Predicting Energy Balance Status of Holstein Cows using Mid-Infrared Spectral Data

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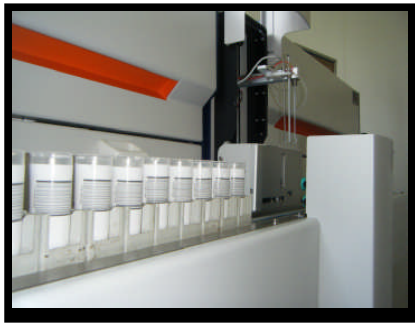
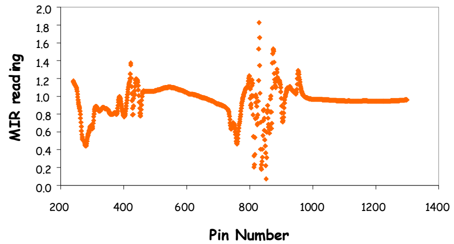
Introduction

- Energy balance (output-input) is a heritable indicator of health & fertility in dairy cows
- Useful for multi-trait breeding programme
- BUT
  - Expensive to measure (correctly)
  - Measurement not feasible on commercial herds
  - Little data available
- Methods to <u>model</u> energy balance exist
  - Require expensive phenotypes
  - Rely on phenotypes not always available

Example of Energy Balance Prediction

Potential errors





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Milk fat content

Milk protein content

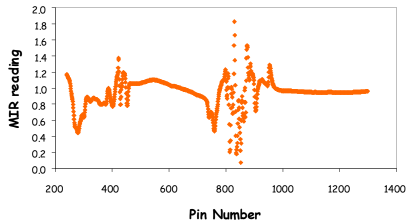
3

Predicted Energy Balance

Objective

- Predict energy balance directly from milk using MIR spectral data

- Can we improve the accuracy of prediction?



Predicted Energy Balance

Materials and Methods

1. Data Collection

- Langhill experimental herd of Holstein cows (SAC, Scotland)
  - Two genetically divergent lines
  - Two feeding systems
- Routinely recorded phenotypic traits
  - Milk, fat, protein, DMI, live weight & BCS
- Random regressions fit to get daily solutions
  - Fixed effects: experiment group, year-season of calving, calving age, year-by-month of record
  - Random effect: cow*Σ(DIM)
  - Models fit within parity
  - Data retained between 1990-2010

Materials and Methods

2. Calculation of energy balance

- Two separate measures *(Banos & Coffey, 2010)*
  - Direct_EB = inputs – outputs

    incl. milk production, DMI, weight, BCS & diet
  - Body energy content (EC) = predicted protein and lipid weights from BCS and LWT

ALSO

- Daily deviation from mean direct_EB (dev_EB)
  - Cows own deviation within parity

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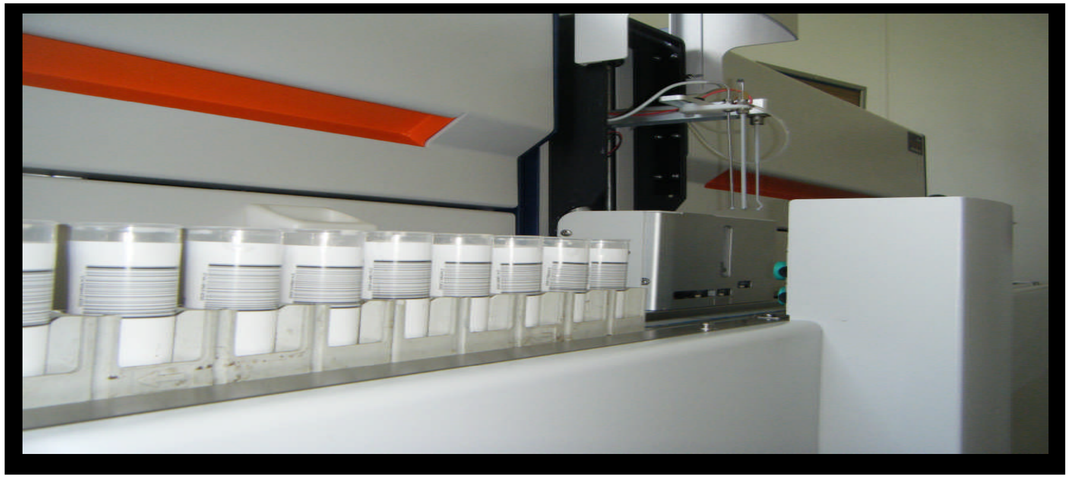
Materials and Methods

