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Preliminary exploration of extreme floods in two Italian watersheds through UNSEEN ensemble scenarios

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ECSS 2025 Utrecht 20/11/2025

TRANSLATE, project climate risk information from ensemble weather and climate predictions

Finanziato dall'Unione europea NextGenerationEU

Ministero dell'Università e della Ricerca

Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA

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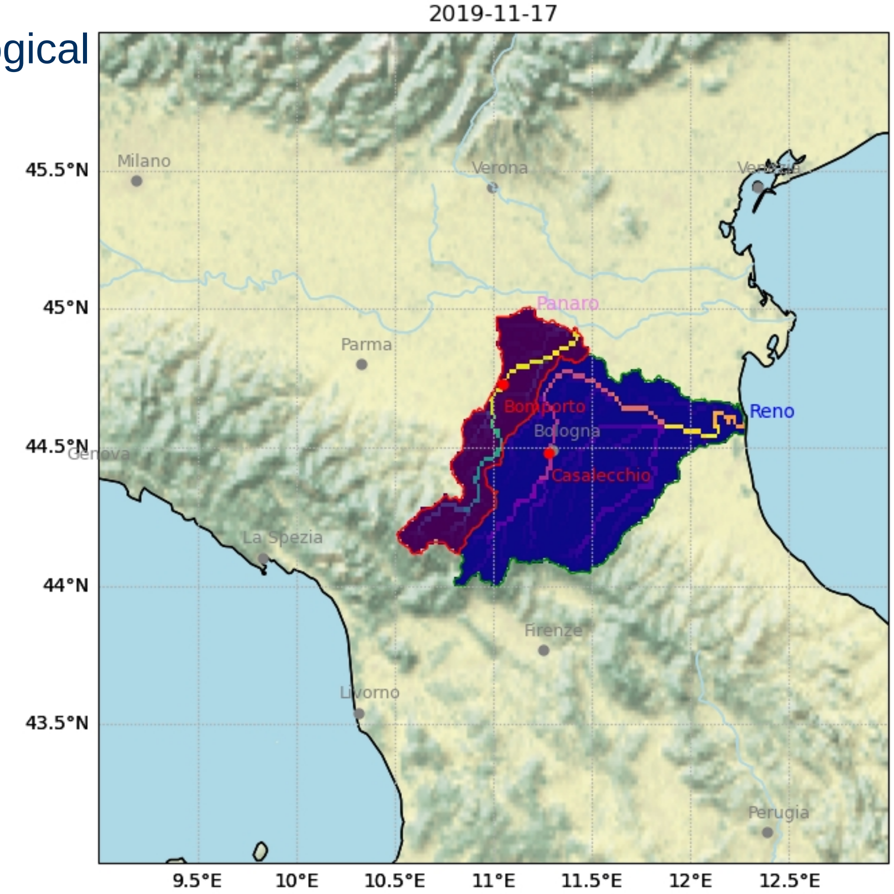
Why studying the River Discharge (RD) of Panaro (Bomporto) and Reno (Casalecchio)?

Emilia-Romagna region (Italy) was hit by several hydro-meterological extremes in recent years. E.g. in the last 7 years we observe:

Date	Station	River	Max Inst. RD [m³/s]	Daily Mean RD [m³/s]
2 February 2019	Casalecchio	Reno	1280	NA
5 December 2020	Spilamberto	Panaro	960	495
27 February 2024	Casalecchio	Reno	?	459
23 January 2021	Casalecchio	Reno	700	422
17 May 2023	Casalecchio	Reno	?	374
18 May 2023	Bomporto	Panaro	?	368



Is it by chance or because of an external forcing change?

We try an UNSEEN approach: using ensemble reforecasts (made by the EFAS hydrological model) we try to determine if the RD extreme events are due to **external forced changes** or if they are more compatible with the **internal atmospheric variability** estimated by the ensemble.

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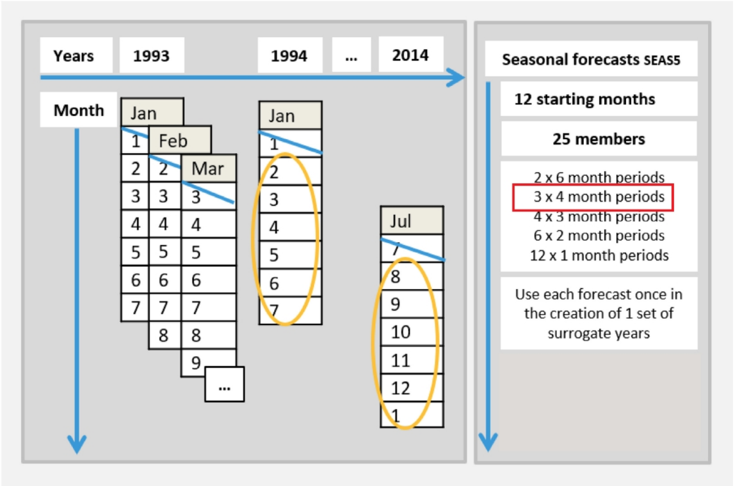
River Discharge data studied to analyze the Panaro and Reno:

1. Observed river discharge data by "ARPAE": 1923-2023 daily-mean RD, from which we derive also the RD annual maxima.



Klehmet, K., Berg, P., Bozhinova, D., Crochemore, L., Du, Y., Pechlivanidis, I., Photiadou, C., & Yang, W. (2024). Robustness of hydrometeorological extremes in surrogated seasonal forecasts. International Journal of Climatology, 44(5), 1725–1738.

2. "**Historical** EFAS" RD: deterministic forecasts made by LISFLOOD hydrological model, forced with "daily observed data" (using high-res. **EMO1 observational rain** dataset and **ERA5** as **large scale** forcing) and calibrated on ARPAE RD. Since 1992. Spatial resolution: 1.3x1.9 km.

3. "Reforecast EFAS" RD: ensemble forecasts by same LISFLOOD, forced with **SEAS5** seasonal reforecast (**25 members**, initialized the first day of month and valid for the next ~7 months), since 1992 (but we use data only since 2000, because before SEAS5 is not considered reliable). Resolution: RD 1.3x1.9 km, but SEAS5 forcing model at only 22x31 km.

4. "**Surrogate** trimestral EFAS" RD: 25 reforecast EFAS timeseries started from **four different initial times** (first of Apr, May, Jun and Jul 1999), skipping the first three months for *statistical independence* of members, and concatenated until 2023. In this way we obtain **100 timeseries** of surrogate RD.

