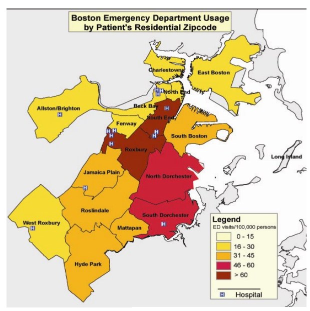
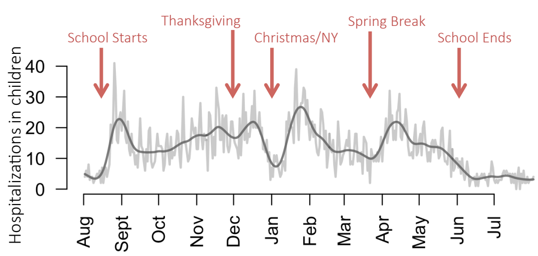
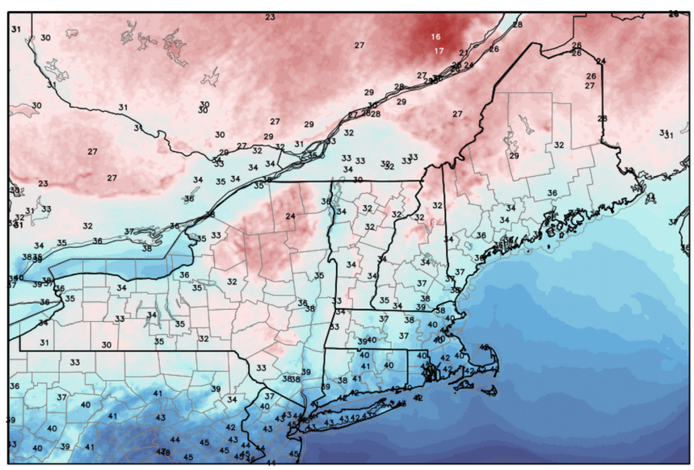
Analytic Solutions for Real-Time Biosurveillance
Models for Risk of Asthma Exacerbations in Urban Environments

CDRL – A007.3
HDTRA1-15-C-0004
Consultancy Report







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Models for Risk of Asthma Exacerbations in Urban Environments
Consultancy Report

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I. Acknowledgements

ISDS is extremely grateful to the Boston Public Health Commission (BPHC) for spearheading the development of the use case and for providing the event venue. We thank all the participants for contributing their tremendous subject matter expertise to the discussion. This work supported by contract # HDTRA1-15-C-0004 to ISDS from the Defense Threat Reduction Agency (DTRA). Opinions expressed do not necessarily reflect the views of DTRA, BPHC, or the ISDS Membership.

Models for Risk of Asthma Exacerbations in Urban Environments: Consultancy Participants

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II. ISDS and Analytic Solutions for Real-Time Biosurveillance

The International Society for Disease Surveillance (ISDS) is a 501©(3) organization with a mission to advance the science and practice of health surveillance worldwide. In health surveillance we include the overlapping fields of public health surveillance, animal health surveillance, zoonotic disease surveillance, and surveillance of the environment to monitor health threats and provide situational awareness. ISDS advances its mission through a broad portfolio of activities involving multi-stakeholder collaborations to provide capacity-building assistance to members and the surveillance community worldwide; actively shape national and international health surveillance policy; and expand our global surveillance Community of Practice (CoP).

ISDS fills the need for a practical forum and coordinating mechanism for collaboration among subject matter experts (SMEs) from stakeholder groups that may normally not interact but who, when brought together, enable innovative approaches to problems and solutions that are not possible by any one group alone. The objective of the *Analytic Solutions for Real-Time Biosurveillance* project is to advance analytic capabilities in real-time biosurveillance (BSV) by expediting next-generation solutions to currently intractable problems through focused consultancies that join end-user problem owners from civilian and military public health agencies with solution developers in academia, industry, and government. This approach helps to clarify key gaps in surveillance capabilities and to develop the requirements for knowledge management, algorithms, models, visualizations, and other solutions to address these gaps. For more information about this project, see: http://www.syndromic.org/cop/analytic-solutions/isds-consultancies

III. The Boston Use Case

Julia Gunn and Margaret Reid from the Boston Public Health Commission (http://www.bphc.org/) co-submitted a use-case to ISDS for consideration as a consultancy (Appendix A). The ISDS Analytic Solutions Advisory Group (ASAG), consisting of SMEs in surveillance practice, research, and policy reviewed the case and found the problem well suited for a consultancy format. Drs. Howard Burkom and Ian Painter providing expertise on technical matters and SMEs. ISDS provided overall project management and event coordination.

Problem Description

Asthma exacerbation can be triggered by a number of environmental factors and respiratory viral infections. Asthma control plans are essential in preventing exacerbation. An early warning of increased atmospheric/environmental risk would enable public health agencies to alert asthmatic patients and providers. These alerts would also include prevention messaging and allow asthmatics to ensure that their plans are up to date. BPHC seeks analytic methods for forecasting conditions that are associated with asthma exacerbations. The forecast should consider the impact of respiratory infections (rhinovirus, influenza), temperature extremes, anomalous air quality measurements, and pollen. Available data sources are emergency department visit records, weather data, air quality data, and pollen counts.

Regarding the type of solution sought, the prediction calculations and alerting communications must be available at a minimum on a daily basis without impacting other routine processing operations. The stratification of predictions by geography and by demographic factors should be as fine as the data will support. Electronic near real time data feeds are required. The analytical processes must be automated. The model and system needs to support continuous model training.

IV. Agenda

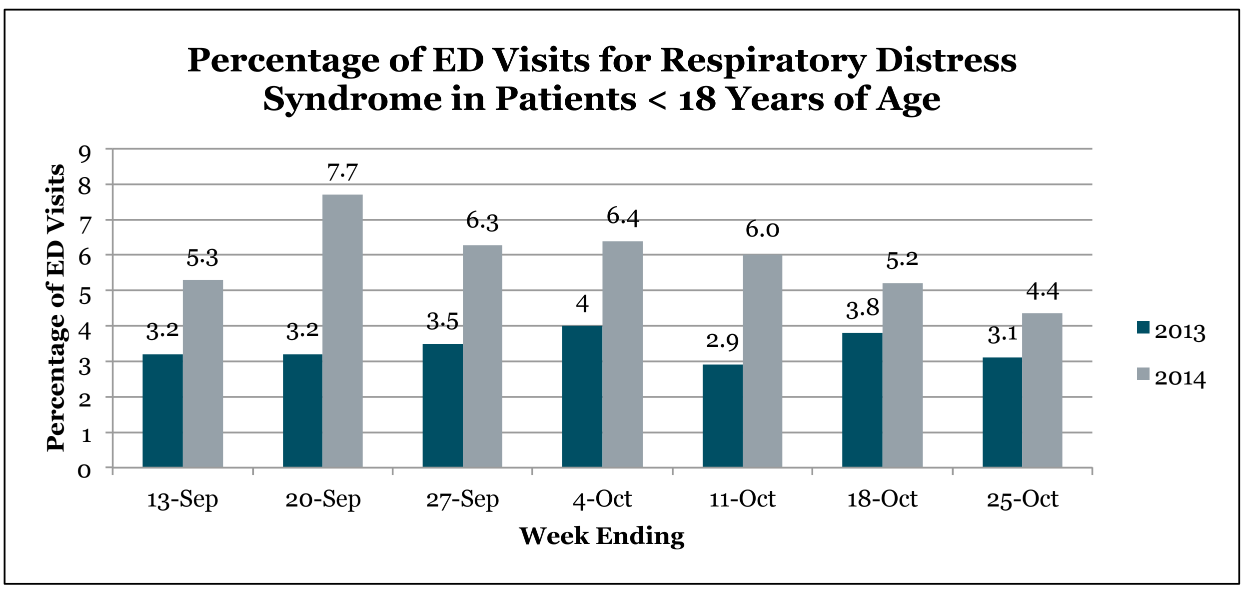
In light of the problem description and the preliminary solution requirements, the goals of this consultancy were to:

1. Identify a practical model to forecast environmental conditions that are likely to result in asthma exacerbations;
2. Define systems requirements to automate the processing notifications of issues (environmental and technical).
3. Communicate environmental conditions and actions to a variety of stakeholders at different levels of the socio-ecological model.

For meeting notes and presentation slides, see Appendices B – L.

Consultancy Day 1: March 30, 2016	
9:00	**Meet and Greet with Continental Breakfast**
10:00	**Welcome to the BPHC** *Monica Valdes Lupi,* Executive Director, BPHC
10:15	**Welcome to the Consultancy – Introductions** *Laura Streichert,* ISDS
10:45	**Use Case Goals and Requirements** *Julia Gunn,* BPHC
11:00	**The Asthma Problem in Boston** *Margaret Reid*, Director, Division of Healthy Homes and Community Supports, BPHC • What is the BPHC program? • What are the factors that make asthma worse and may cause asthma? • If we could anticipate events, what would we like to know? • How would we use this information? *Moderated Group Discussion*
12:00	**Lunch Provided**
12:45	**Syndromic Surveillance for Asthma** *Julia Gunn,* BPHC • Boston's Syndromic surveillance system • What makes it particularly useful? (ex: near real time info) • Examples of how we use it for asthma • Summary of data features: ▪ Date range of benchmark set ▪ Number of hospitals and total records ▪ Relevant data fields ▪ Summary of syndrome classification ▪ Age distributions *Moderated Group Discussion*
1:45	**Environmental Data Sources** *Steve Babin*, JHU/APL, moderator *Haig Iskenderian,* MIT Lincoln Laboratory, presenter *Ivanka Stajner,* NOAA, presenter • Relationship to exacerbations, availability and timeliness, quality, coverage and resolution (time and space) • Weather: temperature, solar radiation, precipitation • Air Quality: Ozone, PM2.5, Sulfur Dioxide • Pollen, mold, allergens • Other environmental risk factors? • How to combine with healthcare-seeking data *Moderated Group Discussion*
2:45	**Coffee Break**

3:00	**Modeling Approaches** *Howard Burkom*, JHU/APL, moderator, presenter *Rosalind Eggo,* London School of Hygiene and Tropical Medicine, presenter *Kathy Ensor,* Rice University, presenter *Anna Buczak,* JHU/APL, presenter *Jon Levy,* Boston University School of Public Health, presenter • Basic concept • Past applications • Advantages, disadvantages, obstacles for exacerbation risk modeling in City of Boston with available data *Moderated Group Discussion*
4:30	**Group Discussion** Determining utility, practicality, cost, timeliness, availability, and relevance. • How can it be brought to bear on asthma? Are there other criteria? • Are there data sources that meet the criteria that we have not yet considered?
4:45	**Wrap-Up and Plan for Day 2**
5:00	**Adjourn**
6:30	**Group Dinner –** Teranga Restaurant, 1746 Washington St, Boston, MA 02118



Consultancy Day 2: March 31, 2016	
8:00	**Continental Breakfast**
8:30	**Recap of Day 1 and Goals for Day 2** *Julia Gunn*, BPHC
9:00	**Translating the Model** *Margaret Reid*, BPHC • What is the utility of models for decision-making at different levels? • How would we communicate information to different audiences? • How will information be communicated to and used by different stakeholders? *Moderated Group Discussion*
9:30	**Operationalizing the Model** *Julia Gunn,* BPHC, moderator *George Mathew*, MIT Lincoln Laboratory, presenter *Karen Stark,* Digital Infuzion, presenter • How do we operationalize a model into an automated system? • System architecture • Informatics including what the output would look like • Privacy and security requirements • Performance metrics • Automated updating of the model *Moderated Group Discussion*
10:30	**Break**
10:45	**Moderated Group Discussion** *Julia Gunn,* BPHC • What do we need to build and what would it take? (e.g., money, time, technology) • Are there available resources? • BPHC data request procedures • Other Uses • Future Considerations
12:00	**Next Steps and Closing** *Laura Streichert,* ISDS
12:15	**Working Lunch** Meeting Hotwash and Open Discussion
1:30	**Adjourn**

V. Evaluation Results

Fourteen participants completed the online survey. The respondents described their primary position as: Local PH practitioner (1); State PH practitioner (1); CDC or other federal public health agency representative (1); other federal agency (e.g. NOAA); Academic researcher (8); Other (2), who identified themselves as an Epidemiologist and pediatrician and a researcher and developer in an FFRDC.

A pre-consultancy call was held in preparation for the in-person meeting. The purpose of the pre-consultancy call was to review the context and goals of the meeting, summarize the problem, present the agenda, identify SME presenters, discuss consultancy logistics, and answer any participant questions. All respondents indicated "neutral" or "agree" in regards to achieving the goals of the pre-consultancy call, as seen in the table below. In the evaluation of the pre-consultancy call 53.85% of participants agreed that the pre-consultancy call clarified the purpose and the goals of the consultancy.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Did not attend call	Total	Weighted Average
The pre-consultancy call clarified the purpose and goals of the consultancy	**0.00%** 0	**7.69%** 1	**0.00%** 0	**53.85%** 7	**15.38%** 2	**23.08%** 3	13	4.00
The consultancy agenda was clearly presented during the pre-consultancy call	**0.00%** 0	**0.00%** 0	**0.00%** 0	**46.15%** 6	**30.77%** 4	**23.08%** 3	13	4.40
The pre-consultancy call clarified any questions you had about the consultancy	**0.00%** 0	**7.69%** 1	**23.08%** 3	**38.46%** 5	**7.69%** 1	**23.08%** 3	13	3.60
The pre-consultancy call resolved any concerns regarding logistics of the consultancy	**0.00%** 0	**15.38%** 2	**15.38%** 2	**23.08%** 3	**23.08%** 3	**23.08%** 3	13	3.70
I felt fully prepared for the consultancy after attending the pre-consultancy call.	**0.00%** 0	**7.69%** 1	**38.46%** 5	**30.77%** 4	**0.00%** 0	**23.08%** 3	13	3.30

When evaluating how well the consultancy objectives were met during the meeting, the participants deemed all of the objectives to be "partially" or "fully" met, as seen in the table below. 75% of participants indicated that the objectives of "describing the asthma problem in Boston" and "understanding the features and availability of environmental data sources," were fully met.

	Objective not met at all	Objective partially met	Objective fully met	Not present for the discussion	Total
To describe the potential value of being able to model risk factors that exacerbate asthma in Boston.	0.00% 0	41.67% 5	50.00% 6	8.33% 1	12
To describe the asthma problem in Boston	0.00% 0	16.67% 2	75.00% 9	8.33% 1	12
To describe how Boston Public Health Commission would use the information if they could anticipate factors that trigger asthma attacks.	8.33% 1	58.33% 7	33.33% 4	0.00% 0	12
To describe the patterns of syndromic surveillance for asthma surveillance in Boston.	0.00% 0	41.67% 5	58.33% 7	0.00% 0	12
To understand the features and availability of environmental data sources (e.g., weather, particulate data)	0.00% 0	25.00% 3	75.00% 9	0.00% 0	12
To present results of a sample of models for asthma surveillance.	0.00% 0	25.00% 3	66.67% 8	8.33% 1	12
To describe strategies for translating a model for asthma.	0.00% 0	50.00% 6	41.67% 5	8.33% 1	12
To describe functional requirements for operationalizing a model in Boston.	0.00% 0	50.00% 6	41.67% 5	8.33% 1	12
To provide a a greater understanding of how the consultancy work fits into the long term goals of the Biosurveillance Ecosystem (BSVE).	16.67% 2	58.33% 7	16.67% 2	8.33% 1	12

One of the primary functions of ISDS and the Boston consultancy is to bring together SMEs from different fields and mechanize multi-stakeholder collaborations. After attending the consultancy, 83% of participants indicated that they would contact another consultancy attendee; 42% of participants are interested in requesting syndromic surveillance data from the BPHC; and 75% of participants responded that they would look into the data sources presented at the meeting.

Open-ended responses to—*What did you gain from attending this consultancy?*—included:

- Limited understanding of asthma problem in Boston
- Appreciation for asthma problem in Boston
- Better understanding of models
- The role of colds in asthma
- Very interesting information from a variety of engaging presenters
- Excellent ideas for implementation for Houston.
- Better understanding of existing data sources -Path forward to better utilize BPHC syndromic data
- I very much enjoyed learning from and listening to the diverse talks and appreciating the complexity of this project.

