



# ANALTYICAL TOOLS PROVIDING EPIDEMIOLOGICAL INSIGHT FOR EVENT-BASED SURVEILLANCE

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# PRESENTATION OUTLINE

**Exploiting Twitter and Google Trends** Exploiting case count data Exploiting air traffic data

Current

work

**Future** 

work





### Data analytics for aberration detection and identification of susceptible populations

#### 1st October 2015 to 31st May 2016 Twitter data from **Data acquisition** 13 million of tweets Pruss et al (2017) English, Spanish, Portuguese **GitHub** Keywords "zika", "ZIKV" and "zica" **Proprietary** platforms Cost English, Korean, Russian GUI limited formatting/querying Google Trends Free gTrendsR Volume of search terms over package

time & space

Relative volume





# Data analytics for aberration detection and identification of susceptible populations

# **Data processing**



Remove re-tweets

Re-tweets by indicated by date and within **Tweet** 



43% of remaining tweets are original

Geolocate tweets

1% users provide coordinates



50% tweets populated with coordinates (and resolution of geolocator)

Classify content of tweets

NLP and machine learning classifiers (e.g. Miller et al. 2017)



**Symptoms** Infection Prevention **Treatment** 

Current work

**Future** work





# Data analytics for aberration detection and identification of susceptible populations

**Analytical tools** 



identification of susceptible populations

Aberration detection of symptoms

Augmenting

- Exploit clues from EBS data
- Output from classifier

Environmental / social determinates

Geolocated classified tweets **Disease susceptibility** 

Current work

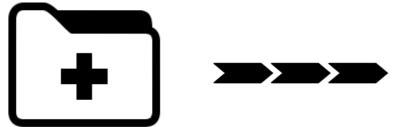
**Future** work

# **Exploiting EBS extracted case count data**



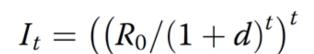
#### Forecasting cases through time

Case data



NLP extracted cases Official surveillance reports Incidence Decay and **Exponential** Adjustment (IDEA) model





Number of confirmed/suspected cases,  $I_t$ Basic reproductive number, RO Discount factor, d Serial interval, t

- Forecasts epidemiological curve
- Estimates potential for disease spread
- Can signal change in outbreak
- Simple
- Not validated for real-time outbreaks

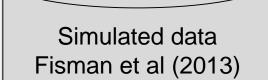


How few weeks of case data can provide reasonable model output?



# **Exploiting EBS extracted case count data**

#### How many weeks of data are needed for reliable model output?







Four serial intervals, t

PAHO surveillance data for ZIKV

> 46 countries Jan. 2015 to Dec. 2016 Backfilled data to index case

Observed surveillance data: Cumulative incidence and frequency of

cases

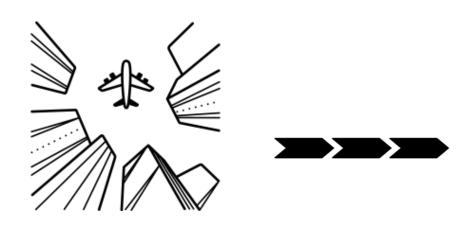
SIR model

5-7 serial intervals, *t*, High variation

> Depends on country, data transformation

Smooth case data? (e.g. Majumder et al.)

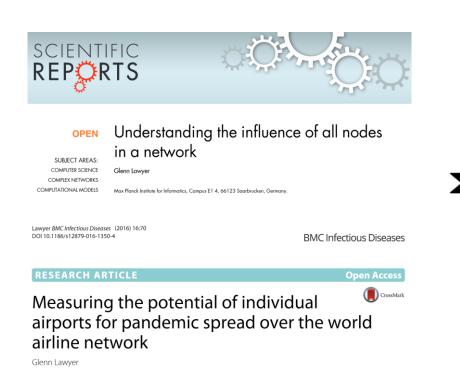




- Disease spread through air travel
- Meta-population compartmental models
- Simpler tools?
- Just passenger volume data → inadequate

Current work

**Future** work



Can ExF predict the risk of disease spread earlier than the **IDEA** model?

- Passenger volume data AND network topology → better!
- Airport expected force of infection (ExF)

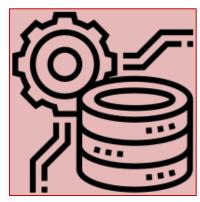


#### Assessing ExF as early predictor for reported travel-acquired ZIKV cases in Canada

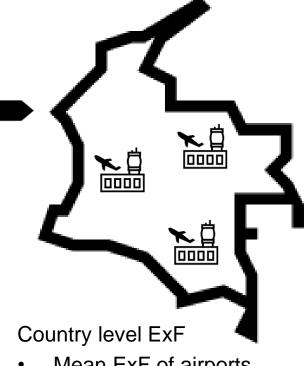
# Data acquisition

- 46 countries in Americas
- Air traffic data (BlueDot/IATA)
- Reported travel-acquired cases
- Other covariates

# Data processing



- Currently 29 countries
- Aggregating ExF to spatial resolution of case data



- Mean ExF of airports
- Max ExF of airports
- CoV ExF of airports

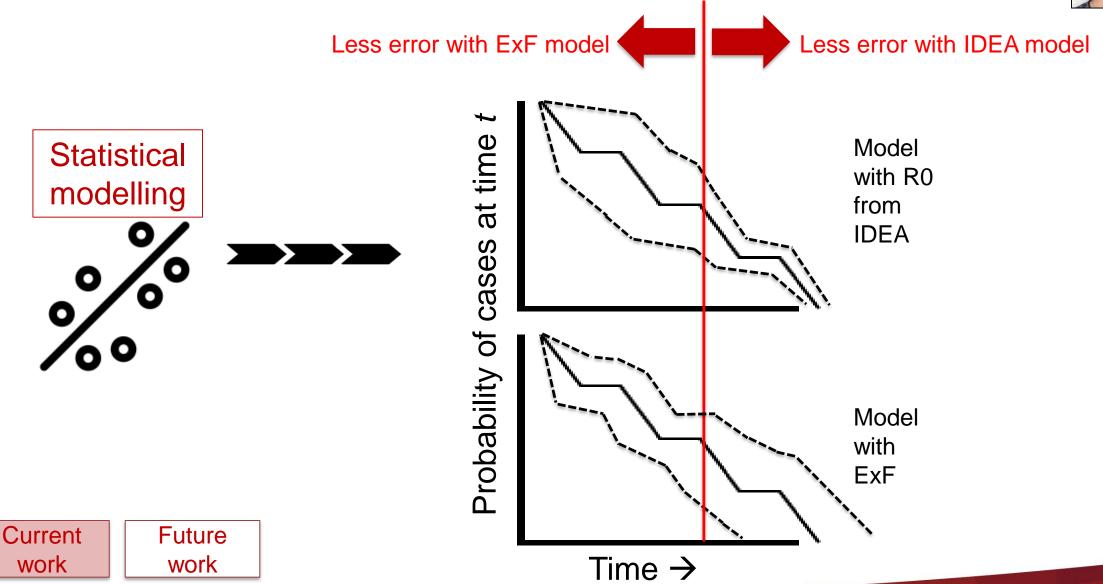
Current work

**Future** work

# **Exploiting air traffic data**







# Closing remarks

#### Challenge of developing data-driven models when data are scarce

- Get InSIGHT earlier: SIR  $\rightarrow$  IDEA  $\rightarrow$  ExF
- Exploit data extracted from EBS systems
- Exploit other data sources
- Integrate data types where possible







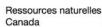


























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