Seasonal Influenza

Radina P. Soebiyanto[1,2]
Richard Kiang[1]

[1]NASA Goddard Space Flight Center, Code 610.2, Greenbelt, MD
[2]Universities Space Research Association, Columbia, MD

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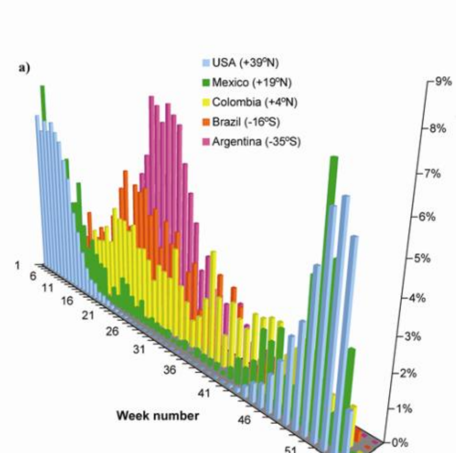
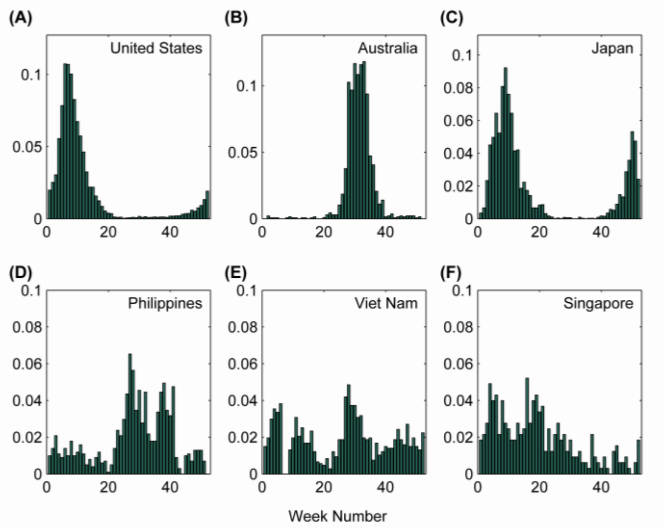
- Part 1
  - Seasonal influenza as part of *"Avian, Seasonal, Pandemic Influenza"* Project
- Part 2
  - *"Modeling Global Influenza Risks using NASA Data"* Project

Influenza Background

- Worldwide annual epidemic
  - Infects 5 – 20% of population with 500,000 deaths
- Economic burden in the US ~US$87.1billion
- 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



Source: Viboud et al., 2006



Influenza Background

- Factors that have been implicated in influenza

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

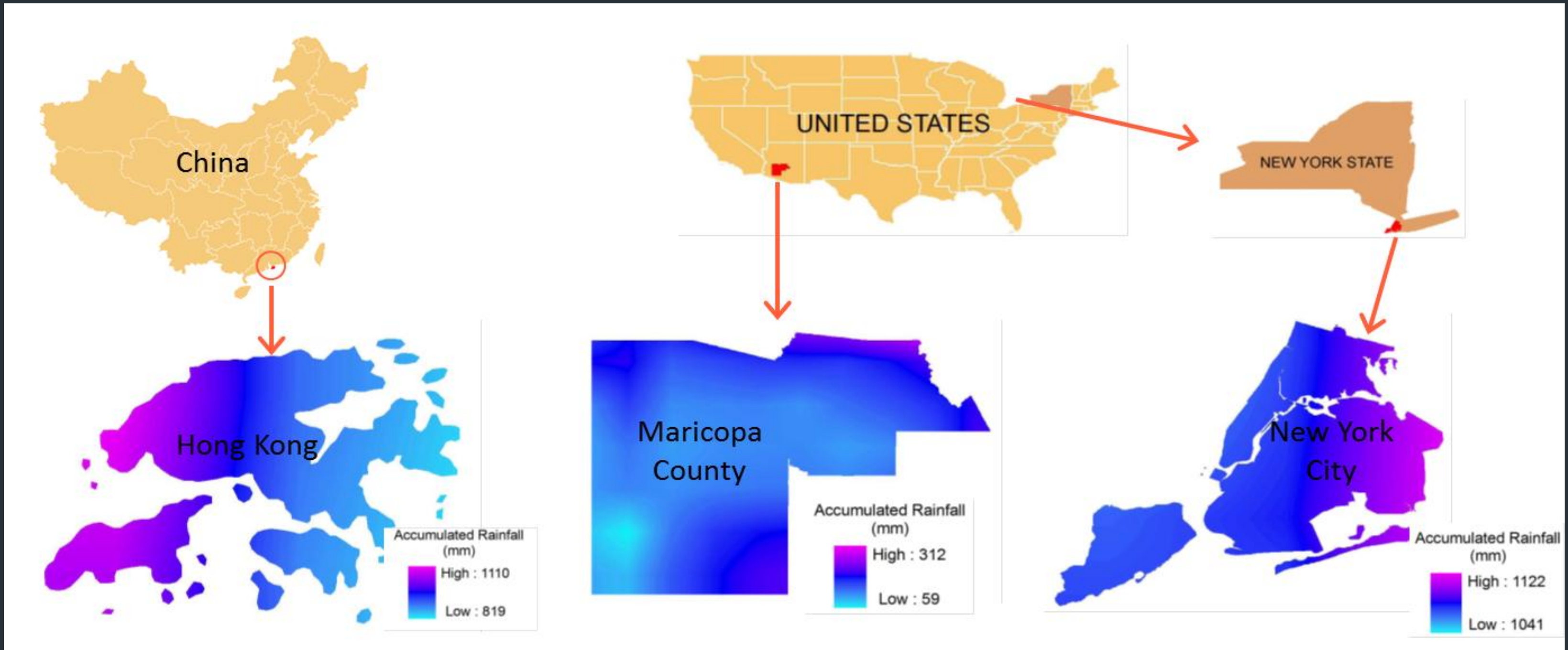
Part I: *“Avian, Seasonal, Pandemic Influenza”* Project

