Global Sensitivity Analysis: who, when and why

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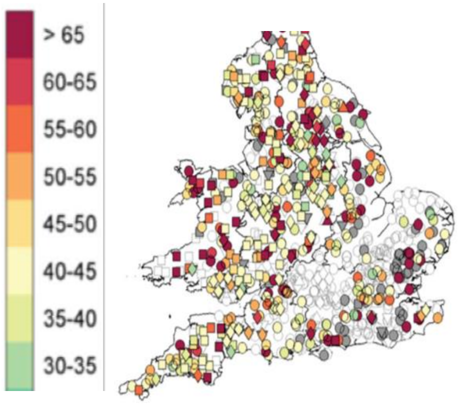
Environmental modelling is affected by large uncertainties

- The data we use to build (calibrate) and test models are affected by large errors and gaps (and new sensors won’t fill them all!)

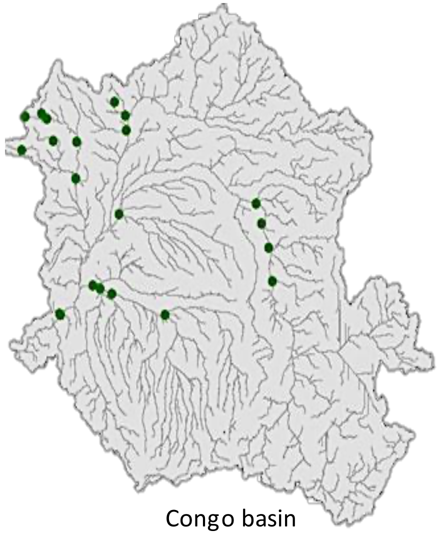
Example: river flow data

Relative uncertainty [%] in low flow data

Coxon et al 2015 *WRR*

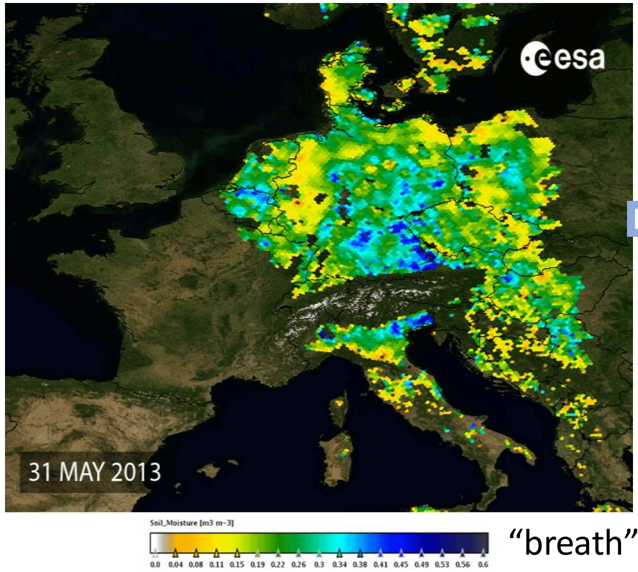


England & Wales (242,500 km^2)



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

Example: soil moisture

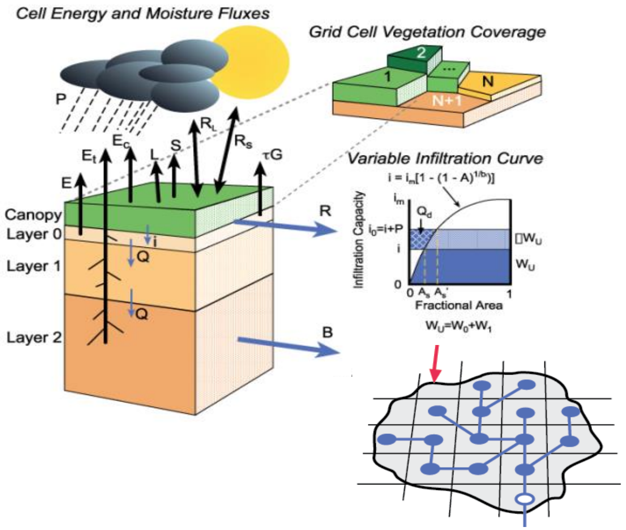


“breath” vs “depth”

Environmental modelling is affected by large uncertainties

- The data we use to build (calibrate) and test models are affected by large errors and gaps
- Models use simplifying assumptions whose adequacy is uncertain

Water flowing over and through hillslopes



Rainfall-runoff processes represented in a mathematical model (VIC)

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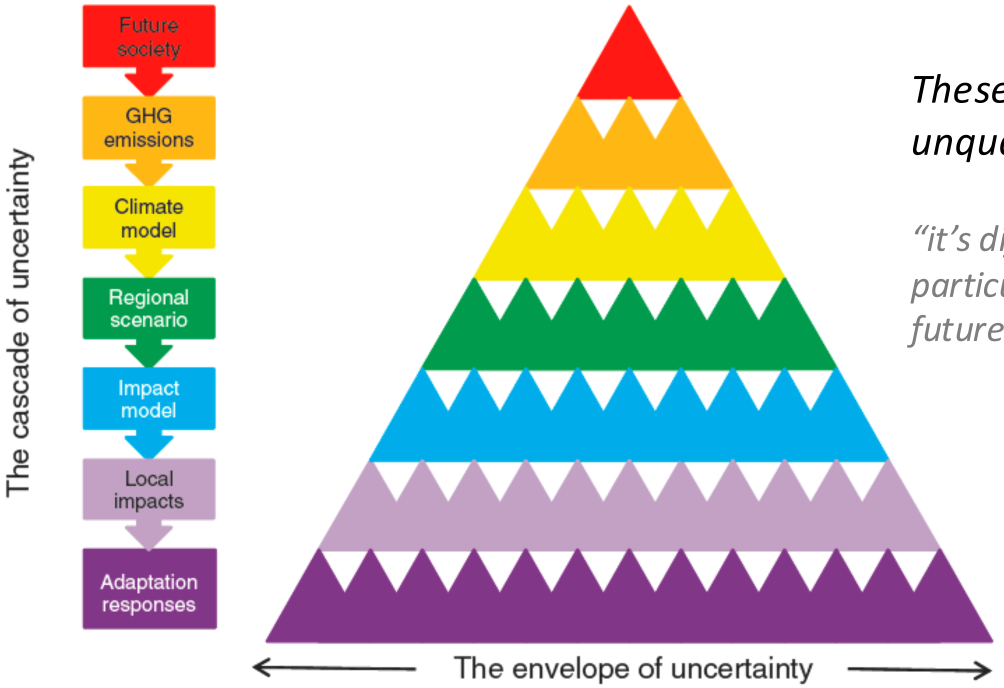
Environmental modelling is affected by large uncertainties

