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# Real-Time Soil Boundary Refinement in Excavation: A GeoBIM Framework Integrating Uncertainty Modeling Tools

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## Abstract

This study investigates the potential of adaptive uncertainty modeling to enhance soil boundary estimation during excavation. A GeoBIM framework integrating Monte Carlo simulation and Kriging interpolation was implemented, enabling real-time refinement of boundary predictions. The results demonstrate significantly improved accuracy and reliability compared to traditional static methods, such as triangulated irregular networks (TINs) and manual excavation, especially in complex environments with limited data. The adaptive model's ability to dynamically learn and improve as excavation data accumulate offers a key advantage for applications requiring high precision and responsiveness. This study highlights the importance of continuous data integration for subsurface modeling. Enhanced soil boundary estimations, when combined with advanced trajectory planning, can lead to more efficient, cost-effective, and environmentally sustainable earthwork operations. This research suggests that adaptive uncertainty modeling can serve as a core technology in automated and intelligent excavation and construction workflows, facilitating smarter and more sustainable earthworks.

**Keywords:** Soil boundary prediction, Uncertainties, Intelligent excavation, Geological mapping, Building information modeling, Advanced trajectory planning, Triangulated irregular networks (TINs), Mean Absolute Error (MAE).

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# 1. Introduction

Construction, one of the world's largest economic sectors, contributes over 10% of global GDP (2023), with annual spending exceeding \$10 trillion and projected to rise to \$15.2 trillion by 2030 — driven largely by urbanization and infrastructure expansion in emerging regions (ConstructConnect, 2023). Yet, despite this growth, productivity in construction has improved by only about 1% annually over the past two decades, lagging well behind industrial and economic averages of 3.6% and 2.8% (McKinsey & Company, 2021). Persistent inefficiencies such as cost overruns, schedule delays, and uncertainty in subsurface conditions continue to limit performance gains. Enhancing accuracy and precision in earthwork operations is therefore essential for improving both efficiency and sustainability. Recent advances in automation, sensor integration, and data-driven methodologies have made it possible to monitor excavation processes in real time and to optimize trajectories, progress, and resource use. Within this technological shift, GeoBIM and uncertainty-based excavation modelling have emerged as key frameworks that link machine-sensed data with probabilistic soil models, enabling adaptive and evidence-based control of earthworks rather than reliance on static assumptions.

Shi et al. (2020) developed an intelligent system for identifying excavator work-cycle phases using main pump pressure data and a support vector machine model, achieving high classification accuracy and enabling real-time monitoring. Similarly, Niskanen et al. (2020) implemented precise four-dimensional soil surface modeling using a fixed two-dimensional (2D) profilometer, achieving ±10 mm accuracy, with practical relevance on-site. Kassem et al. (2021) examined excavation productivity benchmarking with a deep neural network, producing reliable predictions for excavation volumes, while highlighting sensitivity due to manual labor contributions. Panas et al. (2023) noted variations in productivity assessments arising from different initial assumptions, emphasizing the importance of swing angle and excavation depth. Although these studies have improved the accuracy of excavation processes and volume estimates, their application is often limited by predefined excavation models, making adaptation to actual site conditions challenging. Similar limitations also apply to autonomous excavation systems, where outcomes are tightly governed by machine control models.

Recent research by Eraliev et al. (2022) and Zhang et al. (2024) has shown notable progress in measurement technologies, perception methods, and excavation trajectory planning using deep learning and optimization techniques, enhancing operational efficiency and adaptability in dynamic environments. Vierling et al. (2023) developed automated methods for progress tracking and delay detection, which, when integrated into web-based project management platforms, significantly improved excavation project oversight. Despite their advancements, these solutions remain computationally intensive and difficult to apply under practical field conditions.

Several studies (Juola et al., 2024a and Okada et al., 2024 and Kurinov et al., 2020) emphasize the importance of adaptive control systems capable of responding in real time to changing environmental and soil conditions. Common approaches include uncertainty modeling, reinforcement learning (RL), and model predictive control. Some methods also leverage pressure sensor data and force-torque control, in addition to position data, to improve performance across varying soil types (Juola et al., 2024b and Egli et al., 2022 and Fernando et al., 2019). Studies (Svensson and Friberg, 2017 and Schmidinger and Gerard, 2023 and Ijaz et al., 2023) have highlighted the importance of uncertainty modeling for improving map quality and informing design decisions. These studies emphasize the use of robust uncertainty models, improved data acquisition strategies, integrated data management, and the critical role of detailed data in ensuring safe and sustainable engineering solutions. Marschalko et al. (2023) further demonstrated that soil and rock workability, excavation methods, and applied technology significantly affect earthwork costs, underlining the importance of comprehensive geotechnical investigations for accurate cost estimation.

Advanced technologies offer significant potential for earthwork volume estimation, including more efficient data collection and detailed three-dimensional (3D) visualization. However, their accuracy and effectiveness depend heavily on data processing methods, which are often difficult to implement in practice. A deep understanding of the geological and geotechnical conditions of the site is necessary to fully realize the potential of these technologies in the field.

A previous work established by Juola et al. (2024a), employed a sophisticated hybrid methodology that combines Monte Carlo simulation and Kriging interpolation to effectively model uncertainties in the determination of geological boundaries. This innovative approach is rooted in the theoretical principles established by Wellmann et al. (2010) yet finely tuned to accommodate the specific geotechnical conditions prevalent in infrastructure projects by the GeoBIM concept of Tyréns AB.

Previous studies in excavation modeling have largely relied on static terrain representations and fixed boundary assumptions, often lacking the capacity to adapt to real-time changes in soil and environmental conditions. These limitations hinder the accuracy of volume estimation and complicate the integration of data-driven automation frameworks. This study introduces a novel approach that combines adaptive uncertainty modeling with real-time sensor data to refine soil boundary estimates dynamically during excavation. By using real-time pressure sensor data (Juola et al., 2024b), the method enables the accurate definition of soil boundaries in changing environmental and soil conditions. This supports reliable volume estimation and allows optimization frameworks to be integrated for improved excavation performance.

To achieve its objectives, this study seeks to answer the following questions:

- How does adaptive uncertainty modeling reduce errors in soil boundary models?
- How do changes in environmental and soil conditions affect the performance of adaptive uncertainty modeling?
- What is the potential for adaptive uncertainty modeling in automated earthwork operations?

The main contributions of this study are as follows:

- Methodological novelty:
  A real-time adaptive uncertainty modelling framework that integrates Monte Carlo simulation and Kriging interpolation within the GeoBIM environment for continuous, probabilistic refinement of soil boundaries during excavation.
- Experimental validation:
  The framework is evaluated across three field sites with varying geological complexity and data availability, demonstrating improved performance over TIN-based and operator-assisted excavation models.
- Practical implications:
  The adaptive framework establishes a foundation for data-driven, sustainable, and automation-ready earthwork workflows.