- **Objective**
  - 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

Part I: *"Avian, Seasonal, Pandemic Influenza"*

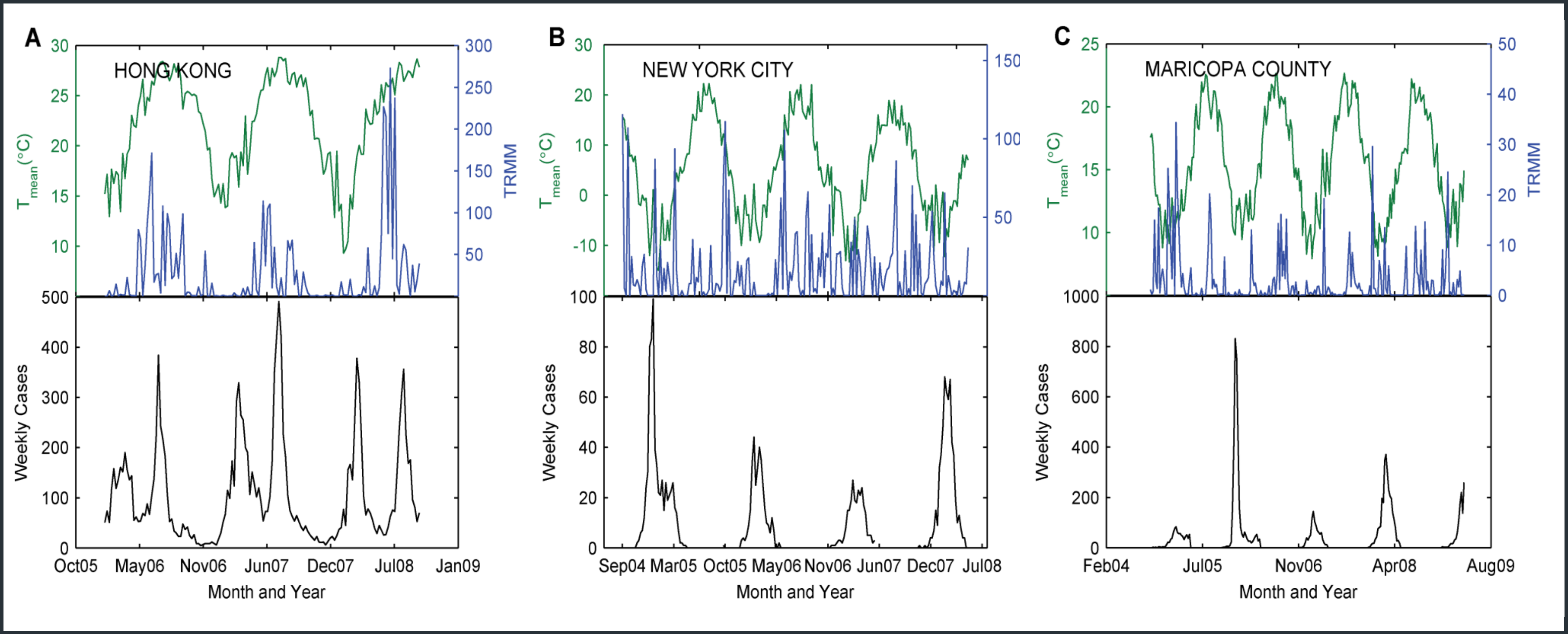
Test Case

	Hong Kong, China	Maricopa County, AZ	New York City, NY
Center Lat.	22° N	33° N	40° N
Climate	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



Part I: *"Avian, Seasonal, Pandemic Influenza"*
Data

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



Part I: *"Avian, Seasonal, Pandemic Influenza"*

Methods

- *Several techniques were employed, including:*

ARIMA (AutoRegressive 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 (NN)

