

Probabilistic geotechnical calculations on dikes

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Acknowledgment

This master's dissertation on "Probabilistic geotechnical calculations on dikes" represents the final milestone of my Master's programme in Civil Engineering at Ghent University. It not only concludes two years of academic effort, but also brings my time as a student to an end: a period during which I learned a lot, both academically and personally. I owe the completion of this thesis to several people who have supported me along the way. Their contributions have been invaluable and I would like to take this opportunity to express my gratitude.

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Notes from the author

This master's dissertation is part of an exam. Any comments formulated by the assessment committee during the oral presentation of the master's dissertation are not included in this text.

Abstract

Traditional geotechnical design practices in Belgium predominantly rely on deterministic or semi-probabilistic methods, which often result in conservative estimates that do not fully account for the inherent variability of soil behaviour. This thesis investigates the practical implementation of fully probabilistic geotechnical calculations, with a focus on predicting dike settlements. The study centres on the Groot Schoor Bornem dike reinforcement project, which is part of the broader Flemish Sigmaplan for flood protection, and integrates extensive field and laboratory data with state-of-the-art probabilistic methods.

A comprehensive methodology is developed, combining PLAXIS 2D finite element modelling with Python-based automation and probabilistic calculations. Key soil parameters are identified through a sensitivity analysis and modelled as stochastic variables based on distributions derived from CPT(u) data and laboratory tests. Latin hypercube sampling is used to generate representative input sets, while a response surface model is trained on a limited number of PLAXIS simulations to enable an efficient large-scale probabilistic analysis. Bayesian updating, using the Markov chain Monte Carlo method, refines the probabilistic predictions by incorporating real-world settlement measurements from the monitoring campaign.

The results show that probabilistic methods not only better capture the variability and uncertainty in settlement behaviour compared to deterministic approaches, but also offer valuable insights into parameter sensitivity and model robustness. This study demonstrates the feasibility and benefits of incorporating probabilistic techniques into routine geotechnical design, paving the way for more reliable and cost-effective infrastructure development as well as data-driven decision-making.

Keywords: probabilistic settlement calculations, numerical modelling, soil parameter distributions, response surface method, Bayesian updating

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Abstract—Traditional geotechnical design practices in Belgium predominantly rely on deterministic or semi-probabilistic methods, which often result in conservative estimates that do not fully account for the inherent variability of soil behaviour. This thesis investigates the practical implementation of fully probabilistic geotechnical calculations, with a focus on predicting dike settlements. The study centres on the Groot Schoor Bornem dike reinforcement project, which is part of the broader Flemish Sigmaplan for flood protection, and integrates extensive field and laboratory data with state-of-the-art probabilistic methods. A comprehensive methodology is developed, combining PLAXIS 2D finite element modelling with Python-based automation and probabilistic calculations. Key soil parameters are identified through a sensitivity analysis and modelled as stochastic variables based on distributions derived from CPT(u) data and laboratory tests. Latin hypercube sampling is used to generate representative input sets, while a response surface model is trained on a limited number of PLAXIS simulations to enable an efficient large-scale probabilistic analysis. Bayesian updating, using the Markov chain Monte Carlo method, refines the probabilistic predictions by incorporating real-world settlement measurements from the monitoring campaign.

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I. INTRODUCTION

Conventional geotechnical design in Belgium often uses deterministic methods in combination with partial safety factors. While these approaches are straightforward and provide safe results, they tend to be overly conservative and do not fully account for the natural variability of soil. As infrastructure projects become more complex and more detailed site data is available, there is a growing need for design methods that better reflect uncertainty. Probabilistic modelling offers a promising alternative, allowing for safer and more cost-effective solutions.

A. Study area and project background

This research focuses on the Groot Schoor dike reinforcement project in Bornem, initiated in 2020 as part of the Flemish Sigmaplan, a large-scale program aimed at

sustainable flood risk management along the Scheldt and its tributaries. The project involves the depoldering of the Groot Schoor site. A new, safer dike has been constructed further inland (indicated in purple in Figure 1), after which an opening will be created in the old Scheldt dike. This intervention will allow the site to be flooded by the tides, facilitating the restoration of unique mudflats and tidal marshes [1].

The project is commissioned by De Vlaamse Waterweg, with Aertssen as the main contractor. The Department of Mobility and Public Works (DMOW) was responsible for the geotechnical site investigations, including field testing, laboratory analyses and the installation of settlement monitoring systems.

For the probabilistic analysis of settlements at the newly constructed dike, cross-section DP26 (highlighted in blue in Figure 1) has been selected as the focus of this study for several reasons. Firstly, it is considered geotechnically complex. Located near the historical Kragewiel—a remnant of a dike breach from 1552—this area features a thick, soft clay layer and reduced soil support on the landward side, making it the most critical section in terms of predicted settlement. Secondly, the site has been thoroughly investigated through extensive field and laboratory testing [2]. Lastly, DP26 is well-instrumented, with high-resolution settlement monitoring data available, making it highly suitable for probabilistic modelling and Bayesian updating [3].



Fig. 1: Overview Groot Schoor site Bornem

B. Research objectives

The primary goal is to develop and validate a probabilistic framework for modelling dike settlements, using advanced numerical and statistical methods. The framework aims to:

- 1) Capture the inherent uncertainty in soil parameters.
- 2) Integrate monitoring data to improve predictions.
- 3) Demonstrate the added value of probabilistic design in real-world projects.

II. AVAILABLE DATA AND INFORMATION

A. Geometry DP26 and construction stages

Based on the design and execution plans provided by DMOV [2], a cross-sectional profile of the dike at location DP26 is drawn. As shown in Figure 2, the newly designed sandy dike (highlighted in yellow) is partially built on top of an older clayey dike (in purple). While this existing dike is partly excavated, it remains in place to serve as an impermeable core. The underlying soil stratigraphy, also defined by DMOV, includes a very soft clay layer (layer S) at the surface. This layer extends beneath the old dike, where centuries of loading have led to increased consolidation and altered soil properties, designated as layers E and Ebis. To reduce anticipated settlement on the Scheldt side (GOG) of the new dike, part of layer S was excavated and replaced during construction.

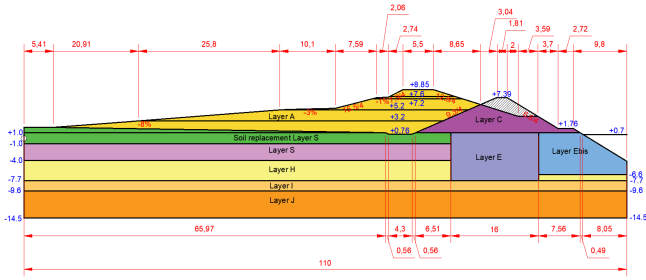


Fig. 2: Cross-sectional plan of DP26

B. Site investigation and laboratory test campaign

From the Databank Ondergrond Vlaanderen (DOV), a substantial number of cone penetration tests (CPTs) are obtained in the vicinity of cross-section DP26. Specifically, six CPTs located on the Scheldt side of the dike, six beneath the existing clayey dike and four on the inland side [4]. The CPT data, providing continuous vertical profiles of cone resistance and pore pressure, serve as the primary basis for deriving the soil stratigraphy (Figure 3) and the probabilistic distributions of key soil parameters through correlations.

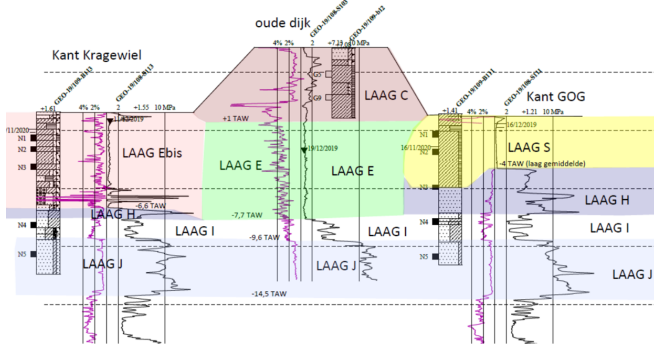


Fig. 3: Soil stratigraphy in DP26 [2]

In addition to CPT data, laboratory testing was performed on selected soil samples retrieved from boreholes. This included oedometer and triaxial tests. The comparison between lab and CPT-derived values allows for the quantification of uncertainty in the derived soil parameter distributions.

C. Monitoring campaign

To monitor the settlement of the newly constructed dike, multiple types of geotechnical instrumentation were installed by DMOV. At cross-section DP26, three key monitoring devices are available: a settlement plate (ZP3), a settlement beacon (ZB3) and a horizontal settlement pipe (Z1). In this study, the main focus is on the settlement beacon ZB3, which is positioned below the crest of the new dike, at the base of the soil replacement. This instrument provides a direct measurement of the vertical displacement at the top of the structure and thus serves as a reliable reference for evaluating total settlement. The full grey line in Figure 4 illustrates the recorded settlements over time at this location.

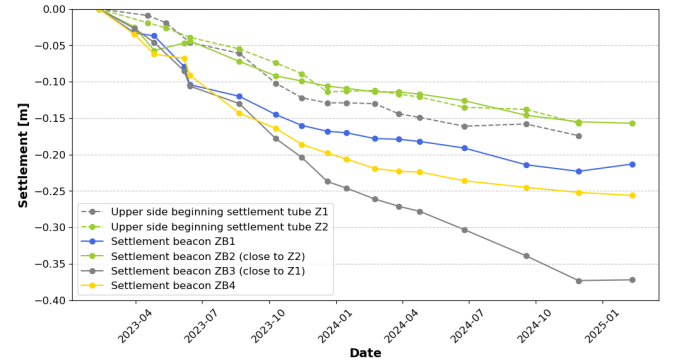


Fig. 4: Monitored settlements with settlement beacons

As shown in Figure 2, the dike is constructed in stages, alternating between elevation and consolidation phases. During elevation, a new wedge of fill is added to increase the dike height. In the subsequent consolidation phase, the soft underlying soils are given time to settle and gain strength. The evolution of dike elevation at DP26, based on measurements at beacon ZB3, is shown in Figure 5. Stepwise increases reflect fill stages, while plateaus indicate consolidation periods.

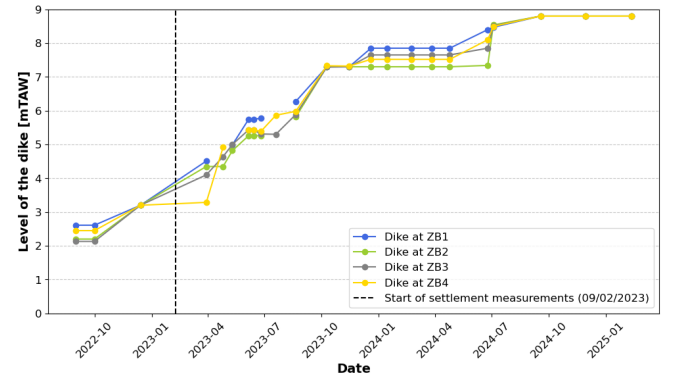


Fig. 5: Evolution of the dike elevation in time

III. NUMERICAL MODEL DP26 IN PLAXIS 2D

Before initiating the probabilistic calculations, a numerical model of the dike must be developed in PLAXIS 2D, as it forms the foundation for simulating settlement behaviour under varying soil conditions and is essential for the large number of model evaluations required in the subsequent analysis. This model, illustrated in Figure 6, incorporates the soil stratigraphy and structural components of both the new and old dike. In PLAXIS 2D, clayey soils are modelled using the Modified Cam-Clay constitutive model, which effectively captures primary consolidation and stress-path-dependent behaviour in clays. For sandy soils, the Hardening Soil Small-Strain model is applied, as it accounts for stiffness degradation at small strains. This is crucial for accurately simulating the response of the deeper sand layers present at the site in Bornem. To enhance efficiency and ensure consistency, the model setup is automated using Python scripting [5].

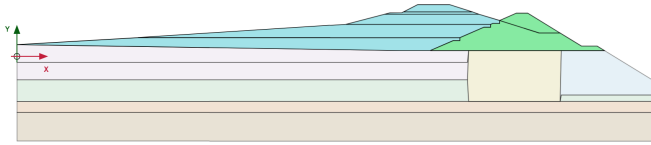


Fig. 6: PLAXIS 2D model of DP26

To simulate the staged dike construction, two modelling options are available for implementation in PLAXIS 2D:

- **Full consolidation modelling:** both elevation and consolidation phases are modelled as time-dependent consolidation steps (Figure 7).
- **Hybrid plastic-consolidation modelling:** elevation steps are treated as undrained plastic calculations, followed by extended consolidation phases (Figure 8).

Both approaches yield a similar final settlement at ZB3, but differ in how they capture time-dependent behaviour. The full consolidation model produces a more realistic curve that closely matches the actual construction timeline. This becomes particularly relevant since field monitoring began 131 days after construction started. When the computed curves are reset to align with this delayed measurement baseline, the hybrid model underestimates the ongoing settlement, while the full consolidation model better reflects the continued influence of earlier construction stages. As such, full consolidation modelling is recommended.

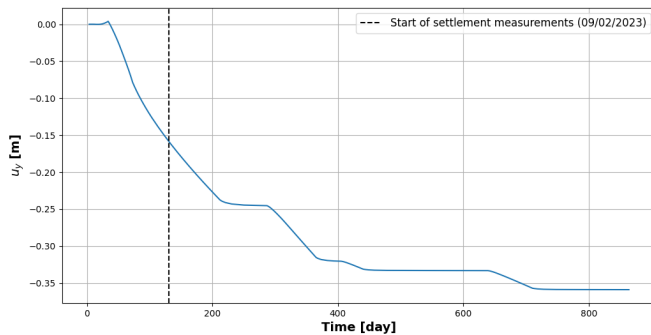


Fig. 7: Full consolidation modelling

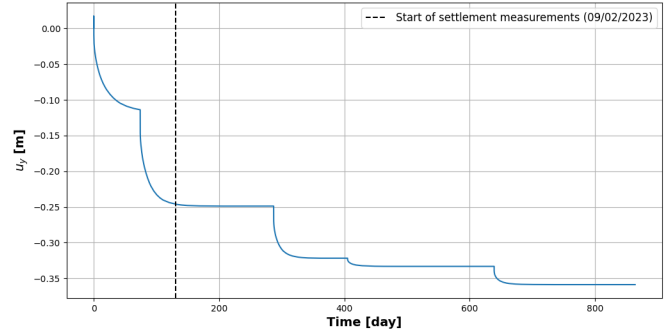


Fig. 8: Hybrid plastic-consolidation modelling

IV. METHODOLOGY FOR PROBABILISTIC CALCULATIONS

This study develops a probabilistic framework for predicting dike settlement, emphasizing uncertainty quantification and real-time data integration. The methodology consists of the following key steps:

- 1) **Sensitivity analysis:** identify the most influential soil parameters affecting settlement to focus the probabilistic modelling on critical variables, thereby reducing unnecessary computational effort.
- 2) **Stochastic soil parameter distributions:** derive probabilistic distributions for sensitive soil parameters using CPT(u) data, supported by laboratory test comparisons to estimate model errors.
- 3) **Latin hypercube sampling (LHS):** generate a well-distributed sample set of input parameters representing soil variability, enabling comprehensive exploration of the input space.
- 4) **Numerical PLAXIS 2D simulations:** generate settlement curves from finite element simulations on a small initial sample set, constrained by the computational cost of PLAXIS simulations.
- 5) **Response surface model (RSM):** develop a surrogate model trained on the numerical simulation results to approximate the input-output relationship, allowing rapid evaluation of settlement predictions for much larger sample set sizes.
- 6) **Extensive probabilistic simulations:** use the RSM to efficiently perform large-scale simulations within probabilistic frameworks, supporting a robust analysis and Bayesian updating.
- 7) **Bayesian updating:** integrate real-time monitoring data to update soil parameter distributions and refine settlement predictions, reducing uncertainty and improving model reliability dynamically throughout the project.

This structured approach combines advanced sampling, surrogate modelling and Bayesian inference to provide a scalable, adaptive and accurate methodology for dike settlement prediction, surpassing traditional deterministic methods that rely solely on fixed input parameters and use monitoring data only for retrospective validation.

V. RESULTS AND DISCUSSION

A. Sensitivity analysis

A sensitivity analysis is performed in PLAXIS 2D to identify which soil parameters should be modelled probabilistically and which can remain at their deterministic values due to their negligible impact on settlement. This is achieved by varying all soil parameters involved in the model within predefined bounds $[p_{\min,i}, p_{\max,i}]$ and assessing their impact on the vertical settlement of the dike, denoted as $f(p_i)$. The analysis produces a sensitivity score $\eta_{ss,i}$, where a higher score indicates a greater effect on settlement [6]. As illustrated in Figure 9, 95% of the variation in settlement behaviour of the dike in DP26 is attributable to changes in four parameters of the soft clay layer S: the overconsolidation ratio (OCR), the vertical permeability ($k_y = k_{vert}$), the compression index (λ) and the recompression index (κ).

$$\eta_{ss,i} = |f(p_{i,max}) - f(p_{i,min})| \rightarrow p_{i,score} = \frac{100 \cdot \eta_{ss,i}}{\sum_{i=1}^n \eta_{ss,i}} \quad (1)$$

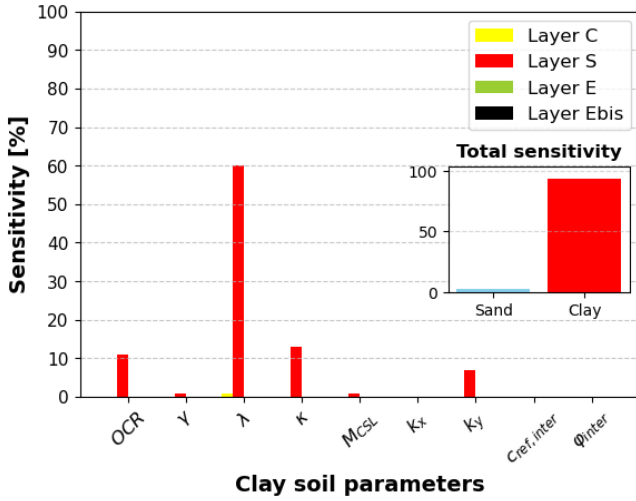


Fig. 9: Sensitivity analysis on soil parameters in DP26

B. Stochastic soil parameter distributions

Before identifying the distributions of the sensitive soil parameters, it should be noted that both the compression (λ) and recompression index (κ) are related to each other in case of very soft clays ($\kappa \approx \lambda/3$) [7]. Moreover, they can be calculated from the initial void ratio (e_0) and the compression constant according to the Flemish formula (C) [8].

$$\frac{C_c}{1 + e_0} = \frac{2.3 \cdot \sigma'}{E_{oed}} = \frac{2.3}{C} \rightarrow \lambda = \frac{C_c}{2.3} = \frac{1 + e_0}{C} \approx 3 \cdot \kappa \quad (2)$$

This illustrates that characterizing the settlement behaviour of clay layer S is best achieved by identifying the distributions of its OCR , k_{vert} , e_0 and C . To determine these distributions, an IMDC workflow has been adapted, linking relevant CPT(u) data to soil layers. At the GOG side of the new dike, six CPT(u) tests provide data for layer S. This data, shown in red in Figure 10, excludes the upper soil surface due to significant accreted material from historic flooding.

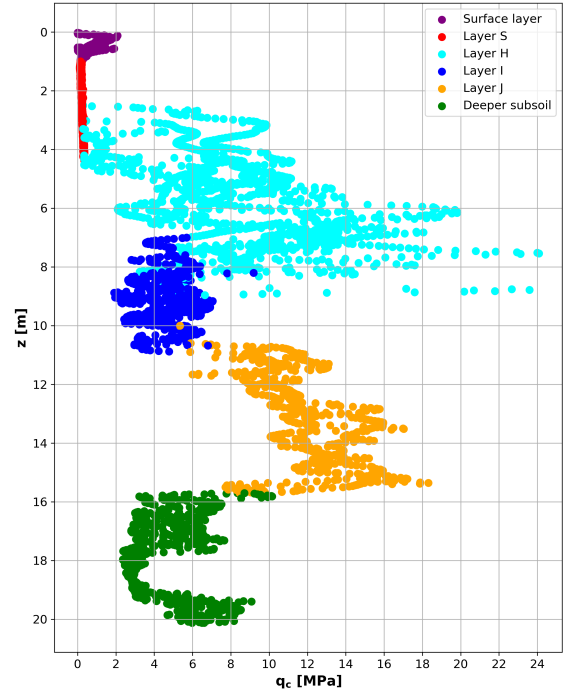


Fig. 10: Cone resistance profiles at the dike's GOG side

Subsequently, derived CPT(u) parameters such as the normalized cone resistance Q_t are calculated, enabling the use of empirical correlations to estimate the target geotechnical parameters. To identify the most suitable correlation for each parameter, available laboratory test data can be used. Given the limited amount of this data, a bootstrapping technique has been applied to construct provisional cumulative distribution functions (CDFs), which are then compared with those derived from the correlated CPT(u) data. This comparison leads to the selection of the following correlations:

- **OCR:** Kulhawy & Mayne (1990) [9].
- **Vertical permeability:** Robertson (2009) [10].
- **Initial void ratio:** Budhu (2010) [8] using the unit weight correlation from Robertson [11].
- **Compression constant:** $C = (\alpha \cdot q_c) / \sigma'_{v,0}$ with α for clays, SB260 (2018) [12].

The selected correlations can then be used to compute probability density functions (PDFs), shown in green in Figure 11. However, since these correlations were developed for soils that may differ from those in layer S, a model (or correlation) error has been estimated in accordance with NBN EN1990 – Annex D [13]. This is done by comparing lab test results with values calculated from CPT(u) data at corresponding locations and depths. Multiplying the model error with the original distributions reveals that poorer correlation performance results in wider, corrected distributions, shown in blue in Figure 11. The correlation performs well for OCR , while for e_0 and C , model error correction mainly shifts the mean with minimal broadening of the PDFs, unlike the more pronounced effect observed for k_{vert} .

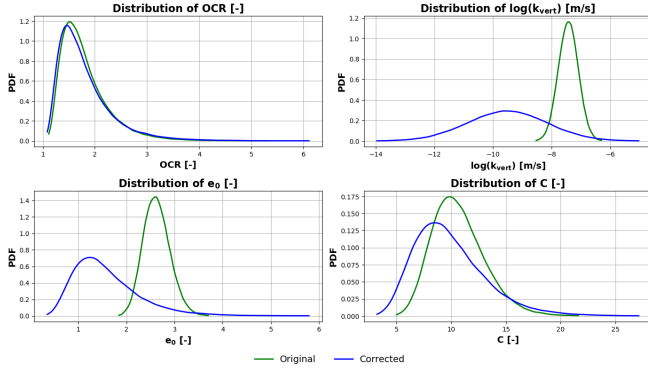


Fig. 11: Soil parameter distributions of layer S

C. Latin hypercube sampling

Latin hypercube sampling (LHS) is used to efficiently generate representative input sets for the probabilistic analysis. For each of the $k = 4$ stochastic soil parameters, the cumulative distribution is divided into m equally probable intervals and a value is randomly selected within each interval. This forms an $m \times k$ sampling matrix based on a permutation matrix $\underline{P}$ of shuffled interval indices and a matrix $\underline{R}$ of uniform random values in $[0, 1]$. The normalized sample positions are computed as $\underline{S} = \frac{1}{m}(\underline{P} - \underline{R})$. Each value $s_{i,j}$ is then mapped to the target distribution using the inverse CDF: $x_{i,j} = F_j^{-1}(s_{i,j})$. This results in m unique sample sets that reflect the statistical properties of the input variables and are used in the PLAXIS settlement simulations [14].

D. Numerical PLAXIS 2D simulations

To reduce the computational cost of repeated PLAXIS evaluations during Bayesian updating, a response surface model (RSM) is developed to approximate settlement behaviour. Therefore an amount of training data is required: $n = 10 \cdot k$, with $k = 4 + 1$ input parameters (four soil parameters and time), 100 LHS sample sets are generated, exceeding the minimum requirement of 50, to balance the one-time computational effort in PLAXIS and RSM accuracy [15]. The resulting computed settlement curves are shown in Figure 12. All curves are reset to zero at the start of the monitoring campaign (indicated by the vertical dotted line) to align with the measured data.

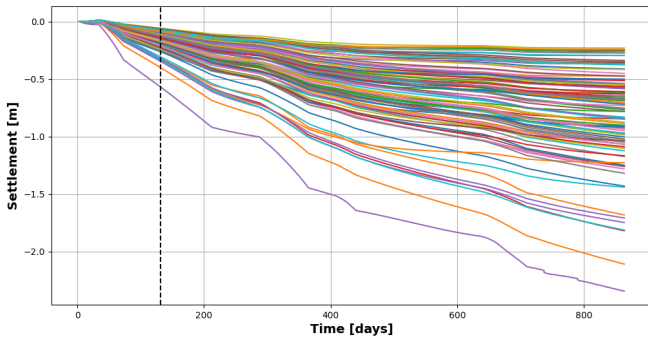


Fig. 12: Numerical simulation of 100 settlement curves

E. Response surface model

As mentioned before, a response surface model (RSM) is constructed to approximate the complex system response $g(\underline{x})$ using a surrogate model $\hat{g}(\underline{x})$. Among various surrogate modelling techniques, Gaussian process regression (GPR) is selected for its ability to capture non-linear, time-dependent settlement behaviour with high accuracy and efficiency, even with a limited number of training samples ($n \leq 100$). Other methods, such as polynomial regression and neural networks, have been investigated but found unsuitable due to limited expressiveness or excessive complexity [16].

The RSM is trained using 80% of the dataset of 100 settlement curves generated with PLAXIS 2D. The input vector is defined as $\underline{x} = [OCR, k_{vert}, e_0, C, \underline{t}]$, where the first four components are soil parameters that remain constant over the range of time $\underline{t}$. The corresponding output $\underline{y}$ is a vector with settlement values at any time instance t . The remaining 20% of the data is reserved for validation. Figures 13 and 14 illustrate the model's performance. The RSM accurately reproduces settlement curves not seen during training. The validation results show a coefficient of determination $R^2 = 0.9961$ close to one and residuals randomly scattered around zero, indicating no autocorrelation and consistent variance (homoscedasticity) [17].

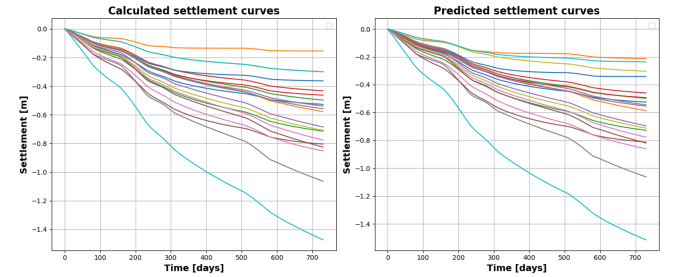


Fig. 13: Calculated (PLAXIS) vs predicted (RSM) curves

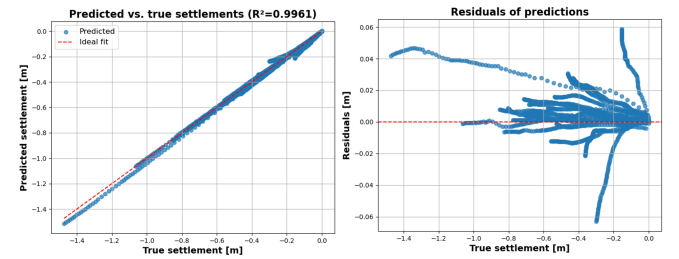


Fig. 14: Validation of the RSM model

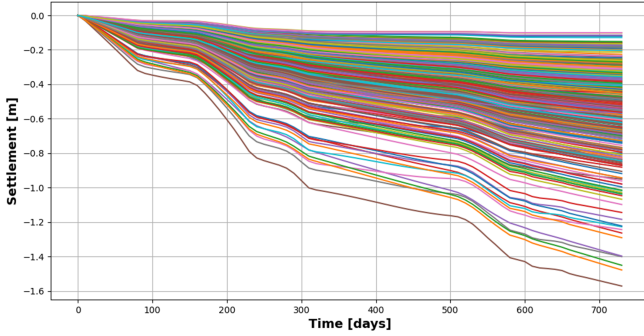
As a Bayesian, non-parametric method, GPR provides both a mean prediction and an uncertainty estimate by defining a distribution over functions. This is governed by a mean function and a kernel that encodes assumptions about function smoothness and correlation. For this study, a hybrid kernel combining a Matérn and White component is adopted to balance smooth approximations with the flexibility to capture abrupt responses and observational noise, typical in geotechnical simulations [18]. The final optimized hyperparameters for each input dimension are summarized in Table I.

Table I: Hyperparameters of the GPR surrogate model

	White	Matérn				
		OCR	k _{vert}	e ₀	C	t
Lengthscale	/	33.2945	27.4955	69.5806	7.5118	1.8652
Variance	$1.7141 \cdot 10^{-6}$	510.8814	510.8814	510.8814	510.8814	510.8814

F. Extensive probabilistic simulations

The trained and validated RSM allows an accurate prediction of a lot of settlement curves in negligible time compared to calculating these curves in PLAXIS 2D. For an LHS sample set with size 500, the RSM reproduces the corresponding 500 settlement curves in 15 minutes (Figure 15), while PLAXIS 2D simulations would take roughly 3000 minutes or 50 hours.

**Fig. 15: Extensive probabilistic simulation using the RSM**

G. Bayesian updating

To refine settlement predictions based on monitoring data, Bayesian updating revises the probability distributions of uncertain soil parameters using Bayes' theorem. Classical closed-form Bayesian methods are unsuitable here due to the non-linear, surrogate-modelled relationship between soil parameters and settlements and the lack of direct parameter observations. Instead, the full joint posterior distribution is approximated using Markov chain Monte Carlo (MCMC), specifically the Metropolis-Hastings (MH) algorithm [19]. MCMC generates a Markov chain whose equilibrium distribution corresponds to the posterior, enabling sampling from complex distributions known only up to a normalizing constant. In each iteration, a candidate parameter vector $\tilde{x}$ is proposed from a proposal distribution $q(\tilde{x} | x_s)$ based on the current state x_s . This candidate can be accepted as the next state x_{s+1} with probability $\alpha(x_s, \tilde{x})$. Here, $f_X(\cdot)$ is the non-normalized posterior (product of prior and likelihood). For symmetric proposal distributions, as is the case for the MH random-walk algorithm: $q(\tilde{x} | x_s) = q(x_s | \tilde{x})$. Hence, the acceptance ratio can be simplified [20].

$$\alpha = \min \left[1, \frac{f_X(\tilde{x})}{f_X(x_s)} \cdot \frac{q(x_s | \tilde{x})}{q(\tilde{x} | x_s)} \right] = \min \left[1, \frac{f_X(\tilde{x})}{f_X(x_s)} \right] \quad (3)$$

A uniform random number $u \sim \mathcal{U}[0, 1]$ determines acceptance: if $u \leq \alpha$, then $x_{s+1} = \tilde{x}$, otherwise $x_{s+1} = x_s$. The procedure is illustrated in Figure 16. After discarding an initial burn-in phase to ensure convergence, the remaining samples represent draws from the posterior, which are propagated through the

surrogate model to produce updated settlement predictions that incorporate parameter uncertainty and observational noise. This MCMC framework thus enables robust, flexible Bayesian updating beyond classical analytic methods [21].

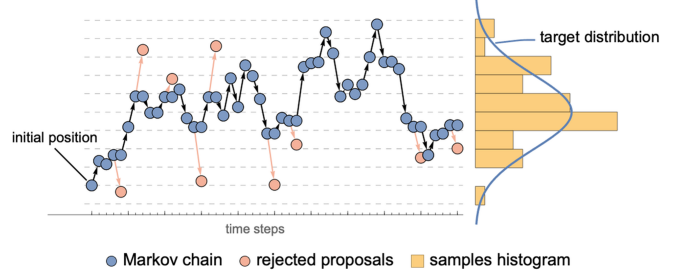
**Fig. 16: Illustration of the MCMC procedure [22]**

Figure 17 illustrates the evolution of the marginal distributions for the four most sensitive soil parameters during the Bayesian updating process. With each update, the distributions become increasingly concentrated, reflecting a systematic reduction in epistemic uncertainty as more monitoring data is assimilated. This sharpening of distributions indicates a clear gain in information about the parameter values, with the narrowing interquartile ranges in the box plots providing a visual confirmation of this trend.

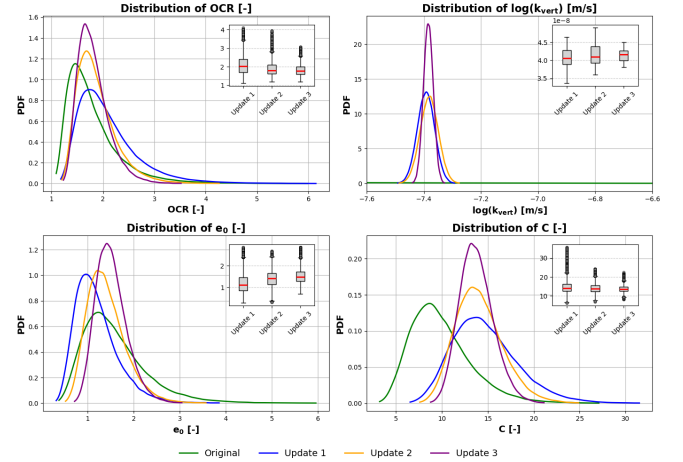
**Fig. 17: Updated soil parameter distributions**

Figure 18 presents the impact of this updating on the settlement predictions. The sequential transition from prior (dotted lines) to posterior (solid lines) predictions demonstrates a convergence toward the observed monitoring data. As shown in the top-right plot, the predictions align closely with measurements after only a few updates, indicating the efficiency of the updating framework. Subsequent updates primarily serve to tighten the credible intervals, represented by the shaded bands, rather than significantly shift the mean predictions. Finally, the bottom-right plot contrasts the initial prior predictions (from Figure 15) with the final posterior, highlighting a substantial reduction in predictive uncertainty. This confirms that the Bayesian updating process not only improves prediction accuracy but also significantly enhances confidence in the model outputs.

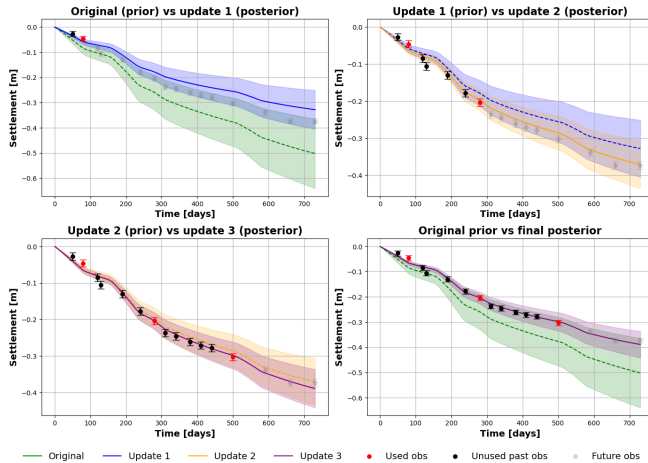


Fig. 18: Updated settlement curves

VI. CONCLUSION AND RECOMMENDATIONS

This study develops a structured and scalable methodology for probabilistic geotechnical modelling, demonstrated through its application to a dike settlement prediction in the Groot Schoor Bornem project. By combining a sensitivity analysis, stochastic modelling, surrogate-assisted simulations and Bayesian updating, the approach captures soil variability and dynamically refines predictions using real-time monitoring data. Compared to traditional deterministic methods, the framework reduces epistemic uncertainty and enhances predictive reliability. It optimises computational efficiency through surrogate modelling, isolates critical soil parameters and adapts to new data throughout the project lifecycle. The results confirm the feasibility and value of integrating fully probabilistic tools into geotechnical practice, supporting data-driven, cost-effective and risk-informed design, paving the way for more resilient infrastructure.

For future work, several enhancements are recommended: extending the RSM to incorporate creep effects alongside primary consolidation, evaluating the framework with alternative constitutive models within PLAXIS and applying the methodology to other geotechnical structures such as retaining walls. Further, using k-fold cross-validation could strengthen RSM robustness. Incorporating spatial variability of soil parameters and updating based on other measurements, such as pore water pressure, may also enhance model accuracy and generalizability.

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Contents

Abstract	ix
List of Figures	xxiii
List of Tables	xxvii
Nomenclature	xxix
1 General introduction	1
1.1 Context and situation of the research project	1
1.1.1 Geotechnical design practices in Belgium	1
1.1.2 Opportunities for advancements in geotechnical design	1
1.1.3 Project Groot Schoor Bornem	3
1.2 Research objectives	3
1.3 Statement on the responsible use of generative AI	4
1.4 Thesis outline and research methodology	4
2 Project Groot Schoor Bornem	7
2.1 Introduction to the Groot Schoor site	8
2.1.1 History	8
2.1.1.1 Early Dike Construction and Expansion (11th - 16th century)	8
2.1.1.2 Dike reinforcement and maintenance (17th - 18th century)	10
2.1.1.3 Modern reinforcements and the Sigmaplan (20th century)	10
2.1.2 Recent construction works for the Groot Schoor site	10
2.2 Cross-sectional geometry and design of the new Scheldt dike	15
2.2.1 Cross-section DP26	16
2.2.2 Soil replacement layer S	17
2.3 Geotechnical site investigation campaign	19
2.3.1 In situ or field tests	20
2.3.1.1 Cone penetration tests (CPT)	20
2.3.1.2 Vane shear tests (VST)	20
2.3.1.3 Measurement of the groundwater table (GWT)	20
2.3.1.4 Boreholes (BH)	20

2.3.2	Laboratory tests	21
2.3.2.1	Triaxial (compression) tests	21
2.3.2.2	Oedometer consolidation tests	21
2.3.2.3	Permeability tests	22
2.4	Geotechnical monitoring campaign	23
2.4.1	Monitoring instruments and techniques	23
2.4.1.1	Settlement plates	24
2.4.1.2	Settlement beacons	25
2.4.1.3	Horizontal settlement pipes	25
2.4.2	Results of the monitoring campaign	26
2.5	Stages during the construction of the new dike	29
2.5.1	Actual construction phases	29
3	PLAXIS 2D modelling	31
3.1	Soil	32
3.1.1	Soil stratigraphy	32
3.1.2	Soil material models	35
3.1.2.1	Material model used for sandy soils	35
3.1.2.2	Material model used for clayey soils	39
3.1.3	Deterministic soil parameters	42
3.2	Structures	43
3.2.1	Geometrical adjustments for numerical stability	43
3.2.2	Mesh optimization and additional simplifications	45
3.3	Mesh	46
3.4	Flow conditions	47
3.5	Staged construction	48
3.5.1	Construction phase modelling options	48
3.5.1.1	Full consolidation modelling (alternative 1)	48
3.5.1.2	Hybrid plastic-consolidation modelling (alternative 2)	48
3.5.1.3	Comparison and recommendations	49
4	Soil parameter distributions	51
4.1	Sensitivity of the soil parameters on the settlement calculation	51
4.1.1	Theoretical background of the sensitivity analysis in PLAXIS 2D Ultimate	52
4.1.1.1	Sensitivity Score	52
4.1.1.2	Relative sensitivity and aggregate sensitivity	52
4.1.2	Result of the sensitivity analysis in PLAXIS 2D	53
4.1.2.1	Sensitivity analysis on soil parameters within individual soil layers	53
4.1.2.2	Global sensitivity analysis on soil parameters of all soil layers	55
4.2	Deterministic values of the non-critical soil parameters	57

4.2.1	Deterministic values of new dike's sand properties (layer A)	57
4.2.2	Deterministic values of the sand replacement's properties (layer R)	60
4.3	Probability distributions of the critical soil parameters	61
4.3.1	Collection and preparation of the CPT(u) data	62
4.3.1.1	Derived CPT(u) parameters	64
4.3.1.2	Soil behaviour type parameters	65
4.3.2	Linking the CPT(u) data to the soil layers	67
4.3.3	Determining the probabilistic distributions and model errors of the critical soil parameters	69
4.3.3.1	Bootstrapping of the laboratory test data	70
4.3.3.2	Probabilistic distributions and model errors: theoretical framework . .	74
4.3.3.3	CPT(u) correlations and model errors: practical application and results	77
4.4	Soil parameter distributions for layer S	90
5	Probabilistic (settlement) calculations	93
5.1	Workflow for the probabilistic calculations	94
5.2	Theoretical framework of the probabilistic calculations	96
5.2.1	Latin hypercube sampling	96
5.2.1.1	Latin hypercube sampling: theoretical background	96
5.2.1.2	Latin hypercube sampling: example	97
5.2.2	Response surface method	99
5.2.2.1	Gaussian process regression: theoretical background	101
5.2.2.2	Gaussian process regression: implementation	104
5.2.2.3	Gaussian process regression: example	107
5.2.3	Bayesian updating	110
5.2.3.1	Markov chain Monte Carlo simulations: theoretical background . . .	112
5.2.3.2	Markov chain Monte Carlo simulations: implementation	116
5.2.3.3	Markov chain Monte Carlo simulations: example	119
5.3	Application of the probabilistic analysis workflow to the new dike in Bornem	125
5.3.1	Sensitivity analysis	126
5.3.2	Stochastic soil parameter distribution	126
5.3.3	Latin hypercube sampling (LHS)	127
5.3.4	Numerical PLAXIS 2D simulations	128
5.3.5	Response surface model (RSM)	129
5.3.6	Extensive probabilistic simulations	131
5.3.7	Bayesian updating	132
5.3.8	Final remarks and discussions	139
5.3.8.1	Probabilistic vs deterministic settlement calculations	139
5.3.8.2	Effect of soil parameter distribution variations on settlement predictions	140
5.3.8.3	Correlations between sensitive soil parameters	141

Conclusion and recommendations	143
5.4 Conclusion	143
5.5 Recommendations for future work	144
Societal reflection	149
References	151
Appendices	159
Attachment A: Execution plans of the site Groot Schoor Bornem	161
Attachment B: Location of the CPTs and BHs on the site Groot Schoor Bornem	164
Attachment C: Location of the settlement monitoring devices on the site Groot Schoor Bornem	165
Attachment D: Definition graphs of the critical state model parameters used in the Modified Cam Clay model	167
Attachment E: Deterministic values for the soil parameters used in the numerical PLAXIS 2D model	168
Attachment F: Numerical stability analysis of the dike construction	171
Attachment G: Mesh quality comparison	173

List of Figures

2.1	Groot Schoor Bornem on a topographical map (Cornelis et al., 2020)	7
2.2	Cross-section of the old winter dike on the Groot Schoor site (Bosmans, 2022)	8
2.3	The origin of the Kragewiel	9
2.4	Working principle of an FCA-CRT (Peeters et al., 2015)	11
2.5	Sigmaplan at Groot Schoor Bornem	12
2.6	Groot Schoor in Bornem	13
2.7	Aerial view on the new ring dike	13
2.8	Aerial view on the large and small Kragewiel	14
2.9	Design plan of cross-section DP26	15
2.10	Dimensions of cross-section DP26 used for the numerical model	17
2.11	Soil replacement of layer S in cross-section DP26	17
2.12	Evaluation of the soil replacement with CPT GEO-22/160-S203.	18
2.13	Location of the CPTs (orange dots) and BHs (green dots)	19
2.14	Relative positioning of the monitoring devices in DP26	24
2.15	Results of the monitoring campaign for settlement beacons	27
2.16	Monitoring results for horizontal settlement pipe Z1, relative to zero measurement	28
2.17	Evolution of the dike elevation in time, measured at the settlement beacons	30
3.1	Soil stratigraphy of cross-section DP26 proposed by geotechnical nota (Couck, 2022)	33
3.2	Boreholes in PLAXIS 2D to define the soil stratigraphy in DP26	34
3.3	Stress-dependent stiffness moduli in the Hardening Soil model (PLAXIS, 2024b)	37
3.4	Dilatancy cut-off in the Hardening Soil model (PLAXIS, 2024b)	38
3.5	Critical state parameters used in the Modified Cam-Clay model (Budhu, 2010)	41
3.6	PLAXIS 2D model of the old and new dike in DP26	43
3.7	Geometry modifications to overcome calculation problems in PLAXIS 2D	44
3.8	Comparison of the plastic analysis at the end of the first elevation phase	44
3.9	Optimization of the mesh quality	45
3.10	Quality of a medium mesh	47
3.11	PLAXIS 2D prediction of the (deterministic) settlement curve at ZB3	49
3.12	PLAXIS 2D prediction of the monitored settlement curve from 09/02/2023 on	50
3.13	Comparison of techniques to reset the settlement curves to zero at 09/02/2023	50

4.1	Sensitivity analysis on soil parameters within individual sandy soil layers	54
4.2	Sensitivity analysis on soil parameters within individual clayey soil layers	55
4.3	Global sensitivity analysis on soil parameters of sandy soils	55
4.4	Global sensitivity analysis on soil parameters of clayey soils	56
4.5	CPTs performed at the locations of settlement plates ZP1, ZP2, ZP3 and ZP4	57
4.6	Coefficient of lateral earth pressure at rest K_0 according to <i>Mayne</i>	58
4.7	Relative density D_r according to <i>Baldi</i>	58
4.8	Determination of the unit weight γ of the sand used in the dike construction	59
4.9	Determination of the HSsmall parameters for the sand of the soil replacement	60
4.10	Location of the CPT(u)s in the vicinity of the Kragewiel	63
4.11	<i>Robertson</i> chart: R_f vs Q_t	66
4.12	<i>Robertson</i> chart: B_q vs Q_t	66
4.13	Cone resistance q_c in function of depth z for the CPT(u)s at the GOG side of the dike	68
4.14	Statistical distribution of the unit weight γ of the soil included in layer S	69
4.15	Parameter distribution in layer S based on bootstrapping of the laboratory test results	73
4.16	Comparison of CDFs for the <i>OCR</i> distribution from CPT(u) and laboratory test data	79
4.17	Model error for <i>OCR</i> before and after recalibration of the correlation of <i>Mayne</i>	80
4.18	Model error for <i>OCR</i> before and after recalibration of the correlation of <i>Kulhawy and Mayne</i>	81
4.19	Model error for <i>OCR</i> using the correlation of <i>Dagger et al.</i>	82
4.20	Fitted PDFs to the probabilistic distribution of k_{vert}	82
4.21	<i>Robertson</i> CDF for the distribution of k_{vert}	83
4.22	Model error for k_{vert} using the <i>Robertson</i> correlation	84
4.23	Fitted PDFs to the probabilistic distribution of k_{vert}	84
4.24	<i>Budhu</i> CDF for the distribution of e_0	85
4.25	Model error for e_0 using the <i>Budhu</i> correlation	86
4.26	Fitted PDFs to the probabilistic distribution of e_0	86
4.27	Comparison of the model error for C by using both correlations of SB260	88
4.28	Comparison of the CDFs for the distribution of C by using both correlations of SB260	89
4.29	Fitted PDFs to the probabilistic distribution of C	89
4.30	Original distributions compared to distributions corrected with the model error	91
5.1	Application of LHS to a simplified dike settlement calculation (Part 1)	98
5.1	Application of LHS to a simplified dike settlement calculation (Part 2)	99
5.2	Hyperparameter optimization of the (squared exponential) kernel (Wang, 2023) . . .	103
5.3	Visual evaluation of regression models	107
5.4	Set-up of an RSM for a simplified dike settlement calculation (Part 1)	108
5.4	Set-up of an RSM for a simplified dike settlement calculation (Part 2)	109
5.4	Set-up of an RSM for a simplified dike settlement calculation (Part 3)	110
5.5	Illustration of the Markov chain Monte Carlo (MCMC) algorithm	113

5.6	Effect of proposal distribution on acceptance rate and correlation of samples (Taboga, 2021b)	115
5.7	Bayesian updating process using the Markov chain Monte Carlo method	120
5.8	Comparison between the prior and posterior settlement prediction	121
5.9	Corner plots for the different updating steps	122
5.10	Sequentially updated soil parameter distributions	123
5.11	Evolution of the mean settlement curve through Bayesian updating	124
5.12	Comparison of the original prior and final posterior settlement prediction	124
5.13	Sequentially updated settlement predictions	125
5.14	Sensitivity analysis of the soil parameters affecting dike settlement in DP26	126
5.15	Soil parameter distributions used in the probabilistic analysis of dike settlements in DP26	127
5.16	LHS of the soil parameter distributions for dike settlement analysis in DP26	128
5.17	Settlement curves resulting from PLAXIS 2D simulations	128
5.18	80 numerically obtained settlement curves used for the training of the RSM	129
5.19	Comparison of calculated (PLAXIS 2D) vs predicted (RSM) settlement curves	130
5.20	Validation of the RSM: comparison of predicted vs actual settlement values and residuals	131
5.21	Extensive probabilistic simulation of 500 settlement curves using the RSM	132
5.22	Bayesian updating process using the MCMC for OCR and k_{vert}	134
5.23	Bayesian updating process using the MCMC for e_0 and C	135
5.24	Comparison between the prior and posterior settlement predictions in each updating step	136
5.25	Sequentially updated soil parameter distributions for DP26	137
5.26	Sequentially updated settlement predictions for DP26	138
5.27	Comparison of settlement curves predicted by the RSM before and after Bayesian updating	138
5.28	Comparison of deterministic vs probabilistic settlement calculations	139
5.29	Effect of an incorrect prior on the posterior distribution of C and the settlement prediction	140
5.30	Corner plots for the sequential Bayesian updating (Part 1)	142
5.31	Principle of the k -Fold cross-validation technique	146
34	Mesh quality for different mesh element distributions (1/3)	173
34	Mesh quality for different mesh element distributions (2/3)	174
34	Mesh quality for different mesh element distributions (3/3)	175

List of Tables

2.1	Geotechnical campaigns and relevant tests for DP26	19
2.2	Construction phases timeline and duration	30
3.1	BH required in PLAXIS 2D to define the soil stratigraphy in DP26 (levels in $mTAW$)	34
3.2	Parameters for modelling sandy soil with the HSsmall model in PLAXIS 2D	39
3.3	Parameters for modelling clayey soil with the MCC model in PLAXIS 2D	42
3.4	Mesh performance for meshes with different coarseness factors	46
4.1	Deterministic values of the sand used in the dike construction (layer A)	59
4.2	Deterministic values of the sand used in the soil replacement (layer R)	60
4.3	Statistical overview CPT(u) data	62
4.4	Derived CPT(u) parameters (Lunne et al., 2002)	64
4.5	Soil behaviour types in the <i>Robertson</i> charts	65
4.6	Statistical overview laboratory test data in layer S	71
4.7	CPT(u) correlations for the derivation of the overconsolidation ratio OCR	78
4.8	CPT(u) correlations for the derivation of the vertical permeability k_{vert}	83
4.9	CPT(u) correlations for the derivation of the initial void ratio e_0	85
4.10	CPT(u) correlations for the derivation of the compression constant C	87
4.11	Overview of the probabilistic distributions and model uncertainty of the key soil pa- rameters	90
4.12	Corrected distributions of the four key soil parameters in layer S	91
4.13	Comparison of statistics between original and corrected distributions	91
5.1	Hyperparameters of the GPR model	108
5.2	Illustrative example: monitoring	119
5.3	Hyperparameters of the GPR model	130
5.4	Summary of the Bayesian updating process using MCMC	133

Nomenclature

Latin symbols I

Symbol	Description	Unit
B_q	Pore pressure ratio	[–]
C	Flemish compression constant	[–]
C_c	Compression index	[–]
C_r	Recompression index	[–]
c_u	Undrained cohesion	[kPa]
c_v	Coefficient of consolidation	[m ² /s]
D_r	Relative density	[–]
E_{50}^{ref}	Secant stiffness in standard drained triaxial test	[kPa]
E_{oed}^{ref}	Tangent stiffness for primary oedometer loading	[kPa]
E_{ur}^{ref}	Unloading/reloading stiffness	[kPa]
e_0	Initial void ratio	[–]
f_s	CPT sleeve friction	[MPa]
F_r	Normalized friction ratio	[–]
$g(X)$	Response function	[–]
G_0	Small-strain shear modulus	[kPa]
G_s	Specific gravity of soil solids	[–]
I_c	Soil behaviour type index	[–]
k	Hydraulic permeability	[m/s]
K_0	Coefficient of lateral earth pressure at rest	[–]
m	Power for stress-level dependency of stiffness	[–]
l	lengthscale (kernel hyperparameter)	[–]
p^{ref}	Reference stress for stiffness	[kPa]
p_{atm}	Atmospheric pressure	[MPa]
q_c	CPT cone resistance	[MPa]
q_n	Net cone resistance	[MPa]
q_t	Corrected cone resistance	[MPa]
Q_t	Normalized cone resistance	[–]
R^2	Coefficient of determination	[–]
R_f	Friction ratio	[%]
$\hat{R}$	Gelman-Rubin statistic	[–]
u_0	Equilibrium pore pressure	[MPa]
u_2	Pore pressure at the shoulder of the CPT	[MPa]
x	Input variable	[–]
y	Output variable	[–]
z	Depth of the CPT	[m]

Greek symbols

Symbol	Description	Unit
α	Acceptance probability for MH algorithm	[–]
Δu	Excess pore pressure	[MPa]
$\gamma_{0.7}$	Threshold shear strain	[–]
γ_d	Dry unit weight of soil	[kN/m ³]
γ_s	Saturated unit weight of soil	[kN/m ³]
κ	Recompression index	[–]
κ	Kernel function GPR	[–]
λ	Compression index	[–]
μ	Mean value of a Gaussian distribution	[–]
M_{CSL}	Slope of the critical state line	[–]
ν_{ur}	Poisson's ratio for unloading/reloading	[–]
ϕ	Angle of internal friction	[°]
ψ	Dilatancy angle	[°]
ρ_{pc}	Vertical settlement of the soil	[m]
σ	Stress	[kPa]
σ	Standard deviation of a Gaussian distribution	[–]
σ_t	Tensile strength	[kPa]
$\sigma_{v,0}$	In situ vertical stress	[MPa]
$\sigma'_{v,0}$	In situ effective vertical stress	[MPa]
$\sigma'_{h,0}$	In situ effective horizontal stress	[MPa]
σ_ξ^2	Variance of the proposal distribution (MH algorithm)	[–]
σ_y^2	Signal variance (kernel hyperparameter)	[–]

Abbreviations

Abbreviation	Description
<i>API</i>	Application programming interface
<i>BH</i>	Borehole
<i>CDF</i>	Cumulative distribution function
<i>CD-TX</i>	Consolidated drained triaxial test
<i>CPT</i>	Cone penetration test
<i>CPT_u</i>	Cone penetration test with pore pressure measurement
<i>CRS</i>	Constant rate of strain (tests)
<i>CU-TX</i>	Consolidated undrained triaxial test
<i>DOV</i>	<i>Databank Ondergrond Vlaanderen</i>
<i>FCA-CRT</i>	Flood control area - controlled reduced tide
<i>FE(M)</i>	Finite element (method)
<i>FORM</i>	First order reliability method
<i>GOG</i>	Gecontroleerd overstromingsgebied
<i>GP(R)</i>	Gaussian process (regression)
<i>GWT</i>	Groundwater table
<i>HS</i>	Hardening Soil model
<i>HS_{small}</i>	Hardening Soil model with Small-Strain Stiffness
<i>IMDC</i>	International Marine and Dredging Consultants
<i>JRC</i>	Joint Research Centre
<i>JCSS</i>	Joint Committee on Structural Safety
<i>LHS</i>	Latin hypercube sampling
<i>MAE</i>	Mean absolute error
<i>MCC</i>	Modified Cam Clay
<i>MCMC</i>	Markov chain Monte Carlo
<i>MH</i>	Metropolis-Hastings
<i>MSE</i>	Mean squared error
<i>OCR</i>	Overconsolidation ratio
<i>PDF</i>	Probability density function
<i>RBF</i>	Radial basis function
<i>RSM</i>	Response surface method (or model)
<i>SORM</i>	Second order reliability method
<i>TAW</i>	<i>Tweede Algemene Waterpassing</i>
<i>UU-TX</i>	Unconsolidated undrained triaxial test
<i>VST</i>	Vane shear test

General conventions

- Vectors are underlined (e.g. $\underline{x}$).
- Matrices are double underlined (e.g. $\underline{\underline{M}}$).
- Prior distributions are designated with a superscript ' (e.g. $f'(x)$).
- Posterior distributions are designated with a superscript " (e.g. $f''(x)$).
- General variables are designated with capital letters (e.g. X).
- Realizations of these general variables are designated with small letters (e.g. x).

1

General introduction

As an introduction to this master's dissertation, this chapter provides the framework in which this research should be situated and tries to highlight the scope as well as the importance of the topic studied. Based on this, the research objectives can be formulated and the methodology to achieve these objectives can be discussed. Finally, the outline of the thesis is presented.

1.1 Context and situation of the research project

1.1.1 Geotechnical design practices in Belgium

Geotechnical design practices in Belgium traditionally rely on deterministic or semi-probabilistic approaches to assess the bearing capacity of structures, analyze the stability of slopes and predict the settlement of soils (Bureau voor Normalisatie (NBN), 2022). These methods use characteristic values for soil properties and apply predefined partial safety factors to account for uncertainties in the soil properties, their determination and the design procedures. While such approaches are widely adopted and provide a framework for safe and effective designs, they often fail to capture variability in outcomes. The partial safety factors are based on expert judgement and are calibrated to ensure acceptable failure probabilities. However, these methods have been criticized for being overly conservative and for not fully utilizing the growing amount of data from site investigations and laboratory testing.

1.1.2 Opportunities for advancements in geotechnical design

Recent advancements in geotechnical software and computational methods, such as PLAXIS 2D, and the adoption of advanced soil models, like the Hardening Soil and Modified Cam-Clay Models, have enabled more refined analyses. These tools allow engineers to simulate complex soil-structure interactions and model non-linear behaviour of soils under various loading conditions. Additionally, automation via Python scripting enables the engineer to perform more calculations in less time and to explore a wider range of design scenarios efficiently.

1 General introduction

Simultaneously, the availability of extensive and high-quality geotechnical data increases through databases, such as Databank Ondergrond Vlaanderen (Vlaamse overheid, s.d.), that collect the results of extensive site investigations, laboratory testing and site monitoring campaigns.

While the general Eurocode framework does support probabilistic design, a deterministic approach to geotechnical design remains prevalent in the Belgian practice. As such, probabilistic geotechnical calculations remain relatively unexplored. Moreover, while the second generation of the Eurocode for geotechnical design is intended to be probabilistically calibrated, a report by Deltares highlights that this calibration has not been fully achieved (Schweckendiek et al., 2024). This shortcoming has prompted the formulation of additional guidance for reliability-based design and assessment of geotechnical structures within the Eurocode framework, as published by JRC (van Den Eijnden et al., 2024).

Building on the increased computational power and data availability, probabilistic geotechnical design approaches emerge as the logical next step. By explicitly accounting for uncertainties through statistical distributions of input parameters, these methods overcome key limitations of deterministic approaches. Instead of producing a single deterministic output, probabilistic methods yield a range of possible outcomes. The latter provides valuable insights into the likelihood and variability of different scenarios (e.g. settlements, bearing capacity). This enables a shift from overly conservative generic designs to optimized, tailored designs and risk-informed decisions that better balance safety, performance and cost-effectiveness.

The large potential of probabilistic calculations lies in their ability to unlock significant benefits for geotechnical practice.

- **Data-driven design:** modern site investigation techniques (e.g. CPTs) and lab tests (e.g. triaxial tests) generate vast datasets. probabilistic methods leverage this wealth of information to define distributions for input parameters, making full use of available information rather than reducing it to single characteristic values.
- **Insight into variability and sensitivity:** by producing a full distribution of outcomes, probabilistic approaches offer deeper understanding of design variability, enabling better performance prediction, identification of critical parameters and sensitivity analysis. This leads to designs that are both more robust to uncertainties and more efficient in terms of cost and resource use.
- **Continuous improvement through monitoring:** integration of real-world data from site monitoring and post-construction performance allows validation and refinement of design assumptions. This feedback loop enhances long-term reliability and improves predictive accuracy, such as for settlement estimates.

1 General introduction

1.1.3 Project Groot Schoor Bornem

In a previous project led by IMDC, in collaboration with the Department of Geotechnics of the Flemish Government, a workflow was developed to generate statistical distributions of soil material model parameters. This methodology used advanced scripting techniques to automate deterministic settlement calculations in PLAXIS, based on parameter samples from these distributions (Somers et al., 2023) (Somers et al., 2024). The success of this initial step into probabilistic analysis highlighted the potential for further development and refinement.

Building on this foundation, the current study focuses on the dike reinforcement project Groot Schoor Bornem, part of the broader Sigmaplan for flood protection in Flanders (Vlaamse Waterweg, 2024a). This project offers a unique opportunity to apply probabilistic methods in a real-world context, supported by on-site measurements suitable for Bayesian updating and comparison between deterministic and probabilistic settlement predictions. Continued collaboration between IMDC and the Department of Geotechnics ensures access to essential data, tools and expertise to support this research.

1.2 Research objectives

As mentioned in paragraph 1.1.1, geotechnical design accuracy, risk assessment and resource optimization can still be improved by bridging the gap between deterministic and probabilistic methodologies. Addressing this gap can be essential in modernizing the geotechnical engineering practice in Belgium and align it with emerging global trends in reliability-based design.

This results in the following main research question at the base of this study: "How can probabilistic geotechnical calculations be systematically implemented in practice and how do their outcomes compare to deterministic calculations and on-site measurements of the settlement in the studied case of the dike reinforcement project Groot Schoor Bornem?" Answering this question is immediately the research objective of this thesis. Sub-objectives related to the main research question are:

1. Accurately modelling the dike geometry and construction stages in PLAXIS 2D using Python scripting and ensuring that the model represents the actual construction process and boundary conditions.
2. Determining the sensitivity of the soil parameters on the settlement predictions.
3. Deriving project-specific statistical distributions of soil parameters from available correlations on field data and developing methodologies to reconcile laboratory test results with field data for improved parameter estimation and uncertainty quantification.
4. Implementing probabilistic calculations next to a PLAXIS 2D analysis using Python scripting and assessing their potential for capturing output variability.

1 General introduction

5. Comparing the accuracy and insight-providing capabilities of probabilistic calculations and deterministic approaches with respect to settlement predictions.
6. Validating probabilistic calculation results against on-site settlement measurements from the Groot Schoor Bornem dike project and updating them with these measurement data to obtain refined posterior predictions.

1.3 Statement on the responsible use of generative AI

During the preparation of this dissertation, generative AI tools (such as ChatGPT and Microsoft Copilot) have been used to a limited but valuable extent to support the research process. Specifically, AI has been employed to assist with debugging Python scripts related to the determination of soil parameter distributions and execution of probabilistic analyses. This significantly improved development efficiency and facilitated the resolution of technical issues. Additionally, AI tools have been consulted for suggestions on improving code structure and enhancing readability. These contributions are especially helpful in the context of creating Python codes that are well documented and maintainable, which is essential for future users. To a lesser extent, AI has been used to generate LaTeX templates for tables and equations based on their counterparts in Microsoft Word or Excel. Additionally, data and graphs initially prepared in Excel can be more easily converted into equivalent Python data frames and visualisations using AI-generated code templates. This has helped to ensure consistency and uniformity in the presentation of plots throughout the dissertation.

At no point has AI been used to generate original research content, perform data analysis or draw scientific conclusions. Its use has remained strictly within the scope of technical, editorial and debugging support. All scientific reasoning, modelling decisions and interpretations have been made independently by the author.

1.4 Thesis outline and research methodology

This master's dissertation is structured into four main chapters, each contributing to the research objectives through a logical progression that reflects the applied methodology. Literature reviews are included within the relevant chapters to enhance cohesion, readability and understanding throughout the text. Below is an overview of the chapters and their content.

Chapter 2: Project Groot Schoor Bornem introduces the case study of the dike reinforcement project Groot Schoor Bornem within the broader Sigmaplan. It outlines the project's context, objectives and importance. Furthermore, a summary of the executed geotechnical site investigations and laboratory testing campaigns is provided. These investigation campaigns serve the collection of soil data, which is the necessary input for the numerical modelling.

1 General introduction

The chapter also explains the cross-sectional geometry and sequential construction stages of the considered dike as well as the occurring soil stratigraphy. In order to understand the subsoil condition, reference is made to historical events on the site. Finally, the chapter concludes with a description of the monitoring campaign that was set up to measure the settlement of the dike during and after construction.

Chapter 3: PLAXIS 2D modelling covers the setup and execution of the PLAXIS 2D Ultimate model. It begins with a discussion of modelling assumptions, followed by a step-by-step explanation of the model setup based on the PLAXIS 2D input interface: selection of appropriate soil models, definition of the soil stratigraphy and geometry, meshing, boundary conditions with respect to the flow conditions and staged construction. The chapter also details the development of Python scripts for automating the model setup, parameter assignment and output extraction.

Chapter 4: Soil parameter distributions presents the methodology for deriving the statistical distributions of soil parameters. It starts with giving an overview of the deterministic soil parameters as determined by the Department of Geotechnics. Based on realistic ranges of the occurring soil parameters derived from the executed laboratory tests and CPTs, global and local sensitivity analyses are performed to identify the key parameters for the settlement predictions. This step requires some engineering judgement as well. Subsequently, the chapter explains how the existing Python scripts and Orange workflows provided by IMDC can be adapted to process the soil data and derive statistical distributions for the identified soil parameters.

Chapter 5: Probabilistic (settlement) calculations develops a methodology to perform probabilistic calculations of the vertical soil settlement. The distributions of the key soil parameters identified through a sensitivity analysis and determined in chapter 4 are used as starting point. Latin hypercube sampling is applied to generate an initial small but well-distributed sample set, which is used as input for the numerical PLAXIS 2D model. The set of settlement curves generated by the finite element method model can then be used to train a response surface model that approximates the settlement response of the PLAXIS 2D model. This response surface model is then used to efficiently generate a large number of settlement curves with much less computational effort compared to the numerical calculations. Finally, this chapter discusses the implementation of Bayesian updating to incorporate real-world settlement data from the monitoring campaign and obtain improved settlement predictions.

The thesis is concluded with a discussion on the key findings, their relevance to geotechnical design practice, recommendations for future research and for the practical implementation of probabilistic methods.

Supporting materials and supplementary analyses are provided in the appendices.

The python scripts developed during this research are available on GitHub ([github.ugent.be](https://github.com/ugent.be)) and can be used as a starting point for future applications of probabilistic geotechnical calculations in PLAXIS 2D: https://github.com/ugent.be/labo-geotechniek/msc_thesis_thibo.