- The data we use to build (calibrate) and test models are affected by large errors and gaps
- Models use simplifying assumptions whose adequacy is uncertain
- We often use models to simulate long-term system behaviour and thus we need to build scenarios of plausible (?) future evolution of the system drivers



These uncertainties are mostly unquantifiable and irreducible

"it's difficult to make predictions, particularly when they concern the future" (Danish proverb)

Wilby & Dessai 2010

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So, what do we do with uncertainty?

- Ignore it

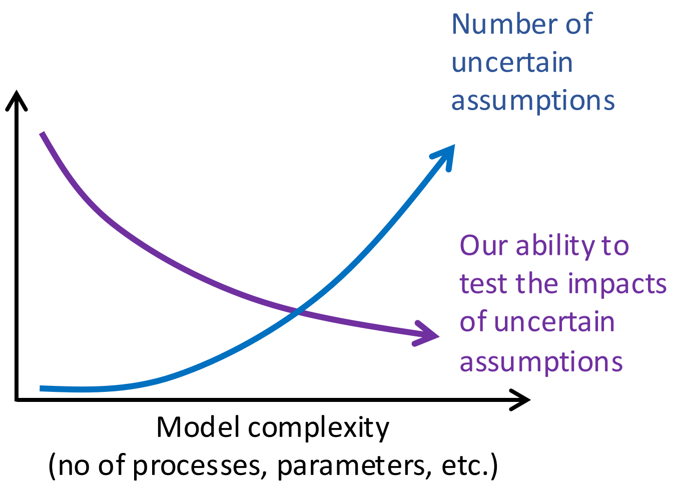
So, what do we do with uncertainty?

- 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* Princeton University Press



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So, what do we do with uncertainty?

- Ignore it
- Fight it
- Acknowledge it
  - uncertainty analysis: to quantify uncertainty in the model output(s) as a consequence of known (assumed) input uncertainties
  - sensitivity analysis: to assess the relative contribution of different input uncertainties to the output(s) uncertainty

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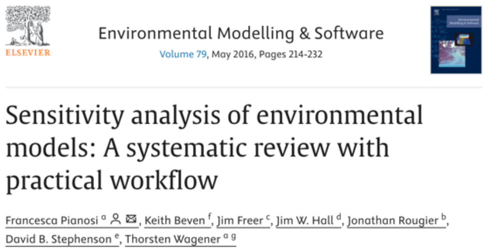
My research journey in this field

NERC Project (2013-2015) on "Risk and Uncertainty in Natural Hazard Assessment"

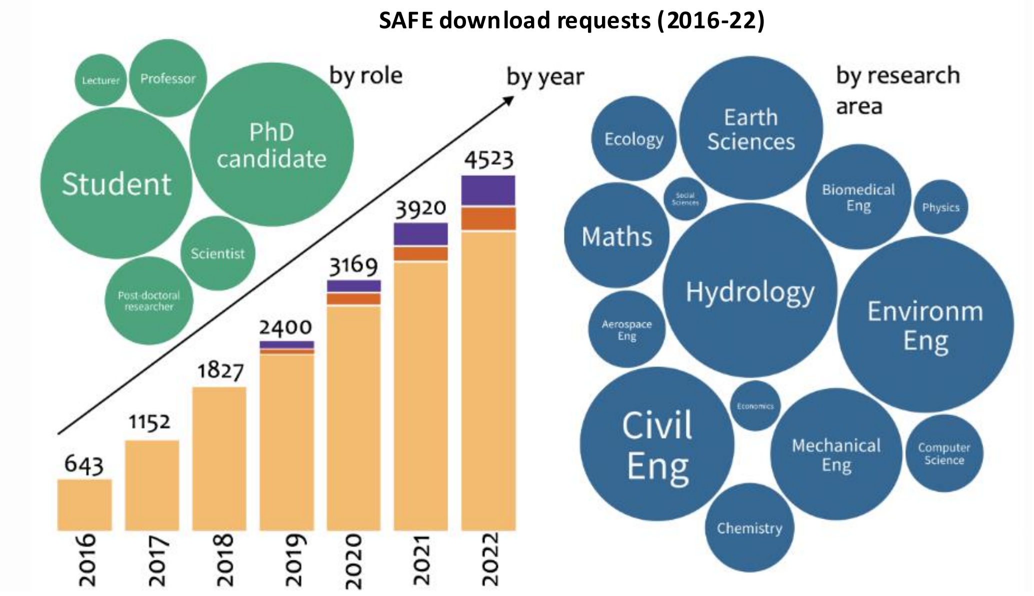
To harmonise and foster uncertainty quantification and attribution across natural hazard modelling sectors

case studies across hazard sectors (floods, windstorms, landslides, etc.)

review of GSA methods and key set-up choices



Open-source software: the SAFE toolbox



Methodological advances
- distribution-based (PAWN) and "given-data" approaches
- analysis of robustness & convergence of sensitivity indices

Can we extract useful insights from small(ish) samples of model's input-output?

