Geological Stratigraphy and Spatial Distribution of Microfractures over Costa Rica Convergent Margin, Central America- A Wavelet-Fractal Analysis

Upendra K. Singh, Thinesh Kumar and Rahul Prajapati,

Department of Applied Geophysics, Indian School of Mines, Dhanbad-826 004, India

Correspondence: upendra_bhu1@rediffmail.com

Abstract

Identification of spatial variation of lithology as a function of position and scale is very critical job for lithology modeling in industry. Wavelet Transform (WT) is an efficacious and powerful mathematical tool for time (position) and frequency (scale) localization. It has numerous advantages over Fourier Transform (FT) to obtain frequency and time information of a signal. Initially Continuous Wavelet Transform (CWT) is applied on gamma ray logs of two different Well sites (Well-1039 & Well-1043) of Costa Rica Convergent Margin, Central America for identifications of lithofacies distribution and fracture zone later Discrete Wavelet Transform (DWT) applied to DPHI log signals to show its efficiency in discriminating small changes along the rock matrix irrespective of the instantaneous magnitude to represent the fracture contribution from the total porosity recorded. Further the data of the appropriate depths partitioned using above mathematical tools are utilized separately for wavelet based fractal analysis (WBFA). As consequences of CWT operation it is found that there are four major sedimentary layers terminated with a concordant igneous intrusion passing through both the wells. In addition of WBFA analysis clearly understand the fractal dimension value is persistent in first sedimentary layers and the last gabbroic sill intrusions Inconsistent value of fractal dimension is attributed to fracture dominant in intermediate sedimentary layers it is also

validate through core analysis. Fractal Dimension values suggest that the sedimentary environments persisting in that well locations bears abundant shale content and of low energy environments.

Key words: CWT, DWT, Fractal, Costa Rica.

Introduction

The nature of any log signal is fluctuating type in accordance to the subsurface geology. A gamma ray log is most vividly used log for lithology identifications. These signals are very noisy in some cases and highly fluctuating in another way. Manual interpretations of such signals are quite difficult and it needs more experience. These difficulties are minimized by kind of wavelet transform method. In our study Continuous Wavelet transform (CWT) is tested on generated synthetic signals and applied to field data. The analyzed results prove that the CWT is highly suitable in geophysical log signals whereas conventional Fast Fourier Transform (FFT) fails in this case because it considers the whole signal in a stationary form. Though WT provides unambiguous results in analyzing the noisy and non-stationary signals, its efficiency of extracting the information from the signal was seen through its wavelet coefficients (Hui and Zaixing, 2010) with wavelet scalogram.

Number of publication has come to identify the lithofacies boundary using various mother Wavelet transform and Fourier transform (Chandrasekhar et al., 2012; Coconi et al., 2010; Dashtian, 2011; Javid and Tokhmechi, Mansinha et al., 1997; Mansinha 2003, 2004; Pan et al., 2007, 2012; Pinnegar and Stockwell, 2007; Stockwell et al., 1996; Sahimi and Hashemi, 2001; Tokhmechi et al., 2009a, b; Yue et al., 2004; Zhang et al., 2011). Some other authors worked on WT to describe the scaling property using magnetic susceptibility data (Fedi, 2003) and Bansal et al., (2010) has determine the presence of fractures using power law scaling behavior of magnetic susceptibility and density variation in continental crust.

In this paper, CWT and Discrete wavelet transform (DWT) are used separately for identifying the lithology using gamma ray log data of well site 1039 and 1043 obtained from Costa Rica Convergent Margin, Central America (expedition 308 scientists 2005) and computed wavelet scalograms. Moreover, the information of fractures zones is analyzed with DWT using density logs data for both wells that provides well featured whereas the log data doesn't carry information of fracture remains featureless. Afterward, a linear relationship is obtained between the fracture density obtained through DWT and identified fractures from water saturation logs using above methods. Apart from wavelet analysis, one of the approach wavelet based fractal analysis (WBFA) techniques applied to attribute the roughness/smoothness of the fractures. The obtained suggest that wavelet transform acts as a microscope to delineate the high and low frequency hidden in the signal separately, wavelet/holder exponent and fractal dimension are highly useful in identification of lithofacies and spatial distribution of fractures.

Mathematical Background

Wavelet Transform

Wavelet transform is mathematical tool that can be used to analyze both stationary and non-stationary signals (Daubechies 1990, 1992) and expand time series into time frequency space. Therefore, this method can find localized intermittent periodicities. For analyzing stationary or non-stationary signal proper mother wavelet has to be substituted and the operation of continuous wavelet transform (CWT) proceeds as the convolution between time series of our interest. The Discrete wavelet transform (DWT) is very useful in case of noisy data it compresses the data by reducing noise and improves the resolution whereas the application of CWT prefers to extract the lithological feature from data. As it exposes the signal to high and low frequency filters to form approximate and detailed coefficients traces out the abrupt changes in the signal. Basically, in geophysical well logs the abrupt change corresponds to its own individual parameter changes which provide us more information about the subsurface stratigraphy. This methodology pertaining to DWT allows us to locate the high frequency changes immersed in the log which cannot be identified manually. For example, gamma ray log is a good lithology indicator but in certain conditions it is highly fluctuating in nature. This nature sometimes perturbs its evaluation. Apart from lithology identification, DWT provides an advantage of analyzing the fracture identifications. Choice of mother wavelet is important factor for analyzing the non- stationary signal. As number of mother wavelets were tested to select the optimum wavelet using well logs signal (Lopez 2006). In this method analysis is based on linearity between logarithm of wavelet coefficients (log σ) and scale. Regression Coefficients R^2 for all log signal from each well has been calculated and linear fit was obtained for Coiflet 4 wavelet. The wavelets do not give the significant change in wavelet coefficients to identify stratigraphy boundary. Thus Coiflet 4 wavelet is best for analysis of this well log data.

2.2 Continuous Wavelet Transform

The concept of continuous wavelet transform can be explained by a basic equation given below:

$$W(a,b) = \frac{1}{a^n}\int_{-\infty}^{\infty} f(x)\varphi\left(\frac{x-b}{a}\right)dx \qquad (1)$$

Where, f(t) is the time series of our interest, φ(t) is the mother wavelet, a is the scaling parameter which is inverse of frequency, b is the translation parameter directly proportional to time and n is the normalizing parameter which is equal to 1 (say). The variance of Wavelet coefficients follows power law relation with the scale which can be given by a simple equation given below;

$$v = x^h$$

Here v is the variance of wavelet coefficients, x is the scale and h is the holder/wavelet exponent.

Holder/Wavelet exponent provides the measure of roughness/smoothness. If the holder exponent values are high, it accounts for smoothness whereas low values of holder exponent emphasis more roughness. After obtaining the holder exponent it can be substituted in the equation given below to obtain the fractal dimension value;

$$2D = 5 - h$$

Where D is the fractal dimension (FD) that is computed using the holder exponent and variance of Wavelet coefficient known as Wavelet based fractal analysis (WBFA).