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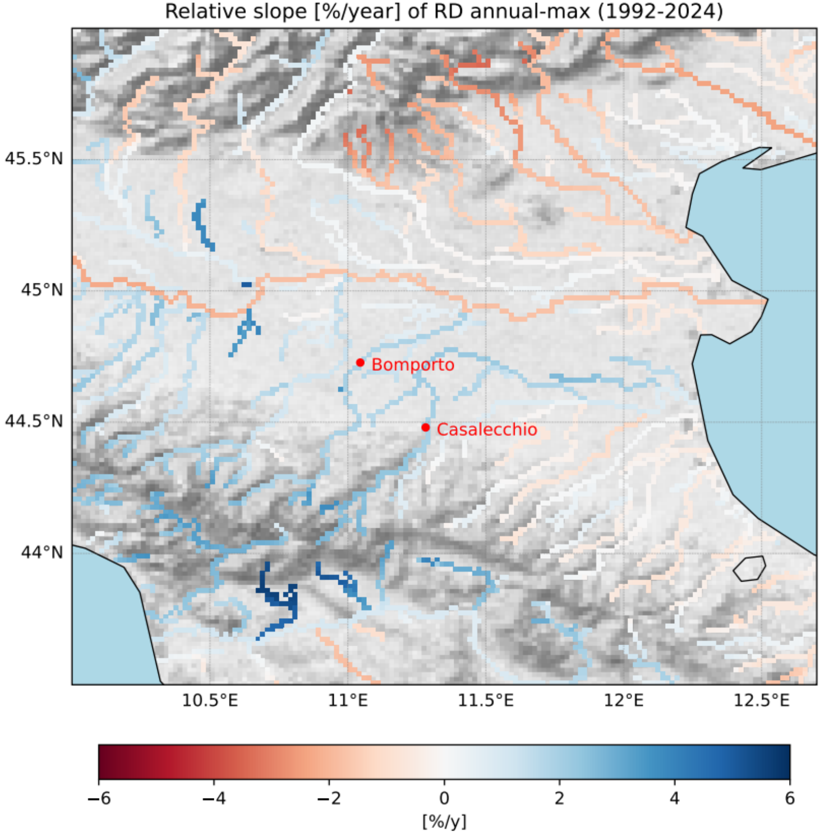
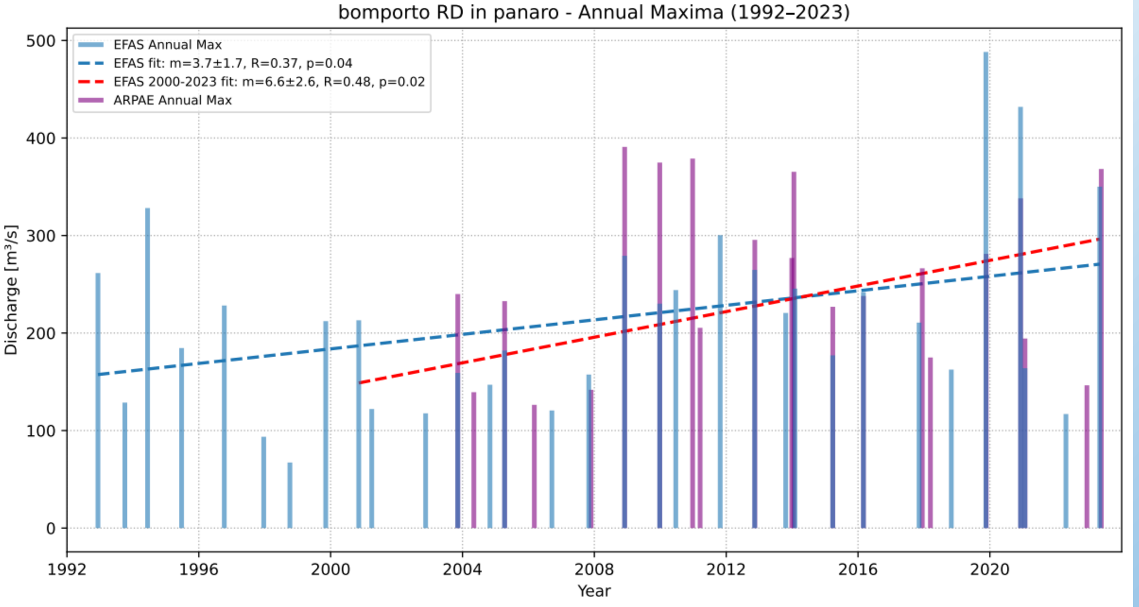
EFAS and ARPAE timeseries: historical trends of annual max RD

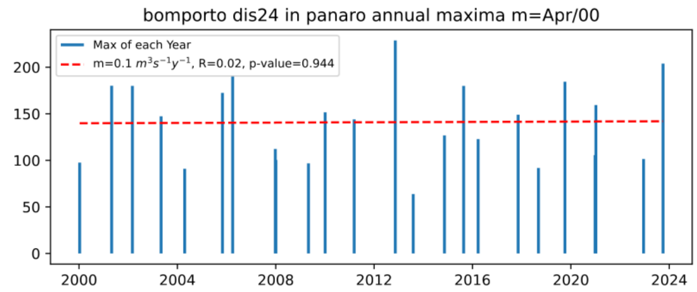
For the EFAS model most of NW Apennines rivers have an increasing trend of their RD annual maxima, while most of Alpine rivers have a decreasing trend.





In Bomporto annual max of historical EFAS has a statistically significant positive trend with slope m=**3.7** m^3/sy (Std.Err.=1.7) and a correlation with time of R=0.37 (p-value=0.04) since 1992, or m= **6.6 m^3/sy** since 2000.
ARPAE data have also a positive trend, even if less statistically significant, probably because affected by the *expansion tanks*, active since ~1985 (hence we do not consider ARPAE trend).

100 surrogate EFAS timeseries and 100 trends of RD annual max:



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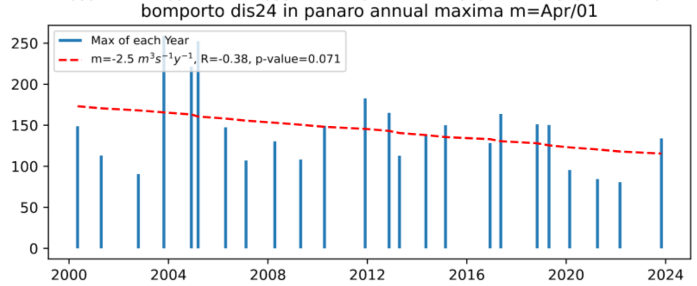

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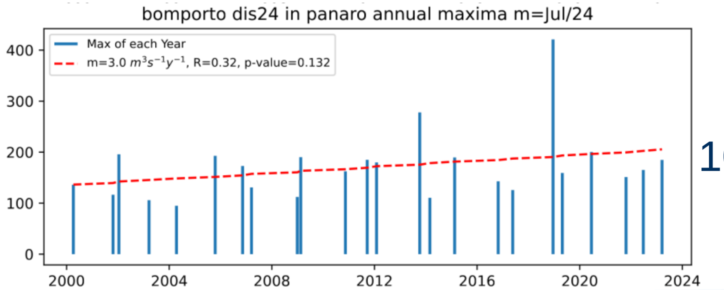

100

- We have 100 EFAS surrogate timeseries: Apr00...Apr24 + May00...May24 + Jun00...Jun24 + Jul00...Jul24 each one with a different linear fit (and hence a different slope **m**) of their RD annual maxima.

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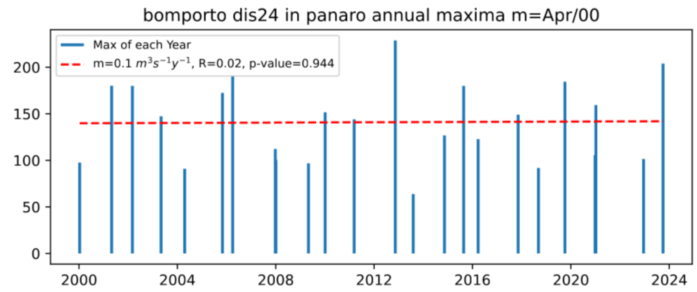

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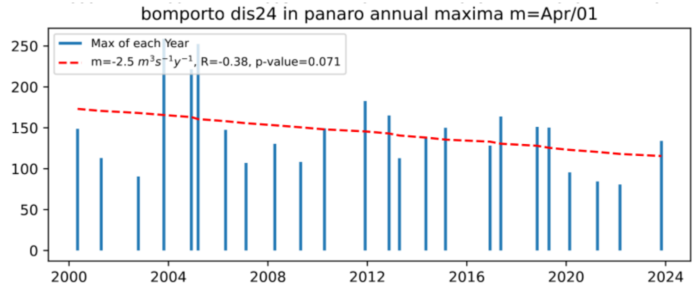

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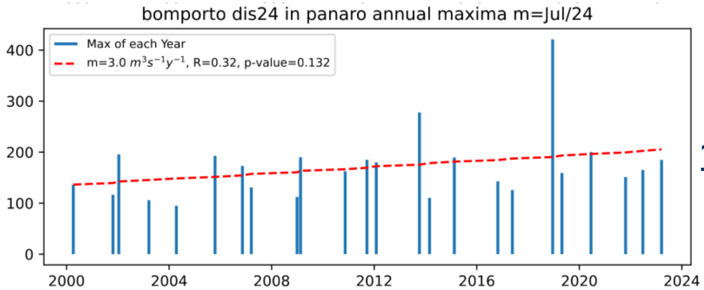

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- Hypothesis:
  the EFAS RD ensemble model describes the “real” climatic variability of the annual maxima in Bomporto station.

