



Predicting the Influenza Season Using AIRS Data

Heidar Thor Thrastarson^{1,2}

1. Joint Institute For Regional Earth System Science and Engineering,
University of California Los Angeles

Joao Teixeira²

2. NASA Jet Propulsion Laboratory, California Institute of Technology

Emily Serman³, Anish Parekh³

3. University of Southern California



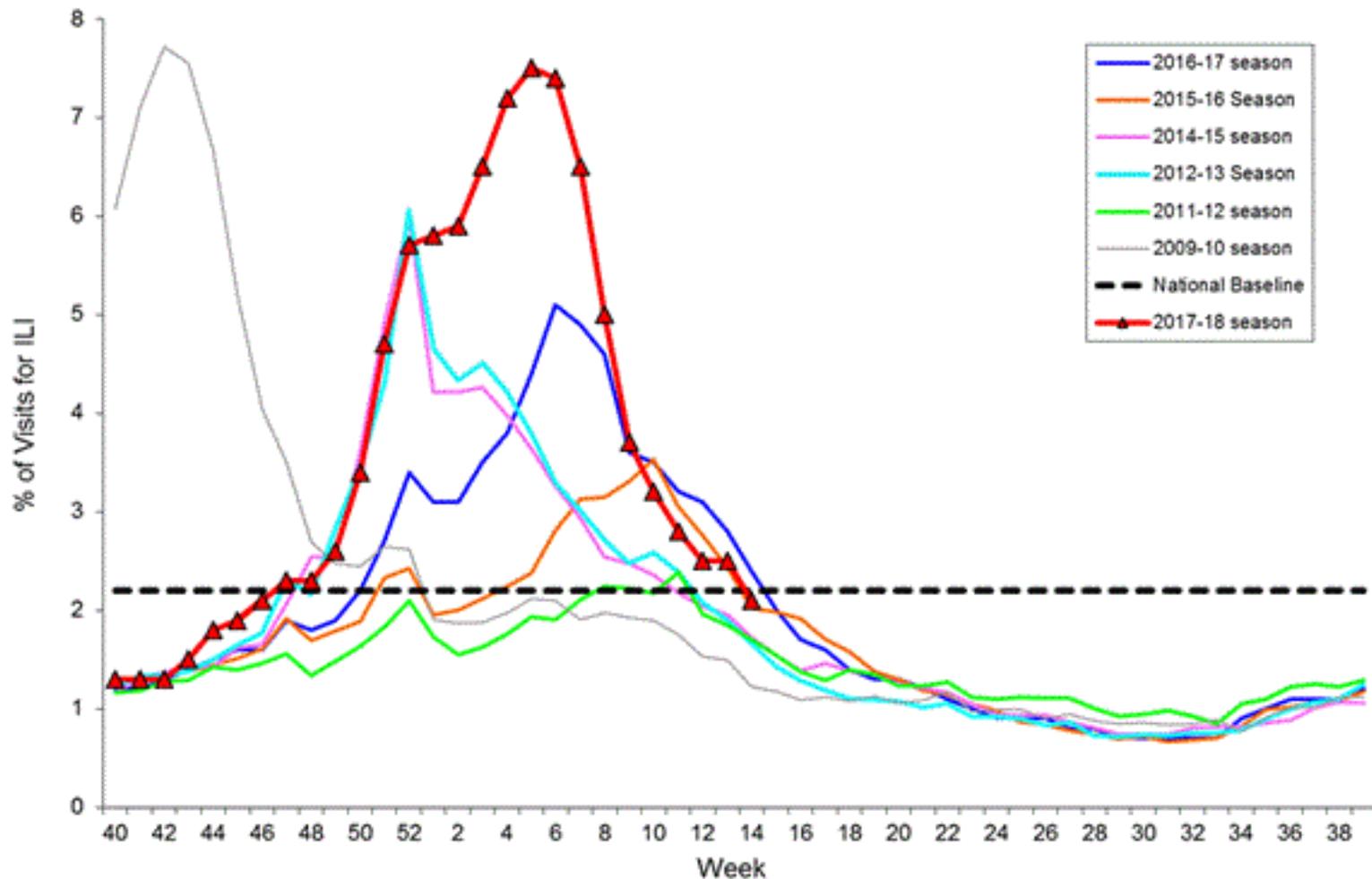
2017-2018 Seasonal Influenza

- CDC update on the flu season in the US:
 - “Hospitalization rates this season have been record-breaking, exceeding end-of-season hospitalization rates for 2014-2015, a high severity, H3N2-predominant season.”
 - “In the past, A(H3N2) virus-predominant influenza seasons have been associated with more hospitalizations and deaths in persons aged 65 years and older and young children compared to other age groups.”
- LA Times: “The flu season nationwide is considered among the worst in a decade.”
- Daily News (February): **“Flu deaths in LA County this season have already doubled the 2016-17 total”**



