007/978-1-4419-9326-78>

<sup>10</sup>Re M, Valentini G (2010). Simple ensemble methods are competitive with state-of-the-art data integration methods for gene function prediction in: *JMLR:Workshop and Conference Proceedings, Mach. Learn. Syst. Biol.* 8(2010)98–111.

<sup>11</sup>Nanni L, Lumini A (2009). An ensemble of support vector machines for predicting virulent proteins, *Expert Syst. Appl.* 36:7458–7462

<sup>12</sup>LandassuriMoreno V, Bullinaria JA (2009). Neural network ensembles for time series forecasting, in: *Proceedings of GECCO'09, Montréal Québec, Canada, 2009*, pp. 8–12.

<sup>13</sup>Hassan HT, Khalid MU, Imran K (2010). Intelligent Object and Pattern Recognition using Ensembles in Back Propagation Neural Network, *International Journal of Electrical & Computer Sciences (IJECS-IJENS)*, Vol. 10, No. 6, pp. 47-54,

<sup>14</sup>Polikar R (2009). *Scholarpedia*, 4 (1) 2776.

<sup>15</sup>Polikar R (2006). Ensemble Based Systems in Decision Making. *IEEE Circuits and Systems Magazine*, Third Quarter, pp. 21-45.

<sup>16</sup>Polikar R (2012). Ensemble Learning. In: Zhang, C. and Ma, Y. (eds.). *Ensemble Machine Learning: Methods and Applications* 8, Springer.

validity was proposed by Anderson, hamil and Talagrand with others.<sup>17,18,19</sup>. Previous studies used numerous training images (TIs) to consider uncertainty in a geological concept in Multiple point Geostatistics (MPG) methods<sup>20,21,22,23,24,25</sup>. Reliability of MPG in reservoir characterization depends on their quality.

### Geologic Setting

The fundamental causative event for the origin of the Niger delta basin was the break-up of south American plate from the African plate<sup>26</sup>. The Benue Trough was formed as part of the widely distributed African rift population which was formed 140 million years ago. The Benue Trough and the Niger delta basin was formed as a composite of several pull-apart rifts, formed by sinistral wrench faulting. The event was followed by structural reorganization in the Santonian, believed to be consequence of the differences in the Atlantic Mesozoic spreading rates<sup>27,28,29</sup>. The continued subsidence of the southern area of Benue Trough due to thermal contraction of the lithosphere formed the Niger Delta Basin<sup>30,31,32</sup>. The evolution of the Niger Delta Basin is controlled by the

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<sup>17</sup> Anderson JL (1996). A method for producing and evaluating prob-abilistic forecasts from ensemble model integrations. *J. Climate*,9: 1518–1530.

<sup>18</sup> Hamill TM (1997). Reliability diagrams for multicategory proba-bilistic forecasts. *Wea. Forecasting*, 12: 736–741. and Colucci SJ, 1996: Random and systematic error in NMC's short-range Eta ensembles. Preprints, 13th Conf. on Probability and Statistics in the Atmospheric Sciences, San Francisco, CA, Amer. Meteor. Soc., 51–56.

<sup>19</sup> Talagrand O, Vautard R, Strauss B (1997). Evaluation of prob-abilistic prediction systems. *Proceedings, ECMWF Workshop on Predictability*, ECMWF, 1–25. [Available from ECMWF, Shinfield Park, Reading, Berkshire RG2 9AX, United Kingdom.]

<sup>20</sup> Jafarpour B, McLaughlin DB (2009). Estimating channelized-reservoir permeabilities with the ensemble Kalman filter: the importance of ensemble design. *SPE J.* 14(2):374–88. <https://doi.org/10.2118/108941-PA>.

<sup>21</sup> Scheidt C, Caers J (2009a). Representing spatial uncertainty using distances and kernels. *Math Geosci.* 41(4):397–419. <https://doi.org/10.1007/s11004-008-9186-0>.

<sup>22</sup> Scheidt C, Caers J (2009b). Uncertainty quantification in reservoir performance using distances and kernel methods: application to a West Africa Deepwater turbidite reservoir. *SPE J.* 14(4):680–92. <https://doi.org/10.2118/118740-PA>.

<sup>23</sup> Lorentzen RJ, Flornes KM, Nævdal G (2012). History matching channelized reservoir using the ensemble Kalman filter. *SPE J.* 17(1):137–51. <https://doi.org/10.2118/143188-PA>.

<sup>24</sup> Lee K, Jeong H, Jung S, Choe J (2013). Improvement of ensemble smoother with clustering covariance for channelized reservoirs. *Energy Explor Exploit.* 31(5):713–26. <https://doi.org/10.1260/0144-5987.31.5.713>.

<sup>25</sup> Lee K, Jung S, Choe J (2016). Ensemble smoother with clustered covariance for 3D channelized reservoirs with geological uncertainty. *J Pet Sci Eng.* 145:423–35. <https://doi.org/10.1016/j.petrol.2016.05.029>.

<sup>26</sup> Burke K (1996). The African Plate. *South African Journal of Geology*, 99, 341–409.

<sup>27</sup> Burke KC, Dessauvage TFJ, Whiteman AJ (1972) Geological history of the Benue valley and adjacent areas In: Dessauvage TFJ, Whiteman AJ (eds) *African Geology*, Ibadan University Press, Ibadan. 187–205

<sup>28</sup> Genik GJ (1992). Regional framework, structural and petroleum aspects of rift basins in Niger, Chad, and the Central African Republic (C.A.R.). *Tectonophysics*, 213(1–2), 169–185. doi:10.1016/0040-1951(92)90257-7

<sup>29</sup> Genik GJ (1993). Petroleum Geology of Cretaceous-Tertiary Rift Basins in Niger, Chad, and Central African Republic. *American Association of Petroleum Geologists Bulletin*, 77, 1405–1434.

<sup>30</sup> Sleep NH (1971). Thermal effects of the formation of Atlantic continental margins by continental breakup. *Geophysical Journal of the Royal Astronomical Society* 24:325–350.

<sup>31</sup> Turcotte DL, Ahern JL (1977). On the thermal and subsidence history of sedimentary basins *J. Geophys. Res.* 82, 3762–3766

<sup>32</sup> Onuoha KM. (1981). Sediment loading and subsidence in the Niger Delta sedimentary basin *J. Min. Geol.* 16(1), 138–140

pre-and syn-sedimentary tectonics<sup>33,34,35,36</sup>. The Hatch field Offshore Niger Delta Basin (Fig.1A .B) consists of thick sequence of clastic sediments covering Km2 area in the southern part of Nigeria. The deposits of the delta are made up of basal Paleocene pro-delta facies which is the Akata formation, the Akata formation is overlain by the Eocene paralic facies of the Agbada formation which is in-turn overlain by the Oligocene fluvial facies of the Benin formation (Fig.2)<sup>37,38</sup>. Previous studies on the tectonics, stratigraphy, sedimentology, petrophysics to mention but a few are well documented by several authors<sup>39,40,41</sup>.

Recent studies in the offshore<sup>42,43</sup> demonstrate the concept of eustatic cyclicity that is valid but perhaps could benefit from the stratigraphic information.<sup>44</sup>Vail defined depositional sequences as consisting of strata bounded by unconformities and their lateral equivalents are only identified in specified sectors of the delta. A definition of a delta wide genetic sequences was put forward by<sup>45</sup> consisting of strata bounded by maximum flooding surfaces within transgressive shales are more readily identifiable in the Niger Delta.

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<sup>33</sup> Evamy RD, Haremboure J, Kamerling P, Knaap WA, Molloy FA, Rowlands PH (1978). Hydrocarbon habitat of tertiary Niger Delta, AAPG Bulletin, 62, No.1

<sup>34</sup> Ejedawe JE (1981). Patterns of incidence of oil reserves in Niger Delta Basin: American Association of Petroleum Geologists (AAPG), v. 65.

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<sup>41</sup> Nton ME, Adesina, AD (2009). Aspects of structures and depositional environment of sand bodies within Tomboy field, offshore western Niger Delta, Nigeria. *RMZ—Materials and Geoenvironment*, 56(3), 284–303.

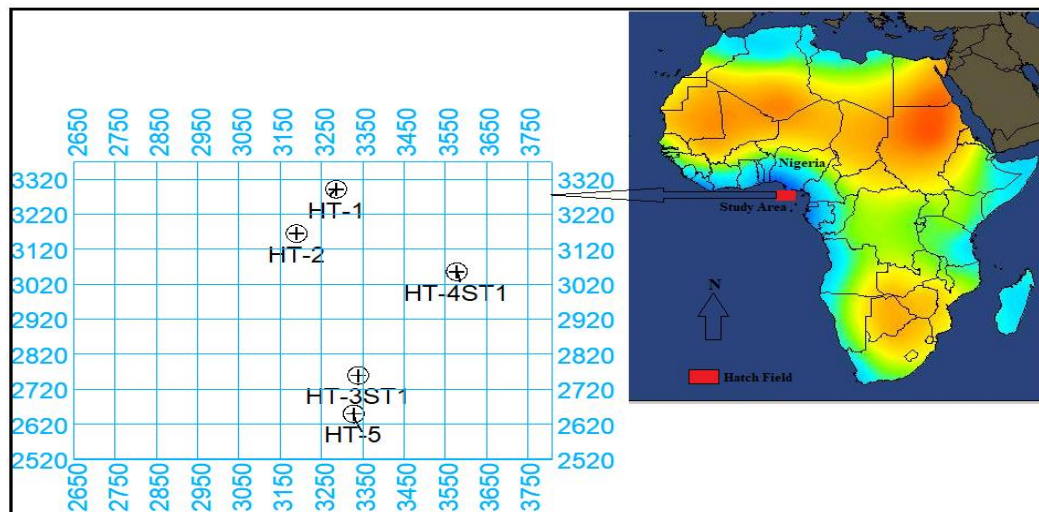
<sup>42</sup> Owoyemi AO, Willis BJ (2006). Depositional patterns across syndepositional normal faults, Niger delta, Nigeria. *Journal of Sedimentary Research* 76, 346–363.