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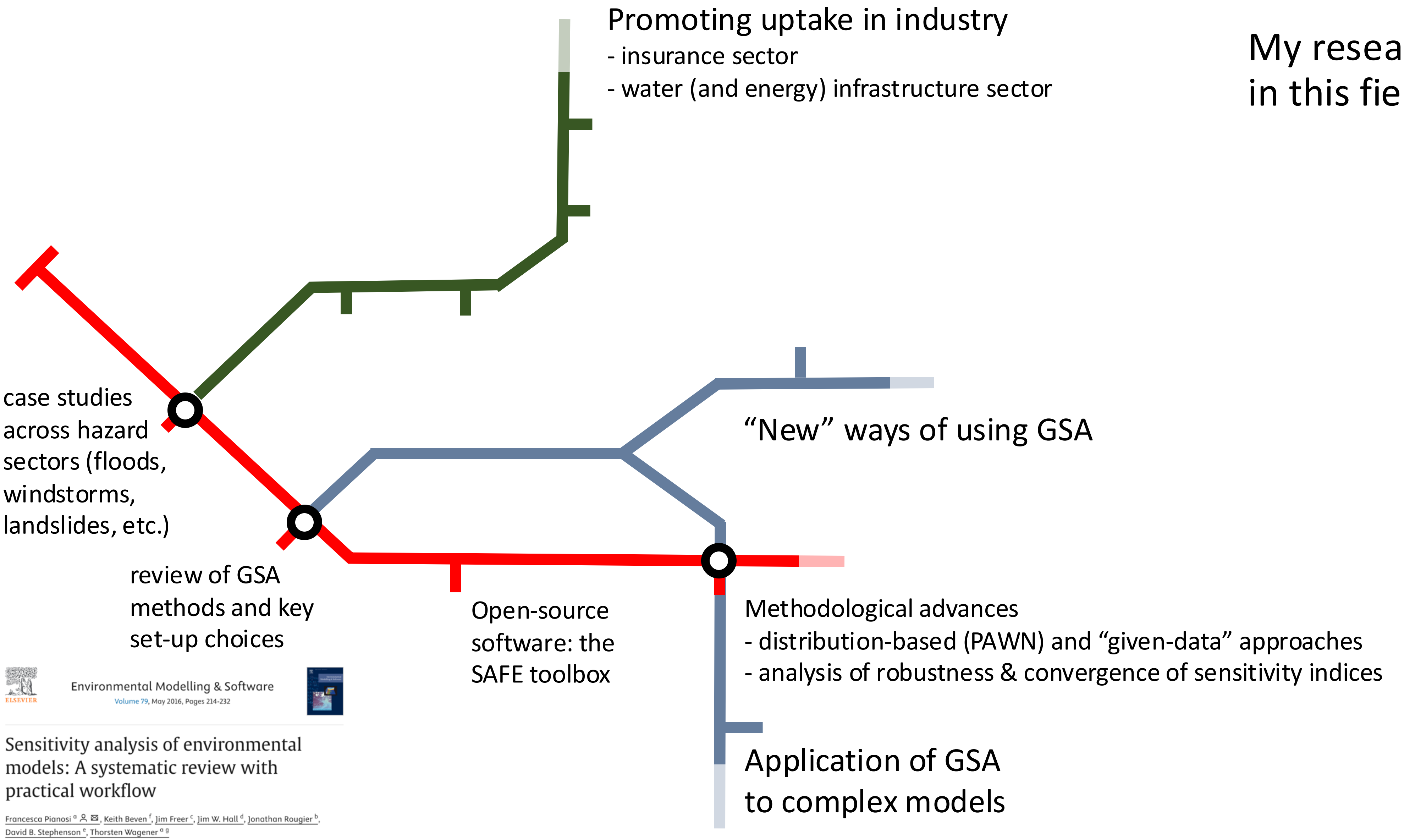

Environmental Modelling & Software
Volume 79, May 2016, Pages 214-232

Sensitivity analysis of environmental models: A systematic review with practical workflow

Francesca Pianosi [a], Keith Beven [f], Jim Freer [c], Jim W. Hall [d], Jonathan Rougier [b], David B. Stephenson [e], Thorsten Wagener [a, g]

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Applying GSA
to complex models

many inputs
many interacting components
long run times

The “GSA paradox” (?):
The models that would most
benefit from scrutiny
through GSA are the ones to
which they are least applied

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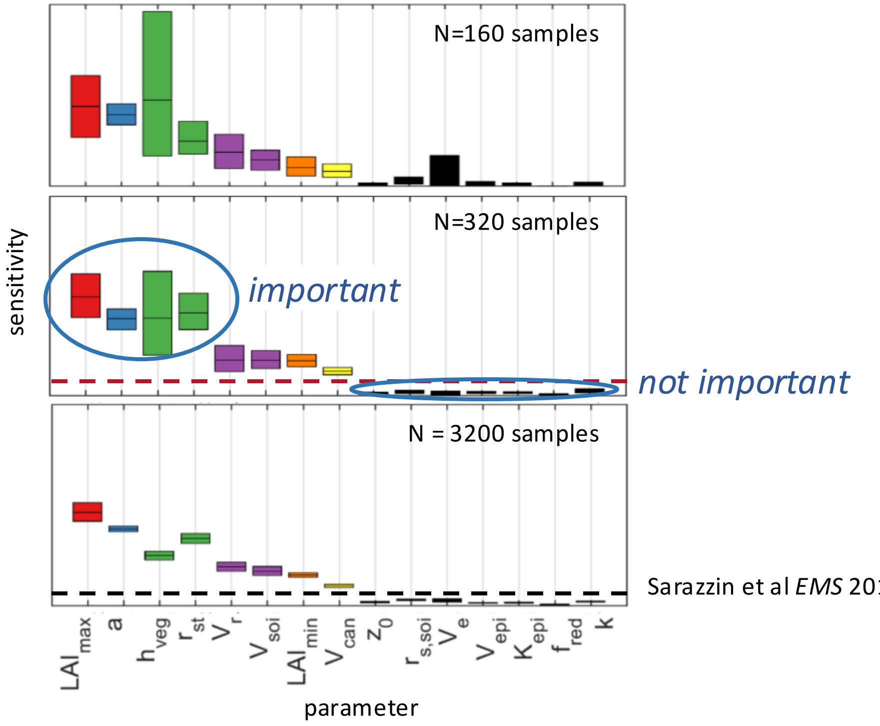
Applying GSA
to complex models

many inputs
many interacting components
long run times

How do we lower down the computational barriers?