1 General introduction

2

Project Groot Schoor Bornem

The site Groot Schoor in Bornem, presented in Figure 2.1, will be the common thread throughout this research project. This chapter starts with an introduction to the site in which reference is made to the historical background of this area and the recent construction works that have been executed. The chapter continues with a description of the cross-sectional geometry and design of the new Scheldt dike, which is the subject of interest in this research. Furthermore, an overview of the site investigations and laboratory tests executed by the Flemish Department of Geotechnics in the framework of the construction of the new dike is given. Also the different construction stages in the construction process of the new dike are discussed. The chapter concludes with a description of the geotechnical monitoring campaign that has been executed to track the settlement behaviour at certain critical cross-sections of the new dike.

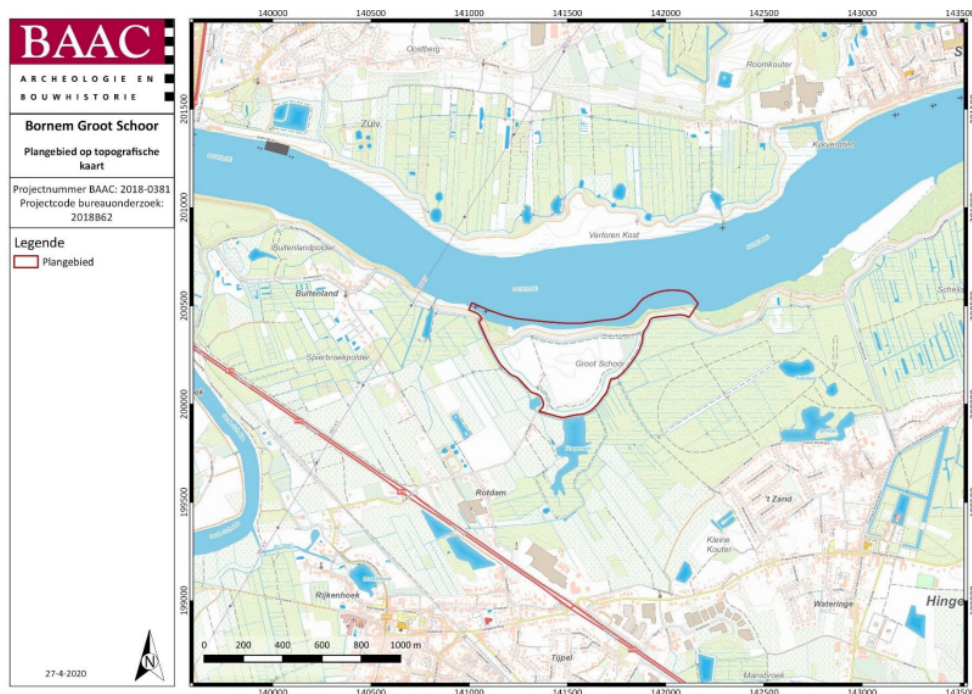


Figure 2.1: Groot Schoor Bornem on a topographical map (Cornelis et al., 2020)

2 Project Groot Schoor Bornem

2.1 Introduction to the Groot Schoor site

The Groot Schoor is an area along the tidal part of the river Scheldt. The site has a long-standing tradition of water management and land reclamation efforts, rooted in the Middle Ages. At that time, the first dikes were established alongside the Scheldt to prevent seasonal flooding and to reclaim land from the Scheldt's marshes and turn it into productive agricultural land. Over the centuries, these protective dike structures evolved in response to severe flooding events that reshaped both the surrounding landscape as well as the approach to flood protection in the region. This gradually resulted in a system of summer and winter dikes.



Figure 2.2: Cross-section of the old winter dike on the Groot Schoor site (Bosmans, 2022)

As part of the current efforts to enhance flood resilience in the framework of Flanders' Sigma-plan, significant construction works have been executed at this site. These constructional improvements aim to protect the land from rising water levels and adapt the dike system to modern flood protection standards while preserving the historical essence of the Groot Schoor area.

In the paragraphs below, a historical overview of the site will be given in order to trace the development of its dikes and flood management strategies. The knowledge of the history of the site is important in order to understand the anomalies in the soil layer profile of the area. Furthermore, the scope of the most recent construction works on the Groot Schoor site will be explained in more detail.

2.1.1 History

2.1.1.1 Early Dike Construction and Expansion (11th - 16th century)

Friars built the first dikes to protect the low-lying lands along the Scheldt River, using simple materials like clay, reed and wood. However, the structures primarily served as summer dikes. Their main function was to protect the fields during the summer months, when the Scheldt is characterized by relatively low water levels.

2 Project Groot Schoor Bornem

By the 16th century, the dikes had been expanded to offer year-round protection, accommodating the needs of a growing population and increasing agricultural activity in the reclaimed lands. Notably, in 1552, a major breach in the Scheldt dike led to the formation of a large tidal pool known as the gully pool or *Kolkgat*. The latter originated from the water flowing in and plunging with tremendous force into the lower polder. The resulting blowout whole was deep and remained filled with water. Efforts to repair this dike breach involved the construction of a new horseshoe-shaped ring dike around the gully pool. This caused a curved trajectory of the dike structure and is one of the indicators to localize past dike breaches. During the 30-year period following the dike breach, siltation of the pool occurred and it gradually filled up with sediment deposits of clay and sand. Around 1586, the *Kolkgat* was almost completely silted up and it became possible to restore the original Scheldt dike in front of the ring dike (Cornelis et al., 2020). Due to the accreted material, the ground level between both dikes is higher than in the surrounding environment. It is located at about $+2.50\text{ mTAW}$. Furthermore, a thicker clay layer inside the Groot Schoor allows the land to be used for agriculture. At the landward side of the dike, two remnants of the breach remain: the large and small Kragewiel. An impression of the origin of the Kragewiel is represented in Figure 2.3 (Willaert, 2022).

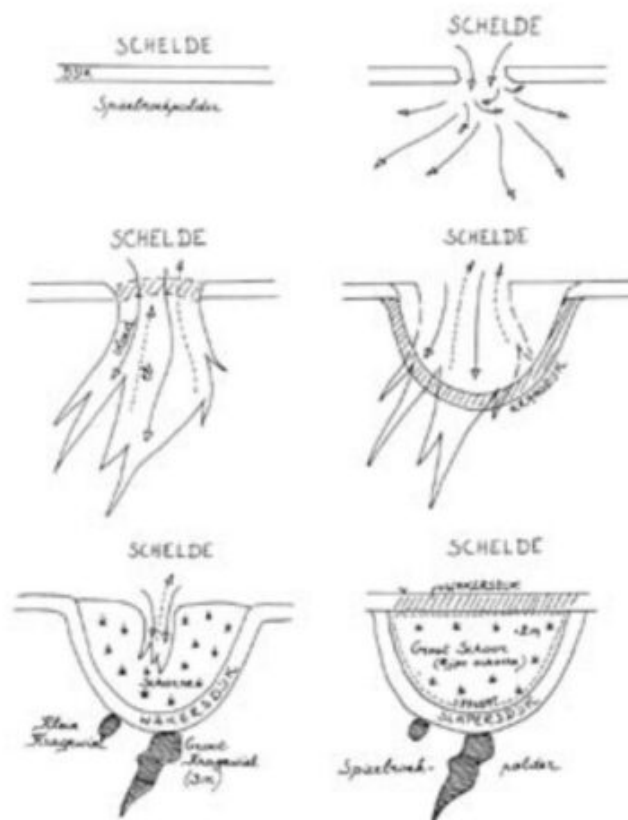


Figure 2.3: The origin of the Kragewiel

2 Project Groot Schoor Bornem

2.1.1.2 Dike reinforcement and maintenance (17th - 18th century)

Over the 17th and 18th century, regular maintenance and reinforcement of the dikes became essential as storm surges and tidal events increased in intensity. Dike construction during this period was influenced by the growing understanding of hydraulic engineering, as dikes were systematically elevated and widened to better withstand floodwaters (Couck, 2022).

2.1.1.3 Modern reinforcements and the Sigmaplan (20th century)

The 20th century brought significant developments in dike engineering in response to a series of severe floods, most notably the storms of 1953 and 1976.

The storm surge of 1953 caused some smaller breaches in the summer dike. These breaches caused the Groot Schoor to flood completely. Furthermore, a large breach was made in the winter dike or ring dike. As a result, the *Spierbroek* and *Hingenebroek* polders behind the ring dike were inundated for some time. As reaction, the dikes of the river Scheldt and Rupel were elevated over 0.50 m to 1.00 m until a level of about +7.75 mTAW in 1954.

During the storm of January 3, 1976, nine breaches occurred in the Groot Schoor near the severely weakened summer dike. The entire site was again under water, but the winter dike persisted. In 1978, new reinforcement works to the summer dike took place. The emphasis was mainly on the widening of the existing Scheldt dikes, resulting in less steep slopes (12/4 at the river side and 16/4 at the landward side of the summer dike) (Couck, 2022).

Under the Sigmaplan, introduced in the 1970s, Groot Schoor became part of a broader flood protection strategy encompassing the Scheldt's low-lying floodplain areas. This plan includes specific measures for flood zone creation and ecosystem preservation, ensuring that the dikes could function both as barriers and as ecological support systems, buffering the region from tidal surges while accommodating natural processes.

2.1.2 Recent construction works for the Groot Schoor site

The recent construction works have been executed in the framework of the Sigmaplan. The main goal of the project is the depoldering of Groot Schoor in order to give the Scheldt more space. In combination with the elevated ring dike, this yields a better protection of Bornem and its surroundings against flooding (Vlaamse Waterweg, 2024b). This and all the other projects in the Sigmaplan will finally result in lower flow velocities and a decrease of the high water levels upstream.

2 Project Groot Schoor Bornem

The construction works are executed in different phases. First the existing ring dike has been widened and strengthened. Also the crest level has been increased compared to the old dike. After finishing the ring dike, an opening will be made into the existing Scheldt dike in order to turn Groot Schoor into a FCA-CRT. This means that the site will be exposed to the tidal regime of the Scheldt. In that way, the ebb and flood will create an erratic landscape with deep channels, freshwater mudflats and salt marshes. These are typical for the intertidal area of the Scheldt, hence their restoration has a large ecological value. The working principle of an FCA-CRT is illustrated in Figure 2.4.

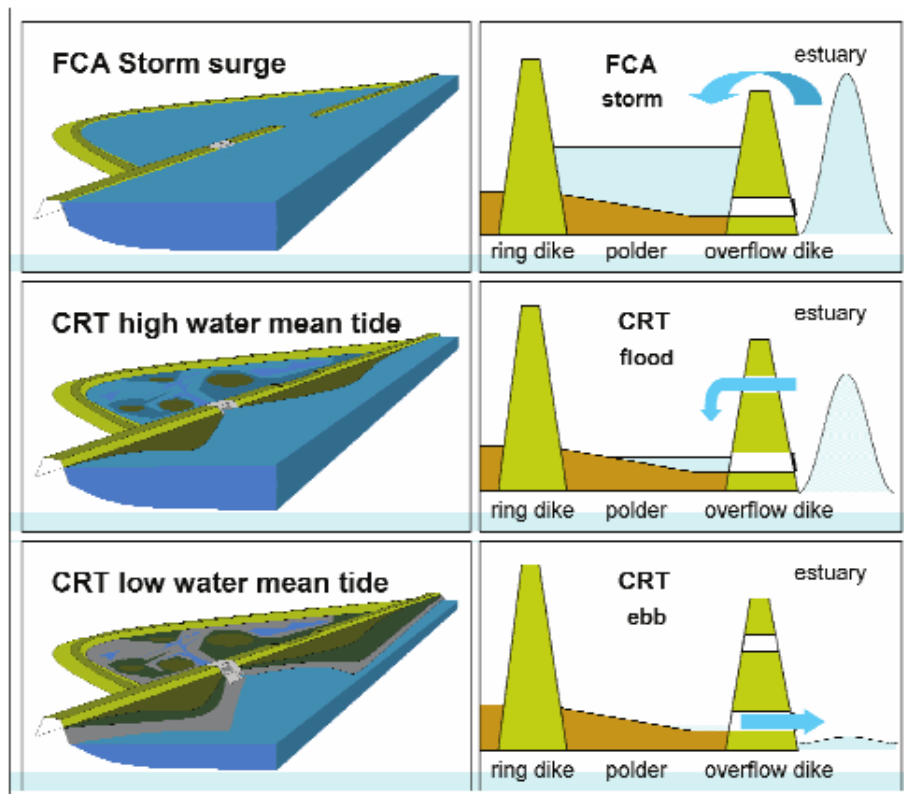


Figure 2.4: Working principle of an FCA-CRT (Peeters et al., 2015)

As a result, depoldering Groot Schoor serves two purposes: on the one hand, it prevents flooding by giving the Scheldt more room to flow and hence restores natural flood resistance. On the other hand re-development of tidal nature can take place, which not only has ecological benefits but also purifies water, increases biodiversity and buffers flooding naturally. A conceptual image on the execution of the Sigmaplan at Groot Schoor in Bornem is displayed in Figure 2.5.

2 Project Groot Schoor Bornem

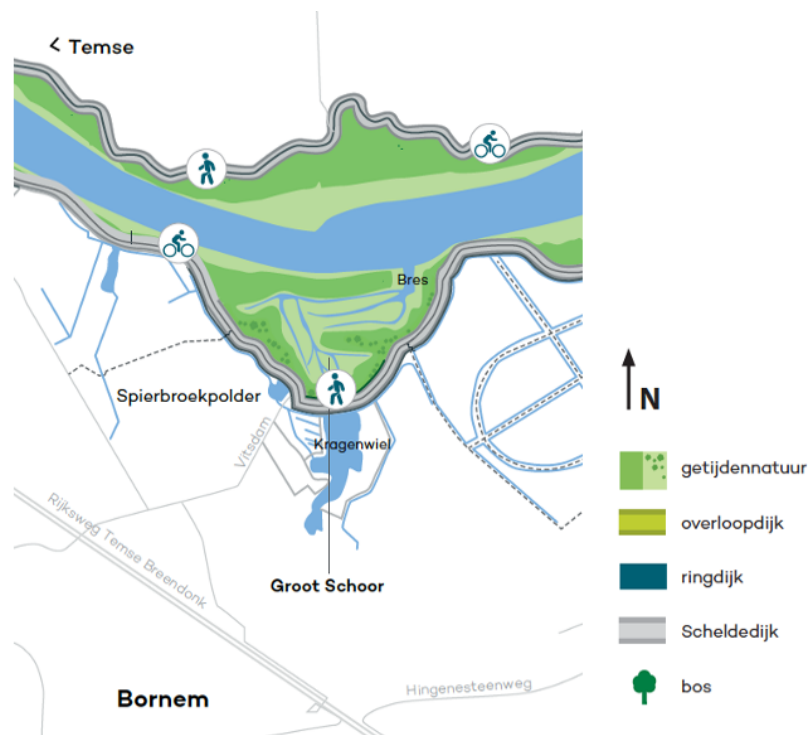


Figure 2.5: Sigmaphan at Groot Schoor Bornem

The following construction works have been executed to upgrade the ring dike: to improve flood protection, the existing ring dike at Groot Schoor has been subjected to a substantial elevation and widening the past few years. Additionally, an embankment covering from heavy clay and rip-rap stones has been constructed on the GOG side of the ring dike to further bolster stability of the dike. To preserve the historical value of the Groot Schoor site, parts of the original dike are preserved to a height of $+4.00\text{ mTAW}$ to $+5.00\text{ mTAW}$, honouring the site's heritage while supporting modern flood resilience. Additionally, incorporating the original clay dike into the new sand structure allows it to function as a water-resistant core. Finally, a drainage network is installed at the base of the landward slope to facilitate controlled water flow and reduce seepage pressure on the dike structure (Couck, 2022).

In sum, the planned construction works at Groot Schoor are a careful blend of engineering and environmental interventions. The project will ensure that Groot Schoor remains resilient in the face of future flooding events, fulfilling its dual role as both a historical landmark and a modern protective structure. Before diving into the profound study of the geotechnical aspects of the site, this section is concluded with some pictures of the site in its entirety in Figure 2.6. A view of the ring dike is given in 2.7 and the large and small Kragewiel are displayed in Figure 2.8 (Couck, 2022).

2 Project Groot Schoor Bornem



(a) River side view on the Kragewiel



(b) Land side view on the Scheldt River

Figure 2.6: Groot Schoor in Bornem



Figure 2.7: Aerial view on the new ring dike

2 Project Groot Schoor Bornem



Figure 2.8: Aerial view on the large and small Kragewiel

2.2 Cross-sectional geometry and design of the new Scheldt dike

The new dike around the Groot Schoor site is designed to meet the modern flood protection standards and to withstand the anticipated water levels in the coming decades. In this research project, the emphasis will be in first instance on a single cross-section of the new ring dike. The chosen cross-section is located near the large Kragewiel and is labelled as DP26 in the design nota of the Flemish Department of Geotechnics (Couck, 2022). In this text, the label DP26 will be adopted for the cross-section. However, in the execution plans of the contractor Aertssen, the considered cross-section is often given another name (DP3 or DP4) (Aertssen infra nv, 2022). The global execution plan is attached in attachment A. The final design plan of cross-section DP26 is displayed in Figure 2.9.

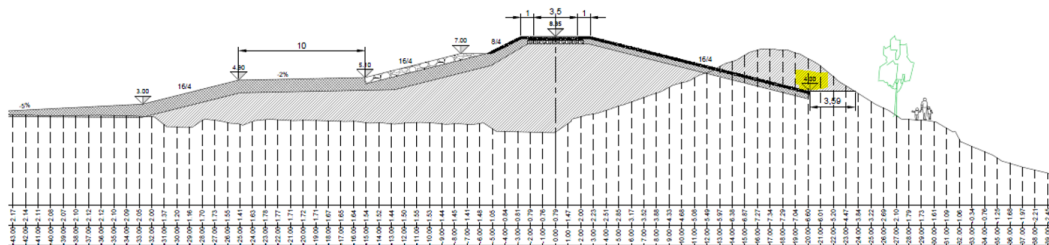


Figure 2.9: Design plan of cross-section DP26

There are multiple reasons for the choice of DP26 as the most interesting cross-section in this thesis about probabilistic geotechnical calculations. First of all, the cross-section is located near the large Kragewiel, which is a remnant of the old dike breach in 1552. The presence of the Kragewiel has a significant impact on the soil layer profile, characterized by a thick and soft clay layer that is not present everywhere in the surrounding environment. This clay layer is present until a depth of about -7.70 mTAW (CPT GEO-19/108-S103). The presence of the Kragewiel at the landward side of the dike results in less support of the soil. As a consequence, DP26 is the cross-section in which settlements are calculated to be most critical. In the nota of the Geotechnics Department, the final settlement in DP26 has been estimated to reach a value of 0.82 m after a period of about 10 months (Couck, 2022).

Furthermore, DP26 is well-instrumented with monitoring devices. A lot of settlement measurement data has been collected in that region throughout the construction process. This high data availability makes the cross-section very suitable for a probabilistic analysis in which updating can be performed.

The design plan of cross-section DP26 (Figure 2.9) is characterized by a crest level of $+8.35 \text{ mTAW}$ and a crest width of 5.50 m . At the river side, the dike has a slope of $12/4$ above $+7.00 \text{ mTAW}$ and $16/4$ below $+7.00 \text{ mTAW}$. Furthermore, a foreshore banket with a width of 10.00 m and a slope of 2% is constructed. This banket provides an ecological habitat while adding a stabilizing layer to the structure. It also helps in dissipating the incident wave energy during storms.

2 Project Groot Schoor Bornem

At the landward side, the slope is 8/4 above +7.00 *mTAW* and 16/4 below and another banket has been created by excavating the old dike until a level of +4.00 *mTAW* for slope stability reasons. This old clay winter dike had a crest level of +7.39 *mTAW*, a river side slope of 9.3/4 and a landward side slope of 6.6/4 (Couck, 2022).

The execution plan, enclosed in attachment A, is quite different from the design plan. The main reason for this is the fact that a soil replacement has been executed below the dike to limit the settlements. Furthermore, the new dike has been elevated until a level of +8.85 *mTAW* in order to ensure the final crest level of the dike to be at least at +8.35 *mTAW* after settling of the soil. This results in increased slopes of the taluds of the actual dike compared to the design.

2.2.1 Cross-section DP26

For the modelling in PLAXIS 2D, the execution plans of the contractor Aertssen are used. Since monitoring has been executed in DP26, the best way to validate the numerical model and update it in a realistic way with real-life on-site data is by modelling the dike as it has been executed. A schematic representation and dimensioning of the studied cross-section DP26 is given in Figure 2.10. On this figure, the different soil layers are displayed as well. Sandy soils are represented by yellow-orange coloured layers, while clayey soils are represented by purple-blue layers. The division of the subsoil in different soil layers is based on the layering found from CPTs and adopted from the design and study nota of the Flemish Department of Geotechnics (Couck, 2022). In Chapter 4, the soil layering will be refined further. As can be seen, a thick layer of clay is present below the old winter dike, which is of a clayey material as well. Since parts of this clay layer have been preconsolidated due to their presence underneath the old winter dike for centuries and properties may have changed due to the accretion of material at the GOG side of the dike, the clay layer is divided into three parts with each their own properties: layer S, layer E and layer Ebis. The figure also shows the addition of the new dike in several layers. This has to do with the construction stages and will be explained in more detail in section 3.5.

The cross-section is drawn in such a way that the geometry of the old dike, new dike and all intermediate construction phases can be modelled by excluding or including layers from the upper part of the figure. On Figure 2.10, red dimensions above and below the cross-section are distances given in meters, while blue dimensions are levels given in meters TAW. The red numbers on the figure indicate the steepness of the slopes.

2 Project Groot Schoor Bornem

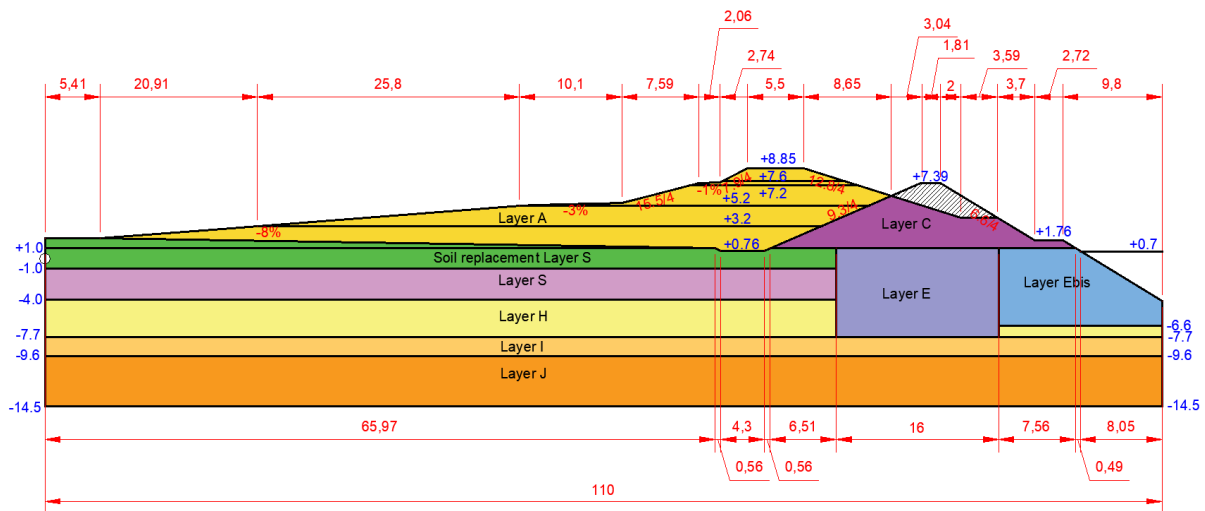


Figure 2.10: Dimensions of cross-section DP26 used for the numerical model

2.2.2 Soil replacement layer S

On Figure 2.10, there is one soil layer hatched in green. This is the upper part of the very soft, non-preconsolidated and accreted clay layer S. As stated before, layer S will be responsible for most of the settlement of the dike and in cross-section DP26, a final settlement of 0.82 m can be expected according to the geotechnical calculation nota (Couck, 2022). To limit this settlement and accelerate the consolidation process, it has been decided during execution to replace part of this layer S. From the execution plans of the contractor Aertssen, it can be observed that in the vicinity of DP26, a soil replacement has been executed until a depth of about -1.00 mTAW , as can be seen on Figure 2.11 and in attachment A. The green hatched layer on Figure 2.10 hence represents the soil replacement in layer S. The soil replacement material is a sandy soil with a higher stiffness than the original clayey soil (Aertssen infra nv, 2023).

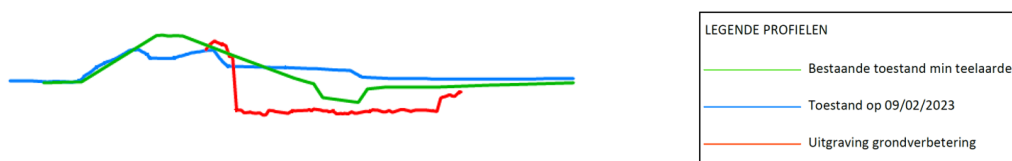


Figure 2.11: Soil replacement of layer S in cross-section DP26

In order to assess the quality of the soil replacement, CPT GEO-22/130-S203 near the large Kragewiel should be compared with earlier soundings taken before the soil replacement such as GEO-19/108-S111 near S203 and GEO-18/015-S12 in the old dike. On Figure 2.12, one can see a slightly higher cone resistance in the zone of $+1.00\text{ mTAW}$ to -1.20 mTAW (see red circle)

2 Project Groot Schoor Bornem

compared to the earlier soundings. This zone features two peaks reaching respectively 4 MPa and 6 MPa , separated by a weaker interval. This variability in cone resistance suggests a non-uniform compaction of the replaced soil and indicates a relatively poor quality. Consequently, the soil replacement cannot be modelled as a uniform layer and reduced soil parameters are used instead (Couck, 2024). The determination of the parameters of the soil replacement will be discussed in more detail in Chapter 4.

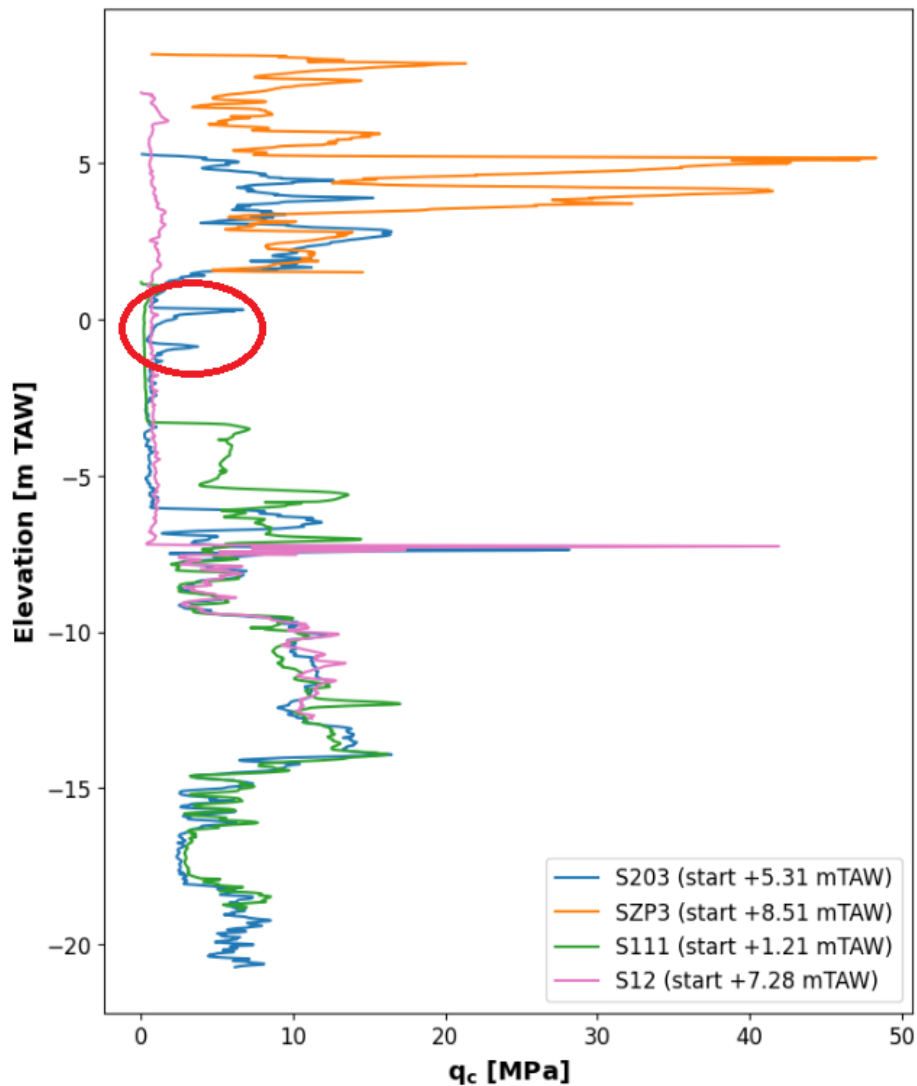


Figure 2.12: Evaluation of the soil replacement with CPT GEO-22/160-S203.

2.3 Geotechnical site investigation campaign

Before starting the design of the new dike, a geotechnical site investigation campaign has been executed by the Department of Geotechnics. The main goal is to obtain a detailed insight into the soil layer profile and soil characteristics (Vincke and Peeters, 2016) (Haelterman, 2008a) (Vincke, 2018) (Couck and Vincke, 2020). Furthermore laboratory tests have been executed on soil samples in order to determine the mechanical properties of the soil (Haelterman, 2008b), (Couck and Vincke, 2022). A summary of the tests, executed in Groot Schoor, that are of interest for the design of the new dike is given in Table 2.1. A global overview of the location of the CPTs and BHs executed on the entire site can be consulted in attachment B. An overview of the tests that are of interest for cross-section DP26 is given in Figure 2.13. In this figure the CPTs are labelled and displayed as orange dots. The BHs are displayed as green dots (Vlaamse overheid, s.d.).

Campaign	Campaign file	Subject	Relevant tests DP26
GEO-07	GEO-07/167	39 CPT (S)	
	GEO-07/168	10 BH (B)	1 GWT (PB)
GEO-12	GEO-12/128		
GEO-18	GEO-18/105	29 CPT (S)	S10, S11, S12, S13
GEO-19	GEO-19/108	12 CPT (S), 4 CPTu (SU), 6 VST (V), 4 GWT (PB)	V12, PB35, S103, V103, S104, S106, S107, V107, S108, S110, S110U, S111, S111U, V111, PB111, S112, S112U, V112, S113, V113, PB113
	GEO-19/109	6 BH (B)	B12, B35, B111, B113

Table 2.1: Geotechnical campaigns and relevant tests for DP26



Figure 2.13: Location of the CPTs (orange dots) and BHs (green dots)

2 Project Groot Schoor Bornem

2.3.1 In situ or field tests

2.3.1.1 Cone penetration tests (CPT)

CPTs are widely used in Flanders to investigate soil profiles by pushing a standardized cone into the ground at a constant rate of 2 cm/s . The test measures the cone resistance q_c and sleeve friction f_s , enabling the identification of soil layers and estimation of the soil's mechanical properties, such as effective cohesion c' and friction angle ϕ' , through established correlations.

At Groot Schoor, CPTu tests were also conducted, which include pore pressure measurements. These allow dissipation tests, where excess pore pressure, built up during penetration, is monitored as it dissipates. In sands, dissipation continues until the porewater pressure has fallen back to the hydrostatic pressure. For cohesive soils, this often takes hours to days and the test is mostly stopped when 50% dissipation is reached (t_{50}). Dissipation tests are used to determine the consolidation properties of the soil such as the hydraulic conductivity k and the coefficient of consolidation c_v .

2.3.1.2 Vane shear tests (VST)

VSTs measure the undrained shear strength of cohesive soils and assess compaction and disturbance effects. A shear vane is inserted in CPT holes at a standardized rate of $6^\circ/\text{min}$ until peak torque is reached (Couck, 2024). Then, eight to ten further revolutions determine the residual torque (Budhu, 2010).

2.3.1.3 Measurement of the groundwater table (GWT)

Groundwater levels are monitored via piezometers with filtered PVC tips and bentonite plugs to block surface water. Pressure loggers record data every 15 minutes. Near the large Kragewiel, the groundwater table fluctuates between $+0.80\text{ mTAW}$ and $+1.05\text{ mTAW}$, with a mean level of $+1.00\text{ mTAW}$. This is higher than the mean water level of the Kragewiel, which is $+0.67\text{ mTAW}$ (Couck, 2022). Tidal levels in the Scheldt range from $+0.50\text{ mTAW}$ at mean low water neap tide to $+6.00\text{ mTAW}$ at mean high water spring tide (Couck, 2024).

2.3.1.4 Boreholes (BH)

Undisturbed and disturbed soil samples were collected using Shelby tubes at various depths in the CPT holes for laboratory testing. These samples are used to determine the mechanical properties of the soil. The various laboratory tests will be discussed in the next section.

2 Project Groot Schoor Bornem

2.3.2 Laboratory tests

2.3.2.1 Triaxial (compression) tests

Triaxial compression tests assess shear strength and deformation on undisturbed cylindrical samples with a diameter of 35 mm. Typically, three samples are taken from a Shelby tube with a diameter of 100 mm. The sample is then enclosed between two porous stones, submerged in a water cel and loaded along the principal stress directions. Compression occurs if $\sigma'_1 > \sigma'_3$ and extension if $\sigma'_1 < \sigma'_3$. σ'_1 is the principal stress that results from the hydrostatic cel pressure and vertical load P_z applied on the cel and σ'_3 occurs due to the horizontal hydrostatic cel pressure. The test is executed under different conditions (Budhu, 2010):

- **Consolidated drained triaxial tests (CD-TX):** determines long-term drained parameters ϕ' , ϕ'_{cs} and moduli E' , E'_s . The sample is consolidated isotropically, followed by a shear phase with constant cel pressure and increasing vertical load P_z .
- **Consolidated undrained triaxial tests (CU-TX):** measures both drained and undrained parameters c_u , ϕ' and ϕ'_{cs} . The test is executed in the same way as a CD-TX, but the isotropic consolidation is followed by an increase of P_z in undrained conditions and the change in porewater pressure is measured as well.
- **Unconsolidated undrained (UU) test:** measures undrained cohesion c_u and modulus E_u . No consolidation occurs before rapid shear in undrained conditions. Therefore, only an isotropic supporting stress is applied on the sample before the vertical load P_z is increased quickly, since no drainage is allowed.

2.3.2.2 Oedometer consolidation tests

The oedometer test simulates 1D compression, restricting lateral deformation. Vertical loads are applied incrementally on a saturated sample in a rigid ring. Each load increment is maintained until the sample has fully consolidated. After the maximum load, the unloading phase may be conducted to evaluate the unloading/reloading behaviour of the soil. The test results in the determination of the compression index C_c , the recompression index C_r and the coefficient of consolidation c_v , which allows to determine the permeability of the soil k . Also the pre-consolidation pressure can be determined, which is the maximum historical stress experienced by the soil (Budhu, 2010).

In the design nota of the Flemish Department of Geotechnics, the compression characteristics of the soil are summarized into a parameter called the Flemish compression coefficient C . This parameter is related directly to the settlement of the soil ρ_{pc} and can be linked to the compression index C_c as well (Couck, 2022).

$$\rho_{pc} = H_0 \cdot \frac{\Delta e}{1 + e_0} = \frac{H_0}{1 + e_0} \cdot C_c \cdot \log \left(\frac{\sigma'_{z,f}}{\sigma'_{z,0}} \right) = \frac{H_0}{C} \cdot \ln \left(\frac{\sigma'_{z,f}}{\sigma'_{z,0}} \right) \rightarrow \frac{C_c}{1 + e_0} = \frac{2.3}{C} \quad (2.1)$$

2 Project Groot Schoor Bornem

2.3.2.3 Permeability tests

The permeability k of the soil can be determined by means of various tests:

- **Triaxial test:** by allowing water to flow through a saturated soil sample in a triaxial cell under controlled hydraulic gradients, the flow rate and pressure drop are measured to determine the permeability of the soil by using Darcy's law.
- **CRS-tests:** the porewater pressure and vertical strain during a constant rate of strain test are recorded. Using these values, the permeability (in function of the effective stress) is back-calculated based on the consolidation rate.
- **Oedometer tests:** allow to derive the coefficient of consolidation c_v of the soil. The permeability can be calculated by the following relation $k = c_v \cdot m_v \cdot \gamma_w$, in which m_v is the modulus of volume compressibility of the soil and γ_w is the specific weight of water.
- **Slug tests (sandy soils):** when a sudden change in water level is induced in a piezometer and the rate of recovery is observed, the horizontal permeability can be determined by using analytical solutions such as the Bouwer-Rice or Hvorslev method (Bouwer and Rice, 1976).
- **Grain size distribution (sandy soils):** empirical formulas such as the Hazen formula can be used.
- **Dissipation tests during CPTs:** k can be derived from the time to 50% pore pressure dissipation during a CPTu.

For cohesive soils, the most suitable method to determine the permeability of the soil is a triaxial test. Followed by CRS tests, dissipation tests and oedometer tests. For cohesionless soils, the most suitable method to determine the permeability of the soil is a slug test. However, the slug test determines rather a horizontal permeability. A value for the vertical permeability of the soil can be obtained from the grain size distribution (Couck, 2022).

2 Project Groot Schoor Bornem

2.4 Geotechnical monitoring campaign

On request of De Vlaamse Waterweg, the Flemish governmental department responsible for the execution of the Sigmaplan, a geotechnical monitoring campaign has been executed by the Department of Geotechnics during the construction of the new dike in order to track the settlement behaviour at certain critical cross-sections.

The need for a monitoring campaign emerged from the fact the site investigation and the initial design calculations predicted the occurrence of large settlements due to the presence of a very soft clay layer prone to consolidation. By monitoring the settlements, the effectiveness of the soil replacement carried out in specific zones under the dike can be evaluated. Moreover, monitoring enables to verify the design assumptions and helps to ensure the long-term reliability of the dike. Finally, it allows the comparison of actual settlements to predicted values derived from design calculations and potential anomalies, such as differential settlements and deviations from expected trends, can be detected.

The geotechnical monitoring campaign for the Groot Schoor project includes a combination of topographic surveys and settlement measurement devices. These instruments were only installed after the dike construction had already begun. This means part of the early settlements could not be captured. Nevertheless, the campaign provides valuable insights into the progression of soil consolidation and settlement behaviour. The results of the campaign serve as basis for:

1. Validating settlement predictions from the design phase.
2. Assessing the effectiveness of soil replacement measures.
3. Updating probabilistic settlement predictions with real-world data.

The location of the various devices installed on the site in Bornem can be consulted in attachment C. The attachment includes a global overview of the monitoring devices on the site Groot Schoor as well as a detailed overview of the monitoring devices in DP26.

2.4.1 Monitoring instruments and techniques

The geotechnical monitoring campaign for the dike reinforcement project employs a variety of instruments and techniques to track vertical settlements of the subsoil during and after dike construction. The combination of tools ensures accurate and large amounts of measurement data. The primary instruments used in the considered campaign are settlement plates, settlement beacons and horizontal settlement pipes. Each instrument serves a specific purpose, enabling data collection at different spatial and temporal scales. The setup and execution of these techniques are described below (Couck, 2024). An overview of the relative positioning of the monitoring devices in DP26 is given in Figure 2.14.

2 Project Groot Schoor Bornem

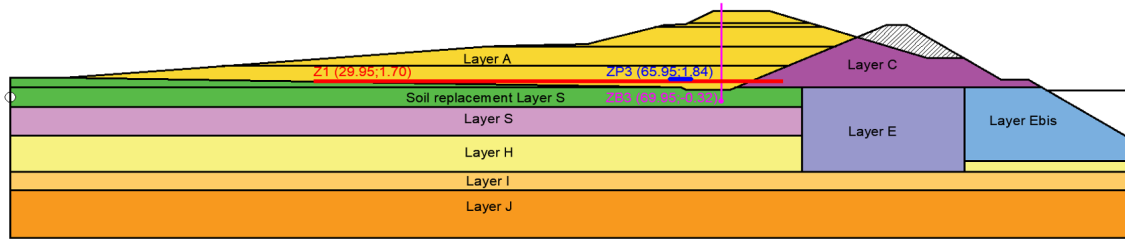


Figure 2.14: Relative positioning of the monitoring devices in DP26

2.4.1.1 Settlement plates

Settlement plates are square concrete plates ($2.00\text{ m} \times 2.00\text{ m}$) installed at the base of the dike embankment to measure vertical settlements at specific locations (Couck, 2024).

- **Installation and setup:** a total of four settlement plates (ZP1-ZP4) were installed on the project site. The plates were placed on the existing ground surface after the start of the dike embankment works, which means initial settlements prior to installation were not recorded. The plates are located at an approximate elevation of $+2.00\text{ mTAW}$. The plate near the large Kragewiel is labelled as ZP3 and is of particular interest in this research.
- **Monitoring method:** settlement is monitored by performing a CPT at the centre of each plate at various construction stages. The CPTs on the four settlement plates were executed on 04/07/2024 and 05/07/2024. At that time the elevation level of the dike was approximately $+8.50\text{ mTAW}$. By comparing the measured depth of the plates at the time of installation with the depth measured on the CPT, in which the concrete plates can be recognized as a sudden huge increase in cone resistance, the settlements can be calculated. For ZP3, a settlement of 0.33 m was measured. Since the Sigmaplan requires an elevation of the dike of $+8.35\text{ mTAW}$, the measured settlement resulted in the decision to further elevate the dike until $+8.85\text{ mTAW}$ to compensate for the settlement.
- **Purpose:** settlement plates provide localized and very accurate settlement measurements and serve as reference points to assess the compaction degree of the dike. The latter should satisfy the conditions imposed by SB260. On previous Figure 2.12, it can be seen from a comparison of CPT S203 (executed in 2023, when the new dike was partially elevated) and CPT SZP3 (performed in 2024, after reaching $+8.50\text{ mTAW}$) that the new dike globally has a large cone resistance and is hence well to very well compacted. Here, the CPTs were performed before the construction works were finished and before the settlements of the subsoil were stabilized. Hence, the measurements obtained from the settlement plates will not be used in the probabilistic calculations.

2 Project Groot Schoor Bornem

2.4.1.2 Settlement beacons

Settlement beacons are topographically surveyed markers installed to measure surface settlements over time (Couck, 2024).

- **Installation and setup:** a total of four settlement beacons (ZB1-ZB4) were installed near the dike embankment. The beacons consist of plates below the dike on which square steel profiles of 2.00 *m* are attached. As the dike height increases, the profiles are extended stepwise with extension pieces of 2.00 *m* to ensure visibility throughout the monitoring campaign. Initial zero measurements were taken on 09/02/2023, again after the start of the dike embankment works. Since the emphasis of this thesis is on DP26, ZB3 is of particular interest.
- **Monitoring method:** topographic surveys have been performed at regular intervals (simultaneously with the settlement pipe measurements) to record the elevations of the soil surface. The results were adjusted for ongoing settlements at the origin points due to being located below the embankment, in the dike's influence zone.
- **Purpose:** settlement beacons provide elevation-settlement trends that can be used both for distinguishing several elevation and consolidation stages during construction as well as measuring the settlement below the dike. Since monitoring occurred at the same time intervals as for the settlement pipes, both measurements can be compared and are complementary to each other.

2.4.1.3 Horizontal settlement pipes

Horizontal settlement pipes are specialized instruments used to measure vertical settlements continuously along the length of the dike. These pipes offer a higher spatial resolution compared to settlement plates and beacons (Couck, 2024).

- **Installation and setup:** two horizontal settlement pipes, Z1 and Z2, were installed beneath the dike embankments at the GOG side of the dike until the core of the new dike, which is the partially excavated old winter dike. Z1 is located near the large Kragewiel, where severe settlements are expected and therefore a significant soil replacement of the upper part of the soft clay layer has been performed. Both pipes were installed at elevations between +1.70 *mTAW* and +2.10 *mTAW* and terminate at a reference point (a rainwater pit). Z1 has a length of 46.00 *m*.
- **Monitoring method:** on regular intervals, the settlement pipes have been surveyed to measure the vertical settlements along the dike axis. These measurements include towing an inclinometer probe through the pipe using a pulley, while recording its inclination. This inclination then allows to calculate the exact position of the pipe in a vertical plane. The measurements are taken at the same time intervals as the settlement beacons.

2 Project Groot Schoor Bornem

- **Purpose:** horizontal settlement pipes provide detailed settlement profiles along the dike axis, which can be used to identify localized settlement anomalies and assess the effectiveness of soil replacement measures. The data obtained from the pipes can be used to update the geotechnical model and refine the probabilistic calculations.

2.4.2 Results of the monitoring campaign

As mentioned earlier in this chapter, the further research will focus on the settlement behaviour at the critical cross-section of the new dike near the large Kragewiel. It has also been highlighted in the previous section that the monitoring results of the settlement beacons and horizontal settlement pipes are most valuable for further use in validating the numeric model and updating the probabilistic calculations. As a consequence, this paragraph only provides an overview of the monitoring results of settlement beacon ZB3 and settlement pipe Z1.

Settlement beacon ZB3 Figure 2.15 shows the results of the monitoring campaign for the settlement beacons. The graph shows the evolution of the vertical settlement, displayed on the vertical axis, over time. In total, 17 measurements have been executed. Surveys have been performed about every two months, with the first measurement taken on 09/02/2023 and the last one on 11/02/2025. The measurements taken at settlement beacon ZB3, near the studied cross-section are displayed as grey dots connected with a full grey line. The graph shows a much larger final settlement value at ZB3 compared to the other beacons. On 28/11/2024, a settlement of 0.37 m has been measured. On top of that, it can be observed that in contrary to the settlement evolution of ZB1, ZB2 and ZB4, which seem to flatten out (creep phase), the settlement of ZB3 is still increasing strongly and no flattening out can be observed. This means the primary consolidation phase was still going on in the subsoil at the moment of this measurement. For this reason, an additional measurement has been executed on 11/02/2025. This last measurement does show flattening out of the settlement behaviour.

The graph in Figure 2.15 also shows the settlement of the reference points of the settlement pipes. These reference points are the rainwater pits located on the GOG side of the dike, where the inclinometer probe measurements start. For the reference point of settlement pipe Z1, measurements are shown as grey dots connected by a dotted line. In contrast to the similar settlement trends of ZB2 and the reference point of Z2 (both shown in green), the settlement evolution and final settlement of ZB3 and the reference point of Z1 differ significantly. As shown in the maps in attachment C, which depict the monitoring device locations, the distance between the settlement beacon and the corresponding reference point is quite large at both the small (ZB2 and Z2) and large Kragewiel (ZB3 and Z1). Since the settlement measured by ZB2 is much smaller than the one measured by ZB3, it can be concluded that the subsoil in the cross-section of the dike near the small Kragewiel is less compressible than near the large Kragewiel.

2 Project Groot Schoor Bornem

Additionally, the larger settlement observed at ZB3 compared to the reference point of Z1 is logical, as soil beneath the dike crest (near ZB3) is subject to greater compression. The presence of a very soft clay layer beneath the dike near the large Kragewiel further explains the significant settlement observed. Near the small Kragewiel, however, the settlement values at ZB2 and the reference point of Z2 are nearly identical. Although one might expect greater settlement beneath the dike, this can be attributed to the absence of highly compressible clay at ZB2 and Z2 (and Z1), in contrast to ZB3. Furthermore, a slight elevation near the reference point of Z2 helps explain the consistent settlement behaviour of ZB2 and Z2 (and Z1), which contrasts with that of ZB3. A last comment on the graph in Figure 2.15 is that the first measurement took place on 09/02/2023, which is about 5 months after the actual start of the dike embankment works. This means that the initial settlements of the subsoil were not captured. The settlement values on all other monitoring dates are relative to the settlement value measured on 09/02/2023. The actual settlement of the subsoil in the vicinity of settlement beacon ZB3, observed during the last measurement on 11/02/2025, is therefore larger than the measured 0.37 m (Couck, 2024).

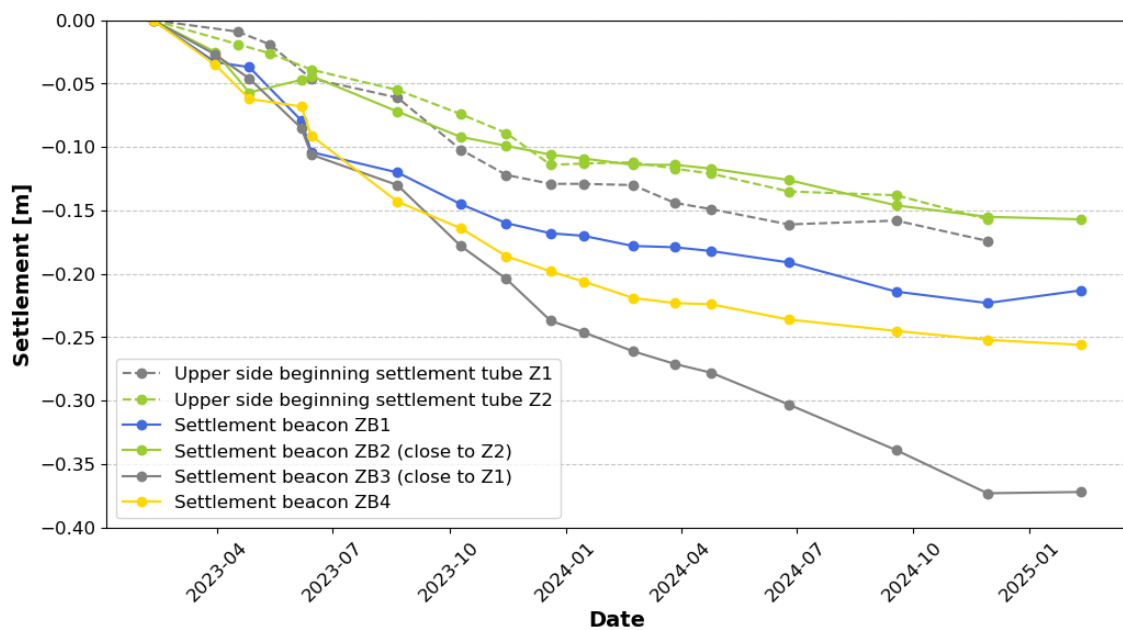


Figure 2.15: Results of the monitoring campaign for settlement beacons

Horizontal settlement pipe Z1 Figure 2.16 shows the settlement profiles below the studied cross-section of the dike relative to the zero measurement conducted on 09/02/2023. On Figure 2.16, the position of ZB3 is indicated with a vertical green line. The final settlement value measured with the inclinometer probe in Z1 at the position of ZB3 is 0.42 m , which is 0.05 m larger than the value found from the point measurement at ZB3. This difference can be attributed to the fact that there is both a transverse distance of about 16 m and a vertical distance of about 2 m between the settlement pipe Z1 and settlement beacon ZB3.

2 Project Groot Schoor Bornem

As mentioned earlier, the settlement pipe Z1 starts in a reference point at the GOG side of the dike and continues until the old winter dike, which forms the impermeable clay core of the new dike. This core is located just landward of the crest of the dike. This can be seen on Figure 2.16 in the fact that the settlement profile already reached its peak before the end point.

When taking a closer look at the results of the last measurement campaigns, it can be observed that settlements at the GOG side of the dike measured on 04/06/2024 and 17/09/2024 don't differ much. This may be an indication that the primary consolidation phase has been completed at that point, roughly two years after the start of the construction works. However, at about 20.00m from the the start of Z1, a sudden jump arises in the settlement profile. As a consequence, a large increase in vertical settlement below the crest of the dike can be observed between the measurement of 04/06/2024 and 17/09/2024. It indicates that the primary consolidation phase below the dike crest is in contrary to the GOG side of the dike, still ongoing. This is in contradiction to the predictions calculated in the design notes of the Department of Geotechnics. As a consequence, an extra measurement campaign has been executed on 28/11/2024, just before demolishing the rainwater pit used as starting point of Z1. When observing the results from this last measurement, it can be seen that there is again an increase in the settlement at the GOG side of the dike, while the settlement below the crest of the dike has been stabilized now. This is a strange observation, which arises the presumption that the jump in the settlement profile measured on 17/09/2024 might be a measurement error. This observation has been confirmed by the Geotechnical Department.

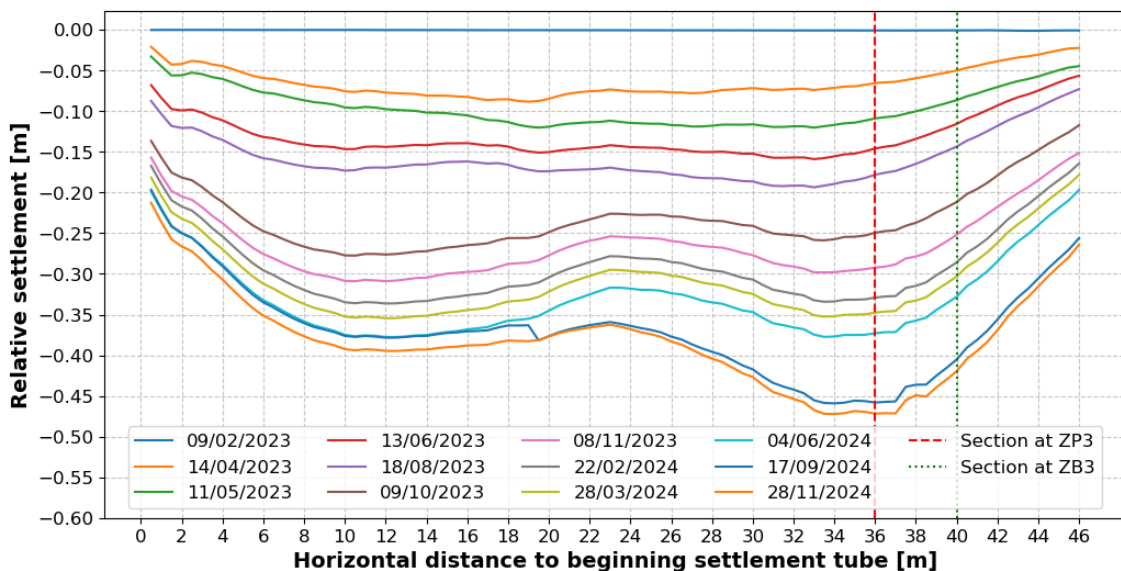


Figure 2.16: Monitoring results for horizontal settlement pipe Z1, relative to zero measurement

2.5 Stages during the construction of the new dike

The construction works have been executed in carefully structured stages to ensure the safety, stability and performance of the new Scheldt dike. The construction started on 01/10/2022 and continued until the end of 2024. Since there was no need to hurry the construction works, a rather slow approach has been adopted in agreement with the contractor Aertssen. This means the construction process has been divided into a series of elevation phases with consolidation phases in between. Each elevation phase applies an additional load on the underlying soil, resulting in settlements. The subsequent consolidation phases allow for the dissipation of pore water pressures and settlement stabilization. The big advantage of this approach is that the soil can consolidate (partly) before the next elevation phase starts. This is essential to avoid significant differential settlements, slope instabilities and unexpected soil behaviour in the soft clay layers and it ensures the long-term stability of the dike in the settlement prone region. Another advantage of this approach is that the soil behaviour can be monitored closely during the construction process.

2.5.1 Actual construction phases

In Figure 2.17, the evolution of the dike elevation in time is displayed. The vertical axis of this graph shows the vertical elevation of the dike in meters TAW and the horizontal axis represents the time. This graph is based on the monitoring results of the settlement beacons (ZB1-ZB4). The stepwise increase in elevation corresponds to the elevation phases, while the plateaus indicate consolidation phases. Since this research focuses on the critical cross-section of the dike near the large Kragewiel, the evolution of the dike elevation at ZB3, displayed in grey, is of particular interest. It can be observed that roughly five elevation phases can be distinguished in the construction process of DP26. In the first elevation phase, the dike reaches a level of $+3.20 \text{ mTAW}$. The second elevation phase brings the dike to $+5.20 \text{ mTAW}$. The third elevation phase increases the dike elevation to $+7.20 \text{ mTAW}$. The fourth elevation phase brings the dike to $+7.60 \text{ mTAW}$. The final elevation phase increases the dike crest to a level of $+8.85 \text{ mTAW}$. Each elevation phase is followed by a consolidation phase, except elevation phase 1. Consolidation phase 4, which follows elevation phase 4 has the longest duration in reality. This is because the construction works were put on hold in the spring of 2023 due to the rainy weather. Based upon the graph in Figure 2.17, Table 2.2 is created. This table summarizes the construction phases and their duration and will be used in Chapter 3 to model the construction phases in PLAXIS 2D.

2 Project Groot Schoor Bornem

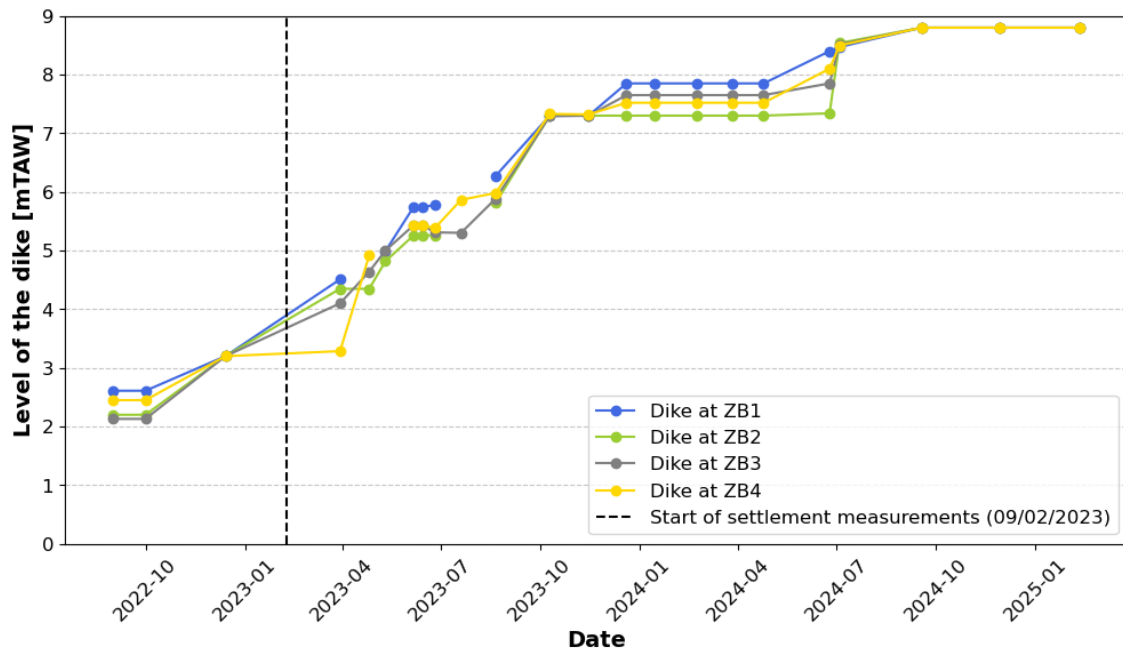


Figure 2.17: Evolution of the dike elevation in time, measured at the settlement beacons

Table 2.2: Construction phases timeline and duration

Construction Phases	Duration [days]	From	Until
Initial phase			
Excavation and soil replacement	34	01/10/2022	04/11/2022
Elevation phase 1	39	04/11/2022	14/12/2022
Consolidation phase 1	1	14/12/2022	14/12/2022
Elevation phase 2	138	14/12/2022	01/05/2023
Consolidation phase 2	75	01/05/2023	15/07/2023
Elevation phase 3	78	15/07/2023	01/10/2023
Consolidation phase 3	40	01/10/2023	10/11/2023
Elevation phase 4	35	10/11/2023	15/12/2023
Consolidation phase 4	199	15/12/2023	01/07/2024
Elevation phase 5	71	01/07/2024	10/09/2024
Consolidation phase 5	154	10/09/2024	11/02/2025
TOTAL	864		

3

PLAXIS 2D modelling

The numerical analysis of the new dike on the Groot Schoor site at cross-section DP26 is conducted using PLAXIS 2D, a specialized finite element software designed for geotechnical applications. PLAXIS 2D is well-suited for modelling soil-structure interactions and is widely used to assess slope stability, groundwater flow and the stress-strain behaviour of geotechnical constructions. It operates in a two-dimensional plane strain or axisymmetric configuration, enabling realistic simulations based on representative cross-sections of the project area.

This study utilizes PLAXIS 2D Ultimate, the most advanced version of the software. It provides extended capabilities such as advanced constitutive soil models, staged construction simulation and consolidation analysis (PLAXIS, 2024a).

The use of PLAXIS 2D inherently involves several assumptions that underpin the numerical analyses (PLAXIS, 2024c) (PLAXIS, 2024d):

- Plane strain conditions are applied (as opposed to axisymmetric).
- Deformations are assumed to be small relative to the structural dimensions.
- The soil is treated as continuum and is homogeneous within each finite element.
- Elastic-plastic soil behaviour is modelled under loading. Advanced soil models can include strain-hardening, creep and small-strain behaviour on top of this general assumptions.
- Effective stress principles are used: the total soil stress is separated into an effective stress and a pore water pressure.
- Groundwater flow is modelled using Darcy's law, in steady-state or transient conditions.
- Incremental loading and staged construction are supported to capture time-dependent processes such as consolidation and creep.
- PLAXIS 2D performs non-linear analyses using the iterative quasi-Newton-Raphson method to ensure convergence. Convergence criteria are used to determine whether the solution is sufficiently accurate. These criteria are typically based on the relative changes in displacements, stresses and pore pressures between successive iterations.

3 PLAXIS 2D modelling

The modelling process in PLAXIS 2D follows five essential steps. Each stage contributes critically to the accuracy and reliability of the simulation. The five steps will be elaborated in detail in the different sections of this chapter. However, a short overview of the steps is given below:

1. **Soil:** modelling begins with defining the soil stratigraphy using borehole data. Each soil layer is assigned a specific material model based on its properties. These models include parameters such as stiffness, strength and initial stress state.
2. **Structures:** geotechnical structures such as dikes, retaining walls and other relevant elements are modelled next. Each structure is defined with appropriate material properties, boundary conditions and loading scenarios to ensure realistic interactions within the soil domain.
3. **Mesh:** the geometry is discretized using a finite element mesh, over which PLAXIS 2D solves the governing equations. To enhance accuracy without compromising computational efficiency, the mesh is carefully refined in regions anticipated to undergo high stress concentrations or significant deformation gradients.
4. **Flow conditions:** groundwater conditions are established by defining the phreatic surface, pore pressure distributions and boundary conditions. These are crucial for analysing dike stability and evaluating seepage and pore pressure development in the soil.
5. **Staged construction:** the final step involves defining the construction sequence, including incremental loading and structural build-up. This staged approach enables the simulation of time-dependent processes such as consolidation and creep settlements, offering a realistic view of dike performance over time.

3.1 Soil

The first step in modelling the new dike in PLAXIS 2D involves defining the soil stratigraphy and assigning appropriate soil properties to each layer. The required soil parameters depend on the constitutive model selected to represent the behaviour of each layer.

3.1.1 Soil stratigraphy

As highlighted in the previous chapter, this study focuses on cross-section DP26 of the new dike at the depoldered Groot Schoor site in Bornem. This section is located directly adjacent to the prominent Kragewiel. The subsoil in this south-western part of the site is characterized by a surface layer of soft clay, formed by sediment deposition after a historical dike breach. At greater depths, the stratigraphy transitions to sandy layers. The geotechnical site investigation report provides a proposed stratigraphic profile for DP26 (Couck, 2022). This includes a subdivision of the surface clay layer into three distinct layers: layer S, layer E and layer Ebis.

3 PLAXIS 2D modelling

This subdivision reflects differences in clay properties resulting from the historical dike construction and flood events context.

- **Layer E:** this layer lies beneath the old dike and consists of clay used to fill a tidal gully following a dike breach. On the one hand, the clayey material probably has some altered characteristics compared to the original clay surface layer. On the other hand, the weight of the dike and the passage of time has preconsolidated this layer over several centuries, likely increasing its stiffness and shear resistance.
- **Layer Ebis:** this layer is similar in origin to layer E, as it also results from the fill of the tidal gully. However, it is situated beside the old dike, meaning it was not subjected to preconsolidation. Consequently, it has lower resistance characteristics than layer E.
- **Layer S:** this layer forms the surface clay layer on the GOG side of the dike. Unlike E and Ebis, layer S is composed of accreted material deposited naturally during site flooding, after the old dike was built but before the Scheldt dike was repaired. It was not artificially filled and its properties differ accordingly.

An additional note on the soil stratigraphy relates to the absence of the sandy layer H beneath the old dike. This is likely due to human intervention during dike construction. Layer H, presumed to have a sloped geometry and potentially unstable characteristics, may have been intentionally excavated to allow foundation of the dike on the more competent layer I, enhancing overall stability.

The soil stratigraphy proposed by the geotechnical nota is displayed in Figure 3.1.

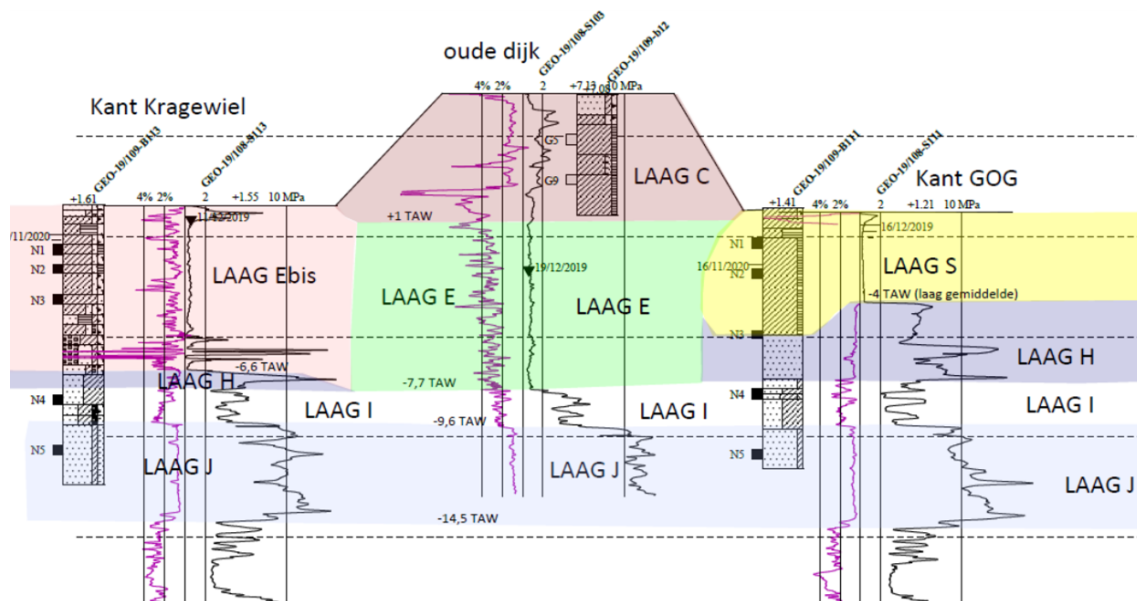


Figure 3.1: Soil stratigraphy of cross-section DP26 proposed by geotechnical nota (Couck, 2022)

3 PLAXIS 2D modelling

In PLAXIS 2D, soil stratigraphy is defined using boreholes. For cross-section DP26, 11 boreholes can be placed along the 110.00 m wide cross-section to define the subsurface layers. The borehole configuration follows the guidelines of the geotechnical nota (Couck, 2022). A visual representation of the boreholes is shown in Figure 3.2 and an overview is provided in Table 3.1.

