

Verification, Validation, and Predictive Capability: What's What?

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Outline

- **Motivation and background**
- **Code and solution verification**
- **Model validation and calibration**
- **Predictive capability**
- **Closing remarks**

Motivation

- **We are in the midst of a revolution in science and engineering**
- **Impact of modeling and simulation are dramatically increasing in geophysical systems because:**
 - **Traditional experiments for the understanding of systems are usually impossible**
 - **Large physical scales and long time spans make simulation most appealing**
 - **Ability to optimize and perturb our designs in unique ways**
 - **Stunning reduction in cost of computing resources**

How can simulation analysts and customers who use simulations determine if the simulation results can be trusted?

Background

- **What elements determine if suppliers and customers can trust simulation results?**
 - Education and training of the computational analysts
 - Development and implementation of quality control processes for simulation activities, e.g., simulation governance
 - **Use of verification and validation procedures**
 - **Estimation of the uncertainties that could impact the results**
- **There are different types of verification and validation:**
 - System V&V
 - Software V&V
 - Simulation V&V
- **All have similar concepts:**
 - Verification: Am I building the product correctly?
 - Validation: Am I building the correct product?

We will focus on simulation V&V and predictive capability

Conceptual Framework of Simulation Verification, Validation and Predictive Capability

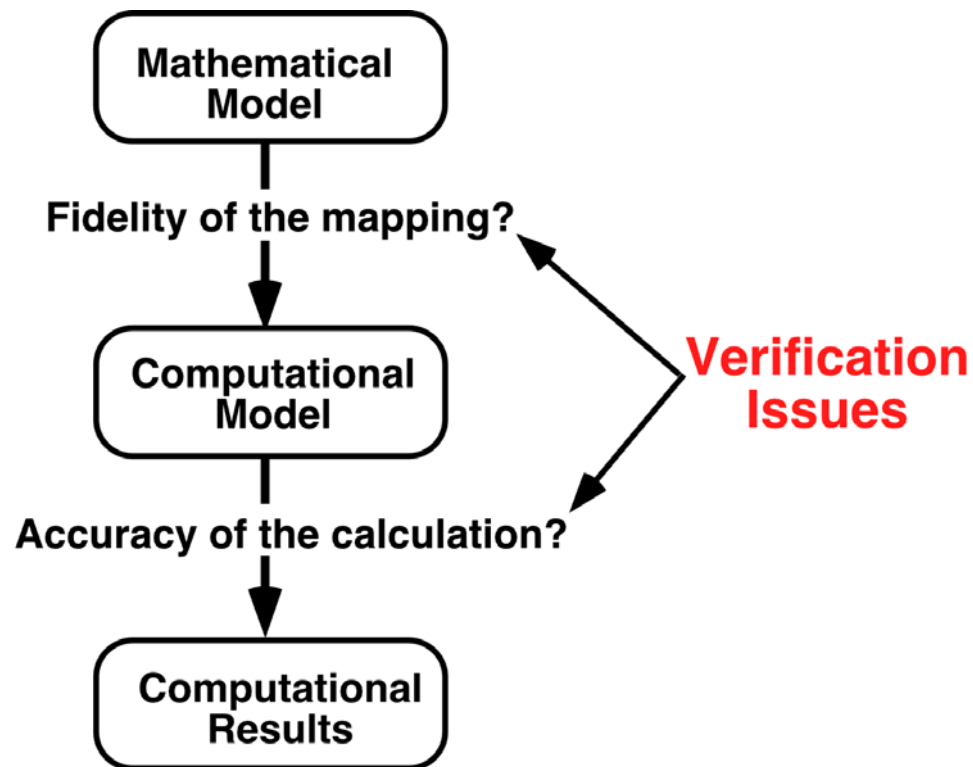
- Verification and validation are built on the philosophy of **skepticism**
 - The fundamental procedure of V&V is **testing**
 - “Show me the evidence that the software and the mathematical models are working properly.”
- Predictive capability is foretelling the state of the system for conditions where **no experimental data** are available:
 - Predictive capability is built on:
 - Fidelity of the physics modeling embodied in the mathematical model
 - Identification and estimation of all sources of uncertainty for the system conditions of interest
 - The procedure is built on uncertainty quantification (UQ) using non-deterministic simulation

**Predictive capability is the primary reason for
conducting simulation**

Formal Definition of Verification (U.S. DoD, AIAA, ASME, ASCE)

Verification: The process of determining that a computational model accurately represents the underlying mathematical model and its solution.

**Verification
assesses
software
reliability and
numerical
accuracy**



Two Types of Verification

First: Code Verification

- **Code verification activities are directed toward:**
 - Finding and removing mistakes in the source code
 - Finding and removing errors in the numerical algorithms

Primary Result: determination of the observed order of numerical convergence in space and time
- **Responsibility for code verification activities:**
 - **Primary: software developers (either commercial or developers within an organization)**
 - **Secondary: simulation analysts (customers of software developers) and customers of the simulation**
- **Status of code verification:**
 - **Commercial software: very few (if any) document the observed order of accuracy of their solutions**
 - **Organizational software: very few organizations document the observed order of accuracy of their solutions**

Two Types of Verification

Second: Solution Verification

- **Solution verification activities are directed toward:**
 - Assuring the correctness of input and output data for each problem of interest
 - Estimating the numerical solution error
- **Sources of numerical solution error:**
 - Round-off error
 - Iterative error
 - **Discretization error**
 - Statistical sampling error
 - Response surface error

Primary Goal: Estimation of the total numerical solution error in the system response quantities (SRQs) of interest

Solution Verification (continued)