2.3 Discrete Wavelet Transform

One- dimensional Discrete Wavelet Transform has been carried out in this task as per the datasets, which are discrete and one dimensional. For the construction of DWT one sets, $a = 2^j$ and $b = 2^j k$, where j and k are both integers. 1-D DWT is given by the following equation,

$$D_j(k) = 2^{-\frac{j}{2}} \int_{-\infty}^{\infty} f(t)\, \varphi\left(2^{-j} t - k\right) dt \qquad (2)$$

Where f(t) is the time series of our interest and k = 1, 2, 3...., n where n being the discrete data array of maximum size. Time series data of our interest is decomposed to approximate and detailed coefficients providing both lower and higher frequency information respectively.

3.0 Results and Discussions

3.1 Application to Synthetic data

A Synthetic signal is generated with three different frequencies such as 3Hz, 5Hz and 10Hz and analyzed by CWT and also applied to synthetic signal added with 25% Gaussian white noise. The result obtained is shown in Figure 1. As the signal is free from noise possessing only its own frequencies the mathematical tools didn't posed any difficulty and the information required are derived without any ambiguity. When the same signal analyzed by the above mentioned techniques after mixing noise, it provides large difference in the results which are shown in Figure 2. The CWT provides an acceptable picture in analyzing the non-stationary as well as the same non-stationary signal mixed with noise. CWT not only removes the ambiguity through by forming wavelet modulus maxima but also through its Wavelet Coefficients. Also it provides a picture of the Time-Frequency localization in interpretable form. An advantage pertaining to wavelet transform is that the Wavelet coefficients records the exact information of the signal even it is noisy. This notion regarding CWT proves it as a good tool for identification of lithology in Well logs. Therefore, this technique can be used in all circumstances to derive the exact information in the signal.

Mostly, Porosity logs are used for this approach and the fluctuating nature of the porosity logs can be correlated to both pores distribution and the fracture (major as well as several micro fractures) as well. DWT differentiates both fractures and the characteristics of the pores in the detailed coefficients (Sahimi and Hashemi, 2001). For demonstration of the techniques, we have generated two type of synthetic well logs (i) assuming well site is fractureless and (ii) well site is fractured. Now wavelet detail coefficient (WDC) for both well site are calculated as sown in in Figure 3(a & b) and Figure 3(c & d). We observed from WDC analysis that will be containing highly differentiable features in terms of spikes or local maxima as shown in Figure 3(d). The noisy data points pertaining to the uniform distribution constitute both low and high values in comparison with its surrounding data points. DWT differentiates these particular locations by means of a spike irrespective of the magnitude of the data points replaced. DWT exposes the signal to low and high frequency filters produces detailed and approximate coefficients respectively.

3.2 Application of Field Data: Costa Rica Convergent Margin, Central America

Costa Rica Convergent Margin in Central America is due to the convergence of Cocos and Caribbean Plates. A seismic migrated section over the region is shown in the Figure 4 showing Well sites 1039, 1040 and 1043. Among these wells sites 1039 and 1043 are taken for study whereas the site 1040 is omitted as it is not passing through certain major litho-units. Logs such as gamma ray and density are taken for study and the gamma ray signals exhibiting sharp spikes which are attributed to presence of interbeded ash layers. From the gamma ray log various lithology are identified and correlated with site adjacent to it. Density Logs are used for identification of spatial distribution of fractures along the rock matrix using DWT. Also the analysis of fractal dimension value through WBFA indicates the presence of fracture in lithology. Core Analysis reports the presence of four sedimentary layers terminated by a concordant Igneous Intrusion Gabbroic Sill. Well site 1039 is taken as the reference and lithology identified through Wavelet Transform are correlated to the site-1043 and the result confirms the subduction zone. As conventional technique such as Fast Fourier Transform fails in providing the time-frequency localization. So the application of wavelet Transform is the only way to find the proper time-frequency localization. The results obtained from CWT analyzed using log data sets prove the lithological successions. This result is significant in certain scale range only. Since scale is inverse of frequency thus small scale and high scale shows high frequency component and low frequency component of signal. Wavelet analysis of signal at small scale shows the very small changes in data which may be associated with noise also while large scale shows the outspread view of signal. The multiscale analysis has important role in computation of wavelet coefficients (Dimri et al., 2005). The scale is linear in a particular range is determined by log(var(cofficients)) versus log(scale) as shown in Figure 5.

The stratigraphic interfaces occurring in the Well log-1039 (Figure 6) appears in the Well log-1043 (Figure 7) after having disruptions in the middle. From the seismic section it is seen that there are four major lithology running from the Well -1039 to Well - 1043 and terminated as Gabbroic Sill. The Well-1040 crossed the above mentioned strata very mildly and it didn’t reach the concordant intrusive structure as reached by the Wells-1039 and 1043. Therefore, for interpretation point of view only the Wells-1039 and 1043 are used. The major successions mentioned after drilling is that the four sedimentary interfaces followed by a Gabbroic sill. The sedimentary succession obtained underneath the reference site-1039 situated in the Cocos Plate found to occur in the site-1043 without any disruption. It is also noted from the observation made by Eric et al., (2000) as the Cocos Plate subducting under the Caribbean Plate the off scarping of the sediments in the Cocos Plate should occur on the overriding plate but on analyzing the chemical composition it was mentioned the sediment lying on the overriding plate was of different composition. This analysis comes in support of the effort of framing the subducting system of Costa Rica using CWT spectrum, it is observed that the sedimentary succession in the site-1039 over the subducted Cocos Plate continuing through the site-1043 without any disruption situated over the overriding Caribbean plate. In accordance to the locations of the Wells and the continuity of the sedimentary successions existing in the both sites (1039 and 1043) as traced by correlation of Wavelet scalogram (Figure 8) where Figure 8 suggests that the Cocos plate is being subducted under the Caribbean plate. Application of DWT applied to porosity log of both the well 1039 & well 1043 to identify the presence of fracture in lithology figure 9 (a & b).

The lithology identified through time and frequency localization tools are used for the WBFA by taking their data points separately. Table 1 shows the FD values of various lithofacies over both wells. The FD values are computed these varies from 1.21 to 1.49 in the well-1039 and 1.20 to 1.44 in the well-1043 and associated coefficient of determination, R^2 (%) are also calculated for both wells. We observed the FD and coefficient of determination over both wells and found that there are transitional changes between sandy shale and shaly sandstone due to variation in FD values and this variation corresponds to a gradual transition between different sedimentary environments. Hence, the FD values can be used as a well log attribute.

Here the FD values are greater than 1.2 that emphasize the presence of high shale content and low energy environment in depth range 210 to 330m and 315 to 430m as reported by (Lopez 2006) in the presence of sandstone over the well sites 1039 and 1043 respectively

(Figure 10 &11). In spite of the presence of sandstone, the FD values are exceeding 1.2 indicating the dominance of shale content and these values are found to be not consistent from reference and 1043 site. In prior depth ranges, the inconsistency of FD values are attributed to the presence of fractures from the structural observations obtained in well site but in the above mentioned depth ranges the inconsistency as well as from the holder exponent values it is noted that the roughness exists in the particular lithology. The analyzed results are well correlated with the core samples.

