

Focus Period Linköping 2022

Multilayer Hybrid Models for Power Outage Analysis of a Brazilian Distribution Company

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Introducing myself



- ✓ Full Professor (2019) of Applied Statistical Methods in the Department of Production Engineering at the Federal University of Minas Gerais/Brazil.
- ✓ I really enjoy data modelling.
- ✓ Research interests are: **statistical models** applied to the electrical sector, applied statistics, network analysis, **spatial statistics**, **time series analysis**, **artificial neural network** theory and applications.

Research Motivation

Statistical/computational modeling of **CEMIG-D** business model using databases and technical knowledge (2019-2021)

Generation



Transmission



Distribution




Hybrid AI – Where data-driven and model-based methods meet



The distribution company with the largest concession area in Brasil (**562.760 km²**)



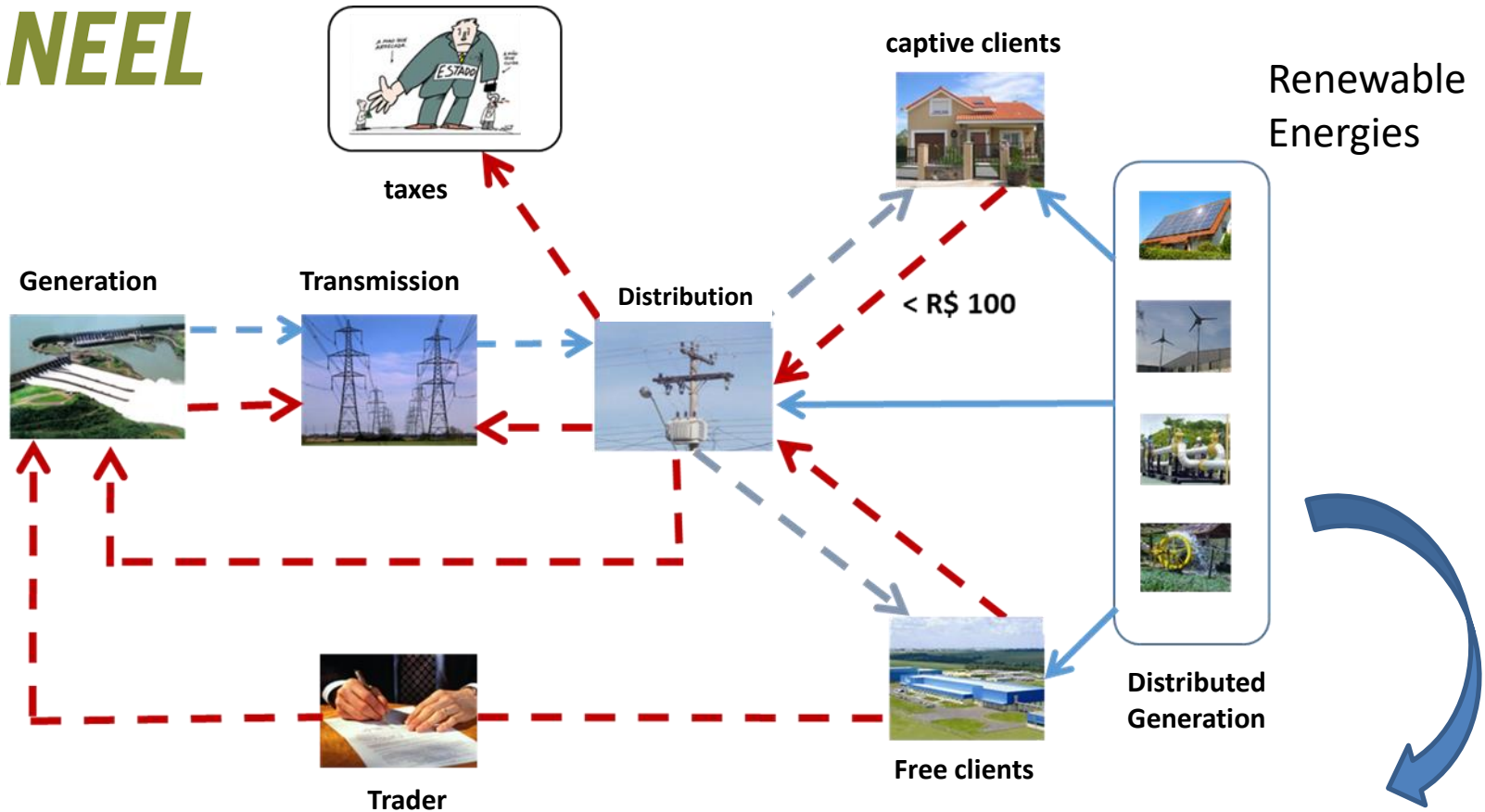
Statistical/computational modeling of **CEMIG-D** business model using databases and technical knowledge (2019-2021)



R&D Objective:

- To develop a computational system to simulate CEMIG-D business model using structural equation models, correlation matrices, regression models, machine learning models and artificial neural networks.
- The project was successfully finished in August 2021. The project received two awards in Brazilian Energy Conferences.

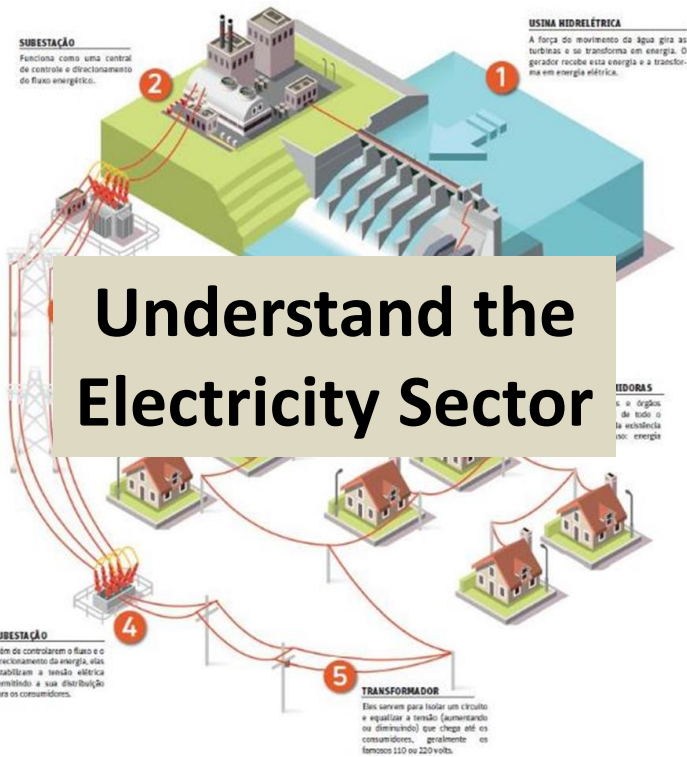
The Brazilian Energy Distribution Business Model