- Artificial intelligence technique
- Widely applied for
  - approximating functions,
  - Classification, and
  - pattern recognition
- Takes into account nonlinear relationship
- Radial Basis Function NN with 3 nodes in the hidden layer
- Only climatic variables and their lags as inputs/predictors

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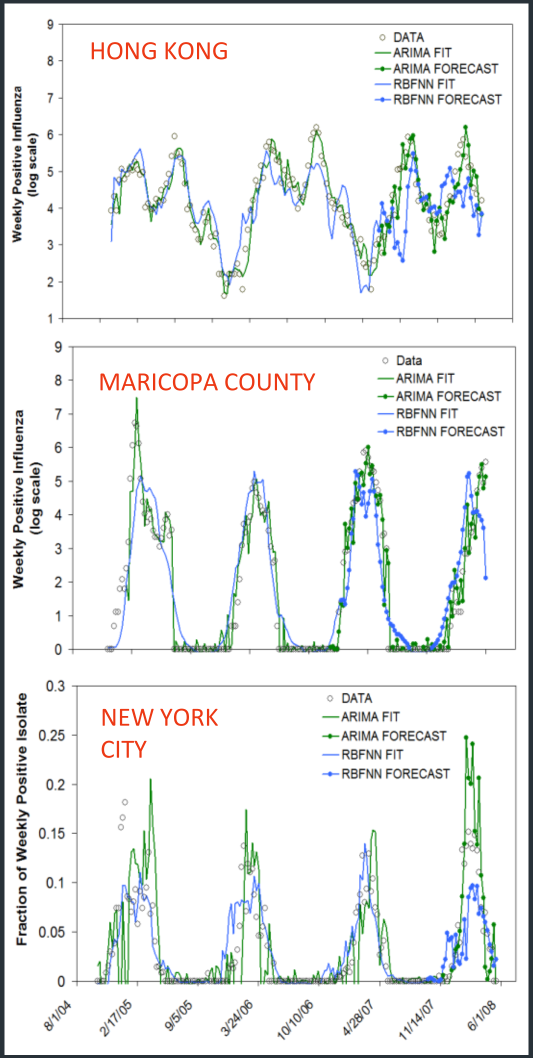
Role of Environments



- 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 seems to be the common determinants for influenza in all regions

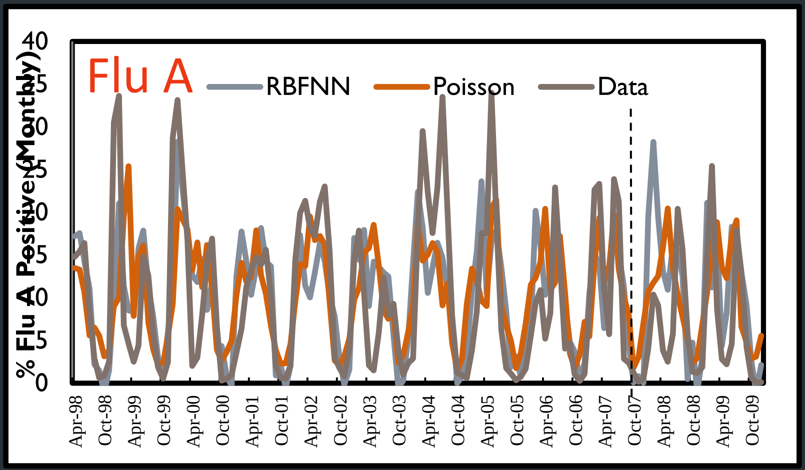
Part I: *"Avian, Seasonal, Pandemic Influenza"*

