Block 2.4: The TSIR model and model validation

Objectives in this section

- Models can be used to quantitatively interpret data.
- Data can be used to set parameters in models.
- Probability gives us guiding principles for comparing models and data.
- Incorporating sources of uncertainty into models gives them flexibility but it also gives us a lot of new model considerations.

The TSIR model applied to England and Wales

The TSIR model is a natural modification of the chain-binomial.

$$I_t = \beta_{t-1} S_{t-1} I_{t-1}^{\alpha} \varepsilon_{t-1},$$

$$S_t = S_{t-1} + B_{t-1} - I_t,$$

$$C_t \sim \text{Binomial} \{I_t, r_t\}$$

- Finkenstadt and Grenfell 2000 is a key paper introducing this model.
- The choice of time step as 2 weeks is practical based on the data but also related to equating incidence and prevalence in the model.

Tangent

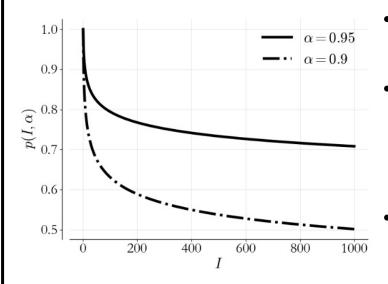


You'll read often that the α exponent models "network effects".

• The exponent is pragmatic – models with it outperform models with α set to 1.

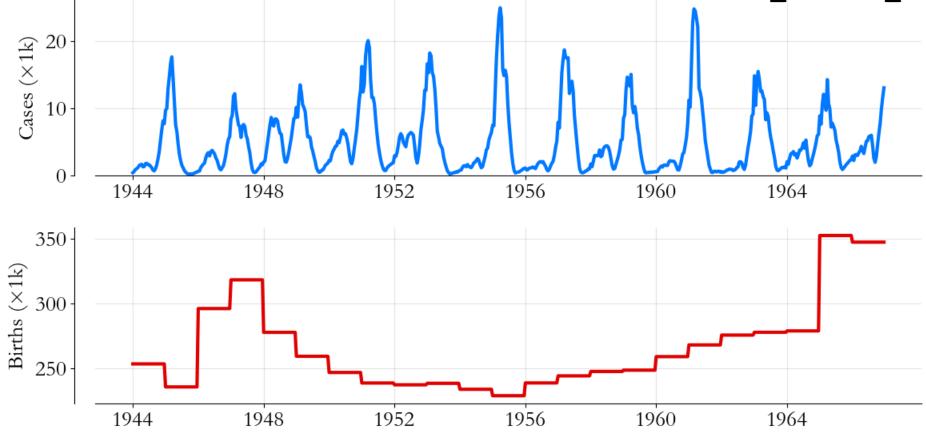


$$\mathbf{A} = egin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1I} \ a_{21} & a_{22} & a_{23} & \dots & a_{2I} \ dots & dots & dots & \ddots & dots \ a_{S1} & a_{S2} & a_{S3} & \dots & a_{SI} \end{bmatrix}$$



- All edge weights $a_{ij} = 1$ implies $S \times I$ edges.
- with probability p, $a_{ij} = 1$ = 0 otherwise, then we expect $SI \times p$ edges.
- We can choose $p(I, \alpha) = 1/I^{1-\alpha}$





$$I_t = \beta_{t-1} S_{t-1} I_{t-1}^{\alpha} \varepsilon_{t-1},$$

$$S_t = S_{t-1} + B_{t-1} - I_t,$$

 $C_t \sim \text{Binomial}\{I_t, r_t\}$

If you want to install Python:

https://www.anaconda.com/download

Let's write some (pseudo)code

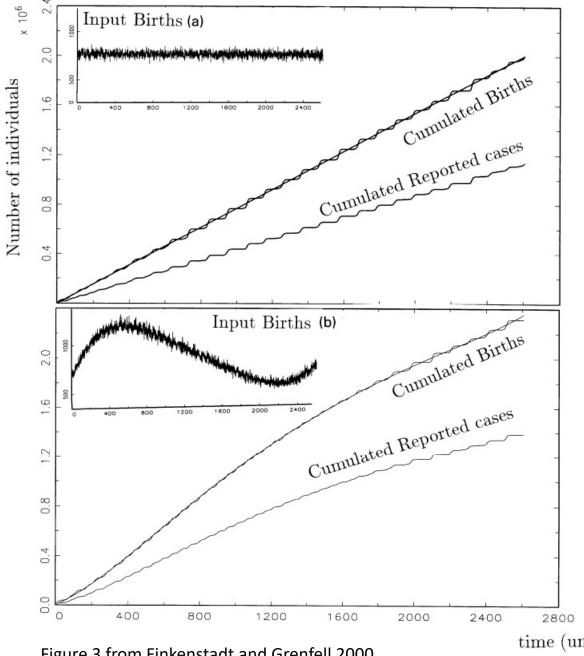


Figure 3 from Finkenstadt and Grenfell 2000

time (units)

