65th LCA Discussion Forum
Zurich - May 24, 2017

Prospective LCA modelling
How to deal with uncertainties ?

Part I : A new approach based on GSA

Part II : The Graphene Case study

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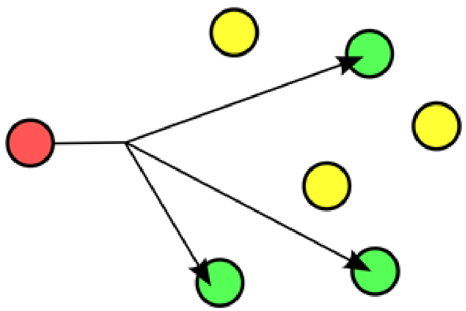
Part I

Global sensitivity analysis in LCA of emerging technologies:

Accounting for inputs' variability



Martino Lacirignola (**ADEME**, FR)
Paula Pérez-López, Philippe Blanc, Isabelle Blanc (**Centre O.I.E. - MINES ParisTech**, FR)
Robin Girard (**Centre PERSEE - MINES ParisTech**, FR)
LCA of emerging technologies: addressing high uncertainty on inputs' variability when performing global sensitivity analysis; Science of the Total Environment, 578 (2017) 268-280

LCA for emerging technologies

Emerging technologies

- Wide data gap
- No pilot/large-scale data?
- Incomplete technology development
- Unknown future applications
- Data quality concerns

Increased level of

UNCERTAINTY

How to deal with uncertainty in LCA of emerging technologies?

Case study: Enhanced Geothermal Systems (EGS)

EGS: an emerging technology to exploit geothermal resources where water, heat or rock permeability are not sufficient for a conventional geothermal system

- Deep wells: 2.5 – 5 km ➡ Drilling
- Reservoir stimulation (enhancement) ➡ Fracturing the rock (e.g. by water pumping)
- For binary systems ➡ Organic Rankine cycle
- Ground-water use

⬇

Environmental impacts ?

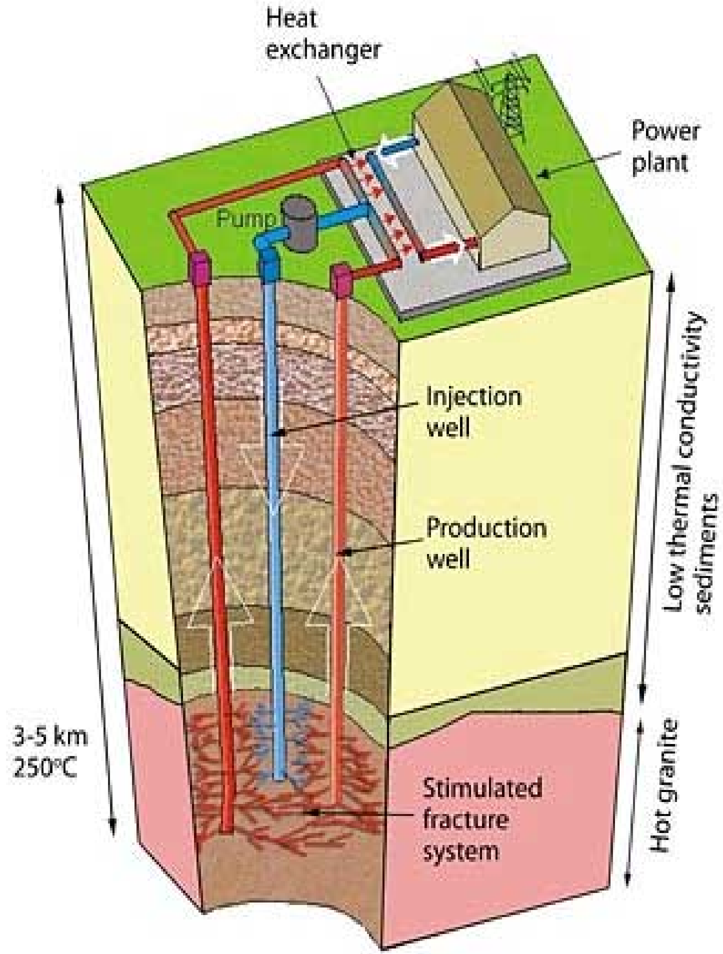


Image: geothermalworldwide, 2016

General modelling framework for LCA

LCA model
$f(X)$

INPUTS → LCA model → **OUTPUTS**

INPUTS

Vector $X_A=(x_1, x_2,\dots,x_p)$

($x_1, x_2,\dots,x_p$: parameters)

↓

p-dimensions vector

↓

Can be linked to FU of scenario A

OUTPUTS

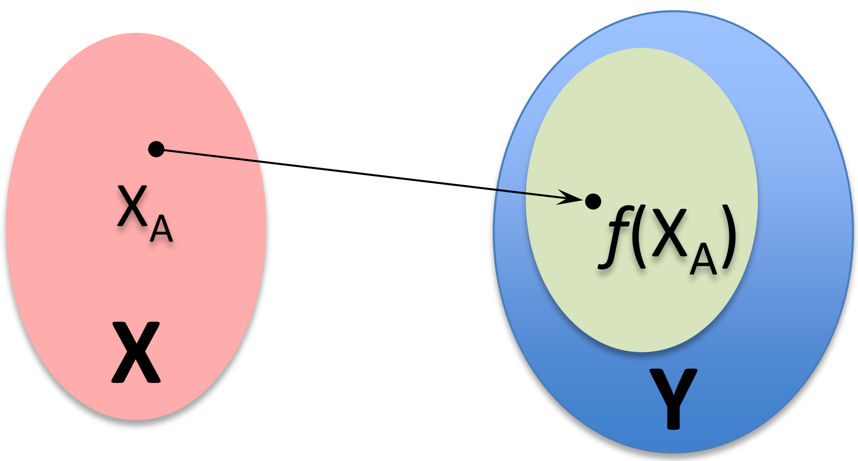
Scalar $y=f(X_A)$

↓

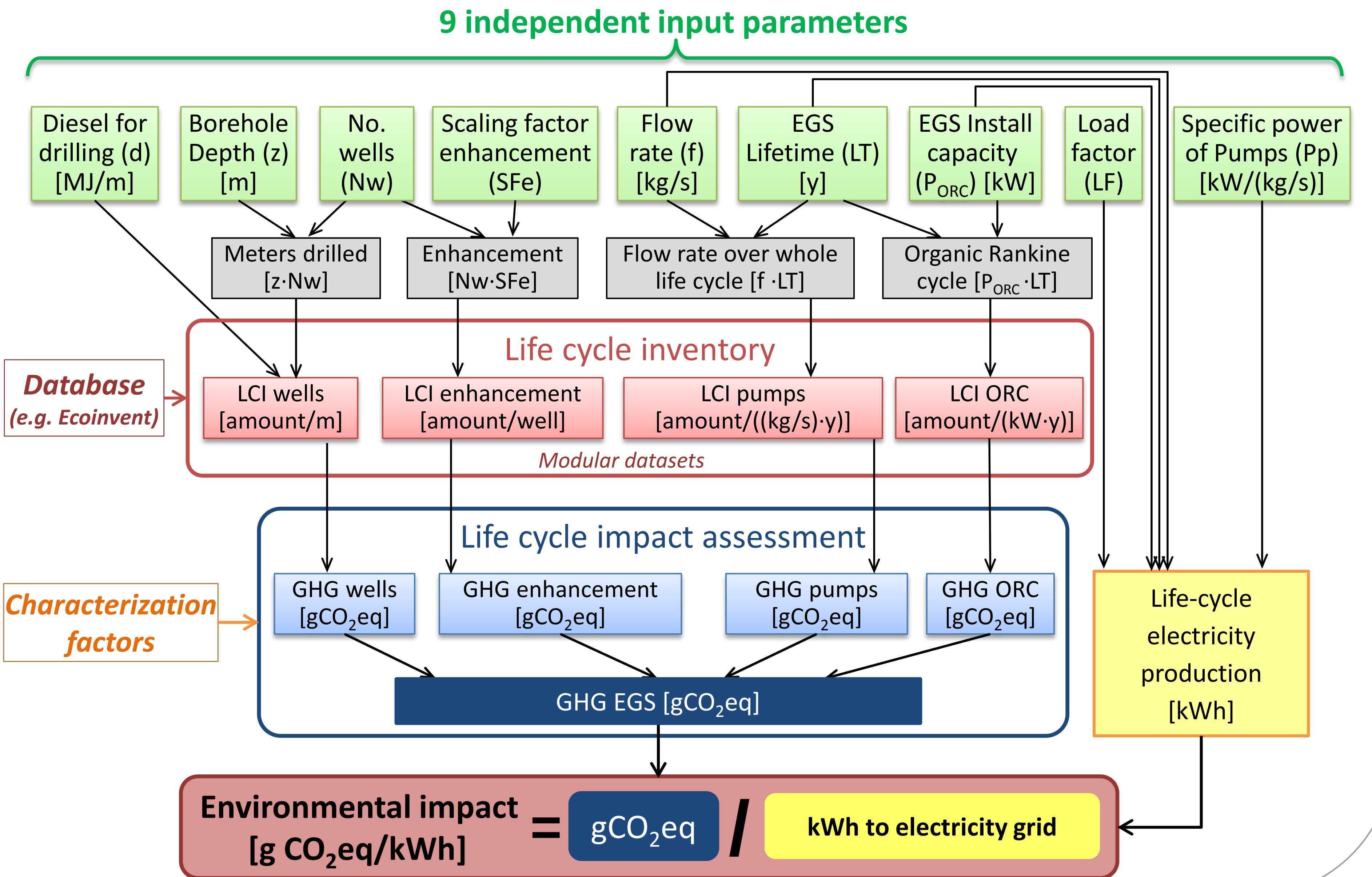
single numeric value

↓

corresponding to the environmental impact of scenario A



EGS: LCA model (GHG emissions)



EGS: Input parameters

Symbol	Parameters	Baseline scenario
z	Borehole depth	4000 m
Nw	Number of wells	3 wells
d	Fuel for drilling	5000 MJ/m
LT	Lifetime	30 y
f	Produced flow rate	62.5 kg/s
P_{ORC}	Installed capacity ORC	2375 kW
SFe	Enhancement scaling factor	5.25
LF	Load factor	0.90
P_p	Specific power of pumps	6.1 kW/(kg/s)

EGS: LCA model (GHG emissions)

