SCHT

Smart Climate Hydropower Tool:

An artificial intelligence based service for hydropower production seasonal forecast

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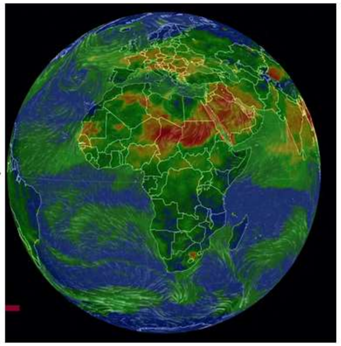
Open Big Data Copernicus

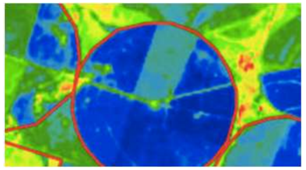
Artificial Intelligence Algorithms

Environmental Models

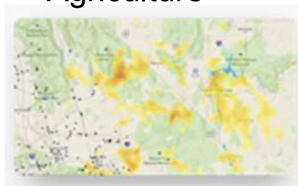
Cloud Web Platform

CLIMATE SERVICES

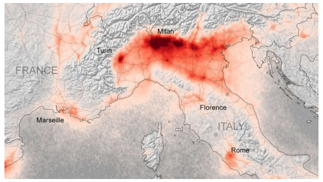




Agriculture



Natural Hazard

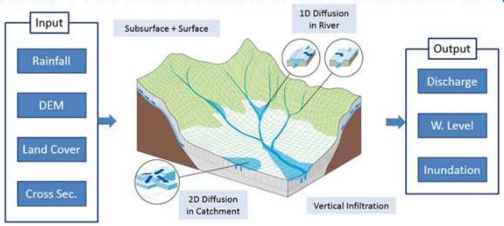


Air Quality

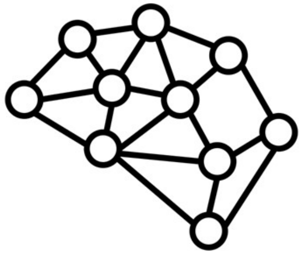
Renewable Energy

SCHT: AI-based Climate Services (CS)

- **THE NEEDS**: Energy and Water Management requires climate service to cope with climate challenges
- **PURPOSE**: Evaluate how much Copernicus Seasonal Forecasts and AI algorithms may contribute to reduce uncertainty of hydropower production due to natural inflows variability
- **STANDARD CS**: Feed Seasonal ECV Forecast into complex hydrological Deterministic Models (EHYPE):
  - Time and data consuming (topo, landuse, soil)
  - requires the involvement of hydrological modeling expert
  - Multiple sites = Multiple Models



- **INNOVATIVE AI-based** : Combination of Copernicus Seasonal Forecast with Data Science (AI and ML) Time Series algorithms.
  - Democratize the practical use of seasonal-forecast-based climate services
  - Less time and data requirements – No background in hydraulics requested
  - Suitable for multiple site applications
  - Web App



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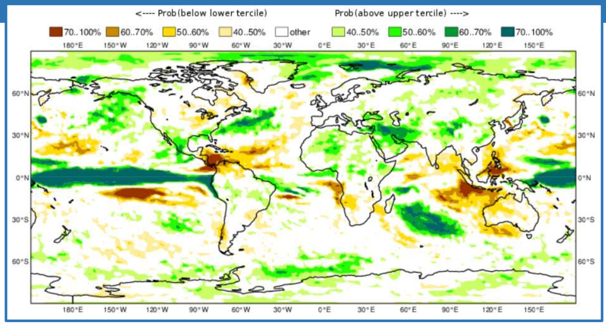
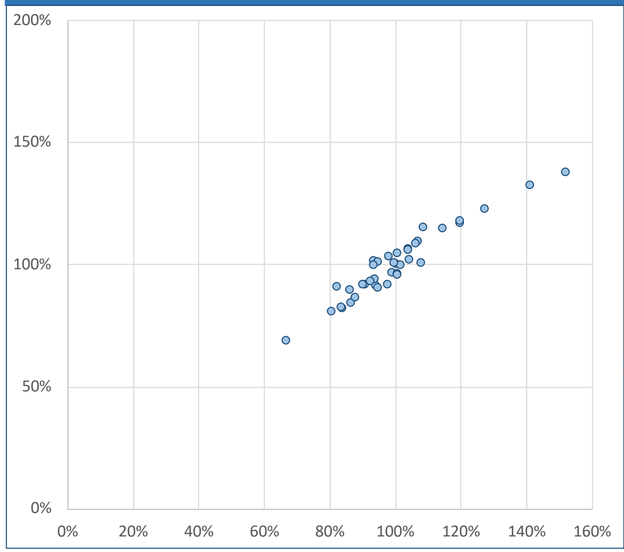
SCHT CS VALUE for ENEL Green Power

