



A MODELLING ASSESSMENT OF THE IMPACT OF CONTROL MEASURES ON HPAI TRANSMISSION IN POULTRY IN GREAT BRITAIN

ECMTB 2026 minisymposium: Modelling avian influenza dynamics

Presenter: Ed Hill (University of Liverpool, UK)

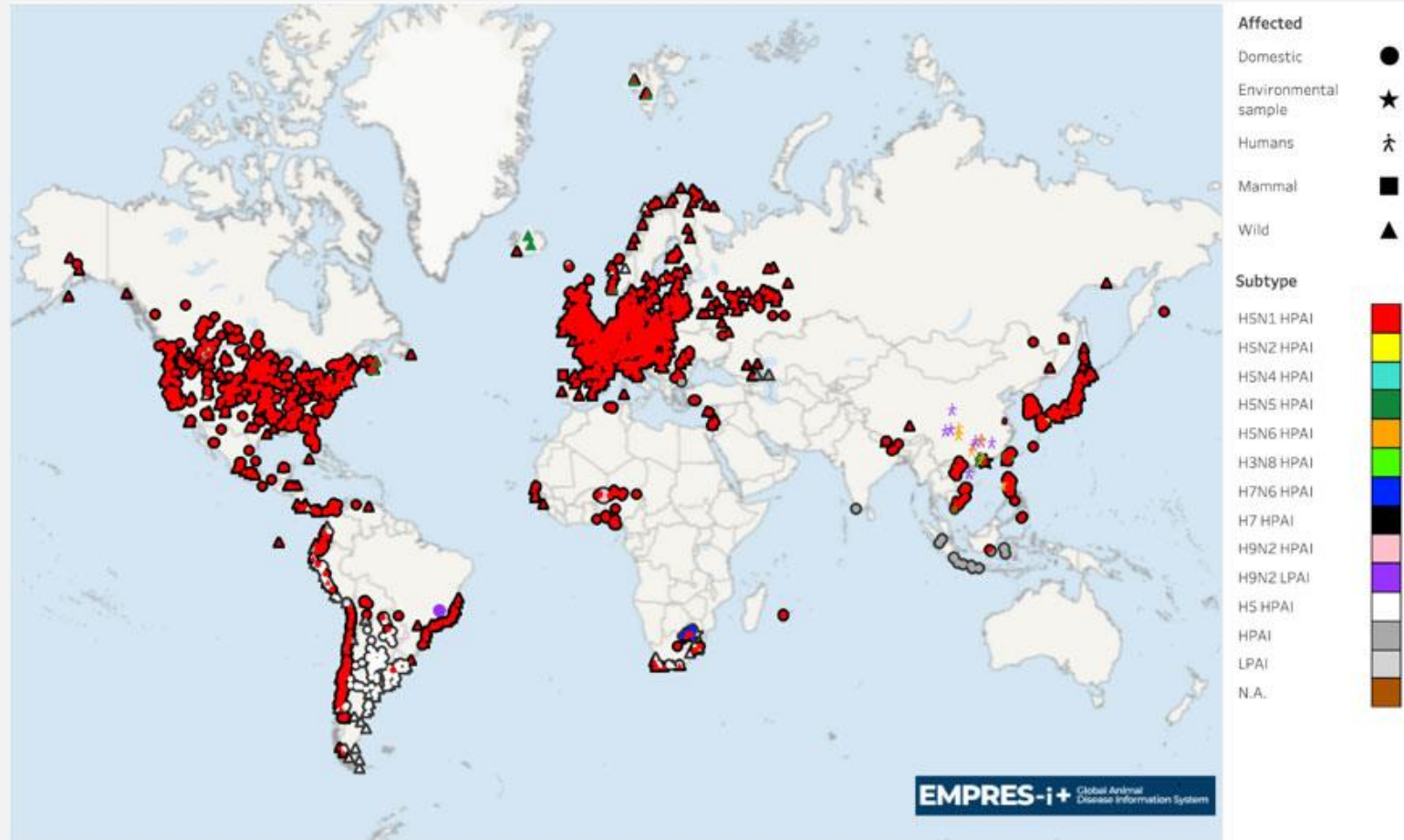
Co-authors: Chris Davis (UK Health Security Agency & University of Warwick, UK), Chris Jewell (Lancaster University, UK), Kristyna Rysava (University of Warwick, UK), Robin Thompson (University of Oxford, UK), Mike Tildesley (University of Warwick, UK).

16 July 2026



Highly Pathogenic Avian Influenza (HPAI)

- Since 2021, the emergence of H5N1 clade 2.3.4.4b has caused substantial outbreaks in both wild birds and poultry.
- Great Britain had its largest outbreak of H5N1 in the 2022–2023 season.
- HPAI has been circulating within Great Britain in the wild bird population with persistence over summer months.

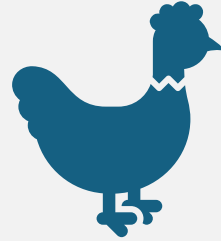


Global distribution of AIV with zoonotic potential observed in the period 1 October 2022 to 30 September 2023. Source: <https://www.fao.org/animal-health/situation-updates/global-aiv-with-zoonotic-potential/en>

Aims of this project



Create a framework to fit a mathematical model to HPAI outbreak data in poultry that could be applied to future outbreaks.



Assess the spatial risk of HPAI outbreaks in poultry and how transmission might change in time.



Investigate the potential for spread within the poultry industry.

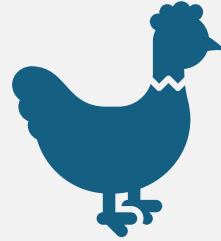


Consider the impact of potential interventions on the spread of HPAI.

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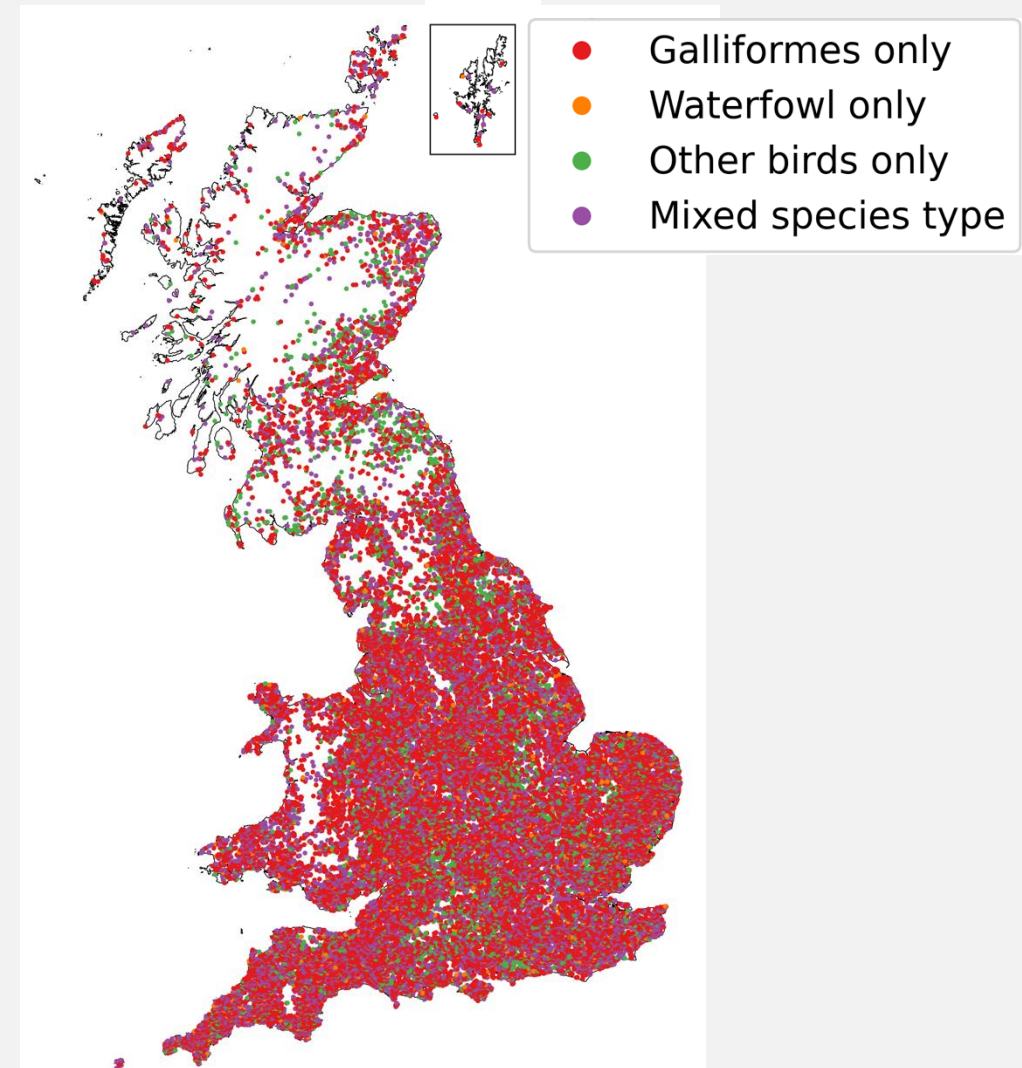
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Poultry premises of Great Britain

