Multi-attribute Probabilistic Neural Network for Near-Surface Field Engineering

Application.

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Abstract

Unconfined Compressive Strength (UCS) is an important rock parameter needed for engineering design of structures built on top or within the interior of rock formations. In a site investigation project, the UCS is typically obtained discretely by point-to-point measurement and interpolated. This method is less than optimal to resolve meter-scale UCS variations of a heterogenous rock, such as carbonate formations, for which property changes occur within data spacing. We investigate the geotechnical application of multi-attribute analysis based on near-surface reflection seismic data to probe rock formations for their strength attributes at meter-scale variability. Two Late Jurassic outcrops located in central Saudi Arabia serve as testing sites: A) the Hanifa Formation in Wadi Birk and B) the Jubaila Formation in Wadi Laban. The study uses core and 2D seismic profiles acquired in both sites from which we constrain UCS, acoustic velocity, density, and gamma ray values. A positive linear correlation between UCS and acoustic impedance (AI) along the core indicates that seismic attributes can be utilized as a method to laterally extrapolate the UCS away from core location. Seismic colored inversion serves as input for neural network multi-attribute analysis and validated with a “blind test”. Results from data at both outcrop sites indicate a high degree of consistency with absolute UCS

error of ~5%. We also demonstrate the applicability of predicted UCS profiles to interpret mechanical stratigraphy and map lateral UCS heterogeneities. These findings provide a cheaper alternative to constrain UCS from limited core data on a field-scale site engineering project.

1. Introduction

Unconfined Compressive Strength (UCS) is an important rock parameter required in the engineering design for both surface and underground structures (Aladejare 2020). UCS is a needed input parameter for the prediction of deformation modulus (Sonmez et al. 2006), rock mass index (Palmstrom 1996) and Hoek-Brown failure criterion (Eberhardt 2012). Compressive rock failure initiates at a granular scale when grain contacts experience micro-scale tensile cracking and frictional sliding that eventually coalesce into a through-going macroscopic shear plane (Zoback 2007). Accurate constraints on UCS are needed for safe, sturdy, and economic design of structures built on top or within the interior of rock formations.

Typically, UCS is derived from core plugs using direct methods such as the standardized International Society for Rock Mechanics (ISRM) uniaxial compression test (Ulusay and Hudson 2014) or correlated from petrophysical measurements with intact rock samples (Al-Osta et al. 2018). Irrespective of the methodology, UCS values are generally measured on point-to-point basis. This implies that quantifying meter-scale UCS variability requires measurements from multiple spatial locations. This is economically not viable – in particular for small to mid-size engineering projects. Alternatively, geotechnical site investigation projects may conduct refraction travel time tomography and multi-channel analysis of surface waves (MASW) to laterally map continuous P-wave and S-wave velocities (Butchibabu, Khan, and Jha 2019). Such velocity profiles are then utilized as inputs to constrain rock moduli and further as a proxy for compressive rock strength. However, refraction travel time tomography

commonly suffers from failure to detect hidden layers whilst standard pseudo-2D MASW cannot resolve shear-wave velocity with lateral dimension shorter than the receiver spread length (Mi et al. 2017). These two methods are not capable of resolving UCS variability at the meter scale. Thus, an affordable methodology is required that probes a rock formation's strength properties at sufficiently higher resolution.

In this context, seismic multi-attribute analysis is a methodology that utilizes one or more reflection seismic attributes to predict petrophysical properties (Russell et al. 1997). This technique is commonly applied in the petroleum industry as a quantitative interpretation methodology for reservoir characterization. The latest advancements in multi-attribute analysis involve machine learning methods such as neural network and self-organizing map to improve the resolution and the predictive capabilities of seismic attributes (Herrera, Russell, and Flores 2006; Yenugu, Marfurt, and Matson 2010; Roden et al. 2017; West et al. 2002). Despite its proven capability to predict reservoir properties, no documented geotechnical application exists that utilizes this method for near-surface lateral UCS characterization. The objective of this study is to investigate the applicability of multi-attribute analysis for geotechnical site investigation. We utilize near-surface reflection seismic data to predict and map UCS away from limited number of control points. We test this methodology on the laterally heterogeneous Late Jurassic carbonate rock formations from two different outcrop sites (Figure 1A). Since the depositional facies of these formations are known to be laterally heterogeneous (Al-Mojel, Razin, and Dera 2020; Jacquemyn et al. 2018), these two outcrops provide a unique opportunity to investigate the applicability of seismic multi-attribute analysis for a near-surface UCS prediction.

