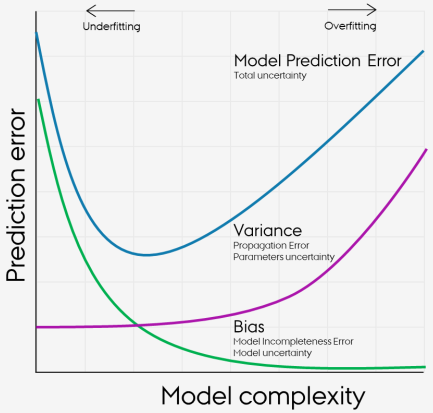
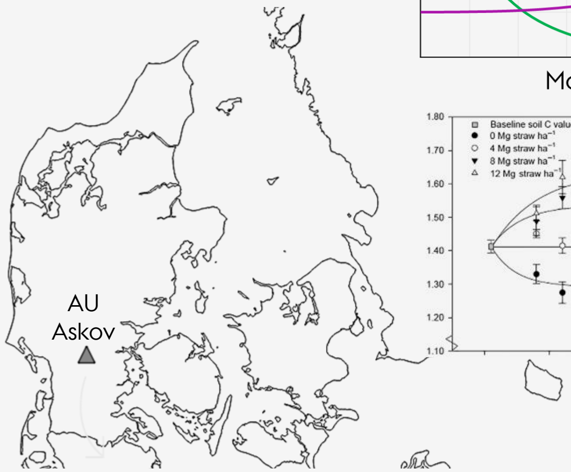
LONG-TERM PLOT SCALE VARIABILITY TO EXPLORE SOIL CARBON TURNOVER MODELING UNCERTAINTIES: A C-TOOL IMPLEMENTATION

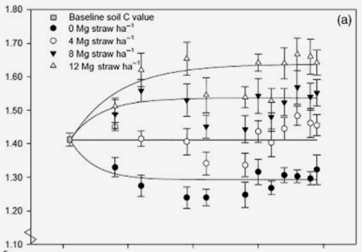
Simple flexible

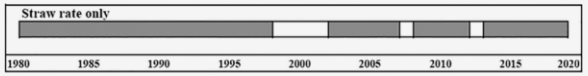
Main sources of uncertainty
- C input calculations
- Parametrization of initial pool distribution

Lack of long-term data





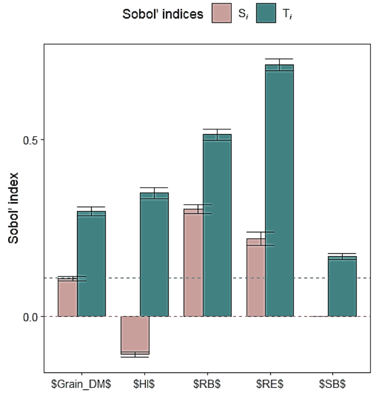




We implemented C-TOOL at plot level, based on precise data from barley straw disposal at plot level to explore uncertainties and validate it performance

How sensitive are C input calculations to allometric parametrization?

Variance-based SA on allometric



Root exudates and root biomass are the most sensitive parameters

How have we run multiple scenarios?

R implementation

What are the sources of the lack of fit?

VCA on residuals

VCA (%) Errors on Topsoil C Stock	
Initialization+HI+RE+RB+RE	9.6
Year	*16.1*
Block	*17.6*
Initial Soil C	*22.4*
Residual	34.2

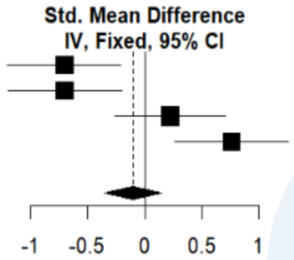
Focus on the initial soil C parametrization

Using a fixed amount of root biomass presented better than using standard allometric

How accurate is the model in predicting the temporal plot variability of SOC?

Arrange a simulation design and evaluate Predictive Error

Straw rate	Simulated Mean	Simulated SD	Observed Mean	Observed SD	Weight	Std. Mean Difference IV, Fixed, 95% CI
0	37.63	1.78	39.27	2.71	24.7%	-0.70 [-1.20; -0.21]
4	41.84	1.03	43.22	2.55	24.7%	-0.70 [-1.20; -0.20]
8	45.83	0.84	45.36	2.92	26.1%	0.22 [-0.26; 0.70]
12	49.00	1.44	46.99	3.42	24.5%	0.76 [0.26; 1.26]
Total (95% CI)					**100.0%**	**-0.10 [-0.35; 0.14]**



All the alternative parametrizations RMPE<15 %

Further studies: global SA to get robust uncertainty and sensitivity estimation

Sharing is encouraged

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DEPARTMENT OF AGROECOLOGY

EGU GENERAL ASSEMBLY
24 APRIL 2023

FRANCA GIANNINI-KURINA
POSTDOC

SOLIDUM PETIT IN PROFUNDIS · UNIVERSITAS ARHUSIENSIS

MODELLING SOIL CARBON
USING **C-TOOL**

AARHUS
UNIVERSITY
DEPARTMENT OF AGROECOLOGY

EGU GENERAL ASSEMBLY
24 APRIL 2023

FRANCA GIANNINI-KURINA
POSTDOC

CONTENT

About models and modelling Soil Carbon

What is C-TOOL and what is not?

- Structure
- Inputs and outputs

What it has been done around C-TOOL

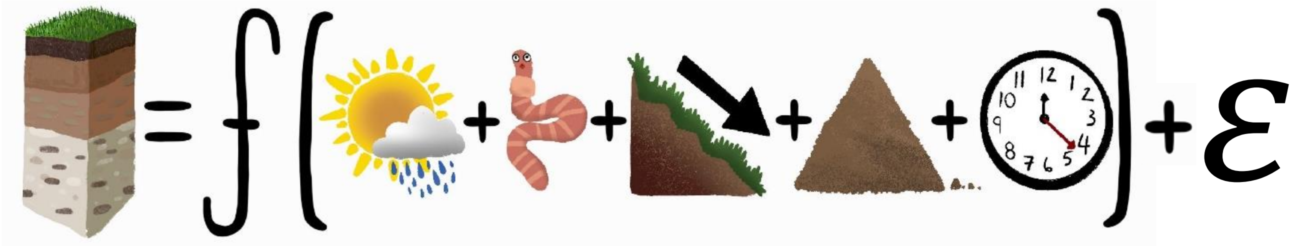
What we have been doing

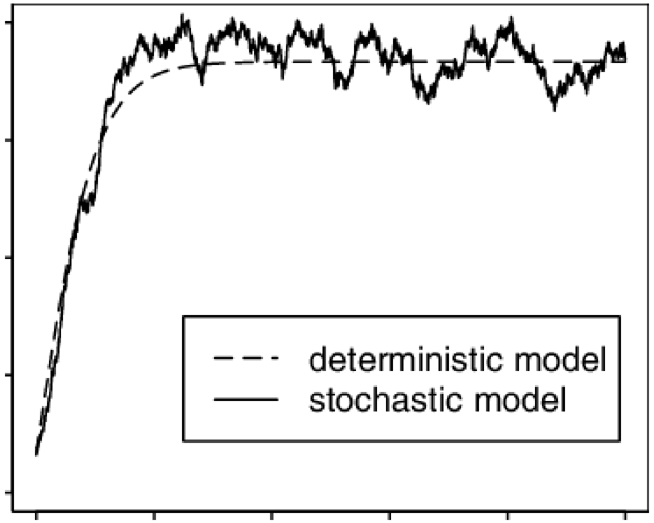
- Implementation
- Sensitivity on C inputs calculations
- Validation
- Simulation

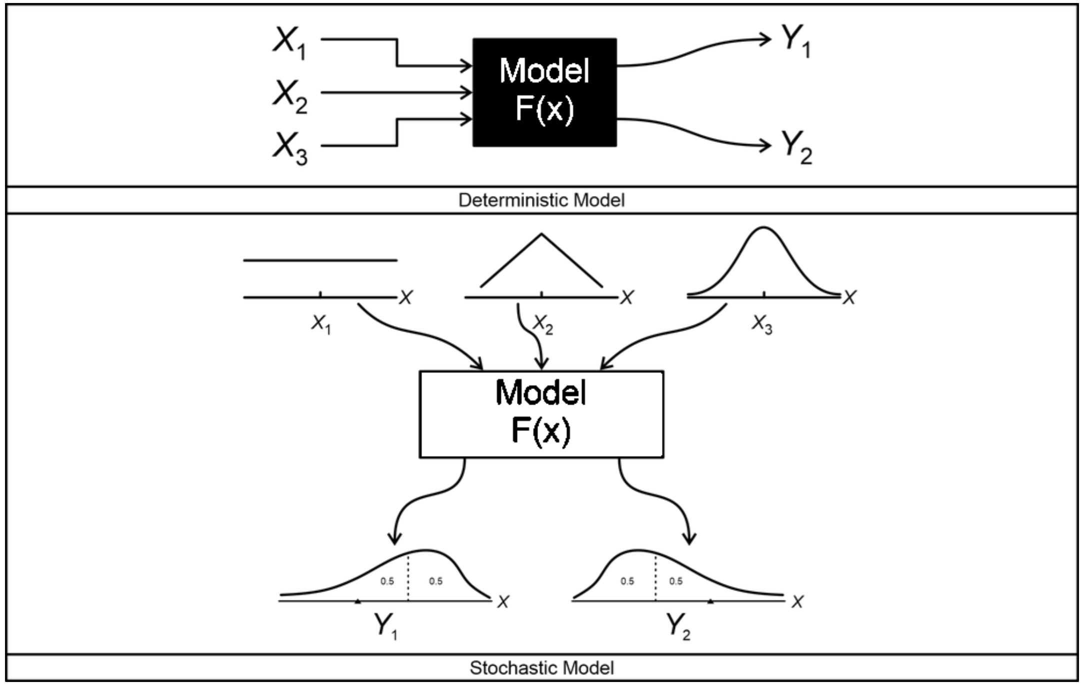
Further works

ABOUT MODELS AND MODELLING SOC

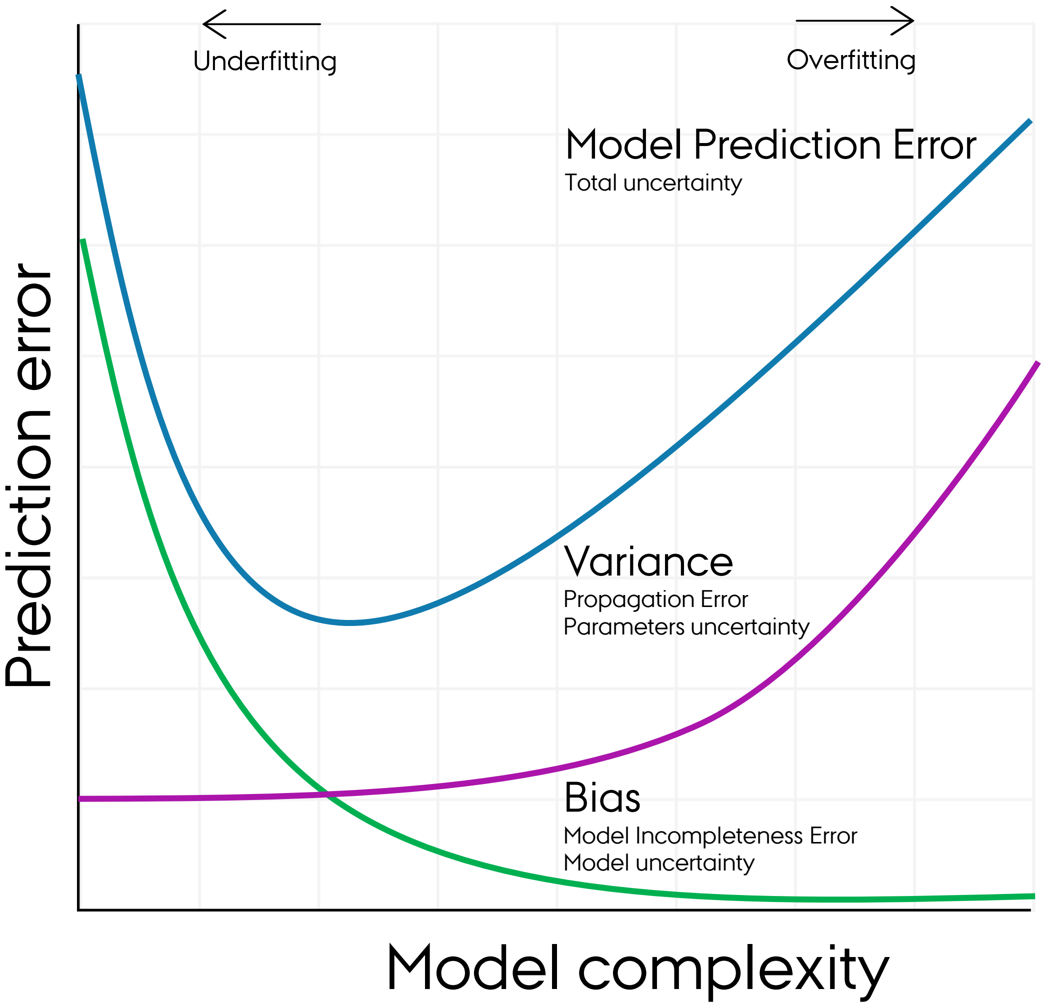
Deterministic vs. stochastic







ABOUT MODELS



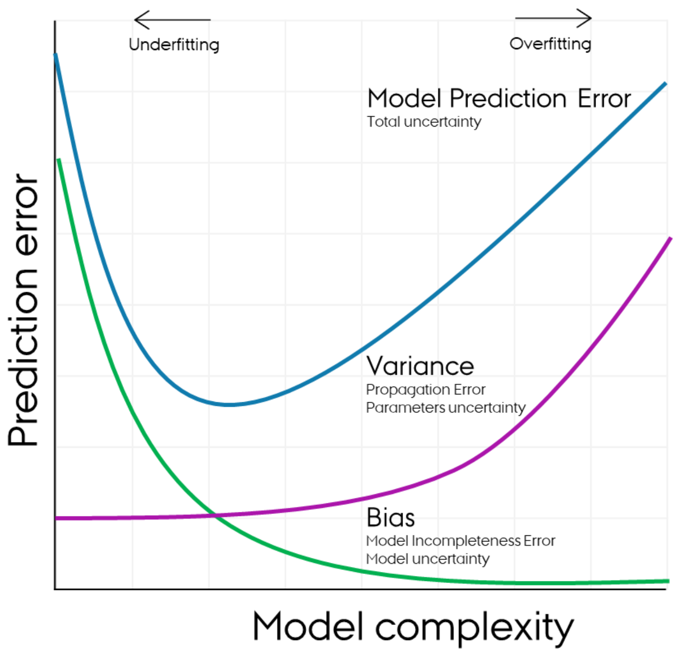
Adapted and not that adapted from... everyone

(Guenet, Le Noé et al. 2022)

WHAT IS C-TOOL AND WHAT IS NOT?

A simple tool for simulation of soil carbon turnover

(Taghizadeh-Toosi, Christensen et al. 2014, Taghizadeh-Toosi 2015)



Model complexity

C Balance | **C-TOOL** | RothC | DNDC | Century 100 DayCent | APSIM DAISY

WHAT IS C-TOOL AND WHAT IS NOT?

