Conception optimisée du bâtiment par la SIMUlation et le Retour d'EXpérience, 00009 (2012)
DOI:10.1051/iesc/2012simurex00009

Can simulation results be trusted?

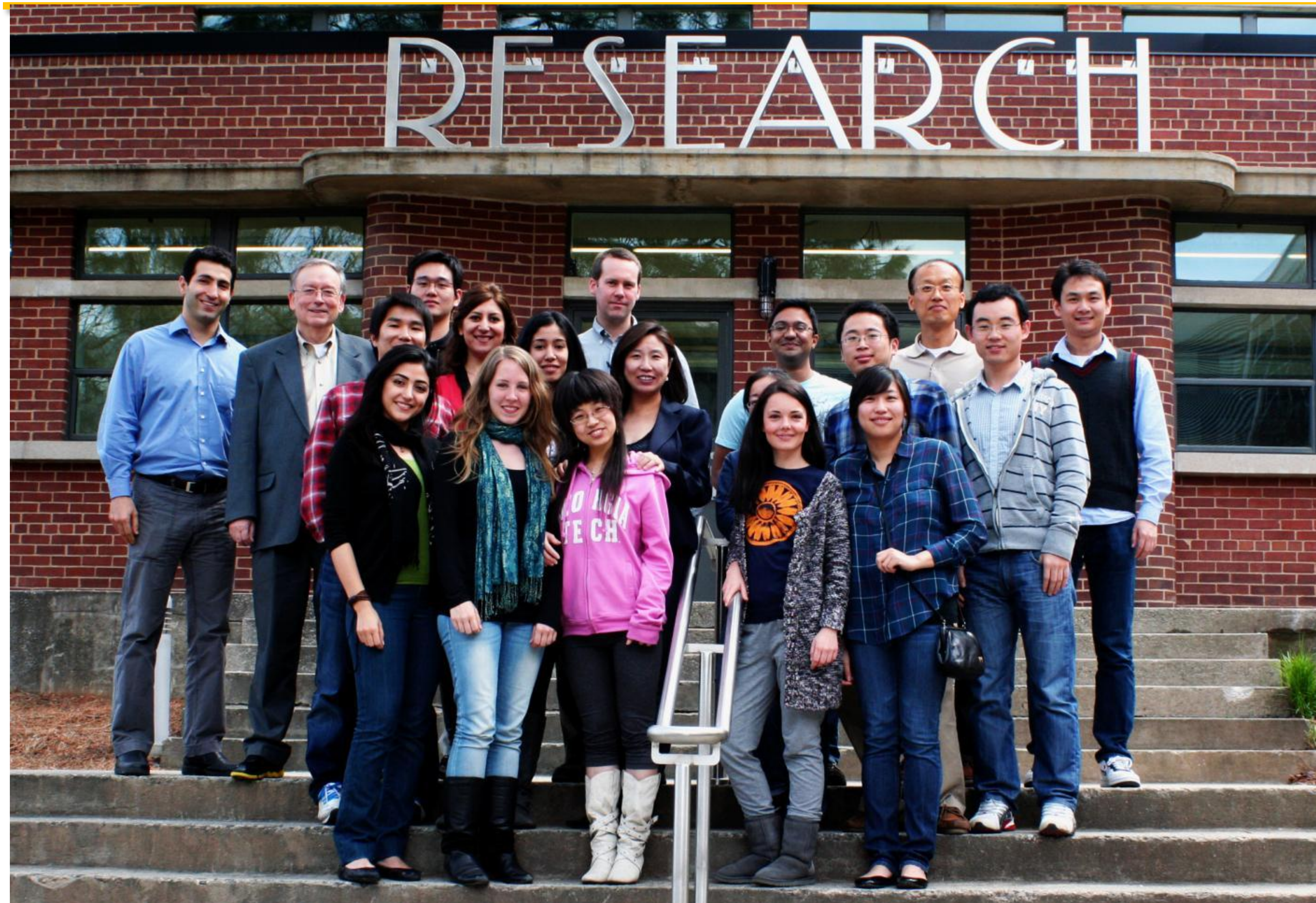
Fried Augenbroe, fried@gatech.edu
Georgia Tech

A preliminary answer

LOCIE-CNRS

Etienne and his PhD students engaged in building energy simulation

HPB Group @ Georgia Tech



Sensible questions

1. How uncertain are current simulation results?
2. How do they impact our use in practice and our decisions?
3. Can they be made transparent?
4. Can they be reduced by using higher fidelity models?
5. Can we translate them into measures of risk and adapt our decision models?

A high level view at models

1. NEED: Models need to be there for a reason

2. GOAL: Support a decision with necessary level of confidence

COROLLARY:
- Sometimes no model exists (early design support fallacy)
- Confidence needs to be transparent and symmetric (Akerlof)
- High fidelity models may be over-engineered for certain problems
  - Reduced order models are back!
  - Calibration of reduced order models sometimes the best of both worlds
  - Example: work by Yeonsook Heo on retrofit decisions in BS11 proceedings

Background

Origins of uncertainty in building simulations

- Physical parameters ← Not as easy as you think
- Model discrepancy ← “Dark Matter”
- Observation errors
- Deterioration effects
- Surprise
- Modeler’s ignorance (indifference)

Needs for uncertainty analysis

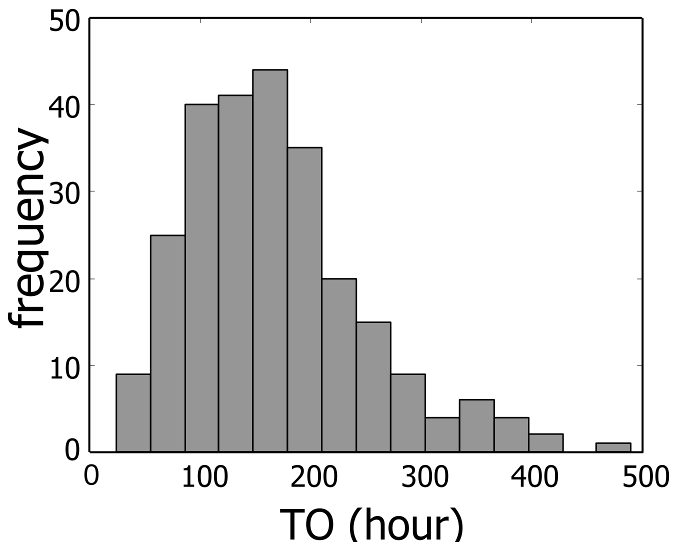
- To support risk-conscious decision making
- To explore the true variability and sensitivity of outcomes

Early work: de Wit (TU Delft), McDonald (ESRU)

Technique:

- Uncertainty Quantification (Underdeveloped)
- Monte Carlo Sampling
- Sensitivity Analysis, Parameter Ranking
- Screening (dominant parameters)

Outcome:



Traditional outcome:

Based on design idealization
TO = 143.5 (lucky shot)

Work over last decade

Tremendous progress in propagation techniques:

- Spectral methods
- Intrusive methods

Statistics society: SAMSI workshops

Last week SIAM-UQ conference

For buildings:

- Raising awareness: OK (from 0 to 30% in BS proc.)
- Rigorous UQ: little progress
- UQ framework: non existent
- Penetration in practice: zero

NSF EFRI-SEED Award 1038248

Risk conscious design and retrofit of buildings for low energy

2 M$, 8/2010- 08/2014

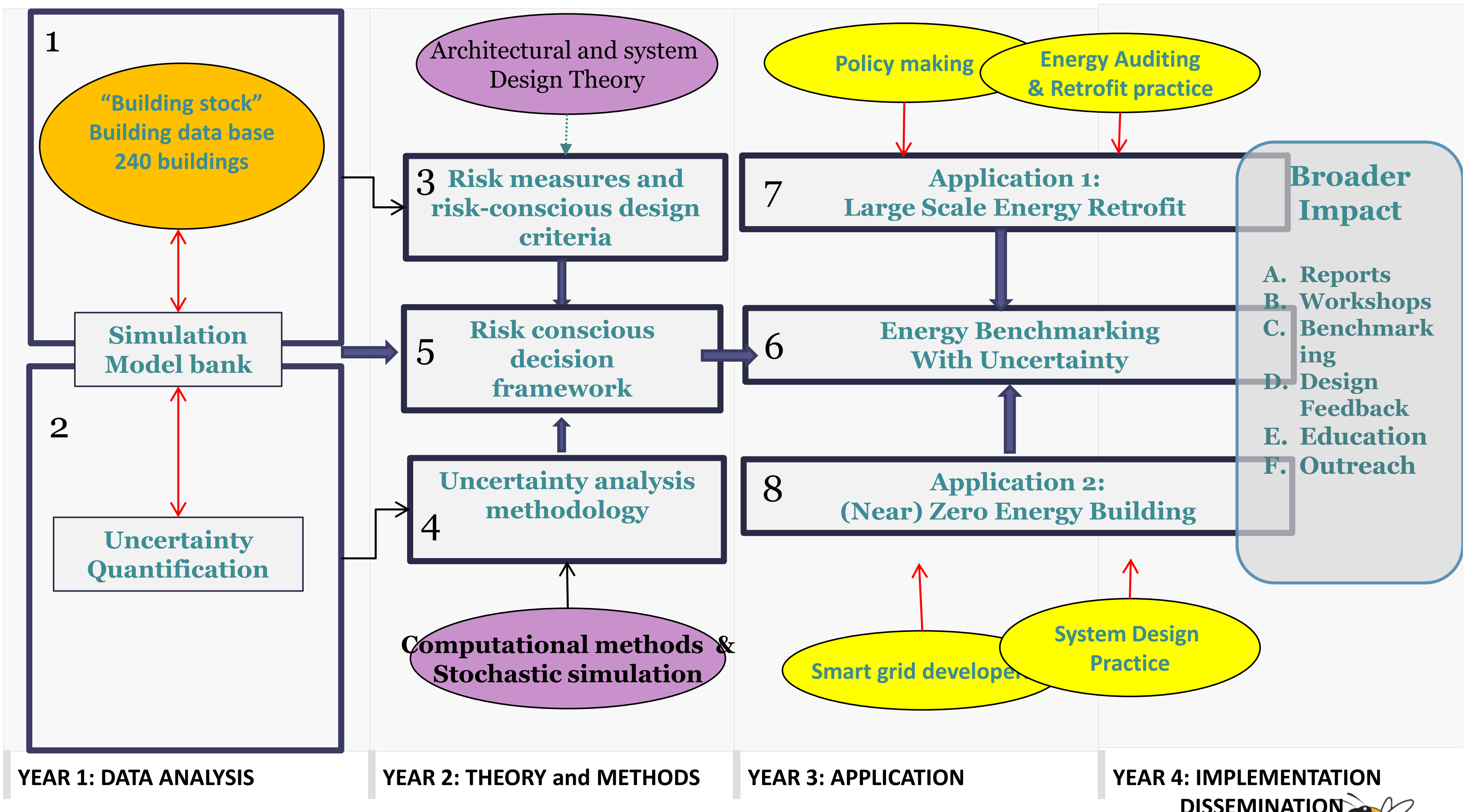
Godfried Augenbroe (PI)
Jeff Wu
Chris Paredis
John Peponis
Ali Malkawi

Georgia Tech College of Architecture

Overarching objectives

1. The scientific community will acknowledge that current tools are inadequate vis-à-vis the complexity, unpredictability and "messiness" of buildings
2. Risk-conscious design methods will lead to systematically better performing buildings and large energy savings
3. Uncertainties at the macro, meso and micro scales of influence will be better understood and quantified
4. Picking winners and losers among proposed building energy solutions will be enhanced by comprehensive risk analyses
5. Benchmarking building energy technologies at the whole building scale under uncertainty will become routine in design evolution
6. The introduction of risk-conscious design measures will forever change our thinking about how we integrate energy systems in buildings
7. New fields of building science will emerge that study the correlation between architectural and system features, and underperformance risks

Project Plan



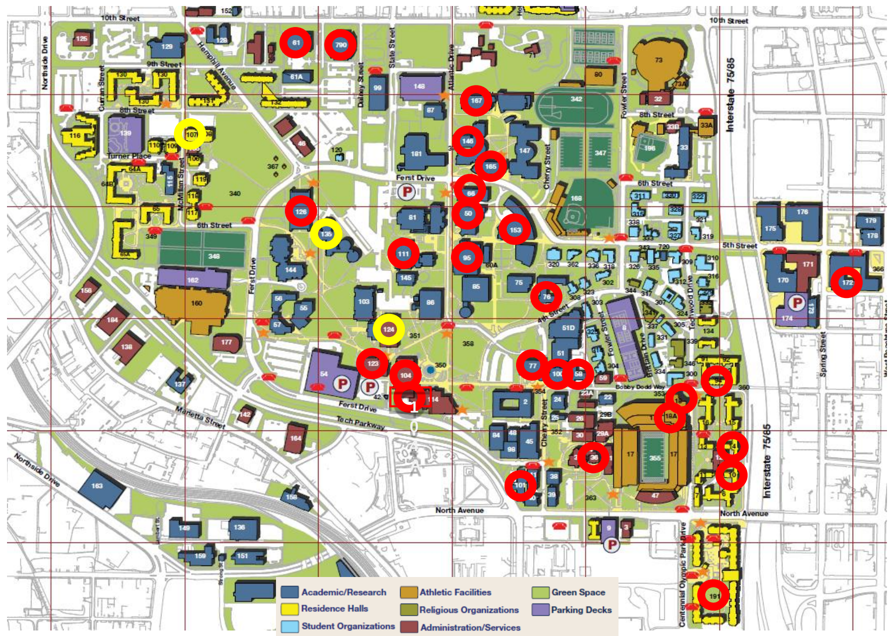
Immediate targets

- Acknowledge the inadequacy of current tools given the complexity, unpredictability and “messiness” of buildings
- Pick winners and losers among proposed building energy solutions by comprehensive risk analyses

