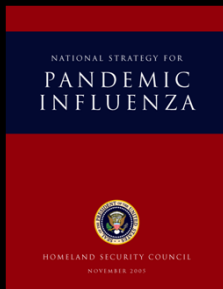


National Strategy for Pandemic Influenza



THREE PILLARS

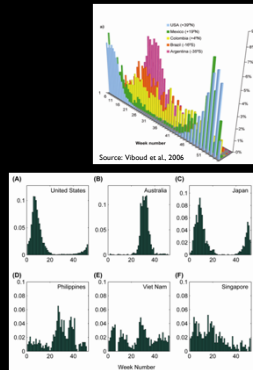
- Preparedness & Communication ←
- Surveillance & Detection ←
- Response & Containment ←

OBJECTIVES

- Systematically investigate the effect of meteorological and climatic factors on seasonal influenza transmission
- Understanding influenza seasonality provides a basis on how pandemic influenza viruses may behave
- Develop framework for influenza early warning and pandemic influenza early detection
- Assess and determine the dominating meteorological and environmental factors on influenza incidences at the major population centers
- Using the identified dominant factors, develop climatic-based model to forecast influenza
- Estimate short and mid-term influenza cases at those population centers based on their climatological profiles or climate forecast
- Examine differential sensitivity of the meteorological variables to influenza virus strain types

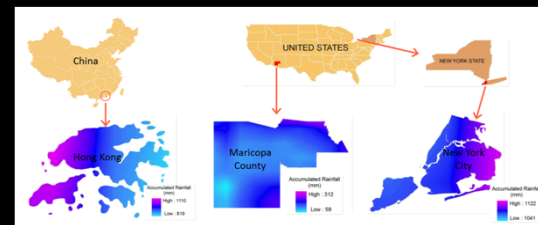
BACKGROUND

- Worldwide annual epidemic
Infects 5-20% of population with 500,000 deaths
- Economic burden in the US
~US\$87.1 billion
- Spatio-temporal pattern of epidemics vary with latitude
Role of environmental and climatic factors
- Temperate regions: distinct annual oscillation with winter peak
- Tropics: less distinct seasonality and often peak more than once a year



Examples

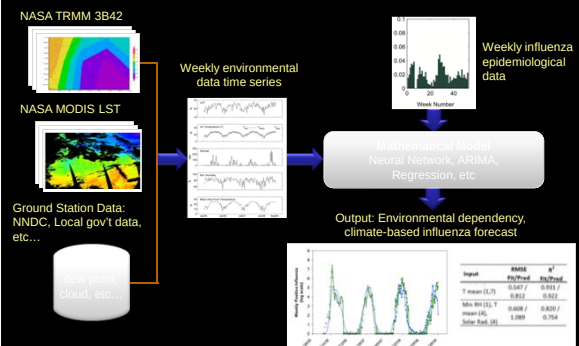
	Hong Kong, China	Maricopa County, AZ	New York City, NY
Center Lat.	22° N	33° N	40° N
Climate	Tropical & Sub-Tropical	Sub-Tropical	Temperate
General Condition	Hot & humid during summer. Mild winter, average low of 6°C	Dry condition. Mean winter low is 5°C, and summer high is 41°C	Cold winter, average low of -2°C. Mean summer high is 29°C



Factors Implicated in Influenza Transmission

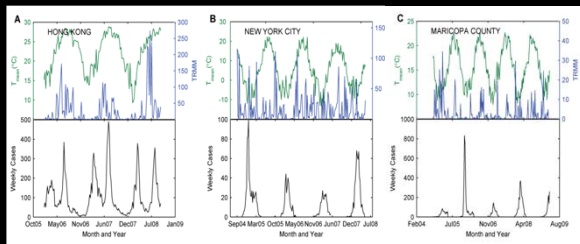
Process	Factors	Relationship
Virus Survivorship	Temperature	Inverse
	Humidity	Inverse
	Solar irradiance	Inverse
Transmission Efficiency	Temperature	Inverse
	Humidity	Inverse
	Vapor pressure	Inverse
Host susceptibility	Rainfall	Proportional
	ENSO	Proportional
	Air travels and holidays	Proportional
	Sunlight	Inverse
	Nutrition	Varies