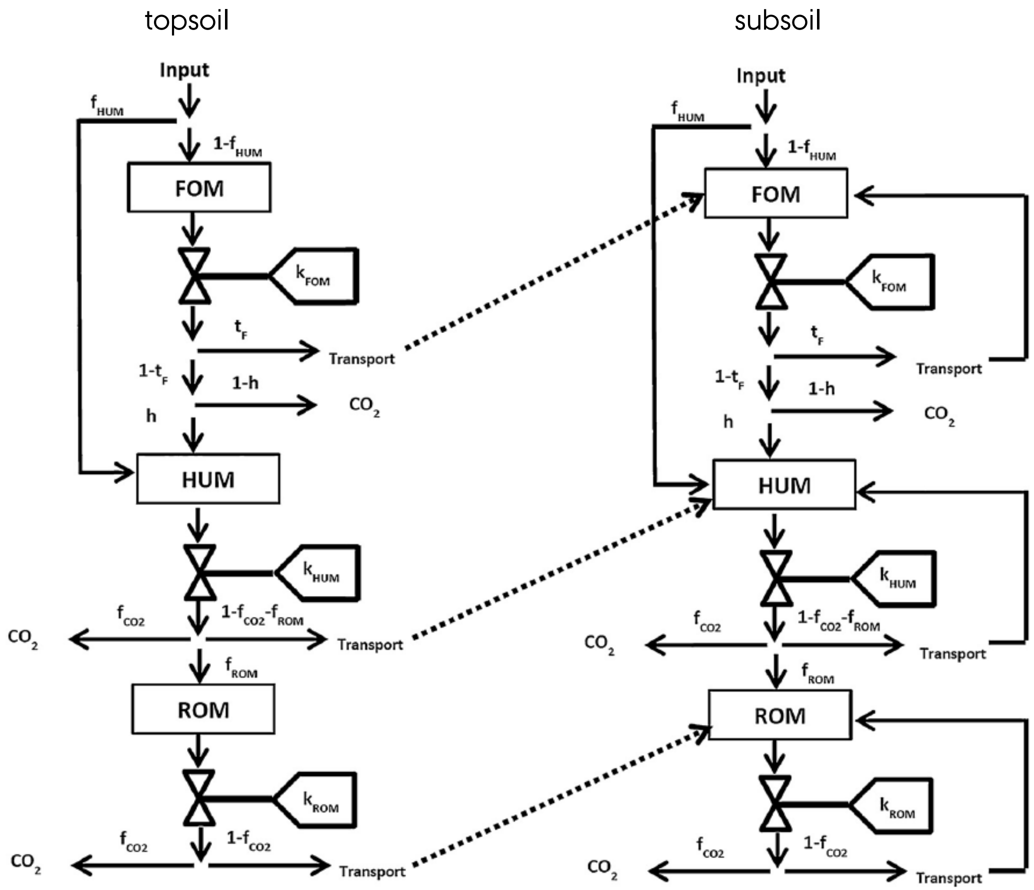


Fig. 1. C-TOOL model structure for top and subsoil; FOM: fresh organic matter, HUM: humified organic matter, ROM: resistant organic matter, f_{HUM}: fraction of input going to HUM (f_{HUM} is >0 for manure and 0 for plant residues), k_{FOM}: decomposition rate of FOM, k_{HUM}: decomposition rate of HUM, f_{ROM}: fraction of FOM going to ROM, k_{ROM}: decomposition rate of ROM, t_F: the fraction going to downward transport, h: humification coefficient, f_{CO_2}: fraction of released CO_2. *Note*: The rate constants and fraction are the same for both topsoil and subsoil.

3

conceptual SOC pools

°C

temperature driven

C inputs to and turnover in topsoil and subsoil

C transport from topsoil to subsoil, and CO_2

does not consider:
soil water as a limiting factor
effects of soil tillage intensity nor bulk density changes during the simulation period

WHAT IS C-TOOL AND WHAT IS NOT?

Allometric calculation for c inputs

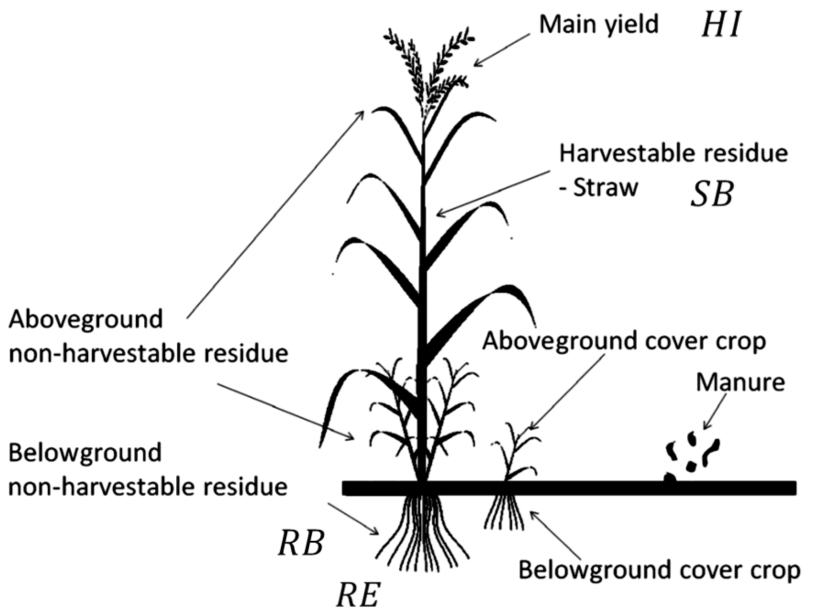
$$C_{resid} = \left(\left(\frac{1}{HI}\right) - 1 - SB\right) \times (Grain_{DM} \times 0.43)$$

$$C_{below} = RB/((1 - RB) \times HI)) \times (Grain_{DM} \times 0.43))$$

$$\boldsymbol{C_{top} = \begin{cases} 0 + (RE \times C_{below})\ if\ C_{resid} < 0 \\ C_{resid} + (RE \times C_{below})\ if\ C_{resid} > 0 \end{cases}}$$

$$\boldsymbol{C_{sub} = (1 - RE) * C_{below}}$$

$$\boldsymbol{C_{man}}$$



(Keel, Leifeld et al. 2017)

WHAT IT HAS BEEN DONE AROUND C-TOOL

ELSEVIER
Ecological Modelling 151 (2002) 1–14
ECOLOGICAL MODELLING
www.elsevier.com/locate/ecolmodel

A flexible tool for simulation of soil carbon turnover

Bjørn M. Petersen [a,*], Jørgen E. Olesen [b], Tove Heidmann [a]
[a] Department of Agricultural Systems, Danish Institute of Agricultural Sciences, Research Centre Foulum, P.O. Box 50, DK-8830 Tjele, Denmark
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Received 12 July 2000; received in revised form 28 February 2001; accepted 21 March 2001

Ecological Modelling 292 (2014) 11–25
Contents lists available at ScienceDirect
Ecological Modelling
journal homepage: www.elsevier.com/locate/ecolmodel
ELSEVIER

C-TOOL: A simple model for simulating whole-profile carbon storage in temperate agricultural soils

CrossMark

Arezoo Taghizadeh-Toosi [a,*], Bent T. Christensen [a], Nicholas J. Hutchings [a], Jonas Vejlin [a], Thomas Kätterer [b], Margaret Glendining [c], Jørgen E. Olesen [a]
[a] Aarhus University, Department of Agroecology, Blichers Allé 20, P.O. Box 50, 8830 Tjele, Denmark
[b] Swedish University of Agricultural Sciences, Department of Ecology, P.O. Box 7044, Ulls Väg 16, 750 07 Uppsala, Sweden
[c] Rothamsted Research, Department of Computational and Systems Biology, West Common, Harpenden, Herts AL5 2JQ, UK

Agricultural Systems 145 (2016) 83–89
Contents lists available at ScienceDirect
Agricultural Systems
journal homepage: www.elsevier.com/locate/agsy
ELSEVIER

Modelling soil organic carbon in Danish agricultural soils suggests low potential for future carbon sequestration

CrossMark

Arezoo Taghizadeh-Toosi *, Jørgen E. Olesen
Aarhus University, Department of Agroecology, Tjele 8830, Denmark

www.nature.com/scientificreports
SCIENTIFIC REPORTS

OPEN Consolidating soil carbon turnover models by improved estimates of belowground carbon input

Received: 01 June 2016
Accepted: 09 August 2016

Arezoo Taghizadeh-Toosi[1], Bent T. Christensen[1], Margaret Glendining[2] & Jørgen E. Olesen[1]

www.nature.com/scientificreports
scientific reports
Check for updates

OPEN Filling gaps in models simulating carbon storage in agricultural soils: the role of cereal stubbles

Arezoo Taghizadeh-Toosi[1,2] & Bent T. Christensen[1]

Plant Soil
https://doi.org/10.1007/s11104-020-04500-9
REGULAR ARTICLE
Check for updates

Visiting dark sides of model simulation of carbon stocks in European temperate agricultural soils: allometric function and model initialization

Arezoo Taghizadeh-Toosi · Wen-Feng Cong · Jørgen Eriksen · Jochen Mayer · Jørgen E. Olesen · Sonja G. Keel · Margaret Glendining · Thomas Kätterer · Bent T. Christensen

European Journal of Soil Science
European Journal of Soil Science, November 2017, 68, 953–963
doi: 10.1111/ejss.12454

Large uncertainty in soil carbon modelling related to method of calculation of plant carbon input in agricultural systems

S. G. Keel[a], J. Leifeld[a], J. Mayer[b], A. Taghizadeh-Toosi[c] & J. E. Olesen[c]
[a] Agroscope, Research Division Agroecology and Environment, Climate and Air Pollution Group, Reckenholzstrasse 191, 8046, Zurich, Switzerland, [b] Agroscope, Research Division Agroecology and Environment, Soil Fertility and Soil Protection Group, Reckenholzstrasse 191, 8046, Zurich, Switzerland, and [c] Department of Agroecology, Aarhus University, Blichers Allé 20, 8830, Tjele, Denmark

WHAT WE HAVE BEEN DOING

Implementation

Input

Data file

Yearly C inputs

Input file

Parametrization of soil and rates between pools.

Temperature data

Monthly temperature for the simulation period

Output

Total amount

C content in each pool in subsoil and topsoil

CO2

Emissions from each pool in subsoil and topsoil

Transport

C transport between pools

R articulation

A code (`sim_building`) generates a table (`tbl_fill`) where each row is a scenario and each column a parameter

Based on `tbl_fill` table a code (`make_data`) generates a list (`aver`) in which each element for each scenario contains other list with :

- the scenario id
- the data table with the calculated C inputs
- and the input file

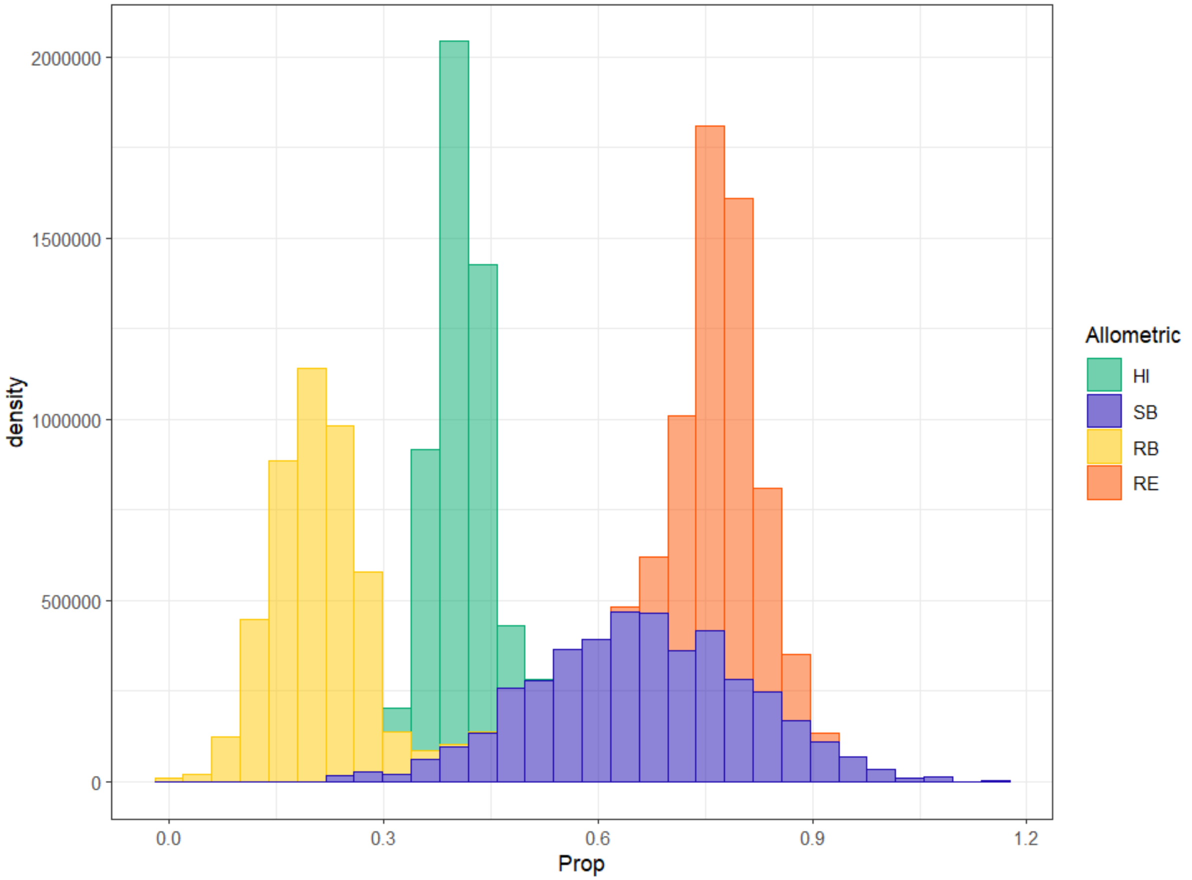
For each element in this list other code (`run_ctool`) code makes a folder copy the c-tool executable and runs the model in it.

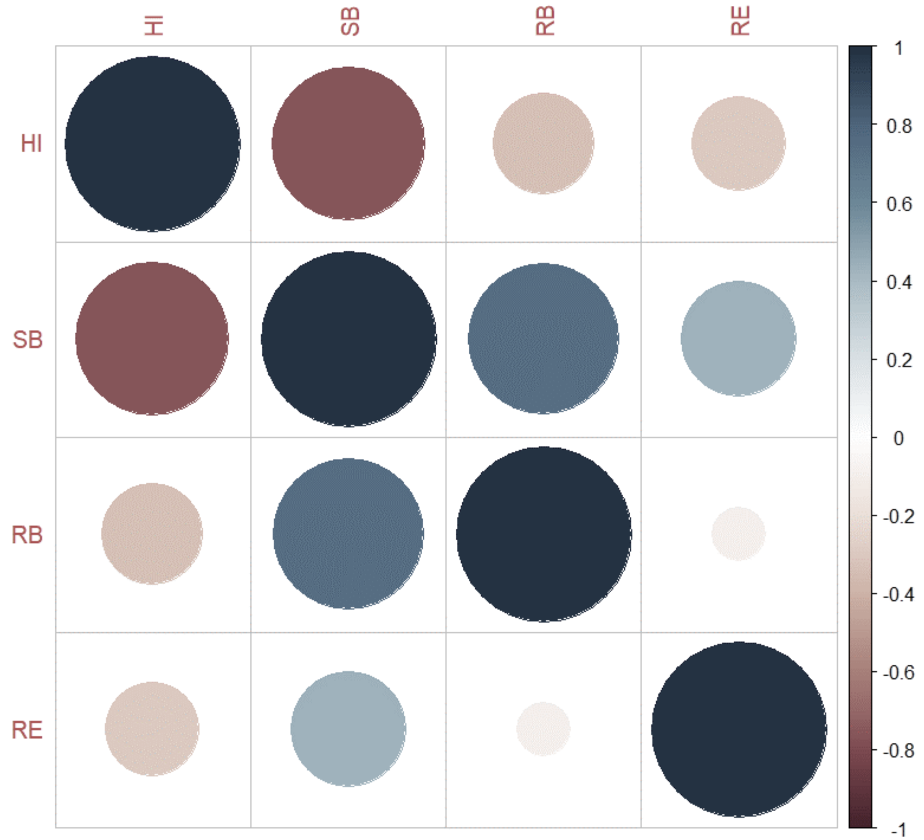
Finally, `outputs` code reeds the outputs in each folder and copy its to a single final data table

