Calibration robuste d'un modèle hydrologique de transfert de pesticides par métamodélisation

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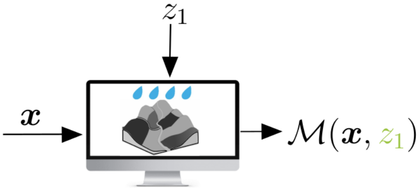
Introduction: Model calibration = minimization of a cost function



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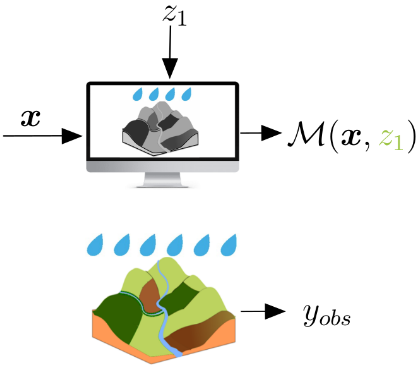

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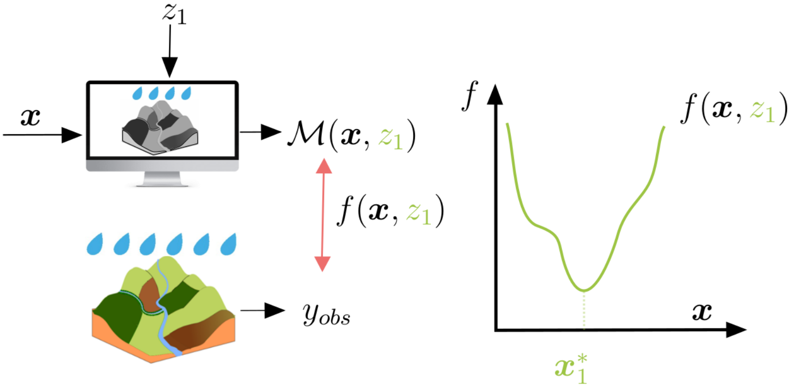

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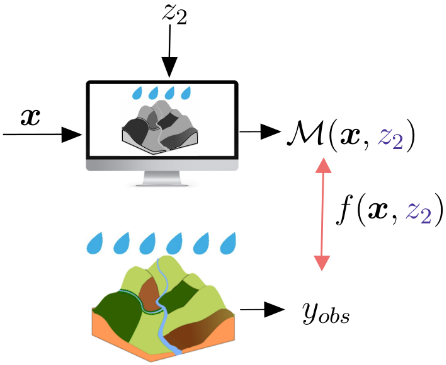

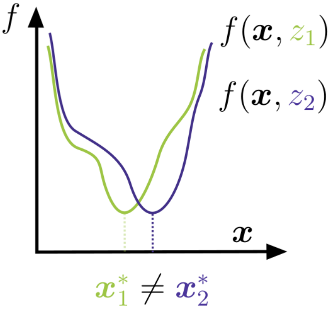

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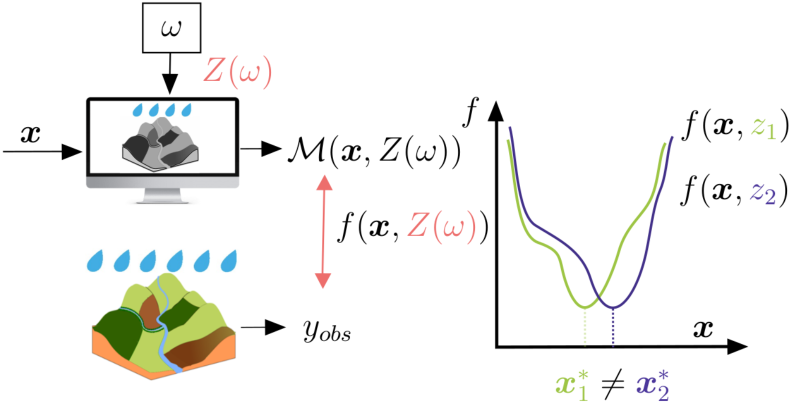

