

3D-S-wave-LLM: three-dimensional shear wave velocity forecasting by large language models

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Abstract

This study addresses the issue of spatial coverage blind spots induced by the limited three-dimensional (3D) shear wave (S-wave) velocity resolution of conventional surface wave imaging methods. To resolve this problem, a 3D S-wave velocity forecasting method based on large language models (LLMs) is proposed. Specifically, we design a prompting template tailored to the 3D S-wave velocity forecasting task combined with a 3D S-wave velocity field grid traversal strategy. The approach converts previously inverted 3D S-wave velocity data into a 3D S-wave velocity prompt sequence dataset with spatiotemporal sequence characteristics. Then, by fine-tuning the LLM using a standard trainer, the fine-tuned LLM is leveraged to forecast S-wave velocities in areas of the study region where coverage is incomplete. Experimental results demonstrate that LLM models (after fine-tuning via prompting techniques and optimization through data engineering) exhibit a good forecasting performance and generalization ability in the scenario of 3D S-wave velocity prediction. These results validate the feasibility and reliability of the proposed method. The findings of this study can be applied to high-resolution S-wave velocity imaging and provide a valuable reference for in-depth investigations of complex geological structures within the geoscience field.

Keywords three-dimensional (3D) shear wave (S-wave) velocity, large language models (LLMs), shear wave (S-wave) velocity forecasting

1 Introduction

S-wave velocity is one of the crucial physical parameters of rocks within the earth's interior, reflecting properties such as rock density and elastic modulus. S-wave velocity is not only of great significance in seismic exploration but also

indispensable in the field of geology. By means of S-wave velocity, it is possible to gain a deeper understanding of the structure and composition of subsurface rocks. It plays a vital role as fundamental information in pre-stack seismic inversion, fluid identification, and other related aspects^[1]. Traditional methods for extracting S-wave velocities, such as acoustic logging and rock physics testing^[2], typically provide one-dimensional (depth profiles) or two-dimensional (profile sections along survey lines) S-wave velocity information. These conventional methods

deliver valuable local or sectional insights, suitable for near-surface engineering surveys and site effect assessments. However, when precisely characterizing complex geological structures or gaining deeper understanding of geodynamic processes, existing research predominantly employs surface wave imaging techniques based on background noise^[3] to invert the 3D S-wave velocity structure within the earth's interior^[4–8].

Significant progress has been made in studying complex geological structures through 3D S-wave velocity inversion based on surface wave imaging methods. However, practical applications still face limitations and shortcomings, primarily manifested in two aspects. First, insufficient or constrained resolution prevents clear delineation of geological structures in inversion results. In practice, due to limitations in station distribution and coverage density of ray paths, resolution significantly degrades in marginal areas. For instance, in studies of the northeastern margin of the Tibetan Plateau^[9], while structures deeper than 75 km in the central region were well-recovered, resolution diminished in marginal areas due to sparse data coverage. Similarly, in Hanzhong Basin inversions^[10], short-period surface wave data provided weak constraints on shallow layers, leading to unstable results in regions with significant lateral velocity variations. Second, the high computational cost of surface wave imaging data processing limits its application in real-time monitoring or rapid response scenarios. Background noise data are typically acquired through long-term continuous recording, generating massive volumes requiring processing^[11], calculating cross-correlations, extracting dispersion curves, and performing 3D tomography inversion demands substantial computational resources and time^[12]. Especially during large-scale, high-resolution imaging, this issue becomes more pronounced.

With the rapid advancement of artificial intelligence (AI) and improvements in computational capabilities, AI technologies are increasingly being applied in earth sciences, particularly in the field of geological structure research. For instance, research utilizing semantic