Climate Services

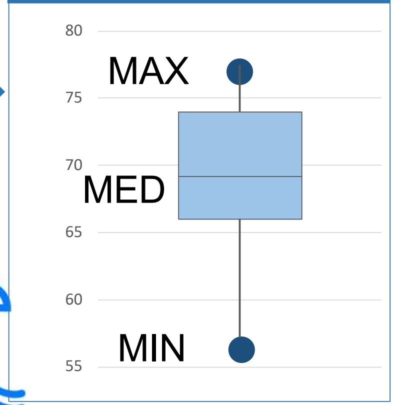


BUSINESS solutions

Precipitation vs Capability



Annual Capability variability GWh



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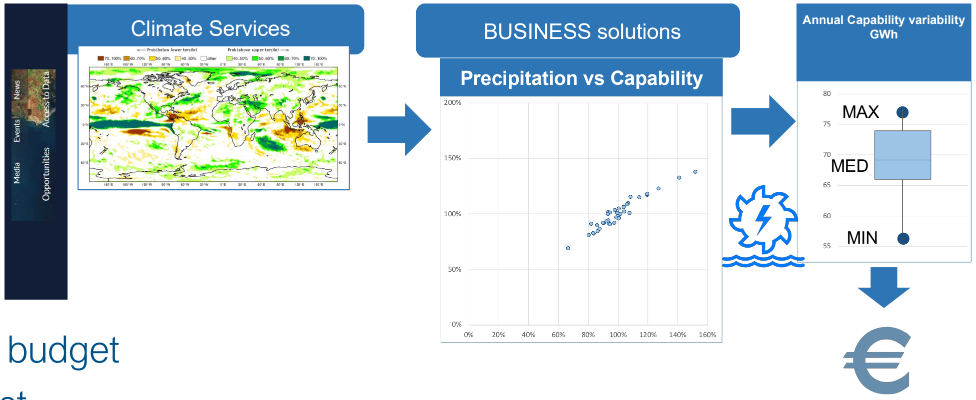
Where is the value in forecasting for HP ?

Problems

- The Technical point of view: Knowing in advance means planning management of the reservoir to boost production
- The Financial one = Deviation between the scheduled annual production and actually achievable production requires:
  - Corrective sales / purchase of energy
    - If you buy increasing unit costs during the year
    - If you sell redundancies have decreasing benefits in the year round.

Objective

- Knowing as early as possible deviation at the year end between budget producibility and final production to be able to undertake the most advantageous corrective actions.



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Case Studies

BETANIA

GUAVIO

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Case studies in Colombia: Betania

Central Hidroeléctrica Betania

Production 2000 GWh/year, Rio Magdalena

Catchment area ≈ 13’000 km2

Images courtesy of ENEL

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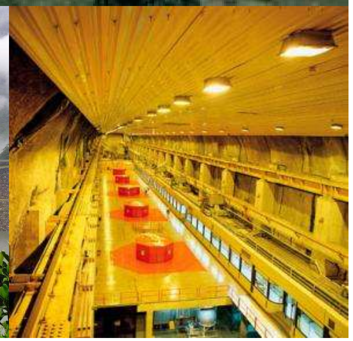
Case studies in Colombia: Guavio

Central Hidroeléctrica El Guavio

production 5500 GWh/year , Rio Guavio,

Catchment area ≈ 1’500 km2



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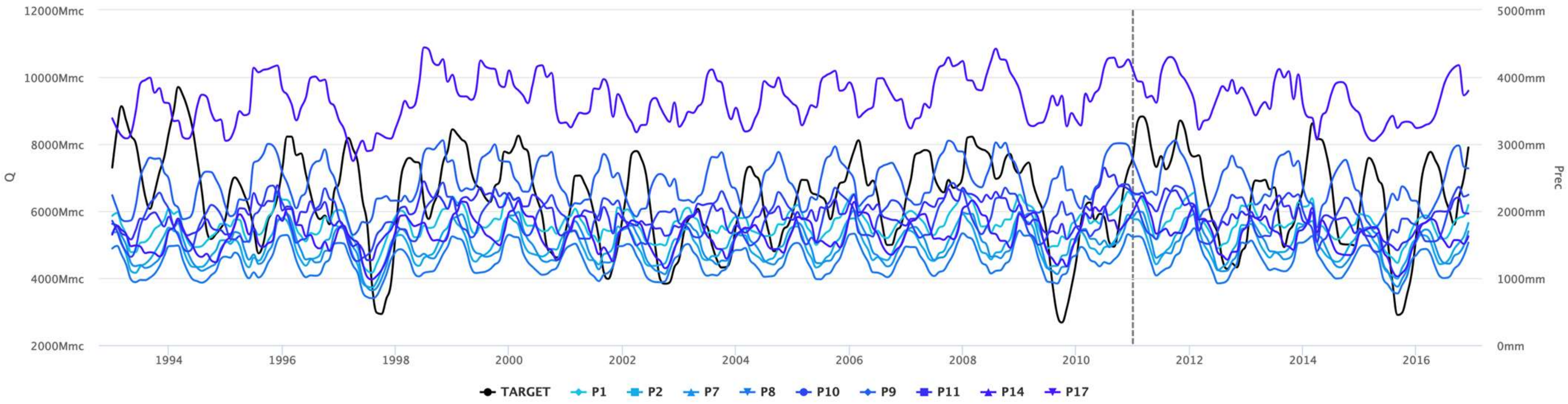
Target and Features

from 1993-01-01 to 2016-12-01			
Machine	RMSE	Nash-Sutcliffe	# sample
TARGET	0	1	288