3. Mid Infrared Spectral (MIR) data

- Monthly samples from all cows sent for MIR analysis
  - September 2008 – December 2009
  - Light shone through each milk sample
  - 1,060 wavelength readings for each sample



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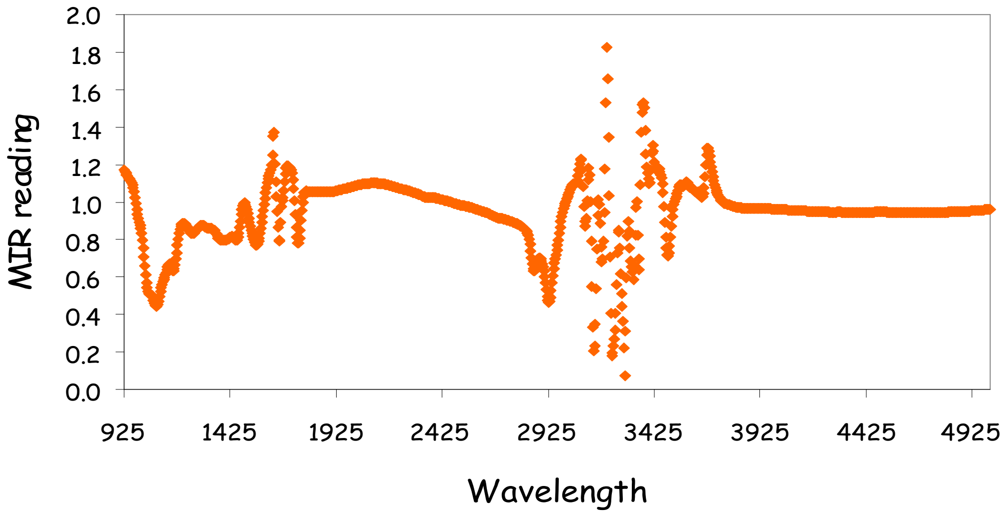

Materials and Methods

4. Prediction equations

- Partial least squares analysis (PROC PLS, SAS)
- Two models – MIR only
  MIR + milk yield
- AM, PM & MD yields analysed separately
  - 1,199 AM, 1,127 PM and 1,148 MD records available
- Cross validation method (max 20 factors)
- Also external validation
  - 25% of data set independently tested
- Best model has the highest R^2 for EXT. validation