knowledge bases and ontology techniques demonstrates that AI can automatically identify geological structures based on rock characteristics and predict the next structural unit within known stratigraphic sequences^[13]. Other studies apply 3D generative AI to tasks such as fault system simulation and fold belt analysis. By integrating drilling or surface survey data, these approaches effectively reduce uncertainties in subsurface interpretation^[14]. Although surface wave imaging techniques can obtain 3D S-wave velocity structures of study areas through methods such as background noise cross-correlation and dispersion curve extraction, limitations in seismic station density, observation cycles, and data coverage often result in spatial coverage gaps^[15] in inversion results. This not only affects the understanding of regional tectonic patterns but also constrains the verification of deep dynamic mechanisms and the accuracy of strong earthquake risk assessments. To summarize, traditional surface wave imaging methods face limitations including insufficient resolution, high computational costs, and spatial coverage blind spots. In contrast, LLMs with powerful sequence modeling capabilities, have demonstrated significant advantages in simulation and forecasting tasks, offering promising solutions to these challenges. Given this, this study leverages the cutting-edge advantages of AI technology and the practical demands of surface wave imaging inversion. Using the inverted 3D S-wave velocity data, it utilizes LLM methods to further predict the incomplete S-wave velocity coverage within the study area.

The proposed 3D S-wave velocity prediction method offers multiple advantages. First, this novel prediction approach possesses 3D S-wave velocity data completion capabilities, alleviating spatial coverage blind spots or resolution limitations inherent in traditional surface wave imaging methods. It provides a more comprehensive data foundation for subsequent geological structure analysis. Second, this new prediction method simplifies the inversion calculation process, reducing computational costs for large-scale, high-resolution imaging. Traditional surface wave imaging methods require two core conditions for 3D S-

wave velocity inversion; a dense network of observation stations and complex inversion calculations^[16], creating a significant trade-off between cost and efficiency. The proposed prediction method replaces the full-area observation inversion approach by leveraging already-inverted data combined with outward prediction capabilities, effectively reducing computational costs. Finally, this research can stimulate new research directions and application scenarios, such as conducting more refined dynamic assessments of strong-motion earthquake hazards, promoting the deep integration of artificial intelligence with geological structure research, and better serving the development of the Earth sciences field.

2 Related work

2.1 3D S-wave velocity

3D S-wave velocity is a spatial distribution parameter describing the elastic properties of subsurface media. Its core lies in locating the propagation velocity values of S-wave through 3D spatial coordinates (longitude, latitude, depth)^[17–18]. A 3D S-wave velocity structure model can demonstrate how S-wave velocity varies with changes in latitude, longitude, and depth within specific regions of the Earth's interior. Inversion and imaging of 3D S-wave velocity are crucial for understanding complex geological structures within the Earth, assessing seismic hazards, and exploring oil, gas, and geothermal resources^[19–20].

2.2 S-wave velocity forecasting

This paper addresses research on S-wave velocity forecasting across two domains. In the oil and gas exploration field, traditional S-wave velocity forecasting methods can be categorized into empirical formula methods and S-wave velocity forecasting methods based on rock physics models. Empirical formula methods^[21–23], grounded in statistical analysis, offer a straightforward approach to estimating S-wave velocity. Rock physics modeling methods primarily involve studying various rock physics models in conjunction

with actual geological conditions^[24]. By calculating the equivalent elastic parameters of rocks, these methods derive S-wave velocities, yielding more accurate results than empirical formula methods^[25–27]. Advances in machine learning have introduced novel approaches to S-wave forecasting, such as utilizing support vector machines for velocity prediction^[28–29]. Deep learning methods have also been applied to S-wave velocity forecasting, including using artificial neural networks for prediction^[30], constructing S-wave forecasting models with gate recurrent unit (GRU)^[31], long short term memory (LSTM)^[32], extreme gradient boosting (XGBoost)^[33] neural networks and so on. Within geological structure research, background noise tomography is commonly employed to obtain S-wave velocities through inversion of Rayleigh wave or surface wave dispersion curves^[34]. However, research focusing on further forecasting of these inverted S-wave velocities remains relatively scarce.

2.3 LLM-based forecasting methods

Recently, LLMs have achieved superior performance in forecasting tasks, benefiting from extensive parameterization and large-scale training data^[35–36]. LLM-based forecasting methods can be categorized as time series-based or prompt-based, depending on whether prompts are included in the input^[37]. Early work explored pure prompting techniques for time series forecasting^[38]. Subsequent studies demonstrated that combining time series with prompts^[39–40] or leveraging pre-trained LLM knowledge^[41–42] can enhance performance. The aforementioned research achievements in the field of artificial intelligence can provide reference for the task of forecasting 3D S-wave velocities in geological structure studies.

