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**Probabilistic transient FE digital twins applied
to landslide prediction**



I. OPENING REMARKS

Plasselb 1994 (FR)



Verschiez 2021 (VD)



Plasselb 2014 (FR)



Schwanden 2023 (GL)





I. OPENING REMARKS

Brienzen 2023 (GR)



Saas-Fee 2024 (VS)



Orsières 2023 (VS)



Blatten 2025 (VS)





I. OPENING REMARKS - The event

On Saturday, 30 January 2021, a landslide occurred in the municipality of Ollon, Switzerland.

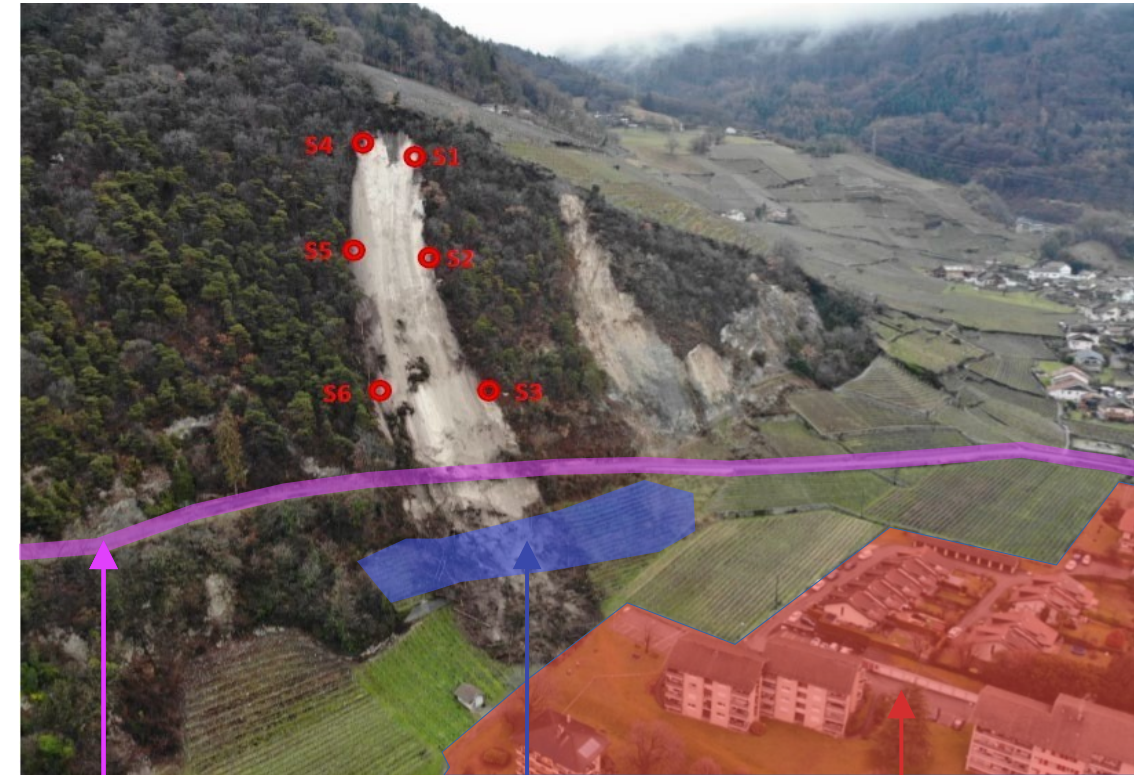
- 8,000 m³ of displaced volume
- No injuries were reported but the landslide came close to buildings
- Led to a several-moth closure of the road

The authorities commissioned the Yverdon School of Engineering to carry out in-situ sampling along the landslide scarp to determine the mechanical properties of the soil. On the six samples collected :

- Grain-size distribution + Permeability tests
- Water content and density + Atterberg limits
- Two series of drained triaxial tests

Goal of the probabilistic study

- Probabilistic model
- Numerical model
- Time-dependent uncertainty propagation



Road

Vineyards

Building area



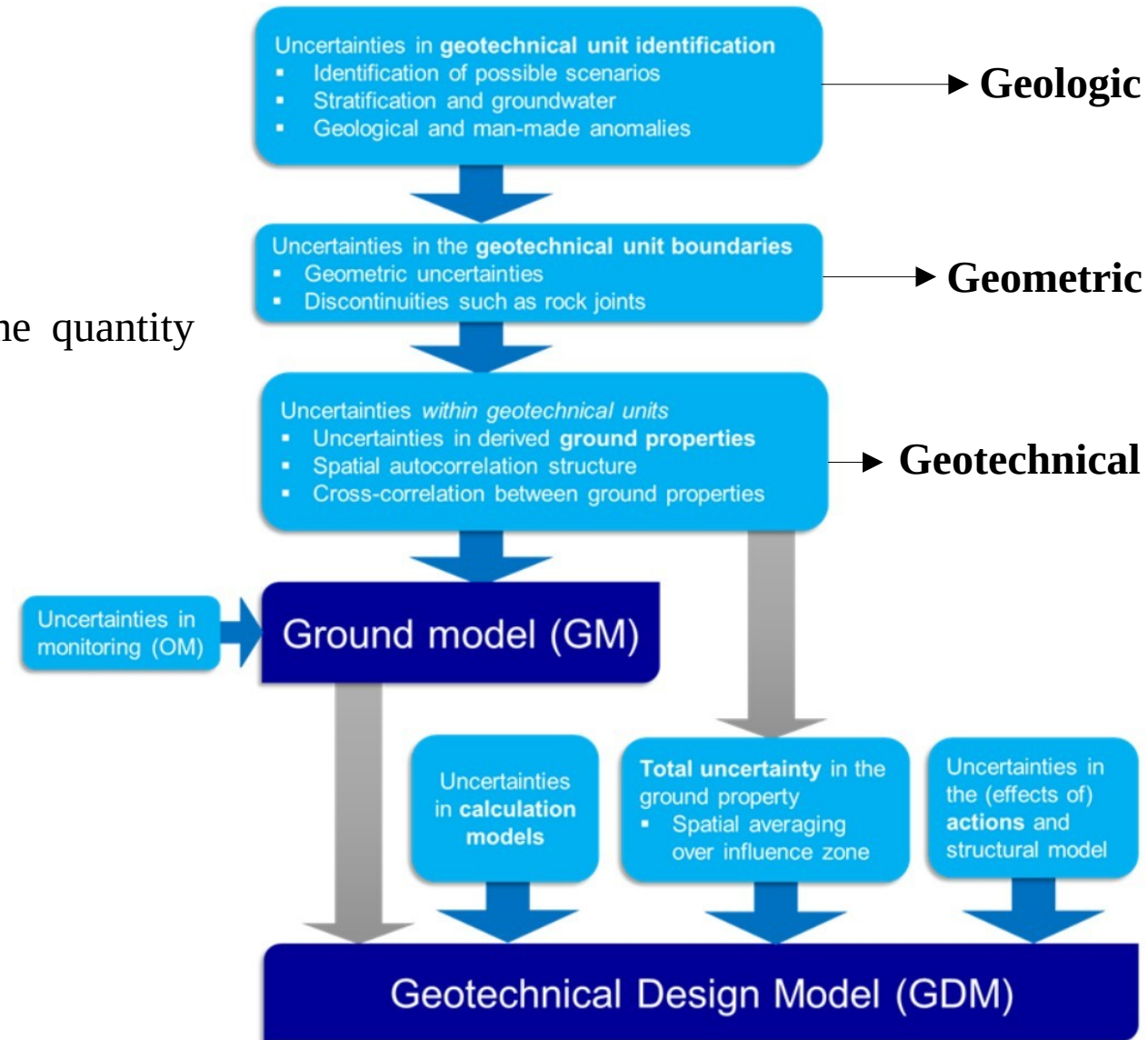
II. PROBABILISTIC MODEL - Introductory remarks