Open-ended responses to— *What worked well during the consultancy?* — included:

- Ample time for free discussion during and after talks
- A good group
- Most of it - meeting flowed well and content was compelling
- It was a great (somewhat eclectic) group of scientist and well-organized program.
- Experts were willing to share their work and opinion

- I appreciated the small group size and the engaging dialogue that represented different points of view. If there had been time, perhaps some additional discussion on other "warning system" structures, design, that may also work to help address BPHC's needs would have been interesting (e.g., additional audience, spatial, and temporal considerations).

Open-ended responses to— *What would you change in the consultancy?* — included:

- Dinner location
- Not much - maybe more time for structured group discussion or directed case work would have helped yield specific deliverables
- At little bit more insight as to what role "a consultancy" plays.
- I would start the meeting with norms/ground rules. At one point, one of the attendees was not being considerate of a speaker. I think this would have been limited or even avoided if we had a set of ground rules about communication, listening, etc.

VI. Next Steps

- 42% of respondents expressed interest in getting access to BPHC data.
- 75% of participants expressed interest in the presented data sources.
- 21 participants indicated interest in working collaboratively on a manuscript to submit to OJPHI. Follow up calls are being scheduled.
- Explore opportunities for funding for model development.

Appendix A: Use Case

Public Health Practice Problem Definition	
Models for Risk of Asthma Exacerbations in Urban Environments	
CONTACT INFORMATION	
Submitter name:	**Julia Gunn**
Jurisdiction or affiliation:	**Boston Public Health Commission (BPHC)**
Phone:	**617-534-5606**
Email:	**jgunn@bphc.org**
Co-submitters and affiliations:	**Margaret Reid, Boston Public Health Commission**
PROBLEM DESCRIPTION	
Summarize the problem: Asthma exacerbation can be triggered by a number of environmental factors and respiratory viral infections. Asthma control plans are essential in preventing exacerbation. An early warning of increased atmospheric/environmental risk would enable public health agencies to alert asthmatic patients and providers. These alerts would also include prevention messaging and allow asthmatics to ensure that their plans are up to date. BPHC seeks analytic methods for forecasting conditions that are associated with asthma exacerbations. The forecast should consider the impact of respiratory infections (rhinovirus, influenza), temperature extremes, anomalous air quality measurements, and pollen. Available data sources are emergency department visit records, weather data, air quality data, and pollen counts.	
SOLUTION REQUIREMENTS	
Describe the type of solution you are seeking (e.g., anomaly detection, signal validation, data quality characterization): The prediction calculations and alerting communications must be available at a minimum on a daily basis without impacting other routine processing operations. The stratification of predictions by geography and by demographic factors should be as fine as the data will support. Electronic near real time data feeds are required. The analytical processes must be automated. The model and system needs to support continuous model training.	
Describe what type of solution would enable you to implement it in your practice setting (e.g., Do you need an algorithm? Do you need code? If you need code, does it have to be written in any particular programming language?). • Analytic program – must be supported by SqL, will consider SAS or R • Integration into existing health department surveillance systems • Exporting outputs (neighborhood; city map) – heat map • Automated alerting • Continuous model training (code, IT systems)	
Describe who will use the solution. For example, how many users will there be and what level of skill do the users have? Are the users all within a single jurisdiction/organization? The BPHC asthma program in the Division of Healthy Homes and Community Supports would be the end user of the system. The number of BPHC end users is anticipated to be less than five. Automated alerting of an aberration to the asthma program staff would be beneficial. The output would be messaged to the asthma community using other communication systems.	

Note any other constraints: Information is processed every day
VALIDATION
Does a gold standard exist with which to validate the proposed solutions? ☐ Gold standard exists within the provided data set (e.g., an outbreak signal nested within baseline data) ☐ Gold standard exists in a separate data set, which can be provided to the workgroup (e.g., laboratory data to validate ED data) ☐ Gold standard exists but cannot be furnished × Gold standard does not exist
INPUT DATA
List the minimum data elements that can be provided to address the problem: • Syndromic surveillance ED visits 2008-2015 (Asthma and ILI syndrome) • Weather data (available on line) • Pollen data (available on line) • Air quality data (available on line)
How much historical data can be provided? 8 years

Appendix B: Summary of Notes

(See presentation slides in Appendices below)

<u>Use Case Goals and Requirements</u>

The Problem

- Asthma
  - Asthma exacerbations are common and numerous.
  - Current interventions focus on individual actions.
- Boston
  - Diverse neighborhoods with varying distributions of children, racial and ethnic makeup, and commonly used languages.
  - Health inequities disproportionately affect certain groups within Boston.
- Data
  - BPHC has ED reports for the past 8 years.
  - Looking for appropriate environmental data streams to bring into the model.

The Goals

- Identify a practical model to forecast environmental conditions that are likely to result in asthma exacerbations.
- Define systems requirements to automate the processing notifications of issues (environmental and technical).
- Communicate environmental conditions and actions to a variety of stakeholders at different levels:
  - Policy
  - Community
  - Organizational
  - Interpersonal
  - Individual

Requirements

- Data streams: electronic, near real time (24 hours), Boston specific
- Model: automated processes, daily outputs, ideally in SQL but will consider SAS or R.
- System: auto notification, multiple data stream inputs, private and secure to protect health information.

<u>Environmental Data Sources</u>

Haig Iskenderian, MIT Lincoln Laboratory
Ivanka Stajner, NOAA

There are numerous environmental data sources at the local and national level, with varying quality.

- Local
  - Hourly and sub-hourly reports are good for analysis of real time weather and tracking weather changes within an individual day:
    - ASOS (Automated Surface Observing Program)
    - CWOP (Citizen Weather Observation Program)
  - Daily weather summaries are good for historical data and when changes within the day are unimportant:
    - COOP (National Weather Service (NWS) Cooperative Observer Program).
    - CoCoRaHS (Community Collaborative Rain, Hail, and Snow Network).

- National
  - Air Quality: http://airquality.weather.gov/
  - Dust, ozone, and smoke: ftp://tgftp.nws.noaa.gov/SL.us008001/ST.opnl/DF.gr2/DC.ndgd/GT.aq/
  - PM2.5: http://para.nomads.ncep.noaa.gov/pub/data/nccf/com/aqm/para/
  - Historical data available on request.

Weather prediction models differ in resolution and require different computer involvement.

- 3km model forecasting out to 15 hours, 24 times per day.
- 12km model that forecasts out to 84 hours, 4 times per day.
- For a neighborhood model you will need a fine model (1km or 3km).

Modeling Approaches

A discrete event simulation model of pediatric asthma exacerbations:
Jonathan Levy, Boston University School of Public Health

- Discrete event simulation (DES) is a systems science approach involving modeling of a complex systems that evolves over time and is used for many health policy analyses.
- Overarching idea: examine the effects of small changes in exposure on asthma health care utilization outcomes, where observational studies are underpowered.
- Pollution sources:
  - NO2, PM2.5, and Mold
- Model application:
  - Simulate a large number of children to detect potentially small changes in outcomes and costs.
  - Evaluate/validate outputs from baseline simulation.
  - Apply model to approximate benefits and costs of alternative intervention strategies.

Epidemics of the "common cold" and the dynamics of sever asthma exacerbation:
Rosalind Eggo, London School of Hygiene and Tropical Medicine

- Linking virus transmission to asthma:
  - Need to know virus prevalence to determine how at risk the population is; data at a large scale are not available from surveys or samples.
  - Use a model of realistic respiratory virus transmission to infer prevalence.
- Conclusions:
  - Common cold transmission model provides a harmonious explanation for the patterns of severe asthma exacerbations seen in Texas.
  - Prevalence of infection is a shifting baseline of risk to the population driven by contact patterns of children in school.
  - Variation in school calendars can alter the risk baseline in a strongly non-linear way.

Disease Prediction
Anna Buczak, JHU-APL

- Goal: create a capability that transforms how decision makers predict the incidence of infectious disease, enabling them to reduce morbidity and save lives through effective mitigation efforts.
- Predicting Infectious disease Scalable Method (PRISM):
  - Provides a novel disease prediction method
    - Predictions performed for several diseases: dengue and malaria.
    - Prediction of peak location for influenza.
  - Flexible, scalable methodology:

        - Predictions are at various geographical resolutions: province, district, region, county.
- Method of analogues for influenza successfully predicts (4 weeks out):
    - Incidence at peak
    - Total number of cases

Toward Asthma Air Aware Day Alert for Houston, TX
Kathy Ensor, Rice University

- Objectives:
    - Identify the most severe days
    - Make school nurses aware of pollution and its potential impact
    - Do no overwhelm the already overwhelmed system
- Approach:
    - Employed case-crossover design + conditional logistic regression to determine the risk from multiple pollutants.
    - Concentration response was used to identify concentration levels suitable to employ warning.
    - Created a model to predict the high-risk days based on pollution.
- Asthma Warning System Pilot:
    - Model uses simple inputs:
        - NO_2 levels observed from 9pm to 2am the night before
        - 8 hours maximum ozone level for the day before
        - Forecast of weather (apparent temperature, cloud cover, and precipitation for the day of
    - Alert is issued between 5 and 6am via e-mail to school nurses.
    - The nurses would then prepare accordingly if a warning was given.

Bayesian Network Approaches
Howard Burkom, JHU-APL

- Concept: Population-based Bayes Networks
    - Method of combining information from the monitored population.
    - Not Bayesian statistics in the sense of hierarchical modeling, fixed/random effects (could incorporate).
    - Not an agent-based Bayesian model representing every individual as a separate node with properties.

<u>Translating the Model</u>

Feasibility:
- Data streams for the model need to be identified and prioritized based on the target populations in Boston.
    - Can we use syndromic data to find the most important stressors in clusters of high-risk groups?

Impact:
- Reduce racial and ethnic disparities in ED and hospitalizations.
- Reduce geographic disparities.

Intervention Levels:
- Policy/System
    - Alerting school nurses

- Alert policy could follow extreme cold/heat alerts in Boston
  - Cross-institution communication is central to addressing this problem
- Community
  - Communication targets based on language and location
- Organizational
  - Focus around school-based intervention with nurses?
- Interpersonal
- Individual

Operationalizing the Model

Operationalizing Models
George Mathew, MIT Lincoln Laboratory

Milestones:
- Requirements gathering
- Architecting
- Project plan: how to implement
- Resource Allocation: getting human capital and funding from all of the agencies
- Development/Integration
- Piloting
- Production
- System Usage Issue Tracking
- System Refactoring/Models Refactoring
- Upgrades

Approaches:
- Incremental: go for the low hanging fruit
- Full Scale Implementation

Themes and Next Steps

Themes:
- Form policy changes across the socio-ecological model.
- Build on partnerships and inter-agency communications.
- Alerting people without actions will create panic.
- Using data will create the immediate actions that need to be taken and will inform staffing policies (e.g. school nurses).
- Simple data streams, no more than 6 input variables.
- Model sustainability.

Next Steps:
- Funding: CDC, BSVE, R21, NIH, NSF
- Share data with developers
- Create special session about the model at 2016 ISDS conference.
- Formulate an incremental model

Appendix C: Forecasting Boston Slides

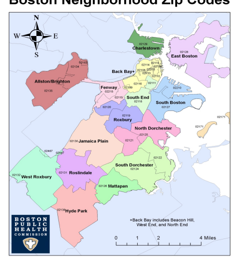
Forecasting Asthma: Boston Use Case

The problem: Asthma

- Asthma and exacerbations are common
- Multiple triggers
  - Viral illness (Influenza, RSV)
  - Air quality
  - Pollen
  - Many others
- Current efforts have focused on individual interventions
- Early warning
  - Notify health providers, patients
  - Prevention messages
- Policy considerations

Neighborhood	Zip Code
Boston	
Allston/Brighton	02134
	02135
	02163
Back Bay (Beacon Hill, Downtown, West End)	02108
	02109
	02110
	02114
	02116
	02199
Charlestown	02129
East Boston	02128
Fenway	02115
	02215
Hyde Park	02136
Jamaica Plain	02130
Mattapan	02126
North Dorchester	02121
	02125
North End	02113
Roslindale	02131
Roxbury	02119
	02120
South Boston	02127
	02210
South Dorchester	02122
	02124
South End	02111
	02118
West Roxbury	02132

Boston Neighborhood Zip Codes



Goals

- Identify a practical model to forecast environmental conditions that are likely to result in asthma exacerbations
- Define system requirements to automate the processing and notification of issues (environmental and technical)

Information age: Systems approach

- Increasing availability of electronic data
- Near real time data
  - Climate
  - Health care
  - Air quality
- Technology to operate analytical systems
- Communication systems for response

1

Requirements

- Data streams
  - Electronic
  - Near real time
  - Boston specific
- Models
  - Automated processes (every day)
  - Function in SqL, will consider SAS or R
  - Processing times
  - Daily outputs
- System
  - Autonotification
    - BPHC program staff of environmental problems
    - Technical staff of system failure
    - Output communicated to other systems
  - Multiple data streams with differing data structure
  - Privacy/security – protected health information

Practical Model

- There is no gold standard
- Time sensitive for response
- Reasonable processing time

Appendix D: The Asthma Problem in Boston

The Asthma Problem in Boston

International Society for Disease Surveillance Consultancy
March 30-31, 2016
Boston Public Health Commission

Margaret Reid, RN MPA
Director; Division of Healthy Homes and Community Supports
Boston Public Health Commission

Presentation Objectives

- To inform subsequent conversations through providing:
  - Boston asthma data on trends, overall burden and disproportionately burdened populations
  - Introduction to asthma and outdoor environmental factors
  - BPHC asthma program description
  - Thoughts on communication strategies and a framework for applying models

Health Inequities Experienced by Boston Residents

Indicator	Year(s)	Race/Ethnicity			
		Asian	Black	Latino	White
Chronic Disease					
Asthma (Percent of Adults)	2013	2.8% (0.2-5.3)	11.9% (9.4-14.4)	11.9% (8.8-15.1)	11.8% (9.5-14.2)
Asthma Emergency Department Visits (per 1,000 residents)	2012	2.8	21.8	12.7	4.1
Diabetes Hospitalizations (per 1,000 residents)	2012	0.6	3.9	2.3	1.4
Diabetes Deaths (per 100,000 residents)	2012	n<5	39.5	23.9	14.3
Heart Disease Hospitalizations (per 1,000 residents)	2012	4.1.	13.6	9.9	9.0
Heart Disease Deaths (per 100,000 residents)	2012	44.6	155.9	80.2	144.9
Hypertension (Percent of adults)	2013	16.2% (9.9-22.4)	36.7% (33.0-40.5)	26.2% (22.0-30.3)	18.6% (16.7-20.6)
Obesity (Percent of adults)	2013	15.3% (8.9-21.6)	33.0% (29.3-36.8)	27.3% (23.1-31.6)	16.2% (13.9-18.4)

NOTES: Gray text in tables represents rates based on counts less than 20 and should be interpreted with caution. Black text in tables represents rates based on counts of at least 20.

Shaded in red are rates or percentages that are higher/worse than the corresponding rate for White residents.

Asthma ED Visits* by Age, FY2004-FY2013

FY	Ages 0-2	Ages 3-5	Ages 6-17	Ages 18-44	Ages 45-64	Ages 65+
2004	369.0	334.7	176.6	89.6	121.6	66.9
2005	299.3	294.6	161.6	86.7	112.7	61.4
2006	346.8	344.0	172.4	84.1	102.0	61.7
2007	323.9	328.5	150.6	81.9	97.4	57.1
2008	351.7	388.2	166.9	86.9	105.9	66.1
2009	279.9	315.9	145.7	81.1	112.7	64.0
2010	278.6	322.0	149.3	79.2	103.7	60.7
2011	196.7	271.7	141.8	72.8	104.7	63.4
2012	180.4	266.0	148.9	66.1	100.1	58.0
2013	203.4	293.9	147.4	72.7	103.6	69.6
% Change 2004-2013**	-47	-16	-17	-22	-10	No Significant Trend

* Age-specific rates per 10,000 residents **Based on trend analysis using regression ($p<0.05$)
NOTE: This analysis includes ED visits that resulted in hospitalizations and observation stays. ED visits that resulted in hospitalizations are included in both ED visit analyses and hospitalization analyses.

