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Sensitivity Analysis of Shield Tunnel-Induced Ground Settlement to Stratigraphic Spatial Variability: From Random Field Simulation to Causal Decoupling

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and code that support the findings of this study are available from the corresponding author upon reasonable request.

Abstract: Geological spatial variability introduces considerable uncertainty into shield-tunnelling-induced settlement prediction, particularly in weathered granite formations with irregular stratigraphic interfaces and pronounced stiffness contrasts. To progressively quantify, explain, and predict this uncertainty, an integrated framework combining random-field simulation, controlled numerical experiments, and symbolic regression was developed. First, a validated PLAXIS 3D model was combined with coupled Markov chains and conditional random fields to simultaneously represent stratigraphic uncertainty and the spatial variability of geotechnical parameters within individual strata. Eleven independent geological realizations produced maximum surface settlements, S_{max} , ranging from -11.25 to -14.63 mm, with a variation of 3.38 mm, confirming that geological spatial variability can cause practically significant settlement uncertainty. Second, to identify the dominant geological controls underlying settlement variability, 37 one-variable-at-a-time numerical experiments were performed by independently varying the deformation modulus (E), cohesion (c), friction angle (ϕ), and number of strata in the excavated stratum and the overburden. The sensitivity ranking was $E_{exc} > E_{upper} > c_{exc}$. Variations in E_{exc} , E_{upper} , and c_{exc} caused changes in S_{max} of 3.72, 2.57, and 1.09 mm, respectively, whereas the effects of friction angle and stratification were below 0.18 mm. These results demonstrate that deformation modulus is the dominant parameter and that the excavated stratum and overburden should be evaluated independently, as they mainly govern deformation generation and transmission, respectively. Finally, the identified dominant parameters were used to develop an explicit symbolic-regression equation. The model achieved $R^2 = 0.806$, $MAE = 0.265$ mm, and $RMSE = 0.454$ mm, while SHAP analysis reproduced the sensitivity ranking obtained from the controlled experiments. The proposed framework advances settlement analysis from uncertainty characterization and mechanism identification to rapid, physically interpretable prediction.

Keywords: shield tunnelling; ground surface settlement; spatial variability; random field; parameter sensitivity; symbolic regression

1 Introduction

Shield tunnelling has become the predominant construction method for urban metro systems owing to its high construction efficiency, minimal disturbance to surface activities, and adaptability to complex geological conditions. According to Mao et al. (2021), urban rail transit has expanded rapidly worldwide, with more than 58 cities in mainland China operating metro systems exceeding 12,000 km in total length, over 80% of which were constructed using shield tunnelling. Over the past two centuries, shield technology has evolved from manual excavation to highly mechanized earth pressure balance (EPB) and slurry pressure balance (SPB) systems, enabling greater excavation depths, larger diameters, and improved adaptability to complex ground conditions (Qiao et al., 2024; Feng et al., 2026). More recently, the increasing application of ultra-large-diameter shield tunnels (diameter ≥ 14 m) and stacked tunnel configurations has further expanded the engineering capability of shield tunnelling (Han et al., 2026; Hu et al., 2025). Nevertheless, shield excavation inevitably causes ground loss and soil disturbance, leading to surface settlement that may threaten adjacent buildings, underground utilities, and existing tunnels. Consequently, accurate prediction and effective control of tunnelling-induced settlement remain fundamental challenges in underground engineering.

Research on settlement prediction has evolved from empirical approaches to numerical simulation and, more recently, data-driven methods. Peck (1969) first proposed the Gaussian settlement trough for single tunnels, which was subsequently extended by Attewell and Woodman (1982), Attewell et al. (1986), Fang et al. (1994), Mair and Taylor (1997), and Loganathan and Poulos (1998), establishing the theoretical foundation for settlement prediction. However, empirical and analytical models are inherently limited in representing geological heterogeneity and the complex interaction between ground conditions and construction processes. With advances in computational geomechanics, three-dimensional finite element analysis has become a principal tool for investigating tunnelling-induced ground deformation. Representative studies include tunnel–structure interaction analysis (Mroueh and Shahrouh, 2003), three-dimensional TBM-EPB modelling (Lambrughi et al., 2012), twin-tunnel excavation in soft ground (Do et al., 2014), close-proximity undercrossing of

existing tunnels (Chen et al., 2018), equivalent-layer analytical prediction (Zhou et al., 2020), and ground response curve analysis considering boundary effects and gravity (Zhang et al., 2026). Meanwhile, field monitoring has provided essential datasets for model calibration and validation. Previous investigations have reported the spatiotemporal characteristics of ground settlement in silty soils (Chen et al., 2011), monitored settlement in saturated sandy cobble formations (Zhang et al., 2013), extended the Peck method to subsurface settlement prediction (Fang et al., 2014), and clarified the settlement mechanism of small-radius curved shield tunnels (Feng et al., 2022).

Recent advances in data-driven approaches have introduced a new paradigm for settlement prediction. Suwansawat and Einstein (2006) first applied artificial neural networks (ANNs) to predict the maximum surface settlement induced by earth pressure balance tunnelling. Subsequent studies compared the performance of various intelligent algorithms (Ahangari et al., 2015), demonstrated the feasibility of random forests (Zhou et al., 2017), and employed ANN-based machine learning for settlement prediction (Chen et al., 2019). Hybrid metaheuristic-machine learning and soft-computing approaches were further evaluated by Zhang et al. (2020, 2021), followed by the widespread adoption of XGBoost, support vector regression, and ensemble learning methods (Cao et al., 2021; Lu et al., 2023; Zhao et al., 2023; Zhou et al., 2023; Song et al., 2024). More recently, deep-learning techniques have further improved predictive performance. Liu C. et al. (2026) proposed a spatiotemporal surrogate modeling framework, Chen et al. (2025) integrated the Peck equation into GRNN and LSTM models, and Hu et al. (2026) developed a physics-informed neural network driven by both data and physical principles. Wang et al. (2026a) combined numerical simulations, empirical equations, and interpretable AutoML using a dataset of 2,000 samples, while Wang et al. (2026b) proposed an AutoML-based regressor-chain model for coupled multi-output prediction of twin shield tunnels. Interpretable machine-learning frameworks based on particle swarm optimization, extremely randomized trees, ensemble learning, and SHAP analysis have also been developed to identify the dominant controlling factors (Liu et al., 2025; Liu W.Y. et al., 2026). Despite their high predictive accuracy, these models typically rank static geological parameters together with dynamically controlled construction variables (e.g., advance rate, chamber pressure, and grouting volume) within a unified statistical framework. Because construction parameters fluctuate more frequently and over a wider range than the spatial variability of geological properties, the predicted settlement is often dominated by construction-induced statistical variations rather than the intrinsic mechanical characteristics of the ground. Consequently, machine-learning models are effective in capturing statistical correlations between construction parameters and settlement, but are generally unable to physically isolate the independent contribution of individual geological factors.

Previous studies have substantially advanced the methodology of settlement prediction; however, most implicitly assume that geological parameters can be represented by deterministic values and that their spatial variability has only a secondary influence on settlement. This assumption has increasingly been challenged. Owing to variations in depositional history, weathering, and tectonic processes, natural soils exhibit pronounced spatial variability and autocorrelation. Vanmarcke (1977) first introduced random field theory to characterize spatial variability using the mean, coefficient of variation, and scale of fluctuation. Phoon and Kulhawy (1999a, 1999b) systematically summarized the statistical characteristics of geotechnical parameters, while Griffiths and Fenton (2004) established the random finite element method, demonstrating the significant influence of spatial variability on bearing capacity and slope stability. In shield tunnelling, Miro et al. (2015) first applied three-dimensional random finite element analysis to investigate the effects of geological uncertainty on tunnel-induced ground movements. Huang et al. (2017) showed that the coefficient of variation and scale of fluctuation of soil stiffness govern the statistical characteristics of tunnel convergence and settlement. Luo et al. (2020) demonstrated the importance of spatial variability in excavation reliability assessment, whereas Cheng et al. (2020) introduced conditional random fields constrained by site investigation data to improve the reliability of settlement prediction. Hu et al. (2025) further reported that deterministic analyses tend to underestimate ground settlement for stacked shield tunnels. For shield tunnelling in karst regions, Qiao et al. (2024) integrated XGBoost, SHAP analysis, and Sobol sensitivity analysis to quantify the relative contributions of geological and construction parameters, showing that geological factors account for approximately 60% of settlement variability, compared

with 40% for construction parameters.

More importantly, existing random-field studies generally treat the tunnel stratum and the overlying strata as a single system when performing sensitivity analysis, overlooking a fundamental mechanical distinction. For tunnelling-induced surface settlement, the excavation stratum acts as the deformation source, where stress relief is directly induced by tunnel excavation, whereas the overburden serves primarily as the deformation transmission pathway. These two strata therefore play fundamentally different mechanical roles, and the influence of the same parameter should be evaluated separately according to its geological role. However, current global sensitivity analyses rank all geological parameters within a unified framework, failing to distinguish the respective contributions of source-zone and transmission-zone properties. This limitation is particularly critical in weathered granite formations widely distributed in South China. Such formations are characterized by (i) a pronounced stiffness contrast between the soft Quaternary overburden (deformation modulus of 3–30 MPa) and the underlying weathered granite (>58 MPa); (ii) highly undulating weathering interfaces, where multiple weathering grades may be encountered within a short tunnel section; and (iii) an incomplete stratigraphic sequence, with Quaternary deposits directly overlying the weathered granite without transitional sedimentary layers. These characteristics produce a much stronger contrast in stiffness and mechanical roles between the excavation stratum and the overburden than in homogeneous or soft-ground conditions, thereby introducing greater uncertainty into settlement prediction. Nevertheless, previous random-field studies have mainly focused on soft clay, sandy cobble, and loess formations (Huang et al., 2017; Cheng et al., 2020; Hu et al., 2025), while systematic investigations of weathered granite formations remain scarce.