In civil engineering settings, the main sources of uncertainty are:

- **Inherent variability** : natural randomness of a quantity
- **Measurement error** : our tools to measure
- **Model uncertainty** : our predictions
- **Statistical uncertainty** : due to limited information of some quantity (e.g. number of observations or laboratory tests)

In a geotechnical context, EN 1997-1 distinguishes the Ground Model from the Geotechnical Design Model used for verification. The GM is directly and hierarchically influenced by the following sources of uncertainty :

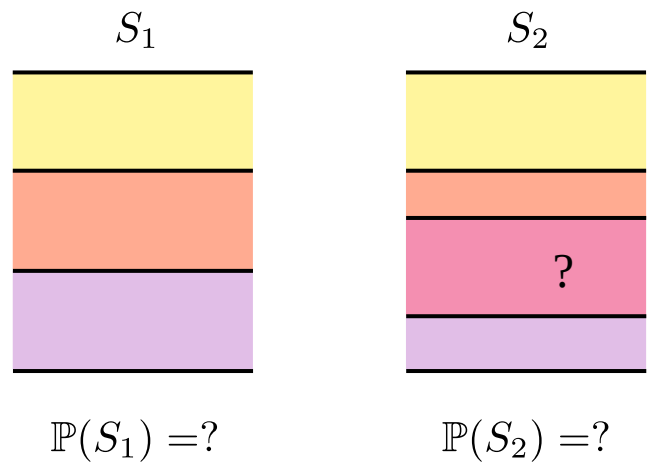
- **Geologic uncertainty**
- **Geometric uncertainty**
- **Geotechnical uncertainty**





Geologic uncertainty

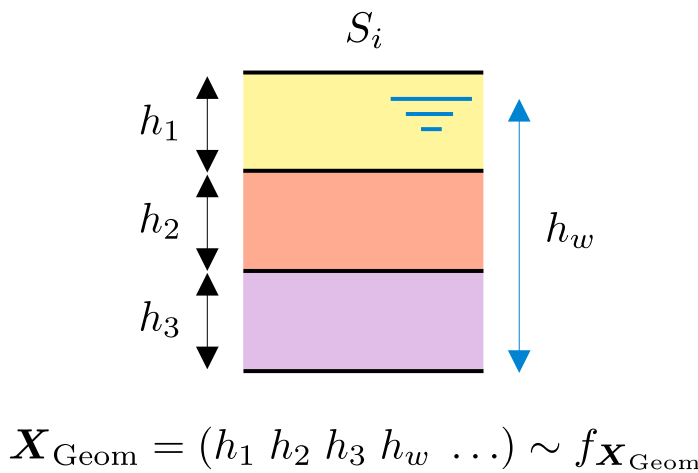
Identify the different scenarios and their associated probabilities of occurrence.



Model is dynamic

Geometric uncertainty

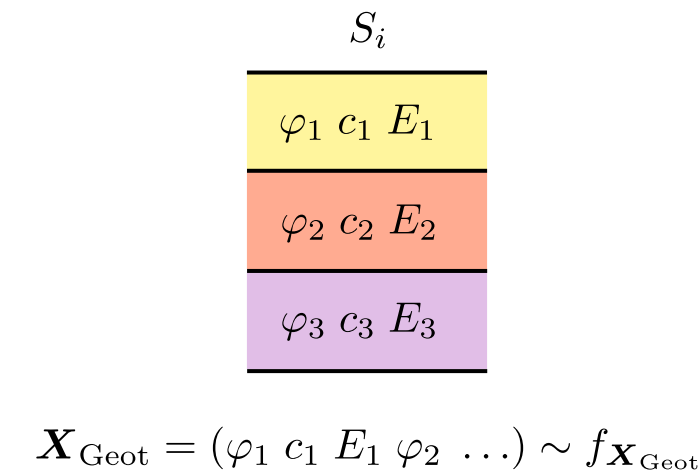
Given a scenario, identify the uncertainties related to its geometry.



Mesh and BC are dynamic

Geotechnical uncertainty

Given a (possibly) variable geometry identify the uncertainty of the soil properties in layers.



Material properties are dynamic

The earlier uncertainty quantification is introduced within the GM, the more complex its propagation becomes! This study covers only the Geotechnical uncertainty, so that the **two first ones** are imposed as **deterministic conditions**.



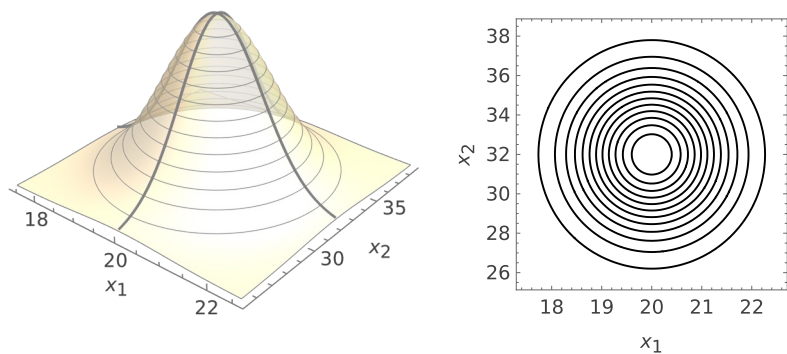
II. PROBABILISTIC MODEL - Uncertainty in ground properties

Formally, a random vector is a mapping $\mathbf{X} : \Omega \rightarrow \mathcal{D}_{\mathbf{x}} \subset \mathbb{R}^d$ from the sample space (all possible outcomes) to the state space. The object $\mathbf{X} = (X_1 \dots X_d)$ can be considered as a vector whose components are random variables with marginal cumulative distribution functions (CDF) $F_{X_1}, \dots, F_{X_d}$, where $F_{X_i} : \mathcal{D}_{x_i} \rightarrow [0, 1]$. The joint density of $\mathbf{X}$ can then be linked to the marginal densities by a so-called copula function $C : [0, 1]^d \rightarrow [0, 1]$ such that the joint CDF $F_{\mathbf{X}} : \mathcal{D}_{\mathbf{x}} \rightarrow [0, 1]$ reads

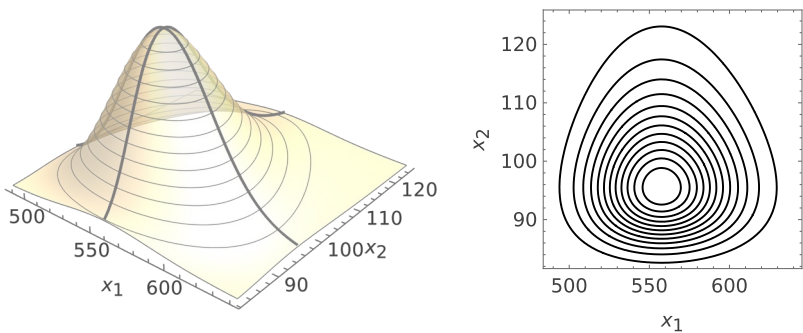
$$F_{\mathbf{X}} = C(F_{X_1}(x_1), \dots, F_{X_d}(x_d))$$

Each marginal $f_{X_i}(x_i; \theta)$ might be parametric and thus fully defined by two distribution parameters which are related to the mean and the standard deviation of a specific quantity.

