



# Permeability prediction from wireline logging and core data: a case study from Assam-Arakan basin

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## Abstract

Permeability is an important petrophysical parameter of hydrocarbon reservoirs for oil and gas production. Formation permeability is often measured in the laboratory test using core samples. However, when few core samples are available to calculate the permeability in the field, estimation of permeability becomes a challenging task. In study area, the Chandmari field of upper Assam-Arakan basin with the availability of only seven core samples and conventional logs such as density, porosity, resistivity and gamma ray data from few wells, the estimation of permeability becomes a difficult task. Therefore, in the present study an attempt is made to estimate the permeability from well log and core data using Buckles' method approach in Langpar and Lakadong + Therria sandstone reservoir of Eocene–Paleocene geologic age in the field under the assumption and geological support that reservoirs in the study area are clean sand having very less shale control and are homogenous reservoir with little/no heterogeneity. In this study, petrophysical evaluation from log data and that from core data are integrated for the analysis of the reservoir characteristics. The relationship between porosity and water saturation which is required to distinguish mobile from capillary bound water or irreducible water saturation is used to estimate the irreducible water saturation. The estimated irreducible water saturation which is an essential parameter for water cut and permeability estimation is used for estimating the permeability in the field. The estimated permeability in the reservoirs using Buckles' method ranging from 1500 to 4554.38 mD is well matched with the permeability estimated from core sample. The estimated permeability results suggest that the oil reservoir has the higher permeability than the gas reservoir. The permeability estimation relationship can further be used for the estimation of permeability in the inter-well region of Chandmari oil field.

**Keywords** Buckles' number · Porosity · Permeability · Well log · Core data · Assam-Arakan basin

## Introduction

An oil/gas reservoir is a heterogeneous geological structure having large inherent complexity properties (Verma et al. 2012). Basic reservoir properties such as porosity, permeability and hydrocarbon saturation are directly linked to the storage capacity, fluid flow capacity, type of rock and amount of hydrocarbon in pore volume, respectively (Verma et al. 2012; Singha and Chatterjee 2014; Chatterjee and Mukhopadhyay 2002). The permeability is an important and primary rock property to access the fluid movement within the reservoir. It is the most difficult property to determine and predict. The permeability value for a single-fluid flow

can be predicted using empirical relationships, capillary models and hydraulic radius theories (e.g. Scheidegger 1953, 1954, 1974; Bear 1972; Houpeurt 1974). It usually increases with the size of pores in sandstone reservoirs, but it is complicated for carbonate reservoirs (Abdideh et al. 2013). Both the permeability and porosity of a rock is result of depositional and diagenetic factors that combine grain size, pore geometry and grain distribution (Mortensen et al. 1998). Sometimes, sand or/and sandstone reservoir contains the high permeability for the coarser grain at a low porosity and the presence of fine grain causes the low permeability at the high porosity (Mortensen et al. 1998; Nelson 1994; Beard and Weyl 1973; Holmes et al. 2009). Many investigators (Archie 1942; Tixier 1949; Wyllie and Rose 1950; Pirson 1963; Timur 1968; Coats and Dumanoir 1974; Schlumberger Ltd 1987; Kapadia and Menzie 1985; Bloch 1991; Ahmad et al. 1991) attempted to capture the relation of permeability function with model. However, these studies

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only contributed to the better understanding of the factor controlling permeability but not the actual relationship. They demonstrated that it is only an illusion that a ‘universal’ relation between permeability and variables from wireline logs can be found (Mohaghegh et al. 1997). The permeability value of the rock is frequently measured by core data in the laboratory experiment considering various apparatuses and different pressure and time conditions (Behnoud far et al. 2017; Tadayoni and Valadkhani 2012; Holmes et al. 2012). The empirical method which uses certain core data such as effective porosity and water saturation to predict permeability values in the entire wells is somewhat realistic in the sense that it makes calibration/comparison/matching of the predicted and core data values and is categorized as a direct method of permeability prediction. Artificial neural networks have been widely applied to estimate the reservoir permeability from the petrophysical data and well logs (Jamshidian et al. 2015; Aminian and Ameri 2005). A comparison of nonparametric approaches, namely the alternating conditional expectations (ACE), generalized additive method (GAM) and neural network (NNET), have shown that ACE is better than other two (Rafik and Kamel 2016). There are various indirect methods for determining permeability using geophysical well log data, but their results are often unsatisfactory (Mohaghegh et al. 1997; Molnar et al. 1994). The regression method which is based on statistical method of deterministic formulation tries to predict a