Applications:

- (Near) Zero energy buildings
- Large scale energy retrofit

Task 1: Model base



122 UPenn and 30 Georgia Tech buildings:

- Modeled at 4 levels of fidelity
- GT buildings monitoring in-use data

Augmented by DOE database of prototype buildings

Multi fidelity model base

GT_2: Models

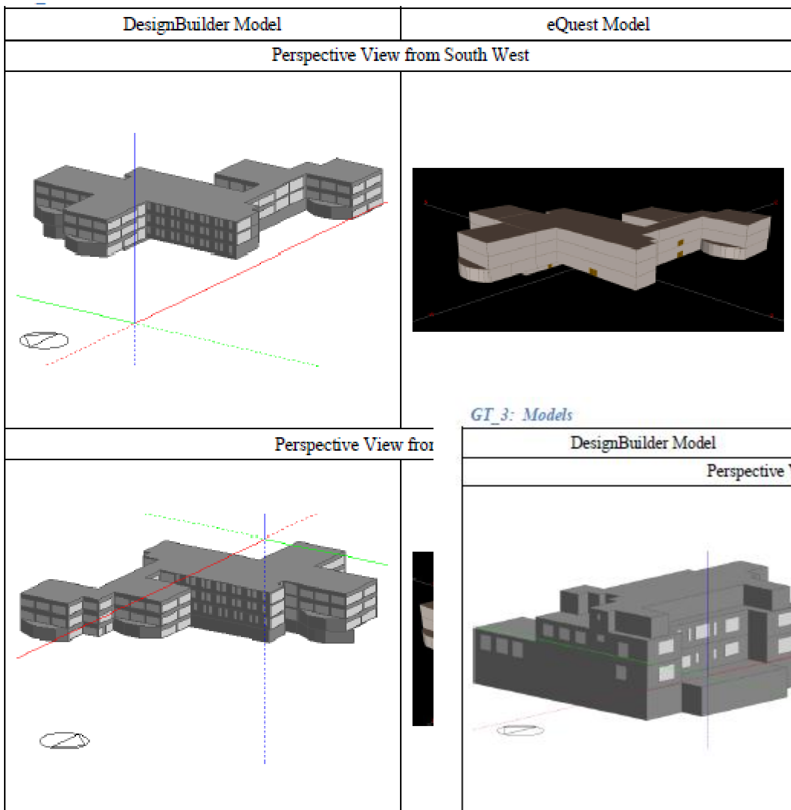


Table 4 GT_2 Building Simulation Modeling Screen Capture

GT_3: Models

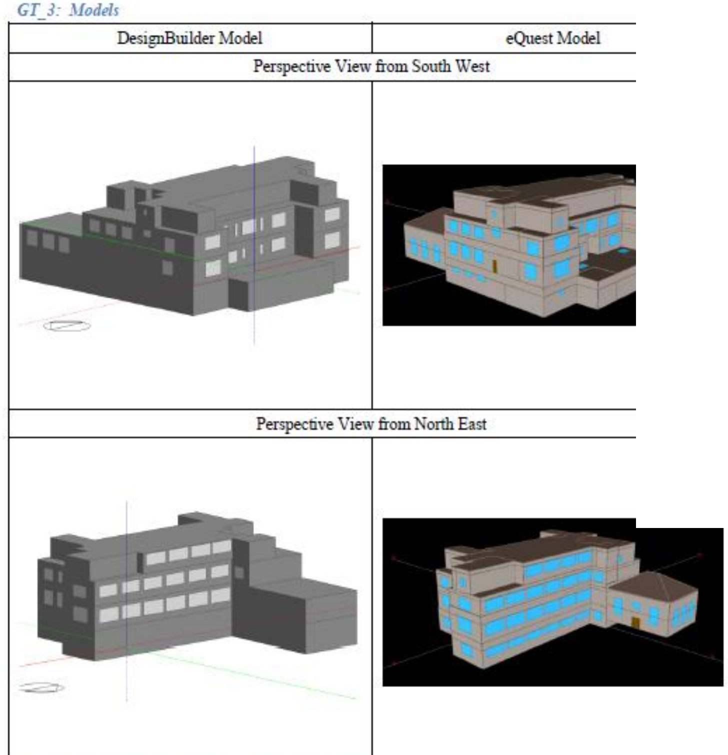
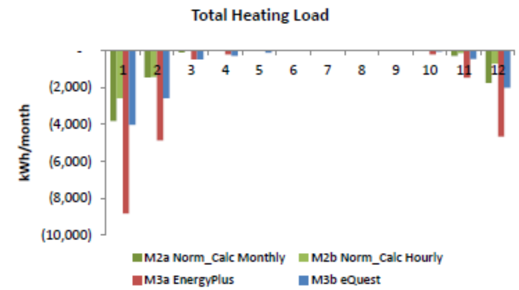
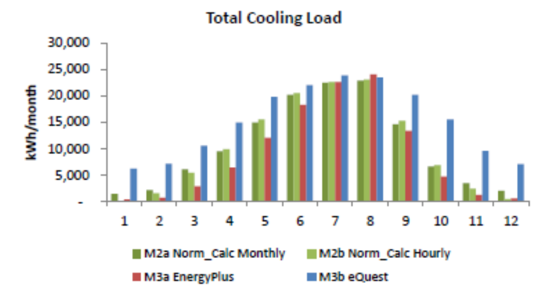
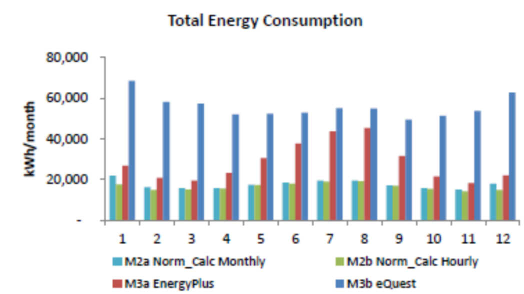


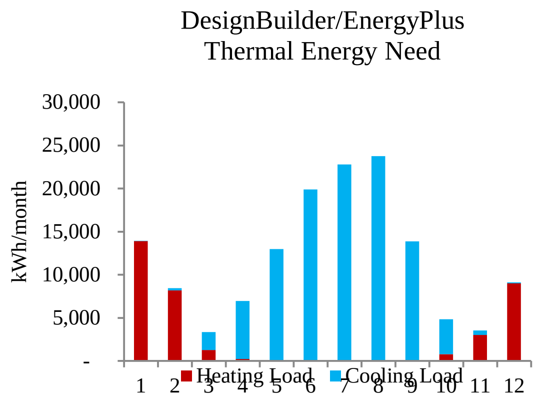
Table 5 GT_3 Building Simulation Modeling Screen Capture

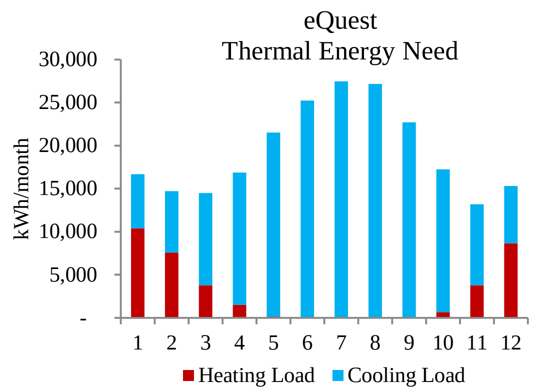


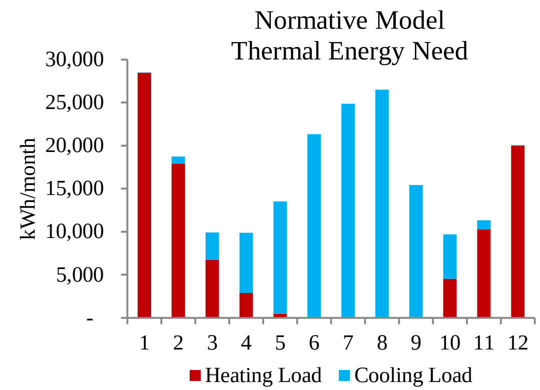


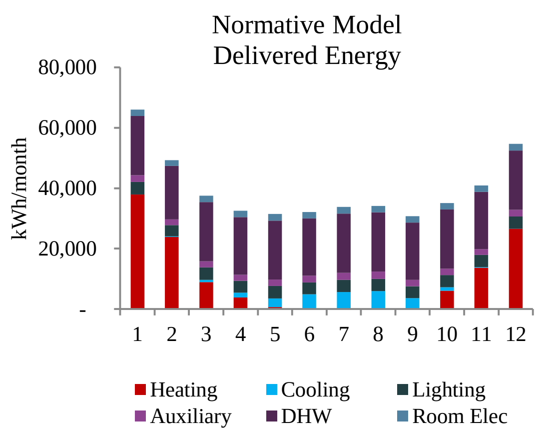


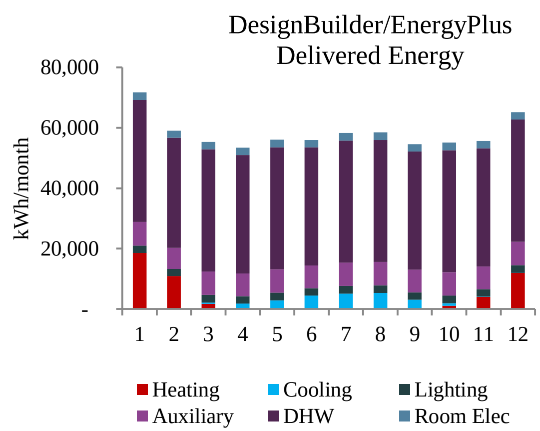
Task 1: Simulation Results

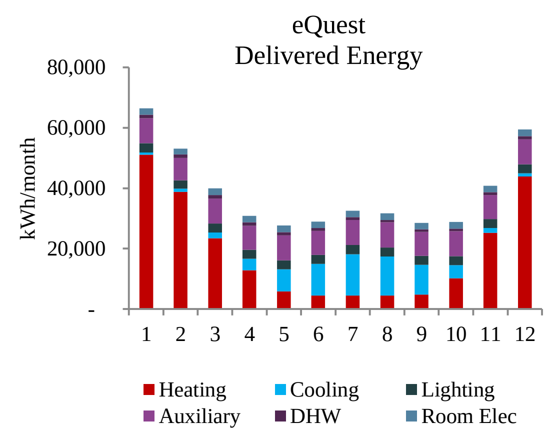






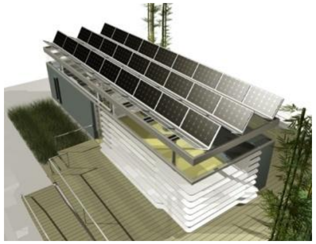


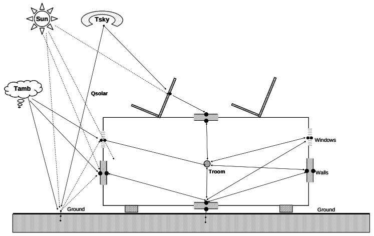


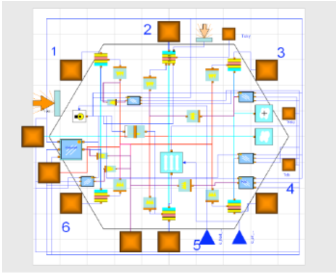


Building energy modeling

- State of the art
  - Idealized Model (design spec)
    Large level of indifference and/or ignorance
    Suspected model discrepancy, but where?
  - Space discretization: finite element model
    DAE system $M\, dx/dt + S(x, u)\, x = f(u)$
    State variables x
    Control variables: u
  - Computer code for numerical time integration and post-processing of state variables







Representation→ Model → Computational structure

Use of model base

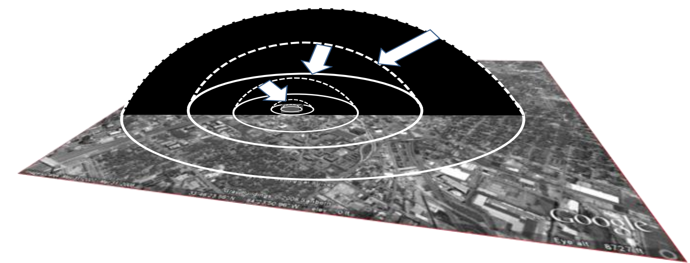
1. Basis of Uncertainty Analysis in 2nd year (Task 4, 5, 6)
   - Step 1: UQ
   - Step 2: model uncertainty
2. Estimate model discrepancy for each model
3. Test-cases for UA methods for different measures (Task 4)
4. Regression into statistical black box models (ongoing)
   - UPenn buildings used for development
   - GT buildings used as test set
   - Follows in tradition of Phil Steadman
5. Discovery of extraneous factors in consumed energy prediction
   - Which non-energy factors make buildings underperform?