7. Conclusions

Lithology identification is a tedious job in well logging and it is the most important one for reservoir characterisation. To identify Presence of structural feature such as fracture by quick look interpretation methods is very difficult using well log data. Formation micro imager (FMI) log often used to identify it is very expensive. Thus methodology used for lithology and fracture identification using wavelet transform and wavelet based fractal analysis using holder exponent can be a useful stuff to extract the different lithological feature as well as stratigraphy feature.

For structural feature identification from various lithology holder exponent and fractal dimension values can be utilised and in the presence of some extra information as that of the structural observations from well sites the results can be more promising. In order to avoid the assistance of extra information more datasets are needed from the same area so that on application of WBFA on various lithologies passing through the area provides concrete idea on lithology and Structural features using holder exponent and fractal dimension values.

Acknowledgement

The authors are thankful to both of the anonymous reviewers for constructing critical comments to improve our manuscript.

Figure and Table Captions

Figure 1: Shows the Continuous Wavelet Transform (CWT) using a synthetic time series data.

Figure 2: Shows the Continuous Wavelet Transform (CWT) of a synthetic noisy time series data.

Figure 3: (a) synthetic well logs data over the fractureless well site, (b) Discrete wavelet detail coefficient (DWC) of fractureless well site, (c) synthetic well log data over the fractured well site, and (d) Discrete wavelet detail coefficient (DWC) of fracture less well site.

Figure 4: Shows the seismic migrated section showing the Wells (after Erik et al, 2000)

Figure 5: shows the scale of interest shows variance of wavelet coefficients versus scale of gamma ray of well site 1039 and 1043.

Figures 6: showing Continuous Wavelet Transform (CWT) using gamma ray signal and the Wavelet Coefficient at an altitude-32 of the gamma ray log of the Well location-1039

Figure 7: showing Continuous Wavelet Transform (CWT) using gamma ray signal and the Wavelet Coefficient at an altitude-32 of the gamma ray log of the Well location-1043

Figure 8: Represents the lithology identification using the gamma ray log of the Well site 1039 and 1043 by the lines drawn on the scalogram and it represents the subduction zone in the areas obtained from the seismic migrated section.

Figure 9: (a) Shows the discrete detailed and approximate coefficients and the spikes represents the possible fractures at well location 1039, (b) shows the Discrete detailed and Approximate coefficients and the spikes represents the possible fractures at well location 1043

Figure 10: Shows variance of Wavelet coefficients versus scale of density log of well site-1039 and 1043 which shows consistent holder exponent and fractal dimension values indicating that wells contains similar sedimentary environment.

Figure 11: Shows the FD values of both well sites of 1039 and 1043.

Table 1: Shows the FD values of the appropriate lithology identified and the circled depth ranging and its appropriate fractal dimension values showing deviation of the vales from the reference site 1039.

Table 2: Shows the ranges of fractal dimension values.

References

Bansal A. R., Gabriel G., Dimri V.P., Power law distribution of susceptibility and density and its relation to seismic properties: An example from the German Continental Deep Drilling Program (KTB), Journal of Applied Geophysics, 72(2010) 123-128.

Brown, R. A.: Interpretation of three-dimensional seismic data, 6th edition, American Association of Petroleum Geologists (AAPG) Eds., 540 pp., 2004.

Coconi-Morales E., Ronquillo-Jarillo G. and Campos-Enríquez J.O., Multi-scale analysis of well logging data in petrophysical and stratigraphic correlation: Geofísica International, 2010,49 (2), 55-67, 2010

Chandrasekhar E., Rao E. V. Wavelet Analysis of geophysical well log data of Bombay Offshore Basin, India, Mathematical Geosciences, 2012, 44, 901–928.

Dashtian, H., Jafari, Z., Lai, K., Sahimi M., Masihi, M., Analysis of cross correlation between well logs of hydrocarbon reservoirs. Transp Porous Med, 2011, 90, 445-464.

Daubechies, I., The wavelet transform time-frequency localization and signal analysis: IEEE Transaction on Information Theory, 1990, 36, No. 5.

Dimri V.P., Vedanti N. and Chattopadhyay S., Fractal analysis of aftershock sequence of the Bhuj earthquake: A wavelet- based approach, current science, vol.88, no 10, 25 may 2005

Erik Moritz, Stefan Bornhold, Hildegard Westphal, Martin Meschede, Neural network interpretation of LWD data (ODP Leg 170) confirms complete sediment subduction at the Costa Rica convergent margin, Earth and Planetary Science Letters, 2000, 174, 301-312.

Expedition 308 Scientist 2005, Overpressure and fluid flow processes in the deep water Gulf of Mexico: slope stability, seeps, and shallow-water flow. IODP Preliminary Report, 308.

Fedi, M.: Global and local Multiscale Analysis of Magnetic Susceptibility Data, Pure Appl. Geophysics, 160, 2339-2417, 2003

Hui Liu and Zaixing Jian. Wavelet Transform of geophysical well logging signal and Its application to sequence division, 3rd International Congress on Image and Signal Processing, 2010, 3470-73.

J. F. Yu and Z. X. Li., Wavelet Transform of Logging Data and Its Geological Significance. Journal of China University of Mining &Technology, 2003, 32 (3): 336-339.

J. T. Li, J. F. Yu and Z. X. Li., The demarcating of Stratigraphic sequence based on wavelet Transform of well-logging data. Coal Geology & Exploration, 2004, 32 (3): 48-50.

Javid M., and Tokhmechi B., Formation interface detection using Gamma Ray log: A novel approach Journal of Mining & Environment, 2012, 3, 1, 41-50.

Lopez M. and Aldana M., Facies rcognition using wavelet based fractal analysis and waveform classifier at the Ortupano-A Field, Venezuela, Nonlin. Processes Geophys., 14,325-335, 2007

Mansinha, L., Stockwell, R. G., Lowe, R., Eramian, M., and Schincariol, R. A., Local S-spectrum analysis of 1-D and 2-D data, Physics of the Earth &Planetary Interior, 1997,103, 329-336.

Pan, S., Hsieh, B., Lu, M. and Lin, Z., Identification of stratigraphic formation interfaces using wavelet and Fourier transforms: Computers & Geosciences, 2008, **34**, 77–92.

Pinnegar, C. R. Mansinha, L., Time-local Fourier analysis with a scalable, phase-modulated analyzing function: The S-transform with a complex window, Signal Processing, 2004, 84, 1167-1176,

Pinnegar, C. R. Mansinha, L., The S-transform with window of arbitrary and varying shape, Geophysics, 2003, 68, 1, 381-385.

Pratt, W.K., Digital Image Processing, John Wiley & Sons, 1978, 330-333.

Sahimi, M., and Hashemi, M., 2001, Wavelet identification of the spatial distribution of fractures: Geophysical Research Letter, 28,4, 611–614.

Stockwell, R. G., Mansinha, L., and Lowe, R. P. Localization of complex spectrum: The S-Transform, IEEE Transactions on Signal Processing 1996, 144, 998–1001.

Stockwell R.G., Why use the S-Transform? AMS Pseudo–differential operators: partial differential equations and time–frequency analysis, 2007, 52, 279–309.

