Centrum Wiskunde & Informatica

Uncertainties in simulations for climate and renewable energy

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Outline

- Climate simulations
- Simulation & uncertainty
- Rare events
- UQ and energy

Sources of uncertainty in climate simulations

As summarized in IPCC AR6 WG1 report (2021):

- Uncertainties in radiative forcing (incl emission scenario uncertainty)
- Climate response uncertainty
- Natural / internal climate variability (e.g. ENSO)

Uncertainties in computational models

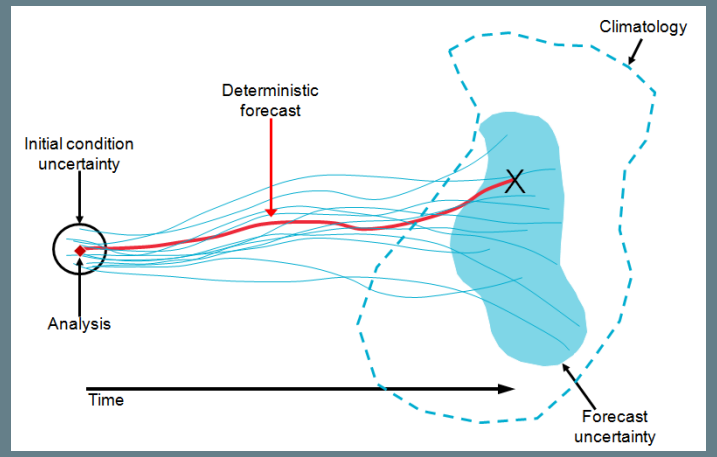
- Input parameters
- Initial conditions
- Boundary conditions and forcing
- Chaotic dynamics
- Intrinsic stochasticity
- Model form uncertainty / model structural error

Uncertainties in computational models

- Input parameters: λ
- Initial conditions: $x(t_{start})$
- Boundary conditions and forcing: $f(t)$
- Chaotic dynamics: small change in $x(t_{start})$ gives large change in Q
- Intrinsic stochasticity: noise / random numbers used in S
- Model form uncertainty / model structural error: uncertainty about form of S

<u>Example</u>: quantity Q at time T, computed with simulator S (e.g. based on discretized PDE)

$Q = S\big(T, x(t_{start}), \lambda, f(t)\big)$, with system state x

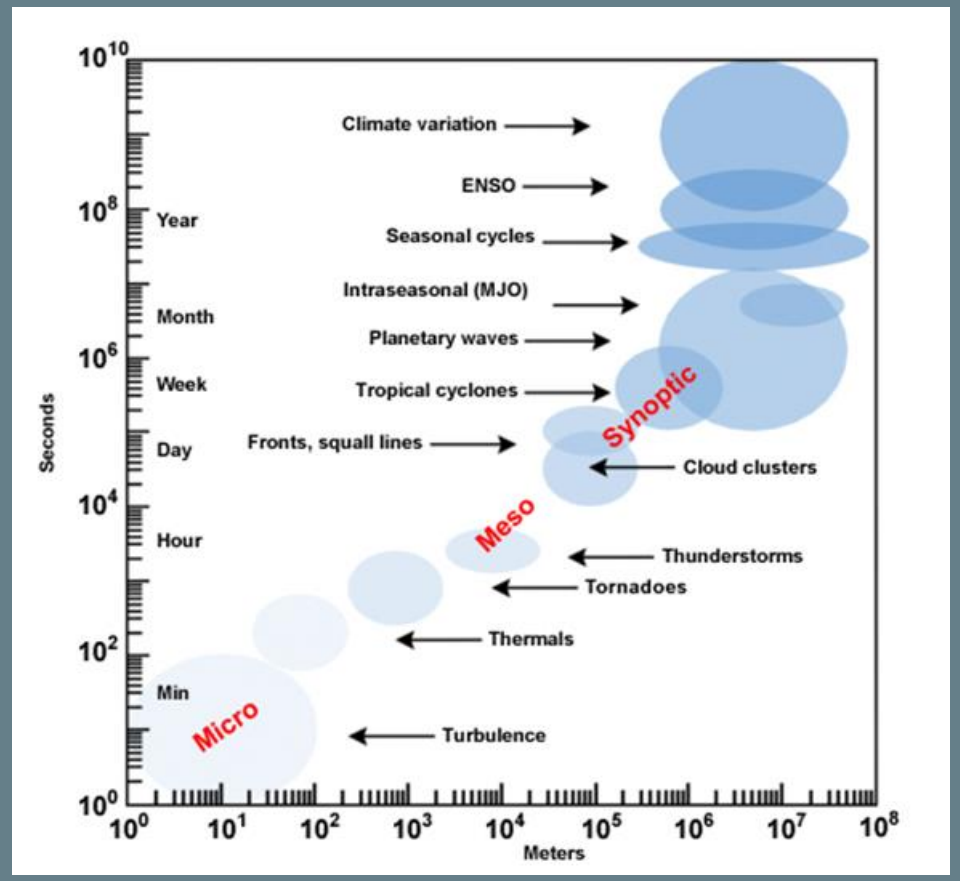


(Figure: UK Met Office)

Climate: multiscale system

Relevant physical and dynamical processes over wide range of space and time scales

Computationally (much..) too expensive to simulate global climate system over long time, while resolving all processes

