

European Council for an Energy Efficient Economy

Ex-post energy savings assessment methodologies using smart-meter data: the case study of a switch from direct electric heating to an air-to-air heat pump

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Context and objectives



- Carbon neutrality in 2050
- Enhance energy independency
- Energy efficiency first principle

→ Electrification of end-uses (transportation, building space heating, industrial process…)
→ Heat pump: efficiency and renewable energy



- Limitation of future increase of electricity consumption
- France: 9 million dwelling w/ direct electric heating

→ Retrofit of direct electric space heaters with an air-to-air heat pump

Replacement of electric convectors with heat pumps (100,000 -150,000 dwellings/y)
Energy futures 2050 (2023-2035: first step towards carbon neutrality)

The case study: Single Family Housing in north of France



Construction	Roof insulation & windows	Smart meter	PHEV	HP
1989	1999 - 2015	2018-06	2021-01	2021-05

- Living area: 130 m² with converted attic
- Electric Domestic Hot Water with storage (200l)
- 2 towel warmers in bathrooms
- Plug-in Hybrid Electric Vehicle
- Appliances and others
- number of people and habits has not changed…

DE space heating
- Total power installed: 12 kW
- 8 units
- Efficiency: ≃ 0.96

retrofit

HP space heating
- Total nominal power installed: 4.1 kW
- Total thermal power: 18 kW
- 2 external units (Efficiency: SCOP = 4.7 / SEER =7.9)
- 6 internal units