Tokhmechi, B., Memarian, H., Rasouli, V., Ahmadi N. H. and Moshiri, B. Fracture zones detection using wavelet decomposition of water saturation log. J. Petrol. Sci. Eng., 2009a, 69, 129-138.

Tokhmechi, B., Memarian, H., Ahmadi N. H. and Moshiri, B., A novel approach for fracture Zone detection using petrophysical logs. J. Geophys. Eng., 2009b, 6, 365-373.

Yue, W.Z., Tao, G., Liu, Z.W., Identifying reservoir fluids by wavelet transform of well logs. In: Proceedings of the SPE Asia Pacific Oil and Gas Conference and Exhibition, Perth, Australia, 2004, (SPE 88559).

Zhang Xiao-Feng, Pan Bao-Zhi, Wang Fei, and Han Xue, A study of wavelet transforms applied for fracture identification and fracture density evaluation, Applied Geophysics, 2011, 8, 2, 164-169

Figure 1

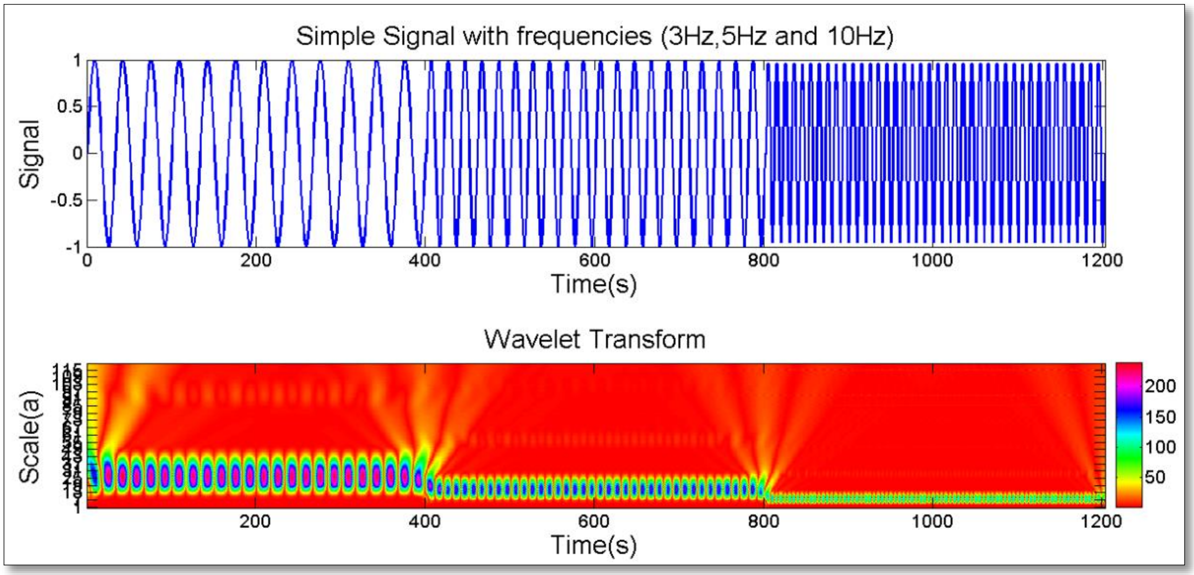

Simple Signal with frequencies (3Hz,5Hz and 10Hz)
Signal
Time(s)
Wavelet Transform
Scale(a)
Time(s)
200
150
100
50

Figure 2

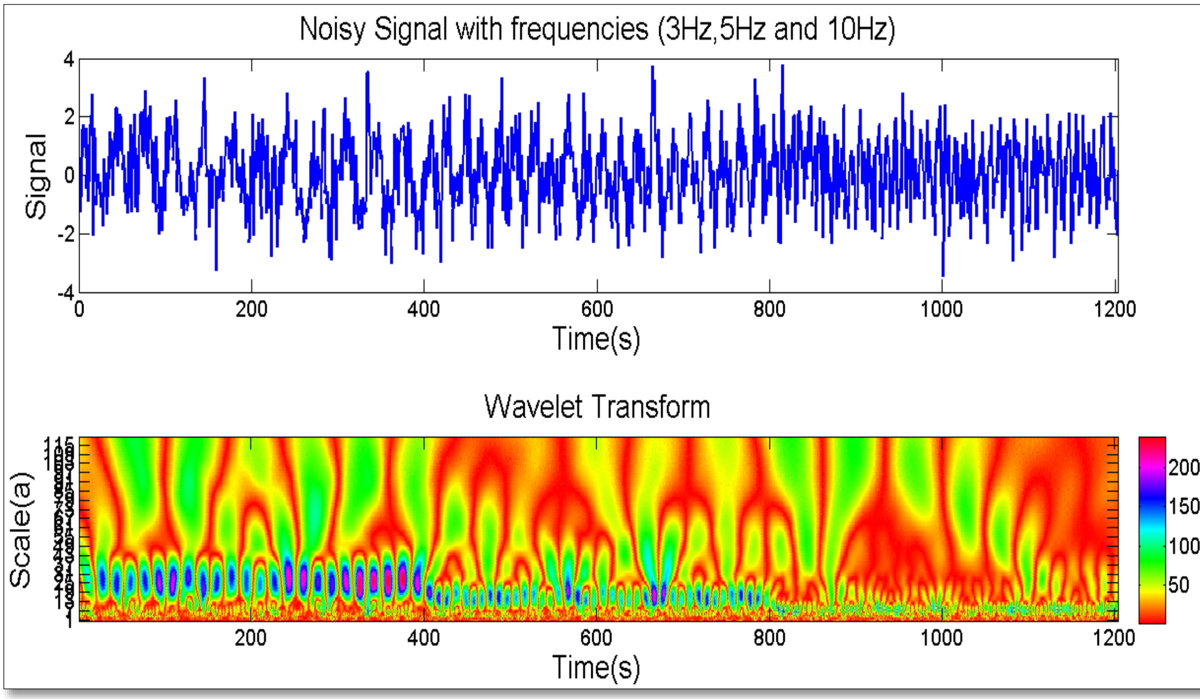

Noisy Signal with frequencies (3Hz,5Hz and 10Hz)
Signal
4
2
0
-2
-4
0
200
400
600
800
1000
1200
Time(s)
Wavelet Transform
Scale(a)
200
150
100
50
200
400
600
800
1000
1200
Time(s)

