



TESTING CENTER FOR OIL AND GAS LEMIGAS

SCIENTIFIC CONTRIBUTIONS OIL AND GAS (SCOG)

Vol. 49. No. 3, September: 233 – 255 - <https://journal.lemigas.esdm.go.id>

ISSN: 2089-3361, e-ISSN: 2541-0520

Published by:

LEMIGAS

Lithofacies Versus Well Identity as Controls on Fracture Porosity in Malay Basin Carbonates: A Two-Scale Statistical Decomposition

Simeão Lourenco Correia da Silva^{1,2}, Muhammad Luqman Hasan^{1,2}, Dejen Teklu Asfha^{1,3}, and Krisna Oka Mahendra^{1,3}

¹Center for Subsurface Seismic Imaging and Hydrocarbon Prediction, Universiti Teknologi Petronas, 32610 Seri Iskandar, Perak Darul Ridzuan, Malaysia.

²Petroleum Engineering Department, Universiti Teknologi Petronas, 32610 Seri Iskandar, Perak Darul Ridzuan, Malaysia.

³Department of Geoscience, Universiti Teknologi Petronas 32610 Seri Iskandar, Perak Darul Ridzuan, Malaysia.

*Corresponding author: Simeão L. C. da Silva (simeao_24007382@utp.edu.my)

Simeão L. C. da Silva: <https://orcid.org/0009-0004-8478-4013>

Received: 06 April 2026; Revised in revised form 03 July 2026; Accepted 21 August 2026
Available online 30 September 2026.

ABSTRACT - Carbonate fracture characterization typically conditions fracture porosity (Fpor) on lithofacies classification, on the assumption that facies labels capture the geological controls on fracture development. This study evaluates this premise by employing a two-scale statistical decomposition of Fpor variance across 537 samples from 13 wells within a single field in the Malay Basin. The analysis uses FMI-derived Fpor as the reference and the operator's three-class lithofacies scheme (clean limestone, mixed carbonate, tight shaly carbonate) as the facies framework. The lithofacies classification produces a statistically detectable but quantitatively small effect on Fpor (one-way ANOVA $F = 3.85$, $p = 0.022$, $\eta^2 = 0.014$; Kruskal-Wallis $H = 12.80$, $p = 0.0017$, $\epsilon^2H = 0.020$), accounting for 1.4 to 2.0% of total variance. Tukey HSD pairwise testing localizes the signal to a single contrast between clean limestone and mixed carbonate ($p\text{-adj} = 0.016$); mixed and tight shaly carbonate classes are statistically indistinguishable ($p\text{-adj} = 0.482$). Well identity, in contrast, accounts for approximately 27% of total Fpor variance (Kruskal-Wallis $\epsilon^2H = 0.271$), an effect more than thirteen times larger than the facies effect. Ward hierarchical clustering on standardized per-well statistics partitions the wells into three internally consistent clusters that cross-cut lithofacies composition. Depth is excluded as a confounding variable through within-class correlation analysis. The dominant control on fracture porosity in this dataset operates at the well scale, not the facies scale. Geological similarity between the target and training wells is the binding constraint on the quality of blind-well fracture prediction. These results indicate that carbonate fracture-prediction workflows should replace facies-only conditioning with well-partitioned validation and well-scale distributional descriptors, since the current three-class lithofacies scheme resolves less than one-fifteenth of the variance that well identity alone explains. Structural compartmentalization is a plausible candidate mechanism, though untestable with the present dataset.

Keywords: fracture porosity; lithofacies classification; carbonate reservoir; Malay Basin; statistical decomposition.

How to cite this article:

Simeão L. C. da Silva, Muhammad Luqman Hasan, Dejen Teklu Asfha, and Krisna Oka Mahendra, 2026, Lithofacies Versus Well Identity as Controls on Fracture Porosity in Malay Basin Carbonates: a Two-Scale Statistical Decomposition, Scientific Contributions Oil and Gas, 49 (3) pp. 233-255.



© 2026 The Author(s). Published by LEMIGAS under the Creative Commons Attribution-ShareAlike 4.0 International License (CC BY-SA 4.0)

<https://doi.org/10.29017/scog.v49i3.2131> | 233

1. Introduction

Carbonate reservoirs supply a substantial fraction of global hydrocarbon production, and many of the most productive examples are matrix-tight systems in which natural fractures provide the dominant permeability pathway (Aguilera 1976; Kargarpour 2020; Nelson 1985). In such reservoirs, fracture porosity (Fpor) controls the flow capacity, sweep efficiency, and ultimate recovery, with even small absolute differences in Fpor translating into substantial production-rate variability across a field. Characterizing the spatial distribution of Fpor from sparse well control is therefore a binding constraint on development planning. Direct measurement is restricted to wells imaged with borehole image logs; predictions into the surrounding volume rely on geological proxies, and the choice of proxy determines the geological scales at which predictions can succeed.

Borehole image logs, principally the formation micro imager (FMI), provide the closest available proxy to direct fracture observation in subsurface intervals. FMI-derived Fpor serves as the operational ground truth for fracture characterization at well locations and as the conditioning data for inter-well prediction. Standard predictive workflows propagate Fpor from imaged wells into unimaged volumes using lithofacies classification as the organizing variable. The underlying assumption is that facies labels, generated from conventional wireline logs and calibrated against core or analog data, capture sufficient geological context governing fracture development to serve as stratification variables for Fpor modeling. This assumption underpins most carbonate fracture modeling workflows (Aghli et al., 2020; Bagheri & Mohebian 2025) and is built into the geostatistical procedures of major reservoir simulation packages. Its empirical foundations have not been systematically tested in many basins.

Carbonate fracture systems are known to vary at scales below conventional facies resolution. Mechanical stratigraphy at decimeter to meter scale, dolomitization fronts, cement distributions, and stylolite networks all develop largely independently of bulk lithofacies labels (Humphrey et al., 2020). Fracture propagation, aperture preservation, and network connectivity respond more directly to brittle-ductile mechanical contrasts and to local diagenetic state than to the gross compositional categories captured by petrophysical facies schemes. Inter-well variability in fracture intensity, aperture, and connectivity has been documented in carbonate fields globally (Marrett et al., 1999; Ortega et al., 2006), typically as a qualitative observation about reservoir compartmentalization rather than a quantified comparison against the facies-scale signal. The empirical question of how much fracture-relevant variance lithofacies actually resolves, and how much resides at the well scale, has not been systematically addressed for many production-relevant carbonate provinces.

The Malay Basin hosts substantial carbonate gas reservoirs whose development depends on accurate fracture characterization (Tjia 1994). The basin's carbonate intervals are typically tight, naturally fractured, and laterally heterogeneous, with reported production behavior frequently diverging from facies-based predictions and these discrepancies often stem from a complex pore system where permeability is governed predominantly by fracture networks rather than primary matrix porosity (Garland et al., 2012; Talebian et al., 2021). The basin offers a useful test case because it combines operational stakes, sufficient well control for a multi-well statistical analysis, and a standardized petrophysical workflow that produces consistently classified lithofacies labels across operator wells. The dataset analyzed here is drawn from one such field, with 13 wells imaged by FMI and labeled under the same classification protocol.

We address the facies-versus-well question through a two-scale statistical decomposition of Fpor variance in a 537-sample dataset drawn from 13 anonymized wells in a single field in the Malay Basin. The analysis is structured around four specific questions. First, does lithofacies classification produce statistically distinguishable Fpor populations, and if so, how much variance does the classification resolve? Second, is depth a controlling variable for Fpor within each lithofacies class, or can depth be excluded as a confounding factor? Third, is the variation in Fpor controlled primarily by lithofacies, depth, or well identity, and what is the relative magnitude of each effect? Fourth, how does within-class variability manifest at the well scale, particularly in wells whose lithofacies composition is constrained to a single class? FMI-derived Fpor provides the ground truth throughout, and the operator's 3-class lithofacies scheme (LITH 0: clean limestone; LITH 1: mixed carbonate; LITH 2: tight shaly carbonate) provides the facies framework. Each test is reported with both p-values and effect-size measures

(η^2 , ϵ^2H , rank-biserial r) to separate statistical detection from geological magnitude. The results establish that lithofacies classification, as currently applied in this dataset, captures only a small fraction of fracture porosity variance, and that the dominant signal resides at the well scale. The two-scale decomposition we develop is straightforward in implementation but consequential in interpretation. It identifies where the predictive signal actually resides, and it constrains what predictive workflows must represent to succeed at blind-well prediction. We interpret the finding geologically, identify the candidate mechanisms consistent with the observed cluster structure, and develop the implications for fracture prediction workflows that rely on facies-based conditioning. The paper is organized as follows: Section 2 summarizes the geological setting; Section 3 describes the dataset and statistical methods; Section 4 presents the analytical results; Section 5 discusses the geological interpretation and predictive implications; and Section 6 concludes.

A limitation should be flagged at the outset: the dataset analyzed here carries no structural or seismic information. Well identities and locations are anonymized at the data provider's request, and no fault maps, seismic attributes, or well-specific structural picks (dip, azimuth, fault correlation) were made available to the authors. Recent 3D seismic work elsewhere in the Malay Basin (Jonge et al., 2024) illustrates the kind of structural framework that could, in principle, be integrated with the well-scale patterns identified here; the present study is deliberately restricted to the conventional wireline log and FMI-derived dataset described in Section 3, and the structural interpretation offered in Section 5 is accordingly framed as a set of candidate mechanisms rather than a tested explanation.

1.1 Geological setting

The Malay Basin is one of several Cenozoic extensional basins that developed across the Sundaland continental block during the late Eocene to Oligocene (Hall 2013; Pubellier & Morley 2014). Sundaland itself records a Late Permian to Triassic amalgamation of Asian terranes (Metcalfe 2017), and its Cenozoic interior subsequently fragmented into a system of rift basins arranged across the Sunda Shelf. The Malay, Penyu, West Natuna, and Pattani basins share this rift history, with linked subsidence and inversion phases driven by India–Eurasia collision to the north and Sunda Trench subduction to the south (Pubellier & Morley 2014). The Malay Basin occupies a central position within this basin system, offshore Peninsular Malaysia and southern Thailand (Figure 1). The field analyzed in this study is located within the Malay Basin proper; its precise location is not disclosed at the data provider's request.

The Malay Basin contains up to 14 km of Cenozoic sedimentary fill above a thinned continental crust, with stretching factors β reaching values close to 4 in the basin centre and decreasing toward 1.2 at the flanks (Madon & Watts 1998; Shahar 2008). Three tectonic phases structure the basin fill. Late Eocene to Oligocene synrift extension produced N–S oriented en-echelon ridges and grabens (Mansor et al., 2014). Rapid Early to Middle Miocene post-rift subsidence followed, accommodating thick sediment accumulation under regional thermal contraction. From the Middle to Late Miocene, regional compression generated a phase of structural inversion, producing anticlines along reactivated rift faults, en-echelon E–W folds, and sinistral and dextral wrench movements along the Hinge Fault Zone (Tjia 1994). Plio-Pleistocene sag completes the tectonic sequence. The basin remains thermally subsiding, with present surface heat flow ranging approximately 33 to 42 mW m⁻² and corresponding geothermal gradients of 23 to 30 °C km⁻¹ (Madon & Watts 1998).

Malay Basin stratigraphy is conventionally subdivided using an alphabetic Group A–M seismic-stratigraphic framework that maps onto the basin's tectonic phases (Madon & Watts 1998). The lower groups (M–I) record synrift to early post-rift fill, dominated by lacustrine and fluvial-deltaic deposits. The middle groups (H–F) document fully developed post-rift subsidence under coastal-plain and marginal-marine conditions and include the source-rich shales together with the principal sandstone reservoirs of the basin's petroleum system. The upper groups (E–A) record marine transgression following Late Miocene inversion, with shallow-marine clastics and intermittent carbonate deposition across the basin (Bishop 2002). The carbonate intervals of interest in this study sit within this upper post-inversion section, deposited on structural highs under shallow-marine conditions (Figure 2). Southeast Asian Cenozoic carbonates developed under equatorial, bioclast-dominated conditions, with rare oolitic or pisolitic textures, restricted evaporite and dolomite associations, and persistent clastic influence from

the surrounding orogenic source areas (Wilson 2002). Carbonate platform initiation across the Sundaland margin was strongly controlled by tectonic topography: isolated platforms developed over antecedent structural highs account for more than 75% of the region's economic carbonate hydrocarbon discoveries, even though only about 30% of platforms initiated as isolated features (Wilson & Hall 2010).

