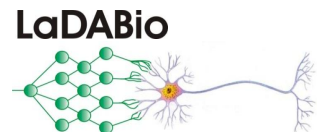




# The Role of Biorefineries in the Transition to a Low Carbon Economy

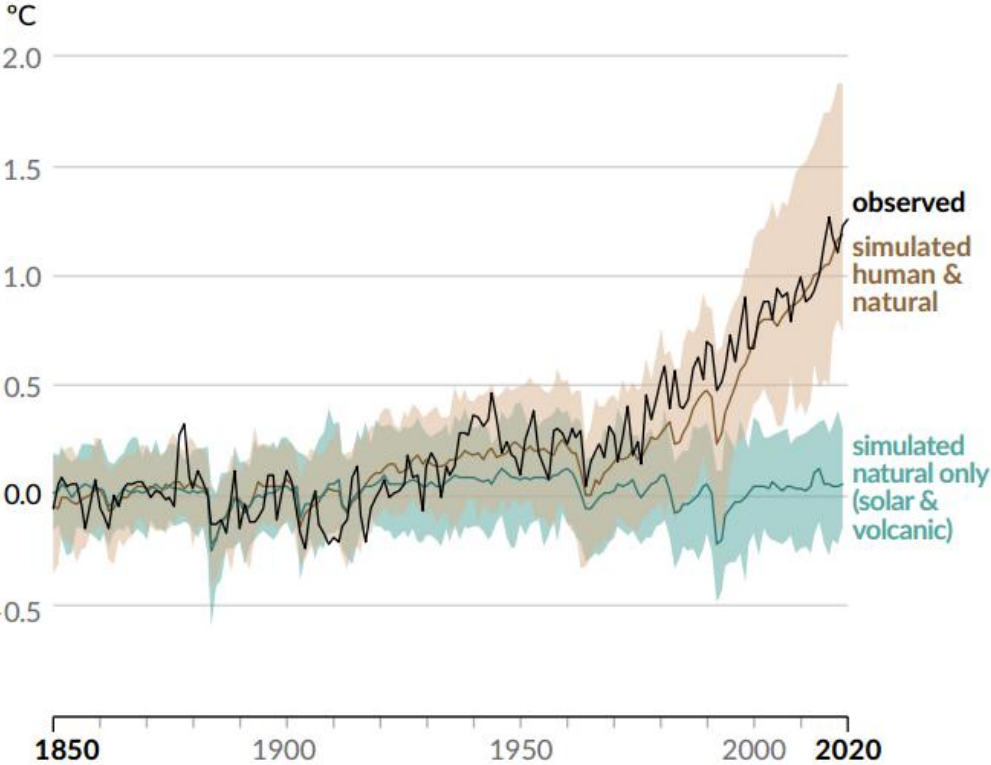
Prof. Felipe Fernando Furlan  
Federal University of São Carlos  
Brazil



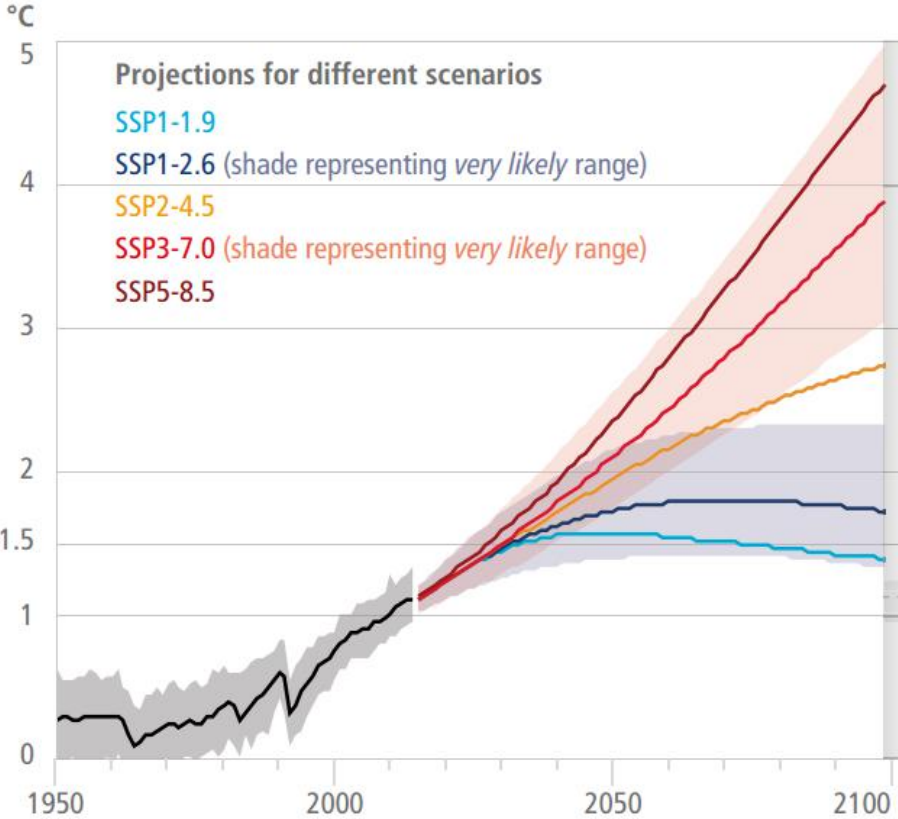


# Climate Crisis

(b) Change in global surface temperature (annual average) as **observed** and simulated using **human & natural** and **only natural** factors (both 1850–2020)



(a) Global surface temperature change Increase relative to the period 1850–1900



IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change

IPCC, 2022: Summary for Policymakers. In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change

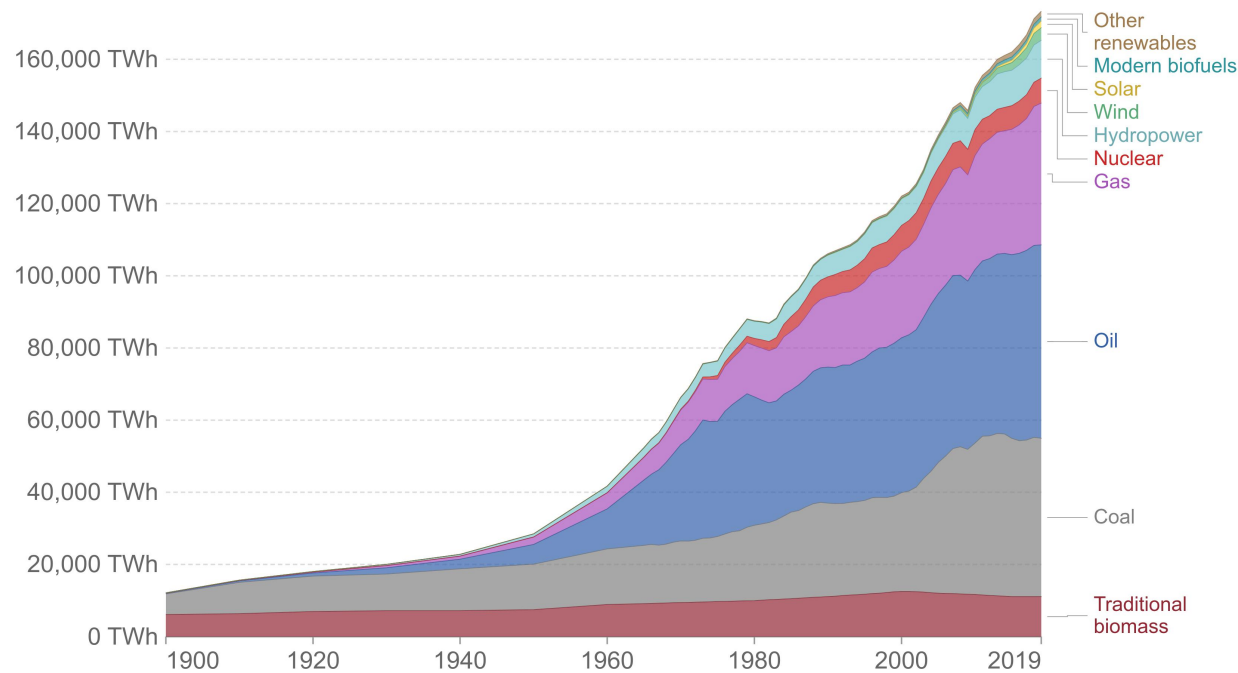


# World's energy matrix

## Global primary energy consumption by source

Primary energy is calculated based on the 'substitution method' which takes account of the inefficiencies in fossil fuel production by converting non-fossil energy into the energy inputs required if they had the same conversion losses as fossil fuels.

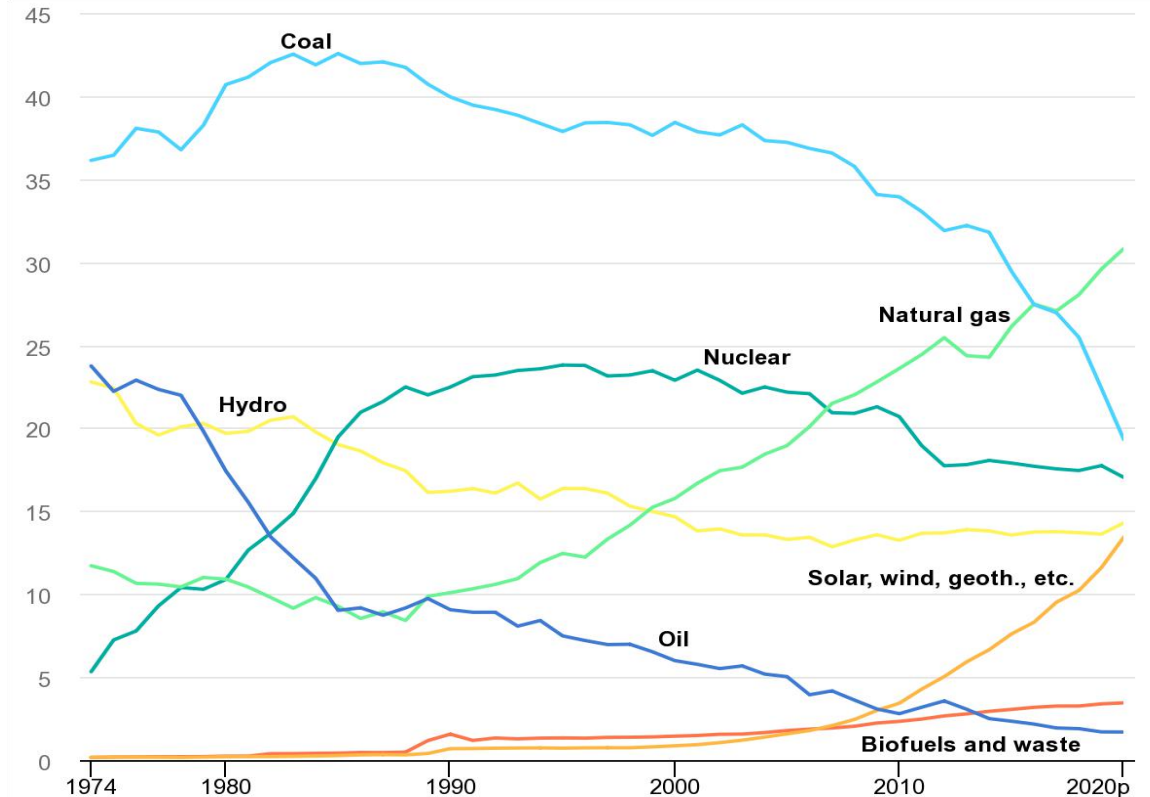
Our World in Data



Source: Vaclav Smil (2017) & BP Statistical Review of World Energy

OurWorldInData.org/energy • CC BY

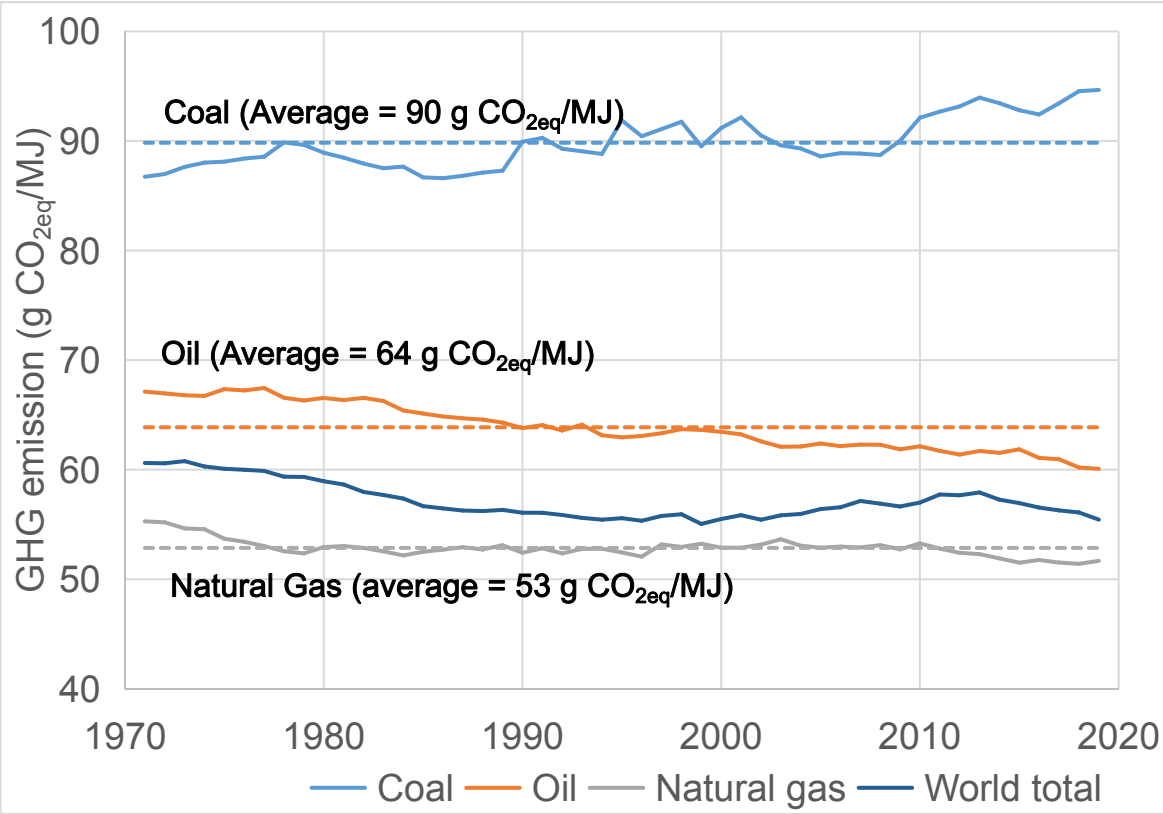
## Contribution of different primary sources in electric energy production in OCDE countries.



