## Modelling Advisory Group (MAG)

# Hydrological Uncertainty Workshop

## Global Sensitivity Analysis using the SAFE toolbox

23 September 2025


**Francesca Pianosi**
University of Bristol


Access to software, papers, example: https://safetoolbox.github.io/


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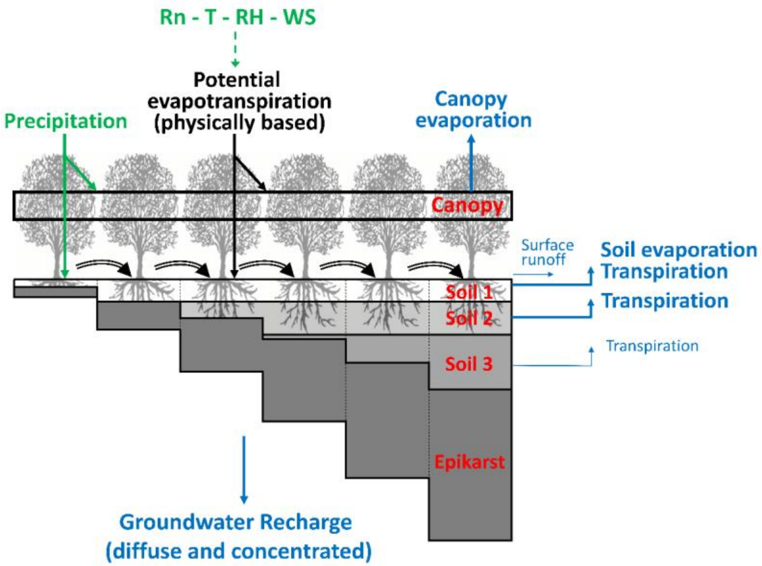
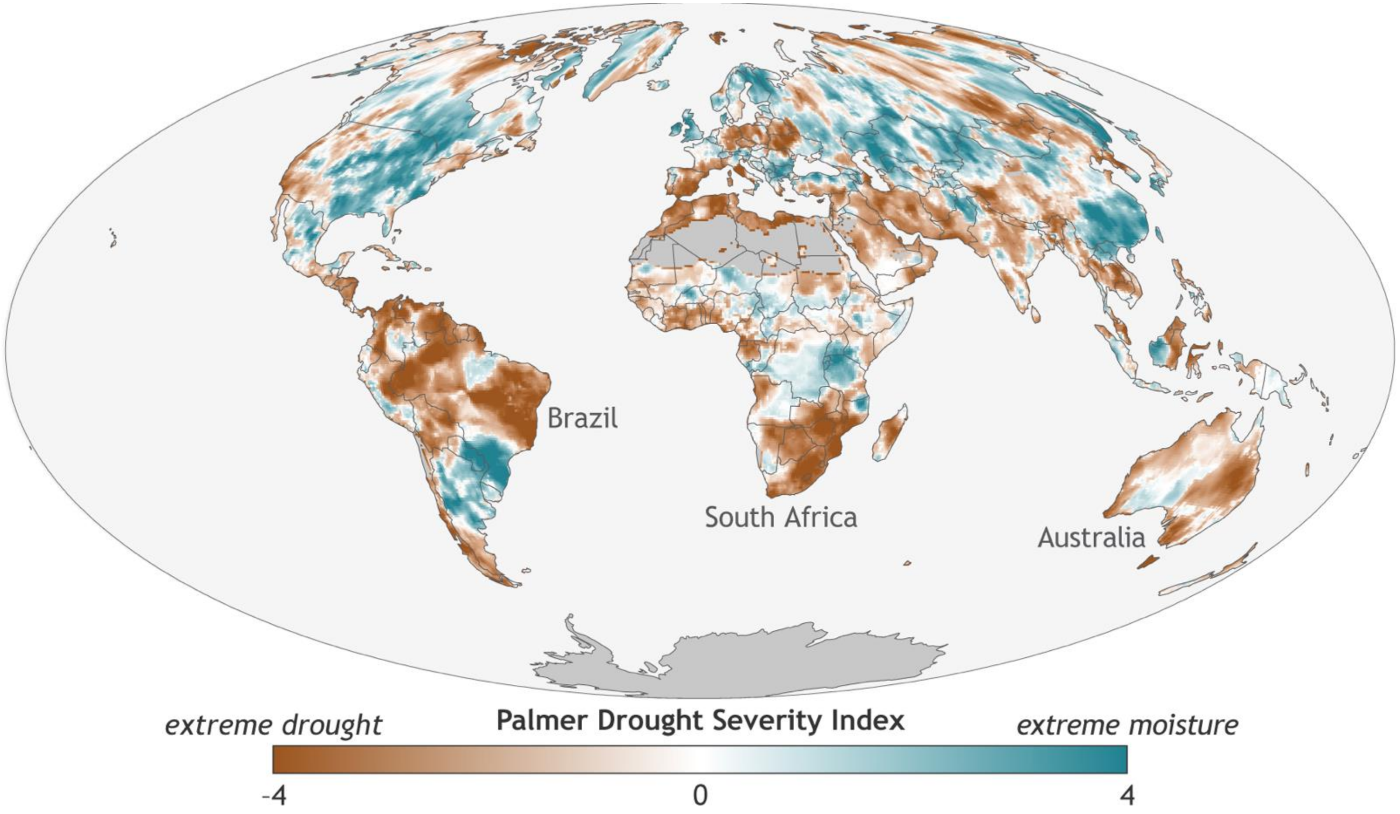
Computer models are essential tools in hydrology to advance our science and inform water resources management decisions at different spatial and temporal scales




francesca.pianosi@bristol.ac.uk

# Despite their differences, all models are built following a similar process

conceptualization
> perceptual model

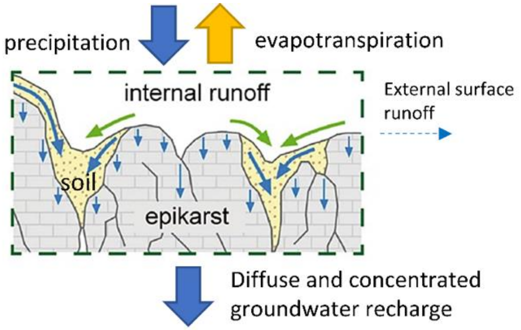
translation into equations
> mathematical model

implementation into a computer code
> computer model

calibration
> computer model tailored to a specific location/system

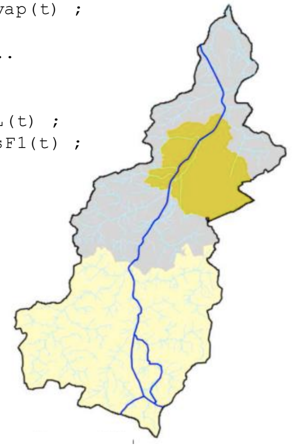
evaluation

use of the model for prediction
(short-term forecasting, what if analysis, etc.)




$$\frac{1}{A}\frac{\partial Q}{\partial t}+\frac{1}{A}\frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right)+g\frac{\partial y}{\partial x}-g(S_o-S_f)=0$$

```
function Q_sim = hymod_sim(par,prec,evap)
Sm =max(eps,par(1));beta =par(2);alfa=par(3);
Rs=par(4);Rf=par(5); N=length(prec);
for t=1:N
    F   = 1 - (1-sm(t)/Sm)^beta ; Pe(t)   = F*prec(t) ;
    sm_temp = max(min(sm(t) + prec(t) - Pe(t),Sm),0);
    Pe(t)=Pe(t)+max(sm(t)+prec(t)-Pe(t)-Sm,0)+...
          min(sm(t)+prec(t)-Pe(t),0);
    W = min(abs( sm(t)/Sm ),1) ; Ea(t)= W*evap(t) ;
    sm(t+1) = max(min(sm_temp-Ea(t),Sm),0);
    Ea(t)= Ea(t)+ max(sm_temp-Ea(t)-Sm,0)+...
          min(sm_temp-Ea(t),0);
    QsL(t)    = Rs * sL(t) ;
    sL(t+1)   = sL(t) +  (1-alfa)*Pe(t) - QsL(t) ;
    sF1(t+1)  = sF1(t) +  alfa*Pe(t) - Rf * sF1(t) ;
    QsF(t)    = Rf * sF1(t) ;
end
Q_sim = QsL+QsF;
```



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# Despite their differences, all models are built following a similar process … which is paved with uncertainties and subjective choices

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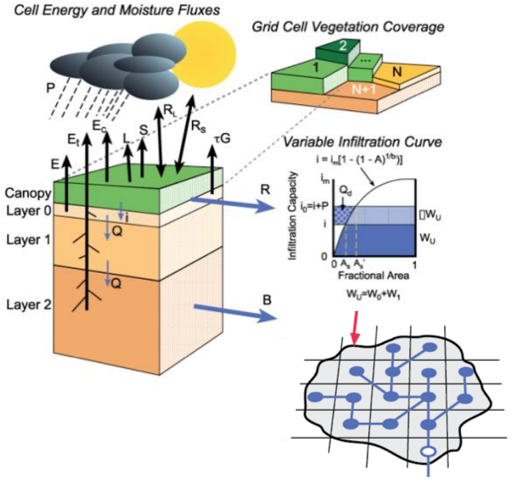
use of the model for prediction
(short-term forecasting, what if analysis, etc.)

- simplifying assumptions whose adequacy is uncertain

Water flowing over and through hillslopes




Rainfall-runoff processes represented in the VIC model

francesca.pianosi@bristol.ac.uk

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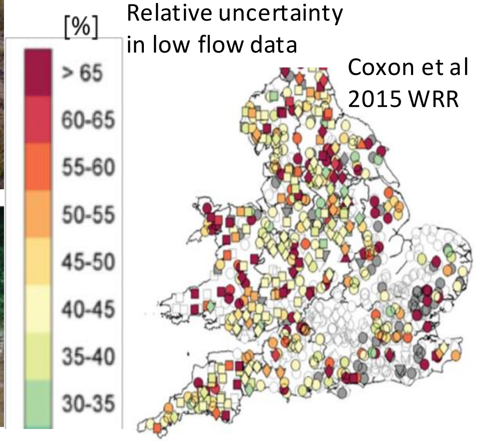
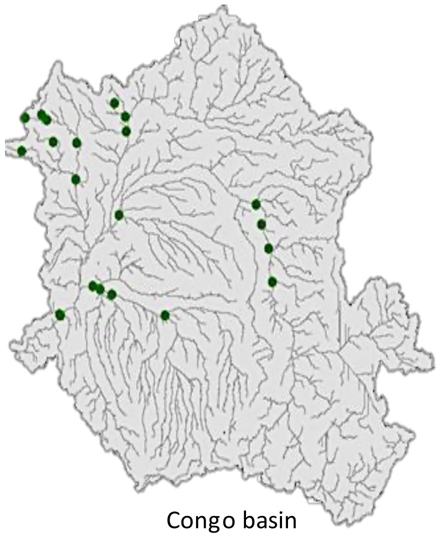
(short-term forecasting, what if analysis, etc.)