conditional average or expectation of permeability (Draper and Smith 1981; Wendt et al. 1986; Yao and Holditch 1993; Doveton 1994). The newest method, called virtual measurement (McCormack 1991; Wiener 1991; Osborne 1992; Mohaghegh et al. 1994a, b), makes use of artificial neural and fuzzy logic as model-free function estimator and flexible tool that can learn the pattern of permeability distribution in a particular field. These methods which solely use data for the permeability calculation do not perform adequately once new data are used (Mohaghegh et al. 1997). The ability of virtual measurement to predict permeability values for entire wells without prior exposure to log/core data and ability to learn from external and then generalize the learning to solve new problem set it apart from all methods using solely log data for this purpose.

The Assam-Arakan basin in India is one of the most petroliferous basins producing oil and gas commercially. In the present study, an attempt is made to predict the permeability in the inter-well region of Chandmari oil field of upper Assam-Arakan basin using few well log and core sample data. Buckles’ equation with the help of Willy-Rose relation and Timur’s constant has been used to predict permeability values using two well log data (Well-A and Well-B) for Langpar and Lakadong + Therria (Lk + Th) sandstone reservoir of Eocene–Paleocene age in the upper part of the basin (Fig. 1). The predicted permeability of the two wells is validated by the few core samples for selected depth intervals,

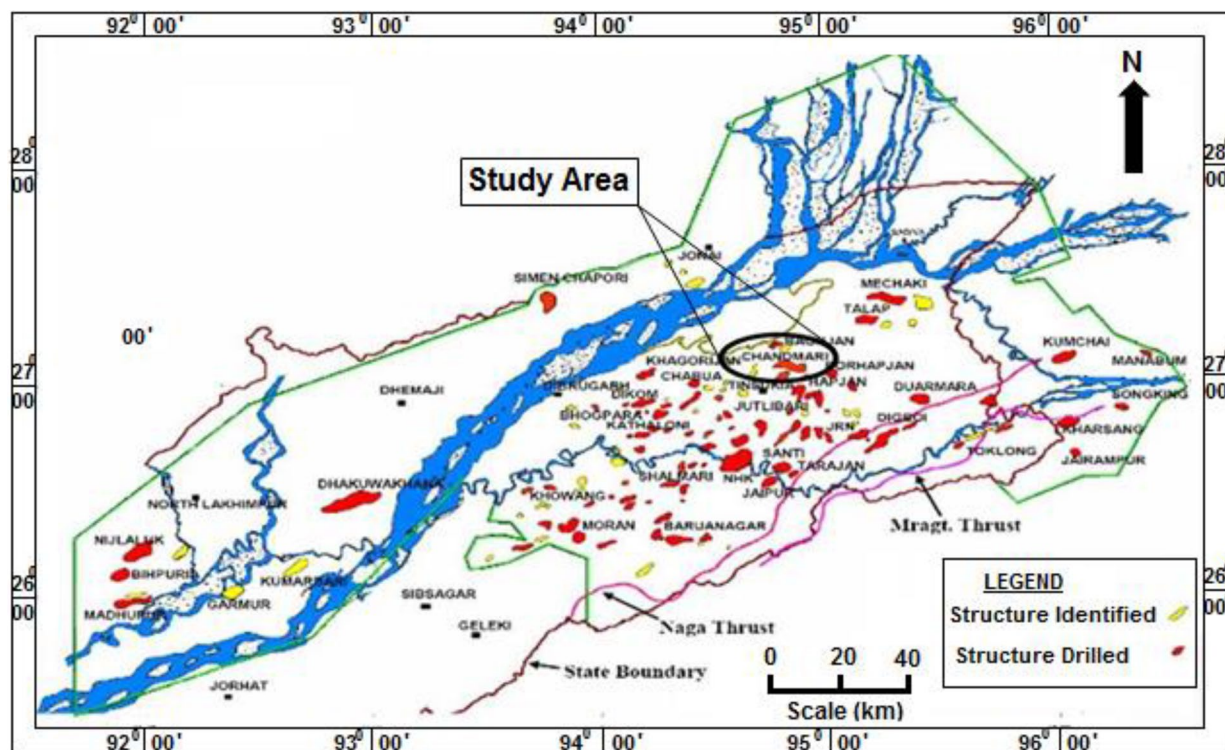


Fig. 1 Geological map of upper Assam-Arakan; study area is marked by black circle near Chandmari region. (After Mandal and Dasgupta 2013)