General Framework



DATA

- Weekly lab-confirmed influenza positive
- Satellite-derived data
 - Precipitation – TRMM 3B42
 - Land Surface Temperature (LST) – MODIS
- Daily environmental data were aggregated into weekly
- Ground station data



Role of Vapor Pressure or Absolute Humidity

- Poisson regression model
- Vapor pressure included as input
- Improve model performance in the temperate region

	Vapor Pressure Excluded		Vapor Pressure Included	
	RMSE	R ²	RMSE	R ²
Hong Kong	65.0037	0.593	74.188	0.478
Maricopa County	48.836	0.808	52.946	0.781
New York City	0.0248	0.66	0.0237	0.69

METHODS

Several techniques are employed, including:

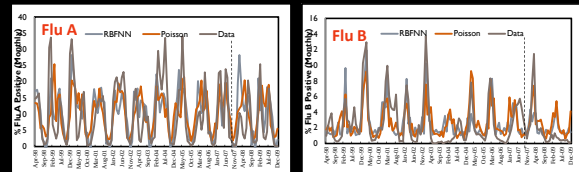
ARIMA (Auto-Regressive Integrated Moving Average)

- Classical time series regression
 - Accounts for autocorrelation and seasonality properties
- Climatic variables as covariates
- Previous week(s) count of influenza is included in the inputs
- Results published in PLoS ONE 5(3): 9450, 2010

Neural Network

- Artificial intelligence technique
- Widely applied for approximating functions, classifications, and pattern recognition
- Radial Basis Function NN with 3 nodes in the hidden layer
- Only climatic variables and their lags as input/predictors

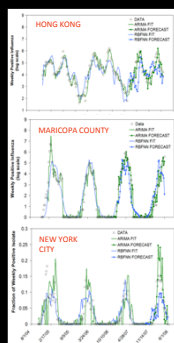
Environmental Sensitivity of Types



Inputs	Flu A	Flu B
	Mean Dew Pt, T min (2), Rainfall (3)	T max (1), Wind Speed, Flu B (2)
RMSE	6.432	1.825
R ²	0.497	0.594

- Flu A does not depend on the number of previous cases
 - Environments counts for ~50% of Flu A variability
- Flu B has dependency to previous cases

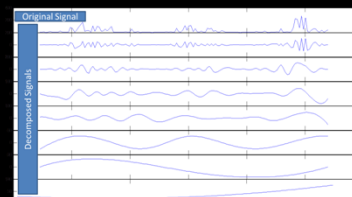
Role of Environments



- NN models show that ~60% of influenza variability in the US regions can be accounted by meteorological factors
- ARIMA model performs better for Hong Kong and Maricopa
 - Previous cases are needed
 - Suggests the role of contact transmission
- Temperature is a common determinant for influenza in all regions
- Reasonably accurate prediction

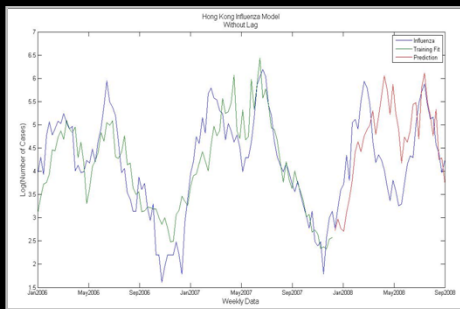
Hilbert-Huang Transform

- A NASA developed mathematical technique (Huang et al. 1996) to decompose signal into a finite set of linear and stationary signals – Intrinsic Mode Functions (IMF)
- Complex time series can be decomposed into a finite and often small number of components
 - Applicable to nonstationary and nonlinear processes
 - Broad applications in Earth sciences, engineering, image processing, biomedical sciences, etc.



Example:
Decomposition of TRMM time series

Hong Kong Time Series Modeled with HHT



Input Variables

EVAP (1)
RHMIN (3.5)
TRMM (4)
SUN (4)
CLOUD (6)

