Cross-Validation Assessment of Random Regression Models for Dry Matter Intake

Interbull Annual Meeting

Bled, 2024

Matias F. Schrauf, Birgit Gredler-Grandl, Renzo Bonifazi, Jeremie Vandenplas, Jan ten Napel,
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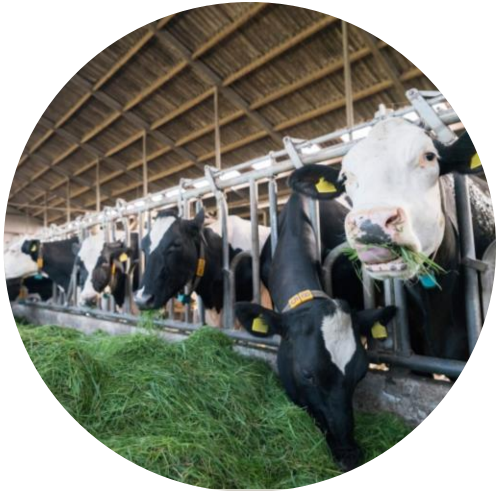

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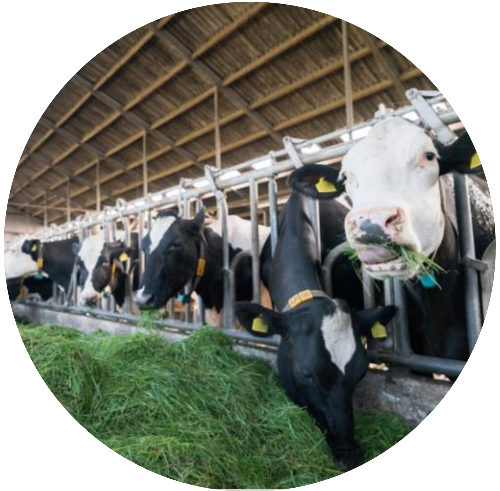

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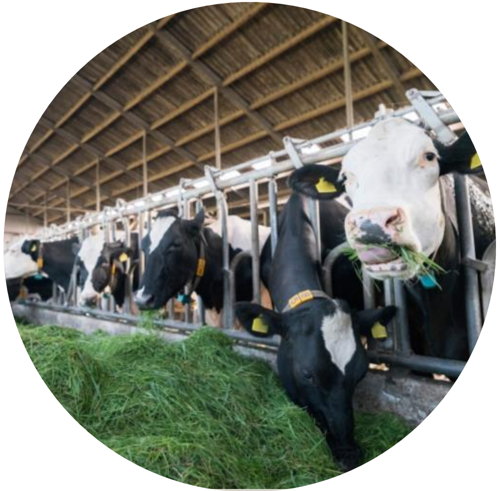

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Dry Matter Intake

Genetic Evaluation for Dry Matter Intake (DMI)

- To select for feed efficiency
- We calculate EBVs for DMI, instead of residual traits

Expensive trait to measure

Few records in the beginning

Simple repeatability model

E-chapter 40. Dry matter intake

Current data

Now we have accumulated DMI data from:

+10K Holstein cows

+20K lactations

+1 million DMI records

Current data

Now we have accumulated DMI data from:

+10K Holstein cows

+20K lactations

+1 million DMI records

Opens opportunity for improved modelling!

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Multi-trait dynamic model for genetic RFI

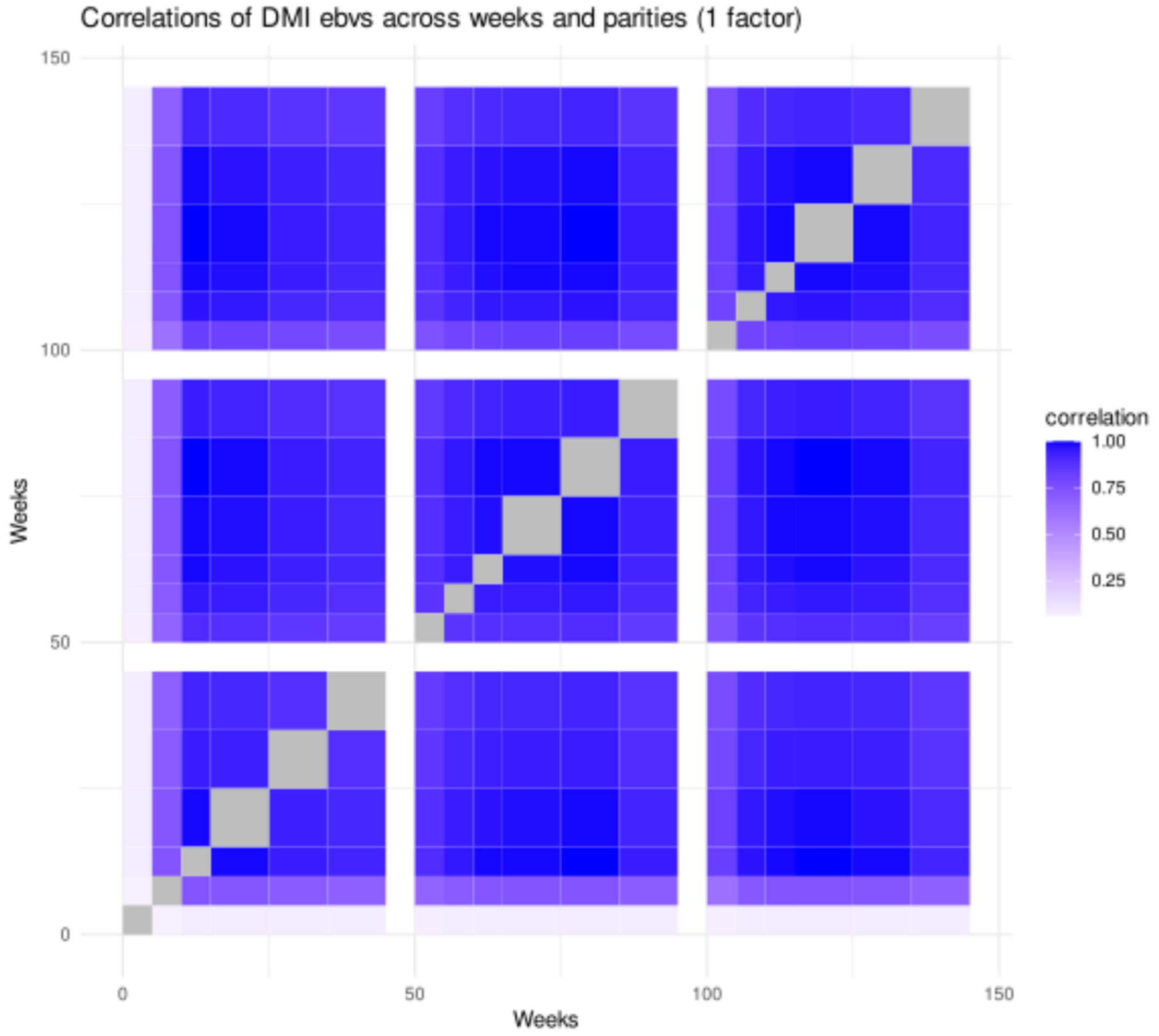
- Multi-trait ⇒ adjusted by MilkE, MBW and dMBW
- Dynamic ⇒ RRM for traits on lactation day
- Genetic ⇒ adjustment on the genetic level

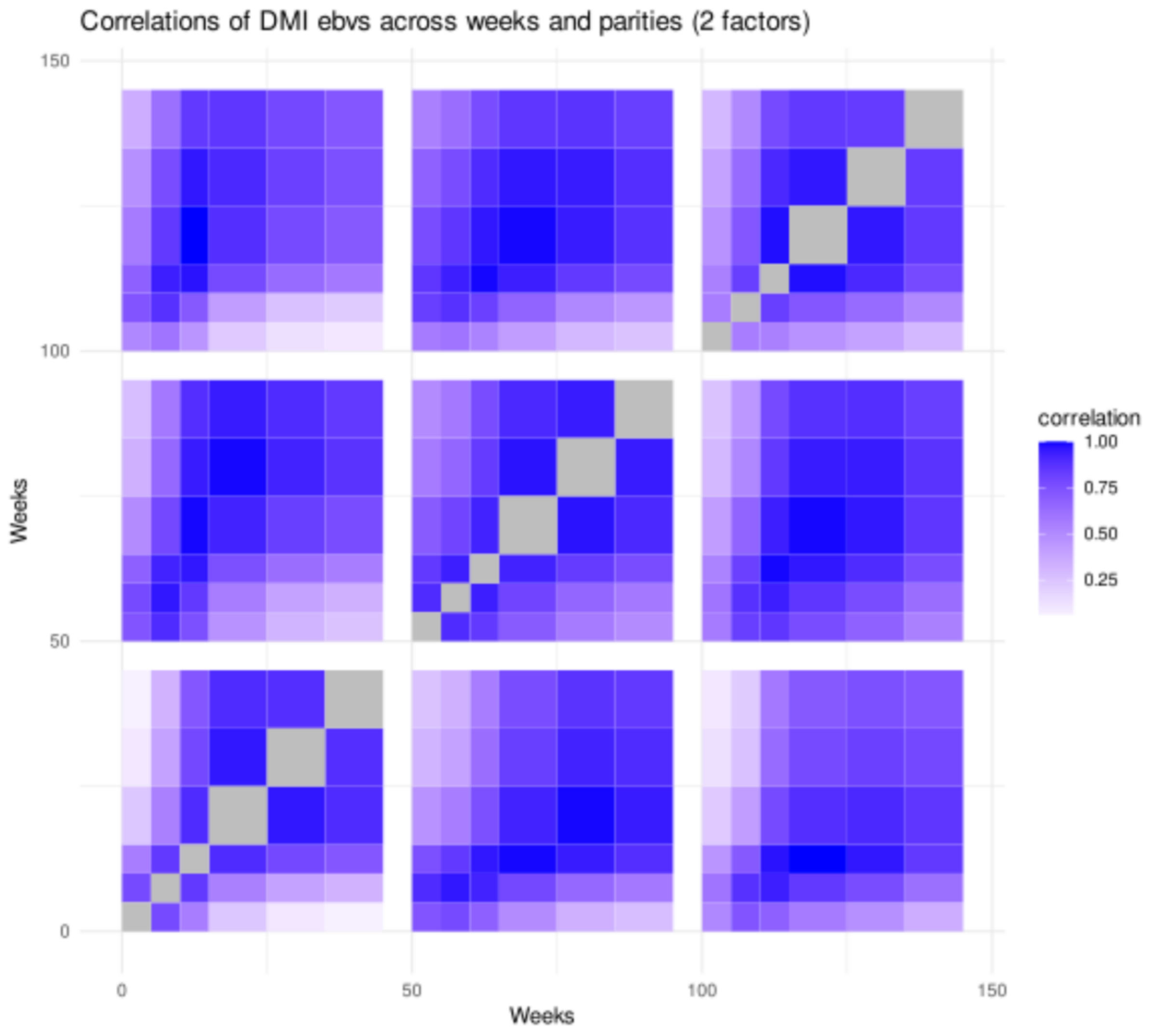
Islam et al., 2020 Khanal et al., 2022 Stephansen et al., 2023 Houlahan et al., 2023

