

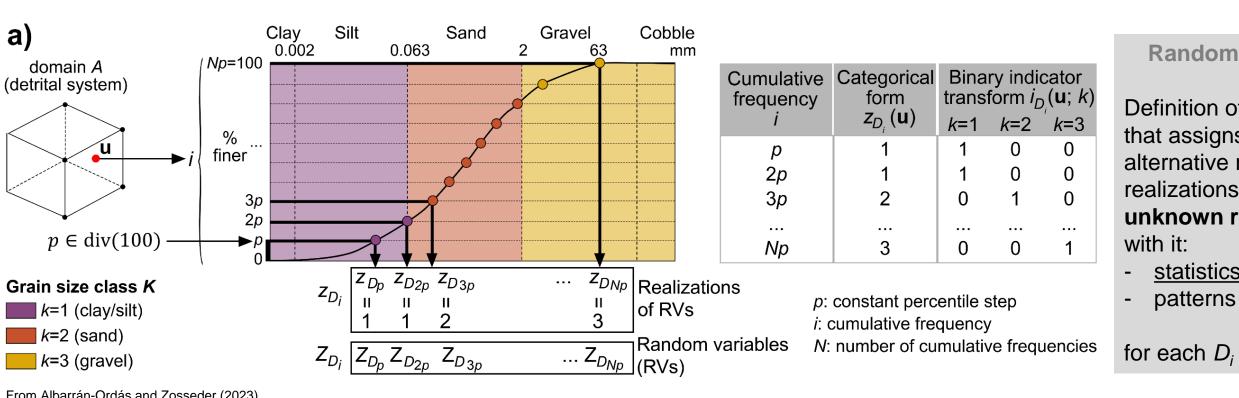
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## 3-D stochastic geological modelling of the sediment texture in detrital systems: prediction of fictive grain size distributions and uncertainty quantification

### INTRODUCTION

#### Geological 3-D modelling of the grain size distribution (GSD): the D<sub>i</sub> models method

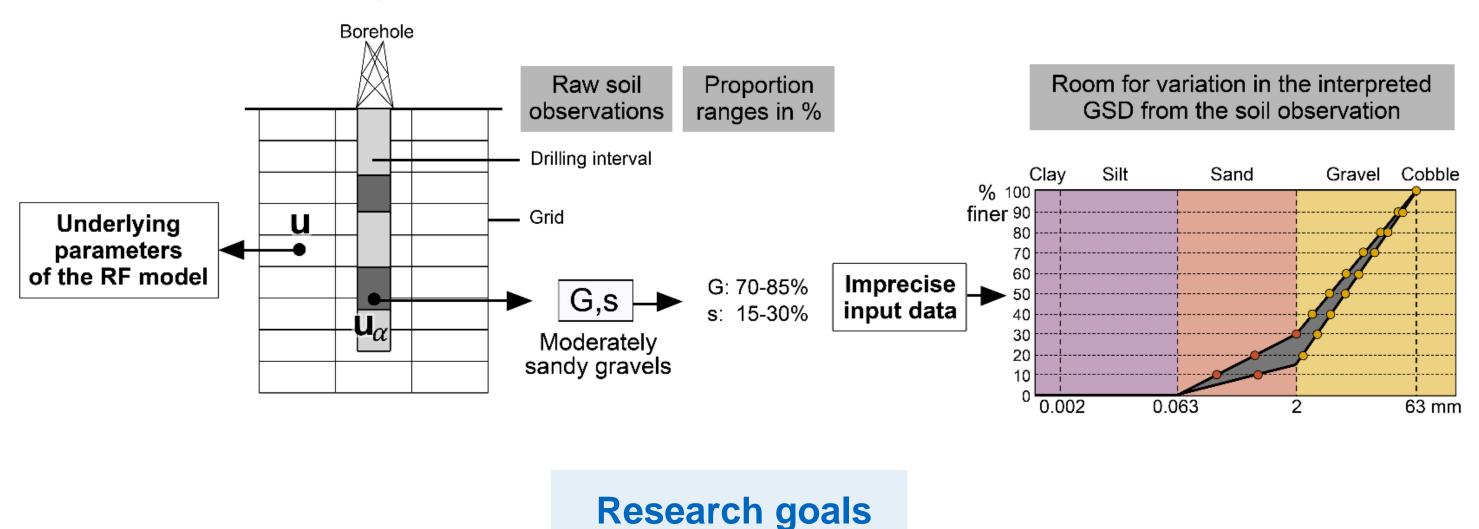
The D<sub>i</sub> models method mimics the GSD characterization at each cumulative frequency in the random function space



