Combining non-seismic and seismic information for geological understanding - a case study

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Abstract. Non-seismic methods such as gravity and magnetic prospecting can provide valuable complementary information in oil and gas exploration in complex with seismic data. The integration of seismic and non-seismic research has become increasingly important in recent years due to advancements in technology and the use of artificial intelligence. The integration of these methods allows for a more comprehensive understanding of the subsurface and can improve the accuracy of predictions. Three examples highlight the potential benefits of integrating potential field data into the seismic interpretation process, including improved accuracy in predicting structural surfaces, the ability to predict discontinuous disturbances, and the ability to restore the depth-velocity model are given. The potential benefits of integrating, particularly in the context of sites located in Siberia, are pointed.

1 Introduction

Non-seismic geophysical methods can play a significant role in improving the quality of scientific and technical assessments in oil and gas prospecting. These methods are relatively cheap and efficient compared to seismic methods, and they can provide complementary information that can help reduce the costs of field development. The benefits of integrating non-seismic methods with seismic methods have been widely recognized by researchers in the field [1,].

The classical methods for non-seismic methods interpretation, which were developed to solve ore geophysics problems, can be applied to hydrocarbon accumulations to some extent. However, the subtler tasks of studying the geological structure of oil and gas fields require more advanced and specialized approaches. The integration of potential field geophysical methods with seismic data can help increase the confidence in identifying hydrocarbon accumulations, as well as improve the understanding of the geological structure of the fields.

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The research work being presented explores these topics and seeks to gain new understanding of the utilization of non-seismic methods in oil and gas exploration.

1.1 Geophysical data interpretation overview

There are two main approaches to interpreting geophysical data that are not seismic in nature: qualitative and quantitative methods.

The quantitative approach is further broken down into various methods. Some of the classical methods of interpretation of potential fields that are commonly used in the exploration of ore deposits and hydrocarbon accumulations are as follows:

1. Assessing the depth of an anomalous object using the shape of the anomaly with methods such as characteristic points, tangents, analytical connected with depths, and other geometric parameters of the anomalies, while constraining the source to a simple geometric shape.

2. Localizing single point fields due to inhomogeneities in the medium through the deconvolution of the Euler and Wenner methods [3].

3. Estimating the source parameters from point 1 using transformations, specifically by analysing the width of the gradient anomalies [4].

4. Downward calculating of the potential field using various filtering and transformation techniques, including Fourier transforms, to gain insight into the distribution of sources in the lower half-space.

5. Selection of model methods which should include pallet and mounting [5].

6. Implementing a combined approach that involves imposing constraints on specific parameters during the search for solutions within a particular layer [6, 7].

The primary techniques for interpretation (inverse methods) were developed in the previous century and currently, it appears unlikely that there will be any significant advancements in the interpretation methods separate from non-seismic methods. It is therefore evident that it is not possible to eliminate the inherent ambiguity of the inverse problem solution. The way to enhance the interpretation quality is to incorporate various data sources, including wellbore geophysics, seismic, non-seismic methods, and geochemistry.

The combination of seismic and non-seismic geophysical methods is a key aspect of the geophysical exploration process. To begin the process of combining these methods, the results from each method are compared independently, such as by comparing the results of a seismic survey and gravity prospecting, as depicted in Figure 1a.

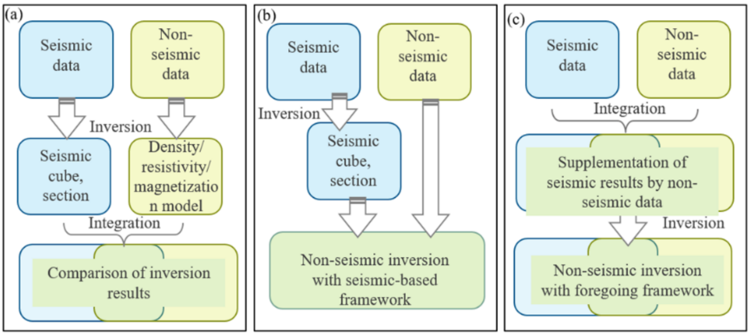

Fig. 1. General scheme of classical approaches to the combined use of seismic and non-seismic geophysical materials in interpretation. Explanations in the text.

Once this comparison has been performed, the results from the non-seismic methods are interpreted within the structural framework established by the wellbore and seismic results (Figure 1b).