- Requires a dynamic modelling of the DMI genetic component

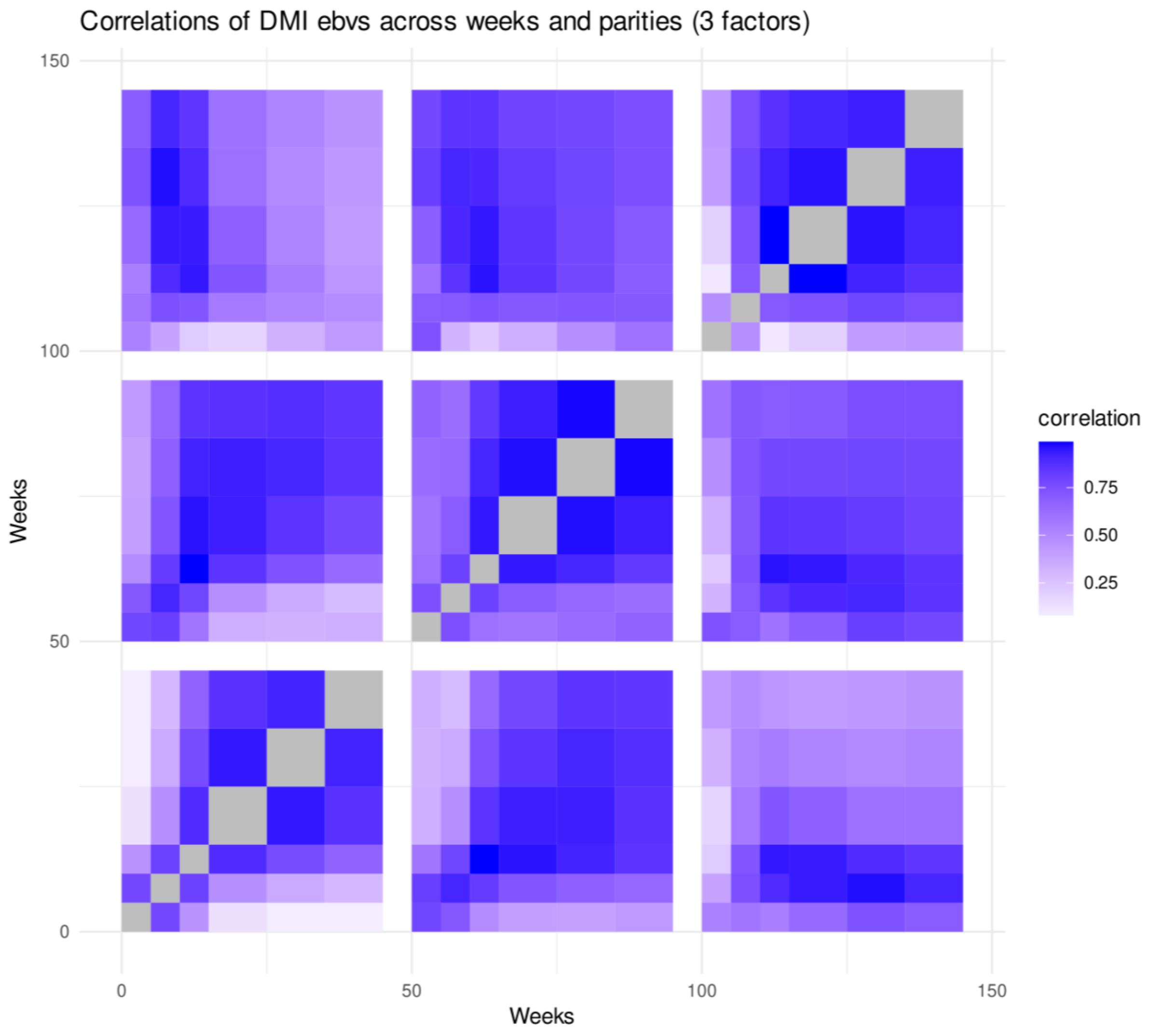
Improvements in Statistical Software

- Newer versions of ASReml
  - XFA parameterization for variance structures
  - Allows for incremental increase in complexity

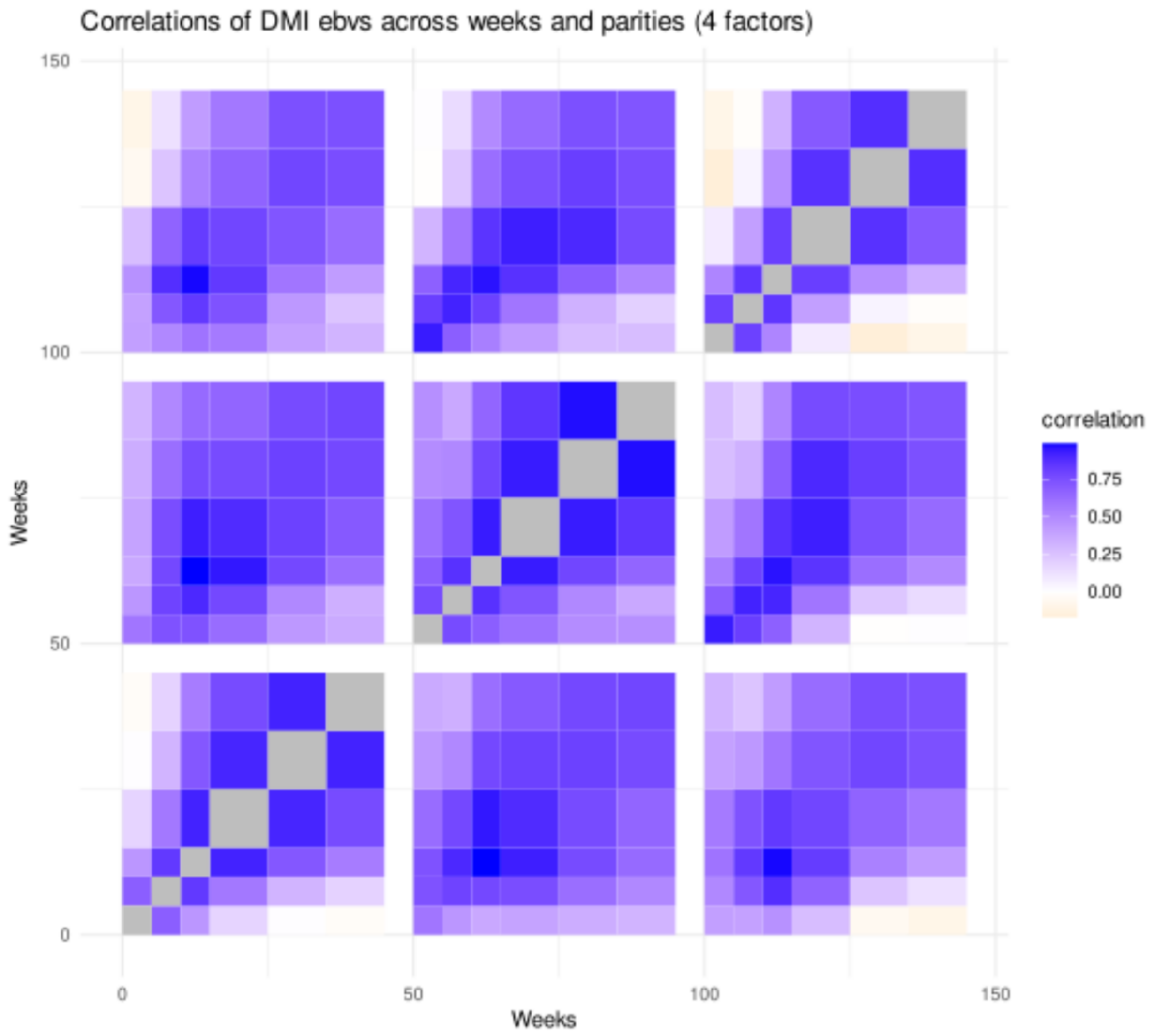

Correlations of DMI ebvs across weeks and parities (1 factor)
Weeks
0
50
100
150
Weeks
0
50
100
150
correlation
1.00
0.75
0.50
0.25



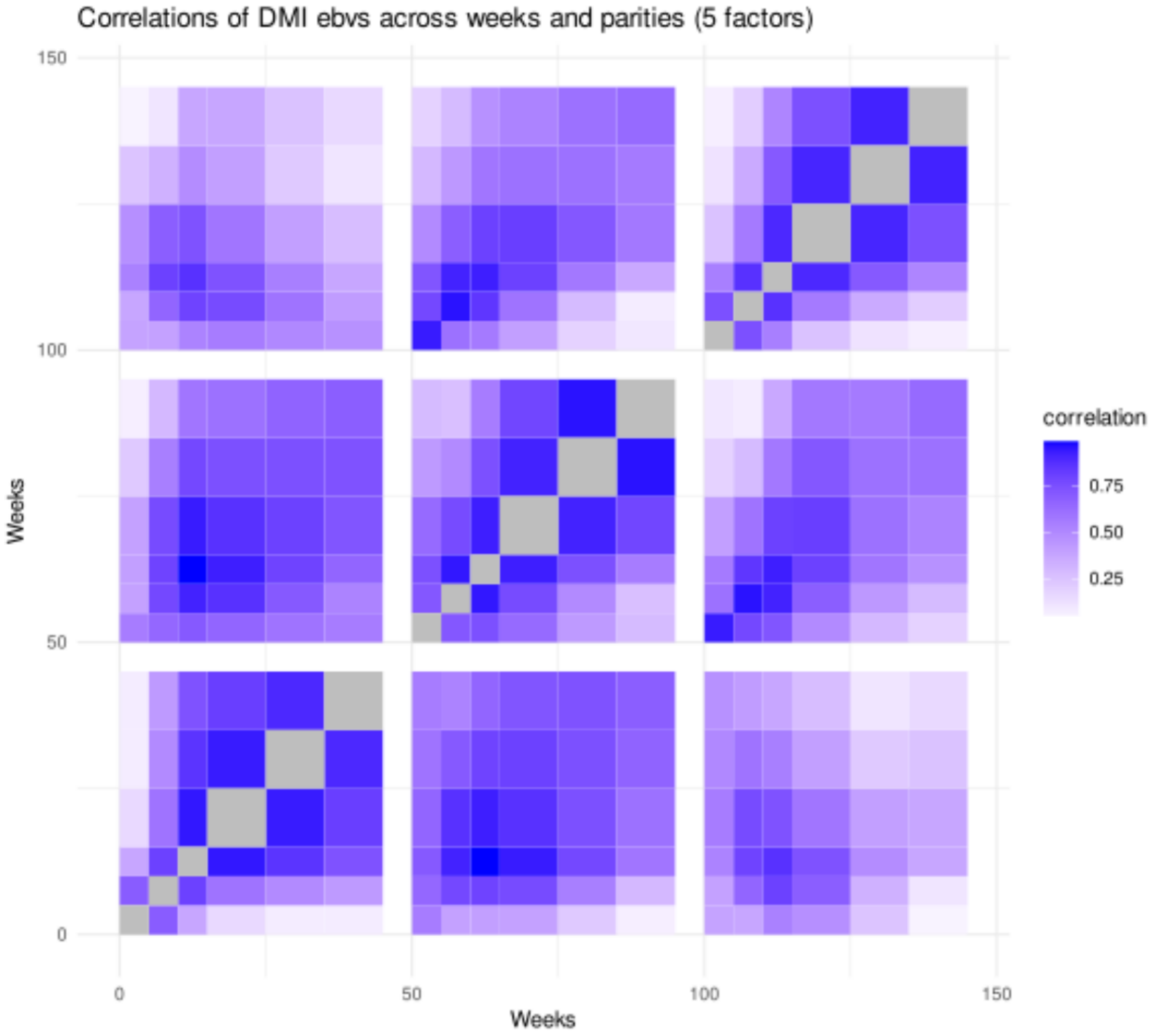
Correlations of DMI ebvs across weeks and parities (2 factors)
Weeks
Weeks
0
50
100
150
0
50
100
150
correlation
1.00
0.75
0.50
0.25