The daily overall consumption from the smart meter

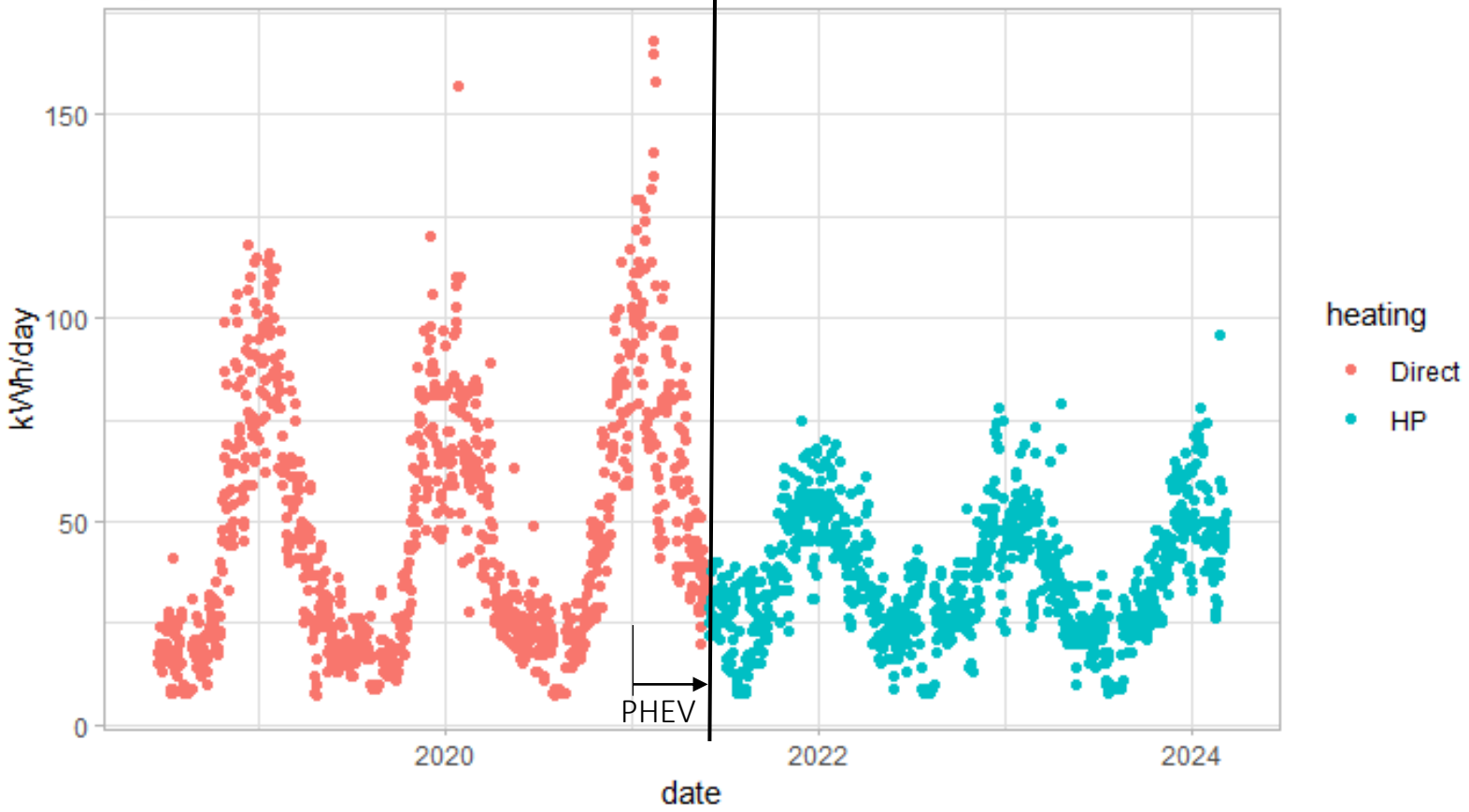


- Data from June 2018 to February 2024
- All end-uses

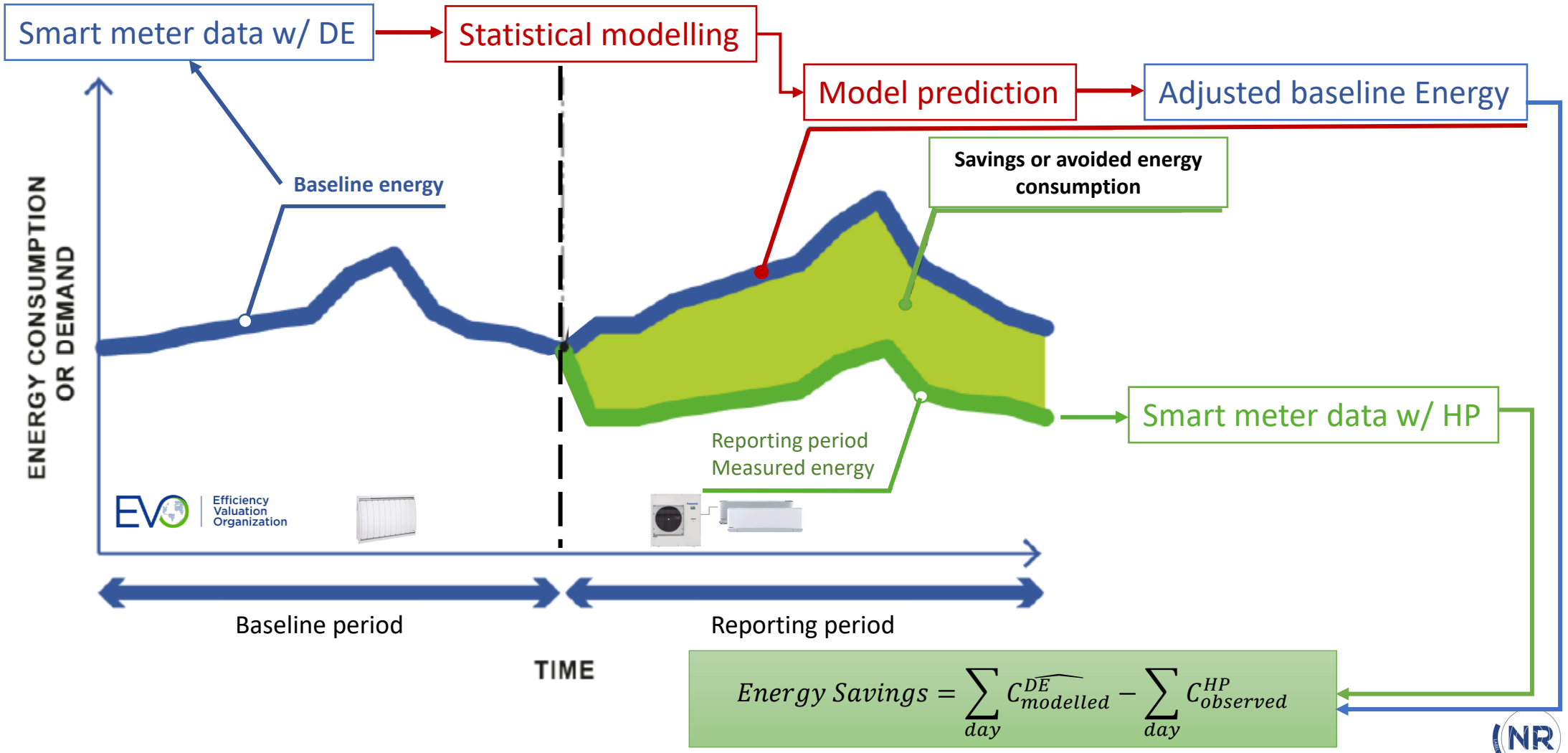
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- Weather data: open data