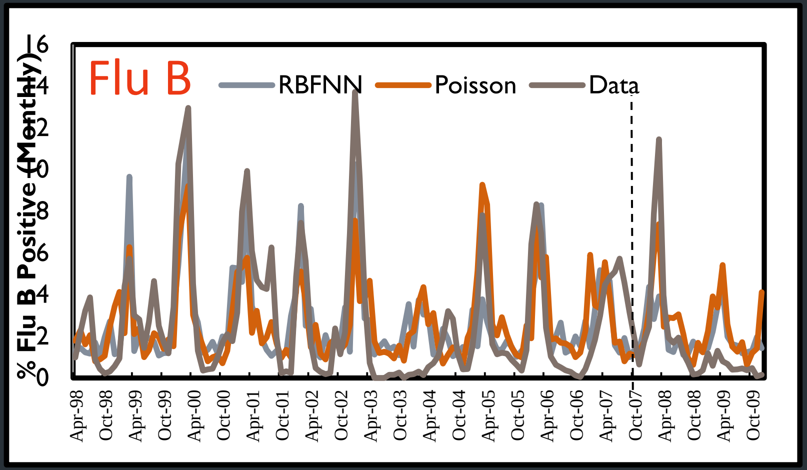
Role of Vapor Pressure/Absolute humidity

- 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

Part I: *"Avian, Seasonal, Pandemic Influenza"*
Environmental sensitivity to (sub)types



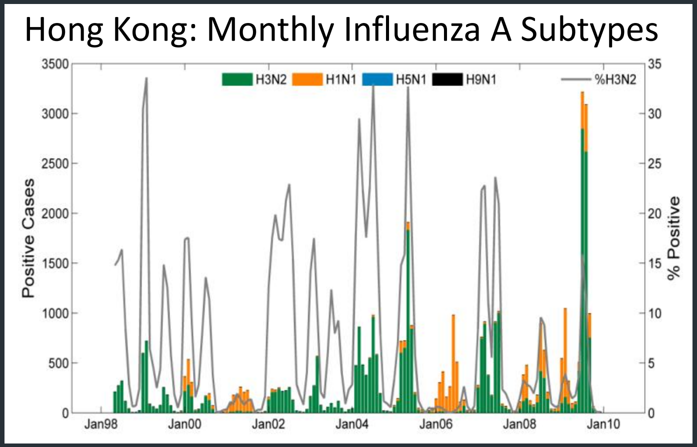


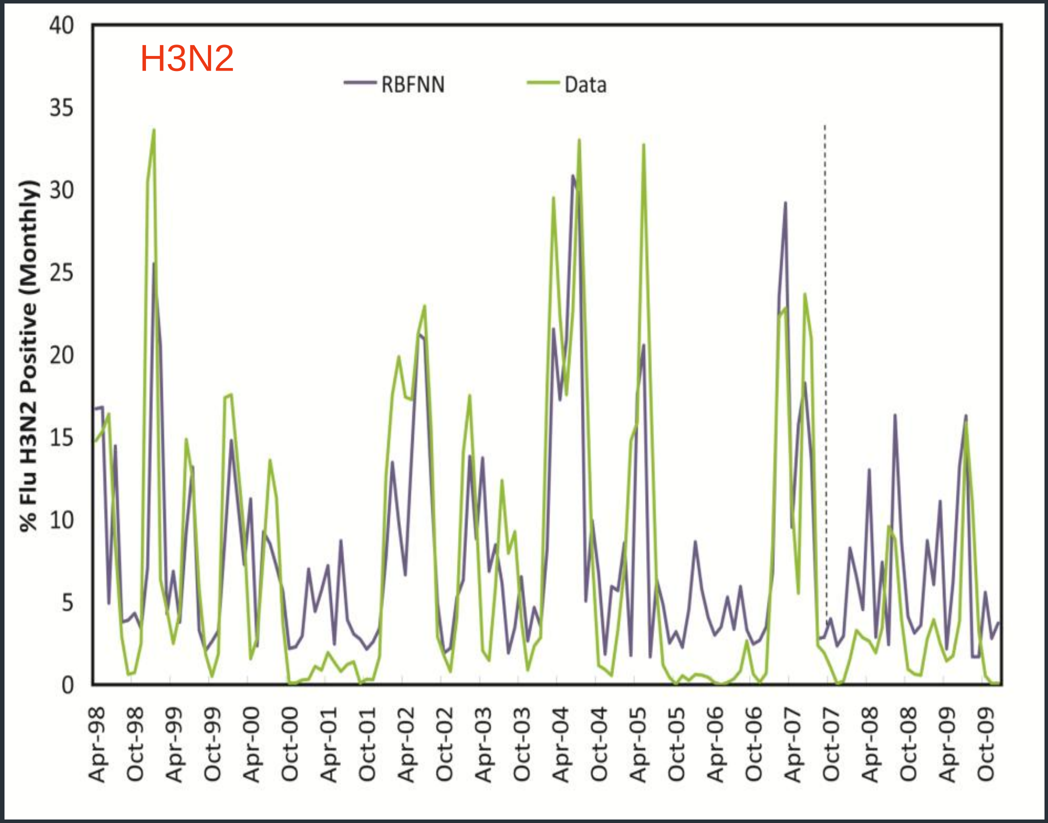
	Flu A	Flu B
Inputs	Mean Dew Pt., T min (2), Rainfall (3)	T max (1), Wind Speed, Flu B (2)
RMSE	6.432	1.825
R^2	0.497	0.594