and on basis of that a relation has been established with the porosity data derived from the core sample. The prime importance of this study is that once the basic porosity, water saturation and permeability relations are established using the core data, the same relations can further be used in other wells from the same reservoir where core data are not available.

## Geological setting

This upper part of Assam-Arakan basin is bounded by Himalayan orogenic belt in the north, a thrust belt in the southern side, Mishimi hills in northeastern side and the shield of Mikir hills in the west (Pahari et al. 2008; Sekhar Deb and Barua 2010). A Basement High trends found parallel to River Brahmaputra where thirteen wells have been drilled by national oil companies. Sedimentary sequences ranging in age from Late Mesozoic to Cenozoic are exposed in the Assam-Arakan basin (Balan et al. 1995; Mandal and Dasgupta 2013). The study area, Chandmari oil field is located in the crested part of Basement high and bounded by two NE-SW-trending major faults in the northern and southern sides of the structure (Sekhar Deb and

Barua 2010). The structure is composed by few numbers of minor faults dipping in both the north and south directions and trending almost parallel to the main fault. These minor faults are trending nearly parallel to the main fault.

The generalized stratigraphic succession in the study area is given in Fig. 2. The main reservoir rocks are the Sylhet formation (Eocene), Kopili formation inter-bedded sandstones (Late Eocene–Oligocene), Tura (basal) marine sandstones and Surma Group alluvial sandstone reservoirs (Mandal and Dasgupta 2013). The most productive reservoirs in the upper basin are the Barail (Oligocene–Miocene) sands and the Tipam group (Miocene) massive sandstones. Other formations are Girujan (Miocene), Namsang (Pliocene) and Siwalik/Dhekiajuli (Recent) (Balan et al. 1995; Mandal and Dasgupta 2013). Langpar formation (Paleocene) is followed by the basement at Pre-Cambrian age. Lakadong + Therria sand reservoir of Sylhet formation and Langpar formation have been found in the area. The main hydrocarbon potential is confined to the Langpar formation and the lower part of Sylhet formation (Lakadong + Therria units). These formations constitute fine- to coarser-grained sandstone and occasionally coal deposit and limestone/calcareous band with thickness varying from 140 to 170 m (Sekhar Deb and Barua 2010).

Age		Group	Formation
Pleistocene		Alluvium	
T E R T I A R Y	Pliocene	Dihing Group	Dhekiajuli Formation
	Miocene	Dupitila Group	Namsang Formation
		Tipam Group	Girujan Formation
			Tipam Formation
	Oligocene	Barail Group	Argillaceous Unit
			Arenaceous Unit
	Eocene	Jaintia Group	Kopili Formation
			Sylhet Formation
	Palaeocene		Langpar Formation
	Pre Cambrian		Basement

Fig. 2 Generalized stratigraphic formation of the upper Assam-Arakan basin. (After Sekhar Deb and Barua 2010)

## Methodology

The several empirical methods have been constructed based on the correlation between porosity, irreducible water saturation, and permeability (Tixier 1949; Timur 1968; Coats and Dumanoir 1974; Coates and Denoo 1981). However, the relationships between porosity and irreducible water saturation are best described by Buckles 1965, Chilingar et al. 1972 and Doveton 1994. Buckles' proposed that porosity and irreducible water saturation are hyperbolically related as follows (Buckles 1965).

$$\Phi \times S_{wi} = C \quad (1)$$

The above relation (Eq. 1) can be linearized to

$$\log S_{wi} = \log C - \log \phi \quad (2)$$

where  $\phi$  is the porosity,  $S_{wi}$  is irreducible water saturation, and  $C$  is a constant whose magnitude is related to the rock type.

The simplest quantitative method of permeability prediction from logs with the support of core studies has been keyed to empirical equations of the type

$$K = P\Phi^Q \quad (3)$$

where  $P$  and  $Q$  are constants determined from core measurements and applied to log measurements of porosity to generate predictions of permeability ( $K$ ).

