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Predicting water discharge on alpine catchments with downscaled seasonal forecasts

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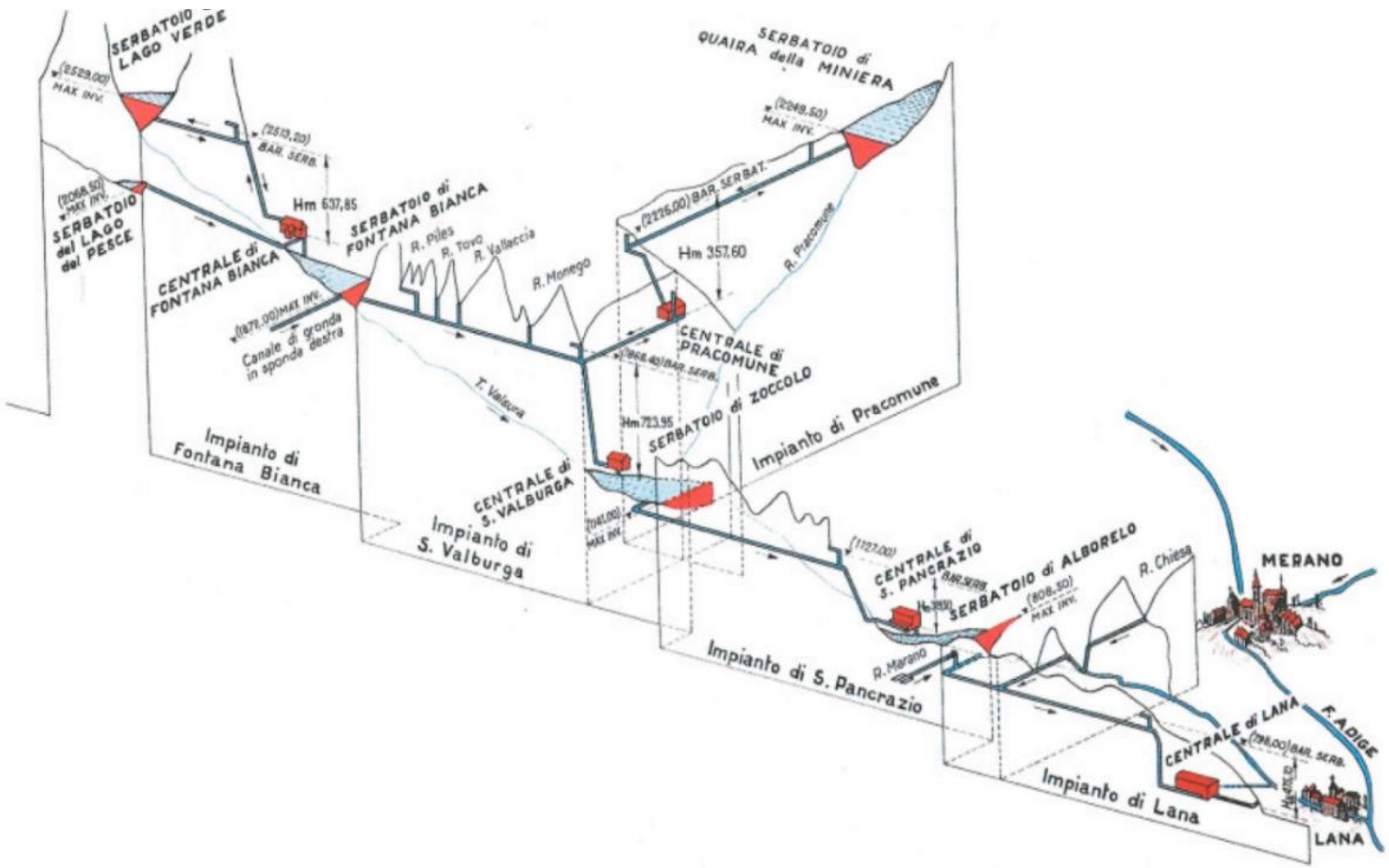
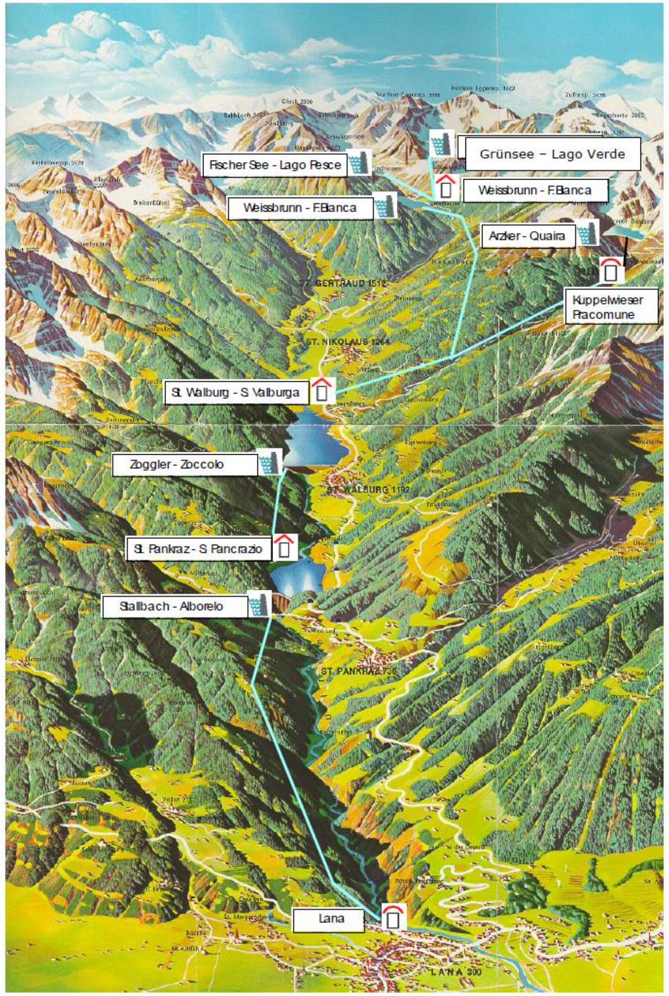
Motivations

Runoff seasonal forecast, from one to several months ahead, is a relevant application for **hydropower plant management**. A reliable estimation of the seasonal runoff can be used to:

- Improve the management of the level of the basins to **optimize** the current and future **energy production**
- Predict the energy that will be produced by a specific hydropower plant system, enabling an **enhanced management on the energy market**
- Improve the management of the hydropower basins to **prevent the risk of floods** and to **reduce the impact of drought**