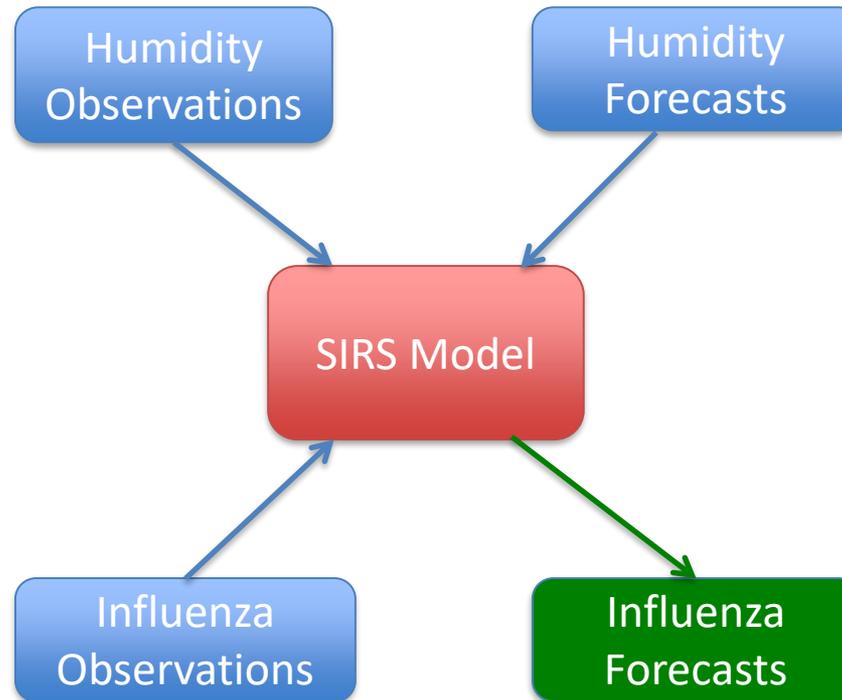
US Influenza Seasons

Percentage of Visits for Influenza-like Illness (ILI) Reported by the U.S. Outpatient Influenza-like Illness Surveillance Network (ILINet), Weekly National Summary, 2017-2018 and Selected Previous Seasons



AIRS-Flu System Overview

- Daily updating most recent values for near-surface H₂O mixing ratio, AIRS level 3 data (v6)



- Influenza data assimilated
- Center for Disease Control (CDC):
 - Regional, weekly surveillance records for the proportion of doctor's visits for influenza-like illness (ILI)
 - Combined with lab virology results for the percentage of influenza positive samples

- NCEP forecasts for near-surface humidity
- The output is the number of infected and susceptible people in a population (city/state/region)



SIRS Model

$$\frac{dS}{dt} = \frac{N - I - S}{L} - \frac{\beta IS}{N} - \alpha$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \frac{I}{D} + \alpha$$

Specific
humidity



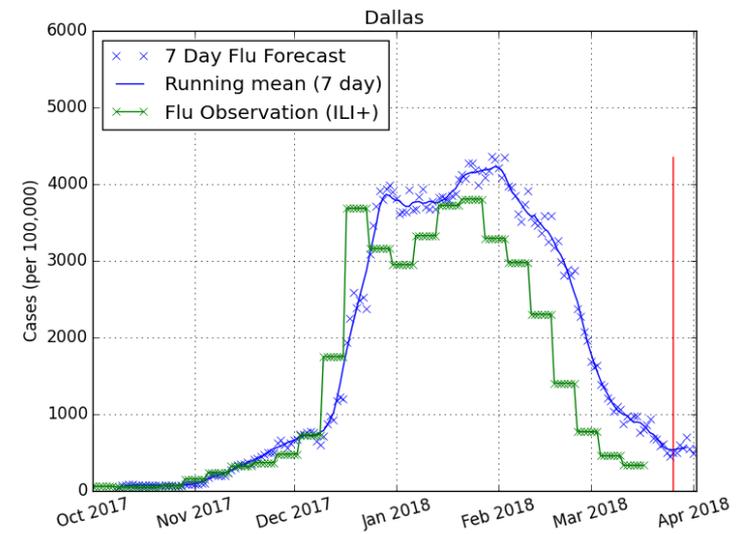
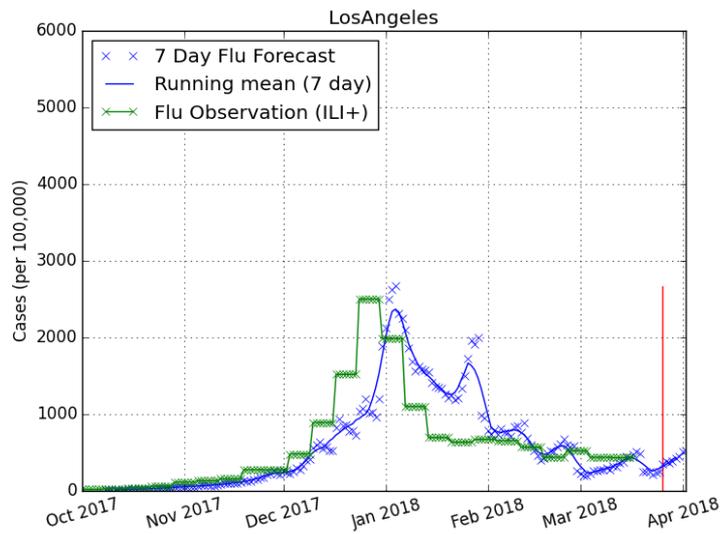
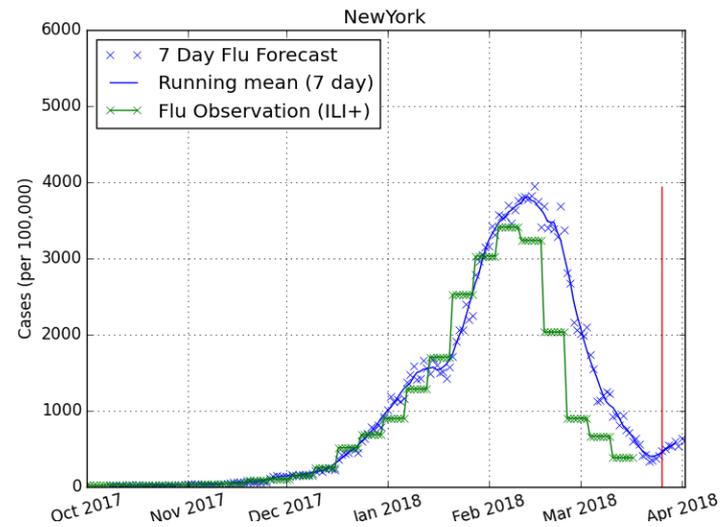
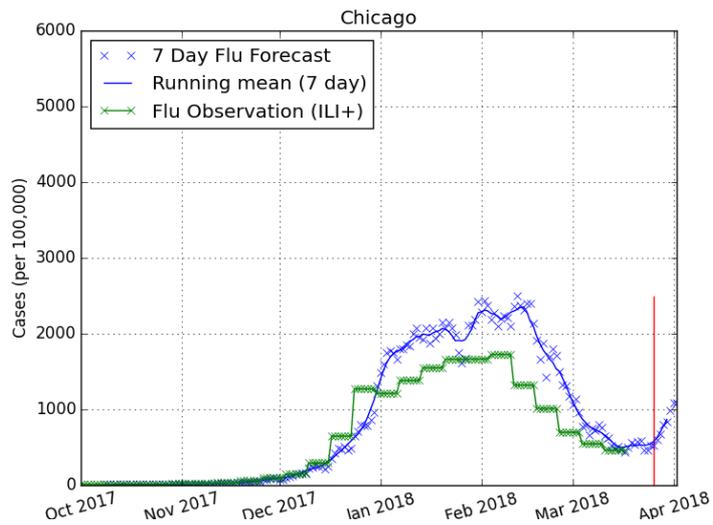
$$\beta = \frac{R_0}{D} = \frac{1}{D} [R_{0min} + (R_{0max} - R_{0min})e^{aq}]$$

