Using compartmental models for the evaluation of syndromic surveillance systems in England

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What is syndromic surveillance?

- Syndromic surveillance collects, analyses, and disseminates data on **disease symptoms** to provide early warnings about public health threats in **near-real-time** (Buehler et al., 2009).
- A key rationale of syndromic surveillance is that it may detect health threats **faster than traditional surveillance systems** (e.g. laboratory reports).
- This may permit more timely, and hence potentially more effective public health action to reduce morbidity and mortality.

Syndromic surveillance

- The investigation of potential outbreaks faces a great deal of **uncertainties**
  - Similar symptoms/syndromes between diseases
  - Each outbreak has a unique manifestation
    - What will the next big event look like?
  - Health-care seeking behaviour
  - Reporting uncertainties
    - Diagnosis is as good as the ability of the medical professional
  - Population coverage of the systems

Syndromic surveillance in England

- In England, the Real Time Syndromic Surveillance Team (ReSST) at Public Health England (PHE) obtains and analyses data from four National Health Service (NHS) healthcare settings:
  - A telehealth consultation system (NHS-111)
  - in-hours General Practitioner consultations (GPIHSS)
  - out-of-hours and unscheduled General Practitioner consultations (GPOOHSS)
  - emergency department attendances (EDSSS)

Aberration detection

- The syndromic indicators (e.g. counts of fever, cough, diarrhoea, gastroenteritis) from these syndromic surveillance systems are compared on a daily basis with the expected number of consultations to identify **anomalous patterns** (aberrations)
- To do so, they use a statistical multi-level model (RAMMIE)
- A data value outside expected bounds is an indicator of **potentially important unusual activity**.
  - Although exceedances may be random events of little concern.

Aberration detection capabilities

- To fully evaluate the role of syndromic surveillance within public health, it is critical to **assess the types of events that can be detected**, how long such systems take to detect the event, and of equal importance, those events that cannot be detected.

Knowledge gap

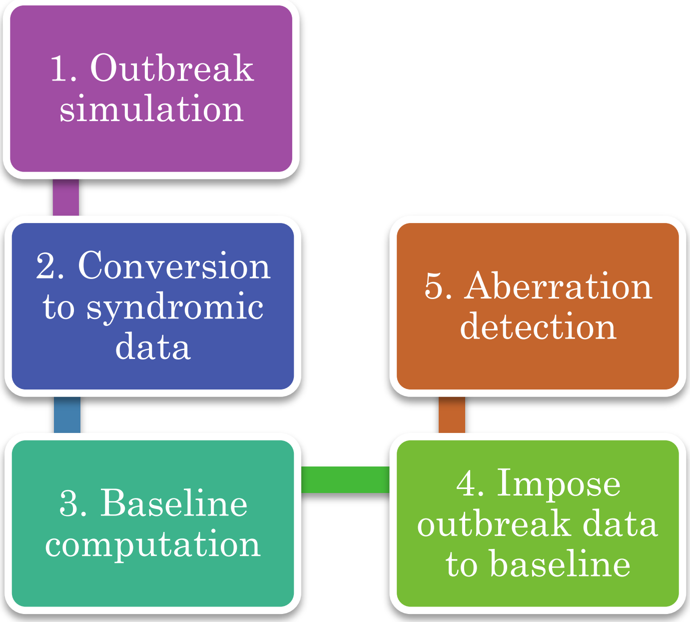
- Research evaluating the performance of syndromic surveillance systems is scarce.
- Most previous studies have used:
  - a single disease type (Fan et al., 2014)
  - one or two syndromic data sources (e.g. Bordonaro et al., 2016).
- No studies have investigated whether detection capabilities vary according to time of year

Knowledge gap

- Previous studies have seldom considered the uncertainties arising from:
  - potential differences between outbreaks,
  - the probability of people consulting health services monitored by a syndromic surveillance system,
  - The proportion of people being coded to a particular syndromic indicator by a health professional.

Addressing the gap

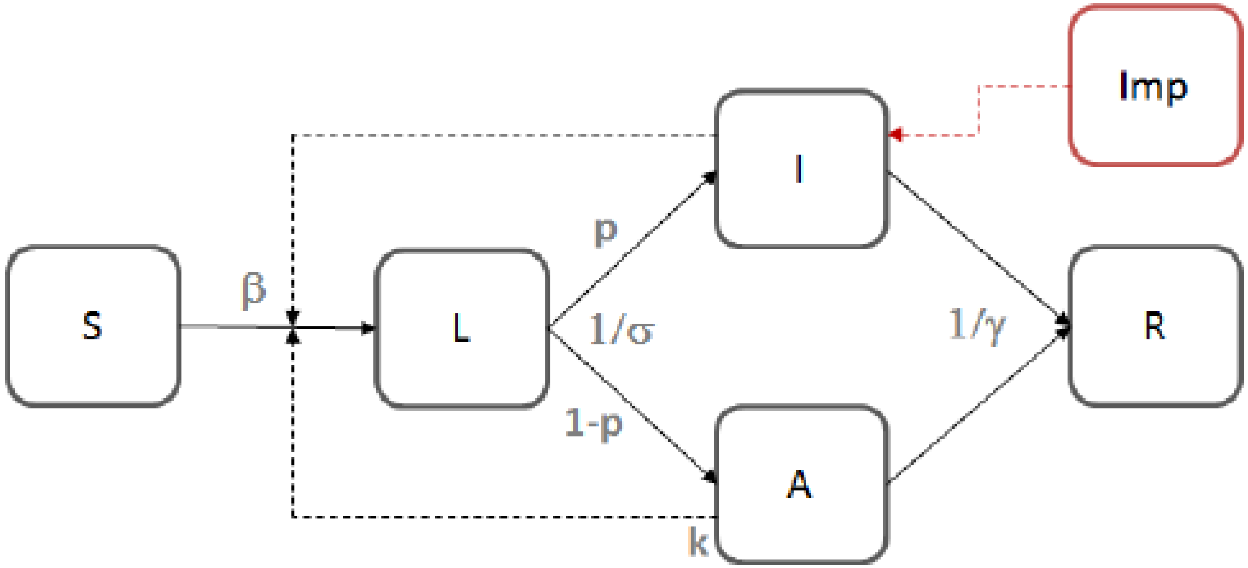
- We developed an evaluation framework for the evaluation of syndromic surveillance systems that aims to account for these uncertainties and allows their investigation
- The framework has five main stages



