

Exceptional service in the national interest



Convergence of Operations Research with Safety and Security

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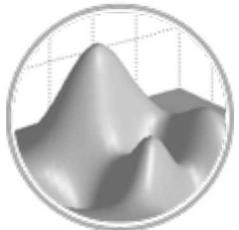
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Research Group Skills



Modeling of Complex Systems

Rigorous systems modeling (steady-state and transient)
Large-scale, non-traditional, networked systems



Nonlinear and Discrete Mathematical Programming

Large-scale algorithms and problem formulation
Parallel algorithms for structured problems (e.g., uncertainty)



Software and Scientific Computing

Open-source domain-specific tools (WST, WNTR, EGRET)
General modeling and optimization tools (Pyomo, Schur-IPOPT)

Mathematical Programming

$$\begin{array}{ll} \min_{\mathbf{x}} & f(\mathbf{x}) \\ \text{s.t.} & c(\mathbf{x}) = 0 \\ & d^L \leq d(\mathbf{x}) \leq d^U \\ & x^L \leq \mathbf{x} \leq x^U \end{array} \quad \begin{array}{l} \text{Objective Function} \\ \text{Equality Constraints} \\ \text{Inequality Constraints} \\ \text{Variable Bounds} \end{array}$$

Mathematical programming (i.e. Optimization)

Problem types classified according to:

- Linearity/Nonlinearity of objective and constraints
- Continuous/Discrete/Mixed variables

LP, QP, NLP, MILP, MINLP

Useful for much more than... “optimization”

Convergence of Operations Research and ...

P2SAC, MKOPSC

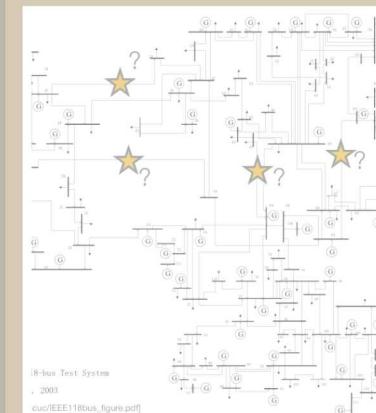
Safety Systems Design

THE 100 LARGEST LOSSES
1972–2011
LARGE PROPERTY DAMAGE LOSSES IN THE HYDROCARBON INDUSTRY
22nd EDITION



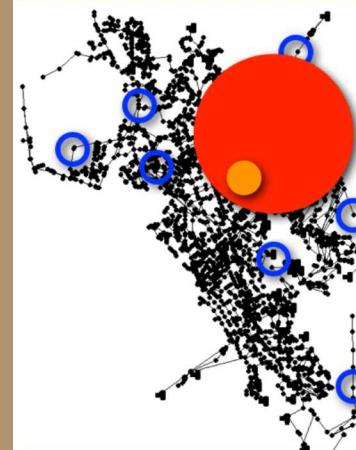
FERC, Sandia

Powergrid Optimization



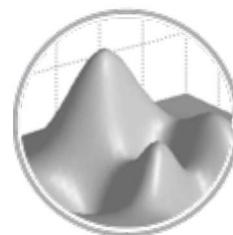
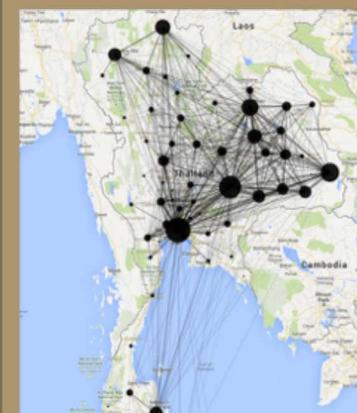
EPA, Sandia

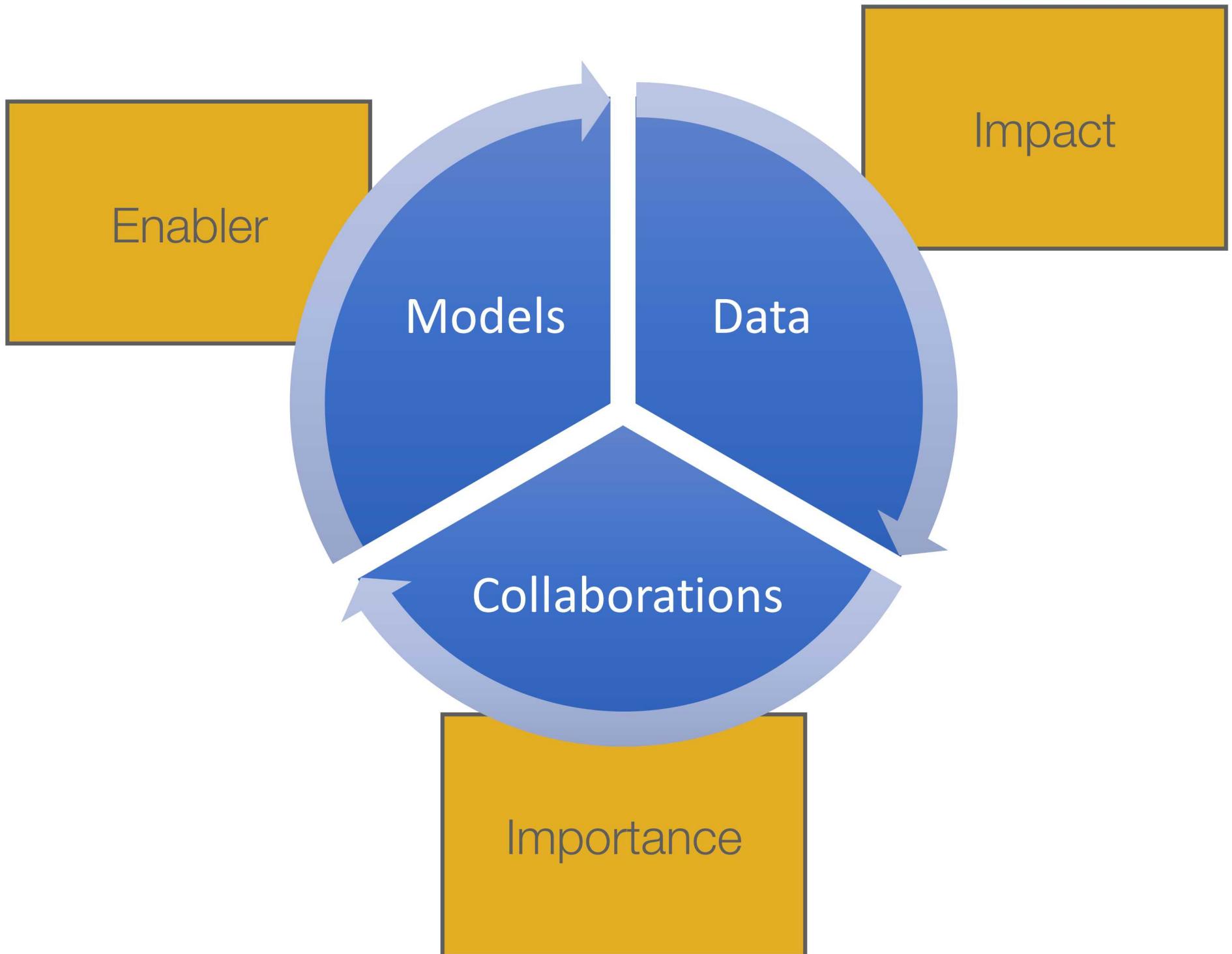
Water Security



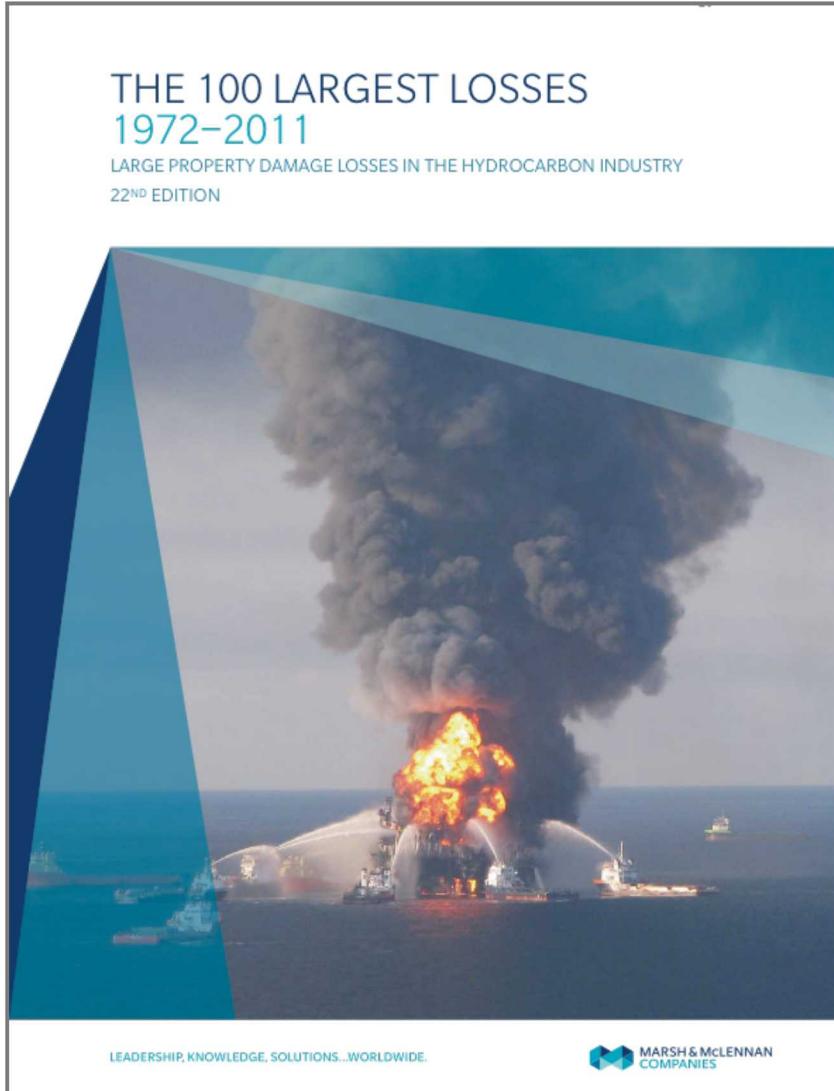
U. Florida, Hopkins

Infectious Disease Spread





The need for improved gas detector placement



Marsh (2012). The 100 largest losses 1972-2011.
London, United Kingdom.

