Direct inversion for reservoir parameters from prestack seismic data

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Abstract

Reliably estimating reservoir parameters is the final target in reservoir characterisation. Conventionally, estimating reservoir characters from seismic inversion is implemented by indirect approaches. The indirect estimation of reservoir parameters from inverted elastic parameters, however, will produce large bias due to the propagation of errors in the procedure of inversion. Therefore, directly obtaining reservoir parameters from prestack seismic data through a rock-physical model and prestack amplitude variation with offset (AVO) inversion is proposed. A generalised AVO equation in terms of oil-porosity (OP), sand indicator (SI) and density is derived by combining a physical rock model and the Aki–Richards equation in a whole system. This makes it possible to perform direct inversion for reservoir parameters. Next, under Bayesian theorem, we develop a robust prestack inversion approach based on the new AVO equation. Tests on synthetic seismic gathers show that it can dramatically reduce the prediction error of reservoir parameters. Furthermore, field data application illustrates that reliable reservoir parameters can be directly obtained from prestack inversion.

Keywords: reservoir parameter, prestack seismic inversion, direct inversion, sand indicator, oil-porosity

1. Introduction

Prediction of reservoir parameters is crucial for the exploration and development of reservoirs because these parameters provide information for field evaluation and well location determination. Reservoir characterisation, whose ultimate goal is to obtain reservoir parameters, does not only limit inelastic parameter inversion from seismic data. Usually, elastic parameters are only intermediates for obtaining reservoir parameters. It means that when the elastic parameters are taken from seismic data, a secondary inversion is required to obtain reservoir parameters from elastic ones (Downton & Ursenbach 2006). Seismic data contain valuable information for reservoir evaluation and prestack seismic inversion provides an effective approach to obtain these reservoir parameters. Amplitude variation with offset (AVO) information is reliable to perform reservoir characterisation with improved certainty (Avseth et al. 2001a).

Over the years, some scholars have studied how to obtain reservoir parameters from seismic data. A multiple linear regression to predict reservoir parameters from selected seismic attributes is proposed (Hampson et al. 2001). Neural network methods also provide useful statistical approaches to reservoir parameters from seismic data (Ahmadi et al. 2013). In these statistical approaches, several seismic attributes, extracted from poststack or prestack seismic data,
are used for neural network training. Reservoir parameters are obtained through extended elastic impedance inversion (Aleardi 2018). The ‘sweet spots’ in reservoir parameters are predicted successfully (Song et al. 2019).

Statistical rock physics are introduced to get reservoir parameters in lithology identification and pore fluid prediction, combing well log data analysis and prestack seismic inversion (Mukerji et al. 2001a; Avseth et al. 2001b; Mukerji et al. 2001b). A fast, probabilistic inversion method based on a mixture density network to jointly estimate porosity and shale volume from P- and S-wave impedances, which are obtained from seismic inversion, is proposed (Shahraeeni et al. 2012). A time-lapse AVO difference inversion for predicting reservoir parameters is developed (Zhi et al. 2016). Based on Bayesian theory, nonlinear sparse inversion of prestack seismic data is performed (Zhang & Dai 2016).

Prestack seismic inversion is a well-established method to get lithology and fluid parameters. A nonlinear method of reservoir AVO inversion with the Zoeppritz equation has been developed (Mazzotti & Zamboni 2003; Wang 2003). A new type of weighted stacking, which combines the linear approximation of seismic reflection coefficients with linear physical rock models, has been introduced. This method can directly estimate band-limited porosity and shale volume (Saltzer & Finn 2005). Hydrocarbon identification through frequency-dependent AVO inversion has also been realised (Luo et al. 2018).