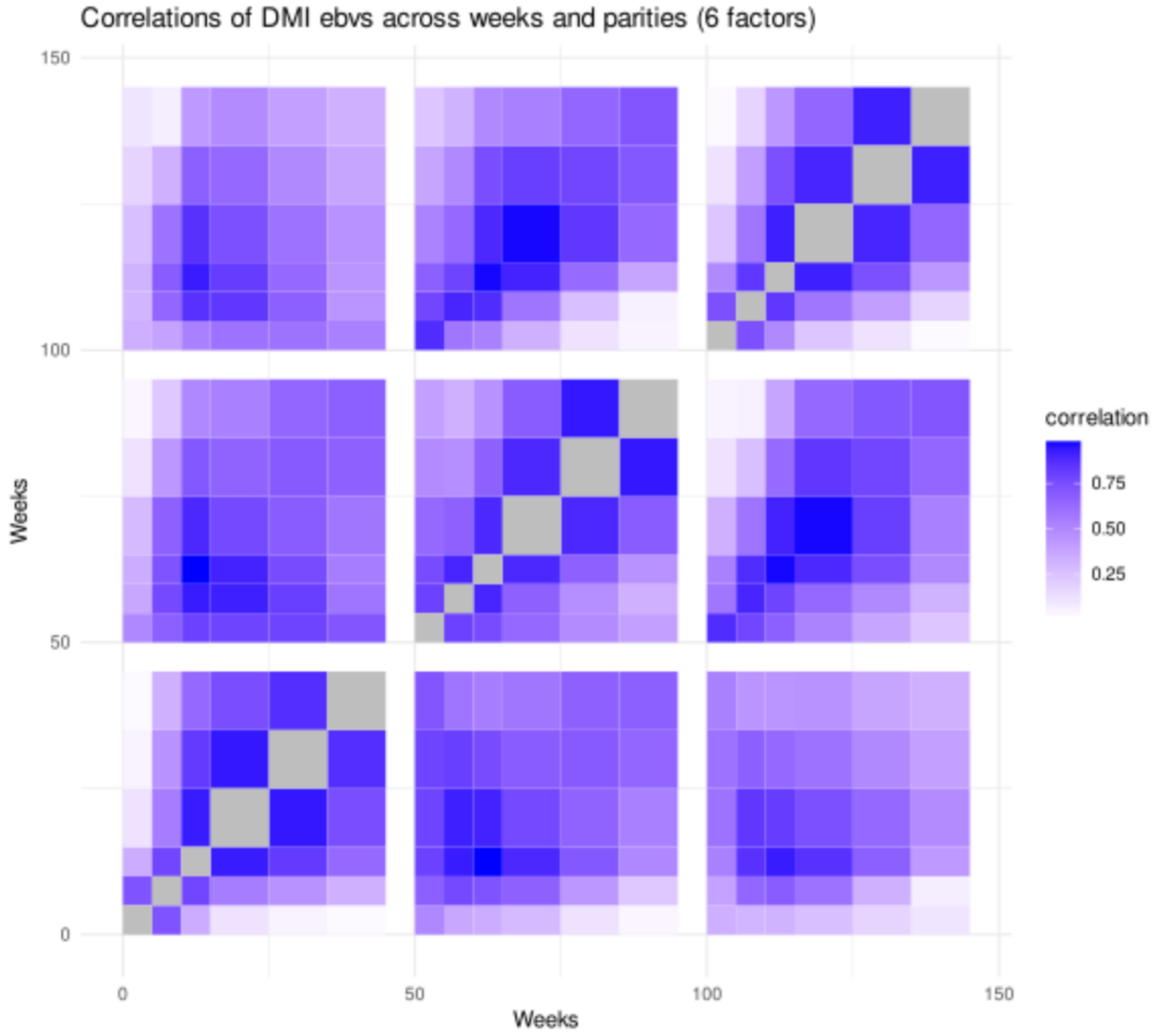
Correlations of DMI ebvs across weeks and parities (3 factors)
150
100
50
0
Weeks
0
50
100
150
Weeks
correlation
0.75
0.50
0.25



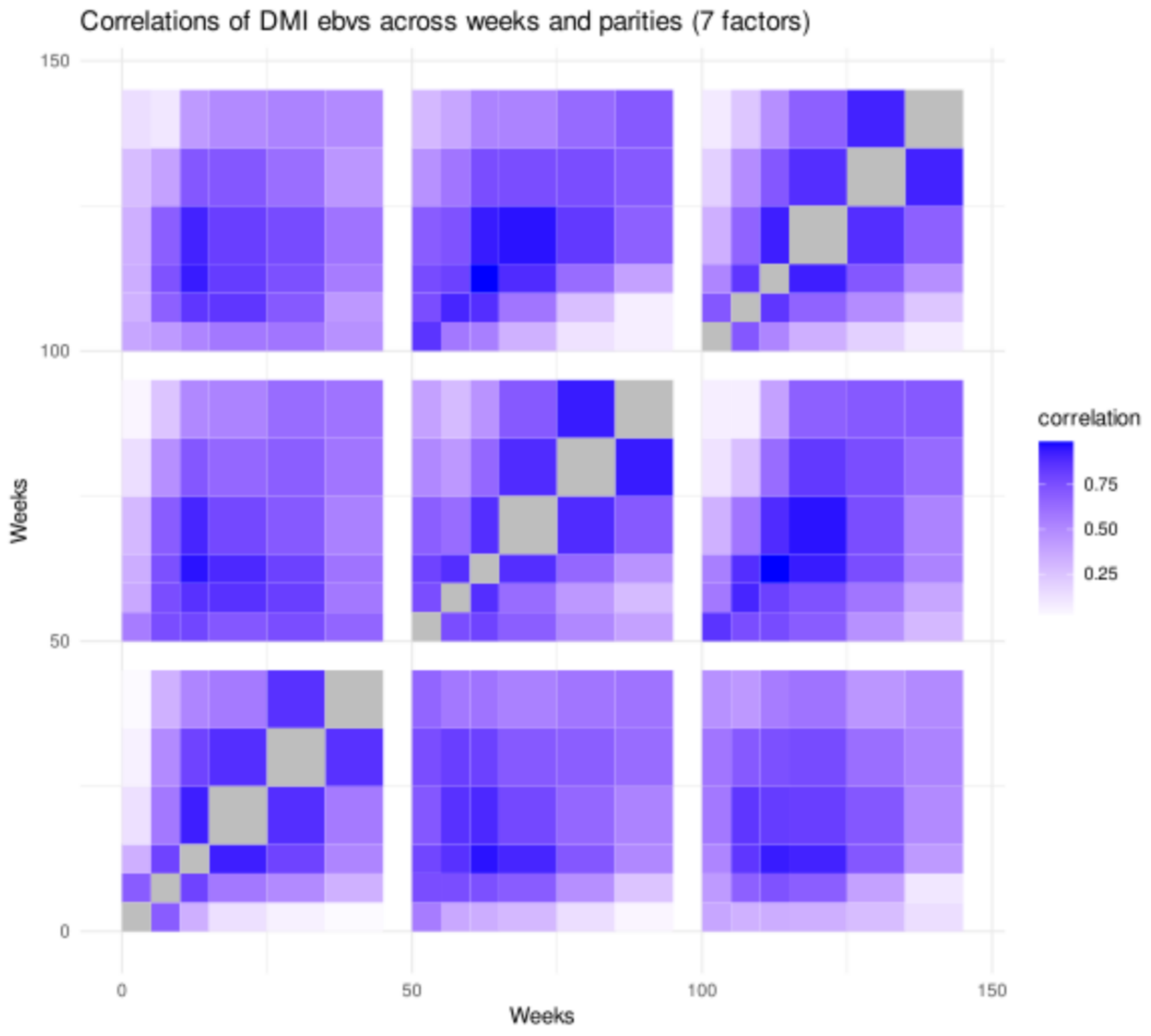
Correlations of DMI ebvs across weeks and parities (4 factors)
Weeks
0
50
100
150
correlation
0.75
0.50
0.25
0.00

