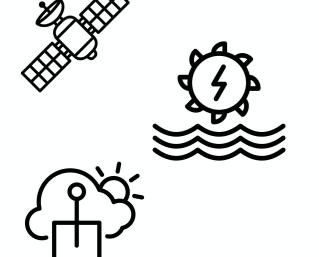
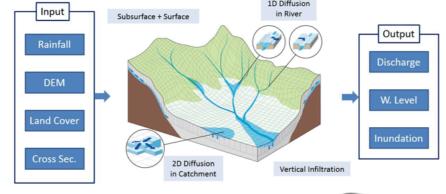


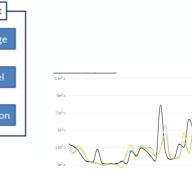
Al for Downstreaming and Tailoring Hydrological Forecast Intelligence to final Users



- <u>NEEDS</u>: Energy and Water Management requires <u>forecast</u> for optimal usage of the resource
- A Data Centric approach: Copernicus CDS, EOBS, Forecast Datasets are GROWING
- The *Business as usual* Way to *Go*: Feed complex hydrological Deterministic Models (Eventually adding Al on top or at the bottom of the CHAIN) with EOBS, ground station data, DTM, Soil And forecast
 - Time and data consuming (topo, landuse, soil)
- Requires the involvement of hydrological modeling expert
- Multiple sites = Multiple Models Many companies already offer service
- Many companies already offer service / software- NO INNOVATION













Al for Downstreaming and Tailoring Hydrological Forecast Intelligence to final Users



- Al for DATA DRIVEN forecast: Combination <u>Operational Forecast</u>, <u>EOBS</u>, <u>and</u> Data Science (Al and ML) for ana effective down streaming of forecast intelligence
 - <u>Democratize</u> the practical use of seasonal-forecast-based climate services
 - Less time and data requirements No background in hydraulics requested Only local discharge data needed (rainfall/ temperature station if available)

• And for web applications

• And for web applications

"Simplicity is the ultimate sophistication"



Where is the value in forecasting for HP?





Betania 2000 GWh/year Rio Magdalena Central Hidroeléctrica El Guavio 5500 GWh/year Rio Guavio



Locla used data are monthly iucoming disharge to the 2 reservoirs recorded in the last 20 years





First application – Hydropower for EGP Where is the value of Al forecasting for HP?



Problems

- Technical: Knowing in advance means planning management of the reservoir to increase production
- **Financial** = 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

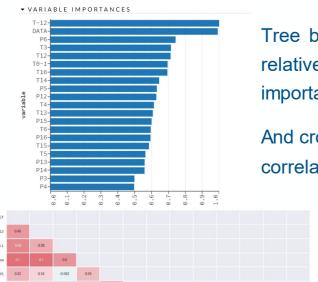


Al lightweight workflow setup



Exploiting power of AUTOML

Selecting most informative FEATURES available operationally (i.e. P,T Seasonla FORECAST from Copernicus CDS)



Tree based relative variable importance

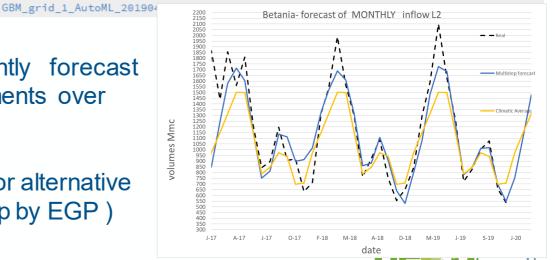
And cross correlation

> Using AI to get consistently forecast performances improvements over benchmarks

(i.e. Climatic average or alternative simple regeressors setup by EGP)



	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
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	GBM_grid_1_AutoML_20190404_203847_model_78	872708.6184079287	934.18
	$Stacked Ensemble_Best Of Family_AutoML_20190404_203847$	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
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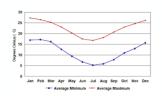






