Feasibility of influenza forecasting system based on meteorological data

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Investigators

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Photo # NH 41731-A Influenza precaution sign at the Naval Aircraft Factory, Philadelphia, 19 Oct. 1918

Background: Effect of Meteorological Variables on timing of influenza epidemics

- Absolute Humidity (Shaman et al, 2009 and 2010)
- Solar Radiation (Charland et al, 2009; Shaman et al, 2010)
- Temperature (Lowen et al 2007; Shaman et al, 2009 and 2010)
- Relative Humidity (Lowen et al 2007; Shaman et al, 2010)

Objectives

Based on meteorological series, averages and/or anomalies:

- Predict timing of epidemics

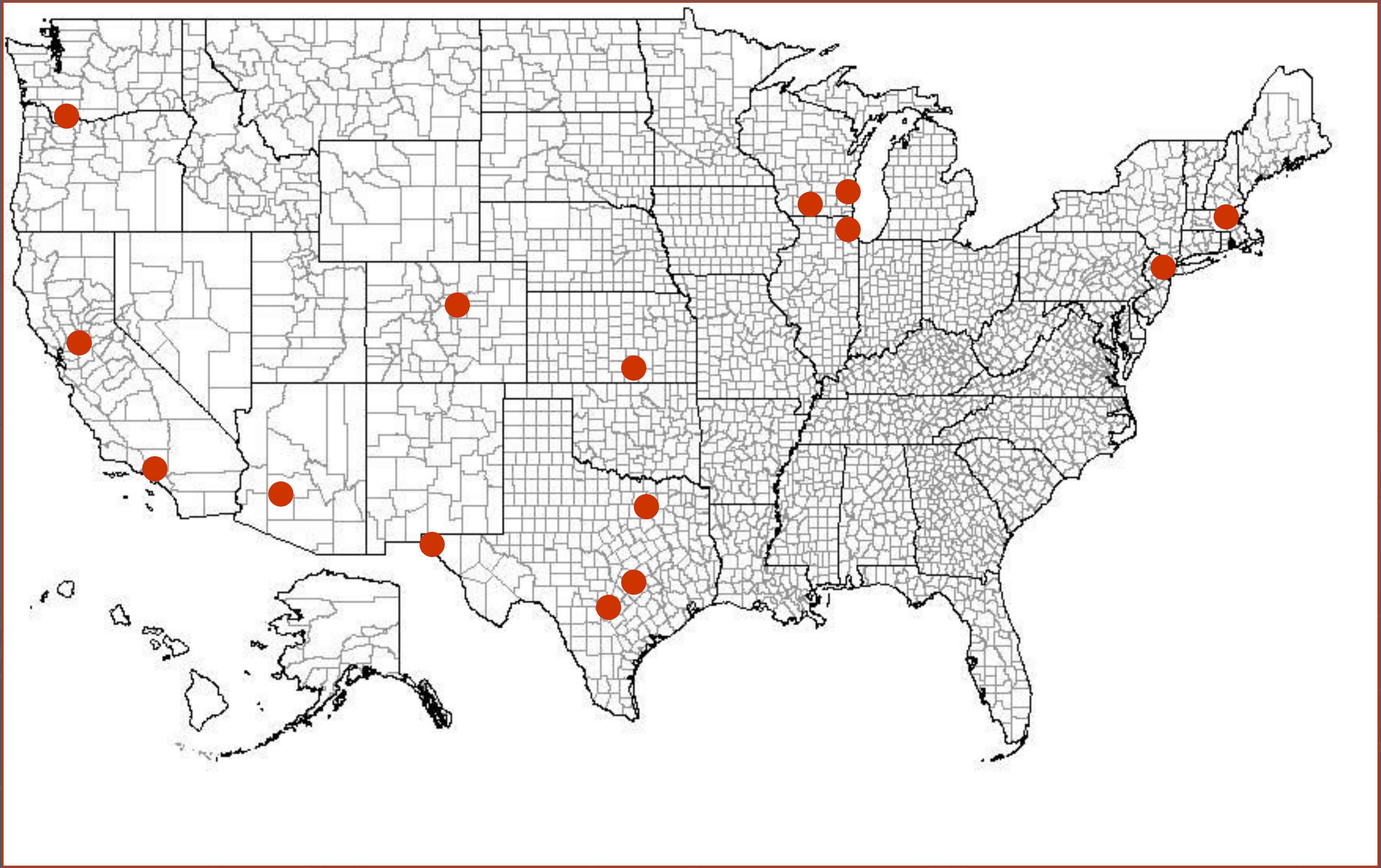
1. Onset
2. Peak

- Predict number of influenza infections per time unit

Data

- Patient record: county, ICD-9 code, date of admission (2-day resolution)
- all counties in 17
