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Early Warning of Ground Settlement and Sensitivity Analysis for Super-large Earth Pressure Balance Shield

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Abstract

Ground surface settlement induced by large-diameter shield tunneling poses a significant risk to adjacent structures and the urban environment, making accurate prediction and interpretable analysis of its governing factors essential for construction safety management.

This study proposes a Simple Temporal Fusion Transformer (STFT) framework for dynamic, one-step-ahead prediction of shield tunneling-induced surface settlement, taking the Tanglangshan Tunnel section of the Shenshan Railway project as a case study. The framework integrates multi-source time-series inputs-including geological parameters, shield machine operational variables, and historical settlement observations-within a hierarchical deep learning architecture.

Comparative experiments against LSTM, GRU, and TCN baselines confirm that the proposed STFT model achieves the highest prediction accuracy, with an overall R^2 of 0.983, RMSE of 2.02 mm, and MAE of 0.92 mm across all test rings. Its advantage is most evident under geotechnically complex conditions, as exemplified by its performance on Ring 40 where it substantially outperforms all benchmarks. Furthermore, SHAP analysis reveals that the model's predictions are physically interpretable, identifying spatial position, geological conditions, and key tunneling parameters including total contact force, total thrust, and excavated soil volume as the most influential features.

The proposed framework provides a reliable and physically interpretable tool for real-time settlement prediction and risk-informed decision-making in urban shield tunneling construction.

Keywords

Shield tunneling, Ground surface settlement, Simple Temporal Fusion Transformer, Multi-source feature fusion, SHAP interpretability.

1 Introduction

Shield tunneling has become one of the most widely adopted construction methods in urban underground rail transit owing to its high safety, rapid advance rate, and limited surface disturbance. However, underground excavation inevitably redistributes earth pressure and disturbs the surrounding strata, inducing ground surface settlement that, if uncontrolled, can threaten overlying infrastructure and public safety. Therefore, accurate prediction and effective control of settlement induced by shield tunneling have become one of the core issues in tunnel construction.

Traditional prediction methods include empirical and semi-empirical approaches, analytical methods, and numerical simulations. However, empirical methods and analytical methods tend to focus on the final surface settlement, making it difficult to achieve dynamic prediction of the settlement process. While numerical simulations can model the process of settlement in detail, they are often computationally expensive, and thus ill-suited for meeting the real-time demands of settlement prediction on active construction sites.

With the rapid development of computer technology and artificial intelligence, machine learning has emerged as a powerful tool for predicting ground settlement during shield tunneling. Support vector machines (SVM) (Lu et al. 2023) and random forests (Kim et al. 2022), as efficient machine learning algorithms, have been widely applied and well recognised in settlement prediction during shield tunneling construction. More recently, emerging algorithms such as Extreme Gradient Boosting (XGB) (Su et al. 2022) and Light Gradient Boosting Machine (LGBM) (Zhu et al. 2025) have also demonstrated considerable potential in predicting ground settlement.

Although machine learning methods perform well in general regression tasks, they treat each sample independently and cannot model the temporal dependency inherent in settlement sequences. Moreover, most existing studies focus exclusively on predicting the maximum settlement at the tunnel axis, neglecting the dynamic evolution of the settlement trough over time. To address these limitations, this study proposes the Simple Temporal Fusion Transformer (STFT), a hierarchical dual-scale architecture that explicitly distinguishes intra-day excavation step dynamics from inter-day settlement evolution. By integrating geological descriptors, TBM tunneling parameters, and historical settlement observations within a unified Transformer encoder–decoder framework, the STFT enables accurate one-step-ahead prediction of the spatiotemporal settlement distribution during shield tunneling.