Conventionally, estimating reservoir characters from seismic inversion has been implemented by indirect approaches (Zhang et al. 2009). Under this indirect approach, seismic data are inverted into elastic parameters first; these elastic parameters are then converted to reservoir parameters by physical rock models taking from well log analysis (Bosch et al. 2010). Obviously, this is an indirect way to predict reservoir parameters from seismic data. The indirect way of reservoir parameter extraction from prestack seismic data causes much uncertainty and accumulated error, which reduces the prediction accuracy of reservoir parameters (Wang et al. 2006). Besides, the internal connection between seismic data and reservoir parameters is weak. To avoid generating unstable reservoir parameters, we integrate a physical rock model and the Aki–Richards equation to produce a generalised AVO equation in terms of such reservoir parameters as oil-porosity (OP), sand indicator (SI) and density. This generalised AVO equation establishes a connection between prestack seismic data and reservoir parameters. It makes a direct inversion for reservoir parameters possible. Stable reservoir parameters can be obtained from direct prestack inversion.

2. Characterisation of reservoir parameters

OP and SI are very effective reservoir parameters for hydrocarbon-containing target prediction and evaluation. Usually, spontaneous potential (SP), and gamma ray (GR) logs are used in lithological identification. However, in certain situations, SP and GR cannot distinguish reservoirs reliably. Alternatively, the ratio of resistivity (RT) and acoustic (AC) logs can effectively identify sand reservoirs. We define this ratio value as SI. As figure 1 shows, SI clearly indicates sandstone and conglomerate from mudstone. It shows that when the SI factor is less than 1.5, it belongs to shale layers. When the SI value is greater than 1.5, it belongs to sand reservoirs. The the larger value of SI, the better the reservoir property.

Porosity and oil saturation are another two important parameters for reservoir evaluation. Layers with high porosity or oil saturation may become a sweet spot, which refers to a favorable area containing oil. However, there is not always a tight correlation between porosity and oil saturation. Layers with high porosity do not necessarily contain oil, and layers with high oil saturation may have no exploitation value if the porosity is not high. Therefore, neither of the two parameters can be used alone to accurately evaluate sweet spots. OP is the product of porosity and oil saturation and a high OP value means the layer has both high porosity and oil saturation simultaneously. Hence, OP is a more reasonable parameter to delineate sweet spots. Let $\phi_o$, $\phi$, $S_o$ represent OP, porosity and oil saturation, respectively, then

$$\phi_o = \phi \times S_o.$$  

Figure 2 shows the probability distribution of sweet spots and OP in a production layer. Area I and II represent type I and II sweet spots, respectively. It can be seen that layers with high OP values are also areas of high-quality sweet spots.

This analysis illustrates that SI and OP have great advantages in sweet-spot characterisation. It is necessary to invert them from seismic data.
There are many physical rock models to describe the correlations between elastic parameters (including P- and S-wave velocity) and reservoir parameters (such as SI and OP). These physical rock models can be introduced to obtain reservoir parameters from seismic data. There are three types of physical rock model: theoretical models, empirical models and statistical models. Among these, theoretical physical rock models require rigid conditions in parameter selection, which make real data application difficult. The empirical equations do not have the capability to adapt different geological circumstances. However, the statistical models obtained from well data analysis are most reliable for a specific survey.

Relations between velocity, porosity and shale volume have been established (Tosaya & Nur 1982; Castagna et al. 1985; Han et al. 1986). Inspired by their conclusions, normal equations between P- and S-wave velocity, OP and SI are established through statistical regression

\[ V_p = A_p + B_p \phi_o + C_p S, \]
\[ V_s = A_s + B_s \phi_o + C_s S, \]

where \( V_p \) is P-wave velocity, \( V_s \) is S-wave velocity, \( \phi_o \) is the OP parameter and \( S \) is the SI parameter, respectively. \( A_p, B_p, C_p, A_s, B_s \) and \( C_s \) are coefficients that can be determined from statistical regression of well logging data.

From equation (2) we can get

\[ S = \frac{\left( B_s V_p - B_p V_s \right) - \left( A_p B_s - A_p B_p \right)}{C_p B_s - C_s B_p}, \]
\[ \phi_o = \frac{\left( C_s V_p - C_p V_s \right) - \left( A_p C_s - A_s C_p \right)}{B_p C_s - B_s C_p}. \]

Define

\[ D_1 = C_p B_s - C_s B_p, \quad E_1 = A_p B_s - A_s B_p, \]
\[ D_2 = B_p C_s - B_s C_p, \quad E_2 = A_p C_s - A_s C_p. \]