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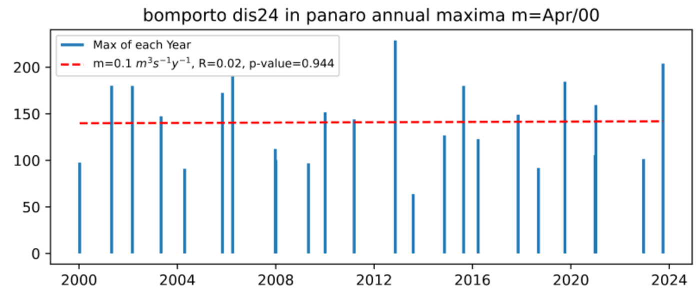

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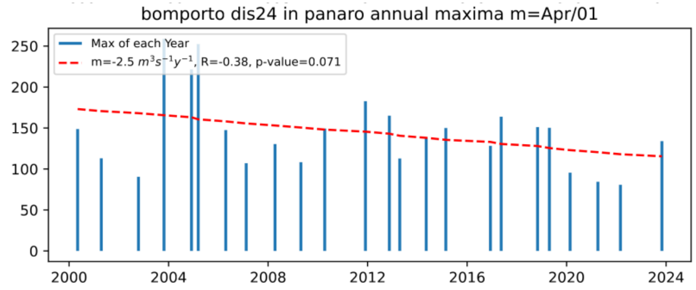

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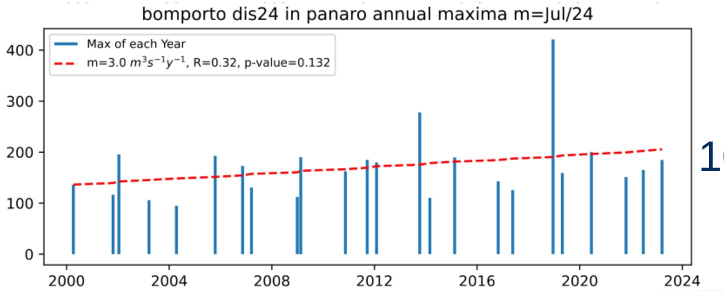

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- Three questions:
  1. How the variability of the RD intensity of the 100 realizations of annual maxima compares with the -unique- historical EFAS annual maximum?
  2. How is the distribution of the 100 m slopes (surrogate trends)? In particular, the historical EFAS slope is an outlier of this distribution?
  3. How the seasonal cycle of surrogate compares with the historical?

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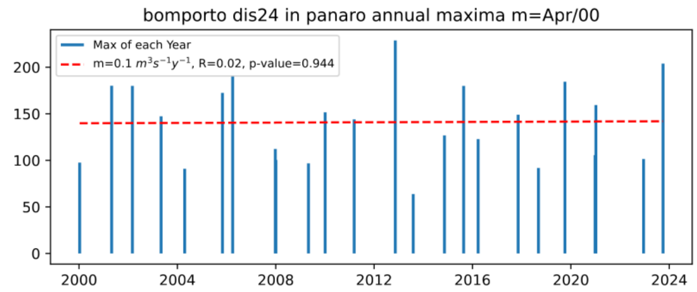
100 surrogate EFAS timeseries and 100 trends of RD annual max:



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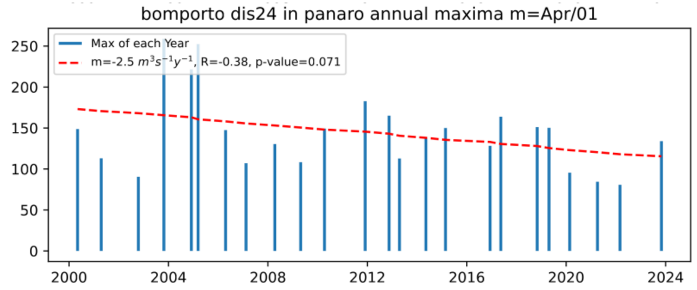

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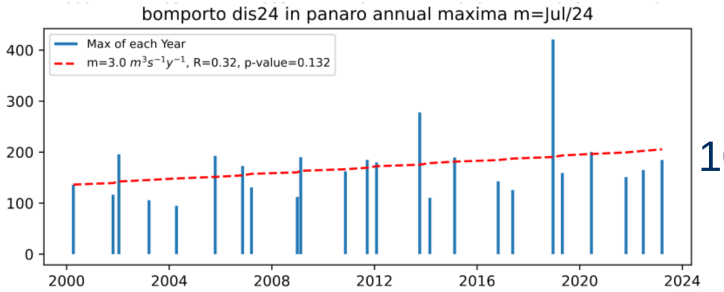

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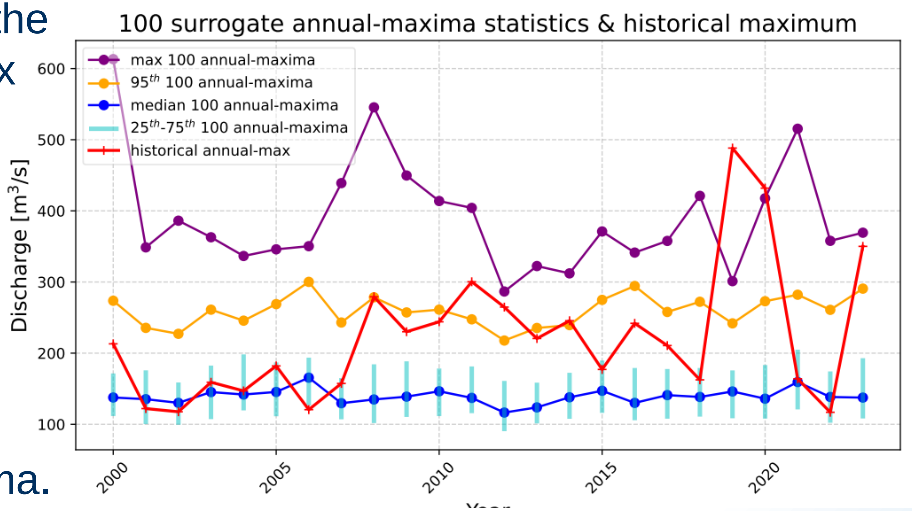
- Definitions:
  <m> = common signal of external forced changes = **S**
  Stand_Dev(m) = noise of the internal atmospheric variability = **N**
  Signal/Noise ratio = **S/N**. S/N>1 means a strong external forcing.

There is a discrepancy between surrogate and historical annual max values and trends:

24 Annual Maxima: the historical annual max (positive trend) is often above the mean of the 100 surrogates maxima (no trend). In 2019 and 2020 it is above the maximum of all 100 surrogate maxima.



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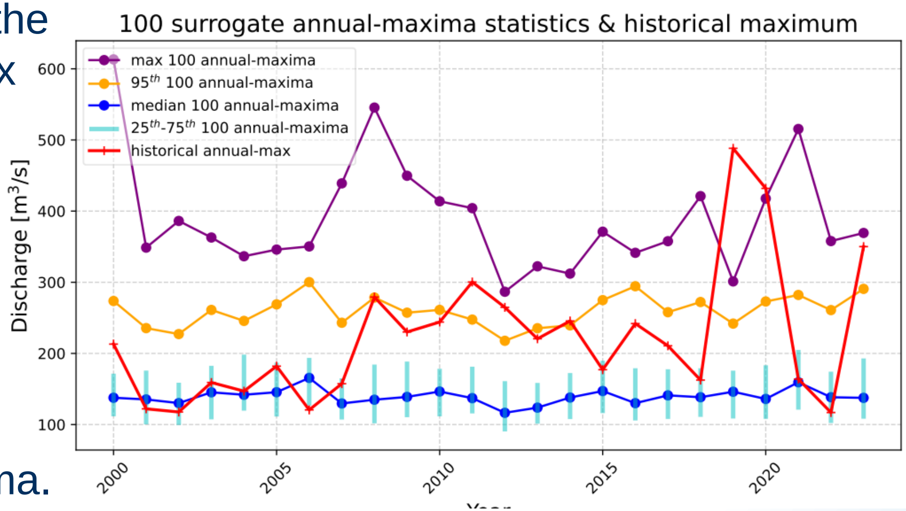

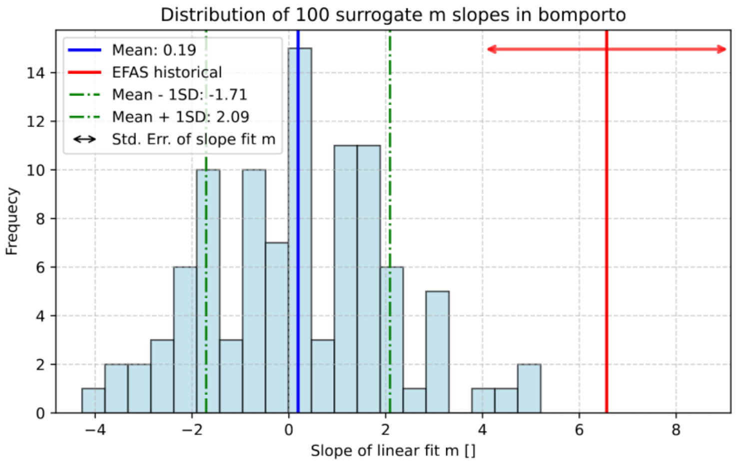

The mean slope of the 100 surrogates (S) is only 0.19 m³/sy, which is much lower than the positive trends of the historical EFAS in the same period (6.6 m³/sy is an outlier). The ensemble spread of slopes is SD=1.9, leading to S/N = 0.10: in this ensemble there is no clear external forcing emerging from the internal variability.