https://github.com/francagiannini/initial-ctool

WHAT WE HAVE BEEN DOING

Sensitivity and Uncertainty analysis on C input calculations

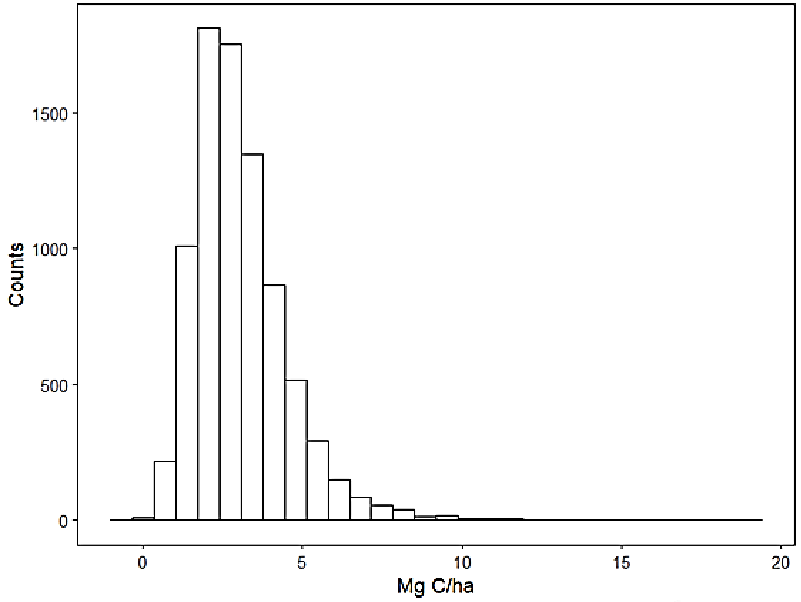


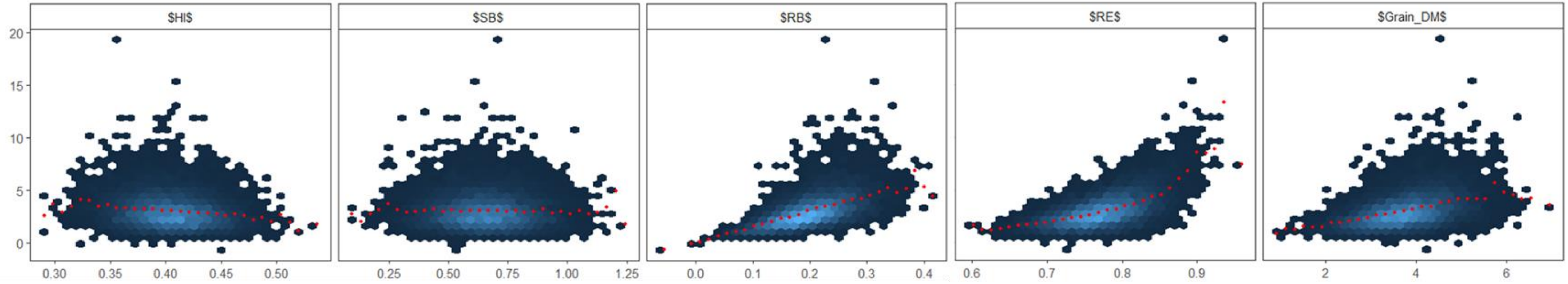


(Saltelli, Annoni et al. 2010, Saltelli, Aleksankina et al. 2019, Razavi, Jakeman et al. 2021)

WHAT WE HAVE BEEN DOING

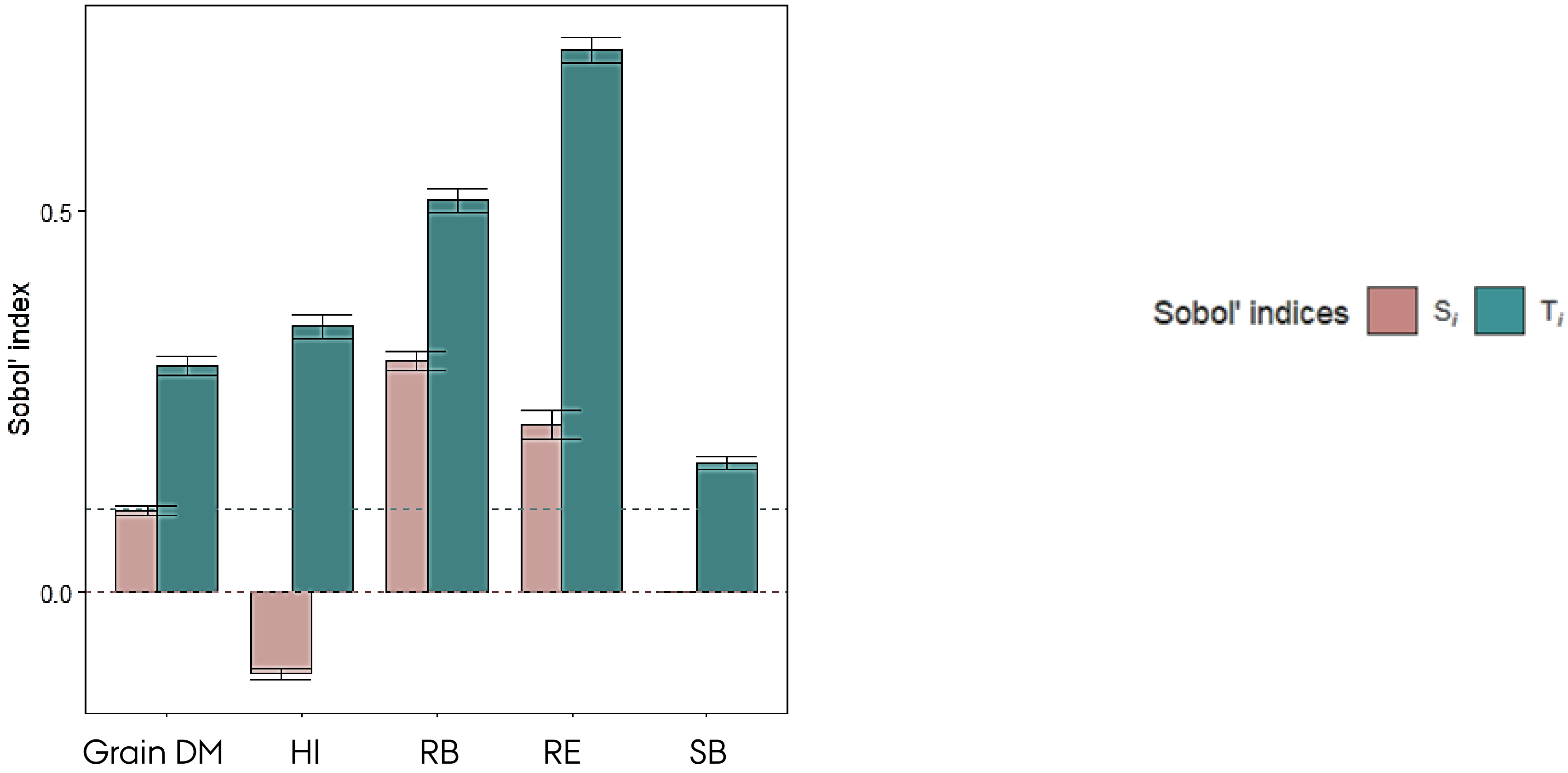
Uncertainty on C input calculations





WHAT WE HAVE BEEN DOING

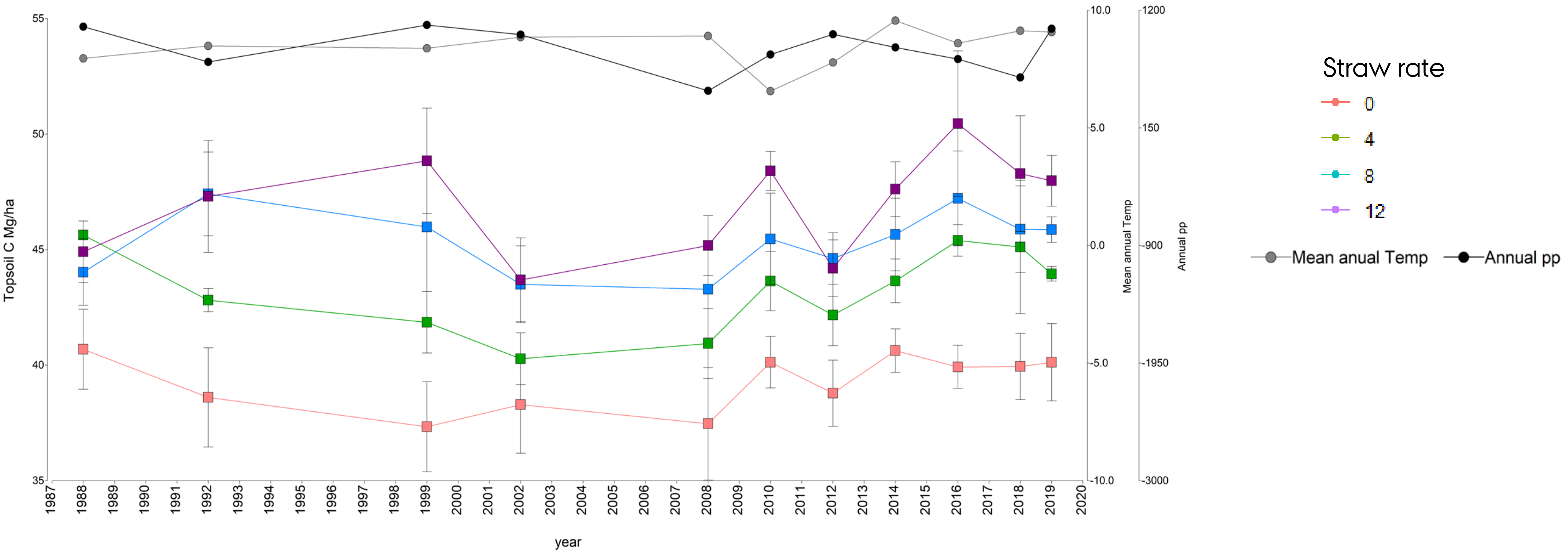
Sensitivity on C input calculations



(Saltelli, Annoni et al. 2010, Saltelli, Aleksankina et al. 2019, Razavi, Jakeman et al. 2021)

WHAT WE HAVE DONE

Validation

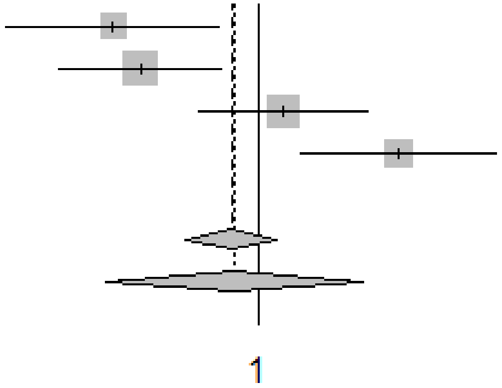


WHAT WE HAVE BEEN DOING

Validation

Study	Simulated Total	Simulated Mean	Simulated SD	Observed Total	Observed Mean	Observed SD	Ratio of Means	ROM	95%-CI	Weight (common)	Weight (random)
0	33	37.71	1.9978	33	39.27	2.7063		0.96	[0.93; 0.99]	18.2%	24.0%
4	33	41.82	1.2110	33	43.22	2.5543		0.97	[0.95; 0.99]	31.7%	25.8%
8	33	45.67	1.1215	33	45.36	2.9165		1.01	[0.98; 1.03]	29.0%	25.6%
12	33	48.86	1.6820	33	46.99	3.4154		1.04	[1.01; 1.07]	21.2%	24.6%
Common effect model	**132**			**132**				**0.99**	**[0.98; 1.01]**	**100.0%**	**--**
Random effects model								**0.99**	**[0.96; 1.03]**	**--**	**100.0%**

Heterogeneity: $I^2 = 87\%$, $\tau^2 = 0.0012$, $p < 0.01$



All parametrization

<15% RMSPE

relative to observed mean

best parametrization 8.18%

WHAT WE HAVE BEEN DOING

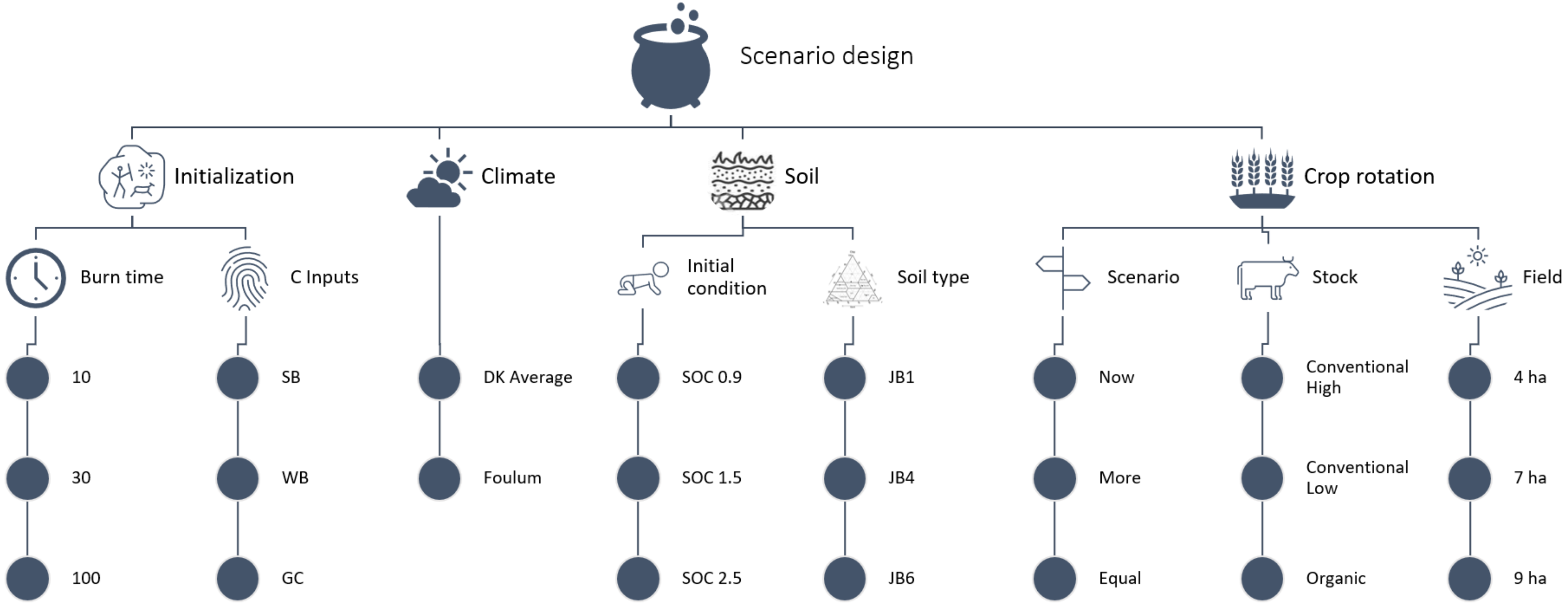
Validation

Residuals VCA

Factor	VCA
CC	0
Initialization	0
HI	2.22
RE	3.73
Block	12.6
Initial SOC	15.9
Residual	28.5
RB (Fixed or HI dependent)	37.2