- 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

Part I: *"Avian, Seasonal, Pandemic Influenza"*

Environmental sensitivity to (sub)types





- Neural Network
  - Inputs: Mean Pressure (3), Sunlight (1), H3N2 Cases (1)
  - RMSE: 5.8766, R^2: 0.5662

Part I: *"Avian, Seasonal, Pandemic Influenza"*

Conclusion

- Demonstrated the role of environmental variables in influenza dynamics in areas with varying climatic condition
  - Temperature as the common dominating factors
  - Vapor pressure (as a measure of absolute humidity) may play more roles in temperate region
  - Differential sensitivity of influenza types and subtypes to environment
- Short-term prediction of influenza can be performed with the use of remote sensing and ground station data
  - Especially the peak timing

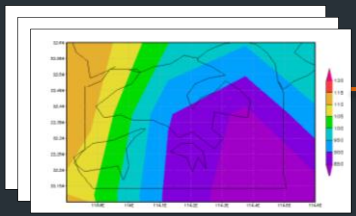
Part 2: *"Modeling Global Influenza Risks Using NASA Data"*

- Objective
  - 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 next season's 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

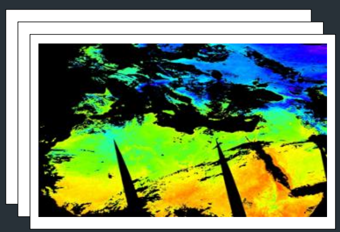
Part 2: *"Modeling Global Influenza Risks Using NASA Data"*

