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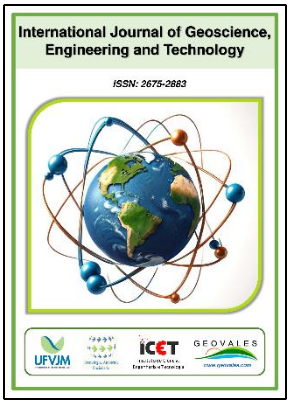

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Statistical Approach to Gamma Ray Signature of Clean Shales, Limestones and Sandstones: Case Study of Benin's Offshore Coastal Sedimentary Basin

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Abstract

Shale, sandstones, limestones, and dolomites are geological formations that play key roles in forming and trapping hydrocarbon systems. The knowledge of GR signature of clean shales, limestones and sandstones is significant for more precise identification of formations. This study aims to propose a statistical technique for determining the gamma ray log signature of clean shales, sandstones, limestones, and dolomites. This approach of combines the GR log statistical processing method and the bootstrap mean estimation method. The case study has helped to determine Benin's offshore sedimentary basin clean formations GR signature at the scale of the petroleum block 1. The results show that Benin's block 1 clean shale GR signature is 122.57 GAPI with a confidence interval of [116.41GAPI; 128.26GAPI] while its clean limestone or sandstone GR signature is 16.63 GAPI with a confidence interval of [12.84GAPI; 20.51GAPI]. As a result, over the qualitative analysis of a block 1 well GR log data, the clean shale and clean sandstone baselines to be used have to correspond to these GR signatures. Moreover, these clean formations GR signatures have to be taken into account over formations shale volume computation.

Keywords: Statistical Approach, Gamma Ray Signature, Clean Shale, Clean Sandstones, Benin's Offshore Coastal Sedimentary Basin.

1. Introduction

Shale, sandstones, limestones, and dolomites are geological formations that play key roles in the process of formation and trapping of hydrocarbon systems. Indeed, when hydrocarbons are generated from a source rock, they migrate and gather in commercial volumes into reservoirs that are porous and permeable rocks, imprisoned by rocks called cap or seal rocks (Djoï, 2024a). The source rocks are in general made of shales and limestones while sandstones, limestones and dolomites constitute hydrocarbons reservoir formations (Adepapo et al., 2014). Like limestones, which can serve as source rocks and reservoirs, shales are not only found as source rocks but also as seal or cap rocks in the petroleum systems (Tuttle, Charpentier and Brownfield, 1999; Adepapo et al., 2014).

Over the exploration and discovered fields appreciation phases, log data analysts determine wells stratigraphic columns or identify the different formations penetrated by a well on the basis of lithology logs, the main used being gamma ray, spontaneous potential (SP), sonic wave and neutron-density logs (Djoï, Nwosu and Ikiensikimama, 2022).

The gamma ray (GR) log is a continuous recording of the intensity of the natural radiations emanating from the formations penetrated by a borehole versus depth, the sources of natural radioactivity being the isotopes of potassium (^{40}K), thorium (^{232}Th) and uranium (^{238}U) contained in the formation minerals (Bassiouni, 1994). As lithology log, GR log is usually used to identify boundaries, primarily shale units from other lower radioactivity formations (limestonesand sandstones), and to quantify formations shale volume (Karakan, 2009).

The first one of the two types of GR log, the total or standard GR log which measures only the total radioactivity, helps in identifying shales and porous formations without being able to differentiate the responses of limestones and sandstones (Oberto, 1948). The challenge of separating limestones, sandstones, and dolomites is overcome with the second type of gamma ray log, the natural gamma ray spectrometry (NGS) log, that measures in addition to the total radioactivity the concentrations of potassium, thorium, and uranium (Baron, Cariou and Thorion, 1989).

Several studies have revealed that the knowledge of GR signature of clean shales, limestones and sandstones, which are the GR characteristic values of these different formations, is significant for more precise identification of formations. For Djoï (2024b), clean shales are formations with a hundred percent of shale while clean limestones and sandstones are those with zero percent shale. As proved by Oberto (1984), Karacan (2009), Szabó (2011), and Djoï (2024b), when using the total gamma ray, clean limestones and sandstones are characterized by the minimum GR recorded at a zone scale and shales by maximum GR. The minimum and maximum GRs at a region scale are known as the GR log signature of clean shales, limestones and sandstones. It can be seen in the work performed by Fadiya, Alao and Adetuwo (2018), Mohammed (2021) and Djoï, Nwosu and Ikiensikimama (2022) that these GR log signatures are needed to compute the gamma ray index which is used in the different models of formations shale volume determination.

