A Bayesian Approach to Model Calibration for *B. anthracis* Risk Assessment

Tao Hong and Patrick L. Gurian

Department of Civil, Architectural and Environmental Engineering, Drexel University

Background

The series of 2001 anthrax letter attacks not only caused the deaths of 5 people and hundreds of millions of dollars in clean up costs, but also identified several critical knowledge gaps relating to risk characterization, and decontamination of bioterrorism agents of concern. Characterization of a biological attack requires a practical approach to estimate the total release quantity, as well as ground-truthed mathematical models to evaluate the subsequent dispersion and human health risks. Establishing a decontamination standard also requires knowledge of how microbes have been dispersed in the environment, how long they will persist in the environment, and how subsequent transport processes, such as re-aerosolization, might lead to human exposure.

The Bayesian Monte Carlo (BMC) technique is a robust tool for model calibration. While classical model calibration methods require inputs to be either parameters fit to match the calibration data or fixed constants, the BMC approach allows inputs to be defined by probability distributions that reflect prior knowledge of their likely values. Posterior probability distributions are then developed by comparing the model predictions with observed data. Informative prior distributions can be developed in this domain because many parameters describing the indoor environment, such as turbulence intensity and air exchange rates, fluctuate, but within reasonable bounds. By drawing not only on the data, but also prior knowledge, BMC methods may be able applied in situations where classical model calibration would be unable to identify parameters (i.e., cases where the model would be overfit to the available data).

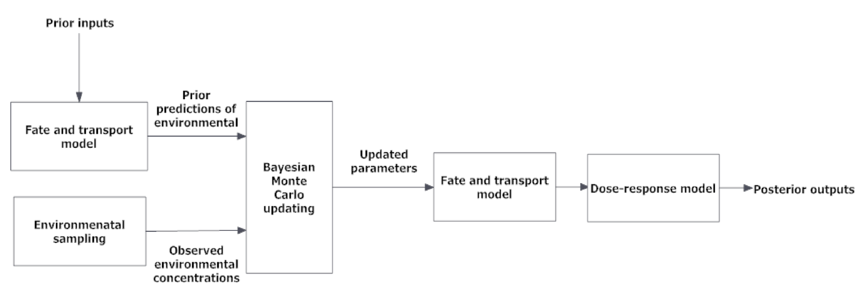

Fig. 1 Flow chart of BMC updating

In this study, the BMC method is applied to the indoor particle fate and transport model developed by Sextro et al. and applied by Hong et al. Field data collected from the Hart Senate Office Building, after a letter containing *B. anthracis* spores was opened, is employed to update distributions for model parameter values. While the available field data may not be sufficient to fully identify all parameters using classical model calibration techniques, when used in a BMC updating procedure they may allow for more informative parameter distributions to be developed. At a minimum, the BMC procedure can ascertain if the observations conflict substantively with the surrogate-based parameter estimates used previously.

Method

Risk Assessment model

The risk assessment model has two components, a fate and transport model, predicting the distribution of released *B. anthracis* spores in an office, and a dose-response model, estimating human health risk from inhalation of the released *B. anthracis* spores. A schematic plot of the modeled office is provided in Figure 2. The office includes seven compartments: air, tracked floor, untracked floor, walls, ceiling, heating ventilation and air conditioning (HVAC), and the nasal passages of occupants of the office. *B. anthracis* spores in the air can deposit to the tracked floor, untracked floor, walls, and ceilings; can be removed by the HVAC filter, can exit the office after passing the HVAC filter, and can be inhaled by the occupants. Most of the movements are irreversible, however, *B. anthracis* spores deposited on the tracked floor have the ability to reenter the air due to human-caused resuspension. *B. anthracis* spores are modeled as being released instantaneously to the air compartment and completed mixed. The fate and transport of released *B. anthracis* particles is described by a set of ordinary differential equations (Eq. 1), for which a detailed solution can be found in Hong.