While the modeling framework introduced in this study is tested across three representative field sites, the scope is intentionally focused on demonstrating the core functionality and adaptability of the proposed method. This deliberate constraint allows the underlying principles of real-time uncertainty modeling to be isolated, validated, and positioned as a scalable foundation for future research in more diverse geological conditions.

## 2. Methods

In this study, we compare our proposed adaptive uncertainty model to the commonly used TIN surface model and operator-assisted TIN excavation. Both models are established to represent excavation and terrain surfaces in geotechnical and infrastructure projects, making them a natural reference for comparison. The accuracy of both methods is evaluated by comparing the modeled excavation surfaces to the actual measured surfaces.

### 2.1 Performance of the TIN Surface Model

TINs are widely used in geoengineering and GIS for modeling complex terrain surfaces due to their ability to accommodate irregularly distributed data points. Unlike regular grids, TINs provide a flexible and detailed surface representation by connecting elevation points into nonoverlapping triangles, most commonly via Delaunay triangulation. This method ensures uniform triangle shapes by maximizing the minimum internal angles, thus improving mesh quality and terrain depiction.

TIN modeling is particularly well suited for representing uneven and detailed surfaces and has been widely applied in earthworks and geodetic measurements to assess excavation shapes and volumes (Wu and Amaratunga, 2003). In excavation modeling workflows, TINs are used to generate 3D representations of target excavation geometries. This process typically involves (1) integrating ground investigation data to define excavation depth and geometry, (2) generating a triangulated mesh based on Delaunay interpolation that captures slope angles and pit floor levels, and (3) exporting the resulting TIN model in a compatible format for machine control systems (Fig. 1).

While effective in general surface representation, TIN models are sensitive to input data quality and spatial distribution. Inadequate or uneven data coverage can result in interpolation errors, particularly in slope estimation and volume calculations. Preprocessing by geotechnical professionals—such as filtering outliers and ensuring consistent spatial density—is essential to mitigate such issues. However, these manual adjustments increase the model preparation effort and may introduce distortions. Despite their utility, the inherent limitations of TIN-based methods—especially under complex stratigraphy or sparse data conditions—highlight the need for more adaptive modeling approaches, as explored in this study.

In our study, the excavation models created using common modeling tools are represented as TIN surface models. These common excavation surface models are compared to models created utilizing adaptive uncertainty modeling. This comparison is made by measuring the Mean Absolute Error (MAE) of said models against true measured excavation surfaces. Excavation surface models created with common Delauney interpolation were viewed with two distinct approaches: 1) a TIN surface model created with initial data points only and 2) an operator-assisted TIN excavation model created with Delauney interpolation from initial data points, allowing for pilot intervention during excavation.

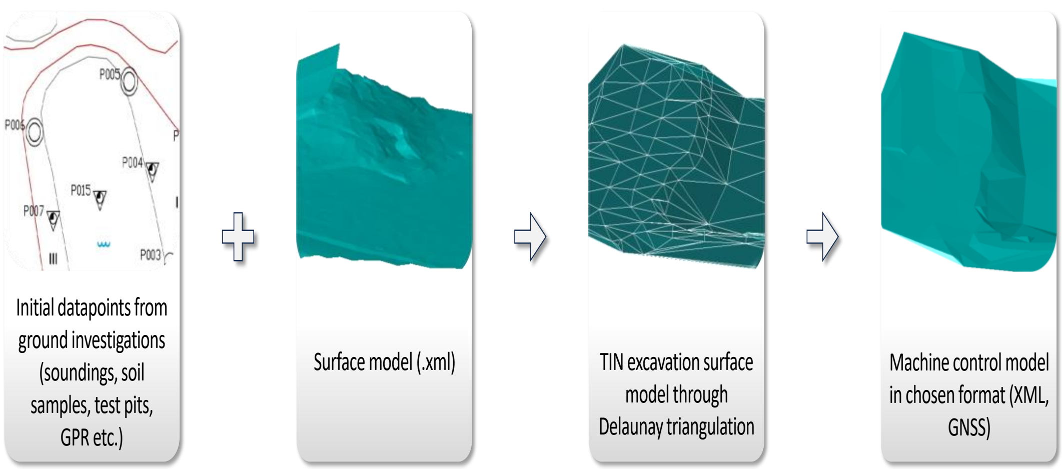


**Figure 1: Workflow of excavation modeling using common TIN surface modelin**

## 2.2 Performance of the GeoBIM Model

Building on the workflow of common TIN surface modeling (Fig. 1), our study incorporates adaptive updates from uncovered soil boundary levels during excavation into an uncertainty modeling tool. Initial ground investigation data are used to calculate a surface model via the Tyréns GeoBIM uncertainty tool, generating a detailed estimation of the targeted excavation boundary. This model is exported to excavators as a machine control surface. As the true soil boundary is revealed during excavation, the observed data are fed back into the uncertainty model, updating the estimation dynamically. This adaptive approach improves volume estimates, identifies areas of high uncertainty, and enables more accurate and flexible excavation planning with reduced cut-and-fill errors.

The modeling workflow follows a structured GeoBIM implementation. The project area is georeferenced using a coordinate system and digital elevation model (DEM), and geotechnical investigation points with interpreted layer depths and uncertainty bounds are imported. These inputs are stored in a centralized database and used to generate an initial Kriging-based uncertainty model. A Monte Carlo simulation with 500 realizations is performed over a 2 × 2 m grid to propagate spatial uncertainty. During excavation, observation data from the excavator—considered ground truth—are incrementally imported (at 20%, 40%, etc.). After each update, the model is recalculated using the same Kriging–Monte Carlo framework, refining surface predictions and reducing uncertainty in near real time. A block diagram of the method is presented in Figure 2.