- BH1 is located on the GOG side, furthest from the dike, while BH11 is positioned on the Kragewiel side.
- Although BH2 to BH5 appear redundant (with identical soil layer levels), they have been included to define the ditch on the GOG side of the dike. In particular, BH3 and BH4 modify the top level of layer R (a sublayer of Layer S) to +0.76 mTAW instead of the default +1.00 mTAW. Layer R represents the top part of clay layer S, which is to be replaced by sand during early construction.
- BH6 and BH7, though closely spaced, are needed to distinguish layer S from layer E. Similarly, BH8 and BH9 separate layer E from layer Ebis.

These refinements in borehole placement ensure that transitions in soil behaviour are accurately captured, particularly around the old dike where material properties vary significantly due to past interventions.

Table 3.1: BH required in PLAXIS 2D to define the soil stratigraphy in DP26 (levels in mTAW)

Layers	Borehole 1		Borehole 2		Borehole 3		Borehole 4		Borehole 5		Borehole 6		Borehole 7		Borehole 8		Borehole 9		Borehole 10		Borehole 11	
x [m]	0.00		65.97		66.52		70.82		71.38		77.80		78.00		93.80		94.00		101.45		110.00	
Material	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
Layer R	2.00	-1.00	1.00	-1.00	1.00	-1.00	1.00	-1.00	1.00	-1.00	1.00	-1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	-4.18	-4.18
Layer S	-1.00	-4.00	-1.00	-4.00	-1.00	-4.00	-1.00	-4.00	-1.00	-4.00	-1.00	-4.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	-4.18	-4.18
Layer E	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	1.00	-7.70	1.00	-7.70	1.00	1.00	1.00	1.00	-4.18	-4.18
Layer Ebis	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-4.00	-7.70	-7.70	-7.70	-7.70	1.00	-6.60	1.00	-6.60	-4.18	-6.60
Layer H	-4.00	-7.70	-4.00	-7.70	-4.00	-7.70	-4.00	-7.70	-4.00	-7.70	-4.00	-7.70	-7.70	-7.70	-7.70	-7.70	-6.60	-7.70	-6.60	-7.70	-6.60	-7.70
Layer I	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60	-7.70	-9.60
Layer H	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50	-9.60	-14.50

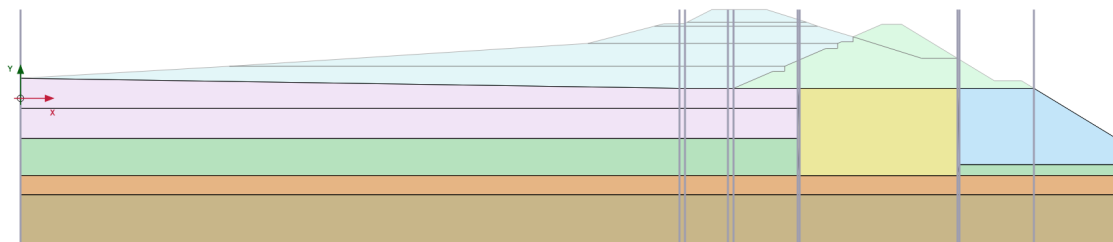


Figure 3.2: Boreholes in PLAXIS 2D to define the soil stratigraphy in DP26

3 PLAXIS 2D modelling

3.1.2 Soil material models

The subsoil in cross-section DP26 is composed of clay and sand, each exhibiting distinct mechanical behaviours under loading. A crucial step in the initial phase of modelling in PLAXIS 2D is the selection of appropriate soil material models to simulate these behaviours. This choice significantly influences the accuracy of the numerical analysis, as the selected models determine how the soil responds to stress and interacts with structures.

PLAXIS 2D Ultimate provides a wide range of constitutive soil models, both linear and non-linear, to represent various types of soil and their behaviour under different loading conditions. The appropriate model is selected based on several factors: soil type and composition, mechanical properties of the soil, expected stress-strain behaviour under loading and purpose and scope of the numerical analysis

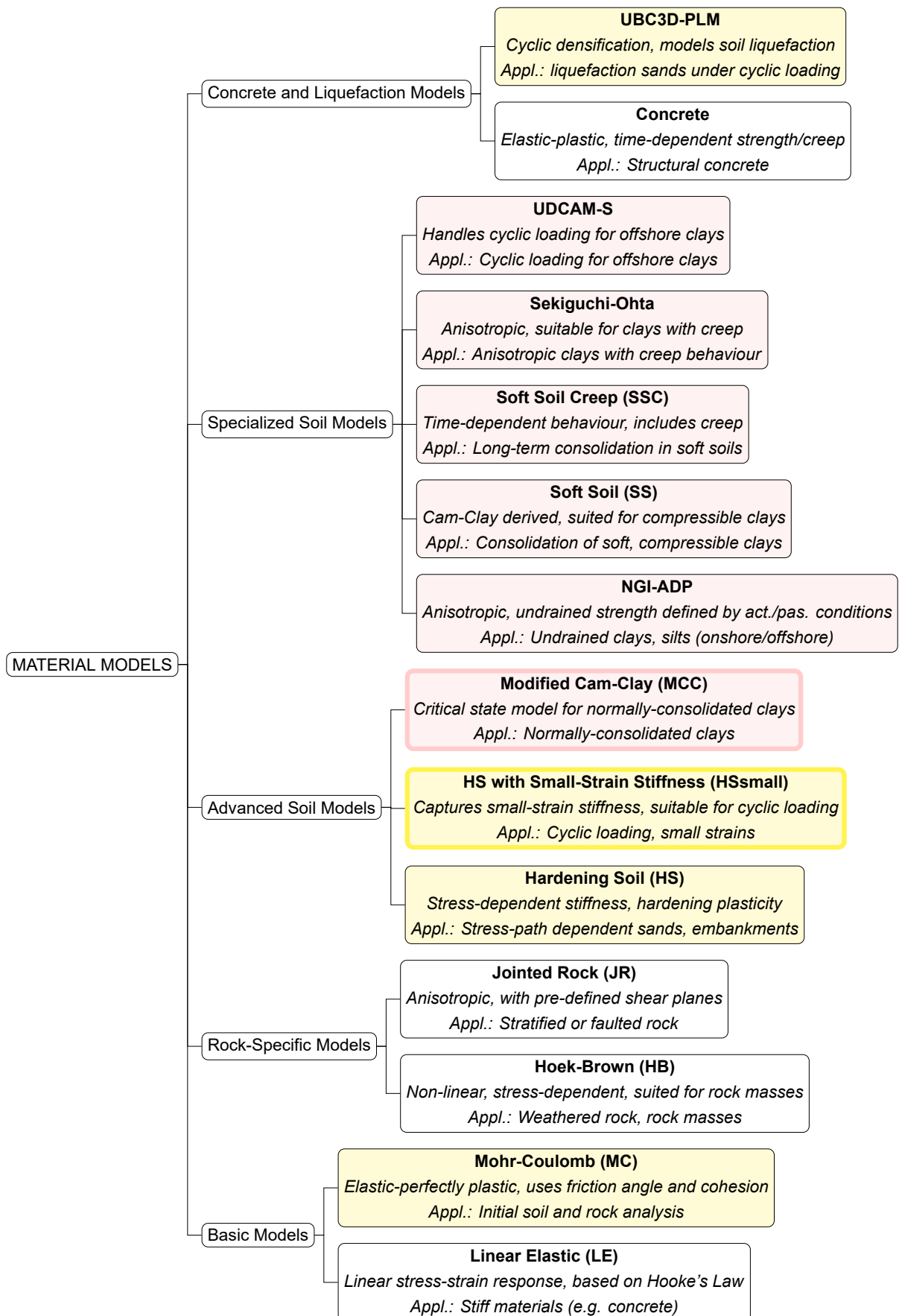
The linear soil material models are used to describe the behaviour of soils that exhibit linear elastic behaviour under loading. They assume that soil deforms proportionally with stress and returns to its original state upon unloading. These models are typically only applicable to simplified or preliminary analyses. The non-linear soil material models are based on the principles of elasto-plasticity. They can capture the irreversible, stress-dependent behaviour of real soils such as clay and sand, including effects such as yielding, strain hardening and consolidation.

The soil material models in PLAXIS 2D Ultimate can be categorized into groups. The scheme on the next page gives a full overview of the soil material models available in PLAXIS 2D Ultimate and their applications. In this scheme, the material models suitable for sandy materials are highlighted in yellow, while the material models suitable for clay and able to capture the time-dependent consolidation behaviour of the clay are highlighted in pink. In the following sections, the soil material models that are most suitable for the soil types in cross-section DP26 will be discussed in more detail (PLAXIS, 2024b).

3.1.2.1 Material model used for sandy soils

For the modelling of the sandy soil, four material models are eligible in first instance: the Mohr-Coulomb model, the Hardening Soil model, the Hardening Soil model with Small-Strain Stiffness and the UBC3D-PLM model. The Mohr-Coulomb model, while simple and widely used, is not well-suited for capturing the non-linear and stress-dependent behaviour of sands. On the other hand, the UBC3D-PLM model is too complex for the scope of this project and is more appropriate for seismic or highly dynamic analyses (PLAXIS, 2024b). This leaves two viable candidates: the Hardening Soil model and the Hardening Soil model with Small-Strain stiffness. Both are briefly evaluated below.

3 PLAXIS 2D modelling



3 PLAXIS 2D modelling

Hardening Soil model (HS) The Hardening Soil (HS) model is a robust and widely used model for simulating the non-linear, stress-dependent behaviour of soil. It improves upon simpler models like Mohr-Coulomb by incorporating features such as plasticity, hardening and stress-dependent stiffness. Key characteristics include:

- **Stress-dependent stiffness:** the model includes three stiffness moduli: the secant stiffness in triaxial tests (E_{50}), the oedometer stiffness (E_{oed}), and the unloading/reloading stiffness (E_{ur}). These values depend on the confining stress and increase according to a power-law relationship with exponent m and reference pressure p^{ref} (typically 100 kPa in PLAXIS). Definitions are shown in Figure 3.3.

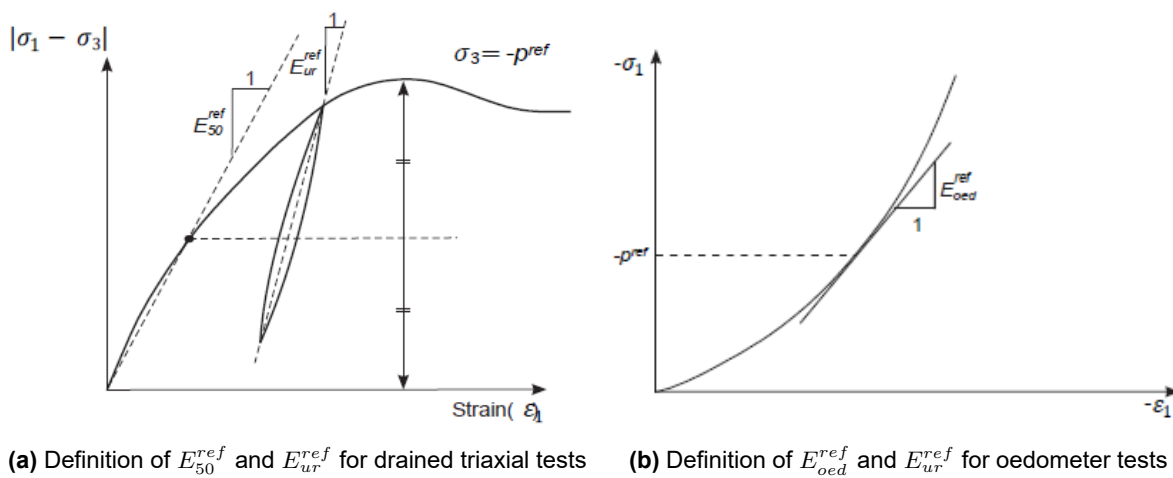


Figure 3.3: Stress-dependent stiffness moduli in the Hardening Soil model (PLAXIS, 2024b)

- **Shear and volumetric hardening:** soil behaviour under shear is modelled using a conical shear hardening surface, while compression is handled through an elliptical volumetric hardening cap. These yield surfaces enable more accurate predictions of settlement and plastic strain development. It also allows to define separate E_{50}^{ref} and E_{oed}^{ref} moduli, of which the former controls the magnitude of the plastic strain associated with the yield surface and the latter the plastic strains originating from the yield cap. The elastic region can be limited further by means of a tension-cut off.
- **Non-linear unloading/reloading behaviour:** the HS model uses a separate stiffness modulus (E_{ur}) to model the hysteresis observed during unloading and reloading cycles.
- **Dilatancy cut-off:** for drained conditions, the model allows limiting volumetric expansion at large shear strains using a dilatancy cut-off. As shown in Figure 3.4, this feature halts dilatancy once a critical void ratio is reached. It should however be noted, that this is not applicable under undrained conditions, where the void ratio remains constant. In such cases, the dilatancy angle ψ should be set to zero.

3 PLAXIS 2D modelling

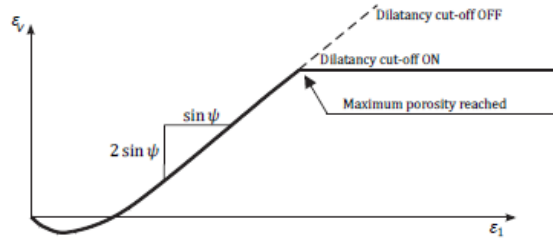


Figure 3.4: Dilatancy cut-off in the Hardening Soil model (PLAXIS, 2024b)

Despite its versatility, the HS model has several limitations when it comes to modelling sandy soils. It does not accurately capture small-strain stiffness, which is crucial for realistic deformation predictions, especially under cyclic or low-strain loading. Furthermore, it assumes linear elasticity below the yield point, whereas sands exhibit non-linear behaviour even at very small strain levels. Finally, it lacks provisions for stiffness degradation and damping, making it unsuitable for dynamic or time-dependent loading conditions (PLAXIS, 2024b).

Hardening Soil model with Small-Strain Stiffness (HSsmall) To overcome the limitations of the standard HS model, the HSsmall model incorporates the effects of small-strain stiffness degradation, which is critical for sandy soils. In reality, soils exhibit a rapid decay in stiffness as strain increases, even below the conventional yield threshold. This degradation follows an S-shaped curve when stiffness is plotted against the logarithm of strain. The HSsmall model builds upon the HS model, but introduces two additional parameters:

- G_0^{ref} : maximum shear modulus at strains $\epsilon < 10^{-6}$, referenced to a confining stress p^{ref} .
- $\gamma_{0.7}$: shear strain at which the shear modulus degrades to 70% of its maximum value.

This enhancement allows the model to capture the non-linear stiffness degradation that occurs even at very small strain levels; behaviour typically undetectable in standard laboratory tests due to their limited strain resolution. Consequently, the HSsmall model is particularly well-suited for simulating realistic settlements in sandy soils under both static and cyclic loading conditions. It is especially effective for modelling dynamic loading scenarios or construction phases involving small, incremental deformations, where accurate prediction of deformation behaviour depends heavily on the stiffness at small strains.

Notably, this improved accuracy is achieved with minimal additional complexity, requiring only two extra parameters beyond those used in the conventional HS model. Given the characteristics of the sandy sublayers in cross-section DP26, located deeper in the profile and thus experiencing smaller strains, the HSsmall model is adopted in this study for modelling sandy soils. A summary of the parameters used to define the HSsmall model in PLAXIS 2D is presented in Table 3.2.

3 PLAXIS 2D modelling

Table 3.2: Parameters for modelling sandy soil with the HSsmall model in PLAXIS 2D

Symbol	Unit	Description
Failure parameters as in the Mohr-Coulomb model		
c	$[kPa]$	(Effective) cohesion
ϕ	$[^\circ]$	(Effective) angle of internal friction
ψ	$[^\circ]$	Dilatancy angle
σ_t	$[kPa]$	Tension cut-off and tensile strength
Basic parameters for soil stiffness		
E_{50}^{ref}	$[kPa]$	Secant stiffness in standard drained triaxial test
E_{oed}^{ref}	$[kPa]$	Tangent stiffness for primary oedometer loading
E_{ur}^{ref}	$[kPa]$	Unloading/reloading stiffness (default: $E_{ur}^{ref} = 3 \cdot E_{50}^{ref}$)
m	$[-]$	Power for stress-level dependency of stiffness
Small-strain parameters		
G_0	$[kPa]$	Small-strain shear modulus
$\gamma_{0.7}$	$[-]$	Threshold shear strain
Advanced parameters (default setting advised)		
ν_{ur}	$[-]$	Poisson's ratio for unloading-reloading (default $\nu_{ur} = 0.2$)
p^{ref}	$[kPa]$	Reference stress for stiffnesses (default $p^{ref} = 100 \text{ kPa}$)
K_0^{nc}	$[-]$	K_0 -value for normal consolidation (default $K_0^{nc} = 1 - \sin(\phi)$)
R_f	$[-]$	Failure ratio (default $R_f = 0.9$)
$\sigma_{tension}$	$[kPa]$	Tensile strength (default $\sigma_{tension} = 0 \text{ kPa}$)
c_{inc}	$[kPa/m]$	Increase in cohesion with depth (default $c_{inc} = 0 \text{ kPa/m}$)
Other parameters		
OCR	$[-]$	Overconsolidation ratio
e_0	$[-]$	Initial void ratio
γ	$[kN/m^3]$	Unit weight
k	$[m/s]$	Permeability (vertical and horizontal)

3.1.2.2 Material model used for clayey soils

For modelling the clayey soils in cross-section DP26, six constitutive models are considered at first glance (PLAXIS, 2024b): the UDCAM-S model, the Sekiguchi-Ohta model, the Soft Soil Creep model, the Soft Soil model, the NGI-ADP model and the Modified Cam-Clay model (MCC). Among these, the MCC model is selected as the most appropriate for this study.

The NGI-ADP, UDCAM-S and Sekiguchi-Ohta models are not further considered due to their high complexity and demand for advanced input parameters (e.g. anisotropic and destructuration-related parameters), which are not available from the performed laboratory testing.

3 PLAXIS 2D modelling

The Soft Soil and Soft Soil Creep models are specifically designed to simulate highly compressible clays. The Soft Soil Creep model also includes time-dependent creep behaviour. However, based on settlement monitoring data (see section 2.4), the observed secondary settlements in DP26 are rather limited and also not the subject of this thesis. Consequently, the added complexity and computational cost of the Soft Soil Creep model is not justified.

While the Soft Soil model shares similarities with MCC and requires fewer parameters, it lacks the ability to adequately represent stress-path-dependent and long term behaviour. Moreover, if compression and recompression indices are available, the MCC model offers broader validity and better theoretical grounding within critical state soil mechanics. Therefore, the MCC model is preferred.

Modified Cam-Clay model (MCC) The Modified Cam-Clay model is a critical state-based elastoplastic model that effectively captures the behaviour of normally consolidated and lightly overconsolidated clays under varying stress conditions. It is particularly suited for stress-path-dependent simulations, such as those occurring beneath dikes. The MCC model includes both volumetric changes due to shearing and primary consolidation, without requiring additional parameters related to creep or secondary settlement. This makes it ideal for short- to medium-term settlement analysis, as is the case for cross-section DP26 (PLAXIS, 2024b).

The model relies on a set of critical state parameters, most of which can be derived from standard oedometer tests. These include the compression index λ , the recompression index κ and the preconsolidation pressure p'_c . A graphical representation of these parameters is shown in Figure 3.5 and additional definitions are available in attachment D (Budhu, 2010).

- **The preconsolidation ratio R_0 :** the ratio by which the current mean effective stress in the soil was exceeded in the past (i.e. the *OCR* for isotropically consolidated soils) and is derived from the ratio of the preconsolidation mean effective stress p'_c to the current mean effective stress p'_0 .

$$R_0 = \frac{p'_c}{p'_0} \quad (3.1)$$

- **The compression index λ :** the slope of the normal consolidation line in the $(e, \ln(p'))$ -plane. This parameter is linked to the compression index C_c .

$$\lambda = \frac{C_c}{\ln(10)} = \frac{C_c}{2.3} \quad (3.2)$$

- **The recompression or unloading/reloading index κ :** the average slope of the unloading/reloading curves in the $(e, \ln(p'))$ -plane. This parameter is linked to the recompression index C_r .

$$\kappa = \frac{C_r}{\ln(10)} = \frac{C_r}{2.3} \quad (3.3)$$

3 PLAXIS 2D modelling

- **The critical state line (CSL):** the line that represents the failure state of soils. In the (p', q) -plane, the critical state line has a slope M_{CSL} , which is related to the friction angle of the soil in the critical state. In the $(e, \ln(p'))$ -plane, the critical state line has a slope λ and is parallel to the normal consolidation line.

$$M_{CSL} = \begin{cases} M_c = \frac{6 \cdot \sin(\phi'_{cs})}{3 - \sin(\phi'_{cs})}, & \text{Axisymmetric compression} \\ M_e = \frac{6 \cdot \sin(\phi'_{cs})}{3 + \sin(\phi'_{cs})}, & \text{Axisymmetric extension} \\ M_{ps} = \sqrt{3} \cdot \sin(\phi'_{cs}), & \text{Plane Strain} \end{cases} \quad (3.4)$$

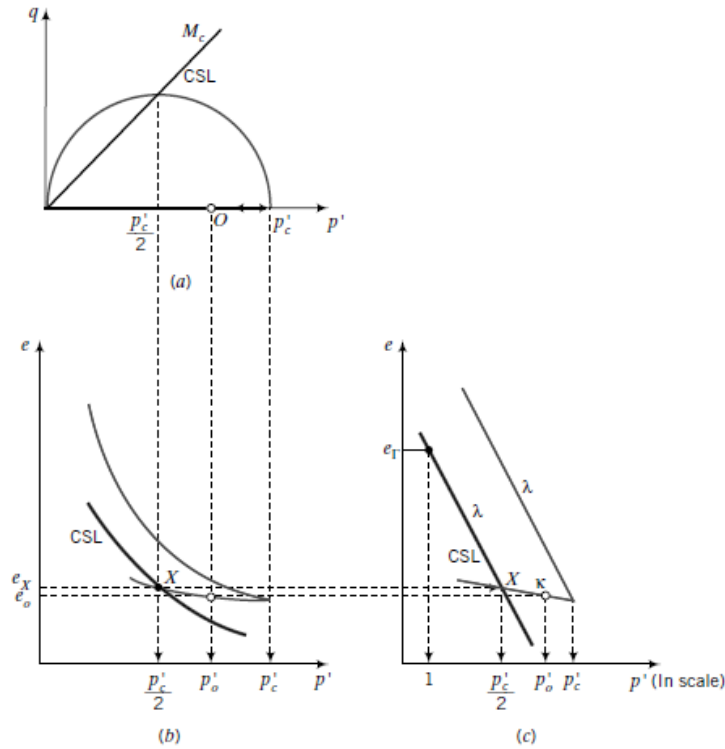


Figure 3.5: Critical state parameters used in the Modified Cam-Clay model (Budhu, 2010)

Since this study focuses primarily on primary consolidation due to dike loading, without significant creep, the MCC model provides the necessary accuracy for modelling stress-dependent settlement behaviour without overcomplicating the analysis. Its lower computational cost and moderate parameter requirements further support its selection for cross-section DP26. The parameters required to define the clayey soil layers using the MCC model in PLAXIS 2D are summarized in Table 3.3.

3 PLAXIS 2D modelling

Table 3.3: Parameters for modelling clayey soil with the MCC model in PLAXIS 2D

Symbol	Unit	Description
Parameters for stiffness		
λ	$[-]$	Cam-Clay compression index
κ	$[-]$	Cam-Clay swelling index
ν_{ur}	$[-]$	Poisson's ratio
e_0	$[-]$	Initial void ratio for loading/unloading
Parameters for strength		
M_{CSL}	$[-]$	Tangent of the critical state line
K_0^{nc}	$[-]$	Coefficient of lateral stress in normal consolidation derived from M_{CSL}
Other parameters		
OCR	$[-]$	Overconsolidation ratio
γ	$[kN/m^3]$	Unit weight
k	$[m/s]$	Permeability (vertical and horizontal)

3.1.3 Deterministic soil parameters

For the initial deterministic analysis, soil parameters are derived from laboratory tests and site investigation data, as outlined in the geotechnical nota (Couck, 2022). A complete overview of the adopted values is provided in Attachment E. Key assumptions and modelling choices are discussed below, while further refinement of deterministic parameters for selected non-critical soil layers is deferred to section 4.2.

Sandy layers are modelled as drained, since their behaviour is governed by effective stresses and they do not generate excess pore pressures. Clayey soils, however, are modelled using the MCC model, which assumes undrained behaviour. In PLAXIS 2D, the MCC model only supports the 'Undrained A' type, where strength and stiffness are defined in terms of effective stress, but pore water is assigned a very high bulk modulus to enforce incompressibility. This results in excess pore pressures even above the phreatic surface, unlike the 'Undrained B' type used in other models, where undrained shear strength is defined directly.

The dilatancy cut-off remains disabled, as no numerical issues arise with this setting. Advanced HSsmall parameters (Table 3.2) are kept at default values, except for permeability, which is based on lab results and converted from $[m/s]$ to $[m/day]$ using a factor of 86400. The gap closure option is enabled.

3.2 Structures

In the 'Structures' tab of the PLAXIS 2D input interface, geometric entities, structural elements and soil boundary conditions are defined (PLAXIS, 2024c). To model cross-section DP26, this tab is used to insert the geometries of both the old clayey winter dike and the new sandy dike constructed partially on top of it. The geometry is based on the cross-sectional plan in Figure 2.10. By subdividing the dike bodies into several polygonal parts, gradual and time-dependent excavation and construction can be simulated later in the 'Staged Construction' tab (section 3.5). The resulting PLAXIS 2D model is shown in Figure 3.6.

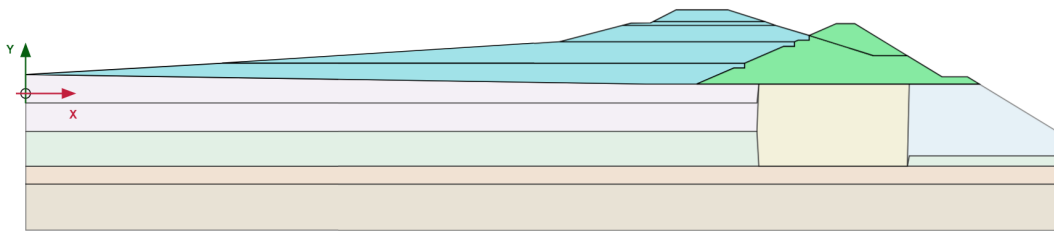


Figure 3.6: PLAXIS 2D model of the old and new dike in DP26

3.2.1 Geometrical adjustments for numerical stability

When comparing Figure 3.6 with Figure 2.10, slight modifications to the geometry can be observed. These were introduced to resolve calculation issues caused by singular points in the original geometry, particularly at the interface between construction layers of the new dike and the GOG side of the remaining old dike. Figure 3.7 highlights the problematic points using blue circles, while the geometric modifications introduced to resolve these issues are shown in red.

In the original layout, a soil layer constructed in a later stage intersected the old dike at a single point. This led to numerical instability: the stress concentration at this singularity triggered unrealistic displacements of up to 1.52 m and caused the calculations to fail early on, in particular when the dike construction proceeds into a new elevation phase due to the additional load in the singular point.

To resolve this, small staircase-like incisions are introduced on the GOG side of the old dike. These incisions ensure that the interface between the new dike layers and the old dike does not converge into a single point, thereby eliminating the singularity issue. This modification allows PLAXIS 2D to calculate stresses and displacements more accurately, avoiding unrealistic results and ensuring convergence during the staged construction phases. The maximum displacement is also reduced to a more realistic value of 0.15 m at the interface between the GOG side of the old dike and the top of the first addition of the new dike.

3 PLAXIS 2D modelling

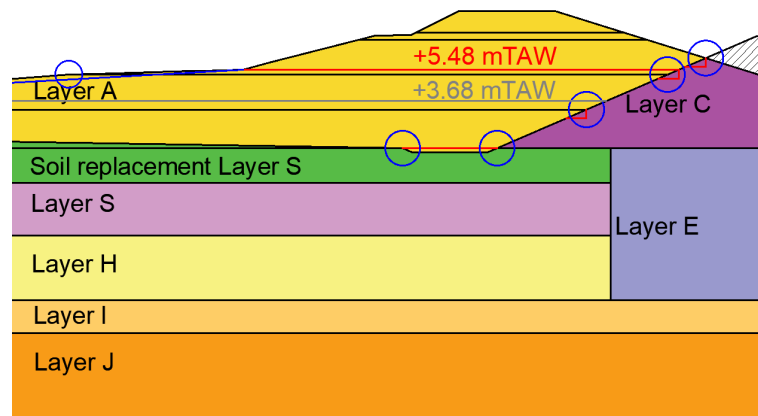


Figure 3.7: Geometry modifications to overcome calculation problems in PLAXIS 2D

Appendix F provides more detailed illustrations of this numerical stability analysis. The first set of figures presents the results for the original geometry containing problematic singular points, while the second set corresponds to the adapted geometry with incisions. In addition to the cross-sectional geometries, the appendix includes displacement results and a plastic point analysis at the end of the first elevation phase, which leads to failure in the case of the original geometry. This analysis helps to identify zones in the soil where plastic deformation occurs and is also depicted in Figure 3.8.

By adapting the dike geometry, red failure points resulting from inconsistencies caused by PLAXIS 2D's misinterpretation of the geometry, are successfully avoided. In the adapted model, only a few failure points appear at the geometrical boundaries of clusters and no significant accumulation of plastic points is observed. This indicates that the geometry has been optimized with respect to the original design. In contrast, the original model shows a large concentration of failure points near the toe of the dike and around the ditch, which may suggest that the ditch contributes to the calculation failure. Additionally, the newly added dike layer displays an unrealistic amount of tension cut-off points, indicating excessive tensile stresses in the soil. These stresses are likely caused by the large total displacement triggered at the singular points, effectively causing the soil mass to 'collapse and tear apart'. In response, PLAXIS 2D attempts to stabilize the model by introducing tensile stresses that artificially hold the soil together, an unrealistic behaviour that ultimately leads to calculation failure.

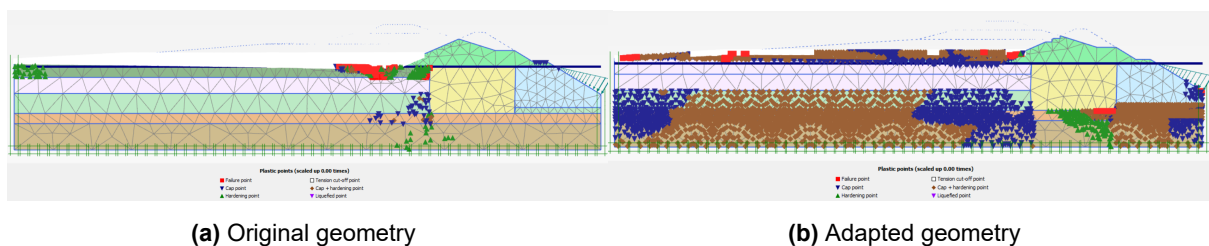


Figure 3.8: Comparison of the plastic analysis at the end of the first elevation phase

3 PLAXIS 2D modelling

3.2.2 Mesh optimization and additional simplifications

Figure 3.7 also highlights the ditch on the GOG side of the old dike and the intersection between a construction layer of the new dike and the riverside slope of the new dike by blue circles. While these specific features do not directly lead to failure in the PLAXIS 2D calculations, they do complicate the generation of a high-quality mesh. This is because they require the inclusion of very fine mesh elements within clusters that could otherwise be meshed more coarsely, as illustrated in Figure 3.9. As a result, the total number of mesh elements increases for a given coarseness factor, leading to a significant rise in the overall calculation time of the PLAXIS 2D model. Since removing the ditch from the numerical model and shifting the construction layer boundary upwards by 0.28 m to $+5.48\text{ mTAW}$ does not influence the subsoil settlement analysis, adapting the dike geometry at these locations is a rational and efficient choice. This allows the use of coarser mesh elements in larger clusters, thus optimizing computational performance without compromising accuracy.

For similar reasons, the thin clayey surface layer, applied in practice on top of the new dike as an impermeable barrier, is omitted from the PLAXIS 2D model. This layer has no significant effect on the settlement analysis and would only lead to an unnecessary increase in mesh elements and computation time. Although it could be argued that a difference in unit weight between the clayey and sandy top layers might influence the results, both materials have the same dry unit weight of $\gamma_d = 17\text{ kN/m}^3$. Therefore, the difference in weight is negligible and no additional load needs to be applied to account for the omitted clayey top layer.

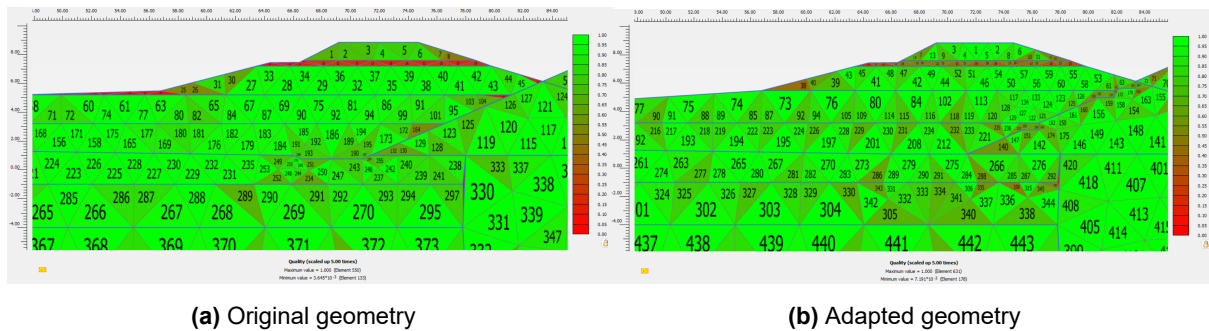


Figure 3.9: Optimization of the mesh quality

Finally, the grey line at $+3.68\text{ mTAW}$ in Figure 3.7 represents the construction level at which the monitoring campaign commenced. This reference line is not implemented in the PLAXIS 2D model itself but is included solely for illustrative purposes, to help visualize the state of the dike at the onset of monitoring.

3.3 Mesh

As discussed in the previous section, generating a high-quality mesh is essential for reducing the simulation's calculation time while preserving result accuracy. In this model, 15-node triangular elements are used to model both subsoil and dike. These elements offer fourth-order interpolation for displacements and utilize twelve Gaussian points for numerical integration. Due to their high precision, especially in stress calculations and failure-prone geotechnical problems, 15-node elements are preferred over 6-node triangles, despite their increased memory requirements and slower computation performance (PLAXIS, 2024c).

PLAXIS 2D defines the mesh element size using a global meshing parameter l_e , which depends on the model's geometric dimensions and a relative element size factor r_e .

$$l_e = r_e \cdot 0.06 \cdot \sqrt{(x_{max} - x_{min})^2 + (y_{max} - y_{min})^2} \quad (3.5)$$

Table 3.4 presents a performance summary of the geometrically updated PLAXIS 2D model for various mesh coarseness factors. For each element distribution, the associated r_e , total number of mesh elements and nodes and corresponding calculation time are listed. Each mesh has been tested through a full calculation on the same model (without soil replacement, explaining the relatively large displacements). The maximum total displacement is employed as an indicator for evaluating the quality of the simulation results. The following trends are observed:

- Increasing mesh coarseness generally reduces calculation time. This reduction stabilizes between $r_e = 1.00$ and $r_e = 2.00$.
- The coarsest mesh (with $r_e = 8.00$) drastically reduces CPU time, but compromises result accuracy: it predicts a maximum total vertical settlement of -0.859 m , deviating by 2.50 cm from the theoretical reference value of approximately -0.885 m (Couck, 2022).

Although the difference may seem minor, it is numerically significant and would affect subsequent analyses. Importantly, the error can be avoided by selecting a different mesh coarseness. As a result, the coarsest mesh is deemed unsuitable. In contrast, the medium, coarse and very coarse meshes yield displacement predictions closely matching the reference values, while significantly reducing computation time, making them more efficient choices.

Table 3.4: Mesh performance for meshes with different coarseness factors

Element distributions	r_e [-]	Number of elements	Number of nodes	CPU time [s]	Total maximum displacement [m]
Finest possible	0.03	39402	317297	8474	-0.8852
Very fine	0.50	2005	16431	326	-0.8850
Fine	0.67	1600	13105	273	-0.8847
Medium	1.00	1236	10117	208	-0.8851
Coarse	1.33	1137	9299	221	-0.8876
Very coarse	2.00	966	7901	205	-0.8883
Coarsest possible	8.00	285	2387	117	-0.8594

3 PLAXIS 2D modelling

For mesh quality, element quality values between 0.30 and 1.00 are considered acceptable. Due to the model's geometric complexity (e.g. including the staircase-like incisions on the GOG side), the mesh always contains a limited number of low-quality (red) elements. As expected, finer meshes produce slightly more accurate results, but at the expense of substantially increased computation time. A detailed, illustrated comparison of mesh performance across all mesh sizes is provided in Appendix G. Since this numerical model will be used in probabilistic calculations involving multiple runs, computational efficiency is crucial. An ideal run time of approximately three minutes per simulation is targeted. Among the candidate meshes, the medium mesh achieves the best trade-off between CPU time, displacement accuracy and mesh quality. It contains fewer low-quality elements, particularly in critical zones such as the wedges near the river side of the new dike.

Conclusion: the dike model for DP26 will be meshed using the medium element distribution predefined in PLAXIS 2D, ensuring optimal balance between numerical performance and result fidelity. The quality of this mesh is depicted in Figure 3.10.

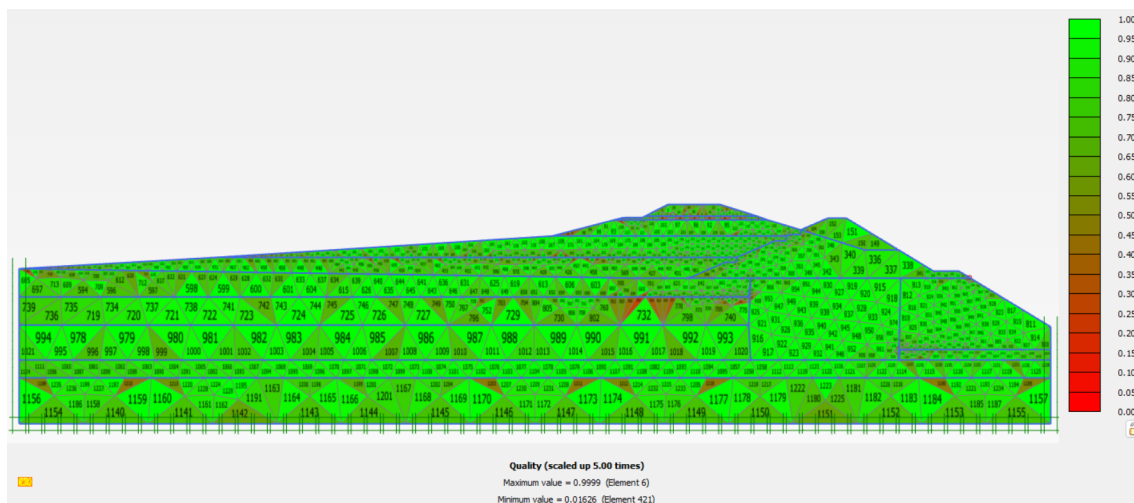


Figure 3.10: Quality of a medium mesh

3.4 Flow conditions

As mentioned in the paragraph 2.3.1.3 regarding the measurement of the groundwater table, the average groundwater level in the studied cross-section is approximately $+1.00 \text{ mTAW}$. This global phreatic level is applied uniformly over the entire cross-section. As a consequence, no hydraulic gradient and hence no groundwater flow is present in DP26. While this represents a simplification of the real conditions, it is justified by the relatively stable groundwater level and the fact that the dike is not situated in an area where significant fluctuations in groundwater levels occur. Moreover, neglecting groundwater flow simplifies the analysis and contributes to a reduction in calculation time.

3.5 Staged construction

The final step in modelling cross-section DP26 in PLAXIS 2D involves defining the sequence of construction stages. PLAXIS 2D offers several options for modelling these stages. The process begins with the initial phase, which represents the state where the old dike is still present. This configuration results in initial vertical $\sigma'_{v,0}$ and horizontal effective stresses $\sigma'_{h,0}$. The latter is related to the initial vertical effective stress through the coefficient of lateral earth pressure K_0 : $\sigma'_{h,0} = K_0 \cdot \sigma'_{v,0}$. To generate these initial stresses, PLAXIS 2D provides multiple options. In this case, the K_0 -procedure is used, which applies a predefined K_0 -value to establish the initial stress state. This method is particularly well-suited to geotechnical problems involving predominantly horizontal soil stratification, such as in DP26. Other available methods include the 'Gravity Loading procedure' and the 'Field Stress method'. The former simulates stress development from soil self-weight but neglects overconsolidation, while the latter allows stress input from external sources or earlier models and is typically used in more complex scenarios (PLAXIS, 2024c).

3.5.1 Construction phase modelling options

For modelling the construction of the new dike, several calculation types are available: plastic, consolidation, safety, dynamic, fully coupled flow-deformation and dynamic with consolidation. For settlement analyses, the plastic (an (un)drained elastoplastic analysis, ignoring consolidation and time) and consolidation calculations (a time-dependent analysis capturing deformation and excess pore pressures dissipation, which requires the input of permeability and time intervals) are most relevant. There are two viable strategies for defining the construction sequence.

3.5.1.1 Full consolidation modelling (alternative 1)

In this approach, both the elevation ($t = t_{elevation}$) and consolidation phases ($t = t_{consolidation}$) are modelled as consolidation calculations, with time intervals (t) reflecting their actual durations, as listed in Table 2.2. This method closely mirrors the real-world construction process and matches measured settlement curves well over the entire time domain. However, due to the higher complexity of consolidation analyses, calculation times are slightly longer and more variable compared to the second alternative.

3.5.1.2 Hybrid plastic-consolidation modelling (alternative 2)

Here, elevation phases are modelled using plastic calculations (with $t = 0$) and consolidation phases remain time-dependent. The actual duration of each elevation step is added to the time interval of the following consolidation phase ($t = t_{elevation} + t_{consolidation}$). While plastic calculations capture immediate deformation, they neglect excess pore pressure dissipation.

3 PLAXIS 2D modelling

This is compensated by extending the duration of the following consolidation step, thereby ensuring accurate long-term settlement behaviour. Although this method does not accurately predict the settlement at every point in time, it results in the same final settlement values as alternative 1, while offering shorter and more consistent calculation times.

3.5.1.3 Comparison and recommendations

Figure 3.11 compares the deterministic settlement curves calculated by PLAXIS 2D at the location of settlement beacon ZB3 (see Figure 2.14) for both alternatives in the actual case of a soil replacement of the surface part of layer S. Both curves indeed converge to a similar final settlement value. The curve from modelling alternative 1 is smoother and more realistic due to the greater accuracy of consolidation calculations, whereas the curve from alternative 2 is more idealized. The figures also indicate the start of the settlement monitoring campaign on 09/02/2023, 131 days after the start of the construction works.

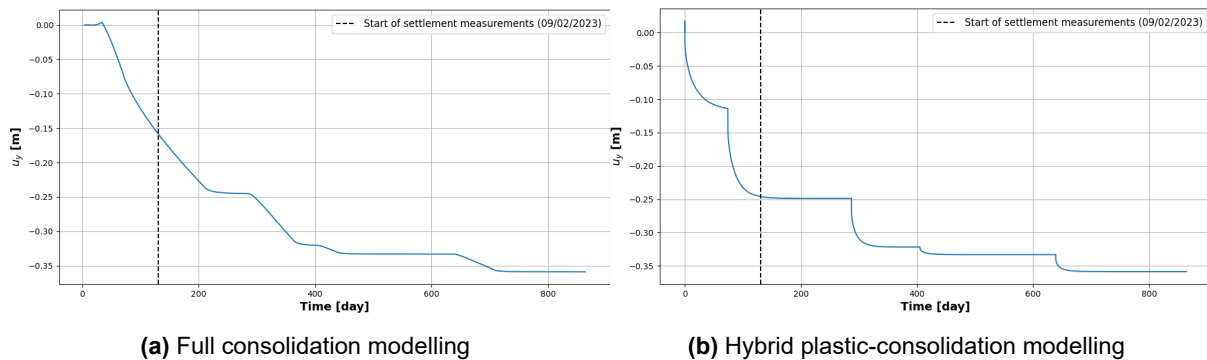


Figure 3.11: PLAXIS 2D prediction of the (deterministic) settlement curve at ZB3

This delay in the start of the monitoring campaign relative to the construction works is important to address, as all monitoring values are calibrated against the zero measurement taken on 09/02/2023. In reality, however, the settlement process had already begun before this date. As a result, the measured values are not directly comparable to the calculated values, since they do not capture the initial settlements that occurred prior to the start of monitoring. To resolve this discrepancy, the settlements predicted by PLAXIS 2D must also be reset to zero on 09/02/2023. This is illustrated in Figure 3.12. The settlement curves shown in this figure are obtained by retaining only the portion of the curves from Figure 3.11 that occurs after 09/02/2023 and shifting their starting point to the origin. This approach allows for a direct comparison with the monitored data. A clear difference between modelling alternatives 1 and 2 can now be observed. Since alternative 2 does not accurately capture the settlement behaviour at every point in time, the predicted settlement at day 131 is not reliable. By coincidence, day 131 falls within a highly sensitive and steep section of the settlement curve, which amplifies the discrepancy between the two approaches.

3 PLAXIS 2D modelling

As a result, the final reset settlement values for alternatives 1 and 2 differ significantly: -0.20 m versus -0.12 m . This highlights the importance of using the full consolidation model when comparing with intermediate monitoring data, especially if the timing of the monitoring campaign is misaligned with the actual start of the settlement process.

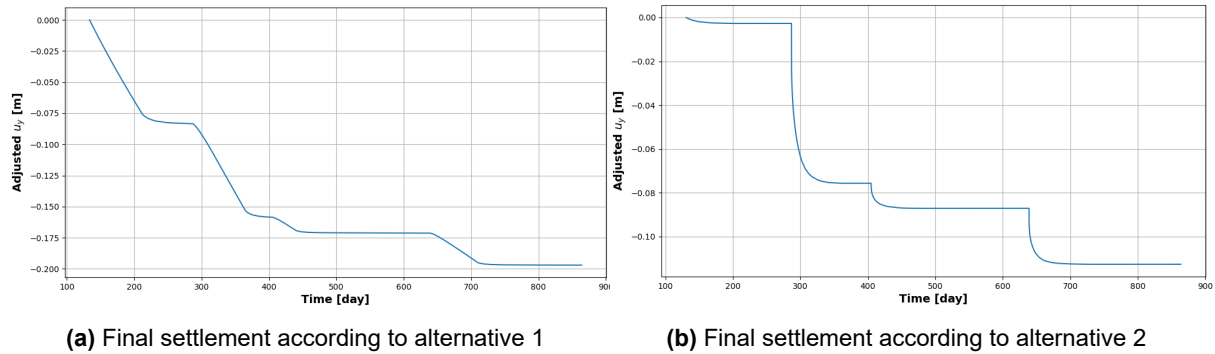


Figure 3.12: PLAXIS 2D prediction of the monitored settlement curve from 09/02/2023 on

It should be noted that starting the settlement calculations only from day 131 after the beginning of construction does not yield accurate results. Although it might seem that the settlement occurring in the first 131 days is simply omitted from the monitoring campaign, the impact of these initial construction activities still influences the settlement behaviour beyond day 131, due to the slow nature of primary consolidation. This effect is illustrated in Figure 3.13, where full consolidation modelling has been used for both curves. In Figure 3.13a, the first 131 days are completely neglected, resulting in a final settlement of -0.11 m . In contrast, Figure 3.13b, which implicitly includes the settlement that occurred during the first 131 days, shows a final settlement of -0.20 m . The additional 0.09 m can be attributed to the long-term influence of the initial construction works on the overall settlement behaviour. The recalibrated simulated final settlement at DP26 is -0.20 m , significantly lower than the measured value of -0.37 m recorded at the end of the monitoring campaign. This indicates that the deterministic analysis is overly conservative, further motivating the development of a probabilistic framework.

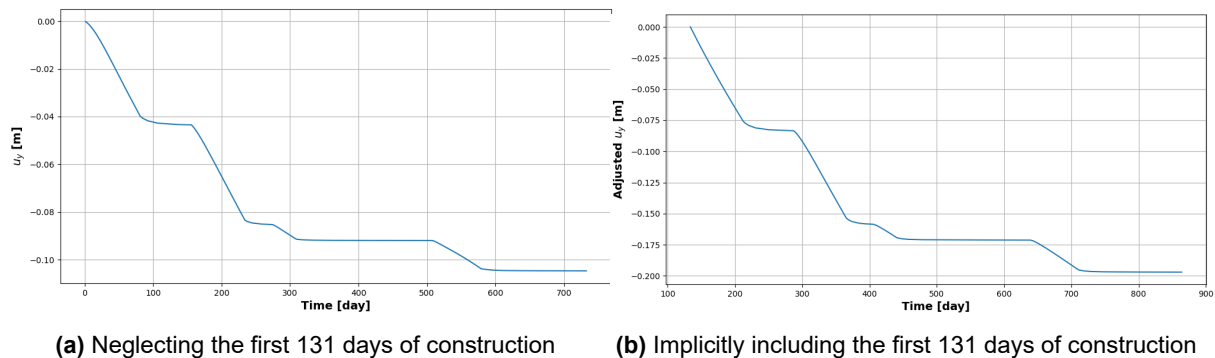


Figure 3.13: Comparison of techniques to reset the settlement curves to zero at 09/02/2023

4

Soil parameter distributions

This chapter lays the foundation for the transition from deterministic to probabilistic settlement calculations. Probabilistic modelling requires the definition of appropriate probability distributions for the relevant soil parameters. As a first step, a sensitivity analysis is conducted to identify which parameters significantly influence the predicted settlement. Parameters that are deemed non-critical based on the sensitivity analysis are assigned fixed deterministic values, typically the characteristic mean values obtained from laboratory testing. In contrast, critical parameters undergo further statistical evaluation to define their probabilistic distributions. To establish these distributions, workflows originally developed by IMDC have been adapted to suit the specific needs of this analysis.

4.1 Sensitivity of the soil parameters on the settlement calculation

Before performing probabilistic analyses, it is essential to identify which soil parameters and layers most strongly influence vertical settlement. A sensitivity analysis offers two main advantages in geotechnical engineering contexts such as this one. First, it helps to reduce computational costs by determining which parameters should be treated probabilistically and which can remain deterministic. This approach ensures computational resources are focused only on parameters that significantly affect model outcomes. A threshold value is applied to distinguish between influential and non-influential parameters. Secondly, a sensitivity analysis provides insight into parameters with the greatest influence on the system's behaviour, thereby highlighting areas of uncertainty. This knowledge can guide further investigation efforts, such as additional laboratory or in-situ testing, to refine parameter estimates and improve the model's accuracy.

Several methodologies exist for performing sensitivity analyses. In this study, the built-in sensitivity analysis tool in PLAXIS 2D Ultimate is employed. This tool assesses parameter sensitivity by varying selected parameters within predefined bounds and observing the resulting changes in output. This approach enables efficient identification of critical parameters that merit a more detailed probabilistic assessment. To fully appreciate the methodology used, the following section outlines the theory behind sensitivity analyses in PLAXIS 2D (PLAXIS, 2024d).

4 Soil parameter distributions

4.1.1 Theoretical background of the sensitivity analysis in PLAXIS 2D Ultimate

4.1.1.1 Sensitivity Score

The sensitivity score, denoted by $\eta_{SS,i}$, quantifies the influence of an input parameter x_i on a specific model output. It is a robust metric for identifying key sources of uncertainty, as it is not influenced by the relative percentage change from a reference value. The score is defined as the absolute difference between the maximum and minimum model outcomes when x_i is varied within its predefined bounds. Here, $f(x)$ represents the relationship between the input parameter and the output of interest, in this case, the vertical settlement computed by PLAXIS 2D. The bounds $x_{i,\max}$ and $x_{i,\min}$ correspond to the highest and lowest values obtained from laboratory or field data, while the characteristic mean is used as the central reference.

$$\eta_{SS,i} = |f(x_{i,\max}) - f(x_{i,\min})| \quad (4.1)$$

To account for parameter uncertainty, each x_i is varied across its full range, and the FEM model is used to compute the resulting variation in output. This ensures that the calculated settlement reflects the potential variability introduced by uncertain soil properties. For this study, the output of interest is the vertical displacement u_y at the monitoring location ZB3.

4.1.1.2 Relative sensitivity and aggregate sensitivity

To compare the sensitivity of each parameter relative to the others, a normalized sensitivity score $x_{i,\text{score}}$ is introduced, where n represents the total number of parameters under consideration. This normalization expresses each parameter's influence as a percentage of the total, facilitating direct comparison and highlighting the most critical parameters.

$$x_{i,\text{score}} = \frac{100 \cdot \eta_{SS,i}}{\sum_{j=1}^n \eta_{SS,j}} \quad (4.2)$$

In cases involving multiple performance criteria (e.g., displacements, forces, safety factors), the sensitivity score $\eta_{SS,i}$ is calculated for each parameter across all relevant outputs. These individual scores are then summed to obtain the total sensitivity score for each parameter across all criteria and construction steps. To quantify each parameter's overall influence, a total relative sensitivity score $\alpha(x_i)$ is defined. Here, m is the number of performance criteria and n is the total number of parameters considered. This aggregate score provides a comprehensive measure of each parameter's contribution to the model response.

$$\alpha(x_i) = \frac{100 \cdot \sum_{j=1}^m (\eta_{SS,i})_j}{\sum_{i=1}^n \sum_{j=1}^m \eta_{SS,i}} \quad (4.3)$$

4 Soil parameter distributions

In the current analysis, only one performance criterion is relevant: the vertical displacement. As a result, the aggregate score $\alpha(x_i)$ simplifies to the normalized sensitivity score $x_{i,\text{score}}$. The scores are expressed as percentages, with higher values indicating a greater influence on the output.

It is important to note that sensitivity outcomes depend strongly on the selected performance criterion. Hence, defining appropriate output metrics is essential and should be guided by sound engineering judgement. In this case, vertical settlement is clearly the most relevant criterion for evaluating the influence of soil parameters on dike behaviour.

4.1.2 Result of the sensitivity analysis in PLAXIS 2D

Given the extensive number of soil parameters included in the PLAXIS 2D model, the sensitivity analysis is carried out in two stages, as a single global analysis would be computationally prohibitive. With 88 soil parameters under consideration, each requiring at least three calculations (for the lower bound, mean value and upper bound), and often necessitating parameter variation, an alternative approach has been adopted.

The first stage involves performing sensitivity analyses within individual soil layers to identify the most influential parameters for each layer. In the second stage, a global sensitivity analysis is conducted using only these selected parameters to determine which ones most significantly affect the overall settlements. In this analysis, all parameters collectively sum to 100%.

As previously mentioned, the vertical soil displacement u_y at the location of settlement beacon ZB3 is chosen as the output of interest. The precise position of ZB3 relative to the dike geometry is shown in Figure 2.14.

4.1.2.1 Sensitivity analysis on soil parameters within individual soil layers

Figure 4.1 presents the results of the sensitivity analyses for individual sandy soil layers. The bars in the diagram represent the sensitivity scores of various soil parameters with respect to the vertical settlement. Since the analyses are performed separately for each sandy layer, the sensitivity scores for a single layer, indicated by bars of the same color, sum to 100%.

In layer A, the unit weight of the soil γ has the most significant influence on the dike settlement. This is expected, as layer A forms the dike body. Its weight directly contributes to the total load imposed on the subsoil. Additionally, the effective angle of internal friction ϕ' and the effective cohesion c' also affect settlement. In contrast, parameters such as $G_{0,\text{ref}}$, $\gamma_{0.7}$, ψ and R_{inter} exhibit negligible influence and are therefore excluded from the global sensitivity analysis.

Layers H, I and J, located beneath the dike body, show a different sensitivity profile. Here, the unit weight γ is no longer a dominant factor, which can be attributed to the overlying clayey layers that primarily govern both the magnitude and duration of the settlement.

4 Soil parameter distributions

In layer J, the deepest sand layer, the small-strain stiffness parameters $G_{0,ref}$ and $\gamma_{0.7}$ emerge as the most influential ones. Due to the lower strain levels typically experienced at such depths, deformation occurs mainly in the small-strain range. The HSsmall model captures this behaviour, with $G_{0,ref}$ and $\gamma_{0.7}$ controlling the stiffness degradation under increasing strain. Thus, small-strain stiffness plays a crucial role in load transfer and soil response at this depth.

In layer I, the effective friction angle ϕ' and particularly the effective cohesion c' are the most critical parameters. The high sensitivity of c' is likely due to the layer's composition: although classified as sandy, it contains a significant amount of clay, resulting in elevated cohesion values that influence settlement more than other parameters in this layer.

For layer H, the elastic moduli $E_{oed,ref}$ and $E_{ur,ref}$ significantly impact vertical settlement. This is consistent with the layer's structural role in bearing the cumulative load from all overlying strata. Its resistance to deformation under stress is key to controlling the settlement of the overlying clay layers and is primarily governed by its elastic stiffness.

In all three layers H, I and J, the parameters ψ and R_{inter} show no influence on vertical settlement and are hence excluded from the global sensitivity analysis.

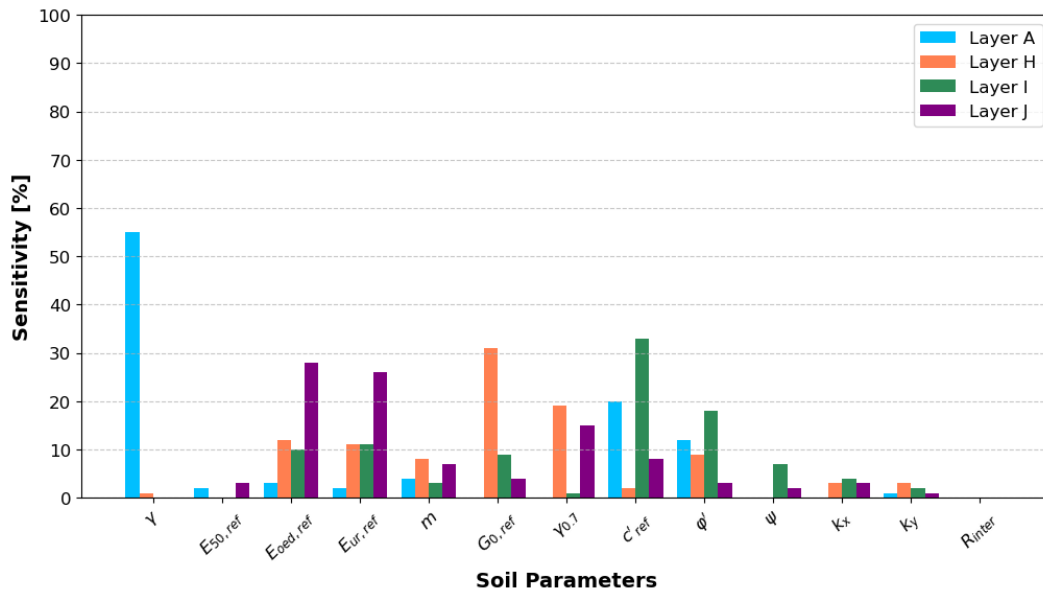


Figure 4.1: Sensitivity analysis on soil parameters within individual sandy soil layers

Figure 4.2 displays the results of the sensitivity analyses for individual clayey layers. For layers C, S, E and Ebis, nearly all parameters of the MCC model influence the dike's vertical settlement. The only exceptions are the interface parameters $c_{ref,inter}$ and $\phi_{ref,inter}$, which show negligible sensitivity. The pronounced sensitivity to parameters such as the overconsolidation ratio, unit weight, (re-)compression indices and permeability is in line with Terzaghi's settlement theory, since these parameters control the compressibility and drainage behaviour of clays.

4 Soil parameter distributions

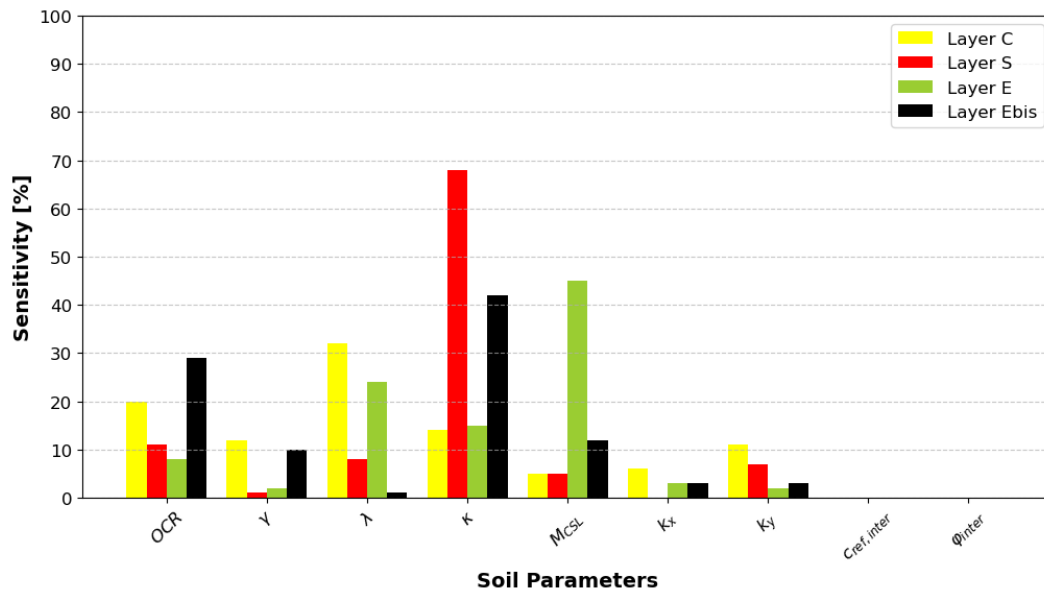


Figure 4.2: Sensitivity analysis on soil parameters within individual clayey soil layers

4.1.2.2 Global sensitivity analysis on soil parameters of all soil layers

Figure 4.3 shows the results of the global sensitivity analysis for the sand parameters. The weight and effective cohesion of the sand used in dike construction each contribute 1%, indicating a small but noticeable effect on settlements. Overall, sand property variations have minimal impact and will therefore be treated deterministically.

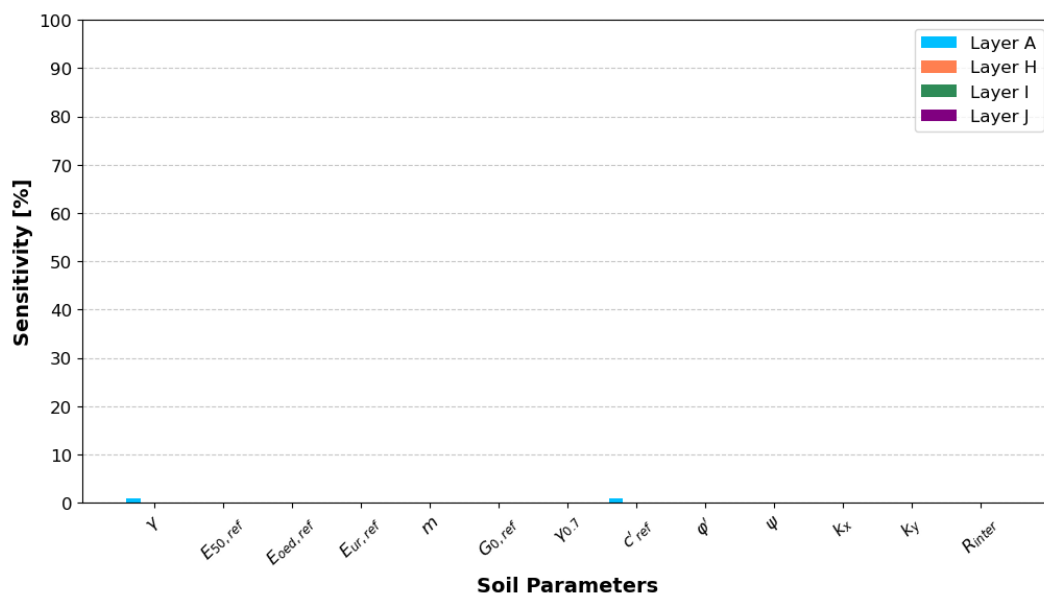


Figure 4.3: Global sensitivity analysis on soil parameters of sandy soils

4 Soil parameter distributions

Figure 4.4 presents the results of the global sensitivity analysis for the clay parameters. As anticipated, the soft clay layer S exhibits the highest sensitivity with respect to settlement. In particular, the overconsolidation ratio OCR (11%), compression index λ (60%), recompression index κ (13%) and vertical permeability $k_y = k_{vert}$ (7%) of layer S dominate sensitivity scores. Together, these four parameters account for 95% of the dike's settlement sensitivity to changes in soil properties. They will therefore be treated probabilistically in the subsequent probabilistic analysis. The other clay parameters have a minimal impact and will be handled deterministically.