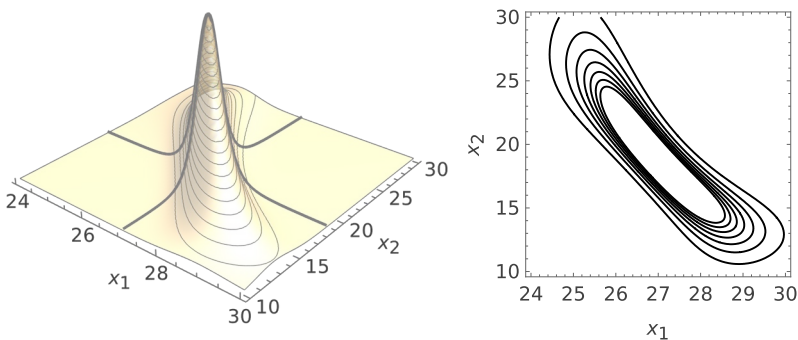
Friction angle vs self weight



Tensile strength vs a load



Friction angle vs cohesion





II. PROBABILISTIC MODEL - Uncertainty in ground properties

Let us assume that we want to fully characterize the uncertainty associated with the friction angle and cohesion of a compacted fine-grained alluvial soil taken from Di Matteo et al. (2013). The following elements need to be defined:

- 2x parametric distributions + 1x copula family + (1x random field distribution) → **8x (10x) Unknowns !**
- 4x distribution parameters + 1x copula parameter + (1x autocorrelation length)

$\mu_{X_1} = 26.9^\circ$

$\sigma_{X_1} = 1.3^\circ$

$\Rightarrow X_1 \sim \mathcal{LN}(\lambda_1, \zeta_1) = \mathcal{LN}(3.29, 0.05)$

$\mu_{X_2} = 19.7 \text{ kPa}$

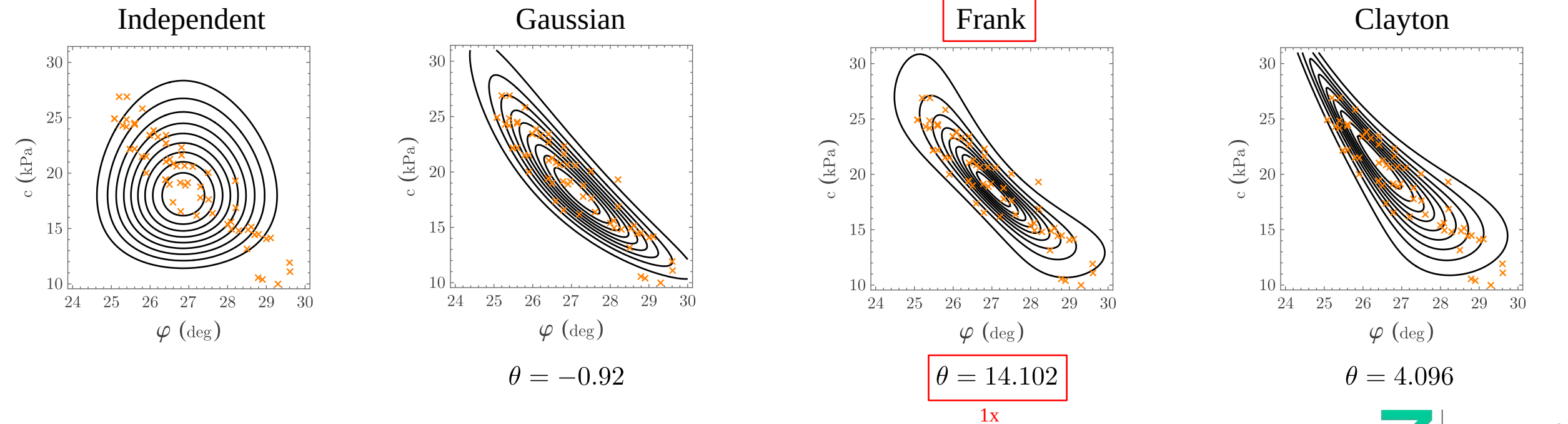
$\sigma_{X_2} = 4.9 \text{ kPa}$

$\Rightarrow X_2 \sim \mathcal{LN}(\lambda_2, \zeta_2) = \mathcal{LN}(2.95, 0.25)$