$$\frac{dM}{dt}=\begin{pmatrix}\dot M_{air}\\ \dot M_{tf}\\ \dot M_{utf}\\ \dot M_{w}\\ \dot M_{f}\\ \dot M_{ec}\\ \dot M_{ce}\\ \dot M_{n}\end{pmatrix}=\begin{pmatrix}[(1-e)p-1]\frac{Q}{V}-(\lambda_{tf}+\lambda_{utf}+\lambda_w+\lambda_{ce}+\frac{I e_n}{V}) & \mu_2 & 0&0&0&0&0&0\\ \lambda_{tf} & -\mu_2 & 0&0&0&0&0&0\\ \lambda_{utf} & 0&0&0&0&0&0&0\\ \lambda_w & 0&0&0&0&0&0&0\\ ep\frac{Q}{V} & 0&0&0&0&0&0&0\\ (1-p)\frac{Q}{V} & 0&0&0&0&0&0&0\\ \lambda_{ce} & 0&0&0&0&0&0&0\\ \frac{I e_n}{V} & 0&0&0&0&0&0&0\end{pmatrix}\begin{pmatrix}M_{air}\\ M_{tf}\\ M_{utf}\\ M_{w}\\ M_{f}\\ M_{ec}\\ M_{ce}\\ M_{n}\end{pmatrix} \quad \text{(Eq. 1)}$$

where the number of spores are denoted by M_{air} (air), M_{tf} (tracked floor), M_{utf} (untracked floor), M_w (walls), M_f (filter), M_{ec} (external compartment) M_{ce} (ceiling), and M_n (nasal passages). The total HVAC air flow rate is Q (m^3/min), p is the fraction of total air flow that is recirculated into the building HVAC system, e is the efficiency of the filter at removing particles, and V is the volume of the room (m^3). Removal to the occupants' nasal passages is modeled with I (m^3/ min), denoting the breathing flow rate and e_n the efficiency of the nasal passages at removing particles. Resuspension from the tracked floor due to occupants walking and other activities is modeled as a first order process with rate constant μ_2 (min^{-1}). Deposition from the air compartment is modeled as a first-order process with rate constants (min^{-1}) of λ_{tf} (deposition to tracked floor), λ_{utf} (untracked floor), λ_w (walls), and λ_{ce} (ceiling), which can be expressed by parameters representing the indoor air flow conditions .

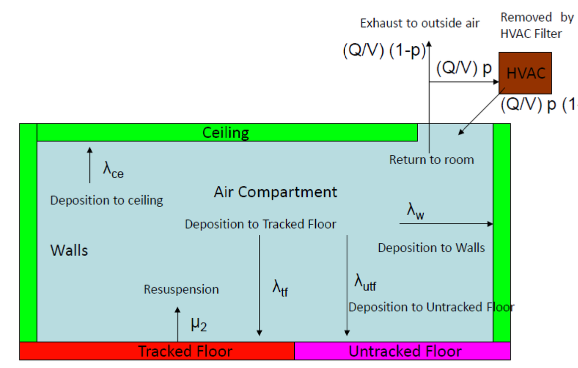

Fig. 2 Schematic of the modeled office

$$\lambda_w=\frac{A_w}{Vol}\times\frac{2}{\pi}\sqrt{Dk_e} \quad \text{(Eq. 2)}$$

$$\lambda_c=\frac{A_c}{Vol}\times\frac{V_t}{e^{\frac{\pi V_t}{2\sqrt{Dk_e}}}-1} \quad \text{(Eq. 3)}$$

$$\lambda_{tf(utf)}=\frac{A_{tf(utf)}}{Vol}\times\frac{V_t}{1-e^{-\frac{\pi V_t}{2\sqrt{Dk_e}}}} \quad \text{(Eq. 4)}$$

$$V_t=\frac{gD^2(\rho_p-\rho_{air})}{18\mu_{air}} \quad \text{(Eq. 5)}$$

where D (m^2/min) is the particle diffusivity, K_e (min^{-1}) is turbulence intensity, and V_t (m/min) is particle settling velocity, which is given in Eq. 5 as a function of the particle's diameter (D), the viscosity of air (μ_{air}), the density of the particle (ρ_p), and the density of air (ρ_{air}).