<sup>43</sup> Magbagbeola O, Willis BJ (2007). Sequence stratigraphy and syndepositional deformation of the Agbada Formation, Robertkiri field, Niger Delta, Nigeria. *American Association of Petroleum Geologists Bulletin* 91, 945–958

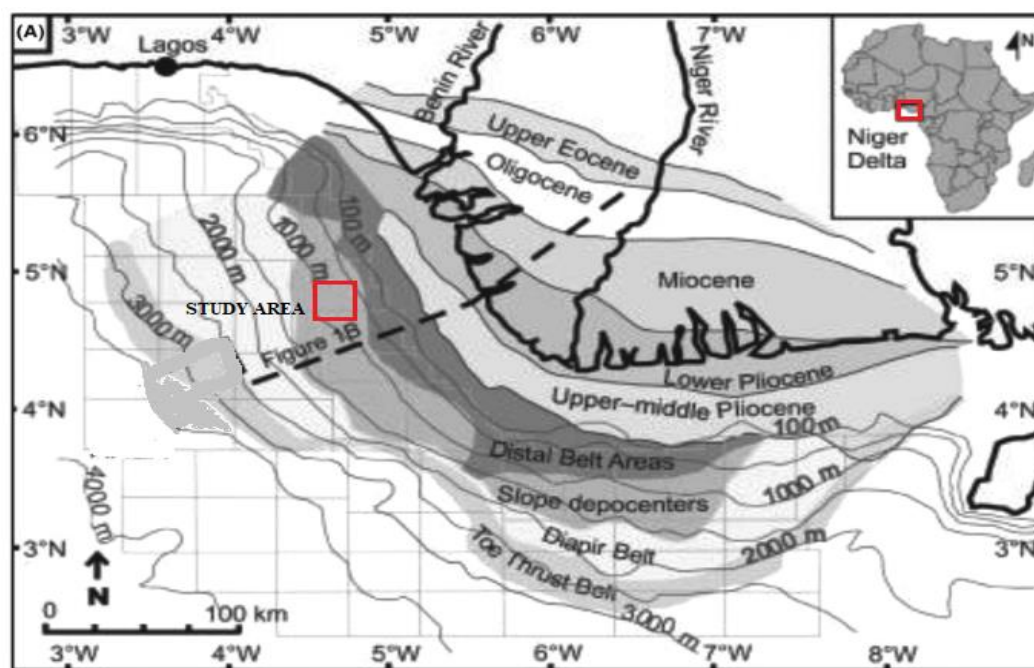
<sup>44</sup> Vail PR (1987). Seismic stratigraphy interpretation, using sequence stratigraphy. Part I: Seismic stratigraphic procedure. [In:] A.W. Balley (Ed.): *Atlas of seismic stratigraphy 1*. American Association of Petroleum Geologists Studies in Geology 27, 1–10.

<sup>45</sup> Galloway WE (1989). Genetic stratigraphic sequences in basin analysis 1: Architecture and genesis of flooding surface bounded depositional units. *American Association of Petroleum Geologists Bulletin* 73, 125–142.

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



B Map showing the compressional toe-of-slope thrust belt of the Niger Delta After<sup>46</sup>.

<sup>46</sup>Heiniö P, Davies RJ (2006). Degradation of compressional fold belts: Deep-water Niger Delta. AAPG Bulletin, 90(5), 753–770. doi:10.1306/11210505090

## B. Degradation of compressional fold belts: deep-water Niger Delta.

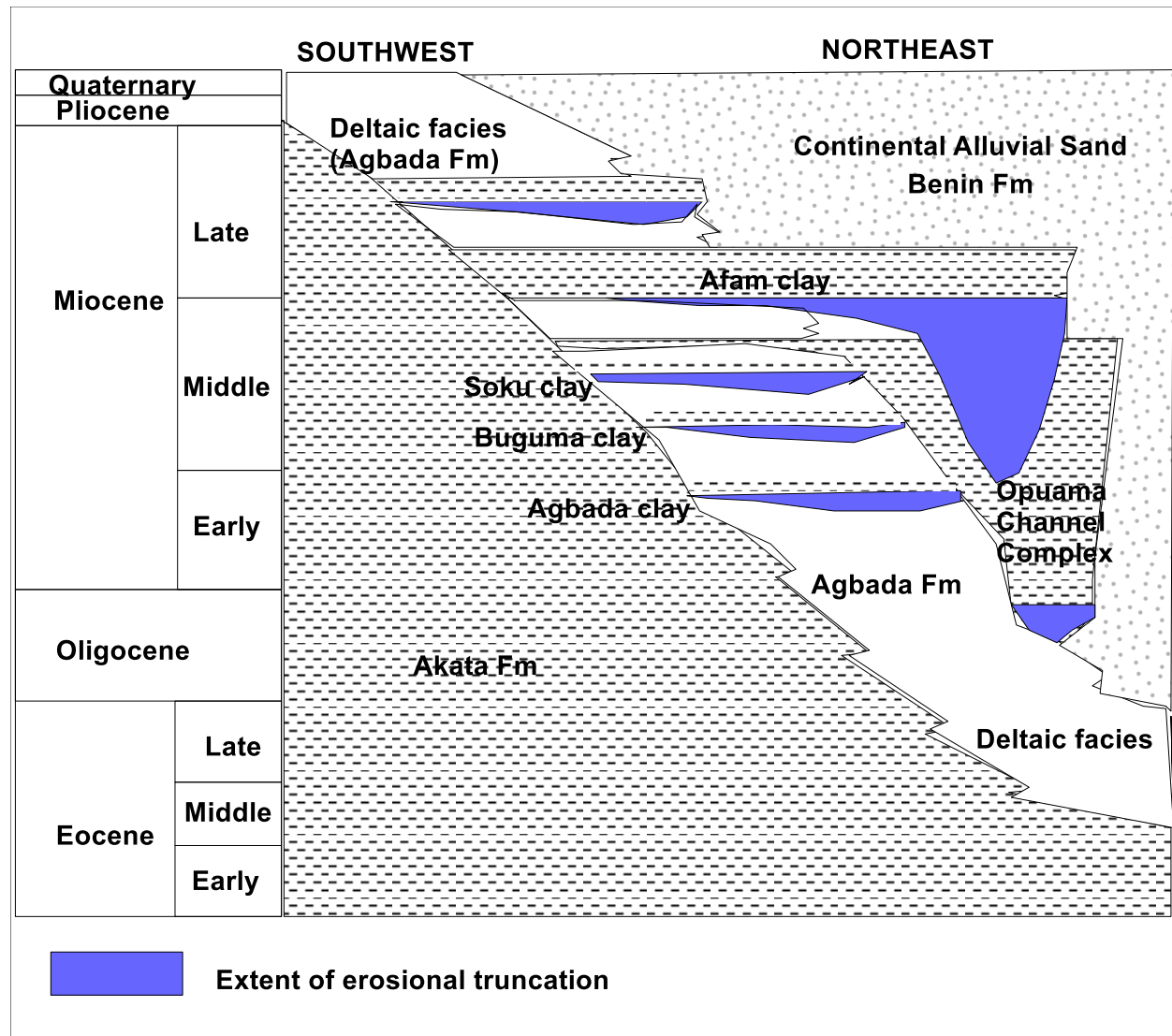


**Fig. 2** Stratigraphic column showing formations in the Niger delta modified from<sup>47</sup>

### Materials and Method of Study

There are many geostatistical methods for lithofacies modelling. In this study, the Multiple-point geostatistics (MPG) method employing the Single Normal Equation Simulation (SNESIM) and the Filter-based Simulation (FILTERSIM) was applied to lithofacies modelling in the Hatch field Niger Delta Basin. The study was carried out to select the best algorithm between SNESIM and FILTERSIM by validation of the model using ensemble histogram that will be best applied in the

<sup>47</sup> Owoyemi AOD (2004). The sequence stratigraphy of Niger Delta field, offshore Nigeria. Msc thesis, Texas A&M University.

study area. Five well log data, seismic data and a 3D object-based generated training image were used for the study. The seismic data was used to identify channel fills on the seismic data. A simulation grid was defined for both reservoir-D and reservoir-E. Derivation of volume of shale<sup>48</sup>. A simulation grid with dimension 157x100x5 was designed for reservoir-D and 204x120x5 for reservoir-E. Lithofacies properties distributed across the simulated grid. The reservoirs in the field were named reservoir-D and reservoir-E. The lithofacies log were correlated across the field.

### Volume of Shale Parameter Evaluation

The volume of shale was calculated using equation 1 for gamma ray index that was further substituted in equation 2 to get the volume of shale<sup>49</sup>.

$$I_{GR} = \frac{GR_{LOG} - GR_{Min}}{GR_{Max} - GR_{Min}} \quad (1)$$

Where  $I_{GR}$ =Gamma ray index,  $GR_{LOG}$ =Gamma ray from log,  $GR_{Min}$ =Minimum gamma ray,  $GR_{Max}$ = Maximum gamma ray log. The volume of shale was determined using Equation (2).

$$V_{Sh} = \frac{I_{GR}}{3 - 2 * I_{GR}} \quad (2)$$

Where  $V_{sh}$ =Volume of shale.

### SNESIM Algorithm of Multiple Point Geostatistics

This algorithm is a Multiple Point Geostatistics method and it is a pixel based. The method is used to generate complex realization such as sinuous channels<sup>2</sup>. The concept behind SNESIM algorithm is quite simple, each voxel or pixel node is simulated sequentially in a haphazard or random order. Facies is drawn with conditional probabilities that are often extracted from a given training image which represents a prior knowledge of the reservoir<sup>50</sup>. The SNESIM is a sequential simulation algorithm much in style like the common Sequential Gaussian simulation and sequential indicator simulation. The SNESIM algorithm relies on the idea of simulating each grid cell facies or petrophysical property sequentially along a random path, the simulation of the cells is constrained by well or seismic data or both<sup>51,52</sup>.

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<sup>48</sup> Asquith G, Krygowski D (2004) Basic well log analysis: AAPG Methods in Exploration, 16, 31-35.

<sup>49</sup> Stieber SJ (1970) Pulsed neutron capture log evaluation - Louisiana Gulf Coast. Fall Meeting of the Society of Petroleum Engineers of AIME. October 4-7, p. 1-7. <https://doi.org/10.2118/2961-MS>.

<sup>50</sup> Gomez J and Srivastava R (1990). "ISIM3D: An ANSI-C Three-Dimensional Multiple Indicator Conditional Simulation," *Computer & Geosciences*, **1990**, 16, 395–410.

<sup>51</sup> Aliakbar B, Omid A, Abbas B, Meysam T (2016). Facies modeling of heterogeneous carbonates reservoirs by multiple point geostatistics. *J Pet Sci Technol* 6(2):56–65

<sup>52</sup> Jika HT, Onuoha KM, Dim CIP (2019) Application of Geostatistics in Facies Modelling of Reservoir-E "Hatch Field" Offshore Niger Delta Basin, Nigeria. *J Petrol Explor Prod Technol*. <https://doi.org/10.1007/s13202-019-00788-1>.

## FILTERSIM Algorithm of Multiple Point Geostatistics

The FILTERSIM algorithm meaning Filter based simulation algorithm mainly includes three steps in the simulation process and the steps include filter and filter scores, pattern classification and multiple point sequential simulation.

### Filter and filter scores

The filtersim algorithm of the multiple point geostatistics is based on the use of designed filters using data template in fixed size to scan the training image<sup>53</sup>. The weight can be gained from the calculated data event through the filter. The mathematical expression of this statement is given in equation 3.

$$Y^m(u) = \sum_{k=1}^k f_m(P_k) * pat(u + P_k) \quad (3)$$

There are M different filters ( $f_m(P_k)$ :  $m=1, \dots, M$ ) in the formula, the number of nodes in the data template is  $k(k=1, \dots, n)$ ,  $pat(u + P_k)$  is attribute value of the node.