Figure 3

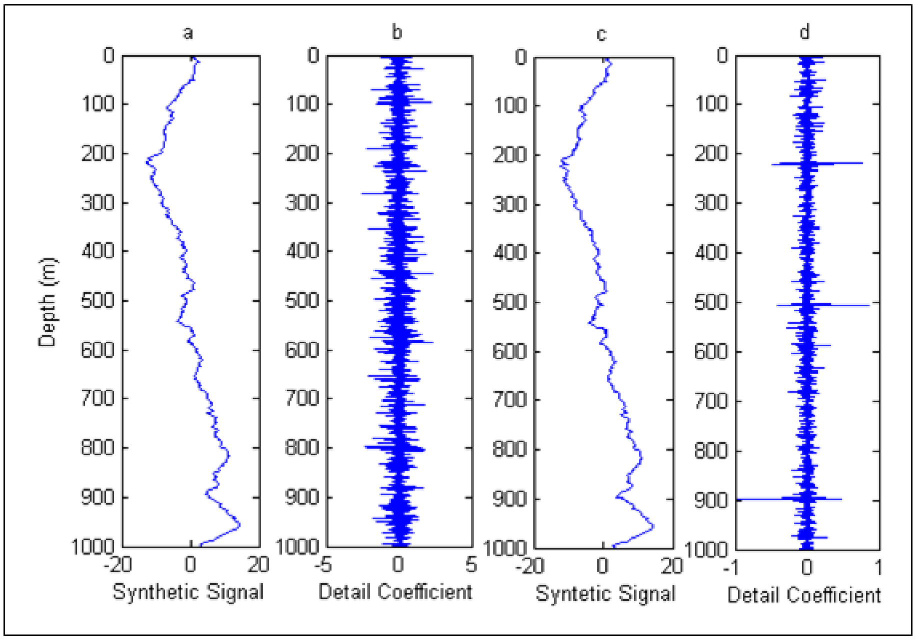

a
b
c
d
Depth (m)
0
100
200
300
400
500
600
700
800
900
1000
-20
0
20
-5
5
-1
1
Synthetic Signal
Detail Coefficient
Syntetic Signal
Detail Coefficient

Figure 4

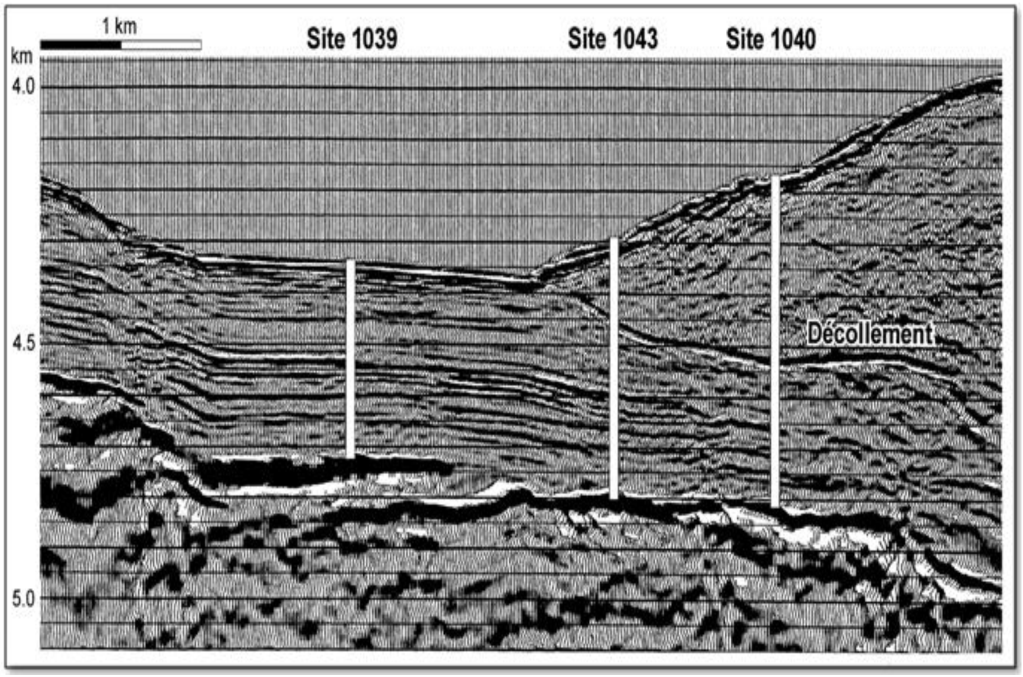
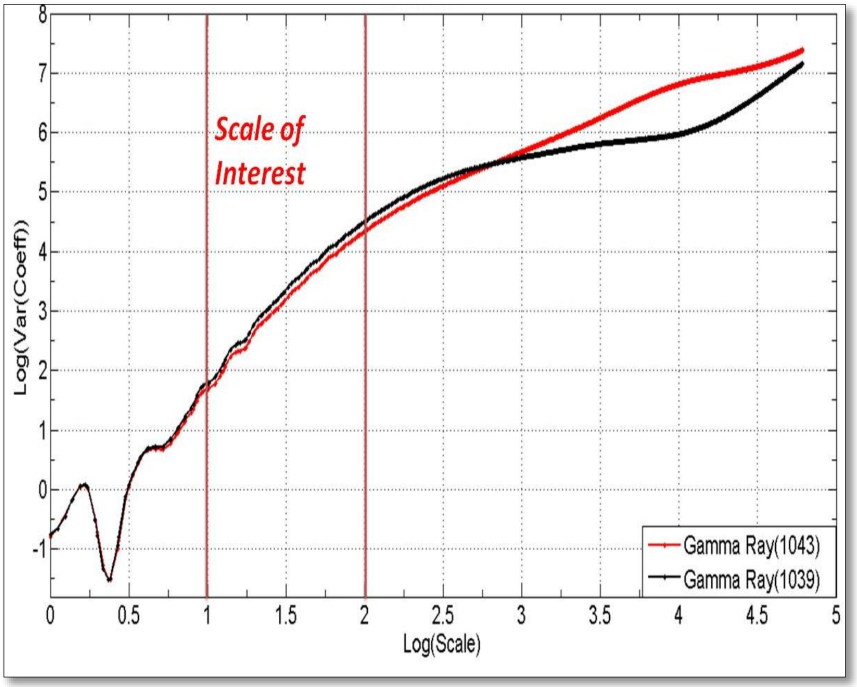


Figure 5



Scale of Interest
Log(Var(Coeff))
Log(Scale)
Gamma Ray(1043)
Gamma Ray(1039)