Hydropower plants in Ulten Valley

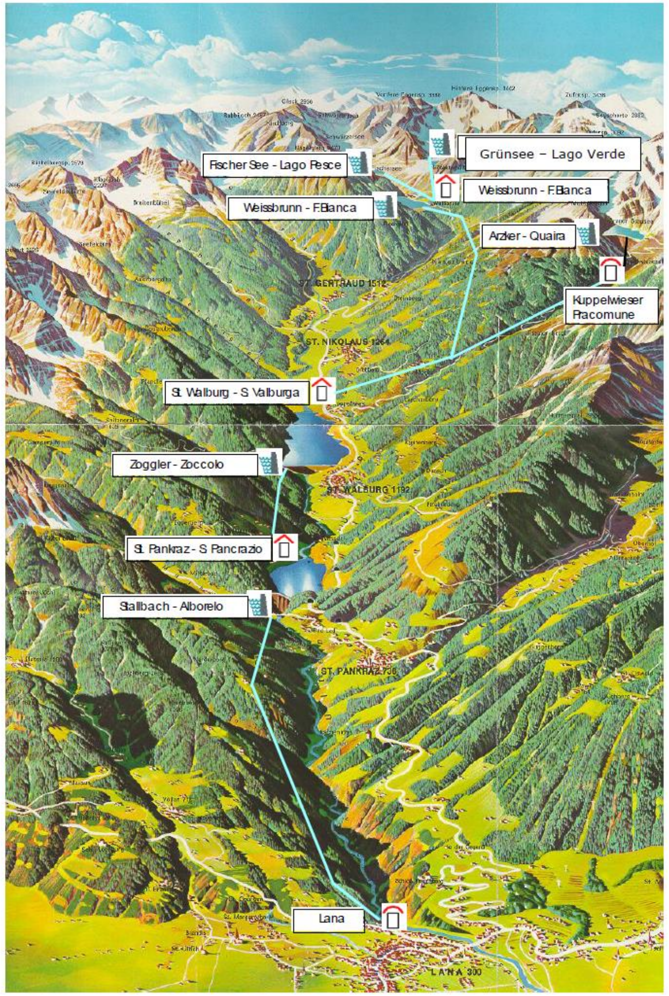




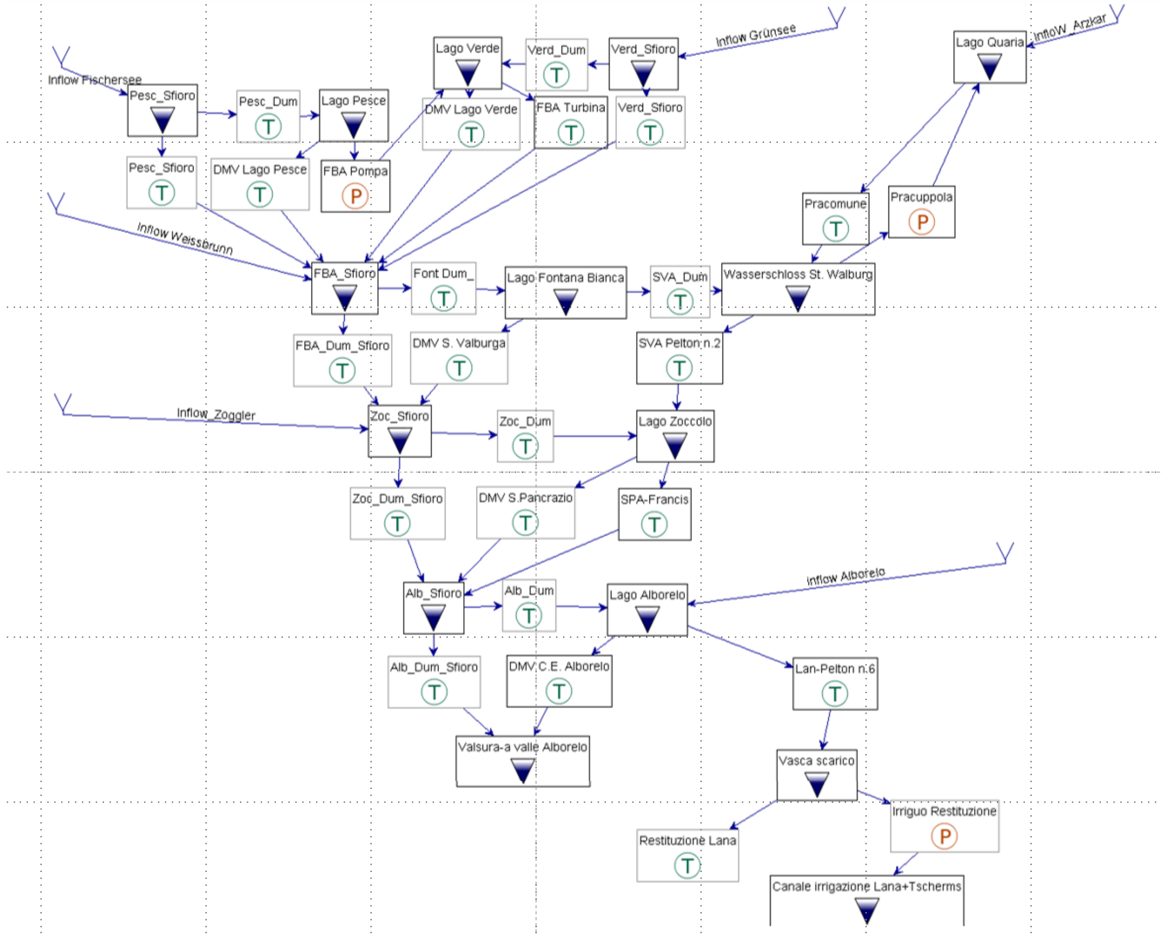
Hydropower plants in Ulten Valley

One of the most important hydropower plants system in South Tyrol:
→ **6 hydropower plants** in series (6 turbine and 1 pump stations)
→ **Total volume of basins > 57000 · 10^3 m^3**
→ **Maximum total power ≈ 250 MW**
→ **Maximum energy per year ≈ 390 GWh**

Impianto	Fontana Bianca	Pracomune (turbine)	Pracomune (pump)	Santa Valburga	San Pancrazio	Lana	Alborelo
Name of basin	Verde / Pesce	Quaira	Fontana Bianca	Fontana bianca	Zoccolo	Alborelo	
Volume of basin [$\cdot 10^3$ m^3]	6.700	11.700	1.265	1.265	35.000	2.400	
Maximum power (P_{max}) [MW]	10	39	40	44	34	120	0,3
Annual mean energy production [GWh]	15	16	-	86	91	180	1



The "Hydro-tool" model



INPUTS

- Predicted natural runoff in the basin
- Initial reservoir level
- Predicted energy price
- Obligations in plant management, e.g. min/max reservoir level, max water emptying speed, min environmental flow, etc.

OUTPUTS

- Reservoir **water volume** to optimize the energy production during the forecast period
- **Energy production forecast**

Objective

To develop a method for **runoff seasonal forecast**, **from one to several months ahead** that:

- Can produce reliable **inputs** for the **Hydro tool model**, to optimize the hydropower plant management in the Ulten Valley
- Makes use of **seasonal forecast** data
- Can be **easily applied in other areas**, i.e. minimum in-situ data availability is required

Hydro-tool model

INPUTS

- **Predicted natural runoff in the basin**
- Initial reservoir level
- Predicted energy price
- Obligations in plant management, e.g. min/max reservoir level, max water emptying speed, min environmental flow, etc.