DE space heating
HP space heating

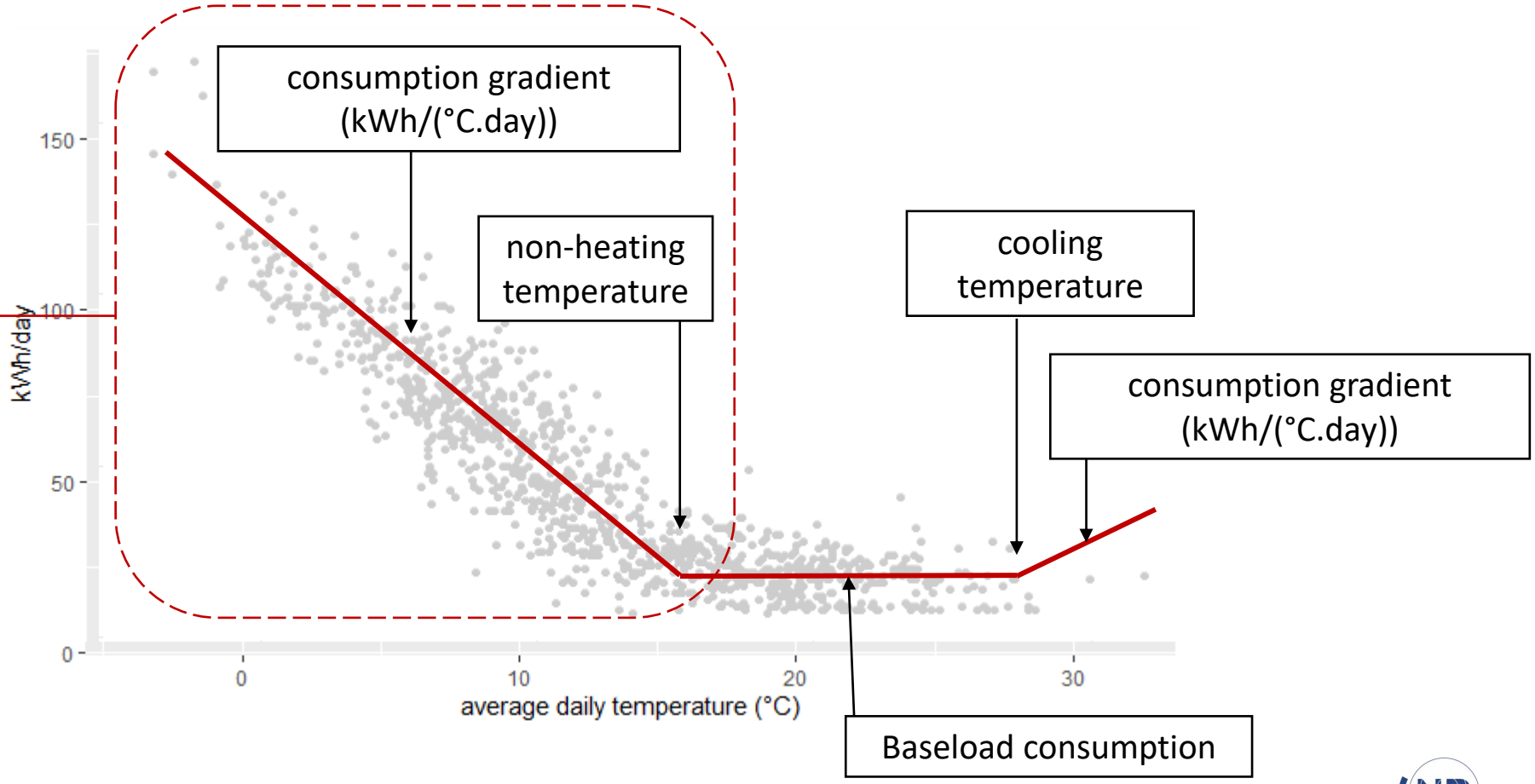
IPMVP Framework - International Performance Measurement and Verification Protocol