This study aims to propose a statistical technique for determining the gamma ray log signature of clean shales, sandstones and limestones.

The approach will help log data analysts in determining the gamma ray log signature of clean shales, limestones, sandstones, and dolomites for specific areas that can be used for further clean shales, limestones and sandstonesidentification in these areas and formations shale volume computation from GR log analysis.

The case study will be performed for determining the GR log signature of clean shales, limestones and sandstones of the eastern north part of Benin's offshore coastal sedimentary basin.

2. Materials and Methods

2.1. Materials

The area of study of the case study is the current petroleum block 1 of Benin's offshore coastal sedimentary basin which is located at the eastern north part of that basin.

The main materials used for the case study are GR log data, Microsoft Excel, and Python Notebook. GR log data of nineteen (19) wells from the area of study have been used for the case study. Microsoft Excel and Jyputer Notebook have been used for GR log data manipulation. Python Notebook has been the tool used for statistical computations.

2.2. Methods

The statistical approach proposed by the current study is a combination of the GR log statistical processing method set by Djoï (2024a) and the boostrap mean distribution. It helps to determine the GR log signature of the formations of interest for specific areas of interest.

The technique proposes three different activities: (1) data manipulation, (2) GR log signature determination at the well scale, and (3) GR log signature determination at the region scale. The flowchart of this approach is summarized in Figure (1).

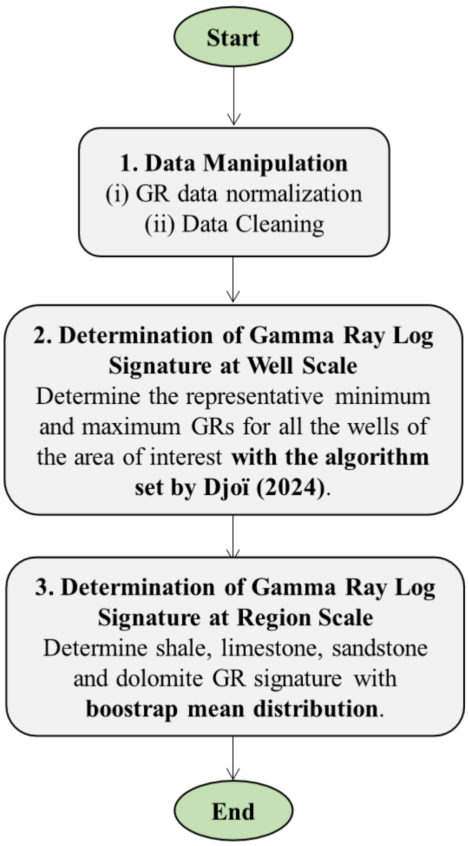

Figure 1 – Flowchart for clean shale, limestone and sandstone GR signatures determination.

2.2.1. Data Manipulation

The first activity to be performed over clean sedimentary formations GR log signature determination is the data manipulation. It consists of (1) GR data normalization to the reference GR scale and (2) data cleaning.

(1) GR Data Normalization

Since the formations GR signature determination is carried out from GR log data collected on a certain number of wells of the area of interest, the GR log data must be converted to the same GR scale, called here reference GR scale, when the same used GR scale is not used for the wells. This process is known as GR data normalization. Indeed, there are two types of GR scales that are 150-GAPI and 200-GAPI scales. Under 150-GAPI and 200-GAPI scales, the maximum GR value to be recorded by the logging probes must be 150 GAPI and 200 GAPI respectively.

The essence of GR data normalization is that a given value of GR must indicate a formation with the same characteristics for different wells. The formula for GR data normalization is given by Equation (1).

$$GR_{conv} = \begin{cases} \frac{3}{4} GR_{mes}, if\ GR_{ref} = 150\ GAPI \\ \frac{4}{3} GR_{mes}, if\ GR_{ref} = 200\ GAPI \end{cases} \quad (1)$$

With GR_{conv} the converted GR value, GR_{mes} the measured GR value and GR_{ref} the GR reference scale.

One must be aware of the fact that, for a given well, the GR data conversion is required when the well GR scale is different from the reference scale chosen for GR signature determination. That is, when for instance the reference scale is 200 GAPI, only GR log data recorded under 150 GAPI must be normalized and vice versa.

