# Climate Services for the Hydropower sector Turning Climate Science into solutions for Hydropower production

Webinar Thursday 12 November 2020

#### **Smart Climate hydropower Tool**

An artificial intelligence-based service for hydropower production seasonal forecast

















Green Power

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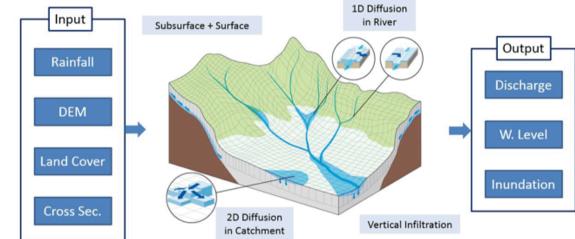
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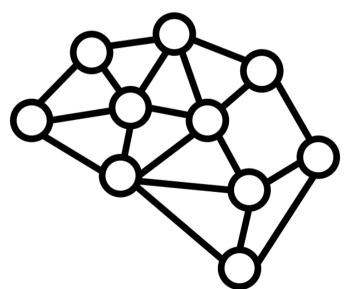
Climate forecast enabled knowledge services

# SCHT: Al-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 Al 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 (Al and ML) Time Series algorithms.
  - <u>Democratize</u> 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





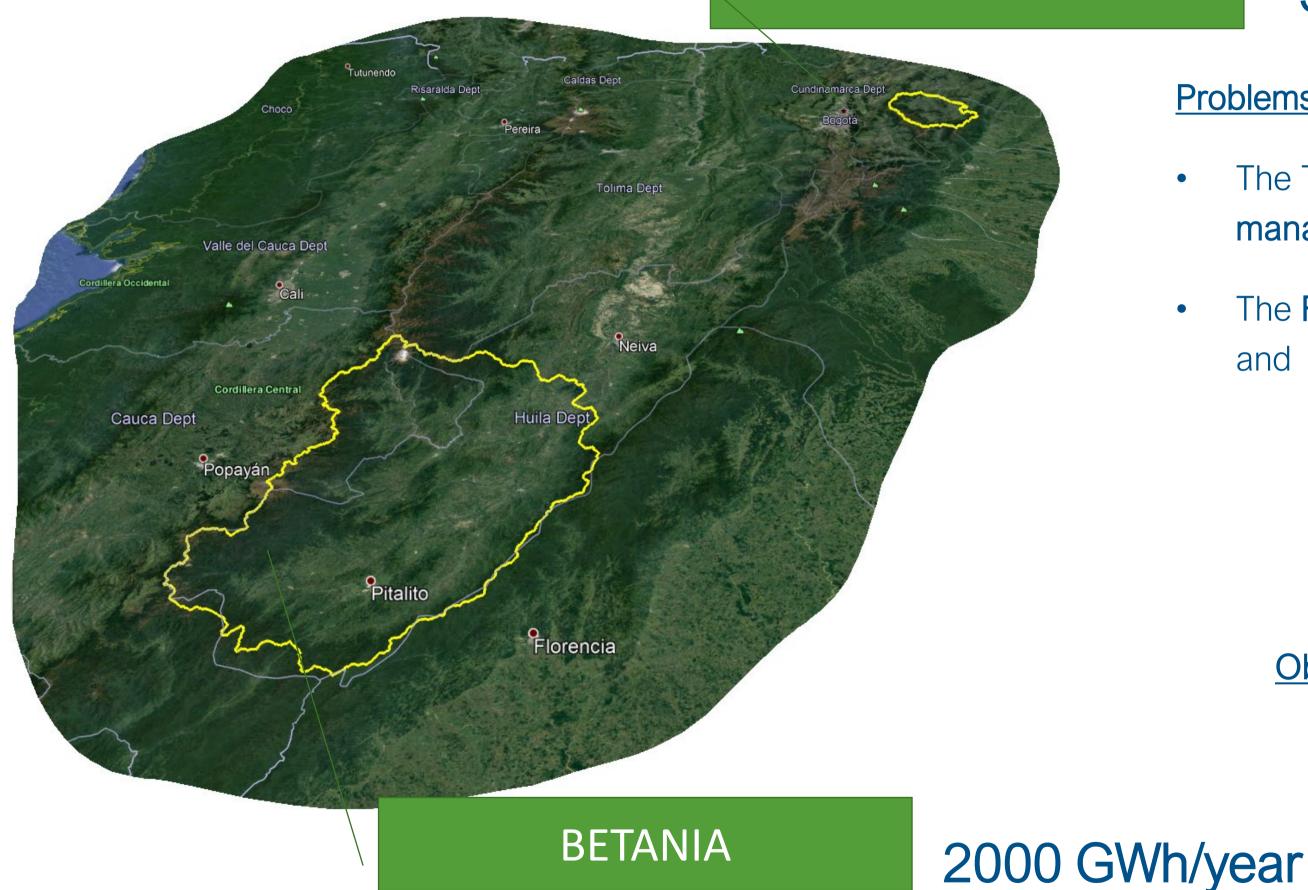




#### Case Studies- by EGP Where is the value in forecasting for HP?



5500 GWh/year



#### **Problems**

- The Technical point of view: Knowing in advance means planning management of the reservoir to increase 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**

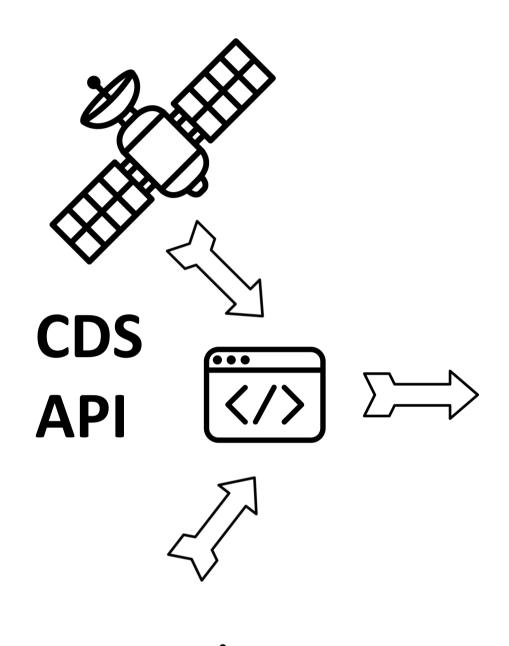
Knowing as early as possible deviation at the year end between budget producibility and final production to be able to undertake the most advantageous corrective actions.