In addition to the fate and transport model described above, a risk assessment model is included to quantify the hazard posed by inhaling *B. anthracis* spores. An exponential dose-response model (Eq. 6) is selected for particle sizes less than or equal to 5μM, while a beta-Possion dose-response model is used for 10μM particle (Eq. 7).

$$Risk(dose)=1-e^{-kdose} \quad \text{(Eq. 6)} \qquad Risk(dose)\approx 1-(1+\frac{dose}{\beta})^{-\alpha} \quad \text{(Eq. 7)} \qquad dose=Inh\int_{t_1}^{t_2}C_{air}(t)dt \quad \text{(Eq. 8)}$$

where *Risk (dose)* is the probability of positive response (death) corresponding to a certain exposure level, *k* is the parameter of exponential dose-response model, and α, β are parameters of a beta distribution describing variability in survival probability. The dose is estimated by integrating the concentration of *B. anthracis* over the exposure time (Eq. 8).

Measurement Data

The measurement data are based on sampling of the Hart Senate Office Building after a letter containing *B. anthracis* spores was opened as one of the 2001 series anthrax attacks. Three rounds of sampling were conducted employing two types of sampling schemes: semiquiescent sampling and active sampling. Air concentrations were measured in each sampling schemes, and the differences were attributed to levels of human-caused resuspension. Besides air concentrations, fabric office dividers' concentrations were sampled from vertical surfaces, and horizontal concentration were sampled from the carpet, as shown in Table 2. Based on the details obtained from Weis' paper and personal communications, the modeling period is divided into 6 stages (Figure 3 and Table 1), beginning with a 1 hour exposure period followed by different sampling and settling periods. Final concentrations computed from each stage served as the following stage's initial conditions. After the first 2 hours, the HVAC system was shut down to prevent the dispersion of *B. anthracis* spores.

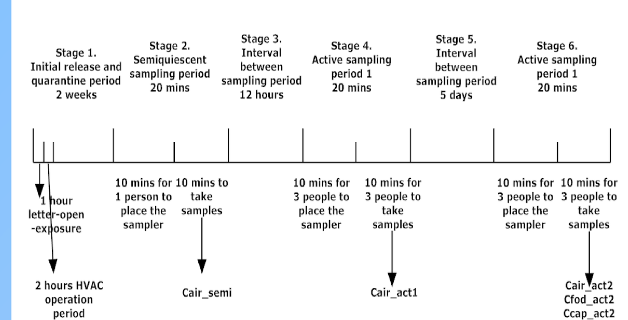

Fig. 3 Time series of different model stages

Table 1. Information of different modeling stages

Stage name	Stage number	Description	Simulation duration	Number of people simulated	HVAC status	Simulated parameter
Initial release and quarantine period	1	Anthrax letter open period	15 mins	10	on	
		Vaccant period	1 week 6days 23 hours and 45 minutes	0	off	
Semiquiescent sampling period	2	Sampler setup	10 mins	1	off	
		Taking samples	10 mins	0	off	C_{air_semi}
Interval between sampling period	3		12 hours	0	off	
First round active sampling period	4	Sampler setup	10 mins	3	off	
		Taking samples	10 mins	3	off	C_{air_act1}
Interval between sampling period	5		12 hours	0	off	
Second round active sampling period	6	Sampler setup	10 mins	3	off	
		Taking samples	10 mins	3	off	C_{air_act2} C_{fod_act2} C_{cap_act2}