### Pattern Classification

After applying the M filters over a K-category training image, each of the training pattern is linked with a unique filter score vector of size  $K \times M$  ( $K=1$  for continuous variables). The same training patterns will have the same  $K \times M$  scores<sup>53</sup>. After partitioning the filter score space, similar patterns can be grouped together. The current available classification know as cross (partitioning) or K-mean clustering classification was put forward<sup>54</sup>. The classification is done by dividing each filter score space independently into equal frequency bins or classes. If the number of bins are increased it will result in better classification but with a larger number of pattern classes. Completion of partitioning leads to each training pattern class characterized by an average pattern termed prototype. A prototype is simply the average of the pattern class. For a continuous training image with a search template  $T_j$ , the pattern prototype is defined as

$$prot(h_j) = \frac{1}{c} \sum_{i=1}^c pat(u_i + h_j), j = 1, \dots, J$$

$h_j$  is the  $j$  th offset location in the search template  $T_j$ , the letter  $c$  is the number of training replicates within that prototype class  $u_i$  ( $i=1, \dots, c$ ) is the center of a specific training pattern belonging to that class. The within class probability is approximated by sampling replicates of  $c$  pattern. For a category variable

$$prot(h_j) = \{prot^k(h_j), k = 1, \dots, K\},$$

<sup>53</sup> Zhang T, Switzer P, Journel AG (2006) Filter-based classification of training image patterns for spatial simulation. Math Geosci 38(1):63-80

<sup>54</sup> Wu J, Boucher A, Zhang T (2008) A SGeMS code for pattern simulation of continuous and categorical variables: FILTERSIM. Comp & Geosci 34(12):1863–1876

Where  $prot^k(h_j) = prob(z(u_0 + hj) = k)$ , and  $u_0$  is the center of template  $T_j$ .

### Sequential Simulation

Simulation proceeds by randomly visiting all the grid nodes on the simulation grid in a sequential manner. At each simulation location  $u$ , a search template  $T_j$  with the same size as the filter template is used to extract the conditioning data event<sup>53</sup>. A prototype closest to the data event, based on some distance function is found. A training pattern is randomly selected from the closest pattern class and pasted on the simulation grid.

### Results and Discussion

The loading of the seismic data revealed channel fills in the field (Fig.3). Further works was also carried out using well log data and training images to confirm the presence of channel fills in the field. Lithofacies correlation was carried out and the result presented in Fig.4. The result shows that the lithofacies in the field is composed of an alternating sequence of sand and shale.

An object-based training image was generated that shows the distribution of channel sand in the field displayed with its histogram (Fig.5) and (Fig.6). The mean and variance of the training image is 0.60083 and 0.239835 (Fig.6). The histogram of the mean and variance of all the realization were plotted using XLSTAT software for both SNESIM and FILTERSIM algorithm for both reservoir-D and reservoir-E.

The SNESIM simulation of reservoir-D revealed thirty realizations showing distribution of lithofacies and channel sand presented in (Fig.7). The SNESIM results for reservoir-D mean, variance and lithofacies proportions is presented in Table 1 and Table 2. Plotting of mean and variance of all the realization to get an ensemble histogram for mean and variance for reservoir-D is presented in (Fig.8) and (Fig.9). The results gave the mean of means of 0.598 and mean of the variance as 0.240. The results show great similarities to that of the training image. The method was also applied to reservoir-E, thirty realizations were generated for reservoir-E and presented in (Fig.10). The results show distribution of lithofacies and channel sands in the field. The mean, variance and lithofacies proportions for all the realization are presented in Table 3 and Table 4. The histogram of the mean and variance of the ensemble is presented in (Fig.11) and (Fig.12). The plot of the ensemble histogram means, and variance revealed values of 0.599 and 0.240 that equally shows close similarities to that of the training image.

In the FILTERSIM simulation of lithofacies thirty realization for reservoir-D were generated and results presented in (Fig.13). The results show the distribution of lithofacies and channel sand in the field. The mean, variance, and proportions of lithofacies within the reservoir is presented in Table 5 and Table 6. The plot of mean and variance of all the realization revealed an ensemble histogram for mean and variance presented in (Fig.14) and (Fig.15). The mean of the means for reservoir-D is 0.681 and the mean of the variance is 0.217. In the same way the lithofacies and channel sand distribution of reservoir property for reservoir-E using FILTERSIM is presented in Fig.16. The mean, variance and lithofacies proportions for the thirty realization are presented in Table 7 and Table 8. The plot of mean and variance ensemble histogram is presented in Fig.17 and Fig.18. The mean and variance of the ensemble is 0.683 and 0.216 respectfully. The result shows

that the SNESIM results shows closer similarity with the training image than FILTERSIM results and thus recommended for reservoir property simulation in Hatch field.

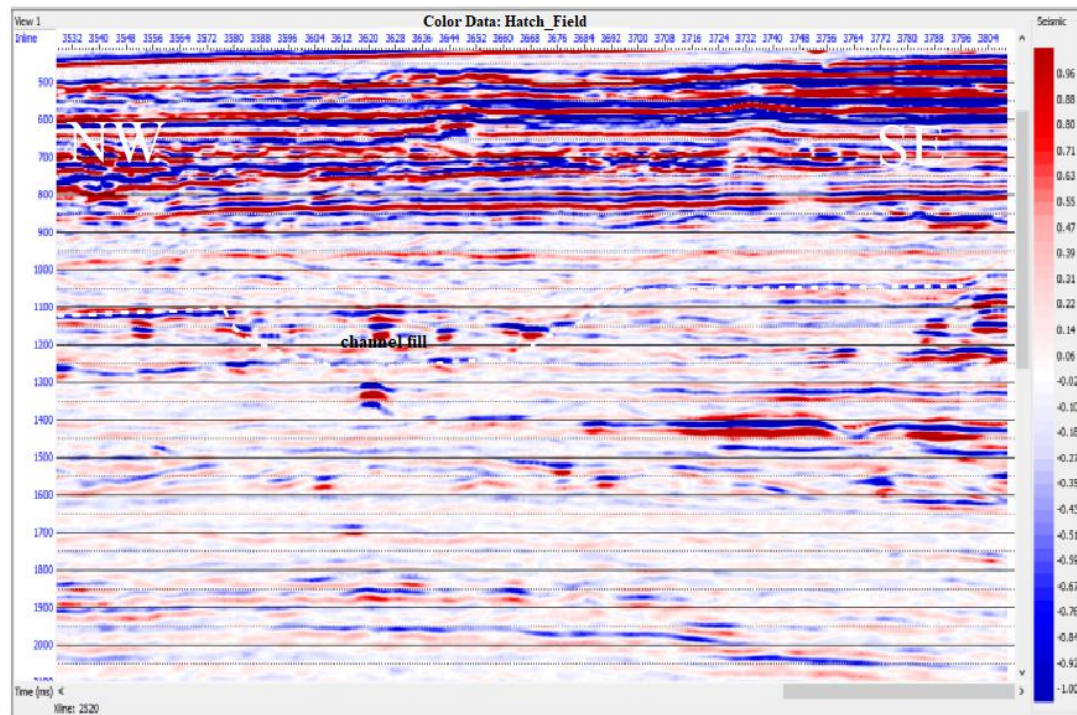


Fig.3. Identifying channel fills on crossline 2520 based on reflection characteristics with the bowl shape and white dotted line indicating the channel fill

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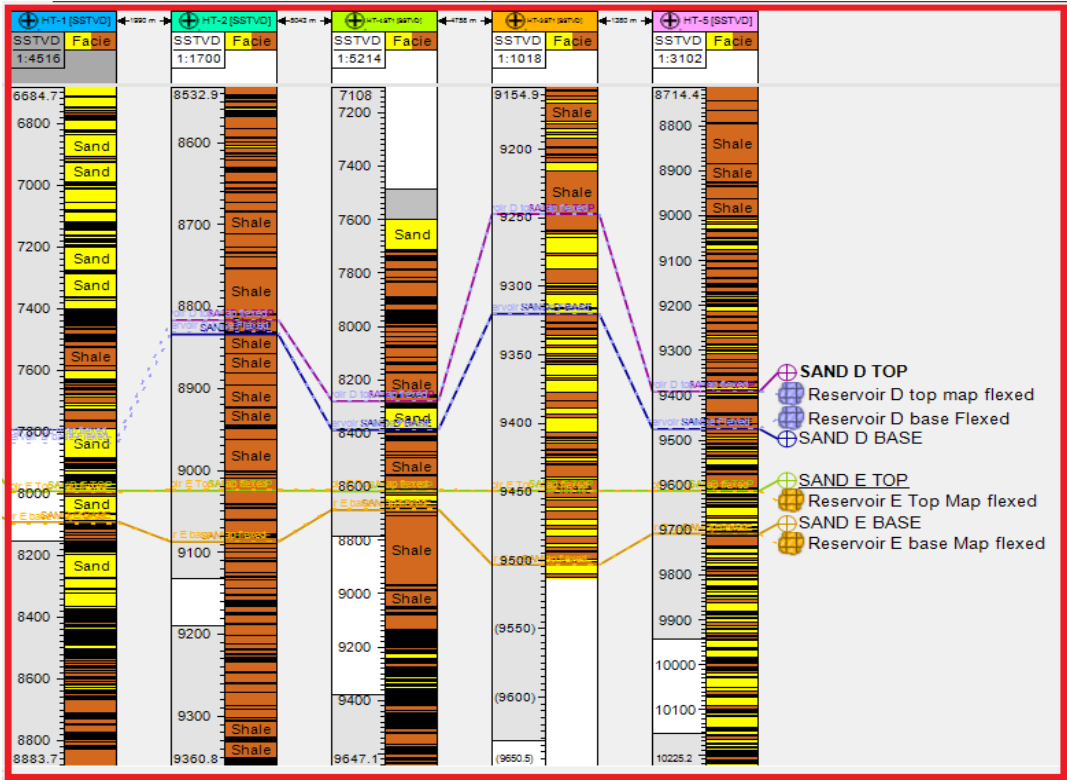


Fig. 4. Litho-facie log correlation showing reservoir intervals and their lithofacies in the five wells in Hatch field Niger Delta Basin

