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Universität Stuttgart
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Recent advances in optimizing field campaigns

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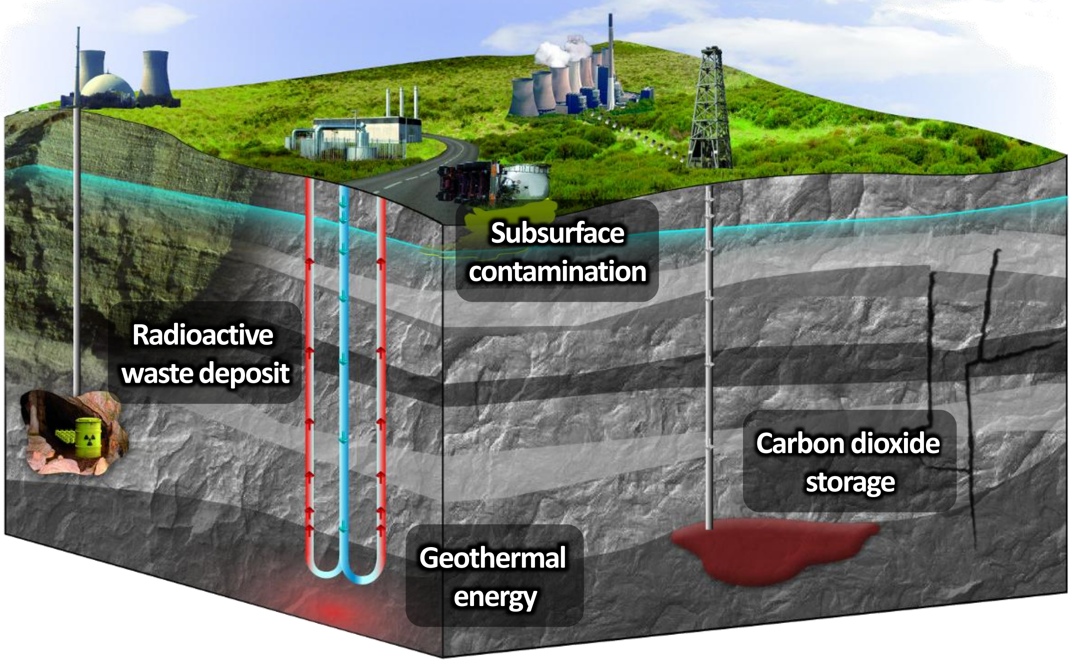
Prediction Uncertainty

…an omnipresent challenge:

- Open system
  (boundaries, forcing)?
- Model concepts
- Scales of
  heterogeneity
- Scarce data
- Measurement
  errors



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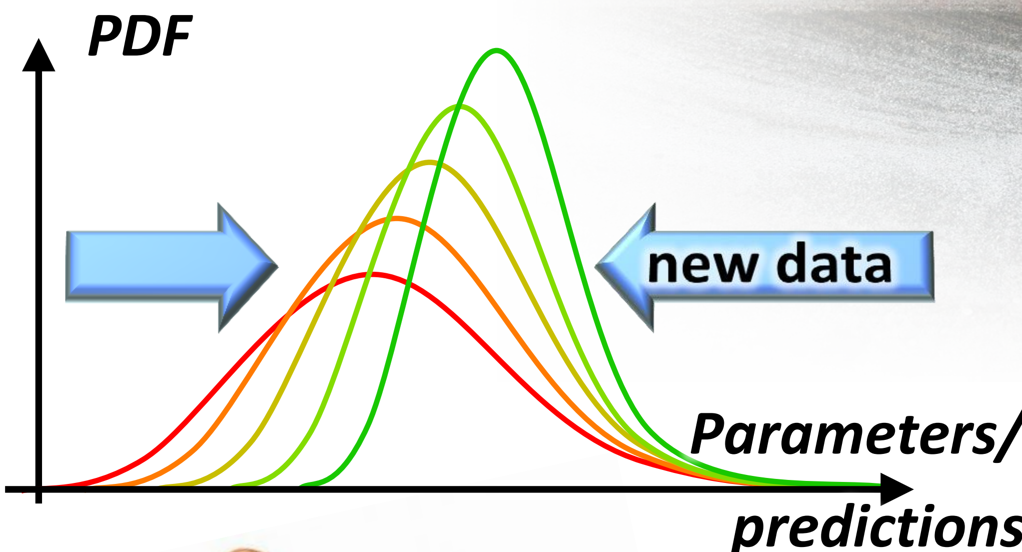
Field Investigation?



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Experimental design

…is blueprint of experiment/campaign:

- Apparatus/system
- Conditions
  - System forcing (active/passive)
  - Boundary/initial conditions
- Observation type (what data)
- Sampling pattern (where)
- Sampling schedule (when)

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Optimal design: challenges

Prior enve-lope?

1.) Stochastic/geostatistical model:
realistic envelope to uncertainty p(θ)

↓

2.) Define utility of desired data:
task-driven information needs U=f(d)

↓

3.) For a given design:
Quantify utility of future data U(d)

↓

4.) Optimize design: d_{opt}=arg max U(d)
maximize utility (e.g., cost-benefit)

(loop back from 4.) to 3.))