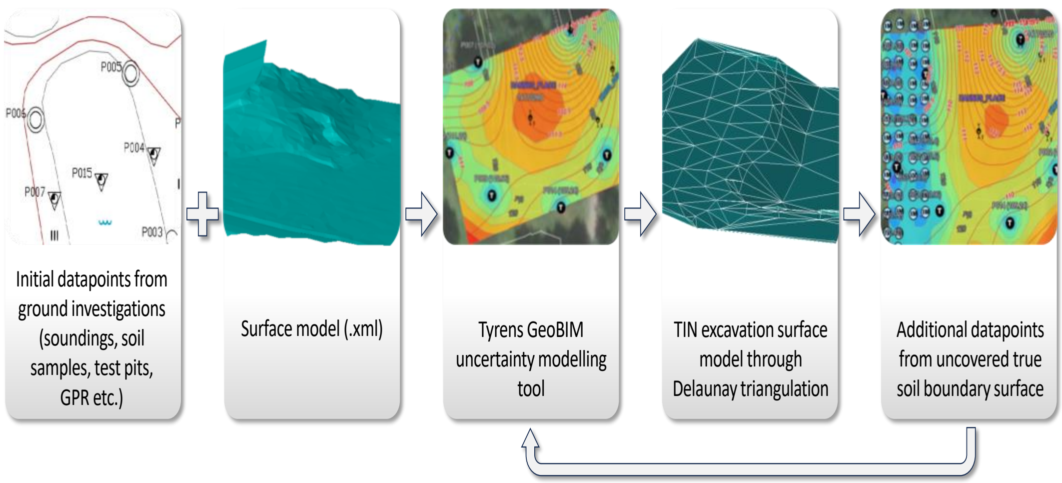


**Figure 2: Workflow of excavation modeling using adaptive uncertainty modeling**

### 2.2.1 Adaptive Uncertainty Modeling

The implementation of the uncertainty model was carried out in collaboration with Tyréns AB (Sweden), who integrated the model into their GeoBIM concept with direct connectivity to a comprehensive geotechnical database. To improve computational efficiency, the uncertainty modeling was implemented in a 2D framework, generating surfaces that represent the geological boundaries of interest. The modeling process was executed using Python on a server, with user interaction enabled through a Microsoft Teams interface.

The uncertainty modeling follows an iterative framework in which random boundary-level values are sampled from the uncertainty distributions defined for each measurement point by Svensson et al. (2022). Each iteration yields a possible soil boundary surface, and the ensemble of simulations is used to derive uncertainty surfaces that support adaptive boundary updates. Variations in boundary-level inputs across iterations allow assessment of how point-level uncertainty propagates to the overall surface model, with this study focusing on the error associated with the most probable contour elevation.

### 2.2.2 Adaptive Feedback Mechanism for Real-Time Soil-Boundary Updates

In the proposed excavation framework, the process forms a closed real-time feedback loop that continuously refines the machine-control model as new ground data are acquired. On-board sensing, rapid data assimilation, and automated model redeployment are coupled to maintain alignment between the digital excavation surface and the evolving true soil boundary.

1. **On-board boundary sensing.**

As shown by Juola et al. (2024b), hydraulic-cylinder pressure sensors mounted on the excavator bucket detect abrupt changes in resistive force when cutting across soil boundaries. The field computer records these depth-coded pressure spikes at a spatial resolution comparable to conventional sounding rigs, with time stamping and georeferencing provided by the machine-control system.

2. **Data transfer and preprocessing.**

Sensor logs are wirelessly uploaded to standard geotechnical mapping software, where pressure breakpoints are automatically parsed into sounding points. The inferred boundary elevations are then exported in a format compatible with the GeoBIM uncertainty modeling environment.

3. **Iterative uncertainty update.**

Newly derived boundary points are appended to the existing measurement set and assimilated into the GeoBIM generator described in Section 2.2.1. A new Monte Carlo simulation is executed on the server, producing updated estimates of the soil boundary and associated confidence limits.

4. **Model redeployment to the field.**

The revised surface is converted into a TIN and deployed as a machine-control model (e.g., Trimble, Leica, or Topcon formats). The update is transmitted to the excavator cab display, replacing the previous guidance surface without interrupting production.

This workflow is built on methods by Svensson et al. (2022) and Juola et al. (2024a). While Svensson et al. validated their model only once after excavation, Juola et al. introduced a progressive, multi-stage protocol in which the evolving model was continuously compared against measured soil boundaries. To establish a robust reference surface, Juola et al. (2024a) applied a tiered validation strategy. First, only 30 % of the available soundings were used for model calibration, with the remaining 70 %—spatially stratified—reserved for independent MAE-based validation. Second, targeted undisturbed soil cores were collected from representative 20 × 20 m grid cells, providing higher-precision stratigraphic elevations and reducing posterior variance. Finally, during excavation, the exposed boundary was systematically logged on a 5 × 5 m grid using total-station measurements, yielding a dense representation of the true boundary surface.

Through this multiresolution validation approach, Juola et al. (2024a) demonstrated that adaptive, continuously updated models produce substantially tighter and more reliable posterior prediction intervals than single-step verification strategies.

### 2.2.3 Surface Modeling Using Monte Carlo Simulation and Kriging Interpolation

Predicting geological and geotechnical properties—including both design parameters and layer boundaries—inevitably involves multiple sources of uncertainty. These arise primarily from natural variability and investigation-related errors, with common mitigation approaches including Bayesian statistics (Prästings, 2019 and Van de Schoot, 2021) and Monte Carlo analysis (Bárdossy and Fodor, 2001).

In this study, geometrical uncertainties were quantified using Monte Carlo simulation combined with geostatistical Kriging interpolation (Oliver and Webster, 2015). Individual uncertainties assigned to each sounding and the distance to the nearest borehole were used as inputs, enabling estimation of both distance-related uncertainty and the propagation of boundary-level errors from individual soundings across the modeled layer boundary. While both approaches rely on spatially distributed data, they differ in how uncertainty is represented and inferred; together, they provide a robust basis for spatial prediction and uncertainty assessment in subsurface modeling.

Within this adaptive GeoBIM framework, two complementary uncertainty domains are modeled: geometrical uncertainty, arising from the spatial interpolation of soil boundaries, and design-parameter uncertainty, originating from measurement or interpretation errors at investigation points. The model takes as input the coordinates of boreholes or soundings $(x_i, y_i, z_i)$ and their associated standard deviations $\sigma_i$. Ordinary Kriging is first used to estimate the boundary surface and its covariance structure based on a linear variogram. A Monte Carlo loop then perturbs input elevations according to their uncertainties and regenerates the surface for each realization. After multiple iterations (typically $N = 500–1000$), ensemble statistics are computed to derive the most probable boundary surface $\bar{Z}(x)$, upper and lower confidence envelopes, and a spatial uncertainty map $\sigma_Z(x)$extendable to three-dimensional probabilistic volumes. The required number of Monte Carlo iterations is dependent on the spatial resolution of the computational grid: for coarser grids, fewer realizations are sufficient to achieve stable mean absolute error convergence, whereas finer grids require higher iteration counts to reach comparable statistical consistency. Increasing the number of realizations improves convergence but proportionally increases computation time, introducing a trade-off between uncertainty resolution and update latency in real-time adaptive workflows. Together, these outputs provide the probabilistic basis for real-time soil boundary refinement within the adaptive GeoBIM workflow (Fig. 3).