- 2002 to 2008
- Influenza year July 1 - June 29 (182 2-day intervals)
- Formed time series of #hospitalizations/2-days
- Preliminary analyses: 15 counties with best signal-to-noise ratio

15 counties



Meteorological Data

- Precipitation
- Solar radiation
- Vapor Pressure Deficit
- Maximum Temperature

Methods

I. Wavelet Coherency Analysis: lead/lag relationship between hospitalization and input series

II. Lagged Regression (Transfer Function Models)

III. Regression of timing of epidemic onset on timing of meteorological anomalies and climate variables

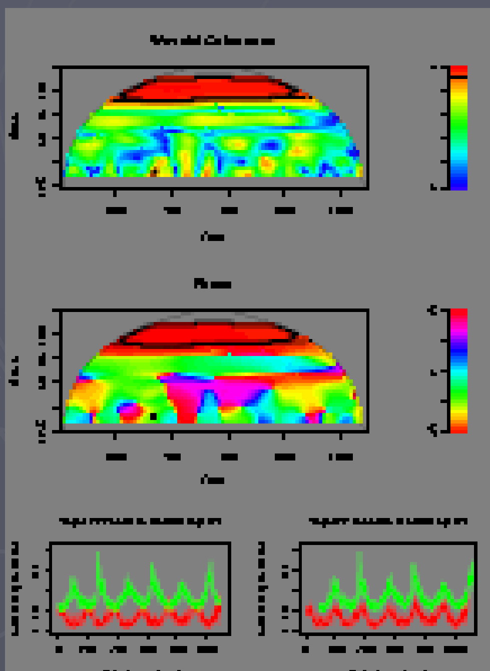
IV. Regression of peak timing on timing of meteorological anomalies and climate variables

V. To come: Spatial Analysis of rates of hospitalizations in relation to meteorological/socio-demographic factors

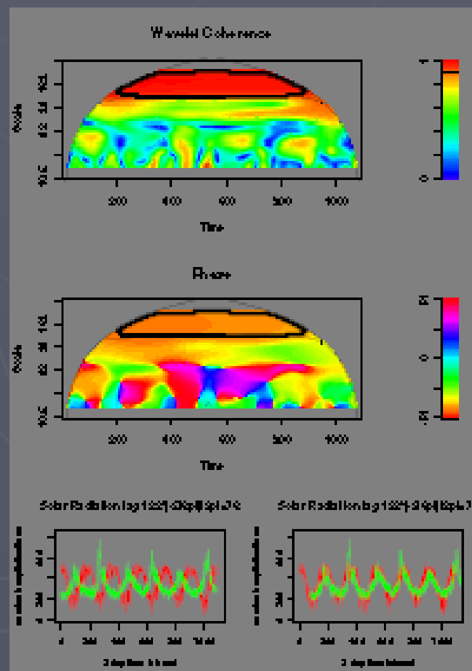
I. Wavelet Coherency Analyses

Results: Wavelet Coherency (LA)