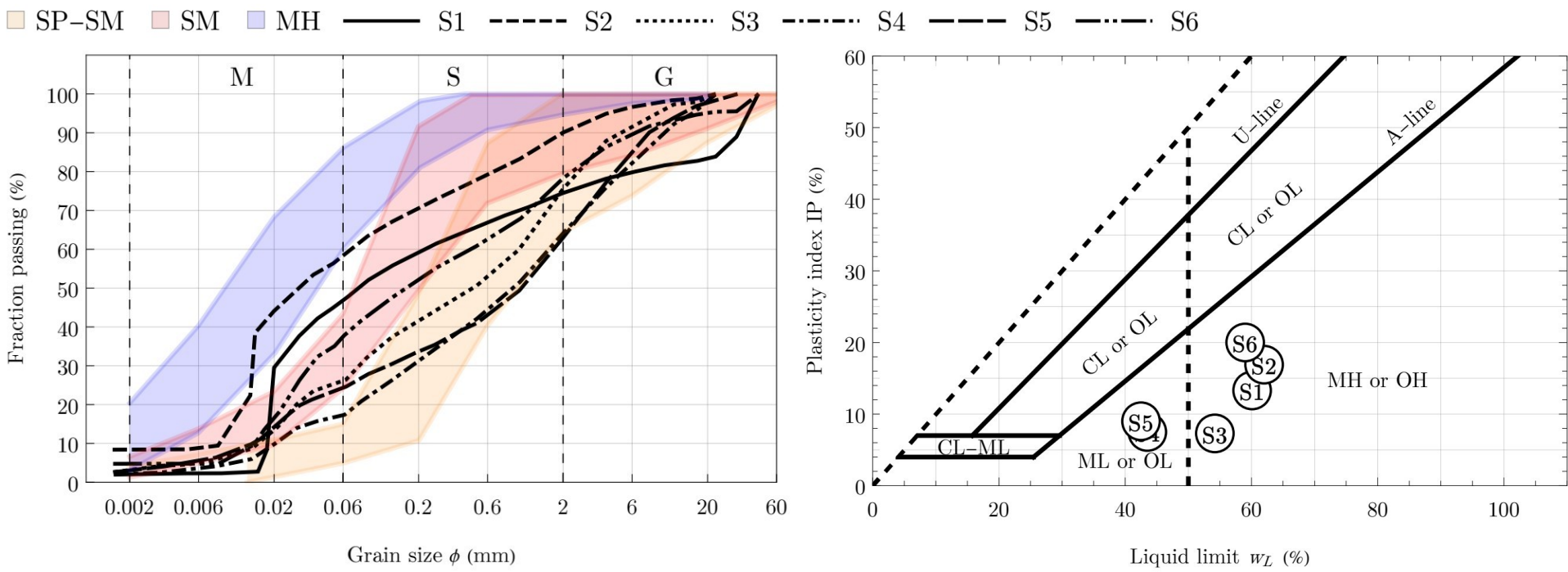
2x

2x

2x



Parameter	Symbol	Unit	S1	S2	S3	S4	S5	S6
Water content	w	%	1.7	8.8	11.1	6.5	4.8	7.0
Liquid limit	w_L	%	60.1	62.0	54.2	43.5	42.5	59.0
Plastic limit	w_P	%	46.9	45.1	46.9	35.9	33.5	39.0
Initial void ratio	e_0	%	52.0		52.4		62.9	
Permeability	k	$\text{m s}^{-1} \times 10^{-7}$	1.80		2.08		2.71	
Unit weight	γ	kN m^{-3}	12.0		12.6		15.0	
Friction angle	φ	deg			30.4		31.7	
Dilatancy angle	ψ	deg						
Cohesion	c	kPa			6.6		9.7	

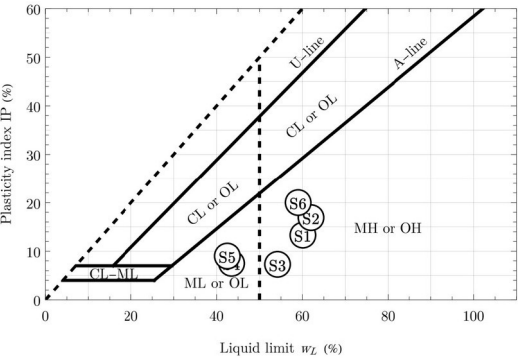
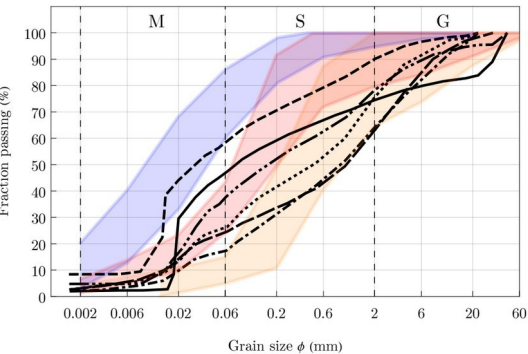


Silty sands (SM or SP-SM)



II. PROBABILISTIC MODEL - The prior distribution

Basic laboratory tests



Scientific and/or normative content

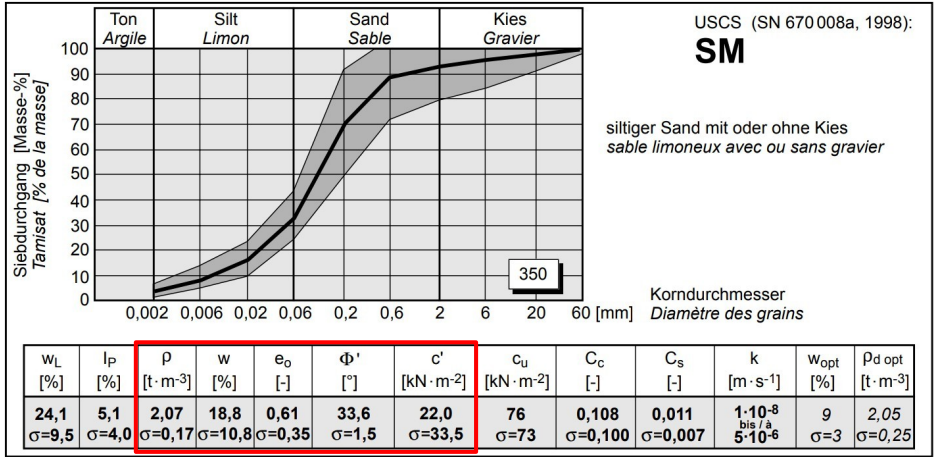


Table A.2 (NDP) — Indicative values of coefficient of variation for different ground properties

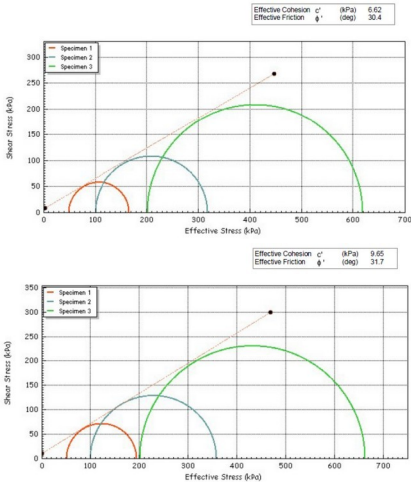
Soil / Rock Type	Ground property	Symbol	Coefficient of variation Vx (%)
All soils and rocks	Weight density	γ	5-10
Fine-grained soils	Shear strength in total stress analysis	c _u	30-50
All soils and rocks	Peak or residual effective cohesion	c' _p c' _r	30-50
All soils and rocks	Angle of friction	φ	5-15
All soils and rocks	Shear strength at failure	τ _f	15-25

Prior distribution

Parameter	Symbol	Unit	f' _{X_i}	μ' _{X_i}	σ' _{X_i}
Unit weight	γ	kN m ⁻³	$\mathcal{LN}$	13.2	0.66
Water content	w	%	$\mathcal{LN}$	18.8	10.8
Initial void ratio	e ₀	%	$\mathcal{LN}$	61.0	35.0
Friction angle	φ	deg	$\mathcal{LN}$	33.6	1.50
Cohesion	c	kPa	$\mathcal{LN}$	22.0	33.5
Unit weight	σ _γ		$\mathcal{U}$	11.3	6.55
Water content	σ _w		$\mathcal{U}$	0.22	0.13
Initial void ratio	σ _{e₀}		$\mathcal{U}$	1.61	0.93
Friction angle	σ _φ		$\mathcal{U}$	4.10	2.02
Cohesion	σ _c		$\mathcal{U}$	21.6	12.5



Advanced laboratory tests



Bayesian inverse analysis

$$f''_{\mathbf{X}}(\mathbf{x}) = a \mathcal{L}(\mathbf{x}) f'_{\mathbf{X}}(\mathbf{x}),$$