To conclude this section, a final remark is warranted regarding the differing sensitivities of the compression index λ and recompression index κ for layer S. In Figure 4.2, which shows the layer-specific analysis, κ has a higher sensitivity than λ . In contrast, the global analysis in Figure 4.4 assigns greater importance to λ . This discrepancy can be explained by the fact that the sensitivities for λ and κ are interchangeable depending on the current stress state relative to historical stress states in the soil. Layer S, with $OCR \approx 2$, extends from $+1.00 \text{ mTAW}$ to -4.00 mTAW . The transition between dominance of κ or λ depends on whether the soil is in an overconsolidated or normally consolidated state. In overconsolidated conditions, where the current stress is below the maximum historical stress, settlement behaviour is governed by κ , which controls the soil's response during unloading and reloading. Conversely, when the stress exceeds past values (normally consolidated conditions), λ becomes the controlling factor as it governs primary compression. Therefore, in layer S, the upper portion remains in an overconsolidated state and is influenced by κ , while the deeper parts experience higher stresses and transition into a normally consolidated state, where λ becomes dominant. This stratified behaviour explains the shift in sensitivity observed between both analyses for the same layer.

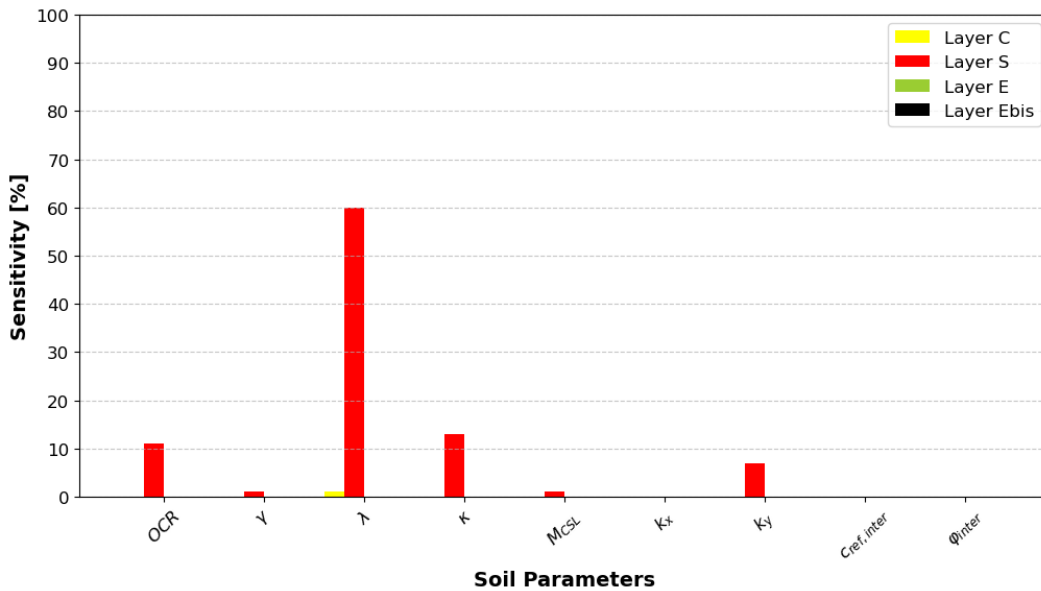


Figure 4.4: Global sensitivity analysis on soil parameters of clayey soils

4 Soil parameter distributions

4.2 Deterministic values of the non-critical soil parameters

The previous section has demonstrated that only four of the 88 soil parameters significantly influence settlement behaviour and will be analysed probabilistically. The remaining parameters show negligible variability and are treated as deterministic, with characteristic values derived from lab tests and CPTs, as detailed in Chapter 2. For sand layers H, I, J and clay layers C, E and Ebis, values are taken from the Geotechnical Department's calculation note (Couck, 2022) and listed in attachment E.

In contrast, the properties of the sand in the new dike (layer A) and soil replacement (layer R) are not detailed in the note, due to their dependence on sand quality and compaction during construction. These are assessed using CPTs conducted during and after the works. The resulting property values are also included in attachment E.

4.2.1 Deterministic values of new dike's sand properties (layer A)

This section focuses on identifying the properties of the sand used in the dike construction. Initially, the contractor was consulted for insights into the construction sand. However, due to the use of various sand batches throughout the project, precise HSsmall model parameters could not be provided. Therefore, an analysis based on CPTs has been performed. The analysis uses CPTs carried out on settlement plates ZP1, ZP2, ZP3 and ZP4, located within the newly constructed dike body, referred to as SZP1, SZP2, SZP3 and SZP4, respectively. These data are obtained from the DOV database (Vlaamse overheid, s.d.). Although only SZP3 was conducted at the investigated cross-section DP26, the dike has been constructed uniformly across the site, allowing the other CPTs to be considered representative as well for the sand properties of the dike. The CPTs are displayed in Figure 4.5. All four CPTs start at a level of about +8.50 *mTAW* and continue over the height of the dike body down to the top of the settlement plates, located respectively at +1.77 *mTAW* (ZP1), +1.80 *mTAW* (ZP2), +1.84 *mTAW* (ZP3) and +2.06 *mTAW* (ZP4).

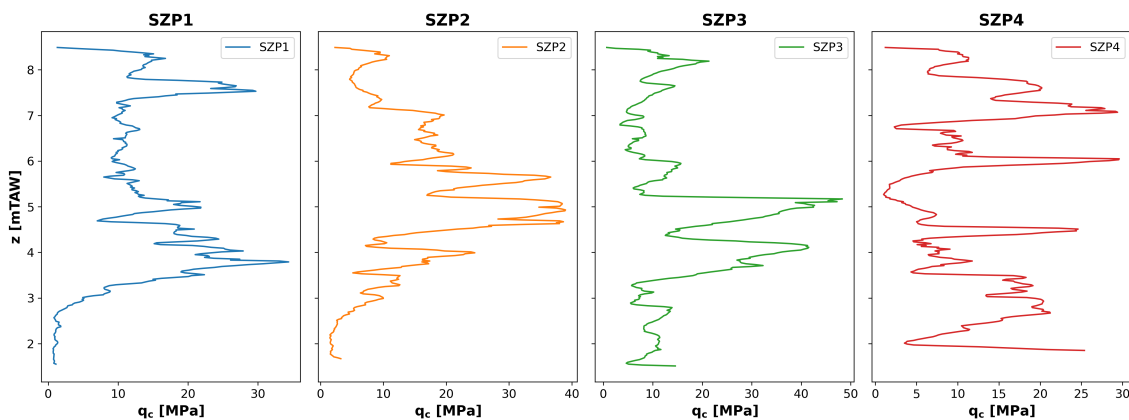


Figure 4.5: CPTs performed at the locations of settlement plates ZP1, ZP2, ZP3 and ZP4

4 Soil parameter distributions

First, the coefficient of lateral earth pressure at rest K_0 is determined by applying the correlation of *Mayne* (equation (4.4)) (Mayne, 2007). Figure 4.6 presents the calculated K_0 -values for the four CPTs, including the mean values of the coefficient of lateral earth pressure at rest over depth. These values are used as input to calculate the relative density D_r of the sand.

$$K_0 = 0.192 \left(\frac{q_t}{p_{atm}} \right)^{0.22} \cdot \left(\frac{p_{atm}}{\sigma'_{v,0}} \right)^{0.31} \cdot OCR^{0.27} \quad (4.4)$$

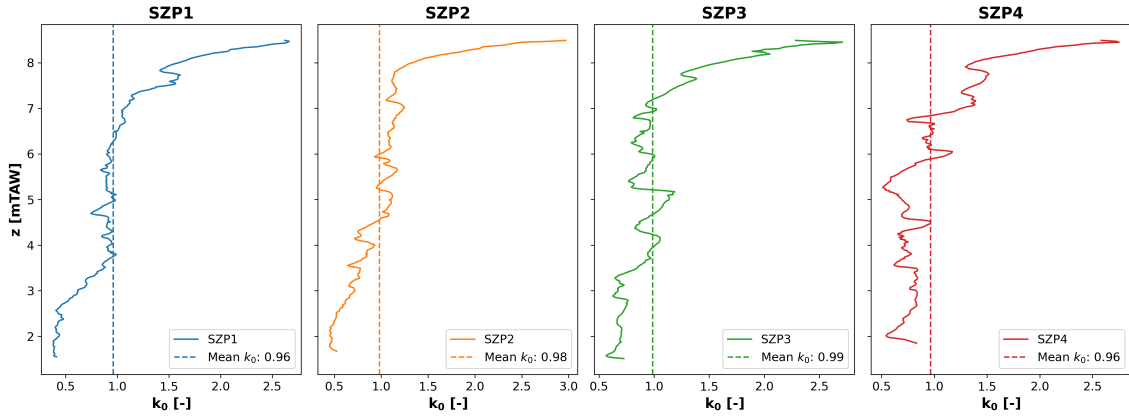


Figure 4.6: Coefficient of lateral earth pressure at rest K_0 according to *Mayne*

Next, the relative density D_r of the sand is determined using the correlation of *Baldi* for overconsolidated sands (equation (4.5)) (Baldi et al., 1986): The correlation of *Jamiolkowski* could not be used, as it requires vertical effective stresses exceeding 50 kPa, which is not the case here. Similarly, the *Baldi* correlation for normally consolidated sand is deemed unsuitable because $K_0 > 0.45$. Figure 4.7 shows the calculated relative density D_r for the four CPTs.

$$D_r = \frac{1}{2.61} \cdot \ln \left(\frac{q_c}{181 \cdot (\sigma'_m)^{0.55}} \right) \text{ and } \sigma'_m = \frac{\sigma'_{v,0} + 2 \cdot K_0 \cdot \sigma'_{h,0}}{3} \quad (4.5)$$

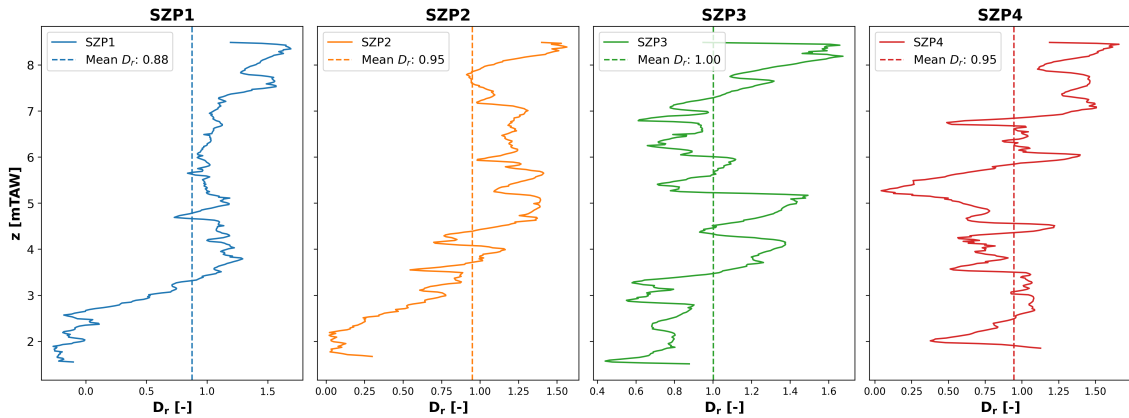


Figure 4.7: Relative density D_r according to *Baldi*

4 Soil parameter distributions

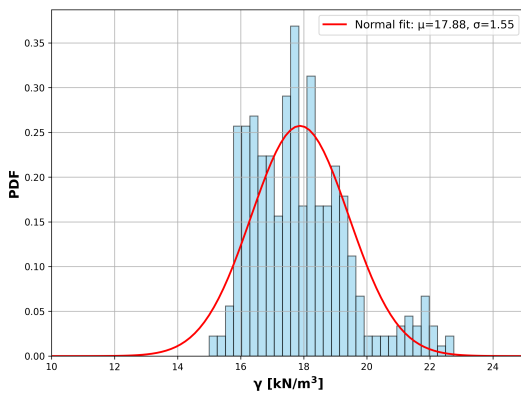
Finally, the parameters of the HSsmall model can be determined based on the mean value of the relative density (always smaller than 1) of the sand with the tool in Groundhog (Stuyts, 2023). Here, the mean of the four mean values of the relative density over the depth for the four CPTs yields $D_r = 0.945$. This results in the HSsmall parameters listed in Table 4.1.

Table 4.1: Deterministic values of the sand used in the dike construction (layer A)

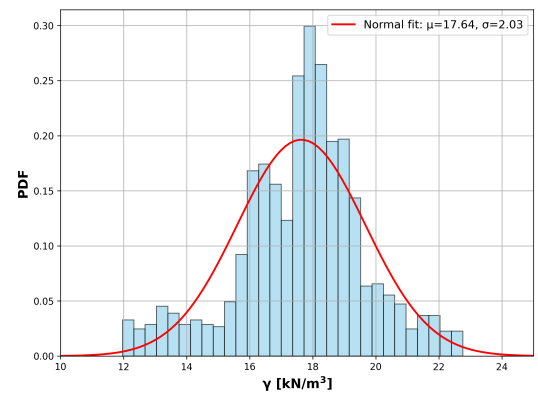
Parameter	Value	Parameter	Value	Parameter	Value
$\gamma_{unsat} [kN/m^3]$	18.78	$E_{50}^{ref} [kPa]$	56700	$m [-]$	0.4047
$\gamma_{sat} [kN/m^3]$	20.51	$E_{oed}^{ref} [kPa]$	56700	$\gamma_{0.7} [-]$	$1.06 \cdot 10^{-4}$
$E_{ur}^{ref} [kPa]$	170100	$G_0^{ref} [kPa]$	124260	$\phi_{eff} [^\circ]$	39.81
$\psi [^\circ]$	9.81	$R_f [-]$	0.8819		

To conclude this, the unit weight γ of the sand used in the dike construction can be determined to verify the reliability of the values in the table above. Therefore, the below correlation of *Robertson and Cabal* (equation (4.6)) can be used on the CPT data (Robertson and Cabal, 2014). Figure 4.8 shows the resulting histograms and fitted normal distributions for the unit weight. A good agreement between the two figures can be observed. The standard deviation in Figure 4.8b is slightly higher due to the inclusion of more datapoints. Furthermore, the mean calculated unit weight is slightly lower than the dry unit weight reported in Table 4.1. Minor peaks around $21.5 kN/m^3$ in the histograms can be attributed to the presence of saturated sand near the toe of the new dike.

$$\gamma = \left[0.27 \cdot \log(R_f) + 0.36 \cdot \left(\log \left(\frac{q_t}{p_{atm}} \right) + 1.236 \right) \right] \cdot \frac{\rho_w \cdot g}{1000} \quad (4.6)$$



(a) Based on CPT SZP3



(b) Based on CPTs SZP1, SZP2, SZP3 and SZP4

Figure 4.8: Determination of the unit weight γ of the sand used in the dike construction

4 Soil parameter distributions

4.2.2 Deterministic values of the sand replacement's properties (layer R)

For the analysis of the soil replacement in DP26, CPT S203 can be used. Figure 2.12 in section 2.2.2 illustrates the effect of the soil replacement on the cone resistance of the soil by comparing CPTs S111 and S12 (conducted prior to the soil replacement) with CPT S203 (performed after the soil replacement). Additionally, the compaction of the sand within the dike body can be observed by comparing CPT S203 with CPT SZP3. The latter was carried out at a later stage and shows significantly higher cone resistance values, indicating a denser and more compacted sand layer within the dike body.

To determine the characteristics of the sand used for the soil replacement using CPT S203, the same procedure described in the previous paragraph is applied. By calculating the coefficient of lateral earth pressure at rest using the *Mayne* correlation and the relative density via the *Baldi* correlation, the parameters for the HSsmall model can be derived. The full calculation procedure is illustrated in Figure 4.9. In Figure 4.9a, it is observable that the cone resistance profile exhibits two distinct peaks as a result of the soil replacement and its non-optimal compaction. These peaks indicate zones of sandy behaviour, which are particularly relevant for characterizing the replacement material. Figures 4.9b and 4.9c focus on the upper peak, located between approximately $+0.50 \text{ mTAW}$ and -0.10 mTAW , to derive the representative soil parameters for this layer. The resulting soil properties are tabulated in table 4.2.

Table 4.2: Deterministic values of the sand used in the soil replacement (layer R)

Parameter	Value	Parameter	Value	Parameter	Value
$\gamma_{unsat} [kN/m^3]$	16.00	$E_{50}^{ref} [kPa]$	15000	$m [-]$	0.6219
$\gamma_{sat} [kN/m^3]$	19.40	$E_{oed}^{ref} [kPa]$	15000	$\gamma_{0.7} [-]$	$1.75 \cdot 10^{-4}$
$E_{ur}^{ref} [kPa]$	45000	$G_0^{ref} [kPa]$	77000	$\phi_{eff} [^\circ]$	31.13
$\psi [^\circ]$	1.13	$R_f [-]$	0.9688		

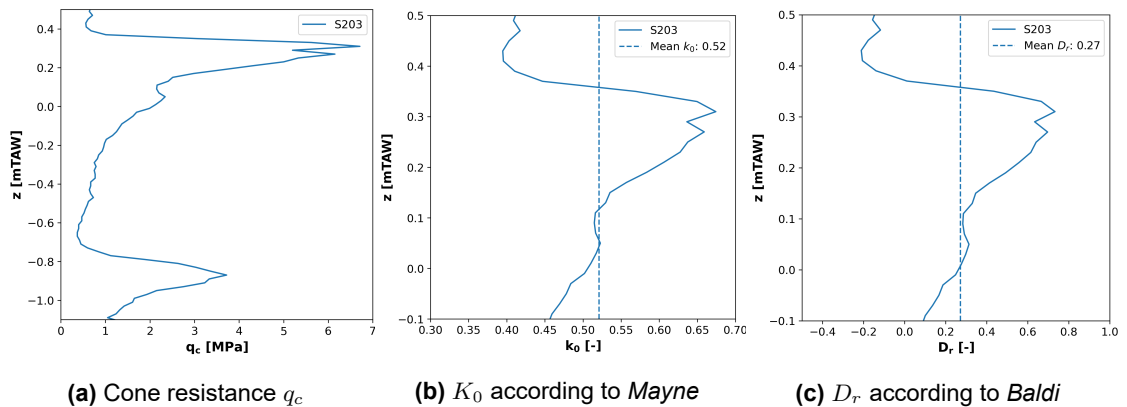


Figure 4.9: Determination of the HSsmall parameters for the sand of the soil replacement

4 Soil parameter distributions

4.3 Probability distributions of the critical soil parameters

The sensitivity analysis in section 4.1 highlights the importance of further investigating the statistical distributions of key parameters for the very soft outcropping clay layer S. These parameters include the overconsolidation ratio OCR , the compression index λ , the recompression index κ and the vertical permeability k_{vert} . To determine their distributions, an existing workflow developed by IMDC is applied and adapted. Originally designed to establish probability distributions for soil parameters in offshore sand nourishments (Somers et al., 2023), the workflow is tailored to HSsmall modelled soil. However, since the soft clay is modelled using the Modified Cam-Clay model, the workflow requires modifications to accurately derive the probability density function (PDF) or cumulative distribution function (CDF) for the relevant clay parameters.

The procedure consists of four main steps, each supported by a dedicated Orange workflow to automate the process. Orange is a data visualization and analysis tool that facilitates the creation of workflows for automated data processing. It is particularly suited to this task, as it allows for the integration of multiple data sources, such as CPT(u) data from site investigations and laboratory test results, and the application of statistical methods to derive PDFs for the critical soil parameters. The methodology and reasoning behind each step are outlined below.

1. **Collection and preparation of the CPT(u) data:** CPT(u)s available near the Kragewiel site are collected as GEF files from DOV. These files are processed through a Data Uniformer Tool, which structures the data into different levels for further analysis in Orange. The raw CPT(u) data is then used to calculate derivative and normalized parameters.
2. **Linking the CPT(u) data to the soil layers:** by plotting the cone resistance q_c and shaft friction resistance f_s over depth, the soil layers can be identified, allowing each CPT(u) datapoint to be assigned to a specific soil layer.
3. **Determining the PDFs by CPT(u) correlations:** literature-based CPT(u) correlations are used to estimate clay parameters relevant for settlement. If sufficient CPT(u) data is available within layer S, a histogram of the target parameter can be created, enabling the derivation of its PDF and CDF. The most suitable correlation(s) are selected by comparing these results with lab test data. Bootstrapping the lab data provides an independent histogram, allowing for comparison with the CPT(u)-derived CDF to assess correlation accuracy.
4. **Quantifying the model uncertainty by comparing CPT(u) and laboratory test data:** since the CPT(u)-based correlations were developed for specific clay types and the soft clay in Bornem (layer S) may behave differently, model uncertainty must be addressed. This is done by comparing lab test results with CPT(u)-derived parameters at matching depths and locations. The observed discrepancies are used to adjust the PDFs of the probabilistic parameters, ensuring the distributions reflect the actual behaviour of layer S.

4 Soil parameter distributions

4.3.1 Collection and preparation of the CPT(u) data

In total, 16 CPT(u)s can be used to characterize the subsoil in the vicinity of the Kragewiel. These CPT(u)s have been executed before the construction of the new dike started and can be roughly categorized into three groups: CPT(u)s at the GOG side of the old dike, CPTs underneath the old dike body and CPTs at the Kragewiel side of the old dike. The CPT(u)s at the GOG side of the old dike are most relevant for the current study since layer S outcrops in this zone. The location of the CPT(u)s is displayed on Figure 4.10. A statistical overview of the CPT(u) data is given in Table 4.3. In this table, n_{data} represents the number of data points available in each layer and each zone. μ_{q_c} and σ_{q_c} respectively represent the mean and standard deviation of the measured cone resistance q_c .

Table 4.3: Statistical overview CPT(u) data

GOG side old dike	GEO-19/108-S110, GEO-19/108-S110U, GEO-19/108-S111, GEO-19/108-S111U, GEO-19/108-S112, GEO-19/108-S112U		
<i>Layer</i>	n_{data}	$\mu_{q_c} [MPa]$	$\sigma_{q_c} [MPa]$
Layer S	790	0.22	0.05
Layer H	1333	8.23	4.23
Layer I	694	4.50	1.24
Layer J	749	11.86	2.29
Underneath old dike	GEO-18/015-S10, GEO-18/015-S11, GEO-19/108-S103, GEO-18/015-S12, GEO-19/108-S104, GEO-18/015-S13		
<i>Layer</i>	n_{data}	$\mu_{q_c} [MPa]$	$\sigma_{q_c} [MPa]$
Layer C	1069	1.32	0.72
Layer E	2074	1.05	0.52
Layer I	1512	11.52	10.02
Layer J	686	11.85	1.71
Kragewiel-side old dike	GEO-19/108-S106, GEO-19/108-S113, GEO-19/108-S107, GEO-19/108-S108		
<i>Layer</i>	n_{data}	$\mu_{q_c} [MPa]$	$\sigma_{q_c} [MPa]$
Layer Ebis	833	0.95	1.20
Layer H	905	9.45	9.24
Layer I	247	4.80	1.13
Layer J	493	10.14	1.61

4 Soil parameter distributions



Figure 4.10: Location of the CPT(u)s in the vicinity of the Kragewiel

These 16 CPT(u)s can be extracted from DOV and processed using the Data Uniformer Tool provided by IMDC. This tool identifies and corrects formatting errors in the CPT(u) data and structures it into different hierarchical levels, each represented by a separate Excel file.

On level 0, each CPT(u) test is assigned a row in the corresponding Excel file, with columns containing the test ID, the cone type, the cone area, the coordinates of the location of the test and the height of the starting point of the test, expressed in $mTAW$. From the latter two, the division of the CPT(u)s into three groups according to their location can be verified. While the CPT(u)s at both sides of the old dike have a starting height of about $+1.50 mTAW$, the six CPTs executed through and underneath the old dike body started at about $+7.20 mTAW$. All CPT(u)s have been executed with a $10 cm^2$ cone area and a net area ratio a of 0.75. This net area ratio is the slope of the line obtained by plotting the cone resistance against the applied the pressure.

On level 1, each row in the corresponding Excel file contains a datapoint. For each datapoint, the corresponding CPT(u) test ID, the depth d of the datapoint and the bare CPT(u) parameters are listed. These bare parameters include the cone resistance q_c , the sleeve friction f_s and eventually the pore pressure at the cone shoulder u_2 . The latter is only available for datapoints registered by a piezocone. This type of cone has only been used for the CPTu tests GEO-19/108-S110U, GEO-19/108-S111U and GEO-19/108-S112U. All other CPTs have been executed with a standard electrical cone.

These two Excel files are used as input for the first Orange workflow. The first Orange workflow essentially extends the level 1 Excel file by calculating derivative parameters as well as soil behaviour type parameters for each CPT(u) datapoint.

4 Soil parameter distributions

4.3.1.1 Derived CPT(u) parameters

The CPT(u) parameters derived in the first workflow are tabulated in Table 4.4. Their calculation requires the definition of the following constants: the atmospheric pressure $p_{atm} = 0.1013 \text{ MPa}$, the density of water $\rho_w = 1000 \text{ kg/m}^3$, the gravitational acceleration $g = 9.81 \text{ N/kg}$ and the minimal soil unit weight $\gamma_{min} = 12 \text{ kN/m}^3$.

Table 4.4: Derived CPT(u) parameters (Lunne et al., 2002)

Quantity	Unit	Formula
Equilibrium pore pressure u_0	MPa	$u_0 = \frac{d \cdot \rho_w \cdot g}{1000 \cdot 1000}$
Excess pore pressure Δu	MPa	$\Delta u = u_2 - u_0$
Corrected cone resistance q_t^a	MPa	$q_t = q_c + u_2 \cdot (1 - a)$
In situ total vertical stress $\sigma_{v,0}$	MPa	$\sigma_{v,0} = \frac{d \cdot g}{1000}$
In situ effective vertical stress $\sigma'_{v,0}$	MPa	$\sigma'_{v,0} = \sigma_{v,0} - u_0$
Net cone resistance q_n	MPa	$q_n = q_t - \sigma_{v,0}$
Friction ratio R_f	%	$R_f = \frac{f_s}{q_t} \cdot 100$
Pore pressure ratio B_q	—	$B_q = \frac{\Delta u}{q_n}$
Normalized cone resistance Q_t^b	—	$Q_t = \frac{q_t - \sigma_{v,0}}{\sigma'_{v,0}}$
Normalized friction ratio F_r^b	—	$F_r = \frac{f_s}{q_t - \sigma_{v,0}} \cdot 100$
Soil unit weight γ	kN/m^3	$\gamma = (0.27 \cdot \log(R_f) + 0.36 \cdot (\log(q_t/p_{atm}) + 1.236)) \cdot \frac{\rho_w \cdot g}{1000}$

^a This correction is needed due the unequal area effect, caused by the pore water pressure measurement at the shoulder of the piezocone.

^b This is a normalization according to formulas of Wroth to account for the influence of overburden stress.

Most of the CPT data in this study were collected using a standard cone without pore pressure measurement (i.e. no piezocone or CPTu). As a result, the pore water pressure at the shoulder of the cone u_2 is not available for these tests. Since normalized CPT parameters require effective stress calculations, an assumption regarding pore pressure is necessary to estimate the vertical effective stress $\sigma'_{v,0}$. In the absence of direct measurements, it is common practice to assume a hydrostatic pore pressure distribution: $u_2 = u_0$. This assumption implies that the excess pore pressure Δu is equal to zero.

While this hydrostatic assumption is widely accepted and generally accurate in coarse-grained soils such as sands, it introduces limitations in soft, low-permeability soils like clay. In such materials, cone penetration can generate significant excess pore pressures that are not captured under hydrostatic conditions, potentially affecting effective stress estimates. However, in this study, the primary clay layer of interest is located at shallow depth. At such depths, both total and pore pressures are relatively low, which limits the generation of excess pore pressure during penetration. Therefore, the error introduced by assuming hydrostatic conditions is expected to be minor in this context.

4 Soil parameter distributions

Furthermore, the impact of this assumption is further mitigated in the analysis of layer S, which is located on the GOG side of the dike. As shown in Table 4.3, each CPT in this area is accompanied by a corresponding CPTu test, providing direct measurements of u_2 . This availability of pore pressure data allows for a more reliable and accurate analysis, reducing reliance on hydrostatic assumptions for this layer. This fortunate availability also ensures a more correct interpretation of soil behaviour and reinforces the validity of the subsequent analyses.

Lastly, it is worth noting that the normalized CPT parameters derived from this approach serve as input for an initial soil parameter distribution estimate in a Bayesian updating framework. This method is robust to some degree of uncertainty in the prior assumptions: as long as the observational data are sufficiently informative, the updating process can converge towards accurate inferences, even if the initial estimates deviate from reality (Caspeelee, 2024).

4.3.1.2 Soil behaviour type parameters

Finally, the first workflow also calculates the soil behaviour type parameters, using the method proposed by *Robertson* (Lunne et al., 2002). This method defines a soil behaviour type index $I_c [-] = ((3.47 - \log(Q_t))^2 + (\log(F_r) + 1.22)^2)^{0.5}$ that can be linked to several zones or soil behaviour types. The soil behaviour type can also be identified by plotting Q_t and R_f (Figure 4.11) or Q_t and B_q (Figure 4.12) on the well-known *Robertson* charts, from which the corresponding soil behaviour type can be read from Table 4.5.

Figures 4.11a and 4.12a show the *Robertson* charts for all soil layers in the studied cross-section. One can observe that the majority of the subsoil falls within the soil behaviour type categories 3, 4, 5 and 6, corresponding to clays, sands and mixtures of both. Figures 4.11b and 4.12b present CPTu data specifically for layer S. The color coding in these graphs denotes different depth intervals, revealing that layer S is distinctly stratified. This stratification, visible as successive color bands, indicates the presence of multiple fine soil layers in layer S, which are likely the result of repeated flooding in the area in front of the dike. Despite the presence of numerous thin layers, the overall composition remains consistent, consisting predominantly of clay and clayey silt. Figure 4.12b indeed reveals the availability of pore pressure measurements in layer S, since measured values for u_2 result in a pore pressure ratio B_q for clayey soil that is larger than zero.

Table 4.5: Soil behaviour types in the *Robertson* charts

Zone	Soil behaviour type	Zone	Soil behaviour type	Zone	Soil behaviour type
1	Sensitive, fine-grained	4	Silt mixtures: clayey silt to silty clay	7	Gravelly sand to sand
2	Organic soils (peats)	5	Sand mixtures: silty sand to sandy silt	8	Very stiff sand to clayey sand
3	Clays: clay to silty clay	6	Sands: clean sands to silty sands	9	Very stiff fine-grained

4 Soil parameter distributions

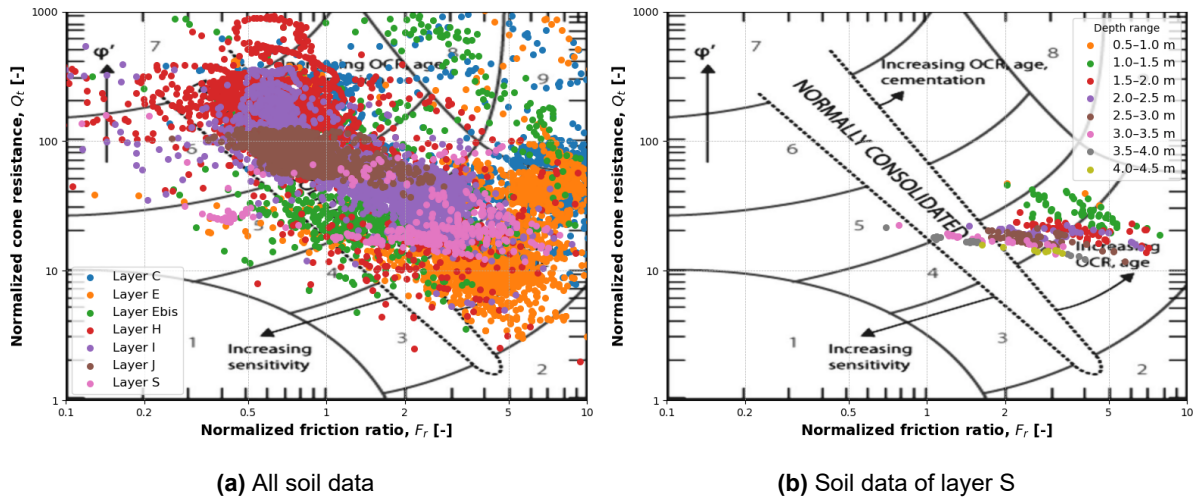


Figure 4.11: Robertson chart: R_f vs Q_t

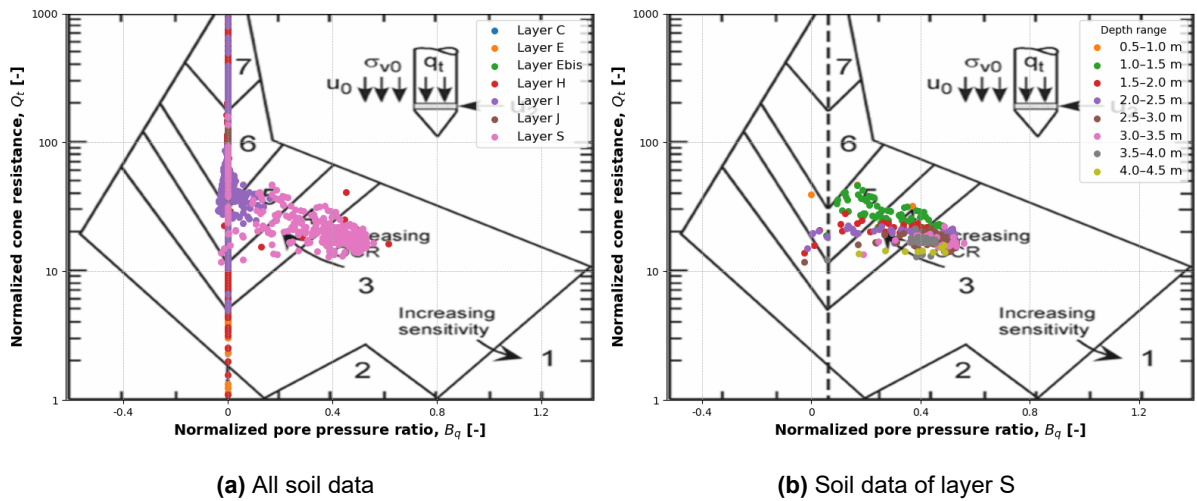


Figure 4.12: Robertson chart: B_q vs Q_t

The soil behaviour type classification can be very helpful in linking the CPT(u) data to the corresponding soil layers. However, factors such as variations in stress history, in situ stress conditions, mineralogy and void ratio can influence the accuracy of the classification. To ensure that the soil parameter distributions within layer S are as reliable as possible, it is essential to exclude data points from adjacent layers. Additional criteria, such as unit weight, will therefore be employed to more precisely delineate the boundaries of soil layer S.

4 Soil parameter distributions

4.3.2 Linking the CPT(u) data to the soil layers

In the second workflow, particular emphasis is placed on accurately linking all CPT(u) data points to their corresponding soil layers. As previously discussed, this step is essential for deriving meaningful statistical distributions that are truly representative for the specific soil layer under consideration. If data points from adjacent layers are inadvertently included, the resulting statistics can be significantly distorted. For instance, incorporating CPT(u) measurements from a sand layer into the analysis of a clay layer can lead to biased distributions, since the mechanical behaviour and strength parameters of sands often introduce extreme values that are not representative for clayey materials.

To ensure the reliability of the derived distributions, several assessment criteria are applied. A first step involves a preliminary classification starting from the soil layering defined by the Geotechnical department. Based on the soil behaviour type index I_c and the cone resistance q_c , this stratigraphy is further refined. When CPTu data is available, the measured pore pressure offers an additional, valuable criterion for distinguishing between clays and sands. Clays, due to their low permeability, exhibit undrained behaviour during cone penetration. This results in a substantial excess pore pressure build up above the hydrostatic pressure line. In contrast, sands behave in a drained manner: their high permeability allows pore water to dissipate rapidly, meaning that no significant excess pore pressure develops and the measured values generally follow the hydrostatic profile. This contrast is also reflected in the pore pressure ratio B_q , defined as the ratio of excess pore pressure to the net cone resistance. In clayey soils, B_q -values are significantly greater than zero, indicating undrained conditions, while in sandy soils, B_q tends to be close to zero. This distinction is clearly visible, for example, in Figure 4.12b, where a typical response for clay can be observed.

These parameters form the basis for an initial delineation of soil layer boundaries. While this first classification remains relatively coarse, it plays a crucial role in separating data by dominant soil type and mechanical behaviour. This separation provides the foundation for more refined, layer-specific analyses in the subsequent stages of the workflow.

For the CPT(u)s performed on the GOG side of the dike, this preliminary soil stratification is illustrated in Figure 4.13a. To assess the accuracy of this layering, particularly with respect to clay layer S, one can evaluate the distribution of a representative clay parameter to identify potential outliers or inconsistencies. A useful indicator for this purpose is the unit weight of the soil, which is known to be relatively constant for a given soil type and can therefore signal the presence of data points that may not belong to the intended layer. The unit weight within layer S can be estimated using the empirical correlation given in equation (4.6). The resulting distribution is presented in Figure 4.14a, which shows both a histogram of the calculated values and a fitted normal distribution. According to JCSS guidelines, the standard deviation of the unit weight for a specific soil type is typically around 5% of the mean value (Baker et al., 2006). Here, the mean unit weight is 14.79 kN/m^3 , with a standard deviation of 1.11 kN/m^3 (7.5%).

4 Soil parameter distributions

While this value is still within an acceptable range, the distribution exhibits a noticeable tail extending up to 19 kN/m^3 , which is considerably high for a clayey soil and suggests possible contamination of layer S from non-clay materials.

Re-examining the cone resistance profile in Figure 4.13a reveals that the upper few decimetres of the layer exhibit significantly higher cone resistance values compared to the rest of layer S. This observation indicates that the uppermost zone is likely not composed of pure clay, but rather a heterogeneous mixture of clay, silt and sand. This may result from repeated flooding events and anthropogenic surface activities in the area, which have likely disturbed the original topsoil. Also in Figure 4.11b, this can be observed as the orange (and green) dots in Zone 5 (and Zone 4).

Based on these findings, it is reasonable to exclude this surface layer from the extent of clay layer S. The revised stratification is illustrated in Figure 4.13b. That this decision is justified is demonstrated by the updated unit weight distribution shown in Figure 4.14b. After refinement, the distribution becomes more narrowly concentrated around a mean value of 14.39 kN/m^3 , with a much smaller standard deviation of 0.39 kN/m^3 , equivalent to just 2.7% of the mean. This improved consistency confirms that the surface layers had previously distorted the characterization of layer S. With the refined layering in place, the analysis can now proceed with greater confidence in the statistical integrity of the data.

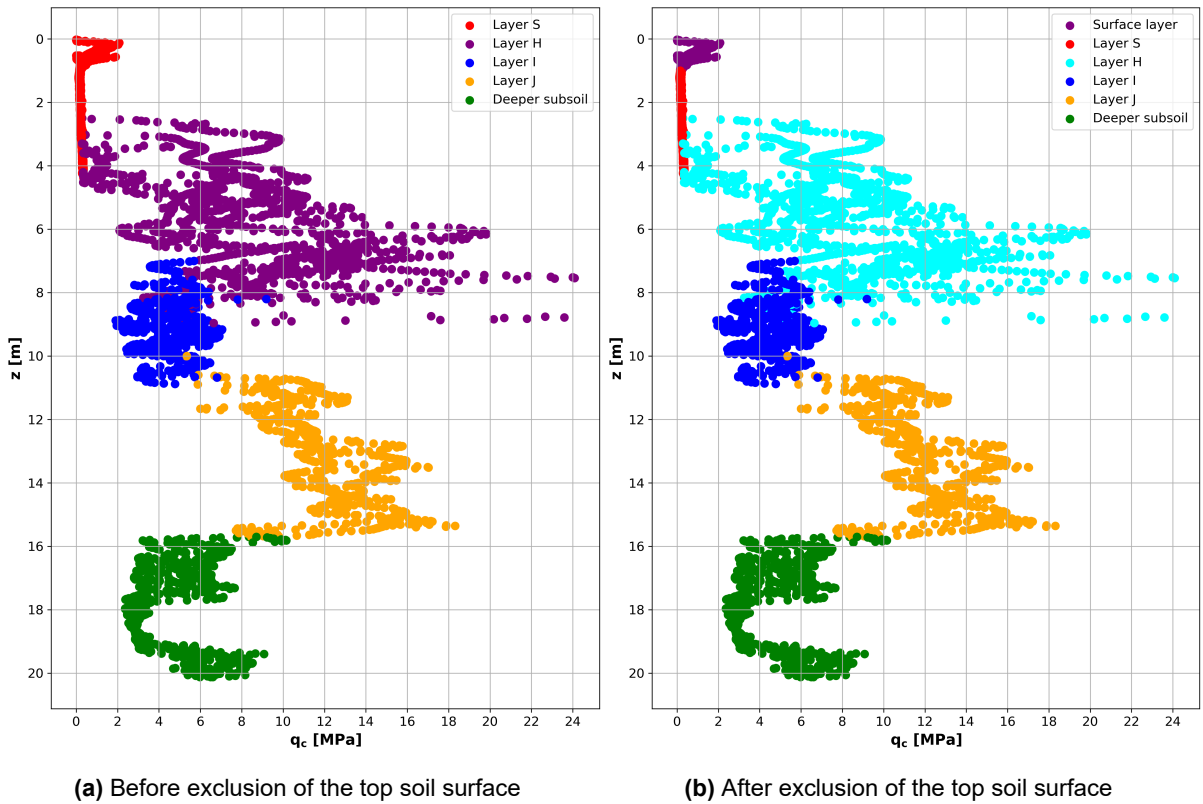


Figure 4.13: Cone resistance q_c in function of depth z for the CPT(u)s at the GOG side of the dike

4 Soil parameter distributions

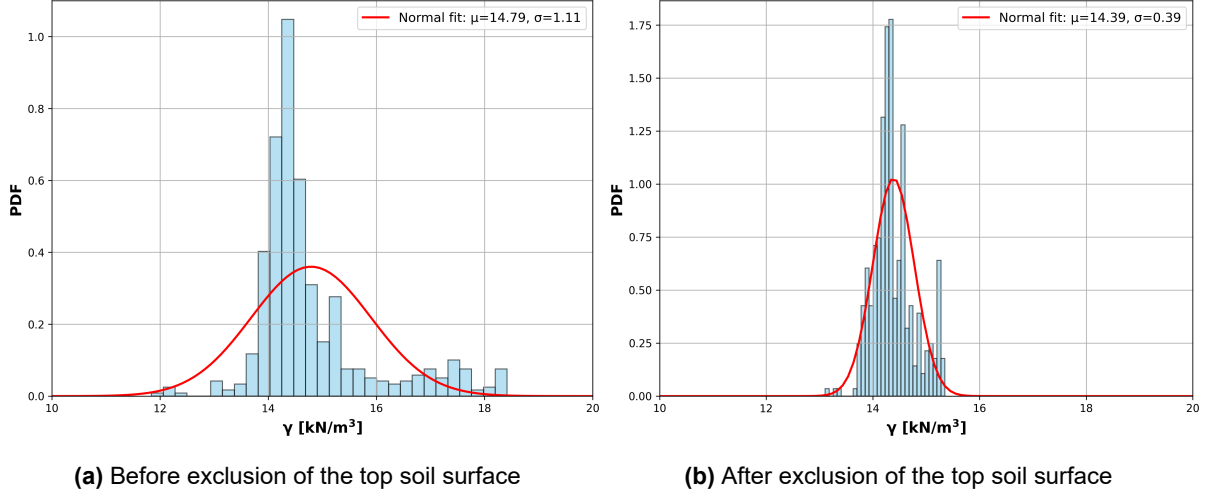


Figure 4.14: Statistical distribution of the unit weight γ of the soil included in layer S

4.3.3 Determining the probabilistic distributions and model errors of the critical soil parameters

Now that all CPT(u) data has been collected, processed and accurately linked to the corresponding soil layers, the subsequent step involves deriving the statistical distributions of sensitive geotechnical parameters. The literature offers numerous empirical correlations for estimating parameters such as the overconsolidation ratio, vertical permeability, compression index and recompression index based on CPT(u) results. However, these correlations are typically developed and calibrated using data from specific soil types, which may not align with the characteristics of soil layer S under investigation. To determine the applicability of each correlation to layer S, the parameter values derived from these empirical relationships are systematically compared against available laboratory test results. This comparison allows for the identification of correlations that yield consistent and representative values for the soil conditions in question.

It should be noted that neither correlations nor laboratory tests are available for directly determining the compression index λ or the recompression index κ . However, both empirical correlations and laboratory measurements do exist for the Flemish compression constant C , which is related to the compression index C_c and the recompression index C_r , as demonstrated in equation (2.1). From these values, the parameters λ and κ can be derived as well, as can be seen below (Budhu, 2010).

$$C_c = \frac{\Delta e}{\log(\sigma'_1/\sigma'_2)} \longleftrightarrow \Delta \varepsilon = \frac{\Delta e}{1 + e_0} \longleftrightarrow E_{oed} = \frac{\Delta \sigma'}{\Delta \varepsilon} \quad (4.7)$$

$$\Delta \varepsilon = \frac{C_c \cdot \Delta \log \sigma'}{\log(10) \cdot (1 + e_0)} \longrightarrow E_{oed} = \frac{\log(10) \cdot (1 + e_0) \cdot \sigma'}{C_c} \longrightarrow C_c = \frac{2.3 \cdot (1 + e_0) \cdot \sigma'}{E_{oed}} \quad (4.8)$$

4 Soil parameter distributions

For the compression index λ the following relations hold (PLAXIS, 2024b).

$$\lambda = \frac{C_c}{2.3} = \frac{(1 + e_0) \cdot \sigma'}{E_{oed}} \rightarrow \lambda = \frac{(1 + e_0) \cdot p^{ref}}{E_{oed}^{ref}} = \frac{(1 + e_0) \cdot p^{ref}}{E_{oed} \cdot \frac{p^{ref}}{\sigma'}} \quad (4.9)$$

$$E_{oed}^{ref} = E_{oed} \cdot \left(\frac{p^{ref}}{\sigma'} \right)^m \quad \text{with } m = 1 \text{ for clays} \quad (4.10)$$

$$\frac{C_c}{(1 + e_0)} = \frac{2.3 \cdot \sigma'}{E_{oed}} = \frac{2.3}{C} \rightarrow C = \frac{E_{oed}}{\sigma'} \rightarrow \lambda = \frac{(1 + e_0)}{C} \quad (4.11)$$

For the recompression index κ the following relations hold (PLAXIS, 2024b)

$$\kappa = \frac{C_r}{2.3} = \frac{C_c}{2.3 \cdot (5 \text{ à } 10)} \quad (4.12)$$

$$E_{50}^{ref} = 2 \cdot E_{oed}^{ref} \text{ and } E_{ur}^{ref} = 3 \cdot E_{50}^{ref} \rightarrow E_{ur}^{ref} = 6 \cdot E_{oed}^{ref} \quad (4.13)$$

$$\kappa = \frac{(1 + e_0) \cdot 2 \cdot p^{ref}}{E_{ur}^{ref}} = \frac{(1 + e_0) \cdot 2 \cdot p^{ref}}{6 \cdot E_{oed}^{ref}} \rightarrow \kappa = \frac{(1 + e_0)}{3 \cdot C} \quad (4.14)$$

This derivation has an important implication: since both the compression index λ and the recompression index κ can be derived from the Flemish compression constant C and the initial void ratio e_0 , they cannot be treated as independent parameters within the Bayesian updating framework. As a result, it is more consistent and theoretically sound to adopt C and e_0 as the sensitive and independent parameters representing the soil's compressibility and recompression behaviour. Accordingly, the four parameters for which statistical distributions will be established, based on both CPT(u) data and laboratory test results, are the overconsolidation ratio OCR , the vertical permeability k_{vert} , the Flemish compression constant C and the initial void ratio e_0 .

4.3.3.1 Bootstrapping of the laboratory test data

A statistical overview of the relevant laboratory test results for layer S is presented in Table 4.6. These tests were conducted on undisturbed soil samples extracted from boreholes BH35 and BH111, located on the GOG side of the dike. In total, five samples from layer S were analysed, allowing for the experimental determination of key soil parameters, as summarized in the table. The overconsolidation ratio was determined using CRS tests. The vertical permeability of the cohesive soil samples was obtained through triaxial testing, which is considered the most suitable method for this purpose, as discussed in section 2.3.2.3. The initial void ratio (e_0) was identified based on water content tests, while the Flemish compression constant (C) was derived from one-dimensional oedometer tests (Couck, 2022).

4 Soil parameter distributions

Table 4.6: Statistical overview laboratory test data in layer S

Test location (depth below surface)	OCR [–]	k_{vert} [m/s]	e_0 [–]	C [–]
B35-1 (1.00 – 1.50 m)	6.60	$1.60 \cdot 10^{-8}$	1.14	30.33
B35-2 (2.00 – 2.50 m)	2.24	$1.02 \cdot 10^{-8}$	1.61	12.00
B35-3 (3.00 – 3.50 m)	1.76	$2.35 \cdot 10^{-10}$	2.42	10.33
B111-1 (1.50 – 2.00 m)	2.34	$2.50 \cdot 10^{-8}$	2.38	9.50
B111-2 (3.00 – 3.50 m)	1.79	$1.60 \cdot 10^{-9}$	2.26	8.67
Mean value μ	2.95	$1.06 \cdot 10^{-8}$	1.96	14.16
Standard deviation σ	1.84	$9.22 \cdot 10^{-9}$	0.50	8.16

For the project in Bornem, a relatively extensive site investigation and laboratory testing campaign has been carried out. However, despite these efforts, the resulting dataset for layer S still contains only five test values per key parameter. This limited sample size is insufficient to construct a meaningful histogram or reliably fit a statistical distribution from which a cumulative distribution function (CDF) could be derived. Such a CDF is needed to compare the laboratory-based results with those obtained via empirical correlations, in order to evaluate their applicability and performance.

To address the challenge of limited laboratory test data, an issue frequently encountered in geotechnical practice, the bootstrap resampling method is employed. In this study, bootstrapping is used to estimate the statistical distribution of key soil parameters in layer S based on a small set of experimental data. The method is particularly well-suited for situations where the sample size is small and the underlying population distribution is unknown or cannot be assumed. Bootstrapping operates by repeatedly resampling, with replacement, from the original dataset to generate a large number of synthetic samples, each equal in size to the original. These resampled datasets may contain repeated values, reflecting the idea that each observation in the original dataset represents a plausible member of the underlying population. For each resample, the soil parameter of interest is recalculated and the resulting collection of values forms an empirical approximation of the parameter's sampling distribution (Trainer, 2021). This procedure is rooted in the principles of statistical inference. In geotechnical engineering, it is often impractical to measure every possible realization of a soil parameter. As a result, engineers rely on limited samples to infer the broader behaviour of the soil. Bootstrapping allows to approximate the distribution of these soil parameters, even when classical statistical tools like the Central Limit Theorem are not applicable due to small sample sizes. By generating thousands of bootstrap replicates, a more robust estimate of the CDF is obtained.

By all means, attempting to fit a parametric probability distribution directly to the five available laboratory test results per parameter is not recommended, as such limited data yields unstable and unreliable distribution estimates.

4 Soil parameter distributions

Bootstrapping, in contrast, leverages the existing data more effectively to generate statistically meaningful inferences.

Figure 4.15, shows the estimated distributions of the four relevant soil parameters in layer S, based on bootstrapping of the laboratory results and making use of 10000 sample draws. The resulting distributions of the mean parameter values are presented as histograms, with the fitted normal, log-normal and gamma distributions overlaid in red, yellow and blue respectively.

In probability and statistics, many continuous probability distributions are characterized by three key parameters: the location, scale and shape. These parameters describe different aspects of the distribution's characteristics, such as its position, spread and overall form.

- **Location parameter:** determines the central position of the distribution along the horizontal x -axis. It shifts the entire distribution without affecting its shape or spread.
- **Scale parameter:** controls the spread of the distribution by stretching or compressing it along the x -axis. A larger scale leads to a wider distribution, while a smaller scale results in a more concentrated distribution.
- **Shape parameter:** influences the shape of the distribution and determines characteristics such as skewness and kurtosis (peakedness). The shape parameter varies depending on the distribution.

From the location l , scale s and shape parameters h of the three fitted distributions, the mean μ and standard deviation σ of the estimated soil parameters can be determined using the below formulas (Caspeele, 2024).

- **Normal distribution:** $\mu = l$ and $\sigma = s$.
- **Log-normal distribution:** $\mu = e^{\ln(s)+0.5 \cdot h^2}$ and $\sigma = \sqrt{(e^{h^2} - 1) \cdot e^{2 \cdot \ln(s)+h^2}}$.
- **Gamma distribution:** $\mu = h \cdot s$ and $\sigma = \sqrt{h} \cdot s$

With reference to Figure 4.15, it should be emphasized that the gamma distribution, although sometimes used for fitting purposes, does not carry a physical interpretation in the context of soil parameter distributions. Consequently, the focus is placed primarily on the normal and log-normal distributions, which are more consistent with the expected behaviour of geotechnical parameters. The normal distribution is suitable for modelling symmetric data, whereas the log-normal distribution is more appropriate for positively skewed data, a common characteristic in geotechnical properties such as permeability and compressibility.

A final important consideration applies specifically to the overconsolidation ratio (OCR), which by definition cannot be less than one, as values below this threshold would imply a normally consolidated state rather than overconsolidation.

4 Soil parameter distributions

To account for this physical constraint, the OCR can be modelled using a log-normal distribution with a location parameter $loc = 1$, ensuring that all sampled values exceed the minimum threshold. Alternatively, a truncated normal distribution can be employed, bounded below by $OCR = 1$. In the latter approach, the lower bound is transformed into standard normal space using $(1 - \mu)/\sigma$, and the resulting value is applied in the *scipy.stats* Python library using the `truncnorm()` function. This allows for statistically consistent modelling while adhering to the geotechnical limitations of the parameter.

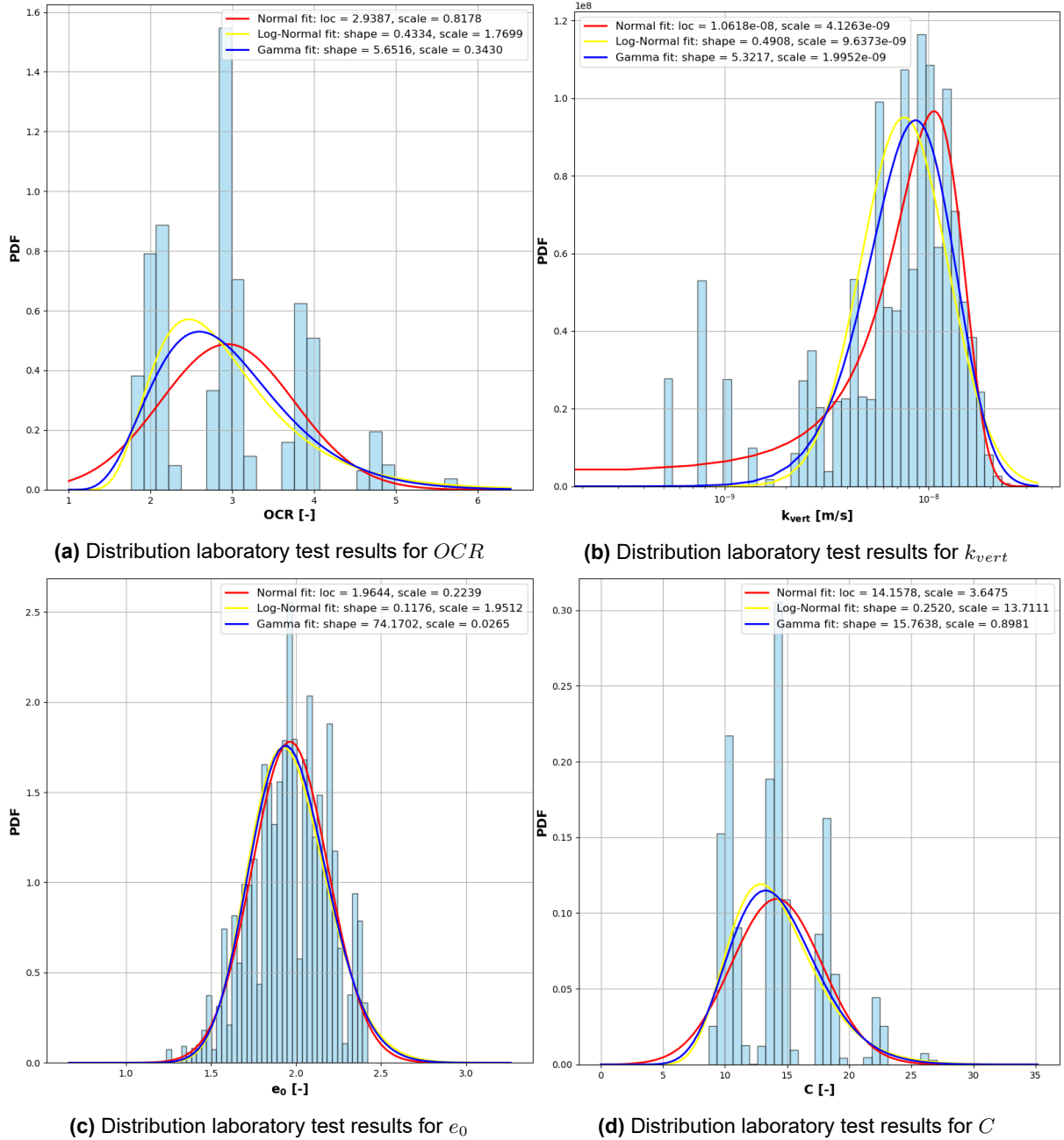


Figure 4.15: Parameter distribution in layer S based on bootstrapping of the laboratory test results

4 Soil parameter distributions

4.3.3.2 Probabilistic distributions and model errors: theoretical framework

CPT(u) correlations and statistical distributions A first key result in the final outcome of this chapter is the determination of the probabilistic distributions of the overconsolidation ratio, vertical permeability, initial void ratio and compression constant for the clay in layer S. Now that approximate distributions have been fitted to the laboratory test data using the bootstrap resampling method, one might wonder why these distributions are not used directly to characterize the soil parameters required for the probabilistic settlement calculations. The reason lies in the inherently limited size of the laboratory dataset. Even after applying bootstrapping, the number of original data points remains small compared to the vast quantity of CPT(u) data available. Consequently, the distributions derived from the CPT(u) data are statistically more reliable than those based solely on the laboratory test results.

This limitation is clearly illustrated in Figure 4.15, where the histograms based on the laboratory data appear discontinuous, showing sharp peaks around the observed test values and significant gaps in between. Although bootstrapping helps to smooth out these gaps, it cannot fully resolve them, especially for parameters with inherently wide distributions such as the overconsolidation ratio in Figure 4.15a and the Flemish compression constant in Figure 4.15d.

The primary advantage of using CPT data is the large volume of available measurements, which supports the generation of robust statistical distributions. However, this approach requires the use of empirical correlations to convert CPT(u) data into the soil parameters of interest. As discussed earlier, these correlations are typically calibrated on soil types that may differ significantly from the soft clay encountered in layer S. This is where the bootstrapped laboratory data plays a crucial role. While the laboratory-derived distributions may lack statistical robustness, they provide valuable insight into the actual soil conditions in layer S, since they are based on direct measurements of the in-situ soil.

Therefore, these laboratory-based CDFs serve as a reference to evaluate the reliability of the CPT-based correlation-derived distributions. By comparing both sets of distributions, it becomes possible to assess the applicability of each correlation to the local soil context. Moreover, once the most appropriate correlation is identified, the model error (i.e. the systematic discrepancy between the correlation-predicted values and the laboratory measurements) can be quantified and explicitly accounted for in the probabilistic framework.

In section 4.3.3.3, the probabilistic distributions of the four critical clay parameters (OCR , k_{vert} , e_0 , and C) are derived and presented using correlations based on CPT(u) data. For each correlation, the parameter values are calculated at all available CPT(u) measurement points within layer S. This results in a large dataset for each parameter, from which a histogram can be constructed. A normal or log-normal probability density function (PDF) is then fitted to the data. The corresponding cumulative distribution function (CDF) is subsequently used to assess the quality of each correlation by comparing it visually with the CDFs derived from laboratory test data.

4 Soil parameter distributions

The overall methodology remains the same for all four parameters. Only the correlations used as input differ. Since layer S is classified as a fine-grained soil, only correlations developed for cohesive soils will be considered. Correlations developed for coarse-grained soils consistently produced inferior results and are consequently excluded from further consideration.

Quantification of the model error according to NBN EN1990 Annex D A second key objective of this chapter is to quantify the model error associated with the proposed probabilistic distributions. To complete the discussion on the derivation of statistical distributions for the soil parameters, it is crucial to assess the uncertainty introduced by the empirical correlations used for parameter estimation. This model uncertainty arises from inherent discrepancies between the predicted values obtained from these correlations and the actual soil behaviour observed in practice. To quantify this uncertainty, the methodology outlined in Annex D of NBN EN1990 is applied (Bureau voor Normalisatie (NBN), 2002). Specifically, the model error is assessed by comparing laboratory test results with values estimated from empirical correlations at the same locations and depths, following the procedures prescribed in the standard.

Table 4.6 provides an overview of the laboratory test results, including the corresponding test depths and locations. The selected empirical correlations are used to calculate the clay parameter of interest from CPT(u) data measured at sounding locations GEO-18/108-S111(U) and GEO-18/015-S35, which are closest to the respective borehole locations 1445-GEO-19/109-B111 and 1445-GEO-19/109-B35. By averaging the calculated values over the same depth intervals as the laboratory samples listed in Table 4.6, five pairs of experimental and calculated values are obtained for the clay parameter, which allow for a direct comparison.

To evaluate the accuracy of the empirical correlation, a scatter plot can be created by plotting the calculated values $r_{t,i}$ on the horizontal axis and the corresponding experimental values $r_{e,i}$ on the vertical axis. The relationship described in equation (4.15) applies, where b represents the slope of the least-squares best-fit through the data points. This parameter b can be interpreted as a correction factor for the correlation. In the case of a perfect correlation, all data points would lie exactly on the 45°-line, indicating $b = 1$.

$$r_e = b \cdot r_t \text{ with } b = \frac{\sum_{i=1}^n r_{e,i} \cdot r_{t,i}}{\sum_{i=1}^n r_{t,i}^2} \quad (4.15)$$

Furthermore, the error ratio θ_i can be computed for each test as the ratio of the experimental to the calculated values. Taking the natural logarithm of this ratio yields the log error ratio Δ_i . The mean model error μ is then derived by calculating the average $\bar{\Delta}$ of the log error ratios Δ_i and converting it back from the logarithmic to the original space. Besides the average, the variance of the error ratios σ_{Δ}^2 can be determined as well, from which the coefficient of variation V_{θ} can be calculated. From the coefficient of variation and mean model error, the standard deviation of the model error σ_e in the original space can be obtained.

$$\theta_i = \frac{r_{e,i}}{r_{t,i}} \longrightarrow \Delta_i = \ln(\theta_i) \quad (4.16)$$

4 Soil parameter distributions

$$\bar{\Delta} = \frac{1}{n} \cdot \sum_{i=1}^n \Delta_i \text{ and } \sigma_{\Delta}^2 = \frac{1}{n-1} \cdot \sum_{i=1}^n (\Delta_i - \bar{\Delta})^2 \quad (4.17)$$

$$V_{\theta} = \sqrt{\exp(\sigma_{\Delta}^2) - 1} \quad (4.18)$$

$$\mu_e = \exp(\bar{\Delta} + 0.5 \cdot \sigma_{\Delta}^2) \text{ and } \sigma_e = \mu \cdot V_{\theta} \quad (4.19)$$

To account for model uncertainty, the final probabilistic distribution of the clay parameter is obtained by multiplying its estimated distribution with the model error, which is assumed to follow a (log-)normal distribution. This error is characterized by the previously derived mean and standard deviation in standard space. A correlation is considered more reliable when the mean model error is close to one and the standard deviation is small, indicating both low bias and high consistency. A mean greater than one implies systematic underestimation of the parameter, while a mean less than one suggests overestimation. Similarly, a smaller standard deviation reflects more consistent predictions, whereas a larger one indicates greater variability, reducing confidence in the correlation, even if the mean is close to unity.

The assumption of a log-normally distributed model error is justified in this context, as it reflects the physical and statistical characteristics of the soil parameters being analysed. These parameters are strictly positive and tend to exhibit multiplicative uncertainty rather than additive deviations. modelling the error as log-normal ensures that the resulting values remain physically meaningful (positive) and aligns with the behaviour of processes where the magnitude of uncertainty scales with the parameter value.

The presence of a model error leads to a shift and stretching of the soil parameter distributions, which are then used as input for reliability-based analyses. However, these analyses do not require precise input distributions. Instead, they rely on a Bayesian updating procedure that refines the soil parameter distributions at each step based on actual observations. As a result, the prior distributions are continuously improved, becoming progressively more accurate throughout the analysis process. Deviations in the exact distribution of the model error are hence not critical.

It is important to note that model error is calculated in the logarithmic domain. This approach offers several advantages: it transforms multiplicative relationships into additive ones, improves numerical stability, normalizes skewed data and ensures physical consistency. Moreover, it aligns with reliability-based design frameworks, such as those in the Eurocode, by allowing for normally distributed variables in probabilistic analyses.

4 Soil parameter distributions

4.3.3.3 CPT(u) correlations and model errors: practical application and results

In the below paragraphs, both the statistical distributions as well as the model errors of the four key soil parameters (OCR , k_{vert} , e_0 and C) are derived from the available CPT(u) data. For each parameter, the methodology outlined in section 4.3.3.2 has been applied.

Probabilistic distribution of the overconsolidation ratio OCR Table 4.7 summarizes the available correlations for estimating the overconsolidation ratio (OCR) from CPT(u) data, which are potentially applicable to clay layer S. The accompanying notes provide context regarding the calibration basis of each correlation, including the soil types and validity ranges, which are essential for evaluating their relevance to the specific geotechnical conditions of layer S.

Figure 4.16a compares the CDFs of OCR values derived from these correlations with those obtained from laboratory tests. All CPT(u)-based correlations tend to overpredict the OCR relative to the laboratory data. Among them, the correlation by *Dagger et al.* yields a CDF that most closely matches the experimental distribution, making it the most suitable correlation in its original form.

However, to improve the fit, the correlations of *Mayne* and *Kulhawy and Mayne* may be recalibrated by using the model error quantification method described in section 4.3.3.2. By iteratively adjusting the calibration coefficients to minimize the model error, improved values of these coefficients can be obtained: $k_{Mayne} = 0.1101$ and $k_{Kulhawy} = 0.0873$. A comparison between the initial and final model errors in case of the correlation of *Mayne* is shown in Figure 4.17. For the correlation of *Kulhawy and Mayne*, this is illustrated in Figure 4.18.