To address these gaps, this study investigates shield tunnelling in the weathered granite formation of the Shenzhen Intercity Railway using PLAXIS 3D through a progressive framework comprising numerical modelling, random-field simulation, controlled parametric analysis, and symbolic regression (Fig. 1). First, a three-dimensional numerical model was established and validated against both field monitoring data and the Peck empirical method to ensure reliable simulation of settlement in the soft-over-hard geological setting (Section 2). Subsequently, a dual-uncertainty framework integrating Markov-chain stratigraphic simulation and conditional random-field parameter assignment was developed to simultaneously characterize discrete stratigraphic uncertainty and continuous spatial variability of soil properties (Section 3). This framework was employed to quantify the influence of inherent geological variability on settlement responses and to evaluate the settlement range potentially underestimated by deterministic analyses. Based on the random-field framework, a series of controlled parametric experiments was then conducted to decouple the effects of Young's modulus (E), cohesion (c), friction angle (ϕ), and stratification, with particular emphasis on distinguishing the respective contributions of the excavation stratum (source zone) and the overburden (transmission zone) (Section 4). Finally, the resulting dataset was expanded using Latin hypercube sampling, and symbolic regression was employed to derive an explicit three-parameter prediction equation that balances predictive accuracy and physical interpretability (Section 5). The derived model was further validated through SHAP-based global sensitivity analysis to examine its consistency with the conclusions obtained from the controlled experiments.

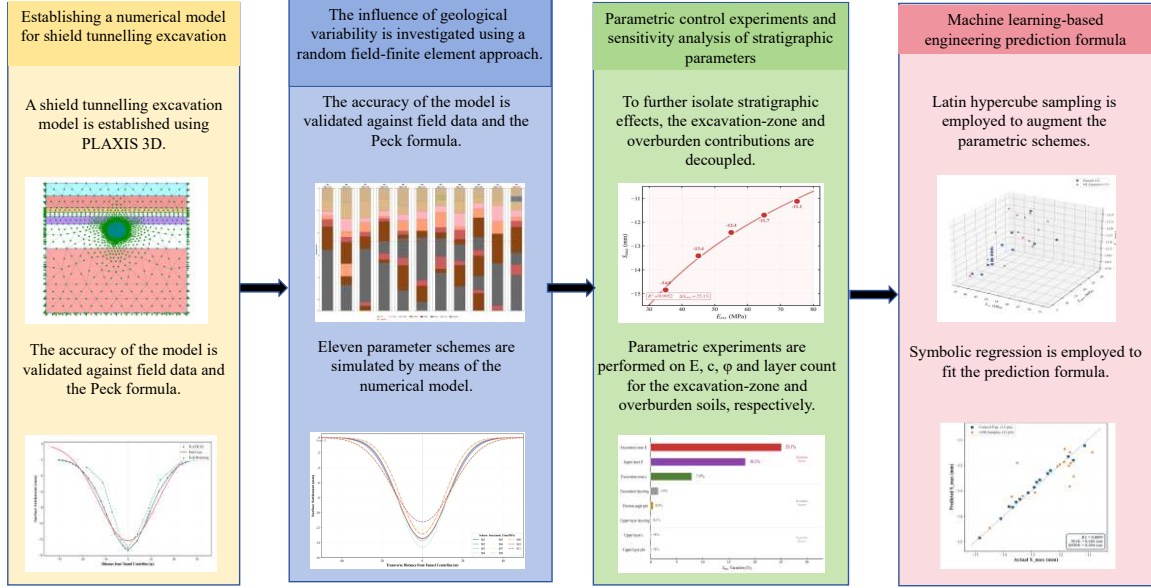


Fig. 1. Workflow of the proposed methodology.

2 Engineering background and PLAXIS 3D numerical model

2.1 Engineering background

The case study is based on the Shenzhen Airport–Dayawan Intercity Railway, specifically the section between Pingshan Station and Julong Station. The tunnel was constructed using an earth pressure balance (EPB) shield with an average burial depth of approximately 20 m and passes predominantly through the weathering profile of Yanshanian granite. Located on the southeastern margin of the South China Fold Belt, Shenzhen is underlain by extensive Yanshanian granite, which has developed a thick and well-defined weathering profile under long-term subtropical weathering. Statistical analysis of core logging and laboratory test data from 60 boreholes identified seven representative strata, including miscellaneous fill, sandy clay, completely weathered granite, soil-like highly weathered granite, blocky highly weathered granite, moderately weathered granite, and slightly weathered granite, arranged in descending order of weathering degree.

It should be noted that the geotechnical parameters listed in Table 1 are presented as ranges to reflect the inherent variability observed among different boreholes. For example, the deformation modulus of completely weathered granite varies from 30 to 61 MPa, while its cohesion ranges from 23.1 to 44.2 kPa. Such spatial variability of geological properties represents an intrinsic characteristic of the site and constitutes the primary focus of the random-field analysis presented in this study.

Table 1 Physical and mechanical properties of the major geological strata .

Merged Soil Type	E/kPa	c/kPa	$\varphi/^\circ$	$\gamma/(\text{kN}/\text{m}^3)$
Fill	8 ~ 12	19.9 ~ 26.1	21.6 ~ 25.0	17.00
Completely Weathered Granite (FWGr)	30 ~ 61	23.1 ~ 44.2	25.4 ~ 35.3	18.00
Earthy Strongly Weathered Granite (ESWGr)	59 ~ 94	25.3 ~ 40.1	29.2 ~ 37.2	18.00
Blocky Strongly Weathered Granite (BSWGr)	31 ~ 40	21.4 ~ 27.0	28.1 ~ 31.6	18.00

Merged Soil Type	E/kPa	c/kPa	$\varphi/^\circ$	$\gamma/(\text{kN/m}^3)$
Moderately Weathered Granite (MWGr)	38 ~ 64	21.4 ~ 31.5	27.5 ~ 35.9	18.00
Slightly Weathered Granite (SWGr)	45 ~ 68	22.6 ~ 35.9	26.7 ~ 33.3	18.00
Sandy Clay	19 ~ 44	20.1 ~ 30.3	25.1 ~ 28.0	17.50

2.2 PLAXIS 3D finite element model

2.2.1 Model configuration

A three-dimensional finite element model was established using PLAXIS 3D 2022. The model employed 10-noded tetrahedral elements, which provide a good balance between computational accuracy and efficiency for three-dimensional geotechnical analyses. The calculations were performed using the Pardiso multicore direct solver, which is well suited for medium-scale nonlinear problems. The engineering SI unit system was adopted throughout the analysis, with force in kN, length in m, and time in days.

The model dimensions were 60 m $\times$ 40 m $\times$ 55 m (X $\times$ Y $\times$ Z), which were verified through preliminary analyses to be sufficient for eliminating boundary effects. Normal displacement constraints were applied to the lateral boundaries while allowing vertical movement, the model base was fully fixed, and the ground surface was treated as a free boundary. The tunnel had a circular cross-section with an excavation radius of 4.0 m, corresponding to a single-track metro shield tunnel with an outer diameter of 8.0 m. The segmental lining was modelled using thick shell elements with a thickness of 0.35 m, representing C50 precast reinforced concrete segments. The tunnel model was 36 m long, comprising a 20 m excavation section and a 16 m trailing buffer zone. Along the longitudinal direction, the tunnel was divided into 18 slices with an interval of 2 m to simulate the staged excavation process.

All soil strata were modelled using the Mohr–Coulomb elastic–perfectly plastic constitutive model, which is widely adopted in geotechnical engineering because of its simplicity, clear physical interpretation, and suitability for shallow tunnel problems dominated by strength and deformation. The segmental lining, shield shell, and grouting material were simulated using linear elastic models. The lining and shield shell were defined as non-porous materials, whereas the grouting material was treated as a conventional porous medium. The material properties adopted for the lining, shield shell, and grouting material in the reference PLAXIS 3D model are summarized in Table 2.

Table 2 Material properties adopted in the reference PLAXIS 3D model.

Material	Constitutive Model	$\Gamma/(\text{kN/m}^3)$	E /kPa	ν	c /kPa	$\varphi/^\circ$
Concrete Lining	Linear Elastic	27.0	31,500,000	0.23	—	—
TBM Shield	Linear Elastic	247.0	200,000,000	0.20	—	—
Grout	Mohr-Coulomb	21.0	500,000	0.25	200	35

2.2.2 Simulation of the shield tunnelling process

The numerical simulation of the shield tunnelling process constitutes the core of the proposed model. The tunnelling procedure was implemented in PLAXIS 3D using the Tunnel Designer module, which automatically simulates the excavation cycle through a three-step workflow consisting of feature definition, construction sequencing, and state-driven activation. The tunnel boring machine (TBM) was represented by three functional zones: (1) the excavation zone, where soil elements at the

tunnel face were progressively deactivated to simulate cutterhead excavation; (2) the shield zone, where prescribed volume contraction was applied to the tunnel perimeter to reproduce ground convergence caused by shield passage (i.e., ground loss); and (3) the tail zone, where the segmental lining was installed and grouting pressure was applied to simulate synchronous backfill grouting and lining support. This simulation strategy reproduces the spatiotemporal characteristics of shield tunnelling by accounting for the influence of completed excavation, lining installation, and grouting behind the tunnel face on the advancing excavation front and the surrounding ground. Through the staged activation and deactivation of soil elements, structural components, and loading conditions, the model captures the longitudinal evolution of the ground stress field and the continuous development of surface settlement during tunnel excavation.