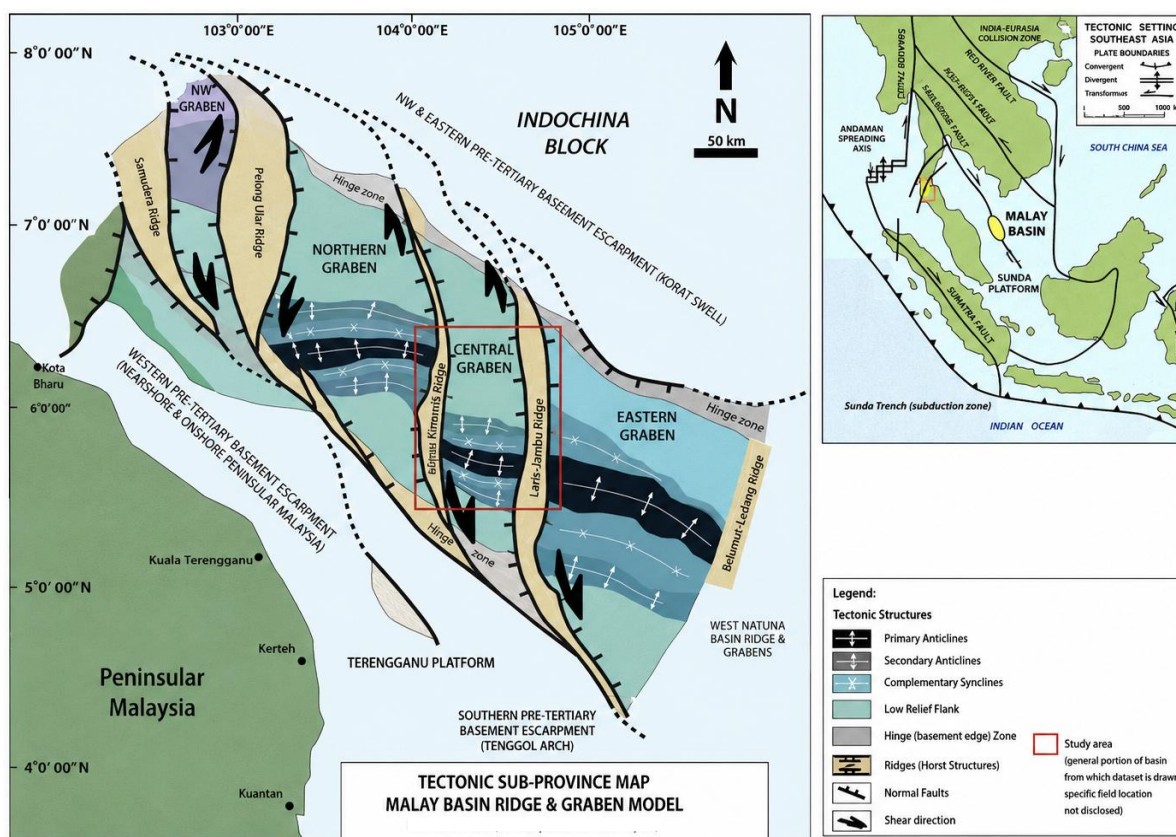


Figure 1.

Regional location and tectonic framework of the Malay Basin within the Sundaland passive-margin system. Inset shows Sundaland and surrounding active margins (Sunda Trench to the south, India–Eurasia collision to the north). Main map identifies the Malay, Penyu, West Natuna, and Pattani basins, the Hinge Fault Zone, and the principal Middle to Late Miocene inversion folds. The study area rectangle indicates the general portion of the basin from which the dataset is drawn; specific field location is not disclosed. Modified after (Mansor et al., 2014; Pubellier & Morley 2014).

Diagenetic modification of these carbonates spans marine, meteoric, and burial environments. Detailed work on analogous Miocene buildups of Central Luconia (offshore Sarawak) documents moldic porosity reaching 45% in the best intervals, alongside calcite and dolomite cementation, stylolitic compaction, and burial-related porosity destruction (Janjubah et al., 2017). Late dissolution and microfracturing locally restore permeability against this background of progressive cementation. Fracture systems in Malay Basin carbonates arise from at least two distinct processes operating across the basin's history. Tectonic fractures formed during the Middle to Late Miocene inversion phase, with orientations controlled by the regional compressional stress field and locally by reactivated rift faults (Maddon 2007; Tjia 1994). Wrench-related en-echelon and conjugate fracture sets are consistent with transtensional and transpressional movements along major bounding fault zones. Diagenetic fractures developed independently from burial compaction, stylolite-associated brittle failure, and dissolution along bedding-parallel surfaces. Analogue work on Central Luconia carbonate platforms documents fault-related selective cementation, with fracture-intensity peaks coinciding with low-porosity mounds (Rankey et al., 2019), demonstrating that fracture development and porosity preservation vary at sub-platform scale and across short lateral distances. Outcrop fracture-network analysis on Sarawak limestone buildups confirms that fracture intensity, topology, and connectivity vary substantially within a single carbonate unit (Ong & Jamaludin 2023). Both tectonic and diagenetic mechanisms contribute to the fracture porosity targeted in this study.

Generalized Cenozoic stratigraphy of the Malay Basin

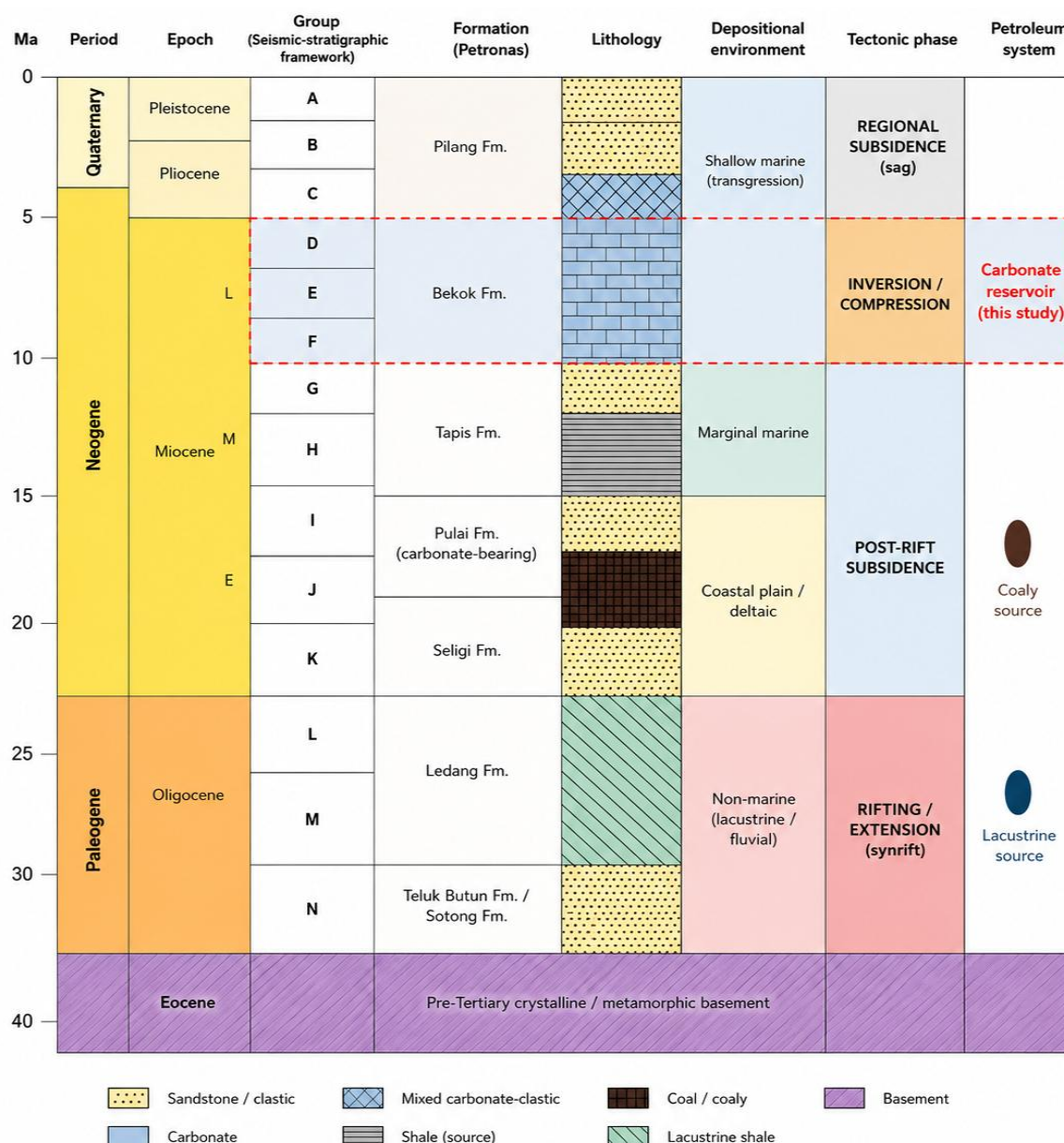


Figure 2.

Generalized Cenozoic stratigraphy of the Malay Basin showing the alphabetic Group A–M seismic-stratigraphic framework, lithologies, and corresponding tectonic phases (synrift, post-rift, inversion, sag).

The shaded band marks the upper post-inversion carbonate interval from which the dataset is drawn.

Source-rock interval (Group H–I) shown for petroleum-system context. Modified after (Bishop 2002; Madon et al., 2020).

Malay Basin gas reservoirs occur primarily in the post-rift sandstone groups and, in subordinate fashion, in the upper post-inversion carbonate intervals (Madon et al., 2006). The basin's central depocenter is gas-rich, with hydrocarbon accumulations concentrated in late-inversion anticlinal traps and in combined structural-stratigraphic configurations (Bishop 2002). Carbonate reservoirs in these and analogous regional fields are commonly tight, with matrix permeabilities of order 1 mD or below, and depend on natural fracture networks for economic flow. Regional analogue studies of Late Miocene Malaysian carbonate buildups report that fractured carbonate platforms host a substantial fraction of national gas reserves, with reservoir quality varying significantly within and between platforms despite broadly similar bulk lithology (Janjubah et al., 2017). The field analyzed here is one such tight, fracture-controlled carbonate gas reservoir, and the well-scale F_{por} variability quantified in subsequent sections is consistent with the within-platform heterogeneity documented across the region.

2. Dataset and methods

2.1 Dataset and variables

The dataset consists of 537 samples drawn from 13 wells in a single field in the Malay Basin. The wells are anonymized as W1 through W13 throughout this paper; the field name and operator are withheld at the data provider's request. Per-well sample counts range from 23 (W9) to 66 (W3), reflecting both the length of the FMI-imaged interval in each well and the density of usable fracture observations within those intervals. The 13 wells together span 808 ft of vertical range, from −2,532 to −3,395 ft TVDSS.

Fracture porosity (Fpor) is the primary target variable throughout the analysis. Each Fpor value is derived from FMI image-log interpretation performed by the operator under their standard petrophysical workflow. We treat the resulting Fpor values as the operational ground truth and do not re-interpret the underlying image data; the uncertainty in this interpretation is discussed in Section 5.4. The FMI interpretation delivered to the authors is limited to the Fpor value at each depth sample; no structural picks (dip, azimuth, or fault correlation) were provided with the dataset, so the structural characterization of individual wells lies outside the scope of the present study. Grouping variables include the lithofacies label (3-class categorical), well identity (13-class categorical), and depth in TVDSS (continuous). Two auxiliary continuous variables, shallow resistivity (RS) and deep resistivity (RT), are used in Section 4.6 to characterize log–Fpor relationships.

