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Prise en compte d'incertitudes externes dans l'estimation de paramètres d'un modèle de transfert d'eau et de pesticides à l'échelle du bassin versant

Katarina Radišić¹²³

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²Univ. Grenoble-Alpes, Inria, CNRS, Grenoble-INP, LJK

³INRAE, RiverLy, Lyon-Villeurbanne

Context : Landscape management in the service of water quality

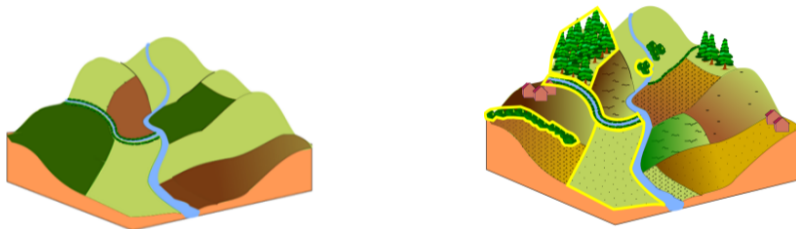


Figure: Landscape elements influence pesticide transfer dynamics,
image credit Rouzies et al. (2018) (hal-02608211)

Context : The PESHMELBA model

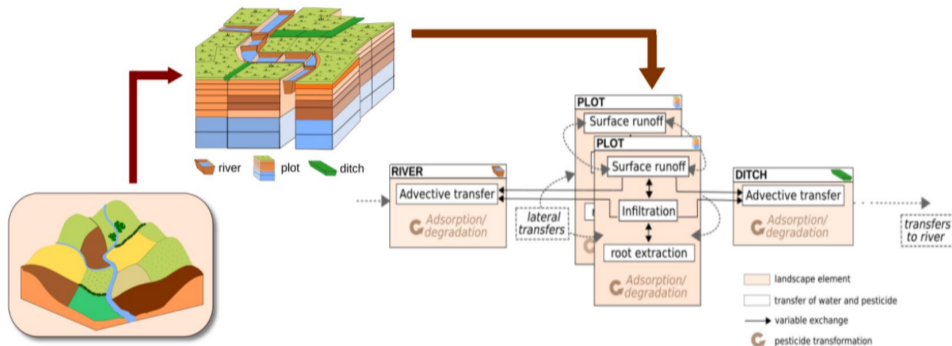


Figure: The catchment of assembled parcels, their vertical decomposition, and the main processes of water and pesticide transfer in PESHMELBA, (Rouzies et al., 2019) doi : 10.1016/j.scitotenv.2019.03.060, image credit E. Rouzies

Context : The PESHMELBA model

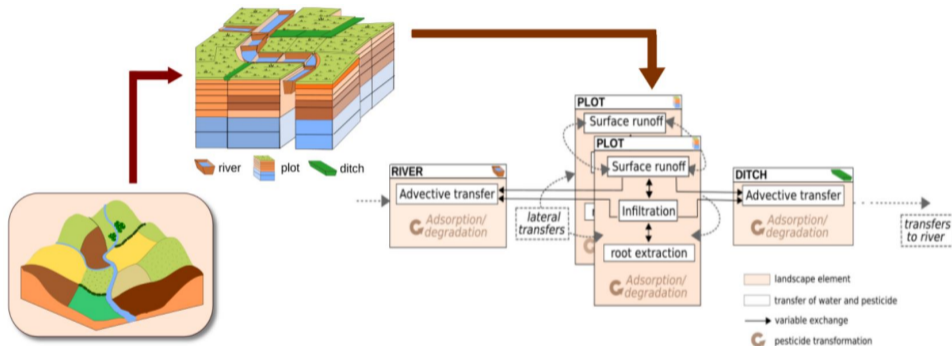


Figure: The catchment of assembled parcels, their vertical decomposition, and the main processes of water and pesticide transfer in PESHMELBA, (Rouzies et al., 2019) doi : 10.1016/j.scitotenv.2019.03.060, image credit E. Rouzies

Complex model with many parameters -> needs to be calibrated.



