

# New phenotypes from milk MIR spectra: challenges to obtain reliable predictions

Grelet C.<sup>1</sup>, Dardenne P.<sup>1</sup>, Soyeurt H.<sup>2</sup>, Fernandez J.A.<sup>1</sup>, Gengler N.<sup>2</sup>, Vanlierde A.<sup>1</sup>, Dehareng F.<sup>1</sup>

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# **Context**

Prediction of phenotypes by MIR -Fast -Cost effective -Easy to use in routine

Potentially usable for large scale applications -Management of cows -Genetic studies ROUTINE

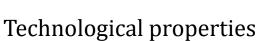
VALIDATED

 $\rightarrow$  Exponential researches to create MIR models

# Context

Milk quality







Cow phenotype



Outliers, detection of contaminants



Estimating Fatty Acid Content in Cow Milk Using Mid-Infrared Spectrometry Potential estimation of major mineral contents in cow milk H. Soyeurt,\*†<sup>1,2</sup> P. Dardenne,‡ F. Deh using mid-infrared spectrometry P. Mayeres,\*#<sup>2</sup> and N. Gengler\*||<sup>2</sup> Prediction of individual milk proteins including free amino acids H. Soyeurt,\*1 D. Bruwier,\* J.in bovine milk using mid-infrared spectroscopy and their correlations with milk processing characteristics A. McDermott,\*† G. Visentin,\*† M. De Marchi,† D. P. Berry,\* M. A. Fenelon,‡ P. M. O'Connor,‡ O. A. Kenny,‡ and S. McParland\*

Prediction of coagulation properties, titratable acidity, and pH of bovine milk using mid-infrared spectroscopy

M. De Marchi,\*<sup>1</sup> C. C. Fagan,† C. P. O'Donnell,† A. Cecchinato,\* R. Dal Zotto,\* M. Cassandro,\* M. Penasa,\* and G. Bittante\*

Potential use of milk mid-infrared spectra to predict individual methane emission of dairy cows

Mid-infrared prediction of lactoferrin content in bovine milk: . Dehareng A. Vanlierde<sup>1</sup> potential indicator of mastitis

> H. Soveurt<sup>1,2†</sup>, The potential of Fourier transform infrared spectroscopy of milk F. Dehareng<sup>6</sup>, Hsamples to predict energy intake and efficiency in dairy cows<sup>1</sup> M. Coffey<sup>5</sup>, L Development of Fourier transform mid-infrared calibrations

6. McParland to predict acetone, β-hydroxybutyrate, and citrate contents in bovine milk through a European dairy network

c. Grelet,\*1 c Prediction and validation of residual feed intake and dry matter intake F. G. Colinet. in Danish lactating dairy cows using mid-infrared spectroscopy of milk

N. Shetty,<sup>1</sup> P. L Assessing the effect of pregnancy stage on milk composition of dairy cows using mid-infrared spectra

> A. Lainé,\* C. Bastin,\*1 C. Grelet, H. Hammami,\* F. G. Colinet,\* L. M. Dale,\*2 A. Gillon, J. Vandenplas,\*§3 F. Dehareng, + and N. Gengler\*

Jse of a multivariate moving window PCA for the untargeted detection of contaminants in agro-food products, as exemplified by the detection of melamine levels in milk using vibrational spectroscopy A. Fernández Pierna, D. Vincke, V. Baeten, C. Grelet, F. Dehareng, P. Dardenne

Milk origin determination



Building of prediction models by using Mid-Infrared spectroscopy and fatty acid profile to discriminate the geographical origin of sheep milk

Marco Caredda <sup>a</sup>, Margherita Addis <sup>a</sup>, Ignazio Ibba <sup>b</sup>, Riccardo Leardi <sup>c</sup>, Maria Francesca Scintu <sup>a</sup>, Giovanni Piredda <sup>a</sup>, Gavino Sanna <sup>G</sup>

# However...

# Huge difference between

Developing a model in a

research context

Using a model to generate

predictions at a large scale



# Huge difference between

### Developing a model in a

### research context

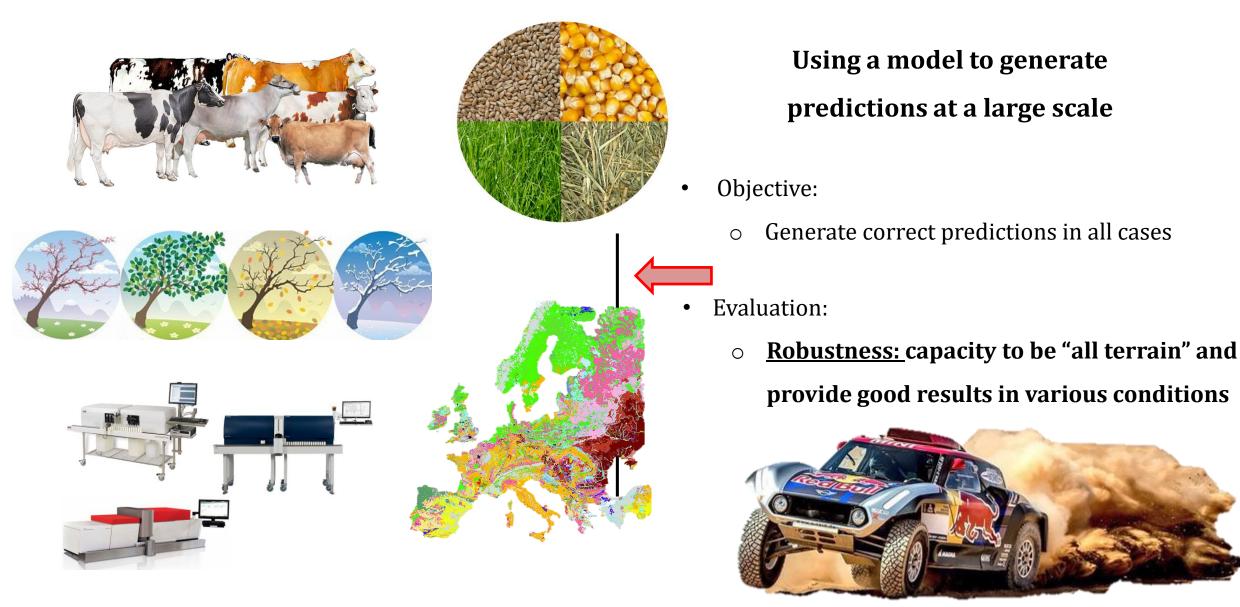
- Objective:
  - Evaluate a potential
  - $\circ$  Publication
- Development
  - $\circ$  Research herds
  - With one or few herds, diets, breeds, countries, MIR instruments
- Evaluation
  - **Performances** (highest R<sup>2</sup>, RMSE)

