

# Understanding and breeding for resilience traits

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- **How does the genetics of animals influence disease prevalence & impact?**
- **How can we use genetics & other control strategies effectively to combat infectious disease?**

## Approach: computational models for data analyses & predictions



# Cattle today face many threats



# Cattle today face many threats



Breeding approaches to  
generate disease-resilient cattle

# When, Why and How to breed for disease resilience?



What are the key challenges and opportunities for breeding for disease resilience?

How may future breeding programmes & dairy farmers benefit from recent research in disease resilience?



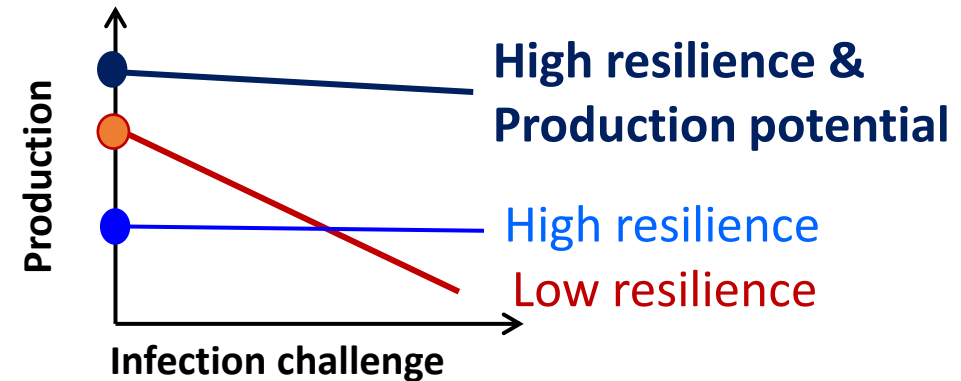
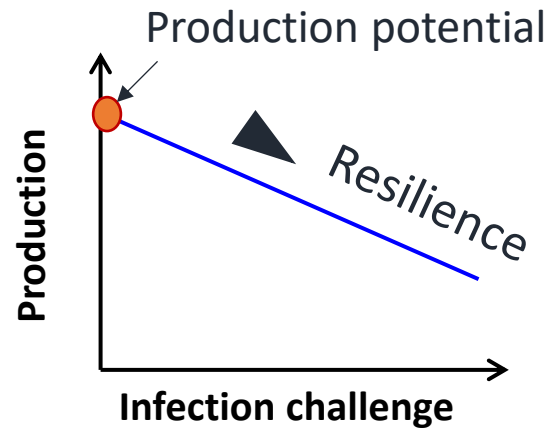


# What is disease resilience and how to measure it?

1. The ability to **maintain high production & health levels** when challenged by infection
  - **Inferred** from modelling reaction-norms
2. The ability to **either maintain or revert quickly to high production and health levels** when challenged by infection
  - **Inferred** from modelling trajectories



# Disease resilience as reaction-norm



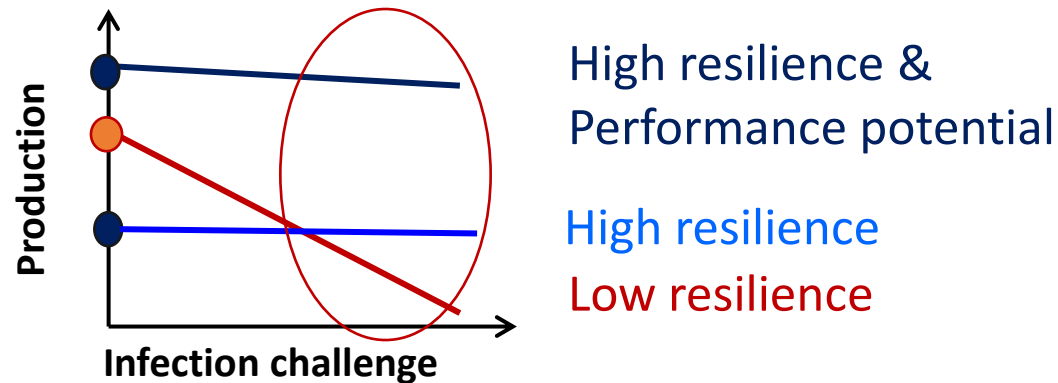
**Reaction-norm:** change in production with increasing infection challenge

**Resilience** = reaction-norm **slope**

**Production potential** = reaction-norm **intercept**

Goal: **high production potential & high resilience**

# When to breed for disease resilience?



Consider breeding for disease resilience when animals are frequently exposed to infections that impact productivity & health



# Improvement of disease resilience is profitable

Species	Disease	Cost per animal (\$)	Genetic gain per animal (\$)	Cost / Gain
Sheep	Parasites	6.2	0.8	7.6
Ruminants	Bluetongue	37.3	14.0	2.7
Cattle	bTB	19.9	3.8	5.2
Pigs	PRRS	10.2	2.2	4.7



*Pieter Knap:  
Genetic Strategy  
Manager, Genus-PIC*

**The cost of combatting disease exceeds any achievable genetic gain in productivity**

# How to breed for disease resilience?

## **Current (black box) indirect selection on resilience:**

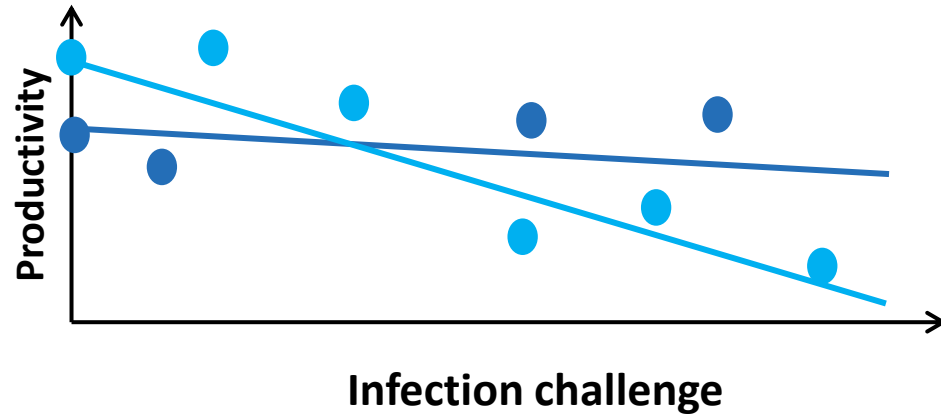
- Select for high productivity in infectious conditions
- Good enough?

## **Key challenges for explicitly selecting for resilience :**

- Reliable resilience phenotypes for genetic evaluations
- Identifying and managing trade-offs between resilience and other traits



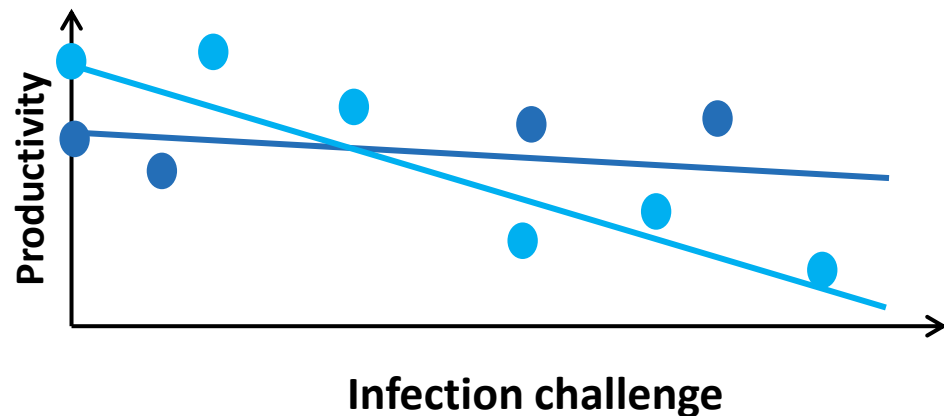
# Statistical challenges for estimating resilience



Estimating resilience slopes requires **multiple performance measures** of individuals **across a range of challenge levels**

- Do genomic data help?
- How sensitive are resilience estimates to phenotyping strategies?

