

**INTEGRATIVE CHARACTERIZATION AND
MODELING OF THE PERMO-TRIASSIC
CARBONATES, SOUTHCENTRAL SAUDI ARABIA**

BY

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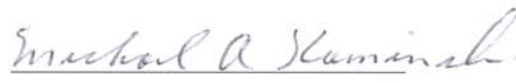

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“In the memory of father, strength for mother, hope for brother and home”

To my beloved family and to the Pearlsboat |

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LIST OF ABBREVIATIONS

ANN	:	Artificial Neural Network
DT	:	Delta-T: Acoustic slowness (transit-time)
DTCO	:	Delta-T of compressional wave
DTSM	:	Delta-T of shear wave
ECS	:	Elemental capture spectroscopy
GR	:	Gamma ray
LLD	:	Laterolog deep resistivity
MF	:	Microfacies
NPHI	:	Neutron-porosity
RHOB	:	Bulk density

|

ABSTRACT

Full Name : Abdallah Abdelkarim Hassan Abdelkarim
Thesis Title : Integrative Characterization and Modeling of The Permo-Triassic Carbonates, Southcentral Saudi Arabia
Major Field : Geology
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Due to its contribution to the low carbon budget, natural gas resources became a desired target for the energy transition. The Permo-Triassic succession is one of the most prolific gas intervals in Saudi Arabia and the Gulf region. This research aims to characterize and model late Permian-Early Triassic carbonate reservoir microfacies in Southcentral Saudi Arabia, incorporating core and well-log data. In the study area, core samples were deeply buried and characterized by dominant SEM intercrystalline microporosity (3-18%) and extremely low permeability, indicating a tight, unconventional reservoir setting. Ten carbonate microfacies were identified, covering various carbonate textures ranging from mudstone to grainstone and floatstone. XRD mineralogy analysis exhibited dolomite-rich at the upper part, where best reservoir quality was recorded in terms of intercrystalline microporosity and fractures, while calcite dominates at the lower part of the core section. Quartz and illite were slightly noted and were particularly associated with organic-rich mudstone microfacies. XRF elemental geochemistry agreed with mineralogy results, representing a good proxy for mineral composition. In all microfacies, the occurrence of fractures, stylolites, poor sorting, and organic matter reduces and distorts acoustic velocities for given microporosity, regardless of carbonate texture. The core analysis results showed decent agreement with the wireline logs concerning calcite-dolomite segregation, elemental geochemistry, and general acoustic variation. Geostatistical and artificial neural network

(ANN) modeling were used to investigate spatial variability and correlation in different Permo-Triassic members in the study area. The modeling results intend to substrate for cost-efficient procedures in early exploration stages. Incorporating the basic geomorphology of the epicontinental platforms with geostatistics provides better certainty for lateral reservoir prediction, which optimizes well planning and exploration strategies on the field scale. In this context, directional variograms showed spatial continuity in geochemical composition with minimal variation and negligible nugget effects. Thus, all studied Permo-Triassic members exhibited long major ranges in Ca and S as dominant elemental capture spectroscopy (ECS). Minor ranges were comparable to the major ones, indicating clear zonal anisotropy. Vertical variograms showed variable ranges as they were influenced by member thickness. Model outputs honored the geological input data in all modeled properties. The ANN modeling aims to utilize and evaluate the performance of several model architectures to predict the elemental composition and Permo-Triassic members, using an integration of ECS, mineralogy, and other well-log data, including acoustic transit-time (DT), neutron porosity (NPHI), bulk density (RHOB) and gamma ray (GR). Principal component analysis (PCA) shows that the input training data could be grouped into three major components that capture more than 80% of the variance. Three ANN architectures with different properties were designed and evaluated to address the regression and classification. The simplest model (Architecture_1) steadily performed best, balancing model complexity with predictive accuracy. Architecture_2 and _3 have also shown comparable results but with less accuracy. This finding emphasizes the importance of model selection in geological applications, where simpler models can often yield time-effective results for reservoir prediction, especially during exploration, with limited data and less computational burden.

ملخص الرسالة

الاسم الكامل: عبد الله عبد الكريم حسن عبد الكريم

عنوان الرسالة: توصيف ونمذجة تكاملية للكربونات البيرمية - الترياسية في جنوب وسط المملكة العربية السعودية

التخصص: الجيولوجيا

تاريخ الدرجة العلمية: ديسمبر ٢٠٢٣

أصبحت موارد الغاز الطبيعي هدفاً مرغوباً في عملية تحول الطاقة وذلك بسبب مساهمتها في تقليل الانبعاثات الكربونية. تُعدّ تتابعات السحنات الكربوناتيّة البيرمية المتأخرة - الترياسية المبكرة (البيرمية-الترياسية) واحدة من أكثر النطاقات المحتوية على الغاز في المملكة العربية السعودية ومنطقة الخليج بشكل عام. يهدف هذا البحث إلى توصيف ونمذجة هذه السحنات في جنوب وسط السعودية باستخدام العينات الصخرية وسجلات الآبار. في منطقة الدراسة، هذه التتابعات وُجدت على أعماق سحيقة وتتميز بمسامية بين-بلورية دقيقة ومتفاوتة، ونفاذية منخفضة للغاية، مما يشير إلى أنها تمثل خزان نفطي ضيق وغير تقليدي. تم التعرف على عشر سحنات كربوناتيّة بأنسجة رسوبية متفاوتة. أظهر تحليل المعادن بالأشعة السينية أن الجزء العلوي غني بالدولوميت مع توفر أفضل مسامية، والتي تتعلق بتوفر المسامية الدقيقة والتكسرات، بينما يسيطر الكالسييت على الجزء السفلي من العينات الصخرية. وُجد الكوارتز والإليت بشكل طفيف وارتبطا بشكل خاص بالسحنات الطينية الغنية بالمواد العضوية. توافقت نتائج التركيب العنصري للأشعة السينية مع نتائج تحليل المعادن، مما يوفر مؤشراً جيداً للتكوين المعدني. أظهر البحث أنه وفي جميع السحنات المدروسة، يقل وجود التكسرات، الاستيلوليت، الفرز الحبيبي، والمواد العضوية من سرعات الموجات الصوتية لنفس المسامية، بغض النظر عن سحنة الكربونات. أظهرت نتائج تحليل العينات الصخرية توافقاً جيداً مع سجلات الآبار فيما يتعلق بنطاقات الكالسييت والدولوميت، التركيب العنصري، والتباين في سرعة الموجات الصوتية بشكل عام. فيما يتعلق بنمذجة الكربونات البيرمية-الترياسية، تم استخدام النمذجة الجيوإحصائية والشبكات العصبية الاصطناعية للتحقيق في التباين المكاني، التكوين العنصري، والمضاهاة في أعضاء البيرمي-الترياسي المختلفة في منطقة الدراسة. تهدف نتائج النمذجة إلى توفير إجراءات فعّالة من حيث التكلفة والوقت في مراحل الاستكشاف المبكرة. يساهم تكامل جيومورفولوجيا وخصائص المنصات القاريّة مع النمذجة الجيوإحصائية في تحسين دقة التنبؤ الجانبي للخرانات النفطية، مما يحسن تخطيط الآبار واستراتيجيات الاستكشاف على مستوى الحقل. في هذا السياق، أظهرت الرسوم التباينية الإتجاهية استمرارية مكانية في التكوين العنصري مع تباين طفيف. وبذا فقد توافقت نتائج النمذجة الجيوإحصائية لأي نموذج مع البيانات المعطاة. تهدف نمذجة الشبكات العصبية الاصطناعية إلى تقييم أداء عدة هياكل نموذجية للتنبؤ بالتكوين العنصري وتوزيع أعضاء البيرمي-الترياسي المدروسة، وذلك باستخدام بيانات التركيب العنصري، المعادن، وبيانات سجلات الآبار الأخرى. في هذا الصدد، تم تصميم وتقييم ثلاثة هياكل للشبكة العصبية الاصطناعية وخصائص مختلفة. أظهر تحليل المكونات الرئيسية أن بيانات التدريب يمكن تجميعها في ثلاثة مكونات رئيسية. النموذج الأبسط (نموذج_١) قدّم أفضل أداء من حيث التوازن بين تعقيد النموذج والدقة التنبؤية. كذلك سجل النموذجين الآخرين أداءً جيداً، ولكن بدقة أقل وحسابات ومواصفات شبكية أكثر تعقيداً. تؤكد هذه النتائج على أهمية اختيار النموذج المناسب في التطبيقات الجيولوجية وأخذ النماذج المبسطة بعين الاعتبار، لا سيما في مرحلة الاستكشاف النفطي، حيث يمكن لمثل هذه النماذج أن توفر نتائج فعّالة مع بيانات محدودة، في وقت وجيز وبحسابات أبسط.

CHAPTER 1

INTRODUCTION

1.1 Preface

The increasing energy demand imposes exploitation of all kinds. Particularly, any kind of energy that is considered as an environmentally-friendly. Among other fossil energies, non-associated gas has the lowest contribution to the global carbon budget, an issue which is highly required for the energy transition plan (IPCC, 2006; Shearer et al., 2014; McGlade et al., 2014; McGlade and Ekins, 2015). It is reported that about 60% of the world's petroleum reservoirs are accumulated in carbonate rocks (e.g., Ahr, 2011; Jia, 2012). The Permian-Triassic Khuff reservoirs host one of the world's greatest non-associated gas reserves ever discovered (Al-Jallal, 1987; Al-Dukhayyil, 2007; Koehrer et al., 2010; Koehrer et al., 2012) (Figure 1.1). Around 15-20% of the world's gas reserves are hosted by the Khuff carbonates (Al-Aswad, 1997; Koehrer et al., 2010). In Saudi Arabia and other Arabian Gulf countries, the Khuff Formation is always an exploration target for non-associated gas reserves and, less importantly, for crude oil (Dasgupta et al., 2002; Al-Qattan, 2014). Geologically, the subsurface setting of the Khuff Formation has revealed a simplified, flattened carbonate ramp characterized by a minor slope gradient. This setting is favorable for developing a layer-cake of micro- and macro-facies associations that are correlatable and predictable for long distances with a good degree of certainty (Al-Jallal, 1995; Insalaco et al., 2006; Al-Dukhayyil, 2007). Nevertheless, the formation is more complex, as reflected by vertical and horizontal heterogeneities. These heterogeneities, particularly in the lateral trend, are

controlled by the post-depositional setting (Dasgupta et al., 2002; Al-Qattan, 2014; Al-Qattan and Budd, 2017). The Permian-Triassic Khuff Formation is composed of several carbonates and evaporites cycles, with the domination of shallow marine clastics in the basal part of the formation. The carbonates-evaporites alteration was developed in shallow to marginal marine ramp platform, which was part of the Epeiric Sea in the northeastern areas of the Neo-Tethys Ocean, prevailed by arid climate (Al-Jallal, 1995; Konert et al., 2001; Hughes, 2009; Koehrer et al., 2010) (Figure 1.2). The shoreline extension of that epeiric sea exceeded 2500km along the strike and above 1500km along the dip direction with a gentle basin-ward slope; this setting implies reservoir continuity (Koehrer et al., 2010). Geostatistical modeling is widely used in the oil and gas industry for demonstrating the directional variability patterns of the property under study. As a keystone for reservoir modeling, variogram analysis is required to judge the degree of continuity or heterogeneity (Olea, 1994; Gringarten and Deutsch, 2001). Different geomechanical tests are used to characterize the reservoir rock properties in terms of stiffness, which is mainly related to the porosity and mineralogy of the rock sample. In carbonate rocks, besides the indigenous difference in lithofacies texture and composition, different diagenetic processes produce different chemistry, mineralogy, and thus porosity, which is indicated by the difference in acoustic and geomechanical properties and hence the reservoir properties in high-resolution scale (Ameen et al., 2009). Accordingly, this research attempts to build a relationship between lithofacies and their acoustic properties by considering the carbonate reservoir units' composition, pore typing, geochemistry, and mineralogy.

STRATIGRAPHY		FORMATION	MEMBER	GENERALIZED LITHOLOGY	RESERVOIR
TRIASSIC LOWER		Sudair	Lower		
			Khuff A		Khuff A
			Khuff B		Khuff B
			Khuff C		Khuff C
			Khuff D		
			Khuff E		
PERMIAN UPPER		Khuff			
PERMIAN LOWER		Unayzah			
CARBONIFEROUS		Berwath			

Figure 1.1. The stratigraphic position of the late Permian-early Triassic Khuff Formation in Saudi Arabia, with respective potential gas reservoirs (Dasgupta et al., 2002).

1.2 Problem Statement and Research Motivation

Due to the increasing demand for energy resources, besides its characteristics as a low contributor to the global CO₂ budget, the natural non-associated gas has become a potential exploration target. Permo-Triassic carbonates represent one of the most gas-prolific intervals in Saudi Arabia. Even though Permo-Triassic carbonate lithofacies tend to have continuous layer-cake patterns, which imply reservoir continuity, different geological and petrophysical studies have demonstrated the spatial heterogeneities of these carbonates in the subsurface

(Alsharhan and Nairn, 1994; Al-Jallal, 1995; Dasgupta et al., 2002; Al-Dukhayyil, 2012; Al-Qattan, 2014). Thus, understanding the heterogeneity of these carbonates, using integrative laboratory and modeling techniques, is crucial for enhanced reserves estimation and recovery.

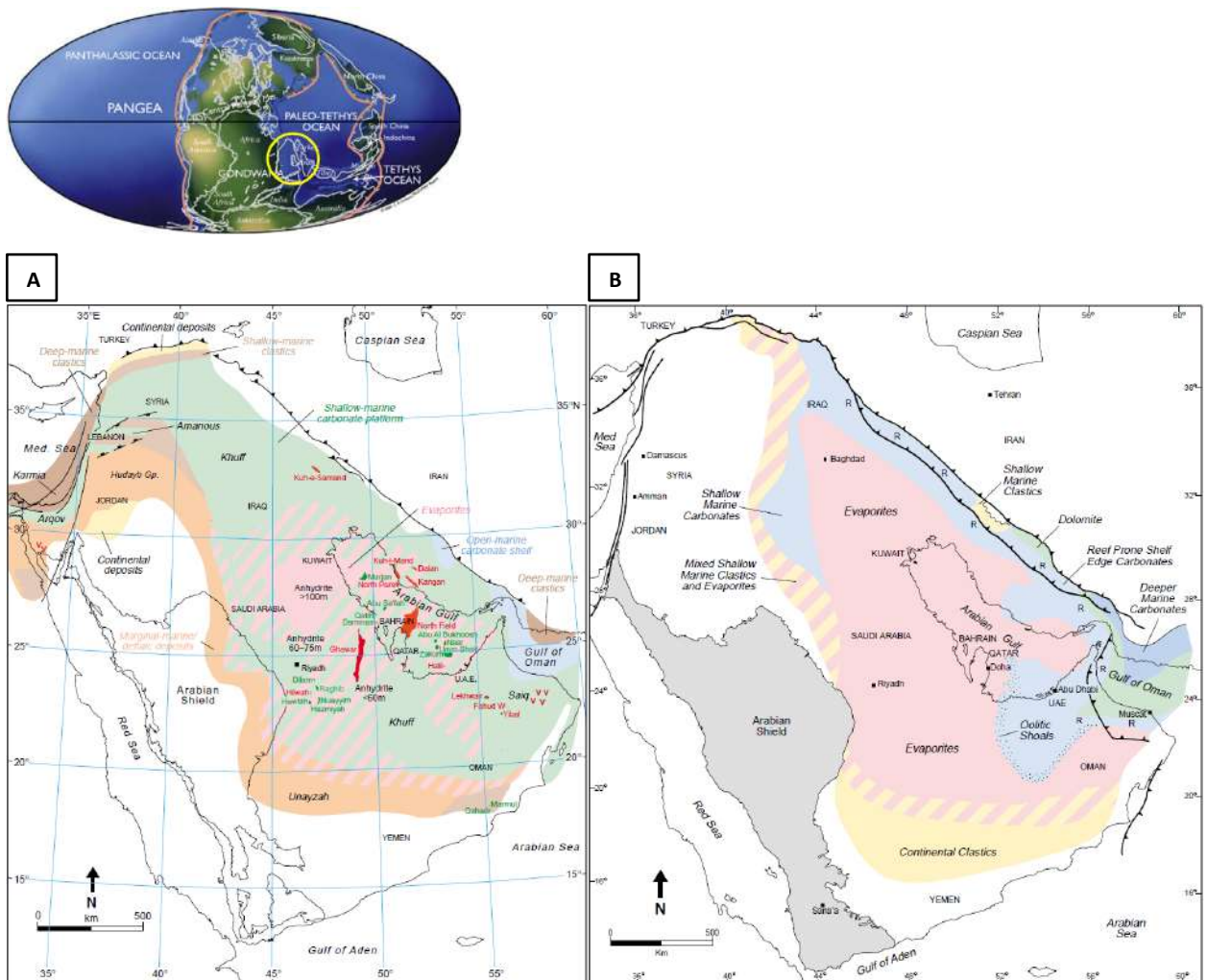


Figure 1.2. Late Permian paleo-globe and paleofacies. The late Permian paleo-globe of Gondwana shows the Neo-Tethys shelf partially inundating the Arabian Plate (yellow circle). **A** and **B.** Paleofacies map of the Arabian Plate during the late Permian (deposition of Khuff carbonates and evaporites and their regional equivalents in the epeiric sea of the northeastern passive margin of the Neo-Tethys). The present-day distribution of Khuff gas (red spots) and oil (green spots) reservoirs is also shown. The giant North Field of Qatar mainly produces gas from Khuff carbonates (Ziegler, 2001). Note, in **B**, the mixed shallow

marine and tidal-flat evaporites all over the platform and mixed shallow marine clastics and evaporites westward along the Noe-Tethyan shoreline (Konert et al., 2001). The Permian globe is modified from (Scotese, 2003).

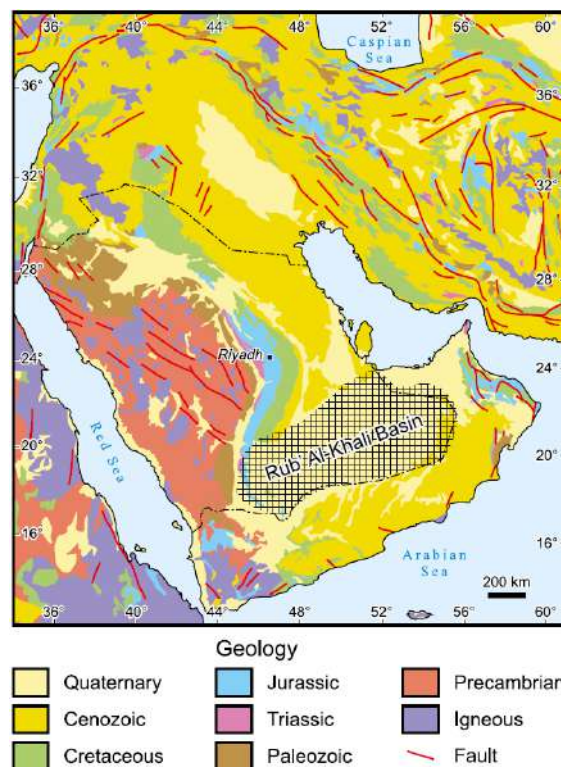


Figure 1.3. Location of the Rub' Al-Khali Basin, a huge Quaternary sand sea blanketing the Arabian Platform's Phanerozoic strata in southern Saudi Arabia (Stewart, 2016).

1.3 Research Objective

This integrative study aims to characterize and model the Permo-Triassic carbonate reservoir microfacies in a field located in southcentral Saudi Arabia. Consequently, the main objective is to characterize and model the Permo-Triassic carbonates regarding reservoir properties such as porosity, elemental geochemistry and mineralogy as implications for reservoir quality. Using core and well-logs data, a set of tasks is required to satisfy the main research objective as follows.

- Detailed carbonate microfacies analysis using available cores and well-logs. This is the general skeleton for the subsequent laboratory works.
- Study the porosity patterns of these carbonates qualitatively and quantitatively.
- Investigate the acoustic properties as a crucial tool for tight carbonates, using available cores and well-logs.
- Explore the elemental geochemistry and mineralogy of the Permo-Triassic carbonates using available cores and well-logs.
- Investigate the potential of variability modeling and ANN in regional correlation and prediction purposes, in the light of studied reservoir properties.

1.4 Dataset and Methods

1.4.1 Dataset

The data used in this study includes conventional well-logs and cores from six wells in the Rub' Al-Khali Basin (Figure 1.3). The well-log data used in this study includes the lithology indicators such as GR, besides acoustic, resistivity, neutron-porosity (NPHI), and bulk density (RHOB); the latter serve as porosity and lithology indicators. The dataset is a courtesy of the Saudi Arabian Ministry of Energy.

1.4.2 Methods

The integration of laboratory and modeling tasks is planned to perform the objective of this research. The characterization and modeling represent the two major aspects of this research. The general framework of the characterization part relies on the high-resolution microfacies characterization from core samples and well-logs. This part targets the uppermost part of a

late Permian member, representing a potential natural gas interval. This aspect includes a detailed description of the available cores as required to define the microfacies composition and characteristics. Based on the lithology variation and the mineralogy input, powder samples will be obtained from selective zones along the core. Accordingly, representative XRD and petrography-based mineral maps were applied to the powder sample to obtain a mineralogy signature. XRF scan was applied on the slabbed core and used as a proxy to correlate it with mineralogy. The acoustic properties of the whole-core were correlated to the porosity (qualitative and quantitative). Well-logs were used for validation but dominantly for modeling purposes, including 3D geostatistical modeling and ANN of rock properties. The modeling part represents the field scale concerned with large-scale variability and correlation. For the modeling part, 3D modeling was performed through directional variography analysis, the keystone for 3D reservoir property modeling. In this context, well correlation constrains the property modeling. Details of methods followed for characterization were elaborated in Chapter 3, while Chapters 4 and 5 include details for geostatistical and ANN modeling methods, respectively.

CHAPTER 2

LITERATURE REVIEW

2.1 Tectonic Evolution of the Arabian Plate

Many accretion events occurred in the Arabian Plate during the late Precambrian. These accretions occurred between the amalgamated microplates to form a consolidated shield. Among these accretion events, the most important Amar Collision occurred when the Ar-Rayn Microplate drifted westward and collided with the Arabian Shield. As a result, the N-S Amar suture developed along the colliding zone (640-620Ma) (Figure 2.1). Three main tectonic stress regimes have influenced the structural geology and the related depositional patterns of the Arabian Platform (Edgell, 1992). Those regimes occurred during the middle Proterozoic, the Proterozoic-Mesozoic, and the Cenozoic periods (Figure 2.2), illustrated in the following. During the middle Proterozoic, three main structural fault trends were developed in the Arabian Plate. Those are the north, northwest, and northeast trends. These structures are concisely described as follows. I) The north-trending structures, located east of the Arabian Plate, resulted in the development of the Summan Platform, Ghawar Anticline, Dibdibah Trough, and Qatar Arch (Figure 2.3). II) The northwest-trending structures located in the Arabian Shield. After the Amar Collision, an extension stage was initiated as intrusions of granitic A-type plutons were developed. This extension stage concluded by developing the sinistral Najd Fault System when the Arabian Plate drifted about 300km, creating a series of NE rifts (Al-Husseini, 2000). III) The northeast-trending structures: located in the Arabian Gulf region in the east of the Arabian Peninsula, those

included the northeast-trending rift basins of Oman, the Arabian Gulf Basin, and the Zagros Thrust Mountains. These basins were classified as pull-apart basins attributed to the left-lateral dislocation, which was triggered by the Najd Fault System (Al-Husseini, 2000). These tectonic settings control the later Phanerozoic sedimentary succession of the Arabian Plate, which in turn influences the sedimentary patterns, including sediment types and distribution (Konert et al., 2001; Bell, 2004). The middle Proterozoic structures have been sporadically reactivated by the later Proterozoic-Mesozoic stress regime. Particularly, this included Ghawar Anticline, Qatar Arch, and Dibdibah Trough. At the Cenozoic, two major vertical shear zones took place in the Precambrian basement due to the prevailing stress regimes. These shear zones occurred at about N20°W and N36°E. The first shear is a left-lateral strike-slip fault, while the later shear is right-lateral (Edgell, 1992). The Arabian Plate was affected by a major tectonic event at the late Devonian, resulting from the formation of the Pangaea Supercontinent due to the Gondwana-Laurasia collision. The Hercynian Orogeny, which lasted for roughly 25Ma, was behind the removal of thousands of meters of sediments in the uplifted areas, and the hiatus surface produced by this event is called the Pre-Unayzah Unconformity (Alsharhan and Nairn, 1994; Wender et al., 1998; Konert et al., 2001, Sharland et al., 2001; Al-Husseini, 2004). Continental stretching and rifting affected the west of Pangaea during the end of the early Permian. As a result, the Cimmerian Continent was separated from Gondwana. This separation led to the creation of the Neo-Tethys Ocean (Alsharhan and Nairn, 1994). In the Arabian Plate, the separation caused a regional uplift, which in turn produced the regional Pre-Khuff Unconformity. Contemporarily, a late Permian regional marine transgression of the Neo-Tethys was developed to create the first widespread and well-developed carbonates succession in the Arabian Plate (Khuff

Formation) (Alsharhan and Kendall, 1986; Al-Jallal, 1995). Today, the Arabian Peninsula is bordered by different tectonic boundaries. The extensional regime includes seafloor spreading in the Red Sea, the Gulf of Aden and the Arabian Sea and to the west, southwest, and south of the plate; compressional regime along Zagros thrust belt to the east and northeast; subduction zone of Makran Zone in Oman in the southeast; and transform regime along the Dead Sea and Gulf of Aqaba in the northwest, and along Owen-Sheba Fault Zone at the southern and southeastern boundaries (Konert et al., 2001; Ziegler, 2001) (Figure 2.4).

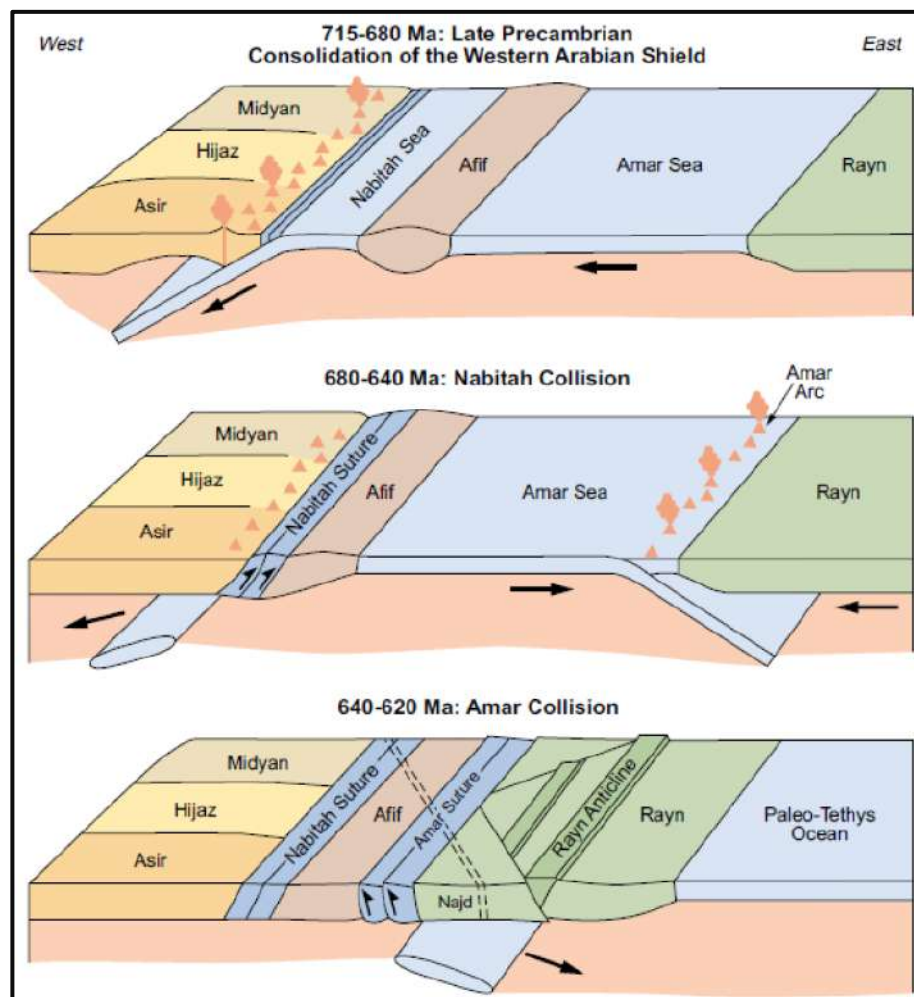


Figure 2.1. The tectonic evolution of the Arabian Shield basement complex showing significant micro-plate collisions and amalgamations; the most important among all is the Amar collision (640-620Ma) (Al-Husseini, 2000).

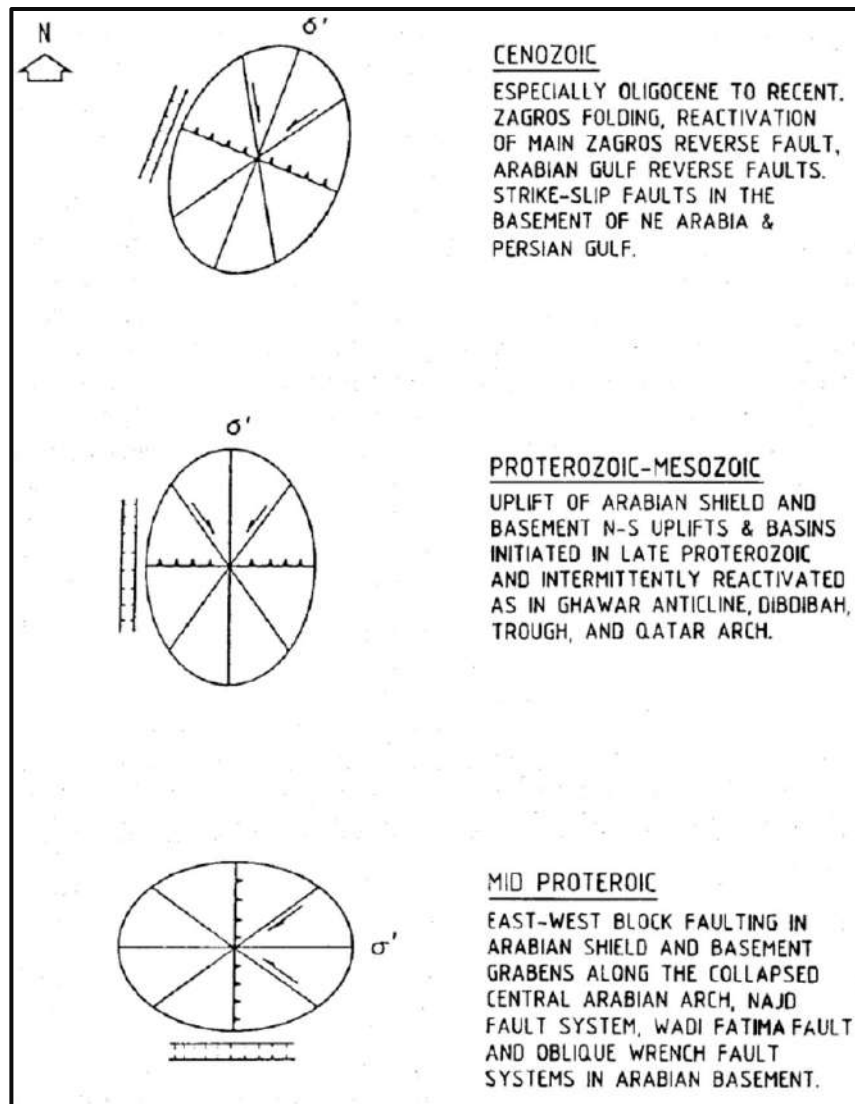


Figure 2.2. Major stress regimes in the Arabian Plate during the middle Proterozoic, the Proterozoic-Mesozoic, and the Cenozoic (Edgell, 1992).

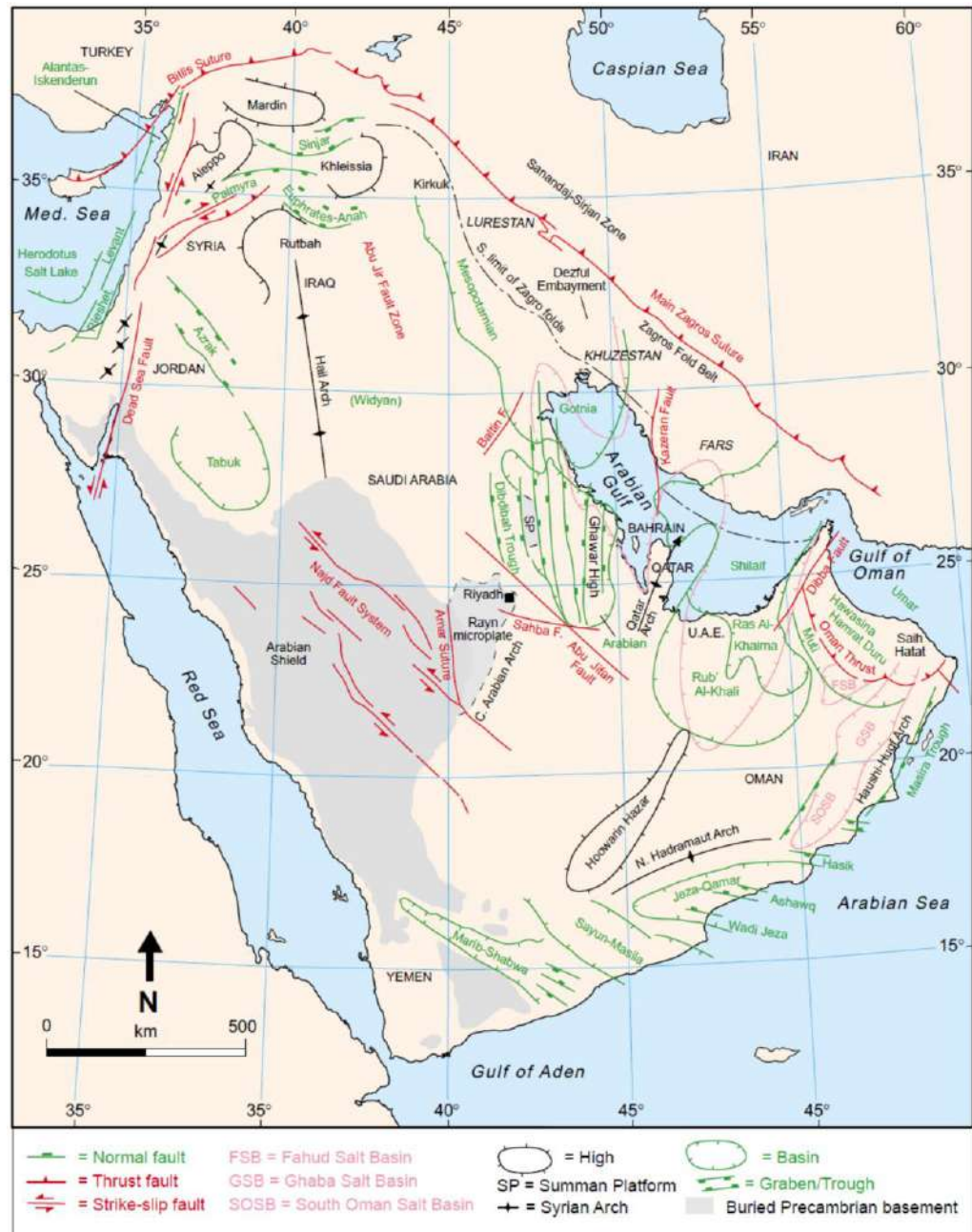


Figure 2.3. The tectonic and structural map of the Arabian Plate shows the dominant structural trends (Ziegler, 2001).

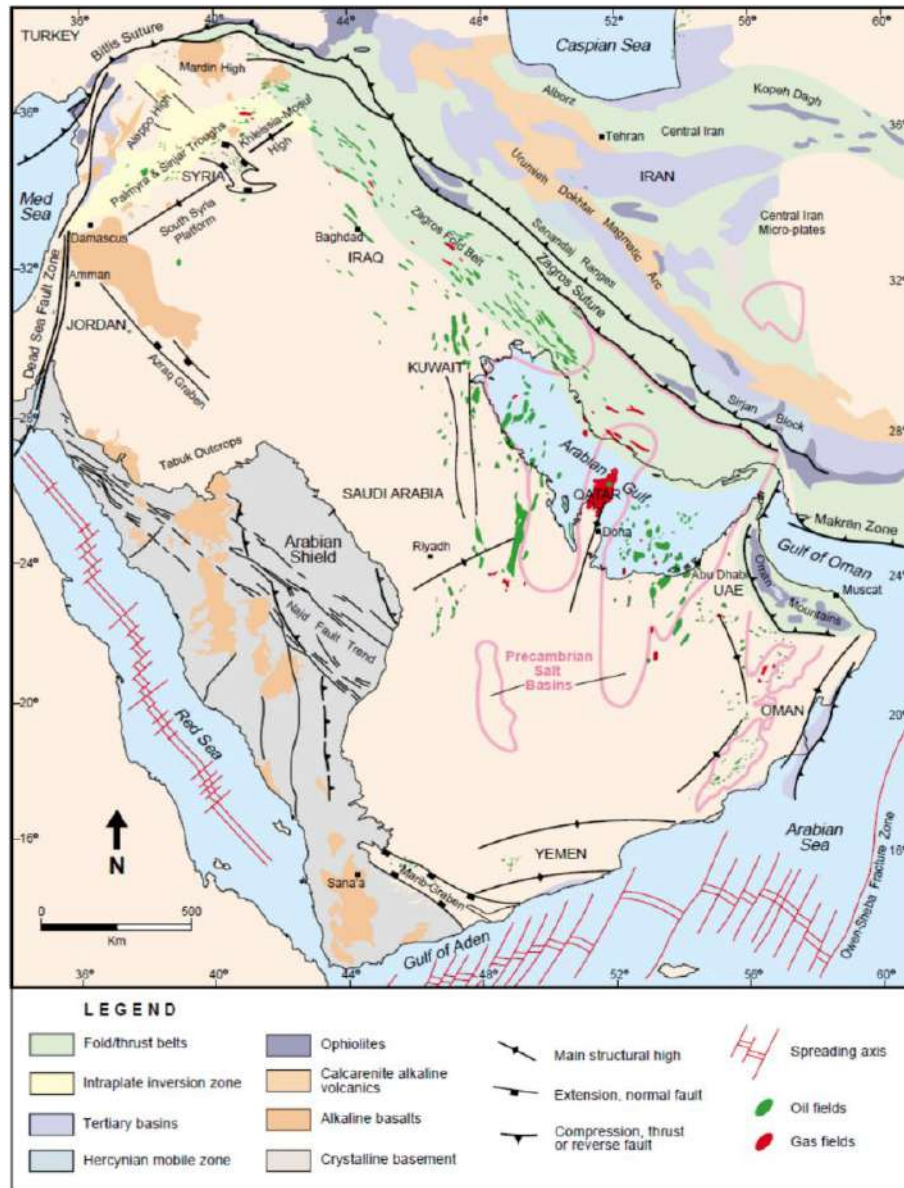


Figure 2.4. Present-day major tectonic margins surrounding the Arabia Plate. All kinds of plate tectonic margins occur in this region: collision along the Zagros suture zone, Seafloor spreading margins in the Red Sea and the Gulf of Aden, and transform margin in the Dead Sea, Gulf of Aqaba and Owen-Sheba zone (Konert et al., 2001).

2.2 Arabian Plate Paleo-latitudes

Besides the aspects of Arabian Plate tectonic evolution on the development of the Arabian platform and associated sedimentary successions, the wandering of the plate through the Phanerozoic also has an influence on the origin and distribution of the sediments (Figure 2.5). Several schematic paleofacies maps were generated, which are mainly controlled by paleogeography, hence the paleoclimate (Konert et al., 2001; Ziegler, 2001). During the late Precambrian, the Arabian Plate was part of Gondwana and attached to the present-day African Plate. The location of the Arabian Plate was close to the equator, with E-W orientation. During the early Paleozoic, the plate started to move southward in an anti-clockwise drifting; an extensive glacial event was developed west of the plate as it was located in higher southern latitudes. This was followed by a clockwise rotation angle of about 100° during the Ordovician-Carboniferous, without a significant latitudinal change. Another glacial event took place during the late Carboniferous, affecting Oman, Yemen, and wide areas in southern Arabia (Konert et al., 2001; Sharland et al., 2001). At this time, the plate started to take its final orientation as the present day geography. Long northward movement occurred during the Permian, from about 25°S to 5°S. The plate remained in its equatorial location during the early Jurassic (Al-Fares et al., 1998). This position was behind the prevailing carbonate platform during the Jurassic. The opening of the Atlantic Ocean during the Cretaceous had drifted the African and Arabian plates northward from about 5°N to 10°N, while the Red Sea opening had tilted these plates eastward (Sharland et al., 2001) (Figure 2.5).

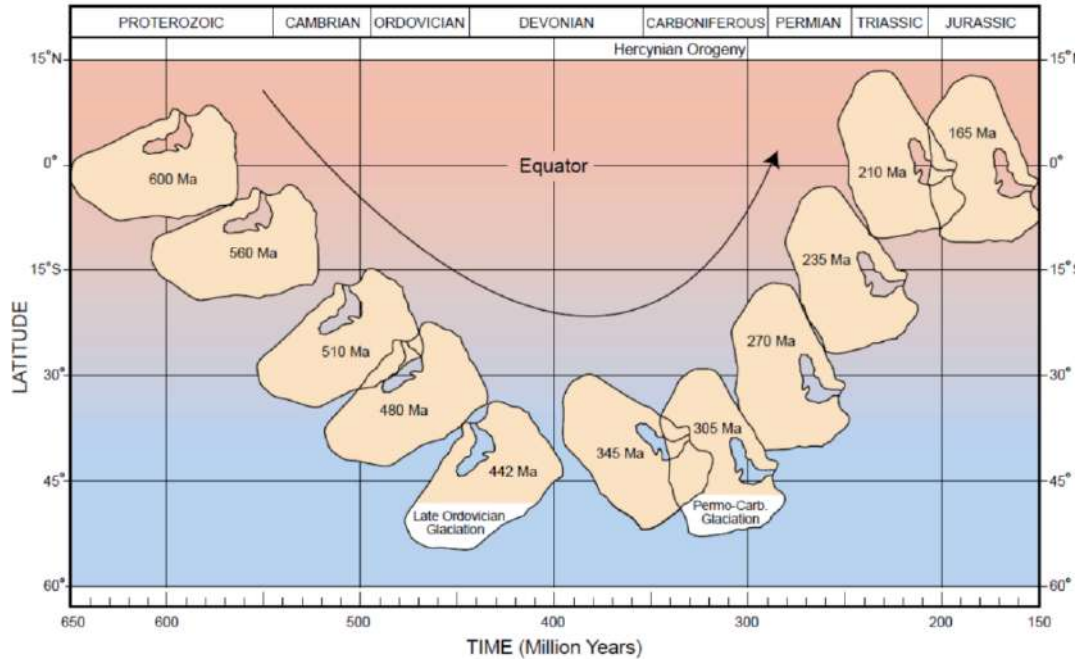


Figure 2.5. Anti-clockwise latitudinal drifting of the Arabia Plate during the Proterozoic-Jurassic. An approximated drift of roughly 20 latitudinal degrees occurred during the late Permian (Konert et al., 2001).

2.3 Tectonic Evolution of the Rub' Al-Khali Basin

The Rub' Al-Khali Basin is located below the Rub' Al-Khali Desert, which covers large areas south of the Arabian Peninsula. The basin, predominantly located in Saudi Arabia, is also shared and bordered by Oman, Yemen, and the United Arab Emirates (Figure 1.3). There is no surface expression to tell about the subsurface geology of the basin except at the western and northwestern flanks, where the basement complex and the Phanerozoic succession are exposed out along the eastern border of the Arabian Shield complex. Therefore, the structural and sedimentary evolution of the Rub' Al-Khali Basin was mainly studied through magnetic, gravity, and seismic reflection imaging besides well data (Stewart, 2016). The structural evolution extends from the late Precambrian to Neogene periods. The approximate deepest zones imaged by seismic reflection are at a depth of 13km in the

undrilled areas of the Precambrian rifts. The structural evolution of the Rub' Al-Khali Basin is believed to be influenced by three principal events, those are, the Hormuz salt diapirism, the Hercynian event, and the evaporites successions during the Permian, Jurassic, and Tertiary. These events are briefly elaborated in the following (Stewart, 2016). Contrary to the impact of Hormuz salt diapirs (late Ediacaran – early Cambrian) on the structural style of some petroleum fields in Oman and the United Arab Emirates (e.g., Al-Barwani and McClay, 2008; Thomas et al., 2015), no similar structural styles were observed from seismic reflection in the interior of the Rub' Al-Khali Basin. The exception was reported in the middle of Wajid Graben, where an isolated dome was observed. However, it can also be interpreted as an inversion structure or an igneous plutonic intrusion (Stewart, 2014). The Carboniferous Hercynian event produced a major break in the Arabian Plate stratigraphic succession. Isolated paleo-highs, arches (including Qatar Arch), and sub-basins were generated. The thickness of Cambrian-Devonian (Pre-Hercynian) succession in Jafurah and Eastern Rub' Al-Khali Basin indicate arches elevation of about 2-4km relative to shouldering basins. Although the Phanerozoic evaporites successions were documented to be tectonically active in the Zagros thrust setting (Sepehr et al., 2006), these evaporites (Permian, Jurassic, and Tertiary) have no proven influence on the structural evolution of the Rub' Al-Khali Basin (Stewart, 2016). As mentioned earlier, the evaporites of the Khuff Formation played an important role as a top seal for internal Khuff plays. Moreover, it was used as a stratigraphic datum for sequence stratigraphy and correlation, e.g., in Ghawar Field (Al-Jallal, 1995; Al-Dukhayyil, 2012; Al-Qattan, 2014). In the Rub' Al-Khali Basin, the Khuff Formation is located at a depth of about 5km, with a thickness of 0.5-1km. The formation contains 5-10% evaporites, with individual bed thickness up to several meters in

some areas (Alsharhan, 1993, 2006). The evaporites of the Khuff Formation have a general trend of westward thinning until becoming relatively absent in the outcrop (Vaslet et al., 2005).

2.4 The Permo-Triassic Khuff Formation

2.4.1 Geological Setting

The Khuff Formation was first identified by (Steinke et al., 1958, cited in Powers et al., 1966) near Ayn Khuff, where the type section is exposed as nearly 170m thick. A more completed reference section was studied in the Wadi Ar-Rayn Quadrangle (Figure 2.6). Along the eastern border of the Precambrian Arabian Shield, the formation was reported in many localities, either unconformably overlying the shield or the older Paleozoic succession (Power et al., 1966; Vaslet et al., 2005). This unconformity is an indication of the major early Permian continental stretching and rifting events that occurred in the west of Pangaea (Wander et al., 1998). The basal siliciclastic succession of the formation was named and classified by different authors, either as Unayzah member (Delfour et al., 1982) or as Unayzah Formation (Al-Laboun, 1982; El-Khayal and Wagner, 1985) or named as Ash Shiqqah Member instead of Unayzah Member (Vaslet et al., 2005) (Figure 2.7). In the outcrop, the Khuff Formation is composed of five members. These members were described by many authors (e.g., Powers et al., 1966; Delfour et al., 1982; Le Nindre et al., 1990; Vasle et al., 2005). These members are, from older to younger, As-Shiqqah Member, Huqayl Member, Duhaysan Member, Midhnab Member, and Khartam Member (Vaslet et al., 2005) (Figure 2.7).

2.4.2 Stratigraphic and Depositional Setting

During the deposition time of the Khuff Formation, the Arabian Plate was characterized by a thermal collapse along the Arabian passive continental margin, which continued during the northward drift. This setting produced prevalent transgression during the beginning of the late Permian. In Saudi Arabia, five members were identified in the subsurface, from older to younger. Those are Khuff-E, -D, -C, -B, and -A. Each of these members represents a gradual transgressive-regressive cycle starting with the deposition of transgressive grainstones and grain-supported carbonates and ending with regressive mudstones and evaporates (Al-Jallal, 1995). Such a setting was also reported in the Khuff outcrop bordering the Arabian Shield (Vaslet et al., 2005) (Figure 2.8); for instance, the basal Khuff clastics in the outcrop represent the early transgressive Khuff-E in the subsurface. Moreover, these depositional cycles can be correlated to the global ones of the late Permian eustatic cycles proposed by (Haq et al., 1987). The Khuff Formation lies within the tectonostratigraphic megasequence (AP6), according to Sharland et al. (2001). The basal boundary of this megasequence represents the pre-Khuff unconformity (255Ma). The reservoir units of Khuff carbonates are represented in the transgressive porous and tight limestones and dolomites of Khuff-A, -B, and -C, while the regressive mudstones and evaporites represent the intraformational seals (Dasgupta et al., 2002). The depositional sub-environments of the Permian-Triassic Khuff Formation represent subtidal to intertidal carbonates, shoals, lagoons, sandbars, supratidal, and sabkhas. A recent analogous of the arid hypersaline sabkha conditions prevailed in Khuff time can be observed in the present day southern shores of the Arabian Gulf. Similar to today's sabkha patterns were observed along cores cut through the subsurface Khuff Formation (Al-Jallal, 1989).

2.4.3 Dating of the Khuff Formation

The biostratigraphy used as the dating framework of the Khuff Formation in central Saudi Arabia was built upon the extensive occurrence of benthic foraminifera, ostracods, and algae (Vaslet et al., 2005) (Figure 2.9). Other marine fauna were also identified and assisted in constructing the chronostratigraphy and paleo-environment. This includes, but is not limited to, nautiloids, orthocones, echinoderms, ammonoids, and bryozoans. The conodonts, diagnostic for the late Permian in many areas of the Tethyan realm, were encountered in a single reworked calcarenite of Midhnab Member in outcrop (Nicora et al., 2006). Geochemically, Al-Jallal (1989) and Al-Dukhayyil (2012) reported a sharp negative shift in carbon isotope ($\delta^{13}\text{C}$) at the basal part of the Khuff-B reservoir in Ghawar Field, eastern Saudi Arabia, similar to that shift was observed in Oman (Krystyn et al., 2003). This shift was interpreted as an indicator of the Permian-Triassic extinction event. In general, the regional dating of Khuff members in the Arabian Gulf region has an acceptable consistency; the complexity within this context appears from the thickness variation of the depositional units in the regional sense (Al-Qattan, 2014; Al-Qattan and Budd, 2017).