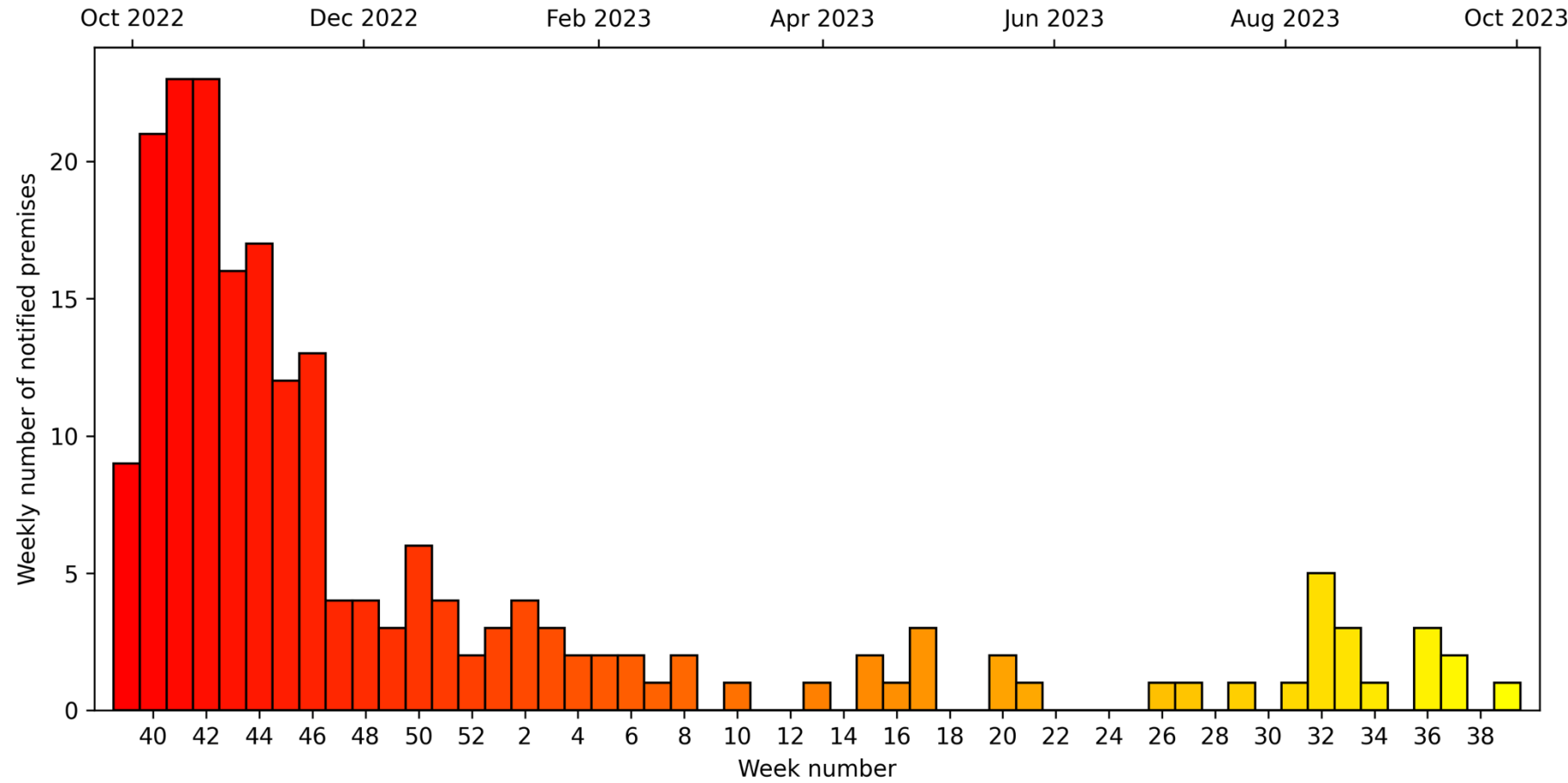
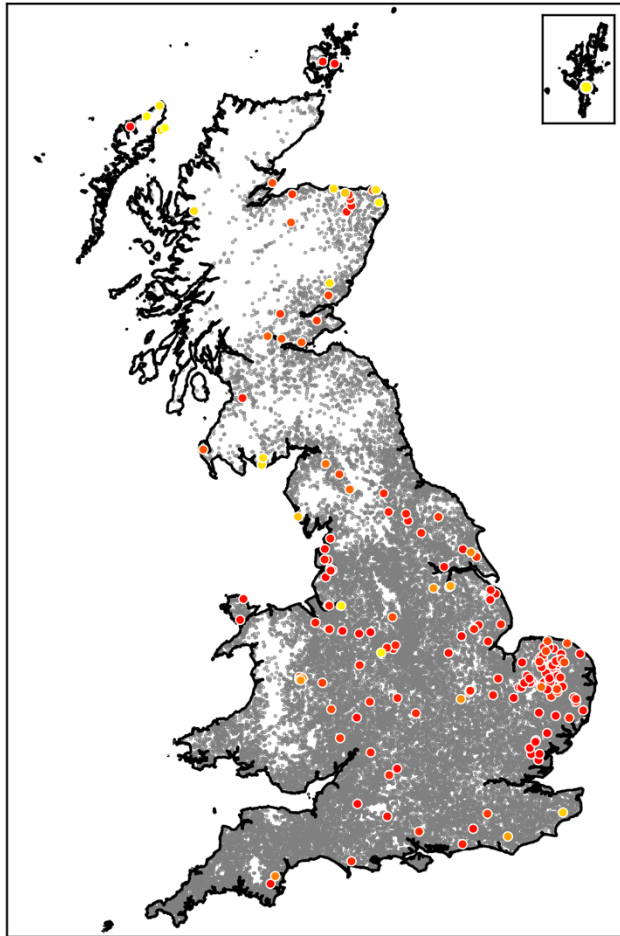
Demographic data – as registered on 01 December 2022.

Bird type	Number of premises	Number of birds
Galliformes	26 013	281.8 million
Waterfowl	1 205	4.2 million
Other	4 871	43.2 million
Mixed	12 539	N/A
Total	44 628	329.2 million

With thanks to the Animal & Plant Health Agency for provision of data.



Weekly H5N1 infected premises (2022/2023)



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Modelling approach

Epidemiological unit
Poultry premises.

H5N1 disease status

Compartmental model based on the time a premises changes infection state.

Species specific

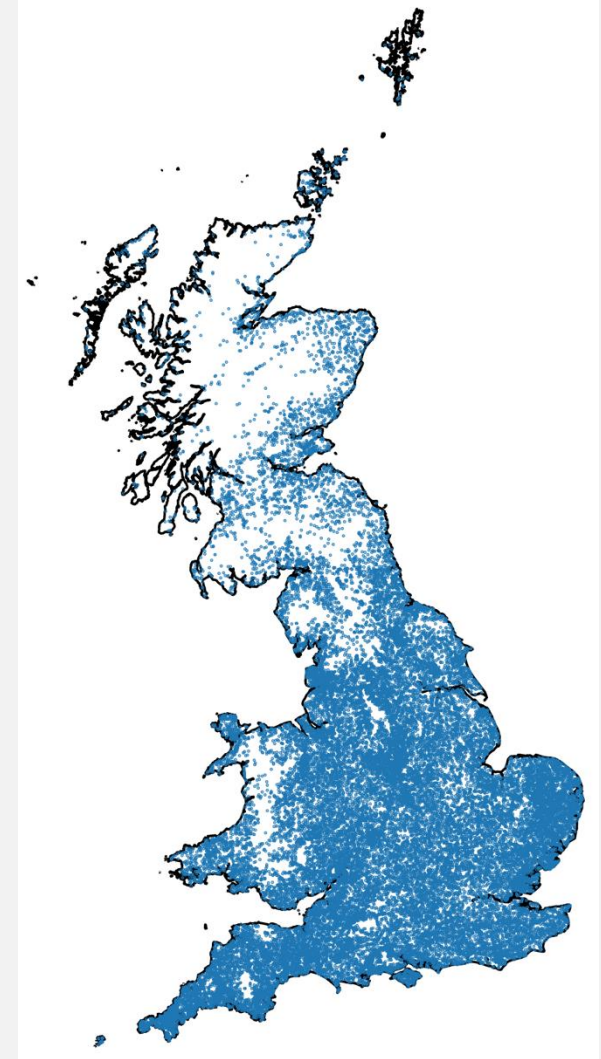
Three bird species structure.
(Galliformes, waterfowl, other)

Spatially explicit

Distance kernel in the transmission rate.

Timestep

Simulate the model in discrete time in days.