# Simulation studies



[Front Genet.](#) 2023; 14: 1127530.

Published online 2023 May 12. doi: [10.3389/fgene.2023.1127530](https://doi.org/10.3389/fgene.2023.1127530)

PMCID: PMC10213464

PMID: [37252663](https://pubmed.ncbi.nlm.nih.gov/37252663/)

Exploring the value of genomic predictions to simultaneously improve production potential and resilience of farmed animals

[Masoud Ghaderi Zefreh](#),<sup>✉1,\*</sup> [Andrea B. Doeschl-Wilson](#),<sup>1</sup> [Valentina Riggio](#),<sup>1</sup> [Oswald Matika](#),<sup>1,2</sup> and [Ricardo Pong-Wong](#)<sup>1</sup>

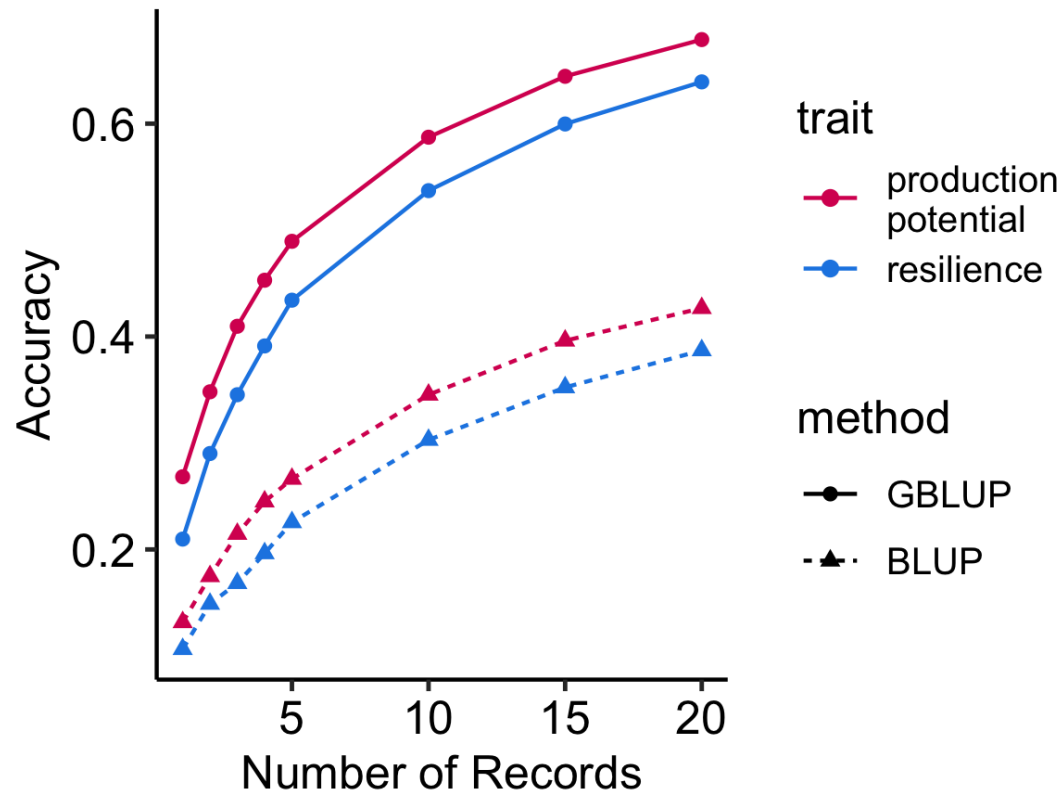


- Simulate reaction-norms of a population of genotyped animals exposed to different challenge levels
  - Assume potential trade-off between production potential & resilience
- Evaluate how prediction accuracies & response to selection depend on genotyping and phenotyping strategies

*Ghaderi-Zefreh et al., Front. Gene. 2023*



# Much improvement in prediction accuracies with genomic data & repeated records



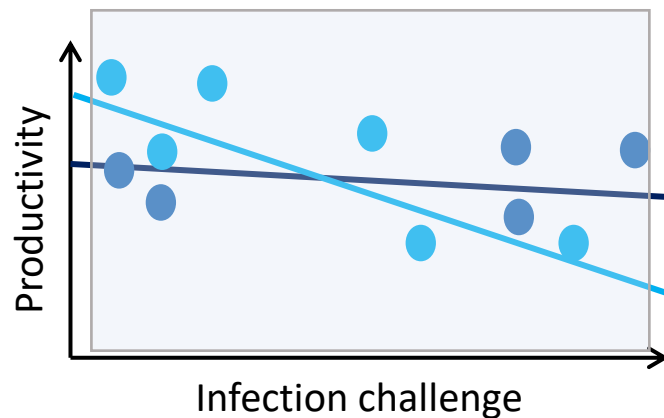
- Prediction accuracies greatly improve with number of records
- Genomic data provide good prediction accuracies even for limited records
- Selection for high production potential & resilience possible with genomic prediction

# What if we only have data from good or poor conditions?

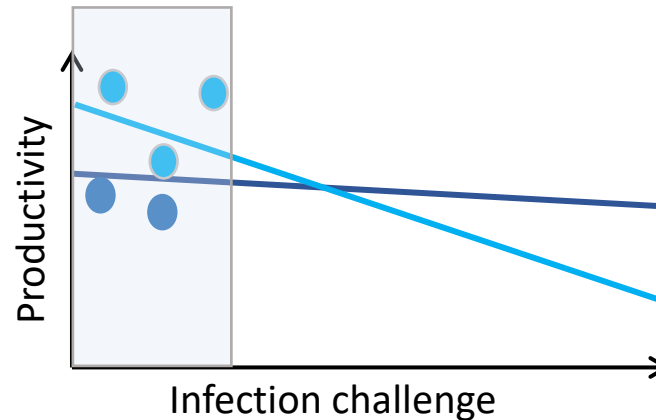
Can we still improve production potential & resilience?

- without explicitly estimating these traits?

