



# Validation & Verification and Uncertainty Quantification at Sandia

**Brian M. Adams**  
*Sandia National Laboratories*  
*Optimization and Uncertainty Quantification*

**July 18, 2008**

**Research Consortium for Multidisciplinary  
System Design Workshop**  
***MIT, Boston, MA***



# Outline

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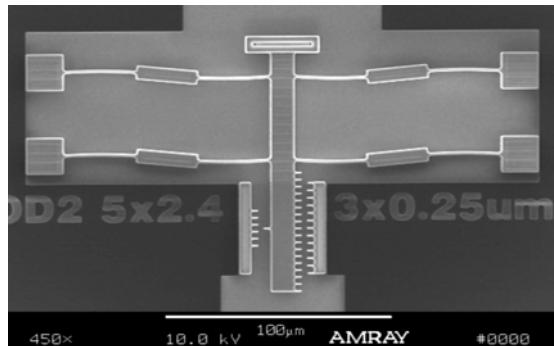


***To be credible, simulations must be verified, validated with data, and deliver a best estimate of performance, together with its degree of variability or uncertainty.***

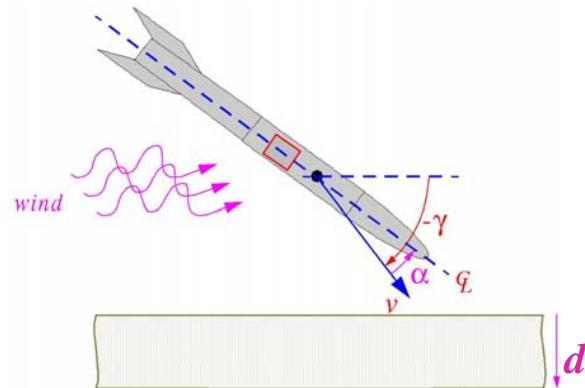
- Credible simulation and V&V
- Characterizing and propagating uncertainty for risk analysis and validation
- Intro to aleatory and epistemic UQ in DAKOTA
- Application examples:
  - UQ for CMOS7 ViArray UQ
  - Sandia's QASPR program: computational model-based system qualification

*Slide credits: Mike Eldred, Laura Swiler, Tony Giunta, Joe Castro, Genetha Gray, Bill Oberkampf, Matt Kerschen, others*

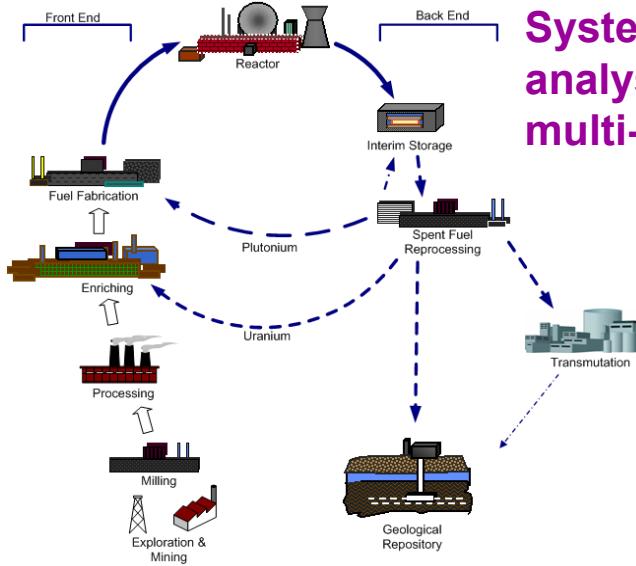
# Insight from Computational Simulation



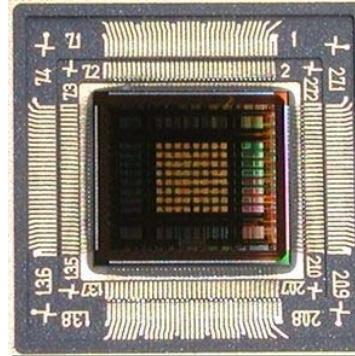
# Micro-electro-mechanical systems (MEMS): quasi-static nonlinear elasticity, process modeling



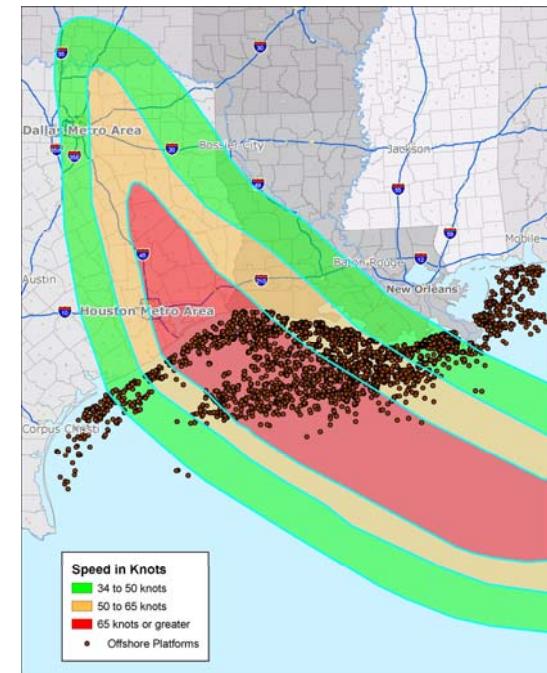
# Earth penetrator: nonlinear PDEs with contact, transient analysis, material modeling



# Electrical circuits: networks, PDEs, differential algebraic equations (DAEs), E&M



## Systems of systems analysis: multi-scale, multi-phenomenon



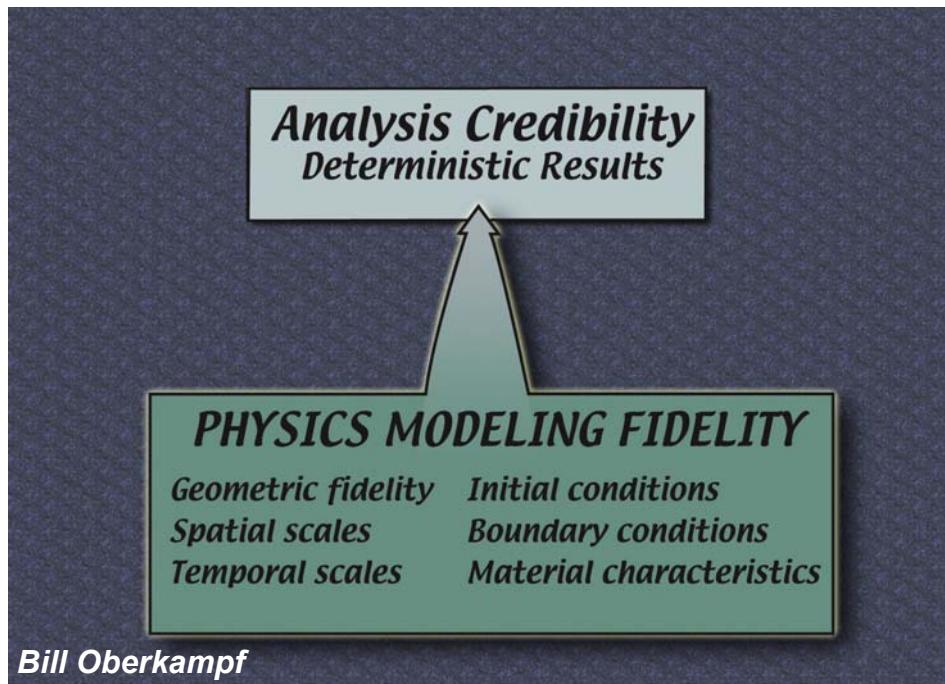
# Hurricane Katrina: weather, logistics, economics, human behavior



# Credible Simulation

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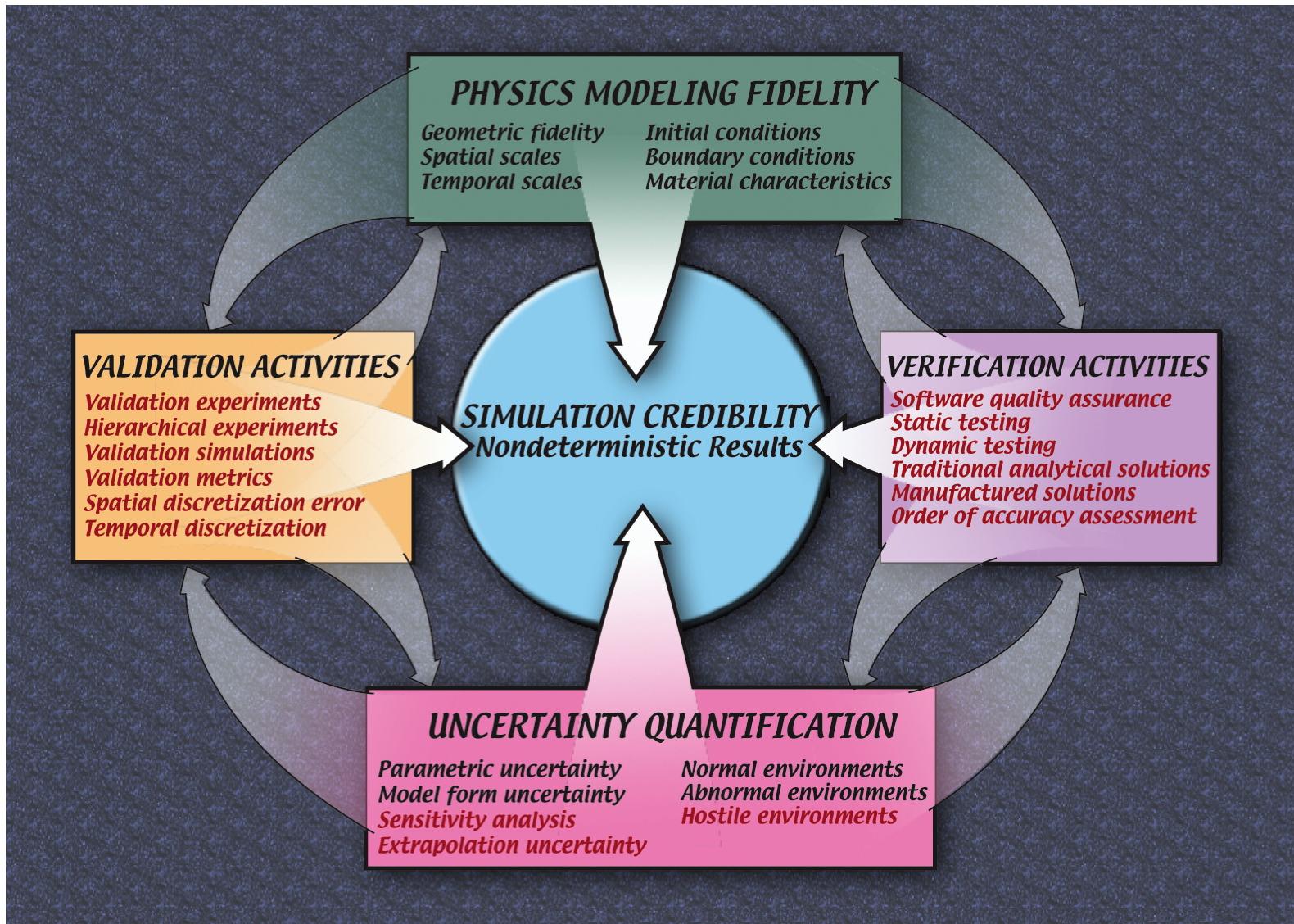
- Ultimate purpose of modeling and simulation is (arguably) insight, prediction, and decision-making → *need credibility for intended application*