Let's write some (pseudo)code

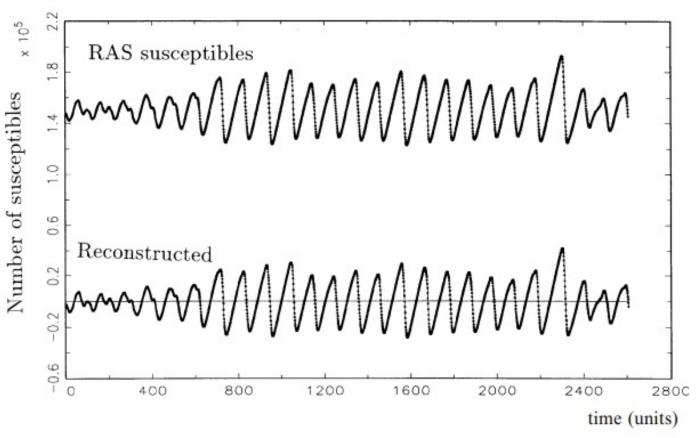
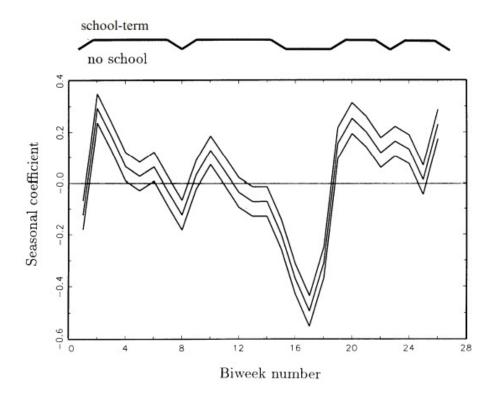
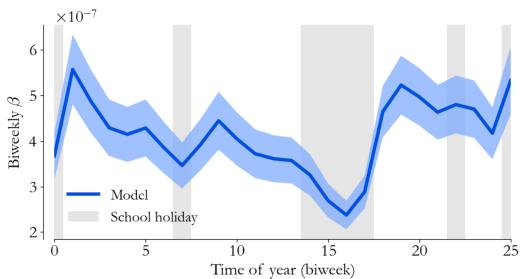
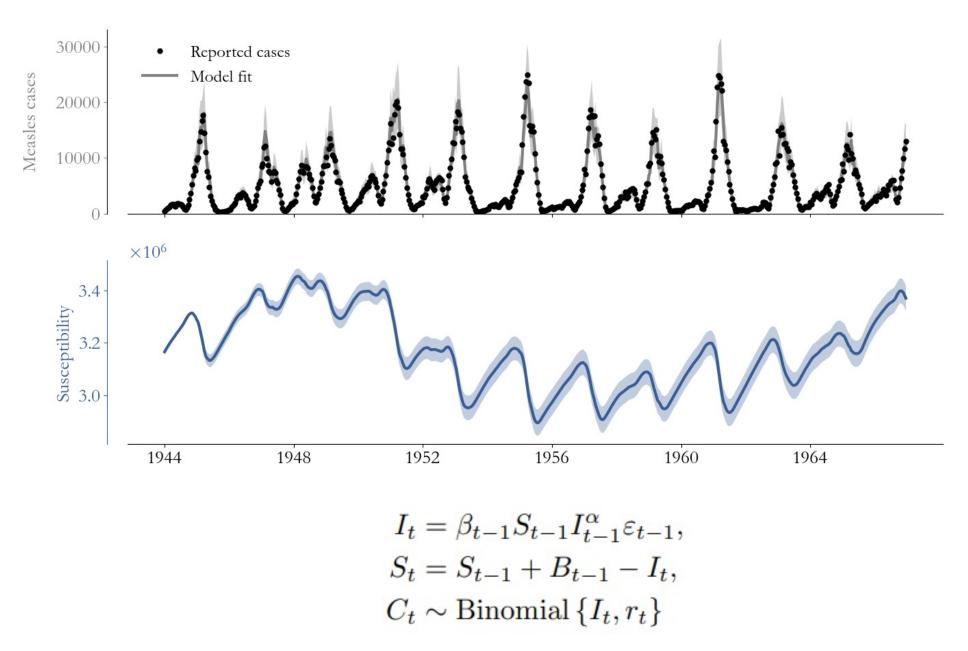