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Prior envelope?

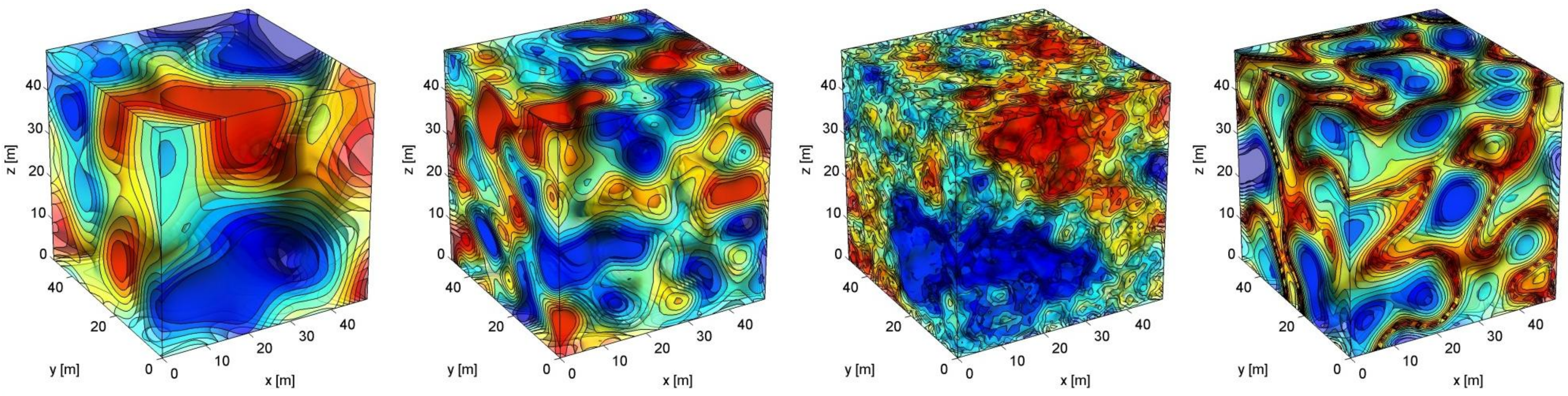
Example: geostatistical model uncertain!

– Bayesian geostatistics *(Kitanidis, WRR 1986)*

What could be uncertain?

– Variance, length scales, anisotropy, smoothness
(Matérn covariance) *(Nowak & al, WRR 2010,*
(BMA) *S. Neumann & al, AWR 2012)*

– Trend/zonation models *(M. Fienen & al, WRR 2008)*



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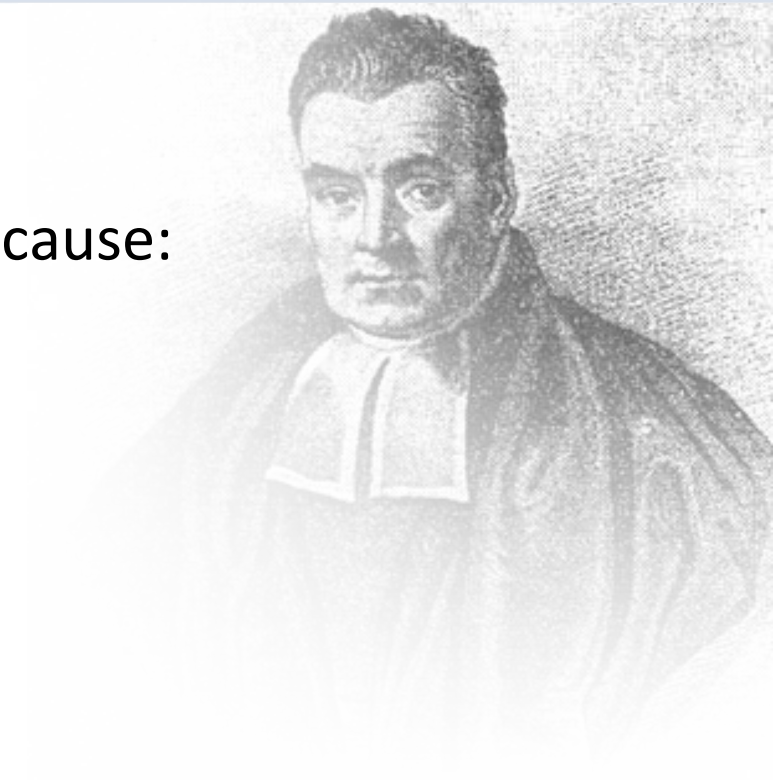
What to do?