3 Methodology

3.1 Template-based prompting

Although 3D S-wave velocity data are fundamentally a geophysical parameter with spatial dimensions, it can be transformed into a sequence data format processable

by LLM through space-sequence modeling via time-series processing. By designing prompt templates tailored to the 3D S-wave velocity prediction task, the LLM is guided to focus on key information for performing 3D S-wave velocity predictions.

Using template-based description is an effective and efficient approach to achieve the data-to-text transformation. In this work, we explicitly introduce templates for the 3D S-Wave data and Table 1 lists the templates and the corresponding examples.

Table 1 Templates for transforming 3D S-wave numerical to 3D S-wave prompt

Type	Template	Example
Input prompt	Context	From longitude 101.00° to 101.50°, latitude 36.00° to 36.50°, depth 0.00 km to 0.00 km, the S-wave velocity are 3.148 5, 3.237 1, 3.268 3, 3.365 6, 3.268 7, 3.077 9, 3.332 3, 3.365 6, 3.257 6, 3.257 0, 3.313 6, 3.379 7, 3.423 1, 3.352 9, 3.284 9, 3.301 5, 3.304 5, 3.307 1, 3.309 7, 3.309 7, 3.306 7, 3.298 2, 3.319 4, 3.314 6, 3.386 6 km/s. The general trend value of S-wave velocity change is ΔS km/s, and the average velocity change rate is $\Delta S\%$.
	Question	Based on the known coordinates, S-wave velocity, and auxiliary information for the {Step_in} points, what is the S-wave velocity for the next {Step_out} points (longitude {Next_Start_Longitude}° to {Next_End_Longitude}°, latitude {Next_Start_Latitude}° to {Next_End_Latitude}°, depth {Next_Start_Depth} km to {Next_End_Depth} km)?
Output prompt	Answer	In the range of longitude {Next_Start_Longitude}° to {Next_End_Longitude}°, latitude {Next_Start_Latitude}° to {Next_End_Latitude}°, depth {Next_Start_Depth} km to {Next_End_Depth} km, the predicted S-wave velocity are: {V1, V2, ..., VStep_out} km/s.

In a nutshell, the template consists of two main components: input prompt and output prompt. The input prompt can be divided into a context section and a question section. The context provides the historical information needed for prediction, while the question section can be viewed as a query about the future. The output prompt is the answer to the question.

In the context section, the 3D coordinates of {step_in} known points must be provided, including latitude, longitude, and depth, along with the specific S-wave velocity corresponding to each point. Additionally, we have designed prompt auxiliary information, including the overall change trend ΔS and the average velocity change percentage $\Delta S\%$, which is used to assist the language model to understand the

overall trend of S-wave velocity changes within the given area. In the question section, the forecast step size is {step_out}, meaning the S-wave velocity is forecasted backward for {step_out} points starting from the last known point. In the answer section, the forecasted S-wave velocities for the subsequent {step_out} points need to be provided.

$$\Delta S = \left\{ \sum_{i=1}^T \delta S_i \right\}$$
$$\delta S_i = V_i - V_0$$

(1)

$$\Delta S\% = \left\{ \frac{1}{T} \sum_{i=1}^T S_i \times 100\% \right\}$$
$$S_i = \frac{\delta S_i}{V_0}$$

(2)

The primary principle for designing templates that

transform 3D S-wave numerical data to 3D S-wave prompt is as follows.

1) Contextual data aggregation: use placeholders such as Start_Longitude to End_Longitude to describe the range of 3D spatial coordinates, avoiding the need to list each point individually. Let $\{V_1, V_2, \dots, V_{\text{step_in/step_out}}\}$ denote the sequence data, with ΔS and $\Delta S\%$ summarizing the trends in data variation.

2) Forecasting coordinate rules: declare the forecast data range within the 3D via parameters such as Next_Start_Longitude and Next_End_Longitude, ensuring the model sequentially traverses the latitude-longitude grid. The entire dataset is split into multiple sequences using a slide window, where the window size equals the observation length Step_in + forecast length Step_out. The slide step size is set to 1 as default.