Figure 4 from Finkenstadt and Grenfell 2000





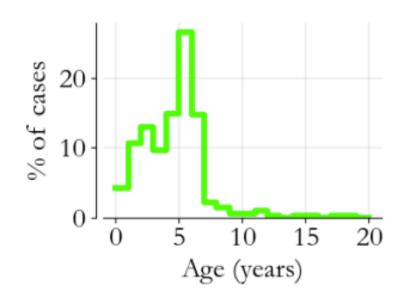
Let's write some (pseudo)code

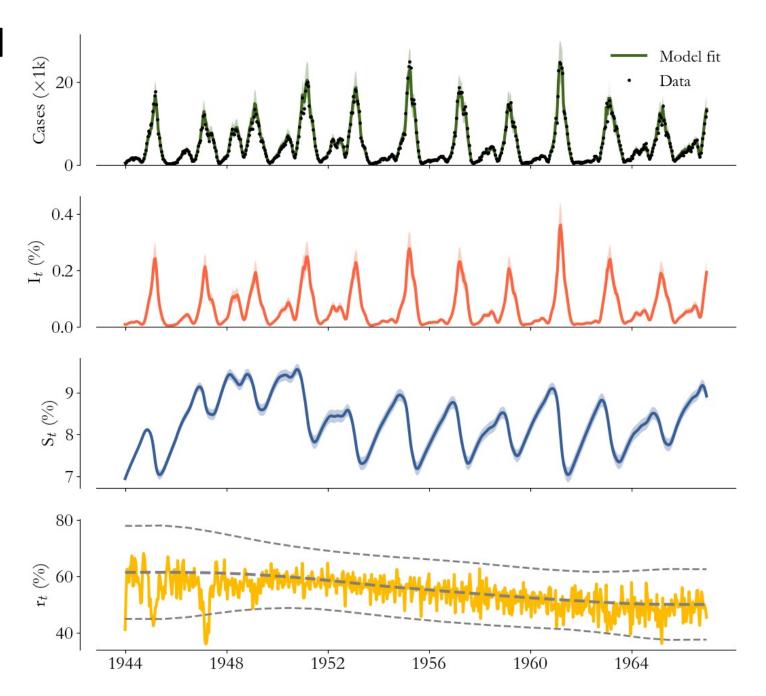


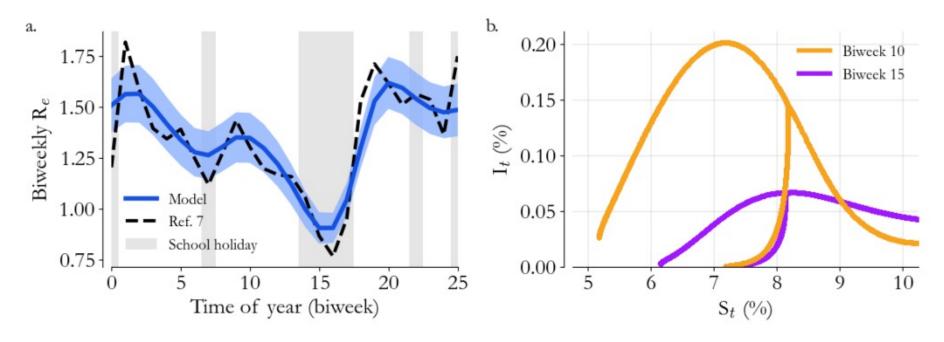
How do we validate a model like this?