Ensemble (mean 40/50 members) Forecasted Prec/Temp



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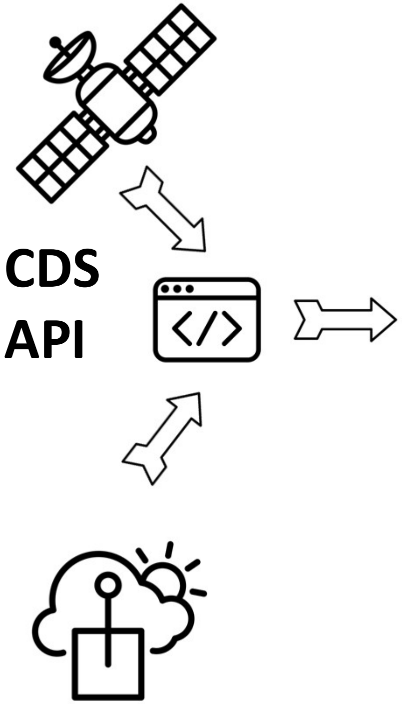
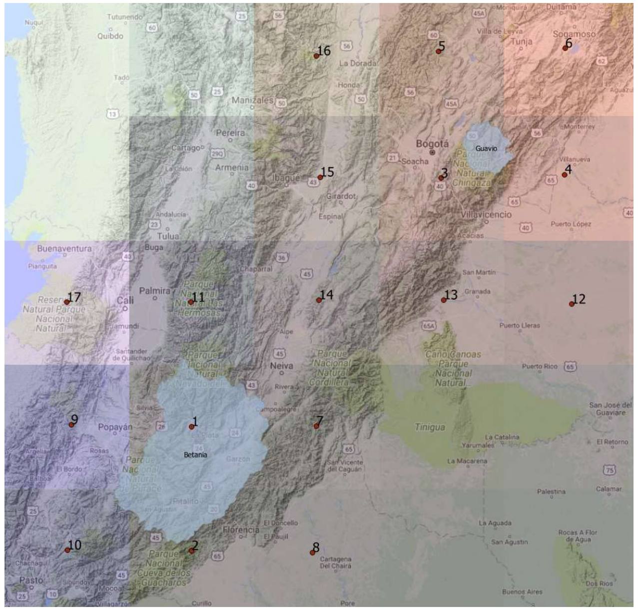
Preprocessing – Pixels Selection





Correlation between cumulated volumes
and hindcasted rainfall (anomalies from average climatology)

- (monthly) Copernicus Seasonal Hindcast (P,T)
- @100 km resolution

Are this signals (cor)related to target volumes ?

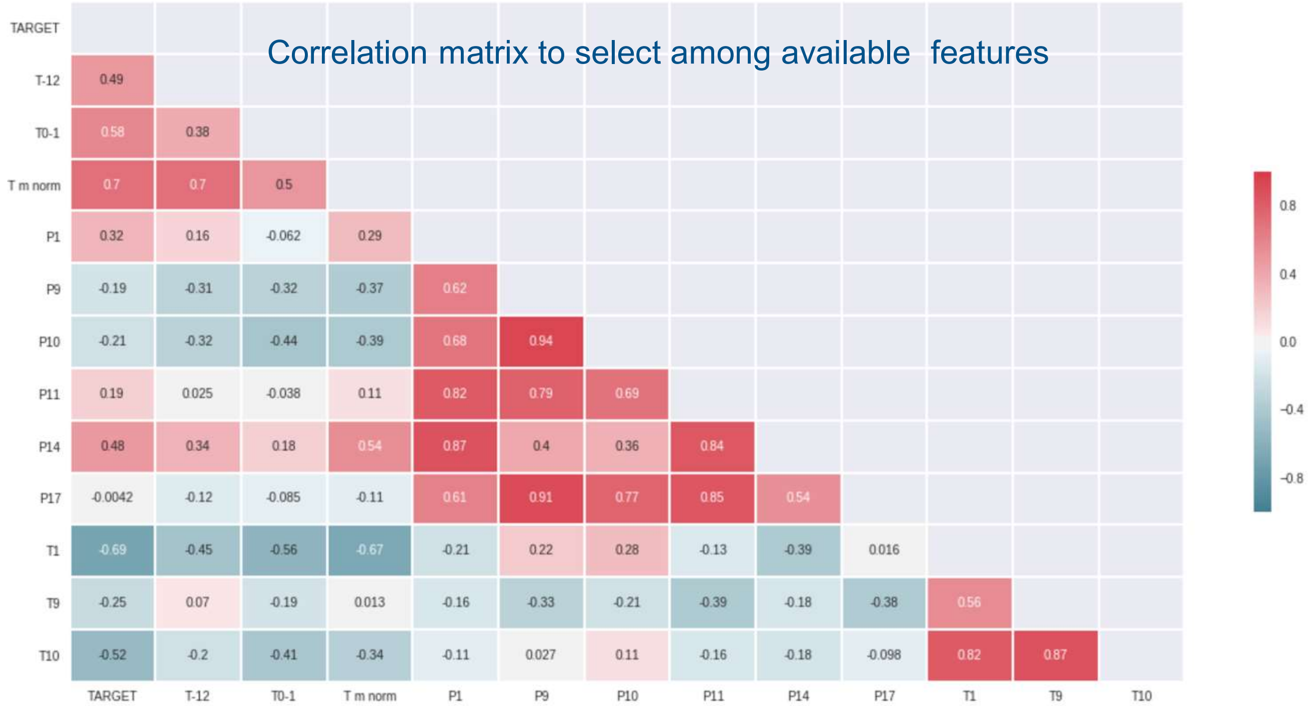
	Skill_Guavio_Cumulative values						Skill_Betania_Cumulative values				
	Lead 0_1	Lead 0_2	Lead 0_3	Lead 0_4	Lead 0_5		Lead 0_1	Lead 0_2	Lead 0_3	Lead 0_4	Lead 0_5
P1	0.18	0.23	0.25	0.25	0.24	P1	0.38	0.44	0.48	0.49	0.51
P2	0.23	0.30	0.33	0.33	0.32	P2	0.39	0.46	0.50	0.51	0.53
P3	0.21	0.21	0.19	0.16	0.15	P3	0.23	0.25	0.27	0.28	0.30
P4	0.32	0.34	0.33	0.28	0.25	P4	0.20	0.23	0.26	0.27	0.29
P5	0.16	0.13	0.11	0.07	0.07	P5	0.16	0.15	0.16	0.18	0.20
P6	0.33	0.34	0.33	0.27	0.25	P6	0.19	0.19	0.19	0.19	0.20
P7	0.24	0.28	0.30	0.28	0.27	P7	0.38	0.45	0.48	0.49	0.51
P8	0.25	0.31	0.34	0.33	0.32	P8	0.38	0.45	0.50	0.51	0.52
P9	0.02	0.04	0.07	0.09	0.09	P9	0.27	0.36	0.43	0.48	0.53
P10	0.08	0.11	0.15	0.18	0.18	P10	0.31	0.39	0.46	0.50	0.53
P11	0.06	0.08	0.08	0.08	0.07	P11	0.31	0.36	0.40	0.43	0.46
P12	0.29	0.33	0.32	0.28	0.24	P12	0.20	0.26	0.30	0.31	0.34
P13	0.26	0.29	0.29	0.25	0.24	P13	0.31	0.36	0.39	0.40	0.42
P14	0.15	0.17	0.17	0.15	0.14	P14	0.32	0.37	0.41	0.42	0.45
P15	0.05	0.07	0.09	0.07	0.05	P15	0.23	0.26	0.30	0.32	0.34
P16	0.07	0.05	0.04	0.03	0.03	P16	0.19	0.20	0.22	0.24	0.27
P17	0.01	0.05	0.08	0.11	0.11	P17	0.24	0.33	0.41	0.47	0.51
T1	0.01	-0.02	0.02	0.06	0.08	T1	-0.09	-0.12	-0.13	-0.14	-0.15
T2	0.01	-0.02	0.02	0.06	0.08	T2	-0.08	-0.12	-0.13	-0.14	-0.15
T3	0.00	-0.03	0.01	0.05	0.07	T3	-0.08	-0.12	-0.13	-0.15	-0.15