3) Input-output alignment: output (answer) parameters named Next_* are identical to the 3D coordinate ranges in the input (question), eliminating

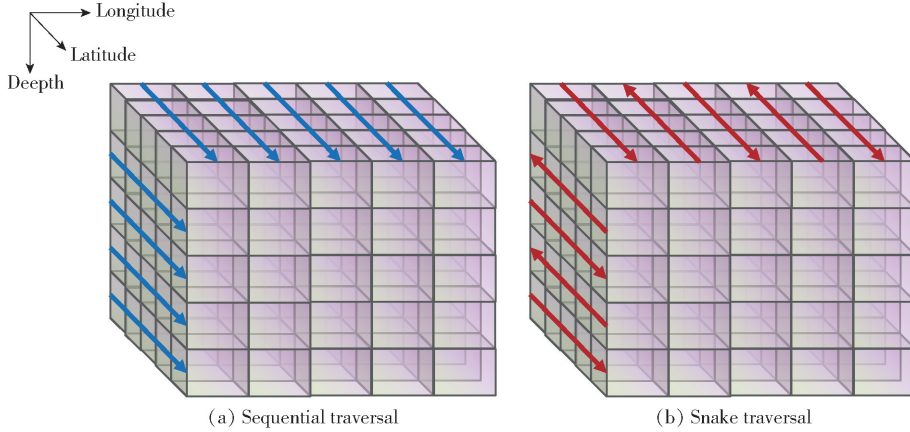


Fig. 1 Sequential traversal and snake traversal

1) Sequential traversal: expand in strict lexicographical order following “depth layer-longitude column-latitude row”. Within each layer, first fix depth and longitude, then sample along latitude in monotonically decreasing order, ensuring a linear mapping between the spatial index and the one-dimensional sequence.

2) Snake traversal: within the same depth layer, alternately reverse the latitude traversal direction to ensure spatial continuity between the end and start nodes of neighboring longitude columns. Between

ambiguity. All forecast velocity values are uniformly expressed in km/s, aligning with the original data units.

4) Scalability: the template supports dynamic replacement of placeholders, which is applicable to different practical forecasting requirements for 3D S-wave velocity.

3.2 Data engineering

Time series modeling possesses a mature theoretical framework and methodological advantages in dynamic data forecasting and trend analysis^[43]. For effectively capturing potential spatio-temporal correlation features within 3D S-wave velocity fields, we adopt a time series modeling approach to transform the 3D S-wave velocity field into a spatio-temporal sequence. Furthermore, we proposed two grid traversal strategies, the comparison of the two traversal methods is depicted in Fig. 1.

layers, achieve closed-loop traversal by mirroring the longitude order, thereby flattening the 3D grid into a single path which is closed spatially and continuous in measurement.

3.3 Model framework

We explored the performance of three model framework applications after implementing the prompting templates and data engineering strategies proposed in this paper within a 3D S-wave velocity prediction scenario: Transformer-based models, pure

prompting techniques, and prompt-based LLMs. The three model frameworks are illustrated in Fig. 2.