2 Database and settlement control standards

2.1 Data sources

The dataset was collected from the Tanglangshan Tunnel section of the Shenshan Railway, a 3,412 m tunnel excavated by a dual-mode EPB/TBM with a cutting diameter of 14.29 m and a lining outer diameter of 13.8 m. Overburden depth ranges from 17.2 m to 168 m. The tunnel traverses completely weathered, strongly weathered, and weakly weathered sandstone, transitioning into weakly weathered granite, with the initial 200 m characterised by a composite soft-over-hard stratum.

Settlement during shield tunneling is governed by tunnel geometry, geological conditions, and tunneling parameters (Suwansawat et al. 2006). Three static parameters are adopted: overburden depth (H_1), and thicknesses of strongly (H_2) and weakly (H_3) weathered sandstone at the tunnel face. Zhao et al.(2025) showed that shield thrust, cutterhead torque, and advance rate are key to surface settlement. Accordingly, 13 related tunneling parameters are selected as model inputs. The area within 5 m ahead and 20 m behind the face is most affected by shield-soil friction (Hong et al. 2025). Given this, the distance from the monitoring point to the face D and its change rate ΔD are included as predictive features. Ground surface settlement is measured at intervals of 5–10 rings and a monitoring frequency of once per 24 hours. The statistical ranges of all input parameters are summarised in Table 1.

2.2 Establishment of dataset

To enhance the reliability of the dataset, abnormal measurement points are removed through data cleaning, and by filling isolated missing values in tunneling parameters via nearest-neighbour interpolation. All features were standardised using Z-score normalization.

After preprocessing, seven rings (15, 22, 30, 40, 50, 60, 70) were selected. Using a sliding window approach, geological and tunneling parameters were aligned by ring and time to construct the time series (see Fig. 1). This process generated 801 multivariate time-series samples that integrate geological conditions, tunneling parameters, and spatial relationships.

Table 1. Range of data values.

Data	Max	Min	Ave	Data	Max	Min	Ave	Data	Max	Min	Ave
D (ring)	10	0	4	Sp (mm/min)	24.40	5.29	17.97	SV (m³)	607	311	378
L (m)	21.76	16.07	17.98	Pte (bar)	0.45	0.00	0.16	T (kN·m)	31639	1501	13892
H_1(m)	10.06	0.00	5.74	Pch (bar)	5.00	0.97	2.97	Tc (kN·m)	25717	5444	14866
H_2(m)	5.33	0.15	2.84	Pe (bar)	3.62	1.21	2.22	Vc (m³)	337.03	4.38	23.36
H_3(m)	13.65	1.47	5.23	Vs (m³)	84.20	18.80	31.61	Ptt (kN)	110034	67529	89558
Spc(rpm)	1.98	1.17	1.51	Vse (m³)	6.70	0.00	0.70	Fc (kN)	40526	18277	31334



Fig. 1 Illustration of Sliding Window.

3 Methodology

3.1 STFT model

The standard TFT (Lim et al., 2021) employs a generic GRN-VSN-LSTM-Self Attention pipeline for forecasting. This pipeline is designed for general-purpose forecasting where input structure and feature relevance are unknown. Shield tunneling settlement data, however, has a well-defined hierarchical structure: each day contains an ordered sequence of S intra-day excavation steps, and settlement evolves across inter-day trends. The STFT replaces the GRN-VSN-LSTM pipeline with a dual-scale Transformer that explicitly aligns each component with one of these two physical temporal scales (see Fig. 2).

Step Transformer. A shared Transformer Encoder is applied independently to each day's step-feature matrix $X_t \in R^{(S\times F)}$, mapping it to a single day-level embedding h_t^{step} via masked mean pooling over valid steps. Weight sharing across all historical and future days ensures that the resulting embeddings occupy a consistent latent subspace. The self-attention within this encoder captures inter-step dependencies, while pooling implicitly weights each step by contextual relevance.

Static covariate encoding. The four static covariates (H_1, H_2, H_3, L) are encoded by a two-layer FFN into a context vector $c_{stat} \in R^d$, which is then broadcast and concatenated to each day-level embedding. Unlike the conditional gating of GRN, this direct injection is appropriate because the geological and positional role of these variables is structurally fixed rather than instance-dependent.

