



Quantifying resilience in growing pigs with weight and feed trajectories: the impact of observation frequency and duration

Wim Gorssen, Carmen Winters, R. Meyermans, L. Chapard, K. Hooyberghs,

S. Janssens, A. Huisman, K. Peeters, H. Mulder and N. Buys

Session 20 “Innovative approaches to pig and poultry production”

wim.gorssen@kuleuven.be



KU LEUVEN

Background

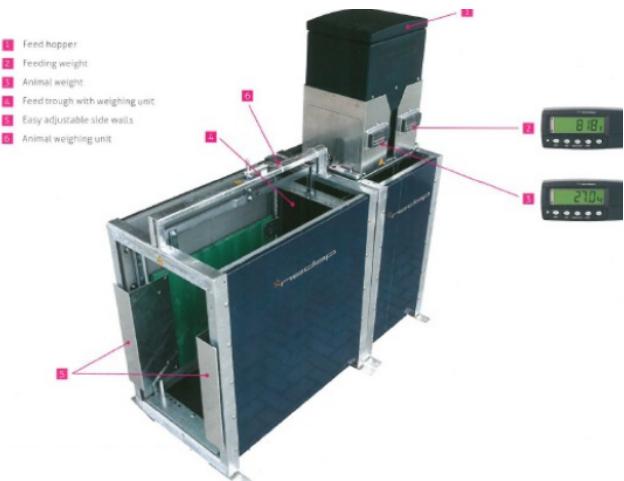
“A few decades ago, we used to refer to these robustness traits as “secondary traits”—and by now, they have evolved to hot item #1 in livestock breeding”