Figure 6

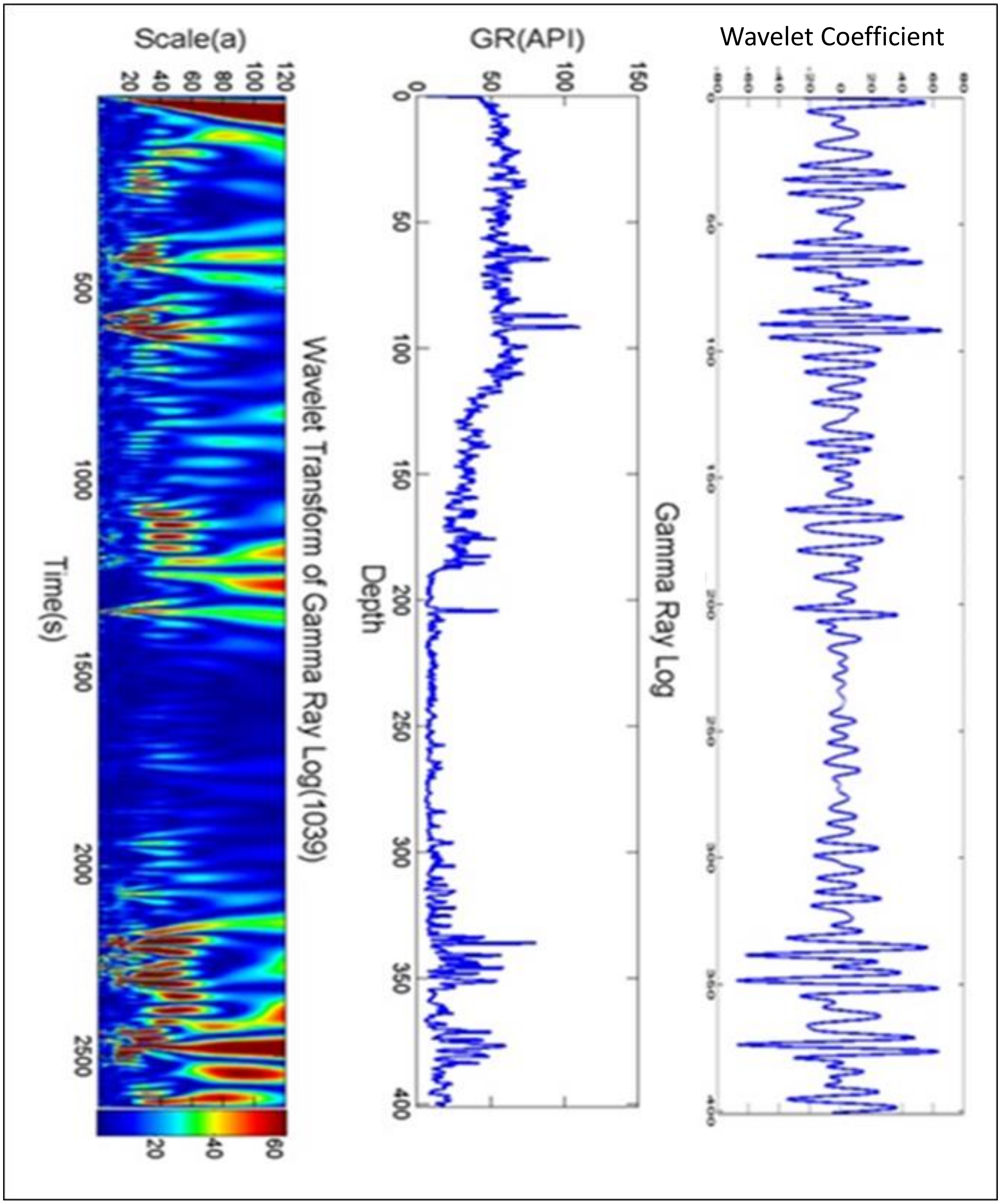
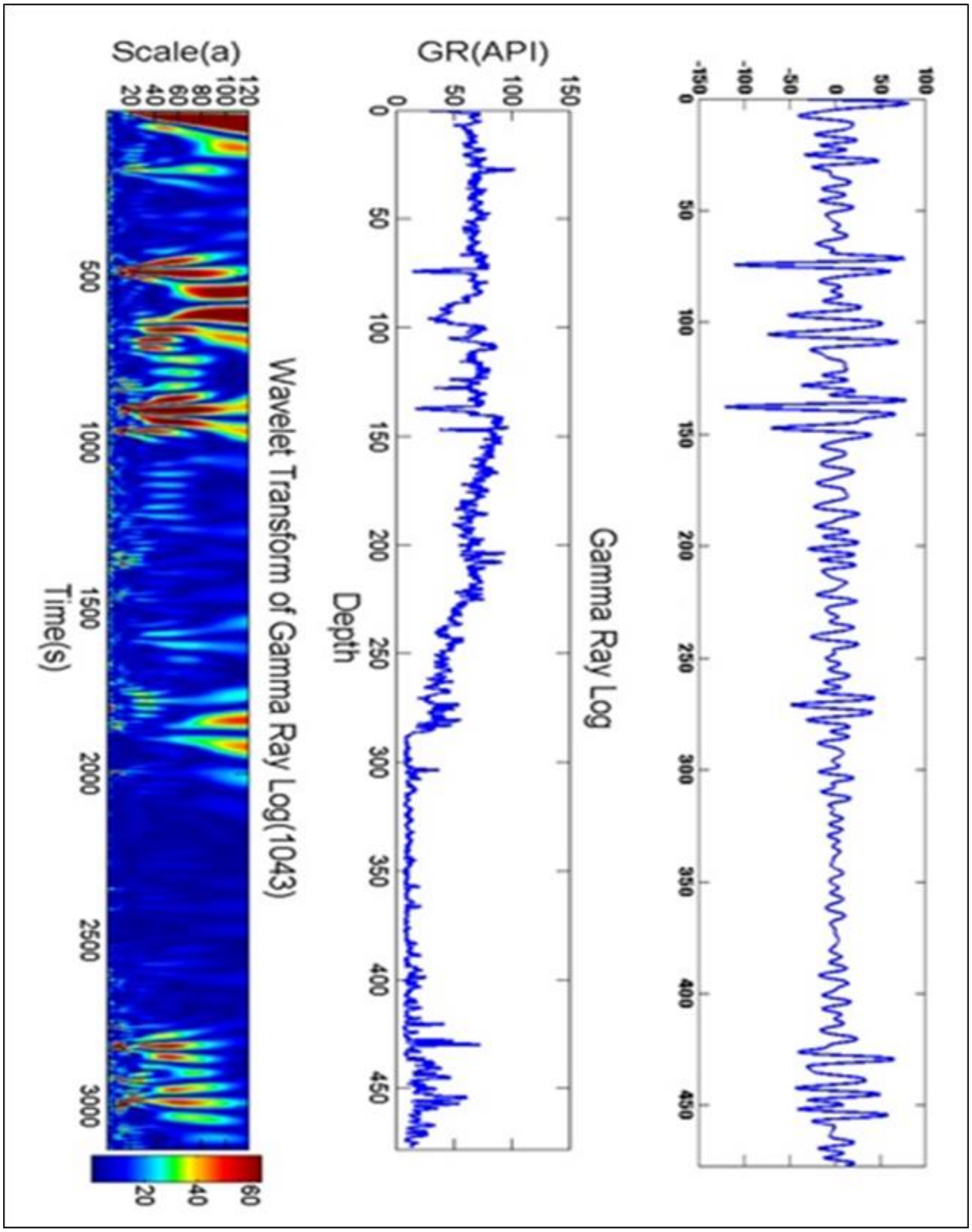

Wavelet Coefficient
Gamma Ray Log
GR(API)
Depth
Scale(a)
Wavelet Transform of Gamma Ray Log(1039)
Time(s)

Figure 7



Gamma Ray Log
GR(API)
Depth
Wavelet Transform of Gamma Ray Log(1043)
Scale(a)
Time(s)