2.4.4 Khuff Petroleum Play: From the Source to the Reservoir

The Khuff carbonates host the world's largest recoverable gas reserve, with about 750 TCF of gas. The first discovery in the Permian-Triassic Khuff Formation was in 1949, when non-associated gas was discovered in the Awali Field, Bahrain. Succeeding gas plays were discovered in the United Arab Emirates, Iran, Oman, and Saudi Arabia. However, among these discoveries, the largest pool of Khuff gas was discovered in 1971, as the world's largest reserve of non-associated gas is accumulated in the northern dome (North Field) of the Khuff

reservoir (Figure 1.2). In Saudi Arabia, the first prolific gas was discovered in Damman Field in 1957 (Alsharhan and Nairn, 1994), before further discoveries occurred in Ghawar, Berri, Abu Safah, Qatif, Khurais, and Harmaliya fields (Beydoun, 1988). There are two possible source rocks for the Khuff gas reservoirs; the early late Permian units of Khuff Formation and the early Paleozoic Qusaiba shales of the Qalibah Formation. The latter represents the main potential source rock for the whole Paleozoic petroleum system in Saudi Arabia (Alsharhan and Nairn, 1994). In the Arabian Gulf region, both source rocks have shown fair to good potentiality with 0.3-1.1 wt% organic matter (Mahmoud et al., 1992). An alternative source rock was also proposed from the cracking of crude oil in the Khuff Formation into gas, particularly in the deep zones (Grunau, 1977). This alternative source was further considered in Saudi Arabia (Kasnick and Engen, 1989) and also in Abu-Dhabi, UAE (El-Bishlawy, 1985), northern Oman (Bos, 1989), and Bahrain (Janahi and Mirza, 1991) where sweet gas reserves were reported. The gas reserve in these areas is dominated by methane as a principal gas (89%) with small amounts of nitrogen, carbon dioxide, and heavier hydrocarbons, with a maximum of 5% hydrogen sulfide. For these potentiality and favorable gas properties, the Khuff Formation in Saudi Arabia, among other Gulf countries, is an important alternative for cleaner energy exploitation. The porosity and permeability of Khuff carbonates are generally low, although the dolomitization is mostly increasing the reservoir quality. The mudstones, mud-supported packstones, and wackestone have low porosity (about 2.5%) and permeability (around 1md), especially in deeply-buried reservoirs. Nevertheless, the reservoir quality is frequently enhanced by fractures. Better primary porosity occurs in the intertidal setting, where sand-size oolitic grainstones are dominant in the high-energy shoal environment (Alsharhan, 1993; Alsharhan and Nairn,

1994). In lateral and vertical directions, the reservoir quality is a function of dolomitization, fractures, cementation (mostly by anhydrite), and leaching. Qualitatively, the porosity ranges between depositional intergranular to post-depositional moldic porosity. The porosity controls the permeability, more significantly in the lithofacies characterized by dominant primary porosities. However, leaching of matrix, cement or grains, besides the fracturing act as permeability boosters (Konert et al., 2001). Charging of Khuff carbonate reservoirs has some uncertainty concerning the migration pathways, principally in those fields where the basal shales of Khuff Formation hinder the vertical migration. However, it is most likely the reactivation of the older faults provided vertical migration conduits and pathways (Wender et al., 1998). The shales of the early Triassic Sudair Formation represent the regional cap rock of Khuff reservoirs (Al-Jallal, 1995). Dasgupta et al. (2002) studied the Khuff Formation in the Uthmaniyah Sector of Ghawar Field. Using core data, two wells have shown anhydrite-cemented tight carbonates in Khuff-C Member. Anhydrite cementation is common in Khuff reservoirs. This feature is a result of percolation of anhydrite-rich fluid into the underlying mudstones and grainstones and destroying its porosities. In contrary, cores from other wells have shown good intergranular porosity dominated in grainstones, dolograins and dolomudstones facies. Al-Dukhayil (2012) investigated the sequence stratigraphic and chemostratigraphic frameworks of the Permian-Triassic data from Ghawar Field in eastern Saudi Arabia. The author identified seven high-frequency surfaces that form the Khuff-C Member. The author reported a generally rare occurrence of anhydrites in the late Permian Khuff-C. In contrary, rich anhydrites zones were developed in Khuff A and B. The dominant reservoir lithofacies in Khuff-C was also found in the oolitic grainstone at the topmost of the high-frequency sequence. In Khuff-A and -B members, good non-

dolomitized oolitic grainstones reservoir units that are distal from tidal flat evaporites were also reported. Al-Qattan and Budd (2017) studied the dolomite and dolomitization of Khuff-C carbonates in Ghawar Field. Six hundred core plugs and their thin sections were used to characterize the porosity and permeability of limestones, dolostones, and dolomitic limestones. The porosity was found to be suitable to represent the reservoir quality, while the permeability showed very low order, more significantly in dolostone lithofacies, ranging between 0.1 to 0.3md in its best cases. The approach of considering only the porosity of Khuff dolostones as a representative of its reservoir quality was also introduced by other authors (e.g., Ehrenberg et al., 2016; Ehrenberg et al., 2007). However, although it showed widely scattered clusters, the porosity-permeability cross-correlation always tends to exhibit a generally positive relationship in Khuff carbonates and other regional equivalents (Rahimpour-Bonab et al., 2010; Amel et al., 2015). Not all diagenetic features were observed in all lithofacies. For instance, the Khuff-C limestones are characterized by aragonite dissolution, anhydrites and calcite cementation, and replacing of earlier grains and calcite with anhydrites. The latter feature is common in dolostones reservoirs. Based on petrography, the authors classified the dolomites into mimetic fabric preserving, non-mimetic fabric preserving and fabric destructive dolomites (Al-Qattan and Budd, 2017).

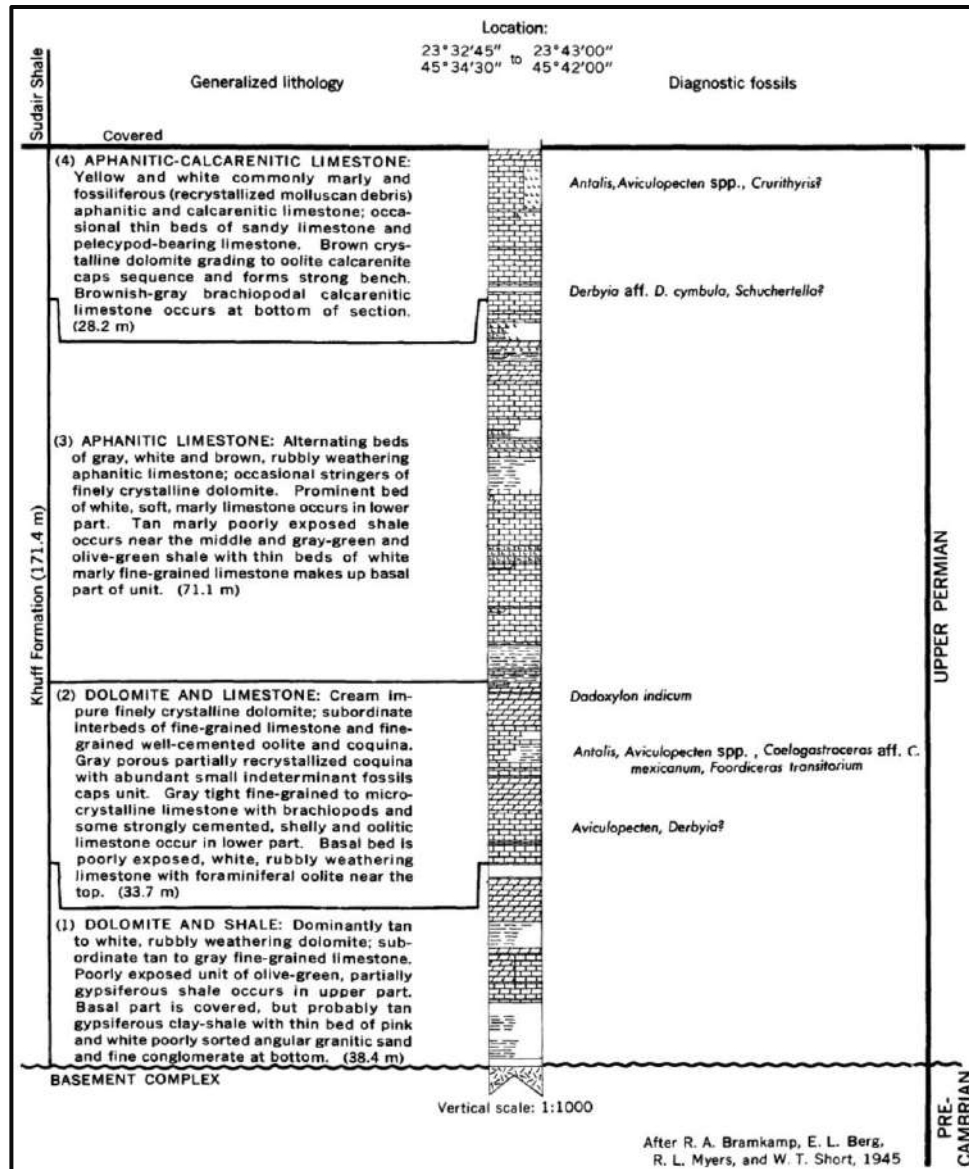


Figure 2.6. The reference section of the Khuff Formation outcrop in Ar-Rayn Quadrangle, central Saudi Arabia. The diagnostic fossils were used for dating and building the biostratigraphy of the formation (Powers et al., 1966). The formation was thoroughly described in other quadrangles by (Vaslet et al., 2005).

Khuff Formation type section, Ad Dawadimi quadrangle, Saudi Arabia

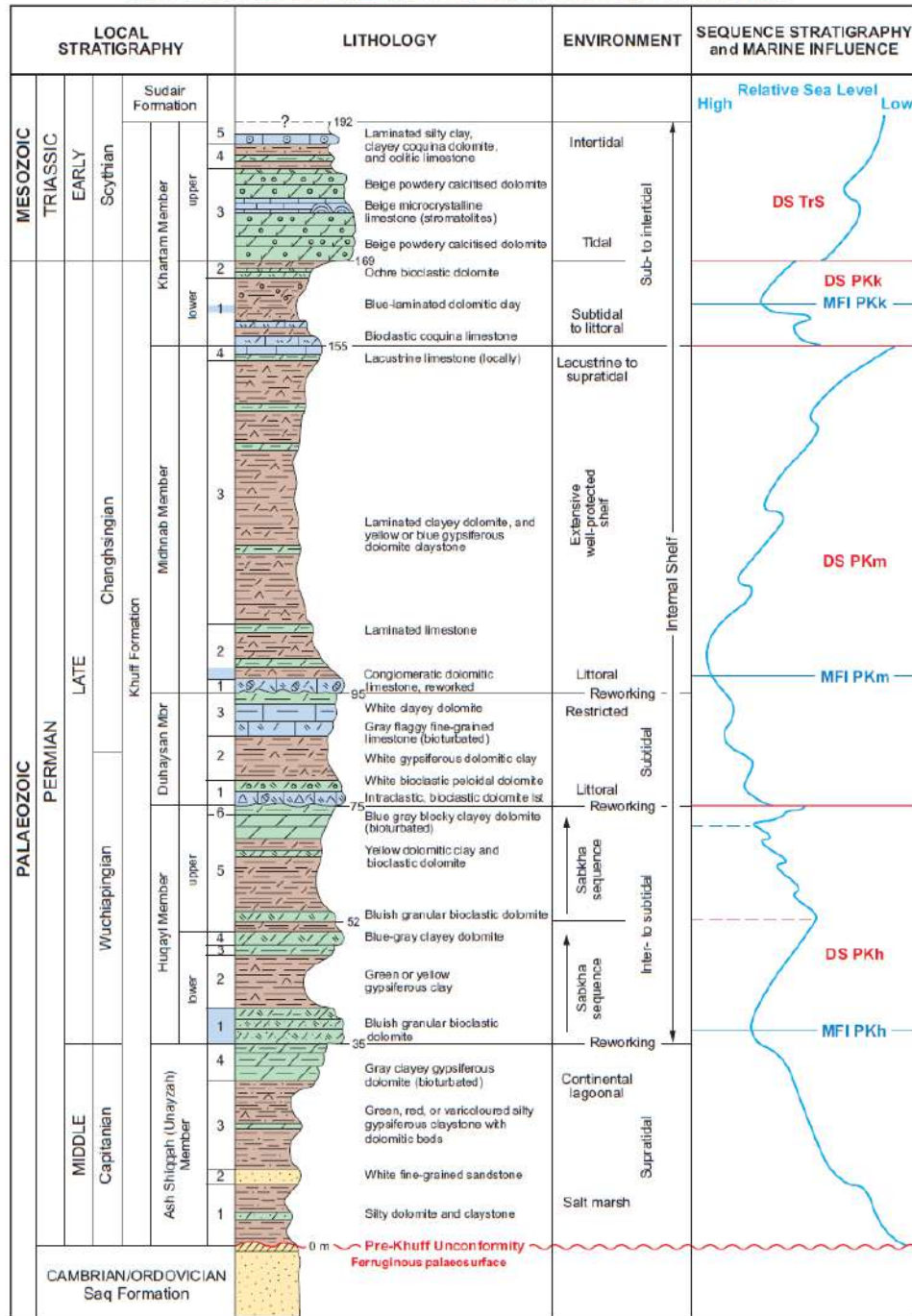


Figure 2.7. Composite section of Khuff Formation outcrop in Ad-Dawadimi Quadrangle in central Saudi Arabia, with the local stratigraphy of the five Khuff members (Delfour et al., 1982). Regressive evaporites lithofacies are missing in the uppermost member (Khartam Member, the equivalent of Khuff-B in the subsurface), while reported in the lower members in different localities (Vaslet et al., 2005).

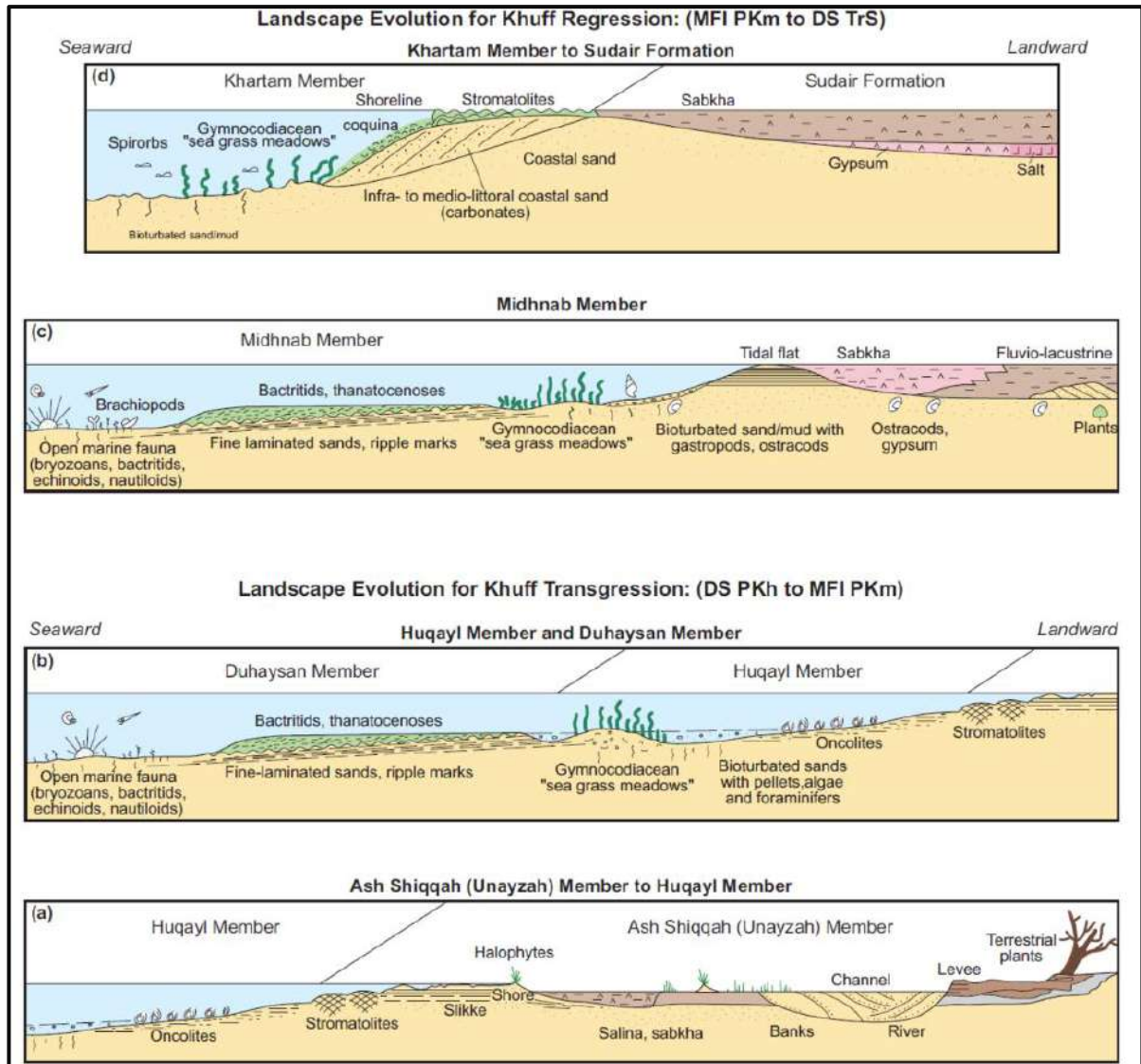


Figure 2.8. Khuff Formation transgression and regression. **a.** and **b.** Sketches represent Khuff transgression (DS PKh-MFI PKm), resulting in the deposition of Ash Shiqqah-Huqayl members (a) and Huqayl-Duhaysan members (b). **c.** and **d.** Khuff regression (MFI PKm to DS TrS), resulting in the deposition of Midhnab Member (c) and Sudair Formation shales (d) (Vaslet et al., 2005).

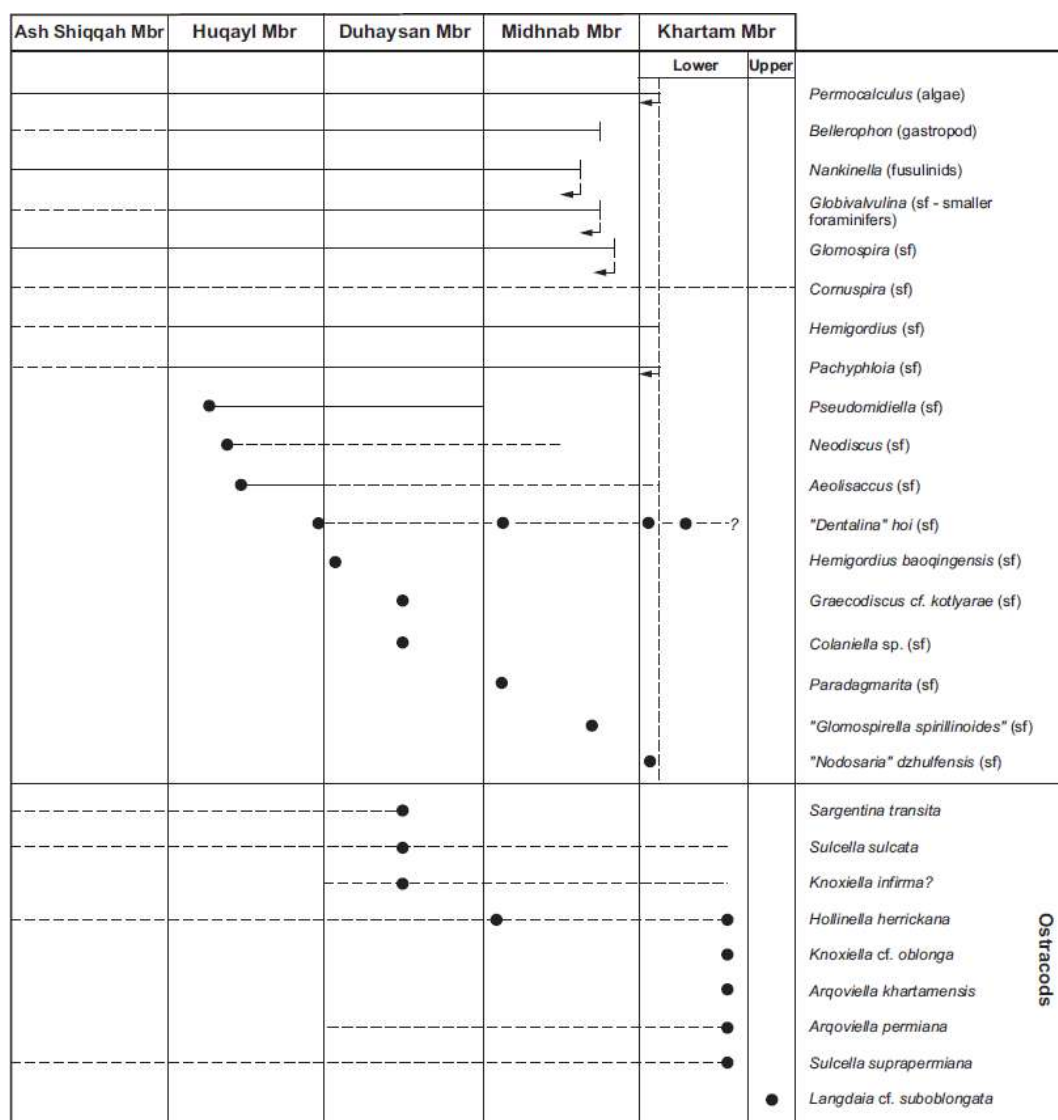


Figure 2.9. The principal late Permian micropaleontological fauna obtained from Khuff Formation exposures in central Saudi Arabia and mostly observed in samples from the clayey units of Huqayl, Duhaysan, Midhnab, and lower Khartam members. The LADs (last appearance datum) of some significant foraminifera are illustrated by the backward arrows (Vaslet et al., 2005).

CHAPTER 3

HIGH-RESOLUTION RESERVOIR

CHARACTERIZATION

3.1 Introduction

Small-scale heterogeneity in the carbonate microfacies is a vital aspect that needs consideration for better reservoir characterization and reserve exploitation. In its conventional and unconventional (tight) settings, carbonate microfacies hold considerable heterogeneity due to complex physical, chemical, and biological processes that led to their formation and deposition. Besides, the post-depositional reaction susceptibility of these sediments is also a player in carbonate heterogeneity. In contrast to detrital siliclastic reservoirs, the lithification of carbonates arises from these post-depositional, diagenetic processes. These processes frequently preserve the final porosity framework, even after prolonged subsurface burial and compaction (Anselmetti and Eberli, 2001). This setting implies possible unconventional sweet spots in deeply buried tight carbonates. Carbonate reservoirs host about 50-60% of the world's petroleum reserve (Vanorio et al., 2008; Mousavi et al., 2012; Madhubabu et al., 2016; Sun et al., 2017). Natural gas progressively becomes a desirable target for fuel resources due to its low participation in the carbon budget compared to crude oil (Aguilera and Aguilera, 2012; McGlade et al., 2014; McGlade and Ekins, 2015). The Permo-Triassic carbonates of the Middle East host about 15-30% of the world's proven gas reserves, with roughly 750 tcf of gas reserves (Al-Aswad, 1997; Konert et al., 2001; Koehrer et

al., 2011). The Permo-Triassic carbonates of the Middle East host about 15-30% of the world's proven gas reserves, with roughly 750 tcf of gas reserves (Al-Aswad, 1997; Konert et al., 2001; Koehrer et al., 2011). The reservoir intervals in the late Permian play of Saudi Arabia are gas-prone, and no oil was potentially reported (Alsharhan and Nairn, 1994; Dasgupta et al., 2002; Poppelreiter, 2013). Many workers have investigated the aspects influencing acoustic velocities in sedimentary rocks, including porosity as the major influencer. However, other factors such as pore size, permeability, sedimentary textures, density, mineralogy, and overall diagenetic imprints, are also responsible for wave propagation behavior (Gardner et al., 1974; Raymer et al., 1980; Anselmetti and Eberli, 1993; Anselmetti and Eberli, 1999; Anselmetti and Eberli, 2001; Eberli et al., 2003; Kenter et al., 2007; Baechle et al., 2008; Weger et al., 2009; Kleipool et al., 2015; Soete et al., 2015; Regnet et al., 2019; Teillet et al., 2020; Garia et al., 2021). The depositional, stratigraphic, diagenetic, and petrophysical settings of the Permian-Triassic conventional and tight carbonates in Saudi Arabia and its regional stratigraphic equivalents, including Dalan and Kangan formations have been documented by numerous researchers (e.g., Al-Jallal and Al-Husseini, 1995; Sharland et al., 2001; Reading, 2009; Khalifa, 2005; Alsharhan, 2006; Moradpour et al., 2008; Esrafil-Dizaji and Rahimpour-Bonab, 2009; Rahimpour-Bonab et al., 2010; Amel et al., 2015; Adam et al., 2018; Nazari et al., 2019; Salih et al., 2021; Salih et al., 2023). To our best knowledge, no documented study covers the impact of depositional and petrophysical settings on acoustic velocity in the subsurface reservoir interval of the late Permian carbonates. The earlier definition of "microfacies" has related it to thin section investigated petrography and paleontology (Brown, 1943; Cuvillier, 1952). Later, that

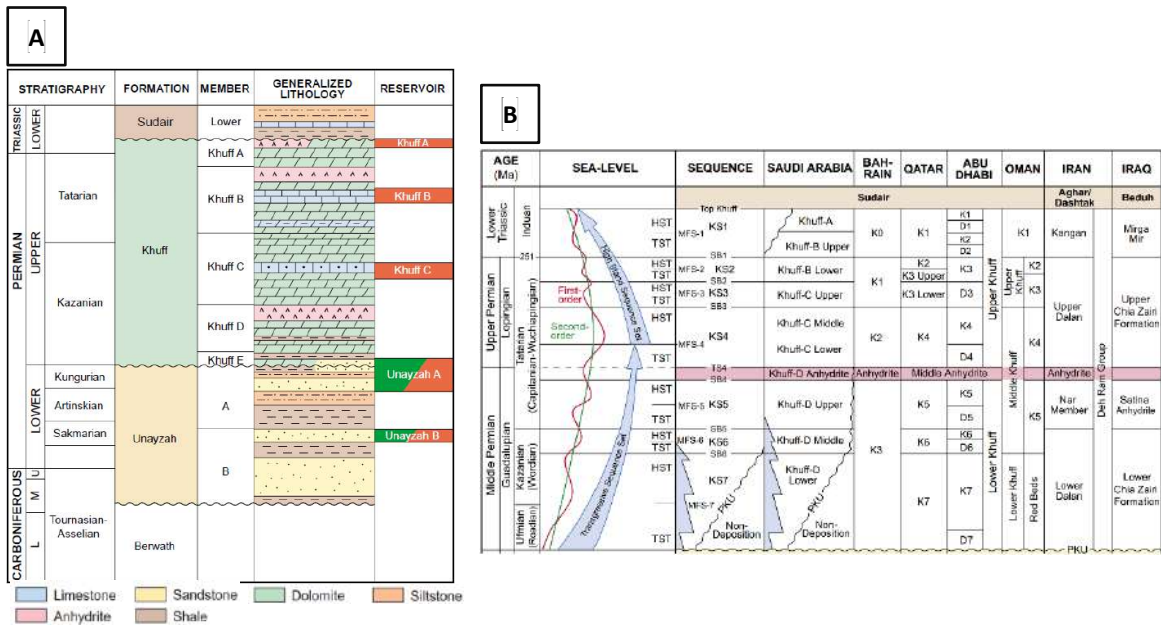
definition was outdated to cover more scales of investigation, including polished slabs and rock samples (Flügel and Munnecke, 2010). In this study, the nature of investigated samples as tight, deeply-buried carbonate microfacies prefaces other controlling factors, rather than porosity, to be involved. Thus, this study investigates the impact of microfacies characteristics, petrophysical properties, mineralogy, and elemental geochemistry on acoustic velocity. In detail, these factors include features such as crystal shape and size, porosity, pore size and type, mineral content, elemental geochemistry as a proxy for mineralogy, fractures, stylolites, and organic content. This research investigates these factors as they occur in different carbonate microfacies. The logging procedures conducted in this study represent a unique approach, having the advantage of continuity compared to discrete plug estimations obtained from specific points along the core. The scale of investigation in this study is far beyond the resolution of seismic, well-logs, and even plug scales. Millimeter scale variability was logged across different microfacies; hence, velocity variation was recorded. In addition, the acoustic wave survey was applied parallel to the layering. This procedure ensures the best acoustic velocity for individual layers compared to the borehole acoustic sonde, which measures the travel time across the layers and laminae between the source and receiver(s). This matter creates uncertainty wherever thin interbedding or interlamination is encountered.

3.2 Geological setting

Representing the first major marine transgression following the Hercynian Orogeny, the Permo-Triassic carbonates and their regional equivalents were deposited in shallow marine carbonate ramp of an epi-continental sea, under generally low-energy and poorly circulated depositional conditions. Permo-Triassic Dalan and Kangan formations in Iran

are the isochronous equivalents of the Saudi Arabian Permo-Triassic succession in the region (Figure 3.1). In this context, the studied late Permian (late Lopingian) is the equivalent of Upper Dalan (K3 and K4 members) (Sharland et al., 2001; Strohmenger et al., 2002; Alsharhan, 2006). The ramp architecture is characterized by very low relief (gentle slope) with localized shoal bodies and lagoons (Sharland et al., 2001; Konert et al., 2001; Alsharhan, 2006; Insalaco et al., 2006). In Saudi Arabia, the middle-late Permian strata were subdivided into five shoaling upward sequences, including three reservoir sequences. Stratigraphically, these sequences are arranged from younger to older as A, B, C, D, and E, the latter composed of basal clastics (Al-Jallal, 1987; Dasgupta et al., 2002) (Figure 3.1). As a response to the eustatic sea level fluctuation, each member represents a separated depositional cycle that commences as transgressive subtidal carbonates (grainstones and grain-supported microfacies), shallowing upwards into regressive intertidal and sabkha successions (mudstones, mud-supported and evaporites microfacies). The transgressive subtidal grainstones act as potential prolific reservoir zones, capped and sealed by regressive supratidal mudstones and evaporites (Alsharhan, 2006; Reading, 2009). This repetitive succession across the Permo-Triassic carbonates is regionally capped and sealed by shales of Sudair Formation or its equivalent formations (Figure 3.1). In the subsurface setting, the thickness of middle-late Permian succession varies from around 200m in the central fields of the Arabian Platform and exceeds 1300m in the eastern and southeastern parts (Al-Jallal and Al-Husseini, 1995; Strohmenger et al., 2002). The reservoir quality of late Permian carbonates is a function of lateral continuity and truncations of geobodies. Besides, the diagenetic overprints, such as cementation and chemical compaction caused by great burial depth, have

frequently reduced the original reservoir quality (Dasgupta et al., 2002; Ehrenberg et al., 2007; Poppelreiter, 2013). Several offshore and onshore fields of the Arabian Shelf have shown less than 12% average porosity in the late Permian and its equivalents. Nevertheless, the occurrence of natural fractures proved to enhance the permeability in many fields, even in low porosity settings (Dasgupta et al., 2002; Ehrenberg et al., 2007). The current study area is located in southcentral Saudi Arabia. The structural and sedimentary evolution of the Rub' Al-Khali Basin were mainly studied through magnetic, gravity, and seismic imaging besides well data. The approximate deepest zone imaged by seismic reflection was at 13km depth in the undrilled areas of the Precambrian rifts. The stratigraphic column extends from the late Precambrian to Neogene periods (Stewart, 2016).



3.3 Data and Methods

An overall 30 ft (9.14 m) whole-core section was cut from the top of the deeply-buried late Permian carbonates in well-X, Rub' Al-Khali Basin, southcentral Saudi Arabia. The core was collected from a depth zone of 10-15k ft (3-4.6 km). Most of the whole-core was severely fractured, not slabbed, or missed from the succession. Certainly, 13.12 ft (4.0 m) polished slabs of the whole-core were appropriate for petrophysical, geochemical, mineralogical, and organic geochemical analyses (Figure 3.2). The essential analysis of this study was based on continuous acoustic velocity measurements across the polished core slabs. These microfacies were encountered across the core slabs, where more than one microfacies occasionally occurred in a single slab. The microfacies were characterized based on textural, geochemical, mineralogical, and organic content perspectives using petrography, micro-XRF, XRD, SEM, and their combination (qemscan analysis), besides TOC. Porosity was analyzed through petrography and SEM. Organic matter was investigated qualitatively through petrography and quantitatively through TOC% analysis.

3.3.1 Core Scanning and Petrography

The polished core slabs were scanned with a high-resolution Epson™ scanner to investigate the naked-eye macro-features such as layering, lamination, fractures, stylolites, bioclasts, and intraclasts. A total of 23 thin sections were carefully cut to cover the different microfacies encountered across the carbonate strata. These samples were stained with blue epoxy to visualize the available pore spaces before being stained with alizarine-red S to differentiate between dolomite and calcite crystals (Dickson, 1966). All samples were scanned using Axioscan-Z1™ machine for petrography with (5x-40x)

magnification and visualized using ZEN-lite 3.2 (Zeiss™) software. The carbonate textural classification scheme (Dunham, 1962) and its modified version (Embry and Klovan, 1971) were followed to classify each microfacies. Pore type was classified following (Choquette and Pray, 1970) scheme.

3.3.2 Elemental Geochemistry

X-ray fluorescence (XRF) was performed using the M4 Tornado micro-XRF (Bruker™) machine to produce high-resolution vertical elemental profiles along the polished slabs. The machine utilizes a microfocus source of rhodium (600μA with 50kV) for detecting elemental spectroscopy at approximately 20 μm spot size. Two silicon-drift detectors are used to collect the spectrum from the samples under vacuumed conditions of about 20 mbar, with an X-ray beam penetration of 2mm underneath the sample surface. To ensure the best coverage with high certainty, reading interval of 2mm was adjusted with a 10-second reading period. The purpose of these profiles is to provide auxiliary data that act as a proxy for limited mineralogical data obtained via XRD. A representative 2D elemental map was also generated to visualize element distribution with microfacies layering.

3.3.3 Mineralogy

In order to have the mineralogical output of the studied section and to calibrate the elemental profiling obtained by XRF, a total of 32 chip samples were collected, powdered, and analyzed for X-ray diffraction (XRD). X'Pert³ Malvern Panalytical™ machine was used with scanning range angles of 10°-90° to cover a wide spectrum of minerals. The main mineralogical groups targeted include carbonates and silicates; the

latter includes quartz and clay minerals. Representative thin sections were further used to generate 2D mineralogy maps. These maps were generated using qemscan-650F (CSIRO-FEI™), which represents an advanced petrography that integrates scanning electron microscopy (SEM), energy dispersion spectroscopy (EDS), and species identification protocol (SIP). This protocol includes a mineralogy library that is used to identify different minerals on the scanned surface depending on their specific energy dispersion. Qemscan technique was used in many works for similar purposes (e.g., Gottlieb et al., 2000; Ayling et al., 2012; Qian and Gerson, 2015). Carbon-coating (Quorum EMS 150R ES) was applied on the selected thin sections in a specific representative area (1 cm²), with 5 µm point spacing to get high-resolution maps. X-ray beam voltage of 15kv and 10nA electric current was used for scanning. The technique was also used to define micro-pores in the scan area. The scanning results were processed and then visualized by the attached iDiscover™ software.

3.3.4 SEM Imaging

Microscale imaging is crucial for investigating micro-features, such as the shapes and sizes of microcrystals and micro-pores. Conventional techniques for determining porosity, like saturation and helium porosimetry, were inappropriate to give insights into microporosity due to the nature of these unconventional carbonates as tight, microporous, and extremely low permeable. SEM images were captured from 72 gold-coated chip samples using a vacuumed JEOL™ JSM/7900F machine. The Udden-Wentworth (U-W) scale, extended for carbonate rocks, was used for SEM crystal size analysis (Flügel and Munnecke, 2010).

3.3.5 TOC Analysis

24-hour oven-dried powdered samples were selected to analyze total organic carbon (TOC). TOC was estimated as milligrams of organic carbon per kilogram of rock sample (mg/kg). The values were then converted into percentages (TOC%). Using relative percentage difference (RPD) as part of QC/QA measures, selected samples were analyzed twice to ensure the homogeneity of the powdered sample for precise analysis.

3.3.6 Well-Logs

A batch of bulk density (RHOB), neutron-porosity (NPHI), geochemistry, and interpreted lithology logs was used to validate microfacies distribution, characteristics, and laboratory analysis. Environmentally corrected NPHI was estimated from the corrected neutron log, while density-porosity was estimated using the equation (3.1). Coupled neutron-density (ND) porosity was estimated based on equation (3.2) to deal with a potential gas-bearing reservoir. All these porosities were calibrated with SEM visually-estimated microporosity. The volumetric photoelectric absorption index (U) was also used to calibrate mineralogy and thus lithology. This index (equation 3.3) is a supplementary log to density tool, indicating low-energy GR absorption per electron of atoms forming rock minerals. Consequently, a specific mineral has a specific index based on its matrix density (Glover, 2000; Luthi, 2001). This characteristic made the photoelectric index a good indicator for lithology, particularly when calibrated with neutron and density logs.

$$\phi_D = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_f} \quad (3.1)$$

$$\emptyset_{ND} = \sqrt{\frac{\emptyset_N^2 + \emptyset_D^2}{2}} \quad (3.2)$$

$$U = P_e \cdot \rho_e \quad (3.3)$$

Where:

$\emptyset_D$: density-porosity (%). $\emptyset_N$: neutron-porosity (%). $\emptyset_{ND}$: neutron-density porosity (gas-bearing formation) (%). ρ_{ma} : matrix density (g/cc). ρ_b : Formation bulk density (g/cc). ρ_f : Pore-fluid density (g/cc). U : Volumetric photoelectric absorption index (barns/electron). P_e : Specific photoelectric absorption index (barns/electron). ρ_e : Unit density of mineral.

3.3.7 Microporosity Measurement

72 microporosity values were visually obtained from the high-resolution SEM images using the point-count technique by Image-J™ software. These 72 values represent the maximum and minimum microporosity for each microfacies per sample (Figure 3.2, Table 3.2). For this purpose, several chip samples for each core sample were picked and used for microporosity estimation to constrain the minimum and maximum values. The constrained values allow for generating threads of microporosity for each sample along the studied core section. In this context, the Excel™ 2010 random function was used to generate the microporosity. The software uses the Mersenne Twister algorithm, commonly used for pseudo-random number generation as it has a long period of searching with good statistical properties (Matsumoto and Nishimura, 1998). Excel adopts the time system seed to initialize the Mersenne Twister algorithm and assign the starting point for number generation from a specified value. Time seed ensures that numbers generated each time are different and lie within the specified range (minimum

to maximum). This repetition allows different correlation coefficients (r) between the random numbers and each of the p- and s-wave velocities until the best fit is achieved. Later, averages of the best-generated microporosity were calibrated with density-porosity and NPHI for validation.

3.3.8 Permeability Measurement

Nitrogen permeability was measured using the Autoscan logging system by NER™. The permeability probe applies the maximum possible pressure on the sample surface to ensure measuring stable and continuous gas flow rates, thus detecting the permeability. The duration of each measurement depends on the time required for gas flow to be stabilized, which depends on microfacies properties. Due to its low density compared to air, nitrogen is preferred for measuring permeability in tight reservoir settings.

3.3.9 Acoustic Velocity

Acoustic wave velocity is an essential tool to characterize tight carbonate reservoirs. The studied core section represents the deeply-buried, tight, and confined carbonate reservoir target obtained for exploration purposes. Accordingly, the acoustic measurements were adequate to conduct under atmospheric conditions. Continuous compressional and shear acoustic measurements were synchronously recorded from the top to the bottom of the core slabbed samples (Figure 3.2). To ensure the best coverage of acoustic waves per microfacies, the logging intervals were adjusted between 2mm and 8mm depending on microfacies variation and thickness. The Autoscan logging system by NER™ was used, equipped with an acoustic velocity

probe. The probe contains a source and a detector, 5 cm apart. The probe orientation was adjusted horizontally, parallel to sedimentary layering to ensure specific microfacies measurements of velocity.

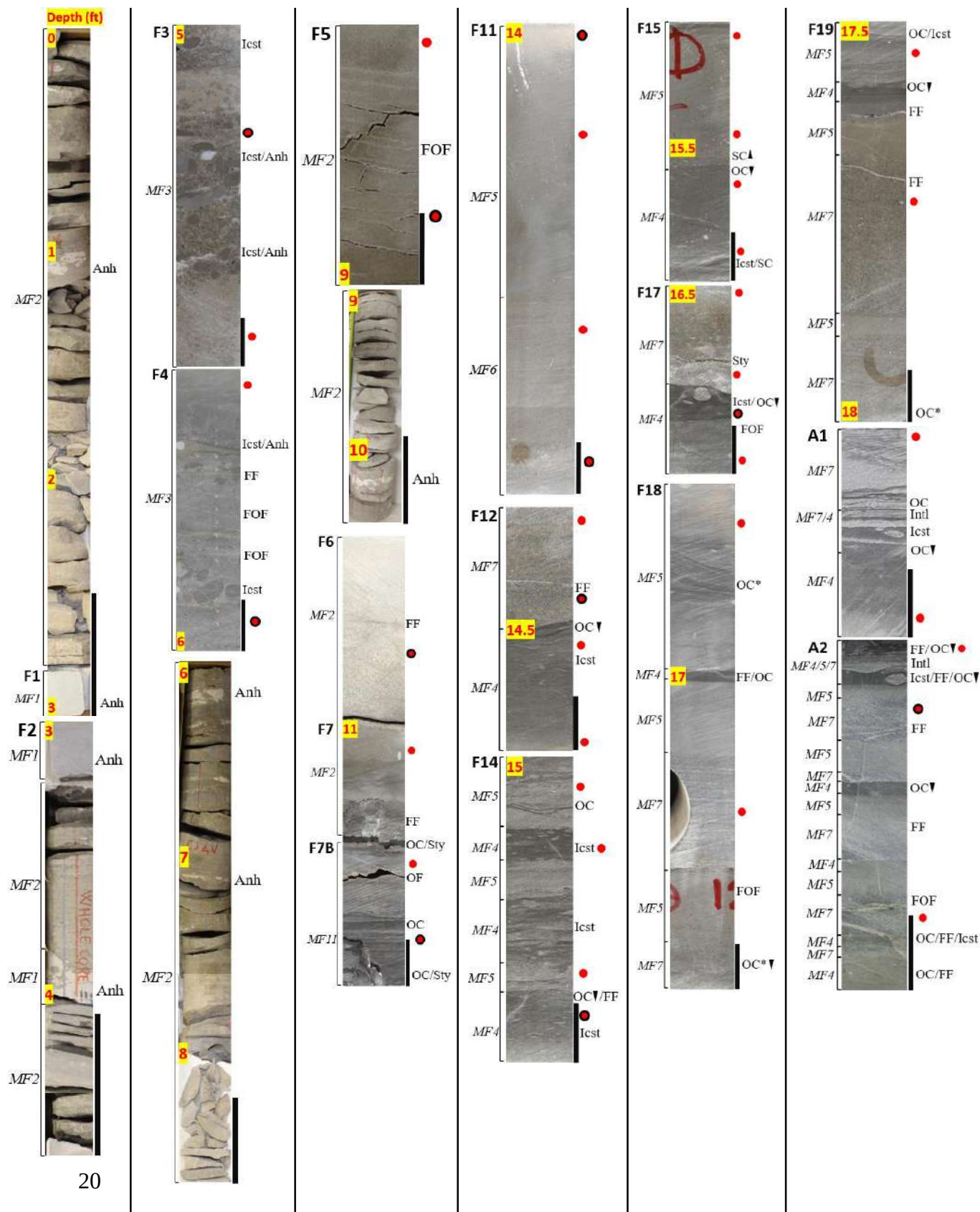
3.4 Results

3.4.1 Microfacies Characteristics

The microfacies encountered along the core section were classified into five categories: 1-evaporites (MF1), 2- mudstone and mud-dominated microfacies (MF2, MF4, MF5, and MF6), 3- grainstone and grain-supported microfacies (MF3, MF10, MF7, and MF9), 4- Mixed microfacies (microbialites) (MF11), and 5- floatstone microfacies (MF8). These microfacies were investigated to record the variable behavior of acoustic p- and s-wave velocity, and link it directly to the visual, geochemical, and mineralogical observations of the respective microfacies. Table 3.1 summarizes the major microfacies properties, including sedimentary textures and structures, compositional allochems and trace fossils, diagenetic features, porosity, and pore types.

Evaporites (MF1)

The studied section of the late Permian carbonates is capped by evaporites, representing the intraformational seal of this reservoir interval. These evaporites are composed of anhydrite, and also occur as separated thin layers (6 cm and 7 cm) embedded within the carbonate sequence. Sparse nodules of evaporites were also



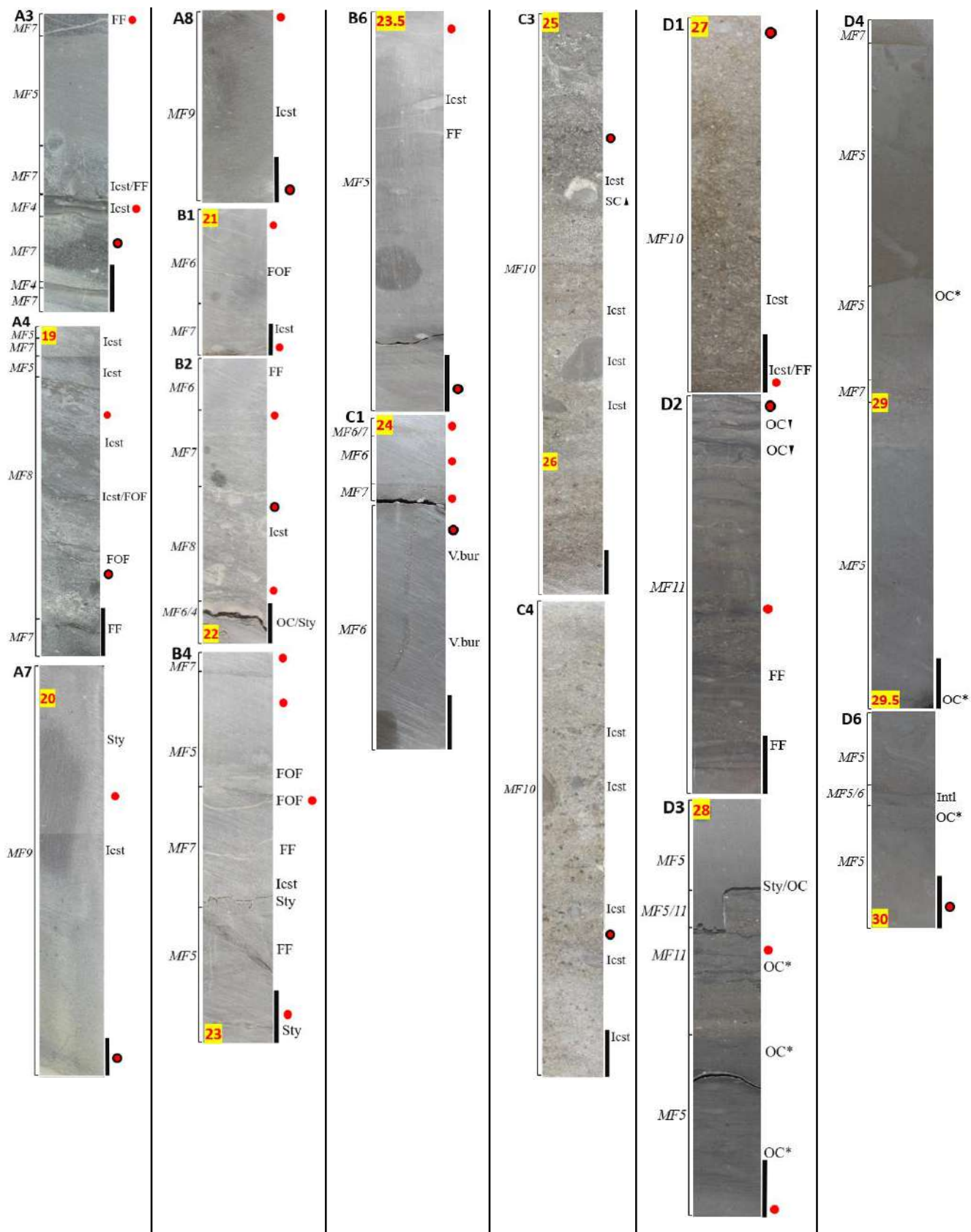


Figure 3.2. Whole-core and slabbed samples of the carbonate microfacies obtained from Well-X, with microfacies distribution (*MF#*), sample ID (coded from top to bottom as F#, A#, B#, C#, and D#), arbitrary depth (0-30 ft), sample locations, and general sedimentary features. Whole-core samples unsuitable for petrophysical analyses were excluded (includes intensively fractured core at the top of the section between 0-10 ft). Samples between (11.25-14 ft) were missed from the section. MF1: Evaporites, MF2: Dolomitic mudstone, MF3: Intraclast skeletal peloidal grainstone, MF4: Organic-rich mudstone, MF5: Massive mudstone, MF6: Massive peloidal wackestone, MF7: Skeletal peloidal packstone, MF8: Floatstone, MF9: Echinoderm bioclastic packstone, MF10: Bioclastic peloidal grainstone, MF11: Microbialite. Abbreviations: Icst (mud intraclasts), FOF (filled to open fractures, i.e., partially open), FF (filled fractures; i.e., closed), Sty (stylolite), Anh (anhydrite), intl (interlaminated), OC (organic content), OC* (delicate organic content), SC (skeletal content), and V.bur (vertical burrow). Red dots indicate chip samples used for SEM, and black-bordered red dots indicate samples used in both petrography and SEM. Scale bar in the whole-core: 15.2 cm (0.50 ft), in the core slabs: 2 cm (0.79 inch).

encountered frequently within MF2 and less within MF3 (Figure 3.2). Evaporites were excluded from further analysis as they represent non-reservoir (seal).