Baseline and Benchmark

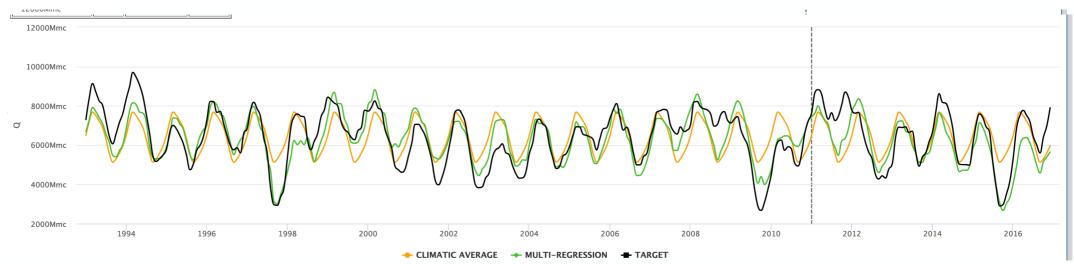




BASELINE: What you have for free: trivial bench - climatic average



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





Best Model Results Vs Baselines-RMSE

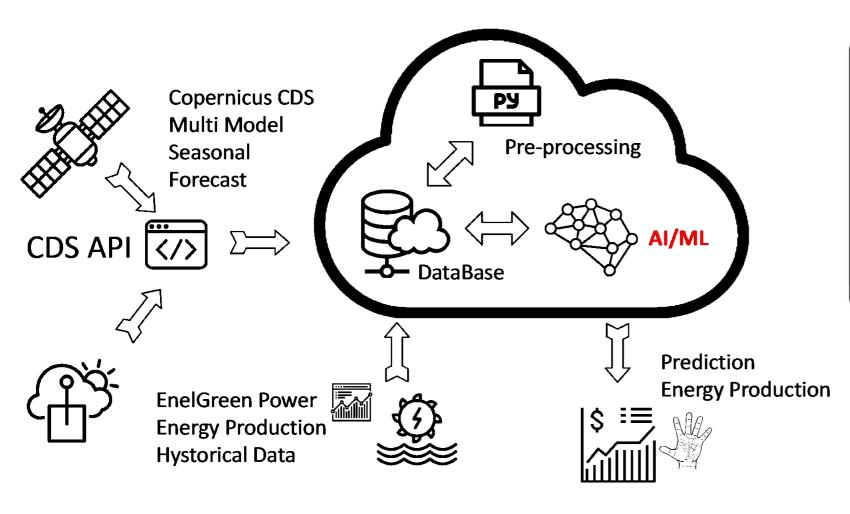


	BETANIA 6 Months RMSE (1E6 mc) Cum. Vol 6 Months	GUAVIO 3 Months RMSE (1E6 mc) Cum. Vol 3 Months
Deep Learning (LSTM)	697	116
SVR	819	116
Multi-regression (by EGP)	960	135
Climatic Average	1000	136