WHAT WE HAVE BEEN DOING

Simulation

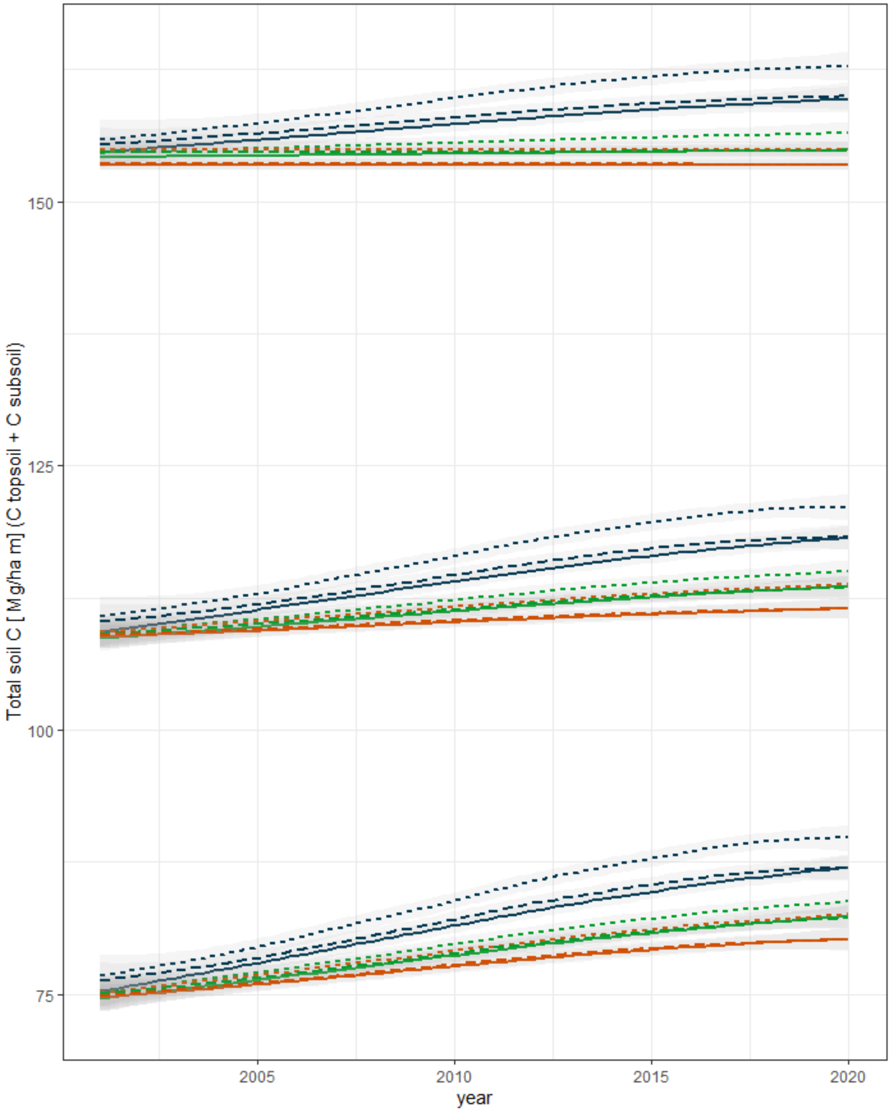


WHAT WE HAVE BEEN DOING

Simulation

WHAT WE HAVE BEEN DOING

Simulation



Proportion of grass

- Equal
- More
- Now

Farm type

- Conventional farm high stock
- Conventional farm low stock
- Organic farm

Further works

C input calculations on grass rotations

Global sensitivity analysis

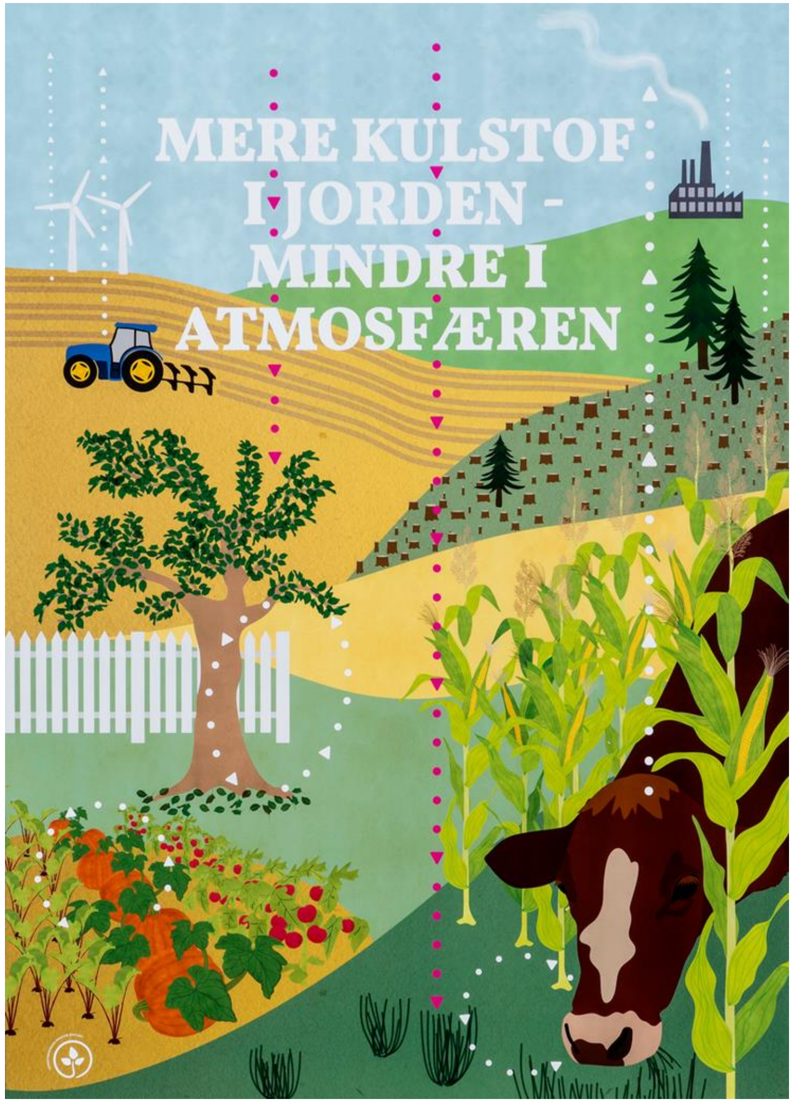
Backward prediction/estimation of initial condition

National scale variability

Simulation

Related to other C turnover models

- Comparison
- Ensambling



Mere kulstof i jorden, mindre i atmosfæren, 2016. Udgivet af Landsforeningen Praktisk Økologi.

Thanks for getting until here

AARHUS UNIVERSITY

We are looking forward to hearing from you!

Any questions and feedback is highly appreciated please contact us!

francagk@agro.au.dk

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SENSITIVITY ALLOMETRIC

October 2022

THE QUESTION

how the variability on allometric impacts the output variability of the model?

… and we should prioritize their impact

How wrong can it be?

ALLOMETRIC CALCULATION

$$C_{resid} = \left(\left(\frac{1}{HI}\right) - 1 - SB\right) \times (Grain_{DM} \times 0.43)$$

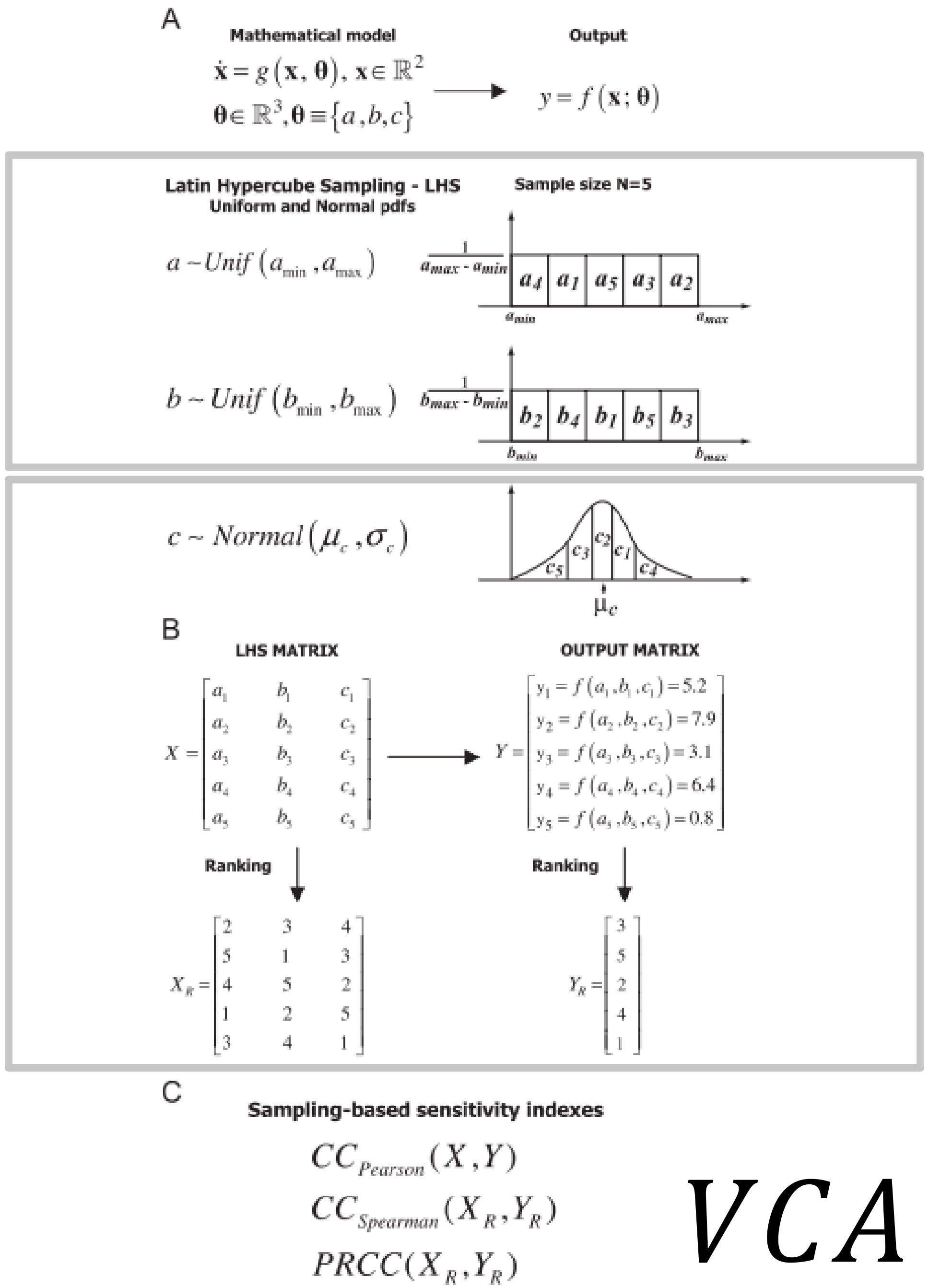
$$C_{below} = RB/((1 - RB) \times HI)) \times (Grain_{DM} \times 0.43))$$

$$\boldsymbol{C_{top} = \begin{cases} 0 + (RE \times C_{below})\ if\ C_{resid} < 0 \\ C_{resid} + (RE \times C_{below})\ if\ C_{resid} > 0 \end{cases}}$$

$$\boldsymbol{C_{sub} = (1 - RE) * C_{below}}$$

Uniform uncorr

Gaussian corre



VCA

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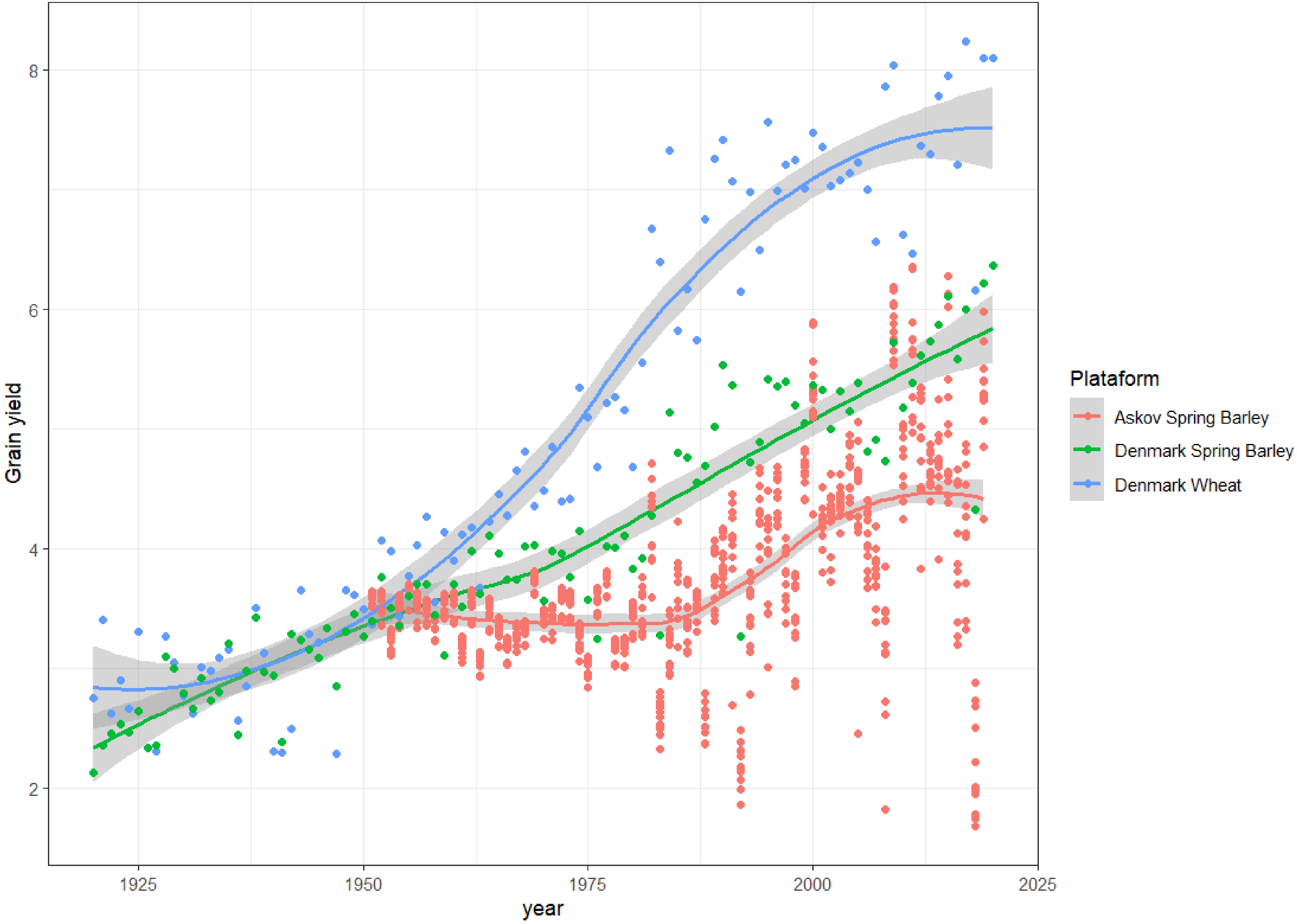
YIELDS



