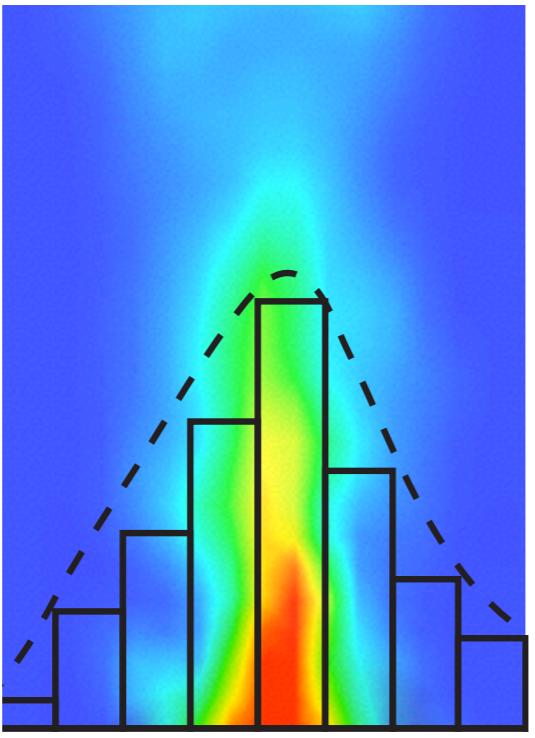




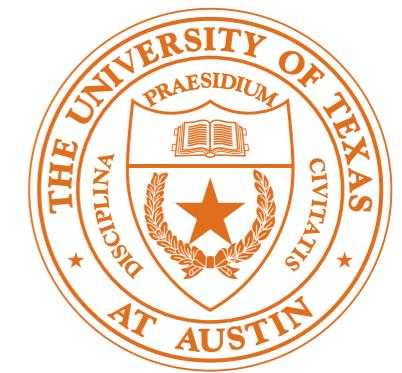
A Parameter Uncertainty Framework for Fire Scenarios Using a Bayesian Inference Approach

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NIST



Outline

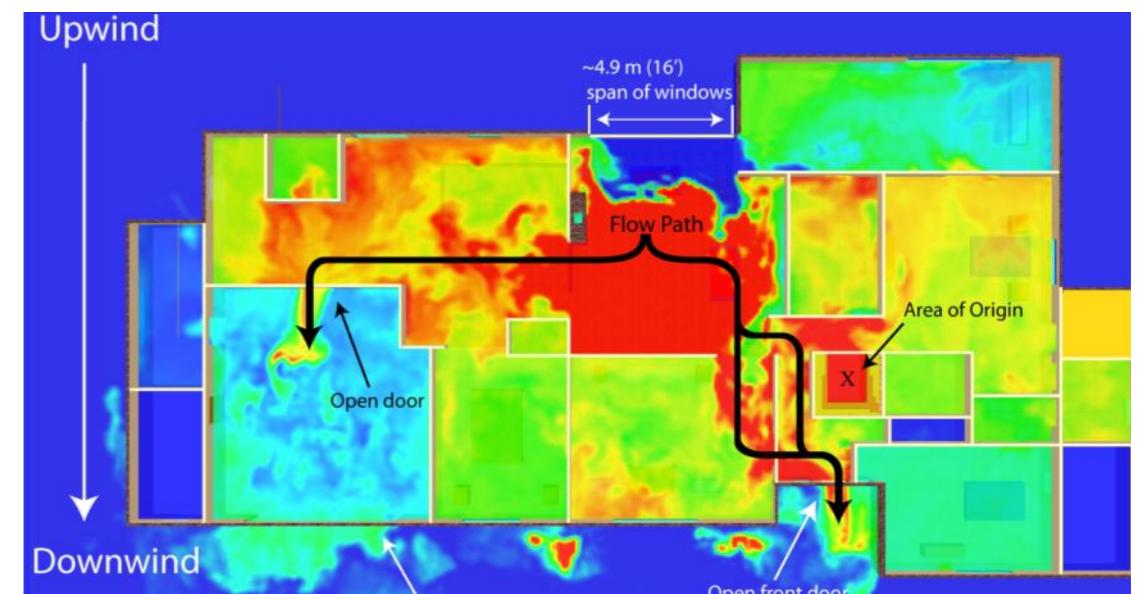
- Motivation
- Problem Statement
- Research Objectives
- Bayesian Inference Framework
- Examples Using Bayesian Inference in Fire Scenarios:
 - 1) Estimating Fire Size
 - 2) Estimating Material Properties
 - 3) Estimating Fire Location
- Conclusions

Motivation

Fire modeling tools can be applied to model validation exercises, fire and arson investigations, and reconstructions of firefighter line-of-duty deaths (LODDs) and injuries.



Barowy and Madrzykowski, 2012



Barowy and Madrzykowski, 2012

The location and intensity (i.e., heat release rate) of a fire in a compartment are important model inputs that govern the evolution of thermal conditions in the fire compartment.

Motivation

Compartment fires leave behind a record of fire activity and history (i.e., fire signatures).



NFPA 921, 2011 ed.



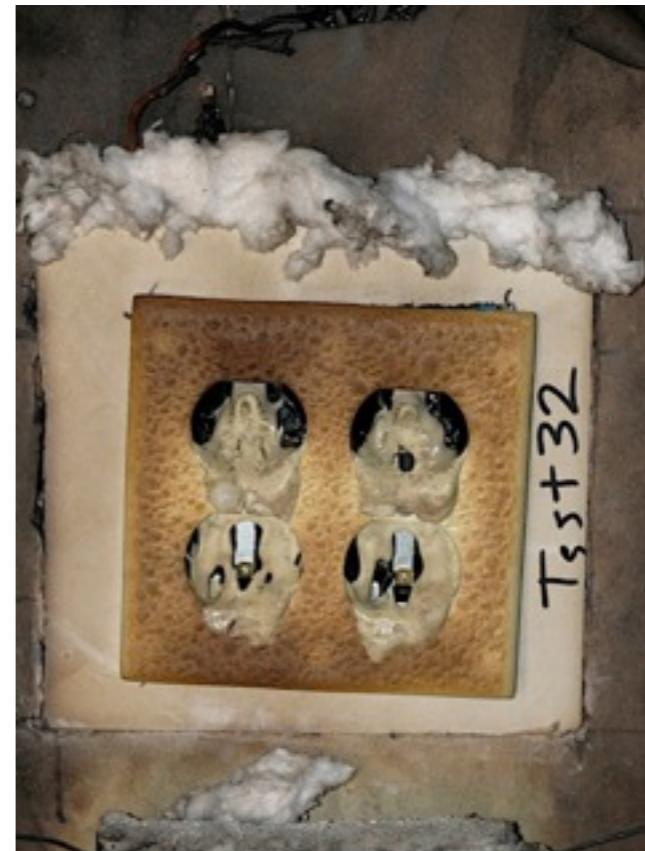
NFPA 921, 2011 ed.

- Gypsum wallboard undergoes chemical reactions/calcination,
- Metal and plastic components melt and deform,
- Soot deposition to surfaces occurs.

Motivation

In fire scenarios, observations of fire damage can be a surrogate for measured data (e.g., degraded gypsum wallboard or melted switch plates and outlets).

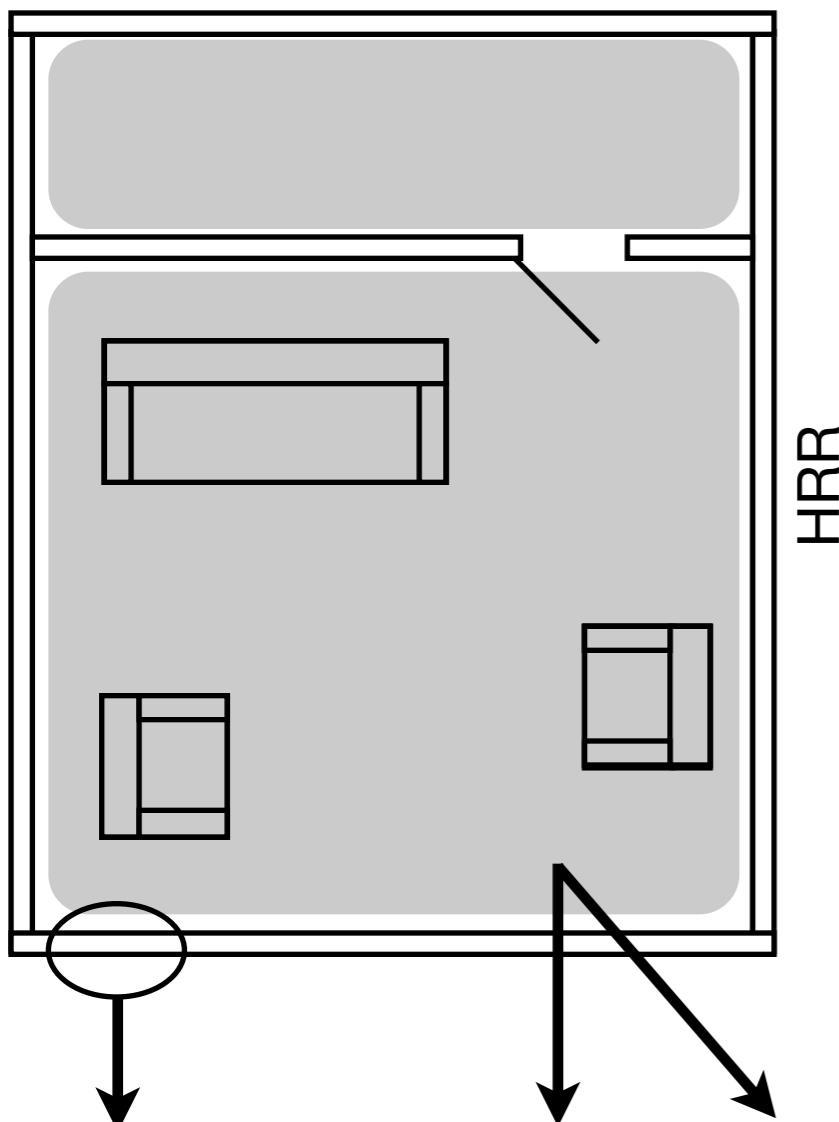
We can use various fire models and inversion techniques to estimate the size and location of a fire in a compartment.