Substitute to equation (3), then

\[ S = \frac{1}{D_1} \left( B_s V_p - B_p V_s - E_1 \right). \]  

Consequently, the contrast of SI is

\[ \Delta S = \frac{1}{D_1} \left( B_s \Delta V_p - B_p \Delta V_s \right). \]

Combining equations (7) and (8), we have

\[ \frac{\Delta S}{S} = \frac{1}{g_1} \left( \frac{\Delta V_p}{V_p} - \frac{B_p}{B_s} \frac{\Delta V_s}{V_s} - E_1 \right), \]

Define

\[ k_1 = \frac{B_s V_s}{B_p V_p}, \quad g_1 = 1 - \frac{B_p}{B_s} \frac{E_1}{V_p}, \]

then equation (9) can be written as

\[ \frac{\Delta S}{S} = \frac{1}{g_1} \left( \frac{\Delta V_p}{V_p} - k_1 \frac{\Delta V_s}{V_s} \right). \]

Similarly, define

\[ k_2 = \frac{C_p V_s}{C_s V_p}, \quad g_2 = 1 - \frac{C_s}{C_p} \frac{E_2}{V_s}, \]

then

\[ \frac{\Delta \phi_o}{\phi_o} = \frac{1}{g_2} \left( \frac{\Delta V_p}{V_p} - k_2 \frac{\Delta V_s}{V_s} \right). \]

From equations (11) and (13), we can get

\[ g_1 \frac{\Delta S}{S} = \left( \frac{\Delta V_p}{V_p} - k_1 \frac{\Delta V_s}{V_s} \right), \]
\[ g_2 \frac{\Delta \phi_o}{\phi_o} = \left( \frac{\Delta V_p}{V_p} - k_2 \frac{\Delta V_s}{V_s} \right). \]

Equation (14) can be further converted to

\[ \frac{\Delta V_p}{2V_p} = \frac{g_2 k_1}{k_1 - k_2} \frac{\Delta \phi_o}{2 \phi_o} - \frac{g_1 k_2}{k_1 - k_2} \frac{\Delta S}{2 S}, \]
\[ \frac{\Delta V_s}{2V_s} = \frac{g_2 k_1}{k_1 - k_2} \frac{\Delta \phi_o}{2 \phi_o} - \frac{g_1 k_2}{k_1 - k_2} \frac{\Delta S}{2 S}. \]

where \( \Delta V_p/2V_p \), \( \Delta V_s/2V_s \) represent the variation ratio of P-wave velocity and S-wave velocity respectively. Similarly, \( \Delta \phi_o/2 \phi_o \) and \( \Delta S/2 S \) represent the variation ratio of OP and SI, respectively. Equation (15) establishes direct relations between P-wave velocity, S-wave velocity, OP and SI.
The Zoeppritz equation indicates that either reflection coefficient or transmission coefficient can be calculated when a P-wave is incident to the interface between two elastic media. Although the Zoeppritz equation can precisely calculate the amplitude of reflection coefficient, it is too complicated to exhibit the influence on amplitude of reflection coefficient when the elastic parameter changes. A number of papers have listed different ways to simplify the Zoeppritz equation through a linearisation method (Bortfeld 1962; Aki & Richards 1980; Fatti et al 1994; Wang 1999). A summary of linearised approximations with different elastic parameters is listed in Russell et al. (2011). Among them, the Aki–Richards equation is mostly used in petroleum exploration. In the Aki–Richards equation, the P-wave reflection coefficient $R$ follows

$$R(\theta) = \frac{g_2}{k_1 - k_2} \left( \frac{k_2}{2} \sec^2 \theta - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta \phi_o}{\phi_o} - \frac{g_1}{k_1 - k_2} \left( \frac{k_2}{2} \sec^2 \theta - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta S}{S} + \frac{1}{2} \left( 1 - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta \rho}{\rho},$$

where $V_p$, $V_s$, $\rho$ and $\theta$ are the average of P-wave velocities, S-wave velocities, densities and incident angles across the interface, respectively; $\Delta V_p$, $\Delta V_s$ and $\Delta \rho$ are the changes in P-wave velocities, S-wave velocities and densities across the same interface, respectively.

