

Large scale transmission experiment reveals substantial genetic variation in both host susceptibility and infectivity affecting disease spread and survival

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Reducing pathogen transmission is paramount for planetary health



Image: freepik.com. Design by Mali Welch

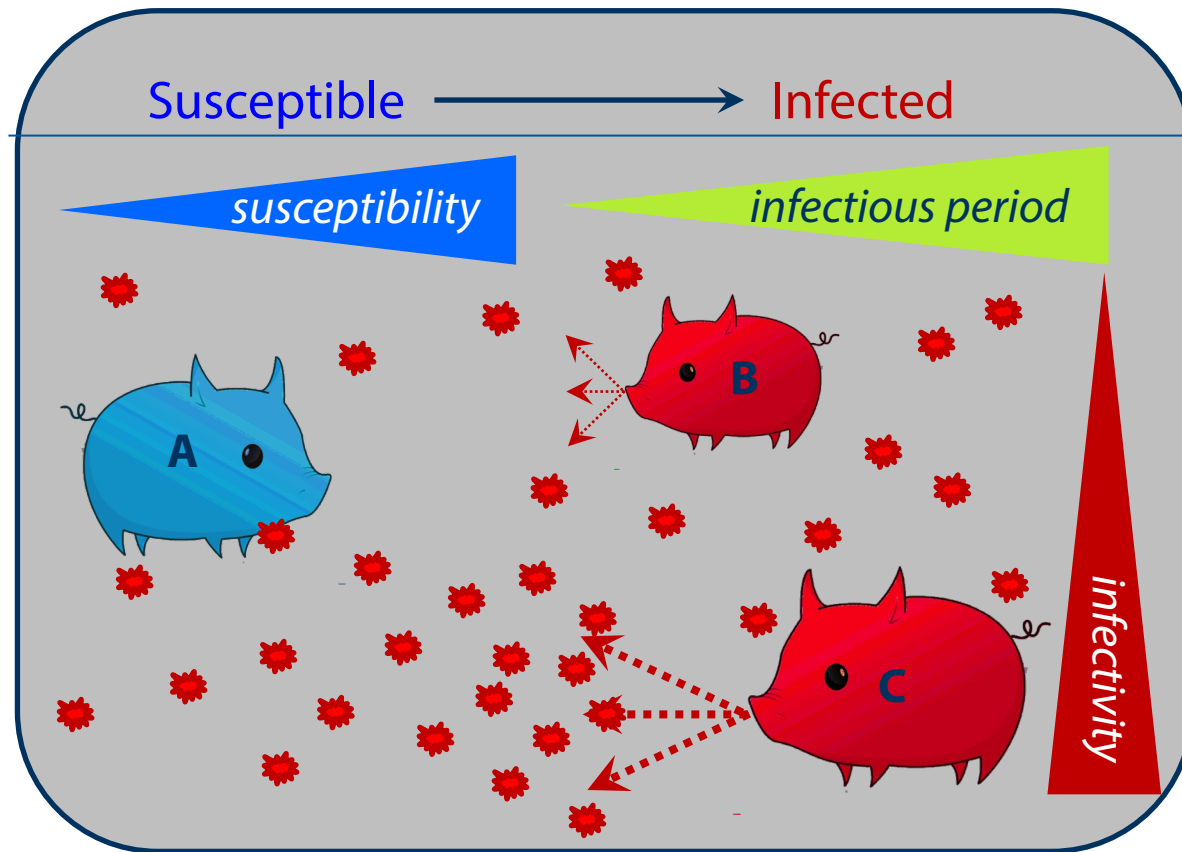
Epidemiological approach:
reduce $R_0 < 1$

Can geneticists help?

How to detect and estimate
genetic variation in host
ability to transmit infection?

Host traits affecting disease transmission

R_0 : expected number of secondary infections caused by 1 **infectious** individual in a **susceptible** population over its infectious lifetime



Susceptibility:

Propensity to acquire infection

Infectivity:

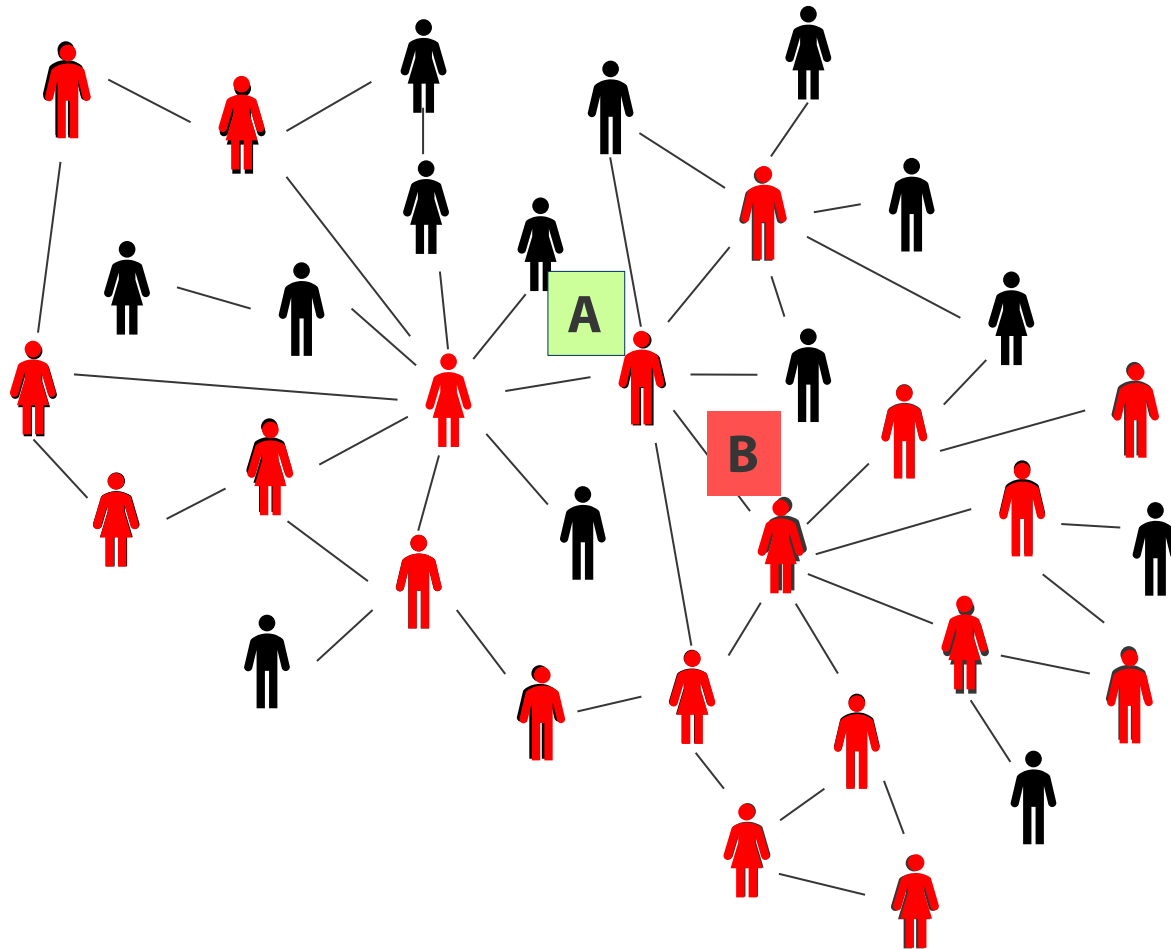
Propensity to transmit infection

Duration of infectious period:

- Related to tolerance (propensity to recover / die)

Latent traits; confounded

How to estimate genetic variation susceptibility, infectivity & tolerance



Data:

- Proxies of individuals' infection times
- From many epidemics

Models that represent infection dynamics

Inference methods that can handle uncertainty

Case study: Scuticociliatosis in Turbot



Skin infection in turbot caused by protozoan *P. Dienterarchi*

- Good genetic model:
 - Easy to create many large full / half-sib families
 - Evidence for genetic variation in resistance

- Good infection model:
 - Possible to generate many independent epidemics with moderate mortality
 - Easy to identify infected fish through visual inspection

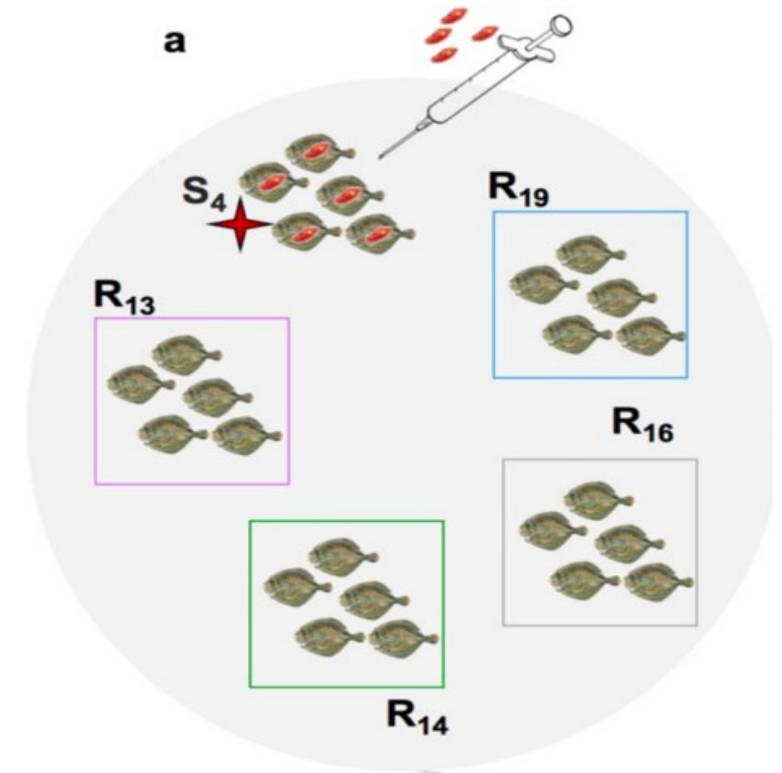


Experimental design

- 1800 fish (60 full-sib families) distributed into 72 isolated tanks (36 per trial)
- 25 fish/tank
 - Epidemics seeded by 5 **seeder fish** from 1 family
 - 20 susceptible **contact fish** from 4 families
- Family composition in each tank optimised for disentangling susceptibility and infectivity

Data (per fish)

- Time of onset of symptoms and death (censored)
- Weight at start of trial, Infection status at start & end
- RAD-seq data (17,690 SNPs) of 1400 fish, imputed to >1.2 Mio SNPs using WGS data of parents