Feature Selection

- Selecting among available features to get most informative ones available operationally

DataBase

Pre-processing



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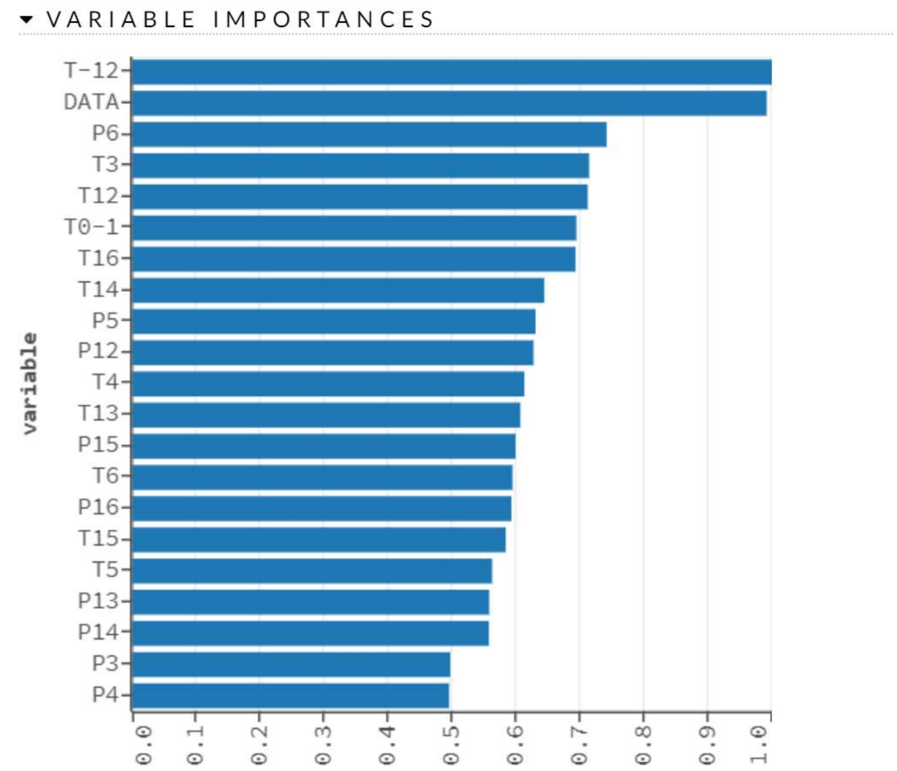
Feature Importance

- Selecting among available features to get most informative ones available operationally

DataBase

Pre-processing



Tree based relative variable importance

AUTO ML example - Betania

H2O.ai

model_id	mean_residual_deviance	rmse
GBM_grid_1_AutoML_20190404_203847_model_91	751935.437897656	867.14
DRF_1_AutoML_20190404_203847	812327.5612870641	901.29
XRT_1_AutoML_20190404_203847	851252.1116687973	922.63
GBM_grid_1_AutoML_20190404_203847_model_71	851279.4798175697	922.64
GBM_grid_1_AutoML_20190404_203847_model_88	860670.2604317574	927.72
GBM_grid_1_AutoML_20190404_203847_model_78	872708.6184079287	934.18
StackedEnsemble_BestOfFamily_AutoML_20190404_203847	881258.2452519641	938.75
GBM_grid_1_AutoML_20190404_203847_model_75	884550.7750331265	940.50
GBM_grid_1_AutoML_20190404_203847_model_105	895843.8989916794	946.49
GBM_grid_1_AutoML_20190404_203847_model_50	904389.176157908	950.99
GBM_grid_1_AutoML_20190404_203847_model_1	911340.8085015629	954.64