IEA, Share of OECD gross electricity production by source, 1974-2020p, IEA, Paris <https://www.iea.org/data-and-statistics/charts/share-of-oecd-gross-electricity-production-by-source-1974-2020p>

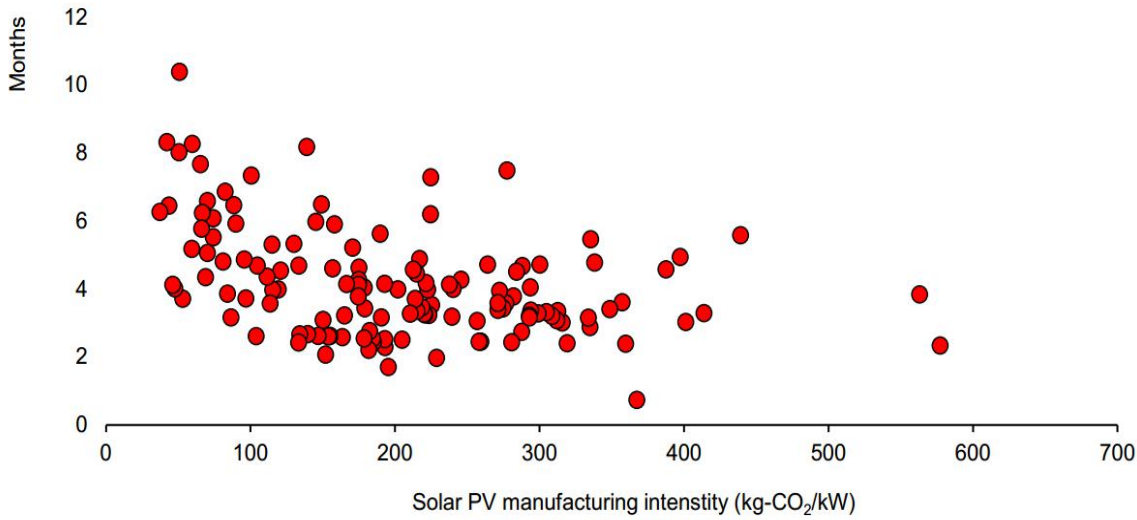


# GHG in Energy production



IEA (2021), *Greenhouse Gas Emissions from Energy*  
bp Statistical Review of World Energy, 71st edition, 2022

## Solar photovoltaic carbon intensity and payback time (each point represents a country)



IEA, Solar PV manufacturing emissions intensity and payback period, IEA, Paris <https://www.iea.org/data-and-statistics/charts/solar-pv-manufacturing-emissions-intensity-and-payback-period>

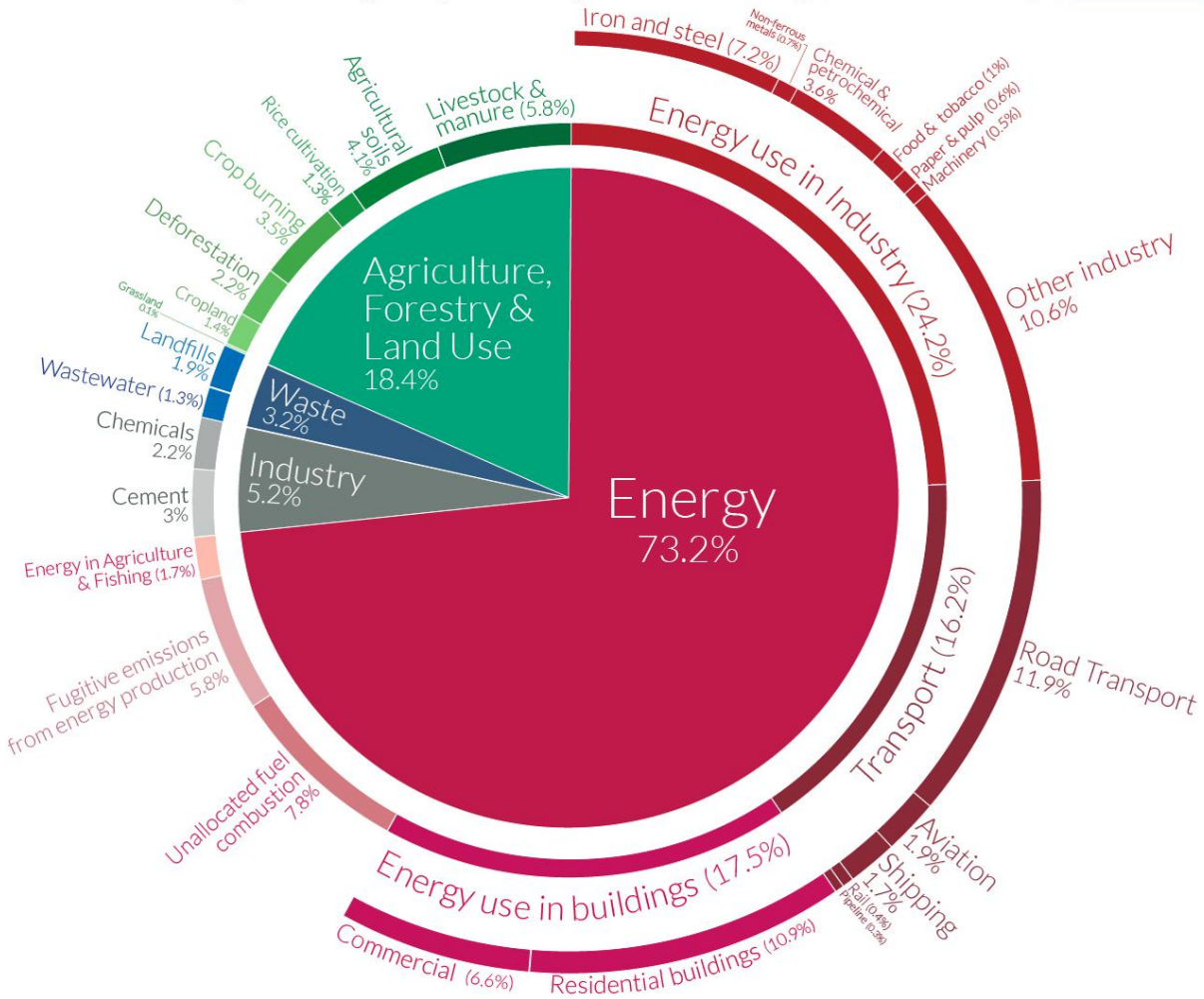


# Greenhouse gas emissions by sector

## Global greenhouse gas emissions by sector



This is shown for the year 2016 – global greenhouse gas emissions were 49.4 billion tonnes CO<sub>2</sub>eq.



OurWorldinData.org – Research and data to make progress against the world’s largest problems. Source: Climate Watch, the World Resources Institute (2020). Licensed under CC-BY by the author Hannah Ritchie (2020).



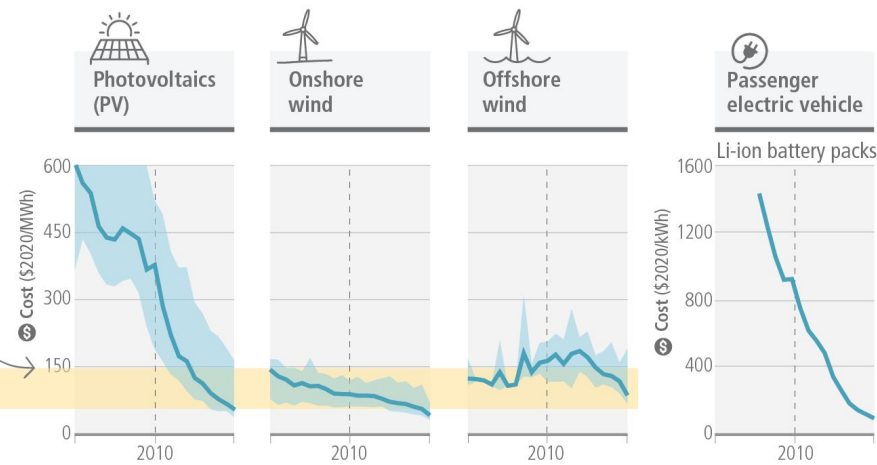


# GHG in Electric Energy production

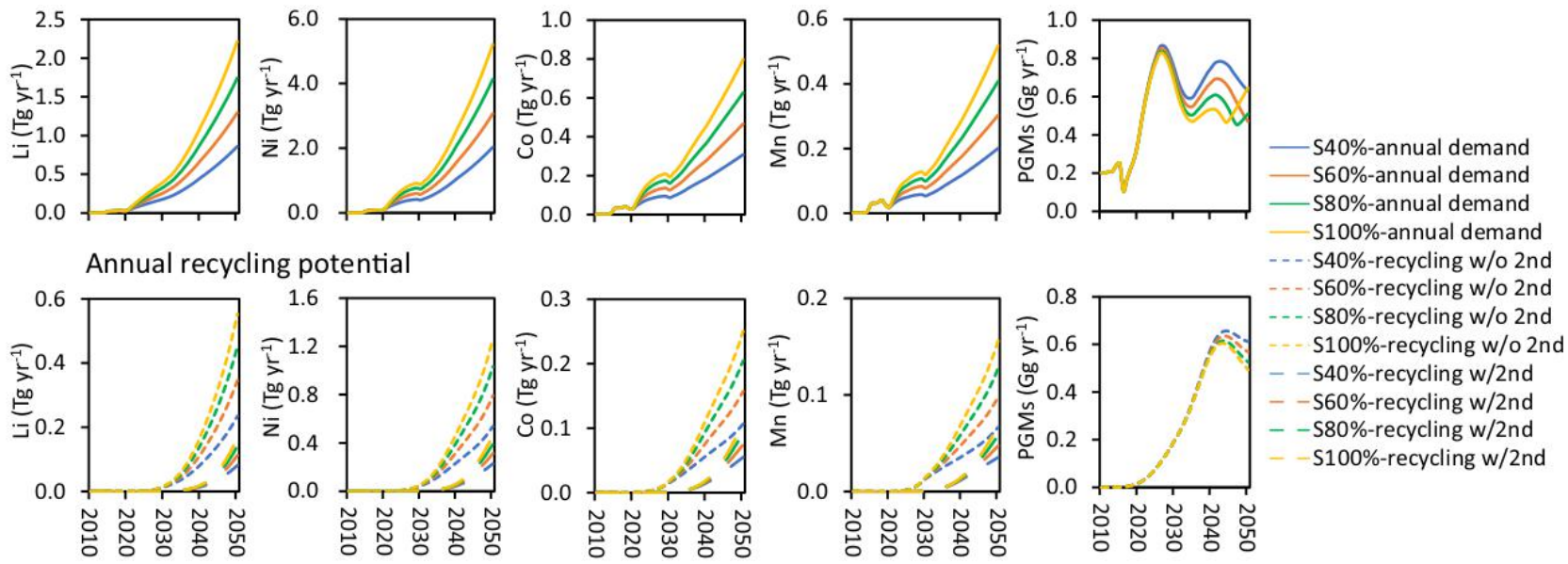
Electrification seems the answer. But car batteries will be a bottleneck in the near future.

Renewable electricity generation is increasingly price-competitive and some sectors are electrifying

**a) Market Cost**  
 Since AR5, the unit costs of some forms of renewable energy and of batteries for passenger EVs have fallen.  
 below this point, costs can be less than fossil fuels  
 Fossil fuel cost (2020)



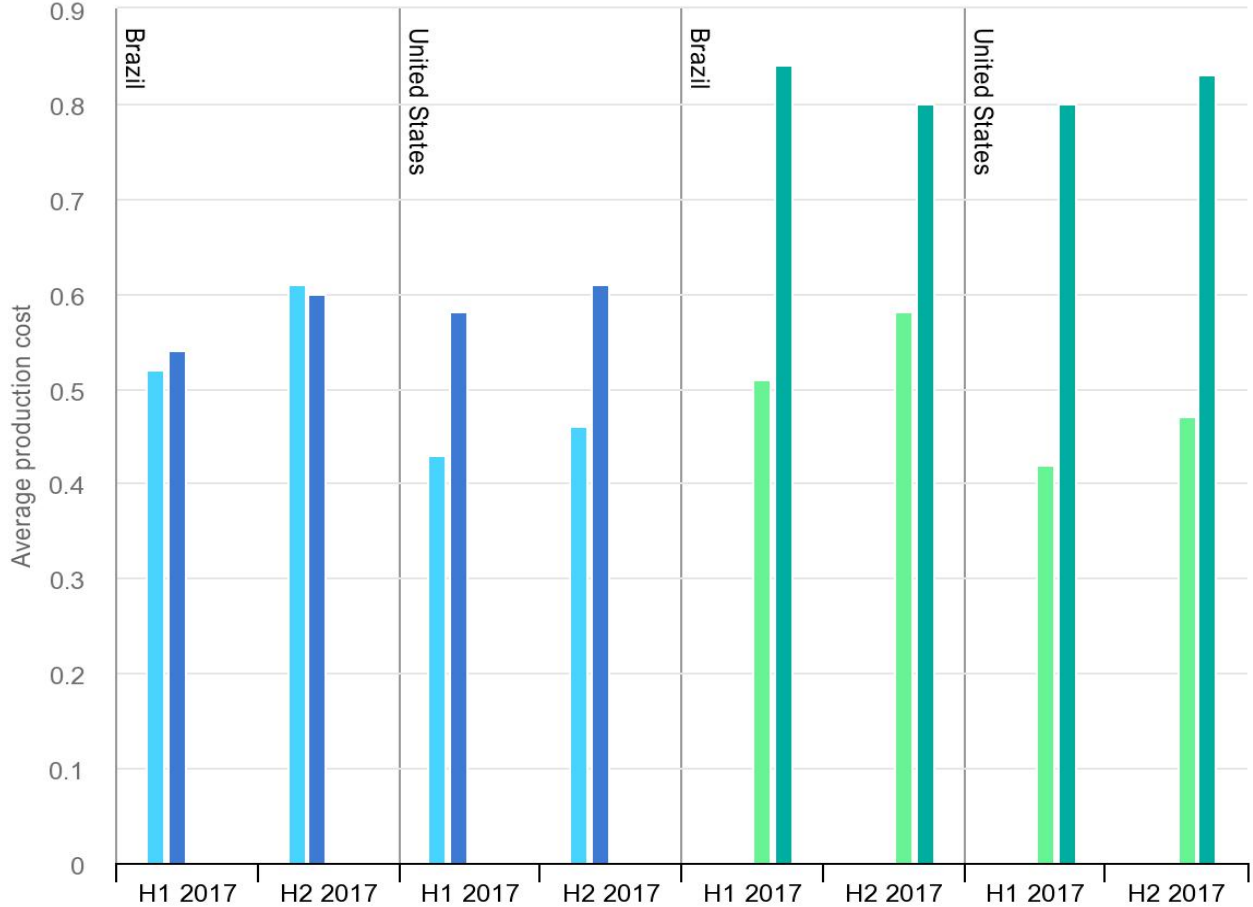
IPCC, 2023: Climate Change 2023: Synthesis Report of the IPCC Sixth Assessment Report (AR6).



Zhang C, Zhao X, Sacchi R, You F. Trade-off between critical metal requirement and transportation decarbonization in automotive electrification, 2023, nature communications, 14, 1616.

# Economic feasibility of biofuels

## Biofuels costs compared to fossil fuel alternatives:



H1: First half of the year, H2: second half

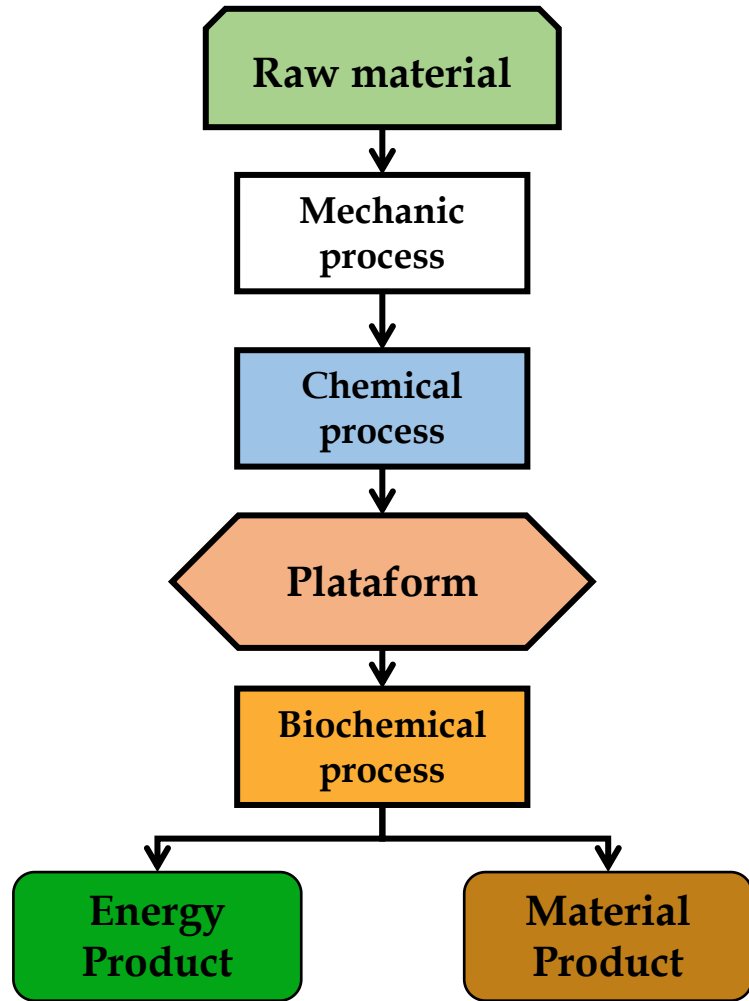
- gasoline
- ethanol
- diesel
- biodiesel

### Europe (2014-2016):

- Ethanol: 15-22 €/GJ (gasoline: 12 €/GJ)
- Biodiesel: 16-21 €/GJ (diesel: 11 €/GJ)

IEA, Biofuel and fossil-based transport fuel production cost comparison, 2017, IEA, Paris <https://www.iea.org/data-and-statistics/charts/biofuel-and-fossil-based-transport-fuel-production-cost-comparison-2017>

# Biorefineries



Acording to the International Energy Agency:

“Biorefinery is the sustainable processing of biomass into a spectrum of marketable products (food, feed, materials, chemicals) and energy (fuels, power, heat)”