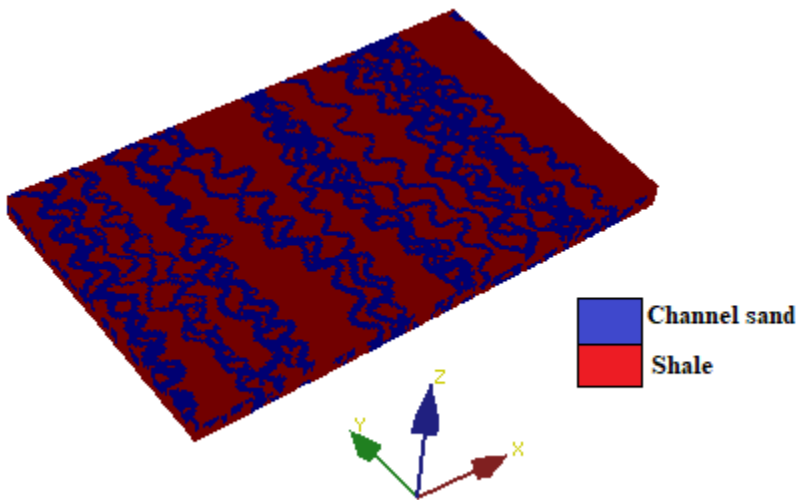


Fig. 5. 3D Object base generated channelized Training Image

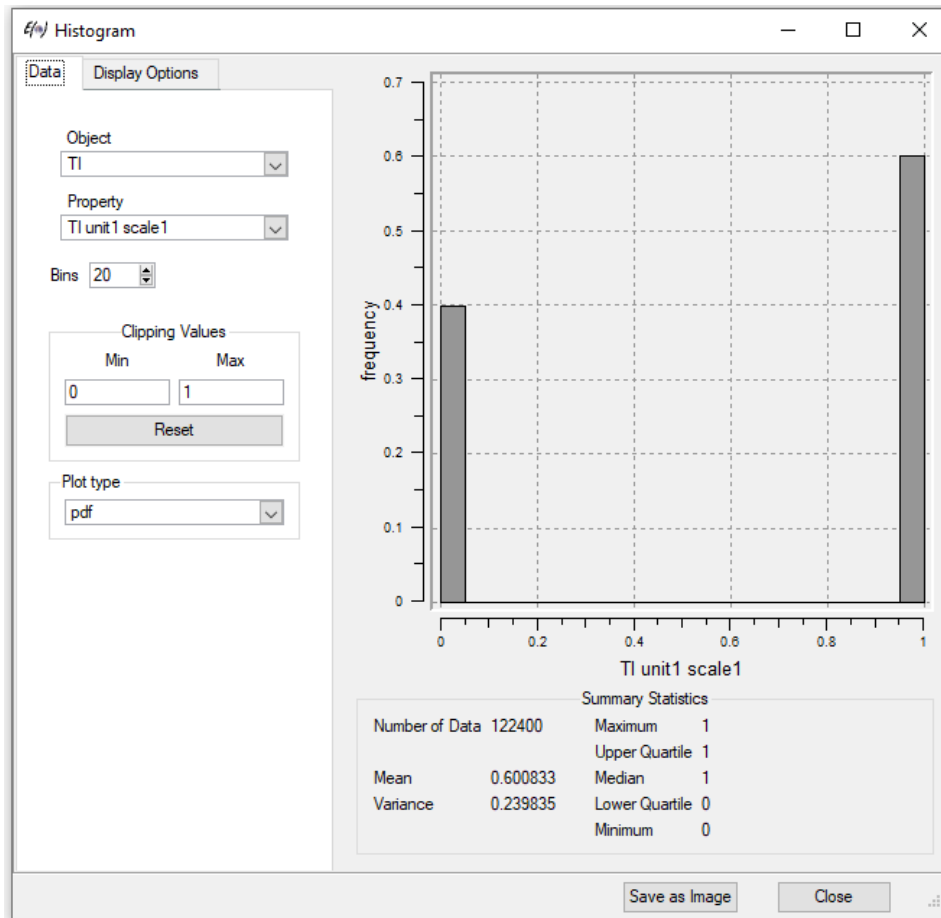


**Fig.6.** Histogram statistics for a channelized training image

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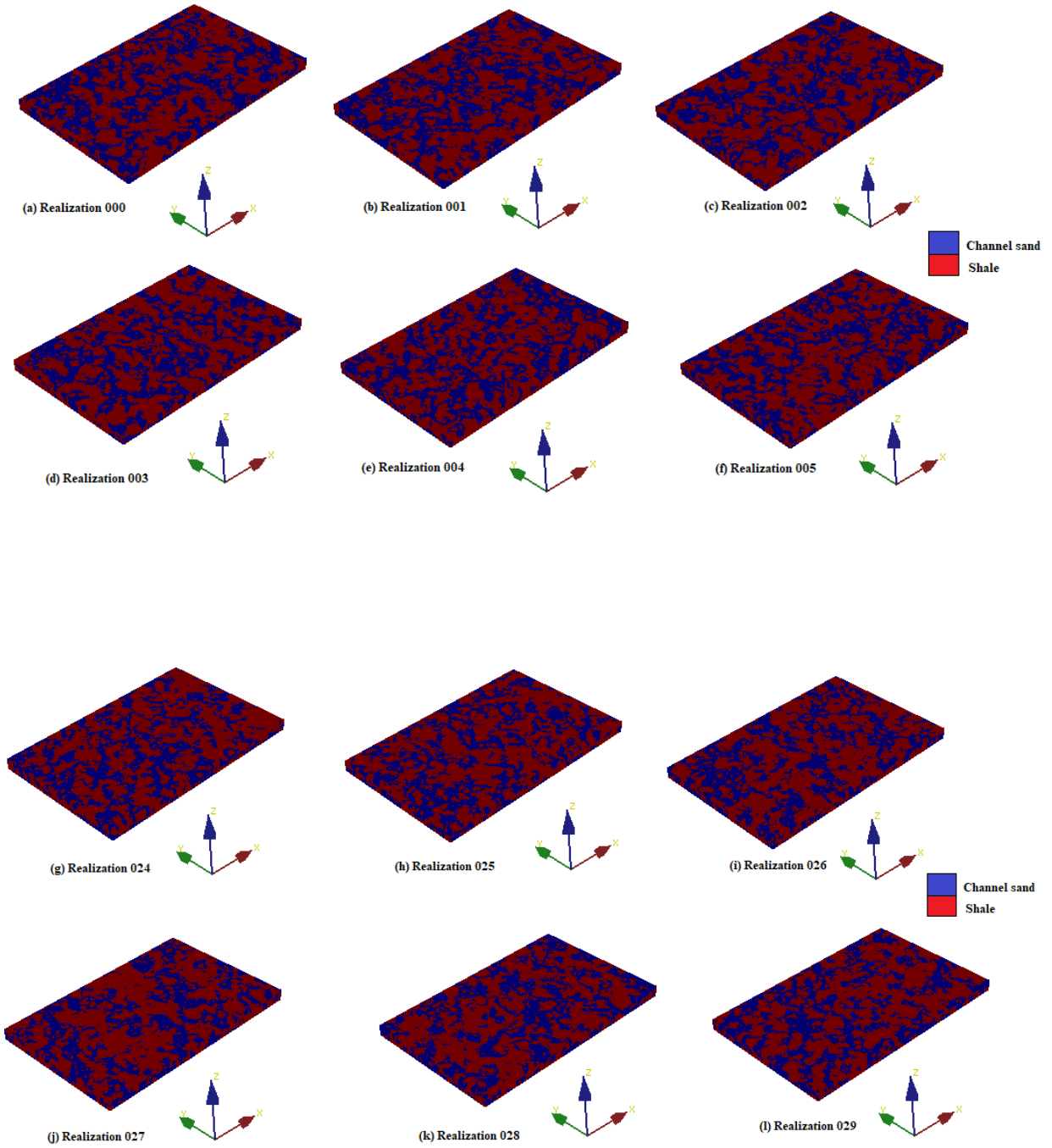


**Fig. 7.** Channelized reservoir model using SNESIM algorithm for reservoir-D

**Table 1.** showing realization mean and variance for reservoir-D using SNESIM algorithm

| Realization | 0        | 1        | 2        | 3        | 4        | 5        | 6        | 7        |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.599758 | 0.595783 | 0.600318 | 0.590981 | 0.594841 | 0.600127 | 0.593911 | 0.59749  |
| Variance    | 0.240051 | 0.240829 | 0.239939 | 0.241726 | 0.241008 | 0.239978 | 0.241184 | 0.240499 |

| Realization | 8        | 9        | 10       | 11       | 12       | 13       | 14       | 15       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.602815 | 0.593847 | 0.607427 | 0.594166 | 0.601172 | 0.58693  | 0.601312 | 0.59879  |
| Variance    | 0.239432 | 0.241196 | 0.238463 | 0.241136 | 0.239767 | 0.242446 | 0.239739 | 0.240244 |

| Realization | 16       | 17       | 18       | 19       | 20       | 21       | 22       | 23       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.605185 | 0.598726 | 0.602064 | 0.595401 | 0.604433 | 0.591592 | 0.603108 | 0.597516 |
| Variance    | 0.238939 | 0.240256 | 0.239586 | 0.240902 | 0.239097 | 0.241614 | 0.239372 | 0.240494 |

| Realization | 24       | 25       | 26       | 27       | 28       | 29       |
|-------------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.593248 | 0.588968 | 0.599172 | 0.60135  | 0.601822 | 0.593274 |
| Variance    | 0.241308 | 0.242088 | 0.240168 | 0.239731 | 0.239635 | 0.241303 |

**Table 2.** Channelized Facies Proportions of Model realization (SNESIM) and Training Image for Reservoir-D

| Realization | 0   | 1    | 2   | 3    | 4    | 5   | 6    | 7    | 8    | 9    |
|-------------|-----|------|-----|------|------|-----|------|------|------|------|
| Sand        | 0.4 | 0.41 | 0.4 | 0.41 | 0.41 | 0.4 | 0.41 | 0.41 | 0.39 | 0.41 |
| Shale       | 0.6 | 0.59 | 0.6 | 0.59 | 0.59 | 0.6 | 0.59 | 0.59 | 0.61 | 0.59 |

| Realization | 10   | 11   | 12  | 13   | 14  | 15  | 16   | 17  | 18  | 19   |
|-------------|------|------|-----|------|-----|-----|------|-----|-----|------|
| Sand        | 0.39 | 0.41 | 0.4 | 0.42 | 0.4 | 0.4 | 0.39 | 0.4 | 0.4 | 0.41 |
| Shale       | 0.61 | 0.59 | 0.6 | 0.58 | 0.6 | 0.6 | 0.61 | 0.6 | 0.6 | 0.59 |

| Realization | 20   | 21   | 22   | 23  | 24   | 25   | 26  | 27  | 28  | 29   | TI   |
|-------------|------|------|------|-----|------|------|-----|-----|-----|------|------|
| Sand        | 0.39 | 0.41 | 0.39 | 0.4 | 0.41 | 0.42 | 0.4 | 0.4 | 0.4 | 0.41 | 0.40 |
| Shale       | 0.61 | 0.59 | 0.61 | 0.6 | 0.59 | 0.58 | 0.4 | 0.4 | 0.4 | 0.59 | 0.60 |