Finally, the full utilization of non-seismic methods is integrated with well-logging, seismic data, and joint inversion of various geological exploration methods to form a comprehensive structural framework (Figure 1c). For instance, in areas with limited wellbore data, the velocity model can be corrected to improve the time-to-depth conversion of the seismic survey. In regions where the seismic coverage is incomplete, machine learning algorithms can be used to predict structural surfaces outside the seismic area based on the non-seismic methods data and their transformations. Machine learning algorithms can identify data regression and dependencies without human intervention or errors and are widely used in research to solve a range of practical problems even in situations where deterministic models are difficult or impossible to form [8; 9].

Machine learning algorithms are classified into various tasks based on the purpose of the study. These tasks can be broadly classified into regression, classification, clustering, data redundancy reduction, and anomaly detection [10, 11].

The regression problem in geoscience can be used to predict or fill in missing information. Currently, there are many methods that are considered for solving the regression problem in forecasting missing information: Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System, Fuzzy Models, Support-Vector Machine, k-Nearest Neighbors, Gaussian Process Regression, Decision Trees, and Random Forest [12].

Similar approaches can be used to predict faults that have been reliably identified in a portion of the area. The material composition of the rocks in the area can be analysed based on well studies and the available dataset. In the absence of wells, it is not possible to reliably tie in the seismic survey in depth, in which case gravimetric data can be used instead. The applications of these techniques are discussed in more detail in the next section.

The field locations presented in Case Studies 1 and 2 are located in Eastern Siberia, an area that is complicated by near-surface trap magmatism. Case Study 3 is located on the shelf of the East Siberian Sea, an area with a very low level of exploration and no drilling.

2 Case studies

2.1 Case study. Prediction of structural surfaces

In this section of the manuscript, the focus is on predicting the crystalline basement surface in an area where the results of airborne and magnetic surveys and 2D seismic surveys are already known. Figure 2 presents a map of the measured magnetic field anomaly at a scale of 1:50,000 (Figure 2a), a map of the gravitational field in the Bouguer reduction at a scale of 1:200,000 (Figure 2b), and a map of the basement surface depth obtained from the primary seismic studies using kriging interpolation (Figure 2c). The territory under study is complex and features salt domes, multiple stages of trap magmatism, and secondary processes of carbonatization, sulfidization, and halitization.

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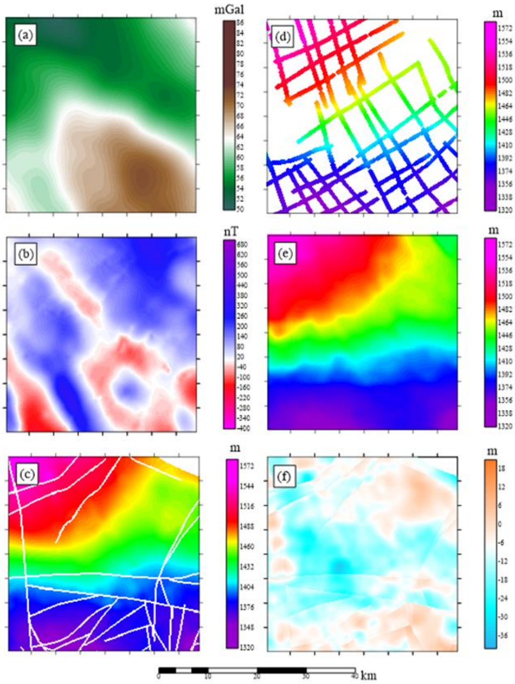

Fig. 2. Input data for research: a-c. Map of the anomalous magnetic field (a), the gravitational field in the Bouguer reduction (b). The map of basement depth obtained from 2D seismic data; white lines provide faults (c). Training sample of foundation surface depths (d), the result of the algorithm (e). The difference map of the foundation surface (comparison of interpolation and regression) (f).

The algorithms and stages used to predict the structural surfaces using non-seismic methods and neural networks trained with seismic survey data are depicted in Figure 2 (d, e, f). The training dataset is displayed in Figure 3d. In this case, an exact basement depth was assumed, and the goal was to predict the structural surface in the areas not covered by seismic surveys. The result of the algorithm is shown in Figure 3e, and the characteristics of the basement surface map produced by the neural network are visually similar to the results of the conventional kriging interpolation. However, when the difference is calculated (Figure 3f), it is evident that the spread of values is close to 50 meters (and further away from the profiles, the difference increases to hundreds of meters). The residual diagram also shows the presence of fault lines, as the algorithm involves smooth surfaces. An explanation of the above algorithm was done before [13, 14].