6 Creation of generic effect categories of uncertainties for design and retrofit scenarios

Task 2: UQ

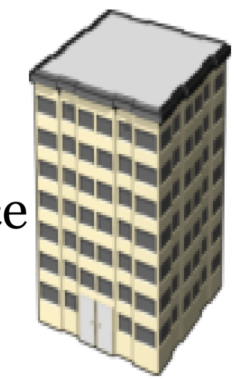
Step 1: UQ at meso-scale level

- 8 microclimate pars



Step 2: UQ at the material systems level

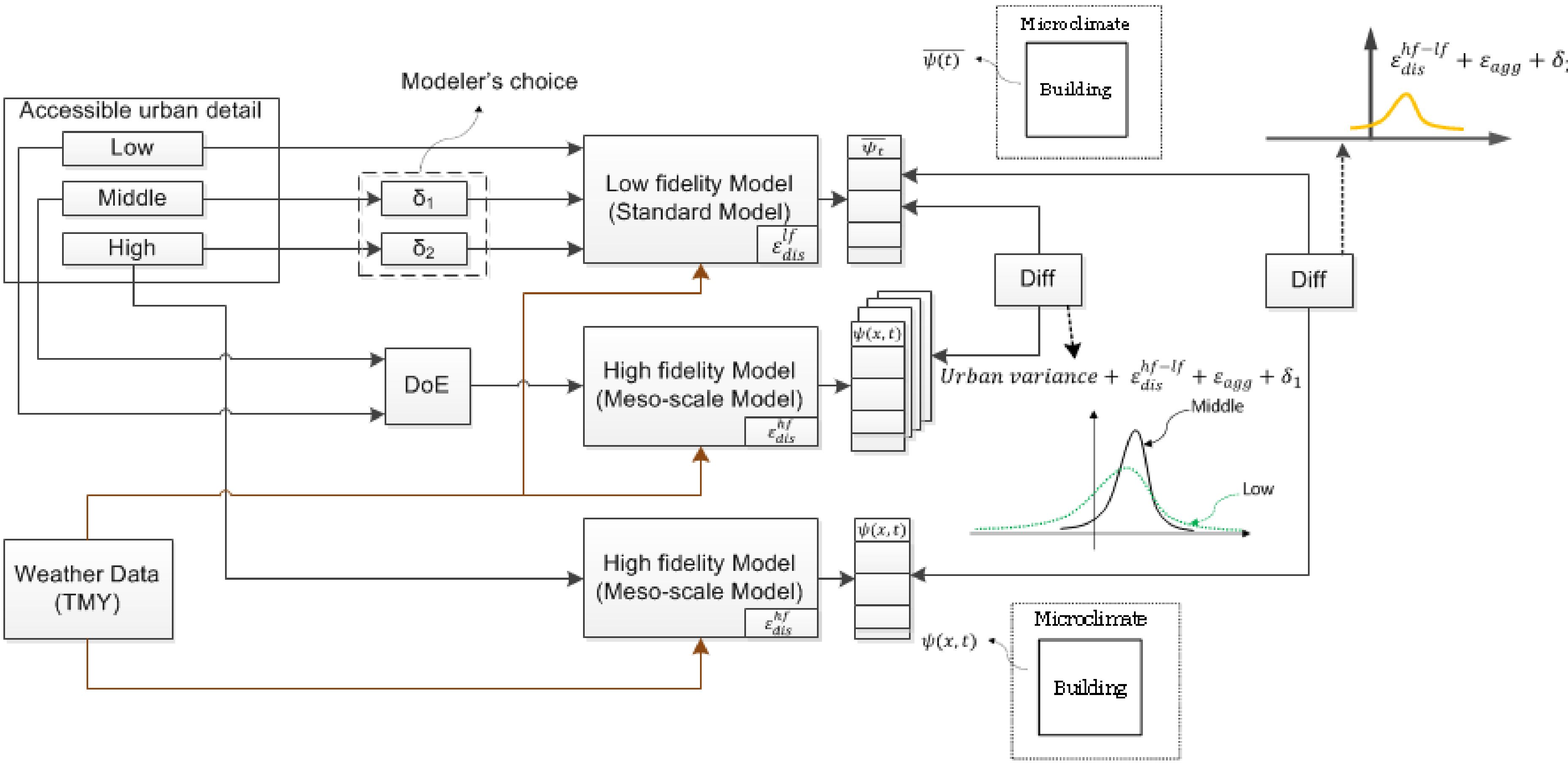
- Mostly physical parameters and modeling assumptions
- System module with uncertainty in performance curves
- Approx 80 pars



Step 3: UQ at the people and processes level

- 5 parameters based on occupancy analytics
- Occupant behavior (stochastic processes)
- Fundamental discussion: scenario or uncertainty?

UQ Framework



Challenges and purpose of UQ:

- Module inadequacy in models
- Insufficient knowledge (e.g., early stage)

Major purpose of our UQ outcomes:

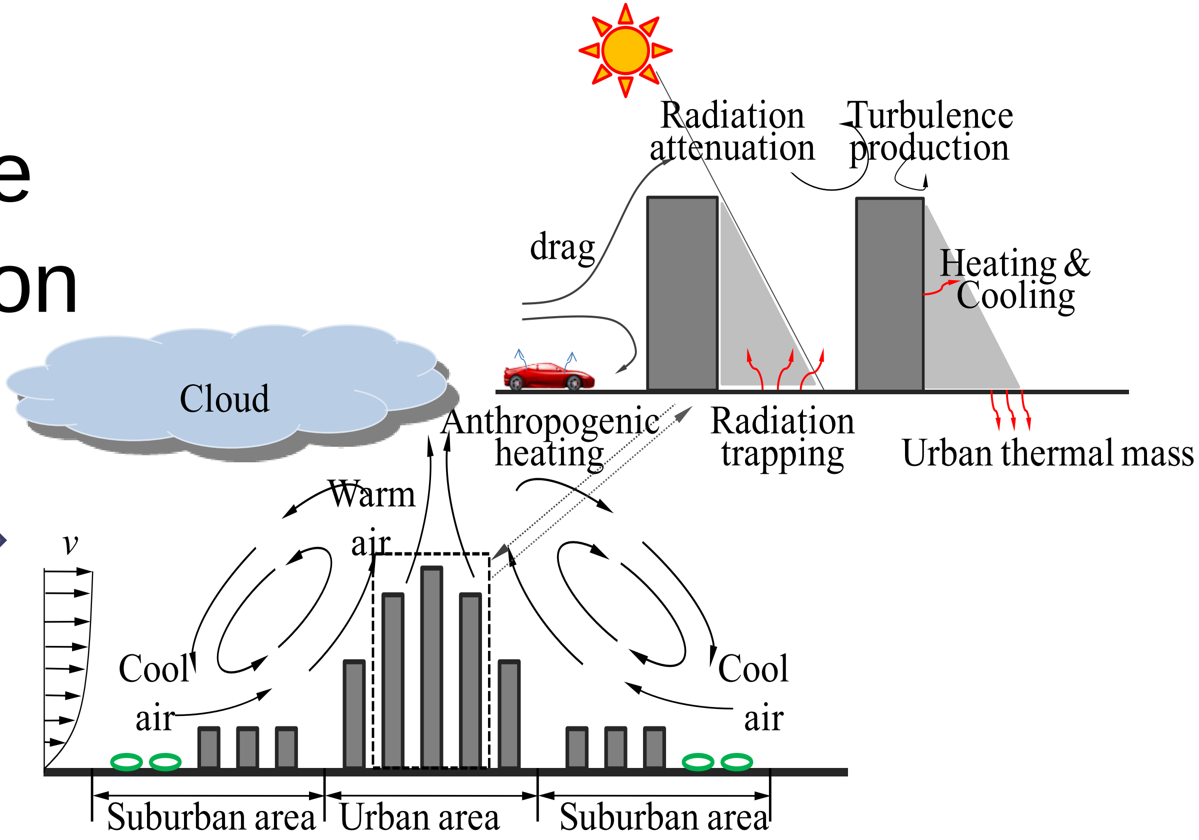
- to propagate uncertainty through the model.
- to rank the impacts of all parameters
- to rank the impacts of model inadequacy;

UQ of Building Microclimates

Microclimate variables:

- Wind speed
- Temperature
- Wind pressure
- Solar irradiation

Meteorological Stations



High level of model sophistication + High knowledge about the urban environments (one particular case)

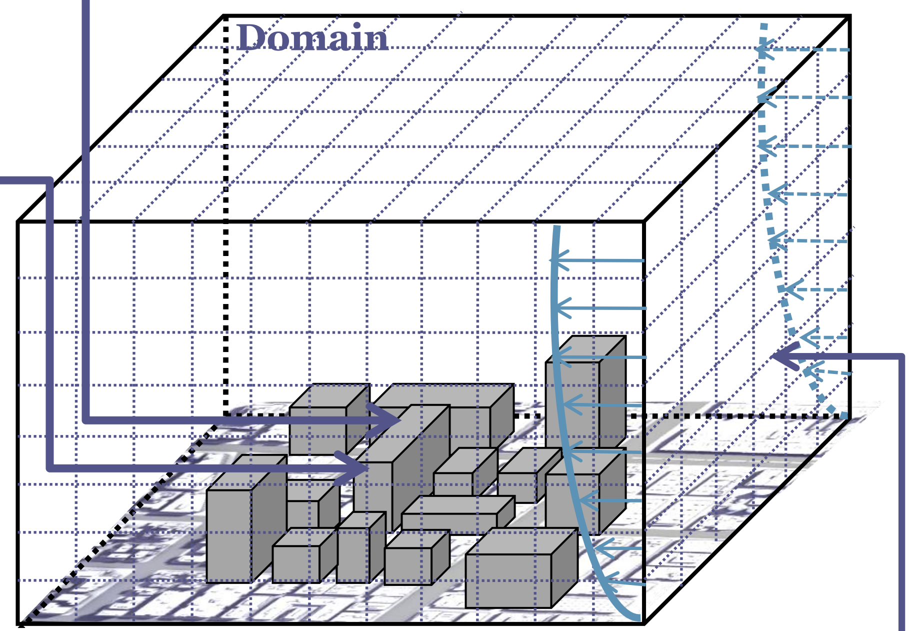
Inputs

Urban Geometry:
Coordinates for urban surface geometry
- 8 coordinates for a building

Thermal Properties:
1. Emissivity
2. Solar reflectance
3. Heat transfer coefficient
- One set of properties for each surface

Boundary Conditions:
1. Temperature Profile
2. Turbulent energy profile
3. Wind Profile
4. Solar Radiation

MESO Model



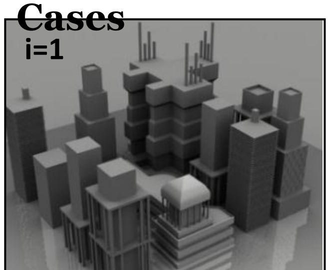
High level of model sophistication

Terrain Description
Flat, open country
Rough, wooded country
Towns and cities
Ocean
Urban, industrial, forest

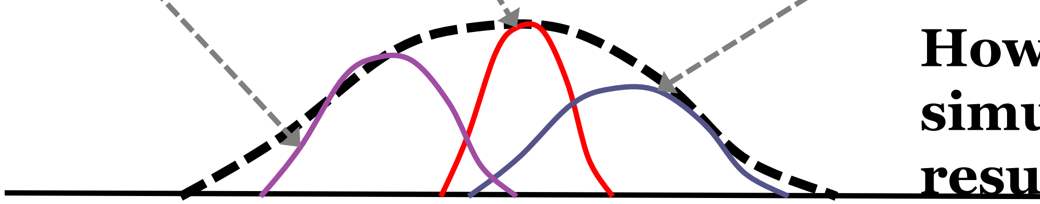
Scenarios

Uncertainty in model parameters

A number of Particular Cases



...



How to aggregate simulation results ?

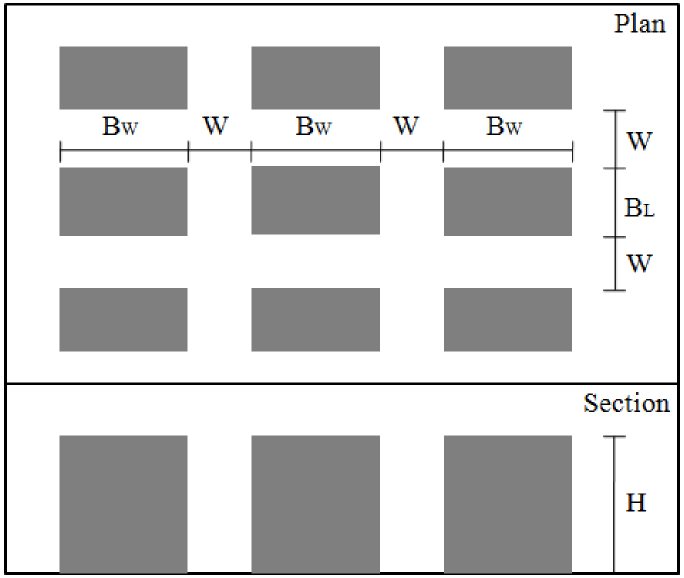
$$V_z = F_i(\underline{M})$$

Local Wind Speed

Standard model ← ASHRAE Fundamentals

$$V_z = V_{met}\left(\frac{\delta_{met}}{z_{met}}\right)^{\alpha_{met}}\left(\frac{z}{\delta}\right)^{\alpha}$$

