75th EAAP Congress, Florence, 1st Sep 2024

Hybrid local and global sensitivity analysis: Evaluation of dairy cow response predicted through INRA 2018 feeding system according to feed characteristics

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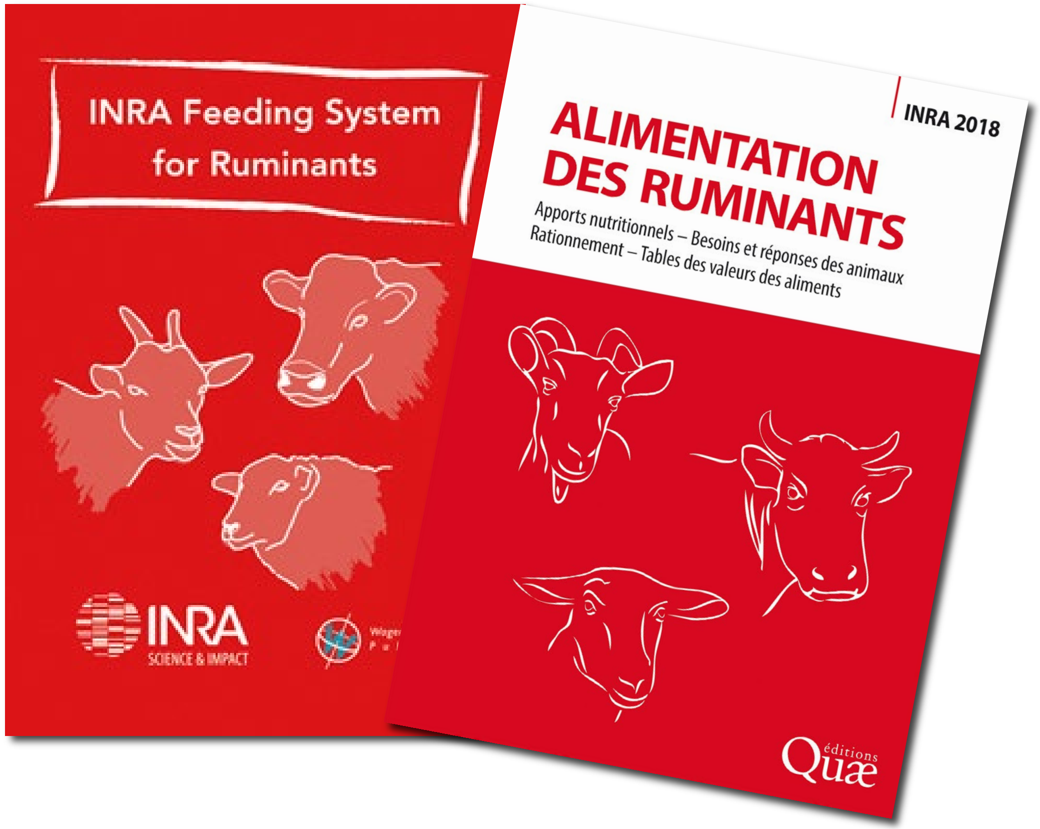

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What is the sensitivity analysis?

1. Sensitivity analysis?

- Which input variables (and how much) caused the variation in output?

2. Objectives

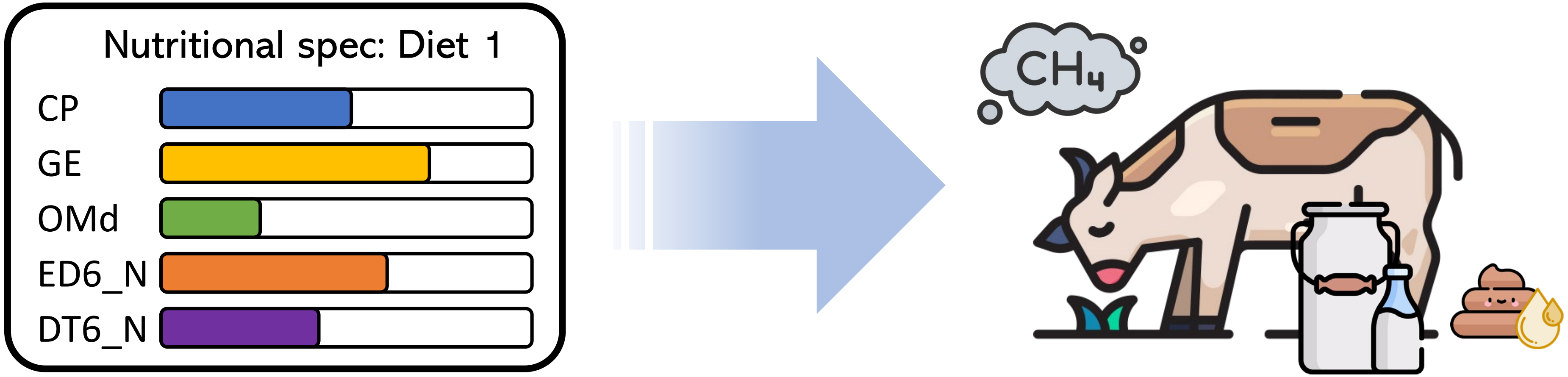
- *Simplification:* remove non-effective or redundant input variable
- *Understanding:* verify the relationship between input and output in a complex system

3. Research object

- How the dairy cow's performances, predicted from the INRA 2018 feeding system, react to variation in feed characteristics?

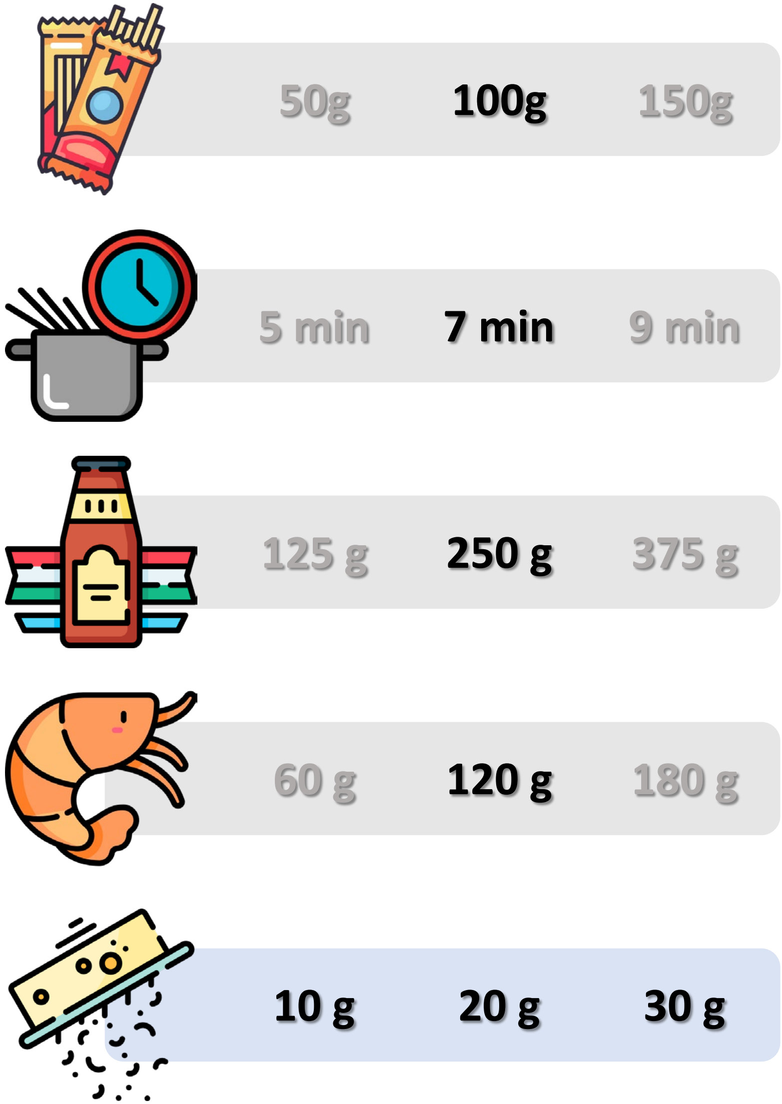
Local approach?