INPUTS → **LCA model** f(X) → OUTPUT

Vector $X_A=(x_1, x_2,\dots,x_p)$

Scalar $y_A=f(X_A)$

$X_A=(z_A, Nw_A, d_A, LT_A, f_A, P_{ORC, A}, SFe_A, LF_A, P_{p, A})$

e.g. X_A=(4000, 3, 5000, 30, 62.5, 2375, 5.25, 0.90, 6.1) → y_A=34.7 g CO_2 eq/kWh

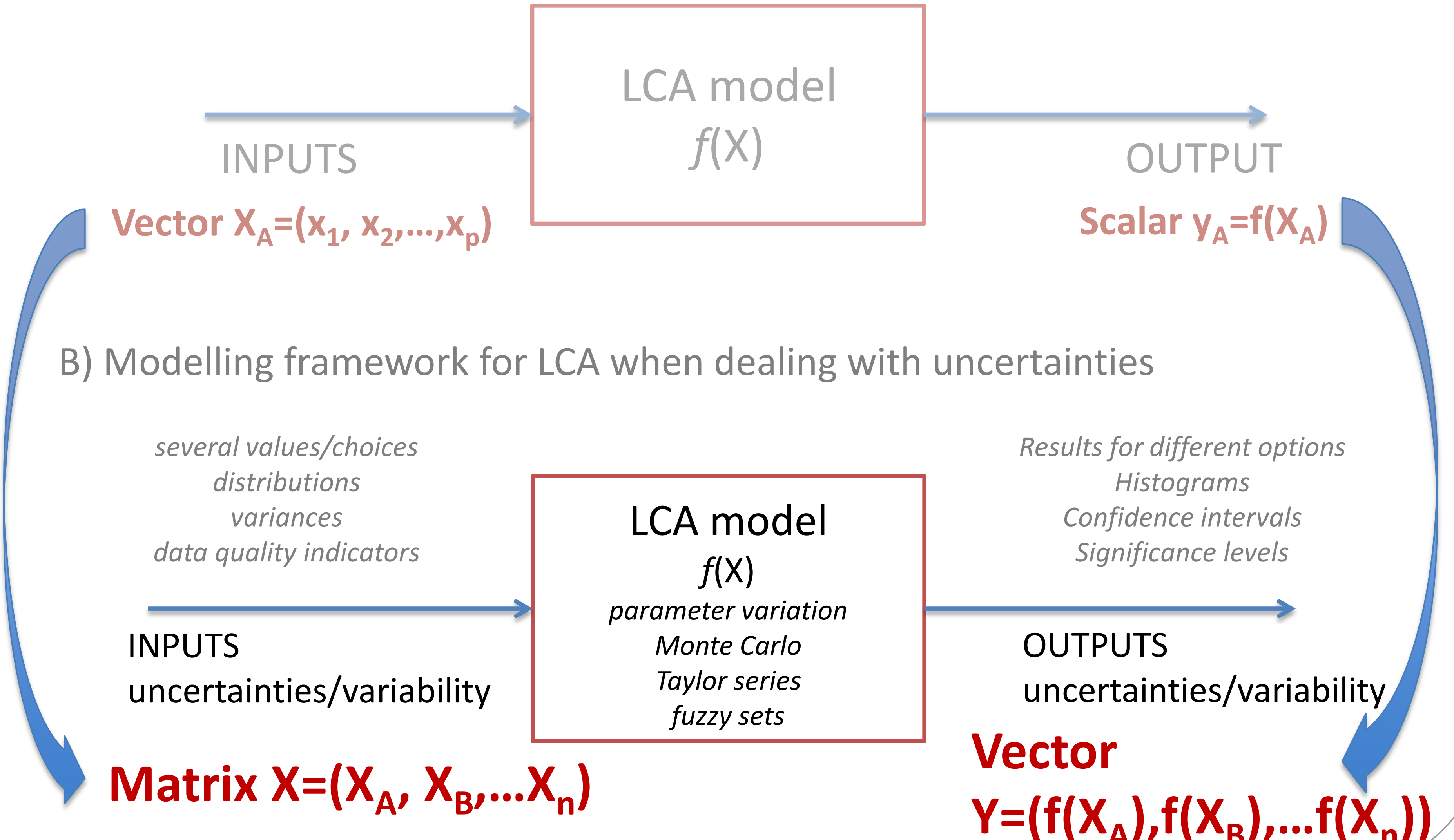
$$GHG_{EGS,\,A}\left[\frac{g\,CO_2eq}{kWh}\right] = \frac{z_A\cdot Nw_A\cdot(\alpha_1+\alpha_2\cdot d_A)+LT_A\cdot f_A\cdot\alpha_3+P_{ORC,A}\cdot LT_A\cdot\alpha_4+Nw_A\cdot Sfe_A\cdot\alpha_5}{LF_A\cdot LT_A\cdot\left(P_{ORC,A}-f_A\cdot P_{p,A}\right)\cdot 8760}$$

With α_1= 498761.36 gCO_2eq/m; α_2=90.56 gCO_2eq/MJ; α_3=487363.03 $gCO_2eq\cdot s/(kg\cdot y)$; α_4=50603.13 $gCO_2eq/(kW\cdot y)$; α_5=25757089.05 gCO_2eq

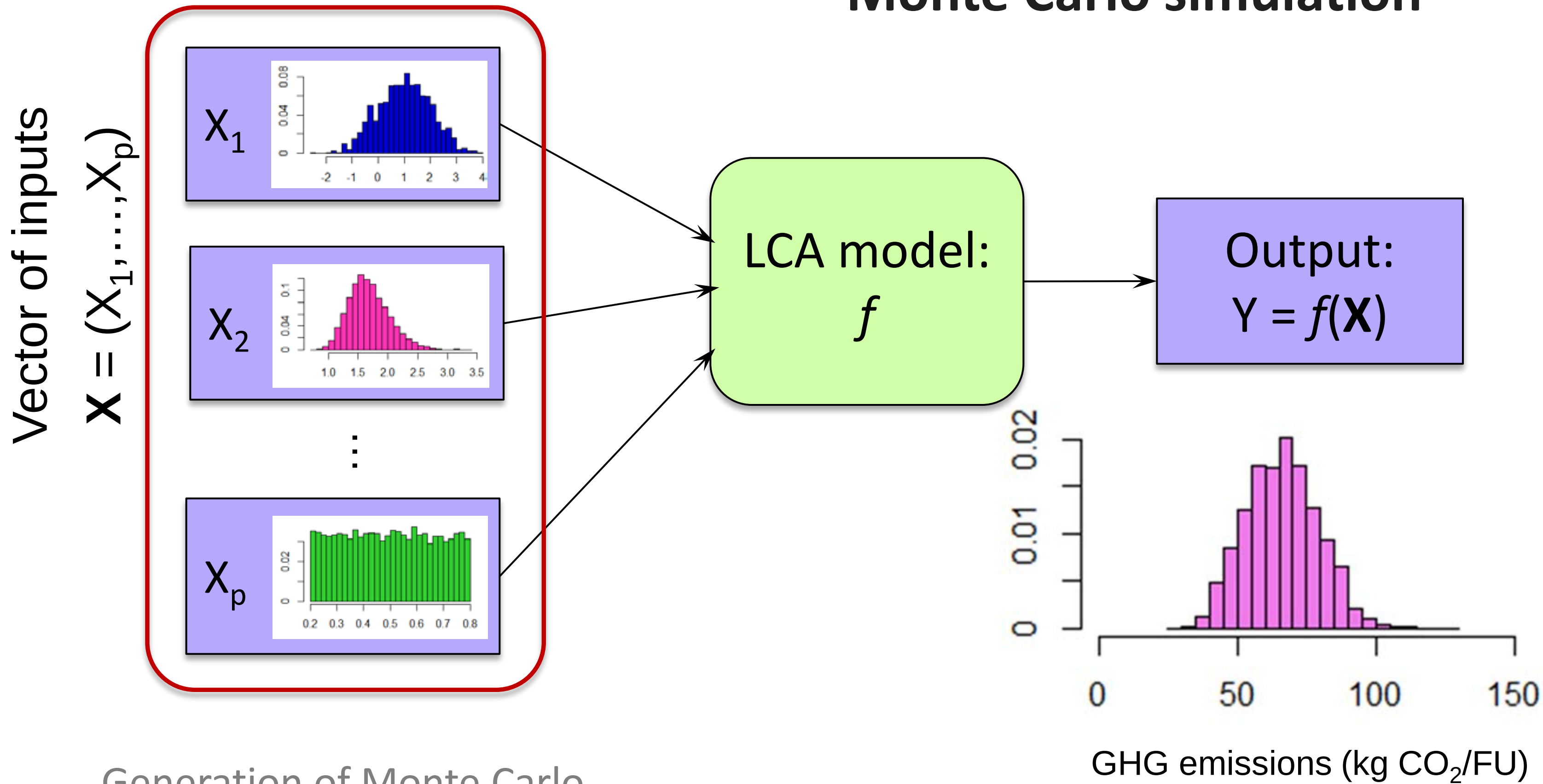
Prospective LCA model: *Variable* Input parameters

Symbol	Parameters	Baseline scenario	Value range
z	Borehole depth	4000 m	2000 – 6000 m
Nw	Number of wells	3 wells	2 – 3 wells
d	Fuel for drilling	5000 MJ/m	3000 – 7000 MJ/m
LT	Lifetime	30 y	20 – 40 y
f	Produced flow rate	62.5 kg/s	25 – 100 kg/s
P_{ORC}	Installed capacity ORC	2375 kW	1250 – 3500 kW
SFe	Enhancement scaling factor	5.25	0.5 – 10
LF	Load factor	0.90	0.85 – 0.95
P_p	Specific power of pumps	6.1 kW/(kg/s)	3.6 – 8.6 kW/(kg/s)

