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RESEARCH

Mapping petrophysical properties with seismic inversion constrained by laboratory based rock physics model

Siddharth Garia[1] · Arnab Kumar Pal[2] · Shreya Katre[2] · Satyabrata Nayak[3] · K. Ravi[2] · Archana M. Nair[2]

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Abstract
Estimation of reservoir properties from seismic data suffers from non-unique solutions. A workflow based on the numerical reformulation of a laboratory-based rock physics model may reduce the non-uniqueness. This study attempts to integrate seismic and well log data of relatively unexplored parts of Upper Assam (UA) basin using inversion driven by laboratory based rock physics model. The laboratory-based rock physics model was developed based on experimental measurements conducted on rock cores from Tipam and Barail formations of the basin. Seismic inversion analysis was performed in OpendTect, an open-source software on post-stack seismic data to derive the acoustic impedance (AI) using coloured inversion. A multilayered feed-forward neural network was developed to spatially populate different petrophysical properties. Laboratory-based correlations between AI, density, porosity were utilised for the AI model from which velocity was computed using multivariate rock physics equation. This derived velocity value was transformed to AI and subsequently trained with well log to populate density (2.23-2.73 gm/cc) and porosity (7-28%) for the entire survey area. A reasonable to high correlation is obtained between bulk density and porosity derived by NN using well log and that derived by laboratory-based model (r = 0.78, 0.91 for Barail and 0.95, 0.94 for Sylhet formation). Thus, integrating datasets of different scale from seismic to core with well log data using neural network helps to derive more realistic models that helps in quantitative decision analysis.

Keywords Acoustic impedance · Upper Assam basin · Seismic inversion · Neural network · Well logs

Introduction

Laboratory based estimation of petrophysical, geomechanical and mineralogical parameters is essential to corroborate data obtained from the well logs (Ambati et al. 2021). Although the well log data have a higher vertical resolution (Leisi and Saberi 2023), but this information is limited in the vicinity of the well from where it is measured. On the other hand, analysis on the core plugs in the laboratory, collected from multiple wells of the same basin, tend to be more representative of a broader lithological unit, especially in case of clastic reservoirs, that offer relatively less heterogeneity as compared to carbonate reservoirs (Zhang et al. 2020; Garia et al. 2021a). It is well established that resolution of investigated petrophysical parameters is quite high for laboratory measurements of cored wells or logging data (Feng 2020). Besides, it is essential to understand the geological trend and reservoir distribution to build a suitable rock physics workflow (Garia et al. 2019; Ali et al. 2020). Therefore, this can be achieved by incorporating laboratory-based analysis or trends into the conventional seismic inversion workflow. The applicability of known statistical trends derived in the laboratory can help to reduce uncertainty, ambiguity related to the most likely interpretation since laboratory data is more exact (Farouk et al. 2021).

The different methods for subsurface characterization involve examination and measurements on core plugs in the laboratory, analyzing the different well log information and interpretation of seismic data. Seismic reservoir characterization requires the transformation of seismic derived parameters such as P-wave, S-wave velocities, acoustic impedance (AI) into parameters describing the

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✉ Archana M. Nair
nair.archana@iitg.ac.in

1 School of Civil Engineering, Lovely Professional University, Phagwara, India

2 Department of Civil Engineering, Indian Institute of Technology, Guwahati, India

3 Senior Geoscientist, PETRONAS, Kuala Lumpur, Malaysia

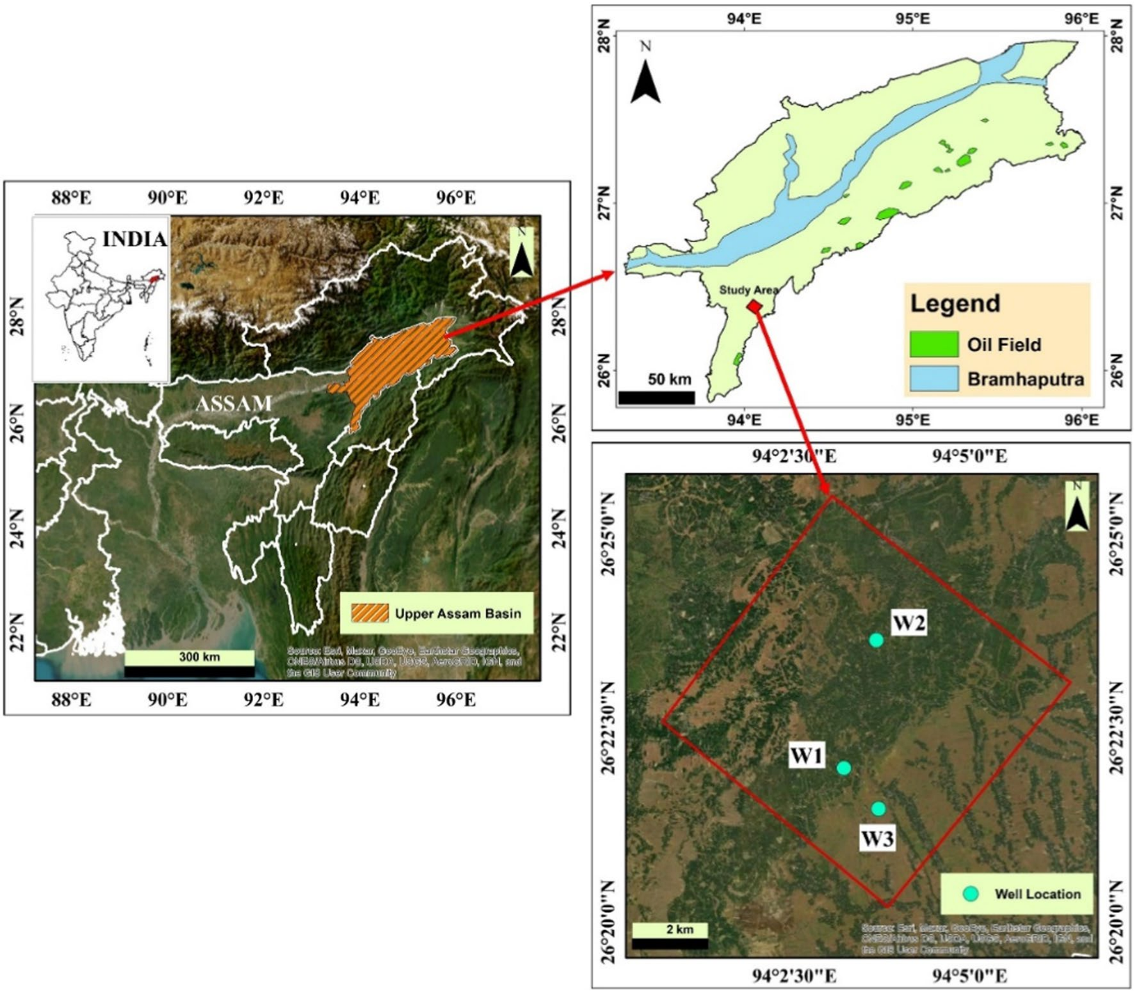


Fig. 1 Geographical location of the study area (part of Upper Assam Basin)

reservoir lithology and conditions (Johansen et al. 2013; Garia et al. 2020). It is difficult to predict desired rock properties from the geophysical measurements without a good rock physics model incorporating all known physical effects (Sayers and Chopra 2009). A large number of rock physics models, which is an essential ingredient for deriving relationships, are available in the literature; however, their relevance is generally constrained by lithology type,

Table 1 Stratigraphic succession of Upper Assam basin (modified after Murty 1984, Deb and Barua 2016)

Age		Group	Formation	Lithos-Units
PLEISTOCENE		Alluvium		
TERTIARY	*Pliocene*	Dihing	Dhekiajuli	Sandstone with bands of clay
	Miocene	Dupitila	Namsang	Mottled clay with greyish, soft sandstone
		Tipam	Girujan	
			Tipam	
		Surma	Bokabil	
	Oligocene	Barail	Argillaceous	Mudstone, shale, sandstone with clay seams
			Arenacceous	Dark grey shale with thin sandstone
	Eocene	Jaintia	Kopili	
			Sylhet	
	Paleocene		Langpar	
PRE CAMBIAN		Basement		