Bayesian updating

The posterior probability $P(\vec{\theta}\,|\,\overrightarrow{C_{obs}})$ of modeled parameters is acquired by updating the parameters of the fate and transport model with the measured *B. antrhacis* spore concentrations:

$$P(\vec\theta\,|\,\overrightarrow{C_{obs}})=\frac{L_{overall}(\overrightarrow{C_{obs}}\,|\,\vec\theta,\overrightarrow{C_{pred}})\times P(\vec\theta)}{\int_{\vec\theta} L_{overall}(\overrightarrow{C_{obs}}\,|\,\vec\theta,\overrightarrow{C_{pred}})\times P(\vec\theta)\,d\vec\theta} \quad \text{(Eq. 9)}$$

$$L_{overall}(\overrightarrow{C_{obs}}\,|\,\vec\theta,\overrightarrow{C_{pred}})=\prod_{\substack{surf=air_semi,\\ air_act1,\,air_act2,\\ fod_act2,\,cap_act2}} L(\vec C_{surf,obs}\,|\,\vec\theta,\vec C_{surf,pred})=\prod_{\substack{surf=air_semi,\\ air_act1,\,air_act2,\\ fod_act2,\,cap_act2}}\frac{\Gamma(\frac{\nu}{2})}{\sqrt{\nu\pi}\,\Gamma(\frac{\nu}{2})}(1+\frac{t^2}{\nu})^{-(\frac{\nu+1}{2})} \quad \text{(Eq. 10)}$$

where $P(\vec\theta)$ is the joint prior probability, subscript obs indexes the observation from surface sampling, and subscript pred represents concentrations predicted by the fate and transport model ($\overrightarrow{C_{pred}}$) as a function of model inputs . $L_{overall}(\overrightarrow{C_{obs}}\,|\,\vec\theta,\overrightarrow{C_{pred}})$ is the overall likelihood of obtaining certain surface measurements ($\overrightarrow{C_{pred}}$) given model prediction ($\overrightarrow{C_{obs}}$), which are conditional on model parameters $\vec\theta$. In this study, the overall likelihood is the joint probability of the concentrations observed during the sequence of 5 different sampling events. Thus the likelihood can be rewritten as a function of the t-distribution (Eq. 10), where ν is the number of degrees of freedom, Γ is the Gamma function. Four hypothetical scenarios are created to explore what could be learned if additional sampling information were available. Scenario 2 is introduced in which roughly 4 times more samples are taken, but the sample means and standard deviations unchanged. Scenario 3 is desired to assess whether knowing the size distribution of the release helps interpret the data. Scenario 4 tests how information from an additional sampling location, the HVAC system filter, affects the updating results. In Scenario 5 both the size distribution of released *B. anthracis* spores and simulated HVAC concentrations are available. Scenario 6 aims to evaluate how the performance of BMC updating will change if incomplete information is provide, in which only concentrations sampled from fabric office dividers and carpet are available.

Results and Discussion

Figures 4 graphically illustrates the changes before and after Bayesian updating for different scenarios by box plots, where the bottom and top of the box are 25th and 75th percentile, the band inside the box is the 50th percentile, and the upper and lower whiskers represent the 5th and 95th percentile, respectively. Parameters resuspension rate (μ_2) of the larger size particle, inhalation risk (Risk), total release quantity (Mass_t), the fraction of total inhaled pathogens over release quantity (Dose/Mass_t), the fraction of recirulated air (P) and released pathogen's size fraction (f) have been successfully updated. The reduced distance between two whiskers indicates less uncertainty existed after updating. Comparing results from Scenario 1 with Scenarios 2 to 6, more information can be extracted from the later four scenarios, indicating that there are two approaches to improve the performance of Bayesian updating. The first approach is to improve the quality of samples, where one can collect additional data to reduce sample errors as Scenario 2, or one can remove the low quality data (difficult to measure) as Scenario 6. After purging the samples, the BMC updating process would highlight the "correct" parameter values by assigning higher weights and remove "noise" parameter values by assigning lower weights. As a result, more updates will be expected in the posterior distributions for parameters to be updated. The second approach is to collecting data with a close correlation to the "target" parameter. First, one needs to analyze model parameters and identify the relationship between parameter outputs and available information. Since we found that the concentrations sampled from the HVAC filter could serve as an indicator of air recirculation rate, which has not been successfully updated in the previous three scenarios. Thus, simulated HVAC concentrations are introduced into Scenario 4 which successfully update the value of air recirculation rate.