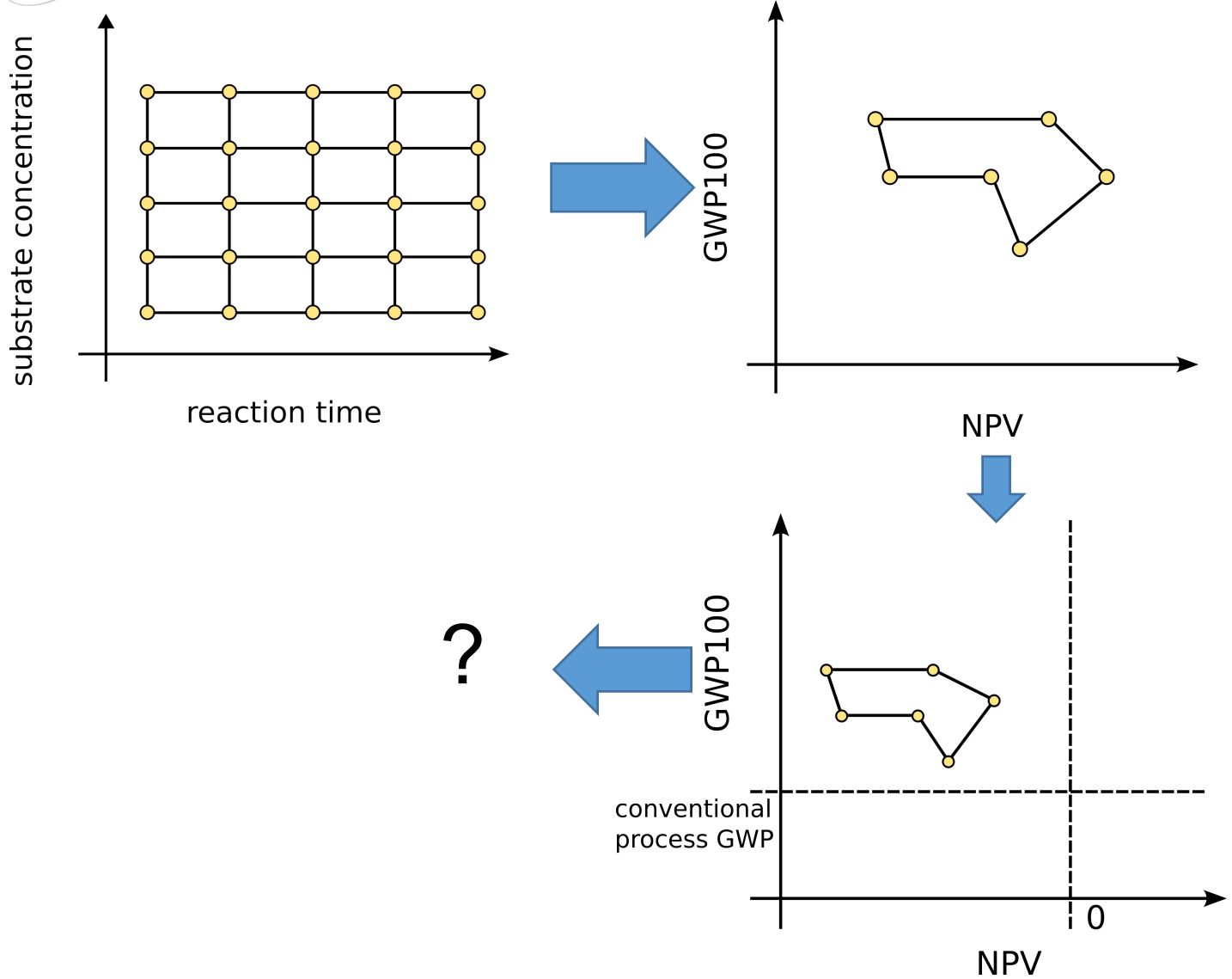
Biorefineries, similarly to oil refineries, are multipurpose plants, with a “backbone” (biofuels) and countless derivatives.

Cherubini, F.; Jungmeier, G.; Wellisch, M.; Willke, T.; Skiadas, I.; Van Ree, R.; Jong, E. Toward a common classification approach for biorefinery systems. *Biofuels, Bioprod. Bioref.* 2009, 3:534-546.





# The problem: These processes are rarely feasible at the experimental conditions



- Optimization will find the best condition. But what if it is not feasible?
- Trying to find feasible conditions means extrapolating the models. Bad idea, specially for biochemical models.
- What information can we get to guide the experimental effort?

# General metrics for biochemical processes

Process metrics	Cost	Annual Production	Biocatalyst yield	Reaction yield	Space-time yield	Product concentration	ee
Units	€/kg	ton/year	$g_{\text{product}}/g_{\text{biocatalyst}}$	%	$g_{\text{product}}/L_{\text{reactor}}/h$	$g_{\text{product}}/L_{\text{reactor}}$	%
Bulk chemical	0.5-10	$10^4$ - $10^6$	$10^3$ - $10^5$	>95	>20	>300	>90
Fine chemical	10-50	$10^2$ - $10^4$	$10^2$ - $10^3$	>90	>2.5	>150	>95
Pharmaceutical chemical	>100	$10$ - $10^3$	$10$ - $10^2$	>90	>1	>60	>95

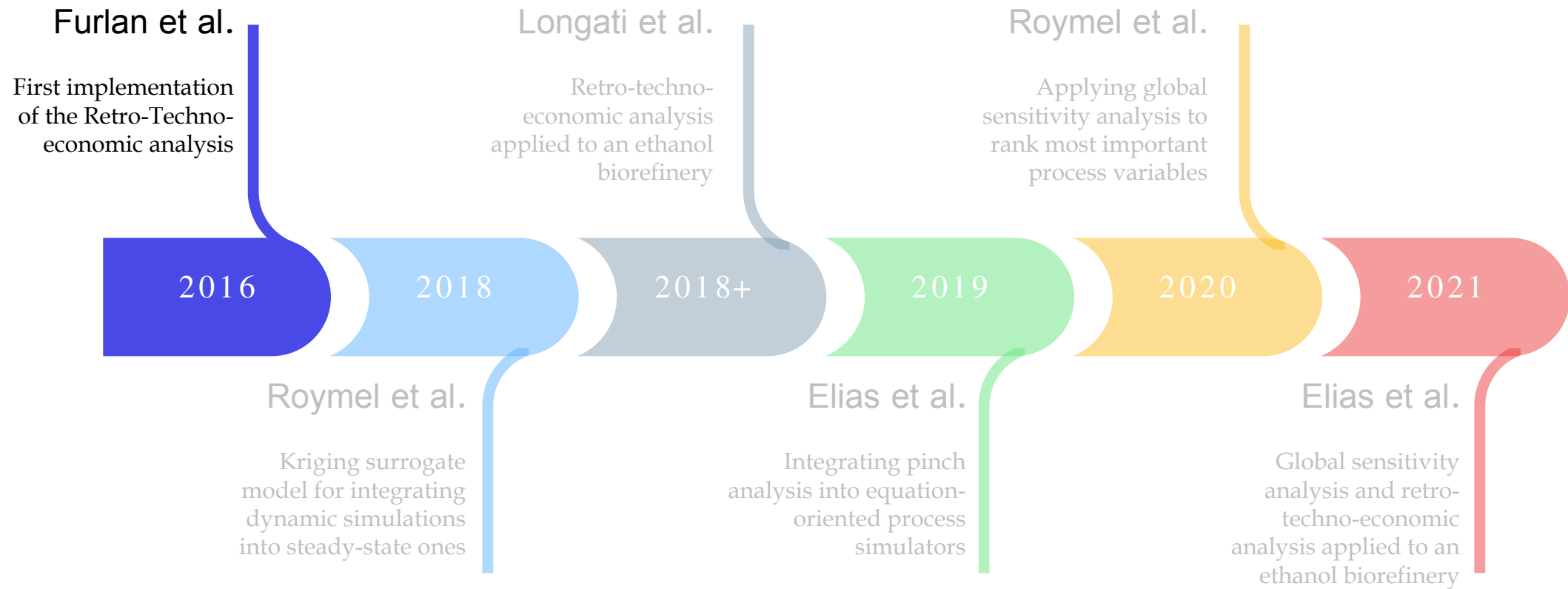
Lima-Ramos, J. A methodology for development of biocatalytic processes, PhD Thesis, Technical University of Denmark, 2013.



**Turning the problem upside down!**

<http://kids.nationalgeographic.com/content/dam/kids/photos/articles/Other%20Explore%20Photos/R-Z/Wacky%20Weekend/UpSide-Down%20Animals/ww-upside-down-animals-humpback-whale.adapt.945.1.jpg>

# The path we took



## Economic and environmental analyses:

- Equations easy to solve, which does not impact the simulation convergence.

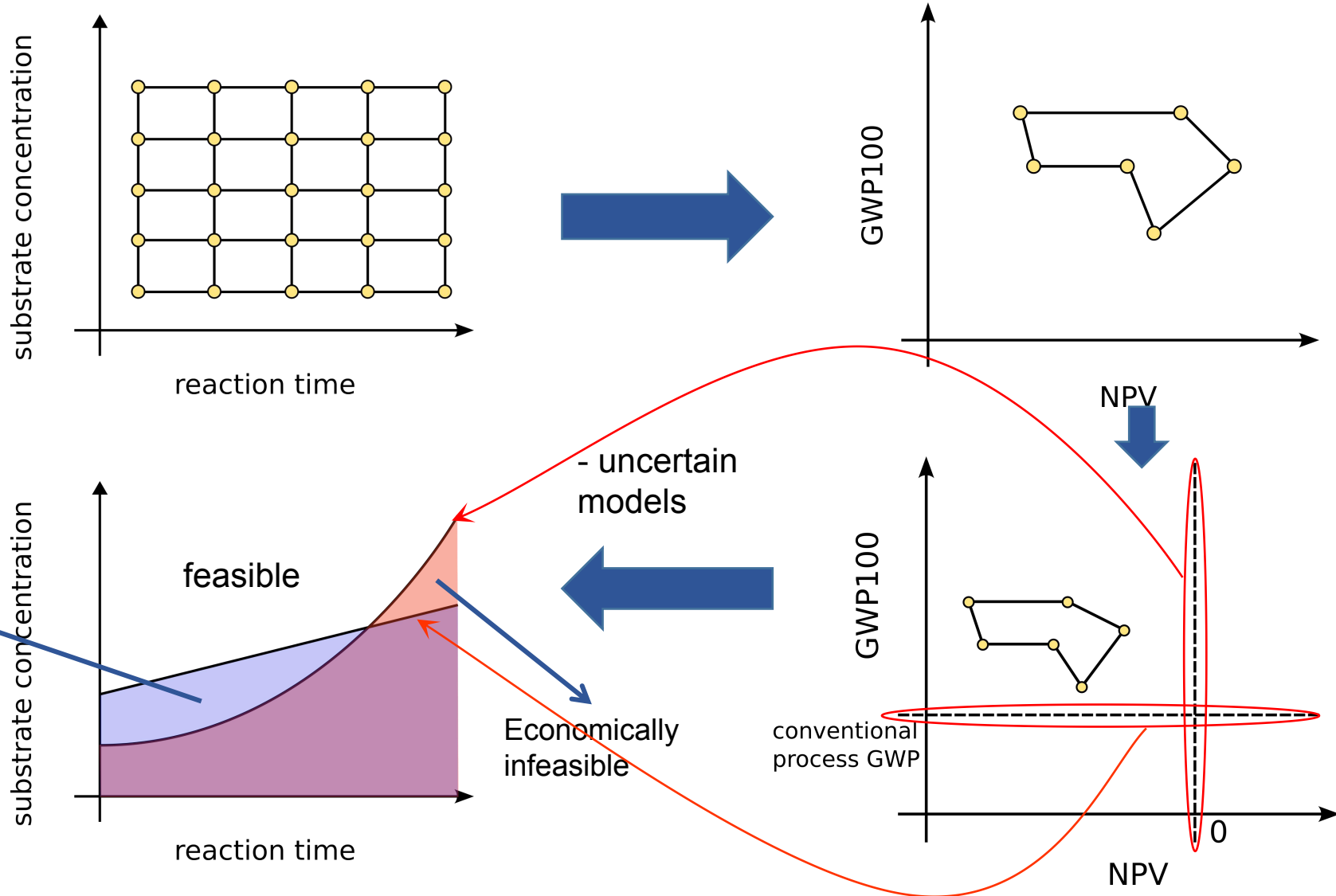
$$NPV = \sum_{i=1}^{Nt} \frac{CF_i(x)}{(1+r)^i} - \sum_{j=1}^{Neq} K_j(A_j(x))^{\alpha_j} \qquad I_i = \sum_{j=1}^M F_j \sum_{k=1}^N \theta_{ik} x_{jk}$$

- We include all equations responsible for both analysis in the simulation procedure, to be solved simultaneously to the process model equations.
- Knowledge about process economic feasibility and impacts are attained at simulation time.



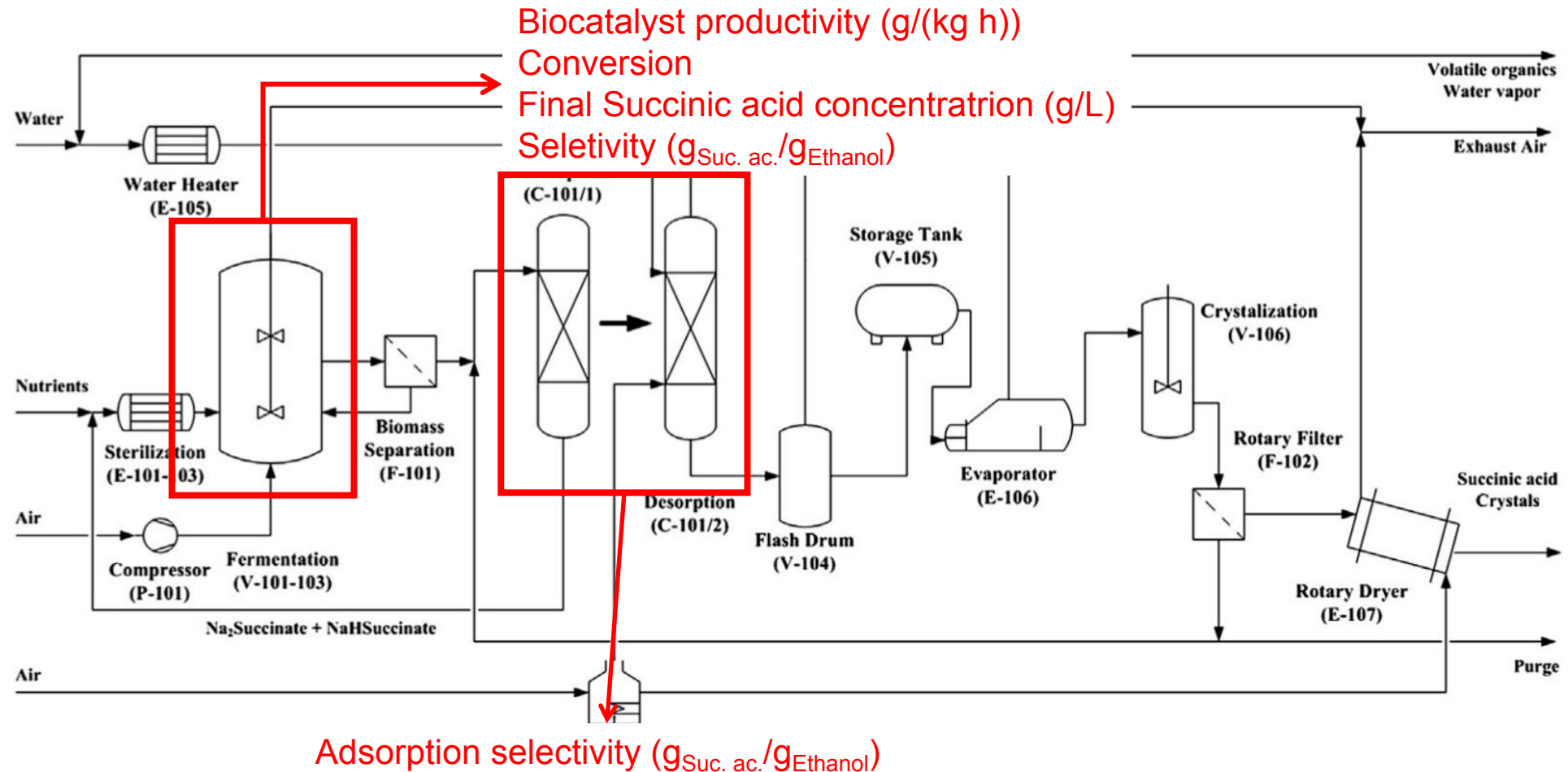


# Furlan: First RTEEA implementation and tests



# Furlan: First RTEEA implementation and tests

## Case study: Succinic acid production from glucose by *Sac. cerevisiae*



Furlan FF, Costa CBB, Secchi AR, Woodley JM, Giordano RC. Retro-Techno-Economic Analysis: Using (Bio)Process Systems Engineering Tools to Attain Process Target Values. Industrial & Engineering Chemistry Research, 2016, 55, 9865-9872.