Technological developments facilitate longitudinal data collection

- Automated feeding stations

Quantifying resilience/robustness

- Deviations from longitudinal data trajectories
 - Weight
 - Feed intake



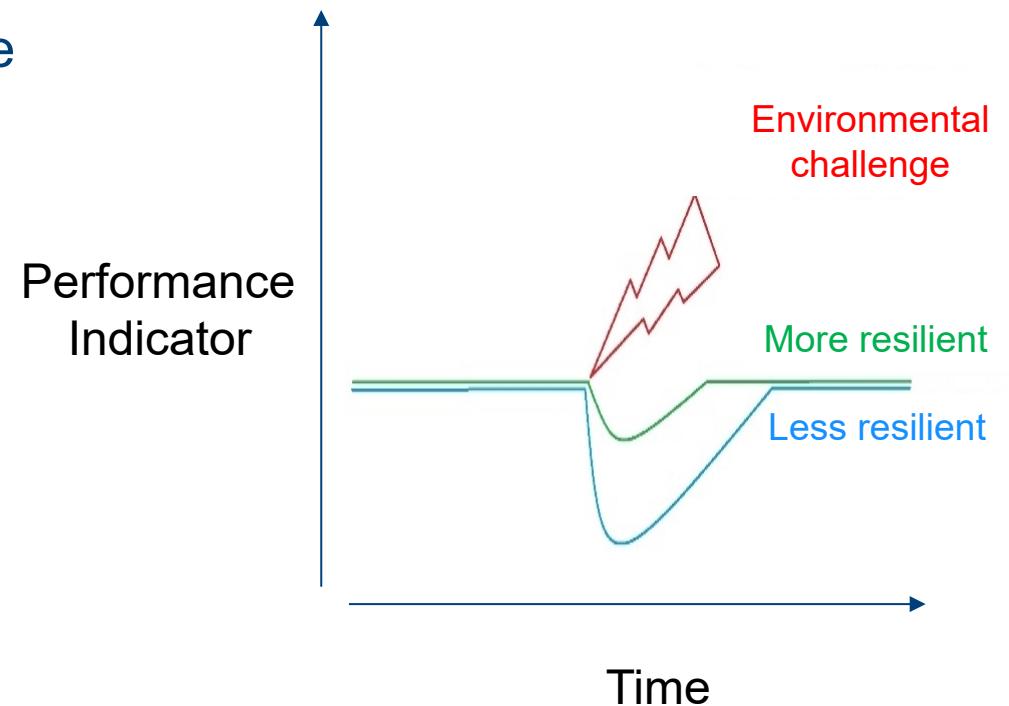
General resilience hypothesis

Animals have a theoretical 'optimal' performance

A challenge will create a deviation from optimal

More resilient animals

- Less severe deviation
- Quick recovery to optimal state

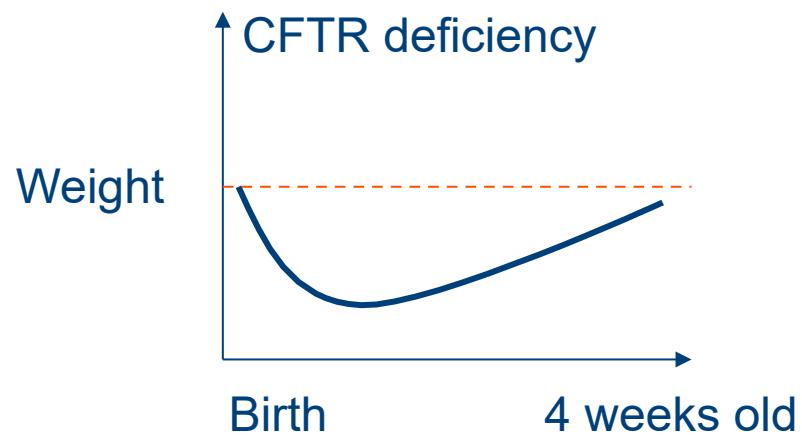


Genetic basis of resilience: case example

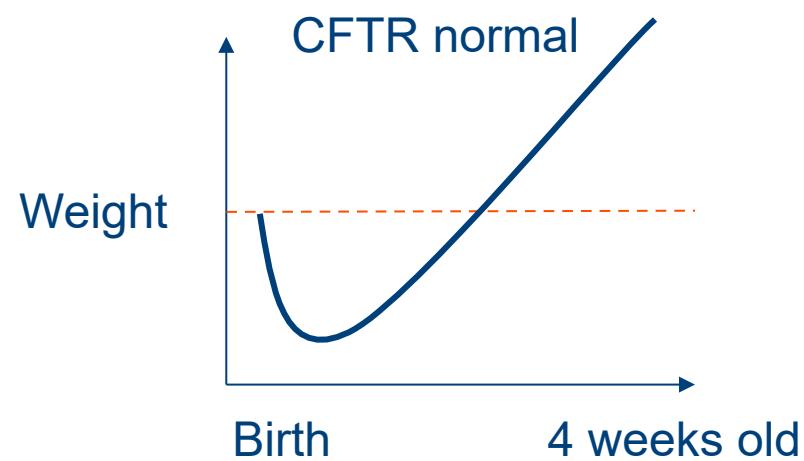
Annemone Gorssen Winters



Fullsibs - genotyped
Parents with good breeding value



Hazel Gorssen Winters



Research objectives

1. Quantify resilience from weight and feed intake data of growing pigs
2. Estimate genetic parameters
3. Evaluate impact of observation frequency and observation duration



Material

Automated feeding station data from purebred Piétrains

Pigs	Weight records	Feed Intake records
5,939	324,478	323,775

Pedigree of minimal 13 generations

- 9,369 pigs in pedigree
- 6,726 pigs with 45K SNP genotypes



KU LEUVEN

Methods

Quality control via custom R-script

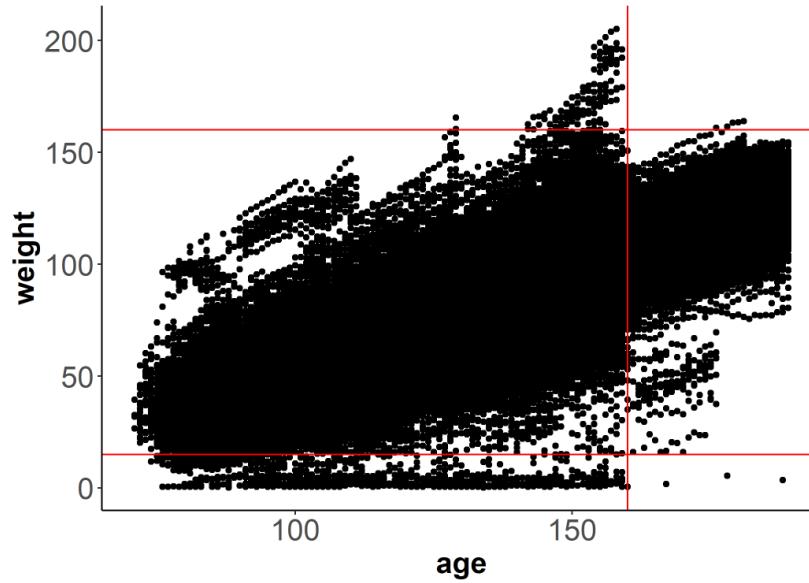
Genetic analyses via remlf90 software: $y = Xb + Za + Wc + e$