$$Q = \int \dot{q}'' dt$$

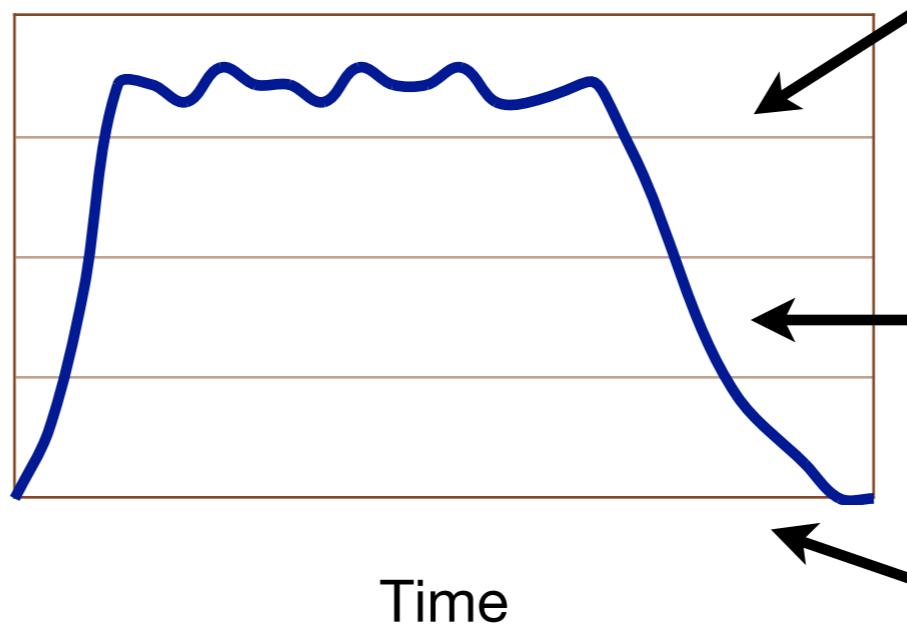
Problem Statement

Compartment fire

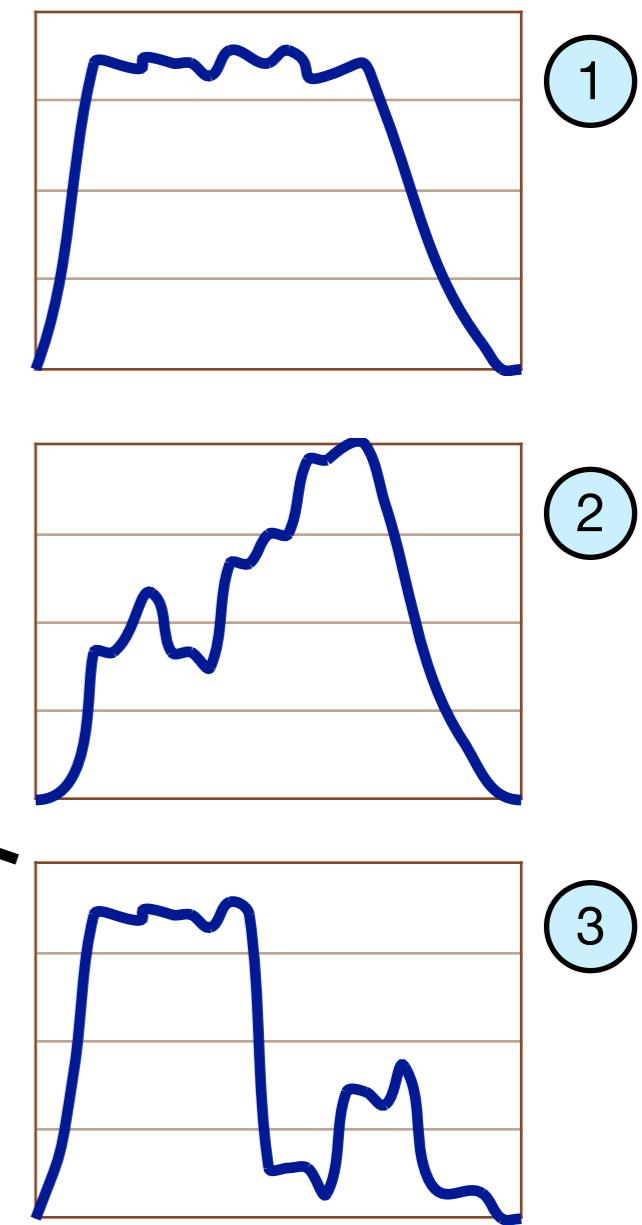


$$T_{gyp}(z) = f(T_u(t), L(t))$$

Actual Fire Scenario



Plausible Scenarios



Institutional Decision Analysis

In institutional settings (businesses, governments, or research organizations), **decisions need to be justified**, and **formal decision analysis** has a role to play in clarifying the relation between [...] a relevant probability model and the resulting estimates.

[...] forensic scientists use a particular quantitative approach to evaluating forensic laboratory results, the Bayesian approach, as a means of **quantifying uncertainty and communicating it accurately to judges, prosecutors, and defense lawyers** [...]

[...] using the Bayesian approach also brings about a particular type of intersubjectivity; [...] **quantifications must be consistent** across forensic specializations, which brings about a **transparency based on shared understandings and practices**.

Institutional Decision Analysis

Numerical scale	Verbal scale	Likelihood ratio interval
+4	The results of the examination extremely strongly support that ...	$lr \geq 1,000,000$
+3	The results of the examination strongly support that ...	$6000 \leq lr < 1,000,000$
+2	The results of the examination support that ...	$100 \leq lr < 6000$
+1	The results of the examination support to some extent that ...	$6 \leq lr < 100$
0	The results of the examination support neither ... nor ...	$1/6 < lr < 6$
-1	The results of the examination support to some extent that ... was not ...	$1/6 \geq lr > 1/100$
-2	The results of the examination support that ... was not ...	$1/100 \geq lr > 1/6000$
-3	The results of the examination strongly support that ... was not ...	$1/6000 \geq lr > 1/1,000,000$
-4	The results of the examination extremely strongly support that ... was not ...	$lr \leq 1/1,000,000$

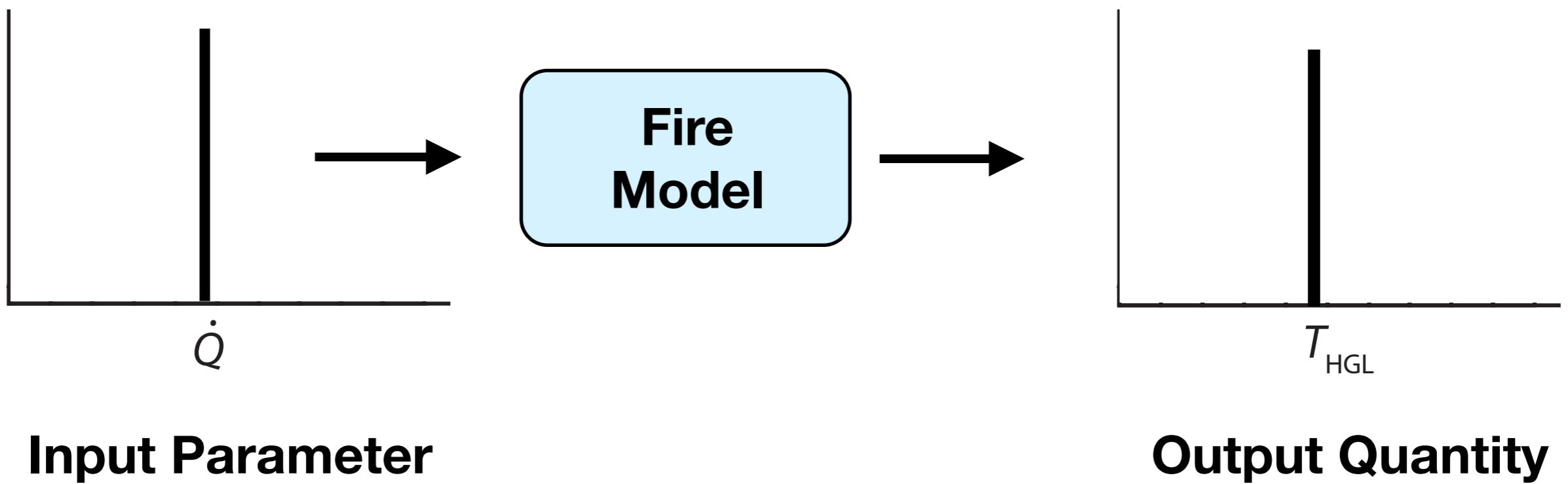
Research Objectives

To describe probability distributions that indicate the **amount of uncertainty in model inputs and outputs**.

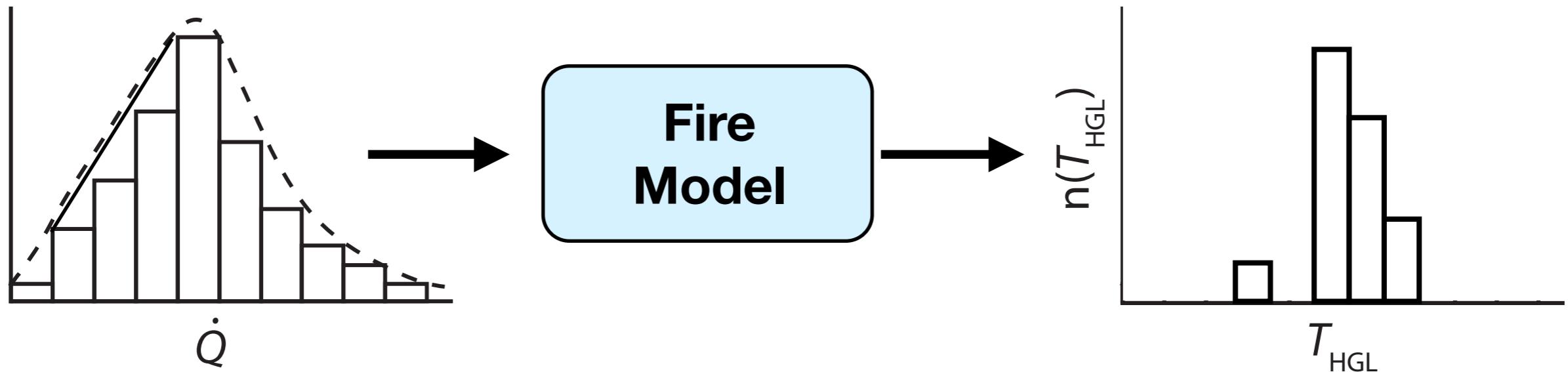
To quantify our **degree of certainty (or degree of belief)** in unknown input parameters for fire scenarios based on:
1) a predictive model and 2) measured (or observed) data.

