Modelling in public health

SE Scientific Communication, 2019

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Background

Infectious diseases cause

Outbreaks:

Influenza, 2009

MERS-Cov (Middle-East Respiratory Syndrome)

Ebola, West Africa, DRC

Zika Virus, Brazil

role of modelling increases

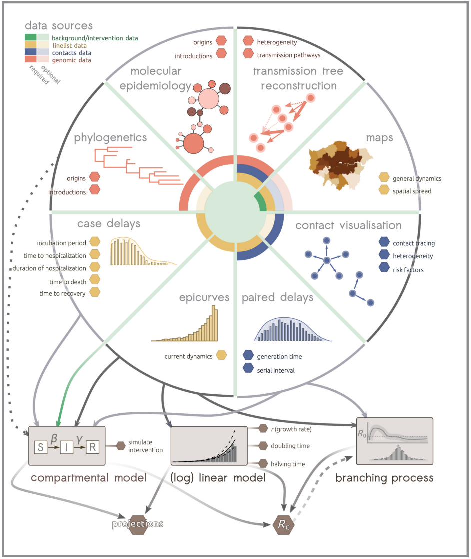
Objective/Goal

during outbreak:
exploit all data
inform response team in real time
in general (also non outbreak situation)
allow evidence based decisions
compare/assess interventions
policy evaluation (before/after in), vaccine programmes
track of WHO targets (HIV, HCV)

Types of models

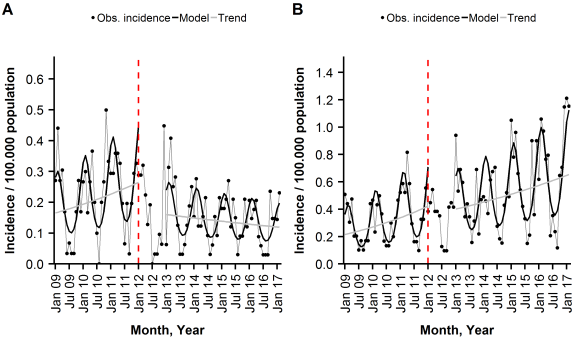
dynamic, mathematical (SIR)
statistical (e.g. Poisson regression)
Bayesian statistics
spacial stats/models
-> visualise outcome

Example of outbreak analytics workflow.



Intervention effect - Invasive Pneumococcal Disease (IPD)

Figure: Monthly incidence of (A) PCV10 ST-IPD and (B) non-PCV10 ex ST 6A-/19A-IPD, among the $\geq$50 years old, observed and modelled by a segmented negative binominal regression, Austria, January 2009-February 2017, shown are overall and seasonal trends.



Richter et al., 2019

IPD2

Serfling-like Model

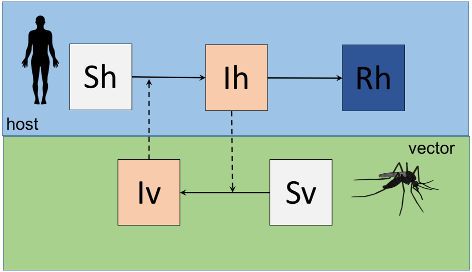
$$
\begin{aligned}
\log\left(Y_t\right) &= \log\left(pop_t\right) + \beta_0 + \beta_1\, t + \beta_2 \sin\left(\frac{2\pi t}{12}\right) \\
&\quad + \beta_3 \cos\left(\frac{2\pi t}{12}\right) + \beta_5\, (t - t_0)^+ \\
&\quad + \mathbb{1}_{t-t_0>0}\left[\beta_4 + \beta_6 \sin\left(\frac{2\pi t}{12}\right) + \beta_7 \cos\left(\frac{2\pi t}{12}\right)\right]
\end{aligned}
$$

with

$$
(x)^+ = \begin{cases} x, & \text{if } x > 0, \\ 0, & \text{otherwise.} \end{cases}
$$

Transmission model of Zika Virus

Vars	Description
S_h	Susceptible Humans
I_h	Infected/Infectious humans
R_h	Humans recovered from infection (with lifelong immunity)
S_v	Susceptible vectors
E_v	Exposed vectors



adapted from
https://www.reconlearn.org/ and Ferguson et al., 2016

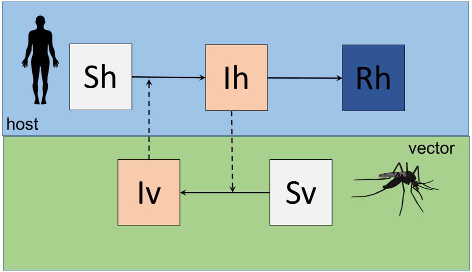
Transmission model of Zika Virus

Humans/Host

$$\frac{dS_h}{dt} = \mu_h N_h - \frac{\beta_h b}{N_h} S_h I_v - \mu_h S_h$$
$$\frac{dI_h}{dt} = \frac{\beta_h b}{N_h} S_h I_v - (\gamma_h + \mu_h) I_h$$
$$\frac{dR_h}{dt} = \gamma_h I_h - \mu_h I_h$$

Vectors

$$\frac{dS_v}{dt} = \mu_v N_v - \frac{\beta_v b}{N_h} I_h S_v - \mu_v S_v$$
$$\frac{dI_v}{dt} = \frac{\beta_v b}{N_h} I_h S_v - \mu_v I_v$$



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other applications

GO
Ebola
Influenza (Nielsen)
Foodborne outbreaks to identify the source of infection (poisson model)

Conclusion

Here comes the conclusion

Any questions?

References

[1] Lukas Richter et al. "Invasive Pneumococcal Diseases in Children and Adults before and after Introduction of the 10-Valent Pneumococcal Conjugate Vaccine into the Austrian National Immunization Program". In: *PloS One* 14.1 (2019), e0210081. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0210081. pmid: 30629620.

[2] Neil M. Ferguson et al. "Countering the Zika Epidemic in Latin America". In: *Science* 353.6297 (July 22, 2016), pp. 353–354. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.aag0219. pmid: 27417493. URL: https://science.sciencemag.org/content/353/6297/353 (visited on 06/19/2019).

[3] Polonsky Jonathan A. et al. "Outbreak Analytics: A Developing Data Science for Informing the Response to Emerging Pathogens". In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 374.1776 (July 8, 2019), p. 20180276. DOI: 10.1098/rstb.2018.0276. URL: https://royalsocietypublishing.org/doi/10.1098/rstb.2018.0276 (visited on 06/18/2019).

[4] R. E. Serfling, I. L. Sherman, and W. J. Houseworth. "Excess Pneumonia-Influenza Mortality by Age and Sex in Three Major Influenza A2 Epidemics, United States, 1957-58, 1960 and 1963". In: *American Journal of Epidemiology* 86.2 (Sept. 1967), pp. 433–441. ISSN: 0002-9262. DOI: 10.1093/oxfordjournals.aje.a120753. pmid: 6058395.