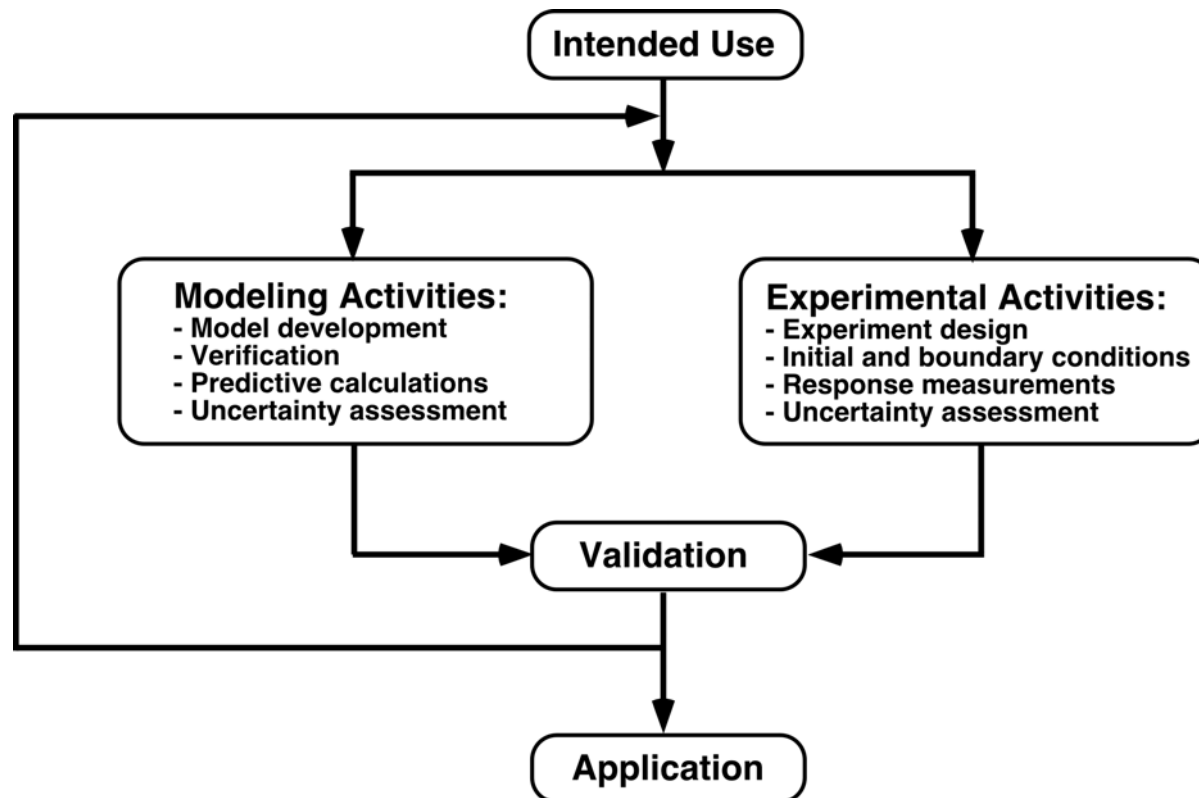
- **Classification of discretization error estimators:**
 - Type 1: DE estimators based on higher-order estimates of the exact solution to the PDEs (Richardson extrapolation, order refinement methods, and finite element recovery methods)
 - Type 2: DE estimator based on estimating the discretization residual of the PDEs (DE transport equation method, finite element residual methods, and adjoint methods)
- **Responsibility for solution verification:**
 - Primary: simulation analysts
 - Secondary: software developers (for implementing estimation tools) and customers of the simulation
- **Status of solution verification:**
 - Very few analysts estimate solution error
 - Very few managers/decision makers ask about solution verification

“But our results agree with the experimental data.”

Formal Definition of Validation (U.S. DoD, AIAA, ASME, ASCE)

Validation: The process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model.

