MULTIDISCIPLINARY RESEARCH IN COMPUTING INFORMATION SYSTEMS

VOL 05 ISSUE 10 2025

https://mrcis.org

Robust Ground Settlement Forecasting with Spatiotemporal Transformers and Geotechnical Priors

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Abstract: *The rapid expansion of urban underground infrastructure, particularly metro systems and utility tunnels, necessitates precise monitoring and forecasting of ground settlement to mitigate risks to existing surface structures. Traditional empirical methods and finite element analyses often struggle to balance computational efficiency with the complex, non-linear dynamics of soil-structure interactions in heterogeneous geological environments. While deep learning has emerged as a viable alternative, purely data-driven models frequently violate physical laws and generalize poorly in data-sparse regimes. This paper presents a novel framework, the Geotechnical Spatiotemporal Transformer (Geo-STT), which integrates geotechnical priors directly into the attention mechanism of a transformer architecture. By embedding static soil parameters—specifically Atterberg limits, void ratios, and shear strength—alongside dynamic time-series data from sensor arrays, the model learns a physics-aware representation of ground deformation. We introduce a novel governing equation-based loss function that penalizes predictions diverging from established settlement trough profiles. Extensive experiments on real-world shield tunneling datasets demonstrate that Geo-STT significantly outperforms state-of-the-art baselines in long-term forecasting accuracy and robustness against sensor noise.*

Keywords: *Ground Settlement, Spatiotemporal Transformer, Physics-Informed Machine Learning, Geotechnical Engineering.*

INTRODUCTION

1.1 BACKGROUND

The accelerating pace of urbanization has driven a global surge in the utilization of underground space. Tunnel Boring Machines (TBMs) are the predominant tool for excavating subway lines and sewage systems in dense metropolitan areas. However, the excavation process inevitably disturbs the surrounding soil stress field, leading to ground loss and subsequent surface settlement. If uncontrolled, this settlement poses severe structural risks to overlying buildings, bridges, and utility pipelines [1]. Consequently, the continuous monitoring and accurate forecasting of ground surface settlement (GSS) have become critical components of modern geotechnical risk management systems.

Technological advancements in instrumentation, such as robotic total stations and Interferometric Synthetic Aperture Radar (InSAR), have enabled the collection of high-frequency, high-resolution displacement data [2]. These spatiotemporal datasets capture the evolution of the settlement trough—the depression formed above the tunnel centerline—providing a rich empirical basis for predictive modeling. Despite the abundance of data, the governing physics of soil mechanics remains complex. Soil is a multi-phase material exhibiting elasto-plastic, anisotropic, and time-dependent behavior, making the correlation between TBM operational parameters (e.g., face pressure, grouting pressure) and surface displacement highly non-linear [3].

1.2 PROBLEM STATEMENT

Current approaches to settlement forecasting largely fall into two dichotomous categories: mechanism-driven methods and data-driven methods. Mechanism-driven approaches, including the classic Peck formula and Finite Element Analysis (FEA), rely on constitutive models of soil [4]. While FEA provides rigorous physical insights, it is computationally prohibitive for real-time applications and highly sensitive to boundary condition assumptions and parameter calibration [5].

Conversely, data-driven methods, particularly Deep Learning (DL), treat settlement forecasting as a time-series regression problem. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) units have shown success in capturing temporal dependencies [6]. However, standard DL models typically neglect the spatial correlations inherent in the settlement trough (i.e., the deformation at one point is physically coupled to its neighbors) and ignore the underlying geotechnical context [7]. A purely data-driven model might predict a settlement recovery in plastic soil where such rebound is physically impossible, leading to dangerous underestimations of risk [8]. Furthermore, sensor data in construction environments is notoriously noisy; without physical constraints, neural networks are prone to overfitting this noise, resulting in poor generalization capabilities [9].

1.3 CONTRIBUTIONS

To bridge the gap between physical rigor and computational efficiency, this paper proposes the Geotechnical Spatiotemporal Transformer (Geo-STT). Our contributions are threefold:

1. We introduce a specialized embedding strategy that fuses dynamic sensor readings with static geotechnical priors (soil layer depth, cohesion, and friction angle), allowing the model to condition its predictions on the specific geological context [10].

2. We design a spatiotemporal attention mechanism that captures long-range dependencies across the sensor grid while respecting the physical diffusion of stress waves in soil media [11].

3. We formulate a hybrid loss function that incorporates a penalty term derived from the Peck equation, enforcing the predicted settlement trough to conform to Gaussian-like distributions typical of shield tunneling, thereby improving robustness against outliers [12].