2. Geographic and Geological Settings

During the Late Jurassic, present-day Saudi Arabia was situated on the eastern side of Gondwana, around the paleo-equatorial area with an arid to semi-arid climate (Fallatah and Kerans 2018; Scotese 2003). A vast shallow water epeiric sea flooded most of the Arabian Plate during this period and this led to the development of an extensive ($\sim 10^3$ km in length) shallow water marine carbonate depositional environment (Ziegler 2001). The Late Jurassic strata in Saudi Arabia consists of the Hanifa, Jubaila, Arab, and Hith formations (Figure 1B). Today these strata are uplifted, with a regional $\sim 1^\circ$ dip to the east, and exposed within an area called the Tuwaiq Mountain escarpment in central Saudi Arabia (Fallatah and Kerans 2018). The two outcrops (Site A and Site B) studied are situated within this ~ 900 km long regional escarpment.

Outcrop site A (Wadi Birk at 23.28124° and 46.64420°) is located 250 km south of Riyadh, the capital city of Saudi Arabia. This location is geomorphologically characterized by approximately 145 m tall flat-top cuestas that are cut by wadi channels. The cliff surrounding this area exposes the entire Hanifa Formation. The interval of interest in this study is the upper 50 m that belongs to the Ulayyah Member. This interval was chosen since the topmost 25 m of the Ulayyah Member (Figure 2A) is characterized by laterally heterogenous stromatoporoid/coral biostromes-bioherms and oncolithic grainstone beds (Al-Mojel, Razin, and Dera 2020).

Outcrop site B (Wadi Laban at 24.640163° and 46.589665° ; Figure 2B) is located within the city of Riyadh, Saudi Arabia. An 800-meter-long roadcut on the Riyadh-Mecca highway within this area exposes up to 26 m thick intervals of the Upper Jubaila (J2) Formation (Jacquemyn et al. 2018). The depositional facies of this roadcut is characterized by 10 to 20 cm thick grainstone-packstone beds, which are intercalated with bioturbated wackestone-mudstone

strata. This succession is incised by laterally heterogeneous and chaotically-bedded conglomeratic rudstone that forms channel-like geometry (Jacquemyn et al. 2018).

3. Methodology and Dataset

3.1. Field Data Acquisition

To simulate a typical data availability for a site investigation in a geotechnical engineering project, cylindrical cores (80 mm in diameter) were drilled and 2D seismic profiles were acquired in both outcrop sites. On site A the core drilled is 50 m long and the total length of 2D seismic profile is 636 m (Figure 3A). The terrain in Site A is very rough. Meter size boulders and rubbles of sharp limestone limit the maximum offset of the seismic line. Thus, we split the profile into three separate segments (segment A, B, and C). The seismic source utilized on this site is a 500 kg accelerated weight drop mounted on a 4x4 (Figure 3E) extreme utility vehicle while the receivers are 30 Hz vertical P-wave geophones. On site B we drilled a 35 m long core and acquired a continuous 600 m-long 2D seismic line on top of the roadcut (Figure 3B). The seismic source in site B is a 750 kg accelerated weight drop mounted on a 6x6 all-terrain vehicle (Figure 3F) while the receivers are 10 Hz vertical P-wave geophones. The geophones in both outcrop sites were planted directly on top of the hard limestone rock by hand drills (Figure 3C). The seismic acquisition parameters for both sites are presented in Table 1.

3.2. Laboratory Measurements

In the laboratory, we measured UCS, acoustic velocity, density, and gamma ray along the two cores from sites A and B. These measurements sample the rock at a scale range from 0.002m to 0.3m. We utilize the resulting properties to generate high resolution and continuous “well logs” which serve as calibration points for the predicted UCS values from the seismic data.

UCS, acoustic velocity and gamma ray were measured on the intact core while density was determined from core plugs drilled at ~30 cm spacing.

We measured the UCS with Epslog's WombatTM and derived a continuous UCS profile along the two outcrop cores. An inclined rectangular cutter coated with polycrystalline diamond compact "scratched" the cores along their entire lengths at a constant horizontal velocity, creating continuous 1 cm-wide and 5 mm-deep flat grooves. The magnitude and inclination of the force acting on the cutter were accurately recorded and UCS values were derived from a relationship between this cutter force and the corresponding depth of cut (Borba et al. 2014). This methodology allows for a rapid UCS determination along the entire core with a 2 mm sampling interval. We calibrated UCS value derived from the scratch test with triaxial tests performed on selected plug samples. To utilize the finely sampled UCS profiles for further analysis with measurement results from core plugs, we "up-scaled" the UCS values using a 120 mm moving average and resampled to core plug interval.