General Framework

NASA TRMM 3B42



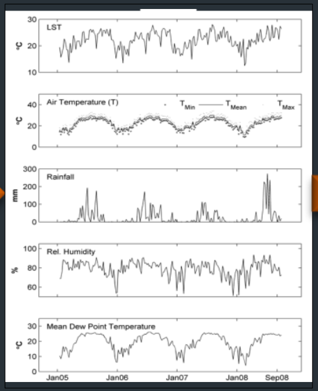
NASA MODIS LST

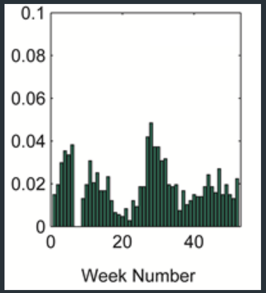


Ground Station Data: NNDC, Local gov't data, etc…

Humidity, dew point, cloud, etc…

Weekly environmental data time series

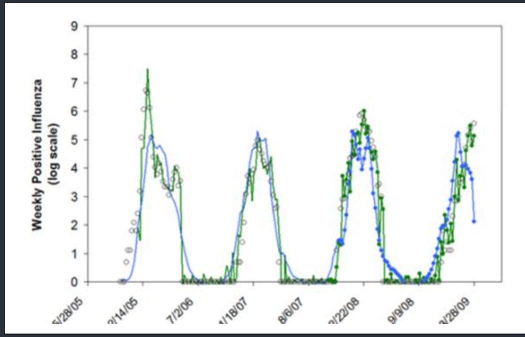




Weekly influenza epidemiological data

Mathematical Model
Neural Network, ARIMA, Regression, etc

Output: Environmental dependency, climate-based influenza forecast

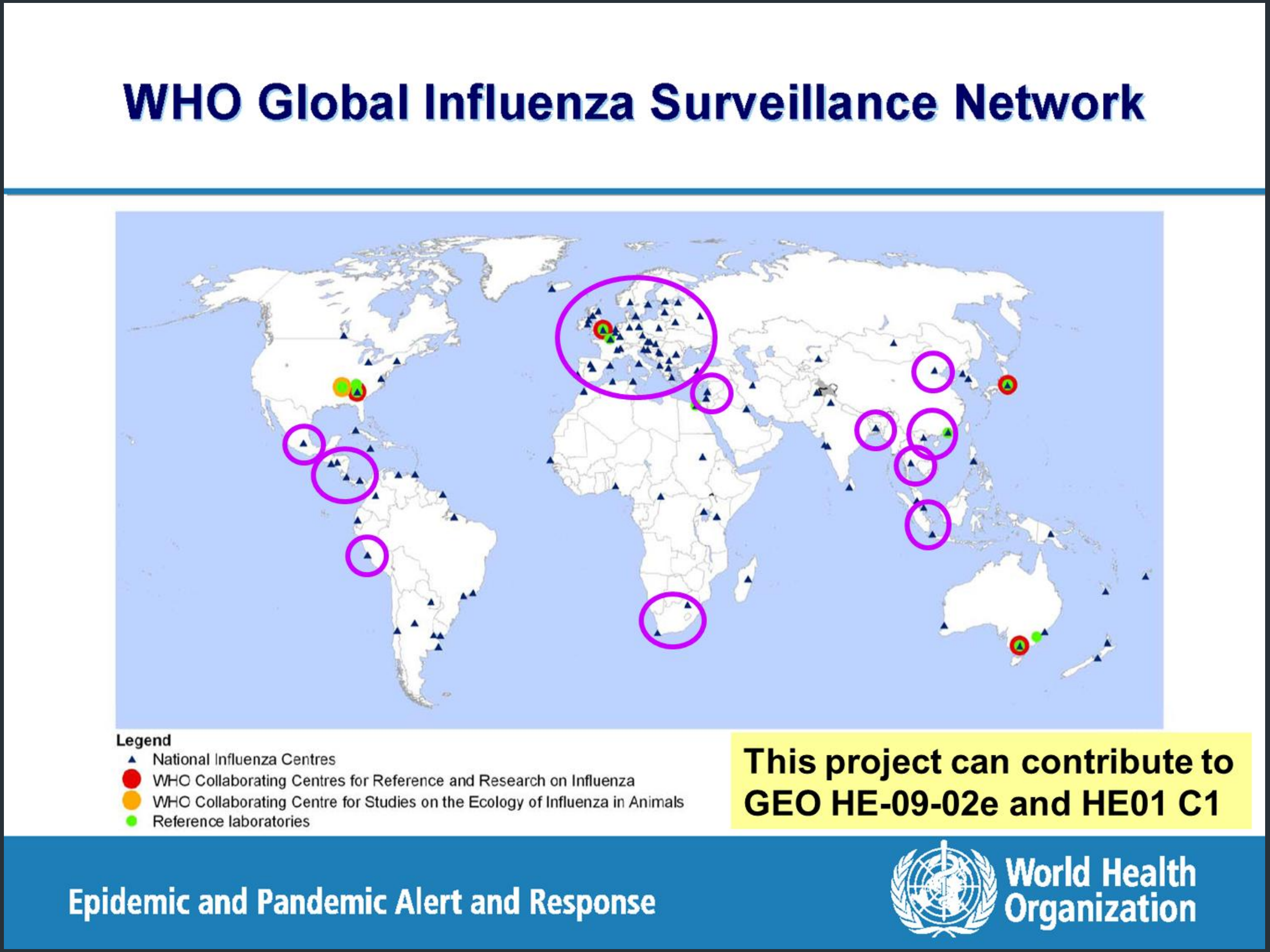


Input	RMSE Fit/Pred	R^2 Fit/Pred
T mean (1,7)	0.547 / 0.812	0.931 / 0.922
Min RH (1), T mean (4), Solar Rad. (4)	0.608 / 1.089	0.820 / 0.754