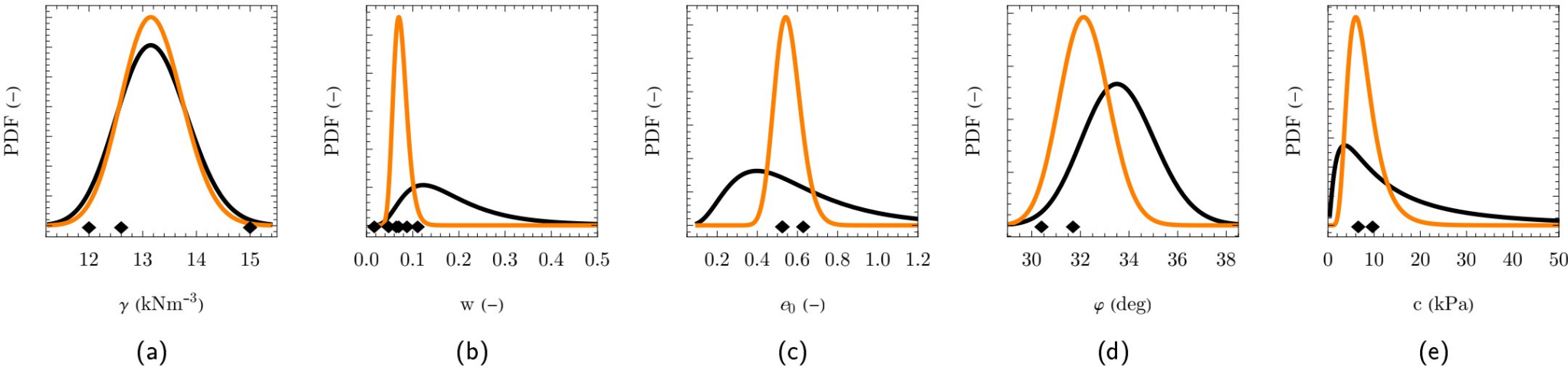
Posterior ← Likelihood ← Prior

$$\mathcal{L}(\mathbf{x}_{\text{aug}}; \mathcal{Z}) = \prod_i \prod_j \mathcal{N}(z_i^{(j)} | x_i, \sigma_i^2)$$

Posterior distribution

Parameter	Symbol	Unit	f''_{X_i}	μ''_{X_i}	σ''_{X_i}
Unit weight	γ	kN m ⁻³	$\mathcal{LN}$	13.2	0.57
Water content	w	%	$\mathcal{LN}$	7.45	1.54
Initial void ratio	e_0	%	$\mathcal{LN}$	55.3	6.51
Friction angle	φ	deg	$\mathcal{LN}$	32.2	1.02
Cohesion	c	kPa	$\mathcal{LN}$	7.88	3.49
Dilatancy angle ^(a)	ψ	deg	$\mathcal{E}$	1.25	1.25

^(a) Not part of the inverse analysis.



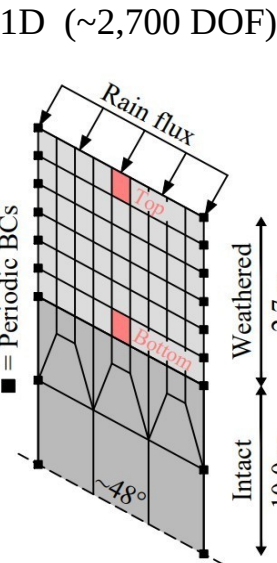
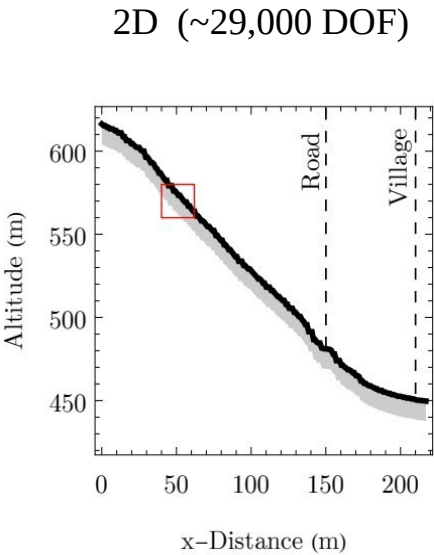
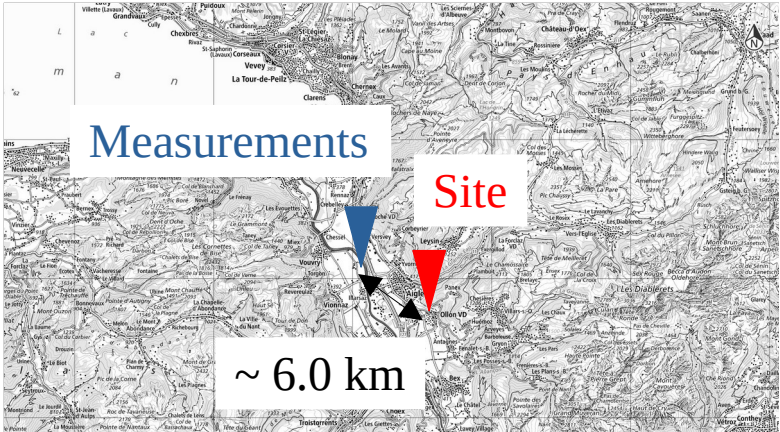


III. NUMERICAL MODEL - Equilibrium and boundary conditions

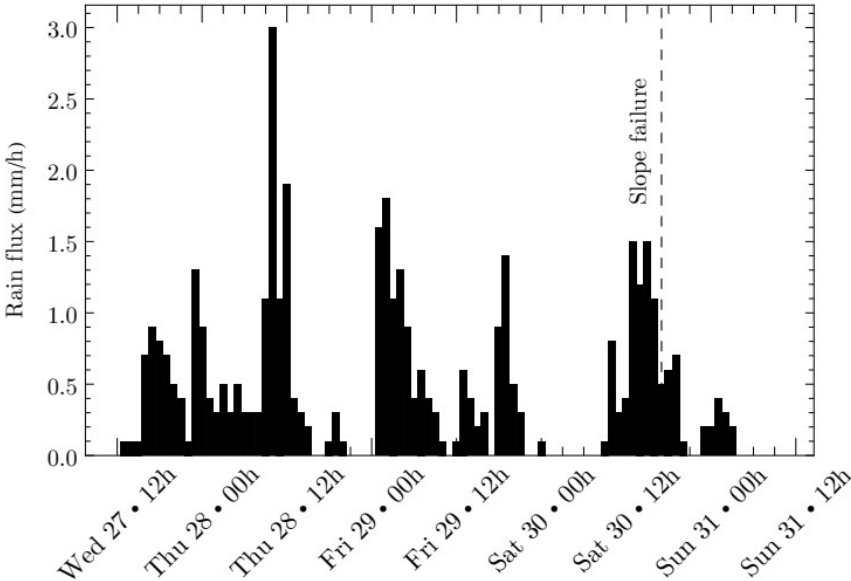
- Two hydro-mechanically coupled models 2D and 1D:
- Weathered gypsum (Mohr-Coulomb) over intact gypsum (elastic),
- Partially saturated (Biot + Van Genuchten).
- Hourly MeteoSwiss rainfall as surface flux over 97-hour window, observed failure at $t = 78$ h.