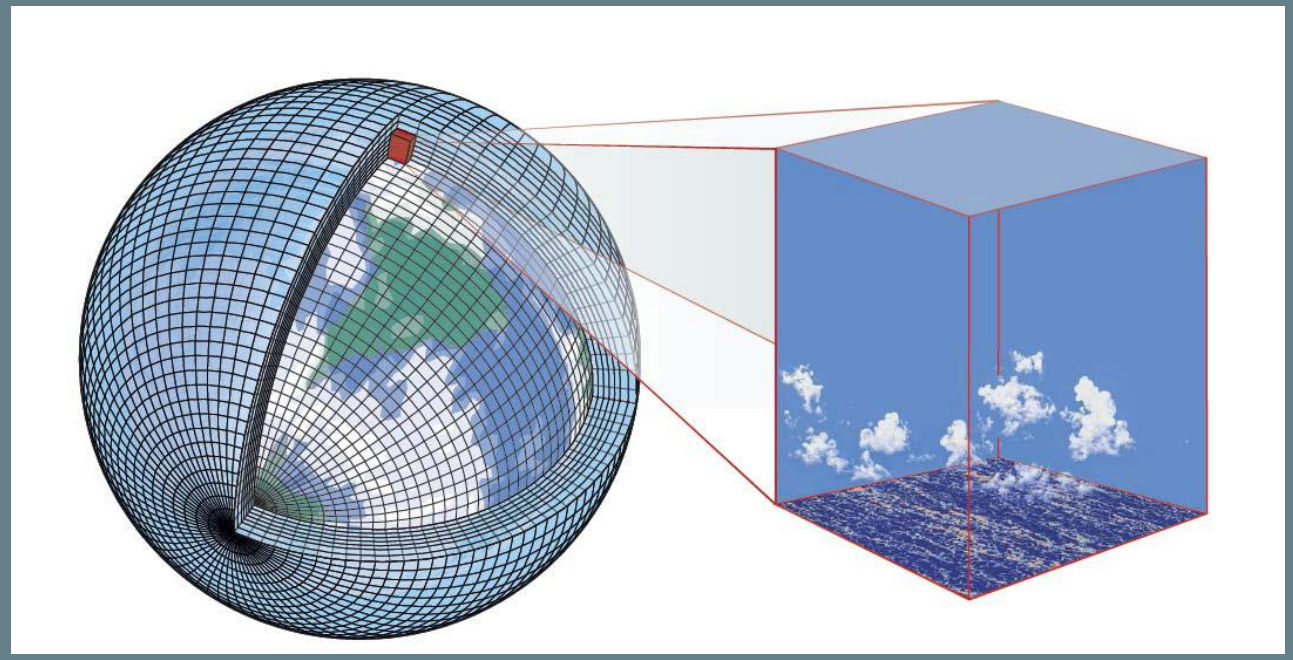


(Figure: COMET/UCAR)

Example: clouds and climate

Clouds: too important to ignore, too expensive to resolve

IPCC AR6 report (2021):
“... clouds remain the largest contribution to overall uncertainty in climate feedbacks”

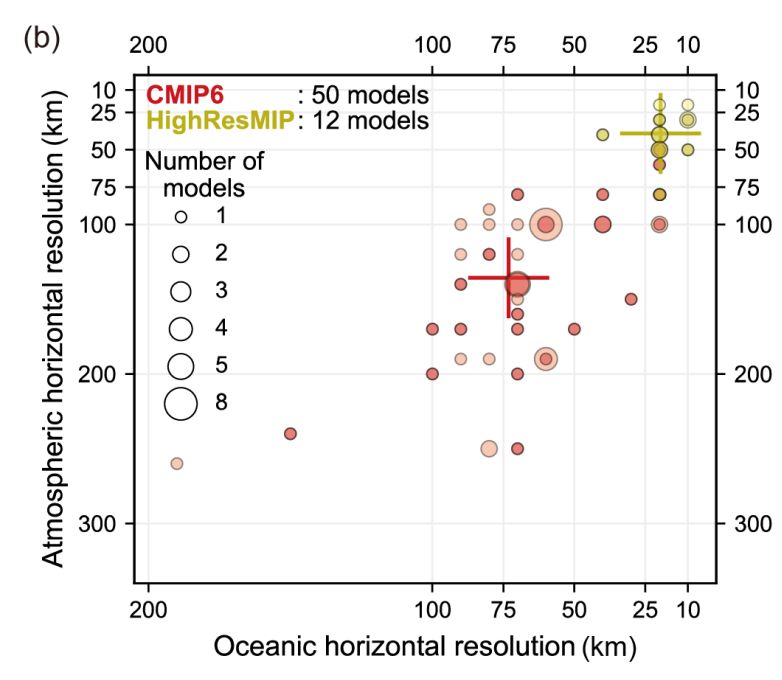


(Figure:Schneider et al, 2017)