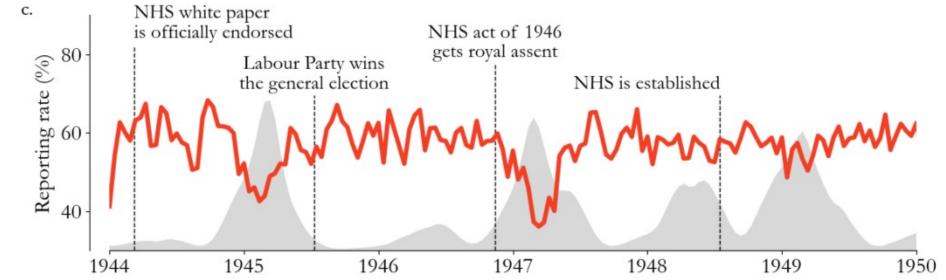
Using a similar approach and some more data we create a more sophisticated model

$$\mathcal{L}(\beta_t, \varepsilon_t, \alpha, r_t, S_0) = \frac{26T - 1}{2} \ln \hat{\sigma}_{\varepsilon}^2 + \frac{(S_0 - \mathbf{E}[S_0])^2}{2\mathbf{V}[S_0]} + \sum_t \frac{(r_t - \mathbf{E}[\tilde{r}_t])^2}{2\mathbf{V}[\tilde{r}_t]}$$



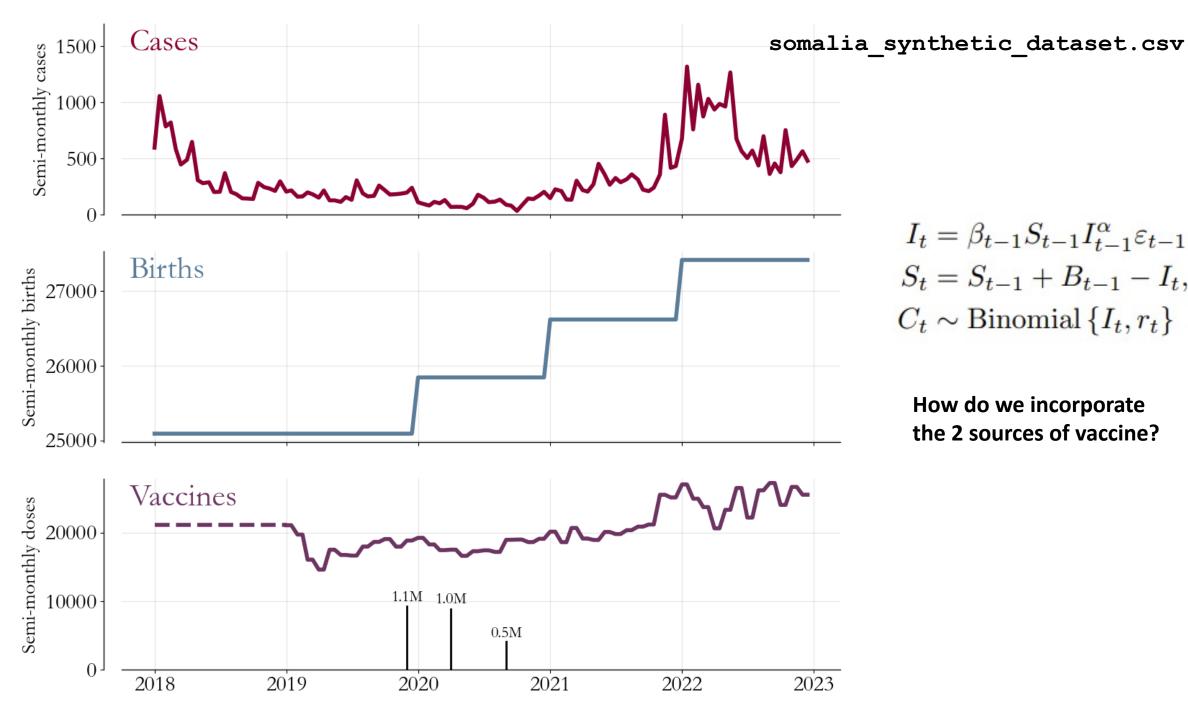






Quantities that are difficult to estimate are then difficult to validate!

The TSIR model applied to SIA impact estimation in Somalia



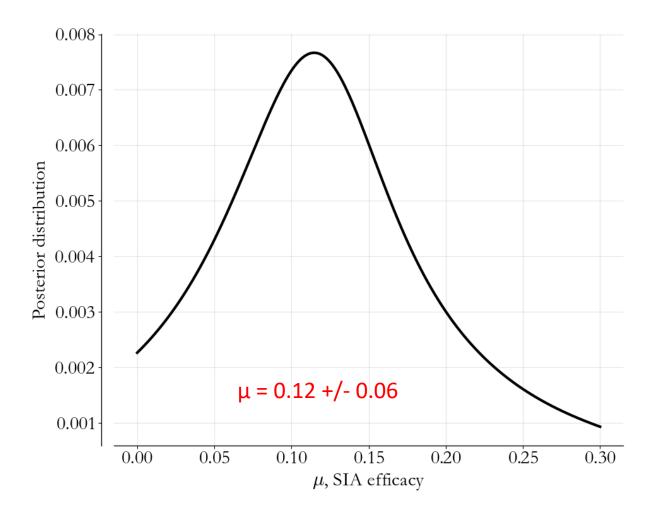
$$I_t = \beta_{t-1} S_{t-1} I_{t-1}^{\alpha} \varepsilon_{t-1},$$