Figure 8

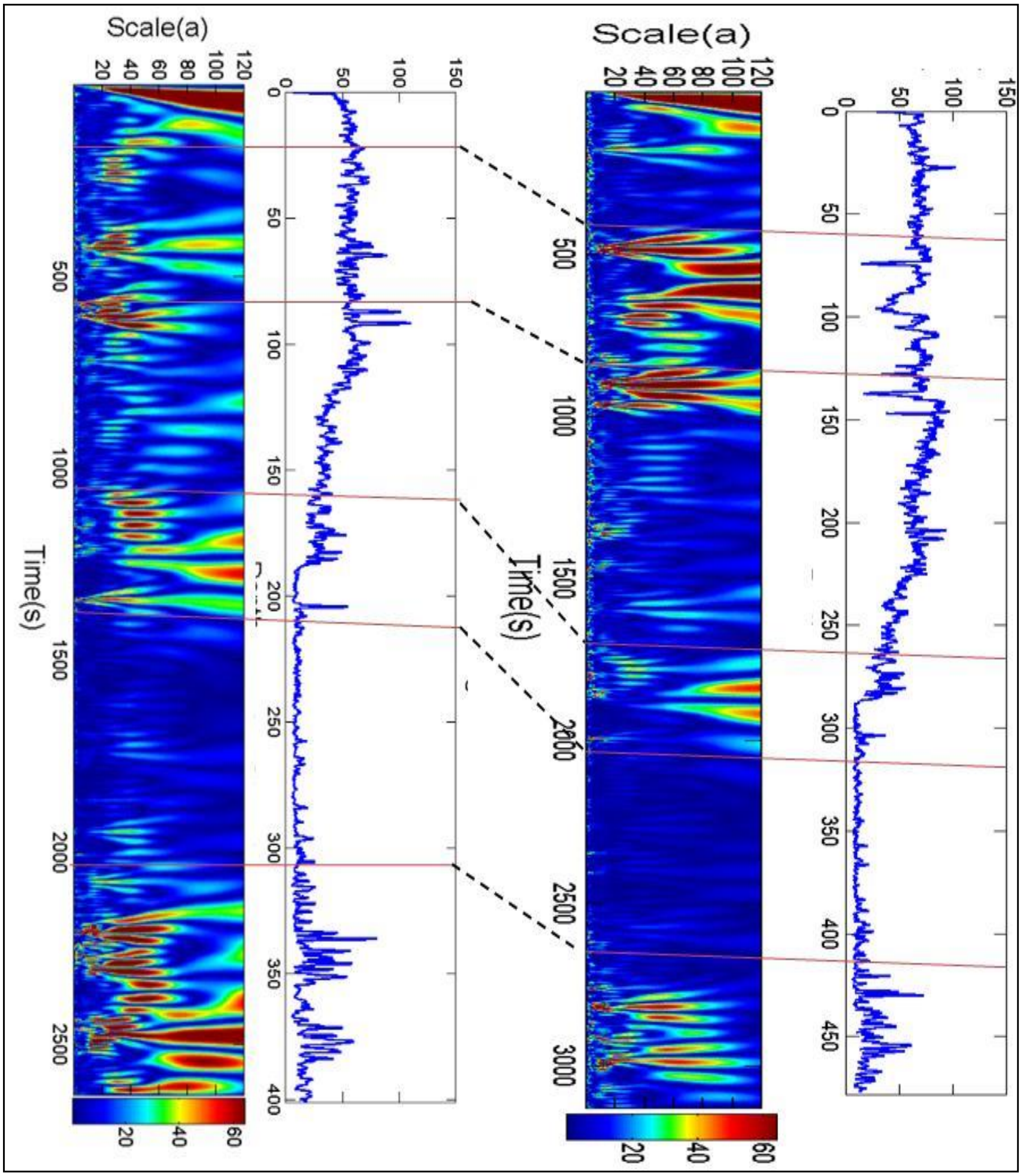


Figure 9

(a) (b)

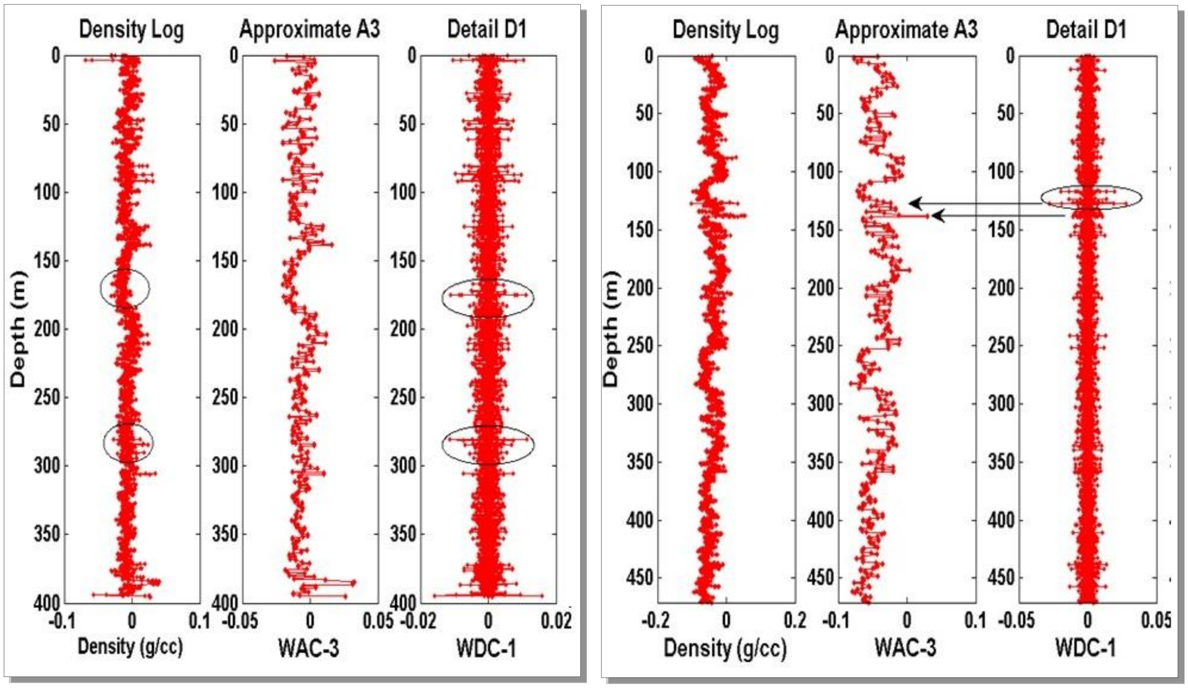

Density Log
Approximate A3
Detail D1
Depth (m)
Density (g/cc)
WAC-3
WDC-1
Density Log
Approximate A3
Detail D1
Depth (m)
Density (g/cc)
WAC-3
WDC-1