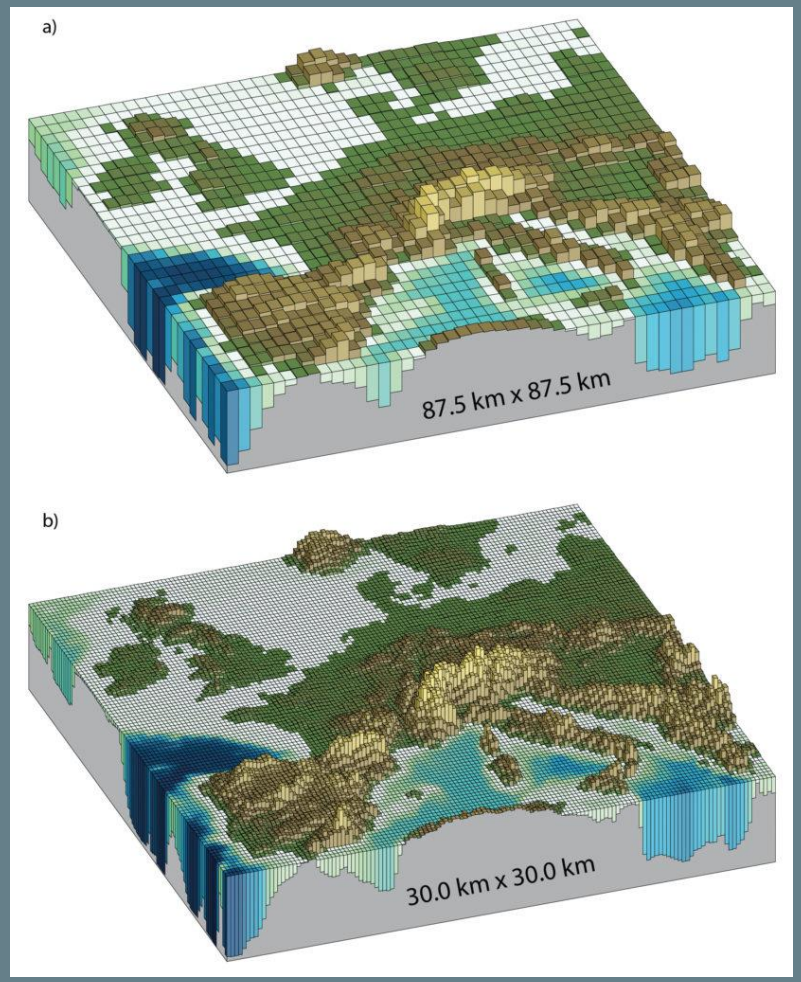
Example: clouds and climate

Clouds: too important to ignore, too expensive to resolve

- Model resolution needed to resolve clouds: ca 100m
- Current (CMIP6) Earth System Model resolution: ca 10km – 200km



(Figure: IPCC, AR6)

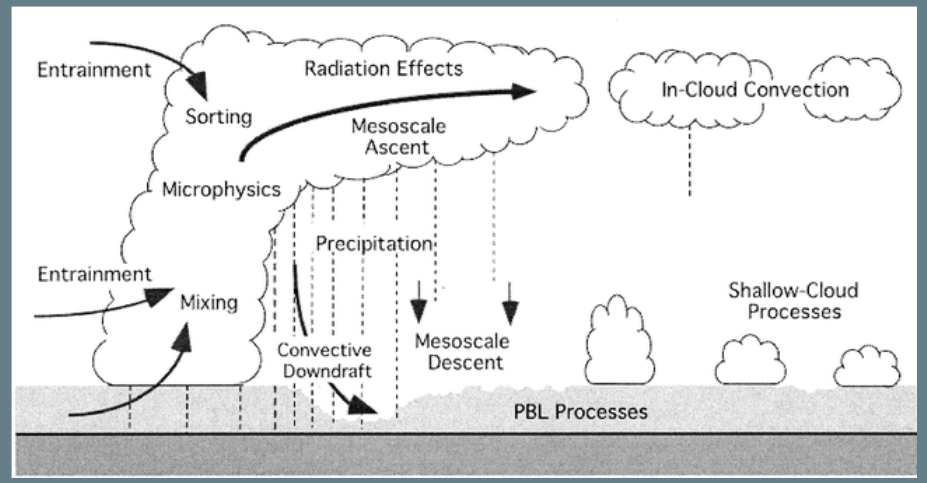


(Figure: IPCC, AR5)

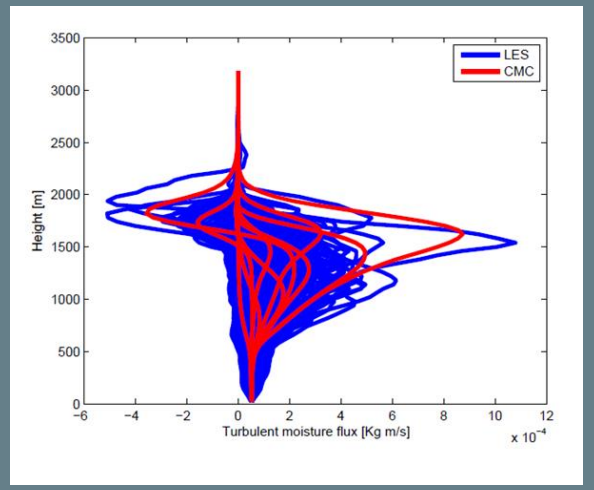
Parameterization

Parameterization: representation of effect of unresolved (small-scale) processes on resolved (large-scale) processes

E.g.: vertical transport of heat and moisture, due to convection & cloud processes



(Figure: Arakawa, 2004)



(Figure: J. Dorrestijn)

Parameterization

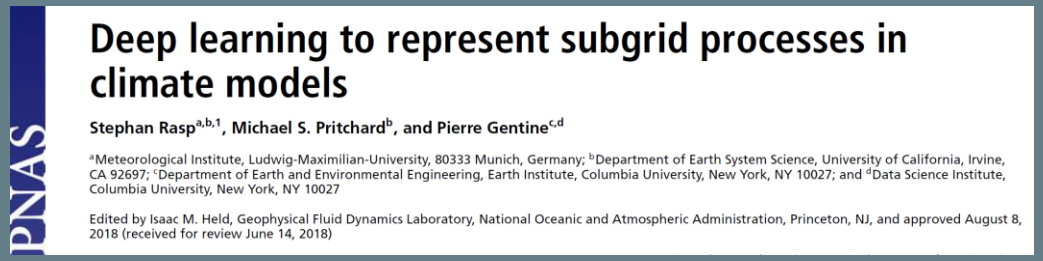
Parameterization (and model closures, constitutive equations, …):
often difficult to derive from first principles → **model uncertainty**