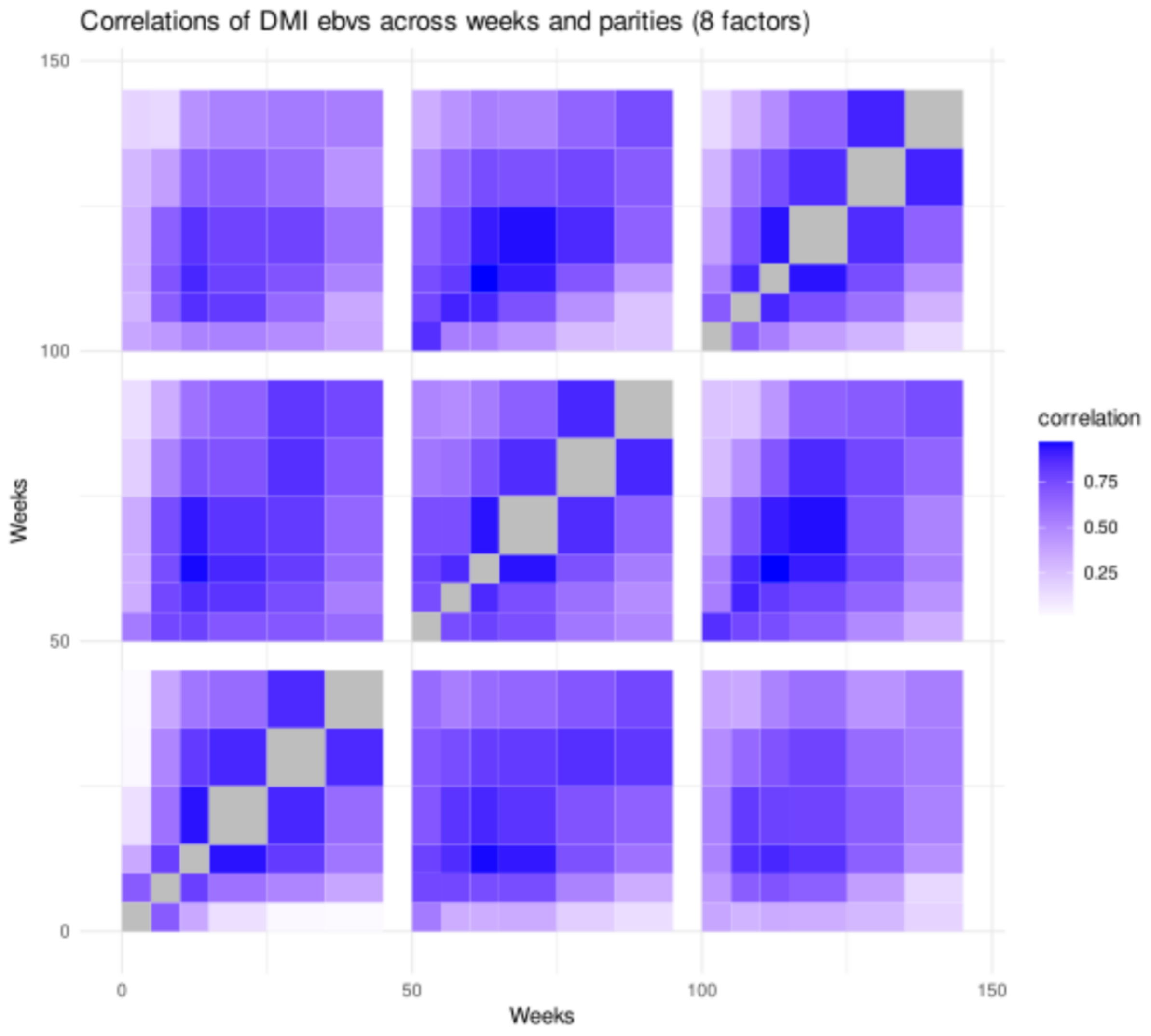


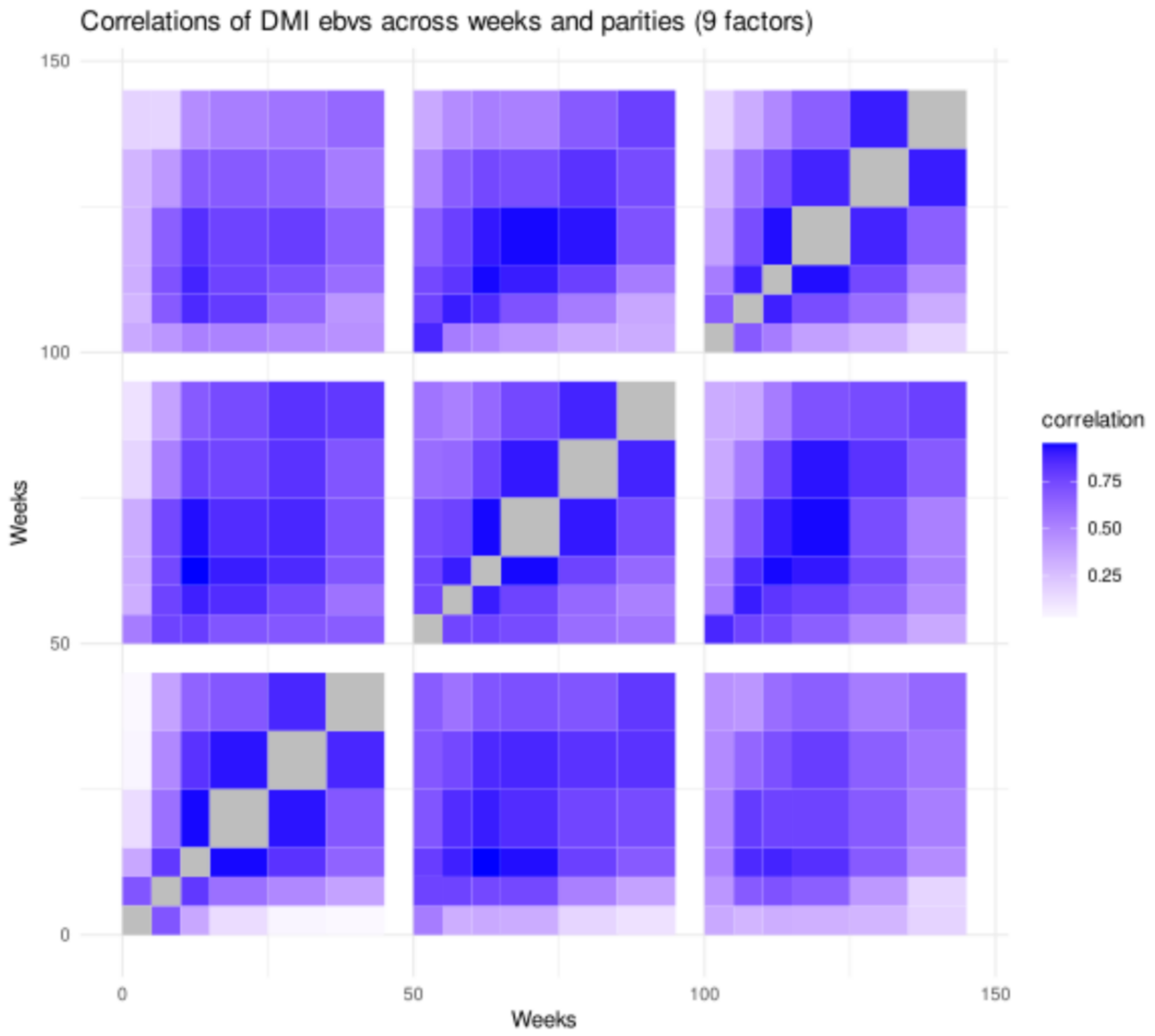
Correlations of DMI ebvs across weeks and parities (5 factors)
Weeks
Weeks
0
50
100
150
0
50
100
150
correlation
0.75
0.50
0.25



Correlations of DMI ebvs across weeks and parities (6 factors)
Weeks
Weeks
0
50
100
150
0
50
100
150
correlation
0.75
0.50
0.25

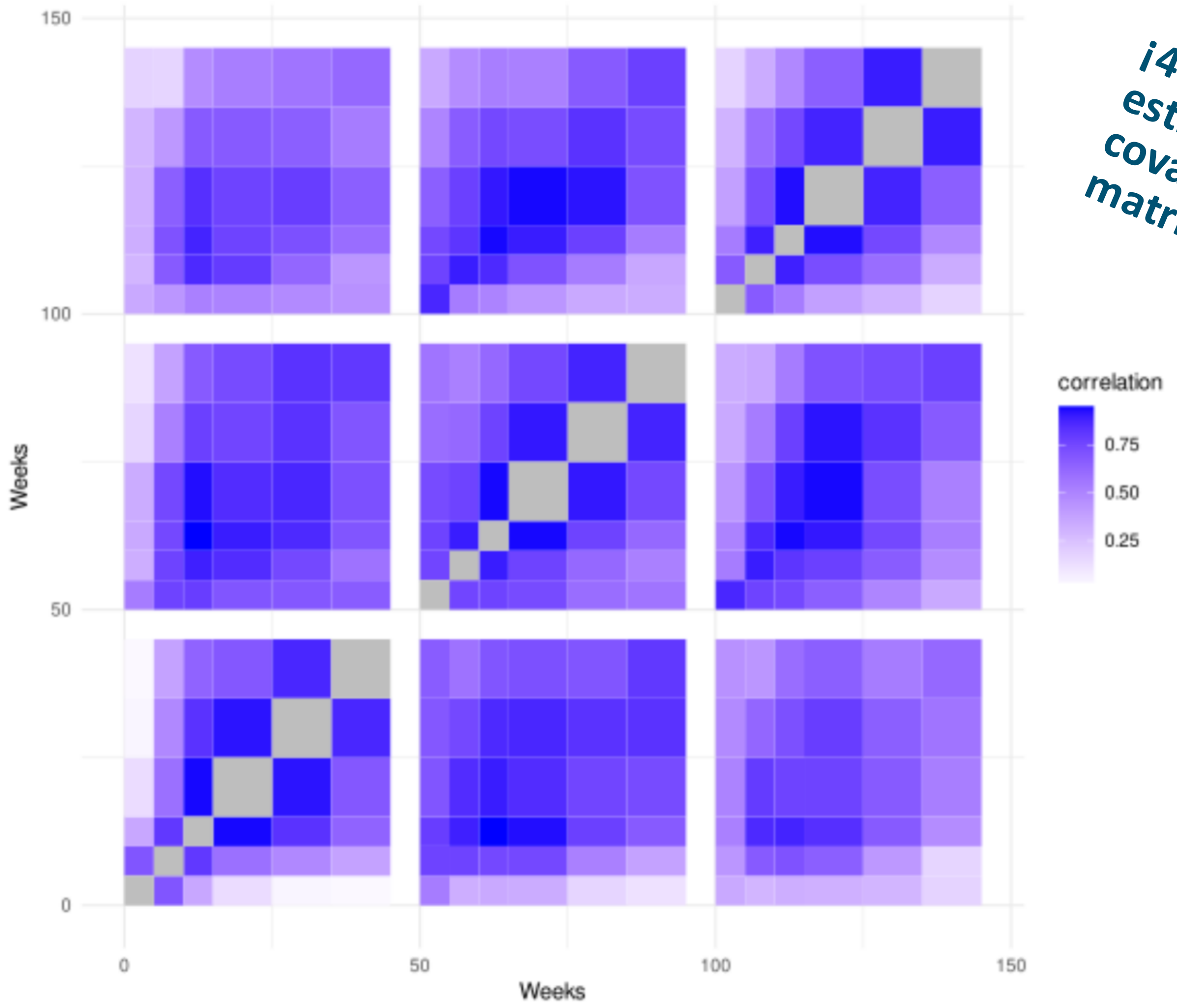

Correlations of DMI ebvs across weeks and parities (7 factors)
Weeks
Weeks
correlation
0.75
0.50
0.25
0
50
100
150
0
50
100
150


Correlations of DMI ebvs across weeks and parities (8 factors)
Weeks
Weeks
0
50
100
150
correlation
0.25
0.50
0.75



Correlations of DMI ebvs across weeks and parities (9 factors)
Weeks
0
50
100
150
correlation
0.75
0.50
0.25

Correlations of DMI ebvs across weeks and parities (9 factors)



¡405 parameters estimated in the covariance matrix!