2.2 Lithofacies classification

Lithofacies labels (LITH 0, LITH 1, LITH 2) are provided by the data owner as part of the operator's standard petrophysical interpretation workflow. The classification draws on integrated analysis of conventional wireline logs, including gamma ray, bulk density, neutron porosity, sonic, and resistivity. It corresponds to clean limestone (LITH 0), mixed carbonate (LITH 1), and tight shaly carbonate (LITH 2). The specific cutoff values and decision rules underlying the classification are proprietary and were not disclosed to the authors. The classification is therefore treated as a given input throughout the analysis, and the implications of this dependency on a vendor-supplied scheme are addressed in Section 5.4.

2.3 Statistical procedures and effect-size measures

The analysis applies parallel parametric and non-parametric tests to each question, with effect-size measures reported alongside p-values to distinguish statistical detection from geological magnitude. Distributional characterization begins with per-LITH and per-well descriptive statistics (sample size, mean, median, standard deviation, coefficient of variation, skewness, interquartile range, minimum, maximum) and a Shapiro-Wilk normality test applied to each LITH class. Normality is rejected for all three classes ($p < 0.001$), and the non-parametric procedures are therefore reported in parallel with their parametric counterparts throughout.

To test the lithofacies effect on Fpor (Section 4.2), we apply one-way ANOVA and Kruskal-Wallis as omnibus tests, followed by Tukey HSD post-hoc pairwise comparisons with the family-wise error rate controlled at $\alpha = 0.05$. Effect sizes are reported as η^2 from ANOVA ($SS_{\text{between}} / SS_{\text{total}}$) and as ϵ^2_H derived from the Kruskal-Wallis statistic, computed as $(H - k + 1) / (N - k)$. Interpretive thresholds follow the conventional small (<0.06), medium ($0.06\text{--}0.14$), and large (>0.14) cutoffs (Berben et al., 2012; Cohen 1988; In & Lee 2024; Richardson 1996).

Within-class depth-Fpor relationships (Section 4.3) are characterized using Pearson and Spearman rank correlations together with ordinary least-squares regression slopes, computed separately for each LITH class to avoid the depth-LITH confound that arises from partially separated depth intervals among classes. Inter-well variability (Section 4.4) is tested with Kruskal-Wallis across the 13 wells, with Mann-Whitney U tests of each well against the pooled remainder, and with Dunn pairwise post-hoc comparisons using Bonferroni correction. The Mann-Whitney effect size is the rank-biserial correlation $r = 1 - (2U / n_1 n_2)$; positive values indicate the focal well sits below the reference distribution, and negative values indicate it sits above. Effect-size dominance, rather than p-value magnitude alone, is used to compare the relative strength of the facies and well effects.

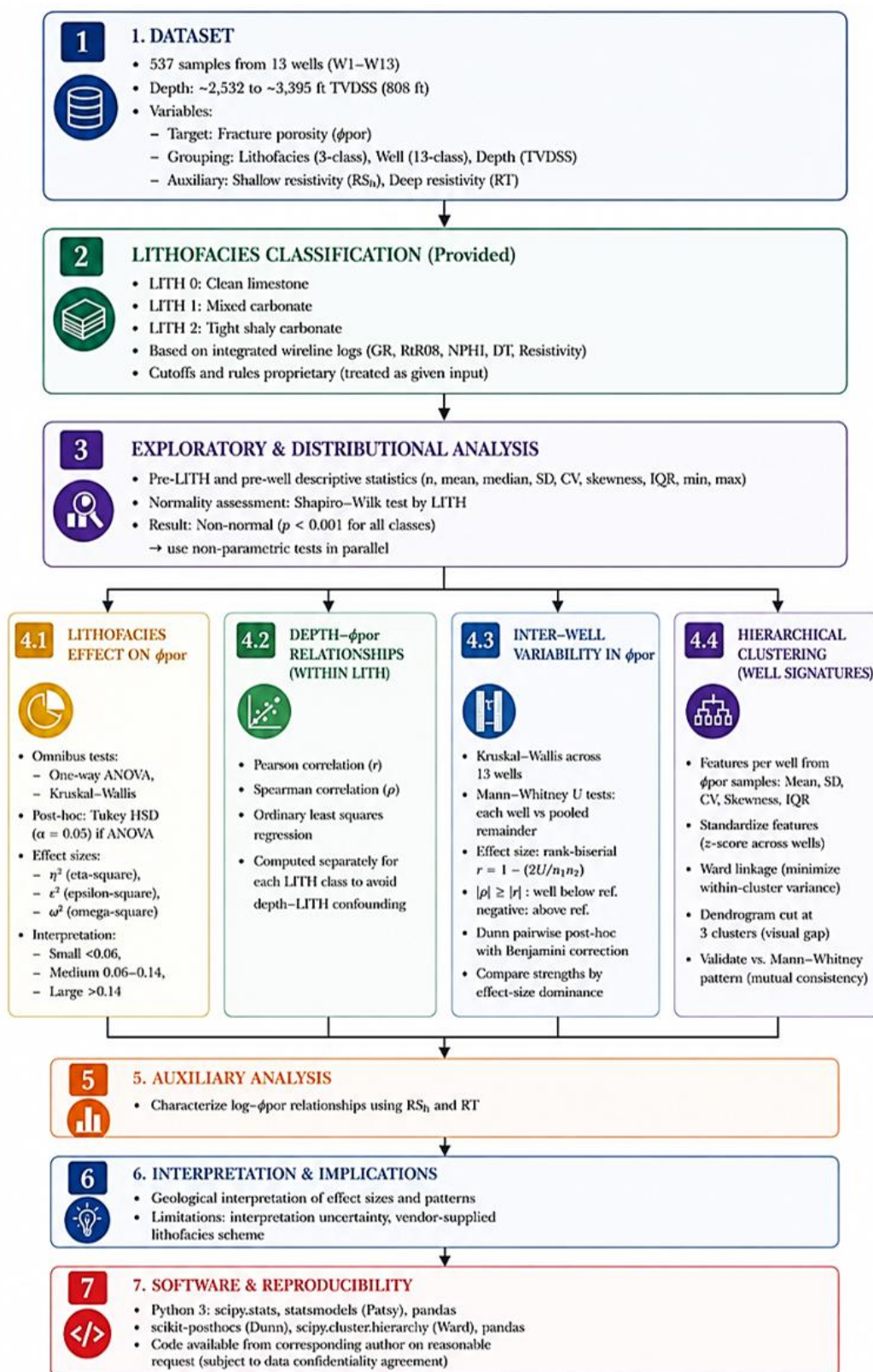


Figure 3.

Analytical workflow for the two-scale decomposition of fracture porosity (Fpor).

Numbered steps denote processing sequence; hierarchical clustering (4.4) follows from the inter-well analysis (4.3).

Lithofacies classification is operator-supplied and treated as a given input.

Full methods are described in Section 3, results in Section 4, and interpretation in Section 5.

2.4 Hierarchical clustering

The well-scale signature identified by the Mann-Whitney battery is characterized further through Ward hierarchical clustering of the 13 wells. The clustering operates on a 5-feature representation of each well's Fpor distribution: mean, standard deviation, coefficient of variation, skewness, and interquartile range. These features capture central tendency (mean), dispersion (SD, CV, IQR), and distributional shape (skewness), and they are computed directly from the per-well Fpor samples without auxiliary covariates. Each feature is standardized (z-score across wells) before clustering, ensuring that the distance metric is not dominated by the variable with the largest absolute scale; CV values are reported in percent and would otherwise dominate the un-standardized distance.

Ward linkage is selected because it minimizes the increase in total within-cluster variance at each merge step, producing compact clusters appropriate to the assumption that wells within a cluster represent an internally consistent population. The dendrogram is cut at a linkage distance corresponding to three clusters, identified visually as the level at which a clear gap appears between merger heights. Robustness of the partition was checked by comparing the three-cluster assignment to the Mann-Whitney significance pattern (Section 4.4); the two partitions are mutually consistent.

2.5 Software and reproducibility

All statistical procedures are implemented in Python 3, using the `scipy.stats` module for ANOVA, Kruskal-Wallis, Mann-Whitney, Pearson and Spearman correlations, and Shapiro-Wilk testing; the `statsmodels` package for Tukey HSD via `statsmodels.stats.multicomp`; the `scikit-posthocs` package for Dunn pairwise comparisons with Bonferroni correction; and the `scipy.cluster.hierarchy` module for Ward linkage and dendrogram construction. Data management is handled in `pandas`. The analysis code is available from the corresponding author on reasonable request, subject to the data confidentiality agreement governing the underlying well-log dataset.

3. Result and discussion

3.1 Fracture porosity distributions by lithofacies class

Fracture porosity is right-skewed in every lithofacies class (Figure 4a; skewness 1.26 to 1.78), with most values clustering between 0.030 and 0.040 and tails extending to roughly 0.18. Shapiro-Wilk tests reject normality for all three classes ($p < 0.001$), so the inferential analyses below use nonparametric methods alongside their parametric counterparts.

The three class means sit within a narrow range (Table 1). LITH 0 (clean limestone, $n = 74$) averages 0.0384 ± 0.0257 ; LITH 1 (mixed carbonate, $n = 205$) averages 0.0485 ± 0.0279 ; LITH 2 (tight shaly carbonate, $n = 258$) averages 0.0456 ± 0.0261 . The coefficient of variation is 66.8% for LITH 0 and close to 57% for both LITH 1 and LITH 2. Pooled across the 537 samples, Fpor has a mean of 0.0451 and a median of 0.0379.

Table 1.
Descriptive statistics of fracture porosity (Fpor) per lithofacies class.
All three classes are non-normal (Shapiro-Wilk $p < 0.001$).

LITH	Description	N	Mean	Median	SD	CV (%)	Min	Skewness
0	Clean limestone	74	0.0384	0.0310	0.0257	66.8	0.0039	1.77
1	Mixed carbonate	205	0.0485	0.0415	0.0279	57.5	0.0000	1.26
2	Tight shaly carbonate	258	0.0456	0.0378	0.0261	57.2	0.0000	1.78
—	Pooled (all classes)	537	0.0451	0.0379	—	—	0.0000	—

The histogram in Fig 4b shows substantial overlap among the three classes, especially in the 0.02-0.06 interval, which contains most observations. Class identity does not produce visually distinct modes. The three KDE peaks are separated by only a small horizontal offset: LITH 0 peaks near 0.025, while LITH 1 and LITH 2 both peak near 0.030 to 0.035 on otherwise similar curves.

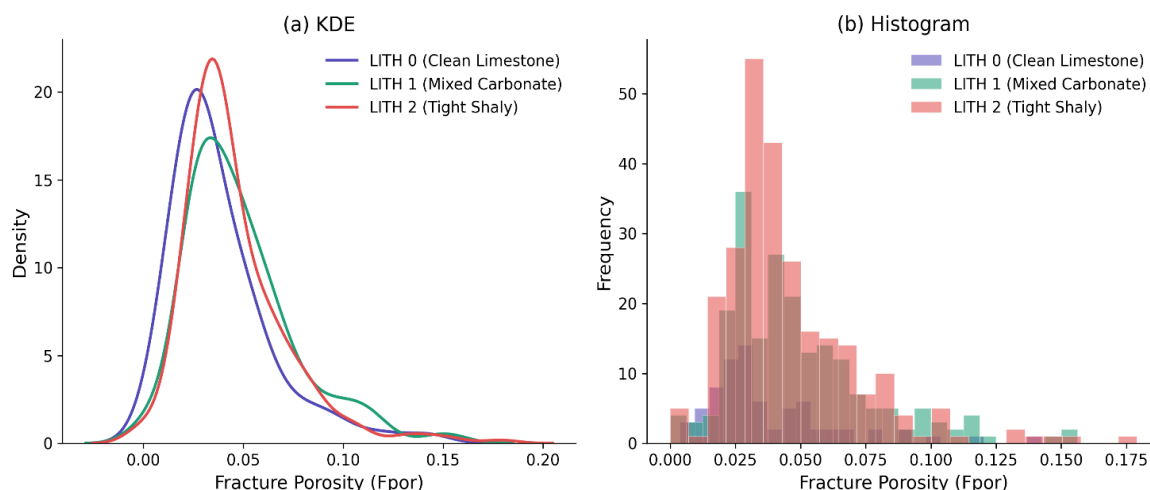


Figure 4.

Distribution of fracture porosity (Fpor) per lithofacies class across the 537-sample dataset.