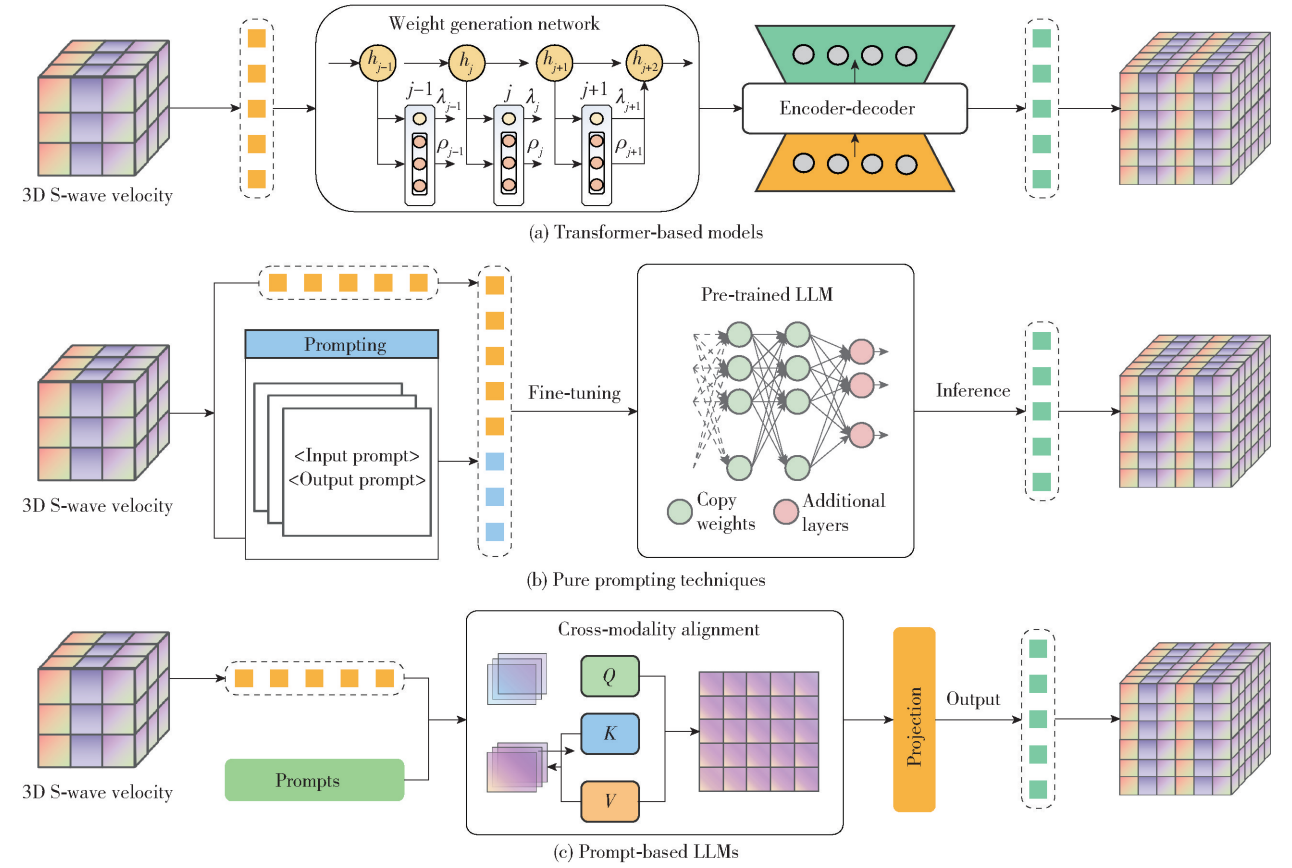


Fig. 2 Three model frameworks

The Transformer-based model framework, depicted in Fig. 2(a), consists of an attention mechanism and a feedforward neural network. A sequence-to-sequence architecture is typically used, in which the encoder processes the input sequence and the decoder generates the forecast sequence.

Our model framework is depicted in Fig. 2(b). First, acquire partially inverted 3D S-wave velocity data within the study area. Next, convert the inverted 3D shear velocity data into a 3D S-wave velocity prompt sequence dataset with spatiotemporal sequence characteristics using the prompting template and the 3D S-wave velocity field grid traversal strategy. Subsequently, fine-tune the language generation model using the prompt sequence dataset and a standard trainer. Upon completion of fine-tuning, save the final model weights, configuration file, and tokenizer. During the prediction phase, for regions within the study area where the 3D S-wave velocity field

is not covered, input prompts are constructed using the same grid traversal strategy and prompting template. These input prompts include the 3D spatial coordinates and shear velocities of known points in the region to be forecasted, as well as the overall trend ΔS and the average velocity change percentage $\Delta S\%$, which are calculated based on the sequence of known points to describe the general trend of 3D S-wave velocity changes in the region. After constructing the input prompt, it is fed into the fine-tuned language generation model. Based on the input context and the problem at hand, the model autoregressively generates textual descriptions of the velocity values for the subsequent Step_out points. Finally, specific numerical prediction sequences are obtained through decoding. The text output generated by the language model is parsed into a structured list of velocity values. Following the inverse mapping of the original grid traversal path, the one-dimensional

prediction sequence is reorganized back into a 3D spatial grid, ultimately forming the predicted structured 3D S-wave velocity data.

In addition, as depicted in Fig.2(c), prompt-based LLM frameworks incorporate text-based prompts as additional input and use cross-modal alignment to integrate data modalities and prompt modalities, thereby aiding the model in understanding the forecasting task.