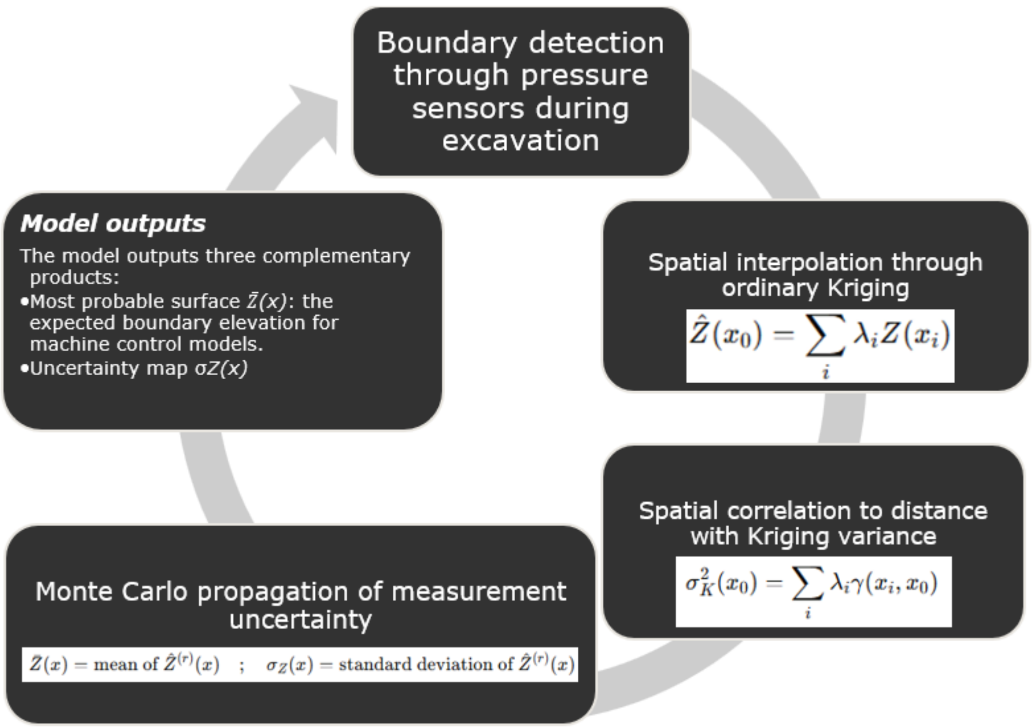


**Figure 3: Adaptive GeoBIM workflow diagram**

### 2.2.4 Modified Gempy Algorithm and Monte Carlo Simulation

The developed algorithm is derived from the open-source Gempy framework (Varga et al., 2019), which combines Monte Carlo simulation with 3D interpolation of geological units to quantify uncertainty. In Gempy, uncertainties are defined for each data point—either stochastically or by interval bounds—and random values are sampled during Monte Carlo simulations.
Because Gempy is designed for large-scale (kilometer-scale) 3D geological modeling (Wellmann et al. 2010) and involves computationally intensive calculations, a modified implementation was developed within the GeoBIM concept for built-environment applications at the meter scale. This adaptation retains the ability to assign individual uncertainties to each data point but reformulates the problem using a 2D representation of geological boundaries to improve computational efficiency.

The algorithm requires three input datasets:

i. Point observations defining the target surface (e.g., soundings, geophysical data, or outcrop observations), each with an interpreted most probable layer elevation and bounds defining its uncertainty distribution.
ii. Ground surface elevations, typically derived from a DEM.
iii. Parameters defining the coordinate system.

The computation proceeds in two steps. First, point data are interpolated to a continuous geological surface using Kriging, yielding a spatial variance that increases with distance from measurement points. Second, an iterative Monte Carlo simulation randomly perturbs boundary elevations within their uncertainty intervals, generating 1,000 realizations to quantify how point-level uncertainty propagates across the surface. The variance from these steps is combined to produce a total standard deviation for each model cell. In addition, upper and lower reasonable boundary surfaces are derived by adding and subtracting two standard deviations from the interpolated surface, with envelopes expanded in cells where deviations exceed this threshold.

### 2.2.5 Kriging Interpolation

Kriging interpolation is a geostatistical technique used to predict spatially distributed variables at unobserved locations based on the spatial correlation of measured data (Bárdossy and Fodor, 2001). It assumes that observations within a spatial domain are correlated, with correlation decreasing as distance increases. This structure is described using a variogram, which relates the variance of pairwise differences between observations to their separation distance. An empirical variogram is derived from the data and fitted with a theoretical model that characterizes the spatial behavior of the variable. Denser data coverage, and thus shorter inter-point distances, generally reduces prediction error.
In soil surface modeling, the Kriging procedure follows a structured workflow.

Spatially distributed soil observations are first collected, after which an empirical variogram is computed and a theoretical model is fitted. Based on this variogram, a system of linear equations is formulated to estimate values at unsampled locations, with weights assigned to observations such that estimation variance is minimized. Solving this system yields the predicted values, along with the Kriging variance, which provides a quantitative measure of uncertainty and reliability of the interpolation.

### 2.3 Test Field Sites

This study investigates the performance of adaptive excavation models compared to traditional TIN surface modeling methods across three distinct field sites. These sites were deliberately selected to represent typical cut-and-fill scenarios commonly encountered in earthworks, where excavation is carried out to remove upper layers of poorer-quality soil—typically characterized by low bearing capacity or cohesive soil parameters—and to expose underlying friction soils with more favorable geotechnical properties. Such stratigraphic configurations are frequently observed in practical construction settings, particularly in infrastructure and foundation projects. Consequently, the selected test sites not only reflect realistic engineering challenges but also capture a representative range of soil conditions, boundary complexities, and data availability scenarios (Table 1). This diversity provides a robust and practical evaluation framework for assessing the effectiveness and adaptability of the proposed excavation modeling approach.

**Table 1: Overview of field site characteristics**

| Parameter | Site 1 | Site 2 | Site 3 |
|---|---|---|---|
| Area ($m^2$) | 1 335 | 4 223 | 3 657 |
| Soil profile | Cohesive/moraine | Cohesive/moraine | Frictional/moraine |
| Boundary z-variance (m) | 1.61 | 5.14 | 12.65 |
| Data distribution | Even coverage | Partial coverage | Perimeter only |
| Uncertainty of soundings | ± 4 cm | ± 4 cm | ± 20 cm |

Site 1 represents a compact, well-instrumented area with uniform conditions, providing a high-confidence baseline for comparison. Site 2 introduces moderate topographic variability and incomplete data coverage, reflecting typical mid-scale infrastructure environments. Site 3 presents the most challenging configuration, characterized by strong heterogeneity, limited interior data, and higher measurement uncertainty. Collectively, these sites span a practical gradient from data-rich to data-sparse contexts, enabling comprehensive evaluation of the proposed adaptive modeling workflow across varying geological and operational scenarios.

The three field sites represent contemporary, typical infrastructure projects in active use, and are therefore classified as critical infrastructure. Consequently, no photographic documentation of the excavations is available for publication.

Nevertheless, all analyses presented herein are based on digitally reconstructed surface and boundary models (Fig. 4), derived from total station surveys and core sampling data, ensuring accurate representation of site conditions.