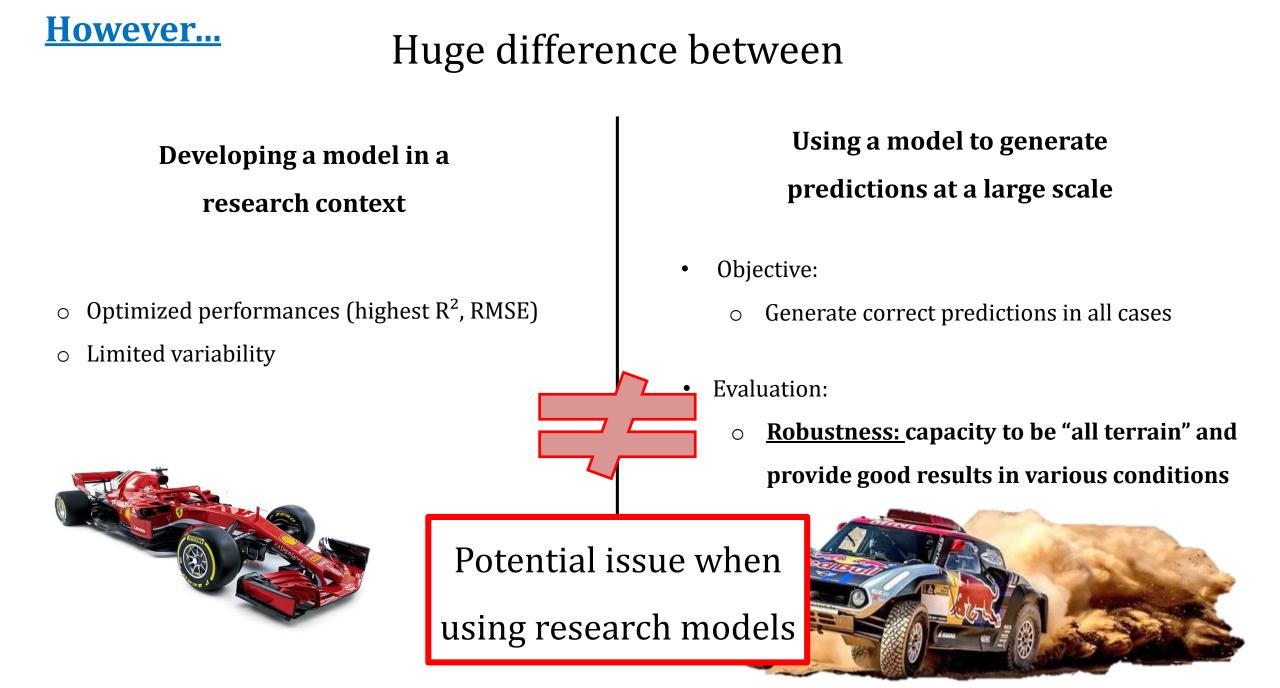
Using a model to generate

predictions at a large scale

# However...

# Huge difference between





# **Objective...**

Evaluate the impact of different factors on Robustness :

- Inclusion of variability in the model (breeds, days in milk...)
- Sampling scheme (oriented vs. random)
- Model development (spectral areas, PLS factors)
- Spectral standardization

Evaluated by :

• Error in external validation (RMSEP)