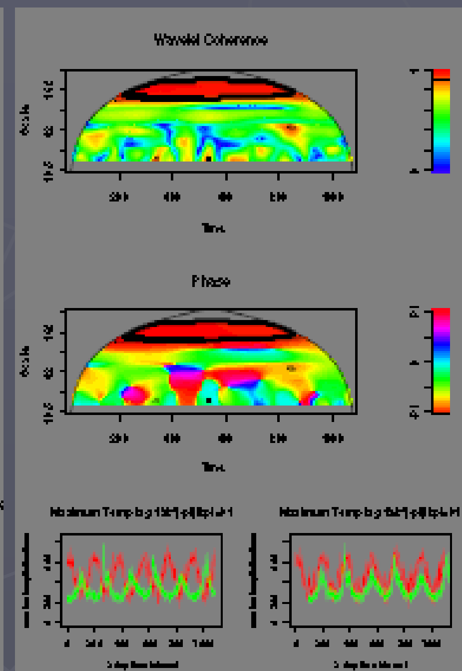
Vapor Pressure Deficit



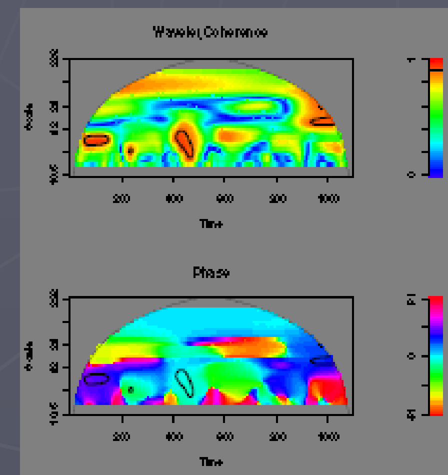
Solar Radiation



Maximum Temp



Precipitation



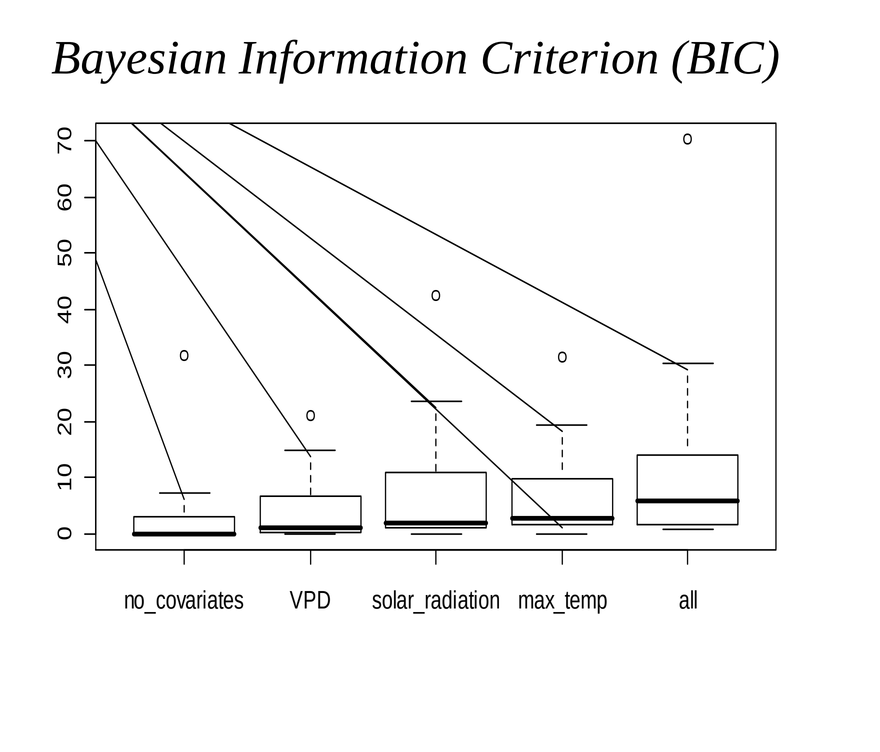
R software and Package SOWAS

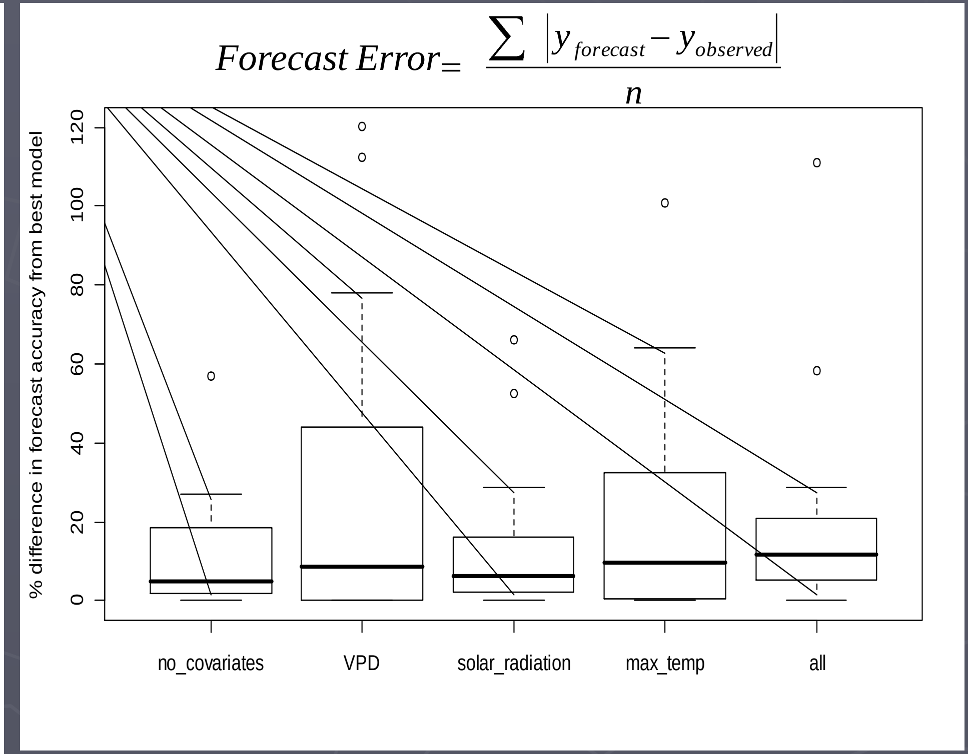
Transfer Function Models of relationship of hospitalization series and meteorological series

Results: Lagged Regression

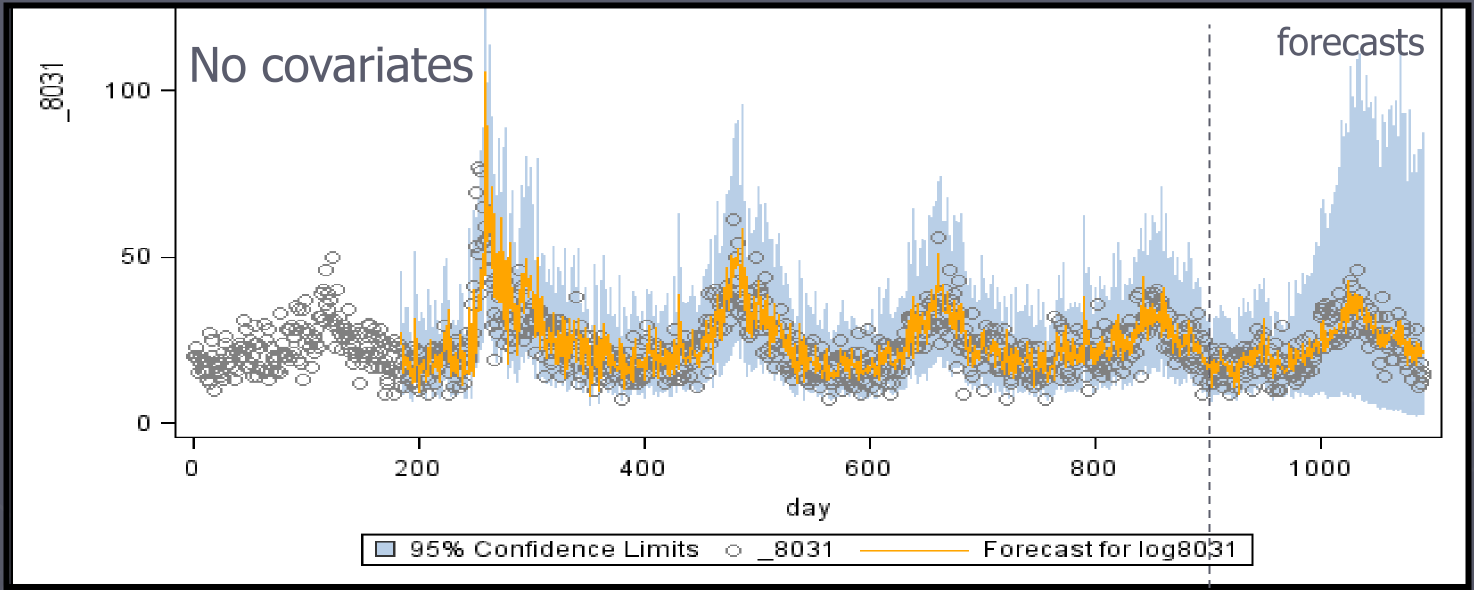
- Cross-correlation coefficient to find appropriate lag
- Regressed hospitalization series on lagged meteorological series
- Compared fit and forecast accuracy of models:
  - with single inputs to model
    (i.e. VPD, sol. rad., max. temp.)
  - with all inputs
  - with no inputs
- Fit statistic Bayesian Information Criterion (BIC)
- forecast accuracy=$\sum |y_{forecast} - y_{observed}| / n$