Part 2: *"Modeling Global Influenza Risks Using NASA Data"*

Current Status

- Countries/regions that have been approached for this project



Part 2: *"Modeling Global Influenza Risks Using NASA Data"*

Current Status

- Tested Hilbert-Huang Transform (HHT) method using Hong Kong data
- Ensemble Empirical Mode Decomposition
  - Decompose signal into a finite set of linear and stationary signals, Intrinsic Mode Functions (IMF)
- Used the decomposed signals in a Poisson regression
  - Stepwise fit for input selection

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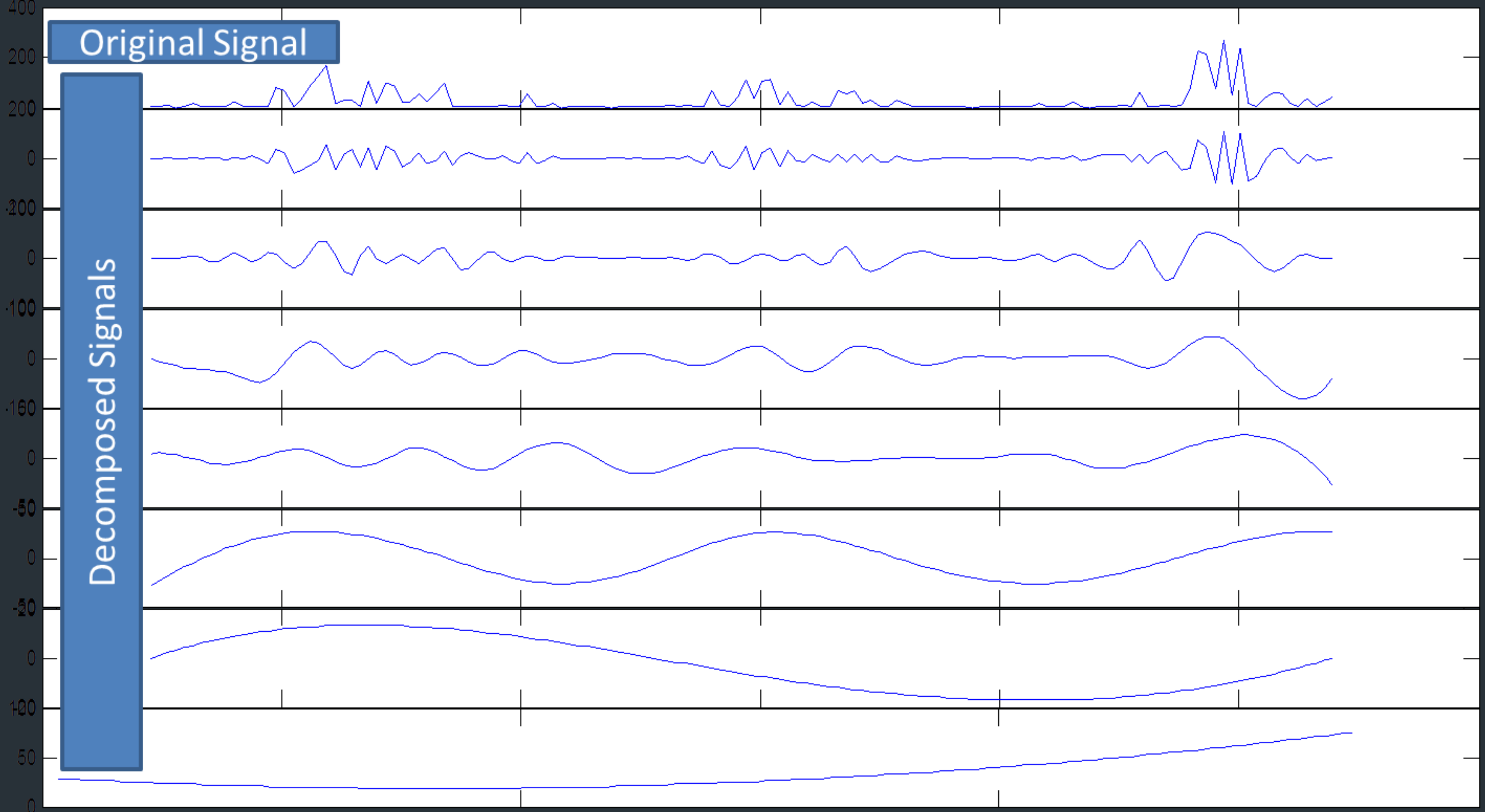
Current Status – HHT Results