(a) Kernel density estimates for LITH 0 (clean limestone, $n = 74$), LITH 1 (mixed carbonate, $n = 205$), and LITH 2 (tight shaly carbonate, $n = 258$). All three distributions are right-skewed (skewness 1.26 to 1.78), with closely overlapping modes near 0.025-0.035. (b) Stacked histogram showing distributional overlap among the three classes; the bulk of observations falls between 0.020 and 0.060.

3.2 Lithofacies effect on Fpor

One-way ANOVA detects a significant difference among the three class means (Figure 5; $F = 3.85$, $p = 0.022$), and the Kruskal-Wallis test confirms it ($H = 12.80$, $p = 0.0017$). Both effect sizes are small: ANOVA-based $\eta^2 = 0.014$, and the Kruskal-Wallis equivalent $\epsilon^2 H = (H - k + 1) / (N - k) = 0.020$. Lithofacies classification accounts for 1.4 to 2.0% of total Fpor variance, well within the small-effect range under the standard $\eta^2 < 0.06$ cutoff (Table 2).

Tukey HSD pairwise comparisons localize the effect to a single contrast. LITH 0 differs significantly from LITH 1 (mean difference 0.010, $p\text{-adj} = 0.016$), while LITH 0 versus LITH 2 is not significant (mean difference 0.007, $p\text{-adj} = 0.106$), and LITH 1 versus LITH 2 is far from significant (mean difference -0.003 , $p\text{-adj} = 0.482$). The omnibus signal arises entirely from the LITH 0 to LITH 1 separation; the remaining two contrasts cannot be distinguished from the null.

Lithofacies class is therefore a statistically detectable but quantitatively minor control on Fpor, and the effect itself is narrowly localized: only the clean limestone class (LITH 0) separates from the others, while the mixed and tight shaly carbonate classes (LITH 1 and LITH 2) are statistically interchangeable on this measure. The p -values reflect the sample size ($n = 537$) more than a wide separation between classes. Within-class variance is sufficiently wide that the facies label alone cannot reliably predict the Fpor of an individual sample, and in practice the 3-class scheme reduces to a 2-class one (LITH 0 versus LITH 1+2).

3.3 Depth-Fpor relationships

Within-class Pearson correlations between Fpor and depth (TVDSS) are weak and statistically nonsignificant: $r = 0.051$ for LITH 0 ($p = 0.663$), $r = -0.102$ for LITH 1 ($p = 0.145$), and $r = -0.077$ for LITH 2 ($p = 0.219$). Spearman correlations are similarly negligible ($|r| \leq 0.023$, all $p > 0.74$). The pooled correlation across all samples reaches nominal significance ($r = -0.099$, $p = 0.022$) but is practically zero; the pooled signal arises from mixing samples drawn from facies classes occupying partially separated depth intervals (Table 3).

Table 2.

Inferential tests of the lithofacies effect on Fpor.

The ANOVA-based η^2 and the Kruskal-Wallis-based ε^2H are reported as complementary effect-size measures. Asterisk (*) denotes Tukey HSD pairwise contrasts significant at the family-wise error rate of $\alpha = 0.05$.

Test	Statistic	df	p-value	Effect size
One-way ANOVA	F = 3.85	2, 534	0.022	$\eta^2 = 0.014$
Kruskal-Wallis	H = 12.80	2	0.0017	$\varepsilon^2H = 0.020$
Tukey HSD: LITH 0 vs LITH 1	mean diff = 0.010	—	0.016 *	—
Tukey HSD: LITH 0 vs LITH 2	mean diff = 0.007	—	0.106	—
Tukey HSD: LITH 1 vs LITH 2	mean diff = -0.003	—	0.482	—

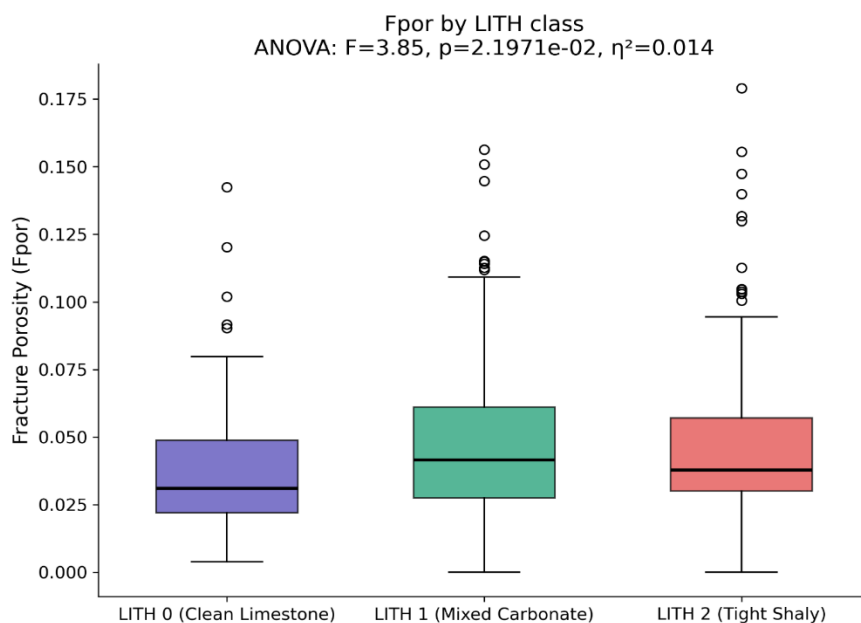


Figure 5.

Box plots of Fpor by lithofacies class.

Boxes span the interquartile range, the central line is the median, whiskers extend to $1.5 \times \text{IQR}$, and points beyond the whiskers are plotted individually. Summary statistics: ANOVA F = 3.85, $p = 0.022$, $\eta^2 = 0.014$. Tukey HSD post-hoc testing identifies the LITH 0–LITH 1 contrast as the only significant pairwise difference ($p\text{-adj} = 0.016$); LITH 1 and LITH 2 are statistically indistinguishable ($p\text{-adj} = 0.482$).

Table 3.

Depth–Fpor correlations within and across lithofacies classes.

Within-class correlations are weak and non-significant for all three classes; the nominally significant pooled correlation reflects partially separated depth intervals among classes rather than a within-class trend.

Group	N	Pearson r	Pearson p	Spearman ρ	Spearman p	Slope (Fpor/ft)
Pooled (all)	537	−0.099	0.022	−0.097	0.025	-1.3×10^{-5}
LITH 0	74	+0.051	0.663	+0.016	0.891	$+2.6 \times 10^{-5}$
LITH 1	205	−0.102	0.145	+0.023	0.749	-1.7×10^{-5}
LITH 2	258	−0.077	0.219	+0.015	0.808	-1.2×10^{-5}

Within-class regression slopes are essentially flat: $+2.6 \times 10^{-5}$ Fpor/ft for LITH 0, -1.7×10^{-5} for LITH 1, and -1.2×10^{-5} for LITH 2. The scatter in Figure 6, shows substantial vertical spread at every depth interval, without a systematic trend in any of the three panels. This rules out depth as a candidate explanation for the inter-well variability reported in Section 4.4. The wells span 808 ft vertically (−2,532 to −3,395 ft TVDSS), and the between-well differences in Fpor are not attributable to systematic depth-dependence within facies.

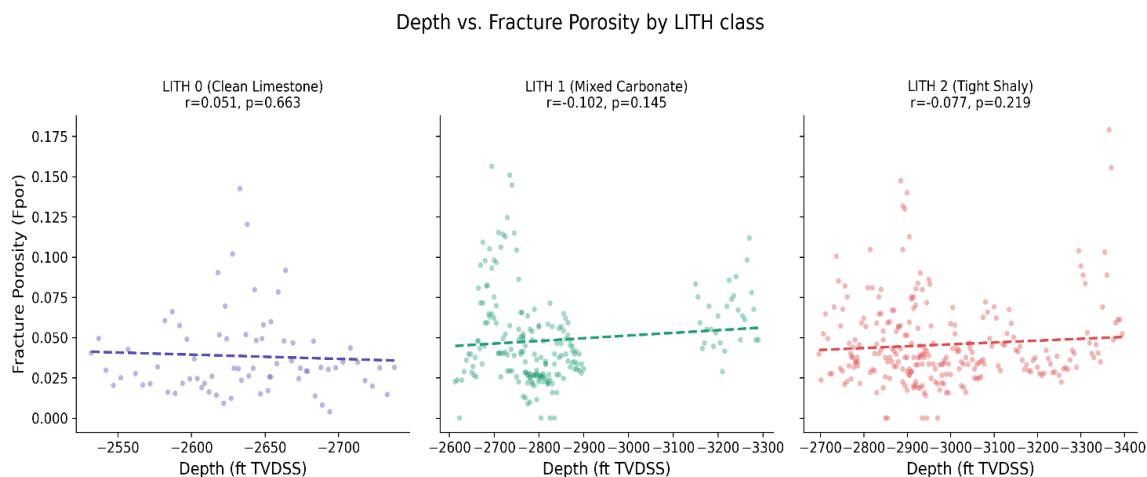


Figure 6.

Depth versus Fpor scatter plots by lithofacies class.

Within-class Pearson correlations are weak and statistically nonsignificant: LITH 0 $r = 0.051$ ($p = 0.663$), LITH 1 $r = -0.102$ ($p = 0.145$), LITH 2 $r = -0.077$ ($p = 0.219$). Dashed lines show within-class linear regressions with slopes near zero in every panel. Depth ranges differ across classes, reflecting the stratigraphic position of each facies in the sampled wells.

3.4 Inter-well variability and clustering

Treating well identity as the grouping variable, the Kruskal-Wallis test across the 13 wells returns $H = 154.12$ ($p = 8.3 \times 10^{-27}$), with effect size $\epsilon^2 H = (154.12 - 12) / (537 - 13) = 0.271$. Well identity accounts for approximately 27% of Fpor variance, about 13 times the variance attributable to lithofacies class.

Per-well descriptive statistics (Table 4) show that mean Fpor ranges from 0.0274 (W13) to 0.0738 (W8), a 2.7-fold spread that exceeds the 1.3-fold spread between LITH classes. CV across wells ranges from 33% (W5) to 68% (W10). There is no monotonic relationship between mean and CV: W7 has a high mean (0.0679) with intermediate CV (42%), while W2 has a lower mean (0.0530) with comparable CV (53%). The box plots in Figure 7, summarize the per-well distributions.

Table 4.

Per-well descriptive statistics with Ward-clustering assignment.

Wells are anonymized (W1–W13). LITH composition indicates the lithofacies classes present in the well's sampled interval. Cluster assignment is from Ward hierarchical clustering on standardized statistics (mean, SD, CV, skewness, IQR).