70% attributed to fires and explosions

BSEE (2012), HSE (2007) and PSA (2012) data do not indicate a decreasing trend.

Less than 50% of all known releases are detected by gas detectors (HSE, 1997 & 2003)

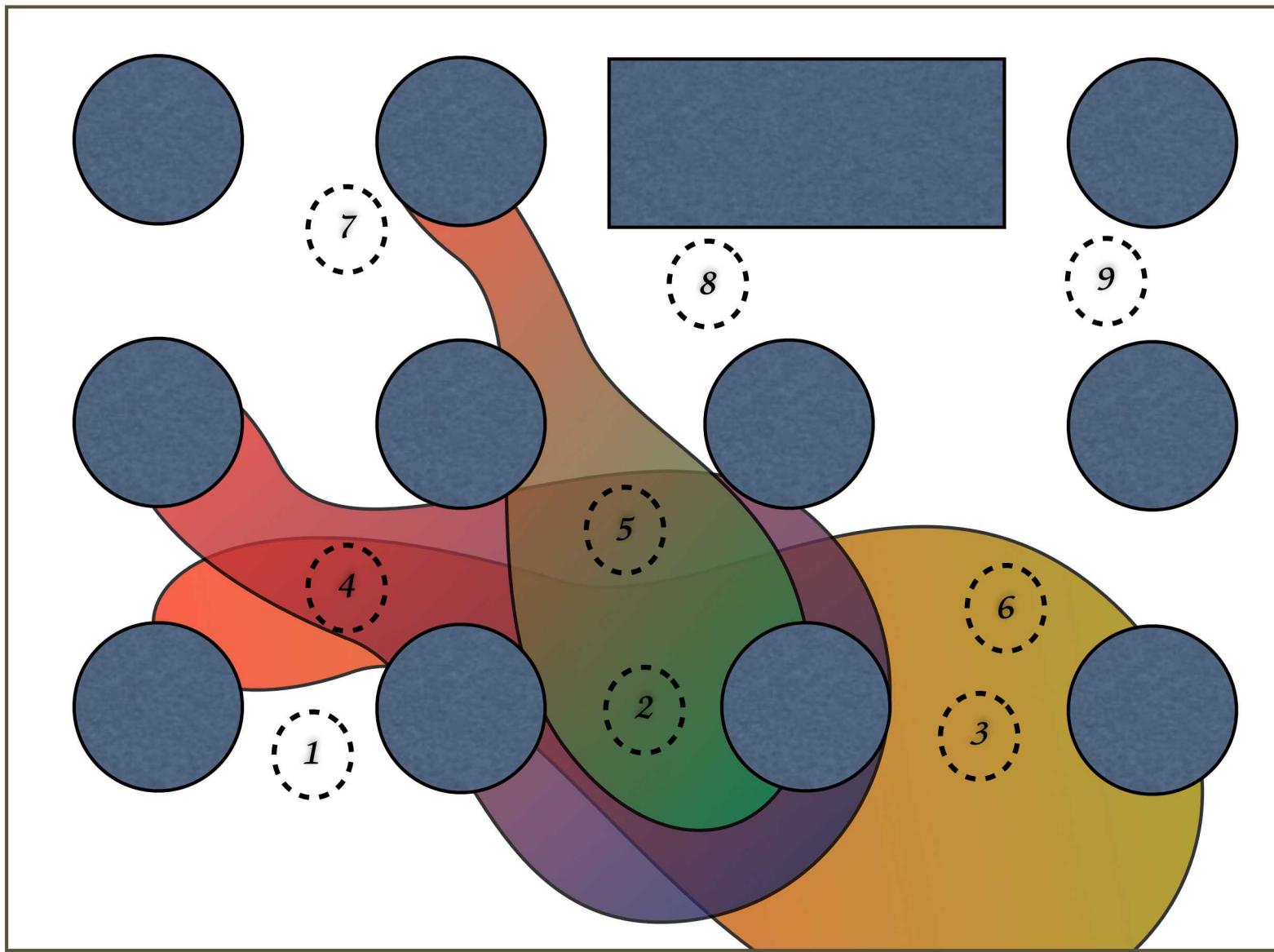
-

Significant uncertainty (leak location, weather, process conditions, etc.)

Highly complex geometries (difficult to model)

Design of gas detector systems currently done with rule-of-thumb, semi-quantitative methods.

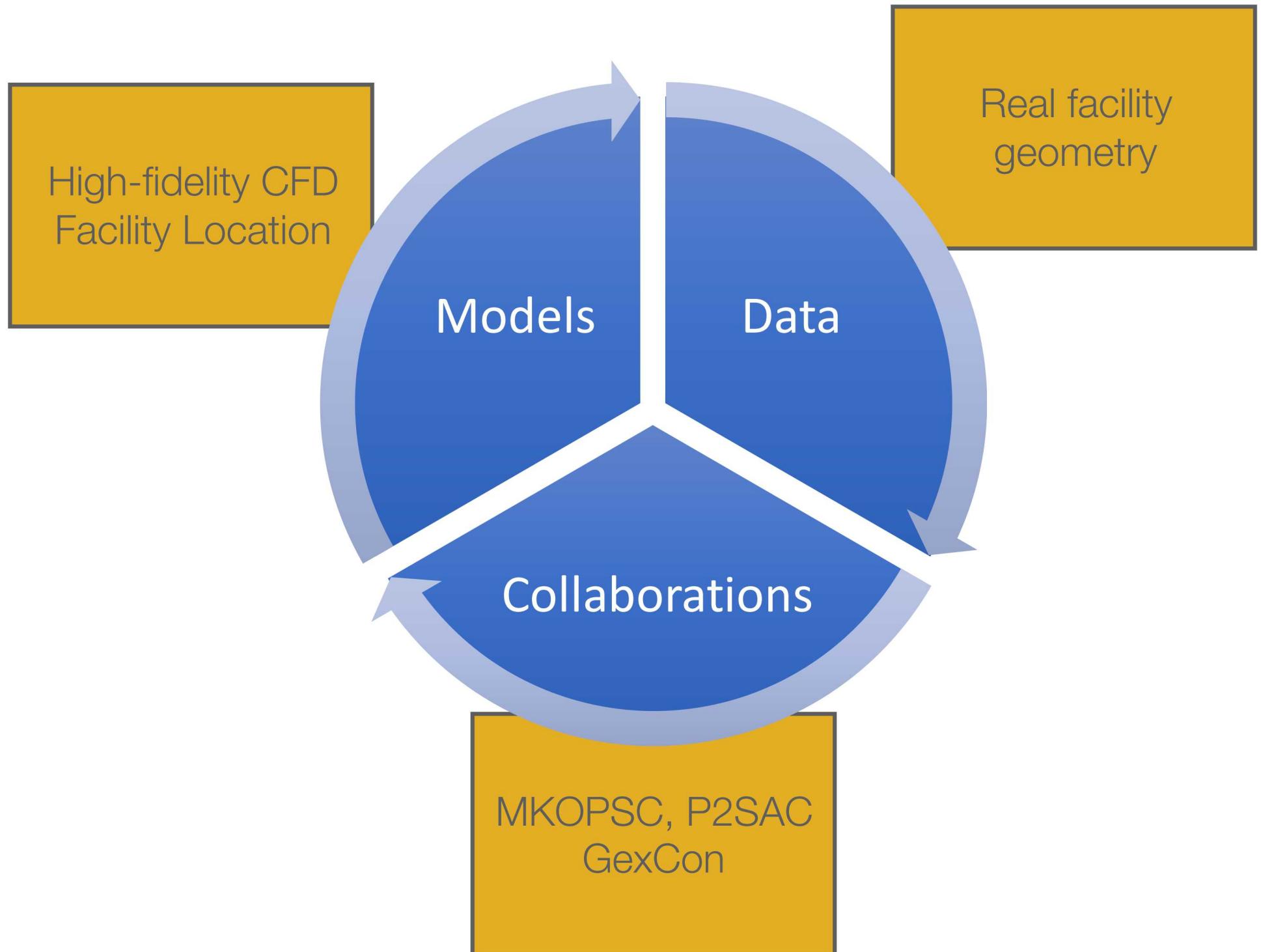
Optimal Placement of Detectors



Optimal Placement of Gas Detectors

- Significant uncertainty in:
 - Leak location
 - Weather conditions
 - Process conditions
- Problem scope:
 - Hundreds or thousands of scenarios
 - Hundreds or thousands of potential locations
 - Several different technologies
- Other challenges:
 - Most effective objective metric
 - Leak dispersion in complex geometries
 - Combinatorial explosion of decisions





Optimization-based Approach

$$\min \sum_{a \in \mathcal{A}} \alpha_a \sum_{i \in \mathcal{L}_a} d_{a,i} x_{a,i}$$

$$\text{s.t.} \quad \sum_{i \in \mathcal{L}_a} x_{a,i} = 1 \quad \forall a \in \mathcal{A}$$

$$x_{a,i} \leq s_i \quad \forall a \in \mathcal{A}, i \in \mathcal{L}_a$$

$$\sum_{i \in \mathcal{L} \setminus \{D\}} s_i \leq p$$

$$s_i \in \{0, 1\} \quad \forall i \in \mathcal{L}$$

$$0 \leq x_{a,i} \leq 1 \quad \forall a \in \mathcal{A}, i \in \mathcal{L}_a$$

- Minimizes the expected detection time across all events
- Summation of probabilities of detection of scenario **a**
- A sensor location can only claim detection if a sensor exists in that location
- Constraint limiting the number of sensors allowed
- Binary variable reflecting existence of a gas detector
- Probability of ‘first to detect’ within the range of [0,1]

Gas Detector Placement Research

Water
Community

Sensor placement in municipal water
networks (Berry et al, 2005)

Designing contamination warning systems
for municipal water networks using
imperfect sensors (Berry et al, 2009)

Gas
Detection
for
Process
Industries

SP
(Legg et al, 2012b)
Initial formulation

*What about sensor
failure?*

*How does this
compare with
practice?*

*Are the number
of scenarios
sufficient?*

*Should we be
concerned with
mean behavior or
tail-behavior?*

*Non-uniform failure probabilities
(type, location, time)*

Operations
Research
Literature

Backup Covering models and facility unavailability models for the LSCP and MCLP.
Reliable PMP (**RPMP**) (Snyder & Daskin, 2005)

Gas Detector Placement Research

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Gas
Detection
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Industries

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Initial formulation

SP-U & SP-UV
(Benavides et al, 2014a)
Imperfect detector
considerations: Unavailability
and Voting