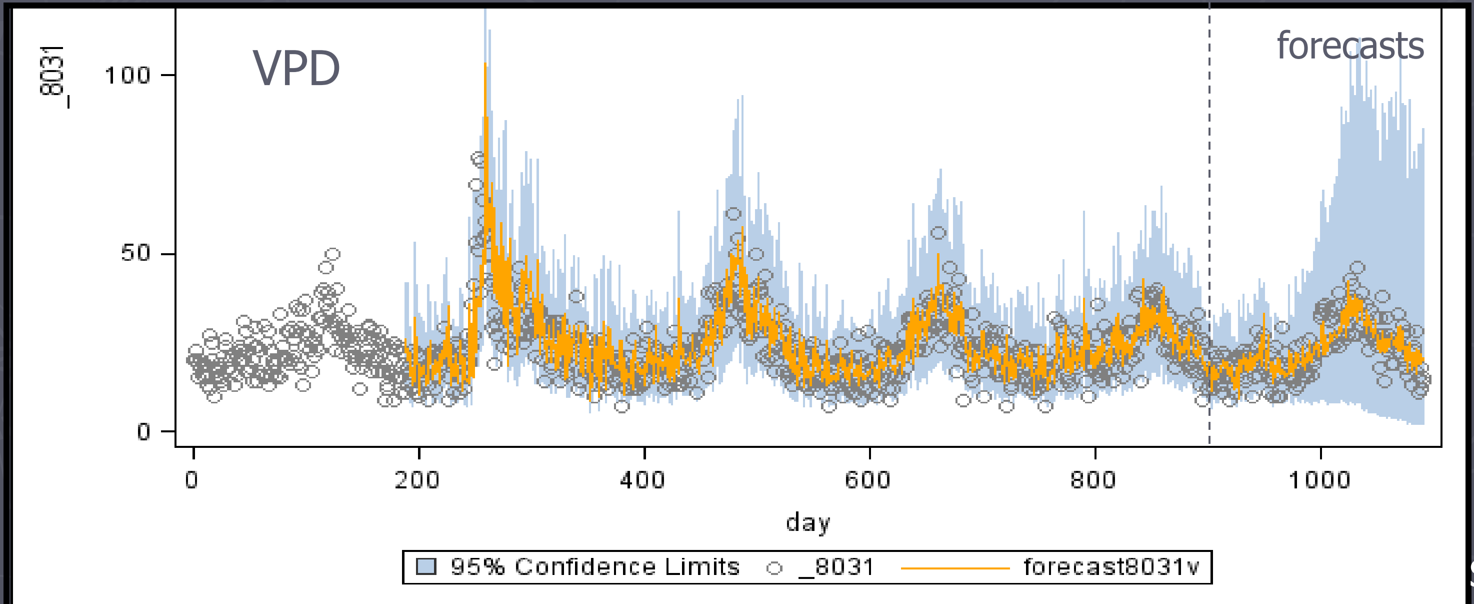
Results: % increase in BIC and forecast error w.r.t. best model