Acoustic velocities are measured using the ultrasonic transducers integrated in Epslog's WombatTM. The velocity was measured on the flat surface of the previously "scratched" groove using piezoelectric crystal probes that transmit and receive acoustics signals at 300 kHz frequency at 4 cm resolution. We picked the first break p-wave arrival time that propagated along the scratch groove to derive an acoustic p-wave velocity "log" along the core. We calibrated these velocities with p-wave measurements on dry (non-saturated) selected core plugs using a low frequency resonant column device. The resulting acoustic velocity log was smoothed using a 12 cm running average and resampled to core plug sampling interval.

We measured spectral gamma ray at 20 cm spacing with a handheld Radiation Solution™ gamma ray spectrometer which utilizes a 103 cm³ Bismuth Germanate Oxide as the radiation detector. We calibrated the spectrometer with surrounding environmental background gamma ray intensity before measurements. The duration of each acquisition point was 2 minutes to ensure data stability. Measurement outputs provide % K (Potassium), ppm of U (Uranium) and ppm of Th (Thorium) from which we calculated total gamma ray count in API units following Luthi (2001). We resampled the measured gamma ray data to core plug sampling interval.

Density values were derived using the Metarock PDP-300™ helium gas porosimeter. The device utilizes isothermal helium expansion phenomena and Boyle's law to constrain grain density, bulk density, and porosity of each core plug sample. We only utilize bulk density values for further analysis in this study.

We identified lithofacies as part of petrographic analyses on the slabbed cores calibrated with thin sections made from trim ends of the core plugs. The thin sections were impregnated by blue-dyed resin and stained with Alizarin red to visualize porosity and non-calcite minerals. We followed the modified Dunham classification (Embry and Klovan 1971) to describe the depositional textures and utilized these for depositional facies description.

All lab-measured properties, petrographic description, and synthetic seismograms of the cores are displayed in a well correlation panel that mimic standard well log display in the petroleum industry (Figure 4). Lithofacies classification and identification of both cores (Table 2) follow the studies by Al-Mojel, Razin, and Dera (2020) and (Chandra et al. 2021).

3.3. Near-Surface Reflection Seismic Data Processing

The objective of P-wave seismic reflection processing in this study is to utilize seismic data as a proxy to reliably predict UCS away from well control points. Near-surface reflection seismic can be viewed as a scaled-down version of reflection seismology commonly utilized in the petroleum industry. In this context, it is modified for shorter offset, shorter geophone spacing, lower fold, and lighter acquisition equipment (Pelton and Butler 2005). For the data acquired from both sites A and B, we followed the near-surface processing steps outlined by Baker (1999) with some modifications outlined in Table 3 to adapt to our dataset. The dominant frequency of the processed seismic data is ~120 Hz in site A and ~75 Hz in site B. Thus, both datasets can also be utilized to investigate the effect of different dominant frequency to the applicability of multi-attribute analysis to predict compressive rock strength.

Next, we generated zero-offset synthetic seismograms using acoustic velocities and densities from the cores convolved with Ricker wavelets using dominant frequency similar to the seismic data (120 Hz for site A and 75 Hz for site B). Average acoustic velocities of the cores were utilized to perform time-depth conversion for both cores and seismic data. We compared the synthetic seismograms (without stretch and squeeze) with processed seismic data to assess the processing quality (Figure 5). Resulting correlation coefficients are ~0.8 for site A and ~0.75 for site B. This good match between synthetics and seismic data indicates that the processed seismic image is a close approximation to bandlimited acoustic reflectivity.

It is important to mention that at site B (Wadi Laban) the well is located ~20 m to the northeast from the seismic line. We projected its log data into the seismic line by cross-correlating the synthetic seismogram with the actual trace from the northeastern-most part of the seismic data.

The projected location of the well in the line is determined by the location of seismic trace that has the highest cross-correlation coefficient with the synthetic seismogram.

4. Core Lithofacies and UCS

4.1. Core Lithofacies

The interval of interest in outcrop site A is the upper ~50 m part of the Ulayyah member of the Hanifa Formation. We adopt the classification by Al-Mojel, Razin, and Dera (2020) to identify six lithofacies along the core (Table 2, Figure 4A). The lowermost 15 m of the core is characterized by bioturbated peloidal lime wackestone-packstone facies (BPLM) with a relatively low gamma ray signature. This facies is followed by an erosional contact and the intraclast, peloidal, skeletal grainstone (IPSG) facies with higher gamma ray values. The contact between these two facies at ~45 m depth is interpreted in Al-Mojel, Razin, and Dera (2020) as the second composite sequence boundary of the Hanifa Formation. Henceforth, the succession from this contact to the top of the core is described as the Hanifa Composite Sequence-2 (HCS-2). The lower ~20 m part of this HCS-2 is characterized by intercalation between IPSG-BPLM, and nodular bioturbated peloidal mudstone to wackestone (NBPM) facies with higher gamma ray signatures. This higher gamma ray value is attributed to the increase in argillaceous content during the early deposition of HCS-2. On the outcrop, the lower ~20 m part of HCS-2 exhibits a typical “layer-cake” parallel bedded geometry. The upper ~25 m part of HCS-2 is characterized by a relatively low gamma-ray signature and the occurrence of coral/stromatoporoid boundstone (CSB) and coral/stromatoporoid floatstone (CSF) facies. The low gamma ray signature is attributed to the decrease of argillaceous content which indicates a cleaner shallow-water carbonate deposition far from clastic influx. The CSB/CSF facies is a laterally heterogenous complex characterized by stromatoporoid/coral developing biostromal to biohermal build-up morphologies and stromatoporoid/coral detritus