To apply a **statistical parameter inversion framework** to various fire scenarios to determine: 1) fire size, 2) fire location, and 3) material property parameters.

Single Model Inputs and Outputs



Uncertainty and Distributions in Models



Input Parameter

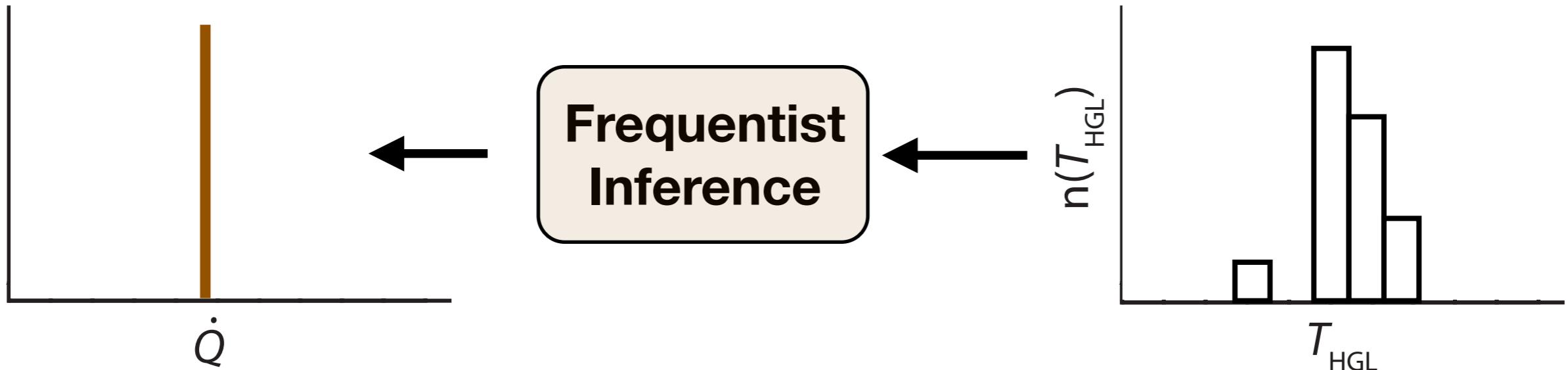
Consider the different use cases:

- Propagation of uncertainty (output distribution)
- FDS verification & validation process (model bias)
- Calculate distribution of input parameters given measured data

Output Quantity

Frequentist Inference Method

Frequentist Approach



Input Parameter

Inputs are fixed but unknown constants that do not depend on the data.

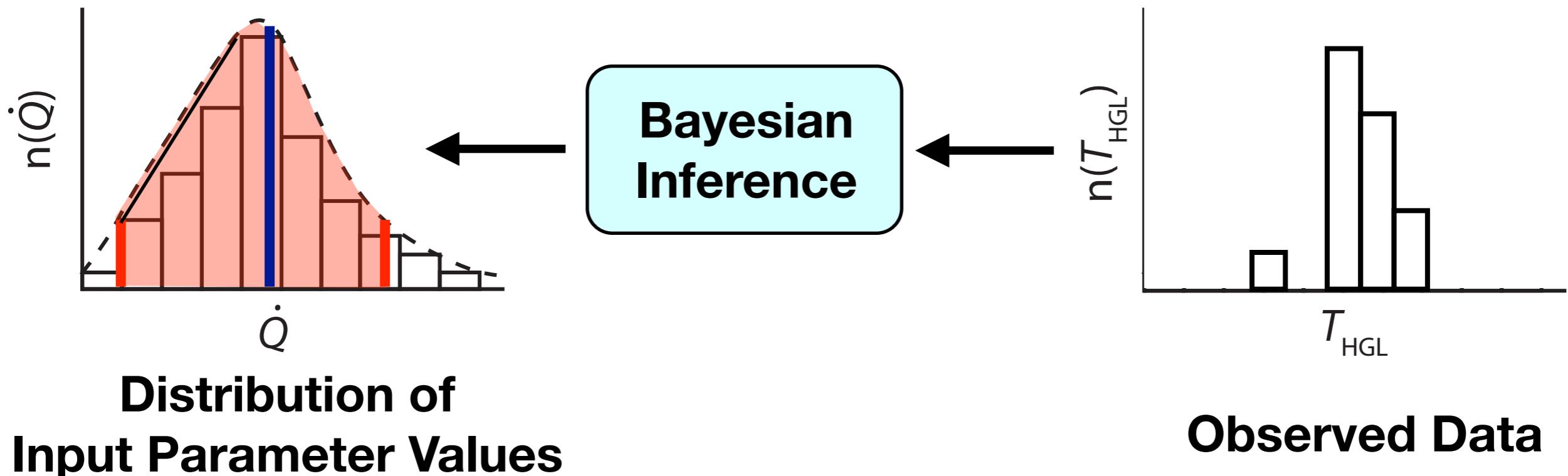
Uncertainty is expressed in terms of repeatability.

Observed Data

Data are repeated random samples (with some frequency).

Bayesian Inference Framework

Bayesian Approach



Inputs are unknown random variables that we are uncertain about and depend on the data.

We model the data-generating process.

Data are fixed observations from a true distribution.

Bayes' Theorem

Definition of Bayes' Theorem

$$\widehat{P(A|B)} = \frac{\overbrace{P(B|A) \cdot P(A)}^{\text{Likelihood} \quad \text{Prior}}}{\underbrace{P(B)}_{\text{Normalizing constant}}}$$

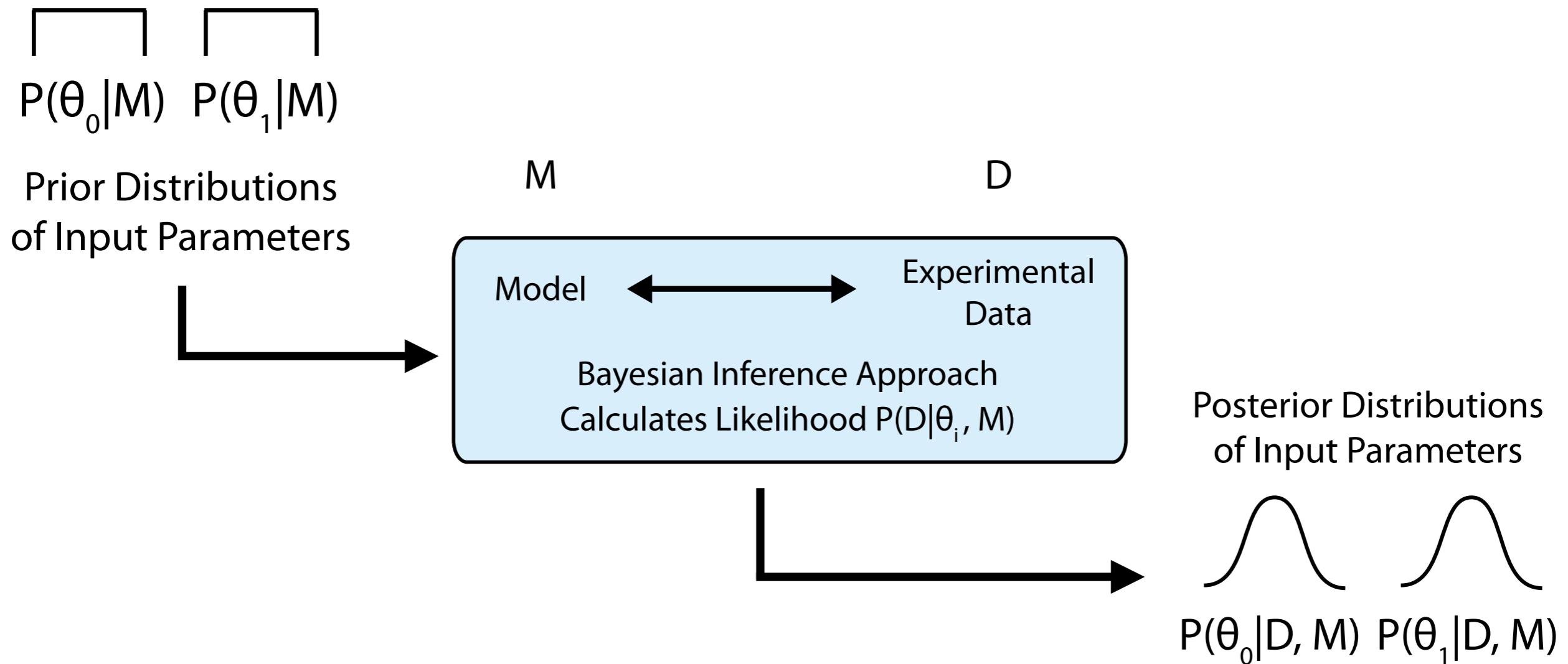
Bayes' Theorem for Model Applications

$$P(\theta|D, \mathcal{M}) \propto P(D|\theta, \mathcal{M}) \cdot P(\theta|\mathcal{M})$$

Unknown parameter Model
Data
Posterior Likelihood Prior

Bayesian Inference Framework

The Bayesian inference process



Applications of Bayesian Inference

Examples using Bayesian inference in fire scenarios

1. Estimate fire size using measured heat flux data.
2. Use the FDS fire model to estimate material properties using measured mass loss data.
3. Estimate fire location using heat flux data.