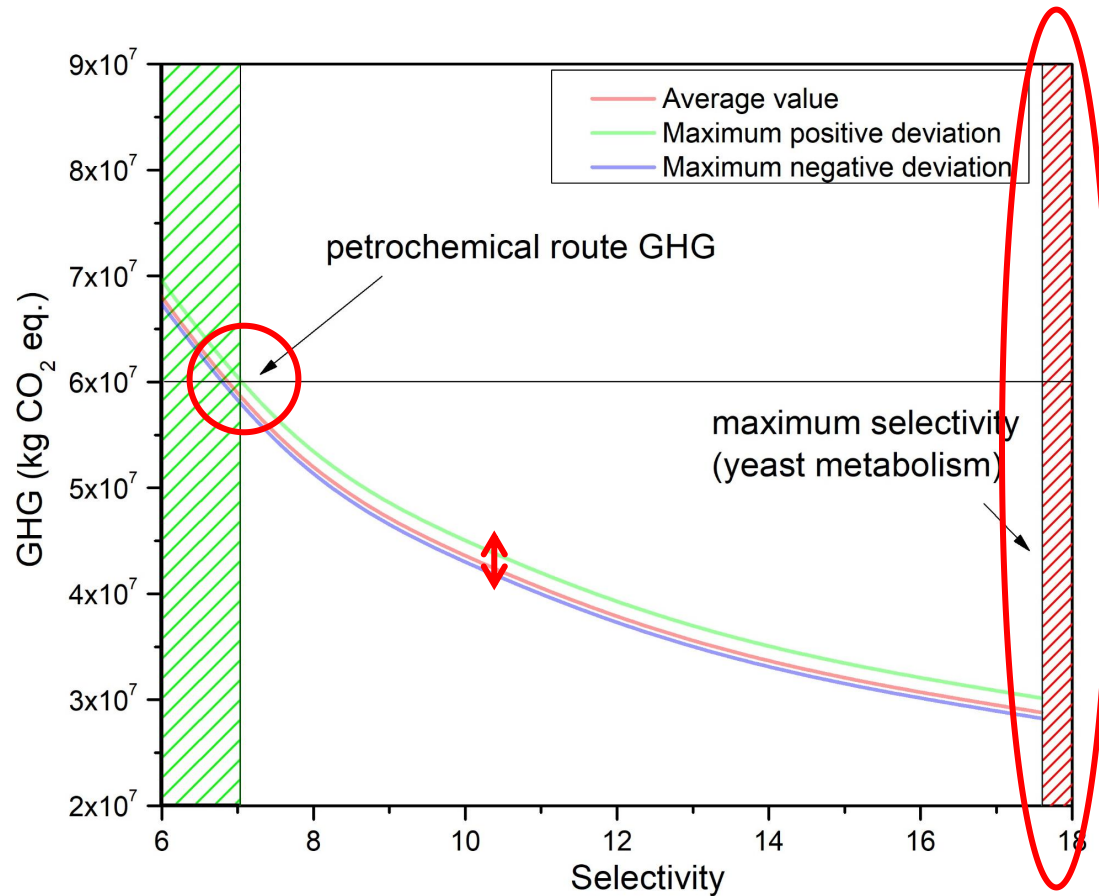
# Furlan: First RTEEA implementation and tests “Global” sensitivity analysis

Simultaneous modeled variables	variables considered					R <sup>2</sup>	
	Csa	Pr	Conv	Selet	Sel_ad	NPV	GHG
5	1	1	1	1	1	0,996	0,994
4	1	1	1	1	0	0,996	0,994
3	1	1	0	1	0	0,996	0,994
2	1	1	0	0	0	0,923	0,086
	0	1	0	1	0	0,109	0,994
1	0	0	0	1	0	0,001	0,994
	1	0	0	0	0	0,672	0,039

Elias AM; Furlan FF, Ribeiro MPA, Giordano RC. Retro-Techno-Economic-Environmental Analysis (RTEEA) from the cradle: a new approach for process development. European Symposium on Computer Aided Process Engineering, 2018, Graz, Austria.

# Furlan: First RTEEA implementation and tests

## Results: GHG emission



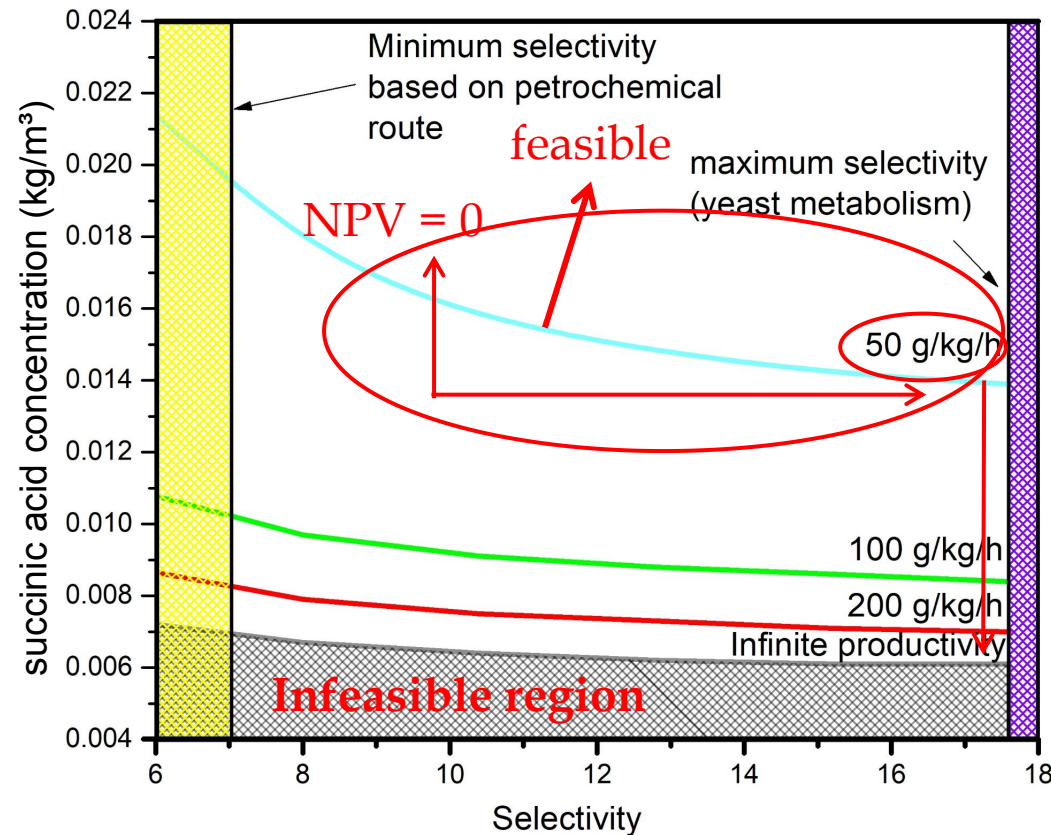
Greenhouse gas emissions from petrochemical route = 1.94 kg CO<sub>2</sub>eq/kg succinic acid. Equivalent to a selectivity of 7.0

Limit imposed by the yeast metabolism on selectivity (equal to 17.6)

Effect on GHG caused by all the other variables

# Furlan: First RTEEA implementation and tests

## Results: Economic feasibility



Biocatalyst productivity (g/ (kg h)).

The effect of biocatalyst productivity decreases sharply. Hardly justify increasing it beyond 100 g/kg/h.

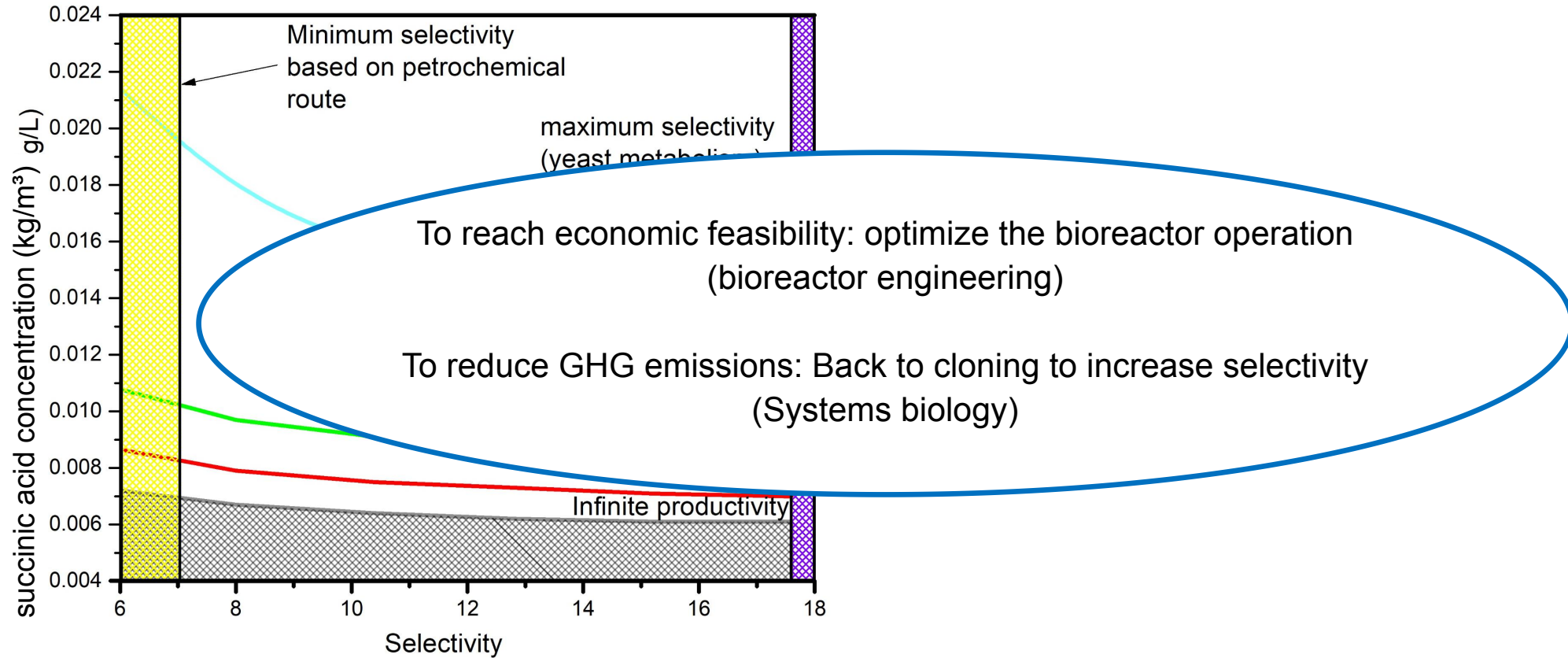
Infinite biocatalyst productivity limit (equals to a zero reaction time) Therefore, the minimum feasible product concentration is 7 g/L

Increasing selectivity does not help much. It's better to increase the maximum product concentration.



# Furlan: First RTEEA implementation and tests

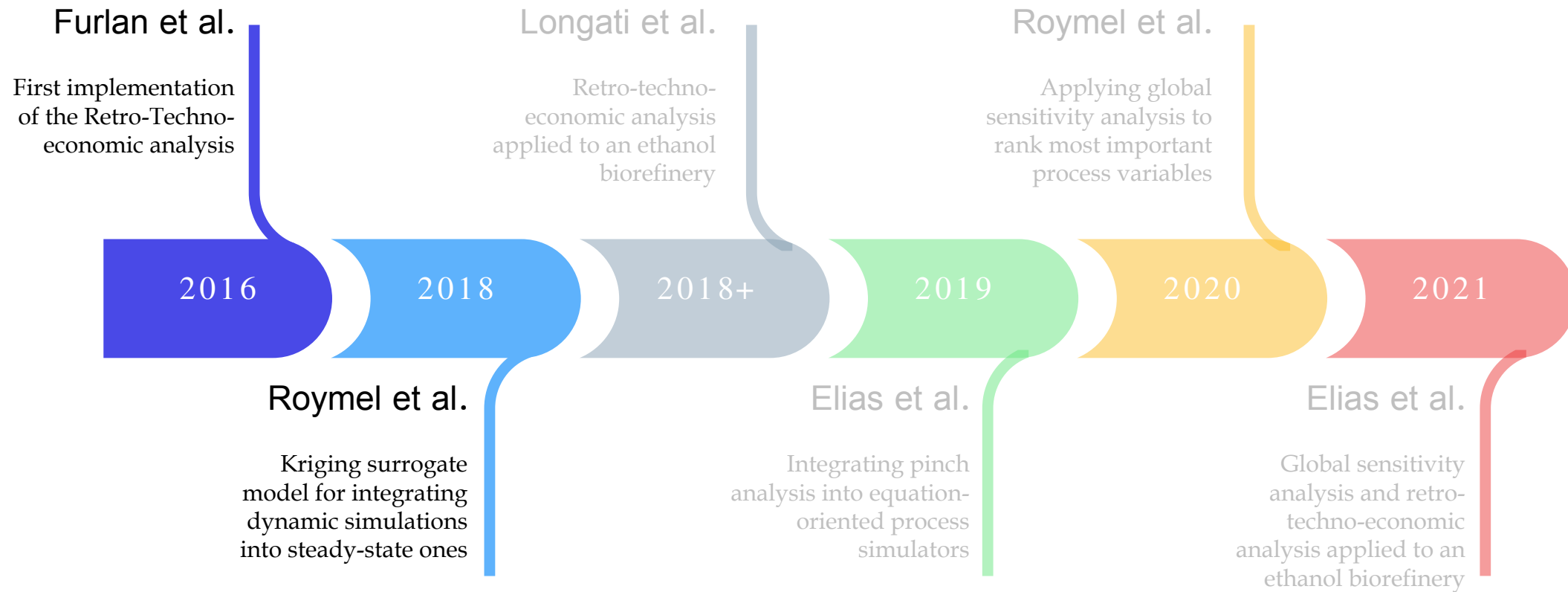
## Results: Economic feasibility



Elias AM; Furlan FF, Ribeiro MPA, Giordano RC. Retro-Techno-Economic-Environmental Analysis (RTEEA) from the cradle: a new approach for process development. European Symposium on Computer Aided Process Engineering, 2018, Graz, Austria.



# The path we took





## Roymel: Kriging-based metamodels to integrate dynamic models into whole plant steady-state simulations

There are several types of models for Kriging, but to approximate the behavior of nonlinear systems, the most used are ordinary Kriging and universal Kriging.

$$\hat{y}(x) = \mu(x) + z(x)$$

In this model, the first term represents the variation in the mean of the response variable and the second term represents the stochastic part of the response.

Characteristics:

- Perfect interpolator;
- $\mu(x)$  is normally a low order polynomial;
- $z(x)$  is normally an exponential function of the distance between points;

# Roymel: Kriging-based metamodels to integrate dynamic models into whole plant steady-state simulations

Model of enzymatic hydrolysis of sugarcane bagasse describing the conversion of cellulose as a function of solids fraction, enzymatic load and reaction time.

$$\frac{dC}{dt} = -r_1 - r_2$$

$$\frac{dG_2}{dt} = 1.056r_1 - r_3$$

$$\frac{dG}{dt} = 1.111r_2 + 1.053r_3$$

$$\frac{dH}{dt} = -r_4$$

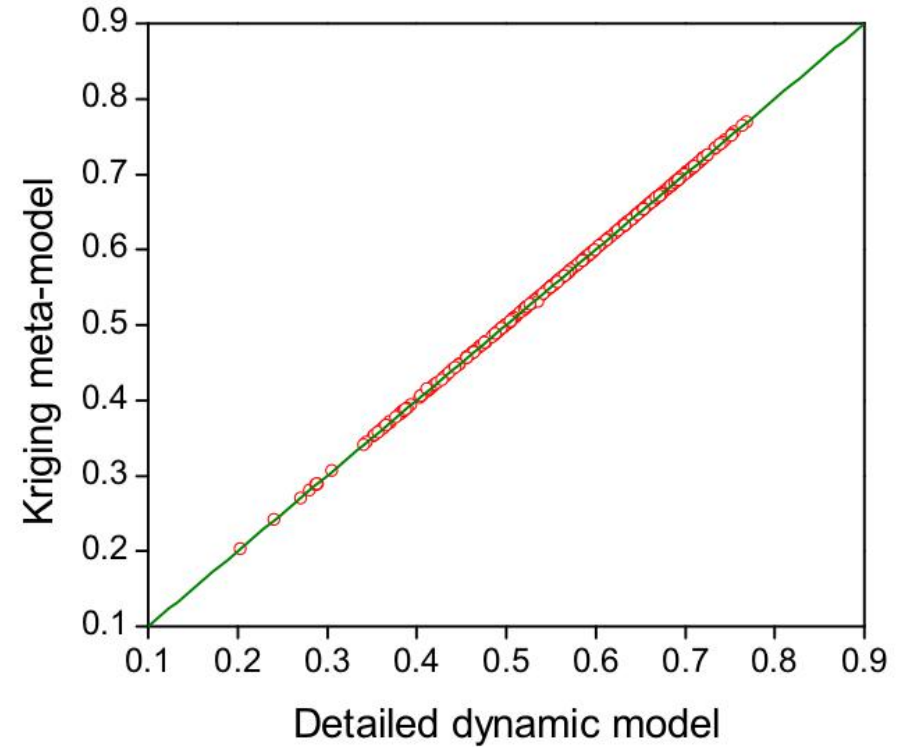
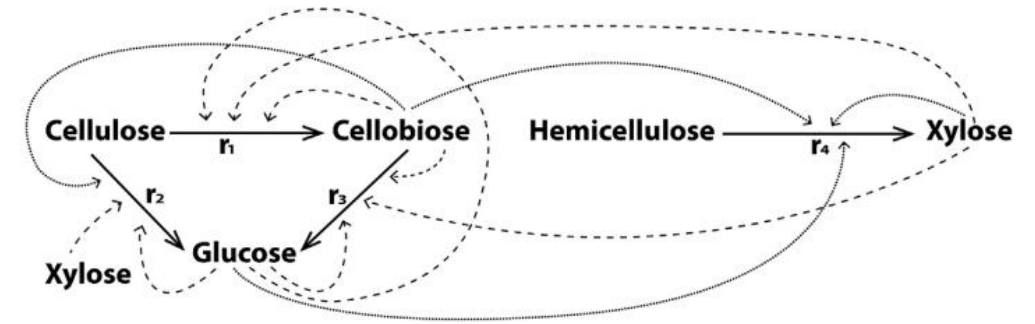
$$\frac{dX}{dt} = 1.136r_4$$

$$r_i = \frac{k_{ir} E_{BC} R_s S}{1 + \frac{G_2}{k_{iG_2}} + \frac{G}{k_{iG}} + \frac{X}{k_{iX}}}$$