floating in muddy or grainy matrix. Lastly, the uppermost 7 m of the core is characterized by interbedded oncoidal-peloidal rudstone-grainstone (OPRG) with IPSG facies which forms a prominent cross bedding and foresets structure.

Lithofacies along the core from site B were previously interpreted by Chandra et al. (2021). and we adopt these for our study (Table 2, Figure 4B). The lower ~20 m of the core is characterized by LFT1 interbedded with several dm to m thick LFT2. Intermittently, this succession is interrupted by a few cm to dm-thick poorly sorted intraclast-peloidal rudstone beds (LFT4) with sharp and erosive bases. On the outcrop scale, the LFT4 forms channel-like geometries that scoured the underlying strata. The contact between LFT2 and LFT1 at 14.5 m is identified in Chandra et al. (2021) as a sequence boundary that separates the lower Jubaila Composite Sequence-1 from the upper Jubaila (J2) Composite Sequence-2. The upper 15 m of the core is characterized by coarser texture. The lithofacies succession in this interval is characterized by LFT1 that graded up into LFT2 and meter-thick beds of LFT3 at the top of the core. The LFT4 is less prominent in the upper part of the core.

4.2. Statistical Relationships Between UCS, Acoustic Impedance and Lithofacies

Cross-plots of core UCS values against core acoustic impedance (AI) color-coded by lithofacies reveal the following:

In Site A (Figure 6A, 6C, and 6E), UCS values range from ~17 MPa to ~70 MPa with a mean, median, and standard deviation of ~45 MPa, ~46 MPa, and ~11 MPa, respectively. Similarly, AI values range from ~2720 m.g/cc.s to ~11200 m.g/cc.s with a mean, median, and standard deviation of ~7835 m.g/cc.s, ~8140 m.g/cc.s, and 1609 m.g/cc.s respectively. UCS values linearly correlate with AI following a moderate correlation coefficient of 0.5 ($R^2=0.95$). The

UCS-AI data points do not group into lithofacies, suggesting a lesser influence on the correlation. An exception are the coral/stromatoporoid boundstone and floatstone facies (CSB and CSF) since these exhibit the highest average UCS and AI values respectively at ~52 MPa and ~9,276 m*g/cc*s. Also, we find that some of the anomalous high peaks (~70 MPa) in the UCS log relate to well-lithified and well-cemented fossilized coral heads. Thus, in these two cases lithofacies exert some control on the corresponding strength and acoustic impedance.

In Site B (Figure 6B, 6D, and 6F) AI and UCS values are generally higher than site A. UCS values range from ~32 MPa to ~120 MPa with a similar mean and median value of ~68 MPa (standard deviation = ~18 MPa). AI values range from ~7550 m.g/cc.s to ~14500 m.g/cc.s with mean and median value of ~10300 m.g/cc.s (standard deviation = ~1406 m.g/cc/s). AI values plotted against the UCS color-coded by lithofacies show a strong positive linear correlation with a coefficient of 0.97 ($R^2=0.94$). Similarly to site A, the UCS-AI data do not cluster by their depositional lithofacies; rather they are dispersed. Chandra et al. (2021) and Ramdani et al. (2020) attribute diagenesis and microporosity as the dominant controlling factors over petrophysical properties, including UCS and AI. The influence of diagenesis and microporosity to the petrophysical properties as well as the explanation behind lower AI and UCS values in site A requires more thorough investigation and is outside of the scope for this study.

The linear relationship between UCS and acoustic properties observed in this study is consistent with other studies such as Çobanoğlu and Çelik (2008) and Al-Osta et al. (2018). In the following, we exploit this finding further and evaluate seismic multi-attributes for their capabilities to predict compressive rock strength away from well control points under moderately to strongly correlated target logs.