- Accept structural uncertainty, because:
  - Uncertain even after sampling
  - High impact on prediction goal
  - You will learn nothing about what you claim to know already
- Include & tackle this uncertainty in optimal design!
- Method: “Bayesian geostatistical design”:
  - Model identification as (implicit/secondary) objective / MOO
  - Robustness against too narrow priors

  (W. Nowak, F.P.J. de Barros and Y. Rubin, WRR 2010)

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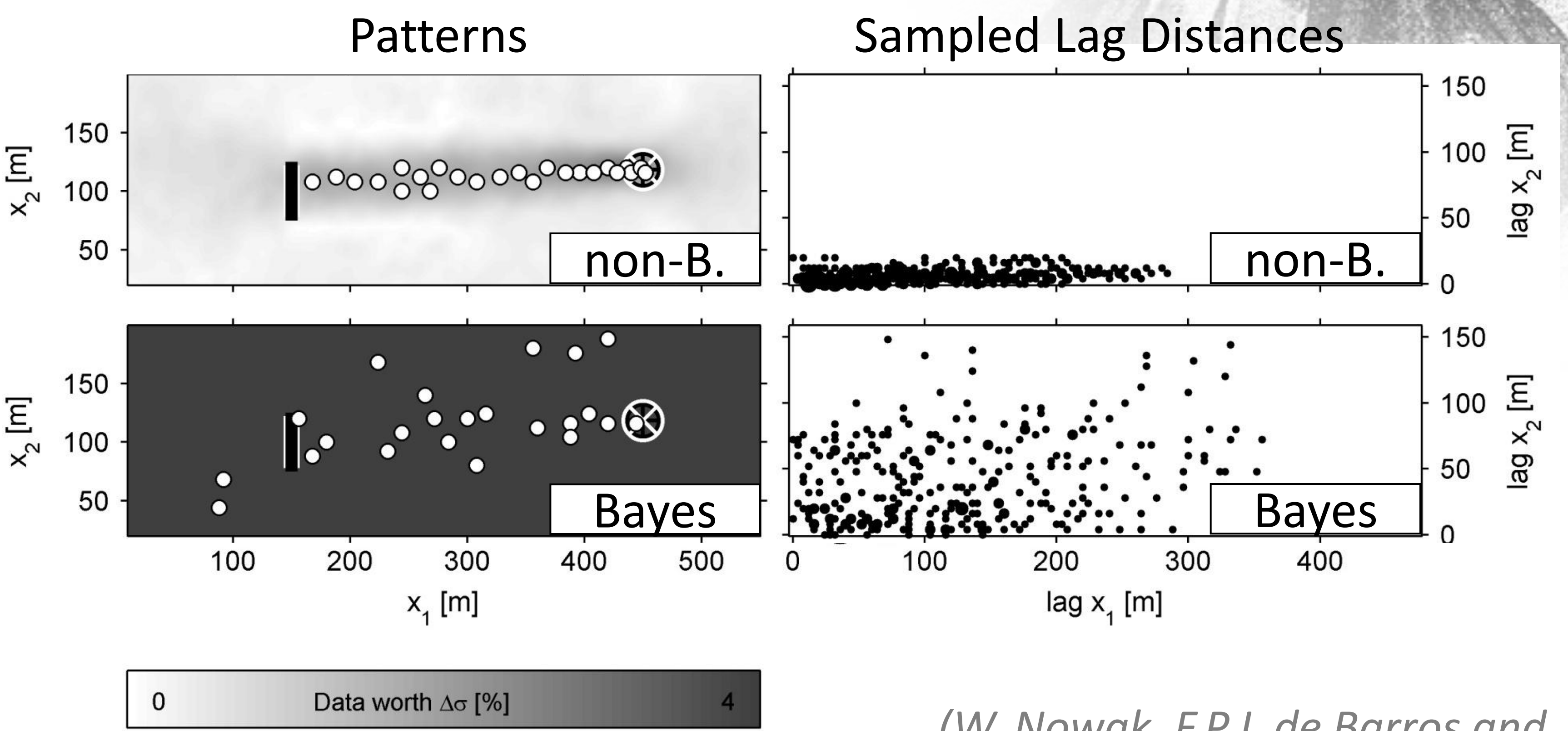
Bayesian geostat. Design



(W. Nowak, F.P.J. de Barros and Y. Rubin, WRR 2010)

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Optimal design: challenges

Information needs?

1.) Stochastic/geostatistical model:
realistic envelope to uncertainty

↓

2.) Define utility of desired data:
task-driven information needs

↓

3.) For a given design:
Quantify utility of future data

↓

4.) Optimize design:
maximize utility (e.g., cost-benefit)

(loop back from 4.) to 3.))

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Information needs?

