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OPTIMIZING TBM PARAMETERS THROUGH SURFACE SETTLEMENT MONITORING USING SURROGATE MODELLING APPROACH

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Introduction

Tunnels offer efficient transportation infrastructures in urban areas such as the Grand Paris Express in France. In urban areas, a densely built environment is exposed to the surface settlements caused by tunneling and, consequently, vulnerable buildings and infrastructures can be damaged.

Figure 1 : Overcoming Challenges in Tunnel Projects in Urban Areas

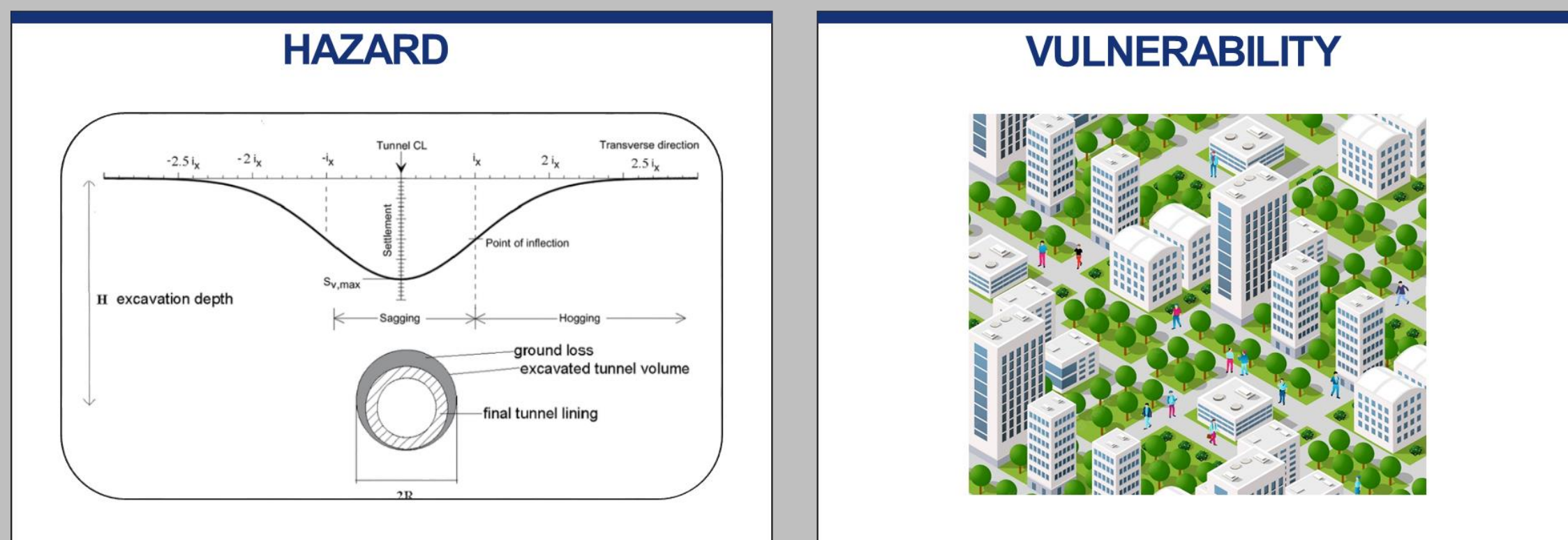


Table 1: Assumptions used for the simulation of the TBM excavation process

Model Parameters	Implementation within the model	Type
TBM	Uniformly distribute pressure along the length of the shield, immediately after excavation of the face	Boundary condition
Face Pressure + Jack Forces	Apply Hydrostatic pressure that varies with depth along the excavated vertical face	Boundary condition
Overcutting	The diameter of the excavated soil slice is larger than the diameter of the TBM face, indicating that a larger area of soil is being excavated with each slice.	Geometry
Grout & Lining	Volumic material	Geometry
TBM weight	Apply a downward surface pressure along the shield length immediately after excavating the face	Boundary condition
Injected Grout Pressure	Apply hydrostatic pressure that varies with depth on the excavated wall immediately following the TBM tail	Unlimited
Grout Hardening	The deactivation of injected grout pressure and the subsequent step-by-step evolution of mechanical behavior (from a liquid to a solid state)	Material
TBM Conicity and Strain / Lining joints	The finite element parametric model that was chosen does not take into account those factors, which may have implications for the accuracy of the model and the validity of its results	Geometry and Material