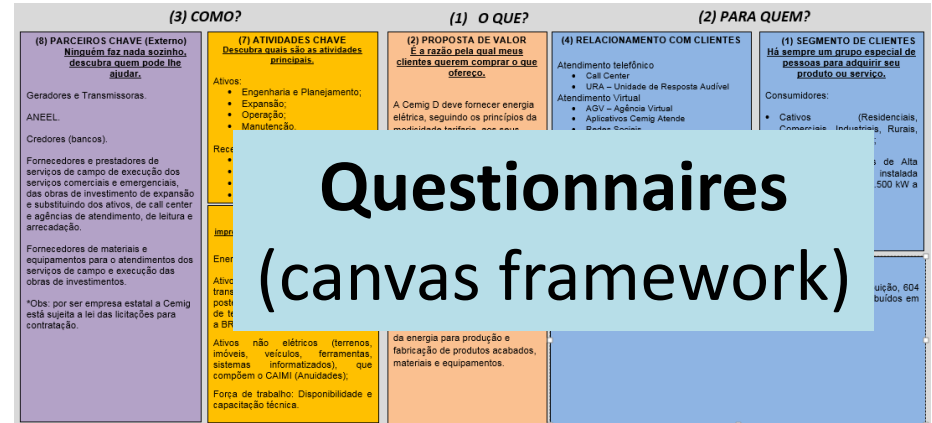
■ Energy Flow (MWh)
■ Cash Flow (R\$)

Consumer/Producer: the distribution system as a battery backup (photo-voltaic generation)

Extensive qualitative analysis using frameworks

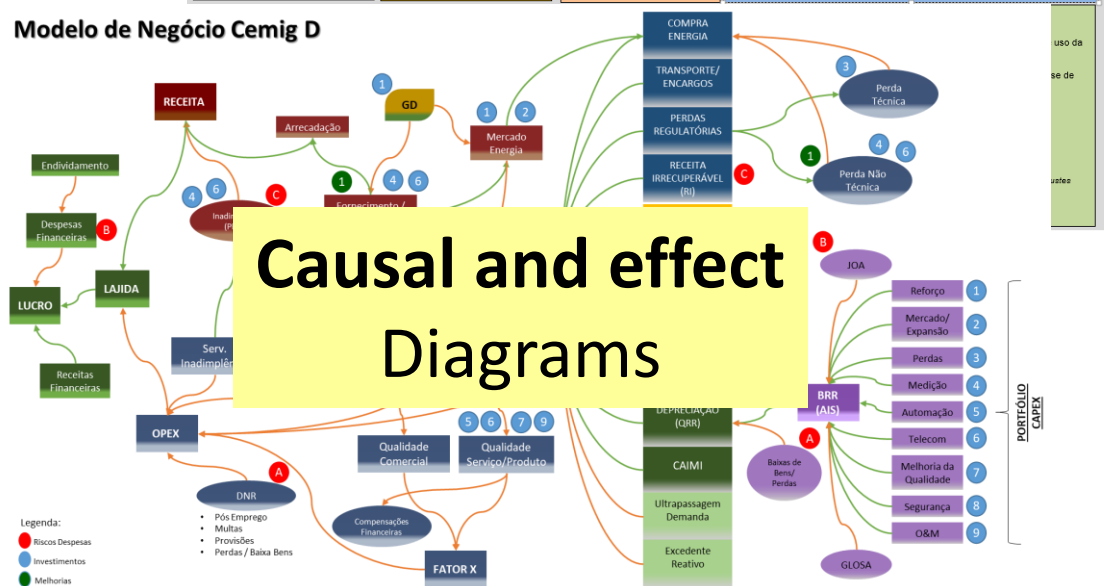


Understand the Electricity Sector



Questionnaires (canvas framework)

Modelo de Negócio Cemig D

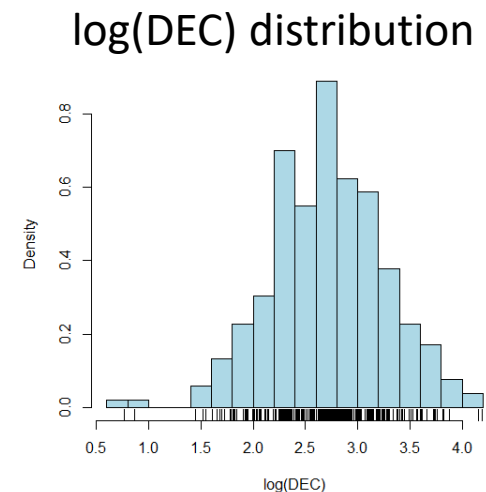
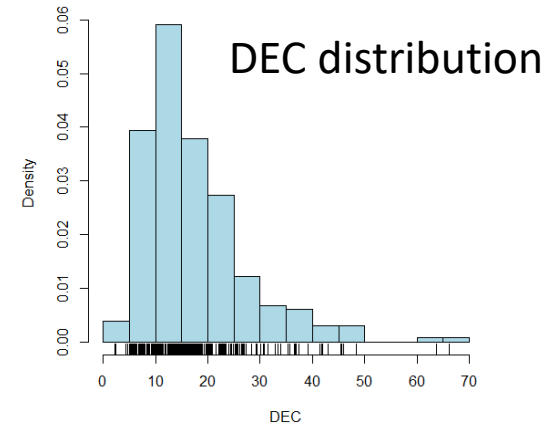
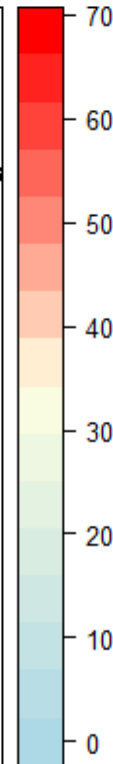
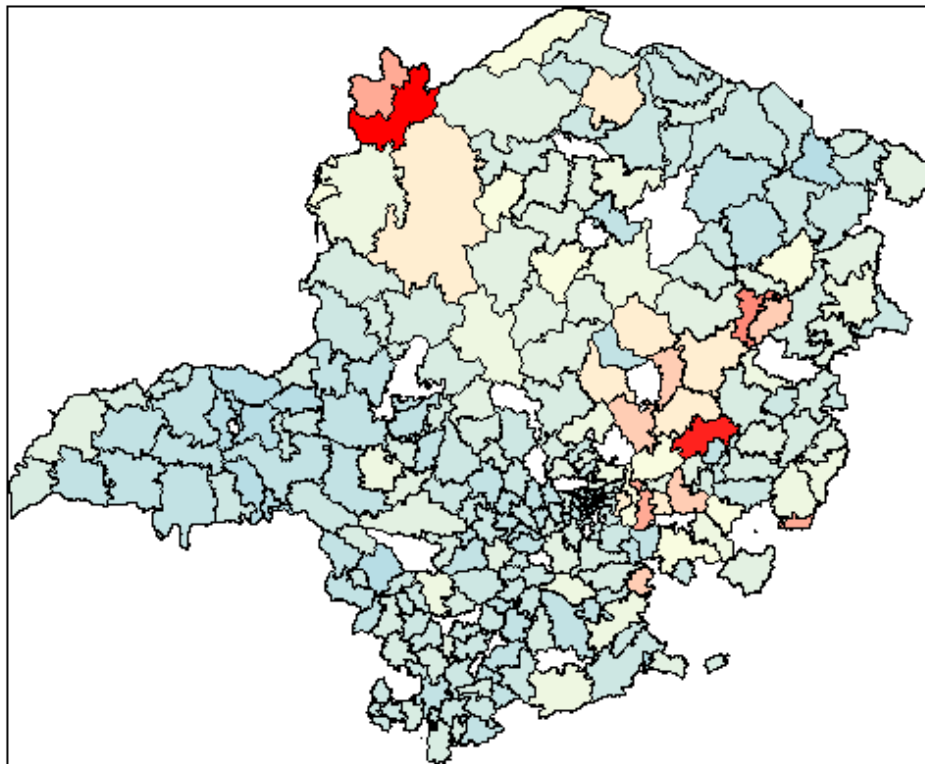