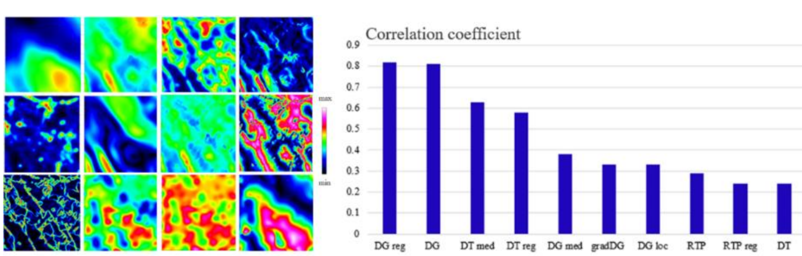

Fig. 3. Some of considered transformants (gravitational, magnetic, pseudo-gravitational fields, their gradients, traced anomaly axes, regional, local components, etc.) and the contribution of transformants to the formation of the basement surface.

Analysis of the correlation between transformants and the predicted results for a slightly larger area than shown in the figure 3 shows that the greatest contribution to the prediction of the absolute elevation of the basement was made by:

- the regional component of the gravitational field (DG reg) - correlation coefficient = 0.82
- the gravitational field (DG) - correlation coefficient - 0.81
- the mid-frequency component of the magnetic field (DT med) - correlation coefficient = 0.63
- the regional component of the magnetic field (DT reg) - correlation coefficient = 0.58,
- the mid-frequency component of the gravitational field (DG med) - correlation coefficient = 0.38,
- the gravitational field gradient (gradDG) - correlation coefficient = 0.33,
- the high-frequency component of the gravitational field (DG loc) - correlation coefficient = 0.33,
- the magnetic field reduced to the pole (RTP) - correlation coefficient = 0.29,
- the regional component of the magnetic field reduced to the pole (RTP reg) - correlation coefficient = 0.24,

the magnetic field (DT) - correlation coefficient = 0.24. For the rest of the transformants, the modulus correlation coefficient is less than 0.2.

The result in Figure 3b confirms the priori notions that in assessing the depth of the basement, one would first of all use the magnetic, gravitational fields and their regional components.

This analysis demonstrates the potential for non-seismic methods to be used in conjunction with seismic survey data to improve the accuracy of predictions and to fill in gaps in the data where seismic surveys are not available. The combination of different geophysical methods, including seismic and non-seismic, provides a more comprehensive understanding of the subsurface structure and helps to identify and map subsurface features such as faults and hydrocarbon reservoirs. The use of machine learning algorithms, in this case neural networks, can also greatly enhance the accuracy of predictions by incorporating the vast amount of information available from multiple sources. The results shown in Figure 4 indicate that the prediction of subsurface structures using non-seismic methods and seismic data is feasible and can provide valuable information for subsurface exploration and resource development.

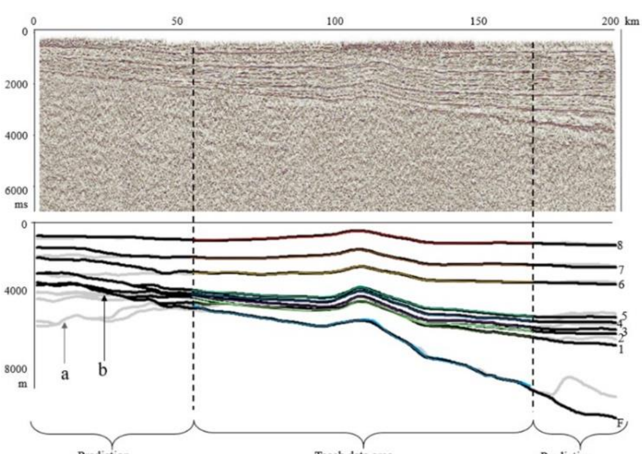

Fig. 4. Time seismic section, graphs of the reflecting horizons depth according to the forecast (variant with incomplete transformations - grey (a) and optimum number of transformants - black (b) lines) and specified in the training (in the centre, colour lines).

2.2 Case study. Prediction of faults

The next step is to predict the faults scheme. The initial interpretation of the original 2D seismic survey yielded the faults as thin black lines as shown in Figure 5a and Figure 5b. Using these faults, a training sample was generated in which an abstract parameter, assumed to be the fault factor, ranges from 0 to 1 depending on the proximity to the fault. The above algorithm was represented earlier [15].