Ongoing work

The process of validating modeling assumptions and calibrating the model using sensor data (Figure 3) involves running numerous simulations to fine-tune the numerical model (outlined in Figure 2) until an accurate representation of the observed data is achieved. The ultimate aim of calibration is to identify the optimal set of input parameters that effectively explain the monitored data.

Once the numerical model is calibrated, a **surrogate model** can be built by revisiting the input space and focusing solely on the **TBM parameters**. This approach enables a precise assessment of the impact of a specific set of input driving parameters on the settlement curve. Employing an active learning strategy can substantially reduce the number of simulations necessary while maintaining excellent performance levels.

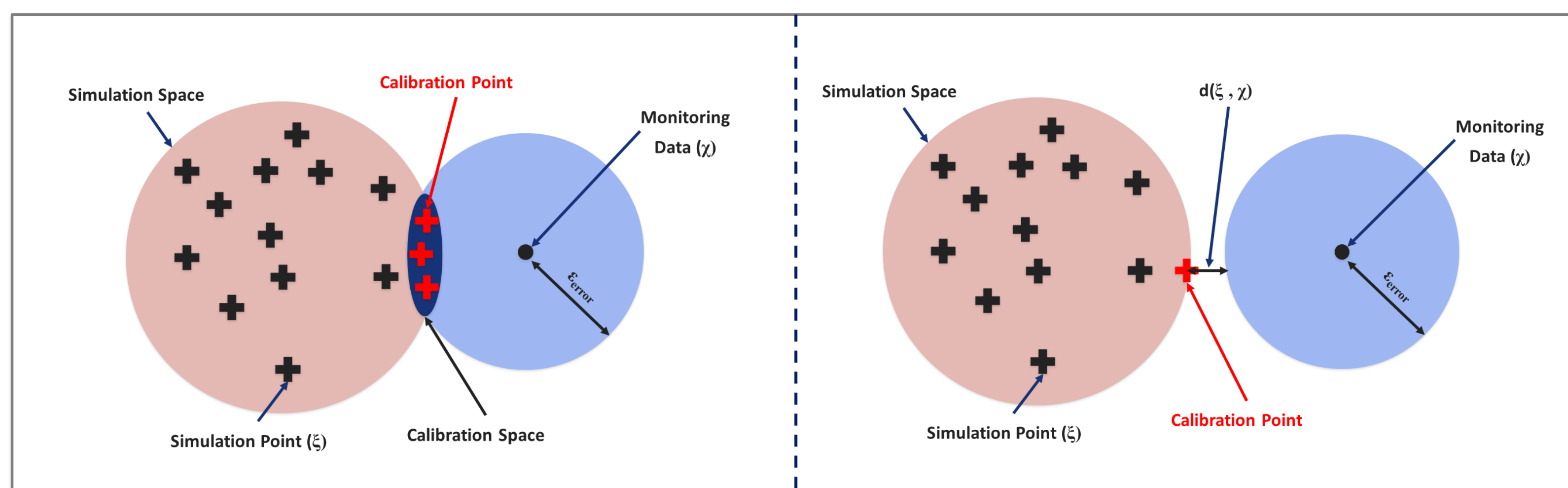


Figure 3 : Calibration Approach Flow Chart [4]

Understanding a Simulation Points as the concatenation of a set of Inputs and Outputs

Objectives

The design of tunnel boring machines (TBM) and the choice of driving parameters have a significant impact on induced settlements [1]. A digital tool prototype is developed to minimize the surface settlement induced by tunneling works by picking the right TBM driving parameters. To carry out this research work, 4 steps are considered:

1. Building of a **3D finite element model** to simulate the **TBM excavation process in an urban area**.
2. **Calibration** of the model with **monitoring data**
3. Construction of a **surrogate model** to **predict a 3D settlement curve** faster than the finite element model.
4. Development of a digital tool for dynamic control of tunneling parameters. With the history of settlements and tunneling associated parameters

State Of The Art

- 2D finite element models are often used for simulating TBM excavation due to their simplicity and speed, but **3D models are more accurate**. However, **surrogate models** can be used to improve or simplify numerical models, so a surrogate model based on a 3D model is needed for accurate predictions.
- Assumptions must be made to simulate the TBM excavation process using a 3D finite element model. These assumptions are summarized in **Table 1 based on a state-of-the-art review** and include **TBM driving parameters** and the **hardening phenomenon**.
- To model soil behavior accurately, the **Hypoplastic or Hardening Soil model** would be appropriate, but implementing these models requires a high number of parameters that increase complexity. Thus, **simpler models such as Mohr Coulomb or Drucker Prager laws will be studied first**.

Parametric Finite Element Model Presentation

A **parametric 3D finite element approach** was implemented, with assumptions outlined in Table 1 to construct a surrogate model and perform sensitivity analysis and calibration. A Python script was developed to streamline the process, enabling users to input various parameters such as face pressure, mortar pressure, and mechanical properties. The model was then simulated using **ABAQUS** software to estimate surface settlements.

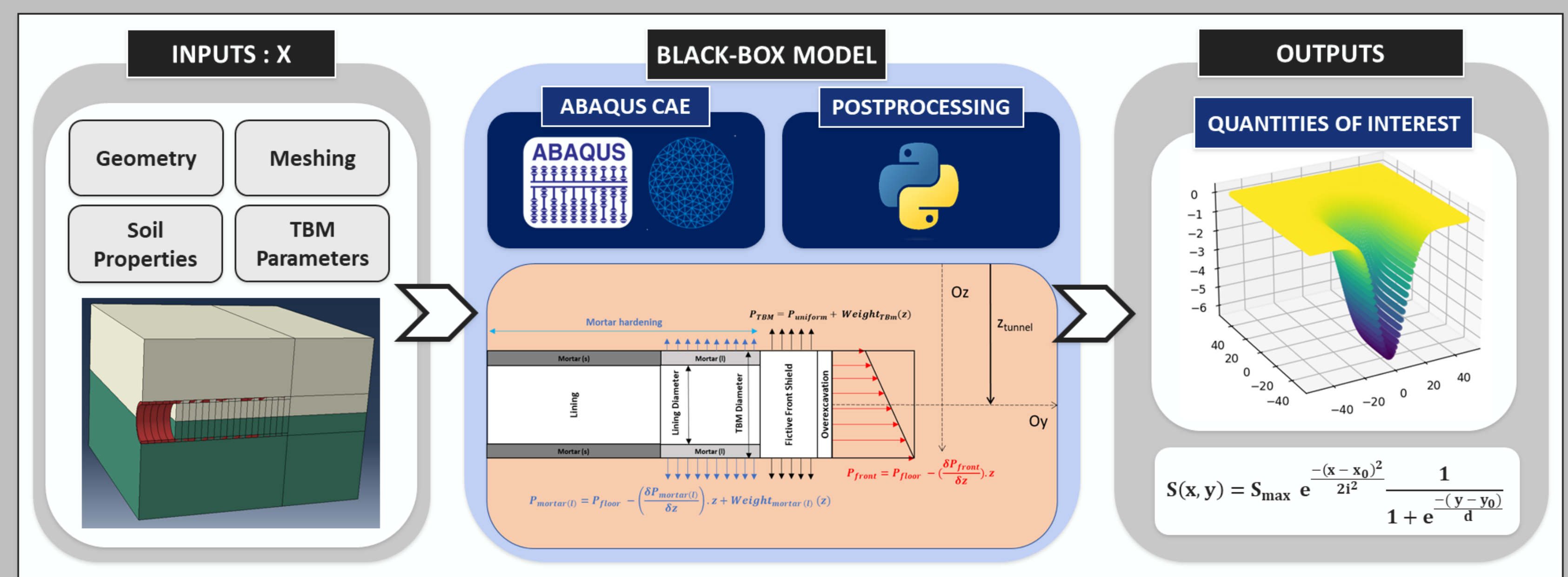


Figure 2 : Automation of the 3D TBM excavation finite element simulation [3]