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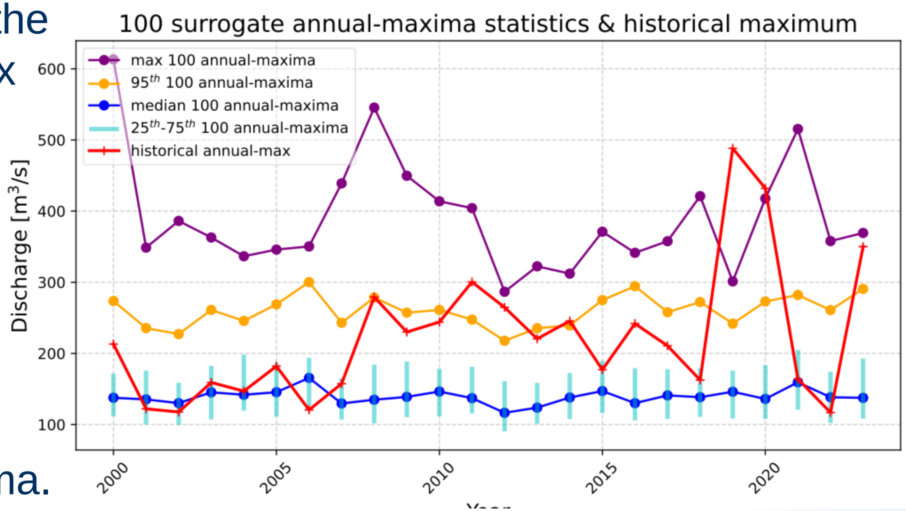

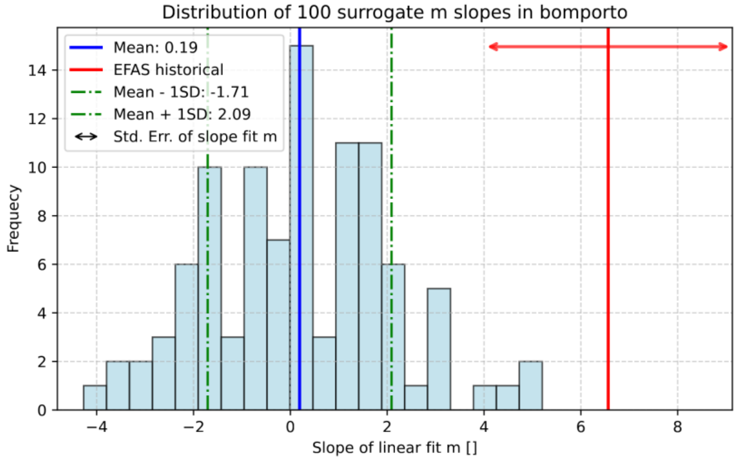

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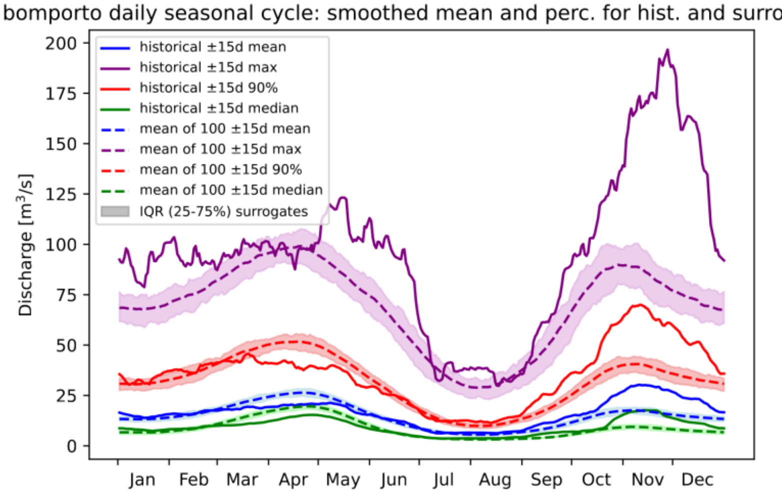

Lastly, this discrepancy is seasonal-dependent, with the strongest underestimation occurring between mid-October and December. Why?

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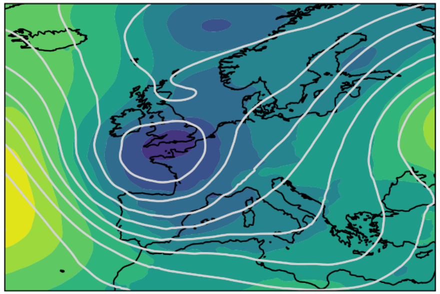
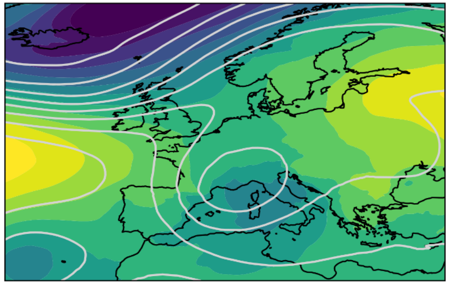
Synoptic analysis for the Bomporto first 6 annual max:

Dataset	**Reference date**	**Reference RD [m³/s]**	**Historic freq. [%]**	**Surrogate freq. [%]**
Historical EFAS (11688 days)	20191117	488	0.154	0.153
	20201205	432	0.565	0.500
	20230502	350	0.180	0.126
	19940612	328	3.294	3.381
	20111026	300	3.140	2.670
	20081201	279	1.258	1.358
Surrogate EFAS (922300 days)	20001011 May_05	613	0.009 (1 case)	0.013
	20081006 May_03	545	0.779	0.556
	20211013 Jun_18	515	7.893	9.454
	20090903 Jul_23	450	0.462	0.516
	20071006 Jul_03	439	0.342	0.268
	20200607 Jun_23	421	7.997	8.907

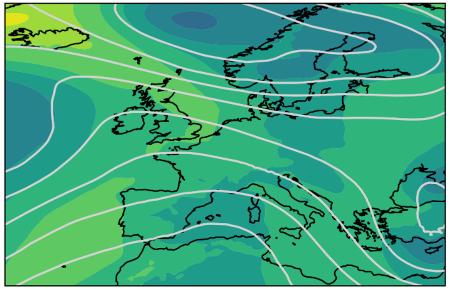
2019-11-17; 488.2 m3/s



2020-12-05; 431.9 m3/s



2023-05-02; 350.1 m3/s



The frequency of days "similar" to a given synoptical condition (correlation of Z500 and MSLP > 0.7) is of the same order in the historical world (ERA5) as in the surrogate world (SEAS5), hence *SEAS5 represents well the variability of ERA5 circulations leading to RD extremes.* However, configurations similar to these maxima *are much more frequent than RD extremes* and can be associated also to very low RD.