SP-UV Validation
(Benavides et al, 2014b)
SP-UV vs. Current detector
placement practices in the
industry

SP-C
(Legg et al, 2012a)
Coverage constraints and
the resilience of the
formulation to unforeseen
scenarios

(Benavides et al, 2016)
Non-uniform
unavailability
(1 backup level only)

SP-CVaR
(Legg et al., 2012c)
Improves the
tail-behavior of the
distributions of detection
times

(J. Liu et al,
MKOPSC Symposium)
Non-uniform unavailability
(no limitation)

Operations
Research
Literature

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Optimal Gas Detector Placement

Mathematical optimization is computationally tractable (and useful) - Several formulations exist with realistic assumptions

Optimization methods based on dispersion studies outperform common methods for gas detector placement

Methods that use dispersion information outperform those that do not

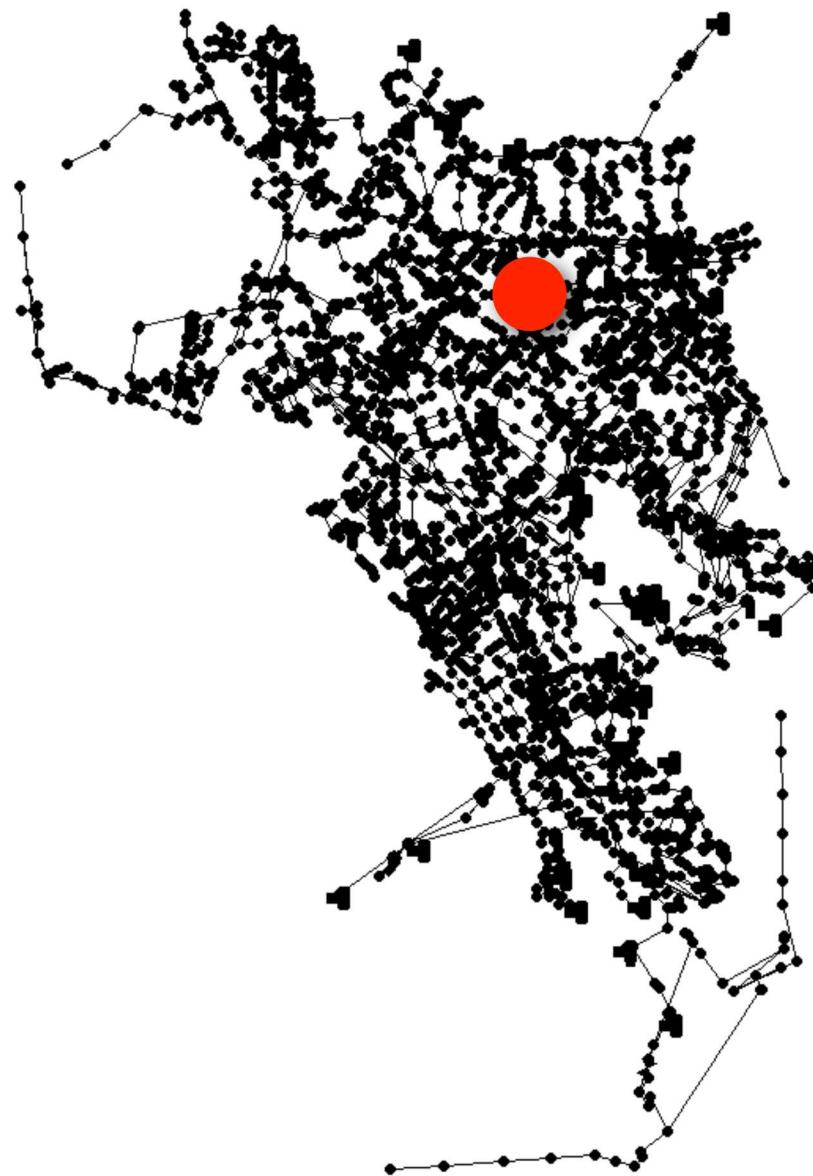
Methods that use optimization outperform those that do not

The volumetric approach (one of the most common) behaves the poorly (worse than random) with the data studied

Similar results for all 4 data sets

Similar results when incomplete data used for placement (75% / 25%)

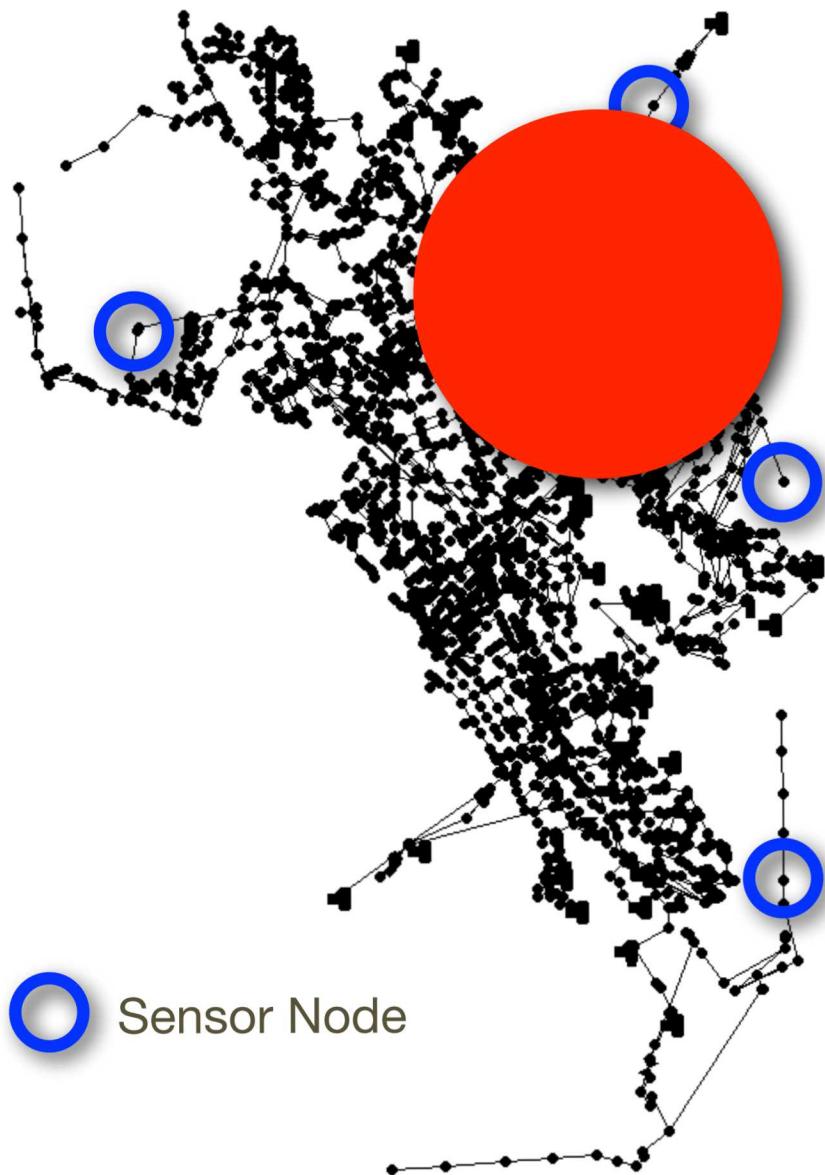




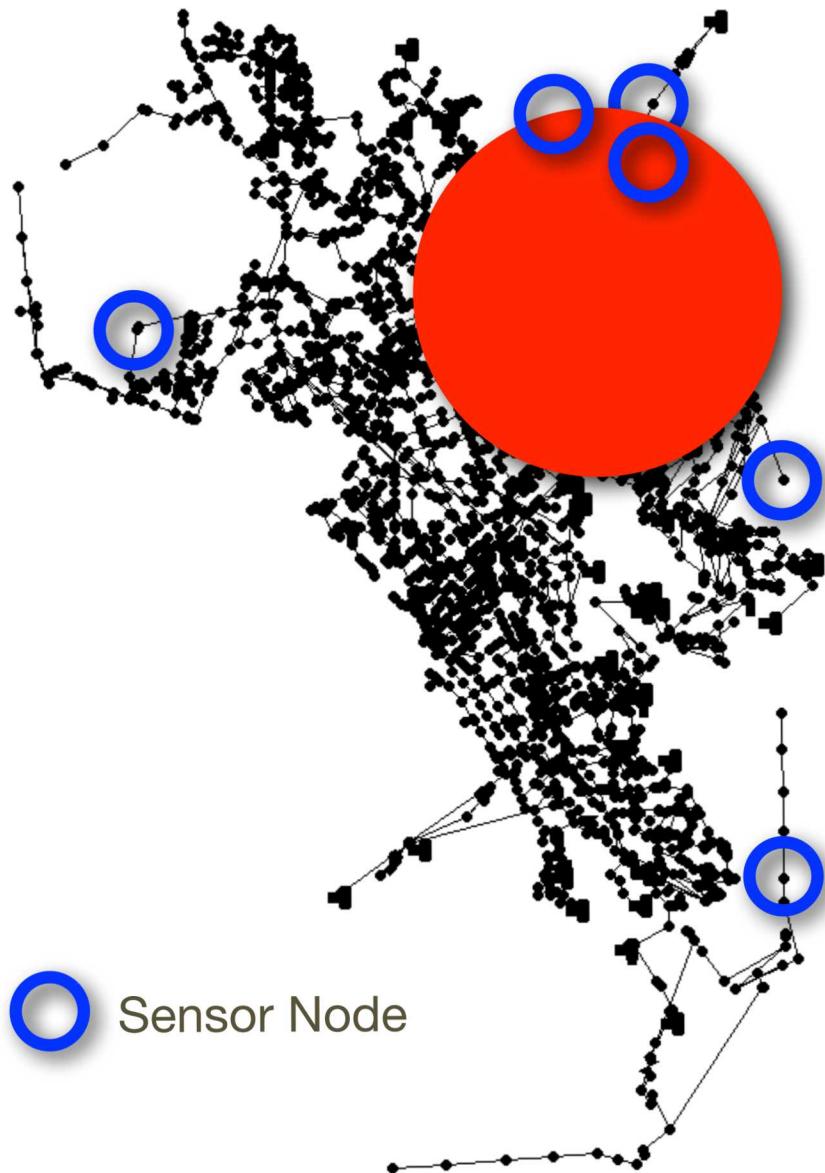


How do I best protect the
public and the infrastructure?