Global approach?



01 Local vs. Global sensitivity analysis

Target output: The taste of pasta



1. Local analysis (One-at-a-time)

- Change only one condition at a time (e.g. cheese)
- The remaining variables are fixed to standard values (e.g. pasta, time, sauce, shrimp)

[Expecting conclusion]

- Non-linear positive relationship with cheese amount

[Strength]

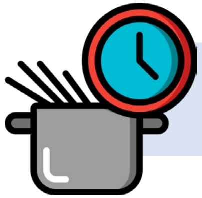
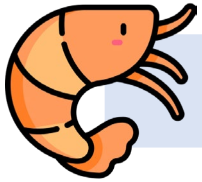
- Fast and easy to analyse
- Easy to understand the impact

[Weakness]

- Cannot consider interactions

Local vs. Global sensitivity analysis

Target output: The taste of pasta

	50g	100g	150g
	5 min	7 min	9 min
	125 g	250 g	375 g
	60 g	120 g	180 g
	10 g	20 g	30 g

2. Global analysis

- Change multiple conditions simultaneously

[Expecting conclusion]

- Amount of pasta & sauce were highly interacted
- Amount of shrimp & cheese were highly interacted
- Boiling time was significant but did not interact with others

[Strength]

- Can consider interactions

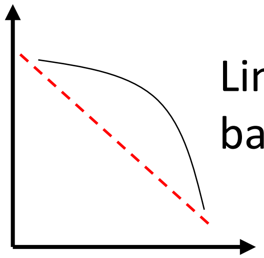
[Weakness]

- High performing time
- Not easy to interpret

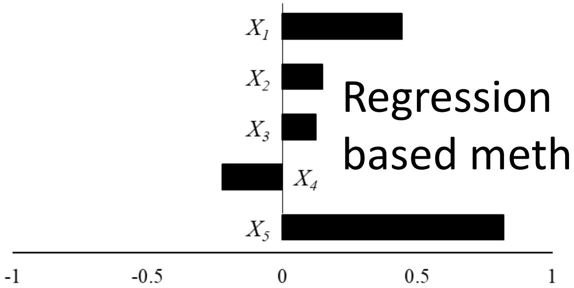
Local vs. Global sensitivity analysis

1. Local analysis (= one-at-a-time method)
- Evaluate the influence one-by-one
- Strength: Fast, Easy, Intuitive
- Weakness: Limited information

2. Global analysis
- Simultaneously evaluate the influence of multiple variables
- Strength: Consider interactions
- Weakness: High computing time, Complicate

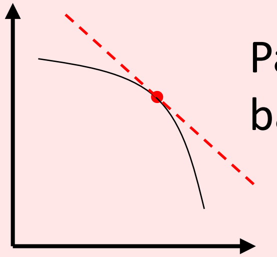


Linear regression based method



Regression based method

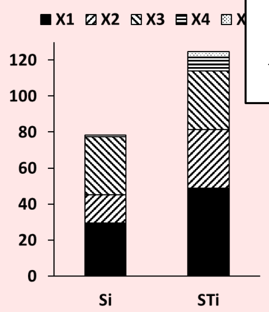
✓ Not affected by simulation range



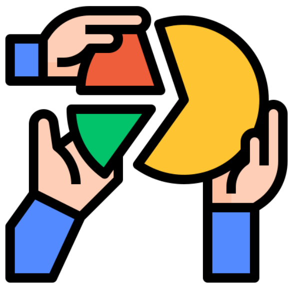
Partial derivative based method

Complimentary to each other

✓ Applicable to non-linear & non-monotonic model
✓ Interaction can be quantified



Variance based method



Simulation conditions

Table 1. Diet composition (% DM) for multiparous

	RF	GH1	GH2	GH3*	GS	CS
Diet composition						
Fresh perennial ryegrass	72.9	-	-	-	-	-
Grass hay (1st growth)	-	54.2	-	-	-	-
Grass hay (2nd growth)	-	-	84.2	52.9	-	-
Grass silage	-	-	-	-	62.1	-
Corn silage	-	-	-	-	-	75.6
Soybean meal	3.6	-	-	-	4.2	13.6
Rapeseed meal	-	21.1	-	18.6	-	-
Barley	-	-	-	-	-	10.8
Corn	23.6	24.7	15.8	28.6	33.7	-
Nutritive values						
CP (g/kg DM)	143	150	183	150	140	141
GE (kcal/kg DM)	4339	4448	4527	4456	4481	4495
OMd (% DM)	73.9	61.3	70.2	62.6	69.8	68.3
ED6_N (% DM)	66.3	58.2	63.1	58.7	64.5	62.5
dr_N (% DM)	86.0	79.3	86.9	80.6	82.7	83.5

*3kg with fixed amount

1. Reference point

1) Animal condition

- 2nd parity multiparous in 14 wks of lactation
- 37.5 kg/d of MY and 1,121 g/d of MPY
- 608 kg of BW (BCS 2.29)