Source: IPMVP, General accepted M&V principles

Temperature sensitivity of electricity consumption

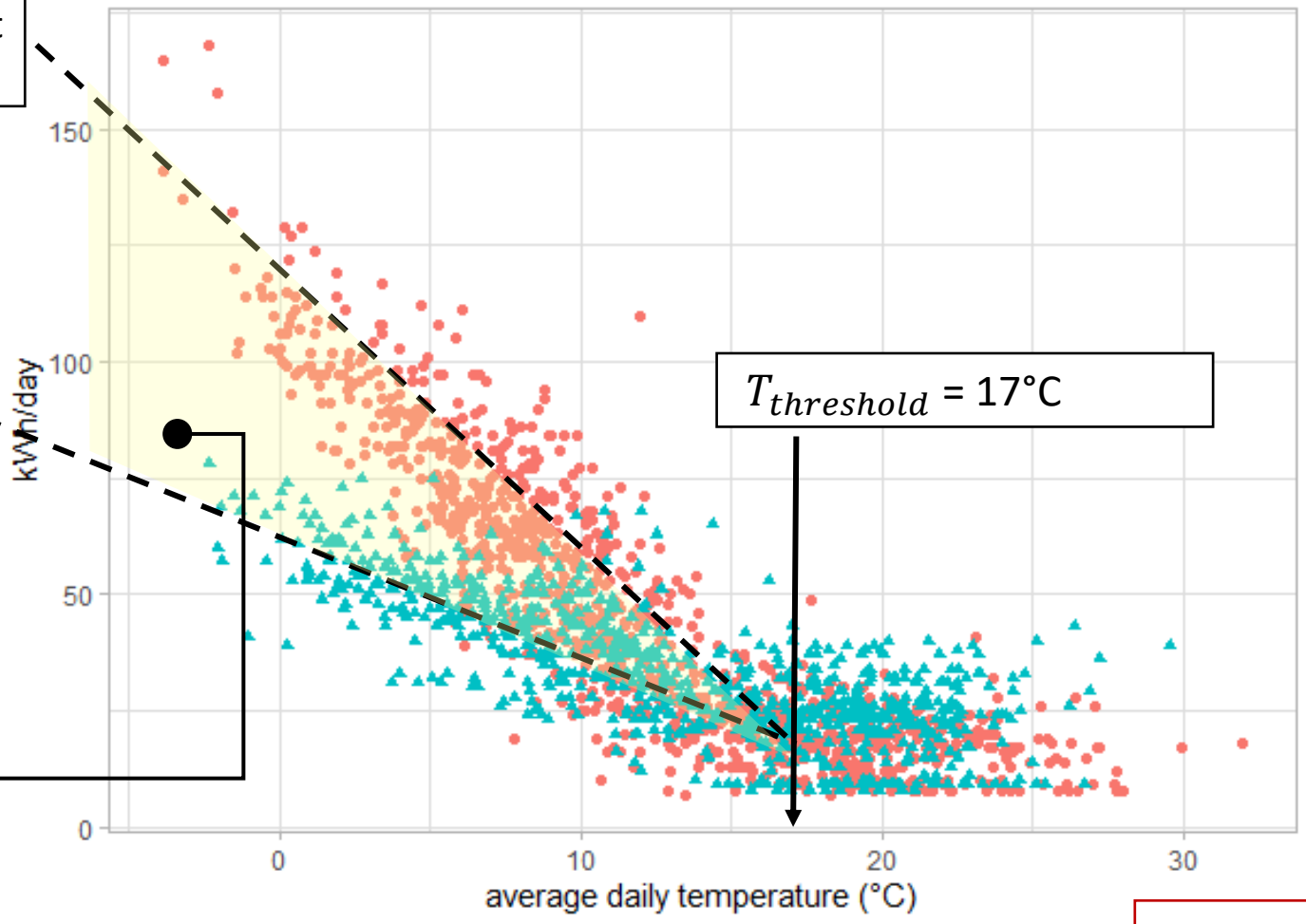
Data used
To assess the
energy savings



Effect of HP installation on consumption gradients

DE consumption gradient (kWh/(°C.day))

HP consumption gradient (kWh/(°C.day))



Gross energy savings

$$Energy\ Savings = \sum_{d}^{T\ obs.} \widehat{C^{DE}_{modelled}} - \sum_{d}^{T\ obs.} C^{HP}_{observed} = \sum_{d} \left(\widehat{C^{DE}_{d}} - C^{HP}_{d}\right) = \sum_{d} \left(\left[\mathbf{s}\left(\boldsymbol{X_i^d}\right) + \boldsymbol{\varepsilon}\right] - C^{HP}_{d}\right)$$

baseline modelling
- *Xi*: explanatory variables
- *s*: regression function
- *ε*: error term

Observed daily consumption

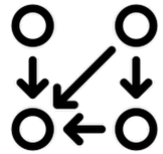
The modelling of the baseline

Model list:
- OLS - Ordinary Least Square (aka linear regression)
- QR - Quantile Regression
- PLSR - Partial Least Square Regression
- EARTH - Enhanced Adaptive Regression Through Hinges (aka MARS*)
- SVM - Support Vector Machine
- RF - Random Forest
- XGBoost - Extreme Gradient Boosting
- Gam - Generalized Additive Models
- qGAM - Quantile GAM
- Prophet – forecasting time series based on non linear additive model
- SL – Superlearner (Staking model)

Sampling by random selection: Train 80% + Test 20%

Test performance:
- MAPE: Mean Absolute Percentage Error
- MAE: Mean Absolute Error
- RMSE: Root Mean Squared Error
- R^2: Coefficient of Determination

Explained variable:
- Daily consumption – all end-uses
- w/ Tday < T threshold



Explanatory variables:
- Temperature
  - Day average, Day-1, Day-2
  - Day min and Day max
- Relative Humidity
- Wind
  - Direction, Speed
- Atmospheric Pressure