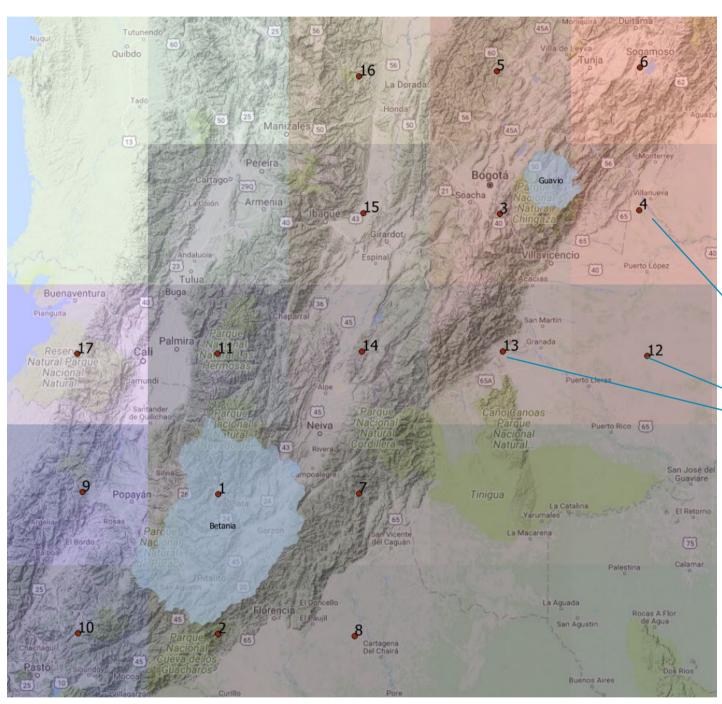






# How we did it- preprocessing

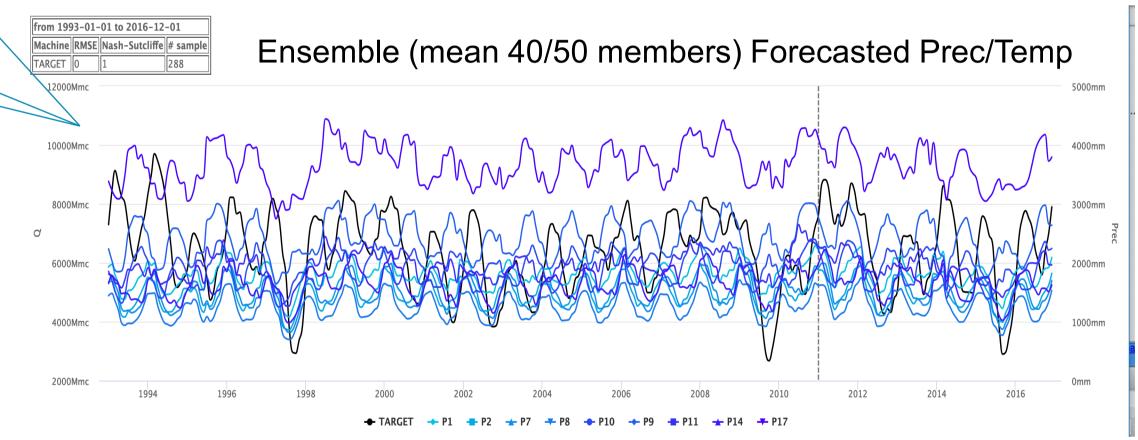




Correlation between cumulated volumes and hindcasted rainfall (anomalies from average climatology)

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

Are this signals (cor)related to target volumes?