- Animal effect (a)
- Fixed effects (b)
 - Sex
 - Farm
 - Maximum age
- Contemporary group effect (c)
 - Farm * Compartment * Date of entrance farm

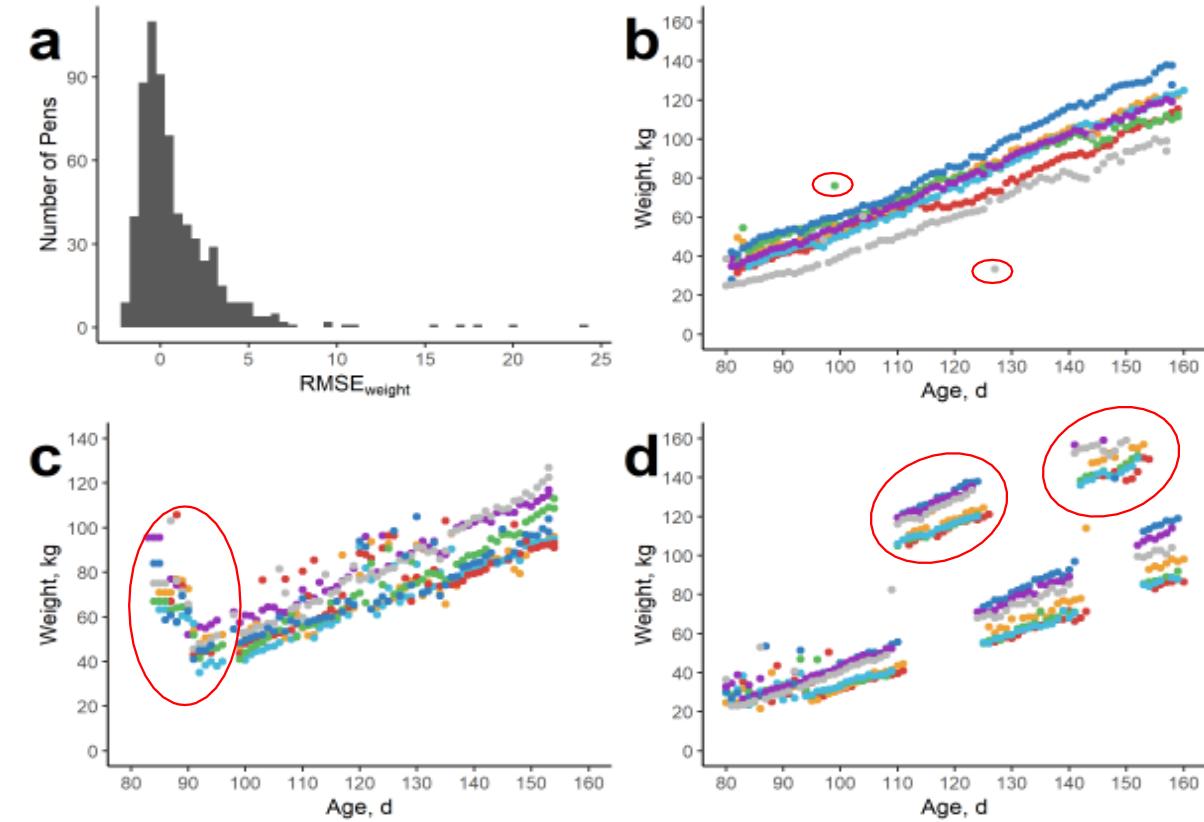


Quality control is crucial when looking at deviations!