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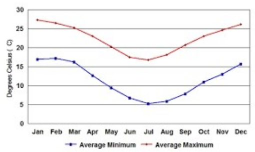
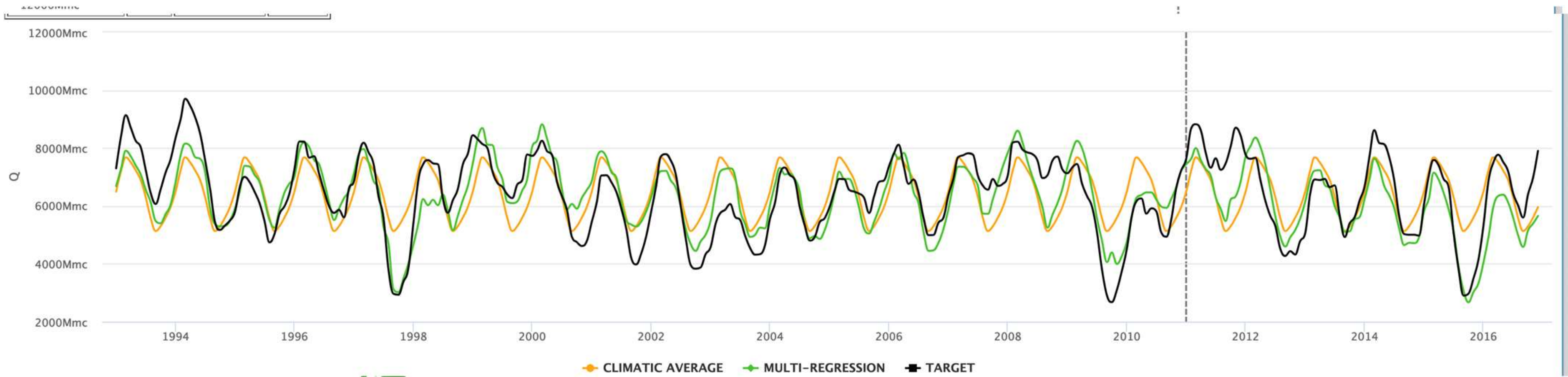
Baseline and Benchmark



BASELINE : What you have for free : trivial bench - climatic average

BENCHMARK: What you can setup with an excel spreadsheet - multiregression with same input features - EGP



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Best Model Results Vs Baselines- RMSE

	BETANIA 6 Months RMSE (1E6 mc) Cum. Vol 6 Months	GUAVIO 3 Months RMSE (1E6 mc) Cum. Vol 3 Months
Deep Learning	697	116
SVR	819	116
Multi-regression	960	135
Climatic Average	1000	136

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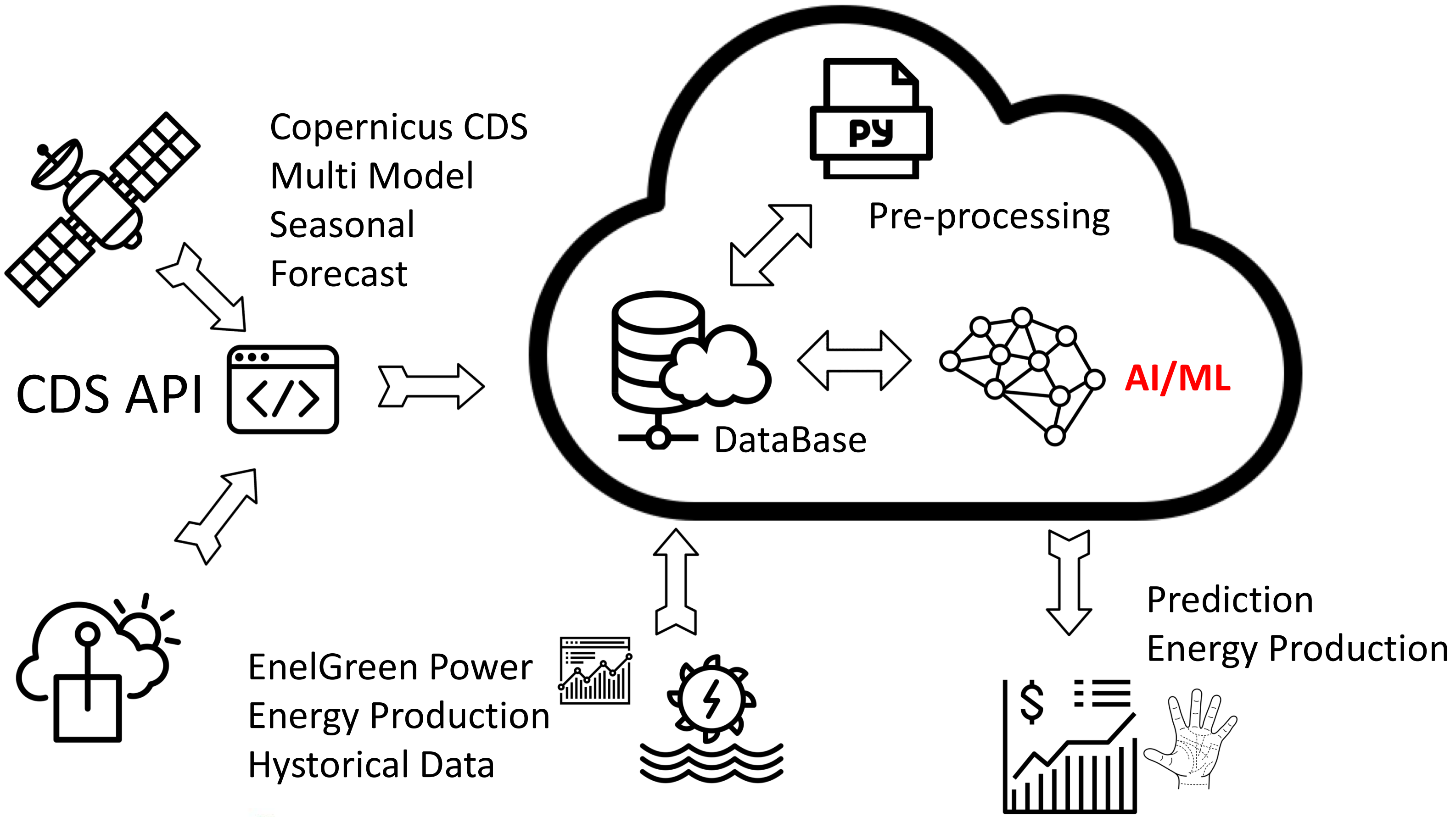
SCHT Operational Cloud-Web CS