Dolomitic mudstone (MF2)

This microfacies occupies most of the studied section, with a cumulative thickness of about 9 ft (274.3 cm). However, most of this thickness was excluded from further petrophysical analyses since it was severely fractured and poorly recovered during borehole operation. Cumulative of 0.80 ft (24.4 cm) was suitable for acoustic and elemental analysis, even though this thickness was rich in natural fractures parallel to sub-parallel to the bedding (Figure 3.2). This microfacies comprises massive, tight dolomitic mudstone, with scarce allochems and no sedimentary structures. MF2 represents the most porous unit among the studied carbonate microfacies. Dolomite crystals are pervasive as fine- to medium-grained, euhedral to subhedral, and responsible for the well-developed intercrystalline microporosity compared to other

microfacies. XRD recorded the richest dolomite as up to 90% with 10-15% magnesium (Mg-content) (Figures 3.8 and 3.11).

Intraclast skeletal peloidal grainstone (MF3)

With a total thickness of 0.88 ft (26.8 cm), this microfacies is dominated by well-sorted pellets, lesser content of skeletal allochems (mainly well-sorted bivalves and other unidentified fragments), and rare ooids. Occasional mud intraclasts occurred mainly at the middle part of the slab and less frequently at the lower part. All these components align horizontally to bedding, except for some sub-horizontal mud intraclasts. The size of mud intraclasts roughly reaches 2 cm in the slab and around 300 μm in thin sections (Figures 3.2 and 3.3). This heterolithic composition indicates deposition in a high-energy setting. The matrix porosity is well-blocked by microcrystalline equant calcite cement (Figure 3.3). Infiltration of hypersaline water through overlying porous and fractured dolomitic-rich strata was indicated by sparse of evaporite nodules sporadically observed in MF3 (Figure 3.2).

Organic-rich mudstone (MF4)

A total of 0.83 ft (25.3 cm) of this microfacies was logged through the studied core section. The microfacies often represents the finer part interbedded with an overlain coarser microfacies (MF7), as observed in samples F12 and F17. It is composed of fine crystalline mudstone (4-8 μm in median), rich in organic content that forms inclusions or micro-laminae (Figure 3.3). Dolomite content (less than 30%) was also observed in this microfacies. Compared to other microfacies, the elemental analysis also revealed noticeable content of silicon (Si), potassium (K), aluminum (Al), and sulfur (S). A negligible content of evaporites was also noted, which may indicate that the S-content

in this microfacies was due to organic matter degradation. Comparative content was also noted in the microbialite (MF11) (Figure 3.8).

Massive mudstone (MF5)

The 3.91 ft (119.2 cm) cumulative thickness of this microfacies occurs as tight, microcrystalline, calcite-rich, massive mudstone . This microfacies often occurs adjacent or interbedded with skeletal peloidal grainstone (MF7), and occasionally with coarser peloidal wackestone (MF6). Most MF5 slabs revealed dolomite content of less than 20% (Figure 3.11).

Massive peloidal wackestone (MF6)

This microfacies composes of 0.95 ft (29 cm) massive peloidal wackestone. Dolomite crystals are concentrated in the pellets interior, which are fully dolomitized with a median crystal size of 18 μm . Conversely, calcite blocks the matrix with larger crystals (31.9 μm in median). Dolomite crystals are anhedral to subhedral, forming fabric-preserving non-mimetic dolomite.

Skeletal peloidal packstone (MF7)

This microfacies cumulatively occupies 1.80 ft (55 cm) of the total studied section. The composition of this microfacies is comparable to that of MF3, i.e., skeletal grains (bivalves and unidentified fragments) and pellets in a well-cemented matrix. Moreover, both microfacies exhibited a presence of 60-70% calcite in XRD, primarily within their matrix. Nevertheless, it is notable that in MF7, skeletal grains have undergone dissolution and subsequent filling by calcite cement. This was evident in the significantly higher average calcium (Ca-content) in MF7, exceeding 90%, in contrast to the averages of $\approx 75\text{-}82\%$ observed in MF3 (Figure 3.11). Furthermore, it should be

noted that the pellets and skeletal grains in MF7 were poorly-sorted, compared to those in MF3 (Figure 3.3). Frequent fractures occurred in MF7, as noted in different slabs (Figure 3.2).

Floatstone (MF8)

Floatstone is coarse-grained allochthonous matrix-supported carbonates (Embry and Klovan, 1971). This microfacies was encountered in two samples in the studied core section, with a cumulative thickness of 0.39 ft (11.9 cm). The matrix is dominated by fine crystalline calcite, and the grainy assemblage is composed of various-sized skeletal grains (brachiopods and bryozoans), pellets, and poorly-sorted mud intraclasts. Fractures were observed in sample A4, including partially open fractures at the middle of the samples and closed ones at the lower part (Figures 3.2 and 3.3). Less frequent fractures were recorded in sample B2. Mud intraclasts were larger in sample B2, reaching up to 2.5 cm in diameter (Figure 3.2).

Echinoderm bioclastic packstone (MF9)

This microfacies is composed of 0.93 ft (28.2 cm) of skeletal packstone. Echinoderm fragments, besides unidentified skeletal bioclasts and rare fragments of gastropods and bryozoans, forming the skeletal component. These skeletal grains were replaced by calcite crystals with average crystal sizes of 5 μm and 12 μm in the two MF9 samples (A7 and A8), respectively. The matrix is rich in microscale stylolites and contains dolomicrite that forms envelopes coating most skeletal allochems (Figure 3.3).

Bioclastic peloidal grainstone (MF10)

This microfacies composes a cumulative thickness of 1.77 ft (54.1 cm) of coarse-grained, massive, well-cemented grainstone. This heterogeneous microfacies

comprises mainly poorly-sorted pellets, with scatters of skeletal bioclasts, including gastropods and bryozoans, besides rare echinoderm and multi-chambered foraminifera. Petrography showed average crystal sizes ranging between 6.5 μm and 16.2 μm in the fine dolomitic interior of skeletal components and coarser calcitic outer shell and matrix, respectively (Figure 3.3). Besides intercrystalline microporosity, MF10 is frequently characterized by disconnected and scattered fenestral and rare moldic micro- and macro-pores.

Microbialite (MF11)

This microfacies comprises of thin laminae (2-10 mm) of organic matter intercalated with coarser components (pellets and unidentified skeletal fragments), occupying a cumulative thickness of 0.47 ft (14.5 cm). It was encountered in the dolomitic-rich (0-11.25 ft) and calcitic-rich parts (14-30 ft), with a thickness of 0.08 ft (2.5 cm) and 0.39 ft (12 cm), respectively. Si-content appears higher in the organic-rich lamina than in the intercalated skeletal-rich component. The behavior was also observed in organic-rich mudstone (MF4) with relatively higher quartz and thus illite contents, as indicated by XRF and XRD (Figures 3.8 and 3.11).

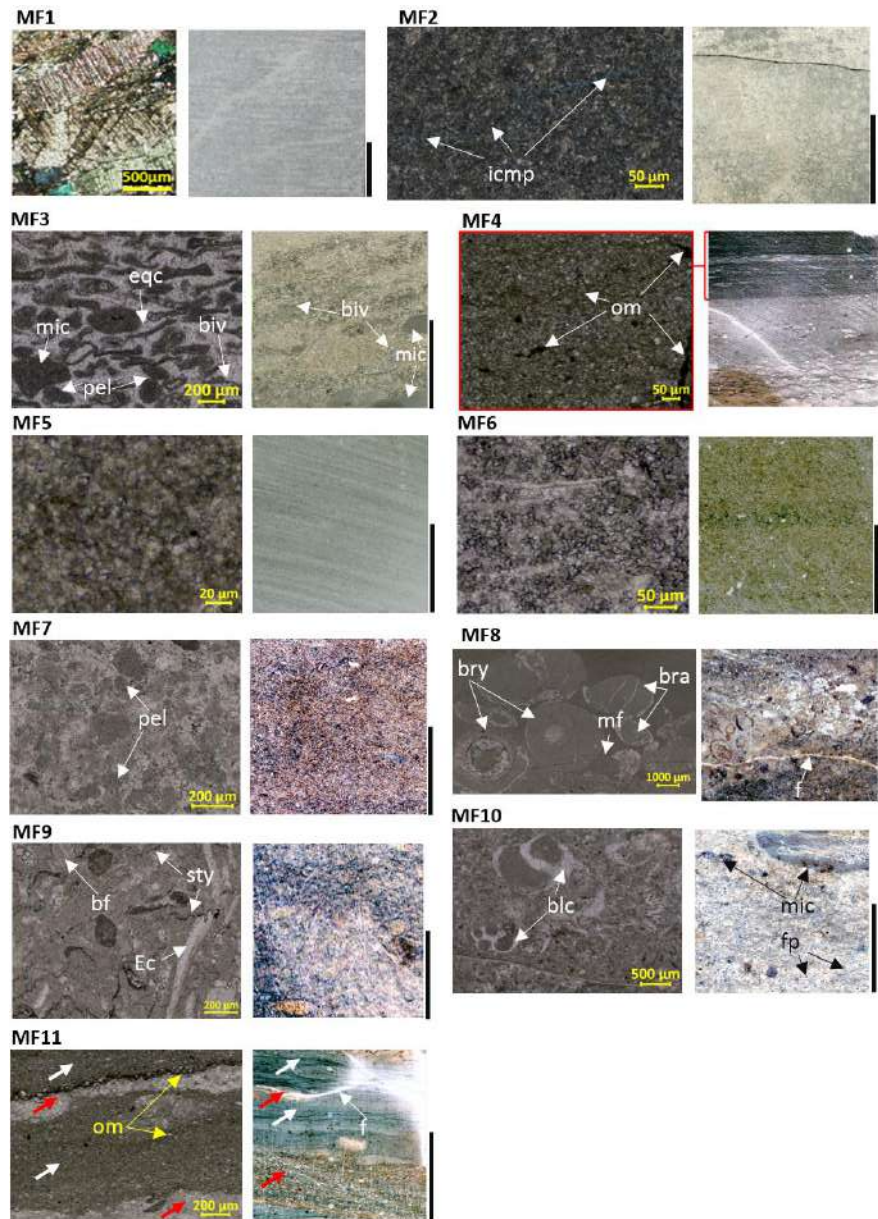
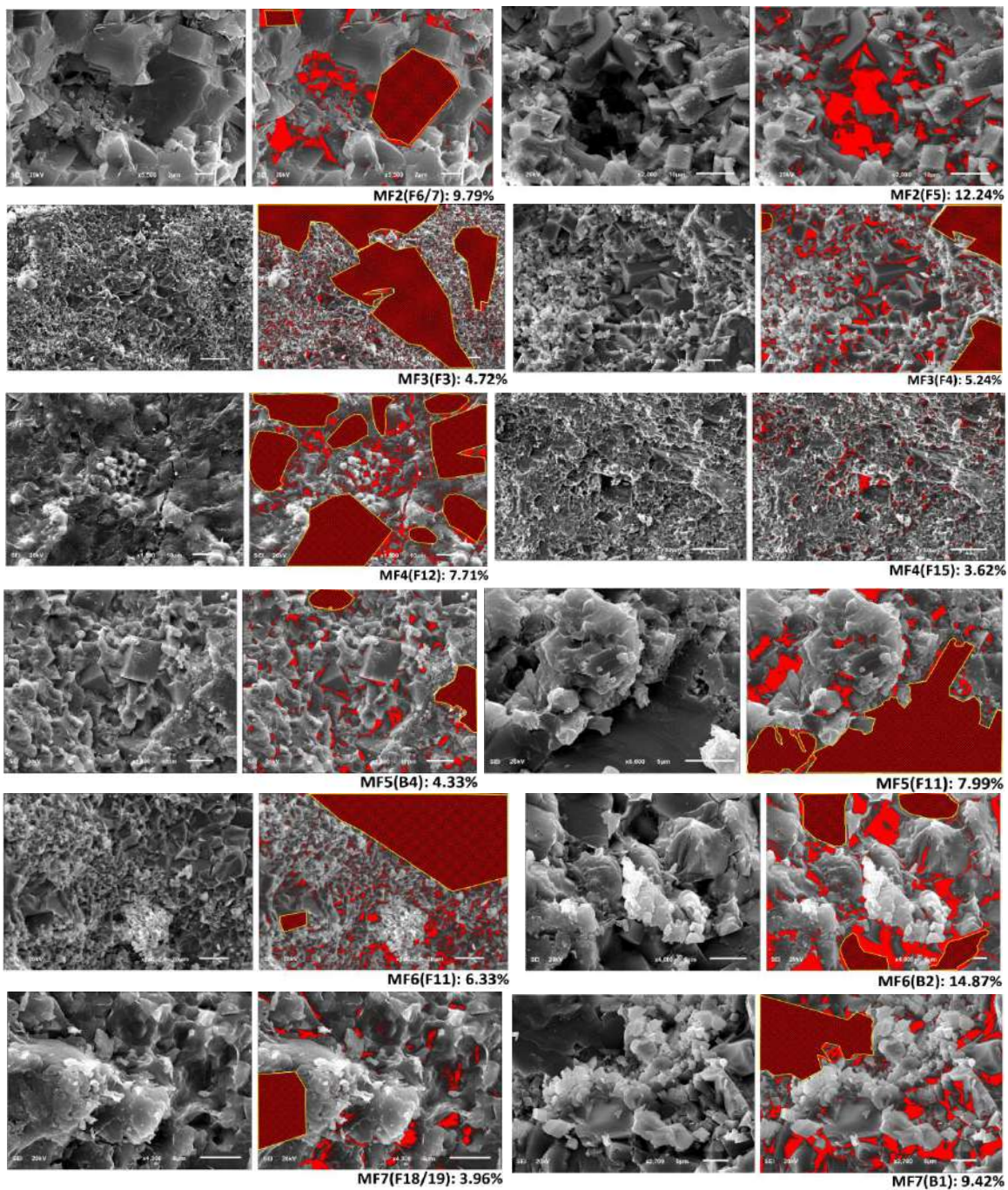


Figure 3.3. Representative petrography (left) and high-resolution slab images (right) of the eleven microfacies in the studied core section (0-30 ft). Note the well-sorting in MF3 and poor sorting in heterogeneous microfacies; MF8, MF9, and MF10 (C3/4). The arrows in MF11 indicate the alternation between dark-color fine microbial mats (white arrows) and coarser skeletal-rich laminae (red arrows). Abbreviations: icmp (intercrystalline microporosity), eqc (equant calcite cement), mic (mud intraclast), biv (bivalve), pel (pellets), om (organic matter), f (fracture), mf (microfracture), bra (brachiopod), bry (bryozoans), bf (benthic foraminifera), sty (stylolite), Ec (echinoderm fragment), blc (blocky calcite cement), fp (fenestral porosity). Scale bar in slab images: 1 cm (0.39 inch). Detailed microfacies characteristics are elaborated in section 4.1 and summarized in Table 3.1.

Table 3.1. Summary of the microfacies characteristics. See Table 3.2 for median values of crystal and pore sizes.

Microfacies (code)	Microfacies photographs	Sedimentary structures	Texture and crystal size (median diameter)	Fossils/ Trace fossils	Diagenetic overprint	Pore type/ porosity% (min-max)/pore size (median)
Layered evaporites (MF1)	Figures 3.2, 3.3	Layered Evaporites (1-10 cm), occasional nodules within adjacent microfacies	Medium to coarse crystalline: 100-500+ μm	None	Pore/fracture filling as infiltrate into adjacent microfacies (MF2 and MF3)	NA
Dolomitic mudstone (MF2)	Figures 3.2, 3.3, 3.12A	Massive, horizontal fractures	Cryptocrystalline to very fine crystalline (4.3-5.4 μm)	Rare unidentified bioclasts	Dolomitization, evaporites-filling, stylolite, fractures	Intercrystalline/ 9.79-18.3%/ 0.4-0.5 μm^2
Intraclast skeletal peloidal grainstone (MF3)	Figures 3.2, 3.3, 3.12B	Graded bedding, lack of matrix mud	Poor sorting. Mud intraclasts 200 μm -2 cm. Pellets: 200-300 μm . Skeletal grains: 200-1000 μm . Elongated, well-sorted pellets of medium size. Cryptocrystalline (3.2-3.7 μm)	Bivalves, pellets, rare ooids, and benthic foraminifera	Cementation, occasional vuggy pores filled with blocky calcite, matrix with equant calcite cement, fractures	Intercrystalline/ 4.7-12.46%/ 0.5 μm^2
Organic-rich mudstone (MF4)	Figures 3.2, 3.3	Thin laminations of organic matter	Cryptocrystalline micrite to very fine crystalline (4.5-8.2 μm)	Rare bivalves and other unidentified bioclasts	Dolomitization	Intercrystalline/ 3.5-9.97%/ 0.04-1.8 μm^2
Massive mudstone (MF5)	Figs.3.2, 3.12C, 3.12D	Rare allochems, millimeter-scale laminations associated with delicate organic content	Cryptocrystalline to very fine crystalline (2.7-6.7 μm)	Occasional unidentified skeletal bioclasts	Immature dolomite crystals with anhedral faces	Intercrystalline/ 3.6-16.3%/ 0.4-3.1 μm^2
Massive peloidal wackestone (MF6)	Figure.3.3	None	Cryptocrystalline to very fine crystalline matrix (2.1-7.2 μm)	Pellets, unidentified bioclasts, including	Dolomitization, skeletal molds	Intercrystalline/ 5.65-14.91%/ 0.7-23.1 μm^2

				bivalves/vertical burrows	filled with blocky calcite, fractures	
Skeletal peloidal packstone (MF7)	Figures 3.2, 3.3, 3.12D, 3.12E, 3.12F	None	Moderately- to poorly-sorted, medium to coarse pellets (100-200+ μm), with skeletal biota around similar size or larger. Cryptocrystalline to very fine crystalline (2.7-9.8 μm)	Rounded to subrounded pellets. Skeletal assemblage of bivalves, gastropods, and benthic foraminifera	Dolomitized pellets, calcitized skeletal grains, stylolites, fractures	Intercrystalline/4.0-14.7%/ 0.32-13.0 μm^2
Floatstone (MF8)	Figures 3.2, 3.3	None	Heterolithic texture (floatstone) of a muddy matrix, skeletal allochems, and mud intraclasts (various sizes)	Brachiopods, skeletal debris of bryozoans, unidentified fragments, and benthic foraminifera	fractures, stylolite,	Intercrystalline/5.4 14.9%/ 0.30-0.32 μm^2
Echinoderm bioclastic packstone (MF9)	Figures 3.2, 3.3	Massive	Cryptocrystalline to fine crystalline dolomitic matrix (4.5-11 μm), various-sized skeletal allochems (100-2000 μm)	Pervasive Echinoid fragments, bryozoan fragments	Equant matrix cementation, stylolites	Intercrystalline/3.2-12.79%/ 1.0-4.1 μm^2
Bioclastic peloidal grainstone (MF10)	Figures 3.2, 3.3, 3.12G, 3.12H	Massive, with locally graded bedding	Poor sorting: cryptocrystalline to very fine crystalline (2.2-5.7 μm) dolomitic matrix, coarser calcitized skeletal frames (50+ μm). Occasional mud intraclasts (up to 2.5 cm)	Sparse pellets, skeletal biota including gastropods, bivalves, rare benthic foraminifera	Fine matrix of anhedral to subhedral equant cementation, evaporite filling	Intercrystalline, with some skeletal molds and fenestral pores/ 7.9-10.1%/ 0.3-1.3 μm^2
Microbialite (MF11)	Figures 3.2, 3.3	Thin lamination of organic films blanketing coarse components of skeletal/non-skel. allochems. The latter also occurs as lenses within the organic films	Heterolithic texture: cryptocrystalline micrite organic-rich lamina (3.4-4.6) with poorly- sorted fine to coarse crystalline (10-50 μm and larger) skeletal/non skeletal allochems	Unidentified skeletal fragments	Cementation, stylolites, fractures	Intercrystalline/ 5.4-14.5%/ 0.4-2.9 μm^2



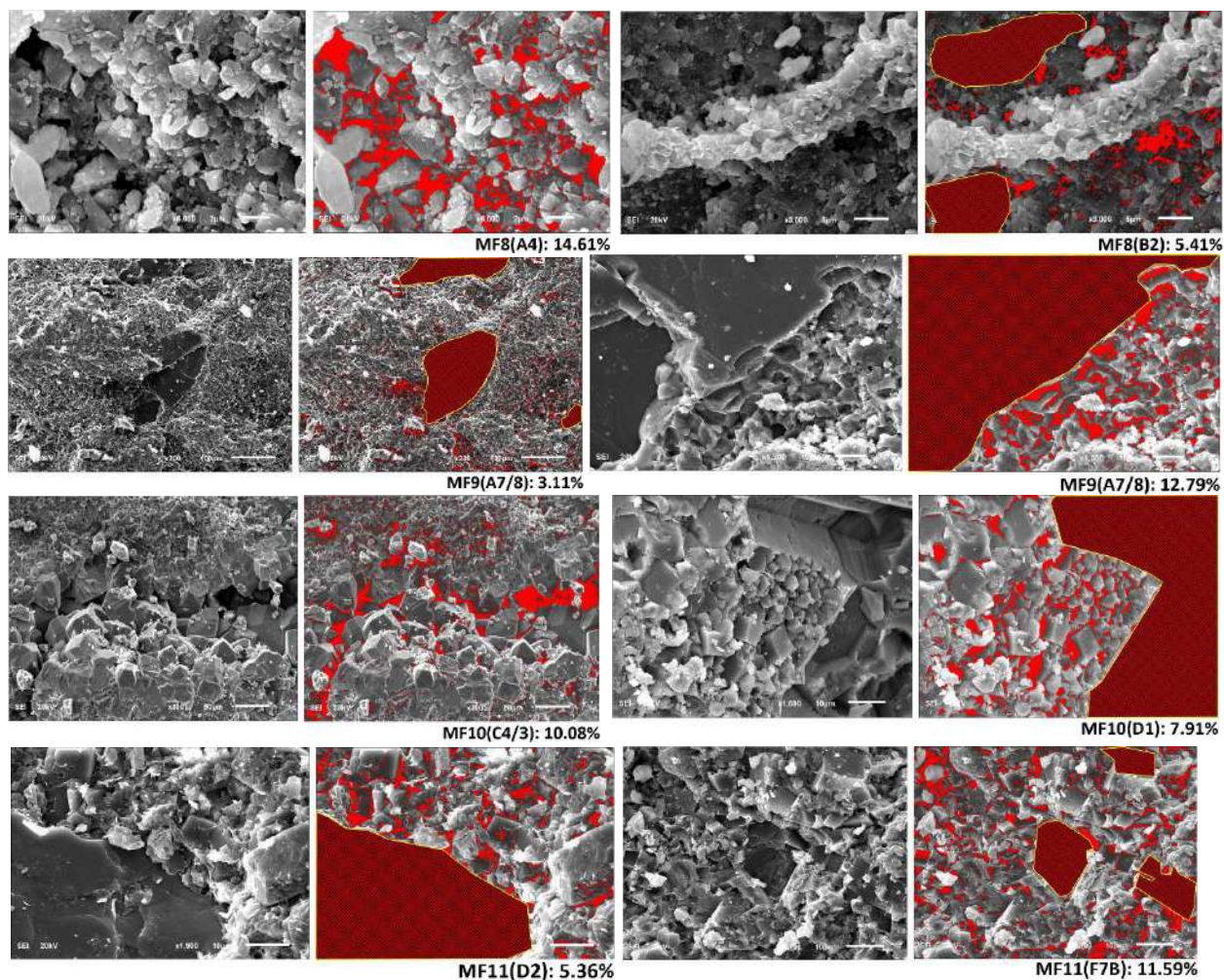


Figure 3.4. Representative SEM point-count microporosity estimations using color threshold (stained in red) in different samples and microfacies. Intercrystalline microporosity prevails, with local occurrence of intraparticle micropores, e.g., MF4(F12). The patterned, yellow-bordered polygons indicate areas excluded from porosity estimation to avoid interference with the color threshold. Note the type of crystal contact, e.g., punctic contact in MF2, MF8, and MF10, serrate contact in MF6 and MF7, and coalescent and meshed contact in MF4, MF5, and MF9. See section 4.3 for details.

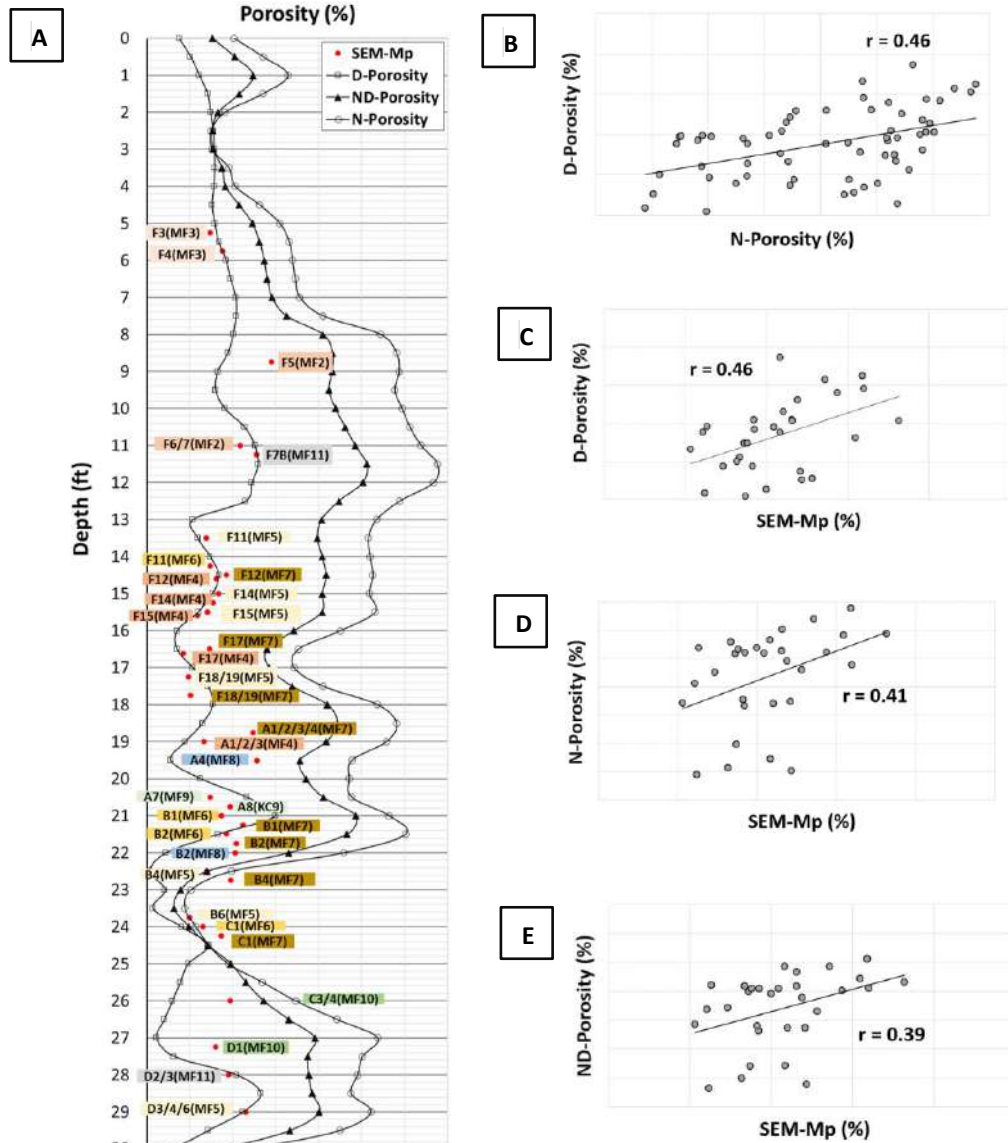


Figure 3.5. (A) Chart of porosity derived from wireline logs, including Density (D-porosity), neutron (N- porosity), and coupled neutron-density (ND-porosity) logs. Porosity increases rightward. The averaged SEM microporosity (SEM-Mp), obtained from (Table 3.2), was also plotted at their actual or best approximate depth in the wireline log scale (0.5 ft interval). Cross relationships showing the direct correlation of D-porosity with N-porosity **(B)**, and averaged SEM-Mp against D-porosity **(C)**, N-porosity **(D)**, and ND-porosity **(E)**. The best agreement was noted between SEM-Mp and D-porosity **(C)**. Note: In **C**, **D**, and **E**, SEM-Mp represents samples that have equivalent log porosities in **A**.

Table 3.2. Detailed summary of statistical parameters for crystal diameter, pore size, and microporosity acquired from high-resolution SEM images from different samples of different microfacies. Samples were arranged based on their actual distribution in the slabbed core samples from top to bottom (0-30 ft) (Figure 3.2). Crystal diameter represents the length of maximum diameter, while pore size indicates pore area. All samples are intercrystalline microporous. Abbreviations: N (number of measurements), Min (minimum value), Max (maximum value), Avg (average), Med (median), SD (standard deviation), and CV (coefficient of variation).

Sample#	Microfacies#	Crystal size (diameter, μm)							Pore size (μm^2)							Microporosity (%)						
		N	Min.	Max.	Avg.	Med.	SD	CV	N	Min.	Max.	Avg.	Med.	SD	CV	N	Min.	Max.	Avg.	Med.	SD	CV
F3	MF3	86	1.34	11.80	3.49	3.21	1.66	0.48	143	0.10	20.76	1.60	0.46	3.03	1.89	43	4.72	10.75	7.37	7.06	1.57	0.21
F4	MF3	269	0.87	38.54	5.02	3.71	4.04	0.80	783	0.11	77.67	2.58	0.46	7.21	2.79	44	5.24	12.46	8.82	8.66	2.15	0.24
F5	MF2	92	0.84	11.15	4.29	4.28	2.33	0.54	136	0.11	22.12	2.47	0.49	4.67	1.89	31	12.24	18.30	14.53	14.44	1.80	0.12
F6/7	MF2	162	1.76	24.29	6.03	5.38	2.95	0.49	86	0.10	8.68	0.79	0.35	1.25	1.58	29	9.79	12.43	10.87	10.77	0.78	0.07
F7B	MF11	69	1.34	10.96	4.02	3.39	1.91	0.48	360	0.10	15.30	1.10	0.44	1.92	1.75	11	12.57	12.96	12.72	12.60	0.41	0.03
F11	MF5	88	2.85	11.92	5.86	5.57	1.83	0.31	141	1.01	98.19	5.65	2.07	13.33	2.36	25	5.92	7.99	6.90	6.99	0.51	0.07
F11	MF6	76	2.08	15.83	5.67	2.10	4.43	0.78	175	5.04	70.15	15.45	10.04	14.16	0.92	18	6.33	8.35	7.39	6.88	0.60	0.08
F12	MF7	26	1.51	5.98	3.08	2.74	1.27	0.41	31	0.21	6.28	1.40	0.82	1.53	1.09	19	7.09	12.46	9.24	8.96	1.63	0.18
F12	MF4	34	2.74	44.92	6.43	4.79	6.97	1.08	60	0.50	32.22	4.12	1.77	6.05	1.47	15	7.71	8.85	8.05	8.11	0.20	0.02
F14	MF5	109	1.56	15.44	5.86	5.53	2.51	0.43	203	0.51	51.85	3.09	1.54	5.43	1.76	19	5.35	10.33	8.36	8.26	1.43	0.17
F14	MF4	61	1.39	13.03	4.89	4.46	2.35	0.48	32	0.20	30.30	2.41	0.77	4.15	1.72	25	5.41	9.97	7.72	7.83	1.31	0.17
F15	MF5	69	0.45	11.43	1.68	2.68	0.97	0.58	101	0.01	2.34	0.21	3.08	1.84	8.76	25	5.96	7.63	7.04	7.12	0.54	0.08
F15	MF4	-	-	-	-	-	-	-	28	0.10	4.76	0.61	0.26	1.03	1.69	19	3.62	7.25	5.86	5.99	1.14	0.19
F17	MF7	46	4.82	33.18	10.84	9.82	4.81	0.44	303	0.53	106.53	3.37	1.23	8.45	2.51	18	4.02	9.58	7.30	7.40	1.54	0.21
F17	MF4	130	3.34	25.13	8.79	8.15	4.05	0.46	67	0.11	16.28	1.98	0.32	3.69	1.86	15	3.53	5.18	4.25	4.23	0.54	0.13
F18/19	MF5	134	1.59	19.60	6.26	5.87	2.71	0.43	212	0.53	52.76	2.71	1.25	5.36	1.98	71	3.60	6.82	4.85	4.73	0.76	0.16
F18/19	MF7	52	4.14	18.73	7.46	7.05	2.80	0.38	943	0.32	45.16	1.82	0.89	2.71	1.49	59	3.96	6.15	5.06	4.98	0.64	0.13
A1/2/3/4	MF7	31	2.46	9.60	4.69	4.36	1.61	0.34	63	0.11	25.34	1.61	0.32	4.09	2.54	56	10.72	13.94	12.37	12.47	0.96	0.08
A1/2/3	MF4	43	2.73	11.48	6.57	6.19	1.80	0.27	712	0.02	8.65	0.20	0.04	0.68	3.40	18	4.97	7.62	6.68	6.96	0.80	0.12
A4	MF8	155	0.64	8.75	3.37	3.00	1.52	0.45	68	0.10	8.07	0.70	0.32	1.22	1.74	30	10.97	14.61	12.79	12.71	1.07	0.08
A7	MF9	77	1.79	11.88	5.02	4.52	2.29	0.46	85	0.50	23.44	2.19	0.99	3.24	1.48	68	3.11	12.79	7.35	8.53	2.77	0.38
A8	MF9	41	7.70	19.17	12.05	11.15	3.06	0.25	916	2.04	295.60	6.71	4.07	13.39	2.00	30	8.11	11.75	9.73	9.74	0.94	0.10
B1	MF6	42	3.02	9.98	5.49	5.40	1.60	0.29	806	0.21	48.66	1.56	0.67	3.17	2.03	29	5.65	12.09	8.66	8.53	2.04	0.24
B1	MF7	66	3.06	18.98	8.10	7.28	3.22	0.40	121	1.02	79.78	5.82	2.01	10.69	1.84	12	9.42	14.11	11.17	10.19	1.65	0.15
B2	MF6	114	3.58	23.73	7.72	7.21	2.88	0.37	126	0.51	38.12	1.29	4.23	17.91	13.88	19	5.65	14.87	9.26	8.88	2.60	0.28
B2	MF7	109	2.41	11.40	5.01	4.52	2.01	0.40	278	0.16	67.55	2.48	0.74	5.90	2.38	18	8.38	12.84	10.44	10.20	1.44	0.14
B2	MF8	48	0.86	4.32	2.20	2.03	0.83	0.38	188	0.10	53.71	1.32	0.26	4.76	3.61	29	5.41	14.88	10.26	10.07	2.41	0.23
B4	MF5	81	2.19	11.24	6.04	5.74	2.19	0.36	159	0.13	14.47	1.80	0.73	2.60	1.44	29	4.33	8.60	6.95	7.30	1.20	0.17
B4	MF7	47	1.85	11.98	4.88	4.47	1.87	0.38	545	0.10	101.72	1.79	0.32	6.67	3.72	19	6.47	14.71	9.74	9.83	2.22	0.23
B6	MF5	69	1.22	5.68	2.78	2.68	0.97	0.35	136	1.16	11.53	3.51	3.08	1.84	0.52	45	4.41	5.60	4.95	4.98	0.31	0.06
C1	MF6	47	3.24	11.74	6.43	5.77	2.12	0.33	471	0.51	79.06	2.88	1.54	4.85	1.68	25	5.80	7.21	6.53	6.53	0.44	0.07
C1	MF7	35	1.92	7.47	4.17	4.05	1.25	0.30	113	0.10	57.69	2.48	0.48	6.45	2.60	10	8.60	8.72	8.67	8.67	0.04	0.00
C3/4	MF10	87	0.70	11.34	2.67	2.18	1.79	0.67	66	0.10	26.93	1.35	0.30	3.66	2.71	104	9.40	10.08	9.67	9.65	0.71	0.07
D1	MF10	80	2.37	11.94	6.44	5.73	2.50	0.39	87	0.51	17.18	2.44	1.28	3.03	1.24	54	7.91	8.06	7.99	8.00	0.04	0.01
D2/3	MF11	214	1.26	11.81	4.80	4.62	1.73	0.36	203	1.34	43.65	4.73	2.86	5.28	1.12	54	5.36	14.54	9.52	8.48	3.08	0.32
D3/4/6	MF5	99	3.57	17.49	7.00	6.71	2.27	0.32	197	0.10	14.79	1.21	0.38	2.19	1.81	99	8.33	16.32	11.49	11.15	1.57	0.14

Table 3.3. Summary of statistical parameters of the flow rate and gas permeability. Notice the median values are indicative of flow rate and permeability compared to average values, which have a tendency to extreme values (outliers). All studied samples have shown extremely low permeability (less than 0.1 mD), regardless of microfacies. Abbreviations: N (number of measurements), Min (minimum value), Max (maximum

Depth (ft)	Flow rate (cc/min)						Permeability (mD)					
	N	Min.	Max.	Avg.	Med.	SD	N	Min.	Max.	Avg.	Med.	SD
0-11.25	109	1.687	500.57	56.01	2.20	130.08	106	0.07	265.51	5.42	0.09	26.70
14-18	251	1.665	139.44	4.79	1.82	15.81	251	0.07	9.07	0.26	0.07	1.04
18-21	66	1.732	502.60	40.55	1.82	131.63	63	0.07	490.41	10.23	0.07	63.63
21-24	83	1.68	500.16	36.05	1.85	114.51	81	0.07	31.48	0.88	0.07	3.66
24-27	86	1.615	500.13	30.77	1.95	108.09	85	0.06	61.96	2.25	0.08	9.60
27-30	102	1.679	500.06	17.07	1.81	84.15	99	0.07	2.14	0.11	0.07	0.22

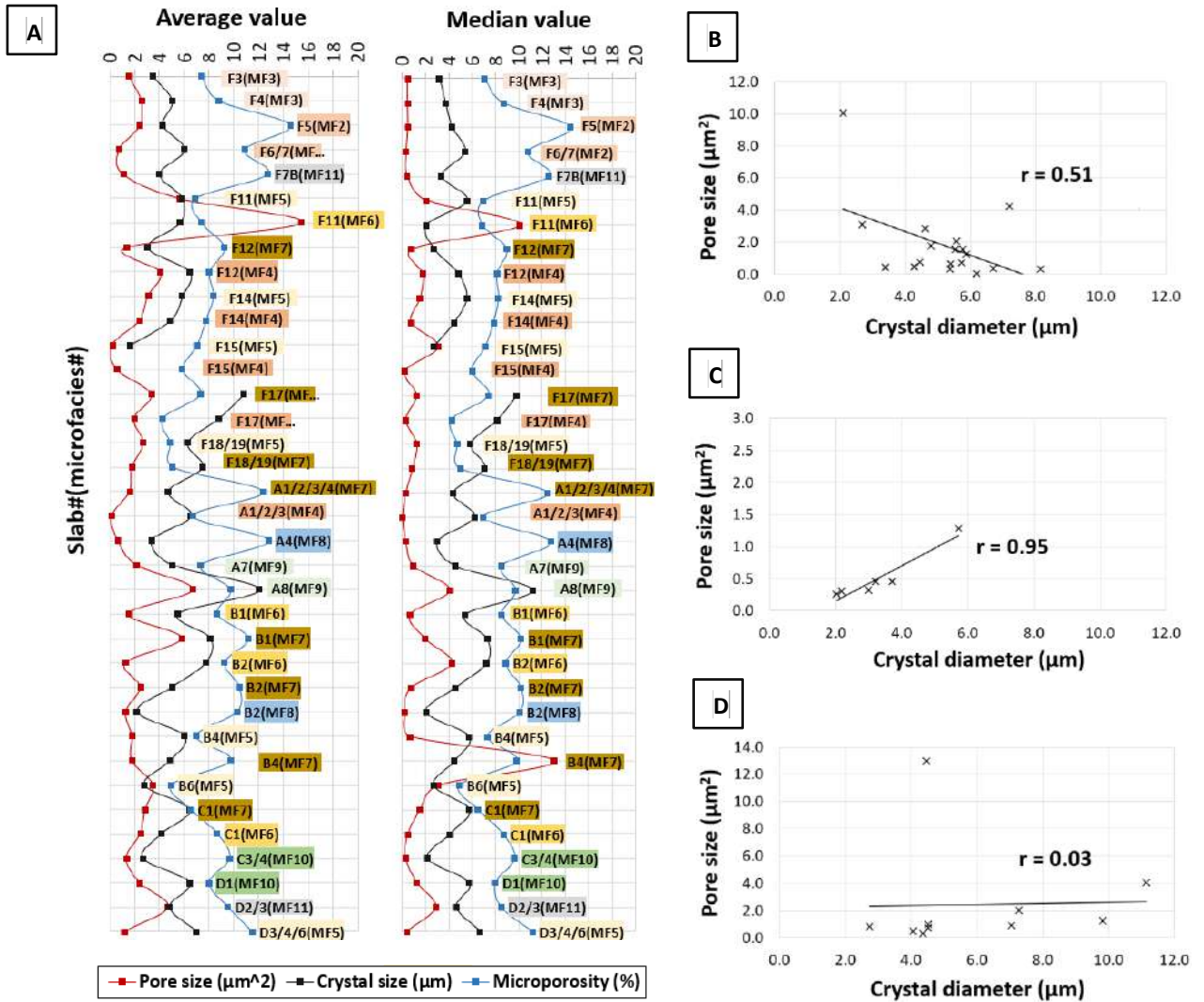


Figure 3.6. (A) Distribution of the average (left) and median (right) pore sizes, crystal sizes, and microporosity in different slabbed samples and microfacies in the studied late Permian carbonate microfacies. The relationships between pore size (median) and crystal size (median) are shown in mudstones, microbialite, and mud-dominated microfacies (MF2, MF4, MF5, MF11, and MF6) (B), in grainstones and floatstone (MF3, MF10, and MF8) (C), and in packstones (MF7 and MF9) (D). Details of the statistical analysis are in Table 3.2.

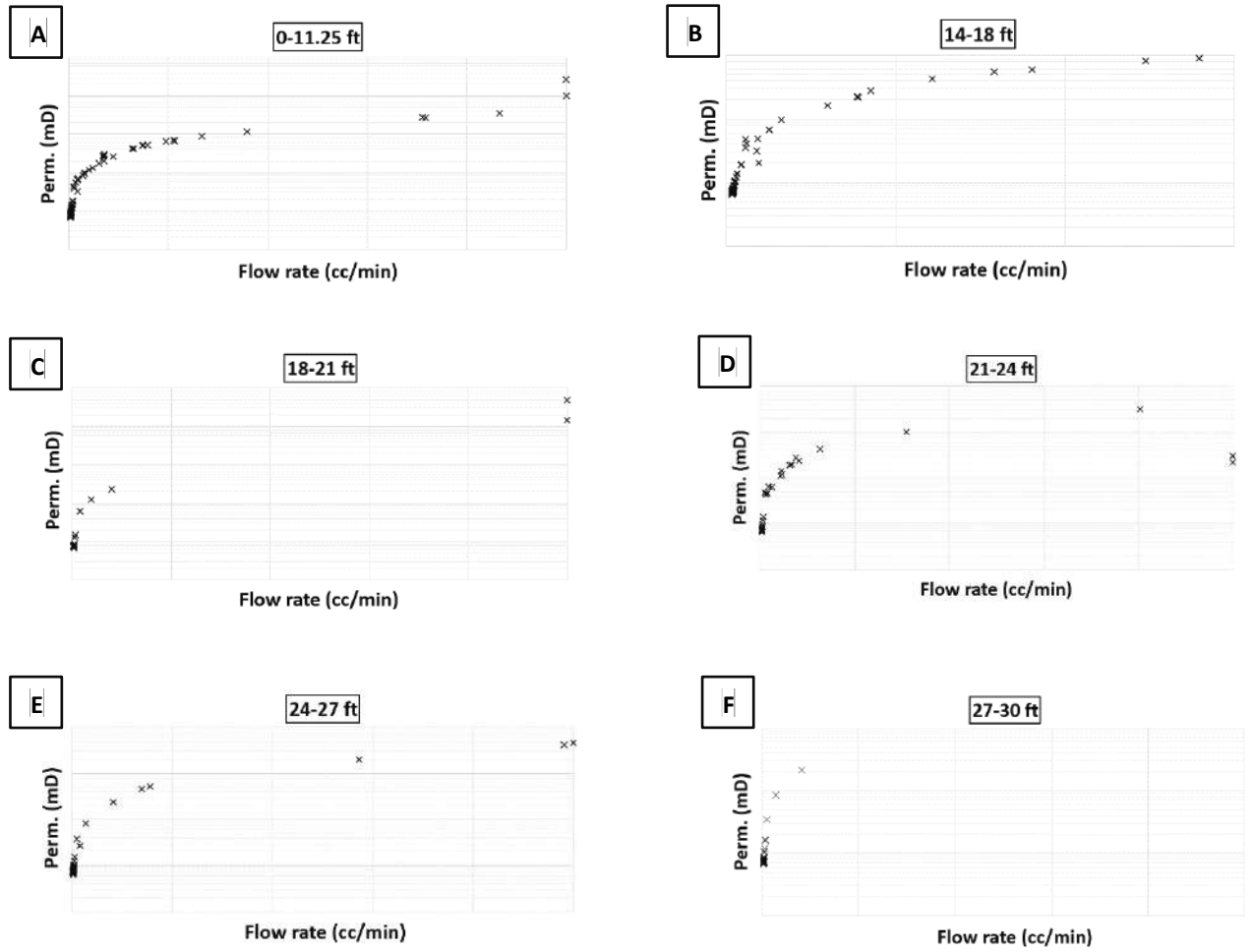


Figure 3.7. Relationship between flow rate and related gas permeability of all slabbed core samples in the studied section (0-30 ft), permeability represented in log scale. The permeability increases upward, and the flow rate increases rightward. All core slabs showed extremely low flow rates and thus, permeability. Limited high values indicate the occurrence of multiscale fractures as observed in slabbed samples and petrographic thin sections. Details of flow rate and permeability are in Table 3.3. Statistics related to data points are shown in Table 3.3.

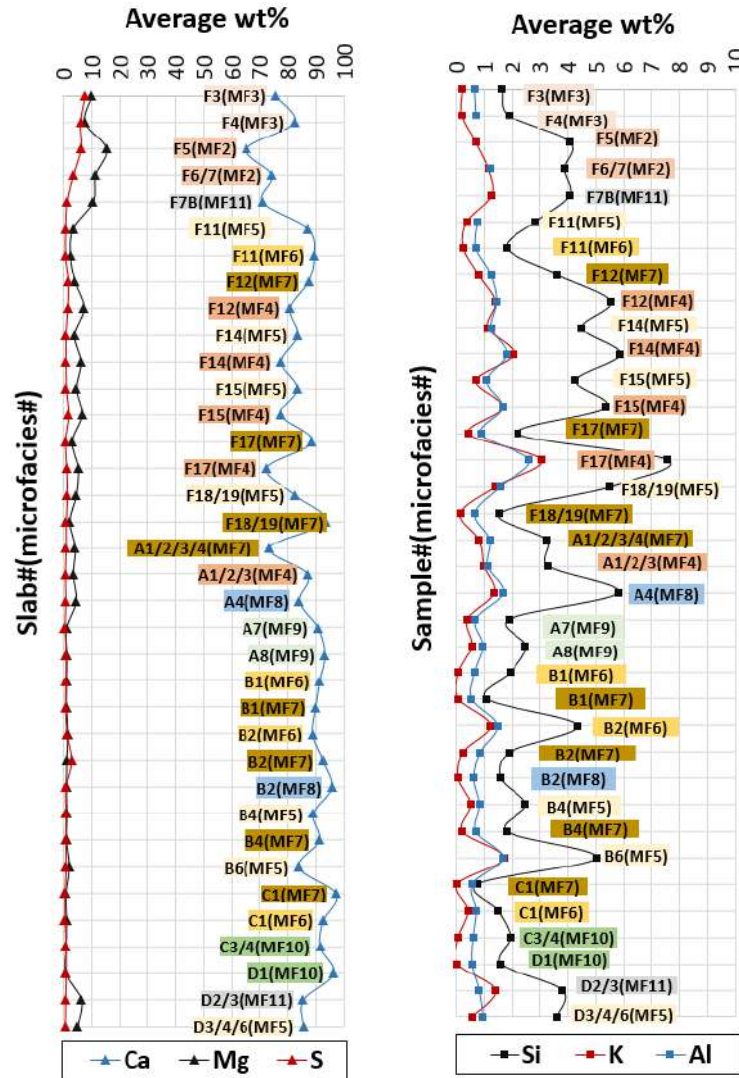


Figure 3.8. Distribution of average weights (%) of the dominant elements in different slabbed samples and microfacies encountered in the studied core section. Note the higher Mg content at the upper part of the section (0-11.25 ft), compared to the rest of the section, and the reverse content of Ca in the same context. Ca (calcium), Mg (magnesium), S (sulfur), Si (silicon), K (potassium), and Al (aluminum). MF2: Dolomitic mudstone, MF3: Intraclast skeletal peloidal grainstone, MF4: Organic-rich mudstone, MF5: Massive mudstone, MF6: Massive peloidal wackestone, MF7: Skeletal peloidal packstone, MF8: Floatstone, MF9: Echinoderm bioclastic packstone, MF10: Bioclastic peloidal grainstone, MF11: Microbialite.