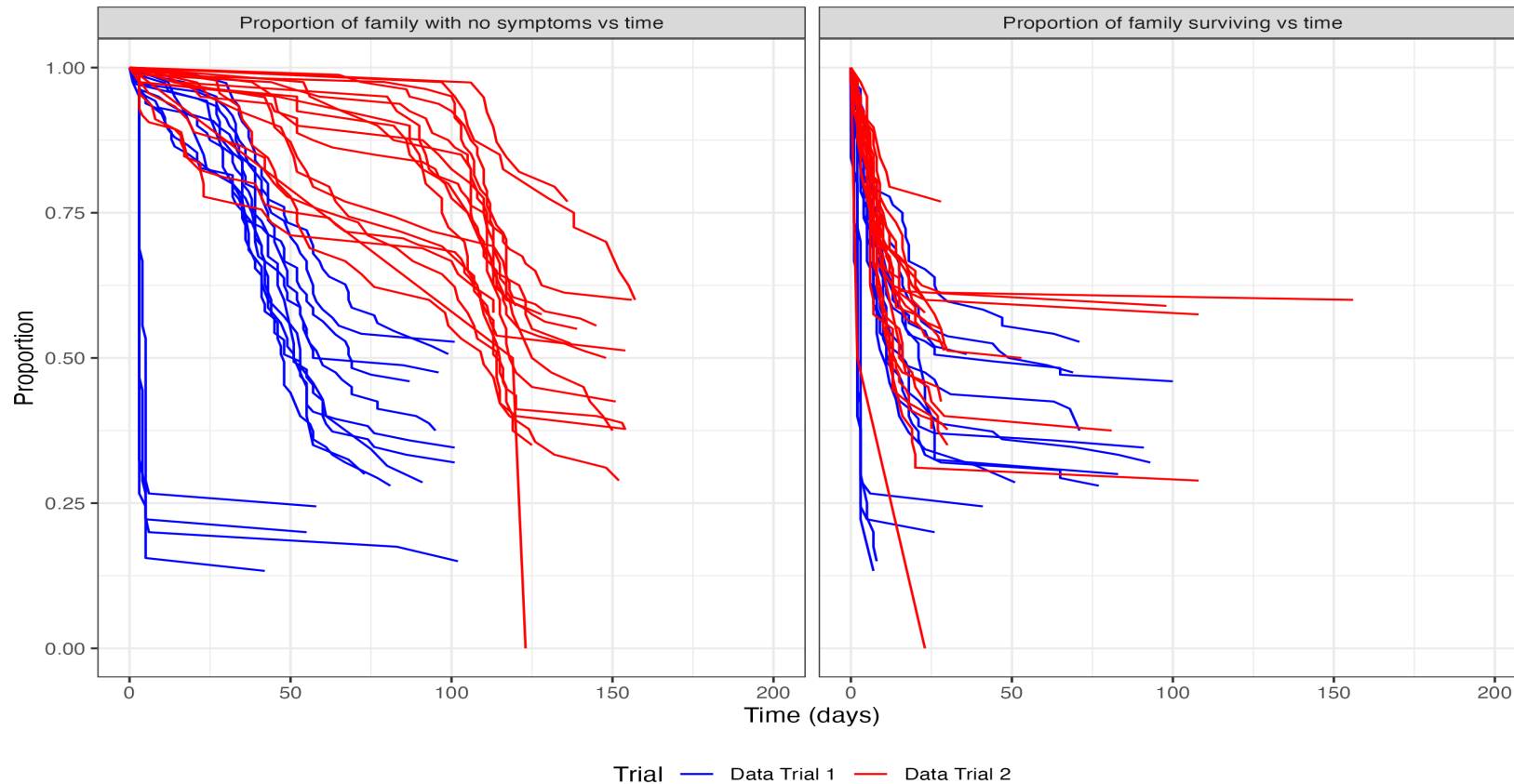
Anacleto et al., Sci Rep. 2019; Saura et al., Front. Gene. 2019.

Kriaridou, Optimizing genotype imputation..., PhD thesis, 2024

Infection and survival profiles per family

Time to onset of symptoms

Time from symptoms to death





Inferring genetic parameters & SNP effects for susceptibility, infectivity & tolerance: SIRE software



Inference Tools for Epidemiological Analysis and Modelling

- › Home
- › BICI
- › SIRE
- › SIRE-PC
- › Contact

Susceptibility, Infectivity and Recoverability Estimation

In the era of rapid expansion of the human population with increasing demands on food security, effective solutions that reduce the incidence and impact of infectious diseases in plants and livestock are urgently needed. Even within a species hosts differ widely in their response to infection and therefore also in their relative contribution to the spread of infection within and across populations. Three key epidemiological host traits affect infectious disease spread: susceptibility (propensity to acquire infection), infectivity (propensity to pass on infection to others) and recoverability (propensity to recover quickly). Disease control strategies aimed at reducing disease spread may, in principle, target improvement in any one of these three traits.



(Manual)



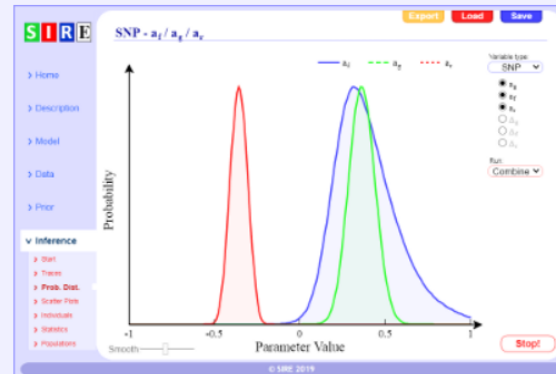
(Linux)



(Mac)



(Windows)



Illustrative screenshots - SIRE features an easy to use point and click interface that facilitates data input and displays a variety of output visualisations that aid interpretation of the results.