Computational Framework

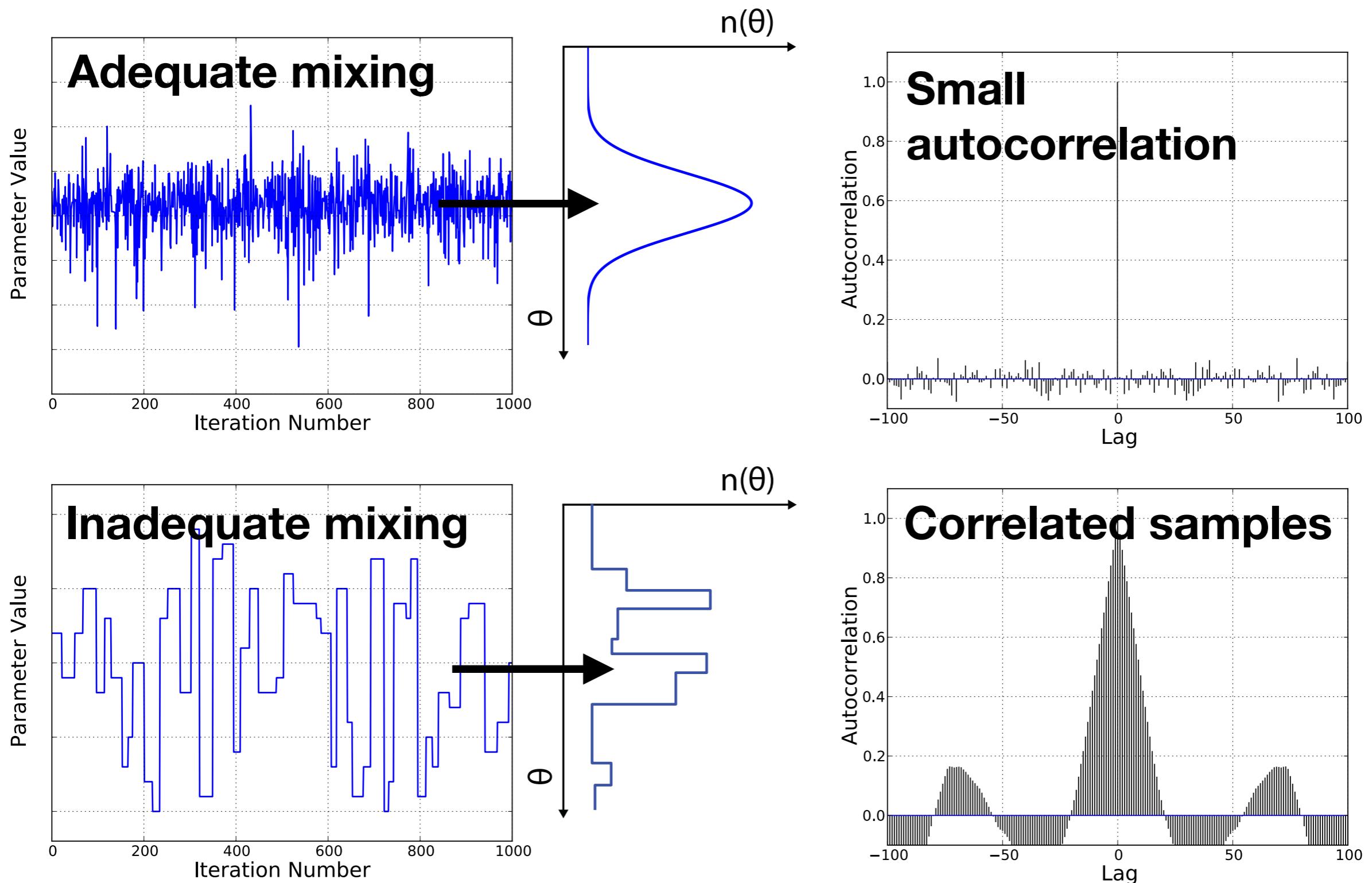
Fire modeling and visualization tools:

- Empirical correlations
- Consolidated Model of Fire and Smoke Transport (CFAST)
- Fire Dynamics Simulator (FDS)
- Smokeview (SMV)

Computational, analysis, and visualization tools:

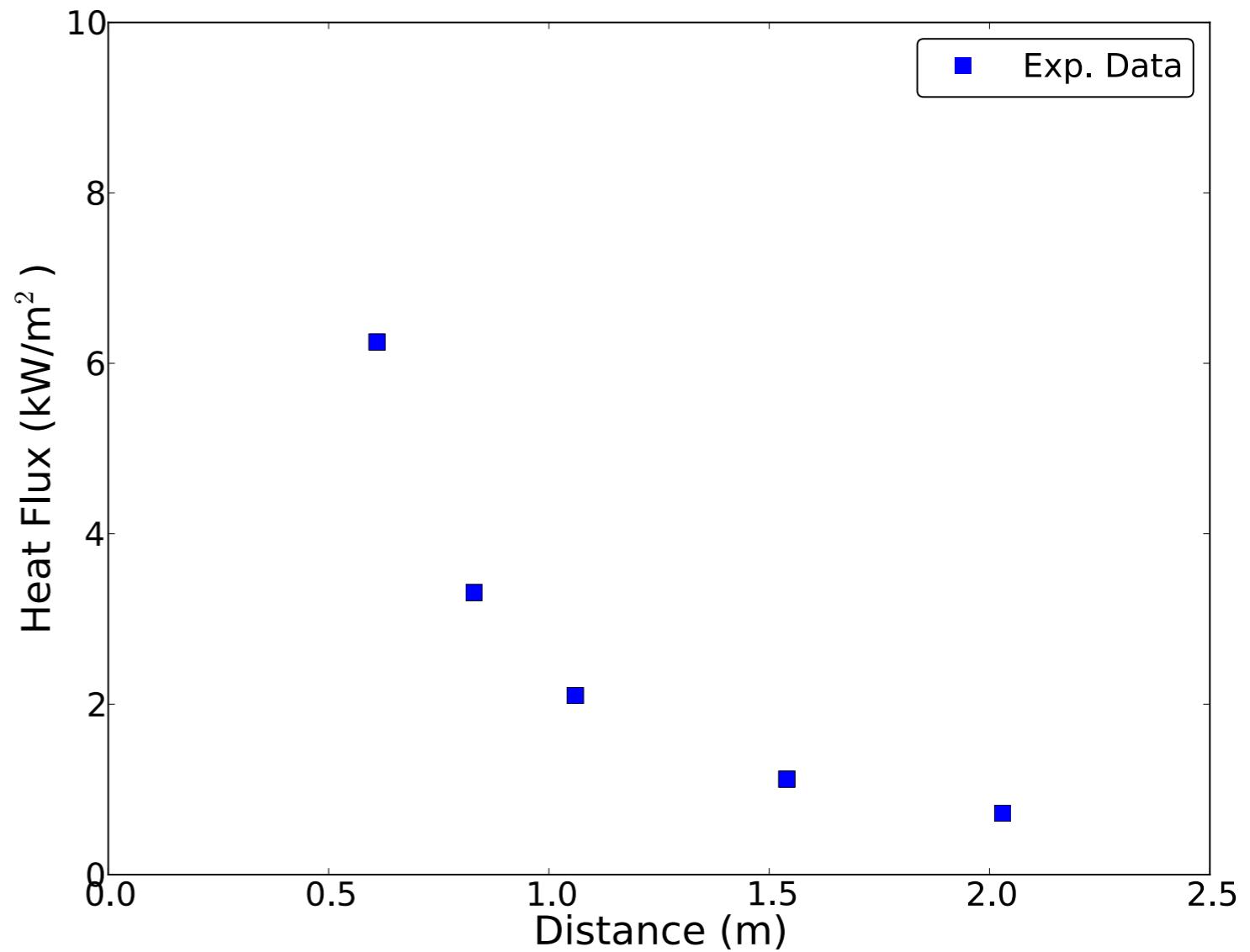
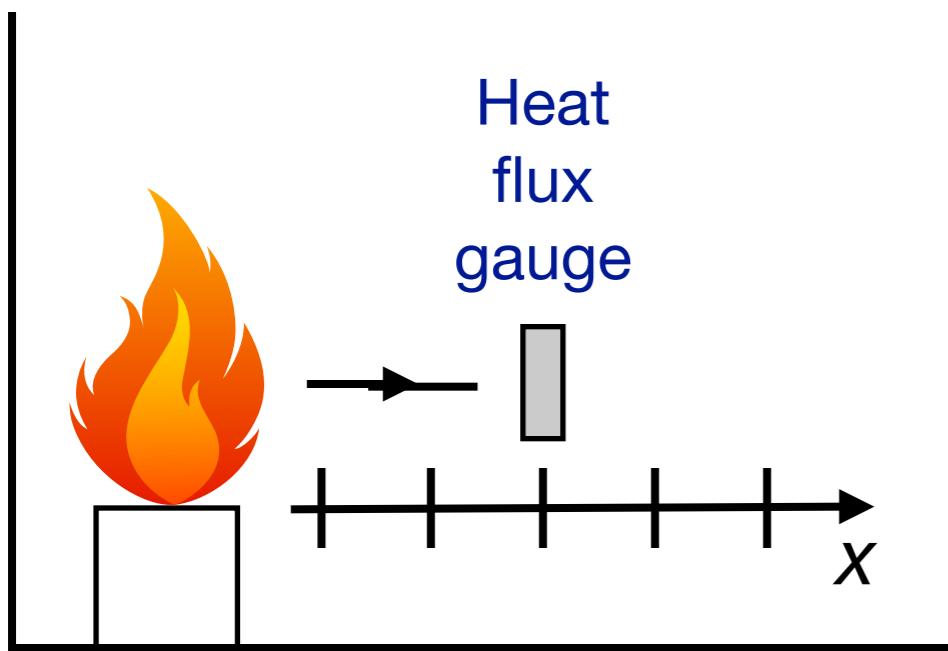
- Python
- Numeric Python (NumPy)
- Scientific Python (SciPy)
- Math plotting library (matplotlib)
- Bayesian Inference in Python (PyMC)

Results of Bayesian Inference



Example 1 - Estimating Fire Size

Fleury heat flux experiments; Measured heat flux vs. distance data;
100 kW propane burner



R. Fleury, "Evaluation of Thermal Radiation Models for Fire Spread Between Objects," Master's thesis, University of Canterbury, Christchurch, New Zealand, 2010.