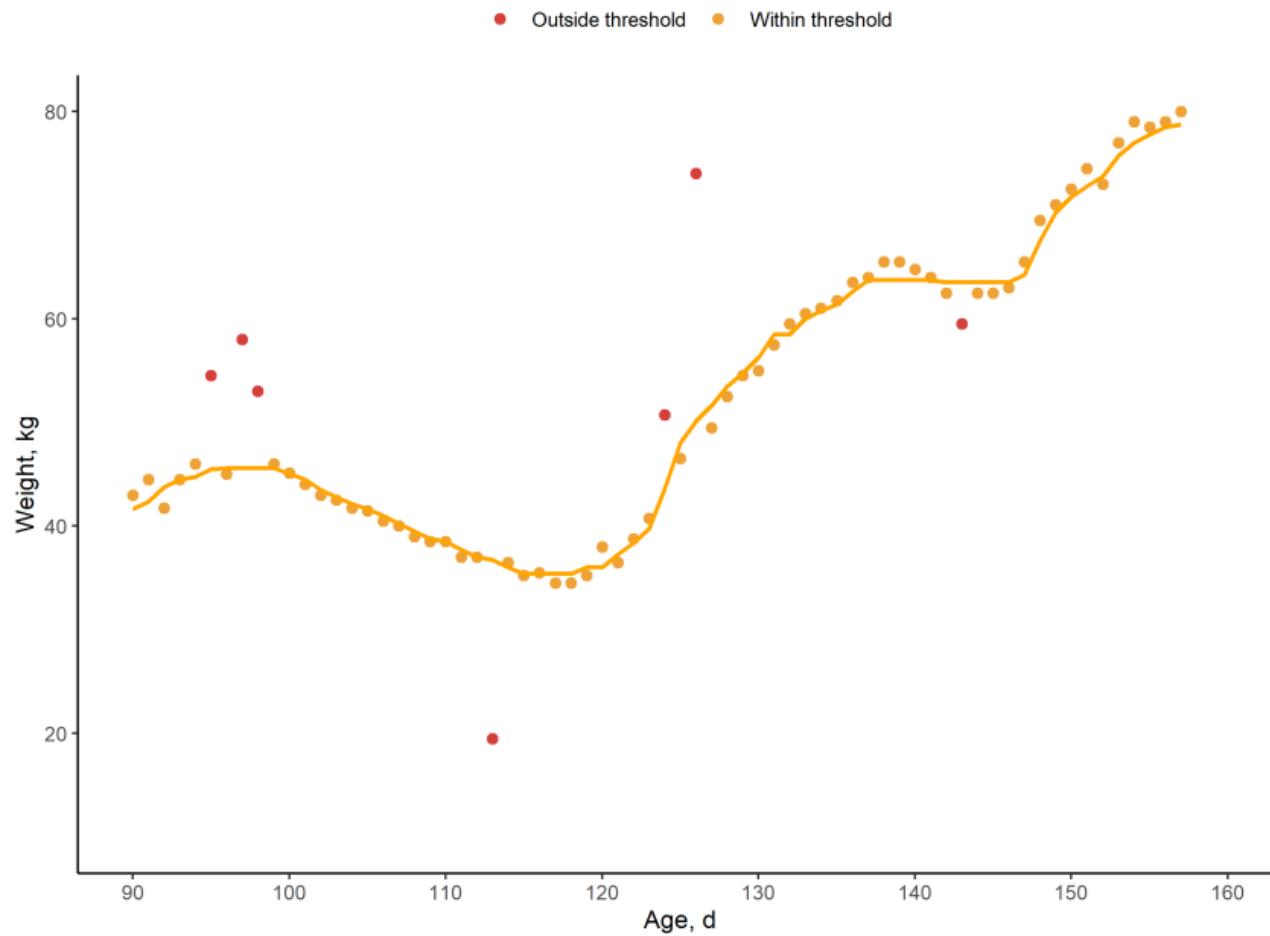
1. Remove clear outliers



2. Pen level QC



3. Individual quality control with rolling average method



Quantifying resilience from weight data

Deviations of observed vs expected

- Natural logarithm of variance (Invar)
- Standardized age trajectory of 95-155 days