DATA SOURCE: Acute Hospital Case Mix Databases, Massachusetts Center for Health Information and Analysis (CHIA)
DATA ANALYSIS: Boston Public Health Commission Research and Evaluation Office

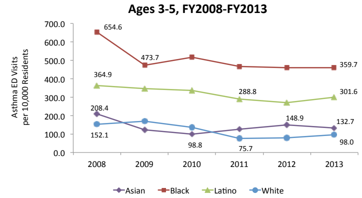
Asthma Hospitalizations* by Age, FY2004-FY2013

FY	Ages 0-2	Ages 3-5	Ages 6-17	Ages 18-44	Ages 45-64	Ages 65+
2004	80.8	62.7	34.6	9.8	32.0	38.4
2005	71.6	56.0	31.1	9.4	30.8	37.4
2006	104.8	81.7	40.8	9.8	26.9	36.7
2007	97.0	87.3	39.8	9.6	26.7	34.9
2008	128.5	93.4	42.0	9.9	31.7	41.5
2009	114.3	89.5	45.7	10.6	35.9	41.6
2010	99.1	101.5	38.2	11.7	36.1	41.7
2011	89.5	78.8	40.0	9.5	34.8	41.1
2012	73.0	89.1	39.0	7.7	26.8	31.1
2013	67.5	71.7	36.0	7.6	25.4	34.0
% Change 2004-2013**	No Significant Trend	+26	No Significant Trend	-14	No Significant Trend	No Significant Trend

* Age-specific rates per 10,000 residents **Based on trend analysis using regression ($p<0.05$)
NOTE: This analysis includes ED visits that resulted in hospitalizations. ED visits that resulted in hospitalizations are included in both ED visit analyses and hospitalization analyses.

DATA SOURCE: Inpatient Hospital Discharge Database, Massachusetts Center for Health Information and Analysis (CHIA)
DATA ANALYSIS: Boston Public Health Commission Research and Evaluation Office

Asthma ED Visits by Race/Ethnicity, Ages 3-5, FY2008-FY2013



NOTE: This analysis includes ED visits that resulted in hospitalizations and observation stays. ED visits that resulted in hospitalizations are included in both ED visit analyses and hospitalization analyses.

DATA SOURCE: Acute Hospital Case mix Databases, Massachusetts Center for Health Information and Analysis (CHIA)
DATA ANALYSIS: Boston Public Health Commission Research and Evaluation Office

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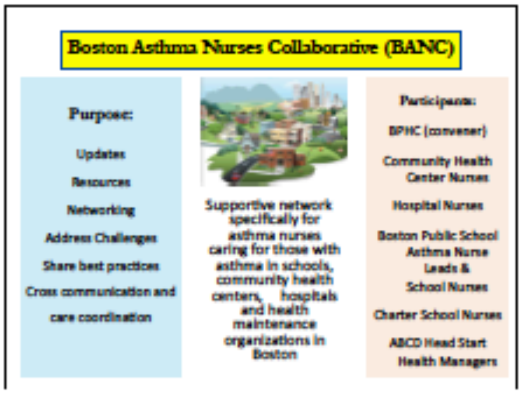
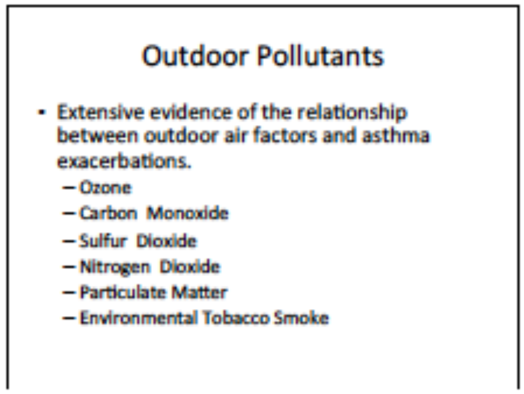
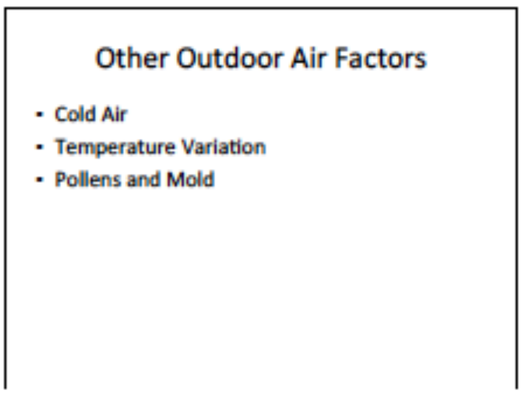
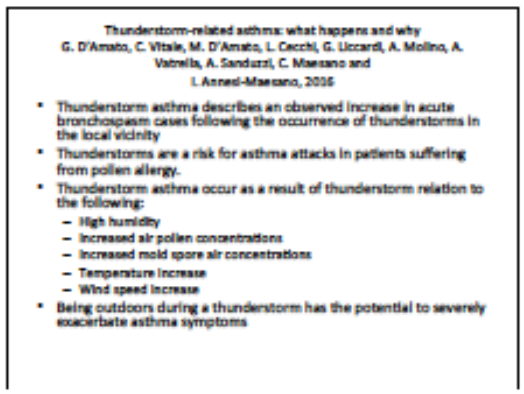
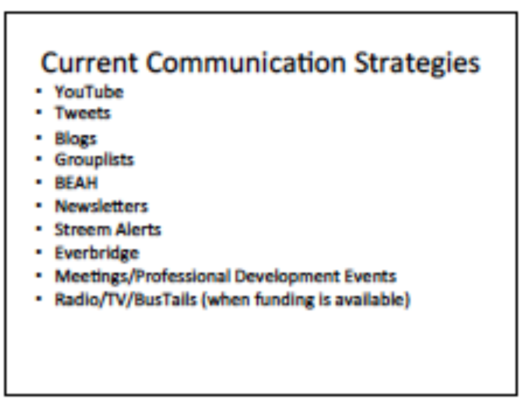
Appendix E: Syndromic Surveillance Slides

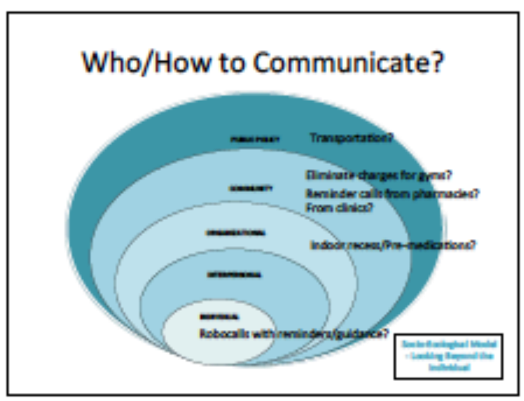












Syndromic Surveillance: Boston

Syndromic Surveillance Reporting Regulations

- BPHC Board of Health regulation first passed in 2004 requires:
  - Hospital emergency departments to report syndromic data
  - Information to be sent includes:
    - Visit date
    - Unique patient identifier (HIPAA-compliant)
    - Age, gender, and race/ethnicity
    - Zip code of primary residence
    - Chief complaint (Within 24 hours)
    - ICD-9/10 codes when available (First three)
    - Disposition
  - Daily electronic transfer

Boston Syndromic Surveillance System

- Developed in 2004 for the Democratic National Convention – Go live July 2004
- All 10 Boston emergency departments report daily visits for the previous 24 hours
- Automatic electronic transfer
- Chief complaints are categorized into various syndrome groups
- Analyzed for increased activity, significant events, or situation awareness

Chief Complaints

Chief Complaint Dictionary

Fever	Respiratory	Cough	Hypoxia	SOB	Cold
chiles	atelectasis	bringing up blood	color change	apnea	cold
chills	brionchitis	cogh	color off	apneic episode	cold sx
cough+fever	brochiolitis	copugh	cyanosis	breathing difficulty	cong
debrile	bronchiolitis	couch	cyanotic	breathing fast	congear

EMT-P to Standardize Data

Natural language processing program

Created by the University of North Carolina

Uses Perl, Java, and the National Institute of Health's Unified Medical Language System©

EMT-P and UMLS: The Boston Experience

- Training – Not all terms map
  - Hd = dialysis
  - scd = sickle cell disease
  - ooc = out of control
- One to Many (EMT-P)
  - Boston - Many to One
- Terms with multiple meanings
  - OD: Overdose vs Right eye
  - ST: Sore throat vs Sinus tachycardia
  - Context matters

Preprocessing Input	Output
FEVER, VOMMITING, BODY PAIN	body pain fever vomiting
N/V/D	diarrhea nausea vomit
NVD	diarrhea nausea vomit
THROWING UP	vomiting
NAUSEA VOMITING DIARHEA	diarrhea nausea vomit
ABD PAIN;NAUSEA;EMESIS;DIAHERRA	abdominal pain diarrhea emesis nausea
Cugh	cough

Impact

- Decrease processing time
- Fewer unique terms
  - Original (unaltered chief complaints): 22, 748 unique words.
  - Standardized: 14,893 unique words
- Facilitates identification of new terms – Ongoing language evolution
  - Standardization
  - Evolving health care problems (STEMI)
  - Evolving care (Narcan)

Asthma		
adthma	asthme	reactive airway
ashma	astma	reactive airway disease
ashthma	astmma	status asthmaticus
ashtma	asttmma	weezing
asntha	athma	wheeing
astha	athama	wheeezing
astham	bronchospasm	wheeze
asthama	bronchospasms	wheeze.
asthamtic	exac.asthma	wheezes
asthma	heezing	wheezing
asthma-adult	r a d	wheezy
asthma-pediatric	r.a.d	whezzing
asthmas	r.a.d.	
asthmatic	rad	
[illegible]	[illegible]	

ILI Syndrome Definition

CDC Definition
Influenza-like Illness:
Fever (≥100° F [37.8° C], oral or equivalent) -AND- Cough and/or sore throat (in the absence of a known cause)

⬇

BPHC Syndrome Definition
ILI Narrow: Flu or ("Fever" and ("Cough" OR "Sore throat"))

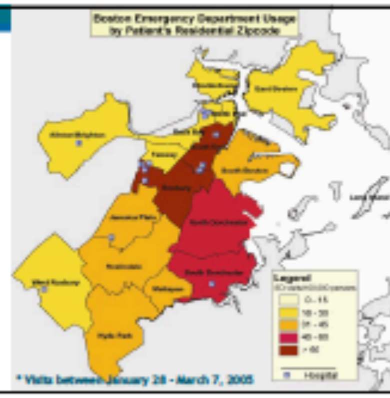
Flu Wheezing

⬇ ⬇

ILI Asthma

Regions associated with Boston emergency department visits: February-March, 2016

	Number of Visits
All	64,313
Boston	34,627 (54%)
Massachusetts (Excluding Boston)	26,461 (41%)
New England/ New York	1,625 (3%)
Other US	842 (1%)
Unknown	758 (1%)



Day of the week effect

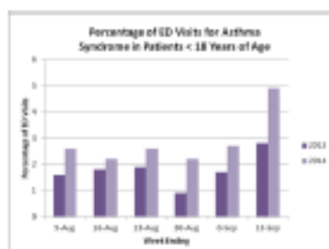
	Number of Asthma Visits
Sunday	116
Monday	122
Tuesday	118
Wednesday	113
Thursday	103
Friday	106
Saturday	104

Enterovirus D68 (EV-D68)

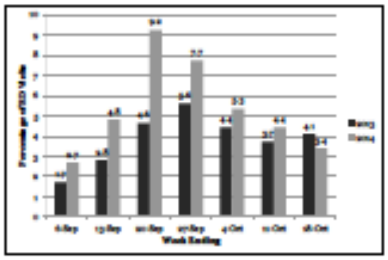
- One of more than 100 non-polio enteroviruses
- 2014, national outbreak associated with severe respiratory disease
  - Children with asthma were at high risk
  - Supportive treatment only

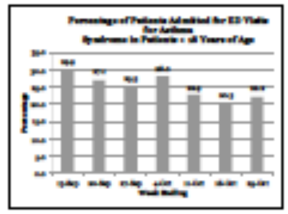
Biosurveillance Challenges

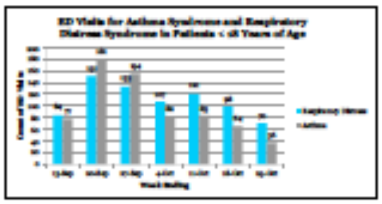
- Limited laboratory testing
- No case definition
- No reporting requirement
- Bridge asthma and infectious disease surveillance

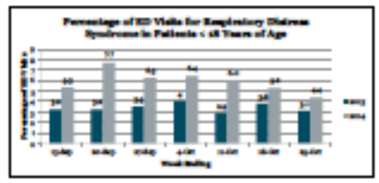


Percentage of Asthma Syndrome Visits: <18 Year Olds: 2013 vs. 2014









Response

- Surveillance
  - Syndromic surveillance (current and historical visits for asthma)
- Health care sites
  - Enhanced infection control
  - Monitoring albuterol stocks
- Public health guidance and alerts including asthma specific information
- Pushed information via the BPHC asthma program networks
- Schools: Up to date asthma control plans

Influenza, 2012-2013

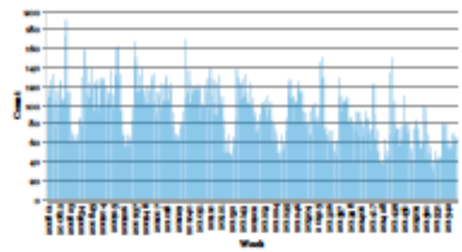
The never ending flu season: 2013-2014

Influenza 2014-2015

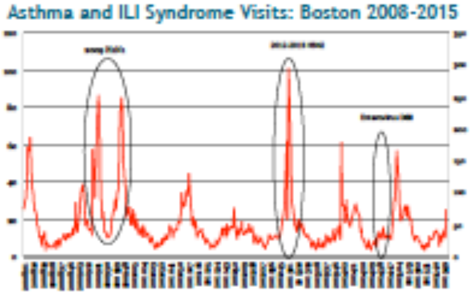
Number of visits for Boston residents: 2008-2015

- Asthma
  - All: 22,827
  - 18 years of age and younger: 14,978
- ILI
  - All: 21,227
  - 18 years of age and younger: 10,823

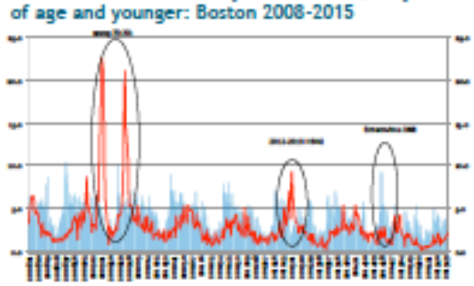
Asthma Syndrome Visits: Boston 2008-2015



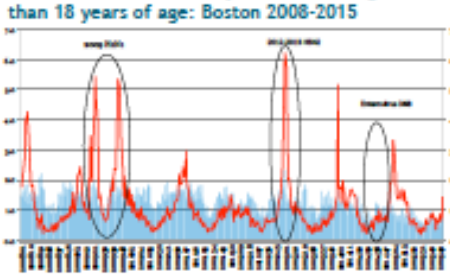
Asthma and ILI Syndrome Visits: Boston 2008-2015



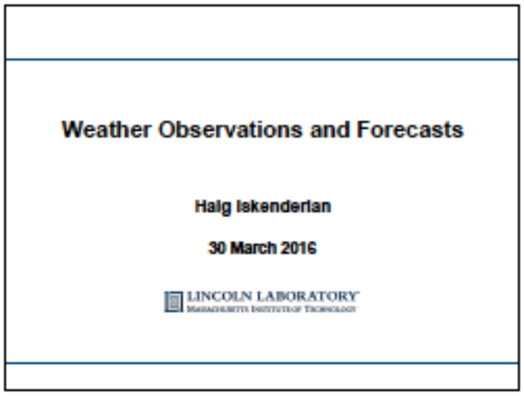
Percent asthma and ILI syndrome visits, 18 years of age and younger: Boston 2008-2015