- frugal methods that require smaller sample sizes
- methods to deal with complex, correlated inputs
- accept imperfect but meaningful results



Sarazzin et al *EMS* 2016

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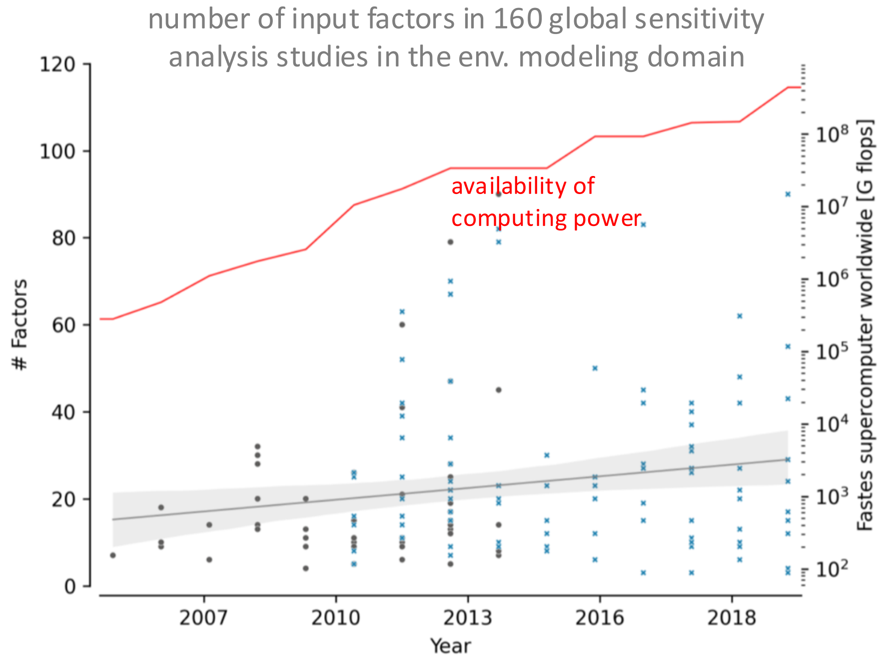
Applying GSA to complex models

many inputs
many interacting components
long run times

Computational burden is not the only barrier to uptake!



complexity of GSA application has not increased in line with growth in available computing power!

Reinecke et al *SESMO* 2024

Applying GSA
to complex models

many inputs
many interacting components
long run times

The extent to which uncertainty is explicitly considered depends on “values” more (?) than on technical constraints:

- Modelling culture
- View of the role of modelling for public decision-making
- Market acceptance (for commercial models)

High-fidelity, high-resolution

- models as *“perfect pictures”*
- role of modelling is *“to produce truth”*
- uncertainty as undesirable

GSA resistant

Parsimonious, mechanistic

- models as *“metaphors”*
- role of modelling is *“to assist in problem solving”*
- uncertainty as inevitable

GSA adopter

Data-driven, black box

- models as *“crystal balls”*

??

??

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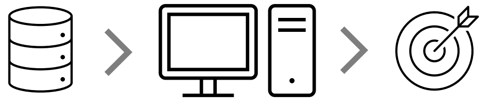
New ways of using GSA: model evaluation

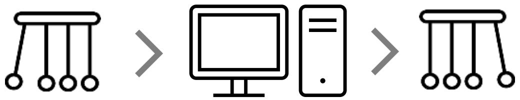
Wagener et al 2022
On the evaluation of climate change impact models *WIREs-CC*
doi:10.1002/wcc.772

"Data-based" evaluation:



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

"Response-based" evaluation:



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

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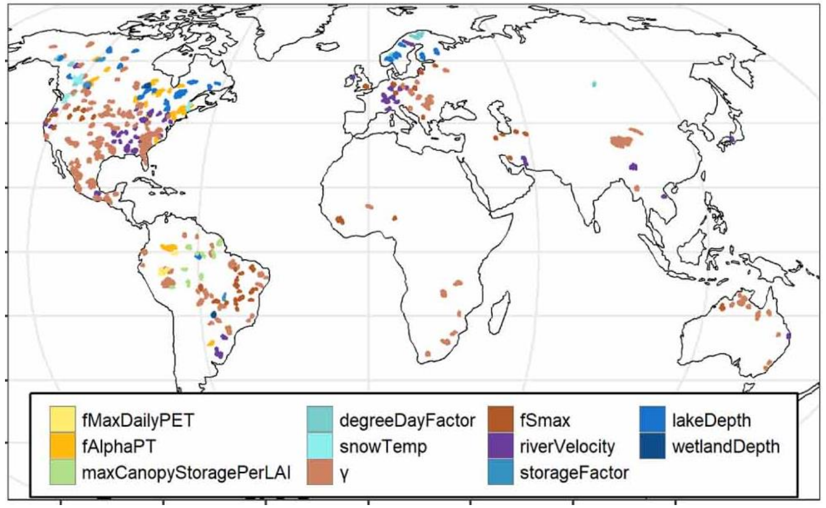
New ways of using GSA: model evaluation

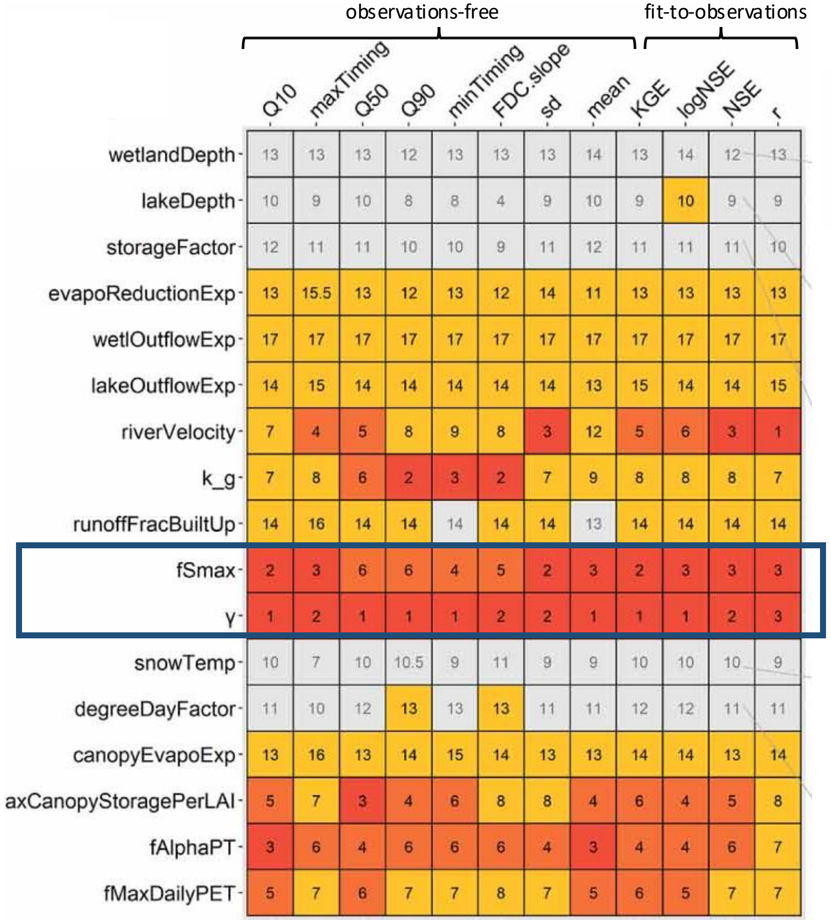
Example application to global hydrological model WaterGAP3