1. Observed weights vs predicted gompertz weights

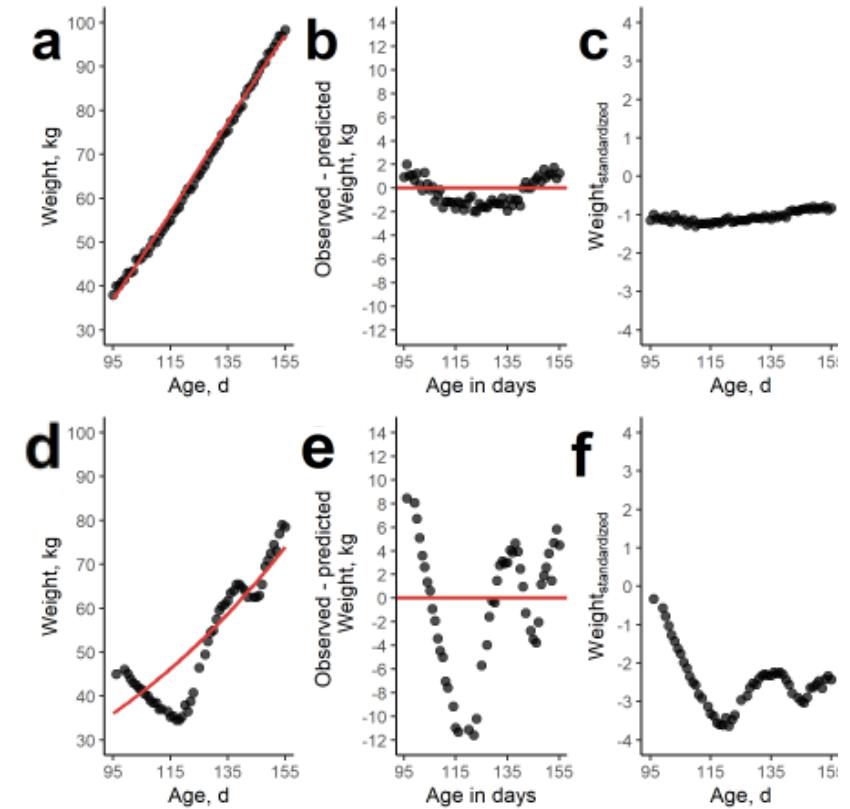
- $\text{Lnvar}_{\text{weight}}$

2. Standardized weights per age

- $\text{Lnvar}_{\text{weight_standardized}}$

→ Higher Invar, lower resilience

→ More deviations from optimal performance

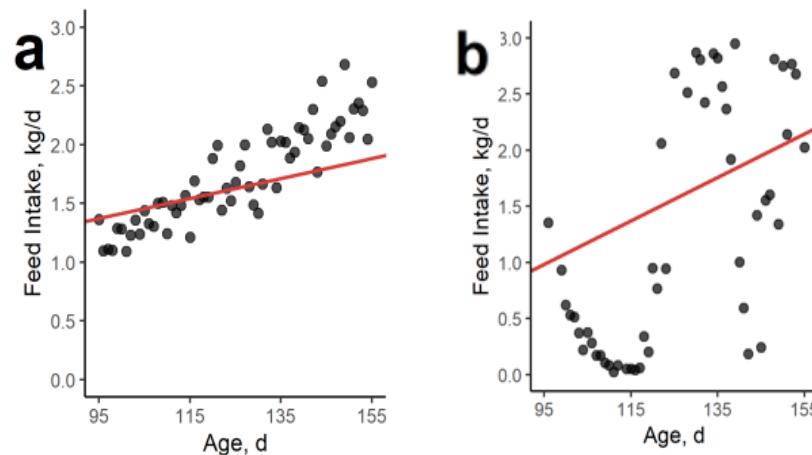


Quantifying resilience from feed intake

Deviations of observed vs expected

- Natural logarithm of Mean Squared Error (MSE)
- LnMSE_{FI}

→ Higher LnMSE , lower resilience



Heritability estimates

Low to moderate heritability resilience traits

Feed Intake deviations higher heritability estimate

→ Note: without adequate QC, h^2 estimates were <5%!