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    - Allows for incremental increase in complexity

Improvements in Statistical Software

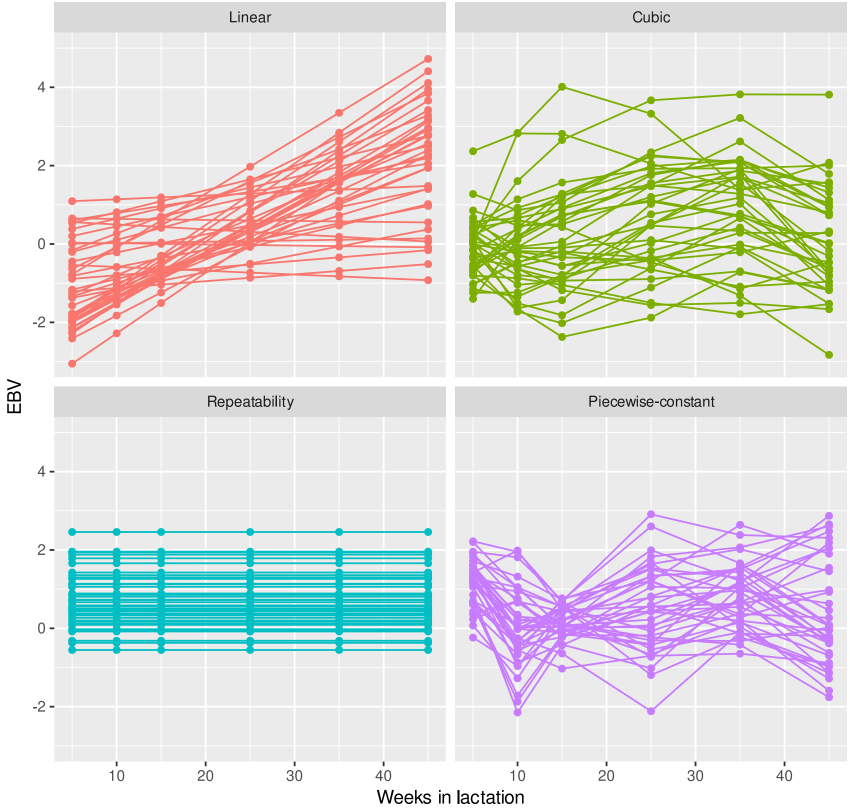
- Newer versions of ASReml
  - XFA parameterization for variance structures
  - Allows for incremental increase in complexity
- Newer versions of MiXBLUP
  - efficient ssSNPBLUP running on GPUs

Random Regression Models

Random Regression Model

Random regressions
on days in milk (nested in parity)

- Linear
- Cubic
- Repeatability
- Piecewise-constant



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MiXBLUP

Cross-Validation Assessment

Validation approaches

- Parametric
  - Likelihood, AIC, BIC

- Non-parametric
  - CV on DRPs

Validation approaches

- Parametric
    - Likelihood, AIC, BIC
- Semi-parametric
    - LR-method
- Non-parametric
    - CV on DRPs

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Semi-parametric

Compares EBVs from partial data, with EBVs from full data.

Model	rho	mse
Linear	0.25	1.09
Cubic	0.20	1.03
Repeatability	0.28	0.65
Piecewise-constant	0.41	0.48

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Repeatability	0.28	0.65
Piecewise-constant	0.41	0.48

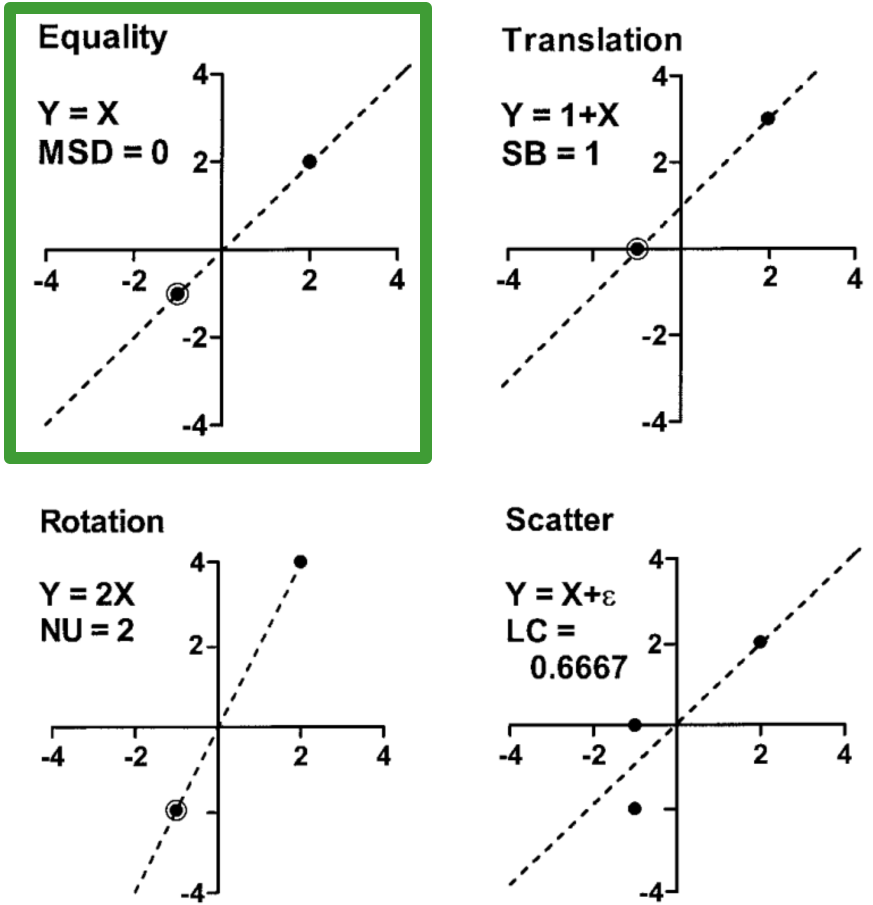
Used PWC model fitted with full data as the prediction target

Validation metrics

Possible discrepancies

- Level bias -> SB
- Inflation/deflation -> NU
- Accuracy -> LC

MSE = SB + NU + LC



Gauch et al., 2003

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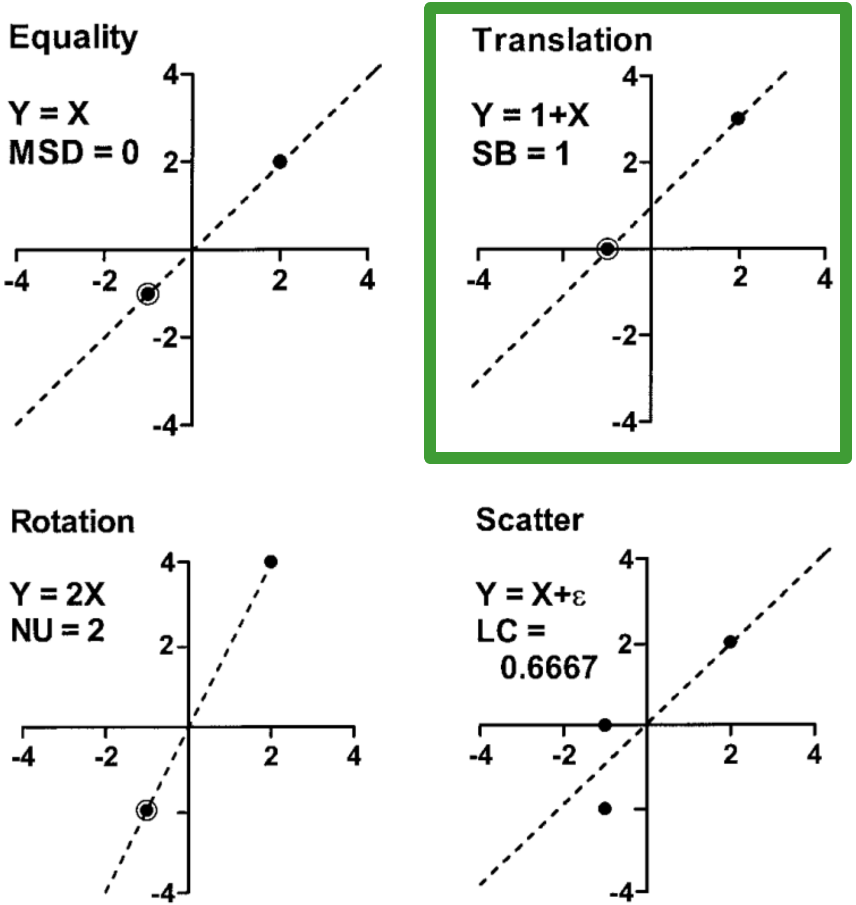

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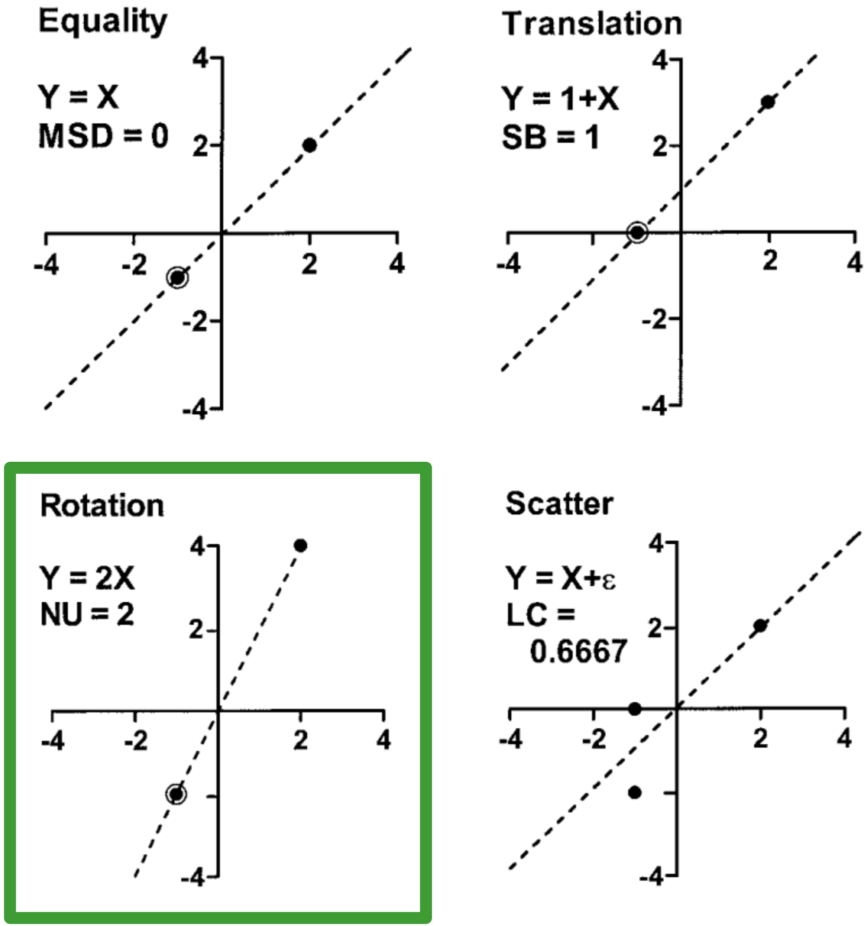