The application of the training dataset on the specified network gave the result shown in Figure 5c and demonstrating the predominance of not latitudinal, but meridional directions in tectonics. Subsequent works confirmed that the area is characterized by the meridional strike of deep faults. The accuracy of the interpretation of course increases with an increment in the amount of the dataset used for training. An accurate estimate of the permissible data error is about 10%. Furthermore, to switch to the usual linear type of faults, the anomaly axes were traced using the well-known algorithm presented in 2017 [16]. This can be used to obtain a diagram of faults, due to seismic data at the intersection with seismic profiles, and on the rest of the area - by a set of methods. The results obtained from the application of the training dataset on the specified network have shown that the network is capable of accurately predicting the faults scheme in the study area. The prediction of the faults scheme is essential in geoscience, as it helps in understanding the structural and tectonic evolution of the area and also in resource exploration and exploitation. The accuracy of the interpretation can be increased by using a larger dataset for training, and by using additional methods to switch to the usual linear type of faults [17, 18]. The estimated permissible data error for the interpretation is about 10%. These results highlight the potential of machine learning algorithms in predicting geological structures and improving our understanding of geological processes.

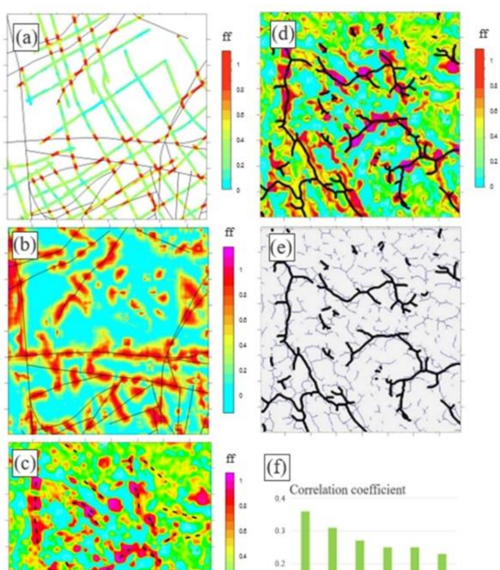

Fig. 5. The training sample of the fault factor according to the primary seismic interpretation (a), the result of the algorithm (b). The result of the algorithm operation is shown after adding additional seismic materials (a fragment of 3D observations is outside the area of the represented area) and faults axes highlighted by the interpreter (c). Fault factor and the result of linear tracing of faults (d). In the

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center - the result of linear tracing of faults with different detail of the input data (e). The contribution of transformants to the formation of the result field (f).

In this case, there were no high correlation coefficients (Fig.5e) and a wide range of transformations with a correlation coefficient of 0.2-0.3 (others are even less):

- the analytical signal of the magnetic field local component (AS DT loc) - correlation coefficient = 0.36,
- the local component of the magnetic field (DT loc) - correlation coefficient = 0.31,
- the mid-frequency component of the magnetic field (DT med) - correlation coefficient = 0.27,
- the gradient of the local component of the magnetic field (gradDTloc) - correlation coefficient = 0.25,
- the second vertical derivative of the magnetic field (DTzz) - correlation coefficient = 0.25,
- the second vertical derivative of the local component of the magnetic field (DT loc zz) - correlation coefficient = 0.23.

Below (Fig. 6) is the sectional view showing the comparison of the fault factor parameter and seismic data. In figure 8c, there are abundant discontinuous outbursts, which can be seen in the wave field. On the right, the field is smoother, and the fault factor value is low.

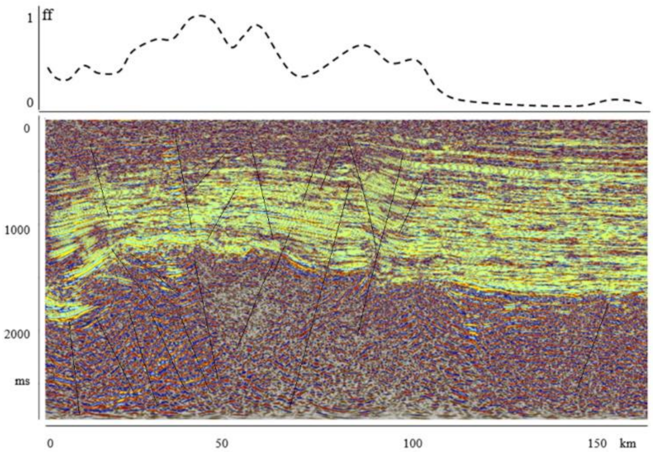

Fig. 6. Fault factor values and time seismic section.