- simplifying assumptions whose adequacy is uncertain
- errors and gaps in the data we use to build and test models

Example: river flow data




England & Wales
(242,500 km$^2$)



Congo basin
(3,700,000 km$^2$)

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- simplifying assumptions whose adequacy is uncertain
- errors and gaps in the data we use to build and test models

*These uncertainties can be "aleatory" (=due to intrinsic randomness, e.g. from noise in measurement devices) or "epistemic" (=due to lack of knowledge, e.g. on the mechanics of a particular process)*

*Aleatory and epistemic uncertainties are - to some extent - quantifiable and reducible*

francesca.pianosi@bristol.ac.uk

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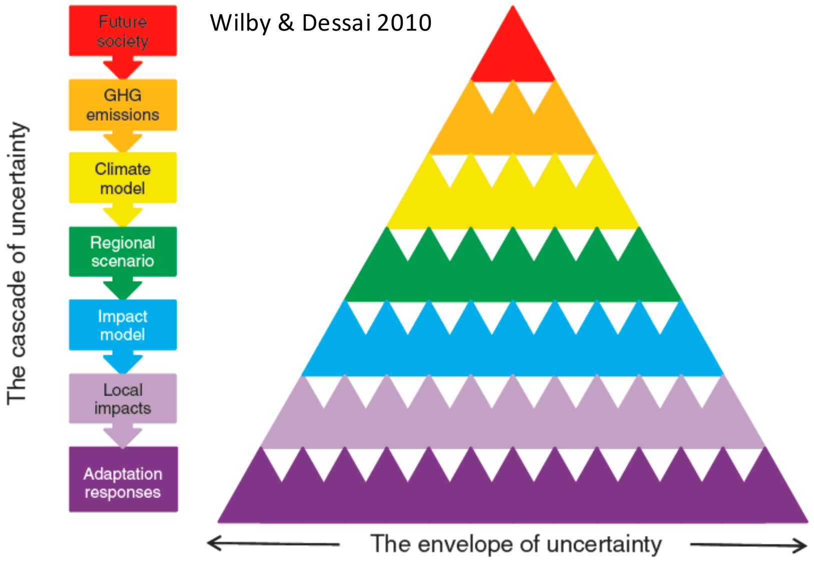
use of the model for prediction
(short-term forecasting, what if analysis, etc.)

- simplifying assumptions whose adequacy is uncertain
- errors and gaps in the data we use to build and test models
- If we use models to simulate long-term system behaviour, then we need to build scenarios for how the system drivers will evolve in the future




*These uncertainties are "deep" ( = there is no consensus regarding the appropriate way to represent them)*

*Deep uncertainties are unquantifiable and irreducible*

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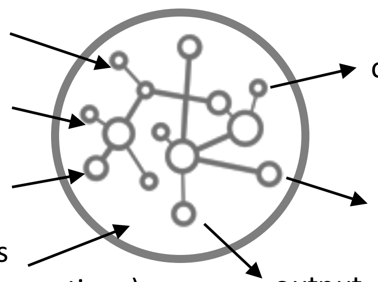
# Uncertainty in >>> Uncertainty out

"**input uncertainties**" when the 'right' value or choice for some of the model input factors is uncertain




"**output uncertainty**" as a consequence of input uncertainties

francesca.pianosi@bristol.ac.uk

# Uncertainty in >>> Uncertainty out
# So, what do we do with it?

- Ignore it

francesca.pianosi@bristol.ac.uk

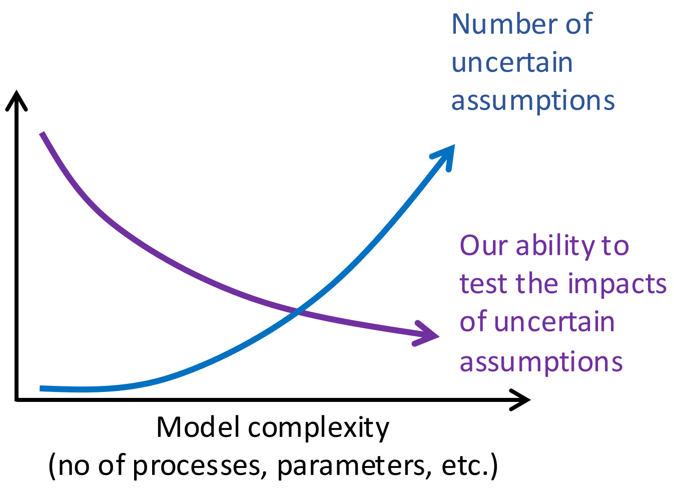
# Uncertainty in >>> Uncertainty out
# So, what do we do with it?

- Ignore it
- Fight it

  - more monitoring, fieldwork, experiments, thinking, etc.: yes 🤓
  - more detailed and "realistic" models: meh 🤔

  The complexity paradox: *"A complex model may be more realistic, yet it is ironic that as we add more factors to a model, the certainty of its predictions may decrease even as our intuitive faith in the model increases (…) The more we strive for realism by incorporating as many as possible of the different processes and parameters that we believe to be operating in the system, the more difficult it is for us to know if our tests of the model are meaningful"*

  Oreskes 2003 *The role of quantitative models in science*

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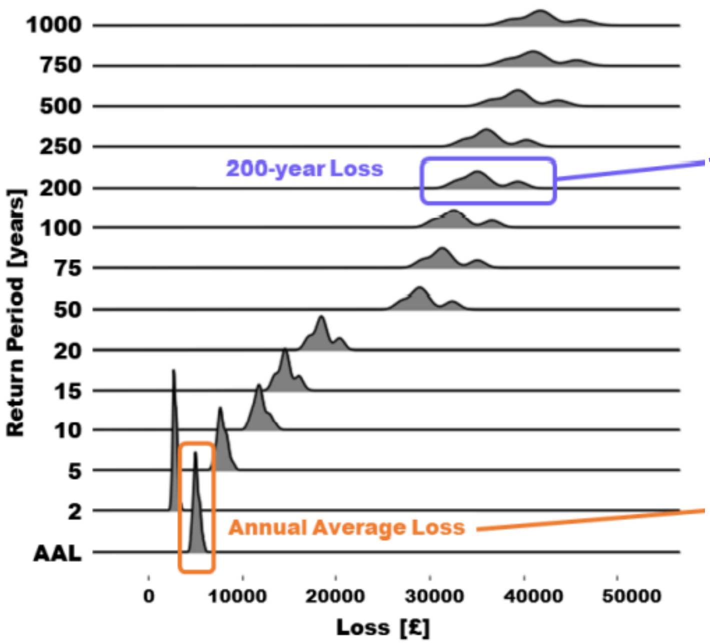
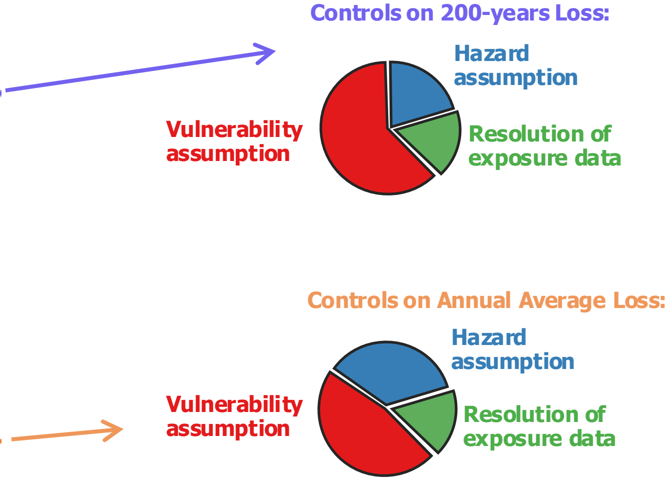
# Uncertainty in >>> Uncertainty out
So, what do we do with it?

- Ignore it
- Fight it
- Acknowledge it

## Uncertainty analysis:
quantify uncertainty in the model output(s) as a consequence of known (assumed) input uncertainties

## Sensitivity analysis:
assess the relative contribution of different input uncertainties to the output(s) uncertainty




francesca.pianosi@bristol.ac.uk

# What kind of questions can we answer through uncertainty and sensitivity analysis and who are these interesting for?

- Questions to prioritise efforts for model improvement

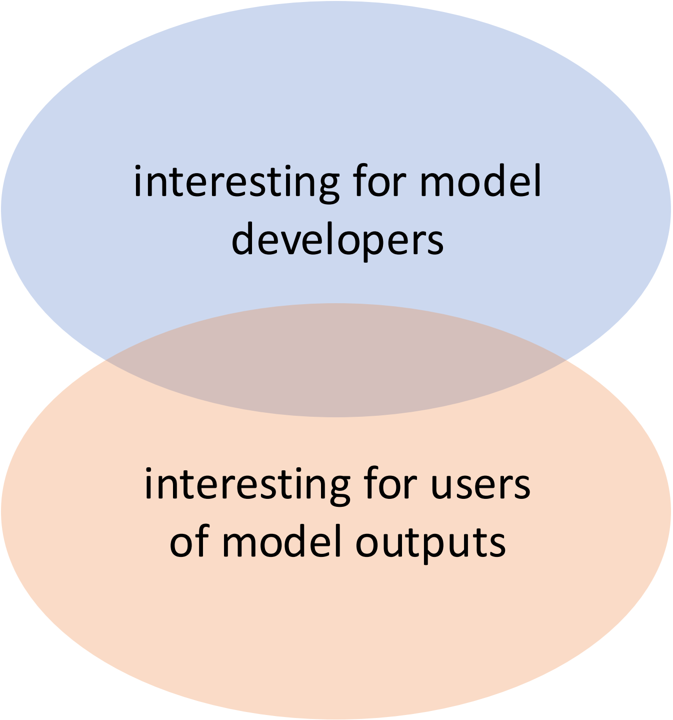
*What are the input data, parameters or model components that control the model outputs uncertainty most and where reduction of uncertainty would be most beneficial?*

- Questions to evaluate models and establish they are fit for purpose

*Does the "right" inputs/components control the "right" outputs? Are model outputs sufficiently controlled by the "decision levers" relative to other input uncertainties?*

- Questions about the systems behaviour (under the assumption: system=model)

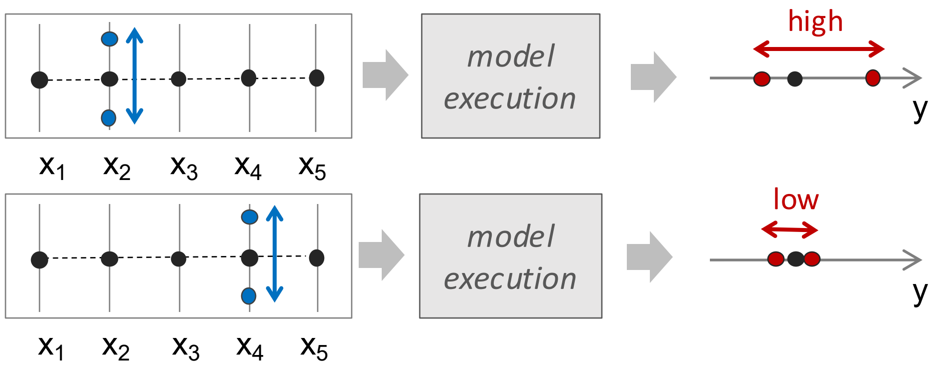
*What are the key drivers of the system in the face of deep uncertainty? Are there "robust" decisions that work sufficiently well across a range of uncertainties?*




francesca.pianosi@bristol.ac.uk

# Two ways of approaching Uncertainty and Sensitivity Analysis

Local approaches: investigate the sensitivity of the output (y) to varying the uncertain inputs ($x_1$,$x_2$,….) **one at the time** around a **baseline**




Limitation:

- ignore interactions
- results only valid for the chosen baseline: output uncertainty and sensitivity may be very different for a different baseline

Global approaches: investigate the sensitivity of the output (y) to varying all uncertain inputs **simultaneously** across their entire variability space (no baseline!)

francesca.pianosi@bristol.ac.uk

# Global approaches are based on repeated executions of the model against different inputs' combinations and a statistical analysis of the resulting input-output dataset

[1] characterize uncertainty in input factors

[2] propagate input uncertainties through the model

[3] quantify output uncertainty

[4] attribute output uncertainty

RUNNING
MONTE-CARLO SIMULATIONS

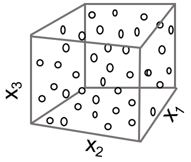
ANALYSING
INPUT-OUTPUT DATASET

characterize uncertainty in the inputs

(e.g. via a list of possible values, variability range, probability distribution.)