Validation
deals with
physics
modeling
fidelity

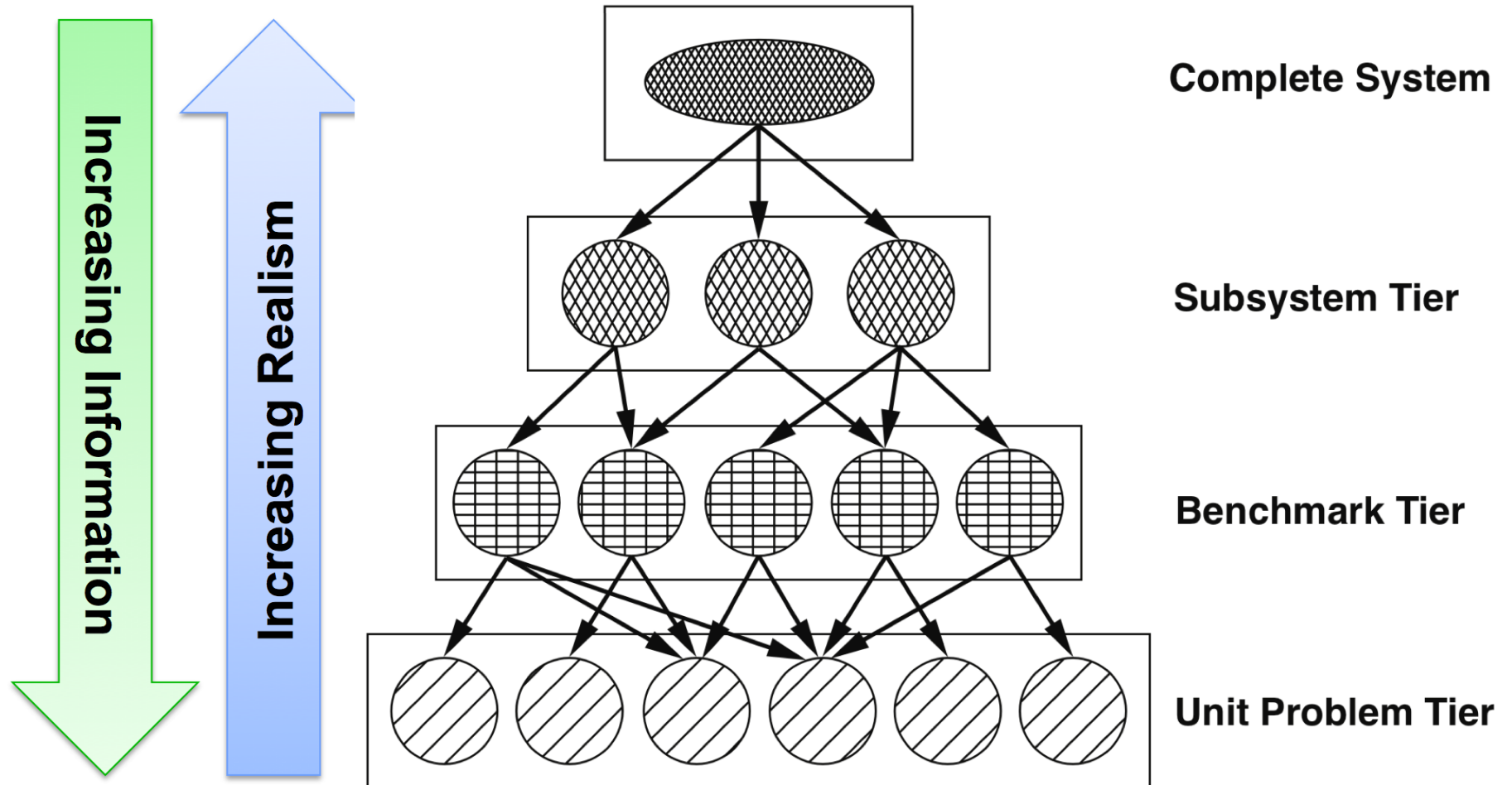


(Ref: ASME Guide, 2006)

Goals and Tools of Validation

- **Tactical goals of validation:**
 - Quantification of the effects of mathematical modeling assumptions and approximations by comparison of simulation results with experimental measurements, i.e., quantification of model form uncertainty
 - Quantification of model form uncertain (distinct from parametric uncertainty)
- **Strategic goals of validation:**
 - Improve mathematical modeling to increase predictive capability
 - Improve the separation of model form uncertainty from input parameter uncertainty
- **What are the primary tools of validation?**
 - High quality validation experiments
 - Validation metrics: mathematical operators to quantify the difference between simulation and experimental outcomes

Validation Experiment Hierarchy for Engineering Systems



(Ref: AIAA Guide, 1998)

Model Calibration

Calibration: (AIAA and ASME definition) The process of adjusting physical modeling parameters in the computational model to improve agreement with experimental data

- Also known as: parameter estimation, model tuning, model updating
- Calibration is commonly conducted **before** formal validation activities
- Ex: Calibration of erosion parameters, calibration of subsurface porosity and permeability, and calibration of chemical and biological parameters

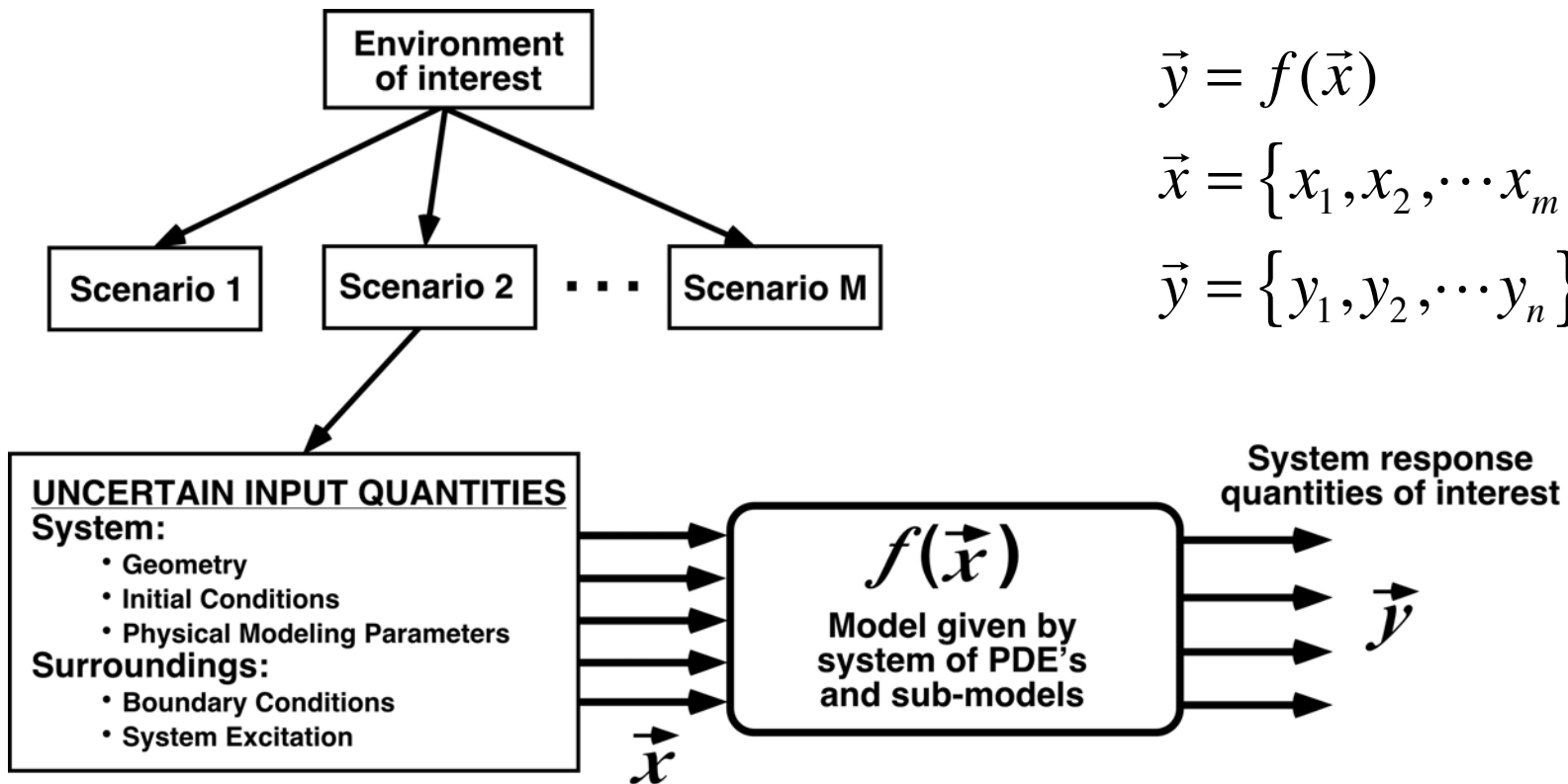
Approaches to model calibration:

- Frequentist (classical) approaches
- Bayesian updating:
 - Parameters are considered as probability distributions
 - Probability distributions represent belief likelihoods
 - Parameters are updated using Bayes formula when new experimental data become available

Where Do We Stand: Validation Activities

- **Common approach to validation is actually **model calibration**:**
 - Parameters in the model, either scalars or probability distributions, are adjusted to improve agreement with experimental data
 - Simulations are usually reliable when the models are used for very similar systems and conditions for which the models are calibrated
 - Weaknesses in the models are not uncovered, but masked, when model calibration becomes dominant
- **To improve confidence in our simulations, validation should:**
 - Improve the separation of calibration and validation activities
 - Emphasize the assessment of simulation accuracy by using blind-predictions of experimental data
 - Improve cooperation and synergism between experimentalists and computational analysts

Predictive Capability: Reliance on Non-Deterministic Simulations



- **Key sources of uncertainty:**
 - Identification of environments and scenarios that the system could experience
 - Input uncertainties in the system and in the surroundings
 - Model form uncertainty, i.e., uncertainty in $f(\vec{x})$
 - Numerical errors in \vec{y}

Types of Uncertainties

Aleatory uncertainty: uncertainty due to inherent randomness

- Also referred to as variability and stochastic uncertainty

Aleatory uncertainty is a characteristic of the system of interest

- **Examples:**

- Variability weather conditions, e.g., wind speed, rain fall, temperature
- Variability in properties of natural and manmade materials
- Variability in excitation, e.g., frequency and amplitude of earthquakes

Epistemic uncertainty: uncertainty due to lack of knowledge

- Also referred to reducible uncertainty, knowledge uncertainty, and subjective uncertainty

Epistemic uncertainty is a characteristic of our knowledge of the system

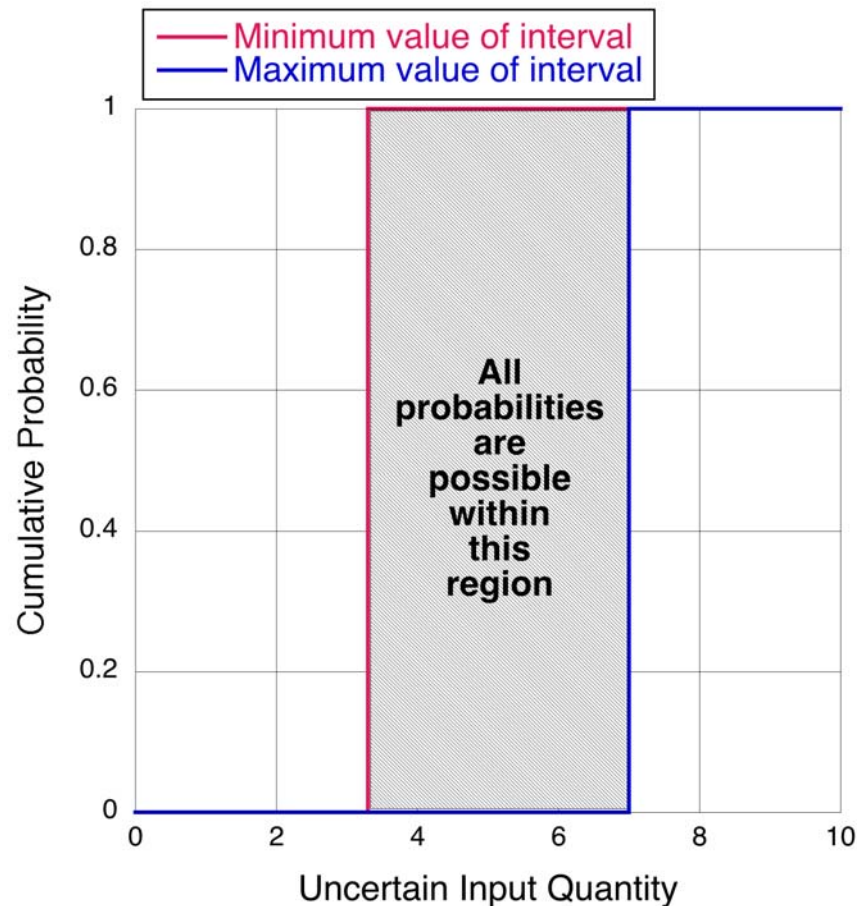
- **Examples:**

- Poor understanding of physical phenomena, e.g., underground transport
- Poor understanding of accident scenarios and event/failure trees
- Model form uncertainty, e.g., failure of large man-made structures

(Ref: Kaplan and Garrick, 1981; Morgan and Henrion, 1990; Ayyub and Klir, 2006)