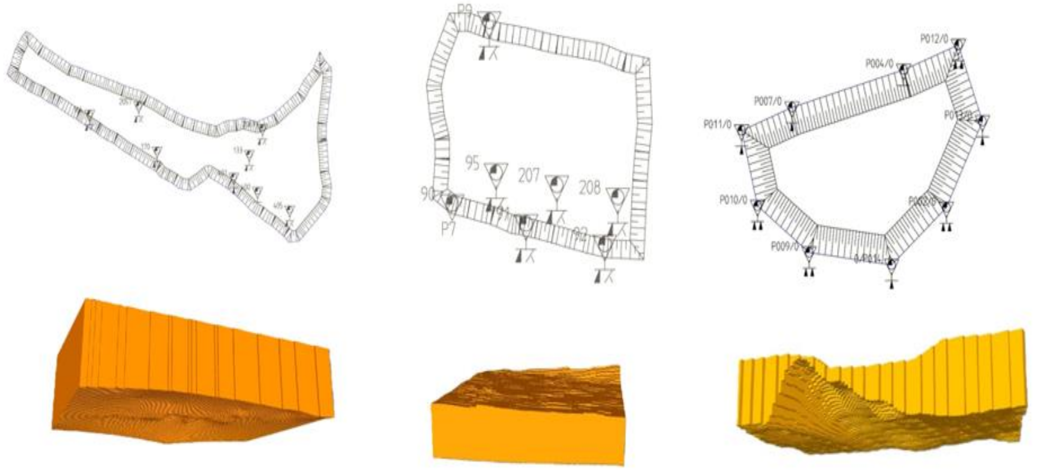

**Figure 4: Excavation area of a) Site 1, b) Site 2, and c) Site 3, with initial ground investigation points**

These three sites, with their varying characteristics, provide a comprehensive basis for evaluating the effectiveness of adaptive excavation models in diverse real-world scenarios. For this, 500 Monte Carlo iterations were conducted per update phase, where each model instance was interpolated using Kriging to propagate uncertainties from individual geotechnical data points throughout the model surface (Fig. 5). The grid resolution was standardized to 2 × 2 m cells across all investigated sites. Computation time per full simulation cycle (500 realizations) ranged between 8–15 minutes, depending on the site area and number of data points, using standard desktop hardware. Latency between field observation uploads (e.g., excavator-integrated measurements) and updated model outputs remained below 5 minutes per update stage, enabling near-real-time refinement of subsurface models during construction operations.

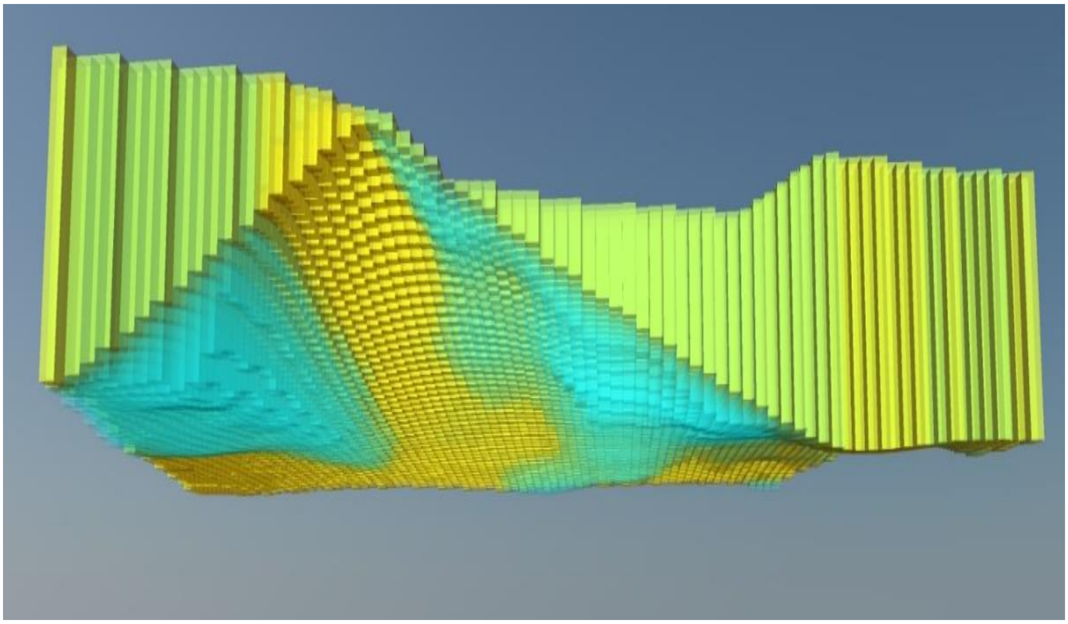

**Figure 5: Boundary surface development from 20% update (orange) to 100% (blue) update at Site 3**

Field measurements were collected using a Leica TS16 total station (angular accuracy ±1″, distance precision ±(1.5 mm + 2 ppm)) combined with GNSS control points for coordinate referencing. Elevation points were recorded at 5–10 m spacing along excavation profiles, supplemented by manual core sampling and visual boundary logging. The instrumentation setup and installation procedure, including the data synchronization workflow between the total station and GeoBIM environment, are described in detail in Juola et al. (2024a and 2024b).

# 3. Results

The accuracy of soil boundary estimation was assessed at three distinct field sites—Site 1, Site 2, and Site 3—each characterized by different soil conditions, boundary complexities, and data availability. The primary metric used for this evaluation was the MAE, which quantifies the average deviation between the modeled and true soil boundaries. MAE was chosen because distance is a key measure in excavation work, and it effectively captures the extent of deviation in boundary estimation.

## 3.1 Performance of the TIN Surface Model

Across all sites, the traditional TIN excavation model—based on Delaunay triangulation and relying solely on initial survey data—produced the highest MAE values. This consistently poorer performance highlights the model's limited ability to account for complex or variable soil boundaries (Fig. 5). Specifically, the TIN model yielded an MAE of 0.77 at Site 1, 0.99 at Site 2, and a significantly higher

1.82 at Site 3. The particularly poor performance at Site 3 reflects its high boundary variability and sparse internal sampling, emphasizing the model's sensitivity to boundary complexity and lack of comprehensive input data.

### 3.2 Performance of the Operator-Assisted TIN Excavation

The "Excavated pit with piloted excavator" method, representing conventional operator-controlled excavation utilizing the traditional TIN excavation model as the basis for excavation and allowing human intervention in clear problematic areas during excavation, showed more varied performance (Fig. 6). It achieved excellent accuracy at Site 1 (MAE = 0.03), likely due to an evenly distributed set of sounding points that enabled precise machine control. However, accuracy decreased markedly at Site 2 (MAE = 0.74) and Site 3 (MAE = 0.68). This variability suggests that while human-operated excavation can be precise under ideal conditions, it is more prone to error when facing incomplete data or complex terrain. In such cases, the control model guiding the excavation lacks the precision required for high accuracy.