Thus, faults are corrected with transformants associated with the local component of the magnetic field. This is understandable in this area, since the intrusion of magnetic diorite traps into the upper part of the sedimentary cover occurred along faults.

2.3 Case study. Velocity-depth model correction

In seismic survey fields that are remote or new, there is frequently a limited amount of geological and geophysical information, making it challenging to properly and accurately perform the depth referencing of seismic materials in the time domain [19]. To overcome this issue, obtaining data from potential fields such as the gravity survey is necessary. The goal is to adjust the velocity-depth model using the results of seismic density inversion. The process of refinement involves making corrections to the interval velocities on a layer-by-layer basis by selecting the density distribution to minimize the difference between the model and the observed fields.

The input data required for seismic density modeling is the distribution of interval velocities for each layer, which can then be converted into density values using the Gardner equation (1974). This equation was experimentally derived and is accurate for most conditions, leading to a solution that corresponds to the real geological environment. Although there may not always be a direct relationship between velocity and density, the equation has proven to be effective based on a large sample of data. The conversion process should be guided by general geological understanding of the distribution of density properties in the section, as well as any available prior geological and geophysical information from the study region.

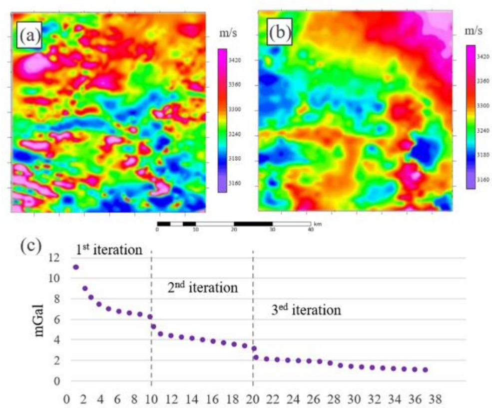

Fig. 7. Distribution of average velocities in the target formation based on velocity analysis (a) and using gravity data to form a low-frequency model (b). Matching error depending on the iteration number (c).

To correct the velocity-depth model using potential fields, the primary step is the seismic density inversion. The main stratigraphic horizons obtained from seismic survey data serve as the model framework and each horizon is assigned a density distribution that is consistent in depth and across the lateral, converted from interval velocities. The layers are identified based on the stratigraphic units. It is worth noting that the density inversion is performed layer by layer and involves multiple iterations until the standard deviation between the observed field and the model field reaches the survey error values, as shown in Figure 7.

The integration of seismic and gravity data through joint inversion enables the selection of a model that is most consistent with the density and acoustic property data. At the conclusion of the inverse relationship-based density inversion, the density distribution across reference horizons was transformed into interval velocity values. The effectiveness of this technique has been previously demonstrated using model data [20].

Trials of this algorithm on several pilot projects have exhibited remarkable success in resolving the challenge of creating a velocity-depth model in the absence of high-quality geological and geophysical information. When the histograms of interval velocities were compared, the difference in mean values was never more than 2.3%, with the main modifications observed in ranges where significant shifts towards higher or lower velocities occurred.

The analysis of results suggests that the interval velocity data obtained from seismic data processing contains a high-frequency component and a fragmented structure, which can be attributed to a limited observation network and the use of kriging in areas where profiles are missing. Including potential field data in the depth-velocity model enables the introduction of a low-frequency component, thereby enabling prediction of data in regions where seismic observations are absent.

The results in this study demonstrate that the algorithms used are adequate, meet expectations, and fall within the acceptable range, with a geological explanation possible. While the results have not been directly verified through drilling or other means, error estimates were performed through cross-validation. The errors obtained in all areas studied at this stage of the research do not exceed the permissible error range.

3 Conclusions

The suggested methods can be utilized for analyzing geological and geophysical data in uncharted areas with limited or no further field research. This study did not address the usefulness of non-seismic techniques for static adjustments in seismic exploration, nor the utilization of electrical exploration data for training neural networks, and multi-feature classifications of 3D models. Future studies will focus on an integrated approach while taking into account these omitted aspects, particularly in regions where non-seismic methods are being increasingly utilized in research, alongside the examination of new production territories.

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