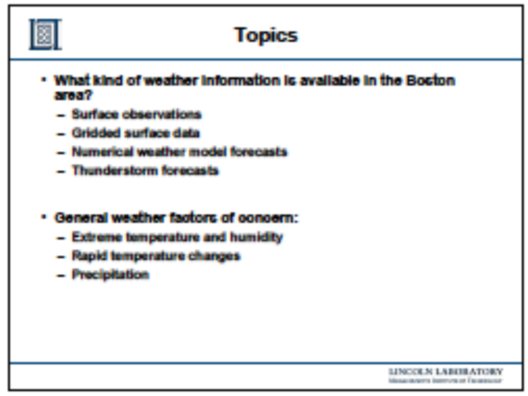


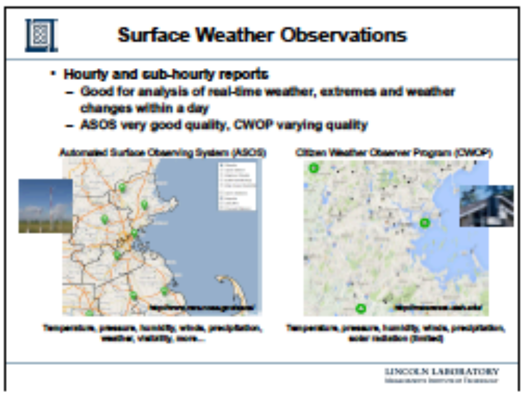
Percent asthma and ILI syndrome visits, greater than 18 years of age: Boston 2008-2015

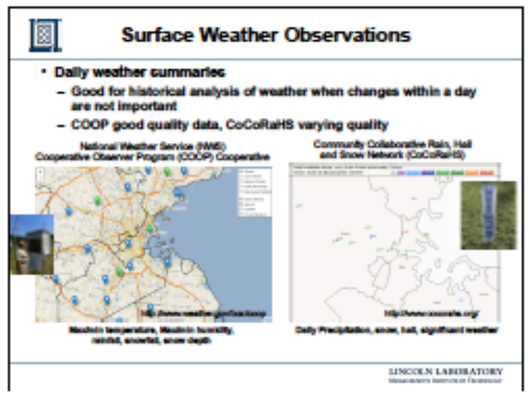


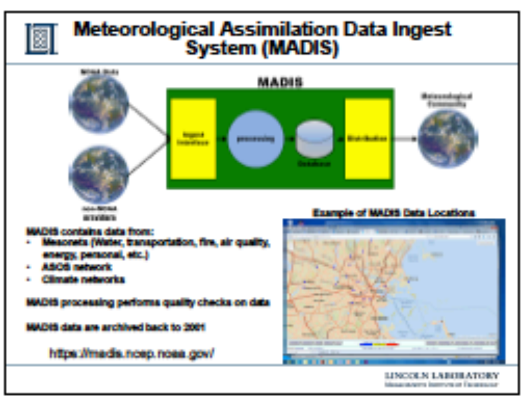
Appendix F: Weather Observations and Forecasts Slides

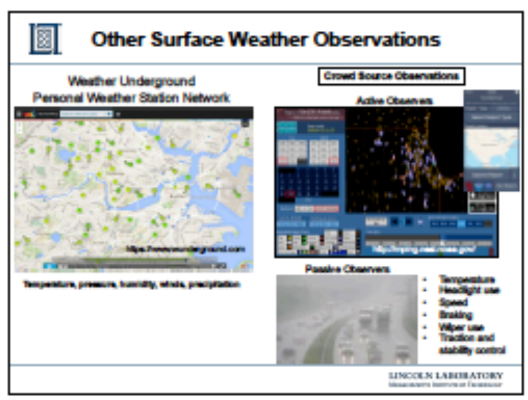








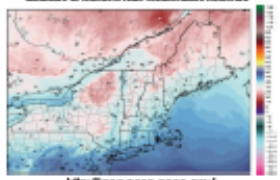




Gridded Analyses

- Real-time Mesoscale Analysis (RTMA)
  - Assimilates many sources of weather data
  - Creates surface weather analyses (temperature, humidity, winds, pressure, cloud, visibility)
  - 2.5 km horizontal resolution updated hourly

Example of NOAA RTMA Temperature Analysis



http://mag.ncep.noaa.gov/

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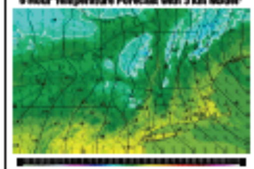
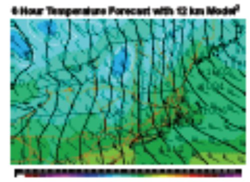
Numerical Weather Forecasts
Differences in Horizontal Resolution

6-Hour Temperature Forecast with 3 km Model[1]



6-Hour Temperature Forecast with 12 km Model[2]



[1]NOAA's 3 km High Resolution Rapid Refresh (HRRR) model makes forecasts out to 15 hours, 24X per day
[2]NOAA's 12 km North American Mesoscale (NAM) model makes forecasts out to 84 hours, 4X per day

- Other weather models provide forecasts out to 2 weeks in the future
- Weather models provide forecast of pressure, temperature, humidity, winds, precipitation, clouds, visibility, many other quantities

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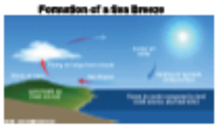
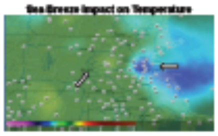
Sea Breeze

Formation of a Sea Breeze



Sea Breeze Impact on Temperature



- Sea breeze can cause rapid temperature, wind, and air quality changes
- Fine-scale observations and models needed to diagnose and forecast

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Thunderstorm Observations

Radar Depiction of Precipitation Intensity

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Radar Mosaic

Combine multiple radars into single radar scene

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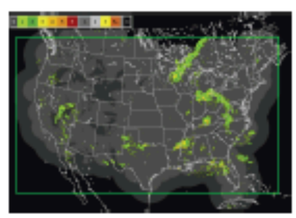
0-8 Hour Thunderstorm Forecast for the Federal Aviation Administration



- Tracking of thunderstorms tends to do better for first few hours of forecast
- Numerical models tend to do better after first few hours of forecast
- Combine thunderstorms tracking and HRRR numerical model
- 1 km resolution first 2 hours, 3 km thereafter out to 8 hours
- Updated every 5 min first 2 hours, every 15 minutes 2-8 hours

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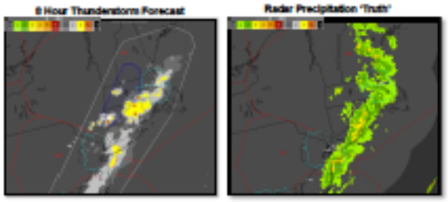
Thunderstorm Forecasting Northeast Example

6 Hour Thunderstorm Forecast

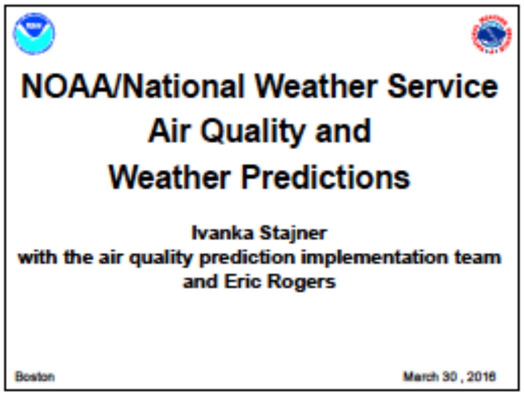
Radar Precipitation 'Truth'

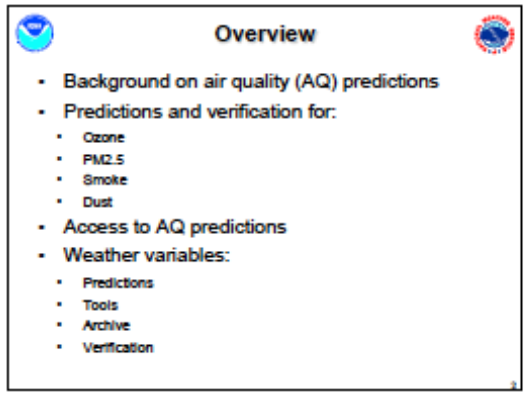


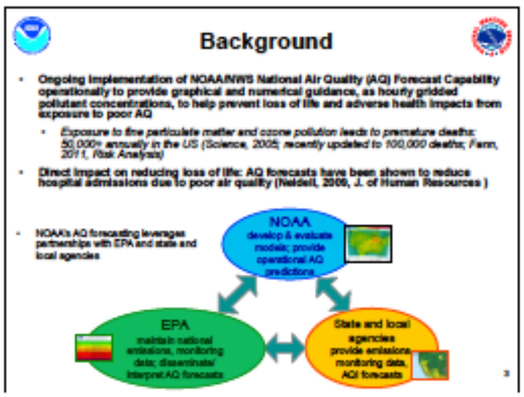
Summary

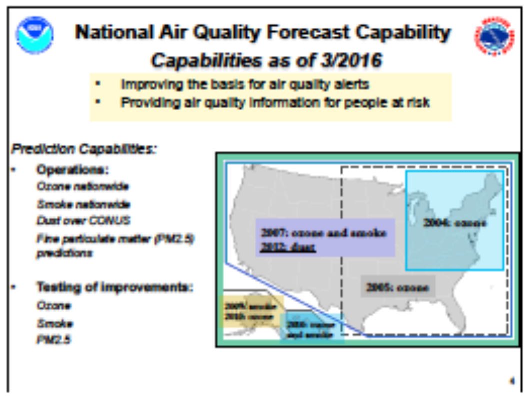
- Numerous sources of surface weather observations exist
  - Sub-daily vs. daily
  - Varying data quality
  - MADIS quality controls and archives many surface observations
- Observations can be gridded to create a continuous surface analysis field
- Numerical weather models use observations to predict weather conditions
  - Varying grid resolution, updates, forecast length
- Thunderstorm forecasts blend radar precipitation tracking and numerical models

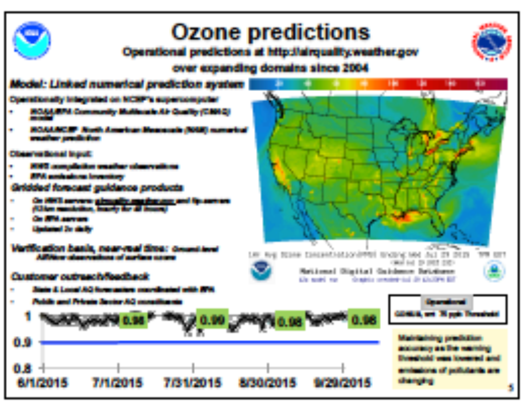
Appendix G: NOAA/National Weather Service Air Quality and Weather Predictions

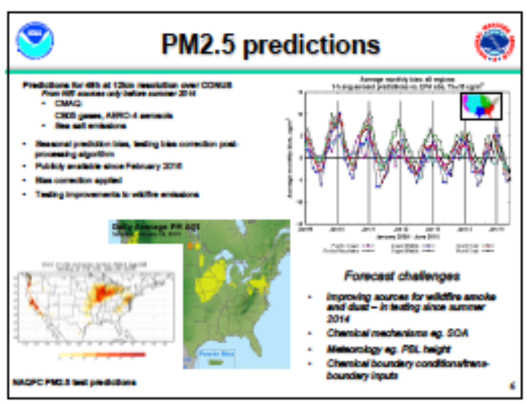






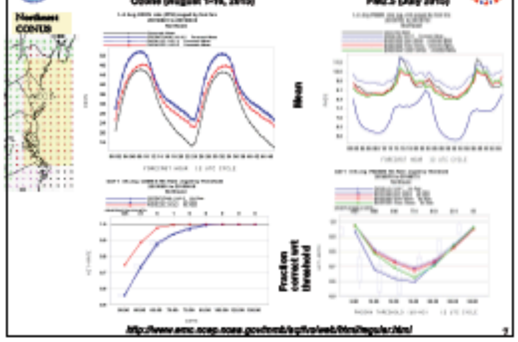






Verification (NE CONUS)

Ozone (August 1-16, 2015) | PM2.5 (July 2015)



http://www.emc.ncep.noaa.gov/mmb/aq/cmaq/web/html/regular.html

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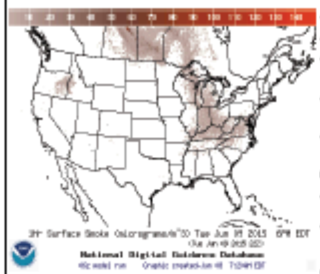
Smoke predictions



- Smoke predictions for CONUS (continental US), Alaska and Hawaii
- NESDIS provides wildfire locations
- Bluesky provides emissions estimates
- HYSPLIT model for transport, dispersion and deposition (Rolph et al., WAF, 2009)
- Increased plume rise, decreased wet deposition, changes in daily emissions cycling
- Developed satellite product for verification (Kondragunta et al. AMS 2008)

Recent updates includes

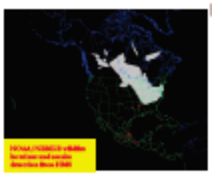
- Automated detection of fires in Canada, Mexico and Central America
- 3-D particle model approach (rather than horizontal puff) to properly represent the additional fires identified with automatic fire detection

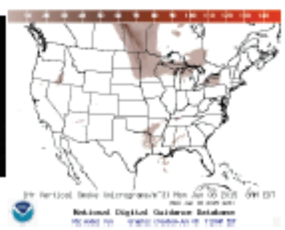
Current testing includes

- Updated BlueSky System for smoke emissions

8

Canadian wildfire smoke 6/9/2015



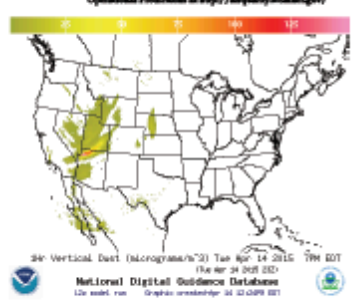


Canadian wildfire smoke intrusion into CONUS was captured well in NOAA's smoke predictions

9

CONUS dust predictions

Operational Predictions at http://airquality.weather.gov/



Standalone prediction of airborne dust from dust storms:

- Wind-driven dust emitted where surface winds exceed thresholds over source regions
- Source regions with emission potential estimated from MODIS deep blue climatology for 2003-2006 (Ginoux et. al. 2010).
- Emissions modulated by real-time soil moisture.
- HYSPLIT model for transport, dispersion and deposition (Draxler et al., JGR, 2010)
- Wet deposition updates in July 2013
- Developed satellite product for verification (Ciren et.al., JGR 2014)

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Access to AQ predictions

For ozone, smoke and dust:

Current graphical predictions are available at

http://airquality.weather.gov/

Current grib files are available at

ftp://tgftp.nws.noaa.gov/SL.us008001/ST.opnl/DF.gr2/DC.ndgd/GT.aq/

Historical data can be requested at the following link:

http://www.ncdc.noaa.gov/has/HAS.StationYearSelect?datasetname=9950_01&subqueryby=STATION&applname=&outdest=FILE&dtypesort=dtypeord&stationsort=id

Desired product can be requested by choosing the WMO headers. As the request gets processed a link is sent in the email to pick up the data.