Scenarios

- We developed scenarios to evaluate our framework:
  - **A national outbreak of influenza** similar to A(H1N1)pdm09 (swine flu) occurring in England as a consequence of international travelling
  - A local outbreak of cryptosporidiosis in a metropolitan area as a consequence of failure in a water treatment plant

1. Outbreak simulation: Influenza



$$\frac{dS}{dt} = -\beta S(I + kA)$$

$$\frac{dL}{dt} = \beta S(I + kA) - \sigma L$$

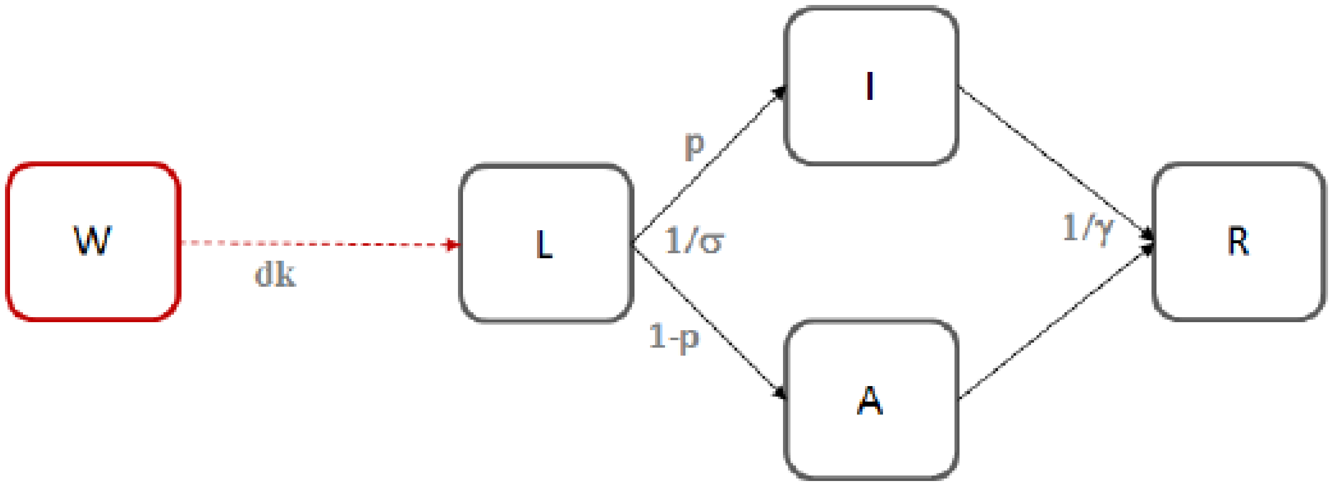
$$\frac{dI}{dt} = p\sigma L - \gamma I$$