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SIRE: Susceptibility-Infectivity-Recoverability Estimation

- Bayesian (MCMC based) inference

¹ <https://github.com/theiTEAM/SIRE1.0>

² <https://github.com/theiTEAM/SIRE2.0>

¹ Pooley et al., *PloS Comp. Biol.* 2020;

² Pooley et al., under review 2024

Genetic model for the 3 epidemiological host traits

Susceptibility $\mathbf{g} = \mathbf{X}\mathbf{b}_g + \mathbf{a}_g + \boldsymbol{\varepsilon}_g$

Infectivity $\mathbf{f} = \mathbf{X}\mathbf{b}_f + \mathbf{a}_f + \boldsymbol{\varepsilon}_f$

Tolerance $\mathbf{r} = \mathbf{X}\mathbf{b}_r + \mathbf{a}_r + \boldsymbol{\varepsilon}_r$

Fixed effects:

Mode of infection (injection or contact),
trial, weight at start

$$\begin{pmatrix} \mathbf{a}_g \\ \mathbf{a}_f \\ \mathbf{a}_r \end{pmatrix} \sim \text{MVN}(0, \mathbf{A} \otimes \boldsymbol{\Omega})$$

↑
H-matrix constructed
from sequence &
pedigree data

$$\boldsymbol{\Omega} = \begin{pmatrix} \Omega_{gg} & \Omega_{gf} & \Omega_{gr} \\ \Omega_{gf} & \Omega_{ff} & \Omega_{fr} \\ \Omega_{gr} & \Omega_{fr} & \Omega_{rr} \end{pmatrix}$$

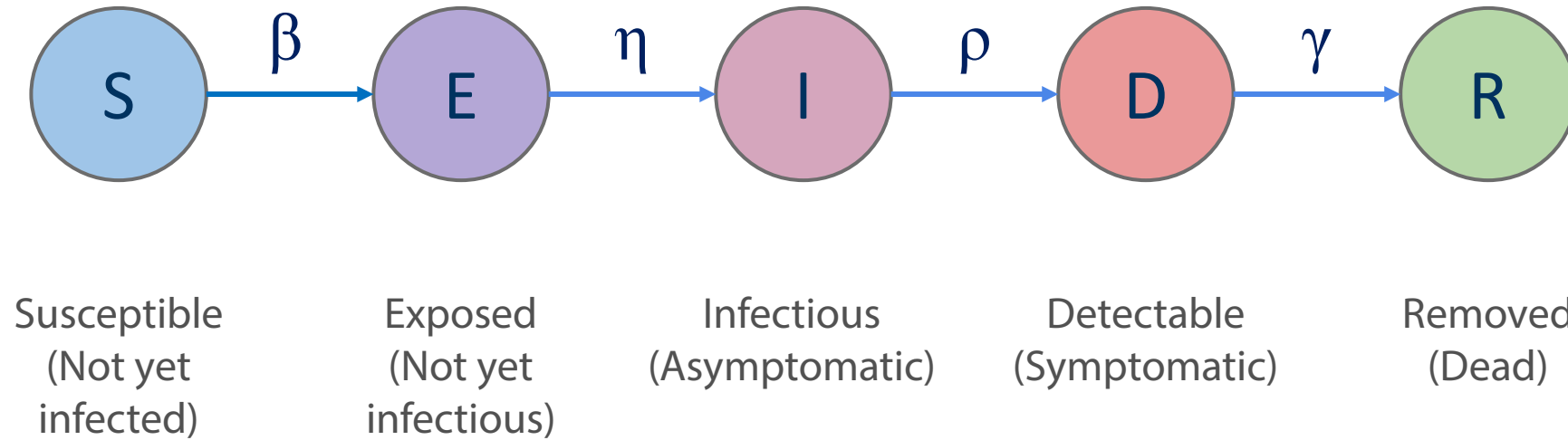
Genetic
covariances

$$\begin{pmatrix} \boldsymbol{\varepsilon}_g \\ \boldsymbol{\varepsilon}_f \\ \boldsymbol{\varepsilon}_r \end{pmatrix} \sim \text{MVN}(0, \mathbf{I} \otimes \boldsymbol{\Psi})$$

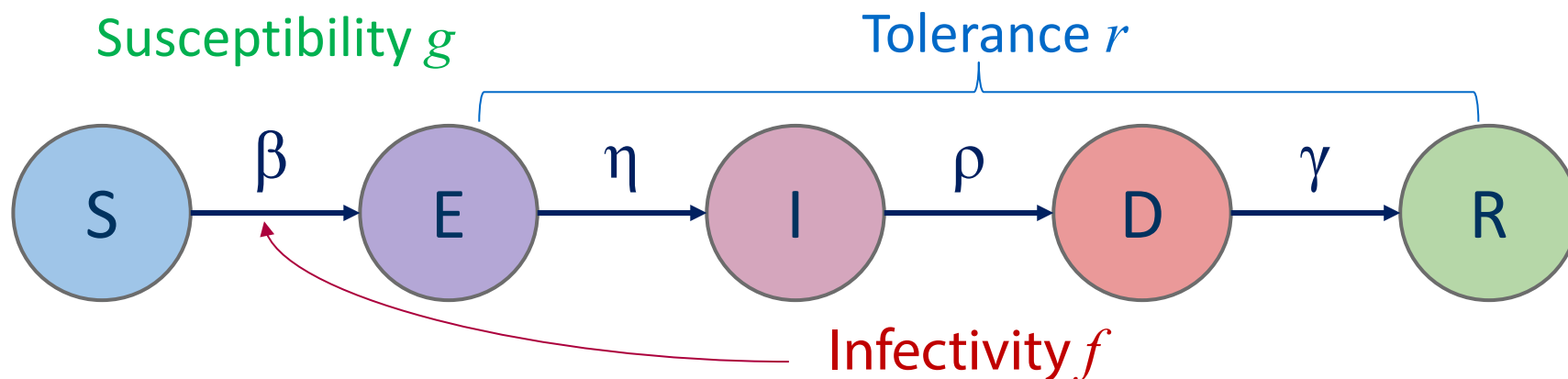
$$\boldsymbol{\Psi} = \begin{pmatrix} \Psi_{gg} & \Psi_{gf} & \Psi_{gr} \\ \Psi_{gf} & \Psi_{ff} & \Psi_{fr} \\ \Psi_{gr} & \Psi_{fr} & \Psi_{rr} \end{pmatrix}$$