It should be noted that only the correlations of *Mayne* and *Kulhawy and Mayne* are suitable for recalibration, as they were originally developed based on very specific soil types. In contrast, the correlation proposed by *Dagger et al.* was calibrated using a much broader range of soil conditions, making it more universally applicable and less likely to benefit from further recalibration.

The two recalibrated correlations yield the updated CDFs shown in Figure 4.16b. Both *Mayne* and *Kulhawy and Mayne* now produce very similar and significantly improved fits to the laboratory data, slightly underestimating the experimental CDF. As mentioned before, the *Dagger et al.* correlation slightly overestimates the experimental CDF, but also provides a good fit. The result of the model error calculation for the *Dagger et al.* correlation is shown in Figure 4.19.

From Figures 4.17b, 4.18b and 4.19, it can be observed that the correlation by *Kulhawy and Mayne* performs better than that of *Mayne*. Although both yield a mean model error $\mu_e = 1.00$, the *Kulhawy and Mayne* correlation exhibits a lower standard deviation $\sigma_e = 0.28$, compared to $\sigma_e = 0.52$ for the *Mayne* correlation, indicating more consistent predictions. Moreover, the *Kulhawy and Mayne* correlation is also preferred over that of *Dagger et al.*.

4 Soil parameter distributions

While both correlations show comparable standard deviations, the *Dagger et al.* correlation systematically overestimates the OCR values, resulting in a significantly lower mean model error $\mu_e = 0.56$. This substantial deviation from unity indicates a persistent bias, making the recalibrated *Kulhawy and Mayne* correlation the most reliable among the three.

Based on the evaluation of model performance, the correlation by *Kulhawy and Mayne* is thus selected as the most suitable for estimating the overconsolidation ratio in layer S. Figure 4.20 displays the fitted probability density functions to the distribution of the OCR . Among the fitted distributions, the log-normal distribution, displayed in yellow, clearly provides the best fit. This is logic since only positive values of the overconsolidation ratio occur.

Table 4.7: CPT(u) correlations for the derivation of the overconsolidation ratio OCR

Name correlation	Year	Correlation
Mayne ^a	2006	$OCR = k_{Mayne} \cdot \frac{q_t - u_2}{\sigma'_{v,0}}$
Kulhawy & Mayne ^b	1990	$OCR = k_{Kulhawy} \cdot \frac{q_t - \sigma'_{v,0}}{\sigma'_{v,0}}$
Dagger et al. ^c	2018	$OCR = 0.33 \cdot Q_t^{1 - \frac{0.28}{1 + (I_c/2.65)^{25}}}$
Josza (method A) ^d	2013	$OCR = 18.306 \cdot z^{-0.887}$
Josza (method B)	2013	$OCR = 29.101 \cdot z^{-0.803}$
Josza (method C)	2013	$OCR = 66.512 \cdot z^{-0.822}$

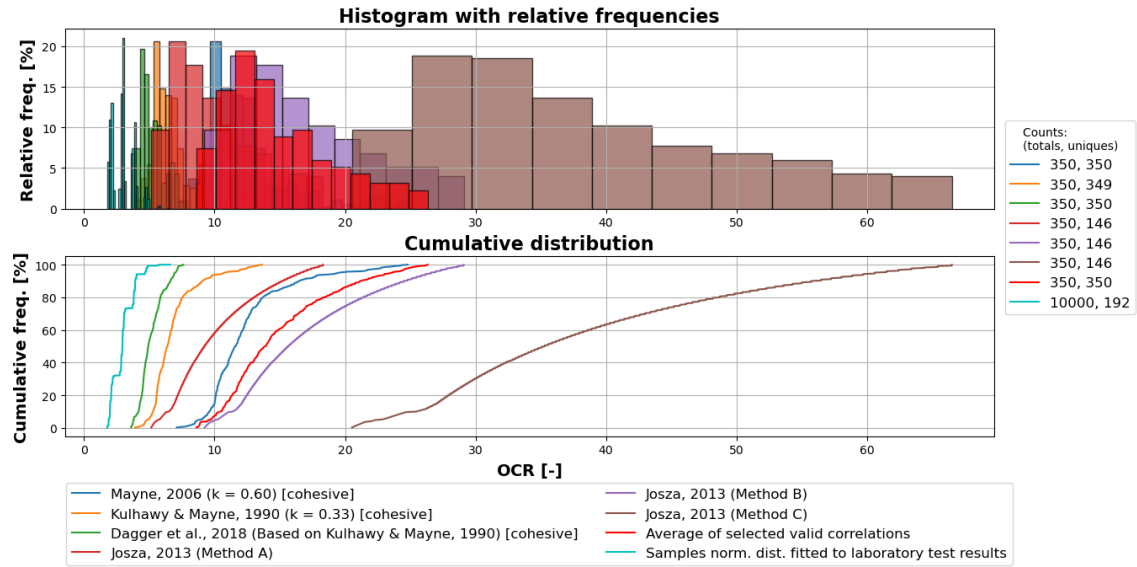
^a The correlation is calibrated on stiff clays from the Baton Rouge site (Louisiana) and soft to firm Bootlegger Cove Clay from Anchorage (Alaska): $k_{Mayne} = 0.60$ (Mayne, 2006).

^b The correlation is calibrated on 47 different laboratory-tested intact and fissured clays: $k_{Kulhawy} = 0.33$ (Kulhawy et al., 1990).

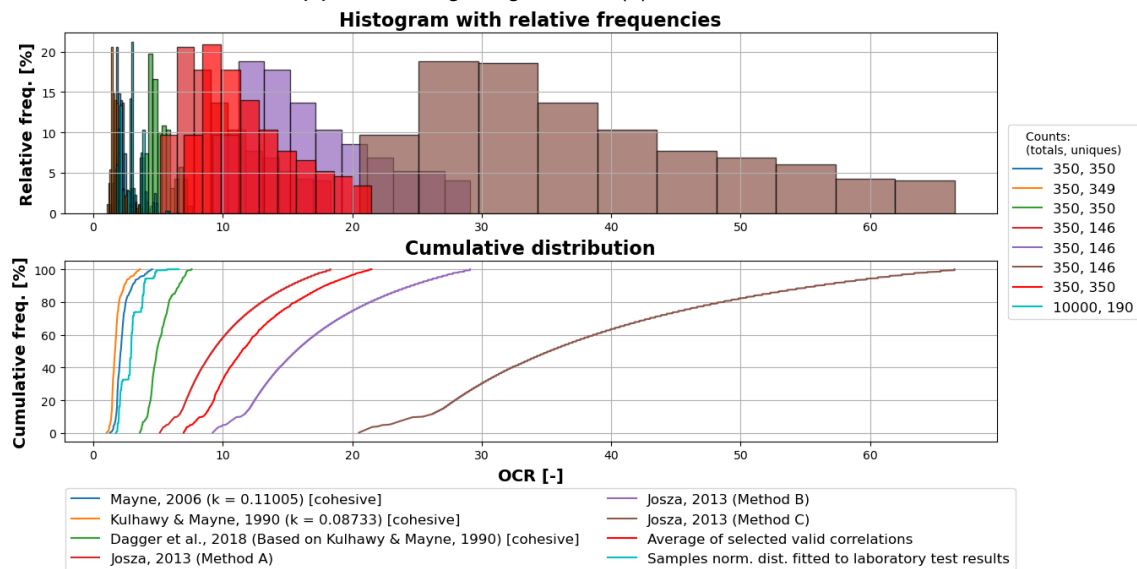
^c The correlation is based on the correlation of *Kulhawy and Mayne*, but generalized to accommodate mechanisms of preconsolidation such as ageing, desiccation, repeated cycles of wetting and drying and repeating freeze thaw cycles. The power m' is calibrated on Hibernia sand, Euripides sand, Holmen sand, Po River sand, Blessington sand, Piedmont SM silt, Piedmont ML silt, Pentre silt, Vagverket silt, Mjardevi silt, Gunnestad silt, Tomhill glacial silt, Upper and Lower Troll clay, Burswood clay, Northwestern NGES clay, Bothkennar clay, Amherst NGES clay, Baton Rouge clay and Brent Cross clay (Dagger et al., 2018).

^d The correlations are calibrated on 22 soil samples from 7 boreholes and 53 characteristic points from 13 CPT diagrams executed at 53 different depths along the Danube River in Dunaujvaros (Hungary). The OCR decreases with depth z , depending on its determination method. The upper 3 m thick clay layer yields unrealistically high OCR -values due to the combination of the low effective vertical stress and high cone tip resistance. Method A provides the lowest values, followed in turn by methods B and C. The calculated correlation coefficient of the mathematical functions are respectively 0.9335, 0.8621 and 0.8223 (Józsa et al., 2013).

4 Soil parameter distributions



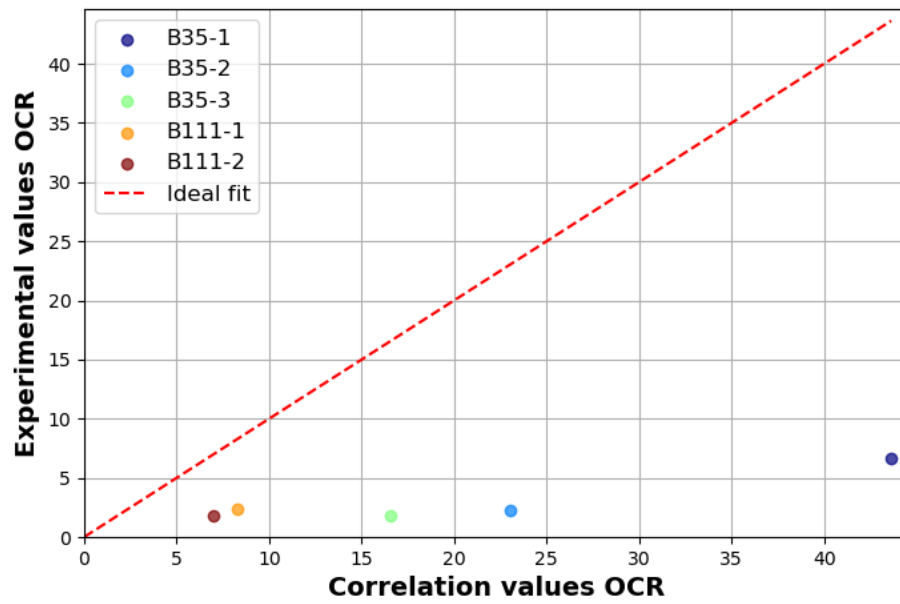
(a) CDFs using the given CPT(u)-based correlations



(b) CDFs using recalibrated CPT(u)-based correlations

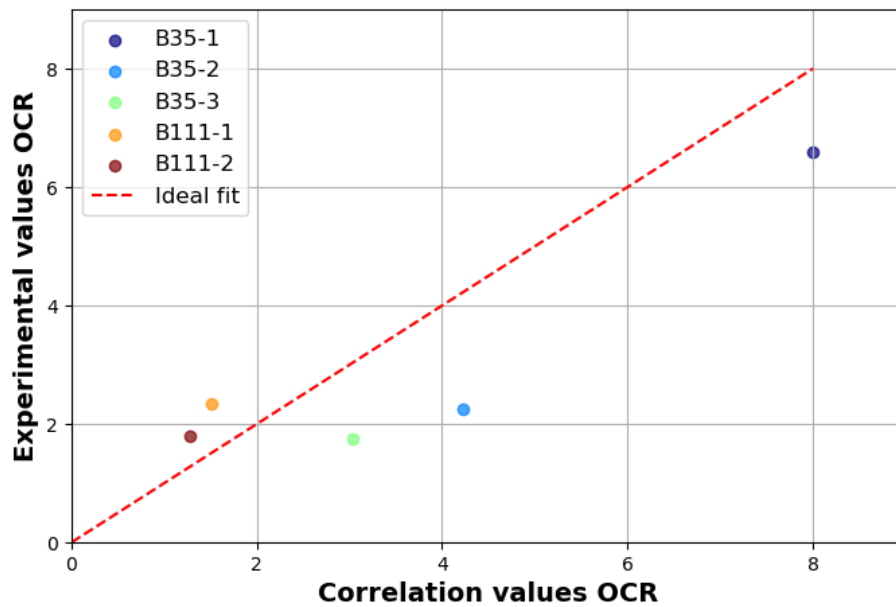
Figure 4.16: Comparison of CDFs for the OCR distribution from CPT(u) and laboratory test data

4 Soil parameter distributions



Mayne, 2006 (coh.)
Mean model error: 0.1834
Standard deviation of model error: 0.0960

(a) Before recalibration: $k_{Mayne} = 0.60$

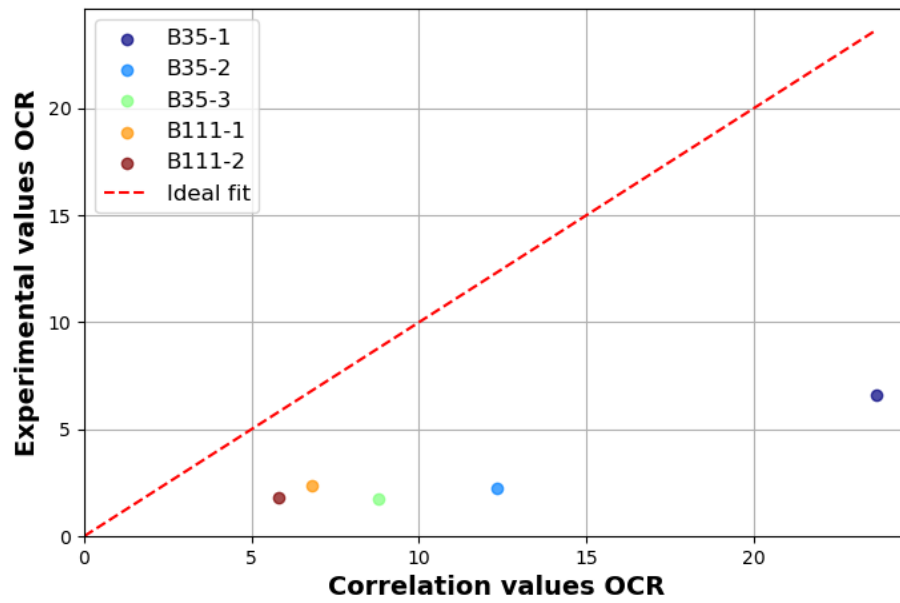


Mayne, 2006 (coh.)
Mean model error: 1.0000
Standard deviation of model error: 0.5231

(b) After recalibration: $k_{Mayne} = 0.1101$

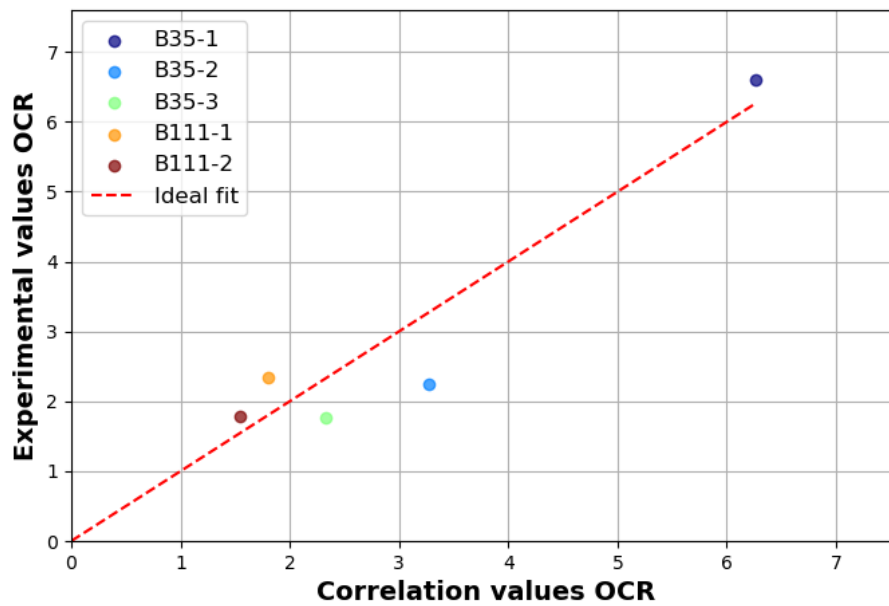
Figure 4.17: Model error for *OCR* before and after recalibration of the correlation of *Mayne*

4 Soil parameter distributions



Kulhawy and Mayne, 1990 (coh.)
Mean model error: 0.2646
Standard deviation of model error: 0.0747

(a) Before recalibration: $k_{Kulhaway} = 0.33$



Kulhaway and Mayne, 1990 (coh.)
Mean model error: 1.0000
Standard deviation of model error: 0.2821

(b) After recalibration: $k_{Kulhaway} = 0.0873$

Figure 4.18: Model error for *OCR* before and after recalibration of the correlation of *Kulhaway and Mayne*

4 Soil parameter distributions

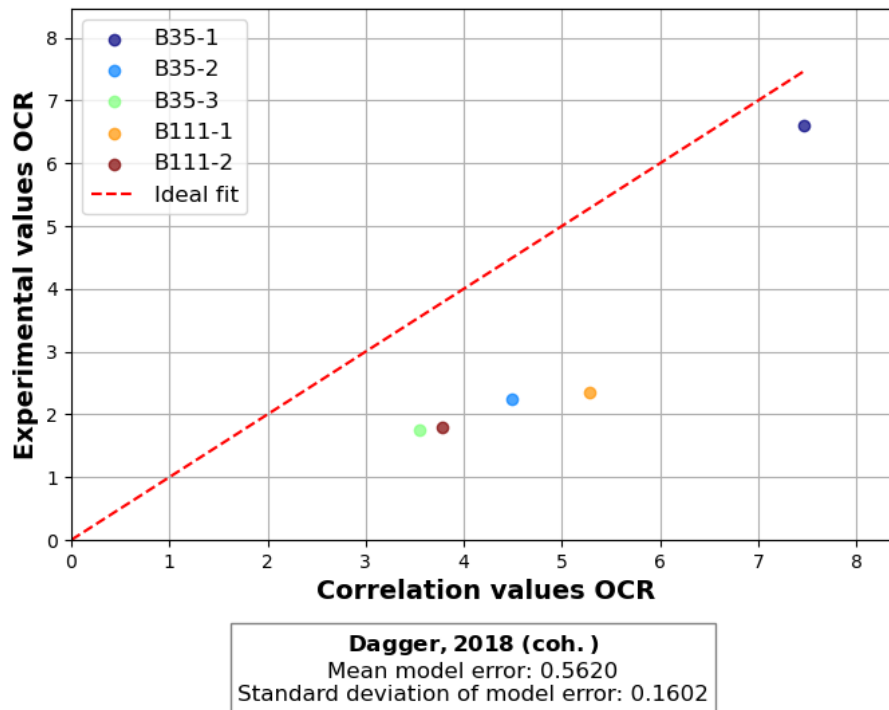


Figure 4.19: Model error for OCR using the correlation of *Dagger et al.*

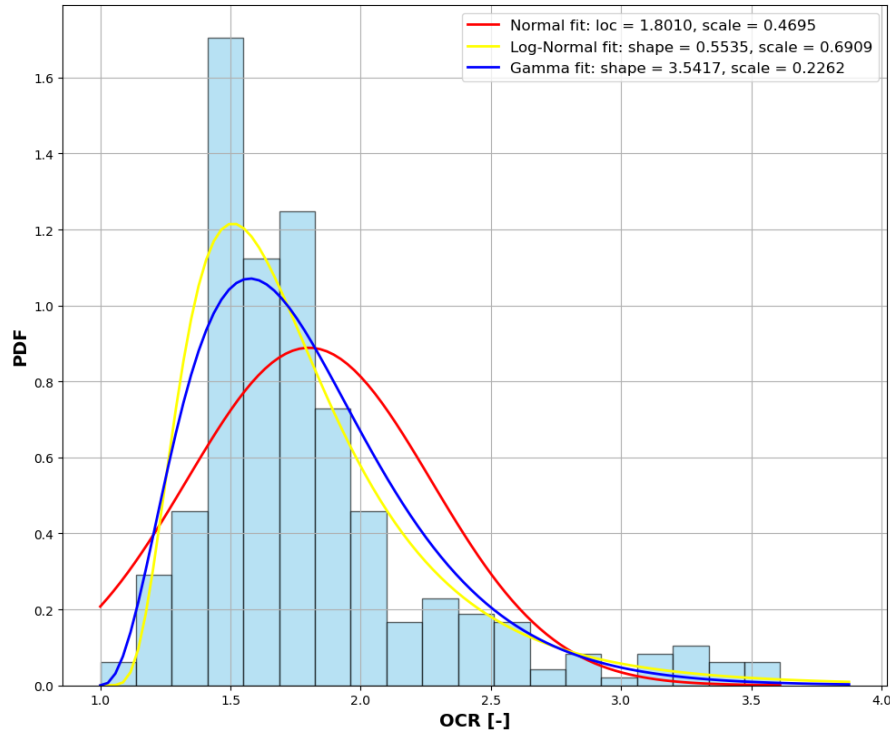


Figure 4.20: Fitted PDFs to the probabilistic distribution of k_{vert}

4 Soil parameter distributions

Probabilistic distribution of the vertical permeability k_{vert} For the vertical permeability k_{vert} , only one empirical correlation has been identified in the literature: the *Robertson* correlation. This method utilizes the soil behaviour type index I_c and is applicable to both coarse- and fine-grained soils. Further details regarding the correlation and its derivation are provided in Table 4.8, with accompanying notes explaining the basis of its development.

However, the accuracy of the *Robertson* correlation is limited, as reflected in its model error characteristics. As shown in Figure 4.22, although the mean model error $\mu_e = 0.84$ is relatively close to unity, the standard deviation $\sigma_e = 86.16$ is extremely high (almost order of magnitude 10^2) indicating substantial variability. As a result, the application of this model error significantly alters the distribution of k_{vert} when incorporated into the probabilistic analysis through multiplication with this distribution.

This overestimation is also evident in the cumulative distribution function presented in Figure 4.21, which shows a clear divergence from the experimental data. The probability density functions fitted to the k_{vert} -distribution are shown in Figure 4.23, where the log-normal distribution, indicated by the yellow line, provides the best fit to the data.

Table 4.8: CPT(u) correlations for the derivation of the vertical permeability k_{vert}

Name correlation	Year	Correlation
Robertson ^a	2009	$k_{vert} = \begin{cases} 10^{0.952-3.04 \cdot I_c} & \text{if } 1.0 < I_c \leq 3.27 \\ 10^{-4.52-1.37 \cdot I_c} & \text{if } 3.27 < I_c \leq 40 \end{cases}$

^a The correlation is modified from *Lunne et al.* and relies on the soil behaviour type charts of *Robertson et al.*. It reflects that an increasing I_c indicates more fine-grained soils, resulting in decreasing permeabilities. It is calibrated on a wide variety of sand and clay mixtures, primarily found at Huntington Beach (California) (Robertson, 2010).

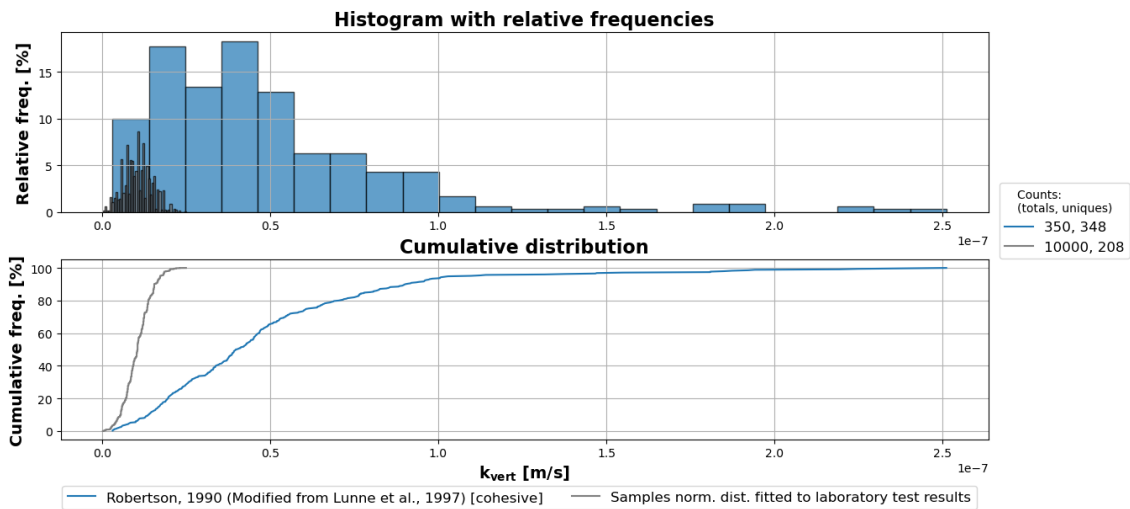


Figure 4.21: *Robertson* CDF for the distribution of k_{vert}

4 Soil parameter distributions

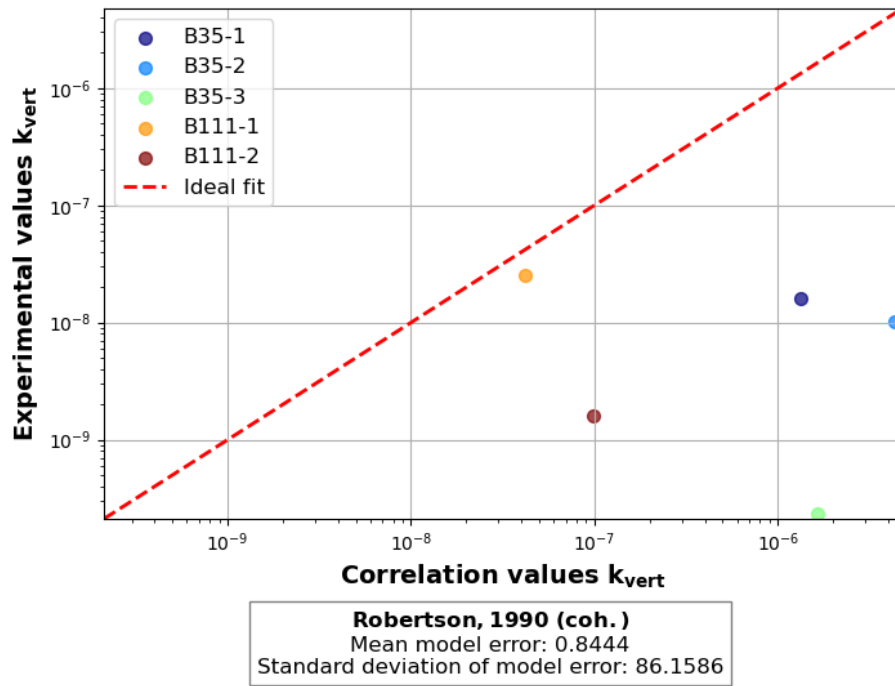


Figure 4.22: Model error for k_{vert} using the *Robertson* correlation

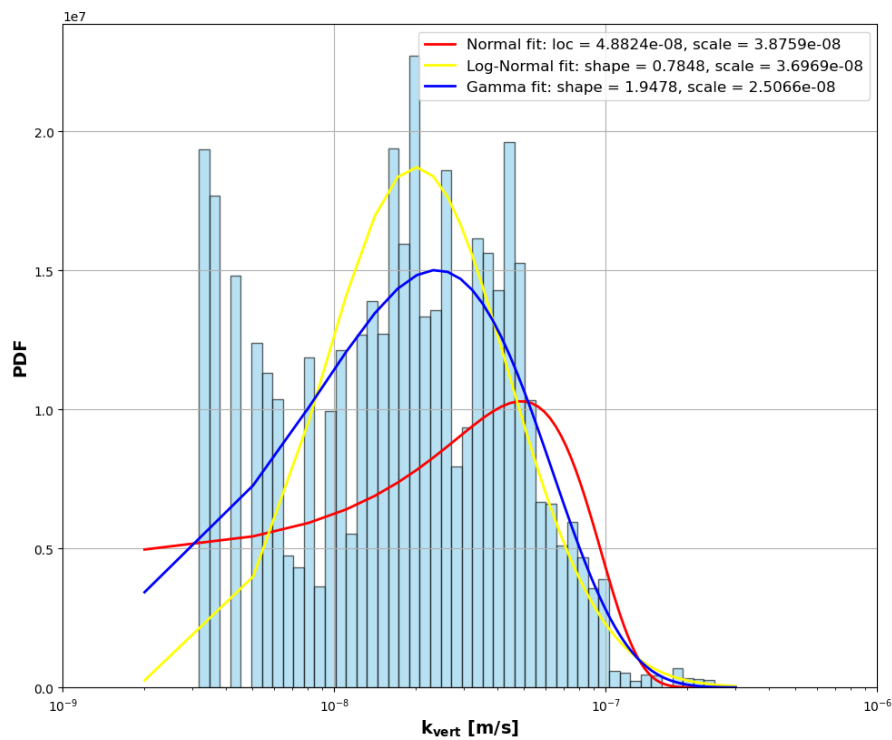


Figure 4.23: Fitted PDFs to the probabilistic distribution of k_{vert}

4 Soil parameter distributions

Probabilistic distribution of the initial void ratio e_0 The initial void ratio e_0 is estimated from CPT(u) data using a correlation proposed by *Budhu*, which is based on the saturated unit weight γ_s and the specific gravity G_s of the clay. The corresponding calculation is summarized in Table 4.9. In this study, G_s is assumed to be constant and equal to 2.70, a typical value for clay soils. While slight natural variations in G_s may occur, their influence on the resulting e_0 distribution is minor and becomes negligible when the distribution is used within a Bayesian updating framework.

The model error associated with this correlation is illustrated in Figure 4.25, with the cumulative distribution function and fitted probability density functions shown in Figures 4.24 and 4.26, respectively. The correlation yields a mean model error of $\mu_e = 0.60$ and a standard deviation of $\sigma_e = 0.26$, indicating moderate performance. While the bias suggests a tendency to over-predict e_0 , the relatively low variability implies a consistent error pattern. Again, the log-normal distribution provides the best fit to the data, as indicated by the yellow line in Figure 4.26. This is logic since only positive values of e_0 occur.

Table 4.9: CPT(u) correlations for the derivation of the initial void ratio e_0

Name correlation	Year	Correlation
Budhu ^a	2010	$e_0 = \frac{\frac{\gamma_s}{(g \cdot \rho_w)/1000} - G_s}{1 - \frac{\gamma_s}{(g \cdot \rho_w)/1000}}$

^a The calculation is based on a theoretical formula and makes use of the saturated unit weight γ_s of the clay considered (calculated with the correlation of *Robertson and Cabal*, equation (4.6)) and its specific gravity $G_s = 2.70$ (Budhu, 2010).

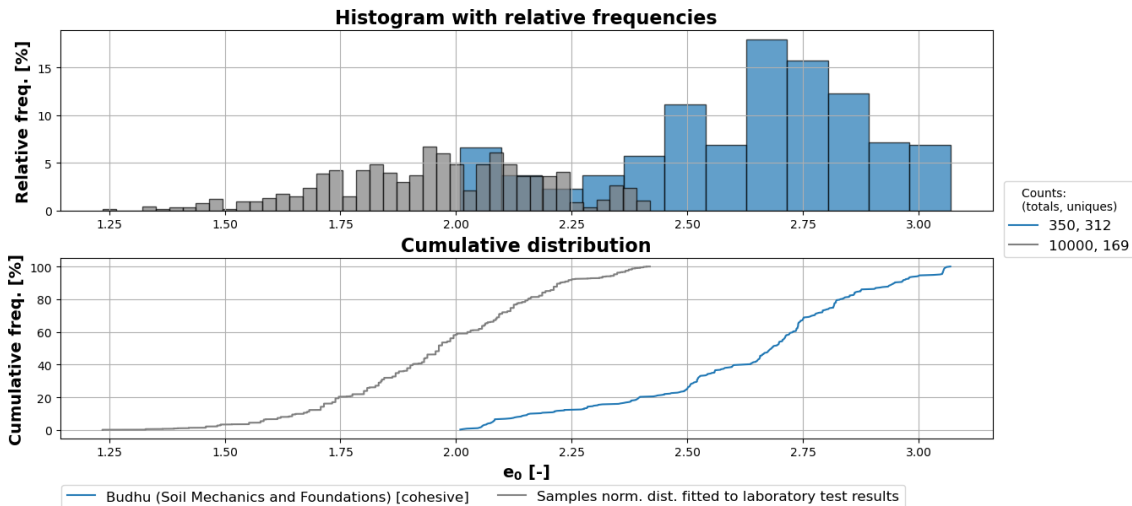


Figure 4.24: *Budhu* CDF for the distribution of e_0

4 Soil parameter distributions

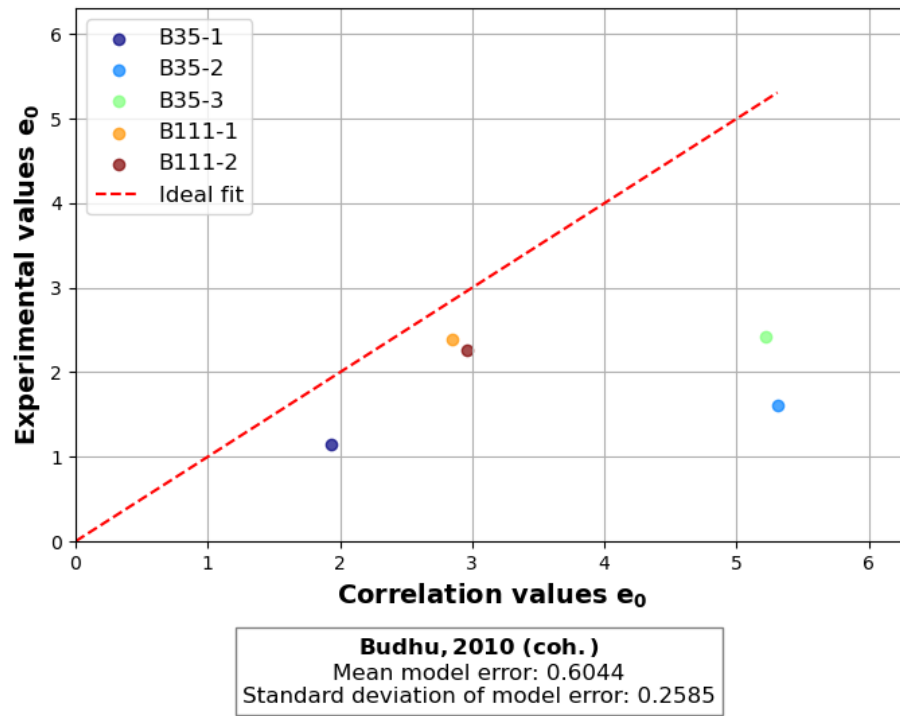


Figure 4.25: Model error for e_0 using the *Budhu* correlation

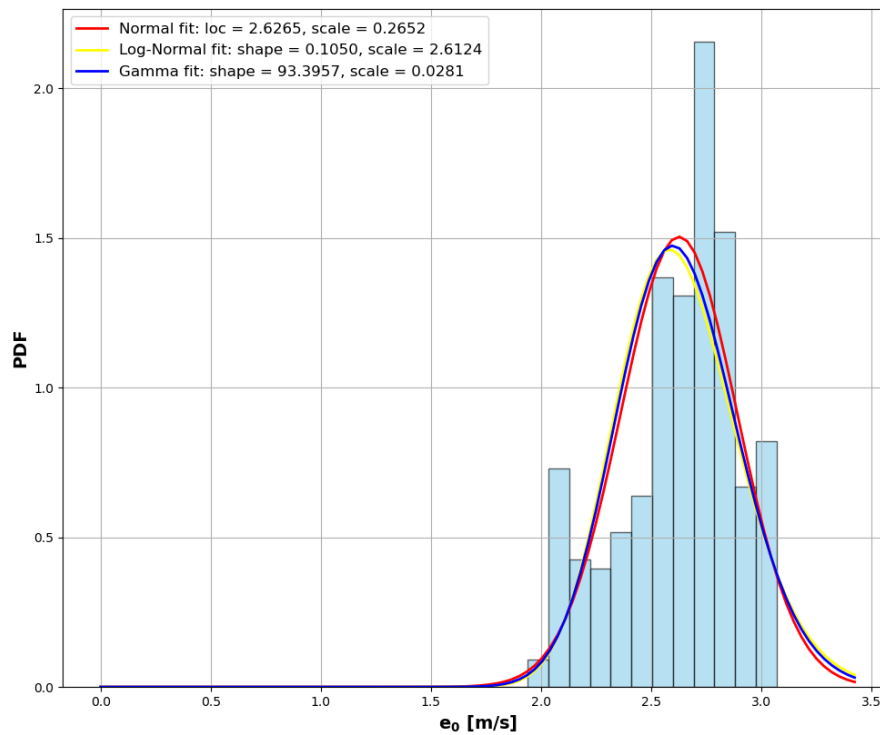


Figure 4.26: Fitted PDFs to the probabilistic distribution of e_0

4 Soil parameter distributions

Probabilistic distribution of the compression constant C The compression constant C is derived from the cone resistance q_c using the methodology outlined in SB260. The relevant equations are listed in Table 4.10. Among the available correlations, the one developed for clayey soils proves to be the most appropriate, based on both model error comparison (Figure 4.27) and a visual assessment of the cumulative distribution functions (Figure 4.28). This correlation yields a mean model error $\mu_e = 0.93$ and a standard deviation $\sigma_e = 0.23$, indicating strong agreement with laboratory test results. In contrast, the correlation for intermediate soils exhibits significantly higher variability and bias, with $\mu_e = 2.32$ and $\sigma_e = 0.57$, making it less suitable for the soil conditions under consideration.

Figure 4.29 presents the fitted probability density functions for the distribution of C . As expected, the log-normal distribution offers the best fit, which is consistent with the inherently positive nature of the compression constant.

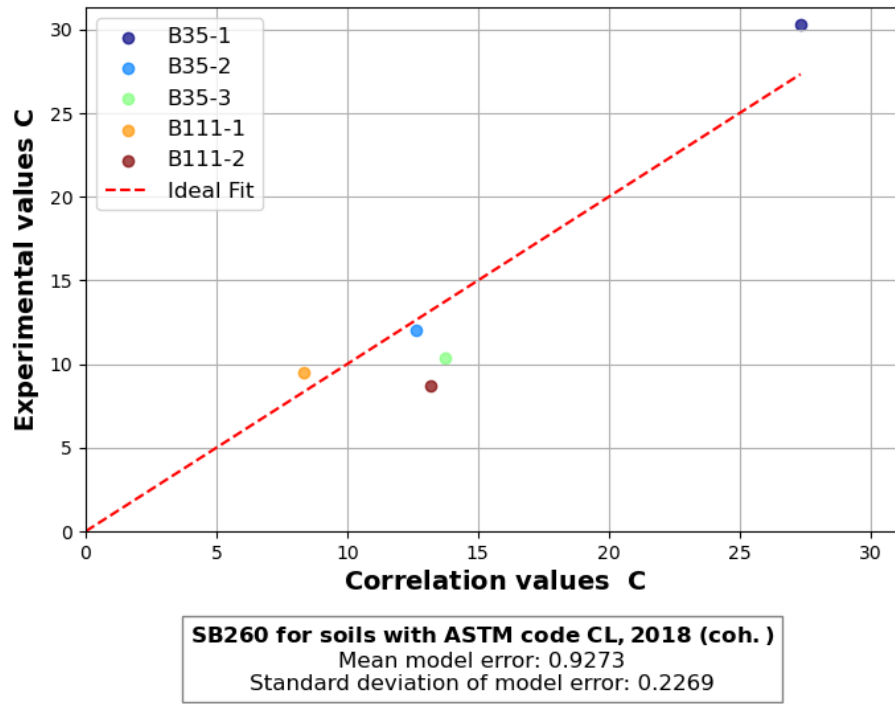
Table 4.10: CPT(u) correlations for the derivation of the compression constant C

Name correlation	Year	Correlation
SB260 (clayey soils) ^a	2018	$\alpha = \begin{cases} 5.0 \cdot q_c & \text{if } 0.0 \leq q_c < 0.7 \\ 3.0 \cdot q_c & \text{if } 0.7 \leq q_c < 2.0 \\ 1.5 \cdot q_c & \text{if } q_c > 2.0 \end{cases}$
SB260 (intermediate soils) ^b	2018	$\alpha = \begin{cases} 2.0 \cdot q_c & \text{if } 0.0 \leq q_c < 2.5 \\ 4.0 \cdot q_c - 5 & \text{if } 2.5 \leq q_c < 5.0 \end{cases}$

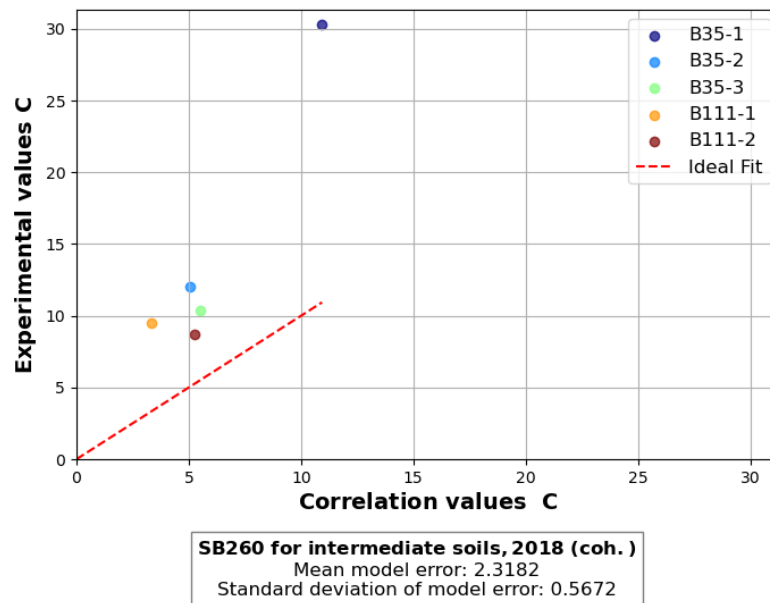
^a When settlements are calculated based on CPT(u) data, the compression constant C is estimated from the cone resistance q_c . The parameter is approximately related to the oedometer modulus E_{oed} by the expression $E_{oed} = C \cdot \sigma'_{v,0}$. For cohesive soils, it also holds that $E_{oed} = \alpha \cdot q_c$, hence $C = (\alpha \cdot q_c) / \sigma'_{v,0}$. From this last expression, the numerator is tabulated. The ASTM label CL refers to cohesive clays (Departement Mobiliteit en Openbare Werken, 2018).

^b The transitional soil types refer to clayey or silty sand, as well as sandy silt to clay (Departement Mobiliteit en Openbare Werken, 2018).

4 Soil parameter distributions



(a) Correlation SB260 for clayey soils



(b) Correlation SB260 for clayey soils

Figure 4.27: Comparison of the model error for C by using both correlations of SB260

4 Soil parameter distributions

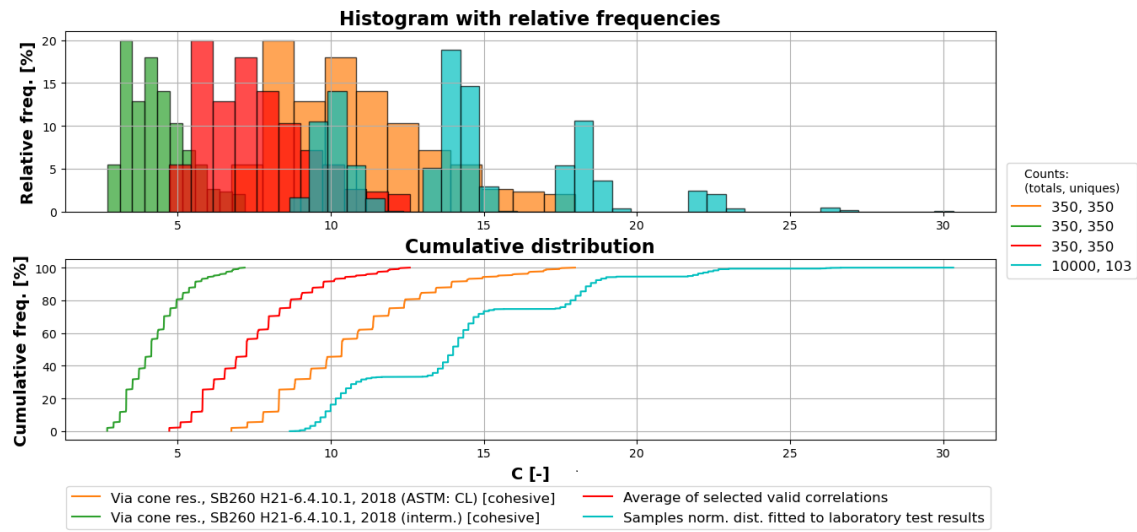


Figure 4.28: Comparison of the CDFs for the distribution of C by using both correlations of SB260

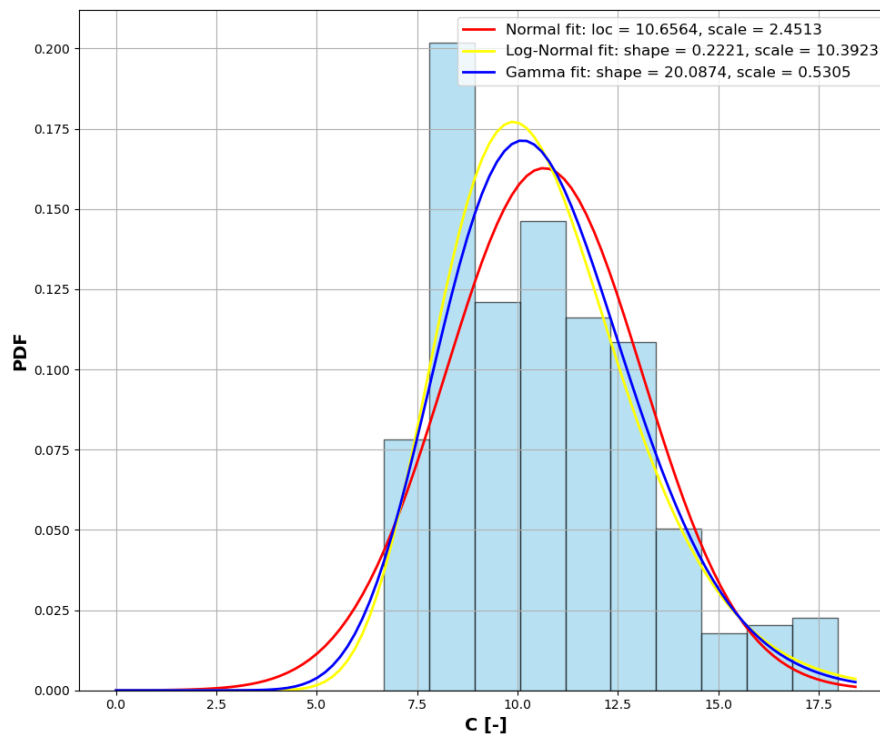


Figure 4.29: Fitted PDFs to the probabilistic distribution of C

4 Soil parameter distributions

4.4 Soil parameter distributions for layer S

To conclude this chapter, Table 4.11 presents a comprehensive summary of the log-normal distributions characterizing the four key clay parameters in layer S that influence dike settlement. The table lists the location, scale and shape parameters of each distribution, along with the corresponding mean model error μ_e and standard deviation σ_e . The table summarizes the outcomes of the CPT(u)-based analyses, validated against laboratory test results, as discussed in the preceding sections.

Table 4.11: Overview of the probabilistic distributions and model uncertainty of the key soil parameters

Clay parameter layer S	Probabilistic distribution				Model uncertainty	
	Distribution type	loc	scale	shape	μ_e	σ_e
$OCR [-]$	LN	1.0000	0.6909	0.5535	1.0000	0.2821
$k_{vert} [m/s]$	LN	0.0000	$3.6969 \cdot 10^{-8}$	0.7848	0.8444	86.1586
$e_0 [-]$	LN	0.0000	2.6124	0.1050	0.6044	0.2585
$C [-]$	LN	0.0000	10.3923	0.2221	0.9273	0.2269

As mentioned before, the final distributions of the soil parameters are obtained by multiplying the estimated distributions with the model error. Since both the soil parameter X and the model error E follow a log-normal distribution, their product Y also follows a log-normal distribution (Caspeele, 2023).

$$X \sim \mathcal{LN}(\mu_X, \sigma_X^2) \text{ and } E \sim \mathcal{LN}(\mu_E, \sigma_E^2) \longrightarrow Y = X \cdot E \sim \mathcal{LN}(\mu_Y, \sigma_Y^2). \quad (4.20)$$

Based on the location, scale and shape parameters of the log-normal distribution of the soil parameter, its mean μ_X and standard deviation σ_X in log-normal space can be calculated.

$$\mu_X = \ln(scale) \text{ and } \sigma_X = shape \quad (4.21)$$

For the model error, the mean μ_E and standard deviation σ_E in log-normal space are calculated as follows from the given mean μ_e and standard deviation σ_e in standard space:

$$\mu_E = \ln(\mu_e) - \frac{1}{2} \ln\left(1 + \left(\frac{\sigma_e}{\mu_e}\right)^2\right) \text{ and } \sigma_E = \ln\left(1 + \left(\frac{\sigma_e}{\mu_e}\right)^2\right) \quad (4.22)$$

The mean μ_Y and standard deviation σ_Y of the product Y can be calculated as follows:

$$\mu_Y = \mu_X + \mu_E \text{ and } \sigma_Y = \sqrt{\sigma_X^2 + \sigma_E^2} \quad (4.23)$$

The shape of the final distribution is equal to the log-normal standard deviation σ_Y and the scale is equal to the exponential of the mean μ_Y . The mean and standard deviation of the final distribution in normal space can be calculated as follows:

$$\mu_y = \exp\left(\mu_Y + \frac{1}{2} \cdot \sigma_Y^2\right) \text{ and } \sigma_y = \sqrt{(\exp(\sigma_Y^2) - 1) \cdot \exp(2 \cdot \mu_Y + \sigma_Y^2)} \quad (4.24)$$

4 Soil parameter distributions

The final probabilistic distributions of the four key soil parameters in layer S, corrected for model uncertainty, are summarized in Table 4.12. Table 4.13 provides a comparison between the original and corrected means (μ_x, μ_y) and standard deviations (σ_x, σ_y) in normal space. These changes are also visualized in Figure 4.30. As shown, incorporating model uncertainty leads to a notable increase in standard deviation across all parameters, reflecting greater variability. Additionally, the means of the distributions for k_{vert} , e_0 , and C shift significantly as well.

Table 4.12: Corrected distributions of the four key soil parameters in layer S

Clay parameter layer S	Corrected probabilistic distribution			
	Distribution type	loc	scale	shape
$OCR [-]$	LN	1.0000	0.6650	0.6188
$k_{vert} [m/s]$	LN	0.0000	$3.0592 \cdot 10^{-10}$	3.1411
$e_0 [-]$	LN	0.0000	1.4517	0.4231
$C [-]$	LN	0.0000	9.3606	0.3278

Table 4.13: Comparison of statistics between original and corrected distributions

Clay parameter layer S	Original distributions		Corrected distributions	
	μ_x	σ_x	μ_y	σ_y
$OCR [-]$	1.8053	0.4821	1.8053	0.5501
$k_{vert} [m/s]$	$5.0301 \cdot 10^{-8}$	$4.6412 \cdot 10^{-8}$	$4.2471 \cdot 10^{-8}$	$5.8961 \cdot 10^{-6}$
$e_0 [-]$	2.6268	0.2766	1.5876	0.7029
$C [-]$	10.6518	2.3952	9.8773	3.3267

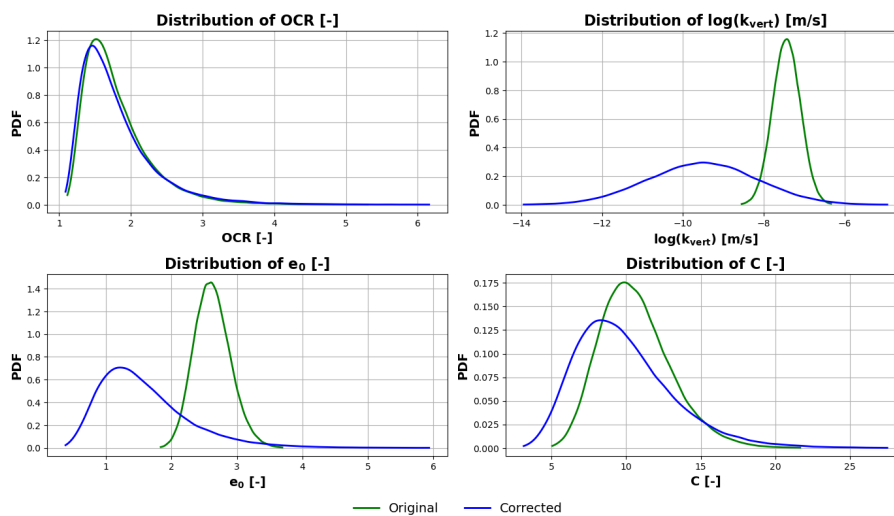


Figure 4.30: Original distributions compared to distributions corrected with the model error

4 Soil parameter distributions

5

Probabilistic (settlement) calculations

This chapter presents a probabilistic framework for calculating dike settlements, marking a departure from traditional deterministic methods. In current engineering practice, settlement is typically computed deterministically, with monitoring data used only retrospectively to compare predicted and observed values. This approach limits the ability to assess reliability and doesn't allow proactive decision-making. Here, the objective is to develop and implement a comprehensive probabilistic workflow that incorporates uncertainty and integrates real-time monitoring data. This allows for more accurate, adaptive settlement predictions throughout the project lifecycle. Furthermore, the workflow builds upon results discussed in earlier chapters.

In this workflow, Bayesian updating is used to incorporate monitoring data. This enables prior distributions of soil parameters to be refined based on observed values. This results in posterior distributions that reflect improved system knowledge, enhancing model accuracy and robustness over time. The proposed methodology culminates in a dynamic probabilistic settlement model that continuously integrates field data. This represents a significant advancement over static models by enabling ongoing refinement of predictions.

The adaptive nature of this approach offers several key benefits: it reduces uncertainty early in the project, supports timely and informed decision-making and facilitates adjustments to the dike design and monitoring strategy as needed. Ultimately, this method enhances risk management, supports compliance with design requirements and improves the overall reliability of the flood protection system.

The full methodology is explained step by step in the following section. This is followed by the theoretical background of the probabilistic calculations, focusing on the techniques used in the proposed workflow. To make the approach easier to understand and follow, each technique is illustrated using a simple example. Finally, the developed probabilistic method is applied to the dike at DP26 and the results are analysed and discussed.

5 Probabilistic (settlement) calculations

5.1 Workflow for the probabilistic calculations

This section outlines the general workflow used in this chapter to perform the probabilistic calculations. The approach is designed to be efficient, scalable and accurate, making it suitable for complex engineering problems such as dike settlement predictions. By implementing techniques such as the use of response surface models, the computational cost of the workflow is reduced. This allows for large-scale probabilistic analyses that would be too demanding with traditional methods. The method is especially effective in high-dimensional spaces, where many stochastic variables (soil parameters) influence the outcome. Latin hypercube sampling is used to ensure well-distributed samples across the input space, improving the quality of the results. A final key benefit of this workflow is its ability to improve prediction accuracy over time. By updating the model as new data becomes available, the method supports more informed decision-making throughout the project.

1. **Sensitivity analysis:** before starting the probabilistic calculations, a sensitivity analysis is carried out to identify the most influential soil parameters affecting dike settlement. This step is essential to determine which parameters have a significant impact and are therefore worth modelling probabilistically, and which have minimal influence and can be kept at their default values. By doing so, unnecessary probabilistic modelling is avoided, which can save a considerable amount of time and computational effort. The principles and results of this sensitivity analysis have already been presented in Chapter 4.
2. **Stochastic soil parameter distributions:** for the soil parameters identified as having a significant impact on dike settlement, their probabilistic distributions can be determined using CPT(u)-based correlations. In addition to the extensive CPT(u) data available, laboratory test results can also be used for comparison. This comparison allows the performance of the correlations to be evaluated against actual soil conditions, as reflected in the lab tests. As a result, the model error associated with the derived distributions can be estimated. The underlying principles and results of this process have already been discussed in Chapter 4.
3. **Latin hypercube sampling (LHS):** the distributions of the influential soil parameters are sampled and randomly combined using LHS. This results in a series of random input parameter sets. These sets form the basis of the probabilistic approach, where the outcomes under different conditions, each represented by a unique input set, are computed and compared.

5 Probabilistic (settlement) calculations

4. **Numerical simulations in PLAXIS 2D:** the randomly generated input parameter sets are used as input for the numerical PLAXIS 2D model developed in Chapter 3. For each input set, a corresponding settlement curve is calculated. By evaluating a large number of such cases, a probabilistic distribution of the final dike settlement can be obtained. However, running the PLAXIS 2D model for each sampled input is computationally expensive: each simulation (with post-processing) takes approximately 450 seconds. In a Bayesian updating framework, which may require tens of thousands of iterations, using the full numerical PLAXIS 2D model would lead to impractically long computation times, often stretching into weeks. To overcome this, the proposed workflow starts with a limited application of LHS, generating a relatively small but representative number of input combinations. Following the rule of thumb, a sample size of $n = 10 \cdot k$ is used (Loeppky et al., 2009), where k is the number of probabilistic variables (five in this case, including time). These input combinations are then evaluated using the PLAXIS 2D model, producing settlement curves over time for each sampled case. This initial step enables efficient exploration of the input space while keeping computational costs manageable. The resulting settlement curves are then used as a training dataset to develop a response surface model, which replaces the need for repeated full-scale numerical simulations in the later stages of the workflow.
5. **Response surface model (RSM):** the data from the initial PLAXIS 2D simulations is used to train an RSM, which acts as a surrogate for the full numerical PLAXIS model. The RSM approximates the relationship between the input parameters and the output response, here the vertical settlement of the dike. This surrogate model enables rapid and computationally efficient evaluations (several simulations per second), making it feasible to conduct the large number of simulations required for probabilistic and Bayesian analyses. To ensure reliability, the RSM is validated against the original PLAXIS 2D results, confirming that it accurately captures the system's behaviour.
6. **Extensive probabilistic simulations:** once the RSM is constructed and validated, it is used to perform a much larger set of probabilistic simulations. An extensive new set of input samples is generated using LHS and these are evaluated using the RSM of the computationally intensive PLAXIS 2D model. This allows for rapid generation of a large dataset of settlement predictions and enables the implementation of Bayesian updating into the workflow.
7. **Bayesian updating:** observations from the settlement monitoring campaign, discussed in Chapter 2, are incorporated into the probabilistic model to refine predictions and reduce uncertainty. This step systematically combines prior information (sampled with LHS and evaluated with the RSM) with new field data, resulting in a posterior distribution that more accurately represents the soil's behaviour. The updated model provides improved predictions of future settlements and remains robust and adaptive as additional information becomes available.

5 Probabilistic (settlement) calculations

5.2 Theoretical framework of the probabilistic calculations

This section explains the theoretical background of all steps in the probabilistic settlement calculation methodology proposed in section 5.1. The focus will be on the Latin hypercube sampling, the development of a response surface model and the implementation of the Bayesian updating framework. More information about the setup of the numerical PLAXIS 2D model can be found in Chapter 3. The sensitivity analysis and determination of the soil parameter distributions was treated in Chapter 4.

5.2.1 Latin hypercube sampling

Latin hypercube sampling (LHS) is a stratified sampling technique designed to efficiently explore input parameter spaces by ensuring that each variable's range is evenly sampled. LHS was originally developed to improve the accuracy of stochastic analyses. It divides each variable's distribution into intervals of equal probability and selects one value from each, maintaining statistical independence between variables. This structured approach leads to more uniform coverage of the input space compared to traditional Monte Carlo methods. As such the risk of undersampling critical regions is reduced (McKay et al., 1979).

A key advantage of LHS is its ability to achieve comparable or superior accuracy with significantly fewer samples, which is particularly beneficial when computational resources are limited. In fact, studies have shown that LHS can provide similar results to standard Monte Carlo sampling at roughly half the sample size. Additionally, LHS is flexible, allowing for mapping onto various distributions, such as Gaussian or log-normal, by using the inverse cumulative distribution functions (CDF). This makes it broadly applicable to complex engineering problems, including those involving non-linear behaviours like subsoil settlement (Olsson et al., 2002). Furthermore, LHS performs well in high-dimensional input spaces where multiple variables influence the system's behaviour and a large number of samples is required to explore the input space. Unlike methods such as first (FORM) and second order reliability methods (SORM), which rely on linear approximations of failure surfaces, LHS provides more accurate estimates in complex or non-linear response domains (Davis et al., 1987). This makes it particularly well-suited for the probabilistic modelling of dike settlements in the proposed workflow, where five input parameters are considered: four soil parameters that strongly impact settlement behaviour, along with time. The latter is included as a variable to capture the evolution of the settlement.

5.2.1.1 Latin hypercube sampling: theoretical background

As mentioned previously, LHS is a stratified sampling method because it divides the input space into equally probable intervals and ensures that each interval is sampled exactly once in each dimension. This results in a more uniform and representative sampling of the input space compared to traditional random sampling methods (Davis et al., 1987).

5 Probabilistic (settlement) calculations

1. **Division of the input domain:** for k random variables and m chosen samples, the cumulative distribution range of each variable is divided into m equally probable intervals. This ensures the entire input domain, with dimension k is systematically covered.
2. **Sampling plan construction:** from each interval of the distribution of each of the variables, a value is randomly selected. Therefore two matrices are generated: one $m \times k$ matrix $\underline{P}$ of which each column is a random permutation of integers representing the interval indices $1, \dots, m$ and a second $m \times k$ matrix $\underline{R}$ of independent random numbers from the uniform $[0, 1]$ distribution. The sampling plan $\underline{S}$ can be defined and each element $s_{i,j}$ represents the normalized position of a sample within the interval: $\underline{S} = 1/m \cdot (\underline{P} - \underline{R})$.
3. **Mapping to the target distributions:** the sampled probabilities $s_{i,j}$ are transformed to match the desired marginal distribution of the input variable, using its CDF F_x : $x_{i,j} = F_x^{-1}(s_{i,j})$. This ensures the samples reflect the statistical properties of the variables.
4. **Reduction of spurious correlations (optional):** various advanced techniques exist to address correlations in LHS, such as Cholesky transformations, Iman and Conover's rank correlation method and Stein's shifting method for multivariate or spatial distributions. These are not applied in this study. The use of standard LHS without correlation adjustment is justified by the assumption of independence among the input variables (which will be checked later). As established in the previous chapter, independent distributions for the four sensitive soil parameters were derived from CPT(u) data. Moreover, spatial variability has not been considered. Soil properties are assumed to be uniform within each layer, making random field modelling unnecessary. While incorporating correlation handling may improve model realism, the current approach provides a practical and sufficiently accurate basis for the probabilistic analysis of settlement (Pebesma et al., 1999).

5.2.1.2 Latin hypercube sampling: example

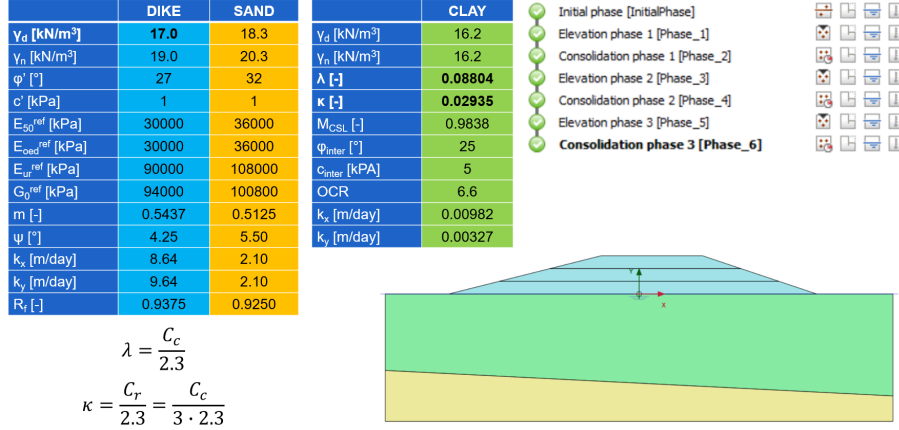
To illustrate the probabilistic methodology, a simplified example of a dike settlement calculation is introduced. This example, consisting of a dike with a basic geometry made up of three construction layers overlying a thick clay layer and underlain by sand, serves as a conceptual basis for developing the Python scripts. In this simplified case, it is decided to treat all soil parameters as deterministic except for two: the unit weight of the dike fill-up sand γ_d and the compression index of the clay layer below C_c . These two parameters are modelled as stochastic and are given a distribution based on guidelines of the JCSS (Baker et al., 2006).

- Dry unit weight γ_d fill-up material dike: $\mu = 17 \text{ kg/m}^3$ and $\sigma = 0.10 \cdot \mu = 1.7 \text{ kg/m}^3$.
- Compression index C_c clay subsoil: $\mu = 0.1794$ and $\sigma = 0.25 \cdot \mu = 0.0451$.

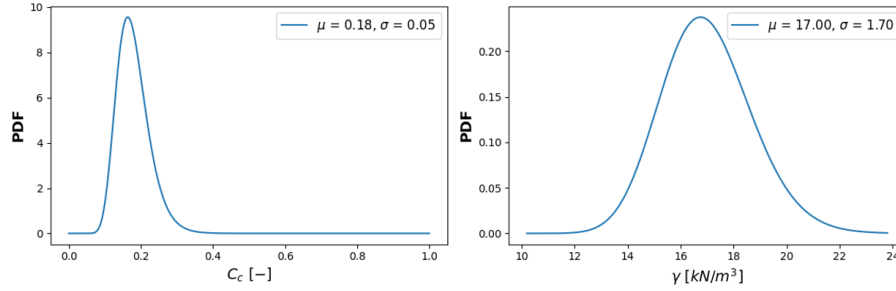
While this is a simplification of the real-world dike problem at DP26 in Bornem, it offers a practical and manageable framework to test and validate the probabilistic techniques. With only two

5 Probabilistic (settlement) calculations

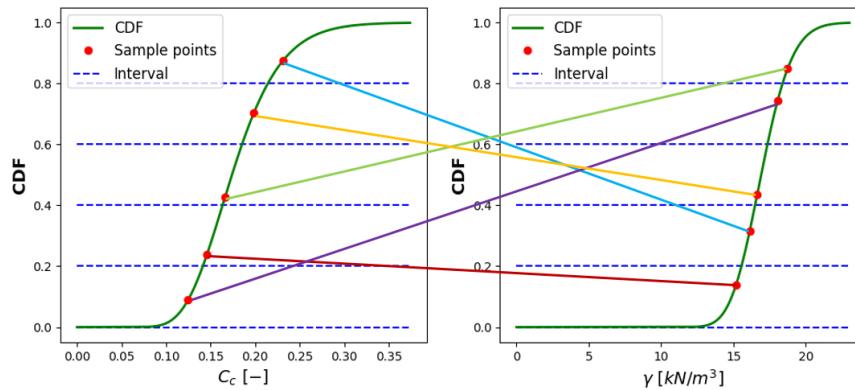
stochastic inputs, results can be easily visualized and interpreted through 2D plots, aiding in verification of the LHS method. Figures 5.1a to 5.1f illustrate the outcome of five LHS-generated samples. Although five samples are insufficient to characterize the full probabilistic distribution of dike settlement, the example serves as a clear demonstration of the methodology. In practice, a much larger sample set is needed to derive meaningful results, for which a response surface model will be introduced in the next section.