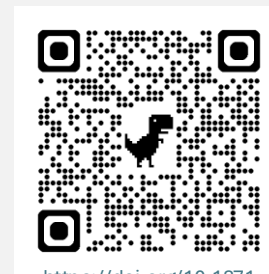
<https://doi.org/10.1371/journal.pcbi.1013874>

Modelling approach

Poultry premises:



$$\lambda_j(t) = \varepsilon(t) + \sum_{i \in \mathcal{I}(t)} \beta_{ij} + \gamma_2 \sum_{i \in \mathcal{N}(t)} \beta_{ij}$$



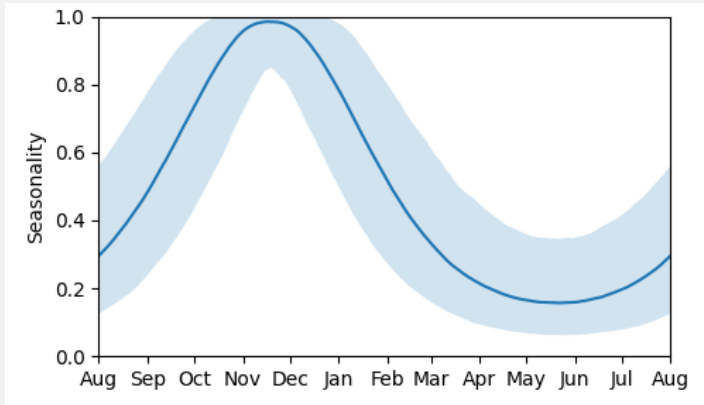
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Modelling approach

Poultry premises:



Baseline infectious pressure



$$\lambda_j(t) = \varepsilon(t) + \sum_{i \in \mathcal{I}(t)} \beta_{ij} + \gamma_2 \sum_{i \in \mathcal{N}(t)} \beta_{ij}$$



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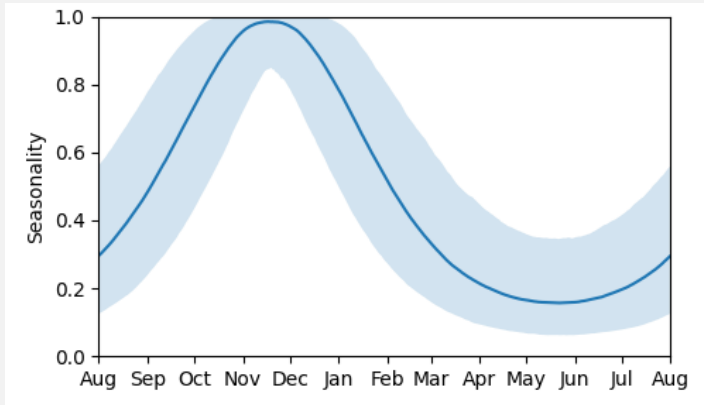
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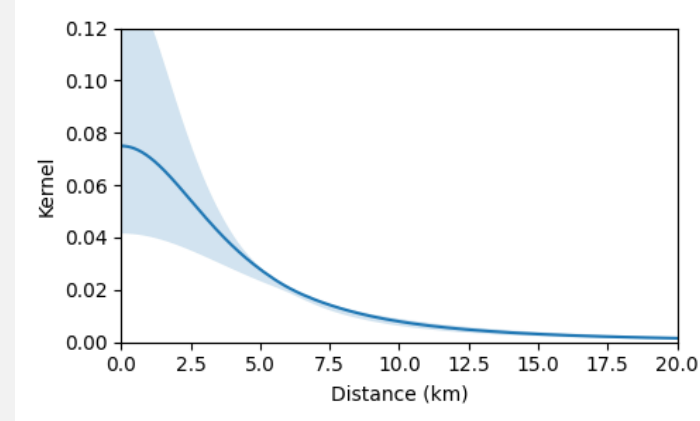
Baseline infectious pressure

Infection from infected premises

Infection from notified premises



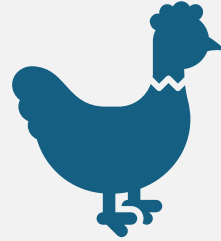
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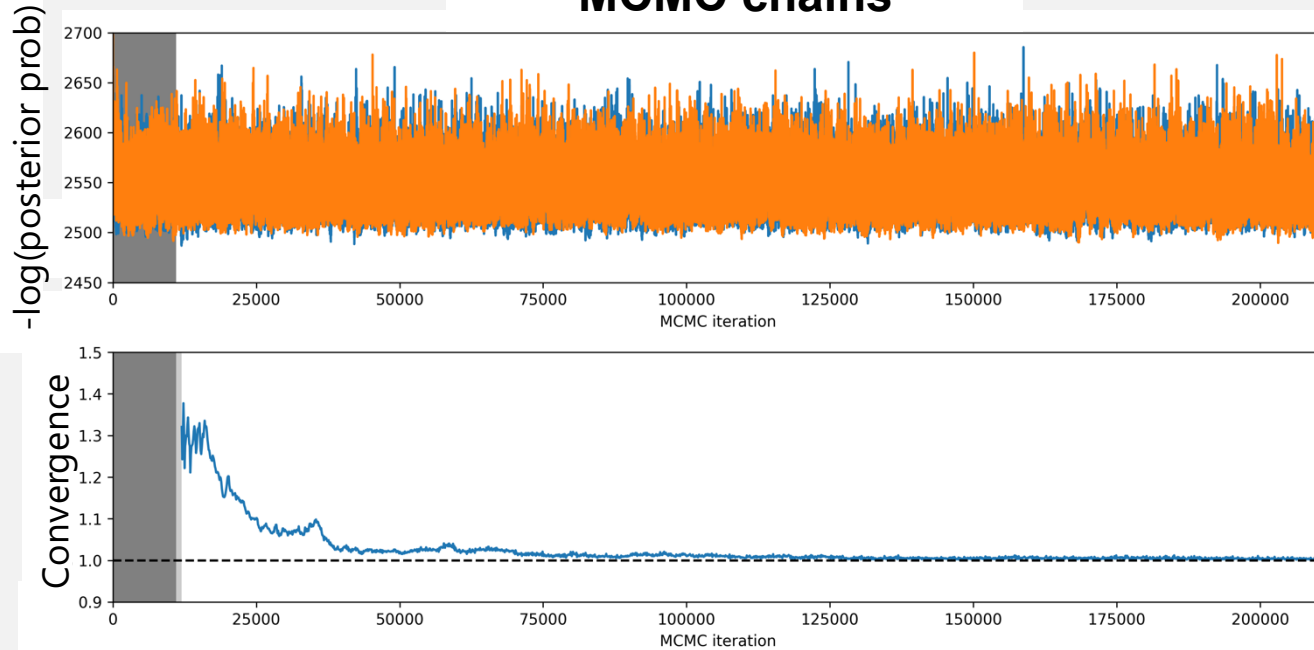
Model fitting and simulations (2022/2023)



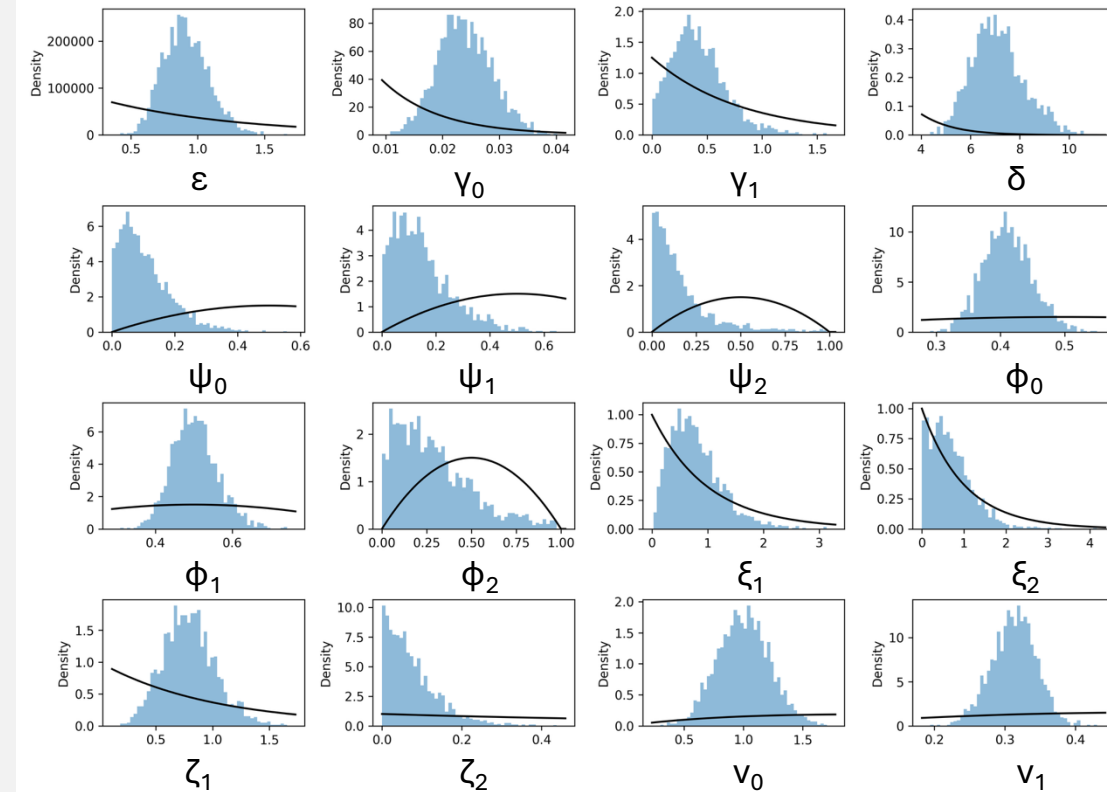
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- Used reversible-jump Markov chain Monte Carlo (MCMC) to estimate 16 model parameters plus the time to notification for each infected premises.
- We used the obtained parameter estimates to run 10,000 model simulations.