- N Population size
- S Susceptible persons
- I Infectious (= infected) persons
- L Average immunity duration
- D Mean infectious period
- α Rate of (travel-related) import of virus into model domain
- β Contact rate
- R_0 (Daily) basic reproductive number
- a (Negative) coefficient in contact rate exponential
- q Specific humidity

Quasi-Operational Prediction System applied to US cities

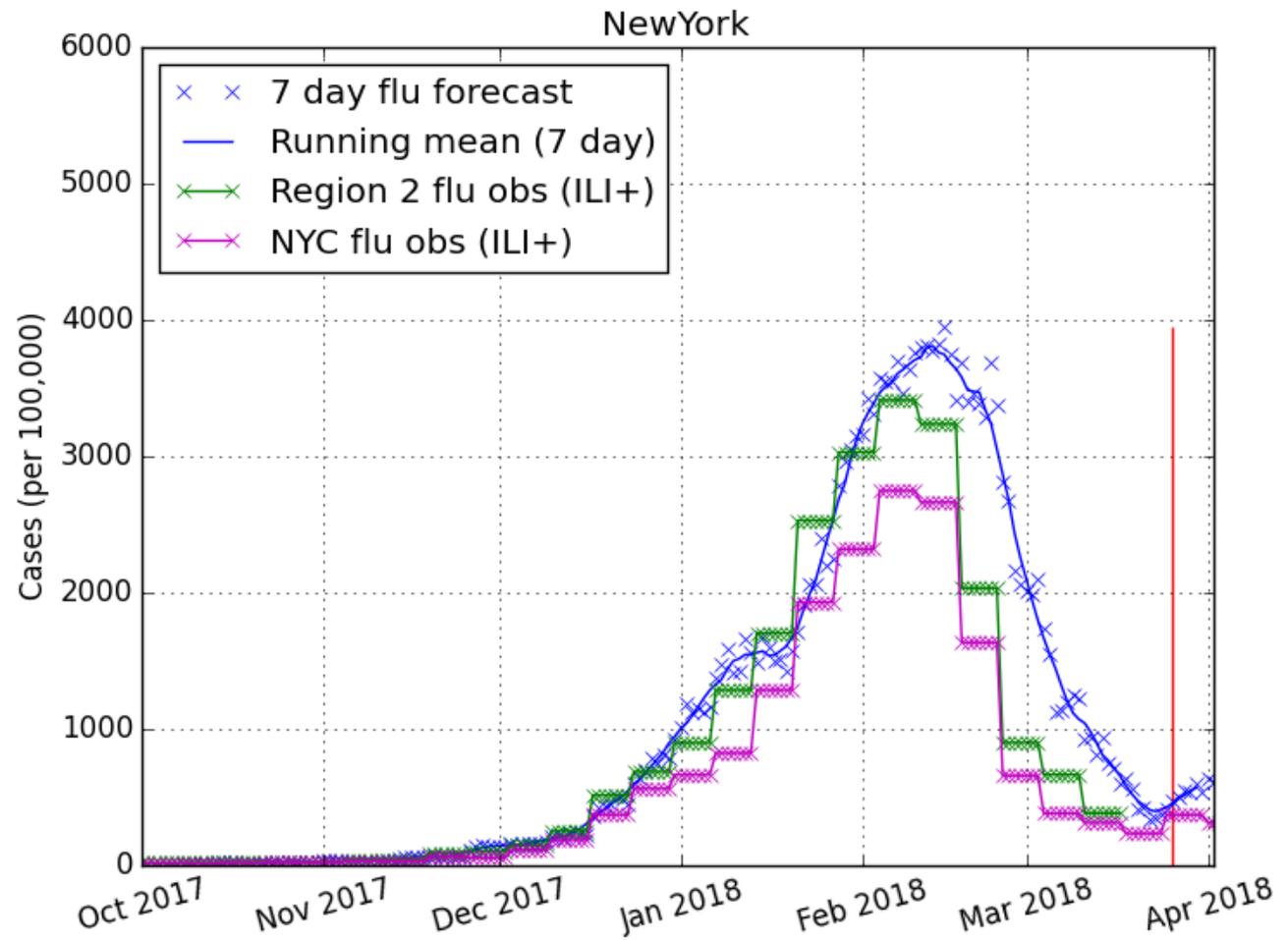
- Important question: At which spatial scales is the humidity-driven model most applicable and useful?
 - Our strategy has been to focus first on city level
 - Emily Serman's research indicates humidity-flu link seems to work on city, state and regional level
- Quality/availability of 'observational' data for flu is a big limitation
 - US (HHS) regional data most readily available
 - Observational data for influenza incidence from CDC regional level assimilated when available (couple of weeks lag time) to make analysis and re-initialize model
 - What we have is Influenza-Like Illness (ILI) indices from doctor's visits and lab results for % influenza positive, which we combine, but it's not the same as actual incidence
 - Previous model results and observations usually weighted equally
 - City level data often available later, from local authorities (pdf format), and can be used to compare (with caveats...)
- Ensembles (100 members) of forecasts run with different model parameter values drawn from distributions reflecting limited constraints
- We have results now from running real-time for two full seasons
 - 2016-2017 results used to calibrate for 2017-2018