Cross-attention decoder. Following the inter-day Causal Self-Attention Encoder, which produces the contextualised historical representation $H_{enc} \in R^{(T\times d_{model})}$, the future day embedding e_{t+1} — encoding both the planned intra-day excavation operations and the static context—serves as the query in a stack of cross-attention decoder layers:

$$z = \mathrm{softmax}(e_{t+1}H_{enc}^{T}/\sqrt{d_k})H_{enc} \quad (1)$$

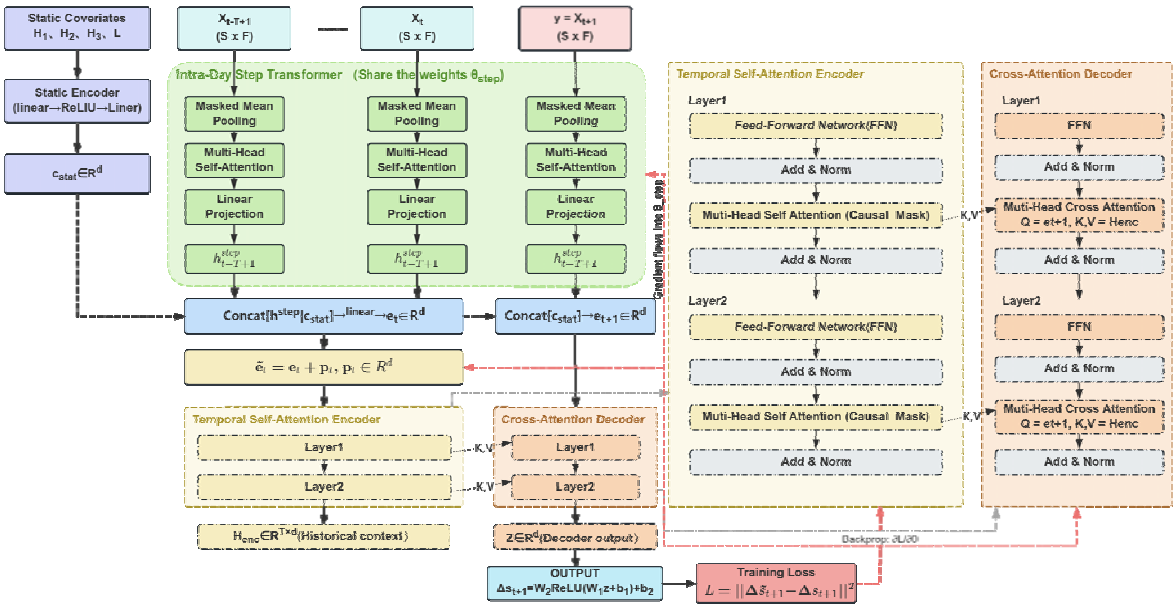


Fig. 2 Architecture of the Simple Temporal Fusion Transformer (STFT) Model.

3.2 SHAP interpretation and analysis

SHAP (SHapley Additive exPlanations) (Xue et al. 2024) is a model-agnostic interpretability method grounded in cooperative game theory that quantifies each feature's marginal contribution to individual predictions by computing Shapley values across all possible feature subsets. Unlike information gain or correlation-based methods, which are tied to specific model structures or assume linear relationships, SHAP provides theoretically consistent local and global feature attributions applicable to arbitrary nonlinear models. In this study, the GradientExplainer variant of SHAP is employed to identify the shield tunneling parameters that most significantly influence ground surface settlement predictions.

4 Model Training and Results Analysis

4.1 Experimental Setup and Evaluation Metrics

Since samples from the same ring share structural and temporal characteristics, random partitioning would introduce data leakage. A six-fold cross-validation strategy is therefore adopted: each fold designates one ring as the test set and aggregates the remaining rings as the training set. Ring 15 is excluded from serving as a test fold due to its insufficient sample count. Three regression metrics are used for evaluation: the coefficient of determination R^2, mean absolute error (MAE), and root mean square error (RMSE).