Wyllie and Rose (1950) proposed an empirical equation which is modification of the Carman–Kozeny (1937) equation that substituted irreducible water saturation for the specific area term. As the specific surface area is quite difficult to measure directly by conventional methods and therefore it is linked with pore size, this in turn controls the irreducible water saturation.

$$K = P \frac{\Phi^Q}{S_{wir}^R} \quad (4)$$

The equation functions as a powerful surrogate variable for specific surface area, and this accounts for the improvement in permeability estimates when incorporated with porosity. The constants  $R$  and  $Q$  are measured from core measurements and then applied to well log data. This is one of the oldest permeability estimation methods available and is reliable when calibrated to core data.

In hydrocarbon zones above the transition zone, irreducible water saturation is taken equal to water saturation ( $S_w$ ) values from any shale-corrected method. Below the hydrocarbon zone (i.e. in the water and transition zone), we calculate the irreducible water saturation using the following formula.

$$S_{wir} = \frac{C}{\phi / (1 - V_{cl})} \quad (5)$$

where  $V_{cl}$  is the volume of clay and  $C$  is Buckles' constant.

If irreducible water saturation is fixed, the permeability is calculated using the formula (Eq. 4) given by Wyllie and Rose (1950). Since the reservoir is Lanpor and Laka-dong + Therria sandstone formation, we used Timur (1968) values of constants for sandstone in the generalized equation of Wyllie and Rose (1950) which is also known as Timur's parameters, as follows.

$$P = 3400 \text{ (For Oil)}, 340 \text{ (For Gas)}, Q = 4.4, R = 2.0$$

## Results and discussion

The well log data for this study are shown in Figs. 3 and 4. The curve on track 4 depicts the intergranular porosity (purple color) calculated from the ELAN Plus volumetric analysis (using Techlog (GeoFrame) ELANPlus modules of Schlumberger) and core data (blue color), respectively. ELAN Plus gives the quantitative petrophysical analysis of multi-mineral lithology using a number of optimized simultaneous equations and models. It is different from the traditional petrophysical analysis because it solves a set of equations to estimate the volume of each formation component first. Then, it measures the properties such as porosity, water saturation, volume of shale from the derived volumes and does not compute the formation properties from a number of fixed formulas step by step (Schlumberger 2013). The intergranular porosity curve (PIGN), water saturation and clay volume ( $V_{cl}$ ) have been determined by carrying out petrophysical interpretation of wireline log data. The default values of Timur's parameters recommended for sandstones are modified after calibrating it with the available core data in both the wells individually. Following good match of porosity curve with the core data, Buckles' constant has been determined corresponding to both the Langpar and Lk + Th reservoirs separately. The Lk + Th formation is having the finer sandstone, whereas the deeper Langpar sandstone reservoir is relatively coarser. The estimated values of Buckles' number in both reservoirs support the fact that Buckles' number increases for finer-grained rocks. The log curve on track 5 shows the derived permeability using Wyllie and Rose (1950) formula and core data, respectively, whereas the ELAN Plus volume is presented on the last track 6 (Figs. 3, 4). The crossplot between porosities values derived from density log (on X-axis) and ELAN interpretation (Y-axis) are analyzed, and a straight line curve is drawn to fit the data points. The crossplot between the porosities estimated from two different inputs show a very good correlation coefficient, 91% in Well-A (Fig. 5) and 73% in Well-B (Fig. 6). A liner relationship between porosity derived from density log and effective porosity obtained from ELAN interpretation using conventional petrophysical software (Techlog, Schlumberger) which is also calibrated with the core data, is established and is shown in Figs. 5 and 6 for both the Well-A and Well-B,