$$\frac{dA}{dt} = (1 - p)\sigma L - \gamma A$$

$$\frac{dR}{dt} = \gamma(I + A)$$

$$R_0 = \beta N_0 \left[\frac{p + k(1 - p)}{\gamma}\right]$$

1. Outbreak simulation: Cryptosporidium



$$\frac{dL}{dt} = \sigma L$$

$$\frac{dA}{dt} = (1-p)\sigma L - \gamma A$$

$$\frac{dI}{dt} = p\sigma L - \gamma I$$

$$\frac{dR}{dt} = \gamma(I + A)$$

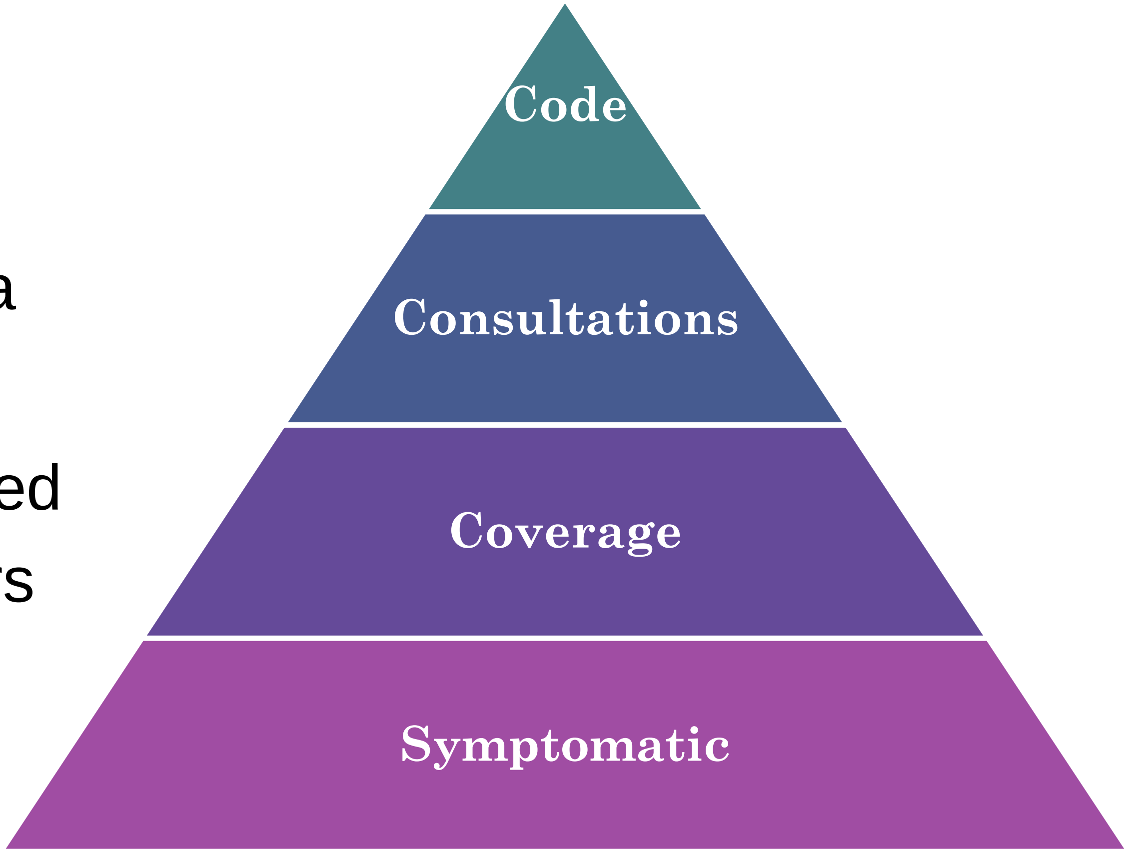
Model parameters

- To explore uncertainty, we simulated models using the 10th, 50th, and 90th percentiles of the distribution of values for each of the following parameters:

Influenza	Cryptosporidium
R_0	Number of exposed people
Incubation period	Number of oocysts released
Infectious period	Probability of infection
Fraction of asymptomatic	Incubation and infectious period
Infectivity reduction on asymptomatic	Proportion of asymptomatic

2. Conversion to syndromic data

- Each system has a different coverage
- Not all symptomatic people will consult a health-care system
- People may be coded to different indicators by health professionals



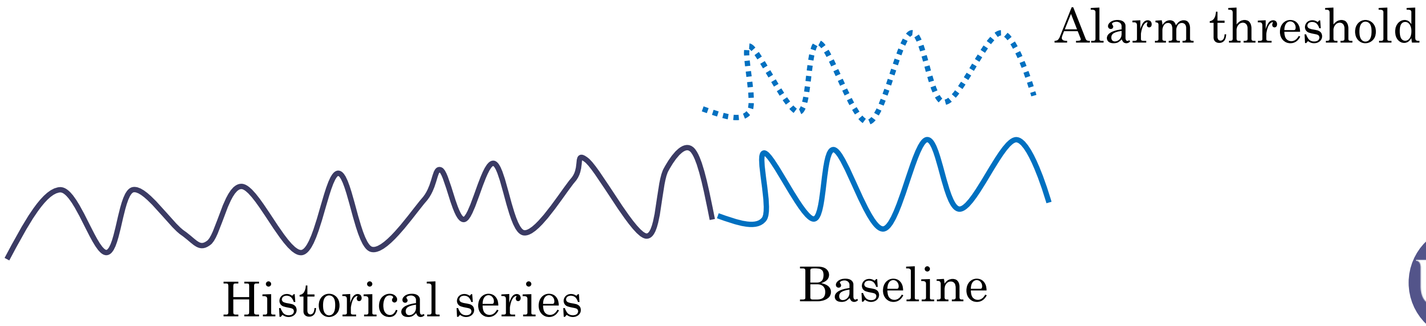
2. Conversion to syndromic data

- Not all symptomatic people will report on the first day of symptoms
- We used a health-seeking behaviour model

$$P_tI_t = \begin{bmatrix} p_1 i_1 & 0 & 0 & 0 & \dots & 0 \\ p_1 i_2 & p_2 i_1 & 0 & 0 & \dots & 0 \\ p_1 i_3 & p_2 i_2 & p_3 i_1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ p_1 i_t & p_2 i_{t-1} & p_3 i_{t-2} & p_4 i_{t-3} & \dots & p_t i_{t-5} \end{bmatrix} \begin{matrix} \text{Day 1} \\ \text{Day 2} \\ \text{Day 3} \\ \vdots \\ \end{matrix}$$