Predictions (Denver - no covariates and VPD)





SAS software

Regression of timing of epidemic onset on climate variable and timing of meteorological anomalies

Methods

- F-statistic to identify epidemic onset and average of meteorological variables and anomalies before onset
- Bayesian hierarchical models with random effects for influenza year (2002-03…2007-08)
- Deviance Information Criterion (DIC) for model fit
- forecast accuracy $=\sum|y_{forecast} - y_{observed}| \,/\, n$
- WinBUGS 1.4 software

Results: Regression Onset

***<u>Four</u>* week average of variable**	***Beta Coefficient***	***95% Credible Interval***
Vapor Pressure Deficit	-0.0018	(-0.0049, 0.0013)
Solar Radiation	-0.022	(-0.054, 0.0097)
Maximum Temperature	-0.54	(-0.96, -0.11)*

***<u>Two</u>* week average of variable**	***Beta Coefficient***	***95% Credible Interval***
Vapor Pressure Deficit	-0.0023	(-0.0058, 0.0012)
Solar Radiation	-0.023	(-0.053, 0.0078)
Maximum Temperature	-0.55	(-0.93, -0.16)*

Model Fit and Forecast Accuracy: Regression of timing of epidemic onset and meteorological variable averages

Four Week Average of Variable	*DIC*	*Forecast Accuracy*
Vapor Pressure Deficit	525.52	7.74
Solar Radiation	524.90	7.57*
Maximum Temperature	519.70*	7.79
All	523.24	8.38

Two Week Average	*DIC*	*Forecast Accuracy*
Vapor Pressure Deficit	524.01	7.71
Solar Radiation	524.80	7.53*
Maximum Temperature	518.64	8.18
All	517.51*	8.09