Table of contents

Introduction

Methods

Case study

Results

Conclusion



Table of contents

Introduction

Methods

Case study

Results

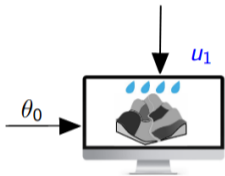
Conclusion



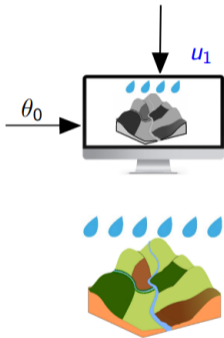
Introduction: From classical to robust calibration



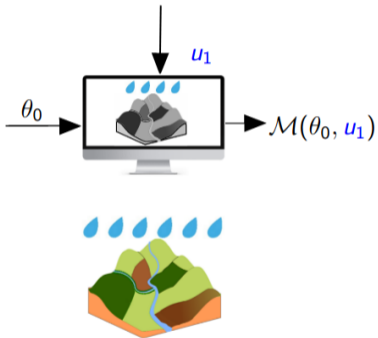
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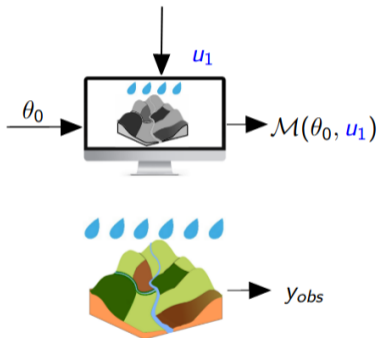
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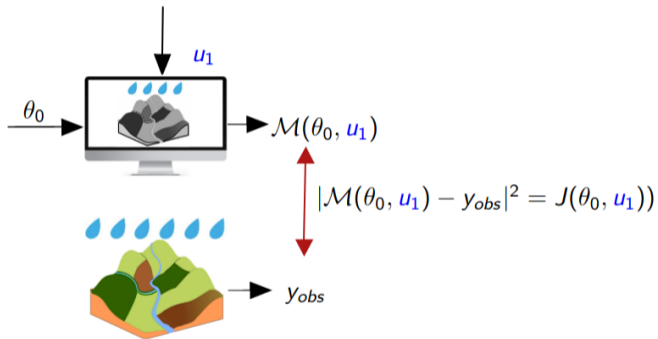
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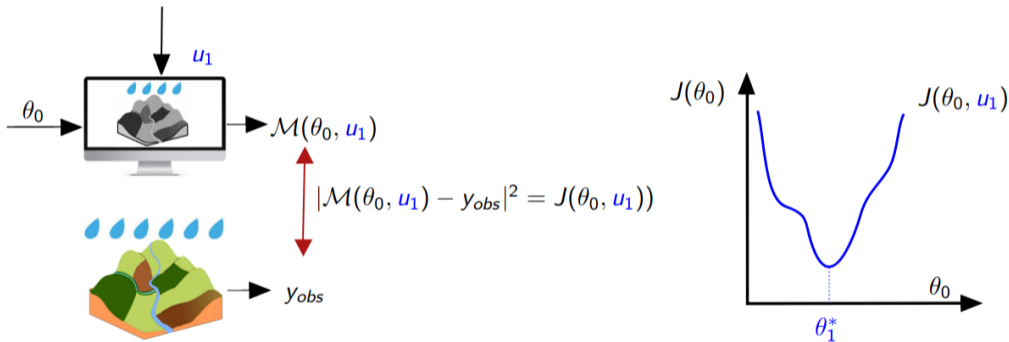
Introduction: From classical to robust calibration