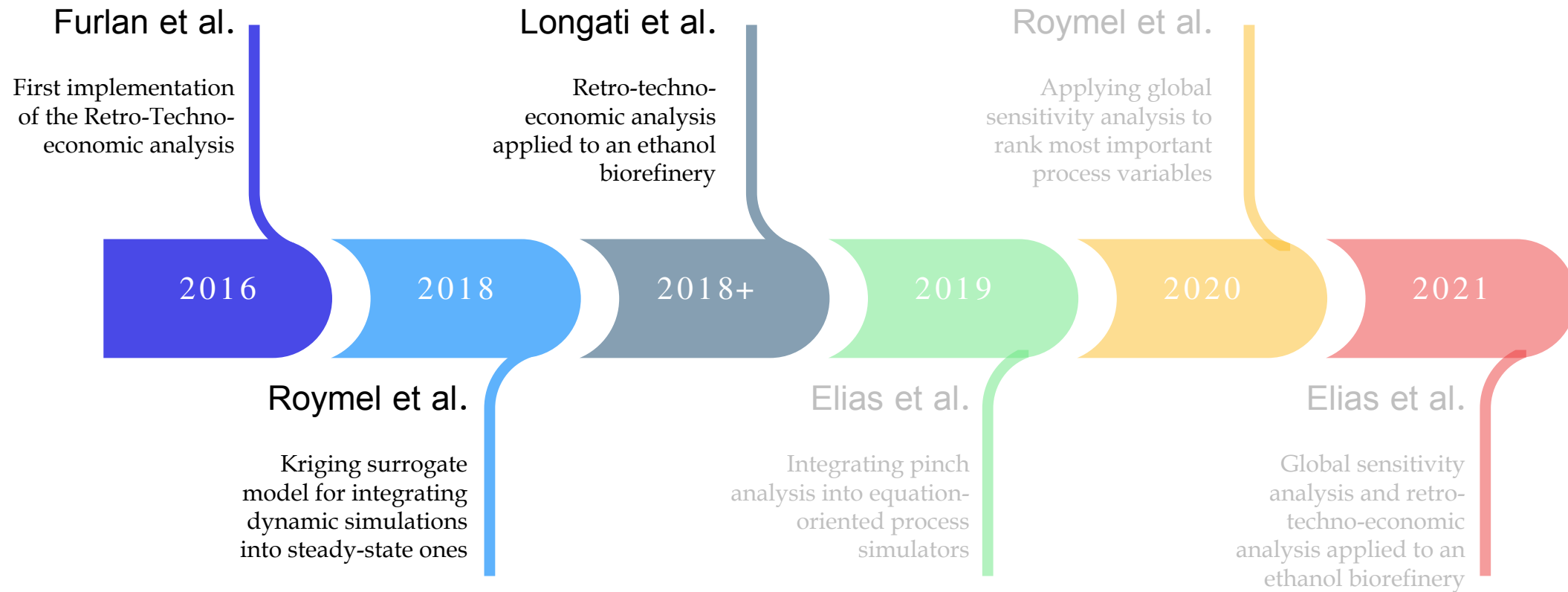
$i = 1, 2, 4$

$$r_3 = \frac{k_{2r} E_F G_2}{K_{3M} \left( 1 + \frac{G}{k_{3IG}} + \frac{X}{k_{3IX}} \right) + G_2}$$

- Universal kriging using a second order polynomial for  $\mu(x)$  and Gaussian function for  $z(x)$ .
- Absolute accuracy of  $10^{-2}$  mol/l.
- Kriging needed 500 points to achieve accuracy, while pure interpolation needed 2409 points to achieve the same result.

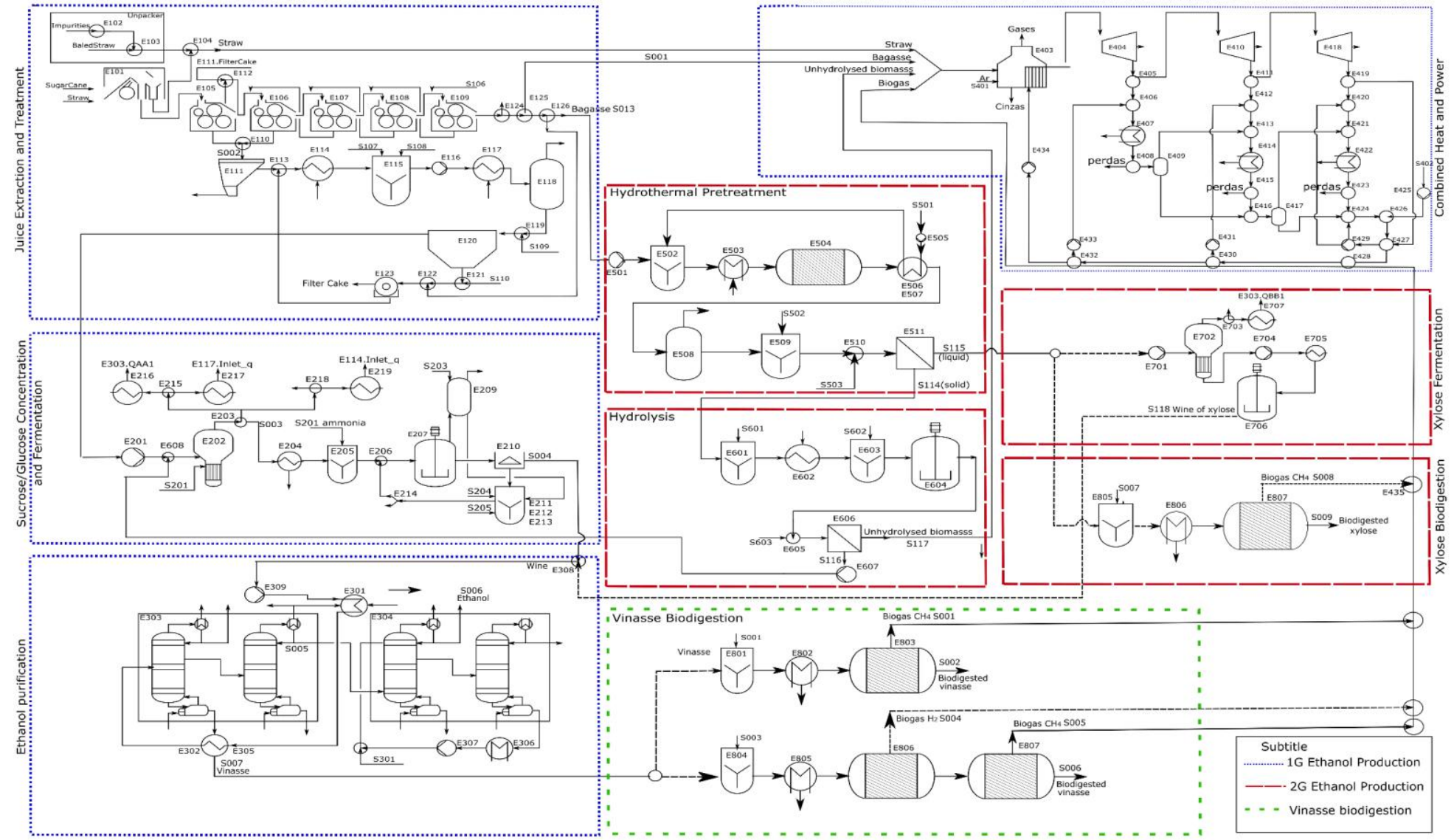


# The path we took



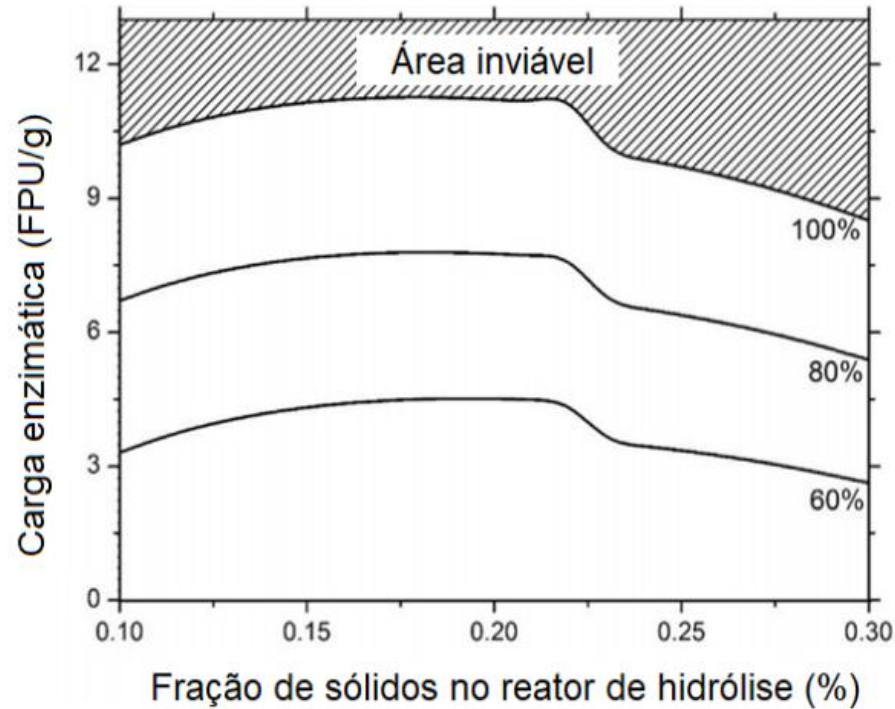


# Longati: RTEA applied to 1G-2G Ethanol biorefinery



Longati, 2018

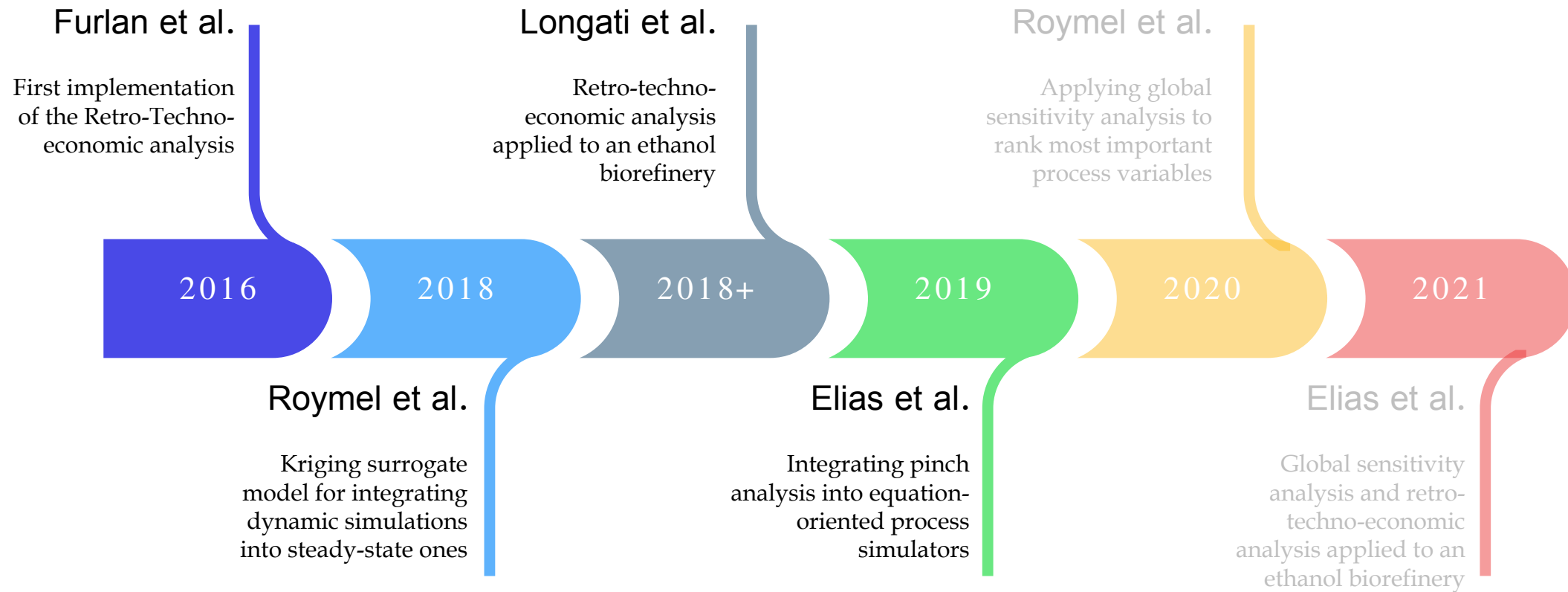
# Longati: RTEA applied to 1G-2G Ethanol biorefinery



- Highest feasible enzyme load of 11.4 FPU/gcellulose.
- Negative curvature due to a tradeoff between solid load in the reactor (increasing final glucose concentration) and glucose recovery in the downstream stages.
- Discontinuities around 22% of solids are due to layout changes in the heat integration.



# The path we took



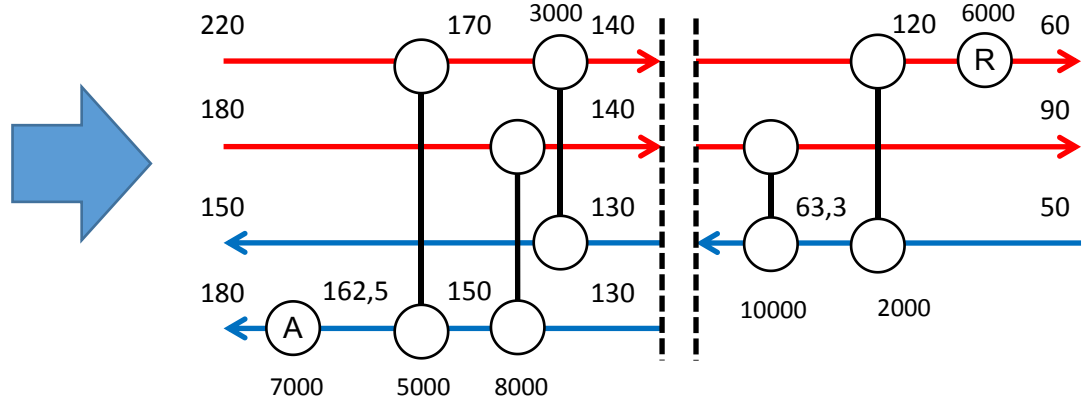
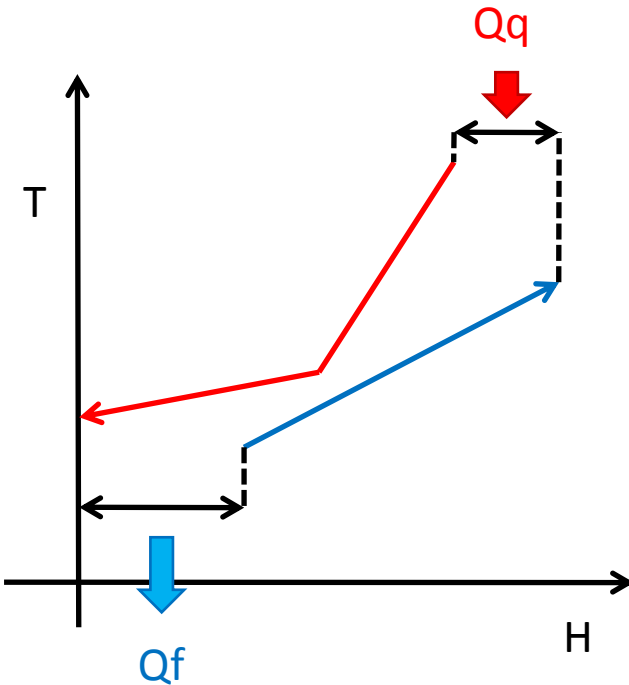


# Elias: Integrating pinch analysis into equation-oriented process simulators

1- Minimum demands for hot and cold utilities

2- Construction of the heat exchanger network

3- Economic analysis



Approximate estimate based on the calculation of investment cost targets.