Kupzig et al 2023
Towards parameter estimation in global hydrological models *Environ. Res. Lett.*
doi:10.1088/1748-9326/acdae8

Most influential parameter on NSE of daily streamflow across 347 gauged catchments



Parameter importance on different output metrics



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

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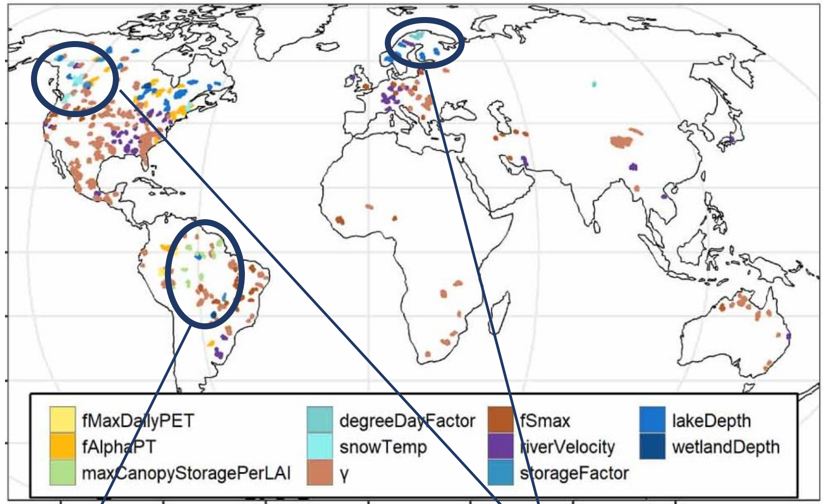
Is the most influential parameter the "right one" at the "right place"?

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

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

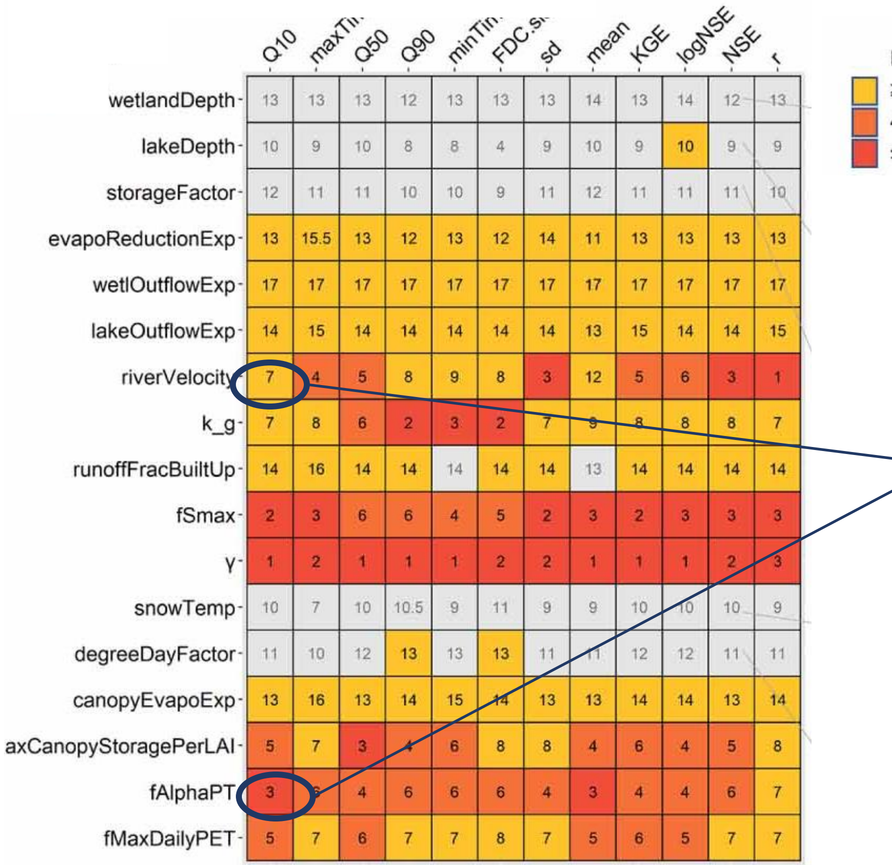
Most influential parameter on NSE of daily streamflow across 347 gauged catchments



CanopyStorage key in forested catchments

☺

SnowTemp key in snowmelt dominated catchments



	Q10	maxTi	Q50	Q90	minTi	FDC.s	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]

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

☹

Model structural error?

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New ways of using GSA: another “GSA paradox”?

- The versatility of GSA makes it more difficult (rather than less) to communicate its value to potential users

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New ways of using GSA: another "GSA paradox"?