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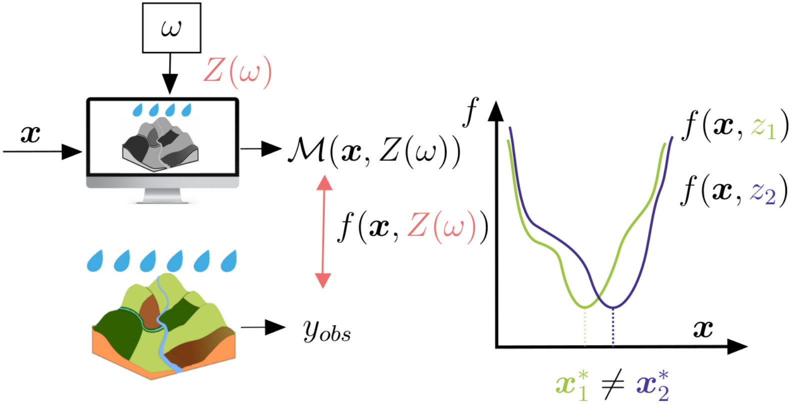

How to minimize a stochastic function? $\longrightarrow$ ***robust calibration***

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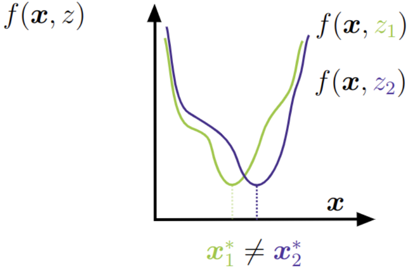
Methods: Robust minimizers



What criterion for the minimization of a stochastic cost function ?

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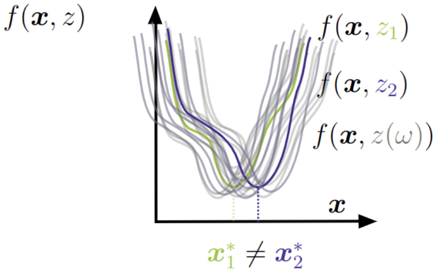

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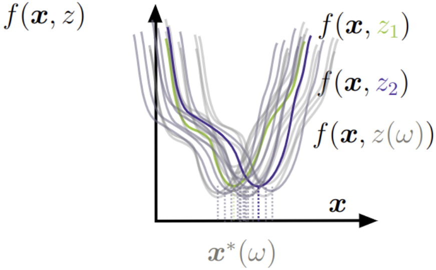

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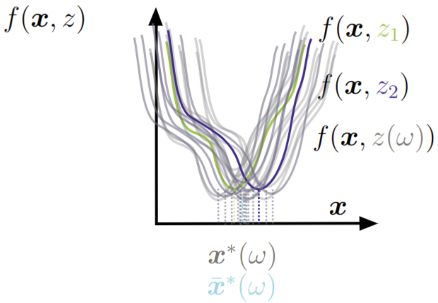

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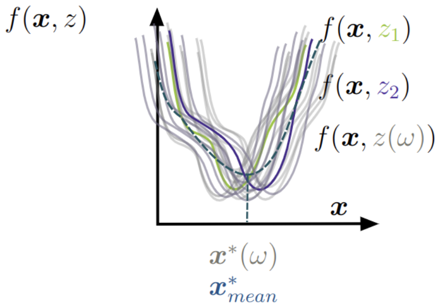

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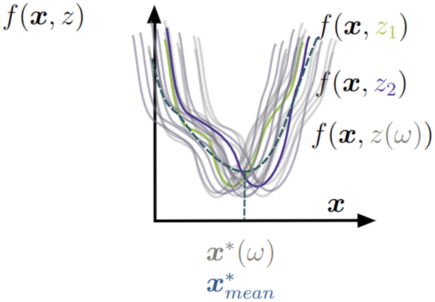