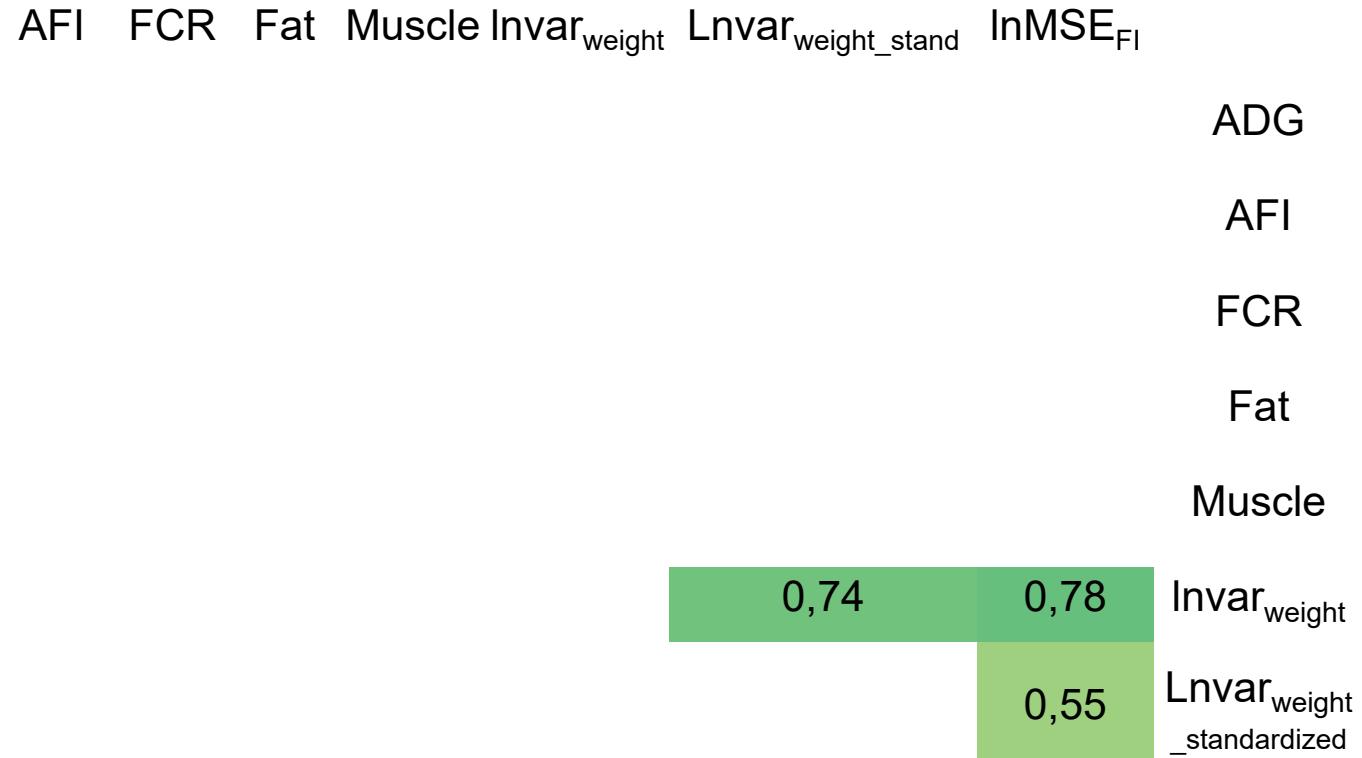
Genetic coefficient of variation 22-30%!

- High potential for genetic improvement

Production traits have moderate to high heritability estimates

Trait	Heritability (SE)	Genetic sd
Lnvar _{weight}	11,0 (2,8)	0,22
Lnvar _{weight_standardized}	12,1 (2,8)	0,30
InMSE _{FI}	23,3 (3,4)	0,29
ADG (g/day)	16,5 (2,6)	67
FI (g/day)	33,8 (3,5)	201
FCR (g/g)	22,9 (3,3)	111
Muscle depth (mm)	36,6 (3,8)	3,9
Fat depth (mm)	52,7 (4,2)	1,2