Meso-scale model ← High Fidelity

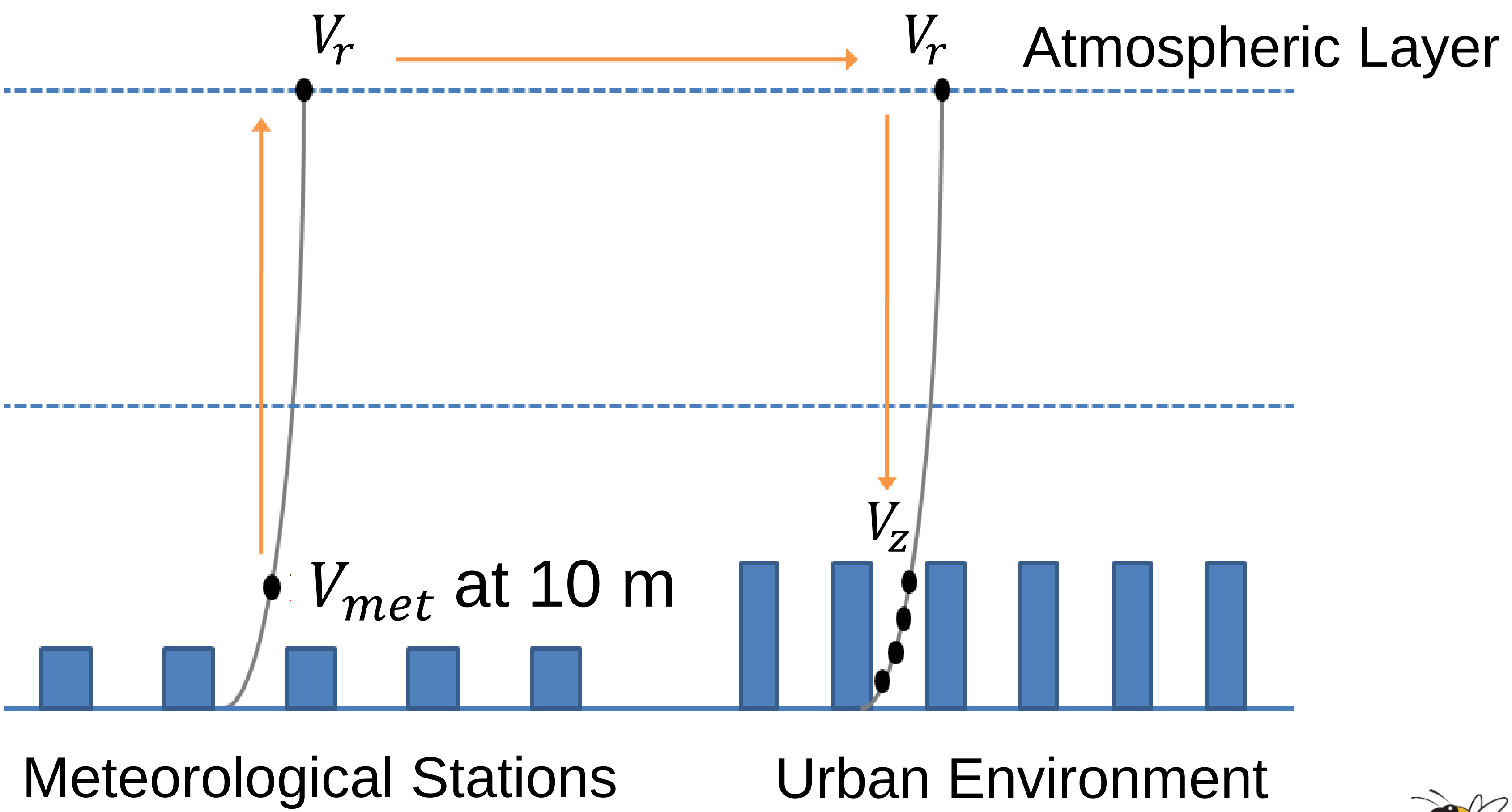


← Community Land Model

Urban parameterization scheme

Local Wind Speed

Procedures to compute local wind speeds from TMY data



Local Wind Speed

Setup for experimental designs

	H		H/W		B_L/B_W	
	min	max	min	max	min	max
Open Country	3	3	0	0.3	0.25	1.00
Urban/Suburban	99 cases				0.25	1.00
Large City centers	26 cases				0.25	1.00

Sample size using Latin Hypercube sampling

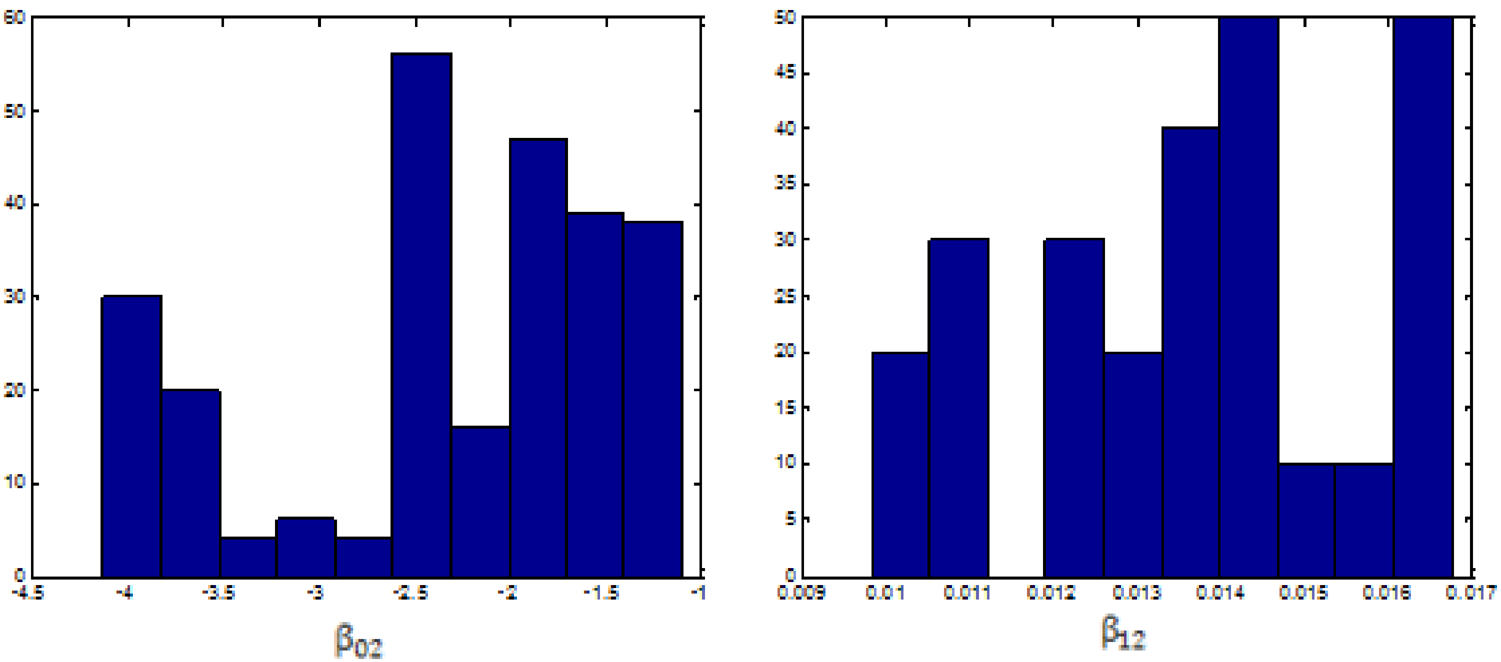
- 260 from large city centers
- 990 from urban and suburban areas
- 50 from open country
- 20 from meteorological stations

Local Wind Speed

Statistical model

$$\text{Diff} = \begin{cases} \beta_{01} + \beta_{11} z + \varepsilon & \varepsilon \sim N(0, \sigma^2) & z \leq \tau \\ \beta_{02} + \beta_{12} z + \varepsilon & \varepsilon \sim N(0, \sigma^2) & z > \tau \end{cases}$$

The R^2 for all the situations is above 0.95.



Histograms of unknown parameters

Statistical Model and Prediction

- Purpose: Model the difference in local wind speed between standard model and meso-scale model.

- The statistical model is as follows:

$$\text{Diff} = \begin{cases} \beta_{01} + \beta_{11} z + \varepsilon & \varepsilon \sim N(0, \sigma^2) & z \le \tau \\ \beta_{02} + \beta_{12} z + \varepsilon & \varepsilon \sim N(0, \sigma^2) & z > \tau \end{cases}$$

- This regression model fits the difference data very well (R^2 all above 0.95) $\Rightarrow$ good prediction accuracy.

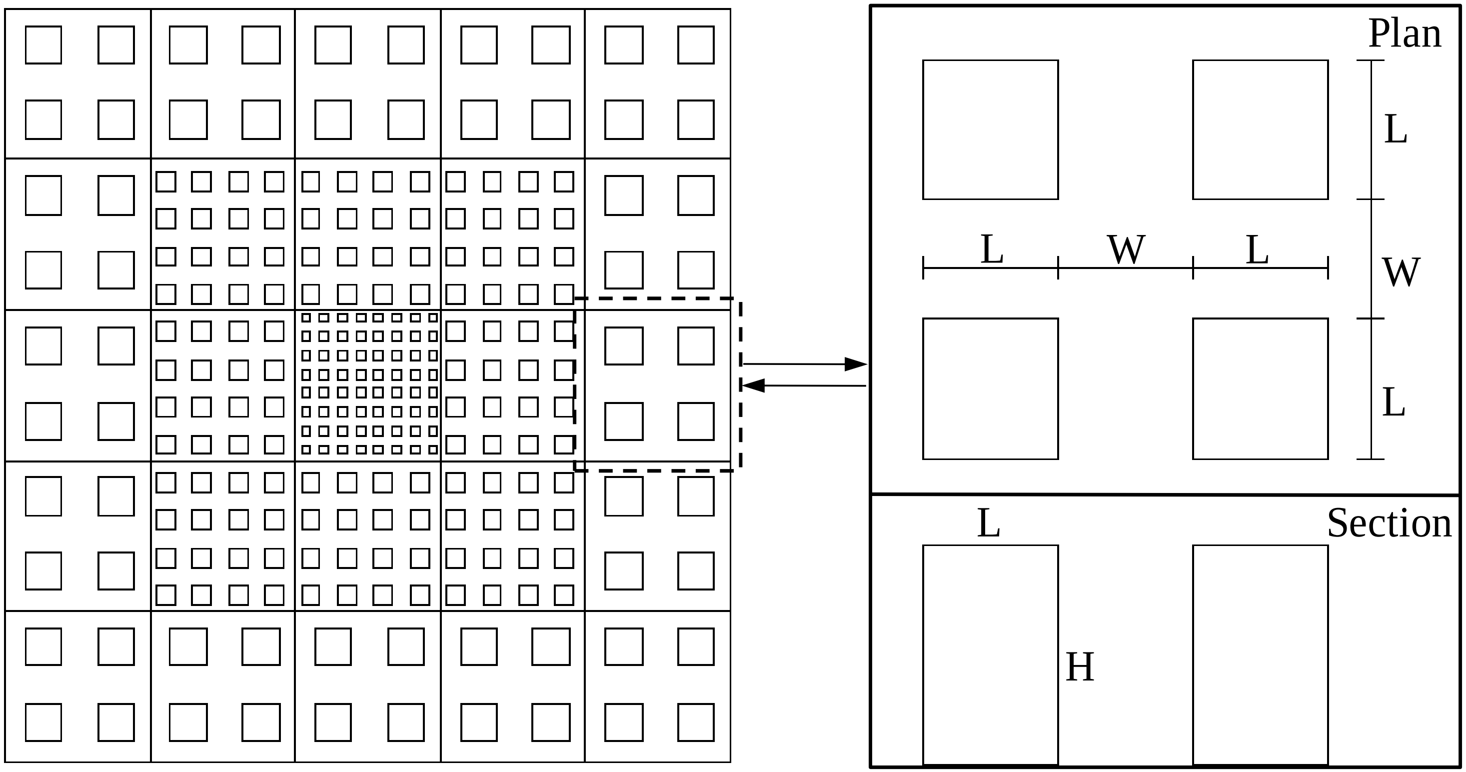
- Significance of results: gives an accurate emulator of the meso-scale model to predict the local wind speed at any height *z* in different terrains; providing UQ of prediction.