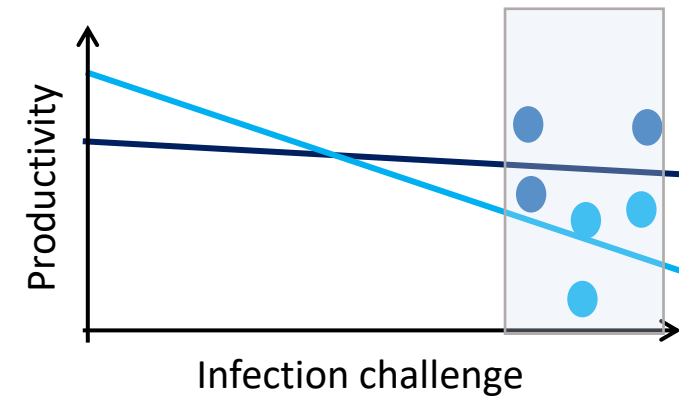
A: good & poor health conditions



B: high health conditions



C: poor health conditions



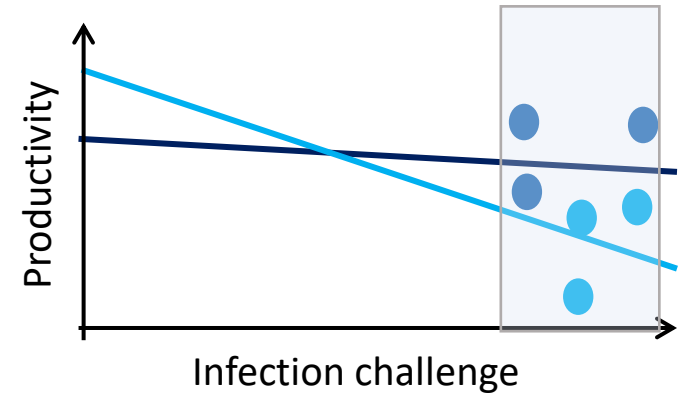
For each phenotyping scenario A-C, simulate 10 generations of selection on

- (i) productivity (GEBV) or
- (ii) index of estimated production potential & resilience

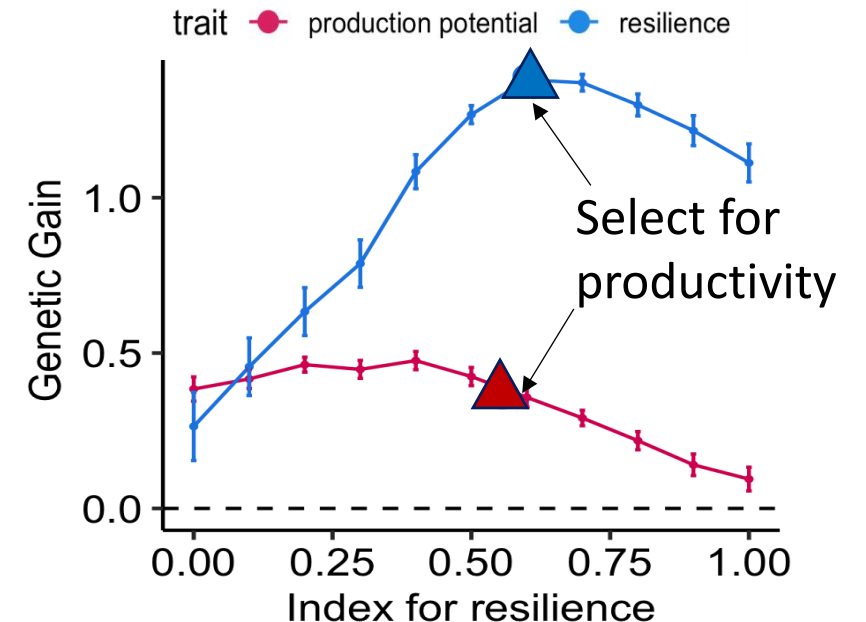


# Predicted genetic gain after 10 generations of selection

C: poor health conditions

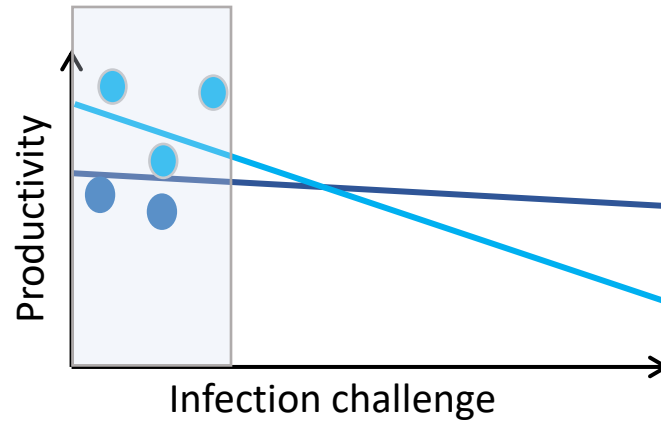


- High genetic gain in resilience
- Limited gain in production potential
- Genetic gain in both traits achieved by selection on productivity alone

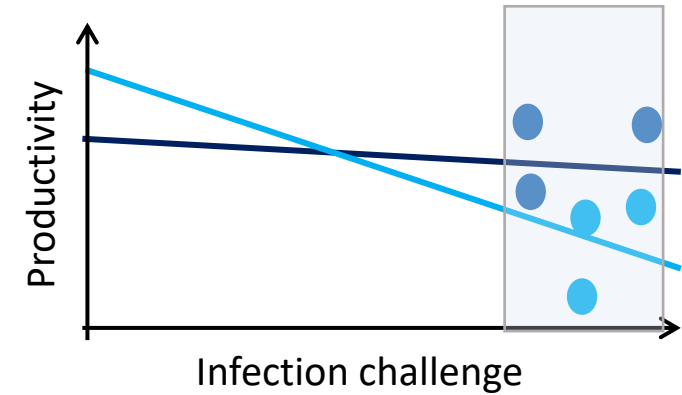


# Predicted genetic gain after 10 generations of selection

**B: high health conditions**

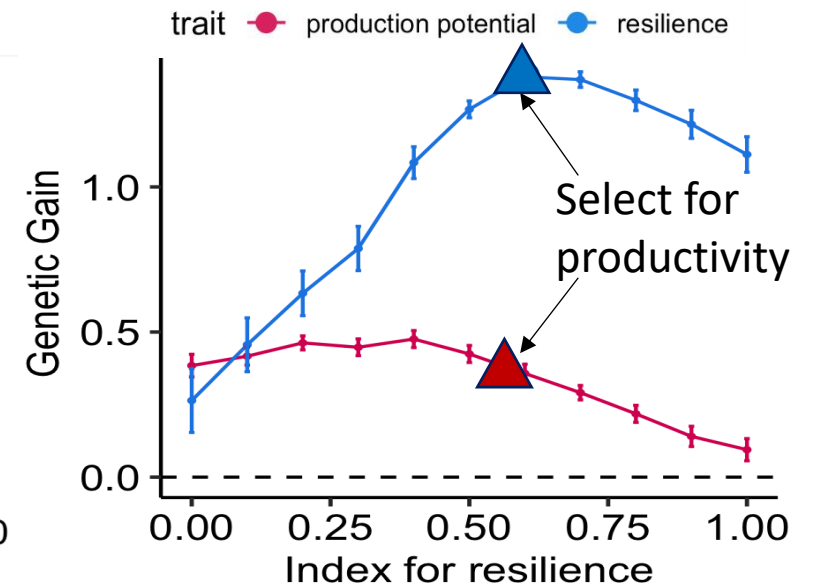
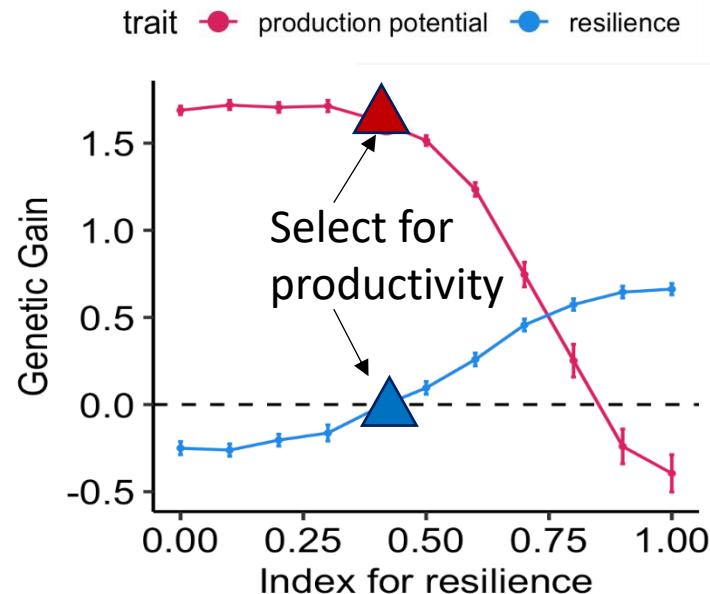