(2) Data Cleaning

Two main tasks lead to data cleaning: (a) odd values detection and treatment and (b) outliers detection and treatment. The development of the procedures is as follows.

a. Odd Values Detection and Treatment

According to Djoï, (2024b), for a given GR scale, any GR value that is negative or greater than the GR scale maximum value is known as an odd value. As highlighted above, the 150-GAPI scale and 200-GAPI scale maximum value is 150 GAPI and 200 GAPI respectively.

The odd values must be removed or deleted from the GR datasets (Djoï, 2024b).

b. Outliers Detection and Treatment

At this step, the outliers of the GR dataset are identified with an appropriate method. Djoï (2024b) proposed outliers detection through boxplot analysis. He added that for a well GR dataset, no matter the technique adopted for outliers identification, they (outliers) must be replaced in the dataset by the mod or the center of the modal class.

2.2.2. Determination of Gamma Ray Log Signature at Well Scale

The clean shale GR signature at a well scale is the representative maximum GR on that well while the clean limestone or sandstone GR signature at a well scale is the representative minimum GR on the well.

For the determination of GR signature at region scale, the GR signatures at well scale must be determined for different wells of the area of interest for which the GR data are available. For that purpose, the statistical approach proposed by the current study requests the use of the method set by Djoï (2024a) for representative minimum and maximum GR determination.

The algorithm set by Djoï (2024a) is the one of Figure (2).

2.2.3. Determination of Gamma Ray Log Signature at Region Scale

The algorithm proposed by the statistical approach of this study for formation GR signature computation is shown in Figure (3). The details are presented as follows.

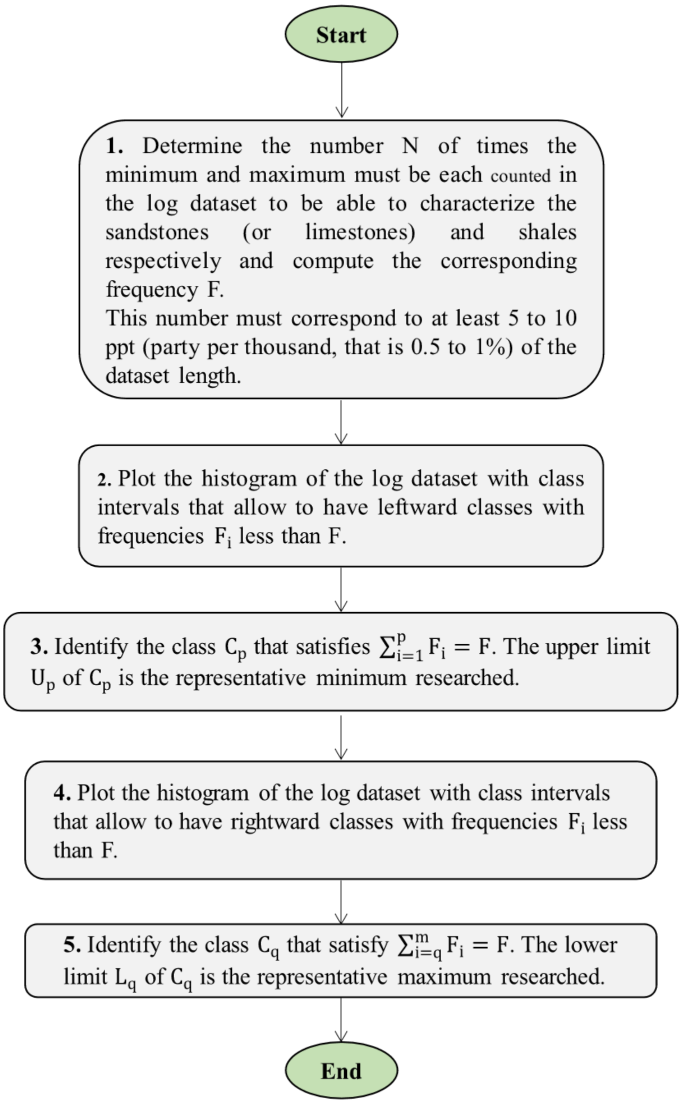

Figure 2 – Algorithm for representative minimum and maximum GR determination (Djoï, 2024b).