A total of 15 construction stages were defined to reproduce the entire tunnelling process, from the initial geostatic equilibrium to the completion of excavation. The construction sequence and corresponding physical processes are summarized in Table 3. The prescribed volume loss ratio was set to 0.4%, which was back-calculated from field settlement measurements in Shenzhen and adopted as the representative ground loss parameter. To simulate the progressive accumulation of ground loss during shield advancement, the volume contraction was applied incrementally to the tunnel boundary over five calculation steps.

Table 3 Definition of the shield tunnelling construction sequence.

Construction Phase	Core Operation
Phase1	K_0 in-situ stress equilibrium, activate face support pressure
Phase2	Excavate the 1st segment, contraction ratio $C = 0$, install lining and grouting at shield tail
Phase4	Contraction ratio $C \rightarrow 0.1\%$
Phase6	Contraction ratio $C \rightarrow 0.2\%$
Phase8	Contraction ratio $C \rightarrow 0.3\%$
Phase10	Contraction ratio $C \rightarrow 0.4\%$ (target value), change distribution to uniform
Phase12	Remove temporary lining formwork, activate ring-sealing grouting pressure
Phase13	Change grouting pressure to uniform normal distribution, $\sigma = 600$ kPa
Phase14	Replace shield tail void material with hardened grout (concrete), unload grouting pressure
Phase15	Remove all temporary loads and auxiliary structures

The coupling between construction stages and the longitudinal tunnel position was achieved using the Advance Step mechanism in the PLAXIS Tunnel Designer. Each advance step defines the construction sequence in the temporal domain, while the corresponding spatial position is automatically mapped through the predefined tunnel alignment, slice spacing, and construction sequence. The 36 m tunnel was divided into two functional sections according to the completion status of the construction cycle. The first section, extending 20 m, represents the completed excavation zone, where the full construction sequence (excavation, volume contraction, grouting, and lining installation) has been completed. The ground response within this section is fully developed and therefore serves as the reference state for evaluating the influence of previous excavation. The second section, extending 16 m, represents the active excavation zone, where continued shield advancement is simulated. This segmentation allows the completed section to provide a fully disturbed reference condition rather than the initial in-situ state, thereby enabling the incremental settlement induced by subsequent excavation stages to be quantified consistently. The construction loading parameters were determined according to the actual shield tunnelling operations of the Shenzhen Intercity Railway and are summarized in Table 4.

Table 4 Construction loading parameters.

Load Type	Load Parameter	Value	Unit	Application Location	Simulation Method
Face Support Pressure	Face Pressure	600	kPa	Tunnel face	Perpendicular acting pressure
Shield Shell External Pressure	Initial reference pressure	120	kPa	Surrounding ring surface of shield	Normal pressure
Shield Shell External Pressure	Pressure increment	15	kPa/m	Tunnel circumferential direction	Linearly increasing with depth

2.2.3 Mesh generation and solution control

The global mesh coarseness factor was set to 0.1, with Enhanced Mesh Refinement (EMR) applied around the tunnel. The refinement parameters were specified as EMRGlobalScale = 1.2 and EMRMinElementSize = 0.005 m. This strategy provided sufficient mesh density near the tunnel to capture the high-gradient displacement and stress fields induced by excavation, while coarser elements were used in the far field to limit the overall computational cost. Depending on the stratigraphic configuration, the final models contained approximately 8,000–12,000 10-noded tetrahedral elements. Each construction stage was solved independently using the Pardiso multicore direct solver. Iterative solvers were not adopted to prevent solver convergence from interfering with the parameter sensitivity analysis.

2.3. Model validation

2.3.1 Validation of the numerical model

To validate the numerical model, Borehole S02 was selected as the reference section. A deterministic geological model (without random fields) was established based on the measured stratigraphic profile and geotechnical parameters at this location. The predicted surface settlement trough was then compared with the Peck empirical solution and the corresponding field monitoring data. Borehole S02 comprises nine geological layers, with a tunnel crown depth of approximately 20 m. The numerical model is illustrated in Fig. 2, and the material properties adopted for each stratum were obtained from laboratory geotechnical tests, as summarized in Table 5.

Table 5 Geotechnical parameters of the S02 stratigraphic profile.

Material Name	Depth Range /m	E /kPa	c /kPa	φ /°	γ / (kN/m ³)	ν
Fill	0.00 ~ 6.71	9,952	19.9	25.0	17.00	0.30
Sandy Clay	6.71 ~ 13.68	19,423	21.2	25.1	17.50	0.28
Blocky Strongly Weathered Granite	13.68 ~ 19.44	31,487	21.4	28.1	18.00	0.27
Moderately Weathered Granite	19.44 ~ 21.98	47,351	24.9	35.9	18.00	0.27
Moderately	21.98 ~ 24.31	47,351	24.9	35.9	18.00	0.27

Material Name	Depth Range /m	E /kPa	c /kPa	φ /°	γ / (kN/m ³)	ν
Weathered Granite						
Slightly Weathered Granite	24.31 ~ 33.90	49,761	22.6	31.4	18.00	0.27
Completely Weathered Granite	33.90 ~ 39.59	59,151	23.1	33.0	18.00	0.27
Earthy Strongly Weathered Granite	39.59 ~ 43.32	84,962	29.5	33.1	18.00	0.27
Earthy Strongly Weathered Granite	43.32 ~ 50.00	93,962	29.5	33.1	18.00	0.27

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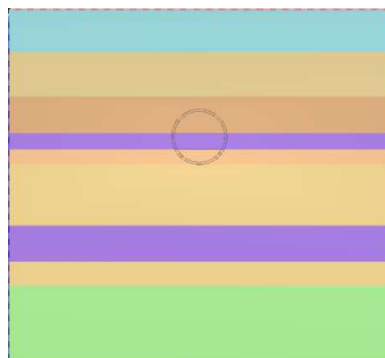


Fig. 2 Three-dimensional numerical model for the S02 validation section.

2.3.2 Validation results

Figure 3 presents the vertical displacement contours of the ground after completion of tunnelling. The calculated surface settlement exhibits an approximately Gaussian trough symmetric about the tunnel centreline. The maximum settlement occurs directly above the tunnel crown and gradually decreases towards both sides, whereas slight heave is observed beneath the tunnel invert because of unloading-induced rebound. The displacement contours are densely distributed above the crown and become progressively sparser towards the flanks, indicating that the deformation is concentrated mainly in the ground immediately overlying the tunnel. These characteristics are consistent with the theoretical settlement patterns described by the Peck equation and the Mindlin elastic solution. The smooth and continuous contour distribution, without anomalous distortion, further confirms the appropriateness of the adopted boundary conditions and material parameters.

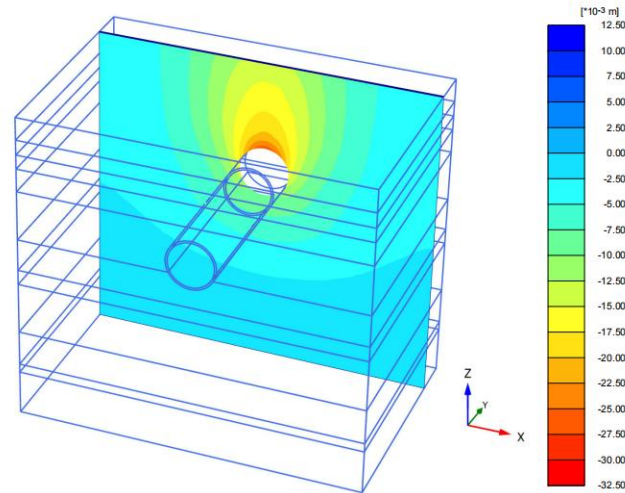


Fig. 3. Vertical displacement contours obtained from the numerical model.

Figure 4 compares the transverse surface settlement troughs obtained from the PLAXIS 3D model, the Peck empirical equation, and field monitoring. The maximum settlement predicted by the numerical model is approximately 31.5 mm, which agrees closely with the Peck prediction of approximately 31.5 mm and the monitored value of approximately 30 mm. The three settlement troughs also show good agreement in terms of overall shape and width. These results demonstrate that the model can reliably reproduce the surface settlement response induced by shield tunnelling in weathered granite formations in Shenzhen. The deterministic model based on Borehole S02 therefore provides a validated reference model for the subsequent random-field-based sensitivity analysis.