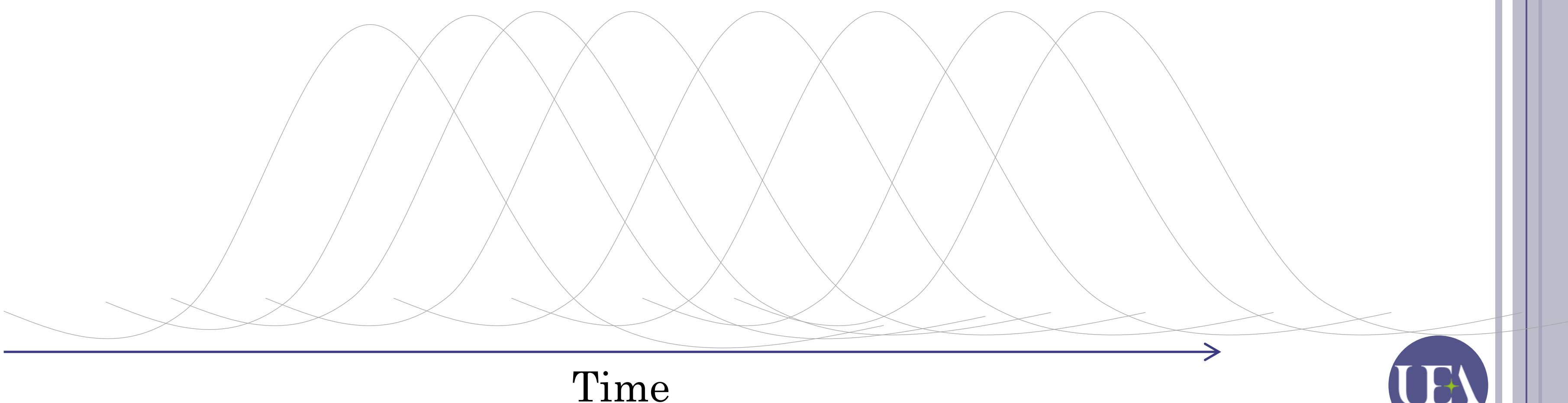
3. Baseline simulation

- Expected number of cases and its 99% confidence intervals for 2015 based on historical data using a mixed effects statistical model
- The upper bound of the CI used as **alarm threshold**
- We simulated 100 time series for each baseline



4. Test data

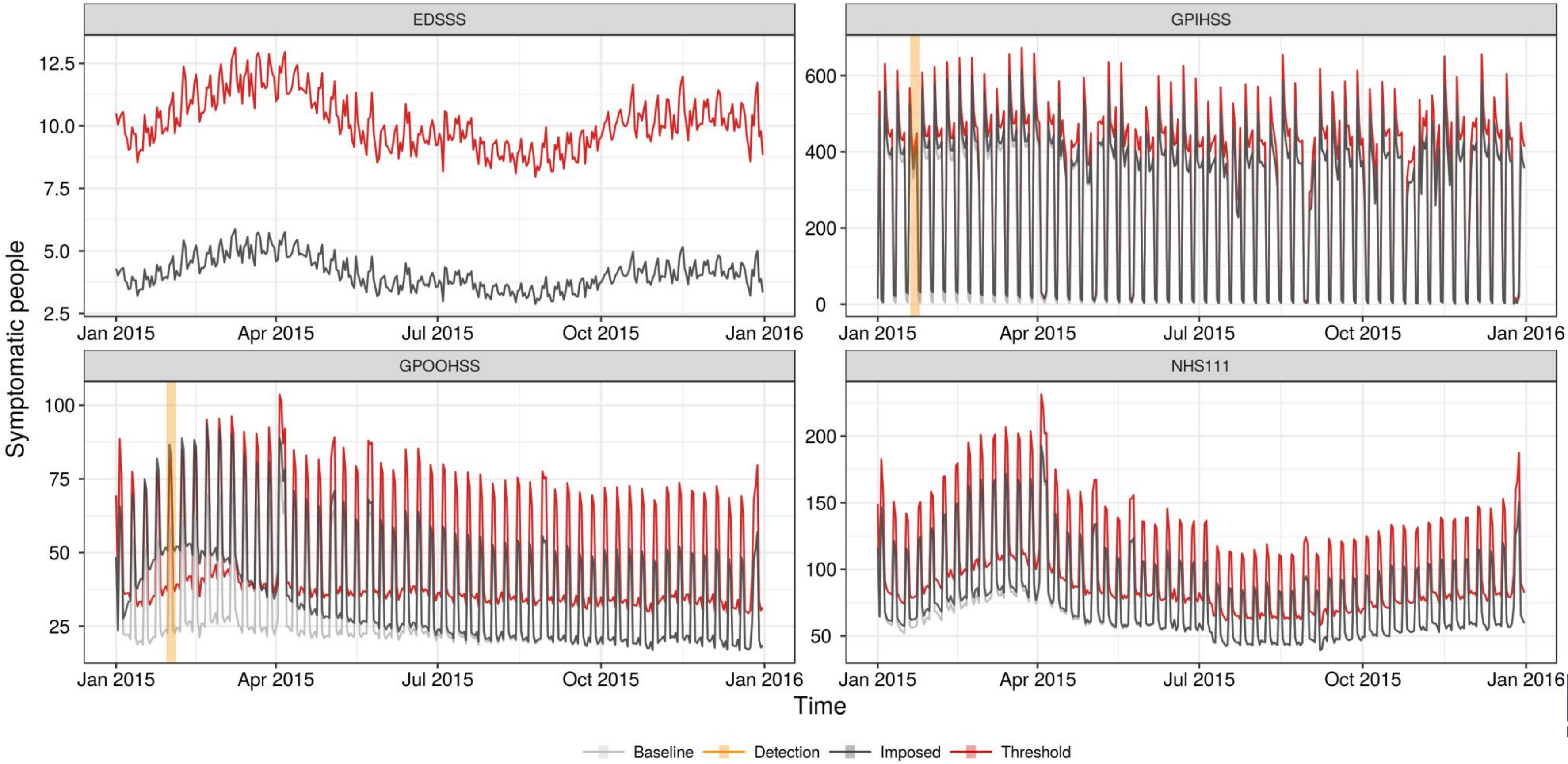
- We added the downscaled outbreak data to the 100 simulated baselines
- Outbreak data were imposed onto the baseline every other day across the whole year