For a dataset with a large number of wells N, GR log signature of clean shales and clean limestones and sandstones are respectively the average of the representative minimum GRs and the average of the representative maximum GRs of the wells of the area of interest. That is, if GR log data is available for a population of N wells of the area of interest and $(GRmin_1, GRmin_2, \dots, GRmin_N)$ and $(GRmax_1, GRmax_2, \dots, GRmax_N)$ the samples of the representative minimum GRs and of the representative maximum GRs respectively, the area of interest clean shale GR signature is given by Equation (2) and the clean limestone and sandstone GR signature is given by Equation (3).

$$GR_{shale} = \frac{1}{N}\sum_{i=1}^{N} GRmax_i \qquad (2)$$

$$GR_{formation} = \frac{1}{N}\sum_{i=1}^{N} GRmin_i \qquad (3)$$

With GR_{shale} is the GR signature of clean shale, $GR_{formation}$ the GR signature of clean limestone or sandstone, $GRmin_i$ the representative minimum GRs and $GRmax_i$ the representative maximum GRs. In Equation (3), formation can be limestone or sandstone.

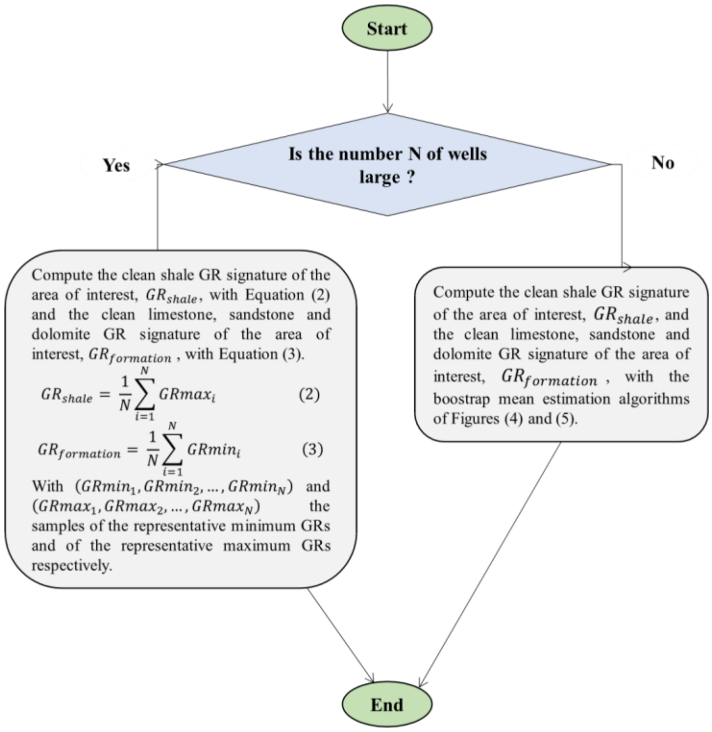

Figure 3 – Algorithm for clean formations GR signature computation.

When the number of wells N is not large, a large number of boostrap mean sample $(GR_{formation}^{*(1)}, GR_{formation}^{*(2)}, \dots, GR_{formation}^{*(B)})$ can be used in place of the original GR samples $(GRmin_1, GRmin_2, \dots, GRmin_N)$ and $(GRmax_1, GRmax_2, \dots, GRmax_N)$ for clean shale, clean limestone and clean sandstone GR signature computation.

Bootstrapping is a computer-based technique that can be used to infer the sampling distribution of almost any statistics via repeated samples drawn from the sample itself, as opposed to the hypothetical resampling from the population (Chong and Cho, 2011). In the case of our study, the boostrap mean estimator must be used. The procedure is as follows.

Let $X = (x_1, x_2, \dots, x_n)$, a statistic x sample from a population.

A boostrap sample $X^* = (x^*{}_1, x^*{}_2, \ldots, x^*{}_n)$ is obtained by randomly sampling n times, with replacement, from the original sample X (Efron and Tibshirani, 1998). The empirical mean $\bar{x}^*$of $X^*$is a boostrap mean of x which is a good estimate $\bar{x}$ (Chen, 2017).

According to Orloff and Bloom (2017) and Efron and Narasimhan (2020), the procedure for computing the boostrap estimate of mean of a statistic x from the sample $X = (x_1, x_2, \ldots, x_n)$ is as follows.

Procedure for boostrap mean estimation

(i) Generate a large number B of boostrap samples $X^{*(1)} = \left(x^*{}_1{}^{(1)}, x^*{}_2{}^{(1)}, \ldots, x^*{}_n{}^{(1)}\right)$, $X^{*(2)} = \left(x^*{}_1{}^{(2)}, x^*{}_2{}^{(2)}, \ldots, x^*{}_n{}^{(2)}\right)$, …, $X^{*(B)} = \left(x^*{}_1{}^{(B)}, x^*{}_2{}^{(B)}, \ldots, x^*{}_n{}^{(B)}\right)$ of x from the original sample $X = (x_1, x_2, \ldots, x_n)$.