2017-2018 Season - US Cities



AIRS-Flu prediction system results for four cities. 7 Day forecasts are shown in as blue crosses (ensemble mean of model results from 7 days prior), ILI+ flu regional 'observations' in green. The blue line is the 7 day running mean of the forecasts. Here, previous seasons' results have been used for calibration.

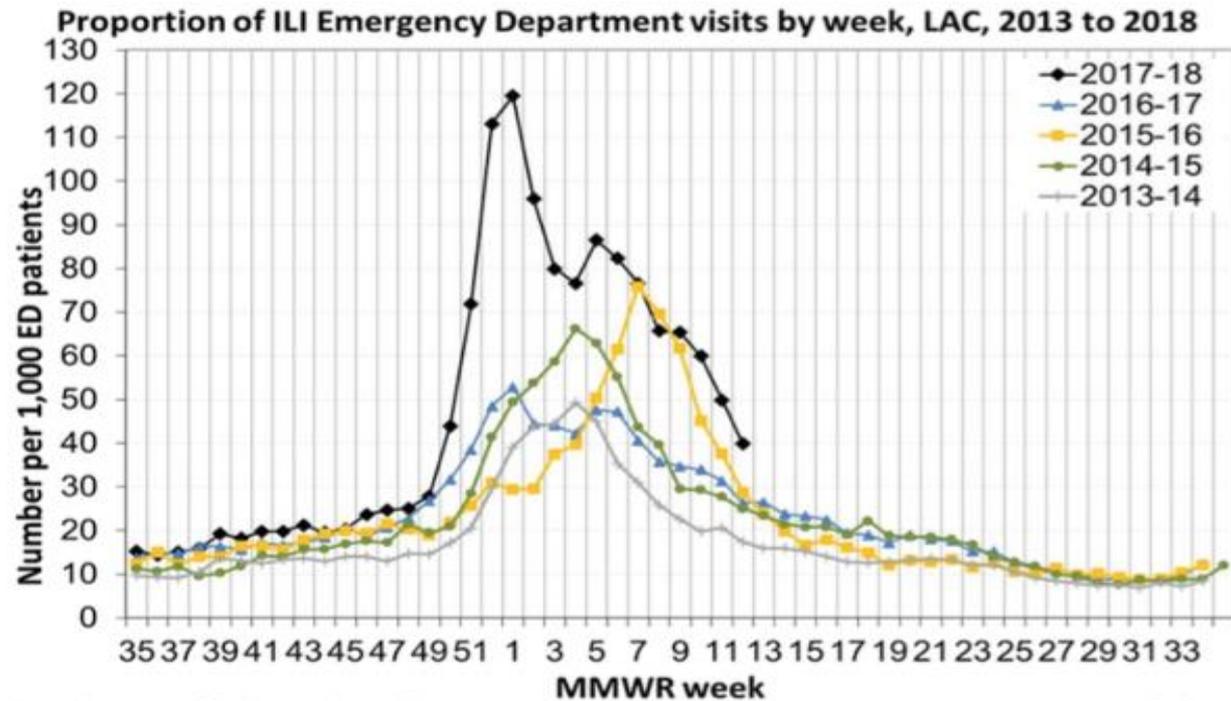
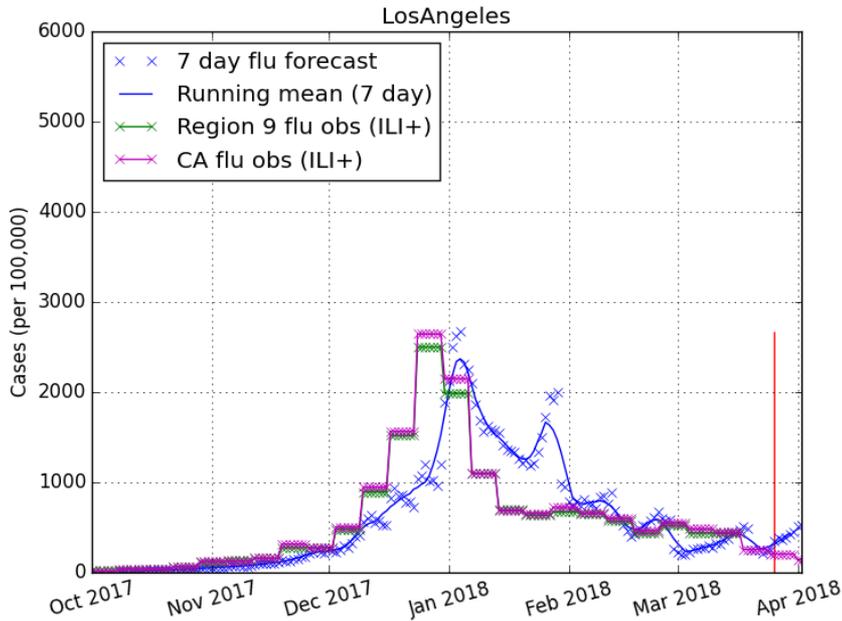
New York City