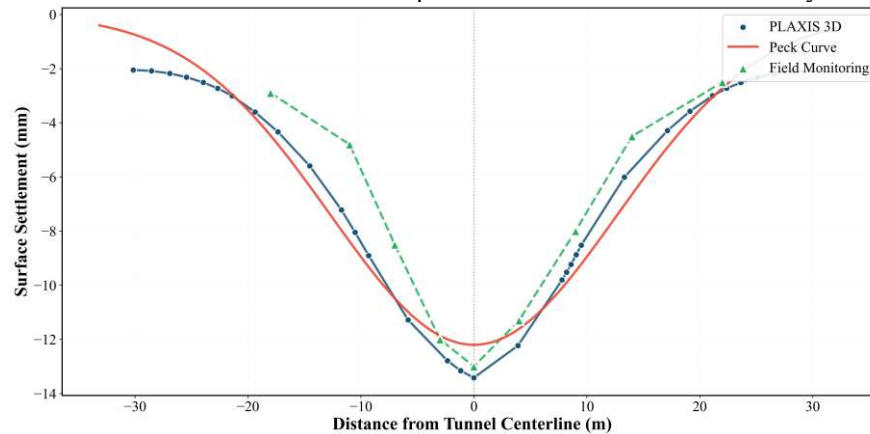


Fig. 4. Comparison of surface settlement troughs obtained from numerical simulation, the Peck equation, and field monitoring.

3 Influence of geological spatial variability on surface settlement: A coupled random field–finite element analysis

3.1 Variability of geological properties

Based on laboratory geotechnical test results from 60 boreholes along the Shenzhen Intercity Railway, the principal geotechnical properties of the weathered granite strata were statistically analysed. According to their spatial relationship with the tunnel, the geological units were classified into two categories: the overburden, comprising all strata above the tunnel crown, and the excavated stratum, representing the geological unit directly intersected by the tunnel excavation. The variability of material properties was then evaluated separately for these two categories. The statistical results are summarized in Table 6. The laboratory data indicate that the geotechnical properties of the weathered

granite profile exhibit pronounced spatial variability. The coefficients of variation range from 4.0% to 16.1%, with the deformation modulus and cohesion showing the greatest dispersion. This variability reflects the combined effects of differential weathering, tectonic disturbance, and groundwater activity during the development of the granite weathering profile, and therefore represents an intrinsic characteristic of the weathered granite formations along the Shenzhen Intercity Railway. These statistical results provide the basis for defining the marginal probability distributions of material properties in the subsequent random-field modelling.

Table 6 Statistical summary of laboratory geotechnical test results from the 60 boreholes.

Parameter	Stratum	Min	Max	Mean	Std. Dev.	CV /%
E /MPa	Overburden	26	42	33.5	4.9	14.6
E /MPa	Excavation	43	57	48.5	4.6	9.5
c /kPa	Overburden	22	28	25.4	2.0	7.9
c /kPa	Excavation	24	36	31.0	5.0	16.1
ϕ /°	Overburden	26	29	27.5	1.1	4.0
ϕ /°	Excavation	28	34	31.5	2.1	6.7

3.2 Dual-uncertainty coupling framework

Natural ground exhibits pronounced spatial variability and autocorrelation in its mechanical properties because of differences in depositional history and weathering processes. Borehole records from 60 locations along the Shenzhen Intercity Railway indicate that, even within the same granite weathering grade, the coefficient of variation of the deformation modulus E_0 can reach 30%–50%, while the elevations of interfaces between adjacent weathering zones may fluctuate by several metres to more than 10 m in the horizontal direction. The extent to which such inherent geological variability affects surface settlement prediction remains unclear. To quantify this effect, a dual-uncertainty coupling framework was developed, comprising two nested stochastic modules that respectively account for the discrete uncertainty of the stratigraphic sequence, namely which stratum occurs at a given location, and the continuous uncertainty of material properties within each stratum.

Module 1: Markov-chain simulation of stratigraphic sequences. Stratigraphic logs from the 60 boreholes were used to derive the vertical transition probability matrix among the seven geological units, ranging from miscellaneous fill to slightly weathered granite. New stratigraphic profiles were then generated using the coupled Markov chain (CMC) method (Elfeki and Dekking, 2001; Li et al., 2016). Unlike a conventional one-directional Markov chain, the CMC approach incorporates both upward and downward transition probabilities, thereby producing stratigraphic sequences that are more consistent with geological reality. In particular, it preserves the asymmetric trend of decreasing granite weathering degree with depth. A total of 11 independent stratigraphic realizations, denoted S01–S11, were generated to a depth of approximately 55 m, covering the complete weathering profile from surface fill to slightly weathered granite.

Module 2: Conditional random-field assignment of material properties. Within each stratigraphic framework generated by Module 1, the marginal distributions of E , c , and ϕ were defined using the means and coefficients of variation listed in Table 1 under the assumption of lognormal distributions. Conditional random fields were then generated using an exponential autocorrelation function. The vertical correlation length θ_v was specified as 2–5 m according to the correlation distances derived from wave-velocity measurements and laboratory tests conducted on weathered granite formations in Shenzhen (Phoon and Kulhawy, 1999a, 1999b). Through this procedure, spatially varying values of E , c , and ϕ were assigned to every finite element integration point within each geological unit, reproducing the natural continuous fluctuation of material properties around their mean values. All random-field realizations employed the same construction parameters as the reference model presented in Section 2, including grouting pressure, contraction ratio C , and excavation sequence. Consequently, any variation in S_{max} can be attributed solely to the spatial variability of geological properties rather than differences in construction conditions.

The principal advantage of the proposed framework is that it overcomes the limitations of

conventional deterministic analyses, in which the ground is typically assumed to be homogeneous or represented by only a few idealized stratigraphic profiles. The framework incorporates both the discrete uncertainty associated with stratigraphic occurrence and the continuous uncertainty associated with within-layer material properties into a unified stochastic modelling scheme. The CMC model first learns the vertical transition probabilities among weathering zones from the borehole records and generates geologically realistic stratigraphic profiles while preserving the asymmetric reduction in weathering degree with depth. Conditional random fields are then superimposed on each realization to assign spatially correlated E , c , and ϕ values to every weathering layer. This hierarchical stochastic strategy simultaneously captures interface fluctuation and within-layer parameter variability, enabling the coupled random field–finite element simulations to reproduce the dual heterogeneity of weathered granite formations more realistically. By accounting for both sources of uncertainty, the framework reduces the settlement prediction bias inherent in deterministic analyses and provides a statistically representative sample space for the subsequent controlled experiments and sensitivity analysis.

3.3 Material properties of the random-field realizations

Figure 7 presents the 11 independent stratigraphic realizations (S01–S11) generated using the coupled Markov chain, together with representative vertical geological profiles. All realizations cover the complete 55 m weathering profile from surface fill to slightly weathered granite, while exhibiting substantial differences in the depth, thickness, and spatial distribution of individual weathering zones. For example, the base of the completely weathered granite layer varies from approximately 18 to 24 m among the realizations, corresponding to a vertical fluctuation of about 6 m and reflecting the natural undulation of weathering interfaces.

To quantify the mechanical differences among the realizations, the equivalent properties of the overburden and excavated strata are summarized in Table 7. The overburden consists of 5–8 layers, with equivalent values of E , c , and ϕ ranging from 26.3–41.9 MPa, 22.2–28.3 kPa, and 26.1–29.1°, respectively. The excavated stratum comprises 1–3 layers, with corresponding equivalent E , c , and ϕ values of 43.5–56.7 MPa, 24.4–36.4 kPa, and 28.6–33.6°, respectively. These results demonstrate that the generated realizations encompass a wide range of stratigraphic configurations and mechanical properties, representing diverse combinations of overburden conditions and excavated strata. The resulting sample space provides a statistically representative basis for evaluating the influence of geological sequence variability on tunnel-induced surface settlement.

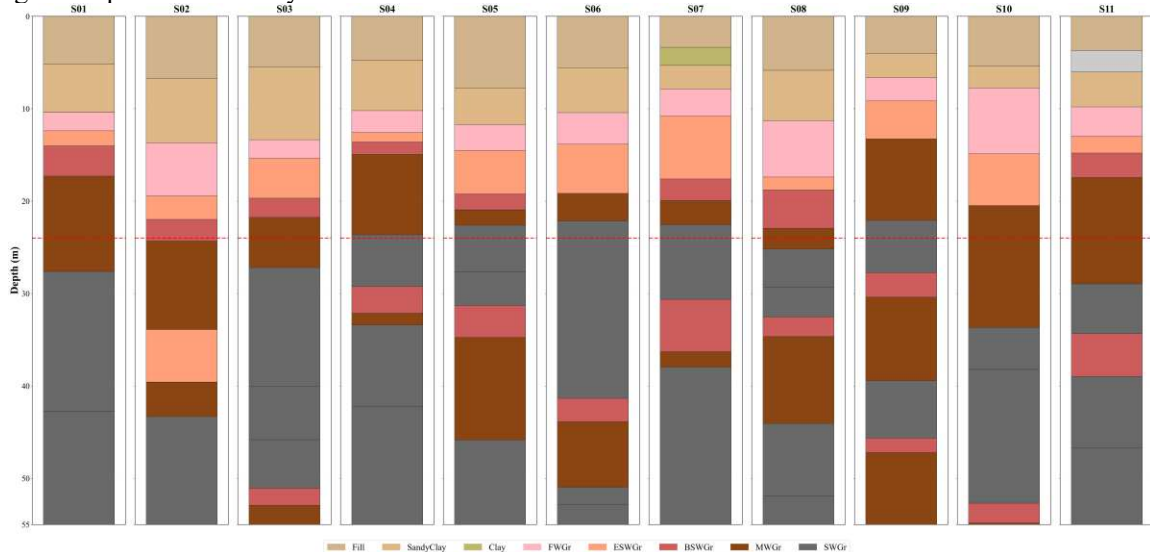


Fig. 7. Stratigraphic profiles of the 11 random-field realizations generated using the coupled Markov chain.