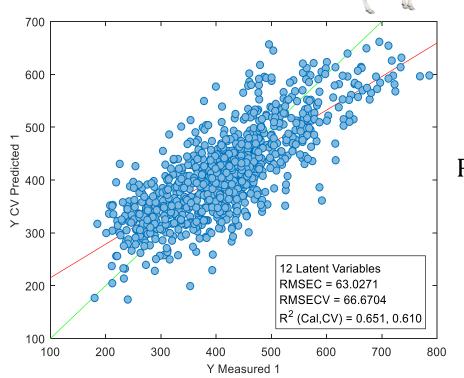
# **Inclusion of Variability**

# **Effect of breeds in the model**

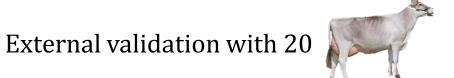
Dataset used: <u>CH4</u> by dairy cows

• 225 Holsteins









RMSEP = 85 g/d

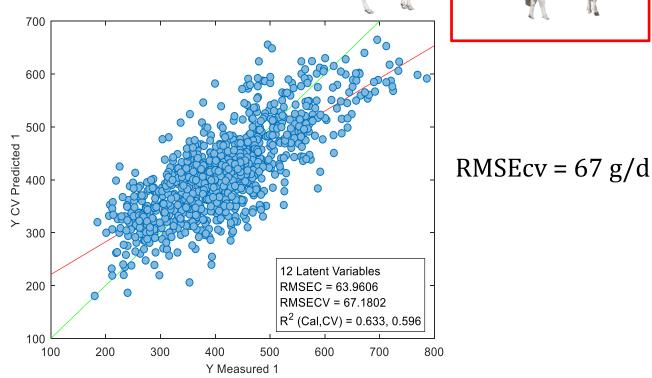
RMSEcv = 67 g/d

# **Effect of breeds in the model**

Dataset used: <u>CH4</u> by dairy cows

• 225 Holsteins

Step 2 : calibration with 225



+ 19



External validation with 20



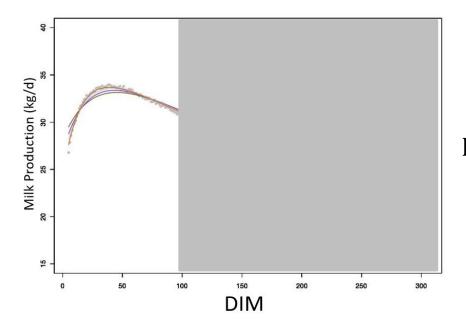
RMSEP = 69 g/d -19%

# **Effect of DIM in the model**

Dataset used: <u>CH4</u> by dairy cows

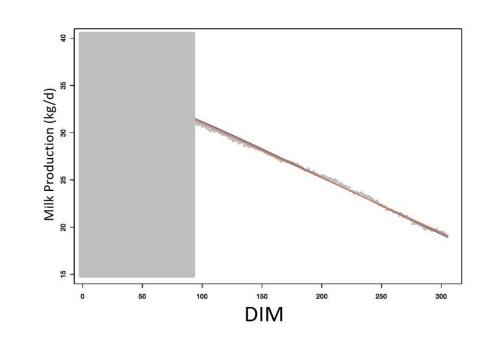
• 350 records from DIM 0 to DIM 100

Step 1 : calibration with beginning of lactation



### External validation with late lactation

• 689 samples from DIM 100 to 320



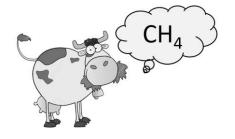
RMSEP = 90 g/d

### RMSEcv = 58 g/d

# **Effect of DIM in the model**

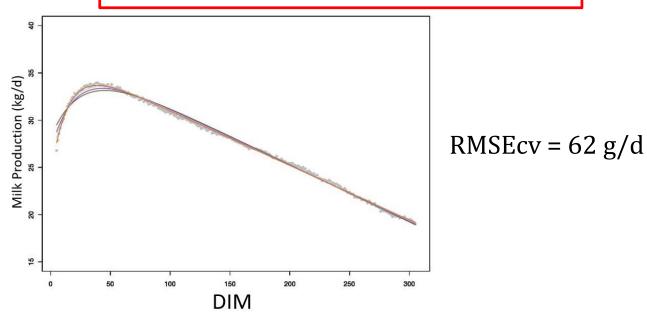
Dataset used: <u>CH4</u> by dairy cows

• 350 records from DIM 0 to DIM 100



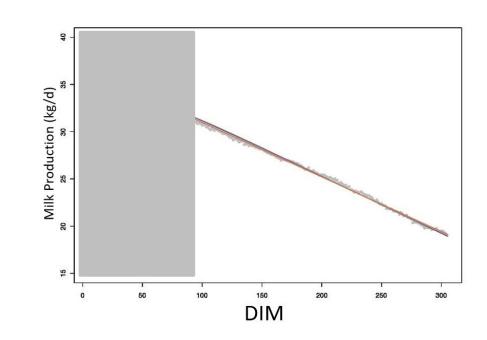
Step 2 : calibration with beginning of lactation