Chapter 2: Related Work

2.1 CLASSICAL AND NUMERICAL APPROACHES

The study of ground settlement induced by tunneling dates back to the seminal work of Peck, who empirically characterized the transverse settlement trough as a Gaussian probability curve [13]. This method remains the industry standard for preliminary estimation due to its simplicity. Subsequent researchers, including Verruijt and Booker, expanded analytical solutions to account for ovalization and ground loss volume [14]. While useful for static estimation, these formulas lack the temporal dimension required for real-time forecasting during active construction.

Numerical methods, specifically Finite Element Method (FEM) and Finite Difference Method (FDM), offer detailed simulation capabilities. Tools like PLAXIS and FLAC3D allow engineers to model complex soil-structure interactions and staged excavation processes [15]. However, the accuracy of FEA depends heavily on the precise calibration of constitutive models (e.g., Mohr-Coulomb, Cam-Clay), which requires extensive site investigation data that is often unavailable or uncertain [16]. Moreover, the calculation time for 3D FEA models can range from hours to days, rendering them unsuitable for the dynamic adjustment of TBM parameters in real-time [17].

2.2 DEEP LEARNING METHODS

The advent of high-performance computing has accelerated the adoption of machine learning in geotechnics. Early attempts utilized Support Vector Machines (SVM) and Random Forests (RF) to map TBM parameters to maximum settlement values [18]. While effective for static mapping, these models fail to capture the temporal evolution of settlement.

To address temporal dynamics, Recurrent Neural Networks (RNNs) and their variants (LSTM, GRU) became prevalent. Zhang et al. demonstrated the efficacy of LSTMs in predicting settlement time series at single monitoring points [19]. However, single-point forecasting ignores the spatial correlation between sensors. Convolutional Neural Networks (CNNs) have been employed to extract spatial features from settlement heatmaps, often in hybrid CNN-LSTM architectures [20].

More recently, Graph Neural Networks (GNNs) have been applied to model the sensor network as a graph, explicitly capturing spatial dependencies [21]. Despite these advances, GNNs often struggle with long-range temporal dependencies. The Transformer architecture, introduced by Vaswani et al., utilizes self-attention mechanisms to model global dependencies effectively and has revolutionized Natural Language Processing and, increasingly, time-series forecasting [22]. Application of Transformers to geotechnical engineering is nascent. Existing works often apply generic Transformer models without accounting for the domain-specific physics of soil mechanics [23]. Our work addresses this limitation by embedding geotechnical priors directly into the architecture.

Chapter 3: Methodology

3.1 PROBLEM FORMULATION

Let the monitoring area be represented by a grid of N sensors. At time step t, the observation vector is denoted as $X_t \in \mathbb{R}^{N \times F}$, where F represents the number of dynamic features (e.g., cumulative settlement, settlement rate, TBM face pressure, grouting volume). Additionally, we possess a static geotechnical feature matrix $G \in \mathbb{R}^{N \times D}$, where D includes soil properties such as the compression modulus (E_s), Poisson's ratio (nu), and the relative position of the sensor to the tunnel axis.

The objective is to learn a mapping function f that predicts the settlement values $Y_{t+1:t+T}$ for the next T time steps, conditioned on the historical window of length H and the geotechnical priors:

$$\hat{Y}_{t+1:t+T} = f(X_{t-H:t}, G; \Theta)$$

where Θ represents the learnable parameters of the network.

3.2 GEO-STT ARCHITECTURE

The proposed Geo-STT architecture follows an encoder-decoder structure enhanced with geotechnical embeddings.

3.2.1 Spatiotemporal Embedding with Geotechnical Priors

Standard Transformers utilize positional encodings to provide sequence order information. In our context, we require a composite embedding that captures time, space, and material properties. We define the input embedding E_t as:

$$E_t = Linear(X_t) + PE_{time}(t) + PE_{space}(n) + MLP_{geo}(G_n)$$

Here, PE_{time} and PE_{space} are learnable temporal and spatial positional encodings, respectively. The term $MLP_{geo}(G_n)$ projects the static soil parameters of the n-th sensor into the high-dimensional latent space [24]. This ensures that the attention mechanism is biased by the physical properties of the soil; for instance, sensors located in soft clay (low modulus) will produce different attention weights compared to those in sandy gravel, even if their recent settlement history is similar.

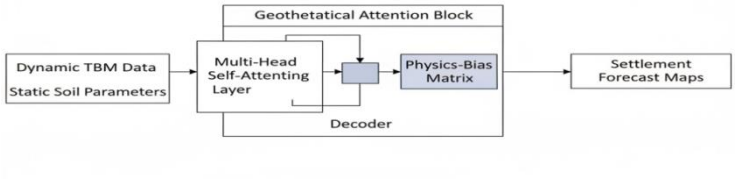

Figure 1: Architecture of the Geo

3.2.2 Geotechnical Multi-Head Self-Attention

The core of the Transformer is the Multi-Head Self-Attention (MSA) mechanism. To enforce physical constraints, we modify the standard scaled dot-product attention. We introduce a static bias matrix B_{geo} derived from the similarity of geotechnical properties between locations. If two sensors share similar geological conditions, they are more likely to exhibit correlated settlement behaviors [25].