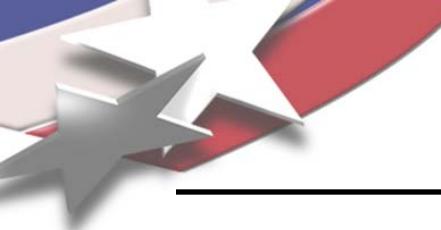


- Historically: primary focus on *modeling fidelity*



# Credible Simulation: V&V and UQ





# Verification & Validation

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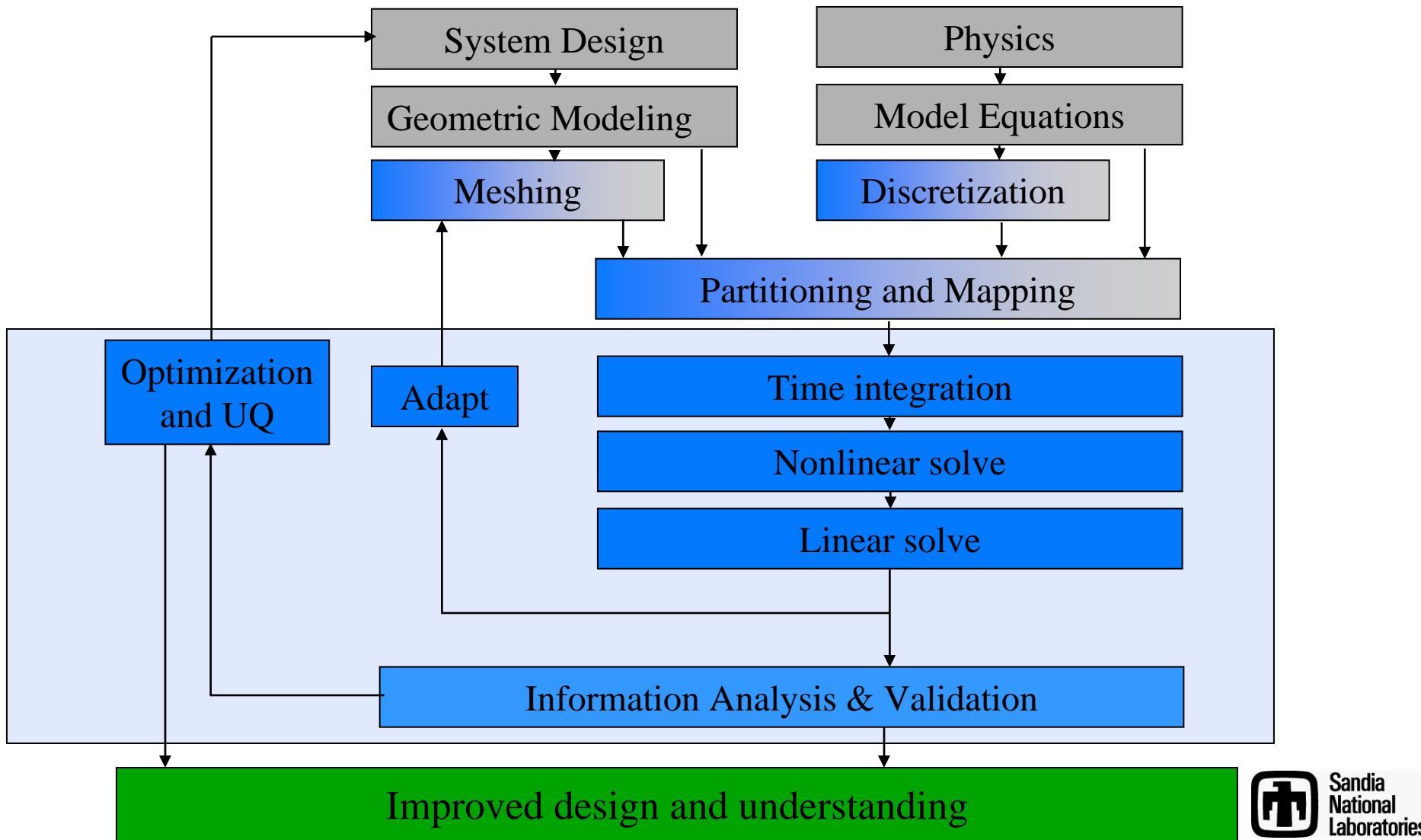
- Ultimately, quantification of margins and uncertainties (QMU):  
How close are my uncertainty-aware code predictions to required performance?
- **Validation:** “Are we solving the right equations?”
  - **A disciplinary science issue:** is the science (physics, biology, etc.) model sufficient *for the intended application?*
  - Involves **data and metrics;** relies on uncertainty quantification (UQ)
- **Verification:** “Are we solving the equations correctly?”
  - **A mathematics/computer science issue:** is our mathematical formulation and software implementation of the physics model correct?
  - **code verification** (software correctness): SQE, especially unit/regression/verification testing; analytic problems, method of manufactured solutions
  - **solution verification:** e.g., exhibits proper order of spatial/temporal/iterative convergence. Algorithms: Richardson extrapolation, finite element error estimation (ZZ, QOI)

$$p = \frac{1}{\ln r} \ln \left( \frac{E_{grid1}}{E_{grid2}} \right)$$

$$\eta^Q \equiv \int_{\Omega} \mathbf{T}(\mathbf{u}_h) : (\mathbf{G}(\nabla \mathbf{z}_h) - \nabla \mathbf{z}_h) \, d\Omega$$

# Algorithms for Computational Modeling & Simulation

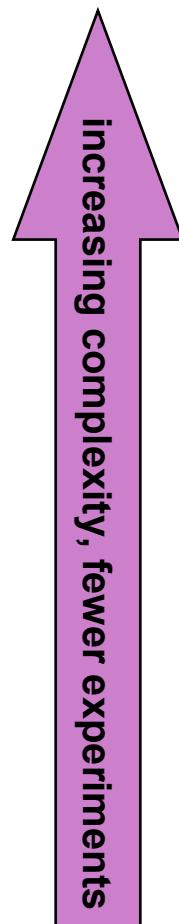
**Are you sure you don't need verification?!**



# Hierarchical Validation Experiments

## (Abnormal Thermal Environment)

**Validation:** “Are we solving the *right* equations?” Based on experimental data and metrics, is the model sufficient *for the intended application*?



Deployed System



Full System



Subassemblies

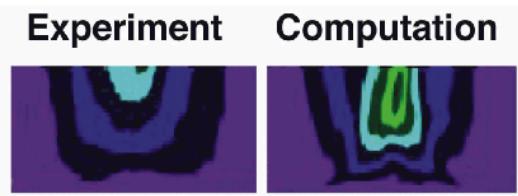


Components

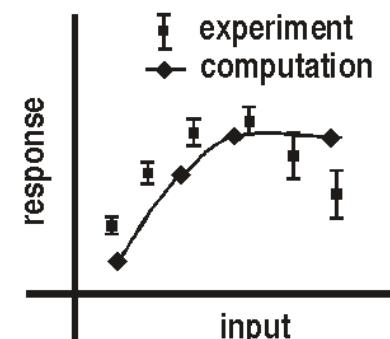
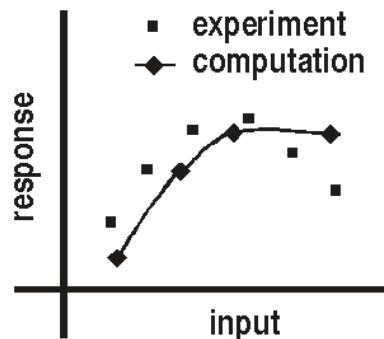


Separable Effects

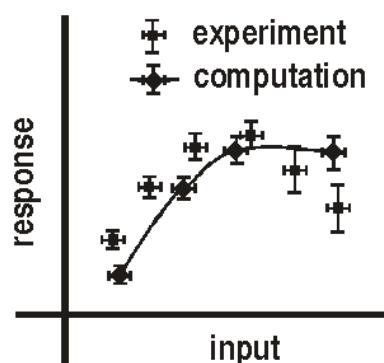
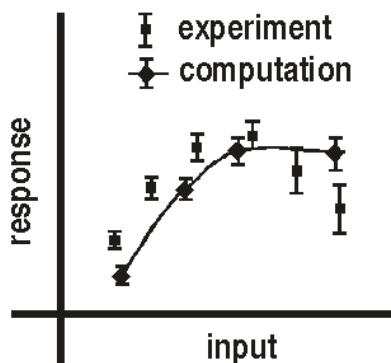
# Validation Metrics: Quantitative Comparison with Experiment