+ 50 records randomly selected between DIM 100 to 320



### External validation with late lactation

• 689 samples from DIM 100 to 320



RMSEP = 78 g/d



# "IR models can only predict what they know"

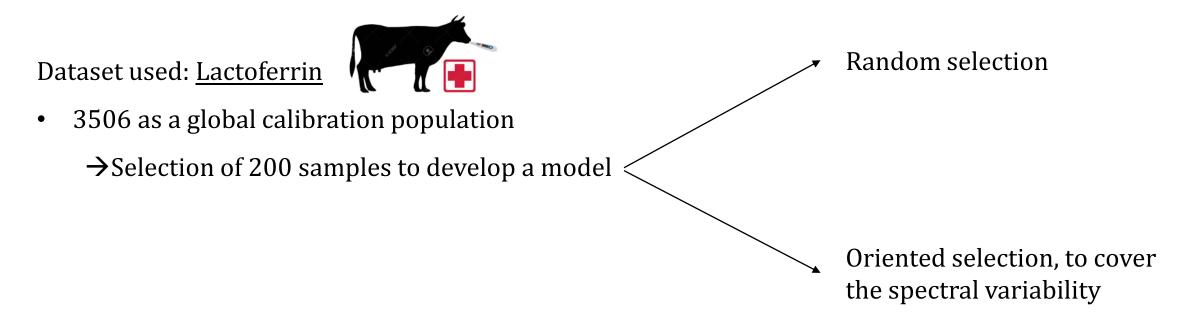
Pierre Dardenne

# *"Extrapolation is dangerous!"*

IR maxim

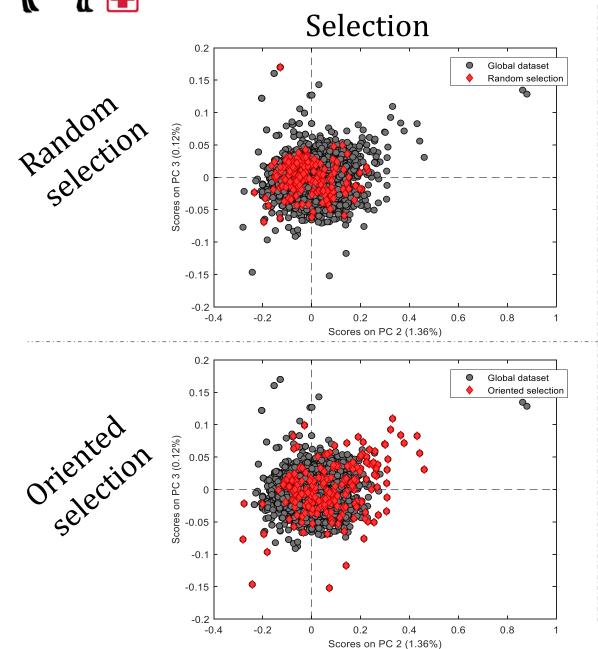
**Sampling method** 

# **Effect of sampling method**



External validation with 400 samples



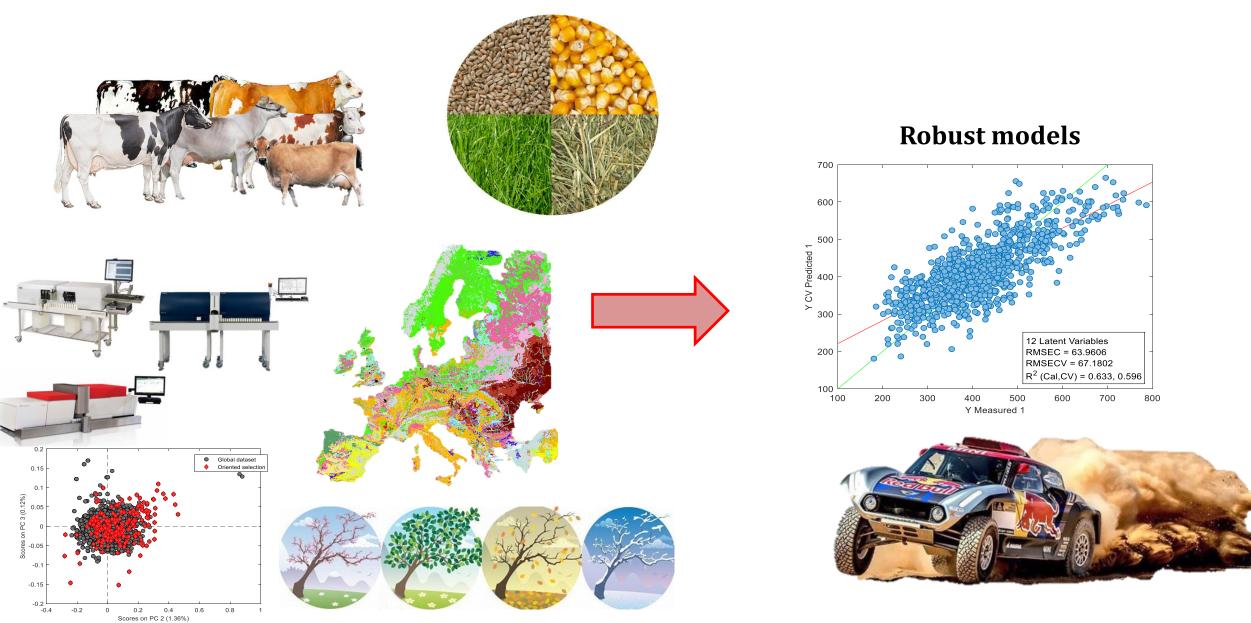


# Cross-validation<br/>(400 external samples)Cross-validation<br/>(400 external samples)• RMSEP = 170 g/L<br/>• 94.4% samples with<br/>GH<3</td>

RMSEcv = 176 g/L

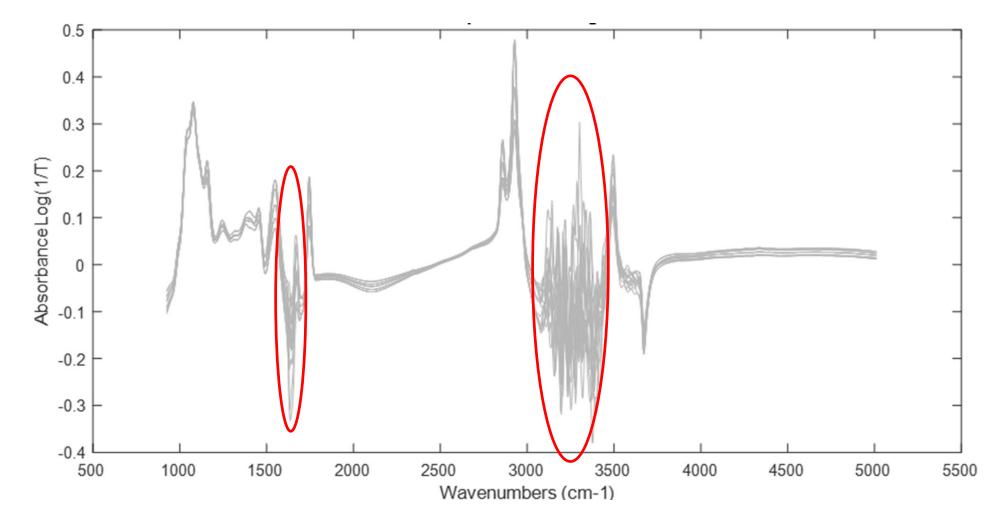
- RMSEP = 146 g/L
- 98.4% samples with GH<3 (-14%)

# IR models can only predict what they know



Model development

# Noisy areas induced by water absorption → usually considered without valuable information and not used





Journal of Dairy Science Volume 101, Issue 3, March 2018, Pages 2260-2272



### Research

Genome-wide association study for milk infrared wavenumbers



Qiuyu Wang, Henk Bovenhuis ዳ 🖾



Genetic and environmental variation in bovine milk infrared spectra

Qiuyu Wang  $\stackrel{\wedge}{\sim}$   $^{\boxtimes}$  , Alex Hulzebosch, Henk Bovenhuis

Genetic analysis of the Fourier-transform infrared spectra of bovine milk with emphasis on individual wavelengths related to specific chemical bonds



G. Bittante, A. Cecchinato 🐣 🖾

Diagnosing pregnancy status using infrared spectra and milk composition in dairy cows

Hugo Toledo-Alvarado \*, Ana I. Vazquez †, Gustavo de los Campos †, Robert J. Tempelman ‡, Giovanni Bittante \*, Alessio Cecchinato \* 은 쯔

But recent studies concluding with the presence of valuable information within those noisy regions

5 identical samples analyzed on 7 Foss instruments + 3 Bentley + 1 Delta

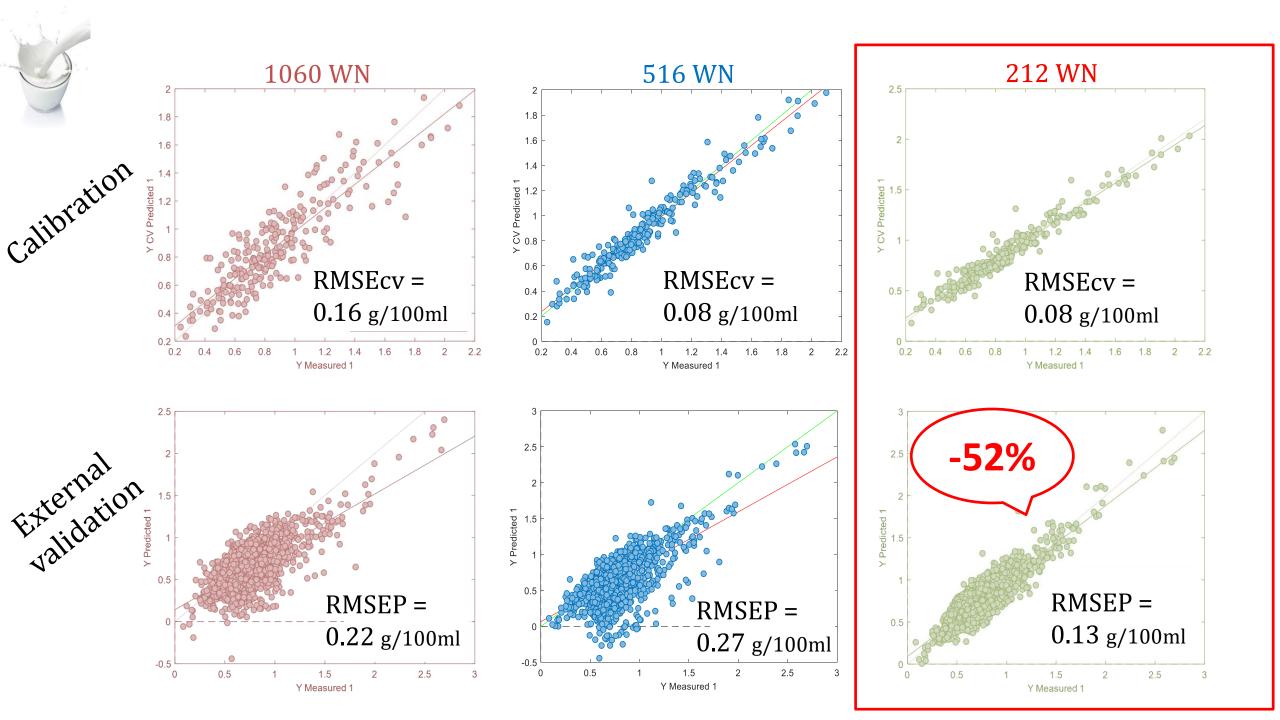
For each wavenumber, correlation between the absorbance values of a reference and the others instruments