- The versatility of GSA makes it more difficult (rather than less) to communicate its value to potential users
- Many studies, reviews, training resources, etc. focus on "how" GSA is performed

characterize uncertainty in the inputs	sample N combinations of inputs	execute the model against each inputs' combination	calculate sensitivity indices
	Which sampling strategy? Which sample size?		*Which sensitivity indices? Which approximation algorithms?*

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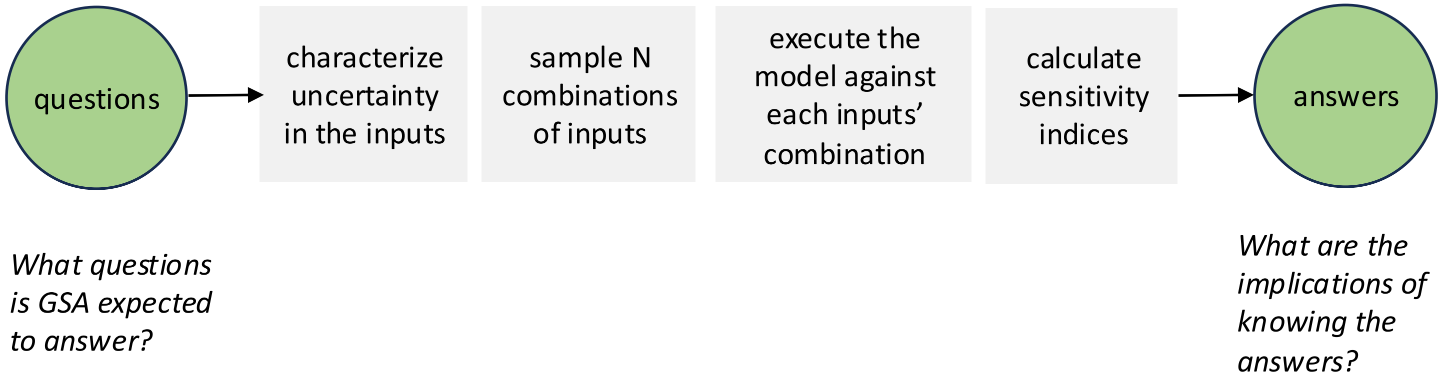
New ways of using GSA: another "GSA paradox"?

- The versatility of GSA makes it more difficult (rather than less) to communicate its value to potential users
- Many studies, reviews, training resources, etc. focus on "how" GSA is performed
- … and possibly not enough on conceptualising why GSA should be performed in the first place



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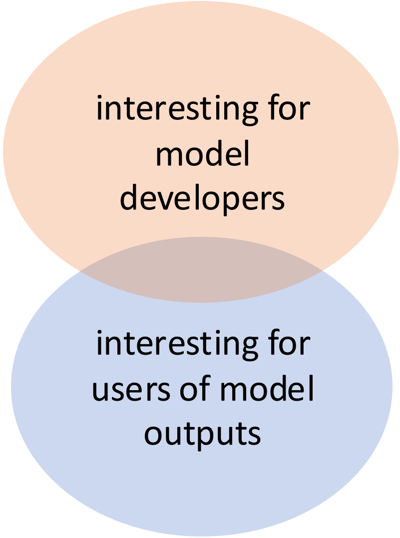
What type of questions can we answer through GSA and who are they relevant for?

- 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?



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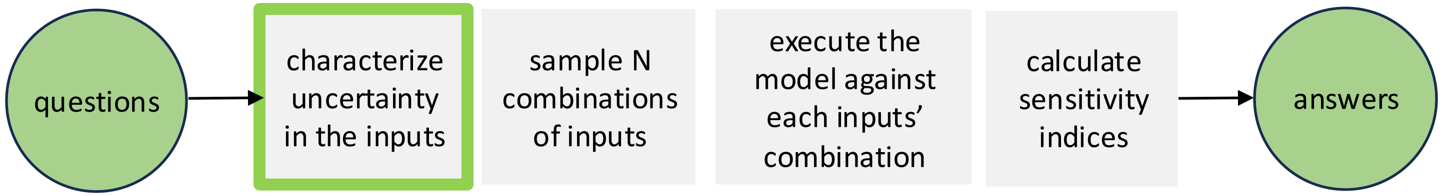
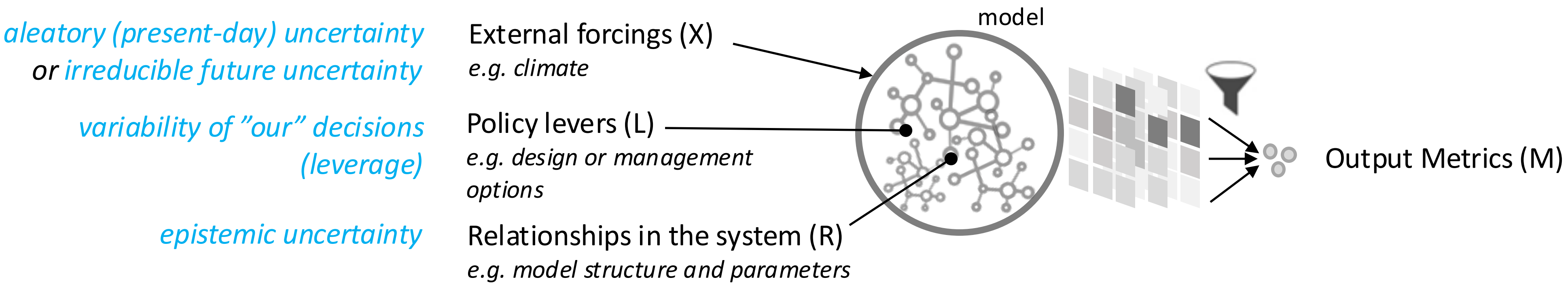
What questions we are asking determines the choice of inputs and outputs but also the meaning of the input variations that we apply



We can use the XLRM Framework for Decision-Making Under Deep Uncertainty (Lempert et al 2004) to frame the GSA experiment



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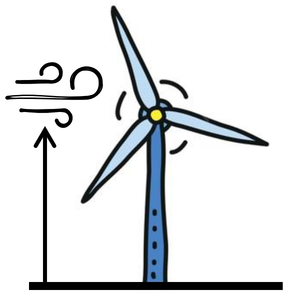
Reframing GSA with the XLRM framework