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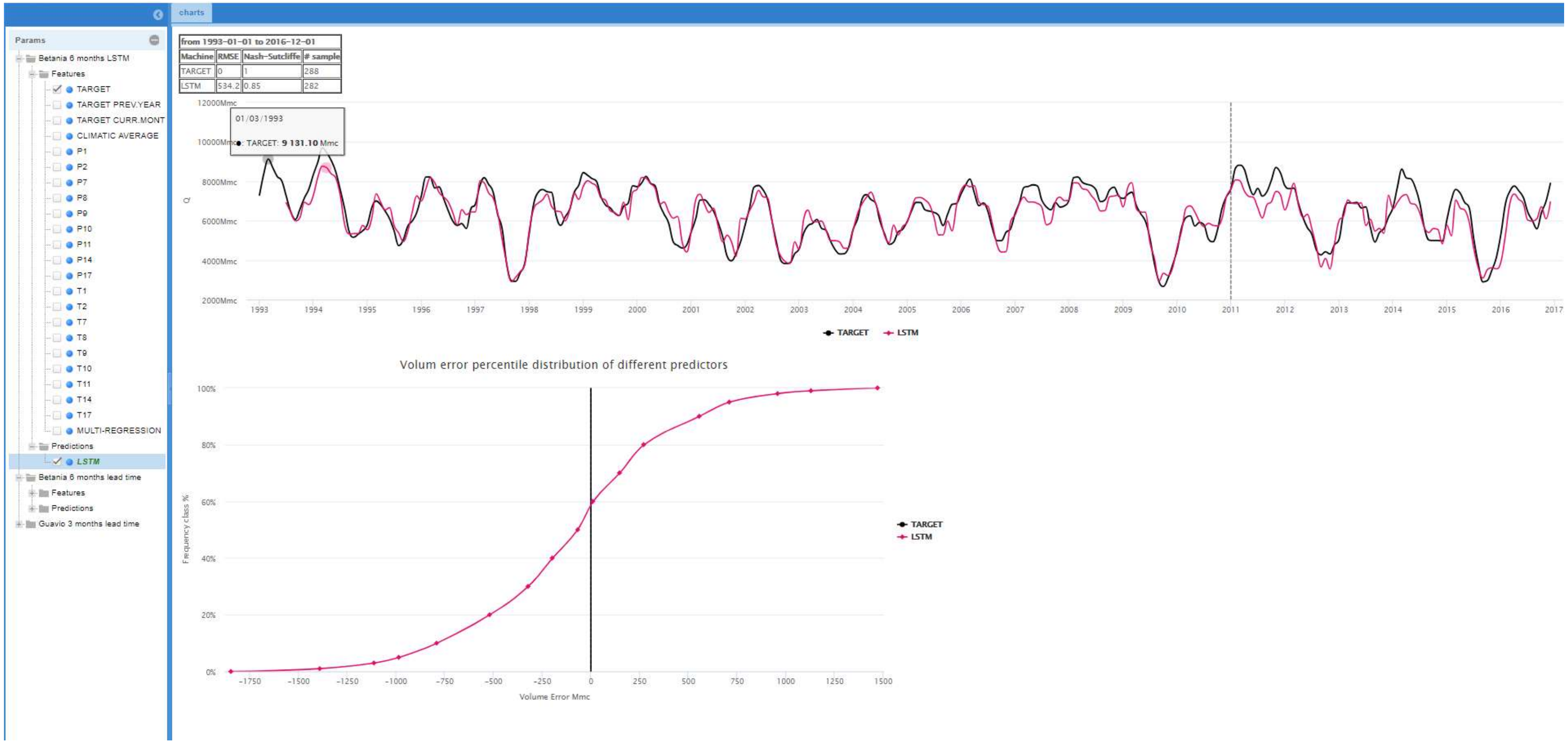
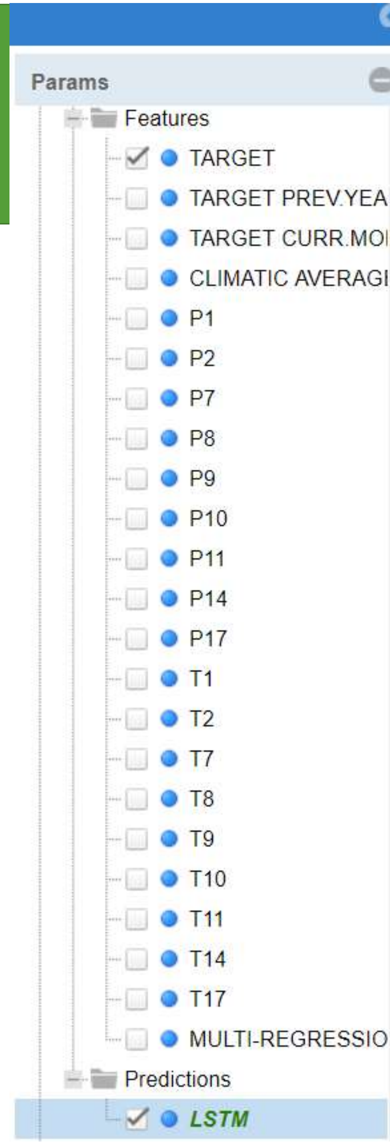
SCHT Web Demo