- **Stochastic** *(e.g. Palmer, 2001; Berner et al., 2017)*


STOCHASTIC PARAMETERIZATION
Toward a New View of Weather and Climate Models

JUDITH BERNER, ULRICH ACHATZ, LAURIANE BATTÉ, LISA BENGTSSON, ALVARO DE LA CÁMARA,
HANNAH M. CHRISTENSEN, MATTEO COLANGELI, DANIELLE R. B. COLEMAN, DAAN CROMMELIN,
STAMEN I. DOLAPTCHIEV, CHRISTIAN L. E. FRANZKE, PETRA FRIEDERICHS, PETER IMKELLER, HEIKKI JÄRVINEN,

- **Data-driven**
  - Fitting stochastic processes *(e.g. Wilks, 2005; Crommelin and Vanden-Eijnden, 2008)*
  - Deep learning *(e.g. Rasp et al., 2018; Bolton and Zanna, 2019)*


PNAS

Deep learning to represent subgrid processes in climate models

Stephan Rasp[a,b,1], Michael S. Pritchard[b], and Pierre Gentine[c,d]

[a]Meteorological Institute, Ludwig-Maximilian-University, 80333 Munich, Germany; [b]Department of Earth System Science, University of California, Irvine, CA 92697; [c]Department of Earth and Environmental Engineering, Earth Institute, Columbia University, New York, NY 10027; and [d]Data Science Institute, Columbia University, New York, NY 10027

Edited by Isaac M. Held, Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration, Princeton, NJ, and approved August 8, 2018 (received for review June 14, 2018)

Multiscale dynamical system

- Coupled ordinary differential equations (ODEs), e.g. from discretizing PDE:

$$\frac{dx}{dt} = f(x) + \sigma, \qquad \sigma = \sigma(y), \qquad \frac{dy}{dt} = g(x, y)$$

- "Macroscopic" variables x, "microscopic" variables y

  Focus here on additive micro-to-macro feedback, $f(x) + \sigma$.

- Discrete time setting, time index $j \in \mathbb{N}$. System evolution:

$$x_{j+1} = F(x_j) + r_j, \qquad r_j := r(y_j), \qquad y_{j+1} = G(x_j, y_j)$$

<u>Aim</u>: - simulate x without resolving $y \rightarrow$ parameterize r
- capture long-term statistics of x

Stochastic parameterization with memory

Evolve / update r by random sampling from conditional probability distribution
$r_{j+1} \mid r_j, r_{j-1}, r_{j-2}, \dots, x_j, x_{j-1}, x_{j-2}, \dots$

in tandem with x updates according to $x_{j+1} = F(x_j) + r_j$

→ Stochastic parameterization of r, with memory (cf. Mori-Zwanzig theory)

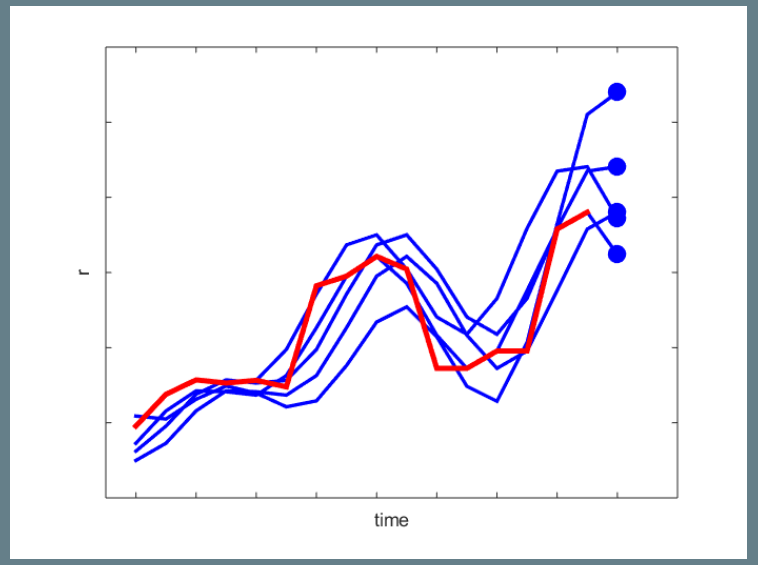
Distribution $r_{j+1} \mid r_j, r_{j-1}, r_{j-2}, \dots, x_j, x_{j-1}, x_{j-2}, \dots$ unknown

Resampling

At each time step:
(i) Update $x_{j+1} = F(x_j) + r_j$
(ii) Sample from $r_{j+1} \mid r_j, r_{j-1}, r_{j-2}, \dots, x_j, x_{j-1}, x_{j-2}, \dots$