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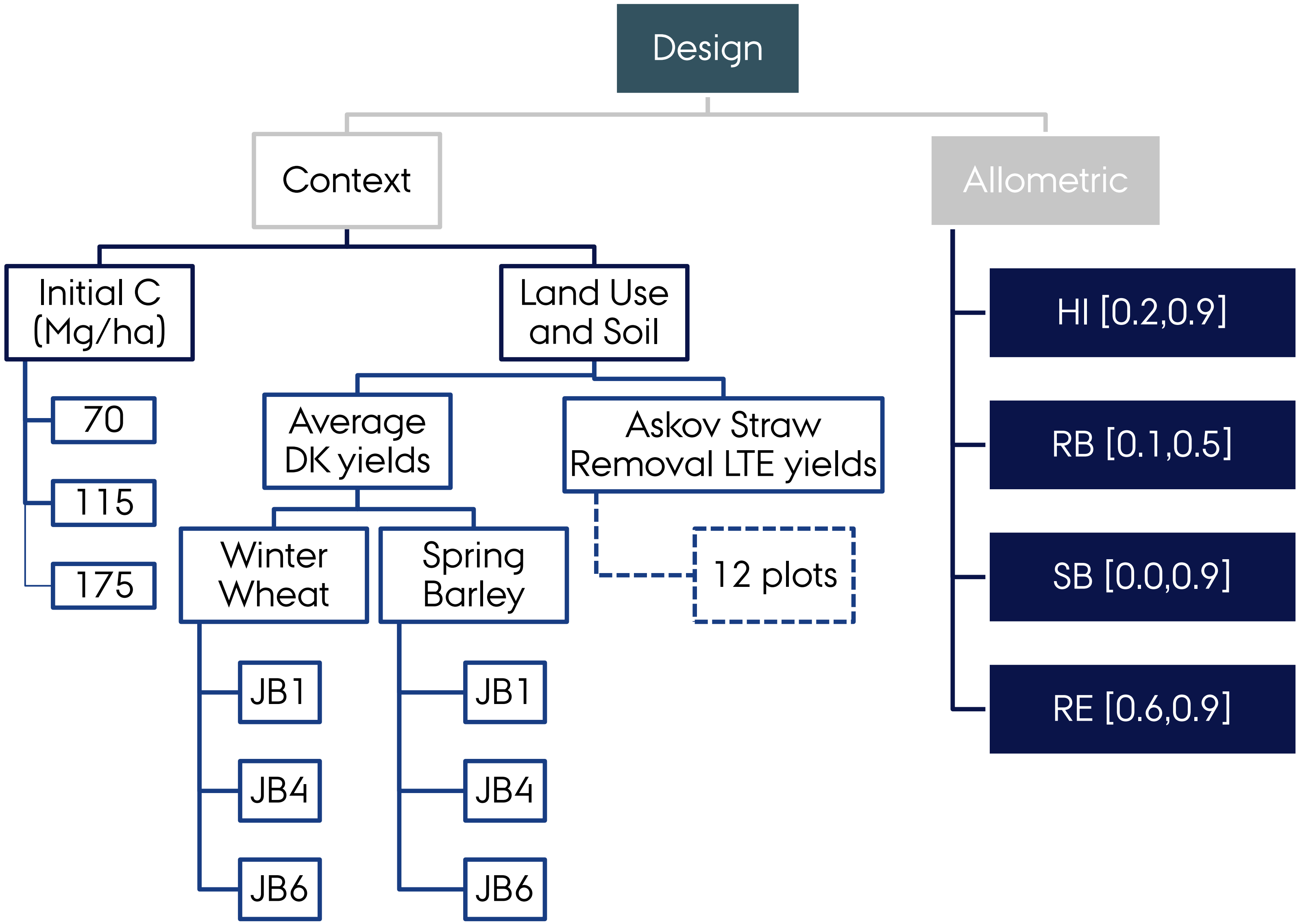
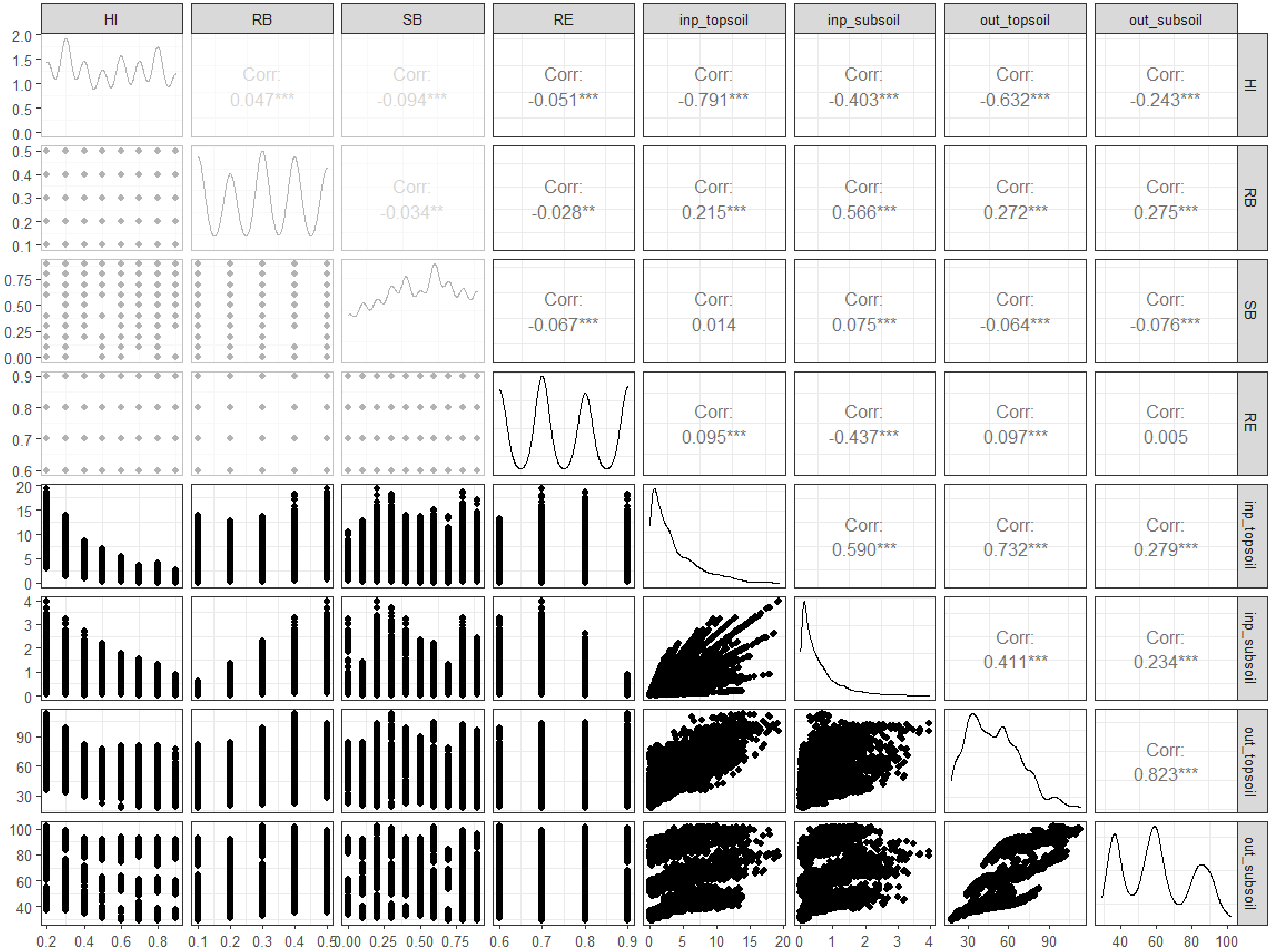

Design
Context
Allometric
Initial C (Mg/ha)
70
115
175
Land Use and Soil
Average DK yields
Winter Wheat
Spring Barley
JB1
JB4
JB6
JB1
JB4
JB6
Askov Straw Removal LTE yields
12 plots
HI [0.2,0.9]
RB [0.1,0.5]
SB [0.0,0.9]
RE [0.6,0.9]

& LINEAR CORRELATIONS



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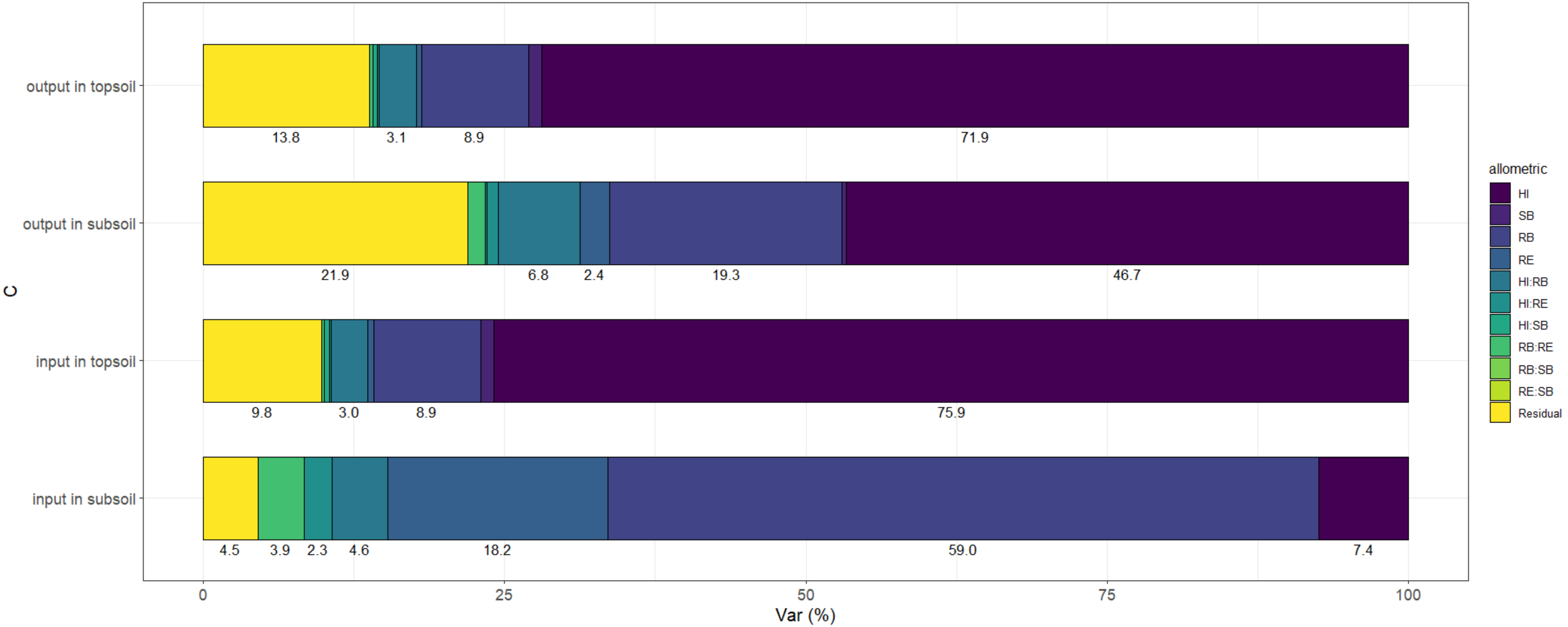
VCA



output in topsoil
output in subsoil
input in topsoil
input in subsoil
C
13.8
3.1
8.9
71.9
21.9
6.8
2.4
19.3
46.7
9.8
3.0
8.9
75.9
4.5
3.9
2.3
4.6
18.2
59.0
7.4
0
25
50
75
100
Var (%)
allometric
HI
SB
RB
RE
HI:RB
HI:RE
HI:SB
RB:RE
RB:SB
RE:SB
Residual

$$C_{topsoil} \ \& \ C_{subsoil} \sim$$
$$year +$$
$$HI + RB + SB + RE +$$
$$HI * RB + HI * SB + HI * RE + RB * SB + RB * RE + RE * SB +$$
$$(1|context)$$

$C_{topsoil}$

	Estimate	Std. Error	t value
(Intercept)	-37.035915	14.818802	-2.499
year	0.052617	0.006902	7.623
HI	-10.828621	2.625343	-4.125
RB	-30.526447	4.592972	-6.646
SB	-11.719620	2.363122	-4.959
RE	0.641305	2.782338	0.230
HI:RB	-32.025630	2.596665	-12.333
HI:SB	2.490117	1.386814	1.796
HI:RE	-44.403693	3.297299	-13.467
RB:SB	12.979863	2.260300	5.743
RB:RE	93.028489	5.478638	16.980
SB:RE	3.658348	3.216040	1.138

$C_{subsoil}$

	Estimate	Std. Error	t value
(Intercept)	52.611996	10.345446	5.086
year	0.007772	0.002888	2.691
HI	-16.287712	1.098573	-14.826
RB	40.294443	1.921937	20.966
SB	-0.240091	0.988848	-0.243
RE	-7.800236	1.164267	-6.700
HI:RB	-24.948882	1.086572	-22.961
HI:SB	0.545299	0.580311	0.940
HI:RE	8.561360	1.379752	6.205
RB:SB	6.513627	0.945820	6.887
RB:RE	-16.074020	2.292547	-7.011
SB:RE	-3.468923	1.345753	-2.578

#BUT…

Environmental Modelling and Software 114 (2019) 29–39

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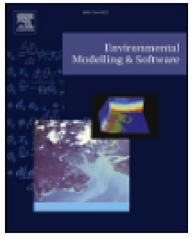
ELSEVIER



Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices

Check for updates

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A B S T R A C T

Sensitivity analysis provides information on the relative importance of model input parameters and assumptions. It is distinct from uncertainty analysis, which addresses the question 'How uncertain is the prediction?' Uncertainty analysis needs to map what a model does when selected input assumptions and parameters are left free to vary over their range of existence, and this is equally true of a sensitivity analysis. Despite this, many uncertainty and sensitivity analyses still explore the input space moving along one-dimensional corridors leaving space of the input factors mostly unexplored. Our extensive systematic literature review shows that many highly cited papers (42% in the present analysis) fail the elementary requirement to properly explore the space of the input factors. The results, while discipline-dependent, point to a worrying lack of standards and recognized good practices. We end by exploring possible reasons for this problem, and suggest some guidelines for proper use of the methods.

SALTELLI ET AL., 2019

Recommendations for best practice

Both uncertainty and sensitivity analysis should be based on a **global exploration of the space of input factors**, be it using an experimental design, Monte Carlo or other ad-hoc designs. The discussion in this paper has demonstrated that **local/OAT methods do not adequately represent models with nonlinearities**.

With some exceptions, **it is advisable to perform both uncertainty and sensitivity analysis**. Once an analyst has performed an uncertainty analysis and is informed of the robustness of the inference, it would appear natural to ascertain where volatility/uncertainty is coming from. At the other extreme, a sensitivity analysis without uncertainty analysis is usually illogical – **the relative importance of a factor on the model output has a different relevance depending on whether the output has a small or large variance**. However, there are cases – for instance, studies to identify the dominant effects on the output for a subsequent model reduction or calibration analysis – where the analyst may be satisfied with a pure SA.

Sensitivity and uncertainty analysis should be focused on a question. Most models have many outputs, and these outputs can be used to answer a range of different questions. The relationship (sensitivity) between the input factors and each different model output can be very different. For this reason, it is essential to focus the sensitivity analysis on the question addressed by the model rather than more generally on the model.

When sensitivity analysis is performed, it should allow the **relative importance of input factors and combinations of factors, to be assessed, either visually (scatterplots) or quantitatively (regression coefficients, sensitivity measures or other**).

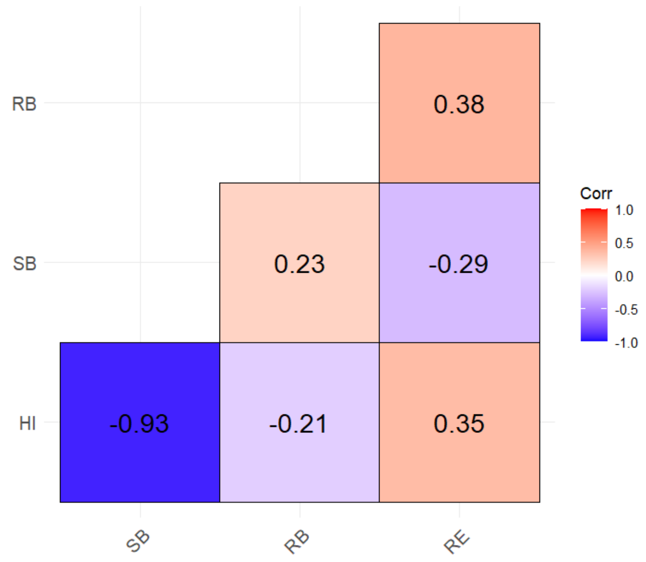
Sensitivity and uncertainty analysis are themselves uncertain, because there is considerable uncertainty in quantifying the uncertainty in input factors, and modellers should be frank about how they arrived at the supposed uncertainties (Saltelli et al., 2013). This should be kept in mind and efforts made to capture the uncertainty of input assumptions as accurately as possible.

Even an apparently perfect uncertainty and sensitivity analysis is no assurance against error. As noted by (Pilkey and Pilkey-Jarvis, 2009) “It is important to recognize that the sensitivity of the parameter in the equation is what is being determined, not the sensitivity of the parameter in nature. [...] If the model is wrong or if it is a poor representation of reality, determining the sensitivity of an individual parameter in the model is a meaningless pursuit.”