5. Continuous Field Scale UCS Extrapolation

5.1. Acoustic Impedance (AI) Inversion

Since p-wave seismic amplitude is a convolution between source wavelet and the earth's acoustic reflective coefficient, seismic amplitude needs to be converted into AI before being utilized as a mean to extrapolate UCS laterally away from the core. To achieve this, we performed colored inversion (Lancaster and Whitcombe, 2000) where AI spectra of the core were used to compute the spectrum of the inversion operator. We plot the amplitude spectrum of the time-converted core AI in log-log scale and a regression line is then fitted which approximate the core AI spectrum (Figure 7A and 7D). An average amplitude spectrum from the seismic line is computed (Figure 7B and 7E) and the difference between core and seismic spectrum is calculated for the inversion operator (Figure 7C and 7F). This operator is then convolved with seismic data and the result transforms seismic amplitude into bandlimited relative AI. Using the low-frequency model derived from the core AI, relative AI is then converted into absolute AI (Figure 8A and 8C). P-wave refraction tomogram from the same seismic line is also posted to illustrate the advantage of colored inversion AI over travel-time refraction tomography in terms of imaging meter-scale lateral acoustic heterogeneity in both outcrops (Figure 8B and 8D).

5.2. Multi-attribute Probabilistic Neural Network Applied to the Seismic AI

The objective of multi-attribute analysis and probabilistic neural network (PNN) in this study is to predict and map UCS away from core data under limited vertical resolution using AI as the primary attribute. The PNN is a mathematical interpolation method implemented through 3-layered feed forward neural network architecture (input layer, pattern layer, and output layer) where the network formulation is based on the probability density estimation of the input layer (Yenugu et al. 2010; Specht 1990). In this study, a linear multi-attribute analysis using

stepwise regression method (Hampson et al. 2001) based on bandlimited relative AI and reflection amplitude were performed to obtain the optimum number of attributes that best estimate the core UCS values. Hampson et al. (2001) averaged 9 traces around the wellbore for their multi-attribute analysis. In this study, our aim is to capture finer-scale lateral variation in properties over highly heterogeneous carbonate formations. Therefore, we utilize one trace at the well location for multi-attribute analysis since averaging more than one trace will likely to smear out the lateral heterogeneity detail that we intend to capture. At well location, a series of standard post-stack seismic attributes (such as complex attributes, instantaneous attributes, etc) are generated and their cross-correlation coefficients with the core UCS are recorded. The number of optimum attributes needed for an optimum transformation is determined by plotting absolute UCS errors against the number of attributes (Figure 9A and 9B).

In Site A, the absolute UCS error converges at ~ 1 MPa using seven attributes. All the attributes in this site are from bandlimited relative AI trace. The attributes are as follows: inverse of AI trace ($1/AI$); instantaneous phase of AI trace multiplied by normalized AI value (amplitude weighted phase); first and second derivative of AI trace; cosine of instantaneous phase calculated from AI trace (cosine instantaneous AI phase); amplitude envelope of AI trace; and second derivative of instantaneous AI trace envelope.

For Site B, the error converges at ~ 7 MPa with the following twelve attributes: inverse of relative AI trace ($1/AI$); cosine of instantaneous phase calculated from relative AI trace (cosine instantaneous AI phase); normalized instantaneous phase of relative AI trace (amplitude weighted AI phase); first derivative of instantaneous relative AI trace; cosine phase of relative AI trace; first derivative of relative AI trace; instantaneous frequency of relative AI trace; second derivative of relative AI trace; running summation of relative AI trace which then

filtered by 50 points smoother (integrated AI amplitude); instantaneous frequency of relative AI trace multiplied by normalized relative AI value (amplitude weighted AI frequency); and instantaneous frequency of the original reflection amplitude. Despite having a higher correlation coefficient, the absolute UCS error in Site B is higher compared to Site A. Thus, the number of attributes needed is also greater. We explain this fact with the larger UCS range to be predicted (i.e., 32 MPa – 120 MPa) and a lower dominant frequency of ~75 Hz at Site B (as opposed to ~120 Hz at Site A).

The attributes selected from multi-attribute analysis at well location were utilized as an input layer for PNN process. The attributes were then trained in PNN architecture to establish the non-linear relationship between attributes and core UCS. Once the network is trained at the well location, the trained neural networks were then applied to predict the UCS using attributes generated for the entire seismic section. Cross correlation between UCS from multi-attribute PNN with actual core-measured UCS shows high correlation and R^2 values at both sites (Figure 9C and 9D). The resulting probabilistic neural network multi-attribute analysis enables us to predict UCS away from well control points (Figure 10A and 10 B). To validate the UCS prediction and examine the neural networks accuracy, an additional shallow (~9.5 m) validation core was drilled at Site A approximately 260 m away from the main core (Figure 10A). We used the scratch testing methodology to determine the UCS values of the validation core. At Site B, we obtained three near-surface core plugs with a hand-drill at random locations (Figure 10B). The strength of three validation plugs were measured using standard triaxial UCS test.