Uncertainties in LCA



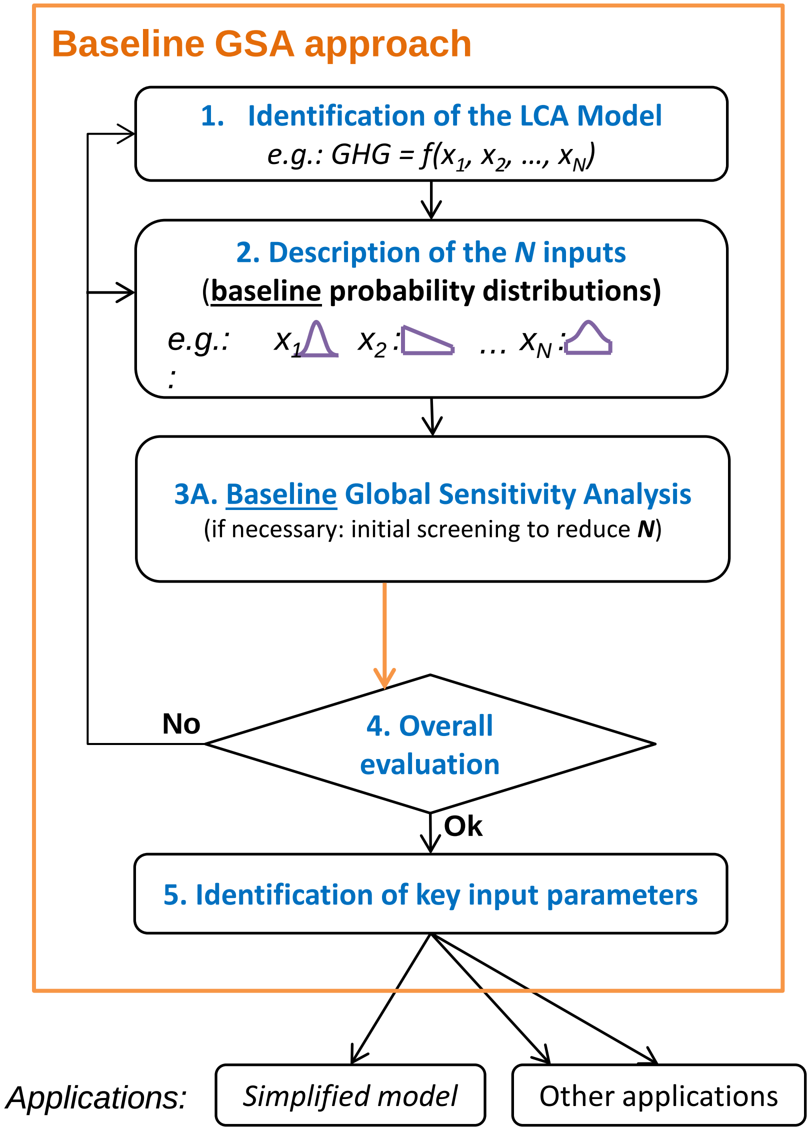
Generation of scenarios by Monte Carlo simulation



Generation of Monte Carlo sample for the inputs

Generation of Monte Carlo sample of the output

Global sensitivity analysis (Sobol method)



$$GHG_{EGS,A}\left[\frac{g\,CO_2eq}{kWh}\right] = \frac{z_A \cdot Nw_A \cdot (\alpha_1 + \alpha_2 \cdot d_A) + LT_A \cdot f_A \cdot \alpha_3 + P_{ORC,A} \cdot LT_A \cdot \alpha_4 + Nw_A \cdot Sfe_A \cdot \alpha_5}{LF_A \cdot LT_A \cdot (P_{ORC,A} - f_A \cdot P_{p,A}) \cdot 8760}$$

(Cucurachi et al. 2016; Lacirignola et al. 2017)

Prospective LCA model: *Variable* Input parameters

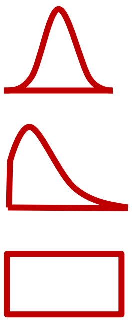
Symbol	Parameters	Value range	Probability distribution
z	Borehole depth	2000 – 6000 m	Uniform
Nw	Number of wells	2 – 3 wells	Uniform
d	Fuel for drilling	3000 – 7000 MJ/m	Uniform
LT	Lifetime	20 – 40 y	Normal distribution centered on LT=30 with σ=3.25
f	Produced flow rate	25 – 100 kg/s	Uniform
P_{ORC}	Installed capacity ORC	1250 – 3500 kW	2375 kW
SFe	Enhancement scaling factor	0.5 – 10	Lognormal distribution with σ=1, μ=0 and peak on Sfe=1
LF	Load factor	0.85 – 0.95	Uniform
P_p	Specific power of pumps	3.6 – 8.6 kW/(kg/s)	Uniform

Baseline Prospective LCA results for EGS

LT

SF

e



f

[…]

Nw

[…]

d

[…]

z

P_{OR}

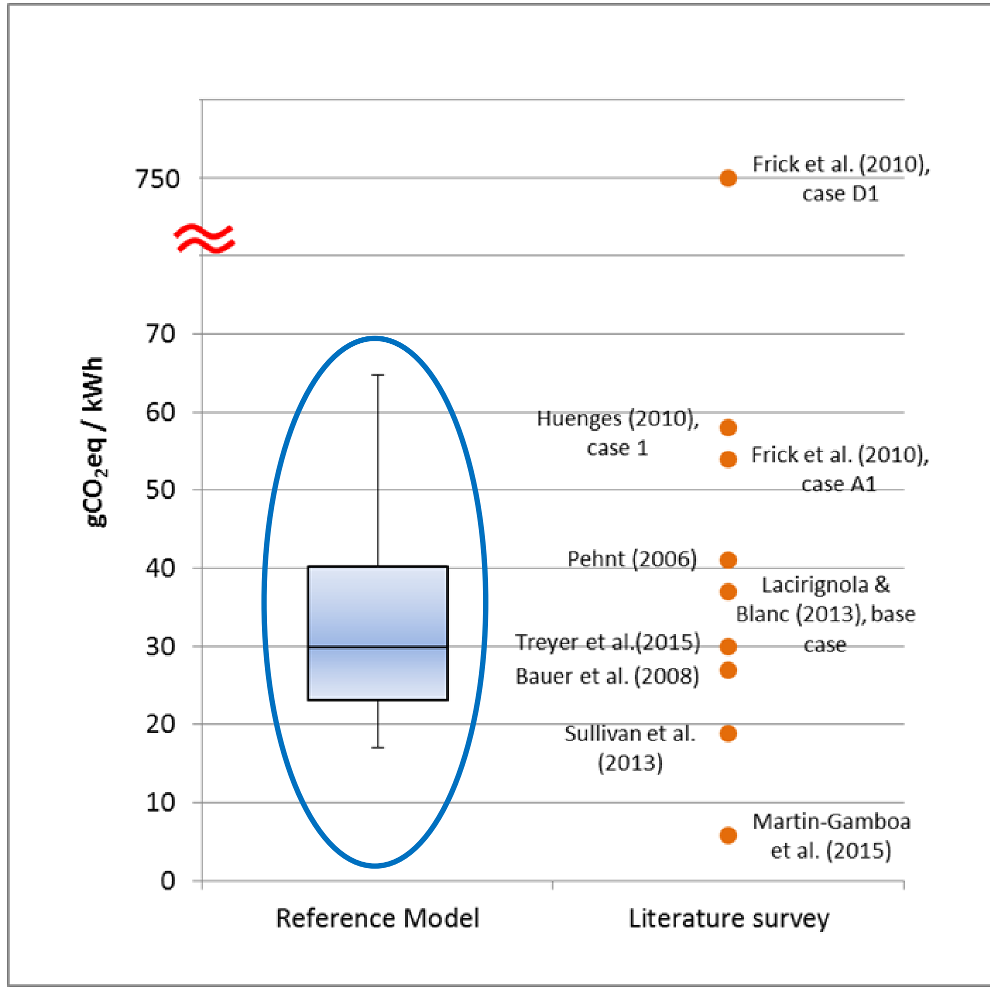
c

P_p

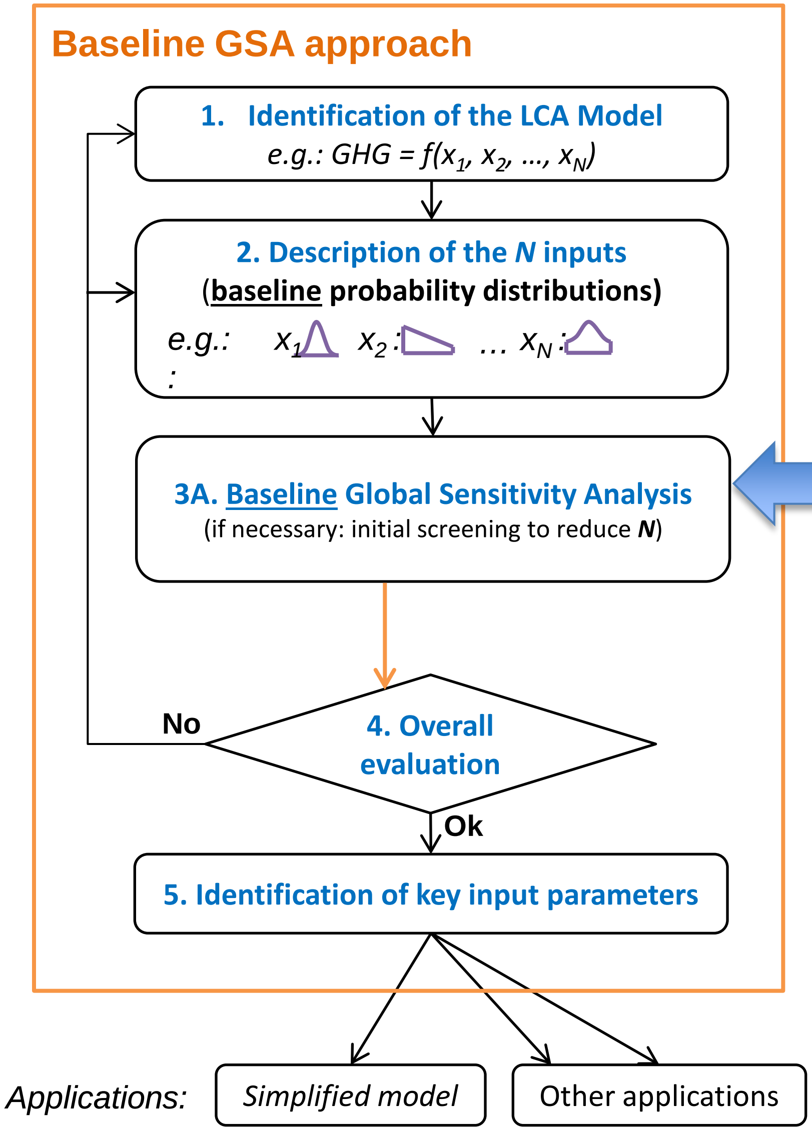
LF

Monte Carlo

500 000 simulations, i.e. 500 000 potential EGS facilities



Global sensitivity analysis (Sobol' method)



$$GHG_{EGS,A}\left[\frac{g\,CO_2eq}{kWh}\right] = \frac{z_A \cdot Nw_A \cdot (\alpha_1 + \alpha_2 \cdot d_A) + LT_A \cdot f_A \cdot \alpha_3 + P_{ORC,A} \cdot LT_A \cdot \alpha_4 + Nw_A \cdot Sfe_A \cdot \alpha_5}{LF_A \cdot LT_A \cdot (P_{ORC,A} - f_A \cdot P_{p,A}) \cdot 8760}$$