Well	LITH	N	Depth (ft TVDSS)	Mean	Median	SD	CV (%)	Skew	Cluster
W1	LITH 1+2	35	–2,786 to –2,613	0.0459	0.0398	0.0218	47.5	0.59	1
W2	LITH 1+2	26	–2,791 to –2,665	0.0530	0.0407	0.0283	53.4	0.75	3
W3	LITH 1+2	66	–3,078 to –2,755	0.0325	0.0320	0.0112	34.4	0.45	1
W4	LITH 1+2	48	–2,990 to –2,755	0.0487	0.0420	0.0311	63.9	0.94	2
W5	LITH 2 only	63	–3,290 to –2,980	0.0395	0.0358	0.0131	33.1	0.90	1
W6	LITH 1+2	57	–2,935 to –2,650	0.0439	0.0397	0.0167	38.0	0.46	1
W7	LITH 1+2	50	–3,395 to –3,150	0.0679	0.0611	0.0286	42.1	1.77	3
W8	LITH 1+2	53	–2,953 to –2,695	0.0738	0.0649	0.0350	47.4	0.77	3
W9	LITH 0 only	23	–2,694 to –2,584	0.0347	0.0262	0.0222	64.0	0.96	2
W10	LITH 0 only	25	–2,738 to –2,618	0.0490	0.0346	0.0332	67.7	1.49	2
W11	LITH 0 only	26	–2,654 to –2,532	0.0315	0.0287	0.0161	51.0	0.62	1
W12	LITH 1 only	28	–2,900 to –2,765	0.0326	0.0300	0.0147	45.1	0.72	1
W13	LITH 1+2	37	–2,943 to –2,765	0.0274	0.0266	0.0163	59.4	0.40	1

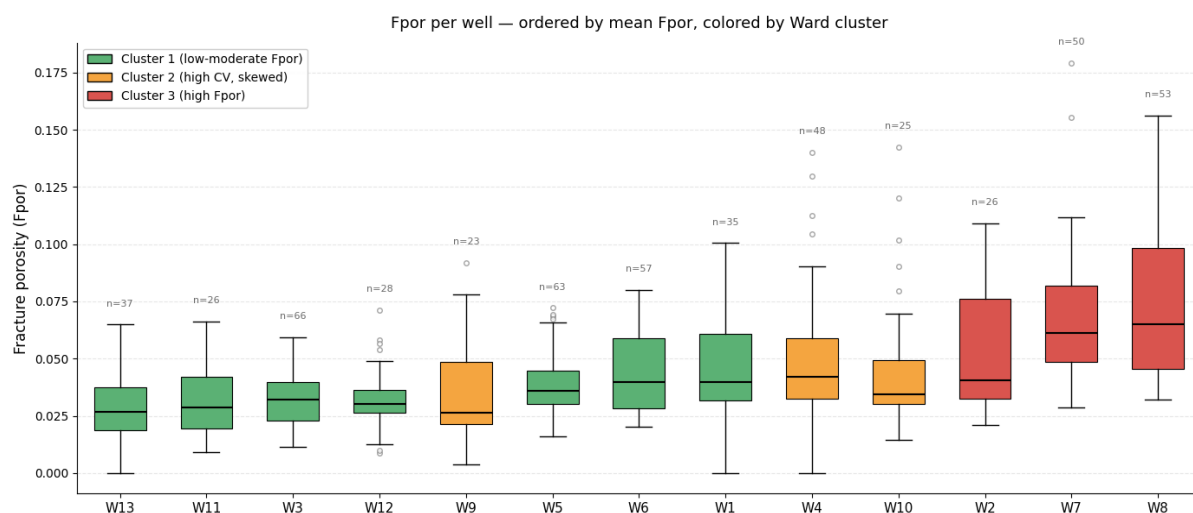


Figure 7.

Box plots of Fpor per well for the 13 anonymized wells in the dataset.

Sample sizes per well are annotated above each box and range from $n = 23$ (W9) to $n = 66$ (W3). Color coding identifies the cluster assignment from Ward hierarchical clustering (Cluster 1: low-to-moderate Fpor; Cluster 2: moderate Fpor, high CV; Cluster 3: highest Fpor). Wells are ordered by increasing mean Fpor.

Mann-Whitney comparisons of each well against the pooled remainder identify seven wells that differ significantly from the dataset baseline at $p < 0.05$ (Table 5). Two wells are significantly elevated: W7 (effect $r = 0.584$, $p < 10^{-5}$) and W8 (effect $r = 0.579$, $p < 10^{-5}$). Five wells are significantly depleted: W3 ($r = 0.354$), W9 ($r = 0.299$), W11 ($r = 0.364$), W12 ($r = 0.319$), and W13 ($r = 0.492$). The remaining six wells, W5 included, do not differ significantly from the baseline.

Table 5.

Mann-Whitney U test of each well against the pooled remainder of the dataset.

Effect r is the rank-biserial effect size; positive values indicate the well is lower than the pooled remainder, negative values indicate higher.

Well	N	Mean (well)	Mean (others)	U	p	Effect r	Significant
W1	35	0.0459	0.0457	9,388	0.497	-0.069	No
W2	26	0.0530	0.0453	7,664	0.186	-0.154	No
W3	66	0.0325	0.0475	10,037	< 0.0001	+0.354	Yes (lower)
W4	48	0.0487	0.0454	12,722	0.337	-0.084	No
W5	63	0.0395	0.0465	13,860	0.355	+0.072	No
W6	57	0.0439	0.0459	14,199	0.640	-0.038	No
W7	50	0.0679	0.0434	19,284	< 10^{-5}	-0.584	Yes (higher)
W8	53	0.0738	0.0426	20,257	< 10^{-5}	-0.579	Yes (higher)
W9	23	0.0347	0.0462	4,143	0.015	+0.299	Yes (lower)
W10	25	0.0490	0.0455	6,315	0.911	+0.013	No
W11	26	0.0315	0.0464	4,227	0.0017	+0.364	Yes (lower)
W12	28	0.0326	0.0464	4,856	0.0045	+0.319	Yes (lower)
W13	37	0.0274	0.0470	4,698	< 10^{-5}	+0.492	Yes (lower)

Ward hierarchical clustering on five standardized per-well statistics (mean, SD, CV, skewness, IQR) produces three clusters (Figure 8). Cluster 1 contains seven wells (W1, W3, W5, W6, W11, W12, W13) with low-to-moderate mean Fpor (0.027 to 0.046) and skewness between 0.40 and 0.90; these are the lower-Fpor wells with relatively well-behaved distributions. Cluster 2 contains three wells (W4, W9, W10) with moderate mean Fpor (0.035 to 0.049) but the highest within-well CV values in the dataset (64 to 68%) and high positive skewness (0.94 to 1.49), indicating distributions dominated by occasional high-Fpor outliers. Cluster 3 contains the remaining three wells (W2, W7, W8), which have the highest mean Fpor (0.053 to 0.074) and elevated IQR values, combining a raised baseline with a wide spread.

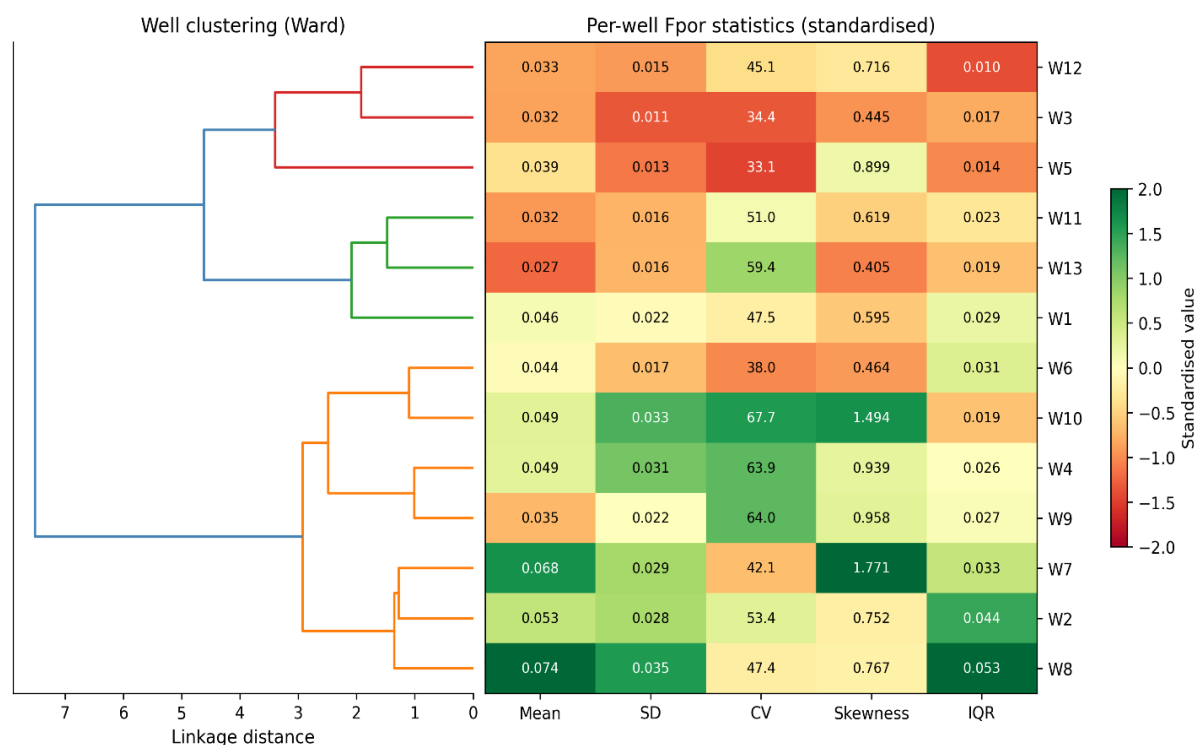


Figure 8.

Hierarchical clustering of the 13 wells by Fpor distributional statistics.

(Left) Ward linkage dendrogram computed on standardized per-well features (mean, SD, CV, skewness, IQR), producing three clusters at a linkage distance of approximately 3.5. (Right) Heatmap of the same standardized statistics underlying the clustering. Cluster 1 ($n = 7$ wells) contains low-to-moderate Fpor wells with controlled variance; Cluster 2 ($n = 3$ wells) contains wells with moderate Fpor but the highest within-well CV; Cluster 3 ($n = 3$ wells) contains the highest-Fpor wells with elevated IQR.

The clusters cross-cut lithofacies composition. Cluster 1 contains wells of mixed LITH 1+2 composition (W1, W3, W6, W13), the LITH 2-exclusive W5, and the LITH 0-exclusive W11. Cluster 3 likewise mixes LITH 1+2 wells (W2, W7, W8). The statistical signature distinguishing the clusters is not reducible to facies composition.

Dunn pairwise comparisons with Bonferroni correction identify 26 of the 78 well pairs as significantly different (Table 6). Most of these pairs involve Cluster 3 wells (W2, W7, W8) tested against Cluster 1 wells, consistent with the elevated Fpor means in Cluster 3.

3.5 Within-class case study: the single-facies well (W5)

W5 is the only well in the dataset composed entirely of LITH 2 samples ($n = 63$; depth range $-2,980$ to $-3,290$ ft TVDSS). Its Fpor distribution has mean 0.0395, median 0.0358, and SD 0.0131. The CV is 33.1%, the second-lowest in the dataset after W3 at 34.4%. A Mann-Whitney test of W5 against the pooled LITH 2 samples from all

other wells ($n = 195$) returns $U = 5,421$ with $p = 0.161$ and effect size $r = 0.117$. Against its facies peers, W5 is not statistically distinguishable in central tendency. By the standard within-class test, the well is unremarkable.

Table 6.

Significant pairwise comparisons between wells from the Dunn post-hoc test (Bonferroni-corrected, $p < 0.05$). Twenty-six of the 78 possible pairs reach significance; W7 and W8 (Cluster 3, highest Fpor) account for the majority of the contrasts.

Well A	Well B	p-adj	Well A	Well B	p-adj	Well A	Well B	p-adj
W1	W7	0.0202	W4	W8	0.0085	W7	W11	< 0.0001
W1	W8	0.0213	W4	W13	0.0018	W7	W12	< 0.0001
W1	W13	0.0098	W5	W7	< 0.0001	W7	W13	< 0.0001
W2	W3	0.0497	W5	W8	< 0.0001	W8	W9	< 0.0001
W2	W13	0.0034	W6	W7	0.0007	W8	W10	0.0106
W3	W4	0.0321	W6	W8	0.0007	W8	W11	< 0.0001
W3	W7	< 0.0001	W6	W13	0.0043	W8	W12	< 0.0001
W3	W8	< 0.0001	W7	W9	< 0.0001	W8	W13	< 0.0001
W4	W7	0.0082	W7	W10	0.0100			

W5 stands apart for three reasons that the facies label does not capture. It is the only well in the dataset composed entirely of a single lithofacies class. Its CV of 33.1% sits well below the LITH 2 population CV of 57.2%, indicating a tighter Fpor distribution than its facies peers. Moreover, the depth profile in Figure 9 shows persistent low-amplitude variation across the full logged interval, unlike the high-amplitude excursions visible in the other LITH 2-bearing wells (W2, W4, W6, W7, W8, W10, W13).