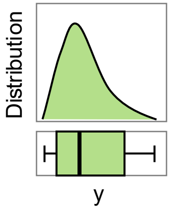
sample N combinations of inputs

(e.g. via random sampling, Latin Hypercube sampling)



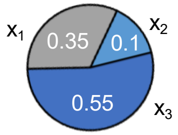

execute the model against each inputs' combination

derive the output(s)' distribution or CIs




calculate sensitivity indices

contribution to output uncertainty




- Elementary Effects method
- Regional Sensitivity Analysis
- Variance-based (Sobol') method
- Distribution-based methods (for example, PAWN)

etc.

francesca.pianosi@bristol.ac.uk

# WHY

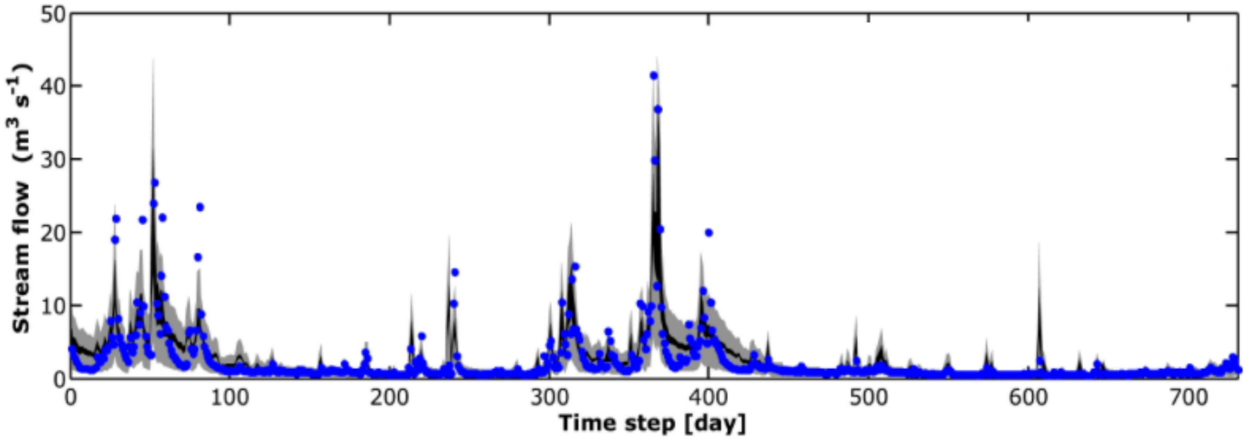
doing UA/SA?

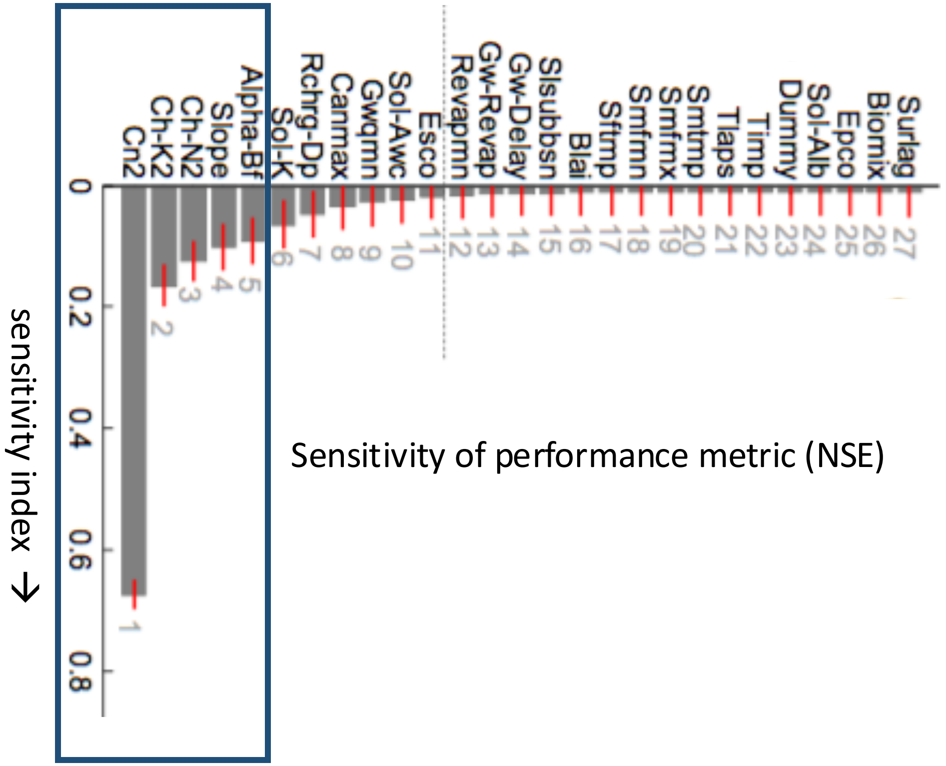
francesca.pianosi@bristol.ac.uk

# Guiding model calibration

If we have output observations to compare with, which model parameters control the predictions accuracy, and thus should be the focus of model calibration?

Application to SWAT model
Zadeh et al *EMS* 2017



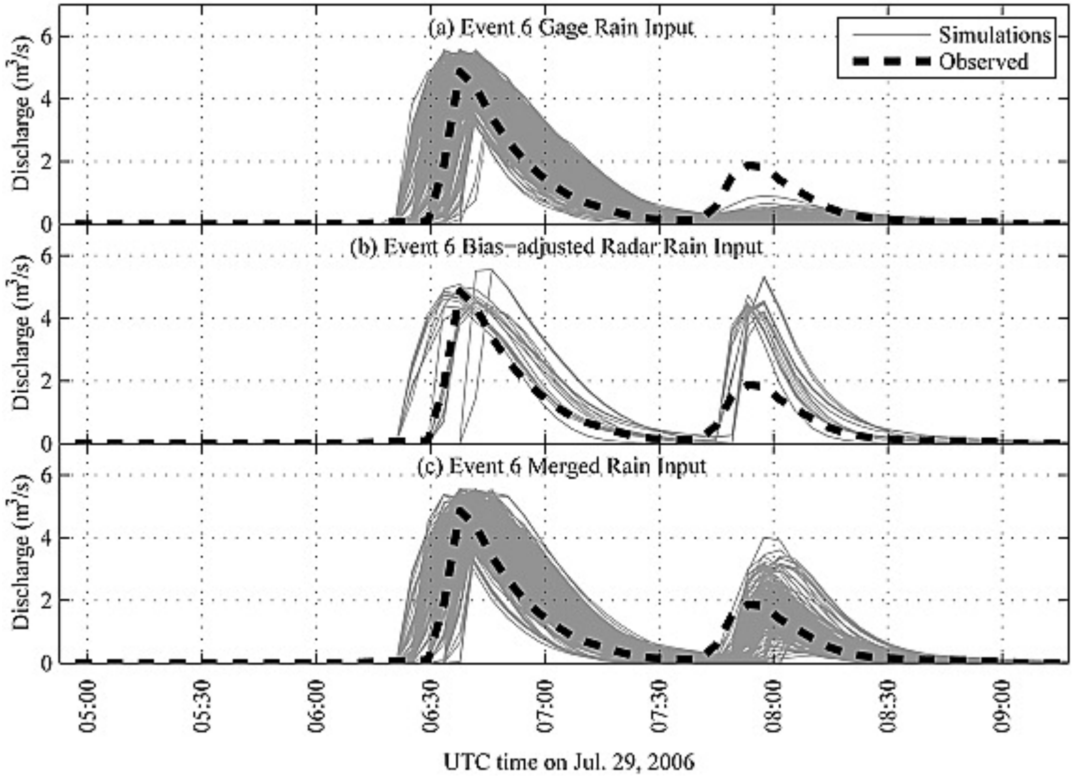

Sensitivity of performance metric (NSE)

francesca.pianosi@bristol.ac.uk

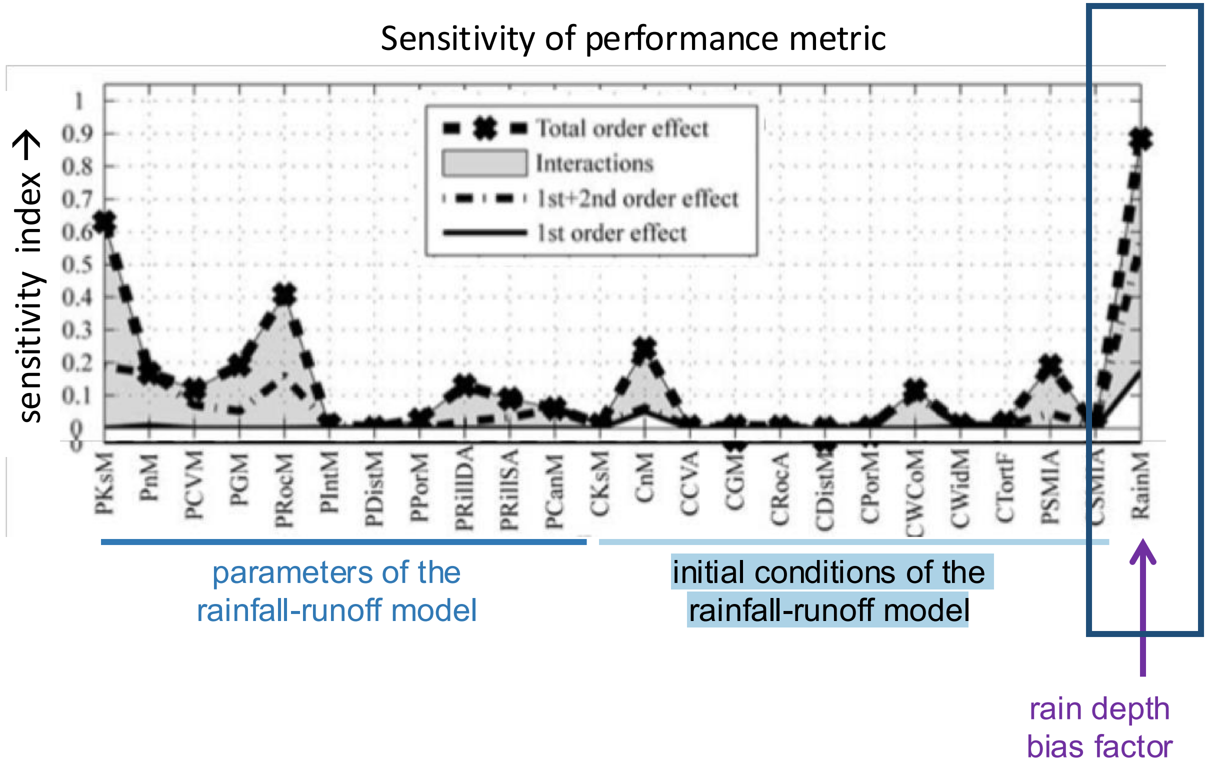
# Guiding model calibration

How much of the model performance is controlled by the uncertainty in parameters of the hydrological model vs uncertainty in parameters used for pre-processing forcing inputs (for example, precipitation)?