OUTPUTS

- Reservoir **water volume** to optimize the energy production during the forecast period
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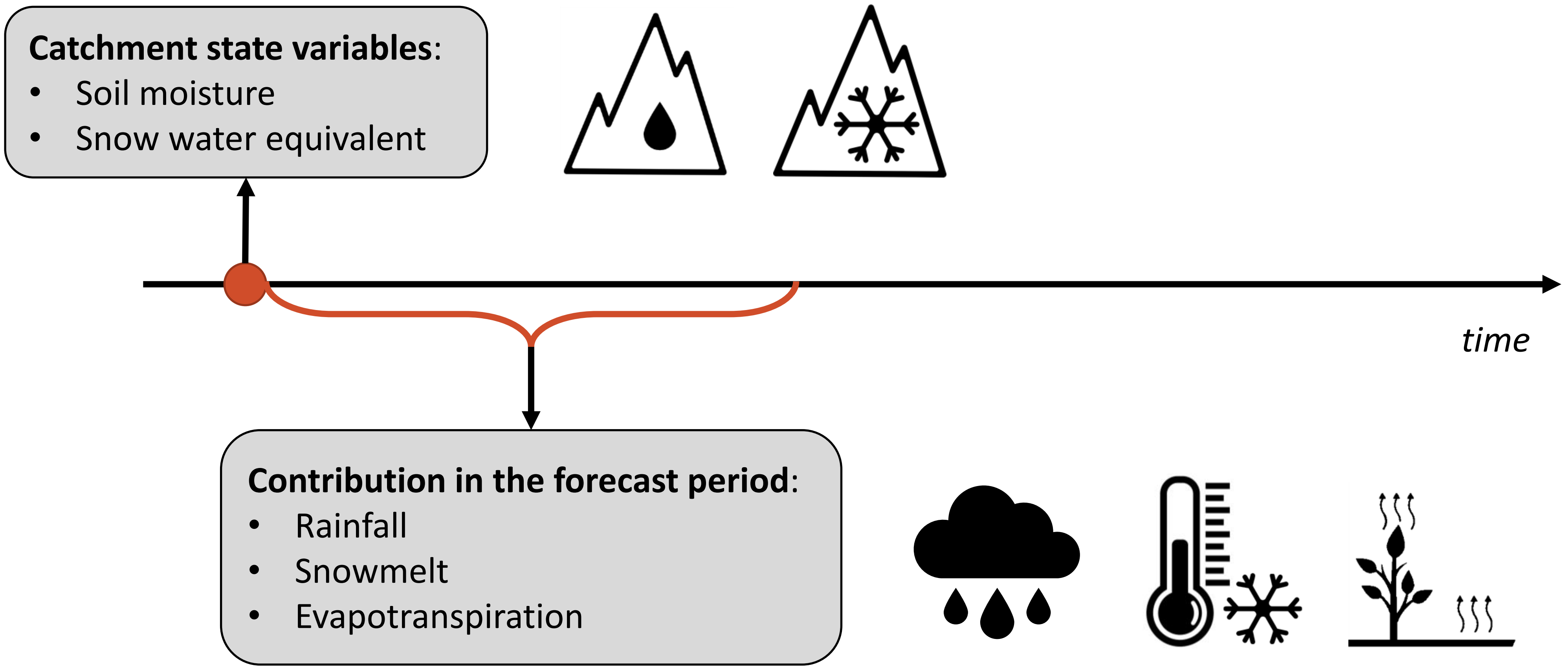
Monthly mean runoff forecast



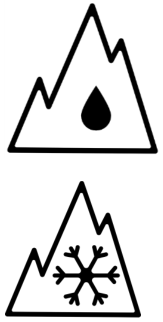
Statistical models for runoff forecast

Statistical models may represent a valuable solution with respect to hydrological model:

Some proxy variables which are representative of all the variables can be selected. No need to estimate exactly each variable (i.e. catchment state, contribution in the forecast period variables)

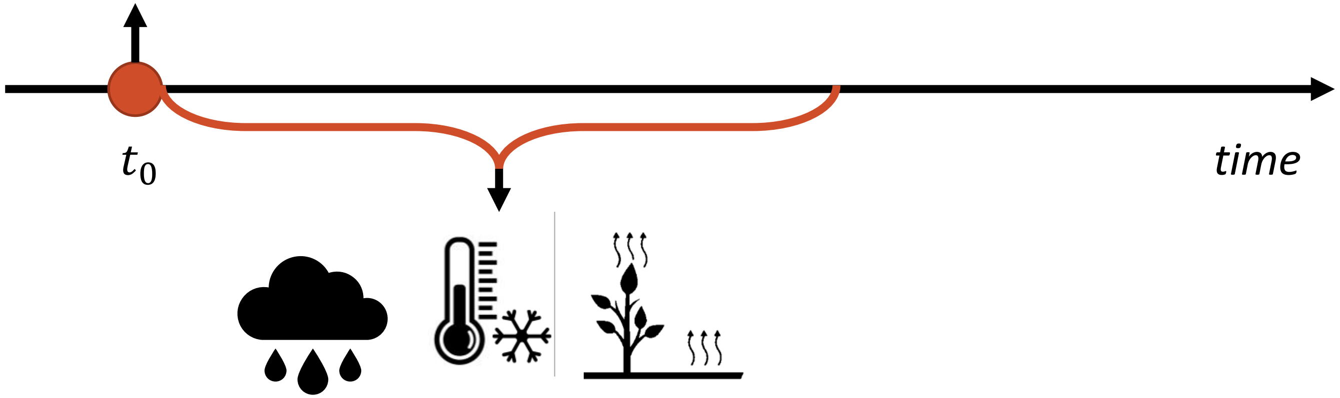
Generally, the prediction function found using a statistical model cannot be extended to other catchments without re-fitting the statistical model

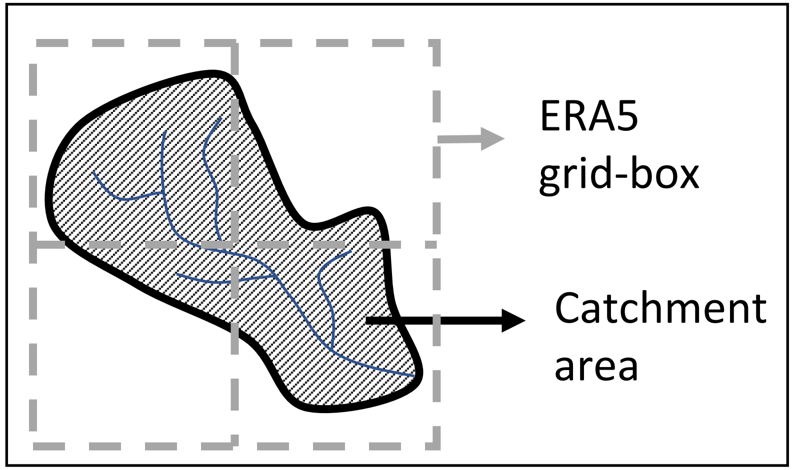
Selected proxy input variables



Selected proxy variables to describe the **catchment state**:

- **Mean runoff of the previous month**
- **ERA5-swe** (considering all grid-box covering the catchment area)





Selected proxy variables to describe the **contribution during the forecast period**:

- **Seasonal forecast (SF) of monthly mean temperature (t2m) and total precipitation (tp)** downscaled at the ERA5 resolution (considering all grid-box covering the catchment area)

Support Vector Regression (SVR)