- Shut down well after contaminant spill?
  (e.g., Frind et al., 2006; Enzenhöfer et al., 2010)
- Is a contaminant release rate critical?
  (e.g., Troldborg et al., 2010)
- Is natural attenuation occurring?
  (e.g., Schwede und Cirpka, 2010)
- Is a proposed remediation design safe?
  (e.g., Cirpka et al., 2004)
- Is a radioactive waste site safe?
  (e.g., Andricevic und Cvetkovic, 1996)
- Is human health risk above critical level?
  (e.g., de Barros und Rubin, 2008; de Barros et al., 2009)
- Is a model adequate to describe a site?
  (e.g., Neuman, 2003; Refsgaard et al., 2006)

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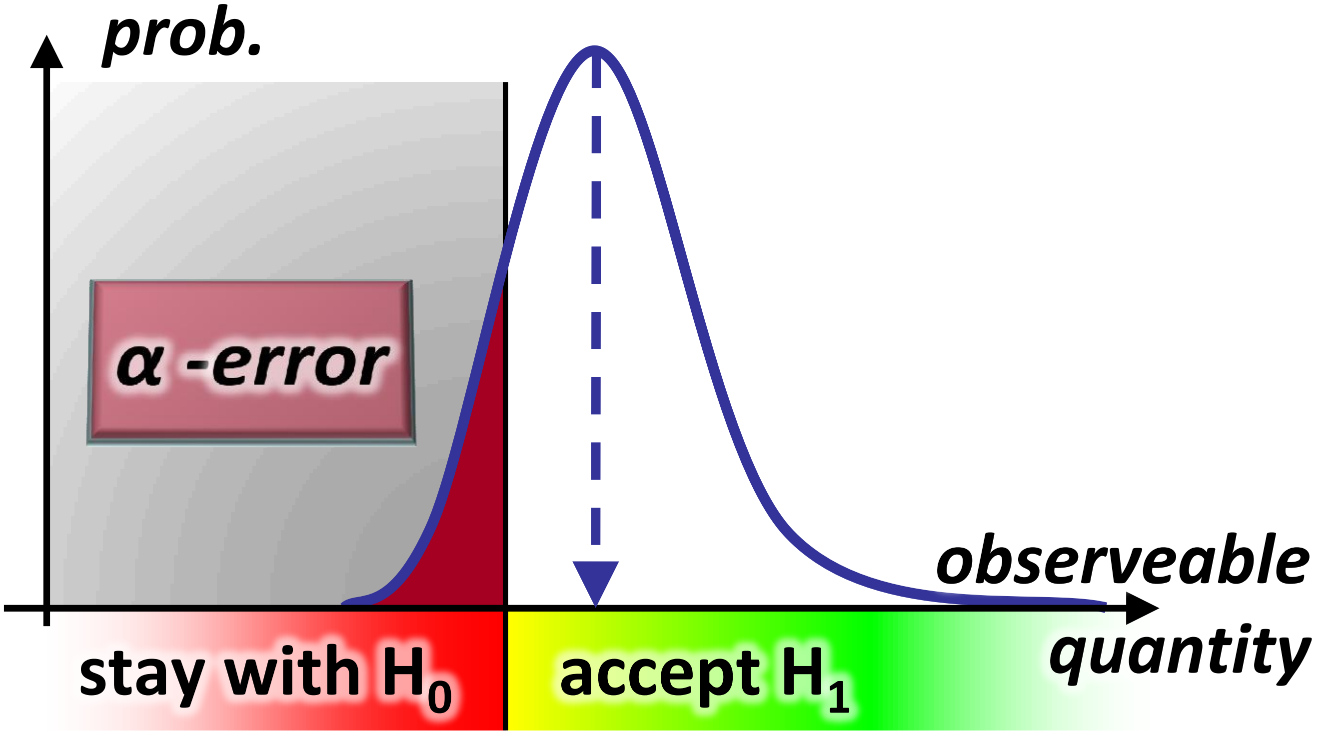
Failure of decisions



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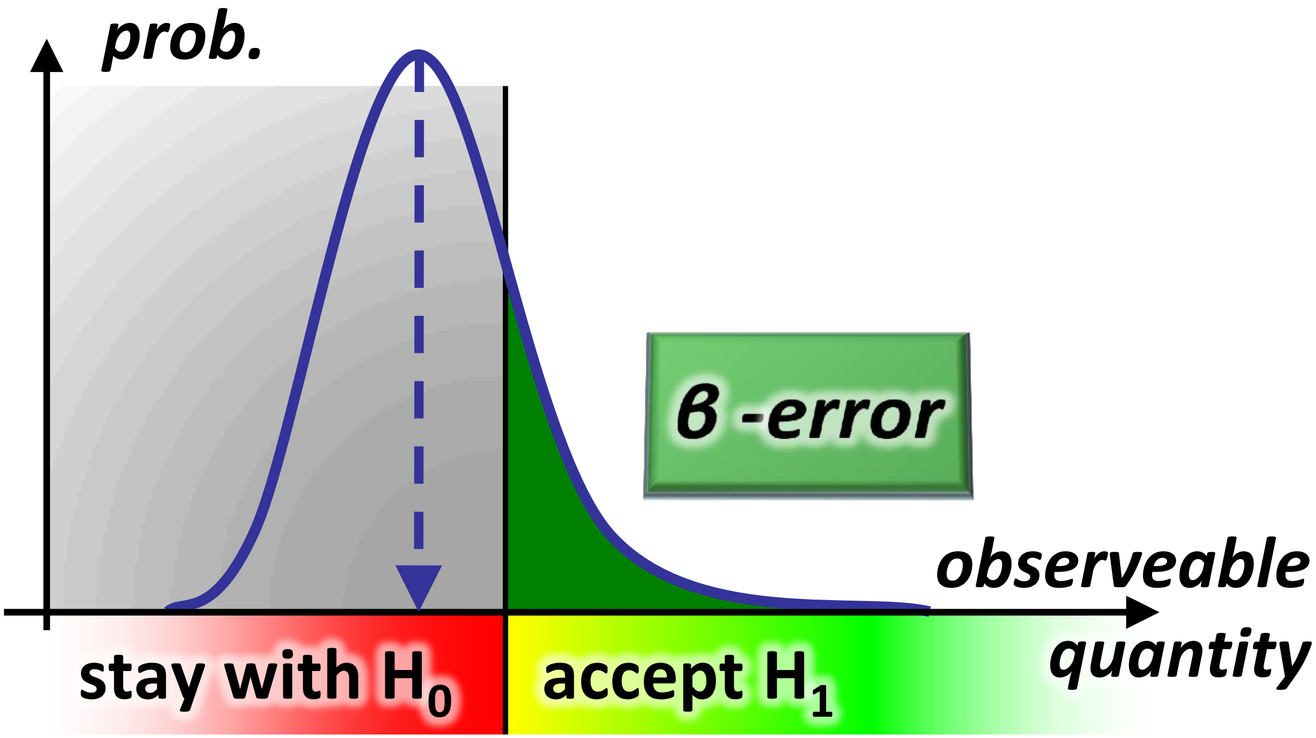
Failure of decisions