Early Warning and Response System

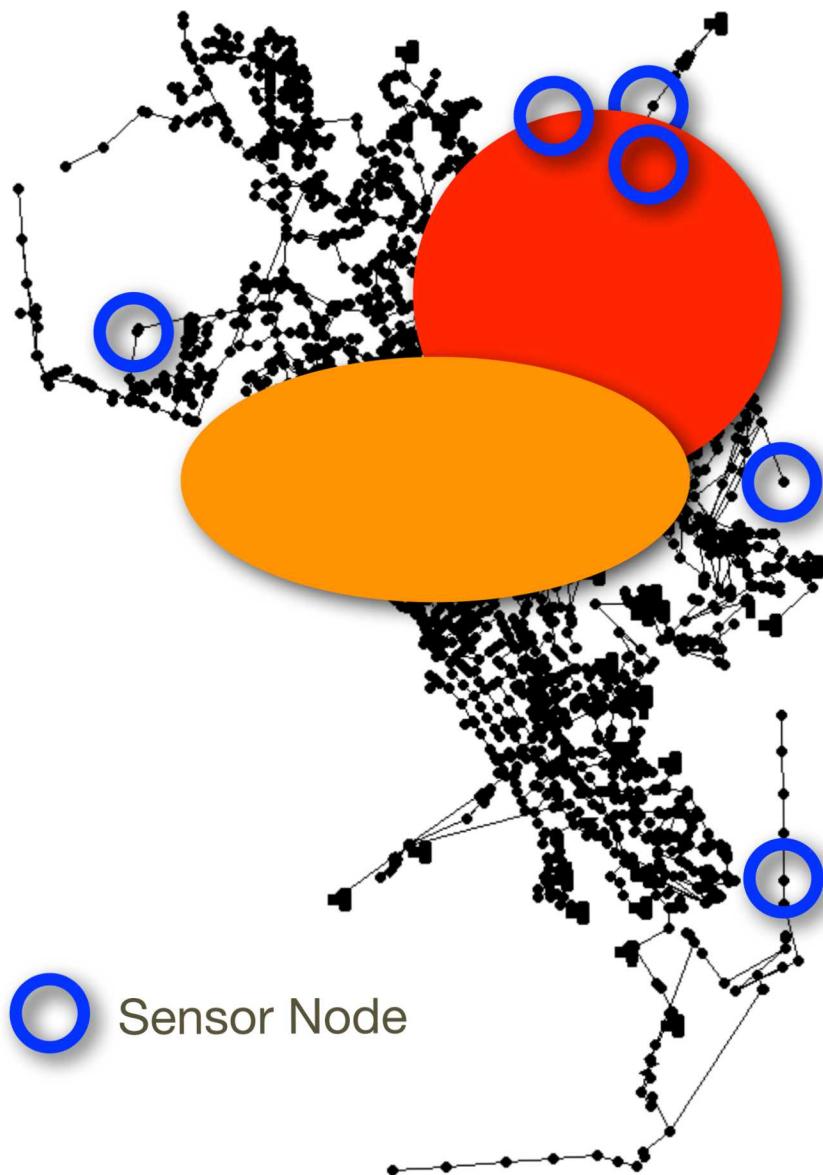


Early Warning and Response System

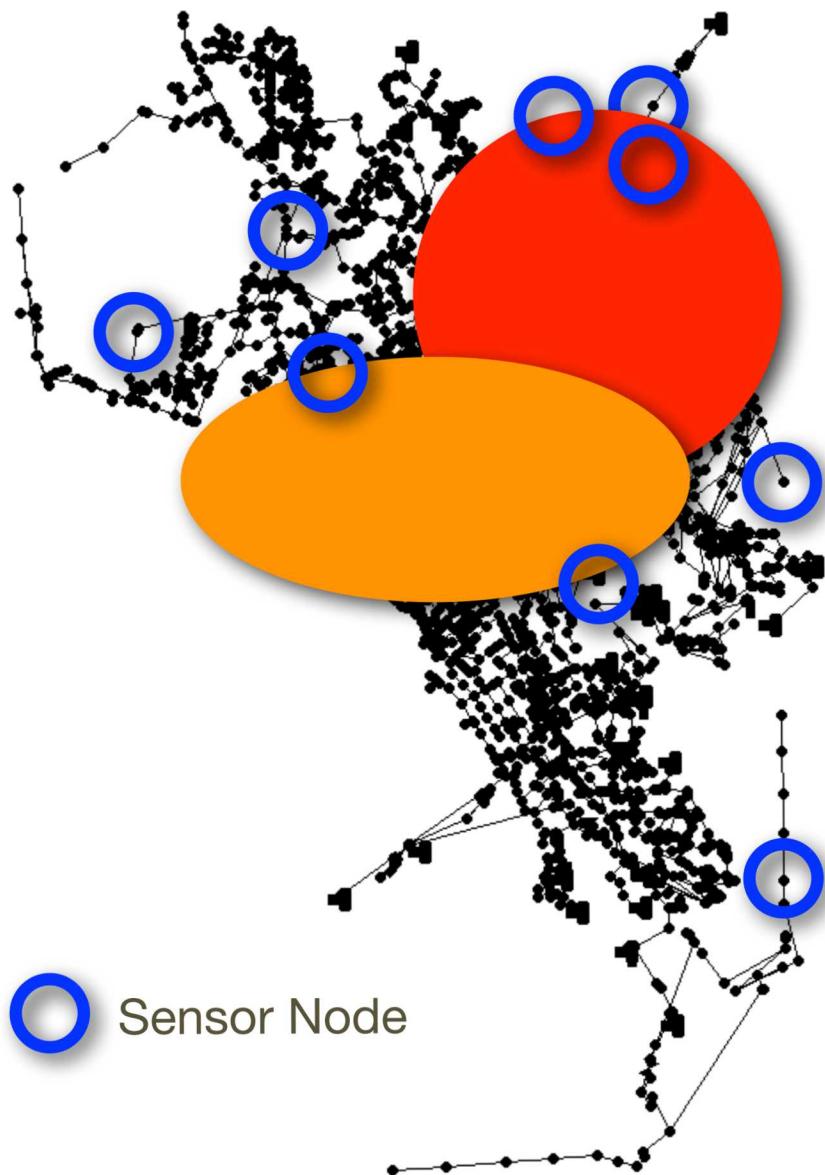


Sensor Node

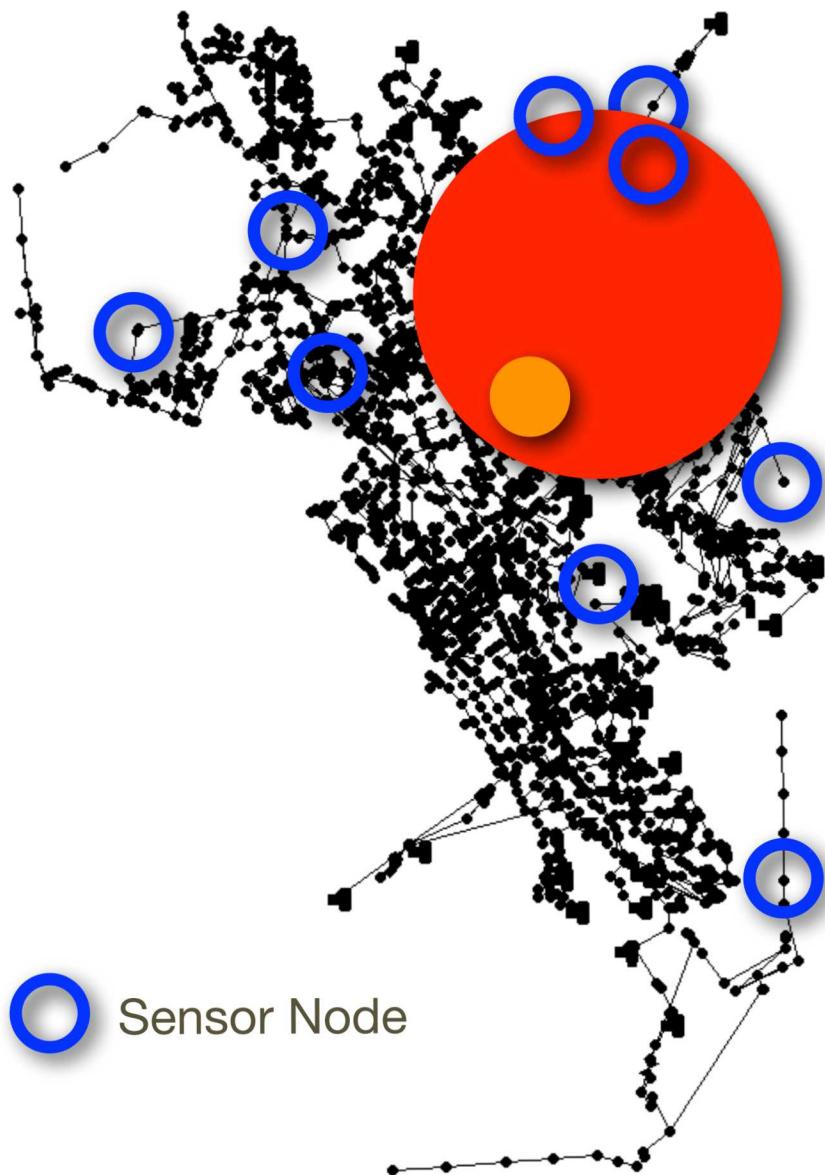
Early Warning and Response System



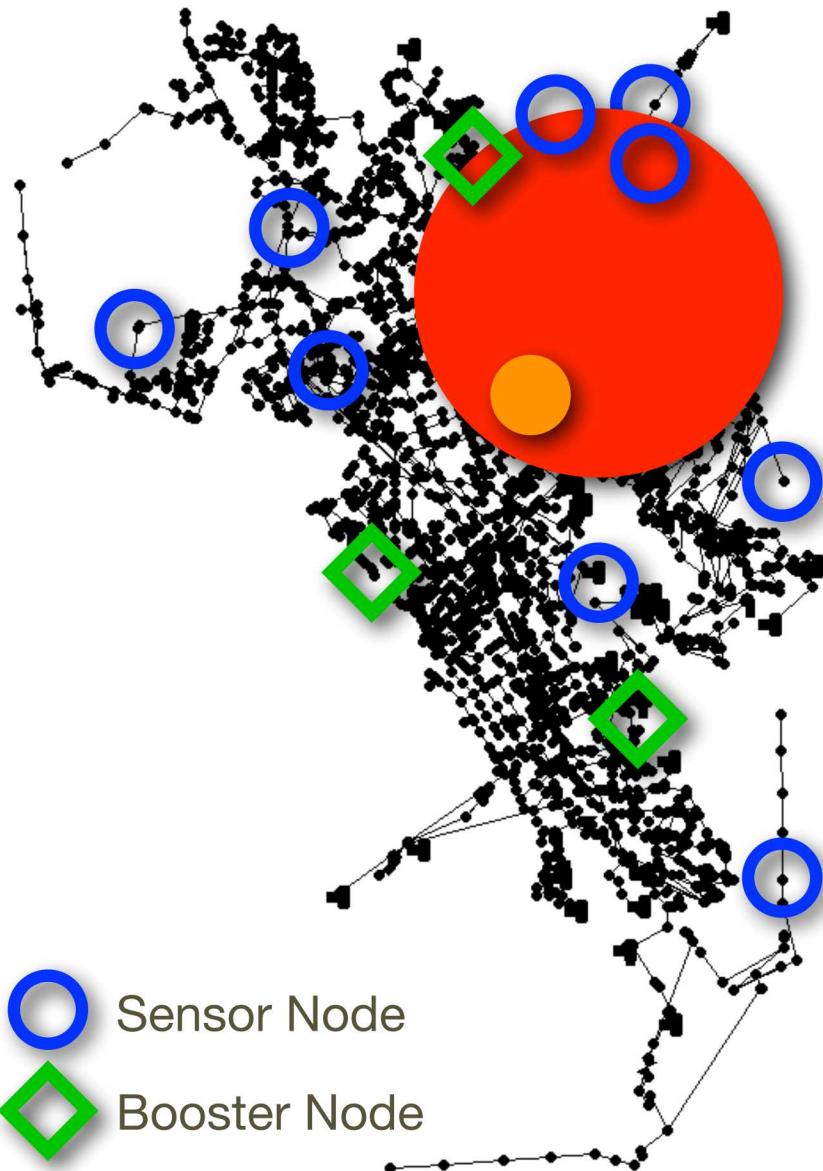
Early Warning and Response System



Early Warning and Response System



Early Warning and Response System



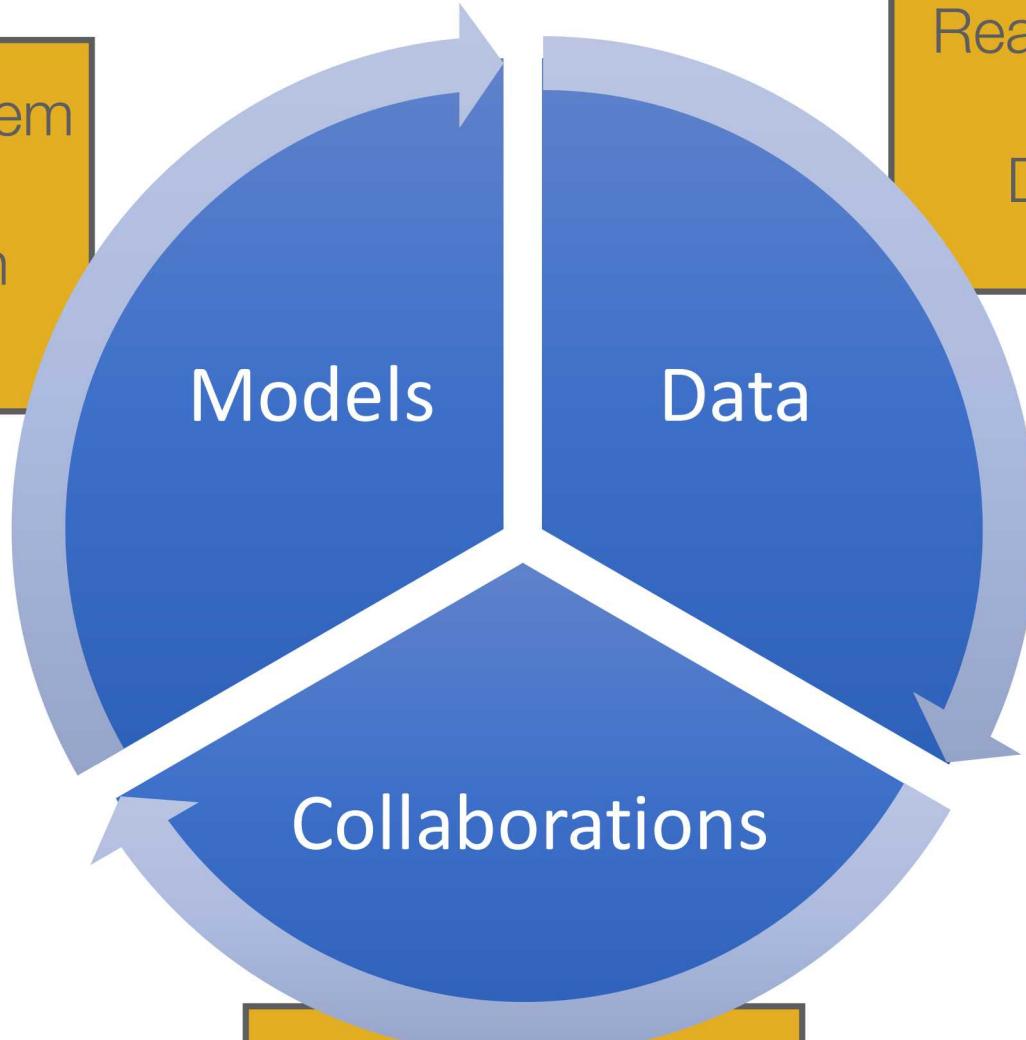
Sensor Technology

Monitoring & Mitigation
System Design

Source/Plume Identification
& Real-time Response

Distribution System
Models
(Reformulation
Needed)

Real (and realistic)
Network
Descriptions



US EPA
Sandia Nat. Lab

Publications in Water Security

Santiago-Rodriguez, J., Bynum, M., Hart, D., Laird, C.D., Klise, K.A., Haxton, T., "Optimal sampling locations to reduce uncertainty in contamination extent in water distribution systems", in progress

Seth, A., Hackebiel, G.A., Klise, K.A., Haxton, T., Murray, R., and Laird, C.D., "A Stochastic Programming Formulation for Disinfectant Booster Station Placement in Water Distribution Systems", submitted.

Seth, Arpan, et al. "Testing Contamination Source Identification Methods for Water Distribution Networks." *Journal of Water Resources Planning and Management* 142.4 (2016): 04016001.

Mann, A.V., Hackebiel, G., Laird, C.D., "Explicit Water Quality Model Generation and Rapid Multi-Scenario Simulation", *Journal of Water Resources Planning and Management*, Volume 14, May 2014, Pages 666-677.