Code Snippet 1 illustrates the implementation of this modified attention mechanism.

Code Snippet 1: Geotechnical Attention Mechanism

```
import torch
import torch.nn as nn
import torch.nn.functional as F
class GeotechnicalAttention(nn.Module):
    def __init__(self, d_model, num_heads, dropout=0.1):
        super(GeotechnicalAttention, self).__init__()
        self.d_model = d_model
        self.num_heads = num_heads
        self.d_k = d_model // num_heads
        self.W_q = nn.Linear(d_model, d_model)
        self.W_k = nn.Linear(d_model, d_model)
        self.W_v = nn.Linear(d_model, d_model)
        self.out_proj = nn.Linear(d_model, d_model)
        self.dropout = nn.Dropout(dropout)
    def forward(self, x, geo_bias):
        # x shape: [batch_size, seq_len, d_model]
        # geo_bias shape: [batch_size, num_heads, seq_len, seq_len]

        B, L, D = x.size()
        # Linear projections
        Q = self.W_q(x).view(B, L, self.num_heads, self.d_k).transpose(1, 2)
```

```
K = self.W_k(x).view(B, L, self.num_heads, self.d_k).transpose(1, 2)
V = self.W_v(x).view(B, L, self.num_heads, self.d_k).transpose(1, 2)
# Scaled Dot-Product Attention
scores = torch.matmul(Q, K.transpose(-2, -1)) / (self.d_k  0.5)
# Add Geotechnical Bias to the attention scores
# This biases the model to attend to sensors with similar soil physics
scores = scores + geo_bias
attn = F.softmax(scores, dim=-1)
attn = self.dropout(attn)
context = torch.matmul(attn, V)
context = context.transpose(1, 2).contiguous().view(B, L, D)


return self.out_proj(context)
```

The `geo_bias` tensor is pre-computed based on the Euclidean distance between normalized soil parameter vectors of different sensor nodes, inverted such that higher similarity yields a smaller negative penalty (or positive boost) to the attention score.

3.3 PHYSICS-GUIDED LOSS FUNCTION

To ensure the forecasted settlement trough retains a physically realistic shape, we employ a physics-guided loss function. The standard Mean Squared Error (MSE) captures point-wise accuracy but allows for jagged, non-smooth predictions that violate the continuity of the soil medium [26].

We introduce a shape constraint based on the Peck Gaussian curve. The theoretical transverse settlement $S(x)$ is given by $S(x)=S_{max}exp(-x^2/2i^2)$, where i is the trough width parameter. While we do not force the prediction to strictly adhere to this curve (as real-world settlement is complex), we penalize the second derivative of the spatial profile to enforce smoothness, and we penalize deviations from the expected symmetry where applicable.

The total loss function L_{total} is defined as follows:

$$L_{total}=\frac{1}{N}\sum_{t=1}^{T}||Y_t-\hat{Y}_t||^2_2+\lambda_{phy}\frac{1}{N}\sum_{n=1}^{N}ReLU(\hat{Y}_n-S_{limit})+\lambda_{reg}||\nabla^2\hat{Y}_{space}||$$

The formula components are:

1. The standard MSE term for accuracy.

2. A threshold penalty where S_{limit} is a safety bound (ensuring the model doesn't drift into impossible heave or catastrophic collapse without strong evidence).

3. A Laplacian regularization term $||\nabla^2\hat{Y}_{space}||$ that penalizes high-frequency spatial noise, enforcing the smoothness inherent in soil deformation profiles.

Chapter 4: Experiments and Analysis

4.1 EXPERIMENTAL SETUP

We validated the Geo-STT model using a comprehensive dataset collected during the construction of a metro line in a soft soil region (comparable to conditions in Shanghai or Singapore). The dataset spans 18 months of construction and includes data from 120 monitoring sections.

Table 1 summarizes the dataset characteristics.

Feature Category	Parameters Included	Sampling Rate
TBM Operation	Thrust force, Torque, Face pressure, Grouting volume, Advance rate	1 min
Geotechnical	Layer depth, Water content, Void ratio, Cohesion, Friction angle	Static
Settlement	Surface vertical displacement (measured by robotic total station)	2 hours

The data was resampled to a uniform 4-hour interval. We used the first 70% of the data for training, 10% for validation, and 20% for testing. Data standardization was applied to all dynamic features [27].