(a) Initialization and definition of the simplified example



(b) Probabilistic distribution of the parameters γ_d and C_c

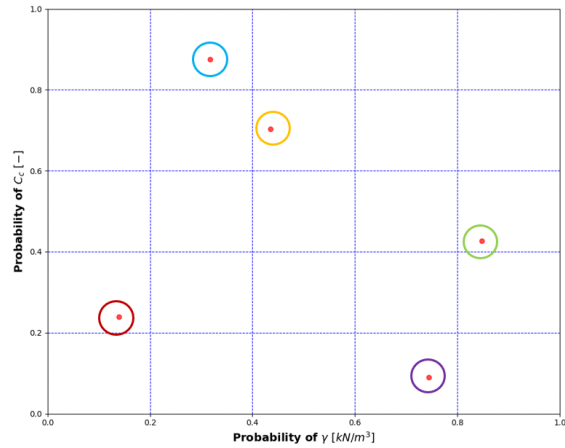


(c) LHS: division the CDFs and random combination forming

Figure 5.1: Application of LHS to a simplified dike settlement calculation (Part 1)

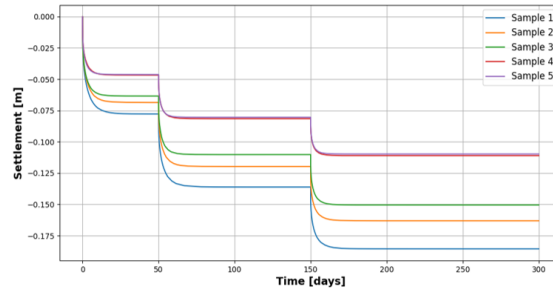
5 Probabilistic (settlement) calculations

	γ_d [kN/m^3]	C_c [—]
Sample 1	16.1296	0.2312
Sample 2	16.6429	0.1986
Sample 3	18.7412	0.1662
Sample 4	15.1808	0.1459
Sample 5	18.0579	0.1248

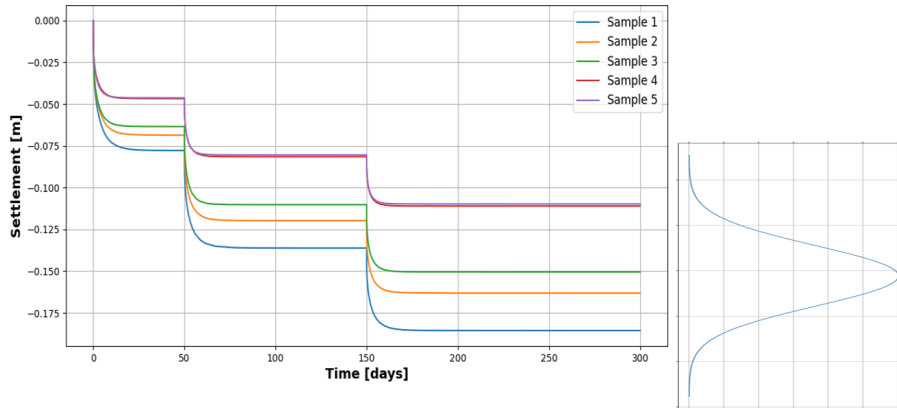


(d) LHS: representation of the random sets of input parameters

	Final settlement [m]
Sample 1	-0.1858
Sample 2	-0.1633
Sample 3	-0.1507
Sample 4	-0.1112
Sample 5	-0.1099
MEAN	-0.1442
STD. DEV.	0.0332



(e) PLAXIS 2D settlement curves corresponding to the LHS input parameters



(f) Distribution of the final settlement based on 5 samples

Figure 5.1: Application of LHS to a simplified dike settlement calculation (Part 2)

5.2.2 Response surface method

The response surface method (RSM) is a technique used to approximate the relationship between a (set of) input variables $\underline{X}$ and a response variable $\underline{Y}$, particularly when the underlying model is complex or computationally demanding, such as those involving FE analyses. Instead of evaluating the response function $g(\underline{X})$ directly, RSM constructs a surrogate model $\hat{g}(\underline{X})$ that mimics the system's behaviour but is significantly faster to compute (Allaix and Carbone, 2011).

5 Probabilistic (settlement) calculations

A key assumption in RSM is that the true system response can be reasonably approximated by a polynomial function, with the required degree of the polynomial depending on the complexity of the system (Rajashekhar and Ellingwood, 1993). The accuracy of the response surface strongly depends on the placement of the sample points used during the design of experiments. Initial approximations may need iterative refinement to improve the surrogate model and ensure reliable predictions (Nguyen et al., 2008).

Several approaches exist for constructing response surfaces. The optimal choice depends on the complexity of the system, data availability and computational resources. The most common techniques are described below.

- **Polynomial regression:** the response function $g(\underline{X})$ is approximated by fitting a polynomial of a certain degree. A commonly used form is the quadratic response surface. Here, the cross-product terms $x_i \cdot x_j$ account for interactions between variables and the coefficients a_0, a_i, a_{ii}, a_{ij} are obtained through iterative regression (Rajashekhar and Ellingwood, 1993).

$$\hat{g}(\underline{X}) = a_0 + \sum_{i=1}^k a_i \cdot x_i + \sum_{i=1}^k a_{ii} \cdot x_i^2 + \sum_{i \neq j} a_{ij} \cdot x_i \cdot x_j \quad (5.1)$$

Polynomial regression is computationally efficient and interpretable, but its accuracy is limited for non-linear or complex relationships. Higher-order polynomials can improve approximation accuracy, but at the cost of increased computational effort and risk of overfitting, particularly in the presence of noisy data. Overfitting can degrade generalization and produce unreliable predictions. A trade-off is thus required between the complexity (degree) of the polynomial and the efficiency of the analysis. In most cases, quadratic or cubic surfaces, potentially enriched with mixed terms, offer a good balance between accuracy and efficiency.

- **Gaussian process regression (GPR):** GPR is a non-parametric, Bayesian regression method that models the response surface as a distribution of functions. It is especially useful when the underlying relationship is unknown or highly non-linear. Unlike polynomial regression, GPR does not assume a fixed functional form and provides probabilistic predictions, offering uncertainty quantification as part of the model. GPR is particularly data-efficient and effective in settings with limited data, making it ideal for systems where experiments or simulations are costly (Rasmussen and Williams, 2006).

GPR assumes the response at any point is a Gaussian random variable. It is defined by a mean function and a kernel function κ , which governs the smoothness and correlation structure of the response surface. It is commonly used with active learning strategies (e.g. Bayesian optimization), allowing iterative refinement of the surrogate by selecting new data points that minimize uncertainty or maximize information gain.

5 Probabilistic (settlement) calculations

- **Neural networks (NN):** neural networks consist of layers of interconnected nodes (neurons) that transform inputs through weighted connections and activation functions. They are capable of approximating highly complex and non-linear relationships and are suited for problems where the system behaviour is difficult to model analytically. However, NNs typically require large datasets, substantial tuning and come with less interpretability compared to simpler models (Ghaemi et al., 2023).

For the probabilistic settlement analysis in this study, GPR is recommended as it offers a favourable balance between model complexity, accuracy and data requirements. It performs well with relatively small training datasets ($n \leq 100$), making it computationally efficient. The interpretability of the kernel function further supports its use. The settlement curves over time effectively serve as the response function $S = g(X)$. The complexity and shape of these time-dependent responses cannot be captured adequately with polynomial regression. Conversely, neural networks would introduce unnecessary complexity for the problem at hand.

5.2.2.1 Gaussian process regression: theoretical background

A Gaussian process (GP) is a non-parametric model used to describe distributions over functions (Krasser, 2018). For any input $\underline{x}_i \in \mathbb{R}^d$, the GP defines a random variable $f(\underline{x}_i)$, such that the joint distribution of a finite number of these variables $p(f(\underline{x}_1), \dots, f(\underline{x}_k))$ is also Gaussian.

$$p(\underline{f} \mid \underline{x}) = \mathcal{N}(\underline{f} \mid \underline{\mu}, \underline{\sigma}) \quad (5.2)$$

- $\underline{f} = (f(\underline{x}_1), \dots, f(\underline{x}_k))$ is the vector of function values at training inputs $\underline{x} = \underline{x}_1, \dots, \underline{x}_k$.
- $\underline{\mu} = (m(\underline{x}_1), \dots, m(\underline{x}_k))$ is the mean vector, with mean function $m(\underline{x}_i)$.
- $\underline{\sigma}$ is the covariance matrix, with entries $\sigma_{ij} = \kappa(\underline{x}_i, \underline{x}_j)$, where κ is a positive definite kernel or covariance function defining similarity between inputs.

It is common to scale the inputs and use a zero mean and a unit variance to improve model stability. The kernel function $\kappa(\underline{x}_i, \underline{x}_j)$ plays a central role by controlling the shape and smoothness of the functions drawn from the GP. If two inputs $\underline{x}_i$ and $\underline{x}_j$ are close (as measured by the kernel), the corresponding outputs $f(\underline{x}_i)$ and $f(\underline{x}_j)$ are expected to be similar.

Suppose you have a set of noise-free observations $\underline{f}$ at known inputs $\underline{x}$ and you want to predict the function values $\underline{f}^*$ at new inputs $\underline{x}^*$. Under the GP prior, the joint distribution of $\underline{f}$ and $\underline{f}^*$ is:

$$\begin{bmatrix} \underline{f} \\ \underline{f}^* \end{bmatrix} \sim \mathcal{N} \left(0, \begin{bmatrix} \underline{k} & \underline{k}^* \\ \underline{k}^{*\top} & \underline{k}^{**} \end{bmatrix} \right) \quad (5.3)$$

- $\underline{k} = \kappa(\underline{x}, \underline{x})$ is the training covariance matrix.
- $\underline{k}^* = \kappa(\underline{x}, \underline{x}^*)$ is the cross-covariance matrix between training and prediction data.

5 Probabilistic (settlement) calculations

- $\underline{k}^{**} = \kappa(\underline{x}^*, \underline{x}^*)$ is the covariance matrix at prediction points.

Using standard rules for conditioning a multivariate Gaussian, the predictive distribution becomes:

$$p(\underline{f}^* | \underline{x}^*, \underline{x}, \underline{f}) = \mathcal{N}(\underline{f}^* | \underline{\mu}^*, \underline{\Sigma}^*) \text{ where } \underline{\mu}^* = \underline{k}^{*\top} \underline{k}^{-1} \underline{f} \text{ and } \underline{\Sigma}^* = \underline{k}^{**} - \underline{k}^{*\top} \underline{k}^{-1} \underline{k}^* \quad (5.4)$$

This yields both the predicted mean $\underline{\mu}^*$ and uncertainty $\underline{\Sigma}^*$ for the outputs at new inputs $\underline{x}^*$.

If the training observations contain Gaussian noise $\underline{y} = \underline{f} + \underline{\epsilon}$, with $\underline{\epsilon} \sim \mathcal{N}(0, \sigma_y^2 \underline{I})$, the noise can be included in the model by adding $\sigma_y^2 \underline{I}$ to the training covariance matrix: $\underline{k}_y = \underline{k} + \sigma_y^2 \underline{I}$. Then the predictive distribution becomes:

$$p(\underline{f}^* | \underline{x}^*, \underline{x}, \underline{y}) = \mathcal{N}(\underline{f}^* | \underline{\mu}^*, \underline{\Sigma}^*) \text{ where } \underline{\mu}^* = \underline{k}^{*\top} \underline{k}_y^{-1} \underline{y} \text{ and } \underline{\Sigma}^* = \underline{k}^{**} - \underline{k}^{*\top} \underline{k}_y^{-1} \underline{k}^* \quad (5.5)$$

Although equation 5.5 accounts for noise in the training data, it still predicts noise-free outputs $\underline{f}^*$. To get predictions that also reflect observation noise, an extra term $\sigma_y^2 \underline{I}$ is added to the predictive covariance:

$$p(\underline{y}^* | \underline{x}^*, \underline{x}, \underline{y}) = \mathcal{N}(\underline{y}^* | \underline{\mu}^*, \underline{\Sigma}^* + \sigma_y^2 \underline{I}). \quad (5.6)$$

Several types of kernel functions exist in GPR, each imposing different assumptions on the structure and smoothness of the underlying function. In the development of the RSM used to approximate the settlement behaviour, an iterative approach reveals that a simple combination of a Matérn and White kernel yields the best results. It provides a robust and physically consistent approximation of the settlement evolution, balancing smooth continuous behaviour with the ability to account for discontinuities and modelling uncertainties. The rationale for selecting these two kernels, as well as the limitations of other commonly used kernels, are discussed below (Pedregosa et al., 2025a).

- **Squared exponential, radial basis function (RBF) or Gaussian kernel:** although widely used due to its smoothness and infinite differentiability, this kernel may not be suitable for capturing the abrupt responses in settlement behaviour caused by load increments. It tends to over-smooth the response, potentially missing sharp transitions. For this reason, it is not used in the RSM, although it could be considered for interpolating smooth sections between load steps.

The RBF employs a lengthscale parameter l that controls how rapidly the correlation between input points decays with distance, thereby determining the smoothness of the resulting function. Points that are close together in the input space ($\|\underline{x}_i - \underline{x}_j\|^2$) yield highly correlated outputs, while the correlation decreases exponentially as the distance increases. In addition, the RBF kernel includes a signal variance parameter σ_y^2 , which governs the vertical scaling or amplitude of the function's output.

$$\kappa(\underline{x}_i, \underline{x}_j) = \sigma_y^2 \exp\left(-\frac{\|\underline{x}_i - \underline{x}_j\|^2}{2 \cdot l^2}\right) \quad (5.7)$$

5 Probabilistic (settlement) calculations

In practice, the kernel hyperparameters (l and σ_y^2) can be iteratively optimized using Bayesian optimization in Python-based implementations. The influence of this hyperparameter tuning is illustrated in Figure 5.2. As the lengthscale l decreases, the fitted GP becomes less smooth and tends to overfit the noise in the data. Conversely, increasing l leads to a smoother approximation that may underfit rapid variations. The signal variance σ_y^2 affects the vertical scaling of the GP: lower values lead to flatter curves, while higher values can result in larger oscillations and potential overfitting. However, compared to the lengthscale, the variance parameter typically has a less pronounced effect on the shape of the fitted function (Wang, 2023).

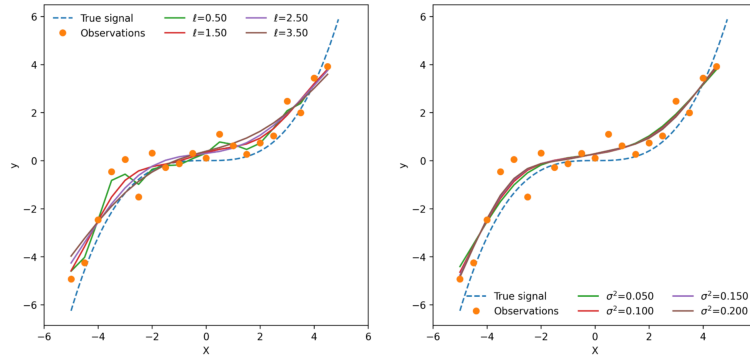


Figure 5.2: Hyperparameter optimization of the (squared exponential) kernel (Wang, 2023)

- **Matérn kernel:** this is a stationary covariance function and a generalization of the RBF kernel (for $\nu \rightarrow \infty$), offering a more flexible trade-off between smoothness and adaptability. It is parameterized by an additional smoothness parameter ν , alongside the standard hyperparameters l and σ_y^2 . For commonly used values such as $\nu = 3/2$ or $\nu = 5/2$, the Matérn kernel can model functions that are once or twice differentiable, respectively. Unlike the RBF kernel, which assumes infinite differentiability and thus overly smooth behaviour, the Matérn kernel is better suited for modelling physical phenomena like soil settlement, which involve both smooth trends and abrupt shifts due to load increments. Moreover, the lengthscale in the Matérn kernel can be defined as a vector, assigning a separate lengthscale to each input dimension. This anisotropic variant allows the kernel to capture direction-dependent behaviour in the input space. In the context of settlement modelling, this enables the model to account for varying sensitivity of the response to different input variables, thereby improving the interpretability and accuracy of the surrogate model. In the kernel formulation, $K_\nu(\cdot)$ is a modified Bessel function, $\Gamma(\cdot)$ is the gamma function and $d(\underline{x}_i, \underline{x}_j)$ is the Euclidean distance between the two input points $\underline{x}_i$ and $\underline{x}_j$: $\|\underline{x}_i - \underline{x}_j\|$ (Rasmussen and Williams, 2006).

$$\kappa(\underline{x}_i, \underline{x}_j) = \frac{1}{\Gamma(\nu)2^{\nu-1}} \left(\frac{\sqrt{2\nu}}{l} d(\underline{x}_i, \underline{x}_j) \right)^\nu K_\nu \left(\frac{\sqrt{2\nu}}{l} d(\underline{x}_i, \underline{x}_j) \right) \quad (5.8)$$

5 Probabilistic (settlement) calculations

- For $\nu = \frac{1}{2}$: the Matérn kernel becomes the exponential kernel:

$$\kappa(\underline{x}_i, \underline{x}_j) = \exp\left(-\frac{1}{l}d(\underline{x}_i, \underline{x}_j)\right)$$

- For $\nu = \frac{3}{2}$: the Matérn kernel is once differentiable (this is the Matérn kernel used here):

$$\kappa(\underline{x}_i, \underline{x}_j) = \left(1 + \frac{\sqrt{3}}{l}d(\underline{x}_i, \underline{x}_j)\right) \exp\left(-\frac{\sqrt{3}}{l}d(\underline{x}_i, \underline{x}_j)\right)$$

- For $\nu = \frac{5}{2}$: the Matérn kernel is twice differentiable:

$$\kappa(\underline{x}_i, \underline{x}_j) = \left(1 + \frac{\sqrt{5}}{l}d(\underline{x}_i, \underline{x}_j) + \frac{5}{3l^2}d(\underline{x}_i, \underline{x}_j)^2\right) \exp\left(-\frac{\sqrt{5}}{l}d(\underline{x}_i, \underline{x}_j)\right)$$

- **White kernel:** this kernel adds identically normally distributed, uncorrelated noise to the diagonal of the covariance matrix. It is used to model observation noise, random modelling errors and numerical artifacts (such as those resulting from the simplified assumptions, natural variability of deterministic parameters or numerical inaccuracies in the PLAXIS 2D simulations). The kernel is characterized by a single hyperparameter σ_n^2 that controls the amount of noise added. By summing this kernel with the Matérn kernel, the RSM avoids overfitting to non-physical variations and focuses on capturing true settlement trends.

$$\kappa(\underline{x}_i, \underline{x}_j) = \begin{cases} \sigma_n^2 & \text{if } \underline{x}_i = \underline{x}_j \\ 0 & \text{if } \underline{x}_i \neq \underline{x}_j \end{cases} \quad (5.9)$$

- **Periodic kernel:** this kernel assumes regular, repeating structures in the data and is hence suitable for modelling strictly periodic behaviour. While settlement due to repeated loading might contain some repeated structure, the non-uniformity and varying time scales of load increments in geotechnical problems make the periodic kernel less appropriate.
- **Constant kernel:** this kernel assumes a uniform mean level across the dataset and is often combined with other kernels. In the context of settlement modelling, such behaviour can be more realistically captured by the Matérn kernel, which already accounts for both global trends and local variations. Therefore, a separate constant kernel is not needed.

5.2.2.2 Gaussian process regression: implementation

To implement GPR for setting up an RSM in Python, several libraries are available. This thesis utilizes the *GPy* library, developed by the Sheffield Machine Learning Group, which offers a comprehensive framework for Gaussian processes. *GPy* includes a wide selection of kernels, likelihood functions and optimization methods, providing significant flexibility for various applications (Zwiessle et al., 2020). Another commonly used library is *Scikit-learn*, which features a set of predefined kernels that can be combined (Pedregosa et al., 2011).

5 Probabilistic (settlement) calculations

The response surface approach is employed to approximate the output of the PLAXIS 2D numerical model and to reduce the computational cost of repeated simulations across varying parameter combinations relevant to settlement prediction. Rather than running PLAXIS 2D at every iteration of the Bayesian updating framework, a surrogate model based on GPR is trained and used to estimate the settlement response (Vereecken, 2022).

The process begins with the generation of input samples using LHS. It is recommended to train the model using a sample set size of $n = 10 \cdot k$, where k is the dimensionality of the input space. An input sample $\underline{x}$ is a vector of $k - 1$ stochastic soil parameters and a time variable t . The soil parameter values remain constant, while time varies within each input matrix $\underline{x}$. Each sample $\underline{x}$ is then evaluated in PLAXIS 2D to obtain the corresponding time-dependent settlement response $\underline{y}$.

Next, the dataset $(\underline{x}, \underline{y})$ is split into training and validation sets. Typically, 80% of the data is used for training and 20% for validation. The split is performed using the *Scikit-learn* function `train_test_split( $\underline{x}$ ,  $\underline{y}$ , test_size=0.2)`. The split is applied at the level of the settlement curves rather than individual data points. This means 80% of the settlement curves is used for training and 20% for validation, which ensures the training data is well-distributed over the entire time range.

The training data $(\underline{x}_{train}, \underline{y}_{train})$ is used to fit the GPR model. During training, the model constructs a covariance matrix based on the chosen kernel and training inputs, capturing the similarity between data points. This enables the model to define a probabilistic mapping from inputs to outputs. The trained surrogate model can then predict both the expected value (mean) and associated uncertainty (variance) of the settlement response for new input combinations, without requiring additional PLAXIS 2D simulations.

Hyperparameter optimization in this study is performed by maximizing the log marginal likelihood of the GP model, as defined by equation (5.10), using gradient-based optimization techniques. The process begins with the initialization of the GP using a selected kernel and the available input-output training data.

To improve robustness and avoid convergence to suboptimal local minima, common in non-convex objective landscapes, the *GPy* method `optimize_restarts(num_restarts=5)` is used. This performs multiple optimization runs from different initial values of the kernel hyperparameters. Each restart minimizes the negative log marginal likelihood, which serves as the objective function balancing model fit and complexity. Setting `verbose=True` provides feedback on the optimization progress by printing the objective function value f for each restart. The optimizer selects the hyperparameters corresponding to the lowest f -value.

$$\log p(\underline{y} | \underline{x}) = \log \mathcal{N}(\underline{y} | 0, \underline{k}_{\underline{y}}) = -\frac{1}{2} \underline{y}^T \underline{k}_{\underline{y}}^{-1} \underline{y} - \frac{1}{2} \log |\underline{k}_{\underline{y}}| - \frac{n}{2} \log(2\pi) \quad (5.10)$$

5 Probabilistic (settlement) calculations

After identifying the best result among the restarts, a final refinement is conducted using the `optimize(max_iters=5000)` method, allowing for more precise convergence by increasing the maximum number of iterations. This two-step procedure enables effective tuning of key kernel parameters, such as the `lengthscale` and `variance`, ensuring the GP model captures the underlying data structure without overfitting. The overall approach aligns with the Bayesian principle of iteratively updating model assumptions based on observed evidence.

The remaining 20% of the data ($\underline{x}_{test}, y_{test}$) is used to validate the model, providing an estimate of its predictive accuracy and generalization capability (Vereecken, 2022). The validation set is not used during the training process, ensuring that the model's performance is evaluated on unseen data. Several methods can be used to check accuracy.

- **Coefficient of determination R^2 :** this metric quantifies the correlation between predicted outputs y_{pred} and true outputs y_{test} obtained from PLAXIS evaluations. For m validation samples, it is defined by equation (5.11). When the number of samples is low relative to the model complexity and the number of input parameters, R^2 may overestimate performance, indicating potential overfitting. In such cases, the coefficient of determination is adjusted, R^2_{adj} , based on the number of unknown parameters ν in the RSM (Bucher, 2009).

$$R^2 = 1 - \frac{\sum_{i=1}^m (y_{test,i} - y_{pred,i}(\underline{x}_{test}))^2}{\sum_{i=1}^m (y_{test,i})^2} \longrightarrow R^2_{adj} = R^2 - \frac{\nu - 1}{m - \nu} \cdot (1 - R^2) \quad (5.11)$$

- **Mean absolute error (MAE):** the average absolute difference between predicted and actual values. It corresponds to the expected value of the absolute error loss. A lower MAE indicates better model accuracy (Pedregosa et al., 2025b).

$$MAE = \frac{1}{n_{test}} \cdot \sum_{i=1}^{n_{test}} |y_{test,i} - y_{pred,i}(\underline{x}_{test})| \quad (5.12)$$

- **mean squared error (MSE):** the average of squared differences between predicted and actual values. A lower validation error indicates better model performance. MSE is sensitive to outliers, as larger errors have a disproportionately higher impact on the overall error metric (Pedregosa et al., 2025c).

$$MSE = \frac{1}{n_{test}} \cdot \sum_{i=1}^{n_{test}} |y_{test,i} - y_{pred,i}(\underline{x}_{test})|^2 \quad (5.13)$$

- **Visual evaluation of regression models:** model performance can also be assessed visually, as shown in Figure 5.3. The first plot compares predicted versus actual values. Ideally, points cluster around the 45-degree line. In real-world settings with irreducible noise (when not all variations of $\underline{y}$ can be explained by features in $\underline{x}$), the best models produce a dense cloud along this diagonal. The second plot shows residuals (prediction errors or differences between the actual and predicted values) versus predicted values.

5 Probabilistic (settlement) calculations

This allows to check whether the model assumptions are met: the expected value of the residuals should be zero, residuals should be uncorrelated across observations (no autocorrelation) and each error term should have the same variance (homoscedasticity). Therefore residuals should be randomly scattered around the horizontal line at zero. Systematic patterns, such as banana-shaped curves, suggest model inadequacies and the need for refinement (Pedregosa et al., 2025d).

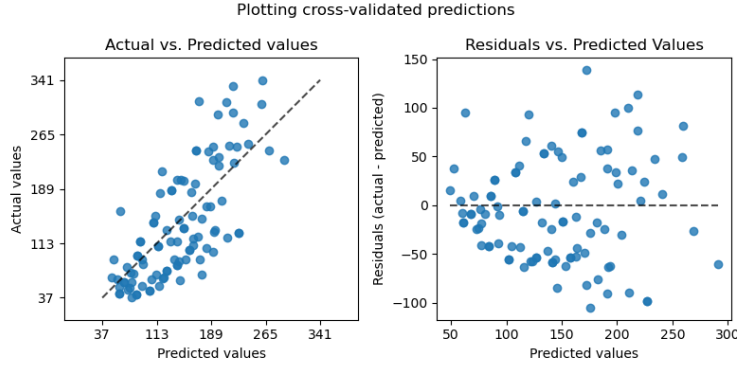


Figure 5.3: Visual evaluation of regression models

5.2.2.3 Gaussian process regression: example

To conclude the explanatory section on the response surface methodology, the simplified example of the dike settlement calculation introduced in section 5.2.1.2 is revisited. In this example, the unit weight of the sand used in dike construction and the compression index of the underlying clay layer are treated as stochastic variables. Including time, the input space becomes three-dimensional: $X = (\gamma_d, C_c, t)$. Based on the rule of thumb $n = 10 \cdot k$, at least 30 settlement curves are recommended for training. Here, 50 samples are generated using LHS (Figure 5.4a) and used to run PLAXIS 2D simulations, resulting in 50 corresponding settlement curves over time $y = S(t)$ (Figure 5.4b).

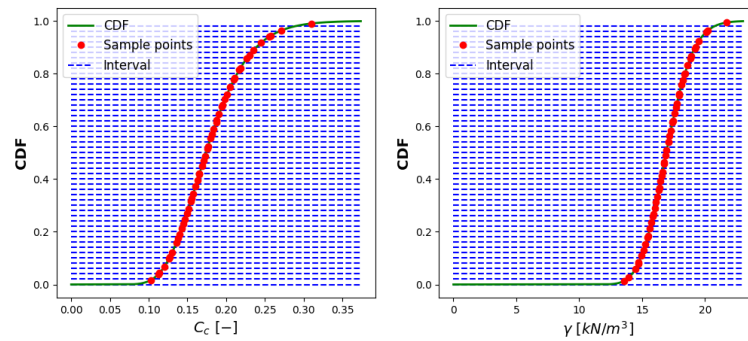
The dataset $(((\gamma_{d,1}, C_{c,1}, [t_0 \dots t_f]) \dots (\gamma_{d,50}, C_{c,50}, [t_0 \dots t_f])); [(S_1(t_0 \dots t_f)) \dots (S_{50}(t_0 \dots t_f))])$ is split into a training set of 40 curves and a validation set of 10 curves. The GPR model has been trained using the 40 training curves (Figure 5.4c) and a Matérn kernel with $\nu = 3/2$ combined with a White kernel. During training, the model computes a covariance matrix that captures the similarities between input points, which is used to probabilistically map inputs to outputs. Hyperparameter optimization has been carried out to minimize the negative log marginal likelihood, resulting in an optimal objective value of $f = -8253.96$. The final hyperparameters are listed in Table 5.1. The model's predictive accuracy is evaluated using the 10 validation curves (Figure 5.4d). The predicted settlements closely matched the actual PLAXIS 2D outputs, with performance metrics indicating excellent agreement: $MAE = 0.002586$, $RMSE = \sqrt{MSE} = 0.000022$, $R^2 = 0.989609$, and $R^2_{adj} = 0.988310$. Additionally, the residuals are randomly scattered around zero with no discernible pattern (Figure 5.4e).

5 Probabilistic (settlement) calculations

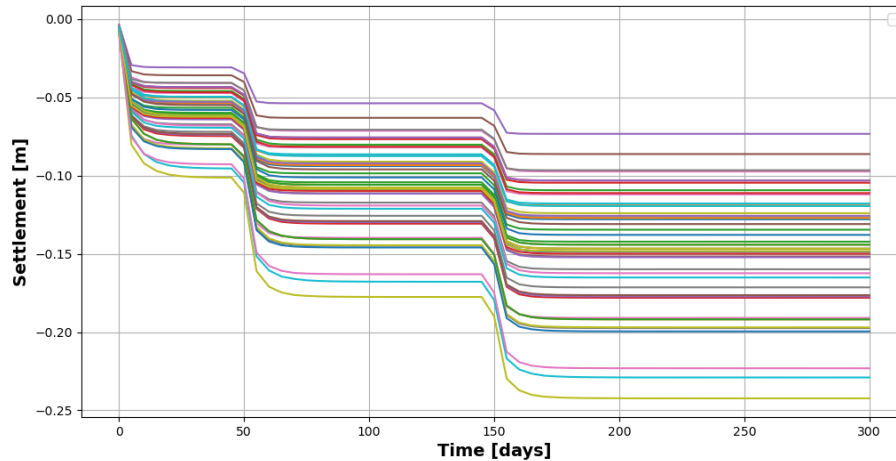
Table 5.1: Hyperparameters of the GPR model

Kernel		Lengthscale	Variance
White kernel		/	$8.3626 \cdot 10^{-15}$
Matérn Kernel	C_c	4.2180	0.6319
	γ_d	4.3357	
	t	0.0829	

To demonstrate the efficiency of the trained surrogate model, 500 new input combinations are generated using LHS (Figure 5.4f) and the corresponding settlement curves are predicted using the GPR model (Figure 5.4g). The generated curves appear physically plausible and the entire prediction process has been completed in approximately 5 minutes. In contrast, running PLAXIS 2D for the same number of samples would have required an estimated 50 hours, clearly illustrating the computational advantage of the GPR-based surrogate model.



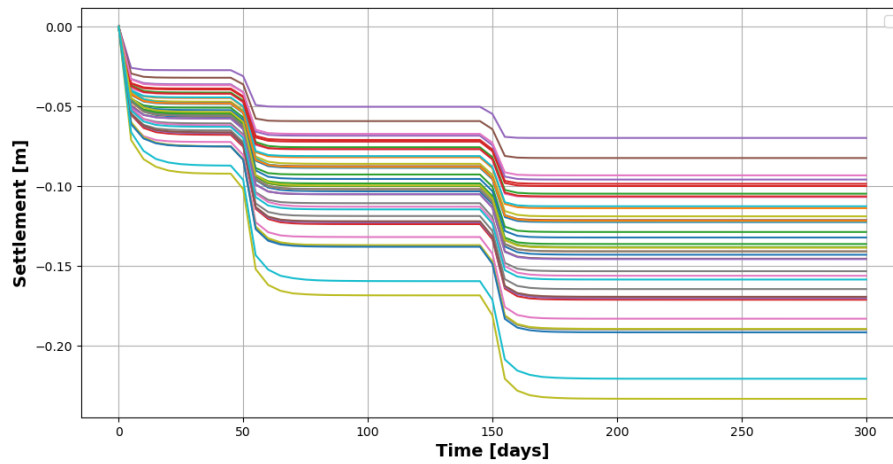
(a) Generation of 50 LHS samples to train and validate the GPR model



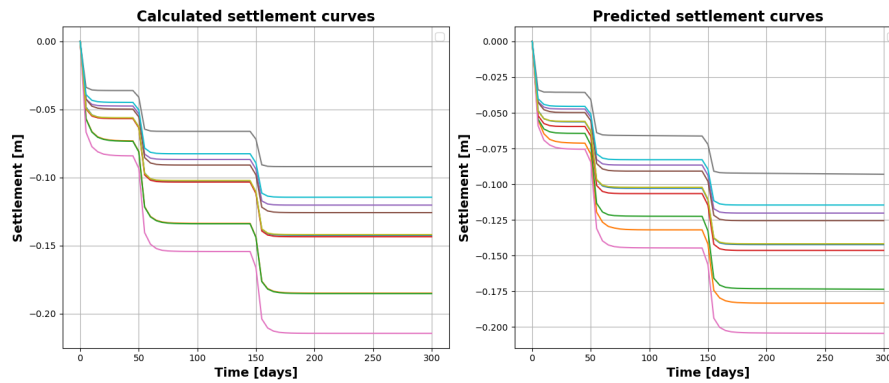
(b) 50 settlement curves generated by PLAXIS 2D, corresponding to the LHS parameters

Figure 5.4: Set-up of an RSM for a simplified dike settlement calculation (Part 1)

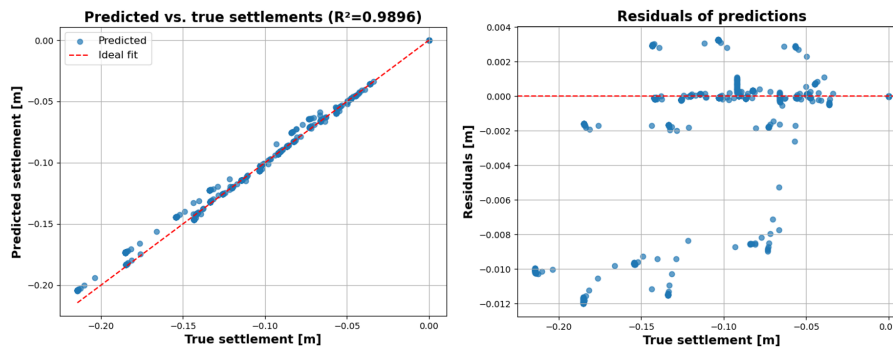
5 Probabilistic (settlement) calculations



(c) Training set: 40 settlement curves



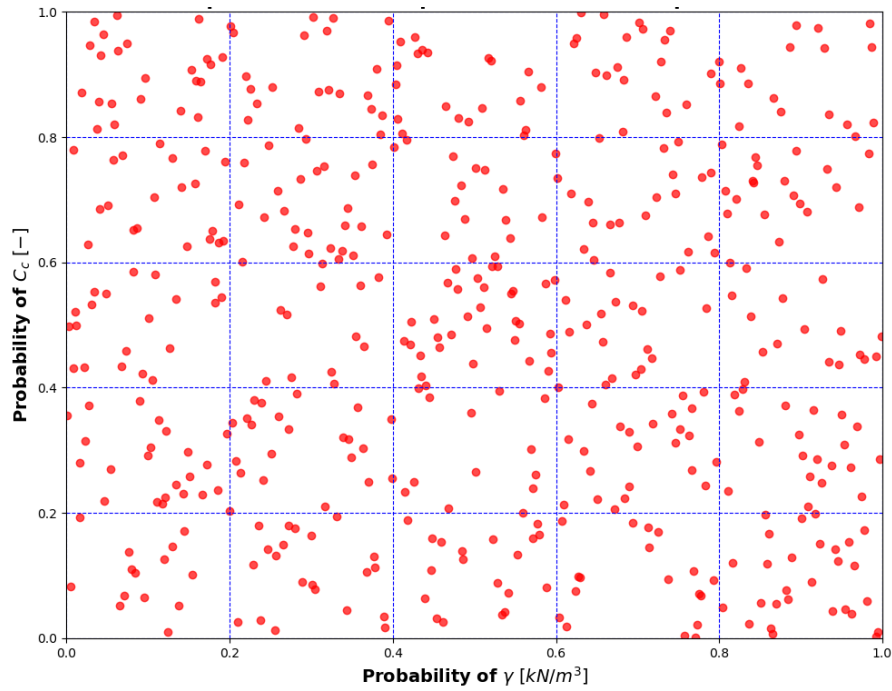
(d) Validation set: comparison calculated and predicted settlement curves



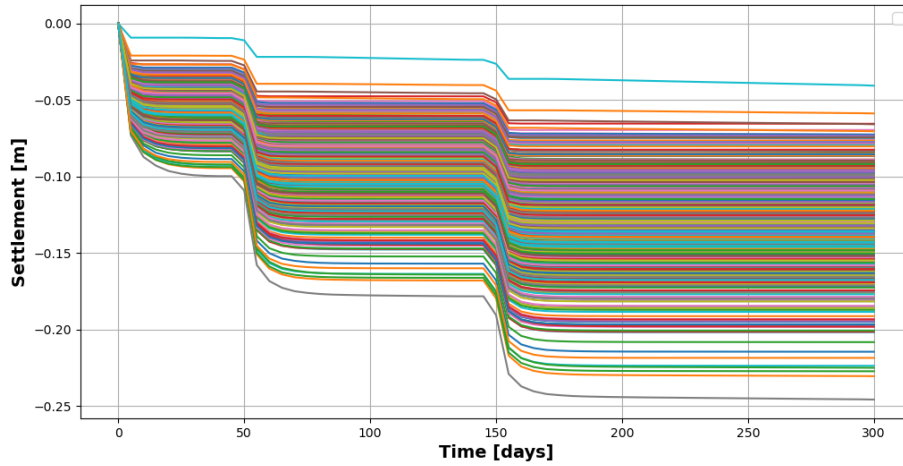
(e) Validation of the GPR model

Figure 5.4: Set-up of an RSM for a simplified dike settlement calculation (Part 2)

5 Probabilistic (settlement) calculations



(f) Generation of 500 new input samples for the GPR model



(g) Prediction of the 500 settlement curves using the GPR model

Figure 5.4: Set-up of an RSM for a simplified dike settlement calculation (Part 3)

5.2.3 Bayesian updating

The final step of the proposed probabilistic workflow is the incorporation of real-world monitoring data through Bayesian updating in order to improve settlement predictions. The base of the Bayesian approach is Bayes' theorem, which states that the posterior probability of a hypothesis H given observed data D is proportional to the likelihood of the data given the hypothesis, multiplied by the prior probability of the hypothesis, scaled by the total probability of the data.

5 Probabilistic (settlement) calculations

$$P(H | D) = \frac{P(D | H) \cdot P(H)}{P(D)} \quad (5.14)$$

In the case of continuous random variables, Bayes' theorem is expressed using probability density functions (PDFs) rather than probabilities. The continuous analogue is given by equation (5.15). Here, $f''_{\underline{X}}(\underline{x})$ denotes the posterior PDF of the parameter vector $\underline{x}$ given data D , $L(\underline{x} | D)$ is the likelihood and $f'_{\underline{X}}(\underline{x})$ the prior. Again, denominator serves as a normalizing constant to ensure that the posterior integrates to one over the parameter space (Caspeele, 2024).

$$f''_{\underline{X}}(\underline{x}) = \frac{L(\underline{x} | D) \cdot f'_{\underline{X}}(\underline{x})}{\int L(\underline{x} | D) \cdot f'_{\underline{X}}(\underline{x}) d\underline{x}} \text{ where } L(\underline{x} | D) = L(\underline{x} | d_1, \dots, d_n) = \prod_{i=1}^n f_X(d_i | \underline{x}) \quad (5.15)$$

In this study, the objective is not to update a single settlement value, but rather to obtain an entire updated settlement curve that more accurately predicts both the final settlement and its evolution over time, based on earlier monitoring data. Therefore, classical Bayesian updating formulas, such as equation (5.16), are insufficient. These formulas update a single value based on the prior distribution of the settlement, denoted by μ' and σ'^2 , and the likelihood of the observed value, characterized by μ_L and σ_L^2 , where the observation is typically a single settlement measurement at the time of updating ($n = 1$). These formulas are based on the assumption that both the prior and likelihood are normally distributed and that the variable being updated (here, the settlement) is directly observed (Nederlof, 2023).

$$\mu'' = \frac{\sigma_L^2 \cdot \mu' + n \cdot \sigma'^2 \cdot \mu_L}{n \cdot \sigma'^2 + \sigma_L^2} \text{ and } \sigma''^2 = \frac{\sigma_L^2 \cdot \sigma'^2}{n \cdot \sigma'^2 + \sigma_L^2} \quad (5.16)$$

More broadly, other methods such as Kalman filtering and multivariate Bayesian updating also depend on linear-Gaussian assumptions and require observations of the model's internal state variables (here, the stochastic soil parameters) or closed-form expressions of the posterior. However, in the current setting, only settlement measurements s_{obs} are available, while the soil parameters p themselves remain unobserved. Moreover, the relationship between these parameters and the settlement response is non-linear and modelled via a trained response surface. As such, the assumptions underlying classical Bayesian updating methods are violated and these approaches are not suitable for this application.

An alternative approach that has been explored in this study is a heuristic method aimed at updating the distributions of the soil parameters based on observed settlement data: first, a large prior sample of soil parameters is generated using LHS. Each sampled parameter set is then passed through the trained RSM to produce a corresponding predicted settlement curve. For a given observation time, the predicted settlement value s_{pred} is extracted and compared to the observed settlement s_{obs} at that time. Considering an assumed observational uncertainty of 0.01 m, all predicted settlement curves for which $s_{pred} \in [s_{obs} - 0.01, s_{obs} + 0.01]$ are selected. The soil parameter sets that generate these "acceptable" curves can be collected.

5 Probabilistic (settlement) calculations

This produces a subset of the original prior sample consisting of parameter combinations that is consistent with the observed settlement at the specified time instance. From this filtered subset, the posterior mean and standard deviation of each soil parameter can be calculated. These mean values can be used as updated estimates for the parameters, while the updated standard deviations can be interpreted as revised measures of uncertainty. The resulting (Gaussian) posterior distributions is then resampled and has been propagated through the RSM to generate updated settlement predictions.

While this method is intuitive and computationally efficient, it comes with important limitations. It approximates the posterior distributions as Gaussian by matching means and variances and does not account for potential non-Gaussian features, such as skewness, heavy tails or multimodality. Furthermore, it neglects parameter correlations, which are often critical in probabilistic modelling. As a result, this approach oversimplifies the underlying distribution and fails to fully represent the true joint posterior. Therefore, a more rigorous Bayesian approach, such as Markov chain Monte Carlo (MCMC), is better suited to capture the full complexity of the updated parameter space.

MCMC offers a principled solution to these limitations. Since the goal is to infer the full joint posterior distribution of the soil parameters, however irregular it may be, and to propagate these samples through the trained RSM to generate an ensemble of updated settlement curves, a sampling method is needed that does not rely on restrictive assumptions such as linearity or normality. Markov chain Monte Carlo (MCMC) fulfils this requirement by constructing a Markov chain whose equilibrium distribution corresponds to the target posteriors. Once the chain has converged, samples drawn from it reflect the full probabilistic structure of the updated parameter space. By evaluating each sample through the surrogate model, the resulting settlement predictions capture the uncertainty and variability inherent in both the measurements and the model itself. As such, MCMC emerges as the most robust and flexible framework for Bayesian updating in this context.

5.2.3.1 Markov chain Monte Carlo simulations: theoretical background

Markov chain Monte Carlo (MCMC) is a class of algorithms used to generate dependent (i.e. correlated) samples from complex target distributions, typically Bayesian posterior distributions, when direct sampling is impractical or infeasible due to the absence of an analytical closed-form expression. To obtain samples from probability distributions, MCMC methods construct a Markov chain. The latter is a sequence of random variables x_i that transition from one state to another based on probabilistic rules. It is characterized by the Markov property, where the probability of moving to a specific state x_i depends only on the previous state x_{i-1} and not on the entire history ($x_{i-2}, x_{i-3}, \dots$) of the chain. By iteratively generating samples, the Markov chain asymptotically behaves as the PDF that has to be sampled (Gelman et al., 2013).

5 Probabilistic (settlement) calculations

Here, the Metropolis-Hastings (MH) algorithm is used to evaluate the Markov chain, which is one of the most popular MCMC algorithms. The methodology is explained below (Caspeele, 2010) and illustrated in Figure 5.5.

1. **Initialization:** chose a starting vector $\underline{x}_0$ as well as a transition or proposal distribution $q(\tilde{\underline{x}} | \underline{x}_s)$, which is a function of the current state $\underline{x}_s$ and generates a new candidate vector $\tilde{\underline{x}}$.
2. **Iteration:** starting from starting vector $\underline{x}_0$, independent and sequential realizations $\underline{x}_s$ are computed from a PDF $f_X(\underline{x})$ for which no analytical solution is available. In each step, the transition between the current state $\underline{x}_s$ and the next one $\underline{x}_{s+1}$ is given by equation (5.17) and the acceptance probability $\alpha(\underline{x}_s, \tilde{\underline{x}})$ of the candidate vector $\tilde{\underline{x}}$ is calculated with equation (5.18).

$$\underline{x}_{s+1} = \begin{cases} \tilde{\underline{x}} \propto q(\tilde{\underline{x}} | \underline{x}_s) & \text{with probability } \alpha(\underline{x}_s, \tilde{\underline{x}}) \\ \underline{x}_s & \text{else} \end{cases} \quad (5.17)$$

$$\alpha(\underline{x}_s, \tilde{\underline{x}}) = \min \left[1, \frac{f_X(\tilde{\underline{x}})}{f_X(\underline{x}_s)} \cdot \frac{q(\underline{x}_s | \tilde{\underline{x}})}{q(\tilde{\underline{x}} | \underline{x}_s)} \right] \quad (5.18)$$

Next, a random number u is generated from a uniform distribution $\mathcal{U}[0, 1]$. The candidate vector $\tilde{\underline{x}}$ is accepted as the next draw from the PDF $f_X(\underline{x})$ with a probability $\alpha(\underline{x}_s, \tilde{\underline{x}})$ in case $u \leq \alpha(\underline{x}_s, \tilde{\underline{x}})$ or rejected in the other case. As such, a sequence of random draws $\underline{x}_s$ from $f_X(\underline{x})$ is generated, although no analytical solution is available for this PDF.

3. **Burn-in period and convergence:** the first $n_{burn-in}$ samples are discarded to ensure that the Markov chain has converged to the target distribution, eliminating bias from the arbitrary initialization. The remaining samples are used for posterior inference. To check convergence of the chain, one can use trace plots, running mean plots or the Gelman-Rubin statistic to verify that the chain has mixed well and reached equilibrium. More information on these convergence diagnostics can be found in section 5.2.3.2.

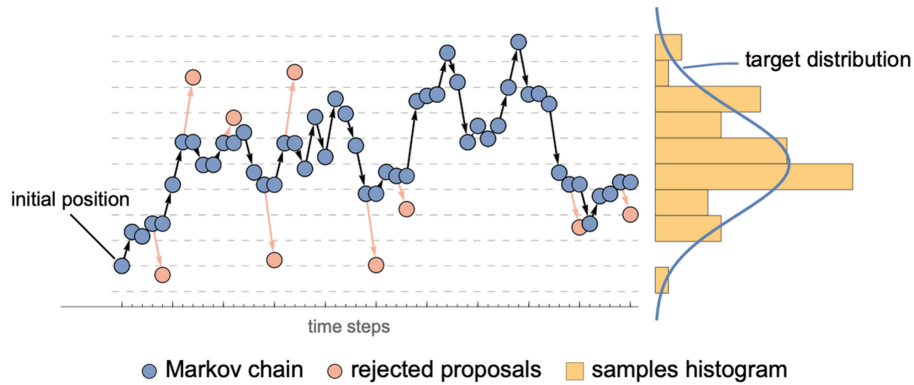


Figure 5.5: Illustration of the Markov chain Monte Carlo (MCMC) algorithm

5 Probabilistic (settlement) calculations

According to the Metropolis-Hastings algorithm, a recommended choice for the proposal distribution $q(\tilde{x} | x_s)$ is obtained by adding a random disturbance ξ to the current state x_s : $\tilde{x} = x_s + \xi$. This random disturbance is generated as a sequence of random and independent draws from a known probability distributions, for example a standard normal distribution $\mathcal{N}(0, \sigma_\xi^2)$, where σ_ξ^2 can be seen as a tuning parameter that controls the size of the perturbation.

An important consequence of choosing the proposal distribution as a random perturbation of the current state (also referred to as the random walk Metropolis-Hastings algorithm) is that the proposal distribution is symmetric: $q(\tilde{x} | x_s) = q(x_s | \tilde{x})$. This means that the acceptance ratio simplifies to equation (5.19) (Navarro, 2023).

$$\alpha(x_s, \tilde{x}) = \min \left[1, \frac{f_X(\tilde{x} = x_s + \xi)}{f_X(x_s)} \right] \quad (5.19)$$

If it holds for the target PDF that points close to each other have similar densities and that there is a high probability region with points far from this region having a much lower density than points in this region, which is most often the case, two extreme cases can be considered. These are illustrated in Figure 5.6 (Taboga, 2021b).

- **Small σ_ξ^2** : the proposal distribution is concentrated around the current state x_s . The acceptance rate is high, but the samples are highly correlated (the Markov chain 'jumps' only a small distance between subsequent states).
- **Large σ_ξ^2** : the proposal distribution is more spread out. The acceptance rate is lower because if x_s is in the high probability region, then the proposals tend to be far from this region and thus they have a low density. The proposals are often rejected and the chain remains stuck at a high-density point for long periods of time, resulting in a highly serially correlated MCMC sample as well.

To avoid these two extremes, the variance of the random walk increments ξ should be accurately tuned. The optimal value of σ_ξ^2 is problem-dependent and can be determined through trial-and-error: start with a guess for σ_ξ^2 and generate a first MCMC sample. Next, examine the trace plots and increase σ_ξ^2 if the trace plot moves very slowly, or decrease σ_ξ^2 if the chain gets stuck at a certain point, visible as a flat line in the trace plot.

5 Probabilistic (settlement) calculations

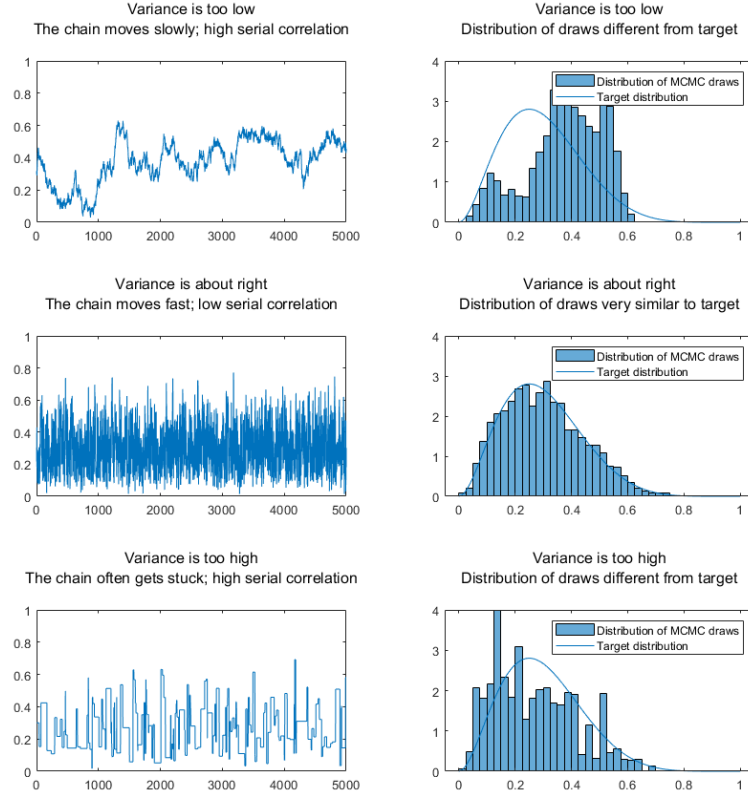


Figure 5.6: Effect of proposal distribution on acceptance rate and correlation of samples (Taboga, 2021b)

To apply MCMC to this problem, the PDF (here, the posterior distribution) from which samples are to be drawn need to be defined. From previous parts, continuous probability distributions have been established for the soil parameters affecting settlement. These are interpreted as the prior distributions. The true settlement value $\hat{s}$ can be predicted using a trained surrogate model M , evaluated at a k -dimensional input vector $\underline{p}$, consisting of $k - 1$ soil parameters p and a time value t . If the surrogate model would be perfect and the true values $\hat{p}$ are exactly known, the RSM would predict the true response value $\hat{s}$. However, due to uncertainties in both measurements and the model itself, the actual observation is represented as: $\hat{s} = M(\hat{p}) + \varepsilon$ where the error term $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ captures both model uncertainty and measurement error. The standard deviation σ_ε is assumed to be constant across the input space (Taboga, 2021a).

Given N observed settlement values s_i corresponding to input vectors $\underline{p}_i$, the likelihood of the observed data can be expressed as:

$$\begin{aligned}
 L(s_1, \dots, s_N \mid \underline{p}_1, \dots, \underline{p}_N) &= \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma_\varepsilon} \exp\left(-\frac{1}{2} \frac{[s_i - M(\underline{p}_i)]^2}{\sigma_\varepsilon^2}\right) \\
 &= \prod_{i=1}^N \frac{1}{\sigma_\varepsilon} \phi\left(\frac{s_i - M(\underline{p}_i)}{\sigma_\varepsilon}\right), \tag{5.20}
 \end{aligned}$$

5 Probabilistic (settlement) calculations

This likelihood function is then used to update the joint prior distribution $f'_P(\sigma_\varepsilon, p_1, \dots, p_{k-1}, t)$ into a posterior distribution using Bayes' theorem, where c is an unknown normalizing constant that ensures the posterior integrates to one.

$$\begin{aligned} f''_P(\sigma_\varepsilon, p_1, \dots, p_{k-1}, t) &= \frac{f'_P(\sigma_\varepsilon, p_1, \dots, p_{k-1}, t) \cdot L(s_1, \dots, s_N \mid \underline{p}_1, \dots, \underline{p}_N)}{\int f'_P \cdot L d\sigma_\varepsilon dp_1 \dots dp_{k-1} dt} \\ &= c \cdot f'_P(\sigma_\varepsilon, p_1, \dots, p_{k-1}, t) \cdot L(s_1, \dots, s_N \mid \underline{p}_1, \dots, \underline{p}_N), \end{aligned} \quad (5.21)$$

An important advantage of the Metropolis-Hastings algorithm and a key reason for its use in Bayesian inference, is that it does not require this constant c to be known. The (posterior) PDF (here, $f''_P(\underline{p}) = f_X(\underline{x})$) can often be written in the form $f_X(\underline{x}) = c \cdot h_X(\underline{x})$, where $h_X(\underline{x})$ is the product of the prior and the likelihood. The normalizing constant c is independent of the parameter vector $\underline{x}$ and can be factored out of the acceptance ratio. This means that the acceptance probability α can be expressed according to equation (5.22). As a result, the constant c cancels out. This is the strength of Metropolis-Hastings: it allows sampling from a distribution even if the full, normalized density is not known. This feature makes MCMC particularly well-suited for the current application, where the posterior over the soil parameters is complex, high-dimensional and only available up to a multiplicative constant.

$$\alpha = \min \left(1, \frac{f_X(\tilde{\underline{x}})}{f_X(\underline{x}_s)} \right) = \min \left(1, \frac{h_X(\tilde{\underline{x}})}{h_X(\underline{x}_s)} \right), \quad (5.22)$$

Following the above method, one obtains the posterior distributions of the soil parameters, since the MCMC algorithm generates samples from the full joint posterior. By marginalizing over the other parameters in the chain, the distribution of each individual soil parameter can be inferred. These marginal distributions reflect the updated knowledge about each parameter after incorporating the observed settlement data and provide a complete probabilistic description of the uncertainty, which can be used for further prediction and analysis.

5.2.3.2 Markov chain Monte Carlo simulations: implementation

Although several Python libraries exist for performing MCMC simulations - such as *emcee*, which implements an affine-invariant ensemble sampler - it is decided to manually implement the Metropolis-Hastings algorithm in this study. An affine-invariant ensemble sampler uses multiple parallel chains (so-called walkers) and automatically adapts to anisotropic or correlated posteriors, making it efficient for complex parameter spaces. However, in this study, the focus is on transparency and full control over the sampling process. Manually implementing the Metropolis-Hastings algorithm ensures that all steps are fully understood and validated. Moreover, it provides the flexibility to tailor the sampler to the problem-specific needs, such as the integration of a surrogate model, definition of a custom likelihood structure and the non-standard form of the posterior. Additionally, it ensures a direct link between each programming step and the theoretical formulation. This approach avoids reliance on a complete black-box method and facilitates diagnostic analysis and debugging throughout the implementation.

5 Probabilistic (settlement) calculations

The code defines functions `log_prior()`, `log_likelihood()` and `metropolis_hastings()`. It initializes a Markov chain at a starting vector $\underline{x}$, consisting of the initial mean values of the soil parameters. In each iteration, new candidate values are proposed for these parameters by adding Gaussian noise to the current state, which aligns with the symmetric proposal distribution, centred at the current state $q(\tilde{\underline{x}} | \underline{x}_s) = \mathcal{N}(\underline{x}_s, \sigma_\xi^2)$ as discussed in section 5.2.3.1.

The acceptance probability is computed by evaluating the log-posterior density, expressed as the sum of the log-prior and log-likelihood, for both the current and proposed states. The prior probability is obtained from known Gaussian distributions of the parameters, while the likelihood is calculated by comparing predicted settlement values (from the surrogate model) to the observed data using equation (5.20). If the new candidate improves the posterior and is accepted with a certain probability, it is added to the chain. Otherwise, the current state is retained. This aligns with the acceptance rule from equation (5.17). The output of this algorithm is a sequence of correlated samples representing draws from the posterior distribution of the soil parameters. These samples form the basis for statistical inference and are later used to generate updated settlement predictions through the response surface model.

To reflect the progressive nature of real-world monitoring, the MH algorithm is embedded within a sequential Bayesian updating framework. Rather than using all available observations at once, the algorithm is run iteratively: at each time step, all settlement measurements up to that point are used to update the posterior. Each new chain is initialized using the posterior mean of the previous step, maintaining continuity across updates. At every iteration, two independent chains (walkers), with slightly different starting values are run in parallel to improve robustness. Each chain itself is generated by 10000 iterations, of which the first 1000 samples serve as burn-in. This allows the chains to reach equilibrium. The resulting chains are then combined to approximate the updated posterior distributions of the sensitive soil parameters.

Convergence of the chains is assessed by using the Gelman-Rubin diagnostic $\hat{R}$ (Gelman and Rubin, 1992), which compares between-chain and within-chain variance to evaluate how well the chains have mixed. Consider J chains of length L (after burn-in), with $x_i^{(j)}$ the i -th sample of the j -th chain. The diagnostic is computed as follows: $\hat{R} = \sqrt{\frac{\frac{L-1}{L}W + \frac{1}{L}B}{W}}$, where:

- Mean of each chain: $\bar{x}_j = \frac{1}{L} \sum_{i=1}^L x_i^{(j)}$ and mean across all chains: $\bar{x}_* = \frac{1}{J} \sum_{j=1}^J \bar{x}_j$
- Between-chain variance: $B = \frac{L}{J-1} \sum_{j=1}^J (\bar{x}_j - \bar{x}_*)^2$
- Within-chain variance: $W = \frac{1}{J} \sum_{j=1}^J \left(\frac{1}{L-1} \sum_{i=1}^L (x_i^{(j)} - \bar{x}_j)^2 \right)$

When the chains have converged, the between-chain variance $B \rightarrow 0$ and $\hat{R} \rightarrow 1$. Values of $\hat{R}$ close to 1 (e.g. below 1.1) are generally accepted as evidence of convergence. Once convergence is confirmed, the retained samples from the chains form the basis for posterior inference and are propagated through the surrogate model to produce updated settlement predictions.

5 Probabilistic (settlement) calculations

In addition to the Gelman-Rubin statistic, running mean plots are used to visually assess convergence of the Markov chains. These plots display the cumulative mean of a sampled parameter against the number of iterations in the MCMC chain. It is always advised to use multiple convergence diagnostics, as there is no single metric that can guarantee convergence on its own. Combining quantitative measures such as the Gelman-Rubin statistic with visual tools like trace plots and running mean plots provides a more robust assessment of whether the Markov chains have sufficiently explored the posterior distribution.

To end this section, two more comments should be made.

First, in the implementation of the Metropolis-Hastings algorithm, the prior, likelihood and posterior probabilities are evaluated in logarithmic form. This practice is common in Bayesian inference for several important reasons. First, working in logarithmic space improves numerical stability. Probabilities and likelihoods often involve extremely small values, particularly when evaluating joint densities over multiple data points, which can lead to numerical underflow when multiplied. Taking the logarithm transforms these products into sums, making the computation more stable and less prone to floating-point errors. Second, many statistical libraries (e.g. *scipy.stats*) provide direct functions for computing log-densities, such as `logpdf()`, which simplifies the implementation and improves computational efficiency. Third, using log space simplifies the computation of the acceptance ratio in the Metropolis-Hastings algorithm. Instead of directly comparing ratios of probabilities, one can compare the difference of their logarithms. This is computationally more stable and avoids the risk of dividing very small numbers. Finally, since the posterior is only known up to a multiplicative constant, working in log space emphasizes that only relative differences in probability are needed for sampling decisions. These advantages collectively make log-space computation the preferred approach in practical MCMC implementations.

$$\alpha = \min \left[1, \frac{f_X(\tilde{x})}{f_X(x_s)} \right] \rightarrow \log(\alpha) = \min [0, \log(f_X(\tilde{x})) - \log(f_X(x_s))] \quad (5.23)$$

Second, the choice of the proposal distribution's standard deviation is a critical tuning parameter that directly affects the performance of the MCMC sampler. As explained in section 5.2.3.1, an optimal balance must be found to ensure both a reasonable acceptance rate and efficient exploration of the parameter space. In this study, the proposal standard deviations are selected through a trial-and-error process, guided by visual diagnostics such as trace plots and running mean plots. A well-tuned proposal distribution improves the mixing of the Markov chain and ensures convergence to the target posterior distribution within a practical number of iterations. In practice, it is recommended to aim for an overall acceptance rate between 20% and 30%, with 23.4% often cited as optimal in high-dimensional problems (Roberts et al., 1997). Values within a broader range of 10% to 60% may still be acceptable depending on the context. To achieve this, the scalar proposal standard deviation σ_ξ should be adjusted iteratively until the empirical acceptance rate falls within the desired window.

5 Probabilistic (settlement) calculations

5.2.3.3 Markov chain Monte Carlo simulations: example

The illustrative example of the simplified dike settlement calculation, first introduced in section 5.2.1.2 and further developed in section 5.2.2.3, is now revisited a final time to demonstrate the full Bayesian updating procedure. The measured settlement values used to perform the Bayesian updating with in this example are given in Table 5.2. According to experts from the Geotechnical Department of the Flemish Government, the uncertainty in the settlement measurements can be estimated at 0.01 m .

Table 5.2: Illustrative example: monitoring

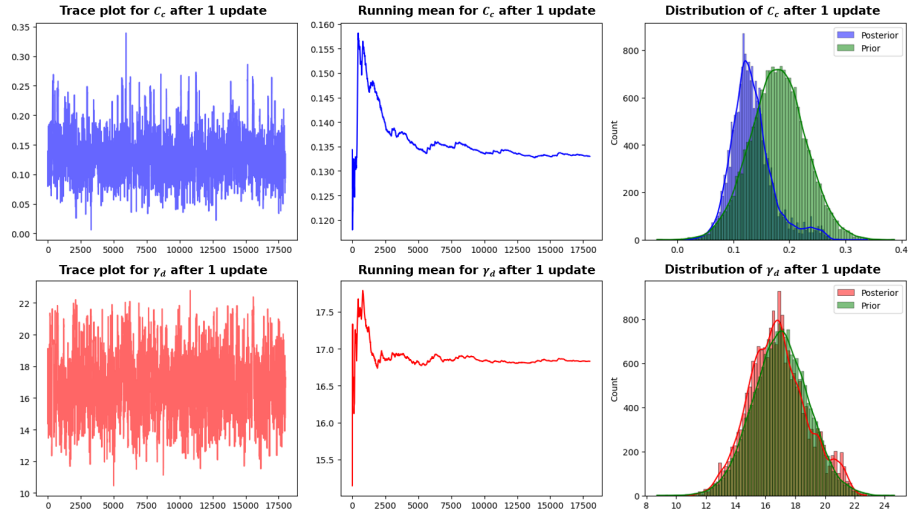
Observation times t_{obs} [days]	25	100	200
Observed settlements z_{obs} [m]	−0.03	−0.15	−0.20

The prior distributions of the soil parameters are shown in Figure 5.1b. The response surface model trained and validated in section 5.2.2.3 is used to predict the settlement at each observation time. For every update, the MCMC algorithm is executed using all available measurements up to that point to refine the posterior distributions of the soil parameters and produce updated settlement predictions. At each stage, two independent Markov chains are run in parallel, each with 10000 iterations, discarding the first 1000 samples as burn-in. The proposal distributions used to explore the parameter space employ a standard deviation of $\sigma_{\xi} = 1.1 \cdot \sigma$, determined through trial-and-error to achieve an acceptance rate between 10% and 60%. Convergence is evaluated using the Gelman–Rubin statistic and running mean plots, ensuring adequate mixing and convergence to the target posterior distribution.