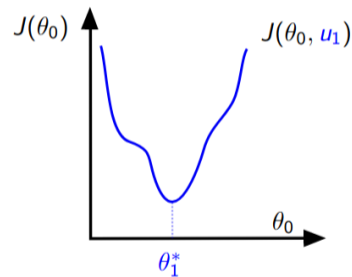
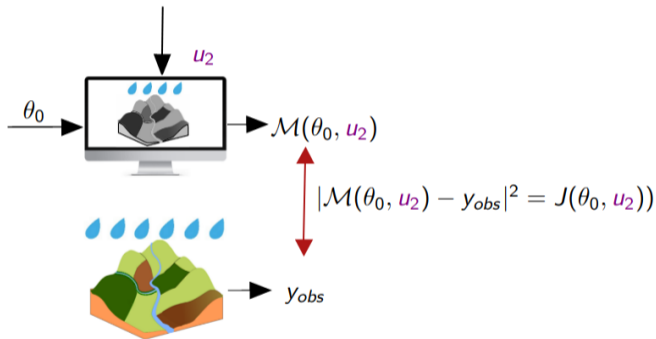
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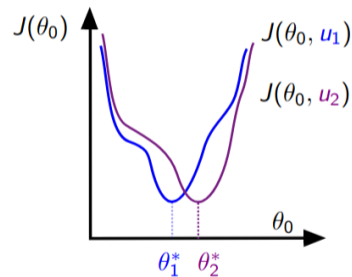
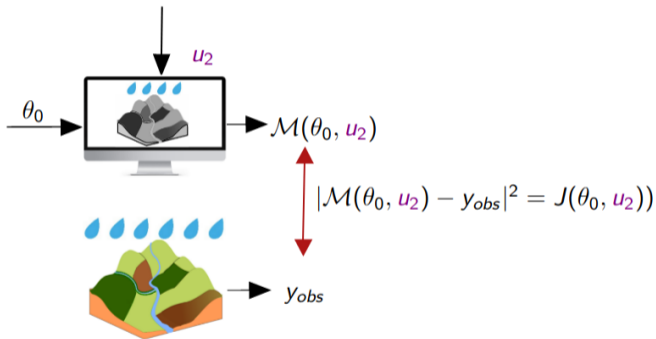
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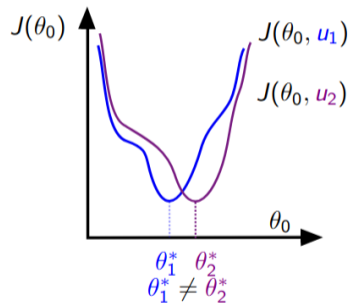
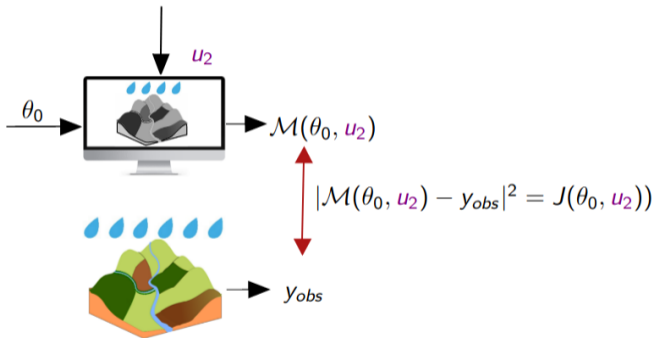
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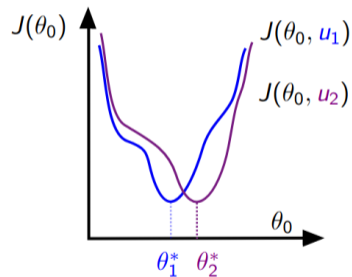