Translating forecast intelligence into Operational Cloud-Web CS

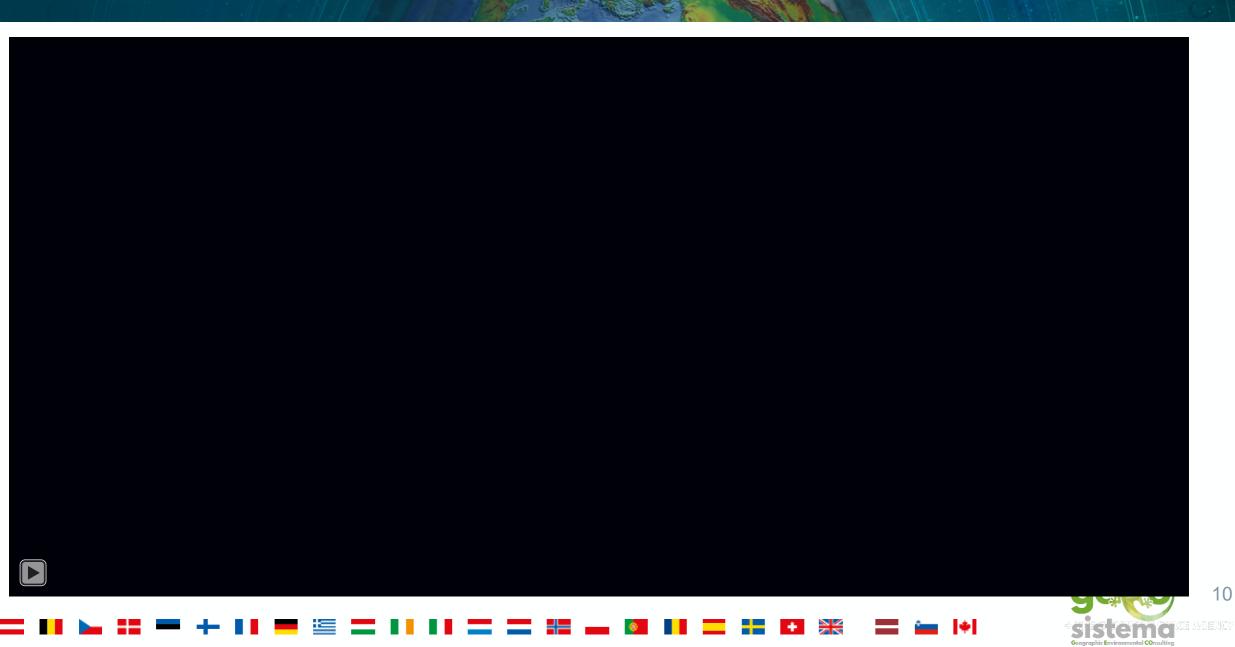






A web service that shows forecast and performances









The added value example for HPIS the provide intelligence good "Enough"?



	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%

A simple test made with EGP: Simulation of expected benefits on annual producibility for budget adjustment twice a year, considering actual and perfect forecast

And current management reservoir rules

(*) with low energy price oh 4 \$c/Kwh (PRE-COVID market condition...)



Second application – Forecast intelligence for Water distribution





Ridracoli Resevoir

- Over 33 Mm3 of capacity
- Small 80km2 mountain catchment
- Distributing drinking water to 3
 Provinces in Emilia Romagna –
 Italy



Second application – Forecast intelligence for Water distribution





Problems

- Technical: Knowing in advance means planning a mix of water resources to be exploited efficiently
- A small, impulsive and very challenging catchment

Objective

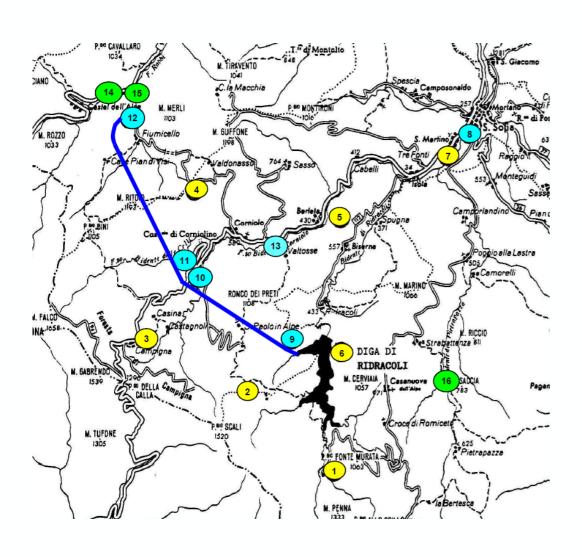
Reducing uncertainty in the average discharge coming to the reservoir for the next 14 days and the next month and testing operational forecast twice a month.





Getting a few Local data for effective downstreaming





- Temperature/prec.
- **Discharge**



Testing ECMWF TIGGE forecast dataset Precipitation and temperature

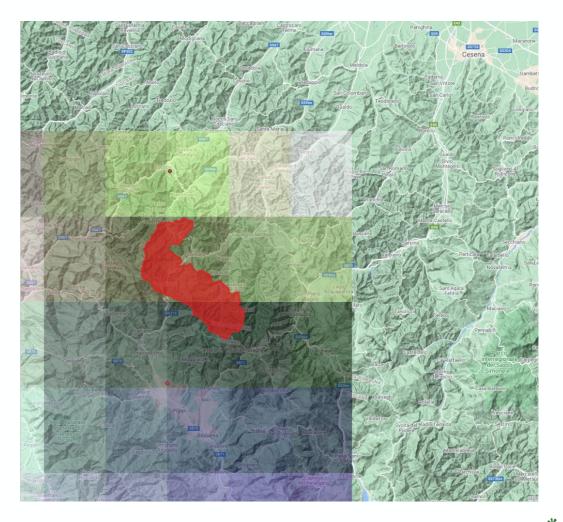


Nearly operational meteo forecast (48 hours delay)