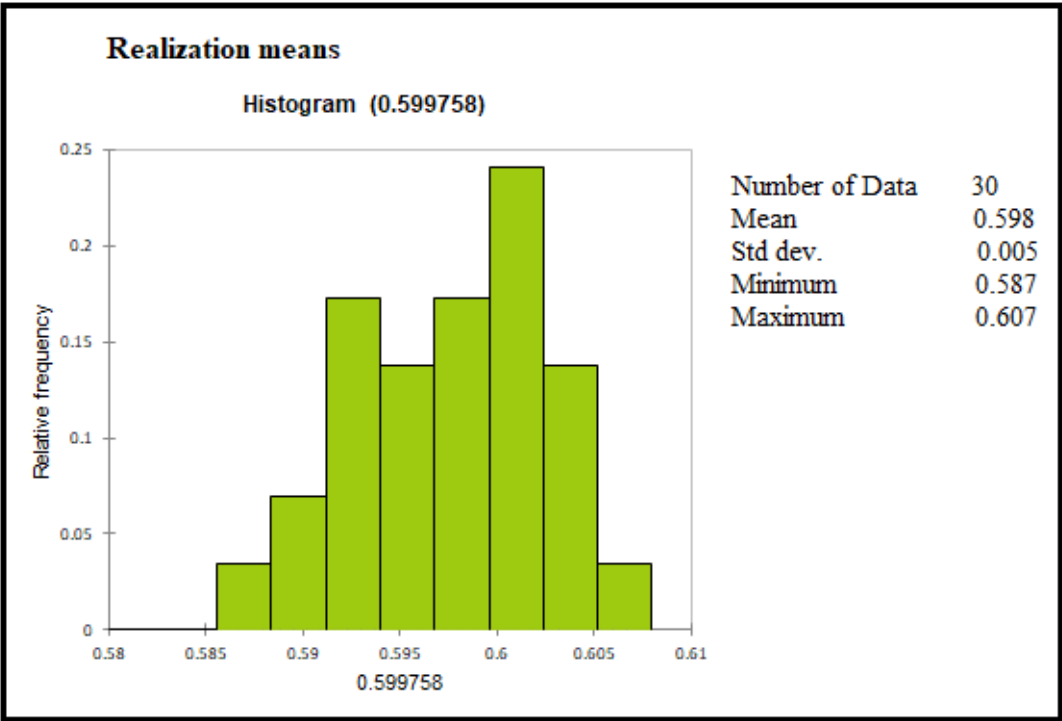


**Fig.8.** Mean ensemble histogram for reservoir-D using SNESIM algorithm

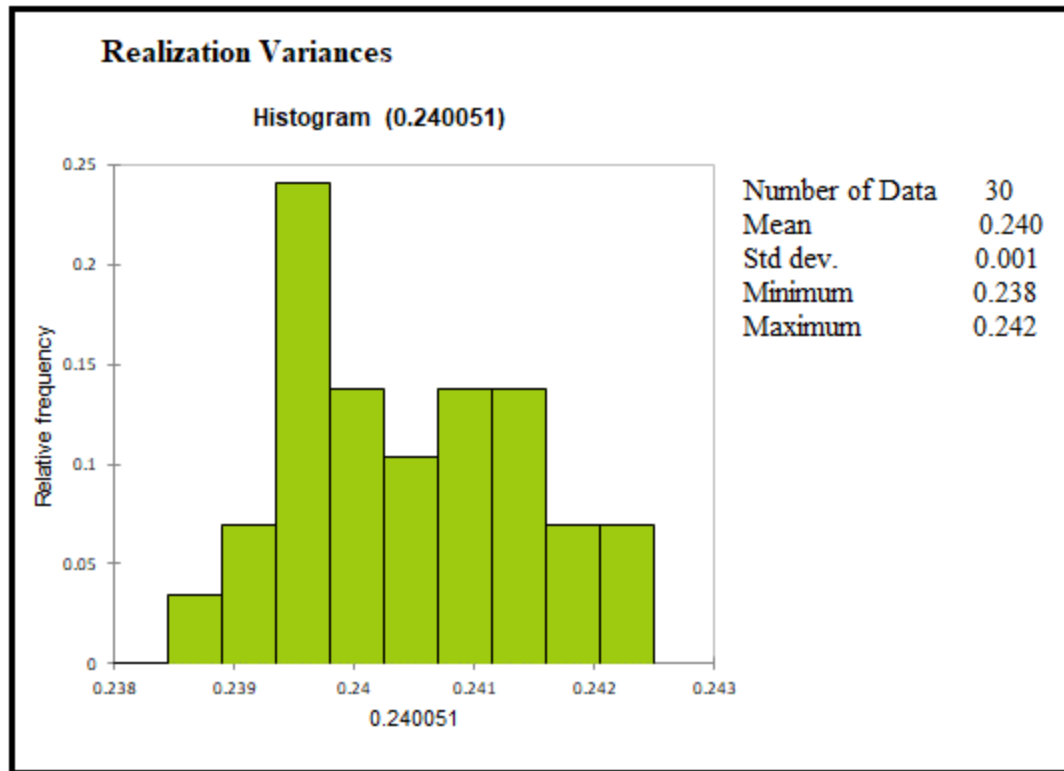
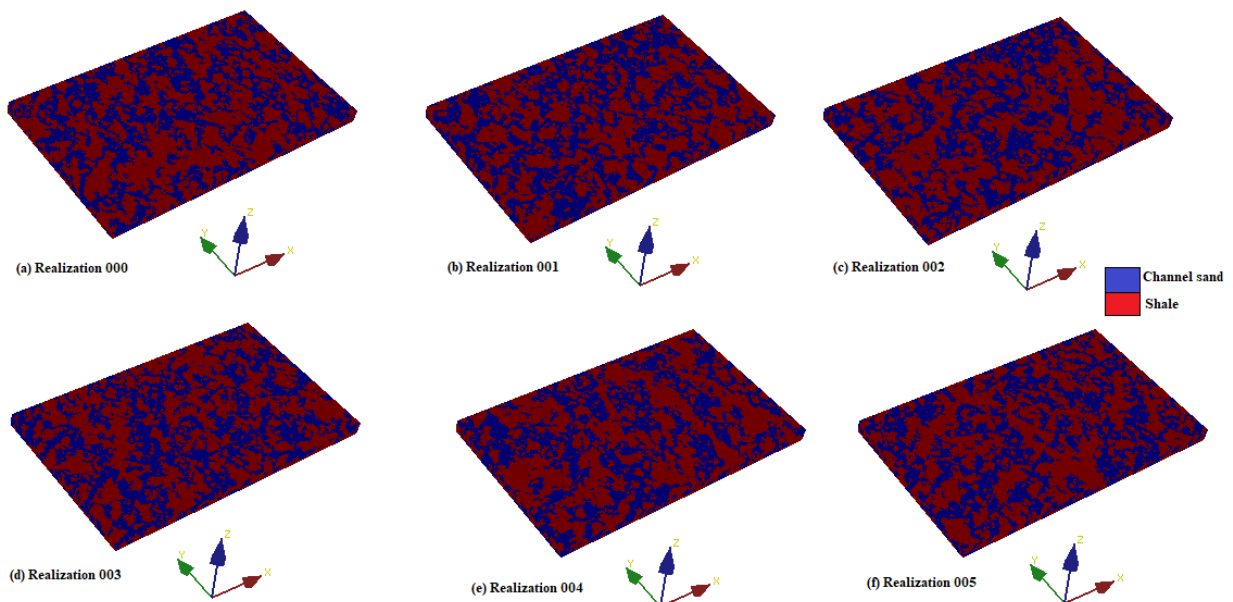


**Fig.9.** Variance ensemble histogram for reservoir-D using SNESIM algorithm



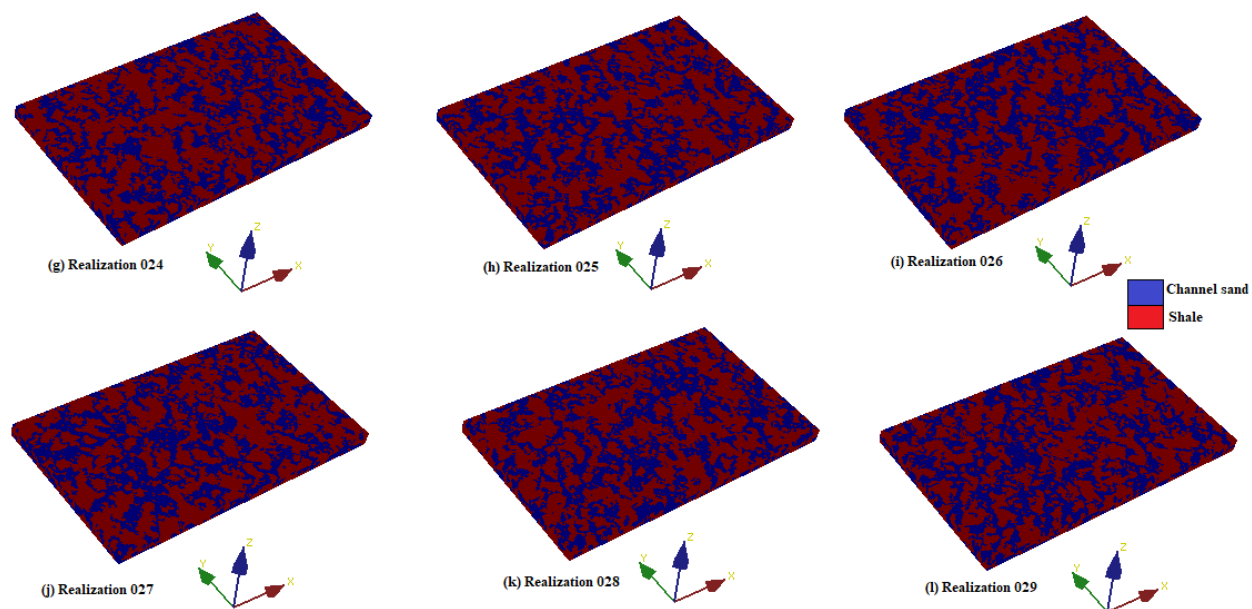


**Fig.10.** Channelized reservoir model using SNESIM algorithm for reservoir-E

**Table 3.** showing realization mean and variance for reservoir-E using SNESIM algorithm

| Realization | 0        | 1        | 2        | 3        | 4        | 5        | 6        | 7        |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.59656  | 0.596209 | 0.600825 | 0.597925 | 0.597778 | 0.597124 | 0.600417 | 0.598407 |
| Variance    | 0.240678 | 0.240746 | 0.239836 | 0.240413 | 0.240441 | 0.240569 | 0.239918 | 0.240318 |

| Realization | 8        | 9        | 10       | 11       | 12       | 13       | 14       | 15       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.594649 | 0.597394 | 0.603309 | 0.600637 | 0.598636 | 0.598807 | 0.597059 | 0.592353 |
| Variance    | 0.241044 | 0.240516 | 0.239329 | 0.239874 | 0.240273 | 0.240239 | 0.240582 | 0.241473 |

| Realization | 16       | 17       | 18       | 19       | 20       | 21       | 22       | 23       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.602018 | 0.605025 | 0.601397 | 0.602402 | 0.59893  | 0.599992 | 0.598742 | 0.593636 |
| Variance    | 0.239594 | 0.238972 | 0.239721 | 0.239516 | 0.240215 | 0.240004 | 0.240252 | 0.241234 |

| Realization | 24       | 25       | 26       | 27       | 28       | 29       |
|-------------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.596127 | 0.602974 | 0.597353 | 0.595245 | 0.596871 | 0.596879 |
| Variance    | 0.240761 | 0.239398 | 0.240524 | 0.24093  | 0.240618 | 0.240616 |