The “blind test” result in Site A shows a correlation coefficient of 0.92 ($R^2=0.85$) with a better predictability at higher UCS value (Figure 10C). The maximum absolute UCS error in Site A

is ~2.9 MPa, which accounts for ~5% of the predicted UCS range. On the other hand, a maximum absolute error of ~5 MPa (~5.6% of the predicted UCS range) is observed for the three validation plugs in Site B (“X”, “Y”, and “Z” in Figure 10D). We acknowledge that the “blind test” for Site B is limited in sample number. Hence, the validation result is less robust compared to Site A. However, given that the three validation plugs were drilled randomly yet the results show some indication of consistency, we are optimistic that the “blind test” result in Site B is also affirming the applicability and reliability of the seismic multi-attribute as a method to predict UCS.

5.3. Mechanical Stratigraphy Interpretation

Four mechanical stratigraphy zones are observed in Site A (Figure 10A). The topmost 7 m interval (zone “O”) is characterized by a continuous ~30–45 MPa of UCS stratum associated with oncolithic and peloidal bioclastic grainstones. The second zone (zone “SC”) is a ~22 m-thick stratum characterized by discontinuous and tabular patches of high UCS bodies (~60–70 MPa) that are associated with stromatoporoid/coral build-up complex. The third zone (zone “LC”) is a 13 m-thick stratum characterized by a continuous ~25–40 MPa of UCS associated with parallel-bedded bioturbated mudstone-wackestone and peloidal bioclastic grainstone strata. The bottommost zone (zone “HCS1”) is characterized by high UCS value (~50–70 MPa) associated with highly compacted mudstones of the top of Hanifa Composite Sequence-1. The contact between Hanifa Composite Sequence-1 and 2 is also observed as a boundary with distinct UCS contrast (“HCS1-HCS2” contact, Figure 10A).

At Site B we observe five mechanical layers (Figure 10B). Layer-1 is a thin stratum (~4 m) characterized by a relatively high UCS values (~100 MPa). Layer-2 is 7 m-thick and characterized by ~40-60 MPa of UCS which laterally intercalated with anomalous patches of

high UCS (~110 MPa). Layer-3 is characterized by high UCS (80-90 MPa) at ~200 m around the core. The thickness of this layer is increasing (from ~12 m to ~14m) and the high UCS region becomes more disjointed away from core location. Layer-4 is characterized by UCS of ~50-60 MPa that pinches out and thinning with the distance. The thickness changes from ~5 m around the core into ~2 m at the end of the profile. Layer-5 is characterized by an 8 m-thick and relatively homogenous UCS (~50-60 MPa) with minor patches of high UCS (~100 MPa). The five mechanical layers identified in this study are consistent with intra-well rock mechanical layers outlined by Chandra et al. (2021). This study further improves their findings by laterally propagating and mapping the heterogeneity of those five layers away from well control point.

6. Conclusions

We have demonstrated the near-surface engineering applicability of probabilistic neural network multi-attribute analysis. A positive linear correlation between UCS and AI exists in the data derived from core. This indicates that seismic properties can be utilized as a reliable means to laterally extrapolate and predict UCS away from core locations. Seismic-derived acoustic impedances are the main input for this multi-attribute analysis. We verify this method at two different outcrop sites which sample a moderately correlated-higher frequency seismic data (Site A) and strongly correlated lower-frequency seismic data (Site B). The highly correlated-lower frequency data (Site B) requires greater number of attributes to converge and minimize the prediction error as compared to Site A. We performed a “blind test” for both sites to validate the UCS prediction and the results reveal a high degree of consistency and high level of reliability with absolute UCS error of ~5%. We also have demonstrated the applicability of the predicted UCS profile to interpret mechanical stratigraphy and map the lateral UCS heterogeneity in the rock formations. The method shown here presents itself as a

cheaper alternative to map UCS in a field-scale site investigation engineering project when only limited well control points exist.

7. References

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497 **Figure and Table Captions**

499 Figure 1. (A) Satellite image of the Arabian Peninsula and the location of the two outcrop sites
500 relative to the Jurassic rock exposures (light blue) as part of the Tuwayq Mountain
501 Escarpments. (B) The Late Jurassic stratigraphic column in central Saudi Arabia. The interval
502 of interest in this study at each site is highlighted by grey shade. Interval of interest in Site A
503 is the upper part of the Ulayyah member of the Hanifa Formation while site B is the upper part
504 of the Upper Jubaila (J2) Formation.