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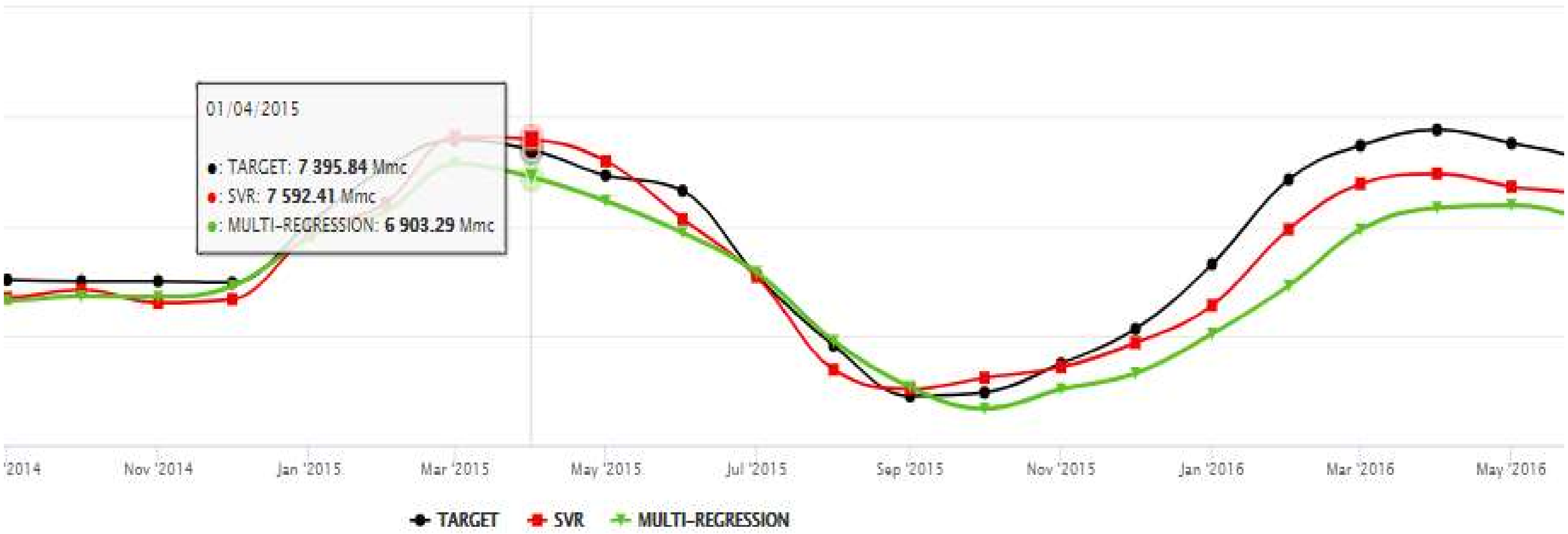
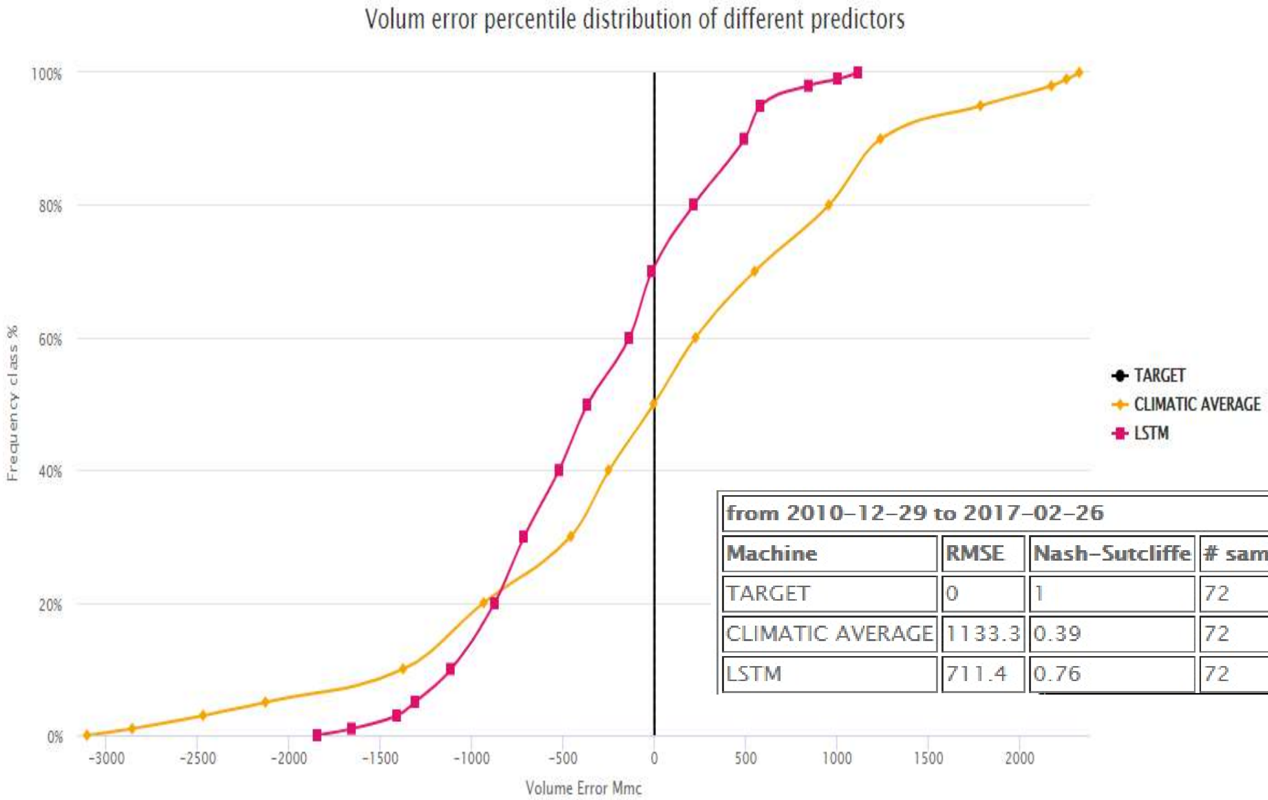