(a) Viewgraph Norm

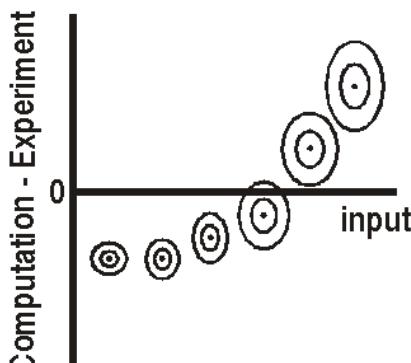


(b) Deterministic  
(c) Experimental  
Uncertainty



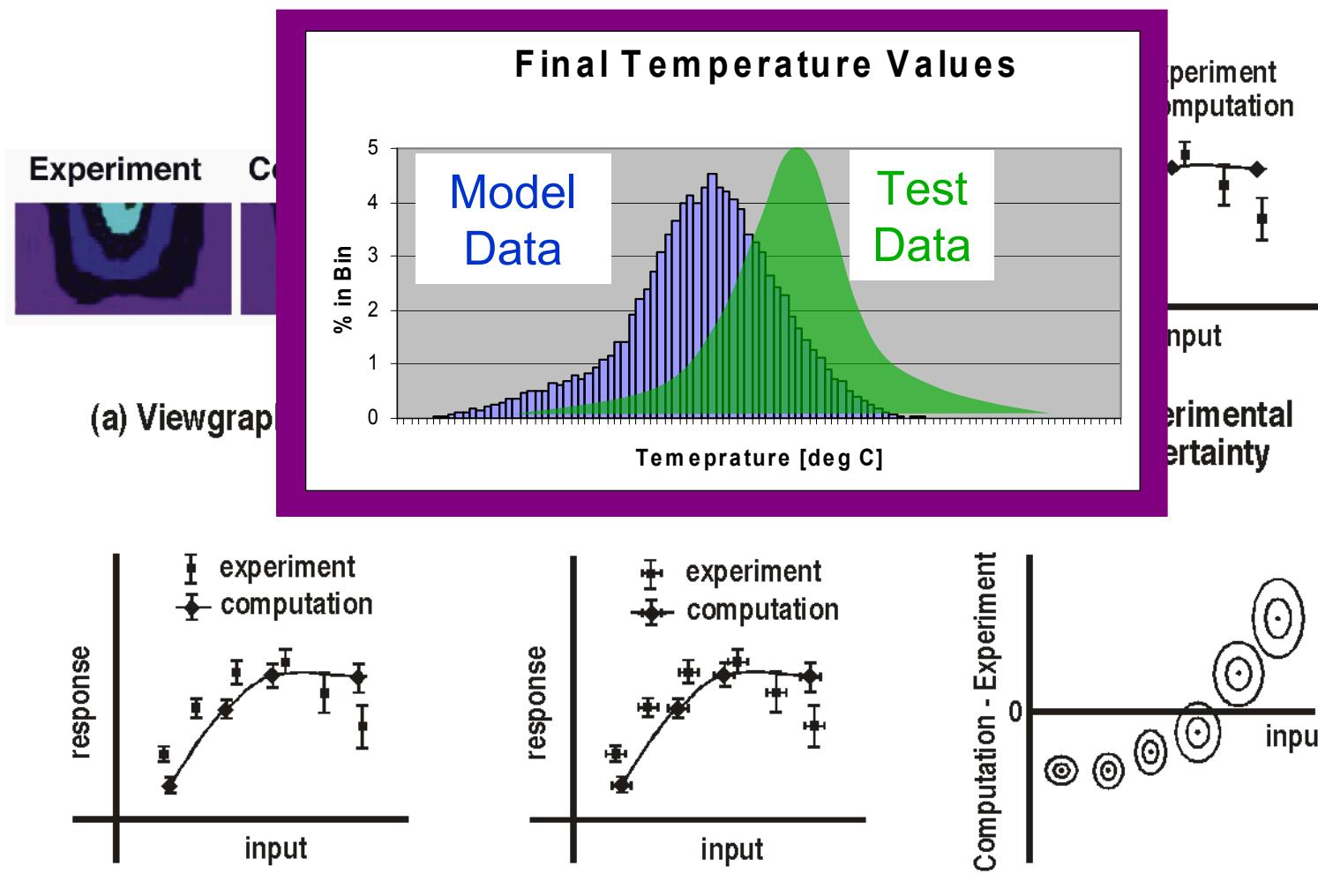
(d) Numerical Error

(e) Nondeterministic  
Computation



(f) Statistical  
Comparison

# Validation Metrics: Quantitative Comparison with Experiment

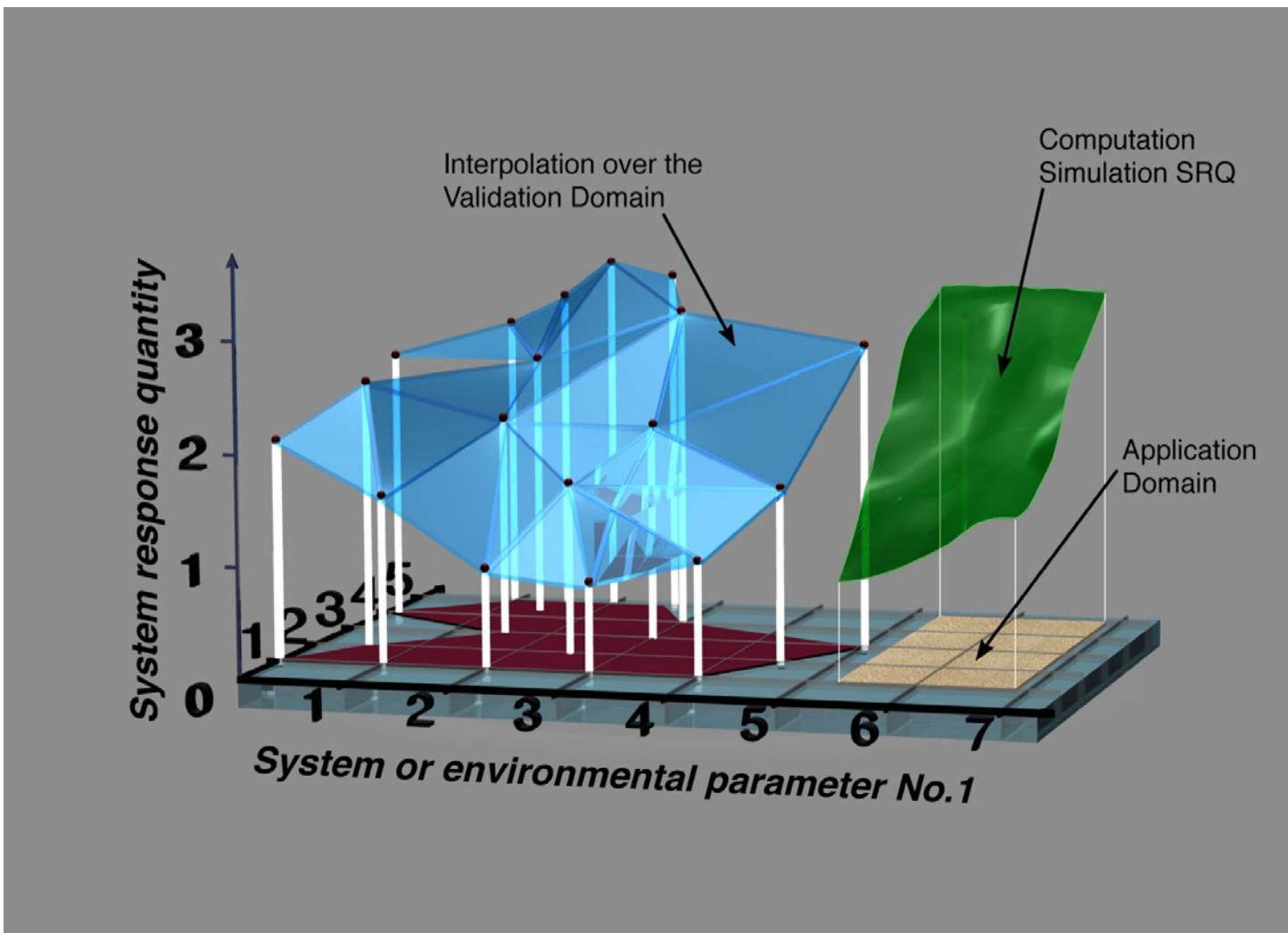


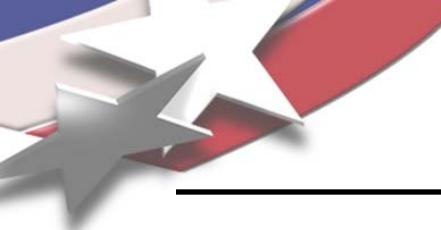
#### (d) Numerical Error

## (e) Nondeterministic Computation

## (f) Statistical Comparison

# Extrapolating Beyond Validation Domain



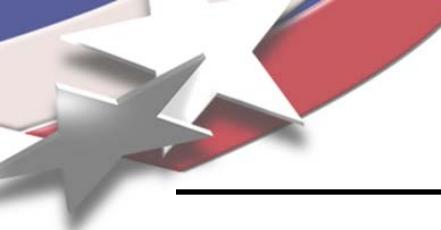


# Uncertainties to Quantify

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*A partial list of uncertainties affecting computational model results*

- **typical parametric uncertainty**, incl. random fields/processes
  - physics/science parameters
  - **statistical variation**, inherent randomness
  - operating environment, interference
  - initial, boundary conditions; forcing
  - geometry / structure / connectivity
  - material properties
  - manufacturing quality
- **model form / accuracy**
- **program: requirements, technical readiness levels**
- **human reliability, subjective judgment, linguistic imprecision**
  
- **numerical accuracy**: mesh, solver, approximation error
- **experimental error**: measurement error, bias

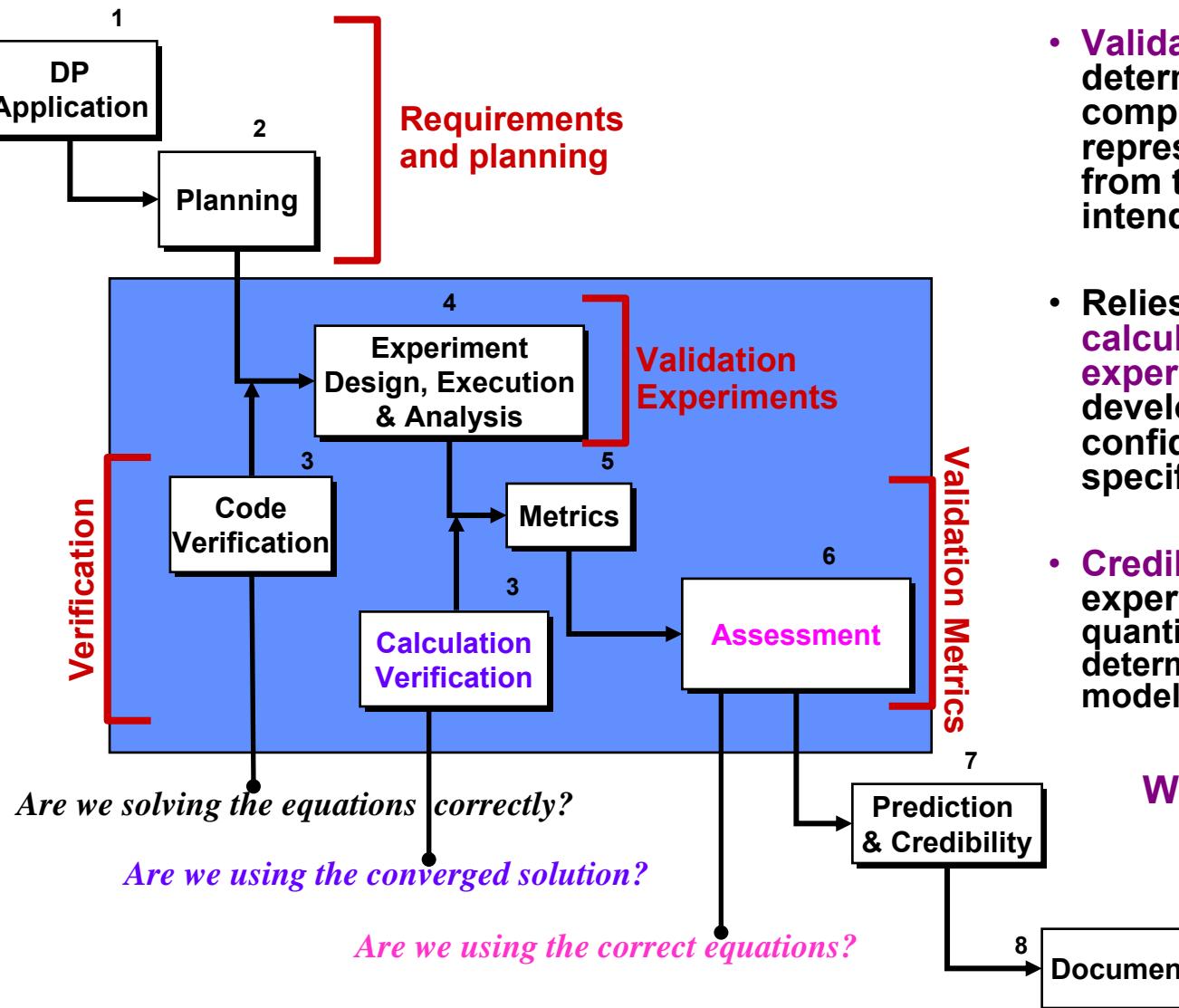


# Why Uncertainty Quantification?

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- A single optimal design or nominal performance prediction is often insufficient for
  - decision making / trade-off assessment
  - validation with experimental data ensembles
- *Need to make risk-informed decisions, based on an assessment of uncertainty*

# Verification & Validation: A Formal, Iterative Process



- **Validation** is “the *process* of determining the degree to which a computer model is an accurate representation of the real world from the perspective of the intended model *applications*.”

- Relies on **comparing code calculations to results of physical experiments**, with the goal of developing and quantifying confidence in codes to predict a specified problem result

- **Credibility** assesses model and experiment relevance, quantification and capture of non-deterministic components, and model adequacy

**Well-characterized result:  
BEST ESTIMATE +  
UNCERTAINTY**

# Coverage Matrix Shows Code Features Exercised in Verification Tests

## **Sierra Capabilities (subset)**

**PDE terms**  
 Conductation (diffusion term)  
 Capacitance (transient term)  
 Src (source term)  
 EnclRad  
 CM (chemistry source term)

**Thermal Conductivity**  
 k0 (constant conductivity)  
 k1 (tabular T-dependant)  
 k2 (user subroutine T-dependant, mostly)  
 k3 (defined variable)  
 k4 (anisotropic constant)  
 k5 (anisotropic tabular T-dependant)

**Heat capacity**  
 Cp0 (constant)  
 Cp1 (tabular T-dependant)  
 Cp2 (user subroutine T-dependent)  
 Cp3 (user variable)

**Density**  
 D0 (constant)  
 D1 (tabular T-dependent)  
 D2 (user subroutine T-dependent)  
 D3 (user variable)  
 D4 (volume dependant)

**Source terms**  
 G0 (constant)  
 G1 (tabular, time varing)  
 G1T (tabular, temp varing)  
 G2 (user subroutine, time or temp varing)  
 G3 (user variable)

**Temperature boundary conditions**  
 T-0 (constant)  
 T-1t (tabular, time dependent)  
 T-2 (user subroutine)

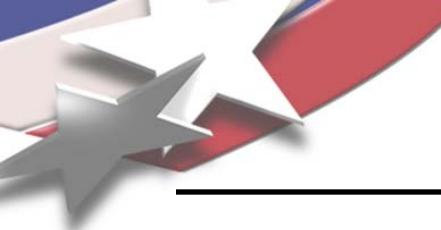
**Flux boundary conditions**  
 Q-0 (constant)  
 Q-1t (tabular, time dependant)  
 Q-1T (tabular, temp dependant)  
 Q-2 (user subroutine)

**Convective boundary conditions**  
 h-0 (constant)  
 h-1t (tabular, time dependent)  
 h-1T (tabular, temp dependent)  
 h-2 (user subroutine)  
 Tref-0 (constant ref temp)  
 Tref-1t (tabular, time dependent, ref temp)  
 Tref-1T tabular, temp dependent, ref temp  
 Tref-2 (user subroutine, ref temp)  
 Tref-B (bulk fluid element)

**Radiation boundary conditions**  
 e-0 (constant emissility)  
 e-1 (tabular, T-dependant)  
 e-2 (user subroutine, T dependent)  
 Trad-0 (constant radiation temperature)  
 Trad-1t (tabular, time dependent rad temp)

## → Fills Gap

**Matrix helps prioritize gaps, create new verification problems to fill most important, w.r.t. intended use.**



# Categories of Uncertainty

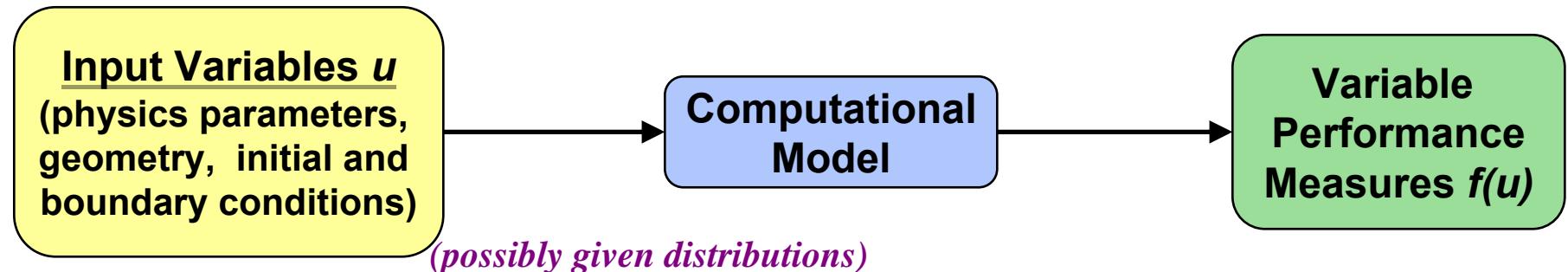
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*Often useful algorithmic distinctions, but not always a clear division*

- **Aleatory** (*think probability density function*)
  - Inherent variability (e.g., in a population)
  - Irreducible uncertainty – can't reduce it by further knowledge
- **Epistemic** (*think bounded intervals*)
  - Subjective uncertainty
  - Related to what we don't know
  - Reducible: If you had more data or more information, you could make your uncertainty estimation more precise
- In practice, people try to transform or translate uncertainties to the aleatory type and perform sampling and/or parametric analysis

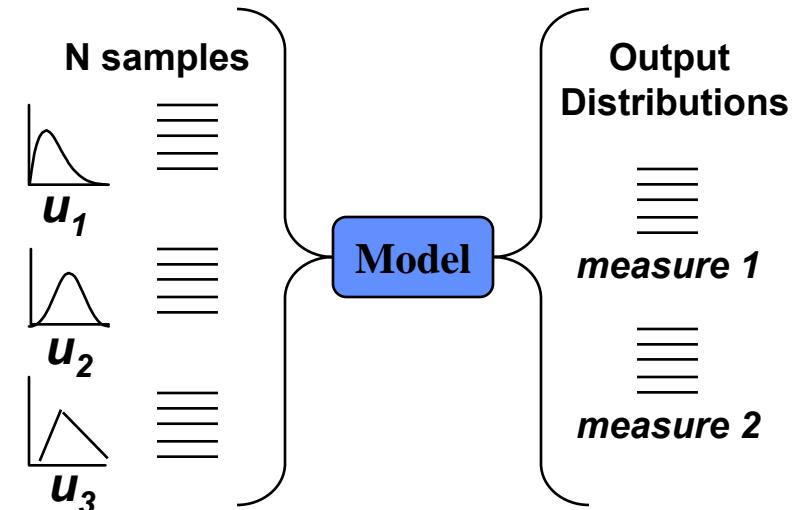
# Uncertainty Quantification

*Forward propagation: quantify the effect that uncertain (nondeterministic) input variables have on model output*