5. Aberration detection

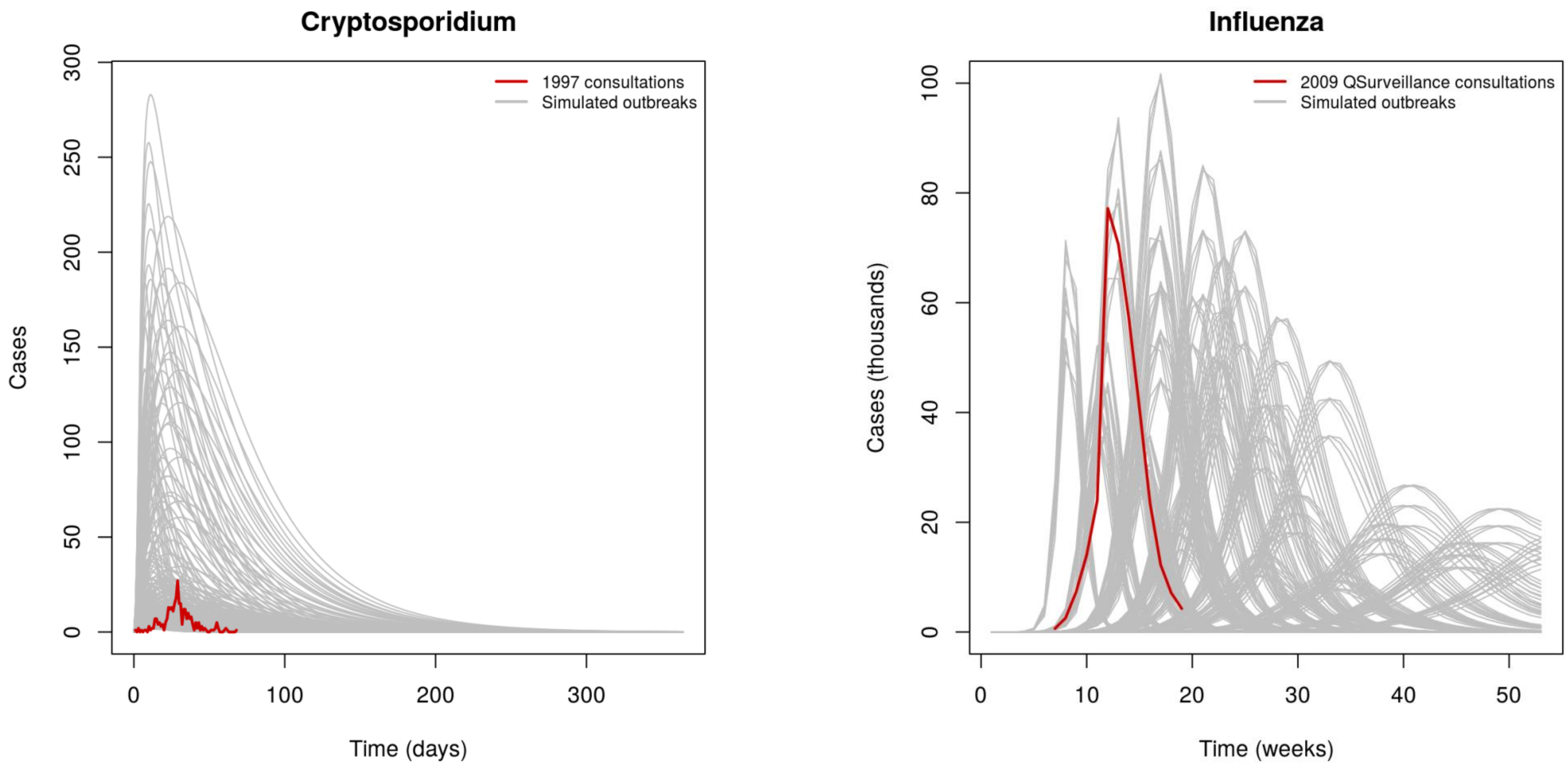
- By chance, about 1% of the simulated baseline data will exceed the alarm threshold
- To reduce the impact of false alarms, we considered detection as the time the alarm threshold was exceeded **for three or more days**.

