Modelling in public health

SE Scientific Communication, 2019

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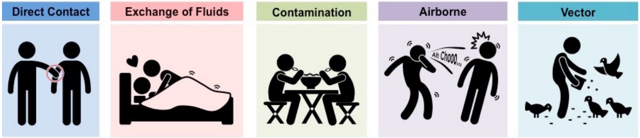
Background

Infectious diseases are a threat to human health
cost lifes and also money
Outbreaks
“sporadic” cases
different transmission chains



Outbreaks

Influenza pandemic “swine flu”

Global, 2009-2010, 100.000–400.000 deaths

Ebola

West Africa, 2014-2016, 11.000 deaths
DRC, since 2018, 1.900 deaths

Zika Virus

Brazil, 2015-2016, ca. 215.000 cases (CHECK!) wolrdwide

Measles

Europe, 2019, ca. 6.300 cases
Austria, 2019, more than 120 cases

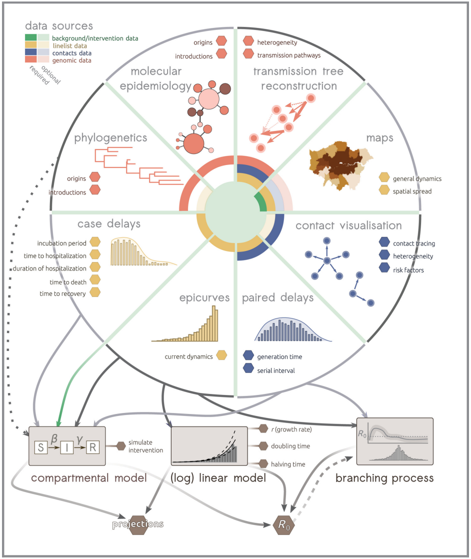
Objective/Goal

during outbreak:
exploit all data
inform response team in real time
non outbreak situations:
health programmes are usually implemented over a long period of time with broad benefits to many in the community
find high impact and cost-effective interventions
allow evidence based decisions
policy evaluation (vaccine programmes, WHO disease elimination targets)
benefits of model:
cheap: Clinical trials are seldom large enough to capture these effects
often little or no data to analyse (new emerging diseases)
mathematical models can help to assess potential threats and impacts early in the process, and later aid in interpreting data from complex and multifactorial systems

Types of models

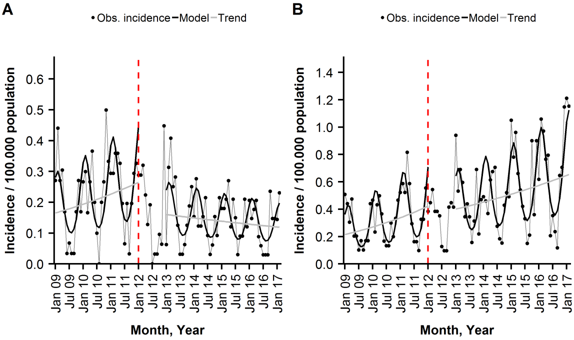
dynamic, mathematical (SIR)
statistical (e.g. Poisson regression)
Bayesian statistics
spacial stats/models
-> visualise outcome / communication

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 ≥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

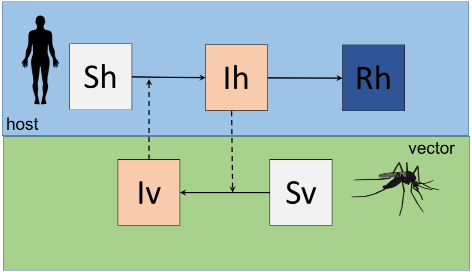
$$\begin{aligned}\log\left(Y_t\right) &= \log\left(pop_t\right) + \beta_0 + \beta_1\, t + \beta_2\, \sin\left(\frac{2\pi t}{12}\right) \\ &\quad + \beta_3\, \cos\left(\frac{2\pi t}{12}\right) + \beta_5\, (t - t_0)^+ \\ &\quad + \mathbb{1}_{t-t_0>0}\left[\beta_4 + \beta_6\, \sin\left(\frac{2\pi t}{12}\right)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

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

$$\frac{dS_h}{dt} = \mu_h N_h - \frac{\beta_h b}{N_h} S_h I_v - \mu_h S_h$$

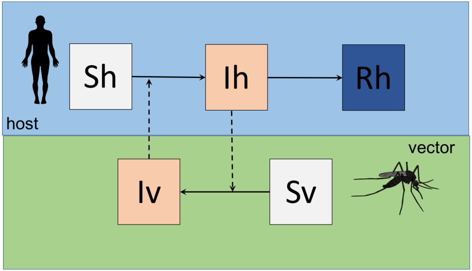
$$\frac{dI_h}{dt} = \frac{\beta_h b}{N_h} S_h I_v - (\gamma_h + \mu_h) I_h$$

$$\frac{dR_h}{dt} = \gamma_h I_h - \mu_h I_h$$

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) Nielsen et al., 2019
Foodborne outbreaks to identify the source of infection (poisson model)

Conclusion/Wrap up

We saw some examples of applied modelling
plays an increasingly important role in helping to guide the most high impact and cost-effective prevent disease
models can be critical tools in guiding public health action.
always comes with limitations (as other studies)
decision makers benefit, so do the affected people still a lot to do -
However, there are a number of challenges in achieving a successful interface between modelling and public health.

Any questions?

References

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[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] J. Nielsen et al. "European All-Cause Excess and Influenza-Attributable Mortality in the 2017/18 Season: Should the Burden of Influenza B Be Reconsidered?". In: *Clinical Microbiology and Infection* (Feb. 18, 2019). ISSN: 1198-743X. DOI: 10.1016/j.cmi.2019.02.011. URL: http://www.sciencedirect.com/science/article/pii/S1198743X19300588 (visited on 04/08/2019).

[4] 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).

[5] 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.