Application to spatially-distributed rainfall runoff model
Yatheendradas et al *WRR* 2008




Sensitivity of performance metric

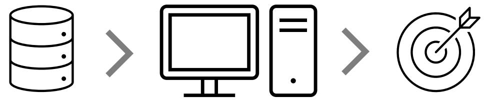



francesca.pianosi@bristol.ac.uk

# Supporting model evaluation

If we do not have output observations, can we at least ensure that the ‘right’ parameters control the model response at the right place?

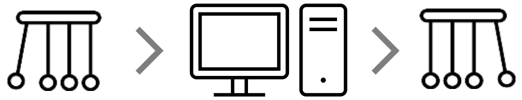
“Data-based” evaluation:



*Fit-to-data: are model outputs consistent with observations?*

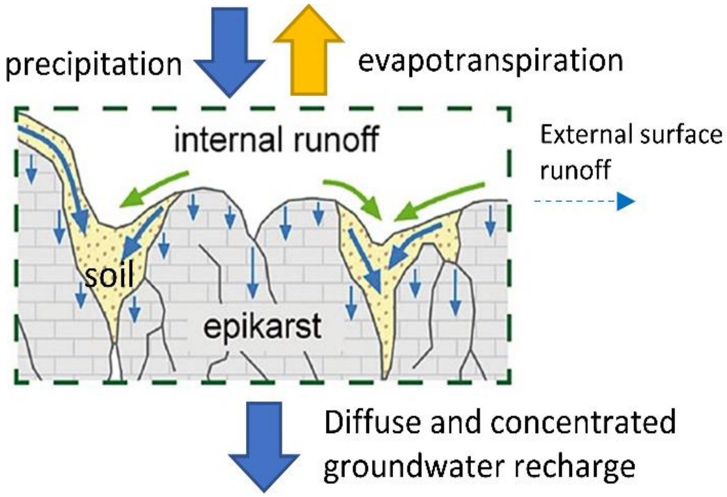
“Response-based” evaluation:

Wagener et al *WIREs-CC* 2022
**doi**:10.1002/wcc.772

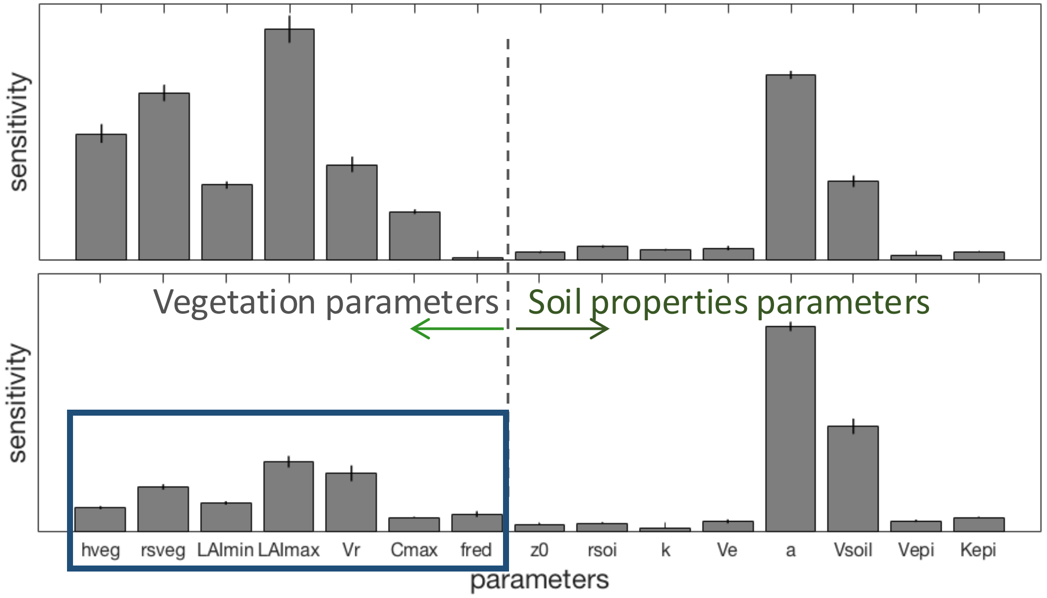


*Is the model input-output response consistent with our understanding of the systems functioning?*

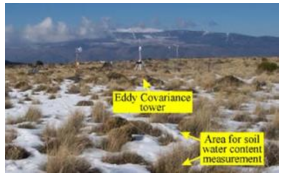
Application to karst groundwater recharge model
Sarrazin et al *GMD* 2018




Sensitivity of annual groundwater recharge




Humid site



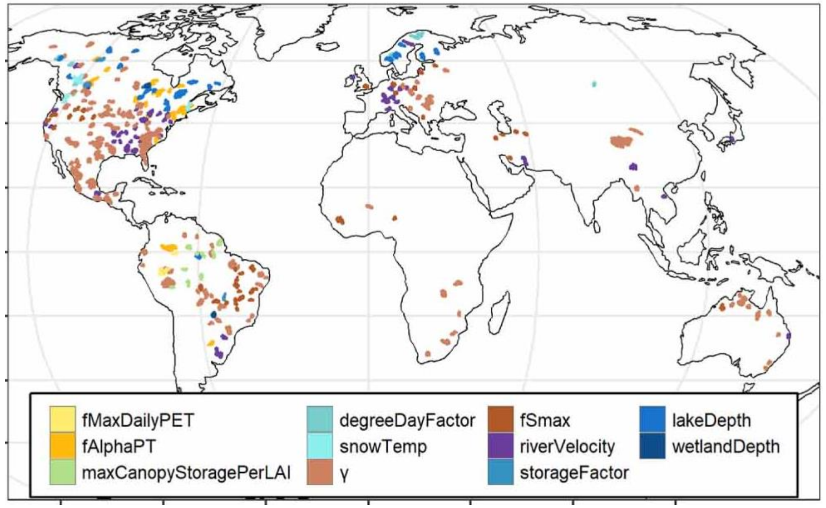
Arid site

francesca.pianosi@bristol.ac.uk

# Guiding model calibration and evaluation

Application to global hydrological model WaterGAP3
Kupzig et al *ERL* 2023
**doi:**10.1088/1748-9326/acdae8

Identifying most influential parameter on NSE of daily streamflow across 347 gauged catchments




Identifying most influential parameters on different output metrics

| | observations-free | | | | | | | | fit-to-observations | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q10 | maxTiming | Q50 | Q90 | minTiming | FDC.slope | sd | mean | KGE | logNSE | NSE | r |
| wetlandDepth | 13 | 13 | 13 | 12 | 13 | 13 | 13 | 14 | 13 | 14 | 12 | 13 |
| lakeDepth | 10 | 9 | 10 | 8 | 8 | 4 | 9 | 10 | 9 | 10 | 9 | 9 |
| storageFactor | 12 | 11 | 11 | 10 | 10 | 9 | 11 | 12 | 11 | 11 | 11 | 10 |
| evapoReductionExp | 13 | 15.5 | 13 | 12 | 13 | 12 | 14 | 11 | 13 | 13 | 13 | 13 |
| wetlOutflowExp | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 | 17 |
| lakeOutflowExp | 14 | 15 | 14 | 14 | 14 | 14 | 14 | 13 | 15 | 14 | 14 | 15 |
| riverVelocity | 7 | 4 | 5 | 8 | 9 | 8 | 3 | 12 | 5 | 6 | 3 | 1 |
| k_g | 7 | 8 | 6 | 2 | 3 | 2 | 7 | 9 | 8 | 8 | 8 | 7 |
| runoffFracBuiltUp | 14 | 16 | 14 | 14 | 14 | 14 | 14 | 13 | 14 | 14 | 14 | 14 |
| fSmax | 2 | 3 | 6 | 6 | 4 | 5 | 2 | 3 | 2 | 3 | 3 | 3 |
| γ | 1 | 2 | 1 | 1 | 1 | 2 | 2 | 1 | 1 | 1 | 2 | 3 |
| snowTemp | 10 | 7 | 10 | 10.5 | 9 | 11 | 9 | 9 | 10 | 10 | 10 | 9 |
| degreeDayFactor | 11 | 10 | 12 | 13 | 13 | 13 | 11 | 11 | 12 | 12 | 11 | 11 |
| canopyEvapoExp | 13 | 16 | 13 | 14 | 15 | 14 | 13 | 13 | 14 | 14 | 13 | 14 |
| axCanopyStoragePerLAI | 5 | 7 | 3 | 4 | 6 | 8 | 8 | 4 | 6 | 4 | 5 | 8 |
| fAlphaPT | 3 | 6 | 4 | 6 | 6 | 6 | 4 | 3 | 4 | 4 | 6 | 7 |
| fMaxDailyPET | 5 | 7 | 6 | 7 | 7 | 8 | 7 | 5 | 6 | 5 | 7 | 7 |

Ranks
≥7 [less important]
4 - 6
≤ 3 [more important]

Some parameters are consistently less important across metrics and basins → exclude from calibration

Some parameters are consistently very important across metrics and basins → prioritise for calibration

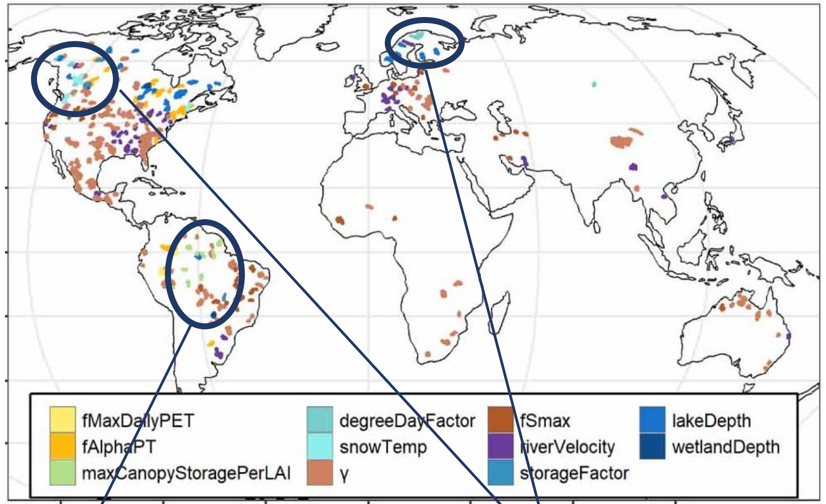
francesca.pianosi@bristol.ac.uk

# Guiding model calibration and evaluation

Application to global hydrological model WaterGAP3
Kupzig et al *ERL* 2023
**doi:**10.1088/1748-9326/acdae8

Is the most influential parameter the "right one" at the "right place"?

Is parameter importance explained by catchment attributes and/or climate zones?