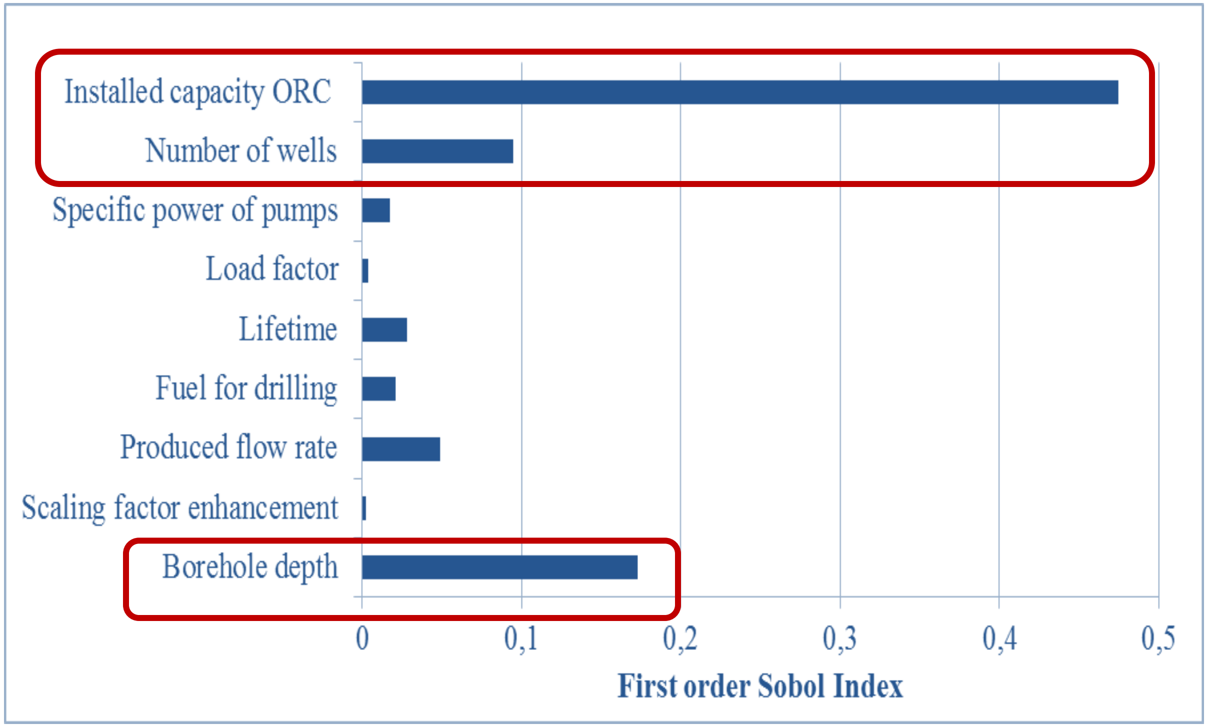
Based on Sobol indices (variance decomposition method) to identify key parameters:

$$S_i = \frac{Var[E(Y|X_i)]}{Var(Y)} = \frac{V_i(Y)}{Var(Y)}$$

$$S_{ij} = \frac{V_{ij}(Y)}{Var(Y)} \qquad S_{ijk} = \frac{V_{ijk}(Y)}{Var(Y)}$$

(Cucurachi et al. 2016; Lacirignola et al. 2017)

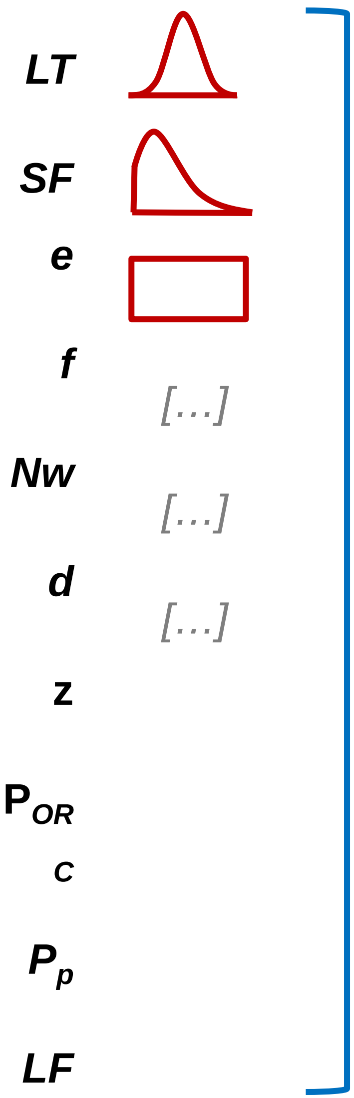
EGS: Baseline GSA results



P_{ORC}, Nw, z

Key parameters responsible for 75% of output variation

EGS: Dependence of GSA results on PDF

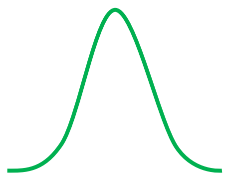


For emerging technologies, characterizing inputs' probability distribution functions (PDF) may be difficult

Which is the effect of changing PDF on inputs' ranking from GSA?

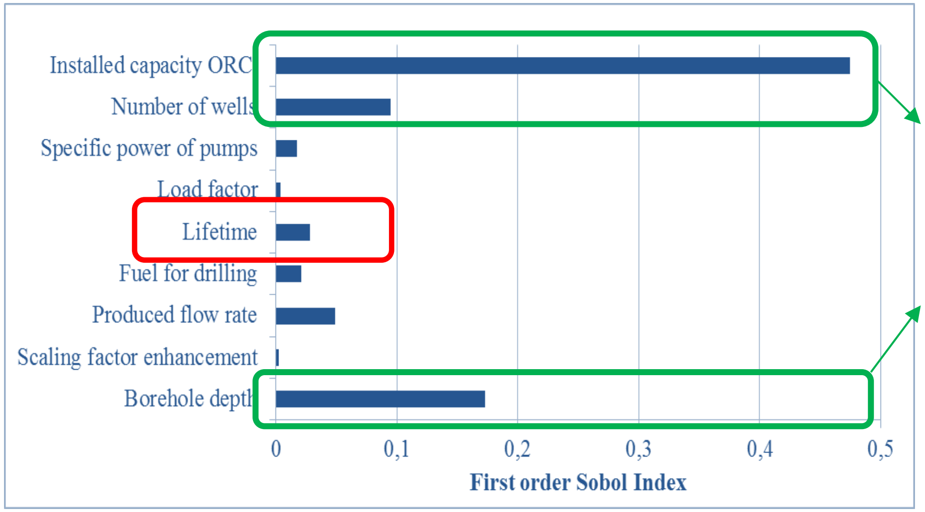
EGS: Dependence of GSA results on PDF

LIFETIME



Normal

Hypothesis (uncertain)

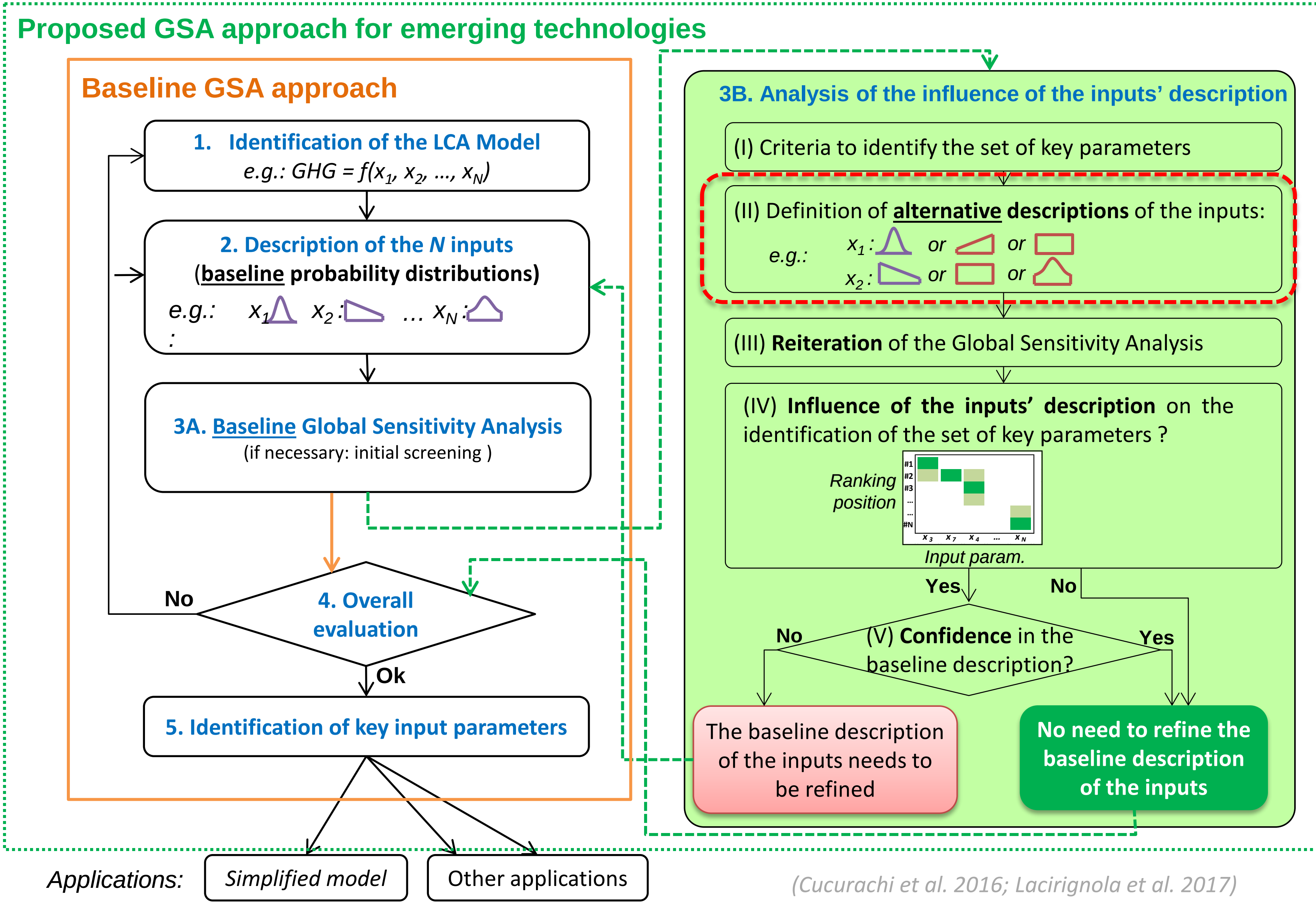


P_{ORC}, Nw, z: Key parameters responsible for 75% of output variation

Uniform

P_{ORC}, LT, z: Key parameters

Global sensitivity analysis (Sobol' method)