Causal and effect Diagrams

The Quality Model (First Case Study)

Duration of Interrupted Energy (DEC)

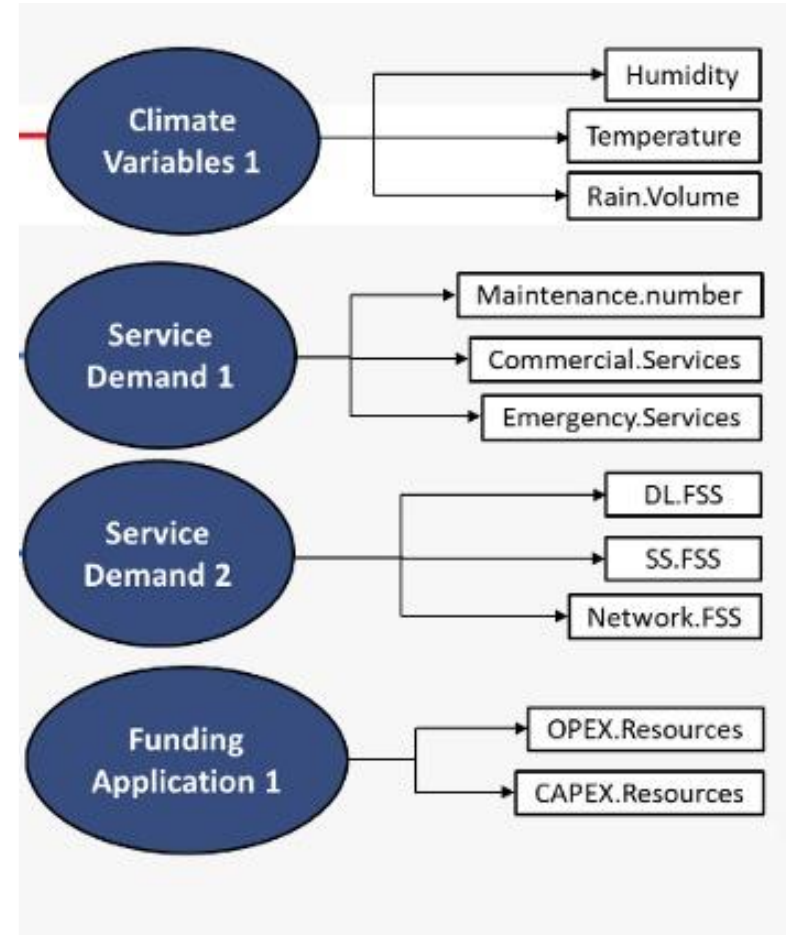
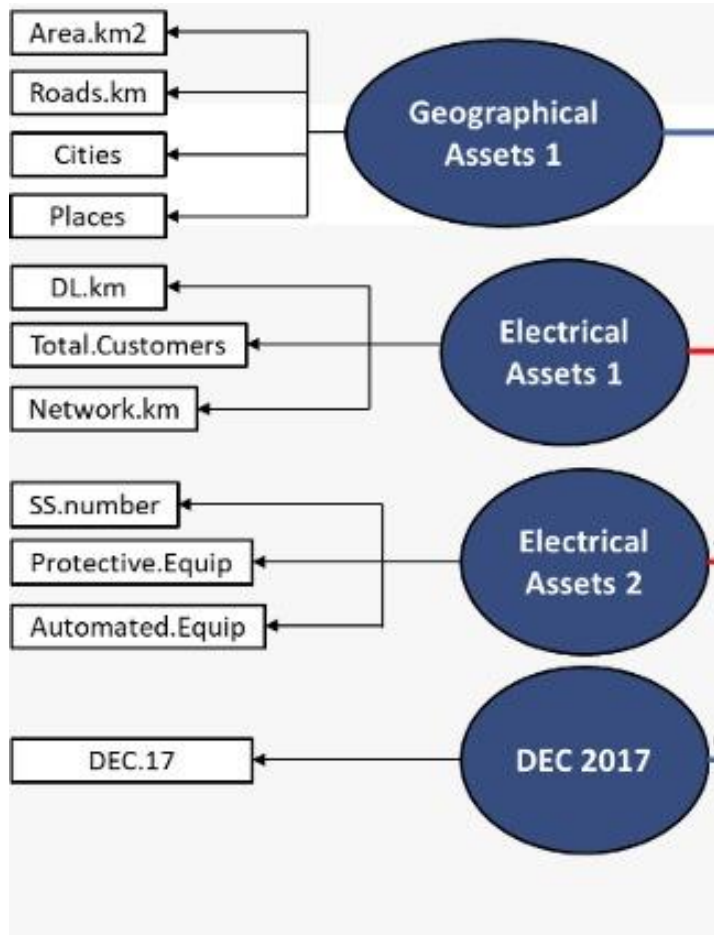
DEC indicator (2017)