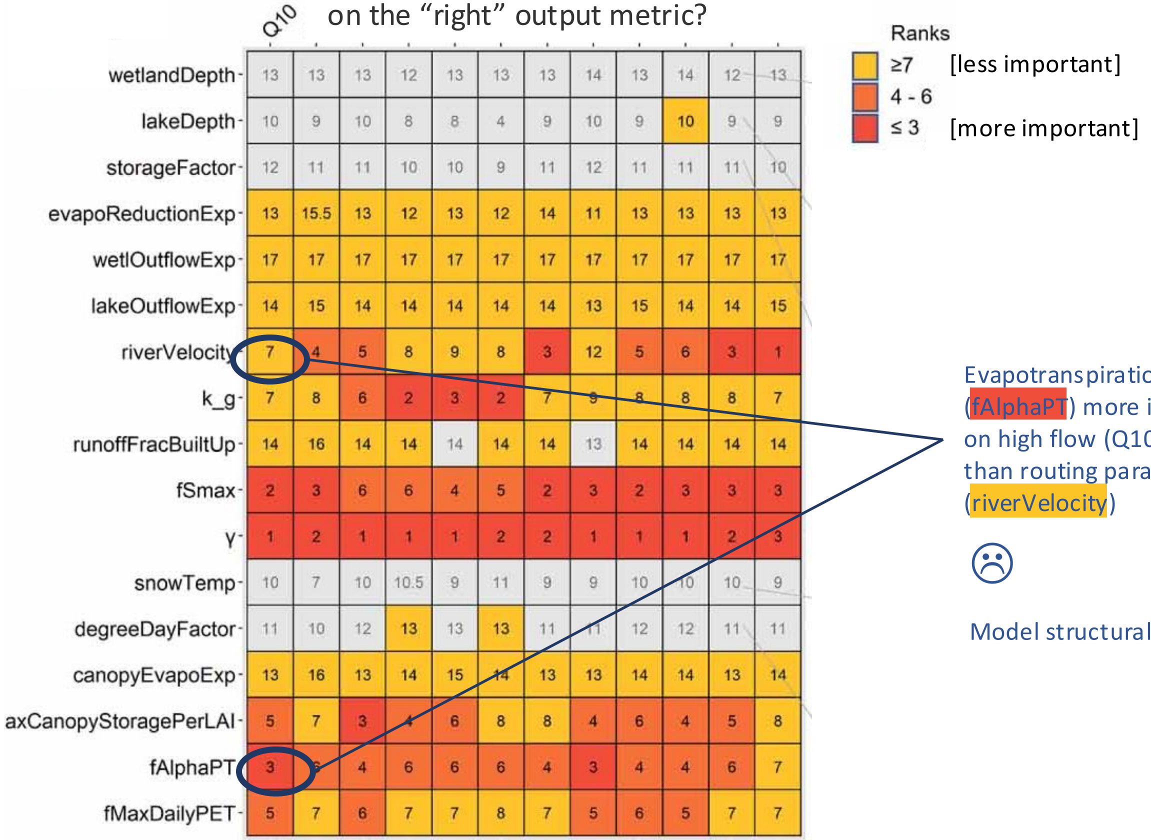



CanopyStorage key in forested catchments

☺

SnowTemp key in snowmelt dominated catchments

Is the "right" parameter most important on the "right" output metric?




Evapotranspiration parameter (fAlphaPT) more important on high flow (Q10) than routing parameter (riverVelocity)

☹

Model structural error?

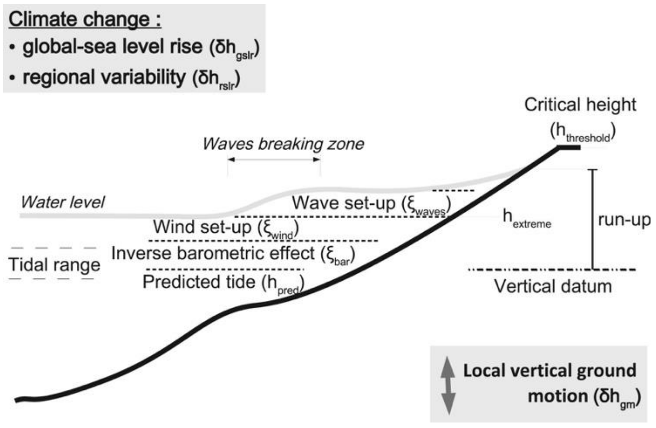
francesca.pianosi@bristol.ac.uk

# Finding controls of system behaviour

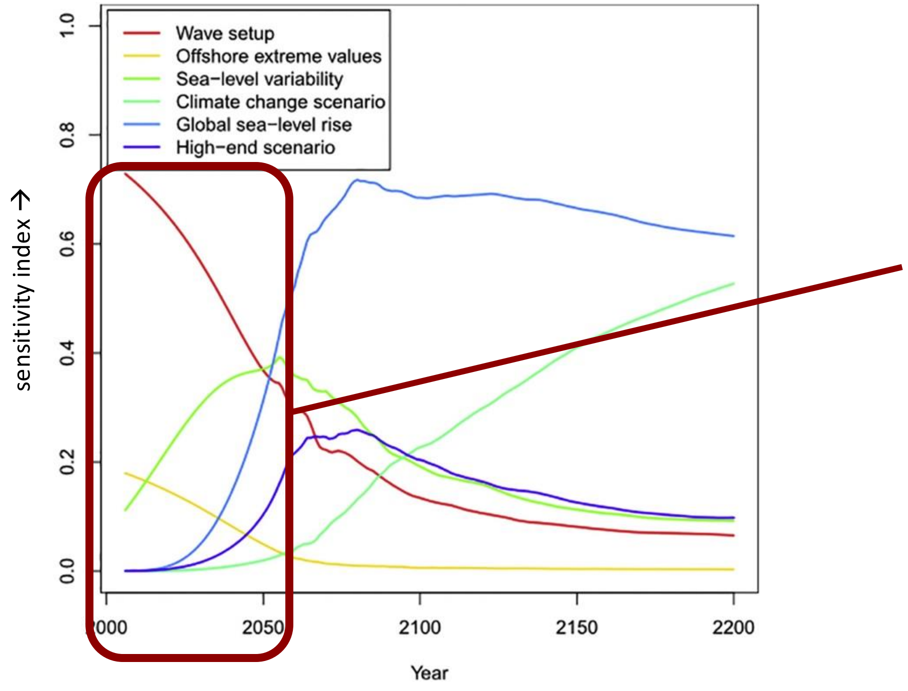
What are the dominant control of the model output?
Are model outputs sensitive to decision-relevant inputs?

*If outputs are more strongly controlled by uncertain assumptions/parameters than by the policy/scenario inputs, then the model will tell us more about the consequences of the assumptions embedded in it than it will tell us about the different policy options/scenarios*

Application to flood defence assessment model
Le Cozannet et al *EMS* 2015
**doi:** 10.1016/j.envsoft.2015.07.021




Sensitivity of coastal defence vulnerability
(= annual probability of exceeding the threshold height of coastal defences)




In the 'mid-term', the model predictions are controlled by the modeller's choice of the (very uncertain) 'wave setup' parameter way more than they are by climate change and sea level rise scenarios

→ the model should not be used for impact assessment on such temporal scales

francesca.pianosi@bristol.ac.uk

# How

to do UA/SA?

# Characterizing uncertainty in input factors

What is the appropriate distribution / range for the uncertain inputs?

| | | | | |
|---|---|---|---|---|
| characterize uncertainty in the inputs | sample N combinations of inputs | execute the model against each inputs' combination | calculate output(s) ranges or distribution | calculate sensitivity indices |

francesca.pianosi@bristol.ac.uk

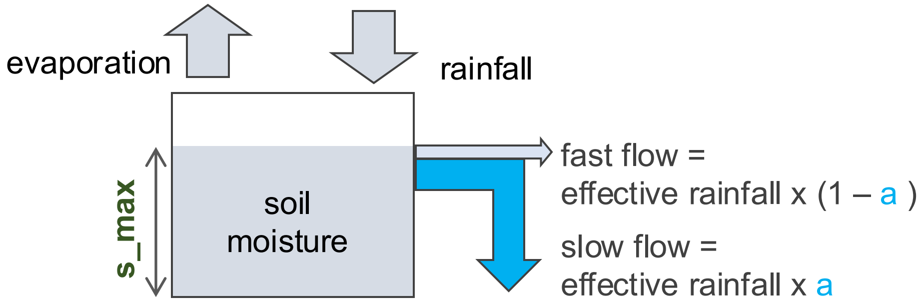
# Characterizing uncertainty in input factors

Depending on the type of input (scalar parameter, time series, discrete modelling choice, etc.) and on our level of uncertainty about it, we can use:

- a list of possible values
    - a uniform distribution within an uncertainty range
        - a probability distribution

… and define them using literature sources, historical observations, experts' judgment, etc.

Sometimes the range (distribution) is univocally defined by the physical meaning of the input, but most often different definitions are possible




The maximum soil capacity (s_max) varies between 0 and an upper bound that may be difficult to define

The repartition coefficient (a) varies between 0 and 1 by definition

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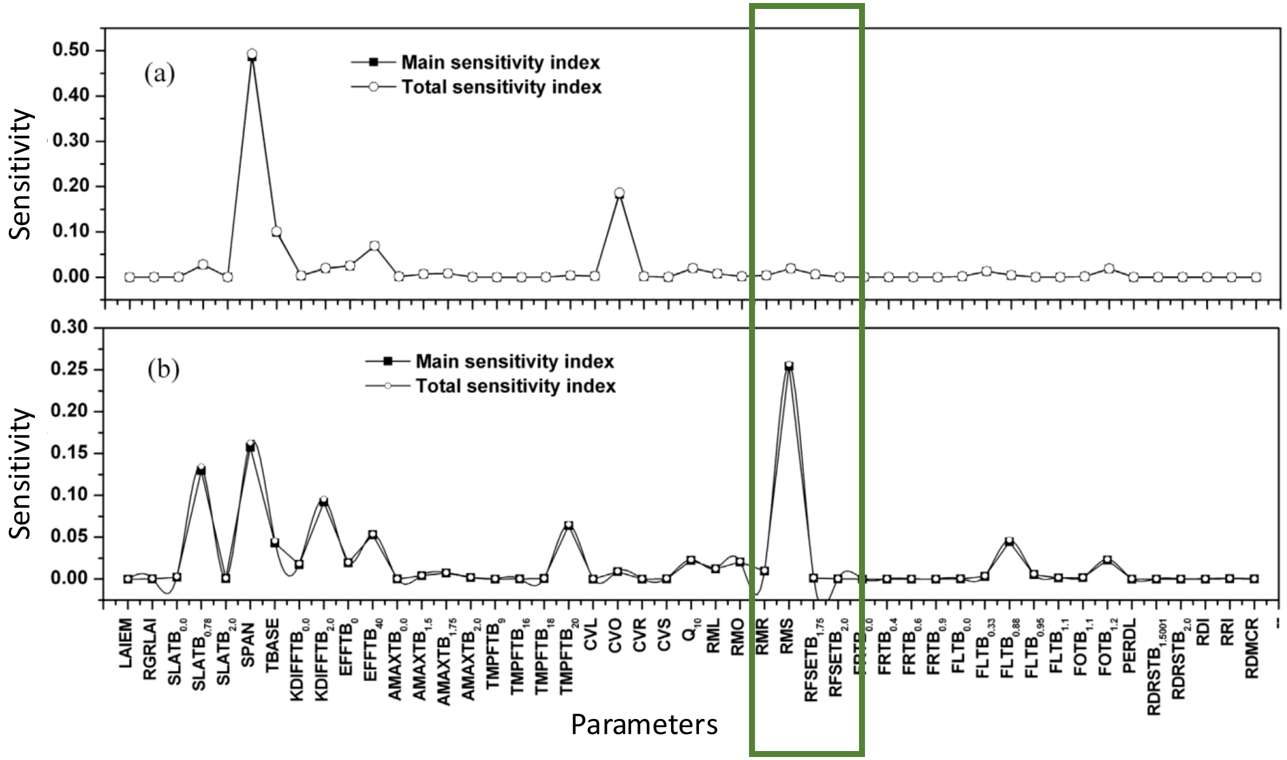
# When different definitions of the inputs ranges (distributions) are possible, the choice can significantly condition UA/SA results