Table 7. Equivalent geotechnical properties of the 11 random-field realizations.

Scheme	N_{over}	E_{over} /MPa	c_{over} /kPa	ϕ_{over} /°	N_{exc}	E_{exc} /MPa	c_{exc} /kPa	ϕ_{exc} /°
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S01	5	31.1	28.3	26.5	1	44.8	36.4	28.8
S02	4	35.2	22.2	28.1	2	56.7	24.8	33.6
S03	5	26.3	26.5	27.0	2	47.3	36.4	32.7
S04	6	26.5	23.2	29.1	2	48.8	26.6	30.9
S05	6	32.2	26.5	28.8	2	43.5	27.4	32.1
S06	5	33.3	26.5	26.3	2	44.7	36.1	28.6
S07	6	40.4	26.9	26.6	1	47.5	34.7	28.0
S08	5	34.3	24.5	28.0	3	56.2	28.1	32.7
S09	5	37.3	26.0	27.8	3	43.5	31.1	31.0
S10	4	30.8	23.4	26.1	2	46.8	36.3	32.9
S11	5	41.9	24.6	27.8	2	53.4	24.4	32.5

3.4 Finite element analysis of the random-field realizations

The 11 stratigraphic realizations were individually incorporated into the PLAXIS 3D reference model. The tunnel geometry, construction sequence, and boundary conditions were identical to those adopted in Section 2, and each realization was analysed independently. The calculated settlement results are summarized in Table 8 and Fig. 6.

Table 8. Finite element results for the random-field realizations.

Scheme	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11
S_{max} (mm)	-13.42	-13.42	-13.78	-14.63	-12.97	-13.6	-12.25	-12.88	-12.78	-13.52	-11.25

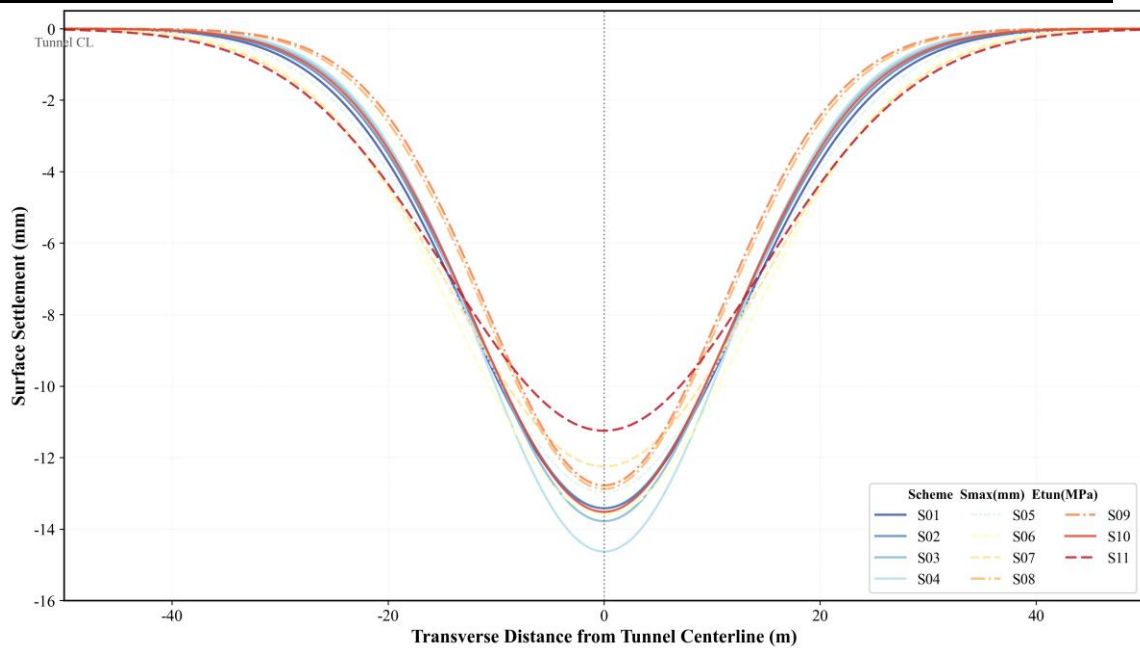


Fig. 6. Surface settlement troughs of the random-field realizations.

Figure 6 presents the transverse surface settlement troughs, while Table 8 summarizes the corresponding maximum surface settlement, S_{max} . All 11 realizations exhibit approximately symmetric Gaussian-shaped settlement troughs, but clear differences are observed in both settlement magnitude and trough width. S_{max} ranges from -11.25 mm for S11 to -14.63 mm for S04, giving a range of 3.38 mm and a relative variation of approximately 30%. Because all realizations used identical construction parameters, including grouting pressure, contraction ratio C , and excavation sequence, these differences can be attributed solely to variations in stratigraphic sequence and the spatial distribution

of material properties. The results therefore provide preliminary evidence that geological variability has a non-negligible influence on tunnel-induced surface settlement.

The 3.38 mm range is also meaningful from an engineering perspective. Daily monitoring records from the Pingshan–Julong section of the Shenzhen Intercity Railway show that, even when the principal construction variables, such as grouting pressure, advance rate, and excavated volume, remained relatively stable, the measured maximum surface settlement at different sections or times ranged from 9.50 to 17.67 mm, corresponding to a variation of 8.17 mm. In the present simulations, a settlement difference of 3.38 mm was produced solely by changing the stratigraphic sequence and spatial parameter distribution while keeping all construction conditions unchanged. This confirms that geological variability contributes substantially to settlement uncertainty.

More importantly, the differences among the 11 realizations result from the coupled effects of multiple geological factors. These include the number of overburden layers, ranging from 5 to 8; the equivalent overburden stiffness, ranging from 26.3 to 41.9 MPa; the number of excavated strata, ranging from 1 to 3; and the equivalent stiffness of the excavated strata, ranging from 43.5 to 56.7 MPa. As an integrated response of the entire ground system, S_{max} reflects the combined influence of these factors. The present set of 11 realizations alone is therefore insufficient to isolate the respective contributions of the excavated-stratum properties, overburden properties, and stratigraphic configuration. Systematic controlled experiments are consequently required to achieve quantitative causal decoupling of E , c , ϕ , and the effects of individual strata. This forms the core of the analysis presented in Section 4.

4 Controlled experiments and sensitivity analysis of geological parameters

The random-field simulations presented in Section 3 demonstrated that geological spatial variability has a significant influence on surface settlement, with S_{max} varying by up to 3.38 mm (approximately 30%) among the 11 realizations. However, these differences arise from the coupled effects of multiple factors, including the properties of the excavated stratum, the overburden, and the stratigraphic configuration, making it difficult to isolate the contribution of each factor.

To quantify the influence of individual geological parameters, a series of 37 controlled numerical experiments was conducted based on the reference model. A one-variable-at-a-time (OVAT) strategy was adopted, whereby only one parameter was varied while all others were held constant. This design enables causal relationships between geological parameters and surface settlement to be identified, rather than simple statistical correlations.

The experiments were organized into four groups. Sections 4.1 and 4.2 investigate the effects of the excavated-stratum properties and structural characteristics, whereas Sections 4.3 and 4.4 examine the influence of the overburden. Section 4.5 synthesizes the results through a sensitivity ranking and mechanistic interpretation. The parameter ranges were determined from the statistical analysis of the 60 boreholes and the recommended values in Table 1. Specifically, E_{exc} was varied from 35 to 75 MPa, E_{upper} from 5 to 30 MPa, and c_{exc} from 25 to 48 kPa. Throughout all experiments, the constraint $E_{upper} < E_{exc}$ was enforced to preserve the characteristic "soft-over-hard" geological profile of the weathered granite formation. This controlled experimental framework establishes the causal basis for the sensitivity analysis and the predictive relationships developed in the following sections.

4.1 Single-parameter analysis of the excavated stratum

The three principal mechanical properties of the excavated stratum—the deformation modulus E_{exc} , cohesion c_{exc} , and friction angle ϕ_{exc} —were varied individually to quantify their independent effects on the maximum surface settlement, S_{max} . The results are summarized in Table 9. Among the three parameters, E_{exc} exerts the strongest influence. As E_{exc} increases from 35 to 75 MPa, S_{max} decreases monotonically from −14.84 to −11.12 mm, corresponding to a total reduction of 3.72 mm, or approximately 0.93 mm for every 10 MPa increase. This nearly linear relationship reflects the greater resistance of a stiffer excavated stratum to unloading-induced deformation, thereby reducing

the settlement transmitted to the ground surface. c_{exc} has a more moderate effect. Increasing c_{exc} from 25 to 48 kPa decreases S_{max} from -13.80 to -12.71 mm, with a total reduction of 1.09 mm. The increase in cohesion enhances the shear strength and local stability of the excavated stratum, thereby suppressing plastic deformation around the tunnel. By comparison, ϕ_{exc} has little influence. As ϕ_{exc} increases from 26° to 32° , S_{max} varies only from -13.37 to -13.44 mm, with a total difference of 0.07 mm, indicating a negligible effect.