## Potential Goals:

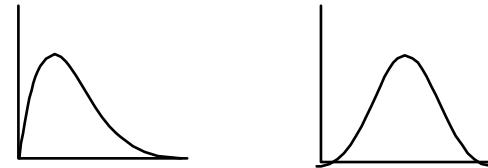
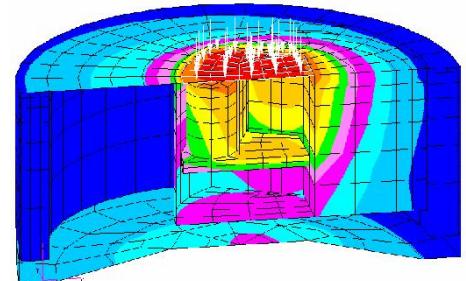
- based on uncertain inputs, determine variance of outputs and probabilities of failure (reliability metrics)
- identify parameter correlations/local sensitivities, robust optima
- identify inputs whose variances contribute most to output variance (global sensitivity analysis)
- quantify uncertainty when using calibrated model to predict



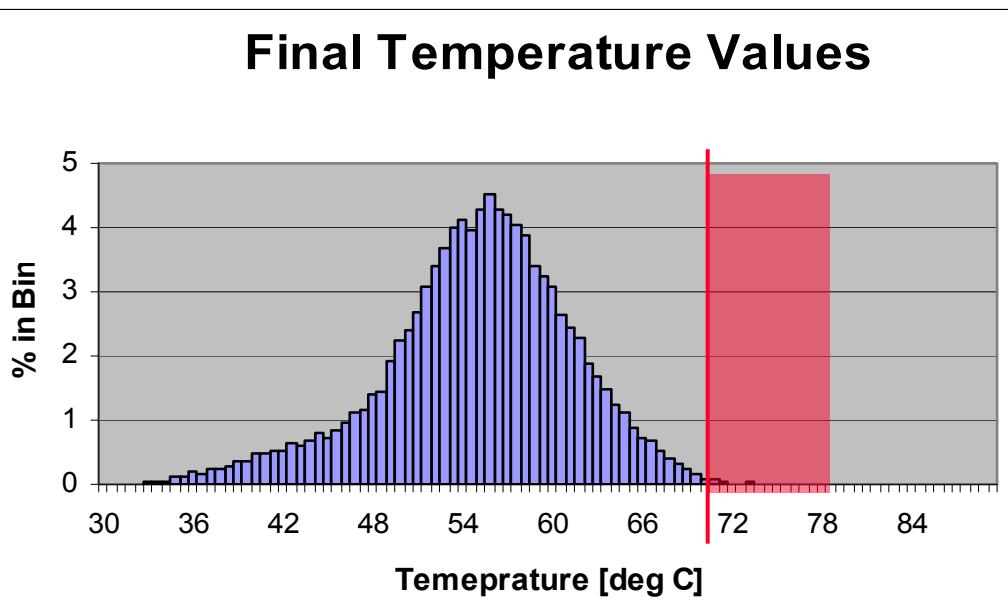
*Typical method: Monte Carlo Sampling*

# Uncertainty Quantification Example

- Device subject to heating (experiment or computational simulation)
- Uncertainty in composition/ environment (thermal conductivity, density, boundary), parameterized by  $u_1, \dots, u_N$
- Response temperature  $f(u) = T(u_1, \dots, u_N)$  calculated by heat transfer code



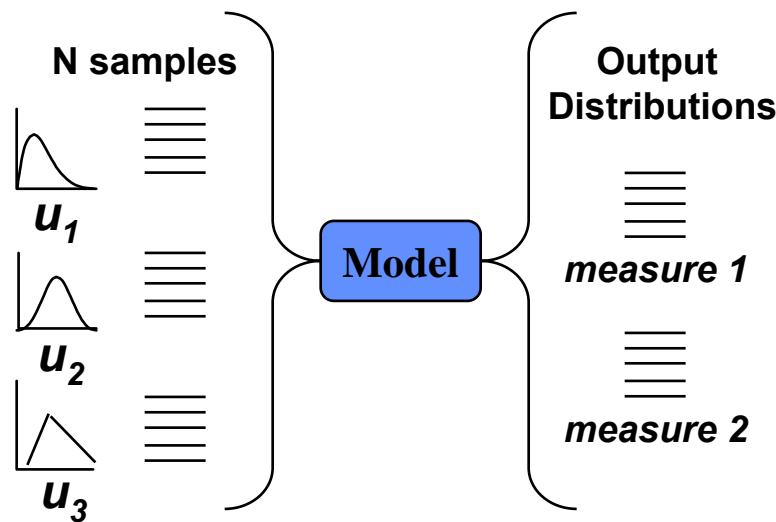
*Given distributions of  $u_1, \dots, u_N$ , UQ methods calculate statistical info on outputs:*



- Probability distribution of temperatures
- Correlations (trends) and sensitivity of temperature
- Mean( $T$ ), StdDev( $T$ ), Probability( $T \geq T_{\text{critical}}$ )

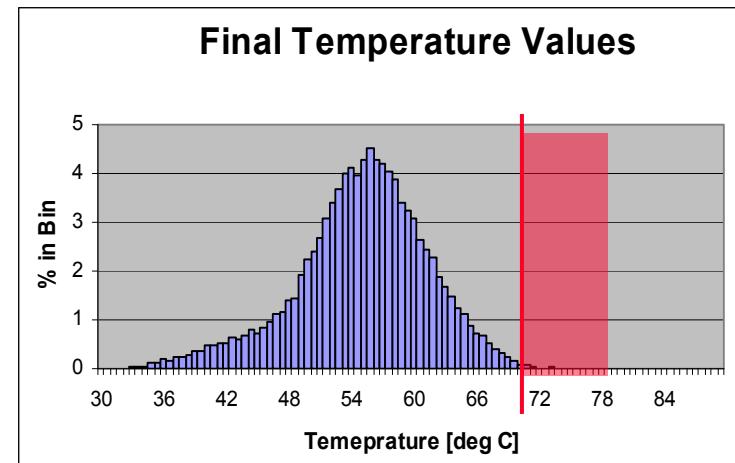
# UQ: Sampling Methods

Given distributions of  $u_1, \dots, u_N$ , UQ methods...



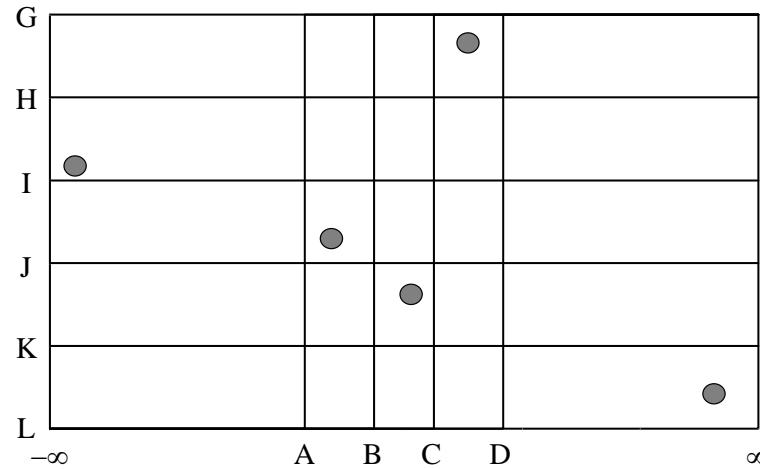
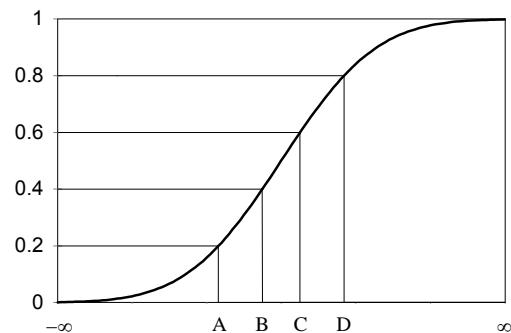
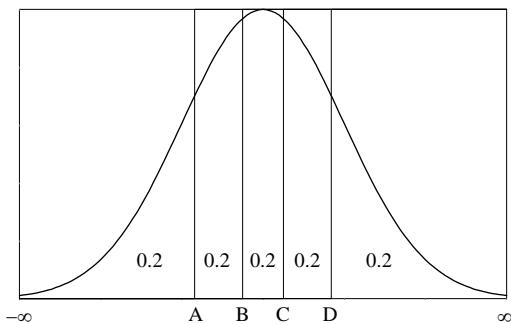
...calculate statistical info on outputs  $T(u_1, \dots, u_N)$

- Monte Carlo sampling
- Quasi-Monte Carlo
- Centroidal Voroni Tessellation (CVT)
- Latin Hypercube sampling



# Latin Hypercube Sampling (LHS)

- Specialized Monte Carlo (MC) sampling technique: workhorse method in DAKOTA / at Sandia
- *Stratified random sampling among equal probability bins* for all 1-D projections of an n-dimensional set of samples.
- McKay and Conover (early), restricted pairing by Iman



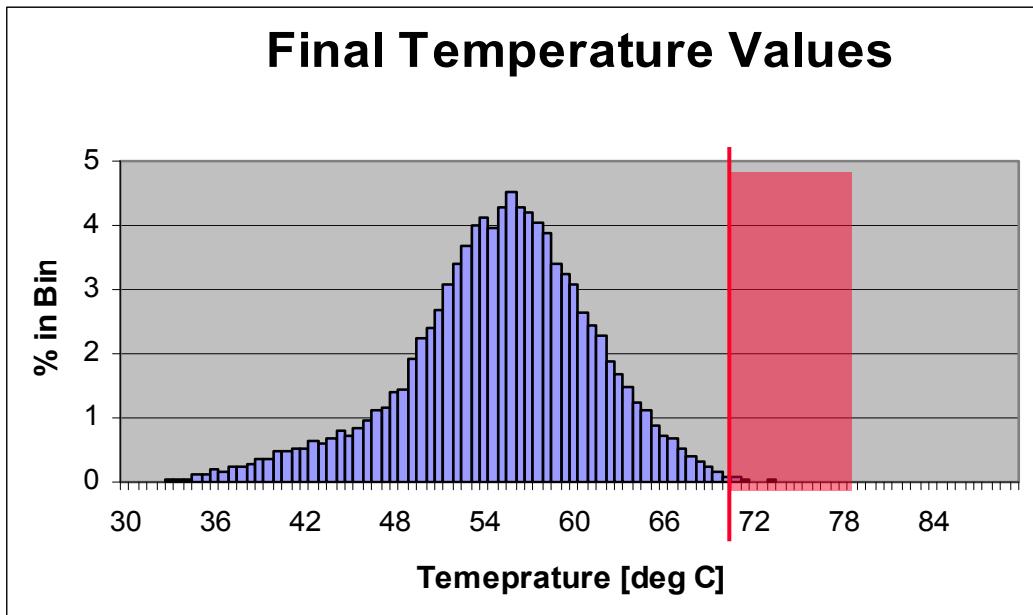
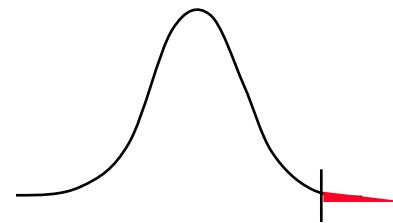
**A Two-Dimensional Representation of One Possible LHS of size 5 Utilizing X1 (normal) and X2 (uniform)**

Intervals Used with a LHS of Size  $n = 5$  in Terms of the pdf and CDF for a Normal Random Variable

# Calculating Probability of Failure

- Given uncertainty in materials, geometry, and environment, determine likelihood of failure

Probability( $T \geq T_{critical}$ )



- Could perform 10,000 Monte Carlo samples and count how many exceed the threshold...
- Or directly determine input variables which give rise to failure behaviors by solving an optimization problem.