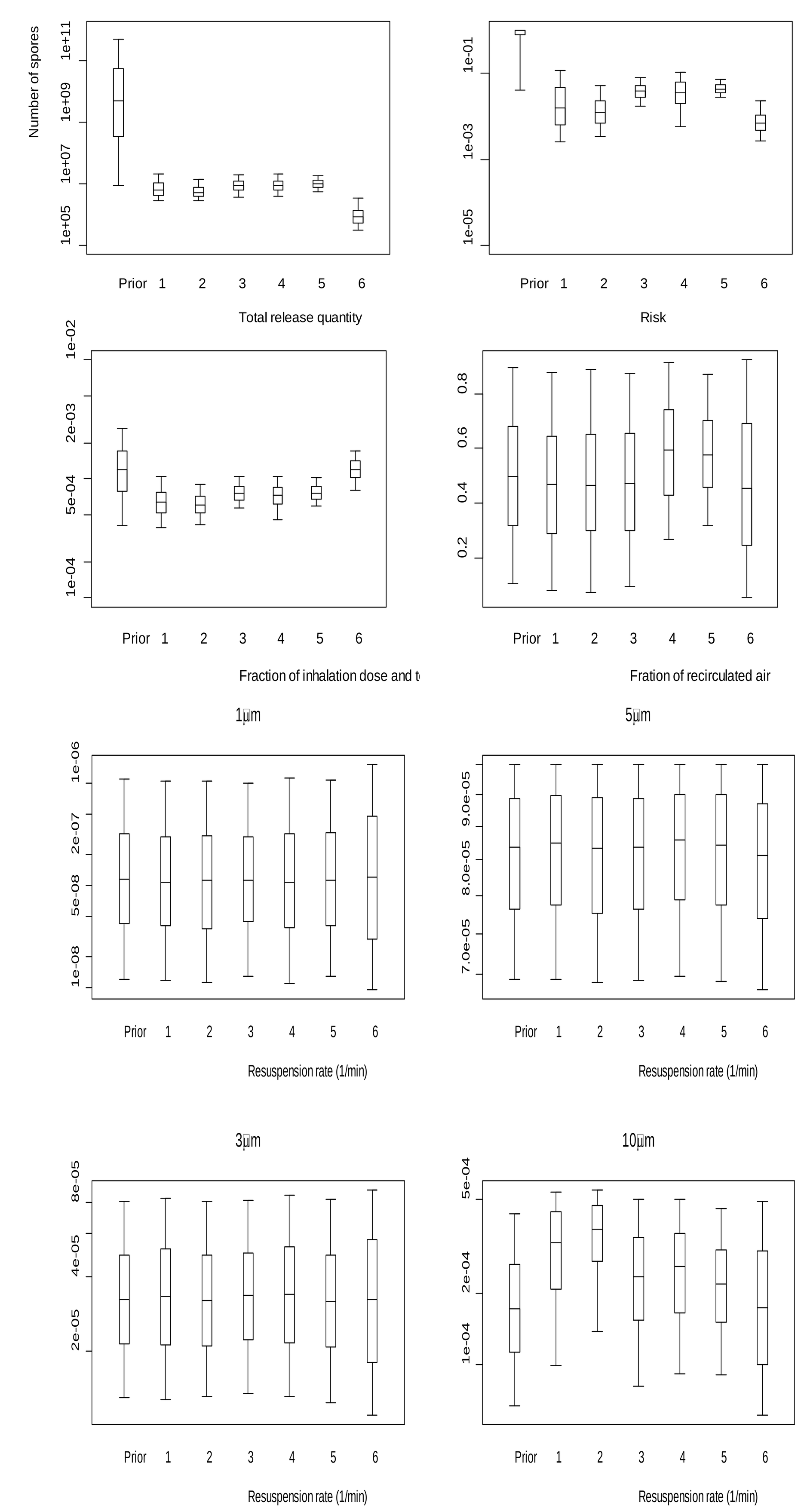

Fig. 4 Prior and posterior CDF for selected parameters

Statistical information on model parameter distributions before and after the different Bayesian updating scenarios is summarized in Table 2. Information extracted from Scenario 2 (data with lower standard errors) indicates that confidence intervals for the total release quantity, the amount of *B. anthracis* escape from the release room, exposure risk, the resuspension rates, and the size fraction of released pathogens are narrower than Scenario 1. The fraction of recalculated air flow (p) is only successfully updated in Scenario 4 (HVAC filter data is provided) and 5 (size distributions are fixed and HVAC filter data is provided); the particle density (ρ_p) is only updated in Scenario 4; the turbulence intensity (ke) is only successfully updated in Scenario 5, implying that the performance of Bayesian updating will be improved if data with a close relationship to the updated parameters are collected. The posterior 90% credible intervals in Scenario 5 are narrower than other scenarios, suggesting that more information might help us to reduce inputs uncertainties. Since air samples are excluded in Scenario 6, only limit number of parameters are updated such like the total released quantity, risk to the exposed people and the fraction of released particle sizes. However, Scenario 6 suggests a large portion (64%) of released *B. anthracis* spores are 1 micron, which is different from results from other scenarios. This phenomenon could be a result of missing air samples, which usually works effectively in differentiating released particle size distribution.

Conclusion

This paper presents an application of BMC method in determining and propagating uncertainty for an integrated fate and transport risk assessment model. The BMC process was found to be able to use available environmental samples to produce order of magnitude estimates of the release quantity and risk to exposed individuals. Substantive reductions in the uncertainties of model parameters was not achieved by the process but neither did the data exclude the model parameter estimates. Besides reducing uncertainties of the inputs, the BMC approach revealed ability to estimate risk, total release quantity, and the resuspension rate of larger particles from post-event sampling. This is important because only little information is available in this field. The whole BMC process is valuable