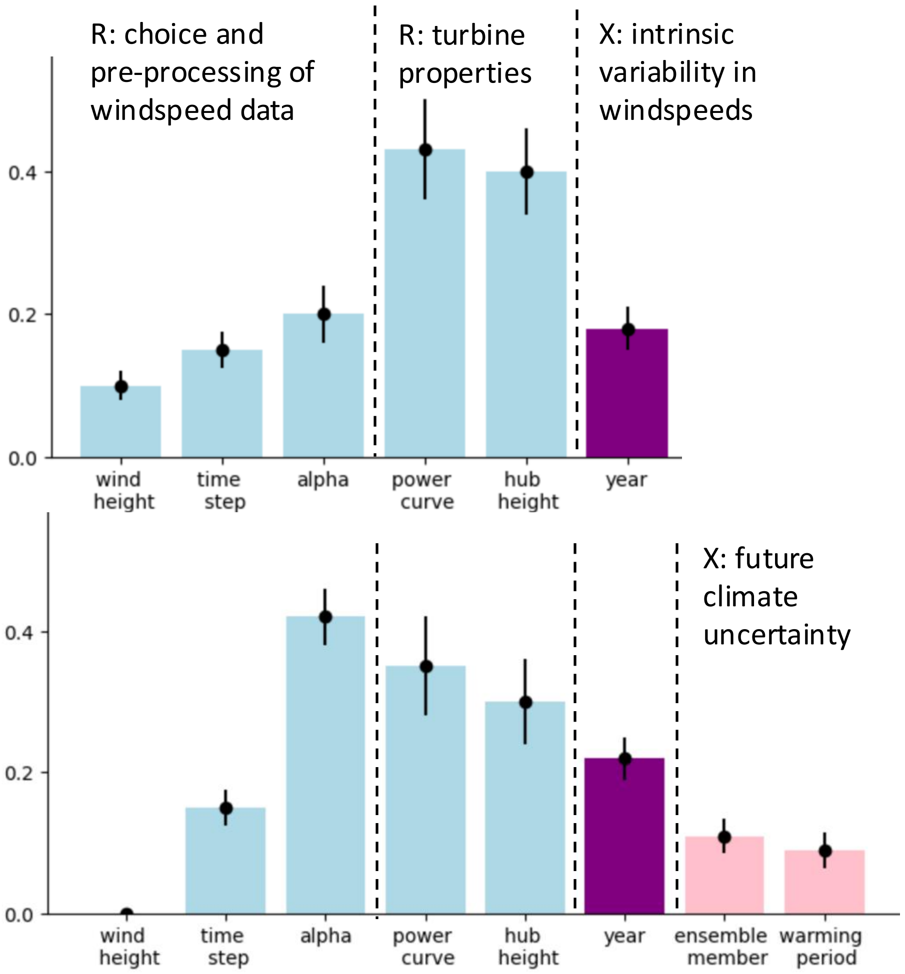


windpower model

Example application to energy and water infrastructure modelling

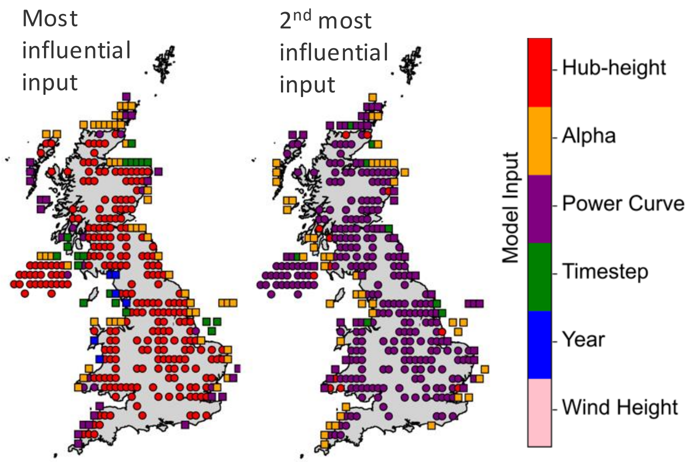
Salwey et al *under prep*

Output M: annual wind power capacity



- aleatory year-on-year wind variability (X) less important than previously thought
- incomplete knowledge of turbine properties (R) plays dominant role

This is confirmed across GB:



> importance of open-access data about existing plants for national-scale energy system stress testing

- climate uncertainty has limited impact on future performance

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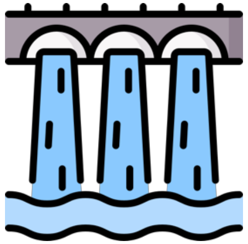
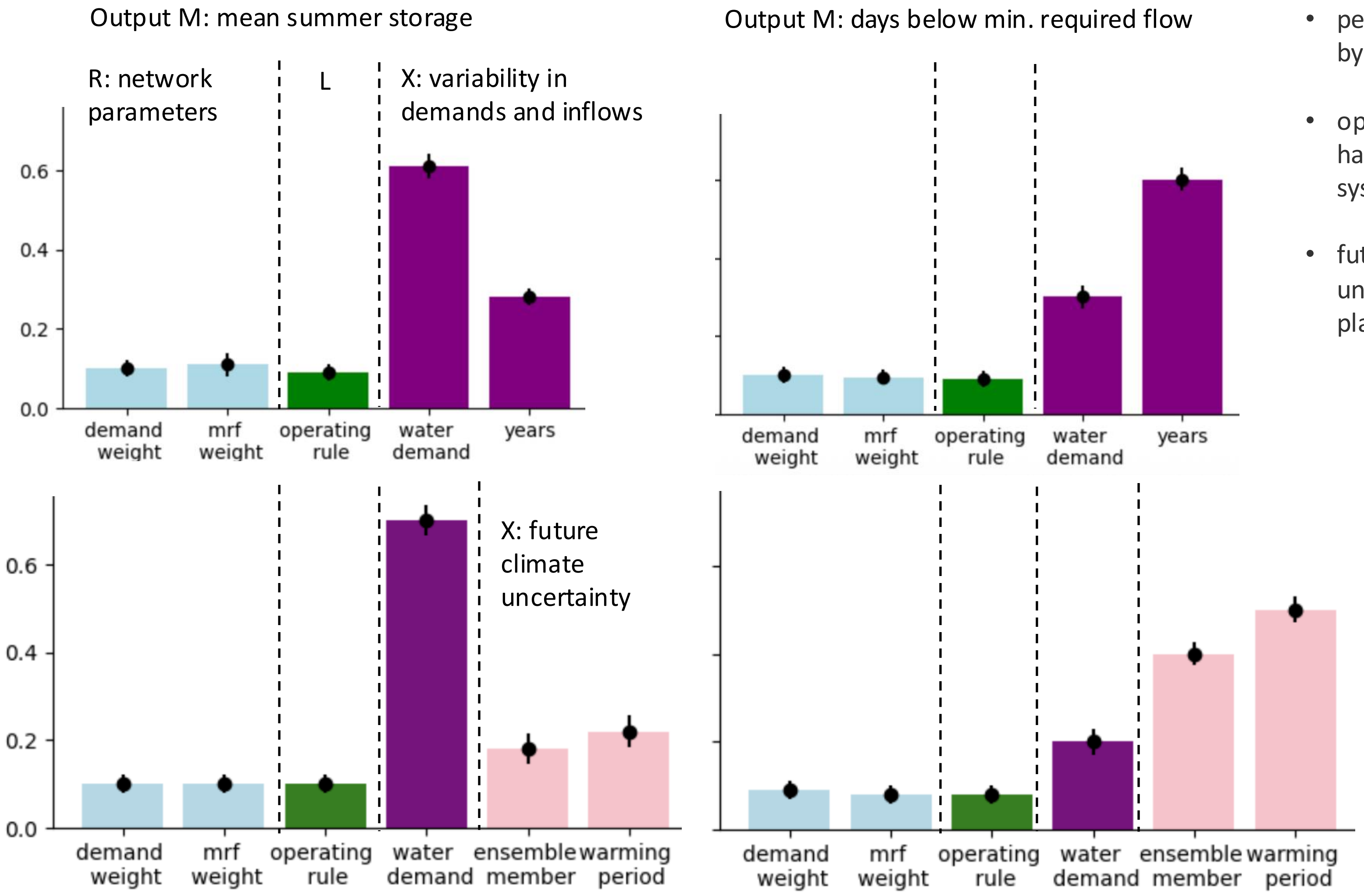
Reframing GSA with the XLRM framework