Urban Heat Island (UHI)

Standard models do not consider the UHI effect

Meso-scale model (TEB Model)

- Urban Parameterization

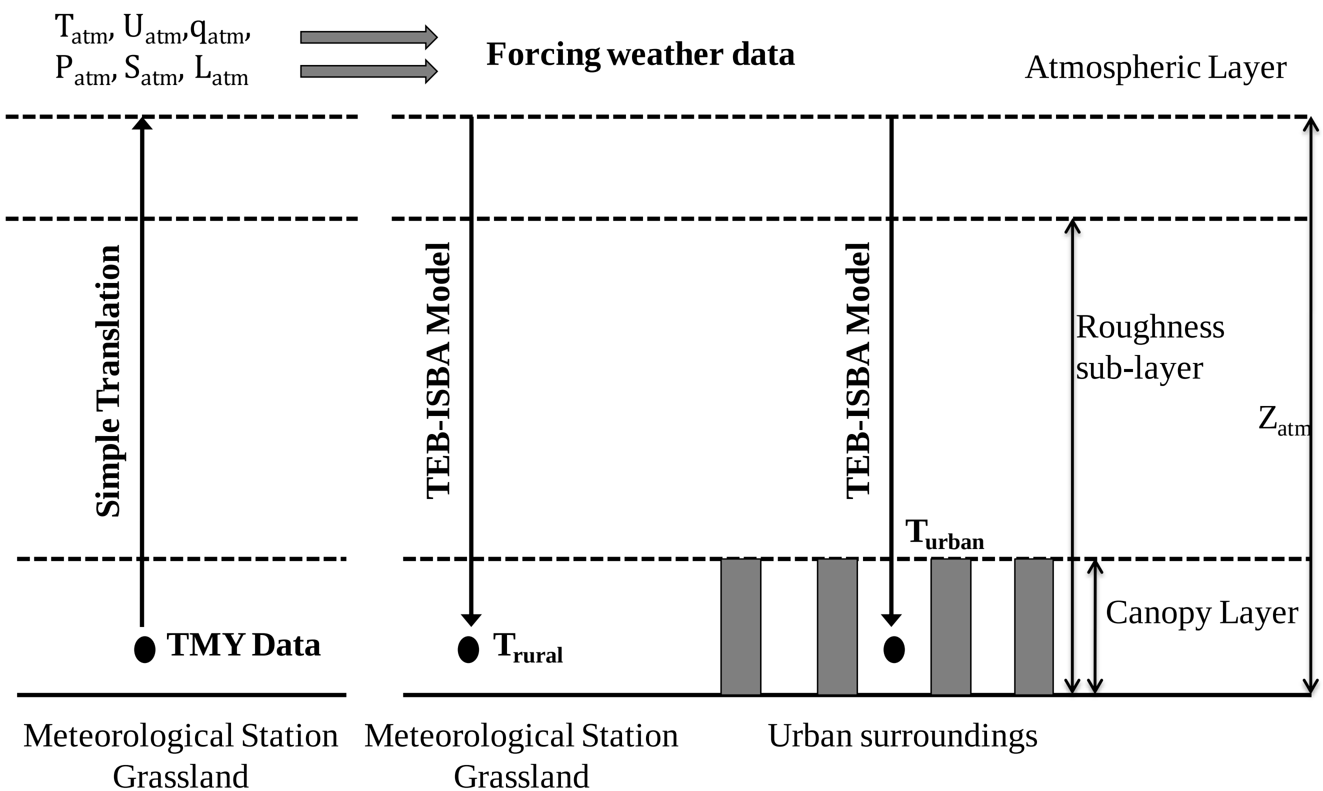


Urban Heat Island (UHI)

Standard models do not consider the UHI effect

Meso-scale model (TEB Model)

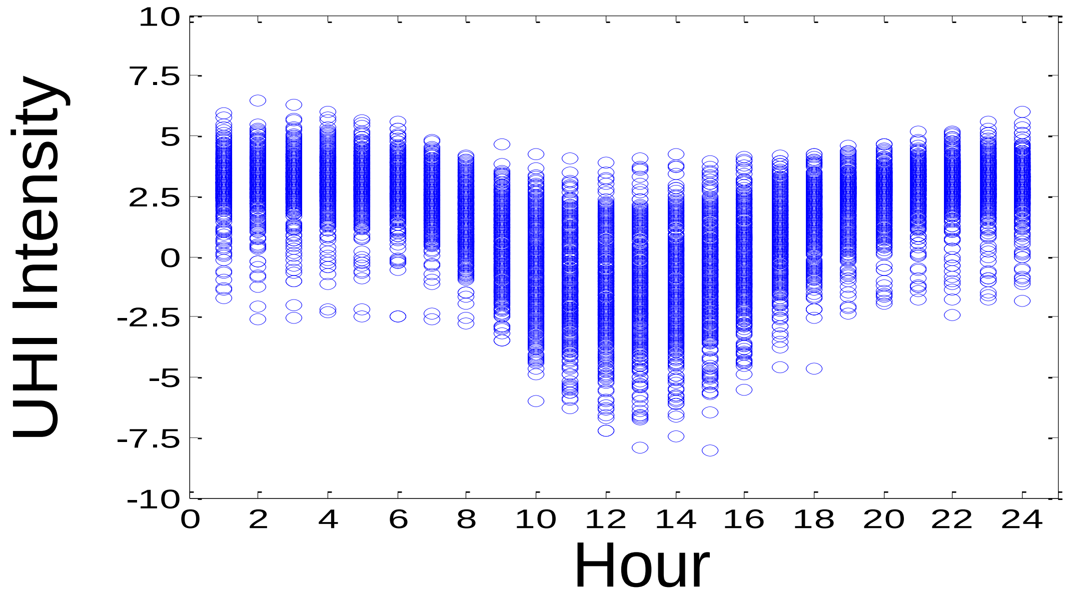
- Urban canyon concept
- Hourly air temperatures with a resolution >= 500m



Procedures to compute urban heat island effect

Urban Heat Island

Results of the TEB model



Setup for experimental designs

Terrain		α_{roof}*	α_{perv}*	H(m)	H:W
Cities	min	40%	12.5%	60	W=25m
	max	85%	71.4%	200	
Urban	min	5%	10%	99 Cases	
	max	90%	80%		

Urban Heat Island

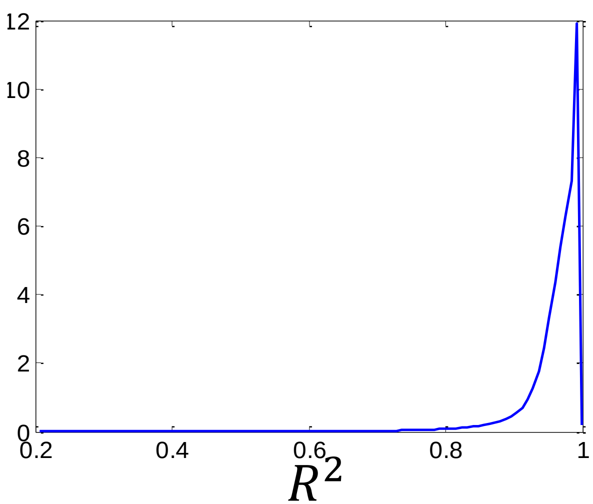
Statistical model

$$\widehat{\Delta T}_j = \hat{\beta}_{0j} + \hat{\beta}_{1j}(z_1 - \bar{z}_1) + \cdots + \hat{\beta}_{pj}(z_p - \bar{z}_p) \qquad (1)$$

$$\bar{\beta}_i^{RIDW}(\boldsymbol{w}_0) = \tilde{\alpha}_0 + \sum_{j=1}^{p} \tilde{\alpha}_j w_{0j} + \frac{\sum_{j=1}^{N} r_{ij} \left\{(\boldsymbol{w}_0 - \boldsymbol{w}_j)^T diag(\boldsymbol{\theta})(\boldsymbol{w}_0 - \boldsymbol{w}_j)\right\}^{-1}}{\sum_{j=1}^{N} \left\{(\boldsymbol{w}_0 - \boldsymbol{w}_j)^T diag(\boldsymbol{\theta})(\boldsymbol{w}_0 - \boldsymbol{w}_j)\right\}^{-1}} \qquad (2)$$

where z is urban geometric variables and w weather variables.

Model evaluation



-Linear model (Eq. (1)) fits the data very well.

-Cross validation suggests that models (1) and (2) combined give good prediction accuracy.

Wind Pressure Coefficient

Standard model: ASHRAE Fundamental

- Wind-tunnel experiments for a stand-alone building.

$$P_W = C_p \rho \frac{V_z^{\,2}}{2} \qquad C_p = 0.6 \ln \begin{pmatrix} 1.248 - 0.703 \sin\left(\frac{\theta}{2}\right) - 1.175 \sin^2(\theta) \\ + 0.131 \sin^2(2\alpha G) + 0.769 \cos\left(\frac{\theta}{2}\right) \\ + 0.07 G^2 \sin^2\left(\frac{\theta}{2}\right) + 0.717 \cos^2\left(\frac{\theta}{2}\right) \end{pmatrix}$$

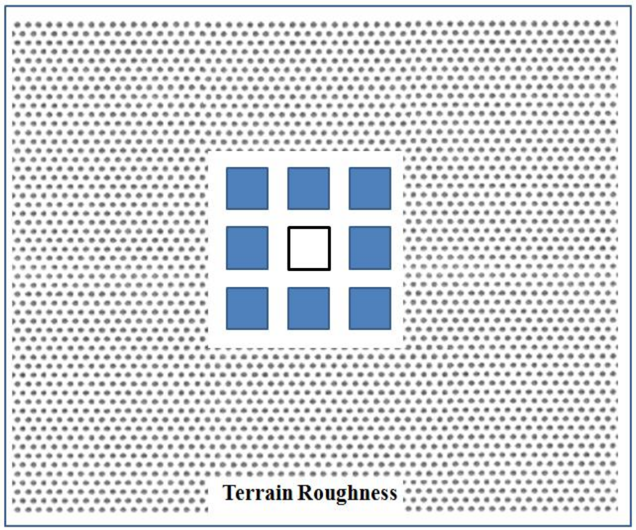
θ, wind incident angle and G the natural log of the building ratio.

High-Fidelity model (TNO Cp generator)

- Based on experimental data
- Require urban context

Wind Pressure Coefficient

Urban parameterization:



	Model parameters
Climate	Wind direction
Urban surroundings	Terrain roughness
	Obstacle basepoint
	Obstacle azimuth
	Obstacle width
	Obstacle length
	Obstacle height

Setup for experimental designs

	H		**H/W**		**H/BL**		**BW/BL**		**Roughness**	
	min	max	min	max	min	max	min	max	min	max
Low-rise Building	99 cases				1	3	1	4	0.03	7.00

Wind Pressure Coefficient

Statistical model

$$\mathbf{Diff} = \begin{cases} \boldsymbol{f_1(\theta) + \varepsilon_1} & \boldsymbol{\varepsilon_1 \sim \mathrm{N}\left(0, \sigma_1^2\right)} \quad \textbf{for } \boldsymbol{\frac{B_W}{B_L} = 1} \\ \boldsymbol{f_2(\theta) + \varepsilon_2} & \boldsymbol{\varepsilon_2 \sim \mathrm{N}\left(0, \sigma_2^2\right)} \quad \textbf{for } \boldsymbol{\frac{B_W}{B_L} = 2} \\ \boldsymbol{f_3(\theta) + \varepsilon_3} & \boldsymbol{\varepsilon_3 \sim \mathrm{N}\left(0, \sigma_3^2\right)} \quad \textbf{for } \boldsymbol{\frac{B_W}{B_L} = 4} \end{cases}$$

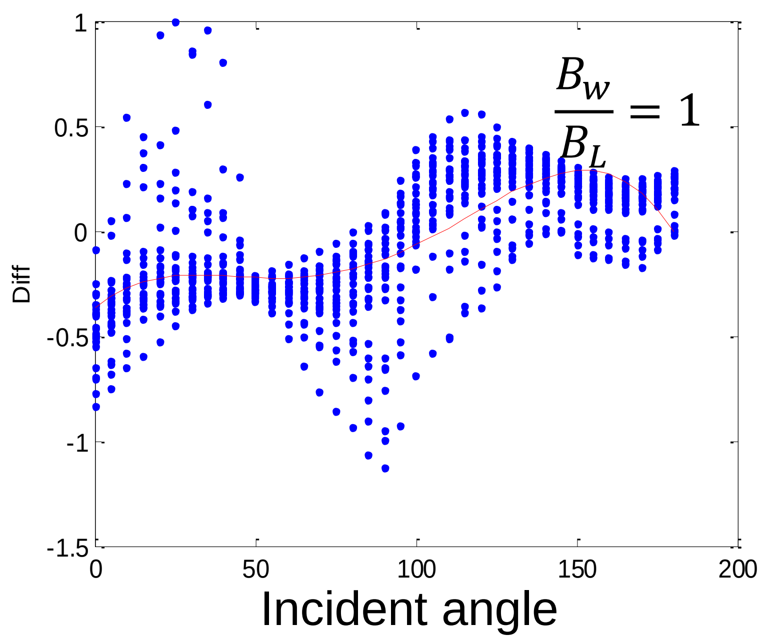
To estimate the $\boldsymbol{f_i(\theta)}$'s, we tried

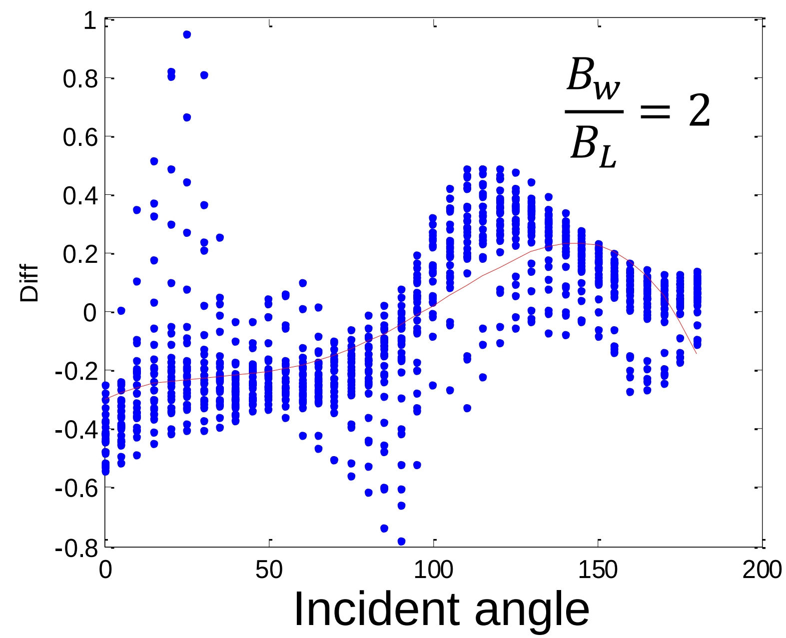
- Smoothing spline;
- Local polynomial regression;
- Stochastic kriging

Wind Pressure Coefficient

Finally, $\boldsymbol{f_i(\theta) = \beta_{0i} + \beta_{1i}\theta + \beta_{2i}\theta^2 + \beta_{3i}\theta^3 + \beta_{4i}\theta^4}$,

$$\textbf{where } \mathbf{i} = \frac{\boldsymbol{B_W}}{\boldsymbol{B_L}}$$





- $\mathrm{B_W/B_L}$ has a significant effect on $\beta's$ and $\sigma's$.
- As for the other values of $\mathrm{B_W/B_L}$, we will use a linear interpolator.