Figure 2. Typical depositional facies heterogeneities encountered at each outcrop site. (A) Stromatoporoid/coral build-up complex and oncolithic grainstone beds in Site A. (B) Conglomeratic rudstone channel in site B.

Figure 3. The location of three segmented seismic lines (blue lines) and core (WB-01) on top of the wadi cuesta in Site A (A). The location of seismic line (blue line) and core (DQ-1) on top of the Riyadh-Mecca roadcut in Site B (B). Drill rig used for coring activities (C). Geophone (white arrow) installation during seismic data acquisition (D). The seismic source at Site A, a 500 kg accelerated weight drop (red arrow) on standby (E). The seismic source at site B (yellow arrow), a 750 kg accelerated weight drop (F) mounted on 6x6 vehicle.

Figure 4. Composite plots integrating lithofacies interpretation with lab-measured gamma ray, UCS, bulk density, acoustic properties, and synthetic seismogram of the cores from Site A (A) and Site B (B) and their corresponding legend (C).

Figure 5. Processed reflection seismic data with synthetic seismograms from the drilled cores at site A (A) and site B (B). The seismic profile in (A) is from line segment A (see Figure 3). A zoom-in panel showing comparison between synthetic seismogram (blue trace) with seismic traces around the core (gray traces) in site A (C) and site B (D). The correlation coefficient between synthetic seismogram and processed reflection data at core location is ~ 0.8 for site A and ~ 0.75 for site B.

Figure 6. UCS-AI cross-plots color-coded by lithofacies for Site A (A) and Site B (B) show positive linear correlations. The correlation coefficient for site A is 0.5 ($R^2=0.95$) while it is 0.97 ($R^2=0.94$) at site B. UCS and AI histograms for Site A (C and E) and Site B (D and F) show a relatively normal gaussian distribution.

Figure 7. Logarithmic spectrum plot of the core AI (blue) with a linear function fit (red) in Site A (A) and site B (D). A comparison between smoothed seismic spectrum (blue) with spectrum of the linear core AI fit (red) with spectrum of inversion operator (black) from site A (B) and Site B (E). The colored inversion operator at Site A (C) and Site B (F).

537

538 Figure 8. The inverted acoustic impedance profile of line segment-A in Site A (A) and seismic
 539 line in Site B (B) with core acoustic impedance posted as a comparison. P-wave refraction
 540 travel-time tomograms from the same profile (C and D) demonstrate the superiority of acoustic
 541 impedance profile over refraction tomogram in resolving lateral acoustic formation
 542 heterogeneities at the outcrop scale.

543

544 Figure 9. Plot of absolute UCS error against number of attributes at Site A (A) and Site B (B).

545 The number of attributes needed for error convergence at site B is greater than Site A. Crossplot

546 between UCS derived from multi-attribute probabilistic neural network (PNN) with core-

547 measured UCS in Site A (C) and Site B (D). Cross correlation coefficient for Site A is 0.92 (R^2

548 $= 0.85$) while Site B is 0.96 ($R^2 = 0.93$).

Figure 10. 2D UCS sections derived from multi-attribute probabilistic neural networks (PNN) for Site A (A) and Site B (B). Core UCS and the location of validation well and near-surface plugs for “blind test” are posted on each profile. Both profiles also include mechanical layer interpretation. UCS profile in (A) is a composite made of the three segment lines (line 1A 1B, and 1C). (C) “Blind test” crossplot between PNN UCS with shallow core UCS from Site A that shows a correlation coefficient of 0.92 ($R^2=0.85$). (D) “Blind test” crossplot between PNN UCS with core plug UCS from site B (X, Y, and Z in Figure 10B) shows a correlation coefficient of 0.97 ($R^2=0.95$).

Acquisition	Parameters	
Site	A	B
Location	Wadi Birk, the Hanifa Formation outcrop	Riyadh, the Jubaila Formation outcrop
Geophone type	Vertical P-wave, 30 Hz	Vertical P-wave, 10 Hz
Source	500 kg accelerated weight drop, mounted on 4x4 XUV	750 kg accelerated weight drop, mounted on 6x6 XUV
Recording length	1000 ms	500 ms
Sampling interval	0.5 ms	0.25 ms
Seismograph	Geometric/Geode 32 bits	Geometric/Geode 32 bits
Acquisition stacks	4	4
Receiver number and spacing	Line 1A: 96, 2 m	Line 1: 120, 5m
	Line 1B: 96, 1.5 m	
	Line 1C: 120, 2.5 m	
Shot number and spacing	Line 1A: 96, 2 m	Line 1: 120, 5m
	Line 1B: 96, 1.5 m	
	Line 1C: 120, 2.5 m	
Profile length	Line 1A: 192 m	Line 1: 600 m
	Line 1B: 144 m	
	Line 1C: 300 m	
Min-Max offset	Line 1A: 0 - 190 m	Line 1: 0 - 595 m
	Line 1B: 0 - 142.5 m	
	Line 1C: 0 - 297.5 m	
Max CMP fold	Line 1A: 96	Line 1: 120
	Line 1B: 96	
	Line 1C: 120	