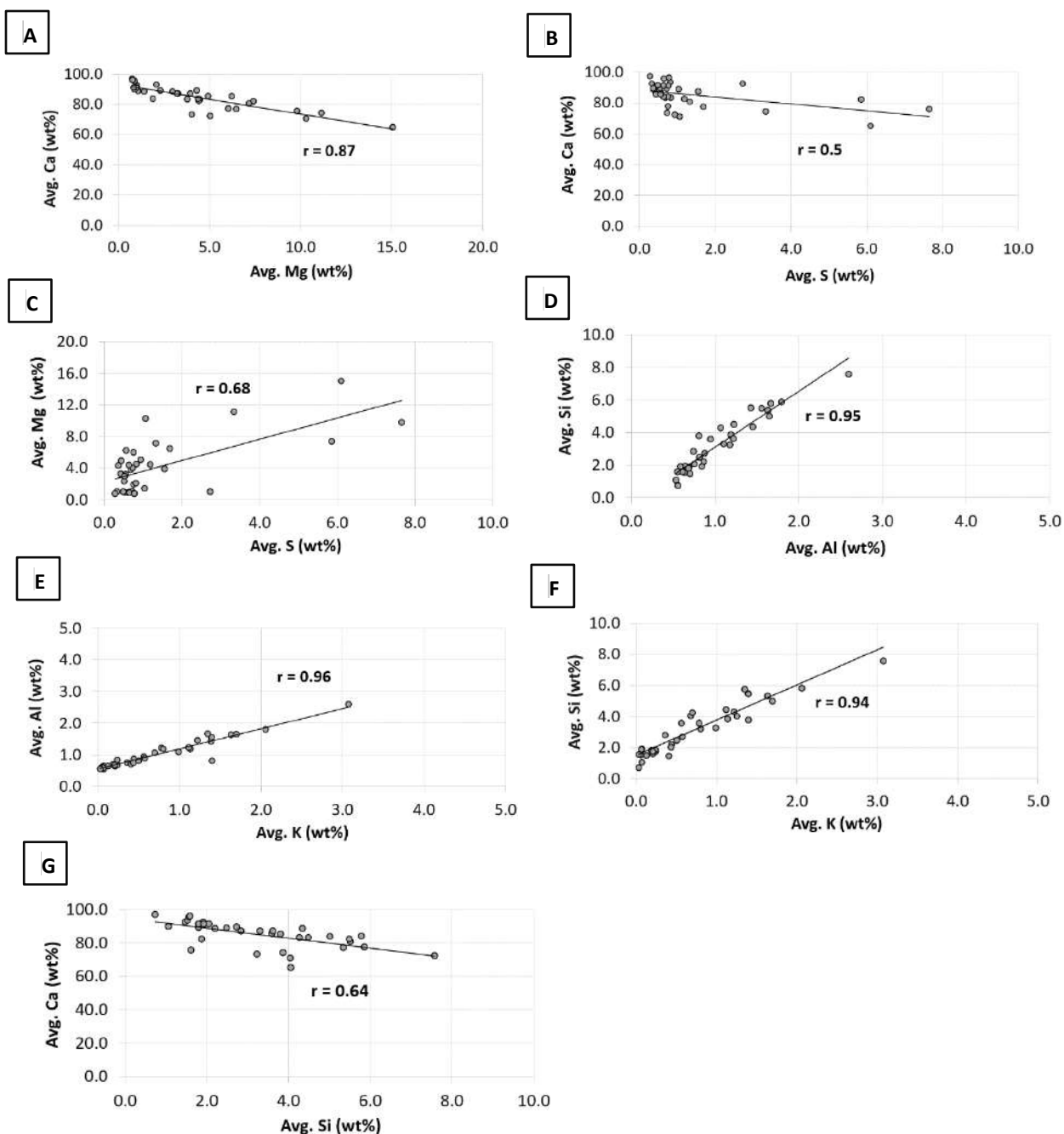
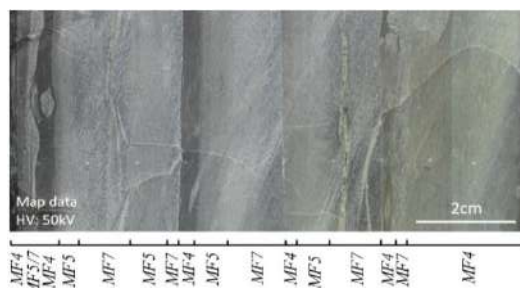


Figure 3.9. Cross-relationships between the dominant elemental spectrums obtained through micro-XRF. Strong reverse relationships were noted between calcium (Ca) and each of magnesium (Mg) and sulfur (S) (**A** and **B**) compared to direct relationships between Si, Al, and K (**D**, **E**, and **F**). Sulfur content (S) is indicative of dolomitization in a hypersaline reflux setting, as indicated by a good direct relationship with magnesium (**C**). Ca and Si; the prevailing elements for carbonate and silica/silicate mineralogy, have revealed the common good reverse relationship (**G**).

Slabbed sample (A2)



Element	%
Magnesium (Mg)	10.05
Silicon (Si)	6.83
Sulfur (S)	1.60
Potassium (K)	1.18
Calcium (Ca)	78.56
Titanium (Ti)	0.19
Iron (Fe)	1.46
Strontium (Sr)	0.10

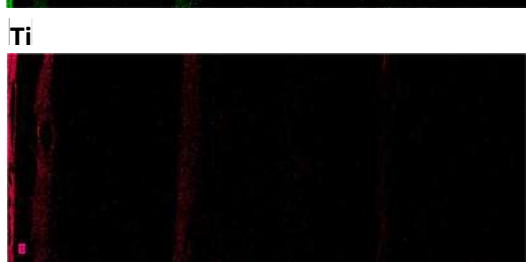
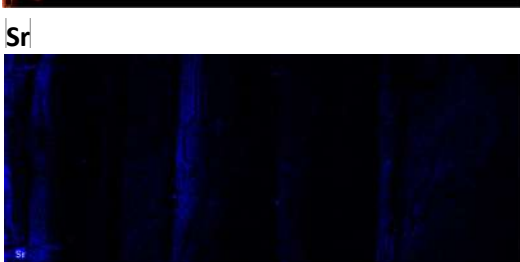
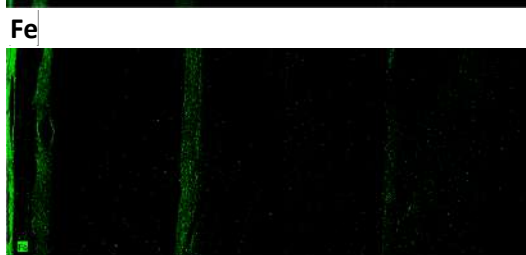
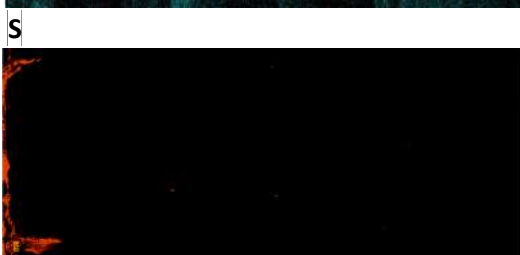
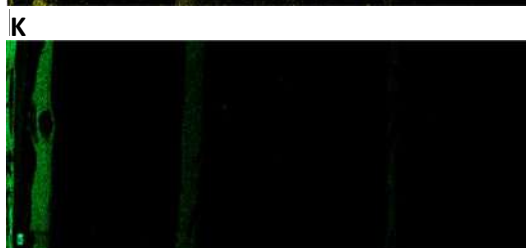


Figure 3.10. Micro-XRF elemental maps of a representative slabbed sample (A2), including major elements (Ca, Mg, and Si). The elemental distribution also conforms with the microfacies stratification observed on the slabbed sample. Sulfur content (S) in this part of the core section (14-30 ft) is minimal compared to the upper one (0-11.25 ft). Si and K maps are relatively identical and conform with organic-rich laminae (MF4), while Ca and Mg maps appear inverse to each other.

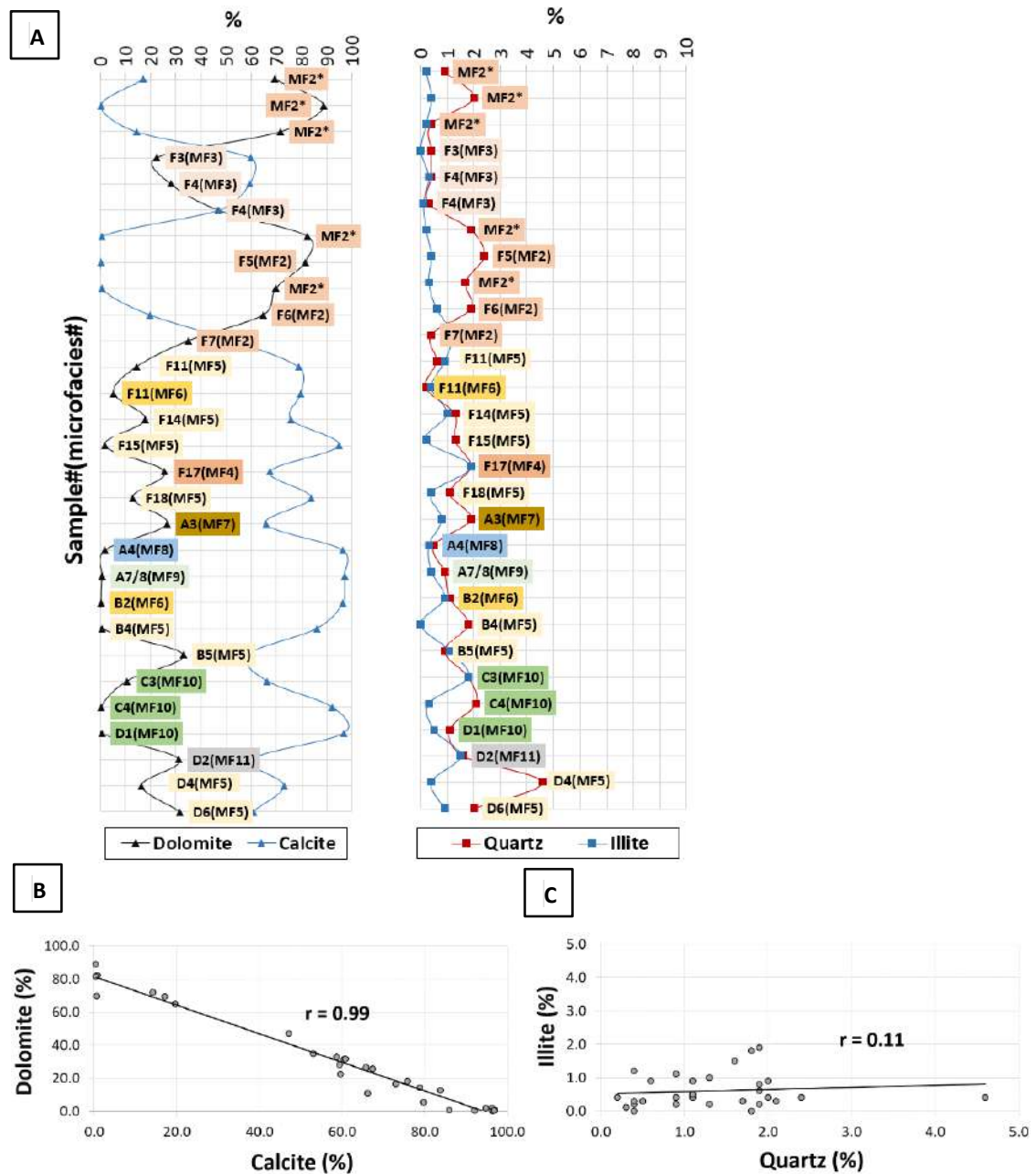


Figure 3.11. A. Distribution of the dominant XRD mineralogy of the studied microfacies in different samples. **B.** Reverse relationship between calcite and dolomite content, where dolomite generally dominates in MF2 (0-11.25 ft; Figure 3.2). **C.** Quartz and Illite showed a poor direct relationship. MF2* indicates samples collected from damaged whole-core pieces in Figure 3.2 (not slabbed). MF2: Dolomitic mudstone, MF3: Intraclast skeletal peloidal grainstone, MF4: Organic-rich mudstone, MF5: Massive mudstone, MF6: Massive peloidal wackestone, MF7: Skeletal peloidal packstone, MF8: Floatstone, MF9: Echinoderm bioclastic packstone, MF10: Bioclastic peloidal grainstone, MF11: Microbialite.

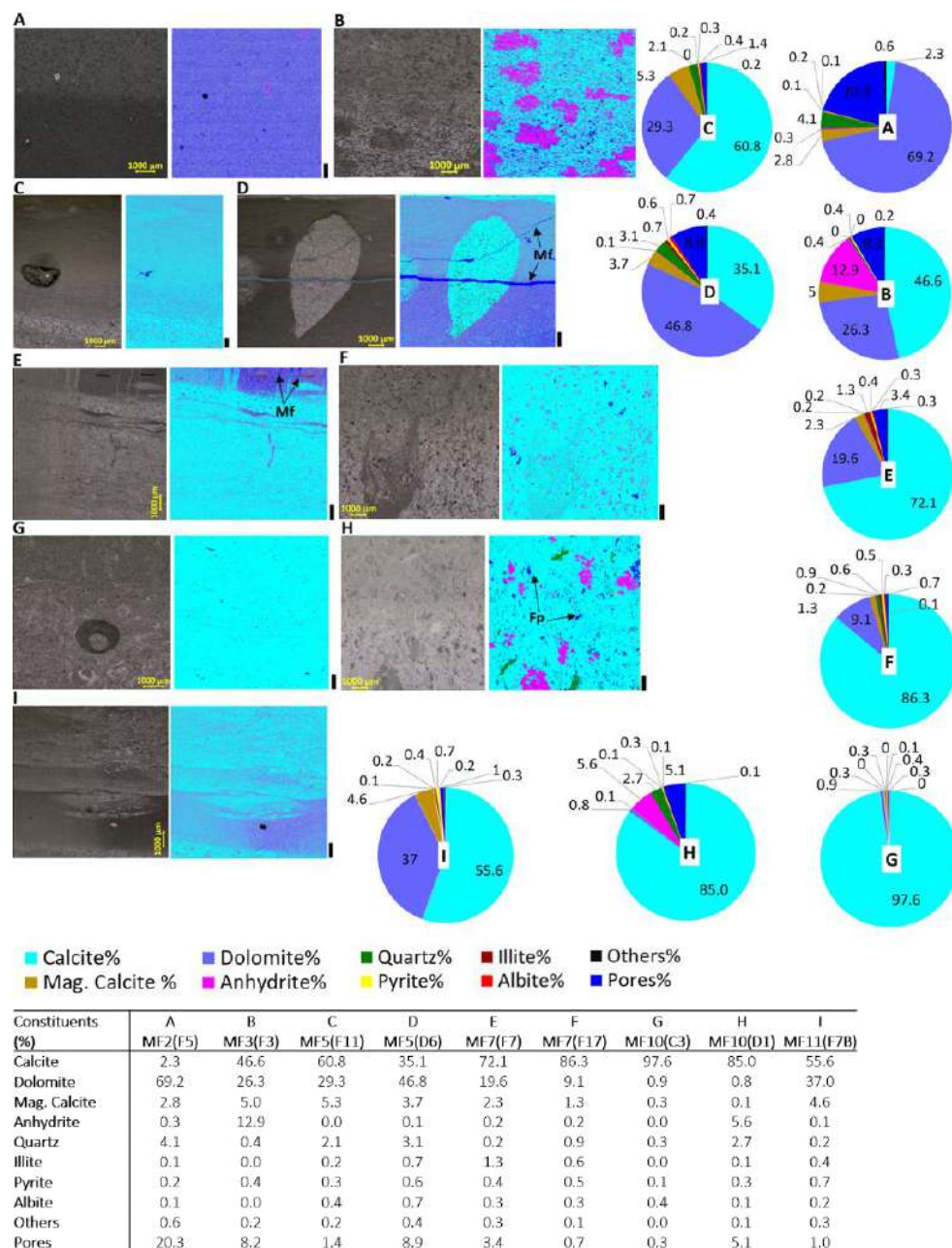


Figure 3.12. Petrography-based mineralogy maps of various microfacies from different samples. **A.** MF2(F5), **B.** MF3(F3), **C.** MF5(F11), **D.** MF5(D6) with inclusion of grain-dominated microfacies (MF7), **E.** MF7(F7) with MF5 at the top, **F.** MF7(F17), **G.** MF10(C3), **H.** MF10(D1) with fenestral micropores (Fp), and **I.** MF11(F7B). Note the dominance of calcite in the grainstones and grain-supported microfacies (**B, E, F, G, H,** and upper part of **I**). Dolomite prevails in mudstone microfacies (**A, C, D,** and lower part of **I**). Microfractures (Mf) are often associated with mudstone microfacies (**D** and **E**). Scale bar: 1 mm (1000 μ m).

3.4.2 Microporosity and Permeability

The studied carbonate microfacies represents a tight carbonate setting, with no significant macro-pores observed in the polished slabs and petrography. An exception was noted in MF10 since fenestral pores and rare molds were observed in slabbed core and petrography, with total porosity around 1.0% (Figure 3.3). In addition, natural fractures, including the open and partially open ones, have poorly contributed to the porosity (Figures 3.2 and 3.3), but significantly enhanced the permeability (Table 3.3, Figure 3.7). SEM revealed a unimodal type of intercrystalline microporosity prevailed in all microfacies (Figure 3.4). For validation, SEM visual microporosity was calibrated with porosity derived from NPHI and RHOB logs. The best correlation was attained between SEM and density porosities, with a correlation coefficient (r) of 0.46 (Figure 3.5). Except for B2/MF6, pore sizes revealed positive skewness, which reflects the homogeneity of pore size as unimodal intercrystalline micro-pores. Three morphologies of microporosity were counted in the studied core section. These types occur either separately as diagnostic for respective microfacies, or in combination with other types for some heterogeneous microfacies (Figure 3.4). These types are; 1- intercrystalline of poorly-sorted sparry calcite (e.g., MF8, MF10), 2- intercrystalline of micrite and dolomicrite (e.g., MF2, MF3, MF5, MF6, MF9, and MF10), and 3- intracrystalline/intraparticle of calcite cement (e.g., MF4 and MF7). Figure 3.4 visualizes microporosity types with representative samples of the microfacies mentioned above. In this study, these types are highly interactive and mostly occur together in different microfacies; thus, investigating the impact of these types on

acoustic velocity was out of the current objective of the study. The limited intracrystalline and macro-pore types are negligible in the studied section compared to prevailing intercrystalline micro-pores. Therefore, this study assumes that the latter pore type has at least the dominant impact on acoustic wave velocity. Quantitatively, the best microporosity was recorded in MF2 and relatively in MF5 and MF11, while other microfacies have shown a wide span of microporosity ranges roughly between 3-15% (Table 3.4, Figure 3.6). Nitrogen permeability measurements showed extremely low values in all microfacies, as obtained from weak gas flow rates. Except for the higher permeabilities (order of 10s and 100s mD) due to the notable micro- and macro-scale fractures, especially at the upper part of the section (MF2), all core intervals exhibited prevailing values around 0.1mD, regardless of microfacies type (Figure 3.7, Table 3.3). This conclusion of permeability setting conforms with the intercrystalline microporosity, implying that the studied section represents a deeply-buried tight carbonate setting.

3.4.3 Crystal Size Analysis

The average crystal size of 12 μm or less was noted in almost all samples of the studied microfacies (Table 3.2, Figure 3.6). Except for F15/MF5, all samples revealed average values greater than median values. Thus, crystal sizes were positively skewed, indicating that most data were clustered in low-value area (Table 3.2). The crystal contacts were classified based on the contact morphology (Loreau, 1972; Tavakoli and Jamalian, 2018). The classification includes point contact (punctic), line contact (serrated), inter-fingering contact (meshed), and welded or fused contact (coalescent). The type of contact is an indicator of the dominant crystal

shape. For instance, punctic contact occurs with euhedral crystals, whereas serrate contact indicates euhedral to subhedral crystals. Meshed contact is indicative of subhedral to anhedral crystals, whereas no crystal contacts are visually resolvable in the coalescent type of contact. In addition, the contact shape may also qualitatively give a clue about porosity, e.g., punctic contact provides better microporosity than other types due to pore space available in this type of contact. The same approach used in this study revealed that carbonate microfacies acquire different contact types as inferred from SEM images (Figure 3.4). Punctic contacts are common in microfacies with better microporosities such as dolomitic mudstone (MF2) and less common in the poorly-sorted microfacies such as MF8 and MF10. The latter microfacies and MF3 have both shown various types ranging from serrate to coalescent with infrequent punctic type as well. Crystal contact ranging from meshed to serrate was observed in MF5, MF6, MF7, and MF9, since these microfacies represent a textural spectrum of mudstone (MF5), wackestone (MF6), and packstones (MF7 and MF9). Serrate to coalescent contacts were observed in organic-rich microfacies (MF4 and MF11). Due to the interactive contact types and the heterogeneity in crystal sizes, SEM showed weak relationships between microporosity and each of the pore and crystal sizes in all microfacies. Thus, a reasonable behavior of microporosity is not attained based on pore and crystal sizes, despite of their occasional fair cross-relationship. (Figure 3.6).

3.4.4. Dolomite Fabrics

Petrographic investigation revealed dolomite fabric ranges between fabric-preserving mimetic to fabric-preserving non-mimetic. No fabric-destructive

dolomite was observed in the studied core section (Figure 3.3). As a general observation, crystal growth (crystal size) increases with the degree of dolomitization, i.e., from fabric-preserving mimetic to non-mimetic. For instance, this observation was obvious from bottom to top, i.e., from MF5 to MF2. The dolomites encountered in the studied core section are mostly non-planar (anhedral) to planar-s (subhedral) non-stoichiometric type (Sibley and Gregg, 1987). Petrography and SEM images have shown none to rare mature dolomite rhombs in the studied samples, except at the uppermost part (dominated by MF2), where a relatively significant amount of dolomite rhombs were observed (Figure 3.4). Accordingly, the Mg-content at the upper part may indicate the occurrence of non-stoichiometric dolomite and dominant poorly-ordered Mg-calcite (calcian) as a prograding stage towards dolomitization. This result accommodates with XRD, XRF, and qemscan analysis as discussed in the mineralogy and elemental geochemistry section.

Fabric-preserving mimetic dolomite

In this dolomite, the depositional textures, internal structure, grains, and crystal geometry and orientation remain preserved. This indicates less dolomite content and maturity than the fabric-preserved non-mimetic and fabric-destructive dolomite (if any), respectively. This fabric was noted in the mudstone microfacies such as MF4 and MF5, and in the fine muddy laminae of MF11.

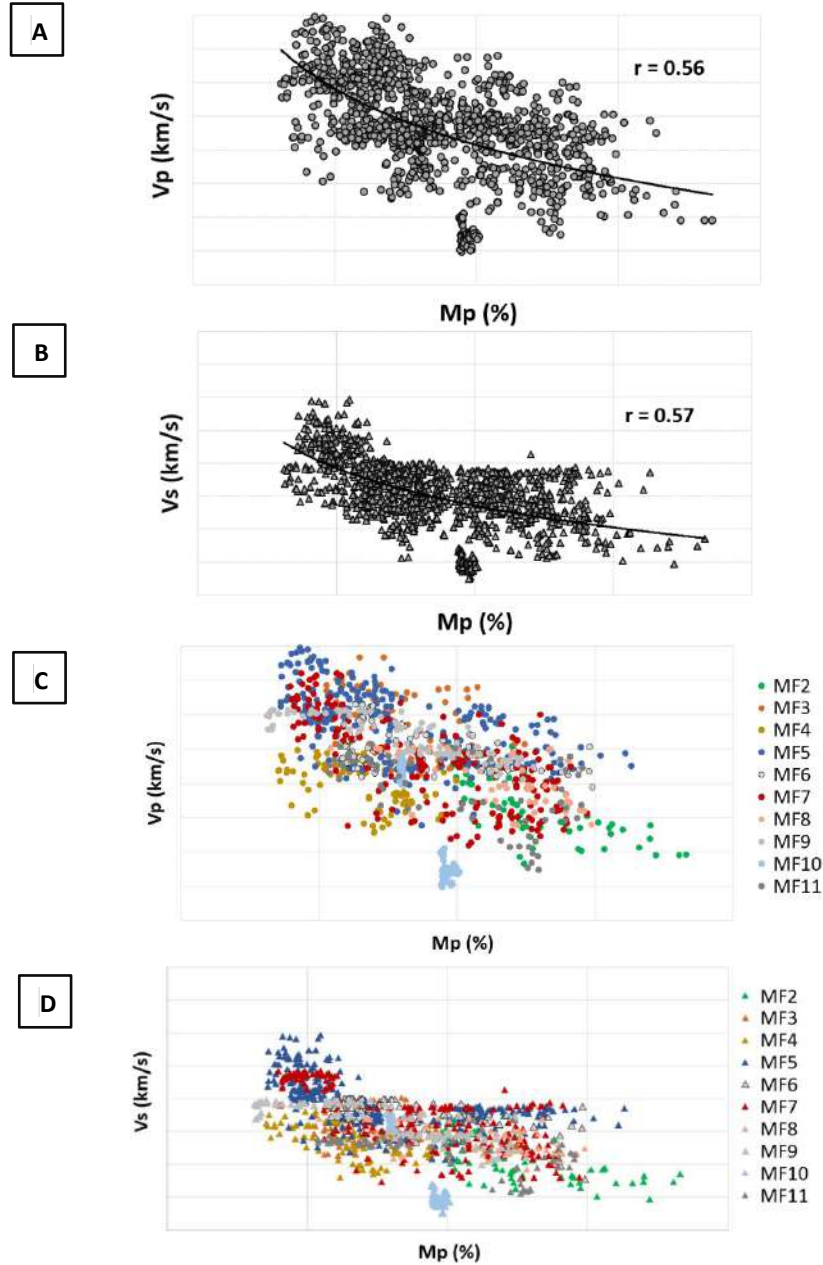
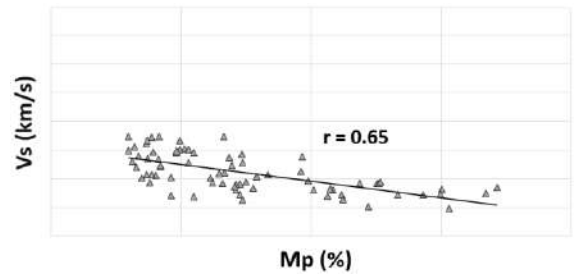
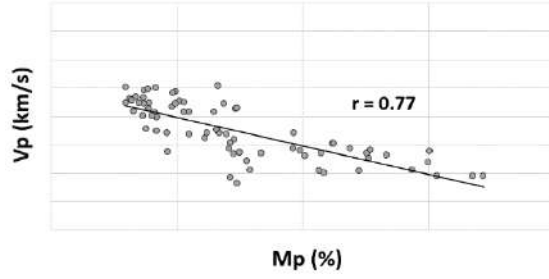
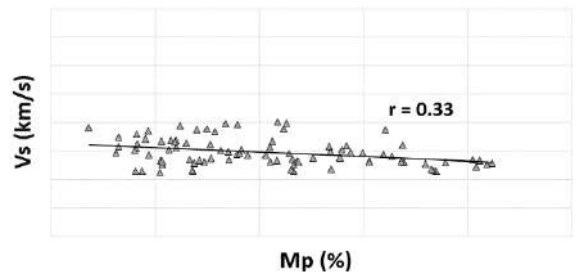
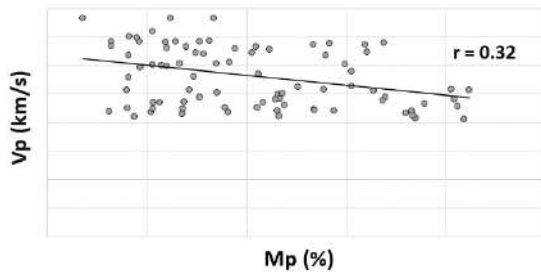


Figure 3.13. Control of microporosity (Mp%) on acoustic p-wave velocity **(A)** and s-wave velocity **(B)** showing reverse relationships. The best fit is explained by non-linear regression, indicating other factors to control these relationships as discussed later. Data points are classified per microfacies for Vp **(C)** and Vs **(D)**. Velocity increases upward and microporosity increases rightward. MF2: Dolomitic mudstone, MF3: Intraclast skeletal peloidal grainstone, MF4: Organic-rich mudstone, MF5: Massive mudstone, MF6: Massive peloidal wackestone, MF7: Skeletal peloidal packstone, MF8: Floatstone, MF9: Echinoderm bioclastic packstone, MF10: Bioclastic peloidal grainstone, and MF11: Microbialite.

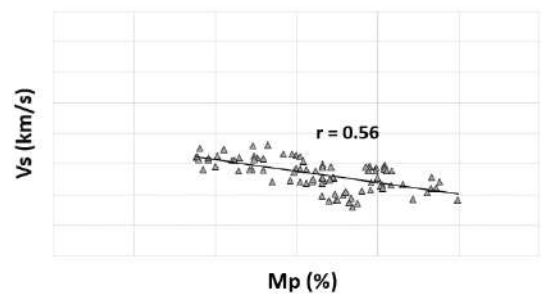
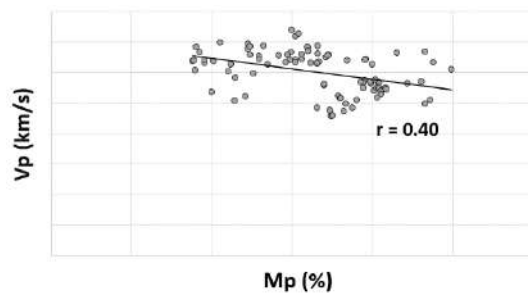
A



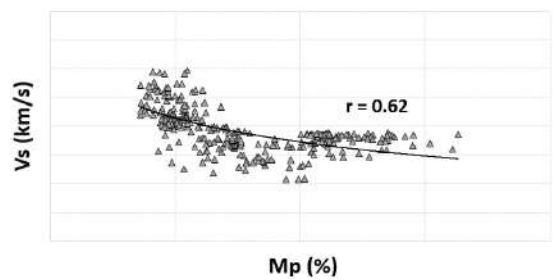
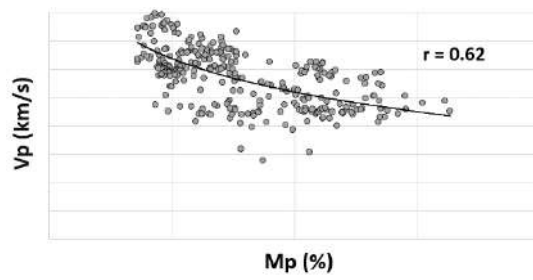
B



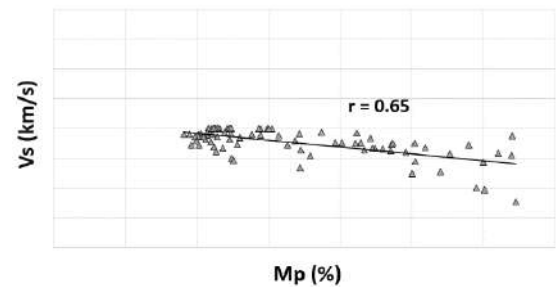
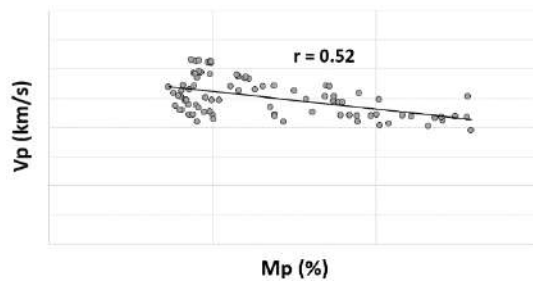
C



D



E



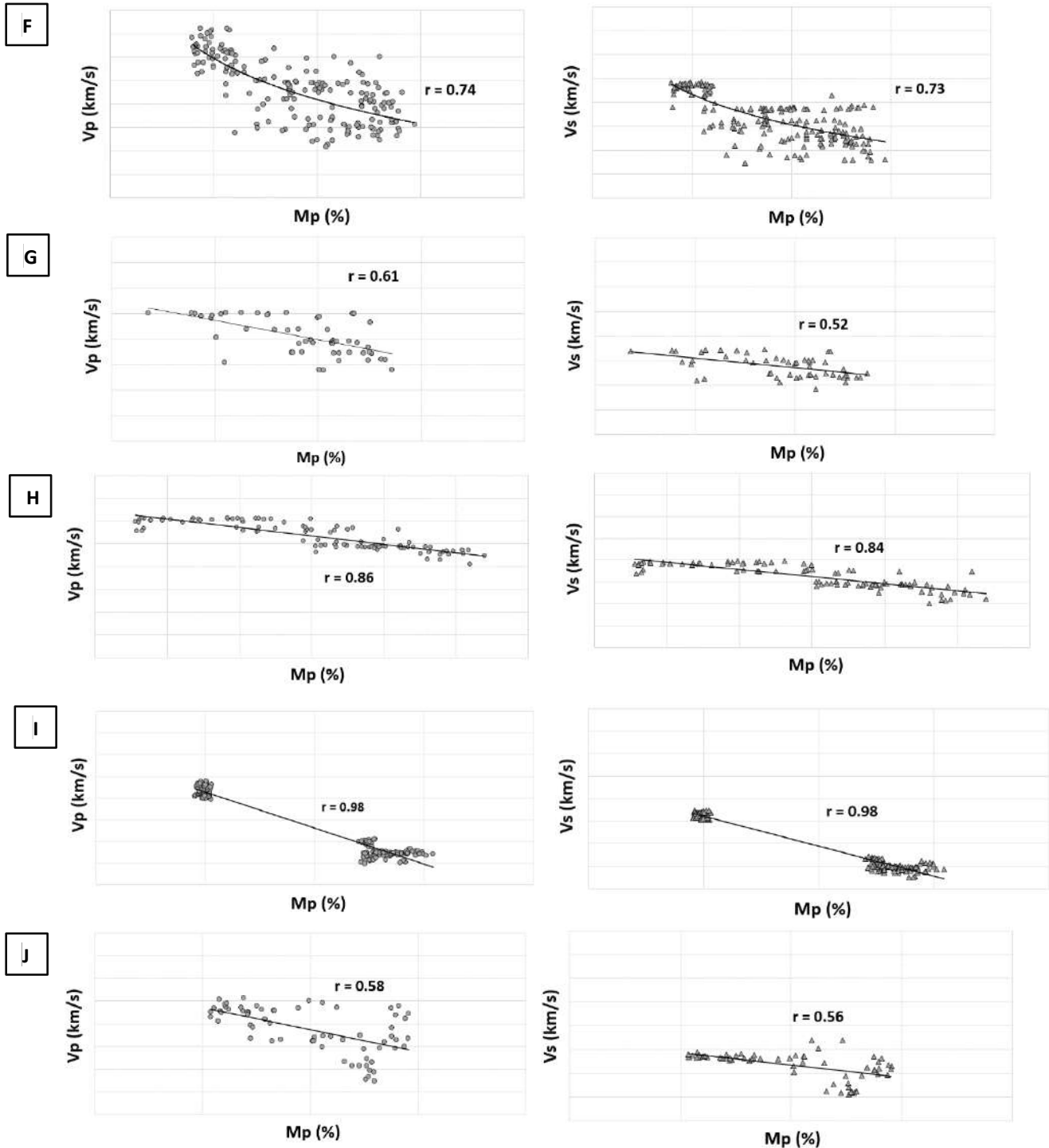


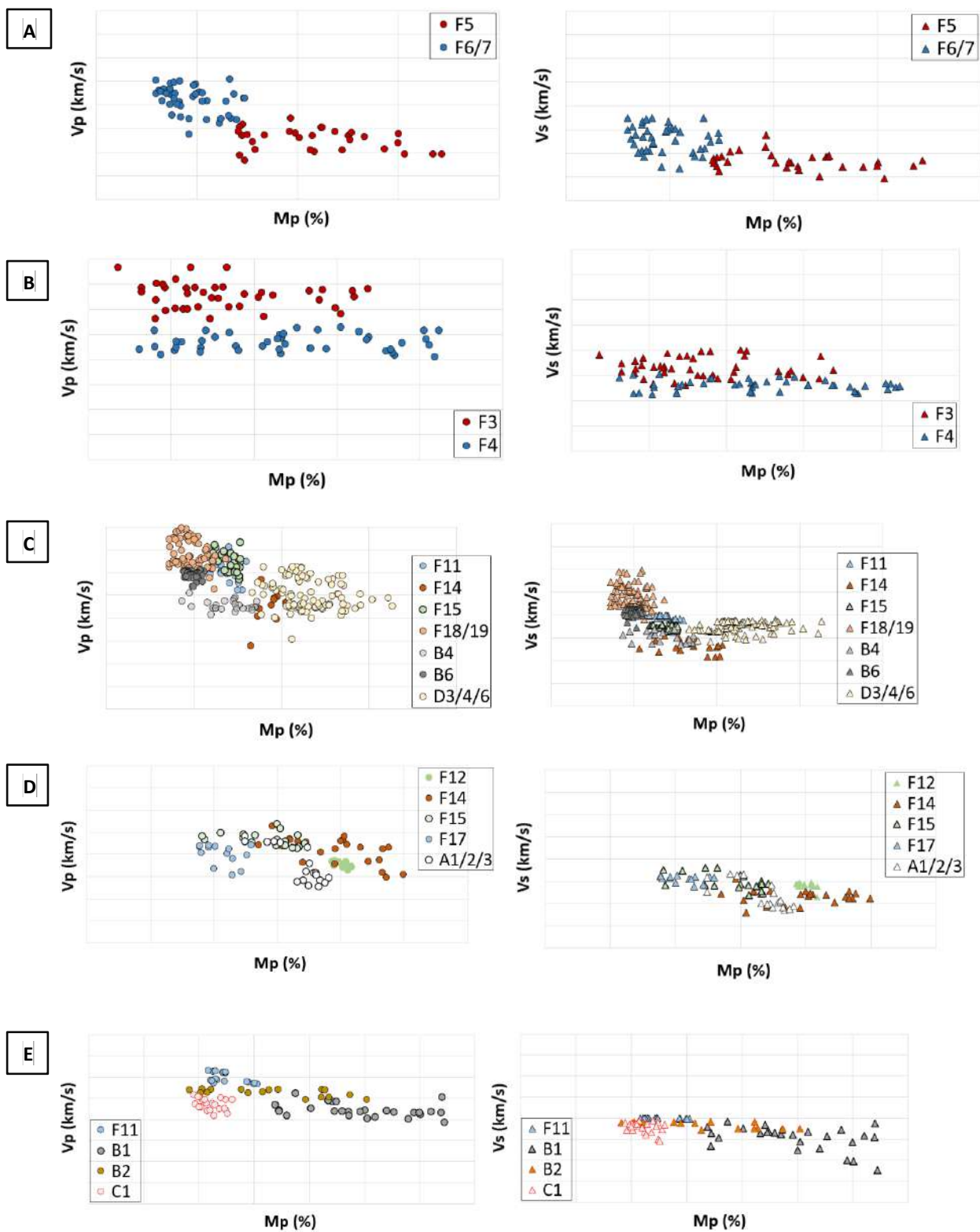
Figure 3.14. Control of microporosity (Mp%) in acoustic p-wave velocity (left) and s-wave velocity (right) in different microfacies, showing weak to fair inverse relationships. The velocity increases upward and the microporosity increases rightward. **A.** MF2, **B.** MF3, **C.** MF4, **D.** MF5, **E.** MF6, **F.** MF7, **G.** MF8, **H.** MF9, **I.** MF10, and **J.** MF11. Note that r values in **(I)** are not indicative and are affected by the two clusters (two samples) of MF10 (Figure 3.15). See Table 3.4 for detailed statistics of these plots.

Table 3.4. Summary of statistical parameters of p-wave (Vp) velocity, s-wave velocity (Vs), and microporosity of different microfacies. Note that individual samples of MF10 (C3/4 and D1) have shown CV of 0.04 (Vp) and 0.06 (Vs) for C3/4, and 0.03 (in both Vp and Vs) for D1 (Figure 3.15). Abbreviations: N (number of measurements), Min (minimum value), Max (maximum value), Avg (average), Med (median), SD (standard deviation), and CV (coefficient of variation).

Microfacies#	N	Vp (km/s)						Vs (km/s)						Microporosity (%)					
		Min.	Max.	Avg.	Med.	SD	CV	Min.	Max.	Avg.	Med.	SD	CV	Min.	Max.	Avg.	Med.	SD	CV
MF2	77	2.82	4.54	3.77	3.74	0.49	0.13	1.47	2.74	2.12	2.06	0.33	0.16	9.79	18.30	12.45	12.00	2.26	0.18
MF3	87	4.06	6.03	4.82	4.64	0.56	0.12	2.13	3.01	2.48	2.44	0.24	0.10	4.72	12.46	8.10	7.65	2.03	0.25
MF4	103	3.28	4.69	3.99	4.13	0.34	0.09	1.79	3.09	2.30	2.28	0.27	0.12	3.53	10.54	6.98	6.91	1.89	0.27
MF5	347	3.39	6.40	4.84	4.89	0.55	0.11	1.40	3.97	2.85	2.84	0.44	0.15	3.60	16.3	7.8	7.02	3.00	0.38
MF6	96	3.94	5.15	4.51	4.47	0.31	0.07	1.77	3.00	2.77	2.84	0.23	0.08	5.65	14.91	8.61	7.79	2.53	0.29
MF7	229	3.09	5.61	4.26	4.23	0.62	0.15	1.56	3.43	2.61	2.60	0.48	0.18	3.96	15.1	9.14	8.71	3.17	0.35
MF8	59	3.38	4.52	3.99	3.94	0.37	0.09	1.75	2.72	2.33	2.32	0.27	0.12	5.41	14.88	11.43	12.02	2.31	0.20
MF9	97	3.51	5.07	4.65	4.58	0.32	0.07	1.32	2.98	2.60	2.60	0.30	0.12	3.11	12.79	8.09	8.53	2.74	0.34
MF10	157	2.48	4.39	3.23	2.76	0.69	0.21	1.25	2.74	1.88	1.54	0.55	0.29	7.91	10.08	9.09	9.53	0.81	0.09
MF11	65	2.74	4.57	3.87	3.97	0.51	0.13	1.56	2.69	2.17	2.30	0.28	0.13	5.36	14.54	10.03	10.20	3.06	0.31

Fabric-preserving non-mimetic dolomite

This type tends to preserve the external feature of the parent grains and matrix and their distribution, along with the overall depositional textures of the host microfacies. However, the grains' internal features are highly affected by dolomitization, and thus, formation of fine dolomite crystals. This fabric was observed in MF2 and MF6, besides grainstones (MF3 and MF10), grain-dominated microfacies (MF7, MF8) and flotstone (MF8).



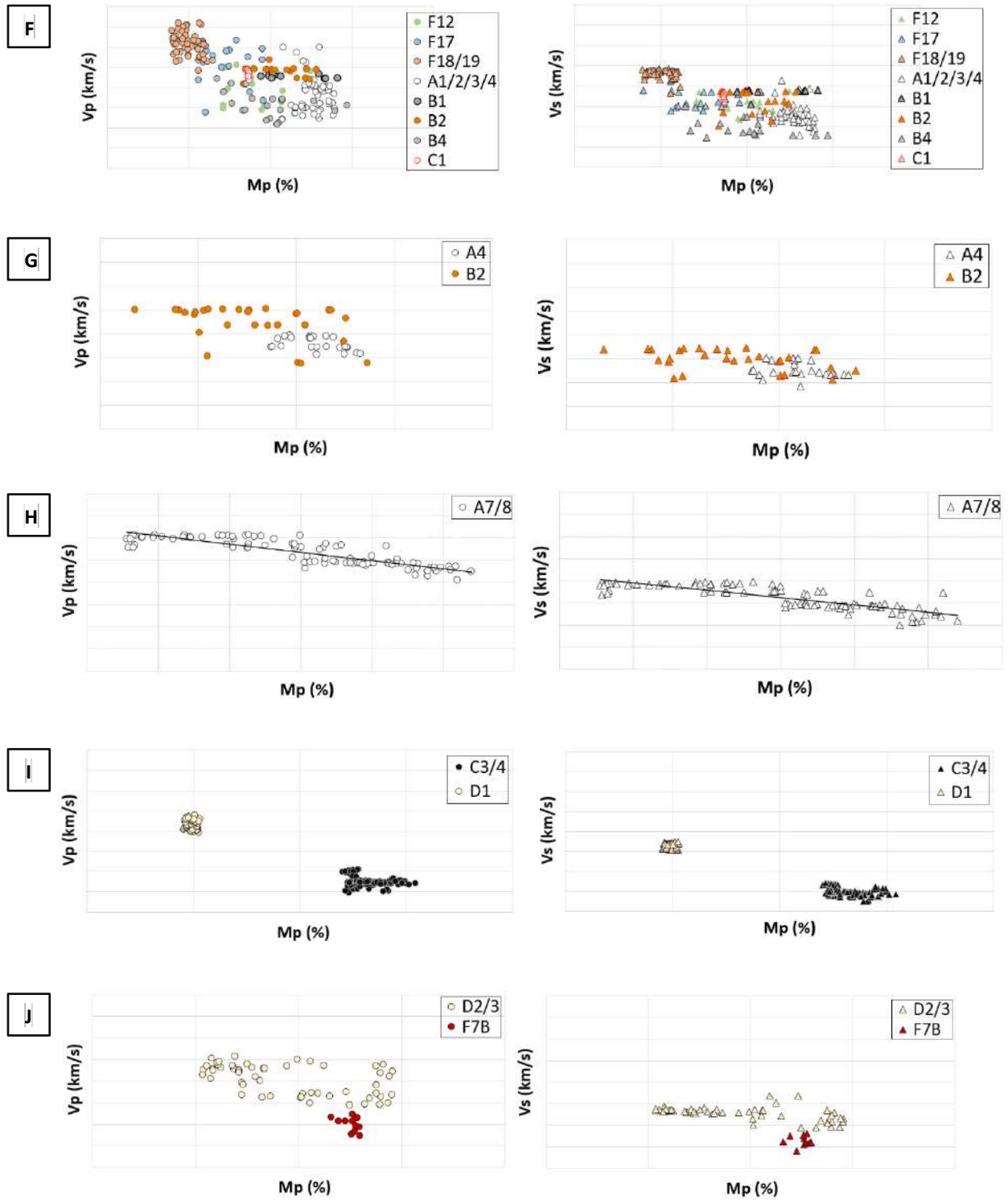


Figure 3.15. Acoustic velocity of p-wave (left) and s-wave (right) versus microporosity (Mp) for samples of different microfacies. Velocity increases upward and microporosity increases rightward. **A.** MF2, **B.** MF3, **C.** MF4, **D.** MF5, **E.** MF6, **F.** MF7, **G.** MF8, **H.** MF9, **I.** MF10, and **J.** MF11.

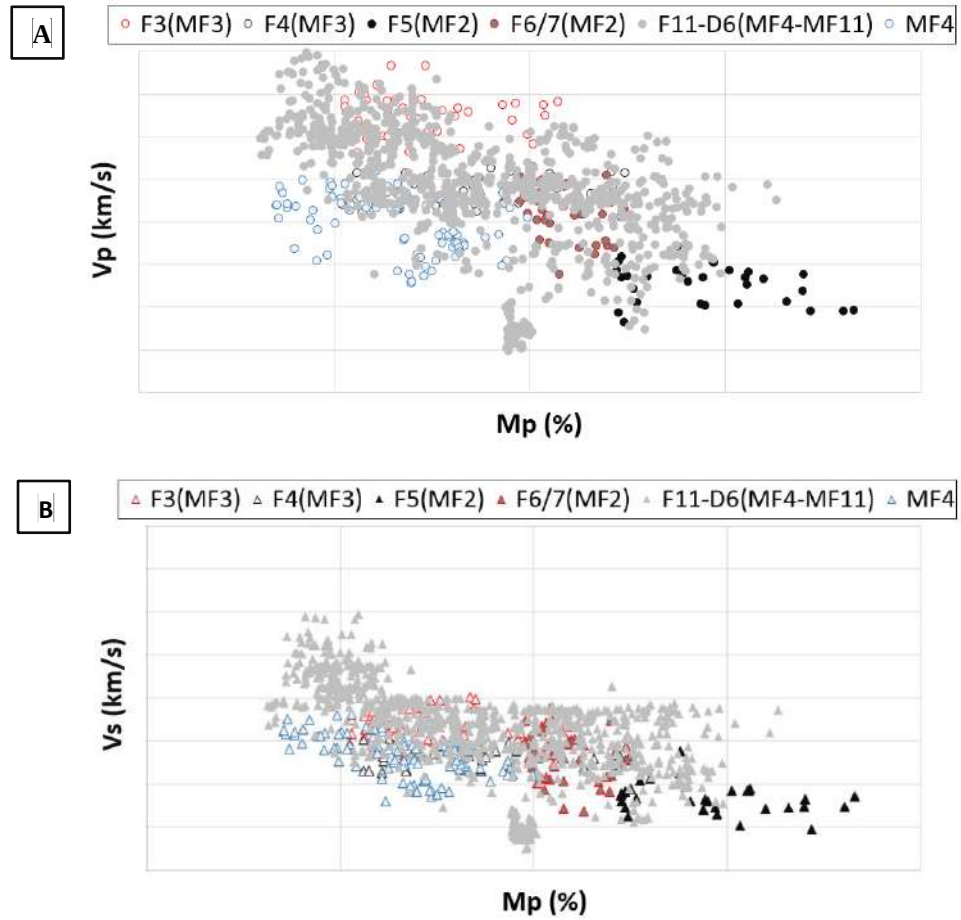


Figure 3.16. Control of mineralogy on the acoustic velocity of p-wave **(A)** and s-wave **(B)**. Velocity increases upward and microporosity increases rightward. The slabbed samples F3(MF3), F4(MF3), F5(MF2) and F6/7(MF2) are located at the upper part of the section (0-11.25 ft), where significant amount of dolomite occur (includes samples with more than 80% dolomite; Figure 3.11). The remaining microfacies and their samples, including MF4, are located between 14-30 ft (Figure 3.2), with higher calcite content (includes samples with more than 90% calcite; Figure 3.11). Note that MF4 also contains above 5% silicon (Si-content) and about 2% quartz and illite contents (Figures 3.8 and 3.11).