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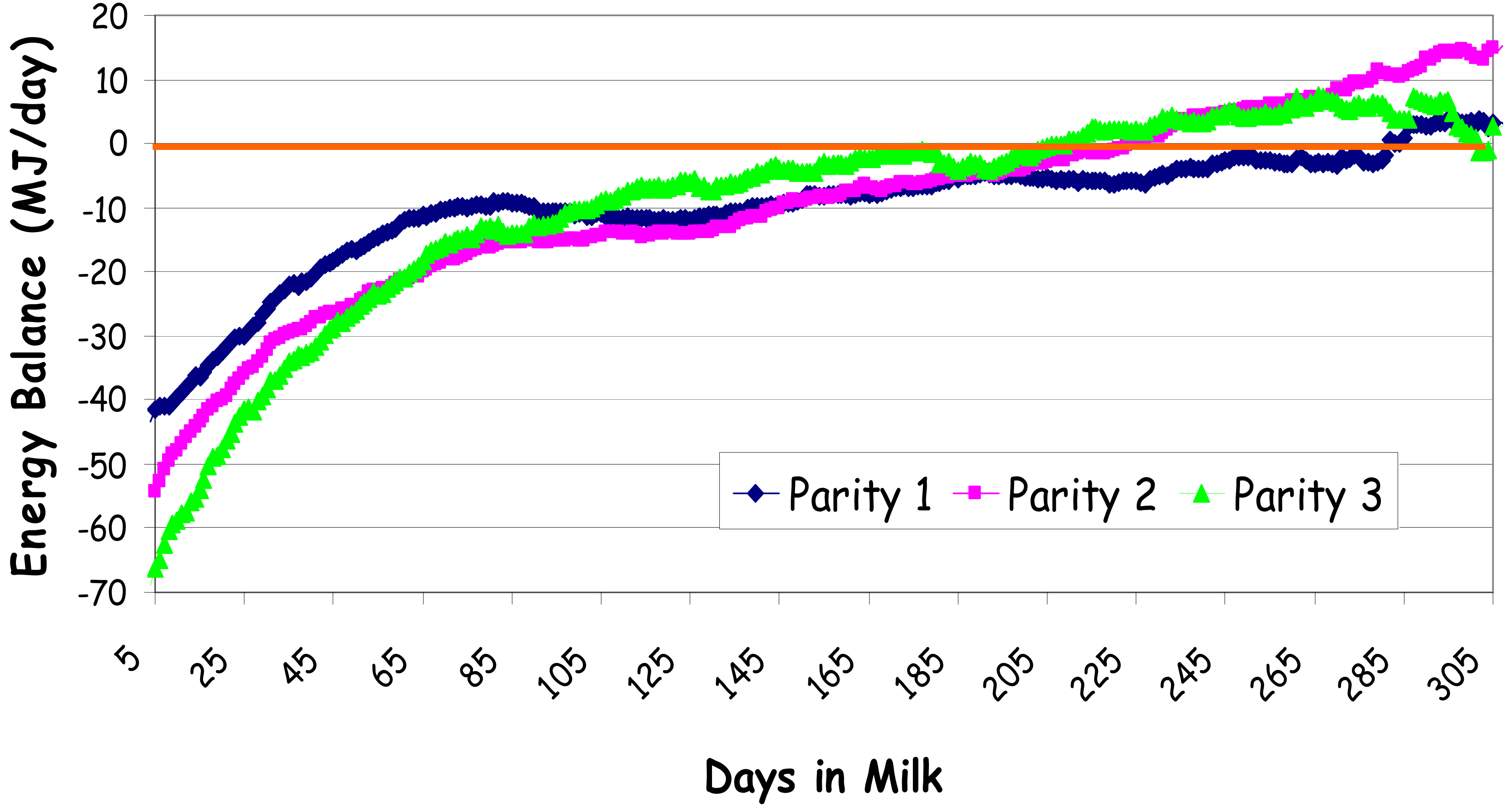
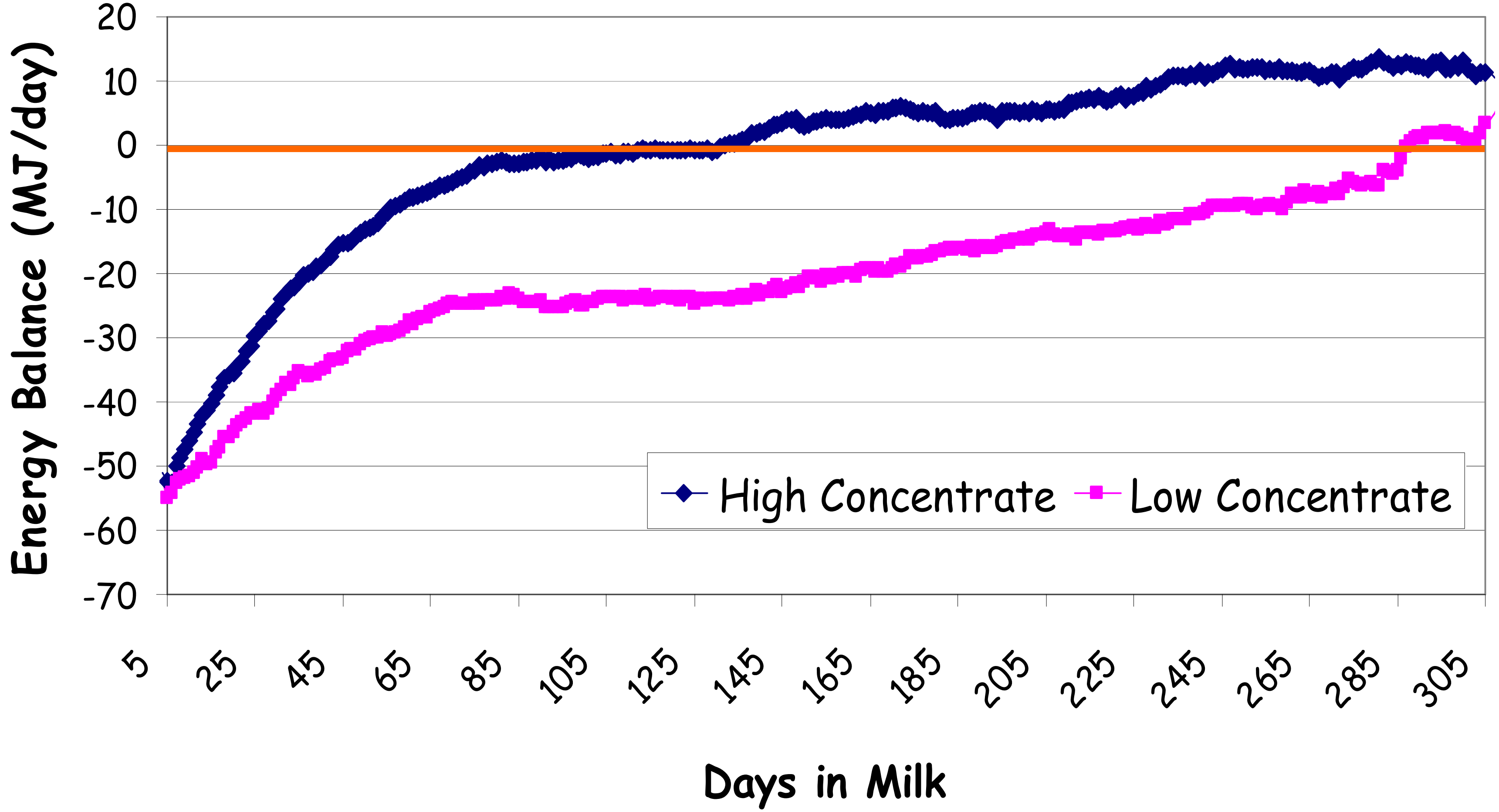
RESULTS