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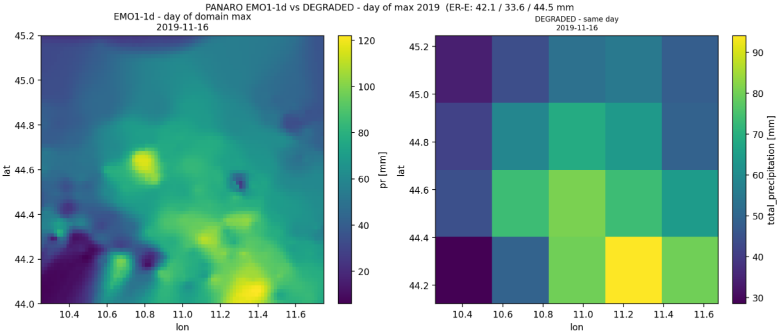
Spatial and temporal analysis of the local rain: mean EMO1 and SEAS5 climo



1. We downgraded the 2000-2022 rain of EMO1 on the SEAS5 grid and computed the "rain bias" on each gridbox.

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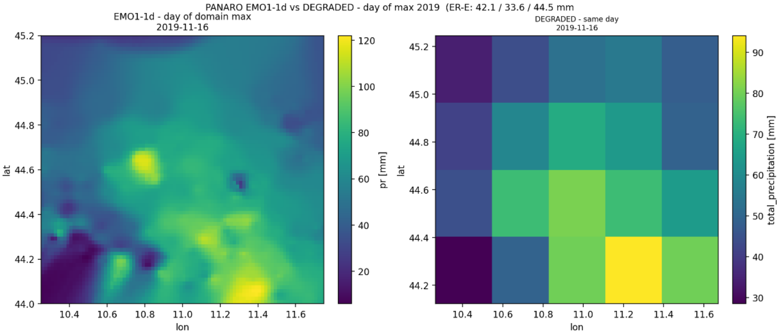

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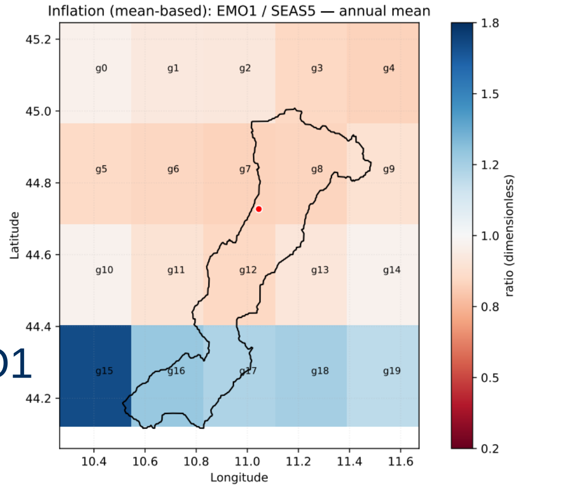

2. EMO1 mean rain has a peculiar spatial climatology, with larger mean rain toward the SW corner (mountains), while SEAS5 rain is more homogeneous. Thus, the map of mean-rain bias (blu-red map) has a spatial distribution, similar to the EMO1 climatology.

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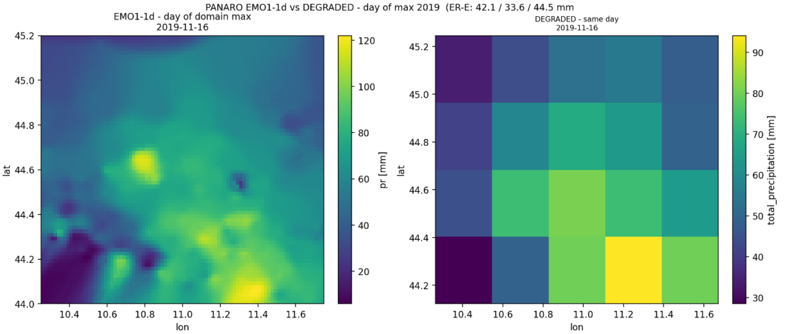

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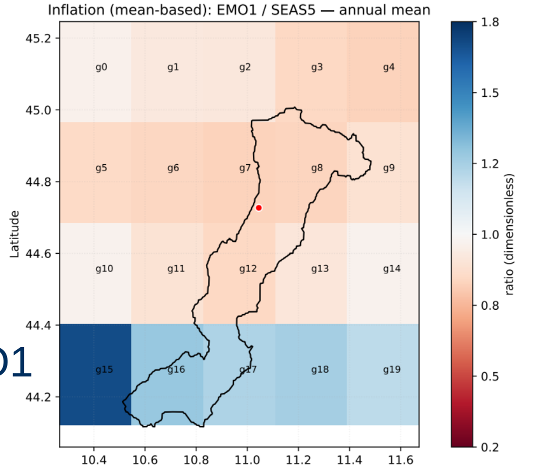

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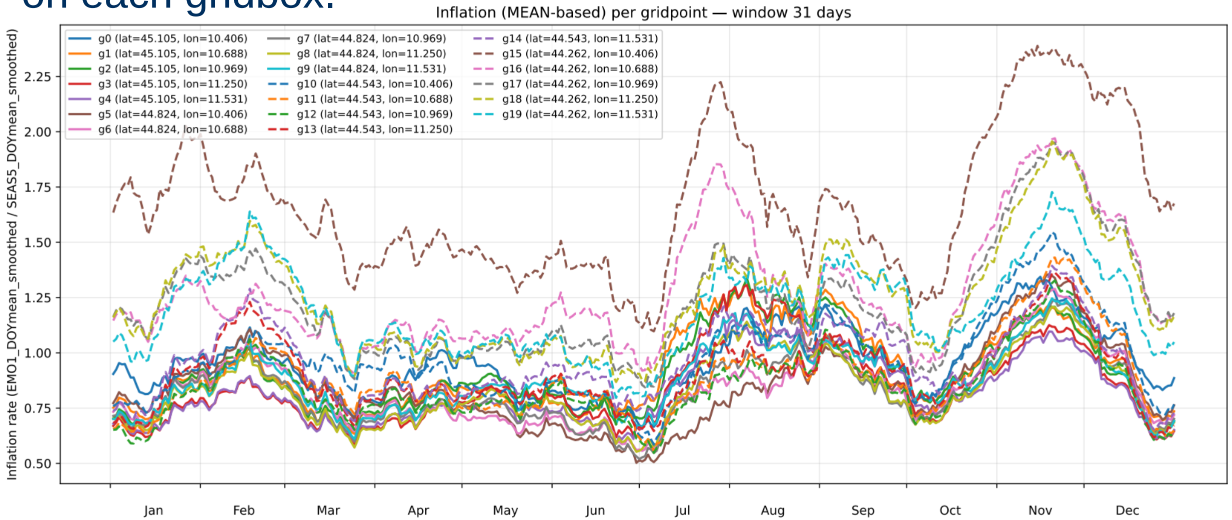

3. If we compute a day-of-year bias-correction for mean rain it is different both for the day-of-year as for each of 20 gridpoints, varying from 0.5 to 2.3.

*Can we use this **rain-bias** correction to correct the **RD bias**?*

Of course, RD is not a linear function of rain...

Hypothesis: can we build a CNN to catch the *non-linear* relationship between rain and RD?

If so, a CNN estimating the historical EFAS RD based on EMO1+ERA5 can be used to infer:

1) RD using the SEAS5 inputs (original rain);
2) RD using the bias-corrected SEAS5 rain.

Lastly we can estimate how RD changes with or without rain correction.

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We developed a dual-domain + dual-task CNN using only EMO1 daily rain in the 2D *local* domain and ERA5 Z500 + MSLP in the *synoptical* domain.