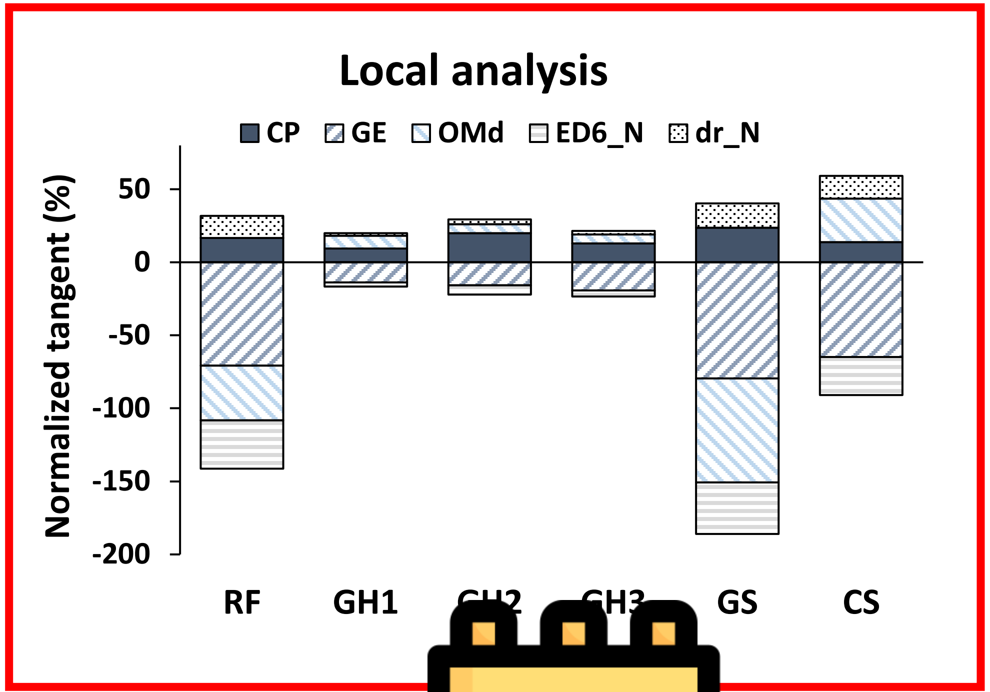
2) 6 common diets formulated (INRAtion®V5)

- RF: Fresh perennial ryegrass based diet
- GH1,2,3: Permanent grass hay based diets
- GS: Permanent grass silage based diet
- CS: Corn silage based diet

2. Simulation

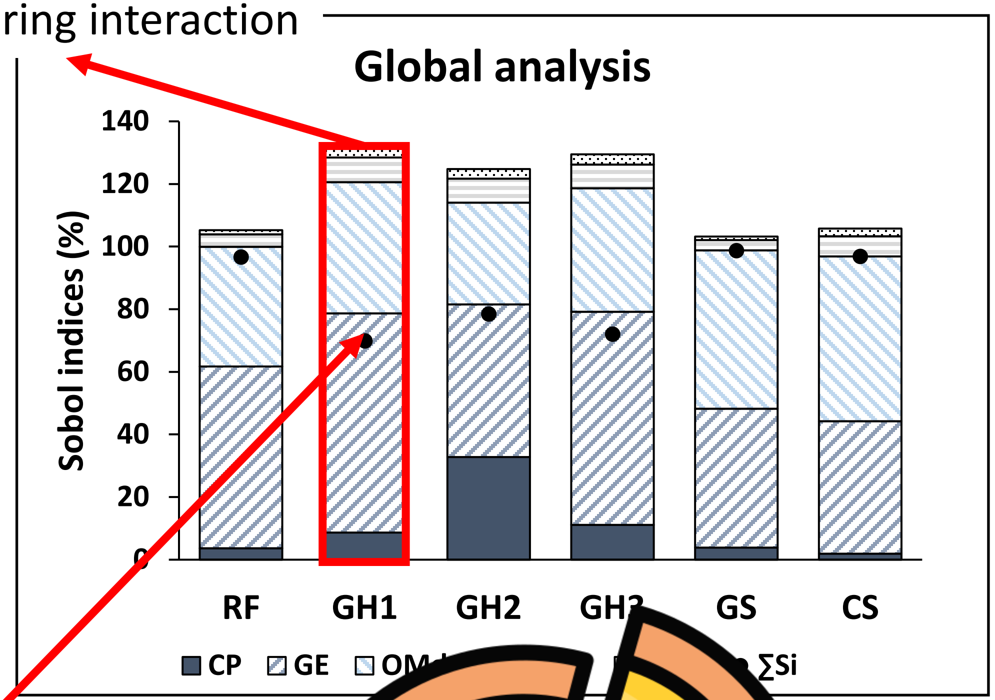
- Around reference situation (±3.0 ~ ±5.5% CV)
  - Local: Latin-hypercube random sampling (N = 50)
  - Global: Quasi-random sampling (N = 10,000)