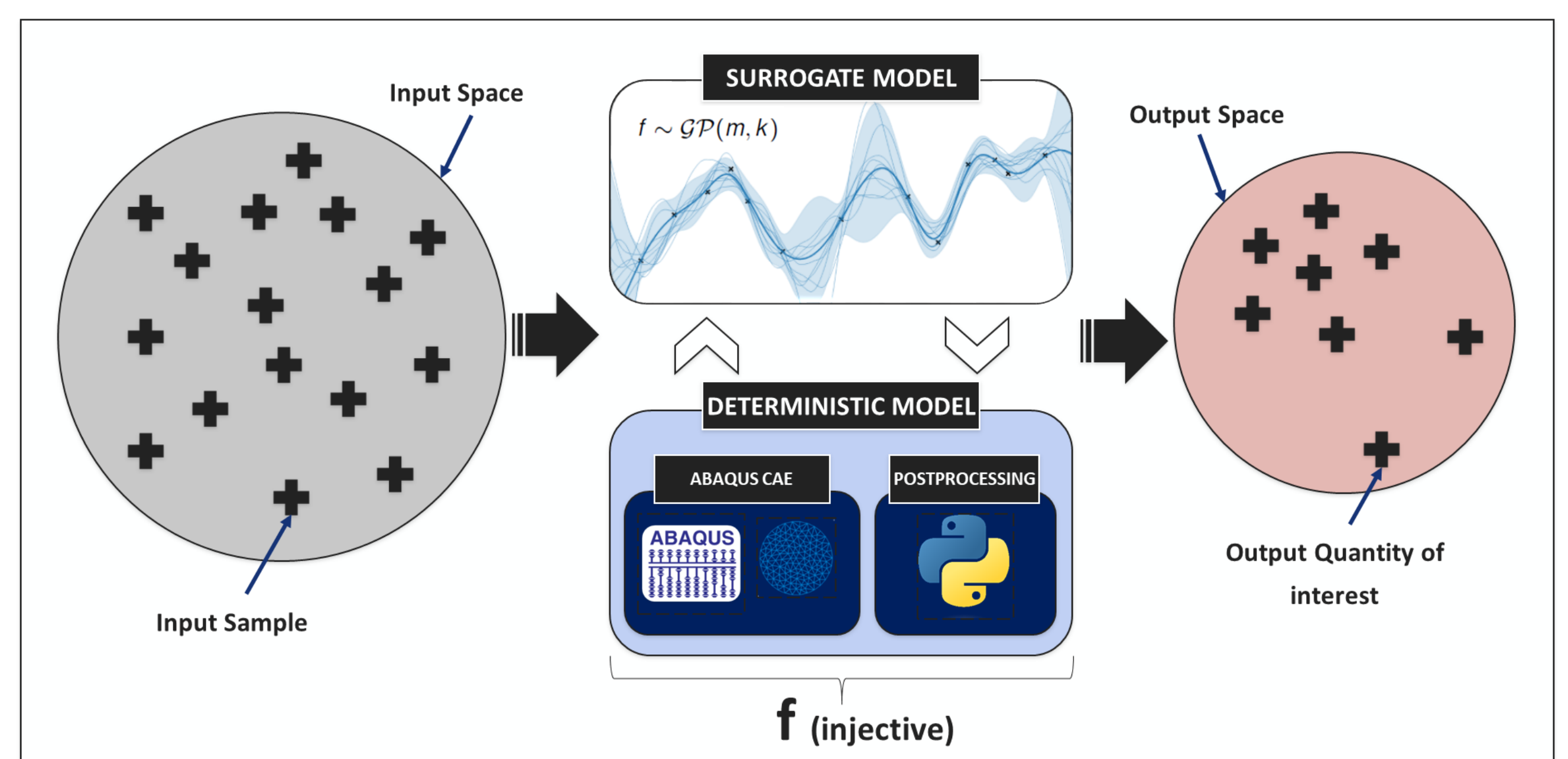


Figure 4: Building a surrogate model [4] of the 3D FE model below by using Gaussian Process [5]