- Here, city level data is available from CDC
- New York City dominates Region 2
- Model peak slightly later and stronger than observed

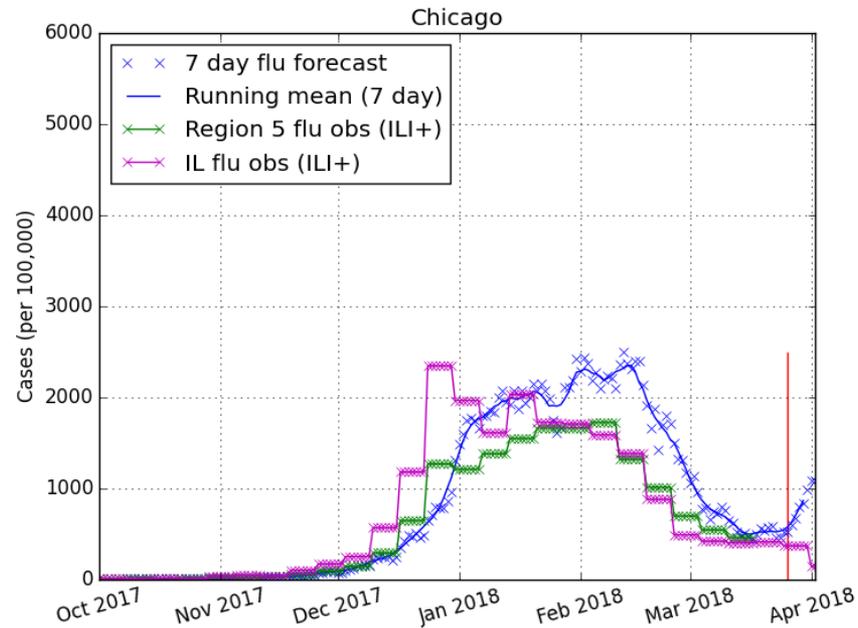
Los Angeles

- CDC only gives region and state data
- But CDPH gives LA County data
- CA dominates Region 9
- But LA quite different
- Model (with LA humidity driving it but regional data assimilated) captures LA better, including 2nd peak (not present in assimilated data), and timing of both peaks