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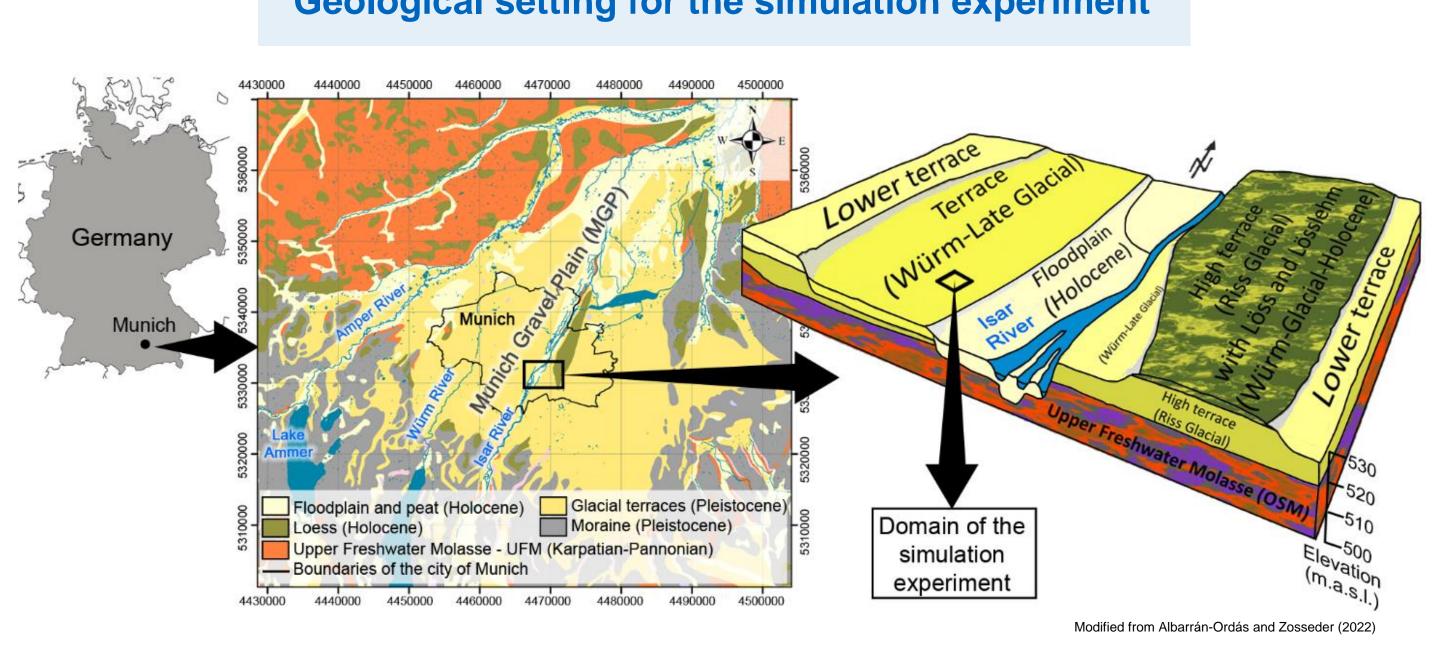
#### Uncertainties in the context of the D<sub>i</sub> models method

• Uncertainties are linked to the developed **Random Function (RF) model**: RVs, (non)-stationarity decisions • Imprecise input data: direct soil observations from drilled materials described in the field are subjected to natural geological variability and systematic imprecisions associated with the inherent generalizations of the standards used and to the subjectivity of on-site personnel



#### 1. Adapting the framework of the $D_i$ models method to integrate uncertainties from imprecise input data

- 2. Developing uncertainty quantification (UQ) measures linked to: a) each D<sub>i</sub>, and b) the whole mixture of clasts
- **3**. Evaluating the ability of the UQ measures **with different RF models**
- 4. Exploring the **uncertainty propagation and impacts** of the adaptation of the geostatistical framework



#### **Geological setting for the simulation experiment**

REFERENCES

ACKNOWLEDGEMENTS

• Albarrán-Ordás, A., Zosseder, K (2022). The Di models method: geological 3-D modeling of detrital systems consisting of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling of varying grain fractions to predict the relative lithological 3-D modeling areas • Albarrán-Ordás, A., Zosseder, K (2023). Uncertainties in 3-D stochastic geological modeling of fictive grain size distributions in detrital systems [Manuscript submitted for publication]