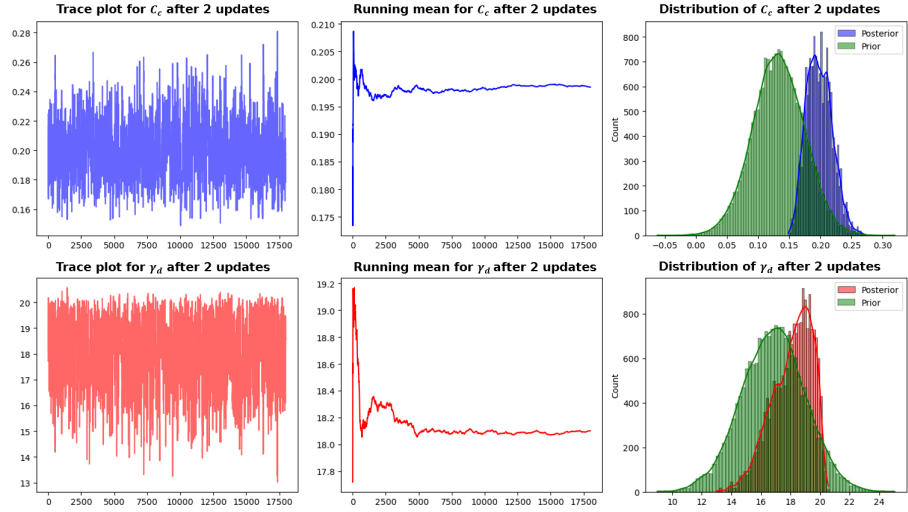
Figure 5.7 illustrates the Bayesian updating process using MCMC with the Metropolis–Hastings algorithm. The figure consists of three subplots, each representing an updating step. Each subplot includes two rows of three panels: the top row corresponds to the clay compression coefficient C_c and the bottom row to the unit weight of the dike sand γ_d . In each row, the first panel shows a trace plot of the Markov chain samples. Compared to the reference in Figure 5.6, these traces exhibit well-tuned proposal distributions, with fast-mixing chains and low serial correlation. The second panel presents the running mean, which stabilizes in all cases. This indicates adequate exploration of the parameter space and convergence to equilibrium. The third panel compares prior and posterior distributions, showing how the observed settlement data refines the parameter estimates. Typically, the posterior distributions are narrower, reflecting reduced uncertainty.

Figure 5.8 compares prior and posterior settlement predictions across the updating steps. The shaded bands represent uncertainty around the mean settlement curves. As more data is incorporated, these bands narrow and predictions become more accurate, demonstrating the effectiveness of Bayesian updating. Notably, each posterior distribution serves as the prior for the subsequent step.

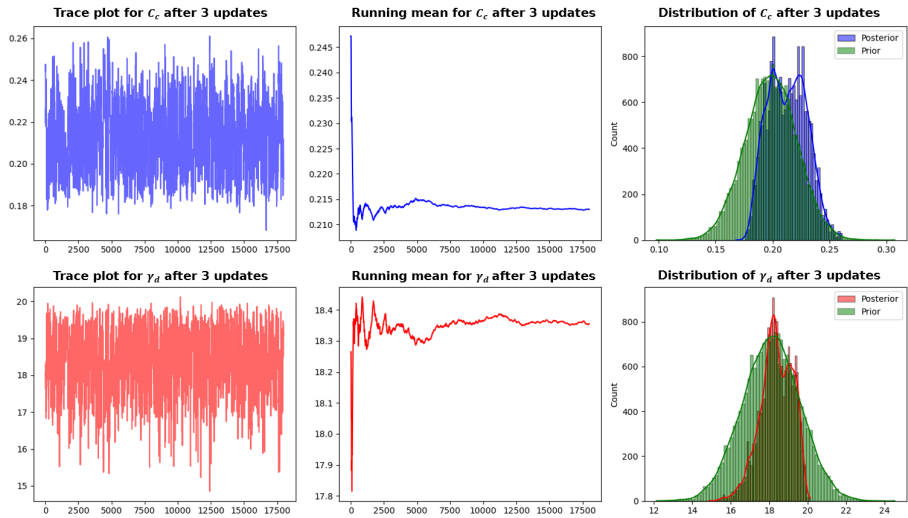
5 Probabilistic (settlement) calculations



(a) Bayesian updating using the first measurement



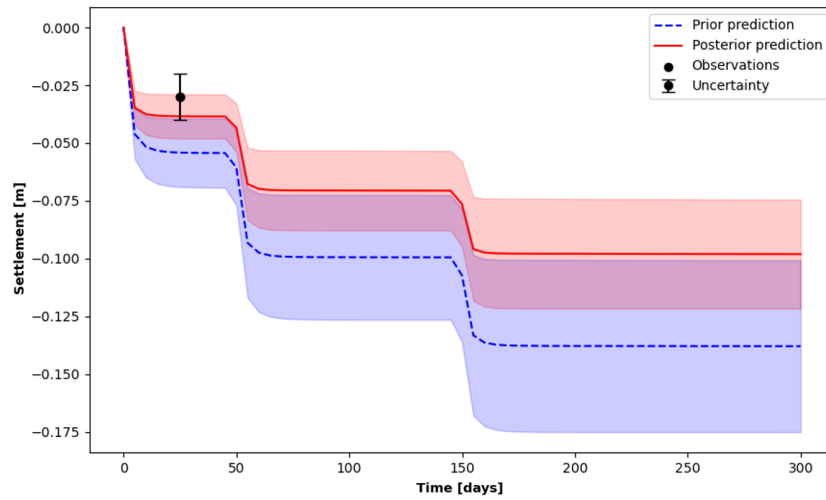
(b) Bayesian updating using the first and second measurement



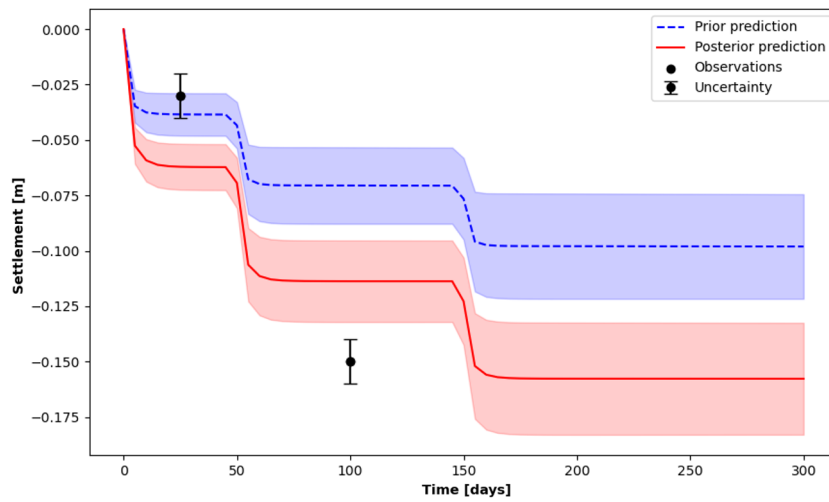
(c) Bayesian updating using the first, second and third measurement

Figure 5.7: Bayesian updating process using the Markov chain Monte Carlo method

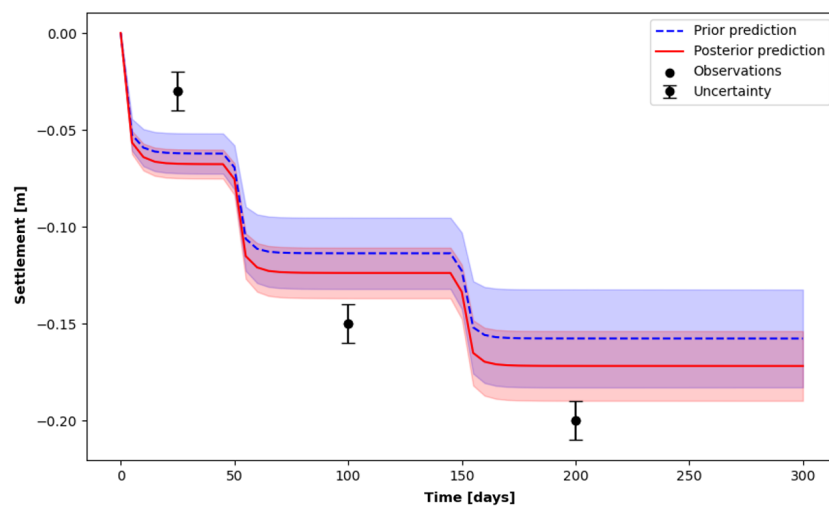
5 Probabilistic (settlement) calculations



(a) Bayesian updating using the first measurement



(b) Bayesian updating using the first and second measurement



(c) Bayesian updating using the first, second and third measurement

Figure 5.8: Comparison between the prior and posterior settlement prediction

5 Probabilistic (settlement) calculations

Figure 5.9 presents corner plots for the different updating steps. The diagonal panels display the marginal posterior distributions of the individual soil parameters, while the off-diagonal panels show their pairwise joint distributions. In the diagonal plots, three vertical dotted lines indicate the mean and the bounds of the 68% credible interval. As more data is incorporated, these distributions narrow and the credible intervals become smaller, reflecting reduced uncertainty. Initially, the joint distribution between the clay compression coefficient C_c and the unit weight of the dike sand γ_d appears circular, indicating independence. As the Bayesian updating progresses, the distribution becomes elliptical, revealing a negative correlation: increases in γ_d are associated with decreases in C_c , and vice versa. This relationship is explained by recalling the theoretical settlement equation from Chapter 2:

$$\rho_{pc} = \frac{H_0}{1 + e_0} \cdot C_c \cdot \log \left(\frac{\sigma'_{z,0} + \Delta\sigma'}{\sigma'_{z,0}} \right) \quad (5.24)$$

where ρ_{pc} is the predicted settlement, H_0 is the thickness of the compressible clay layer, e_0 is the initial void ratio, $\sigma'_{z,0}$ is the initial effective vertical stress and $\Delta\sigma'$ is the increase in effective stress due to loading. The increase in effective stress is given by the unit weight of the dike sand γ_d multiplied by the height of the dike h . To match observed settlements ρ_{pc} , the model compensates between γ_d and C_c . A larger γ_d leads to higher loading, requiring a lower C_c to produce the same settlement. Conversely, a smaller γ_d must be offset by a higher C_c . This trade-off introduces a negative correlation between the two parameters:

- $\gamma_d \uparrow \Rightarrow \Delta\sigma' \uparrow \Rightarrow C_c \downarrow$
- $\gamma_d \downarrow \Rightarrow \Delta\sigma' \downarrow \Rightarrow C_c \uparrow$

The emerging correlation captures the physical interdependence implied by the model and reinforced through data.

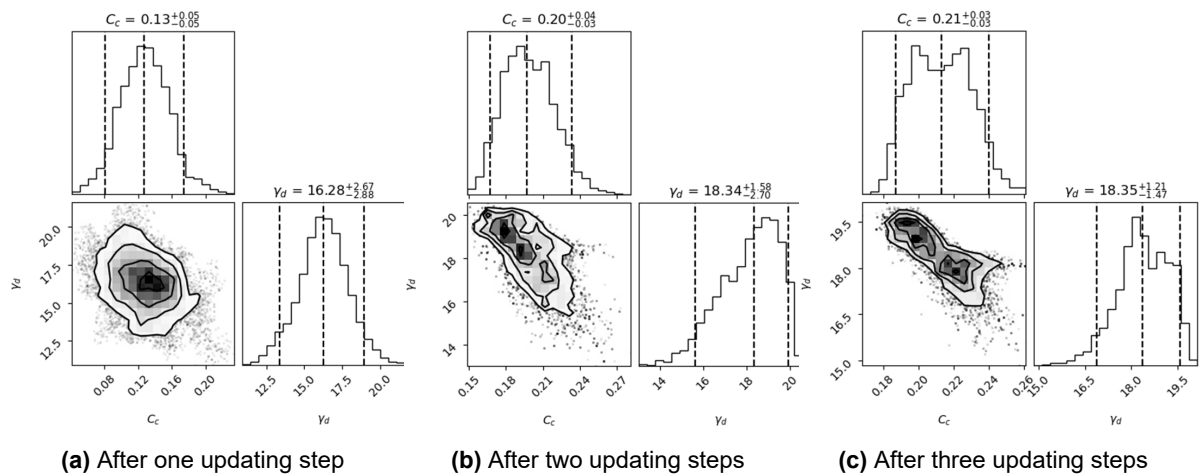


Figure 5.9: Corner plots for the different updating steps

5 Probabilistic (settlement) calculations

Figure 5.10 offers an additional perspective on the reduction of uncertainty in the soil parameter distributions during the updating process. The box plots depict the evolution of the posterior distributions of the clay compression coefficient C_c and the unit weight of the dike sand γ_d after each updating step. Each box represents the interquartile range, with the central line indicating the median. As more data is assimilated, the interquartile range contracts, highlighting the decreasing uncertainty in parameter estimates. The median values shift progressively toward those that better explain the observed settlement data, underscoring the effectiveness of Bayesian updating in refining the model. The updated distributions are also visualized, where the decreasing uncertainty is reflected in progressively narrower distributions.

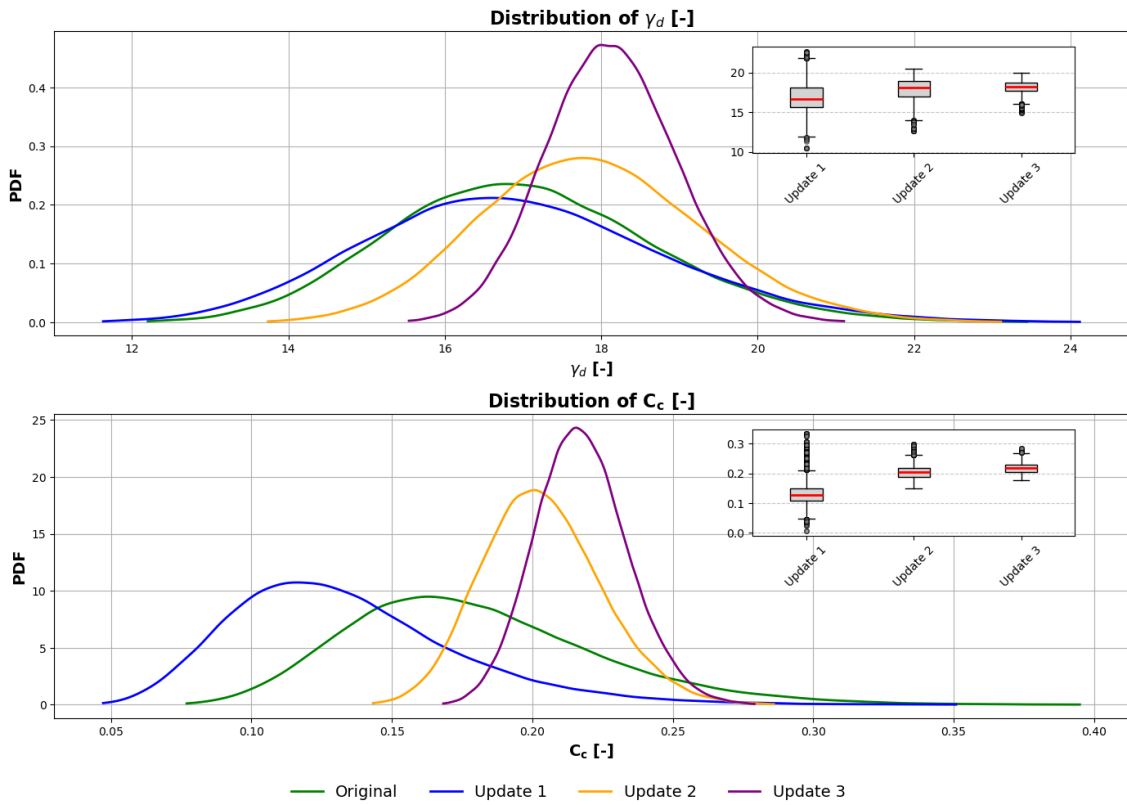


Figure 5.10: Sequentially updated soil parameter distributions

Figure 5.11 shows the evolution of the mean settlement curve throughout the updating process. This curve is generated by evaluating the surrogate model thousands of times using LHS from the updated parameter distributions. With each update, the mean curve moves closer to the observed data, reflecting improved agreement.

5 Probabilistic (settlement) calculations

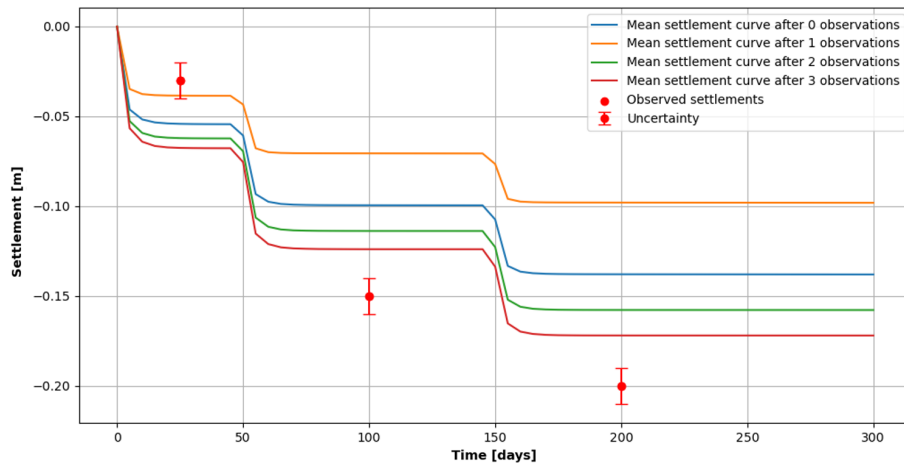


Figure 5.11: Evolution of the mean settlement curve through Bayesian updating

Lastly, Figure 5.12 compares the initial prior settlement prediction, based on the mean values of the prior soil parameter distributions, with the final posterior prediction after three updates. The posterior prediction incorporates all available observations and clearly shows improved alignment with the measured settlements. This demonstrates the progressive enhancement in predictive accuracy achieved through Bayesian updating. For this example, a specific monitoring series is used to test the robustness of the Bayesian updating under both over- and underprediction scenarios. Consequently, the posterior mean settlement curve does not necessarily pass through each observed data point, but rather captures the overall trend. Figure 5.13 summarizes the sequentially updated settlement predictions.

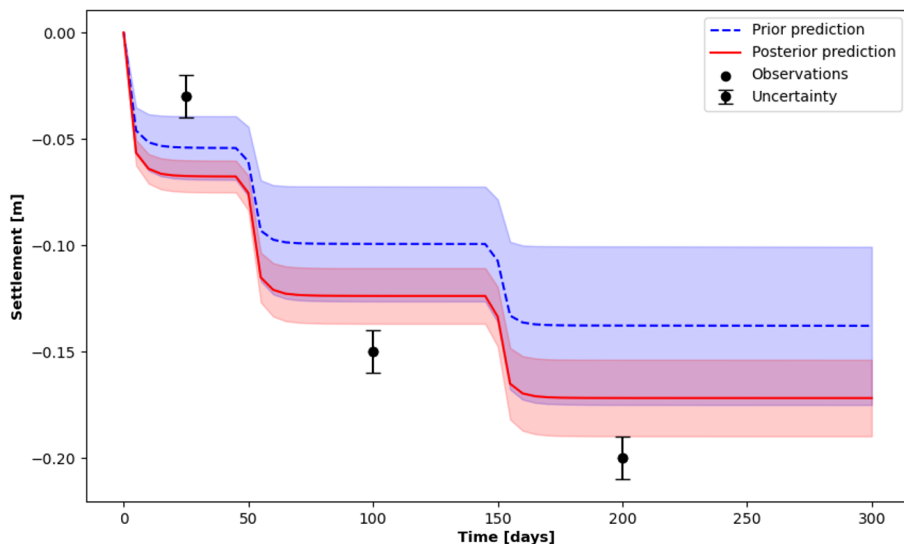


Figure 5.12: Comparison of the original prior and final posterior settlement prediction

5 Probabilistic (settlement) calculations

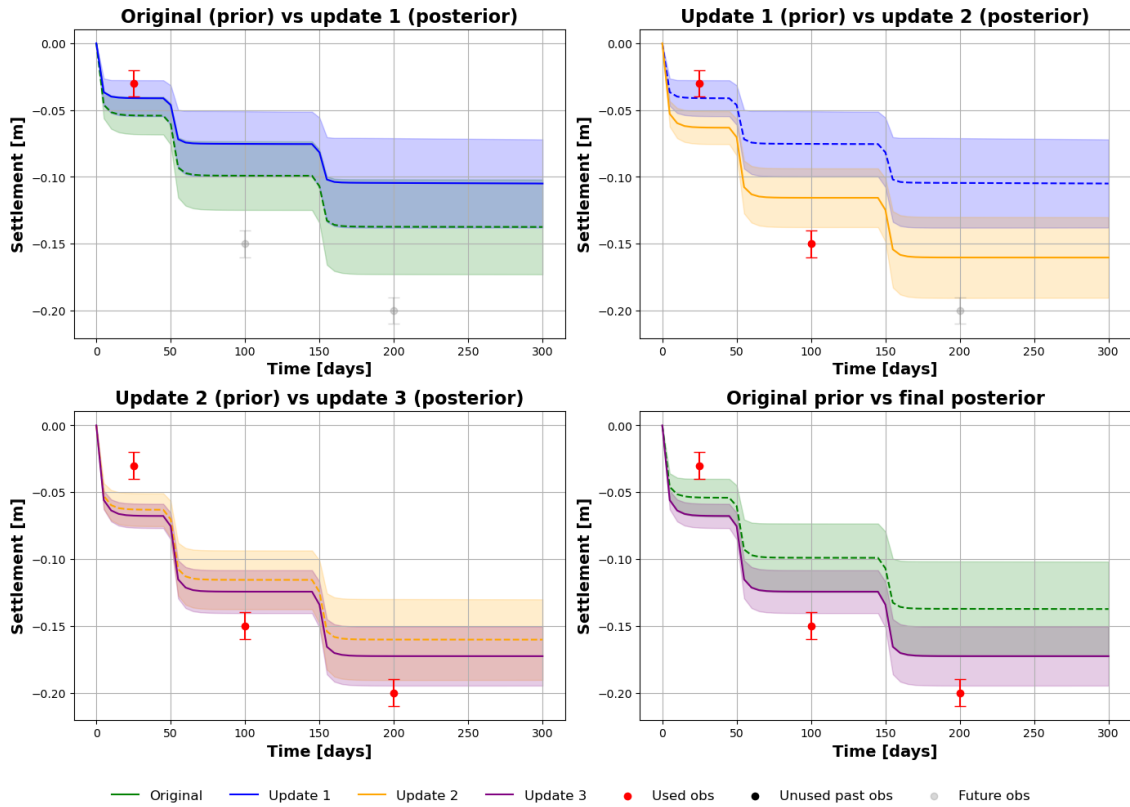


Figure 5.13: Sequentially updated settlement predictions

5.3 Application of the probabilistic analysis workflow to the new dike in Bornem

Now that the probabilistic analysis workflow (section 5.1) for dike settlements has been proposed and all relevant techniques involved in this methodology have been explained and implemented, this chapter is concluded by applying the workflow to cross-section DP26 of the new dike in Bornem. Each step of the workflow is systematically executed and the obtained results are discussed in detail. This case study demonstrates the practical value, applicability and adaptability of the proposed methodology across different dike configurations. It also underscores the strengths of a probabilistic approach compared to traditional deterministic methods, especially in capturing uncertainty and enhancing model robustness. The inclusion of Bayesian updating further improves the reliability of settlement predictions as new data becomes available. Ultimately, this section integrates and synthesizes the key concepts developed in earlier chapters, showcasing how they come together in a unified, coherent analysis.

5 Probabilistic (settlement) calculations

5.3.1 Sensitivity analysis

A sensitivity analysis, detailed in section 4.1, has been performed to identify the most influential soil parameters governing dike settlement. The results clearly indicate that the very soft clay layer S, located on the GOG side of the new dike, dominates the settlement behaviour. Among all input parameters, variations in the overconsolidation ratio, vertical permeability and (re)compression index of layer S account for approximately 95% of the total variability in the predicted settlements. This underscores the critical role of this specific layer in the overall performance of the dike. The findings not only provide a clear focus for parameter distribution identification, but also validate the model's physical realism by aligning with geotechnical expectations: most of the soil settlement can be attributed to the very soft clay layer S. A graphical overview of the sensitivity results is presented in Figure 5.14.

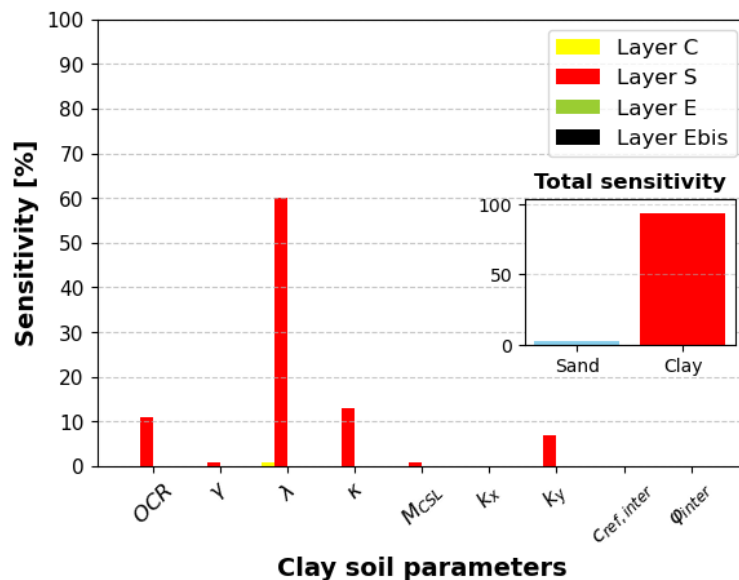


Figure 5.14: Sensitivity analysis of the soil parameters affecting dike settlement in DP26

5.3.2 Stochastic soil parameter distribution

In paragraph 4.3.3, the rationale for selecting the clay parameters OCR , k_{vert} , e_0 and C , as opposed to the alternative set OCR , k_{vert} , λ and κ , has been explained. The remainder of section 4.3 details the methodology for deriving the soil parameter distributions from CPT(u) data using empirical correlations and how these distributions can be corrected with laboratory test results. Figure 5.15 provides a visual summary of this process, showing the initial distributions based on CPT(u) data in green and the adjusted distributions following correction with lab data in blue. The incorporation of laboratory results, while improving parameter realism, often introduces additional uncertainty, particularly when the applied correlations are not well-calibrated to the specific soil conditions encountered in layer S at DP26.

5 Probabilistic (settlement) calculations

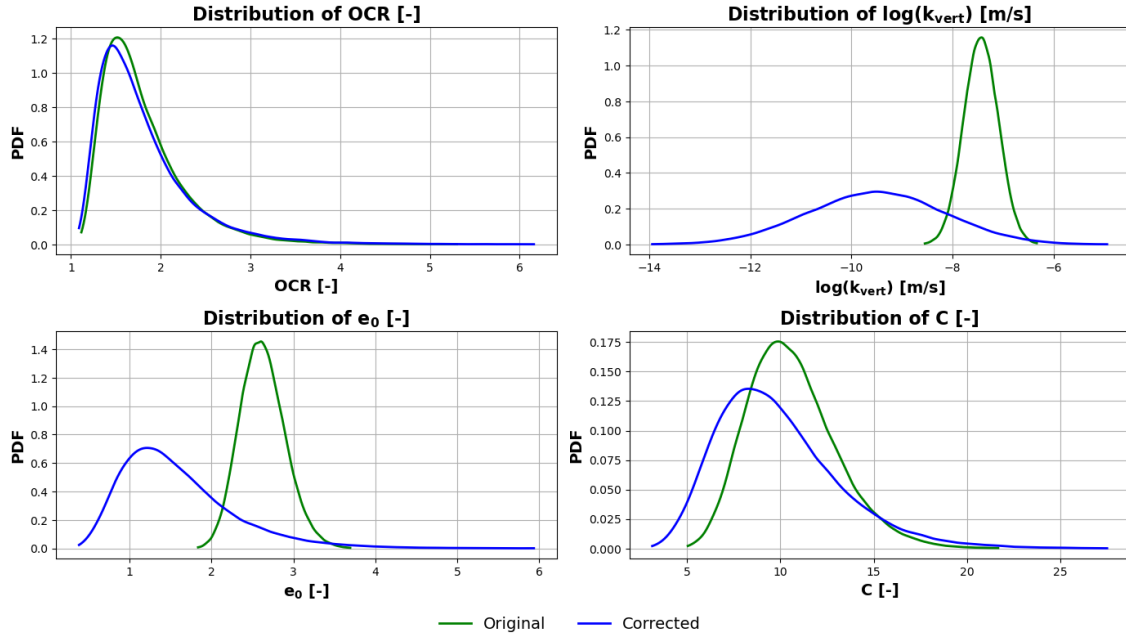


Figure 5.15: Soil parameter distributions used in the probabilistic analysis of dike settlements in DP26

5.3.3 Latin hypercube sampling (LHS)

Next, the probabilistic soil parameter distributions are sampled using Latin hypercube sampling (LHS). A total of 100 LHS samples are drawn from each distribution (Figure 5.16), resulting in four separate pools of 100 samples each. From these pools, one sample is randomly selected from each pool and combined to form a single input set. This process is repeated 100 times, generating 100 distinct input sets for the PLAXIS 2D model and, consequently, 100 corresponding settlement curves. This number of samples exceeds the theoretical minimum required for training a surrogate model, given by $n = 10 \cdot k$, where k denotes the number of input variables. In this case, $k = 4 + 1$, accounting for the four most influential soil parameters and the time variable, as the settlement evolution over time is of primary interest.

The use of 100 samples, double the required minimum, ensures that a portion of the data can be reserved for validation, thereby enhancing the robustness of the surrogate model. This choice represents a strategic compromise: although PLAXIS 2D simulations are computationally expensive, allocating additional model runs for surrogate training is justified by the improved accuracy in approximating the settlement response. Once trained, the surrogate model effectively replaces the need for further PLAXIS evaluations during Bayesian updating, yielding substantial computational savings without sacrificing predictive reliability.

5 Probabilistic (settlement) calculations

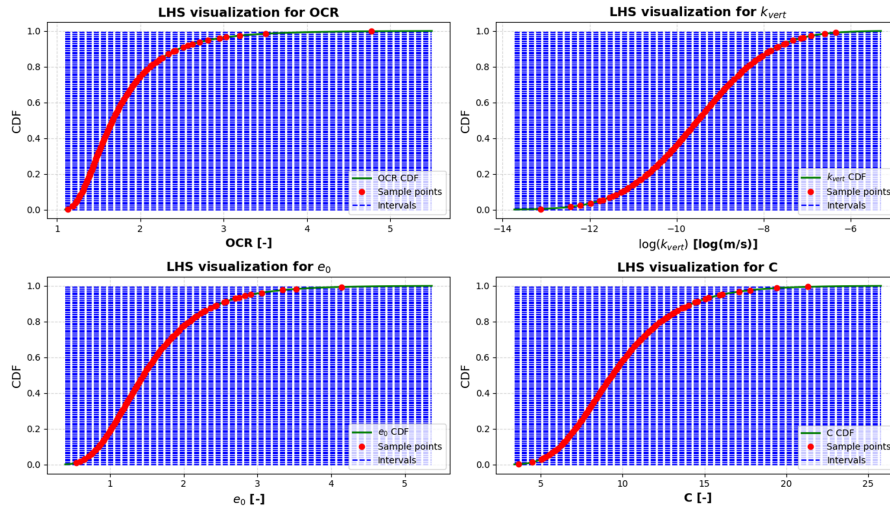


Figure 5.16: LHS of the soil parameter distributions for dike settlement analysis in DP26

5.3.4 Numerical PLAXIS 2D simulations

As previously discussed, the 100 distinct input sets generated via LHS are used to run PLAXIS 2D simulations. Each sample set is evaluated across the full time span of dike construction and subsoil consolidation, 864 days in total, ranging from 01/10/2022 to 11/02/2025. The resulting settlement curves are presented in Figure 5.17a. A vertical dotted line marks the onset of the settlement monitoring campaign, which commenced on 09/02/2023, 131 days after the start of construction.

Because a portion of the settlement has already occurred prior to the start of monitoring, the simulated curves are reset to zero at the monitoring start date, as shown in Figure 5.17b. This normalization ensures consistency between simulated predictions and observed measurements. The reset is justified by the use of a full consolidation calculation in PLAXIS 2D, which, as explained in section 3.5.1, yields realistic settlement behaviour over time and provides a sound basis for comparison with actual field data.

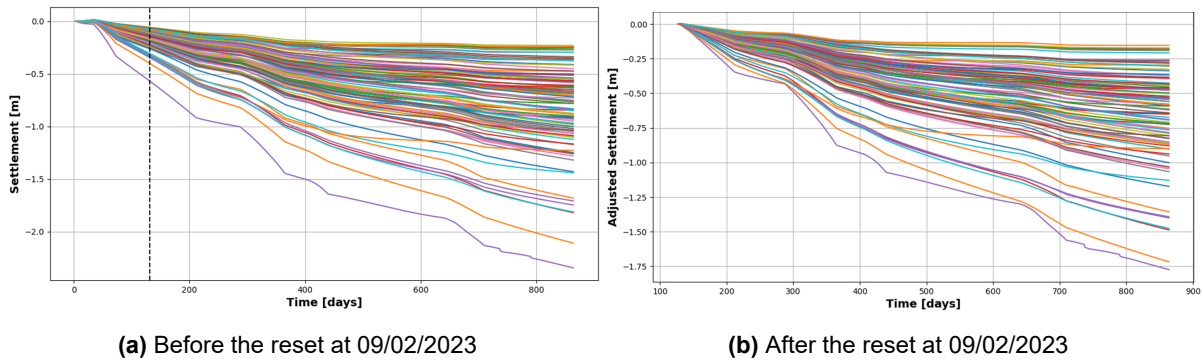


Figure 5.17: Settlement curves resulting from PLAXIS 2D simulations

5 Probabilistic (settlement) calculations

5.3.5 Response surface model (RSM)

The 100 settlement curves generated from PLAXIS 2D simulations are used to train a response surface model (RSM) that approximates the relationship between the four key soil parameters and the settlement response over time. Rather than predicting a single settlement value, the aim is to capture the full temporal evolution while accounting for uncertainty. For this purpose, Gaussian process regression (GPR) is particularly suitable due to its flexibility, ability to model non-linear trends and efficiency with limited training data. In contrast, polynomial regression, which fits a fixed global expression, is less appropriate here, as it struggles with complex, regionally varying behaviors and lacks the ability to quantify prediction uncertainty.

To train the GPR model, 80% of the 100 numerically obtained settlement curves is used for training, while the remaining 20% is reserved for validation. During training, the model learns the relationship between input vectors and their corresponding outputs. The input vector is defined as $\underline{x} = [OCR, k_{vert}, e_0, C, \underline{t}]$, where the first four components represent the key soil parameters and $\underline{t}$ is the time vector. The soil parameters remain constant within each curve's time range. The output $\underline{y}$ is a vector of settlement values corresponding to each time instance t .

To standardize the temporal resolution and improve computational efficiency, each settlement curve is resampled at 10-day intervals. This significantly reduces the training time—from approximately 24 hours (using all 730 time steps: $864 - 131 \approx 730$) to about 2.5 hours—without any notable loss in model performance. The resampling thus ensures both efficiency and accuracy, enabling the model to reliably estimate settlements across varying input conditions and time points. The 80 training curves are displayed in Figure 5.18

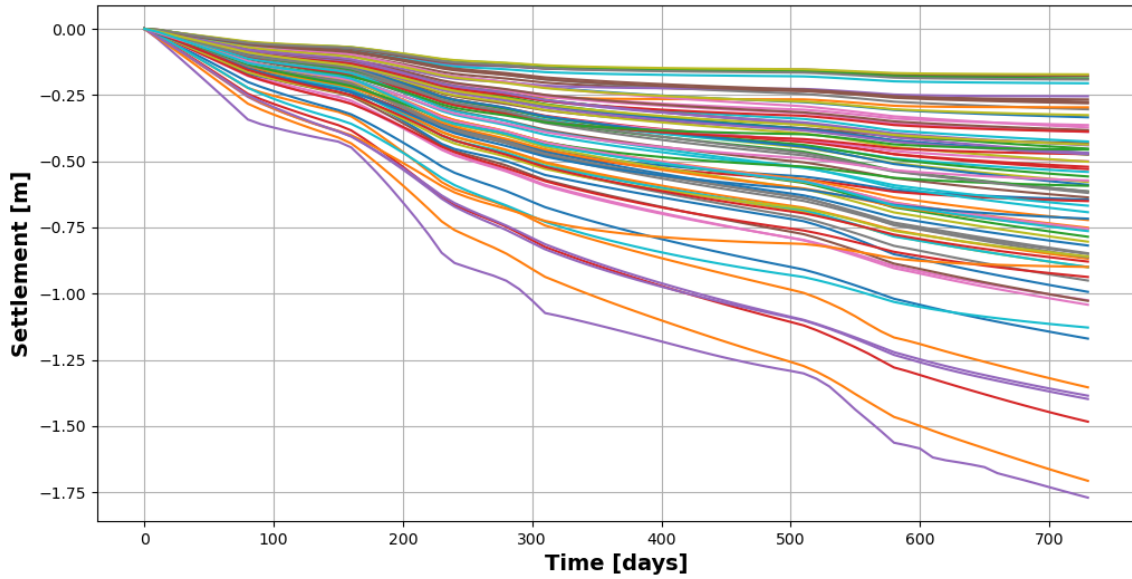


Figure 5.18: 80 numerically obtained settlement curves used for the training of the RSM

5 Probabilistic (settlement) calculations

As described in section 5.2.2, Gaussian process regression (GPR) is a non-parametric Bayesian technique that yields both mean predictions and uncertainty estimates by defining a distribution over possible functions. This distribution is governed by a mean function and a kernel, which encodes assumptions about smoothness and correlation in the data. For this case study, a hybrid kernel that combines a Matérn kernel ($\nu = 3/2$) with a White Noise component is employed. This setup balances smooth approximations with the flexibility to capture abrupt changes and account for observational noise, which are common in geotechnical settlement behaviour.

The kernel hyperparameters are optimized by minimizing the negative log marginal likelihood, resulting in an optimal objective value of $f = -180483.42$. The final optimized hyperparameters for each input dimension are presented in Table 5.3.

Table 5.3: Hyperparameters of the GPR model

Kernel		Lengthscale	Variance
White kernel		/	$1.7141 \cdot 10^{-6}$
Matérn Kernel	OCR	33.2945	510.8814
	k_{vert}	27.4955	
	e_0	69.5806	
	C	7.5118	
	t	1.8652	

The trained GPR model is validated using the remaining 20 settlement curves not included in the training set. Validation involves comparing the GPR-predicted settlement curves with the corresponding PLAXIS 2D simulation results. As shown in Figure 5.19, the model accurately captures the settlement behaviour, with strong visual agreement between numerically calculated and RSM-based predicted curves.

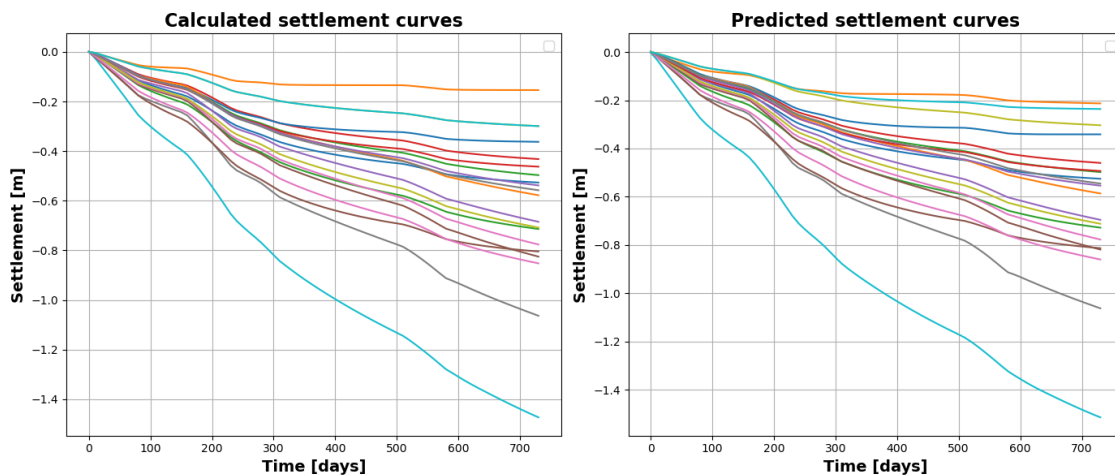


Figure 5.19: Comparison of calculated (PLAXIS 2D) vs predicted (RSM) settlement curves

5 Probabilistic (settlement) calculations

Quantitative performance metrics further confirm the model's accuracy: $R^2 = 0.9961$, $R_{adj}^2 = 0.9951$, $MAE = 0.010525$ and $RMSE = 0.000267$. The high coefficient of determination R^2 indicates that the model explains nearly all variance in the data, while the low mean absolute error (MAE) and root mean square error (RMSE) values reflect the model's precision.

Figure 5.20 provides further validation of the GPR model. The left plot shows a strong correspondence between predicted and actual settlement values, with points closely aligned along the perfect-fit line. The right plot displays the residuals (differences between predicted and actual values) which are generally small and randomly scattered around zero. This pattern confirms the absence of systematic bias and supports the model's high predictive accuracy. The discernible lines in the residual plot correspond to individual settlement curves. For most curves, the residuals remain very close to zero, indicating consistently accurate predictions. Slightly larger deviations are observed in three cases, corresponding to the light green curves in Figure 5.19, where minor discrepancies between predicted and simulated settlements are also visible. However, these deviations are modest and do not significantly impact the overall model performance.

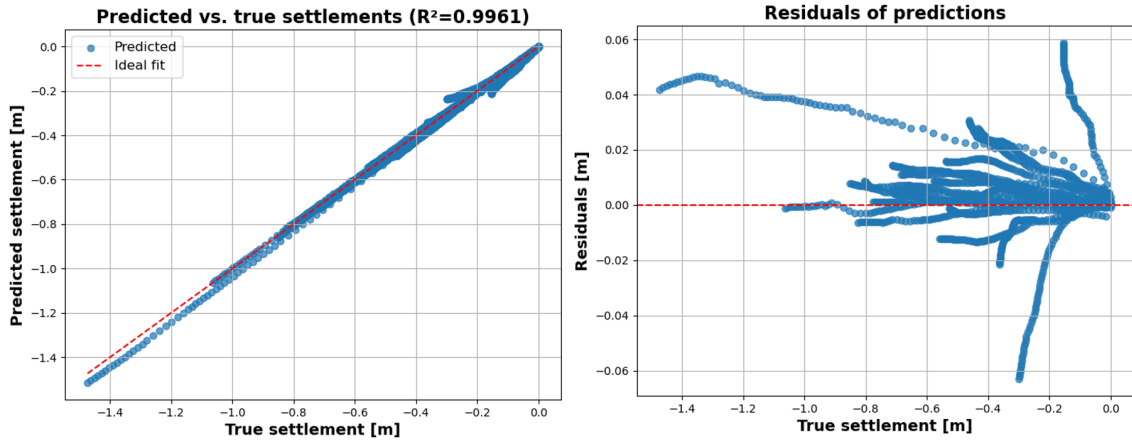


Figure 5.20: Validation of the RSM: comparison of predicted vs actual settlement values and residuals

5.3.6 Extensive probabilistic simulations

To demonstrate the effectiveness of the surrogate model, an extensive probabilistic simulation can be performed. Using LHS, 500 sets of soil parameters are sampled from their distributions. PLAXIS 2D would require approximately 50 hours to calculate the 500 corresponding settlement curves, while the trained RSM only requires 15 minutes to predict the same number of curves. This huge reduction in computational time immediately highlights the value of the surrogate model in practical applications. The 500 predicted settlement curves are shown in Figure 5.21. The initially wide spread of settlement predictions, as shown by these curves, can be substantially reduced by assimilating field monitoring data into the analysis.

5 Probabilistic (settlement) calculations

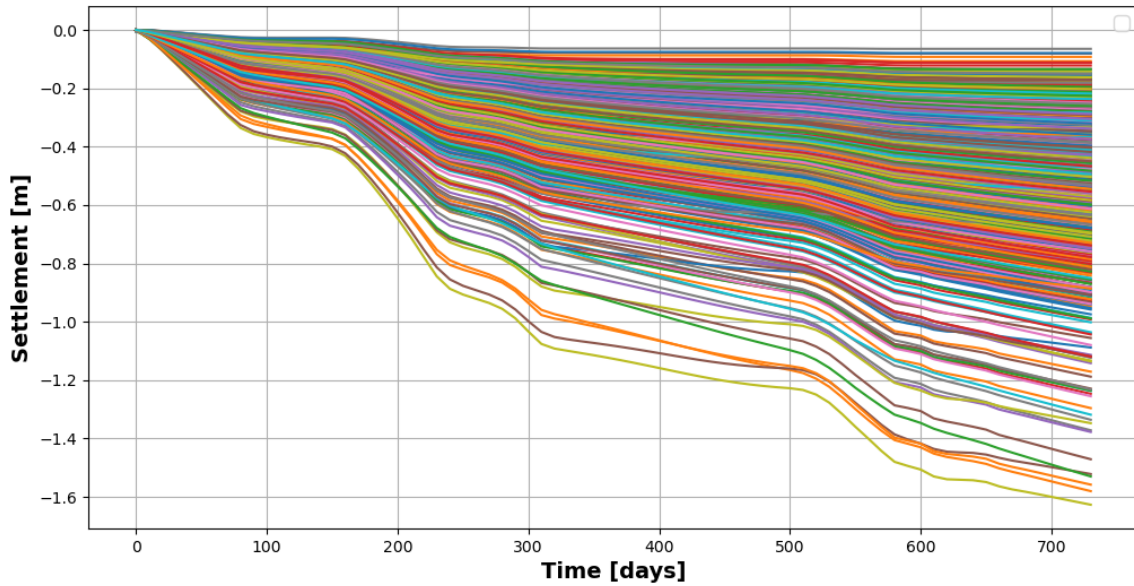


Figure 5.21: Extensive probabilistic simulation of 500 settlement curves using the RSM

5.3.7 Bayesian updating

The final step in the probabilistic analysis workflow is Bayesian updating, which incorporates settlement measurements from the monitoring campaign to refine soil parameter distributions and improve future settlement predictions. In this case, 17 settlement measurements from beacon ZB3 are available, recorded approximately every two months. As new data becomes available, the model updates both the settlement predictions and the underlying soil parameter distributions by integrating the latest measurement with all prior observations. Each update leverages progressively more information, enhancing the accuracy of posterior estimates but also increasing computational demand. To illustrate the updating process while keeping the computational load manageable, three measurements are randomly selected from the full dataset. Specifically, the 2nd, 7th and 13th measurements are used, simulating their sequential availability over time. This approach demonstrates how quickly the updated model approaches the final observed settlement curve, even with only a subset of the available data.

The Bayesian updating is carried out using the Metropolis-Hastings MCMC algorithm, with two independent Markov chains of 10000 iterations each. The first 1000 samples of each chain are discarded as burn-in. Table 5.4 summarizes the results of the updating process. Proposal distribution variances for each parameter have been determined through trial-and-error to maintain acceptance rates between 10% and 60%. Also the recommendations illustrated in Figure 5.6 have been considered in choosing these variances. Since acceptance rates remain within this range (around 40%) across all three updates, the same proposal variances are used throughout the entire updating process.

5 Probabilistic (settlement) calculations

The table also reports the posterior means of the soil parameters after each update, which serve as starting points for the next step in the sequential updating process. Finally, the Gelman-Rubin diagnostic is provided for each parameter in every update. Values close to 1 indicate convergence of the Markov chains to the target posteriors, confirming the reliability of the results.

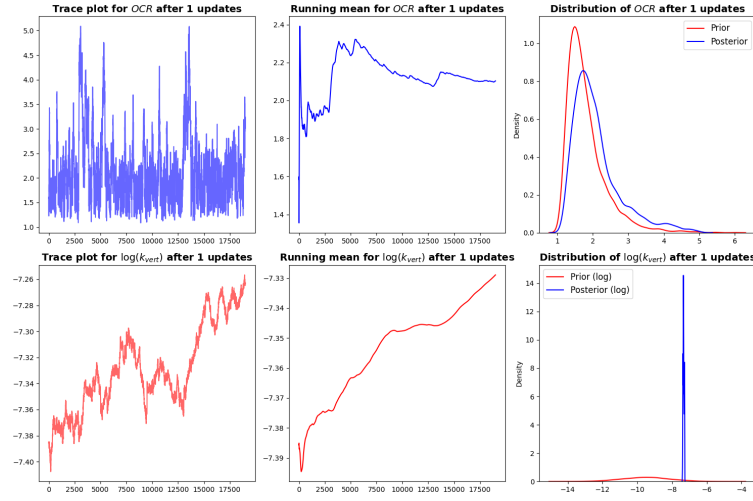
Table 5.4: Summary of the Bayesian updating process using MCMC

	OCR [–]	k_{vert} [m/s]	e₀ [–]	C [–]
Variance proposal distribution	0.12	$8.00 \cdot 10^{-8}$	0.06	1.00
Bayesian updating using the first measurement				
Posterior mean	2.0769	$4.0628 \cdot 10^{-8}$	1.1920	14.7155
Gelman-Rubin statistic	1.003	1.112	1.058	1.009
Bayesian updating using the first and second measurement				
Posterior mean	1.8760	$4.1733 \cdot 10^{-8}$	1.4069	14.0597
Gelman-Rubin statistic	1.018	1.009	1.034	1.008
Bayesian updating using the first, second and third measurement				
Posterior mean	1.8099	$4.1337 \cdot 10^{-8}$	1.5123	13.7605
Gelman-Rubin statistic	1.006	1.027	1.015	1.005

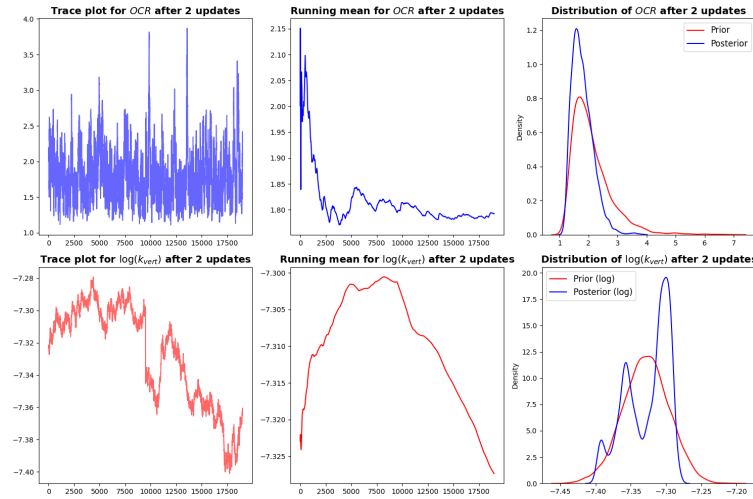
Figures 5.22 and 5.23 illustrate the Bayesian updating process for the soil parameters OCR , k_{vert} , e_0 and C . Each figure contains three subplots corresponding to the sequential updates. Within each subplot, the left panel shows the trace plot of the Markov chains, the middle panel presents the running mean and the right panel compares the prior and posterior distributions. For the overconsolidation ratio, initial void ratio and Flemish compression constant, the trace plots indicate good mixing and low serial correlation, confirming that the chosen proposal variances are effective. The running mean plots converge steadily and the posterior distributions are in general narrower than the priors, reflecting reduced uncertainty after incorporating the measurement data. In the case of vertical permeability, the trace and running mean plots may initially appear problematic due to slow chain movement and noticeable fluctuations in the running mean. However, this is attributed to the very small magnitude of the parameter (on the order of 10^{-8}). The posterior distribution itself is well-defined and the Gelman-Rubin statistics remain close to 1, confirming proper convergence. Thus, the observed fluctuations in the running means are not a cause for concern.

Figure 5.24 compares the prior and posterior settlement predictions across the different updating steps. In addition to the clear shift of the posterior mean curves toward the observed measurements, the shaded bands representing the 68% confidence intervals also become progressively narrower with each update. This reduction in uncertainty highlights how incorporating additional data through Bayesian updating improves the accuracy of the settlement predictions.

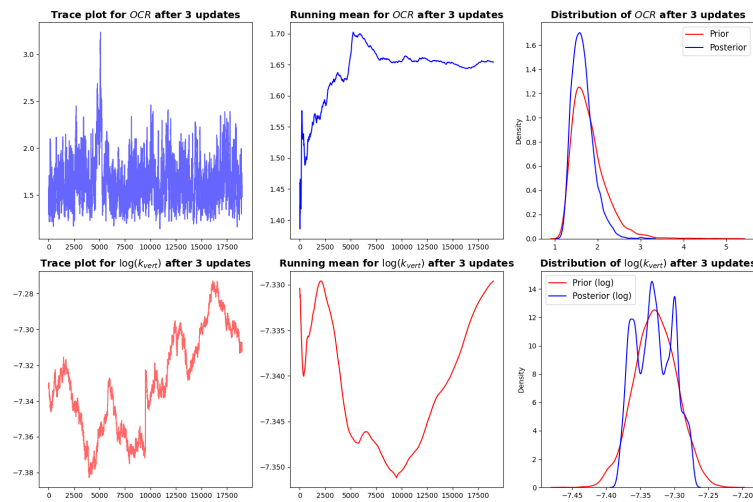
5 Probabilistic (settlement) calculations



(a) Bayesian updating using the first measurement



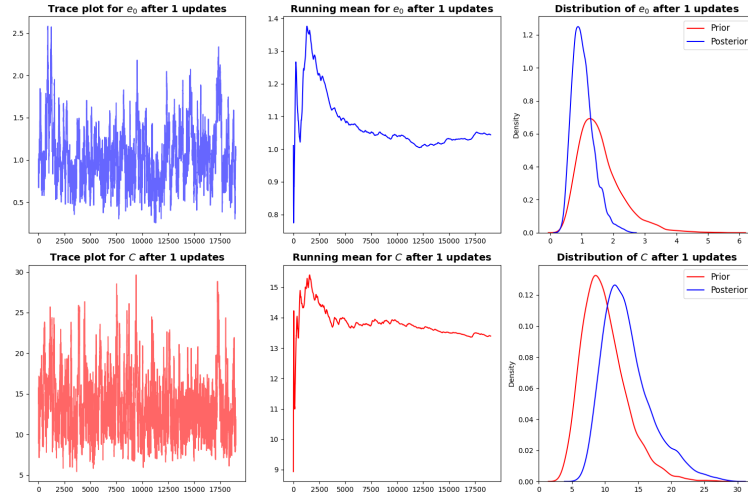
(b) Bayesian updating using the first and second measurement



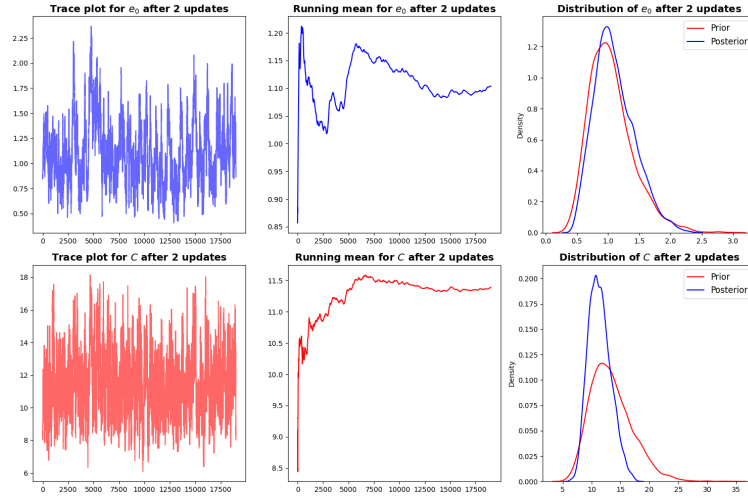
(c) Bayesian updating using the first, second and third measurement

Figure 5.22: Bayesian updating process using the MCMC for OCR and k_{vert}

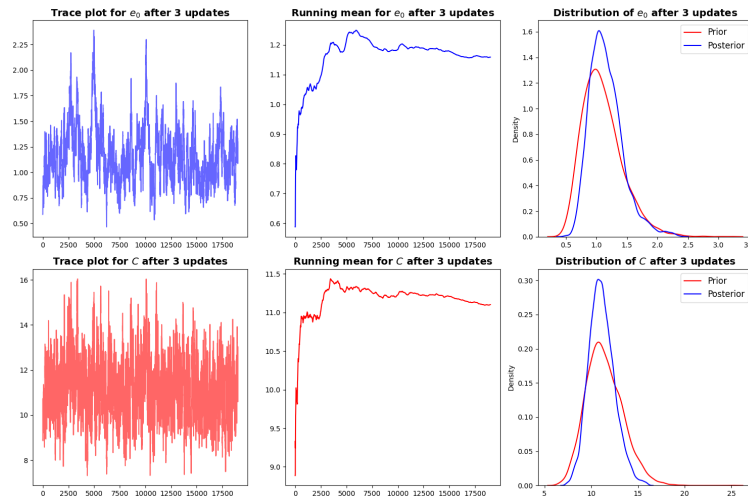
5 Probabilistic (settlement) calculations



(a) Bayesian updating using the first measurement



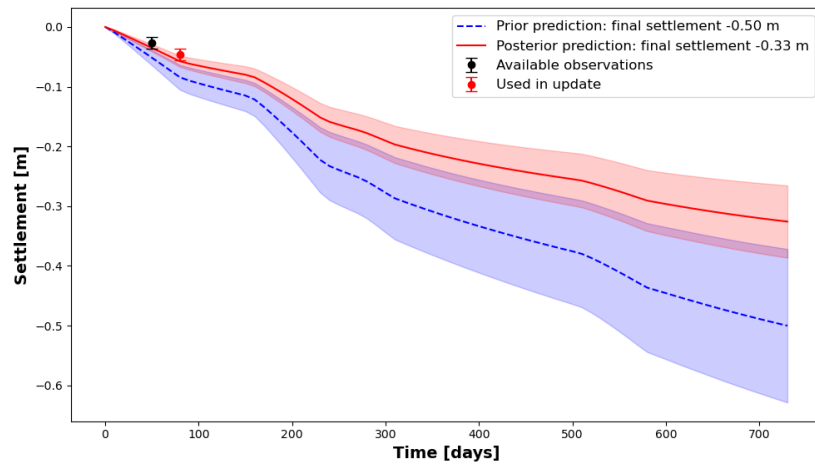
(b) Bayesian updating using the first and second measurement



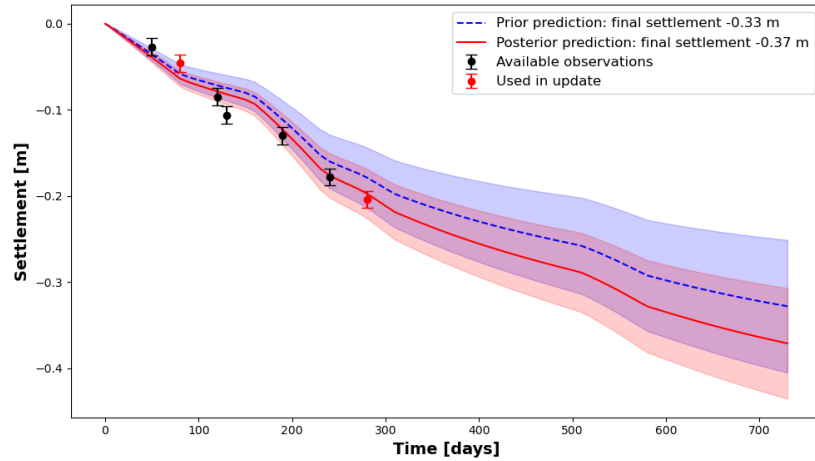
(c) Bayesian updating using the first, second and third measurement

Figure 5.23: Bayesian updating process using the MCMC for e_0 and C

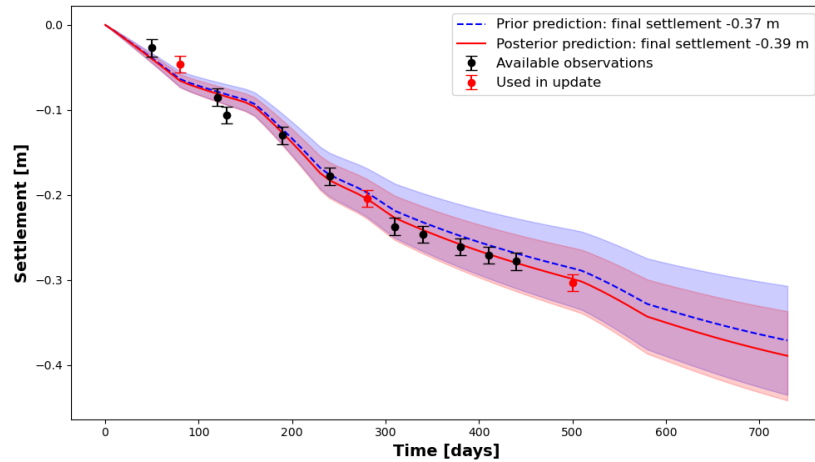
5 Probabilistic (settlement) calculations



(a) Bayesian updating using the first measurement



(b) Bayesian updating using the first and second measurement



(c) Bayesian updating using the first, second and third measurement

Figure 5.24: Comparison between the prior and posterior settlement predictions in each updating step

5 Probabilistic (settlement) calculations

The Bayesian updating process is effectively summarized in Figures 5.25 and 5.26. Figure 5.25 illustrates the sequential refinement of the key soil parameter distributions. With each update, these distributions become increasingly narrow and concentrated, reflecting a clear reduction in uncertainty. This trend is also evident in the accompanying box plots, where the shrinking interquartile ranges indicate growing confidence in the parameter estimates. Figure 5.26 shows the corresponding updates to the settlement predictions for DP26. As additional measurements are incorporated, the posterior mean curves move closer to the observed settlement values, while the shaded 68% confidence intervals narrow progressively. This demonstrates that Bayesian updating not only improves the accuracy of the predictions but also enhances their reliability by quantifying and reducing uncertainty. Notably, already after the first update, the posterior mean settlement curve aligns closely with the observed data. Subsequent updates primarily reduce the uncertainty in the predictions by narrowing the confidence bounds, while the mean settlement estimate remains largely unchanged. This supports the pragmatic choice to use only a subset of available measurements, as it yields strong predictive performance with lower computational demand. Finally, the use of sequential Bayesian updating—where the posterior of one step becomes the prior of the next—enables the model to iteratively build upon existing knowledge. This iterative refinement process lies at the core of the proposed methodology, making it both robust and adaptable to new information as it becomes available.

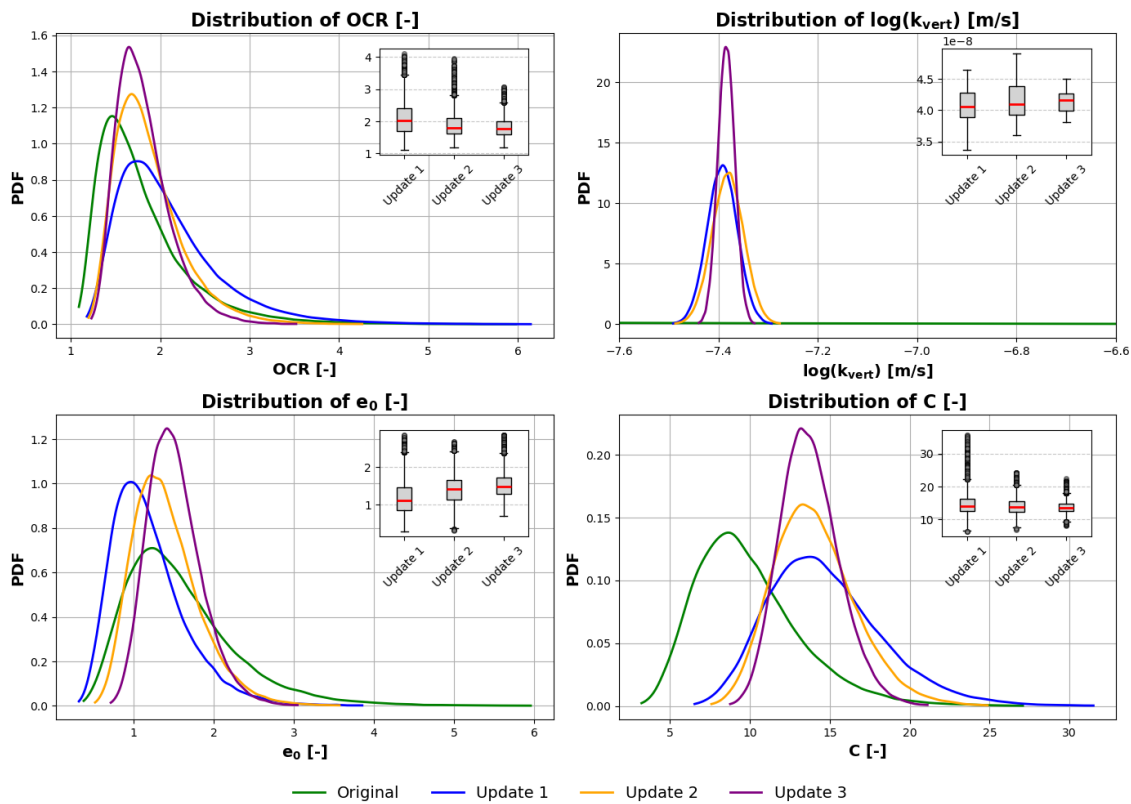


Figure 5.25: Sequentially updated soil parameter distributions for DP26

5 Probabilistic (settlement) calculations

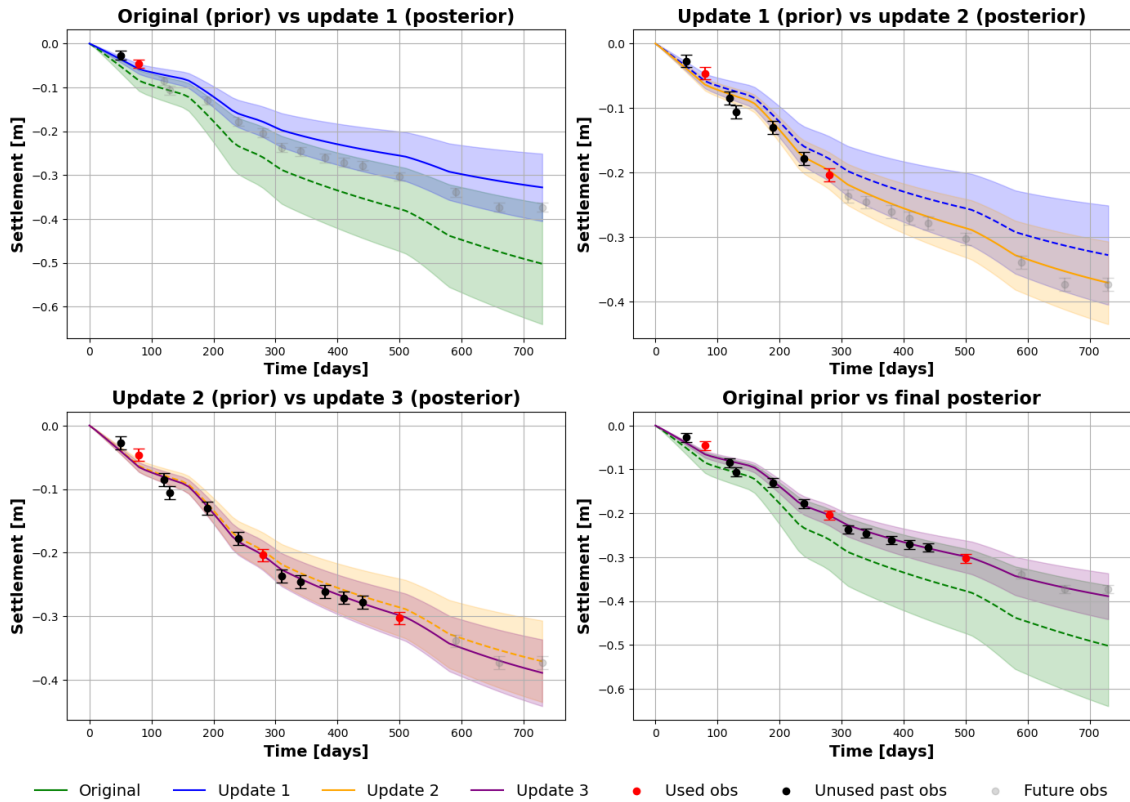


Figure 5.26: Sequentially updated settlement predictions for DP26

The effectiveness of the Bayesian updating process is further demonstrated in Figure 5.27, which compares extensive probabilistic simulations performed before and after updating. In each case, 500 LHS sets are generated from respectively the original prior and final posterior soil parameter distributions. The contrast is clear: the prior simulation, built on uncertain empirical correlations, produces a broad spread of settlement predictions, reflecting high uncertainty. After updating, the posterior simulation yields a much narrower distribution, demonstrating the impact of incorporating real-world observations.