Environmental
covariances

Epidemiological model



Epidemiological model: link to traits of interest



Individual's infection rate: $(S \rightarrow E)$

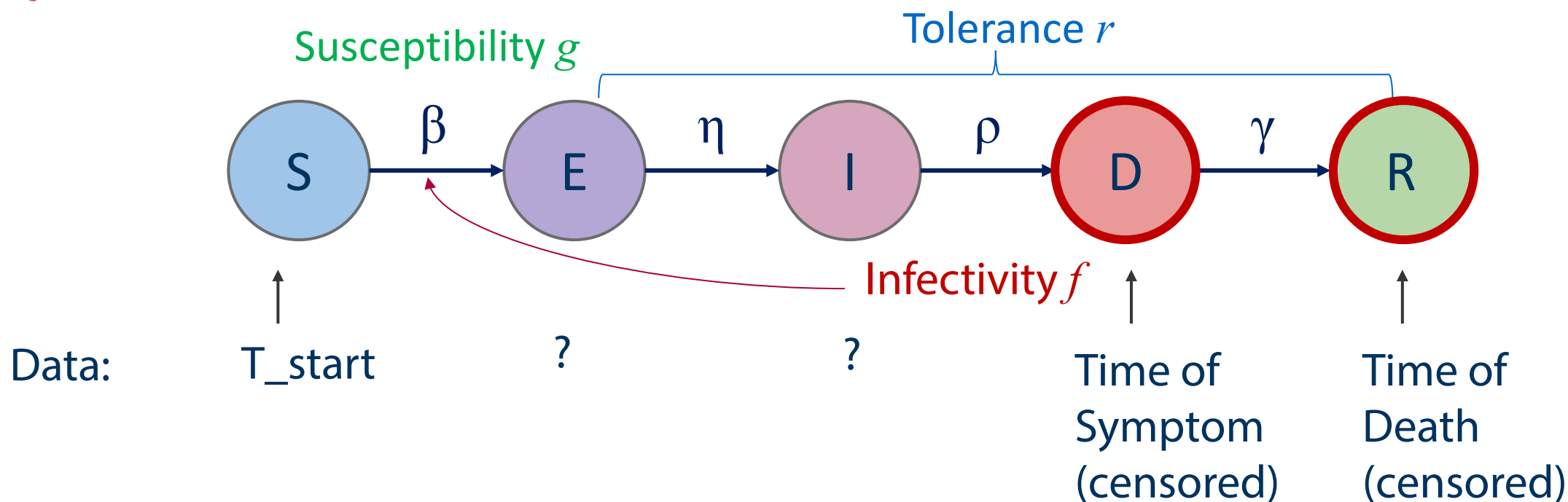
$$\lambda_i(t) = \underset{\substack{\uparrow \\ \text{Random tank effect}}}{\beta_{group}} e^{\underset{\substack{\uparrow \\ \text{Infectious individual} \\ \text{at time } t}}{g_i} \sum_j e^{f_j}}$$

Individual's transition rates

$$\eta_i = e^{r_i} \eta, \quad \rho_i = e^{r_i} \rho, \quad \gamma_i = e^{r_i} \gamma$$

- **Complex, dynamic model, non-linear in susceptibility and infectivity**
- **Not easily implemented as GLMM**

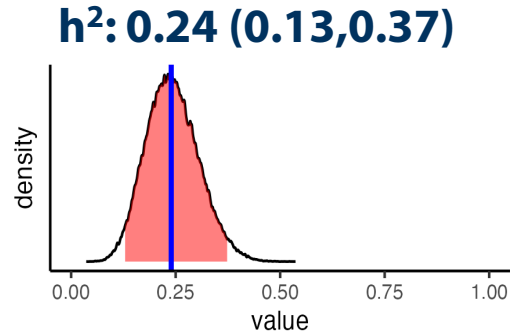
Epidemiological model – link to data



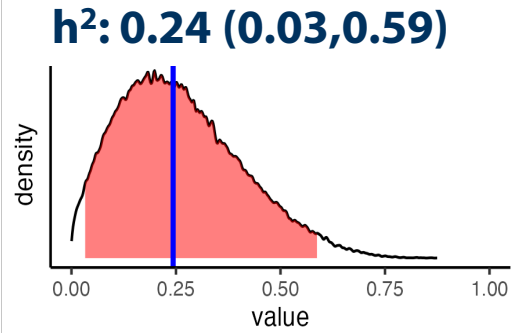
- Moderately informative disease data
- Inference method needs to handle large degree of uncertainty