**Table 4.** Channelized Facies Proportions of Model realization (SNESIM) and Training Image for Reservoir-E

| Realization | 0    | 1    | 2   | 3   | 4   | 5    | 6   | 7   | 8    | 9    |
|-------------|------|------|-----|-----|-----|------|-----|-----|------|------|
| Sand        | 0.41 | 0.41 | 0.4 | 0.4 | 0.4 | 0.41 | 0.4 | 0.4 | 0.41 | 0.41 |
| Shale       | 0.59 | 0.59 | 0.6 | 0.6 | 0.6 | 0.59 | 0.6 | 0.6 | 0.59 | 0.59 |

| Realization | 10   | 11  | 12  | 13  | 14   | 15   | 16  | 17   | 18  | 19   |
|-------------|------|-----|-----|-----|------|------|-----|------|-----|------|
| Sand        | 0.39 | 0.4 | 0.4 | 0.4 | 0.41 | 0.41 | 0.4 | 0.39 | 0.4 | 0.39 |
| Shale       | 0.61 | 0.6 | 0.6 | 0.6 | 0.59 | 0.59 | 0.6 | 0.61 | 0.6 | 0.61 |

| Realization | 20  | 21  | 22  | 23   | 24   | 25   | 26   | 27   | 28   | 29   | TI   |
|-------------|-----|-----|-----|------|------|------|------|------|------|------|------|
| Sand        | 0.4 | 0.4 | 0.4 | 0.41 | 0.41 | 0.39 | 0.41 | 0.41 | 0.41 | 0.41 | 0.40 |
| Shale       | 0.6 | 0.6 | 0.6 | 0.59 | 0.59 | 0.61 | 0.59 | 0.59 | 0.59 | 0.59 | 0.60 |

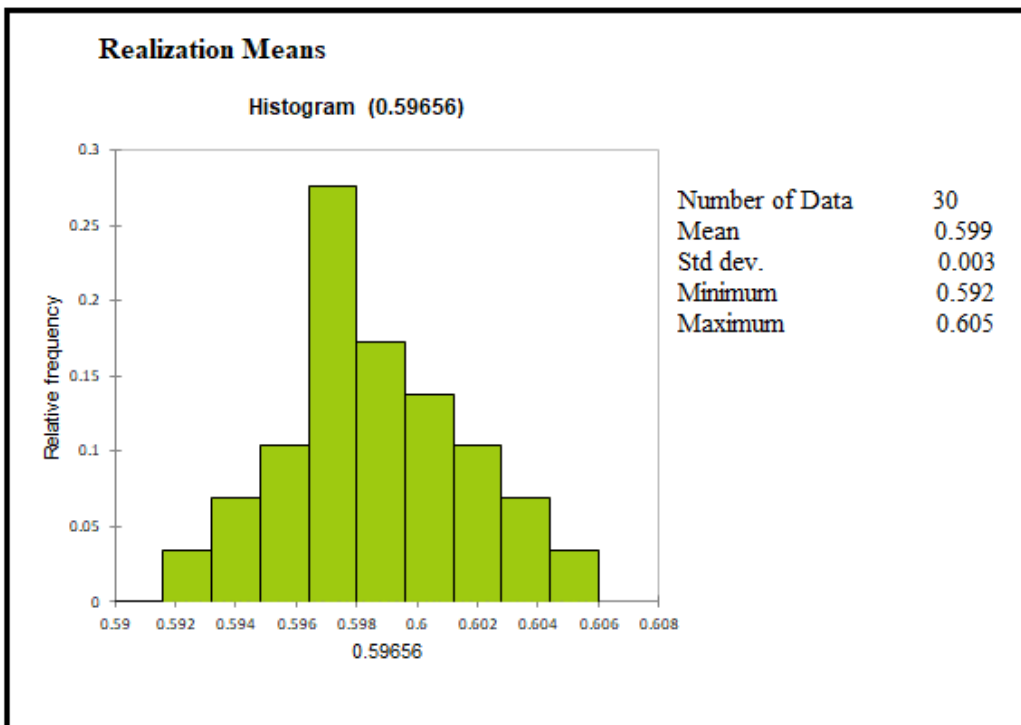


**Fig.11.** Mean ensemble histogram for reservoir-E using SNESIM algorithm

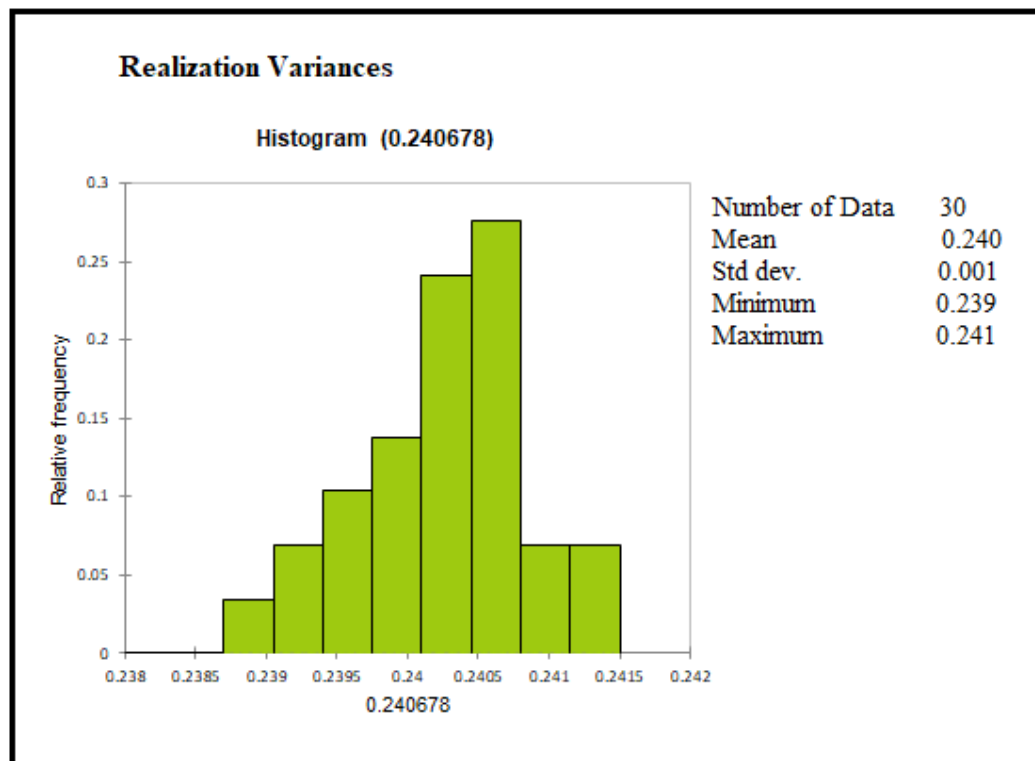
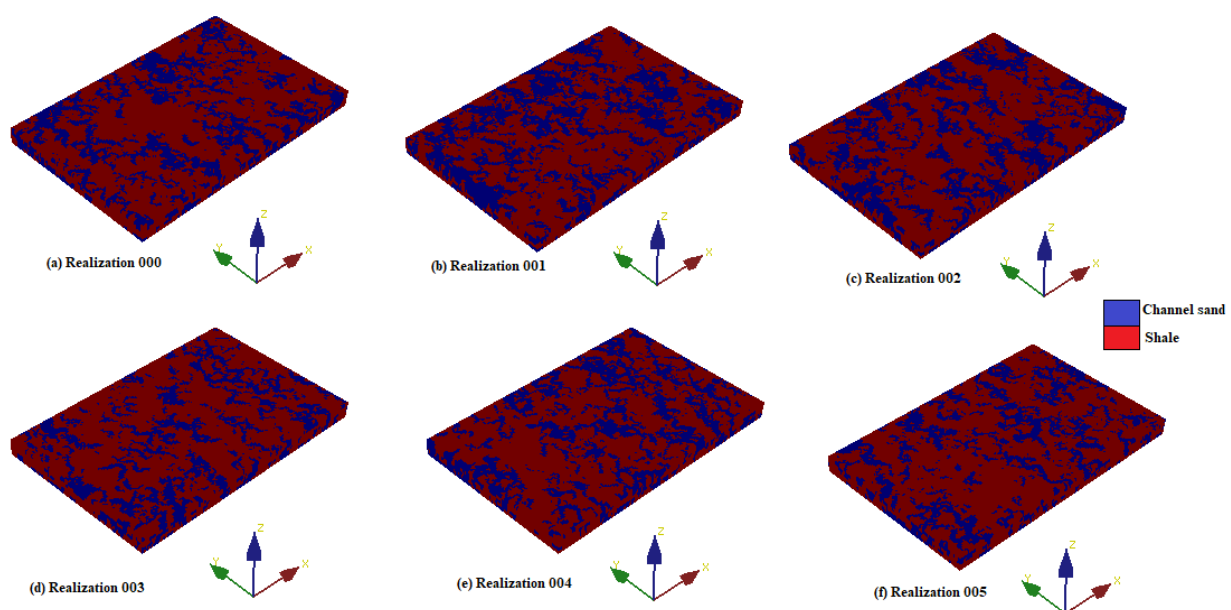


**Fig.12.** Variance ensemble histogram for reservoir-E using SNESIM algorithm



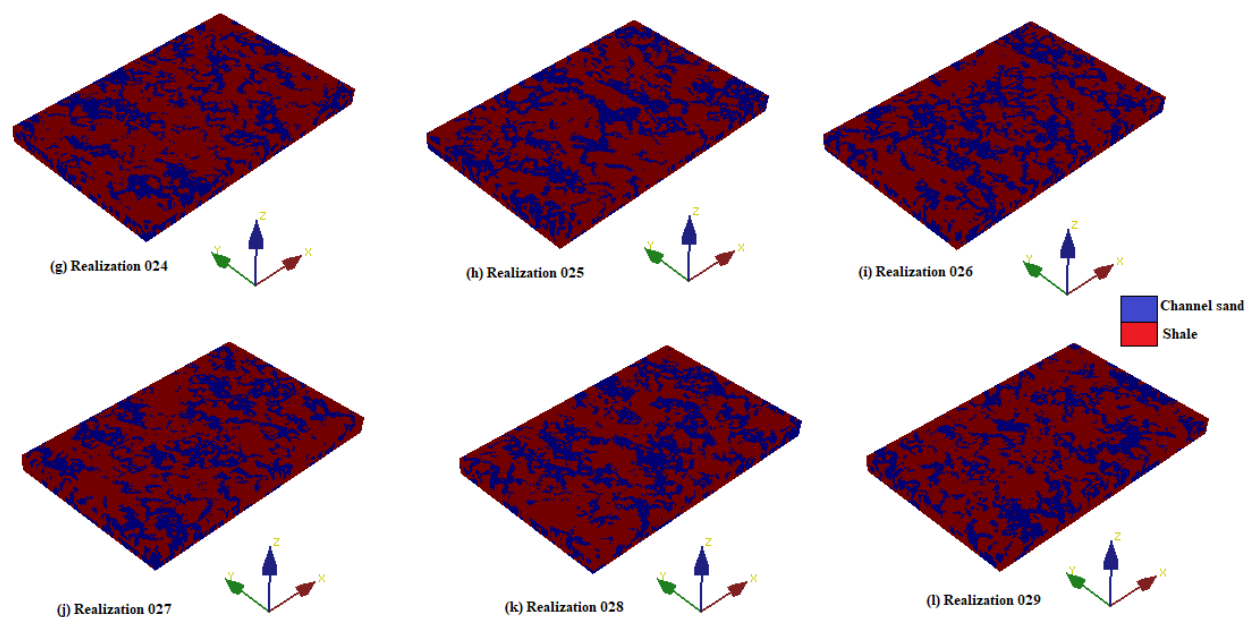


**Fig.13.** Channelized reservoir model using FILTERSIM algorithm for reservoir-D

**Table 5.** showing realization mean and variance for reservoir-D using FILTERSIM algorithm

| Realization | 0        | 1        | 2        | 3        | 4        | 5        | 6        | 7        |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.686917 | 0.657975 | 0.669465 | 0.714318 | 0.684573 | 0.702828 | 0.670076 | 0.666459 |
| Variance    | 0.215065 | 0.225047 | 0.221284 | 0.20407  | 0.215935 | 0.208863 | 0.221077 | 0.222294 |