4 Results

4.1 Experimental setup

4.1.1 Datasets

The paper utilizes 13 months (August 2017—August 2018) of continuous background noise waveform data recorded by 105 broadband seismometers from Sichuan, Chongqing, Gansu, Qinghai, and Shaanxi seismic networks. By extracting the fundamental Rayleigh surface wave dispersion curves within 5 – 40 s, a direct inversion method for surface wave dispersion data^[34] was employed to obtain a 3D S-wave velocity structure model extending to a depth of 120 km, spanning longitudes 98° – 110° and latitudes 39° – 27°, with a spatial resolution of 0.5° × 0.5°.

4.1.2 Baselines and evaluation

We evaluate six baseline models across three

categories: 1) Transformer-based models: the vanilla Transformer^[44], Informer^[45], Autoformer^[46]; 2) prompt-based LLMs: Time-LLM^[39], TimeCMA^[37]; 3) our prompting techniques: 3D-S-Wave.

The evaluation metrics are mean square error (MSE) and mean absolute error (MAE). However, in the third category of practice, due to the uncertainty inherent in the inference process, it cannot be guaranteed that every test instance will successfully extract numerical values from the generated output. To reflect this, we explicitly introduce the missing rate (MR) as an evaluation metric in our assessment. It is defined as $(n_{\text{test}} - n_{\text{decoded}}) / n_{\text{test}} \times 100\%$, where n_{test} is the total number of instances in the test set, and n_{decoded} is the number of generated instances that successfully decode the forecasted values. A lower missing rate indicates better performance.

The test batch size is set to 32 for all methods to guarantee fairness during testing. Each experiment is repeated at least three times with different seeds on GeForce RTX 4070 i9.

4.2 Main results

Table 2 shows the prediction performance of six models across three categories on the 3D S-wave velocity dataset. Overall, models fine-tuned using data engineering and prompting techniques demonstrate strong predictive performance and generalization capabilities in 3D S-wave velocity forecasting tasks.

Table 2 Performance comparisons

Model metric	Transformer		Informer		Autoformer		TimeCMA		Time-LLM		3D-S-Wave		
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MR/%
Sequential-shaped	0.010 8	0.096 0	0.001 7	0.033 5	0.103 2	0.249 0	0.003 0	0.032 6	0.000 3	0.011 2	0.000 5	0.013 1	0.061 6
Snake-shaped	0.013 1	0.106 9	0.002 1	0.038 5	0.363 9	0.449 6	0.002 9	0.032 0	0.000 4	0.010 8	0.000 4	0.012 3	0.123 2

4.2.1 Transformer-based models

The vanilla Transformer model consists of an attention mechanism and a feedforward neural network. It typically employs a sequence-to-sequence architecture, where an encoder processes the input sequence and a decoder generates the forecast

sequence. In forecasting tasks, the vanilla Transformer can capture long-range dependencies within sequences through its self-attention mechanism. Informer is a Transformer model specifically designed for long sequence forecasting. It incorporates probabilistic attention mechanisms and self-attention distillation techniques to enhance the model's efficiency and

accuracy when handling lengthy sequences. Informer demonstrates outstanding performance across numerous prediction tasks, particularly when handling extremely long sequences. Autoformer is a forecasting method that combines autoregressive models with the Transformer architecture. It specifically focuses on capturing long-term dependencies within sequences, introducing a novel self-attention mechanism called the “autocorrelation mechanism” to better handle trend

information.

We evaluated the average performance of the vanilla Transformer, Informer, and Autoformer across three random seed runs, using two data construction methods; sequential-shaped and snake-shaped, under three input and output step (Stp) configurations. Table 3 presents the performance of Transformer-based models forecasting methods on 3D S-wave velocity datasets.