**C: poor health conditions**



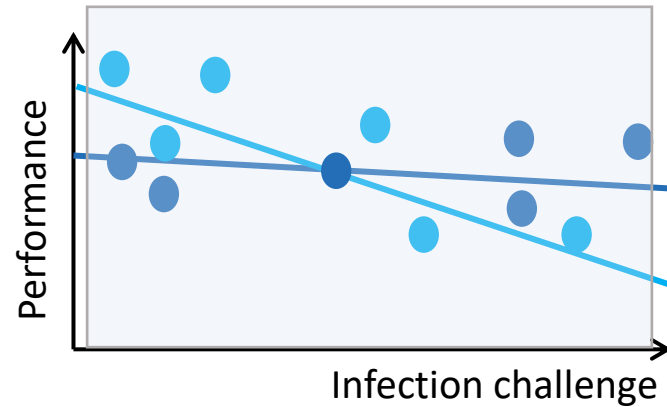
High genetic gain in  
production potential

No improvement in  
resilience unless one  
explicitly selects for it!

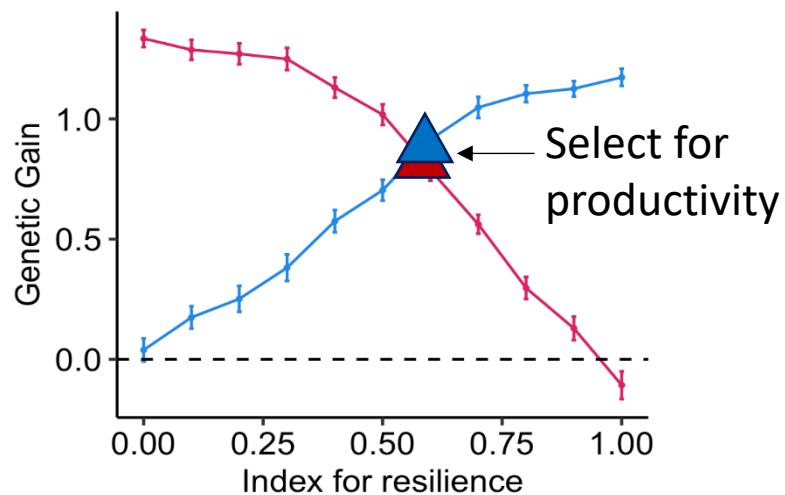


# Predicted genetic gain after 10 generations of selection

A: good & poor conditions



trait —●— production potential —●— resilience



- Best scope for genetic improvement in production potential & resilience
  - And managing trade-offs
- Selection on productivity alone improves both traits



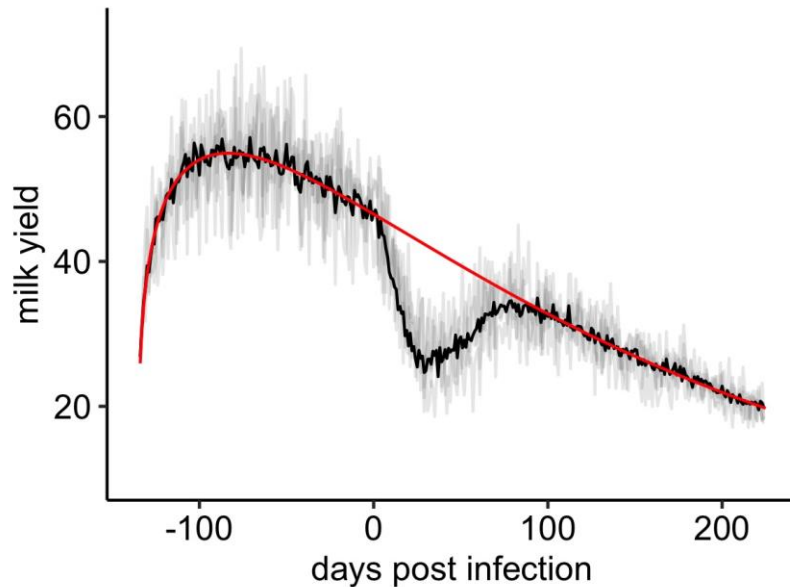
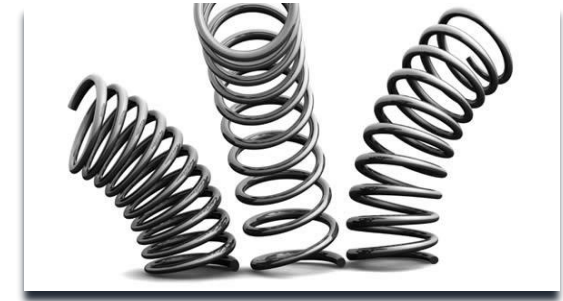
# Key messages from simulation studies

1. Genetic improvement of both production potential and resilience is possible even if there is a trade-off
  - Much more improvement with genomic data & more measurements
2. Genetic gain in either trait depends strongly on the environment in which data are collected
  - Best results when genotypes and phenotypes are collected across a wide range of challenge conditions
3. Selecting on productivity alone can indirectly improve resilience, but only if data are collected in infectious conditions

# Resilience trajectories

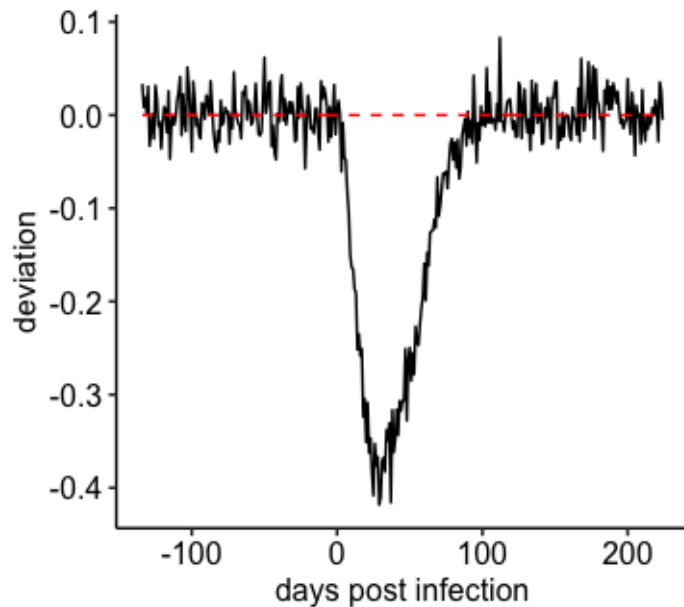
Disease resilience:

The ability of an animal to either **maintain or revert quickly** to high production and health status when exposed to challenges



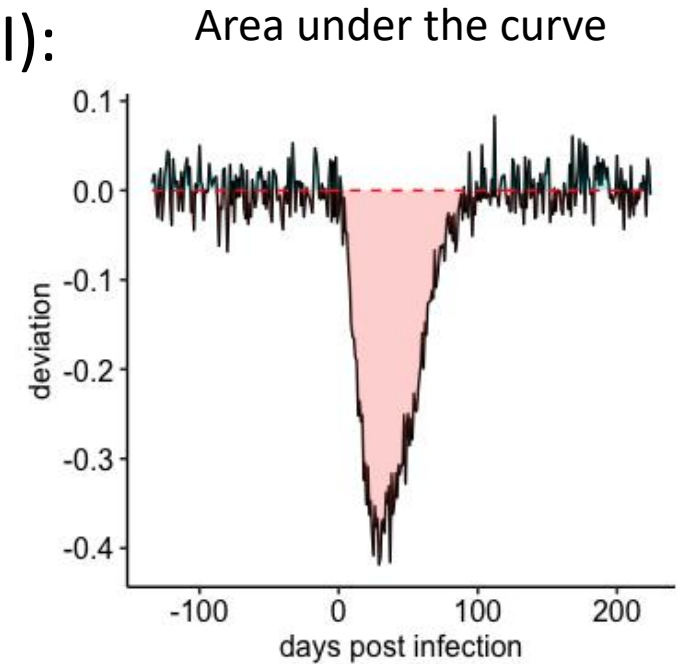
- Characterise animals by their **deviations in the performance trajectory**
- **Resilient animals deviate less from their optimal trajectory & recover faster**
- What is an **appropriate resilience phenotype** to include into breeding goals?