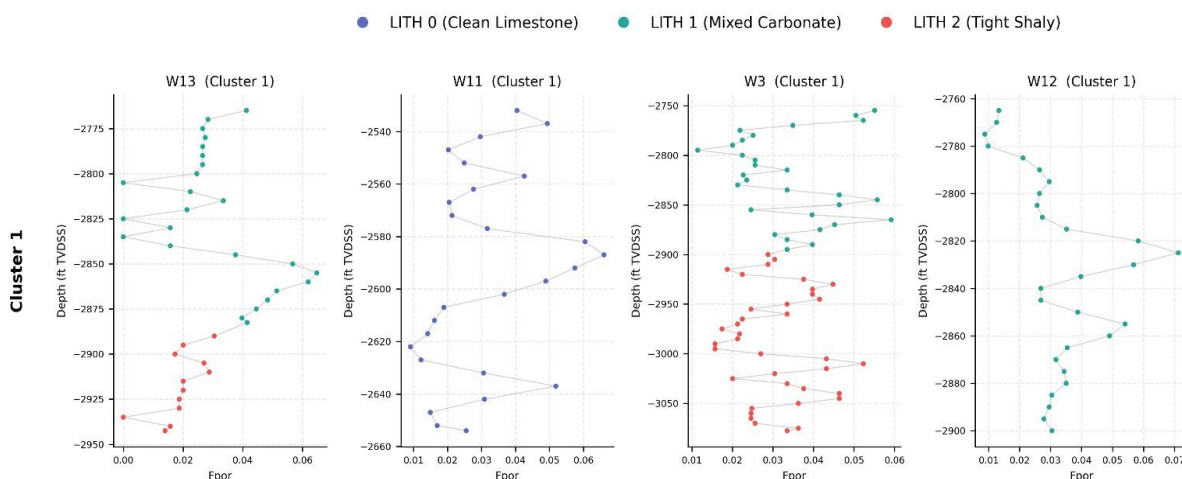
These features illustrate the principal limitation of facies-based fracture characterization in this dataset. A well can occupy a single lithofacies class and have a mean Fpor that is statistically ordinary, yet still carry a distinctive distributional signature in compositional purity, constrained variance, and depth-amplitude character. The well-scale clustering in Section 4.4 captures that signature; the facies label does not.

3.6 Conventional log-Fpor relationships

Cross-plots of resistivity logs against Fpor (Figure 10) show a strong positive monotonic relationship for shallow resistivity (RS vs Fpor: $r = 0.762$, $p < 0.0001$) and a weaker but significant relationship for deep resistivity (RT: $r = 0.432$, $p < 0.0001$). LITH 0, LITH 1, and LITH 2 points are interleaved across both cross-plot planes, with no facies-specific cluster visible along either log axis.

The RS-Fpor correlation is stronger than the correlation of Fpor with any facies-scale or depth-scale variable considered above. This indicates that information predictive of Fpor exists in continuous log space, and that the predictive signal is not stratified by lithofacies label.

Fpor depth profiles by well — organized by Ward cluster



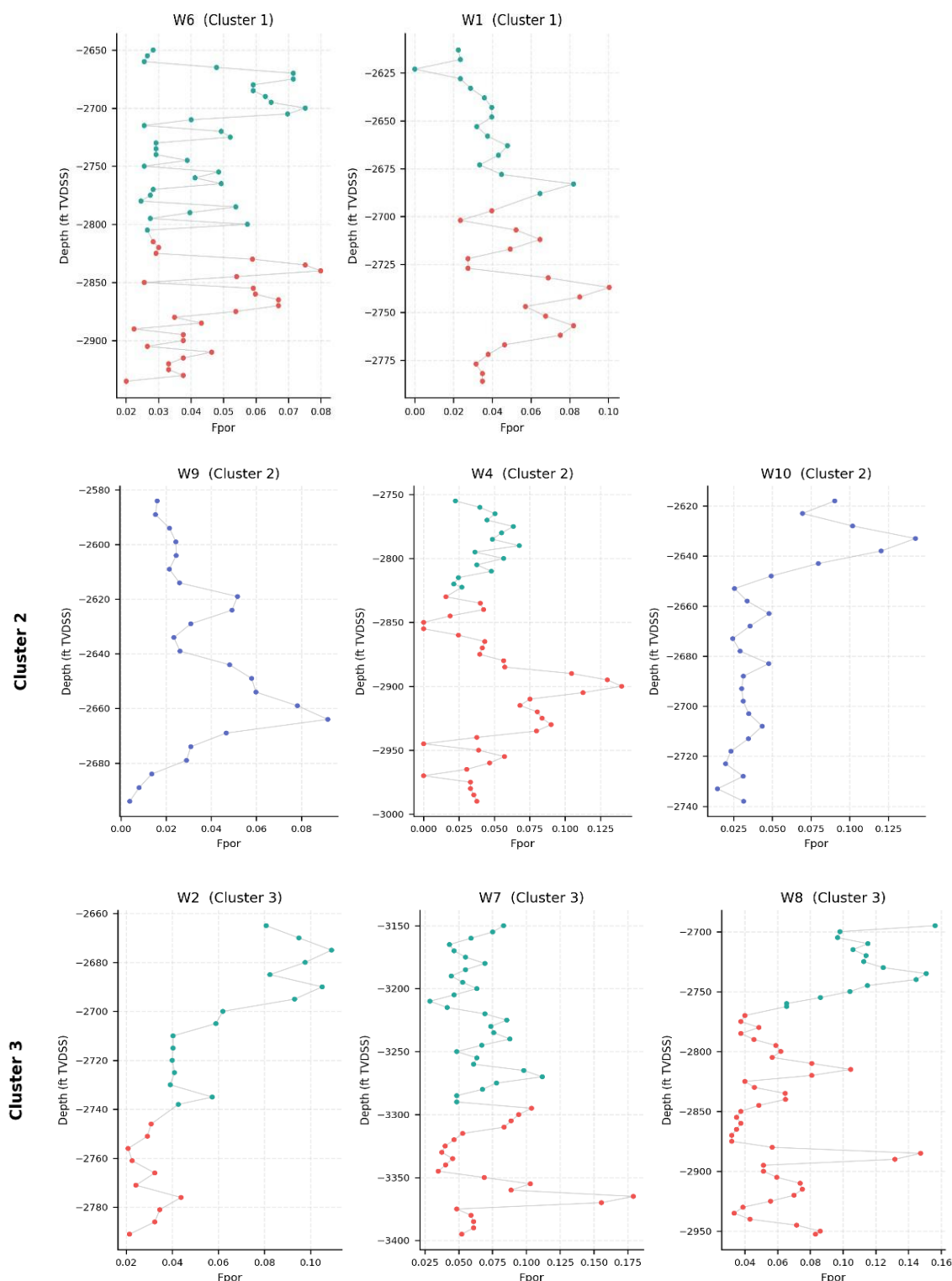


Figure 9.

Fpor depth profiles for all 13 wells, arranged by Ward cluster assignment.

Each panel plots Fpor (horizontal axis) against depth (vertical axis, ft TVDSS) for a single well, with the well name and its cluster given in the panel title. Point colour denotes lithofacies class: LITH 0 (clean limestone) in blue, LITH 1 (mixed carbonate) in green, and LITH 2 (tight shaly carbonate) in red. Row 1 contains the seven Cluster 1 wells (W13, W11, W3, W12, W5, W6, W1), which combine low to moderate Fpor with controlled variance. Row 2 contains the three Cluster 2 wells (W9, W4, W10), distinguished by the highest within-well coefficients of variation in the dataset. Row 3 contains the three Cluster 3 wells (W2, W7, W8), which carry the highest mean Fpor and the widest interquartile ranges. Horizontal and vertical axis limits are set independently for each panel to accommodate the differing Fpor ranges and logged intervals between wells; profiles should therefore be compared by shape and internal variability rather than by apparent spread on the page. W5 (Cluster 1, row 1) is the only single-facies well in the dataset, composed entirely of LITH 2, and shows persistent low-amplitude variation across its full logged interval, in contrast to the high-amplitude excursions seen in the other LITH 2-bearing wells (W2, W4, W6, W7, W8, W10, W13).

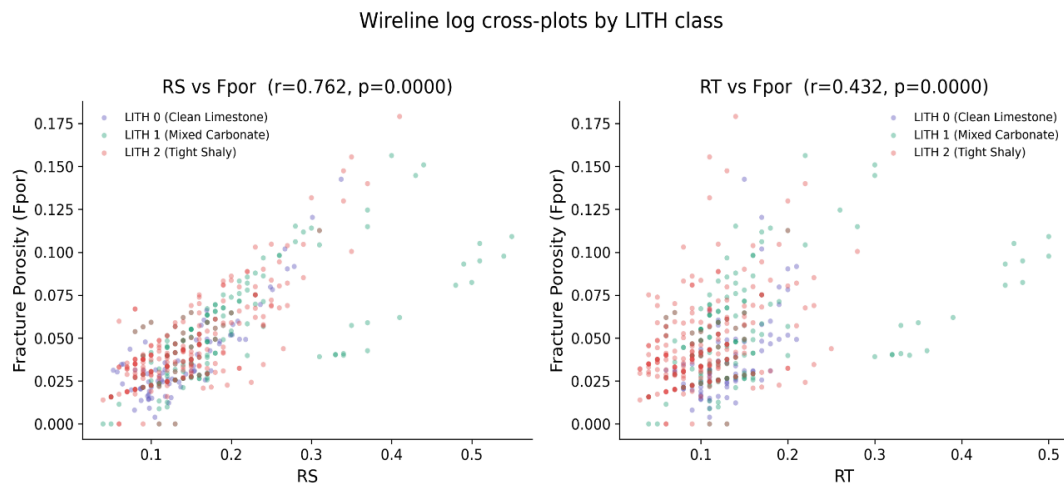


Figure 10.

Wireline log–Fpor cross-plots colored by lithofacies class.

(Left) Shallow resistivity (RS) versus Fpor: $r = 0.762$, $p < 0.0001$. (Right) Deep resistivity (RT) versus Fpor: $r = 0.432$, $p < 0.0001$. LITH 0, LITH 1, and LITH 2 points are interleaved across both planes, showing that the resistivity–Fpor relationship does not stratify by facies.

3.7 Discussion

- **Why the lithofacies effect is small and asymmetric.**

The small effect size of lithofacies on fracture porosity ($\eta^2 = 0.014$; $\varepsilon^{2H} = 0.020$) is consistent with the geological scales at which fracture porosity is generated and modified in carbonate reservoirs. Lithofacies classification, as implemented in the operator's petrophysical workflow, captures bulk mineral composition and shale content, both of which are gross attributes largely independent of the diagenetic, structural, and fluid-flow processes that govern fracture development. Mechanical stratigraphy at decimeter to meter scale, dolomitization fronts, cement distributions, and stylolite networks all vary at scales below the facies level (Lucia 2007). Fracture porosity inherits this sub-facies heterogeneity, and a facies-only classification scheme cannot recover it. The asymmetric pattern within the small lithofacies signal where the LITH 0 separates from LITH 1 and LITH 2, while LITH 1 and LITH 2 remain statistically interchangeable, points toward a single mechanical threshold rather than a graded compositional gradient. Clean limestone (LITH 0) appears to respond to imposed stress and to subsequent diagenetic sealing differently from mixed and shaly carbonate variants. Two candidate mechanisms are consistent with this pattern. First, clean limestone is mechanically more homogeneous and lacks the lithological interfaces that concentrate stress and nucleate fractures in mixed and shaly intervals (Laubach et al., 2016; Ortega et al., 2006). Second, fracture preservation may be lower in clean limestone because diagenetic cementation seals open fractures more efficiently in the absence of clay-bound permeability barriers (Nelson 1985). Either mechanism, or a combination of the two, would suppress preserved fracture porosity in LITH 0 relative to LITH 1 and LITH 2 without further distinguishing the mixed and shaly variants whose mechanical behavior is dominated by shared clay content.

Neither mechanism can be confirmed from the data presented here. The small effect size, the narrow localization of the significant contrast, and the absence of further within-class differentiation are all consistent with inter-well variability (Section 4.4) dominating any facies-level signal. The lithofacies framework provides a coarse first-order partition of Fpor magnitude; the controlling processes operate at finer geological scales than the classification resolves. This contrasts with siliciclastic depositional systems, where facies architecture itself is often the dominant control on reservoir heterogeneity; in the fluvial-to-deltaic Balikpapan Formation of the Lower Kutai Basin, for example, channelised, mouth-bar/delta-front, and prodelta facies show systematic, order-of-magnitude contrasts in porosity and permeability tied directly to depositional process (Wahid et al., 2026). The weak facies signal recovered here therefore appears to be a feature of fracture-dominated carbonate systems specifically, rather than a general property of reservoir heterogeneity.