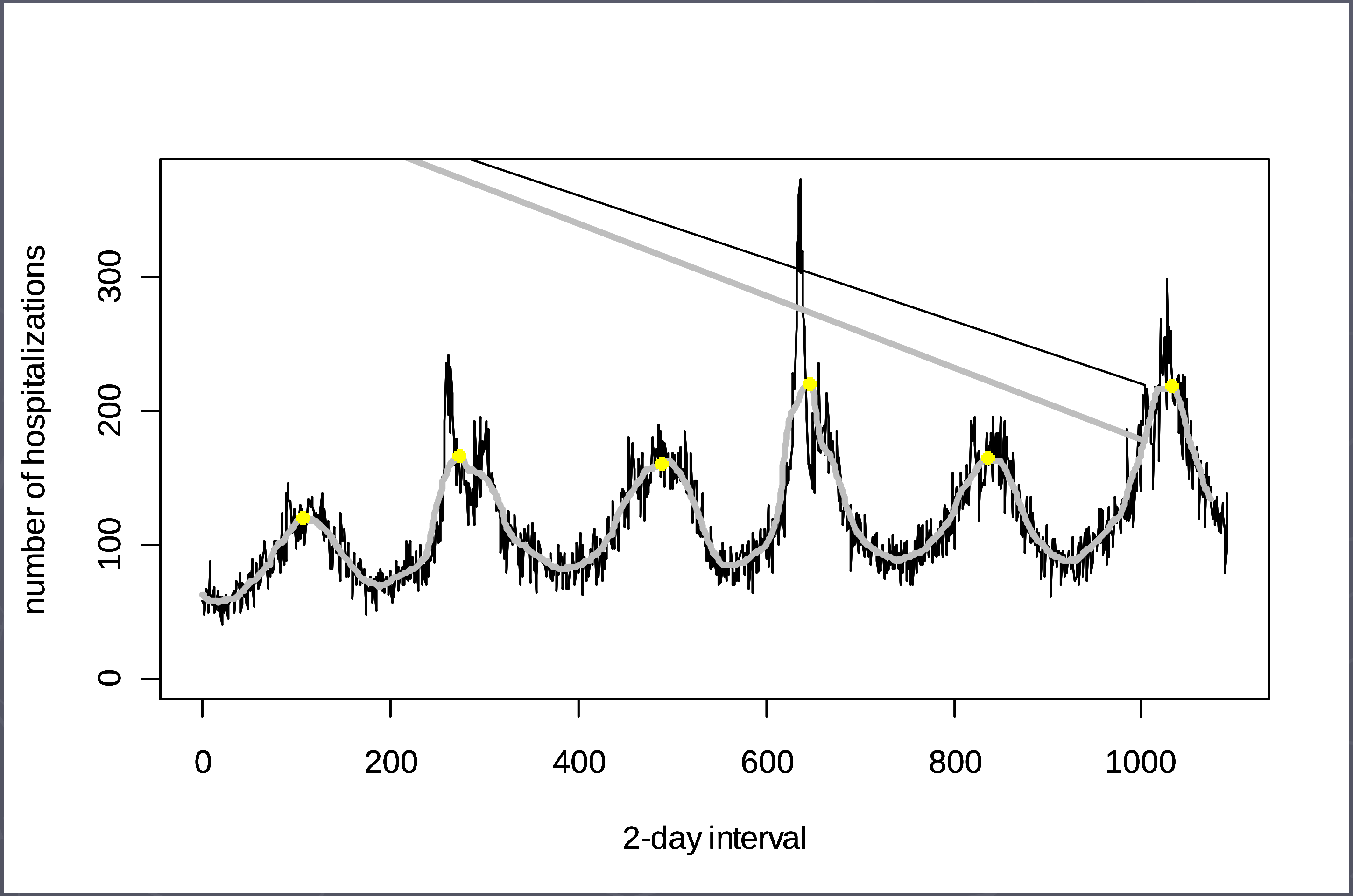
Regression of timing of onset on timing of VPD dropping to below average

- Shaman et al 2010 found that when the absolute humidity fell below the global average the onset usually occurred in the 4 weeks that followed
- Regression coefficient of timing of drop of VPD below average VPD and timing of onset

β=-0.234, 95% CI -0.47, 0.0015

Regression of timing of peak influenza activity on climate variable and timing of meteorological anomalies

Results: Regression Peak timing (Maricopa County, AZ)



Peak timing and 4 week averages

Four week average of variable	*Beta Coefficient*	*95% Confidence Interval*
Vapor Pressure Deficit	-0.0069	(-0.012, -0.0018)*
Solar Radiation	-0.032	(-0.058, -0.0067)*
Maximum Temperature	-0.61	(-0.93, -0.30)*

Variable	*DIC*	*Forecast Accuracy*
Vapor Pressure Deficit	530.57	8.96
Solar Radiation	531.64	8.69*
Maximum Temperature	523.47*	8.88
All	525.11	8.49*

Conclusions

- There may be some benefit to including climate data when predicting epidemic onset and epidemic peak timing
- Problem may lie in year to year variation w.r.t. timing. The average timing of onsets in the 6 influenza seasons of our study ranged from 65 to 81 (2-day interval)

  i.e. 32 days apart
- May be feasible to observe the onset of first epidemic and then predict the peak and onset timings of remaining localities

Future Work

- Incorporating Socio-demographic factors
- Adding counties to analyses
- Spatial Analysis of relative risk of influenza infection
- Other markers of meteorological change and peak

Thank you

AIC