# Statistical resilience indicators based on deviations from a target trajectory



Proposed resilience indicators (RI):

- Mean (square) deviation
- Variance of deviations
- Area under the curve (AUC)
- Lag-1 Autocorrelation
- Skewness



More resilient animals have RI values closer to zero



# Can we trust these resilience indicators?

- **Various studies** applied to short-term disturbances in milk yield in dairy cattle, feed intake & growth in pigs & chicken
- **Generally promising results:**  
E.g. heritable, positively associated with good health & longevity, repeatable, complementary
- **But many potential pitfalls:**
  - Unknown target trajectory
  - Dependence on data features poorly understood
  - Unknown impact on animals' physiology

**The only statistics  
you can trust  
are those you  
falsified yourself.**

wrongly attributed to  
Sir Winston Churchill

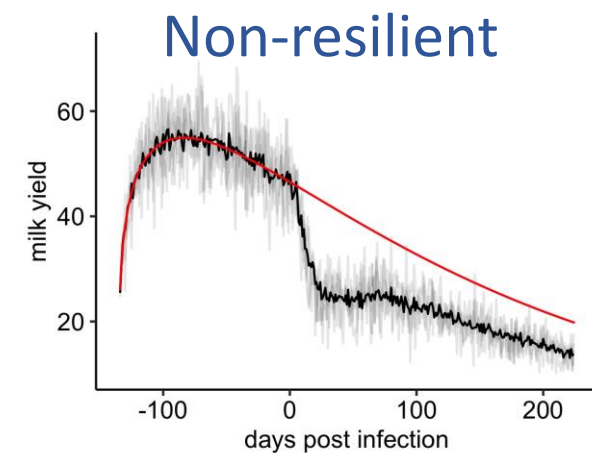
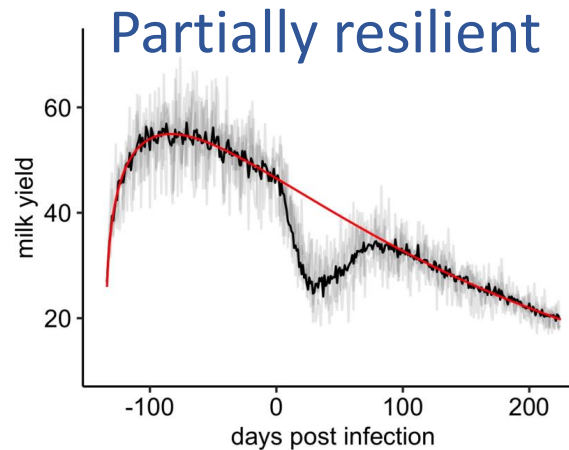
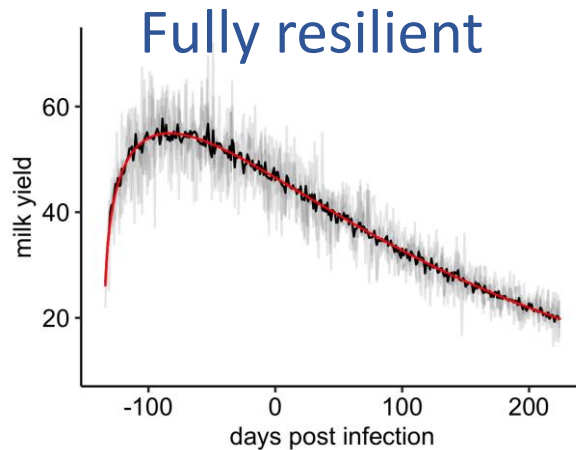


# Simulation studies to validate resilience indicators



*Masoud  
Ghaderi-  
Zefreh*

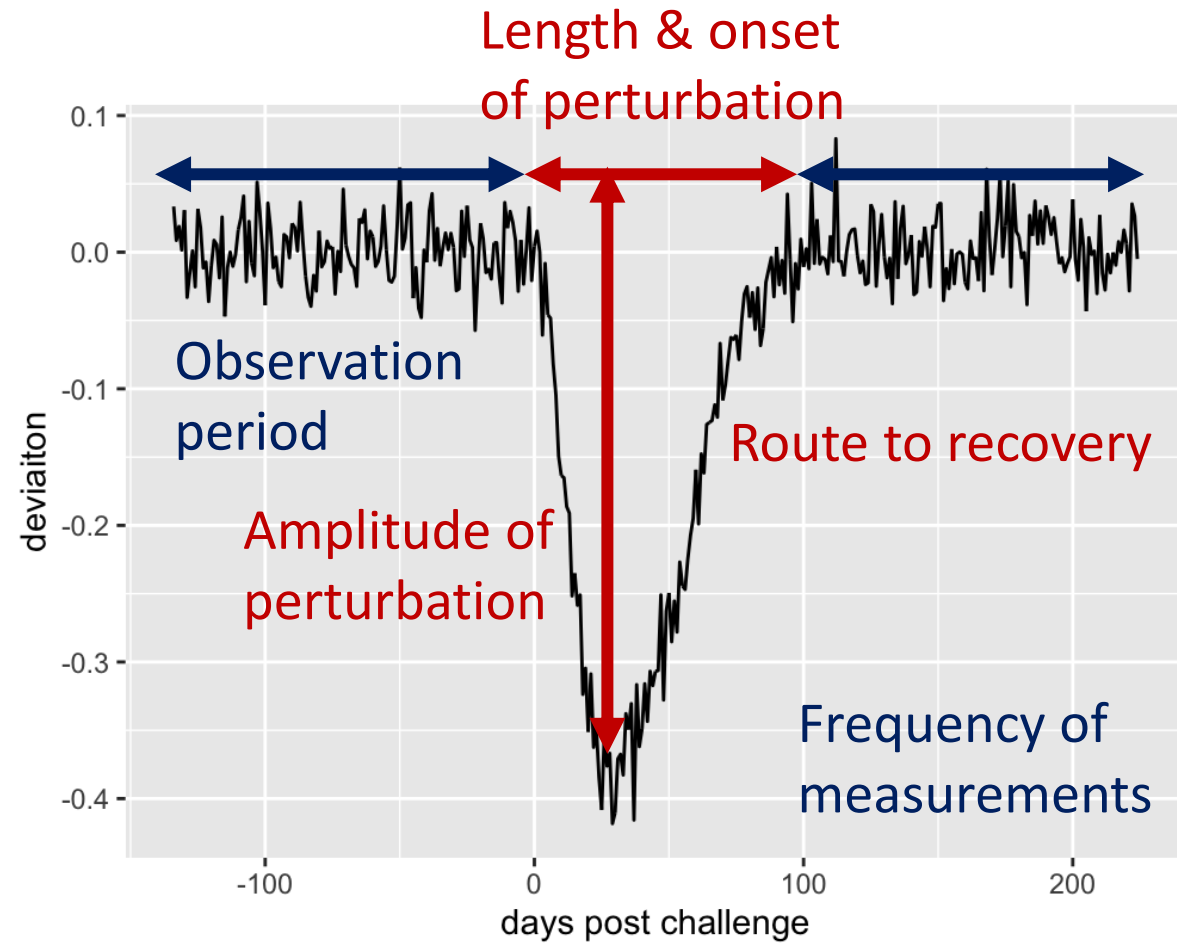
Simulated milk yield profiles under short-term challenge for 3 response types:



## Objectives for validating the statistical resilience indicators

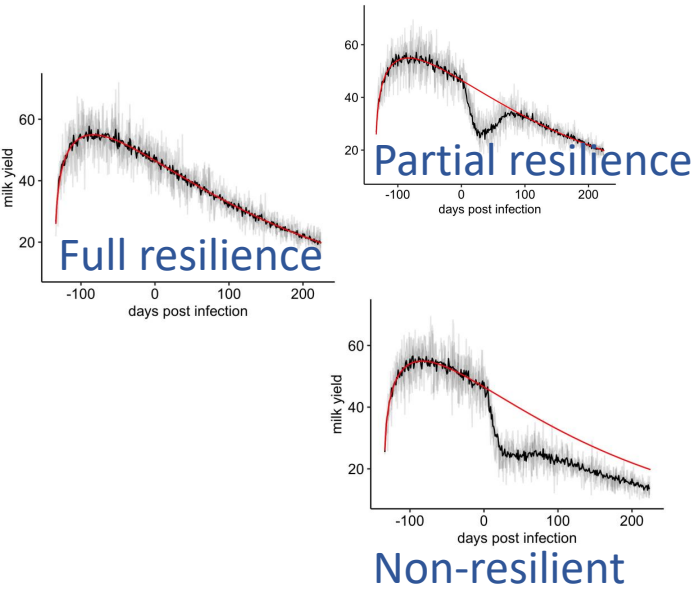
1. Can the RI correctly distinguish between the 3 response types?
2. How sensitive are the RIs to individuals' response and data features?
3. How dependent are RI to the methods for estimating individuals' target trajectories

# Sensitivity of resilience indicators to data features



# Not all resilience indicators can distinguish non-resilient from partially resilient animals

Resilience indicators	Fully vs non-resilient	Fully vs partially resilient	Non-Resilient vs partially resilient
Log-variance deviation	1.00	0.99	<b>0.87</b>
Mean square deviation	1.00	1.00	<b>0.87</b>
Area under the Curve	1.00	0.99	<b>0.81</b>
Lag-1 autocorrelation	0.99	1.00	0.15
Skewness	<b>0.71</b>	0.98	0.09



Strong tendency to mis-classify

Area under the Receiver-Operator-Curve (ROC) for classifying response types based on resilience indicators  
Similar results across different methods for estimating target trajectories

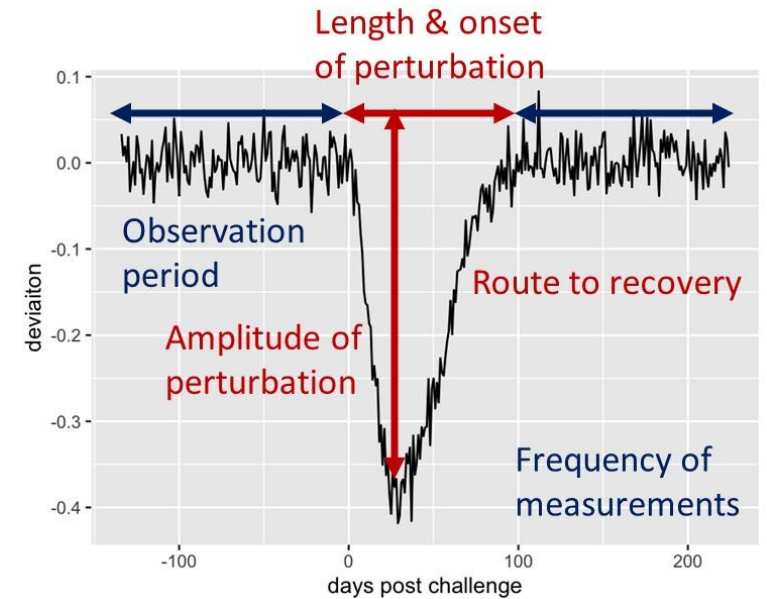


# Sensitivity of resilience indicators to data features

Skewness is generally a poor resilience indicator

Most other resilience indicators are reliable if

- individual performance is recorded frequently & regularly
- sufficient pre- and post-perturbation data exist
- onset of perturbation is known



# Sensitivity of resilience indicators to data features

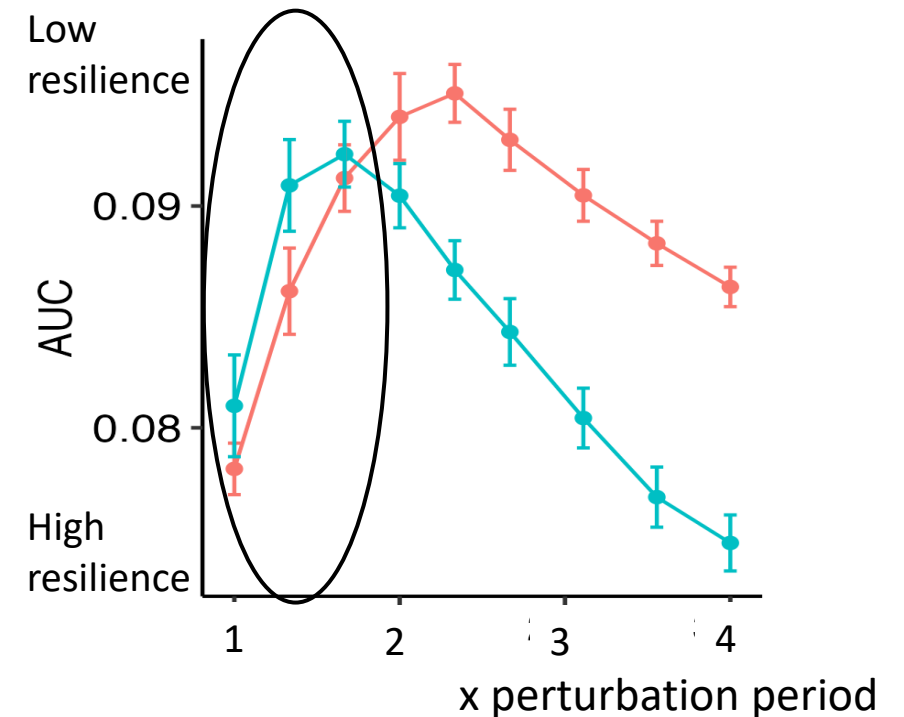
Skewness is generally a poor resilience indicator

Most other resilience indicators are reliable if

- individual performance is recorded frequently & regularly
- sufficient pre- and post-perturbation data exist
- onset of perturbation is known

But serious risk of mis-classifying animal if these criteria are not met

## Sensitivity to length of recording interval



—●— Non-Resilient —●— Partially Resilient

# Summary of results

## 1. Can the RI correctly distinguish between the 3 response types?

Generally yes (apart from skewness)