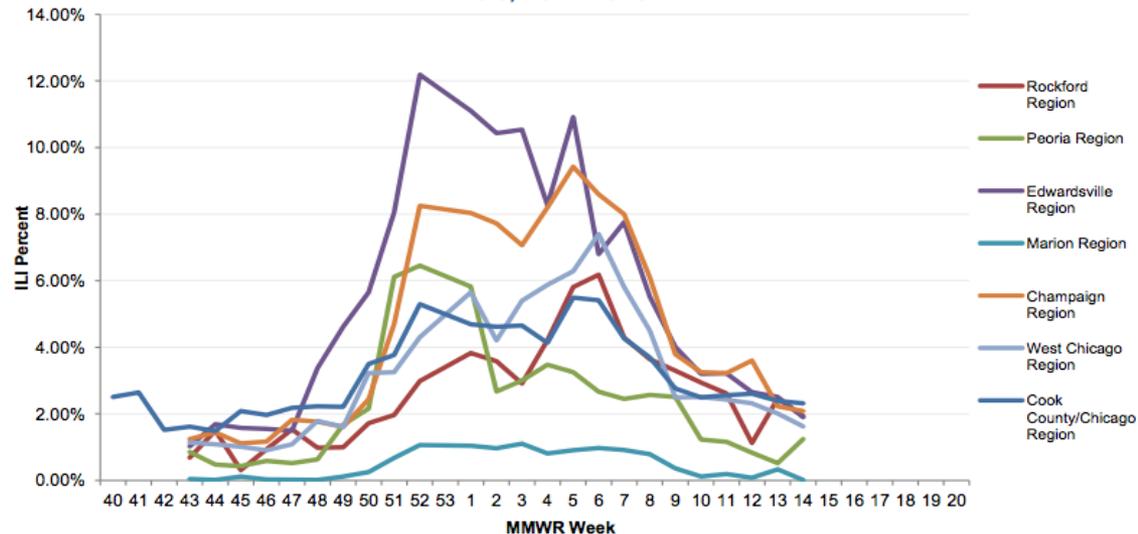


Chicago

- CDC only gives region and state data
- But IDPH gives Illinois data with sub-regions
- IL different from Region 5
- But Chicago more similar to Region 5 than IL
- Model captures Chicago peak timing well (week 6 – mid Feb – a week after Region 5 peak)



Percent of ILI Reported From Sentinel Providers by Region, Illinois, 2017-2018



Dallas

- CDC only gives region and state data
- But Dallas County HHS publishes flu surveillance reports
- Texas dominates Region 6
- Dallas data not yet analyzed but seems similar to Texas
- Model peaks lag observed (TX) peaks

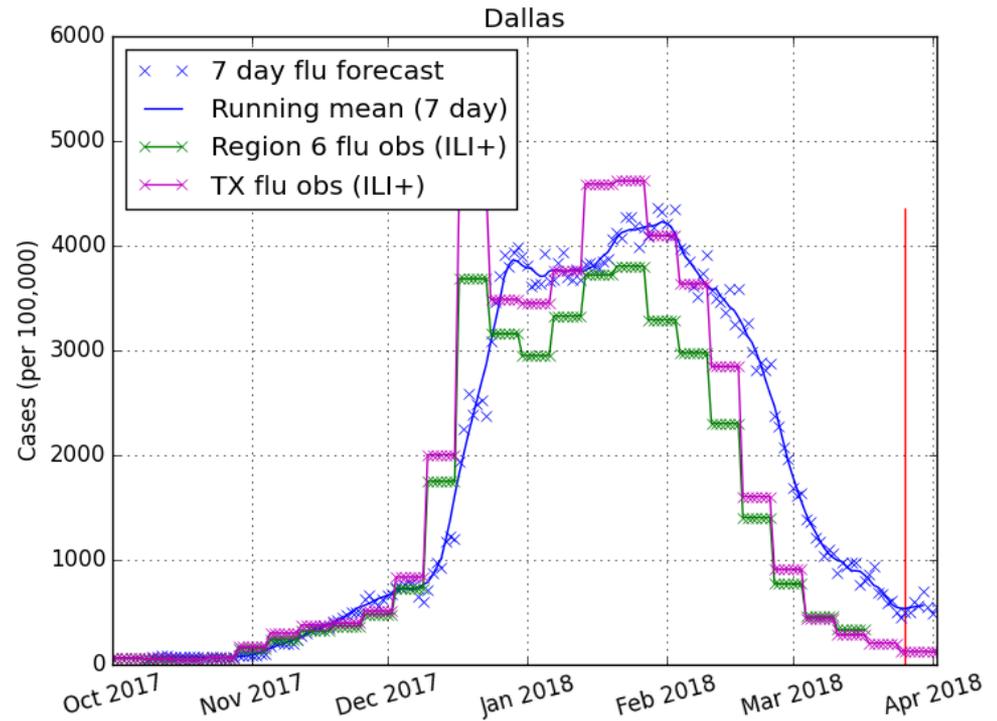
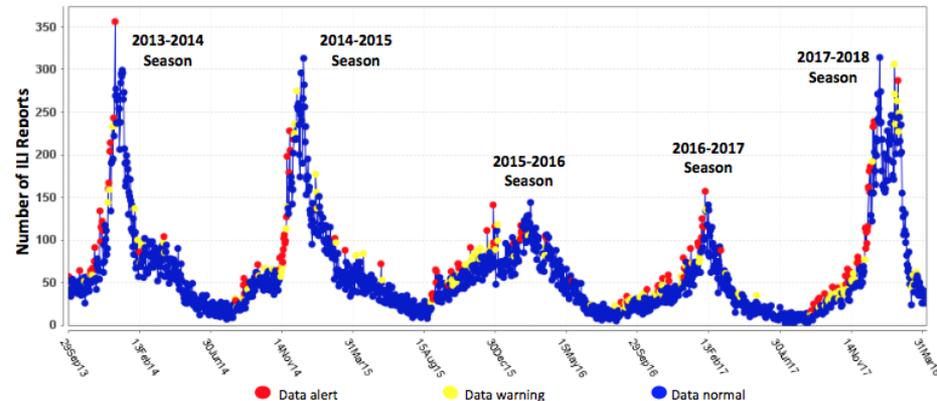
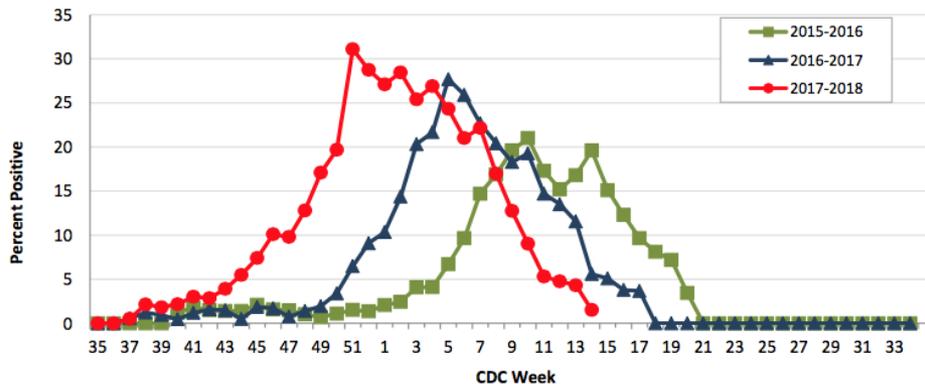