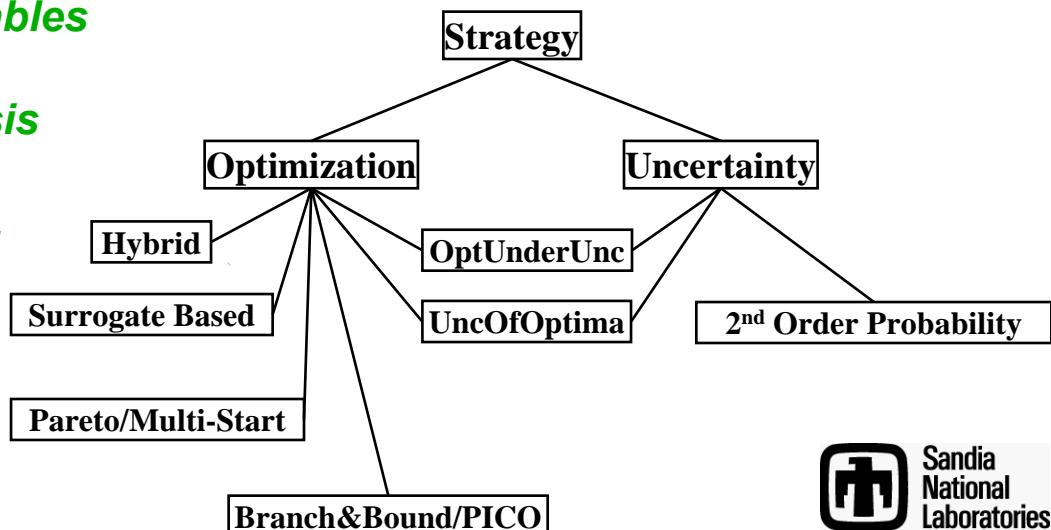


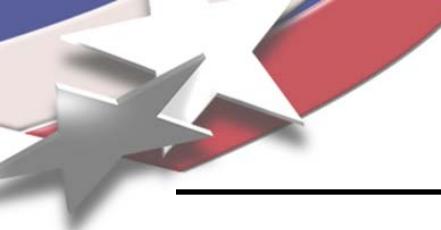
# Alternatives to Sampling

*LHS sampling is robust, trusted, ubiquitous, but advanced methods may offer advantages:*

- for a modest number of random variables, **polynomial chaos expansions** may converge considerably faster to statistics of interest
- if principal concern is with failure modes (tail probabilities), consider **global reliability methods**

*Upcoming (Mike): DAKOTA enables more efficient UQ by combining optimization, uncertainty analysis methods, and surrogate (meta-) modeling in a single framework.*

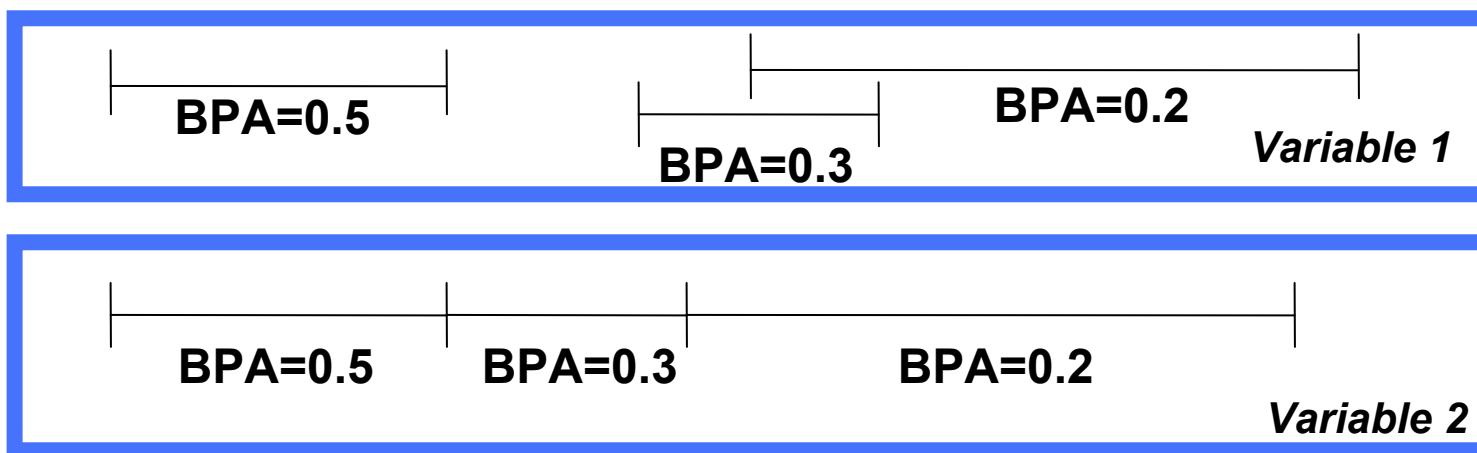




# Challenge: Epistemic UQ

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- **Epistemic uncertainty:** insufficient information to specify a probability distribution
- Subjective, reducible, or lack-of-knowledge uncertainty (given more resources to gather information, could reduce the uncertainty)
- For example:
  - *“I expect this parameter to have a lognormal distribution, but only know bounds on its mean and standard deviation,” or*
  - *Dempster-Shafer belief structures:* “basic probability assignment” for each interval where the uncertain variable may exist; contiguous, overlapping, or gapped

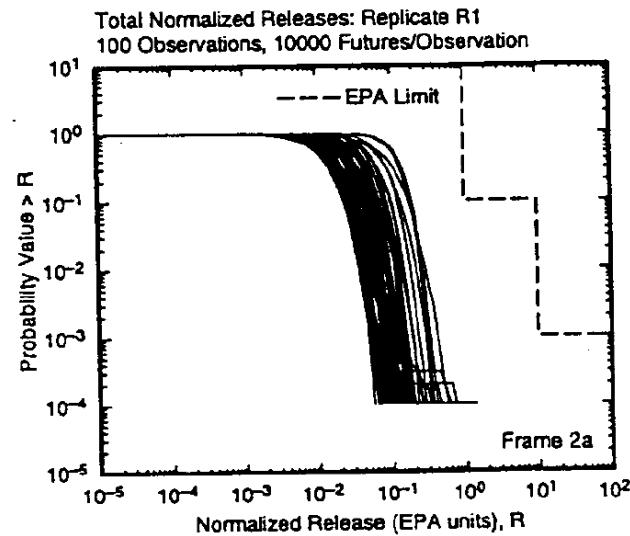


# Propagating Epistemic UQ

## Second-order probability

- Two levels: distributions/intervals on distribution parameters
- Outer level can be epistemic (e.g., interval)
- Inner level can be aleatory (probability distrs)
- Strong regulatory history (NRC, WIPP).

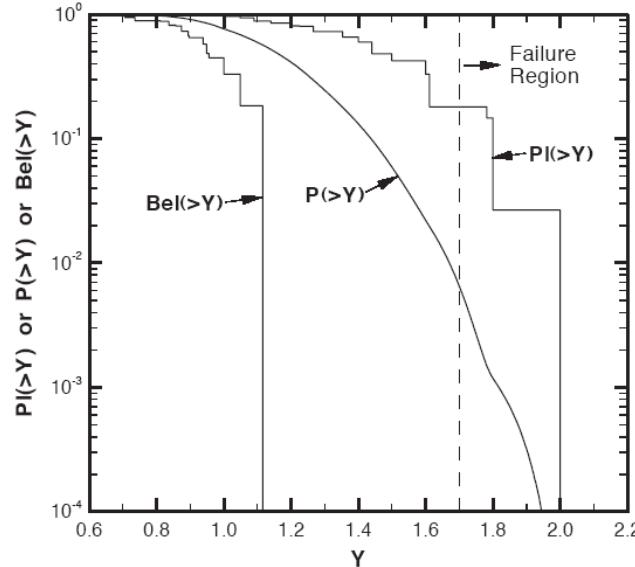
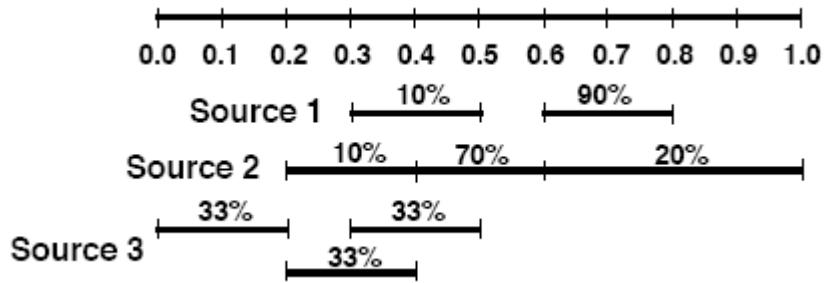
New



## Dempster-Shafer theory of evidence

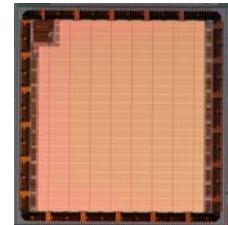
- Basic probability assignment (interval-based)
- Solve opt. problems (currently sampling-based) to compute belief/plausibility for output intervals

New

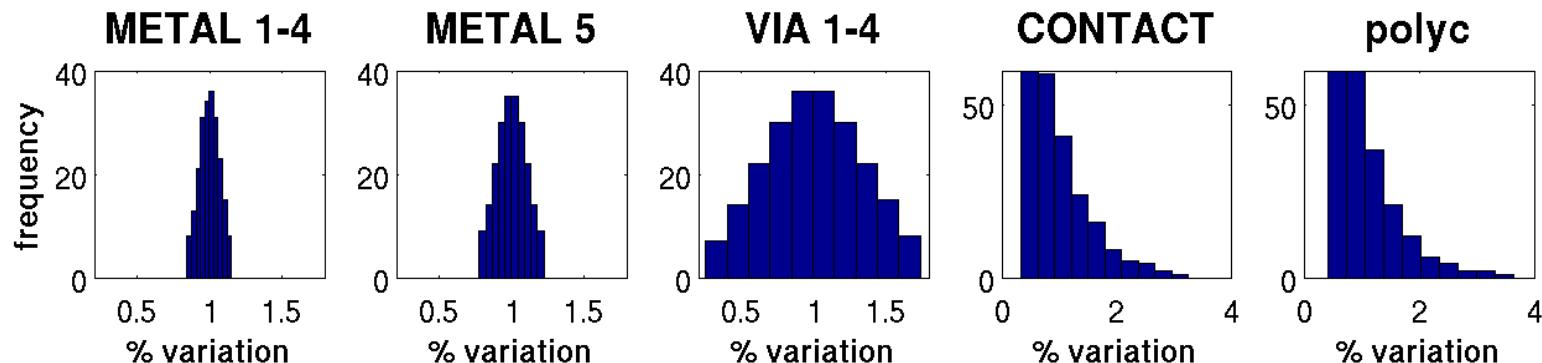


# Circuit UQ Analysis

*Use DAKOTA with Xyce circuit simulator to perform pre-fabrication uncertainty analysis of new CMOS7 ViArray*



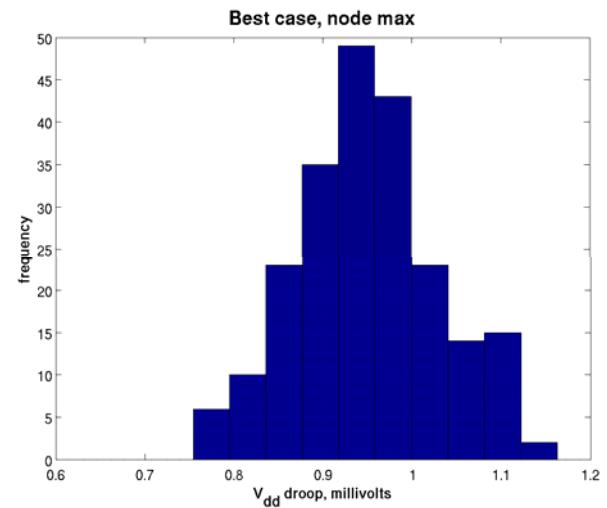
- ViArray: generic ASIC implementation platform
- Target applications: guidance, satellite, command & control
- Assess voltage droop/spike during photocurrent event
- Consider effect of process variation in each ‘layer’ on supply voltages; representative distributions:

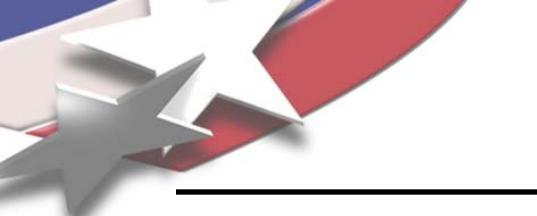


- Truncated normals used for METAL and VIA; truncated lognormals used for CONTACT and polyc.