Susceptibility, infectivity and tolerance are heritable

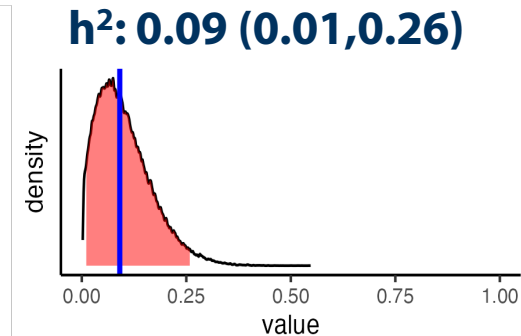
Susceptibility



Infectivity



Tolerance

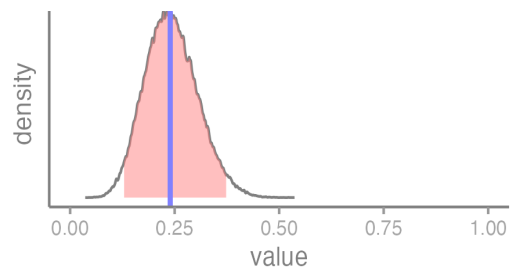


- **Moderate h^2 for susceptibility & infectivity**
- **Low h^2 for tolerance**

Indication for unfavourable genetic correlations

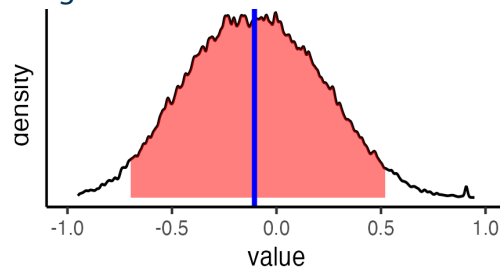
Susceptibility

h^2 : 0.24 (0.13, 0.37)



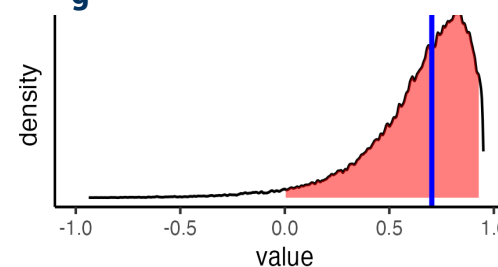
Infectivity

r_g : -0.11 (-0.70, 0.52)



Tolerance

r_g : 0.70 (0.004, 0.93)

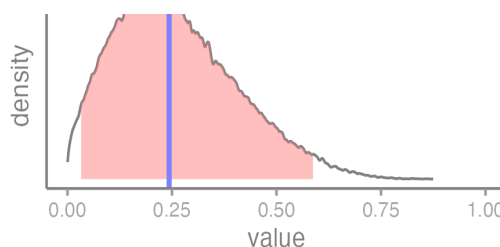


Susceptibility

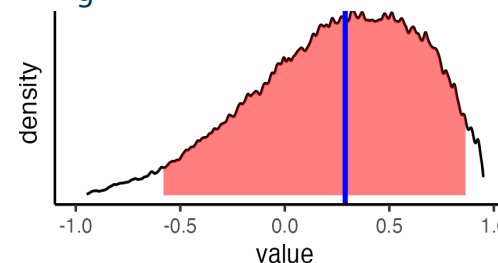
Infectivity

Tolerance

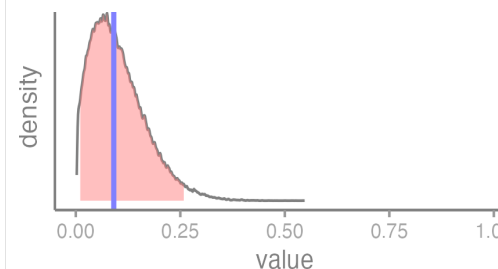
h^2 : 0.24 (0.03, 0.59)



r_g : 0.29 (-0.58, 0.26)

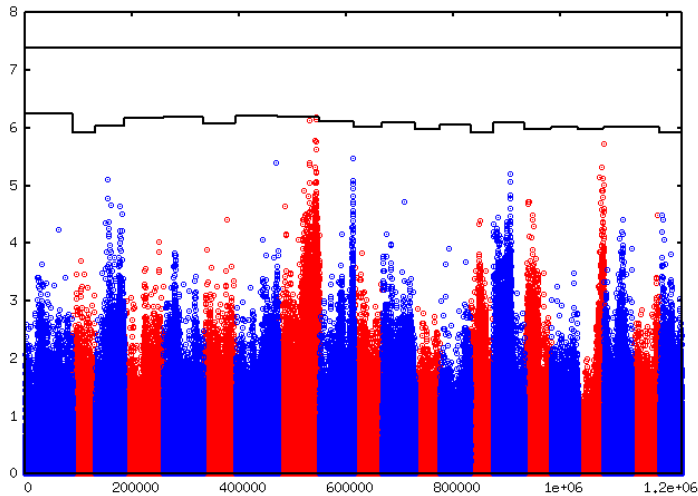


h^2 : 0.09 (0.01, 0.26)