Drivers of the DEC based on technical evidence

idx	Drivers	Expected correlation with DEC
1	Service area (km ²)	positive
2	Extension of roads in the service area (km)	positive
3	Number of municipalities in the service area	positive
4	Number of locations served according to the electrical company definition	positive
5	Extension of distribution lines (km)	positive
6	Extension of distribution network (km)	positive
7	Number of consumers	positive
8	Number of substations	positive
9	Number of electrical protective equipment	negative
10	Number of automated equipment	negative
11	Humidity index (%)	negative
12	Average temperature (oC)	negative
13	Average precipitation (mm)	positive
14	Number of working (maintenance) teams	negative
15	Number of commercial services	negative
16	Number of emergency services	negative
17	Number of interruptions due to falling trees on the distribution lines	positive
18	Number of interruptions due to falling trees at substations	positive
19	Number of interruptions due to falling trees in the distribution network	positive
20	Operational expenditures (OPEX/R\$)	negative
21	Capital expenditures (CAPEX/R\$)	negative

Structural Equation Modelling (SEM)



Then, the unexpected!!!

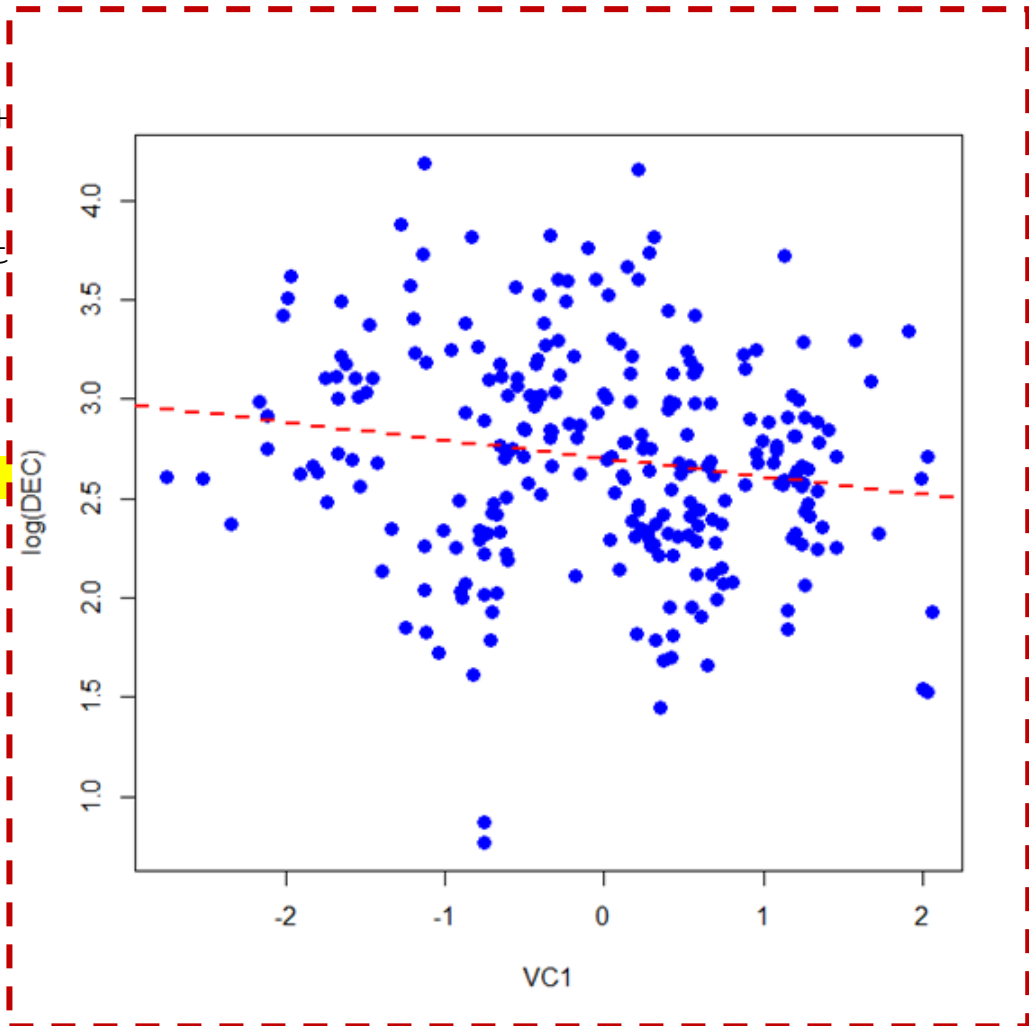


```
lm(formula = DQ ~ AG1 + AE1 + AE2 +
```

```
Coefficients:
```