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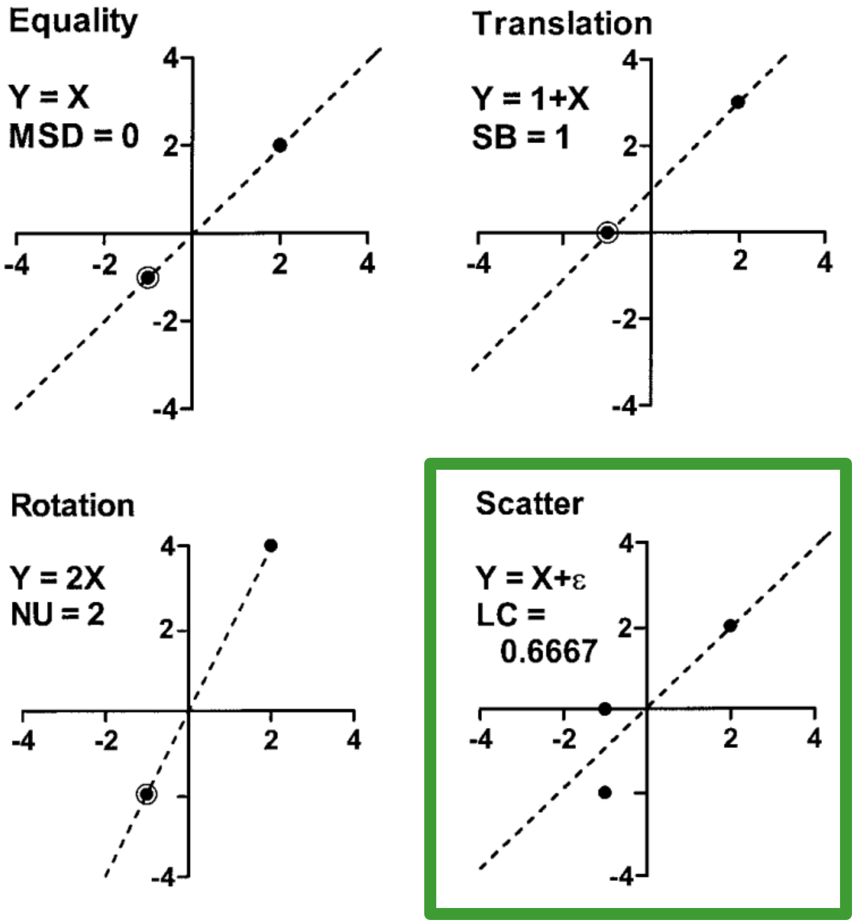

Gauch et al., 2003

Validation metrics

Possible discrepancies

- Level bias -> SB
- Inflation/deflation -> NU
- Accuracy -> LC

MSE = SB + NU + LC

$$\mathbf{LB} = (\overline{X} - \overline{Y})^2$$

$$\mathbf{NU} = (1 - b)^2 V_X$$

$$\mathbf{LC} = (1 - \rho^2) V_Y$$

Gauch et al., 2003

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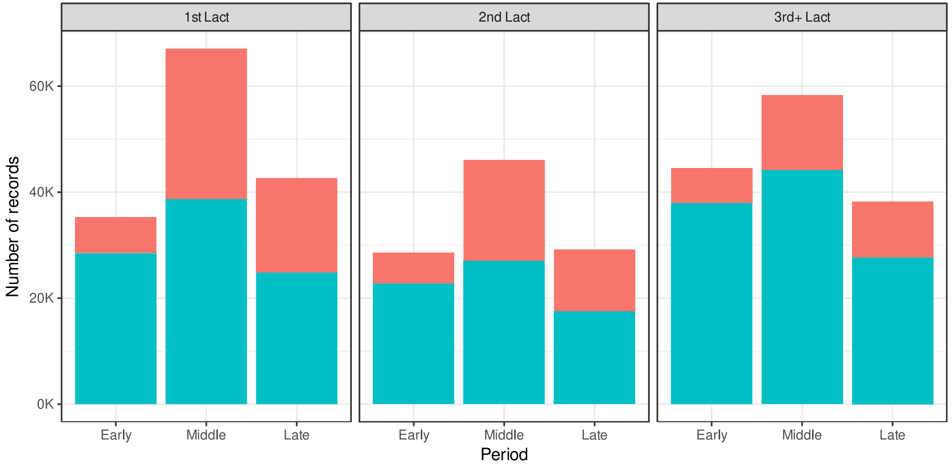
Forward validation