For PM2.5:

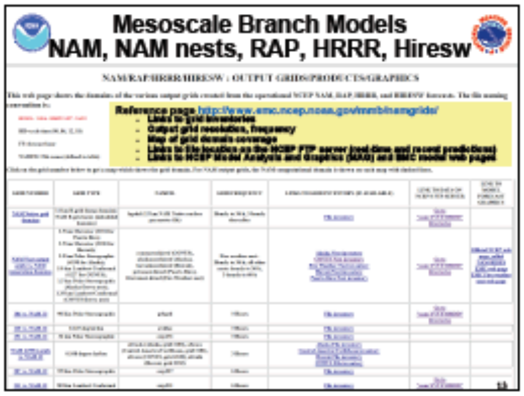
Current grib files are available at *http://para.nomads.ncep.noaa.gov/pub/data/nccf/com/aqm/para/*

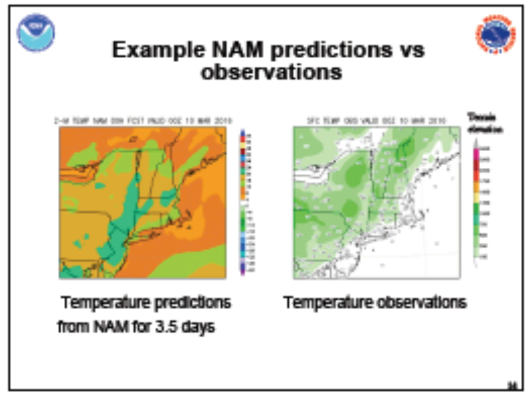
11

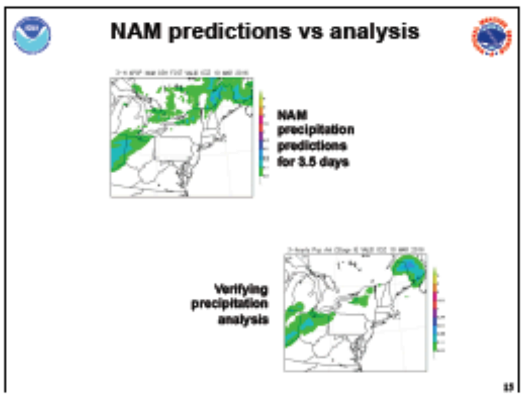
NCEP Weather Model predictions, verification, useful links

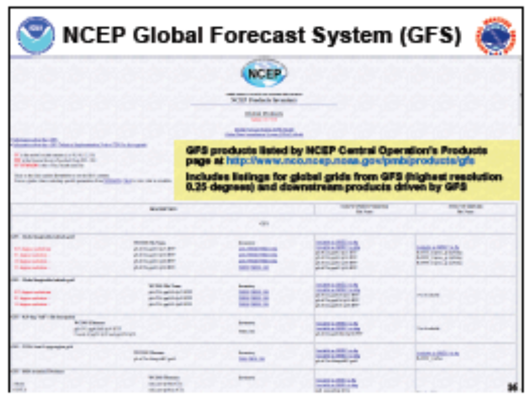
material provided by Eric Rogers (NCEP/EMC)

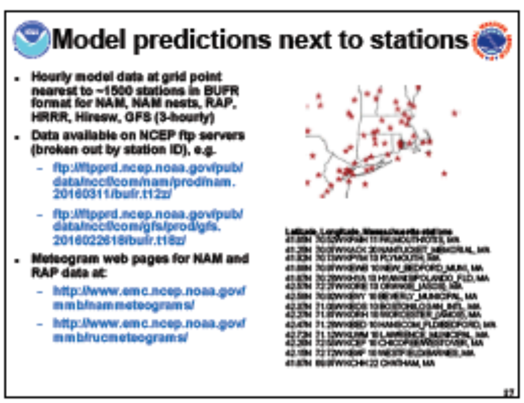
12

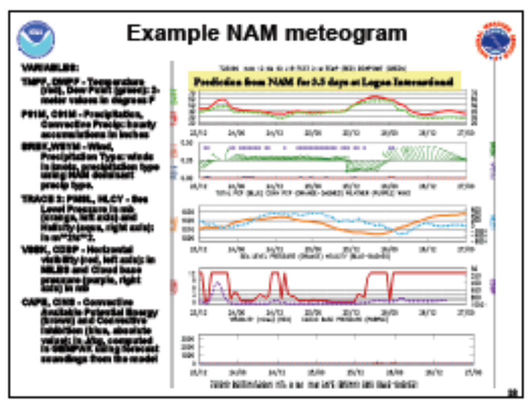

Mesoscale Branch Models
NAM, NAM nests, RAP, HRRR, Hiresw
NAM/RAP/HRRR/HIRESW : OUTPUT GRIDS/PRODUCTS/GRAPHICS
Reference page http://www.emc.ncep.noaa.gov/mmb/namgrids/
- Links to grid inventories
- Output grid resolution, frequency
- Map of grid domain coverage
- Links to file location on the NCEP FTP server (real-time and recent predictions)
- Links to NCEP Model Analysis and Graphics (MAG) and EMC model web pages


Example NAM predictions vs observations
Temperature predictions from NAM for 3.5 days
Temperature observations


NAM predictions vs analysis
NAM precipitation predictions for 3.5 days
Verifying precipitation analysis


NCEP Global Forecast System (GFS)
NCEP
GFS products listed by NCEP Central Operation's Products page at http://www.nco.ncep.noaa.gov/pmb/products/gfs
Includes listings for global grids from GFS (highest resolution 0.25 degrees) and downstream products driven by GFS


Model predictions next to stations
Hourly model data at grid point nearest to ~1500 stations in BUFR format for NAM, NAM nests, RAP, HRRR, Hiresw, GFS (3-hourly)
Data available on NCEP ftp servers (broken out by station ID), e.g.
ftp://ftpprd.ncep.noaa.gov/pub/data/nccf/com/nam/prod/nam.20160311/bufr.t12z/
ftp://ftpprd.ncep.noaa.gov/pub/data/nccf/com/gfs/prod/gfs.2016022618/bufr.t18z/
Meteogram web pages for NAM and RAP data at:
http://www.emc.ncep.noaa.gov/mmb/nammeteograms/
http://www.emc.ncep.noaa.gov/mmb/rucmeteograms/


Example NAM meteogram
VARIABLES:
Prediction from NAM for 3.5 days at Logan International

Tools and archive

- GRIB2 tools: http://www.nco.ncep.noaa.gov/pmb/docs/grib2/
- BUFKIT software to decode/display BUFR station data: http://wdtb.noaa.gov/tools/BUFKIT/
- Long-term archive: http://nomads.ncdc.noaa.gov/index.php

  ftp://nomads.ncdc.noaa.gov/NAM/Grid218/ (NAM predictions for the last year)

  http://www.ncdc.noaa.gov/has/HAS.FileAppRouter?datasetname=NAM218&subqueryby=STATION&applname=&outdest=FILE (NAM predictions since 2006)

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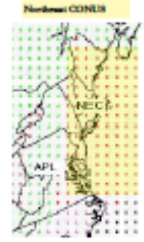
Verification

- Historical precipitation skill scores for NCEP models:

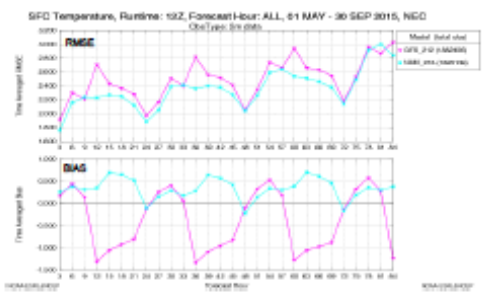
http://www.emc.ncep.noaa.gov/mmb/ylin/pcpverif/scores/

- Real-time NAM, GFS, RAP time series (last 10-30 days) verification vs upper-air and surface data at
  - http://www.emc.ncep.noaa.gov/mmb/mmbpll/mmbverif/
- Real-time HIRESW vs NAM nests time series verification (last 10-30 days) vs upper-air/surface data at
  - http://www.emc.ncep.noaa.gov/mmb/mmbpll/mmbverif.hiresw_new2007/
- Monthly near-surface (2-m Temperature, RH, 10-m Wind) GFS and NAM statistics from Dec 2010-present
  - http://www.emc.ncep.noaa.gov/mmb/research/nearsfc/nearsfc.verf.html



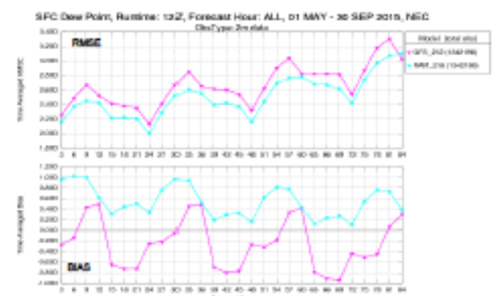
20

NAM vs GFS Surface Temperature RMSE and Bias error (deg C) statistics : Northeast warm season (1 May-30 Sep 2015)



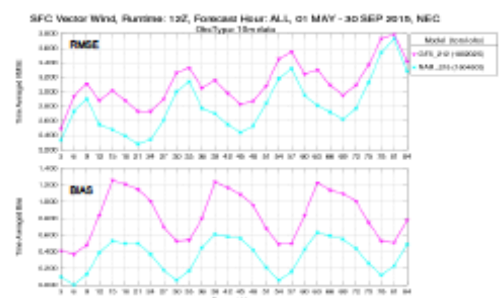
21

NAM vs GFS Surface Dew Point Temperature RMSE and Bias error (deg C) statistics: Northeast warm season (1 May-30 Sep 2015)



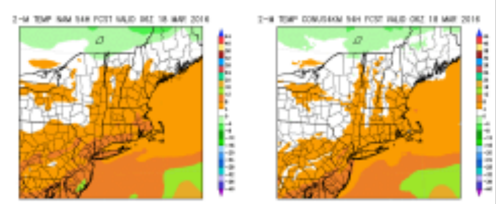
22

NAM vs GFS Surface (10-m) Vector Wind RMSE and Speed Bias error (m/s) statistics : Northeast warm season (1 May-30 Sep 2015)



23

12 km NAM (left) vs 4 km NAM nest (right)



- Finer 4km resolution nest has better depiction of warmer temperatures in Connecticut and Hudson River Valleys
- Nest shows colder temperatures in higher terrain of the Berkshires

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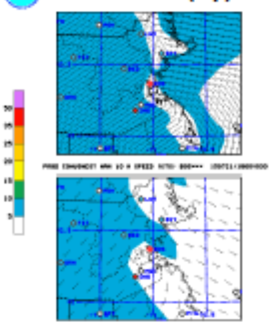
Summary

- NOAA National Weather Service produces operational predictions of:
  - Weather variables (temperature, moisture, wind,…)
  - Ozone
  - PM2.5
  - Smoke
  - Dust
- Examples and links were provided for:
  - Real-time predictions
  - Archive
  - Tools
  - Verification

BACKUP

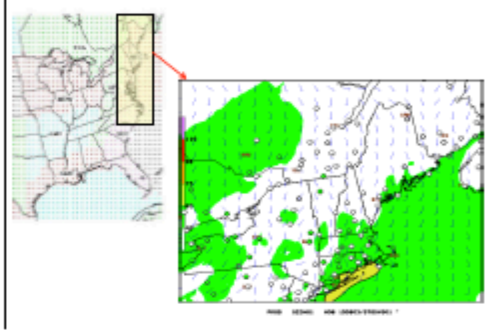
4 km NAM nest (top) vs 12 km NAM (bottom)



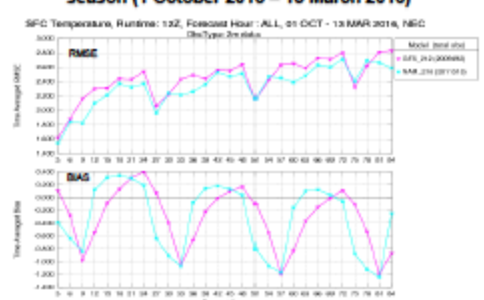
- Finer 4km resolution nest shows stronger wind over coastal ocean
- Also tends to resolve planetary boundary layer height differently in the coastal region

Figure provided by Jeff McQueen

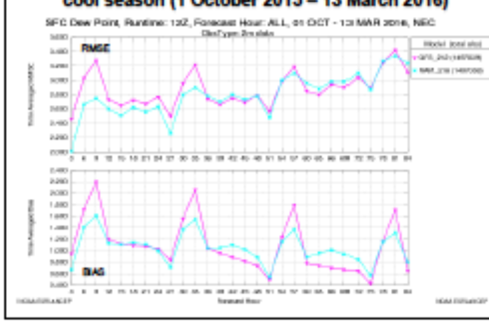
Ozone (North East)

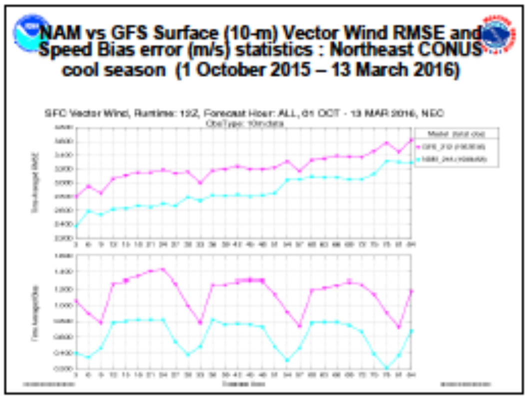


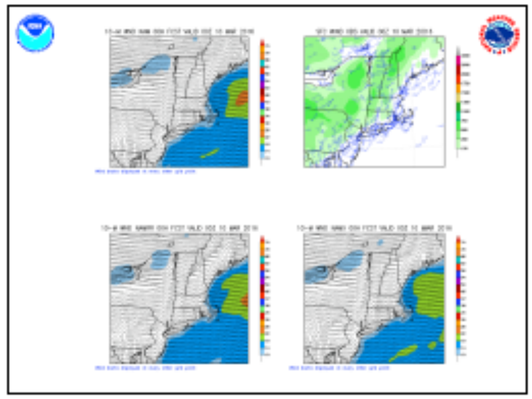
NAM vs GFS Surface Temperature RMSE and Bias error (deg C) statistics : Northeast CONUS cool season (1 October 2015 – 13 March 2016)



NAM vs GFS Surface Dew Point Temperature RMSE and Bias error (deg C) statistics : Northeast CONUS cool season (1 October 2015 – 13 March 2016)




NAM vs GFS Surface (10-m) Vector Wind RMSE and Speed Bias error (m/s) statistics : Northeast CONUS cool season (1 October 2015 – 13 March 2016)
SFC Vector Wind, Runtime: 12Z, Forecast Hour: ALL, 01 OCT - 13 MAR 2016, NEC
ObsType: 10mdata



Appendix H: A Discrete Event Simulation Model of Pediatric Asthma Exacerbation Slides

A discrete event simulation model of pediatric asthma exacerbations

Jonathan Levy
Professor of Environmental Health,
Boston University School of Public Health

Analytic Solutions for Real-Time Biosurveillance
Models for Risk of Asthma Exacerbations in Urban Environments
March 30-31, 2016

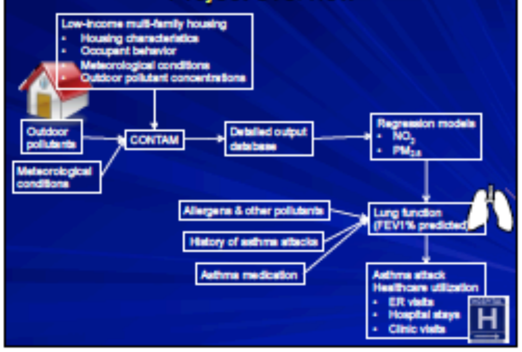
Discrete event simulation (DES)

- A systems science approach involving modeling of a complex system that evolves over time given changes in state variables that occur at defined points in time
  - Accounts for multiple individual attributes
  - Captures interactions and non-linear effects
  - Keeps track of prior history
- Used for many health policy analyses:
  - Schizophrenia, malaria, cardiovascular disease, breast cancer, depression, end-stage liver disease, peptic ulcer disease

Environmental asthma policy model

- Developed by our group under an R21 from NIH
- Applied to case study of energy efficiency upgrade in multifamily housing (HUD)
- Currently being linked with electronic medical record data to parameterize model and characterize feedback loops
  - Overarching idea: Examine the effects of small changes in exposure on asthma health care utilization outcomes, where observational studies are underpowered

Project overview



Pollution sources

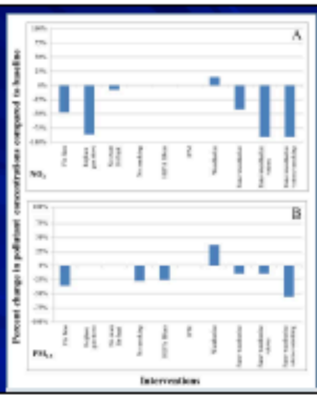
- NO_2: gas stove use, use of gas oven for supplemental heating in winter, outdoors
- $PM_{2.5}$: cooking, environmental tobacco smoke (ETS), outdoors
- Humidity (mold): cooking, breathing, showering, dishwasher