(Cucurachi et al. 2016; Lacirignola et al. 2017)

EGS: Effect of PDFs on GSA results

Parameter	Value range [unit]	Baseline distribution (type 1)	Alternative distributions			
			Type 2	Type 3	Type 4	Type 5
Borehole depth (z)	2,000 – 6,000 [Meters]	Uniform μ: 4,000 σ: 1,155	Δμ: 0% Δσ: –43%	Δμ: –11% Δσ: –8%	Δμ: 11% Δσ: –8%	Δμ: 0% Δσ: –14%
Scaling factor enhan. (Sfe)	0.5 – 10 [Ad.]	Trunc–lognormal μ: 2.10 σ: 1.53	Δμ: 99% Δσ: 65%	Δμ: 150% Δσ: 79%	Δμ: 150% Δσ: 2%	Δμ: 150% Δσ: 53%
Flow rate (f)	25 – 100 [kg/s]	Uniform μ: 62.5 σ: 21.7	Δμ: 0% Δσ: –43%	Δμ: –13% Δσ: –8%	Δμ: 13% Δσ: –8%	Δμ: 0% Δσ: –14%
Fuel for drilling (d)	3,000 – 7,000 [MJ/m]	Uniform μ:5,000 σ:1,155	Δμ: 0% Δσ: –43%	Δμ: –9% Δσ: –8%	Δμ: 9% Δσ: –7%	Δμ: 0% Δσ: –14%
Lifetime (LT)	20 – 40 [Years]	Trunc–gaussian μ: 30 σ: 3.3	Δμ: 0% Δσ: 76%	Δμ: –7% Δσ: 62%	Δμ: 7% Δσ: 62%	Δμ: 0% Δσ: 51%
Load factor (LF)	0.85 – 0.95 [Ad.]	Uniform μ: 0.90 σ: 0.03	Δμ: 0% Δσ: –43%	Δμ: –1% Δσ: –8%	Δμ: 1% Δσ: –8%	Δμ: 0% Δσ: –14%
Pumps specific power (P_p)	3.6 – 8.6 [kW/(kg/s)]	Uniform μ: 6.1 σ: 1.4	Δμ: 0% Δσ: –43%	Δμ: –9% Δσ: –8%	Δμ: 9% Δσ: –7%	Δμ: 0% Δσ: –14%
Number of wells (Nw)	2 or 3 [Ad.]	50% 50% μ: 2.5 σ: 0.5	70% 30% Δμ: –8% Δσ: –8%	30% 70% Δμ: 8% Δσ: –8%	–	–
Installed capacity ORC (P_{ORC})	1,250 – 3,500 [kW]	Uniform μ: 2,375 σ: 650	Δμ: 0% Δσ: –43%	Δμ: –11% Δσ: –8%	Δμ: 11% Δσ: –8%	Δμ: 0% Δσ: –14%

Possible descriptions (probability distribution functions) for each of the 9 input parameters for EGS LCA model

(Lacirignola et al. 2017)

EGS: Effect of PDFs on GSA results

Changing the distribution function for 1 input parameter and keeps other distributions as baseline

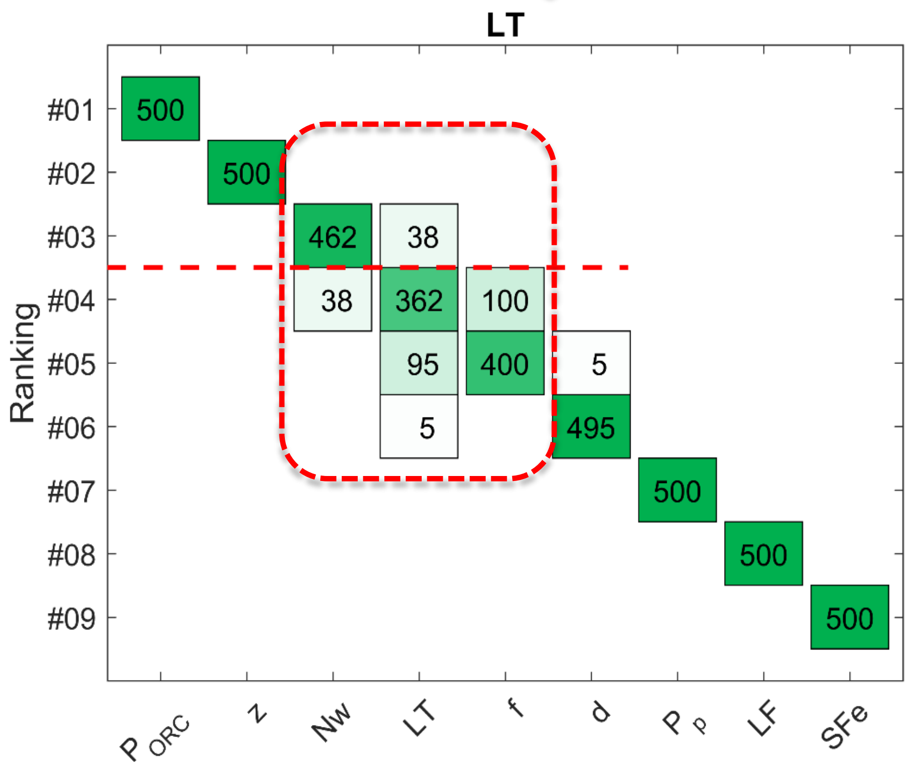
§ GSA	z	SFe	f	d	LF	LT	P_p	Nw	P_{ORC}
§1 (Baseline) ×100 bootstraps	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 2 (×100)	TYPE 2	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 3 (×100)	TYPE 3	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 4 (×100)	TYPE 4	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 5 (×100)	TYPE 5	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 6 (×100)	Baseline	TYPE 2	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 7 (×100)	Baseline	TYPE 3	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 8 (×100)	Baseline	TYPE 4	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
§ 9 (×100)	Baseline	TYPE 5	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
[...]	[...]	[...]	[...]	[...]	[...]	[...]	[...]	[...]	[...]
§ 32 (×100)	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	TYPE 2
§ 33 (×100)	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	TYPE 3
§ 34 (×100)	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	TYPE 4
§ 35 (×100)	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	TYPE 5

(Lacirignola et al. 2017)

EGS: Effect of LIFETIME in inputs' ranking

For example, using the 5 possible distribution functions for **LIFETIME (LT)**:

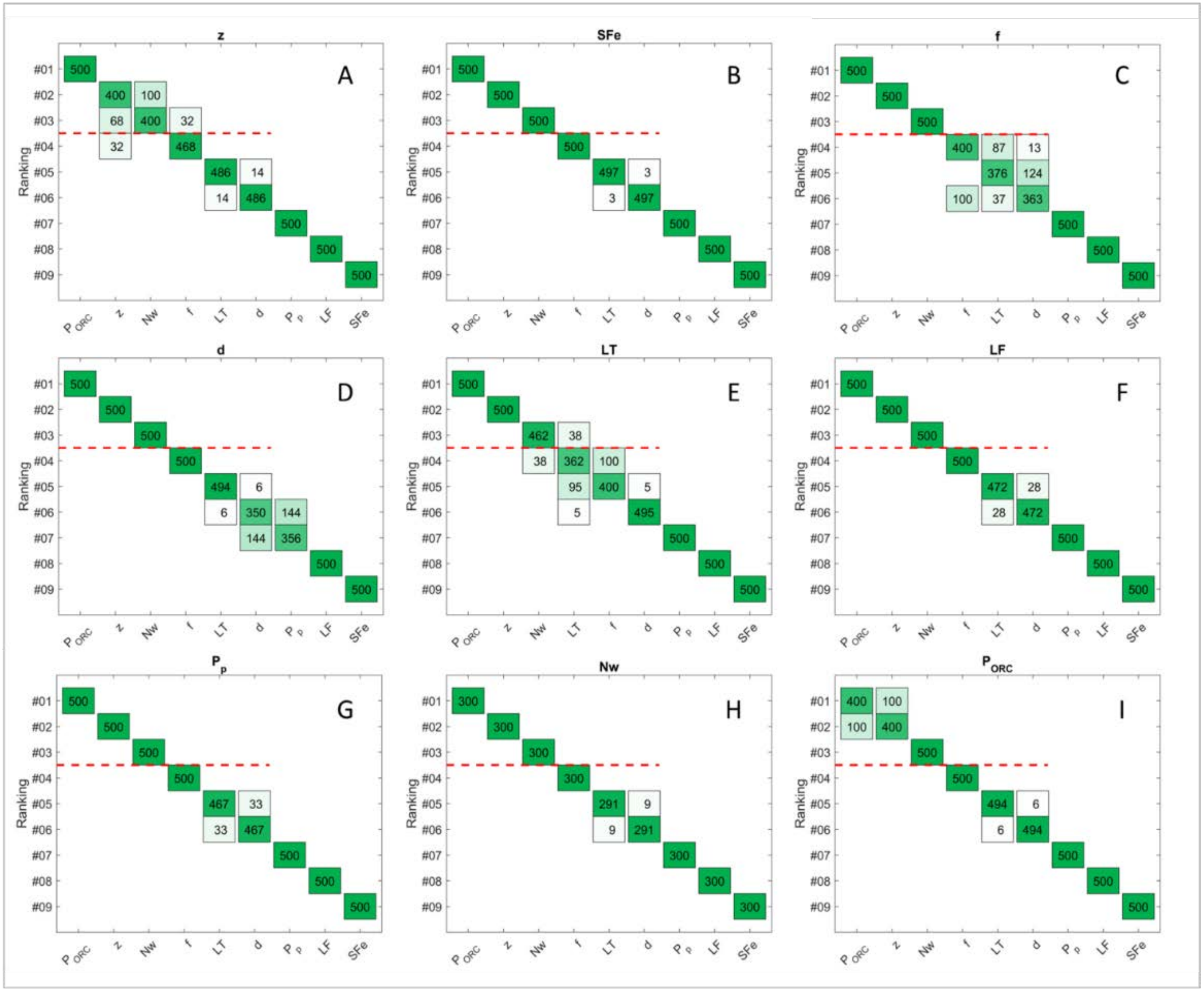
Load factor (LF)	0.85 – 0.95 [Ad.]	Uniform μ: 0.90 σ: 0.03	Δμ: 0% Δσ: -43%	Δμ: -1% Δσ: -8%	Δμ: 1% Δσ: -8%	Δμ: 0% Δσ: -14%