| Realization | 8        | 9        | 10       | 11       | 12       | 13       | 14       | 15       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.700561 | 0.692318 | 0.659847 | 0.692038 | 0.675083 | 0.684471 | 0.697223 | 0.681936 |
| Variance    | 0.209778 | 0.213016 | 0.224452 | 0.213124 | 0.219349 | 0.215973 | 0.211106 | 0.216902 |

| Realization | 16       | 17       | 18       | 19       | 20       | 21       | 22       | 23       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.673121 | 0.675401 | 0.690586 | 0.67214  | 0.694    | 0.652369 | 0.671287 | 0.695032 |
| Variance    | 0.220003 | 0.219237 | 0.21368  | 0.220371 | 0.212367 | 0.226786 | 0.220664 | 0.211965 |

| Realization | 24       | 25       | 26       | 27       | 28       | 29       |
|-------------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.697924 | 0.662318 | 0.677694 | 0.672764 | 0.661261 | 0.695389 |
| Variance    | 0.210829 | 0.223656 | 0.218428 | 0.220155 | 0.223998 | 0.211826 |

**Table 6.** Channelized Facies Proportions of Model realization (FILTERSIM) and Training

Image for Reservoir-D

| Realization | 0    | 1    | 2    | 3    | 4    | 5   | 6    | 7    | 8   | 9    |
|-------------|------|------|------|------|------|-----|------|------|-----|------|
| Sand        | 0.32 | 0.34 | 0.33 | 0.28 | 0.32 | 0.3 | 0.33 | 0.33 | 0.3 | 0.31 |
| Shale       | 0.68 | 0.66 | 0.67 | 0.72 | 0.68 | 0.7 | 0.67 | 0.67 | 0.7 | 0.69 |

| Realization | 10   | 11   | 12   | 13   | 14  | 15   | 16   | 17   | 18   | 19   |
|-------------|------|------|------|------|-----|------|------|------|------|------|
| Sand        | 0.34 | 0.31 | 0.33 | 0.32 | 0.3 | 0.32 | 0.33 | 0.32 | 0.31 | 0.33 |
| Shale       | 0.66 | 0.69 | 0.67 | 0.68 | 0.7 | 0.68 | 0.67 | 0.68 | 0.69 | 0.67 |

| Realization | 20   | 21   | 22   | 23   | 24  | 25   | 26   | 27   | 28   | 29   | TI   |
|-------------|------|------|------|------|-----|------|------|------|------|------|------|
| Sand        | 0.31 | 0.35 | 0.33 | 0.31 | 0.3 | 0.34 | 0.32 | 0.33 | 0.34 | 0.31 | 0.40 |
| Shale       | 0.69 | 0.65 | 0.67 | 0.69 | 0.7 | 0.66 | 0.68 | 0.67 | 0.66 | 0.69 | 0.60 |

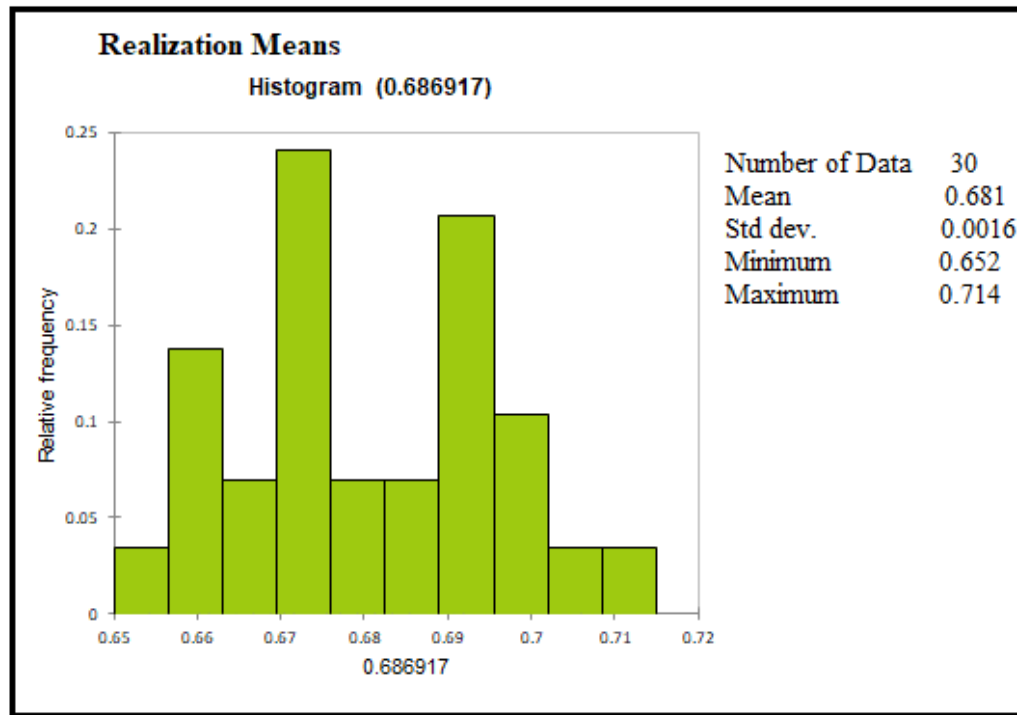


**Fig.14.** Mean ensemble histogram for reservoir-D using FILTERSIM algorithm

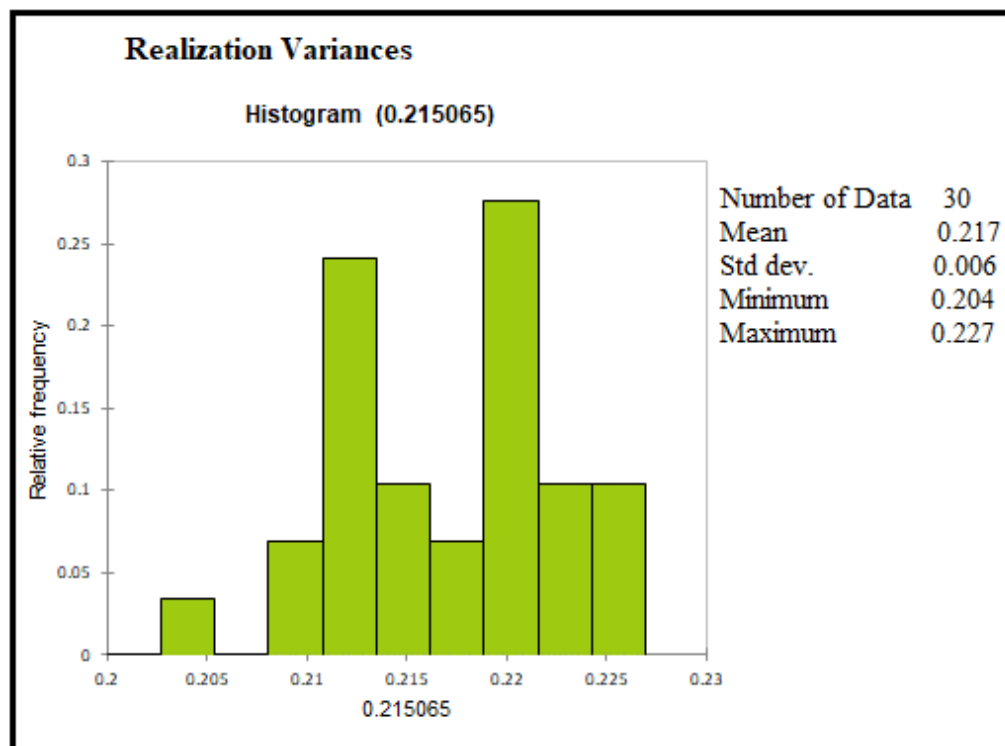


**Fig.15.** Variance ensemble histogram for reservoir-D using FILTERSIM algorithm

Ensemble Histogram a tool for Geostatistical Realization Validation: Hatch Field Niger Delta Basin, Nigeria