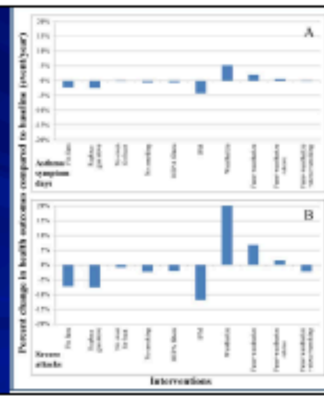
Model application

1. Simulate a large number of children to detect potentially small changes in outcomes and costs
2. Evaluate/validate outputs from baseline simulation
3. Apply model to approximate benefits and costs of alternative intervention strategies

Intervention	Rationale	Modeling
1. Fix kitchen and bathroom fans	Proper spot ventilation will reduce exposure to pollutants associated with cooking and control moisture buildup	Assumed kitchen fan was operated 100% of time during cooking events (100 cfm); turned bathroom fan 'on' during shower events (50 cfm)
2. Replace gas with electric stove	Gas stoves are a source of NO_2 from cooking and supplemental heating; replacement with electric stoves will reduce exposure	Removed NO_2 stove source, simulating the replacement of gas stoves with electric stoves
3. Fix heating system (eliminate inconsistent heating)	Functional heating will eliminate the need to heat with stove, and thus reduce pollutant exposures	Eliminated NO_2 source associated with the use of gas stove for supplemental heating
4. Smoke-free housing policy	Cigarettes are major source of indoor $PM_{2.5}$; removal of this source will lower exposures	Removed smoking sources
5. Use High-Efficiency Particulate Air (HEPA) filter	Will reduce exposure to particles from smoking and other sources	Reduced $PM_{2.5}$ by 25%

Intervention	Rationale	Modeling
6. Integrated Pest Management	Elimination of pest pathways will reduce allergen levels	Eliminated number of homes with holes in wall
7. Weatherize (air sealing, window replacement)	Elimination of air pathways will conserve energy	Moved households in the highest categories of wall infiltration rates (category 2 and 3) down by one category. Category 1, equivalent to an efficient level of air exchange, remains the same
Bundled interventions		
8. Weatherize (#7) + fix exhaust fans (#1)		
9. Weatherize (#7) + fix exhaust fans (#1) + replace gas stove (#2)		
10. Weatherize (#7) + fix exhaust fans (#1) + replace gas stove (#2) + non-smoking policy (#4)		





Linkage to prospective surveillance

- Simulation model with appropriate stressors (e.g., respiratory infections, temperature, air quality) could characterize how daily changes influence outcomes of interest
- Model could be programmed to identify characteristics of high-risk days
  - In general
  - Related to stressors of interest
  - Modifiable subset
- Stressor forecasting could be linked to model outputs to characterize likely high-risk days

What would you need?

- Ability to forecast stressors and behaviors
- Epidemiological evidence connecting stressors with outcomes (directly or indirectly)
- Model with dynamic/seasonal behavior
- Strategy for regular updating and calibration of model

Limitations

- Limited literature linking stressors to lung function, lung function to outcomes
- Challenge to characterize behavioral responses
- Simplified medication assignment
- Need to characterize detailed multivariate attributes of individuals to provide realistic model outputs

Acknowledgements

- Patricia Fabian
- Gary Adamkiewicz
- Amelia Geggel
- Tasha Stout
- Megan Sandel
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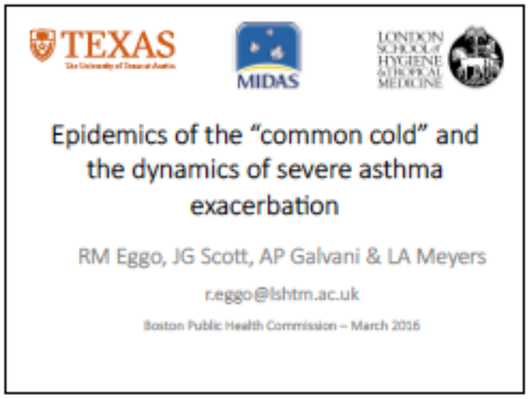
- Kadin Tseng
- Daniel Kamalic
- Lindsay Underhill
- Kimberly Vermeer
- Sharon Lee

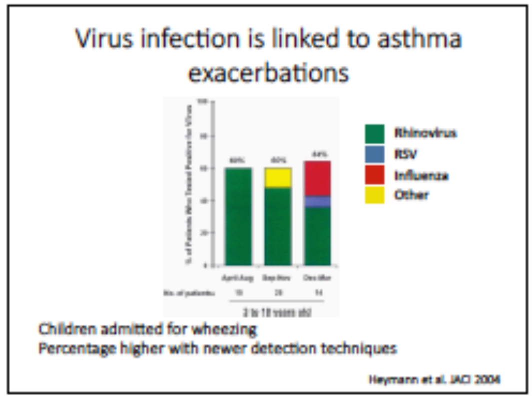
- NIEHS (R21ES017522)
- HUD (MAHHU0008-12)

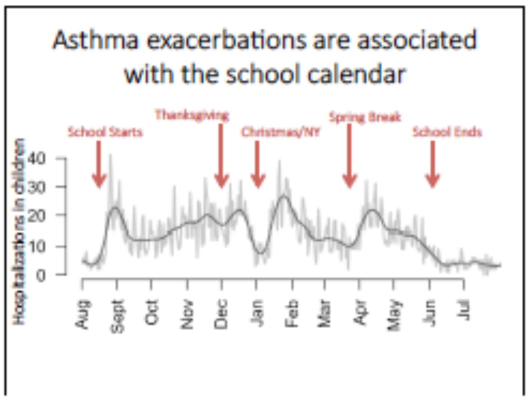
References

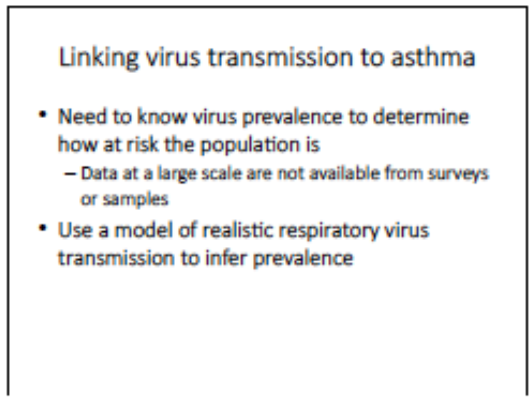
- Fabian MP, Adamkiewicz G, Stout NK, Sandel M, Levy JI. A simulation model of building intervention impacts on indoor environmental quality, pediatric asthma, and costs. J Allergy Clin Immunol 133: 77-84 (2014).
- Fabian MP, Stout NK, Adamkiewicz G, Geggel A, Ren C, Sandel M, Levy JI. The effects of indoor environmental exposures on pediatric asthma: A discrete event simulation model. Environ Health 11:66 (2012).
- Fabian MP, Adamkiewicz G, Levy JI. Simulating indoor concentrations of NO_2 and $PM_{2.5}$ in multifamily housing for use in health-based intervention modeling. Indoor Air 22: 12-23 (2012).
- Adamkiewicz G, Zota AR, Fabian MP, Chahine T, Julien R, Spengler JD, Levy JI. Moving environmental justice indoors: understanding structural influences on residential exposure patterns in low-income communities. Am J Public Health 101: S238-S245 (2011).

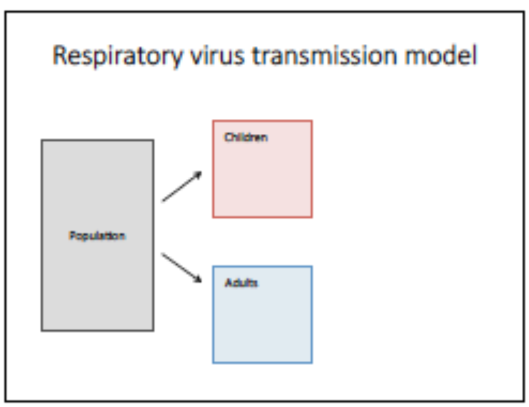
Appendix I: Epidemic of the "Common Cold" and the Dynamics of Severe Asthma Exacerbation Slides

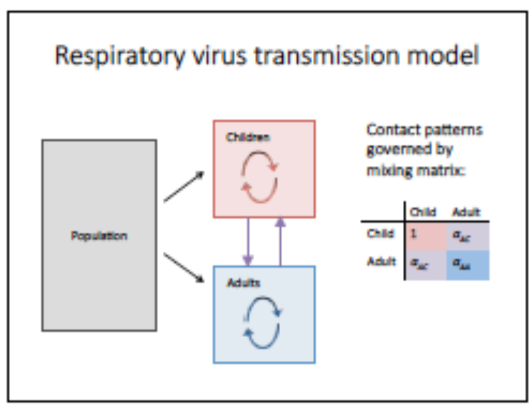




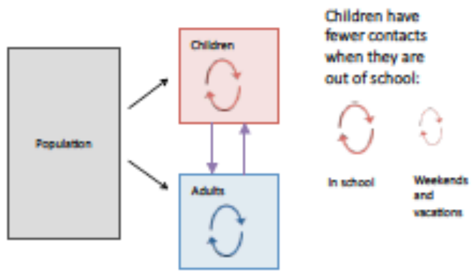




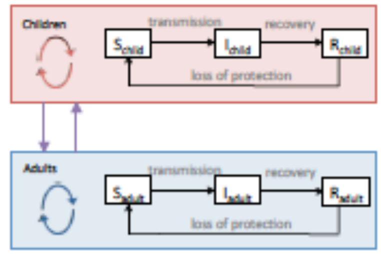


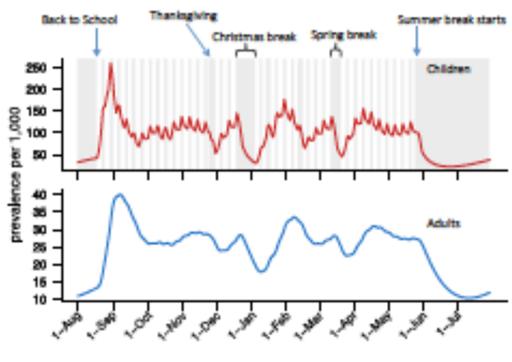


Respiratory virus transmission model



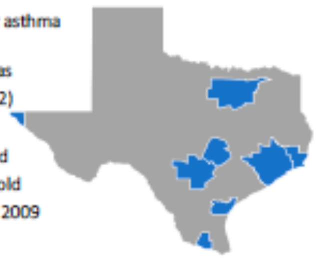
Respiratory virus transmission model





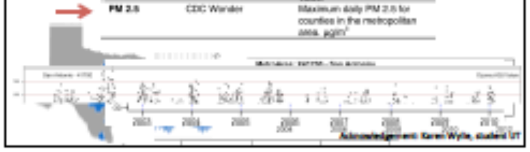
Hospitalization Data

- Hospitalizations for asthma (ICD-9)
- 8 metropolitan areas
- 12.5m people (2002)
- 59% of population
- Child: 5-18 years old
- Adult: 19-55 years old
- Daily data: 2003 to 2009
- More than 65,000 hospitalizations
- Big study, big diverse state



Model Components

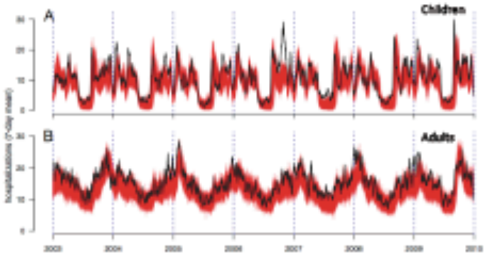
Data	Source	Description
Common Cold	SIRS transmission model	4-day aggregated common cold prevalence
Influenza prevalence	Hospitalization records	Daily state level hospitalizations per million due to influenza, in adults and children. Smoothed
Day of week	Calendar	
Time trend	Daily index value	
Local intercept	Metropolitan boundary	Geographic variation in baseline hospitalization rate
Low temperature	CDC Wonder	Daily minimum temperature in counties in the metropolitan area. Celsius.
Ozone	AIRS	Daily ozone. Air Quality Index value.
PM 2.5	CDC Wonder	Maximum daily PM 2.5 for counties in the metropolitan area. μg/m^3



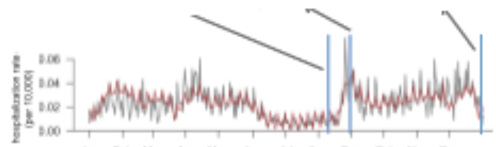
Best fitting model

Data	Source	Description
Common Cold	SIRS transmission model	4-day aggregated common cold prevalence
Influenza prevalence	Hospitalization records	Daily state level hospitalizations per million due to influenza, in adults and children. Smoothed
Day of week	Calendar	
Time trend	Daily index value	
Local intercept	Metropolitan boundary	Geographic variation in baseline hospitalization rate
Low temperature	CDC Wonder	Daily minimum temperature in counties in the metropolitan area. Celsius
Ozone	AIRS	Daily ozone. Air Quality Index value.
PM 2.5	CDC Wonder	Maximum daily PM 2.5 for counties in the metropolitan area. μg/m^3

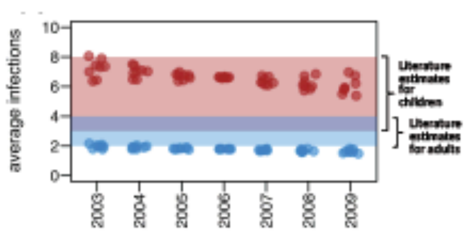
Model Fit



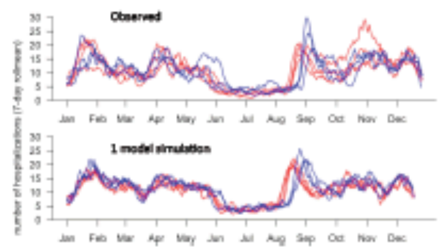
At different times of year the dominant contributing factor changes



Colds per year



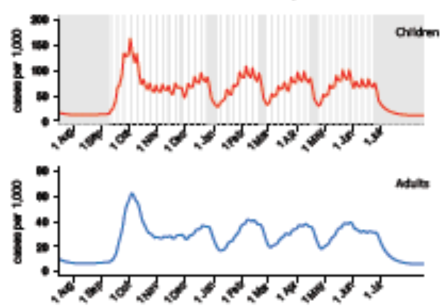
Shift in start date of school



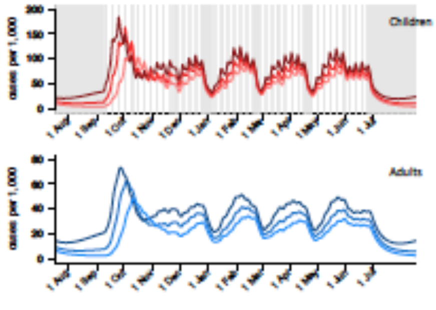
Conclusions

- Common cold transmission model provides a harmonious explanation for the patterns of severe asthma exacerbations seen in Texas
- Prevalence of infection is a shifting baseline of risk to the population driven by contact patterns of children in school
- Variation in school calendars can alter the risk baseline in a strongly non-linear way

Boston - examples



Boston - examples



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Simon Cauchemez – Institut Pasteur
Texas Advanced Computing Center

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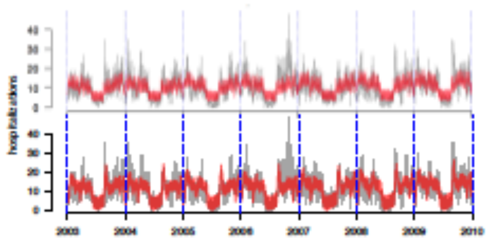
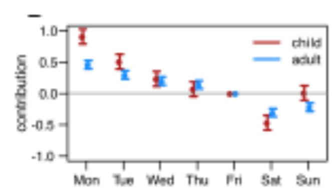
r.eggo@lshtm.ac.uk

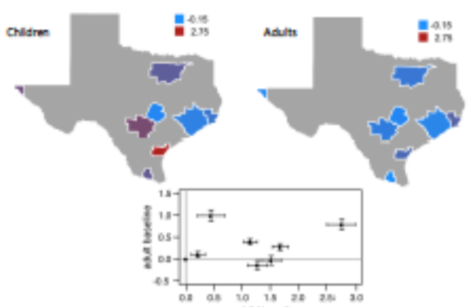
What if kids are just allergic to school?