Solar Irradiation

Solar irradiation

- Direct (Standard model is accurate enough)
- Diffuse (UQ of Perez model-ongoing)
- Ground reflected

UQ of ground reflectance

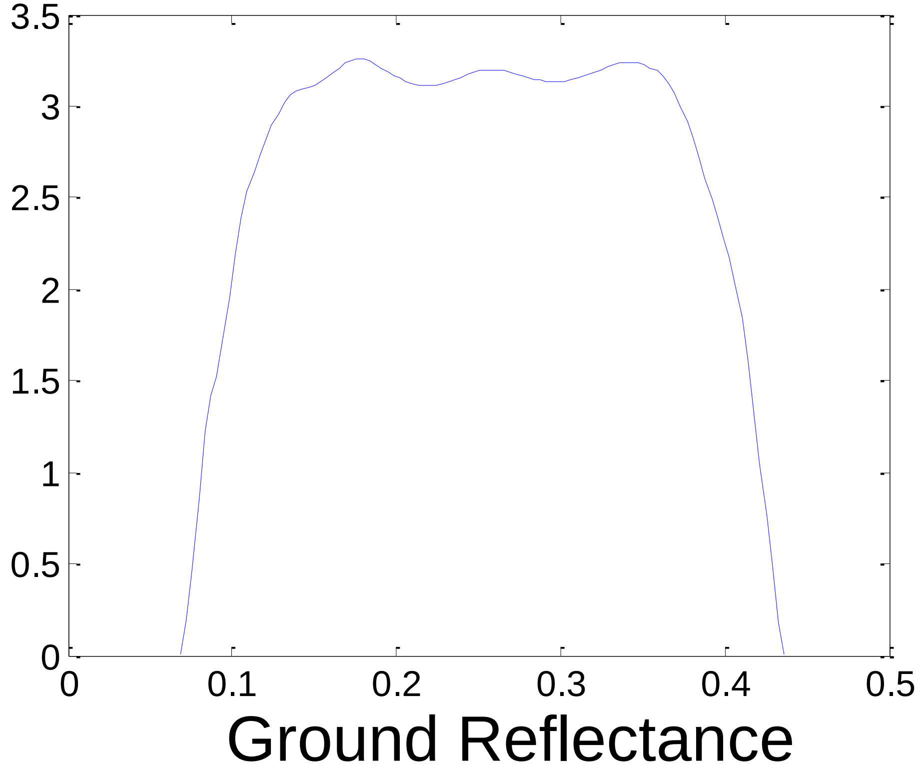
Standard : 0.2

High fidelity: $\rho_{ground} = \rho_{prvd} f_{prvd} + \rho_{imprvd}(1 - f_{prvd})$

Parameters	Large Cities		Urban/Suburban Areas		Open Country	
	Min	Max	Min	Max	Min	Max
f_{prvd}	5%	25%	5%	90%	90%	1
ρ_{imprvd}	0.072	0.44	0.072	0.44	0.072	0.44
ρ_{prvd}	0.05	0.4	0.05	0.4	0.05	0.4

Solar Radiation

Results



In the presence of snow

$\rho_{ground} \in [0.16, 0.49]$ based on literature review.

Outcomes first year

- UQ:
  - Rigorous UQ of multi scale parameters
  - Putting the built environment on the map of UQ
- Unique multi fidelity building model base to run uncertainty tests across discipline
- Identification and verification of low fidelity models as viable alternatives for certain applications; several PhD theses at Georgia Tech deal with this:
  - Retrofit decision making under uncertainty(PhD thesis)
  - Campus energy topology modeling (PhD thesis)
  - Large scale building stock modeling with uncertainty (PhD thesis)

Proceedings of Building Simulation 2011:
12th Conference of International Building Performance Simulation Association, Sydney, 14-16 November.

AGENT-BASED MODELING OF COMMERCIAL BUILDING STOCKS FOR POLICY SUPPORT

Fei Zhao[1], Ignacio J. Martinez-Moyano[2, 3], and Godfried Augenbroe[1]
[1]Georgia Institute of Technology, Atlanta, GA, USA
[2]Argonne National Laboratory, Argonne, IL, USA
[3]The University of Chicago, Computation Institute, Chicago, IL, USA

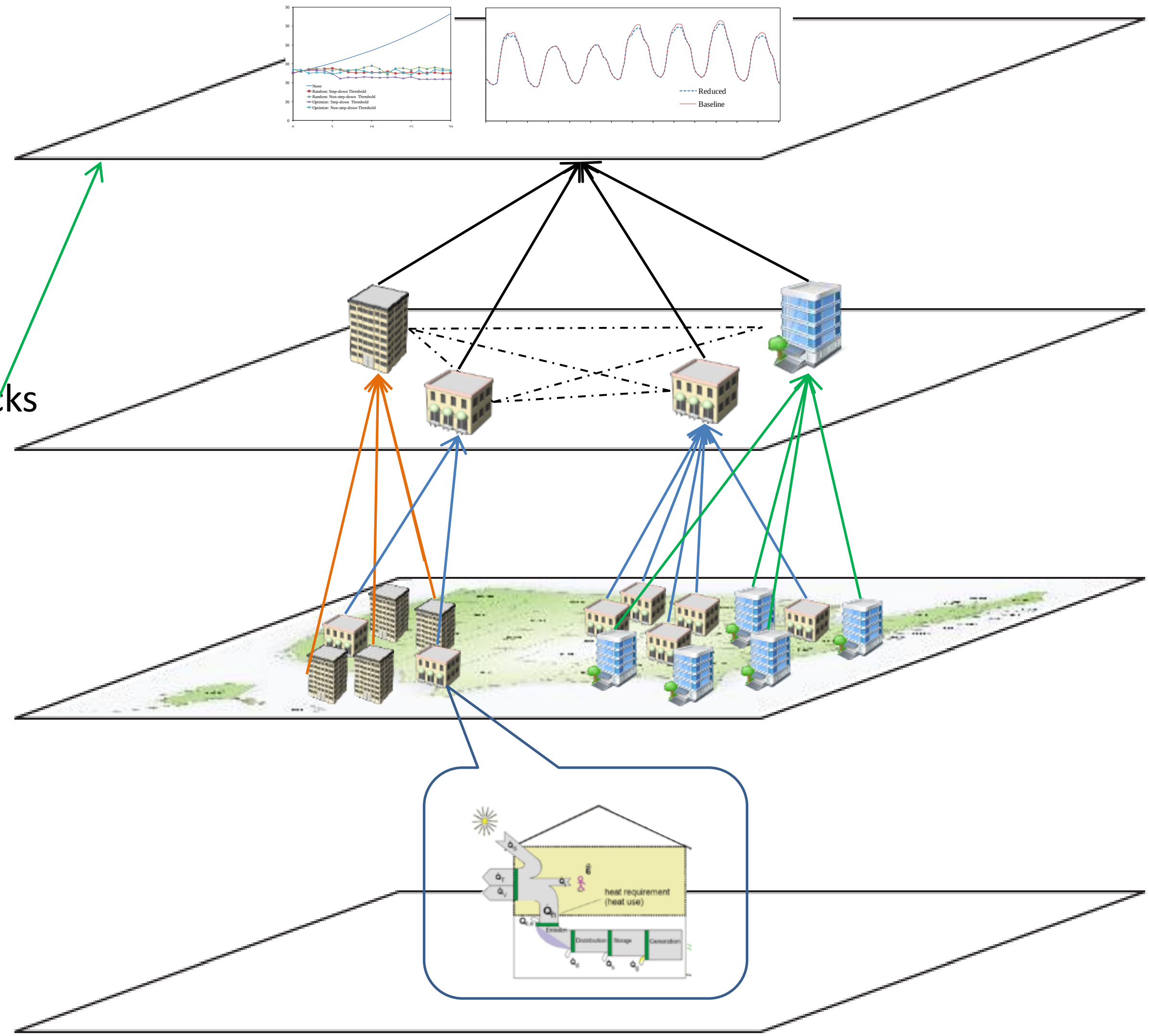
PhD thesis: Modeling Commercial Building Clusters: Building Energy Simulation Beyond the Single-building Level

Impact Level:
Aggregated Indices

Agent Level:
Aggregated Building Stocks

Building Level:
Individual Buildings

Component Level:
Building Systems



Building Simulation 2009

Eleventh International IBPSA Conference
Glasgow, Scotland
July 27-30, 2009

RIGHT SIZING AN OFF-GRID SOLAR HOUSE

Huafen Hu[1], Godfried Augenbroe[1]

[1]College of Architecture, Georgia Institute of Technology
Atlanta, GA, 30332

Figure 2 A front view of the GT solar house

Performance measure	Description	Typical design criterion	Risk based performance measure	Risk conscious design criterion
U	% of time that power service is not available	$U \leq 1\%$ for critical loads	$\text{Risk}(U) = \Pr(U > 1\%)$	$\text{Risk}(U) \leq 10\%$
$\text{Percentage}T_c$	% of exceeding hours of thermal comfort range	$\text{Percentage}T_c \leq 10\%$	$\text{Risk}(T_c) = \Pr(\text{Percentage}T_c > 10\%)$	$\text{Risk}(T_c) \leq 10\%$
$\text{Percentage}T_e$	% exceeding hours of extreme temp range	$\text{Percentage}T_e \leq 1.5\%$	$\text{Risk}(T_e) = \Pr(\text{Percentage}T_e > 1.5\%)$	$\text{Risk}(T_e) \leq 10\%$
R	% energy reduction compared to benchmar	$R \geq 10\%$ for new buildings (LEED)	$\text{Risk}(R) = \Pr(R < 10\%)$	$\text{Risk}(R) \leq 5\%$
E	Annual electric consumption per area	$E \leq 6.0$kWh/sq.ft.	$\text{Risk}(E) = \Pr(E > 6.0)$	$\text{Risk}(E) \leq 5\%$
PY	Payback year of an investment	PY < 15	Risk (PY) = Pr (PY > 20)	Risk (PY) <10%

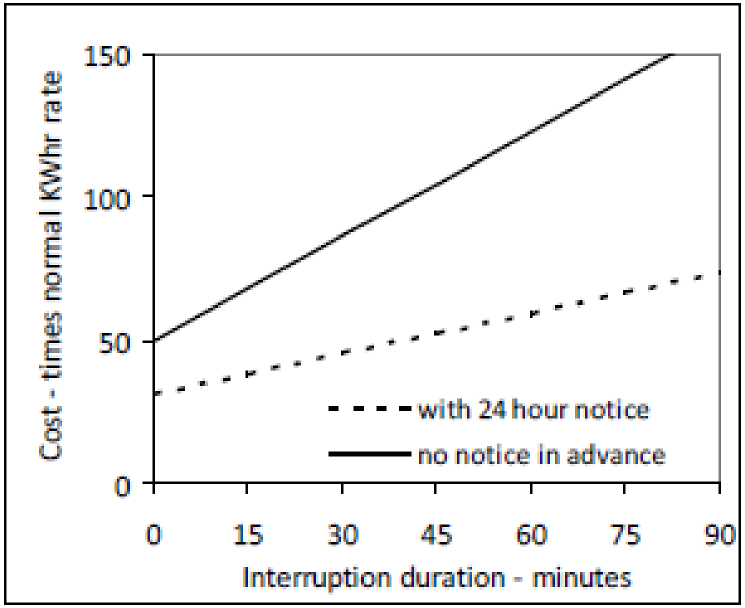


Figure 6 The reduced cost impact if power interruption is noticed to customers 24 hours ahead (Willis, Welch et al. 2001)

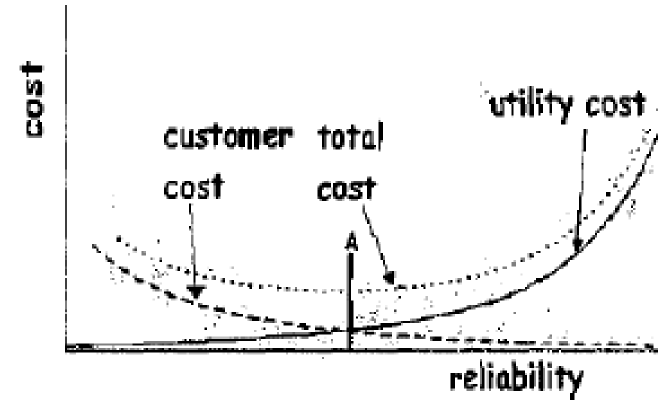


Figure 1 The concept of value-based planning (Kaur, Singh et al. 2004)

Proceedings of Building Simulation 2011:
12th Conference of International Building Performance Simulation Association, Sydney, 14-16 November.