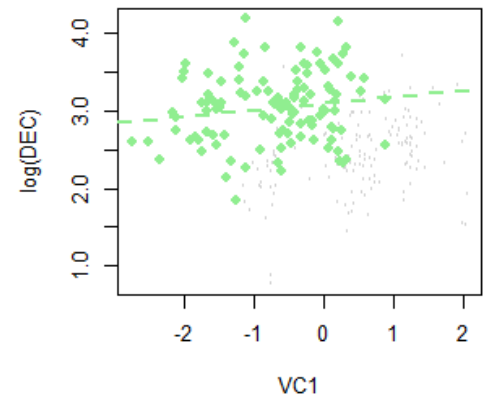
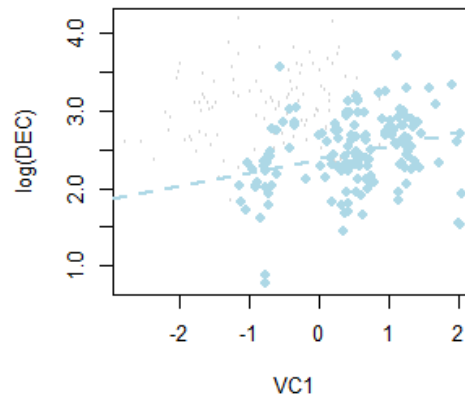
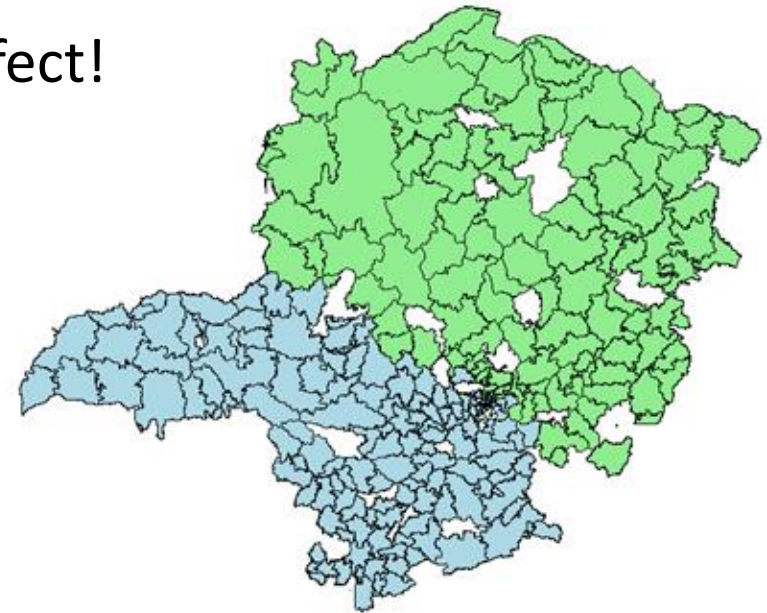
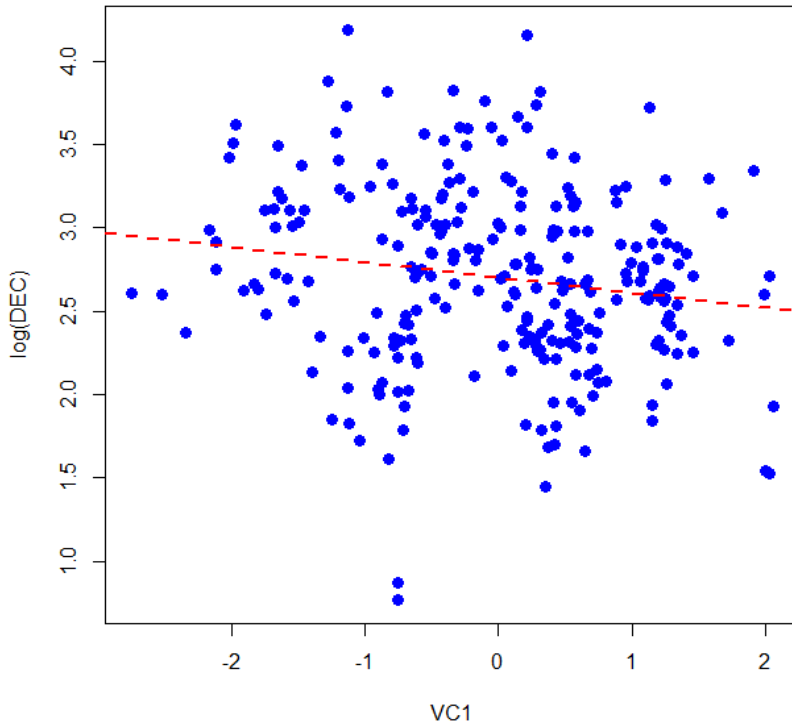
	Estimate	Std. Error	t
(Intercept)	6.103e-17	4.066e-02	
AG1	3.645e-01	8.198e-02	
AE1	-5.087e-01	1.095e-01	
AE2	-6.563e-01	1.132e-01	
VC1	-1.831e-01	4.265e-02	
DS1	-1.297e-01	7.985e-02	
DS2	8.606e-01	8.234e-02	
AR1	2.451e-01	6.649e-02	

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Explanation...

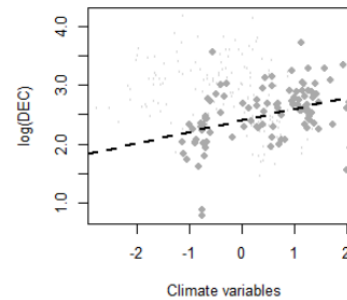
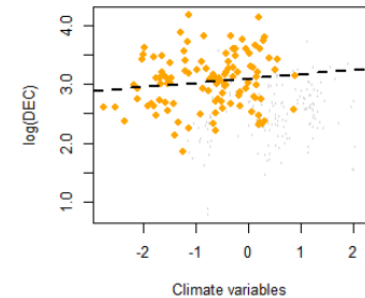
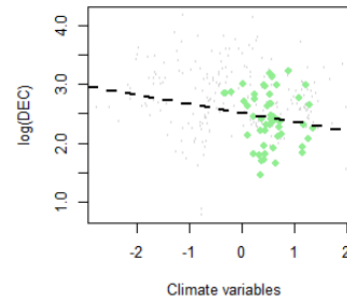
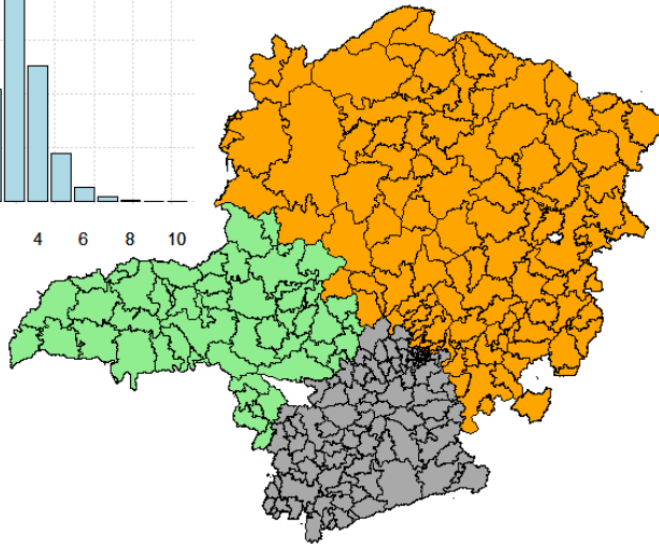
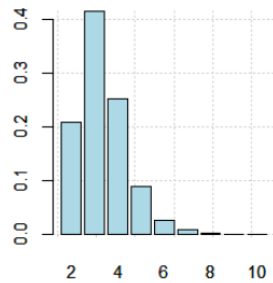
Correlation paradox! Confounding effect!
you name it!



Solution:

- How many geographical clusters?