Example from SA of a crop growth model (Wang et al EMS 2013)




Sensitivity of simulated crop yield based on 'literature' parameter ranges

Sensitivity of simulated crop yield based on 'expanded' parameter ranges

# Choosing the sampling strategy and size

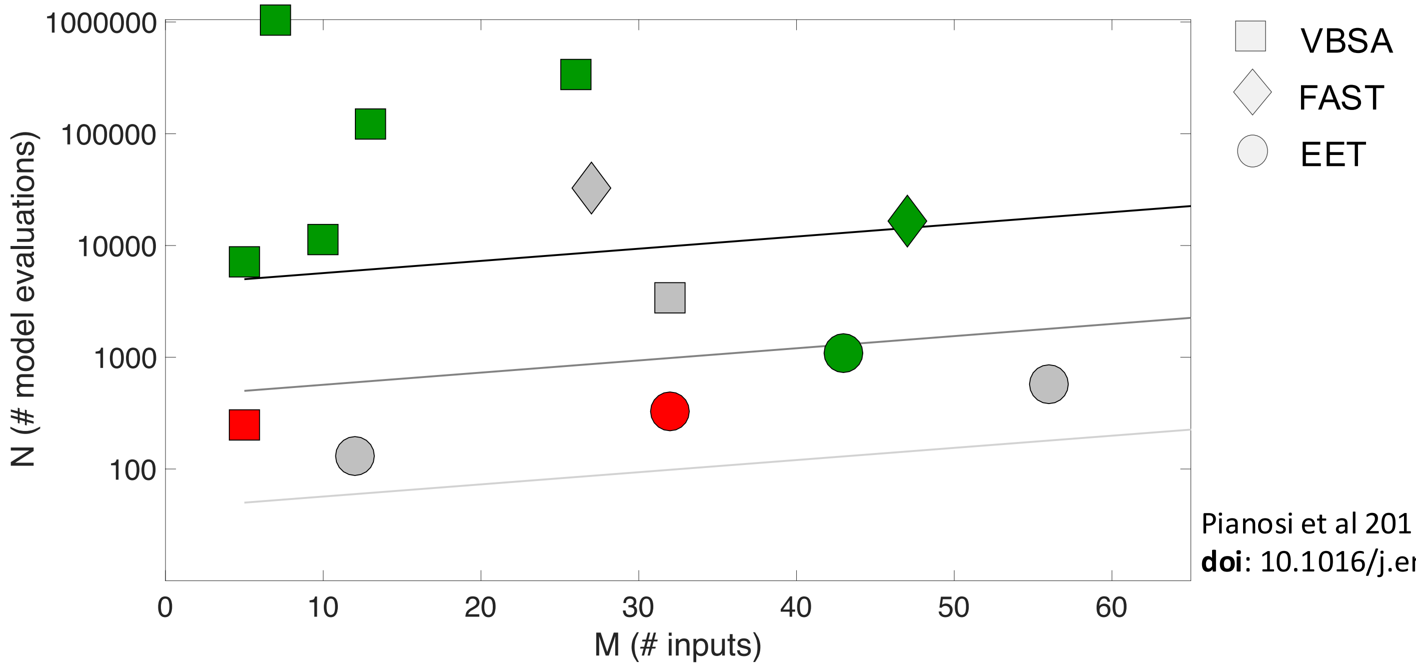
Which sampling technique to use (e.g. random sampling, Latin Hypercube, quasi-random sequences)?

How many samples are needed?

| | | | | |
|---|---|---|---|---|
| characterize uncertainty in the inputs | sample N combinations of inputs | execute the model against each inputs' combination | calculate output(s) ranges or distribution | calculate sensitivity indices |

francesca.pianosi@bristol.ac.uk

In general, the required sample size (N) increases with the number of uncertain inputs (M). However, the proportionality rate varies significantly from one method to another, and from one application of the same method to another

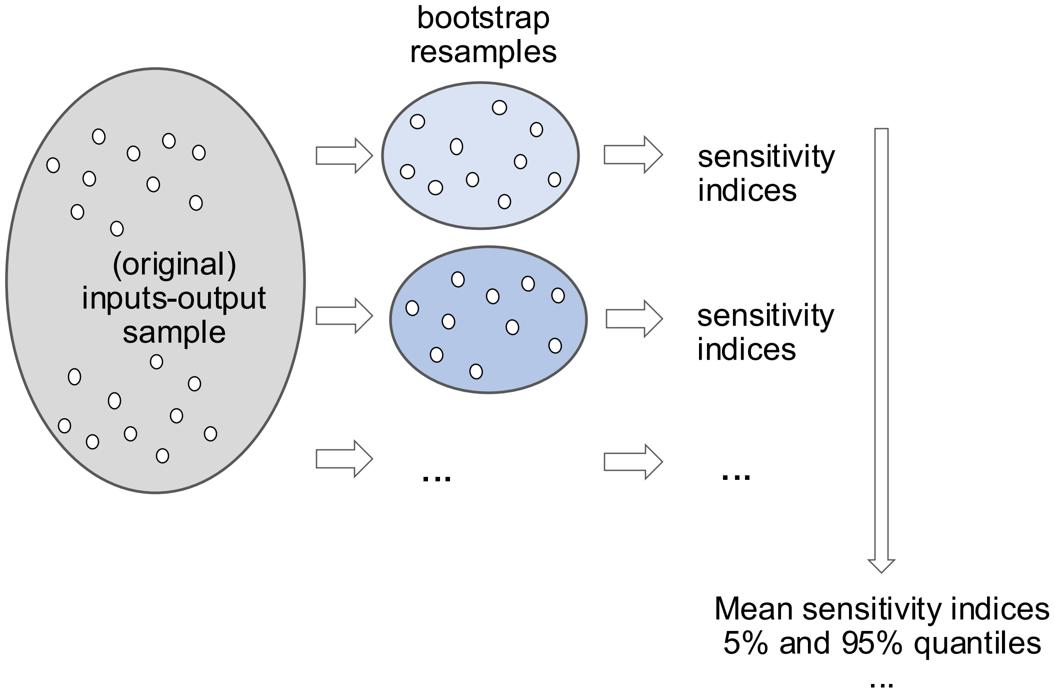


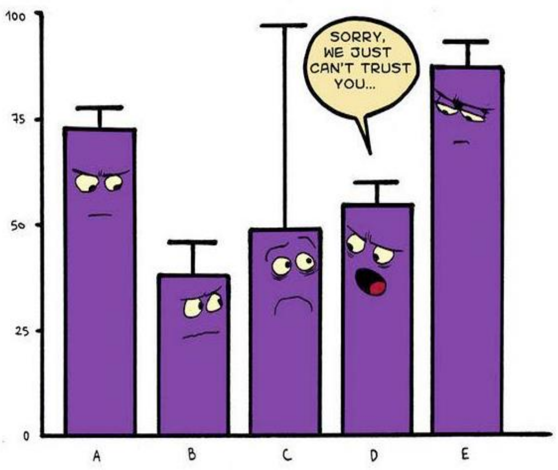

Pianosi et al 2016
**doi**: 10.1016/j.envsoft.2016.02.008

francesca.pianosi@bristol.ac.uk

# Sensitivity indices are calculated from a sample, so if the sample size is small, their values may be poorly approximated

In order to assess the robustness of our sensitivity estimates to the chosen sample, *without re-running the model*, we can use bootstrapping

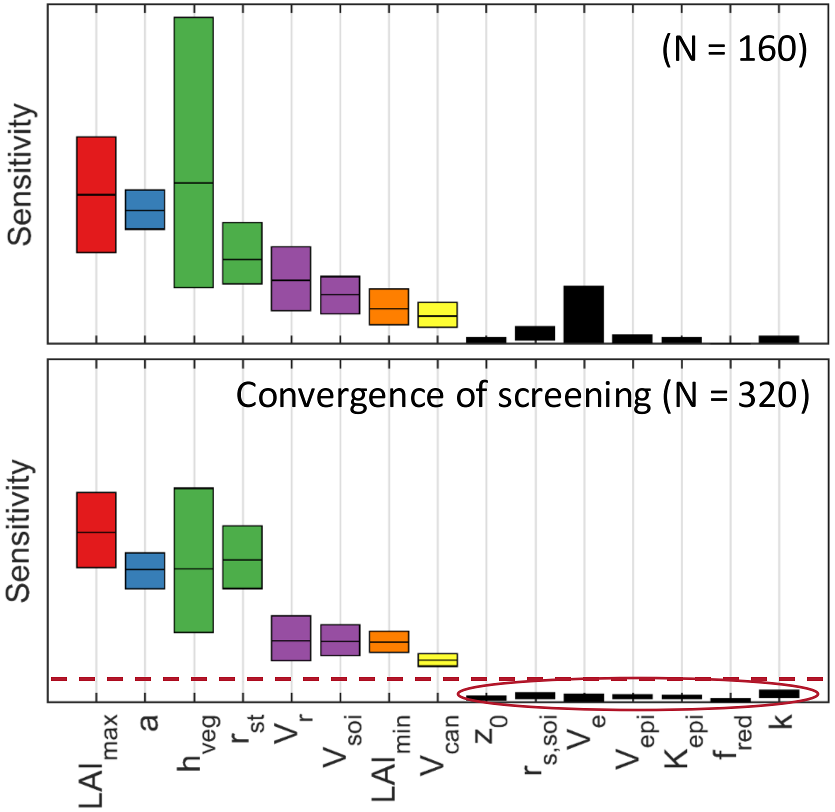


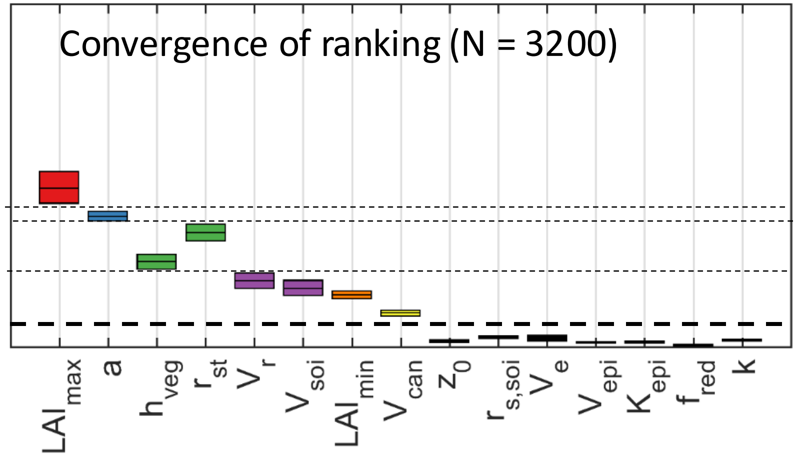

SOURCE: Reading Local Group of the Royal Statistical Society

francesca.pianosi@bristol.ac.uk

If the confidence intervals of our sensitivity indices are not “small enough” we must increase the sample size (what is “small enough” depends on the goal of our GSA)




black line: mean sensitivity index
bar: 90% confidence interval




francesca.pianosi@bristol.ac.uk

# Defining scalar output metric(s)

Which output metrics
should we look at?