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## MATERIAL AND METHODS

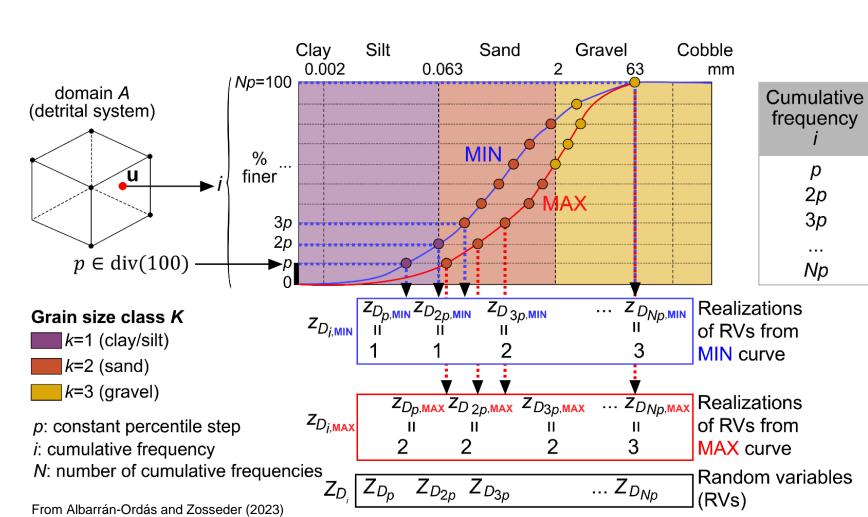


**Random Function Space** 

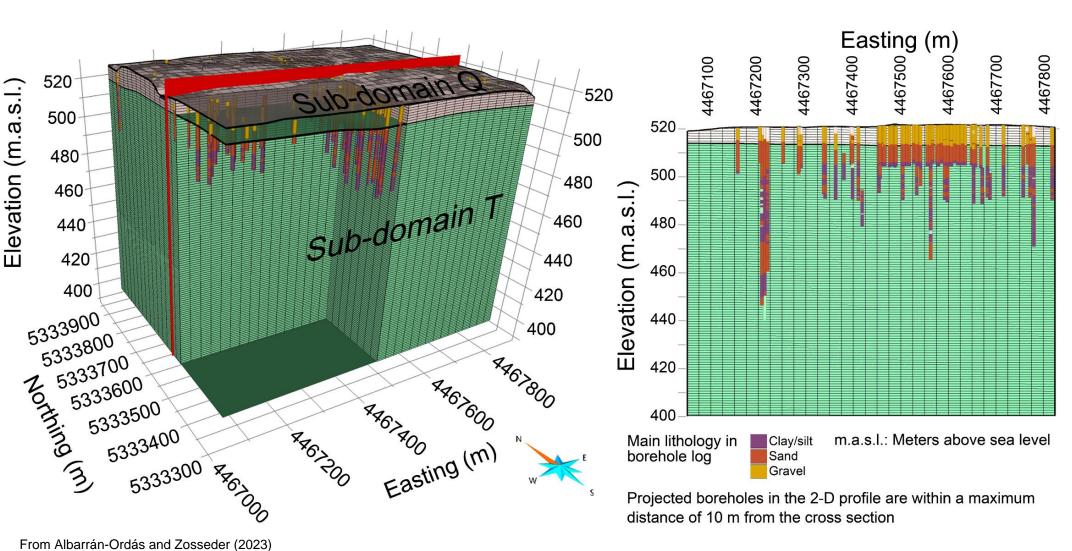
Definition of a **rule for each D**<sub>i</sub> that assigns a collection of native realities (set of realizations) that replaces the unknown reality and shares statistics and

patterns of spatial continuity

#### Adapting the geostatistical framework of the D<sub>i</sub> models method to integrate uncertainties from imprecise input data



