# Remodeling selection to optimize disease forecasts and policies

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# Background:

### **When variation in susceptibility is accounted for…**

- estimated reproduction numbers are higher
- predicted impact of uniform control measures is lower

#### **SI model and selective depletion bias:**

$$
\frac{dS(x)}{dt} = q(x)\mu - \beta \int I(u)du\,xS(x) - \mu S(x), \qquad \frac{dI(x)}{dt} = \beta \int I(u)du\,xS(x) - \mu I(x), \qquad \mathcal{R}_0 = \frac{\beta}{\mu}
$$



MGMG, AM Blagborough, KE Langwig, B Ringwald 2024 Remodelling selection to optimise disease forecasts and policies. *J Phys A: Math Theor 57*:103001.

$$
\frac{dS(x)}{dt} = -\beta \int I(u) du xS(x), \qquad \frac{dI(x)}{dt} = \beta \int I(u) du xS(x) - \gamma I(x), \qquad \mathcal{R}_0 = \frac{\beta}{\mu}
$$



# This talk:

### **Variation in susceptibility can be estimated by remodeling selection when…**

- observational data can be stratified over selection gradients
- experimental data can be generated over selection gradients

# Observational data stratified by region:







### **SI metapopulation model:**

$$
\frac{dS_{A1}}{dt} = (1 - q_A)\mu - \beta(I_{A1} + I_{A2})\alpha_1 S_{A1} - \mu S_{A1}
$$
  
\n
$$
\frac{dI_{A1}}{dt} = \beta(I_{A1} + I_{A2})\alpha_1 S_{A1} - \mu I_{A1}
$$
  
\n
$$
\frac{dS_{A2}}{dt} = q_A \mu - \beta(I_{A1} + I_{A2})\alpha_2 S_{A2} - \mu S_{A2}
$$
  
\n
$$
\frac{dI_{A2}}{dt} = \beta(I_{A1} + I_{A2})\alpha_2 S_{A2} - \mu I_{A2}
$$

$$
\mathcal{R}_{0A} = \left[ (1 - q_A)\alpha_1 + q_A \alpha_2 \right] \frac{\beta}{\mu}
$$

$$
1 - q_A
$$
\n
$$
q_A
$$
\n
$$
\alpha_1
$$
\n
$$
\alpha_2
$$
\n
$$
\alpha_1
$$
\n
$$
\alpha_2
$$

$$
\frac{dS_{B1}}{dt} = (1 - q_B)\mu - \beta(I_{B1} + I_{B2})\alpha_1 S_{B1} - \mu S_{B1}
$$
  
\n
$$
\frac{dI_{B1}}{dt} = \beta(I_{B1} + I_{B2})\alpha_1 S_{B1} - \mu I_{B1}
$$
  
\n
$$
\frac{dS_{B2}}{dt} = q_B\mu - \beta(I_{B1} + I_{B2})\alpha_2 S_{B2} - \mu S_{B2}
$$
  
\n
$$
\frac{dI_{B2}}{dt} = \beta(I_{B1} + I_{B2})\alpha_2 S_{B2} - \mu I_{B2}
$$

$$
\mathcal{R}_{0B} = \left[ (1 - q_B)\alpha_1 + q_B \alpha_2 \right] \frac{\beta}{\mu}
$$



$$
Q = (1 - Q)q_A + Qq_B
$$
  
\n
$$
\mathcal{R}_0 = (1 - Q)\mathcal{R}_{0A} + Q\mathcal{R}_{0B} = \frac{\beta}{\mu}
$$
  
\nMean( $\alpha$ ) = (1 - Q) $\alpha_1$  +  $Q\alpha_2$  = 1  
\nVar( $\alpha$ ) = (1 - Q)( $\alpha_1$  - 1)<sup>2</sup> +  $Q(\alpha_2$  - 1)<sup>2</sup>



### **Endemic equilibrium:**

$$
\frac{\alpha_1(1-q_A)}{\beta I_A \alpha_1 + \mu} + \frac{\alpha_2 q_A}{\beta I_A \alpha_2 + \mu} = \frac{1}{\beta}
$$

$$
\frac{\alpha_1(1-q_B)}{\beta I_B \alpha_1 + \mu} + \frac{\alpha_2 q_B}{\beta I_B \alpha_2 + \mu} = \frac{1}{\beta}
$$



Given  $I_A$  and  $I_B$ **the inverse problem can be solved exactly given the proportion high risk in one** 



0 0.05 0.1 0.15

 $_{A} = 0.3$ 

 $I_B = 0.5$ 

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**A classical metapopulation model would overpredict the impact of an intervention that uniformly reduces susceptibility, such as a vaccine**

## Vaccine trials (low efficacy under high exposure):





$$
\frac{dS_v}{dt}(x) = -\sigma \lambda x S_v(x) + \gamma (q(x) - S_v(x)),
$$
\n
$$
\frac{dI_v}{dt}(x) = \sigma \lambda x S_v(x).
$$

MGMG, SB Gordon, DG Lalloo 2016 Clinical Trials: The mathematics of falling vaccine efficacy with rising disease incidence. *Vaccine* 34:3007.

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# Dose-response infection experiments:

Fish (trout) **Fruit flies** B 1.0 A - Het Controls<br>- - Hom Controls 0.8 distribution of  $0.9$ mortality Proportion Infected<br>
<u>့</u><br>
့် **Wolbachia effects**  $\sim$  Control 0.6  $q(x)$  $\bullet$  Vaccine  $0.4$  $0.2$  $\overline{2}$  $0.0$  $10^4$   $10^5$   $10^6$   $10^7$   $10^8$   $10^9$   $10^{10}$  $0.0$  $0.2$ 0.4 0.6 0.8 1.0 susceptibility, x  $0.0$ dose **Mosquitoes**  $\phi'_\lambda$  $\varphi_{\rho_{\mathcal{I}}}$ **Exposure Concentration** 1.5 А  $B$   $60$ proportion infected  $0.8$ distribution of distribution of 0.75 Wolbachia effects  $0.6$ density vaccine effects  $0.4$  $\widehat{\mathfrak{S}}$  0.50 Ś, **Best fit neremeters**  $a$ pe = 1.53, rate = 1.56 0.5  $0.2$  $0.25$  $0 10<sup>9</sup>$  $0.5$  $10<sup>6</sup>$  $10<sup>7</sup>$  $10^8$  $1.5$  $10<sup>4</sup>$  $10^{5}$  $\mathbf{0}$  $0.00$  $0.50$  $\overline{0.00}$  $0.25$  $0.75$ susceptibility dose (TCID50) p, natural IHNV susceptibility x, susceptibility from vaccination

KE Langwig *et al* 2017 *mBio* 8:e00796-17. KE Langwig *et al* 2019 *Sci Rep* 9:3203.

D Pessoa *et al* 2014 *PLOS Comput Biol* 10:e1003773. JG King *et al* 2018 *Nat Commun* 9:1483.

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# Summary:

- "Selective depletion bias" applies generally when the population mean value of a trait (such as susceptibility) changes over time or across environments due to selective depletion of the frailest (most susceptible) individuals, and this is misinterpreted as individuals (rather than population composition) changing.
- "Remodeling selection" is a novel approach (method) to infer unobserved variation from its effects on observational or experimental data collected over selection gradients.