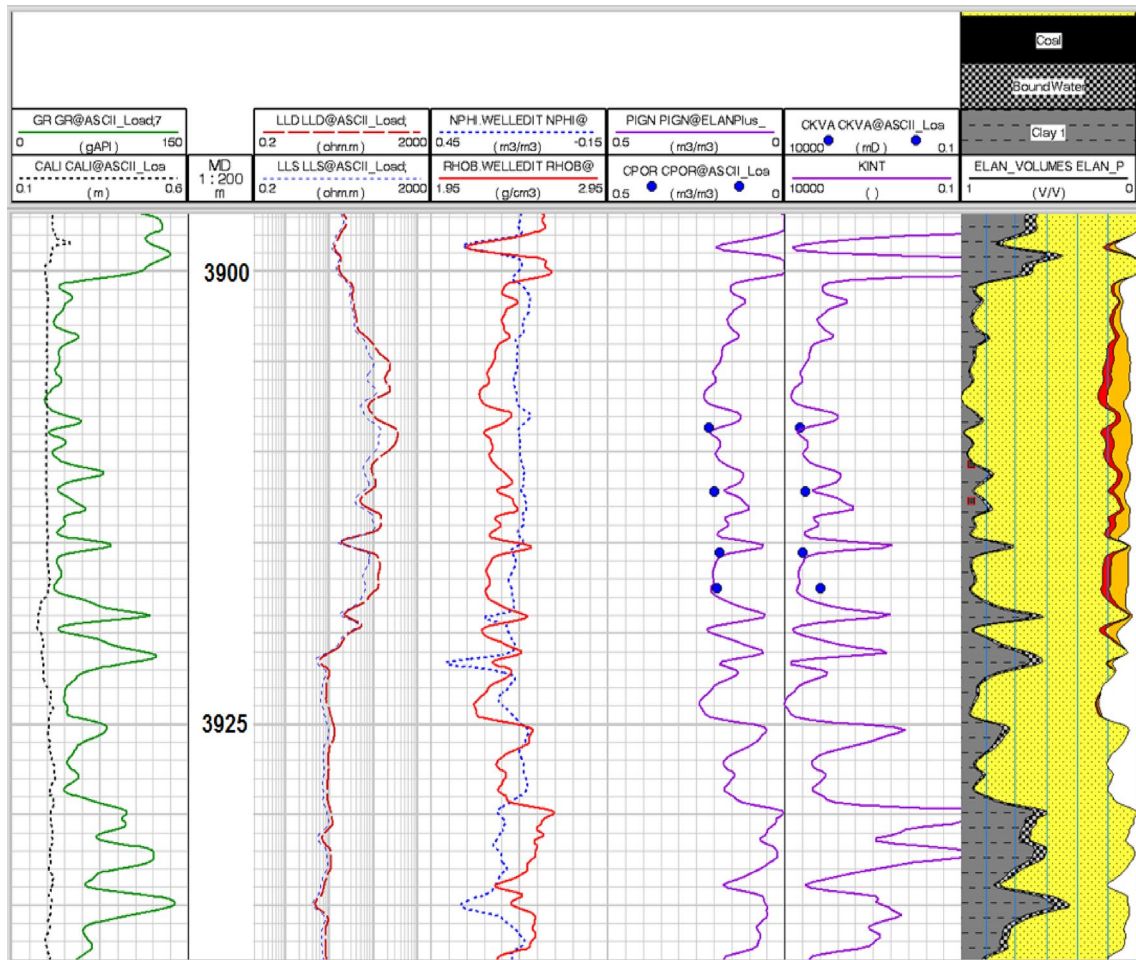


Fig. 3 ELAN interpretation and permeability prediction in Well-A

respectively. This relationship can further be utilized for predicting the permeability in another well in the same area where core data are not available. The sets of equations used for permeability calculation in both the wells are as follows.

**Well-A**

The reservoir sand interval in Well-A is 3900–3921 m with the shale break and volume of shale average (< 10%) in the ranges 3915–3915.3 m and 3918.8–3919.2 m. Hence, it is considered as a clean sand reservoir. Well-A produces oil from Langpar formation of Eocene age. The following sets of equation and parameters are used for the permeability calculation in Well-A.

