

# *Highlights of QUEST Developments and Partnership Activities*

*[www.quest-scidac.org](http://www.quest-scidac.org)*

H. Najm<sup>1</sup>, B. Debusschere<sup>1</sup>, K. Chowdhary<sup>1</sup>,  
R. Moser<sup>2</sup>, V. Carey<sup>2</sup>,

<sup>1</sup>Sandia National Laboratories, Livermore, CA & Albuquerque, NM

<sup>2</sup>University of Texas, Austin, TX

SciDAC PI Meeting  
24–26 Jul 2013  
Rockville, MD

# Outline

- 1 Introduction
- 2 FES Edge Plasma Partnership
- 3 BER Atmospheric Modeling Partnership
- 4 Closure

# Key Elements of our UQ strategy

- Probabilistic framework
  - Uncertainty is represented using probability theory
- Parameter Estimation, Model Calibration
  - Experimental measurements
  - Regression, Bayesian Inference
- Forward propagation of uncertainty
  - Polynomial Chaos (PC) Stochastic Galerkin methods
    - Intrusive/non-intrusive
  - Stochastic Collocation methods
- Model comparison, selection, and validation
- Model averaging
- Experimental design and uncertainty management

# QUEST Team

Institution	Participants
<b>SNL</b>	<b>H. Najm</b> , M. Eldred, B. Debusschere, J. Jakeman, K. Chowdhary, C. Safta, K. Sargsyan
<b>USC</b>	<b>R. Ghanem</b>
<b>Duke</b>	<b>O. Knio</b> , O. Le Maître, F. Rizzi, J. Winokur
<b>UT</b>	<b>O. Ghattas</b> , R. Moser, E. Prudencio, A. Alexanderian T. Bui-Thanh, K. E.-Hiroms, N. Petra, G. Stadler
<b>LANL</b>	<b>D. Higdon</b> , J. Gattiker
<b>MIT</b>	<b>Y. Marzouk</b> , P. Conrad, T. Cui, A. Gorodetsky, M. Parno

# Team Expertise and Capabilities

Institution	Expertise	Tools
<b>SNL</b>	Forward and inverse UQ methods, design under uncertainty	DAKOTA UQTK
<b>USC</b>	Intrusive UQ methods probabilistic modeling	
<b>Duke</b>	Sparse adaptive forward UQ methods	
<b>UT</b>	Large scale inverse problems validation, inverse UQ	QUESO
<b>LANL</b>	Gaussian process modeling, inverse UQ	GPMSA
<b>MIT</b>	Calibration, adaptive sampling, inverse UQ, experimental design	MUQ

# Recent Progress

Software development & integration: SNL, UT, LANL, MIT  
 DAKOTA, QUESO, UQTK, GPMSA, MUQ

Algorithmic developments:

- Hierarchical sparse grid interpolation SNL
- Adaptive basis & sparse representations USC, Duke, MIT
- Compressive sensing, sparsity, & multifidelity SNL
- Missing data & sparse random fields SNL
- Gradient based optimization and MCMC Duke, MIT
- Conditional polynomial representations USC
- Bayesian additive regression trees for massive data LANL
- Extreme scale Bayesian inverse problems UT
- Kernel approx. & discontinuity detection in hi-D MIT

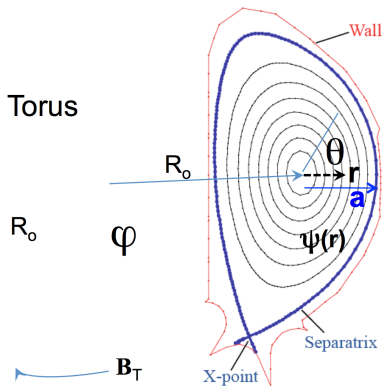
# QUEST Partnerships

DOE	Project Title	Lead PI	QUEST
FES	Center for Edge Plasma Physics Simulation (EPSI)	C.S. Chang Princeton	Moser UT
FES	Plasma Surface Interactions: Bridging from the Surface to the Micron Frontier	B. Wirth ORNL	Higdon LANL
BER	Predicting Ice Sheet & Climate Evolution at Extreme Scales (PISCEES)	P. Jones LANL	Eldred, Ghattas SNL, UT
BER	Multiscale Methods for Accurate, Efficient & Scale-Aware Earth System Modeling	B. Collins LBNL	Debusschere SNL
NP	Nuclear Computational Low Energy Initiative (NUCLEI)	J. Carlson LANL	Higdon LANL
HEP	Computation-Driven Discovery for the Dark Universe	S. Habib ANL	Higdon LANL
HEP	Community Project for Accelerator Science & Simulation (COMPASS)	P. Spentzouris FNAL	Prudencio UT