Example 1 - Estimating Fire Size

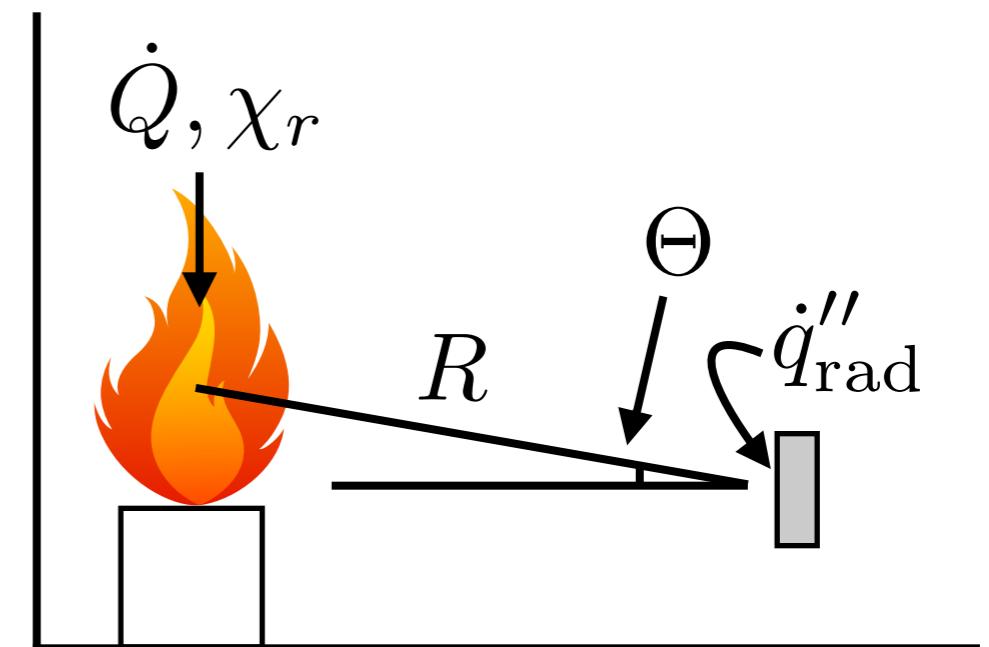
Model: Point source radiation equation

$$\dot{q}_{\text{rad}}'' = \cos(\Theta) \frac{\chi_r \dot{Q}}{4\pi R^2}$$

Known radiative fraction **Unknown fire size parameter**

\dot{q}_{rad}'' \dot{Q}

Measured heat flux data Known distance



Unknown parameter: \dot{Q}

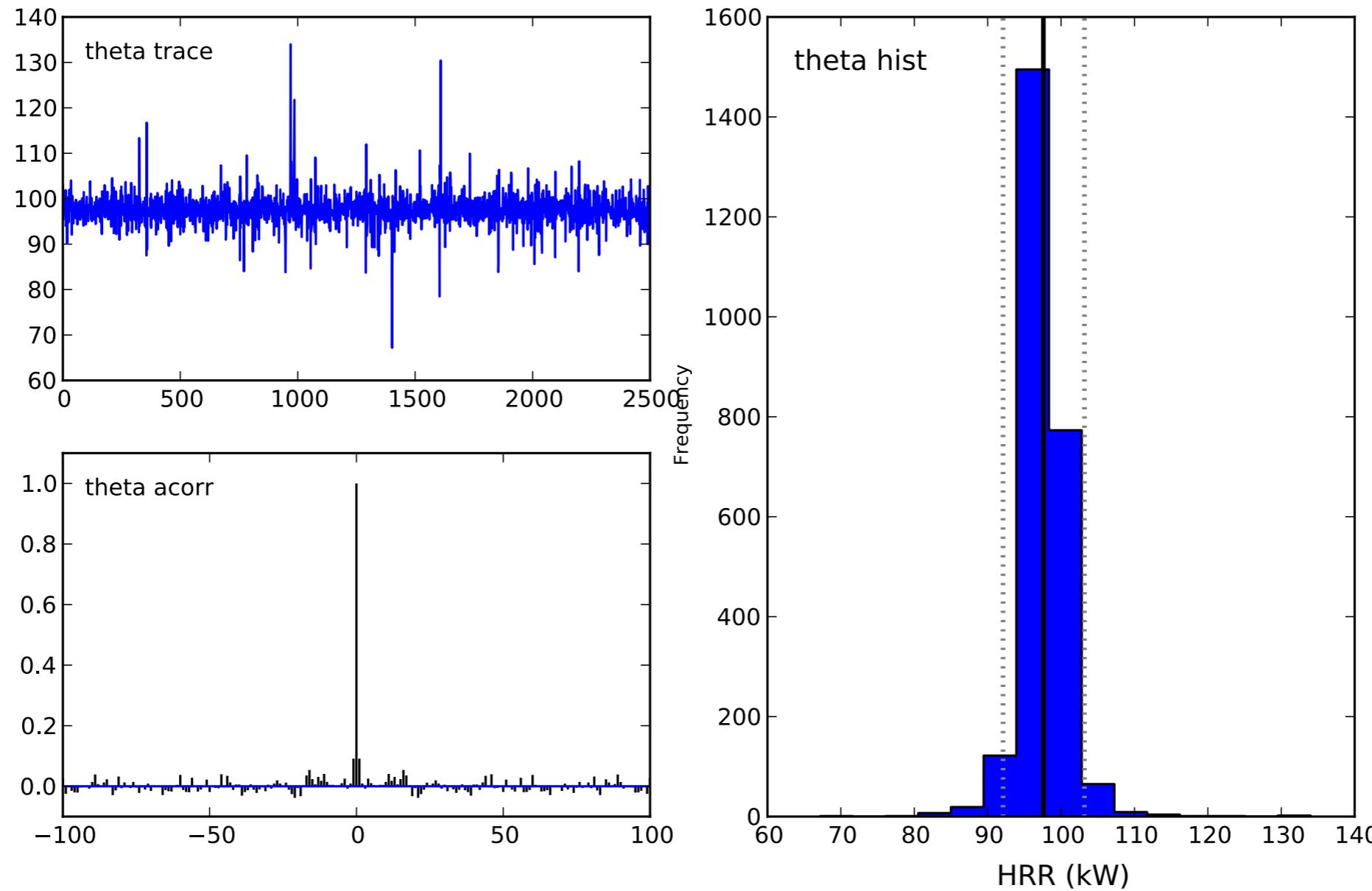
Prior: Uniform distribution: $50 \text{ kW} < \dot{Q} < 300 \text{ kW}$

$$\dot{Q}(i=0) = 200 \text{ kW}$$

Example 1 - Estimating Fire Size

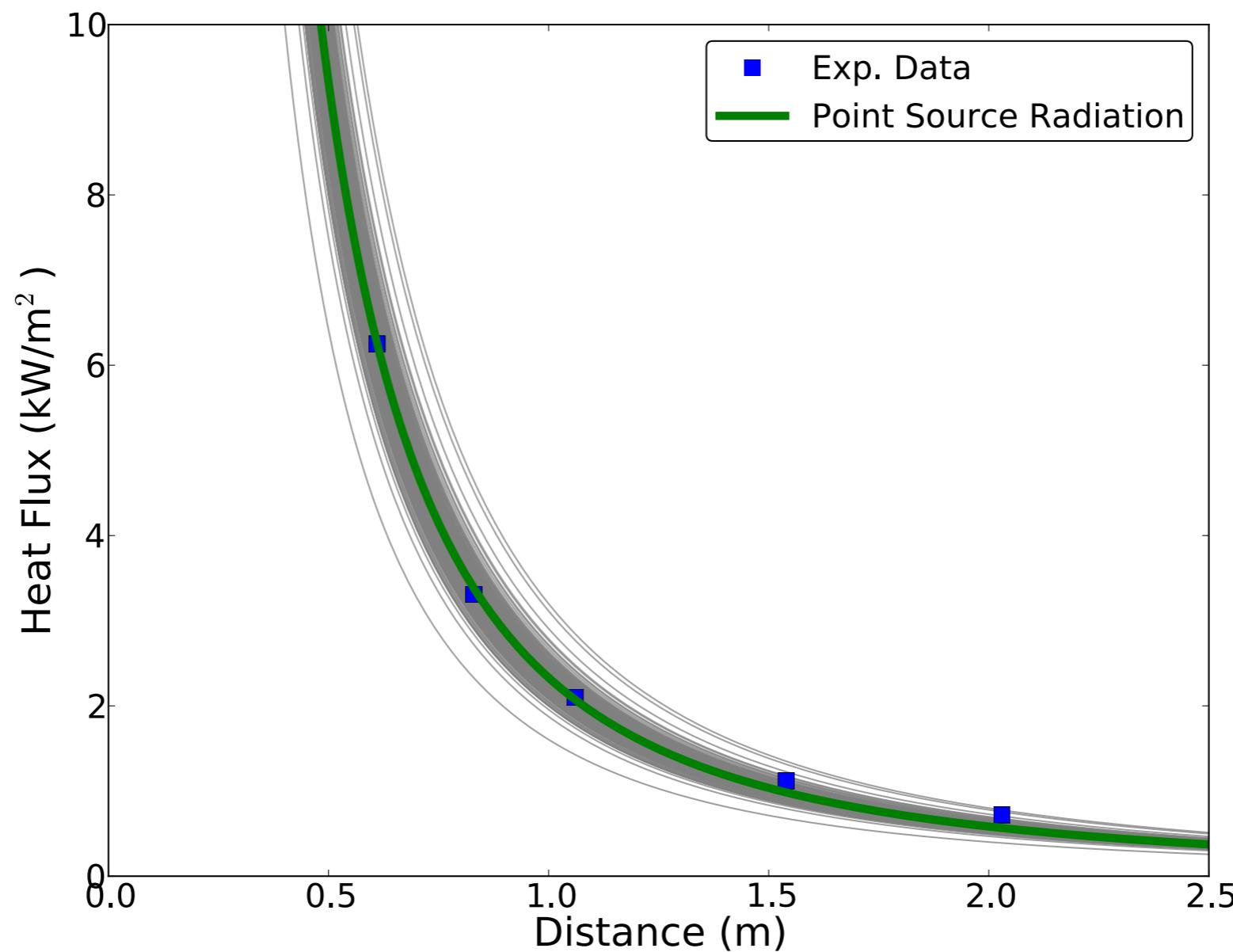
PyMC results for HRR parameter \dot{Q} :

Mean: 97.6 kW; Standard Deviation: 3.1 kW;
95 % credible interval = [92 kW, 103 kW]