(ii) Compute the boostrap means $\bar{x}^{*(j)} = \frac{1}{n}\sum_{i=1}^{n} x^*{}_i{}^{(j)}$ of $X^{*(j)}$, $(1 \le j \le B)$, to get the boostrap mean sample $\left(\bar{x}^{*(1)}, \bar{x}^{*(2)}, \ldots, \bar{x}^{*(B)}\right)$.

(iii) Compute the boostrap estimate of mean of x, $\hat{\bar{x}} = \frac{1}{B}\sum_{j=1}^{B} \bar{x}^{*(j)}$.

The application of this technique to GR signature of clean formations (shale, limestone and sandstone) determination gives the algorithms of Figures (4) and (5).

2.3. Case Study

The case study has been carried out on gamma ray log dataset of nineteen (19) wells (W1 to W19) of current Benin's petroleum block 1 for the block formations GR signatures determination. It has consisted of:

- performing the data manipulation: GR data normalization and cleaning;
- determining GR signatures of the formations of interest (shale, limestone or sandstoneof Benin's petroleum block 1 at well scale with the algorithm set by Djoï;
- determining GR signatures of the formations of interest (shale, limestone or sandstone,) of Benin's petroleum block 1 with the boostrap mean estimation technique.

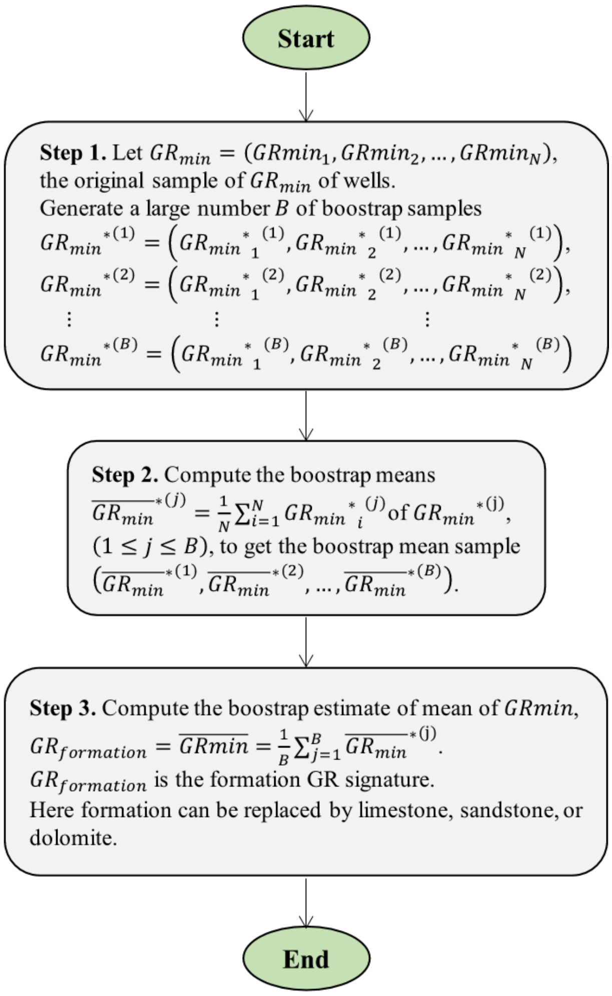

Figure 4 – Algorithm for clean limestone and sandstone GR signature computation with boostrap estimate of mean technique.

3. Results and Discussion

3.1. Data Manipulation

The GR log data have been processed for the nineteen wells. Since GR data have been recorded under 150-GAPI scale for fourteen wells and 200-GAPI scale for five wells, 150-GAPI scale has been chosen as the reference scale and the data have been normalized to that scale for five wells.

Thereafter, odd values and outliers have been identified and treated. Boxplot analysis is used for outliers detection.

Figure (6) shows the histograms of raw and processed GR log data for the well W1. One can see that W1 GR log data is recorded under 200-GAPI scale. The raw data contains negative values and others higher than 200 GAPI. The processed data histogram proves that the data has been normalized and shows no odds values.