#### Simulation experiment: domain and conceptual model



#### Simulation experiment: setups with (non)-stationarity assumptions

Setup	Domain	Indicator kriging algorithm	3-D trend model	Adapted geo-modeling framework
1	Entire	Stationary SK	No	Yes
2	Q and T	Stationary SK	No	Yes
3	Q and T	Non-stationary SK (LVM)	Yes, highly overfit	Yes
4	Q and T	Non-stationary SK (LVM)	Yes, slightly overfit	Yes
5	Q and T	Non-stationary SK (LVM)	Yes, non-overfit	Yes
6	Q and T	Non-stationary SK (LVM)	Same as 5 but only MIN trends	No, finest-grained
7	Q and T	Non-stationary SK (LVM)	Same as 5 but only MAX trends	No, coarsest-grained

#### **Uncertainty quantification (UQ) measures**

• **Uncertainty for each D**<sub>i</sub> in terms of the entropy of the discrete distribution

 $H_{D_i}(\mathbf{u}) = -\sum_{k=1}^{K} p_{D_i}(\mathbf{u}; k) \ln[p_{D_i}(\mathbf{u}; k)]; \quad k = 1, ..., K; \ \mathbf{u} \in A$ 

• **Uncertainty about the whole sediment mixture** as a combined system formed by a collection of RVs:

$$H_{\text{mixture}}(\mathbf{u}) = H\left[Z_{D_{100}}(\mathbf{u}), Z_{D_{100-p}}(\mathbf{u}), \dots, Z_{D_p}(\mathbf{u})\right] = H\left[Z_{D_{100}}(\mathbf{u})\right] + H\left[Z_{D_{100-p}}(\mathbf{u})\right] + \dots + H\left[Z_{D_p}(\mathbf{u})\right]$$

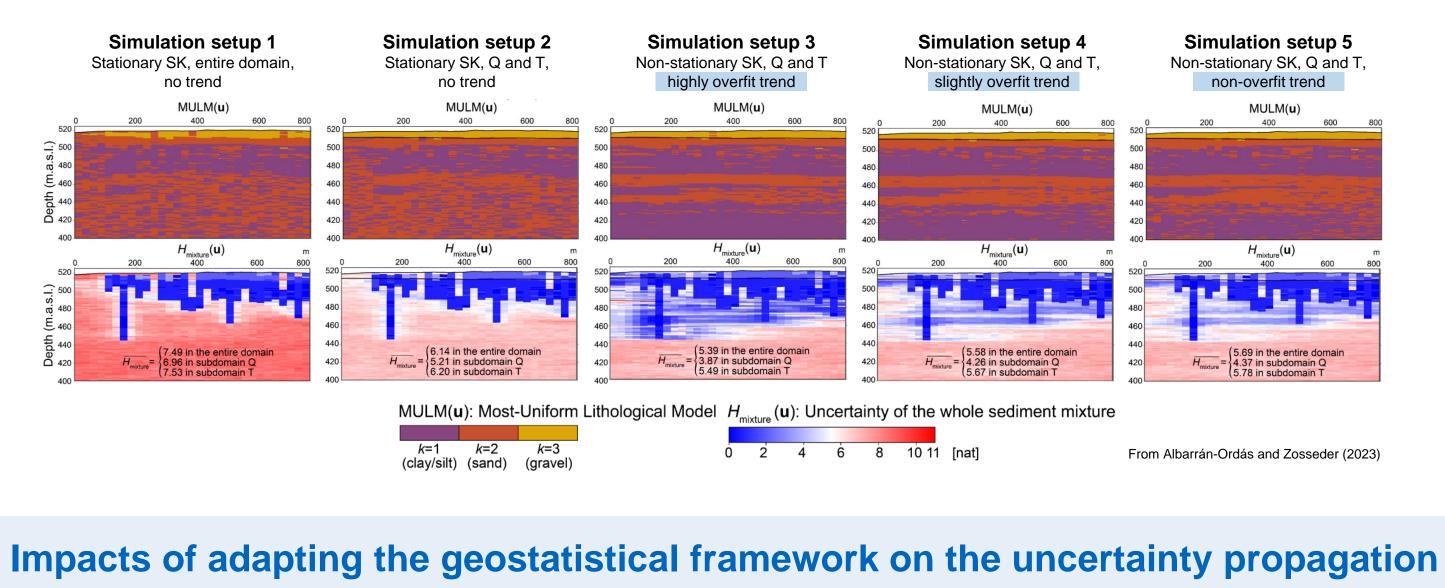
Cumulative frequency	form MIN	Binary indicator transform MIN <i>i</i> <sub>D<sub>j,MIN</sub>(<b>u</b>; k)</sub>			
I	$z_{D_{j,MIN}}(\mathbf{u})$	<i>k</i> =1	<i>k</i> =2	<i>k</i> =3	
р	1	1	0	0	
2р	1	1	0	0	
Зр	2	0	1	0	
Np	3	0	0	1	
ions	Categorical				
rom	form MAX	MAX i <sub>Dj,MAX</sub> (u; k)			
/e	$z_{D_{j,MAX}}(\mathbf{u})$	<i>k</i> =1	k=2	<i>k</i> =3	
	2	0	1	0	
ions	2	0	1	0	
rom	2	0	1	0	
ve					