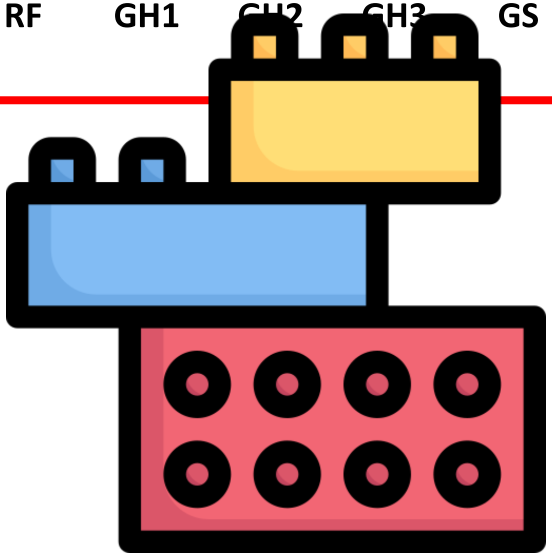
Local vs. Global sensitivity analysis



∑ Total order index

: considering interaction





∑ First order index

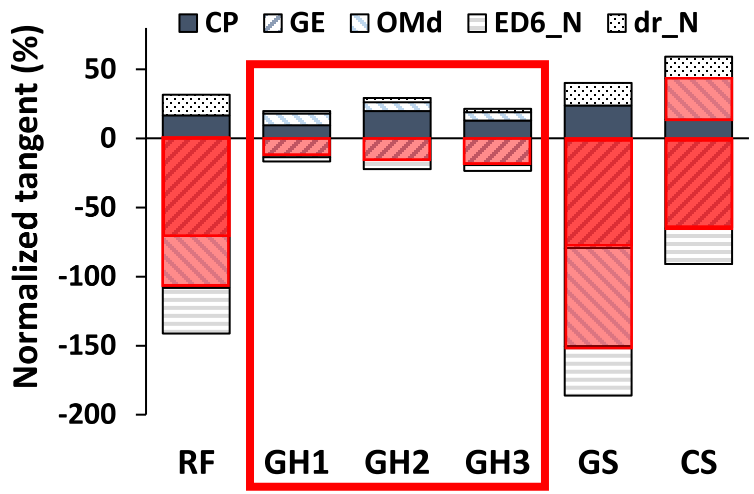
: Disregarding interaction

Interaction

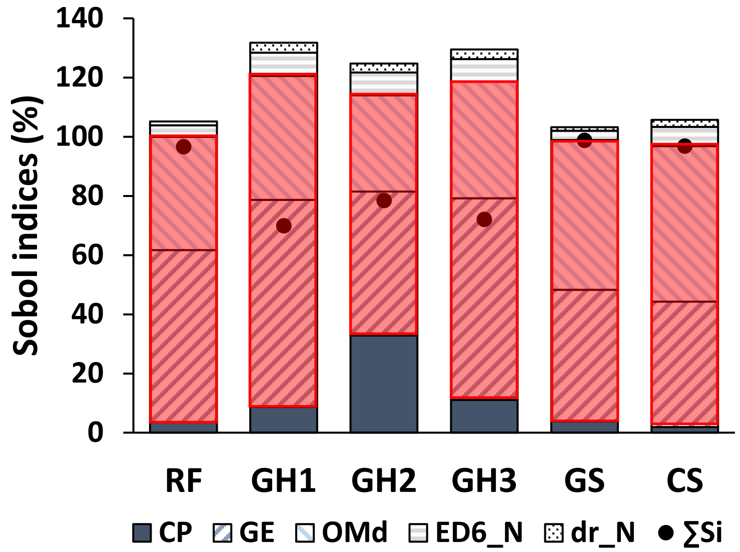
= ∑ Total order index - ∑ First order index

Dry matter intake

Local analysis



Global analysis



General

- Energy related-variables (i.e. GE & OMd) are most important

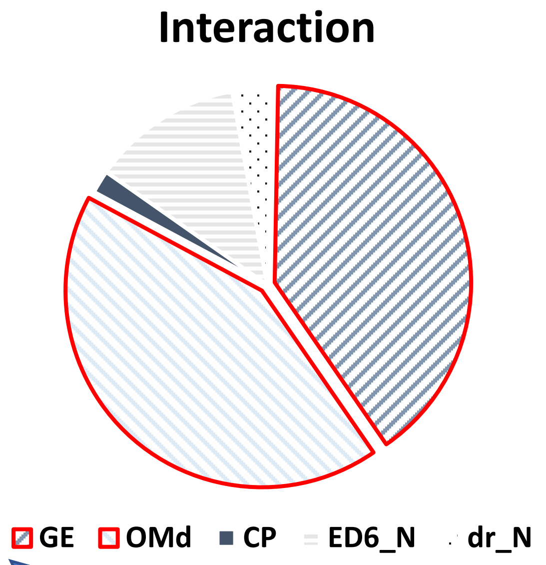
Local Analysis

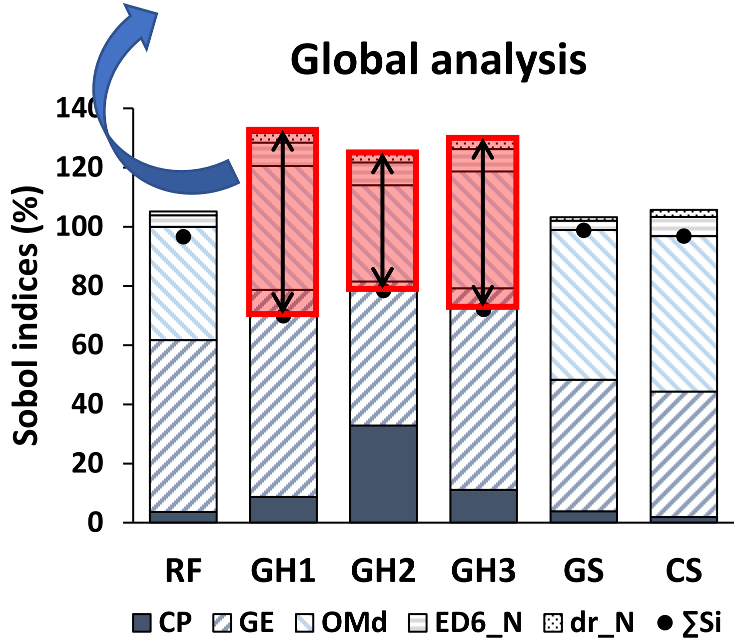
- ***Total variability*** of DMI
  - GH-based diets showed lower variability than non-GH based diets
- ***Direction of change in output*** for each input variable change
  - CP, dr_N: DMI increase (positive)
  - GE, ED6_N: DMI decrease (negative)

Global Analysis

- ***Relative importance*** of input variables
  - Influence of protein-related variables were low

Dry matter intake





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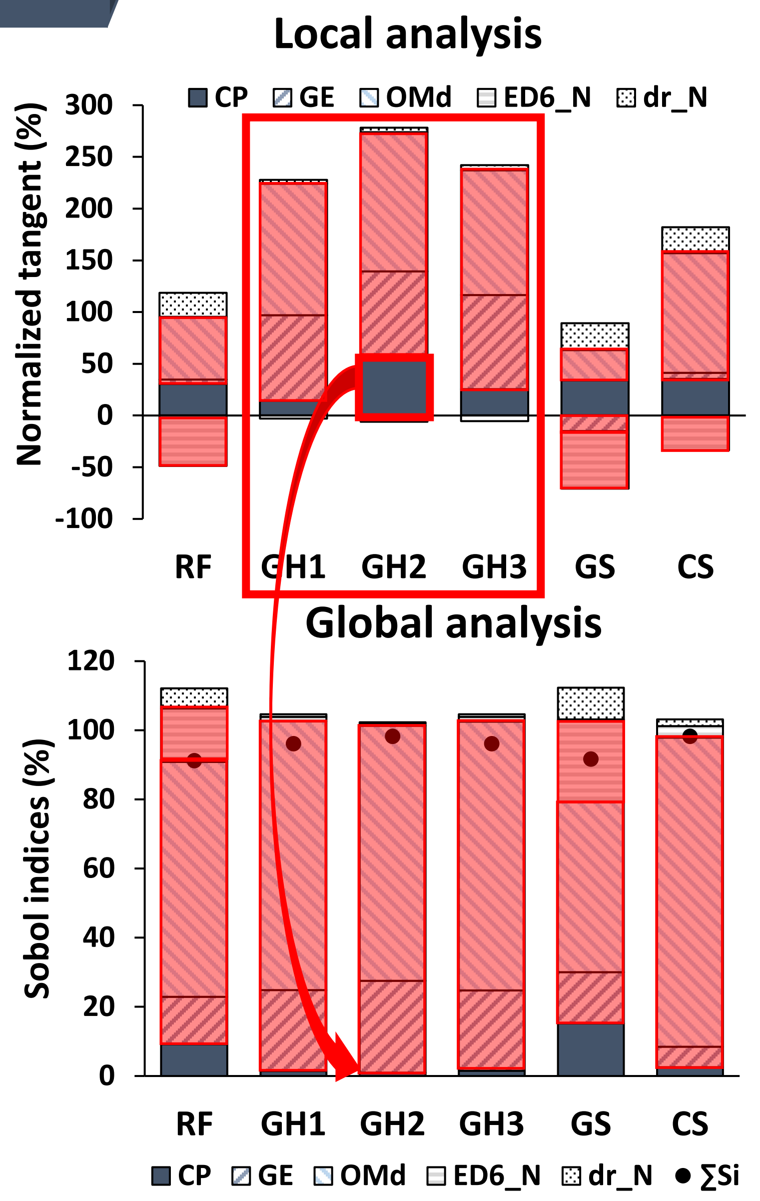
  - GE, ED6_N: DMI decrease (negative)