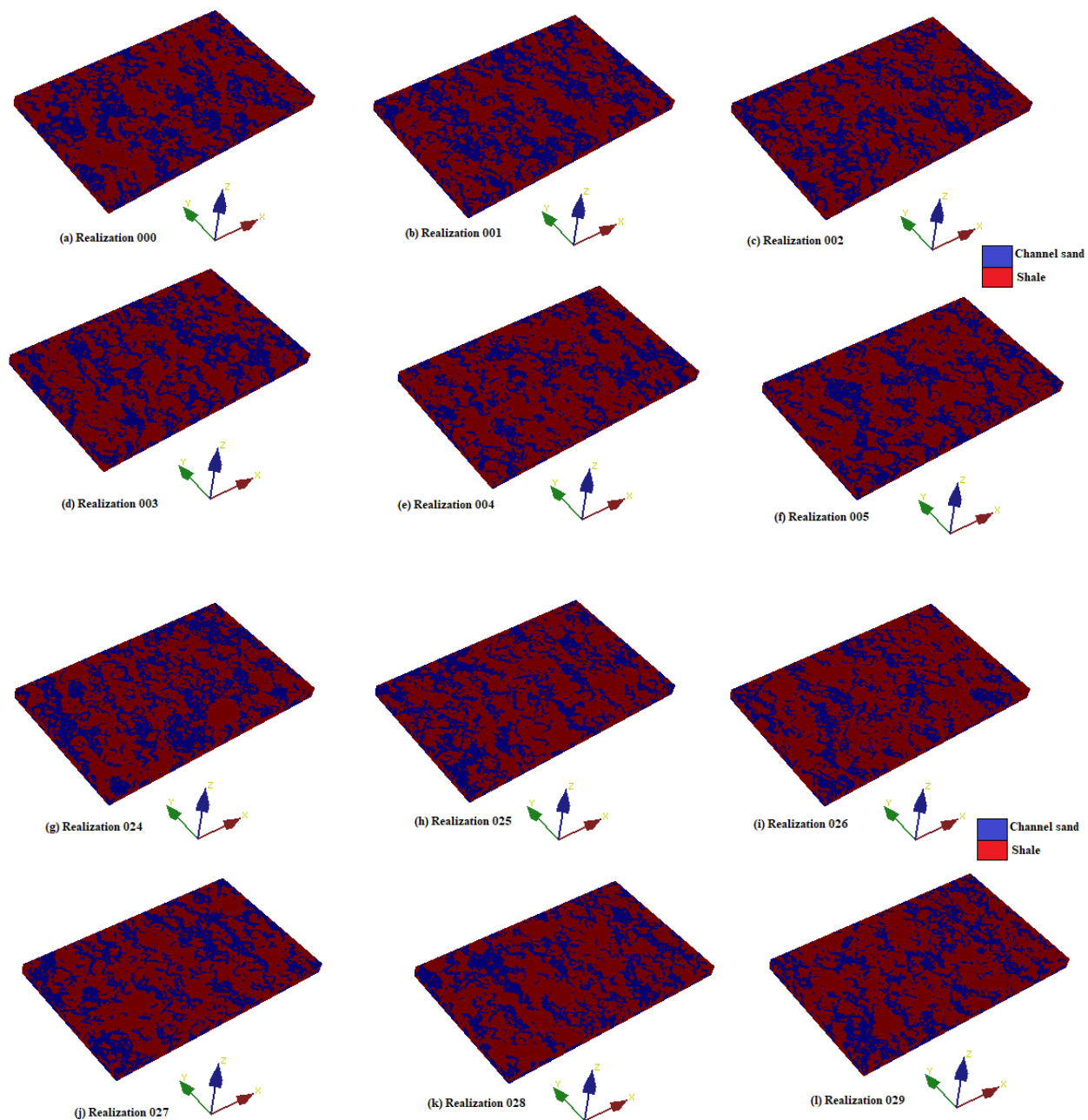


**Fig.16.** Channelized reservoir model using FILTERSIM algorithm for reservoir-E

**Table 7.** Channelized Facies Proportions of Model realization (FILTERSIM) and Training Image for Reservoir-E

| Realization | 0        | 1        | 2        | 3        | 4        | 5        | 6        | 7        |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.676544 | 0.687173 | 0.682222 | 0.661757 | 0.693725 | 0.661283 | 0.696193 | 0.702745 |
| Variance    | 0.218834 | 0.214968 | 0.216797 | 0.223837 | 0.212472 | 0.22399  | 0.21151  | 0.208896 |

| Realization | 8        | 9        | 10       | 11       | 12       | 13       | 14       | 15       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.684003 | 0.658791 | 0.683235 | 0.705351 | 0.684126 | 0.705229 | 0.685033 | 0.696078 |
| Variance    | 0.216145 | 0.224787 | 0.216427 | 0.207833 | 0.216099 | 0.207883 | 0.215765 | 0.211555 |

| Realization | 16       | 17       | 18       | 19       | 20       | 21       | 22       | 23       |
|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Mean        | 0.672288 | 0.689739 | 0.659436 | 0.678056 | 0.676985 | 0.666364 | 0.690458 | 0.681487 |
| Variance    | 0.220319 | 0.214001 | 0.224582 | 0.218298 | 0.218678 | 0.222325 | 0.213728 | 0.217064 |

| Realization | 24       | 25       | 26      | 27       | 28       | 29       |
|-------------|----------|----------|---------|----------|----------|----------|
| Mean        | 0.665057 | 0.691732 | 0.70674 | 0.668145 | 0.680793 | 0.68241  |
| Variance    | 0.222758 | 0.213241 | 0.20726 | 0.221729 | 0.217316 | 0.216728 |

**Table 8.** Channelized Facies Proportions of Model realization (FILTERSIM) and Training Image for Reservoir-E

| Realization | 0    | 1    | 2    | 3    | 4    | 5    | 6    | 7   | 8    | 9    |
|-------------|------|------|------|------|------|------|------|-----|------|------|
| Sand        | 0.32 | 0.32 | 0.32 | 0.34 | 0.31 | 0.34 | 0.31 | 0.3 | 0.32 | 0.34 |
| Shale       | 0.68 | 0.68 | 0.68 | 0.66 | 0.69 | 0.66 | 0.69 | 0.7 | 0.68 | 0.66 |

| Realization | 10   | 11  | 12   | 13  | 14   | 15  | 16   | 17   | 18   | 19   |
|-------------|------|-----|------|-----|------|-----|------|------|------|------|
| Sand        | 0.32 | 0.3 | 0.32 | 0.3 | 0.32 | 0.3 | 0.33 | 0.32 | 0.34 | 0.33 |
| Shale       | 0.68 | 0.7 | 0.68 | 0.7 | 0.68 | 0.7 | 0.67 | 0.68 | 0.66 | 0.67 |

| Realization | 20   | 21   | 22   | 23   | 24   | 25   | 26   | 27   | 28   | 29   | TI   |
|-------------|------|------|------|------|------|------|------|------|------|------|------|
| Sand        | 0.33 | 0.34 | 0.31 | 0.32 | 0.34 | 0.31 | 0.29 | 0.33 | 0.32 | 0.32 | 0.40 |
| Shale       | 0.67 | 0.66 | 0.69 | 0.68 | 0.66 | 0.69 | 0.71 | 0.67 | 0.68 | 0.68 | 0.60 |

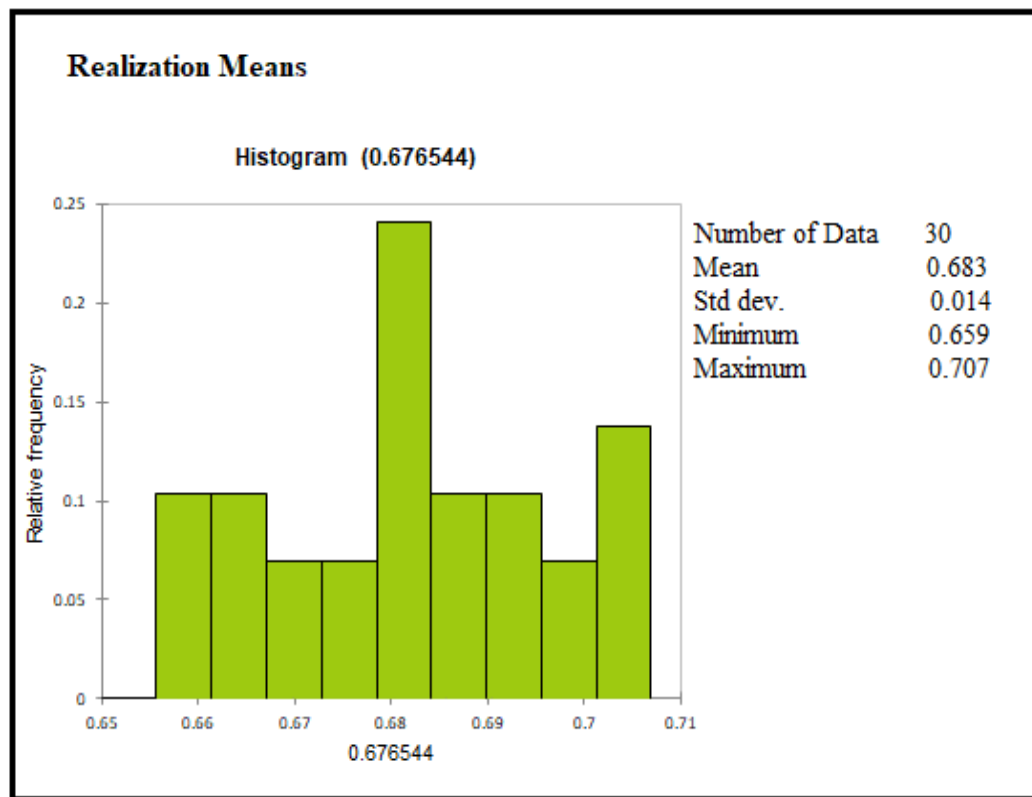


Fig.17. Mean ensemble histogram for reservoir-E using FILTERSIM algorithm

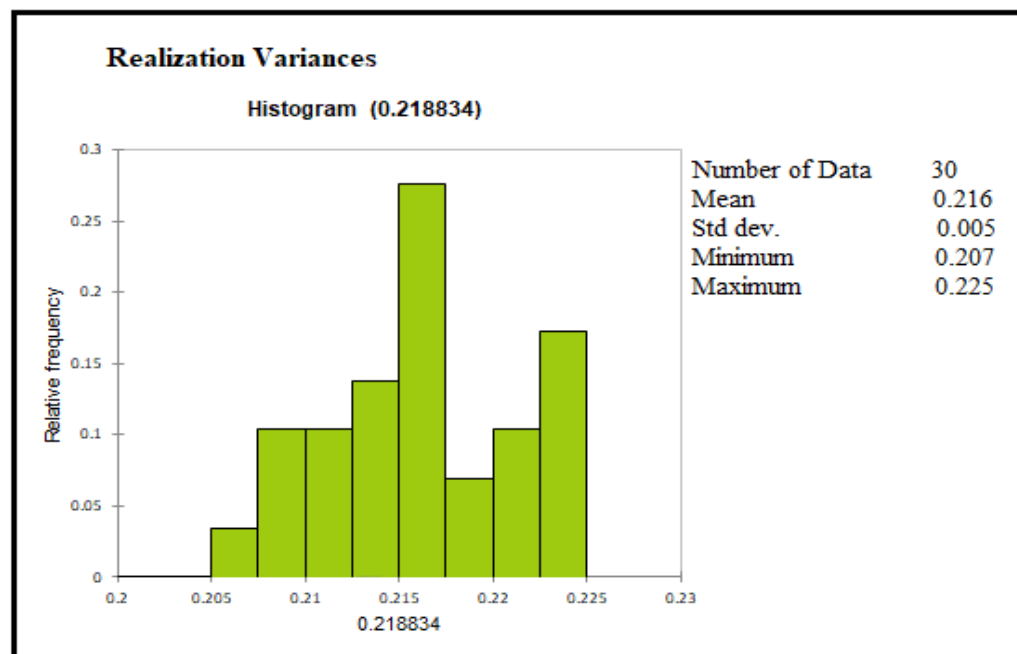


Fig.18. Variance ensemble histogram for reservoir-E using FILTERSIM algorithm

**Conclusion**

The channel fills that were observed on seismic data were confirmed using Multiple point Geostatistics (SNESIM and FILTERSIM). The results of the simulations revealed distribution of lithofacies and channel sand on the two major reservoirs identified in the field. The results of the simulation shows that SNESIM algorithm shows more similarity to the mean and variance of the training image than the FILTERSIM algorithm. Thus, the SNESIM algorithm is a preferred algorithm to be applied in Hatch field Offshore Niger Delta basin.

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