Risk for mis-classifying non-resilient animals

## 2. How sensitive are the RIs to individuals' response and data features?

Risk for mis-classifying non-resilient animals if data are sparse or only collected during challenge period

## 3. How dependent are RI to the methods for estimating individuals' target trajectories

Risk for downward bias in target trajectory estimate, especially for non-resilient animals → cause of mis-classification

# Case study: Bovine Mastitis



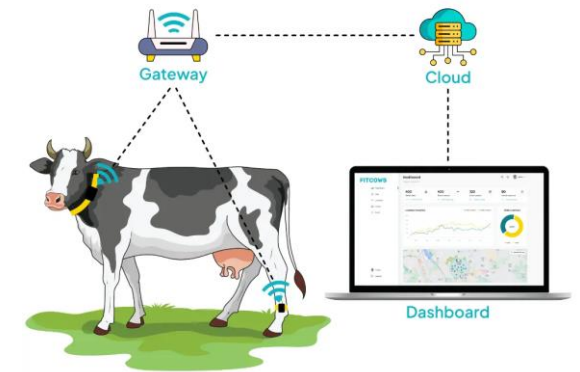
## The problem:

Endemic disease in dairy cattle, causing massive economic losses

Difficult to control (multiple pathogens; sub-clinical mastitis)

## The opportunity:

Construct novel indicators for resilience to mastitis from longitudinal records of milk yield and somatic cell counts from milk robotic data



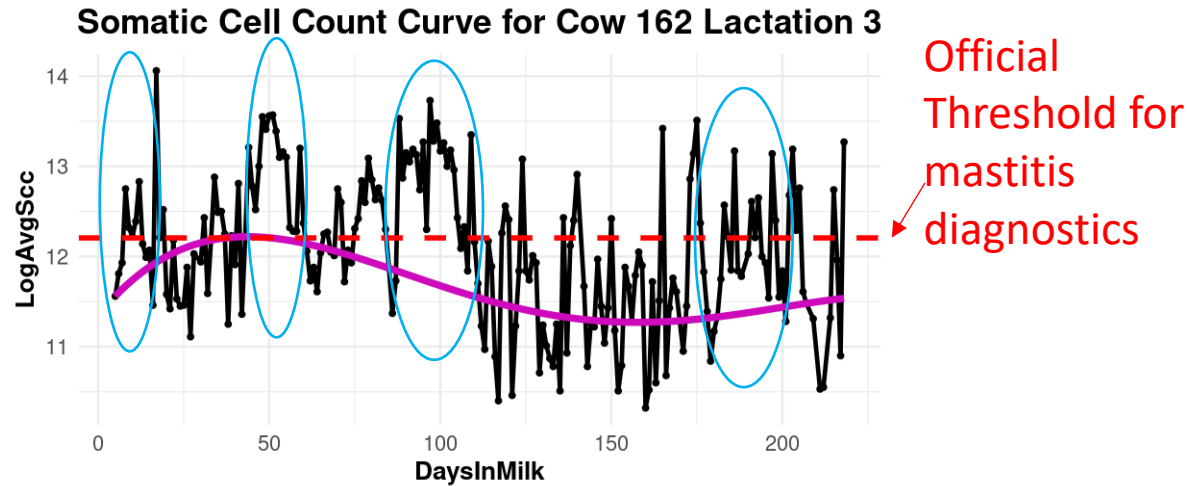
repeated milk & SCC records (from automated milking systems) from >1000 cows, 6 farms



# Case study: Bovine Mastitis



Tijesunimi Ojo

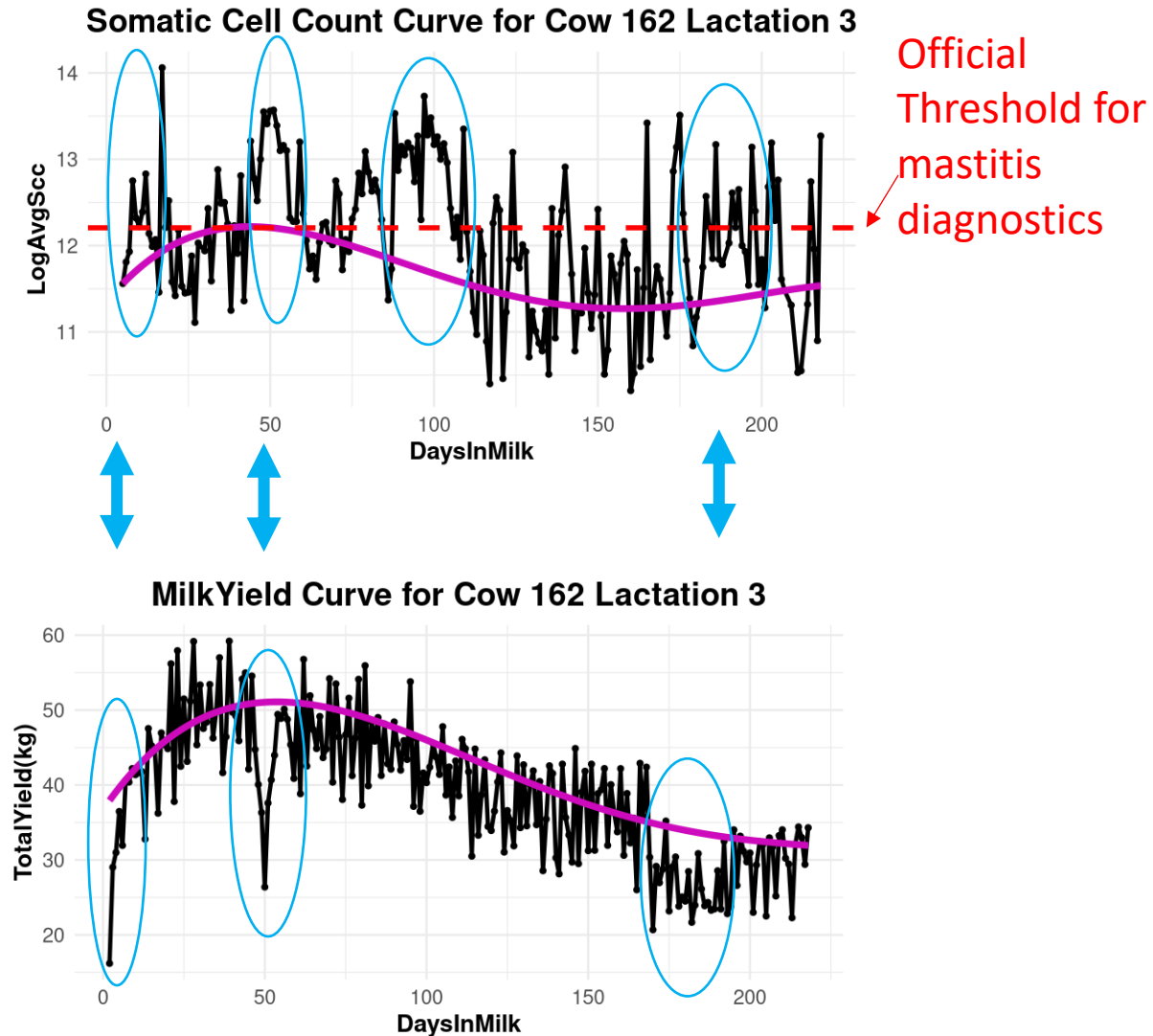


- Official SCC threshold for mastitis poor diagnostics
- Can we construct individual SCC target trajectories and identify & characterise potential mastitis events for each cow?