- An example: Decomposed TRMM data



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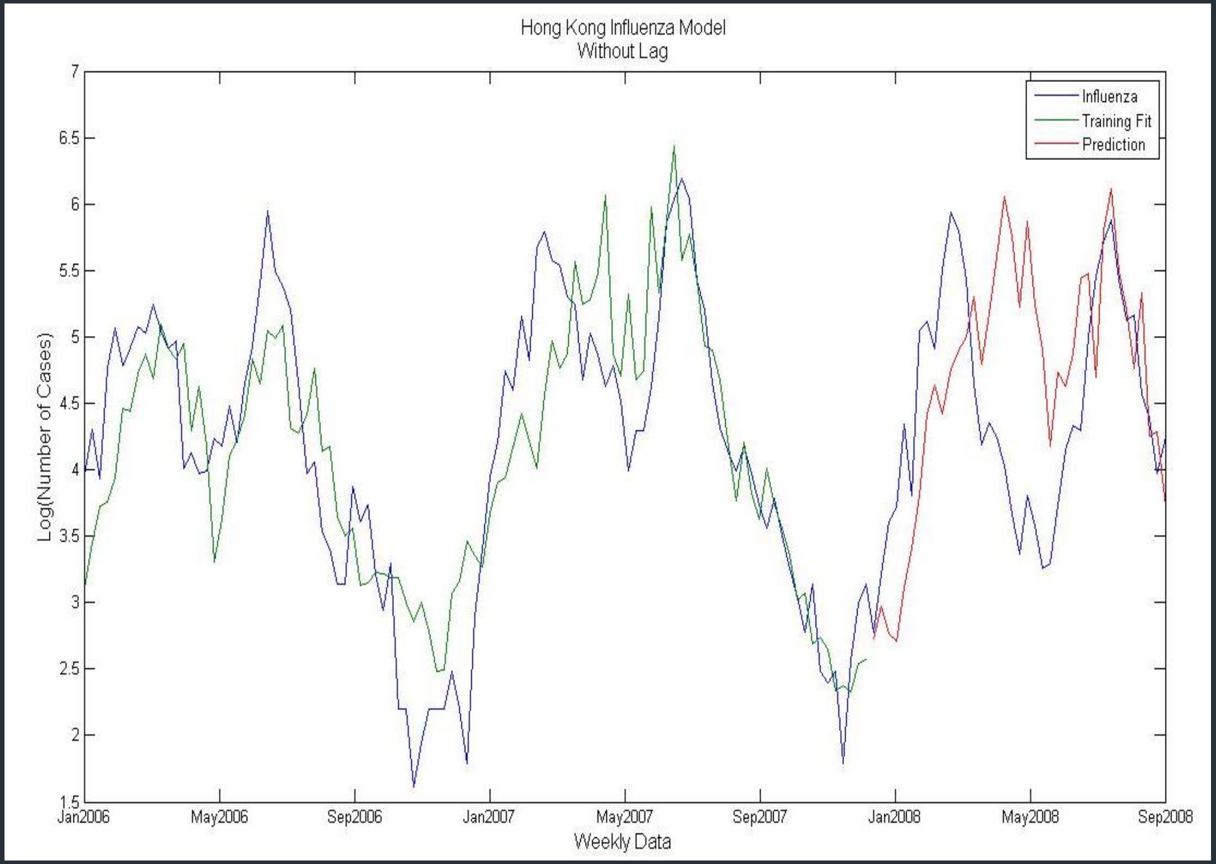
Current Status – HHT Results

Inputs: Minimum RH, TRMM, Sun, Cloud, Evap



Part 2: *"Modeling Global Influenza Risks using NASA Data"*

Next Step

- Influenza epidemiological & environmental data processing and consolidation
  - Recently received data ~3 countries
- Model development for those countries where the epidemiological and environmental data has been processed (~ 2 countries)
- Long-term forecast capability development
- Capacity building with collaborating countries
  - Workshop on using remote sensing data in modeling influenza
- Continue to test other modeling techniques
- Continue to approach other regions for collaboration