*Multivariate Adaptive Regression Splines

Model performance



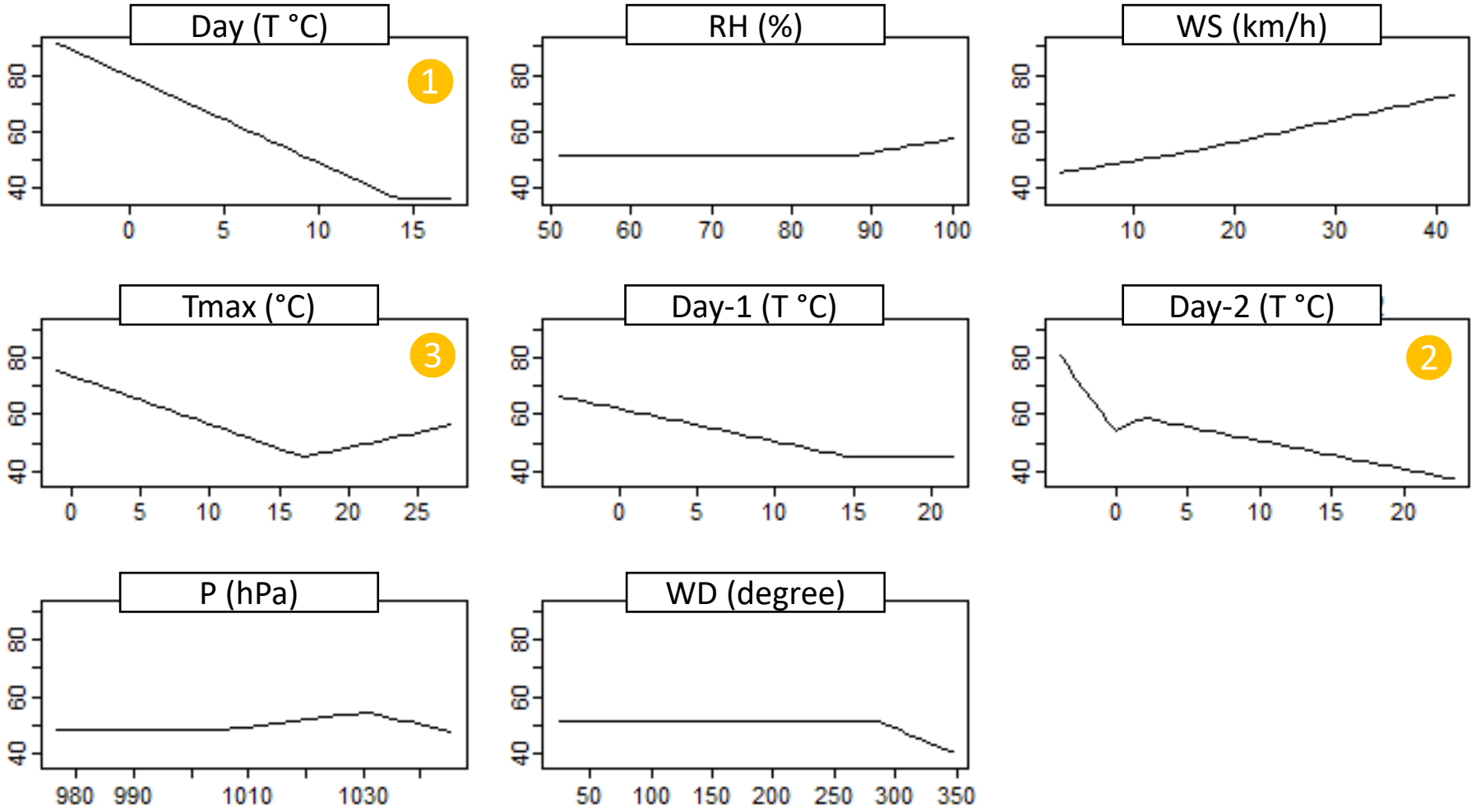
Best model: EARTH - Enhanced Adaptive Regression Through Hinges

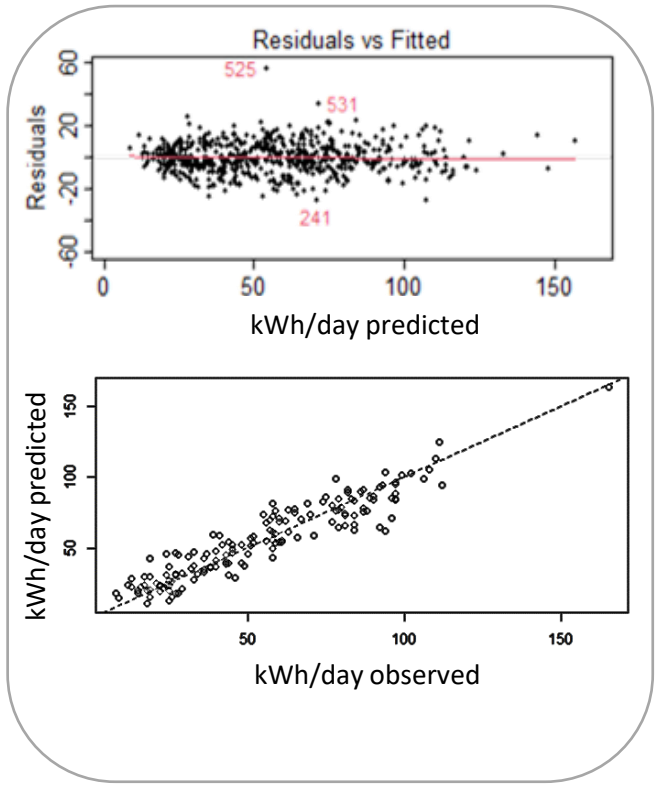
	Model	MAPE (%)	RMSE (kWh)	MAE (%)	R^2 [0 -1]	Type of model
1	Earth	0.197	10.057	7.880	0.879	interpretable
2	SVM	0.199	10.867	8.883	0.858	non-interpretable
3	qGAM	0.200	10.058	7.884	0.879	interpretable
	RF	0.204	10.456	8.043	0.869	non-interpretable
	GAM	0.205	10.235	8.064	0.874	interpretable
	Superlearner	0.209	10.325	8.883	0.872	non-interpretable
	XGBoost	0.210	10.927	8.606	0.857	non-interpretable
	Prophet	0.211	10.009	8.045	0.880	interpretable
	PLSR	0.233	11.286	8.560	0.847	interpretable
	OLS	0.240	11.308	8.749	0.847	interpretable
	QR	0.244	11.519	8.823	0.841	interpretable