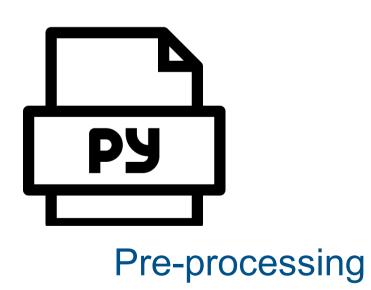


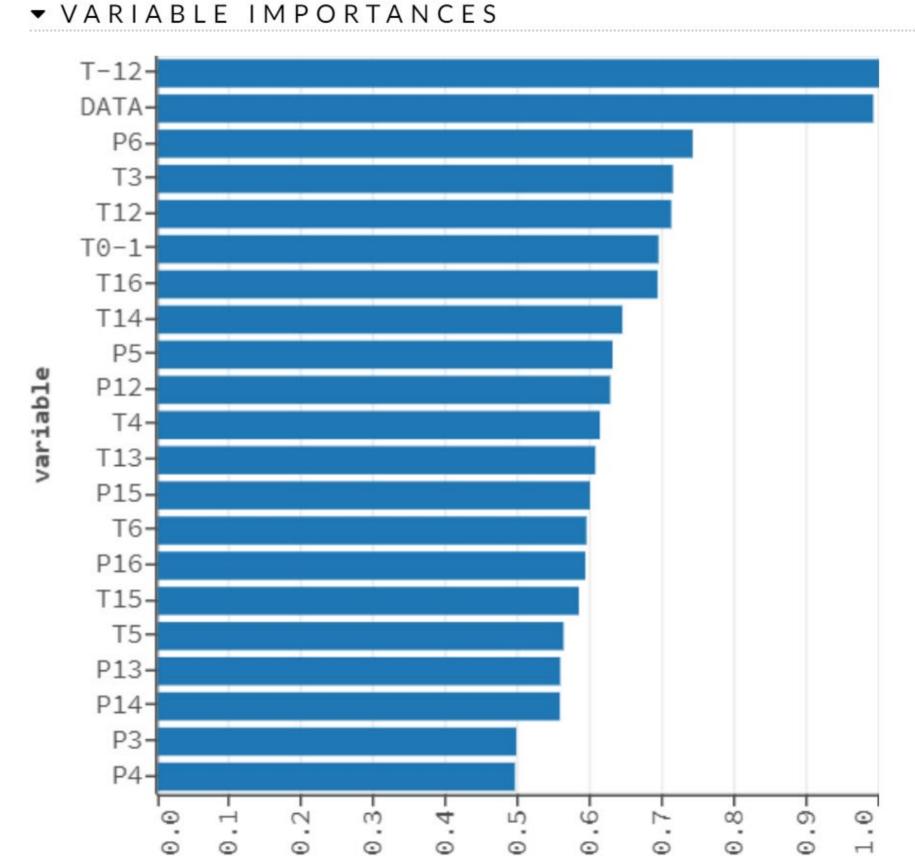


## How we did it- Features selection

Selecting among available features to get most informative ones available operationally









Correlation matrix to select among available features





Tree based relative variable importance



# How we did it- ML training

• Test an AUTOML platform among available ones OR train an algorithm using open libraries

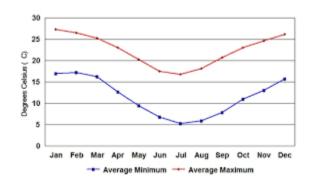
model_id	mean_residual_deviance	rmse
GBM_grid_1_AutoML_20190404_203847_model_91	751935.437897656	867.14
DRF_1_AutoML_20190404_203847	812327.5612870641	901.29
XRT_1_AutoML_20190404_203847	851252.1116687973	922.63
GBM_grid_1_AutoML_20190404_203847_model_71	851279.4798175697	922.64
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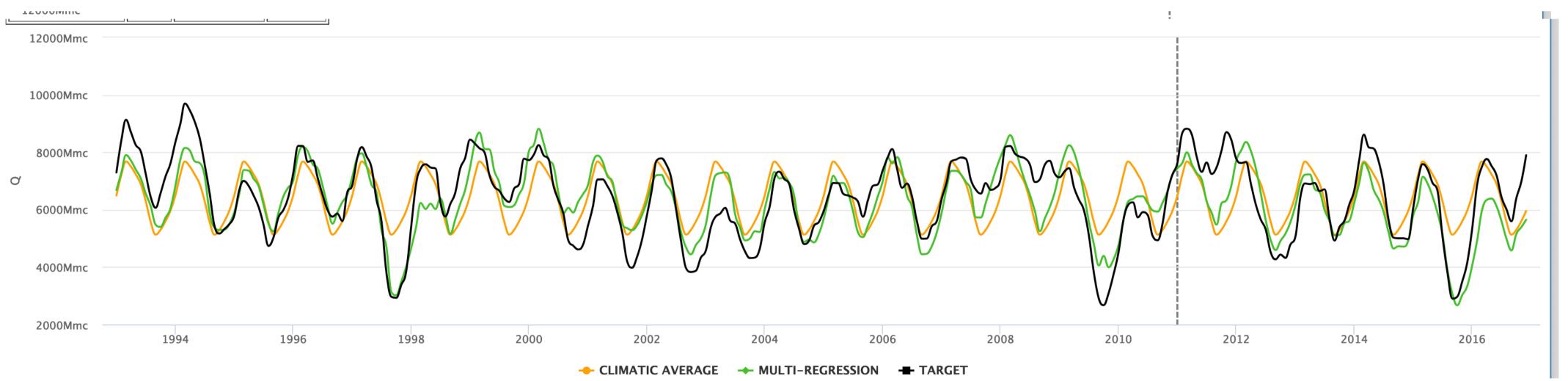
#### Baseline and Benchmark