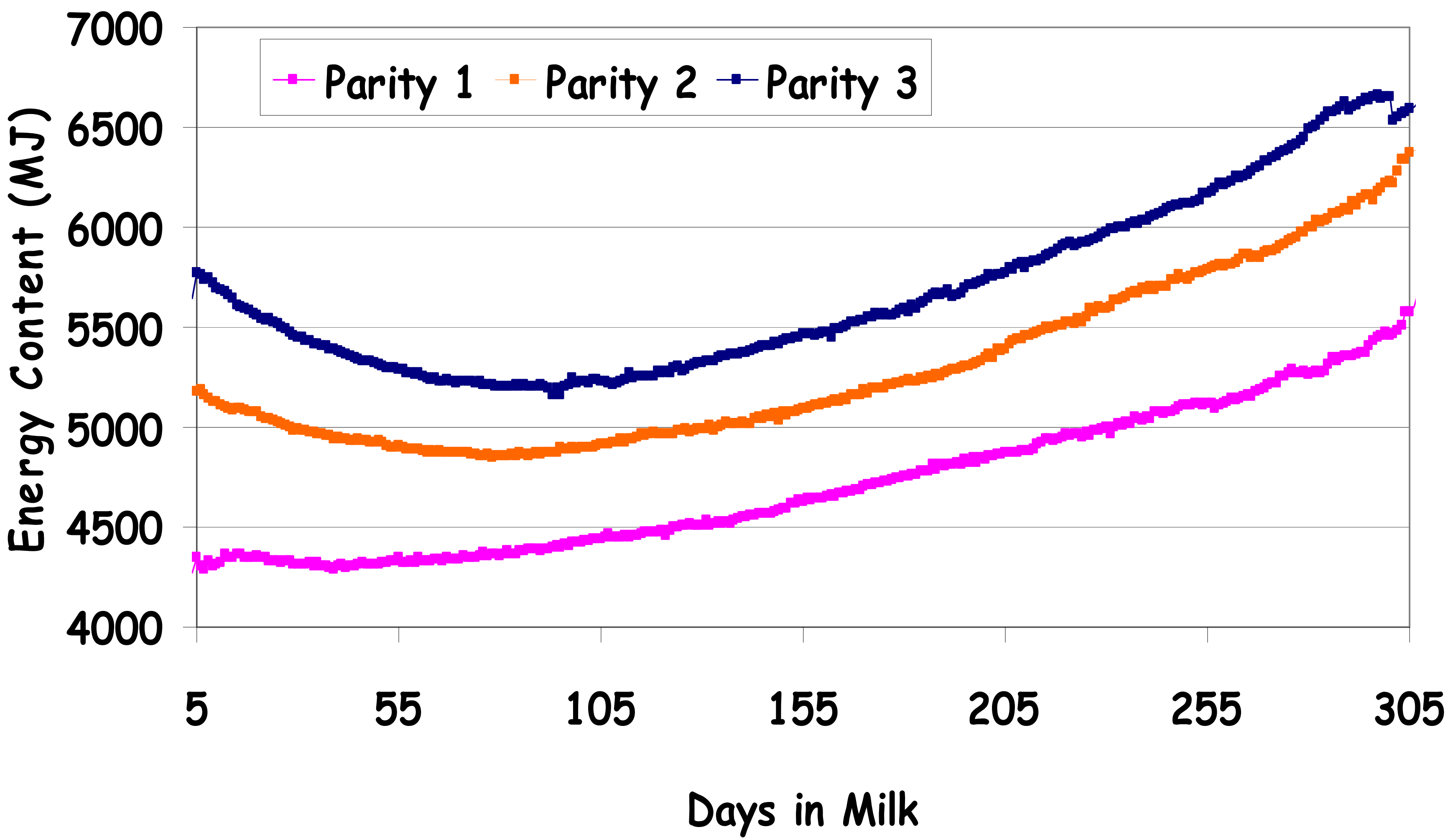
Energy Balance Lactation Curves



Energy Balance - Feed Group



Energy Content Lactation Curves



Cross Validation Results

	R^2	RMSE	Factors
AM			
Direct_EB	0.41	25	18
Energy Content	0.25	1131	17
DEV_ EB	0.40	20	17
MD			
Direct_EB	0.35	26	16
Energy Content	0.23	1144	16
DEV_ EB	0.37	21	16
PM			
Direct_EB	0.32	27	12
Energy Content	0.24	1129	16
DEV_ EB	0.38	21	10

Addition of milk yield as a predictor

Predictors	MIR only		MIR & Yield
AM			
Direct_EB	0.41	→	0.50
Energy Content	0.25		0.25
DEV_ EB	0.40		0.44
MD			
Direct_EB	0.35	→	0.43
Energy Content	0.23		0.22
DEV_ EB	0.37		0.41
PM			
Direct_EB	0.32	→	0.42
Energy Content	0.24		0.24
DEV_ EB	0.38		0.44

Update

- Data collection on-going
- Since collation of results presented, data size (MIR) has doubled
- Analyses re-run

Results updated -

	Previous Results	New Results	
Validation	Cross	Cross	External
AM	R^2	R^2	R^2
Direct_EB	0.41	0.43	0.42
Energy Content	0.25	0.34	0.18
DEV_ EB	0.40	0.45	0.39
MD			
Direct_EB	0.35	0.47	0.44
Energy Content	0.23	0.36	0.19
DEV_ EB	0.37	0.47	0.40
PM			
Direct_EB	0.32	0.53	0.45
Energy Content	0.24	0.38	0.20
DEV_ EB	0.38	0.48	0.39

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Conclusion

- Predicting energy balance directly from milk is more accurate than using fat:protein ratio
- Greater predictive ability when milk yield included in the model
- New data aided improved predictive ability
- Predictive ability for external validation <50%
  - Still a lot of unexplained variation
  - "Noisy" phenotype as measured here
- Work on-going to improve equations

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