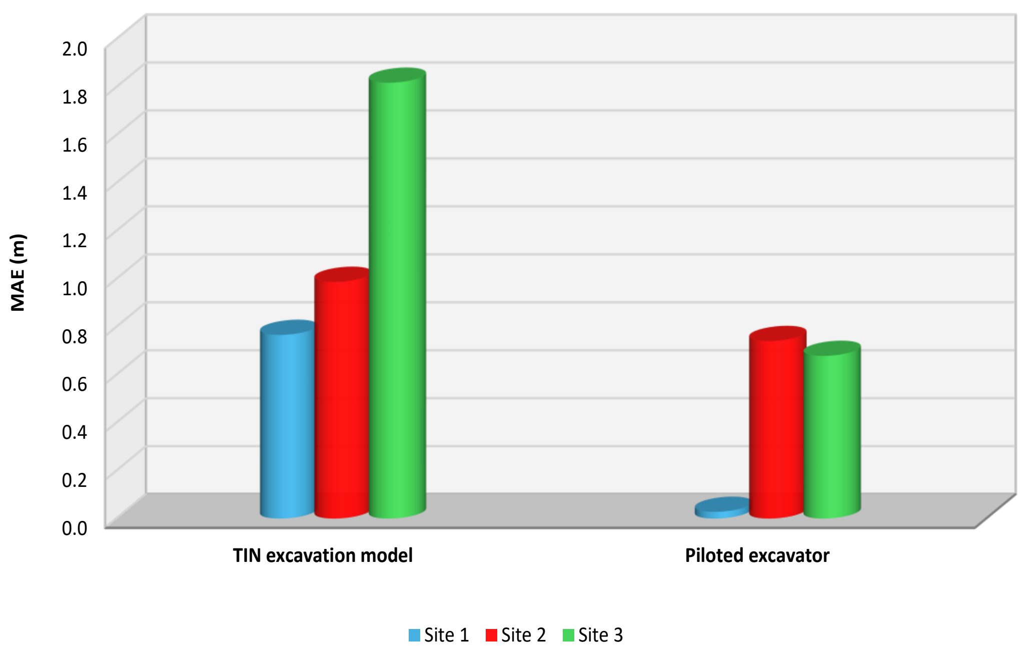


**Figure 6: MAE comparison between TIN model excavation and performance of the TIN model with piloted excavator intervention**

### 3.3 Performance of the GeoBIM model

The GeoBIM excavation model, incorporating Monte Carlo simulation and Kriging interpolation, demonstrated the most adaptive and accurate performance (Fig. 7). This model updated boundary estimates in real time as excavation progressed, integrating new data to refine its predictions continuously. At Site 1, the MAE improved from 0.11, with only initial data to 0.02 after full excavation. Similarly, at Site 2, the MAE dropped from 0.92 to 0.02, indicating substantial accuracy gains as more data became available. The initially high error at Site 2 highlights the model's sensitivity to the initial spatial distribution of sounding points, which limits early-stage accuracy. At Site 3, the GeoBIM model also showed improvement, with MAE decreasing from 0.86 to 0.39 as excavation progressed. However, accuracy plateaued between 40% and 100% excavation, with the MAE stabilizing around 0.42. This reduced improvement is likely due to the site's specific challenges, including a layered soil structure (friction soil over moraine), high variability in boundary shape, and uneven data point distribution, especially along inner boundaries. The coarse granular nature of moraine may also contribute to the model's reduced interpretability in this context, as friction soils are generally more difficult to model accurately than cohesive soil types. Although friction soils exhibit weaker spatial correlation that can reduce kriging accuracy, the associated uncertainty maps reliably captured this effect, demonstrating that measurement density, not soil type itself, governs the effectiveness of uncertainty reduction.

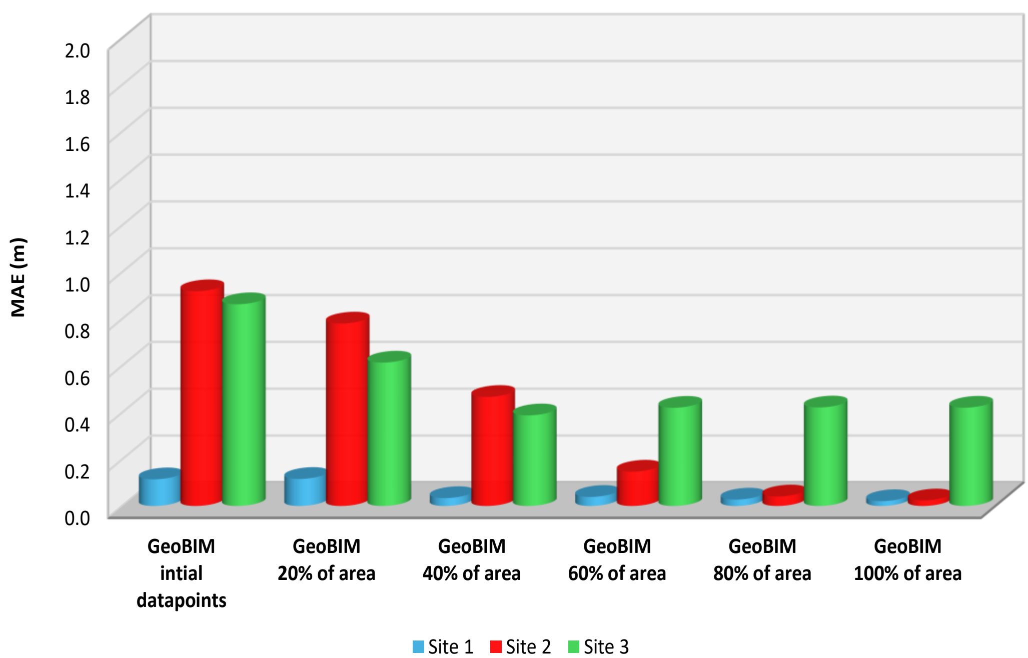


**Figure 7: Progression of MAE during excavation when utilizing GeoBIM models with adaptive boundary-level detection**

Overall, the findings support the hypothesis that adaptive GeoBIM modeling consistently outperforms traditional TIN modeling, particularly in environments with complex soil conditions and sparse initial data (Table 2, Fig. 8). The GeoBIM model's ability to learn from and adapt to incoming data enables progressive refinement of boundary estimations, resulting in superior accuracy (Fig. 9). While performance gains varied by site, the GeoBIM approach was particularly beneficial in challenging settings, such as Site 3, where high boundary variability and limited internal data posed significant obstacles to traditional modeling techniques.