water resource
system model

Example application to energy and water infrastructure modelling

Salwey et al *under prep*



- performance dominated by external drivers (X)
- operating strategy (L) has limited influence on system performance
- future climate uncertainty (X) plays an important role

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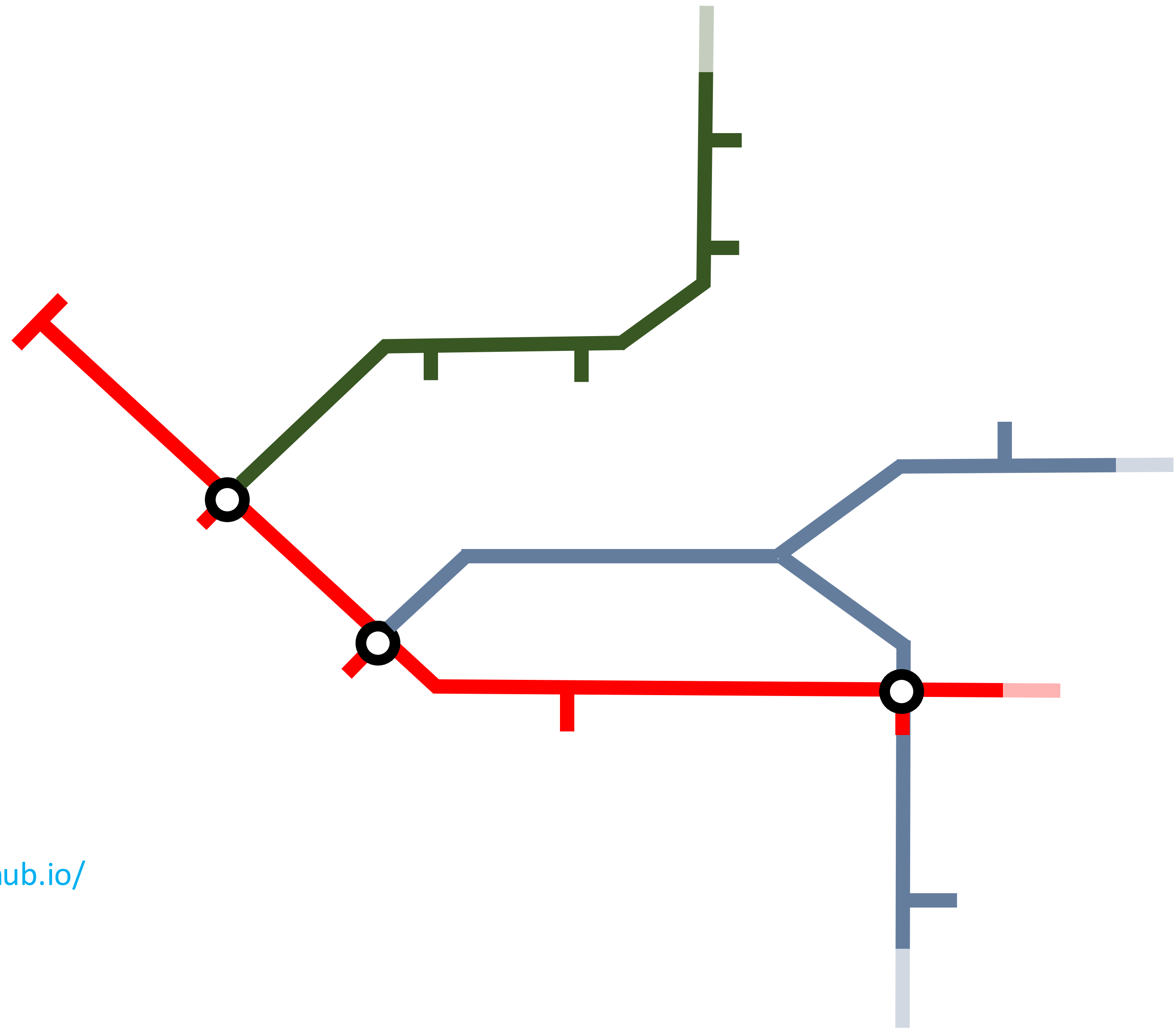
Conclusions

- GSA is even more useful than we think!
- To realise its full potential, we need:

  - approaches applicable to computationally-expensive model and complex input factors

  - understanding and tackling the root causes of resistance against investigation of model uncertainty

  - frameworks and tools to support users in implementing but first of all conceptualising GSA experiments



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

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