@ 10-25 km

P,T,SDWE

Leadtime upt to 10-15 days

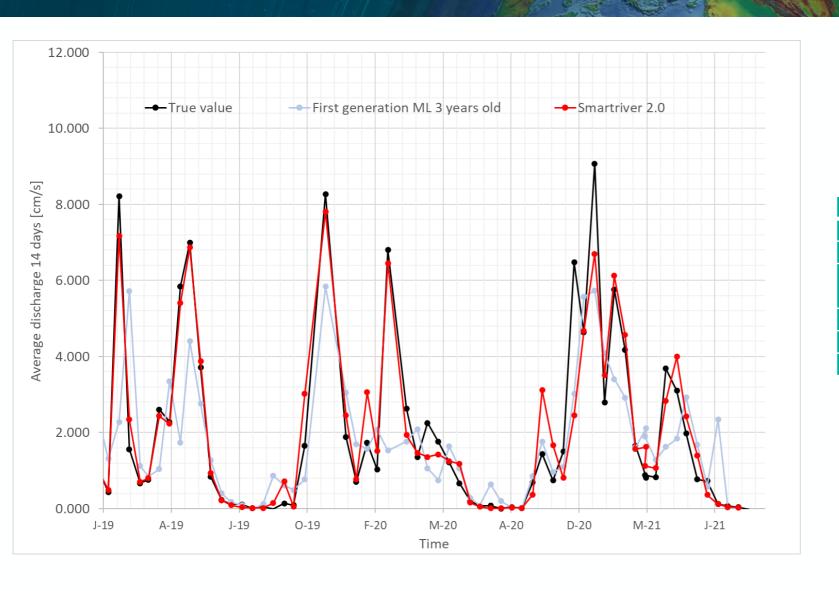






The improved forecast – next 14 days





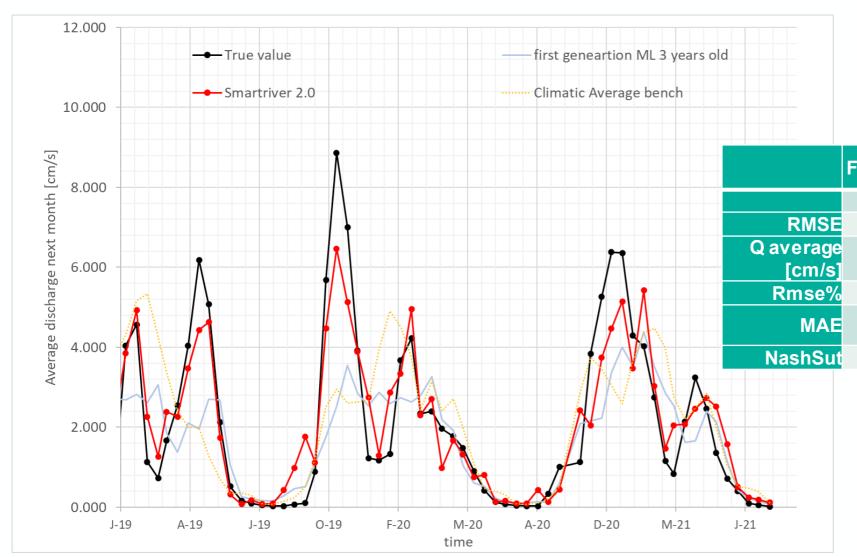
Serious improvement over first generation forecast with simple ML models

	First genration ML	SMARTRIVER 2.0
	19-21	19-21
RMSE	1.42	0.89
Q average [cm/s]		1.84
Rmse%	77%	48%
MAE	0.95	0.53
NashSut	0.6	0.84