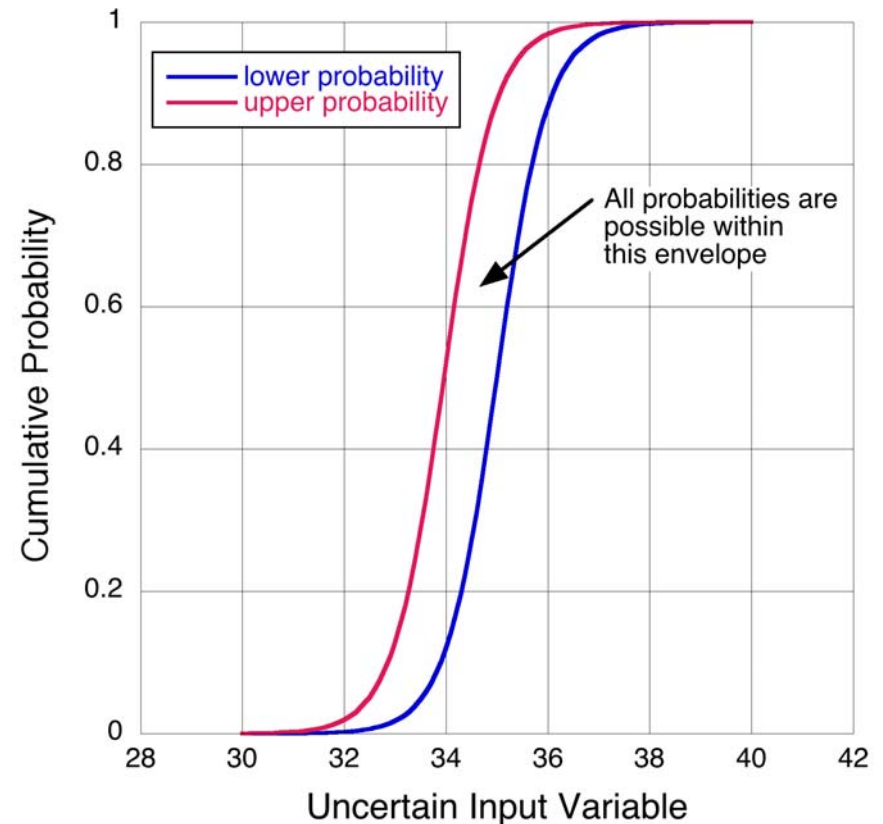
Characterization of Epistemic Uncertainty

A purely epistemic uncertainty is characterized by an interval (a,b)

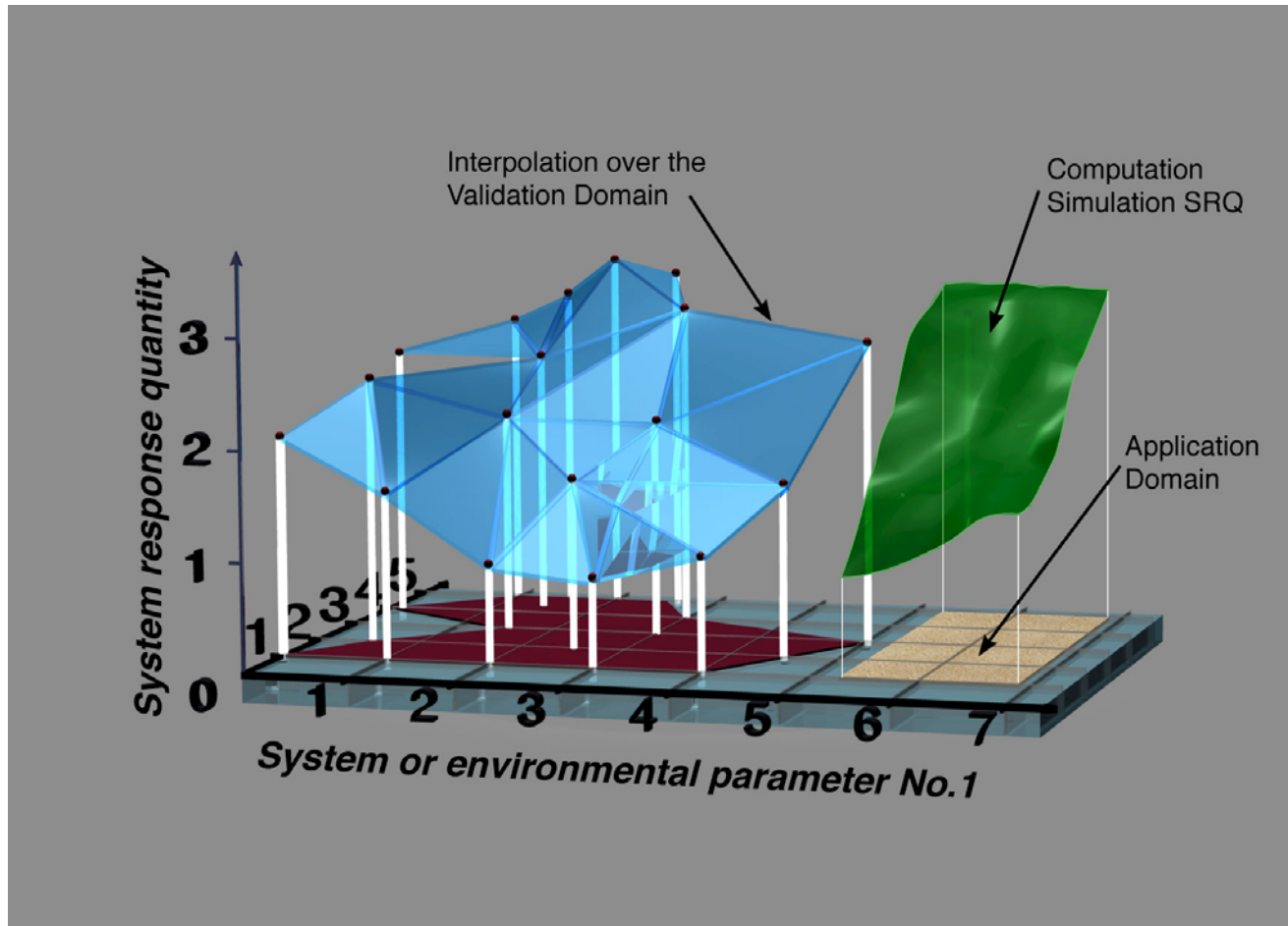


A mixture of epistemic and aleatory uncertainty is characterized by a p-box

This mathematical structure is referred to as an **imprecise probability**.