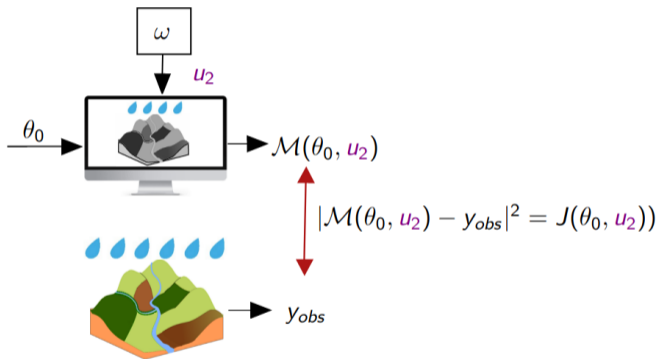
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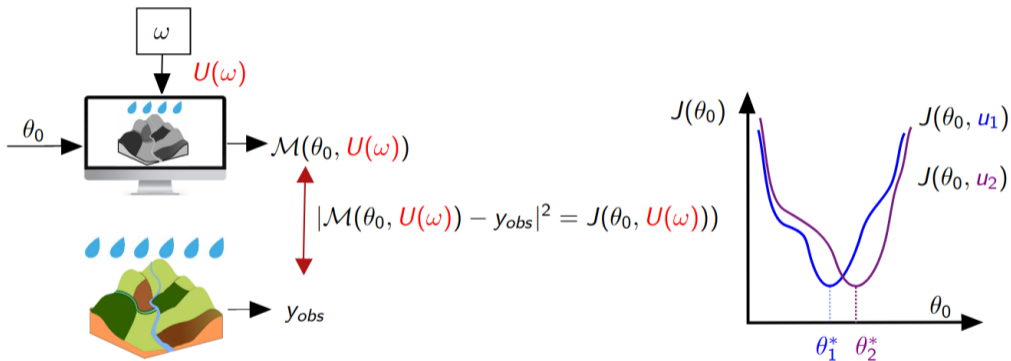
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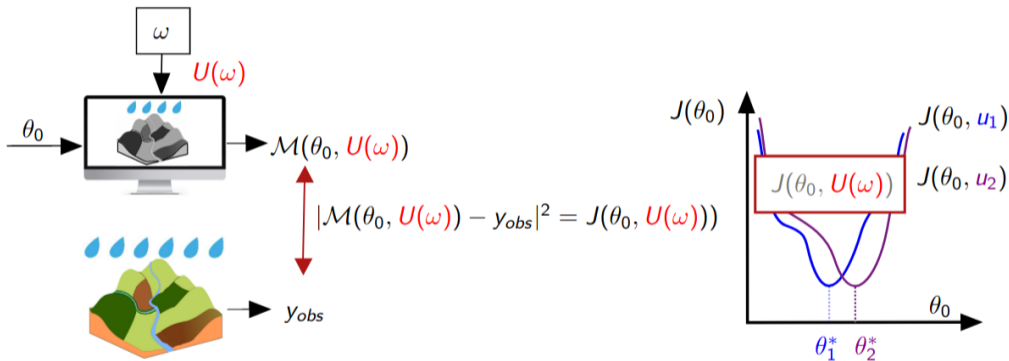
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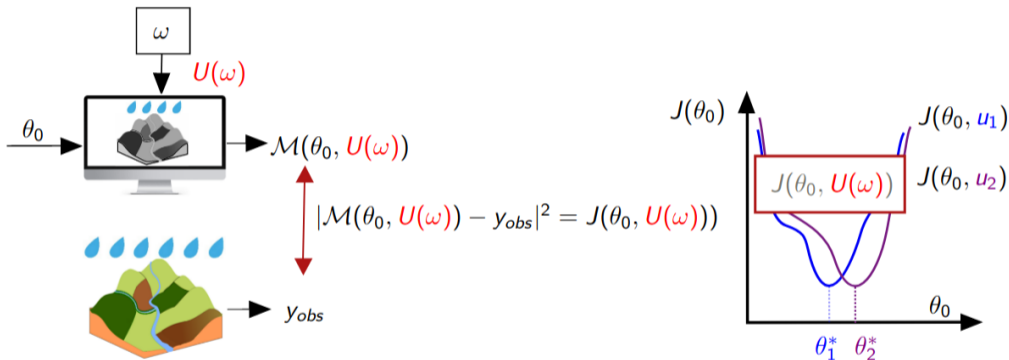
Introduction: From classical to robust calibration