Global Analysis

- ***Relative importance*** of input variables
  - Influence of protein-related variables were low
- ***Interactions*** among the input variables
  - GH-based diets had higher interaction between input variables
  - Mainly from GE and OMd interacting with other input variables

Milk protein yield



General

- Most of the variation occurred mainly due to variations in OMd & GE
- Contribution of ED6_N was non-negligible

Local Analysis

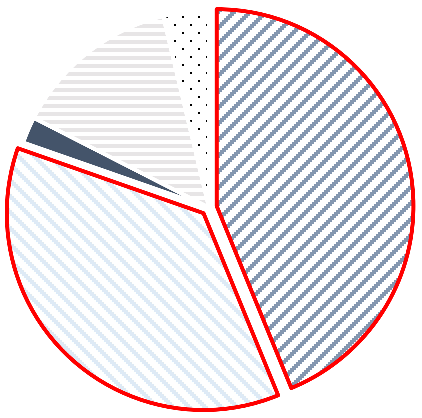
- ***Total variability*** of MPY
  - GH-based diets showed higher variability than non-GH based diets
- ***Direction of change in output*** for each input variable change
  - CP, OMd, dr_N: MPY increase (positive)
  - ED6_N: MPY decrease (negative)

Global Analysis

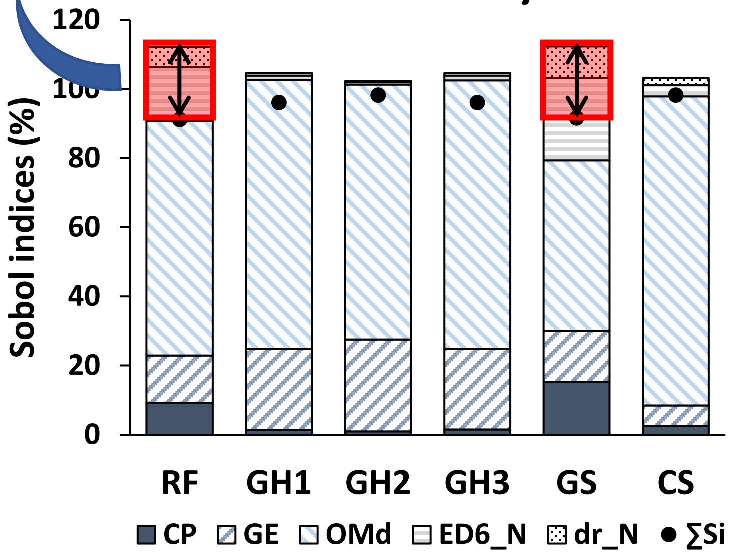
- ***Relative importance*** of input variables
  - In the GH diets, the contribution of protein-related input variables being very low (< 2% of each)
  - Unlike the local analysis, the influence of CP in GH2 diet was minimal

Milk protein yield

Interaction



Global analysis



General

- Most of the variation occurred mainly due to variations in OMd & GE
- Contribution of ED6_N was non-negligible

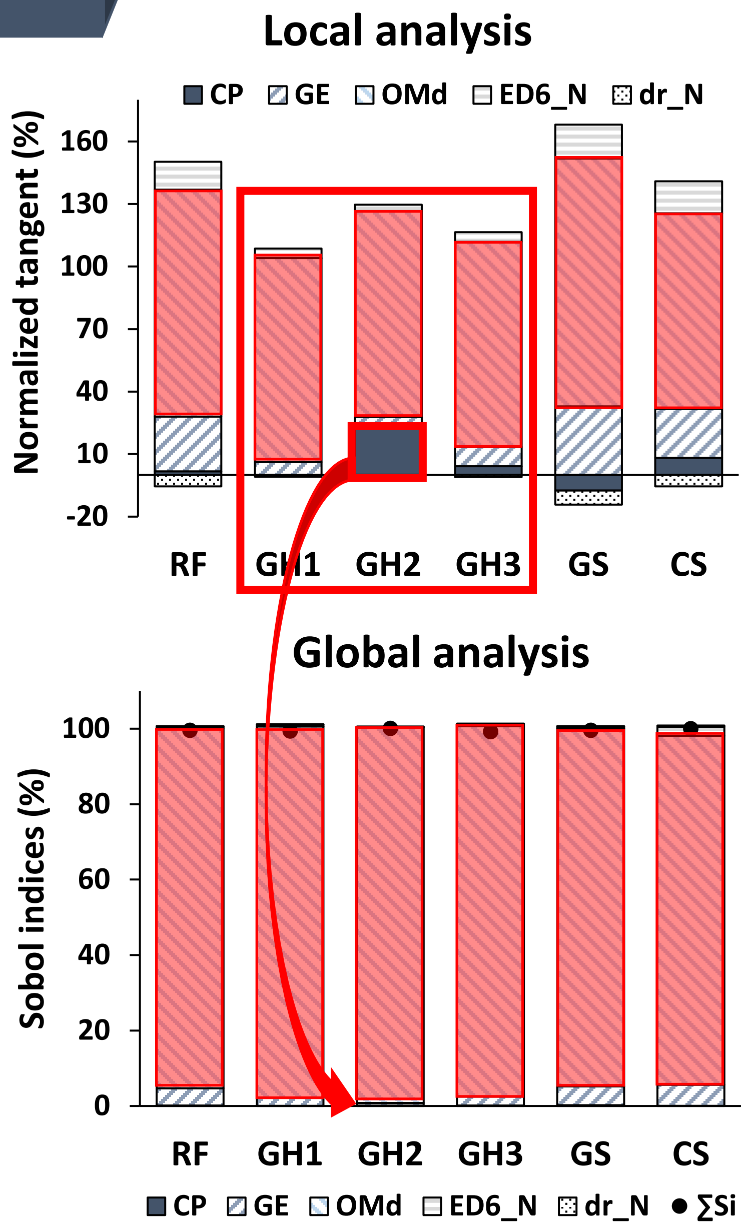
Local Analysis

- ***Total variability*** of MPY
  - GH-based diets showed higher variability than non-GH based diets
- ***Direction of change in output*** for each input variable change
  - CP, OMd, dr_N: MPY increase (positive)
  - ED6_N: MPY decrease (negative)