Effect of explanatory variables – EARTH model

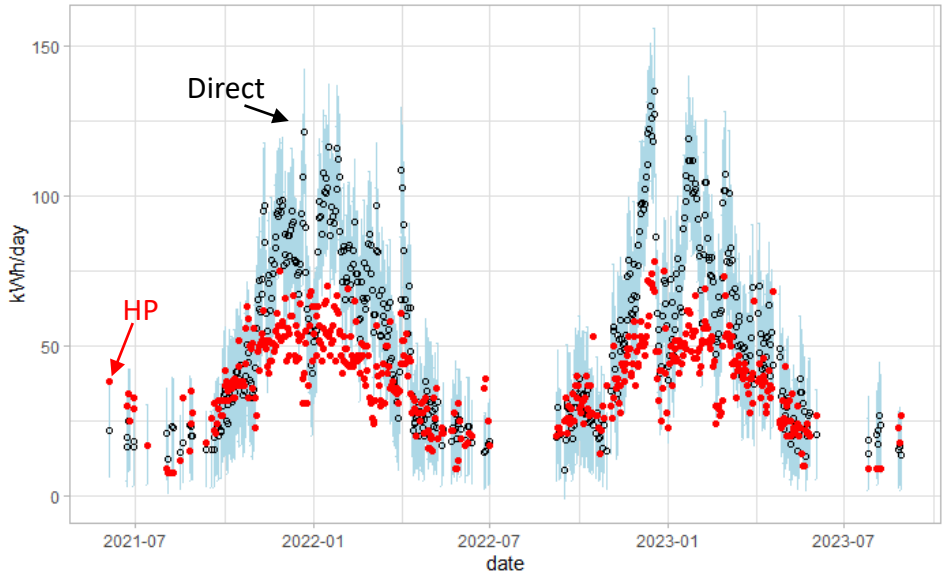
$$\hat{f}(x) = \sum_{i=1}^{k} a_i[\pm(X_i - c)]_+ + b + \epsilon_i$$

c: knot, b: intercept, a_i: coefficients



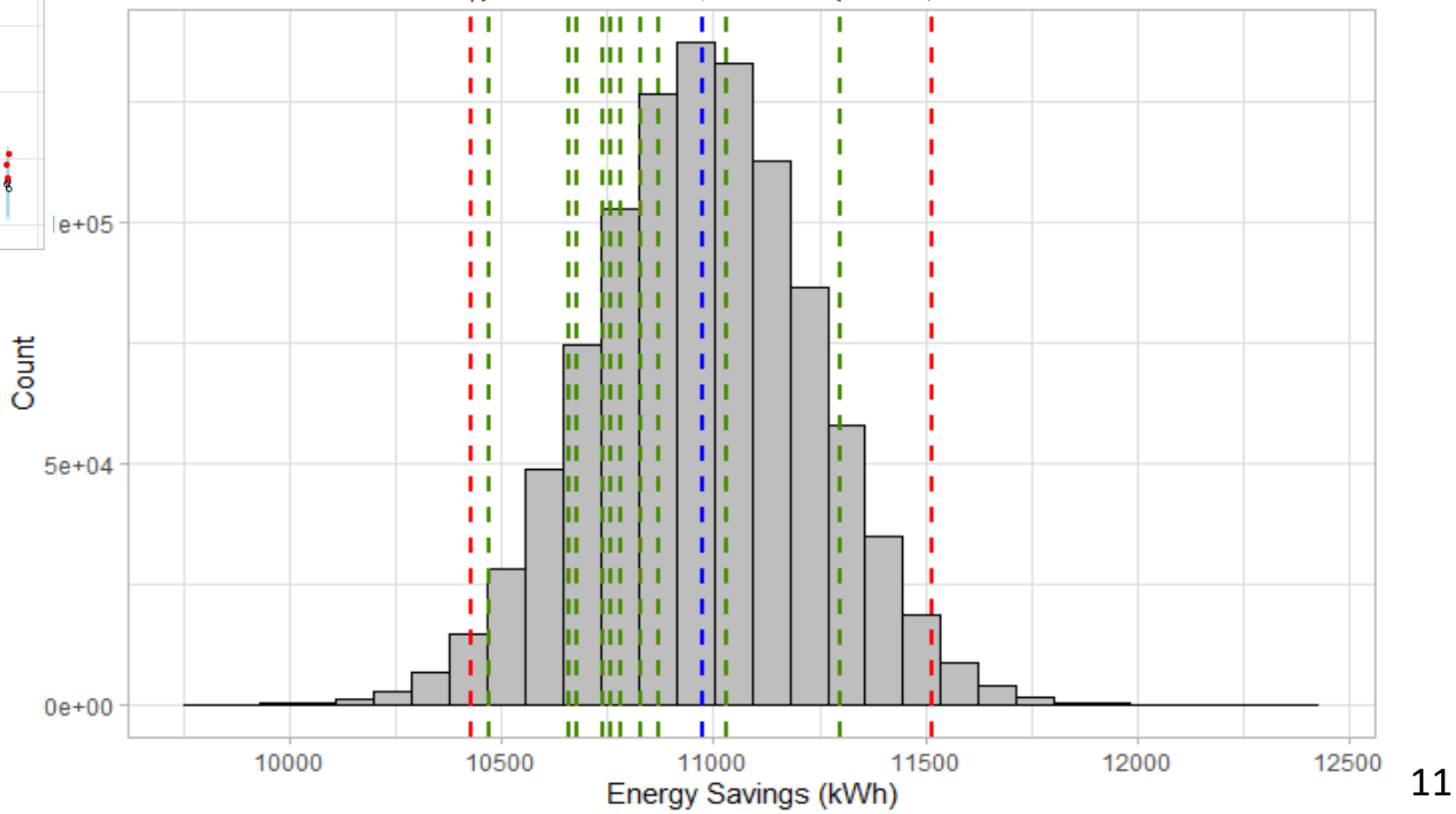


Modelled reference consumption compared to observed consumption over the reporting period