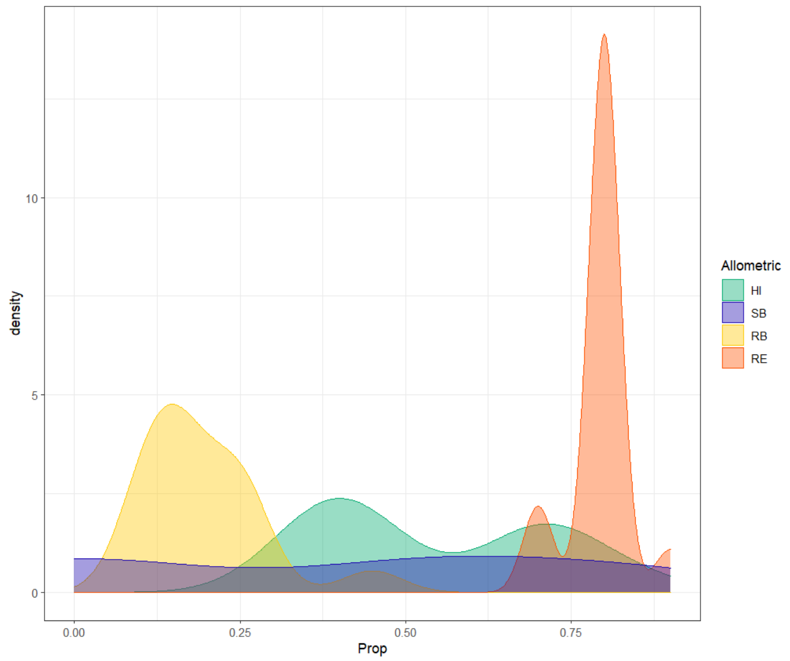
WHAT DO WE KNOW

Crop	HI	SB	RB	RE	Type
WinterWheat	0.45	0.55	0.25	0.7	Grain
SpringBarley	0.45	0.55	0.17	0.8	Grain
WinterBarley	0.39	0.55	0.17	0.7	Grain
Rye	0.38	0.8	0.25	0.8	Grain
Oat	0.4	0.6	0.17	0.8	Grain
CerealsforWholeCropharvest	0.75	0	0.17	0.8	Leaf
OtherCereals,mainlytriticale	0.38	0.8	0.25	0.8	Grain
OilseedRape	0.37	0.9	0.25	0.8	Grain
GrassAndgrassClover	0.7	0	0.45	0.9	Leaf
Potatoes	0.7	0	0.11	0.8	Root
SugarBeets	0.7	0	0.12	0.8	Root
FodderBeets	0.7	0.34	0.12	0.8	Root
SwedishTurnip	0.7	0	0.12	0.8	Root
MaizeForsilage	0.85	0	0.15	0.8	Leaf
Soybean	0.42	0.5	0.1	0.8	Grain
White cabbage	0.37	0.9	0.25	0.8	Leaf

Taghizadeh-Toosi teal,2014

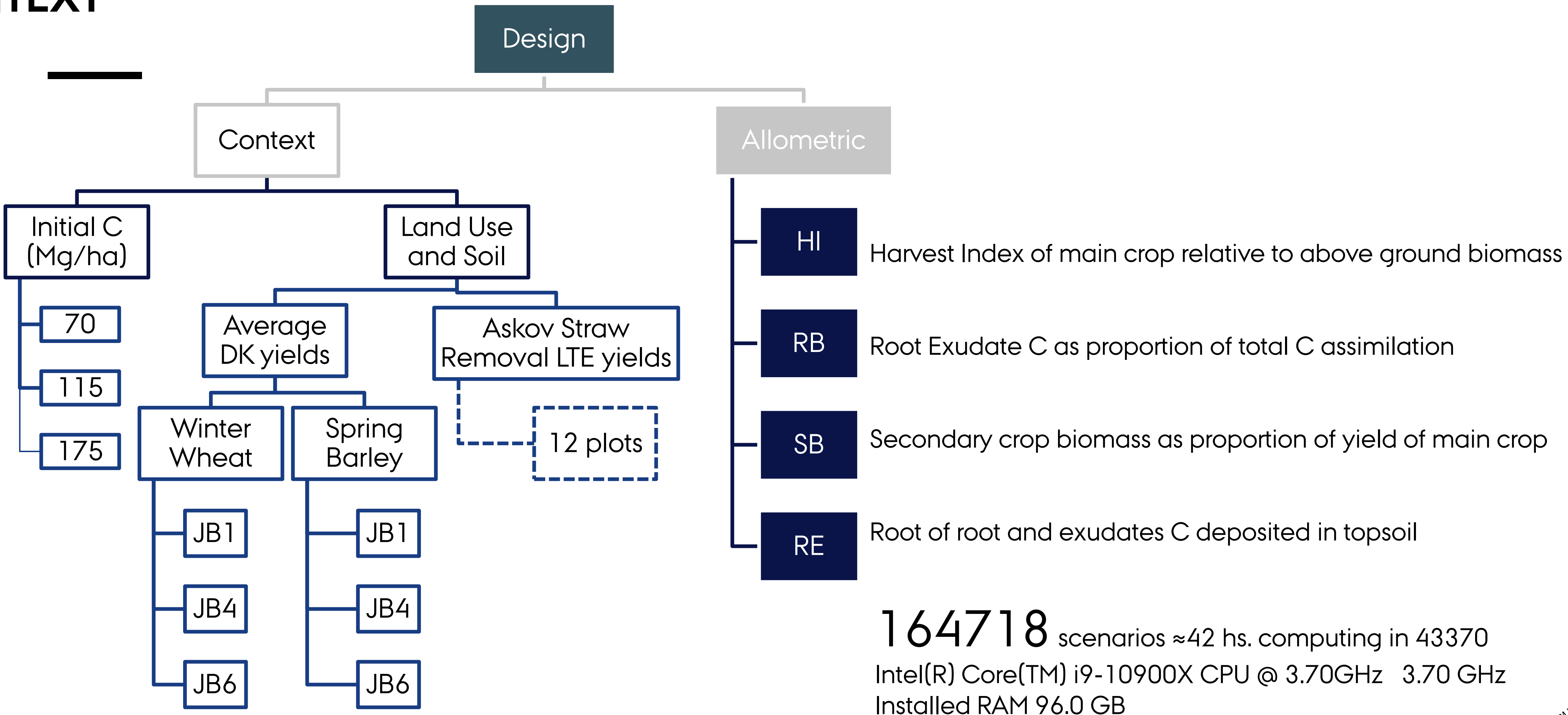


Allometric	HI	SB	RB	RE
HI	0.030	-0.057	-0.003	0.003
SB	-0.057	0.127	0.007	-0.005
RB	-0.003	0.007	0.008	0.001
RE	0.003	-0.005	0.001	0.002



SIMULATION DESIGN

FOCUS IN ALLOMETRIC BUT VARIABILITY IN CONTEXT SCENARIOS THE CONTEXT



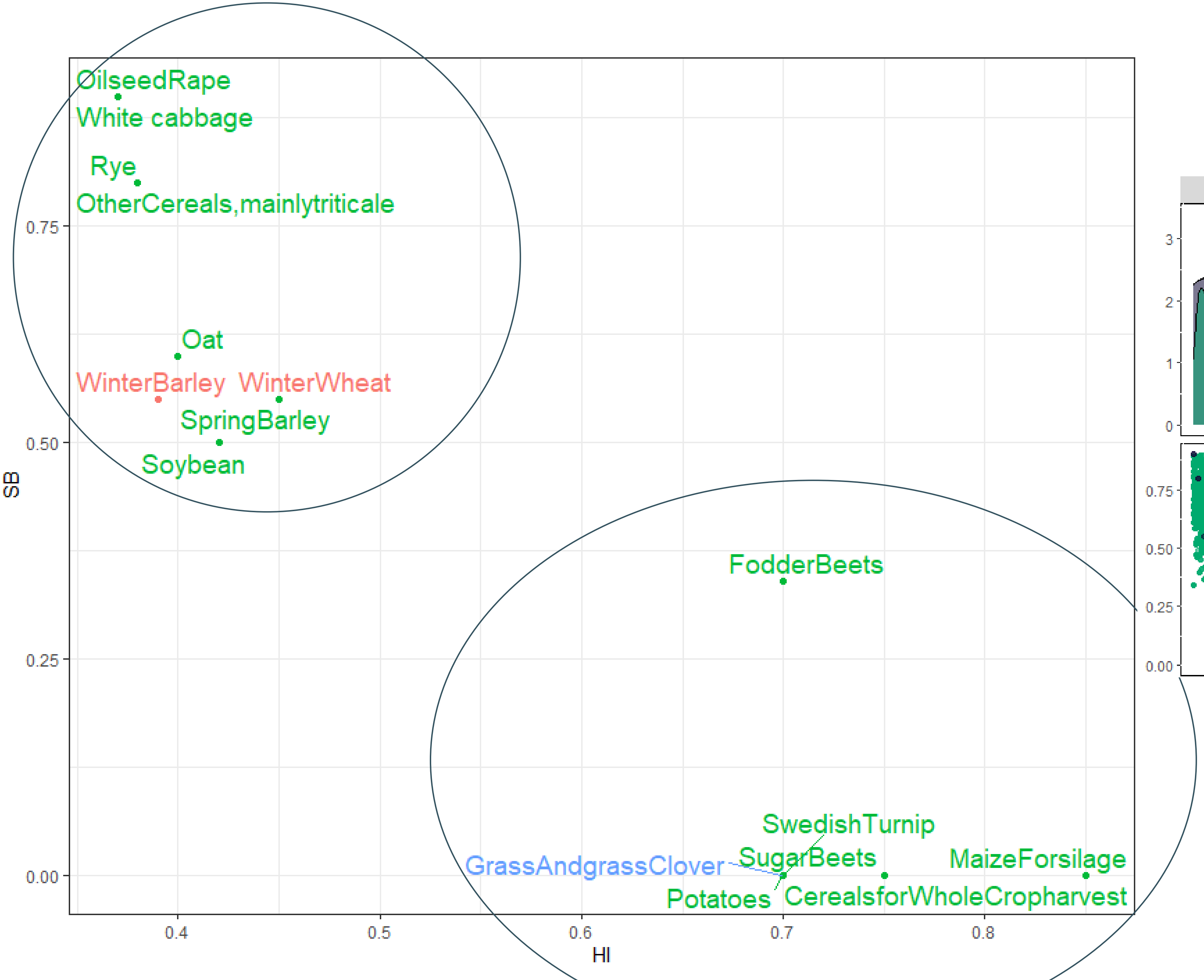
164718 scenarios ≈42 hs. computing in 43370

Intel(R) Core(TM) i9-10900X CPU @ 3.70GHz 3.70 GHz

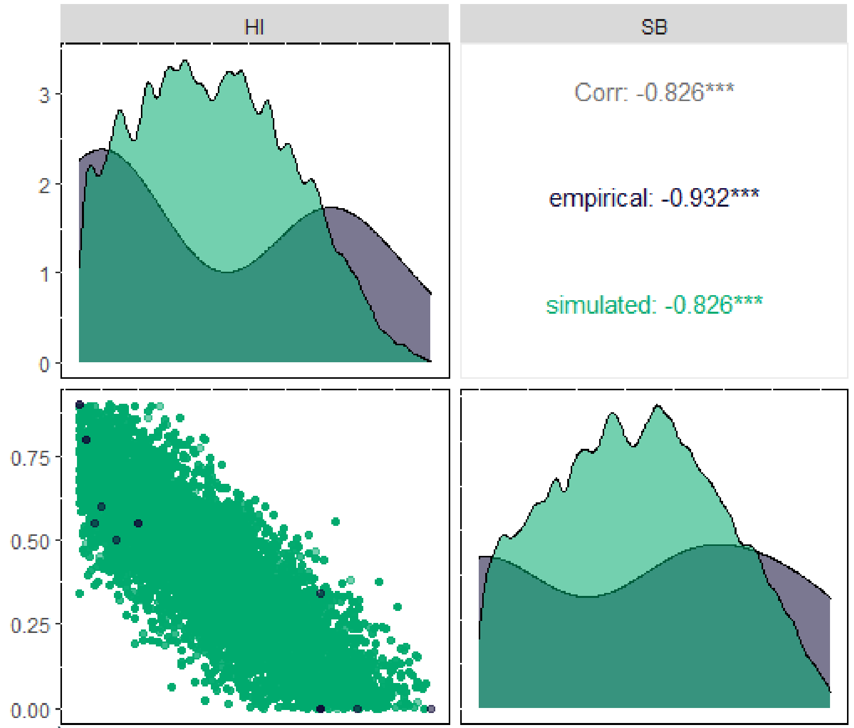
Installed RAM 96.0 GB

Assuming gaussian distribution and Σ

#BUT.BIS...



OilseedRape
White cabbage
Rye
OtherCereals,mainlytriticale
Oat
WinterBarley
WinterWheat
SpringBarley
Soybean
FodderBeets
SwedishTurnip
SugarBeets
GrassAndgrassClover
MaizeForsilage
Potatoes
CerealsforWholeCropharvest
0.75
0.50
0.25
0.00
SB
0.4
0.5
0.6
0.7
0.8
HI



HI
SB
Corr: -0.826***
empirical: -0.932***
simulated: -0.826***
3
2
1
0
0.75
0.50
0.25
0.00