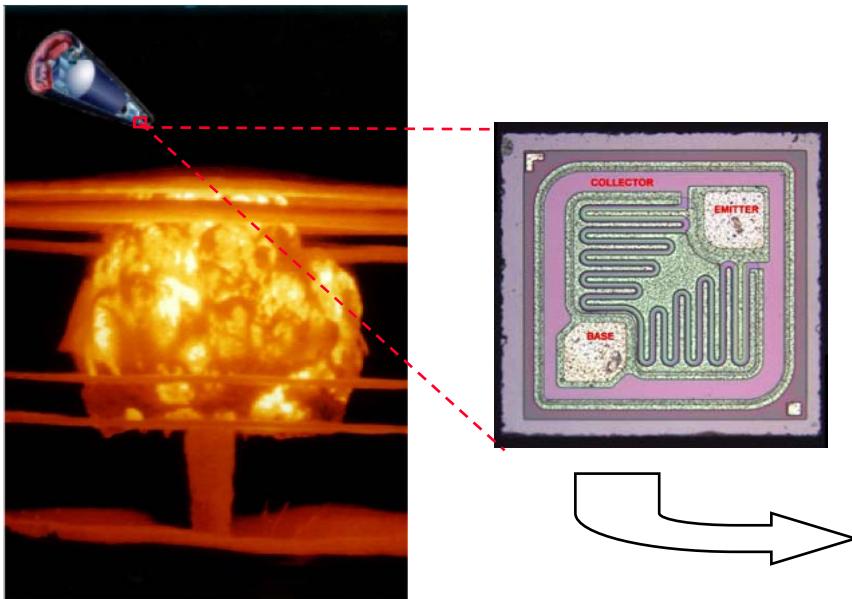
# ViArray: Benefits of UQ

- One ensemble of UQ calculations used to determine most sensitive parameters and output ranges: determined that sensitivity depends on final chip configuration
- Suspicious UQ results led to correcting simulation failures not observed at nominal parameters
- Gave process engineers and circuit designers insight into possible circuit behaviors
- Sensitivity could help guide data collection
- Ongoing work: assess interaction of package parasitics with on-chip parasitics, V&V for photocurrent generation models





# Neutron Radiation Exposure Degrades Electronics



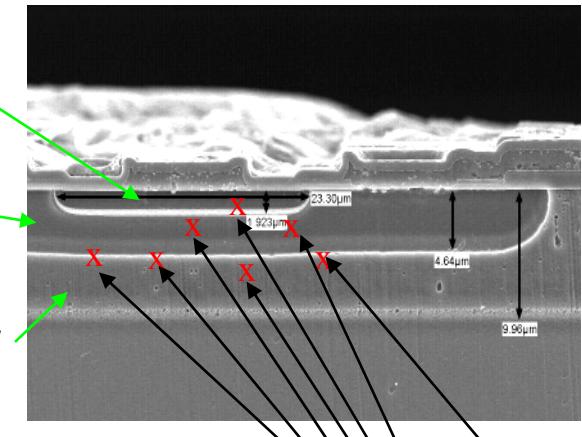
- Military requirement: certify to hostile environment

neutrons create damage

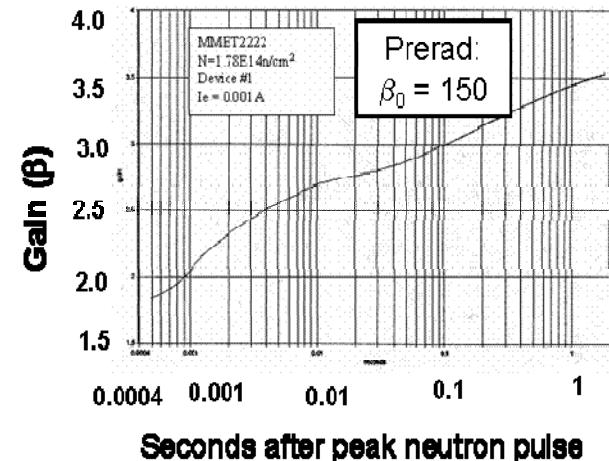
Emitter  
(n-type)

Base  
(p-type)

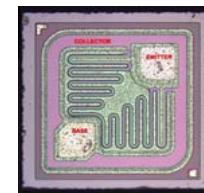
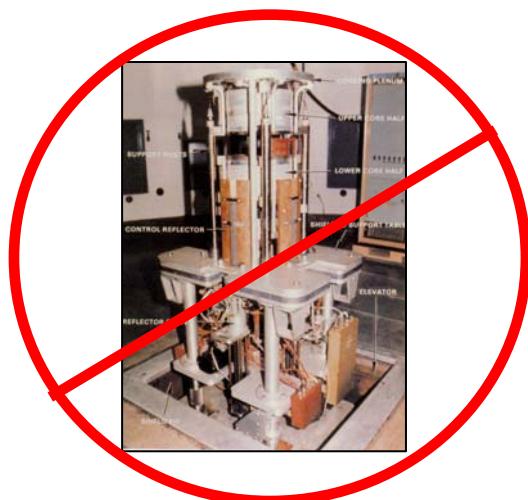
Collector  
(n-type)



damage degrades gain



# Neutron Radiation Exposure Degrades Electronics



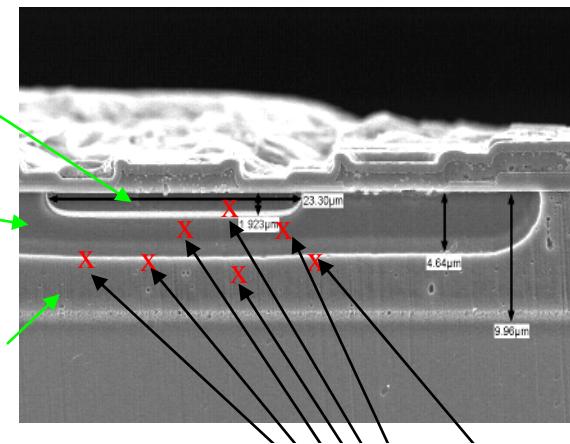
pass/fail  
testing

Emitter  
(n-type)

Base  
(p-type)

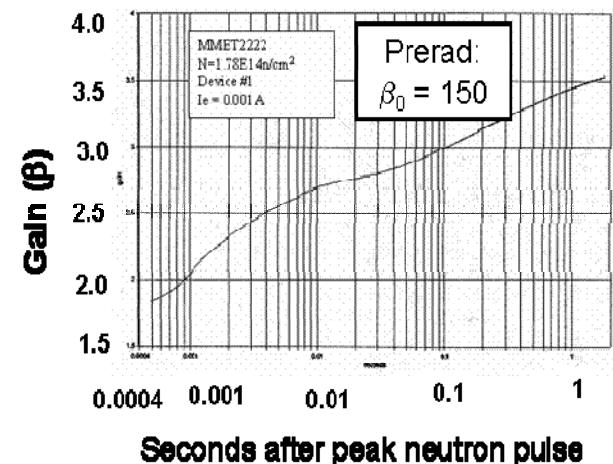
Collector  
(n-type)

neutrons create damage



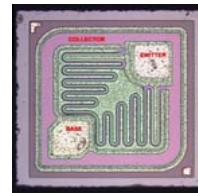
damage degrades gain

- Military requirement: certify to hostile environment
- SPR dismantled end of FY06 to improve security posture



# Neutron Radiation Exposure Degrades Electronics

**QASPR**  
QUALIFICATION ALTERNATIVES TO SPR



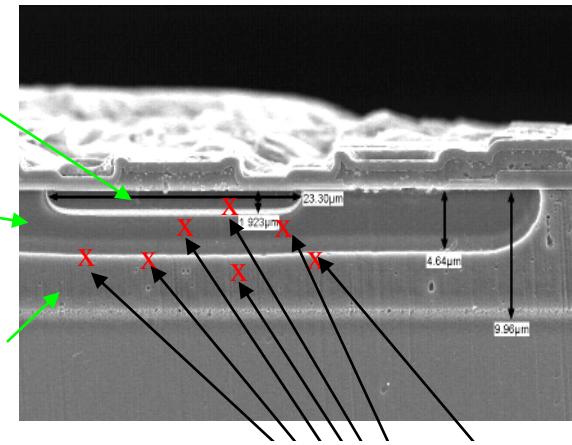
quantified  
uncertainty

Emitter  
(n-type)

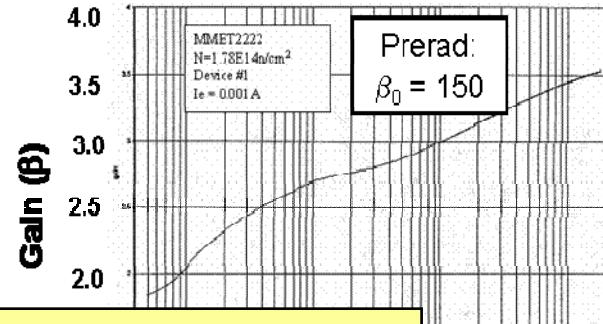
Base  
(p-type)

Collector  
(n-type)

neutrons create damage



damage degrades gain



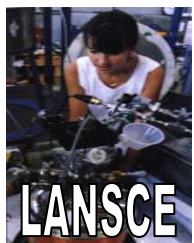
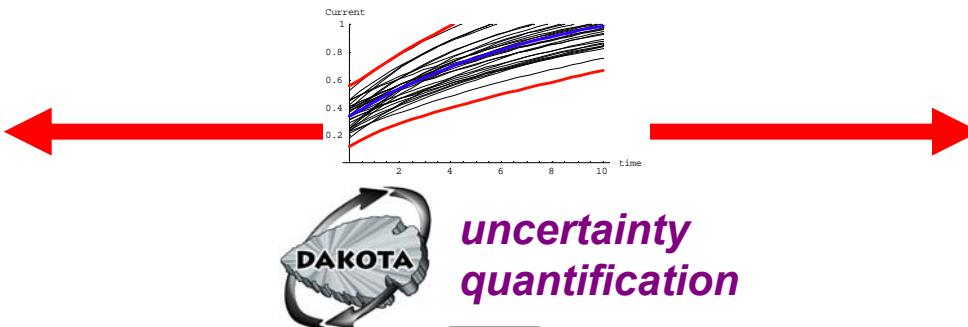
- Military requirement: certify to hostile environment
- SPR dismantled end of FY06 to improve security posture

QASPR (Qualification Alternatives to Sandia Pulse Reactor) methodology will certify qualification via modeling & simulation with quantified uncertainty

# QASPR: Science-Based Engineering Methodology For Qualification

Risk Informed Decisions

Qualification Evidence



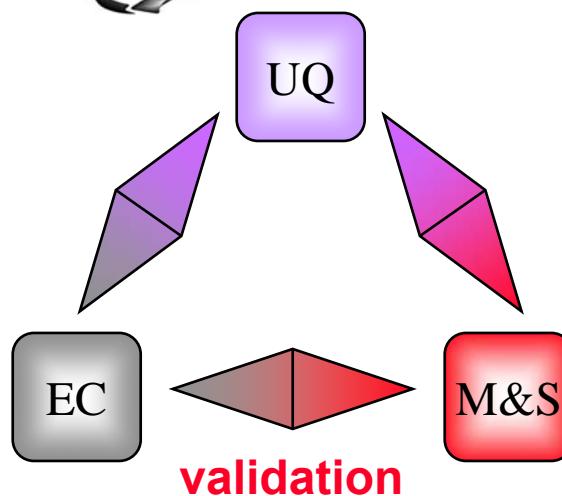
*select experiments in alternate facilities*