**Table 2: Overview of MAE for test sites (meters)**

| MAE Site | TIN excavation model | Pit with piloted excavator | GeoBIM excavation model | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Initial datapoints only | with 20% of area excavated | with 40% of area excavated | with 60% of area excavated | with 80% of area excavated | with 100% of area excavated |
| **Site 1** | 0.77 | 0.03 | 0.11 | 0.12 | 0.03 | 0.04 | 0.03 | 0.02 |
| **Site 2** | 0.99 | 0.74 | 0.92 | 0.78 | 0.47 | 0.15 | 0.04 | 0.02 |
| **Site 3** | 1.82 | 0.68 | 0.86 | 0.61 | 0.39 | 0.42 | 0.42 | 0.42 |

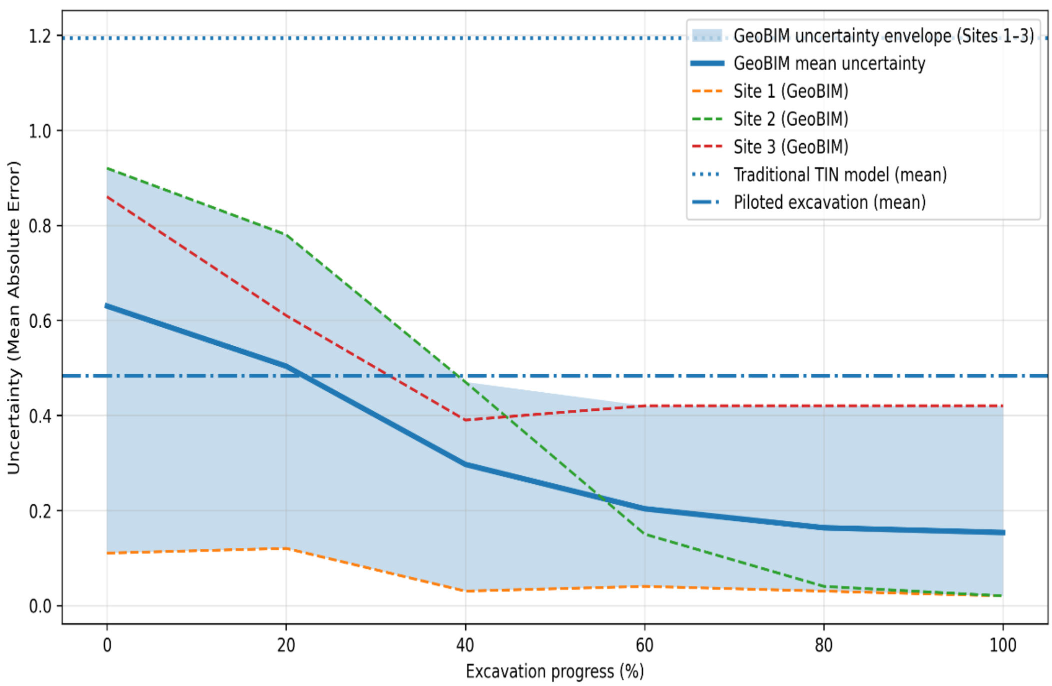


**Figure 8: Uncertainty reduction comparison to excavation progress phase**

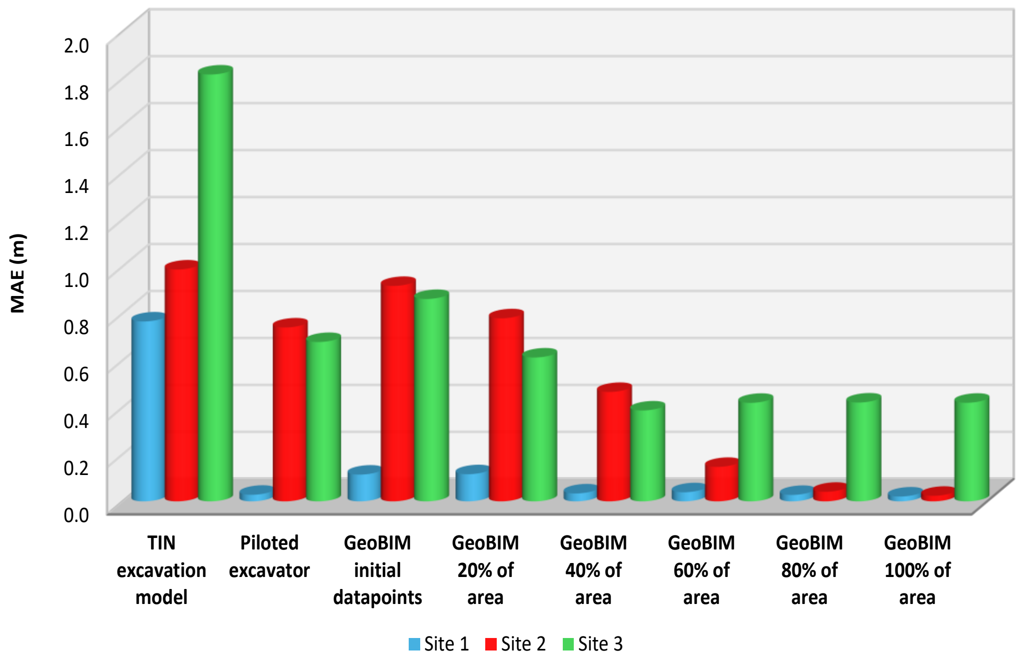


**Figure 9: MAE utilizing various modeling and excavation techniques**

# 4. Discussion

This study evaluated the effectiveness of adaptive GeoBIM modeling for soil boundary estimation during excavation using a GeoBIM approach that integrates Monte Carlo simulation and Kriging interpolation. By comparing this method against the conventional TIN model and a piloted excavator approach across three field sites with varying geological characteristics, we aimed to answer three key questions:

1. How does adaptive uncertainty modeling reduce errors in soil boundary models?
2. How do environmental and soil conditions affect its performance?
3. What is its potential for supporting automated earthwork operations?

## 4.1 Comparative Performance of Modeling Approaches

The results clearly indicate that the adaptive GeoBIM model consistently outperformed both the TIN and piloted excavator approaches across all sites. The TIN model, which relies solely on initial survey data and does not update as excavation progresses, produced the highest MAE values, particularly at Site 3, which featured high boundary variability and sparse internal data points. This highlights the limitations of the TIN model in dynamically changing or geologically complex environments and underlines the necessity of real-time data integration in modern excavation modeling.

The piloted excavator method showed promising results under optimal conditions, as seen at Site 1, where uniform sounding point distribution supported high-precision excavation. However, its accuracy declined significantly at Sites 2 and 3. These findings suggest that human-operated excavation, while effective in controlled settings, becomes more error-prone in complex terrains or when initial data are limited. This variability accentuates the advantages of the GeoBIM model's adaptive data assimilation, which enables it to refine boundary estimations on the fly as new excavation data become available.

To the best of our knowledge, no existing approach combines real-time soil boundary refinement with probabilistic uncertainty modelling in operational excavation workflows, underscoring both the novelty and the applied value of the proposed framework. Compared with other state-of-the-art methods in digital twin development and uncertainty-based terrain modelling, the present framework is distinct in its integration of Monte Carlo–Kriging probabilistic updating with direct field validation across entire excavation areas. Competing approaches, such as reinforcement learning (RL) or static surface estimation techniques, lack the capacity to iteratively refine and quantify uncertainty over full spatial domains with equivalent continuity or statistical depth. Furthermore, no prior studies have reported adaptive simulation of evolving soil boundaries at this operational scale using alternative methodologies.