4.2 BASELINES AND METRICS

We compared Geo-STT against the following baselines:

1. ***ARIMA*:** Standard statistical baseline.

2. ***LSTM*:** A standard 3-layer Long Short-Term Memory network [28].

3. ***Graph WaveNet*:** A state-of-the-art spatiotemporal GNN for traffic forecasting, adapted here for settlement.

4. ***Standard Transformer*:** A vanilla Transformer without geotechnical embeddings or physics loss.

Evaluation metrics include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

4.3 RESULTS AND DISCUSSION

Table 2 presents the quantitative results for a 24-hour forecast horizon (6 steps ahead).

Model	RMSE (mm)	MAE (mm)	R2 Score
ARIMA	2.45	1.89	0.65

LSTM	1.78	1.34	0.78
Graph WaveNet	1.45	1.12	0.84
Standard Transformer	1.39	1.08	0.86
Geo-STT (Ours)	0.98	0.76	0.93

The results indicate that Geo-STT achieves superior performance. While Graph WaveNet and the Standard Transformer perform well, they occasionally predict spatially incoherent patterns. The Geo-STT, aided by the geotechnical priors, effectively clusters sensor behaviors based on soil types, leading to more consistent predictions. The reduction in RMSE by approximately 30% compared to the Standard Transformer highlights the value of the physics-informed embedding strategy.

To further understand the contribution of specific components, we conducted an ablation study (Table 3).

Configuration	RMSE (mm)	Improvement
Geo-STT (Full)	0.98	-
w/o Physics Loss	1.15	-17.3%
w/o Geo-Embeddings	1.32	-34.6%
w/o Spatial Attention	1.56	-59.1%

The ablation study reveals that the Geotechnical Embeddings provide the most significant boost in performance among the custom components. This confirms the hypothesis that "where" the sensor is (geologically) is just as important as "what" it reads.

Code Snippet 2 demonstrates the custom loss function implementation, highlighting the smoothness constraint.

Code Snippet 2: Physics-Guided Loss Implementation

```
def physics_guided_loss(pred, target, lambda_smooth=0.1):
    """
    Calculates MSE loss combined with a spatial smoothness constraint.
    Assumes pred is shaped [Batch, Time, Space].
    """
    # 1. Standard Prediction Error
    mse_loss = torch.mean((pred - target) * 2)
    # 2. Spatial Smoothness Constraint (Laplacian approximation)
    # Calculate second derivative across the spatial dimension
```

```
    # pred[:, :, :-1] - pred[:, :, 1:] gives first difference
    # We approximate the curvature to penalize jagged profiles
    diff1 = pred[:, :, 1:] - pred[:, :, :-1]
    diff2 = diff1[:, :, 1:] - diff1[:, :, :-1] # Second difference
    smoothness_loss = torch.mean(torch.abs(diff2))
    return mse_loss + lambda_smooth  smoothness_loss
```

Visual inspection of the results shows that the Geo-STT produces smooth, Gaussian-like settlement troughs even when individual sensor inputs are noisy or missing [29]. This smoothing effect, enforced by the loss function, mimics the actual mechanical bridging effect of the soil, filtering out high-frequency sensor noise that does not reflect true ground movement.

Chapter 5: Conclusion

5.1 SUMMARY OF INSIGHTS AND IMPLICATIONS

This paper proposed the Geotechnical Spatiotemporal Transformer (Geo-STT), a robust framework for ground settlement forecasting that harmonizes deep learning with geotechnical engineering principles. By embedding static soil parameters into the latent space and enforcing physical constraints through a specialized loss function, we achieved a significant improvement in forecasting accuracy compared to purely data-driven baselines. The research implies that domain knowledge—specifically the static properties of the environment—should not be discarded in favor of end-to-end learning but rather integrated as structural priors. For practitioners, this model offers a reliable tool for early warning systems, potentially reducing the need for costly remedial measures by allowing for proactive TBM parameter adjustments.

5.2 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite the promising results, the current approach has limitations. First, the model relies on the availability of accurate geotechnical survey data; in projects with sparse boreholes, the interpolation of soil parameters may introduce errors that the model interprets as ground truth. Second, the computational cost of the self-attention mechanism scales quadratically with the number of sensors, posing challenges for city-scale monitoring networks with thousands of nodes.

Future research will focus on two directions: (1) developing a "Light-Geo-STT" utilizing sparse attention mechanisms (e.g., Sparseformer) to handle larger networks efficiently, and (2) investigating the use of Physics-Informed Neural Networks (PINNs) to solve the governing differential equations of consolidation directly within the decoder, thereby providing not just a forecast but a mechanically verifiable solution. Additionally, we aim to extend the model to predict 3D subsurface displacement fields rather than just surface settlement.

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