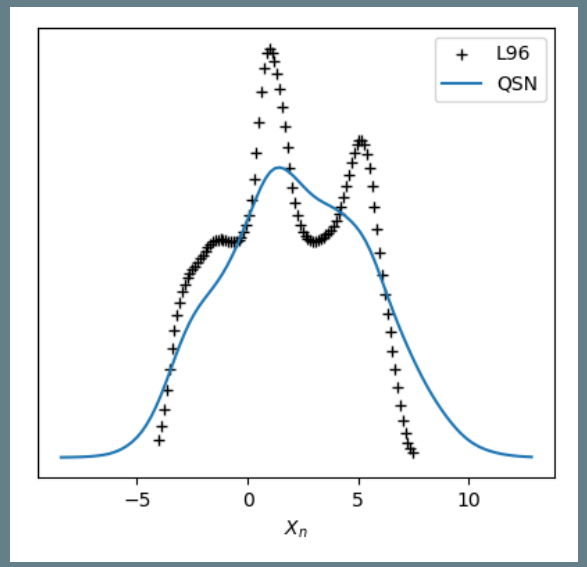
Distribution $r_{j+1} \mid r_j, r_{j-1}, r_{j-2}, \dots, x_j, x_{j-1}, x_{j-2}, \dots$ unknown

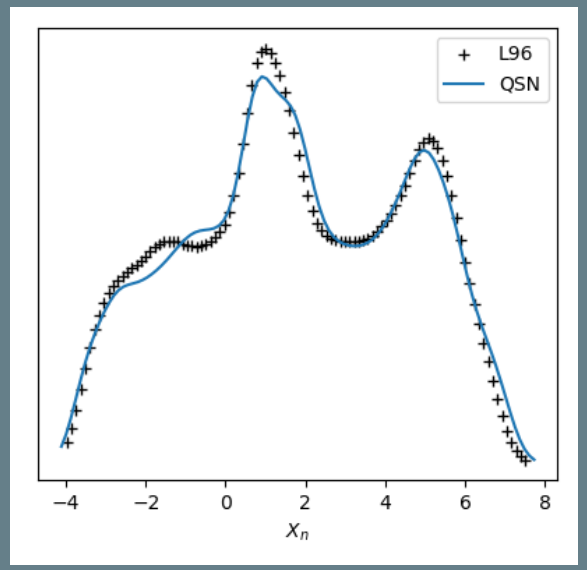
Sample by bootstrapping from observations
$(x_j^o, r_j^o)_{j=1}^N$, $r_j^o := x_{j+1}^o - F(x_j^o)$



Resampling

Numerical tests on L96 model, focus on long-term statistics

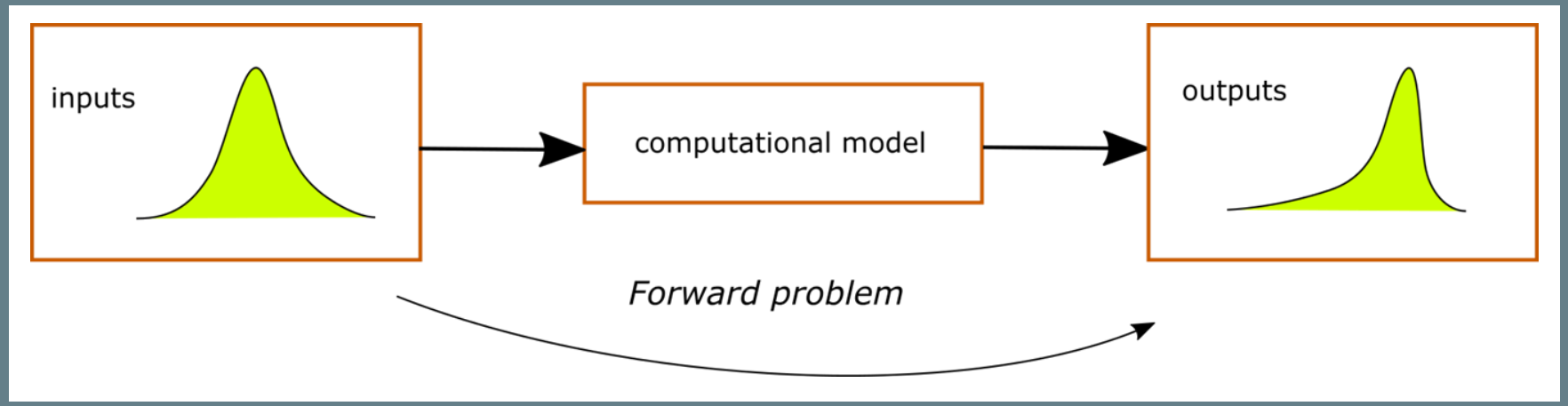




Left: memory depth J=10. Right: memory depth J=75

(Figures from Crommelin & Edeling , Phys. D, 2021)

Uncertainty Quantification (UQ)



UQ: Efficient methods for assessing uncertainties in input and output, with limited number of computational model evaluations