Dataset used: <u>C18\_1 cis9</u> fatty acid

- 250 samples in calibration
- 1572 samples in external validation

Same number of PLS factors



# **Effect of model development: PLS factor selection**

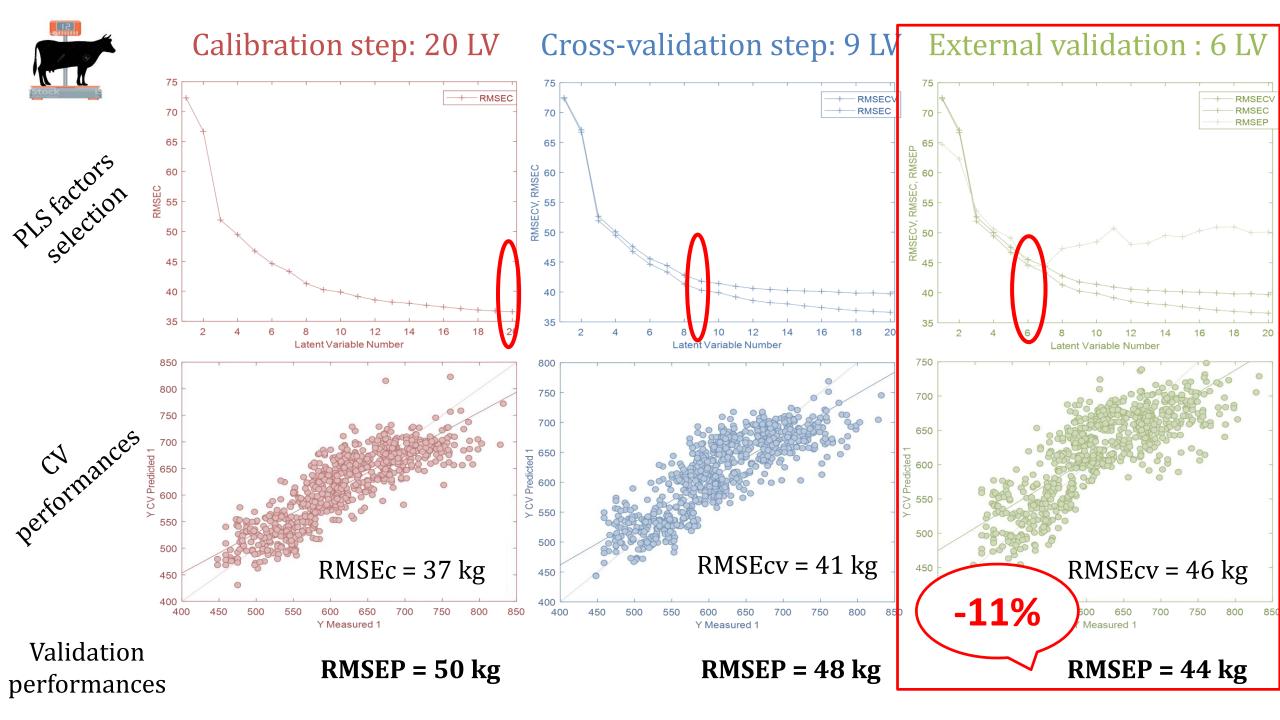
Dataset used: <u>Weight of cows</u>



1033 records from 241 cows

- 75% cows in calibration (781 records)
- 25% cows in validation (252 records)

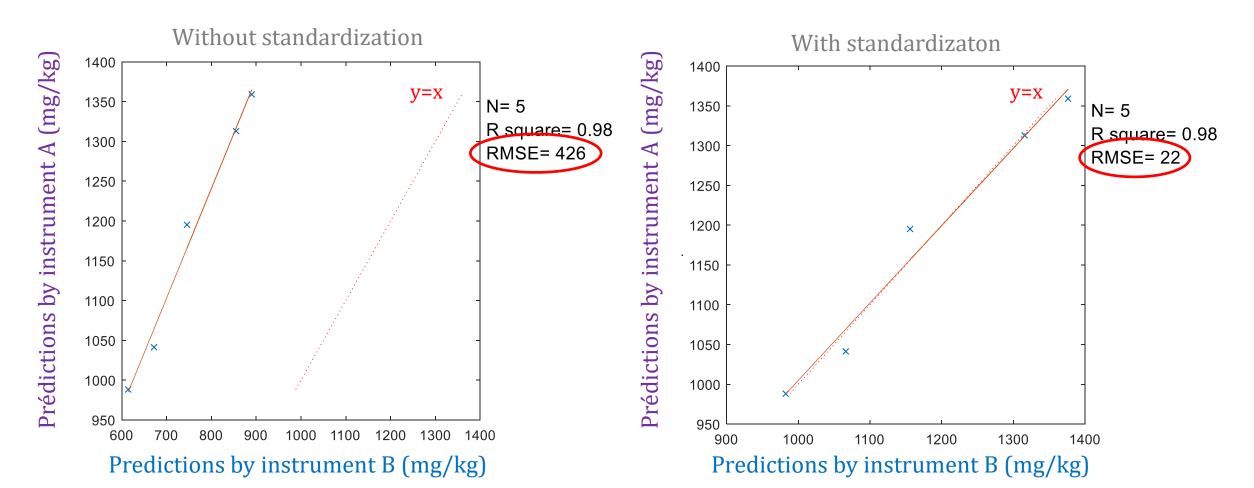
Different ways to choose the PLS factor number



# **Spectral standardization**

# **Spectral standardization**

- <u>Calcium</u> model developed on instrument A
- Model applied on instrument B after analysis of common samples



# **Spectral standardization**

- Calcium model developed on instrument A
- Model applied on instrument B after analysis of common samples

# Bias when using a model into another instrument!!

 $\rightarrow$  Standardization needed to use models at

a large scale



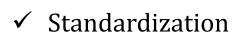


# Take home message

This is only examples, with specific datasets...