# Elias: Integrating pinch analysis into equation-oriented process simulators

## Results: Distance from the optimum

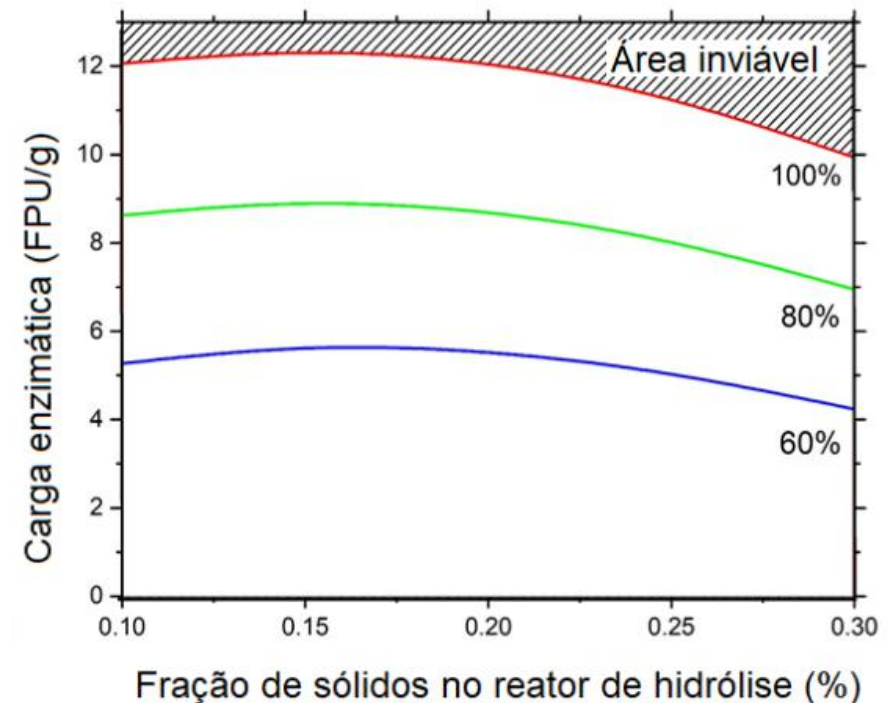
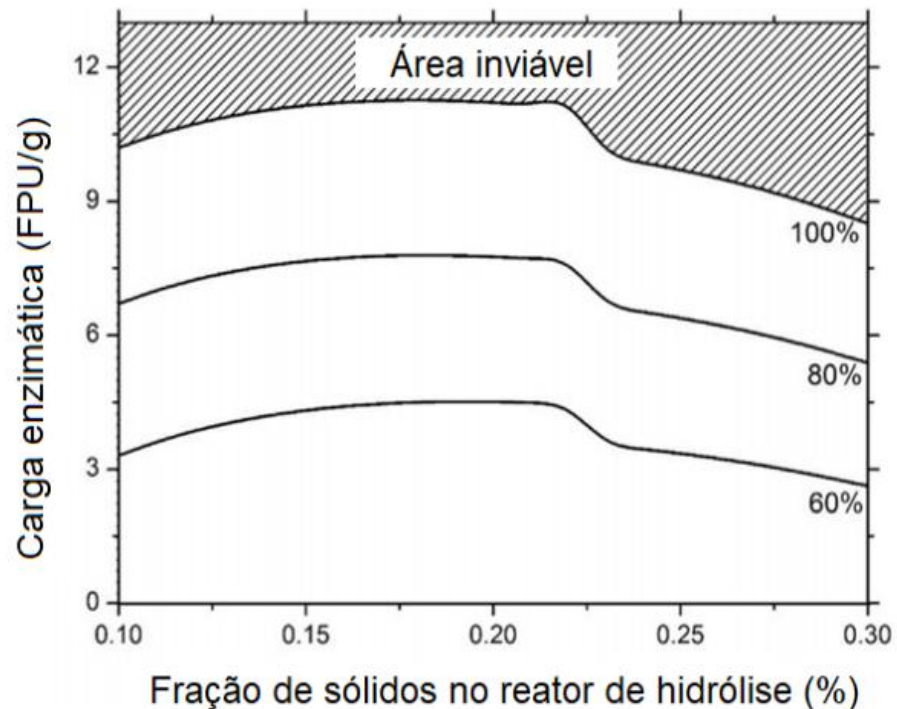
Case study	$\Delta T_{\min}$	# of units	Total annualized cost(US\$/ano)		Deviation from optimum(%)
			Literature	Our work	
1	5	6	117.062,3	127.268,0	8,0
2	10	9	573.205,0	611.322,0	5,7
3	10	10	43.314,0	48.500,2	10,7
4	10	27	1.510.891,0	1.606.330,0	5,9

AM Elias, RC Giordano, AR Secchi, FF Furlan. Integrating pinch analysis and process simulation within equation-oriented simulators. Comp Chem Eng, 130, 106555, 2019.

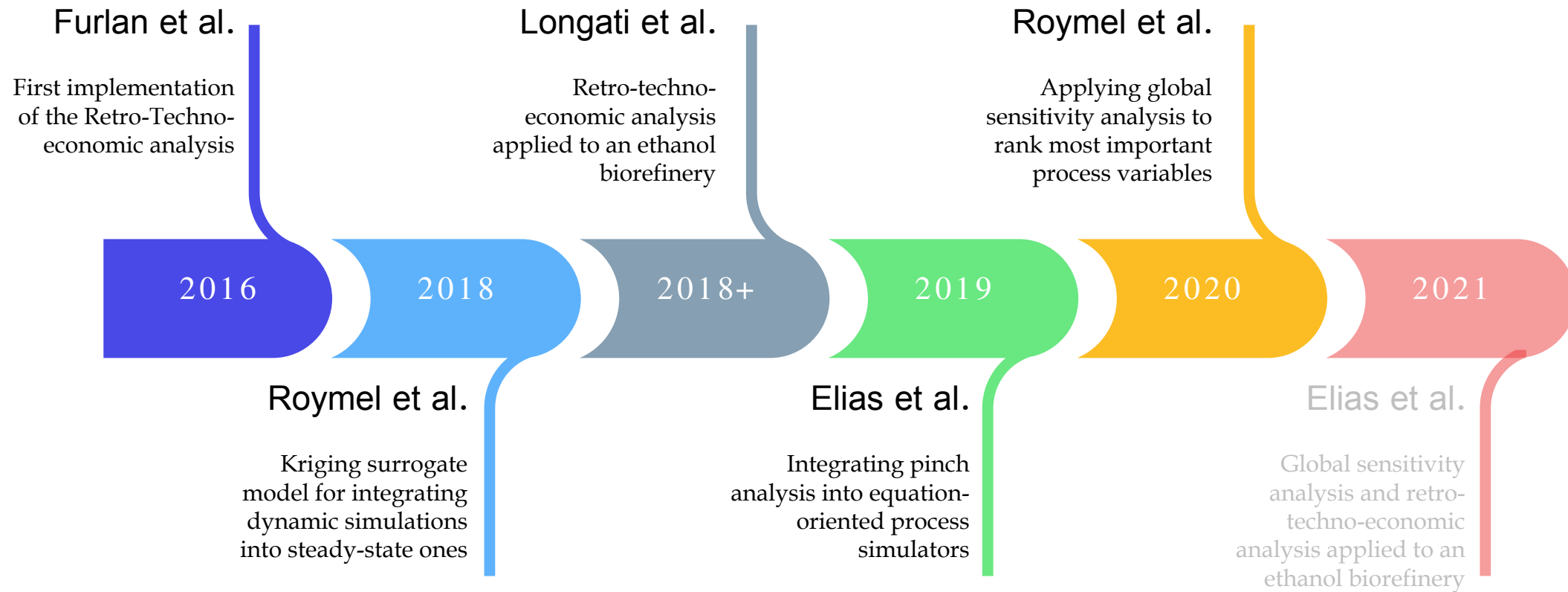
# Elias: Integrating pinch analysis into equation-oriented process simulators

## Results: Pinch analysis applied to a biorefinery

Extra advantage of using Pinch analysis:  
 Replaces the process heat exchanger network with a “virtual” network.  
 Increases simulation robustness and smoothes layout transitions.

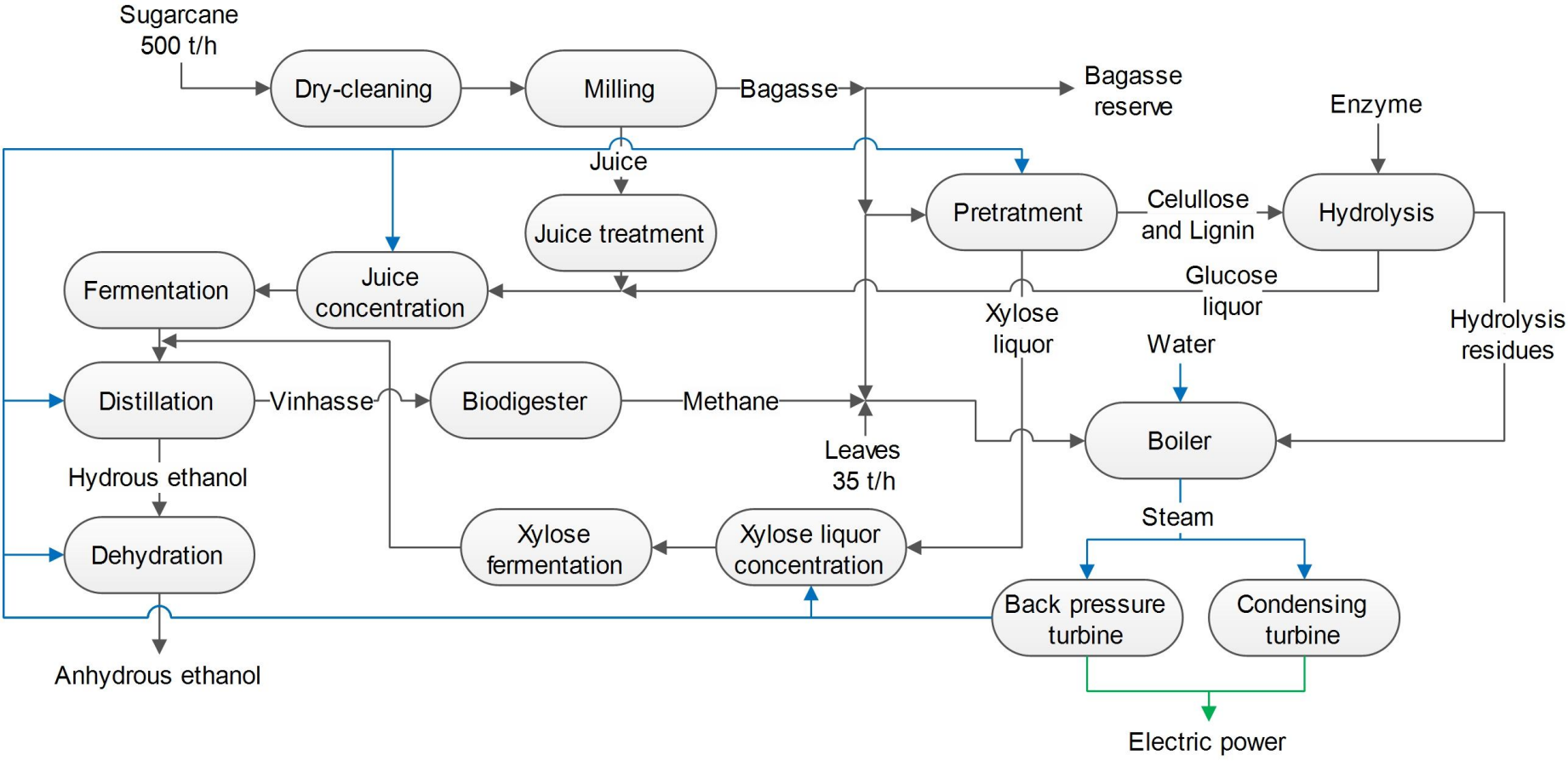


# The path we took





# Roymel: Applying Global Sensitivity Analysis to rank most important variables





# Roymel: Applying Global Sensitivity Analysis to rank most important variables

## Morris Global sensitivity analysis

Elementary effects method:

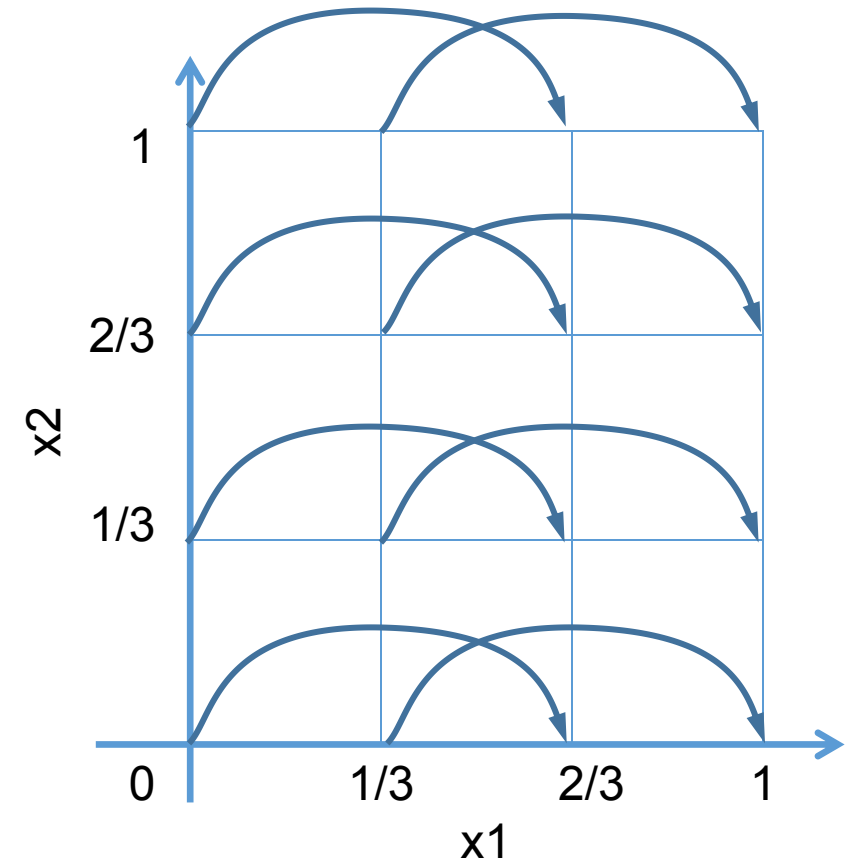
Based on the analysis of the elementary effects of the input variables on the output ones:

$$EE_i = \frac{[Y(X_1, X_2, \dots, X_i + \Delta, \dots, X_k) - Y(X_1, X_2, \dots, X_k)]}{\Delta}$$

$$\mu_i = \frac{1}{r} \sum_{j=1}^r EE_i^j$$

$$\mu_i^* = \frac{1}{r} \sum_{j=1}^r |EE_i^j|$$

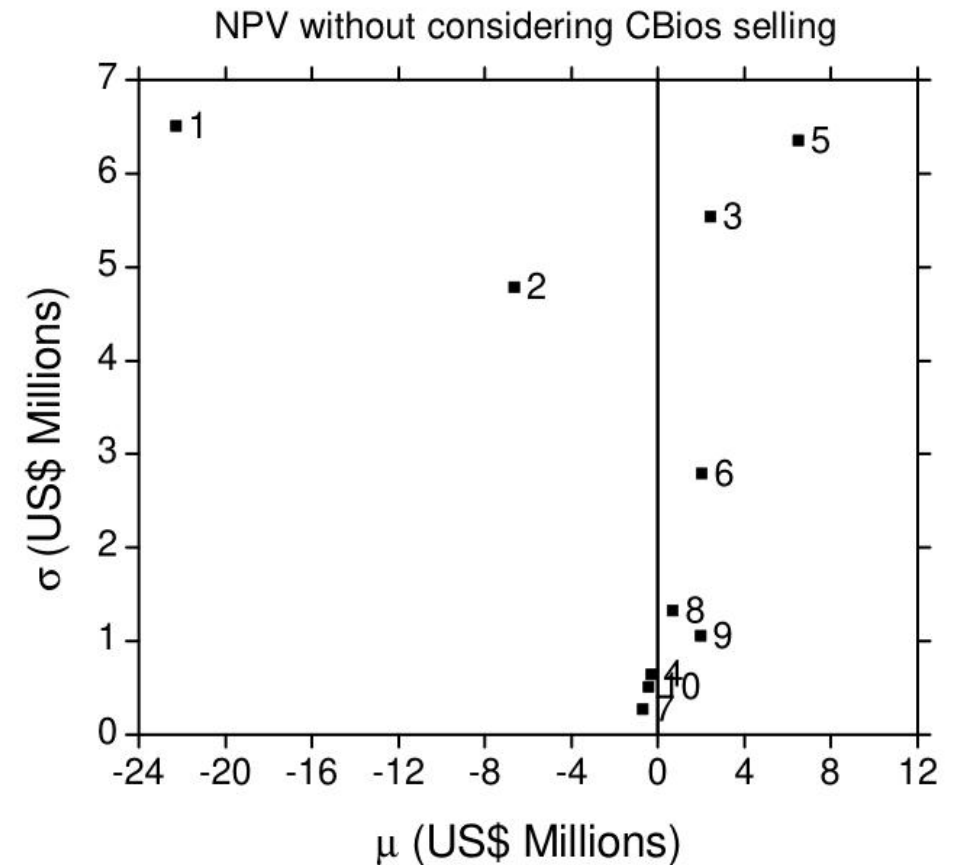
$$\sigma_i^2 = \frac{1}{r-1} \sum_{j=1}^r (EE_i^j - \mu_i)^2$$