- **Geological interpretation of well-scale variability**

Well identity accounts for approximately 27% of Fpor variance, more than an order of magnitude above the facies-scale effect. The geological interpretation of this signal requires identifying processes that operate at the well-to-well rather than the sample-to-sample scale. Four candidate mechanisms are consistent with the observed cluster structure, and the data presented here permit only partial discrimination among them.

Structural compartmentalization is the most direct candidate. Wells located in different fault blocks or tectonic regimes experience distinct stress histories, fracture orientations, and shear-related porosity development (Madon & Watts 1998; Tjia 1994). Cluster 3 wells (W2, W7, W8), with the highest Fpor and elevated IQR, would, in this interpretation, occupy structurally active positions where fracture density and aperture are systematically enhanced. The deeper position of W7 (−3,150 to −3,395 ft TVDSS) and the consistently elevated Fpor of W7 and W8 lend qualitative support to a structural explanation. However, confirmation requires structural mapping, which is not available in this dataset.

Diagenetic heterogeneity at the well scale is a second mechanism. Carbonate reservoirs typically preserve evidence of multiple diagenetic phases such as marine cementation, mixing-zone dolomitization, burial recrystallization, and late hydrothermal alteration, each of which affects fracture preservation, sealing, and reactivation (Esteban & Taberner 2003; Nikbin & Aminshahidy 2025). Cluster 2 wells (W4, W9, W10), with high CV and strong positive skewness, are consistent with a diagenetic signature: a relatively uniform low-Fpor matrix punctuated by isolated high-Fpor intervals, as would arise where focused fluid pathways produced zones of intense dissolution or selective fracture-controlled cementation against a more uniform diagenetic background.

A third candidate is variation in mechanical stratigraphy. Even where facies classification is similar across wells, the detailed bedding architecture and the distribution of brittle–ductile contrasts can differ substantially from well to well (Laubach et al., 2009). Wells whose logged interval contains thinly bedded sequences with frequent mechanical interfaces would develop denser, more uniformly distributed fracture networks than wells dominated by thick homogeneous units. Cluster 1, which groups seven wells with low-to-moderate Fpor and controlled variance, would, in this interpretation, represent the dataset’s background mechanical state, against which Clusters 2 and 3 stand out.

Fluid migration history may contribute independently of structure and diagenesis. Carbonate fracture networks are progressively modified by hydrocarbon emplacement, pressure cycling, and dewatering, and these processes operate at reservoir-compartment scale (Kargarpour 2020). Differences in entrapment timing and reservoir pressure history among the 13 wells would contribute to the well-scale signature documented here.

The cluster structure cannot uniquely identify which combination of these mechanisms operates in this field, but it does establish that the controlling variability is geological rather than random. The three Ward clusters represent stable, internally consistent populations, not measurement noise, and their existence sets a quantitative target for any future characterization effort. Resolving the relative contributions of structure, diagenesis, mechanical stratigraphy, and fluid history would require detailed structural mapping, core-calibrated diagenetic studies, and burial history modeling beyond the scope of the present analysis.

- **Implications for fracture prediction in carbonate reservoirs**

The decomposition of Fpor controls into a small facies-scale effect and a dominant well-scale signal has direct consequences for fracture prediction workflows applied to carbonate reservoirs. Facies-based geostatistical models, in which Fpor is conditioned on a lithofacies framework and propagated across interwell space, systematically miss approximately 27% of the variance at the well scale. The missed component is not random; it is structured, with the well-scale residuals forming discrete clusters that share internal statistical signatures (mean, CV, skewness, IQR). Predicting Fpor without representing this structure means that some wells will be predicted accurately by chance, while others, particularly those belonging to Cluster 2 (high CV, skewed) and Cluster 3 (elevated baseline), will be systematically misrepresented.

Two adjustments follow from this result. First, well-scale distributional descriptors, such as per-well mean, CV, skewness, or membership in the Ward cluster structure, should be incorporated as explicit conditioning variables alongside or in place of lithofacies labels in fracture porosity modeling. The information content of these descriptors is, by the analysis presented here, approximately thirteen times that of facies classification. Second, model performance assessment should be partitioned by well identity rather than by random sample. A predictive workflow that performs adequately under random cross-validation may fail at the well scale, and the failure mode is precisely the inter-well heterogeneity quantified in Section 4.4. Predictive frameworks operating at the well scale, including machine learning approaches investigated for this dataset in a companion analysis (Authors, in preparation), depend on the same well-scale signal documented here.

For blind-well prediction in particular, the practical implication is that prediction quality is governed by the geological similarity between the target well and the wells available for training, not by the algorithmic capacity of the predictive model. A blind well belonging to Cluster 3 will be poorly predicted by a model trained predominantly on Cluster 1 wells, regardless of model choice. This reframes the operational question from 'which model performs best?' to 'whether the target well is geologically representative of the available training set'.

4. Conclusion

In conclusion, we quantified the controls on fracture porosity in a Malay Basin carbonate dataset using two-scale statistical decomposition. Lithofacies classification accounted for between 1.4 and 2.0% of the total Fpor variance ($\eta^2 = 0.014$; $\varepsilon^2H = 0.020$), with the small signal localized to a single pairwise contrast between clean limestone (LITH 0) and mixed carbonate (LITH 1). The mixed and tight shaly carbonate classes (LITH 1 and LITH 2) were statistically indistinguishable in terms of Fpor. In contrast, well identity accounted for approximately 27% of the total variance ($\varepsilon^2H = 0.271$), an effect more than thirteen times larger than the facies effect. The 13 wells were partitioned into three internally consistent clusters whose boundaries cross-cut lithofacies composition.

The dominant control on fracture porosity in this dataset operates at the well scale rather than the facies scale. The three clusters represent distinct populations in the Fpor mean, variance, and distributional shape, and they cannot be reduced to lithofacies labels, depth position, or random measurement noise. The single-facies well in the dataset (W5, composed entirely of LITH 2) illustrates the limitation directly: its Fpor mean is statistically indistinguishable from its facies peers, yet its distributional signature (CV = 33.1%, persistent low-amplitude depth profile) is among the most distinctive signatures in the dataset. Lithofacies classification, as applied here, cannot resolve this type of well-scale uniqueness.

For fracture prediction in this and comparable carbonate reservoirs, the results reframed the operational target. A facies-based geostatistical model systematically missed 27% of the variance at the well scale, with the missed component structured rather than random. Predictive workflows should incorporate well-scale distributional descriptors, and performance should be assessed using well-partitioned validation rather than random cross-validation. Geological similarity between the target and training wells is the binding constraint on the quality of blind-well prediction.

The mechanisms responsible for well-scale variability (candidates include structural compartmentalization, diagenetic heterogeneity, mechanical stratigraphy, and fluid history) cannot be distinguished from the present dataset. Structural compartmentalization is consistent in principle with the fault segmentation typically produced by reactivated rift faults and wrench structures during the Middle to Late Miocene inversion that shaped the basin (Madon 2007; Tjia 1994), recent 3D seismic mapping elsewhere in the Malay Basin indicates that fault-bounded compartments of this kind can exert first-order control on reservoir connectivity even where individual fault throws are modest (Jonge et al., 2024). Diagenetic heterogeneity could produce a comparable well-scale signature if dolomitization or cementation fronts are laterally discontinuous between wells, consistent with the diagenetic variability documented in the analogous Central Luconia platforms (Janjulah et al., 2017). Mechanical stratigraphy operating below facies resolution, and differences in burial and fluid-flow history between wells,

remain equally plausible candidates and are not mutually exclusive with the other two mechanisms. Resolving these issues requires integrated structural mapping, core-calibrated diagenetic studies, and burial history modeling. The decomposition presented here establishes the magnitude of the well-scale signal and identifies the cluster structure within which the geological investigation should be framed.

Limitations

Several limitations constrain the interpretation of these results. The dataset is drawn from a single field in the Malay Basin, and the two-scale decomposition demonstrated here may not generalize directly to other carbonate basins where structural, diagenetic, and fluid-history regimes differ. The qualitative observation that well-scale variability dominates facies-scale variability is likely robust across carbonate settings on geological grounds, but the specific proportions (1.4 to 2.0% for facies versus 27% for wells) should be treated as field-specific.

FMI-derived Fpor carries interpretation uncertainty that we cannot quantify within this study. Fracture porosity from image logs depends on aperture estimation, fracture-versus-non-fracture discrimination, and processing decisions made by the interpreting petrophysicist. The conclusions drawn here are robust to interpretation noise at the magnitude typical of FMI workflows, since both the facies effect and the well effect are statistical signals operating across hundreds of samples; sample-level noise of a few percent on Fpor would not redistribute samples among wells or facies sufficiently to overturn the dominant patterns. Even so, calibration of FMI Fpor against core data, where available, would strengthen the foundation of any predictive workflow built on these labels.

The dataset contains 13 wells with unequal sample sizes ($n = 23$ to 66). The effect-size dominance of well identity over facies ($\epsilon^2_{\text{H}} = 0.271$ versus 0.020) is sufficiently large that unequal group sizes are unlikely to be the source of the contrast, but a bootstrap-based confirmation under stratified equal- N resampling would provide additional robustness against this concern. The lithofacies classification used here (LITH 0, 1, 2) was provided as part of the operator's standard petrophysical interpretation, with the underlying methodology proprietary. The reliance on a vendor-supplied classification scheme introduces an interpretive dependency that we cannot independently audit. The three classes are described by their qualitative composition (clean limestone, mixed carbonate, tight shaly carbonate), and this analysis treats as given.

Finally, the finding that LITH 1 and LITH 2 are statistically indistinguishable in Fpor (Tukey p -adj = 0.482) admits a more pointed reading than the one offered in Section 4.2. The 3-class scheme used here may itself be suboptimal for fracture characterization. An alternative classification, such as distinguishing dolomitic from non-dolomitic intervals, or a core-calibrated rock-typing scheme that incorporates mechanical and diagenetic attributes, could resolve a larger fraction of Fpor variance at the facies scale than the bulk-mineralogy framework analyzed here. The small facies effect ($\eta^2 = 0.014$) is therefore not only a finding about the geology of Malay Basin carbonates; it is also a finding about the limits of the specific classification scheme applied to them. Future work using rock-typing schemes more directly aligned with fracture-relevant attributes is a natural extension of this study.

5. Acknowledgement

This research was supported by the Government of Timor-Leste through the Human Capital Development Fund (Fundo de Desenvolvimento do Capital Humano, FDCH), under whose scholarship the first author carried out this work. The authors acknowledge Universiti Teknologi PETRONAS (UTP) for the institutional framework within which this research was conducted. The work was based within the Centre of Seismic Imaging (CSI), a dedicated research facility whose working environment, drawing together Masters and doctoral candidates, postdoctoral researchers, and faculty across geophysics, reservoir characterization, and subsurface data analytics, shaped the technical and intellectual development of this study in ways that extend beyond any single acknowledgment.

6. Declarations

6.1 Author contributions

Simeão Da Silva: conceptualization, methodology, formal analysis, investigation, data curation, writing – original draft, writing – review & editing, visualization. Muhammad Luqman Hasan: supervision, conceptualization, writing – review & editing. Dejen Teklu Asfha: supervision, writing – review & editing. Krisna Oka Mahendra: validation, resources, writing – review & editing. All authors read and approved the final manuscript.

6.2 Funding statement

This work was supported by the Government of Timor-Leste through the Human Capital Development Fund (Fundo de Desenvolvimento do Capital Humano, FDCH) and Centre for Graduate Studies (CGS-UTP), which funded the first author's postgraduate scholarship. The funder had no role in study design, data collection and analysis, interpretation, or the decision to publish.

6.3 Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

6.4 The use of AI and AI-assisted Technologies

During the preparation of this work, the authors used Grammarly for language refinement. After using this tool, the authors reviewed, verified, and edited the content as necessary and take full responsibility for the accuracy and integrity of the content of this publication, including all statistical results and scientific interpretations.