558

559 Table 1. Seismic acquisition parameters.

Location	Facies Code	Facies Name	Observation	Interpretation	Thin Section/Hand Sample Example
Site A (Al-Mojel, Razin, and Dera 2020)	BPLM	Bioturbated peloidal lime wackestone to packstone	Mudstone-packstone texture. Highly bioturbated laterally extensive units. Top firmground and hardground surfaces. Components are pelletal and peloidal grains with abundant benthic forams	Carbonate inner lagoon
	NBPM	Nodular bioturbated peloidal mudstone to wackestone	Wackestone-mud lean packstone texture. Nodular structure. Contains terrigenous clay. Gradational base tabular units with thin bioturbation. Components are rich with benthic forams	Mixed carbonate-siliciclastic lagoon
	IPSG	Intraclast, peloidal, skeletal grainstone	Grainstone texture with dominant appearance of fine to medium peloids, coated grains, and occasional intraclasts. Scoured and sharp base, lenticular, and occasionally channelized units. Parallel and cross-bedded structure.	Carbonate inner lagoon
	CSF	Coral/stromatoporoid floatstone	Floatstone/rudstone texture. Mainly characterized by cobble-sized stromatoporoid/coral detritus floating in muddy spiculitic or grainy skeletal-peloidal matrix.	Back-barrier lagoon
	CSB	Coral/stromatoporoid boundstone	Stromatoporoid/coral developing biostrome/bioherms morphologies.	Back-barrier lagoon
	OPRG	Oncoidal peloidal rudstone-grainstone	Granule to pebble-sized oncoid grains with grainstone texture. Crossbedded, poorly sorted with skeletal fragments of benthic foraminifera and occasional stromatoporoid/coral clasts.	Back-barrier lagoon

Site B (Chandra et al, 2021)	LFT1	Nodular bioturbated peloidal mudstone-wackestone	Mudstone to wackestone texture. Wavy to nodular bedding with moderate bioturbation by <i>Thalassinoides</i> and <i>Planolites</i> burrows. Main skeletal components are clasts of echinoderms, brachiopods, and benthic foraminifera	Inner lagoon
	LFT2	Bioturbated peloidal lime wackestone to packstone	Wackestone to packstone texture. Massive to slightly nodular, moderately sorted, and strongly bioturbated (<i>Thalassinoides</i> and <i>Planolites</i> burrows). Main skeletal components are fine to coarse-grained clasts of brachiopods, bivalves, and echinoderms. Benthic foraminifera are rarely present.	Highly bioturbated lagoon
	LFT3	Bioclastic to peloidal skeletal packstone to grainstone	Packstone to grainstone texture. Poorly sorted, moderate to strongly bioturbated with fine to coarse grained bioclasts of benthic foraminifera, echinoderms, brachiopods, and gastropods.	Storm-dominated inner platform
	LFT4	Sharp-based intraclast-peloidal skeletal rudstone/floatstone	Rudstone/floatstone texture. Cross-bedded, poorly-sorted, weakly bioturbated with occasional hummocky cross-stratification observed. Sharp basal contact, bored encrusted hardground. Main non-skeletal components are intraclasts and occasional peloidal grains. Skeletal components are clasts of echinoderms, brachiopods, and gastropods.

Table 2. Lithofacies description and observation of the core in Site A and Site B with their respective thin sections and hand samples illustration.

Processing Flow	Objective
Geometry and trace header definition	Assign each recorded trace to their respective spatial location and source-receiver relationship
Trace edit	Manually delete badly recorded trace which will severely deteriorate signal/noise ratio
Top mute	Mute noise above the first break
Time windowing	Focusing the processing effort on the upper part of the data
Elevation statics	Correct the time shift that occurs due to significant elevation difference
Spherical divergence correction	Amplitude correction due to spherical energy decay
F-k filter	Removing ground roll noise
Velocity analysis	Obtain velocities needed for normal moveout correction and common midpoint stacking
Normal moveout correction	Flatten the reflection hyperbola
Cone mute in shot gather domain	Removing the leftover coherent linear noise
Common midpoint stacking	Sum all the traces from the same midpoint to construct unmigrated seismic image and increase signal/noise ratio
Post-stack kirchoff migration	Reposition reflectors into their correct location
Zero phase conversion	Convert minimum phase data into its' zero-phase equivalent for interpretation

Table 3. Seismic processing flow