# Roymel: Applying Global Sensitivity Analysis to rank most important variables

## Results: Morris method

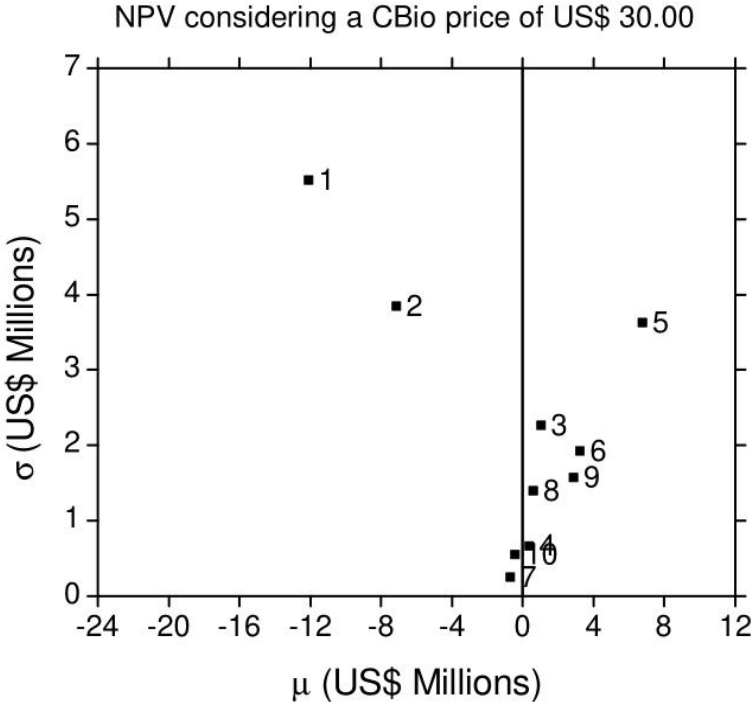
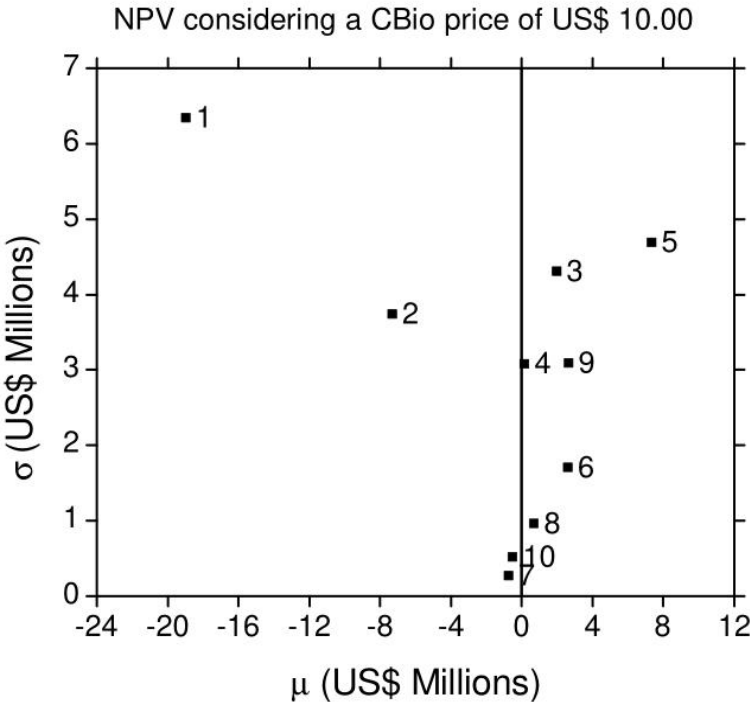
Code	Parameter	$\mu$	$\sigma$
P1	Ratio of bagasse diverted to 2G	-22.25	6.50
P5	Solid fraction in pretreatment	6.52	6.35
P2	Enzyme load in hydrolysis	-6.63	4.78
P3	Solid fraction in hydrolysis	2.43	5.54
P6	Pretreatment yield	2.04	2.78
P9	Fermentation xylose yield	1.99	1.05
P8	Xylose concentration in fermentation	0.70	1.32
P7	Pretreatment residence time	-0.68	0.26
P4	Residence time in hydrolysis	-0.26	0.65
P10	Fermentation residence time	-0.43	0.51





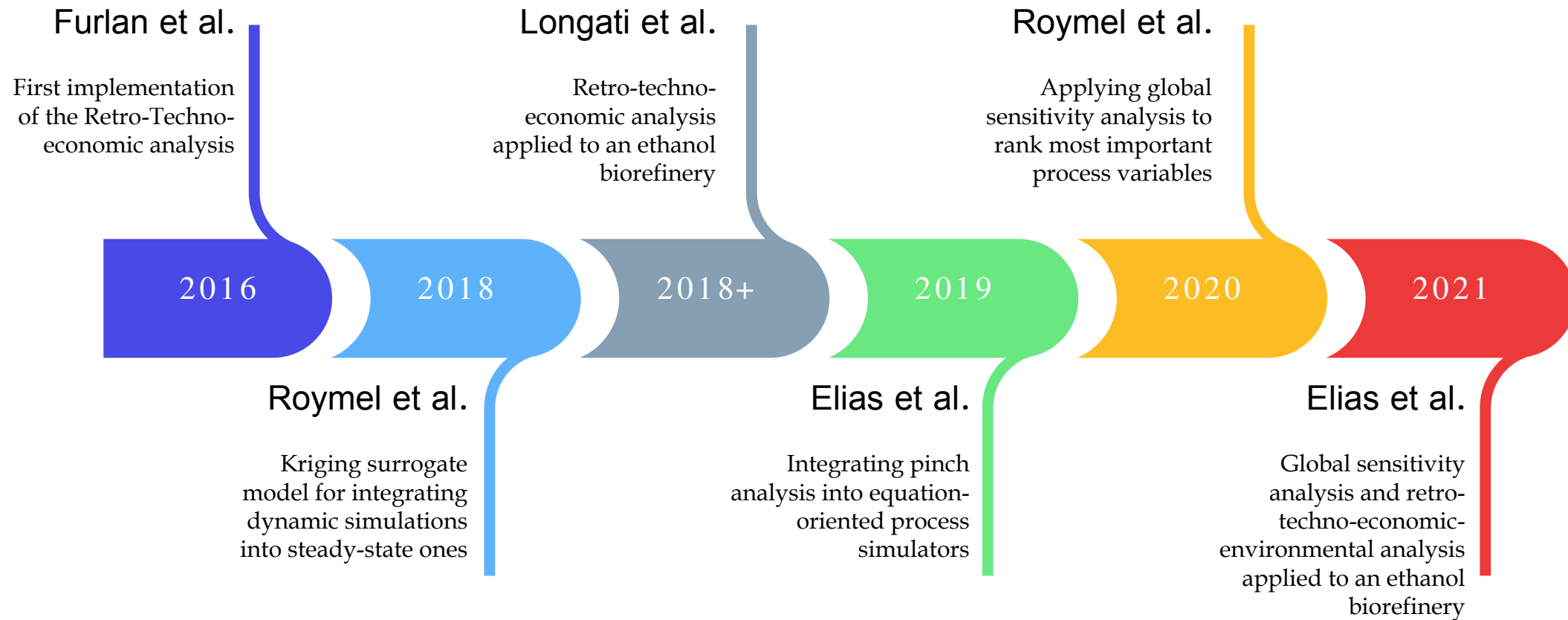
# Roymel: Applying Global Sensitivity Analysis to rank most important variables

## Results: Influence of CBios price



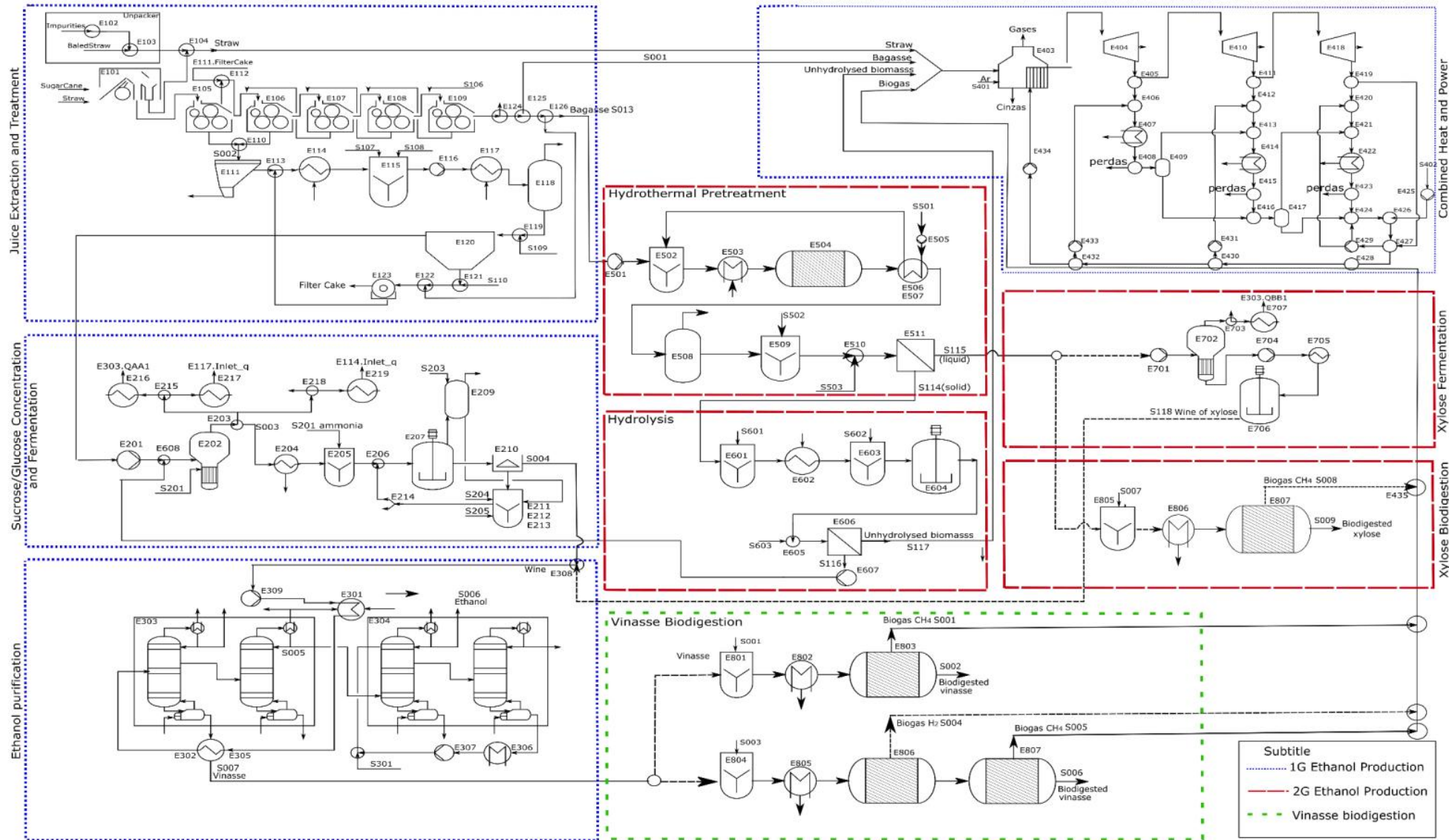
	$\mu$ (CBios = 0)	$\mu$ (CBios = 10)	$\mu$ (CBios = 30)	$\sigma$
P1	-22.25	-18.95	-12.07	~6

# The path we took





# Elias: GSA and RTEEA applied to an ethanol biorefinery



# Elias: GSA and RTEEA applied to an ethanol biorefinery

## Methods: Global sensitivity analysis

Variance based methods:

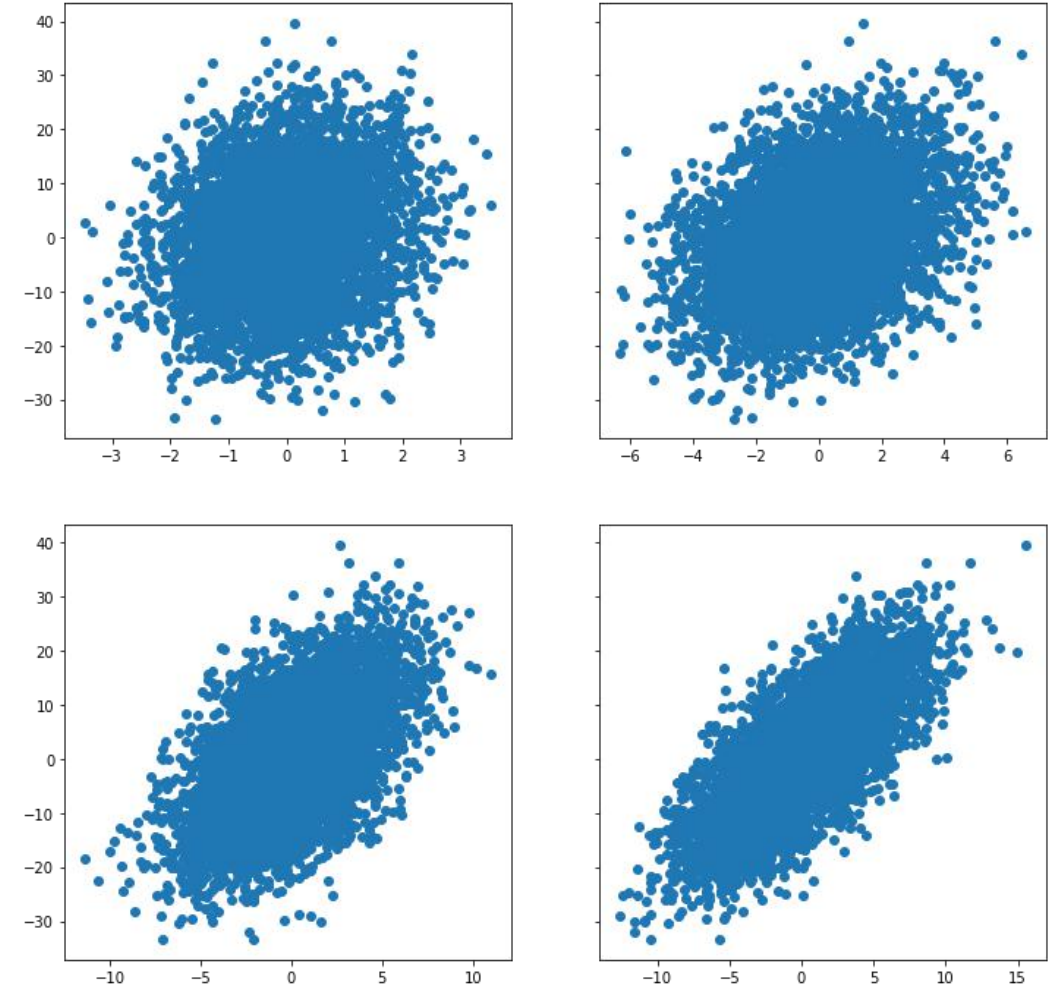
Estimates the sensitivity as the variance of the expected value of the output when the input changes (first order) or the expected decrease in the variance of the output when the input is fixed (total effect).

First-order sensitivity index:

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X_i))}{V(Y)}$$

Total effect:

$$S_{Ti} = \frac{E_{X_{\sim i}}(V_{X_i}(Y|X_{\sim i}))}{V(Y)}$$







# Elias: GSA and RTEEA applied to an ethanol biorefinery

## Results: Global sensitivity analysis

Sobols total effects

Variables	Metrics										
	AD	ODP	HT	FWAET	MAET	TET	AC	EU	GWP100	PO	NPV
PSMF	0.35	0.44	0.47	0.40	0.40	0.50	0.36	0.33	0.28	0.00	0.00
PT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00
PCGC	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.04	0.05
PHXC	0.03	0.03	0.04	0.03	0.03	0.04	0.04	0.04	0.03	0.01	0.00
HSMF	0.03	0.04	0.06	0.04	0.05	0.07	0.03	0.03	0.01	0.02	0.01
HEL	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.07	0.11	0.76	0.68
HC	0.43	0.35	0.34	0.39	0.39	0.32	0.41	0.42	0.41	0.15	0.17
HRT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07
XC	0.14	0.12	0.08	0.12	0.12	0.07	0.10	0.10	0.13	0.02	0.02

Elias AM, Longati AA, Giordano RC; Furlan FF. Retro-Techno-Economic-Environmental Analysis improves the operation efficiency of 1G-2G bioethanol and bioelectricity facilities. Applied Energy, 2021, 282, 116133.