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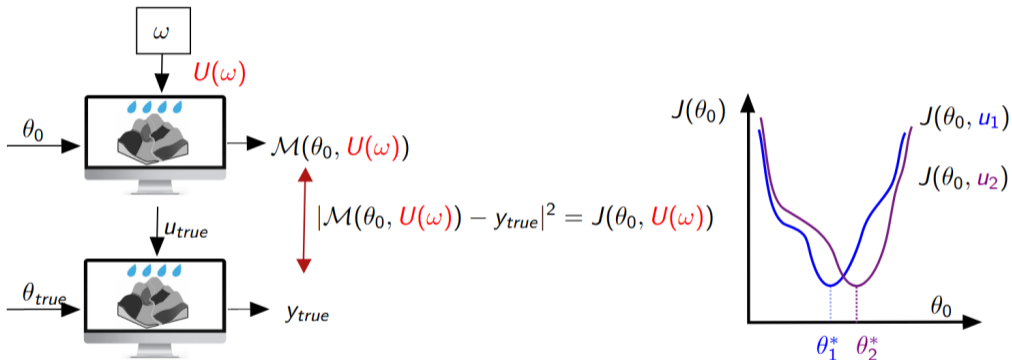


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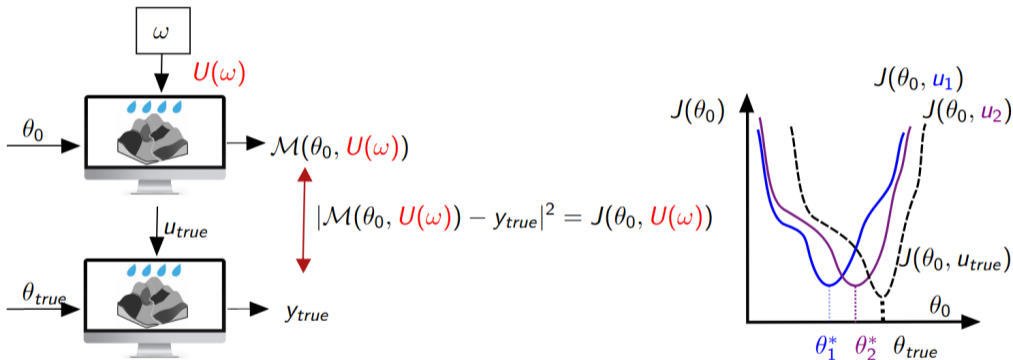
All hydrological model suffer from this.
Here, only rain uncertainties will be considered.

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Table of contents

Introduction

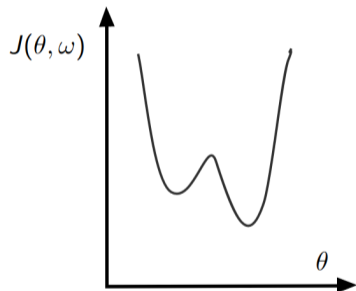
Methods

Case study

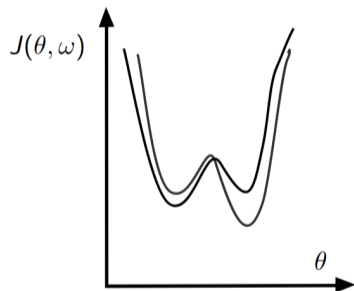
Results

Conclusion

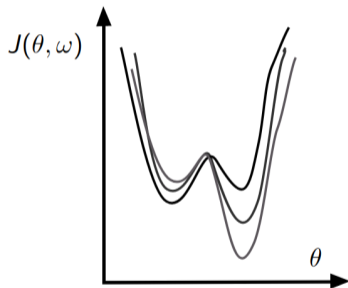
Methods: Definition of robust estimators



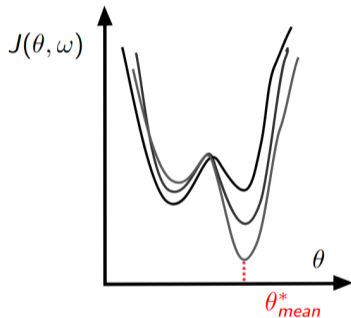
Methods: Definition of robust estimators



Methods: Definition of robust estimators

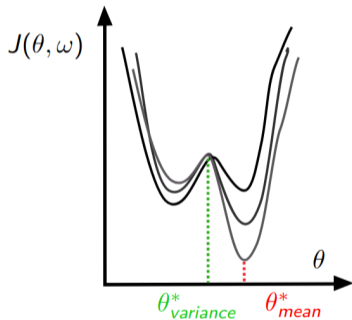


Methods: Definition of robust estimators



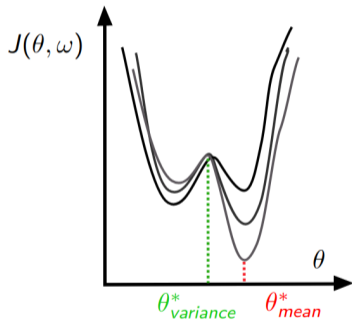
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Methods: Definition of robust estimators



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Methods: Definition of robust estimators



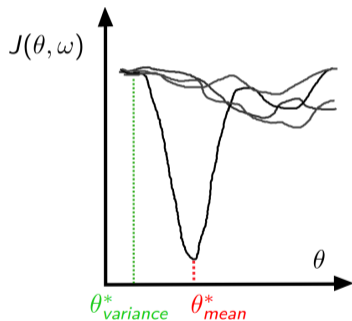
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Other definition of robustness exist.