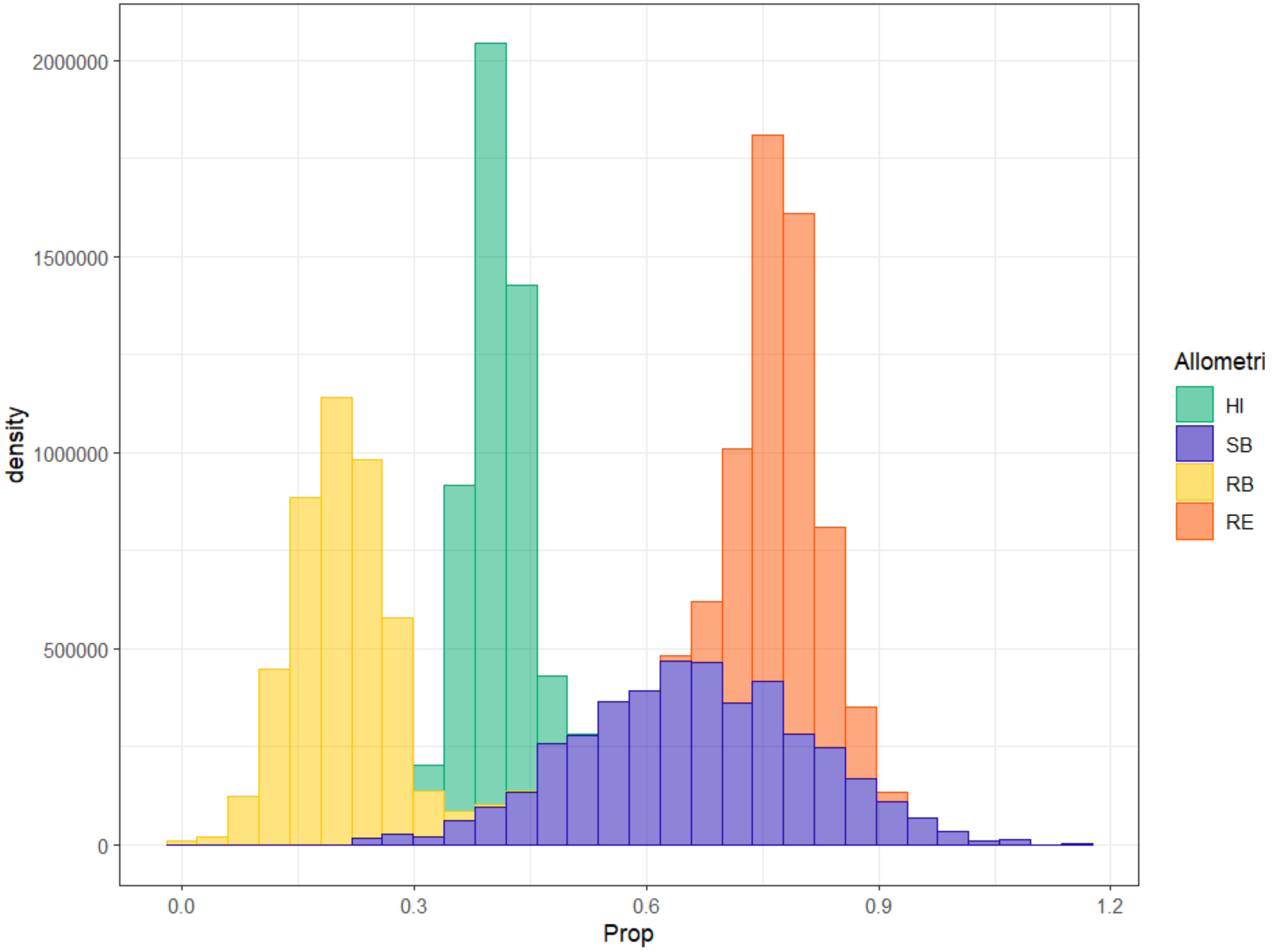
3 CATEGORIES MAYBE

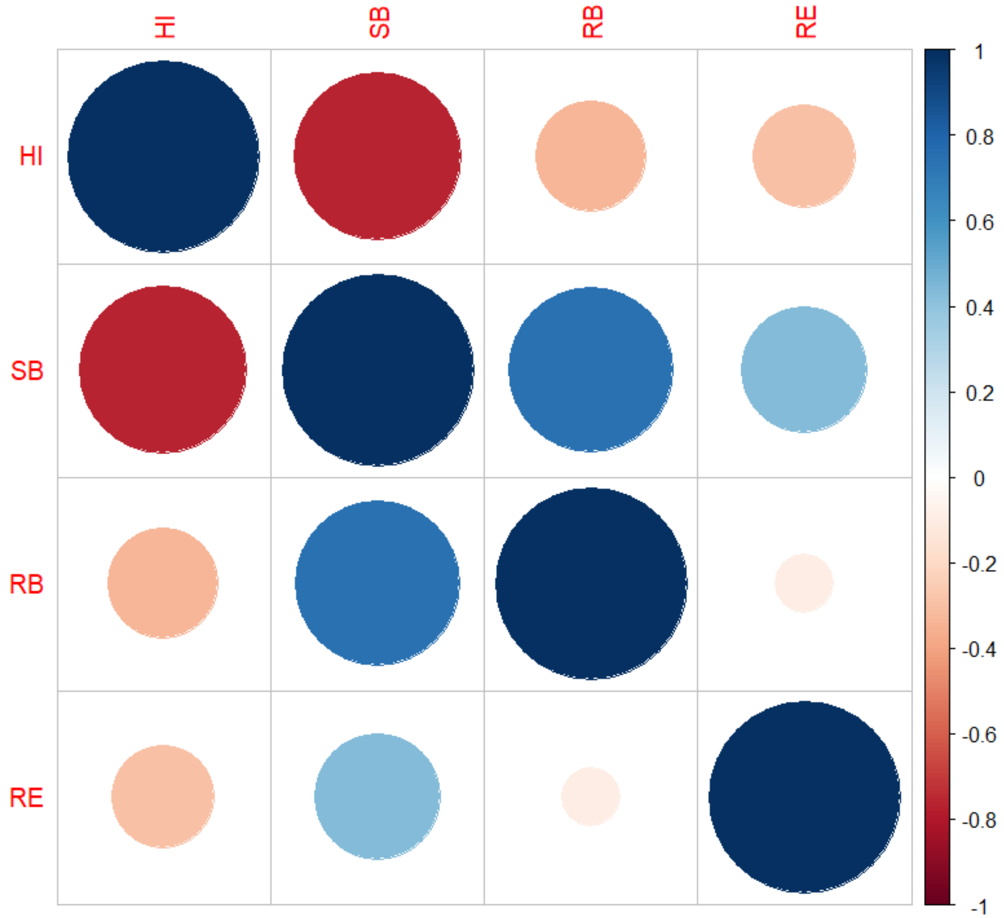
Grain n=9				
$Grain$mean				
	HI	**SB**	**RB**	**RE**
	0.405	**0.65625**	**0.20125**	**0.775**
$Grain$SD				
	HI	**SB**	**RB**	**RE**
	0.031623	**0.152216**	**0.05693**	**0.046291**
$Grain$cor				
	HI	**SB**	**RB**	**RE**
HI	**1**	**-0.76422**	**-0.33725**	**-0.29277**
SB	**-0.76422**	**1**	**0.74081**	**0.430829**
RB	**-0.33725**	**0.74081**	**1**	**-0.09486**
RE	**-0.29277**	**0.430829**	**-0.09486**	**1**

Leaf n=4				
$Leaf$mean				
	HI	SB	RB	RE
	0.766666667	1E-09	0.256667	0.833333
$Leaf$SD				
	HI	SB	RB	RE
	0.07637626	0	0.16773	0.057735
$Leaf$cor				
	HI	SB	RB	RE
HI	1	NA	-0.79361	-0.75593
SB	NA	1	NA	NA
RB	-0.7936145	NA	1	0.998221
RE	-0.7559289	NA	0.998221	1

Root n=3				
$Root$mean				
	HI	SB	RB	RE
	0.7	0.085	0.1175	0.8
$Root$SD				
	HI	SB	RB	RE
	0	0.17	0.005	0
$Root$cor				
	HI	SB	RB	RE
HI	1	NA	NA	NA
SB	NA	1	0.333333	NA
RB	NA	0.333333	1	NA
RE	NA	NA	NA	1

Cereals, Grain





LET'S SEE THE DIFFERENCES IN THE CONCLUSIONS WE ARRIVE

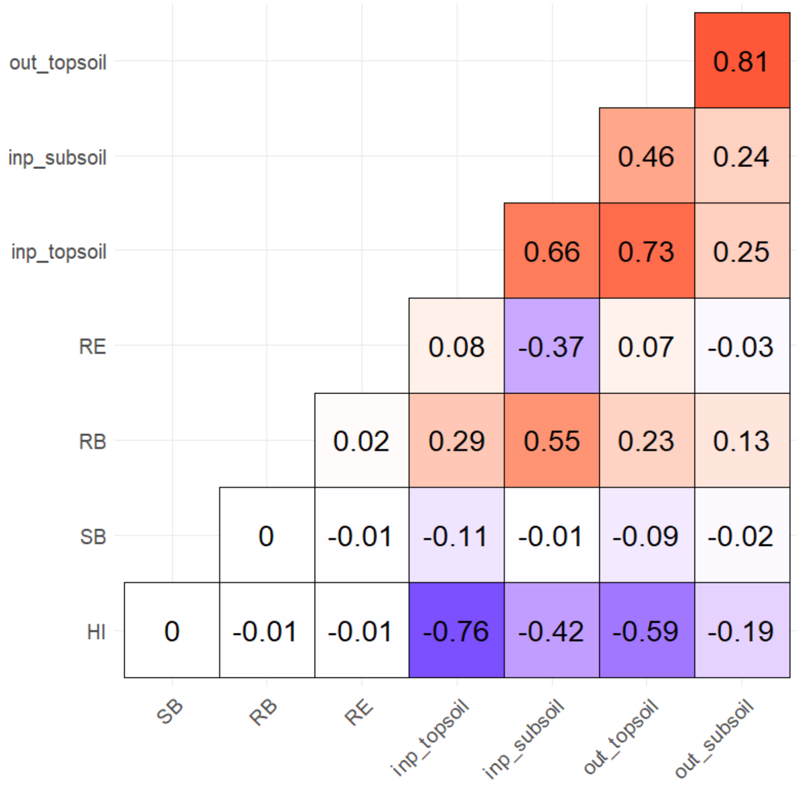
Correlation with Cinputs

?

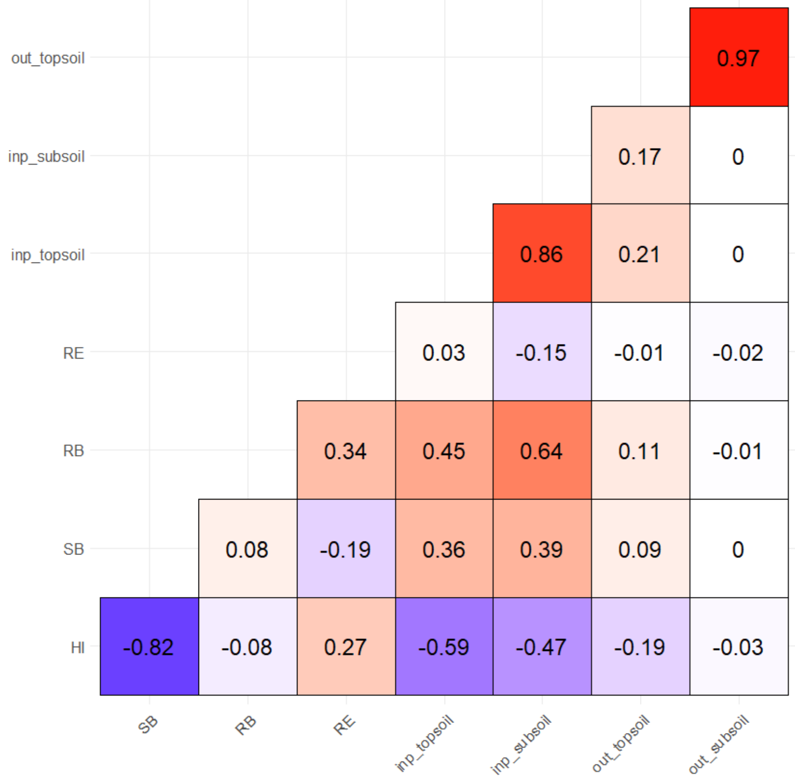
how the variability on allometric impacts the output variability of the model?

...and prioritize their impact

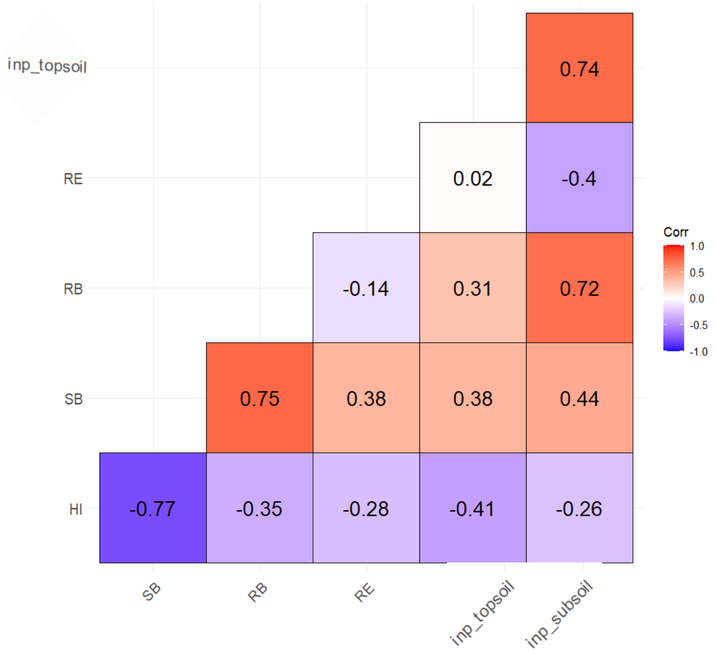
Uniform independent



Gaussian correlated



Gaussian Correlated Cereals



WHICH ARE THE DIFFERENCES IN THE CONCLUSIONS WE ARRIVE

VCA

?

how the variability on allometric impacts the output variability of the model?

…and prioritize their impact

Approach	output	HI	SB	RB	RE	HI:SB	HI:RB	HI:RE	RB:SB	RB:RE	RE:SB	Residual
Uniform Independent	inp_topsoil	75.9	1.1	8.9	0.5	0.4	3.0	0.2	0.0	0.3	0.0	9.8
Uniform Independent	inp_subsoil	7.4	0.0	59.0	18.2	0.0	4.6	2.3	0.0	3.9	0.0	4.5
Uniform Independent	out_topsoil	71.9	1.1	8.9	0.5	0.4	3.1	0.2	0.0	0.3	0.0	13.8
Uniform Independent	out_subsoil	46.7	0.3	19.3	2.5	0.1	6.8	1.0	0.0	1.5	0.0	21.9
Gaussian Correlated	inp_topsoil	38.5	0.0	23.5	0.0	0.0	10.6	0.0	15.4	0.0	0.0	12.0
Gaussian Correlated	inp_subsoil	10.6	0.0	62.1	6.7	0.0	0.0	0.0	13.0	0.0	0.0	7.6
Gaussian Correlated	out_topsoil	41.2	0.0	26.2	0.0	0.0	0.1	11.1	0.0	0.0	11.1	10.5
Gaussian Correlated	out_subsoil	15.3	3.0	14.4	0.0	0.0	0.0	0.0	0.0	0.0	50.9	16.4
Cerial Gaussian correlated	inp_topsoil	6.5	2.2	1.6	0.6	0.6	3.5	3.8	2.0	0.8	0.0	78.4
Cerial Gaussian correlated	inp_subsoil	8.7	0.0	6.8	5.7	8.0	10.5	12.0	7.3	6.5	0.1	34.4

Disclaimer between fixed ranges and continuous

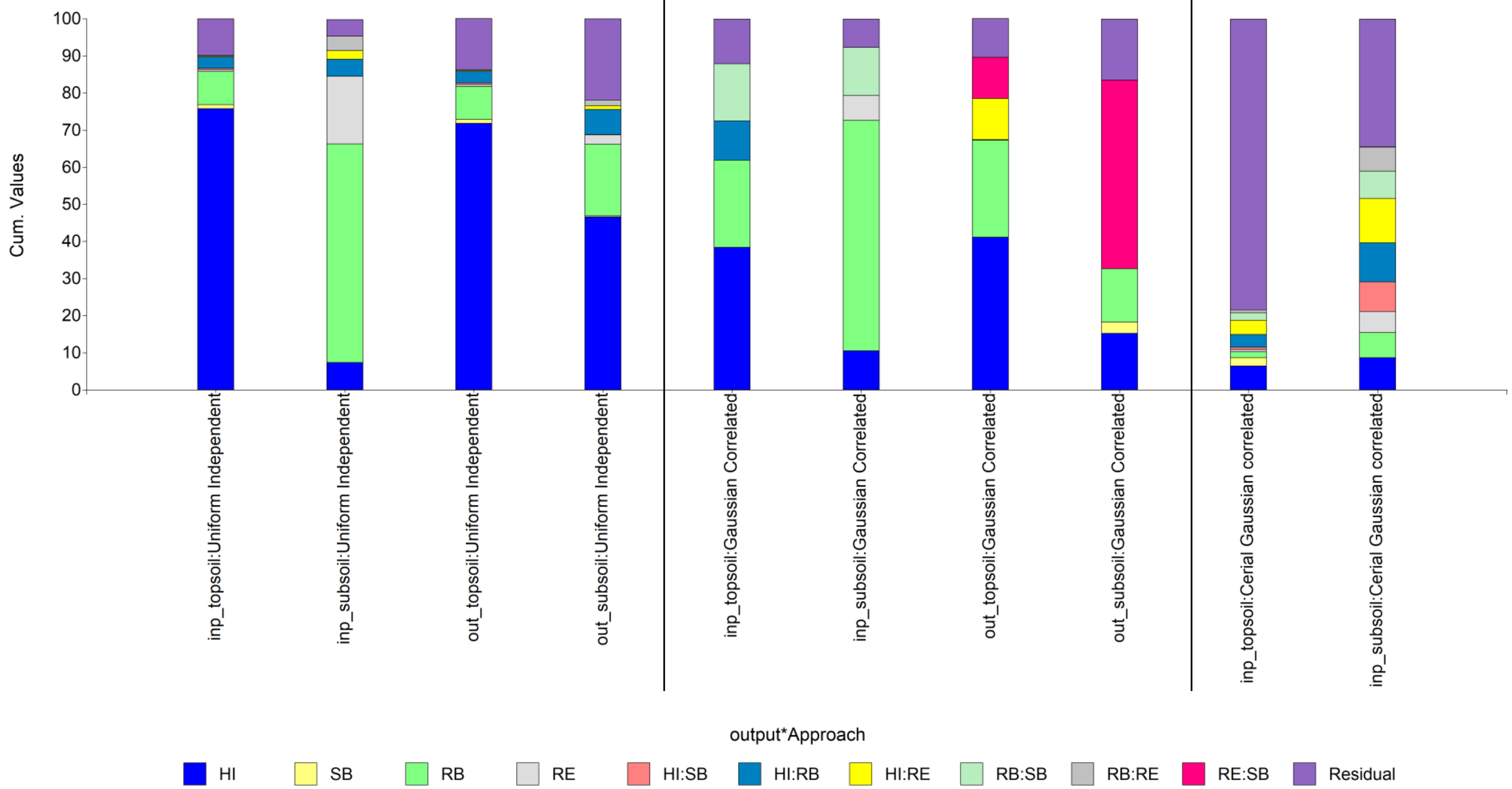
LET'S SEE THE DIFFERENCES IN THE CONCLUSIONS WE ARRIVE

?

how the variability on allometric impacts the output variability of the model?