3.4.5 Factors Controlling Acoustic Velocity

Microporosity and permeability

In order to evaluate the impact of porosity on acoustic velocity, each of the acoustic p- and s-waves was plotted separately against microporosity in different microfacies (Figures 3.13 and 3.14). Due to poor correlation caused by extremely weak to no variation in permeability (around 0.1 mD), the impact of permeability on acoustic velocity was excluded. The microporosity-acoustic velocity relationships also validate the randomly generated microporosity, as the latter correlated to acoustic velocities with the best achievable reverse relationships as weak to moderate correlation coefficients (Figure 3.14). Three aspects of velocity variation were observed from these correlations. First, data points are clustered into groups for each microfacies to indicate general features such as composition and texture, with potential data overlaps between different microfacies (Figure 3.13). Other features impact individual microfacies data points, including fractures, organic content, intraclasts, and stylolitization (Figure 3.2). These features are responsible for the second and third aspects related to variations within the same microfacies and within the same sample, respectively. The third aspect is less important as it indicates the lowest porosity-velocity variation. Further, this aspect may reflect measurements at microfacies boundaries, particularly when thin laminae of different microfacies are adjacent and interlaminated with each other.

Microfacies

Microfacies and textural properties can potentially control acoustic velocity as they primarily influence other petrophysical properties, including porosity and

mineralogy. Velocity-porosity plots were used to understand the impact of different microfacies and textural constituents based on microporosity-velocity data scatter. Mudstones and mud-dominated microfacies such as massive mudstone (MF5) and massive peloidal wackestone (MF6) are genetically related. In general, MF5 has shown higher acoustic velocities than MF6 (Figure 3.13, Table 3.4). Velocity scatters in these microfacies within ≈ 3 km/s and a microporosity range of $\approx 13\%$ in MF5. Whereas MF6 showed a velocity range of ≈ 1 km/s for microporosity range of $\approx 9\%$. Grain-supported microfacies have a velocity range of ≈ 2.5 km/s and ≈ 1.5 km/s for skeletal peloidal packstone (MF7) and echinoderm bioclastic packstone (MF9), respectively, with ≈ 10 - 11% microporosity range. Floatstone (MF8) has also shown a velocity range of ≈ 1 km/s for around $\approx 9\%$ microporosity range. On the contrary, grainstones have a velocity range of ≈ 2 km/s for intraclast skeletal peloidal grainstone (MF3) and bioclastic peloidal grainstone (MF10), within a narrower microporosity range of $\approx 8\%$ and $\approx 2\%$, respectively. The acoustic velocity of microbialite (MF11) scatters within a range of ≈ 2 km/s for $\approx 9\%$ microporosity range, while organic-rich mudstone (MF4) showed a velocity range of ≈ 1 km/s for $\approx 7\%$ microporosity range (Figure 3.14, Table 3.4). Details of quantitative statistical analysis for microporosity and acoustic velocity were elaborated in Table 3.4. The coefficient of variation (CV) of velocity was used to indicate the scatter of data points for each microfacies (Table 3.4). Tackling p-wave (for instance), MF2 and MF5 have comparable CVs of 0.13 and 0.11, respectively. The same comparison was observed between organic-rich microfacies (MF4 and MF11) as 0.09 and 0.13, respectively. Grain-supported microfacies such as MF7 and MF9 (packstones) showed diverse CVs as 0.15 and

0.07, respectively. However, floatstone (MF8), which is supported by large skeletal allochems and mud intraclasts, has shown a comparable CV (0.09) to MF9. Grainstones showed the highest contrast in CV as 0.12 for MF3, and 0.04 and 0.03 for the two samples of MF10 (Table 3.4).

Mineralogy and elemental geochemistry

Porosity-velocity data points were grouped based on mineralogy and elemental geochemistry (Figure 3.16). In general, the data obtained from the upper part of the core section (0-11.25 ft) have shown higher dolomite content, with more than 60% of the total mineralogy; some samples of MF2 have revealed 80-90% dolomite content (Figures 3.11 and 3.12). This part of the section showed low acoustic velocities, more significantly in sample F5, rich in horizontal fractures (Figure 3.2). The dolomite content, boosted by Mg-content proxy (Figure 3.8), is responsible for the significant microporosity as noted through petrography and SEM (Figure 3.2). The lower part (14-30 ft) showed less dolomite content compared to calcite. In some samples, calcite content hits 90% and above, as noted in MF5, MF6, MF8, MF9, and MF10 (Figure 3.11). In grainstones and grain-dominated microfacies, calcite content frequently appears as blocky crystals that clog the available moldic and matrix pore spaces, resulting in higher velocities (Figures 3.3 and 3.16). Quartz and illite occurred in minor contents in the studied core section (Figure 3.11). Except for MF2, quartz is associated with illite in occurrence, strongly evident in MF4 and MF11(F7B). The impact of quartz appears higher in these microfacies compared to others, even though this content slightly exceeds 2%. Like the impact of dolomite, microfacies with quartz have witnessed reduced velocities at a given microporosity

compared to calcite-rich samples. However, the poor quartz and illite contents do not influence porosity as dolomite did; this behavior may be attributed to the fact that neither quartz nor illite was revealed via SEM. MF4 and MF11 were also rich in organic content, yielding velocity reduction. Accordingly, no conclusion could be reached regarding the exact impact of quartz and silicate (illite) on acoustic velocity. Strong relationships between Ca and Mg contents on one side and between Si, Al, and K contents on the other were indicated by reverse trends of Ca and Mg and nearly similar trends of Si, Al, and K contents (Figures 3.8 and 3.9). Mineralogy of the studied section also showed alternating behavior between dolomite and calcite, as indicated by the inverse relationship (Figure 3.11). Qemscan data conforms with XRD, indicating that calcite and dolomite are the prevailing minerals in the studied microfacies (Figure 3.12). While dolomite dominates in mudstone microfacies, calcite prevails in the grainstone and grain-supported microfacies such as MF3, MF10, and MF7. This result reflects the dominance of calcite cement encountered in petrography as blocky and equant calcite cement. In these microfacies, qemscan also revealed replacive dolomite encountered in their pellets (Figure 3.3).

Total organic content (TOC)

Total organic content (TOC) in the studied core section was identified as dark brown to black colored, irregularly thin laminated, possibly fragile, especially within stylolite surface, and mud-rich in texture (Figure 3.2). The organic-rich mudstone (MF4) and microbialite (MF11) exhibit nearly similar average velocities, with values of 3.99 km/s and 3.87 km/s for p-wave velocity and 2.30 km/s and 2.17 km/s

for s-wave velocity, respectively. These values fall below the overall average derived from all microfacies datasets, which stands at 4.31 km/s for p-wave velocity and 2.51 km/s for s-wave velocity (Table 3.4). Notably, MF4 and MF11 demonstrated comparable TOC, reflected in their closely matched acoustic velocities (Figure 3.13 and 3.18, Table 3.4). This observation denotes the impact of the TOC in reducing acoustic velocity, regardless of the heterogeneity of MF11 as interbedded/interlaminated skeletal components with the organic-rich laminae (Figures 3.2 and 3.3).

3.5. Discussion

3.5.1 General Discussion

Carbonate microfacies predominantly comprise calcite, dolomite, or a mixed spectrum of these minerals. These microfacies reflect different biochemical processes. However, many post-depositional processes are responsible for the developing and final characteristics in the paragenetic sequence, such as dissolution, cementation, recrystallization, fracturing, and stylolitization (Longman, 1980; Tucker and Bathurst, 2009; Moore and Wade, 2013). These features impact petrophysical properties such as acoustic velocity by controlling porosity evolution and general microfacies characteristics. Some of these diagenetic features were noted in the studied core section of the late Permian carbonate microfacies. The scale of investigation applied to these samples is finer than the borehole acoustic log and even the conventional plug scale. This study investigated acoustic p- and s-wave velocities in scales ranging between 2-8mm based on microfacies distribution,

thickness, and general sample setting. For instance, following the deep slab inspection, 2mm logging was applied on sample A2 due to the high-frequency microfacies variation, whereas 5mm and 8mm logging was used on samples F11 and C3/4, respectively, as less variation was observed (Figure 3.2). Such scale of investigation provides deeper insights about factors influencing acoustic velocity that were not previously handled in parallel studies, to the best of our knowledge. The core slabs generally exhibited weak to moderate inverse relationships between porosity and acoustic velocity. This inverse relationship is common in carbonate rocks, as noted in several previous works (Raymer et al., 1980; Anselmetti and Eberli, 1993; Anselmetti and Eberli, 1999; Eberli et al., 2003; Kenter et al., 2007; Baechle et al., 2008; Weger et al., 2009; Kleipool et al., 2015; Soete et al., 2015; Regnet et al., 2019; Teillet et al., 2020; Garia et al., 2021; Abdlmutalib et al., 2019; Salih et al., 2023). The weak relationship often reflects complex diagenetic overprint, such as intensive cementation and recrystallization, and is common in very fine microcrystalline microfacies such as mudstones and micrite (Choquette and Pray 1970; Moore and Wade, 2013). This study also indicated that the more microporosity occurs in microfacies, the less acoustic velocity propagates. Similar behavior was also documented in other studies in different carbonate settings (Anselmetti and Eberli, 1993; Eberli et al., 2003; Baechle et al., 2008; Anselmetti and Eberli, 2001; Salih et al., 2021).

3.5.2. Origin of Microporosity

Among different quantitative definitions of microporosity, it is defined as pores with an average diameter of less than 62.5 μm (Choquette and Pray, 1970). It was also defined as pores with diameters of 10 μm or less (Cantrell and Hagerty, 1999). Anselmetti and Eberti, 1999 definition of microporosity refers to optically non-resolvable pores (using an optical microscope); they assigned pore sizes less than 10-20 μm to this type of pores. All those definitions fit the current study. The studied core section is dominated by unimodal intercrystalline microporosity, with positively skewed pore sizes that rarely exceeded 5 μm in average and median values (Table 3.2, Figure 3.6). Thin sections petrography revealed no optically resolvable porosity, except fenestral pores (MF10), which were also noted in the polished slabs. Different formation mechanisms of microporosity were previously elaborated (Pittman, 1971; Bathurst, 1975; Wardlaw, 1976; Cantrell and Hagerty, 1999). These mechanisms include 1- leaching and partial reprecipitation of metastable carbonates such as aragonite and high Mg-calcite (particularity in micritized grains), 2- Inhibition contact against crystal growth, 3- Endolithic boring of grains due to algae and fungi activities in the grains, followed by micrite infill, and 4- Incipient weathering and dissolution. These mechanisms imply that ancient microporosity, such as the late Permian carbonates, occurs due to diagenetic or syn-depositional processes. Among these mechanisms, the reprecipitation of metastable carbonates was noted as the prevailing mechanism in the upper part of the studied section. The evaporitic cab on top of the studied core section represents the source of Mg-rich fluids required for dolomitization (Moore and Druckman, 1981; Cantrell

and Hagerty, 1999). Consequently, partial reprecipitation of Mg-calcite and dolomite is common in the upper part of the section, dominated by naturally-fractured dolomitic mudstone (MF2) (Figure 3.2). This mechanism more likely contributes to controlling microporosity related to dolomite and low Mg-calcite contents in different microfacies including grainstones, such as MF3, MF4, and MF5. On the contrary, the matrix microporosity in all microfacies has developed through crystal growth inhibition in their cemented matrices (Wardlaw, 1976; Cantrell and Hagerty, 1999). No evidence was detected for endolithic boring or incipient weathering and dissolution in the studied carbonate section.

3.5.3. Controls on the Acoustic Velocity

Microfacies characteristics

Although fair microporosity was reported (3-18%; Table 3.2), the investigation exhibited a weak to no relationship between microporosity and permeability in all microfacies. This was attributed to the dominant and unimodal pore type in all microfacies; the interparticle micro-pores, with an average pore size of less than 5 μm , prevailed throughout the studied section (Table 3.2, Figures 3.4 and 3.6). Similar results were also noted in selected microfacies, including organic-rich mudstone (MF4), intraclast skeletal peloidal grainstone (MF3), and thinly-laminated microbialite (MF11) (Abdelkarim and Makkawi, 2022). Apart from intercrystalline microporosity, the cumulative porosity contribution of fenestral and fracture macroporosity observed in C3/4 (MF10) and F5 (MF2) was around 1.0% (Figures 3.2 and 3). Unlike fractures, fenestral macro-pores do not contribute to the permeability, as 0.1 mD nitrogen permeability was recorded in all microfacies, including MF10

(Figure 3.7; Table 3.3). The positive skewness of pore and crystal sizes (average>median) noted in all microfacies may also explain the poor permeability; however, microporosity has shown less positive skewness, i.e., nearly normal distribution (Table 3.2). Accordingly, median values were better representative of crystal and pore sizes than average values (Figure 3.6). Herein, fair relationships were reported between median values of pore and crystal sizes in mudstones and mud-dominated microfacies (MF2, MF4, MF5, MF11, and MF6), and grainstones and floatstones as well (MF3, MF10, and MF8). However, packstones (MF7 and MF9) exhibited no relationship, while MF7 showed a better reverse relationship without MF9. Yet, it is worth mentioning that the data limitation in MF9, MF8, MF2, and MF11 may impact some of these relationships (Table 3.2, Figure 3.6). Nevertheless, poor to no relationship between pore and crystal sizes was attained against microporosity. This situation implies that intensive cementation and tightness of the studied microfacies have yielded unpredictable microporosity, regardless of microfacies. For a given microporosity, the microfacies homogeneity has an impact on increasing acoustic velocity in microfacies with comparable texture and microporosity (e.g., MF5 and MF6). With increasing grain content (skeletal and non-skeletal) in packstones (MF7 and MF9), velocity tends to decrease (Figure 3.13, Table 3.4). Reasonably, reduced velocities were recorded in the poorly-sorted grainstone (MF10) and floatstone (MF8) (Figure 3.13). Grainstone microfacies have shown different behaviors depending on the occurrence of mud intraclasts, fractures, and sorting. MF10 has a low coefficient of variation (CV) in acoustic velocities for individual samples (C3/4 and D1), although its microporosity

values were distributed within the range of the well-sorted MF3 (Table 3.4). However, the latter showed higher CV due to the velocity distortion caused by the possible impact of fractures (even if found locally and partially open; Figure 3.2) and various poorly-sorted components such as intraclasts and evaporites nodules. For a given microporosity, MF3 has the highest acoustic velocity among grainstones and grain-supported microfacies due to intensive calcite cementation and better grain sorting, with the lowest velocities around 4.0 km/s (Figure 3.13, Table 3.4). MF3 is essentially composed of well-sorted pellets and skeletal grains (mainly bivalves), with equant matrix calcite cement (Figure 3.12), and moderately-sorted mud intraclasts occurred mainly at the middle part (F3), and fewer at the lower part of the slab (F4) (Figure 3.2). Fractures associated with F4 yielded reduced velocities than F3, which contains more intraclasts (Figure 3.15). Such impact of sorting has also appeared within MF10. MF10(D1) is finer and well-sorted grainstone that acquired higher velocities than MF10(C3/4) (Figure 3.15); the latter is moderately- to poorly-sorted with various-sized mud intraclasts (Figures 3.2 and 3.12). Another comparable CV was also observed in other poorly-sorted microfacies, such as MF8 and MF9 (Table 3.4). However, the impact of fractures and poor sorting is less in these microfacies compared to MF3. Similarly, MF7 has shown a high CV in acoustic velocities due to the impact of fractures penetrating it in different samples (Figure 3.2). MF7 is interactive with other microfacies such as MF5. These two microfacies occasionally occurred adjacent and interbedded/interlaminated with each other in thin layers (Figure 3.2). This situation may produce some uncertainty in having independent acoustic measurements for each of MF7 and MF5. This

situation may also stand behind the little higher CV in MF5 than other mudstones and wackestones, such as MF4 and MF6, respectively (Table 3.4). This investigation indicates that fractures produce low velocities, regardless of fracture scale and microfacies texture (Schoenberg, 1980; Hudson, 1981). However, closed or cemented (filled) fractures often maintain host rock velocity without a significant drop in acoustic velocity (Anselmetti and Eberli, 2001).

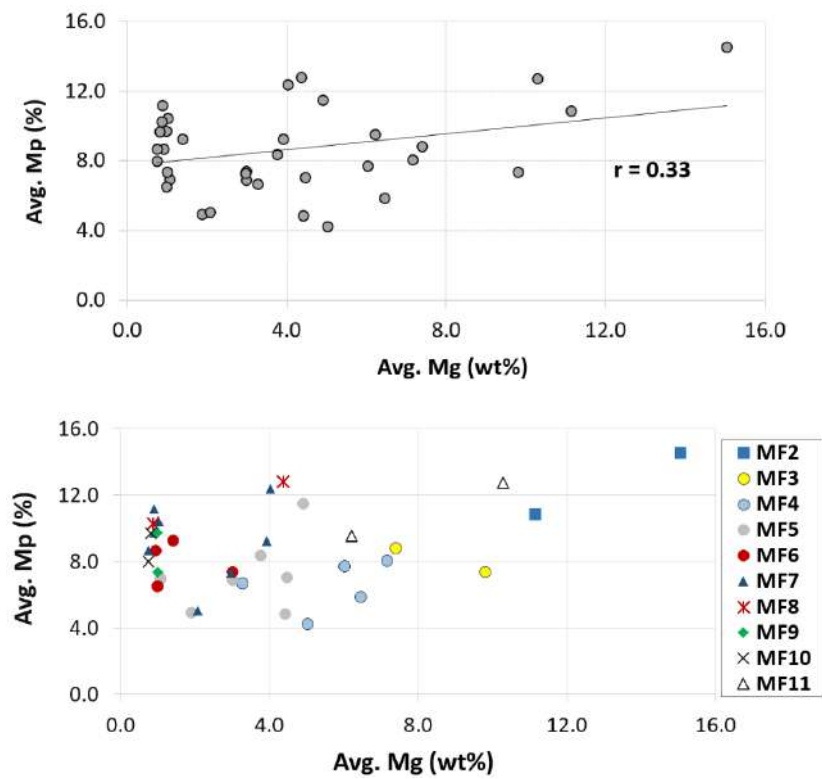


Figure 3.17. The impact of Mg-content on microporosity in different microfacies. Note the impact is more considerable in the dolomitic mudstone (MF2) located at the upper part of the section (0-11.25 ft). Comparable Mg-content was also noted in samples F3(MF3) and F7B(MF11) located at the same interval.

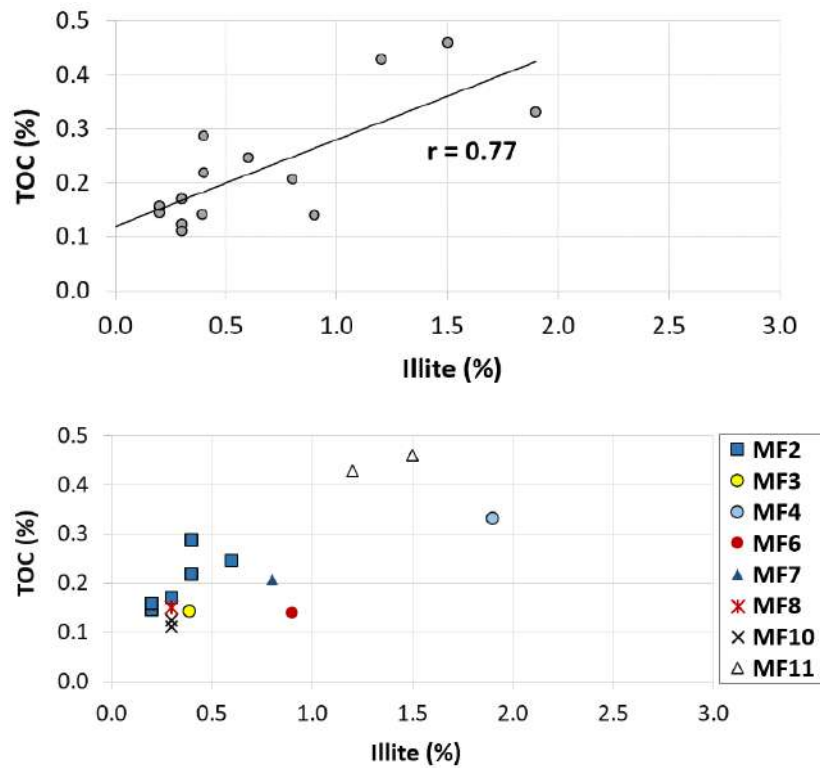


Figure 3.18. Illite content vs. TOC of representative microfacies, including organic-rich ones (MF4 and MF11). Note the good direct proportional correlation, with the higher contents in MF4 and MF11 compared to other microfacies.

Mineralogy and elemental geochemistry

Carbonate minerals have comparable grain densities (2.71 g/cm^3 for calcite and 2.87 g/cm^3 for dolomite). Accordingly, a slight variation in acoustic properties was also noted in consolidated carbonates over a wide range of porosity (V_p/V_s equals 1.9 for limestone and 1.8 for dolomite) (Pickett, 1963). The current results showed that V_p/V_s ratio for all studied microfacies ranges between 1.6 and 1.9, as these microfacies are influenced by mixed mineralogy of dolomite and calcite (Figures 3.11 and 3.12). This situation implies that

variation in acoustic velocity based on bare mineralogy is potentially misleading. The dolomites encountered in the core samples range from mimetic to non-mimetic fabric-preserving dolomite. Some previous studies in the late Permian interval and its regional equivalent revealed prevailing fabric-destructive dolomites, representing potentially porous reservoir units (Rahimpour-Bonab et al., 2010; Al-Qattan and Budd, 2017). The fabric-destructive dolomite is characterized by coarser and well-developed rhombohedral crystals than other dolomite fabrics. The current study showed rare dolomite rhombs and no fabric-destructive dolomitization. Using XRF elemental data as a proxy for mineralogy provided good results in this study, as confirmed by XRD data. Good examples come from Mg and Si contents, which provide proxies for dolomite and illite in MF2 and MF4, respectively (Figures 3.9 and 3.12). Other studies have used elemental proxies and provided decent insights into mineralogy (e.g., Machado et al., 2019; Kim et al., 2021; Hussain and Al-Ramadan, 2022; Fabre et al., 2022). In addition, XRF was used as supplementary data to detect the boundary between the upper and the lower parts of the core. The data shows that Ca-content increases from sample F7B (≈ 11.25 ft) downwards to the bottom of the cored interval, compared to overlain samples, besides a slight drop in S-content and a noticeable drop in Mg-content. Al-Qattan and Budd 2017 also concluded that mudstone-rich microfacies such as barren mudstone, witnessed more dolomitization than grainy-rich microfacies such as shoal grainstone. Moreover, the XRF map was able to pick the smaller scale boundaries between laminae, showing high Mg-content in MF4 compared to the interlaminated MF5 and MF7, which revealed higher Ca-content (Figure 3.10). The richness and strong inverse relationship of Ca and Mg contents (Figures 3.8, 3.9, and 3.10) indicate the influence of these elements and the dominance of calcite and dolomite as observed in

XRD (Figure 3.11). The dominant Ca in all samples compared to other elements (Figure 3.8) is attributed not only to the calcite content dominating the samples between 14-30 ft but also to the Ca-content in both calcite and dolomite in their chemical formulas. Consequently, sample F7B is considered a potential boundary between limestone-rich downward and dolomite-rich microfacies upward (Figures 3.11 and 3.19). The S and Mg contents that distinguish the upper part of the section are indicators of dolomite crystallization due to hypersaline water related to precipitation of the overlain evaporites as an intraformational seal (Sperber et al., 1984; Rahimpour-Bonab et al., 2010; Al-Qattan and Budd, 2017). The reverse relationship between dolomite content and low Mg-calcite was documented in (Anselmetti and Eberli, 2001). The current study also recorded a similar relationship as elemental geochemistry has shown high Mg-content often accompanied by high dolomite content (e.g., in MF2; Figures 3.8 and 3.11) or particularly poorly-ordered dolomite (Figure 3.12). This assumption is enhanced by the rare existence of dolomite rhombs in all studied microfacies, including MF2. Although Si, Al, and K contents are minimal, they showed strong direct relationships (Figures 3.8 and 3.9). Microfacies with relatively notable amount of quartz and illite; which is *a mica-phyllsilicate mineral: (K,H3O) (Al,Mg,Fe) 2(Si,Al) 4O10[(OH) 2,(H2O)]*, such as MF4 and MF11/F7B, have also shown acoustic velocities lower than other microfacies at a given porosity (Figures 3.11 and 3.13). Even with the minor content of quartz observed in MF4 and MF2 (around 2%), a similar impact on acoustic velocity was previously observed in other samples, but with a bit higher quartz content (10-40%) (Salih et al., 2021). This result may indicate that illite in the current data contributes more to reducing velocity in MF4 and MF11 than quartz. However, illite is associated with organic-rich microfacies such as MF4 and MF11 (Figure 3.18). Due to less organic content,

comparable illite contents were observed in other microfacies without disturbing their acoustic velocities (e.g., MF5 in Figures 3.11 and 13). The relationship between elemental content and microporosity showed that the latter is more likely controlled and enhanced by dolomite content, and thus Mg-content, compared to other minerals and elements (Figures 3.16 and 3.17) (Baechle et al., 2008; Fournier et al., 2018; Salih et al., 2023). This impact was obvious at the upper part of the section (0-11.25 ft), where Mg-content (a proxy for dolomite) was notable not only in MF2, but also in samples F3 and F7B of MF3 and MF11, respectively (Figure 3.17).

TOC and stylolitization

TOC has shown a direct relationship with illite content, implying that clay-rich microfacies such as MF4 and MF11 have host higher contents of organic matter compared to other microfacies (Figure 3.18). The relationship between illite occurrence and organic-rich mudstones is well-documented (e.g., Tissot and Welte, 2013; Xia et al., 2019; Abubakar et al., 2022). Due to the low density of organic matter compared to the host rock, these microfacies showed slower acoustic velocities than other mudstones and mud-dominated microfacies (Figure 3.13) (Passey et al., 1990; Eberli et al., 2003; Abdelkarim and Makkawi, 2022). Stylolites form as a concentration of insoluble materials due to pressure dissolution, which also causes a reduction in bed thickness and hence, porosity (Ehrenberg et al., 2016). In this study, these compressional structures occurred parallel to sub-parallel to the bedding and were not diagnostic for specific microfacies. Except for F7 and F7B, no stylolites were encountered at the upper part of the section where dolomite dominates (0-11.25 ft). They occurred in the rest of the section (14-30 ft), which has more calcite content. Such mineralogy control on stylolitization was also documented (Choquette and Steinen, 1980;

Peacock and Azzam, 2006), where stylolites were more frequent in limestones than dolomites. Certainly, five stylolites were picked, in MF2 (F7), MF11 (F7B), MF7 (F17), MF6 (B2) and MF5/11 (D3). Other delicate stylolites in thin section scale were hard to detect on the slab, e.g., MF9 (A7) and MF7/5 (B4) (Figure 3.2). Like the organic-rich microfacies, stylolites are often associated with black, solid organic matter. This organic content occurs within the dissolution surface (i.e., within stylolite as in the current study) and rarely in its vicinity. Other studies also highlighted this observation in carbonate (Alsharhan and Sadd, 2000; Flügel and Munnecke, 2010; Ehrenberg et al., 2016). Also, some stylolites coexist with fractures or intraclasts that may act together to yield reduction and distortion in velocity-microporosity data points, such as MF7/5 (B4) and MF7 (F17) (Figures 3.13 and 3.15). Some high amplitude stylolites, such as MF5/11 (D3), have a vertical component that may also yield distortion in acoustic velocity due to imposed lateral microfacies variation (Figures 3.2 and 3.15). In addition, these surfaces are not diagnostic for specific microfacies, and they indicate compaction, recrystallization, and cementation that may all contribute to porosity reduction in the whole section. For these reasons and the limited occurrence and thickness of organic-rich stylolites in the studied core section, their impact on acoustic velocity is believed to be limited.

3.5.4. Integration with Wireline Logs

SEM visually-estimated microporosity has shown better agreement with density-porosity compared to neutron-porosity and coupled neutron-density (ND) porosity (Figure 3.5). However, the later has shown the best relationship with SEM microporosity in (Abdelkarim and Makkawi, 2022), due to the limited microfacies and data used previously. ND logs provided a general calcite-dolomite segregation. In the absence of gas content, the overlay

of these logs indicates limestone occurrence, whereas the more dolomite exists, the more positive separation occurs (strong shots in ND logs). However, gas content in the reservoir triggers minor neutron shots than oil and water (Glover, 2000). Tying these logs with core observation implies that dolomitization (and thus Mg-content) was prominent in the dolomitic mudstone (MF2) (0-11.25 ft), compared to the Ca-rich lower part (11-30 ft). This observation was also inferred from XRD and mineral micro-maps (qemscan) (Figures 3.11 and 3.12) and also by XRF mineralogy proxy (Figure 3.8). The unexpected, relatively slight separation at the upper part of the core is attributed to the gas content observed in the master log of well-X (total gas above 1%), which led to N-porosity underestimation (Figure 3.19). In contrary, SEM, petrography, and high-resolution images exhibited the best porosity and permeability at the upper part due to higher dolomite and natural fracture contents (Figures 3.2 and 3.3). Compared to the upper part, the wider separation encountered at around 12-16ft resulted from NPHI, which was affected by a notable drop in gas content (less than 0.5%) (Figure 3.19). The borehole acoustic logs have revealed slowness at the upper part where fractures dominate, such low velocity was also noted in F5(MF2). On the contrary, the lowermost part dominated by calcite (as inferred from XRD, XRF, and nearly overlapping ND logs), shows a steady velocity increase with the overall absence of fractures and washout (Figures 3.2 and 3.19). However, there was some ambiguity concerning the acoustic log at the top of the section as an unpredicted less slowness was observed with the occurrence of fractures and potential gas shows. This behavior may be attributed to the borehole conditions leading to local diameter anisotropy (wider hole diameter in one direction) as indicated by the multi-arm (directional) caliper tool of the diameter log, which is related to significant fracture damaging this part (Figure 3.19). Unlike neutron and density

tools which have adjusting arms to keep it wall-stick, such bad hole conditions may lead to eccentricity (tilt) of acoustic tool, leaving ambiguous velocity readings (Glover, 2000; Ellis and Singer, 2007). Besides, this fractured zone also includes un-fractured microfacies (MF3), which can maintain less slowness (higher velocity) (Figure 3.19). The wireline logs have also revealed compatible Ca, Si, and Al trends, besides higher S-content at the top of the section related to the evaporite cap. In addition, iron (Fe-content) was also logged at the upper part, associated with dolomite content (Figure 3.19). These results agree with elemental XRF (Figures 3.8 and 3.9), XRD results (Figure 3.11), and qemscan results (Figure 3.12). Calcite and dolomite mix may stand behind the photoelectric absorption index log (PEFZ) that exceeded the log scale (Figure 3.19), hitting 10 barns/electron as inferred from the wireline LAS file. Another potential cause for the high PEFZ may also attributed to the occurrence of iron (Fe) with dolomite (Figure 3.19). This conclusion is incurred from the fact that PEFZ is a function of the atomic number of rock components, while pore fluids (if any) have a minimal PEFZ (Glover, 2000; Ellis and Singer, 2007). The compatibility of high PEFZ with XRF and XRD results confirms that the studied section represents unconventional carbonates, occupied by intercrystalline microporous and extremely low permeable tight microfacies.

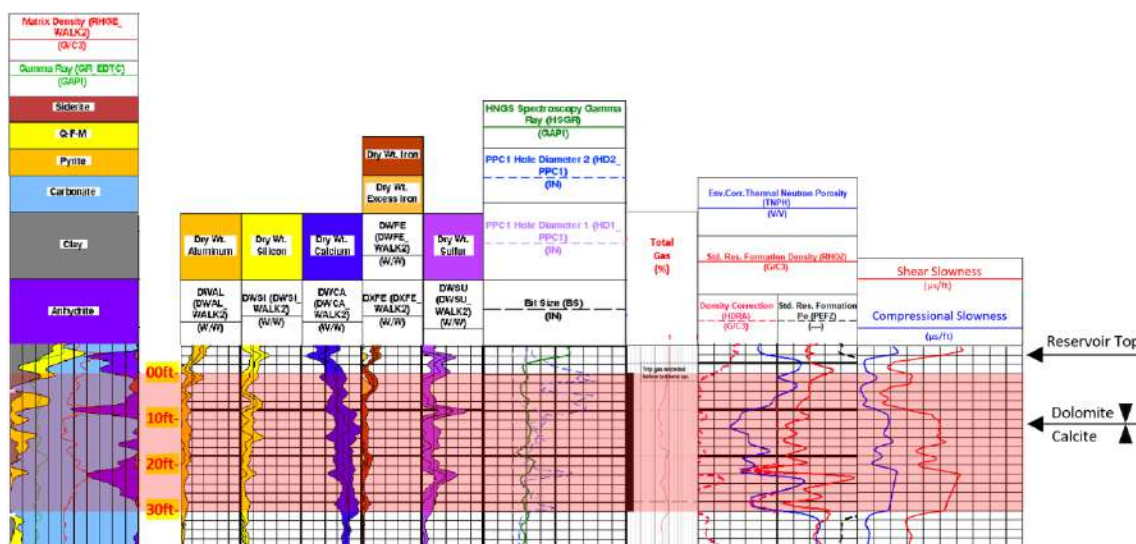


Figure 3.19. Borehole data obtained from wireline and master logs of Well-X, showing lithology of the studied core section (indicated by the red shade). The data include relative elemental weights, GR, caliper, total gas, neutron, density, photoelectric index, and acoustic slowness ($1/V_p$ and $1/V_s$) (no scale). GR positive shots are related to clay content (illite as confirmed by XRD) at the upper part compared to the remaining core section. Note the reverse trends of calcium against silicon and aluminum curves. The approximate boundary between dolomite-rich and calcite-rich parts was allocated with the integrating XRD and micro-XRF data. The reservoir top was allocated using integrative master log and wireline log data. Directional multi-arm caliper indicates diameter anisotropy due to fractures at the upper part. The large diameter in one direction and the divergent neutron-density logs indicate the dominance of dolomite (≈ 0 -12ft) with potential gas shows. Below this, the lower density and higher neutron zone indicates less dolomite and more calcite ratio with less gas content.

CHAPTER 4

GEOSTATISTICAL MODELING OF THE PERMO- TRIASSIC CARBONATES

4.1 Introduction

In the early stages of oil and gas field-scale exploration, geoscientists use seismic reflection to have the first impression of basin structure, large-scale stratigraphy, and potential hydrocarbon entrapments. A tool such as geostatistics may provide valuable insights about the exploration when limited and costly well data are available. Such approach is favorable for large-scale exploration, especially when pre-existing geological knowledge about the platform is helpful. The Rub' Al-Khali Basin extends beneath the enormous sand sea spread in the southern and southeastern areas of Saudi Arabia, covering approximately 300,000 square kilometers (Figure 4.1) (Soliman and Al Shamlan, 1982; Stewart et al., 2016). This basin holds a complete Phanerozoic record, including the Permo-Triassic carbonates which are prolific in Saudi Arabia and elsewhere across the region (Lindsay et al., 2006; Alsharhan, 2014). During the Permo-Triassic, the Arabian Platform was primarily dominated by carbonates and evaporites deposition (Figure 1.2). Only a small amount of siliciclastics was present, found in a limited geographic territory and acting as a border on the landward side of the western platform edge (Konert et al., 2001). The layers of the Permo-Triassic succession are rich in dolomites, limestones, and evaporites spread over the gentle slopes of the basin. The thickness increases towards the northeast and pinches out southwestward. On a large scale, the structure of this Permo-Triassic platform gradually builds upward with

some slight overlaps and thinning out of layers. The slope of the platform is extremely gentle, tilting at an angle between 0.01° and 0.001° . This epeiric platform architecture indicates a very slight slope, which means even small changes in sea level can trigger the shoreline and, thus, wave base to spread across large distances (Van Oosterhout and Pöppelreite, 2014; Aigner and Pöppelreiter, 2011). This unique platform morphology was favorable for the broad deposition of carbonate belts extending regionally (Al-Jallal, 1995; Al-Aswad, 1997; Alsharhan, 2006). The world is currently passing through an energy-transition era, from fossil energy toward clean energy. In this era, less-emission resources such as natural gas are important (Song et al., 2020; Szymczak, 2021; Williams et al., 2021). The recoverable natural gas in the giant North Field of Qatar was approximated at 900 tcf as the region's most prolific late Permian- early Triassic interval (Pöppelreiter and Marshall, 2013). The expanded area of the late Permian platform of the Arabian shelf is unique in all basins related to the Pangaea break-up and Neo-Tethys opening (Van Oosterhout and Pöppelreite, 2014). Around $3.7 \times 10^6 \text{ km}^2$ is the area covered by the Permo-Triassic epicontinental platform, most of which is located in Saudi Arabia. However, this resource is less exploited in Saudi Arabia. Such situation makes the Permo-Triassic succession a potential target for gas exploration in Saudi Arabia. In the exploration and production (E&P), three-dimensional (3D) reservoir models are commonly employed for various purposes to facilitate decisions based on their value. A significant challenge in crafting these 3D reservoir models lies in accurately allocating the recognized facies and their corresponding attributes within the established 3D structural and stratigraphic framework, honoring geological insights and existing well data. To achieve this, various geostatistical approaches are employed, each with its unique set of inputs and foundational assumptions. Predominantly, studies focused on reservoir

characterization rely on variogram-based methods in geostatistical modeling to effectively and precisely capture the complexities of reservoir heterogeneity (McKinley et al., 2004; Caers, 2005; Orellana et al., 2014). The outcomes of simulations derived from these methods are greatly influenced by the data availability, the choice of variogram model, and the geomodeler's expertise in geostatistics and geological understanding (Orellana et al., 2014; Gringarten and Deutsch, 1999). This research aims to evaluate the large-scale variability in the late Permian - early Triassic carbonate properties in the northern part of Rub' Al-Khali Basin, southcentral Saudi Arabia (Figure 4.1). Such investigation is believed to provide a cost-efficient lateral exploration approach for carbonate properties in the epeiric, gentle dipping carbonate ramps. In this context, coupling the lateral variability model with geological insight into the depositional setting would help for better decisions.

4.2 Data and Methods

4.2.1 Data

Conventional well-log data from six vertical wells were used in this study (Table 4.1). These wells are distributed in two nearly perpendicular traverses. One traverse runs parallel to the general platform strike (NNW-SSE), while the other traverse runs parallel to the dip direction of the Arabian Platform (ENE-WSW) (Figure 4.2). The conventional well-logs data included gamma ray, elemental spectroscopy (ECS), deep resistivity (LLD), and RHOB. The ECS data covered the common elements forming carbonates and evaporites (Ca and S), besides quartz and silicate (clay) elements such as Si and Al. The elemental data were used in collaboration with mud logging data for mineralogy identification of the late Permian-early Triassic strata.

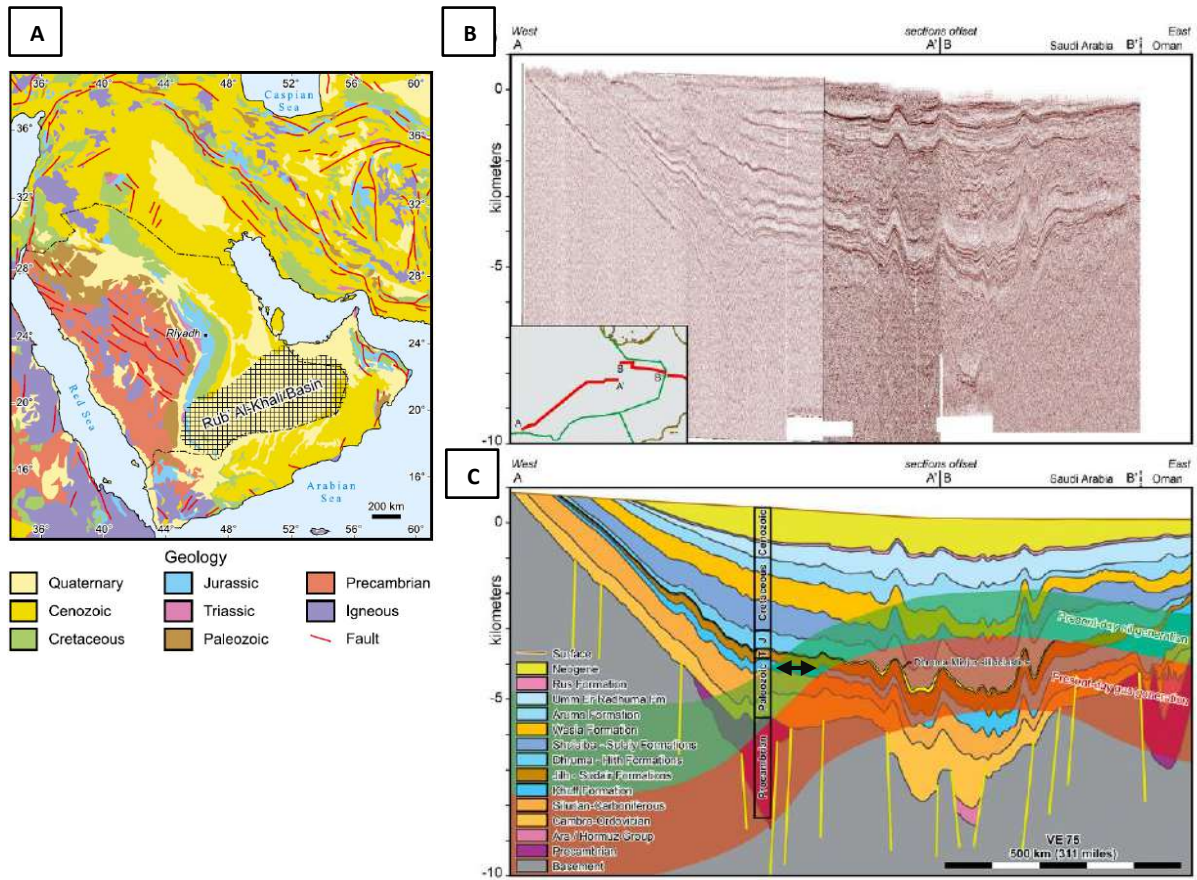


Figure 4.1. Geography and subsurface succession of the Rub' Al-Khali Basin. **A.** Geographic extension of the Rub' Al-Khali desert in southern and southeastern Saudi Arabia. The enormous sand sea blankets the Phanerozoic strata that are exposed in different areas in the western Arabian Platform. **B.** Compiled regional seismic profiles along the general dip direction of the Arabian Platform. **C.** Interpreted Phanerozoic strata from **(B)** (modified from Stewart et al., 2016). The two-headed arrow (roughly 210km) in **(C)** indicates the nearly E-W extension of the modeled area (Figure 4.2A).

Table 4.1. Well-logs used for semivariogram construction and 3D modeling.

Well-log	M1	M2	M3	H	A	S
Ca (w/w)	✓	✓	✓	✓	✓	x
Si (w/w)	✓	✓	✓	✓	✓	x
S (w/w)	✓	✓	✓	✓	✓	x
Density (g/cm ³)	✓	✓	✓	✓	✓	✓
GR (API)	✓	✓	✓	✓	✓	✓
Resistivity LLD (ohm.m)	✓	✓	✓	✓	✓	✓

4.2.2 Methods

Well-log interpretation

Borehole logs provide valuable information about the lithology, porosity, and fluid content (Ellis and Singer, 2007). The carbonate reservoir is composed of limestone, dolomite, or mix. Besides, evaporite minerals may also form a significant fraction of the succession, impacting the reservoir quality. Detrital sediments composed of quartz and clay minerals occur in minor content, significantly in the inner shelf lagoon and outer shelf open marine setting. The following is a summary of the conventional logs used in this study; more details on the theory, instrumentation, and interpretation of wireline logs are elaborated in the literature (e.g., Glover, 2000; Ellis and Singer, 2007; Tiab and Donaldson, 2015).

Gamma ray (GR)

Pure carbonate rocks such as clean limestones and dolomites often exhibit low GR values because the carbonate minerals calcite and dolomite are not radioactive. Low GR values suggest that the rock is likely free of clays or other radioactive materials. Carbonate rocks that contain interbedded shale or clay show higher GR readings. The radioactive isotopes of uranium (U), thorium (Th), and potassium (K) are more concentrated in shales and clays than in pure carbonates. Carbonate rocks may exhibit varying GR responses due to diagenetic features such as fracturing and recrystallization. These processes can lead to the introducing of radioactive minerals into the carbonate matrix. (Tiab and Donaldson, 2015).

Elemental capture spectroscopy (ECS)

ECS sonde employs neutron-induced gamma ray spectroscopy to detect and measure the elemental composition within the targeted rocks. The sonde releases neutrons into the nearby formation, and the atoms in the formation get excited. As these atoms revert to their stable state, they emit gamma radiation that is detected by a high-density bismuth germanate (BGO) detector. BGO ensures highly efficient detection of microcrystals. The emitted gamma radiation has distinct spectral lines unique to each element, which allow for identifying and quantifying different elements based on the gamma ray energy spectrum (Smith et al., 1989; Herron and Herron, 1996; Ellis and Singer, 2007). With information from other logs such as GR, RHOB, and neutron, ECS is used as a proxy to provide the mineralogical and, thus, the lithological composition of the formation.

Resistivity logs

The main purpose of the resistivity log is to detect the formation fluids, including hydrocarbons and formation waters in various salinity (Ellis and Singer, 2007; Glover, 2000). The laterolog, which is used for resistivity logging, is basically designed to focus the current into horizontal layers; this feature makes it ideal for vertical wells. Accordingly, the laterolog provides a measurement closer to the formation's true resistivity, particularly when layers with high resistivity contrast are encountered, e.g., evaporites with clays. Deep laterolog resistivity (LLD) was used to provide better certainty of formation resistivity compared to shallow resistivity which is influenced by borehole conditions.

Density log

Density sonde uses a radioactive source of gamma ray that are emitted into formation. The scatter of gamma ray is a function of electron density in the formation. Accordingly, the log provides insight into mineralogy and lithology. Integrating density with other logs, such as neutron and gamma ray provides better identification for lithology. In carbonate reservoirs, the density log is essential to differentiate among carbonates, evaporites, and siliciclastic input. The density log also provides an estimation of porosity once the matrix density of the rock is known (Ellis and Singer, 2007).

Neutron log

Neutron-porosity (NPHI) tools work by emitting fast neutrons from a source. These neutrons collide with nuclei in the formation, losing energy with each collision. If the formation contains elements with similar atomic mass (hydrogen; abundant in fluids), the neutrons slow down significantly (Tiab and Donaldson, 2015). Once the neutrons are slowed to thermal energy levels, they are captured by the surrounding formation, and this energy is measured by the detectors. For lithology, neutron log might be useful in detecting clay, as it may contain hydrous components.

3D grid construction

A total area of 35,390 km² was assigned for variogram and property modeling (Figure 4.2). Petrel[®] software was used for all stages of modeling, starting from loading data to the final 3D property modeling. Five surfaces were used to constrain the studied four intervals (members) from M-I to M-IV. The late Permian-early

Triassic carbonates were stratigraphically subdivided into four carbonate members. The fourth member is dominated by evaporites and is not considered a potential hydrocarbon reservoir. The top and bottom surfaces were used to construct a simple grid of 50*50 increments (Figure 4.2). Accordingly, 1209*1138*200 grid cells were used to cover the designated volume, ensuring high-resolution modeling. Within this simple grid, layering was equally assigned as 50 layers for each interval to avoid problems with the model runs for much layering.

Upscaling reservoir properties

The upscaling aims to aggregate fine-scale measurements in wireline logging into representative values that can be used in the model, which operates at a larger scale. The goals behind this stage are to reduce data volume along wells, honor the 3D grid resolution, generate final smooth variability and eliminate problems related to heavy computation in 3D models. Eventually, this process helps in data integration and emphasizes any geological trends if found, instead of having noisy short-scale variations that are not interesting during early field-scale exploration. Borehole data were collected as conventional 0.5ft intervals (Figures 4.7 and 4.8). The well-logs of each property in the studied wells were used for upscaling (Figure 4.3). Each 50 layers within the studied zones must be upscaled to the zone grid dimension. When more than one reading is encountered for a model layer, the upscaling procedure goes through those readings to ensure the arithmetic average value. The upscaling was applied for all wells; however, wells with missing logs were excluded during the process.

Semivariogram analysis

The variogram is a fundamental concept in geostatistical reservoir modeling, used extensively to measure and model the spatial variability of various properties like lithofacies, porosity, and other petrophysical attributes. It plays a critical role in understanding and representing the heterogeneity within reservoirs (Gringarten and Deutsch, 1999, 2001; McKinley et al., 2004). The variogram, as defined in many technical papers, is based on a stationary random function with known mean (m) and variance (σ^2), which are location-dependent within the reservoir. Mathematically, the variogram represents the squared vector difference of data values between two locations separated by distance h (equation (4.11)). However, it is mostly represented as semivariogram $\gamma(h)$ by considering one-half of the variogram.

$$2\gamma(h) = E \left\{ \left[Y(u) - Y(u + h) \right]^2 \right\} \quad (4.1)$$

where:

$\gamma(h)$: the semivariogram value for a particular lag distance (h). E : the expected value or the mean of a random variable over its probability distribution. $Y(u)$: the random field at location u . In the context of geostatistics, it could represent a measurement of a property of interest at a specific location. $Y(u + h)$: the random field at a location that is a lag distance (h) away from location (u). u : the lag distance, representing the distance between two points over which the semivariogram is calculated. Semivariograms need to be fitted with one of the theoretical models. The most used models are spherical, exponential, and Gaussian models, each of which has its own properties in addressing spatial variability.

4.3 Results

4.3.1 Well-Log Analysis

This section includes a comprehensive interpretation of well-logs handled in two traverses; parallel to the general strike and dip directions of the platform. The four carbonate-dominated members were described from top to bottom (M-I, M-II, M-III, and M-IV). The well-log analysis is descriptive, i.e., interpreting different responses as high and low readings of well-logs, including ECS, to identify different mineralogy and expected lithology, with the collaboration of mud-log cutting analysis as incurred from well reports. The identified composition mainly includes carbonates and evaporites, besides clay and other detrital components such as quartz and silicate minerals. Figure 4.4 summarizes the approximate percentages of different lithology in the studied members as estimated from well-log interpretation and well reports.