The STFT is implemented in PyTorch and trained with the AdamW optimiser using Huber loss. Three established sequence models, including LSTM, GRU, and TCN, are constructed as baselines under identical cross-validation conditions.

4.2 Model Training and Evaluation Results

Cross-validation results are summarised in Table 2 and Fig. 3. The STFT achieves the best overall performance across all folds, with an overall R^2 of 0.983, MAE of 0.92 mm, and RMSE of 2.02 mm. The advantage of STFT is most pronounced on Ring 40, where baseline models achieve R^2 values between 0.530 and 0.697, while STFT attains an R^2 of 0.892. This result highlights the powerful generalization ability of the STFT model. Across all rings, the MAE of the STFT remains below 1 mm on most folds, satisfying the precision threshold for engineering settlement early-warning applications. These results demonstrate that the STFT model can effectively capture the complex nonlinear relationship between excavation parameters, geological conditions, and settlement development, providing reliable prediction results for ground settlement during shield tunneling.

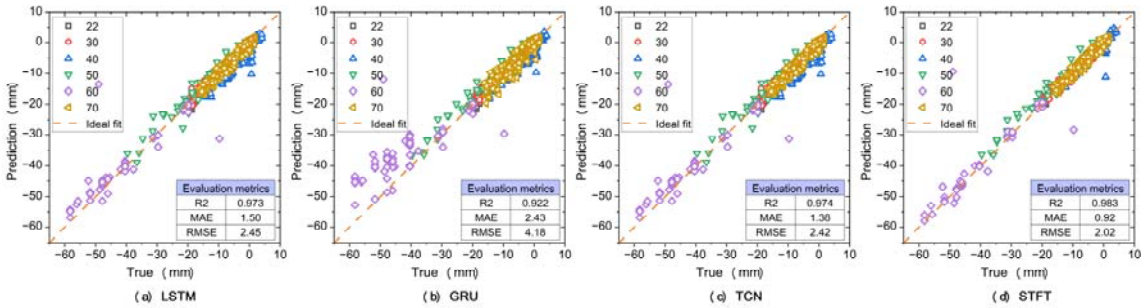


Fig. 3 Scatter plots of prediction results for each model.

Table 2. Summary of evaluation indicators for the six-fold cross-validation Experiment.

Ring	STFT			LSTM			GRU			TCN		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
22	1.11	0.97	0.876	1.11	0.86	0.875	1.20	0.96	0.854	1.21	0.99	0.854
30	0.97	0.73	0.965	1.25	0.99	0.941	1.16	0.89	0.950	1.49	1.16	0.917
40	1.64	0.93	0.892	3.43	2.94	0.530	2.99	2.50	0.642	2.75	2.21	0.697
50	2.52	1.93	0.945	2.53	1.92	0.945	2.63	2.06	0.940	2.83	2.03	0.931
60	3.42	0.83	0.943	3.84	1.99	0.933	8.22	6.10	0.691	3.91	1.60	0.930
70	1.08	0.87	0.946	1.23	0.96	0.930	1.74	1.32	0.858	1.21	0.97	0.932
overall	2.02	0.92	0.983	2.45	1.50	0.973	4.18	2.43	0.922	2.42	1.38	0.974

4.3 SHAP analysis

SHAP analysis is applied over the six cross-folds to quantify each feature's contribution to the settlement predictions. The aggregated results are presented in Fig. 4. Spatial position parameters, specifically the monitoring-point distance L and the excavation face distance D, are identified as the most important features. This finding aligns with the classical Gaussian settlement trough theory. Following them in importance are the geological parameters H_1, H_2 and H_3, reflecting the role of overburden depth and stratigraphy in controlling the propagation range.