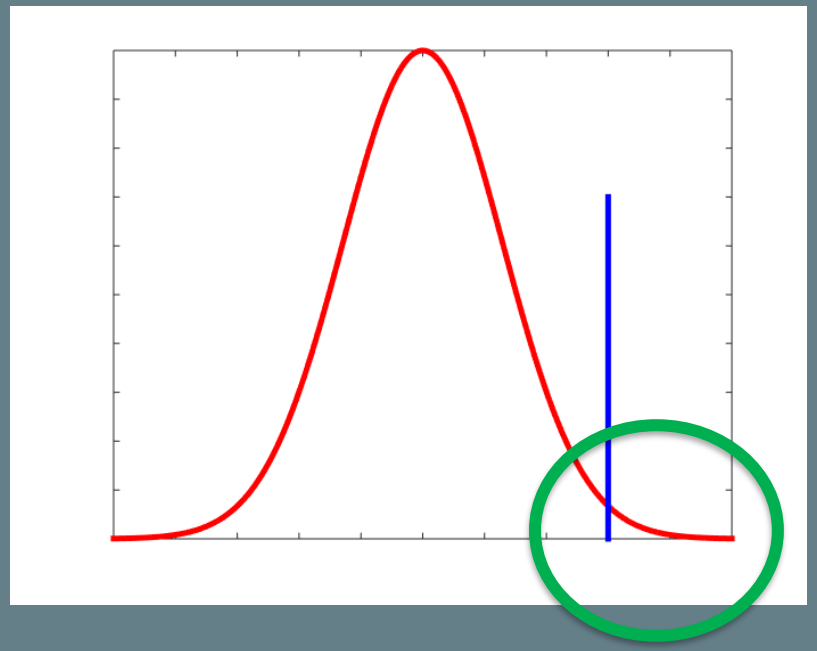
(NB: yearly MSc course Uncertainty Quantification at UvA, fall semester)

Rare Event Simulation

Rare events: the tail of the distribution

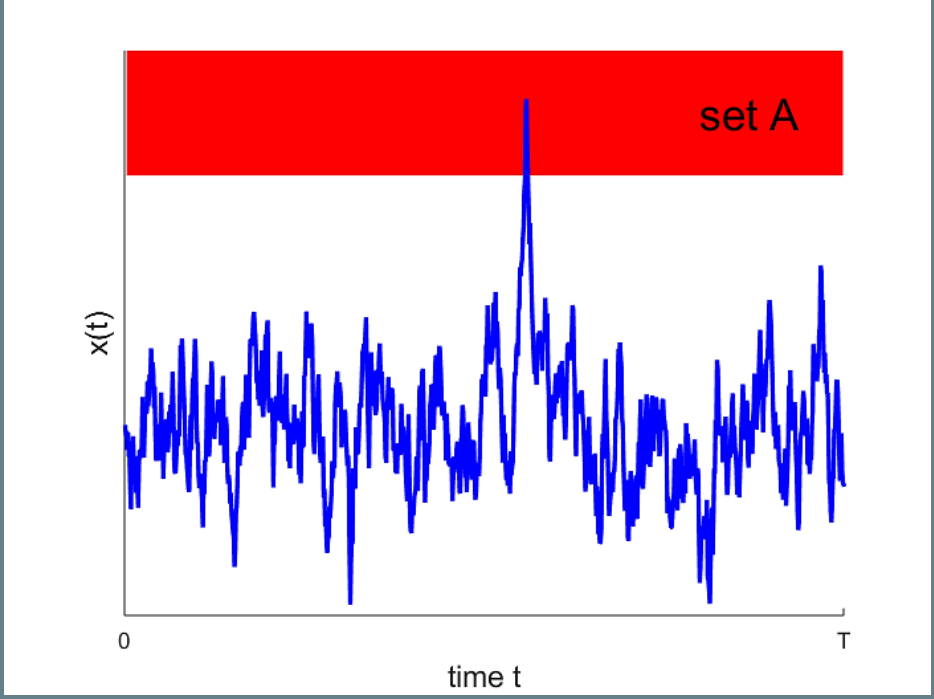
Floodings, hurricanes, power blackouts, structure collapse, …