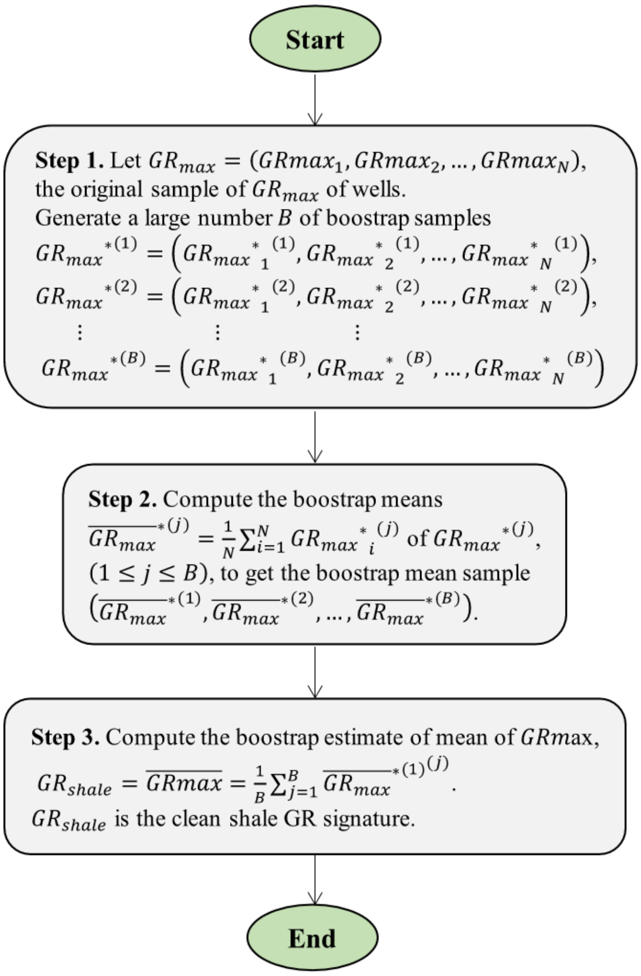

Figure 5 – Algorithm for clean shale GR signature computation with boostrap estimate of mean technique

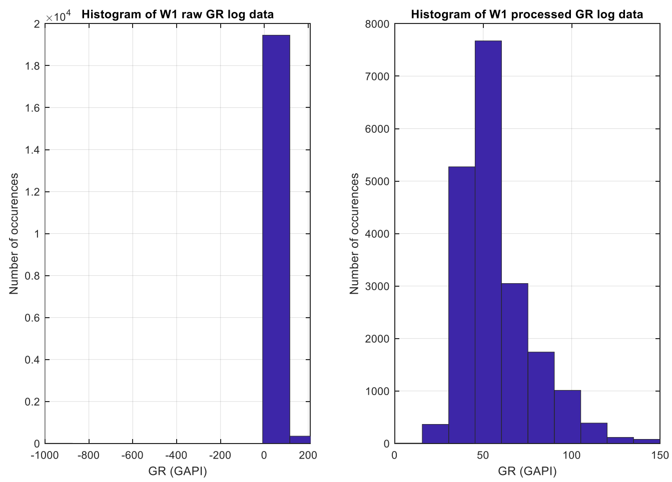

Figure 6 – Histogram of W1 raw and processed GR log data.

3.2. Determination of Gamma Ray Log Signature at Well Scale

The formations (shale, limestone and sandstone) GR signature, that is the representative minimum GR and maximum GR have been determined for different wells with the processed datasets on the basis of the method proposed by Djoï (2024b) in his study on statistical well log data processing.

Figure (7) and Table (1) show the results of this task for shale GR signatures and sandstone GR signatures of the wells. We notice a variability of sandstone and shale GR signatures over wells with sandstone GR signature varying from 3.37 to 30.9 GAPI and 90.9-141 GAPI range for shale GR signature.

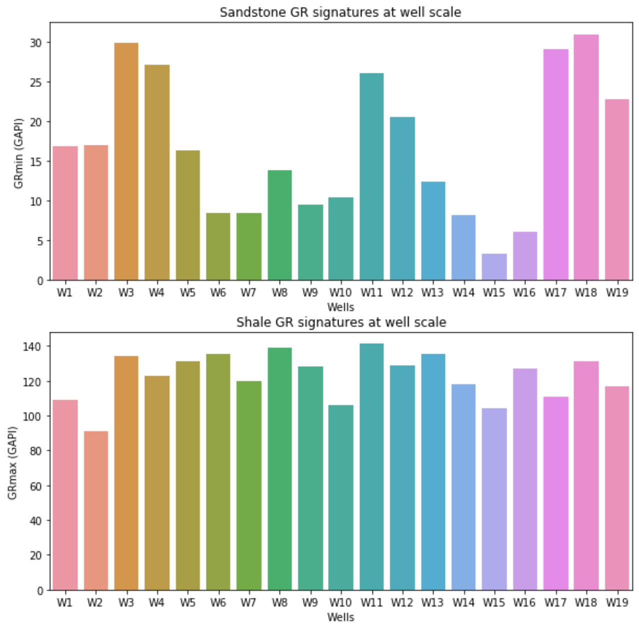

Figure 6 – Shale and Sandstone GR signature of Benin's Block 1 wells.