- Dimensions: 765 x 580 x 133 m Cell size: 25 x 25 x 1 m • Input data: Direct soil observations from 416 boreholes Sub-domains: Q (Quaternary) T (Miocene, Tertiary)
- Grain size classes: k=1 k=2 k=3 (clay/silt) (sand) (gravel) Constant step in the GSD:
- p=10

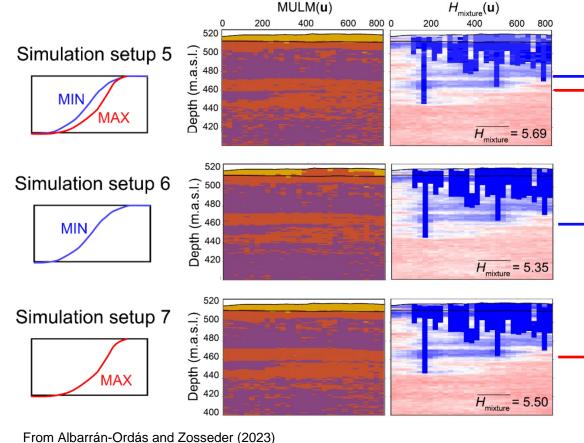
## **RESULTS AND CONCLUSIONS**

# Unsampled location u without correction ensuring

#### Uncertainty quantification (UQ) in the whole sediment mixture



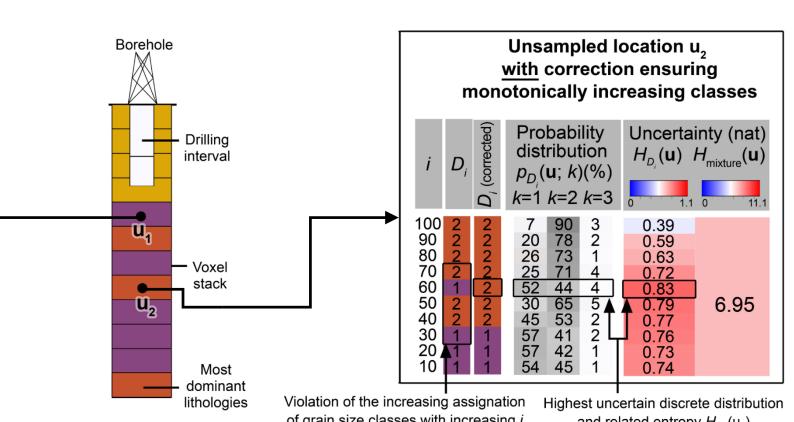
(represented by two extreme unique interpretations of the GSD: MIN, MAX)











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• UQ measures: useful for quantifying and comparing uncertainties, scalable with other conceptual models • Simulating the entire domain leads to a lack of representativeness of spatial statistics: poor estimation (setup 1) • Simulating the **sub-domains** (from setup 2) and including **3-D trends** (3, 4, 5) improve the estimation Trend overfitting leads to overestimation and unfair uncertainties (3, 4). Trend modeling/evaluation: key and critical

• More realistic uncertainty assessment by overcoming the bias caused by ignoring imprecise input data  $\Delta H_{\text{mixture}}$ : Differences of uncertainty -2 -1.5 -1 -0.5 0 0.5 1 1.5 2 [nat] Setup 5 reduces uncertainty with decreasing grain size Most prevailing lithologies after Setup 5 Setup 7 reduces uncertainty with increasing grain size k=2 k=3 Most prevailing lithologies after Setup 5 Conclusions Imprecisions in soil observations from boreholes are integrated into 3D geo-modelling Entropy-based measures quantify the uncertainty of the grain size range of the soil

• A more realistic uncertainty assessment is provided due to overcome potential bias • Better understanding of parameters of the random functions in the D<sub>i</sub> models method The uncertainty scheme supports the decision-making process for practical purposes