Mann, A.V., McKenna, S.A., Hart, W.E., and Laird, C.D., "Real-Time Inversion in Large-Scale Water Networks Using Discrete Measurements", *Computers & Chemical Engineering*, Volume 37, February 2012, Pages 143-151.

Berry, J., Hart W., Laird, C.D., and Uber, J., "A Morphing Technique to Disguise Water Networks", *Proceedings of, EWRI World Environmental and Water Resources Congress 2007*, May, 2007.

Laird, C.D., Biegler, L.T. and van Bloemen Waanders, B.G., "Real-Time, large scale optimization of water network systems using a subdomain approach", In: L.T. Biegler, O. Ghattas, M. Heinkenschloss, D. Keyes, and B. van Bloemen Waanders, Eds., *SIAM Series in Computational Science and Engineering* #3, SIAM, 2007, *Real-Time PDE-Constrained Optimization*, Pages 291-308.

Laird, C.D., Biegler, L.T. and van Bloemen Waanders, B.G., "Mixed-integer approach for obtaining unique solutions in source inversion of water networks", *A.S.C.E. Journal of Water Resources Planning and Management*, Volume 132, June 2006, Pages 242-251.

Laird, C.D., Biegler, L.T., van Bloemen Waanders, B.G. and Bartlett, R., "Contamination source determination for water networks", *A.S.C.E. Journal of Water Resources Planning and Management*, Volume 131, March 2005, Pages 125-134

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Optimal Real-time Sampling Approach

Given a contamination event:

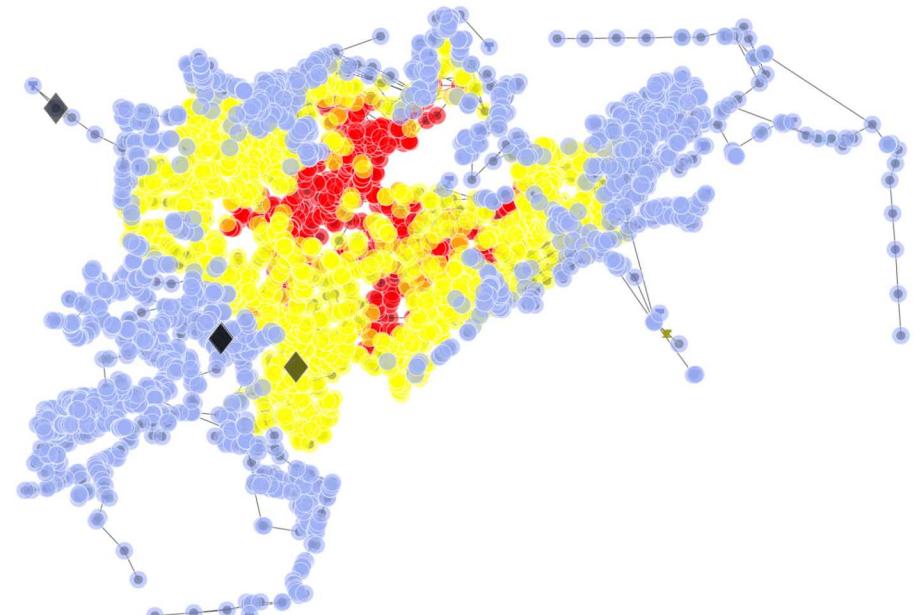
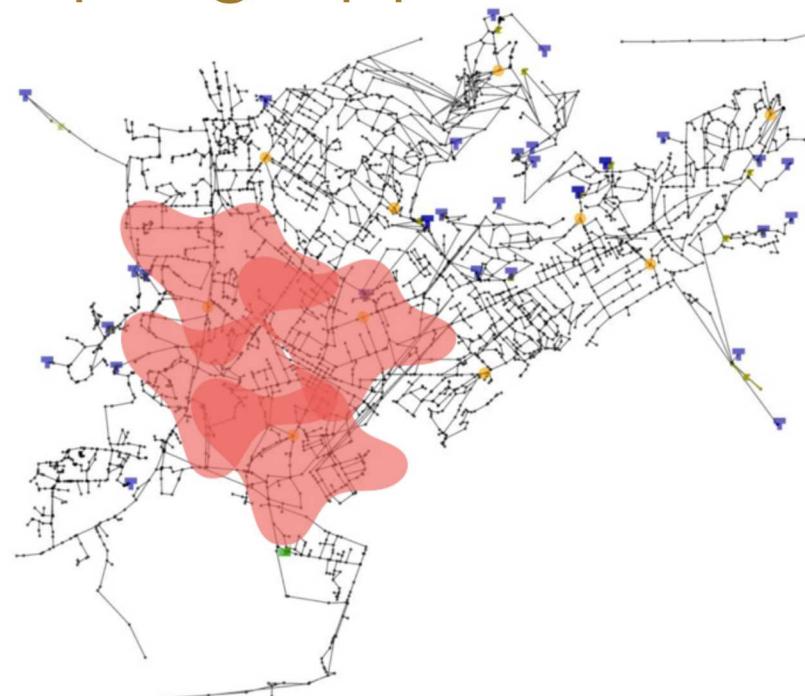
- What is the uncertainty in the plume?
- Where can we take additional measurements to reduce uncertainty?