Dip traverse (S-A-H)

From west to east (proximal to distal), this traverse includes well-S, -A, and -H (Figure 4.2). The considerable similarity between well-A, -M2, and -M3 in terms of lithology distribution and percentages is reasonable since these wells are roughly 50km apart in the epicontinental platform. In the field scale exploration for such gentle-dipping shelf, less heterogeneity is expected in this distance. Well-S is located towards the proximal part of the Arabian Shelf; this location justifies the limited thickness of the late Permian-early Triassic strata in this part, especially in M-I, compared to most of the other wells in the east towards the distal part (Figure 4.4). In well-S, well-logs showed that M-I is capped by interbedded carbonates, clay, and evaporites. The latter increases downward in a relatively reverse manner to clay, which

showed a stable to a decreasing trend. This member is characterized by a lack of quartz-bearing sand-size clastics, which is nearly absent. Similar behavior was also noted in M-II, with a difference in thickness. Less clay was encountered in M-III, concentrated at the lower part. The bottom member (M-IV) is characterized by dominant evaporites exceeding carbonate content. Notable clay content was also recorded at the bottom of M-IV (Figure 4.5). Moving to the east towards well-A and -H, a notable decrease in clay and clastic contents was logged, associated with a decrease in evaporites and evaporitic carbonates in M-I. The well-H witnessed the least contents of the mentioned components compared to well-A and -S, respectively. M-II is also marked by clay and siliciclastic lithology in these wells. The rest of the member is characterized by interbeddings of carbonates and evaporites with comparable evaporite-carbonate ratio (Figure 4.4). Quartz content increases from well-A to well-H, while no content was recorded in well-S, same as M-I in the same well. M-III witnessed less and equivalent evaporitic content between wells-A and -H compared to well-S, which logged higher evaporites content (Figure 4.4), while quartz content also showed increasing towards well-H. The evaporites content in M-IV is conspicuous and nearly equivalent in all wells, with less content noted in strike wells (M1, M2, and M3).

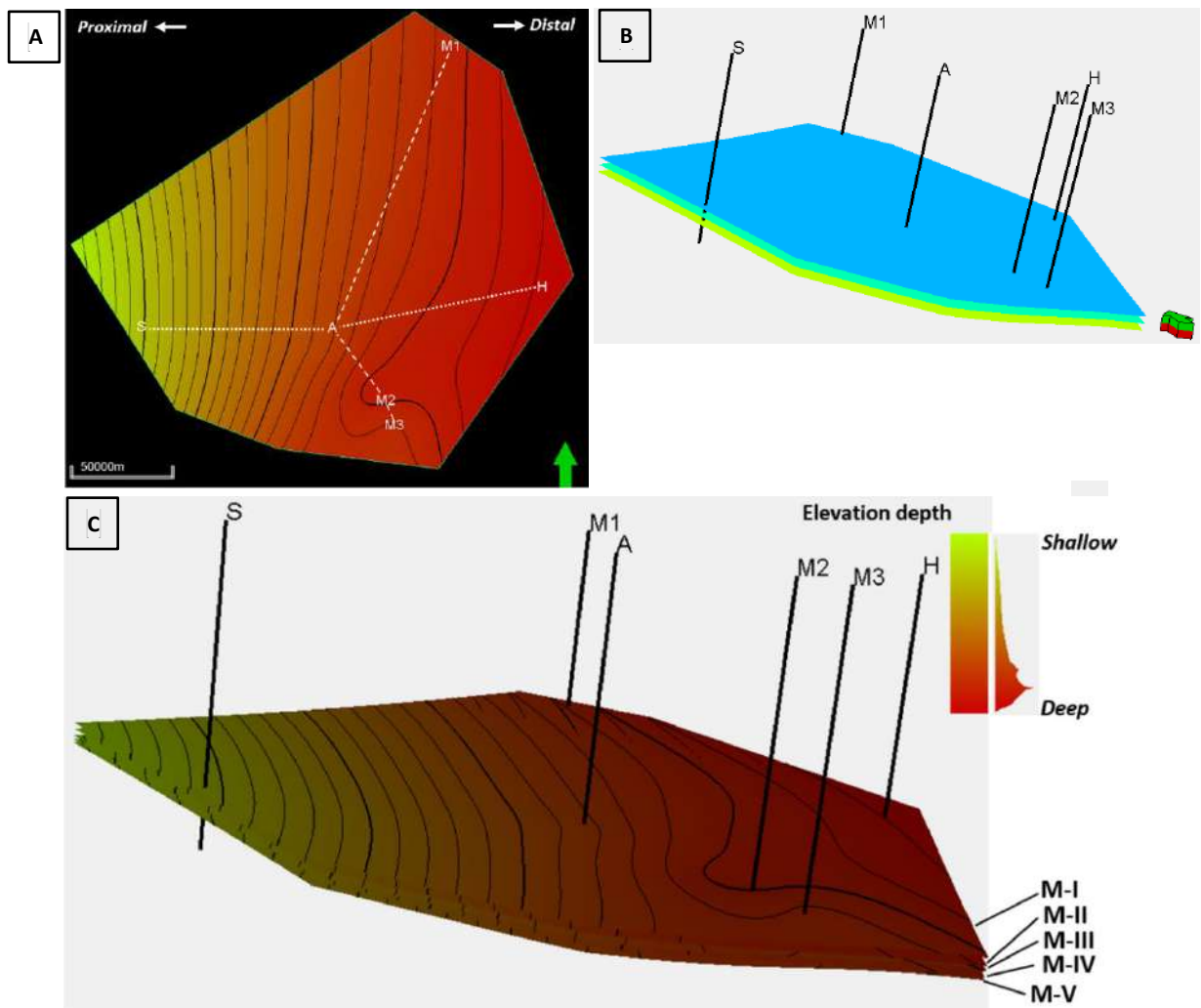


Figure 4.2. The 3D structural model. **A.** Base map obtained from top M-I depth map shows the distribution of wells parallel to general platform strike direction NNW-SSE (M1, A, M2, and M3) (dashed line) and parallel to general dip direction ENE-WSW (S, A, and H) (dotted line). **B.** Simple 3D grid of the study area constructed using top (M-I) and bottom (M-V) surfaces. **C.** Depth map of the five surfaces used to construct the four zones of the model (M-I to M-IV). Note that well-S is located towards the proximal part of the field.

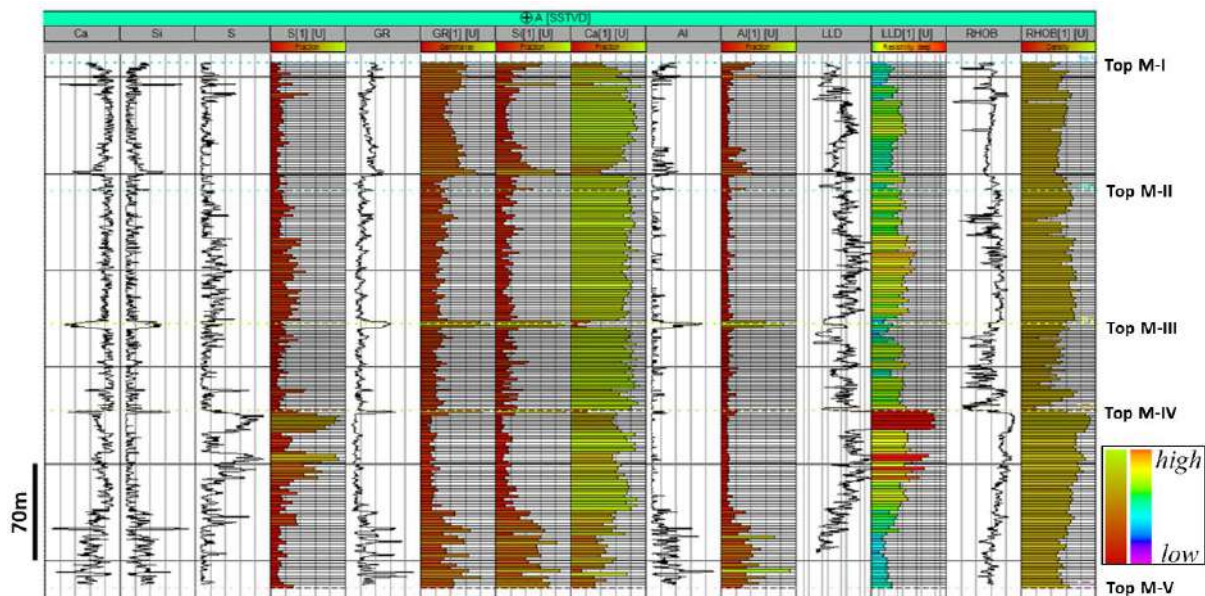
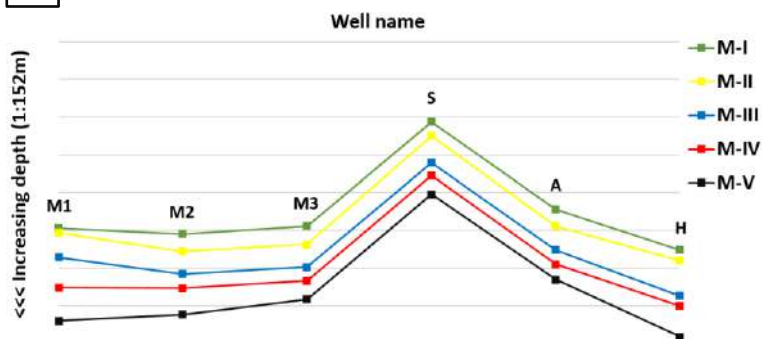


Figure 4.3. Tops of the four members (example from well-A), with the input (uncolored curves) and upscaled (colored curves) well-logs. Color bars indicate the increase in log signature (from left to right). Scale bar $\approx 70\text{m}$ (200ft).

A



B

Member	Carbs:Evap:Qtz:Clay (%) [Thick., m]						Thick., m			
	M1	M2	M3	S	A	H	Avg.	Med.	SD	CV
M-I	71:28:0:1 [16.76]	79:10:5:6 [68.88]	87:3:5:5 [73.76]	79:16:0:5 [54.86]	76:11:8:5 [67.05]	90:5:4:1 [43.58]	54.15	60.96	19.49	0.36
M-II	91:4:0:5 [99.97]	70:17:8:5 [91.44]	83:12:3:2 [91.44]	85:11:0:4 [106.67]	72:14:4:10 [97.53]	75:15:9:1 [143.25]	105.05	98.75	17.86	0.17
M-III	83:14:0:3 [122.83]	76:13:7:4 [57.30]	89:4:3:4 [56.99]	85:12:0:3 [53.34]	85:7:4:4 [57.91]	84:9:7:0 [39.62]	64.67	57.15	26.76	0.41
M-IV	62:32:0:6 [134.41]	51:37:7:5 [106.07]	44:45:7:4 [73.76]	43:52:0:5 [74.67]	46:47:4:3 [60.96]	52:35:10:3 [124.96]	95.81	90.37	27.67	0.29
Total thick. (m)	373.97	323.68	295.95	289.55	283.45	351.42				

Figure 4.4. Mineralogy of the late Permian-early Triassic succession in the study area. **A.** Tops of the late Permian - early Triassic members in different wells. **B.** Approximate contribution of different mineralogy (%) in the composition of studied late Permian-early Triassic strata as incurred from well-logs and mud logs, including carbonates (calcite and dolomite), evaporites (anhydrite), quartz-bearing clastics (quartz and/or silicate minerals), and clay (illite).

Strike traverse (M1-M2-A-M3)

From north to south, this traverse included well-M1, -A, -M2, and -M3 (Figure 4.2). Gamma ray, including spectral logs of K, Th, and U, are not indicative of carbonates. However, high kicks of logs were associated with silicate content (Figure 4.6). This behavior was observed in all six wells, clearly towards the proximal part of the field (well-S). The top of M-I represents the regressive part of the member where silicate minerals were logged. This behavior is clear in the southern part of the study area (well-M3). While the clay and quartz content decrease northward towards well-M1 (Figure 4.6). The central well-A has witnessed less clay content. Besides the high readings of GR, this interpretation was also confirmed by NPHI logs. The hydrogen content within clay minerals stands behind the relatively higher NPHI log compared to the rest of the section, where NPHI and density (RHOB) logs are closely identical. The increase in ND logs is also a function of evaporites occurrences. This behavior is clear in well-M1 where noticeable ECS sulfur and, thus anhydrite occurred (Figure 4.6). Evaporites also cause high kicks on resistivity; this observation was obvious in well-M1. ECS logs accommodate GR for clay content (Si and Al), and with resistivity in evaporites (S), as these logs are sensitive to various contents in respective lithology. Similar to M-I, M-II is marked by a high kick in clay and quartz content, related to the higher content of Si and Al with less content of Ca and steady content of S. This signature was logged in all wells along the platform strike. In wells M3 and A, noticeable content of evaporites was observed interbedded with dolomite. The latter is confirmed by separated ND logs compared to identical logs, indicating calcite dominates in the upper member (M-I) (Figure 4.6). In well-M3, this member witnessed less evaporite content compared to well-M3 and -A and to the overlain member M-I, as indicated by less dolomite as well. The clay content of M-II in

well-M1 is higher than the other two wells (Well-A and -M3), as indicated by a bit higher GR responses; it was also recorded higher GR than the overlying evaporite-rich M-I (Figure 4.6). M-III is marked at the top by significant clay content incurred from relatively higher GR, higher NPHI log, and drop in resistivity log. This observation was clear in well-A and -M3; however, well-M1 is capped by thick evaporites with high resistivity and low GR. Evaporites content in M-III is less than M-II and comparable with M-I for well-A. For well-M3, less evaporites were logged in M-III, but generally comparable to M-I, less than M-II and M-IV, respectively. Well-M1 witnessed higher evaporites content in M-III, similar to M-I and less than M-II. M-IV is marked by thick evaporites in all wells where the thickest evaporites were encountered in all members. Evaporites thickness ranges between roughly 120ft in well-M1 and 90ft in well-M3 (Figure 4.6). The occurrence of massive and interbedded evaporites in M-IV makes this member unsuitable as a reservoir. Reasonably, Thick evaporites in M-IV act as regional correlation datum. Region-wide, this member was not considered a reservoir in any previous work relevant to the late Permian.

4.3.2 Statistical Analysis

Statistical parameters are summarized in (Figure 4.7). Positive histogram skewness was observed in ECS for Si, S, and Al, as those elements were minor contributors to the studied carbonate successions. Reversely, Ca has shown negative skewness. The same distribution was observed in RHOB, which showed negative skewness compared to GR and resistivity logs. Even though the average and median values in some logs (e.g., GR, RHOB, and Ca) are closely similar, nonlinear distribution is still observed in these logs in all members, with less degree compared to other logs (Figure 4.7). Some Ca histograms exhibited bimodal

distribution, clearly in M-I and M-IV compared to M-II and M-III. This was also indicated by a higher coefficient of variation (CV) in M-I and M-IV.

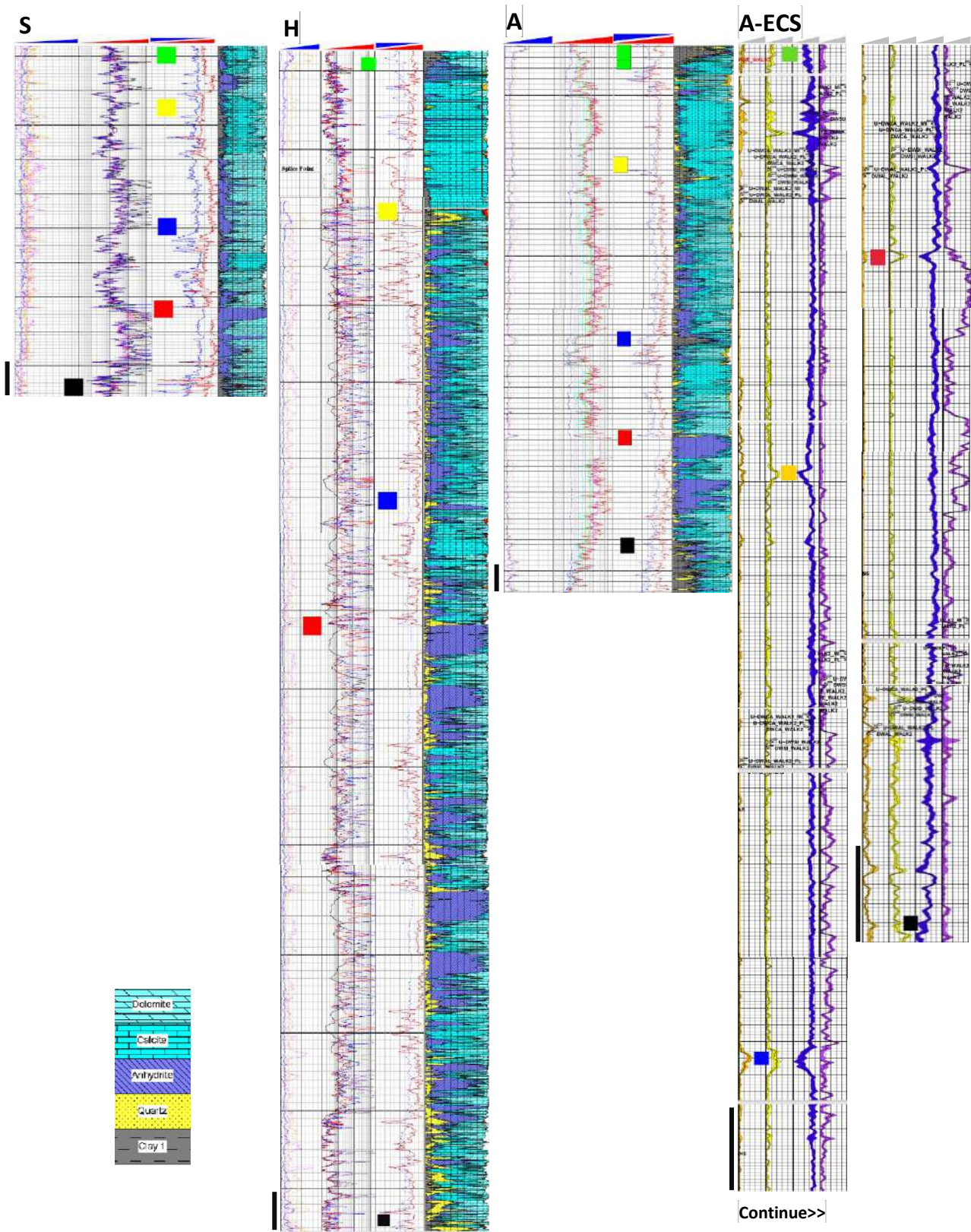
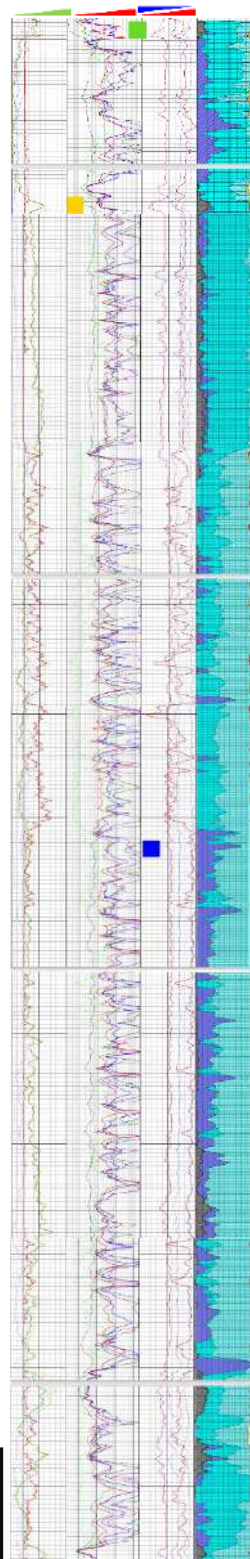
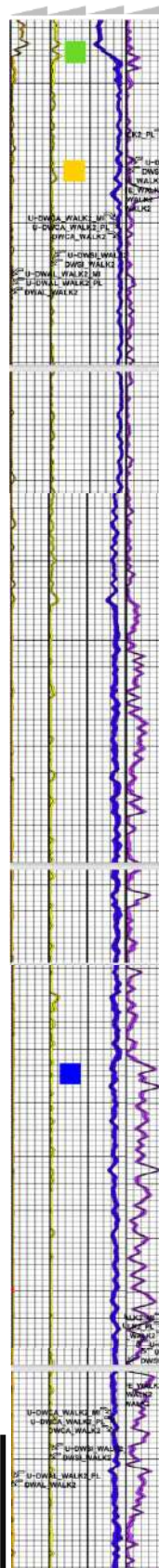
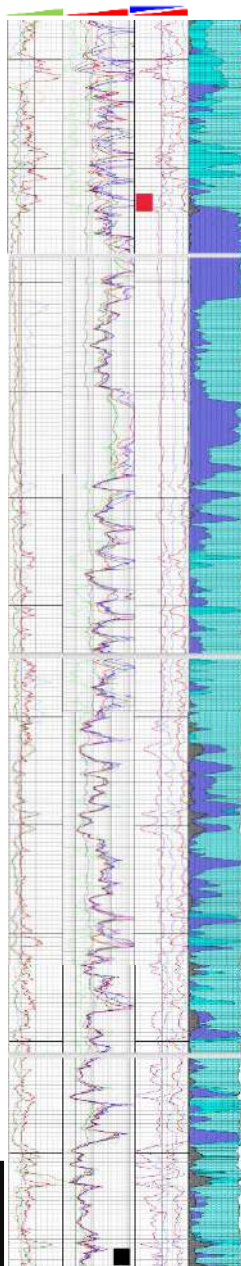


Figure 4.5. Well-logs of the four Permo-Triassic members along dip traverse (well-S, -A, and -H), including representative ECS for well-A. Member tops are indicated by colored boxes in green (M-I), yellow (M-II), blue (M-III), red (M-IV), and black (M-V) representing the basal clastic member. These tops were assigned by integrating well-logs signature and master log of respective wells. See text for details of members' tops and characteristics. Each scale color (header) is similar to the relevant log color. Logs from left to right: GR (green), LLD (red), and combined NPHI (blue), RHOB (red). ECS logs from left to right: Al (pale yellow), Si (yellow), Ca (blue) and S (violet). Scale bar equals 50ft.

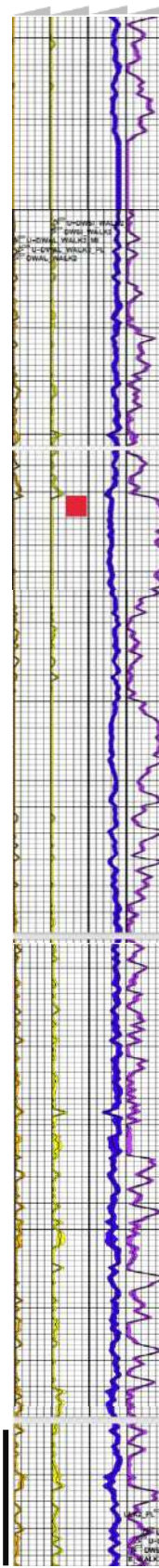
M1



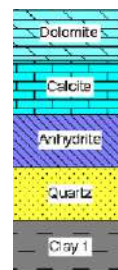
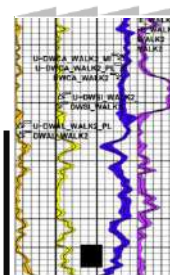
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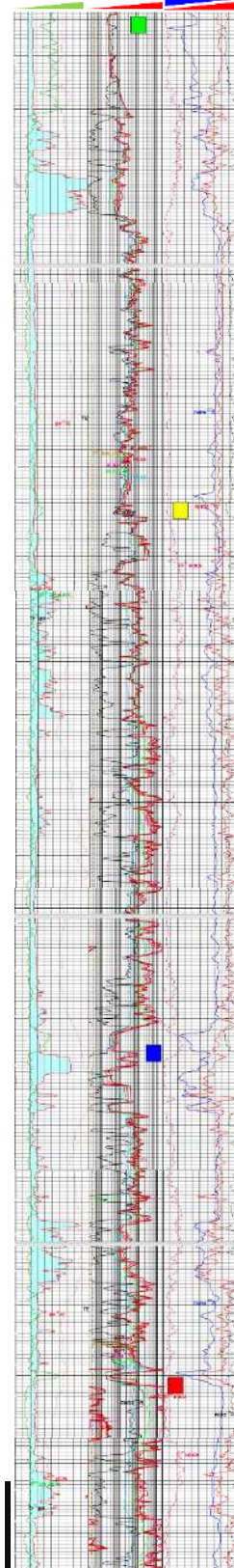
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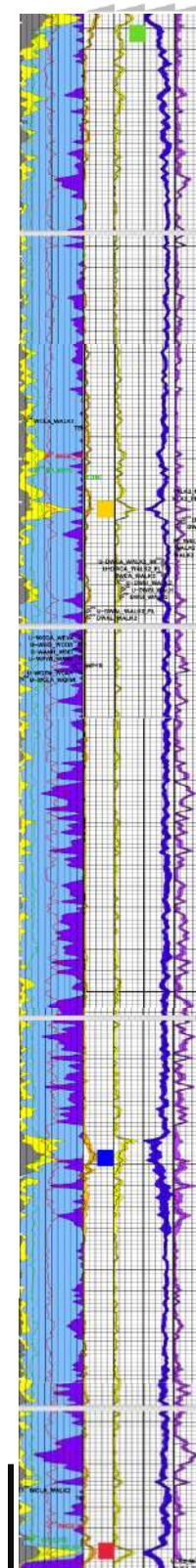
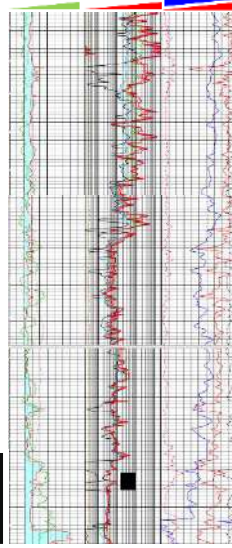
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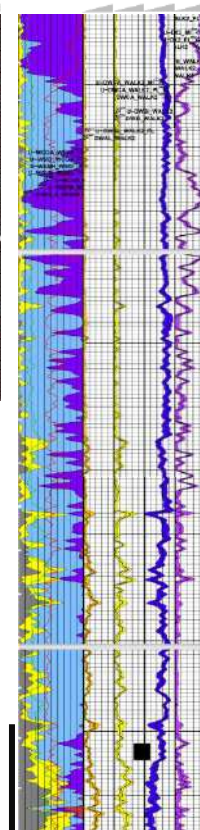
M2



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Continue>>



M3

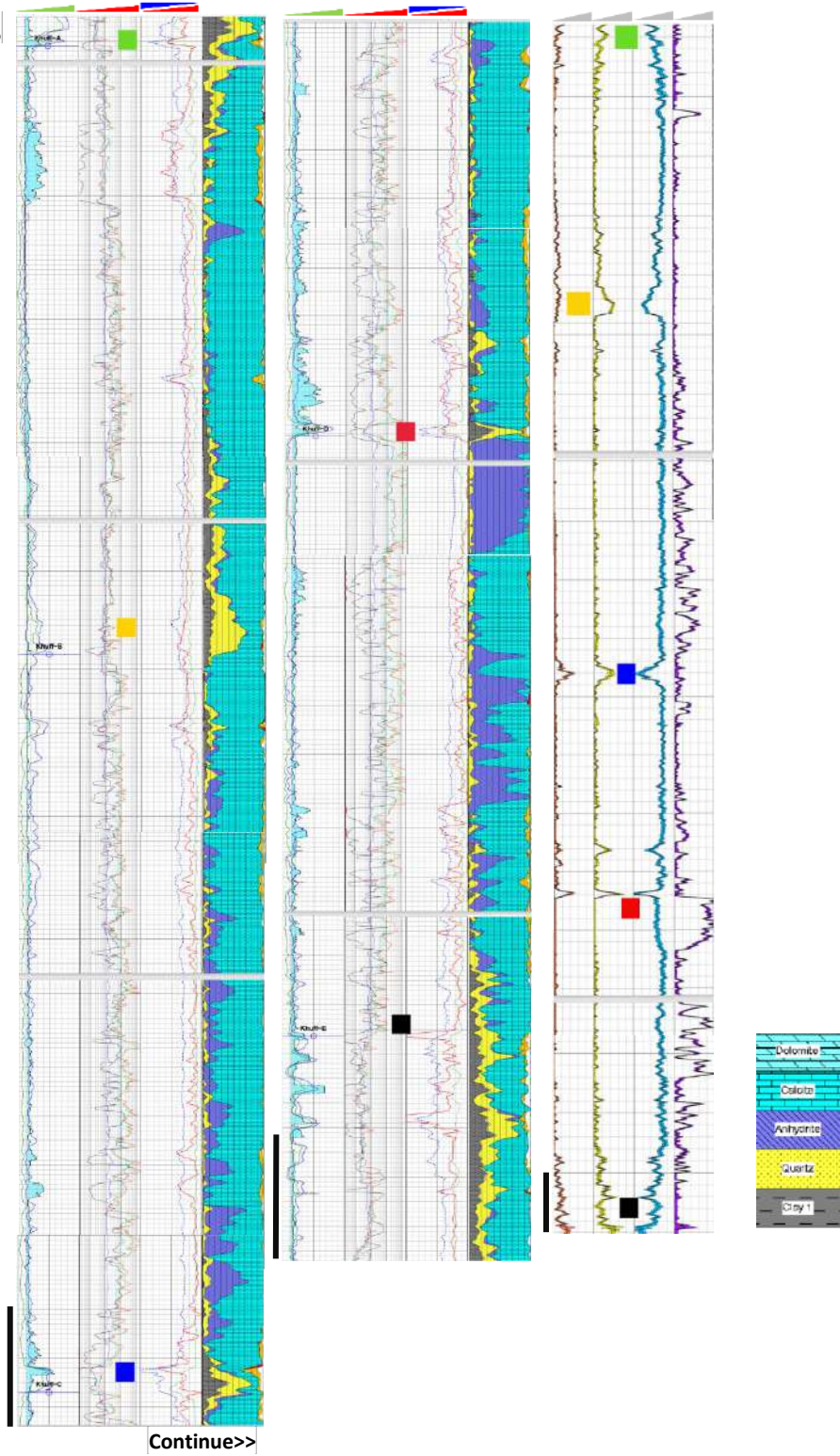


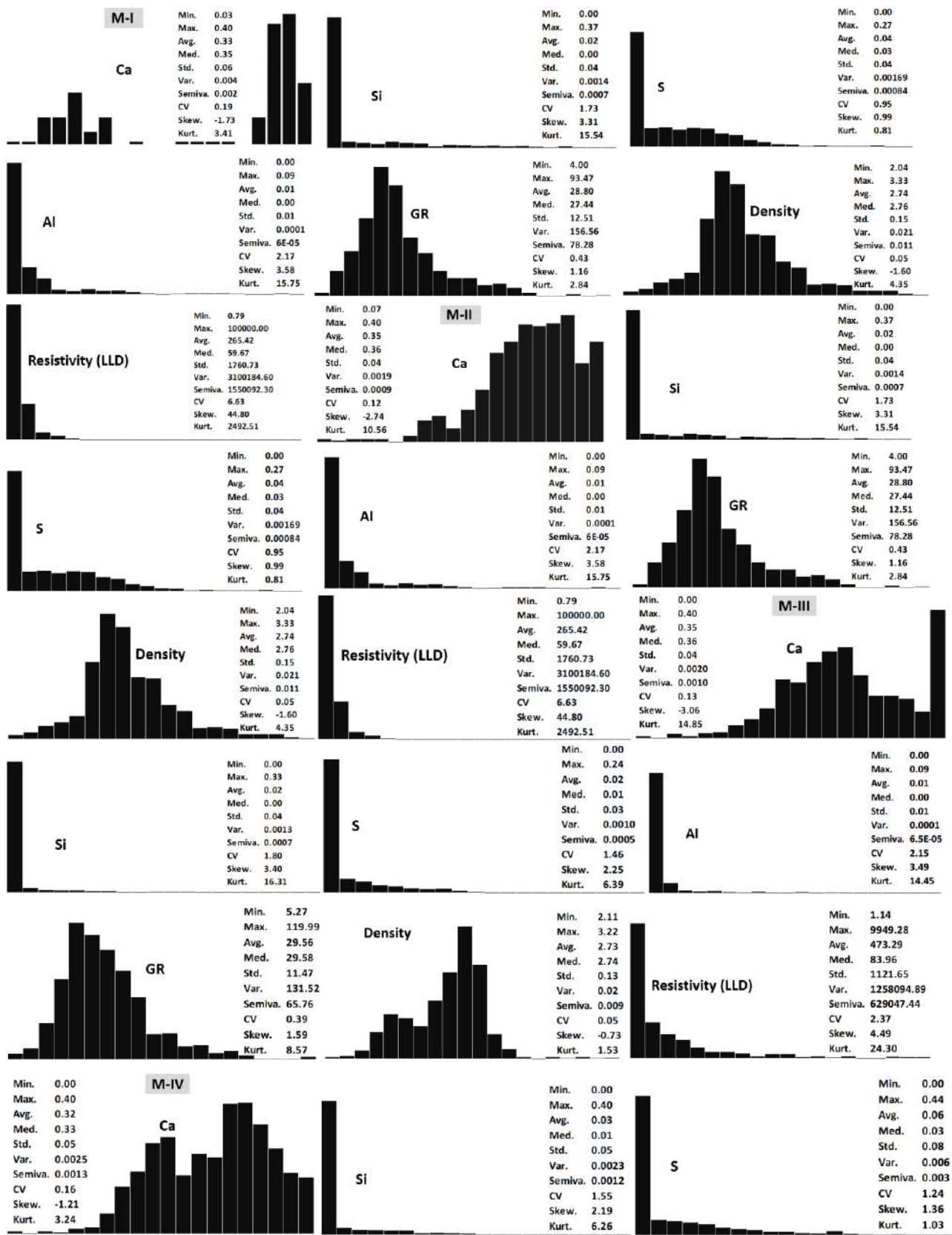
Figure 4.6. Well-logs of the four Permo-Triassic members along strike traverse (well-M1, -M2, and -M3). Member tops are indicated by colored boxes in green (M-I), yellow (M-II), blue (M-III), red (M-IV), and black (M-V) representing the basal clastic member. These tops were assigned by integrating well-logs signature and master log of respective wells. See text for details of members' tops and characteristics. Each scale color (header) is similar to the relevant log color. Logs from left to right: GR (green), LLD (red), and combined NPHI (blue), RHOB (red). ECS logs from left to right: Al (brown), Si (yellow), Ca (blue), and S (violet). Scale bar equals 50ft.

4.3.3 Semivariogram interpretation

Variography analysis is the keystone of this study and represents the input for 3D modeling. Three parameters are considered in variogram interpretation: variogram range, nugget, and sill. Numerous orientations of the semivariogram search cone were tested against available well-log data in the major direction. This includes the general Arabian Platform strike direction (N-S), with some reorientations as NW-SE and NE-SW. In all these directions, the variogram structure remains the same, confirming that N-S is the general strike direction of the platform shelf. The minor direction, by definition, lays perpendicular to the major one to address the direction of less continuity (higher variability). The 3D directional semivariograms were constructed and fitted with the best theoretical model in order to express the 3D variability of the studied properties. Table 4.2 contains semivariogram parameters for all properties in the studied members using exponential and Gaussian models. Petrel[®] software uses a relative sill as a default value of 1.0 for all semivariograms. It acts as a relative value equivalent to the absolute value of half of the data variance (semivariance). The software algorithm uses this approach, as it uses normalized data (standard deviation equals one, mean equals zero) before constructing the semivariogram (half of the variance). The exponential model was the best for fitting all 3D semivariograms,

with a negligible nugget effect that tends to zero (Figure 4.8). The major semivariograms of the ECS showed prominent continuity, with very low variance for tens of kilometers (Table 4.2). The thickness and very low variance of ECS allowed form this notable range. However, M-III in all ECS semivariograms has shown less range, with similar variance. This is attributed to the variable thickness of M-III compared to other members, as indicated by a higher CV (Figure 4.4). Sill values represent half of the total variance for each studied property. A wide radius for each search cone was used to construct a semivariogram that honors all available data (all wells) for each specific member. Therefore, the distance between data points for each data pair is responsible for identifying the major, minor, and vertical ranges and nuggets. Longer ECS major and minor ranges were observed for M-I, MIII, and M-IV, respectively, most obviously in Ca and S. The vertical range of ECS is more sensitive to thickness than major and minor ranges, this behavior was clear in M-I as well- M1 revealed the thinnest interval encountered among other members/wells. This yielded the shortest vertical range among other members (Table 4.2). The nugget effect is minimal; however, 0.18 semivariance was recorded as nugget in Ca (M-IV). This nugget indicates the small-scale variability in Ca due to the dominance of Ca in this member, which is a contributor in both dominant lithology; the carbonates and evaporites. Other properties tend to follow the intrinsic ECS behavior and thus mineralogy of the studied members. RHOB, GR, and formation resistivity are all controlled by lithology. Even though, resistivity is more sensitive to fluid content compared to matrix mineralogy. In this context, GR has shown nearly similar ranges for the top three members, while the bottom evaporitic members revealed much longer range, due to dominant low GR signatures associated with evaporites compared to carbonates. This behavior showed less similarity in the minor range due to

higher variability in the dip direction of the platform, as depicted from clay content (Figure 4.4), clearly in well-H towards the distal part of the field. Similarly, RHOB semivariograms followed the same behavior as ECS, where the longest ranges were picked from M-III and M-IV. Similar variation was noted in minor direction with shorter ranges (Table 4.2). Resistivity is a function of sulfur and evaporite contents, therefore, major and minor ranges revealed comparable variations to that recorded in S content. Qualitatively, geometric anisotropy was observed in all properties based on the difference between the major and minor range (Table 4.2). In all members, the N-S major range (strike direction) is longer than the W-E minor range (dip direction). Reasonably, vertical semivariograms have shown meter-scale ranges due to limited thickness, higher amount of data, and thus higher variability than the aerial extension. Using the Gaussian model in fitting semivariograms has revealed different parameters compared to the exponential model. Particularly, shorter ranges were observed generally in the major and minor directions, with a potential nugget effect, significantly in the vertical direction (Table 4.2). However, geometric anisotropy is still overserved with the Gaussian model.



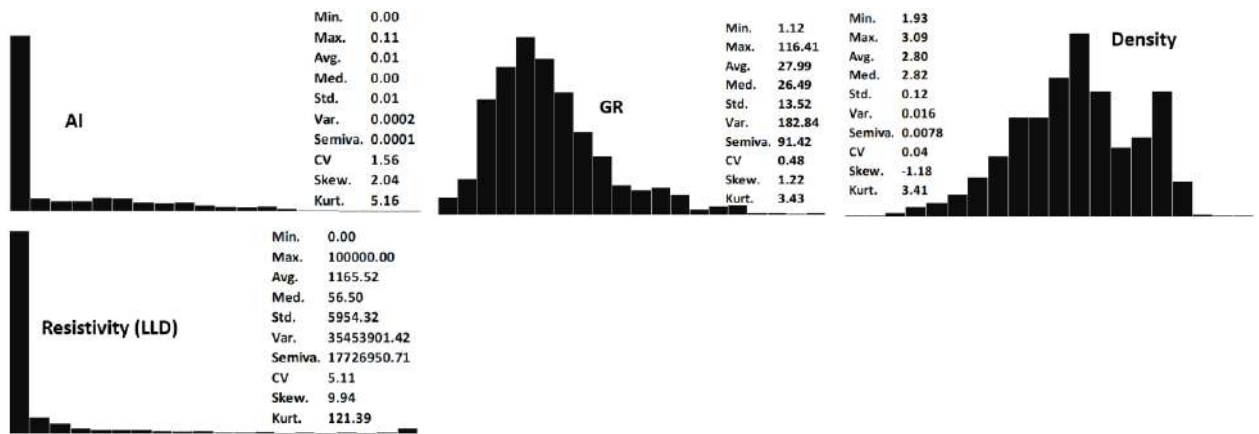
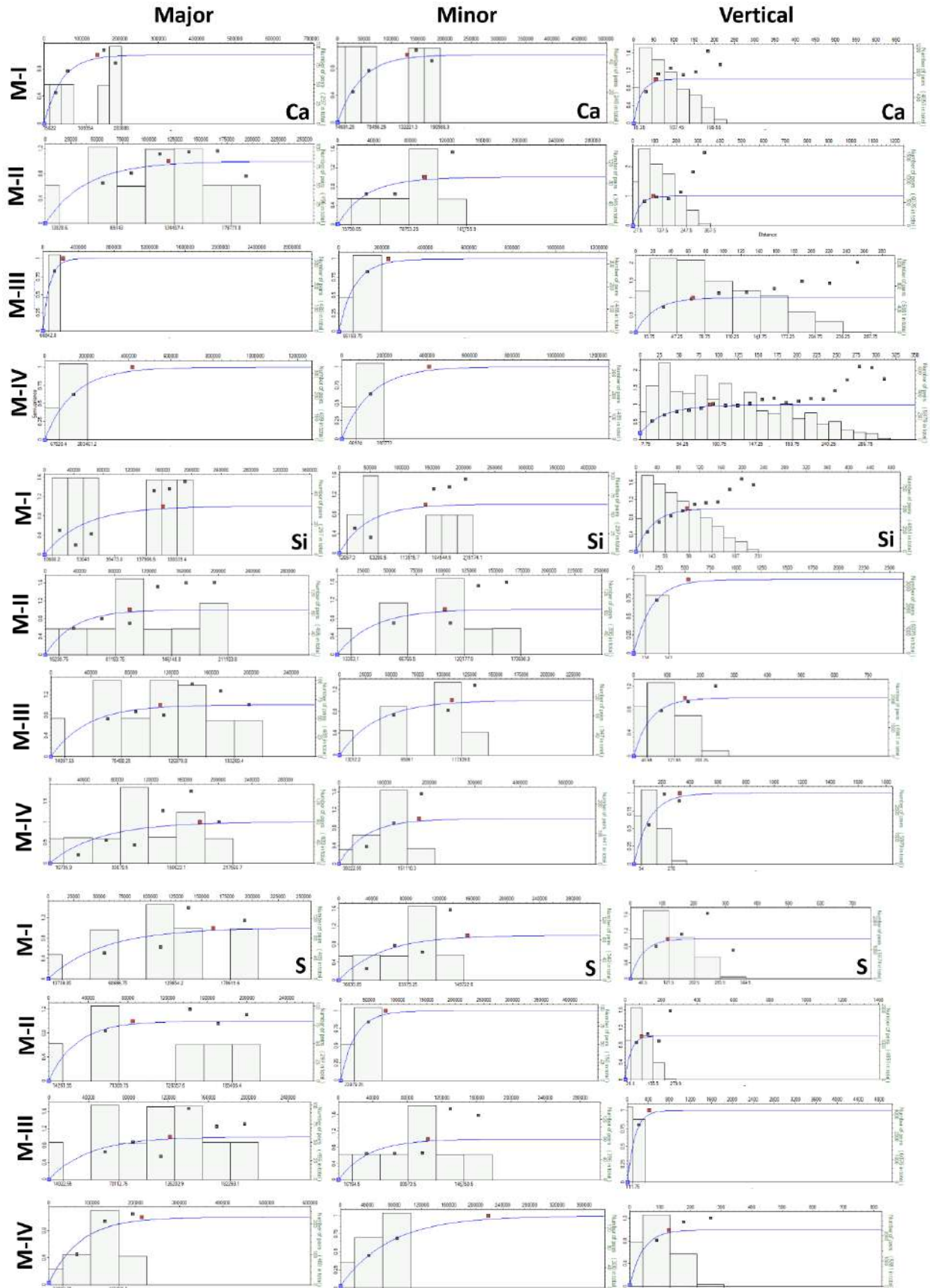


Figure 4.7. Statistical parameters of input well-logs for all Permo-Triassic members (M-I to M-IV), including ECS data (w/w), gamma ray; GR (API), density(RHOB) (g/cm^3), and LLD resistivity (ohm.m).



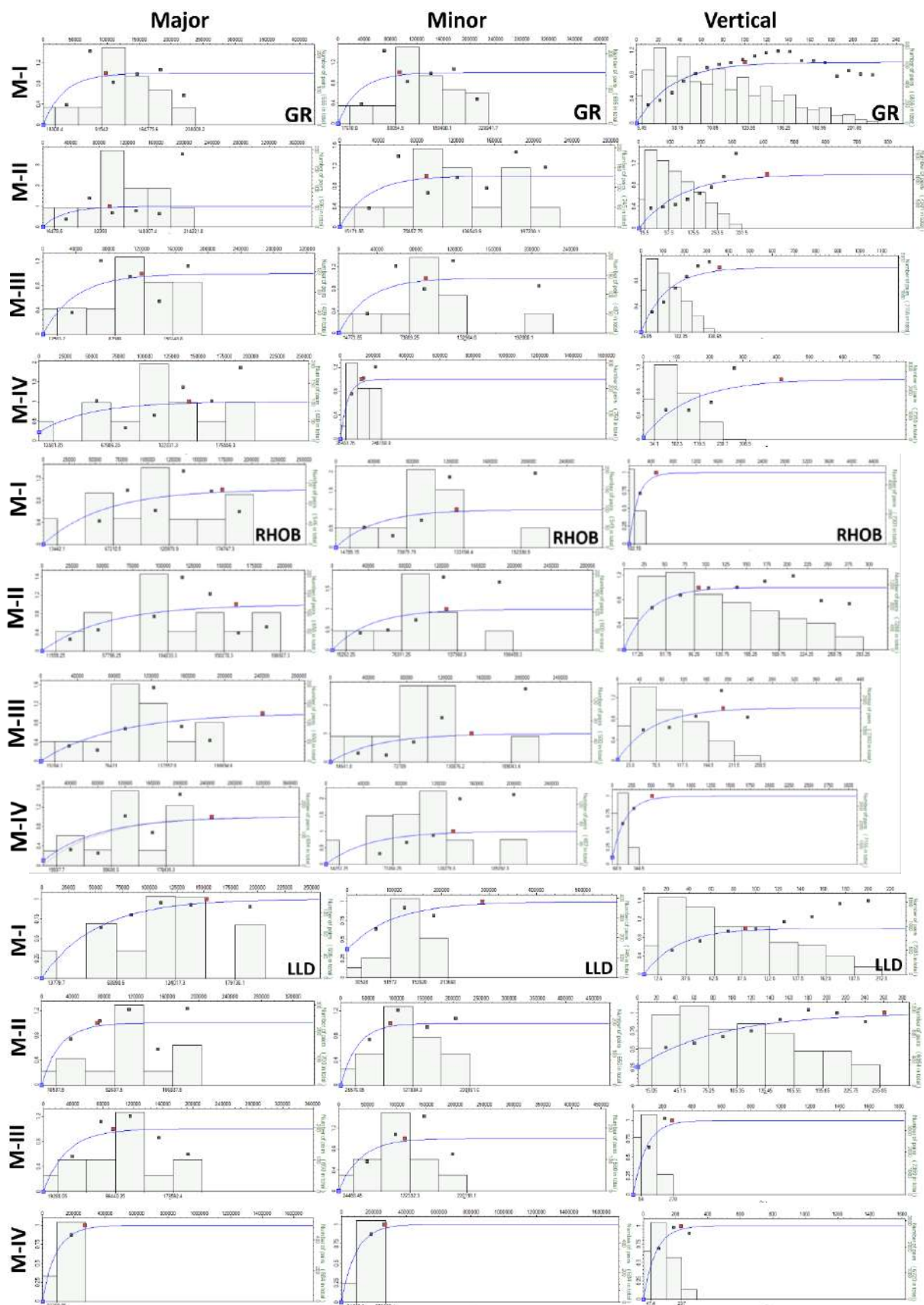


Figure 4.8. Exponentially-fitted directional semivariograms in major (left), minor (middle), and vertical (right) directions for all members arranged from top downwards as M-I, M-II, M-III, and M-IV. Well-constructed semivariograms were attained using exponential fitting with no to minor nugget effects.

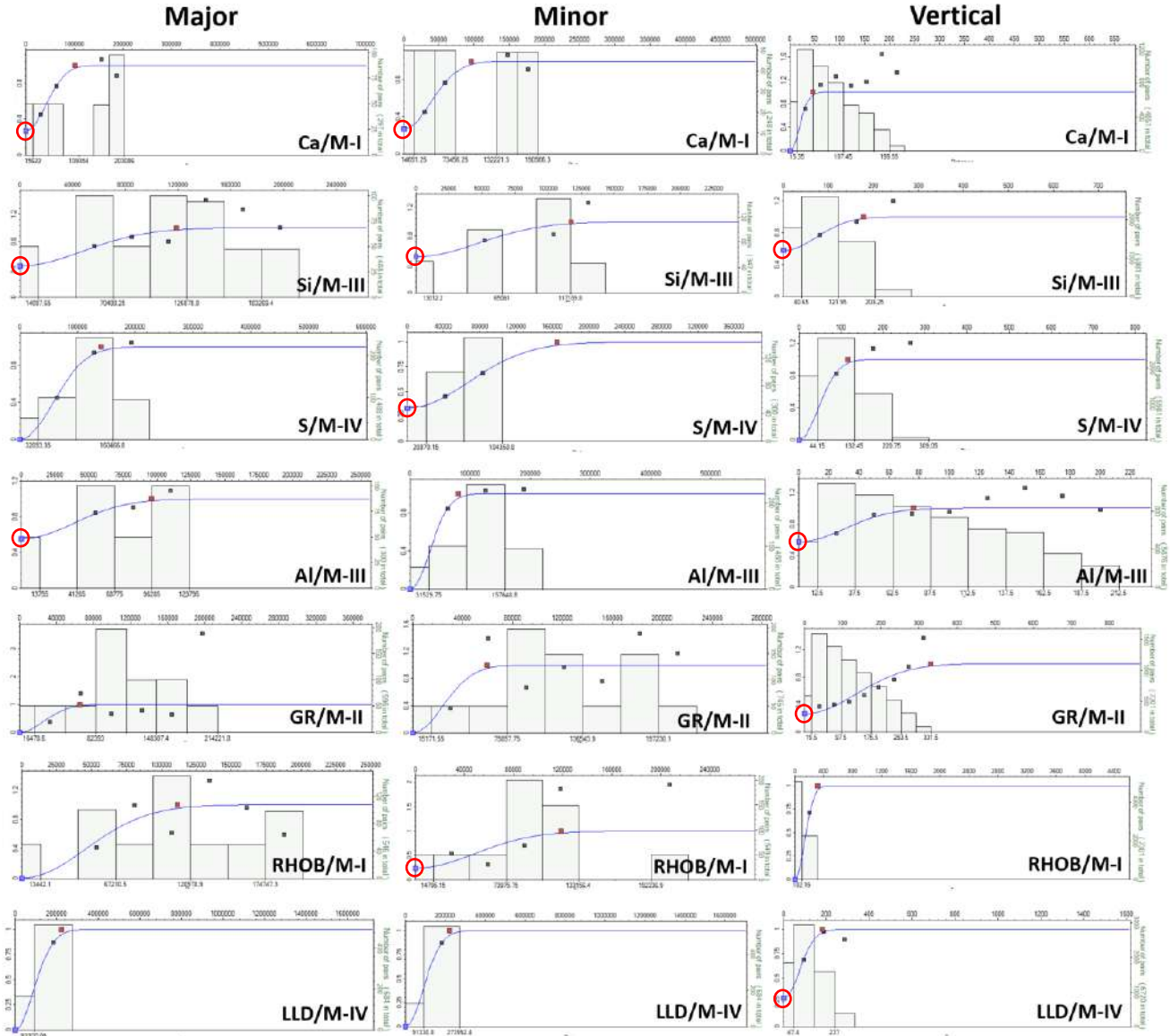


Figure 4.9. Representative Gaussian-fitted directional semivariograms showing significant nuggets as observed in different properties/members.