The improved forecast – next month





Serious improvement over first generation forecast with simple ML models

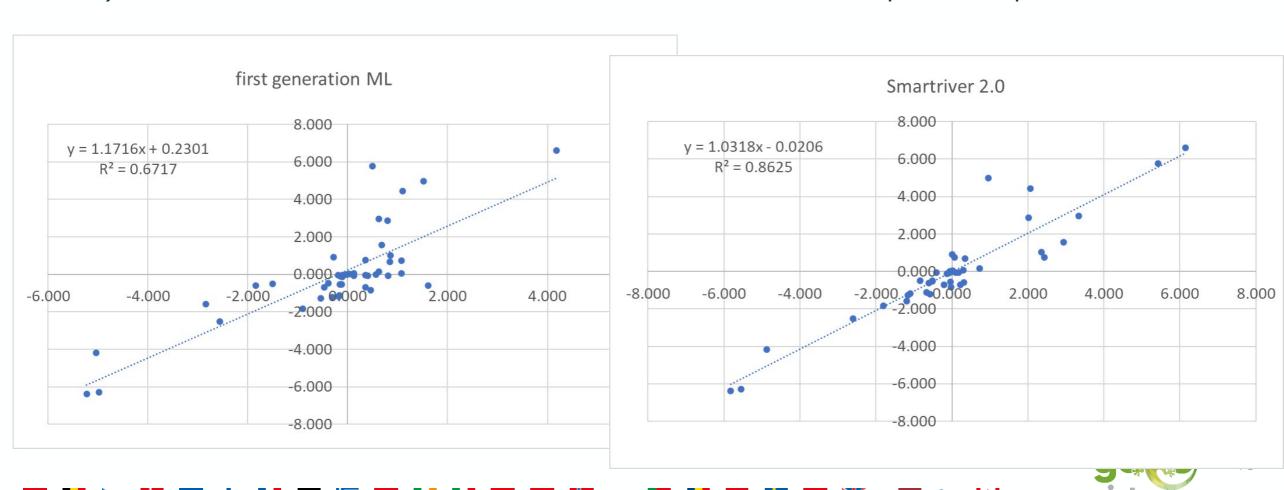
	First gen. ML	Climatic average	SMARTRIVER 2.0
		19-21	
Ε	1.59	1.73	0.93
је			
s]	2.079	2.079	2.079
%	76%	83%	45%
E	0.99	1.07	0.68
ut	0.47	0.37	0.82



Predictive power added by SMARTRIVER



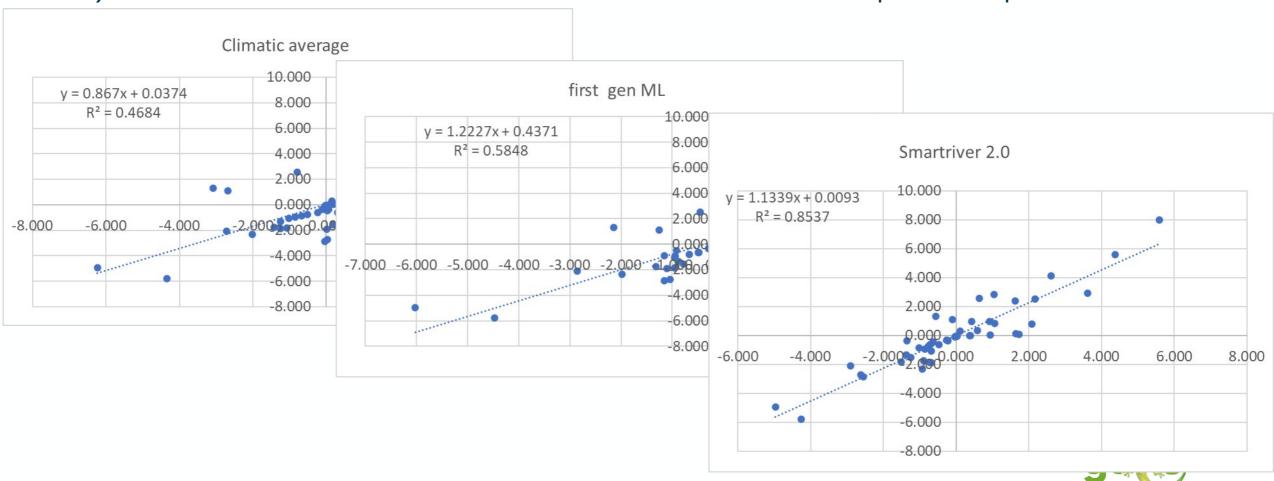
Showing predicted the time-differenced data (next precited time step minus previous recorded one) VS recorded time differenced data is a robust indication of the predictive power:



Predictive power added by SMARTRIVER



Showing predicted the time-differenced data (next precited time step minus previous recorded one) VS recorded time differenced data is a robust indication of the predictive power:



The added value example for HP



- SMARTRIVER AI-based forecast can improve water forecast to usable figures for different target users
- IT's low time and resource consuming and can be replicated in multiple sites virtually WORLDWIDE
 - No needs of complex hydrological models
 - Purely "data" driven
- SMARTIRIVER AI-based forecast realizes effective **Downstream Services** from actual global and growing datastores data stores