3.3. Determination of Gamma Ray Log Signature of Benin's Petroleum Block 1

Benin's petroleum block 1 formation GR signatures have been determined through the statistical technique proposed by this study, the boostrap mean estimation method.

The 19-size GRmin and GRmax samples of Table (1) have been used for formation GR signature computation for Benin's petroleum block 1. 10,000 boostrap samples of these original GRmin and GRmax samples of Table (1) has been generated. The boostrap means and the boostrap mean estimate has been computed through the algorithm of Figures (4) and (5).

The results are summarized in Table (2).

Benin's block 1 clean shale GR signature is 122.57 GAPI with a confidence interval of [116.41GAPI; 128.26GAPI] while its clean limestone or sandstone GR signature is 16.63 GAPI with a confidence interval of [12.84GAPI; 20.51GAPI].

Table 1 – Benin's block 1 clean formations GR signatures at well scale.

N°	Well	Clean sandstone signature = MinGR (GAPI)	Clean shale signature = MaxGR (GAPI)
1	W1	16.9	109
2	W2	17	90.9
3	W3	29.8	134
4	W4	27.1	123
5	W5	16.3	131
6	W6	8.49	135
7	W7	8.4	120
8	W8	13.8	139
9	W9	9.43	128
10	W10	10.4	106
11	W11	26.1	141
12	W12	20.5	129
13	W13	12.4	135
14	W14	8.13	118
15	W15	3.37	104
16	W16	6.14	127
17	W17	29	111
18	W18	30.9	131
19	W19	22.7	117

As a result, the clean sandstones of the block are characterized by a GR value of 16.63 GAPI or must have at least a GR value between 12.84 and 20.51 GAPI. In other words, the clean sandstone baseline to be used while determining the basin stratigraphic column at a well scale from GR log data, must correspond to a GR of 16.63 GAPI or between 12.84 and 20.51 GAPI.

Meanwhile, the clean shales of the block are characterized by a GR value of 122.57 GAPI or must have at least a GR value between 12.84 and 20.51 GAPI. Therefore, over the qualitative analysis of a block 1 well GR log data, the clean shale baseline to be used has to correspond to a GR of 122.57 GAPI or between 116.4 and 128.26 GAPI.

Moreover, these GR signatures have to be taken into account for formation shale volume computation.

Table 2 – Benin's block 1 clean formations GR signatures.

Statistics	Clean Shale GR signature (GAPI)	Clean Sandstone GR signature (GAPI)
Single	122.57	16.63
Confidence interval	[116.41; 128.26]	[12.84; 20.51]

4. Conclusion

When hydrocarbons are generated from a source rock, they migrate and gather in commercial volumes into reservoirs that are porous and permeable rocks, imprisoned by rocks called cap or seal rocks. The source rocks are in general made of shales and limestones while sandstones and limestonesconstitute hydrocarbon reservoir formations. Several studies have revealed that the knowledge of GR signature of clean shales, limestones and sandstones is significant for more precise identification of formations.

This study proposed a statistical technique for determining the gamma ray log signature of clean shales, sandstones and limestonesThe approach has been applied to Benin's petroleum block 1 well log dataset.

The results show that Benin's block 1 clean shale GR signature is 122.57 GAPI with a confidence interval of [116.41GAPI; 128.26GAPI] while its clean limestone and sandstone GR signature is 16.63 GAPI with a confidence interval of [12.84GAPI; 20.51GAPI]. As a result, over the qualitative analysis of a block 1 well GR log data, the clean shale and clean sandstone baselines to be used have to correspond to these GR signatures. Moreover, these clean formations GR signatures have to be taken into account over formations shale volume computation.

We recommend:

- to determine Benin's block 1 formations spontaneous potential signature and other litho-logs signatures;
- to determine formations GR signature for other regions and even at the scale of the Gulf of Guinea.