| characterize uncertainty in the inputs | sample N combinations of inputs | execute the model against each inputs' combination | calculate output(s) ranges or distribution | calculate sensitivity indices |
|---|---|---|---|---|

francesca.pianosi@bristol.ac.uk

# Each output metric is typically sensitive to a small subset of inputs, but which are those inputs will differ from one metric to another

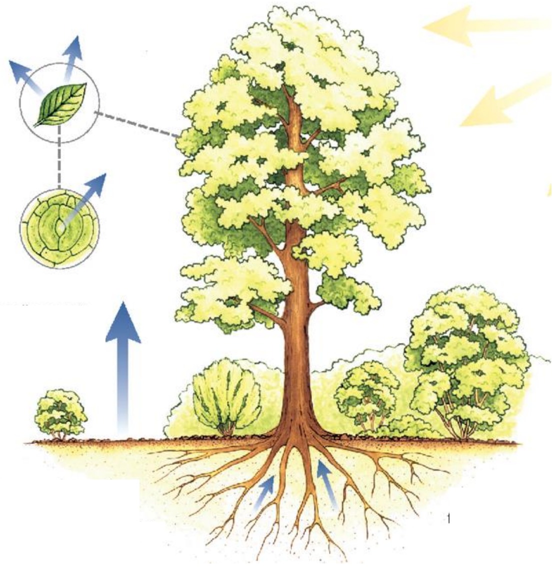
Application to a forest growth model (Song et al EcM 2012)

| Output variables | alphaCx | aWS | CoeffCond | cVPD0 | fN0 | FR | fracBB0 | fracBB1 | fullCanAge | gAc | gammaF1 | gammaR | k | LAIgcx | MaxAge | MaxCond | nWS | pFS20 | pRn | pRx | rAge | rho1 | SLA1 | Tmax | Tmin | Topt | tWaterMax |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| avDBH | 3 | 2 | 12 | | 10 | 6 | | | 19 | | 18 | | 5 | 14 | | 4 | 1 | 9 | 8 | 11 | 20 | | 15 | 17 | 16 | 13 | 7 |
| BasArea | 3 | 2 | 12 | | 9 | 6 | | | | | 18 | | 5 | 14 | 20 | 4 | 1 | 13 | 8 | 11 | 19 | | 15 | 17 | 16 | 10 | 7 |
| StandVol | 2 | | 13 | | 11 | 8 | 20 | 4 | | | 18 | | 5 | 16 | | 3 | 7 | 10 | 9 | 12 | | 1 | 14 | 19 | 17 | 15 | 6 |
| LAI | 3 | 15 | 12 | 20 | 13 | 9 | | | 19 | | 7 | | 8 | 18 | | 4 | 2 | 6 | 10 | 11 | | | 1 | 16 | 17 | 14 | 5 |
| ET | 6 | 19 | 13 | | 16 | 12 | | | | | 9 | | 11 | 20 | 18 | 2 | 4 | 8 | 14 | 15 | 17 | | 5 | 10 | 7 | 1 | 3 |
| fASW | 6 | 20 | 14 | | 19 | 13 | | | | | 15 | | 8 | 18 | 12 | 3 | 5 | 11 | 16 | 17 | 10 | | 4 | 7 | 9 | 1 | 2 |
| Transp | 8 | | 10 | | 19 | 13 | | | | 18 | 12 | | 9 | 20 | 14 | 2 | 6 | 11 | 16 | 17 | 15 | | 7 | 5 | 3 | 1 | 4 |
| WF | 2 | 15 | 12 | 20 | 13 | 8 | | | 19 | | 6 | | 7 | 16 | | 3 | 1 | 5 | 9 | 11 | | | 10 | 17 | 18 | 14 | 4 |
| WS | 1 | 19 | 11 | | 9 | 6 | | | 18 | | 17 | | 4 | 14 | | 2 | 5 | 8 | 7 | 10 | 20 | | 12 | 16 | 15 | 13 | 3 |
| WR | 1 | | 10 | | 9 | 11 | | | | | 20 | 2 | 5 | 16 | 18 | 4 | 13 | 19 | 3 | 6 | 17 | | 14 | 12 | 15 | 8 | 7 |

Input parameters

0.0 0.2 0.4 0.6 0.8 1.0

Sensitivity



francesca.pianosi@bristol.ac.uk

# Choosing a method for calculating sensitivity indices

Which global sensitivity analysis method to use (e.g. variance-based, elementary effects test, regional sensitivity analysis, etc.)?

| | | | | |
|---|---|---|---|---|
| characterize uncertainty in the inputs | sample N combinations of inputs | execute the model against each inputs' combination | calculate output(s) ranges or distribution | calculate sensitivity indices |

francesca.pianosi@bristol.ac.uk

# Different methods defines “sensitivity” in different ways and are more or less suitable for specific purposes or problems

Pianosi et al 2016
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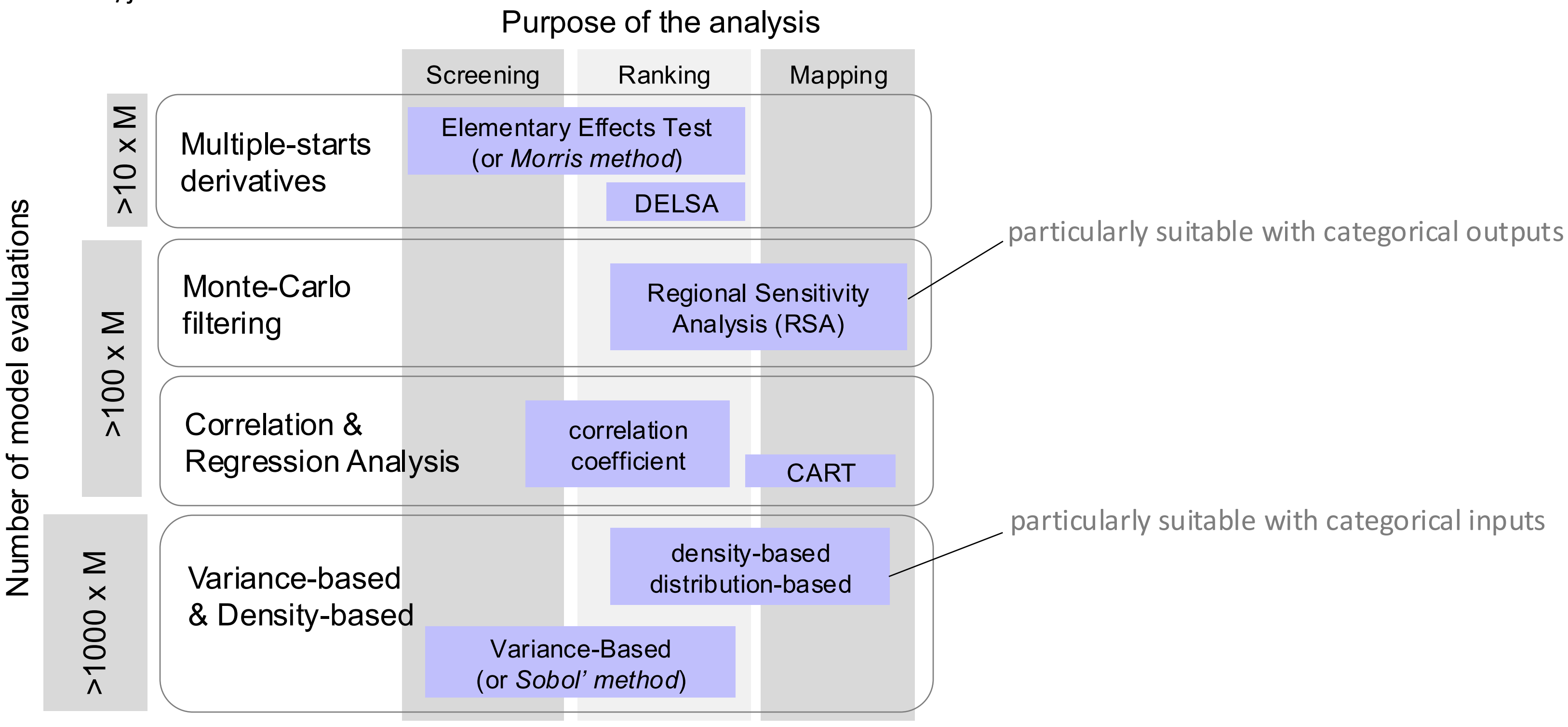
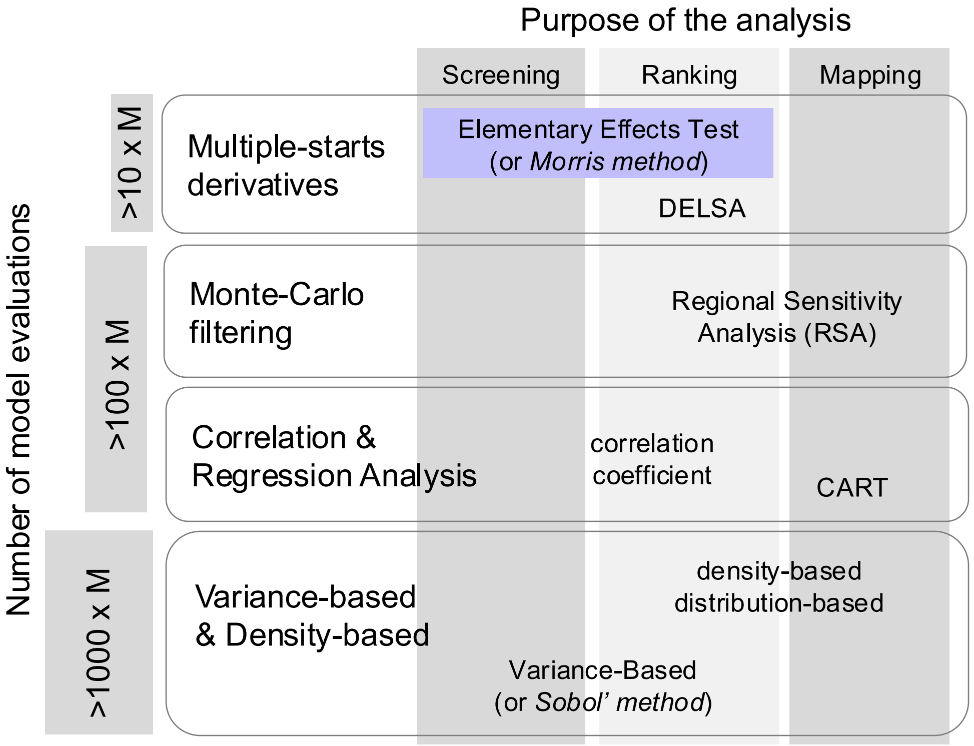



*M = number of input factors*

francesca.pianosi@bristol.ac.uk

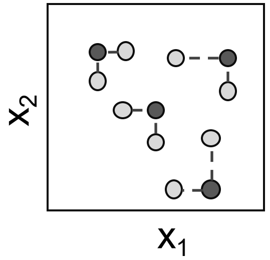
# Elementary Effects Test
(Morris, 1991)