Genetic correlations



Impact of observation frequency and observation duration

Use (costly) feeding stations more efficiently

Lower observation duration

- Shorter time period → test more pigs per station

Lower observation frequency

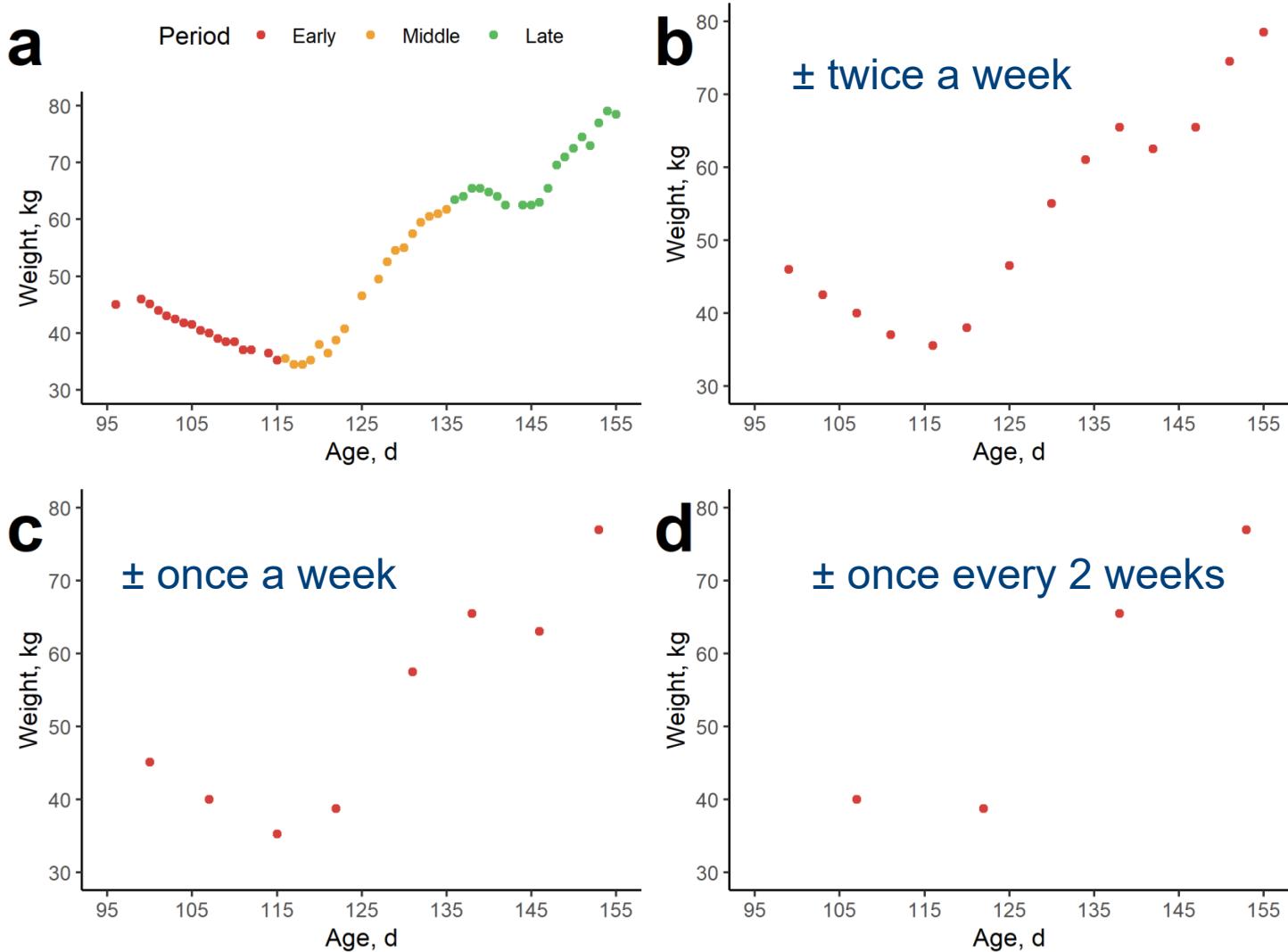
- Only measure pigs every x days
- Rotate → test a group of pigs every x days



What level of missing data is acceptable?

Genetic correlations estimated using bivariate animal models within each trait

Differences in observation period (a) and observation frequencies (b-d)