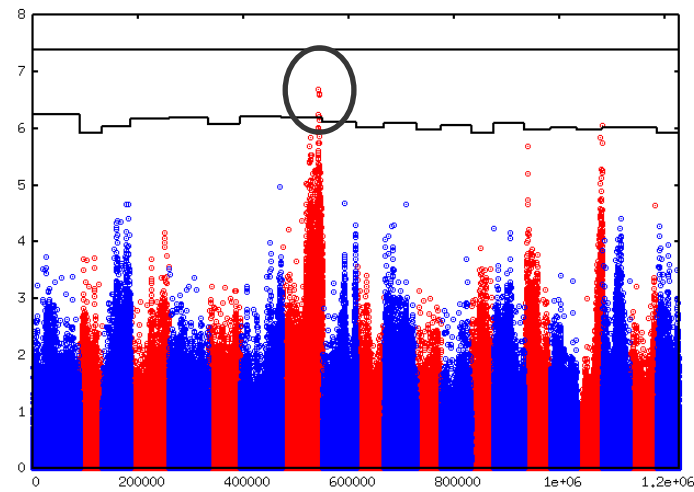


Genetic architecture

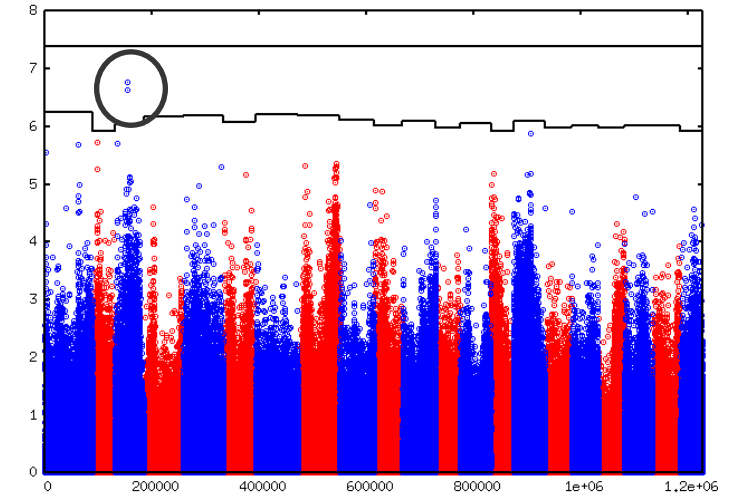
Susceptibility



Tolerance



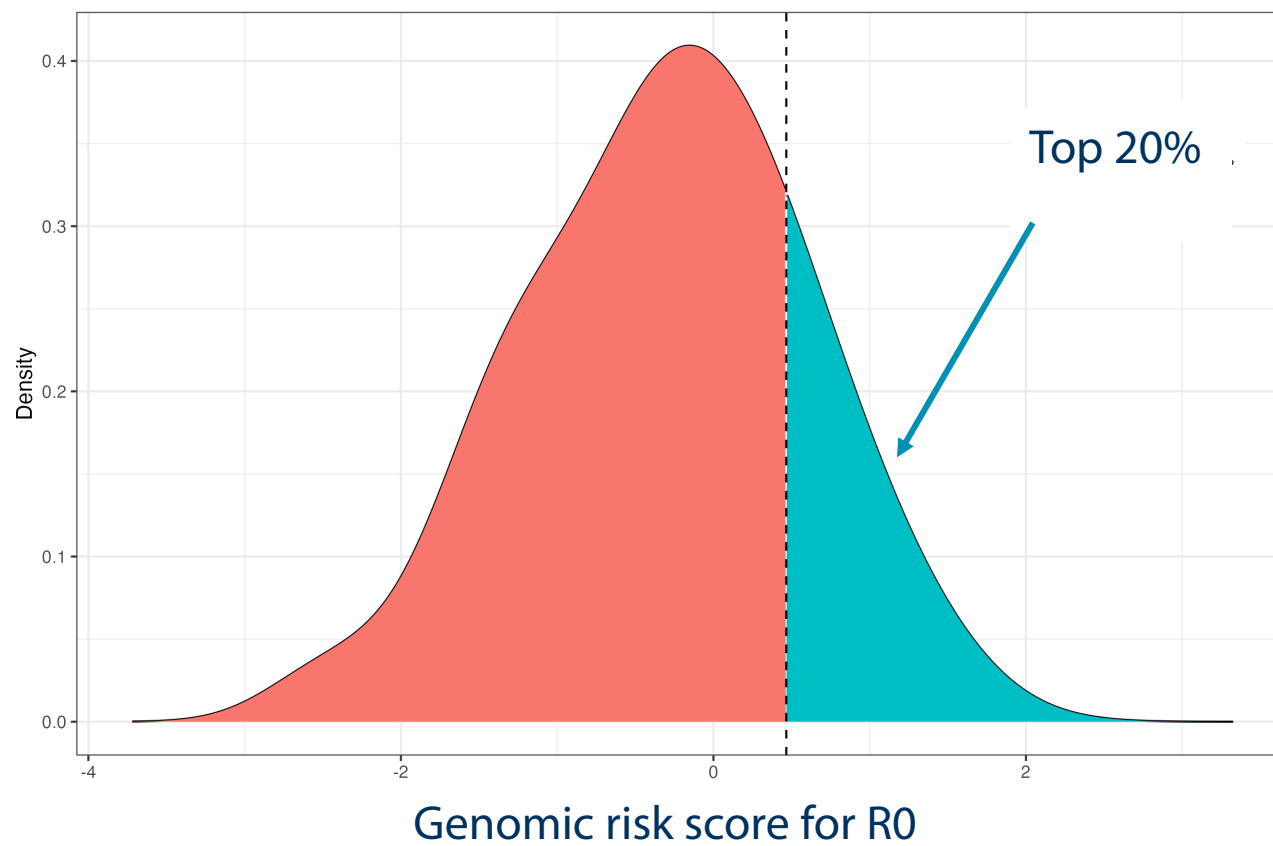
Infectivity



- Polygenic genetic architecture
- Some suggestive variants
 - At different genomic regions