$$C = 0.02, P = 3400, Q = 3.2, R = 2.2$$

Here, few changes in abbreviations,  $PIGN.IN = \emptyset$ ,  $VCL.IN = V_{CL}$  and  $KINT = K$

$$S_{wir} = C / \left( \frac{PIGN}{(1 - V_{CL})} \right) \tag{6}$$

$$KINT = 3400 * \frac{(PIGN)^{3.2}}{S_{wir}^{2.2}} \tag{7}$$

**Well-B**

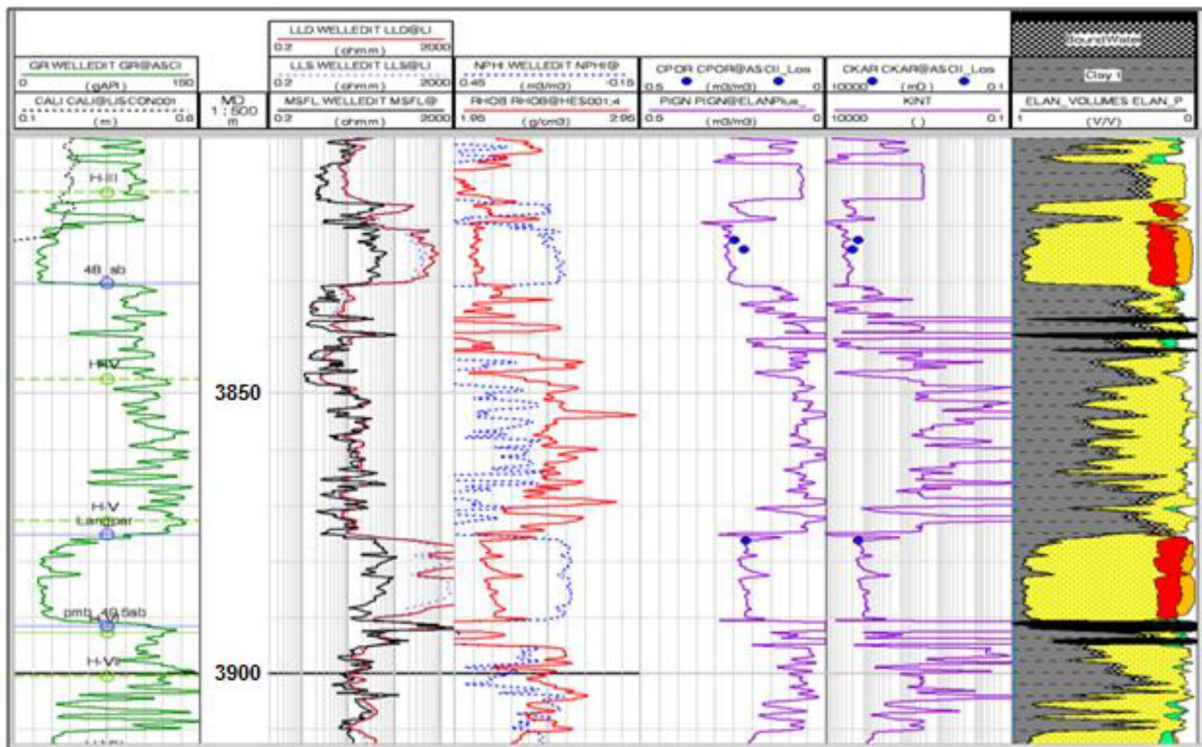
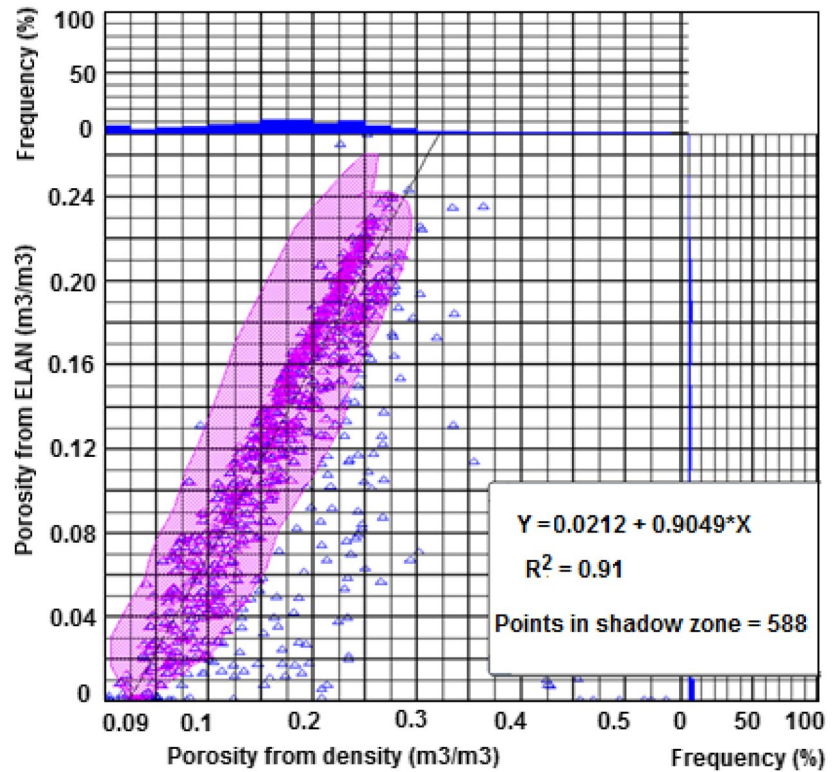
The reservoir sand interval in Well-B is 3820–3830 m (Lk + Th reservoir) and 3872–3892 m (Langpar reservoir), respectively. The well is producing gas from Langpar as well as LK + Th reservoirs of Eocene age, and having volume of shale less than 10% is treated as a clean reservoir. The following sets of equation and parameters are used for the permeability calculation in Well-B.