...but highlight some elements to take into account

- ✓ Look for variability (reference and spectral data)
- ✓ Collaboration to merge datasets!!!
- ✓ Keep models as simple as possible (Wavenumbers and PLS factors)
- ✓ Think spectroscopy (not only mathematics)







# Thank you for your attention!

Grelet C.<sup>1</sup>, Dardenne P.<sup>1</sup>, Soyeurt H.<sup>2</sup>, Fernandez J.A.<sup>1</sup>, Gengler N.<sup>2</sup>, Vanlierde A.<sup>1</sup>, Dehareng F.<sup>1</sup>

<sup>1</sup> Walloon Agricultural Research Centre, B-5030 Gembloux, Belgium <sup>2</sup> Gembloux Agro-Bio Tech, ULiège, B-5030 Gembloux, Belgium



Extensive databases : thousands of feed NIR spectra from years.

## Global models ?

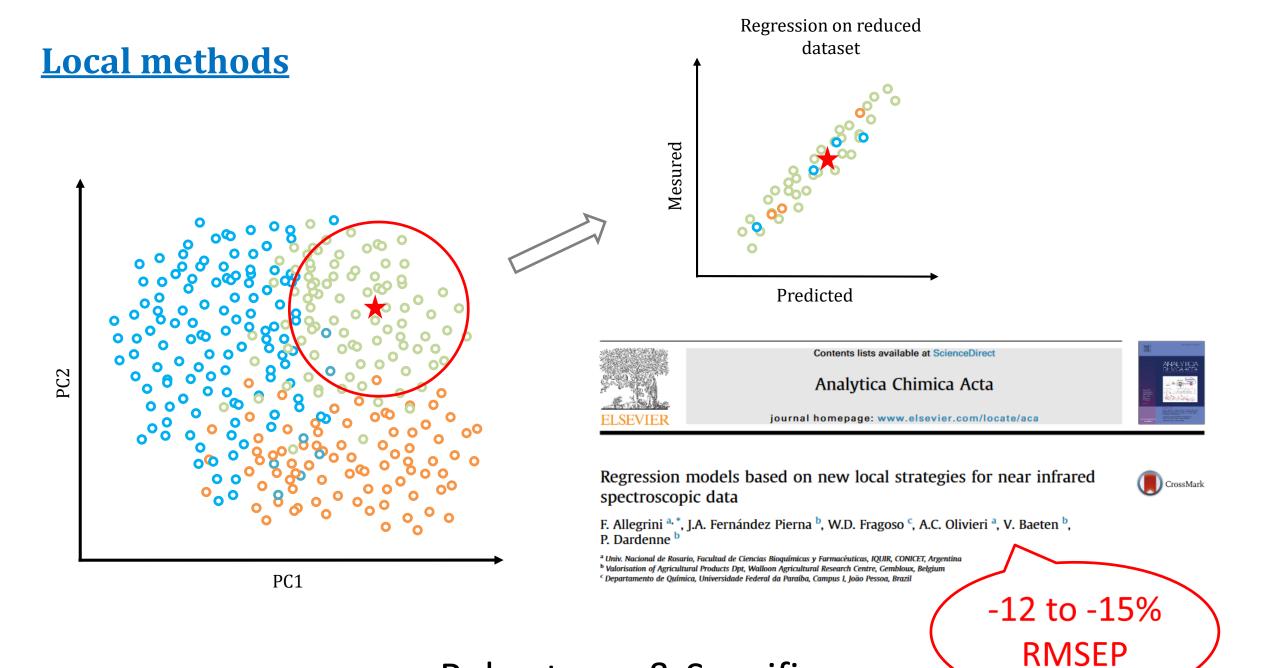
- $\circ$  very robust to sample composition variation
  - $\circ~$  but prediction accuracy decreased

### Specific models for small groups of similar samples ?

o difficult, time consuming, tedious in practice
o increased complexity

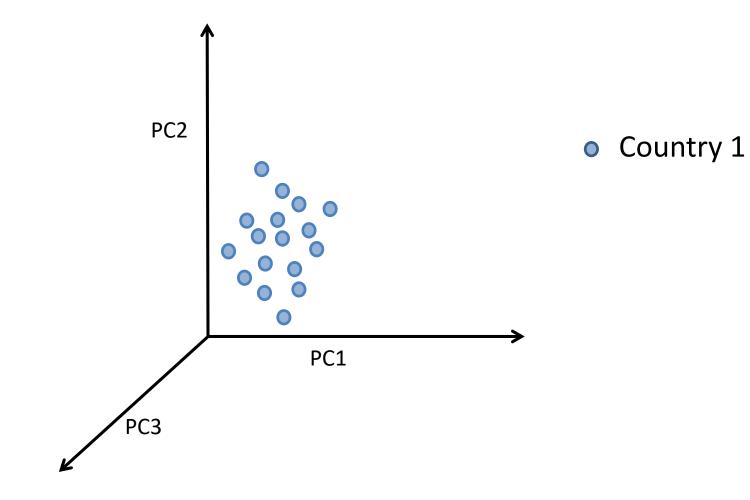
### **Local regression**

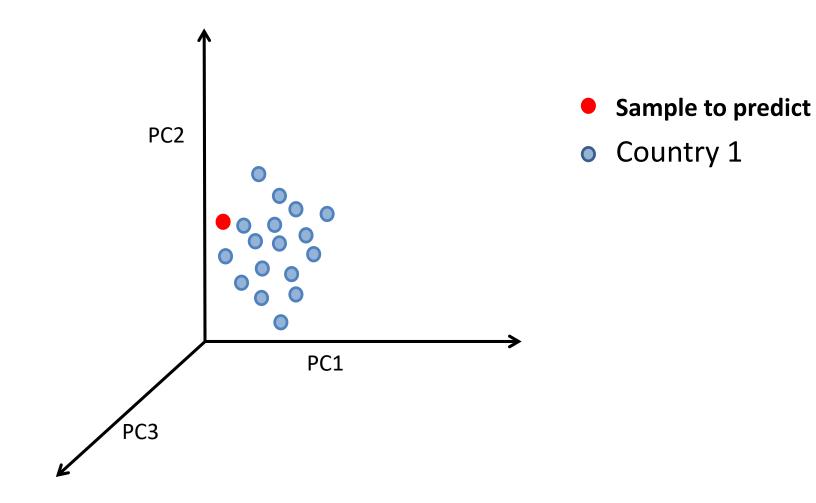
for each sample, compute specific model using a reduced calibration data extracted from a large library