because it can provide insights on the selection and restrictions of model inputs. Precisely estimated parameters assist decision maker correctly and efficiently allocate resource and carry out a series of relative plan in terms of evacuation, and decontamination. In the future, more resources should be allocated to address the question, how to take the advantage of all available observations as well as how to identify important unobserved data.

Table 2 Major model inputs' prior and posterior statistics values

Parameter	Meaning	Diameter	Prior Mean Mean (90% CI)	Posterior Mean (90% CI) Scenario 1 Mean (90% CI)	Scenario 2 Mean (90% CI)	Scenario 3 Mean (90% CI)	Scenario 4 Mean (90% CI)	Scenario 5 Mean (90% CI)	Scenario 6 Mean (90% CI)
Risk	Inhalational risk	`	8.17×10^{-1} (4.59×10^{-2}-1)	3.31×10^{-2} (2.50×10^{-3}-1.17×10^{-1})	1.82×10^{-2} (3.50×10^{-3}-5.13×10^{-2})	4.24×10^{-2} (1.74×10^{-2}-7.83×10^{-2})	4.41×10^{-2} (5.70×10^{-3}-1.04×10^{-1})	4.56×10^{-2} (2.74×10^{-2}-7.15×10^{-2})	8.80×10^{-3} (2.60×10^{-3}-2.33×10^{-2})
Mass_t	Total release quantity		8.39×10^{10} (9.61×10^{6}-5.25×10^{11})	8.76×10^{6} (2.83×10^{6}-2.08×10^{7})	6.62×10^{6} (2.85×10^{6}-1.39×10^{7})	1.02×10^{7} (3.79×10^{6}-1.98×10^{7})	1.05×10^{7} (4.14×10^{6}-2.10×10^{7})	1.09×10^{7} (5.56×10^{6}-1.91×10^{7})	1.17×10^{6} (3.26×10^{5}-3.44×10^{6})
ρ_p	Particle density		2.00×10^{3} (1.20×10^{3}- 2.79×10^{3})	1.86×10^{3} (1.12×10^{3}-2.72×10^{3})	1.93×10^{3} (1.13×10^{3}-2.74×10^{3})	1.99×10^{3} (1.19×10^{3}-2.78×10^{3})	1.84×10^{3} (1.11×10^{3}-2.65×10^{3})	1.99×10^{3} (1.19×10^{3}-2.78×10^{3})	1.94×10^{3} (1.10×10^{3}-2.88×10^{3})
Ke	Turbulence intensity of exposure stage		2.27×10^{-1} (4.58×10^{-2}-4.07×10^{-1})	2.35×10^{-1} (5.52×10^{-2}-4.13×10^{-1})	2.40×10^{-1} (5.18×10^{-2}-4.09×10^{-1})	2.20×10^{-1} (4.45×10^{-2}-4.09×10^{-1})	2.29×10^{-1} (5.47×10^{-2}-4.08×10^{-1})	2.06×10^{-1} (3.15×10^{-2}-3.96×10^{-1})	2.41×10^{-1} (4.47×10^{-2}-3.96×10^{-1})
ACH	Air change rate		1.55 (3.94×10^{-1}- 2.69)	1.67 (4.34×10^{-1}-2.76)	1.66 (4.53×10^{-1}-2.77)	1.64 (4.91×10^{-1}-2.75)	1.69 (5.21×10^{-1}-2.74)	1.72 (5.60×10^{-1}-2.80)	1.79 (6.03×10^{-1}-2.87)
P	The fraction of recirculated air		5.00×10^{-1} (1.07×10^{-1}-8.97×10^{-1})	4.70×10^{-1} (8.13×10^{-2}-8.77×10^{-1})	4.72×10^{-1} (7.24×10^{-2}-8.87×10^{-1})	4.78×10^{-1} (9.37×10^{-2}-8.74×10^{-1})	5.87×10^{-1} (2.68×10^{-1}-9.13×10^{-1})	5.82×10^{-1} (3.16×10^{-1}-8.72×10^{-1})	4.69×10^{-1} (5.50×10^{-2}-9.23×10^{-1})