Global Analysis

- ***Relative importance*** of input variables
  - In the GH diets, the contribution of protein-related input variables being very low (< 2% of each)
  - Unlike the local analysis, the influence of CP in GH2 diet was minimal
- ***Interactions*** among the input variables
  - RF & GS diets had higher interaction between input variables
  - Mainly from GE and OMd interacting with other input variables

Energy in methane



General

- ***Relative importance*** of input variables
  - OMd was the main input variable
  - On average, the influence of CP, ED6_N, and dr_N was not notable

Local Analysis

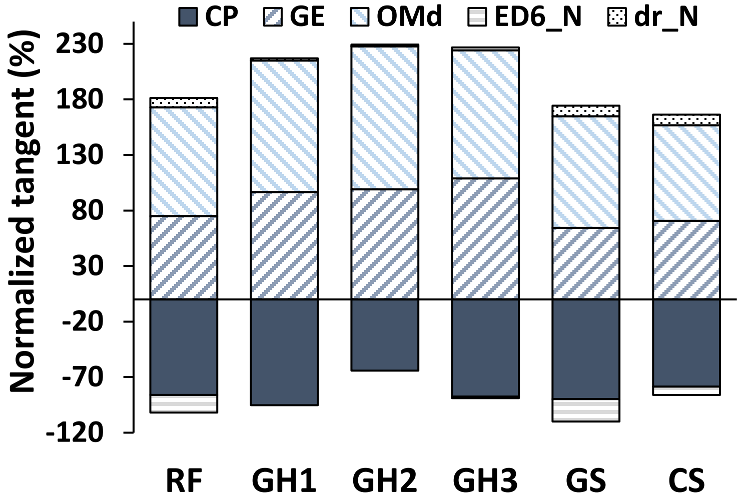
- ***Total variability*** of ECH4
  - The variation of GH diets were slightly lower than non-GH diets
- ***Direction of change in output*** for each input variable change
  - OMd, GE, ED6_N: ECH4 increase (positive)
  - dr_N: ECH4 decrease (negative)

Global Analysis

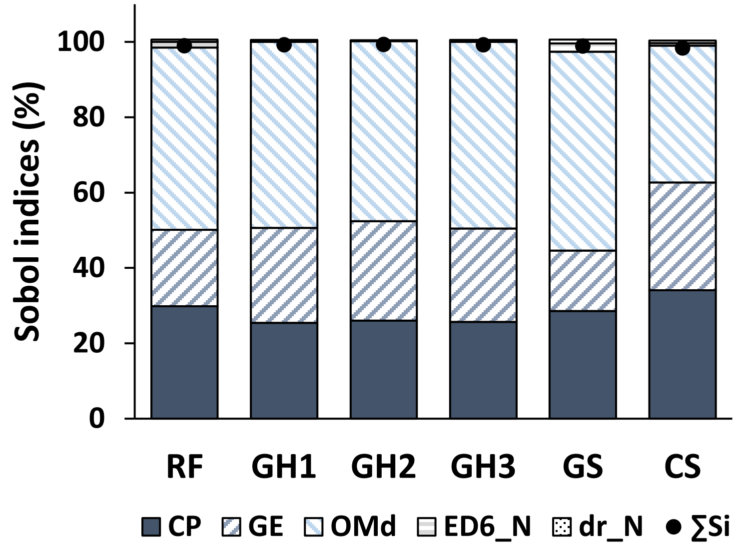
- ***Relative importance*** of input variables
  - Unlike the local analysis, the influence of CP in GH2 diet was minimal
  - The contribution of other 4 input variables being less than 10%
- ***Interactions*** among the input variables
  - No significant interaction between input variables

Nitrogen utilization efficiency (N in milk / N intake)

Local analysis



Global analysis



General

- **No remarkable difference** between two approaches
- Variation of the five input variables were **comparable between diets**
- ***Relative importance*** of input variables
  - Mainly influenced by OMd, GE, and CP
  - ED6_N & dr_N have low influence

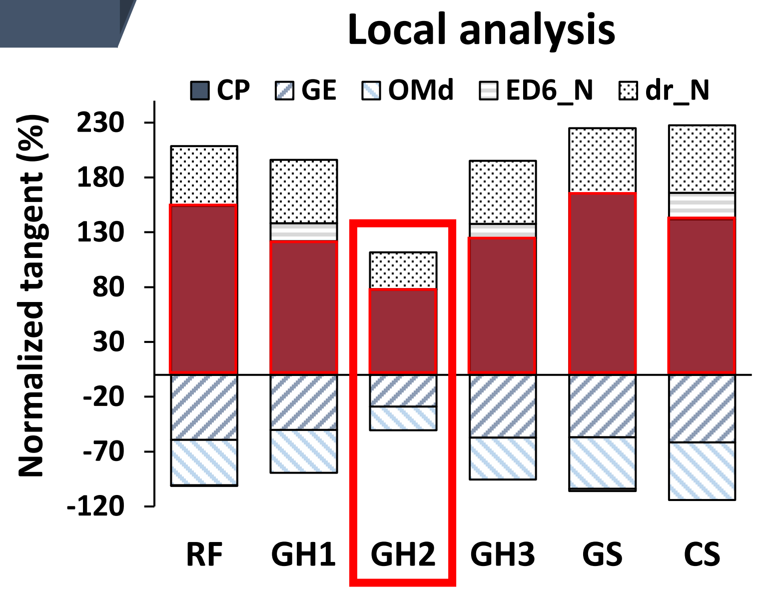
Local Analysis

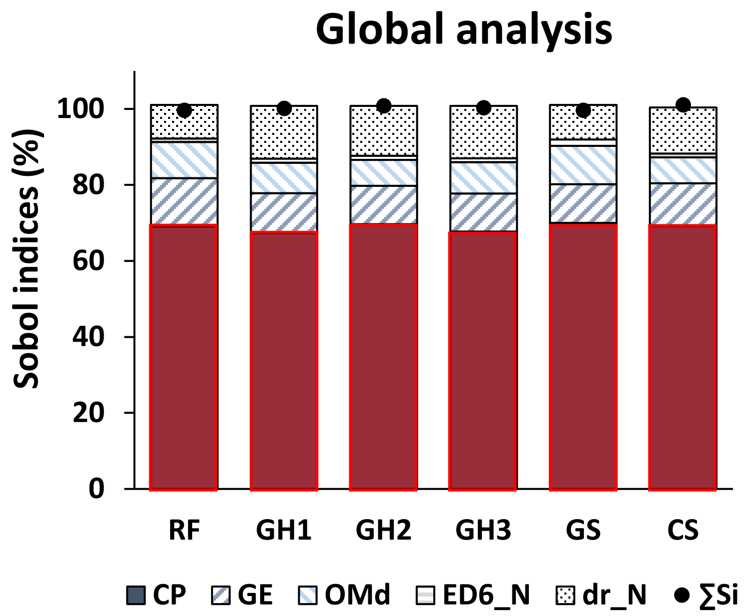
- ***Direction of change in output*** for each input variable change
  - GE, OMd: NUE increase (positive)
  - CP: NUE decrease (negative)