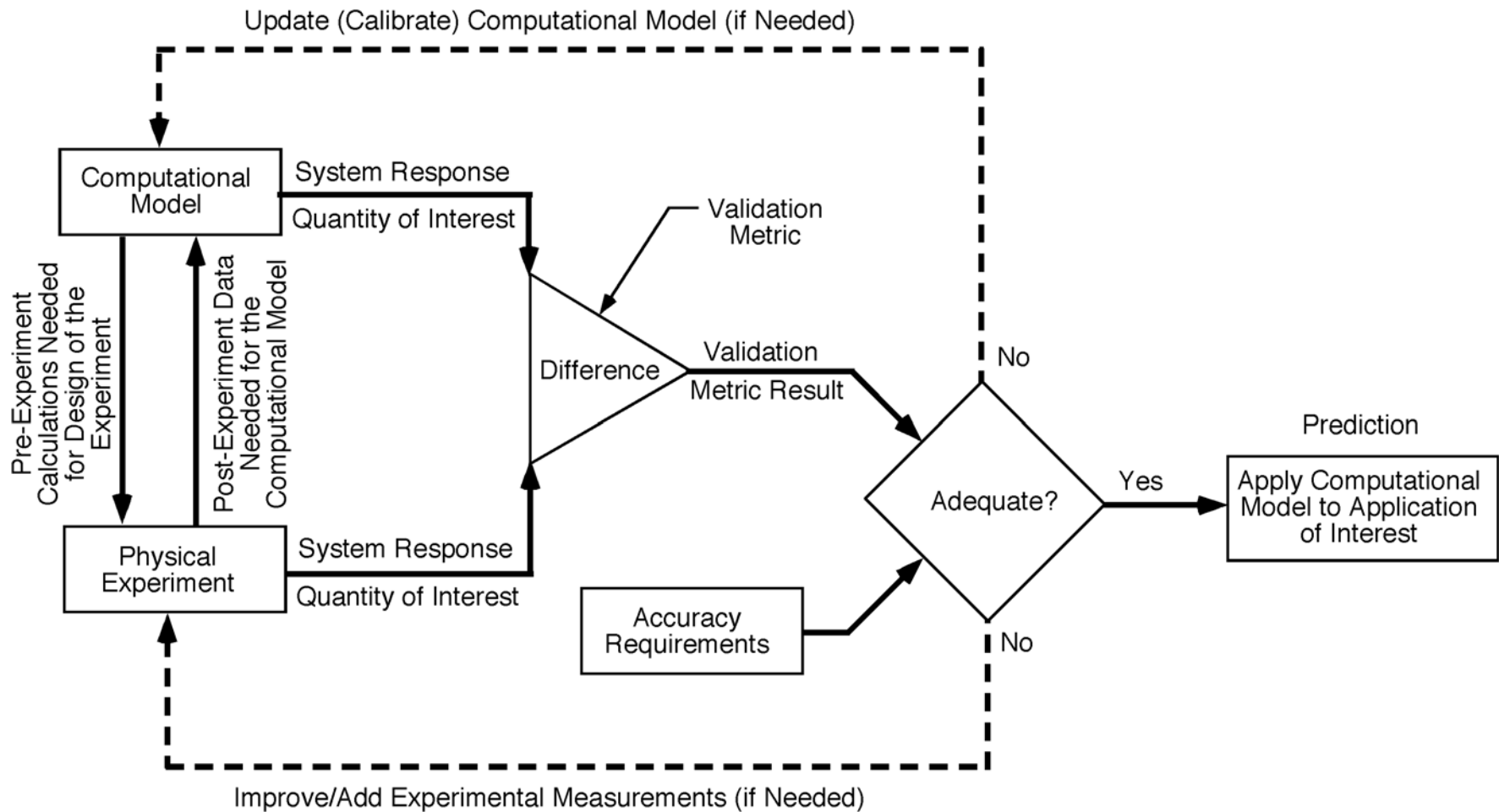
Prediction Far From the Validation/Calibration Domain: Extrapolation



- **Extrapolation can occur in terms of:**
 - Input parameters
 - Higher levels in the validation hierarchy
- **Large extrapolations commonly involve large changes in physics coupling**
- **Large extrapolations should be based on **physics inference, not statistical inference****

(Ref: Oberkampf and Roy, 2010)