The one we choose depends on our goal.

No matter the robustness we choose, they will all be computationally expensive.

Methods: Definition of robust estimators



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Table of contents

Introduction

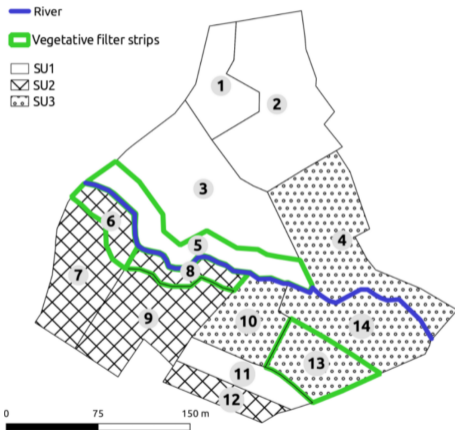
Methods

Case study

Results

Conclusion

Case study: PESHMELBA virtual catchment



- 3 soil types
 - 2 vegetation types
 - 4 soil horizons for each soil type
 - 9 soil parameters for each horizon
- We focus on parcel 4.
 - Calibrate parameters of parcel 4.
 - Observations on parcel 4.
 - Our observations are moisture profiles of the soil column after 100 hours of rain.

Figure: Rouzies et al. 2023

<https://doi.org/10.5194/gmd-2021-425>

Case study: Observations, cost function and rain perturbations

We calibrate only two parameters :

1. the water content in the soil at saturation (**thetas10**)
2. the parameter governing Van Genuchten infiltration equation (**mn10**)

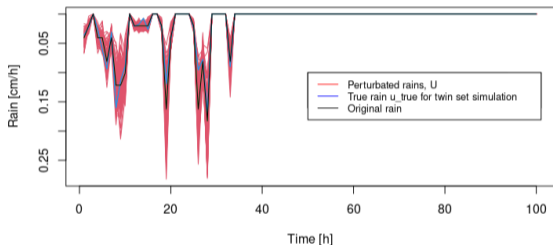
$$thetas_{10} \sim \mathcal{N}(0.3160, 0.0316^2),$$

$$mn_{10} \sim \mathcal{N}(0.1791, 0.0179^2),$$

$$\theta_{true} = (0.164, 0.292).$$

Case study: Observations, cost function and rain perturbations

Perturbed rains



$$J(\theta, u) = (\mathcal{M}(\theta, u) - y_{true})^2 = \sum_{cell_i=1}^{25} (\mathcal{M}(\theta, u)|_{cell_i} - y_{true}|_{cell_i})^2$$

$$y_{true} = \mathcal{M}(\theta_{true}, u_{true}) \in \mathbb{R}^{25}$$

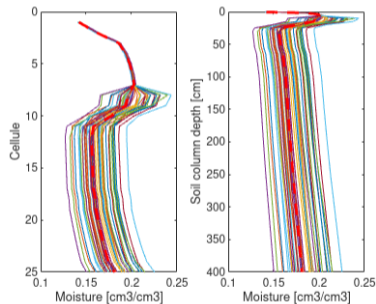


Table of contents

Introduction

Methods

Case study

Results

Conclusion

Results:

We compare the following minimization problems :

1. $\theta^*(u_{true}) = \underset{\theta}{\operatorname{argmin}} J(\theta, u_{true})$
2. $\theta^*(u_{false}) = \underset{\theta}{\operatorname{argmin}} J(\theta, u_{false})$
3. Robust estimators
 - 3.1 $\theta_{mean}^* = \underset{\theta}{\operatorname{argmin}} (\mathbb{E}_U [J(\theta, U)]),$
 - 3.2 $\theta_{variance}^* = \underset{\theta}{\operatorname{argmin}} (\mathbb{V}ar_U [J(\theta, U)]),$