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









### Best Model Results Vs Baselines- RMSE

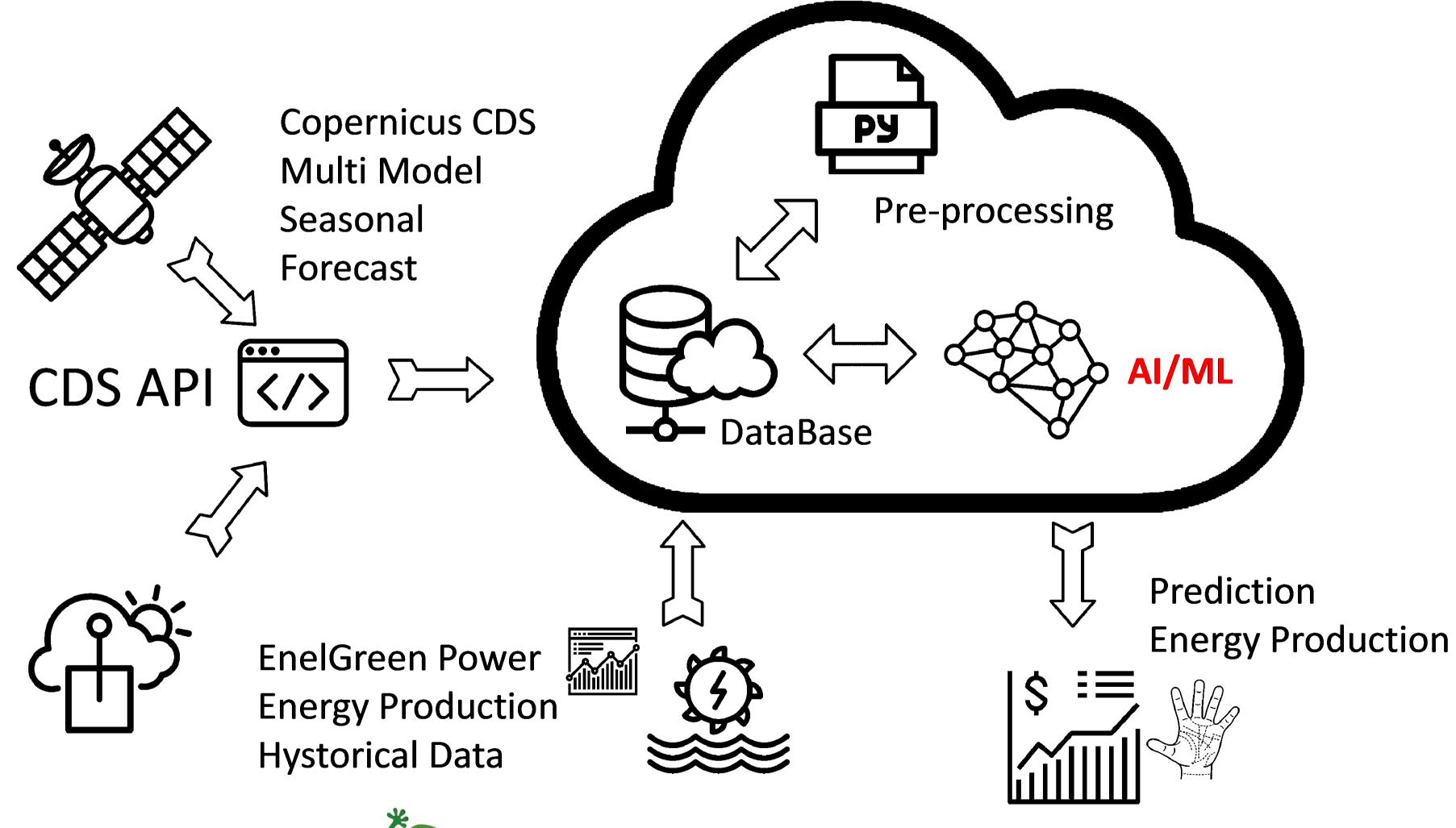
	BETANIA 6 Months RMSE (1E6 mc) Cum. Vol 6 Months	GUAVIO 3 Months RMSE (1E6 mc) Cum. Vol 3 Months
Deep Learning	697	116
SVR	819	116
Multi-regression	960	135
Climatic Average	1000	136







## SCHT Operational Cloud-Web CS







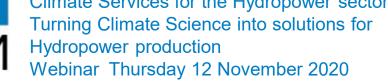


#### SCHT Web Demo



Volume Error Mmc





## Conclusion- an added value example

- Al-based SCHT CS can 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
- Al 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







# Thank you for your attention



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