Selected references

1. Hong, T., P.L. Gurian, and N.F.D. Ward, *Setting Risk-Informed Environmental Standards for Bacillus Anthracis Spores.* Risk Analysis, 2010. **30**(10): p. 1602-1622.
2. Weis, C.P., et al., *Secondary aerosolization of viable Bacillus anthracis spores in a contaminated US Senate Office.* Jama, 2002. **288**(22): p. 2853-8.
3. Shane, S. and S. Staff. *Cleanup of anthrax will cost hundreds of millions of dollars.* 2002 [cited 2002 December 18]; Available from: http://cltv.trb.com/entertainment/bal-te.anthrax18dec18,1,1593731.story.
4. Stuart, A.L. and D.A. Wilkening, *Degradation of Biological Weapons Agents in the Environment: Implications for Terrorism Response.* Environmental Science & Technology, 2005. **39**(8): p. 2736-2743.
5. Price, P.N., et al., *Framework for evaluating anthrax risk in buildings.* Environmental Science & Technology, 2009. **43**(6): p. 1783-1787.
6. Sharp, R.J. and A.G. Roberts, *Anthrax: the challenges for decontamination.* Journal of Chemical Technology and Biotechnology, 2006. **81**(10): p. 1612-1625.
7. Canter, D.A., *Addressing Residual Risk Issues at Anthrax Cleanups: How Clean is Safe?* Journal of Toxicology and Environmental Health, Part A: Current Issues, 2005. **68**(11): p. 1017 - 1032.
8. Reshetin, V.P. and J.L. Regens, *Simulation modeling of anthrax spore dispersion in a bioterrorism incident.* Risk Analysis, 2003. **23**(6): p. 1135-1145.
9. Riley, W.J., et al., *Indoor particulate matter of outdoor origin: Importance of size-dependent removal mechanisms.* Environmental Science & Technology, 2002. **36**(2): p. 200-207.
10. Waring, M.S. and J.A. Siegel, *Particle loading rates for HVAC filters, heat exchangers, and ducts.* Indoor Air, 2008. **18**(3): p. 209-224.
11. Sohn, M.D., et al., *Predicting size-resolved particle behavior in multizone buildings.* Atmospheric Environment, 2007. **41**(7): p. 1473-1482.
12. Miller, S.L. and W.W. Nazaroff, *Environmental tobacco smoke particles in multizone indoor environments.* Atmospheric Environment, 2001. **35**(12): p. 2053-2067.
13. Sextro, R.G., et al. *Modeling the spread of anthrax in buildings.* in *Indoor air 2002.* 2002. Monterey, CA.
14. Brand, K.P. and M.J. Small, *Updating Uncertainty in an Integrated Risk Assessment: Conceptual Framework and Methods.* Risk Analysis, 1995. **15**(6): p. 719-729.
15. Schenker, U., et al., *Using Information on Uncertainty to Improve Environmental Fate Modeling: A Case Study on DDT.* Environmental Science & Technology, 2009. **43**(1): p. 128-134.
16. Gurian, P.L., F. Castro, and Y.-C. Chiu. *A Bayesian Monte Carlo Approach to Model Calibration for Queuing Systems.* in *The 84th Annual Meeting of the Transportation Research Board.* 2004. Washington, DC.