MCMC chains



Posterior parameter distributions



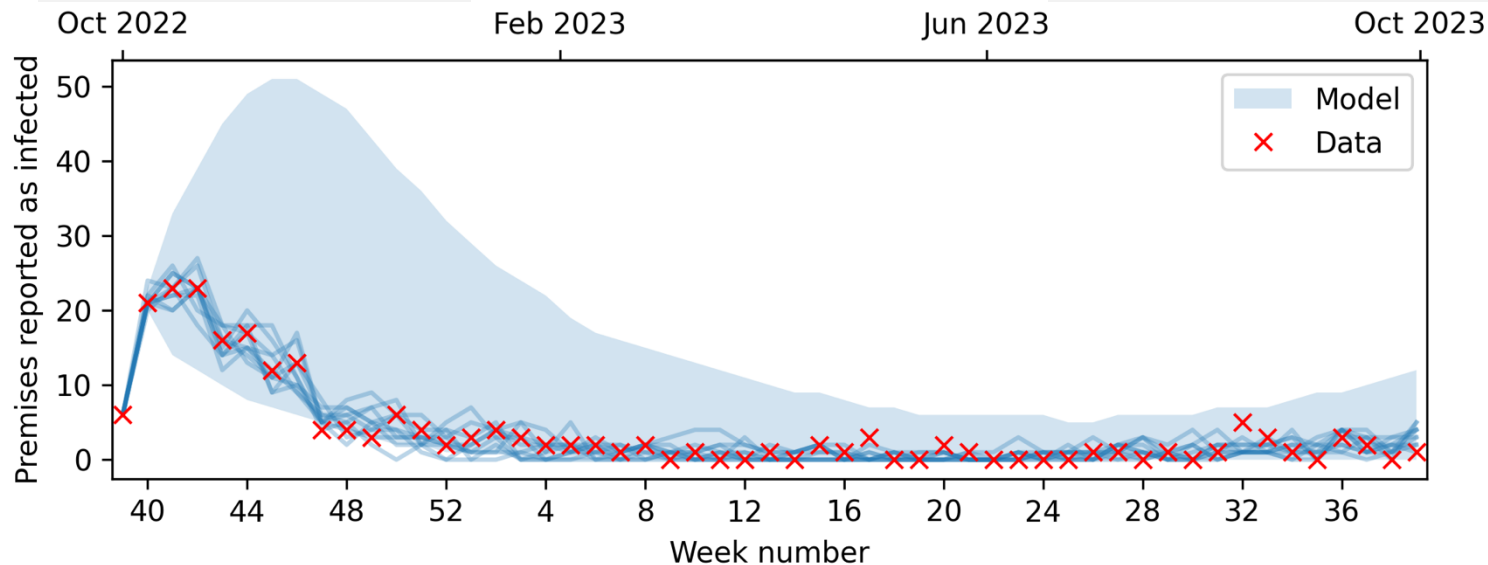
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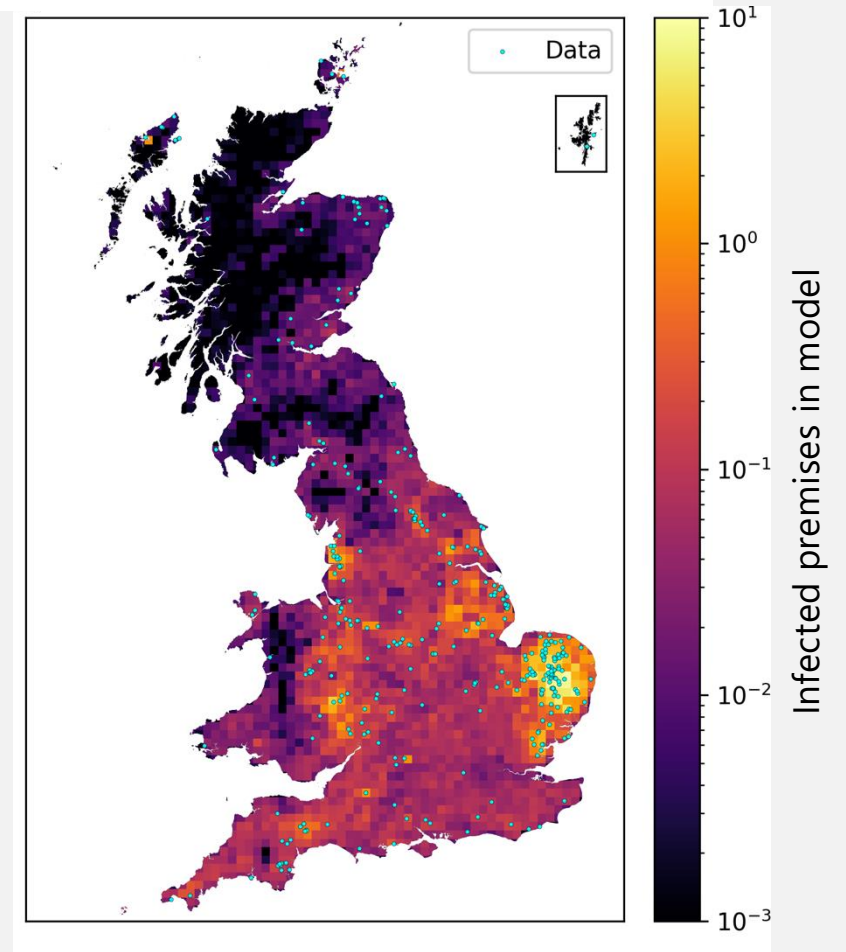
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Temporal model fit



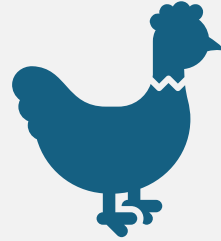
Spatial model fit



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Enhanced biosecurity



<https://doi.org/10.1371/journal.pcbi.1013874>

Enhanced biosecurity in response to local infection could include:

- Increased cleaning and disinfection,
- Reduced contamination risk for water sources, feed storage and housing,
- Reduced risk of contact with wild birds.