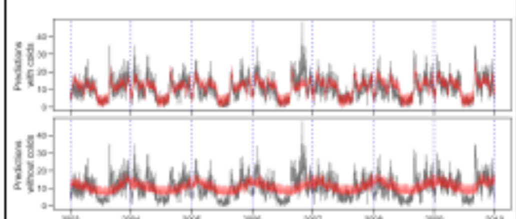
Day of week coefficient



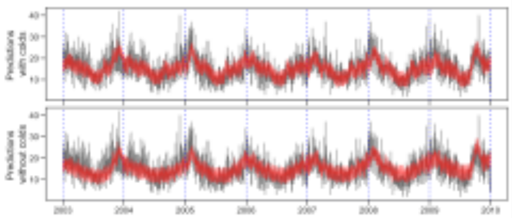
City-specific baseline



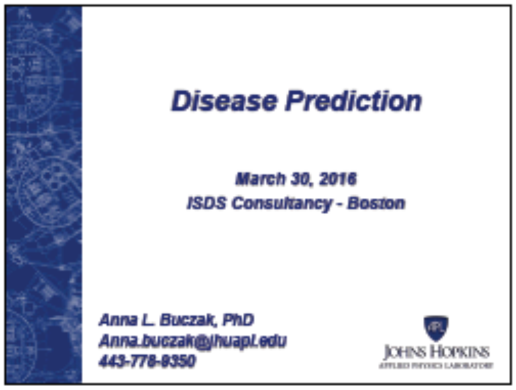
Prediction without colds effect: child

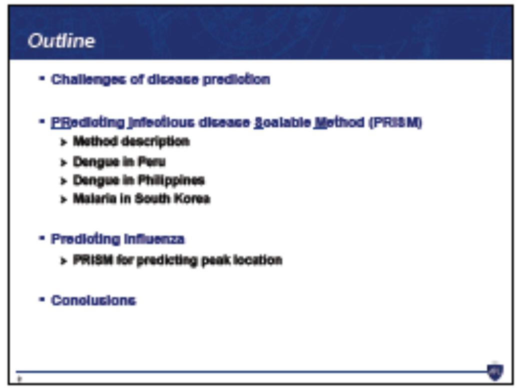


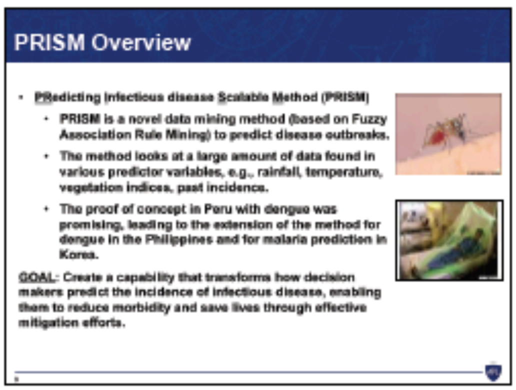
Prediction without colds effect: adult

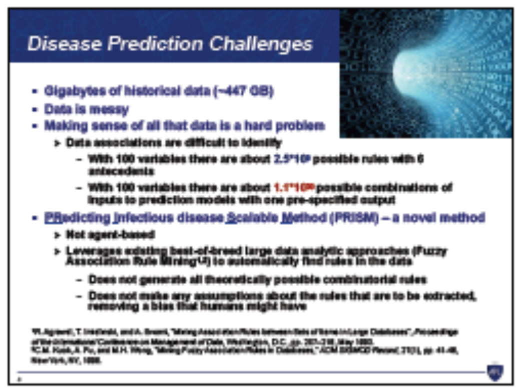


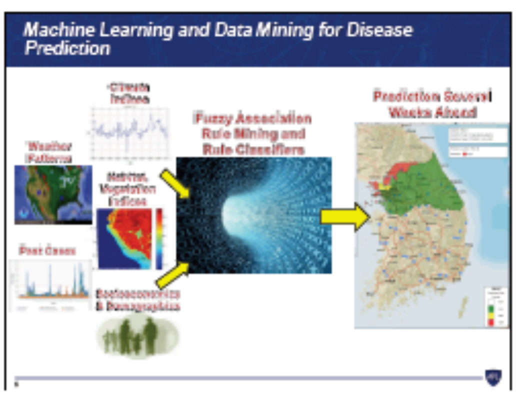
Appendix J: Disease Prediction

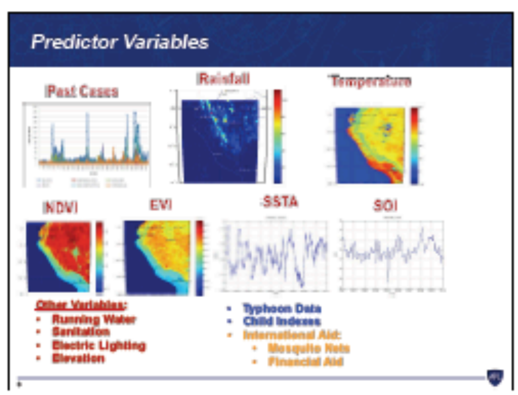




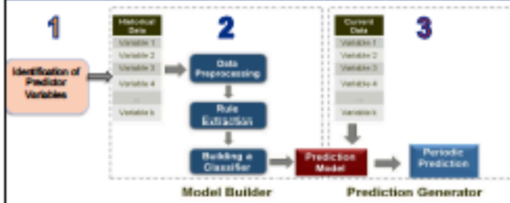








Prediction Methodology



1. Determines all the variables that other researchers found correlated with a given disease (e.g. past incidence, rainfall, temperature, vegetation indexes, socioeconomic).
2. Principal part of the method: uses FARM to build a Prediction Model. Automatically extracts rules from data and chooses a subset of rules to build the classifier (i.e. Prediction Model).
3. Periodic (e.g., weekly) predictions are obtained by running the Prediction Model on new data once a week.

Prediction Results: Dengue in Peru

- Prediction 4-7 weeks into future, 4 weeks at a time
- Prediction done at district level for six Loreto districts
- Results* (6 districts):
  - PPV = 0.806
  - NPV = 0.977
  - Sensitivity = 0.641
  - Specificity = 0.99

PPV: Percentage of time that a prediction of high incidence was made, and a high disease incidence actually occurred

Specificity: proportion of correctly predicted non-outbreaks

*AL Buczak, PT Koshute, SM Babin, BH Feighner and SH Lewis, "A Data-driven Epidemiological Prediction Method for Dengue Outbreaks Using Local and Remote Sensing Data", BMC Medical Informatics and Decision Making, November 2012.

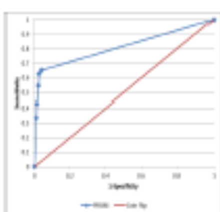
Prediction Results: Dengue in Philippines

- Successful extension of the method to a different country:
  - Model Builder was applied to Philippines province data
  - Trained on 2003-2010 data
    - 40 provinces used in training
  - Tested on 2011 data
    - Tested on 40 and 81 provinces
  - Additionally tested on 2012 data
    - Tested on 40 and 81 provinces
  - Prediction one week at a time, 4 weeks into the future (T+4)
  - Model can be optimized for any of the metrics (e.g., PPV or Sensitivity)
    - PPV=0.778, NPV=0.948,
    - Sensitivity=0.627, Specificity=0.974

PPV: Percentage of time that a prediction of high incidence was made, and a high disease incidence actually occurred

Sensitivity: proportion of correctly predicted outbreaks

ROC



Visualization of Results for Philippines

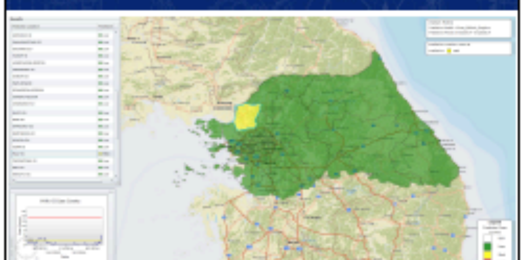
AL Buczak, B Baugher, SM Babin, LC Ramac-Thomas, E Guven, Y Elbert, PT Koshute, JMS Velasco, VG Roque, EA Tayag, IK Yoon, SH Lewis, "Prediction of High Incidence of Dengue in the Philippines", PLOS Neglected Tropical Diseases, 8(4): e2771. doi: 10.1371/journal.pntd.0002771 (2014).

Prediction of Malaria in Korea

- Extension of the method to a different disease and a different country
  - *P. vivax* malaria
- Model Builder applied to South Korea
- Predictions performed at a region level (84 regions)
- Prediction two weeks at a time, 7-8 weeks into the future (T+7_T+8)
- Predictions have three levels:
  - *Low*: 0-2 cases
  - *Medium*: 3-16
  - *High*: 17 or more
  - Number of cases predicted is the aggregate for the two week prediction period

- Metrics:
  - Low: PPV = 0.965, Sensitivity = 0.993
  - Medium: PPV = 0.673, Sensitivity = 0.278
  - High: PPV = 0.842, Sensitivity = 0.801

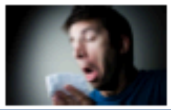
Screenshot: Prediction of Malaria in Korea



AL Buczak, B Baugher, E Guven, LC Ramac-Thomas, Y Elbert, SM Babin, SH Lewis, "Fuzzy Association Rule Mining and Classification for the Prediction of Malaria in South Korea", BMC Medical Informatics and Decision Making 2015, 15:47 doi:10.1186/s12911-015-0170-6

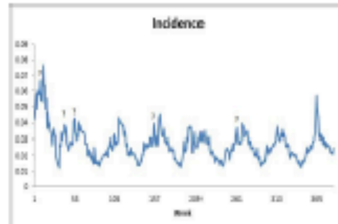
Influenza Prediction - Goal

- Analysis of the military Influenza-like-Illness (ILI) incidence with the goal of prediction of:
  - Weeks of peak ILI incidence
  - Incidence rate at peak
  - Total number of cases



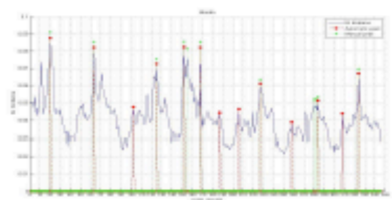
Determination of Peak Location (1)

- Definition of peak is somewhat ambiguous
- Four peak detection algorithms developed



Determination of Peak Location (2)

- Best algorithm still identified some spurious peaks
- Telecon with Matt Biggerstaff from CDC to discuss peak location
- Final algorithm: algorithm 3 with some modifications:
  - Mostly one peak per season
  - When a peak's value was within 5% of the value of the highest peak for a given season, it was added as a peak to overcome problems with reporting



Predictor Variables

- Past Military Influenza like Illnesses (ILI) data (AFHSC)
- Rate of ILI reported (CDC)
- Rate of positive Lab tests for Flu (CDC)
- P&I Mortality Rate (CDC)
- Rate of hospitalization due to Influenza (CDC)
- Rainfall (NASA)
- Temperature (NOAA)
- Relative humidity – derived from temperature and Dew Point
  - Ratio of the partial pressure of water vapor in the air-water mixture to the saturated vapor pressure of water
- Specific humidity – derived from temperature and pressure
  - Ratio of water vapor to dry air in a particular mass
- Atmospheric pressure (NOAA)
- Dew Point (NOAA)
  - Temperature below which the water vapor in a volume of humid air at a given constant barometric pressure will condense into liquid water at the same rate at which it evaporates
- Most predictor variables are used with time stamps T-1, ..., T-12

Results

- Data divided into:
  - Training set: 8/27/2006-7/31/2011
  - Fine-tuning set: 8/1/2010 to 7/31/2011
  - Testing set: 8/7/2011 to 1/6/2013
- Prediction performed for T+4_T+6 (3 weeks) at a time
- Two approaches for building classifiers developed:
  - Build three classifiers: one for predicting a peak at T+4, one for T+5 and one for T+6. Outputs of the classifiers fused by an OR statement: IF (Predicted_Peak_T+4 OR Predicted_Peak_T+5 OR Predicted_Peak_T+6) THEN Predicted_Peak_4_6.
  - One classifier is trained that predicts a peak 4–6 weeks out

Method	PPV	NPV	Sensitivity	Specificity
Fusion	0.3786	0.9350	0.6216	0.8421
One classifier 1	0.5092	0.9692	0.6917	0.9770
One classifier 2	0.6033	0.9665	0.6063	0.9662

AL. Buczak, B. Baugher, E. Guven, L. Moniz, SM. Babin, J_P Chretien. "Prediction of Peaks of Seasonal Influenza in Military Healthcare Data." Accepted for publication by *Biomedical Engineering and Computational Biology Journal* 2016.

Summary

- APL developed a set of methods for disease prediction:
  - PRISM:
    - Provides a novel disease prediction method
      - Predictions performed for several diseases: dengue and malaria
      - Prediction of peak location for influenza
    - Flexible, scalable methodology
      - Predictions are 4-8 weeks out
      - Predictions are at various geographical resolutions: province, district, region, county
  - Method of analogues for influenza successfully predicts (4 weeks out):
      - Incidence rate at peak
      - Total number of cases

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APPLIED PHYSICS LABORATORY

Method of Analogues

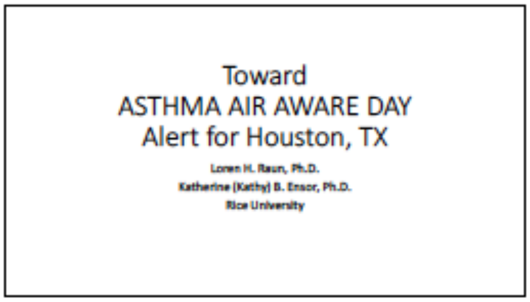
- Method of Analogues uses past time sequences of values to predict future sequences of values

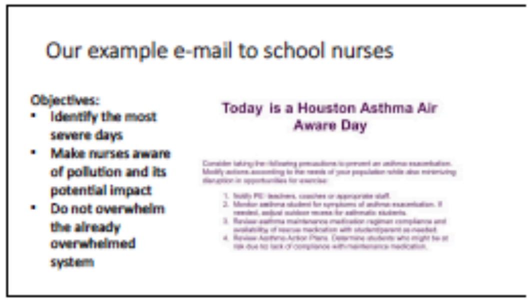
Prediction Metrics

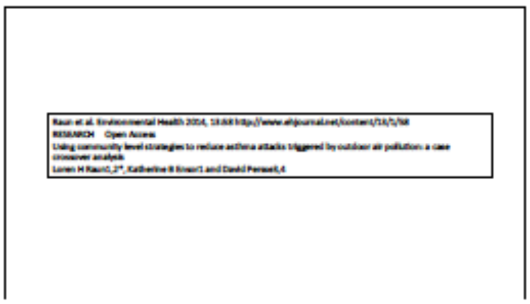
- Prediction accuracy should be quantified:
  - Overall accuracy: proportion of predictions that are correct: (TP+TN)/(TP+TN+FP+FN)
  - Positive Predictive Value (PPV): proportion of positive predictions that are outbreaks: TP/(TP+FP).
  - Negative Predictive Value (NPV): proportion of negative predictions that are non-outbreaks: TN/(TN+FN)
  - Sensitivity: proportion of correctly predicted outbreaks: TP/(TP+FN).
  - Specificity: proportion of correctly predicted non-outbreaks: TN/(TN+FP).
  - False Alarm Rate: proportion of incorrectly predicted non-outbreaks: FP/(FP+TN)

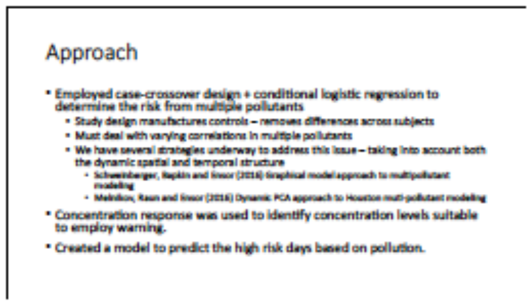
	Actual Positive	Actual Negative
Prediction Positive	True Positive (TP)	False Positive (FP)
Prediction Negative	False Negative (FN)	True Negative (TN)

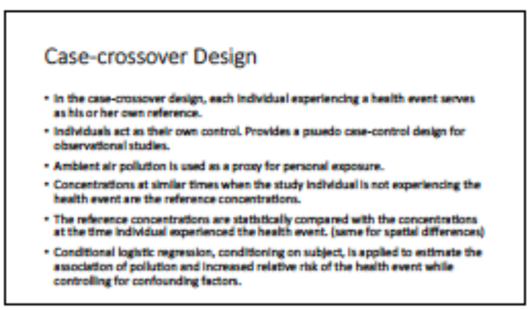
Appendix K: Towards Asthma Air Aware Day Alert for Houston, TX Slides

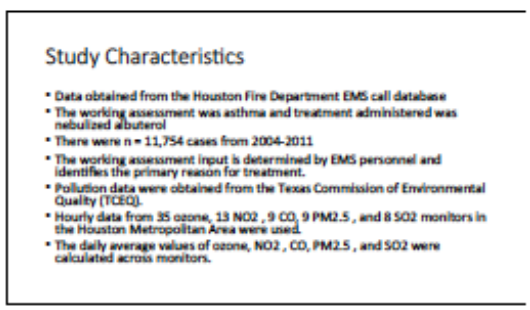




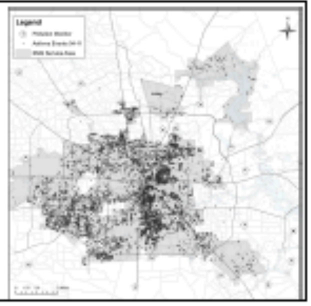






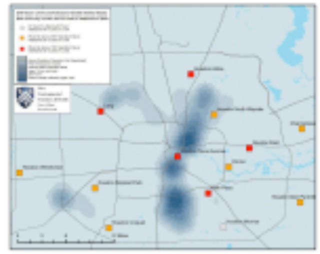


EMS-treated asthma attacks and pollution monitors in Houston, Texas (2004-2011)



Spatial Distribution of Ambulance treated Asthma Attacks

Air quality compliance



A Case for School Nurses

Ambulance treated asthma exacerbations in children.