Energy savings*: **10,973** ± **544** kWh over 2021-06 → 2024-02

Other models



gross savings account for 40% of total consumption (all end-uses)



*95% uncertainty w/ EARTH model

Conclusion and perspective

- IPMVP approach applies to the residential sector even without background/contextual information
- Only use of already available data: smart meter and open data (weather data)

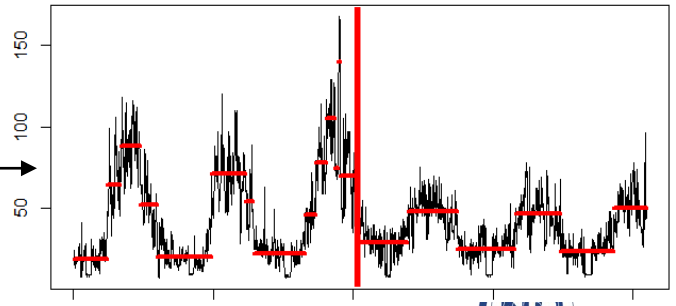
- Different methods of estimating gross energy savings based on daily consumption of all end-uses from a smart meter before and after renovation

- Approach applies notably to both electricity and gas consumption (i.e. daily consumption from a smart meter)

- Even with relatively simple models it is possible to estimate gross energy savings (due to large error compensation) → the major problem does not therefore lie in the choice of the algorithm

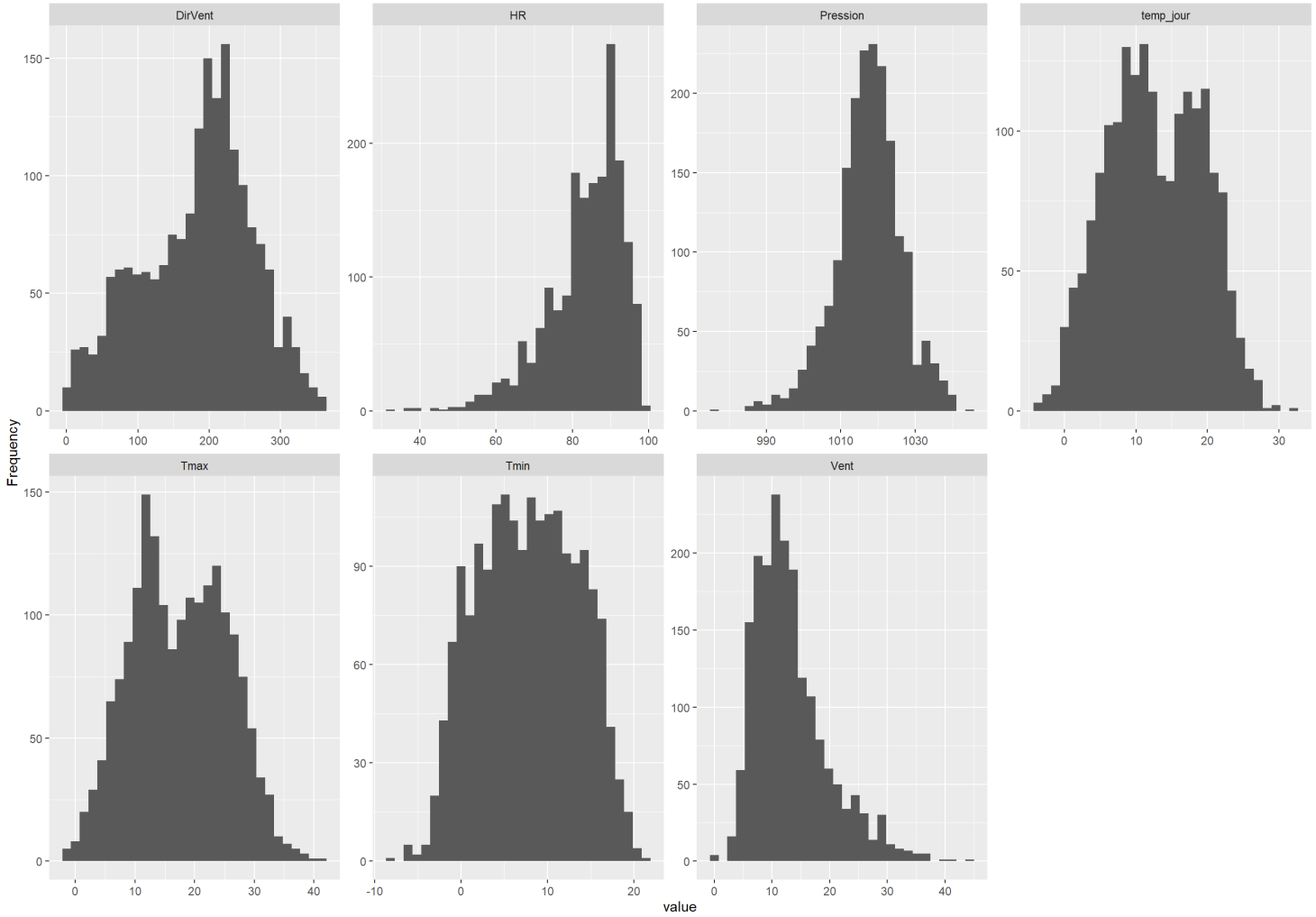
- **Question:** how to process to estimate the net energy savings from gross savings
  → to analyse the evolutions of basic (non-thermosensitive) consumption?
  → to rely on a large statistical panel
  → to conduct field survey w/ quali- and quantitative data