5. Aberration detection



Results

- We analysed 4,422,600 time series per indicator
  - 243 outbreaks × 100 MC baselines × 182 initial dates



Results

- All outbreaks were detected by all systems
- TD decreases as the size of the outbreak increases
- Outbreaks likely to be detected at day 102, 61, and 47 when there are likely to be 9.4, 12.6 and
- 14.2 symptomatic individuals.
- GPIHSS detected the outbreaks considerably before any other system

Current coverage										
		Size 1			Size2			Size 3		
Indicator	Coverage (%)	P_D	T_D	Sym	P_D	T_D	Sym	P_D	T_D	Sym
Influenza										
EDSSS-influenza like illness	7	1.00	158 (81–248)	105.6	1.00	87 (44–136)	110.9	1.00	64 (32–99)	115.0
GPIHSS-influenza like illness	64	1.00	102 (56–162)	9.4	1.00	61 (33–96)	12.6	1.00	47 (25–73)	14.2
GPOOHSS-influenza like illness	65	1.00	146 (74–222)	53.4	1.00	81 (41–124)	59.5	1.00	59 (30–91)	63.3
NHS111 cold-flu	100	1.00	140 (76–232)	72.0	1.00	79 (42–128)	79.6	1.00	58 (30–94)	84.0

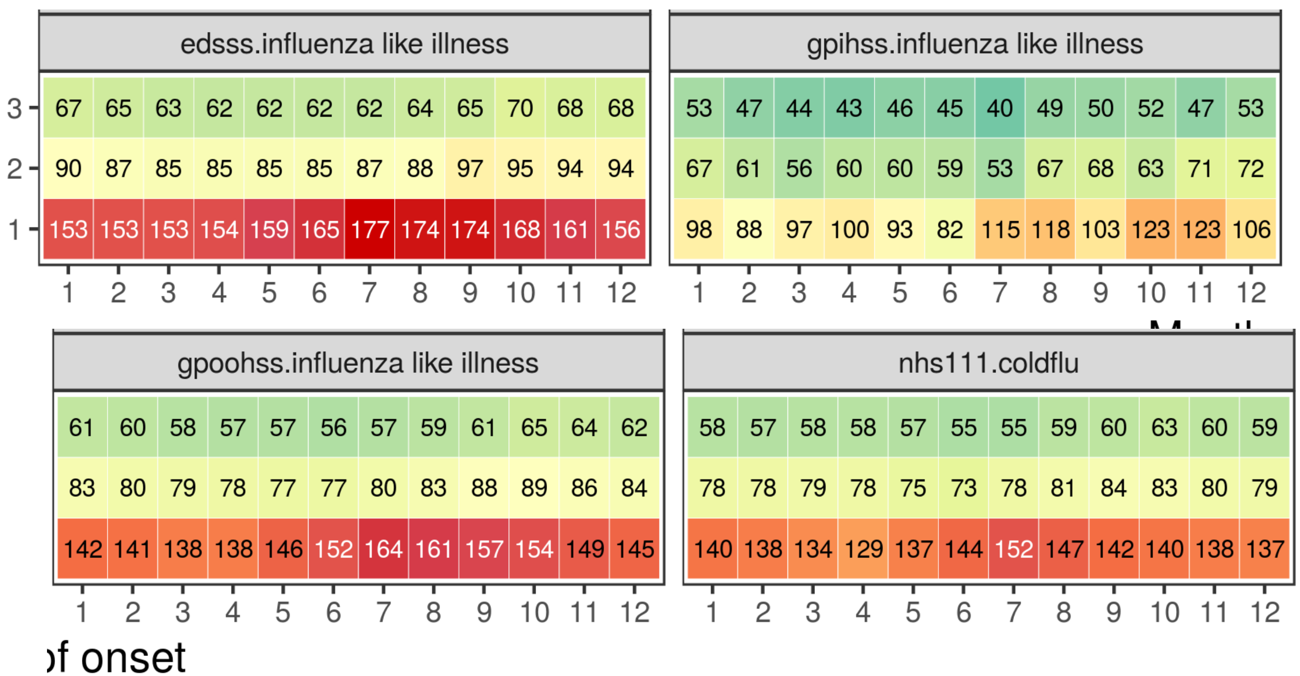
Results

- Not all systems had the same coverage
- What if they did?
  - GPIHSS was still one of the best systems for detection
  - TD reduced slightly

	100% coverage								
	Size 1			Size2			Size 3		
Indicator	P_D	T_D	Sym	P_D	T_D	Sym	P_D	T_D	Sym
EDSSS-influenza like illness	1.00	97 (52–161)	7.4	1.00	56 (31–91)	7.8	1.00 (23–68)	42	8.1
GPIHSS-influenza like illness	1.00	93 (51–148)	6.1	1.00	56 (31–89)	8.1	1.00	43 (23–68)	9.1
GPOOHSS-influenza like illness	1.00	136 (70–208)	34.7	1.00	76 (39–116)	38.7	1.00	56 (29–86)	41.1
NHS111 cold-flu	1.00	140 (76–232)	72.0	1.00	79 (42–128)	79.6	1.00	58 (30–94)	84.0