Table 3 Results of Transformer-based models forecasting methods on 3D S-wave velocity

Model metric			Transformer		Informer		Autoformer	
Dataset	Traversal	Stp	MSE	MAE	MSE	MAE	MSE	MAE
3D S-Wave	Sequential-shaped	5	0.010 8	0.096 0	0.001 7	0.033 5	0.103 2	0.249 0
	Sequential-shaped	25	0.006 4	0.073 1	0.012 2	0.095 6	0.070 6	0.203 8
	Sequential-shaped	50	0.007 9	0.077 9	0.016 5	0.108 8	0.137 5	0.265 5
	Snake-shaped	5	0.013 1	0.106 9	0.002 1	0.038 5	0.363 9	0.449 6
	Snake-shaped	25	0.005 4	0.067 8	0.006 5	0.066 6	0.164 1	0.327 1
	Snake-shaped	50	0.001 2	0.029 0	0.011 5	0.085 4	0.024 3	0.112 4

In a nutshell, under the 3D S-wave velocity forecasting scenario, the three model groups ranked in descending order of performance were Transformer, Informer, and Autoformer. The vanilla Transformer model achieved the best forecasting performance for both 25-and 50-length 3D S-wave velocity sequences. The Informer model demonstrated better performance for the 5-length sequence. Comparing model forecasting performance under two data construction methods, the snake-shaped pattern yielded better forecasting results. This demonstrates that the construction method of the 3D S-wave velocity dataset influences model forecasting effectiveness. Specifically, the snake-shaped data construction method helps models to capture dependencies within the data, which improves forecasting performance.

4.2.2 Prompting techniques

Relevant research on computer vision (CV) and natural language processing (NLP) has demonstrated the effectiveness of pre-trained models that can be fine-tuned for various downstream tasks without the need for

costly training from scratch^[47–48]. Therefore, we fine-tuned and evaluated the performance of six popular language generation models on the 3D S-wave velocity dataset. The language models in the benchmark can be categorized into two types: one follows the encoder-decoder model framework, including efficiently learning an encoder that classifies token replacements accurately (Electra)^[49], bidirectional encoder representations from Transformers (BERT)^[47], and robustly optimized BERT pretraining approach (RoBERTa)^[50]; the other follows the conditional-generation mode framework, including bidirectional and auto-regressive Transformers (Bart)^[51], longformer encoder-decoder (LED)^[52], and text-to-text transfer Transformer (T5)^[53].

First, we converted the 3D S-wave velocity numerical data into natural language using the prompt templates in Table 1. Then, we allocated 20% of the raw datasets prompts_input and prompts_output as the test set, 80% of the remaining data as the train set, and another 20% as the val set. Subsequently, the train and validation set data were converted into standardized JSON format compatible with machine

learning frameworks for model fine-tuning. Finally, we evaluate the performance of the fine-tuned model on the test set. Table 4 presents the performance of prompting

techniques forecasting methods on 3D S-wave velocity datasets.

Table 4 Results of Prompting techniques forecasting methods on 3D S-wave velocity

Framework	Fine-tuning model	Pretrained model size	Metric				
			MSE	MAE	MR/%	Train/s	Inference/s
Encoder-decoder model	Electra	135.0 MB	n/a	n/a	1.0	78	15
	BERT	440.5 MB	n/a	n/a	1.0	276	19
	RoBERTa	501.2 MB	n/a	n/a	1.0	273	26
Conditional-generation model	Bart	557.8 MB	n/a	n/a	1.0	147	244
	LED	647.7 MB	n/a	n/a	1.0	158	89
			0.000 5	0.013 1	0.061 6	257	93
	T5	891.7 MB	0.000 4	0.012 3	0.123 2	257	108

Experimental results show that among the six models across both architectures, only the T5 model can perform correct inference under $T_{in} = T_{out} = 5$ conditions, while other models exhibit high missing rates. Analysis suggests two potential reasons. First, increasing the forecasting steps leads to higher missing rates. In challenging scenarios like multi-step forecasting, models must process and output more information, weakening their sequence comprehension ability, which eventually prevents them from generating semantically and syntactically coherent text. Second, the parameters of the model can affect its performance to a certain extent; the scale of parameters determines the model’s capacity, and low-parameter models are prone to issues such as output logic discontinuity.

While observing the inference performance of the T5 model, its capabilities are significantly better than the best-performing among Transformer-based forecasting methods under equivalent conditions. Which indicates that the multi-step prediction task for 3D S-wave velocity based on prompting techniques is a prospective research direction. Observing the performance of the T5 model under two data construction patterns, its performance in the snake-shaped (Line 9 in Table 4) shows an increase compared to the sequential-shaped (Line 8 in Table 4), which is consistent with the findings from Transformer-based forecasting methods.

