

Groundwater Remediation using Bayesian Information-Gap Decision Theory

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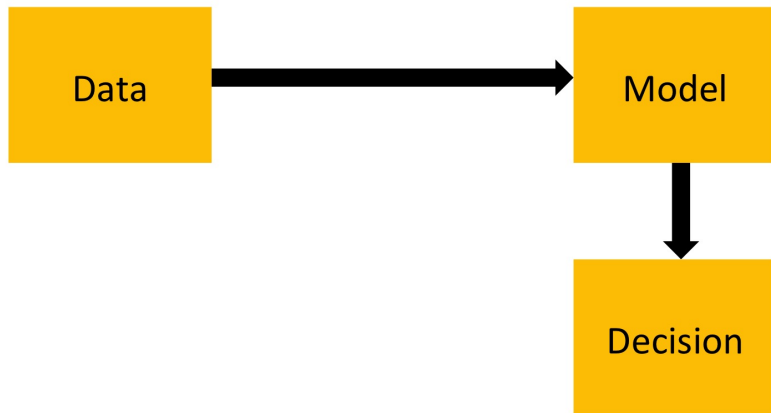
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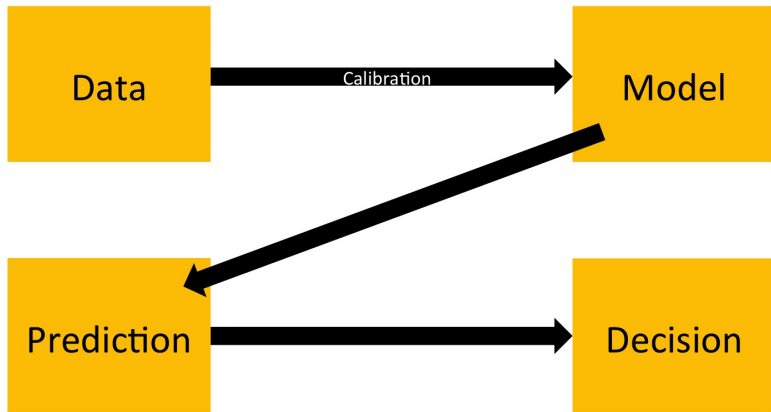
Computational Earth Science, Los Alamos National Laboratory, USA

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Models are often complex

► Parameters

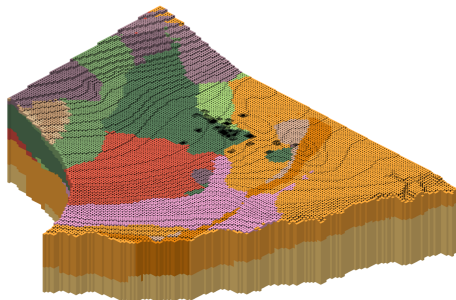
- heterogeneous, anisotropic permeability
- heterogeneous specific storage

► Model Physics

- saturated, confined aquifer
- isothermal, incompressible

► Discretization

- $\sim 10^6$ nodes
- solved with obtuse codes



Shortcomings of this approach

► Parameters

- small scale heterogeneity unrepresented
- uncertainty not considered

► Real Physics

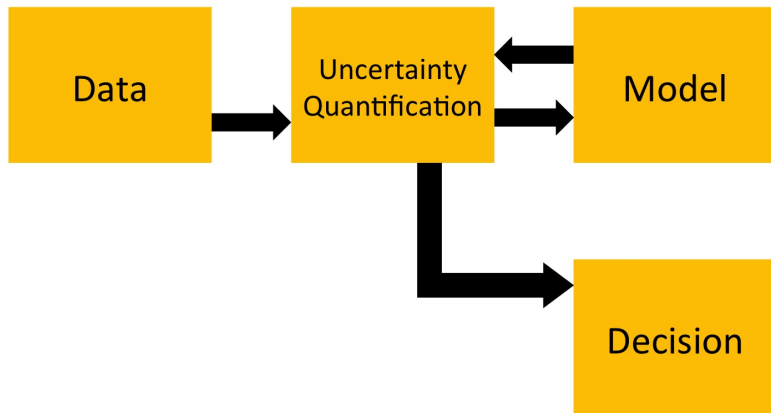
- partially confined aquifer? vadose-zone effects?
- boundary conditions? dual porosity? Noordbergum effect?
- ...
- even more complex once contaminant transport is added