Thus the formal output

$$\mathcal{M}_{\text{FE}} : (t, \mathbf{x}) \in (\mathcal{D}_t \times \mathcal{D}_x) \subset \mathbb{R}^{d+1} \mapsto \text{SF} = \mathcal{M}_{\text{FE}}(t, \mathbf{x}) \in \mathbb{R}$$



$$\begin{cases} \nabla \cdot \boldsymbol{\sigma} + \mathbf{f} = 0 \\ \boldsymbol{\sigma} = \boldsymbol{\sigma}' + \tilde{\alpha} p_w \boldsymbol{\delta} \\ c \dot{p}_w = \tilde{\alpha} \dot{\epsilon}_v + \nabla \cdot \mathbf{q} \\ \mathbf{q} = -\frac{k}{\gamma_w} (\nabla p_w + \gamma_w \nabla z) \end{cases}$$



In a probabilistic context, the safety factor is converted to a time-dependent probability of failure which reads

$$P_f(t) = \int \cdots \int_{\mathcal{D}_f} f_{\mathbf{X}}(\mathbf{x}) \, d\mathbf{x} \quad \text{where} \quad \mathcal{D}_f = \{\mathbf{x} \in \mathcal{D}_{\mathbf{x}} \mid \text{SF}(t) < 1.0\}$$

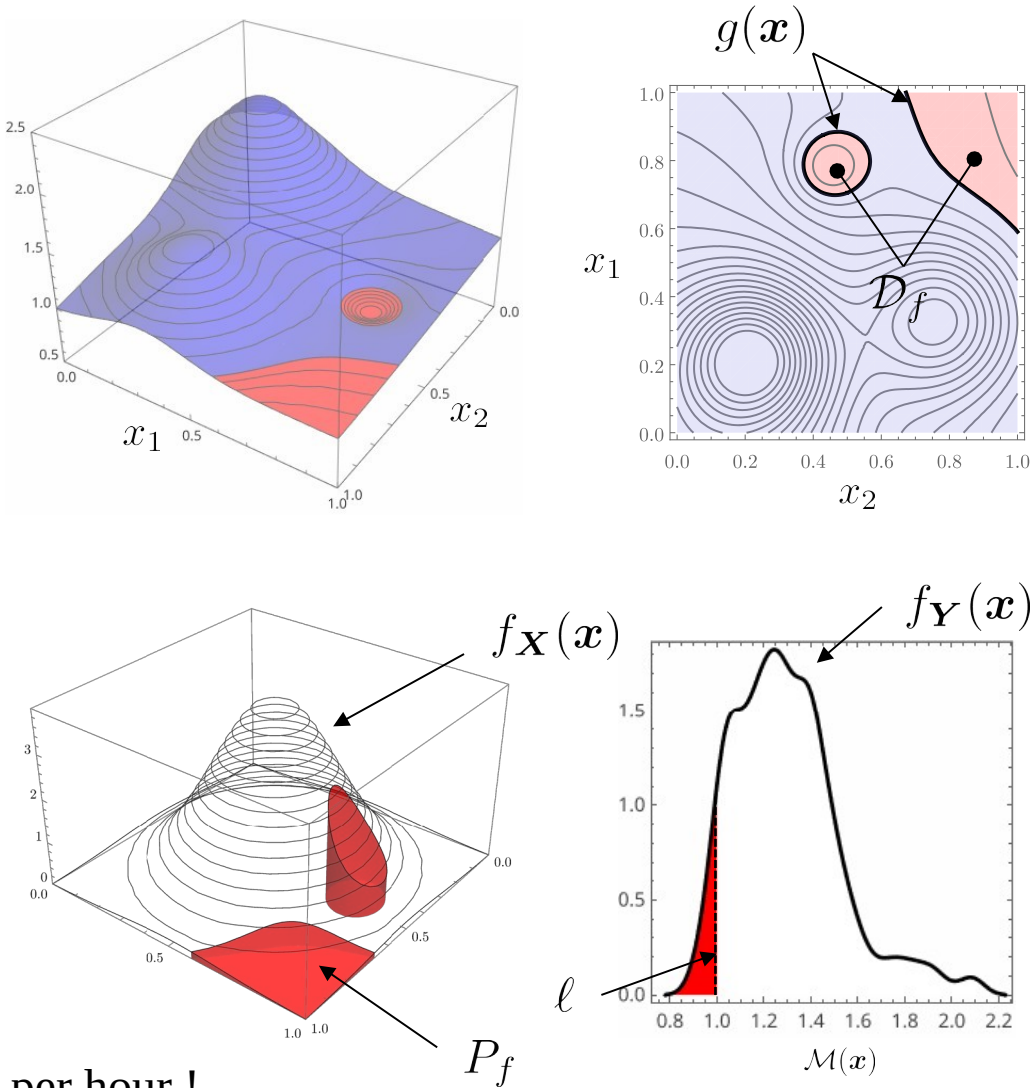
Thus, the time-dependency comes from the evolution of the failure domain. Calculation of the probability is often (always) performed via Monte-Carlo simulation which is too computationally intensive to be directly driven on FE models. So-called *surrogate models* may be used to reduce the computational burden such as a PCK (Gaussian process)

$$\widetilde{\mathcal{M}}(\mathbf{X}) = \sum_{k=1}^p \alpha_k \Psi_k(\mathbf{X}) + \sigma^2 Z.$$

which was trained with *at least* $n = 400$ FE realizations of the 1D model.

To finally account for time dependence, we discretise the time at hourly intervals so that the final model for uncertainty propagation reads

$$\mathcal{M} : \mathbf{x} \in \mathcal{D}_{\mathbf{x}} \subset \mathbb{R}^d \mapsto \mathbf{SF} = \widetilde{\mathcal{M}}(\mathbf{x}) \in \mathbb{R}^{97}. \quad \longrightarrow \text{One stability analysis per hour !}$$