As shown in Fig. 7, the sensitivity of the excavated-stratum parameters follows the order $E_{exc} \gg c_{exc} > \phi_{exc}$. The settlement response induced by E_{exc} is approximately 3.4 times greater than that caused by c_{exc} and 53 times greater than that caused by ϕ_{exc} , identifying the deformation modulus as the dominant parameter controlling tunnel-induced settlement. From an engineering perspective, the 3.72 mm variation associated with E_{exc} is sufficiently large to influence the assessment of surface structures and the specification of construction control criteria. These results suggest that, for weathered granite formations, improving the characterization of the deformation modulus is considerably more important than refining cohesion or friction angle. For the Pingshan–Julong section of the Shenzhen Intercity Railway, the investigated range of E_{exc} (35–75 MPa) spans the transition from completely weathered to soil-like strongly weathered granite, indicating that the variability of E_{exc} contributes far more to settlement uncertainty than the variability of c_{exc} or ϕ_{exc} .

Table 9. Results of the single-parameter analysis for the excavated stratum.

E_{exc} /MPa	S_{max} /mm	Δ vs 45MPa /mm	c_{exc} /kPa	S_{max} /mm	Δ vs 30kPa /mm	ϕ_{exc} / $^\circ$	S_{max} /mm	Δ vs 30° /mm
35	-14.84	-1.43	25	-13.80	-0.39	26	-13.37	+0.04
45	-13.41	± 0.00	28	-13.55	-0.14	28	-13.38	+0.03
55	-12.43	+0.98	30	-13.41	± 0.00	30	-13.41	± 0.00
65	-11.70	+1.71	35	-13.12	+0.29	32	-13.44	-0.03
75	-11.12	+2.29	40	-12.91	+0.50	—	—	—
—	—	—	48	-12.71	+0.70	—	—	—

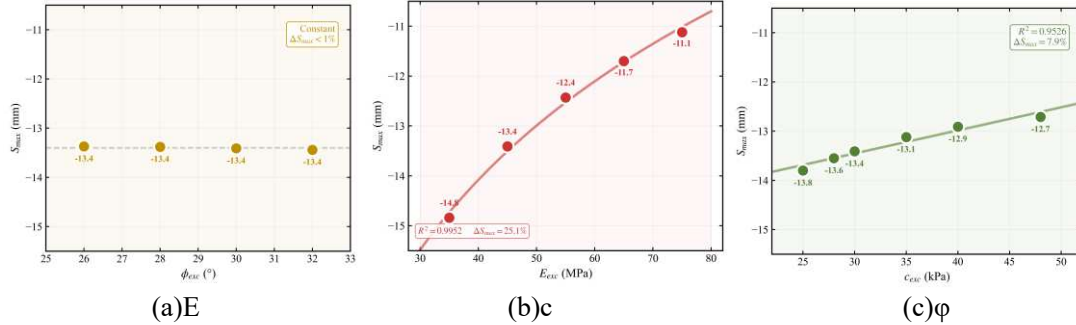


Fig. 7. Sensitivity of surface settlement to the mechanical properties of the excavated stratum.

4.2 Layering effect of the excavated stratum

This section investigates whether the vertical stiffness distribution within the excavated stratum affects the maximum surface settlement, S_{max} , when the equivalent deformation modulus is kept constant. Four layered configurations were designed for this purpose. The results in Table 10 show that the stiffness contrast between layers has a systematic but limited influence on settlement. In Scheme 1 (40/50 MPa, interlayer difference of ± 5 MPa), S_{max} differs from the reference value by 0.14 mm, whereas in Scheme 3 (35/55 MPa, interlayer difference of ± 10 MPa), the deviation increases slightly to 0.16 mm. Although the stiffness contrast doubles, the settlement deviation increases by only about 14%. Scheme 4 (40/45/50 MPa), which adopts a three-layer stiffness gradient, exhibits a deviation of only 0.02 mm despite having the same overall stiffness contrast as Scheme 2, indicating that the stiffness transition between layers also influences the settlement response. Larger stiffness discontinuities lead to stronger stress concentrations and displacement redistribution at layer interfaces, thereby increasing the error associated with the equivalent homogeneous assumption. Nevertheless, even the maximum deviation of 0.16 mm is considerably smaller than the settlement

variation caused by changes in E_{exc} in Section 4.1. These results indicate that, for engineering applications, the detailed vertical stiffness distribution within the excavated stratum has a negligible effect on surface settlement, whereas the equivalent deformation modulus is the governing parameter.

Table 10. Results of the layering-effect analysis for the excavated stratum.

Scheme	Layered Configuration	E /MPa	S_{max} /mm	Δ vs. Baseline /mm	Δ vs. Baseline /%
1	Single layer: E=45	45	-13.41	0.00	0.0
2	2 layers: E=40/50	45	-13.55	-0.14	1.0
3	2 layers: E=35/55	45	-13.57	-0.16	1.2
4	3 layers: E=40/45/50	45	-13.43	-0.02	0.1

4.3 Single-parameter analysis of the overburden

The three principal mechanical properties of the overburden—the deformation modulus E_{upper} , cohesion c_{upper} , and friction angle ϕ_{upper} —were varied individually to quantify their independent effects on the maximum surface settlement, S_{max} . The results are summarized in Table 11. Among the three parameters, E_{upper} has a pronounced influence. As E_{upper} increases from 5 to 30 MPa, S_{max} decreases monotonically from -14.09 to -11.52 mm, corresponding to a total reduction of 2.57 mm, or approximately 0.51 mm for every 5 MPa increase. This trend reflects the role of the overburden as the primary medium through which unloading-induced deformation is transmitted from the tunnel to the ground surface. A softer overburden undergoes larger compression, leading to greater surface settlement, whereas a stiffer overburden attenuates deformation during upward stress transmission. The 2.57 mm variation associated with E_{upper} is therefore of practical engineering significance. However, compared with the 3.72 mm settlement reduction caused by increasing E_{exc} from 35 to 75 MPa (Section 4.1), the influence of E_{upper} is approximately 69% as large, indicating that the stiffness of the excavated stratum remains the primary controlling factor, while the overburden stiffness is the second most important parameter. In contrast, c_{upper} and ϕ_{upper} have virtually no influence. As c_{upper} increases from 12 to 32 kPa and ϕ_{upper} from 20° to 32°, S_{max} remains constant at approximately -13.41 mm.

These results demonstrate a clear contrast in the sensitivity of the overburden parameters. E_{upper} is the only effective controlling parameter, whereas c_{upper} and ϕ_{upper} produce no measurable response. Compared with the weak influence of c_{exc} and ϕ_{exc} observed for the excavated stratum (Section 4.1), the complete insensitivity to c_{upper} and ϕ_{upper} further indicates that the contribution of strength parameters to surface settlement diminishes with increasing distance from the tunnel, while stiffness remains the dominant controlling factor.

Table 11. Results of the single-parameter analysis for the overburden.

E_{upper} /MPa	S_{max} /mm	c_{upper} /kPa	S_{max} /mm	ϕ_{upper} /°	S_{max} /mm
5	-14.09	12	-13.41	20	-13.41
8	-13.67	16	-13.41	22	-13.41
10	-13.41	20	-13.41	25	-13.41
15	-12.82	24	-13.41	27	-13.41
20	-12.33	28	-13.41	29	-13.41
30	-11.52	32	-13.41	32	-13.41

4.4 Layering effect of the overburden

The overburden serves as the medium through which tunnel-induced deformation is transmitted to the ground surface. Its vertical stiffness distribution may therefore influence the attenuation of deformation during upward propagation. To examine this effect, the equivalent deformation modulus of the overburden ($E = 10$ MPa) was kept constant while the number of layers (one to three) and the vertical stiffness distribution (soft-over-hard) were varied. A total of eight PLAXIS 3D simulations

were performed, and the results are summarized in Table 12.

Table 12. Results of the layering-effect analysis for the overburden.

Scheme	Layered Configuration	$S_{\max}$ /mm	Δ vs. Baseline /mm
4-1 (Baseline)	Single layer: $E=10$	-13.41	0.00
4-2	2 layers: $E=9/11$	-13.51	-0.10
4-3	2 layers: $E=7/13$	-13.53	-0.12
4-4	2 layers: $E=6/14$	-13.56	-0.15
4-5	2 layers: $E=5/15$	-13.59	-0.18
4-7	3 layers: C1	-13.53	-0.12
4-8	3 layers: C2	-13.53	-0.12
4-9	3 layers: C3	-13.54	-0.13

Consistent with the findings in Section 4.2, the layering complexity of the overburden has only a negligible effect on $S_{\max}$. Even in Scheme 4-5, which has the largest stiffness contrast (5 MPa in the upper layer and 15 MPa in the lower layer), the maximum settlement differs from the reference case by only 0.18 mm. For the three-layer configurations (Schemes 4-7 to 4-9), the deviations are all less than 1.0%. These results further confirm that, provided the equivalent deformation modulus remains unchanged, increasing the stratification complexity has little influence on surface settlement prediction. Considering the 12 layered configurations examined in Sections 4.2 and 4.4, the maximum deviation is only 0.18 mm, which is substantially smaller than typical field monitoring errors ($\pm 1-2$ mm) and settlement variations induced by fluctuations in construction parameters, such as grouting pressure and advance rate. This demonstrates that the equivalent homogeneous representation is sufficiently accurate for engineering prediction of tunnel-induced surface settlement.