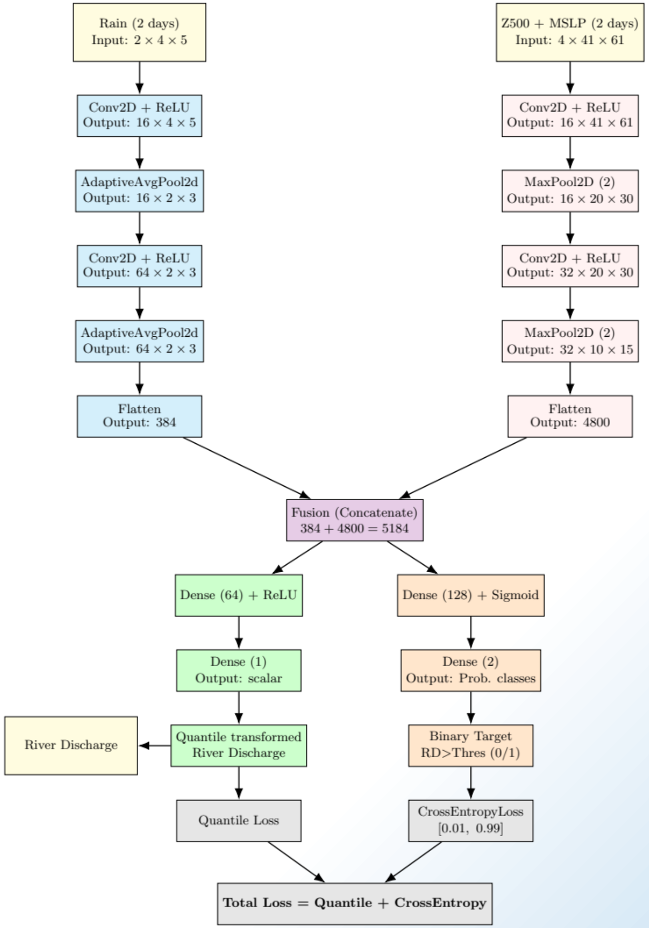

Figure 1: Dual-task architecture for surrogate world: local + synoptic CNNs followed by two heads: regression with QuantileLoss, and classification with weighted CrossEntropyLoss ([0.01, 0.99]). Final loss is the sum of both.

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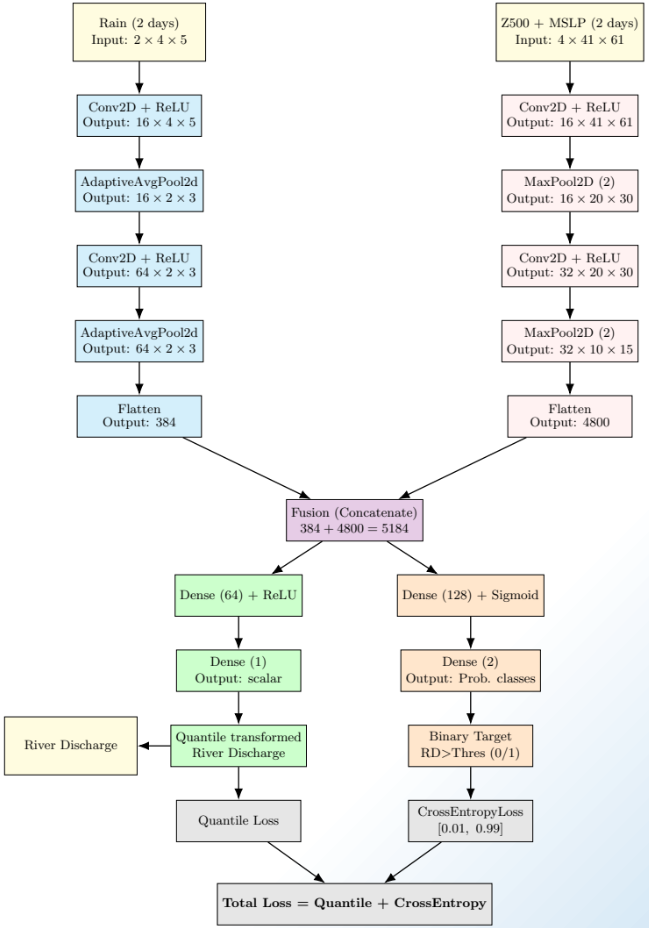

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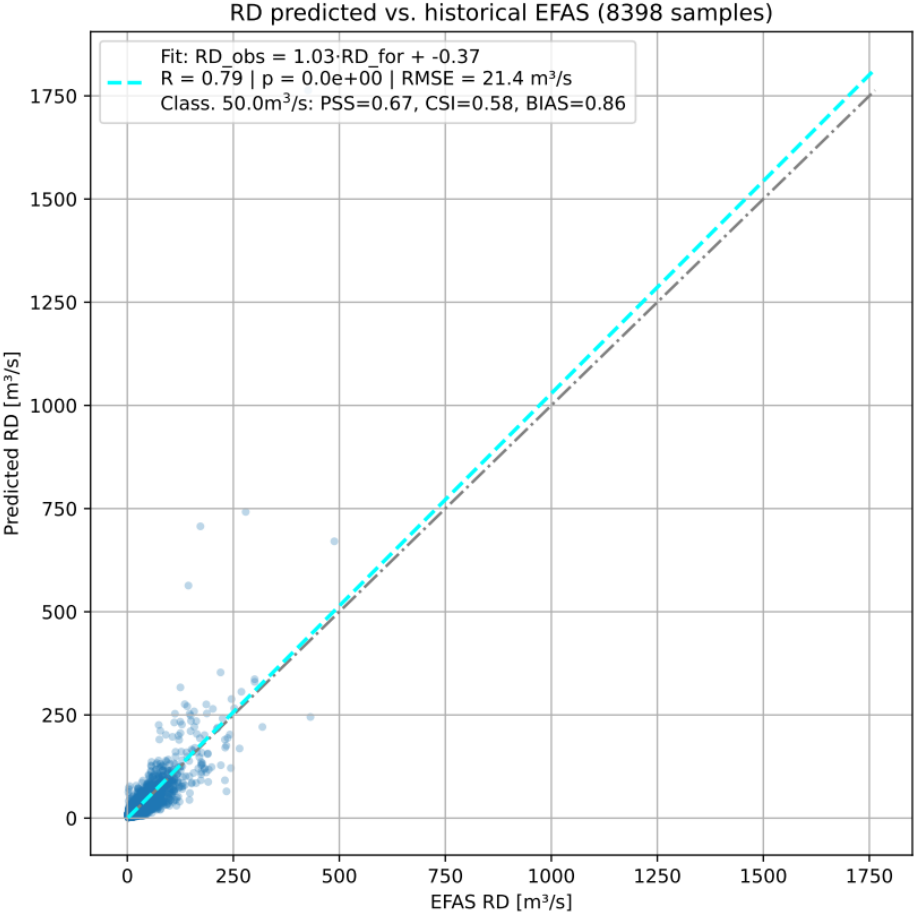
Many hyper-parameters tested:
1) RD preprocessing: Log1p vs. Quantile Transformation (QT)
2) regression loss: quantile loss with many values of q_loss (from 0.5 to 0.95).
3) classification loss: Weighted Cross-Entropy with weights in the [0.05, 0.95] to [0.25, 0.75] range.
4) RD threshold to define the RD binary events (tested 50, 100 and 150 m^3/s).
5) Total loss = Regression + weight * Classification, with weight in the 0.5, 1, 2 range.
6) input length: we tested from 1 to 7 days of inputs (n_days).

The most important parameter was the preprocessing function:
- QT: better performances but all severe RD saturated at the historical max value (488 m^3/s).
- Log1p: no saturation but a few "huge" RD values.

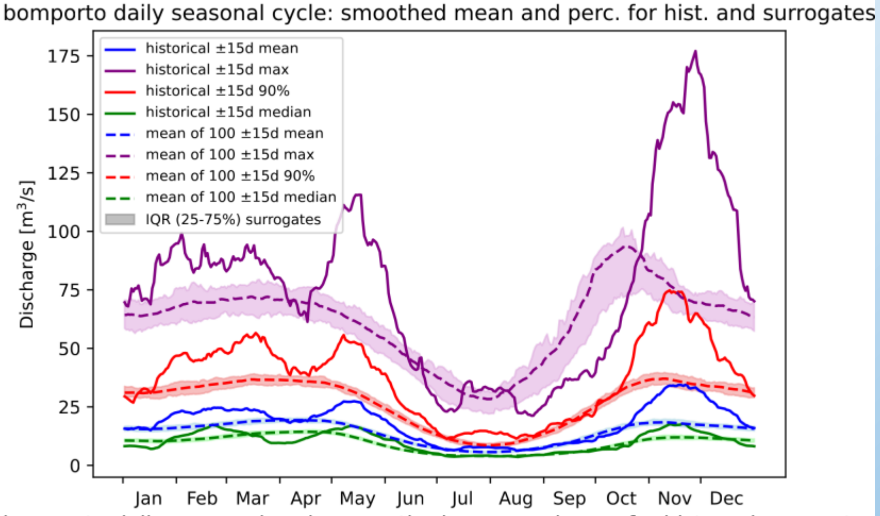
Inference on surrogates with model "88" (n_days=4, log1p): original vs. rain-correction