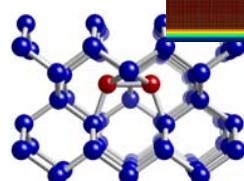
$\gamma, n$  – 100 ms  
long pulse



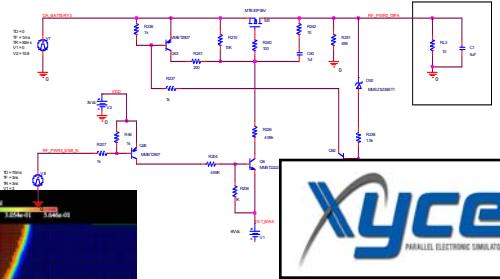
ion – 100  $\mu$ s  
short pulse



*high performance, multi-fidelity, predictive computational modeling*

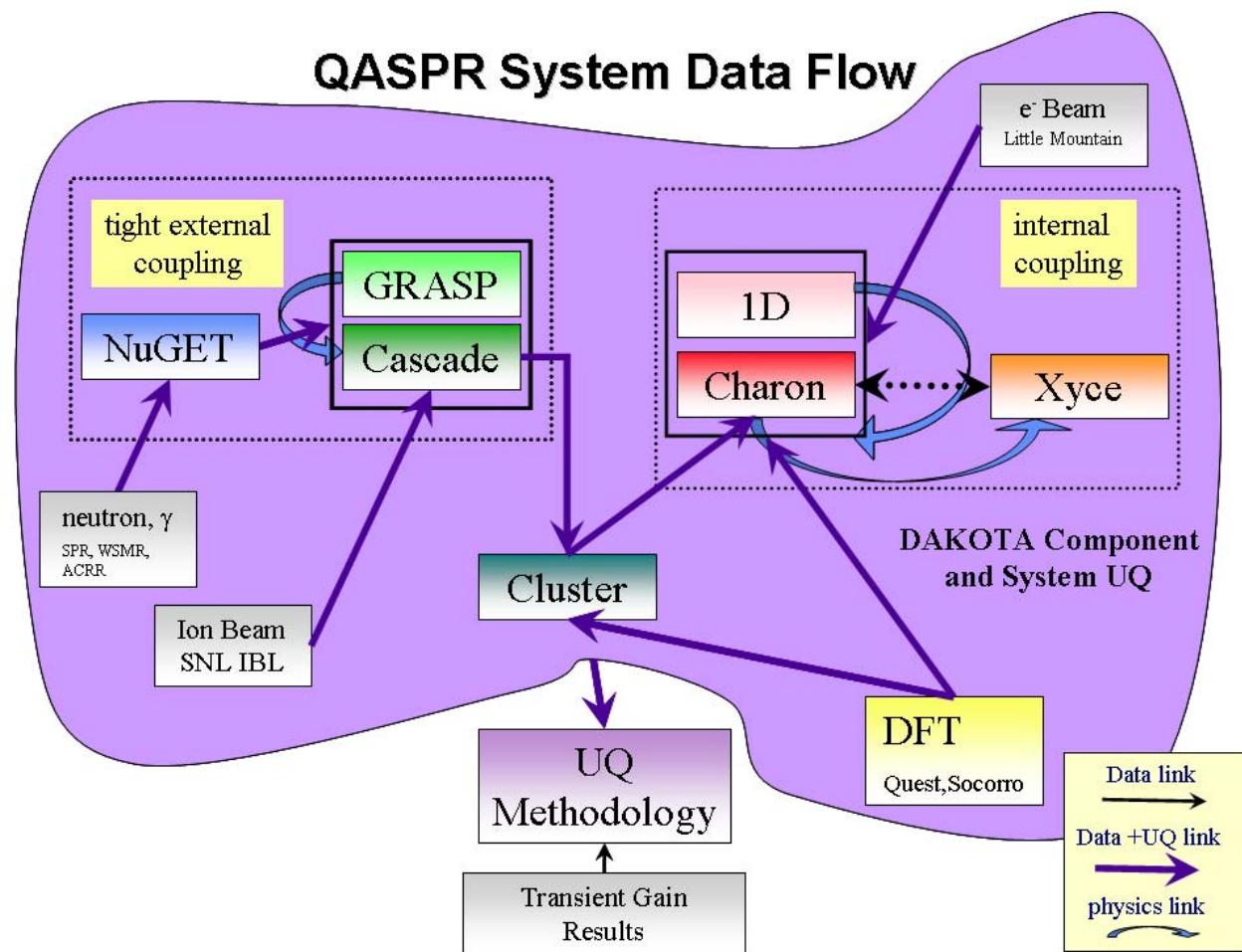


**CHARON**



# V&V for QASPR Components

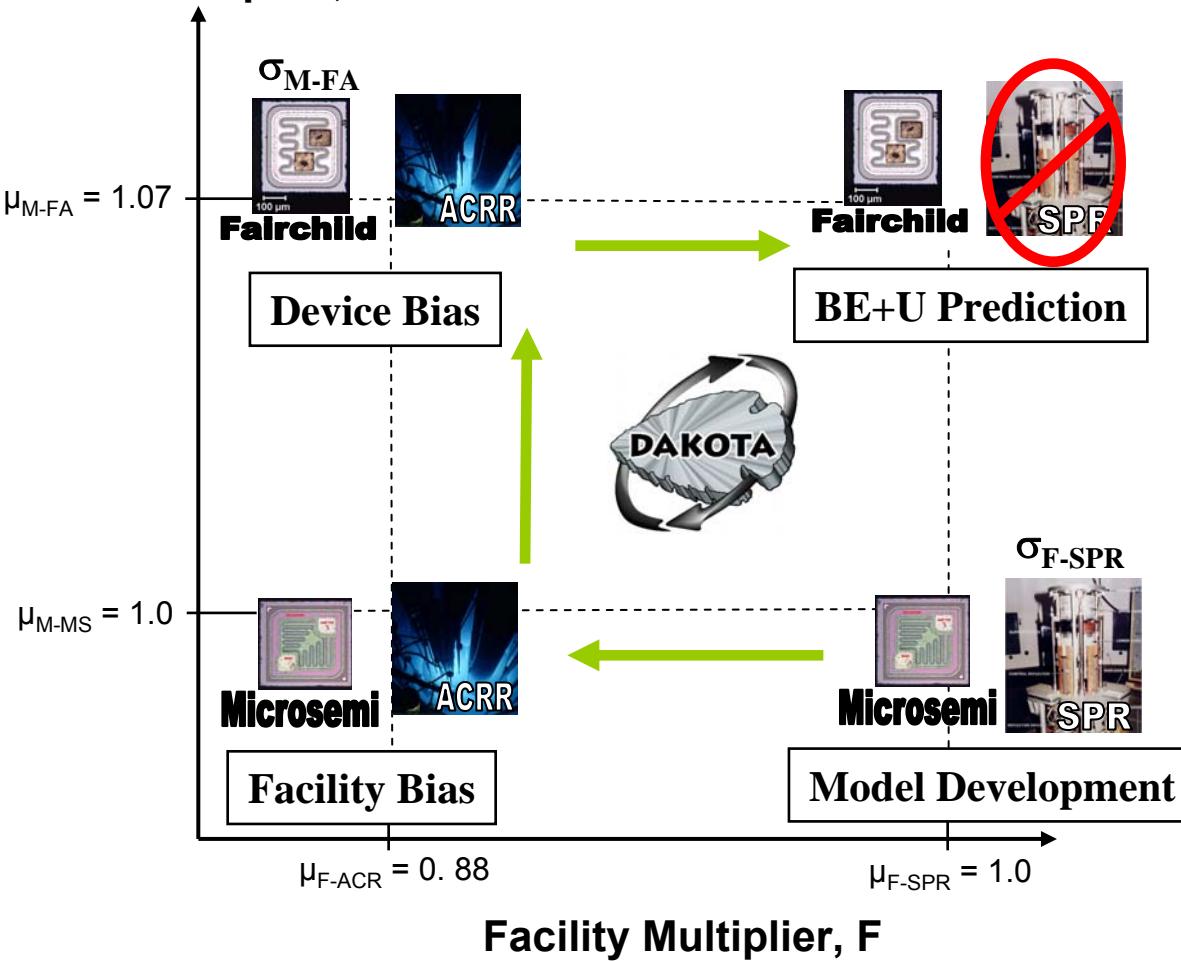
## QASPR System Data Flow



- **Developing formal V&V plans**
- **Each computational code subject to code and solution verification**
- **UQ used to validate device model response against data ensembles**
- **Ultimately systems (circuit) V&V for qualification**

# Device Prototype: UQ Extrapolation to SPR

Device Multiplier, M

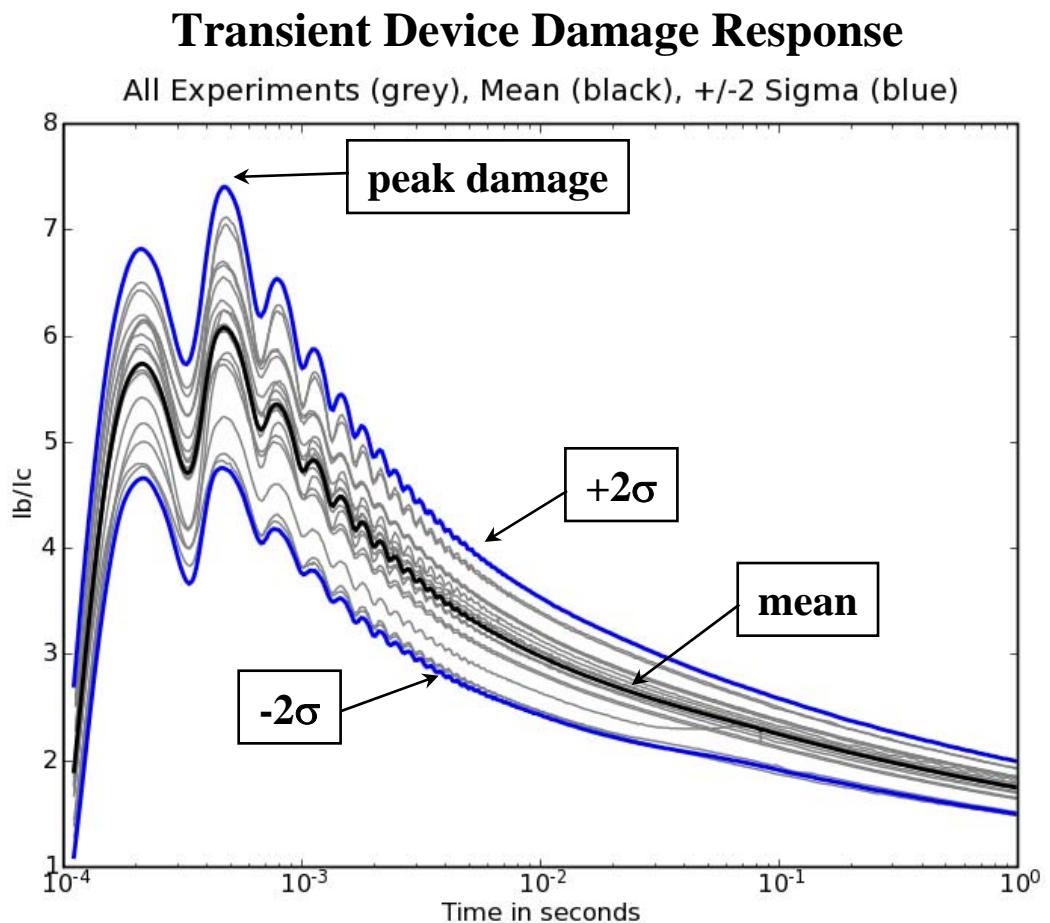


- Calibrated to other facilities, CHARON fills SPR gap
- Uncertainty & bias characterized by 2 degrees of freedom
  - facility multiplier
  - device multiplier
- Uncertainty quantified with D.O.E + statistical approach

End UQ Methodology Goal: Best Estimate  
+ Uncertainty Prediction for SPR

# Model Validation: Blind Prediction

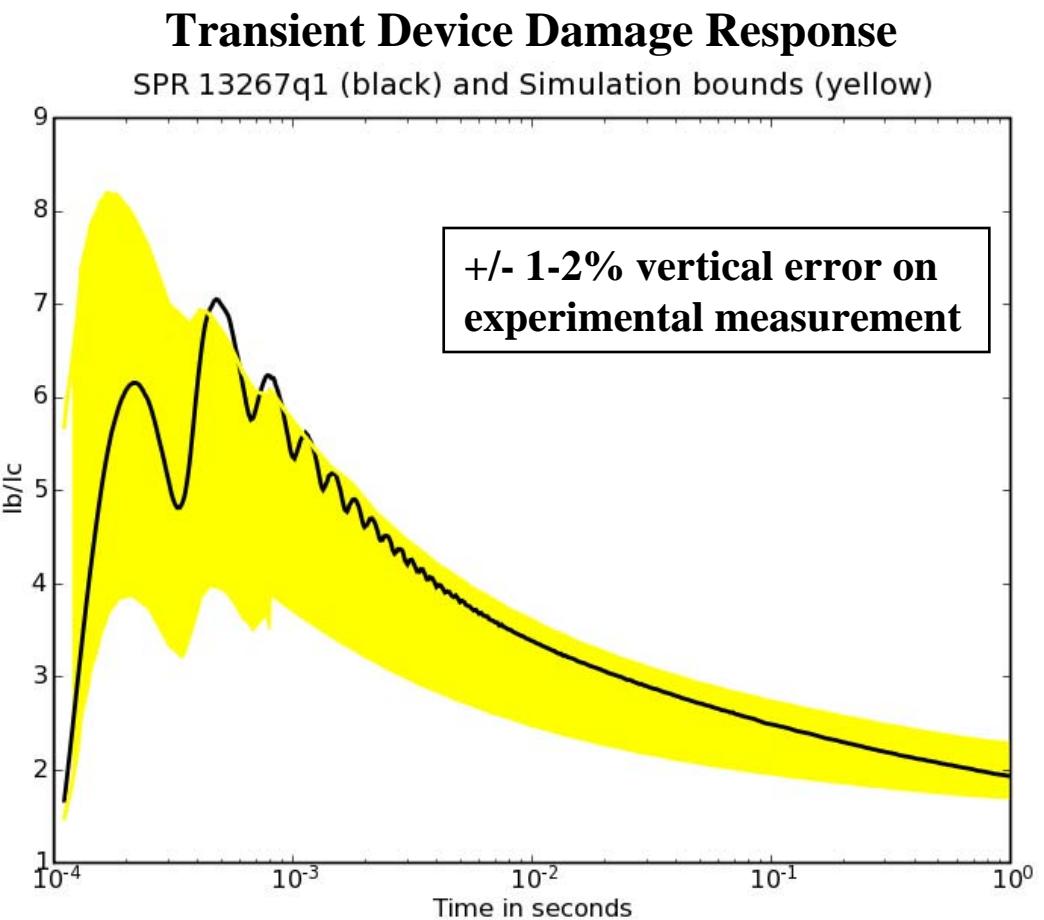
- Fairchild response data within SPR hidden
- First *prototype* of the QASPR methodology (and real validation of the QASPR system)
- Prediction + Uncertainty ( $\pm 2\sigma$  device and facility uncertainty)



UQ algorithms have a critical role in system validation

# Model Validation: Blind Prediction

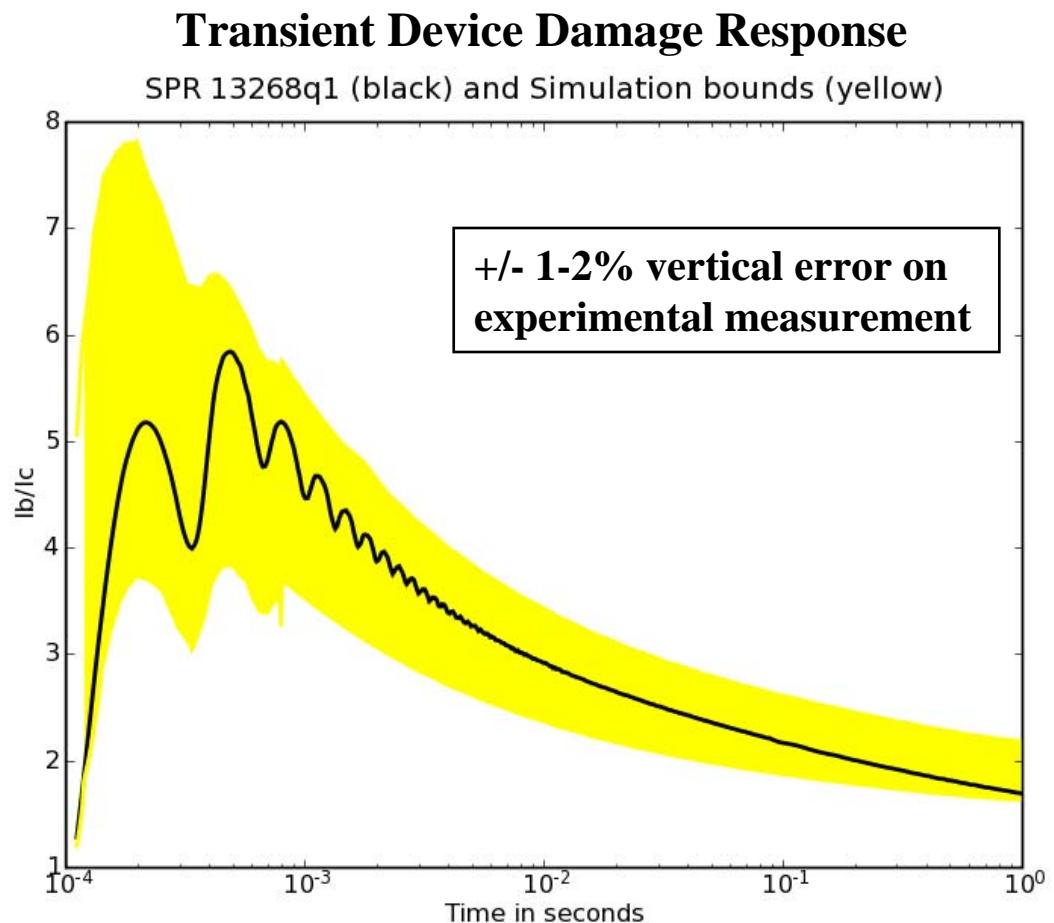
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UQ algorithms have a critical role in system validation