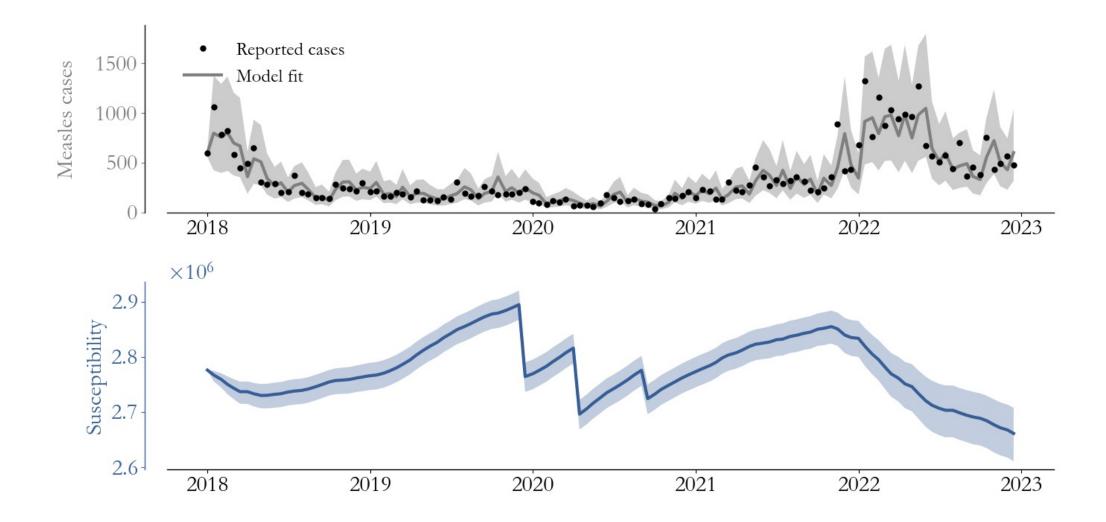
$$S_t = S_{t-1} + B_{t-1} - I_t,$$

$$C_t \sim \text{Binomial} \{I_t, r_t\}$$

How do we incorporate the 2 sources of vaccine?