4.5 Overall sensitivity ranking and physical interpretation

Based on the 37 controlled experiments presented in Sections 4.1–4.4, the independent contributions of the investigated parameters were quantitatively compared, and their sensitivity differences were interpreted from a mechanical perspective. Because the parameter ranges differ (E_{exc} : 35–75 MPa; E_{upper} : 5–30 MPa; c_{exc} : 25–48 kPa; ϕ_{exc} : 26–32°; c_{upper} : 12–32 kPa; and ϕ_{upper} : 20–32°), direct comparison of the parameter values is inappropriate. Therefore, the sensitivity of each parameter was evaluated using the corresponding variation in $S_{\max}$ over its prescribed range, together with a normalized sensitivity defined as the percentage contribution of each parameter to the total settlement variation. The results are summarized in Table 13.

Table 13. Quantitative comparison of the independent contributions of geological parameters.

Parameter	Variation Range	$S_{\max}$ Variation Amplitude /mm	Normalized Sensitivity
E_{exc}	35 → 75 MPa	3.72	25.0%
E_{upper}	5 → 30 MPa	2.57	18.0%
c_{exc}	25 → 48 kPa	1.09	8.0%
Overburden Layering	1 → 3 layers	0.18	< 1.0%
Excavation Layering	1 → 3 layers	0.16	< 1.0%
ϕ_{exc}	26° → 32°	0.07	< 0.5%
c_{upper}	12 → 32 kPa	0.00	0%
ϕ_{upper}	20° → 32°	0.00	0%

The sensitivity ranking can be explained by the mechanics of tunnel-induced settlement. Surface settlement can be regarded as the result of two sequential processes: (i) deformation generation caused by excavation-induced unloading around the tunnel, and (ii) upward transmission of this deformation through the overburden. E_{exc} participates in both processes. A higher E_{exc} reduces unloading-induced volumetric deformation around the tunnel and simultaneously increases the stiffness of the surrounding ground, thereby attenuating deformation during upward propagation. In contrast, E_{upper} affects only the second process by controlling the efficiency of deformation transmission; a stiffer overburden reduces the displacement reaching the ground surface. c_{exc} has a secondary influence

because higher cohesion restricts the development of the plastic zone around the excavation, although its contribution remains limited under the predominantly elastic response of shallow tunnels. The influence of ϕ_{exc} is negligible because the stress state around the tunnel remains well below the shear failure condition. For the overburden, c_{upper} and ϕ_{upper} have no measurable effect, as strength parameters do not participate in the elastic transmission of deformation.

These results highlight the fundamentally different mechanical roles of the excavated stratum and the overburden. The excavated stratum acts as the deformation source, where unloading and stress redistribution occur directly, whereas the overburden functions as the deformation transmission pathway, conveying tunnel-induced deformation to the ground surface. Consequently, both stiffness and, to a lesser extent, strength parameters influence the excavated stratum, while only stiffness governs the response of the overburden. This source–pathway distinction provides the physical basis for the controlled experimental design adopted in this study and explains why conventional global sensitivity analyses, which rank parameters solely according to statistical variability, may obscure these fundamentally different mechanical roles.

5 Engineering prediction formula based on symbolic regression

5.1 Data augmentation and parameter-space coverage

The 37 controlled experiments in Section 4 provided the initial dataset for establishing a parameter-to-settlement prediction model. However, because each experiment varied only one parameter while holding the others at their reference values, the data were concentrated along the parameter-space axes intersecting at the reference case. Regions between these axes, such as combinations of high E_{exc} and low E_{upper} , remained poorly sampled. In real weathered granite formations, multiple parameters vary simultaneously, and their combinations are more complex than those represented by one-variable-at-a-time experiments. To improve parameter-space coverage, 15 additional cases were generated using Latin hypercube sampling (LHS) within the three-dimensional space defined by $E_{exc} = 35\text{--}75$ MPa, $E_{upper} = 5\text{--}30$ MPa, and $c_{exc} = 25\text{--}48$ kPa. As shown in Fig. 8, these cases uniformly fill the previously unsampled regions. The friction angle and layering variables were excluded because Section 4 demonstrated that their effects were negligible: variations in ϕ changed S_{max} by no more than 0.07 mm, while layered configurations deviated from the reference case by no more than 0.18 mm. This reduced the model input dimension from eight variables to three key parameters, corresponding to a dimensionality reduction of more than 60%.

The 15 supplementary cases were recalculated using PLAXIS 3D and combined with 15 selected cases from Section 4 after excluding the ϕ - and layering-related experiments, yielding a complete dataset of 30 cases. Table 14 summarizes the statistical characteristics of the three input parameters. The final dataset combines dense sampling along the principal parameter axes with uniform coverage of the three-dimensional parameter space. The former captures the independent effects of each parameter, while the latter improves the surrogate model's ability to generalize to coupled parameter combinations.

Table 14. Statistical characteristics of the complete 30-case dataset.

Parameter	Min	Max	Mean	Std. Dev.	CV /%
E_{exc} /MPa	35	75	48.2	9.2	19.1
E_{upper} /MPa	5	30	15.0	8.0	53.0
c_{exc} /kPa	25	48	33.4	6.3	18.9
S_{max} /mm	−14.84	−10.85	−12.62	1.03	8.2

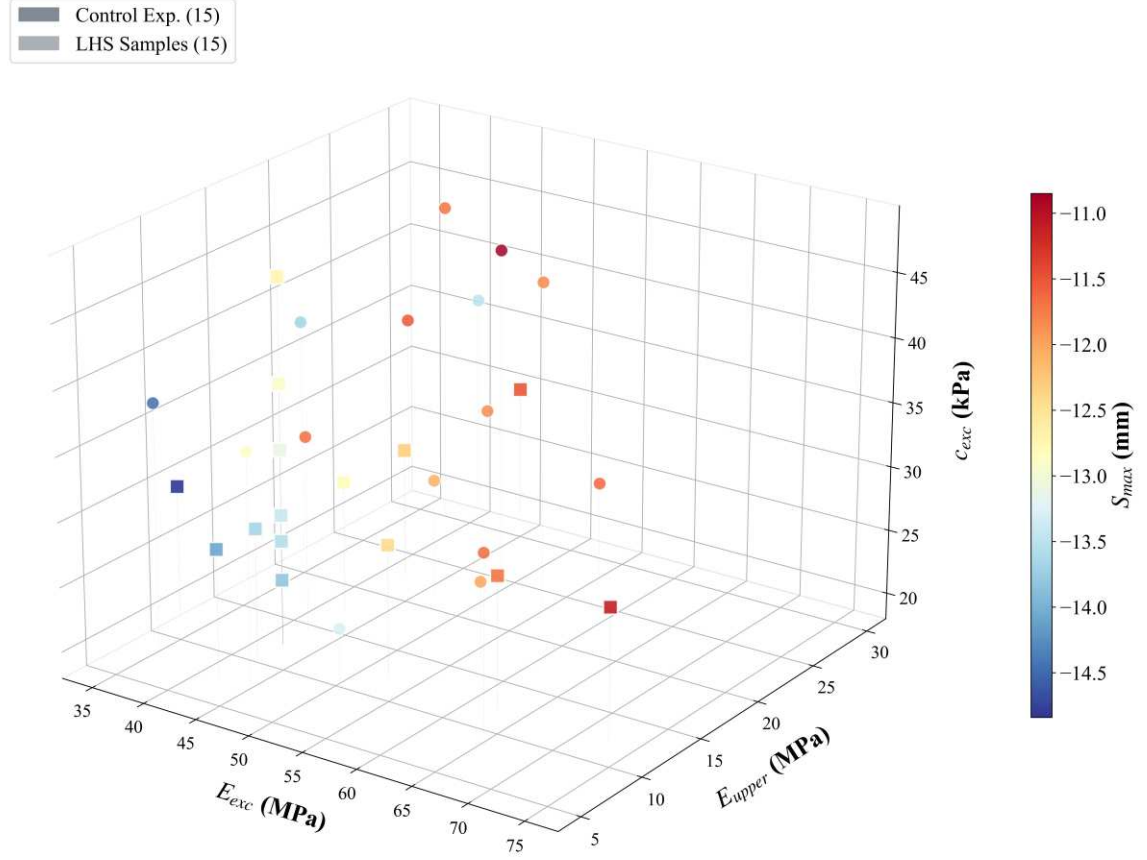


Fig. 8. Coverage of the sample parameter space.