Low probability, high impact

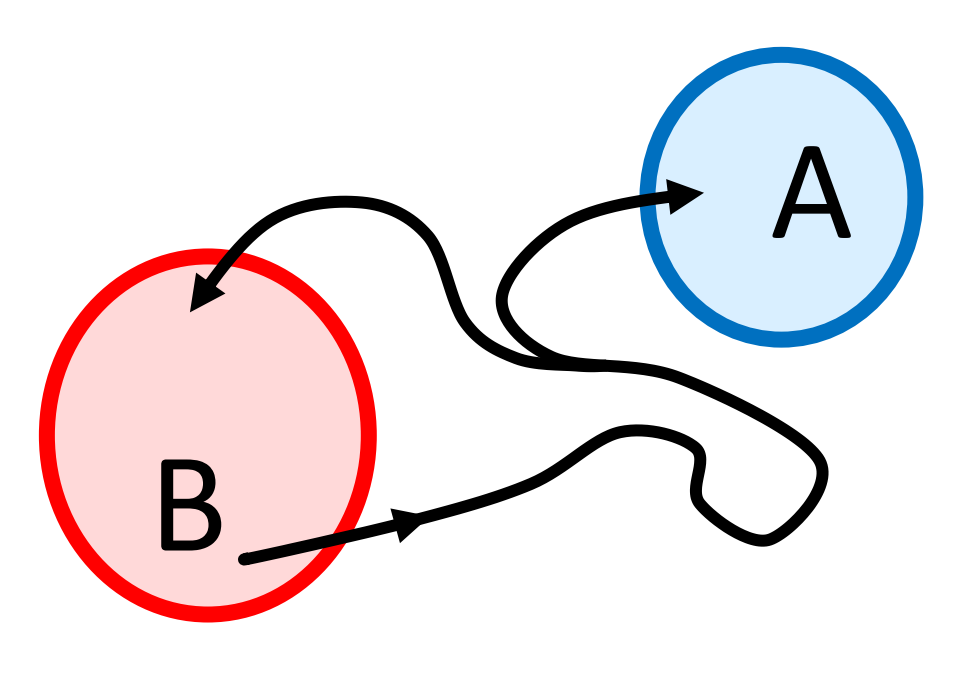


Rare Event Simulation

Extremes



Transitions



Rare Event Simulation

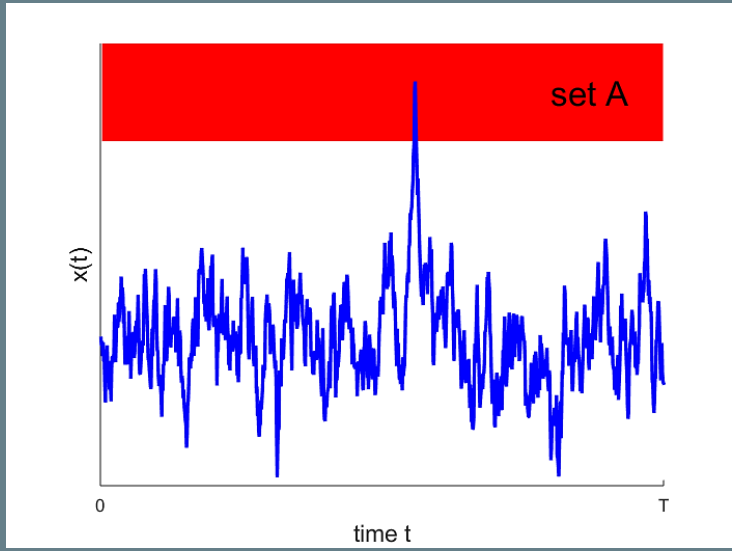
Study rare events in models, e.g.:

- Probability of occurrence
- Typical paths/trajectories towards rare event (precursors / transition paths).

Often, one has to rely on simulation.

<u>Need very long simulations to observe a few events</u>

E.g. $O(10^4)$ years of simulation to see one
1-in-10000 year storm surge.



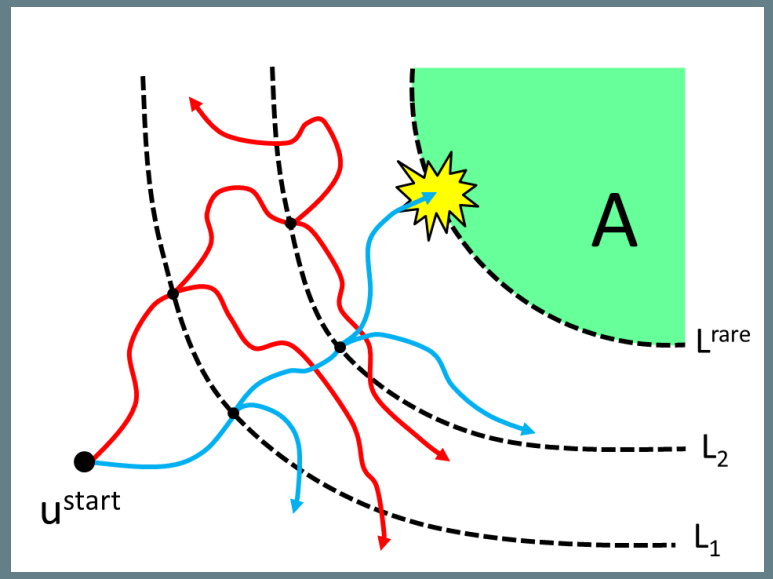
Rare Event Simulation

How to simulate rare/extreme events?
How to estimate their probabilities?

Straightforward Monte Carlo very inefficient for small probabilities

Dedicated techniques to accelerate
MC simulations for rare events:

- multilevel splitting,
- importance sampling.



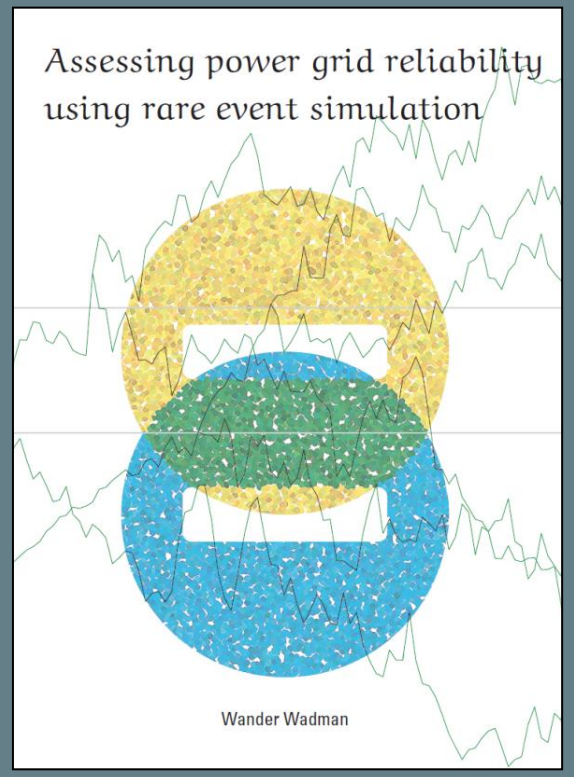
Example: power grids

The energy flow in a power grid is uncertain:

- Demand uncertainty
- Possibility of equipment failure
- Limited predictability of renewable power generation (wind farms, solar panels, ...)

Uncertainties pose risks to the stability of power grids.

How can we quantify these risks?