# EPSI-QUEST UQ Participants

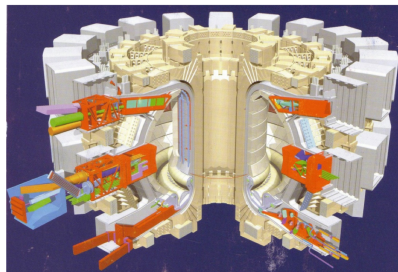
- C.S. Chang, Princeton **EPSI PI**
- Robert Moser, UT-Austin **QUEST Center Lead**
- Martin Greenwald, MIT
- Suenghoe Ku, Princeton
- Julian Cummings, Caltech
- Varis Carey, UT-Austin
- Devon Battaglia, Princeton



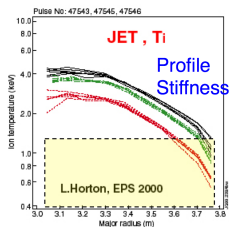
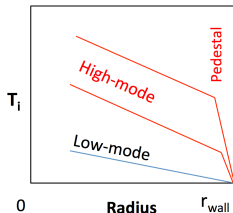


**Poloidal cross-section at a constant toroidal angle**

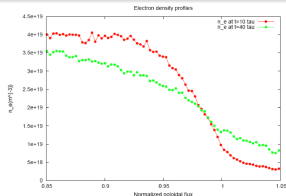
Poloidal magnetic flux label  
 $\psi(r)$ : 1 at  $r/a=1$ , 0 at  $r/a=0$



# Key Problem: Understanding Edge Physics



- Plasma near material wall must stay cold
- Temperature slope limited by **turbulent transport**
  - Ion Temperature ( $T_i$ ) **too low** if fusion core in L-mode
- ITER based on “H-mode” pedestal
  - experimental, Wagner 1982
- Steep pressure gradient induces edge localized modes
- Underlying physics and inherent uncertainties must be understood



# EPSI-QUEST Partnership Plan

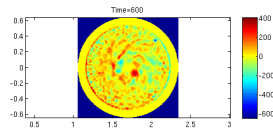
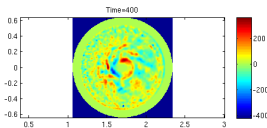
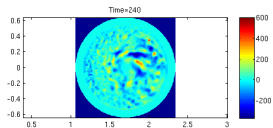
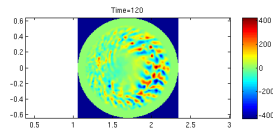
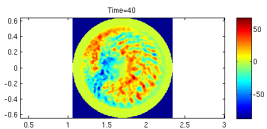
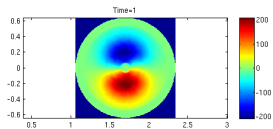
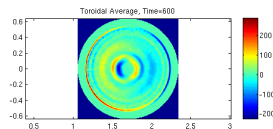
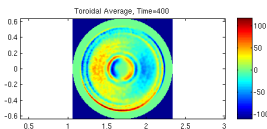
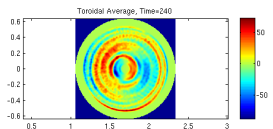
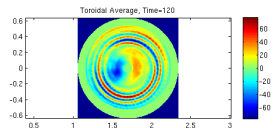
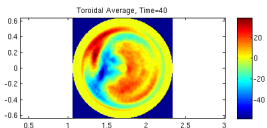
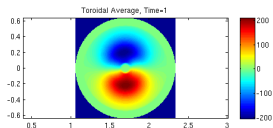
## Primary Thrust

- 1 Identify **key model sensitivities** for gyrokinetic code XGC-1
- 2 Validate/invalidate hierarchy of physics in XGC-1
  - 1 Initial UQ focus: Ion Temperature Gradient (ITG) turbulence
  - 2 Enrich physics, guided by:
    - Validation studies
    - Edge profiles and fluxes