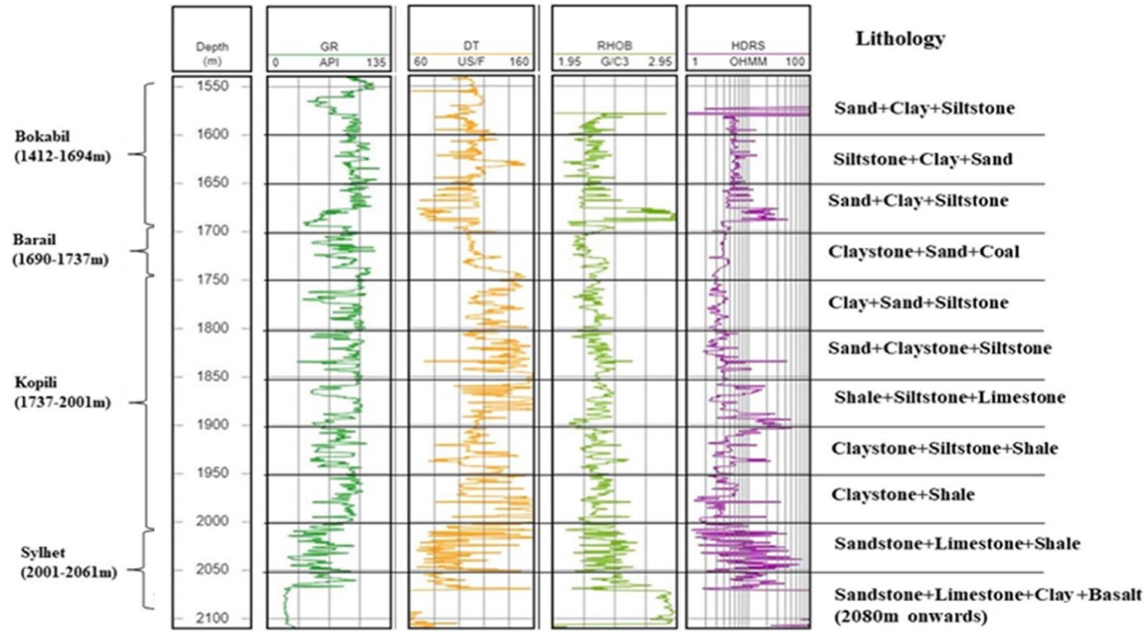
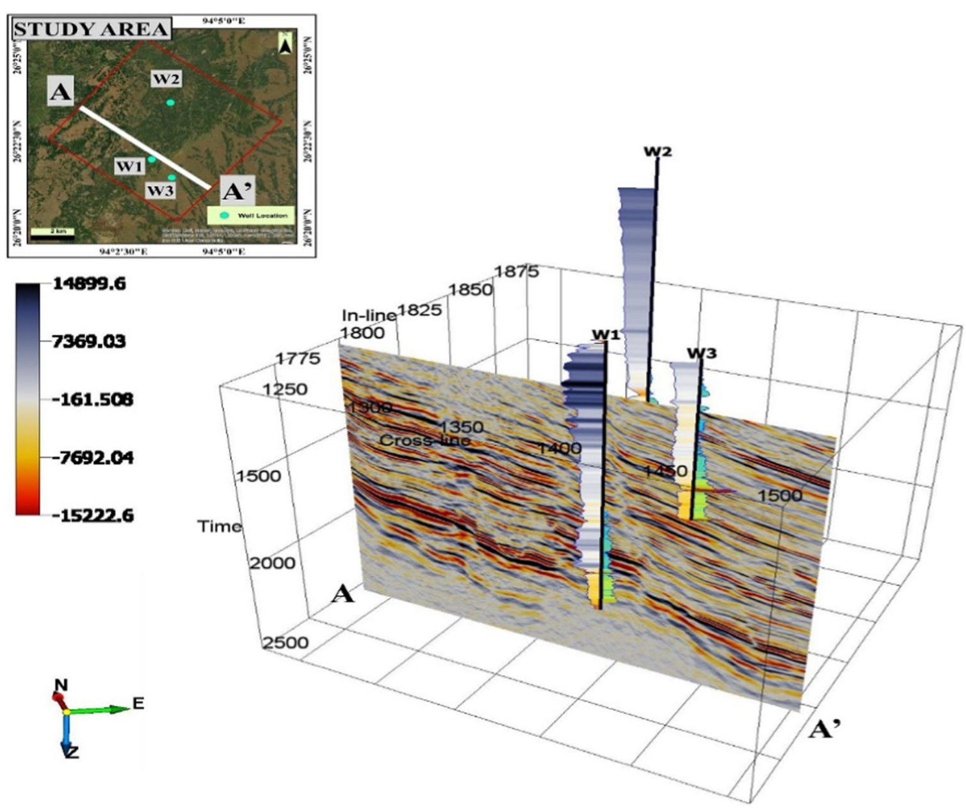


Fig. 2 Log responses obtained for Well 1 along with lithology information and formation details

porosity range, saturation conditions etc. (Johansen et al. 2013). The key requirements of the model are its predictability and its geological relevance (Dvorkin et al. 2014; Pal et al. 2020; Katre et al. 2021; Katre and Nair 2022). These effects when incorporated, would act as a powerful tool for use in seismic interpretation. The key purpose of performing seismic interpretation qualitatively is to recognize and map geological elements and stratigraphic patterns from seismic reflection data (Avseth et al. 2010; Garia et al. 2021b).

Fig. 3 Seismic data along with the three wells with logs (slowness in left and density in right)



However, inversion methods in geophysics do not exploit the multidisciplinary character of the information (Bosch 2004). The rock physics models are controlled by geological factors such as porosity, lithology, fluid characteristics (Ali et al. 2020). The inclusion of complementary information from petrophysics, geology and other fields is crucial for realistic seismic modelling. The choice of inclusion of information is motivated by primarily two reasons – (i) trends captured through petrophysical analysis can easily be extended for inversion based property prediction, and (ii) the trends can be said to be representative of the reservoir conditions. These trends can be included into the conventional rock physics transforms by the application of different neural network models and multivariate statistics. Moreover, inversion based property prediction on the basis of AI traditionally has been addressed by the application of multivariate statistics and, more recently, by neural network (NN) methods (Kadkhodaie-Ilkhchi et al. 2014; Yasin et al. 2020; Othman et al. 2021). The results are generally compared and used to constrain or update a model for estimating the probability of finding the presence of hydrocarbons (Onajite 2021).

In the present study, we propose a workflow to map the different reservoir properties by integrating well data, laboratory-based sandstone rock core data and seismic inversion analysis. The datasets comprising of seismic data, well logs and sandstone core plugs belong to Upper Assam basin in India. This basin is known to be a prolific hydrocarbon producing region which is producing hydrocarbons for more than a century (Mandal et al. 2011). Figure 1 shows the geographical location of the study area and Table 1 shows the stratigraphic succession of Upper Assam basin. The goal of this study is the characterization of a hydrocarbon reservoir through quantitative estimation of porosity and density spatially for different formations by unification of different scales of study, i.e. the focus of this research is to address the challenges of different scales of study (well logs, laboratory based analysis and seismic data) in the context of reservoir characterization and incorporate them in the seismic inversion methodology. Taking this into consideration, the study proposes

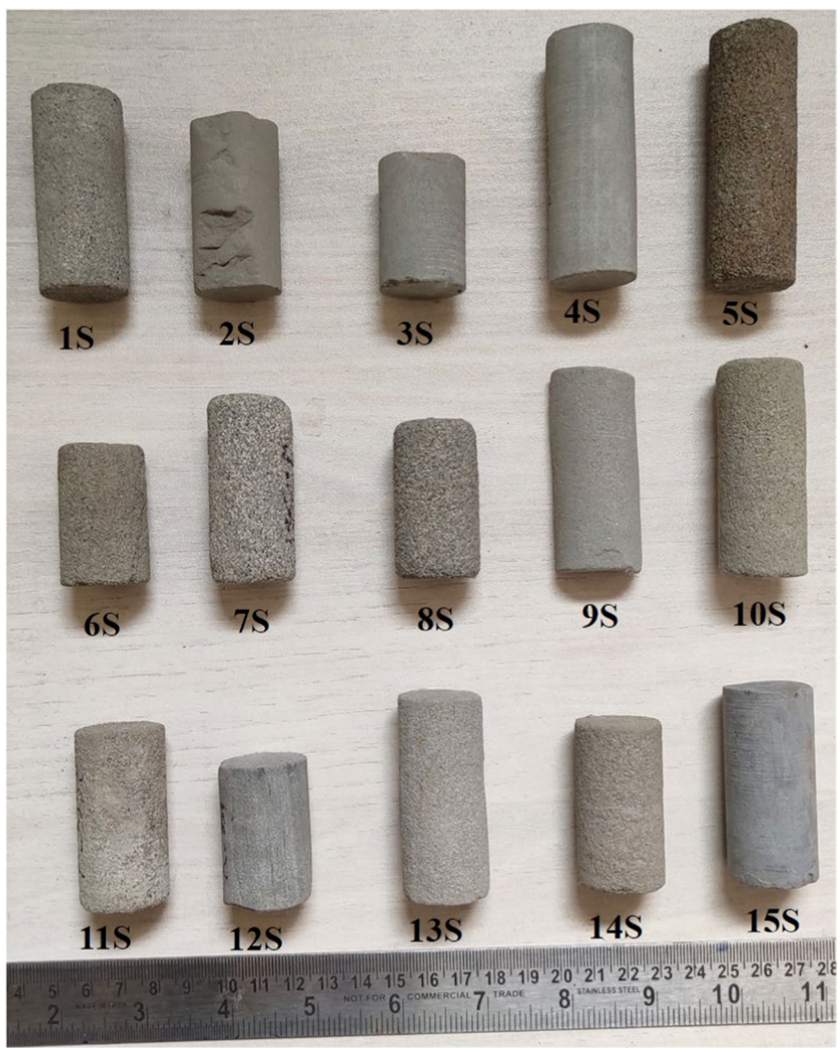


Fig. 4 Investigated sandstone core plugs to derive laboratory generated rock physics model

a new strategy based on integration of well logs, rock core laboratory data and inversion to transform the seismic data to different reservoir properties. Hence, in the present paper, the methodology is given more attention since the laboratory based rock core analysis is incorporated into the inversion methodology. Although the presented results are expected to be more realistic and these correlate with the well log derived parameters, yet, the effect of overburden pressure or stress in the simulation of subsurface models may further need to be investigated. As a result, the present research advocates that the studies reviewed in the literature must be supplemented by incorporating analysis based on laboratory data that captures the small-scale variability, which is indistinct in seismic data. Thus, the proposed workflow focusses on developing a multidisciplinary approach that may aid future researchers in improving reservoir characterization using seismic inversion.