...and prioritize their impact

VCA



ALTERNATIVE
BY CROP TYPE

I-Sensitivity to allometric to C input calculation

- μ and Σ by type (just with cereals?)
- DK yields by region from 2006 to 2021

II-Global sensitivity of CTOOL

- C input variability from I
- Soil by JB classes (Clay, C initial, C/N)
- Monthly temp from DMI grid
- Pool dist???

REVISION

Concept category	Terms
Population	(woodpecker* OR sapsucker* OR Veniliorn* OR Picoid* OR Dendropic* OR Melanerp* OR Sphyrapic*) AND (fire* OR burn* OR wildfire*)
Exposure	((nest* OR reproduct* OR breed* OR fledg*) W/3 (succe* OR fail* OR surviv*)) OR (surviv* OR mortalit* OR death*) OR ('food availab*' OR forag* OR provision*) OR (emigrat* OR immigrat* OR dispers*)
Comparator	[not applicable to research question]
Outcome	(occup* OR occur* OR presen* OR coloniz* OR colonis* OR abundan* OR 'population size' OR 'habitat suitability' OR 'habitat selection' OR persist*)

https://doi.org/10.1111/2041-210X.13268

P: population ~~Winter~~ wheat, ~~Spring~~ Barley
I: intervetion, experimental
~~C: comparison,~~
O: outcome allometric, harvest index, shoot root ratio, root exudates, root biomass

(wheat'* OR 'barley')AND(experimental)AND('Allometric'* OR 'shoot root ratio' * OR 'harvest index'* OR 'root exudates'*OR' root biomass')

(wheat OR barley) AND experimental AND (Allometric OR "shoot root ratio" OR "harvest index" OR "root exudates" OR "root biomass")

(wheat OR barley) AND experimental AND (allometric OR "shoot root ratio" OR "harvest index")AND ("root exudates")AND("root biomass")AND carbon

REVISION #2

(wheat OR barley) AND (Allometric OR ”shoot root ratio” OR “harvest index” OR “root exudates” OR ”root biomass”) AND carbon

In document in title, abstract, and keywords

1975-2023

Subject areas

Agricultural and Biological Sciences (311)
Environmental Science (150)
Biochemistry, Genetics and Molecular Biology (58)
Earth and Planetary Sciences (28)
Veterinary Science and Veterinary Medicine (22)
Engineering (21)
Energy (20)

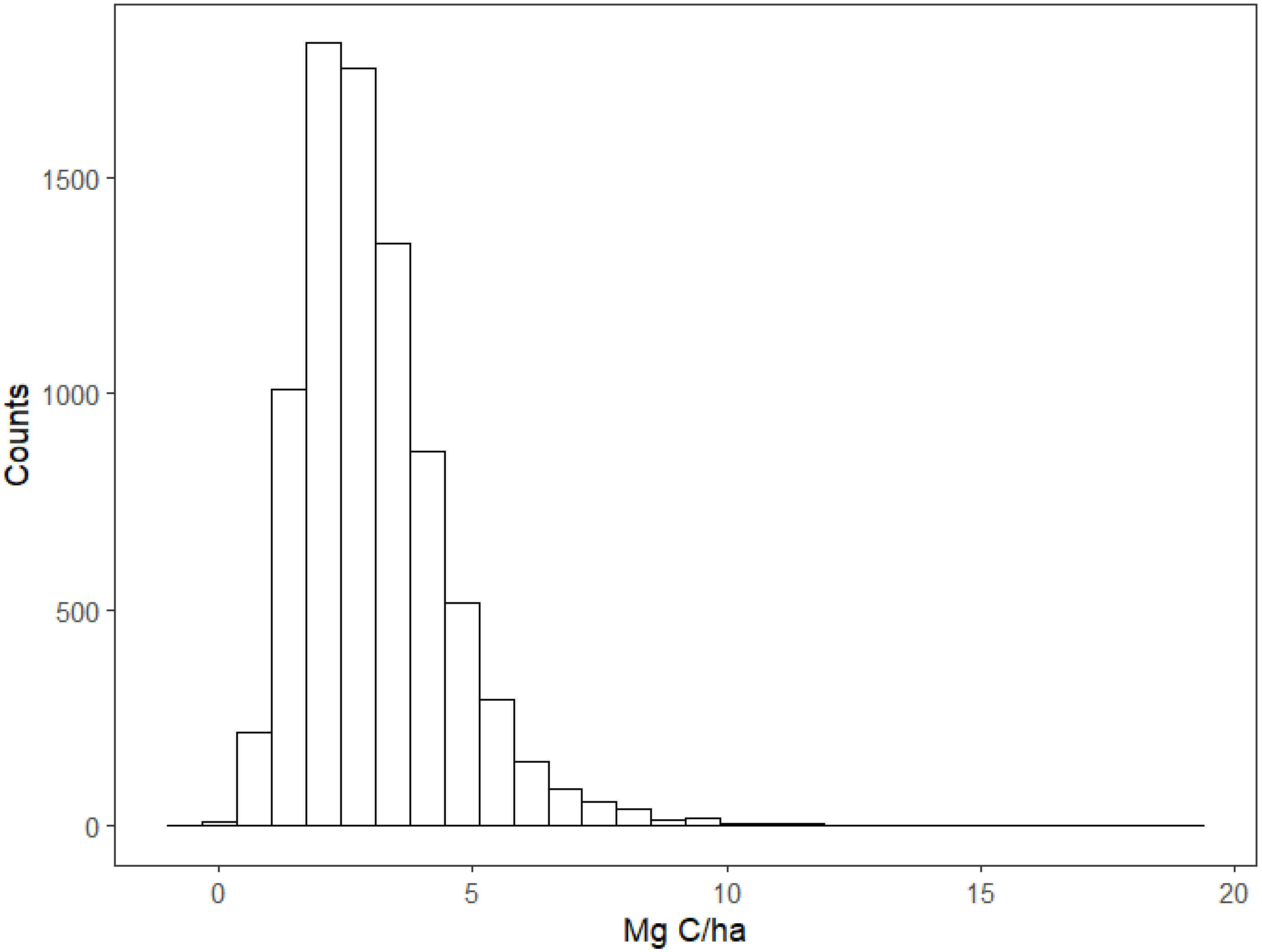
SENSOBOL

DEC 2022

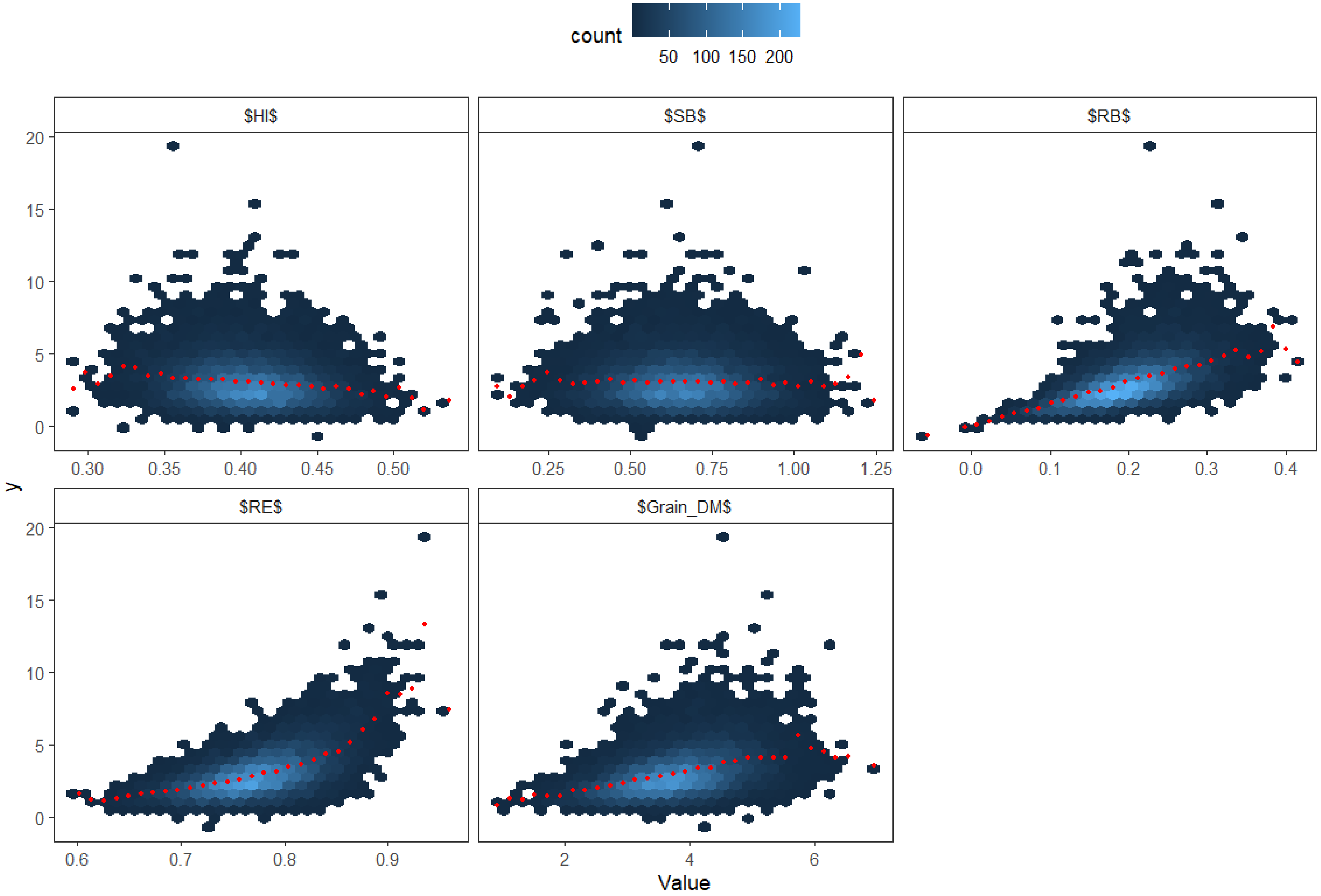
Puy, A., Piano, S. L., Saltelli, A., & Levin, S. A. (2021). Sensobol: an R package to compute variance-based sensitivity indices. arXiv preprint arXiv:2101.10103.

SENSOBOL, UNCERTAINTY

1%	2.5%	50%	97.5%	99%	100%
0.77	1.007	2.787	6.617	7.89	28.30

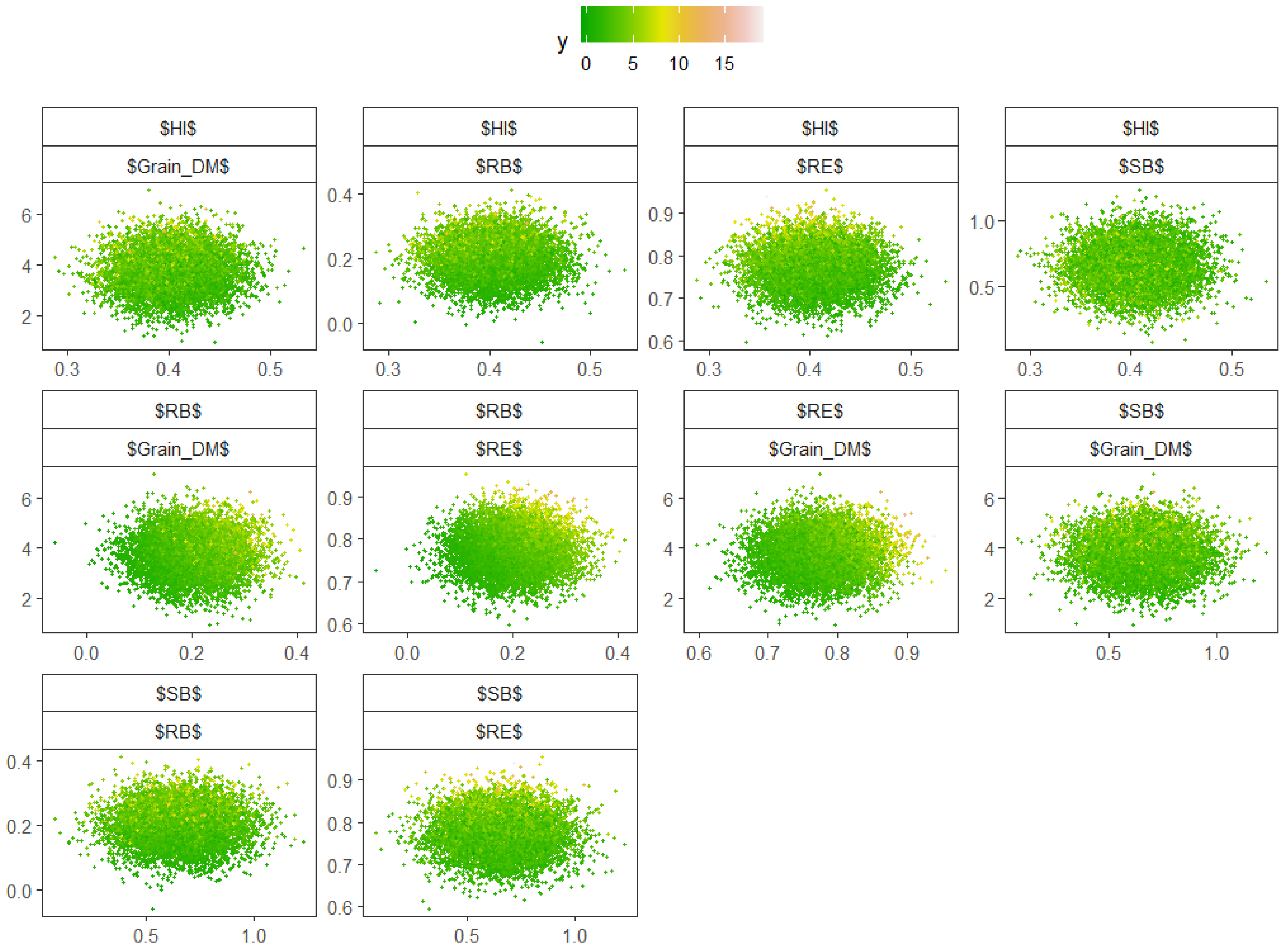


SENSOBOL



count
50 100 150 200
HI
SB
RB
RE
$Grain_DM$
y
Value
20
15
10
5
0
0.30 0.35 0.40 0.45 0.50
0.25 0.50 0.75 1.00 1.25
0.0 0.1 0.2 0.3 0.4
0.6 0.7 0.8 0.9
2 4 6

SENSOBOL



AARHUS
UNIVERSITY
DEPARTMENT OF AGROECOLOGY

SENSOBOL C INPUTS