RISK ANALYSIS OF ENERGY-EFFICIENCY PROJECTS BASED ON BAYESIAN CALIBRATION OF BUILDING ENERGY MODELS

Yeonsook Heo[1,2], Godfried Augenbroe[1], and Ruchi Choudhary[3]
[1]College of Architecture, Georgia Institute of Technology, Atlanta, USA
[2]Decision and Information Sciences, Argonne National Laboratory, Argonne, USA
[3]Engineering Department, University of Cambridge, Cambridge, UK

Bayesian Calibration

- Bayesian approach updates our prior beliefs on true values of uncertain parameters θ in a computer model given observations

Normative Model →

Monthly utility data →

Prior density functions for uncertain parameters →

Bayesian Calibration

Bayes' theorem:

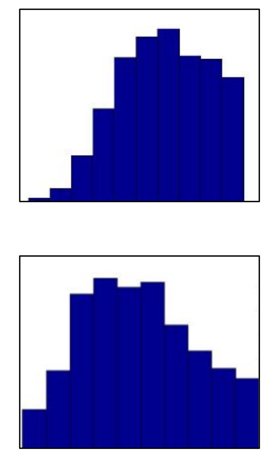
$$p(\theta \mid y) \propto p(\theta) \times p(y \mid \theta)$$

Kennedy and O'Hagan:

$$y(x_i) = \eta(x_i, \theta) + \delta(x_i) + \varepsilon(x_i)$$

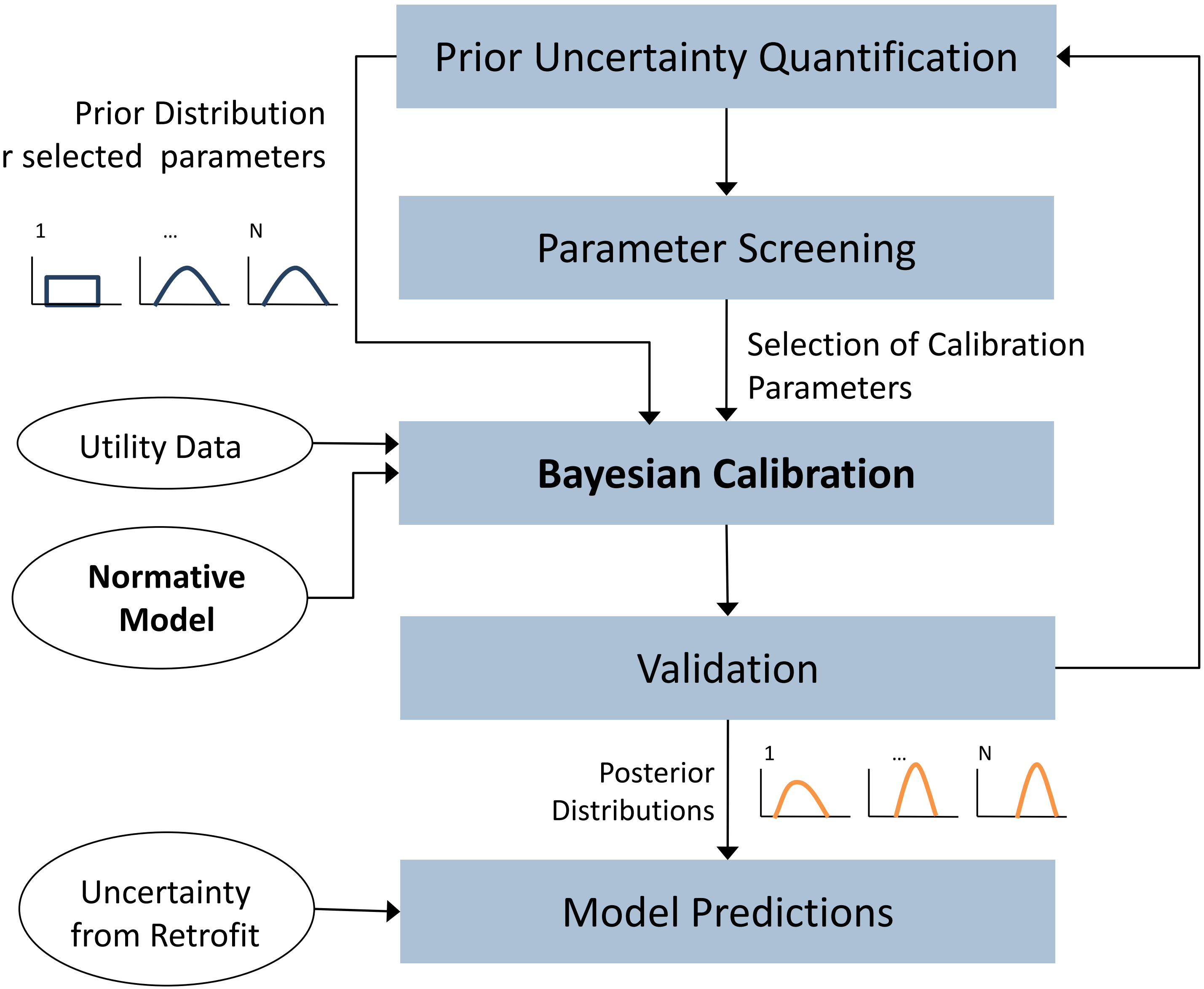
Numeric method:
Markov Chain Monte Carlo

→ Posterior Distributions

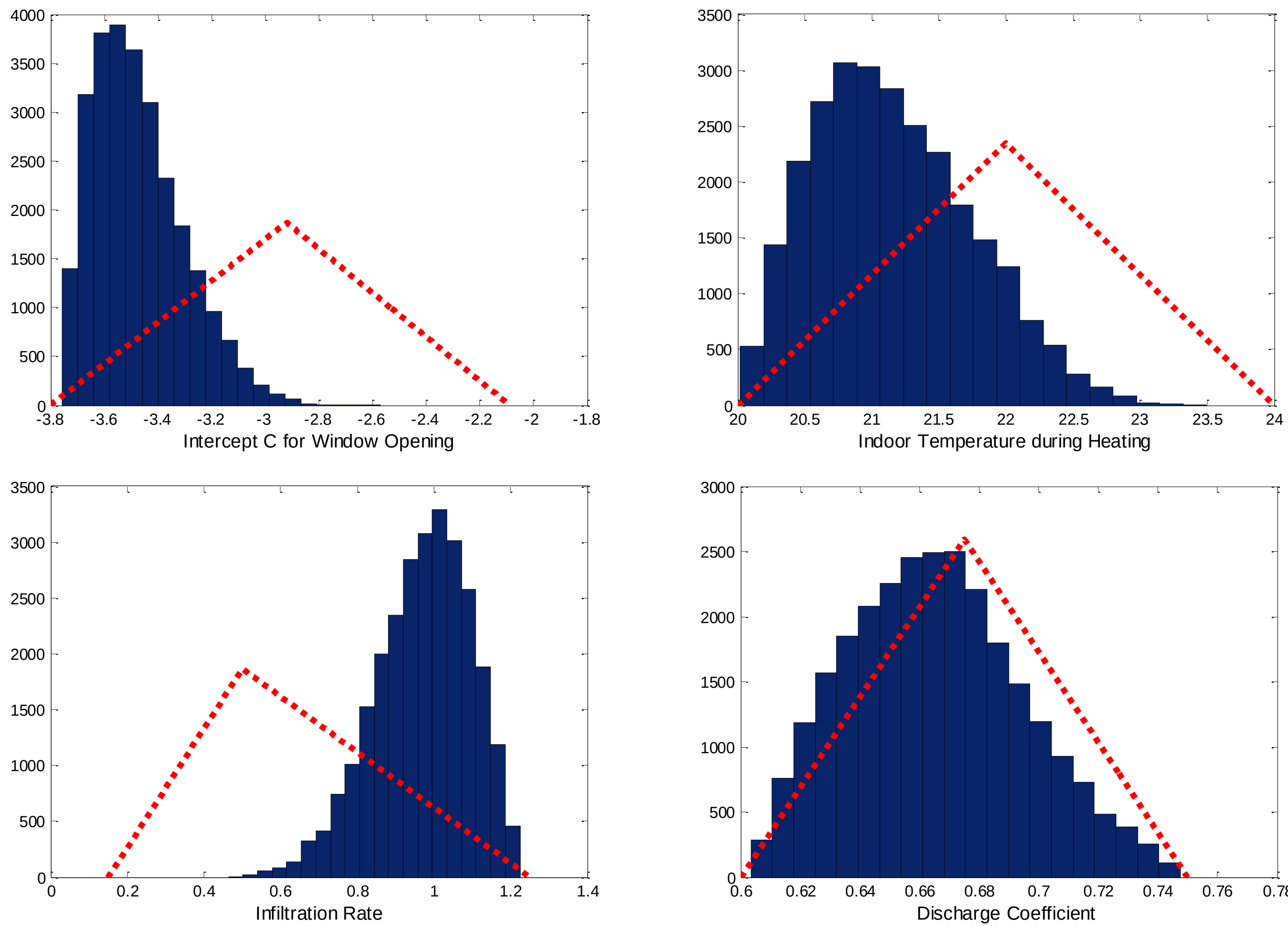


A set of models
(calculating different
intervention scenarios)

Whole Retrofit Analysis Procedure



Step 3: Bayesian Calibration

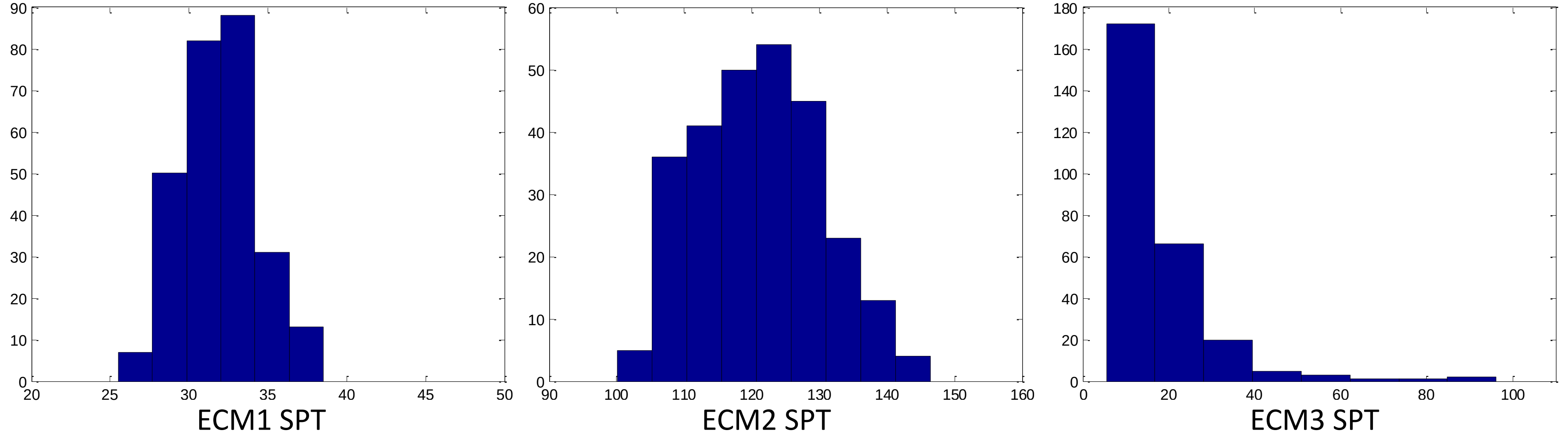


Model Prediction

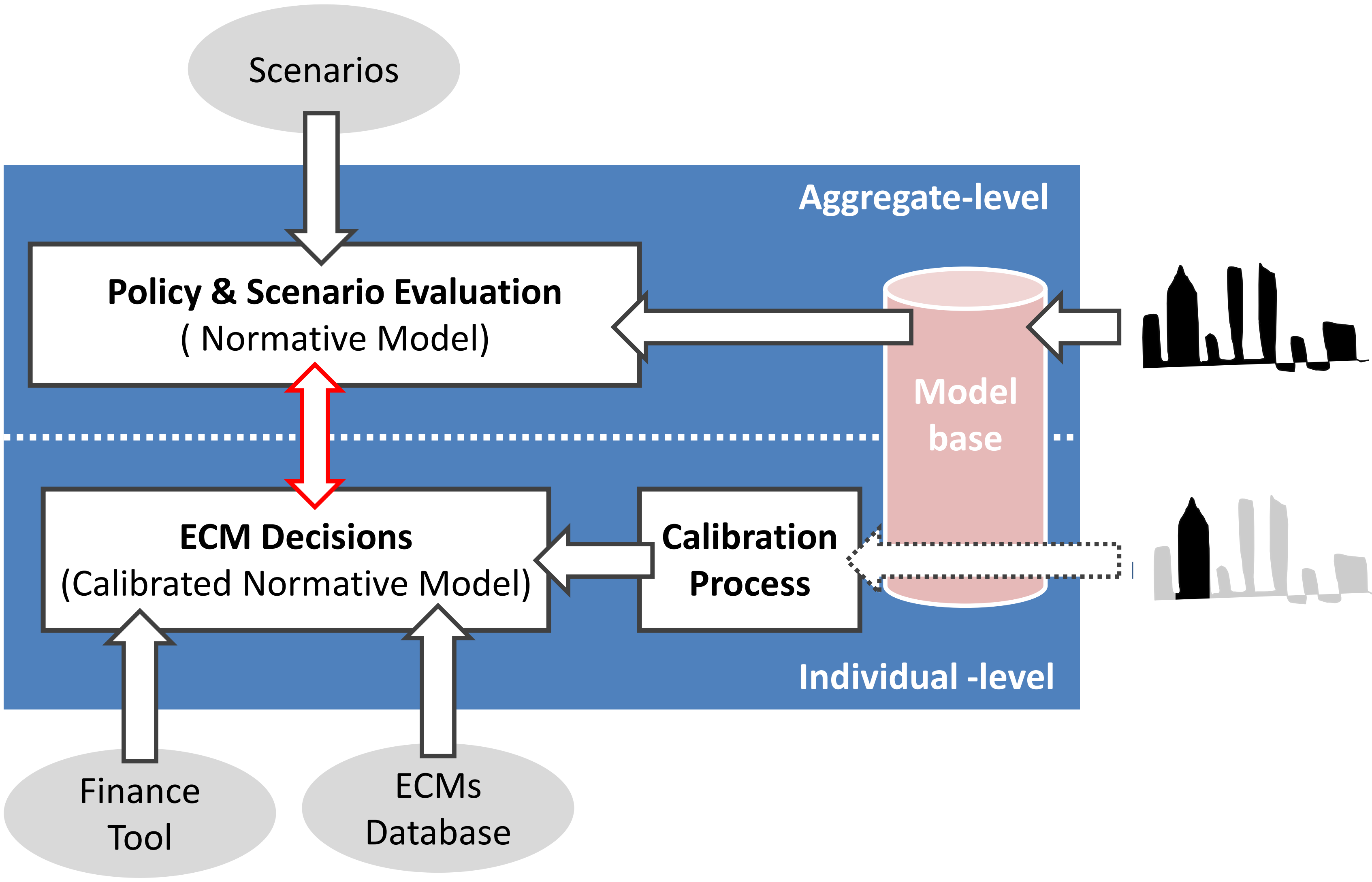
- Candidate Energy Conservation Measures