Methodology

Dataset and methods

Well log and seismic

The present research was conducted on seismic data and well log data (density log, sonic log) of three wells belonging to Upper Assam basin. As per the available well report, Sylhet formation of Well 1 was found to be oil bearing, while the other two wells were found to be water bearing. The typical well log response of Well 1 (oil bearing well) is shown in Fig. 2. For a detailed information with regards to lithology and stratigraphy of the study area, Garia et al. 2022a may be referred.

In the present study, density log was used to derive total porosity (as per Bateman 2015)–

$$\Phi = \frac{(\rho_{ma} - \rho_b)}{(\rho_{ma} - \rho_f)} \tag{1}$$

where ρ_{ma} is the matrix density = 2.65 gm/cc, ρ_f is the fluid density = 1 gm/cc

Due to the confidentiality of the given data provided by NDR (National Data Repository), DGH (Director General of Hydrocarbons), limited information related to seismic data (consisting of approximately 50 km^2 area) were known such as: inline 1756-1895, crossline 1224-1511 and two-way travel time 1000-2500 ms. Figure 3 shows the seismic data along with the location of three wells.

Laboratory-based model derived on sandstone core plugs

Core plugs of the Upper Assam basin, belonging to Tipam and Barail formation (Fig. 4), were investigated for petrographical, petrophysical and acoustic properties examination and correlations were formulated between

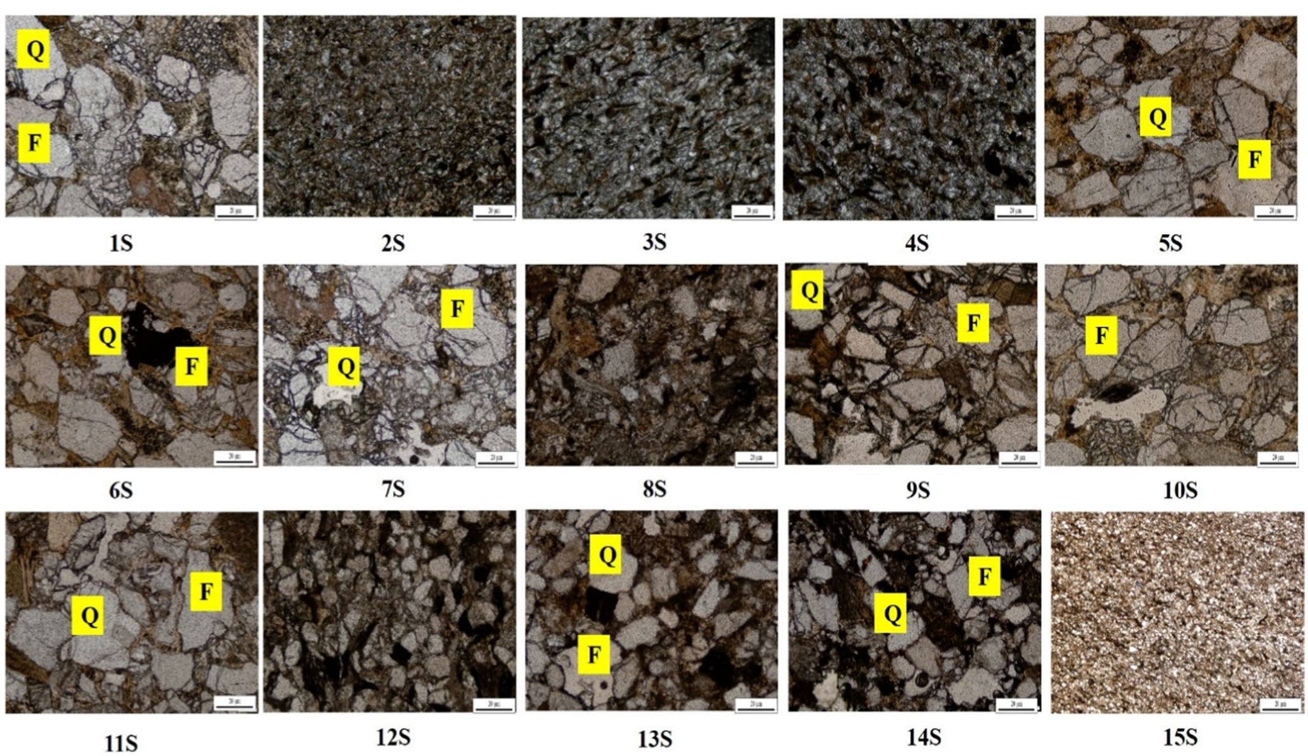


Fig. 5 Thin sections of the investigated sandstone cores (Magnification: 10X, Scale: 50μm) (where Q is Quartz, Fe is Feldspar)

different properties (Garia et al. 2022b; Pal et al. 2018, 2022). The thin section micrographs showing the major minerals present, Quartz and Feldpar, is shown in Fig. 5. Moreover, the minerals present, analysed through X-ray diffraction (XRD) are also shown in Fig. 6. Quartz and Feldspar were found to be the major minerals present in these sandstones.

Based on laboratory measurements, a one to one relationship between AI, bulk density and porosity is shown in Fig. 7. These correlations were used to populate bulk density and porosity from AI cube generated from inversion analysis. The obtained density and porosity were cross-plotted with density and porosity obtained from AI cube when well log data were used as inputs. However, it is observed from the literature that there are multiple parameters that have an effect on V_p (Garia et al. 2019), as a result, a one to one correlation may not provide a realistic assessment. Hence, the correlation between velocity (V_p), density (ρ) and porosity (ϕ) obtained from multivariate analysis (Eq. 2) from examination of core plugs in the laboratory (Garia et al. 2022b) was utilized to derive porosity and density for the entire survey area using inversion.

$$V_p = 4743.62\rho + 51.43\phi - 9873.42 \quad R^2 = 0.852 \tag{2}$$

This equation was used to estimate V_p by application of NN derived density and porosity at the well location (inline 1794, crossline 1392). In this manner, laboratory based attribute was used as an input for NN, thereby incorporating the laboratory based trend in the inversion analysis. Figure 8 presents a flowchart displaying the application of laboratory-based model for petrophysical property prediction using well log data and inversion.

Inversion scheme

Seismic inversion problem aims to infer the subsurface properties such as elastic and petrophysical properties (Ali et al. 2018). It is a convolutional process, which is used to generate AI from the seismic data (Lancaster and Whitcombe 2000; Ismail et al. 2020). In the present study, coloured inversion operator was used to perform inversion analysis. For a detailed procedure regarding coloured inversion method, its merits and demerits, studies by Lancaster and Whitcombe 2000; Neep 2007; Ansari 2014; Datta Gupta and Gupta

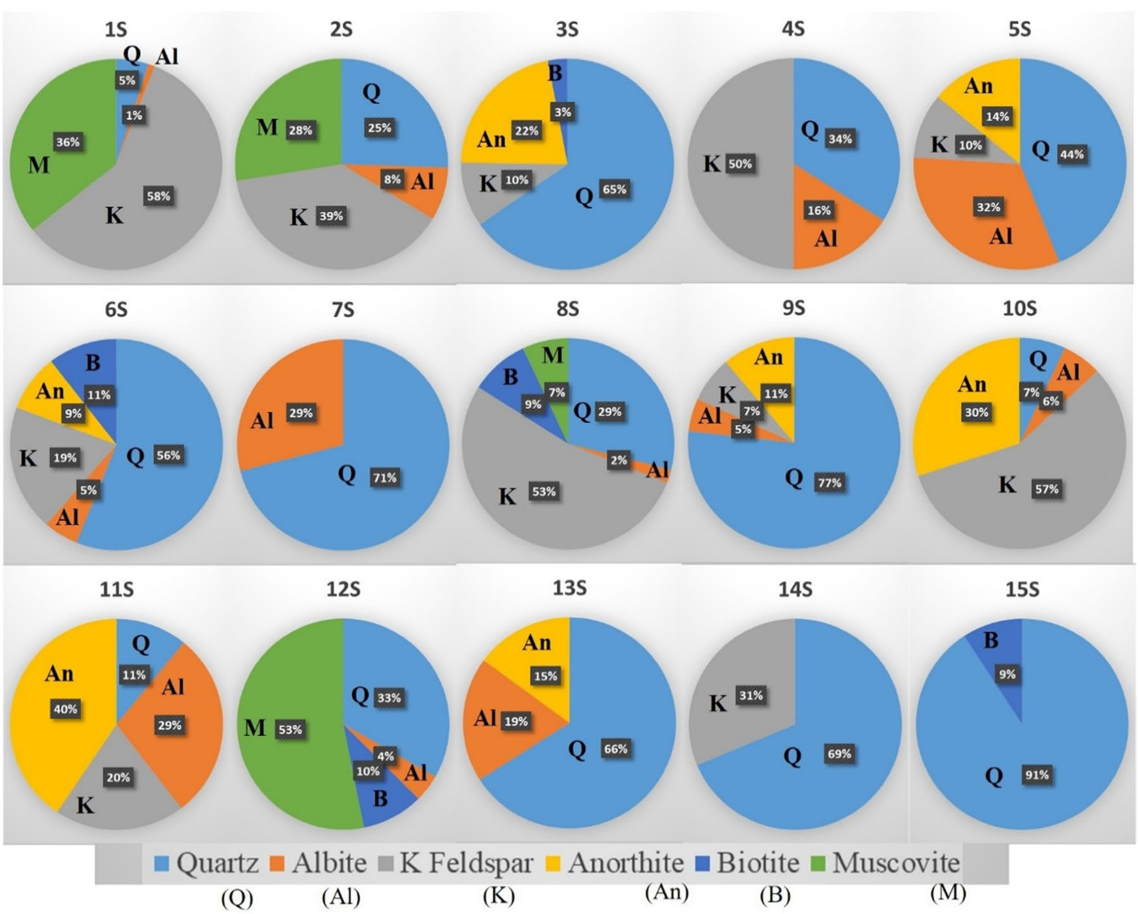


Fig. 6 Mineral composition based on XRD analysis on the investigated sandstone cores