Account for uncertainty in:

- Contamination location, time, profile
- Hydraulics, reaction dynamics

Computational approach:

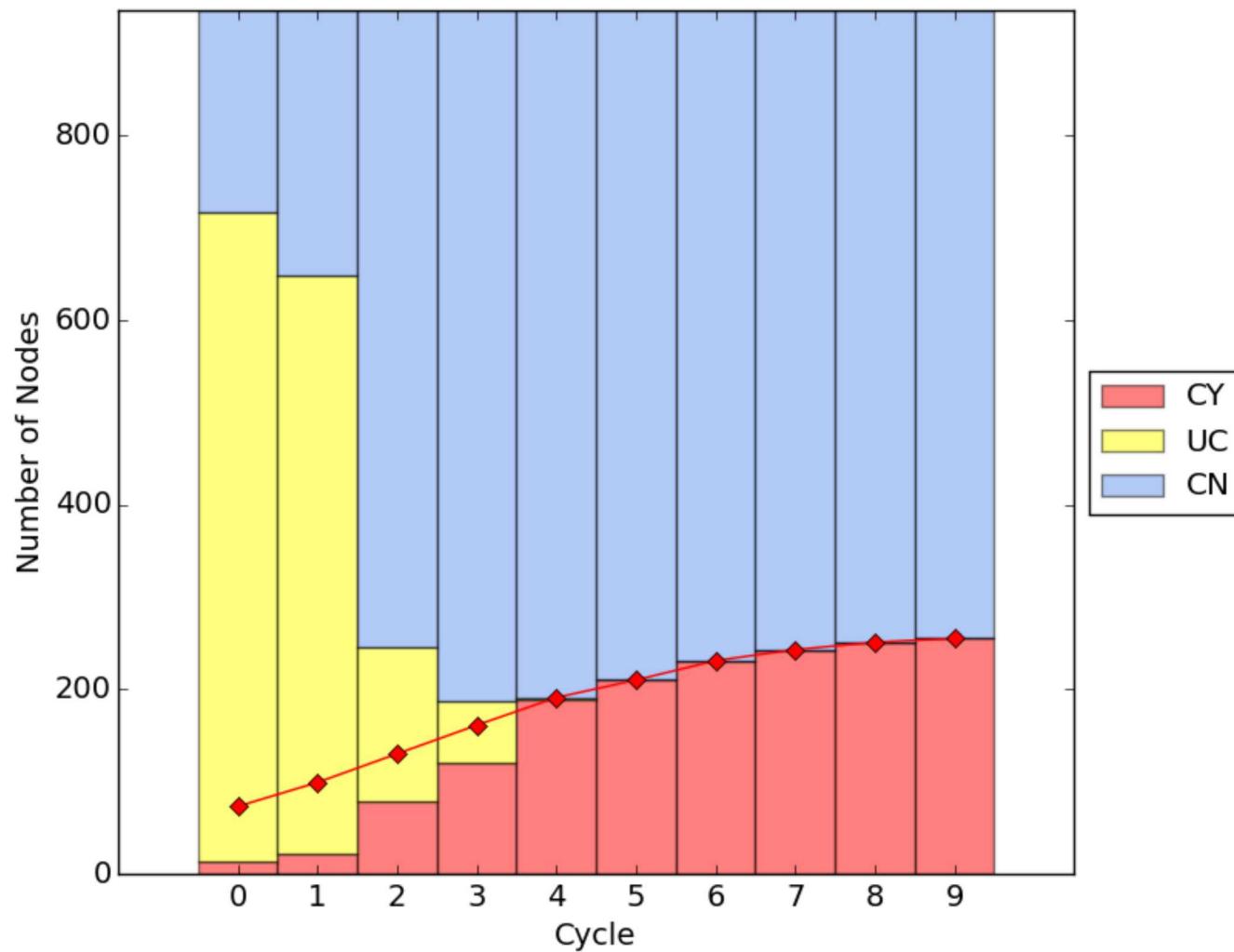
- Pre-compute scenarios (M's)
- Bayesian statistics:
 - update scenario probabilities
 - propagate probability of scenarios to probability of contamination
 - use optimization to find best sampling locations to update the scenario probabilities



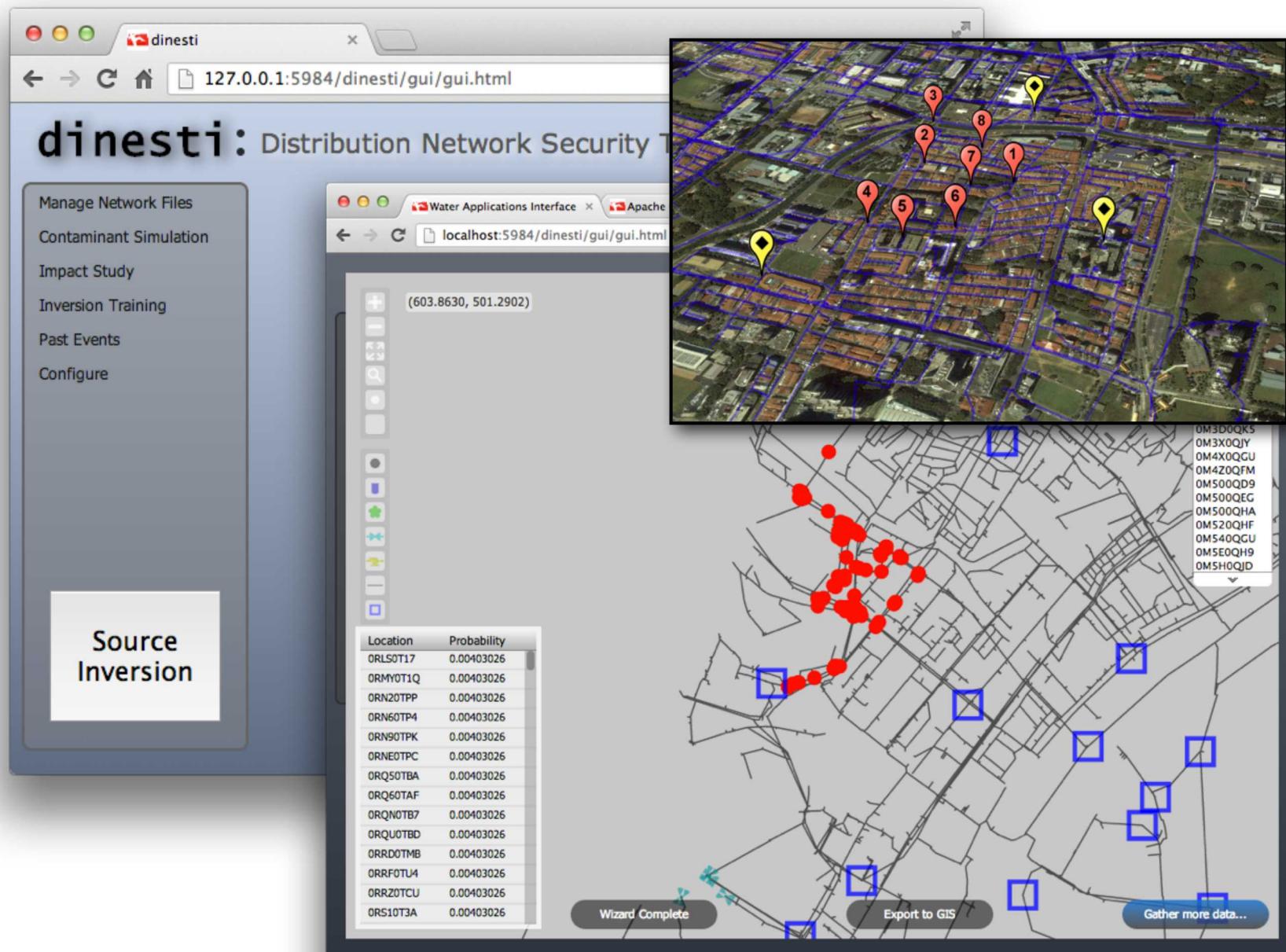
Maximization of number of expected scenarios that mismatch