Figure 10

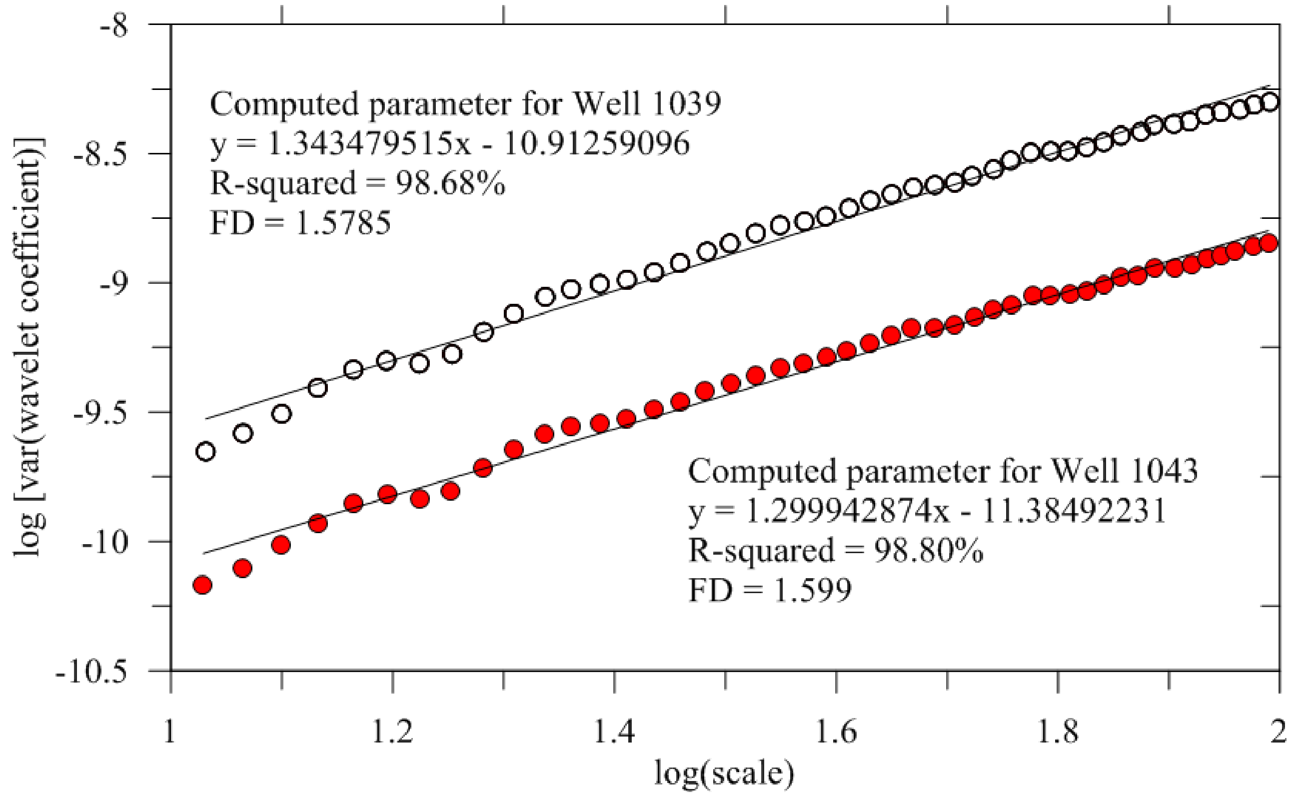

Computed parameter for Well 1039
y = 1.343479515x - 10.91259096
R-squared = 98.68%
FD = 1.5785
Computed parameter for Well 1043
y = 1.299942874x - 11.38492231
R-squared = 98.80%
FD = 1.599
log [var(wavelet coefficient)]
log(scale)
-8
-8.5
-9
-9.5
-10
-10.5
1
1.2
1.4
1.6
1.8
2

Figure 11

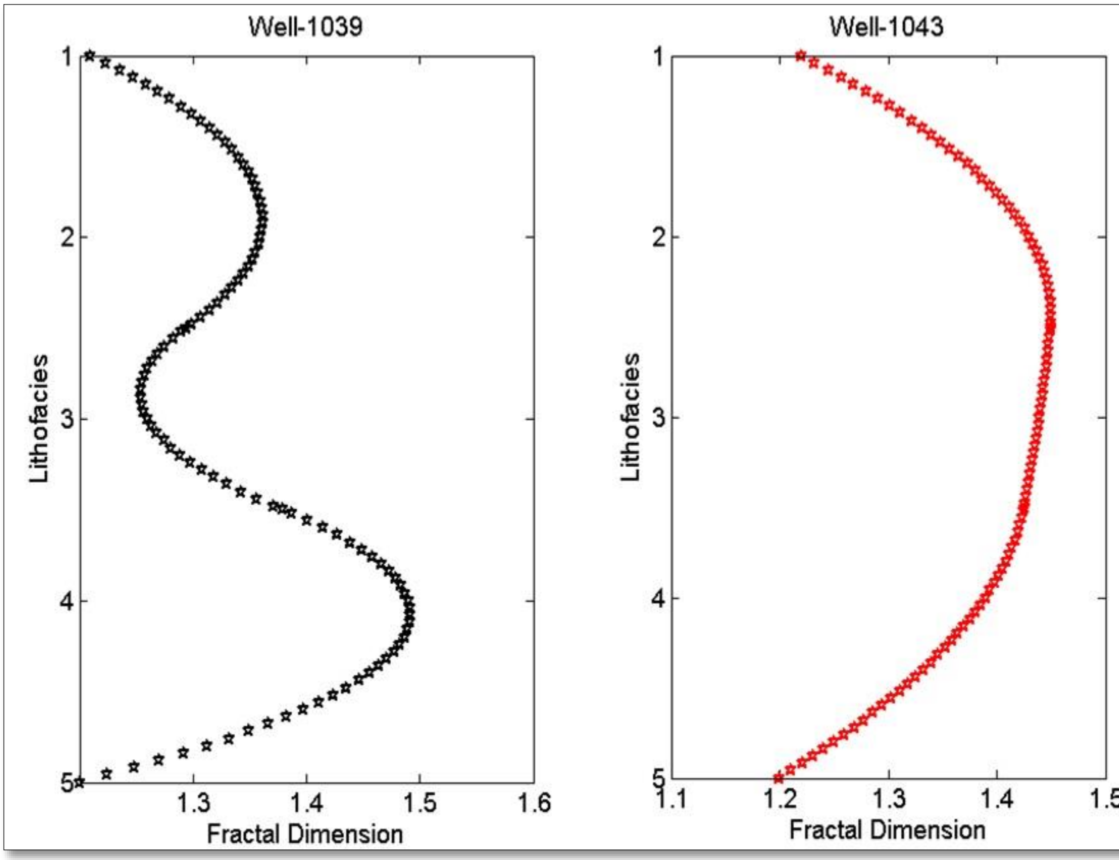

Well-1039
Lithofacies
Fractal Dimension
1
2
3
4
5
1.3
1.4
1.5
1.6
Well-1043
Lithofacies
Fractal Dimension
1
2
3
4
5
1.1
1.2
1.3
1.4
1.5

Table 1

Lithofacies	Depth Range (m.)		Fractal Dimension		Coefficient of determination, R^2 (%)	
	Well 1039	Well 1043	Well 1039	Well 1043	Well 1039	Well 1043
Shale with interbeded ash layer	20-80	60 - 130	1.21	1.22	99.441	99.5988
Shaly sandstone	80 -160	130 - 260	1.36	1.43	99.3234	99.3375
Sandy shale with interbeded ash layer	160 - 210	260-315	1.26	1.44	99.0514	98.8141
Sandstone	210 - 330	315-430	1.49	1.39	98.8141	98.791
Gabbroic sill	330 - 400	430-450	1.20	1.20	99.1356	96.96441

Table 2

Fractal Dimension	Interpretation
< 0.9	High sand content and high energy environment
0.9 to 1.2	Inter-bedded sand and shale
> 1.2	High shale content and low energy environment