Among the tunnel parameters, total contact force, total thrust force, and spoil volume exhibit the highest SHAP values across both the historical and future input branches, as clearly shown in Fig. 4(b) and 4(c). Total contact force and thrust directly quantify the mechanical load on the surrounding ground. Spoil volume captures the deviation between actual and theoretical soil removal. The high and consistent importance rankings of these parameters across all validation folds, corroborated by the results in Fig. 4(d), confirm that their impact is stable and not an artefact of local geological variations.

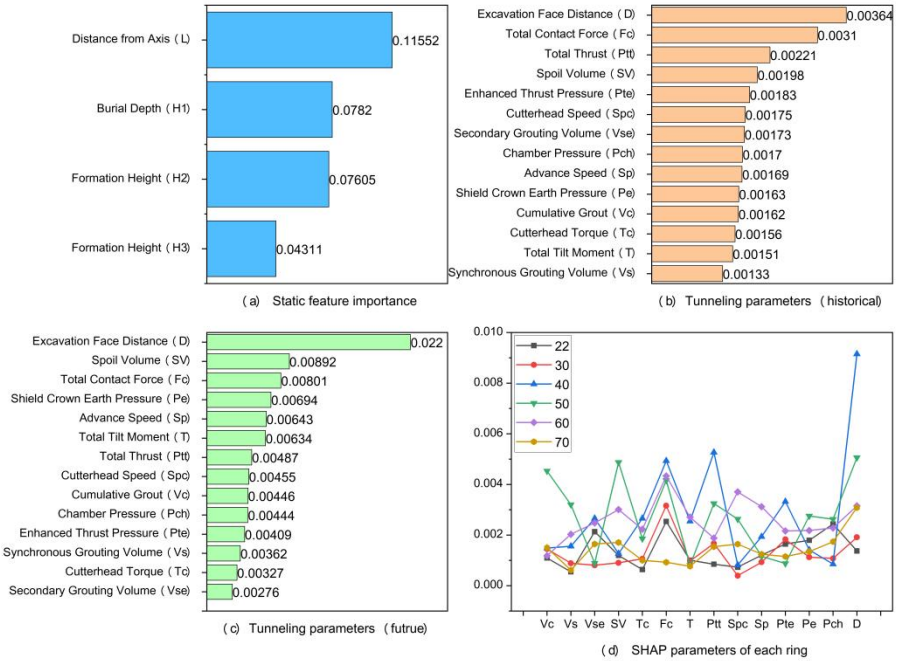


Fig. 4 SHAP analysis result.

5 Conclusions

This study proposes a Simple Temporal Fusion Transformer (STFT) framework for the dynamic prediction of ground surface settlement induced by large-diameter shield tunneling. By integrating multi-source time-series data within a hierarchical dual-scale architecture, the STFT explicitly models the intra-day excavation steps and inter-day settlement trends, effectively capturing the complex spatiotemporal dependencies in the data. Comparative experiments demonstrate that the STFT consistently outperforms established sequence models (LSTM, GRU, TCN), achieving superior prediction accuracy (overall R^2=0.983, RMSE=2.02 mm, MAE=0.92 mm) and exhibiting particularly strong generalization capability under geotechnically complex conditions.

SHAP analysis reveals that the model's predictions are physically grounded. Spatial parameters (L and D) are identified as the most influential factors, which aligns with the classical Gaussian settlement trough theory. Following these are geological parameters (H_1, H_2, H_3) and key tunneling parameters (Fc, Ptt, and SV), reflecting the controlling roles of overburden conditions and mechanical loads on settlement. The stability of these feature importance rankings across all validation folds confirms the robustness of the model's decision-making process.

The primary limitation of this work lies in its validation on a single project dataset. Future research should focus on applying and validating the STFT framework across multiple tunneling projects with diverse geological profiles and shield types. Furthermore, exploring transfer learning strategies to adapt the pre-trained model to new construction environments with limited data would significantly enhance its practical utility and scope of application.

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