Table 4.2. Semivariogram parameters for the four Permo-Triassic members using exponential and Gaussian fitting

Well log	Member	Major semivariogram						Range difference (m)	Minor semivariogram						Range difference (m)	Vertical semivariogram						Range difference (m)			
		Exponential			Gaussian				Exponential			Gaussian				Exponential			Gaussian						
		Range (m)	Sill	Nugget	Range (m)	Sill	Nugget		Range (m)	Sill	Nugget	Range (m)	Sill	Nugget		Range (m)	Sill	Nugget	Range (m)	Sill	Nugget				
Ca (w/w)	M-I	139,377.76	0.002	0.00	101,566.33	0.002	0.27	37,811.43	130,138.65	0.002	0.00	95,505.40	0.002	0.00	0.00	0.00	0.27	34,653.25	16.71	0.002	0.00	14.16	0.002	0.00	2.55
	M-II	119,075.45	0.0009	0.00	106,567.56	0.0009	0.47	12,507.89	95,424.31	0.0009	0.00	98,200.69	0.0009	0.00	0.00	0.05	-2,776.38	28.63	0.0009	0.00	39.87	0.0009	0.70	-11.24	
	M-III	229,401.19	0.001	0.00	175,121.78	0.001	0.00	54,279.41	227,091.32	0.001	0.00	173,358.45	0.001	0.00	0.00	0.00	53,732.87	19.83	0.001	0.00	19.29	0.001	0.01	0.54	
	M-IV	416,020.06	0.0013	0.00	237,548.51	0.0013	0.00	178,471.55	410,521.42	0.0013	0.00	234,408.77	0.0013	0.00	0.00	0.00	176,112.65	27.12	0.0013	0.18	27.79	0.0013	0.52	-0.67	
Si (w/w)	M-I	160,858.59	0.0014	0.00	141,873.18	0.0014	0.00	18,985.41	138,473.75	0.0014	0.00	135,994.12	0.0014	0.00	0.00	0.29	2,479.63	29.26	0.0014	0.00	28.62	0.0014	0.35	0.64	
	M-II	99,513.68	0.0007	0.00	115,678.35	0.0007	0.47	-16,164.67	98,469.06	0.0007	0.00	113,359.94	0.0007	0.38	-14,890.88	163.19	0.0007	0.00	106.52	0.0007	0.00	56.67	0.00		
	M-III	109,227.43	0.0007	0.00	118,794.96	0.0007	0.45	-9,507.53	108,179.95	0.0007	0.00	117,179.76	0.0007	0.45	-8,995.81	46.88	0.0007	0.00	54.22	0.0007	0.57	-7.34	0.00		
	M-IV	177,883.25	0.0012	0.00	137,819.35	0.0012	0.02	40,063.90	176,262.88	0.0012	0.00	137,692.11	0.0012	0.02	38,570.77	100.25	0.0012	0.00	62.75	0.0012	0.00	37.50	0.00		
S (w/w)	M-I	161,475.44	0.00032	0.00	135,492.54	0.00032	0.16	25,982.90	155,750.91	0.00032	0.00	109,985.46	0.00032	0.04	43,765.45	27.28	0.00032	0.00	23.43	0.00032	0.00	23.43	0.00032	0.00	3.85
	M-II	84,810.81	0.00084	0.00	72,742.90	0.00084	0.00	12,067.91	77,997.93	0.00084	0.00	61,160.96	0.00084	0.00	16,836.97	35.71	0.00084	0.00	32.83	0.00084	0.00	32.83	0.00084	0.00	2.88
	M-III	121,686.13	0.001	0.00	124,712.25	0.001	0.32	-3,026.12	103,544.86	0.001	0.00	123,044.15	0.001	0.47	-19,499.29	39.21	0.001	0.02	35.31	0.001	0.02	35.31	0.001	0.00	3.90
	M-IV	217,986.34	0.003	0.00	165,216.36	0.003	0.00	52,769.98	215,652.47	0.003	0.02	140,213.23	0.003	0.33	73,439.24	127.17	0.003	0.00	93.1	0.003	0.00	93.1	0.003	0.00	34.07
Density (g/cm ³)	M-I	171,710.34	0.0116	0.00	118,559.55	0.0116	0.00	53,150.79	125,421.83	0.0116	0.00	111,590.30	0.0116	0.24	13,831.53	27.78	0.0116	0.00	30.71	0.0116	0.53	30.71	0.0116	0.53	-2.93
	M-II	160,176.15	0.011	0.00	112,855.39	0.011	0.17	47,320.76	125,363.82	0.011	0.00	101,869.05	0.011	0.08	23,494.77	149.56	0.011	0.00	96.53	0.011	0.00	96.53	0.011	0.00	53.03
	M-III	240,673.37	0.009	0.00	134,165.01	0.009	0.04	106,508.36	147,325.11	0.009	0.00	119,979.30	0.009	0.01	27,345.81	56.23	0.009	0.00	57.11	0.009	0.43	57.11	0.009	0.43	-0.88
	M-IV	245,815.39	0.0078	0.00	175,196.59	0.0078	0.09	70,618.80	135,560.86	0.0078	0.00	125,131.49	0.0078	0.00	10,429.37	155.52	0.0078	0.00	140.02	0.0078	0.47	140.02	0.0078	0.47	15.50
GR (API)	M-I	97,197.73	230.05	0.00	70,906.00	230.05	0.00	26,291.73	93,718.31	230.05	0.00	68,204.68	230.05	0.00	25,513.63	30.48	230.05	0.00	24.15	230.05	0.23	24.15	230.05	0.23	6.33
	M-II	94,478.25	78.28	0.00	64,984.54	78.28	0.00	29,493.71	89,634.66	78.28	0.00	59,829.05	78.28	0.00	29,805.61	125.37	78.28	0.00	100.76	78.28	0.26	100.76	78.28	0.26	24.61
	M-III	91,148.67	91.42	0.00	467,784.01	91.42	0.73	-376,635.34	89,960.32	91.42	0.00	62,084.13	91.42	0.00	27,876.19	109.14	65.76	0.00	81.8	65.76	0.20	81.8	65.76	0.20	27.34
	M-IV	141,632.28	65.76	0.21	165,464.46	65.76	0.59	-23,832.18	128,625.53	65.76	0.00	102,550.05	65.76	0.00	26,075.48	126.02	91.42	0.03	103.76	91.42	0.33	103.76	91.42	0.33	22.26
Resistivity IUD (ohm.m)	M-I	286,270.78	629047.44	0.00	265,605.53	629047.44	0.35	20,685.25	152,515.59	629047.44	0.37	138,389.73	629047.44	0.43	14,125.86	67.51	629047.44	0.37	27.37	629047.44	0.63	27.37	629047.44	0.63	40.14
	M-II	88,054.36	10423.71	0.00	74,827.95	10423.71	0.47	13,226.41	71,377.08	10423.71	0.00	55,082.23	10423.71	0.00	16,294.85	260.432	10423.71	0.09	63.84	10423.71	0.47	63.84	10423.71	0.47	196.59
	M-III	113,043.32	1550092.3	0.02	89,144.92	1550092.3	0.78	23,898.40	93,144.62	1550092.3	0.05	69,752.48	1550092.3	0.63	23,392.14	69.54	1550092.3	0.02	80.68	1550092.3	0.38	80.68	1550092.3	0.38	-11.14
	M-IV	271,187.48	17726950.7	0.00	223,501.14	17726950.7	0.63	47,686.34	266,906.64	17726950.7	0.00	220,802.16	17726950.7	0.46	46,104.48	90.675	17726950.7	0.00	71.19	17726950.7	0.29	71.19	17726950.7	0.29	19.49

4.3.4 3D Modeling

3D sequential Gaussian models were generated using semivariogram parameters (Table 4.2). As they have shown better variogram structure (Figure 4.8), and due to their behavior in exhibiting a longer range for spatial correlation, exponentially-fitted semivariograms were used to generate the 3D models for all properties (Figure 4.10). Overall, semivariograms have generated acceptable models that honor the expected lateral extension of the properties in an epicontinental, gently dipping platform setting. This was clear in ECS models, more importantly for Ca, the dominant element in carbonates and evaporites. Gaussian model was also tested for fitting semivariograms, and 3D models were generated accordingly, however, they have revealed significant nugget effects compared to the exponentially-fitted ones (Figure 4.9).

4.4 Discussion

4.4.1 The Permo-Triassic Epicontinental Platform

The Permo-Triassic succession of the Arabian Shelf represents a unique opportunity to test the applicability of geostatistics as a cost-effective tool for addressing spatial variability. From the first impression, the lateral extent of the Permo-Triassic deposition in the epicontinental platform implies spatial continuity of the cyclic depositional system and probably the related rock properties. The difference in range values between different Permo-Triassic members was noted for different properties in nearly similar behavior, i.e., higher ranges in M-I, M-III, and M-IV in all directions. This observation can be attributed to Permo-Triassic geomorphology, as the different

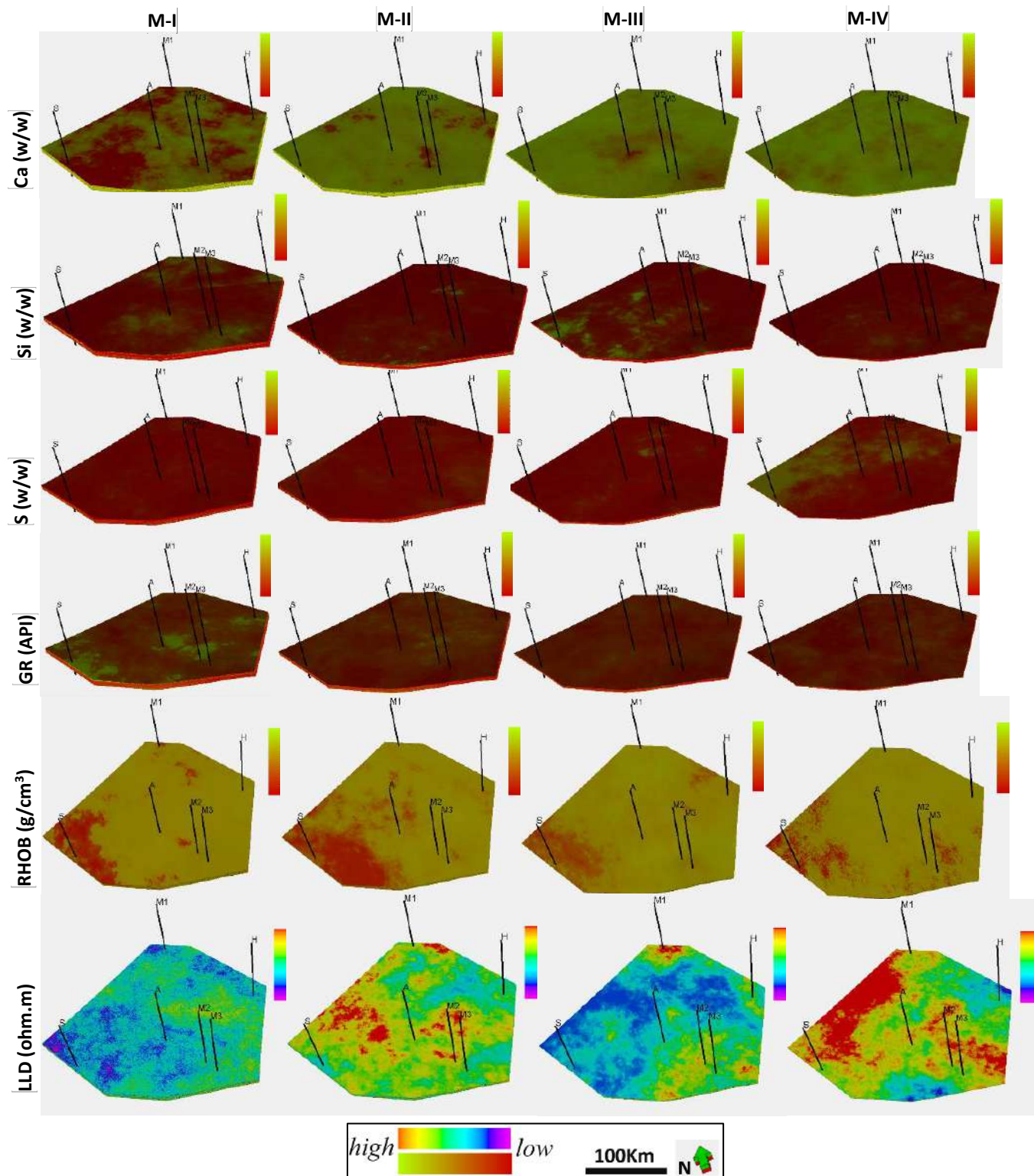


Figure 4.10. 3D models of all studied well-logs. Smooth variation observed in ECS models compared to other conventional well-logs.

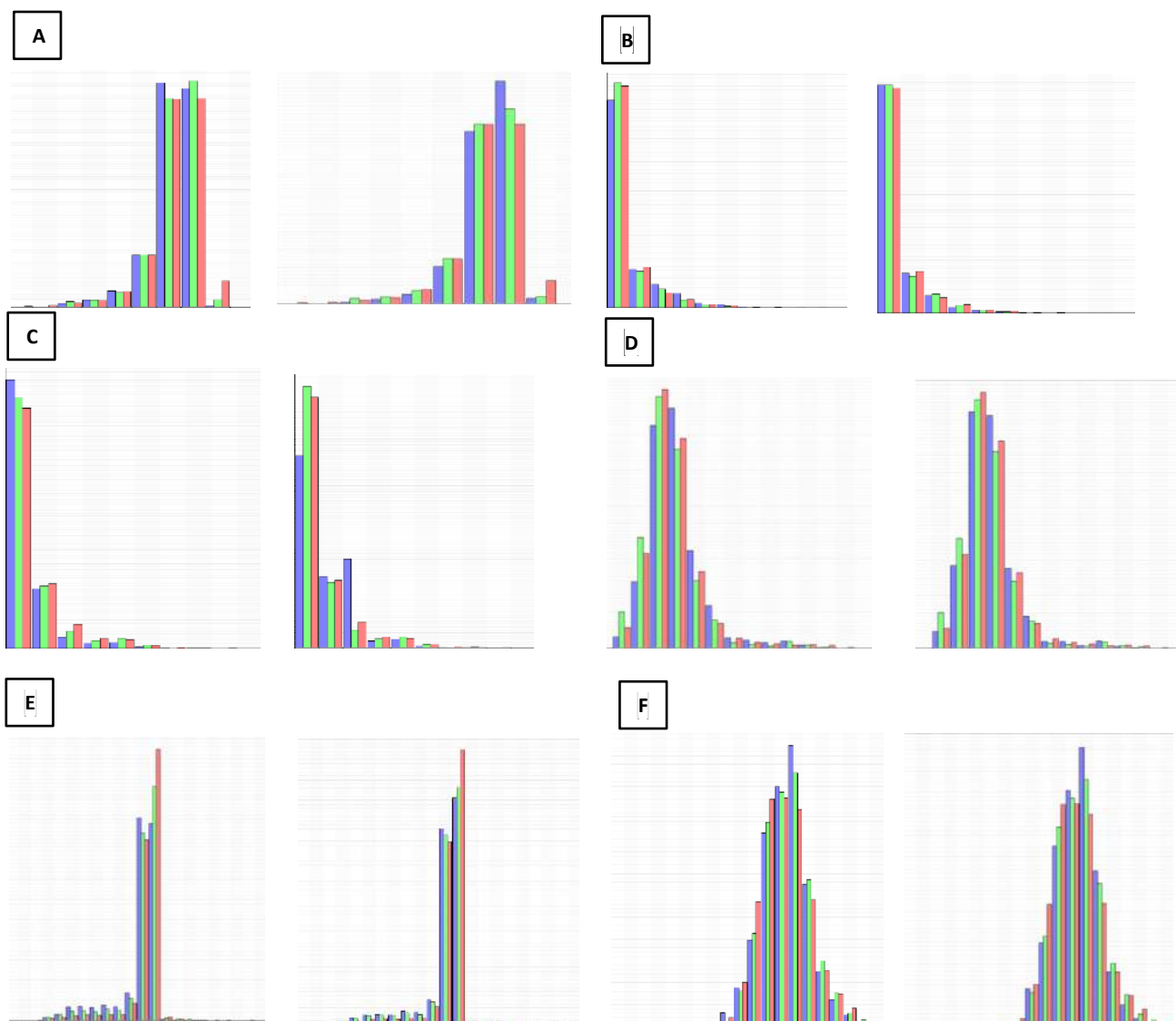


Figure 4.11. Histograms comparing input (red), upscaled (green) and modeled well-logs (red) for exponential- (left) and Gaussian- (right) fitted semivariograms. **A.** Ca (w/w), **B.** Si (w/w), **C.** S (w/w), **D.** GR (API), **E.** density (RHOB) (g/cm^3), and **F.** LLD resistivity (ohm.m).

members reflect cyclic deposition within transgressive-regressive sequences (Alsharhan and Nairn, 1994; Al-Jallal, 1995). The general paleogeography of the Permo-Triassic succession is fairly well-determined (Ziegler, 2001) (Figure 1.2). The water levels were shallow enough

to enable the occurrence of extensive supratidal environments in arid climate. In this context, minor sea-level fluctuations could lead to notable shifts in the sedimentary setting, including the formation of sabkhas, as noted by Alsharhan and Kendall in 1986. This fundamental scenario stretched from Oman to southeast Turkey, as reported by Murris, 1980 and Sharief, 1982, and it is clear that the cyclic patterns observed didn't necessitate a significant change in sea level.

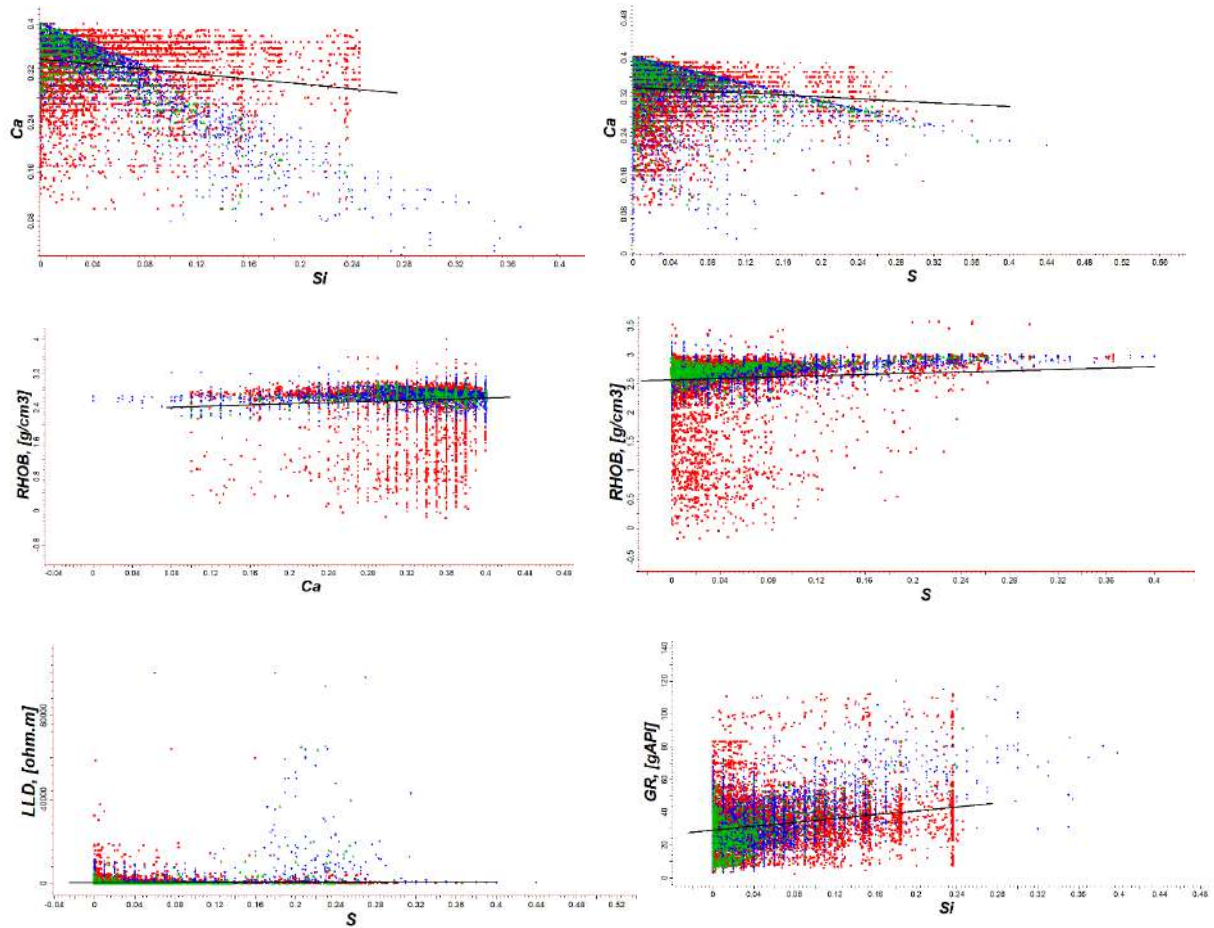


Figure 4.12. Cross-relationships between different well-logs from exponential models data (red). Note the good direct correlations between Si, Al, and GR, moderate correlation between Ca, S, and density (RHOB), and the reverse correlation between Ca and S. LLD resistivity has shown poor to no correlation with S. Blue and green data are the input well-logs and upscaled well-logs, respectively, superimposed in the whole model data.

4.4.2 Model Validation

Petrel[®] software uses a relative sill as a default value of 1.0 for all semivariograms. This value acts as a relative value equivalent to the absolute value of half of the data variance (semivariance). The software algorithm uses this approach, as it uses normalized data (the standard deviation equals one, the mean equals zero) before constructing the semivariogram (half of the variance). This process also helps for the sake of simplicity, which eases the auto-fitting semivariogram by the software. However, in this research, auto-fitting was ignored and the semivariograms were fitted manually for each property in each member to ensure the best semivariogram parameters that properly indicate the variability. An exponential model was found the best for fitting all 3D semivariogram, with a negligible nugget effect that tends to zero. Basically, the exponential model assumes that spatial correlation decreases exponentially with distance, and it is particularly suitable for datasets where the decrease is not abrupt (as with the spherical model), but is more gradual. The exponential model is often preferred for its flexibility and can model a wide range of spatial structures. It is especially useful for continuous processes. The exponential model always ensures the lowest nugget compared to the spherical and Gaussian models, respectively. A lower nugget effect is typically desirable because it indicates less unexplained variability and suggests that the measurements are more precise and the spatial correlation is stronger (McKinley et al., 2004; Caers, 2005; Orellana et al., 2014). The variogram is a fundamental tool used to quantify spatial variability. It plots the variance of the difference between pairs of sample points against the distance separating those points. Dispersion variance can be seen as a particular case of this, where the interest is in the variance within a block or volume of material rather

than between pairs of points. In this regards, the basic statistical parameters, including the variance obtained from different models were compared with original input and upscaled well-logs, acceptable match were attained among them for different logs (Figure 4.11, Table 4.3). Close match that observed in ECS data indicate the intrinsic elemental composition, and thus mineralogy indicated by well-logs. The elemental composition is also directly affecting other logs including GR, density (RHOB), and deep resistivity (LLD). Accordingly, a good cross-relationship between these models was recorded (Figure 4.12). In the Gaussian-fitted semivariogram, the parabolic increase at short distances indicates a high degree of spatial correlation for nearby points. This behavior implies that the studied property (variable) changes smoothly over space, with values at locations close to each other being very similar (Leuangthong et al., 2011). The presence of a nugget in the Gaussian semivariograms, and less in the exponential ones (Table 4.2), suggests the potential occurrence of small-scale variations or a degree of randomness. Nugget can be attributed to various aspects such as measurement error, small-scale variation, or limited sampling. Knowing that borehole log data is among high-frequency and high-accuracy sort of data with least error, especially if the studied interval is thick as the current situation, in addition to the fact that this is a field-scale study with limited well data distributed in large area. Reasonably, the Gaussian model which has negligible variation in small-scale, has revealed a significant nugget due to the low density of sampling, indicating the potential small-scale variability, more significantly in the areal extension (major and minor ranges). On the contrary, the exponential model which respect the small-scale variation, having higher variation near origin (Bohling, 2005) (Figure 4.8). This model generally exhibits a slower approach to

the sill, indicating a longer range of spatial correlation. This suggests that data points further apart are still somehow correlated, with the correlation decreasing gradually with distance. In the context of limited data, the exponential semivariogram with a longer range implies to consider data points that are relatively far from the target location while maintaining a degree of certainty in their spatial correlation. In the epicontinental, laterally extended and gently-dipping platform, it is assumed that exponential fitting is better representative for variability than the Gaussian fitting. Reasonably as the two models have shown comparable parameters that honor the input and upscaled well-logs (Table 4.3). However, the structural setting of the platform needs to be considered as it could impact the rock properties due to potential diagenesis taking place. In this regards, seismic structural cubes, coupled with seismic attribute analysis for rock properties would be valuable for better carbonate properties modeling and characterization.

Table 4.3. Model parameters obtained from exponential and Gaussian 3D models compared to the input and upscaled well-logs. These parameters are cumulative for whole members.

Well log	Data source	Exponential			Gaussian		
		Avg.	Std.	Var.	Avg.	Std.	Var.
Ca (w/w)	Model	0.3369	0.0469	0.0022	0.3267	0.0741	0.0050
	Upscaled	0.3366	0.0478	0.0023	0.3366	0.0478	0.0023
	Input	0.3380	0.0506	0.0026	0.3380	0.0506	0.0026
Si (w/w)	Model	0.0369	0.0480	0.0023	0.0291	0.0384	0.0015
	Upscaled	0.0297	0.0388	0.0015	0.0297	0.0388	0.0015
	Input	0.0282	0.0447	0.0020	0.0282	0.0447	0.0020
S (w/w)	Model	0.0371	0.0452	0.0020	0.0629	0.0535	0.0029
	Upscaled	0.0443	0.0547	0.0030	0.0443	0.0547	0.0030
	Input	0.0423	0.0574	0.0033	0.0423	0.0574	0.0033
Density (g/cm ³)	Model	2.5910	0.4790	0.2295	2.5203	0.5672	0.3217
	Upscaled	2.5519	0.5600	0.3136	2.5519	0.5600	0.3136
	Input	2.6500	0.4396	0.1933	2.6500	0.4396	0.1933
GR (API)	Model	30.35	11.27	126.92	32.29	13.90	193.20
	Upscaled	29.98	14.41	207.58	29.98	14.41	207.58
	Input	31.43	14.56	212.14	31.43	14.56	212.14
Resistivity LLD (ohm.m)	Model	309.0	1536.3	2360254.6	512.9	2153.7	4638254.5
	Upscaled	550.7	3233.5	10455235.0	550.7	3233.5	10455235.0
	Input	545.3	3515.5	12359038.5	545.3	3515.5	12359038.5

CHAPTER 5

APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN THE PREDICTION OF PERMO-TRIASSIC CARBONATES

5.1 Introduction

An in-depth knowledge of the depositional environments of sedimentary strata is essential for predicting their intrinsic attributes, such as composition, and thus petrophysical properties that aid in fluid flow simulation. (Jennings and Lucia, 2003; Marchand et al., 2015; Aziz and Gomaa, 2022). These assessments have predominantly been based on traditional methods such as paleontological and sedimentological features (Tucker and Wright, 2009; Boggs, 2012; Tucker and Jones, 2023). Nonetheless, progress in sedimentary geology has greatly improved the capacity to understand depositional environments by employing chemical elemental information. Elemental composition is one of the most standard approaches for understanding the depositional environment and stratigraphic correlation of different sedimentary strata (Craigie, 2018; Michael et al., 2021). This approach is known for its simplicity of laboratory analyses and exceptional accuracy and precision (Eltom et al., 2017). Elemental data are typically presented and analyzed as ratios, indices, and proxy values arranged in profiles against depth (Ramkumar et al., 2018; Sial et al., 2018). With over a thousand potential combinations of the analyzed elements, pinpointing significant variations that lead to correlating chemostratigraphic boundaries and zones across wells becomes a labor-intensive task. Due to the vast number of combinations,

about 30-40% of the data often remains unutilized in correlations, yet this information could be key to comprehending geological processes. Automation and artificial intelligence (AI) are considered promising approaches to address all these issues. Well-log data from the subsurface can offer vital insights into the spatial variations of depositional lithofacies, the petrophysical characteristics of reservoir zones, and mineralogy, leading to a more thorough evaluation of reservoirs (Zhang et al., 2018; Wood, 2019; Sun et al., 2020; Martin et al., 2021). Moreover, well-log data is usually more readily available in most wells compared to other types of subsurface data, like cores. Therefore, despite several limitations associated with well-log data, a possible connection might be established between well-log data and elemental composition. By combining machine learning (ML) and artificial intelligence (AI) with well-log data to predict elemental composition, significant time and effort typically allocated for laboratory analyses and costly elemental well-logs could be saved, thus, making the overall process more efficient. Several studies utilized well-log data and ML/AI to address multiple issues including prediction of mineralogy (e.g. Asante-Okyere et al., 2021; Laalam et al., 2022; Mustafa et al., 2022), formation matrix volume (Kannaiah et al., 2023), lithofacies (Martin et al., 2021; Mubarak and Koeshidayatullah, 2023), Total Organic Carbon (TOC) (Shi et al., 2016; Mahmoud et al., 2017; Tariq et al., 2020; Chan et al., 2022). Nevertheless, the involvement of elemental composition in the integration of AI/ML and well-log data remains not extensively explored except in some studies of unsupervised techniques (e.g., De Oliveira and Carneiro, 2021; Hussain et al., 2021; Hussain et al., 2022; Larson et al., 2023a; Larson et al., 2023b), that shows a good potentiality of this integrational area. This research aims to utilize and evaluate the performance of several Artificial Neural Network architectures to predict lithological units (members) of a late Permian - early

Triassic carbonate succession using integration of elemental composition and well-log data. Initially, several statistical techniques were applied to discover the nature and pattern of the input dataset. The same architectures' regressors were applied, using well-log data as an input, to predict the composition of major elements in the studied successions. This study suggests ways to employ well-log data to predict elemental composition, saving the time and efforts dedicated to elemental well-logging and laboratory analyses.

5.2 Data and Methods

5.2.1 Data

Well-logs from six vertical wells were used in this study. The targeted interval includes the Permo-Triassic (late Permian - early Triassic) strata, subdivided into four members using five member tops (Figure 4.2). The data used in ANN modeling includes conventional well-logs (GR, RHOB, NPHI, and acoustic slowness of p- and s-wave). In addition, the elemental capture spectroscopy (ECS) logs of the major elements were also incorporated for predicting member identity. The major elemental contributors used as input for modeling include Ca, Si, Al, Fe, and S logs. Mineralogy logs interpreted from conventional logs and elemental geochemistry were also used for member identification. These minerals include carbonates (carb), anhydrite (Anh), quartz-feldspars-mica (QFM), and clay. In total, 14 logs were used for member identification, five of which were used for ECS geochemistry prediction (major elements).

5.2.2 Methods

The principal component analysis (PCA) is a statistical technique that transforms the data into a new coordinate system, with the axes (called principal components (PCs)) ordered by the amount of variance captured from the data. The first principal component captures the most variance; the second captures the second most, and so on. PCA loadings are coefficients that describe how much weight each original variable has in the principal components. They are a measure of the contribution of each feature to a principal component. They are represented by a heatmap, where each cell corresponds to the loading of a feature (rows) on a principal component (columns). One can interpret the principal components by examining which variables have high positive or negative loadings on a principal component in terms of the original variables. For major elements data, the correlation coefficient (CC) is one of the most frequently used statistical analyses to understand element-mineral links. Typically, correlation coefficient values above 0.7 indicate a strong correlation between two variables. Values between 0.6 and 0.7 suggest a moderately strong correlation, while those ranging from 0.5 to 0.6 imply a moderate correlation. Any CC value below 0.5 is considered to reflect a weak correlation. This standard applies to negative CC values as well; for instance, a CC value below -0.7 would denote a significant inverse relationship between two elements (Wold et al., 1987). The correlation heatmap is commonly used to illustrate the degree of linear relationship between variables. The hierarchical clustering analysis was performed to explore the natural groupings within the dataset based on the similarity of features. The resultant dendrogram, as illustrated, provides a visual representation of the clustering process. Each vertical line represents a cluster, and the length of the two legs of the U-shape connection indicates the distance between clusters, with shorter legs suggesting greater

similarity. This dendrogram is an essential tool for data analysis, which enables determining the number of clusters that best represent the underlying data structure. To address the classification and regression objectives of this study, several neural network architectures we designed and evaluated (Figure 2), optimizing for performance and generalization. The architectures (models) are outlined as follows. Architecture_1: This model is a straight feedforward neural network consisting of an input layer that accepts 14 features, including elemental, mineralogical, and well-log data. It sequentially processes data through two dense layers with 512 and 256 neurons, respectively, and applies dropout regularization after each dense layer to prevent overfitting. The final output layer uses 4 neurons, which could correspond to a multi-class classification task with four classes (Figure 5.1). Architecture_2: This expanded network introduces additional complexity, with a deeper structure of four dense layers and dropout applied after each dense layer. The number of neurons in successive layers is 1024, 512, 256, and 128; reducing by half with each layer and culminating in an output layer with 4 neurons. This architecture is designed to capture more complex patterns in the data while still employing dropout to mitigate overfitting (Figure 5.1). Architecture_3: This configuration integrates batch normalization and activation layers after the initial dense layer with 512 neurons. Batch normalization is intended to stabilize and accelerate training by normalizing the input layer for each mini-batch. This process is repeated for the second dense layer with 256 neurons. Dropout is applied after each activation to enhance model robustness (Figure 5.1). Each architecture's layers are activated using non-linear activation functions (not explicitly shown), which are critical for the network to model non-linear relationships in the data. The dropout rates were not specified but are typically set between 0.2 and 0.5. The final layer's activation function would be chosen based on the specific task,

such as softmax for multi-class classification. The architectures were implemented using a modern deep learning framework, ensuring that they could be trained efficiently on available datasets. The design choice for each architecture reflects a trade-off between model complexity and computational efficiency, aimed at achieving the highest predictive accuracy while avoiding overfitting to the training data. These NN architectures were then trained, validated, and tested using our dataset, with performance metrics being recorded to compare the effectiveness of each model configuration. The chosen architectures and their corresponding performance will be discussed further in the Results section. In addition to the neural network architectures previously outlined for classification tasks (Figure 5.1D-F), we employed similar structures adapted for regression analysis. These architectures were rigorously trained and validated using cross-validation techniques to ensure robust performance in predicting continuous target variables. The performance metrics, such as mean squared error (MSE) or mean absolute error (MAE), were carefully monitored to assess the regression models' accuracy. This evaluation is critical in understanding the architectures' predictive capabilities, with detailed results presented in the subsequent sections of this study. The three architectures were applied to the training dataset from well-M3. The produced model was applied to a dataset from unseen well as a blind test (well-M1) for both classification and regression purposes as an additional approach of cross-validation and to evaluate the performance of the architectures to differentiate between the studied lithological units.

5.3 Results

5.3.1 Principal Component Analysis (PCA)

PCA shows that the input training data of major elements and well-log could be grouped into three PCs that capture more than 80% of the variance, leading to a significant reduction of dimensionality with minimal information loss. Over 50% of the variance is explained by the first principal component (PC1). By the time the third component is involved, over 80% of the variance is captured (as suggested by the cumulative explained variance (Figure 5.2). Ten principal components hold the entire variance of the input data.

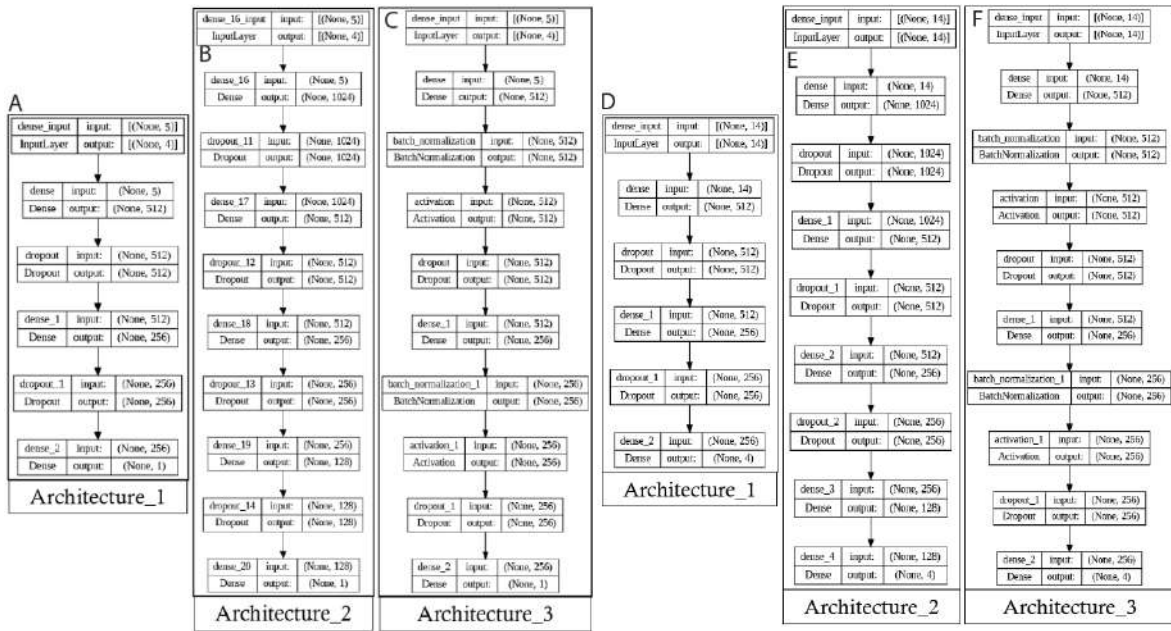


Figure 5.1. ANN architectures applied to predict the elemental composition and Premo-Triassic members: **A.** Architecture_1 consists of two dense layers containing 512 and 256 neurons, respectively. **B.** Architecture_2 consists of four dense layers containing 1024, 512, 256, and 128 neurons. **C.** Architecture_3 consists of two dense layers containing 512 and 256 neurons; each dense layer is followed by a batch normalization layer. Notice we applied the drop out technique to reduce overfitting. The same architectures with more input data were applied for classification to predict the four members, as shown in **D**, **E**, and **F**.

The major PC's are detailed as follows:

- PC1 is positively influenced by Al, Si, Fe, and clay minerals. Relatively lesser positive influence is related to QFM, GR, DTCO, and DTSM. This component is negatively influenced by Ca. The highest positive loadings are normally concentrated in clay minerals and are probably associated with quartz. PC1 reflects detrital material input (Figure 5.2).
- PC2 is positively correlated with S, anhydrite, and RHOB. Ca and carbonate have negative loading on PC2. The highest positive loadings indicate that this PC reflects the effect of anhydrite minerals associated with post-depositional processes.
- NPHI and RHOB have the highest positive and negative loading on PC3, respectively. PC3 probably reflects the impact of porosity.
- PC4 is positively correlated with Si and QFM. It is tightly associated with the quartz component of detrital input.
- PC5 to PC8 have the highest positive and negative loading from well-log data reflecting the influence of rock properties.
- PC9 to PC14 are associated with major elements and minerals, all these components do not explain any variance.

As evident from the loading heatmap, both major elements and well-log data contribute equally to the most important four PCs. Therefore, utilizing the entire input features could improve classification or regression performance (Figure 5.2).

5.3.2 Hierarchical Clustering

From the dendrogram, it is clear that the clustering produced several distinct groups, with the tallest branch (in blue color) representing the largest distance indicative of the least similarity between two major clusters in the dataset (Figure 5.3). Conversely, the shorter branches (in orange and green) represent clusters with greater similarity. The hierarchical structure of the clusters is immediately clear, allowing us to discern the complexity of the relationships between different data points. Cutting the dendrogram at the height of 300 would yield a specific number of clusters, each representing a collection of data points with similar characteristics.

5.3.3 Correlation Coefficients

Among the input elemental, mineralogical, and well-log data, elemental and mineralogical data show a high correlation coefficient (Figure 5.4A). Al is positively correlated (> 0.7) with Si, Fe, QFM, and clay minerals, indicating a very strong mineralogical affinity with clay minerals. Ca shows a strong negative correlation with Al, Si, Fe, clay, and QFM minerals. It only has a positive correlation coefficient with carbonate minerals. S has a strong positive correlation with anhydrite and carbonate minerals only, while weakly correlated with other variables. Among the well-log data, GR has a strong positive correlation with the siliciclastic components. DTSM and DTMO are strongly correlated with each other. Slightly less (yet strong) positive and negative correlation of slowness versus siliciclastic variables and Ca is observed, respectively. RHOB is strongly associated with S and anhydrite. The weak correlation of S is further proved by pair-plot (Figure 5.4B). M-I and M-IV Members are well clustered and separated in most of these correlations except S scatterplots.

5.3.4 Prediction of Major Elements Using Well-Logs

The correlations between well-logs and major elemental composition logs are the basements for predicting these elements (Figure 5.5). In this context, a series of scatter plots were attained, comparing the predicted versus actual values of the major four elements (Si, Ca, Al, and S) using data from well-logs (Figure 5.6). These plots evaluate the performance of three different neural network architectures. The bar chart (Figure 5.6M) presents the Mean Squared Error (MSE) and coefficient of determination (R^2) for both training and testing datasets for each architecture. For Si prediction, Architecture_1 (Figure 5.6A) shows a tighter clustering of points around the best-fit line, indicating good predictions for both the training and testing sets. Architecture_2 (Figure 5.7) has a similar distribution, but more outliers exist, especially in the test set. Architecture_3 (Figure 5.7) appears to have the widest spread of points, suggesting less accurate predictions, especially for higher values of Si. Regarding Ca predictions, Architecture_1 (Figure 5.6D) has a reasonable fit for lower values but shows some divergence at higher values. Architecture_2 (Figure 5.6E) shows a similar pattern to Architecture_1 but with slightly more variance in the test set. Architecture_3 (Figure 5.6F) seems to have a better fit for higher values compared to Architecture_1 and _2, despite having few outliers. For Al predictions, Architecture_1 (Figure 5.6G) shows good predictions with only a few points deviating from the best-fit line. Architecture_2 (Figure 5.6H) has more spread in the test set predictions. Architecture_3 (Figure 5.6I) shows similar performance to Architecture_1 but with slightly more variance in the test set. Regarding S predictions, Architecture_1 (Figure 5.6J) exhibits a good correlation for training data, with a few outliers in the test set. Architecture_2 (Figure 5.6K) shows a slightly wider scatter for the test set compared to the training set. In Architecture_3 (Figure 5.6L),

The scatter plot indicates that this architecture has a comparable distribution of training data points to Architecture_1 but with slightly more spread in the test data. For Si and Al, Architecture_1 consistently has the lowest MSE and highest R^2 for training and testing, suggesting it is the most accurate and reliable for these elements. For Ca, Architecture_3 has a notably better R^2 in the test set, indicating better generalization despite a higher MSE, which suggests it may predict certain ranges of Ca more accurately. For S, Architecture_1 again has the lowest MSE for training and testing, although the R^2 for the test set is not the highest. Architecture_3 shows a competitive R^2 for the test set, suggesting good explanatory power for the variance in Sulfur data, even though the MSE is higher (Figure 5.6M). In summary, Architecture_1 Offers the most consistent performance across all elements, generally achieving the lowest MSE and highest R^2 . It seems to be the best general-purpose model. Architecture_2 Tends to show more scatter in the test sets, which might indicate some overfitting or less robustness to unseen data. It is less accurate than Architecture_1 but more than Architecture_3 for Si and Al, while its performance falls between the two for Ca and S. Architecture_3, while not as consistent as Architecture_1, seems to offer advantages in certain situations, such as with higher concentrations of Ca. For Sulfur, it shows a good R^2 in the test set but with a higher MSE, indicating it captures the trend in the data but with less precision. Figure 5.7 illustrates loss curves for training and validation sets across epochs. Architecture_1 presented a traditional approach with two dense layers followed by dropout regularization. The model exhibited rapid convergence to a stable loss value, indicative of efficient learning. Despite its simpler configuration, the validation loss mirrored the training loss closely, suggesting that the model generalized well to the validation data without signs of overfitting. Architecture_2 incorporated a more complex structure, with additional layers

and a higher number of neurons, potentially increasing the model's capacity to capture complex patterns. Notably, despite its complexity, the validation loss remained comparable to the training loss throughout the training process. This suggests that the model was robust in generalizing despite the increased risk of overfitting associated with its complexity, likely mitigated by effective dropout regularization at multiple layers. Architecture_3 adopted a modern approach by integrating batch normalization with activation layers. This model demonstrated the most rapid initial decrease in loss, settling quickly into a stable and low loss value. The smoothness of the loss curve points to a stable learning process, and the close alignment of training and validation losses indicates exceptional generalization capability. The produced models were applied to predict the elemental compositions of another unseen well; these results are visualized in Figure 5.8. The overall trend and bounding surfaces of the studied lithological units are well predicted using the synthetic elemental composition profiles. Si content predicted by Architecture_1 outlined fine or high-resolution intra-member cyclicity. However, they are significantly higher than the real values along the surfaces of high Si contents. The coarser inter-member boundaries are overlooked by architecture_2 and _3. Overall, the Si values predicted by Architecture_1 are closer to the ground truth values. Ca, Al, and Si predictions in the basal part (most probably in M-IV) have clearer coincidence and match better with the real values.

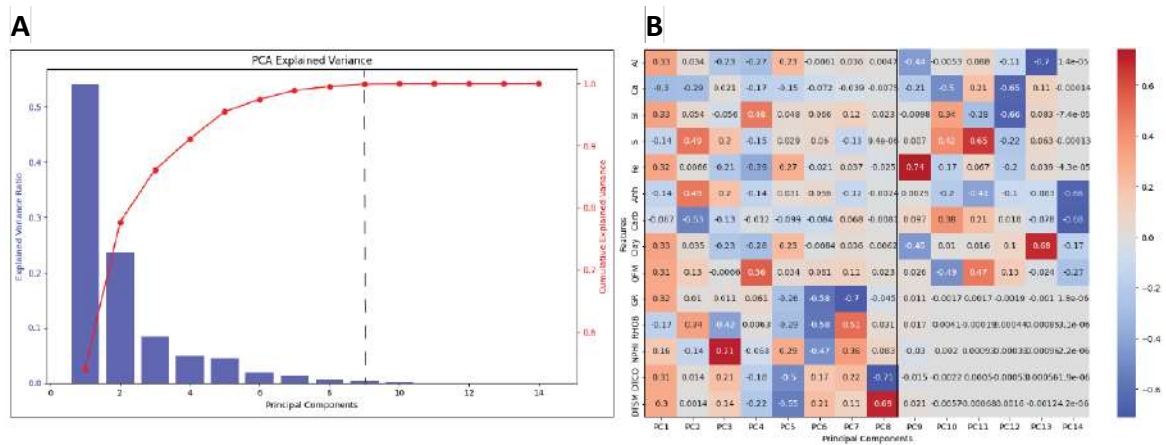


Figure 5.2. Results of the principal component analysis (PCA). **A.** Bar chart and line graph representation of PCA showing the explained variance ratio of each principal component (bar chart) and the cumulative explained variance (line graph) across the principal components, highlighting the proportion of dataset variance captured by each component in the analysis. **B.** PCA Loadings heatmap displaying the correlation coefficients between various geochemical features and the principal components derived from PCA. Each cell represents the loading of a geochemical feature (row) on a principal component (column), with color intensity indicating the strength and direction of the correlation: red for positive and blue for negative loadings.