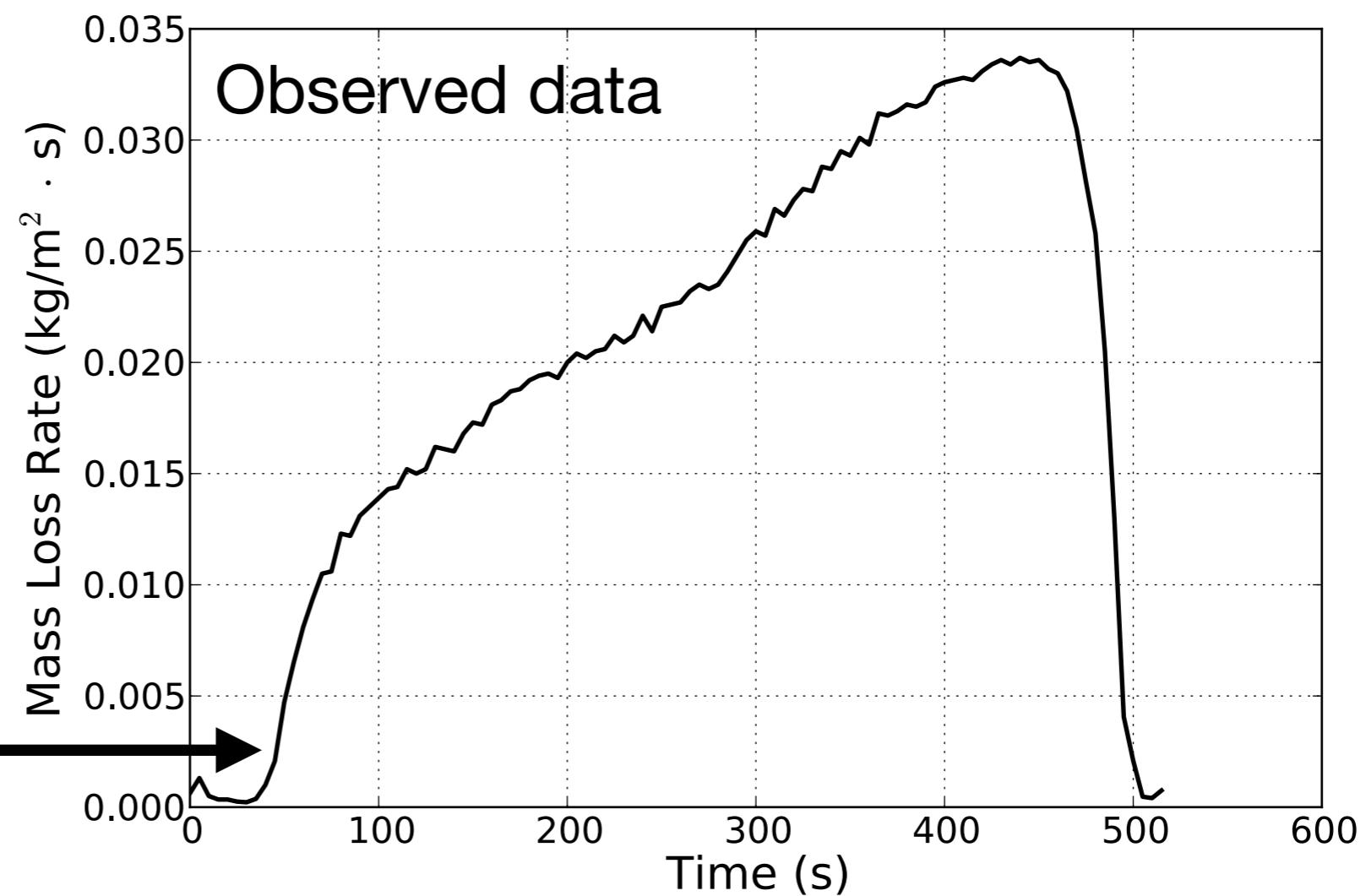
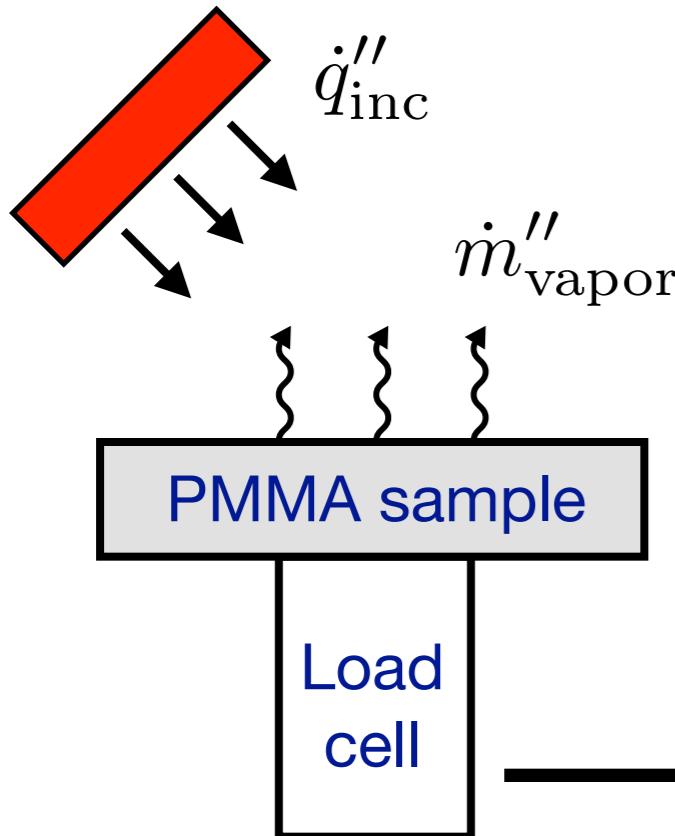
Example 1 - Estimating Fire Size

Results of point source radiation model at posterior mean value (solid green line) and for all values from the posterior distribution (shaded gray area)



Example 2 - Material Property Estimation

Transient mass loss rate of sample in the NIST gasification apparatus: 8.5 mm thick PMMA sample; incident heat flux was 52 kW/m²; 1 cm layer of insulation under the PMMA sample.



Example 2 - Material Property Estimation

To predict the mass loss rate of the PMMA sample exposed to an external heat flux, FDS was run in “solid-phase only” mode in which no gas-phase combustion occurs.

$$\rho_s c_s \frac{\partial T}{\partial t} = \frac{\partial}{\partial x} k_s \frac{\partial T}{\partial x} + \dot{q}_s''' ; \quad \dot{q}_s''' = \frac{\partial \rho_s}{\partial t} \Delta H_r - \dot{q}_r'''$$

↓ ↓ ↓

Specific Heat Thermal Conductivity Heat of reaction

↑ ↑ ↑

Density Function of pre-exponential factor, and activation energy Function of absorption coefficient, emissivity

The pyrolysis model, external heat flux, and 1D heat conduction solver determine the reaction rate of the solid material.

Example 2 - Material Property Estimation

Material properties for PMMA (from literature) and their associated uncertainty values.

Parameter	Literature Value	Uncertainty (%)	Measurement Technique	Source
Absorption Coefficient	2700 1/m	50	FTIR	[119]
Pre-Exponential Factor	8.5×10^{12} 1/s	50	TGA	[120]
Activation Energy	188 000 kJ/kmol	3	TGA	[120]
Emissivity	0.85	20	IS	[121]
Heat of Reaction	870 kJ/kg	15	DSC	[122]
Thermal Conductivity	0.20 W/m · K	15	TLC	[120]
Density	1100 kg/m ³	5	Direct	[120]
Specific Heat	2.2 kJ/kg · K	15	DSC	[122]

Model: FDS

Unknown parameters: Eight material properties

Priors: Uniform distribution around literature values

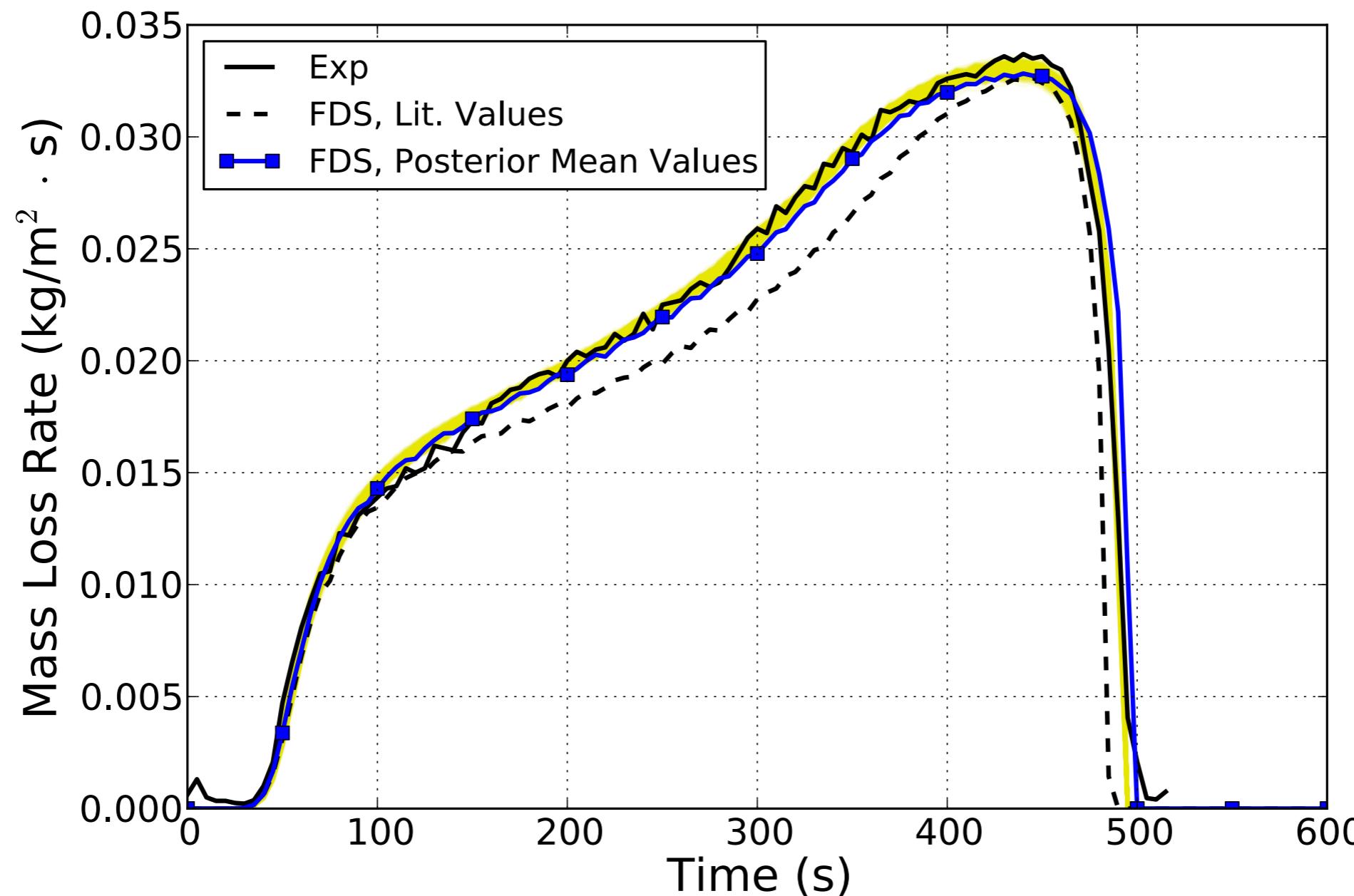
Example 2 - Material Property Estimation

Resulting posterior mean values for the input parameters compared to literature values

Parameter	Units	Posterior Mean Value	Literature Value	Relative Difference
Heat of Reaction	kJ/kg	958	870	10%
Thermal Conductivity	W/m · K	0.22	0.20	10%
Density	kg/m ³	1208	1100	9.8%
Specific Heat	kJ/kg · K	2.0	2.2	9.1%

Example 2 - Material Property Estimation

Results from experiment (black line), literature values (dashed line), posterior mean values (blue line with boxes), and individual realizations over all posterior values (yellow region)



Example 3 - Inverse Fire Localization

A fire is located in a compartment measuring $10 \text{ m} \times 10 \text{ m} \times 2.4 \text{ m}$ with an open door measuring $0.9 \text{ m} \times 2.4 \text{ m}$. A 300 kW propane fire at $(x, y) = (2, 2)$ was used in FDS to generate synthetic heat flux data. Six heat flux gauges are located near the fire at a height of 1.2 m.