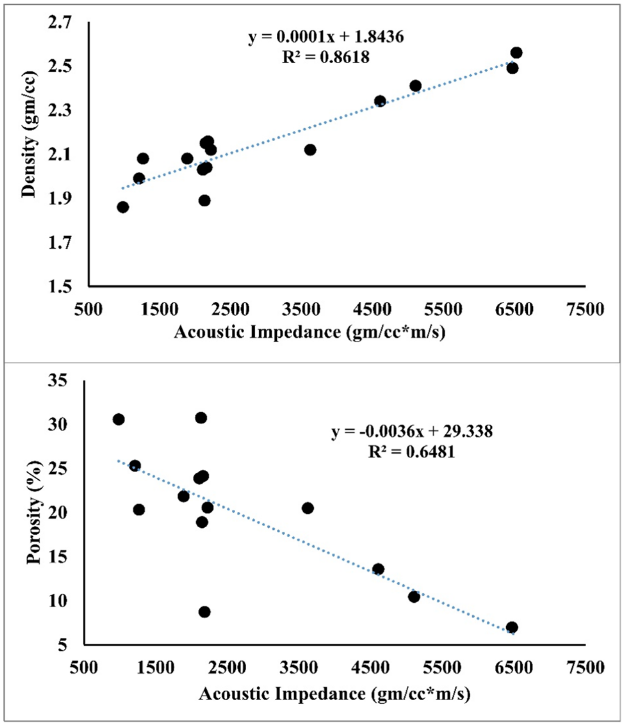


Fig. 7 Cross plot between acoustic impedance (AI) and (**a**) density and (**b**) porosity estimated in the laboratory on sandstone core plugs

2017; Maurya et al. 2020; Ismail et al. 2020 may be referred. Besides coloured inversion, there are several techniques of post-stack seismic inversion available in the literature such as sparse spike deconvolution, model-based analysis, geostatistical methods, multilayer linear calculator, maximum likelihood inversion to predict and map the spatial variation of key parameters. However, different inversion techniques as mentioned above can also be used to develop models and subsequently the adopted methodology may again be trained, tested. Apart from multilayered feed forward neural network, another popular neural network technique available is probabilistic neural network (Maurya et al. 2020). Each of these techniques have its own merits and demerits, which is beyond the scope of this study. For a detailed methodology regarding neural network techniques, studies conducted by Maurya and Singh 2019; Maurya et al. 2020, Kushwaha et al. 2020 may be referred. However, probabilistic neural network technique can also be used to train the present model. For the present study, an open source software - OpendTect was used for carrying out the inversion analysis.

Results and discussions

The different results obtained by performing analysis have been summarised in this section. Initially, seismic inversion was performed on the seismic data with the help of coloured inversion to generate acoustic impedance cube, Thereafter, well logs and subsequently laboratory based trends were used as targets to populate the different properties. The following sections present the different results obtained.

AI and different properties prediction by well logs

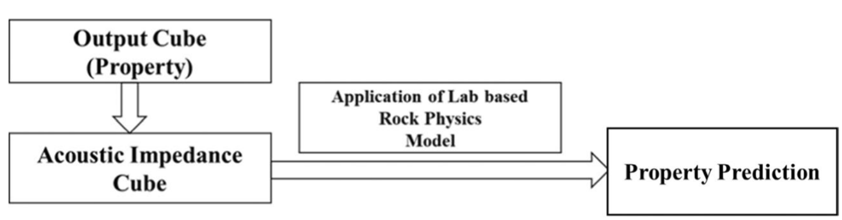
With the help of coloured inversion method, impedance (AI) cube was generated from the seismic data through inversion. The impedance values obtained from neural network considering Well 1 as target varies from 4603 to 14155 (g/cc) * (m/s) as shown in Fig. 9. Based on this AI cube, the different petrophysical and acoustic properties were evaluated by considering Well 1 logs as target. The density log of Well 1 was used as target to spatially populate across the survey area. The density values obtained from neural network varies from 2.14 to 2.73 g/cc as shown in Fig. 10 (a). Similarly, for obtaining the porosity across the survey area, PHID log, obtained from density log of Well 1 was used. The porosity values obtained from neural network varies from 6.7 to 28.8% as shown in Fig. 10 (b).

Petrophysical properties prediction by laboratory model

Using a one to one correlation

The laboratory-based statistically derived trends (Fig. 7), as elaborated earlier, were used to spatially populate the different petrophysical and acoustic properties across the seismic survey, as shown in Fig. 11(a, b). On application of the laboratory-based model (one to one correlation), the range of bulk density varies from 2.14 to 2.73 g/cc. Similarly, on the application of laboratory-based model (one to one correlation), the range of porosity varies from 6.7 to 28.9%.

Fig. 8 Flowchart displaying application of laboratory based model in petrophysical property prediction



The neural network derived results (density and porosity) which were obtained by training well logs (RHOB and PHID respectively) with acoustic impedance (AI) cube derived using coloured inversion were compared with the laboratory derived results. The laboratory derived results were evaluated based on utilizing one to one correlation between AI with density and porosity (Fig. 7). The acoustic impedance (AI) which was derived using coloured inversion, was transformed to density and porosity with the help of one to one correlation equation (as shown in Fig. 7). Thereafter, these estimated parameters, i.e., density and porosity (laboratory derived and well derived), were cross-plotted as shown in Fig. 12 for Barail and Sylhet formations. From the plots, it was observed that the correlation coefficient (r) was found to be 0.95 for density, while 0.95 for porosity. However, it is established from the literature that a one to one correlation may not provide a clear assessment (Garia et al. 2020), hence multivariate regression approach was adopted to further enhance the model.

Using multivariate regression equation

Using Eq. (1), V_p was calculated by using density and porosity derived from neural network analysis. This obtained V_p from Eq. (1) was cross plotted with the velocity derived from neural network analysis using well log (sonic log) and a strong correlation coefficient was obtained as shown in Fig. 13. However, neural network derived velocity values were found to be on a higher side when compared with laboratory derived velocity, i.e., $_{V_p}$ (from NN) = c * V_p (from lab), where c varies from 1.34 to 1.48 for Barail and Sylhet formation.

The velocity obtained from Eq. (1) was transformed to AI (by using neural network derived density) and thereafter trained with the modelled well log to generate density and porosity cube throughout the seismic data. These generated density and porosity models were used to derive velocity based on Eq. (1), thereby integrating laboratory and well modelled components to enhance the seismic reservoir characterization. Thereafter, to check the validity of the obtained velocity model, it was cross plotted with the previously derived velocity model (as elaborated in section "Using multivariate regression equation") for different formations as shown in Fig. 14 (a) and (b). It was observed that the velocity values were almost similar, i.e. V_p (from integrating NN and lab derived model) = c*V_p (from NN), where c varies from 0.97 to 1.08 for Barail and Sylhet formation.

Similarly, density (in g/cc) and porosity (in fraction) slices are also shown considering laboratory-based rock physics model for different formations, i.e., at Barail formation top (z=1660 ms), Barail formation bottom (z=1695 ms), and at Sylhet formation top (z=1925 ms) and Sylhet formation bottom (z=1951 ms), as shown in Figs. 15, 16, 17 and 18.

These generated density and porosity models were compared and plotted with the well-modelled logs. It was found