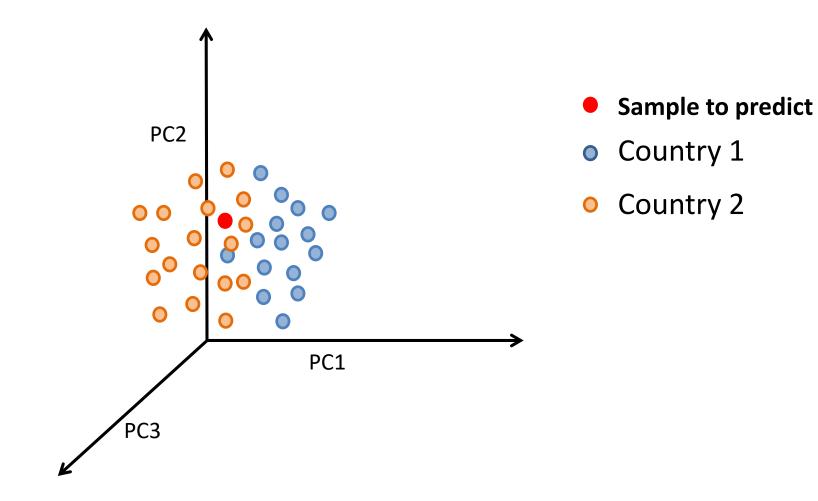


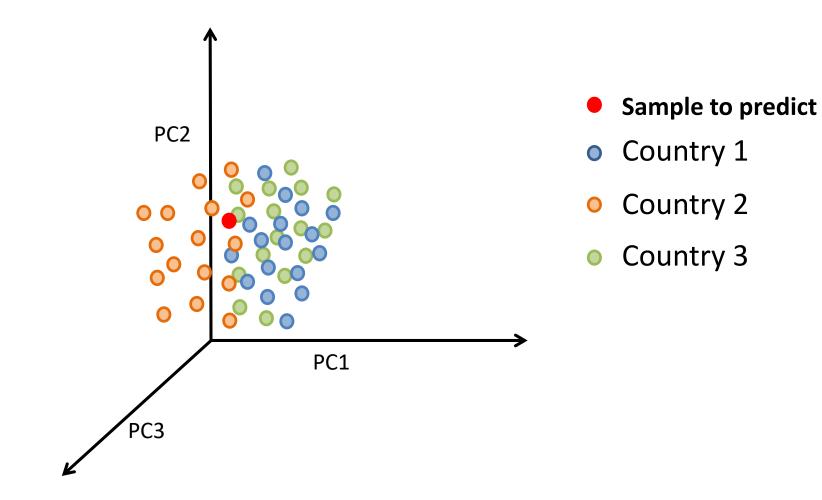
Robustness & Specific

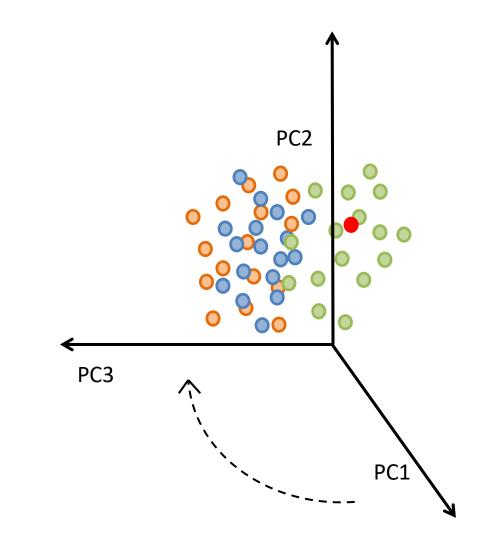
# However...