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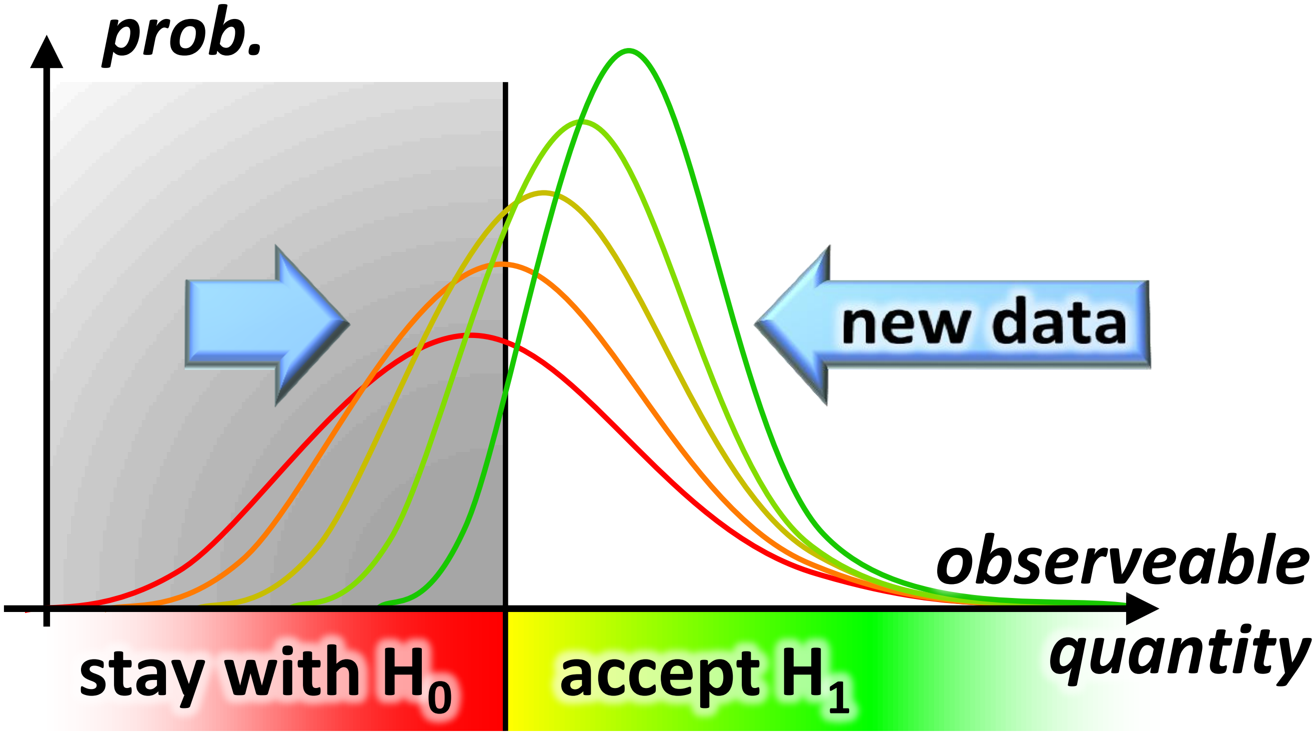
Failure of decisions