Figure 5. Syndromic Surveillance of Emergency Department Visits for Influenza-like Illness (ILI), Dallas County: September 29, 2013 – April 07, 2018



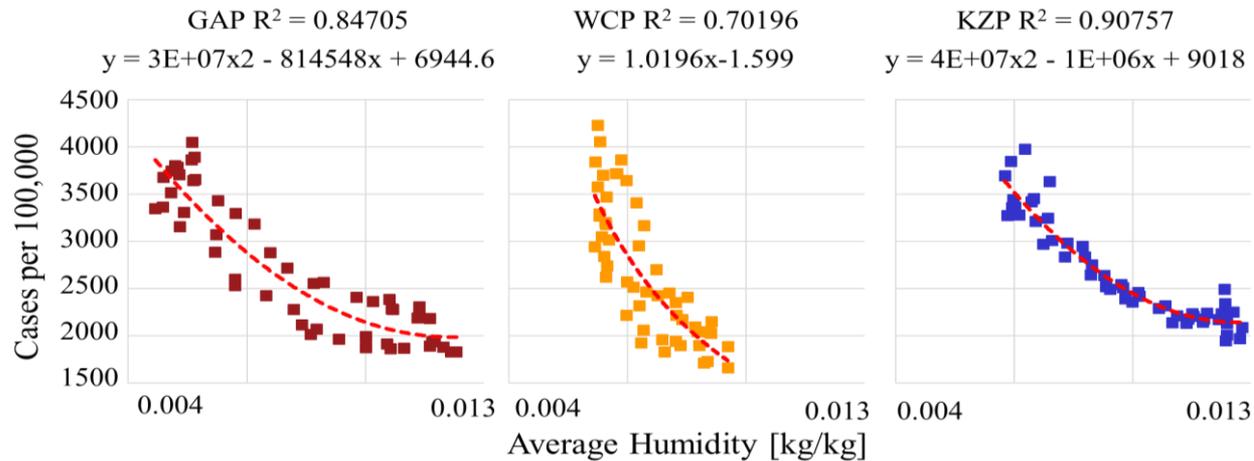
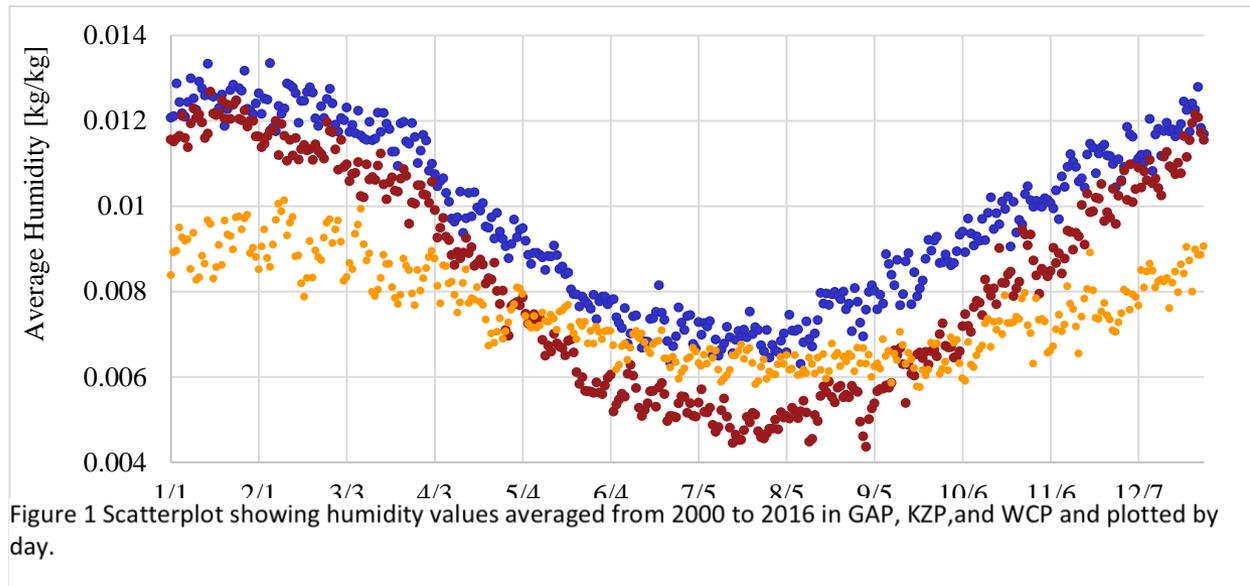
Data source: 18 emergency departments in Dallas County hospitals participating in the Electronic Surveillance System for the Early Notification of Community-based Epidemics (ESSENCE) voluntarily reporting the numbers of persons presenting with self-reported chief complaints of ILI.