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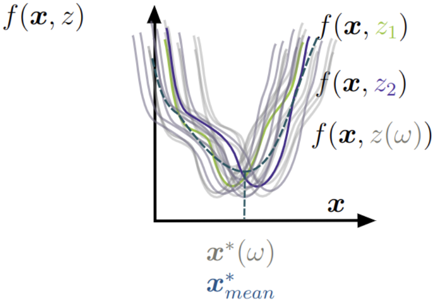

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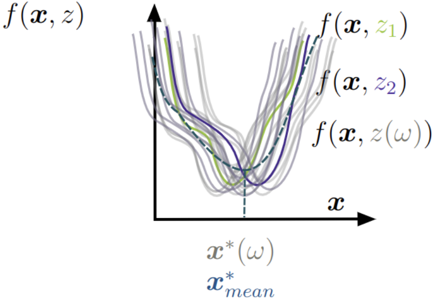

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Very expensive simulations

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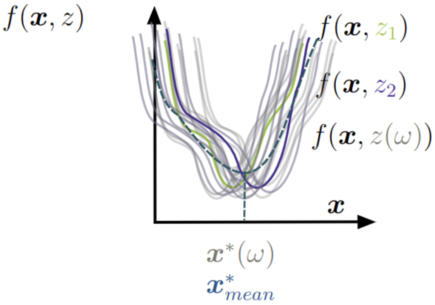

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Very expensive simulations

How to limit number of model evaluations ?

$\longrightarrow$ Metamodels = approximation of the original model (***or of the cost function***): linear regression, neural networks ...

- **Polynomial Chaos Expansion**, Marelli and Sudret 2014
  - can be used for a large number of input parameters (+)
  - uses one-shot experimental designs (can be parallelized) (+)
  - approximate the cost function globally (-)
  - have to be validated (-)

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Case study: PESHMELBA

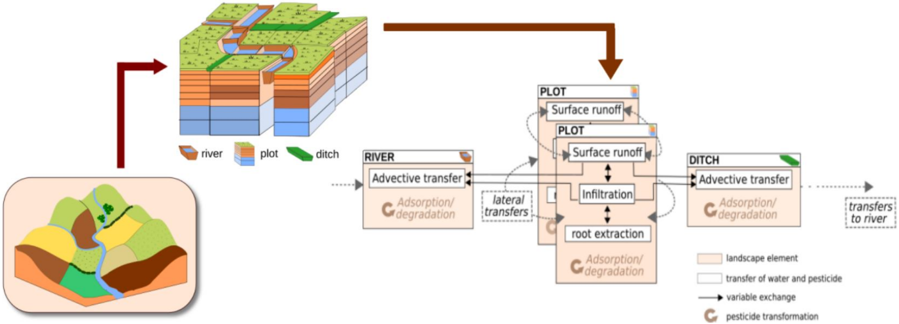

Figure: PESHMELBA model, Rouzies et al. 2019

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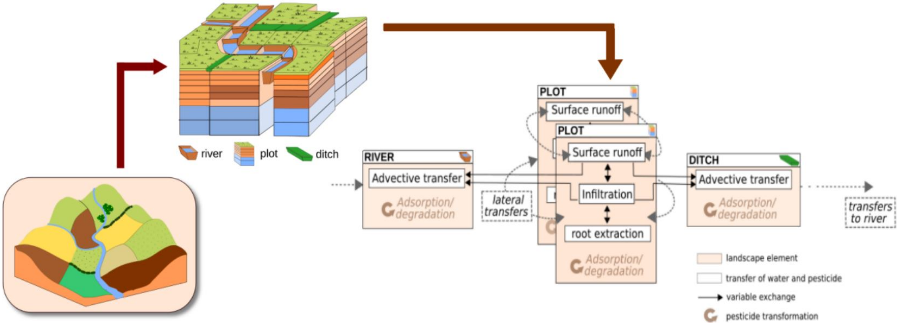