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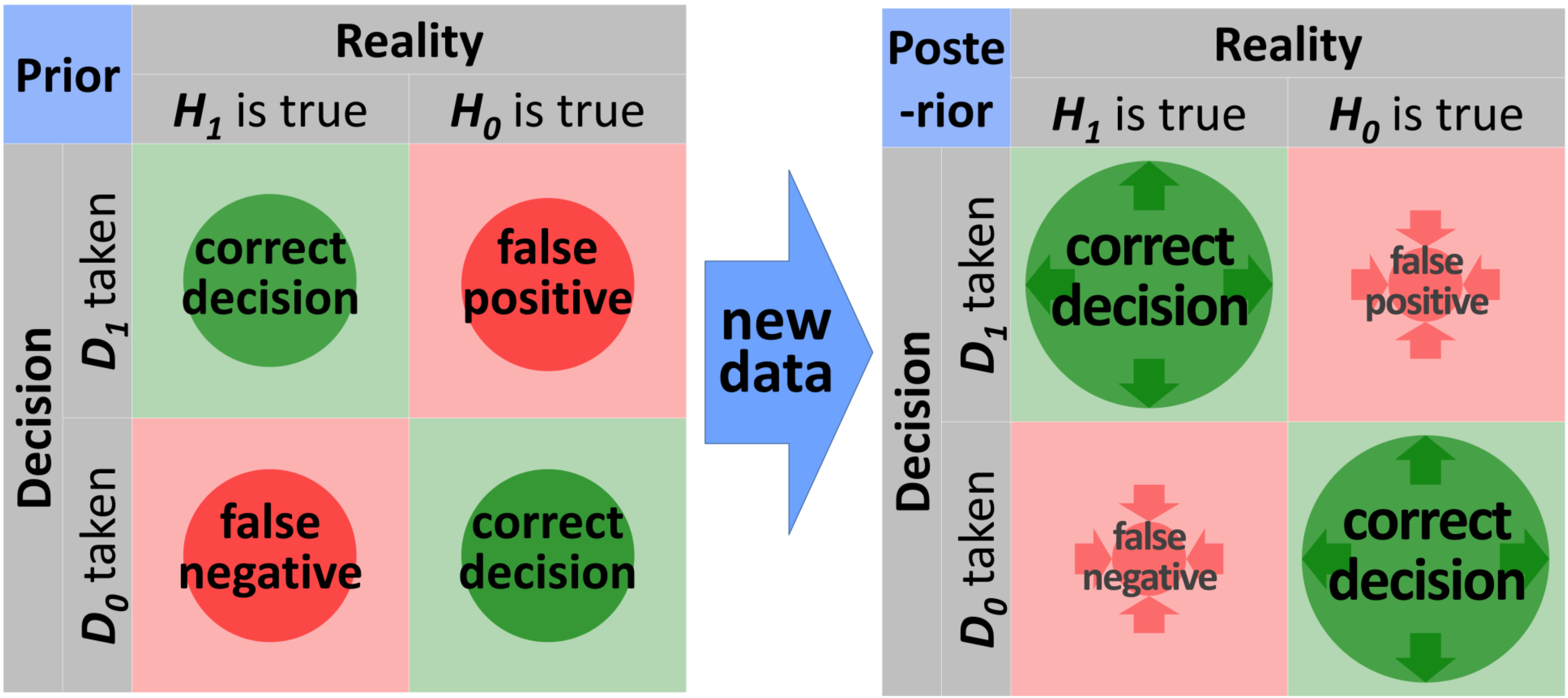
Hypothesis-driven design



- Uses **actual** goals (no surrogates) as objective function
- Searching “scientific truth” avoids “monetization” etc.
- Model assumptions / identification, decision support…

W. Nowak, F.P.J. de Barros and Y. Rubin, WRR2012 (submitted)

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Optimal design: challenges

1.) Stochastic/geostatistical model:
realistic envelope to uncertainty

↓

2.) Define utility of desired data:
task-driven information needs

↓

3.) For a given design:
Quantify ***expected*** utility

↓

pre-posterior analysis →

**3b.) Generate random data sets,
condition & assess utility for all**

↓

4.) Optimize design:
maximize utility (e.g., cost-benefit)

(loop back from 4.) to 3.))