## Secondary Projects: Validation/Reduced Order Modeling

- 1 Improve uncertainty estimates for derived experimental quantities. (Martin, MIT) (*Provides both input profiles for XGC-1 and validation observables*)
- 2 Perform calibration exercises for reduced physics model (Battaglia, Princeton). (*Bayesian calibration using QUESO*)

# Diagnostics of ITG Mode



## Current Status

- Dedicated UQ branch of XGC-1, with access to richer physics as needed
- Postprocessing tools for 1D XGC-1 diagnostic outputs
- Scripts for XGC-1 interface with DAKOTA
- Initial sensitivity results for heating power, numerical parameters (particles, timestep)

## Plans & Challenges

- Development of computationally tractable problems for UQ analysis, with QoI uncertainties that will be representative of the full problem
- Secondary projects
  - Uncertainty in experimental data analysis
  - Bayesian calibration of reduced models

# BER Atmospheric Modeling Partnership

## Multiscale Methods for Enabling Scale-Aware Capability in CESM – PI: William Collins (LBNL)

- QUEST: Bert Deusschere & Kenny Chowdhary (SNL)
- Multiscale Project Collaborator: Vincent Larson (UWM)

***Project goal is to develop climate modeling capability with high fidelity down to scales of key features of interest: cloud systems and ocean eddies***

- Variable resolution unstructured grids
- Multiscale parameterizations of microphysics
- Numerics geared to next-generation comp. architectures
- Verification, validation and UQ

# QUEST supports project UQ and statistics needs

- Provide expertise and tools for enabling UQ
  - Sensitivity analysis, surrogate modeling, forward UQ, calibration
  - Discussions ongoing regarding the selection of the proper QUEST tools
    - Calibration of CLUBB parameters with DAKOTA
    - GPMSA for multi-fidelity calibration
- Quadrature approaches to account for subgrid variability in microphysics
  - Subgrid variability modeled through assumed distributions for the microphysics parameterization inputs
  - Efficient approaches needed to compute averages of microphysics over grid box

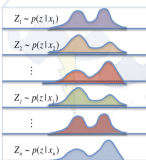
# Traditionally, random sampling can be used to account for sub-grid physics variability

**Autoconversion:** conversion of cloud droplets to rain droplets  
– measured as a rate of mass transfer

## INPUTS

$\vec{x}_j = (\mu_s, \sigma_s, \mu_{\ln N}, \sigma_{\ln N}, \rho_{s, \ln N})$   
for each grid box  $j = 1, \dots, n$

Determine normal-lognormal PDFs at each grid box using the means and variances  $\vec{x}_j$ .



LHS SAMPLING

## OUTPUTS

Autoconversion mean at each grid box:  
 $\langle A(Z_1) \rangle, \dots, \langle A(Z_n) \rangle$

- Autoconversion depends on
  - cloud water mixing ratio  $s$
  - cloud droplet number concentration  $N$
- CLUBB model:
  - $s, N | x_j \sim$  joint normal-lognormal PDF
  - $x = (\mu_s, \sigma_s, \mu_{\ln N}, \sigma_{\ln N}, \rho_{s, \ln N})$
- Currently, at each time step, and grid box
  - PDF is sampled using LHS
- Samples used to compute the autoconversion mean, at each grid box and time step.



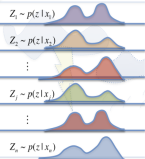
# Quadrature approaches show significant improvement to sub-grid physics calculations

**We can replace Latin Hypercube sampling with a quadrature based approach.**

## INPUTS

$\bar{x}_j = (\mu_s, \sigma_s, \mu_{\ln N}, \sigma_{\ln N}, \rho_{s, \ln N})$   
for each grid box  $j = 1, \dots, n$

Determine normal-lognormal PDFs at each grid box using the means and variances  $\bar{x}_j$ .