Figure: PESHMELBA model, Rouzies et al. 2019

- process-oriented, physically-based, coupling with landscape features

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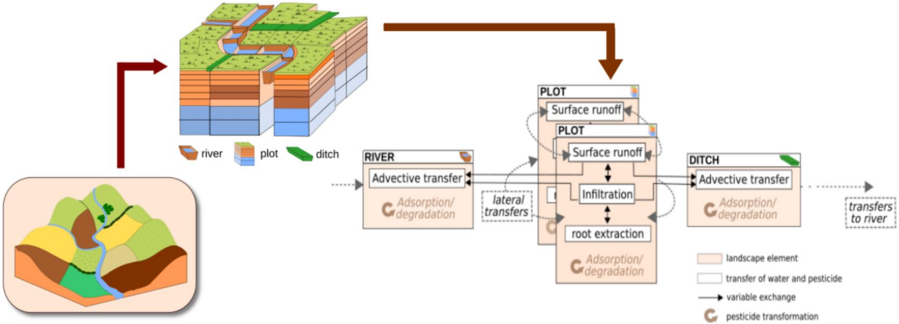

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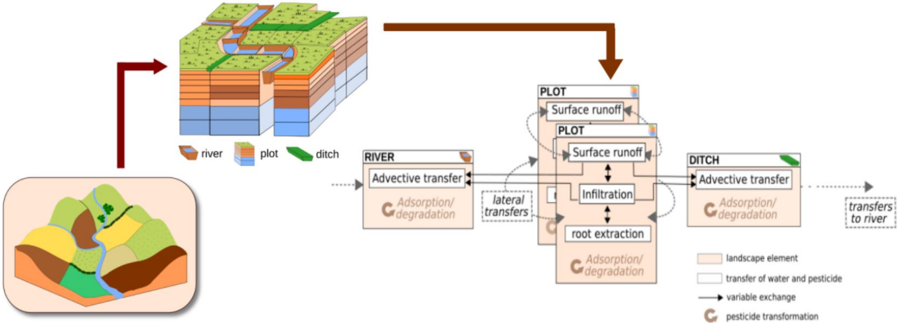

Figure: PESHMELBA model, Rouzies et al. 2019

- process-oriented, physically-based, coupling with landscape features
- simulates water and pesticide transfers on an agricultural catchment
- distributed model, numerous parameters to calibrate

Case study: Moisture profiles

A simplified case study: moisture profile of one plot

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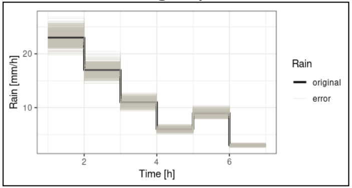
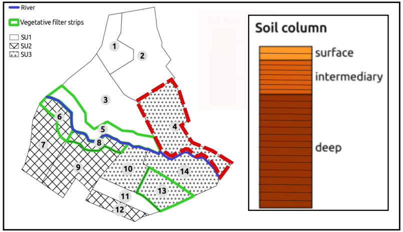
Forcing input



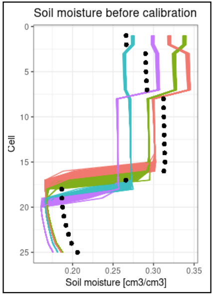
Parameters to calibrate

Name	Definition
$\theta_{s.surf.}$	water content at saturation (surface)
$\theta_{s.inter.}$	water content at saturation (intermediary)
$\theta_{s.deep}$	water content at saturation (deep)
$\theta_{r.deep}$	residual water content (deep)
$mn_{.deep}$	Van Genuchten retention curve parameter (deep)

PESHMELBA configuration



Observation = moisture profile of parcel 4



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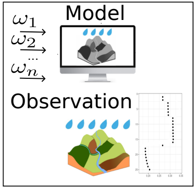
Results: Problem formulation



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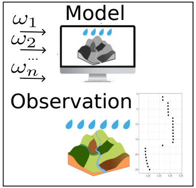