Seasonal effects

- On average, outbreaks starting in Feb-July had a lower TD compare to one starting in Aug-Jan
  - Outbreaks starting in July had TD=40 days compared to TD=47 days if started in November (GPIHSS)



Results Cryptosporidium

- Outbreaks of cryptosporidiosis will be more local in nature
- The ability to detect outbreaks of different sizes varies by indicator.
- Small and medium size outbreaks (i.e. ~854 and ~1,281
- exposed people per day) are not consistently detected
- EDSSS was unable to detect any outbreak

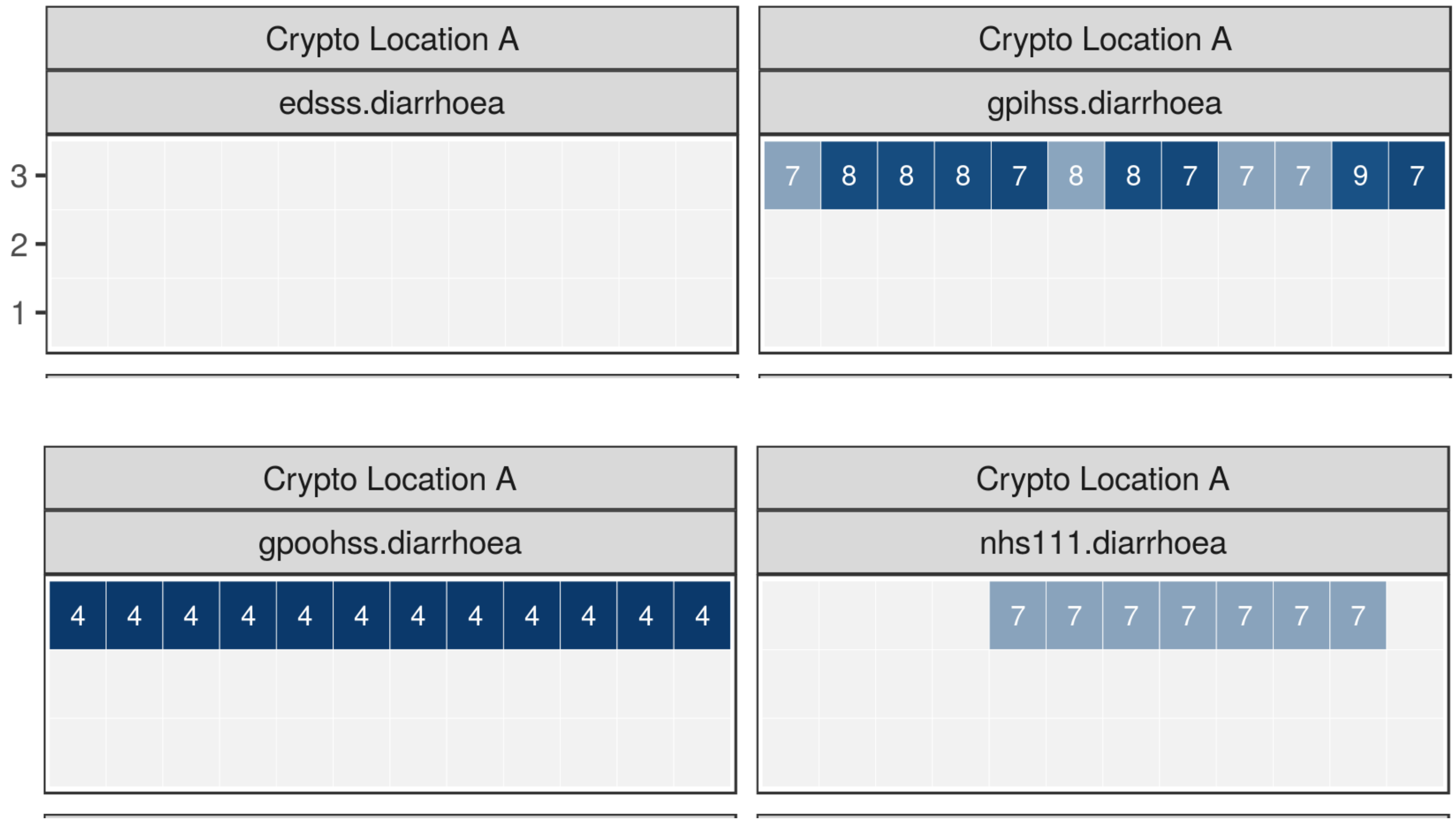
Indicator	Coverage (%)	P_D	T_D	Sym	P_D	T_D	Sym	P_D	T_D	Sym
EDSSS diarrhoea	15	0.00	-	-	0.00	-	-	0.00	-	-
GPIHSS diarrhoea	64	0.14	-	-	0.24	-	-	0.84	8 (2–33)	4.4
GPOOHSS diarrhoea	65	0.18	-	-	0.33	-	-	0.95	4 (2–11)	2.4
NHS111 diarrhoea	100	0.00	-	-	0.00	-	-	0.52	7 (3–21)	5.7