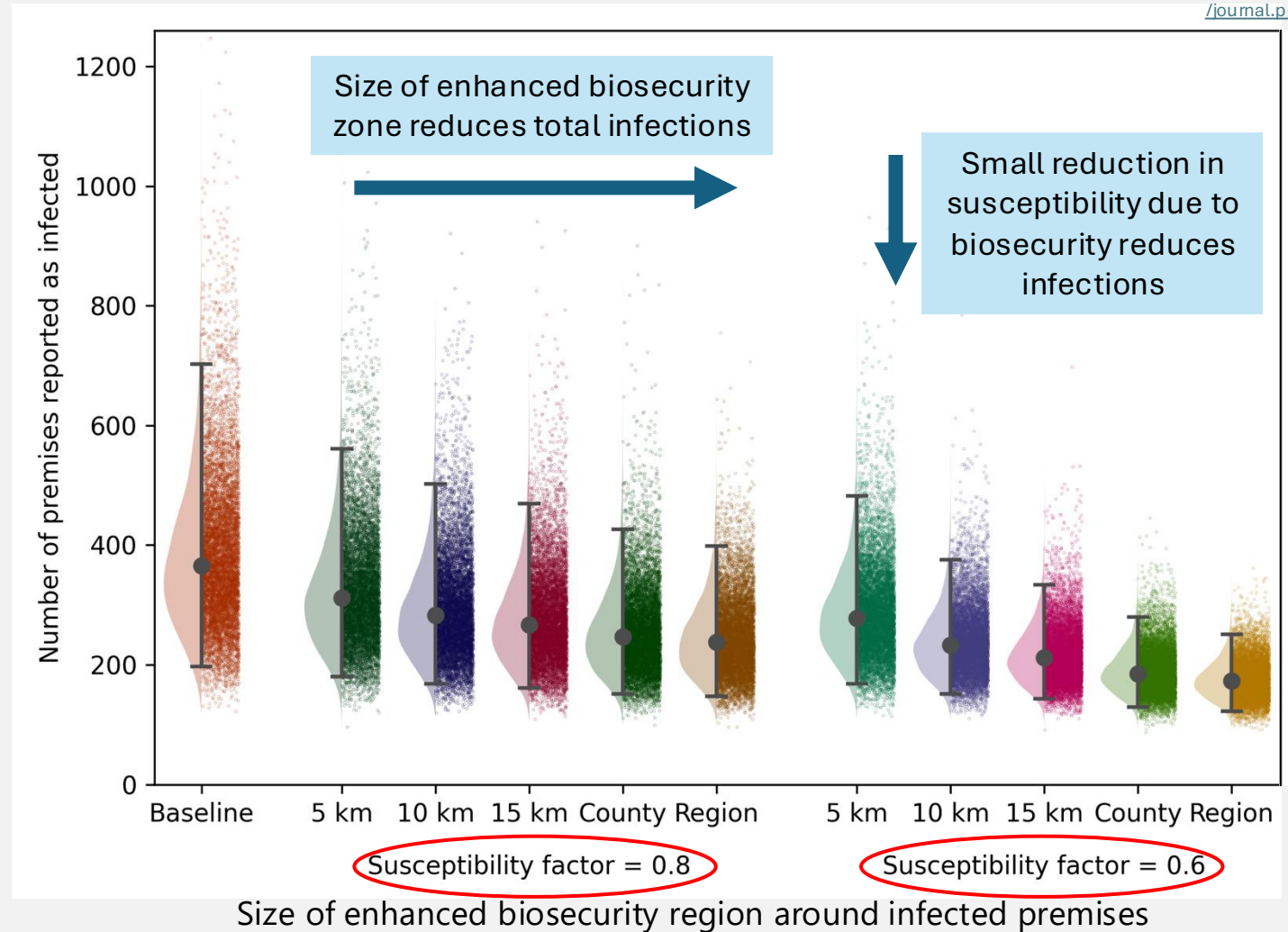
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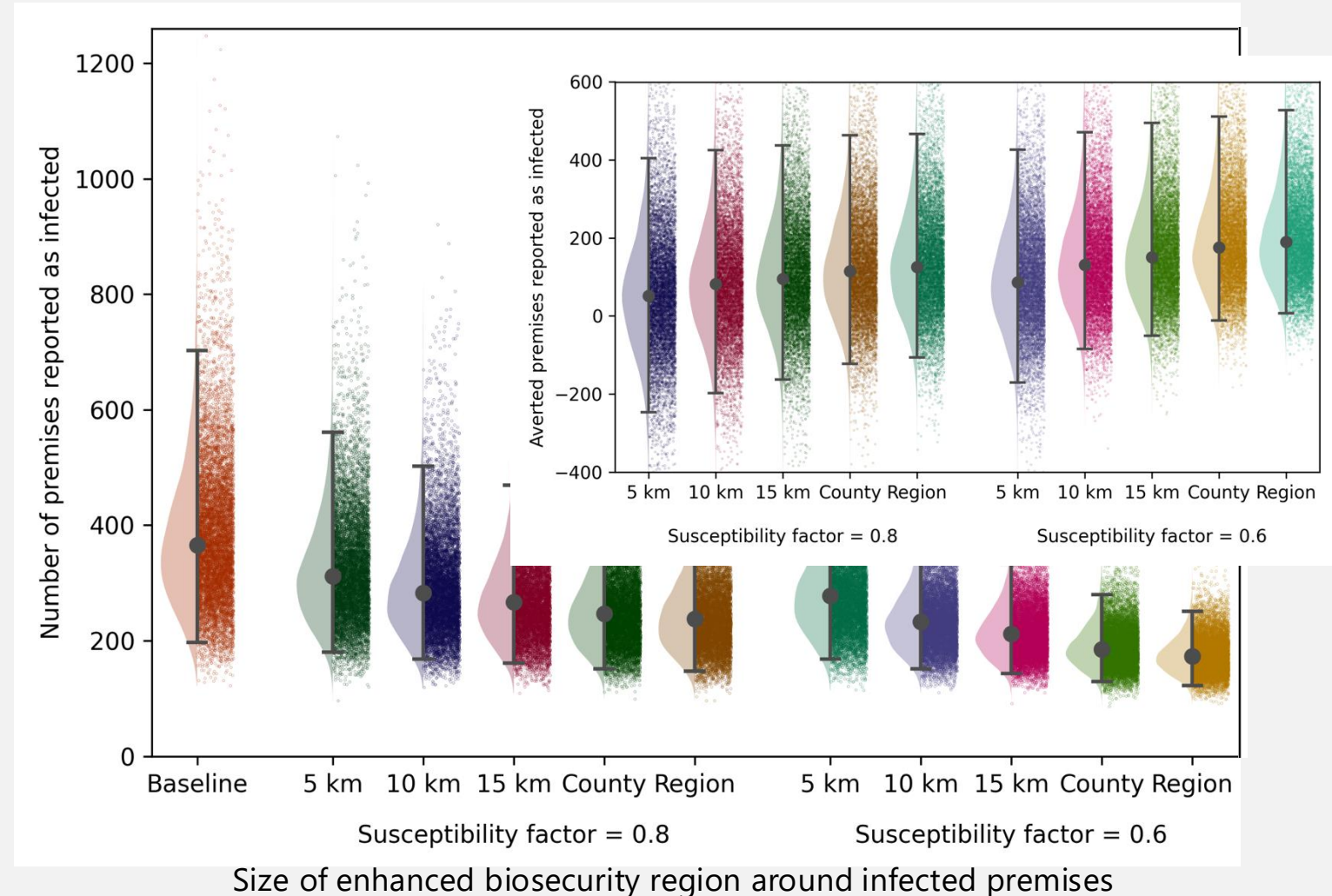


Comparing strategies



Work in progress

- Enhanced biosecurity results in a reduction of susceptibility.
- This can only result in a reduction in infections.
- The mean simulated behaviour shows positive averted infections.
- Many individual simulations show negative number of averted infections.



Sellke construction



Work in
progress

Original method:

For susceptible premises j at time t , the probability of becoming infected by time $t + \delta t$ is:

$$p_j(t) = 1 - e^{-\lambda_j(t)\delta t}.$$

Using Sellke construction:

For susceptible premises, set thresholds $z_j \sim \text{Exp}(1)$.

Premises j becomes infected at time T , the first time when $\sum_{t=0}^T \lambda_j(t)\delta t > z_j$.

Sellke construction



Work in progress

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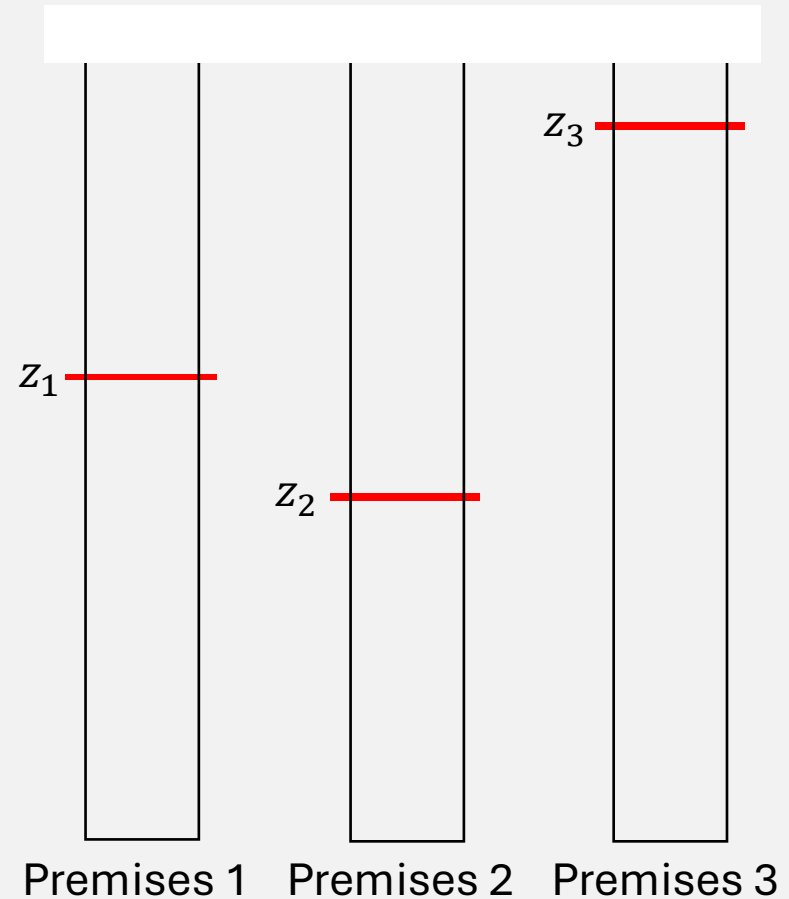
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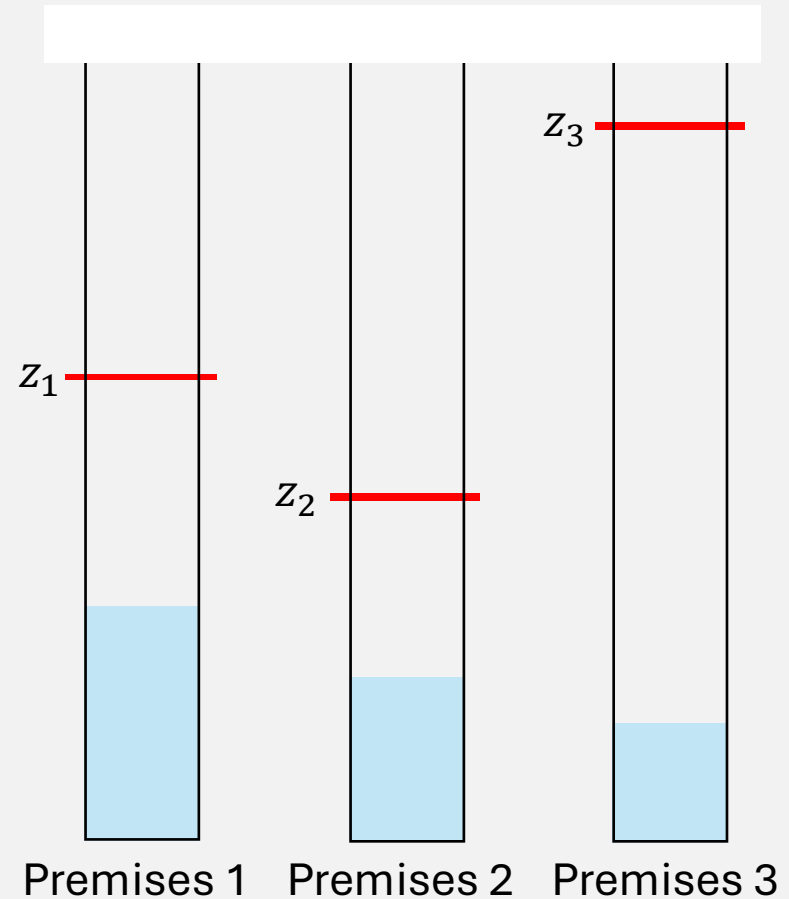
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Day 1