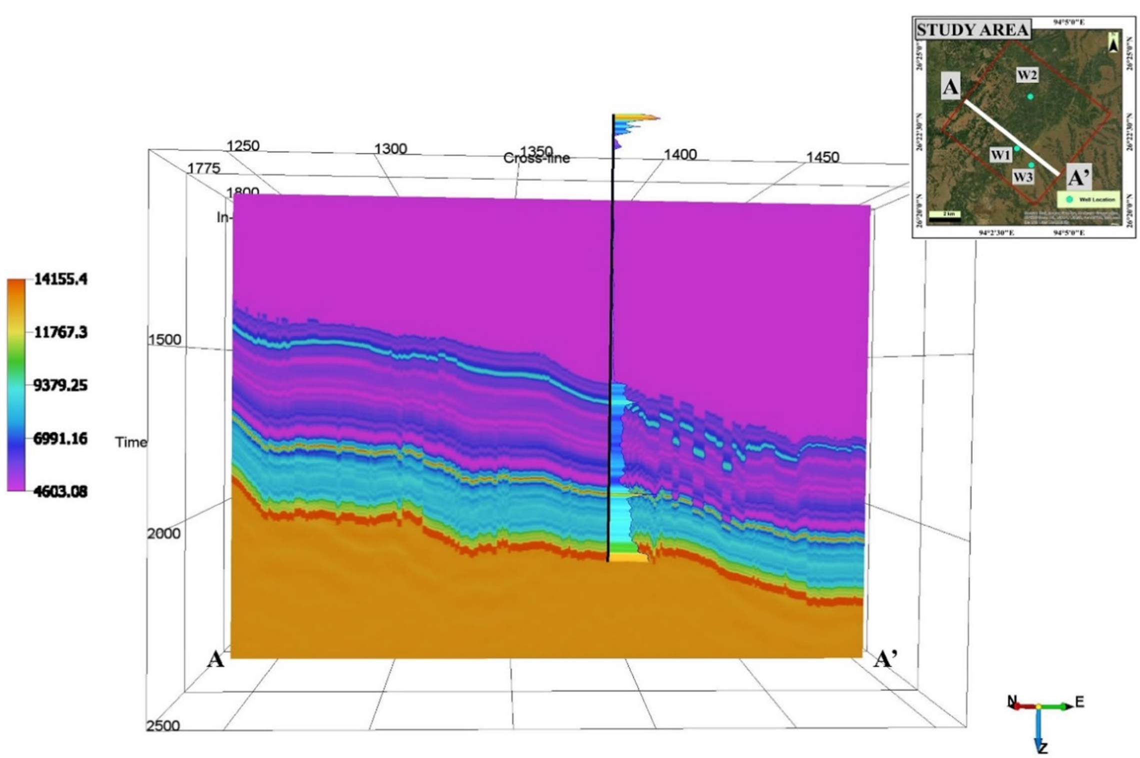


Fig. 9 Impedance (in m/s*gm/cc) generated through inversion analysis considering W1 as target

that there was a reasonable match between the two parameters, i.e., r = 0.78 and r = 0.95 for density for Barail and Sylhet formation, while r = 0.91 and r = 0.94 for porosity for Barail and Sylhet formation as shown in Fig. 19. These modelled parameters constitute of an amalgamation or integration of laboratory and well-modelled components that may be useful in enhancing the seismic reservoir characterization.

Several studies pertaining to the estimation of petrophysical parameters have been reported in the literature for Upper Assam basin (Table 2). For instance, Gogoi and Chatterjee (2019) obtained log derived porosity in the range of 30-36% for Tipam sandstones, 18-30% for Barail sandstones, AI (acoustic impedance) = 5000-11000 m/s*gm/cc and r (correlation coefficient) = 0.98 between inverted and computed porosity. Similarly, Kumar et al. (2018) reported log derived porosity as 15-22% and AI as 4000-16000 m/s*gm/cc, while Garia et al. (2022a, b) obtained laboratory derived porosity as 4.75- 30.7% and density as 1.86-2.56 gm/cc for Tipam and Barail sandstones. Majumdar and Devi (2021) reported log derived density as 1.95-2.95 gm/cc, porosity as 8-33% while Bhuyan et. al. (2022) reported log and laboratory derived porosity as 5-22% and 6.32-22% respectively for Barail sandstones. Hazarika and Gogoi (2021) stated laboratory

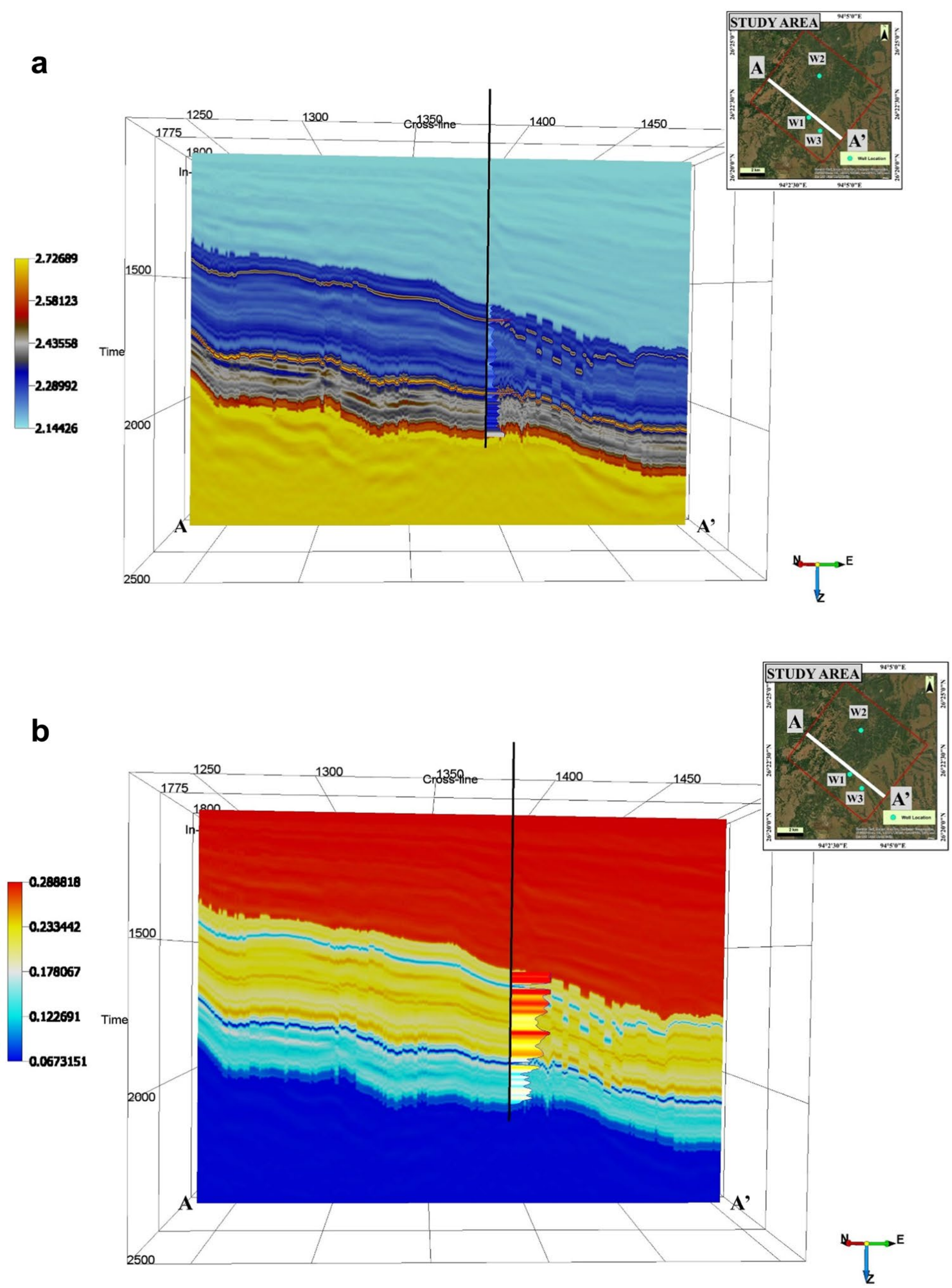


Fig. 10 (**a**) Density (in gm/cc) generated from neural network analysis considering Well 1 as target, (**b**) Porosity (in fraction) generated from neural network analysis considering Well 1 as target