- Positions 1 and 2 always correspond to parameters P_{ORC} and z
- Positions 3, 4, 5 ⇒ influenced by LT distribution

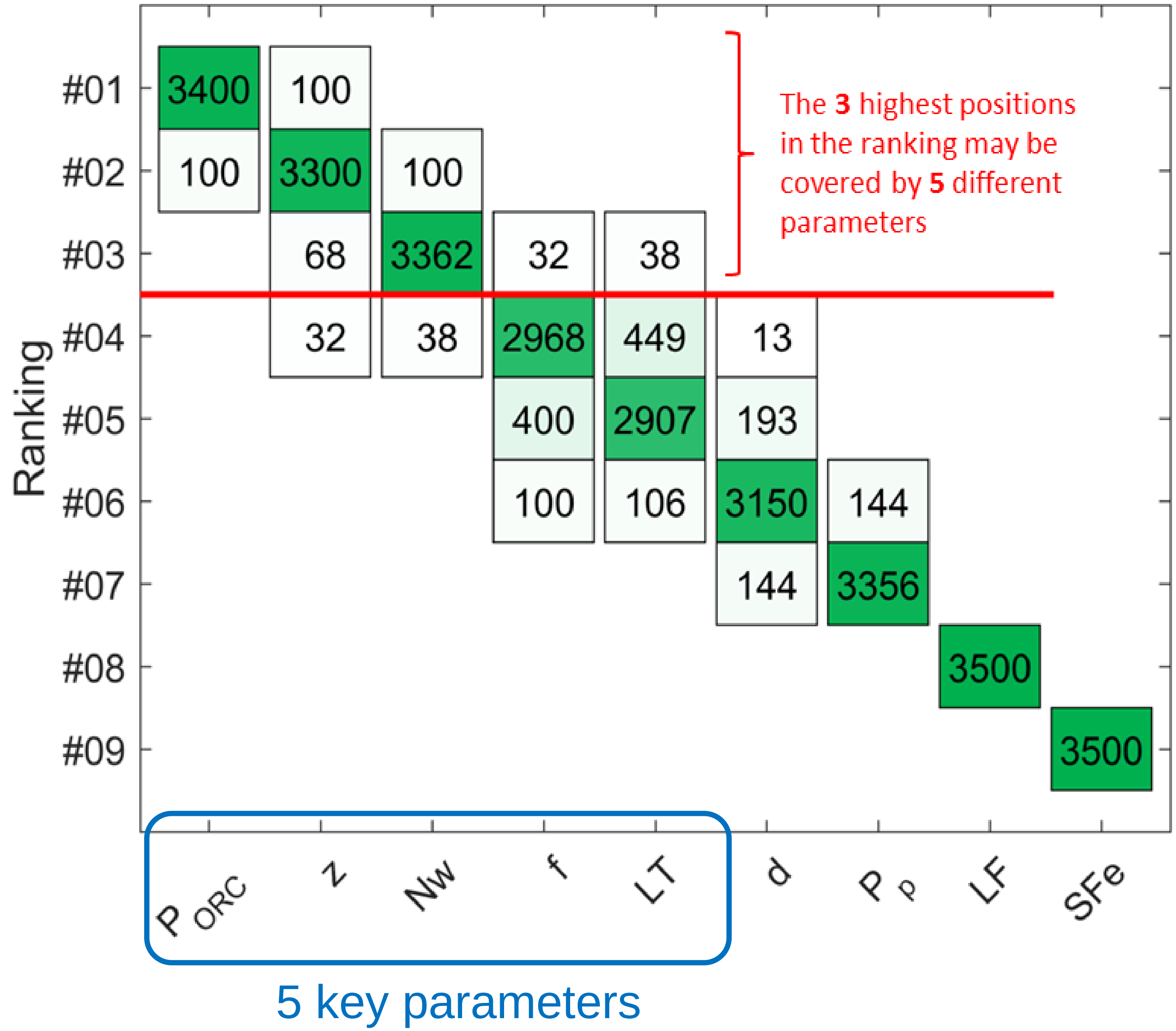
EGS: Effect of PDF on GSA results

For each of the 9 input parameters



EGS: Effect of PDF on GSA results

Considering 3500 rankings after iterative GSA:



EGS: application of GSA results

Identification of **5** key input parameters among the **9** initial ones

→ **Simplified model for LCA of** EGS facilities

5 key parameters

$$GHG_{EGS\_Reduced}\left[\frac{gCO_2eq}{kWh}\right] = f(P_{ORC}, N_w, z, LT, f)$$

$$= \frac{Nw \cdot (\omega_1 \cdot z + \omega_2) + LT \cdot (\omega_3 \cdot f + \omega_4 \cdot P_{ORC})}{LT \cdot (P_{ORC} - f \cdot \omega_5)} \pm 5\ gCO_2eq/kWh$$

$\omega_1 = 120.70\ [gCO_2eq/(m \cdot h/y)]$; $\omega_2 = 5\,161.87\ [gCO_2eq/(h/y)]$;
$\omega_3 = 61.82\ [gCO_2eq \cdot s/(kg \cdot h)]$; $\omega_4 = 6.42\ [gCO_2eq/(kWh)]$; $\omega_5 = 6.10\ [(kW \cdot s)/kg]$;

EGS: application of GSA results

- From complete parametric model

$$GHG_{EGS}\left[\frac{g\ CO_2eq}{kWh}\right] = \frac{z \cdot Nw \cdot (\alpha_1 + \alpha_2 \cdot d) + LT \cdot f \cdot \alpha_3 + P_{ORC} \cdot LT \cdot \alpha_4 + Nw \cdot Sfe \cdot \alpha_5}{LF \cdot LT \cdot (P_{ORC} - f \cdot P_p) \cdot 8760}$$

- .... to simplified model

$$GHG_{EGS\_Reduced}\left[\frac{gCO_2eq}{kWh}\right] = \frac{Nw \cdot (\omega_1 \cdot z + \omega_2) + LT \cdot (\omega_3 \cdot f + \omega_4 \cdot P_{ORC})}{LT \cdot (P_{ORC} - f \cdot \omega_5)}$$

ADVANTAGES

✓ Reduced number of input parameters (From 9 to 5)

✓ For some of the least influencing parameters, data were difficult to obtain → Simplified model facilitates data gathering

Conclusions & perspectives

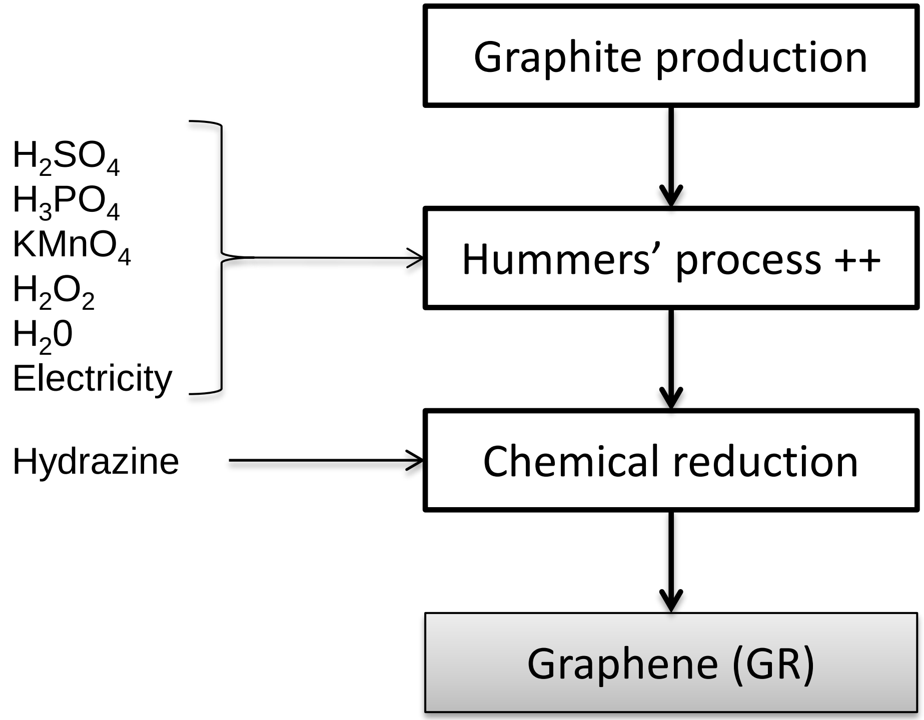
- Need for a specific approach to deal with large uncertainty of **emerging technologies** in LCA
- Global Sensitivity Analysis (GSA) based on variance-decomposition methods (e.g. Sobol) allows **key parameter identification** and ranking
- The protocol proposed for GSA of emerging technologies helped to evaluate the influence of **distribution functions** of input parameters in GSA results
- ⮡ **a simplified parametric equation** to estimate GHG impact from a reduced number of parameters was obtained.
- We aim to apply the same approach to deduce a set of simplified equations for a multi-criteria LCA

Part II: GSA applied to nanomaterials

- Case study: Graphene (GR) production by **chemical reduction process** (Based on publication by Arvidsson et al. 2014)

- No pilot/large-scale data
- Incomplete technology development
- Unknown future applications
- Data quality concerns