7. Glossary of terms and symbols

Term & Symbols	Definition	Unit
Fpor	Fracture porosity, derived from FMI image-log interpretation; the target variable throughout the analysis	fraction (v/v)
FMI	Formation MicroImager; borehole resistivity image log used as the ground-truth source for fracture observation	—
LITH 0	Lithofacies class 0: clean limestone	categorical
LITH 1	Lithofacies class 1: mixed carbonate	categorical
LITH 2	Lithofacies class 2: tight shaly carbonate	categorical
TVDSS	True Vertical Depth Sub-Sea	ft
RS	Shallow resistivity log	ohm·m
RT	Deep (true) resistivity log	ohm·m
N, n	Total sample size (N) and subgroup sample size (n)	count
k	Number of groups compared in an omnibus test	count
CV	Coefficient of variation, SD / mean × 100	%
IQR	Interquartile range of the Fpor distribution	fraction (v/v)
F	One-way ANOVA test statistic	dimensionless
H	Kruskal–Wallis test statistic	dimensionless
U	Mann–Whitney U test statistic	dimensionless
p	Probability value; statistical significance threshold set at $\alpha = 0.05$	dimensionless
η^2 (eta-squared)	ANOVA effect size, $SS_{\text{between}} / SS_{\text{total}}$	dimensionless
ϵ^2H (epsilon-squared-H)	Kruskal–Wallis effect size, $(H - k + 1) / (N - k)$	dimensionless
r	Pearson correlation coefficient, or rank-biserial effect size for the Mann–Whitney test	dimensionless
ρ (rho)	Spearman rank correlation coefficient	dimensionless
α (alpha)	Significance threshold / family-wise error rate for post-hoc testing	dimensionless

8. References

- Aghli, G., Moussavi-Harami, R., & Mohammadian, R. (2020). Reservoir heterogeneity and fracture parameter determination using electrical image logs and petrophysical data (a case study, carbonate Asmari Formation, Zagros Basin, SW Iran). *Petroleum Science*, 17(1), 51–69. <https://doi.org/10.1007/s12182-019-00413-0>
- Aguilera, R. (1976). *Analysis of Naturally Fractured Reservoirs From Conventional Well Logs*. <https://doi.org/10.2118/5342-PA>
- Bagheri, H., & Mohebian, R. (2025). Fracture facies estimation utilizing machine learning algorithm and Formation Micro-Imager (FMI) log. *Petroleum Research*, 10(4), 764–781. <https://doi.org/10.1016/j.ptlrs.2025.04.006>
- Berben, L., Sereika, S. M., & Engberg, S. (2012). Effect size estimation: Methods and examples. In *International Journal of Nursing Studies* (Vol. 49, Number 8, pp. 1039–1047). <https://doi.org/10.1016/j.ijnurstu.2012.01.015>
- Bishop, M. G. (2002). PETROLEUM SYSTEMS OF THE MALAY BASIN PROVINCE, MALAYSIA. *USGS Science for a Changing World*. <https://pubs.usgs.gov/of/1999/ofr-99-0050/OF99-50T/OF99-50T.pdf>
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (Second Edition). <https://doi.org/10.1016/C2013-0-10517-X>
- Esteban, M., & Taberner, C. (2003). Secondary porosity development during late burial in carbonate reservoirs as a result of mixing and/or cooling of brines. *Journal of Geochemical Exploration*, 78–79, 355–359. [https://doi.org/10.1016/S0375-6742\(03\)00111-0](https://doi.org/10.1016/S0375-6742(03)00111-0)
- Garland, J., Neilson, J., Laubach, S. E., & Whidden, K. J. (2012). Advances in carbonate exploration and reservoir analysis. *Geological Society Special Publication*, 370(1), 1–15. <https://doi.org/10.1144/SP370.15>
- Hall, R. (2013). The palaeogeography of Sundaland and Wallacea since the Late Jurassic. *Journal of Limnology*, 72(S2), 1–17. <https://doi.org/10.4081/jlimnol.2013.s2.e1>
- Humphrey, E., Gomez-Rivas, E., Neilson, J., Martín-Martín, J. D., Healy, D., Yao, S., & Bons, P. D. (2020). Quantitative analysis of stylolite networks in different platform carbonate facies. *Marine and Petroleum Geology*, 114. <https://doi.org/10.1016/j.marpetgeo.2019.104203>
- In, J., & Lee, D. K. (2024). Alternatives to the P value: connotations of significance. *Korean Journal of Anesthesiology*, 77(3), 316–325. <https://doi.org/10.4097/kja.23630>
- Janjuhah, H. T., Mohammad A, A., & Parsed Gho, D. (2017). Sedimentology and Reservoir Geometry of the Miocene Carbonate Deposits in Central Luconia, Offshore, Sarawak, Malaysia. *Journal of Applied Sciences*, 17(4), 153–170. <https://doi.org/10.3923/jas.2017.153.170>
- Jonge, A. De, Widyanita, A., Busch, A., Doster, F., & Nicholson, U. (2024). *New Insights into the Structural and Stratigraphic Evolution of the Malay Basin Using 3D Seismic Data: Implications for Regional Carbon Capture and Storage Potential*. [https://doi.org/10.1111/bre.12885DigitalObjectIdentifier\(DOI\)](https://doi.org/10.1111/bre.12885DigitalObjectIdentifier(DOI))
- Kargarpour, M. A. (2020). Carbonate reservoir characterization: an integrated approach. *Journal of Petroleum Exploration and Production Technology*, 10(7), 2655–2667. <https://doi.org/10.1007/s13202-020-00946-w>
- Laubach, S. E., FALL, A., COPLEY, L. K., MARRETT, R., & WILKINS, S. J. (2016). Fracture porosity creation and persistence in a basement-involved Laramide fold, Upper Cretaceous Frontier Formation, Green River Basin, USA. *Geological Magazine*, 153(5–6), 887–910. <https://doi.org/10.1017/S0016756816000157>
- Laubach, S. E., Olson, J. E., & Cross, M. R. (2009). Mechanical and fracture stratigraphy. *AAPG Bulletin*, 93(11), 1413–1426. <https://doi.org/10.1306/07270909094>
- Lucia, F. J. (2007). *Carbonate reservoir characterization : an integrated approach* (2nd ed). Springer.

- Madon. (2007). Overpressure development in rift basins: an example from the Malay Basin, offshore Peninsular Malaysia. *Petroleum Geoscience*, 13(2), 169–180. <https://doi.org/10.1144/1354-079307-744>
- Madon, M., Jong, J., Kessler, F. L., Damanhuri, M. H., & Amin, M. K. A. (2020). Pre-tertiary basement subcrops beneath the malay and penyu basins, offshore peninsular malaysia: Their recognition and hydrocarbon potential. *Bulletin of the Geological Society of Malaysia*, 70, 163–193. <https://doi.org/10.7186/bgsm70202014>
- Madon, & Watts, A. B. (1998). Gravity anomalies, subsidence history and the tectonic evolution of the Malay and Penyu Basins (offshore Peninsular Malaysia). In *Basin Research* (Vol. 10). <https://doi.org/10.1046/j.1365-2117.1998.00074.x>
- Madon, Yang, J.-S., Abolins, P., Abu Hassan, R., Yakzan, A. M., Saiful, &, & Zainal, B. (2006). Petroleum systems of the Northern Malay Basin. In *Bulletin* (Vol. 49). <https://gsm.org.my/articles/702001-100556/>
- Mansor, M. Y., Rahman, A. H. A., Menier, D., & Pubellier, M. (2014). Structural evolution of Malay Basin, its link to sunda block tectonics. *Marine and Petroleum Geology*, 58(PB), 736–748. <https://doi.org/10.1016/j.marpetgeo.2014.05.003>
- Marrett, R., Ortega, O. J., & Kelsey, C. M. (1999). Extent of power-law scaling for natural fractures in rock. *Geology*, 27(9), 799–802. [https://doi.org/10.1130/0091-7613\(1999\)027<0799:EOPLSF>2.3.CO;2](https://doi.org/10.1130/0091-7613(1999)027<0799:EOPLSF>2.3.CO;2)
- Metcalfe, I. (2017). Tectonic evolution of Sundaland. *Bulletin of the Geological Society of Malaysia, Volume 63, June 2017, Pp. 27 - 60*. <https://doi.org/10.7186/bgsm63201702>
- Nelson, R. A. (1985). Geologic Analysis of Naturally Fractured Reservoirs. *Gulf Professional Publishing., Vol 1*. https://books.google.com.my/books?hl=id&lr=&id=7TI516mt3s8C&oi=fnd&pg=PP11&dq=Geologic+Analysis+of+Naturally+Fractured+Reservoirs,+2nd+Ed.,&ots=TjiJsX7eln&sig=aVzWklukJvFkmZeehLx0vGRfsMw&redir_esc=y#v=onepage&q=Geologic%20Analysis%20of%20Naturally%20Fractured%20Reservoirs%2C%202nd%20Ed.%2C&f=false
- Nikbin, M., & Aminshahidy, B. (2025). An integrated petrographic and petrophysical study of diagenetic controls on elastic response in heterogeneous carbonate reservoirs. *Journal of Petroleum Exploration and Production Technology*, 15(10). <https://doi.org/10.1007/s13202-025-02058-9>
- Ong, P. Y., & Jamaludin, S. N. F. (2023). Fracture Network Analysis of Karstified Subis Limestone Build-Up in Niah, Sarawak. *Applied Sciences (Switzerland)*, 13(22). <https://doi.org/10.3390/app132212110>
- Ortega, O. J., Marrett, R. A., & Laubach, S. E. (2006). A scale-independent approach to fracture intensity and average spacing measurement. *American Association of Petroleum Geologists Bulletin*, 90(2), 193–208. <https://doi.org/10.1306/08250505059>
- Pubellier, M., & Morley, C. K. (2014). The basins of Sundaland (SE Asia): Evolution and boundary conditions. *Marine and Petroleum Geology*, 58(PB), 555–578. <https://doi.org/10.1016/j.marpetgeo.2013.11.019>
- Rankey, E. C., Schlaich, M., Mokhtar, S., Ghon, G., Ali, S. H., & Poppelreiter, M. (2019). Seismic architecture of a Miocene isolated carbonate platform and associated off-platform strata (Central Luconia Province, offshore Malaysia). *Marine and Petroleum Geology*, 102, 477–495. <https://doi.org/10.1016/j.marpetgeo.2019.01.009>
- Richardson, J. T. E. (1996). Measures of effect size. In *Behavior Research Methods, Instruments, & Computers* (Vol. 28, Number 1). <https://doi.org/10.3758/BF03203631>
- Shahar, S. (2008). *Durham E-Theses Structural evolution of the Tenggol Arch and its implication for basement fracture patterns in the Malay Basin, Malaysia* [Durham University]. <https://etheses.durham.ac.uk/id/eprint/2233/>
- Talebian, S. H., Enayati Najafabadi, M., & Fahimifar, A. (2021). Application of improved data-driven diagnostics workflow based on coupled hydro-mechanical model for stimulation candidate selection in a complex carbonate reservoir. *SN Applied Sciences*, 3(7). <https://doi.org/10.1007/s42452-021-04695-1>

- Tjia, H. D. (1994). Inversion tectonics in the Malay Basin: evidence and timing of events. In *Geol. Soc. MaLaYJia, BuLletin* (Vol. 36). <https://gsmpubl.wordpress.com/wp-content/uploads/2014/09/bgsm1994027.pdf>.
- Wahid, A., Sultan, Farida, M., Jamaluddin, & Ryka, H. (2026). Depositional facies influence on reservoir heterogeneity in the Balikpapan Formation, Lower Kutai Basin: Insights well log. *Scientific Contributions Oil and Gas*, 49(1), 219–234. <https://doi.org/10.29017/scog.v49i1.1985>
- Wilson, M. E. J. (2002). Cenozoic carbonates in Southeast Asia: implications for equatorial carbonate development. *Sedimentary Geology*, 147(3–4), 295–428. [https://doi.org/10.1016/S0037-0738\(01\)00228-7](https://doi.org/10.1016/S0037-0738(01)00228-7)
- Wilson, M. E. J., & Hall, R. (2010). *Cenozoic carbonate systems of Australasia*. SEPM (Society for Sedimentary Geology). <https://doi.org/10.2110/sepm.sp.095.013>