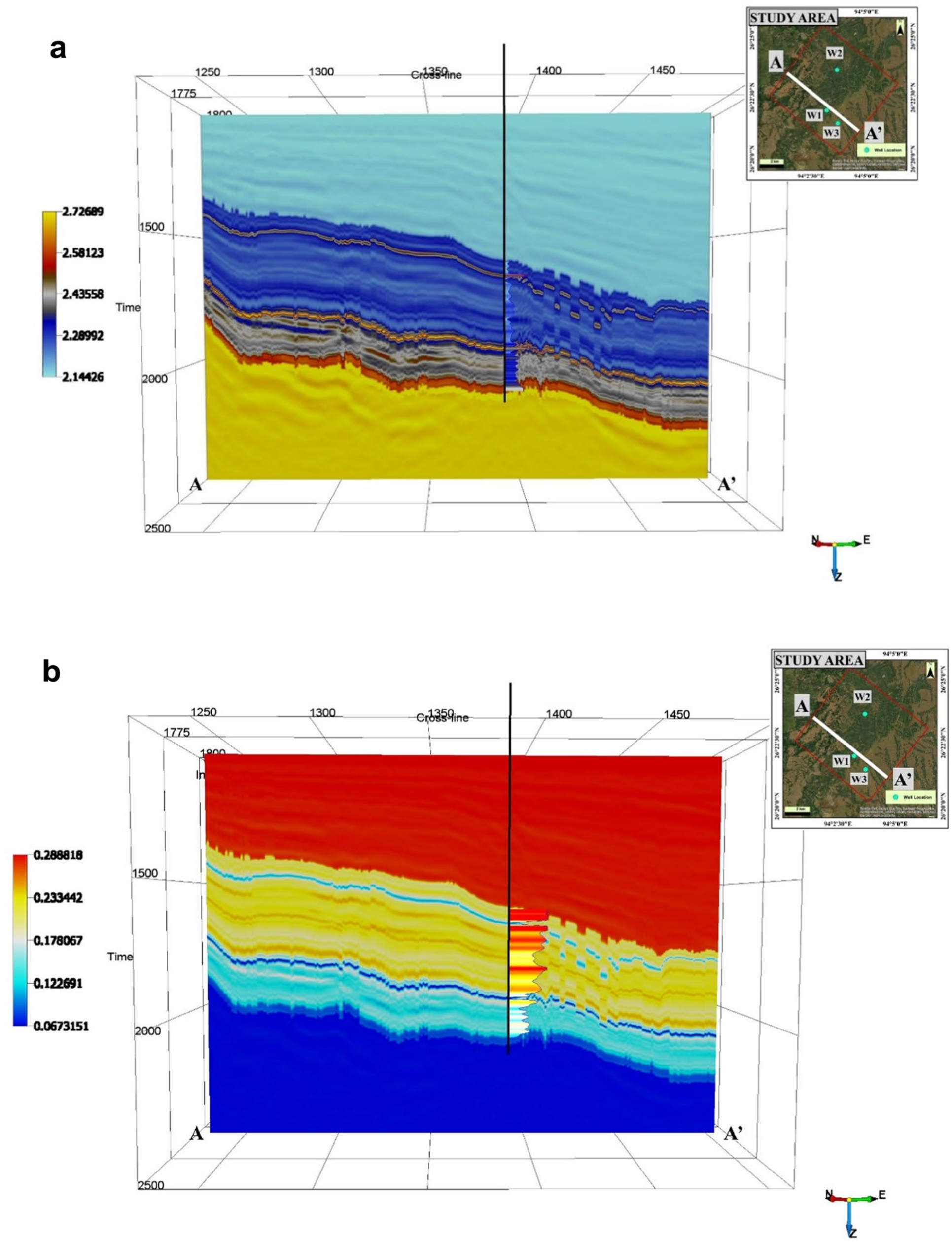


Fig. 11 (**a**) Density (in gm/cc) variation with depth generated from impedance considering laboratory based rock physics model. (**b**) Porosity (in fraction) variation with depth generated from impedance considering laboratory based rock physics model

derived porosity as 18.6-29.2% and Zaei and Rao (2019) estimated average density as 2.4 gm/cc, porosity as 13% for Tipam sandstones. Also, Wandrey (2004), Ishwar and Bharadwaj (2013), Bharali and Borgohain (2013) reported log derived porosity as 7-30%, 27-30% and 15-30% respectively for the Upper Assam basin. On comparing the above results obtained in the literature with the present study, the different parameters such as density, porosity etc. are found to be in range. For instance, in the present study, the range of porosity obtained is 6-28%, density: 2.1-2.7 gm/cc and acoustic impedance (AI): 4600-14000 m/s* gm/cc. These are found to be similar with the studies conducted in the Upper Assam basin, as tabulated in Table 2.

Conclusion

The present study incorporates the rock physics model derived in the laboratory on examination of sandstone rock core plugs of the Upper Assam basin along with the well log data into the seismic inversion methodology. By doing so, a methodology was proposed where the laboratory generated model was incorporated into the NN and subsequently trained with well log data to spatially populate density and porosity for the entire survey area. Generally, well log data are used in the rock physics workflow for quantitative seismic data interpretation. However, it is widely accepted that laboratory-based estimation of different parameters is

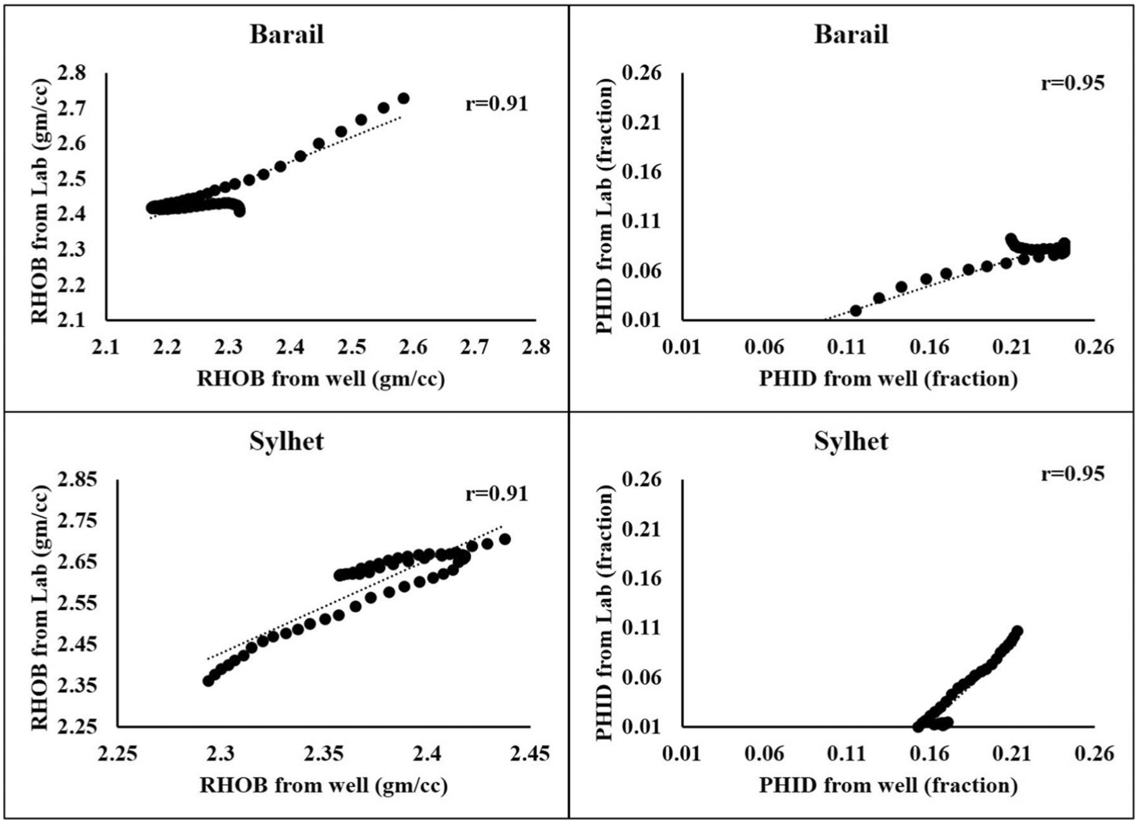


Fig. 12 Cross-plot between density and porosity from laboratory results (one to one correlation) to the density and porosity obtained from neural network

essential to corroborate data obtained from the well logs (Ambati et al. 2021). Therefore, to validate the efficacy of the laboratory-based rock physics model, seismic inversion was performed on the seismic data belonging to the Upper Assam basin on which the laboratory-based model was developed. Integrating the laboratory-derived rock physics model with the conventional seismic inversion workflow, the density varied between 2.23 to 2.73 g/cc, while porosity varied between 7 to 27%. These generated models were compared with well log data, and there was a reasonable agreement between them.

As a result, this research attempts to decipher a probable spatial variation of different reservoir properties for different formations by unification of different scales of study, i.e., involving macro for core data, mega for log data and giga for seismic data. Since investigations performed on core

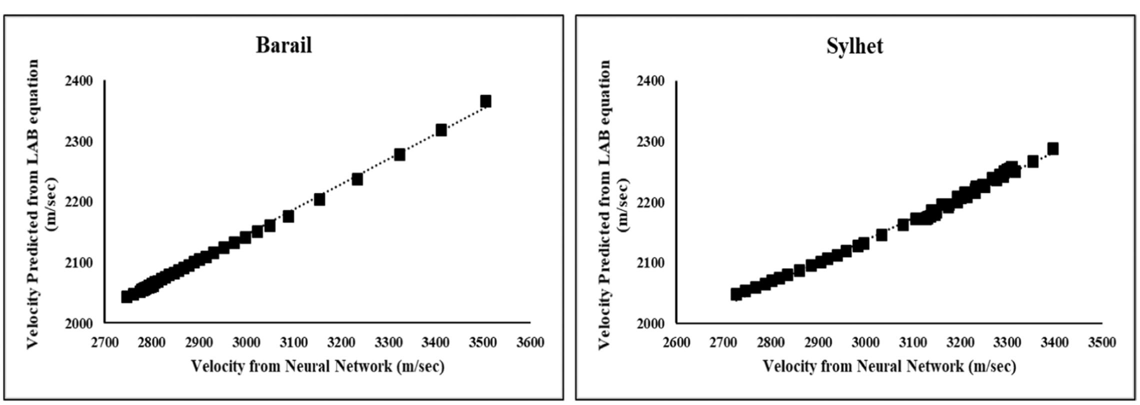


Fig. 13 Cross-plot between velocities from laboratory results to the velocity obtained from neural network, for (**a**) Barail, (**b**) Sylhet formation