■ Posterior probability of the number of clusters



A novel clustering-based spatial regression model applied to consumer power outage indicator
Marcelo Azevedo Costa, Leandro Brioschi Mineti, Álvaro Lédo Ferreira (working paper)

The proposed Bayesian model

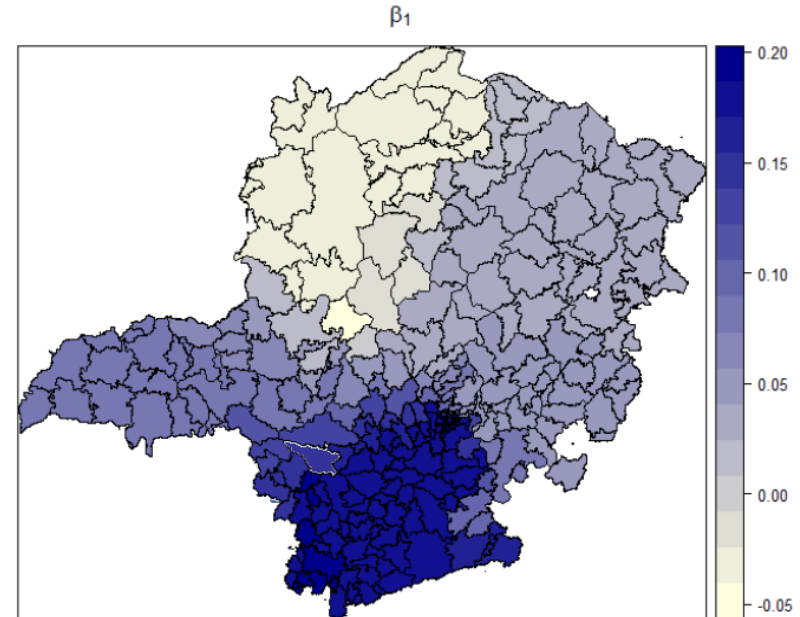
$$Y_i \sim \text{Normal}(\beta_{j0} + \beta_{j1}x_i; \sigma^2)$$

Priors:

$$k \sim (1 - c)^k$$

$$\beta_j | \sigma^2 \sim \mathcal{N}_{p+1}(\mathbf{0}; \sigma^2 (\lambda_0 \mathbf{I})^{-1})$$

$$\sigma^2 \sim IG(a_0, b_0)$$



A Reversible Jump Markov Chain Monte Carlo (RJMCMC) algorithm is proposed to estimate the parameters of the model

Costa, M. A., Mineti, L. B., Mayrink, V. D., & Lopes, A. L. M. (2019). Bayesian detection of clusters in efficiency score maps: An application to Brazilian energy regulation. *Applied Mathematical Modelling*, 68, 66-81.

What if we are missing something?

- Geographical heterogeneity was adjusted and linear regression models were adjusted for each geographical partition.

Predictor variable	Expected sign	Cluster 1			
		univariate	coefficient	P-value	VIF
Climate variable	positive	0.0671	-0.0186	0.6840	1.49
Demand for electrical services I	positive	-0.0068	-0.0027	0.9764	6.21
Demand for electrical services II	positive	0.1118	0.3720	0.0000	3.93
Electrical assets I	positive	-0.0265	-0.3589	0.0002	9.04
Electrical assets II	negative	0.0059	-0.1601	0.1654	13.38
Geographical assets	positive	0.0531	0.0993	0.1090	4.40
Operational and capital costs	negative	0.0359	0.0980	0.0778	2.70

Sample size: 115 electrical areas

What if we are missing something?

- Geographical heterogeneity was adjusted and linear regression models were adjusted for each geographical partition.

Cluster 1:

Demand for electrical services II
Electrical Assets I

Cluster 3:

Demand for electrical services II
Electrical Assets II
Geographical Assets

Cluster 2:

Demand for electrical services I
Demand for electrical services II
Electrical Assets I
Electrical Assets II
Geographical Assets

Hybrid Models for the DEC indicator

Measurement 146 (2019) 425–436



Contents lists available at [ScienceDirect](#)

Measurement

journal homepage: www.elsevier.com/locate/measurement



Failure detection in robotic arms using statistical modeling, machine learning and hybrid gradient boosting



Marcelo Azevedo Costa ^{a,*}, Bernhard Wullt ^c, Mikael Norrlöf ^{c,b}, Svante Gunnarsson ^b



^a Department of Production Engineering, Universidade Federal de Minas Gerais, Brazil

^b Department of Electrical Engineering, Linköping University, Sweden

^c Robotics and Discrete Automation, ABB AB, Sweden

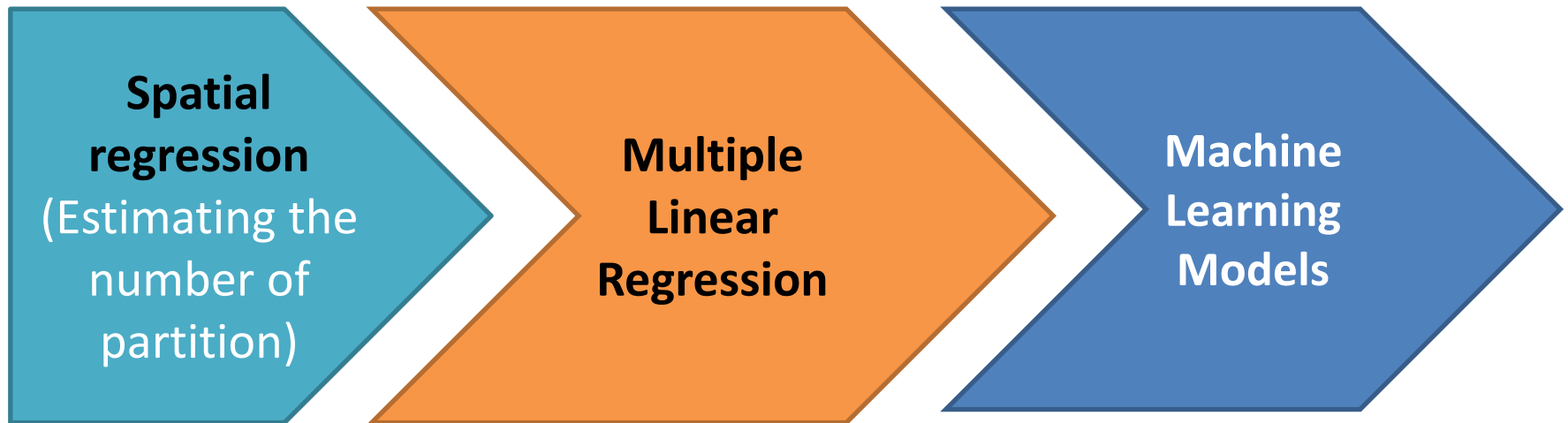
Failure detection in robotic arms using statistical modeling, machine learning and hybrid gradient boosting