Cost function

$$\longrightarrow f(x, \omega_1)$$

$$\longrightarrow f(x, \omega_2)$$

... ...

$$\longrightarrow f(x, \omega_n)$$

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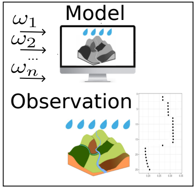

	Cost function		Metamodel
$\longrightarrow$	$f(x, \omega_1)$	$\longrightarrow$	$PCE_{\omega_1}(x)$
$\longrightarrow$	$f(x, \omega_2)$	$\longrightarrow$	$PCE_{\omega_2}(x)$
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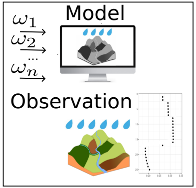

	Cost function		Metamodel		Minimization
$\longrightarrow$	$f(x, \omega_1)$	$\longrightarrow$	$PCE_{\omega_1}(x)$	$\longrightarrow$	$x^*_{\omega_1}$
$\longrightarrow$	$f(x, \omega_2)$	$\longrightarrow$	$PCE_{\omega_2}(x)$	$\longrightarrow$	$x^*_{\omega_2}$
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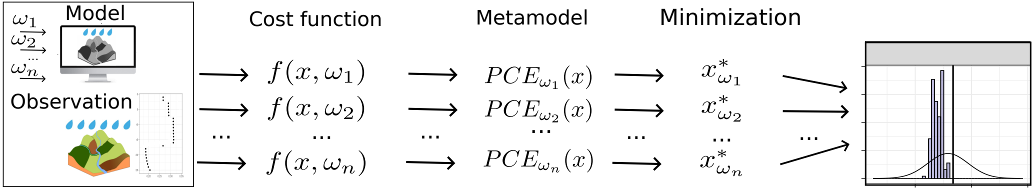

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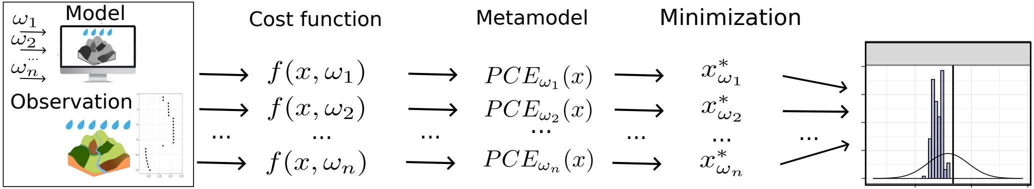

- the spread of minimizer histogram = the uncertainty propagation from forcings to calibrated values

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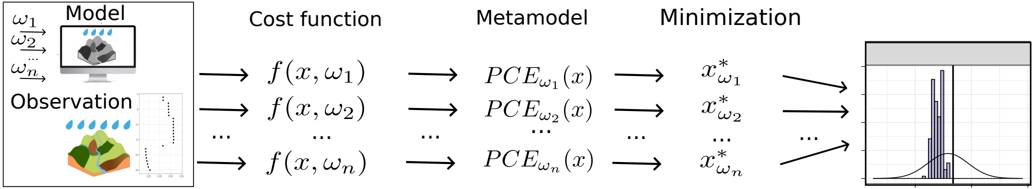

- the spread of minimizer histogram = the uncertainty propagation from forcings to calibrated values
- all metamodels show very good R2 values > 0.95 (validation).

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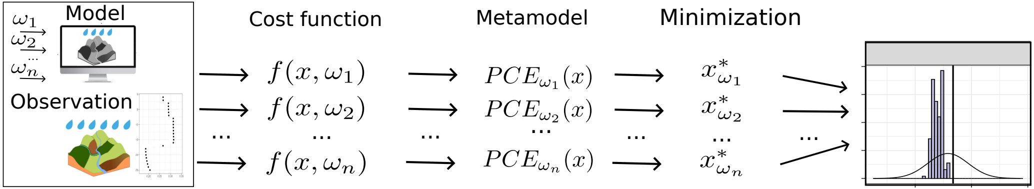