$C = 0.03$  (for Lk + Th reservoir),  $0.02$  (for Langpar formation)

$$P = 3400, Q = 3.2, R = 2.4$$

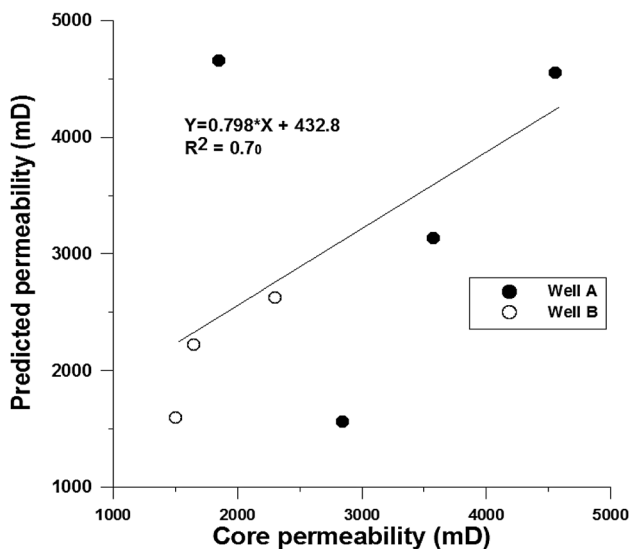
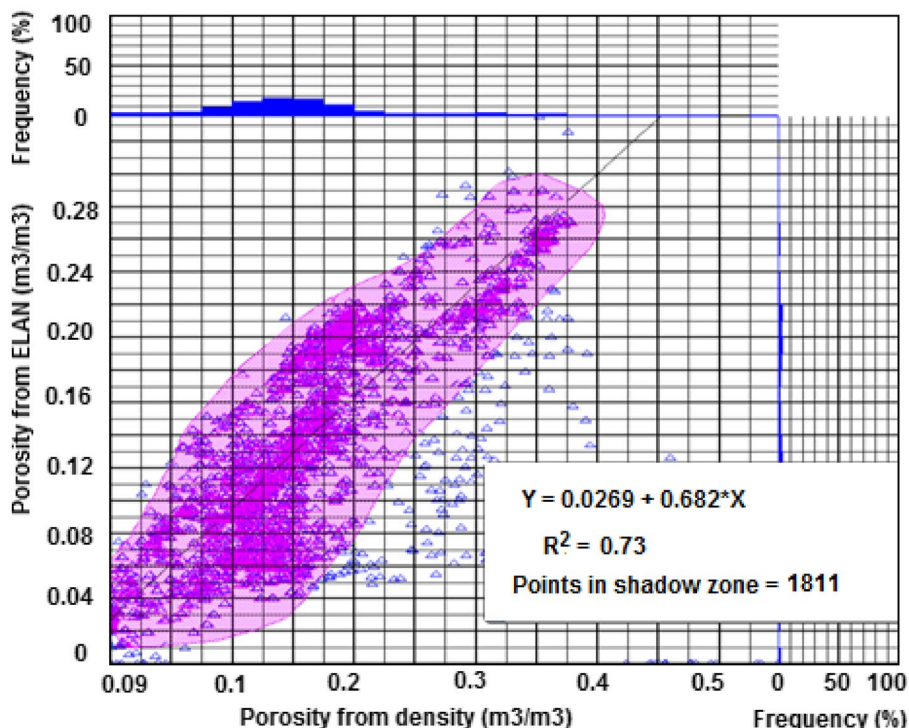
$$KINT = 3400 * \frac{(PIGN)^{3.2}}{S_{wir}^{2.4}} \tag{8}$$