5.2 Physics-informed symbolic regression model

Using the 30-sample training dataset, symbolic regression was employed to establish a predictive relationship between S_{max} and the three key parameters E_{exc} , E_{upper} , and c_{exc} . Symbolic regression is a genetic-programming-based method that simultaneously identifies the mathematical structure and coefficients of a model from a search space comprising arithmetic operators, elementary transformations, and interaction terms. Unlike conventional regression, it does not require a predefined functional form. This flexibility is important because, although elasticity suggests an inverse relationship between settlement and stiffness, the soft-over-hard stratigraphy, the distinct mechanical roles of the excavated stratum and overburden, and possible parameter interactions may cause the actual response surface to deviate from a simple logarithmic model. Subject to the parameter ranges and monotonic trends identified in Section 4, a library of 27 candidate features was constructed, including logarithmic, square-root, reciprocal, quadratic, and exponential transformations of the three variables, together with interaction terms such as $\ln(E_{exc}) \cdot \ln(E_{upper})$ and $E_{exc} \cdot E_{upper}$. All combinations containing two to six terms were evaluated, and the optimal expression was selected using the adjusted coefficient of determination (adjusted R^2) to balance fitting accuracy and model complexity. Because ϕ and the layering variables were shown to have negligible effects in Section 4, only E_{exc} , E_{upper} , and c_{exc} were retained as inputs. The resulting symbolic regression formula is:

$$S_{max} = -36.096 + 1.282 \ln(E_{exc}) \ln(c) - 1.421 \ln(E_{upper}) \ln(c) + 1.819 \ln(E_{exc}) \sqrt{E_{upper}} - 0.0102 E_{exc} E_{upper} \quad (1)$$

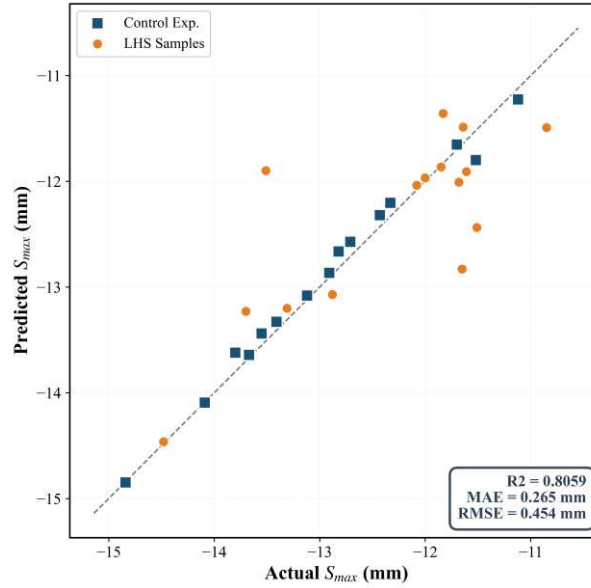


Fig. 9. Performance of the symbolic regression model.

The model achieved $R^2 = 0.806$, $MAE = 0.265$ mm, and $RMSE = 0.454$ mm. Figure 9 compares the calculated and predicted S_{max} values for the 30 samples. The points are distributed approximately symmetrically about the 45° line, indicating no systematic overprediction or underprediction. The larger residuals are mainly associated with the LHS cases, whereas nearly all 15 OVAT samples fall within ± 0.3 mm. This difference arises from the sampling strategies: the OVAT cases lie along orthogonal axes in parameter space, where the response is locally smooth, while the LHS cases cover the full three-dimensional domain, including geologically unbalanced combinations such as a soft overburden overlying a stiff excavated stratum. These regions exhibit stronger nonlinear and interaction effects, producing larger residuals but also providing the information required to identify interaction terms. Future studies could expand the dataset to hundreds or thousands of simulations and employ more flexible machine-learning models to capture higher-order nonlinear interactions and further assess the generalizability of the proposed framework.

5.3 Parameter sensitivity analysis

Although the symbolic regression model provides an explicit analytical relationship between the input variables and S_{max} , the relative importance of each parameter requires further quantification. To this end, SHAP (SHapley Additive exPlanations) was applied to the symbolic regression model (Eq. (1)) to perform a global sensitivity analysis. Based on Shapley values from cooperative game theory, SHAP quantifies the marginal contribution of each input feature by considering all possible feature combinations. This approach provides a consistent and additive measure of feature importance while accounting for both individual and interaction effects.

Figure 10 presents the SHAP values calculated from the 30 training samples. The mean absolute SHAP values are 0.609 for E_{exc} , 0.530 for E_{upper} , and 0.203 for c_{exc} . The resulting importance ranking is $E_{exc} \gg E_{upper} > c_{exc}$, which is fully consistent with the controlled experiments in Section 4 and the structure of the symbolic regression model. Specifically, the contribution of E_{exc} is approximately three times that of c_{exc} , while E_{upper} contributes about 2.6 times more than c_{exc} , confirming that stiffness parameters—particularly the deformation modulus of the excavated stratum—dominate settlement prediction. This finding agrees well with the controlled experiments, in which variations in the deformation modulus produced settlement changes of several millimetres, whereas changes in cohesion resulted in only sub-millimetre responses. The SHAP analysis therefore provides independent statistical evidence that E_{exc} is the most influential parameter governing tunnel-induced surface settlement and offers a quantitative basis for prioritizing site investigation and parameter characterization in engineering practice.

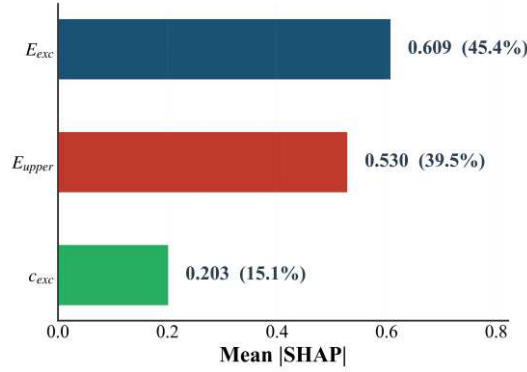


Fig. 10. SHAP-based interpretation of feature importance.

6 Conclusions

This study investigated shield-tunnelling-induced surface settlement in the weathered granite formations of the Shenzhen Intercity Railway using borehole data from 60 sites and three-dimensional PLAXIS simulations. By integrating stochastic geological modelling, controlled numerical experiments, mechanistic interpretation, and symbolic regression, a systematic framework was established to quantify, explain, and predict the effects of stratigraphic spatial variability on surface settlement. The main conclusions are as follows.

(1) The random-field simulations established that geological spatial variability is an important source of uncertainty in shield-tunnelling-induced settlement. A key methodological innovation of this study is the development of a dual-uncertainty modelling framework that integrates coupled Markov chains with conditional random fields. The coupled Markov chains reproduce the spatial variability of stratigraphic sequences, while the conditional random fields describe the within-stratum spatial variability of geotechnical parameters. This framework therefore enables stratigraphic uncertainty and material-property uncertainty to be represented simultaneously rather than treated independently or replaced by deterministic mean values. Across 11 independent geological realizations, the maximum surface settlement, S_{max} , varied from -11.25 to -14.63 mm, giving a total variation of 3.38 mm. Because the tunnel geometry and construction parameters were kept unchanged, this difference can be primarily attributed to geological spatial variability and uncertainty. The results demonstrate that spatial variations in both stratum distribution and geotechnical properties can produce practically significant differences in predicted settlement, and that deterministic analyses based only on mean stratigraphic conditions and average material parameters may underestimate settlement uncertainty.

(2) To further clarify the influence of geological strata on shield-tunnelling-induced settlement, 37 one-variable-at-a-time numerical experiments were conducted to separately investigate the effects of deformation modulus, cohesion, friction angle, and stratification in the excavated stratum and the overburden. The sensitivity ranking was $E_{exc} > E_{upper} > c_{exc}$. Increasing E_{exc} by 40 MPa, E_{upper} by 25 MPa, and c_{exc} by 23 kPa changed S_{max} by 3.72 mm, 2.57 mm, and 1.09 mm, respectively, whereas the settlement variations caused by friction angle and stratification were both less than 0.18 mm. The effects of the remaining factors were comparatively minor. These results demonstrate that the deformation modulus is the dominant geological parameter governing settlement and that the excavated stratum and the overburden should be evaluated as separate geological units because they play fundamentally different roles in tunnel-induced ground deformation. The excavated stratum primarily controls the development of deformation during excavation, whereas the overburden governs the transmission of deformation to the ground surface through its stiffness. This distinction provides a more physically meaningful framework for geological parameter sensitivity analysis than treating the entire soil profile as a single equivalent geological unit.

(3) Within the excavated stratum, larger interlayer stiffness contrasts or steeper stiffness gradients tend to produce slightly greater surface settlement. However, this effect is considerably smaller than that of the equivalent deformation modulus. Therefore, detailed stratification should be considered

when high prediction accuracy is required, whereas an equivalent homogeneous representation is generally sufficient for routine engineering analysis provided that representative equivalent stiffness values are properly determined.

(4) An explicit and interpretable settlement prediction equation was established using symbolic regression, providing a transparent alternative to conventional black-box machine learning models. Latin hypercube sampling was employed to efficiently expand the parameter space, while the three dominant variables identified from the controlled numerical experiments (E_{exc} , E_{upper} , and c_{exc}) were selected as model inputs to ensure that the regression was grounded in physically meaningful parameters. The resulting equation achieved satisfactory predictive performance, with $R^2 = 0.806$, $MAE = 0.265$ mm, and $RMSE = 0.454$ mm. Furthermore, SHAP analysis ranked the parameter importance as E_{exc} (0.609) > E_{upper} (0.530) > c_{exc} (0.203), in close agreement with the sensitivity ranking obtained from the controlled experiments. This consistency demonstrates that the symbolic regression model captures the dominant physical controls on tunnel-induced settlement rather than merely fitting statistical relationships. The proposed equation provides a rapid and interpretable tool for preliminary settlement prediction, geological parameter screening, and engineering decision-making, while the integrated workflow combining controlled numerical experiments, symbolic regression, and explainable artificial intelligence offers a practical framework for developing physics-informed predictive models in geotechnical engineering.

Overall, the study connects geological spatial variability, settlement mechanisms, and practical prediction within a unified framework. The proposed symbolic regression formula provides a rapid and interpretable tool for preliminary settlement estimation, construction risk screening, and investigation planning under comparable geological and tunnelling conditions..

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