Validation (Model Accuracy) Assessment, Calibration and Prediction



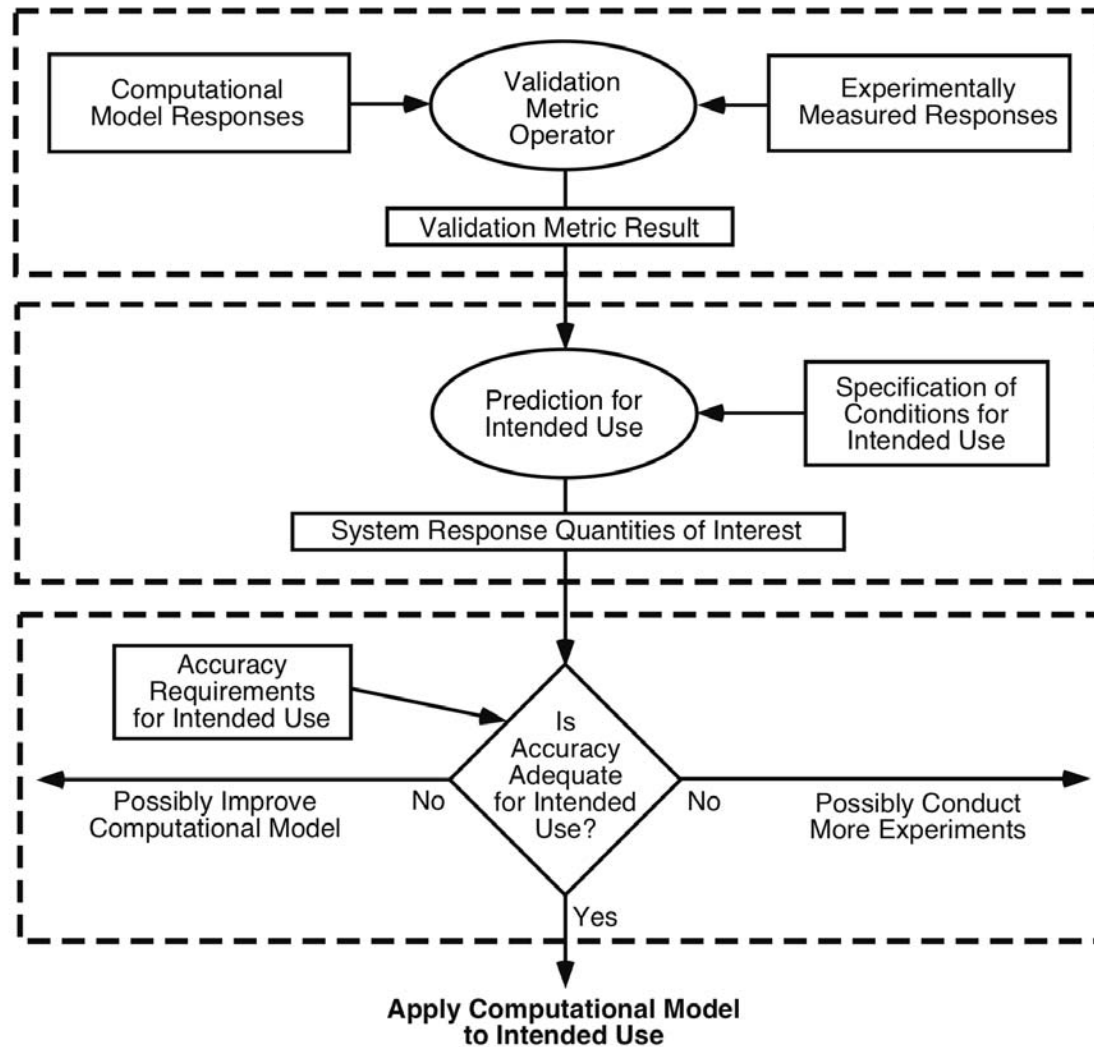
(Ref: Oberkampf and Barone, 2006)

Contrasting Validation, Prediction, and Model Adequacy

Validation
Assessment of Model Accuracy by Comparison with Experimental Data

Prediction
Interpolation or Extrapolation of the Model to the Intended Use

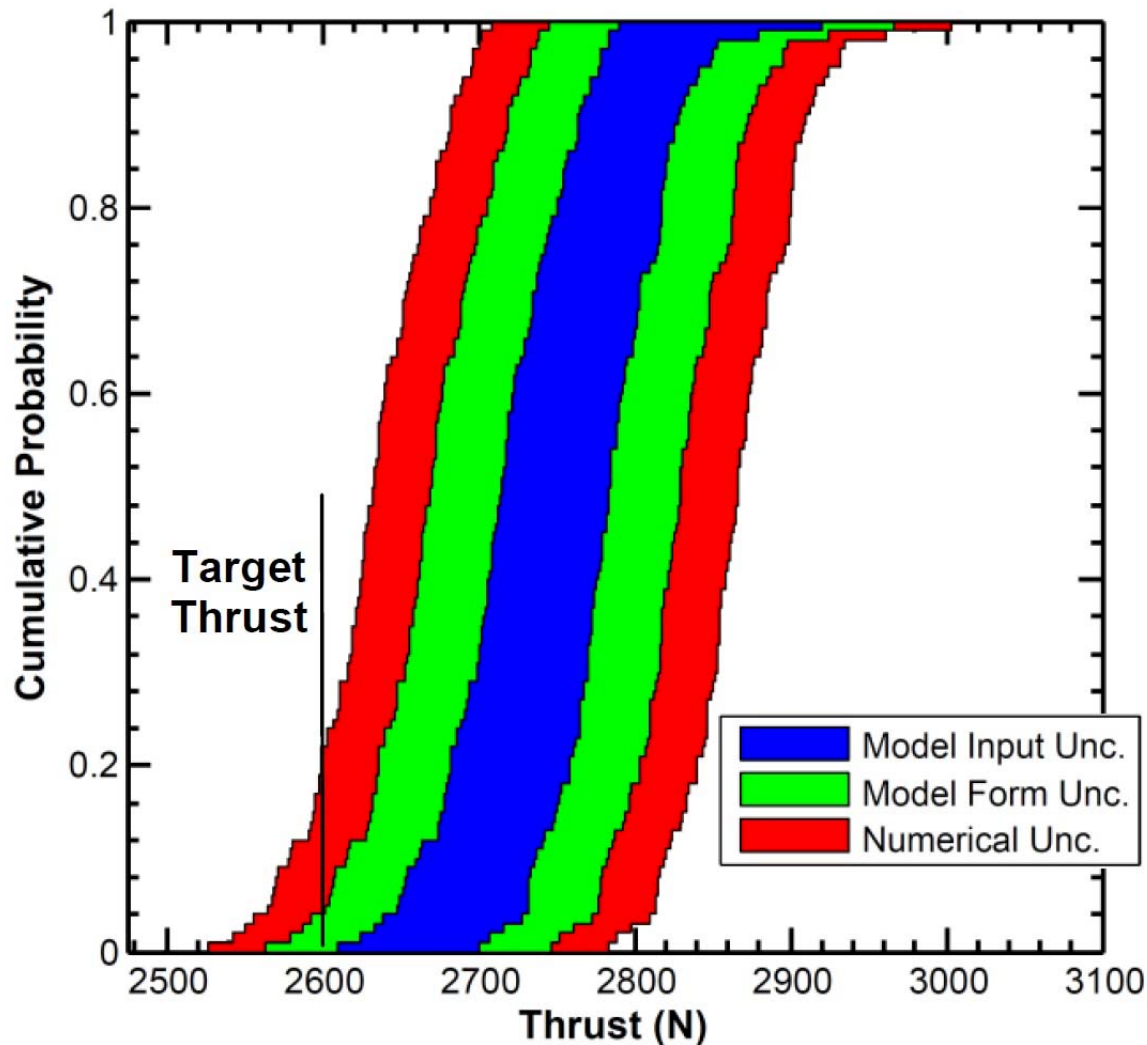
Adequacy
Decision of Model Adequacy for Intended Use