► Discretization

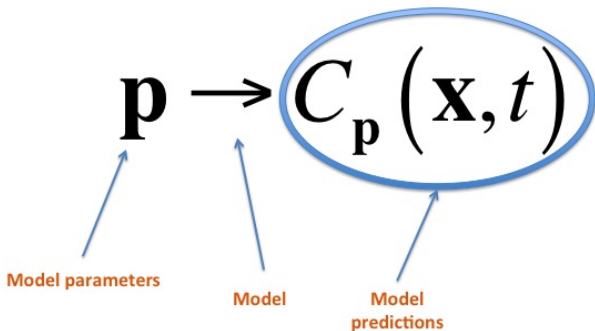
- relatively coarse discretization
- numerical errors

► Therefore

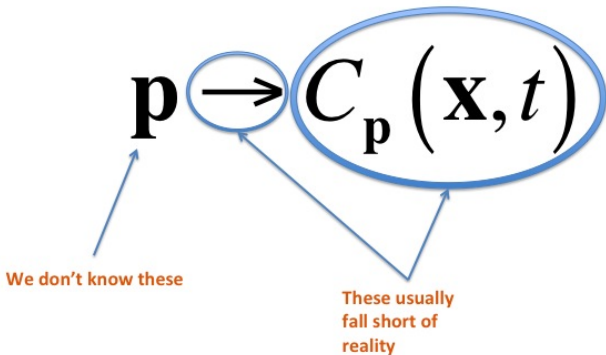
- Address the fact that we do not know the model parameters
- Address the fact that we cannot represent the physics
- Address the fact that we have uncertain observations



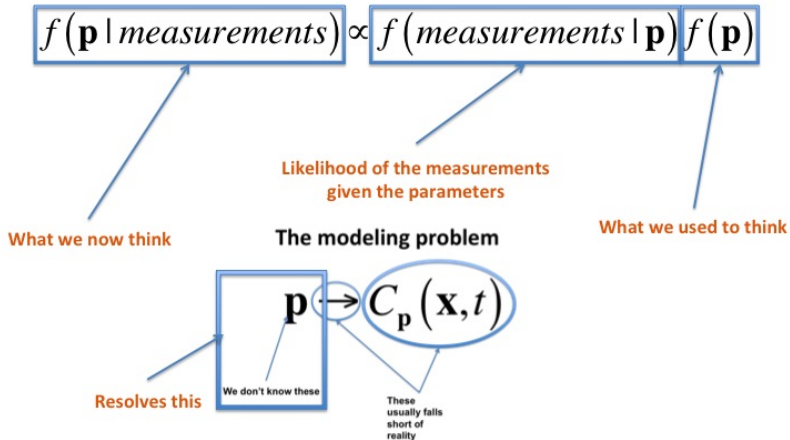
The modeling solution



The modeling problem



The Bayesian solution

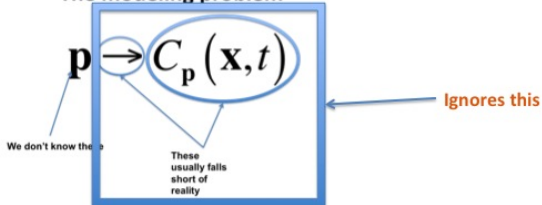


The Bayesian problem

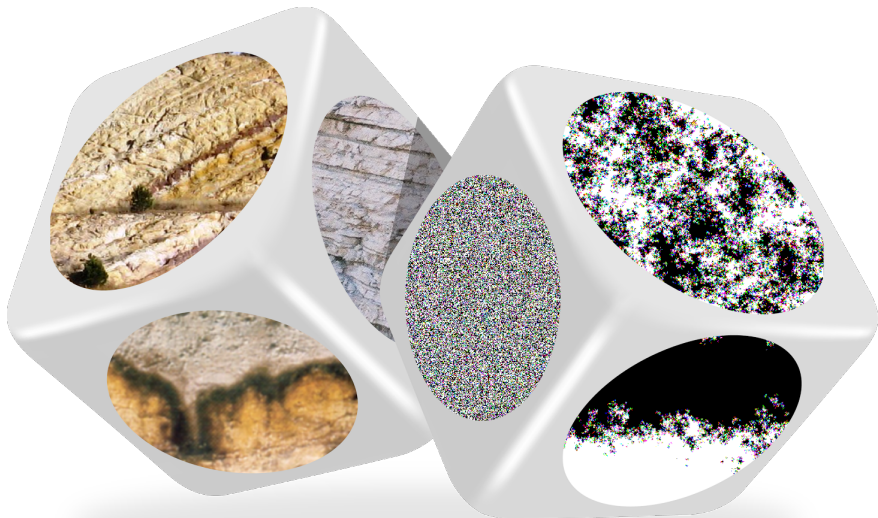
$$f(\mathbf{p} | \text{measurements}) \propto \boxed{f(\text{measurements} | \mathbf{p})} f(\mathbf{p})$$