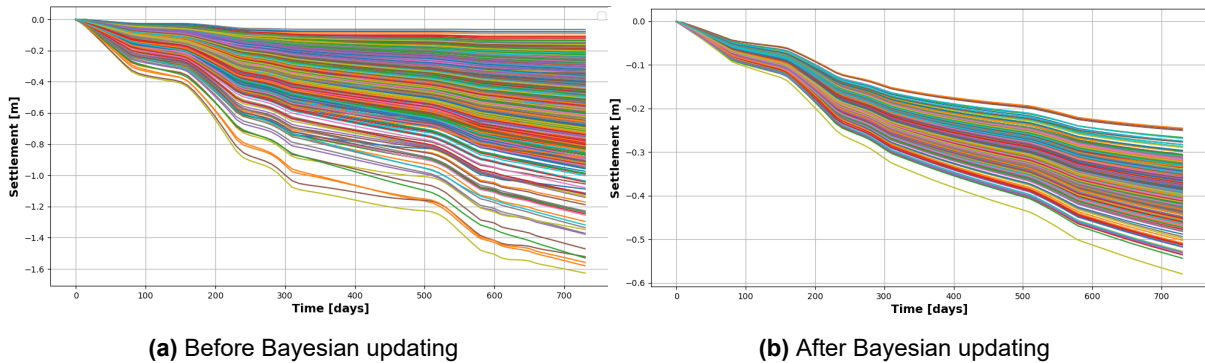


Figure 5.27: Comparison of settlement curves predicted by the RSM before and after Bayesian updating

5 Probabilistic (settlement) calculations

5.3.8 Final remarks and discussions

To conclude this chapter, some final reflections are offered regarding the probabilistic analysis workflow and its application to the critical cross-section DP26 of the new dike in Bornem, located at the Groot Schoor site.

5.3.8.1 Probabilistic vs deterministic settlement calculations

First, the advantages of probabilistic settlement calculations over deterministic approaches are highlighted. Figure 5.28 demonstrates this comparison by juxtaposing deterministic settlement calculations with probabilistic ones. The deterministic approach, shown in Figure 5.28a, relies on fixed characteristic parameter values and yields a single predicted settlement curve. A full consolidation analysis in PLAXIS 2D, with settlements reset to zero at the start of the monitoring campaign, yields a final predicted settlement of approximately -0.20 m . The deterministic approach significantly underestimates the actual measured settlement of approximately -0.40 m at beacon ZB3, potentially leading to unsafe design outcomes where the required dike crest elevation is not maintained over time

In contrast, the probabilistic method, shown in Figure 5.28b, accounts for variability in key soil parameters by sampling from their probability distributions and predicting settlement for each sample set. This results in a range of possible outcomes, represented by a shaded 68% confidence interval around the mean settlement curve. Prior to Bayesian updating, the model slightly overestimates the final settlement, predicting around -0.50 m . However, after incorporating a selection of settlement measurements through Bayesian updating, the prediction is refined to approximately -0.39 m , aligning closely with the observed data.

This progression demonstrates not only the greater accuracy of the probabilistic approach but also its capacity to quantify uncertainty and improve over time as more data becomes available. By dynamically refining predictions, the method supports more informed decision-making and better risk management throughout the dike's lifecycle.

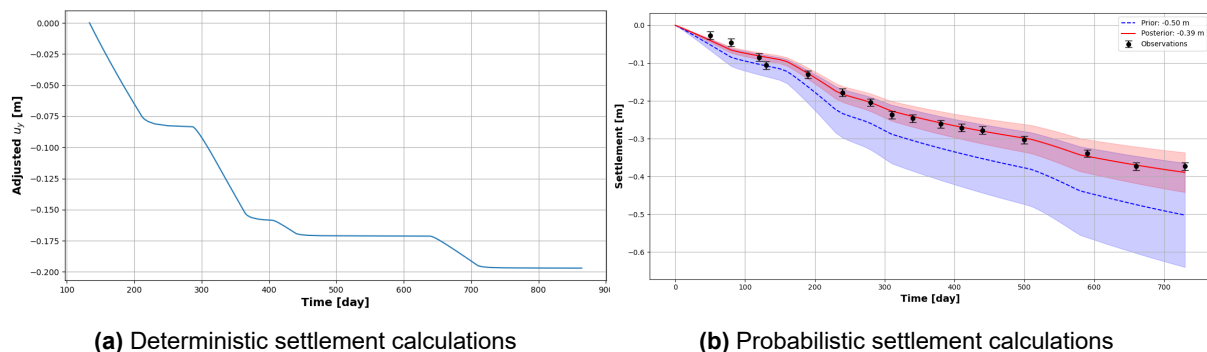


Figure 5.28: Comparison of deterministic vs probabilistic settlement calculations

5 Probabilistic (settlement) calculations

5.3.8.2 Effect of soil parameter distribution variations on settlement predictions

Secondly, some additional clarification is provided regarding the effect of variations in the original prior soil parameter distributions on the settlement predictions in a Bayesian updating framework. Previously, a statement was made that the accuracy of the original priors is not critical, as Bayesian updating will refine them based on observed data and as such naturally converge towards the actual soil parameter distributions. This can for example be seen in the bottom right plot in Figures 5.22a and the top right plot in Figure 5.25. These showcase a significant narrowing of the posterior distribution of k_{vert} compared to its initially broad prior, which was based on uncertain empirical correlations. This clearly demonstrates how Bayesian updating can robustly refine uncertain prior parameter estimates based on observed settlement data, naturally guiding the model toward the true underlying distributions.

This robustness of the Bayesian updating process can be further demonstrated by for example slightly altering the prior distribution of one soil parameter. In Figure 5.29, the mean of the Flemish compression constant is adjusted from 9.8773 to 15.8773. Despite this change, the posterior distribution of C converges—after a few updates—to the same final distribution shown in Figure 5.25. Similarly, the mean settlement prediction shifts from an initial -0.46 m to a final -0.39 m , matching the original result. This shows that Bayesian updating is robust to moderate inaccuracies in the prior, effectively correcting them using observed data. Nevertheless, initial distributions must still be grounded in reality. If the priors are highly unrealistic, even abundant data may not lead to reliable posterior estimates. A proper calculation of the prior distributions hence remains essential, but small errors do not need to be feared as they will correct themselves during the updating process.

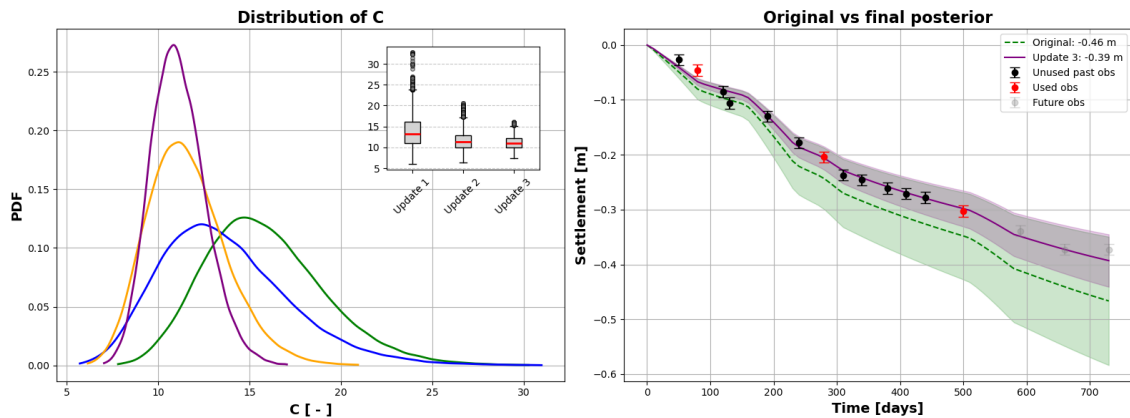


Figure 5.29: Effect of an incorrect prior on the posterior distribution of C and the settlement prediction

5 Probabilistic (settlement) calculations

5.3.8.3 Correlations between sensitive soil parameters

Finally, the assumption made in paragraph 5.2.1.1 is critically examined using Figure 5.30. This assumption states that standard Latin hypercube sampling without adjustments for spurious correlations is valid due to the presumed independence of input variables. The figure displays corner plots showing the evolution of the joint posterior distributions of the four sensitive soil parameters OCR , k_{vert} , e_0 and C across the three successive Bayesian updating steps. Each plot combines marginal histograms along the diagonals with bivariate scatter and contour plots off-diagonal, offering a complete visual overview of parameter uncertainty and potential interdependencies as new settlement data is incorporated.

A clear trend across the three plots is the progressive narrowing of the marginal distributions, which indicates decreasing uncertainty and growing confidence in the parameter estimates. Moreover, the posterior means become increasingly stable with each update, suggesting convergence toward consistent values as the model integrates more observational data.

Particularly insightful are the off-diagonal panels that illustrates the joint distributions between parameter pairs. While there are hints of weak dependencies—such as a mild positive correlation between e_0 and C —most bivariate plots maintain elliptical or nearly circular shapes, signifying minimal to no significant correlation between parameters in the posterior distributions.

This observation has important implications for the probabilistic modelling approach. Specifically, it confirms that omitting parameter correlations during LHS is a valid simplification. In theory, ignoring strong correlations could lead to unrealistic or biased simulation results. However, the analysis shows that such correlations are either absent or too weak to influence the outcome meaningfully. Therefore, treating the input parameters as independent during sampling not only simplifies the computational process but also retains the reliability and accuracy of the model's predictions.

5 Probabilistic (settlement) calculations

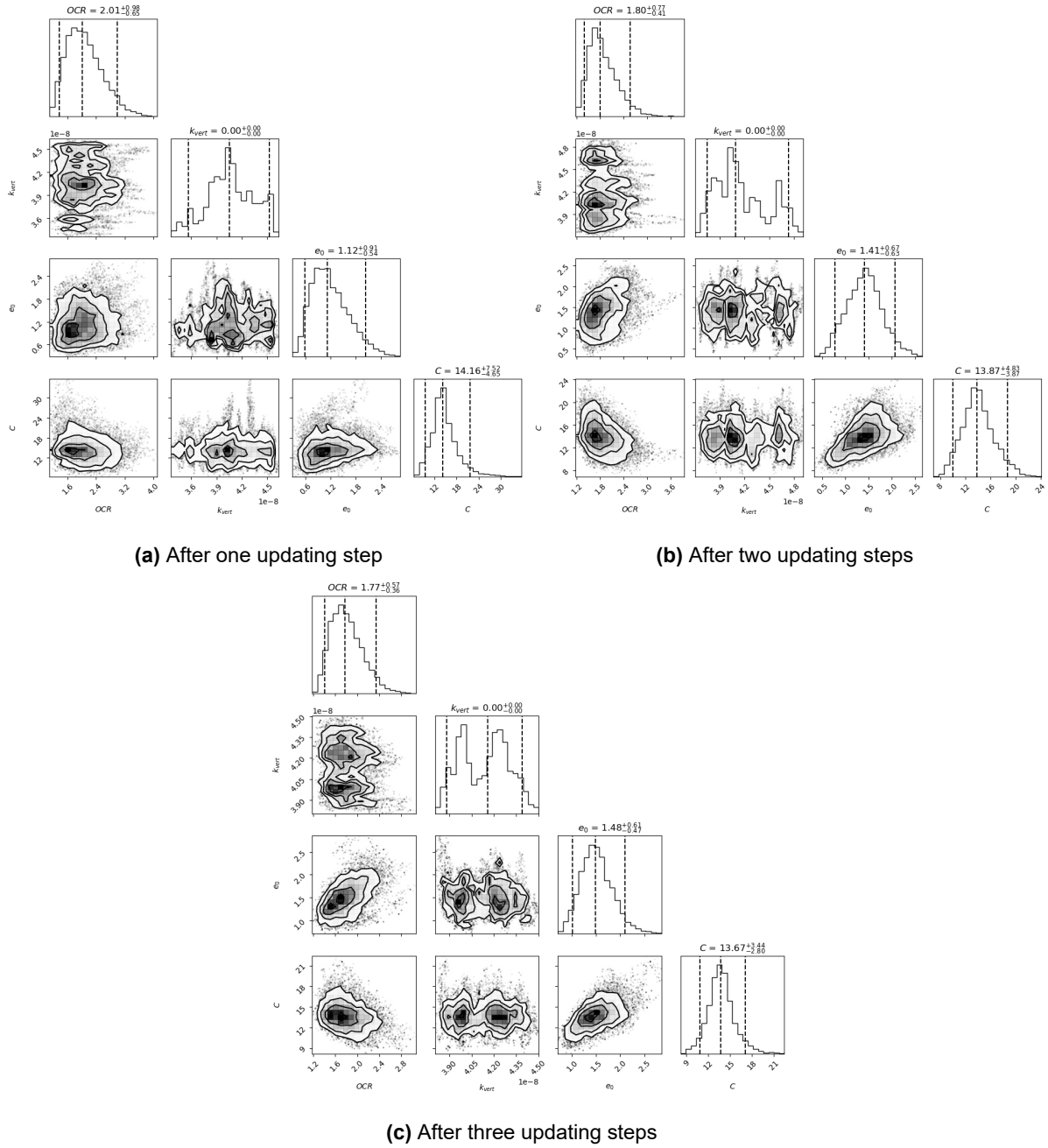


Figure 5.30: Corner plots for the sequential Bayesian updating (Part 1)

Conclusion and recommendations

5.4 Conclusion

This thesis has developed and applied a probabilistic framework to analyse the settlement behaviour of a newly constructed dike at the Groot Schoor site, located along the Scheldt River in Bornem, Belgium. The central aim has been to demonstrate the practical value of probabilistic design in geotechnical engineering by integrating uncertainty quantification and Bayesian updating into the design process.

The study begins with an overview of the Groot Schoor project, identifying cross-section DP26 as the critical point of analysis. A thorough examination of the site's geotechnical context—including dike geometry, soil stratigraphy and available investigation data (CPTs, laboratory tests and settlement monitoring)—provides the foundation for constructing a robust, data-informed probabilistic model.

A detailed numerical model of the dike is built in PLAXIS 2D and automated using Python scripting to enable efficient simulation workflows. Advanced constitutive models have been selected to accurately represent soil behaviour: the Hardening Soil model with Small-Strain Stiffness for sands and the Modified Cam-Clay model for clays. A full consolidation analysis captures the time-dependent interaction between loading and drainage under field conditions.

A sensitivity analysis has been used to identify key soil parameters influencing settlement, focusing probabilistic treatment on the most impactful variables: overconsolidation ratio (OCR), vertical permeability (k_{vert}), initial void ratio (e_0) and the Flemish compression constant (C) of the soft clay layer S. These parameters are assigned probability distributions derived from CPT(u)-based correlations, adjusted for the correlation error through comparison with laboratory data to better reflect local soil behaviour.

Settlement predictions are generated probabilistically by sampling these distributions via Latin hypercube sampling and running the corresponding PLAXIS simulations. The output informs the training of a response surface model, which approximates the full simulation results and enables rapid evaluation of settlement responses across a broad parameter space.

A major strength of the framework is its use of Bayesian updating through a Markov chain Monte Carlo algorithm, which assimilates real-time settlement data from monitoring device ZB3. This process refines the distributions of uncertain parameters, reduces epistemic uncertainty and improves alignment between predicted and observed settlement behaviour. Thereby, it increases model credibility and supports better-informed design choices.

Compared to traditional deterministic methods, the framework offers significant advantages. It facilitates performance-based design by explicitly accounting for uncertainty and variability, delivering a more comprehensive and realistic understanding of geotechnical performance.

5 Conclusion and recommendations

The surrogate model drastically reduces computational demands, while Bayesian updating ensures continual improvement of predictions as new data becomes available.

By uniting uncertainty quantification, data-driven model calibration and efficient numerical tools, this framework enhances both the predictive power and adaptability of geotechnical design. Ultimately, it supports more transparent, resilient and informed engineering decisions and it highlights the transformative potential of probabilistic approaches in modern geotechnical practice.

5.5 Recommendations for future work

To further advance the application of probabilistic methods in geotechnical engineering, the following research directions are recommended:

- **Sensitivity analysis of geometric assumptions:** in this study, a sensitivity analysis has been performed on the soil layers and their constitutive parameters to identify which parameters most significantly influence settlement predictions. A similar methodology could be applied to evaluate the impact of the geometric assumptions made in the subsoil stratigraphy, particularly the division of the soft clay layer at the surface into layers S, E and Ebis. In the current model, soil layer E is defined with fixed dimensions and vertical boundaries. Future research could assess the implications of alternative configurations (e.g. sloped or non-uniform boundaries) through sensitivity analysis, in order to evaluate their effect on the predicted settlements and improve the robustness of the model. Furthermore, an additional sensitivity analysis could be conducted on the thickness of the soil replacement in layer S. Although the execution plans provided in Attachment A allow for determination of the nominal replacement thickness at cross-section DP26, CPT tests indicate that the compaction quality of the replaced soil is not uniform throughout its height. As a result, the entire thickness cannot be assumed to contribute equally to its performance. A sensitivity analysis on the effective thickness could help quantify the influence of this variability on settlement predictions and improve the model's accuracy.
- **Consideration of spatial correlations between soil properties:** in this research, it has been assumed that soil parameters are spatially homogeneous within their respective layers. However, when significant differences in soil behaviour are observed across the cross-section, distinct layers are introduced, as illustrated by the division of the soft clay into layers S, E and Ebis. Although these layers represent the same geological material, they are treated separately due to differences in preconsolidation history and mechanical properties. Nevertheless, spatial variability and correlations between soil parameters within a given layer have not been accounted for in the current model, despite their frequent occurrence in real-world conditions. Future work could incorporate spatial variability and parameter correlations using approaches such as random fields. This would improve the physical realism of the model and potentially enhance its predictive accuracy.

5 Conclusion and recommendations

- **Extension from settlement in points to settlement profiles:** in the current approach, settlement predictions are made for a single point beneath the dike, corresponding to the location of settlement beacon ZB3. However, the methodology can be readily extended to predict full settlement profiles along monitoring devices such as settlement pipes, thereby offering a more comprehensive spatial understanding of deformations. This could be achieved by repeating the established probabilistic analysis at multiple points along the dike or by adapting the methodology to extract settlement values in PLAXIS 2D along a predefined line within the cross-section and subsequently retraining the response surface model for this new output type. Then, the Bayesian updating procedure can be applied using the monitored settlement profiles, as illustrated in Figure 2.16, to enhance the model's accuracy and reliability across the spatial domain.
- **Inclusion of creep (secondary compression):** extending the probabilistic framework to capture long-term settlement behaviour, such as creep or secondary compression, would significantly enhance its relevance for long-term geotechnical performance assessments. Currently, the model considers only primary consolidation and the response surface model is trained solely on the primary consolidation phase of the settlement curves, as the simulations have not been extended far beyond the construction period. In practice, however, secondary compression and creep can play a crucial role in long-term settlement, particularly in soft clay layers. For example, recent monitoring data at beacon ZB3 shows that, after a period of stabilization at approximately -0.37 m , the settlement continued to increase to -0.39 m despite no further elevation of the dike, suggesting ongoing secondary compression or creep effects. To incorporate such time-dependent behaviours, a more advanced constitutive model for soft clay would be required (e.g. the Soft Soil Creep model), which explicitly accounts for creep and secondary compression. Consequently, the sensitivity analysis would likely identify additional creep-related parameters that must be included in the probabilistic framework by determining their distributions. The response surface model would also need to be retrained on a new dataset generated from extended PLAXIS simulations that capture long-term creep behaviour. The Bayesian updating procedure would remain largely unchanged.
- **Integration of additional monitoring data:** in this case study, settlement measurements from the new dike in Bornem have been used as monitoring data incorporated through Bayesian updating. However, the applicability of the Markov chain Monte Carlo method is not limited to settlement data alone. The same updating approach can be extended to incorporate other types of geotechnical measurements, such as pore water pressure. In such cases, the measured pore pressure values can be compared with those predicted by a surrogate model to compute the likelihood function required for Bayesian inference. As long as the parameter of interest is an output that can be simulated in PLAXIS, a corresponding surrogate model can be developed.

5 Conclusion and recommendations

This surrogate model can then be used to conduct extensive probabilistic simulations and compare the results with the available measurements. This flexibility highlights a major strength of the proposed framework: it is not constrained to a specific type of measurement but can be adapted to any observable quantity, provided that a reliable numerical model (e.g. PLAXIS) and surrogate model exist for that quantity. Incorporating diverse types of data into the updating process can further enhance the robustness and accuracy of the model predictions.

- **Incorporation of advanced constitutive models:** the use of alternative or more advanced constitutive soil models, such as the Soft Soil Creep model, which accounts for creep and time-dependent behaviour in clays, could further enhance the realism and predictive capability of the simulations. Incorporating such models would primarily impact the workflow for identifying the relevant soil parameter distributions. Specifically, more sophisticated models often involve additional parameters that govern the long-term settlement behaviour of soils. As a result, it would be necessary to determine which new parameters are most influential for the settlement response and to establish appropriate probability density functions for them. This may require identifying new empirical correlations in the literature to relate these parameters to available CPT(u) data.
- **Cross-validation of the GPR surrogate model:** Instead of a single 80%/20% train-test split, applying k -fold cross-validation can improve the robustness and generalizability of the Gaussian process regression surrogate model. Cross-validation helps prevent overfitting or underfitting, makes better use of limited data and supports hyperparameter tuning of the GPR kernel. In k -fold cross-validation, the dataset is divided into k subsets. The model is trained on $k-1$ folds and validated on the remaining one. This process is repeated k times and the average performance is reported. A 5-fold approach is recommended to balance robustness and computational efficiency. Care must be taken to avoid data leakage, especially when time is a model input, and to ensure each fold remains sufficiently large. Despite the extra computational cost, this method offers a more reliable evaluation of model accuracy.

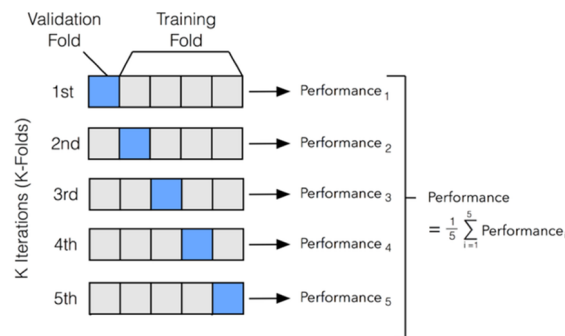


Figure 5.31: Principle of the k -Fold cross-validation technique

5 Conclusion and recommendations

- **Application to other geotechnical problems:** the probabilistic approach developed in this study can be adapted to a variety of geotechnical systems (e.g. retaining walls, deep foundations and slope stability analyses) thereby broadening its practical utility. While the methodology remains the same, modifications to the numerical model and relevant parameters are needed for each application. For instance, in slope stability, it can quantify how soil strength variability affects the factor of safety, while in deep foundation design, it can assess the influence of soil heterogeneity on pile capacity. The framework's flexibility makes it a robust tool for uncertainty quantification and risk assessment across a wide range of geotechnical engineering problems.
- **Evaluation of alternative surrogate models:** other surrogate modelling techniques can be explored (e.g. polynomial regression, polynomial chaos expansion (PCE), artificial neural networks (ANN) or support vector regression (SVR)). These alternatives can be benchmarked against Gaussian process regression (GPR) in terms of predictive accuracy, computational efficiency and ease of interpretation.
- **Comparison of probabilistic inference methods:** while Bayesian updating using Markov chain Monte Carlo has been successfully applied in this study, other probabilistic inference techniques (e.g. approximate Bayesian computation (ABC), variational inference or ensemble Kalman Filters) could be explored in future work. These alternatives may offer advantages in terms of computational efficiency or scalability, which could be particularly valuable for more complex or data-intensive geotechnical applications. Testing different inference methods would help identify the most suitable approach depending on the specific problem context, available data and required accuracy.

5 Conclusion and recommendations

Societal reflection

In a world increasingly challenged by climate change and urban development, ensuring the long-term safety and performance of geotechnical and hydraulic infrastructure such as dikes is of vital societal importance. This thesis presents a probabilistic approach to dike settlement calculations, using Bayesian updating to incorporate real-world monitoring data. This enables a shift from conservative, deterministic design using fixed partial safety factors to performance-based methods that reflect actual site conditions. As a result, decisions made during construction become more data-driven, leading to infrastructure that is safer, more reliable, more efficient and sustainable in its use of resources and better suited to its environment.

This approach aligns strongly with several United Nations Sustainable Development Goals (SDGs). It supports SDG 9 "Industry, innovation and infrastructure" by promoting modern, evidence-based methods in infrastructure design and fostering innovation in geotechnical engineering. It also contributes to SDG 11 "Sustainable cities and communities", as dikes are crucial for protecting populated areas from flooding. By continuously integrating field data into the design process, the long-term resilience and adaptability of these structures to increased flooding risks are improved. Furthermore, it supports SDG 13 "Climate action", given the growing need for infrastructure that can withstand increasingly frequent and severe weather events. These climate-related effects can themselves be modelled stochastically, allowing their uncertainty and impact to be explicitly incorporated into engineering calculations. By adopting a risk-based, probabilistic approach, this framework enables engineers to better anticipate and mitigate the risks associated with extreme weather, ultimately enhancing the climate resilience of critical infrastructure. In this context, the value of monitoring campaigns becomes even more apparent, as real-time data integration supports adaptive decision-making throughout the infrastructure's lifecycle.

Beyond its societal impact, this thesis reflects a broader digital transformation in civil engineering. The use of tools like PLAXIS and Python illustrates a move from rule-based towards risk-based, data-centric workflows. While not applying AI directly, the probabilistic foundation aligns well with future integrations of machine learning and big data into engineering practice.

Finally, this work also brings ethical considerations to the forefront, particularly regarding transparency and communication. Since uncertainty plays a central role in probabilistic modelling, it is essential that results are presented in a clear and understandable way to support responsible, well-informed decisions. While this thesis does not involve personal or sensitive data, the assumptions and choices made during modelling carry an obligation to ensure scientific rigour, reproducibility and integrity throughout the analysis.

In summary, this thesis contributes to the advancement of infrastructure that is not only technically sound but also socially and environmentally responsible: resilient to climate change, resource-efficient and grounded in data-driven, adaptive engineering practices.

5 Societal reflection

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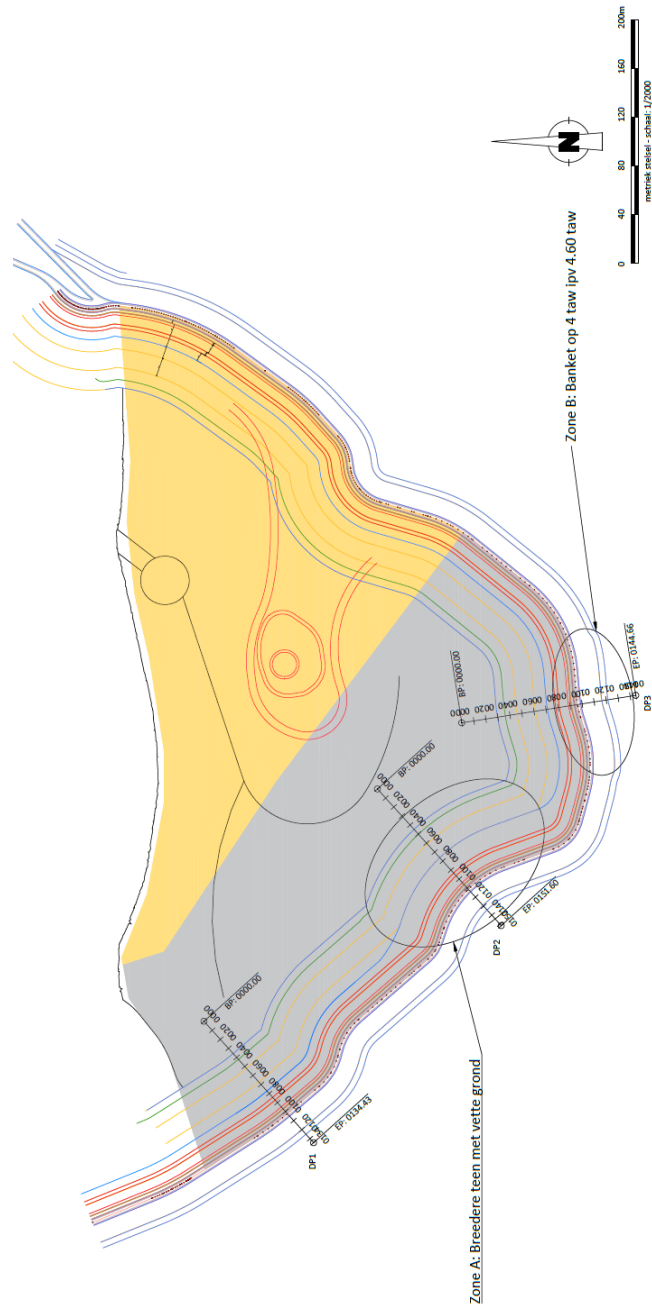
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Appendices

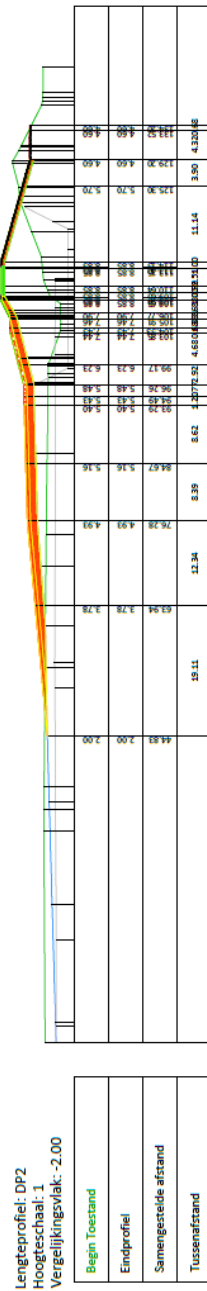
Global overview of the execution plan of Aertssen: the yellow zone is characterized by sandy soils at the surface, the grey zone is characterized by clayey soils at the surface



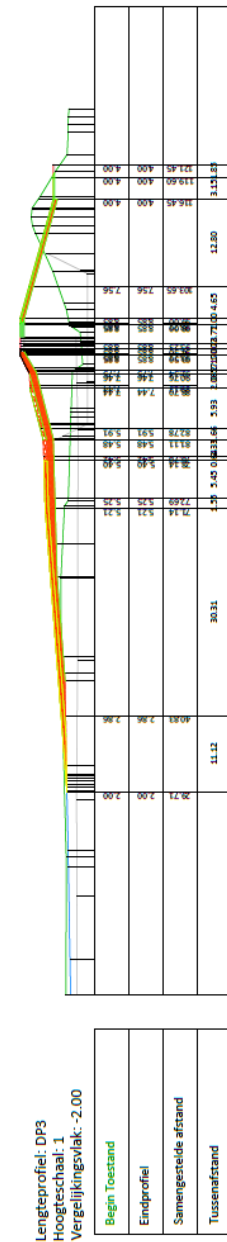
Lengteprofiel: DP 1
Hoogteschaal: 1
Vergelijkingsvlak: -2.00



Zone A DP

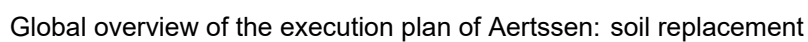


Zone B DP



Schaal: 1/500

Global overview of the execution plan of Aertssen: typological cross-sections



Global overview of the execution plan of Aertssen: soil replacement

Attachment B



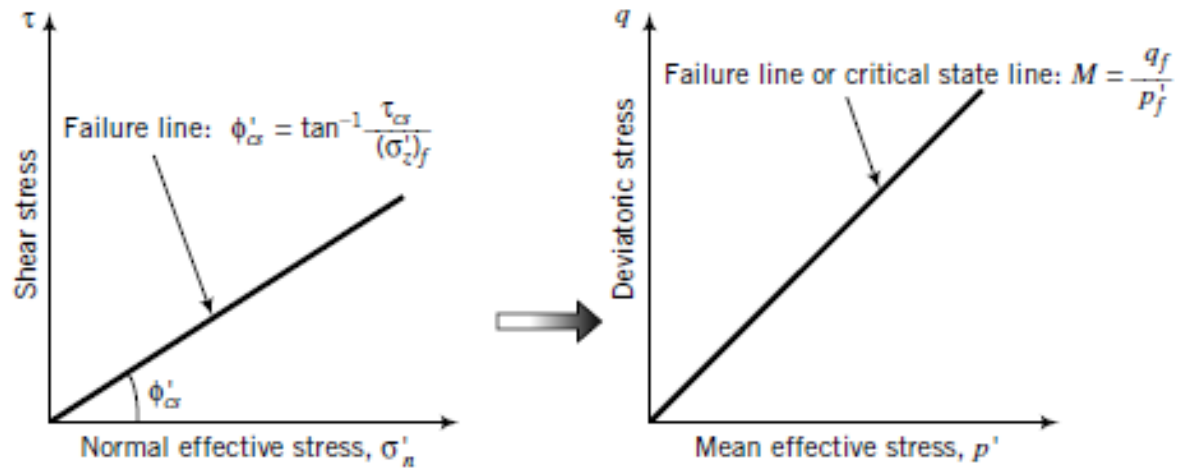
Global overview of the location of the CPTs (orange dots) and BHs (green dots) on the site Groot Schoor Bornem

Attachment C

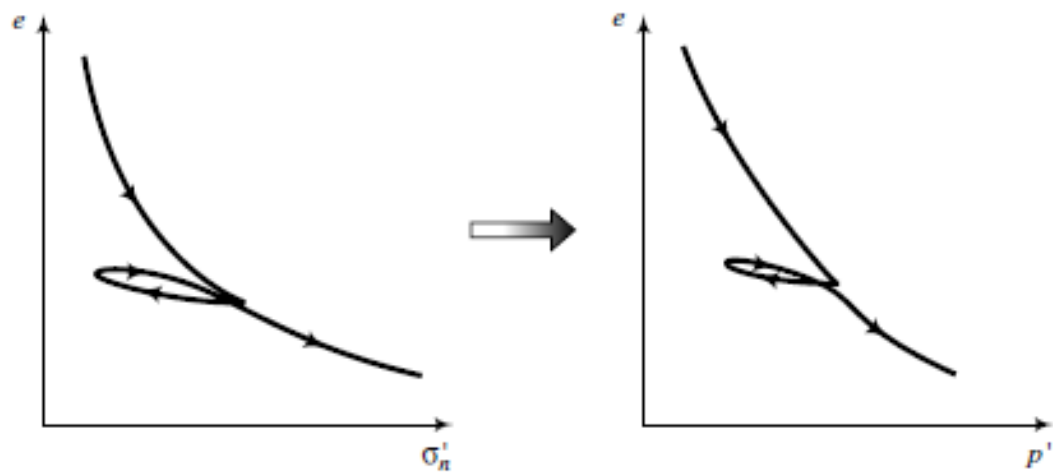


Global overview of the monitoring devices on the site Groot Schoor Bornem

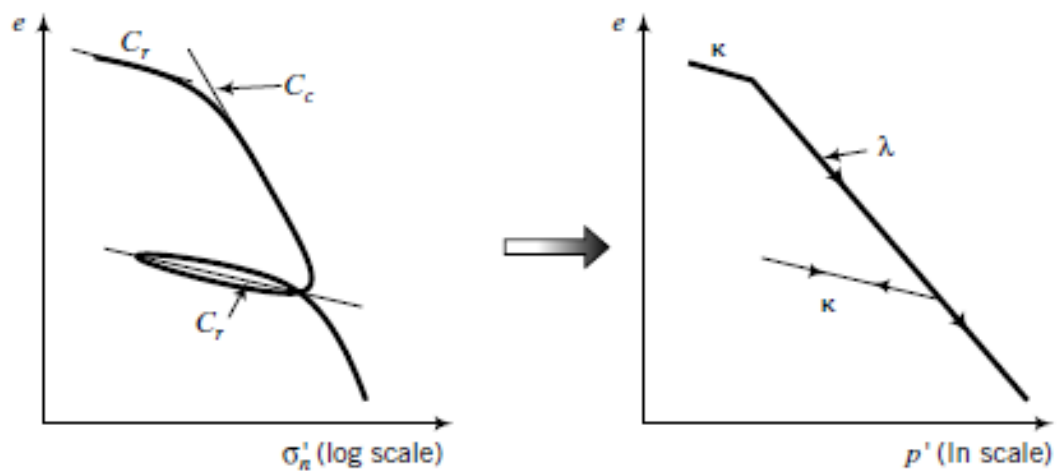
Attachment D



(a)



(b)



(c)

Definition of the critical state model parameters used in the Modified Cam-Clay model

Attachment E

GENERAL		IDENTIFICATION	MATERIAL MODEL	DRAINAGE TYPE	COLOUR (RGB)	COMMENTS	GAMMA UNSAT	GAMMA SAT	DILATANCY CUT-OFF	E INIT
		-	-	-	-	-	kN/m³	kN/m³	-	-
		Layer_H	HS small	Drained	182 226 190	SAND	18.3	20.3	FALSE	0.5
		Layer_J	HS small	Drained	230 181 132	CLAY/SAND	18.3	20.3	FALSE	0.5
		Layer_J	HS small	Drained	200 182 137	SAND – Neogreen	18.3	20.3	FALSE	0.5
		Layer_A	HS small	Drained	161 226 232	SAND – Addition for the new dike	17	19	FALSE	0.5
		Layer_R	HS small	Drained	136 178 133	SAND – Reinforcement subsoil to stabilize the soft clay layer	16	19.4	FALSE	0.5
		Layer_S	Modified Cam-Clay	Undrained A	241 228 246	CLAY – Soft, containing little humus (with vertical channels), North of the old dike	15.0	15.0	FALSE	
		Layer_E	Modified Cam-Clay	Undrained A	236 232 156	CLAY – Locally containing little humus, containing sand, under the old dike	16.2	16.2	FALSE	
		Layer_Ebis	Modified Cam-Clay	Undrained A	159 229 249	CLAY – Locally containing little humus, containing sand, South of the old dike	17.1	17.1	FALSE	
		Layer_C	Modified Cam-Clay	Undrained A	134 234 162	CLAY – Little humus, locally sandy, raising the old dike	17.8	17.8	FALSE	

Deterministic values for the PLAXIS 2D soil parameters (1/3)

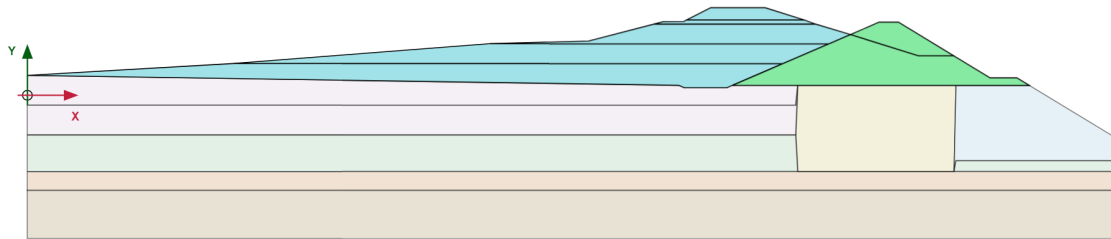
PARAMETERS		E 50 REF	E OED REF	E UR REF	POWER (M)	USE ALTERNATIVES	E INIT	C' REF	PHI'	PSI	GAMMA 0.7		G 0 REF	P REF	LAMBDA	KAPPA	NU UR	M CSL	K 0 NC
		kN/m²	kN/m²	kN/m²	-	-	-	kN/m²	°	°	-	-	kN/m²	kN/m²	-	-	-	-	-
		18000	18000	54000	0.606	FALSE	0.5	1	32	1.750	1.70E-04	80400	100				0.2000		default
		49800	49800	149400	0.441	FALSE	0.5	15	22	8.375	1.17E-04	116400	100				0.2000		default
		36000	36000	108000	0.513	FALSE	0.5	1	32	5.500	1.40E-04	100800	100				0.2000		default
		56700	56700	170100	0.405	FALSE	0.5	1	27	9.813	1.08E-04	124260	100				0.2000		default
		15000	15000	45000	0.622	FALSE	0.5	10	31.13	1.125	1.75E-04	77000	100				0.2000		default
															0.11250	0.03749	0.4500	0.9411	default
															0.08804	0.02935	0.2500	0.9838	default
															0.06196	0.02065	0.3500	0.9838	default
															0.04960	0.01653	0.3500	0.9838	default

Deterministic values for the PLAXIS 2D soil parameters (2/3)

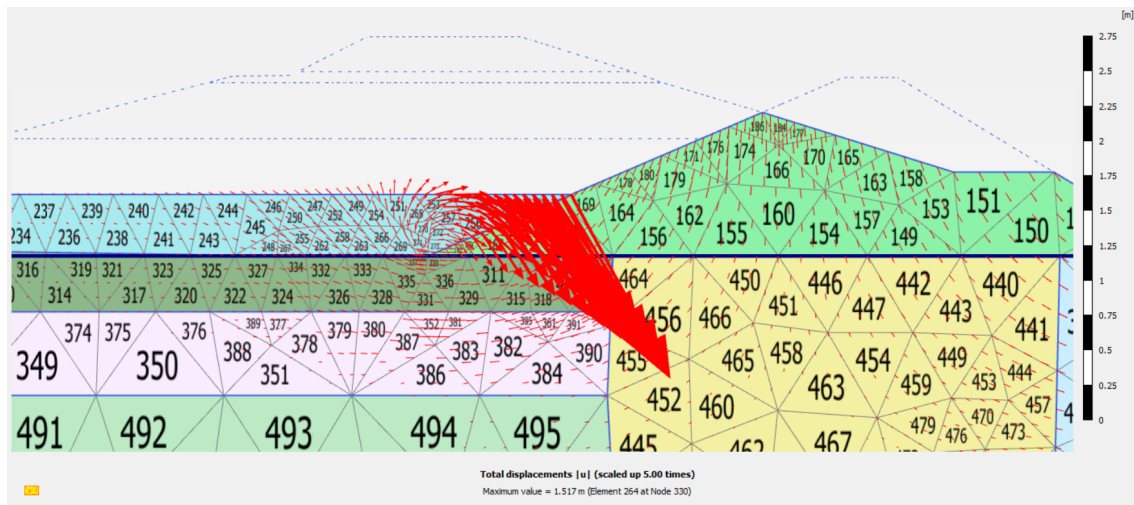
GROUNDWATER															
DATA SET	TYPE	USE DEFAULTS	KX	KY	INTERFACES		STRENGTH	R INTER	STIFFNESS	C REFINITER	PHI INTER	CONSIDER GAP CLOSURE	INITIAL	K 0 SETTINGS	OCR
-	-	-	m/day	m/day			-	-	-	kn/m ²	°	-		-	-
Stand.	Coarse	FALSE	7.080E+00	7.080E+00			Manual	0.9625				TRUE		Auto	1
Stand.	Coarse	FALSE	4.320E-02	4.320E-02			Manual	0.8963				TRUE		Auto	1
Stand.	Coarse	FALSE	2.100E+00	2.100E+00			Manual	0.9250				TRUE		Auto	1
Stand.	Coarse	FALSE	8.640E+00	8.640E+00			Manual	0.8819				TRUE		Auto	1
Stand.	Coarse	FALSE	4.792E-02	4.792E-02			Manual	0.9688				TRUE		Auto	1
Stand.	Coarse	FALSE	1.830E-03	6.110E-04					Derived	1.0000	24.00	TRUE		Auto	2.34
Stand.	Coarse	FALSE	9.820E-03	3.270E-03					Derived	5.0000	25.00	TRUE		Auto	6.6
Stand.	Coarse	FALSE	1.780E-02	5.940E-03					Derived	3.0000	25.00	TRUE		Auto	2.67
Stand.	Coarse	FALSE	1.850E-02	6.180E-03					Derived	5.0000	25.00	TRUE		Auto	2.67

Deterministic values for the PLAXIS 2D soil parameters (3/3)

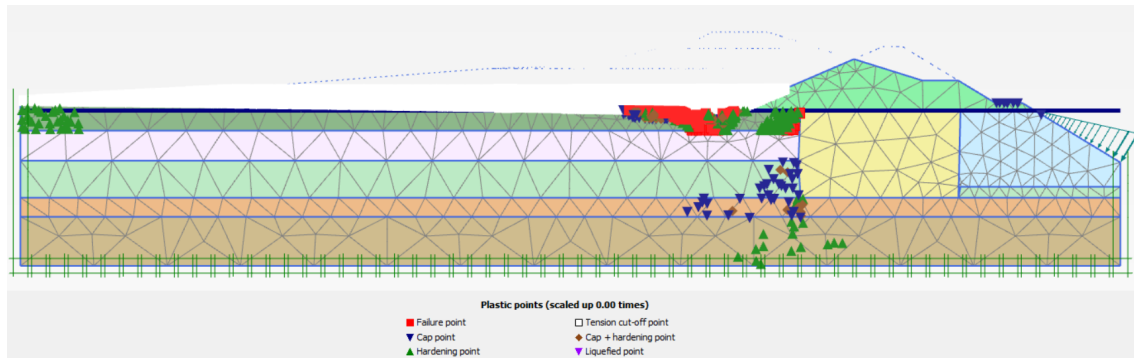
Attachment F



(a) Geometry with singular points

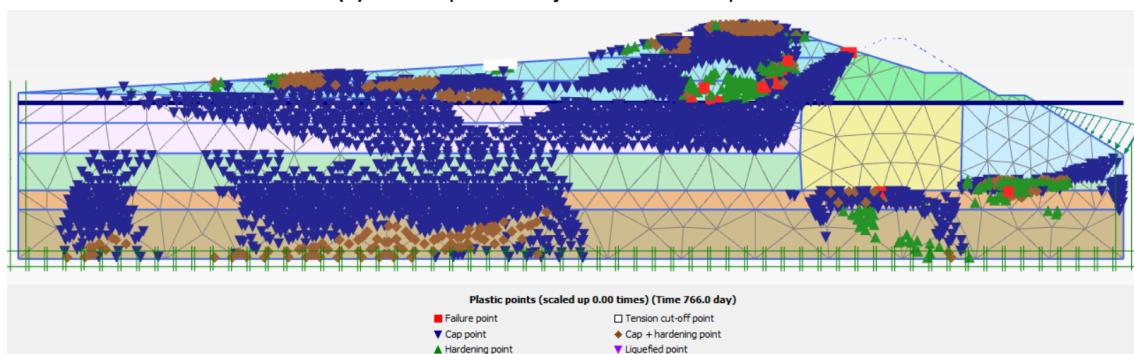
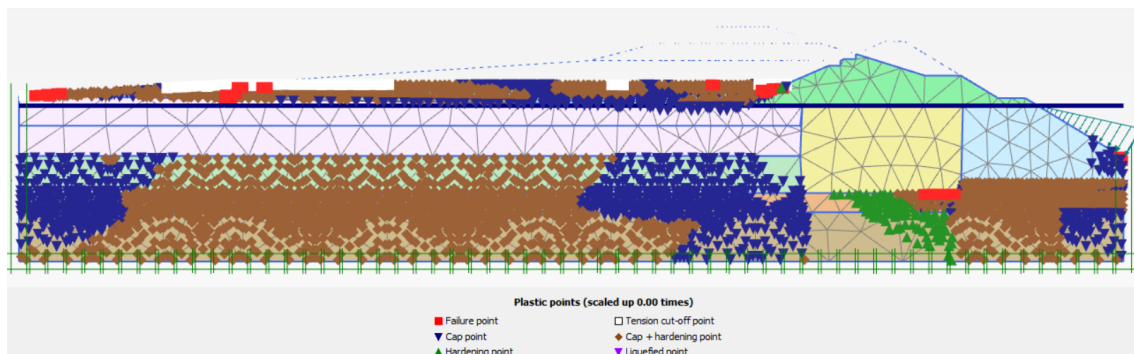
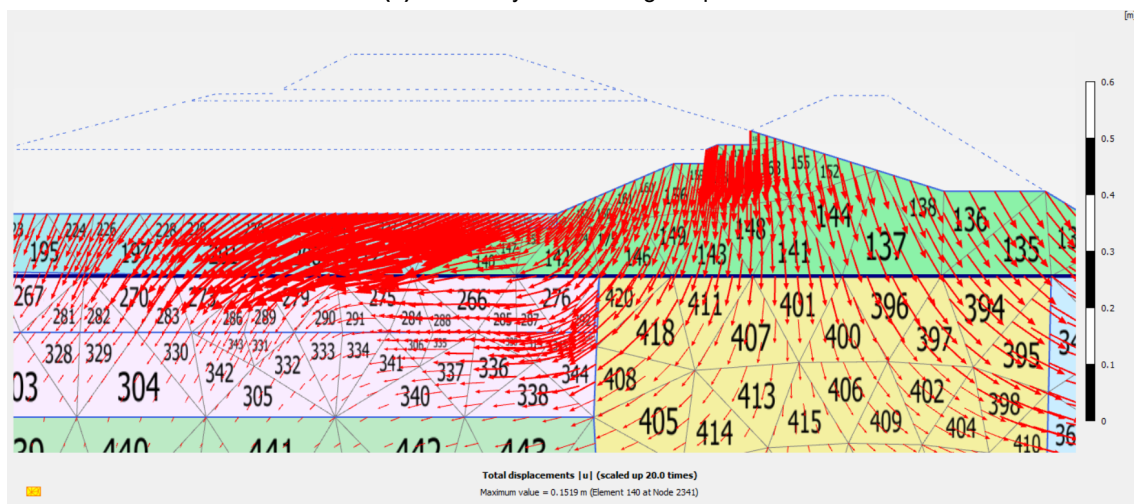
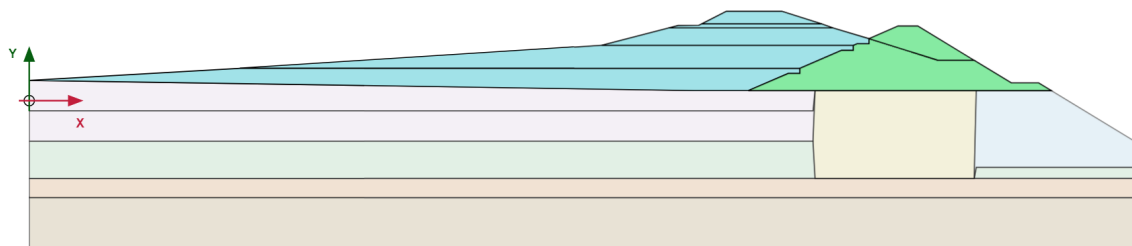


(b) Total displacement in elevation phase 1



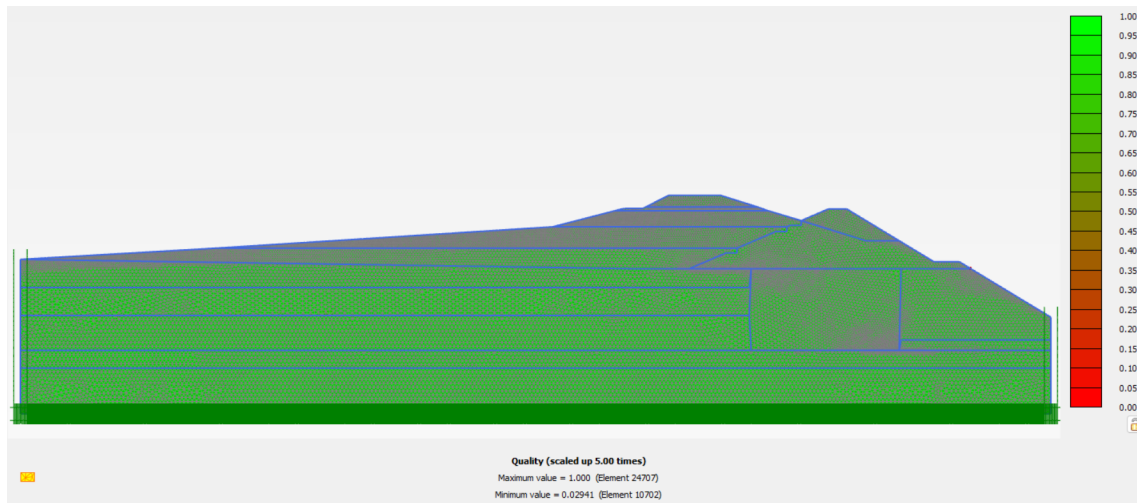
(c) Plastic point analysis in elevation phase 1, resulting in failure

Problematic singular points in the original geometry

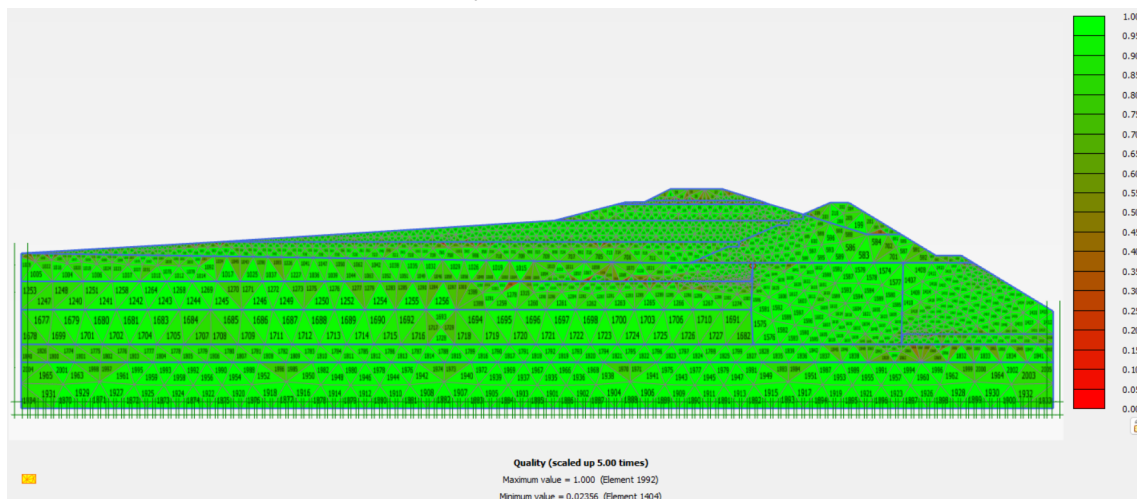


Solution for the singular points in the adapted geometry

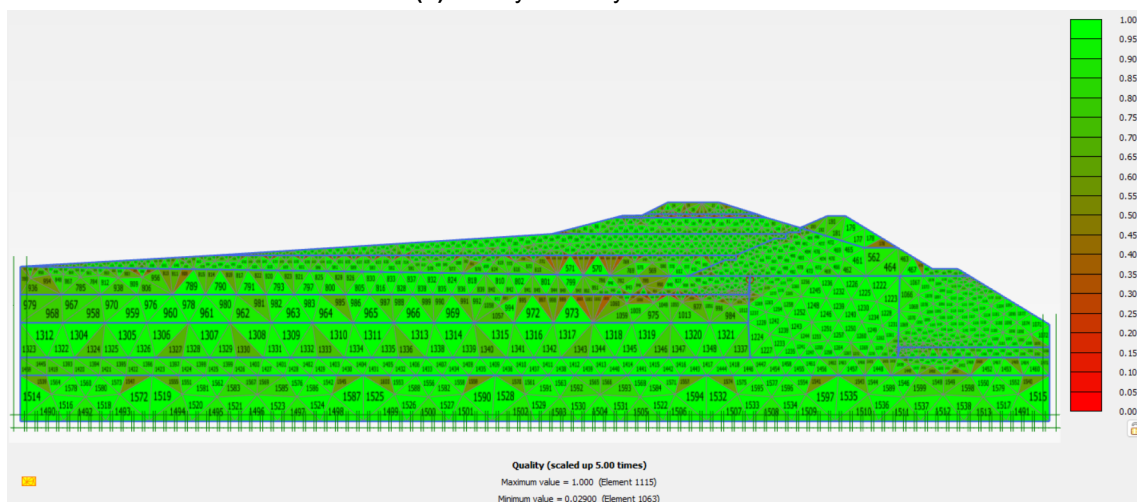
Attachment G



(a) Quality of the finest possible mesh

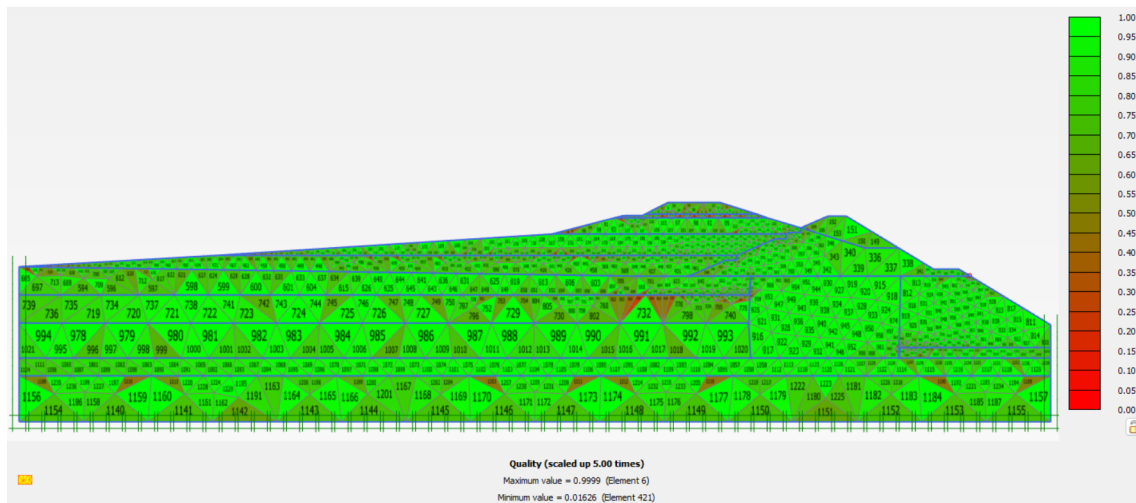


(b) Quality of a very fine mesh

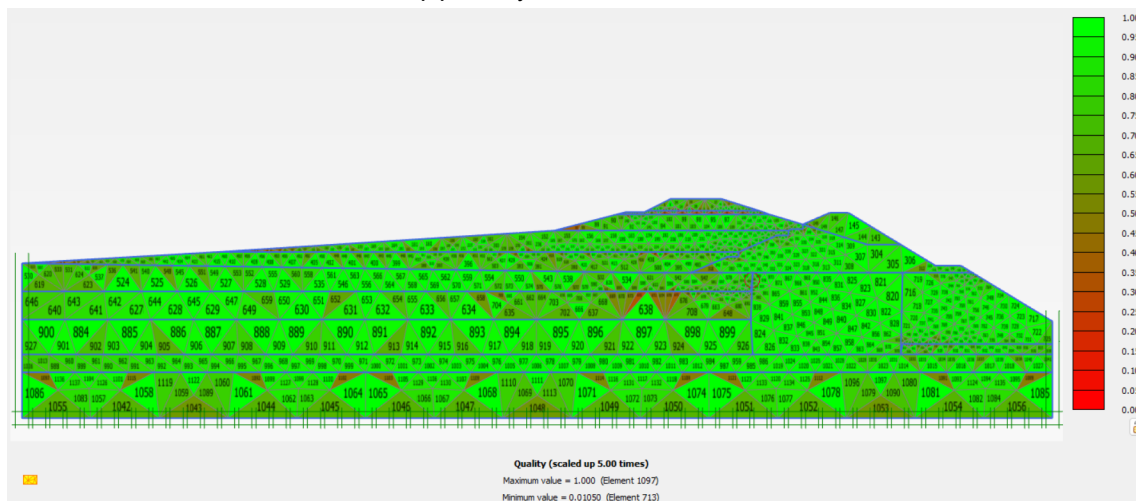


(c) Quality of a fine mesh

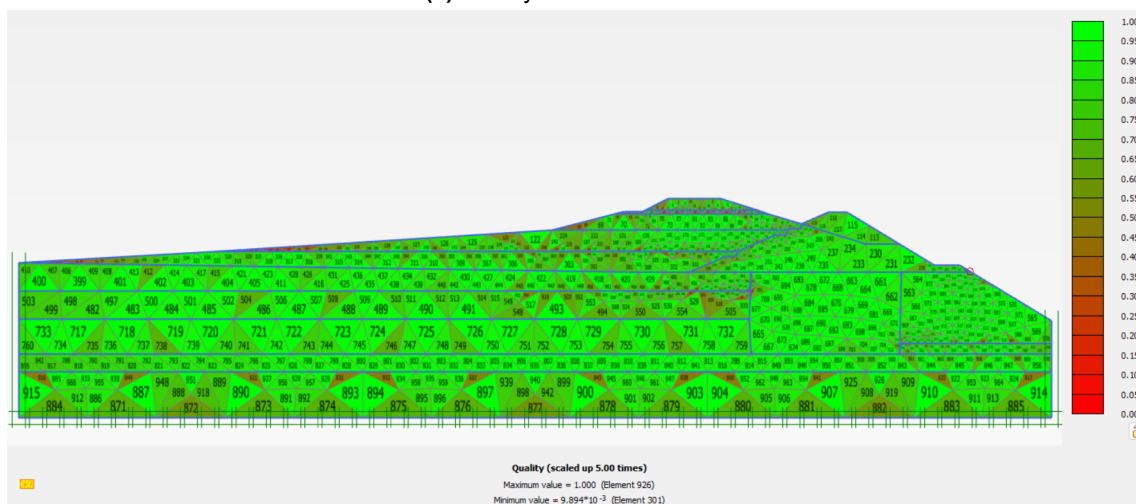
Figure 34: Mesh quality for different mesh element distributions (1/3)



(d) Quality of a medium mesh

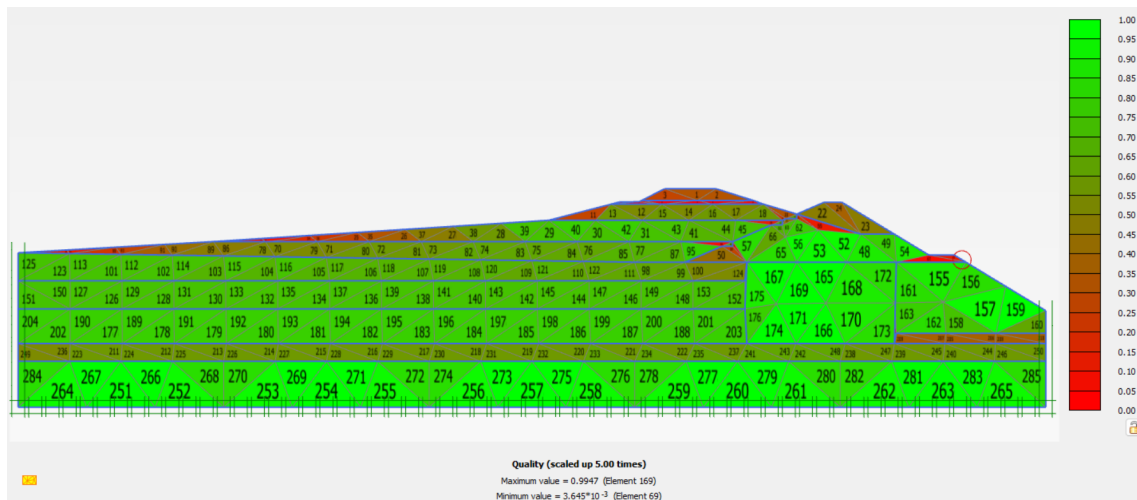


(e) Quality of a coarse mesh



(f) Quality of a very coarse mesh

Figure 34: Mesh quality for different mesh element distributions (2/3)



(g) Quality of the coarsest possible mesh

Figure 34: Mesh quality for different mesh element distributions (3/3)