Climatic Determinants for Seasonal Influenza

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1. INTRODUCTION

Annual Influenza Burden

Worldwide: 5 million severe illnesses and 500,000 deaths

United States: 200,000 hospitalization and >30,000 deaths. Estimated economic burden ~$87.1 billion (Molinari et al., 2007)

Table 1. Factors Implicated in Influenza Transmission

Process	Factors	Relationship
Virus Survivorship	Temperature	Inverse
	Humidity	Inverse
	Solar irradiance	Inverse
Transmission Efficiency	Temperature	Inverse
	Humidity	Inverse
	Rainfall	Proportional
	ENSO	Proportional
Host susceptibility	Sunlight	Inverse
	Nutrition	Varies

Objective

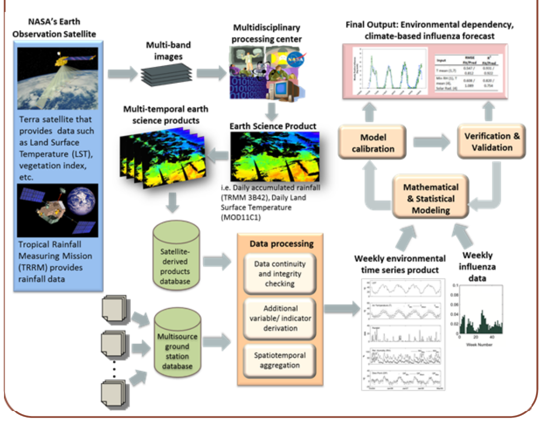
- To understand how climactic and environmental factors affect the efficiency of influenza transmission in different parts of the world so as to enhance multilateral efforts for prevention and control
- This global characterization should enable us to develop better ability to forecast influenza activity worldwide

Study Area

- Here we present current findings from the first phase of our study where we work with countries in North and Central America, and Northern Europe.
- Our results in these regions encompass tropical, sub-tropical and temperate climate

2. APPROACH

Figure 1. Overall approach to modeling influenza using environmental and climatic variables



Methods

- *Autoregressive Integrated Moving Average (ARIMA)*
  - Accounts for seasonality and autocorrelation property
  - General formulation: Let y(t) be the response variable, and $z(t) = y(t) - y(t-1) - \ldots - y(t-d)$
    Then, $z(t) - \phi_1 z(t-1) - \phi_2 z(t-2) - \ldots - \phi_p z(t-p)$
    $= \mu - \theta_1 \varepsilon(t-1) - \theta_2 \varepsilon(t-2) - \ldots - \theta_p \varepsilon(t-p)$
- *Neural Network* (Figure 2)
  - Artificial Intelligence method that mimic the functioning of the brain
  - Capable of capturing nonlinear relationship

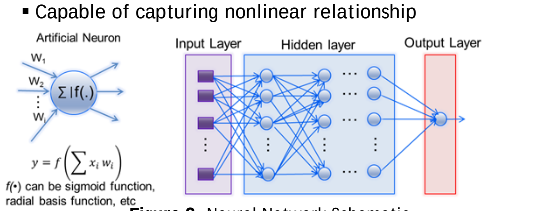
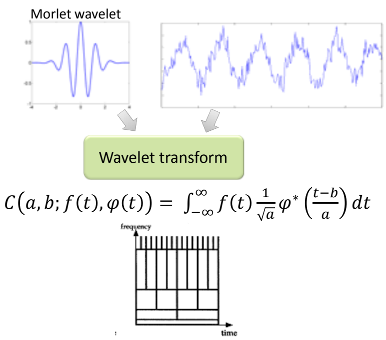


Figure 2. Neural Network Schematic

- *Wavelet*
  - Decompose time series signals into time-frequency space using 'mother' wavelet signal, such as Morlet wavelet (Figure 3)



$$C(a,b;f(t),\varphi(t)) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\varphi^*\left(\frac{t-b}{a}\right)dt$$

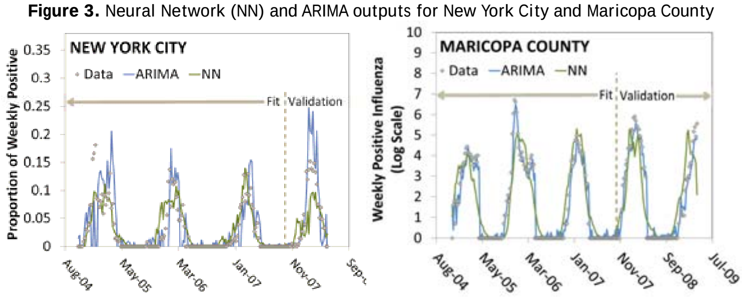
Figure 3. Wavelet transform schematic

3. RESULTS

United States – *New York City (NY) and Maricopa County (Arizona)*

- Influenza data was obtained from the respective Public Health website

Figure 3. Neural Network (NN) and ARIMA outputs for New York City and Maricopa County



	Input	RMSE (Fit/Pred)	R^2 (Fit/Pred)
ARIMA	Mean Dew Pt (4)	0.046/0.022	0.311/0.795
NN	TMAX (1), Rain (3), TMIN (2)	0.044/0.0036	0.731/0.584

	Input	RMSE (Fit/Pred)	R^2 (Fit/Pred)
ARIMA	RHMAX (3), LST(3)	0.575/0.5493	0.911/0.941
NN	RHMIN(1), TEMP(4), SOLAR(4)	0.608/1.089	0.820/0.754

- ARIMA model performs better for Maricopa County – previous cases are needed, suggesting the role of contact transmission
- NN model shows that ~60% of influenza variability in the US regions can be accounted by meteorological factors

Guatemala

- Data was obtained from CDC Regional Office for Central America and Panama
- The relationship between influenza cases were assessed using cross-correlation function (CCF)

Guatemala (Cont'd)

- Pre-whitening was applied before CCF was calculated
- The table shows variables (and the corresponding lag) that were found to be significantly associated with influenza

Variable	Lag
Relative Humidity	2
Mean Temperature	3
Sun	0

Belgium

- Influenza data was obtained from the European Centre for Disease Control and Prevention database

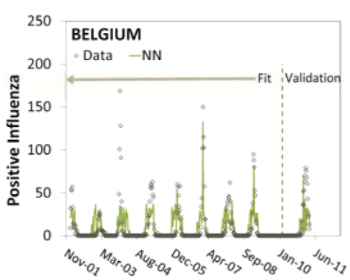


Figure 4. Neural Network (NN) output for Belgium. Inputs are TRMM(3), LSTDAY(1), TEMP(2). Correlation between the NN output and the data is 0.576 for the fit dataset and 0.4822 for validation dataset.

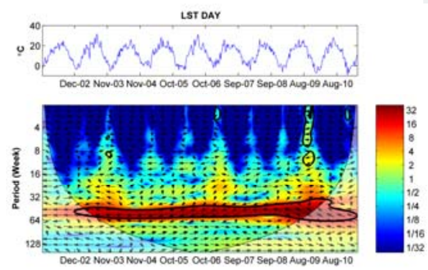


Figure 5. (Top) Time series for Land Surface Temperature (LST) day. (Bottom) Cross wavelet between LSTDAY and the influenza counts. Arrows represent the phase relationships (in-phase pointing right and anti-phase pointing left)

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