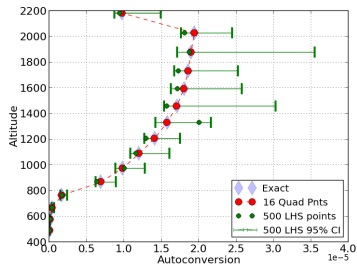


## OUTPUTS

Autoconversion mean at each grid box:  
 $\langle A(Z_1) \rangle, \dots, \langle A(Z_n) \rangle$

**QUADRATURE**

## Latin Hypercube Sampling vs Quadrature



**Figure:** Using a quadrature approach, we can bypass the random sampling and calculate the Autoconversion mean using far fewer points, with even greater accuracy.

# Applying quadrature based approaches to other microphysics processes

- We want to apply this quadrature technique to all microphysics processes with relevant sub-grid variability
- Each process has 1-3 uncertainty parameters
- There are  $\sim 14$  uncertainty parameters in total
- Two implementation approaches
  - ① Use NCAR's sub-column approach
    - Samples all microphysics simultaneously
    - Would require all microphysics to use the same number of quadrature points
  - ② Integrate each microphysics process separately
    - Low-dimensional quadrature tailored to each microphysical process
    - Requires all microphysics to be implemented in separate subroutines

---



---

## Example Microphysics Processes

---

Average evaporation/ condensation rate of cloud water and ice

---

Autoconversion of cloud ice to snow

---

Accretion of cloud water by snow

---

Accretion of cloud water by rain

---

Freezing of cloud droplets and rain

---

Evaporation/ sublimation of precipitation

---

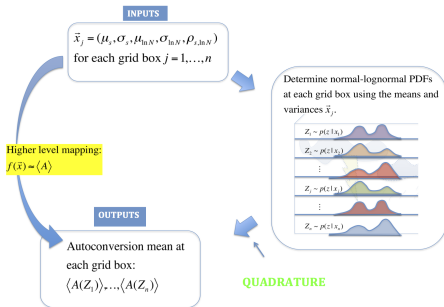
# Integrating each microphysics process separately

In many microphysics processes in a global circulation model like CAM, the number of variable sub-grid parameters is a model choice

Example Microphysics Processes	# of uncertain sub grid parameters	Likely # of quadrature points needed
Average evaporation/ condensation rate of cloud water and ice	3	$4 \times 4 \times 4$
Autoconversion of cloud ice to snow	1	4
Accretion of cloud water by snow	3	$4 \times 4 \times 4$
Accretion of cloud water by rain	2	$4 \times 4$
Freezing of cloud droplets and rain	2	$4 \times 4$
Evaporation/ sublimation of precipitation	3	$4 \times 4 \times 4$

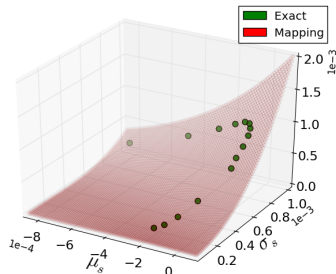
- For calculation of the mean, 4 quadrature points is equivalent to approximating the function of interest with a 7th order polynomial.
- The choice of the number of quadrature points is a trade off between accuracy and cost. However, even a four point quadrature approach shows drastic improvements over Latin Hypercube sampling for the autoconversion mean.
- We are working with Vince Larson (UWM) to prototype this approach in CLUBB.

# Creating a higher level function that maps the inputs directly to the sub-grid microphysics quantities



- This higher level mapping would allow us to bypass the on-the-fly calculation of microphysics completely, with potential for improvements in both speed and accuracy.
- The mapping can be built from a predetermined set of quadrature points or by a growing set of random samples collected over the course of the simulation.

## 5D Mapping (projected in 2D)



**Figure:** We can create a higher level 5D function that maps the means and variances of  $s$  and  $N$  directly to the autoconversion mean. We can use the same mapping as a proxy for the autoconversion mean at every time step.

# UQ algorithms impacting simulation of climate physics

- Quadrature offers a promising approach to account for microphysics subgrid variability with high accuracy and reasonable numbers of samples
- Currently exploring the application of this to all microphysics processes with relevant sub-grid variability
  - CLUBB single column model considered for initial implementation
- Application of QUEST tools in other climate physics areas under discussion

# Closure

- Broad range of ongoing work on UQ software and algorithms development
- A number of SciDAC partnership activities
- Highlighted two example partnerships

Partnerships using UQ methods/tools for:

- Global sensitivity analysis
- model calibration and validation
- microphysics modeling
  - Improved accuracy **and** computational performance