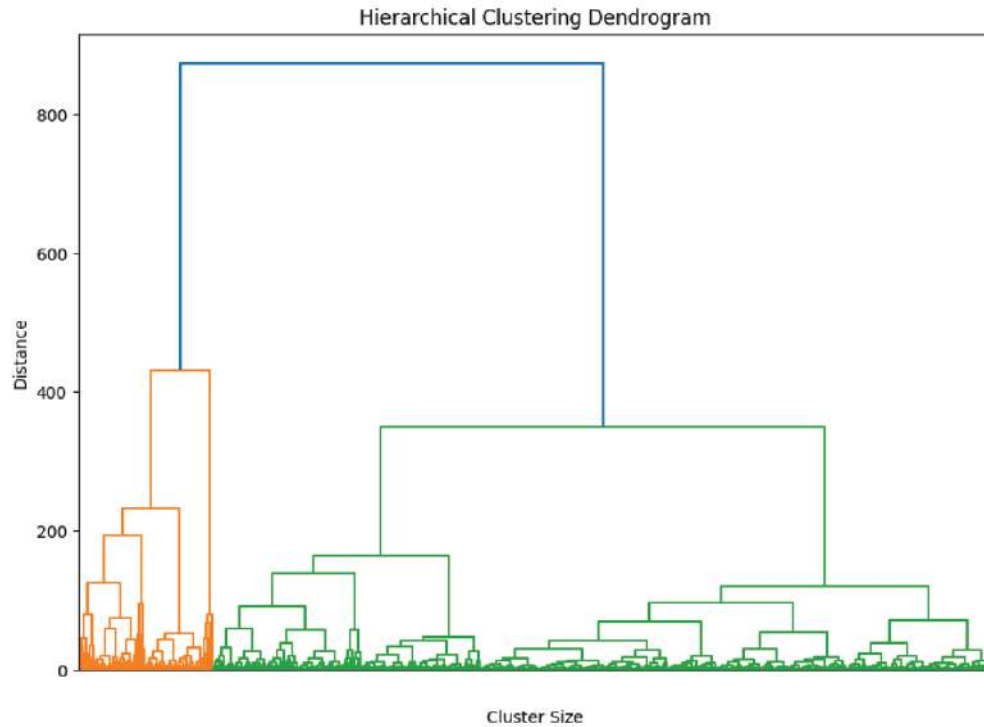
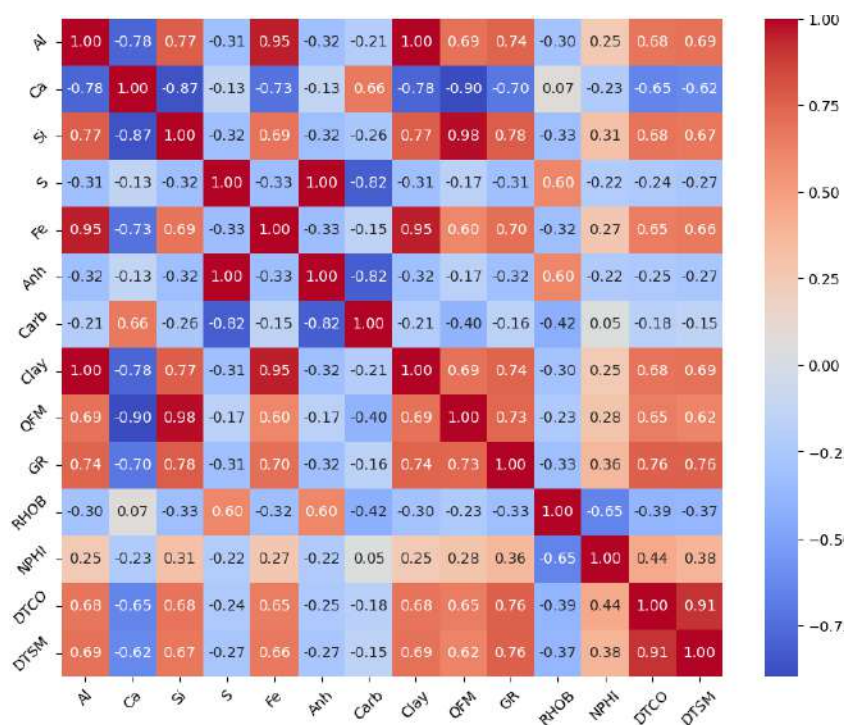


Figure 5.3. Hierarchical clustering dendrogram representing the results of a hierarchical cluster analysis. The vertical axis measures the distance or dissimilarity between clusters, and the horizontal axis represents the individual data points organized into clusters. The length of the vertical lines reflects the distance at which clusters are merged, with the longest line indicating the largest distance between two major clusters. The different colors denote separate clustering stages.

A



B

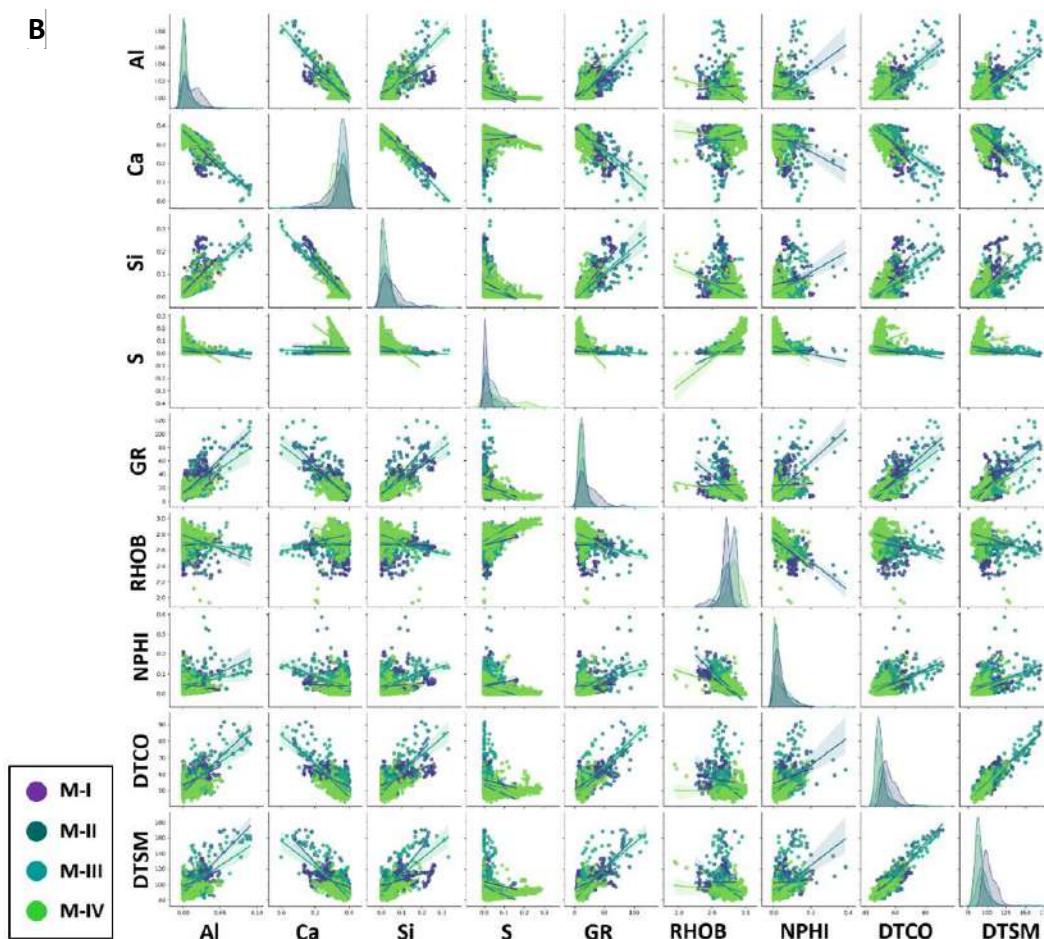


Figure 5.4. Results of the correlation coefficient analysis for the input training data used for classification: **A.** Correlation Heatmap illustrating the pairwise correlation coefficients among various geochemical and well-log parameters. Each square shows the strength of the correlation between two parameters, with 1 indicating a perfect positive correlation, -1 indicating a perfect negative correlation, and 0 indicating no correlation. The color scale ranges from blue for negative correlations to red for positive correlations. **B.** Pair-plot matrix showing the relationships between different geochemical and petrophysical parameters in the Permo-Triassic members. Each plot in the matrix represents the scatter plot of two parameters against each other, with the histogram of each parameter along the diagonal. The plots help to visualize the distribution of individual parameters and the nature of their cross-correlations.

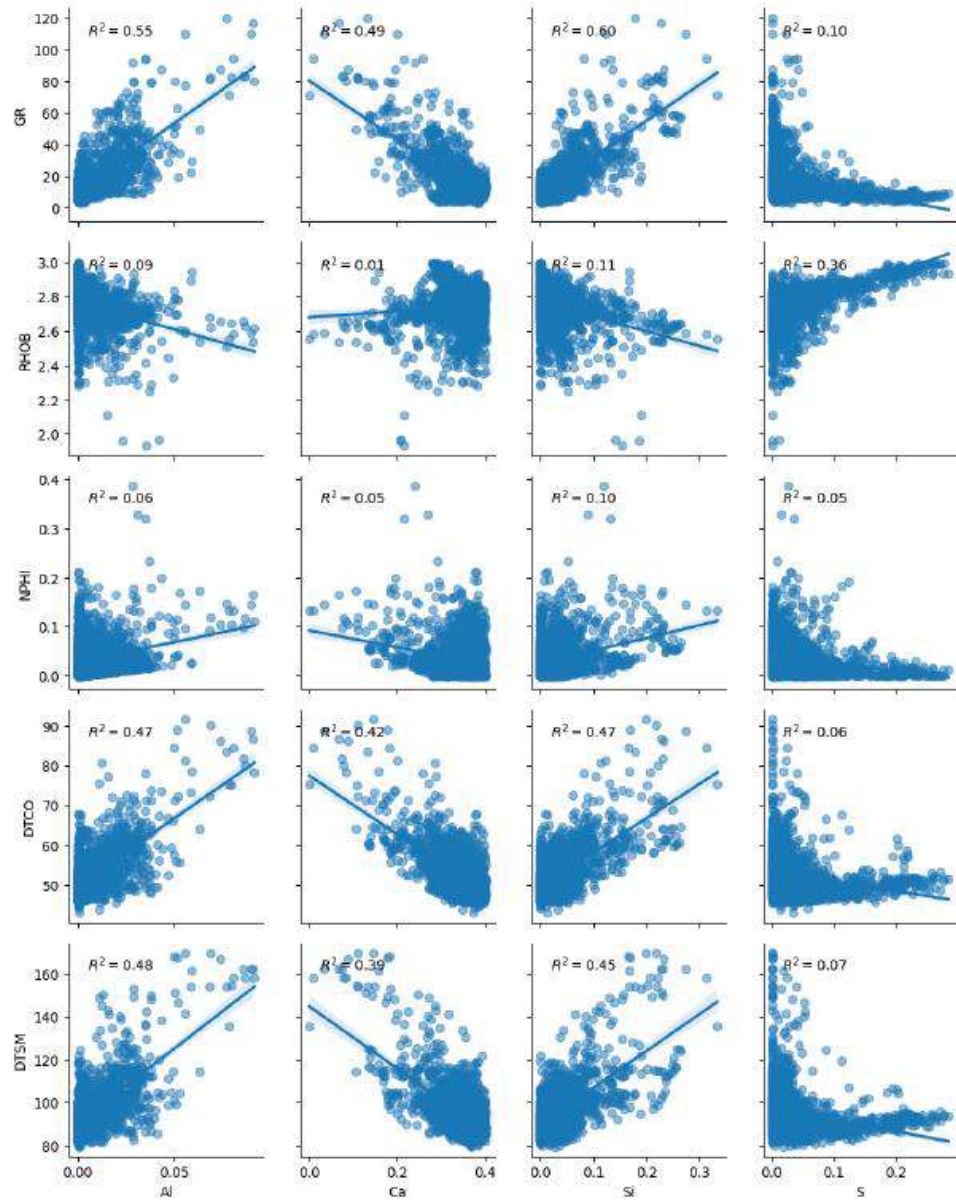


Figure 5.5. Scatterplot matrix showing the relationships between ECS data (Al, Ca, Si, S) and conventional well-logs (GR, RHOB, NPHI, DTCO, DTSM). Each scatterplot shows the correlation between a pair of variables, with the coefficient of determination (R^2) indicating the strength of the linear relationship. The trend lines provide a visual guide to the correlation direction and strength.

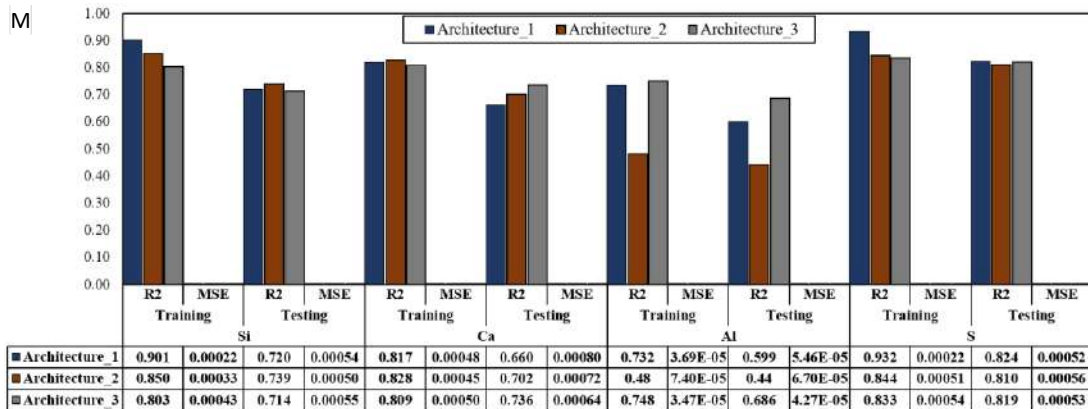
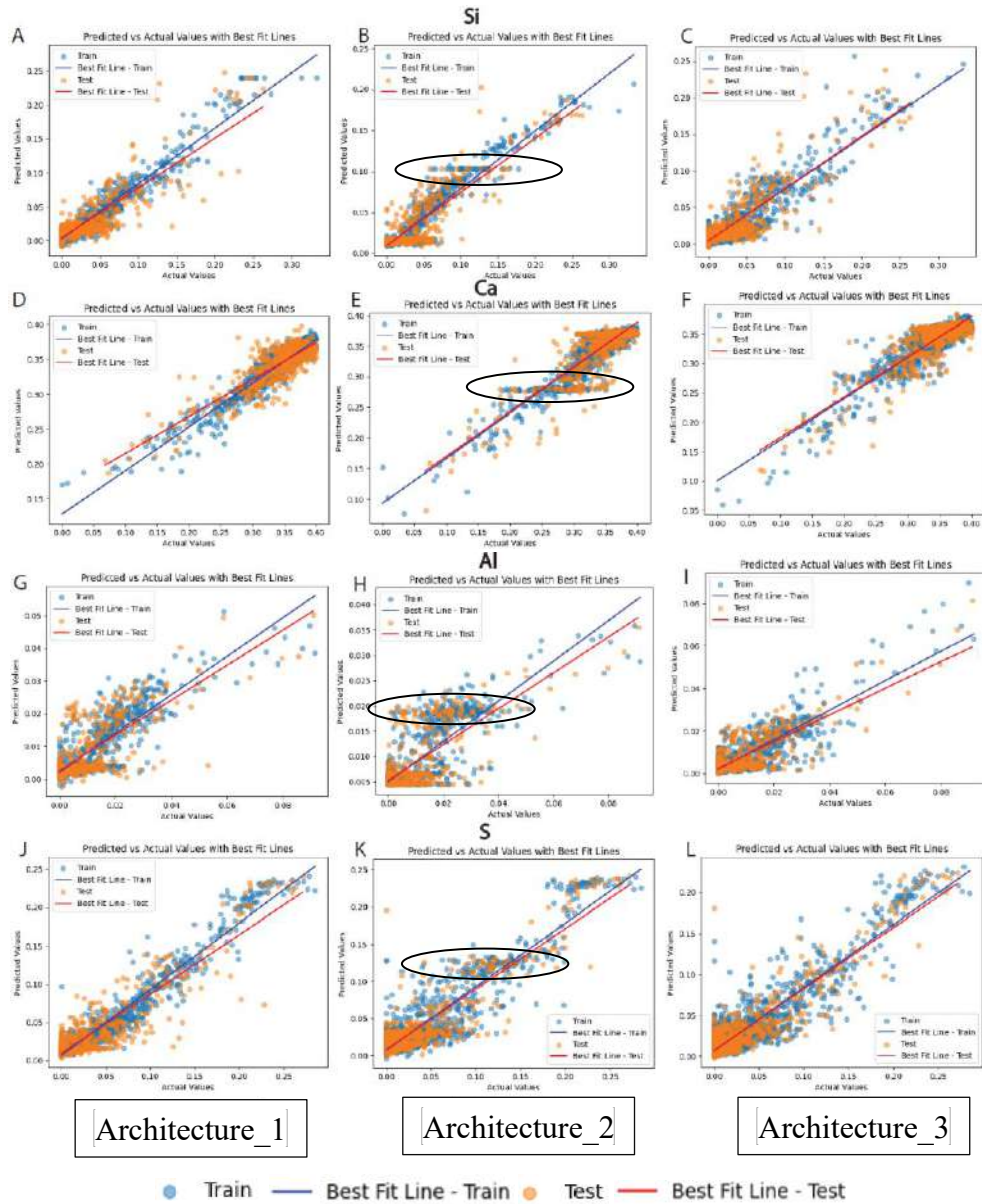


Figure 5.6. Set of regression plots comparing predicted (y-axis) versus actual ECS values (x-axis) for Si (**A-C**), Ca (**D-F**), Al (**G-I**), and S (**J-L**) using different ANN architectures. Each plot includes a 'best-fit' line for training (blue) and test (orange) datasets, illustrating the model's performance. Note the erratic prediction related to Architecture_2 (indicated by ovals). **M.** Bar chart summarizes the performance metrics; R^2 and Mean Squared Error (MSE) for each architecture during training and testing phases, providing a quantitative evaluation of each model's prediction accuracy.

5.3.5 Prediction of the Permo-Triassic Members

Architecture_1 revealed the highest accuracy, achieving 85% and showing higher accuracy compared with Architecture_2 and 3. The latter architectures achieved accuracies of 84% and 81%, respectively. Among the studied members, M-I and M-IV show the highest accuracy, ranging between 81% and 91%. M-I has the highest recall despite the lesser amount of support samples than M-II. The same precision pattern was observed in the F1-score, with M-I and M-IV having the highest scores. When applying the models produced by the three architectures of well-M3 on well-M1, an overall poor accuracy was obtained (<50%) (Figure 5.9, Table 5.1). However, M-I and M-IV show the highest metrics; M-I shows a recall and F1-score of 0.51 and 0.54, respectively. M-IV revealed a recall of more than 60%. In comparing the three architectures, it is evident that Architecture_1 provides the most balanced performance in terms of loss and accuracy, maintaining a close correspondence between training and validation metrics (Table 5.1). Architectures 2 and 3, while achieving high training accuracy, started to show signs of overfitting, as evidenced by the divergence between training and validation curves.

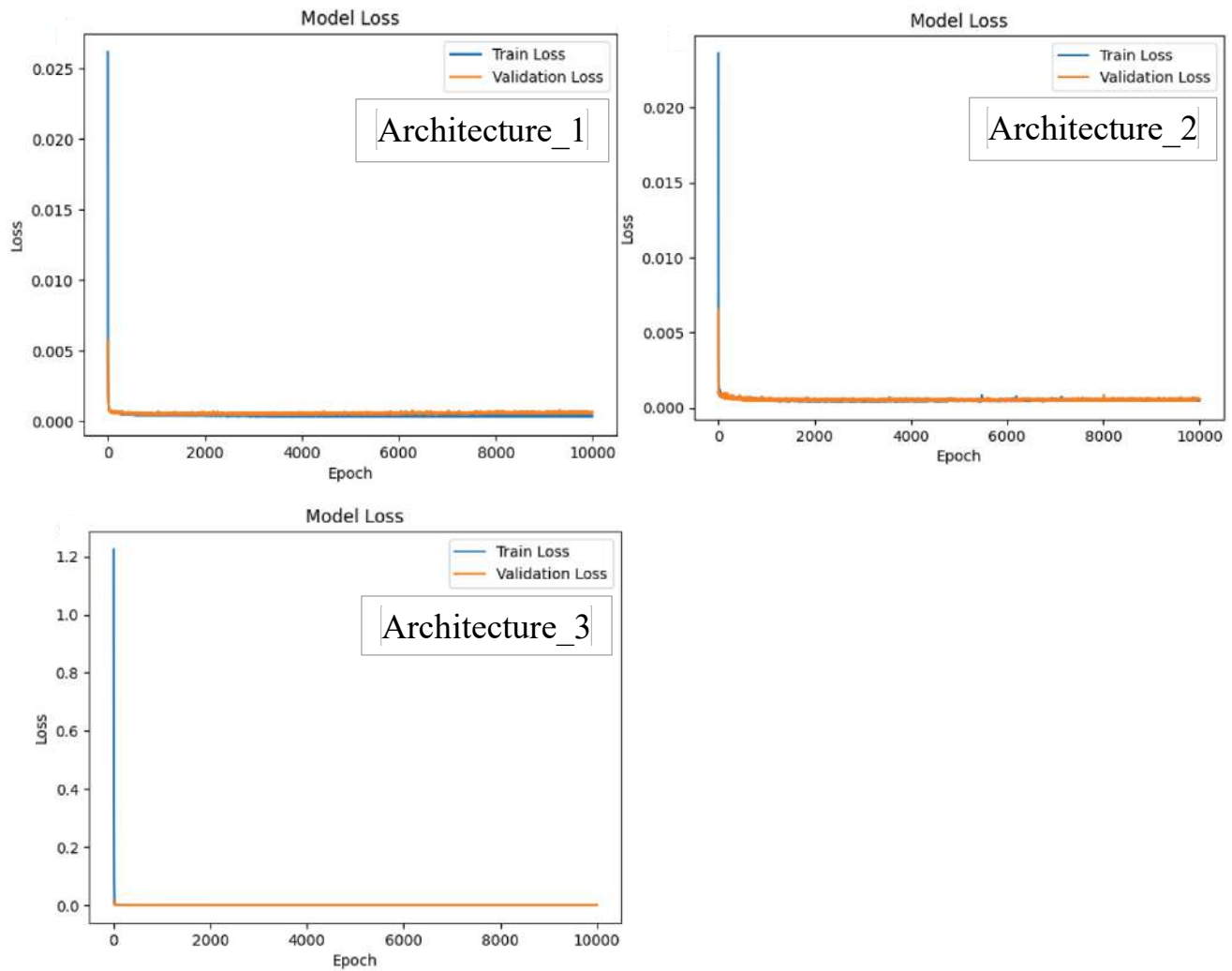
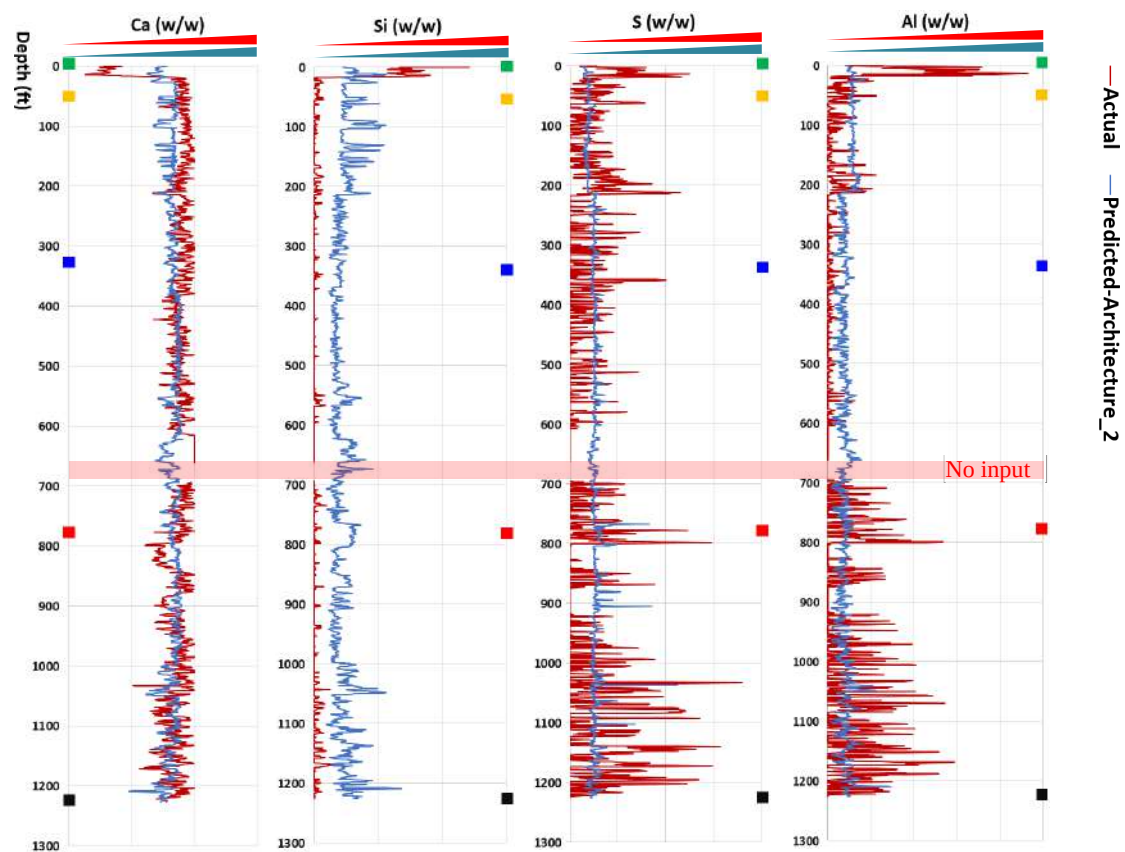
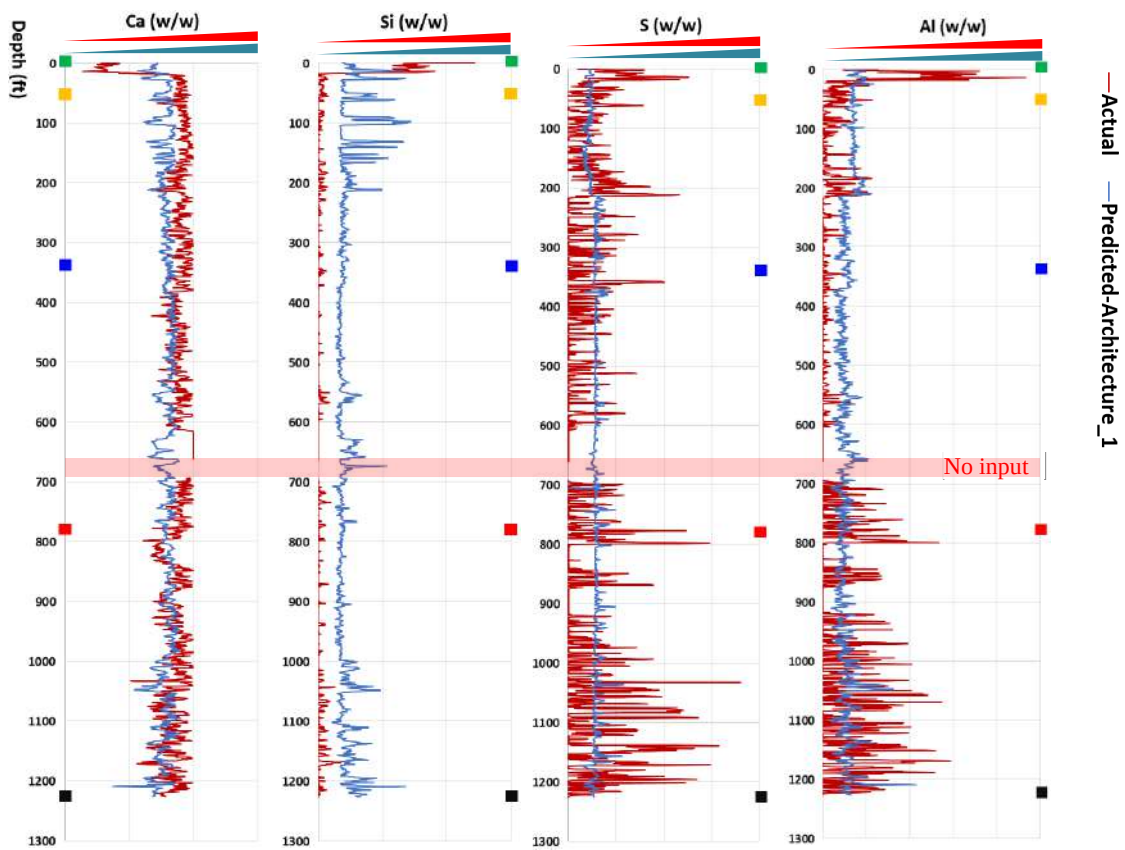


Figure 5.7. Learning curves for the three different neural network architectures showing model loss over epochs to predict overall elemental concentration. The graphs depict the training loss (blue) and validation loss (orange) for each element, indicating how the model's performance improves with each epoch. The spikes in the validation loss of Architecture_2 indicate erratic and poor validation compared to other architectures (Figure 5.6).



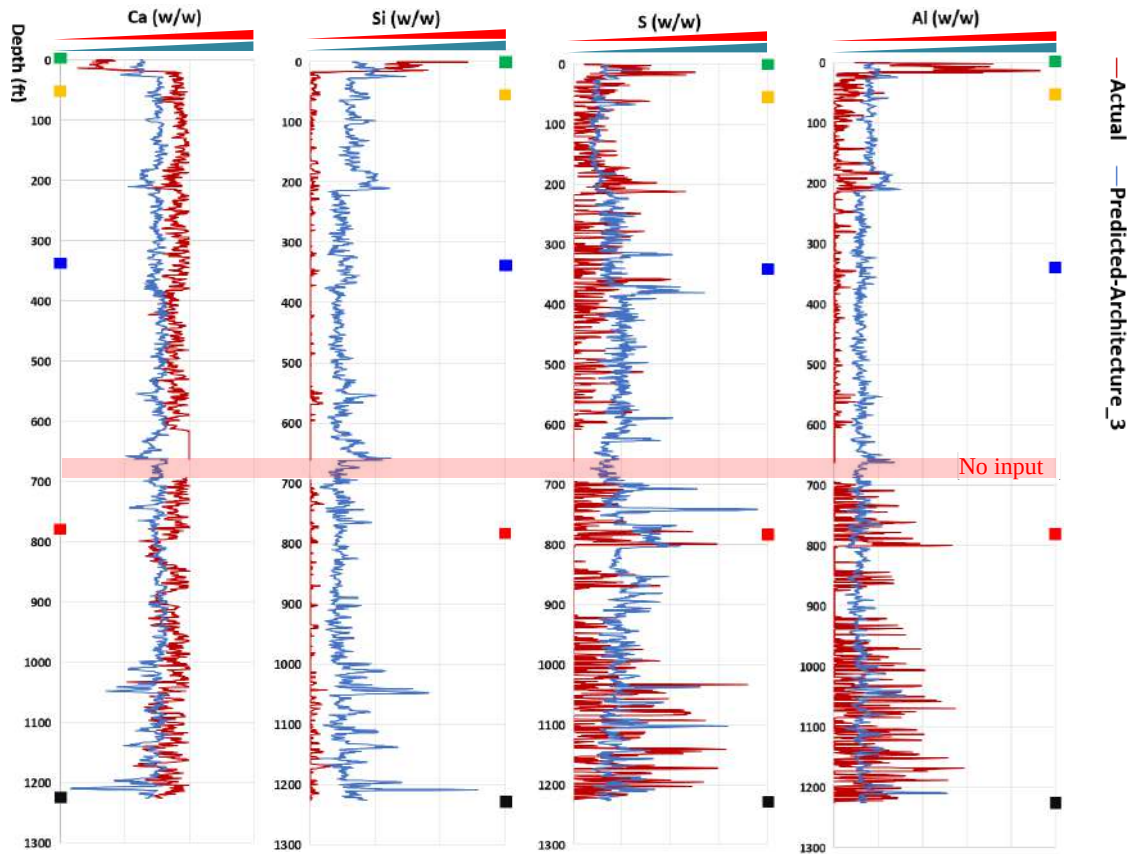


Figure 5.8. Comparisons between the actual ECS (blue curve) and the predicted values (red curve) of Si, Ca, Al, and S in well M1 as generated by the three architectures. Colored boxes indicate the five Permo-Triassic member tops (M-I to M-V; from top to bottom) incurred from well-logs.

5.4 Discussion

In the context of predicting elemental composition using well-logs, it is crucial to select a model that not only well-fits the training data but also performs consistently on unseen data. Based on the loss curves, Architecture_1 seems to be the most promising candidate, although the slight divergence in Architecture_2 and _3 validation loss could be addressed with further model tuning. The final choice of architecture will depend on a trade-off between the complexity of the model, its performance on validation data, and the computational

efficiency. The performance of the three neural network architectures employed in this study presents an insightful comparison regarding the model complexity, learning capability, and generalization performance in predicting elemental compositions from well-logs. Figure 5.10 shows the reverse trends of loss against accuracy in all architectures used for predicting member identity. The choice of the best architecture depends not merely on a singular performance metric but rather on a confluence of factors. Architecture_1, despite its simpler design, not only provided the best fit to the data, as evidenced by the highest R^2 and lowest MSE but also maintained a competitive edge in learning generalizable patterns efficiently. Architecture_1 and _2 achieved comparable final loss values, with Architecture_2 demonstrating a slight edge potentially due to its increased complexity and capacity. The learning behavior in Architecture_3, particularly the stability and rapid decrease in validation loss, suggests that the model quickly reached a strong understanding of the underlying patterns in the data. This indicates good initialization and an effective optimization process, likely facilitated by the batch normalization layers. However, the ultimate goal of predictive modeling is to achieve high accuracy and generalization, as reflected in quantitative performance metrics, which Architecture_1 attained more effectively. The superior R^2 and MSE outcomes associated with Architecture_1 suggest that it could better capture the signal in the training data and generalize these findings to the validation data. The loss curves further support this, where despite less initial stability compared to Architecture_3, Architecture_1 converges to a similarly low loss value, indicating that both architectures eventually learn to predict with similar error margins. Overall, when comparing the three architectures, the simplicity and robustness of Architecture_1 appear well-suited for the prediction tasks in this study. While

Architecture_2 and _3 offer more complexity that could be harnessed for more complicated datasets or different prediction tasks, their performance in this context does not justify the increased computational cost and complexity. Thus, relying on simplified architectures such as architecture_1 is recommended. This situation aligns with previous studies for predicting TOC (e.g., Chan et al., 2022). We further suggest exploring the performance of other conventional methods, such as ensemble machine learning (tree-based algorithms). These methods proved their efficiency (De Oliveira and Carneiro, 2021; Mubarak and Koeshidayatullah, 2023). The best performance of Si and S predictions and the higher accuracy of predicting basal part (M-IV) are tightly linked. Sulfur (S) concentration is strongly correlated with anhydrite mineral and RHOB as evident from the PCA and R^2 results. All these variables are the primary contributors in PC2 that hold more than 20% of the overall explained variance ratio. This also justifies the model's performance in efficiently predicting the fourth member (M-IV) in Well-M1 (Figure 5.9). Comparatively, the top member (M-I) was also predicted as PC1 holds around 50% of the overall variance; this component is influenced by the clastic components (Figure 5.2). However, M-IV prediction is better than that of M-I, which is attributed to the depositional setting of M-IV representing thick, widely-extended evaporites correlated on the regional scale (Al-Jallal, 1995; Konert et al., 2001). Stratigraphically, M-I is located below the massive accumulation of the overlying early Triassic shales, representing the regional cap rock of these carbonates (Al-Jallal, 1995). Al predictions also have good matching with the real values in the basal parts due to the higher abundance of clay minerals in the M-IV than the overlying units, except the uppermost part of M-I, which may indicate the influence of the overlying early Triassic shale-dominated formation that represents the regional seal for underlying carbonates. As

members M-II and M-III do not hold diagnostic characteristics as observed in M-I and M-IV, the model's prediction weakness is justified. Another factor that impacts the prediction is the large distance between Well-M1 and other wells (Figure 4.2). Architecture_3 incorporated batch normalization, which, in theory, should stabilize and speed up the training process. While this architecture did demonstrate fast initial learning, as seen in the sharp descent of the training loss, it did not always translate into superior generalization, as evidenced by the early plateauing of validation loss in some cases. This suggests that batch normalization, while beneficial in many scenarios, may not always be the optimal choice for every dataset, particularly when the dataset size is smaller, or the relationships in the data are not exceedingly complex. Overall, when comparing the three architectures, the simplicity and robustness of Architecture One appear to be well-suited for the prediction tasks in this study. While Architectures_2 and_3 offer more complexity that could be harnessed for more intricate datasets or different prediction tasks, their performance in this context does not justify the increased computational cost and complexity. Relying on simplified architectures is recommended. This result aligns with previous studies for predicting TOC (e.g., Chan et al., 2022). We further suggest exploring the performance of other conventional ML methods, such as ensemble (tree-based algorithms); these methods proved their efficiency (De Oliveira and Carneiro, 2021; Mubarak and Koeshidayatullah, 2023). The best performance of S predictions and the higher accuracy of predicting (M-IV) are tightly linked. Sulfur concentration is strongly correlated with anhydrite mineral and RHOB, as evident from the PCA and correlation coefficient results, all these variables are the primary contributors in PC2 that hold more than 20% of the overall explained variance ratio. Al predictions also

have good matching with the real values in the basal parts due to a higher abundance of clay minerals in the M-IV than the overlying units (except the uppermost part of M-I).

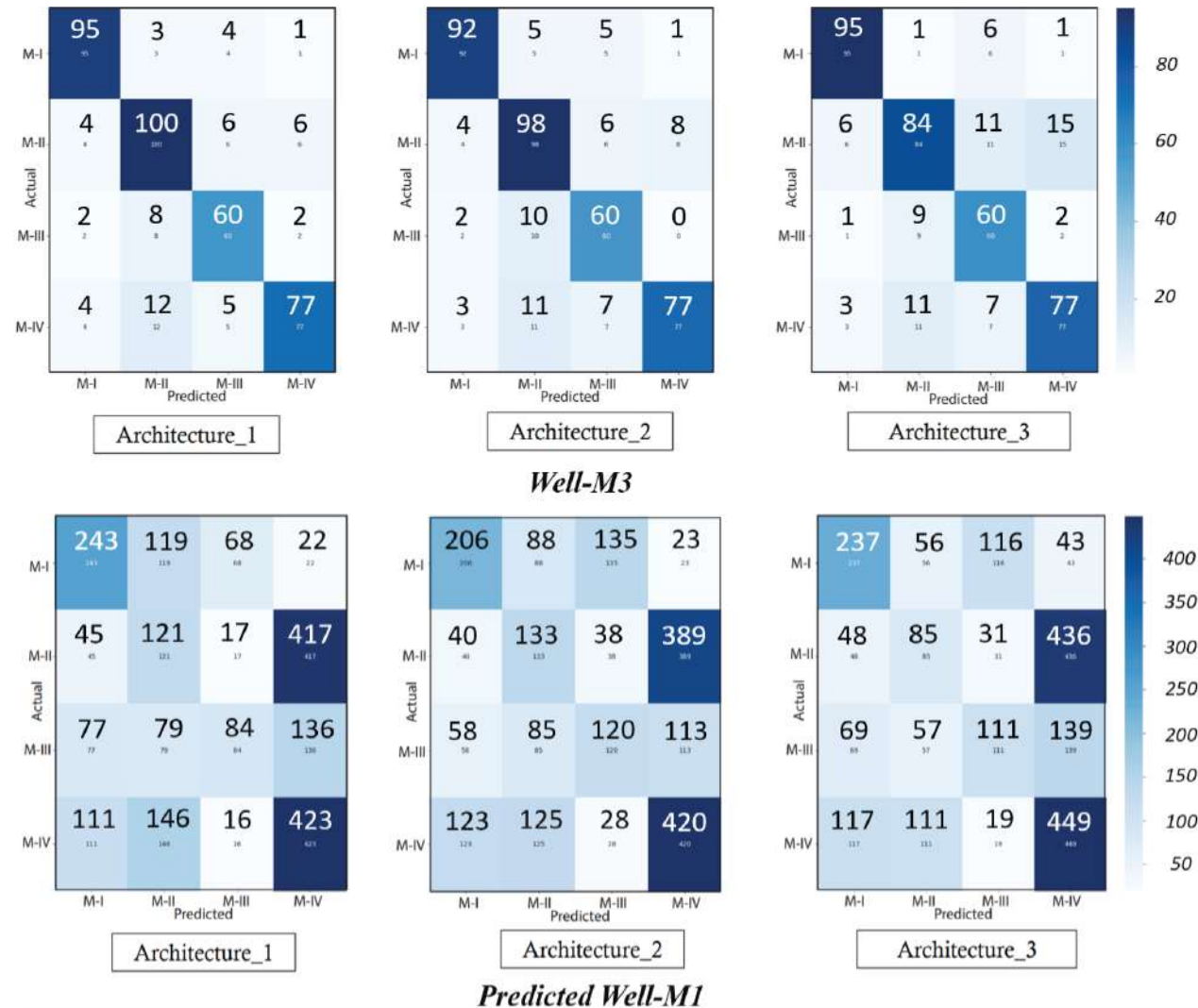


Figure 5.9. Confusion matrix comparing the predicted and actual Permo-Triassic members. The three architectures produced the model using the 20% validation data (389 values) in well-M3. The same architectures were utilized to blindly predict the members in well-M1 (2124 values).

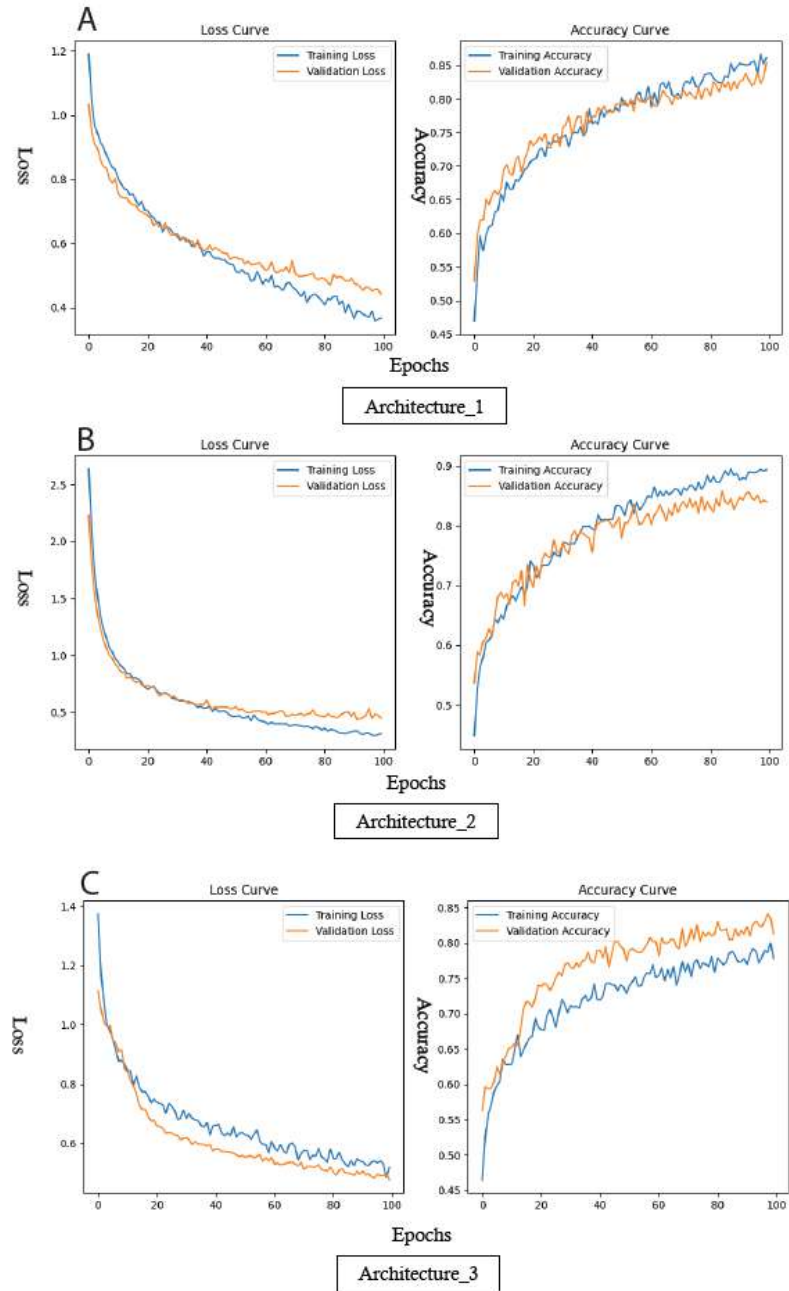


Figure 5.10. Performance evaluation graphs for the three neural network architectures. **A.** Architecture_1, **B.** Architecture_2, and **C.** Architecture_3 showing the training and validation loss curves and the corresponding accuracy curves over 100 epochs. Each set contains a loss curve (left) depicting the decrease in model loss over time, with a closer convergence of training and validation loss indicating better generalization, and an accuracy curve (right) illustrating the increase in model accuracy, where a higher accuracy and a close convergence between training and validation accuracy suggest a better fit.

Table 5.1. Evaluation metrics of the performances of applied ANN architectures in predicting the Permo-Triassic members.

		M-I	M-II	M-III	M-IV	accuracy	macro avg
Architecture1	precision	0.9	0.81	0.8	0.9	0.85	0.85
	recall	0.92	0.86	0.83	0.79		0.85
	f1-score	0.91	0.84	0.82	0.84		0.85
Architecture2	precision	0.91	0.79	0.77	0.9	0.84	0.84
	recall	0.89	0.84	0.83	0.79		0.84
	f1-score	0.9	0.82	0.8	0.84		0.84
Architecture3	precision	0.9	0.8	0.71	0.81	0.81	0.81
	recall	0.92	0.72	0.83	0.79		0.82
	f1-score	0.91	0.76	0.77	0.8		0.81
	Support	103	116	72	98	Total support	389

CHAPTER 6

CONCLUSION

The studied late Permian carbonate microfacies have proven gas potentiality in many fields in the Arabian Platform, including Saudi Arabia. This study utilized an exploratory core section and well-log data from southcentral Saudi Arabia. As revealed by petrography and high-resolution slab images, eleven microfacies occurred along the core section, covering a wide spectrum of sedimentary texture from mudstones and mud-dominated (MF2, MF4, MF5, MF11 and MF6) to grainstones and grain-dominated microfacies (MF3, MF10, MF7 and MF9) and floatstone (MF8), besides evaporites (MF1) belong to the intraformational cap rock. These microfacies are distributed in 13.12ft (4.0 m) polished core slabs from the 30 ft (9.14 m) whole-core interval. The studied late Permian exhibited prevailing intercrystalline microporosity (3-18%) that is not readily observed from conventional petrography. Besides quantifying microporosity, SEM high-resolution images provided a platform for crystal contact analysis that controls porosity distribution. Accordingly, the best porosity was reported in dolomitic mudstone (MF2), rich in punctic crystal contacts. While other microfacies have shown various complex contacts with increasing grain contents, thus, less porosity was noted. The intercrystalline microporosity and extremely low permeability (0.1 mD) in all samples confirm that studied microfacies represent a tight, unconventional reservoir setting. The porosity of these microfacies showed weak to moderate reverse relations to acoustic velocities. Geochemical and mineralogical investigations showed significant dolomite and Mg-calcite contents in the upper part of the core section (0-11.25 ft). Calcite was encountered all over the section but dominated in the lower part (14-30 ft).

The occurrence of dolomite and Mg-calcite has improved porosity, resulting in low velocities in MF2 compared to other microfacies. Other factors have also contributed to reducing and distorting velocity measurements, including microfacies sorting and fractures. The sorting impact was obvious in grainstone and grain-dominated microfacies, where acoustic velocities decreased when the sorting of allochems and intraclasts decreased to poor sorting. This behavior yielded reducing velocities from MF3 to MF8, passing through MF7 and MF9. Fractures yielded reduced, and often distorted, acoustic velocity as appeared in different textures regardless of microfacies. As noted in organic-rich microfacies (MF4 and MF11), the TOC was directly proportional to illite content and yielded low velocities. Occasional bedding-parallel stylolites were also noted as facies-independent features associated with organic matter and occasional fractures. All these features act together in acoustic velocity heterogeneity. Core analysis results showed conformity with data from wireline logs regarding calcite-dolomite segregation and elemental geochemistry. In addition, the NPHI log and gas detectors showed notable gas occurrence at the top of the section (MF2), representing the best reservoir microfacies regarding porosity and fracture intensity. The outcomes of this study offered an opportunity to investigate factors influencing acoustic velocity beyond quantitative and qualitative porosity. Such outcomes introduce better insight into borehole acoustic logs needed for gas exploration in tight carbonates.

In the fourth chapter of this research, 3D geostatistical modeling was applied for an exploration task using limited well data from southcentral Saudi Arabia. The Permo-Triassic carbonate succession in the Arabian Platform is one of the most laterally extended and prolific natural gas targets regionally and worldwide, deposited as transgressive-regressive

cycles in a gently-dipping epi-continental platform. The part aims to enhance the field-scale certainty by presenting a cost-efficient 3D geostatistical modeling of a roughly 35,000 km² field of the Permo-Triassic carbonates based on gamma ray, density, deep resistivity, and elemental geochemistry. Conventional log data from six wells were used for 3D modeling, including NPHI, dominant elemental spectroscopy (ECS) (Ca, S, Si, and Al), and RHOB. The Permo-Triassic succession was subdivided into four members, three of which are potential reservoirs. The intrinsic rock properties obtained from RHOB and ECS guided 3D variability by constraining reservoir intervals. Accordingly, the 3D variograms were constructed for each property and fitted against the best theoretical models. The major and minor directional variograms were identified based on the Arabian Platform geomorphology and validated by the regional variogram of the area. The models were calibrated against input data and enhanced by cross-correlations of intrinsic properties. Directional variograms showed spatial continuity in intrinsic rock properties with minimal variation and negligible nugget effects. Thus, all four members noted long major ranges of roughly 139-416km (Ca) and 160-220km (S). Minor ranges were analogous, spanning around 130-410km (Ca) and 150-210km (S), indicating clear zonal anisotropy. Member thickness governs vertical variograms, with Ca ranges of 17-29m (M-I and M-II) and S range of 27-127m (M-I and M-IV), respectively. Si and Al were less contributors to ECS and got shorter 3D ranges. The RHOB reflects rock composition and showed ranges nearly similar to the ECS in each member. Porosity distribution maintained less contrast among the top three members but notably dropped in M-IV due to the notable S of evaporitic cement.

The fifth chapter of this research successfully demonstrated the potential of using ANN architectures to integrate well-logs with elemental composition for geological predictions.

Among the three architectures evaluated, the simplest model (Architecture_1) consistently showed the best performance, balancing model complexity with predictive accuracy. This finding emphasizes the importance of model selection in geological applications, where simpler models can often yield effective results, especially in the early morning of exploration when limited data is available. The study also highlights the value of machine learning in enhancing geological interpretations, potentially reducing the time and effort required for traditional laboratory analyses. This approach provides a significant step forward in applying artificial intelligence in sedimentary geology for large-scale exploration, offering a more efficient pathway to understand geological settings and reservoir characteristics.

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