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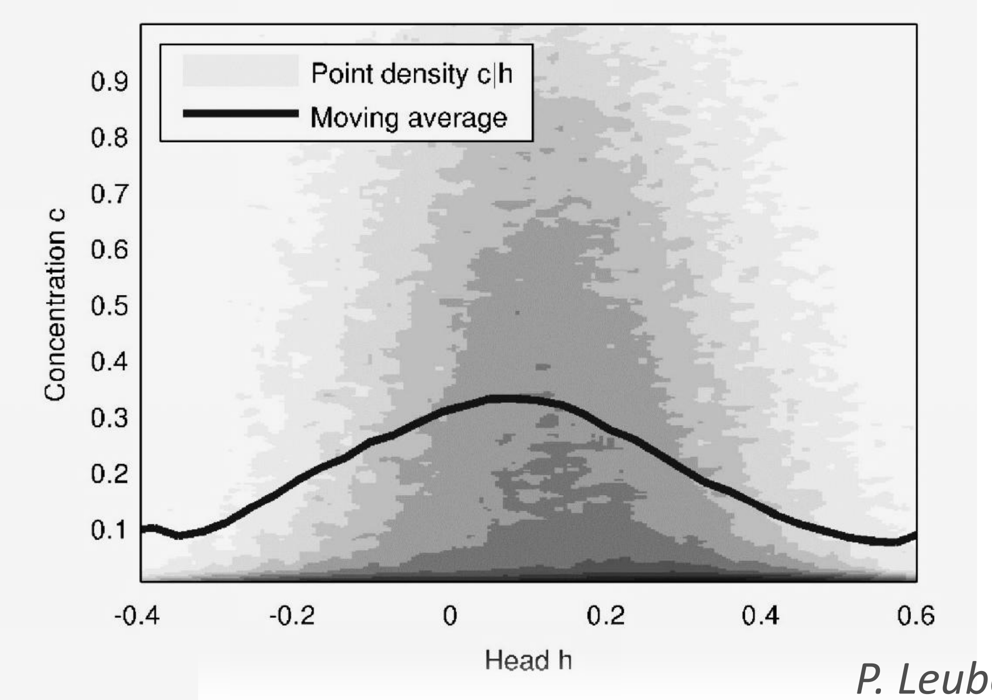
Preposterior Analysis

Preposterior **D**ata **I**mpact **A**ssessment (PreDIA):

- Any task-driven criteria possible
- Fully non-linear method (non-lin. info hidden for linear tools)