Sellke construction



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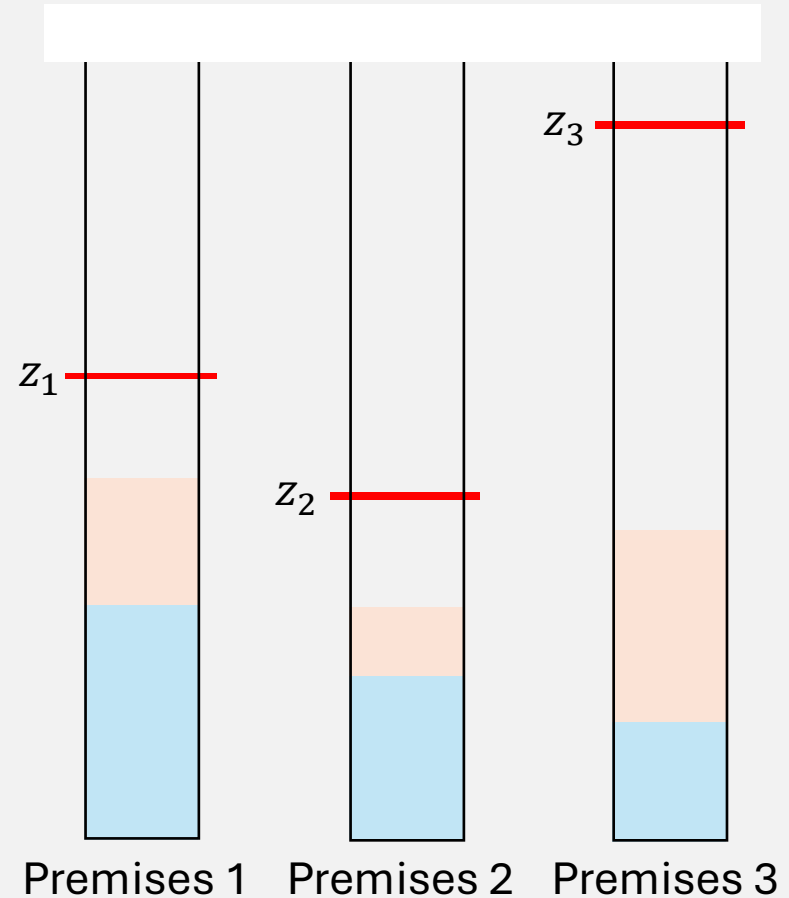
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Day 2



Sellke construction



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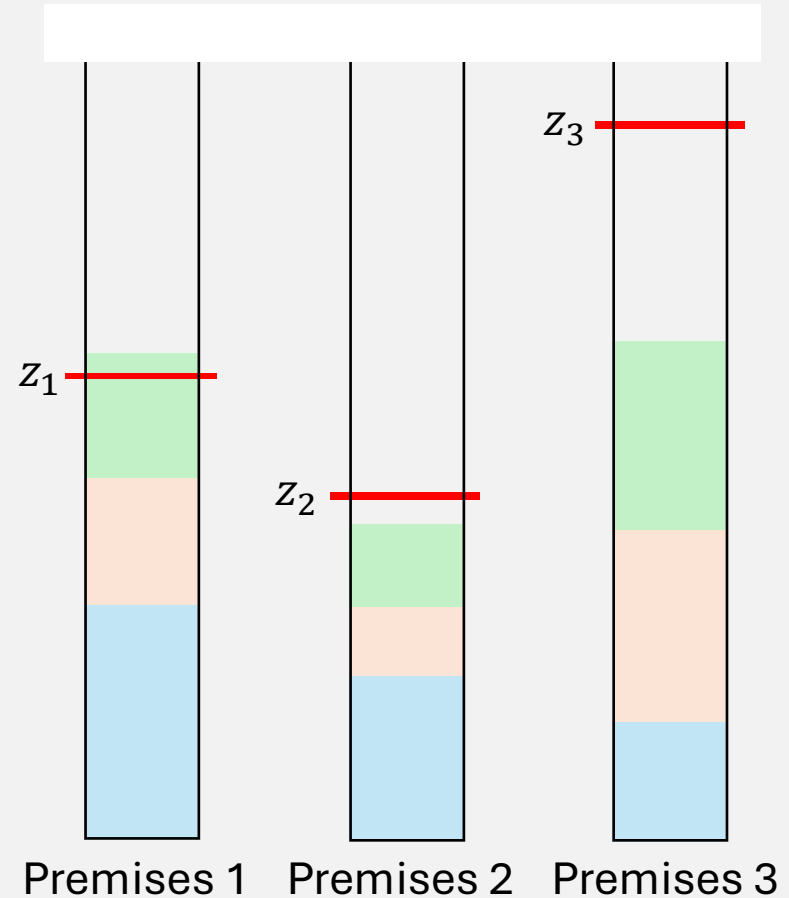
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Day 3: Premises 1 infected



Sellke construction



Work in progress

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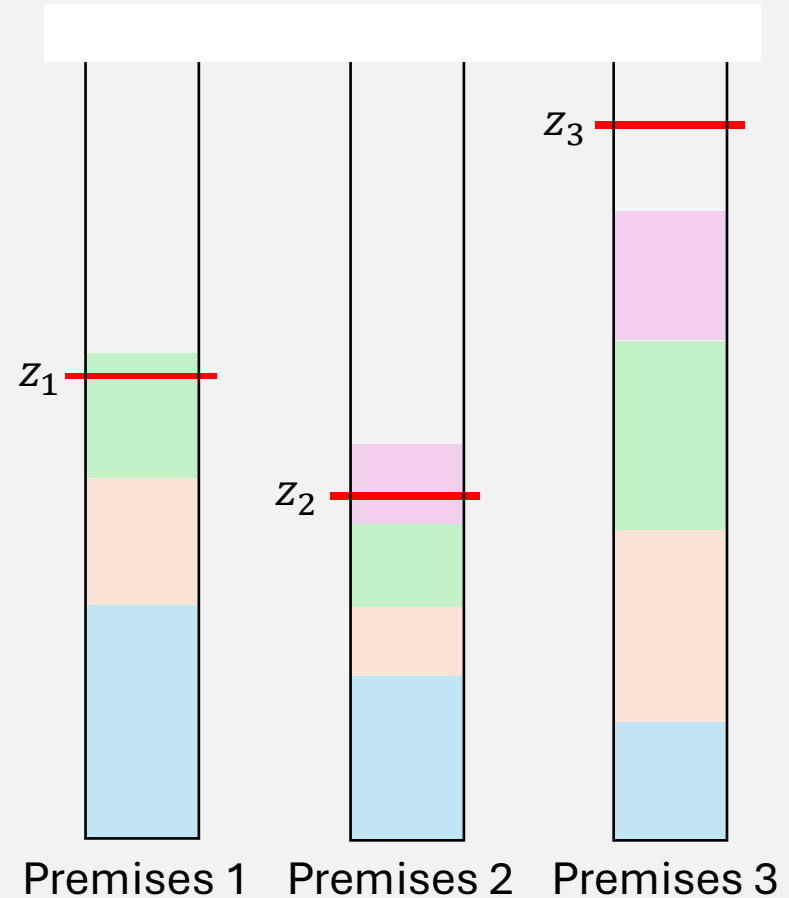
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Day 4: Premises 2 infected