School nurse information

Houston counts

	month	count	med_o3	med_no2	med_no2_1	count_adult_0413
1	a.Jan	1410	29.7299405	13.3041793	54.3397172	1104
2	b.Feb	1259	34.3791667	12.327651	51.313664	974
3	c.Mar	1336	44.1360867	12.9309406	43.3740632	1058
4	d.Apr	1236	47.1703933	8.8719468	35.4877793	901
5	e.May	1040	43.4282467	7.51125	36.125	753
6	f.Jun	880	35.3708618	6.9763601	37.6014704	708
7	g.Jul	915	31.3122674	6.8244476	27.2365312	752
8	h.Aug	1050	40.3374706	7.8461108	31.3810763	766
9	i.Sep	1284	45.4913027	10.2471315	40.930926	949
10	j.Oct	1363	41.1410876	12.0687167	48.2048788	961
11	k.Nov	1316	33.7295117	13.1530537	52.6142146	1006
12	m.Dec	1194	28.7927008	[illegible]	[illegible]	[illegible]

Analysis of relative risk for EMS-treated asthma attacks per IQR increase in single pollutant

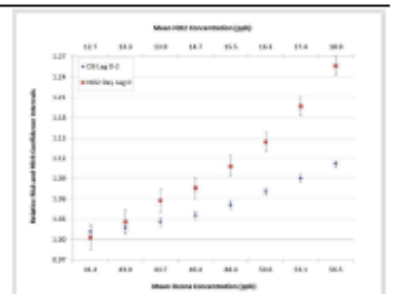
Pollutant	Lag	IQR	All Year RR	All Year 95% CI	WARM April to October RR	WARM April to October 95% CI	COLD November to March RR	COLD November to March 95% CI
NO_2 (ppb)	0 Day*	8	1.12	1.07-1.17	1.08	1.00-1.16	1.14	1.08-1.20
	1 Day		1.04	1.00-1.09	1.02	0.95-1.10	1.05	1.00-1.11
	2 Day		1.03	0.99-1.07	1.06	0.96-1.15	1.01	0.96-1.06
	3 Day		1.02	0.98-1.06	1.05	0.99-1.12	1.00	0.95-1.05
	0 to 2		1.10	1.04-1.16	1.07	0.98-1.17	1.10	1.05-1.16
CO (ppb)	0 Day*	155	1.05	1.02-1.08	1.03	0.98-1.08	1.06	1.03-1.10
	1 Day		1.03	1.00-1.05	1.00	0.95-1.05	1.04	1.00-1.07
	2 Day		1.02	0.99-1.04	1.03	0.98-1.08	1.01	0.97-1.06
	3 Day		1.01	0.98-1.04	1.03	0.99-1.08	1.00	0.96-1.05
	0 to 2		1.04	1.01-1.08	1.01	0.96-1.07	1.06	1.01-1.10
O_3 (8 hour) (ppb)	0 Day	20	1.04	1.01-1.07	1.01	0.98-1.05	1.11	1.04-1.18
	1 Day		1.06	1.03-1.09	1.02	0.98-1.06	1.16	1.09-1.24
	2 Day		1.05	1.01-1.08	1.03	0.99-1.07	1.07	1.01-1.15
	3 Day		1.01	0.98-1.04	1.01	0.98-1.05	0.99	0.93-1.06
	0 to 2*		1.07	1.03-1.11	1.03	0.99-1.08	1.17	1.08-1.27
$PM_{2.5}$ ($\mu g/m^3$)	0 Day*	6	1.02	0.99-1.05	1.05	0.96-1.06	1.00	0.95-1.06
	1 Day		1.02	0.99-1.05	1.03	0.99-1.06	1.00	0.95-1.05
	2 Day		1.04	1.01-1.07	1.05	1.06-1.07	1.06	1.01-1.12
	3 Day		1.03	1.00-1.06	1.03	1.00-1.07	1.01	0.96-1.06
	0 to 2		1.04	1.00-1.07	1.01	0.99-1.08	1.03	0.97-1.10
SO_2 (ppb)	0 Day	2	1.03	0.97-1.08	1.03	0.94-1.12	1.02	0.96-1.09
	1 Day		0.99	0.93-1.05	0.98	0.90-1.07	1.00	0.93-1.06
	2 Day		1.02	0.97-1.07	1.03	0.95-1.12	1.00	0.94-1.07
	3 Day		0.99	0.94-1.04	1.03	0.94-1.12	0.97	0.91-1.08
	0 to 2		1.02	0.94-1.10	1.00	0.89-1.13	1.01	0.92-1.12

* [illegible]

Controlling for holidays and regional temperature (lag 1)

IQR used is approximately representative of year and season range

Forest plots of rolling concentration bins NO2 and Ozone multi-pollutant model concentration-risk



Relative risk for multi-pollutants by quartile bins of concentrations during study period

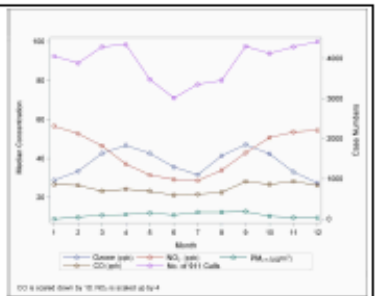
			Q 1 NO_2 ≤7 ppb	Q 2 NO_2 8-11 ppb	Q 3 NO_2 11-15 ppb	Q 4 NO_2 ≥15 ppb
			Relative Risk and Confidence Interval			
Q 1	O_3 < 28 ppb	Cases	957	982	689	508
		Days	249	232	141	117
		O_3	0.93 (0.91-0.94)	0.91 (0.89-0.92)	0.93 (0.92-0.94)	0.93 (0.91-0.95)
		NO_2	0.35 (0.31-0.39)	0.84 (0.81-0.86)	0.96 (0.94-0.99)	1.20 (1.17-1.23)
Q 2	O_3 28-36 ppb	Cases	757	820	574	705
		Days	194	184	122	146
		O_3	1.00 (0.99-1.02)	1.00 (0.99-1.01)	1.01 (1.00-1.02)	1.00 (0.98-1.02)
		NO_2	0.45 (0.41-0.50)	0.83 (0.80-0.86)	0.96 (0.94-0.99)	1.24 (1.21-1.27)
Q 3	O_3 36-48 ppb	Cases	500	972	669	797
		Days	151	235	190	192
		O_3	1.06 (1.05-1.07)	1.04 (1.03-1.05)	1.02 (1.01-1.03)	1.02 (1.01-1.03)
		NO_2	0.56 (0.52-0.61)	0.81 (0.79-0.83)	1.03 (1.00-1.06)	[illegible]
Q 4	O_3 > 48 ppb	Cases	191	746	1074	952
		Days	48	189	249	217
		O_3	1.15 (1.10-1.16)	1.09 (1.08-1.11)	1.07 (1.06-1.08)	1.06 (1.04-1.07)
		NO_2	0.76 (0.67-0.85)	0.86 (0.83-0.90)	1.12 (1.09-1.15)	1.44 (1.38-1.50)

*O_3 Day Lag 0 to 2; NO_2 Day Lag 0

Aggregate pollution findings

- Ozone and NO2 concentrations dip in June and July as do the number of EMS cases.
- July has the lowest frequency of days when the maximum eight hour average concentration of ozone met or exceeded 76 parts per billion at a monitor.
- These lower ozone concentrations in June and July coincide with high daily rain frequency in these months.
- Correlation between daily measures of air pollutant concentrations and apparent temperature indicate the strongest correlations between daily pollutants were between NO2 and CO (r = 0.74) followed by NO2 and SO2 (r = 0.57), by CO and SO2 (r = 0.56), daily PM2.5 and ozone (r = 0.42). The correlation between ozone and NO2 was (r = 0.23).
- The strongest correlation between a pollutant and apparent temperature was for NO2 (r = -0.54).

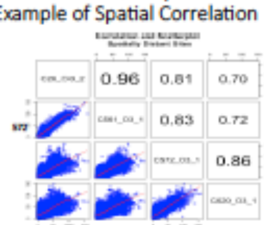
Number of EMS-treated asthma calls in Houston by month and median pollution concentration (2004-2011)



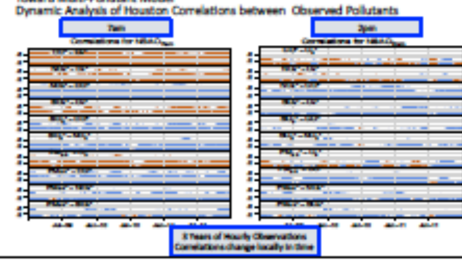
Asthma Warning System Pilot

- Following this research, a pilot study was designed and implemented using a predictive model to create a warning for nurses in the Houston Independent School District.
- The goal is something SIMPLE. Our simple model uses
  - NO2 levels observed from 9pm to 2am the night before
  - 8 hour maximum ozone level for the day before
  - Forecast of weather (apparent temperature, cloud cover, precipitation) for day of
  - Alert is issued between 5 and 6am via e-mail to school nurses
- The nurses would then prepare accordingly if a warning was given.

Air Quality Monitors
Example of Spatial Correlation



Toward Multi-Pollutant Model
Dynamic Analysis of Houston Correlations between Observed Pollutants



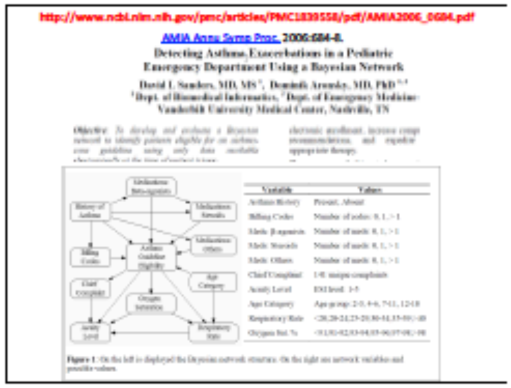
Limitations – so many….but

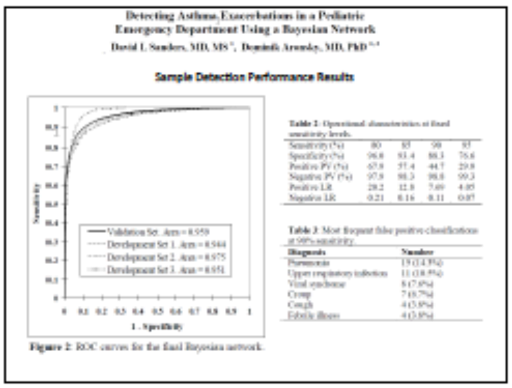
- Observational study with biases
- EMS based – population is not represented as a whole and this is especially true for asthma but fits our goal of reducing EMS calls for asthma.
- We ran our models on the RODS data and obtained similar results. We have also done similar analysis using admissions data for Texas Children's Hospital.
- Multi-pollutant modeling for acute health impact is problematic and we are addressing this issue further.
- Statistical methods can be improved, but not sure we will get better knowledge
  - Spatial-temporal work has been conducted but we were unable to get it published.
  - Fell back to case-crossover with spatial averages.
- Model forecast for warning days – over predicts high risk days, but not severely. Further, the over prediction may be appropriate.

Appendix L: Bayesian Network Approaches Slides

ISDS Consultancy on
Predictive Capability for Asthma
Exacerbations in Boston:
Modeling Session
Bayesian Network Approaches

Howard Burkom
Johns Hopkins Applied Physics Laboratory



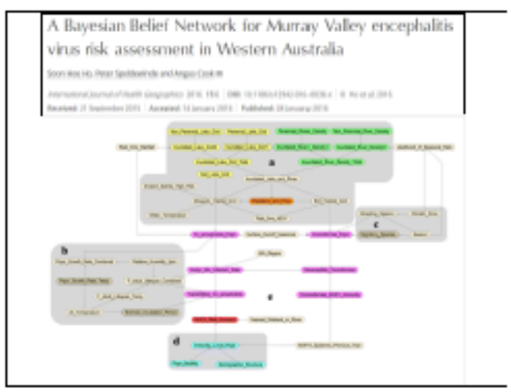


Fusion Capability Designed to Answer:

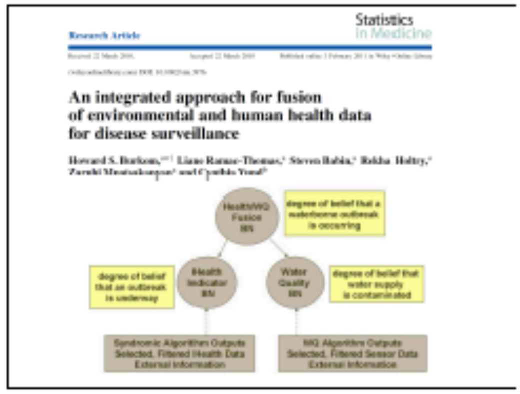
- How would an experienced health monitor make investigation decisions given the luxury of examining all data sources every day?
- How can the principal information supporting these decisions be presented most conveniently?
- What follow-up data details would this monitor find most helpful in deciding whether and how to investigate?

Concept: Population-based Bayes Networks

- Method of combining information from the monitored population
  - Algorithm results from multiple data streams of varying relevance (not raw data)
  - More than a rule set: an analytic umbrella that can also include report-based results, incomplete data updates, other multivariate methods
- Not Bayesian statistics in the sense of hierarchical modeling, fixed/random effects (could incorporate)
- Not an agent-based Bayesian model representing every individual as a separate node with properties




Syndromic
Interactions
Pollution
Allergens
Asthma
Figure 1. HBN structure for asthma detection through fusion of syndromic and environmental data.


Statistics in Medicine
Research Article
An integrated approach for fusion of environmental and human health data for disease surveillance
Health/WQ Fusion BN
degree of belief that a waterborne outbreak is occurring
Health Indicator BN
degree of belief that an outbreak is underway
Water Quality BN
degree of belief that water supply is contaminated
Syndromic Algorithm Outputs
Selected, Filtered Health Data
External Information
WQ Algorithm Outputs
Selected, Filtered Sensor Data
External Information