### 4.2 Adaptive GeoBIM Model Capabilities, Constraints, and Practical Applications

The adaptive nature of the GeoBIM model was particularly evident at Sites 1 and 2, where MAE values declined sharply as more excavation data were incorporated. This progression illustrates the model's ability to learn and improve dynamically, contributing to more accurate and reliable boundary estimations over time.

However, performance at Site 3 plateaued after approximately 40% of the excavation had been completed, with MAE stabilizing despite continued data integration. This limitation appears to stem from several factors:

a complex friction soil over moraine layer,

high boundary variability, and

a sparse distribution of inner boundary data points.

These conditions constrained the model's capacity to refine its estimates, illustrating that even advanced adaptive models face challenges when dealing with coarse-grained soils or extreme geological heterogeneity. Notably, these findings echo prior work by Juola et al. (2024a), whose studies on adaptive geological uncertainty modeling and real-time pressure sensor data utilization emphasized the need for continuous data acquisition and integration to improve subsurface modeling in excavation contexts.

The outcomes of this research align with recent advancements in real-time sensing and adaptive modeling reported by Eraliev et al. (2022) and Zhang et al. (2024). These works showed that deep learning and optimization techniques can enhance the operational adaptability of excavation systems. While these studies focused on trajectory optimization and perception, our work addresses the underlying geological uncertainty — a foundational issue that directly impacts excavation planning and execution.

By combining accurate and continuously refined soil boundary estimations with future trajectory optimization frameworks, automated earthwork operations could become significantly more precise, efficient, and cost-effective. The integration of real-time pressure sensor data, as proposed in this study, adds an additional layer of responsiveness to the modeling process, enabling excavation systems to adapt not only to planned inputs but also to in situ ground conditions. The proposed method introduces a novel and generalizable approach to adaptive soil boundary detection by utilizing pressure sensor data derived directly from the excavator's hydraulic system (Juola et al., 2024b). This sensor-based estimation can be calibrated using a range of available soil mapping techniques—such as cone penetration tests, ground-penetrating radar, or borehole log data—allowing the approach to be tailored to different site conditions and data availability. As a result, the methodology offers broad applicability across diverse geotechnical contexts, making it a practical and scalable solution for real-world deployment in various excavation scenarios.

From a practical standpoint, the adaptive GeoBIM model can be integrated into existing machine control systems to provide continuously updated excavation boundaries during construction. This enables site operators and supervisors to make more informed decisions in real time, reducing over-excavation, rework, and associated costs. Furthermore, the model can be employed in the early planning phases for more accurate mass balance calculations, risk assessments, and bid preparation, enhancing both project predictability and financial control.

### 4.3 Sustainability and Economic Impact

Accurate excavation is essential for controlling costs in large-scale projects, as even minor deviations can lead to substantial financial impacts. For instance, a 1 cm error in a one-hectare excavation area corresponds to a volume of 100 m³. At a cost of €13.76 per m³ (current mean average cost for mass exchange including material, labor, and logistics in Finland), this small measurement discrepancy results in an additional expense of approximately €1,376. Managing such inaccuracies can significantly reduce unnecessary costs, improve project efficiency, and contribute to more sustainable construction practices.

To put this into perspective, consider a 10 km–long road with a width of 7.5 meters. A 1 cm overcut error across this entire length would amount to a volume of 750 m³, translating into an extra cost of approximately €10,320. This calculation underscores how minor errors in excavation, when scaled over large distances, can lead to considerable financial consequences. Hence, maintaining precise excavation models is crucial for cost control and optimal resource management in large infrastructure projects.

Beyond economic efficiency, the adoption of adaptive uncertainty modeling can contribute significantly to the sustainability goals of modern infrastructure projects. By minimizing unnecessary material movement and avoiding over-excavation, this approach reduces fuel consumption and $CO_2$ emissions associated with earthwork logistics. As the construction industry increasingly embraces digitalization and environmental accountability, data-driven excavation models, such as GeoBIM, provide a tangible pathway toward greener and more efficient practices.

### 4.4 Summary of Key Findings

The research addressed the following three core questions:

- **Error Reduction:** Adaptive uncertainty modeling with the GeoBIM approach achieved the lowest final MAE values across all sites, affirming its effectiveness.
- **Environmental Impact:** Complex and variable geological conditions (especially at Site 3) negatively affected model accuracy, highlighting limitations under extreme variability and limited data conditions.
- **Automation Potential:** The ability of the GeoBIM model to assimilate real-time excavation data makes it well suited for automated earthwork systems, where precision and adaptability are essential.

### 4.5 Limitations and Future Research

Despite the promising results, this study has several limitations. First, the validation was conducted using post-processed datasets rather than live data streams, meaning that the system's real-time performance and latency have not yet been tested under actual operating conditions. Secondly, the evaluation was restricted to three field sites with defined and localized soil conditions. Third, the data density and sensor type were fixed in each case, potentially limiting broader generalizability. Finally, the current implementation does not yet include sensor fusion with LiDAR or GNSS, which could further enhance model robustness.

Although the present study was based on post-processed field data, the adaptive GeoBIM framework is computationally optimized for real-time operation. The model structure, including the Monte Carlo–Kriging updating cycle, is capable of processing new sensor data at sub-second intervals under typical excavation data rates.

Future research should investigate:

- The performance of the adaptive utilization of the GeoBIM model in different soil types (e.g., highly cohesive or saturated soils),
- Higher-resolution sensor data integration, such as LiDAR or multispectral imaging,
- Real-time integration test in collaboration with construction machinery automation systems to validate the dynamic performance and latency of the adaptive updates.
- Integration with trajectory optimization algorithms to create a fully adaptive and autonomous excavation pipeline.

By addressing these aspects, future studies can further enhance the practical utility and impact of adaptive uncertainty modeling in earthwork automation and sustainable infrastructure development.

## 5. Conclusion

This study developed and validated an adaptive GeoBIM framework for estimating soil boundaries during excavation. The approach combines Monte Carlo simulation and Kriging interpolation within an iterative updating loop that refines boundary surfaces as new field data become available. Validation across three excavation sites demonstrated that the adaptive model significantly reduced mean absolute error compared with conventional TIN-based approaches, particularly under variable soil conditions.

The results confirm that adaptive uncertainty modeling can substantially improve the accuracy and reliability of digital excavation models. The proposed framework provides a computational basis for real-time integration with machine-control systems, supporting more efficient and automated earthwork operations. Future work will focus on implementing and testing the framework in live excavation environments with sensor fusion and continuous data streams.

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