Recently, reasoning models have demonstrated strong capabilities in handling complex sequence tasks. We utilized the qwen application programming interface (API) to invoke the instruct model qwen2.5-32b-128k-Instruct and the reasoning model qwen 3-32b-128k-Thinking. Due to the high cost of using the API’s fine-tuning services, this section focuses on evaluating the performance of the two un-fine-tuned models in the 3D S-wave velocity forecasting scenario. During evaluation, we used the input prompts from the entire 3D S-wave velocity dataset ($T_{in} = T_{out} = 25$) as queries and collected responses from the API. Table 5 presents the comparison of instruct model and reasoning model on 3D S-wave velocity datasets.

Table 5 Comparison of instruct model and reasoning model on 3D S-wave velocity

Model	Metric				
	MSE	MAE	MR/%	Time-total/ s	Time-per/ s
qwen2.5-32b-128k-Instruct	0.080	0.168	0.285	8 536 (2.371 h)	1.057
qwen3-32b-128k-Thinking	1.796	0.457	3.356	92 686 (25.746 h)	11.477

We observed an intriguing phenomenon; in the 3D S-wave velocity forecasting scenario, qwen2.5-32b-128k-Instruct performs significantly better overall than qwen3-32b-128k-Thinking. Due to the complex inference mechanisms of reasoning models, their

execution time is much higher than instruct models. However, this high time cost does not translate into high performance, which confirms that reasoning models are not universally applicable for solving all problems. This comparison also validates the viewpoint we discussed in the second reason mentioned earlier: model parameters do influence model performance to a certain extent. Furthermore, analysis of the experimental results, the model fine-tuned via our prompting technique can perform better in 3D S-wave velocity forecasting accuracy.

4.2.3 Prompt-based LLMs

Prompt-based LLMs introduce prompts with text as additional input to help the LLMs understand the forecasting task. To evaluate the performance of the prompting technique proposed in this paper in such models, we selected two representative models in the field of time series forecasting as baselines: Time-LLM^[39] and TimeCMA^[37]. We evaluated the average performance of the vanilla Transformer, Informer, and Autoformer across three random seed runs, using two data construction methods: sequential-shaped and snake-shaped, under three stp configurations. Table 6 presents the performance of prompt-based LLMs forecasting methods on 3D S-wave velocity datasets.

Table 6 Results of prompt-based LLMs forecasting methods on 3D S-wave velocity

Models metric			Time-LLM		TimeCMA	
Dataset	Traversal	Stp	MSE	MAE	MSE	MAE
3D S-Wave	Sequential-shaped	5	0.000 3	0.011 2	0.003 0	0.032 6
	Sequential-shaped	25	0.000 1	0.007 5	0.002 1	0.029 3
	Sequential-shaped	50	0.000 2	0.009 2	0.002 3	0.031 7
	Snake-shaped	5	0.000 4	0.010 8	0.002 9	0.032 0
	Snake-shaped	25	0.000 5	0.013 6	0.002 6	0.032 1
	Snake-shaped	50	0.000 3	0.011 4	0.002 5	0.032 9

Experimental results showed that in the 3D S-wave velocity forecasting task, prompt-based LLM performs better than Transformer-based models, while matching the performance of language generation models fine-tuned using prompting techniques.

5 Conclusions

In this paper, we propose a new task, 3D S-wave LLM. It utilizes language models to forecast the unmapped S-wave velocity within the study area, which is based on the 3D S-wave velocity data obtained through inversion. Experimental results demonstrate that models fine-tuned through data engineering and prompting techniques can achieve a good forecasting performance and generalization ability.

We believe that the findings of this study will provide forward-thinking concepts and fresh insights for researchers working in the field of complex geological structure studies. We also believe that the proposed 3D S-wave LLM task will open new directions for 3D S-wave velocity research in geoscience. For example, further enhancing the performance of LLM in 3D S-wave velocity forecasting scenarios, or developing more detailed geological feature studies based on the predicted 3D S-wave velocity structure data. All these ideas need to be considered in future research.

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