- Bootstrap filter
- Average over data Marginalized errors
- Cross-breeding

P. Leube, A. Geiges and W. Nowak, WRR 2012

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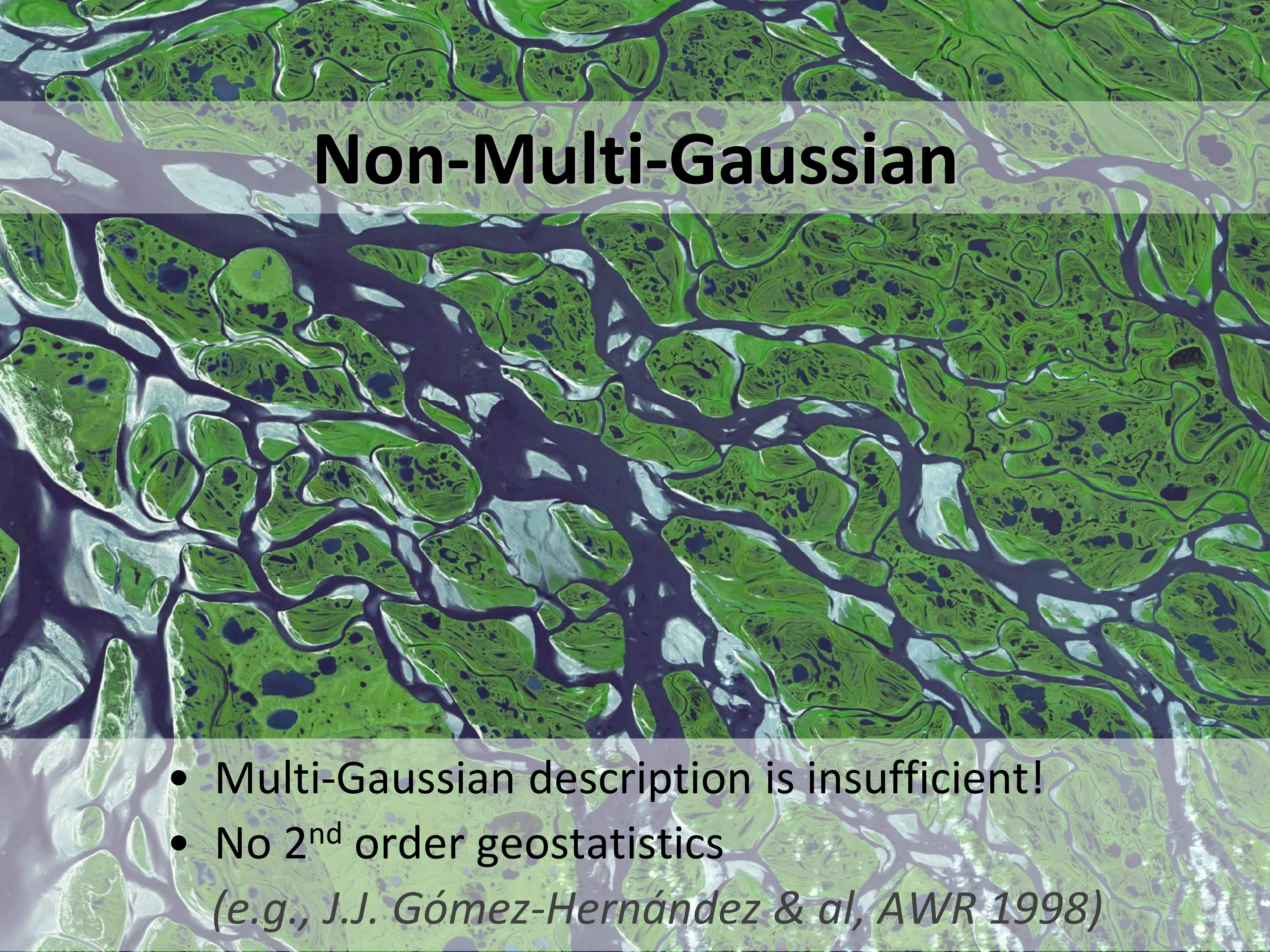
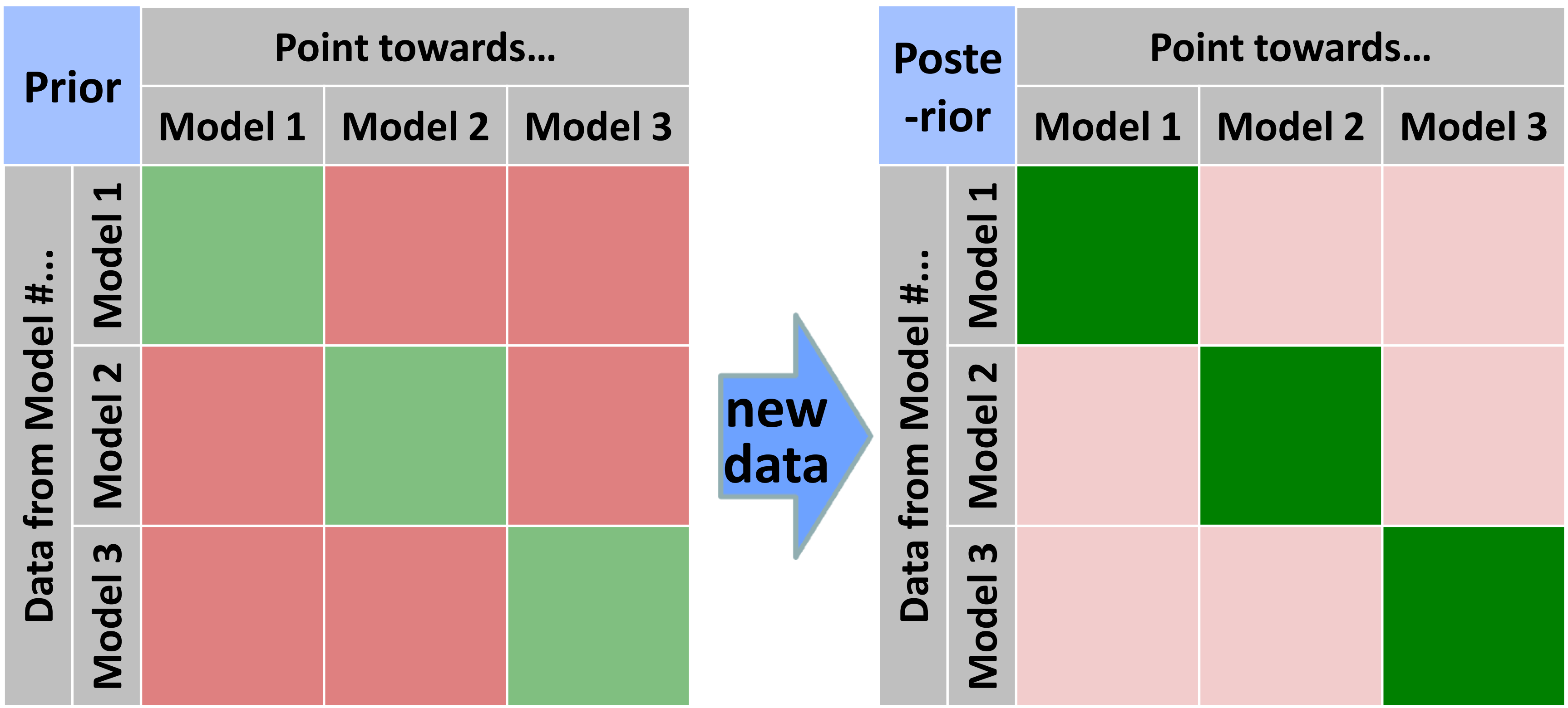


Non-Multi-Gaussian

- Multi-Gaussian description is insufficient!
- No 2nd order geostatistics
  (e.g., J.J. Gómez-Hernández & al, AWR 1998)

Outlook: Model Choice

- What will a good "model choice" design do?



- Hardly any analytical solutions
- Brute-Force (PreDIA), CPU-intensive

Summary & Conclusions

- OD: Quest for perfect information
  - Envelope for prior uncertainty (stay robust w.r.t. priors)
  - Align OD with task at hand (e.g., hypothesis-driven)
  - Fast tools becoming available (e.g., PreDIA)

- Major challenges: 1.) Multivariate structure
  2.) CPU time / real time

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Funding Acknowledgments

- EXC 310/1 SimTech
- IRTG 1398 (NUPUS)
- VW foundation
- State of BW