Sellke construction



Work in progress

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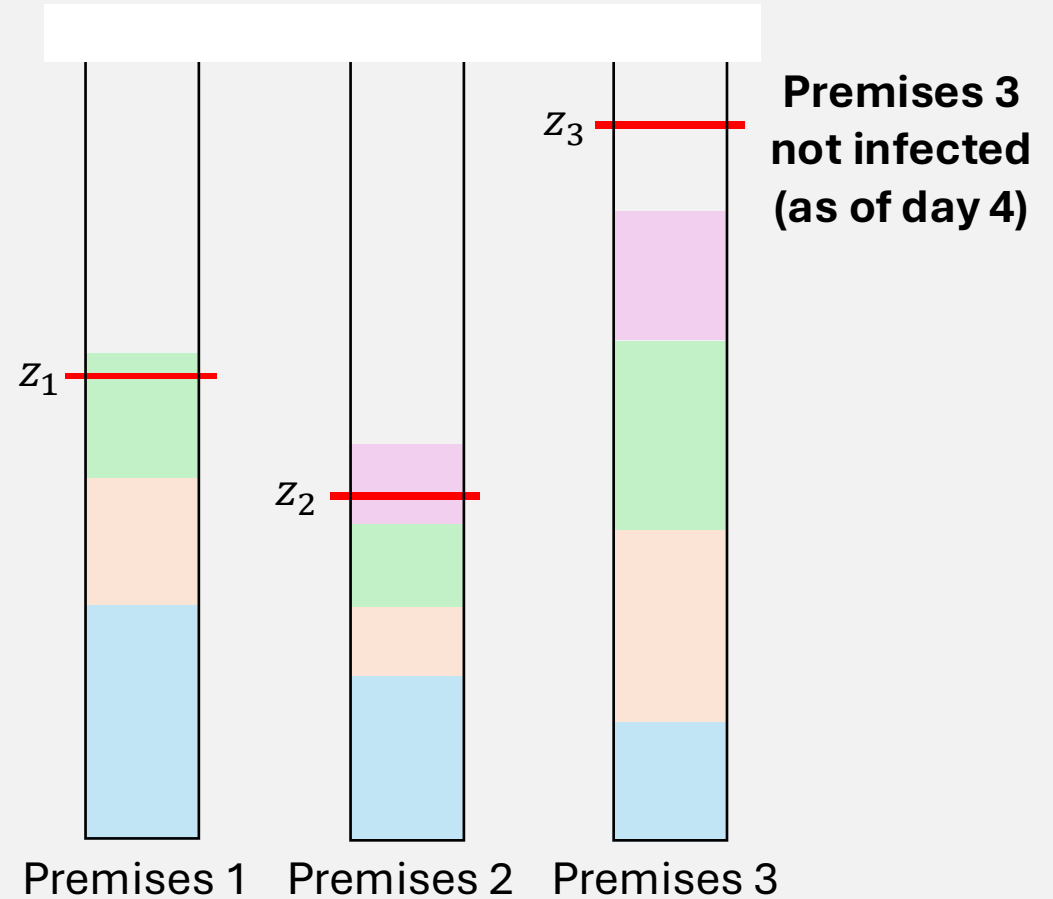
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Sellke construction



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Benefit of Sellke construction:

- 1) Algorithm encodes randomness to the values of the resistance thresholds z_j .
- 2) We can choose the same set of resistance thresholds z_j for each intervention strategy and compare simulations to the baseline.
- 3) Can measure the direct impact of the intervention, removing stochastic simulation uncertainty.

Sellke construction



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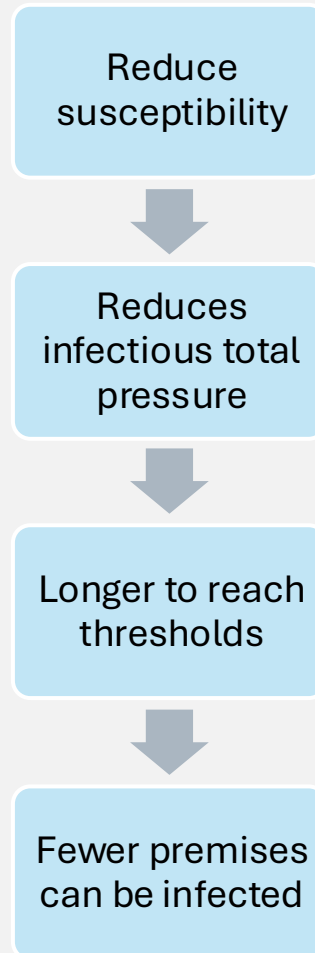
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Preventative vaccination

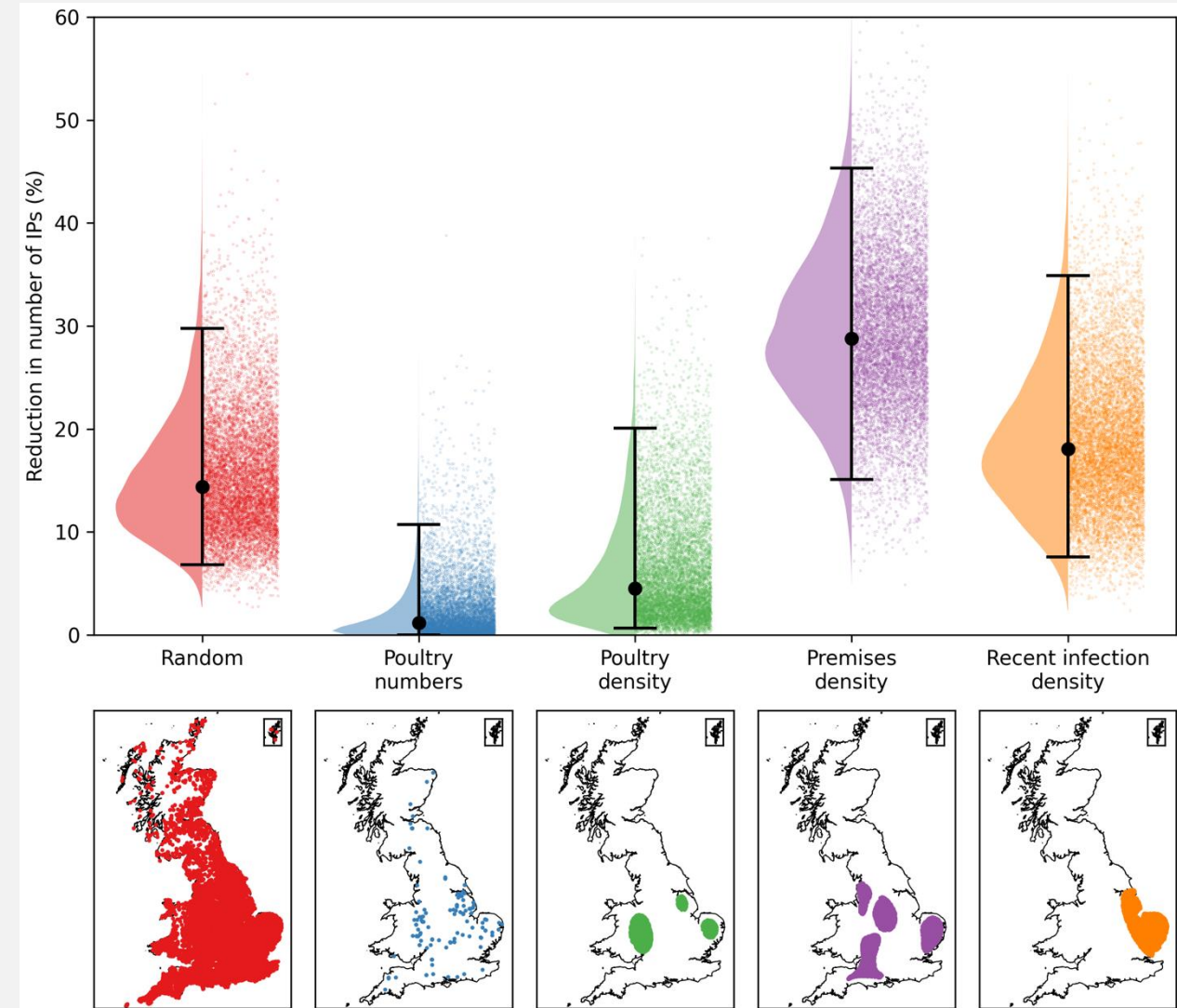


Work in progress

In the UK, use of HPAI vaccinations in poultry is not currently permitted.

The benefits of vaccination are being considered in the UK, with programmes ongoing in European countries.

- Sellke construction used to compare different preventative vaccine strategy allocations.
- The reduction in number of infections is always positive.
- With capacity of 200,000 birds being vaccinated daily, vaccinating in areas with high premises density is the most effective strategy.