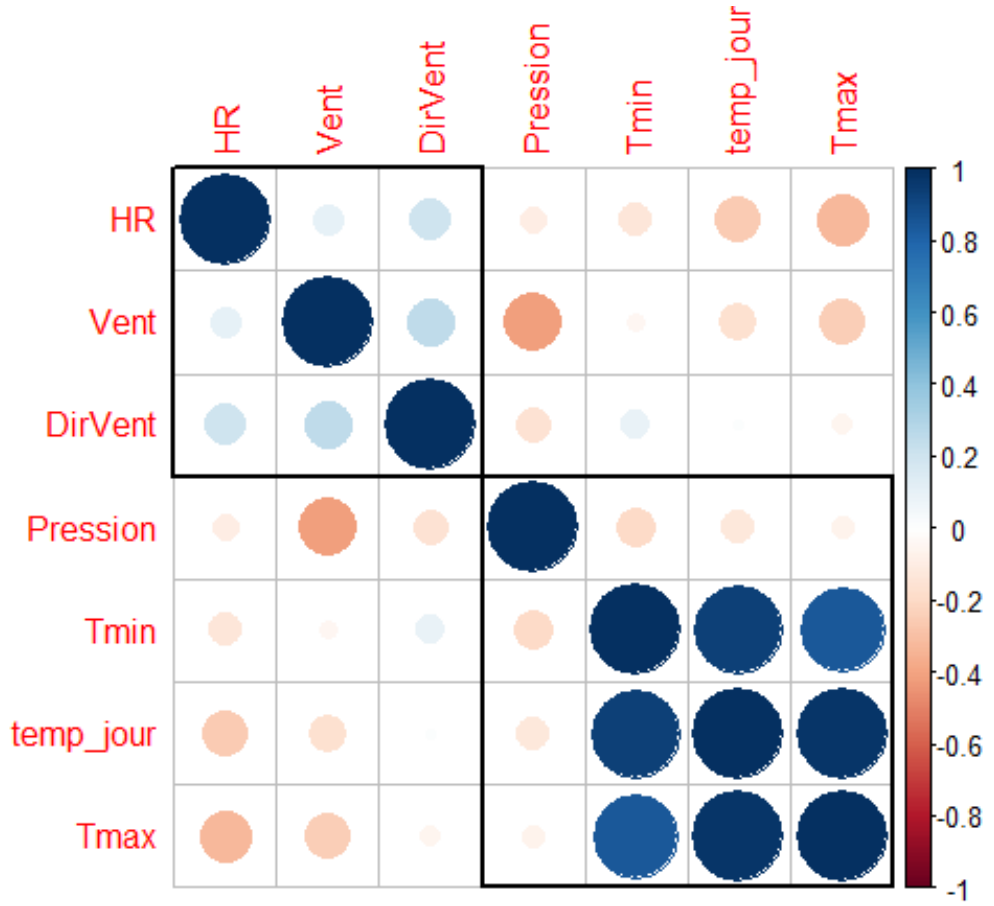
- **Perspective:** automate change detection (change points and structural breaks) → analysis of average power at 30-minute intervals



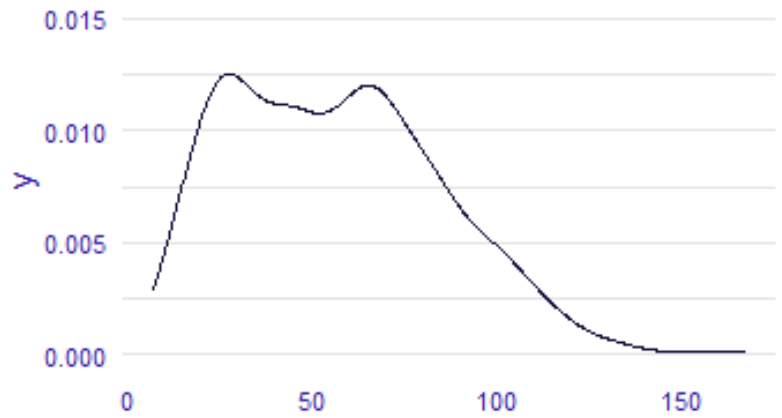

eDF
Thanks

Explanatory variables





Comparison between data (y) and Earth model



Correlation:
0.944