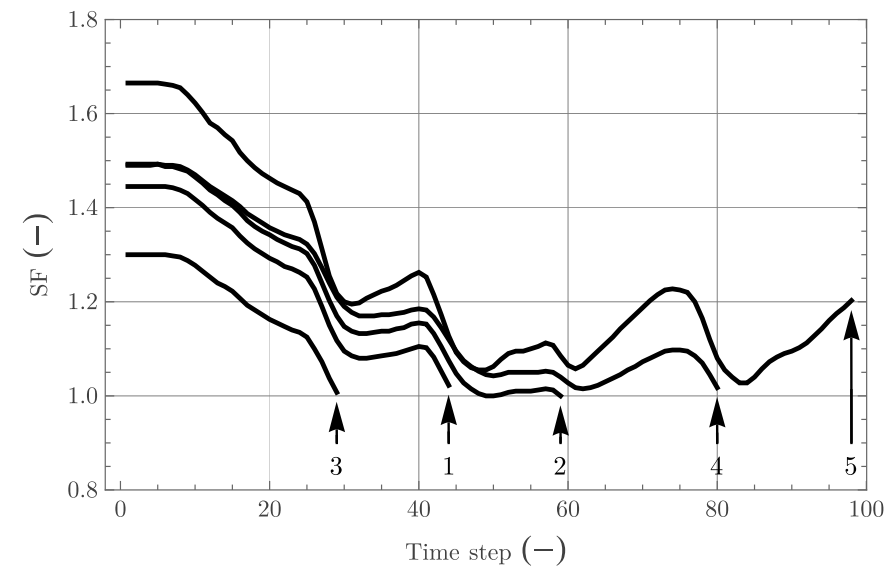




III. NUMERICAL MODEL - Experimental design strategy

Let us draw five samples according to the distribution of the input random vector and evaluate them through ZSoil simulations.

$$\begin{aligned}
 \mathbf{x}^{(i)} \sim f_{\mathbf{X}}(\mathbf{x}) \rightarrow & \begin{matrix} & \gamma & w & e_0 & \varphi & c & \psi \\ 1 & \left(\begin{matrix} 13.15 & 0.11 & 0.54 & 31.80 & 6.38 & 1.55 \\ 2 & 12.34 & 0.10 & 0.55 & 31.43 & 6.47 & 3.90 \\ 3 & 13.53 & 0.06 & 0.60 & 32.68 & 4.29 & 1.98 \\ 4 & 13.15 & 0.08 & 0.62 & 31.97 & 8.19 & 0.48 \\ 5 & 12.72 & 0.07 & 0.37 & 31.25 & 9.93 & 0.50 \end{matrix} \right) \end{matrix} \\
 & \rightarrow \mathcal{M}_{\text{FE}}(\mathbf{x}^{(i)}) \rightarrow
 \end{aligned}$$



Two key observations:

- **no SF below 1.0** - the FE model cannot reach equilibrium in the failure domain
- **no results beyond first failure** - once $SF < 1.0$, the trajectory is censored for all subsequent time steps

Simple solutions taken here:

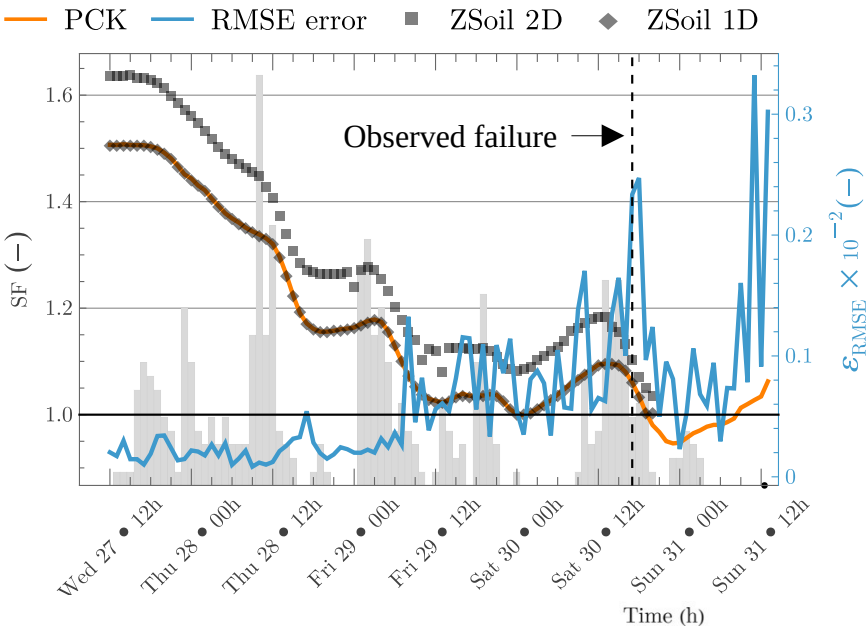
- **Do while** - until every time step is filled with at least 400 training points.
- **Extrapolate** - the PCK trend beyond $SF = 1.0$: assuming the ED is dense enough near the limit-state surface, the extrapolation stays short-range, and only the sign of the prediction matters for P_f .



IV. RESULTS - Deterministic calculations

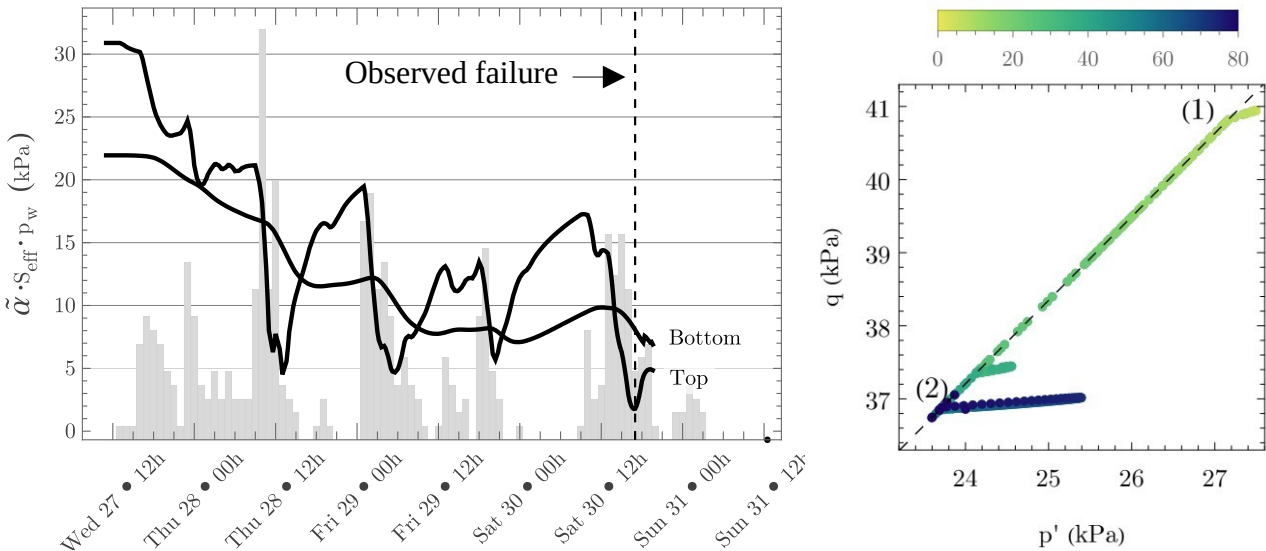
We first consider deterministic calculations with mean values. Among the results, we make the following observations :

- Both the 2D and 1D models exhibit the same behavior and diverge at the same time step ($t \sim 80\text{h}$).
- A difference of about 2h between the **observed** and the **predicted** failure.
- Fair approximation between the mean prediction of the GP and the 1D FE model.
- The precision of the surrogate model, described by the relative mean square error, decreases over time.