We don't know this

The modeling problem



Geologic dice



Bayes' theorem is mathematically rigorous, but its application in science and engineering is not always rigorous. There are two reasons for this:

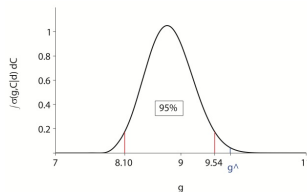
- ▶ We can enumerate the possible outcomes of **dice-rolling**, but not all the possible outcomes for **real-world engineering problems**.
 - ▶ We cannot enumerate all possible permeability fields, and this just covers the first-order physics
 - ▶ NRC: 90% of court-mandated groundwater remediations fail, often due to unanticipated complexities
- ▶ We can precisely determine conditional probabilities for **coin-tossing**, but substantial uncertainty surrounds the conditional probabilities for **real-world engineering problems**.
 - ▶ It is observed that the water level in a well is 1750 [m]
 - ▶ Model A predicts a water level of 1749 [m]
 - ▶ Model B predicts a water level of 1748 [m]
 - ▶ What are the likelihoods of models A and B ?
 - ▶ No one knows

Bayesian problems: estimating gravitational acceleration

$$\frac{dv}{dt} = g - Cv^2, \quad \frac{dz}{dt} = v, \quad z(t_0) = v(t_0) = 0$$

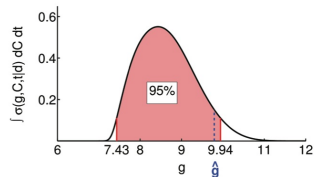


First try (g, C):

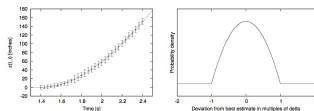


$$E(g|\mathbf{d}) = 8.82 \text{ [m/s}^2\text{]}$$

Second try (g, C, t_0):



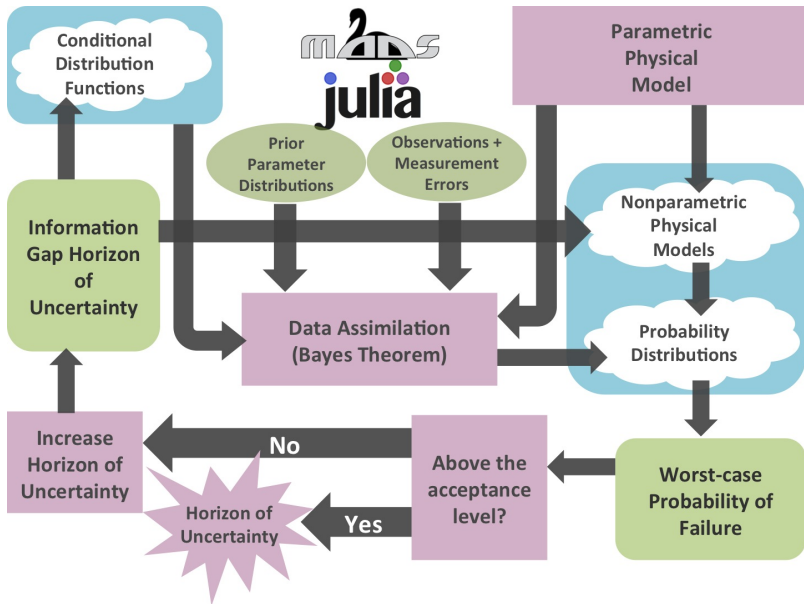
$$E(g|\mathbf{d}) = 8.64 \text{ [m/s}^2\text{]}$$



Allmaras et al. *Estimating Parameters in Physical Models through Bayesian Inversion: A Complete Example*, SIAM Review (2013).