17. Dilks, D.W., R.P. Canale, and P.G. Meier, *Development of Bayesian Monte Carlo techniques for water quality model uncertainty.* Ecological Modelling, 1992. **62**(1-3): p. 149-162.
18. Cox, L.A. and D.A. Popken, *Bayesian Monte Carlo uncertainty analysis of human health risks from animal antimicrobial use in a dynamic model of emerging resistance.* Risk Analysis, 2004. **24**(5): p. 1153-1164.
19. Cox, L.A. and D.A. Popken, *Overcoming confirmation bias in causal attribution: A case study of antibiotic resistance risks.* Risk Analysis, 2008. **28**(5): p. 1155-1171.
20. Sreedharan, P., et al., *Influence of indoor transport and mixing time scales on the performance of sensor systems for characterizing contaminant releases.* Atmospheric Environment, 2007. **41**(40): p. 9530-9542.
21. Sreedharan, P., et al., *Systems approach to evaluating sensor characteristics for real-time monitoring of high-risk indoor contaminant releases.* Atmospheric Environment, 2006. **40**(19): p. 3490-3502.
22. Nazaroff, W.W. and G.R. Cass, *MASS-TRANSPORT ASPECTS OF POLLUTANT REMOVAL AT INDOOR SURFACES.* Environment International, 1989. **15**(1-6): p. 567-584.
23. Lai, A.C.K. and W.W. Nazaroff, *Modeling indoor particle deposition from turbulent flow onto smooth surfaces.* Journal of Aerosol Science, 2000. **31**(4): p. 463-476.
24. Xu, M.D., et al., *DEPOSITION OF TOBACCO-SMOKE PARTICLES IN A LOW VENTILATION ROOM.* Aerosol Science and Technology, 1994. **20**(2): p. 194-206.
25. Bartrand, T.A., M.H. Weir, and C.N. Haas, *Dose-response models for inhalation of Bacillus anthracis spores: Interspecies comparisons.* Risk Analysis, 2008. **28**(4): p. 1115-1124.
26. Haas, C.N., J.B. Rose, and C.P. Gerba, *Quantitative Microbial Risk Assessment.* 1999, New York: Wiley.
27. Weis, C.P., *Personal Communication.* 2010.
28. Ramaswami, A., J.B. Milford, and M.J. Small, *Integrated Environmental Modeling: Pollutant Transport, Fate, and Risk in the Environment.* 2005: John Wiley&Sons.
29. Morgan, M.G. and M. Henrion, *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.* 1992: Cambridge University Press.
30. MathWorks, T. *Matlab.* 2008; Available from: http://www.mathworks.com/.
31. Sohn, M.D., et al., *Rapidly locating and characterizing pollutant releases in buildings.* J Air Waste Manag Assoc, 2002. **52**(12): p. 1422-32.

Acknowledgement

This project was funded through the CAMRA Center of Excellence by a grant from the Department of Homeland Security, Science and Technology Directorate, Office of University Programs and the Environmental Protection Agency.

This research is funded by U.S. EPA - Science To Achieve Results (STAR) Program and U.S. Department of Homeland Security University Programs Grant # R83236201

Drexel UNIVERSITY

CAMRA Center for Advancing Microbial Risk Assessment