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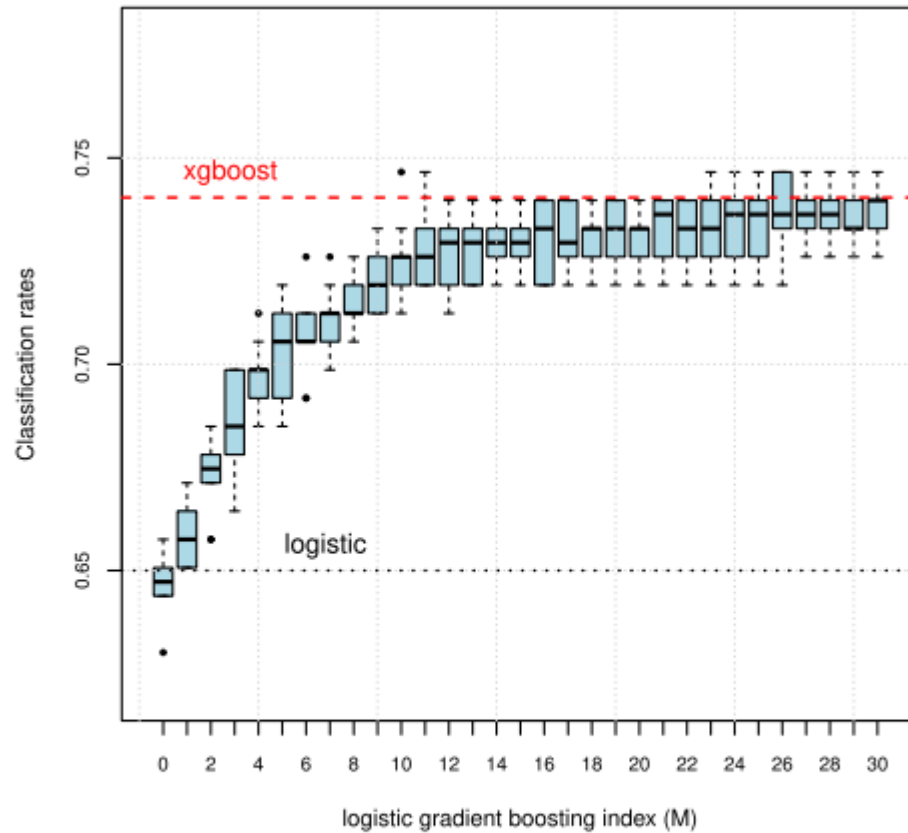
Hybrid Models for the DEC indicator



Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of statistics*, 1189-1232.

CART
Random Forest
xgboost
Neural Networks
...

Boosting a baseline model



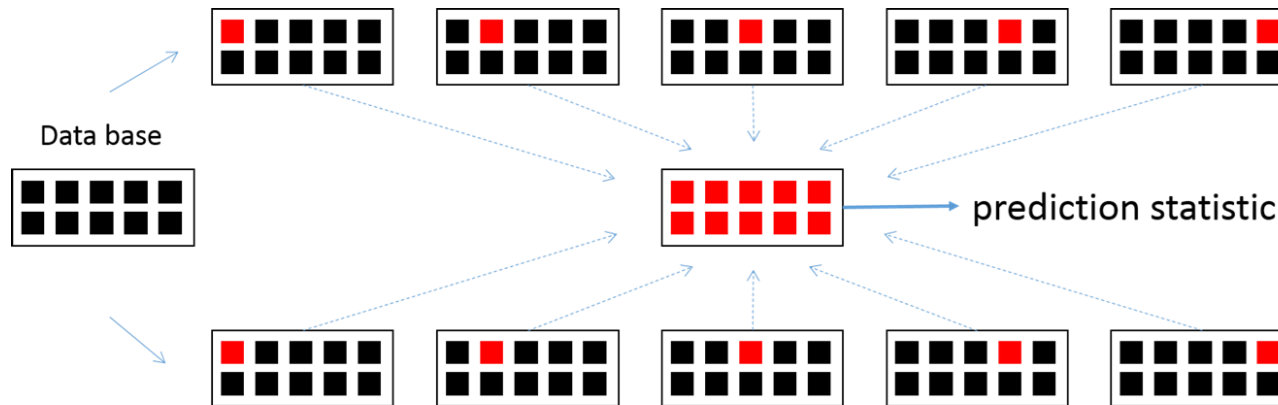
Best model

Base line model

(b) Hybrid gradient boosting with Logistic and Random Forests.

Performance analysis

leave-one-out cross-validation



R^2_{pred}

Predicted
Coefficient of
Determination

Standard Multiple
regression

$R^2_{pred} = 53,6\%$

Spatial
Regression

$R^2_{pred} = 61,79\%$

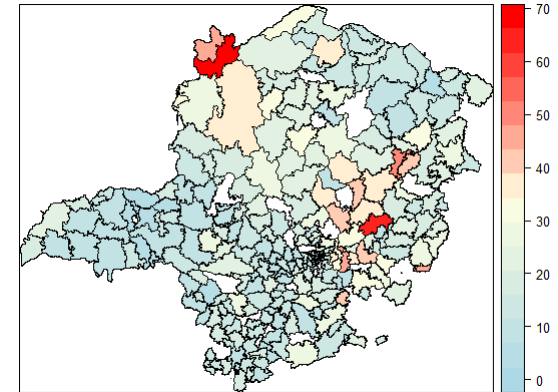
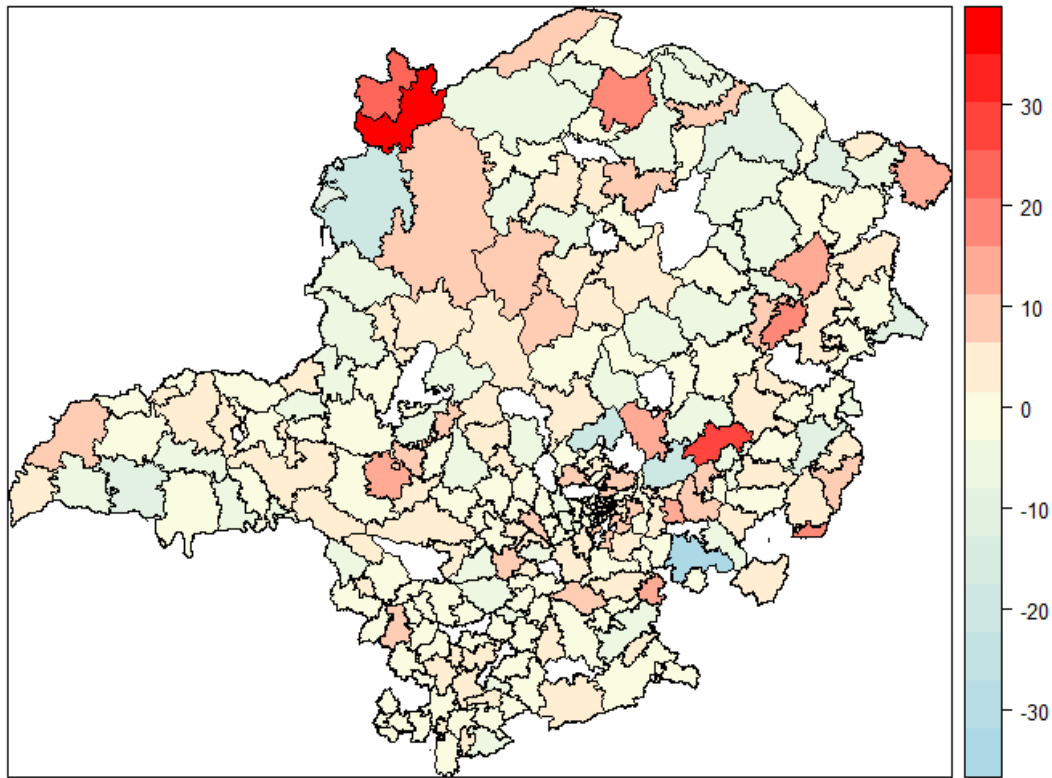
Machine
Learning Models