**Fig. 4** ELAN interpretation and permeability prediction in Well-B



**Fig. 5** Crossplot between porosities derived from density and ELAN interpretation in Well-A

**Fig. 6** Crossplot between porosity derived from density and ELAN interpretation in Well-B



**Fig. 7** Crossplot between predicted permeability from Buckles’ approach and core permeability for the Well-A and Well-B at selected depth intervals

**Permeability relation**

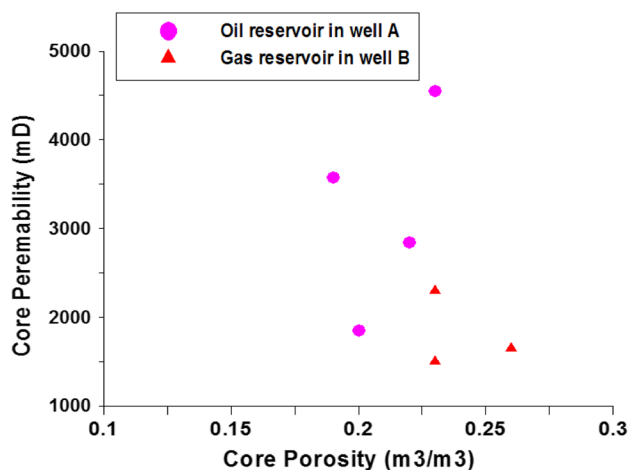
The permeability measured from core data and that predicted from Buckles’ method approach for Langpar reservoir and Lk + Th reservoir in both the wells at selected depth intervals are shown in Fig. 7, which are found to be

in good agreement with each other. The goodness of fit ( $R^2$ ) shows a significant value of 0.70. On basis of this, an equation has been established which can be further applied to calculate permeability of the reservoir where enough well data are not available. As both the permeability and porosity of a rock is result of depositional and diagenetic factors that combine grain size, pore geometry and grain distribution (Mortensen et al. 1998), sometimes reservoir contains high permeability for coarser grain at low porosity and fine grain causes low permeability at high porosity (Mortensen et al. 1998; Beard and Weyl 1973). The gas sands have the lower permeability and higher porosity, whereas the oil sands have the higher permeability and lower porosity as shown in Fig. 8. The gas sands in Well-A are located at the depth interval of 3872–3892 m followed by the oil sand at depth of 3900 m. The Langpar reservoir is relatively coarser in grain size than the Lk + Th reservoir causing its higher permeability and comparatively lower porosity than Lk + Th reservoir.

**Conclusion**

This paper presents a case study of permeability prediction from wireline logging and core data from Assam-Arakan basin. Applicability and suitability of empirical methods for permeability prediction using wireline log and core data are tested, and the suitable one is applied for the purpose. The empirical relationship has allowed





**Fig. 8** Crossplot between predicted permeability from Buckles' approach and core porosity for the Well-A and Well-B at selected depth intervals

estimation of Buckles' number using wireline and core measurements. The formation porosity/irreducible water saturation and permeability from digital well log and core data are estimated using Buckles' method approach. The Buckles' number estimated from empirical relationship using wireline and core measurements can be further utilized to predict permeability in the wells from the same reservoir in which only well log data are available. Hence, from this study it can be concluded that once the basic porosity/water saturation/permeability relations are established using the core data, these relations can be further used in the other wells from the same reservoir where core data are not available. The porosity crossplots indicate a good agreement between log data determined porosity and ELAN interpreted porosity. The predicted permeability from empirical equation and core derived permeability are in good agreement with each other. The estimated values of Buckles' number for both the reservoirs support the fact that Buckles' number increases with the finer-grained rock. Well-A produces oil from Langpar reservoir, whereas the Well-B is producing gas from Langpar as well as LK + Th reservoir of Eocene age. The oil sand in the Langpar reservoir has the higher permeability than the gas sands in Langpar and Lk + Th reservoirs.

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