References

Aguinis, H., Ryan, K.G. and Harry, J., 2013. *Best-Practice Recommendations for Defining, Identifying, and Handling Outliers*. Organizational Research Methods 16(2), pp. 270-301. https://doi.org/10.1177/1094428112470848

Adedapo, J.O., Ikpokonte, A., Schoeneich, E. K and Kurowska, E., 2014. *An Estimate of Oil Window in Nigeria Niger Delta Basin from Recent Studies*. American International Journal of Contemporary Research, Volume 4(9), pp. 114-121.

Baron, J., Cariou, J. and Thorion, R., 1989. *Les diagraphies nucléaires développées par les LPC Principes physiques, mise en œuvre, domaines d'application.* Liaison Labo. P. et Ch – 164, nov-dec 1989 – Ref – 3446. French.

Bassiouni, Z., 1994. *Theory, Measurement and Interpretation of Well Logs*. SPE Text Book Series Vol. 4, Society of Petroleum Engineer, Texas, USA. https://doi.org/10.2118/9781555630560

Chen, Y.C., 2017. *Introduction to Resampling Methods*. Lecture Material 5: Bootstrap, Spring 2017. Available at: <https://faculty.washington.edu/yenchic/17Sp_403/Lec5-bootstrap.pdf> [Accessed 5 September 2024].

Chong, S.K. and Choo, R., 2011. *Introduction to Bootstrap*. Proceedings of Singapore Healthcare, Volume 20(3), pp. 236-240. https://doi.org/10.1177/201010581102000314

Djoï, N.A., 2024a. *Stochastic Approach to Economic Evaluation of Oil Wells in Niger Delta, Nigeria*. Thesis of PhD research. World Bank African Center of Excellence for Oil Field Chemical Research (ACE-CEFOR), University of Port Harcourt, Nigeria.

Djoï, N.A., 2024b. *Well Log Data Statistical Processing for Unbiased Qualitative and Quantitative Analyses: Case Study from the Gulf of Guinea*. International Journal of Geoscience, Engineering and Technology, Volume 9(1), pp 1-19. https://doi.org/10.70597/ijget.v9i1.533

Djoï, N.A., Nwosu, I.J. and Ikiensikimama S.S., 2022. *Hydrocarbon Reservoir Petrophysical Characterization with Statistical Simulations: A Case Study from the Gulf of Guinea*. International Journal of Scientific Research and Engineering Development, 5(2), pp. 298-308.

Efron, B. and Narasimhan, B., 2020. *The Automatic Construction of Bootstrap Confidence Intervals*. Journal of Computational and Graphical Statistics, 29(3), pp. 608–619. https://doi.org/10.1080/10618600.2020.1714633

Efron, B. and Tibshirani, R.J., 1998. *An Introduction to the Boostrap*. Chapman & Hall and CRC Press LLC.

Fadiya, S.L., Alao, O.A. and Adetuwo, A.M., 2018. *A Comparative Study of the Methods of Determining Shale Volume in Radioactive Reservoirs of "AMA" Field, Niger Delta, Nigeria*. International Journal for Research in Emerging Science and Technology, 5(4), pp. 1-39.

Karacan, C.Ö., 2009. *Reservoir rock properties of coal measure strata of the Lower Monongahela Group, Greene Pennsylvania), County (Southwestern from methane control and production perspectives*. International Journal of Coal Geology, 78(1), pp. 47-64. https://doi.org/10.1016/j.coal.2008.10.005

Mohammed, O.A.A., 2021. *Machine learning based shale volume prediction from the Norwegian North Sea*. MSc Thesis, Faculty of Science and Technology, University of Stavanger.

Szabó, N.P., 2011. *Shale volume estimation based on the factor analysis of well-logging data*. Acta Geophysica, 59, Pp. 935-953. https://doi.org/10.2478/s11600-011-0034-0

Oberto, S., 1984. *Fundamentals of well-log interpretation: The acquisition of logging data*. Developments in Petroleum Science, 15A. Elsevier Science Publishers B.V.

Orloff, J. and Bloom, J., 2017. *Bootstrap Confidence Intervals*. Class 24, 18.05. Lecture Material, Spring 2017. Available at: <https://math.mit.edu/~dav/05.dir/class24-prep-a.pdf> [Accessed 5 September 2024].

Tuttle, M.L.W, Charpentier, R.R. and Brownfield, M.E., 1999. *The Niger Delta Petroleum System: 269 Niger Delta Province, Nigeria, Cameroon, and Equatorial Guinea, Africa*. Open-File Report 99-50-H, U.S. Department of the Interior, U.S. Geological Survey. https://doi.org/10.3133/ofr9950H