# Model Validation: Blind Prediction

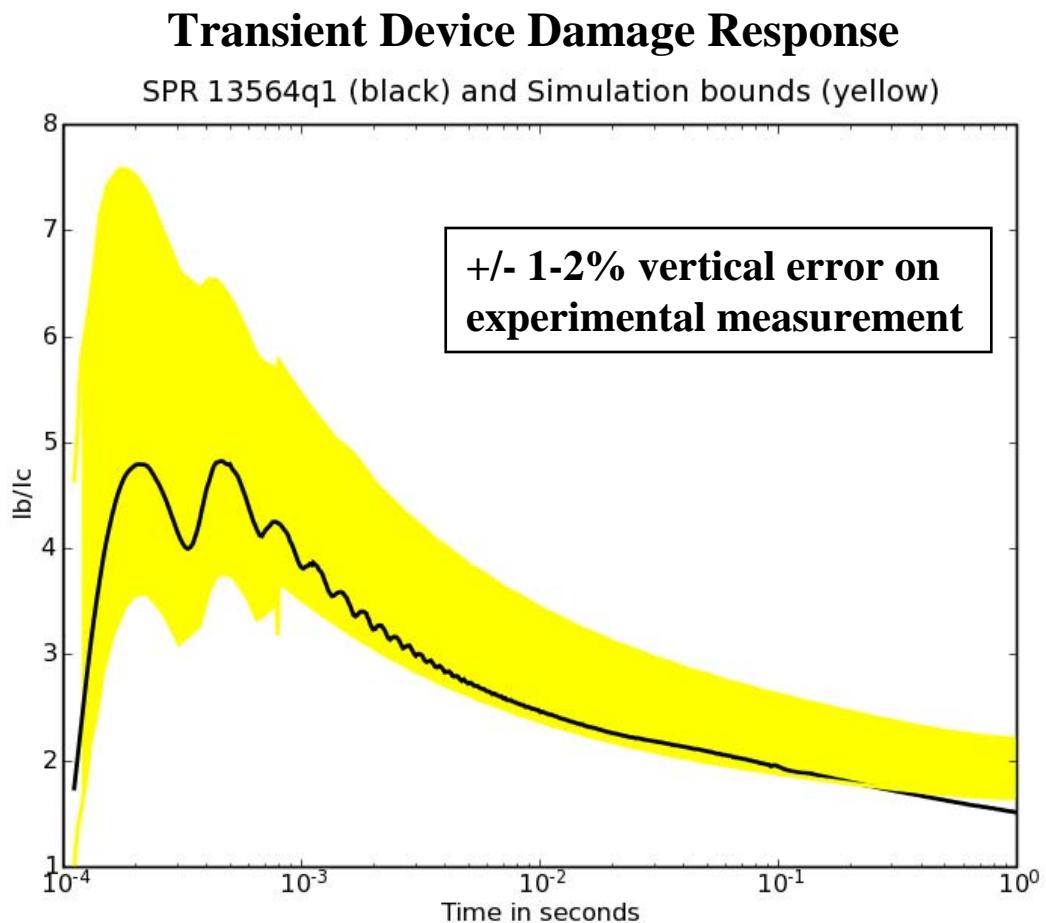
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**UQ algorithms have a critical role in system validation**

# Model Validation: Blind Prediction

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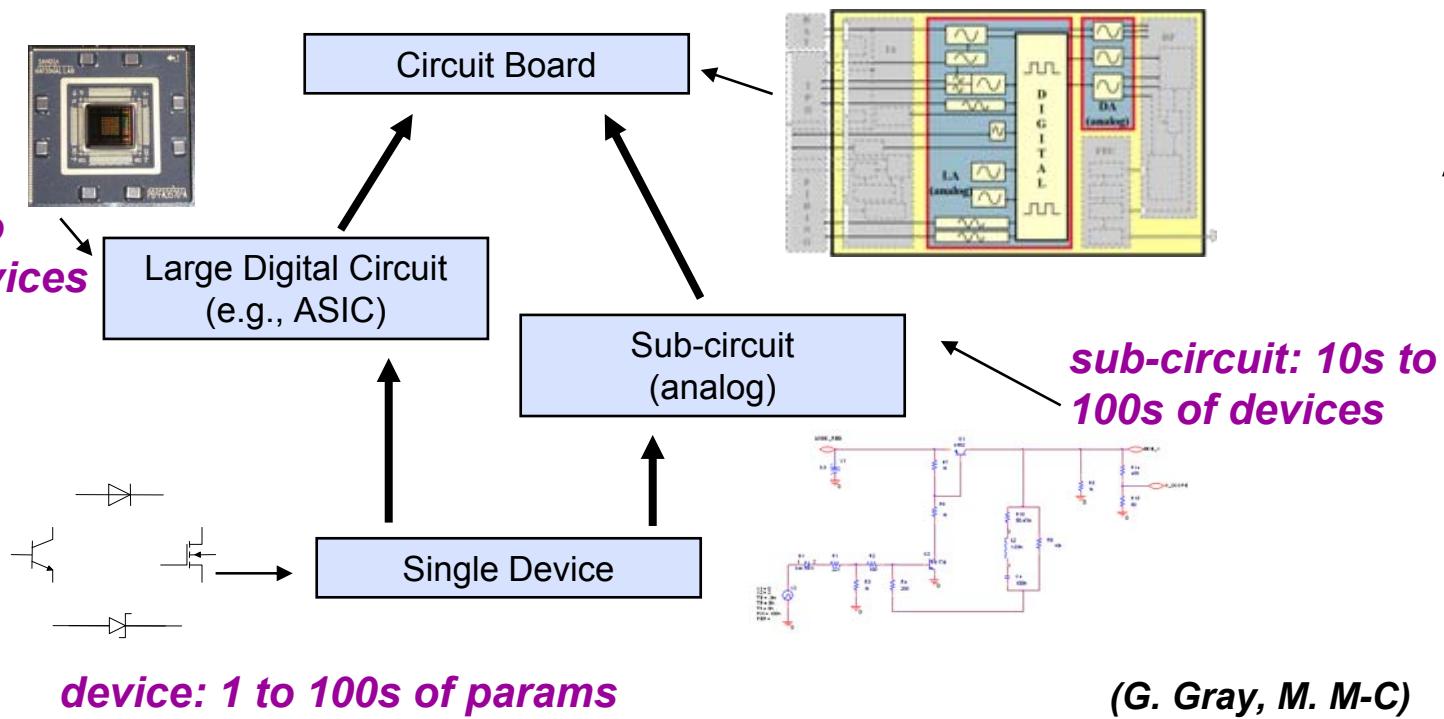


UQ algorithms have a critical role in system validation

# Electrical Modeling Complexity

*complex device models + replicates in circuits*

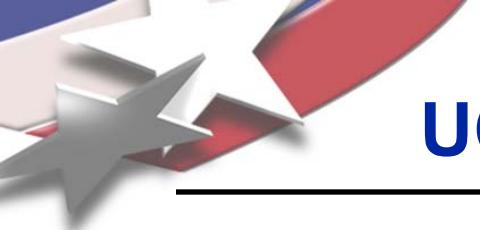
**ASIC: 1000s to millions of devices**



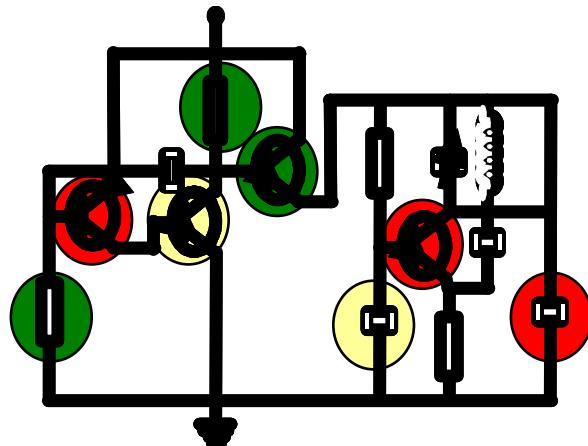
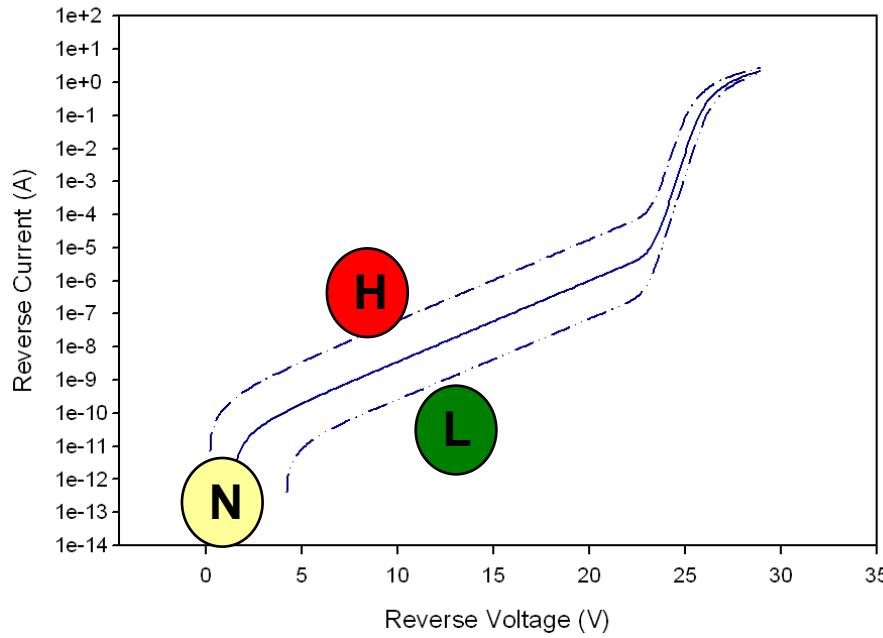
- **simple devices:** 1 parameter, typically physical and measurable
- e.g., resistor @  $100\Omega$  +/- 1%
- resistors, capacitors, inductors, voltage sources

- **complex devices:** many parameters, some physical, others “extracted” (calibrated)
- multiple modes of operation
- e.g., zener diode: 30 parameters, 3 bias states; many transistor models (forward, reverse, breakdown modes)

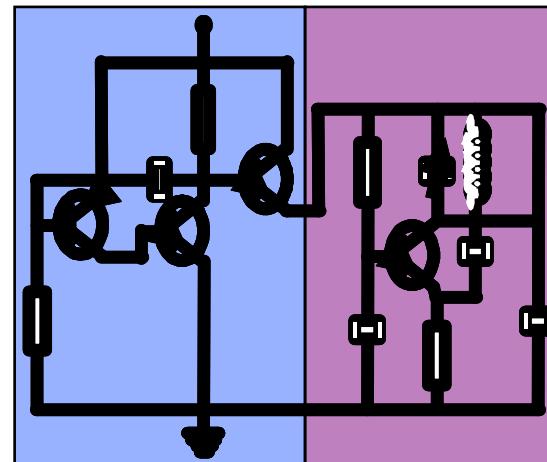
(G. Gray, M. M-C)

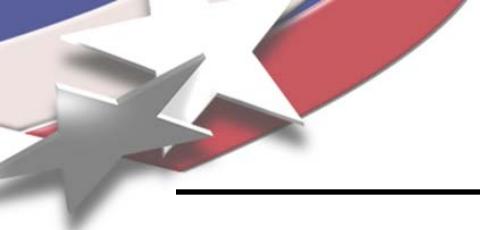


# UQ: Mitigate Explosion of Factors!



- Consider bounding parameter sets?
- Exploit natural hierarchy or network structure?
- Use surrogate/macro-models as glue between levels?
- *Need approaches curbing the curse of dimensionality*





# Summary

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***To be credible, simulations must be verified, validated with data, and deliver a best estimate of performance, together with its degree of variability or uncertainty.***

- Formal V&V process helps certify credible simulation
- Uncertainty quantification algorithms are essential in validation and calibration under uncertainty
- Complex, large-scale simulations demand research in advanced efficient UQ methods

**Thank you for your attention!**

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