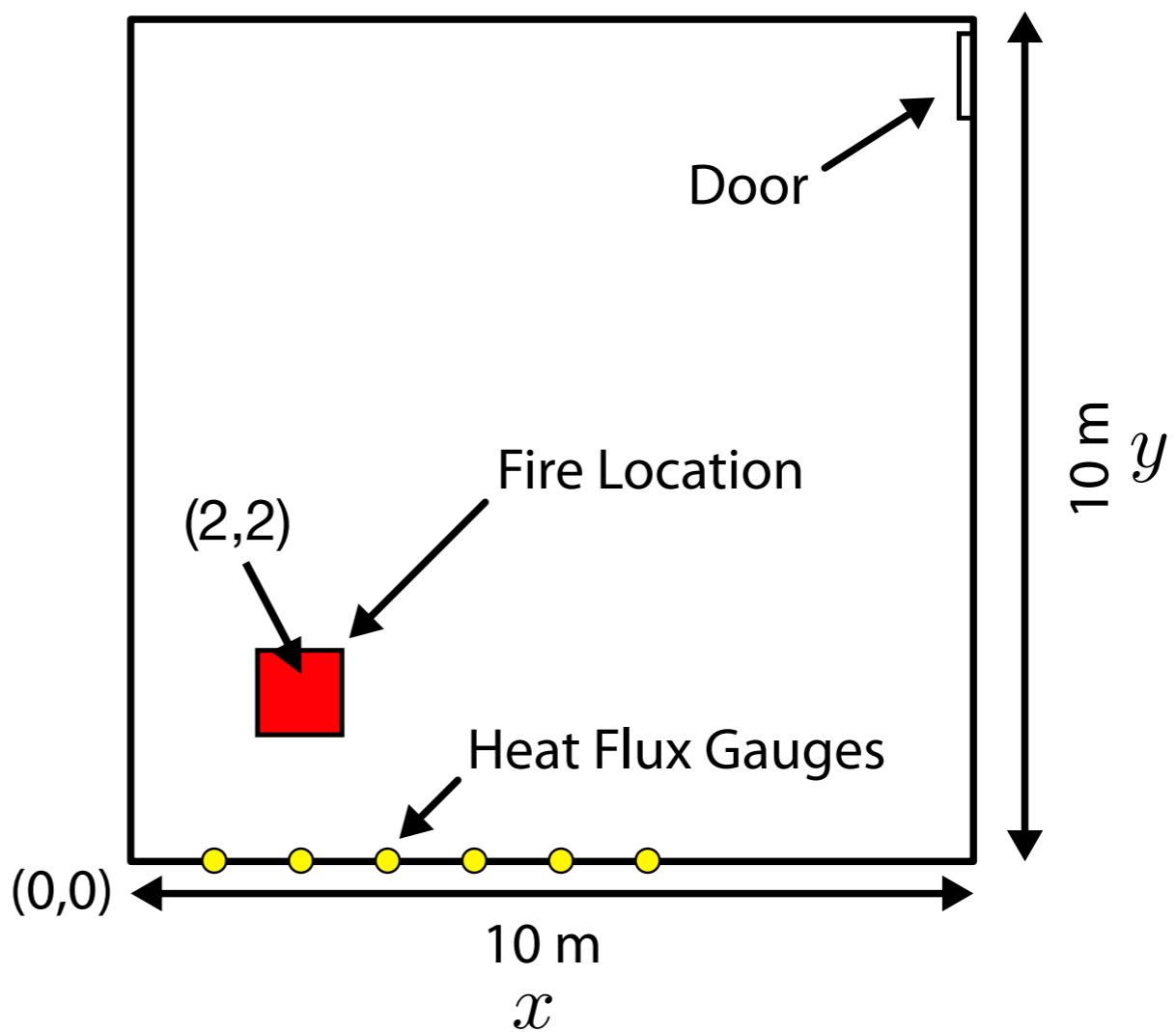
Model: Point source radiation equation

Unknown parameters: x, y

Priors: Uniform distributions

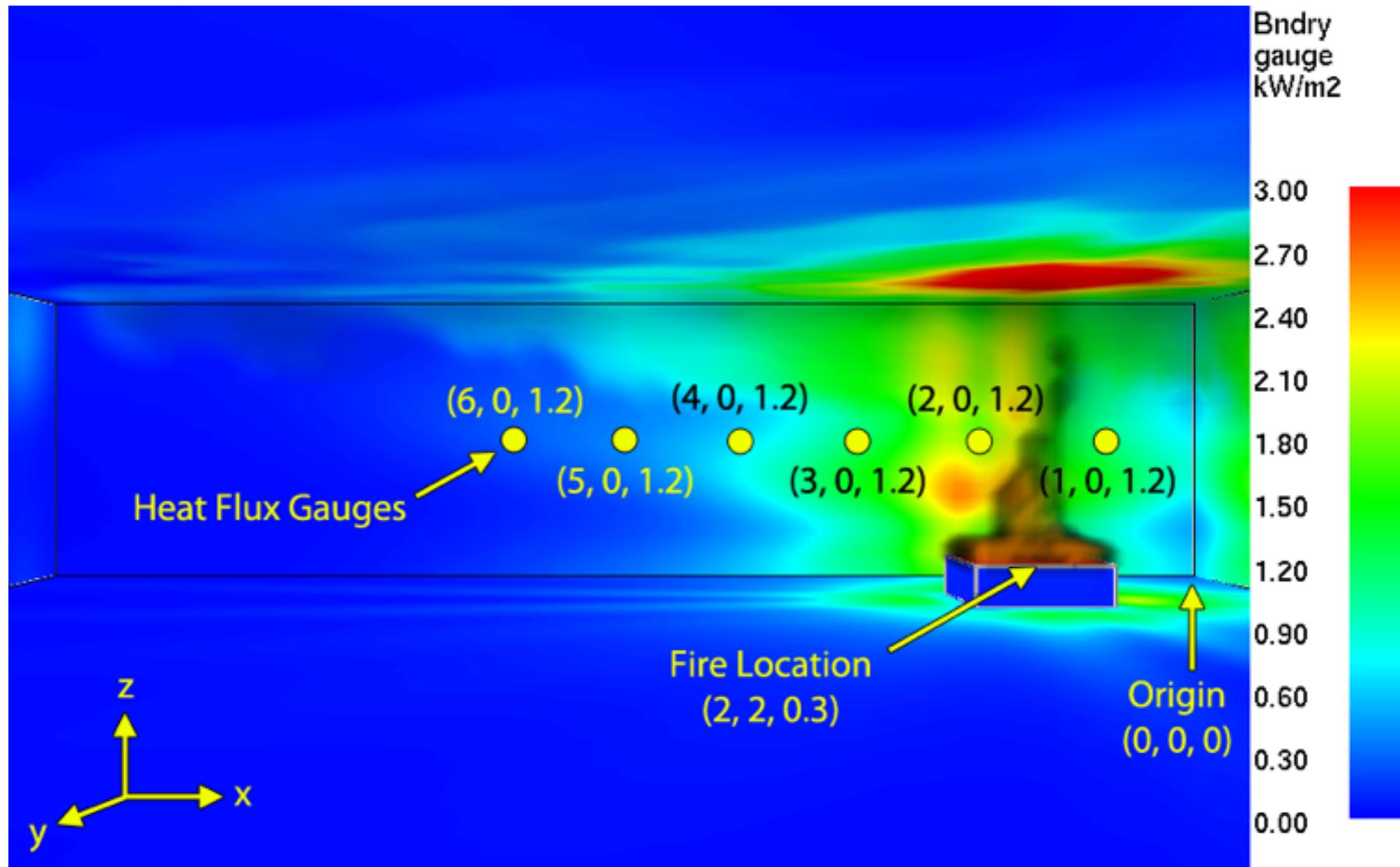
$$0 \text{ m} > x, y > 10 \text{ m}$$

$$x(i=0) = y(i=0) = 5 \text{ m}$$



Example 3 - Inverse Fire Localization

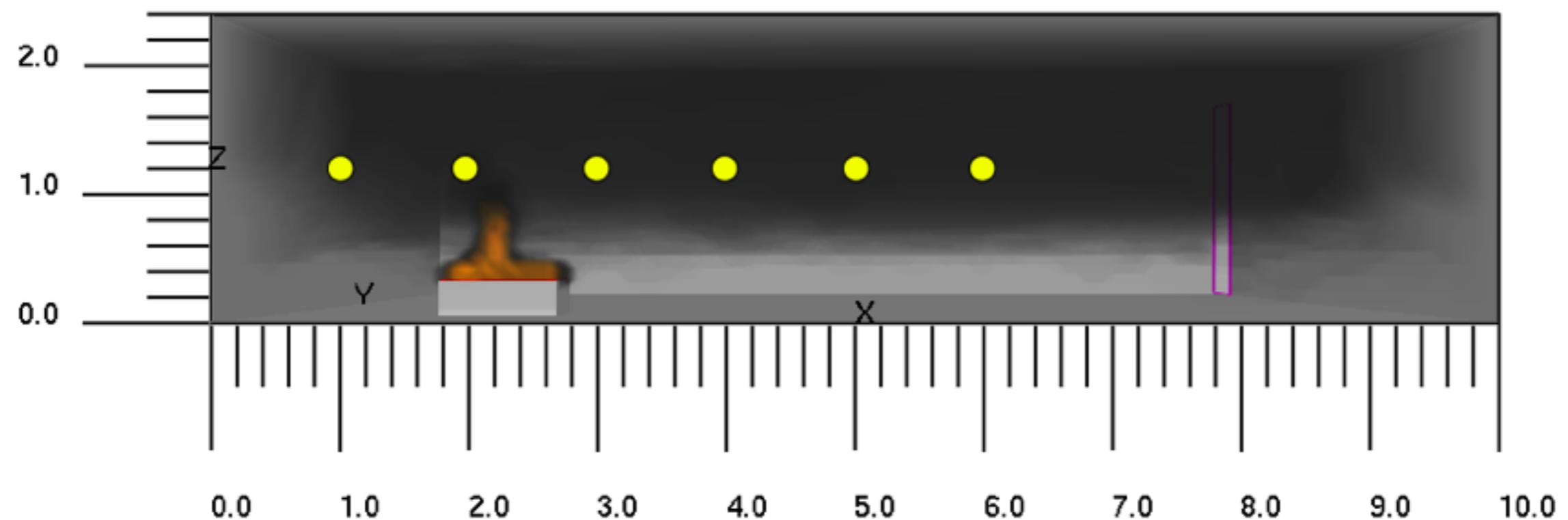
Visualization of gauge heat flux at walls ($T_w = 20^\circ\text{C}$) for 300 kW case



$$\dot{q}_{\text{gauge}}'' = \dot{q}_{\text{r}}''/\varepsilon + \dot{q}_{\text{c}}'' + h(T_w - T_G) + \sigma(T_w^4 - T_G^4)$$