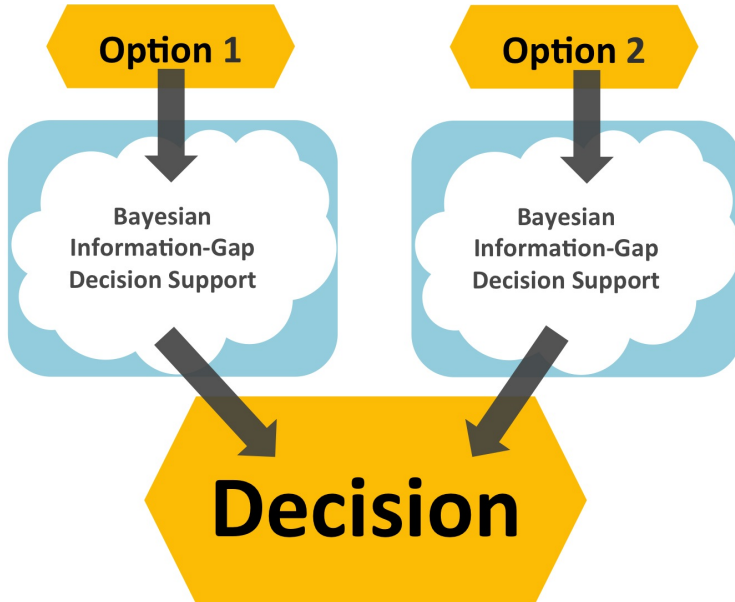
- ▶ **BIG** Decision Theory (DT)
- ▶ **B**ayesian-**I**nformation-**G**ap (**BIG**) Decision Theory (**DT**)
- ▶ Use Bayes theorem to
 - ▶ Assess parametric uncertainty
- ▶ Use information-gap decision theory to
 - ▶ Place the problem in a decision context
 - ▶ Consider the sides of the dice that the Bayesian analysis doesn't see

How to do BIG Decision Theory

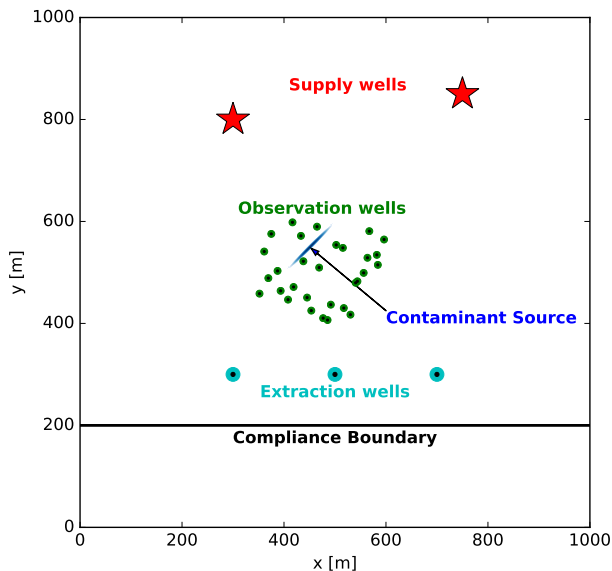


Bayesian Information-Gap Decision Support

How to do BIG Decision Theory



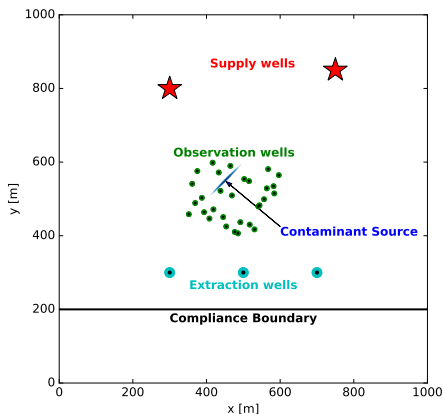
A representative scenario



Remedial options

Remedial options:

- ▶ Use the middle extraction well
- ▶ Use the outer extraction wells
- ▶ Use all extraction wells



BIG Decision Theory Results