Global Analysis

- ***Interactions*** among the input variables
  - No remarkable interaction between input variables (< 1.5%)

Urinary N / Total excreted N





General

- ***Relative importance*** of input variables
  - UN/TN variations were largely influenced by all 4 input variables except ED6_N
  - CP contributed the most, followed by dr_N, GE, and OMd

Local Analysis

- ***Total variability*** of UN/TN
  - Less variation in GH2 diet than the other 5 diets
- ***Direction of change in output*** for each input variable change
  - CP, dr_N: UN/TN increase (positive)
  - GE, OMd: UN/TN decrease (negative)

Global Analysis

- ***Interactions*** among the input variables
  - Ignorable interaction between input variables (< 0.6%)

Summary and Conclusion

1. Summary of results

- The relative importance of each input variables was ***consistent across both approaches***
- ***GE and OMd were the main contributors*** to most outputs (except Urinary N/Total excreted N)
- ***CP was an important contributor*** to N-related outputs (i.e. N utilization efficiency, Urinary N/Total excreted N)
- For DMI & MPY, ***we can get new insights*** by hydrid two approaches
  - But, less effects on environmental output variables (i.e. ECH4, NUE, and UN/TN)

2. New insights gained from a hybrid

- Large interactions between input variables (Global analysis) can be appeared even low total variation (Local analysis)
  - e.g. DMI with Grass hay-based diets (High PDI/UFL)
  - e.g. MPY with Fresh rygrass- & corn silage-based diets (Low PDI/UFL)
- Global SA can improve the understanding of results obtained on Local SA
  - e.g. positive effect of CP on ECH4 with GH2 (Local) may occur through changes in OMd (GSA)

3. Conclusion

- This work showed the ***advantages of a hybrid approach*** with two SA methods for thoroughly understanding and evaluation of ***complex and non-linear models*** such as ruminant feeding systems.

J. Dairy Sci. 107:4558–4577
https://doi.org/10.3168/jds.2023-24361

Sensitivity analysis of the INRA 2018 feeding system for ruminants by a one-at-a-time approach: Effects of dietary input variables on predictions of multiple responses of dairy cattle

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Running head: Hybrid local and global sensitivity analysis

Descriptive title: Sensitivity analysis of the INRA 2018 feeding system for ruminants by hybrid local and global approaches: Comparing the contribution of dietary input variables to multiple response prediction in dairy cattle

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Supple: R scripts for Local & Global sensitivity analysis!!
Under review of the 1st revision (JDS)

THANK YOU FOR YOUR ATTENTION

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Why does ∑STi > 100% ?

- Due to redundant counting of values for interaction when calculate $\sum ST_i$

For example, there are 3 input variables (A, B, C) for an output variable (i)

- $\mathbf{ST_A} = S_A + \mathbf{Inter(A,B)} + \mathbf{Inter(A,C)} + \mathbf{Inter(A,B,C)}$
- $\mathbf{ST_B} = S_B + \mathbf{Inter(A,B)} + \mathbf{Inter(B,C)} + \mathbf{Inter(A,B,C)}$
- $\mathbf{ST_C} = Si_C + \mathbf{Inter(B,C)} + \mathbf{Inter(A,C)} + \mathbf{Inter(A,B,C)}$

- $\sum ST_i = [S_A + Inter(A,B) + Inter(A,C) + Inter(A,B,C)] + [S_B + Inter(A,B) + Inter(B,C) + Inter(A,B,C)] +$

  $[S_C + Inter(B,C) + Inter(A,C) + Inter(A,B,C)]$

  $= S_A + S_B + S_C + \mathbf{2\ Inter(A,B)} + \mathbf{2\ Inter(A,C)} + \mathbf{2\ Inter(B,C)} + \mathbf{3\ Inter(A,B,C)}$

What if there is no interaction between input variables?

- **Sobol index** (Sobol, 1993)
  - Variance-based sensitivity analysis

  (1) First order index (S_i): Evaluate the importance of one input variable (*no interaction*)

  (2) Total indices (ST_i): Evaluate the importance of one input variable considering ***interaction*** with other input variables

  (3) Interaction (STi – Si): Level of interaction with other input variables

- **R program**: *sensobol* packages

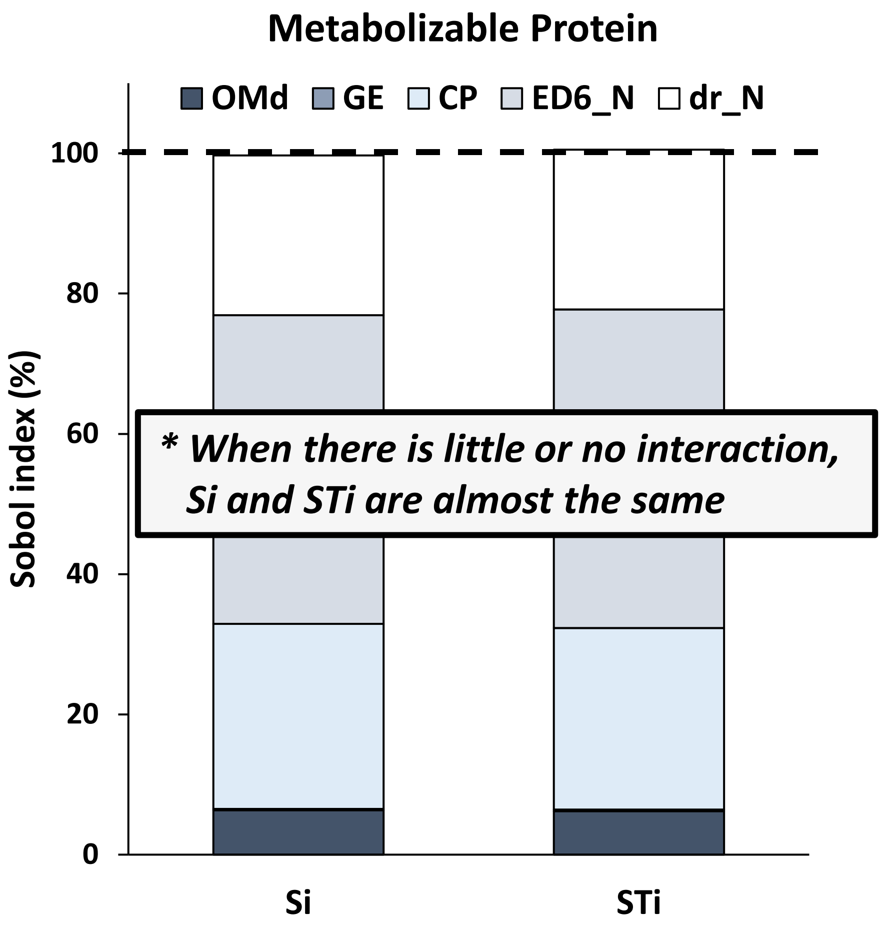

Figure 1. Response of metabolizable protein to change in 5 input variables

Why sobol?