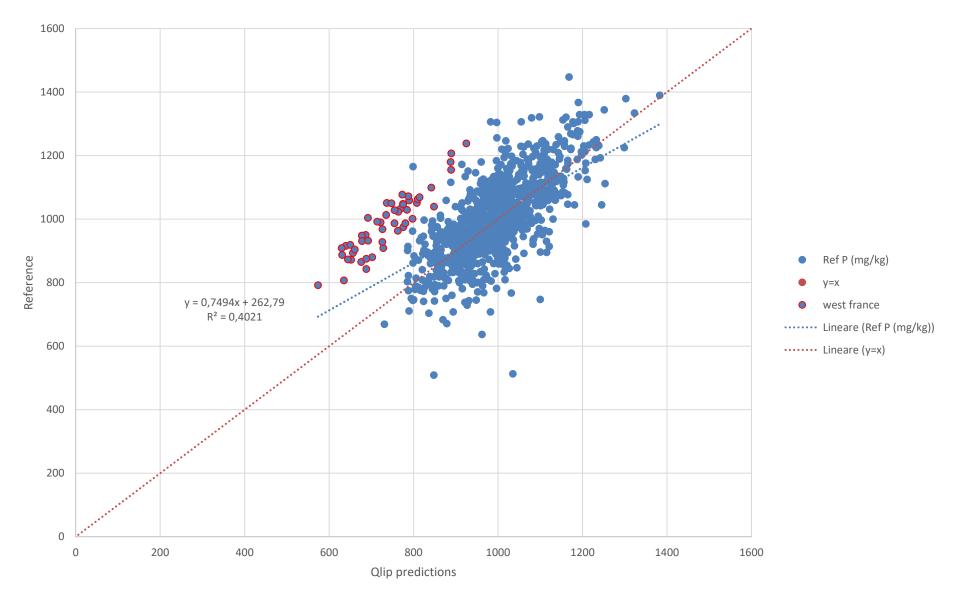


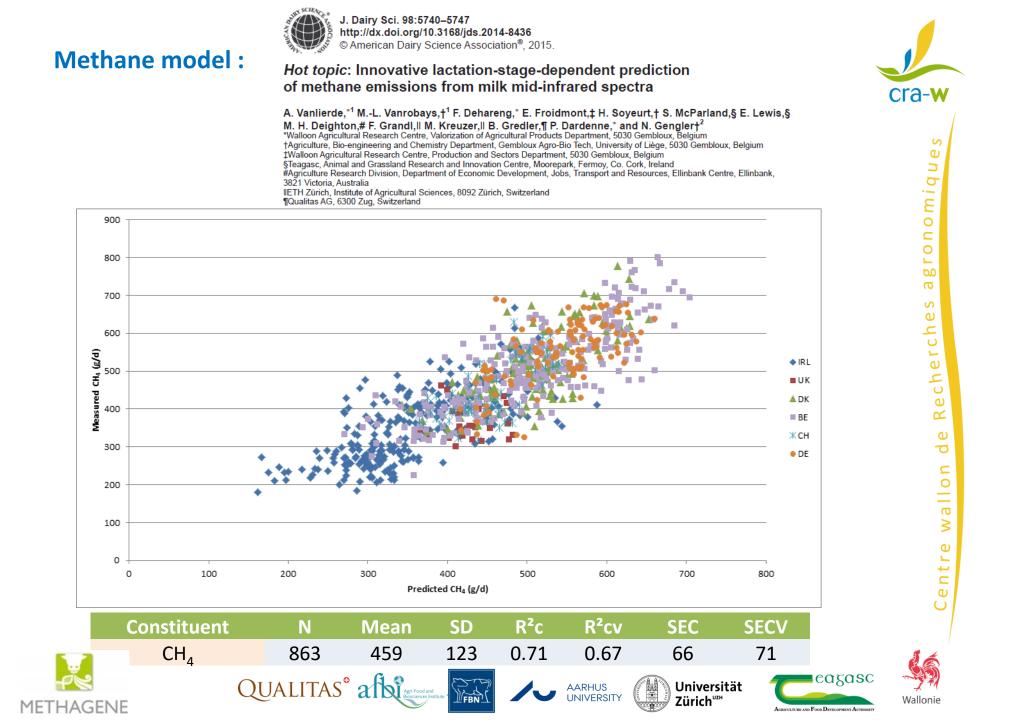


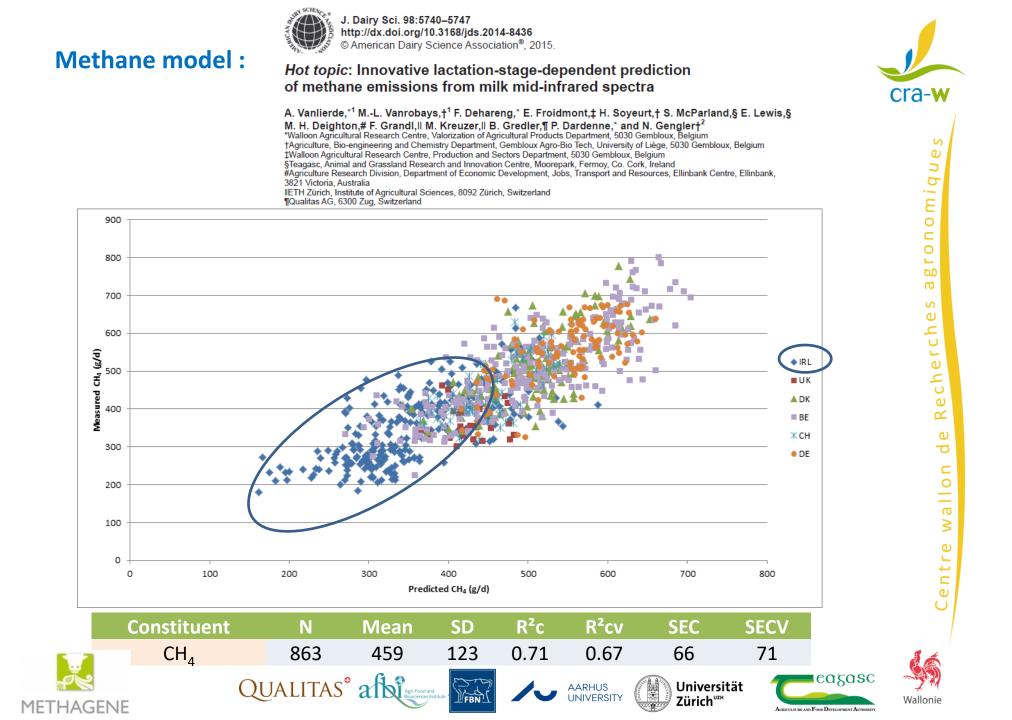


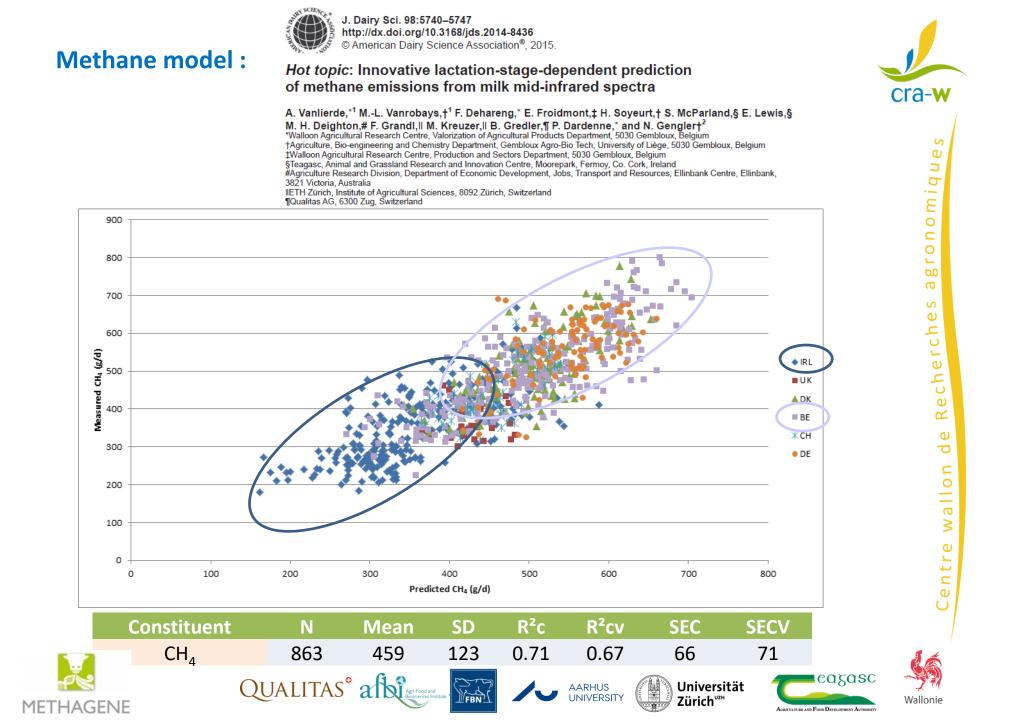
- Sample to predict
- Country 1
- Country 2
- Country 3

# Real test in external validation









5 identical samples analyzed on 7 Foss instruments

For each wavenumber, correlation between the absorbance values of a reference and the others instruments