Results cryptosporidiosis

- Even after increasing the coverage to 100% most outbreaks go unnoticed
- A reduction in the TD is noticed

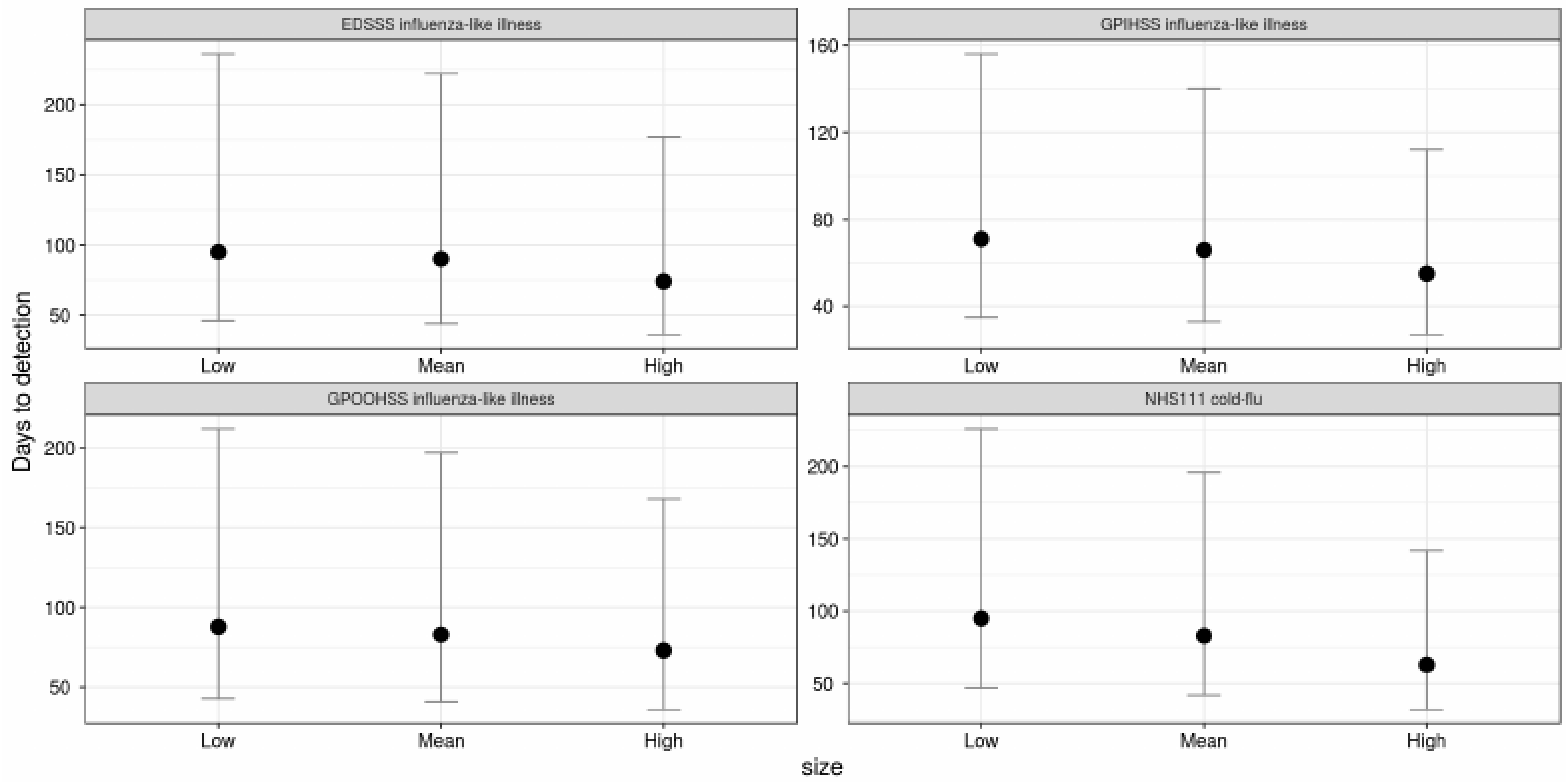
Indicator	Coverage (%)	P_D	T_D	Sym	P_D	T_D	Sym	P_D	T_D	Sym
EDSSS diarrhoea		0.00	-	-	0.00	-	-	0.00	-	-
GPIHSS diarrhoea		0.25	-	-	0.39	-	-	0.92	6 (2–24)	3.6
GPOOHSS diarrhoea		0.34	-	-	0.51	7 (3–20)	0.9	0.99	3 (1–9)	1.8
NHS111 diarrhoea		0.00	-	-	0.00	-	-	0.52	7 (3–21)	5.7

Seasonal effects



Access to healthcare

- No significant effect was detected



- We highlight the importance of using different system-syndrome indicators for event detection.
  - For example, syndromic surveillance data from EDSSS in England are useful for the detection of pandemic influenza but not for the identification of local outbreaks of cryptosporidiosis.
- Interestingly, emergency department data are the most widely used source of syndromic surveillance data worldwide

- The framework allows the exploration of the uncertainties related to the characteristics of the outbreaks as well as the features of the systems
- We argue that our framework constitutes a useful tool for public health emergency preparedness

Thank you!

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