# Case study: Bovine Mastitis



Tijesunimi Ojo



- Official SCC threshold for mastitis poor diagnostics
- Can we construct individual SCC target trajectories and identify & characterise potential mastitis events for each cow?
- Aim: construct mastitis resilience indicators

# Identifying and managing resilience trade-offs

“When the breeding goal is a composite trait, all components must be kept under control. Otherwise selection may come to nothing or make things worse” (Knap 2020)

Potential resilience trade-offs:

- resilience & productivity in disease-free conditions (affecting productivity)
- resistance & tolerance to disease
- resilience & host infectivity (affecting herd resilience)



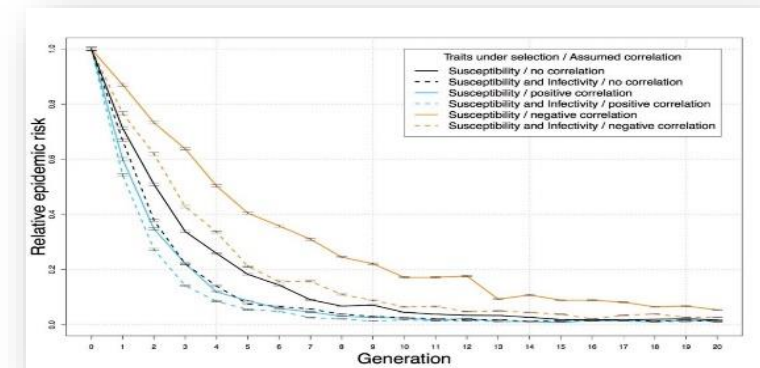
Resilient Super-spreaders  
compromise  
herd resilience

→ Improve resilience &  
decrease infectivity



# Case study : Bovine Tuberculosis

- Persistent zoonotic disease in many countries
- Costly eradication programmes
  - Cattle: Stringent testing & culling; movement restrictions
- TBAdvantage selection index (UK): enables farmers to select bulls with high genetic bTB resistance
- Modelling studies: selection for resistance alone may not be enough





Duygu Madenci



Enrique Sanchez-Molano



# Can / should one breed cattle for low bTB infectivity, in addition to high bTB resistance?

## Objective:

- Detect genetic variance in cattle infectivity from UK national surveillance data
- Assess potential trade-off with bTB resistance and other health and production traits

# Approach

## DATA:

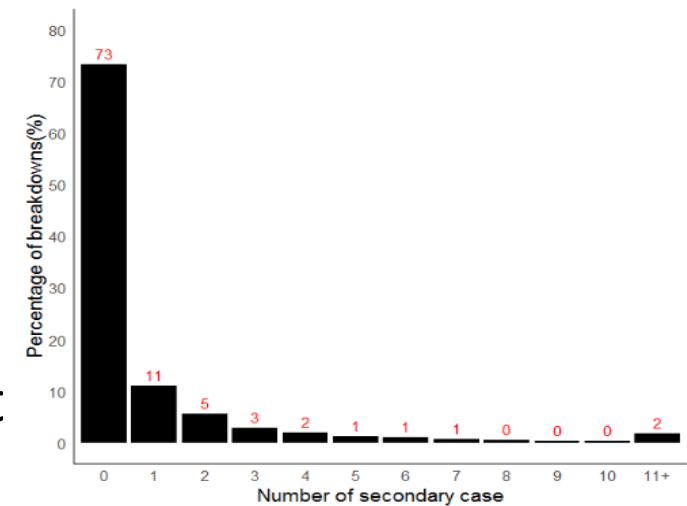
- Same as used in UK national genetic evaluation of bTB resistance
- After filtering: Individual test records of >1Mio Holstein-Friesian cows from >4000 bTB outbreaks (GB, 2000-2021) + pedigree (7 generations, >70K records)

## INFECTIVITY PHENOTYPE (index cases only):

- **Number of secondary cases associated with each index case**

Index case: first identified bTB positive cow in a breakdown

Secondary case: identified bTB positive cows at the follow up test



## GENETIC VARIANCE ESTIMATION:

- Generalized linear mixed models implemented in MCMCglmm R package

# Infectivity variance estimates

Model					
Variance	Hurdle <sup>1</sup>		Zero Inflated Poisson		Geometric
	Binary <sup>2</sup>	Poisson	Binary <sup>2</sup>	Poisson	
$\sigma_s^2$	$<10^{-5}$	<b>0.0328*</b> (0.0004 , 0.1021)	$<10^{-5}$	<b>0.0197*</b> (0.0002, 0.0715)	<b>0.0288*</b> ( $<10^{-5}$ , 0.0979)
$\sigma_e^2$	1.000	1.2990 (1.128 , 1.481)	1.000	3.884 (3.513 , 4.326 )	3.046 (2.692,3.383)

<sup>1</sup> Best model fit

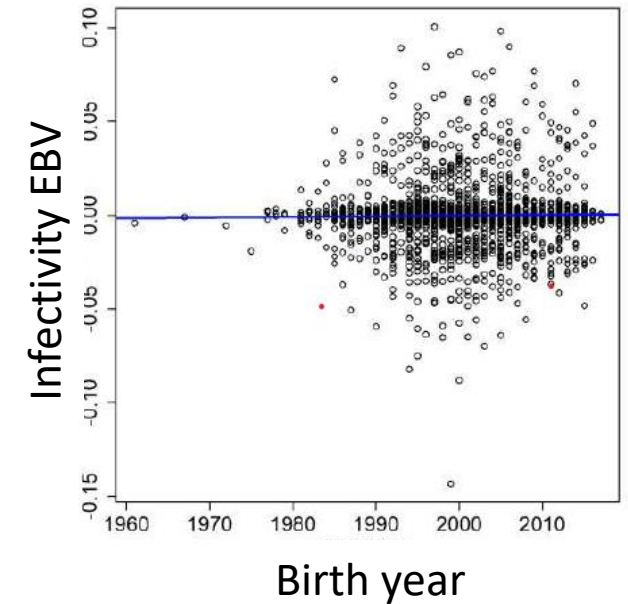
<sup>2</sup> The residual variance,  $\sigma_e^2$ , for the zero-part in both ZIP and Hurdle models fixed at 1

**\*Infectivity EBV of -  $1\sigma_A$  below average  $\approx$  32% - 44% fewer secondary cases**



# Infectivity breeding value correlations

Trait	All sires	Most informative sires
TB Advantage (bTB resistance)	0.008	0.055
Mastitis	-0.029	-0.124
Lameness	0.037	0.182*
Milk yield	-0.012	-0.023
Fat yield	0.012	0.085
Protein yield	0.002	0.091
Lifespan	0.029	0.089
Fertility index	0.006	0.027
Calving interval	-0.004	-0.074



No indirect  
selection for  
infectivity

# Key Lessons – bovine Tuberculosis



1. Strong evidence for genetic variation in infectivity
  - likely under-estimated
2. No evidence that current selection for bTB resistances also reduces bTB transmission
3. Scope for breeding cattle that are both resistant to bTB and less likely to transmit bTB

# Take-home messages

## Breeding for disease resilience

### 1. Is possible and profitable

Especially for endemic diseases

### 2. has potential pitfalls one needs to be aware of

Modelling studies can help identify these & test potential solutions

### 3. requires considerable investment into phenotyping

Big opportunities with non-invasive diagnostics & automated data

# Acknowledgements

- **Masoud Ghaderi-Zefreh**
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- Georgios Banos (SRUC)
- Mike Coffey (SRUC)
- Wilson group members





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**THANK YOU**

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