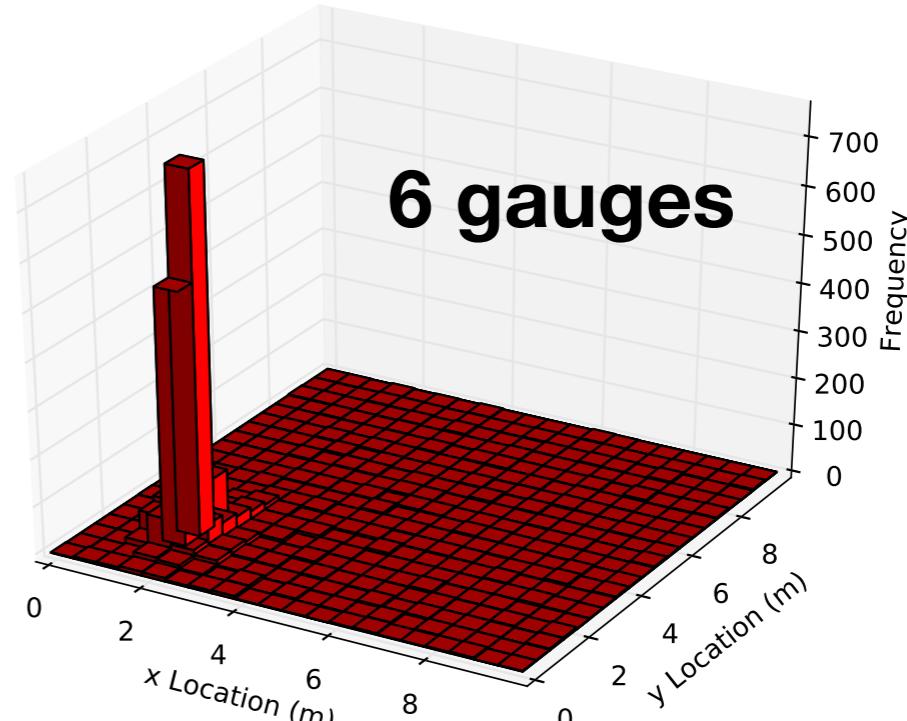
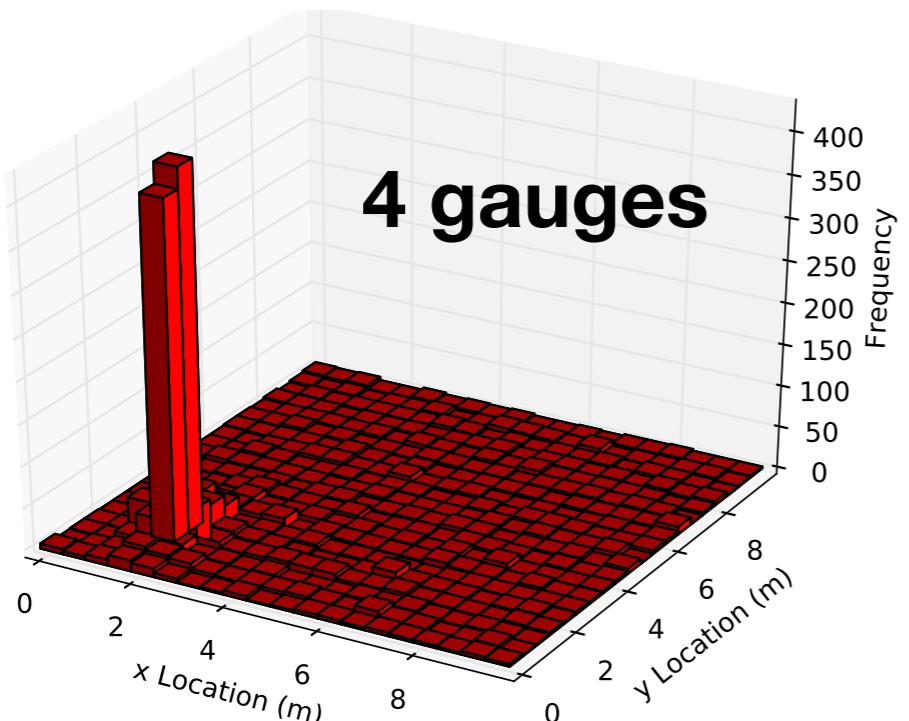
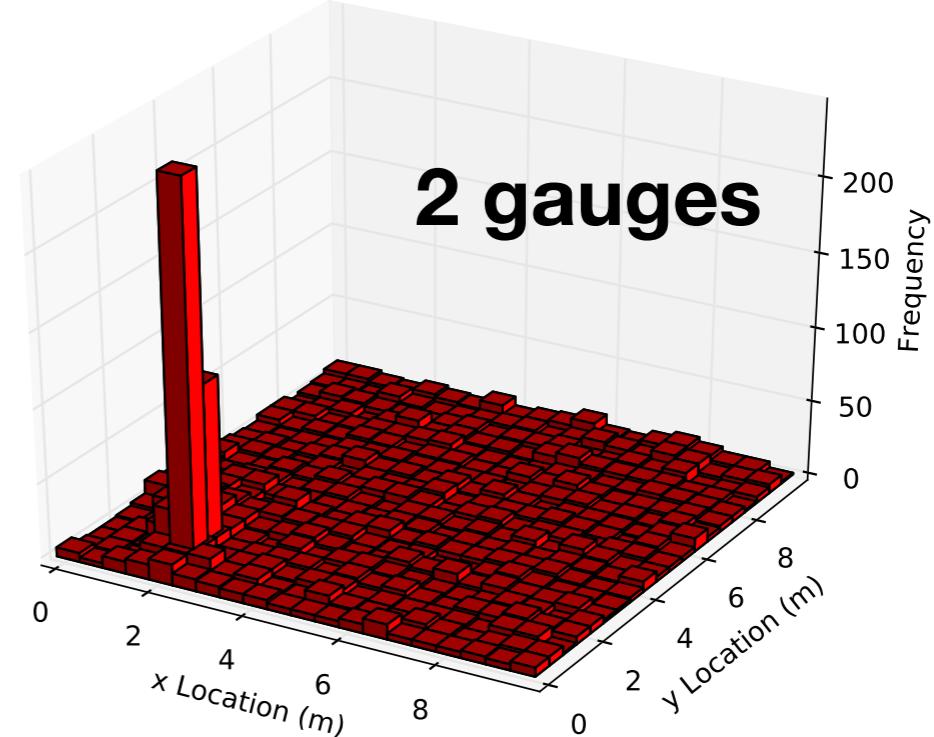
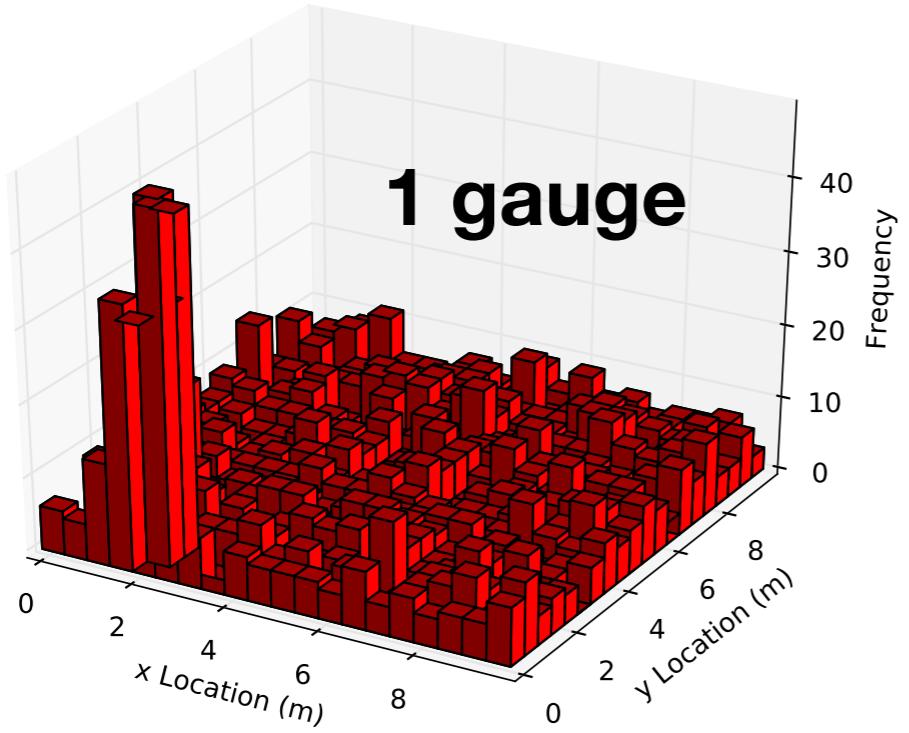
Example 3 - Inverse Fire Localization

Visualization of fire and smoke layer for 300 kW case at 300 s



Example 3 - Inverse Fire Localization

300 kW case using gauge heat flux value at 300 s



Conclusions

A Bayesian inference framework was applied to various fire scenarios (in both univariate and multivariate cases) to determine fire size, fire location, and material properties. This approach can be used to quantify our degree of certainty (or degree of belief) in input parameters or scenarios.

These inversion techniques have applications towards: model validation exercises, risk analyses, probabilistic risk assessments, fire and arson investigations, and reconstructions of firefighter line-of-duty deaths (LODDs) and injuries.

Acknowledgements



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Questions?

- Questions and discussion



koverholt.com

code.google.com/p/bayes-fire



Fire Research Group

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