(Ref: Oberkampf and Trucano, 2008)

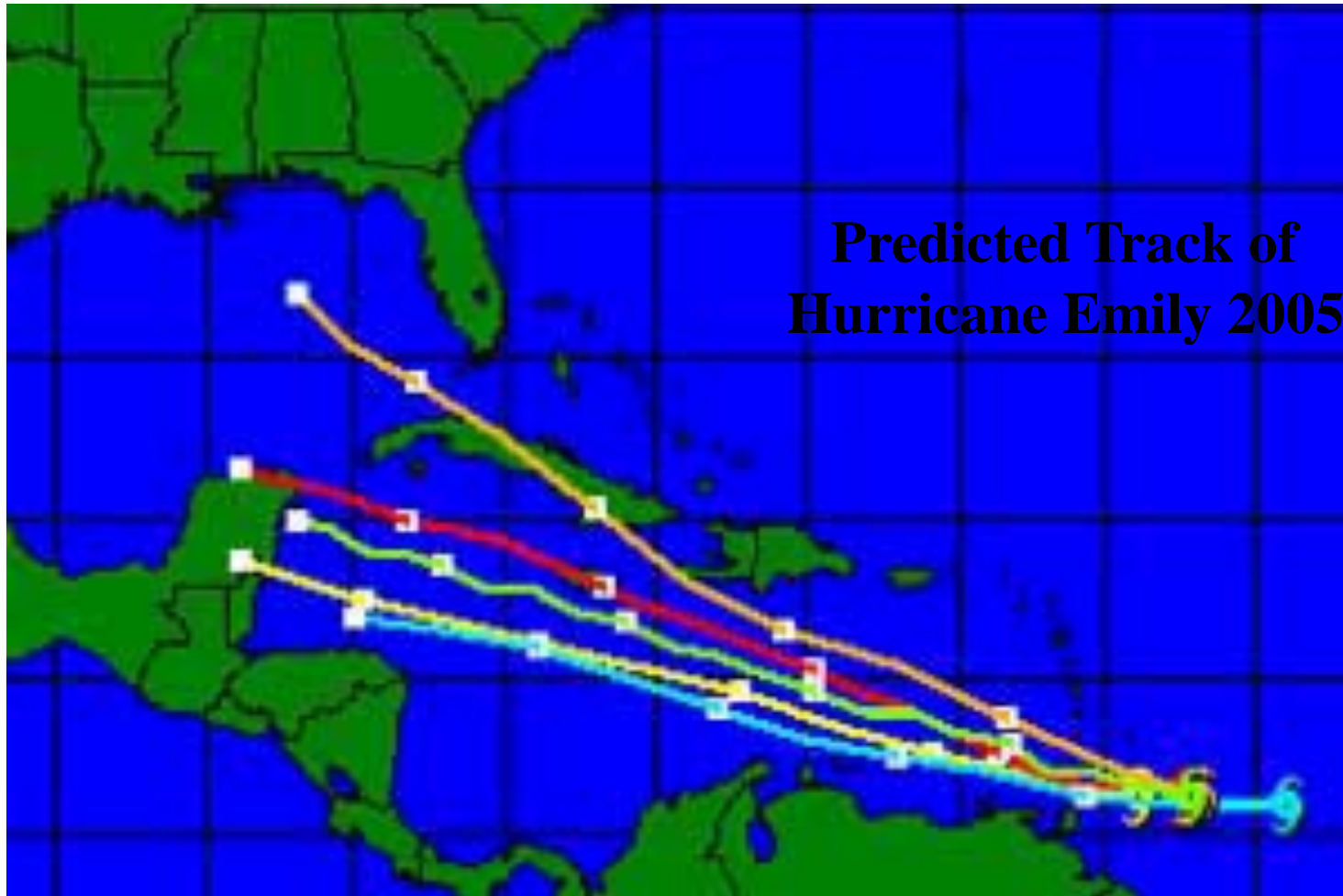
Example of a Probability-Box with Various Sources of Uncertainty

(Roy and Balch, 2012)



- Prediction of thrust from a small rocket motor
- Uncertain inputs to the mathematical model:
 - Total pressure in the motor ~ normal distribution
 - Effect of boundary layer transition ~ interval-valued effect on the expansion ratio of the nozzle
- Epistemic uncertainties in the simulation are:
 - Model form uncertainty
 - Numerical solution error

Example Showing Total Uncertainty Using Alternate Competing Models



(Ref: Green, 2007)

Closing Remarks

- Code and solution verification must be improved to ensure we are building on a solid foundation for simulation
- Validation is focused on assessing the accuracy of mathematical models vis-à-vis experimental measurements
- In geosciences mathematical models are dominated by calibration procedures for model parameters
- Predictive capability:
 - Is focused on what we have **never seen before**
 - When we make predictions far from our validation/calibration database, we should concentrate on capturing total uncertainty

Quote from William H. Press (author of *Numerical Recipes*):

“Simulation and mathematical modeling will power the 21st Century the way steam powered the 19th.”

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