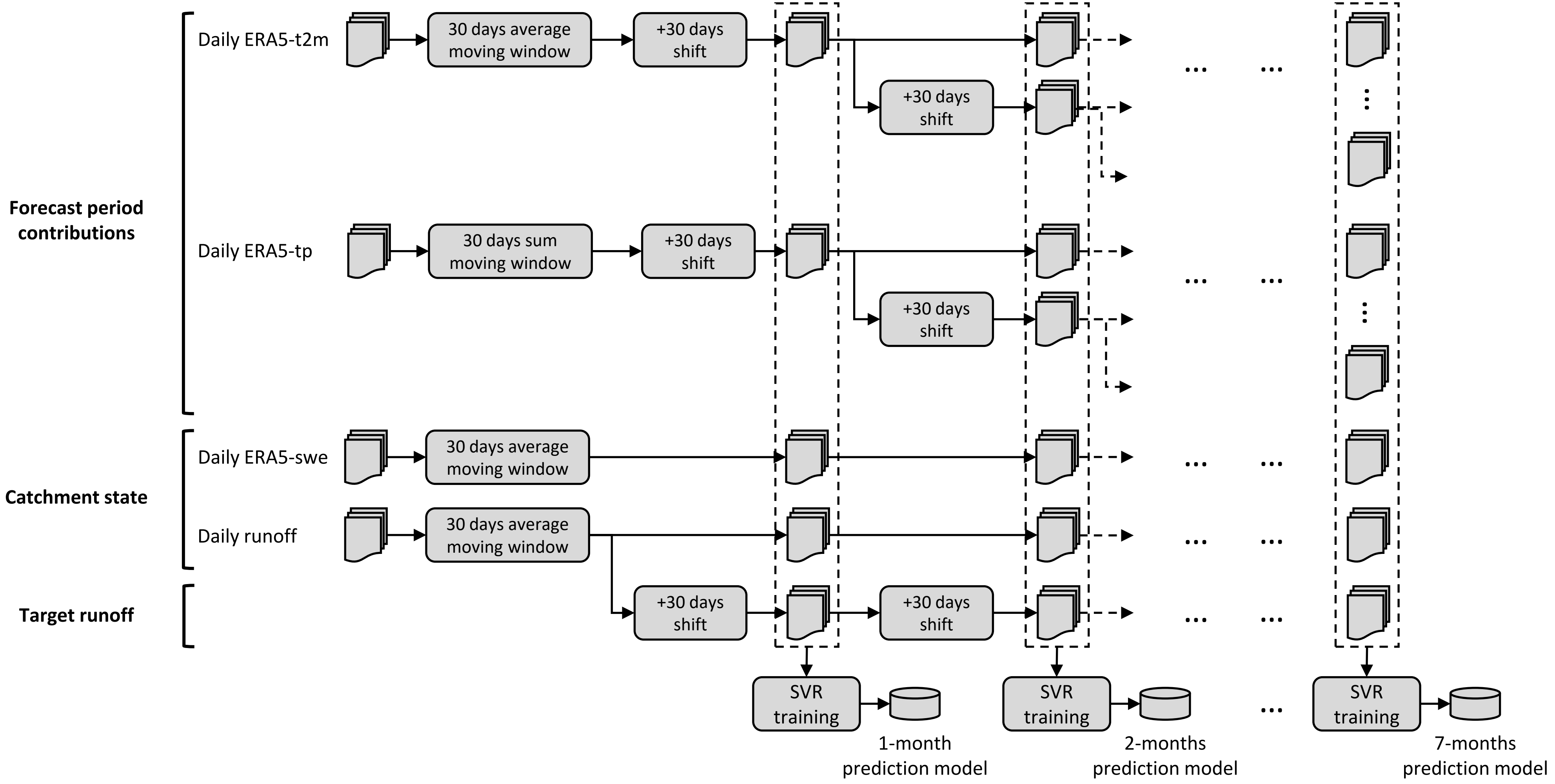
Advantages with respect to other regression algorithms:

- SVR can **easily handle multiple features**, i.e. input variables.
  - With N the number of ERA5 grid-box cells in the catchment and M the lead time months of the prediction, the number of features to be considered are:
    - $N \times M$ temperature + $N \times M$ precipitation features for the **seasonal forecast**
    - N ERA5-swe + runoff at t_0 to describe the catchment state at at t_0

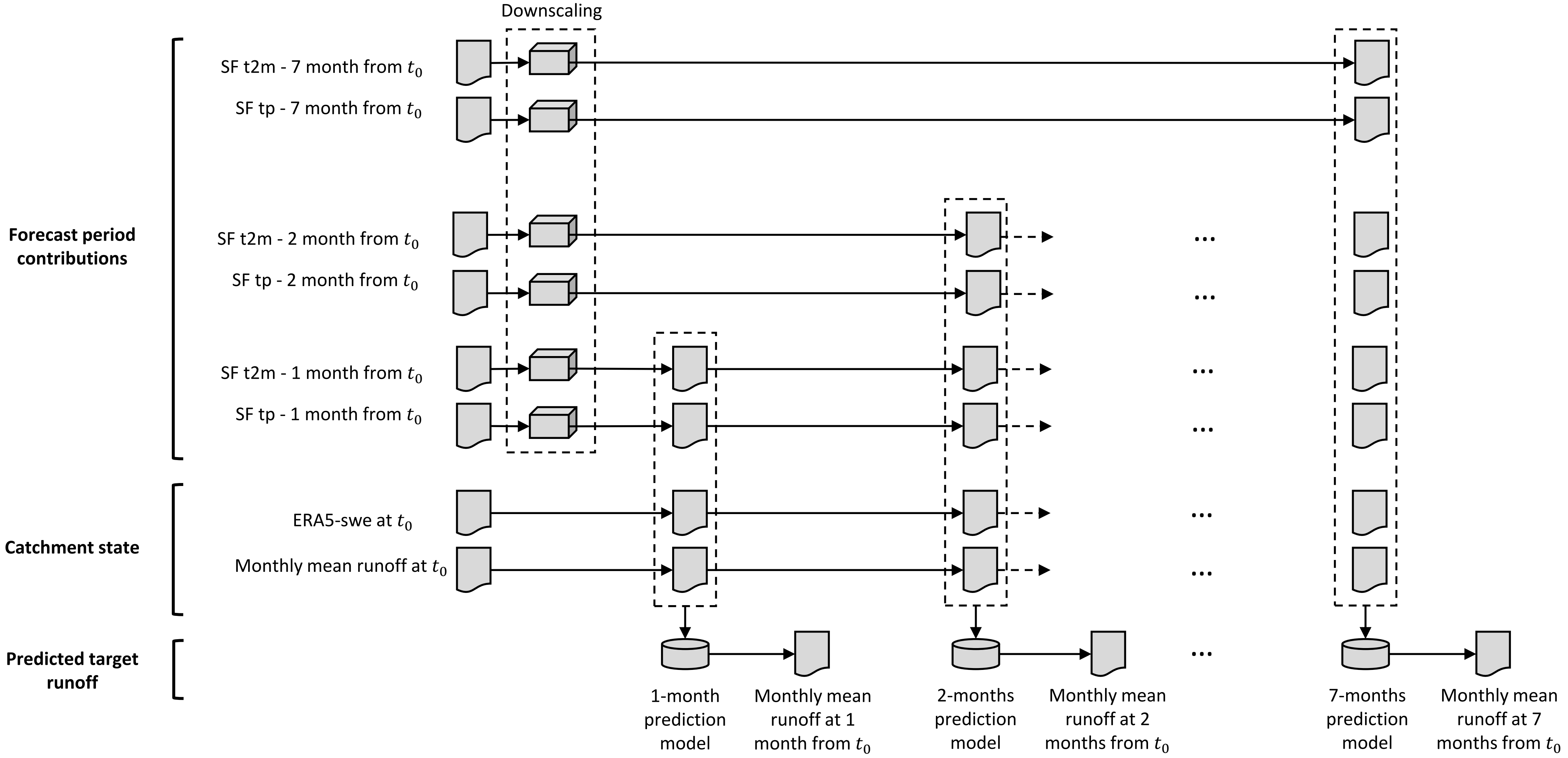
$$\boldsymbol{tot = (2M + 1)N \ + \ 1}$$