Emerging technology

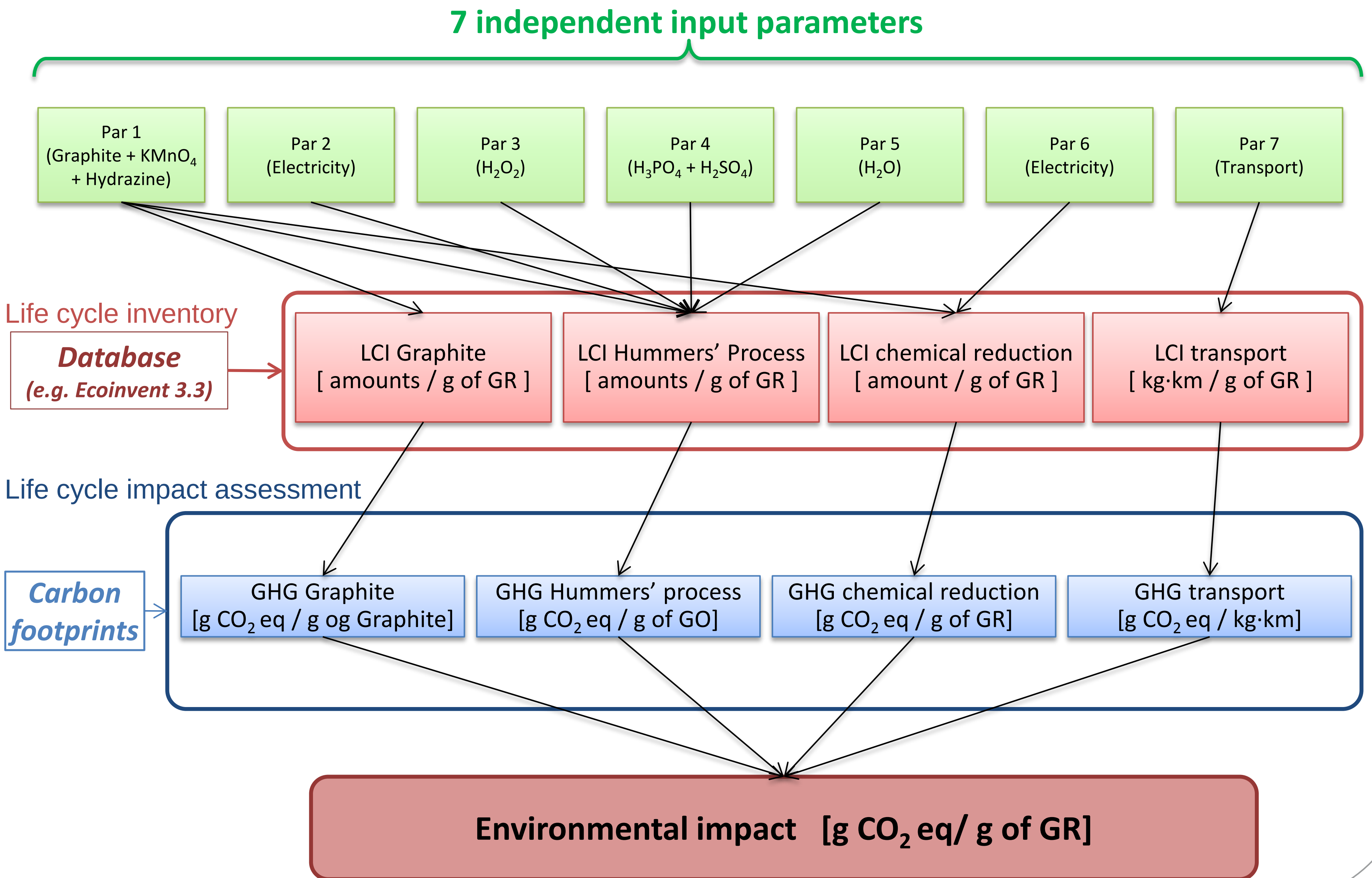


Graphene production: input parameters

Symbols	Parameters	Baseline scenario
Par 1	Graphite + Potassium permanganate ($KMnO_4$) + Hydrazine	2.55 g / g of GR
Par 2	Electricity RER medium voltage - 1	8.5 MJ / g of GR
Par 3	Peroxide (H_2O_2)	4.675 g / g of GR
Par 4	Phosphoric acid (H_3PO_4) + Sulfuric acid (H_2SO_4)	33.15 g / g of GR
Par 5	Deionised water	0.935 g / g of GR
Par 6	Electricity RER medium voltage - 2	0.15 MJ / g of GR
Par 7	Transport - lorry >32 tons class 5	0.259 kg·km / g of GR

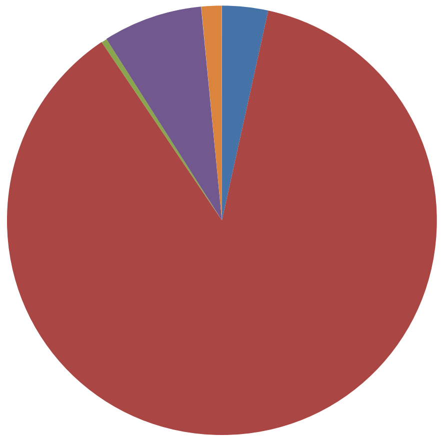
(Based on publication by Arvidsson et al. 2014)

Model for graphene production



Graphene production: Parameters' contribution

Baseline result: 1.7 kg CO2 eq./g of GR



Carbon footprint contribution

1. Electricity for Hummers' process (Par 2)
2. Acids (Par 4)
3. Graphite + $KMnO_4$ + Hydrazine (Par 1)
4. Electricity for chemical reduction (Par 6)
5. Peroxide (Par 3)
6. Transport (Par 7)
7. Deionised water (Par 5)

Graphene production: input parameters

Symbols	Parameters	Baseline scenario	GSD² (Pedigree Matrix)
Par 1	Graphite + Potassium permanganate ($KMnO_4$) + Hydrazine	2.55 g / g of GR	1.51
Par 2	Electricity RER medium voltage - 1	8.5 MJ / g of GR	1.51
Par 3	Peroxide (H_2O_2)	4.675 g / g of GR	1.51
Par 4	Phosphoric acid (H_3PO_4) + Sulfuric acid (H_2SO_4)	33.15 g / g of GR	1.51
Par 5	Deionised water	0.935 g / g of GR	1.51
Par 6	Electricity RER medium voltage - 2	0.15 MJ / g of GR	1.50
Par 7	Transport - lorry >32 tons class 5	0.259 kg·km / g of GR	1.72

(Based on publication by Arvidsson et al. 2014)

Equivalent relative uncertainty

Sobol results– Only lognormal & equivalent uncertainties

		Par 2	Par 6	Par 4	Par 1	Par 3	Par 7	Par 5
		Electricity - 1	Electricity - 2	Acids	Graphite + KMnO4 + Hydrazine	Peroxide	Transport	Water
Ranking	1	100 000						
	2			100 000				
	3				100 000			
	4		100 000					
	5					100 000		
	6						100 000	
	7							100 000

Graphene production: Prospective LCA model

Symbols	Parameters	Baseline scenario	Value range
Par 1	Graphite + Potassium permanganate ($KMnO_4$) + Hydrazine	2.55 g / g of GR	0.85 – 4.25 g
Par 2	Electricity RER medium voltage - 1	8.5 MJ / g of GR	3.4 – 1133 MJ
Par 3	Peroxide (H_2O_2)	4.675 g / g of GR	0.85 – 8.5 g
Par 4	Phosphoric acid (H_3PO_4) + Sulfuric acid (H_2SO_4)	33.15 g / g of GR	22.1 – 44.2 g
Par 5	Deionised water	0.935 g / g of GR	25 – 100 kg
Par 6	Electricity RER medium voltage - 2	0.15 MJ / g of GR	0.06 – 6 MJ
Par 7	Transport - lorry >32 tons class 5	0.259 kg·km / g of GR	0.013 – 5.18 kg·km

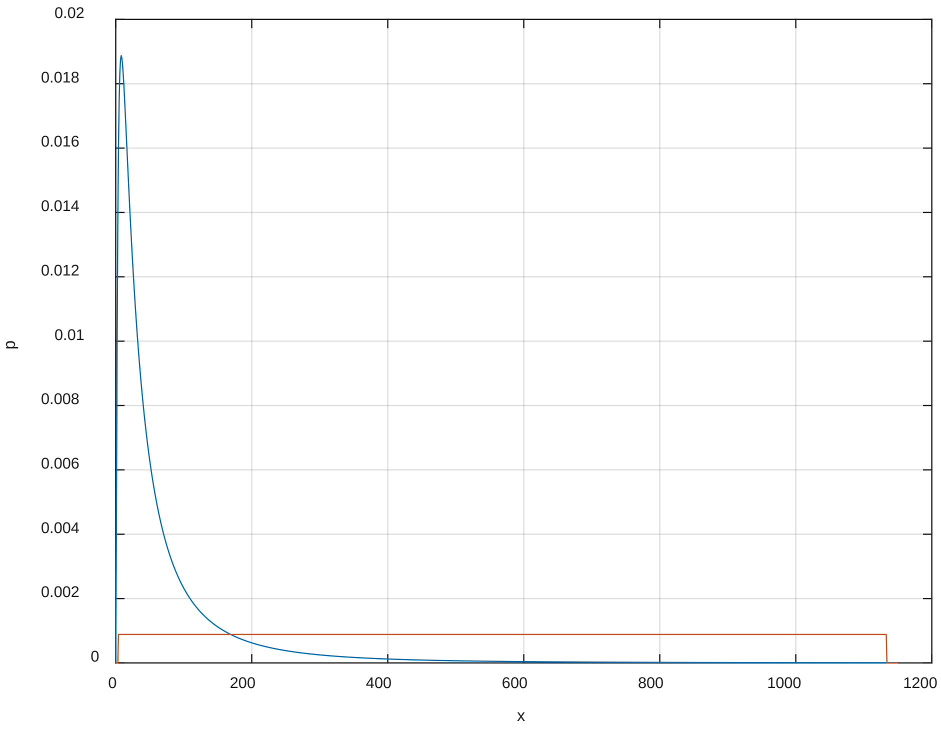
(Based on publication by Arvidsson et al. 2014 and its references)

Inputs for the GSA – All distributions

Parameters	Value range	Baseline distribution	Alternative distributions	
		Type 1	Type 2	Type 3
Par 1	0.85 – 4.25 g	lognormal	Uniform	Triangular
Par 2	3.4 – 1133 MJ	lognormal	Uniform	Triangular
Par 3	0.85 – 8.5 g	lognormal	Uniform	Triangular
Par 4	22.1 – 44.2 g	lognormal	Uniform	Triangular
Par 5	25 – 100 kg	lognormal	Uniform	Triangular
Par 6	0.06 – 6 MJ	lognormal	Uniform	Triangular
Par 7	0.013 – 5.18 kg·km	lognormal	Uniform	Triangular

Inputs for the GSA – Comparison

Difference between lognormal and uniform distribution for electricity used in Hummers' process



Electricity consumption for Parameter 2 (MJ / g of GR)

Pedigree approach propose much lower uncertainty than the value range found in the reference

Results for the GSA – lognormal + uniform

		Par 2	Par 6	Par 4	Par 1	Par 3	Par 7	Par 5
		Electricity - 1	Electricity - 2	Acids	Graphite + KMnO4 + Hydrazine	Peroxide	Transport	Water
Ranking	1	200 000						
	2		100 273	99 727				
	3			100 273	99 727			
	4		99 727		100 273			
	5					200 000		
	6						200 000	
	7							200 000