Substitute equation (15) into equation (16), yielding

$$R(\theta) = \frac{g_2}{k_1 - k_2} \left( \frac{k_2}{2} \sec^2 \theta - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta \phi_o}{\phi_o} - \frac{g_1}{k_1 - k_2} \left( \frac{k_2}{2} \sec^2 \theta - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta S}{S} + \frac{1}{2} \left( 1 - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right) \frac{\Delta \rho}{\rho},$$

where $k_1$, $k_2$, $g_1$ and $g_2$ are obtained from analysis of well logging data. According to equation (17), $\Delta \phi_o/2\phi_o$ and $\Delta S/S$ are the variation ratio of OP and SI across the interface, respectively.
Figure 4. Crossplots of $V_p$, $V_s$ and OP. The SI value of each scatter point is marked in different colors. It indicates that the higher value of OP, the smaller the value of velocity, but the correlation between velocity and OP is not high.

Figure 5. Crossplots of $V_p$, $V_s$ and OP SI is considered in the trend line (different colors represent different SI values). It is better to represent velocities as linear combinations of OP and SI.

Equation (17) creates the direct relation between P-wave reflection coefficient $R$ and reservoir parameters (OP and SI). It establishes the foundation of direct inversion for OP and SI from prestack seismic data.

4. Direct inversion for OP and SI

Rewrite equation (17) as

$$ R\left(\theta\right) = A\left(\theta\right) R_{\phi_o} + B\left(\theta\right) R_{\text{SI}} + C\left(\theta\right) R_p, $$

where

$$ R_{\phi_o} = \frac{\Delta \phi_o}{\phi_o}, \quad R_{\text{SI}} = \frac{\Delta S}{S}, \quad R_p = \frac{\Delta \rho}{\rho}, $$

$$ A(\theta) = \frac{g_2}{k_1 - k_2} \left( \frac{k_2}{2} \sec^2 \theta - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right), $$

$$ B(\theta) = - \frac{g_1}{k_1 - k_2} \left( \frac{k_2}{2} \sec^2 \theta - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right), $$

$$ C(\theta) = \frac{1}{2} \left( 1 - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 \theta \right). $$

When the number of the angle is $M$, equation (17) can be extended to

$$ \begin{bmatrix} R\left(\theta_1\right) \\ R\left(\theta_2\right) \\ \vdots \\ R\left(\theta_M\right) \end{bmatrix} = \begin{bmatrix} A\left(\theta_1\right) & B\left(\theta_1\right) & C\left(\theta_1\right) \\ A\left(\theta_2\right) & B\left(\theta_2\right) & C\left(\theta_2\right) \\ \vdots & \vdots & \vdots \\ A\left(\theta_M\right) & B\left(\theta_M\right) & C\left(\theta_M\right) \end{bmatrix} \begin{bmatrix} R_{\phi_o} \\ R_{\text{SI}} \\ R_p \end{bmatrix}, $$
where \( \theta_1, \theta_2, \ldots, \theta_M \) are different incident angles. Furthermore, for \( n \) samples of each seismic trace, considering the wavelet matrix \( W \), equation (23) will become

\[
\begin{pmatrix}
    d_1 \\
    d_2 \\
    \vdots \\
    d_M
\end{pmatrix} = \begin{pmatrix}
    W A_1 & W B_1 & W C_1 \\
    W A_2 & W B_2 & W C_2 \\
    \vdots & \vdots & \vdots \\
    W A_M & W B_M & W C_M
\end{pmatrix} \begin{pmatrix}
    R_{\phi_1} \\
    R_{\phi_2} \\
    \vdots \\
    R_{\phi_M}
\end{pmatrix},
\]

where

\[
d_i = (d_{i1}^1 \ d_{i1}^2 \ \ldots \ d_{in}^i)^T,
\]

\[
A_i = \text{diag}(A_{\phi_1}^i, A_{\phi_2}^i, \ldots, A_{\phi_M}^i)^T,
\]

\[
R_{\phi_i} = (R_{\phi_1}^i \ R_{\phi_2}^i \ \ldots \ R_{\phi_M}^i)^T,
\]

where \( T \) represents the transpose of matrix. Other parameters can be written similarly.