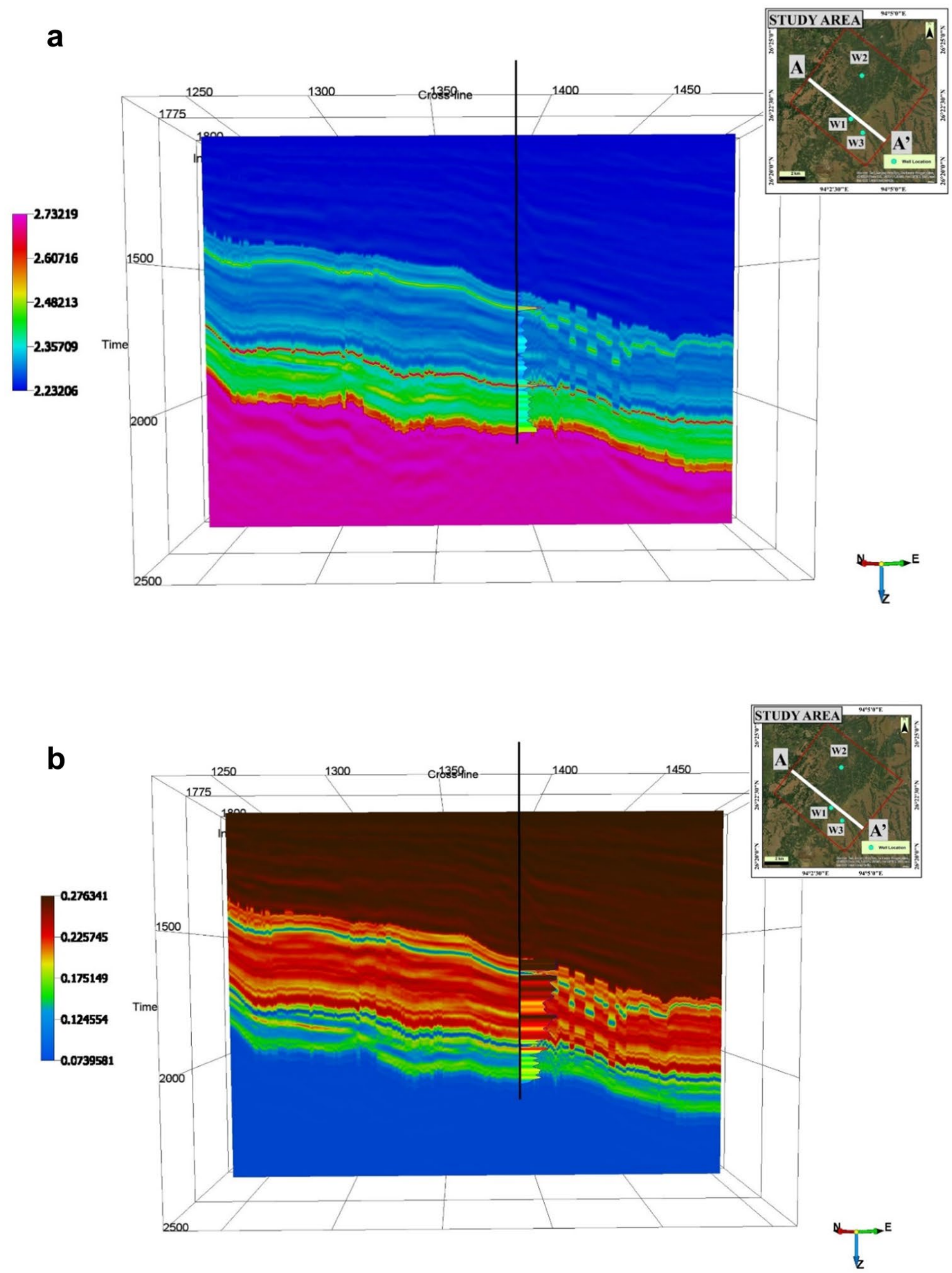


Fig. 14 (**a**) Density (in g/cc) results obtained after incorporating well log and laboratory-generated rock physics model. (**b**) Porosity (in fraction) results obtained after incorporating well log and laboratory-generated rock physics model

plugs at laboratory scale measurements involve minimum assumptions (Kelkar et al. 2002), hence the results (trends) obtained by using the proposed methodology are expected to be more reliable and realistic. The statistical derived trends used for pattern recognition may help to reduce uncertainty, ambiguity related to the most likely interpretation. The proposed workflow provides a framework for reservoir characterization using integrated seismic, well and laboratory-based analysis. This culminates the different factors such as geological, geophysical and seismic that would aid the future researchers to adopt a multidisciplinary approach, thereby providing guidance for the assessment and prediction of productive reservoir zones during the exploration stage.

Integrating different methods may lead to the development of new realistic models, thereby being a guiding force for quantitative decision analysis. The proposed workflow can be successfully applied as an aid in reservoir characterization. This methodology may also attempt to detect the expected small-scale variability noticeable in well log and more prominently in laboratory data, but indistinct in seismic data. The applicability of known statistical trends derived in the laboratory can help to constrain non-unique

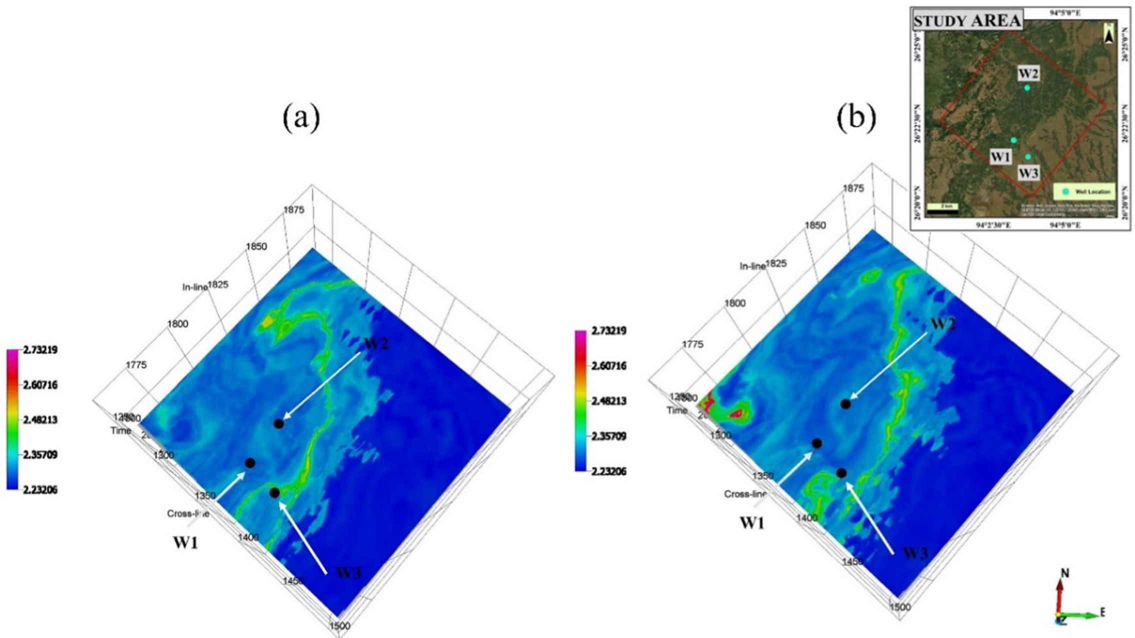


Fig. 15 Density (in g/cc) slice for (**a**) Barail formation top and (**b**) Barail formation bottom generated from neural network analysis obtained after incorporating well log and laboratory-generated rock physics model

geophysical inversions. Although the presented results correlate with the well log derived parameters, further complementary studies involving the effect of overburden pressure or stress in the simulation of subsurface models by using laboratory data can be investigated and may be added as a future scope. Furthermore, the different inversion and neural network techniques (probabilistic neural network) can also be used to develop models and subsequently the adopted methodology may again be trained, tested and compared with the existing results.

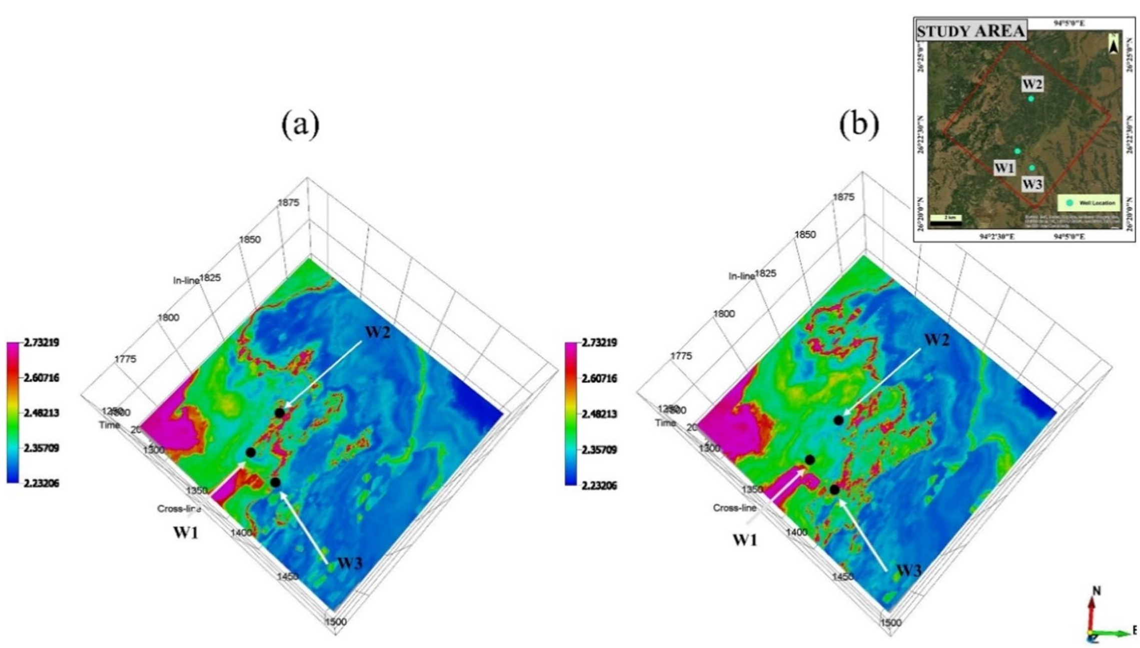


Fig. 16 Density (in g/cc) slice for (**a**) Sylhet formation top and (**b**) Sylhet formation bottom generated from neural network analysis obtained after incorporating well log and laboratory-generated rock physics model