- Big assumption of 'Pearson' and 'Spearman' correlation coefficient
  - 1) Linearity and/or 2) Monotonicity
  - However, most models of the INRA feeding system didn't satisfy this requirement
- What if we apply it to a model that is not linear or monotonicity?
  - $Y1 = 10 \cdot X1 + X2 + X3 + X4 + X5$
  - $Y2 = 10 \cdot X1^2 + X2 + X3 + X4 + X5$

* X1, X2, X3, X4, X5 ← Randomly select between -25 to 25 (n = 700; n = 100 for sobol)

Table 1. Sensitivity indices of input variables for **Y1**

	Pearson	Spearman	Sobol (ST_i)
X1	0.98	0.98	1.00
X2	0.08	0.08	0.01
X3	0.03	0.04	0.01
X4	0.02	0.05	0.01
X5	0.09	0.09	0.01

Table 2. Sensitivity indices of input variables for **Y2**

	Pearson	Spearman	Sobol (ST_i)
X1	0.06	<0.01	0.96
X2	0.06	0.02	<0.01
X3	0.07	0.06	<0.01
X4	<0.01	0.03	<0.01
X5	<0.01	<0.01	<0.01

Sobol analysis sequence using R

1. Create Sobol matrix

	OMd	ED6_N	CP	dr_N	GE
1	0.50	0.50	0.50	0.50	0.50
2	0.75	0.25	0.75	0.25	0.75
…	…	…	…	…	…
n	0.41	0.26	0.30	0.48	0.70

2. Assigning value to the Sobol matrix

Feed1

	OMd	ED6_N	CP	dr_N	GE
1	87.6	44.2	89.1	88.7	4497.5
2	90.9	42.6	92.4	85.5	4664.4
…	…	…	…	…	…
n	86.6	42.7	86.6	88.5	4623.9

Feed2

	OMd	ED6_N	CP	dr_N	GE
1	74.4	69.0	378.7	79.4	4604.7
2	77.2	66.4	392.8	76.4	4775.5
…	…	…	…	…	…
n	73.5	66.5	368.1	79.1	4734.1

Feed3

	OMd	ED6_N	CP	dr_N	GE
1	69.4	67.6	88.0	86.9	4503.2
2	71.9	65.1	91.3	83.6	4670.2
…	…	…	…	…	…
n	68.5	65.2	85.6	86.6	4629.7

3. Extract sobol matrices
- For PrevAlim running

4. **PrevAlim** running
→ Obtain full feed table of each feed

5. **Diet optimizer** running
- Obtain output matrix

6. Calculate Sobol index

Number of sample in sobol matrix

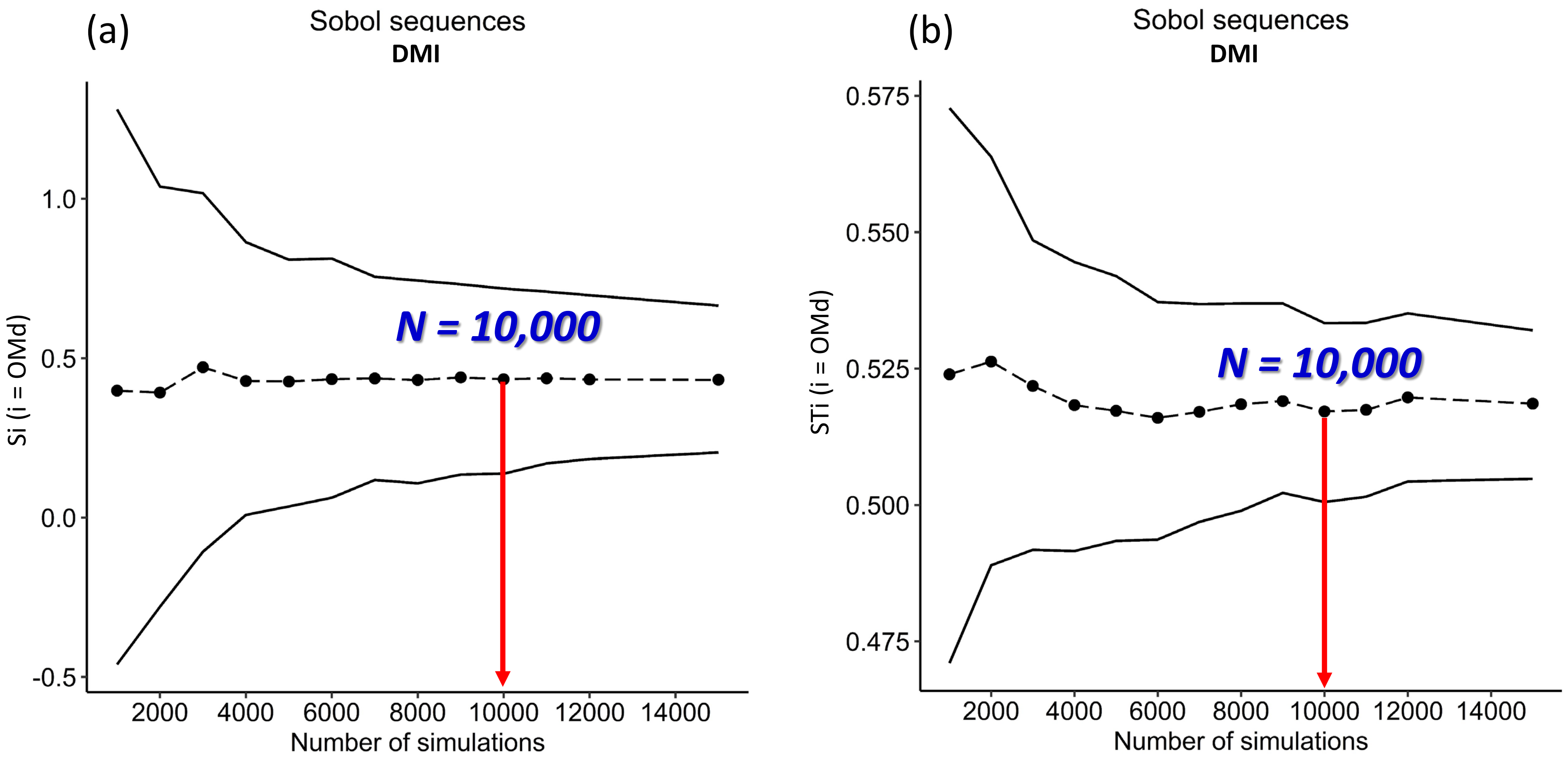

Figure 1. (a) First sobol index (Si, round) and confidence interval (solid line)
(b) Total sobol indices (STi, round) and confidence interval (solid line)