Equation (24) can be written to

\[
d = HR,
\]

where

\[
d = (d_1 \ d_2 \ \ldots \ d_M)^T, \quad H = \begin{pmatrix}
    W A_1 & W B_1 & W C_1 \\
    W A_2 & W B_2 & W C_2 \\
    \vdots & \vdots & \vdots \\
    W A_M & W B_M & W C_M
\end{pmatrix},
\]

\[
R = (R_{\phi}, R_{SI}, R_{P})^T.
\]
Figure 8. Synthetic prestack data and inversion results by different ways. (a) The synthetic prestack data calculated from well logs shown in figure 3 and a 35 Hz Ricker wavelet. (b) The inverted OP and SI from (a) in the direct way, showing that the inverted OP and SI (in red) are highly consistent with measured well logs (in black). (c) The inverted OP and SI from (a) in the indirect way; the correlation is poor between the inverted and measured well logs.

Substituting equation (30) into equation (29)

\[ p(R|d) \propto \prod_{i=1}^{m} \left( \frac{\sigma_i^2}{r_i^2 + \sigma_i^2} \right) \exp \left\{ -\frac{(d - HR)^T (d - HR)}{2\sigma_n^2} \right\} \]

(31)

To get the optimal solution, take its logarithm and omit constants, then

\[ J_R = (d - HR)^T (d - HR) + \sum_{i=1}^{m} \ln \left( \frac{r_i}{\sigma_n} \right)^2 \]

(32)

Where \( J(R) \) is the objective function for prestack seismic inversion, which can be performed through iteratively re-weighted least squares method (Zhang et al. 2014).

5. Well testing

First, the test is done on well logs and synthetic prestack seismic data. Figure 3 shows the well log data, which contain elastic parameters \( (V_p, V_s) \) and reservoir parameters (OP, SI). SI and OP vary from 2.1 to 13.8 and 0.3 to 7.0%, respectively, in this well. As observed from the well logs, high velocity segments show a relatively lower OP.

Figure 4 shows the velocities variation as a function of OP, the SI value of each scatter point is marked in different colors. It illustrates the general decreasing trend of velocity with the increasing of OP values, but their correlation is not high, since a number of scatter points are far away from this trend line. However, when SI is considered in the trend line, as figure 5 shows, the correlation become very strong. It means that velocities can be represented as linear functions of OP and SI, as equation (2) indicated.

Through statistical regression of the well logs, the coefficients in equation (2) are obtained, that is

\[ V_p = 4.61 - 0.09\phi_o + 0.02S \]

\[ V_s = 2.54 - 0.04\phi_o + 0.02S \]

(33)

where the P- and S-wave velocities are in km s\(^{-1}\); \( \phi_o \) is OP value in volume fraction; S is SI value, which is dimensionless.

Equation (33) can be rewritten in an equivalent form

\[ V_p = 4.61 - 0.09(\phi_o - 0.26S) \]

\[ V_s = 2.54 - 0.04(\phi_o - 0.39S) \]

(34)

then the crossplot can be plotted as figure 6. It shows excellent fitting between the velocities and the linear combination of OP and SI.

Furthermore, substituting the OP and SI values of figure 3 into equations (33) or (34), we can get the calculated P- and S-wave velocity. Then the calculated P- and S-wave velocity are compared with the measured velocity data of figure 3, as figure 7 shows. This indicates that the calculated velocities (in red) match the measured ones (in black) very well, exhibiting the reliability of this physical rock model.
Figure 9. Noise tests of the direct inversion method. (a) Synthetic prestack seismic data whose S/N is 2 and (c) synthetic prestack seismic data whose S/N is 1. (b) and (d) show the OP and SI values after performing direct inversions from (a) and (c), respectively. In (b) and (d), the inverted OP and SI are in red, and the measured well logs are in black.
Figure 8a shows the synthetic prestack seismic data using well log data shown in figure 3. The wavelet used in synthesizing is a 35 Hz Ricker wavelet. OP and SI values are inverted from this prestack data by direct and indirect way, respectively, mentioned before. The inversion results are shown in figure 8b and 8c. From figure 8b, it is clear that the inverted OP and SI values (in red) through the direct approach are highly consistent with measured well logs (in black). However, as can be observed from Figure 8c, the correlation is poor between the indirectly inverted value and measured well logs. Hence, it is obvious that a direct inversion for reservoir parameters is more stable than those from indirect inversion.