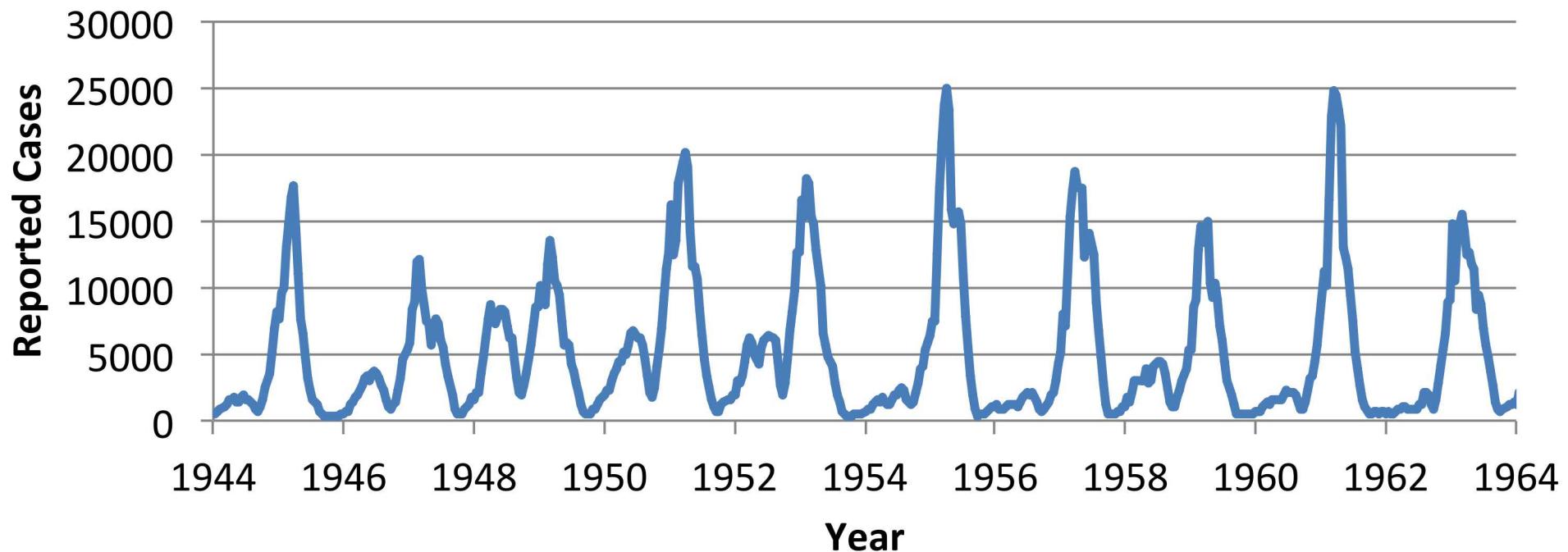
$$\begin{aligned} \max_x \quad & \sum_{s \in S} P_s^{\text{miss}} \\ \text{s.t.} \quad & P_s^{\text{miss}} = 1 - P_s^{\text{match}} \quad \forall s \in S \\ & P_s^{\text{match}} \geq \exp(\tilde{P}_s) \quad \forall s \in S \\ & \tilde{P}_s = \sum_{n \in N} x_n \ln(\alpha_{s,n}) \quad \forall s \in S \\ & \sum_{n \in N} x_n \leq S_{max} \\ & x_n \in \{0, 1\} \forall n \in N \end{aligned}$$

Uncertainty Reduction



Source Inversion Response System

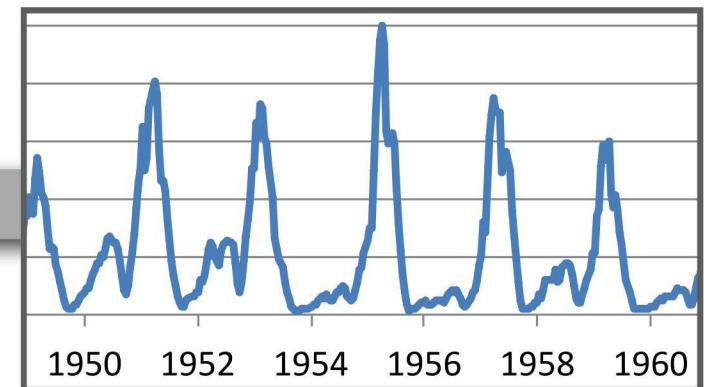
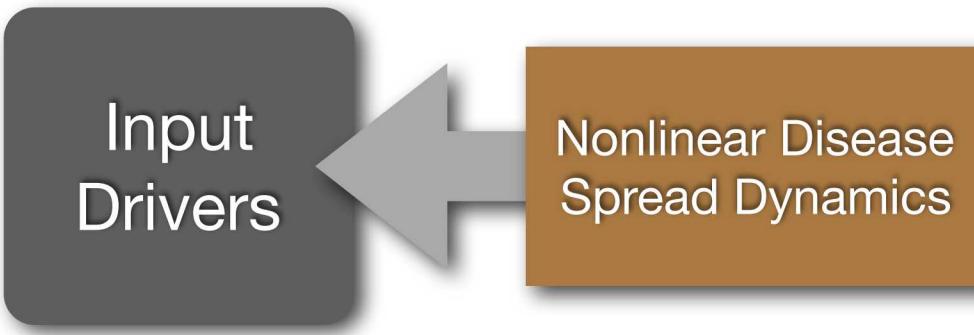
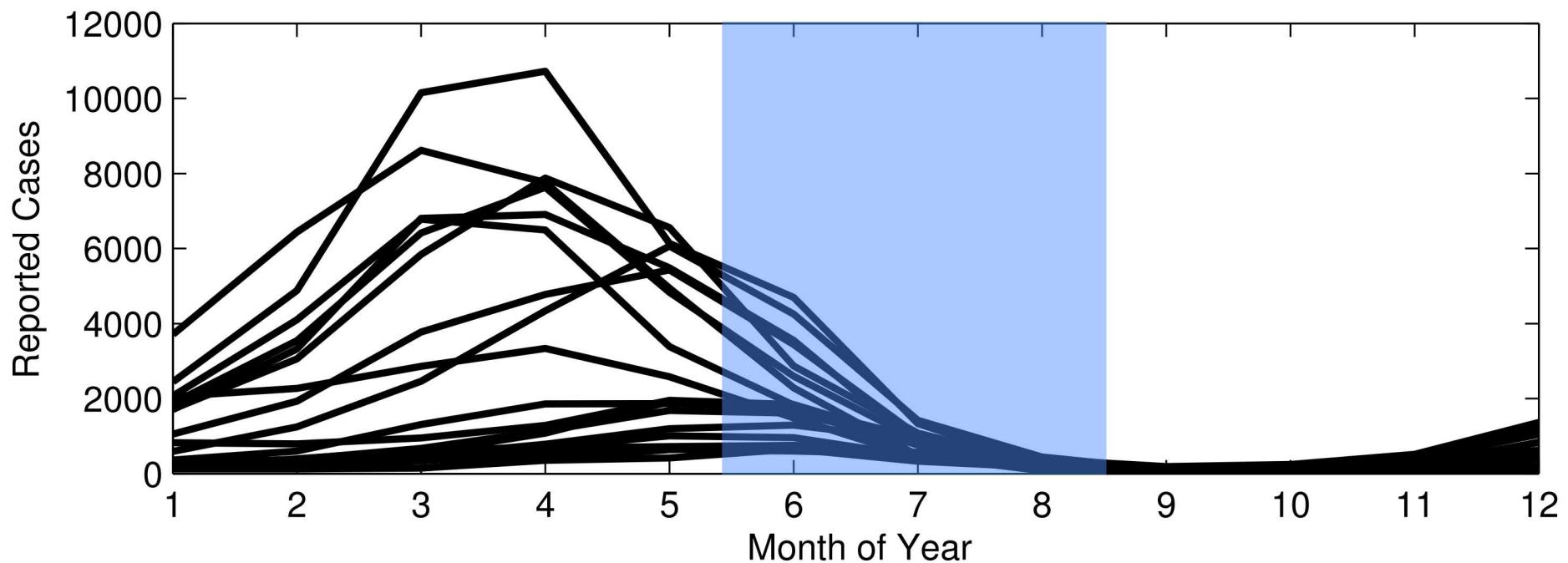


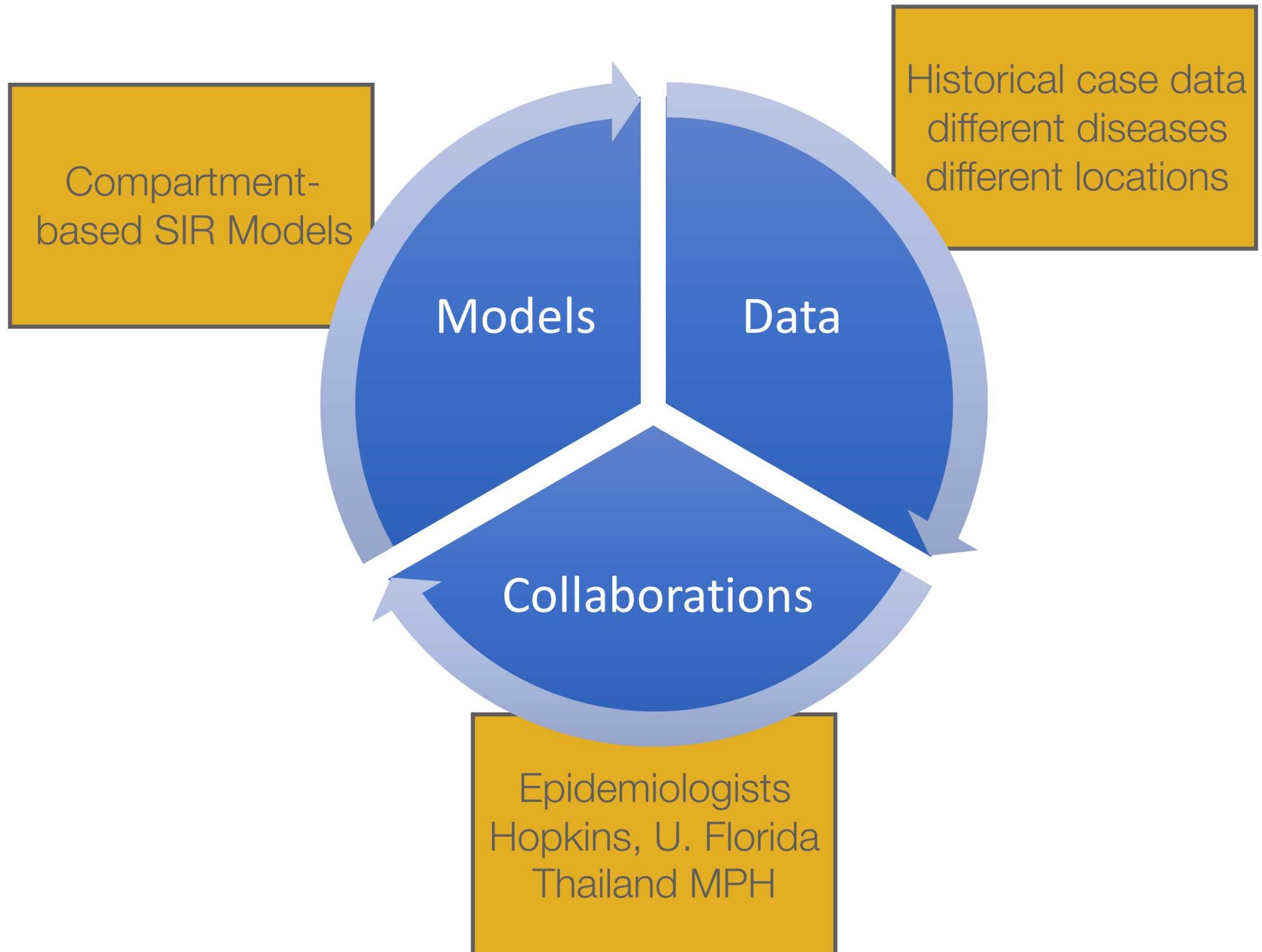


How do we use this data to better understand the spread of infectious disease?