Impact of observation frequency on resilience traits

Lower observation density → heritability drops substantially

- Less information/variance

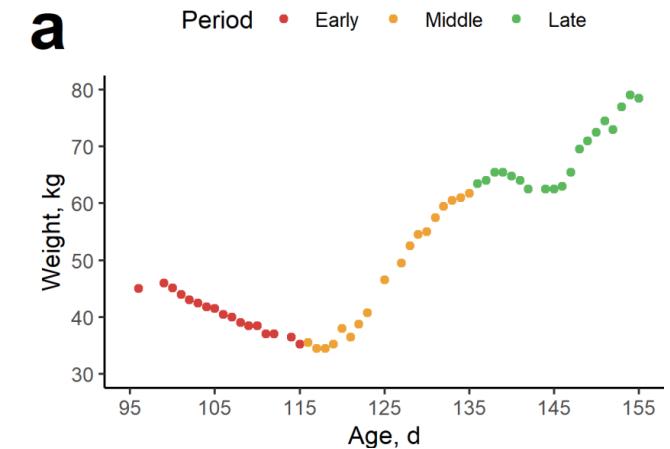
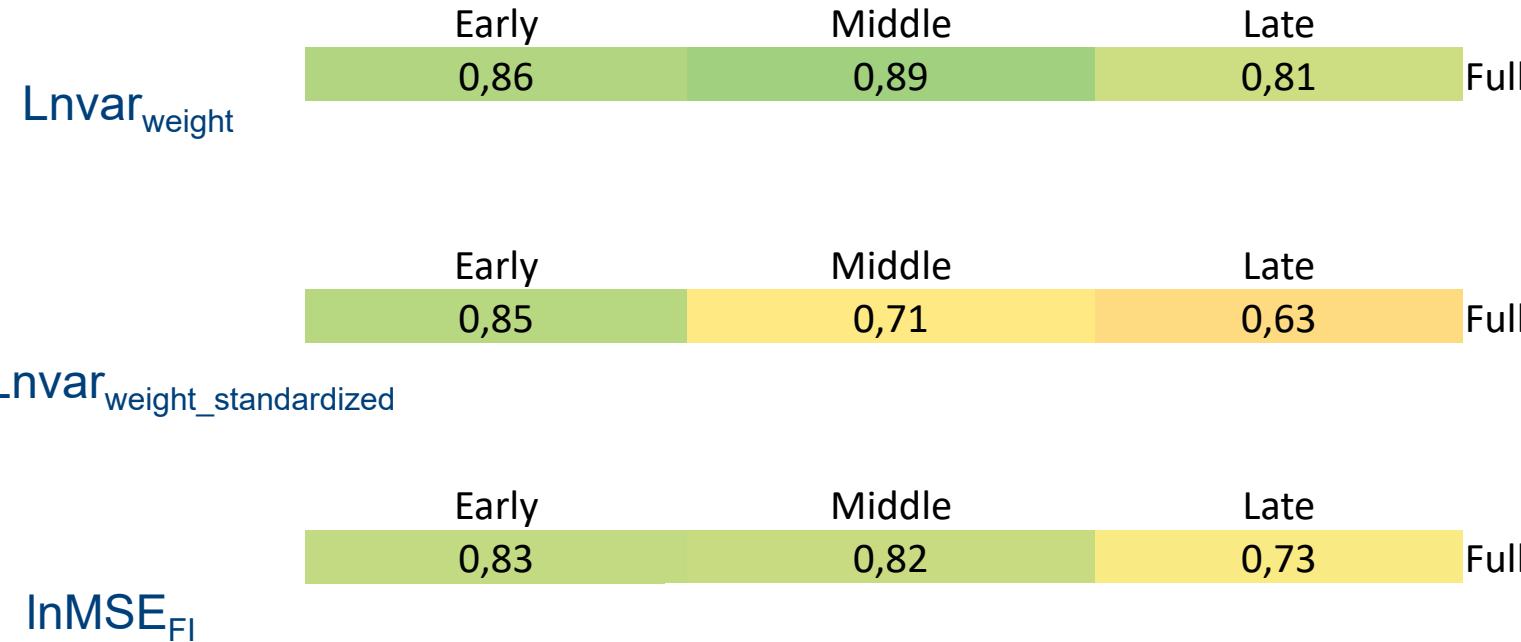
Genetic correlations are high ($r_g > 0,76$), even with only one observation every 14 days
→ Phenotypic correlations also reasonably high ($r_p > 0,43$)

Trait	1 in 4 observations	1 in 7 observations	1 in 14 observations
full dataset	h^2 (se)	h^2 (se)	h^2 (se)
Lnvar _{weight}	14.7 (2.7)	9.2 (1.8)	5.8 (1.3)
Lnvar _{weight_standard}	12.9 (2.7)	10.4 (2.0)	9.3 (1.9)
lnMSE _{FI}	21.6 (2.9)	12.4 (2.1)	5.5 (1.3)

Impact of observation period on resilience traits

High genetic correlations between time periods and full dataset
→ early/middle period higher genetic correlations than late period

Moderate genetic correlations within time periods
→ Resilience traits quite robust to observation period



Want to learn more about this research?

Research | [Open Access](#) | Published: 01 August 2023

A promising resilience parameter for breeding: the use of weight and feed trajectories in growing pigs

[Wim Gorssen](#), [Carmen Winters](#), [Roel Meyermans](#), [Léa Chapard](#), [Katrijn Hooyberghs](#), [Steven Janssens](#), [Abe Huisman](#), [Katrijn Peeters](#), [Han Mulder](#) & [Nadine Buys](#) 

Journal of Animal Science and Biotechnology **14**, Article number: 101 (2023) | [Cite this article](#)



Take-home message

Resilience traits for weight and feed intake deviations are heritable ($h^2=11-23\%$)

- Favorable genetic correlations with FCR

Resilience traits are quite robust to low observation frequencies and short observation period

→ More efficient use of automated feeding stations possible

Validation of resilience traits

- Session 28 (Tuesday, Foyer Amphitheatre Rhone)

15:45 Resilience parameters in fattening pigs are heritable and associated with tail biting and mortality
W. Gorssen, C. Winters, R. Meyermans, L. Chapard, K. Hooyberghs, J. Depuydt, S. Janssens, H. Mulder and N. Buys



Acknowledgments

- Manuel Revilla and Jordi Vila Teixidor for their advice and help

- Data provider



- Funding



Grant IDs: 1S05818N; 1104320N; 1S37119N

Thank you for your attention!