To test the stability of this direct inversion method under noisy seismic data, different levels of random noise are added into the prestack data shown by figure 8a. Figure 9a and 9c represents the synthetic prestack seismic data with different signal to noise ratios (S/N). The S/Ns of prestack seismic data shown in figure 9a and 9c are 2 and 1, respectively. Accordingly, figure 9b and 9d shows the directly inverted OP and SI values from the prestack seismic data of figure 9a and 9c, respectively. Comparing the inverted OP, SI (in red) and the measured well logs (in black), a certain bias can be observed. With the decrease of S/N, the bias becomes larger. However, the inverted OP and SI values are essentially in agreement with the measured well logs. The bias is at a reasonable level and does not seriously affect the result of reservoir prediction. It means that the direct inversion method is feasible when the S/N of prestack seismic data is greater than 1.

6. Field data application

There are three common-angle seismic data cubes (6°, 12°, 21°) provided for prestack inversion. Figure 10 shows one of

Figure 10. Common-angle seismic data for inversion. The parts show different angles of common-angle seismic profile of the same line: (a) 6°, (b) 12° and (c) 12°.

Figure 11. Inverted SI profile, overlapped with poststack seismic data. The left shows the lithology of well Y13. It is clear that areas with high SI correspond to sand layers in this well.
the common-angle seismic profiles, in which figure 10a exhibits a 6° profile, figure 10b exhibits a 12° profile, and so on. Direct inversion for OP and SI is performed according to equation (32). The inverted OP and SI profiles are shown in figures 11 and 12, respectively. Figure 11 is the inverted SI profile, overlapped with poststack seismic data of the same line. The left panel in figure 11 is the lithology of well Y13. It is clear that the areas with high SI values correspond to sand layers in this well. Besides, the thickness of sand layers indicated by SI is consistent with well Y13, demonstrating the correctness of inverted SI in reservoir prediction. Figure 12 shows the inverted OP profile. The high OP layers (in red) are in good agreement with those sweet spots exhibited in well Y13 and Y18, whereas these sweet-spot locations are ambiguous on seismic data. Figures 11 and 12 show that the direct inversion of SI and OP has remarkable effects on reservoir characterisation and sweet-spot analysis.

Figure 13 shows a sand reservoir profile predicted only by interpolation of wells. The reservoir where well H131 crossed is homogeneous. NotethatthedirectionalwellH131isnotusedintheinversionprocedure.
Figure 14. The inverted OP profile along the same lines as figure 13. The reservoir where well H131 crossed is inhomogeneous, showing the reliability of prestack direct inversion for a reservoir description.

7. Conclusion

Obtaining reliable reservoir parameters from seismic data is significant for reservoir characterisation. Prestack inversion is an effective way to obtain useful information of these reservoir parameters.

Usually, reservoir parameters are obtained indirectly. Under the indirect approach, elastic parameters are inverted from the seismic data first; these elastic parameters are then converted to reservoir parameters. Bias existed in the indirect prediction greatly reduces the accuracy of reservoir parameters. To avoid unstable values, we integrate a statistical physical rock model and the Aki–Richards equation to produce a generalised AVO equation in terms of reservoir parameters. This generalised AVO equation establishes a connection between prestack seismic data and reservoir parameters, making direct inversion of reservoir parameters from prestack seismic data possible. Furthermore, under a Bayesian framework, a direct inversion approach to obtaining reservoir parameters from prestack seismic data is developed, from which reliable reservoir parameters can be acquired.

OP and SI are two useful reservoir parameters. Well log and synthetic seismic data tests show that OP and SI directly inverted from prestack seismic data are more reliable than those from indirect approaches. Field seismic data application results indicate that the inverted OP and SI are matched well with the measured well data and are effective at delineating sweet spots. These tests and applications demonstrate the validity of this direct inversion approach in reservoir characterisation.

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Conflict of interest statement

None declared.

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