Genetic Evaluations for Energy Balance A Real Possibility?

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Develop innovative and practical breeding tools for improved dairy products from more robust dairy cows



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Introduction

- Energy balance (output-input) is an indicator of health & fertility in dairy cows
- Useful for multi-trait breeding programme

BUT

- Measurement not feasible on commercial herds
- Little data available
- Milk mid-infrared spectrum accurate predictor of energy balance





Example of Energy Balance Prediction







Objective

Validate prediction equations
 on independent data

•Determine genetic parameters of predicted energy balance



Predicted Energy Balance







1. 2 Data Sets

- Langhill experimental herd (SAC, Scotland)
 2 genetically divergent lines * 2 feeding systems
- Teagasc Moorepark (Ireland)
 Different strains of Holstein-Friesian
- Routinely recorded phenotypic traits
 Milk, fat, protein, live weight, BCS & (DMI)
- Random regressions fit to data separately
 - Models fit within parity
 - Data retained between 1990-2011
- Energy balance (MJ/d) = inputs outputs
 - Incl. milk, fat, protein, LWT, BCS, DMI





2. Mid Infrared Spectral (MIR) data

- MPK samples (AM & PM) analysed weekly
- SAC samples (AM, MD & PM) analysed monthly
 - June / September 2008 January 2011
 - Light shone through each milk sample
 - 1,060 wavelength readings for each sample







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3. Prediction equations

- Partial least squares analysis (PROC PLS, SAS)
- Predictors MIR spectrum + milk yield
- AM, PM & (MD) samples handled separately
- SAC samples (n ≤ 2,989)
- MPK samples (n ≤ 844)
- 3 sets of analyses
 - Calibration develop equations
 - Validation independent test of equations





Calibration & Validation Data









RESULTS





Within Research Data Set

Data Sets		Cross Val		External Validation			
Cal	Val	RMSE	R	Bias (se)	RMSE	R	
SAC							
ΡΜ	ΡΜ	24	0.70	2.18(0.85)	25	0.65	
AM	AM	24	0.70	1.57(0.90)	25	0.67	
MD	MD	24	0.72	-2.35(0.90)	25	0.69	
MPK							
ΡΜ	ΡΜ	19	0.74	3.63(1.70)	21	0.66	
AM	AM	19	0.74	-1.99(1.23)	21	0.67	





Across Research Data Set

Data Sets		Cross Val		External Validation		
Cal	Val	RMSE	R	b (se)	RMSE	R
SAC	MPK					
ΡΜ	ΡΜ	24	0.70	0.11(0.04)	28	0.09
AM	ΡΜ	25	0.69	0.08(0.03)	28	0.09
MD	ΡΜ	24	0.71	0.14(0.03)	28	0.15
ΡΜ	AM	24	0.70	-0.05(0.05)	28	0.03
AM	AM	25	0.69	0.00(0.04)	28	0.00
MD	AM	24	0.71	0.08(0.04)	28	0.07
MD PM AM MD	PM AM AM AM	24 24 25 24	0.71 0.70 0.69 0.71	0.14(0.03) -0.05(0.05) 0.00(0.04) 0.08(0.04)	28 28 28 28 28 28	0.03 0.03 0.00 0.07





Energy Balance - SAC & MPK



Days in milk





PCA of spectra - SAC & MPK







Pooled Research Data Sets

SAC (MD) and MPK (PM)

- Cross Validation
 - RMSE = 27 MJ
 - R = 0.69
- External Validation
 Slope = 0.98 (0.03)
 - Bias = 1.12 (0.88)
 - R = 0.69





Genetic parameters

Heritability of energy balance

- True 0.07 (se =0.05)
- Predicted 0.28 (se = 0.08)

Repeatability of energy balance

- True 0.29 (se =0.03)
- Predicted 0.43 (se = 0.03)

Correlations - true and predicted energy balance

• Genetic = 0.05 (0.42)





Conclusion

- The mid-infrared spectrum is useful as a predictor of energy balance
- Not useful to predict energy balance across systems
- Pooled data across systems gives a robust equation
- Low heritability and low genetic correlation between true and predicted energy balance reported
 - Small data set
- MIR spectrometry is a useful method to routinely collect large volumes of data on energy balance





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