# Elias: GSA and RTEEA applied to an ethanol biorefinery

## Results: Grouping metrics using K-means

	GROUP 1	GROUP 2	GROUP 3
PSMF	0.004	0.443	0.330
PT	0.000	0.010	0.010
PCGC	0.045	0.012	0.021
PHXC	0.005	0.034	0.034
HSMF	0.015	0.052	0.023
HEL	0.724	0.000	0.056
HC	0.158	0.357	0.417
XC	0.020	0.101	0.119
HRT	0.033	0.000	0.000

Group 1: NPV e PO

Group 2: ODP, HT, FWAET, MAET e TET

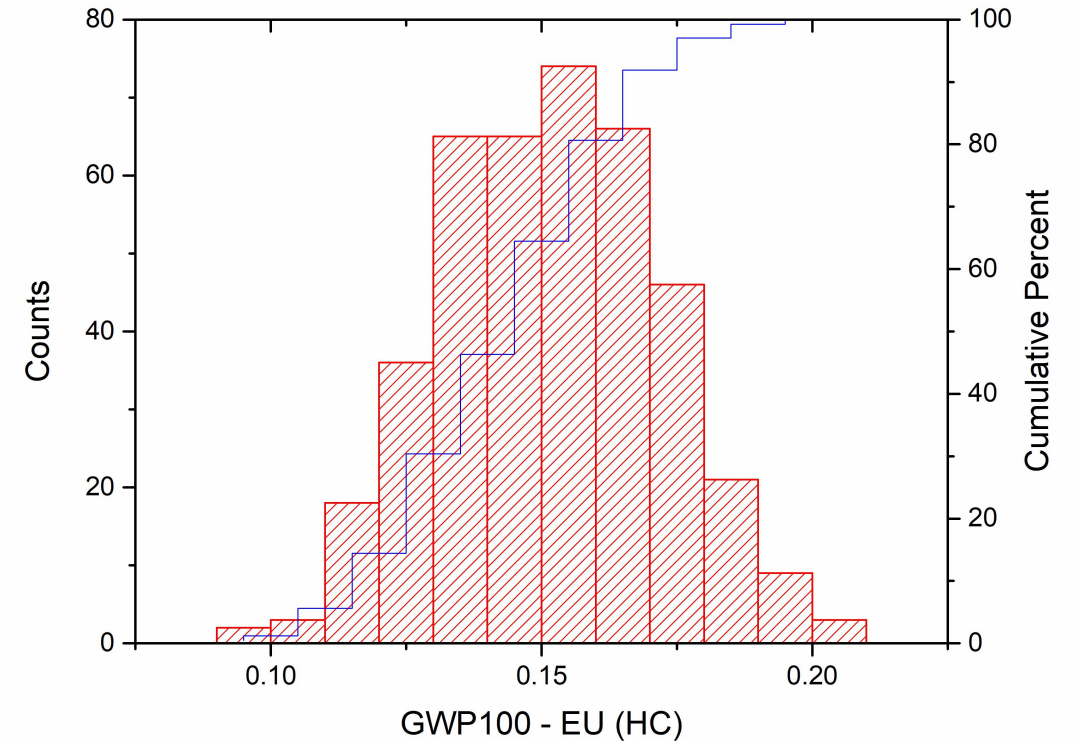
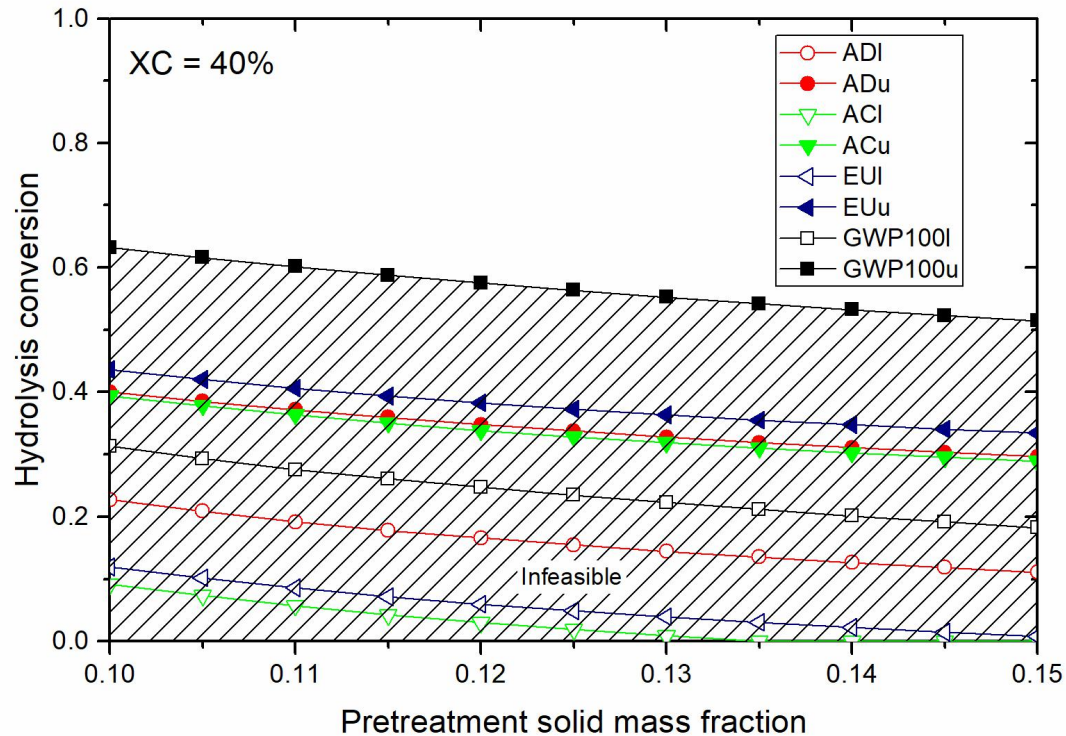
Group 3: AD, EU, AC e GWP100

Elias AM, Longati AA, Giordano RC; Furlan FF. Retro-Techno-Economic-Environmental Analysis improves the operation efficiency of 1G-2G bioethanol and bioelectricity facilities. Applied Energy, 2021, 282, 116133.

# Elias: GSA and RTEEA applied to an ethanol biorefinery

## Results: Isometric curves analyses

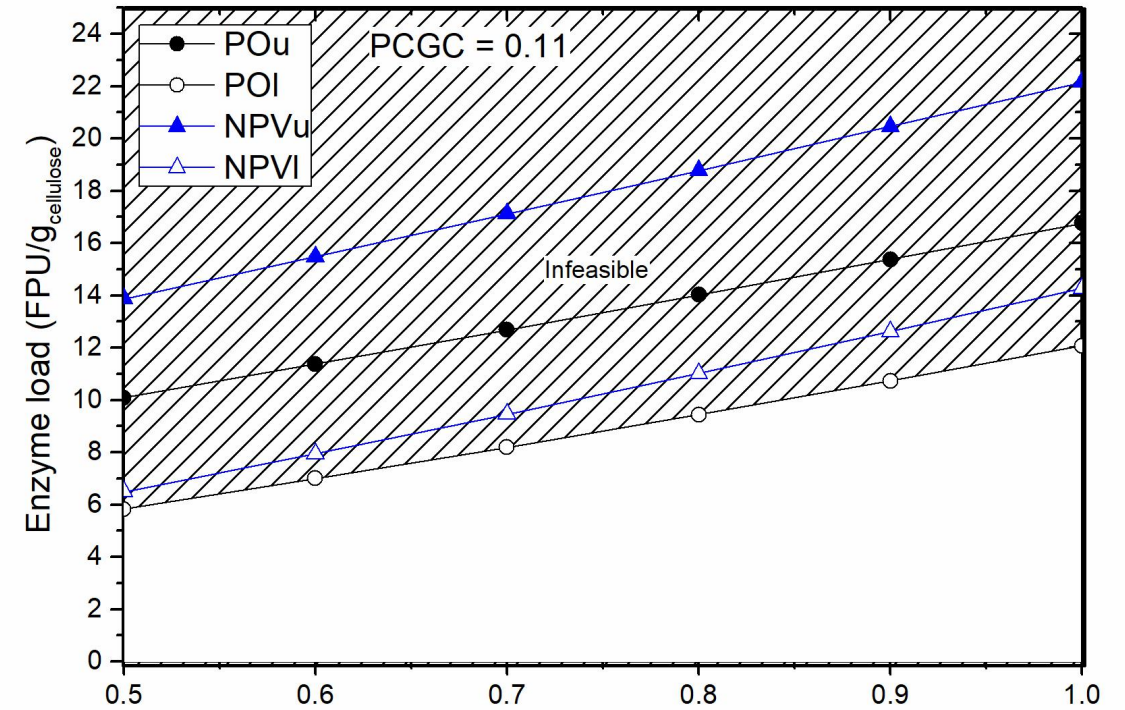
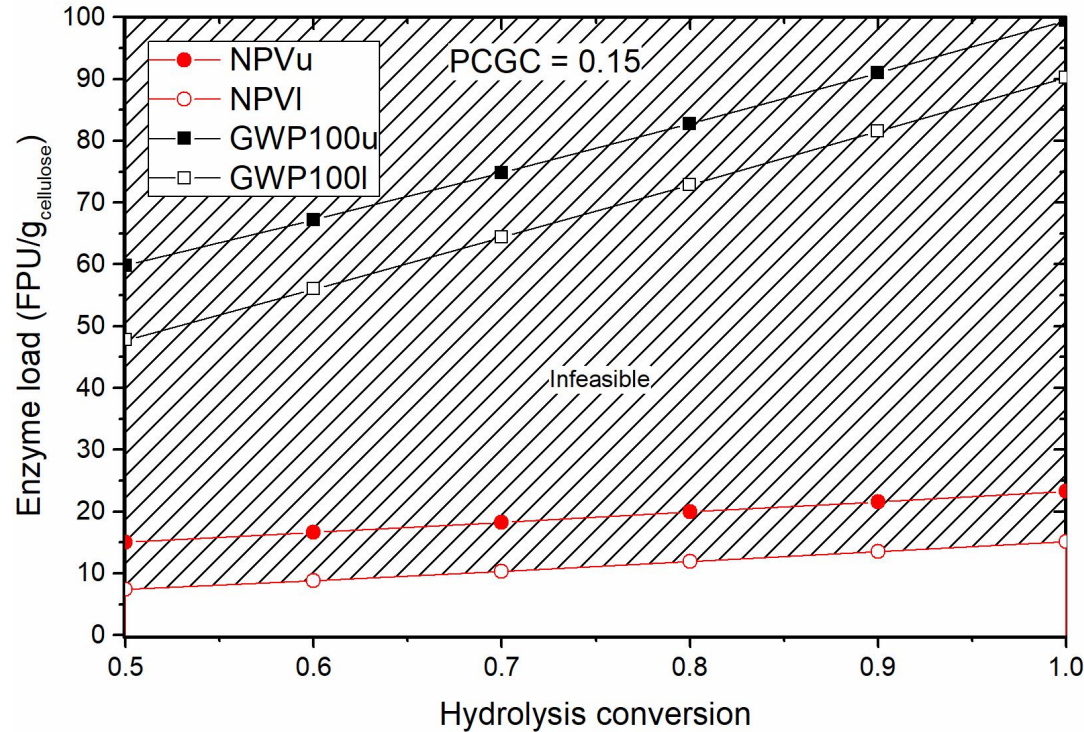
Group 3: AD, EU, AC e GWP100



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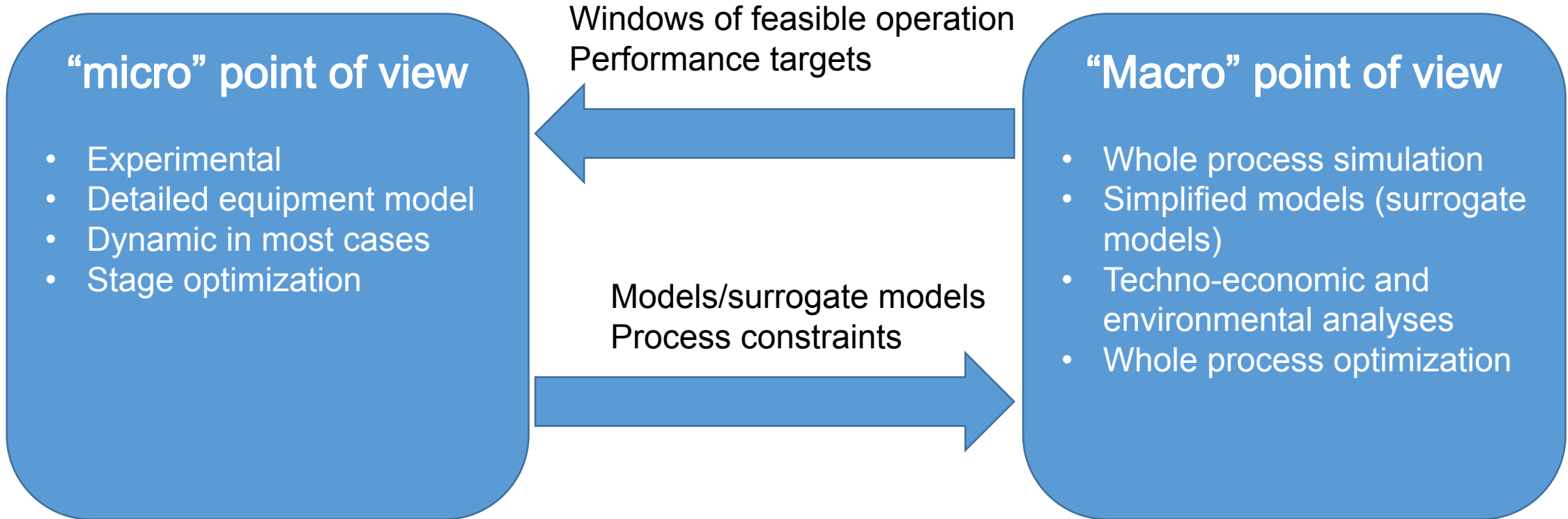
# Elias: GSA and RTEEA applied to an ethanol biorefinery

## Results: Isometric curves analyses



Reprinted from Applied Energy, 282, Elias AM, Longati AA, Giordano RC; Furlan FF., Retro-Techno-Economic-Environmental Analysis improves the operation efficiency of 1G-2G bioethanol and bioelectricity facilities, 116133, Copyright (2021), with permission from Elsevier

# Connecting two points of view





## Summary

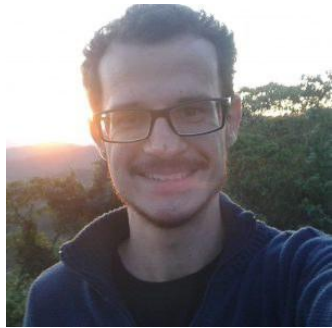
- Transition to a low carbon economy, reaching net zero, is urgent;
- Biofuels, inside a biorefinery perspective, are/will be fundamental to this transition, substituting fossil fuels where electrification is (still) not feasible;
- Biorefineries can turn these biofuels feasible, by associating high added value product to its production process.
- These inovative processes/products under research are rarely studied at lab scale in industrialy feasible operating conditions;
- Construction of windows of feasible operation from process simulation and Techno-economic-environmental analysis, using preliminary experimental data, can guide future experiments towards more industrialy interesting and lower impact conditions.



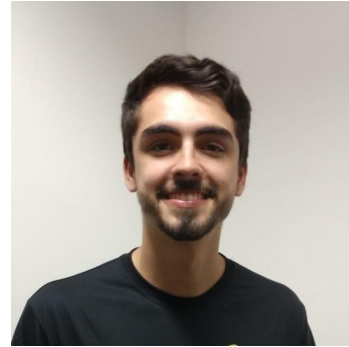


# Research Group

## Undergraduate and graduate students



Felipe Furlan



Gabriel Silva



Christian Martins



Breno Batista

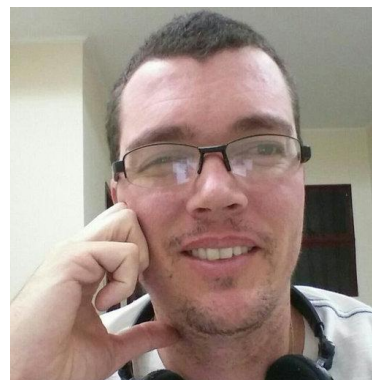
## Former graduate students/colaborators



Simone Carvalho



Andreza Longati



Andrew Elias



Ediane Alves