Emergency responsive vaccination

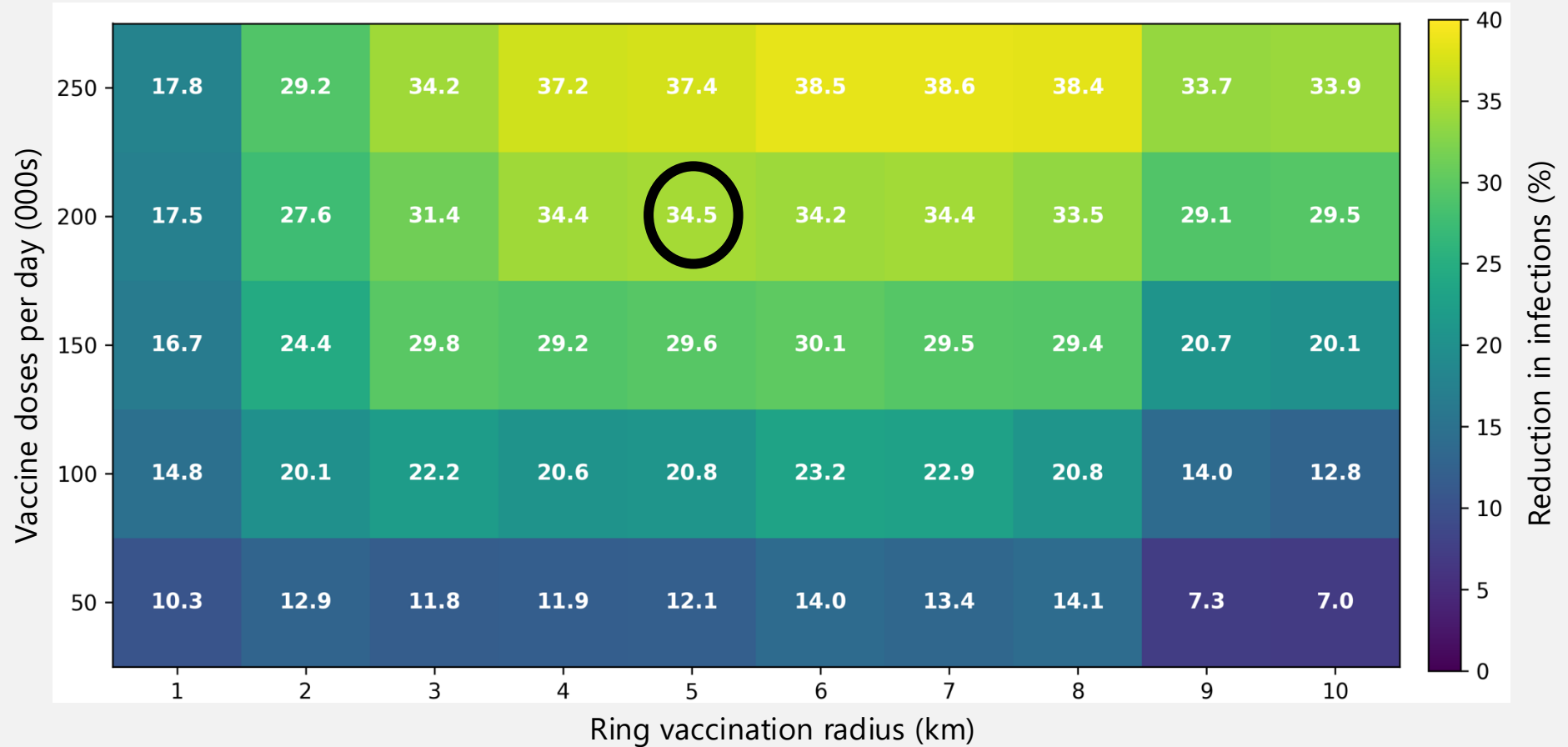


Work in progress

Ring vaccination could be used in response to infected premises.

We can determine optimal vaccination radius for a given number of doses.

For example, at 200,000 vaccine doses per day, of the tested ring vaccination radii a radius of **5km** gave the largest reduction in infections (on average).



Vaccination efficacy



Work in progress

We highlight the importance of a **robust surveillance system** and **high vaccine efficacy**.

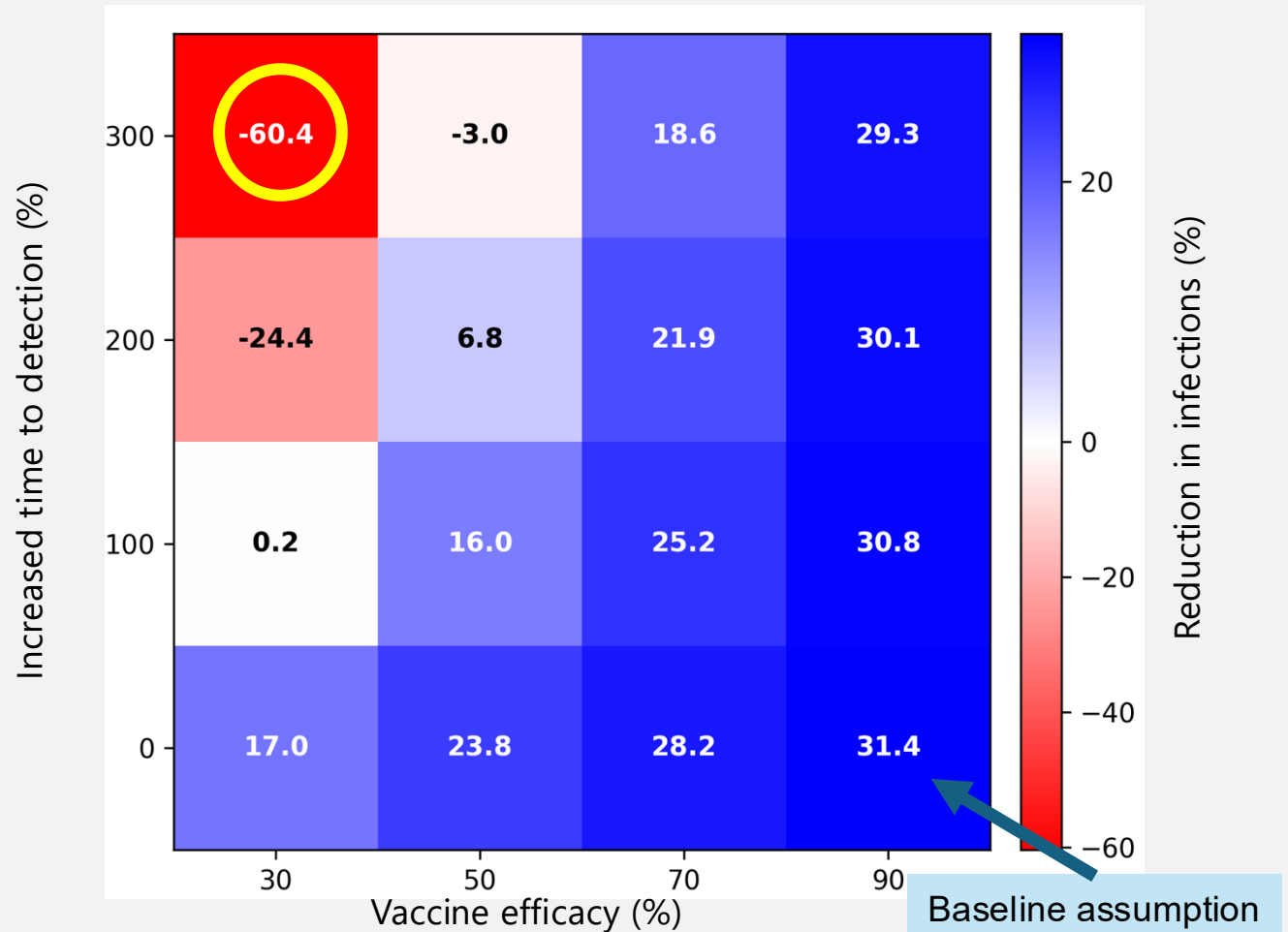
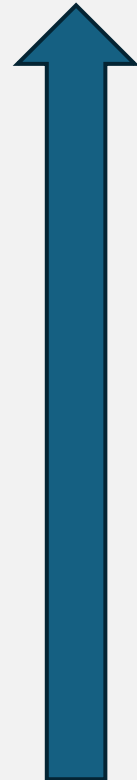
Vaccinated poultry can still become infected and transmit HPAI.

Poultry may show fewer symptoms.

This may increase time to detection for premises.

More *silent spread* may occur before detection.

Could lead to more total infections that without vaccination.



Conclusions



We constructed a spatial HPAI transmission model that was fit to 2022/2023 HPAI outbreak data in poultry in Great Britain.



We would like to investigate further the spatial heterogeneity of wild bird spillover into poultry farms and whether shared ownership of poultry farms increases the transmission risk.



Model can simulate different intervention strategies to assess their impact. Vaccination could be very beneficial reducing the number of infected premises (noting that we have not considered any costs).

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RESEARCH ARTICLE

A modelling assessment of the impact of control measures on highly pathogenic avian influenza transmission in poultry in Great Britain

Christopher N. Davis, Edward M. Hill, Chris P. Jewell, Kristyna Rysava, Robin N. Thompson, Michael J. Tildesley

Citation: Davis CN, Hill EM, Jewell CP, Rysava K, Thompson RN, Tildesley MJ (2026) A modelling assessment of the impact of control measures on highly pathogenic avian influenza transmission in poultry in Great Britain. PLoS Comput Biol 22(1): e1013874. DOI: 10.1371/journal.pcbi.1013874.

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