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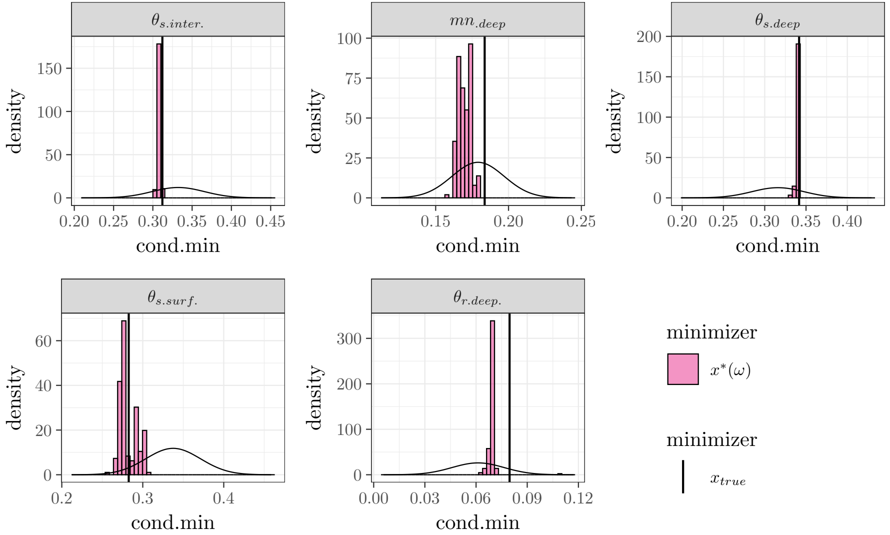
Next: Compare classic minimizers with robust minimizers : x^*_{mean} *and* $\bar{x}^*$.

Results: Minimizers



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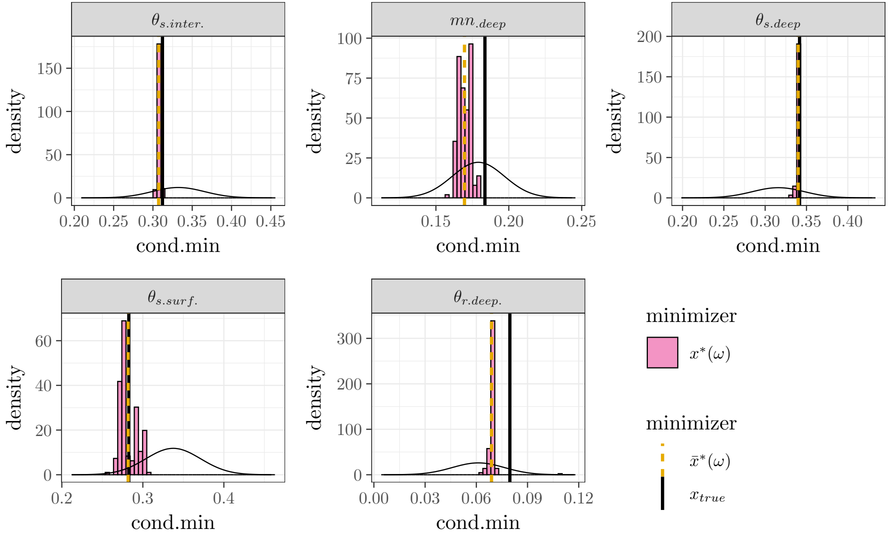