How would you use this data for improved intervention in an emerging childhood respiratory pandemic?

Seasonality in Input Drivers

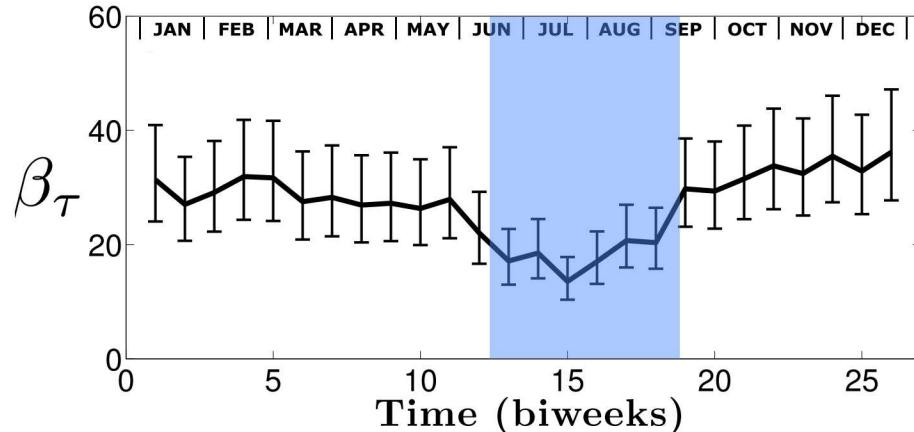




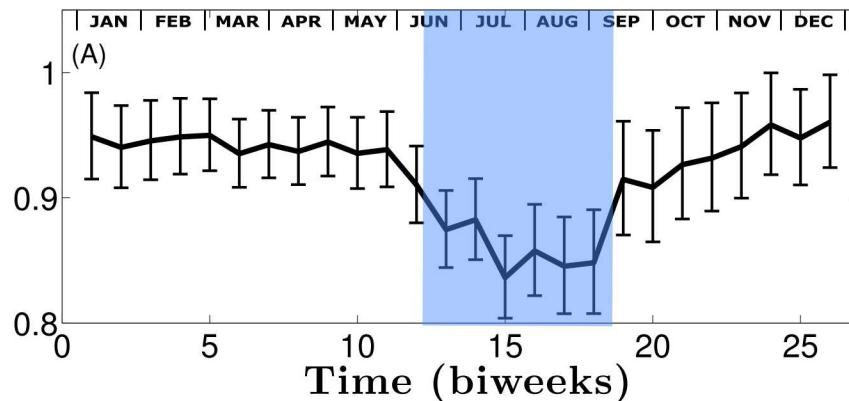
Estimating Seasonal Drivers in Childhood Infectious Diseases

- Childhood Infectious Diseases (e.g., Measles, Chickenpox)
 - Seasonality Induced by School Holidays
 - Pre-Vaccination Era: Everyone Contracts the Disease
 - Still a Significant Problem in Developing Countries & Easily Identified
- Estimation Challenges
 - Long-time Horizons (20-30 years)
 - Data aggregated monthly or biweekly
 - No Susceptible Information
 - Severe Under-reporting of Cases (1/2 for UK, 1/100 for Thailand)
 - Missing (1974, 1979), Substantial Noise, Time-Varying Reporting
- Available Data:
 - England & Wales: 60 (900) Cities 1944-1963
 - US: New York City, Baltimore, TYCO Data
 - Thailand: 76 Provinces 1972-1998
 - Library of Congress

Estimating Seasonal Drivers of Infectious Disease



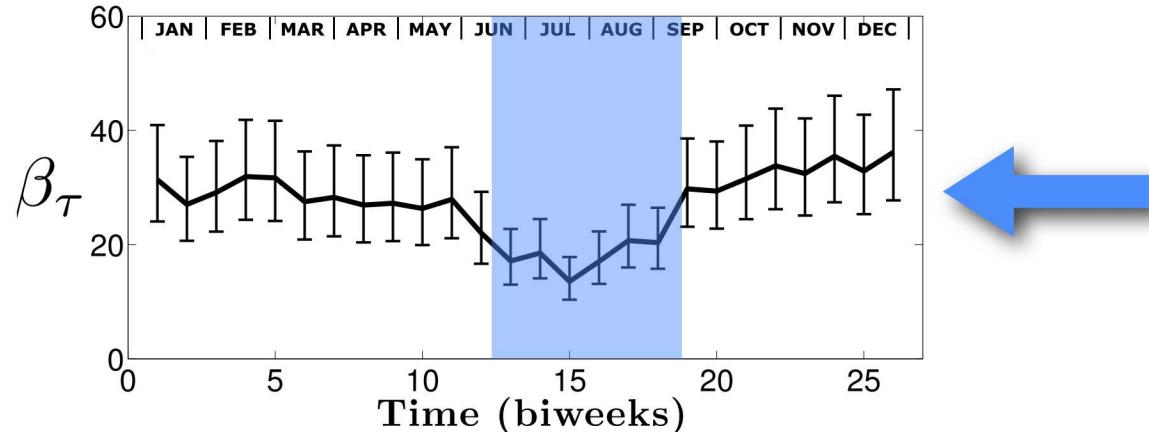
Estimating seasonality in transmission parameter (contacts)



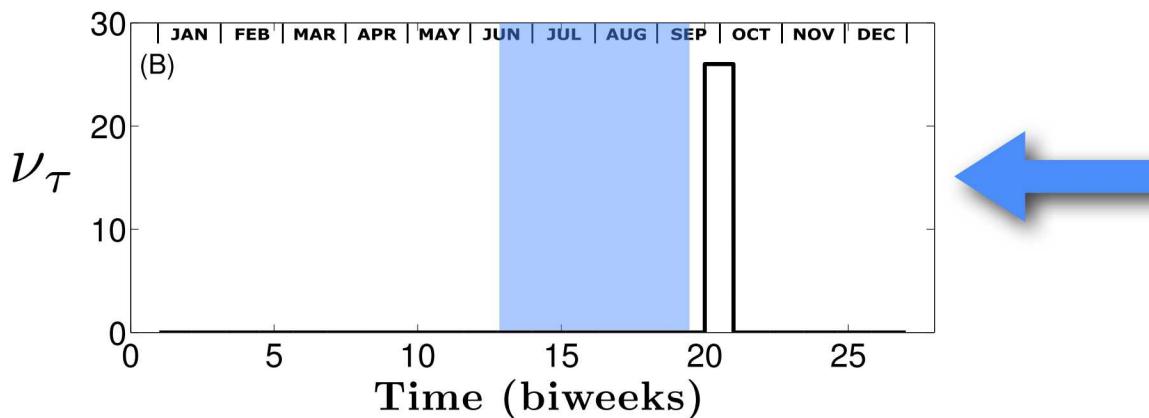
Estimating seasonality in exponential factor (mixing)

Estimated patterns correlate with school holidays and we can quantify impact of school closure

Estimating Seasonal Drivers of Infectious Disease



Estimating seasonality in transmission parameter (contacts)



Estimating seasonality in birth rate

Estimated patterns correlate with school holidays and we can quantify impact of school closure

Publications

Zhen, T., Cummings, D., and Laird, C.D., "A Nonlinear Optimization Approach to the Estimation of Spatial Transmission Parameters in Infectious Disease Spread", in progress

Liu, J., Cummings, D., and Laird, C.D., "MINLP Approaches for Parameter Estimation in Deterministic and Stochastic Disease Models", in progress.

Word, D.P., Young, J.K., Cummings, D.A.T., Iamsirithaworn, S., and Laird, C.D., "Interior-Point Methods for Estimating Seasonal Parameters in Discrete-Time Infectious Disease Models", PLOS One, Volume 8-10, October 2013, Pages 1-13.

Word, D.P., Cummings, D.A.T., Burke, D.S., Iamsirithaworn, S., and Laird, C.D., "A Nonlinear Programming Approach for Estimation of Transmission Parameters in Childhood Infectious Disease Using a Continuous Time Model", Journal of the Royal Society Interface, Volume 9, August 2012, Pages 1983-1997

Word, D.P., Abbott III, G.H., Cummings, D., and Laird, C.D., "Estimating Seasonal Drivers in Childhood Infectious Diseases with Continuous Time and Discrete-Time Models", Proceedings of, American Control Conference (ACC) 2010, Baltimore, MD, June 30 - July 2, 2010, Pages 5137-5142.

Word, D.P., Young, J., Cummings, D., and Laird, C.D., "Estimation of seasonal transmission parameters in childhood infectious disease using a stochastic continuous time model", In: S. Pierucci and G. Buzi Ferraris, Eds., Computer Aided Chemical Engineering, Volume 28, Elsevier, 2010, 20th European Symposium on Computer Aided Process Engineering, Pages 229-234.

Summary and Conclusions

Mathematical programming provides rigorous, computationally tractable, solutions to many problems in safety and security

- Protection of critical infrastructure
- Improved system understanding
- Design of mitigation systems
- Real-time response

Rapid, dramatic improvements in optimization capabilities (modeling tools, algorithms)

Increased data and desire for rigorous analysis from many application areas

Successful convergence in research requires:

- Collaboration: Importance, community
- Data: Impact
- Models: Enabling technology

Acknowledgements

- Current Students/Researchers

- Daniel Laky
- Richard Shu
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- Todd Zhen

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- Ahmed Rabie
- George Abbott III
- Chen Wang
- **Sean Legg**
- **Daniel Word**
- **Angelica Wong**
- Xiaorui Yu
- Gabriel Hackebel
- Shawn McGee

- Collaborators

- D. Cummings - JHSPH
- S. Iamsirithaworn - MPHT
- W. Hart, S. McKenna, J.P. Watson, K. Klise, John Siirila - Sandia
- T. Haxton, R. Murray - EPA
- Johan Akesson, Lund University
- Sam Mannan, TAMU

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