SCHT Web Demo



from 2010-12-29 to 2017-02-26			
Machine	**RMSE**	**Nash-Sutcliffe**	**# sample**
TARGET	0	1	72
CLIMATIC AVERAGE	1133.3	0.39	72
LSTM	711.4	0.76	72

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Conclusion- an added value example

- AI-based SCHT CS can boost and improve seasonal forecast energy production
  - [+1,7%-+0,6%] on 2000GWh/year ≈ 0.5M$/year (*)
  - Better than multi-regression or Climatic Average
- SCHT SC is low time consuming and can be replicated in multiple sites
  - No needs of complex hydrological models
  - Purely "data" driven
- AI and CDS data can boost and democratize Climate Service development

	NO SEASONAL FORECAST	SCHT AI-based CS	PERFECT FORECAST
Years 2000-2016	100.0%	101.7%	103.1%
Years 2011-2016	106.0%	106.6%	108.3%

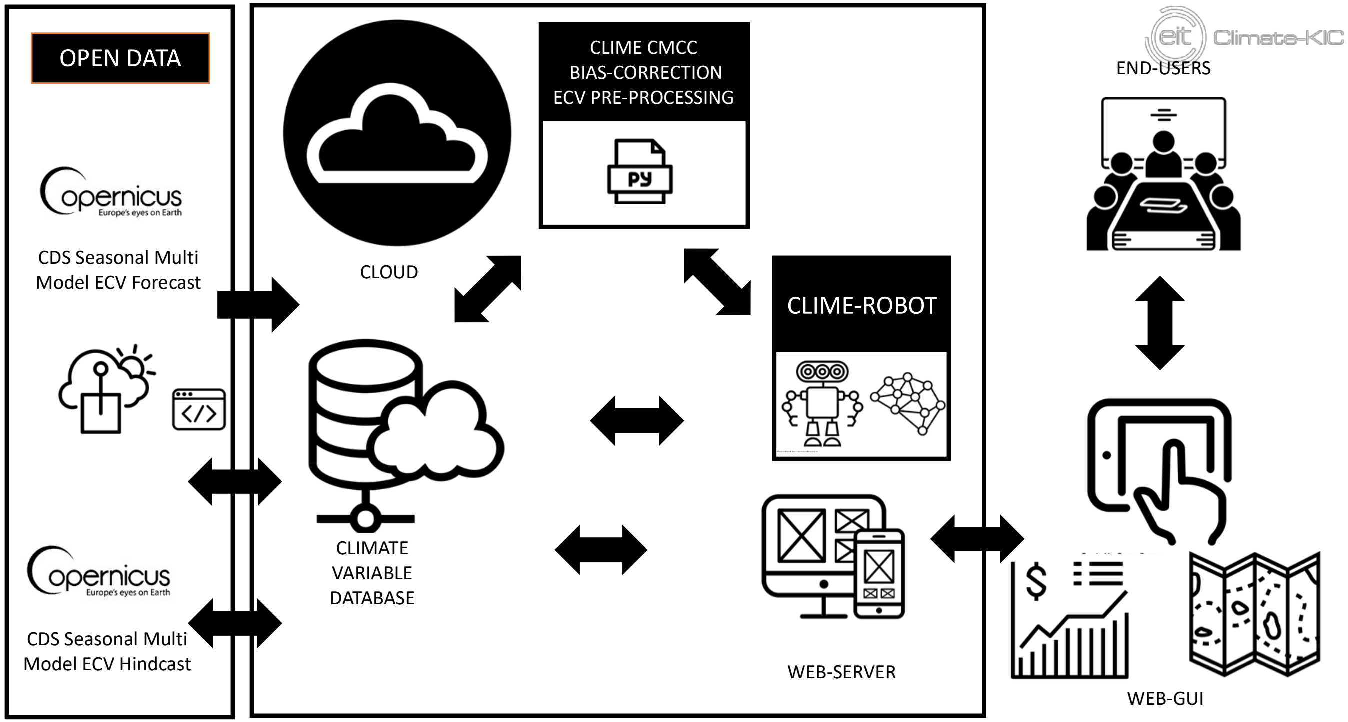
Simulation of expected benefits on annual producibility for budget adjustment twice a year, considering actual and perfect forecast , using hindcast data

(*) with *low* energy price oh 4 $c/Kwh

Next Step: AI-based Climate Platform – ClimeROBOT

Clime-ROBOT: Develop a general platform embedding **AUTO Machine Learning** and the **others cds forecast providers** for improving seasonal time series forecast of a generic climate dependent target variable:

- Water availability
- Energy production
- Irrigation demand
- Tourism
- Industrial production



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Thank you for your attention

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