Results for the GSA – lognormal + triangular

		Par 2	Par 6	Par 4	Par 1	Par 3	Par 7	Par 5
		Electricity - 1	Electricity - 2	Acids	Graphite + KMnO4 + Hydrazine	Peroxide	Transport	Water
Ranking	1	200 000						
	2		100 383	99 617				
	3			100 383	99 617			
	4		99 617		100 383			
	5					200 000		
	6						200 000	
	7							200 000

Results for the GSA – uniform + triangular

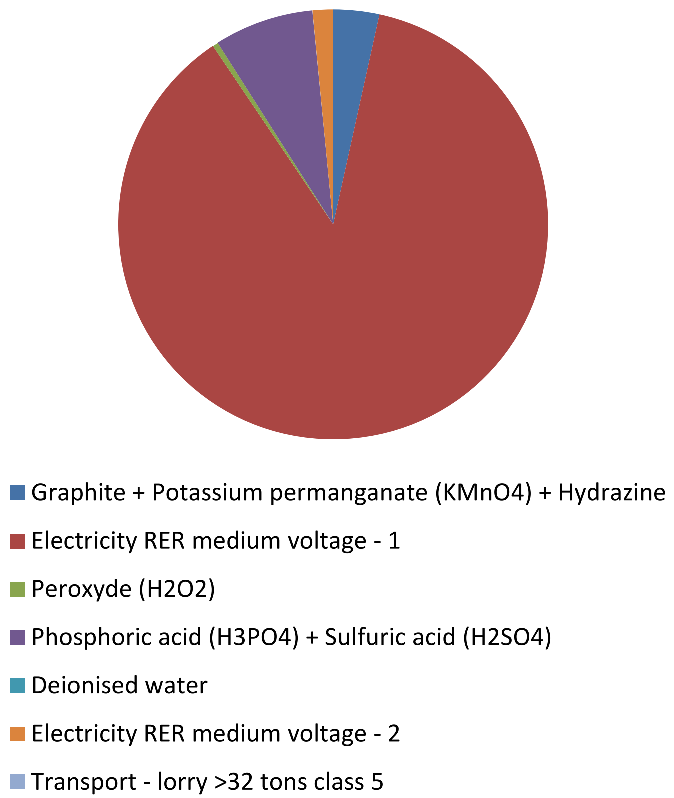
		Par 2	Par 6	Par 4	Par 1	Par 3	Par 7	Par 5
		Electricity - 1	Electricity - 2	Acids	Graphite + KMnO4 + Hydrazine	Peroxide	Transport	Water
Ranking	1	200 000						
	2		200 000					
	3			150 119	49 881			
	4			49 881	150 119			
	5					200 000		
	6						200 000	
	7							200 000

Results for the GSA – All distributions

		Par 2	Par 6	Par 4	Par 1	Par 3	Par 7	Par 5
		Electricity - 1	Electricity - 2	Acids	Graphite + KMnO4 + Hydrazine	Peroxide	Transport	Water
Ranking	1	300 000						
	2		199 867	89 137	10 996			
	3			188 894	111 106			
	4		100 133	21 969	177 898			
	5					300 000		
	6						300 000	
	7							300 000

Graphene production: Parameters' ranking

Baseline result: 1.7 kg CO2 eq./g of GR



Global sensitivity Analysis / Ranking

1. Electricity for Hummers' process (Par 2)
2. Acids (Par 4)
3. Graphite + $KMnO_4$ + Hydrazine (Par 1)
4. Electricity for chemical reduction (Par 6)
5. Peroxide (Par 3)
6. Transport (Par 7)
7. Deionised water (Par 5)

Thank you for your attention

Prospective LCA modelling
How to deal with uncertainties ?

Part I : A new approach based on GSA

Part II : The Graphene Case study

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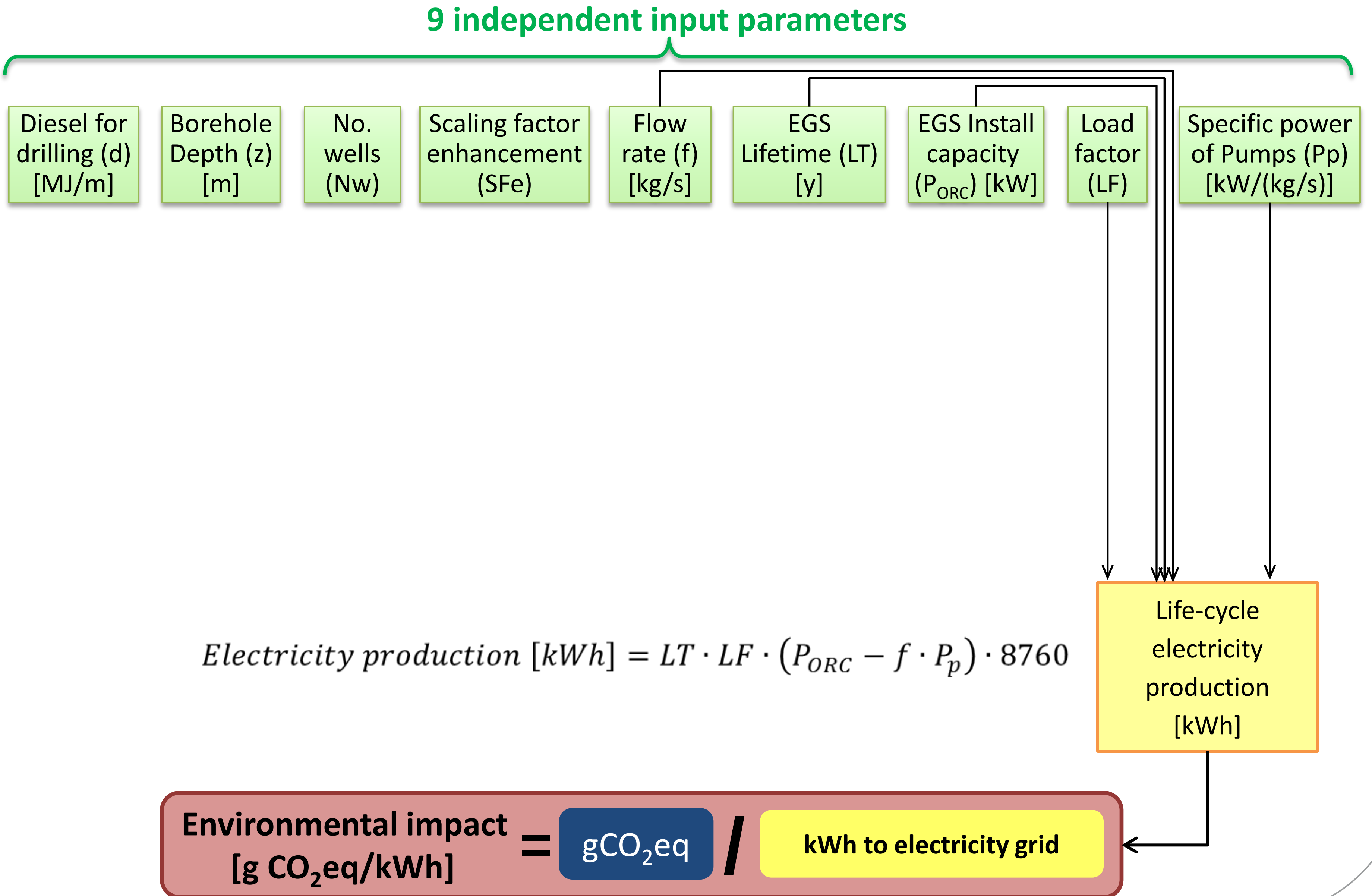
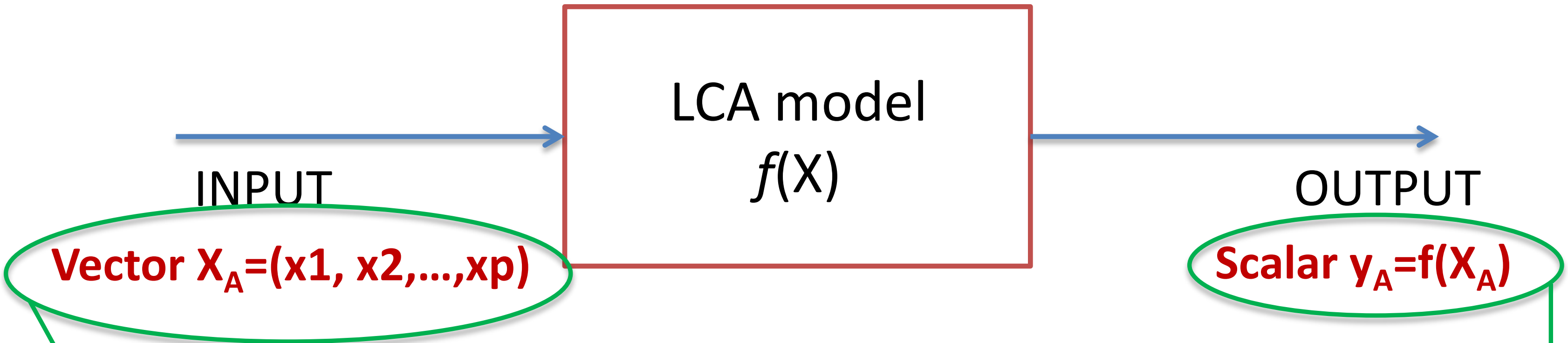
EGS: LCA model (GHG emissions)



$$Electricity\ production\ [kWh] = LT \cdot LF \cdot (P_{ORC} - f \cdot P_p) \cdot 8760$$

EGS: LCA model (GHG emissions)

A) General modeling framework for LCA



$X_A=(z_A, Nw_A, d_A, LT_A, f_A, P_{ORC, A}, SFe_A, LF_A, P_{p, A})$

$$GHG_{EGS,\,A}\left[\frac{g\ CO_2eq}{kWh}\right]=\frac{z_A\cdot Nw_A\cdot(\alpha_1+\alpha_2\cdot d_A)+LT_A\cdot f_A\cdot\alpha_3+P_{ORC,A}\cdot LT_A\cdot\alpha_4+Nw_A\cdot Sfe_A\cdot\alpha_5}{LF_A\cdot LT_A\cdot\left(P_{ORC,A}-f_A\cdot P_{p,A}\right)\cdot 8760}$$

With α_1= 498761.36 gCO_2eq/m; α_2=90.56 gCO_2eq/MJ; α_3=487363.03 $gCO_2eq\cdot s/(kg\cdot y)$; α_4=50603.13 $gCO_2eq/(kW\cdot y)$; α_5=25757089.05 gCO_2eq