Results: Calibration with u_{true} VS u_{false}

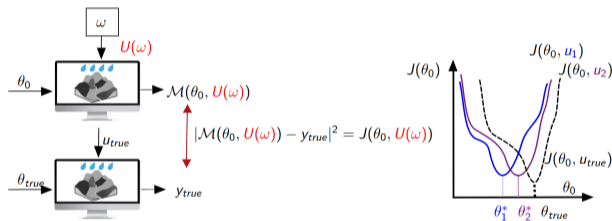
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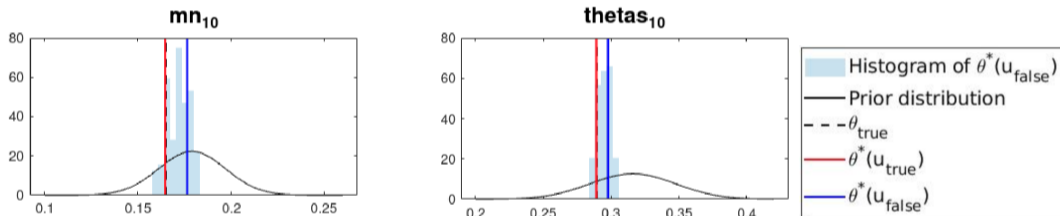


Figure: Minimizers when $u = u_{true}$ in red and when $u = u_{false}$ in blue.

Results: Robust estimators

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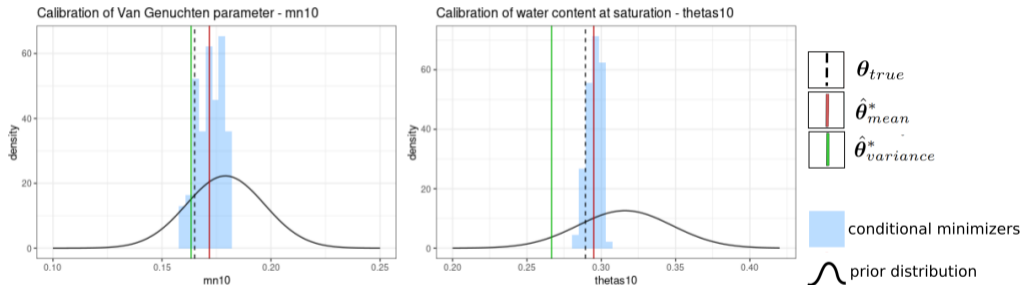
2. $\theta^*(u_{false}) = \underset{\theta}{\operatorname{argmin}} J(\theta, u_{false})$

3. Robust estimators

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Results: Robust estimators



Robust estimators : the minimizer of the mean and variance for the two estimated parameters.



Table of contents

Introduction

Methods

Case study

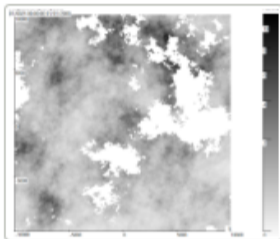
Results

Conclusion

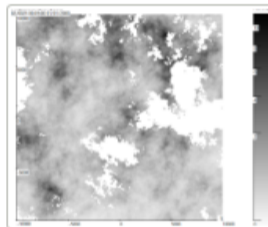
Suite :

- Différentes définitions de robustesse
- Différentes perturbations de pluie
- Le coût numérique de PESHMELBA -> metamodèles
- passage à plusieurs paramètres, plusieurs parcelles
- passage aux pluies spatialisées

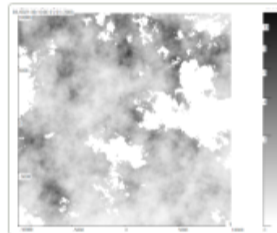
Pluies spatialisées



field_member_001_step_00001.png



field_member_001_step_00002.png



field_member_001_step_00003.png

Figure: Simulations de champs de pluie provenant de SAMPO, (Leblois and Creutin, 2013) doi : 10.1002/wrcr.20190.