- SVR can **easily handle highly non-linear problem**, no assumption on the distribution of the data needed.
  - This is important for example because the effect of temperature on the runoff may be different depending on the season → non-linear behavior

Method workflow (training phase)

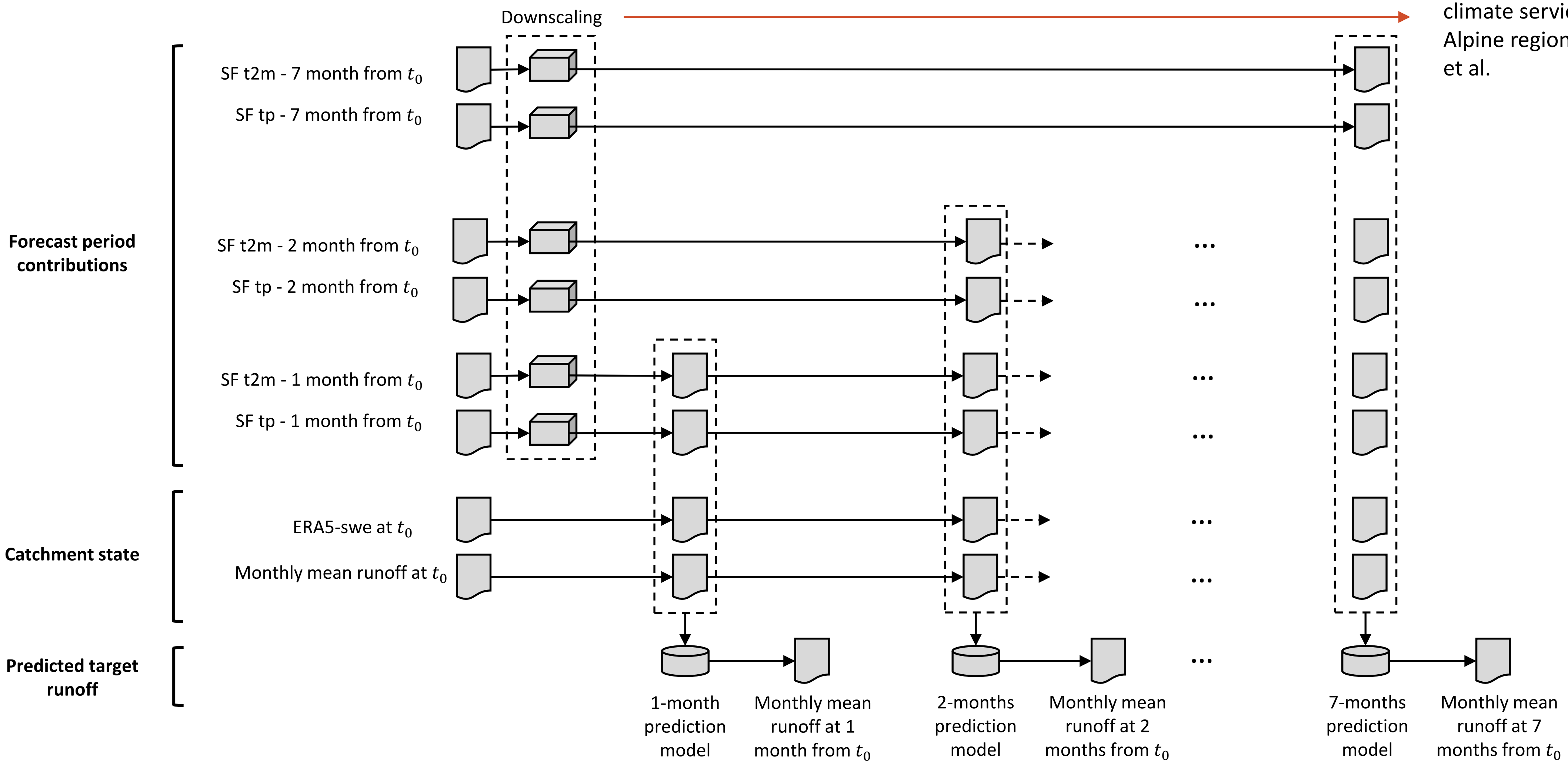


Method workflow (prediction phase)



Method workflow (prediction phase)

For more details: EGU2020-1010 - Downscaling and bias correction of seasonal forecasts to support climate services for the Alpine regions, A. Crespi et al.



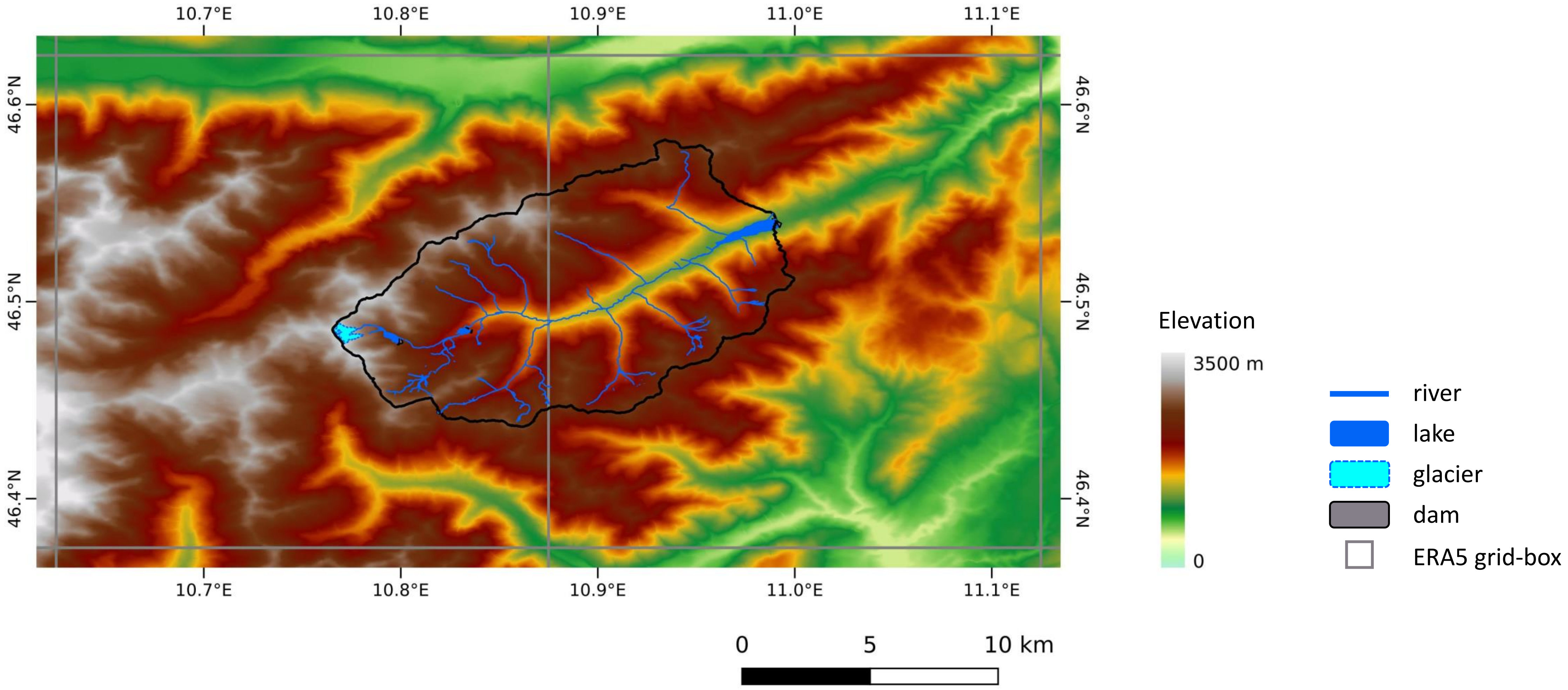
Method performances

Experiment goals:

- To evaluate the **forecast performance** of the proposed method with respect to a **benchmark method**, i.e. **runoff climatology**.
  → Iteratively train and run the forecast excluding one year to test the performance – **Leave one out cross validation (LOO-CV) strategy**

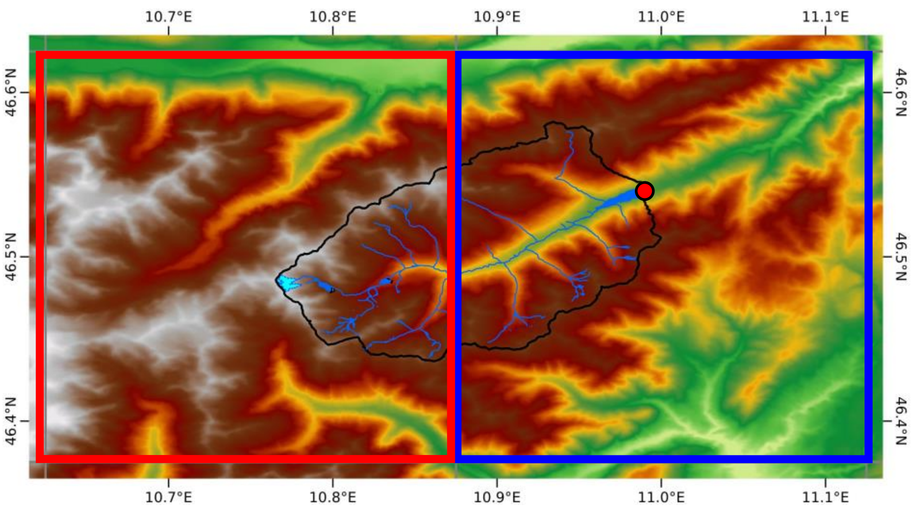
- To investigate whether there is a **limit of applicability** with respect to the **length of the runoff time series**
  → The forecast is repeated using **simulation of runoff time series of different length**

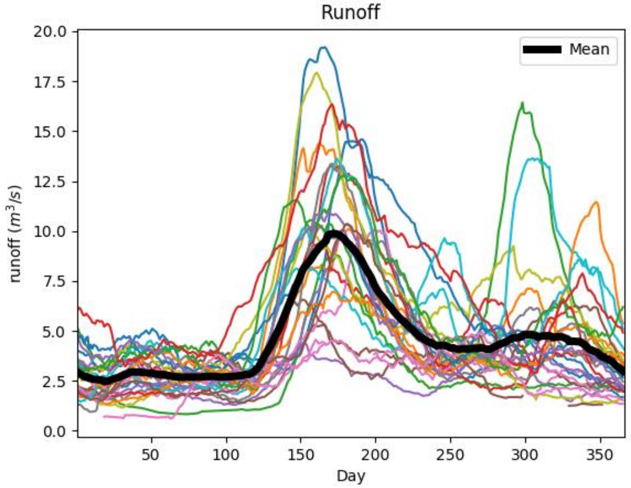
Test site and dataset



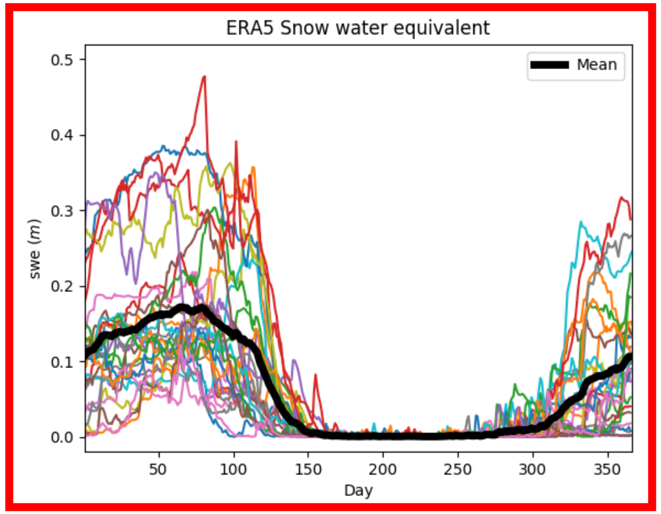
Test site and dataset

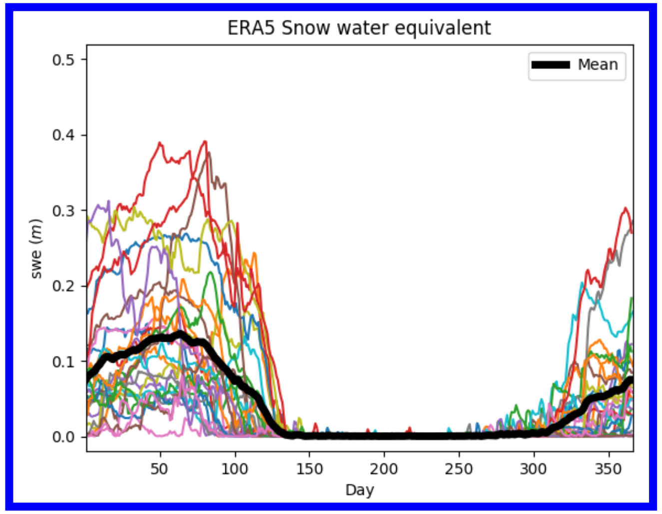
Initial condition variables:





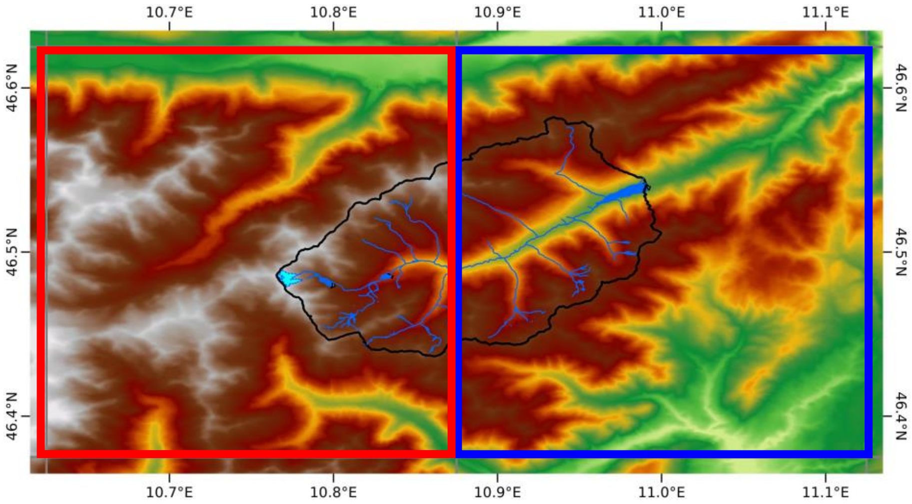
From 1992 to 2017
(~ 9000 samples)