Perspectives

By leveraging the **surrogate model** provided, surface settlement predictions can be expedited compared to using the numerical model alone. This **accelerated prediction capability** enables the theoretical estimation of surface settlement for a given set of TBM driving parameters. By formulating an **optimization problem**, it becomes possible to identify the **optimal TBM driving parameters that ensure surface settlement remains within a desired threshold**. This approach offers significant advantages in terms of time efficiency and the ability to proactively control and manage surface settlement during TBM operations.

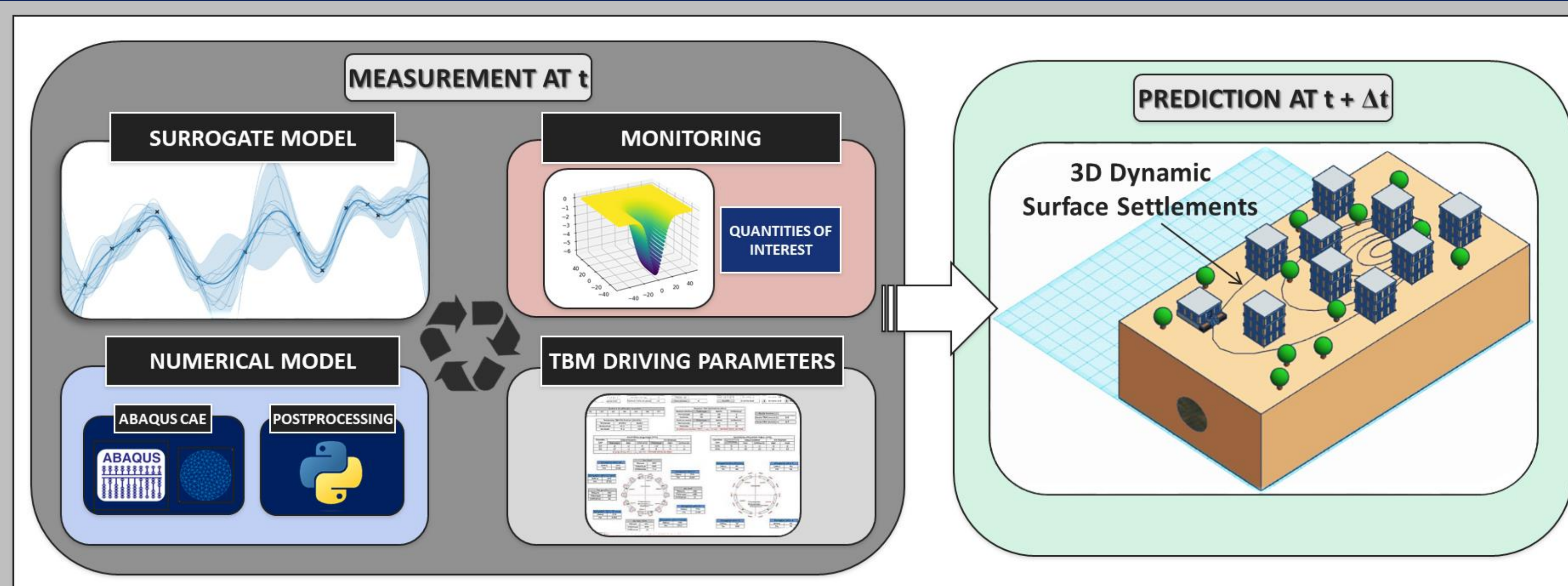


Figure 5 : Digital tool to predict dynamic settlements surface

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