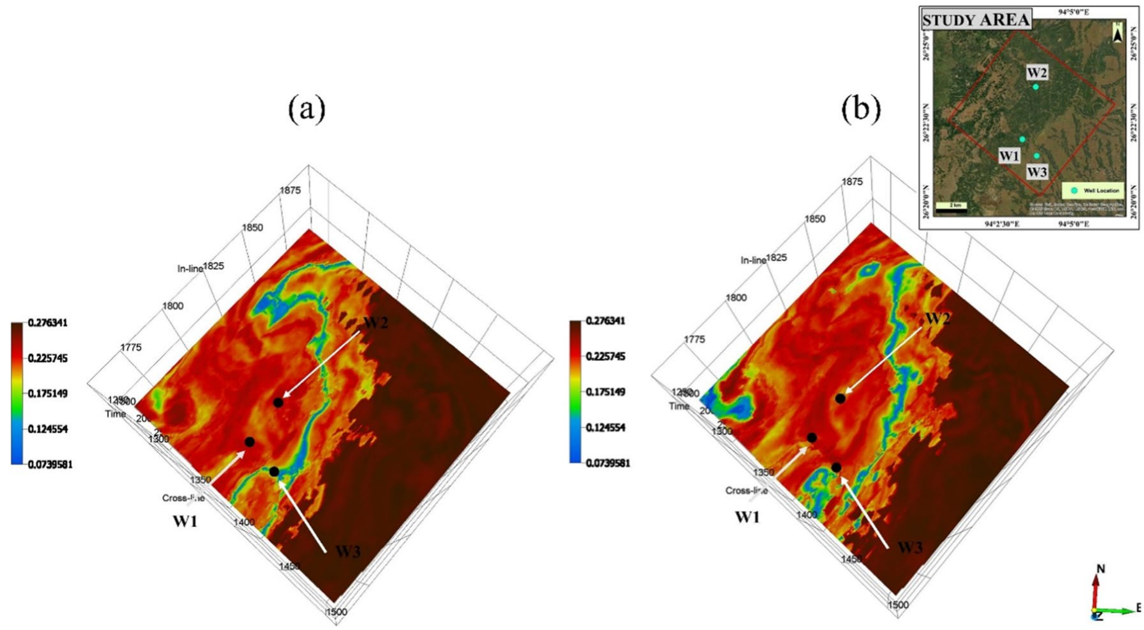


Fig. 17 Porosity (in fraction) slice for (**a**) Barail formation top and (**b**) Barail formation bottom generated from neural network analysis obtained after incorporating well log and laboratory-generated rock physics model

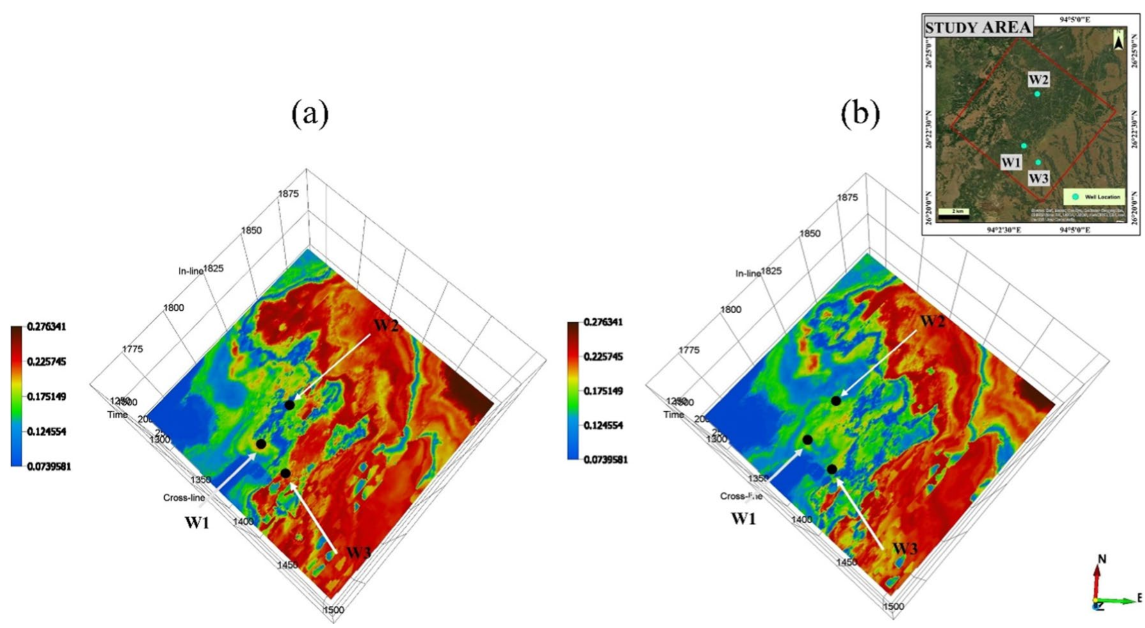


Fig. 18 Porosity (in fraction) slice for (**a**) Sylhet formation top and (**b**) Sylhet formation bottom generated from neural network analysis obtained after incorporating well log and laboratory-generated rock physics model

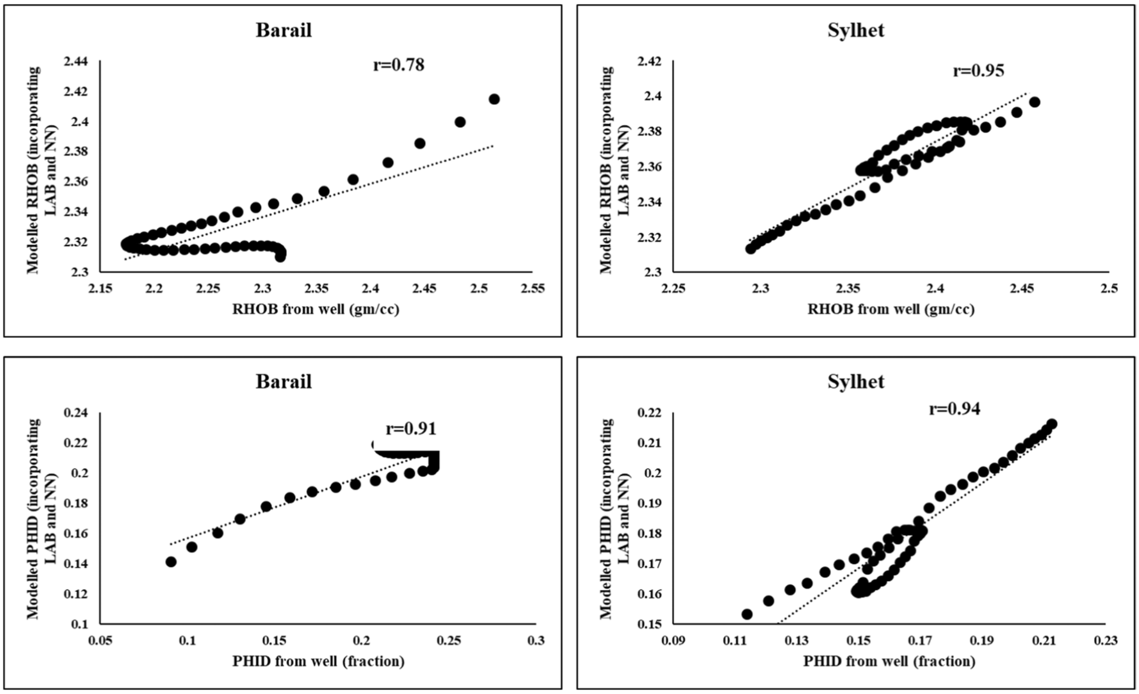


Fig. 19 Cross plot between well log density, porosity with modelled density and porosity results obtained after incorporating laboratory and neural network derived density and porosity for Barail and Sylhet formation

Table 2 Range of petrophysical parameters for the Upper Assam basin reported in the literature

S.No.	Literature	Density		Porosity		Others
		Well derived	Lab derived	Well derived	Lab derived	
1	Garia et al. 2022a, b	-	1.86-2.56 gm/cc for Tipam & Barail	-	4.75-30 % for Tipam & Barail	Acoustic Impedance (AI) = 1000-7000 m/s* gm/cc
2	Bhuyan et al. 2022	-	-	5-22 % for Barail	6.32- 22 % for Barail	-
3	Majumdar & Devi 2021	1.95-2.95 gm/cc	-	8-33 %	-	-
4	Hazarika & Gogoi 2021	-	-	-	18.6- 29.2 %	-
5	Zaei and Rao 2019	-	2.4 gm/cc (average) for Tipam	-	13 % (average) for Tipam	-
6	Gogoi and Chatterjee 2019	-	-	30-36 % for Tipam & 18-30 % for Barail	-	Acoustic Impedance (AI) = 5000-11000 m/s* gm/cc; Correlation coefficient (r) =0.98 between inverted & computed porosity
7	Kumar et al. 2018	-	-	15-22 %	-	Acoustic Impedance (AI) = 4000-16000 m/s* gm/cc

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Author contributions Archana M Nair conceived the research idea, designed the project. Formal Analysis were performed by Siddharth Garia and Arnab Kumar Pal. Methodology, Software and Investigation were performed by Siddharth Garia, Arnab Kumar Pal, Shreya Katre, Satyabrata Nayak and Archana M Nair. The first draft of the manuscript was written by Siddharth Garia and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability All data generated or analysed during this study are included in this published article.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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