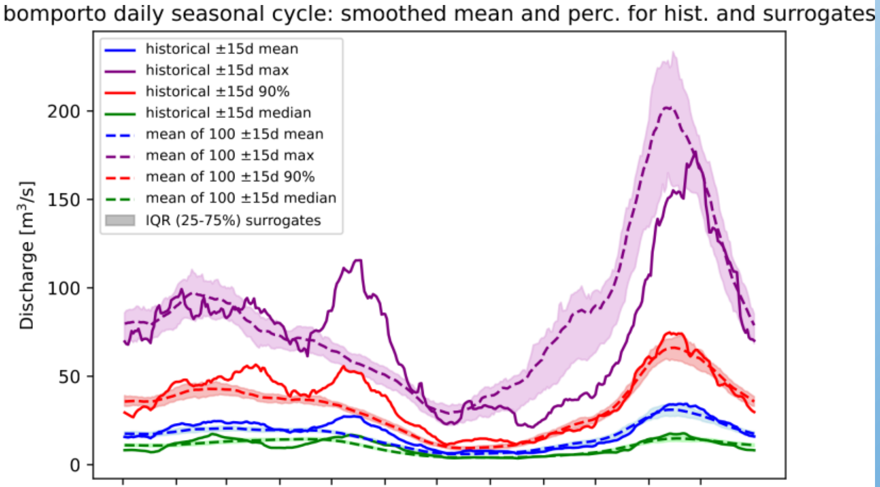
Scatterplot of historical EFAS vs CNN forecasts:



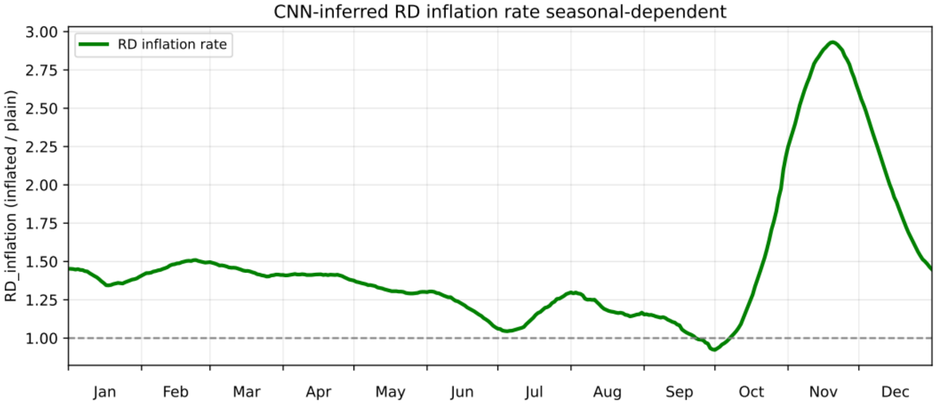
On the right: Above, the seasonal cycle of RD forecasted by the CNN with SEAS5 normal rain (historical continuous, surrogate dashed).

Below, the same but using the corrected SEAS5 rain inputs. It peaks in November.



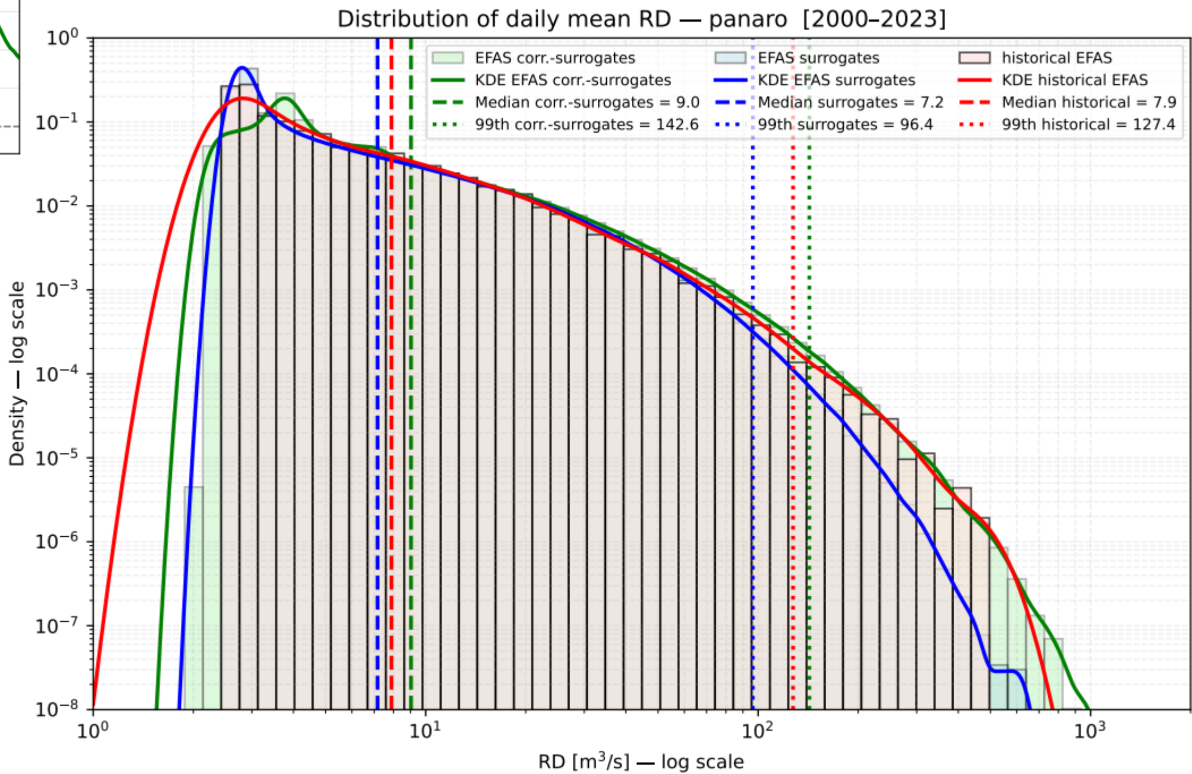


RD results: historical, original and seasonal-dependent bias-corrected surrogates



The seasonal-dependent RD correction rate (derived from the two different annual cycles of the RD max) in Bomporto is about 2.7 times in November.

With this seasonal-dependent correction of RD the distribution of the **new surrogate** overlap above 100 m^3/s much better with the **historical** EFAS than the **original surrogates**. Note the good 99p estimate.



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RD annual max statistic for the surrogate corrected with inflation based on rain-bias:

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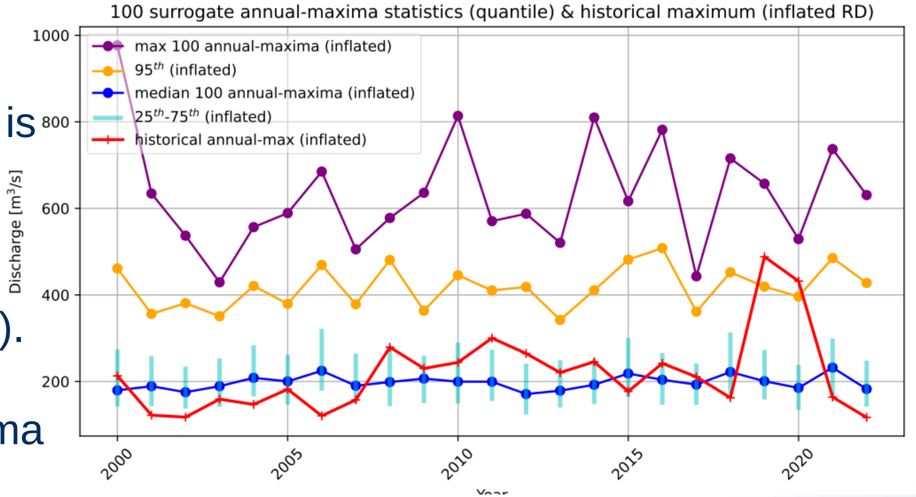