Figure 2. Influenza Positive Tests Reported to DCHHS by Hospital Laboratories: 2015—2018 Seasons



Note: For Figure 2 and all subsequent trend overlays there is no week 53 for the 2015-2016, 2016-17, or 2017-2018 influenza seasons.

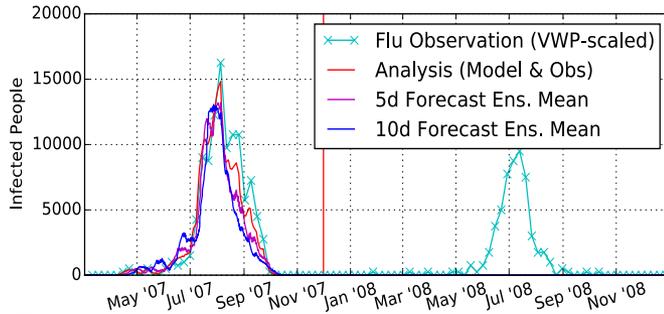
AIRS and Influenza in South Africa



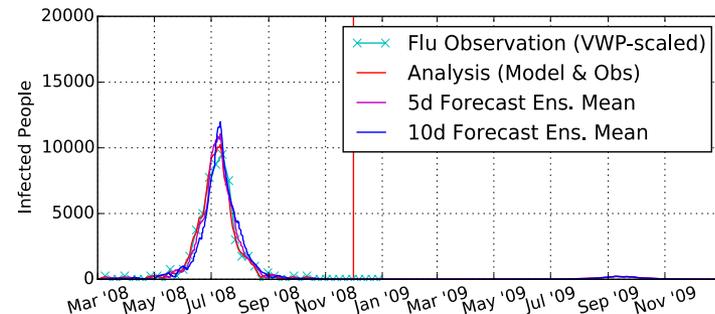
Correlation of influenza case count from GFT database and average humidity.

AIRS and Influenza in South Africa

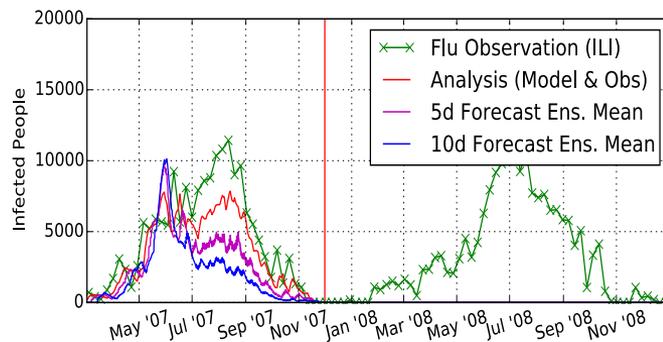
Johannesburg, GT (lat:-26.5° ;lon:28.5°); $t_0 = 2007-03-01$; $\eta=0.2$; $\gamma=50.0$; $n_{ens}=100$



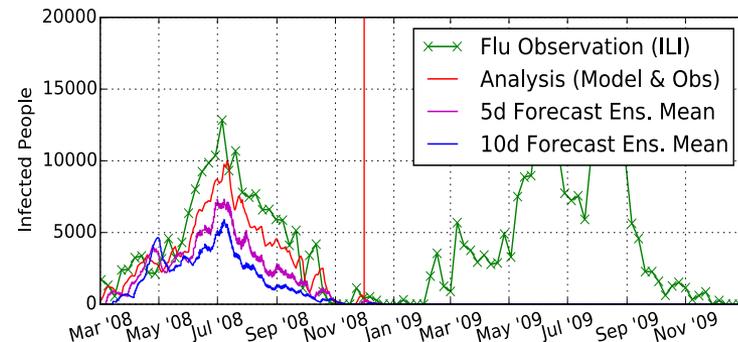
Johannesburg, GT (lat:-26.5° ;lon:28.5°); $t_0 = 2008-03-01$; $\eta=0.2$; $\gamma=50.0$; $n_{ens}=100$



Johannesburg, GT (lat:-26.5° ;lon:28.5°); $t_0 = 2007-03-01$; $\eta=0.2$; $\gamma=1.0$; shift=-1895; $n_{ens}=100$



Johannesburg, GT (lat:-26.5° ;lon:28.5°); $t_0 = 2008-03-01$; $\eta=0.2$; $\gamma=1.0$; shift=-1880; $n_{ens}=100$



Model results for Johannesburg, 2007 (left) and 2008 (right), with VWP (upper) or GFT (lower) data assimilated.



Summary

- Near-surface humidity plays critical role in influenza epidemics
- AIRS near-surface humidity is key component of a quasi-operational (produced daily) influenza prediction system
- For the 2017-2018 flu season our system captures fairly well overall trends (relatively severe season) and timings
- There are encouraging signs that the model can capture features that are not in imperfect assimilated (regional) observations but are present in more specific observations that can be compared at later times (double peak in LA and their timing)



Ongoing/Future Work

- AIRS-Flu code modifications (generalization, state/regional/province level, minor bugs, workflow, flu A and B separation, ...)
- Confidence and uncertainty measures
- More engagement with potential end users, potential trial for the AIRS-Flu system (ZA)
- Longer term seasonal predictions (using AIRS climatology, maybe longer term humidity predictions)
- Modeling spatial/geographical spread