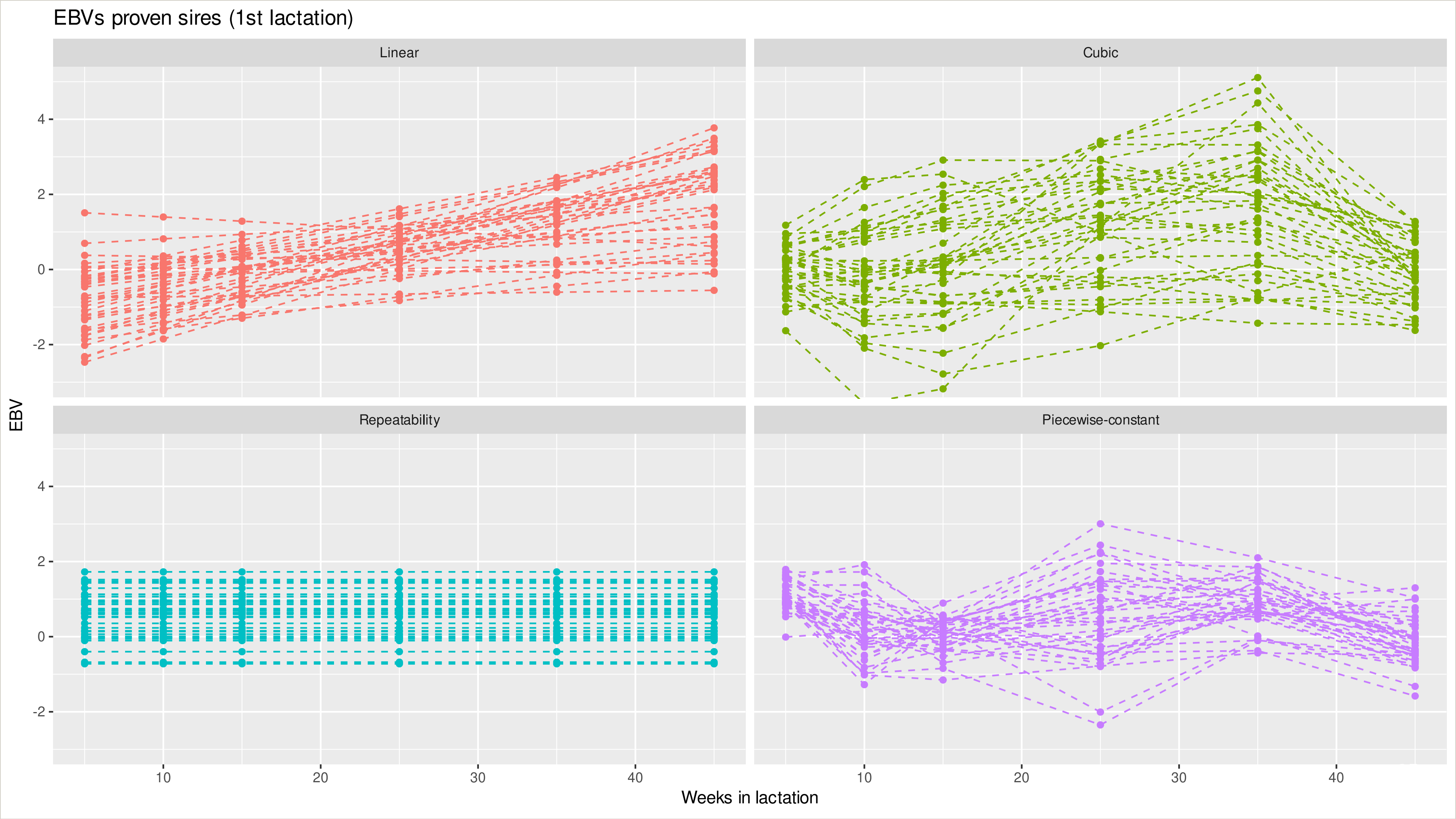
Cutoff date: 2020

Disclaimer: pedigree blups shown here

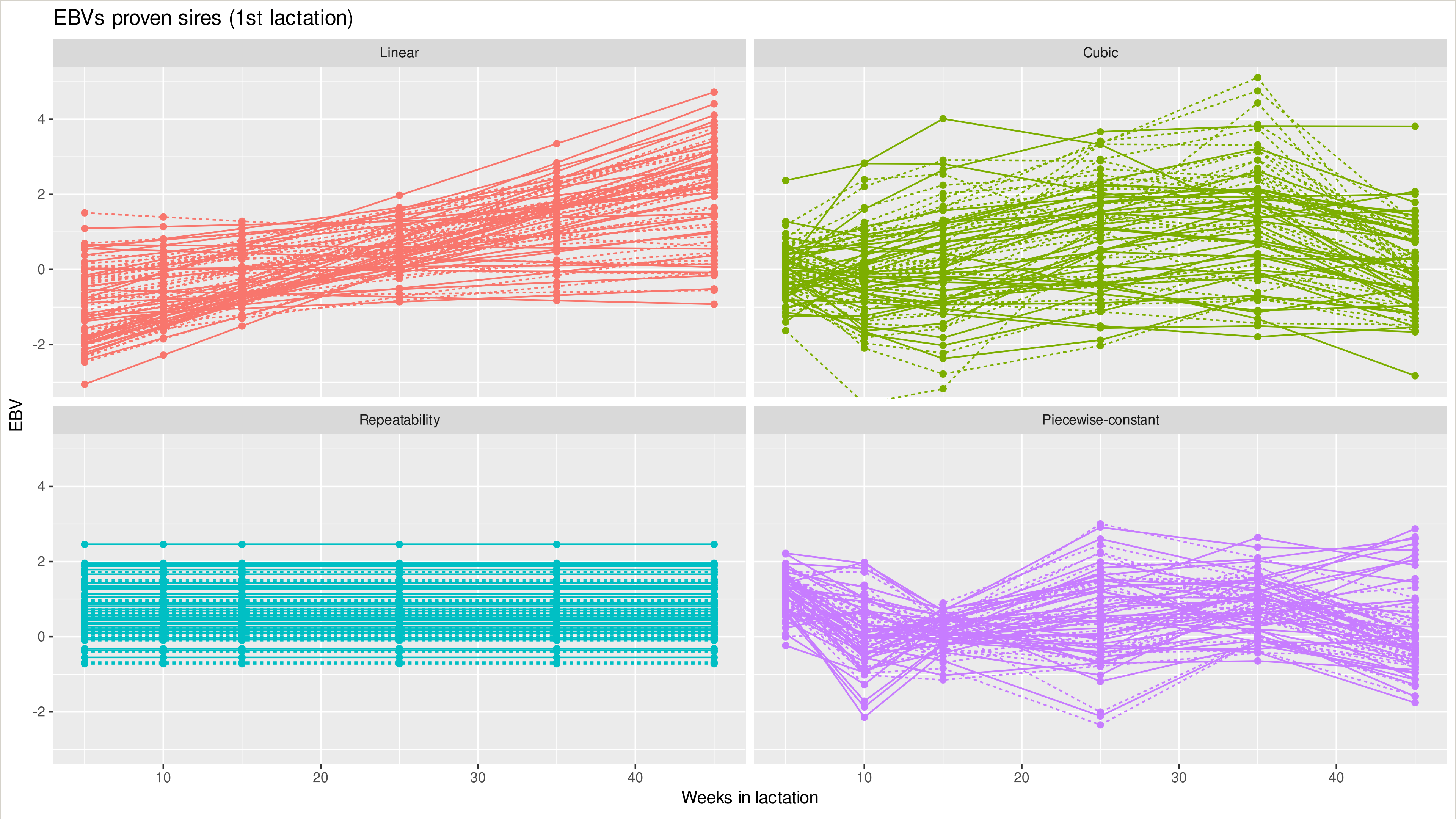
- Focal groups
- validation cows, (0 records in partial , +3 in full) #2958
- young sires, (0 phenotyped daughters in partial, +10 in full) #41
- proven sires, (+10 phenotyped daughters in partial, +1 in full) #38

- Lactation periods
- Early (weeks 5 & 10)
- Middle (weeks 15 & 25)
- Late (weeks 35 & 45)





EBVs proven sires (1st lactation)
Linear
Cubic
Repeatability
Piecewise-constant
EBV
Weeks in lactation
4
2
0
-2
10
20
30
40



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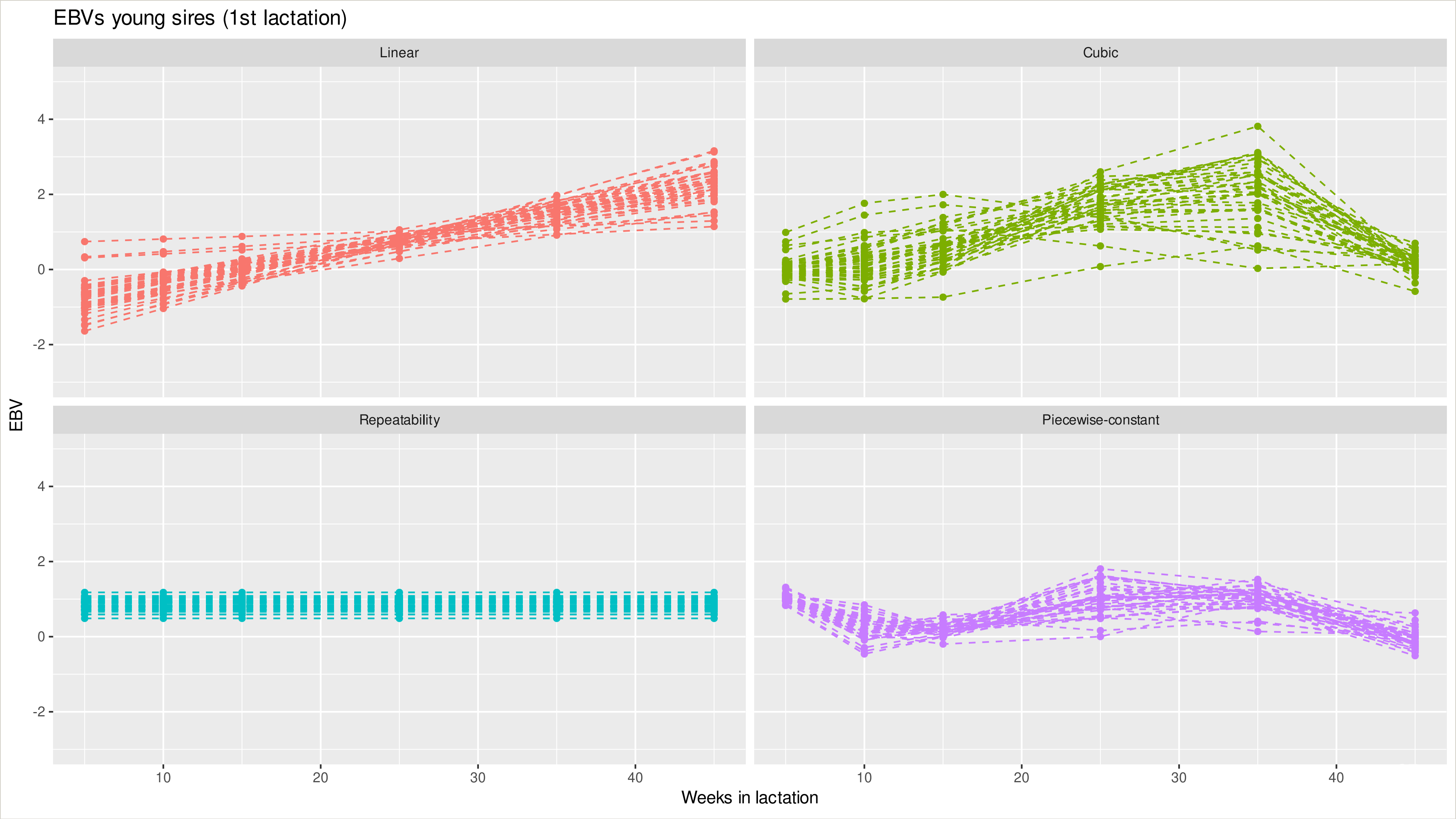
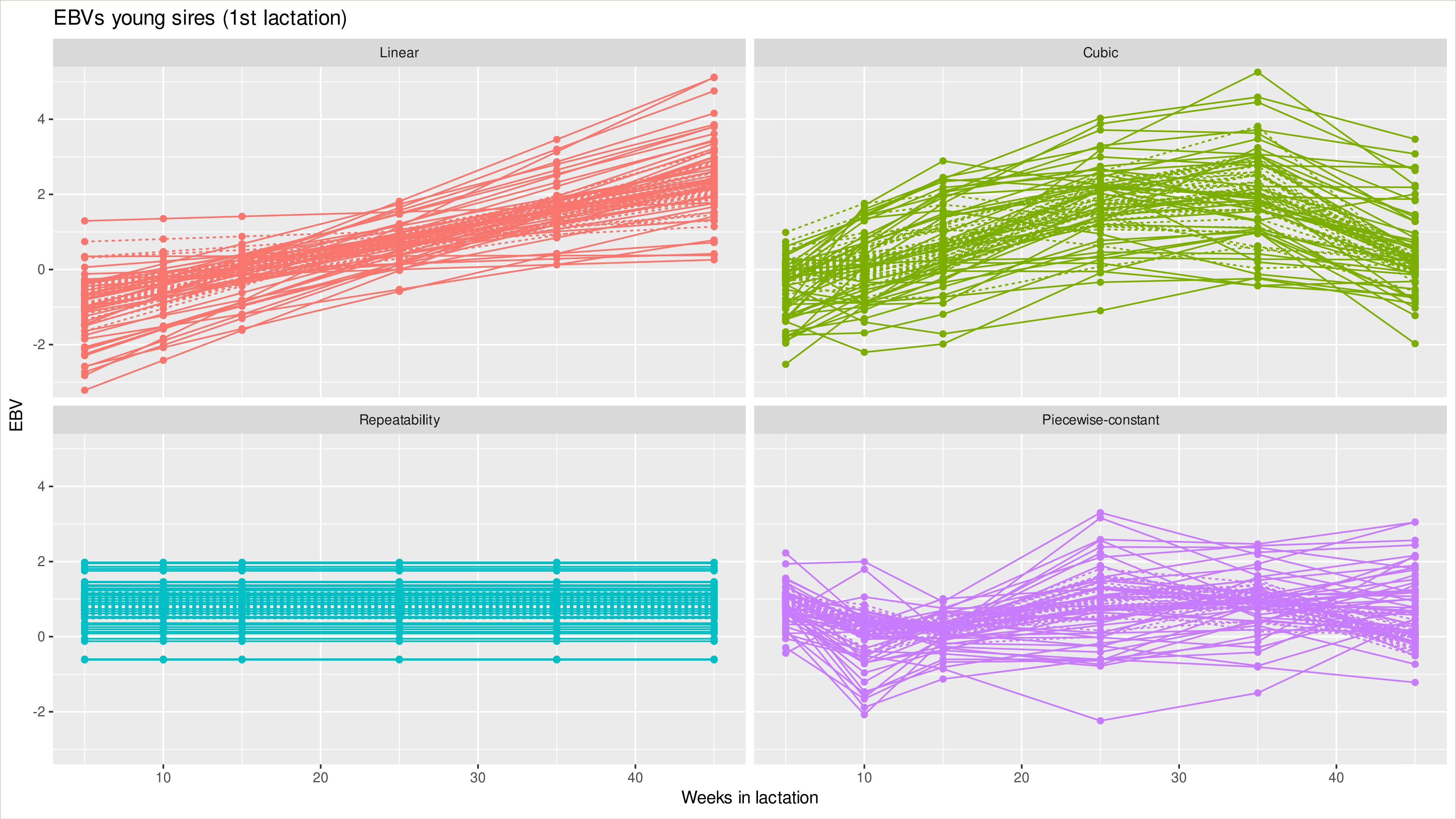
Cubic
Repeatability
Piecewise-constant
EBV
Weeks in lactation
4
2
0
-2
10
20
30
40