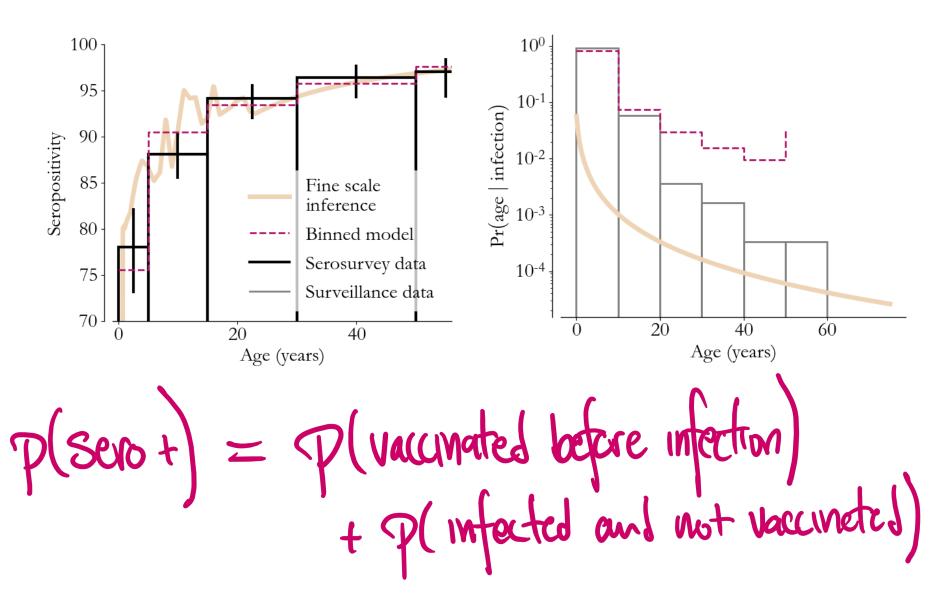
Let's write some (pseudo)code

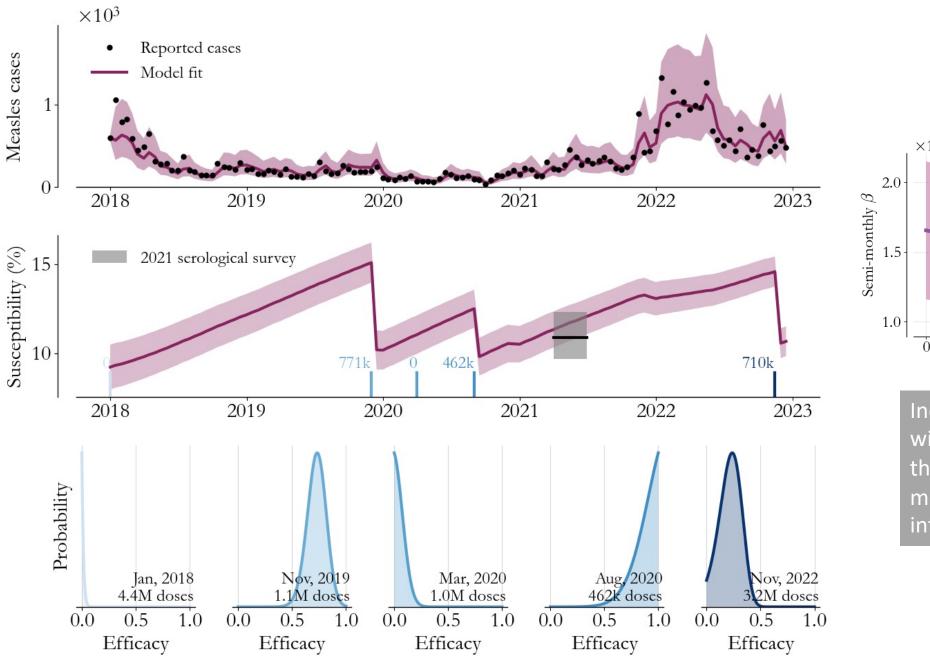


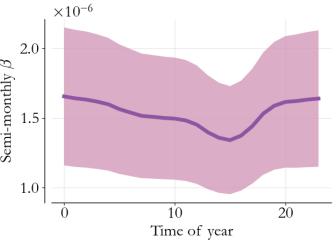


How do we validate a model like this?

We can again incorporate age information, this time from a serological survey in 2021

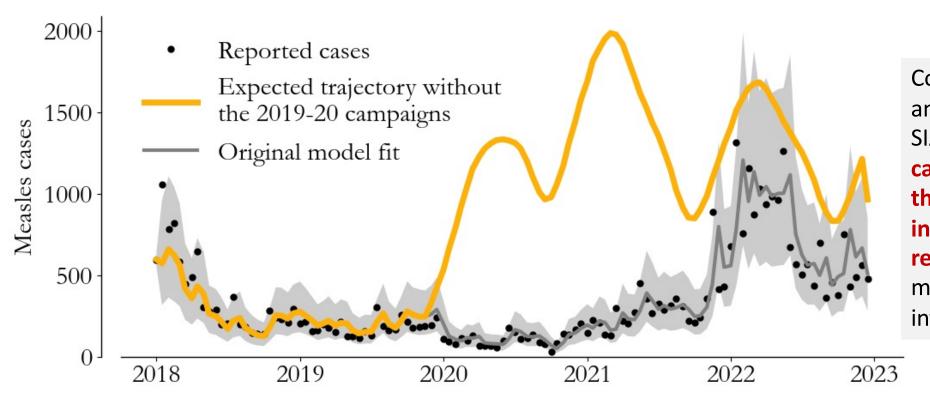






Independent SIA effects with prior information from the serosurvey gives us a more stable model with intuitive inferences.

To illustrate the importance of the 2019-2020 SIAs, we can simulate epidemics in their absence.



Comparing the model with and without the 2019-2020 SIAs, we estimate that the campaigns prevented 64 thousand (52 to 77 95% interval) measles case reports, corresponding to 1.3 million (1.1 to 1.6 95% interval) measles infections.

Examples in this block