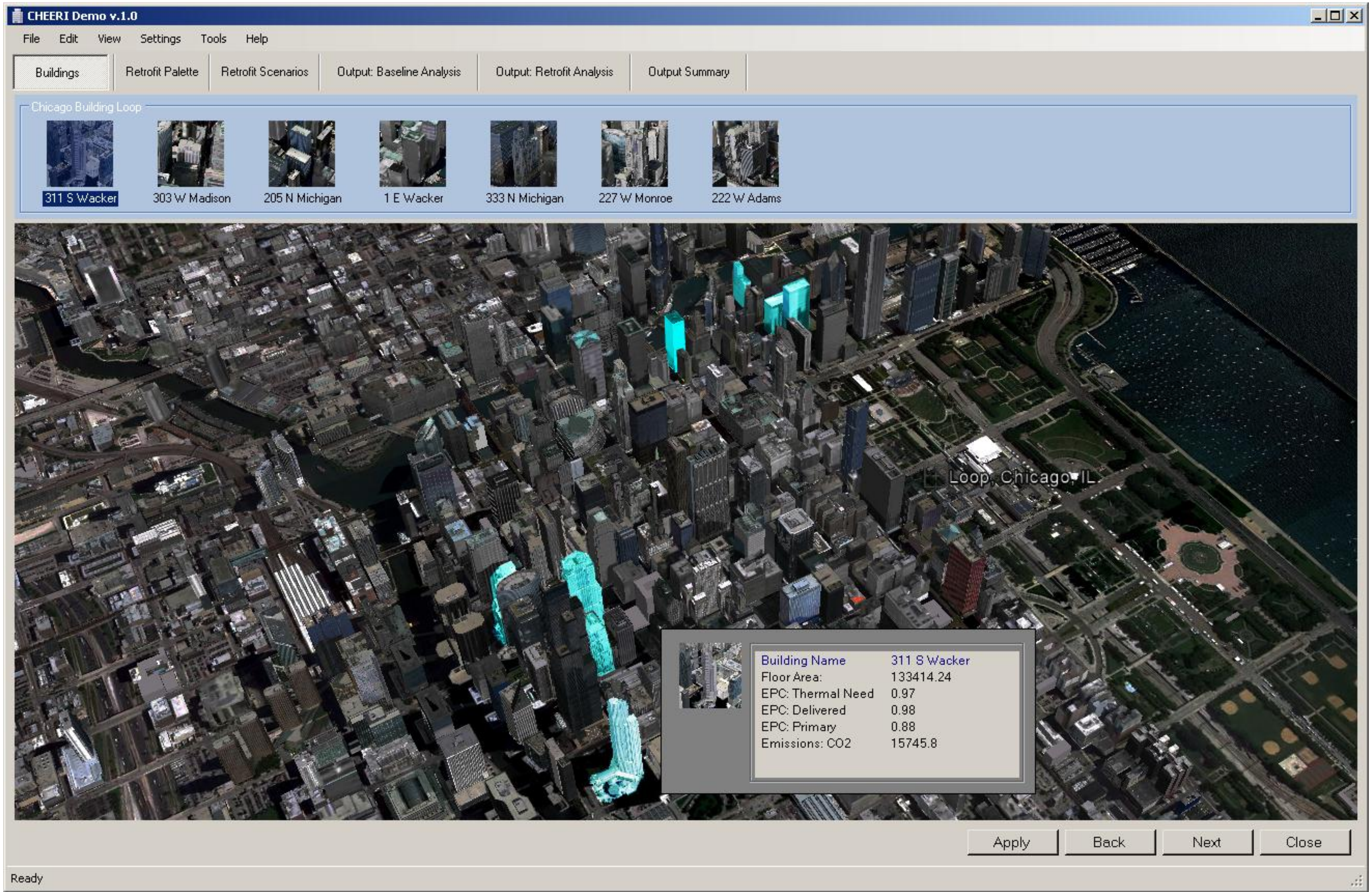
ECM	Model Parameters	Base	Min	Max
ECM1: Insulation Addition	U-value (W/m²K)	0.30	0.27	0.33
ECM2: Window Replacement	U-value (W/m²K)	1.41	1.27	1.55
	Solar Transmittance	0.65	0.63	0.67
	Emissivity	0.05	0.04	0.06
ECM3: Air-tightness	Infiltration Rate Reduction (%)	11	1	31

- Simple Payback Time Predictions



The New Methodology in the Chicago Loop Project




CHEERI Demo v.1.0
File
Edit
View
Settings
Tools
Help
Buildings
Retrofit Palette
Retrofit Scenarios
Output: Baseline Analysis
Output: Retrofit Analysis
Output Summary
Chicago Building Loop
311 S Wacker
303 W Madison
205 N Michigan
1 E Wacker
333 N Michigan
227 W Monroe
222 W Adams
Loop, Chicago, IL
Building Name 311 S Wacker
Floor Area: 133414.24
EPC: Thermal Need 0.97
EPC: Delivered 0.98
EPC: Primary 0.88
Emissions: CO2 15745.8
Apply
Back
Next
Close
Ready

Ongoing research in 2nd year

- Task 3: Risk measures in design and retrofit, driven by:
  - Performance risks: energy, comfort, LOL,
  - Investment risks: ESCO-led, Vendor-led, Investment models
  - Commission (Cx) and diagnostics practices
- Task 4: Uncertainty Analysis: Propagation
  - Tools and methods for sampling and propagation
  - MC approach:"Anytool" wrappers (with some level of intrusion)
    - Sampling techniques
  - Intrusive methods: PC method with newest approaches may be breakthrough (but fully intrusive)
- Task 5: Risk conscious decision framework
  - Combining the outcomes of Tasks 3 and 4
  - Embedded in Workbench where new buildings or building technologies can be tested under uncertainty

Task 4: UA Tools and methods

$$y = f(x, \theta) + \varepsilon(x, \theta)$$

Output | Model | Inputs | Parameters | Structural error

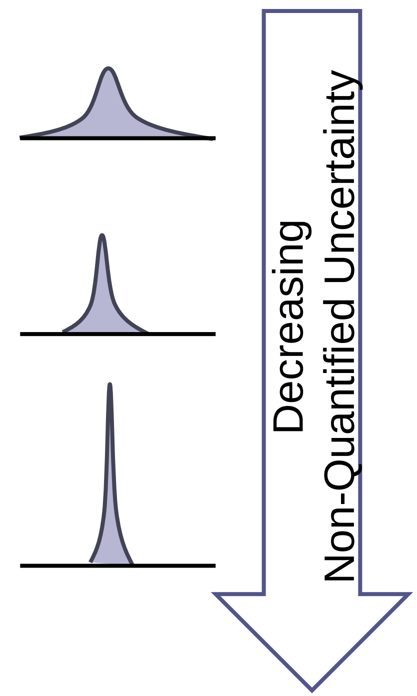
- Structural error is very difficult to characterize
  - Requires large numbers of actual observations

→Reduce structural error as much as possible by:
  - Quantifying uncertainty in inputs & parameters
  - Improving & Extending Building Energy model

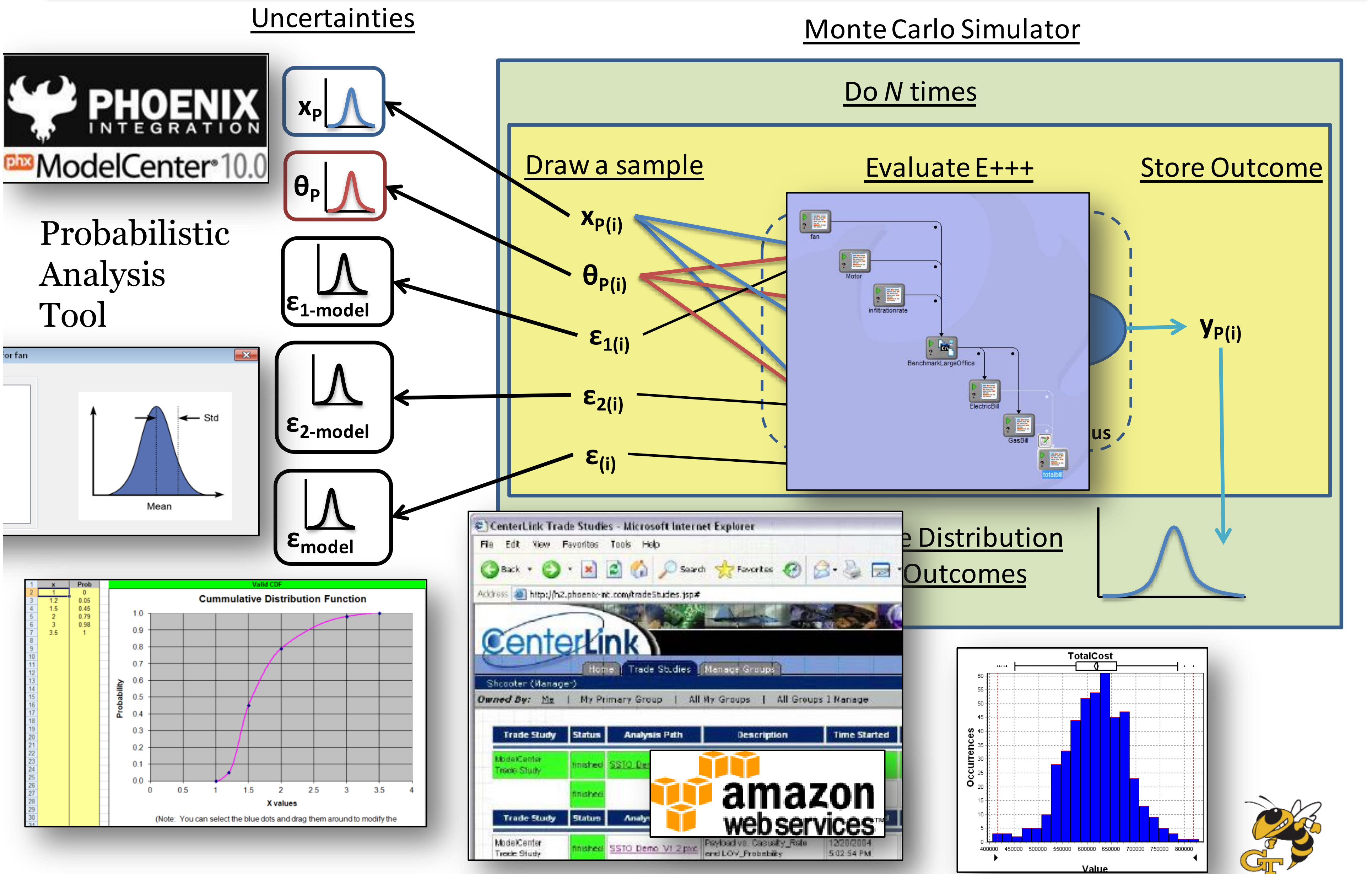
$$y = f(x_D, \theta_D) + \boldsymbol{\varepsilon_D}$$

$$\boldsymbol{y = f(x_P, \theta_P) + \varepsilon_P}$$

$$\boldsymbol{y = f^{+}(x_P, \theta_P) + \varepsilon_E}$$



Monte Carlo with ModelCenter



Year 3 and 4: Applications

- Reality check
- Looking for suitable projects (partnering)
- Decision making in the real world
  - Investment models (symmetric risks)
  - PPA
  - Commissioning/auditing
  - Rating (with confidence interval)
  - "Extreme" buildings: expression of damage to evaluate risk=P(event)* (damage|event)
  - Some of these require long tail accuracy of weather (TMY data unusable)

Current related PhD theses:

- Power simulation: connection to PNNL smart grid simulator
- Stochastic weather simulator: long tail representation
- Façade retrofit study: different underperformance risks for owner and tenant

Conclusions

- Rewriting the book on building performance simulation
  - Recognizing the limitations of energy predictions
  - Model discrepancy vs. limitations of use
  - Compare different model fidelities
- Elevating building energy profession to recognize the importance of UQ
  - Changing the way we interpret energy performance
  - Changing the way we do commissioning and retrofit
- Making energy system development and investment risks transparent
  - Supporting investment decisions under risk
  - Choosing renewable technology winners

THANK YOU!

Many questions ....

..... not enough answers

fried@gatech.edu