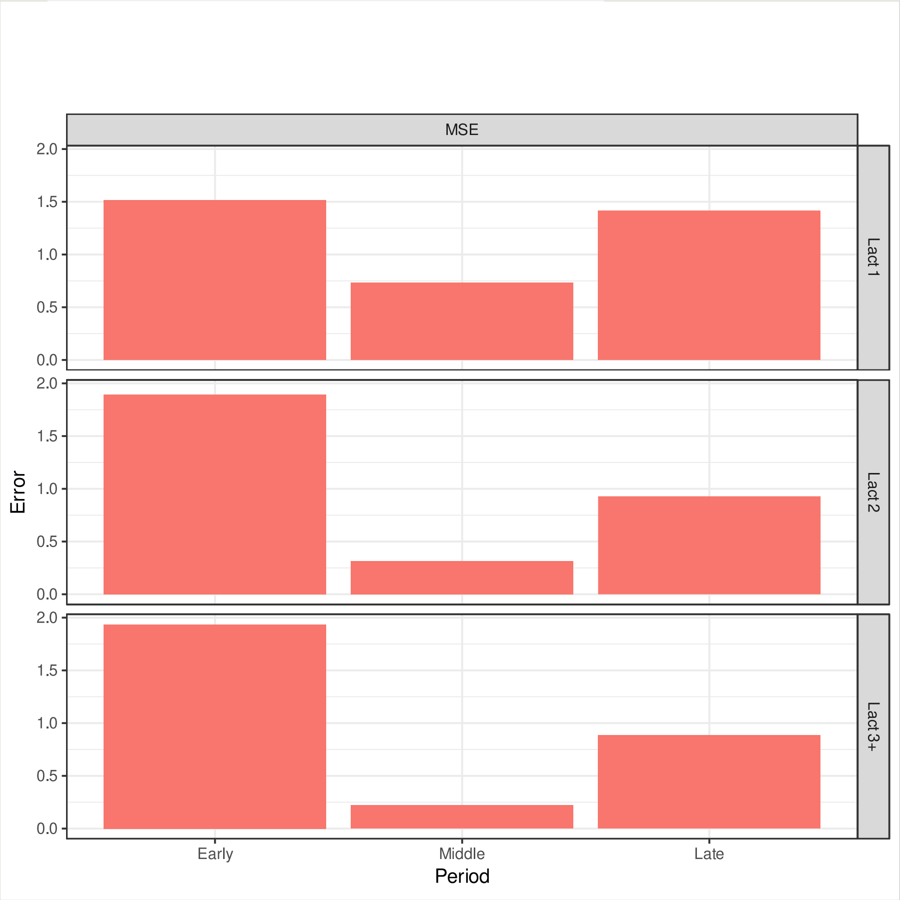

EBVs young sires (1st lactation)
Linear
Cubic
Repeatability
Piecewise-constant
EBV
Weeks in lactation
4
2
0
-2
10
20
30
40


EBVs young sires (1st lactation)
Linear
Cubic
Repeatability
Piecewise-constant
EBV
Weeks in lactation
4
2
0
-2
10
20
30
40

Forward validation for Linear RRM

Simple model predicts well in middle of lactation

And poorly in early and late periods



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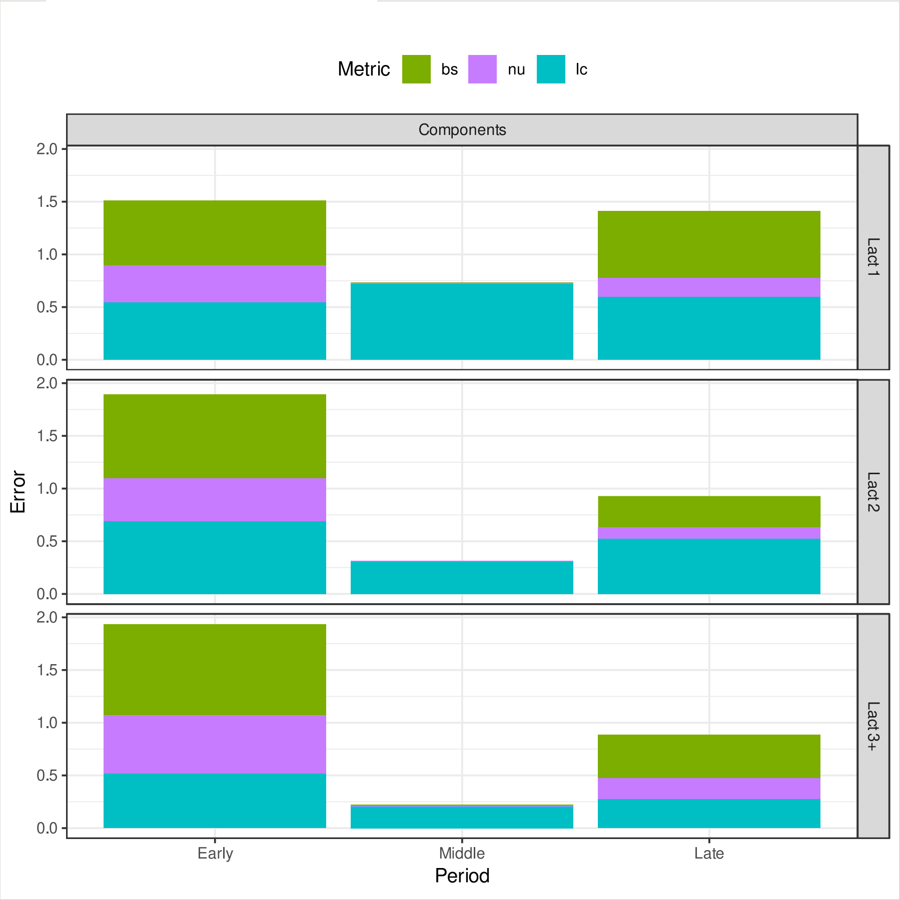
MSE partitioned into components

Level bias due to systematic under- and over-predictions in the extremes of the range

Accuracy is also lower in the middle period, only for 2+ lact.



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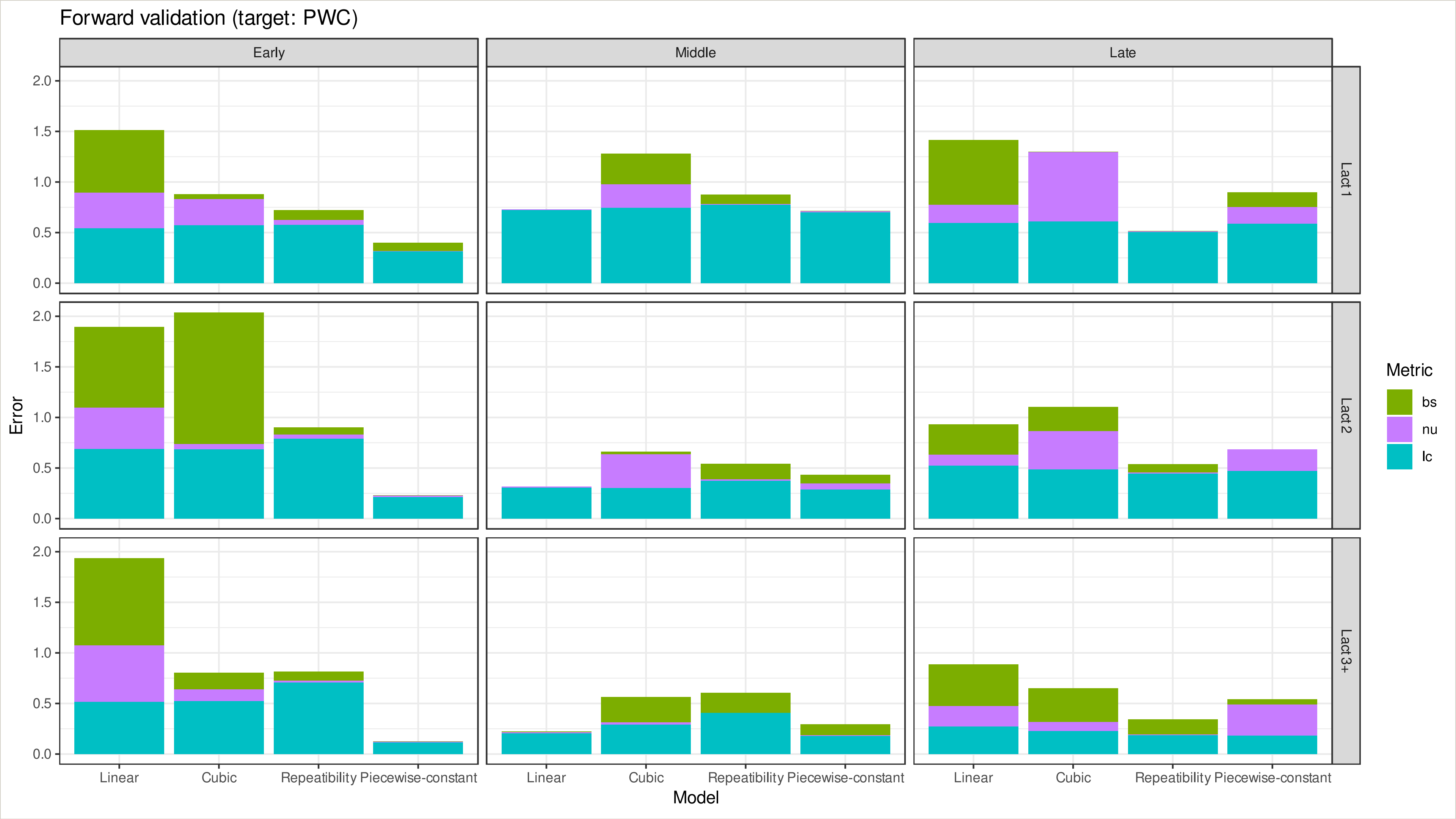
Forward validation (target: PWC)
Early
Middle
Late
Lact 1
Lact 2
Lact 3+
Error
Model
Linear
Cubic
Repeatibility
Piecewise-constant
0.0
0.5
1.0
1.5
2.0
Metric
bs
nu
lc

Discussion

- Cross-validation is crucial for assessing predictive performance
- Predictive accuracy will vary throughout the lactation
- Separating MSE into components can assist interpretation

Discussion

- Other basis for the RRM can be explored (e.g. splines)
- Could PWC be entertained for the evaluation?
    - Against which model could it be validated?
- Different criteria for focal animals may be considered
- Uncertainty in validation metrics should be included

Thanks for your attention!

Questions and comments?

Remember, work in progress,

Suggestions are welcome.

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matias.schrauf@wur.nl