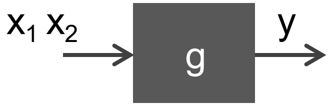



*Sensitivity is proportional to...*
the mean finite differences of the output across the input space

$$S_i = \frac{1}{r}\sum_{j=1}^{r} EE^j$$

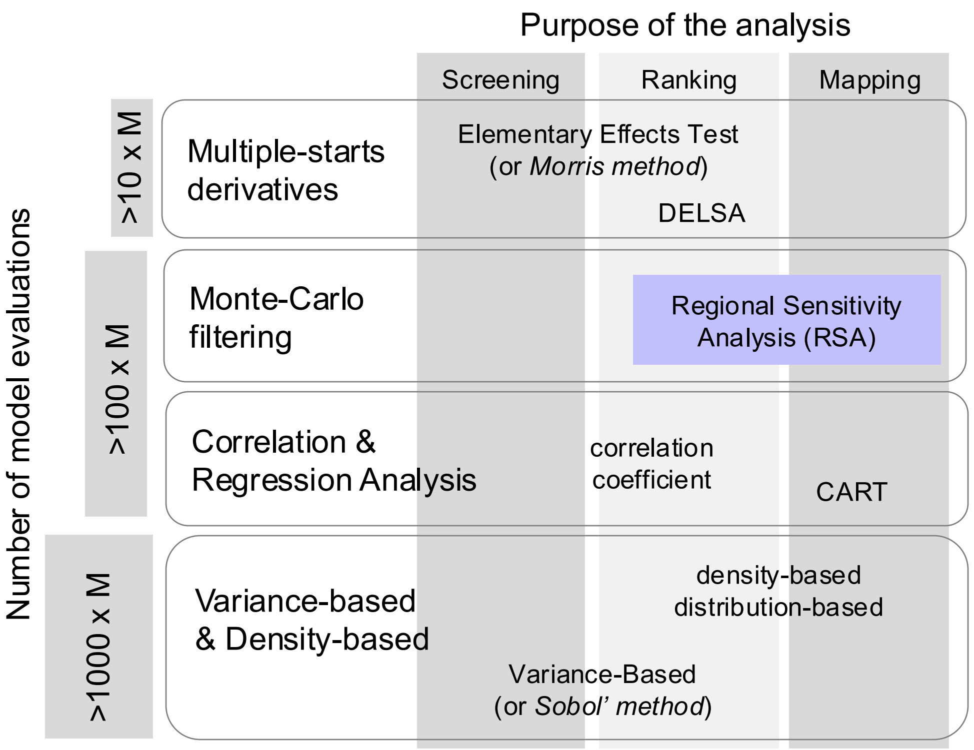
$$EE^j = \frac{g(\bar{x}_1^j, ..., \bar{x}_i^j + \Delta_i^j, ..., \bar{x}_M^j) - g(\bar{x}_1^j, ..., \bar{x}_i^j, ..., \bar{x}_M^j)}{\Delta_i^j} c_i$$




francesca.pianosi@bristol.ac.uk

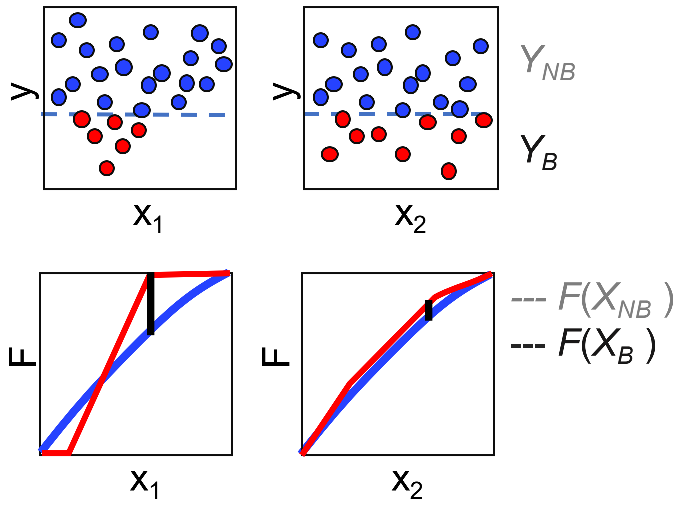
# Regional Sensitivity Analysis (Hornberger & Spear, 1980)




*Sensitivity is proportional to...*

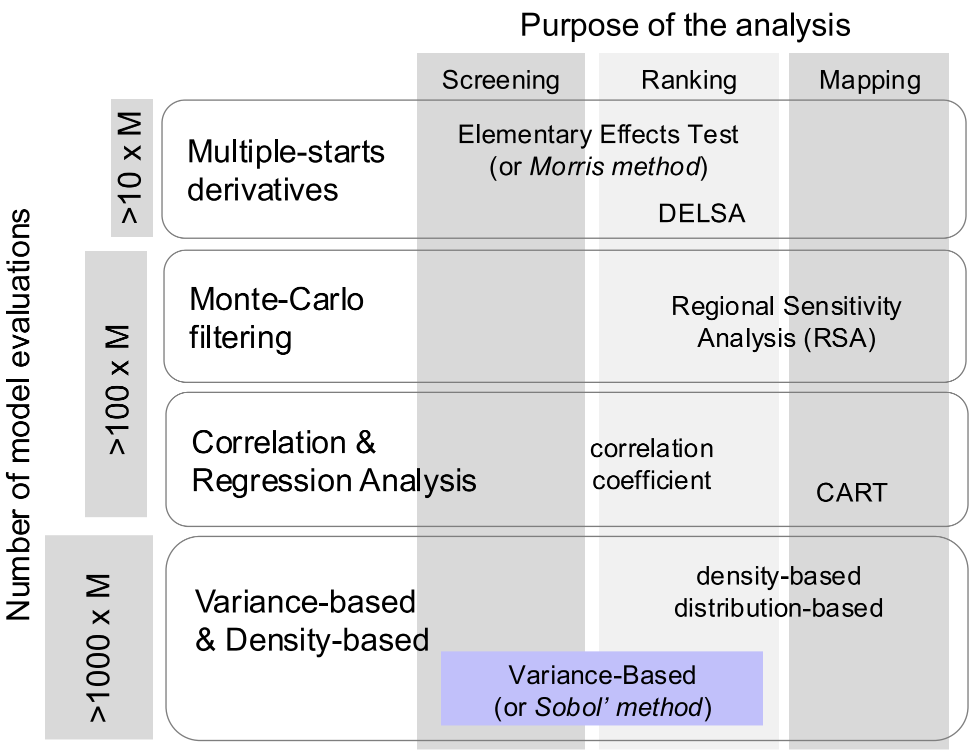
the variation induced in the distribution of an input by conditioning the output

$$S_i = \max_q \left| F_{x_i}(x|x \in X_B) - F_{x_i}(x|x \in X_{NB}) \right|$$




francesca.pianosi@bristol.ac.uk

# Variance-based Sensitivity Analysis (Homma & Saltelli, 1996)




*Sensitivity is proportional to...*
variation induced in the variance of the output by conditioning an input

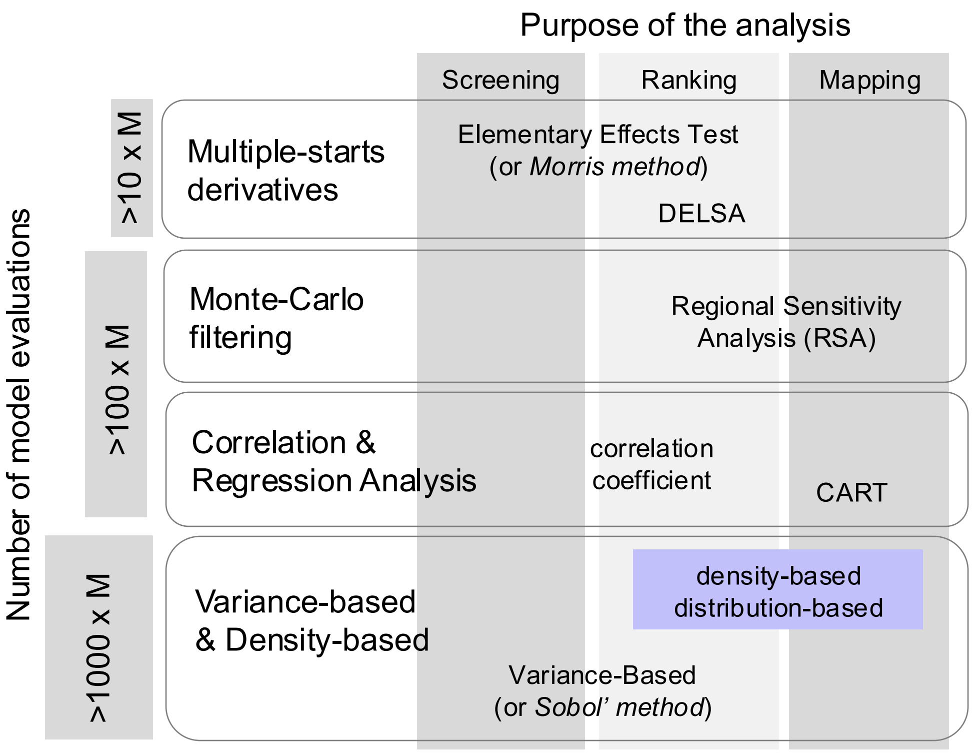
$$S_i = \frac{V_i}{V} = \frac{V_{x_i}[E(y|x_i)]}{V(y)} = \frac{V(y) - E_{x_i}[V(y|x_i)]}{V(y)}$$

$$S_i^T = 1 - \frac{V_{x_{\sim i}}}{V} = 1 - \frac{V_{x_{\sim i}}[E(y|x_{\sim i})]}{V(y)}$$

$$V = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + ... + V_{12...M}$$

francesca.pianosi@bristol.ac.uk

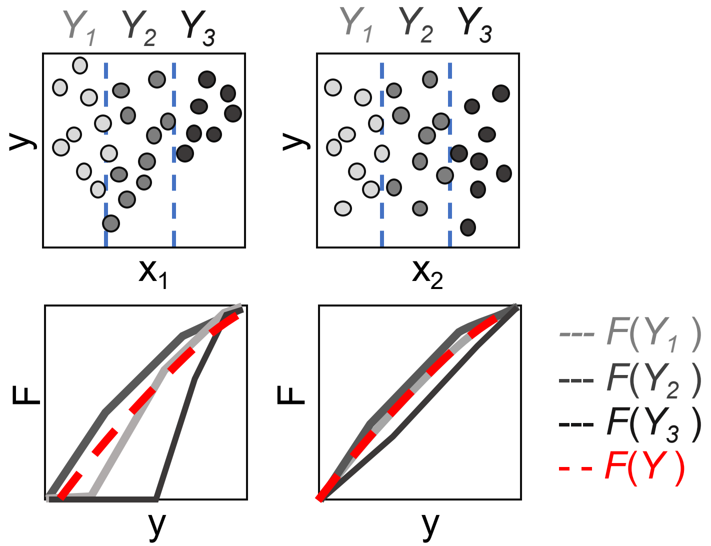
# Distribution-based Sensitivity Analysis (PAWN)
(Pianosi & Wagener 2015)




*Sensitivity is proportional to...*

variation induced in the distribution of the output by conditioning an input

$$S_i = \underset{k}{\mathrm{stat}} \ \max_q \left| F_y(q) - F_{y|x_i}(q|x_i \in I_k) \right|$$




francesca.pianosi@bristol.ac.uk

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francesca.pianosi@bristol.ac.uk