The simulations reveal the following failure mechanism:

- **Hydraulically driven failure** - rainfall infiltration erases $\sim 80\%$ of the initial suction in the weathered layer, with no additional mechanical loading
- **Classical wetting stress path** - p' decreases at nearly constant q until the Mohr-Coulomb envelope is reached

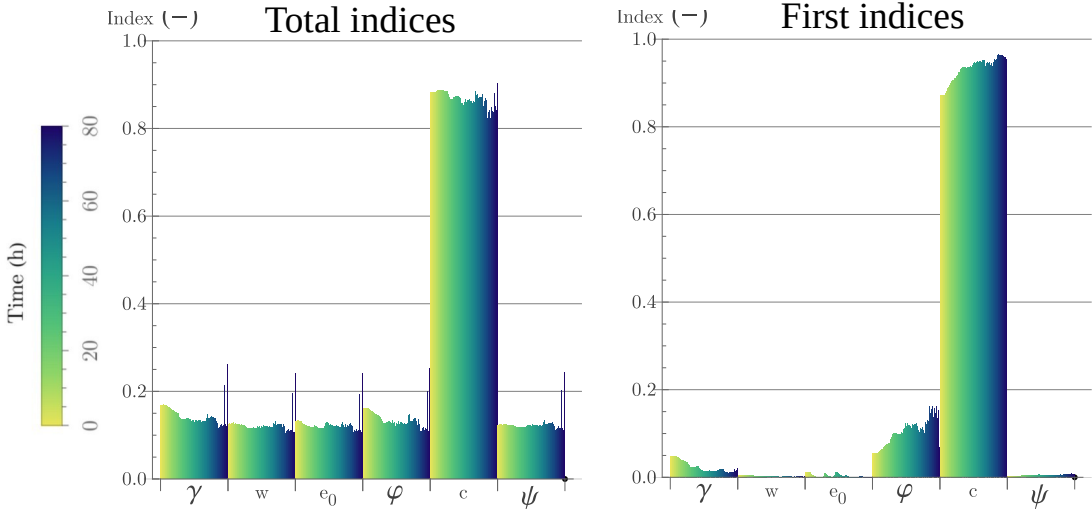
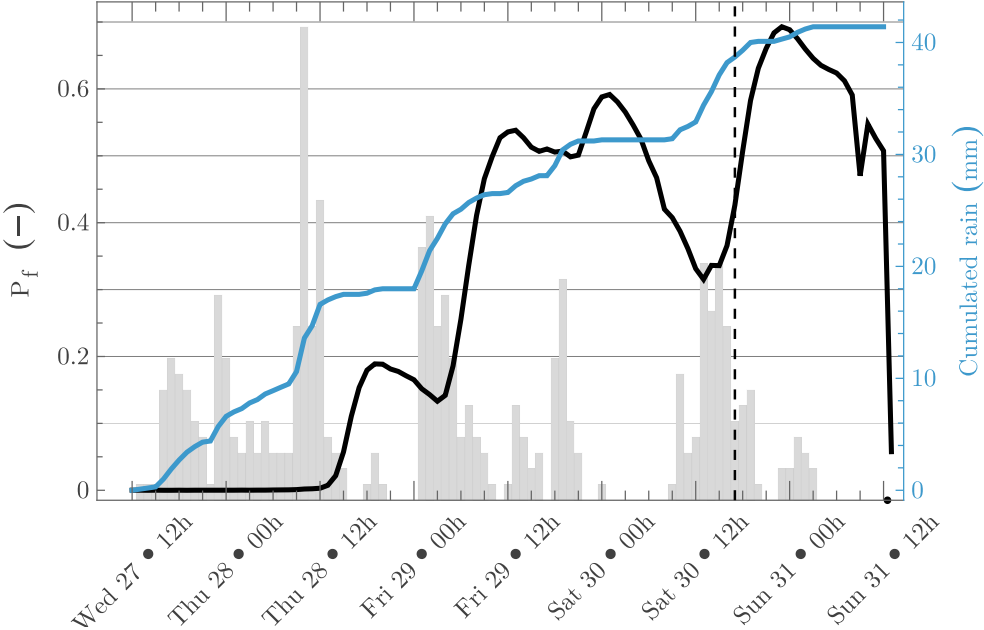




IV. RESULTS - Probabilistic calculations

The probabilistic digital twin delivers time-resolved reliability metrics that can be confronted with target values :

- No dedicated reliability threshold for slopes above low-traffic roads. From EN 1990 (CC0–CC1) and Chowdhury & Flentje (2003), we adopt $P_f=10^{-2}$.
- Target crossed early and massively: 10^{-2} exceeded ~55 h before failure, peak $P_f \approx 0.69$. **A precautionary closure was justified well before the event.**
- Cohesion drives the uncertainty (posterior CoV = 44%): high failure probability partly reflects parameter uncertainty. **Additional triaxial tests would refine the model.**



Promising:

- **Bayesian identification (literature priors + lab data):** transferable when site investigation is limited.
- **From measured to forecast rainfall:** MeteoSwiss nowcasting + 6-hour windows → operational early warning.
- **While-ED strategy:** ≥ 400 training points at every time step, low validation error throughout."

To be extended:

- **Hydraulic variables (k , α):** lab characterization + UQ needed. Suitable priors remain an open question.
- **Towards time-dependent surrogates:** NARX models predict SF(t) from its past values and the rain input — capturing what 97 independent PCKs ignore.



VI. BIBLIOGRAPHY

- Di Matteo, L., Valigi, D., Ricco, R., 2013. Laboratory shear strength parameters of cohesive soils: variability and potential effects on slope stability. *Bull Eng Geol Environ* 72, 101–106. <https://doi.org/10.1007/s10064-013-0459-6>
- EN 1990, 2023. Eurocode. Basis of structural and geotechnical design. British Standards Institution, London.
- Chowdhury, R., Flentje, P., 2003. Role of slope reliability analysis in landslide risk management. *Bull Eng Geol Environ* 62, 41–46. <https://doi.org/10.1007/s10064-002-0166-1>
- Van den Eijnden, B., Knuuti, M., Lesny, K., Löfman, M., Mavritsakis, A., Roubos, A., Schweckendiek, T., Sciarretta, F., Ebener, A., Escher, K., Spross, J., Commend, S., Hehenkamp, M., Arnold, P., Wilhelm, S., Ene, A., Rimoldi, P., Pereira, R., European Commission (Eds.), 2024. Reliability-based verification of limit states for geotechnical structures: guidelines for the application of the 2nd generation of Eurocode 7: geotechnical design. Publications Office, Luxembourg. <https://doi.org/10.2760/1342542>
- Schöbi, R., Sudret, B., 2014. PC-Kriging: a new metamodeling method combining Polynomial Chaos Expansions and Kriging, in: *Proc. 2nd Int. Symposium on Uncertainty Quantification and Stochastic Modeling*, Rouen, France.
- Kucherenko, S., Tarantola, S., Annoni, P., 2012. Estimation of global sensitivity indices for models with dependent variables. *Computer Physics Communications* 183, 937–946. <https://doi.org/10.1016/j.cpc.2011.12.020>