$R^2_{pred} = 67,62\%$

Analysis of the residuals

Log(DEC)

Residuals

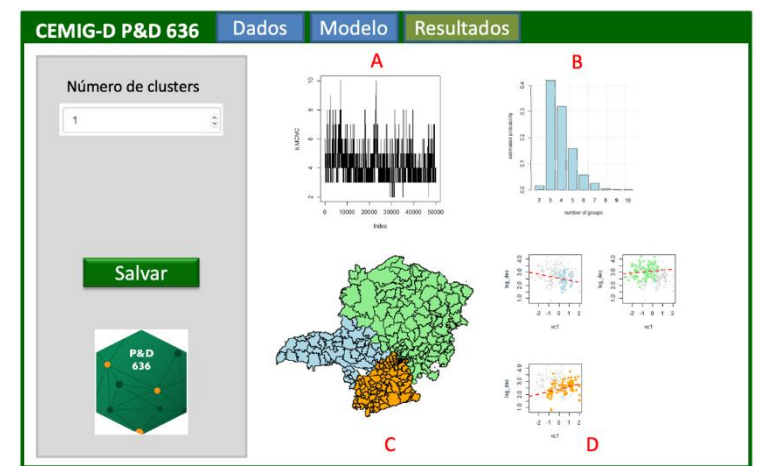
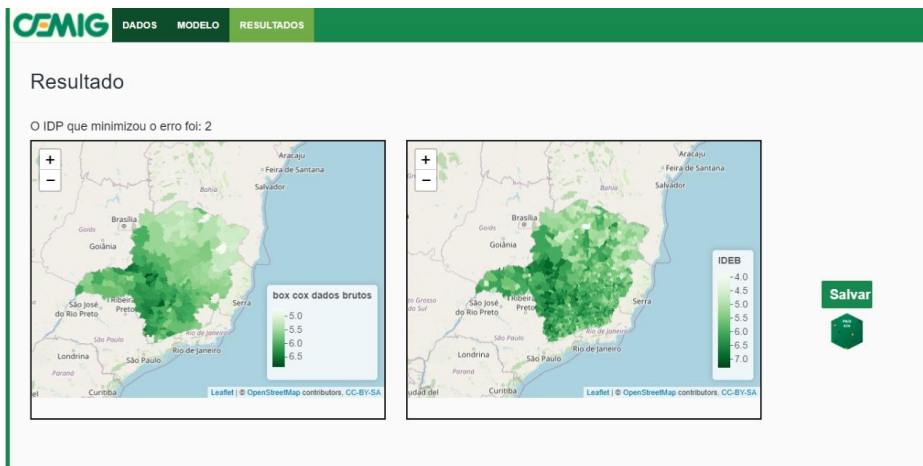
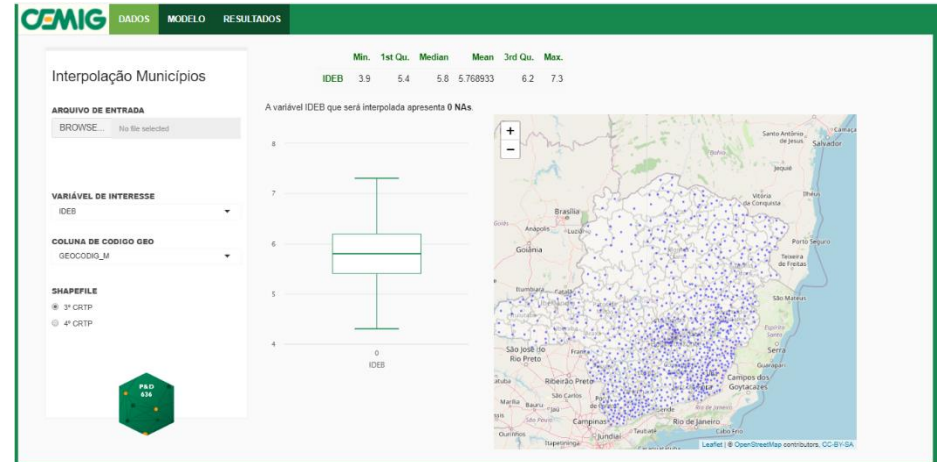
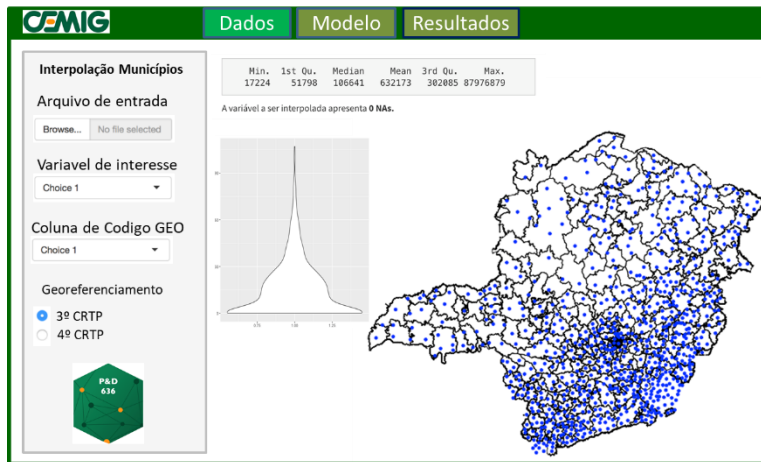


Discussion and conclusion



- Hybrid AI – Where data-driven and model-based methods meet
- Hybrid AI – Where data-drive, **technically-based** and model-based methods meet.

Computational tool (screenshots)



Thanks!



Questions?

Transmission Lines in Brazil



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