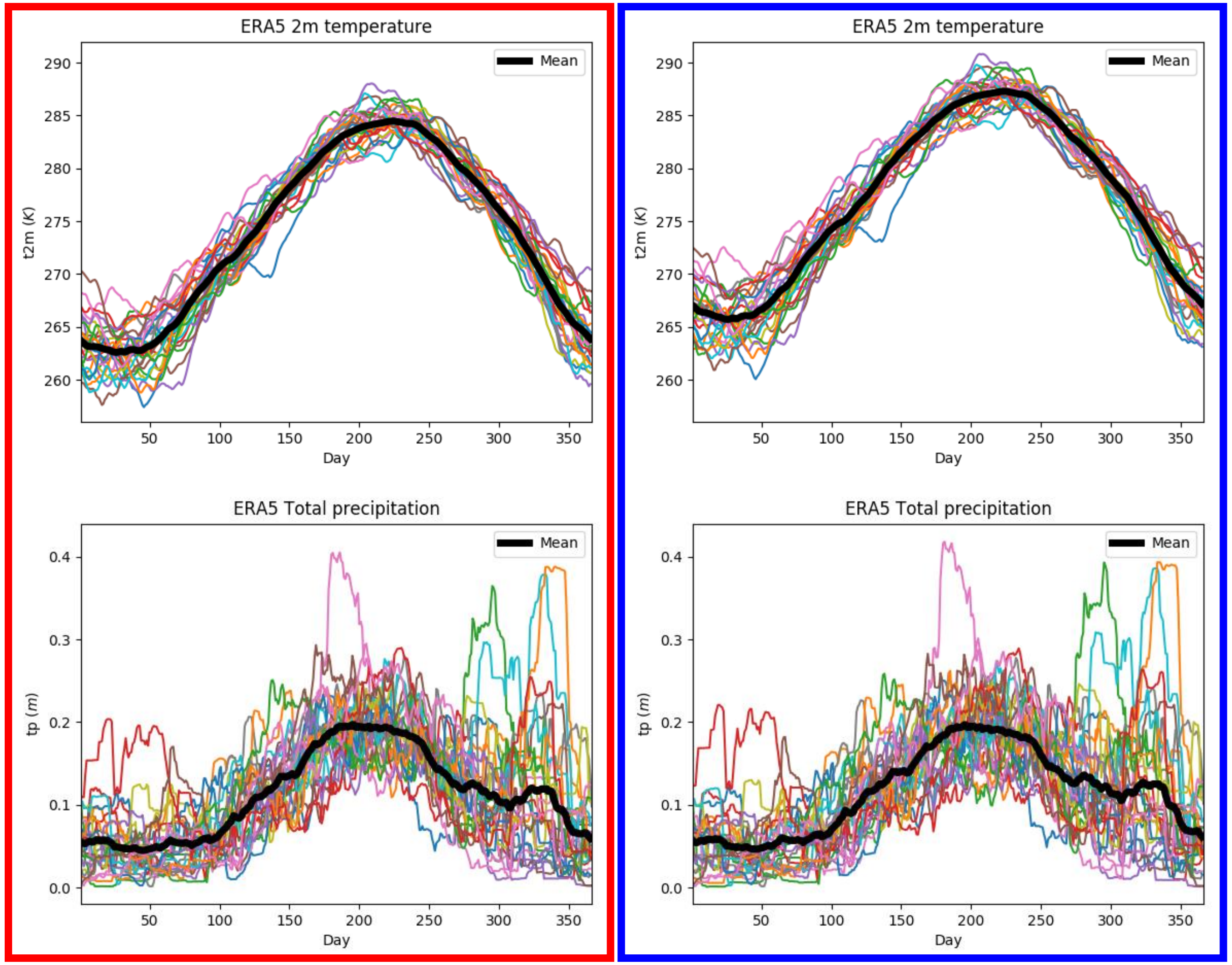




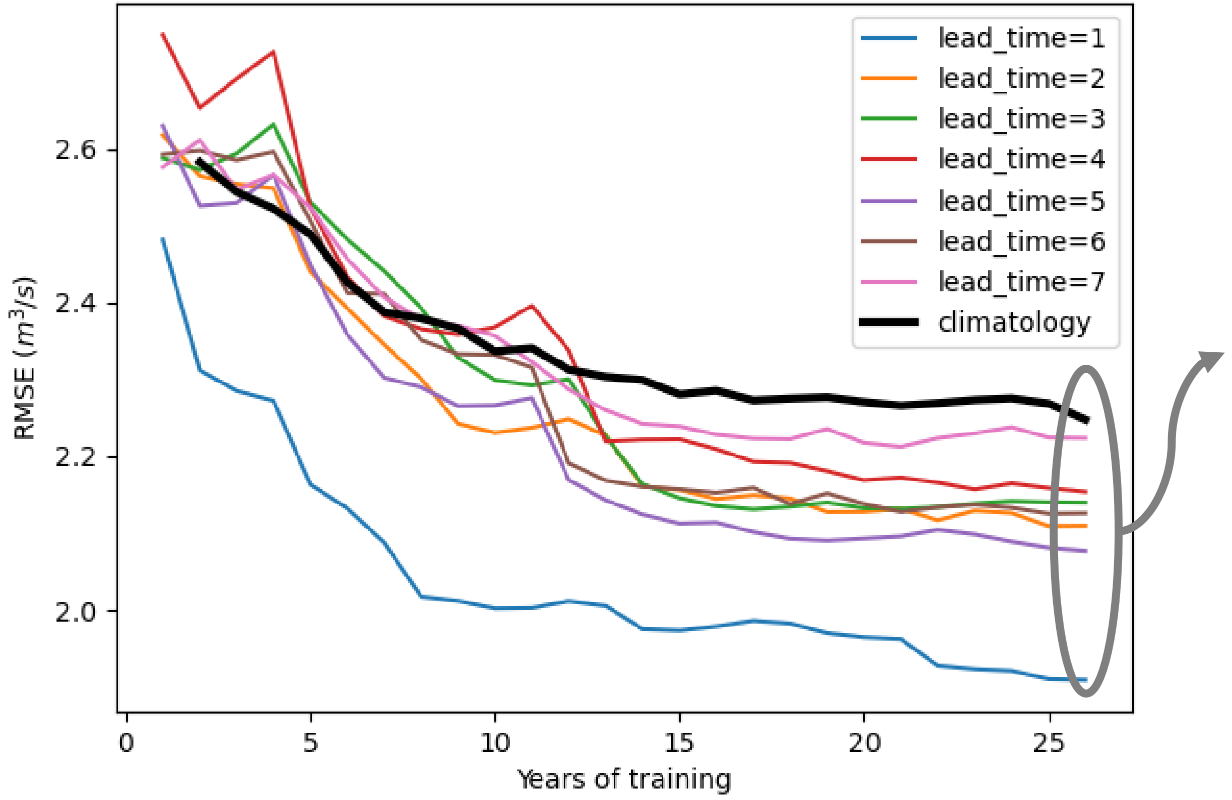
Test site and dataset

Forecast variables:

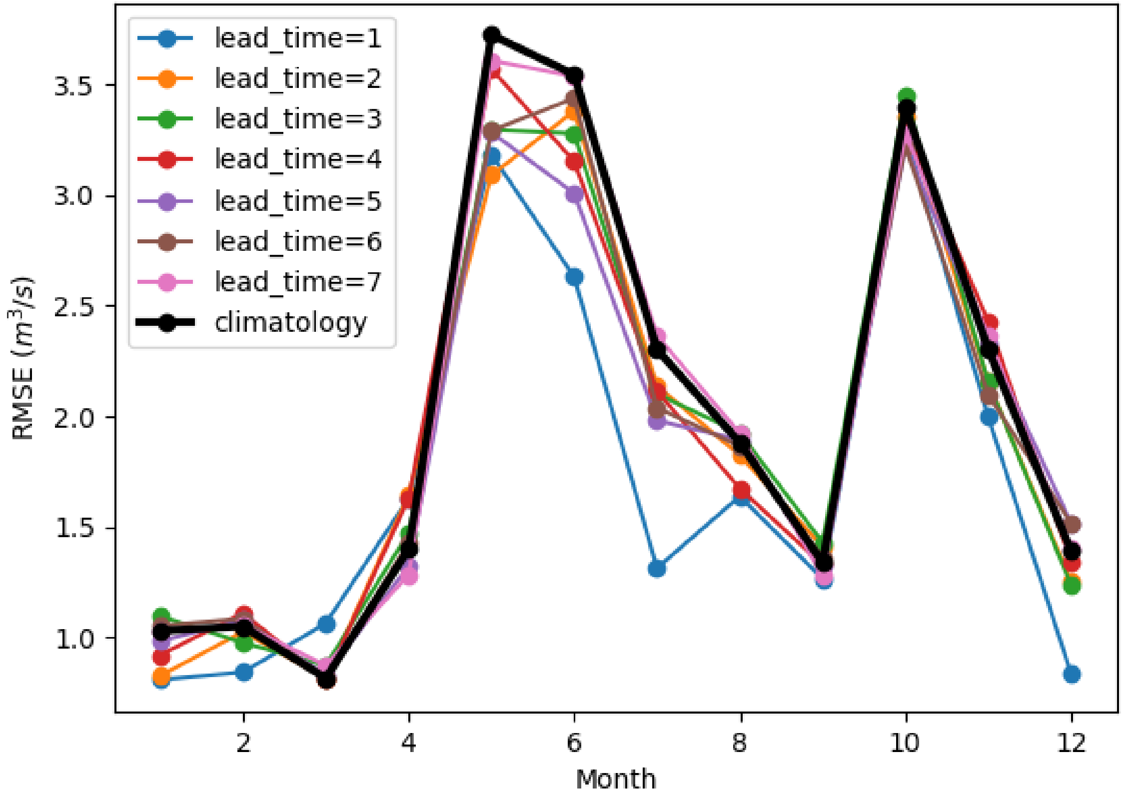




Results



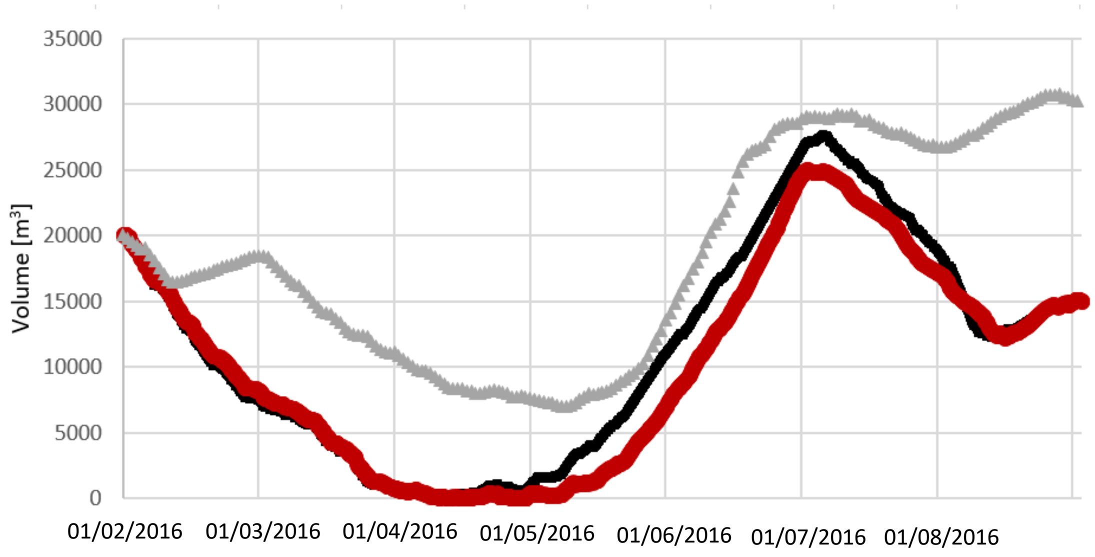
lead_time=1
lead_time=2
lead_time=3
lead_time=4
lead_time=5
lead_time=6
lead_time=7
climatology
2.0
2.2
2.4
2.6
RMSE (m^3/s)
0
5
10
15
20
25
Years of training



lead_time=1
lead_time=2
lead_time=3
lead_time=4
lead_time=5
lead_time=6
lead_time=7
climatology
1.0
1.5
2.0
2.5
3.0
3.5
RMSE (m^3/s)
2
4
6
8
10
12
Month

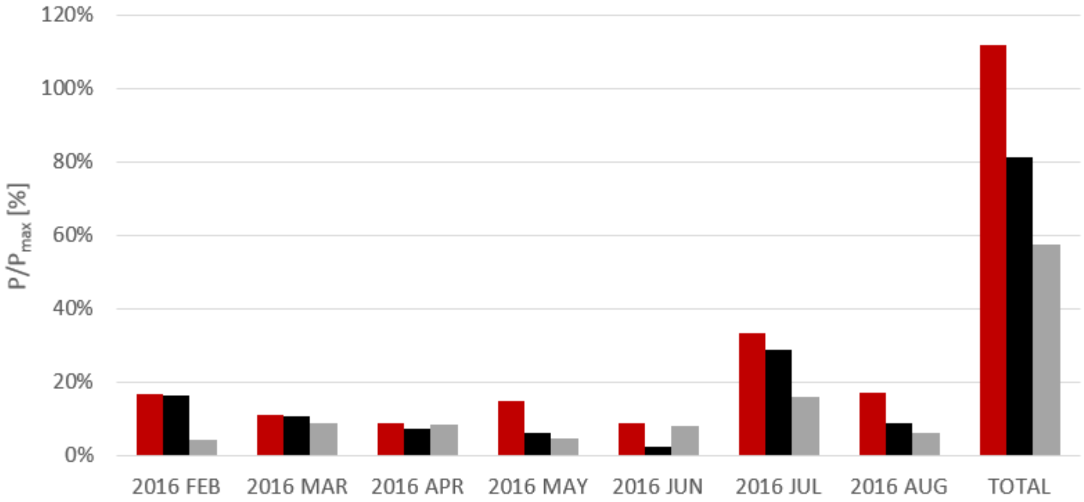
Hydro-tool model results

Modelled water volume in Zoccolo basin to optimize the production in the simulated period.



using runoff climatology as model input
using runoff forecast as model input
Measured water volume

Modelled energy production in case of optimization of the management of the basin



using runoff climatology as model input
using runoff forecast as model input
measured energy production

Conclusions

- For the selected case study **the proposed method outperforms the climatology for monthly mean runoff forecast**. This is particularly evident:
  - for the **1-month lead time**, when the catchment state variables, i.e. swe and runoff of the previous month, play a more relevant role
  - with a **long enough training dataset (> ~15 years)**, when the method outperforms the climatology for all the lead times (from 1 to 7 months)

- The **seasonal forecast of the runoff** obtained with the proposed method can be employed to **improve the management of the basins**. This may lead to an **optimization of energy production** and an **increase of the overall profit**. An evaluation of the gains in these terms for the specific case study in Ulten Valley is currently under investigation