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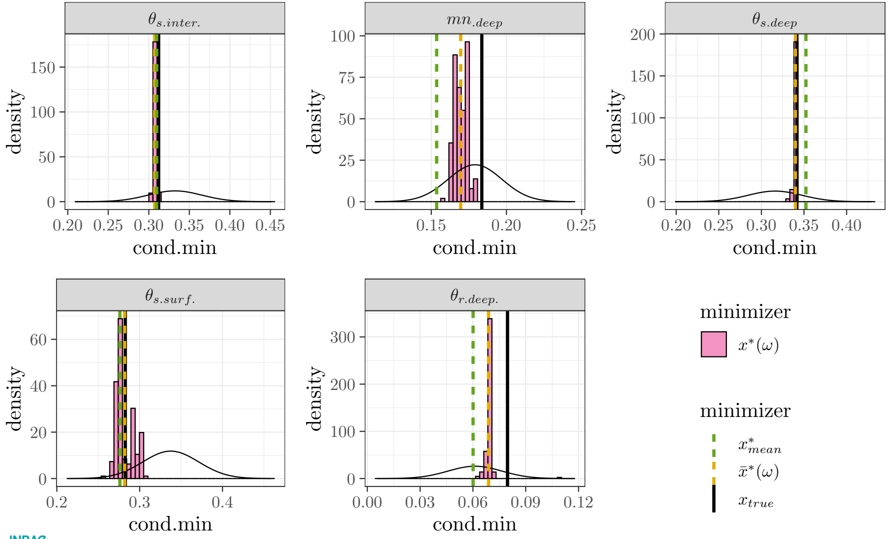

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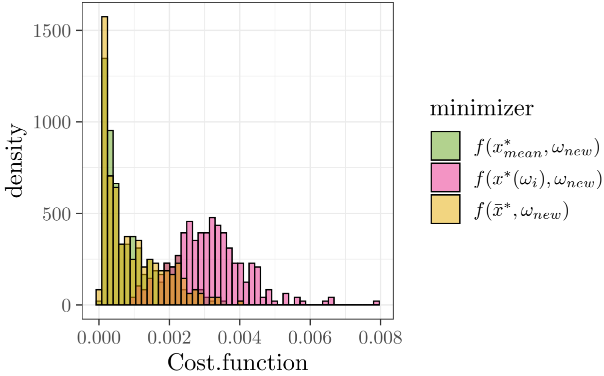

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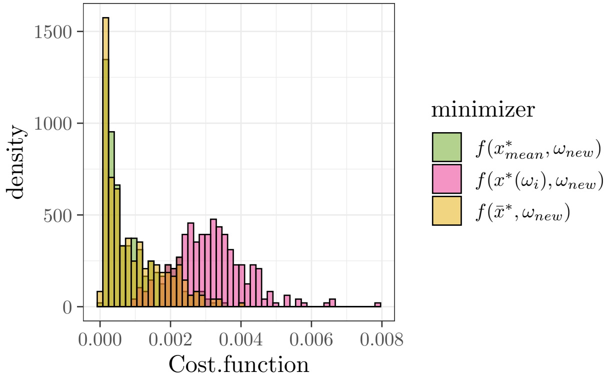

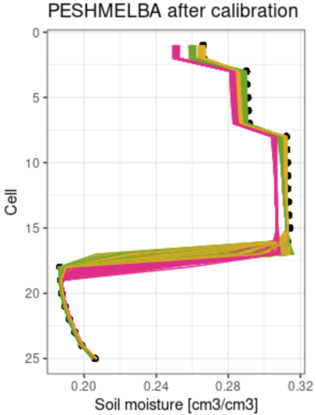

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1. a method is proposed to calibrate models by taking external factors into account (here, rainfall, but the method is valid for any forcing: discretization, evapotranspiration, given a representative sample).

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- complexify case study, passage to catchment scale, study propagation of uncertainty on pesticide application dates to the model calibration

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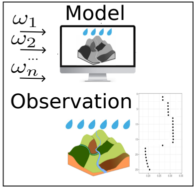
- complexify case study, passage to catchment scale, study propagation of uncertainty on pesticide application dates to the model calibration
- compare Polynomial Chaos Expansion metamodelization with other metamodelization methods
- reduce the number of rain simulations used, interpolation in the rains $\longrightarrow$ stochastic metamodel, Lüthen, Marelli, and Sudret 2023

Conclusion:



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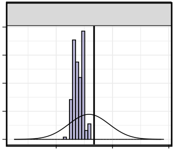

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