Genetic control of disease transmission

Posterior distribution of genomic risk scores of fish for R0

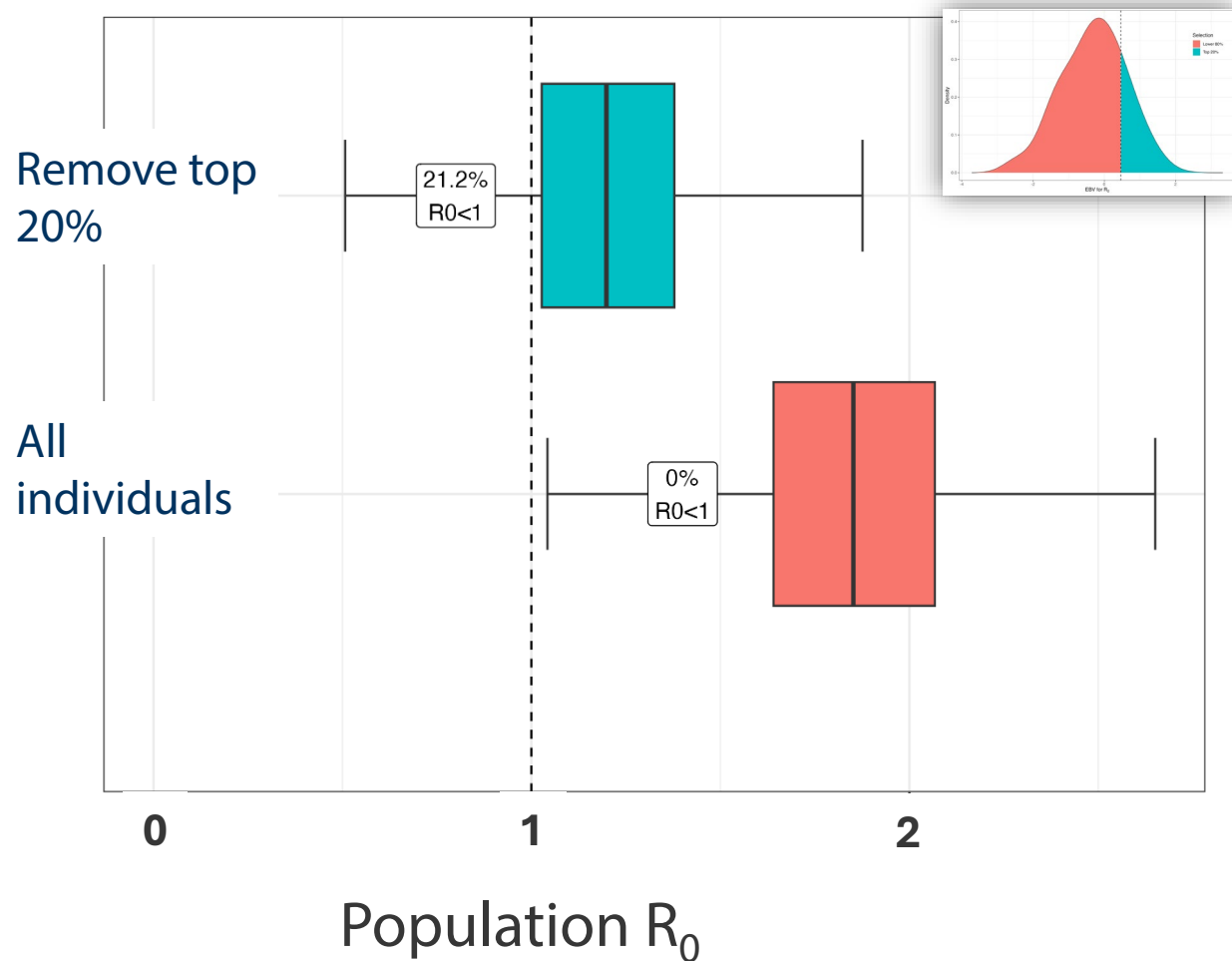


- Aim: Reduce expected $R_0 < 1$:
- We can calculate an individual's genomic risk score for R_0 (Bijma et al., 2022):

$$G_{R0,i} = G_{sus,i} + G_{inf,i} + G_{tol,i}$$

Genetic control of disease transmission

Simulated epidemics (using estimated parameter values)



Early identification of high risk individuals can substantially reduce the risk and severity of disease outbreaks

Conclusions & Implications

1. **We have the tools** to estimate genetic parameters & SNP effects for the epidemiological host traits from imperfect epidemic data



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1. **We have the tools** to estimate genetic parameters & SNP effects for the epidemiological host traits from imperfect epidemic data
2. **First empirical evidence for substantial exploitable genetic variation in infectivity**, in addition to susceptibility & tolerance
 - Potentially antagonistic genetic correlations between traits
 - Polygenic architecture, but some suggestive variants



Conclusions & Implications

1. **We have the tools** to estimate genetic parameters & SNP effects for the epidemiological host traits from imperfect epidemic data
2. **First empirical evidence for substantial exploitable genetic variation in infectivity**, in addition to susceptibility & tolerance
 - Potentially antagonistic genetic correlations between traits
 - Polygenic architecture, but some suggestive variants
3. **Further applications** ongoing ... and **welcome!**



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Infection and survival profiles per family