(PhD thesis W. Wadman, UvA, 2015)

Example: power grids

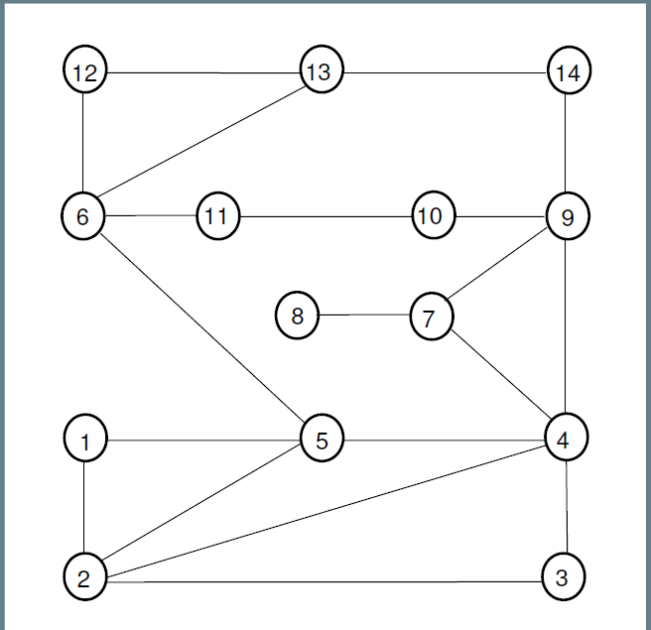
What is Prob(grid failure) by intermittent power generation?

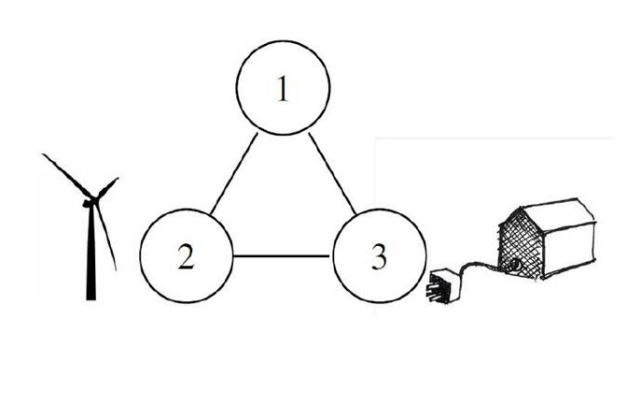
Model power source as stochastic process

Solve power flow equations at every time step:
Coupled nonlinear algebraic equations for network voltages and currents, given power in/output and network topology

Failure: not all voltage and current constraints satisfied

Computational acceleration over straightforward MC:
orders of magnitude





(Figures: D. Bhaumik; W. Wadman)

Uncertainties in power grids and renewable energy generation

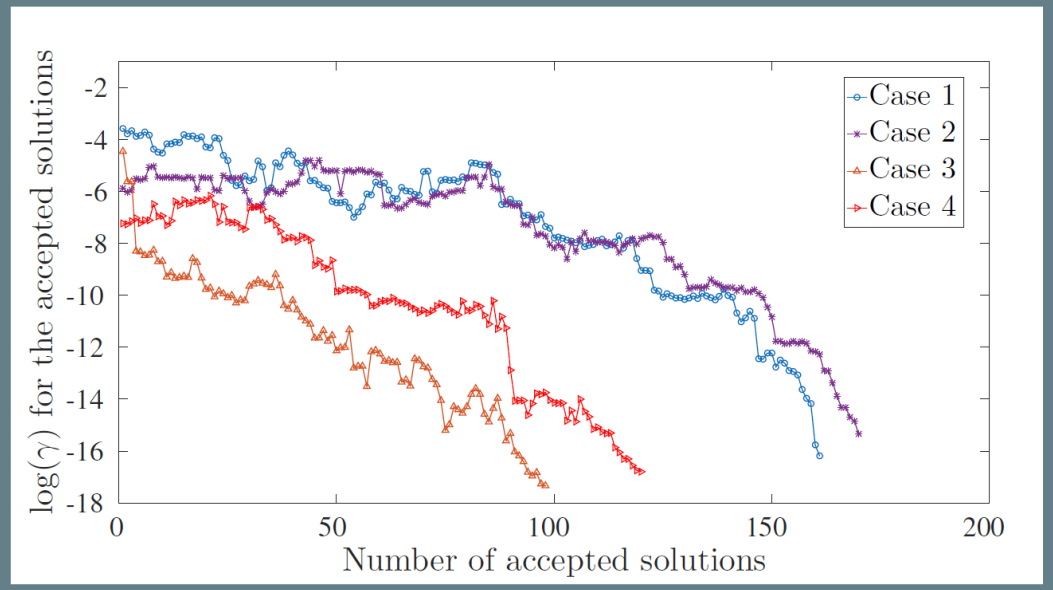
Some further research (aside from methodology development):

PhD thesis A. Eggels, *Uncertainty quantification with dependent input data, including applications to offshore wind farms* (UvA, 2019)

- UQ of hypothetical wind farm energy yield

PhD thesis D. Bhaumik, *Computational techniques for assessing power grids with wind energy and storage* (UvA, 2018)

- Hidden Markov models for wind farm power output, inferred from data
- Optimizing storage placement for maximum grid reliability →



(Figure: D. Bhaumik, PhD thesis)

Conclusion

- Uncertainties in simulations (for climate, energy and beyond) can and should be assessed. Key part of VVUQ: Verification, Validation and Uncertainty Quantification
- Modern mathematical techniques for efficient quantification of uncertainties
- Structural model uncertainty linked to multiscale modeling & simulation
- Rare events: low probability, high impact