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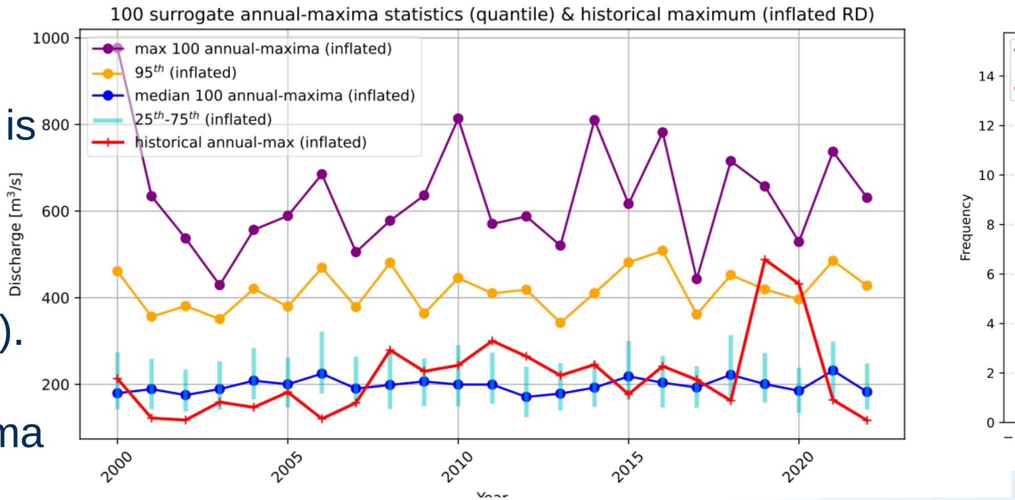

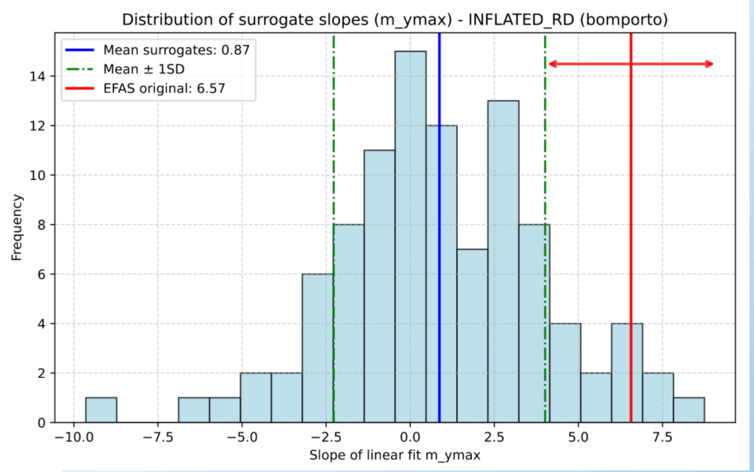

The mean slope of the 100 surrogates (S) increased to 0.87 m³/sy, which is still lower than the positive trends of the historical EFAS but 6.6 m³/sy is not an outlier. The ensemble spread of slopes is SD=3.1, leading to S/N = 0.28. In this corrected-ensemble there is some external forcing signal emerging from the internal variability.

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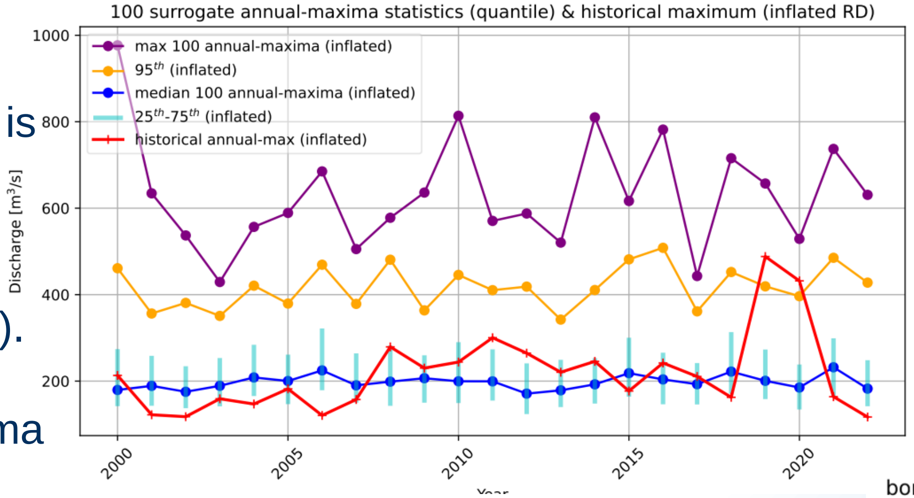

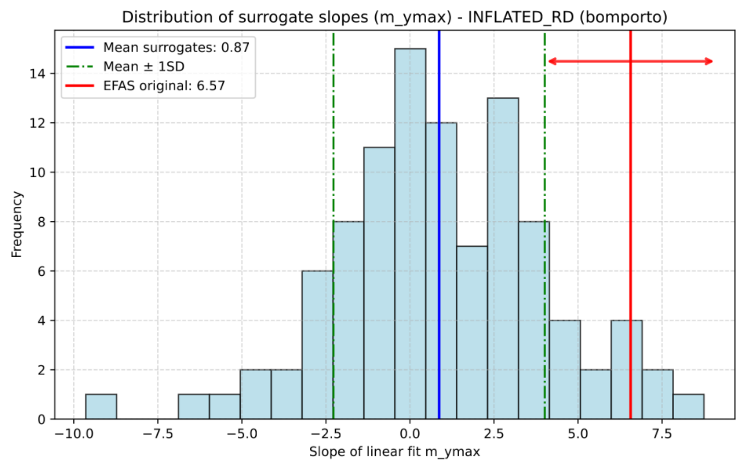

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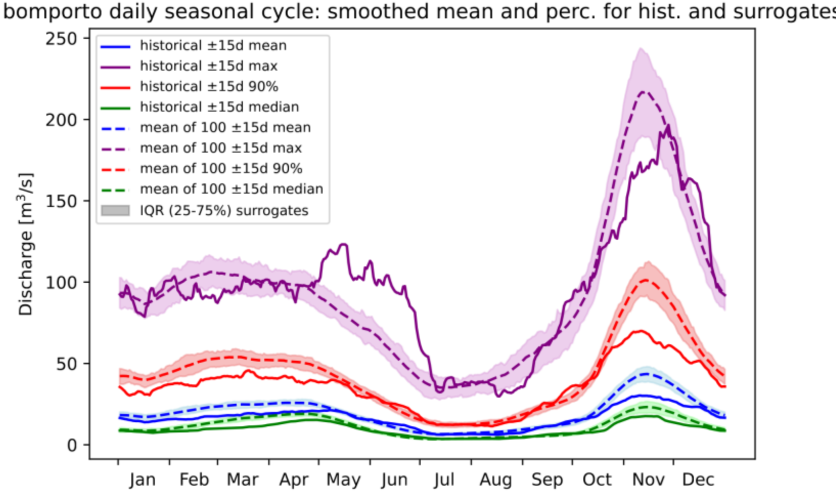
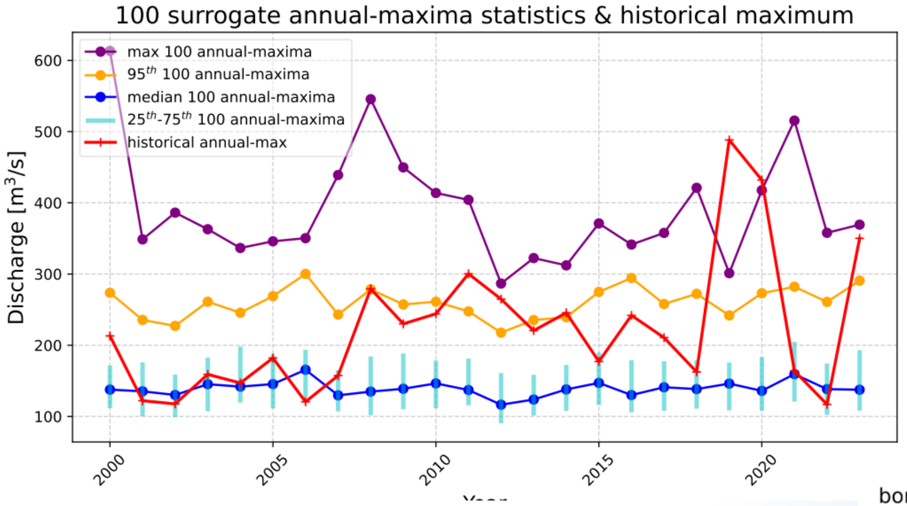
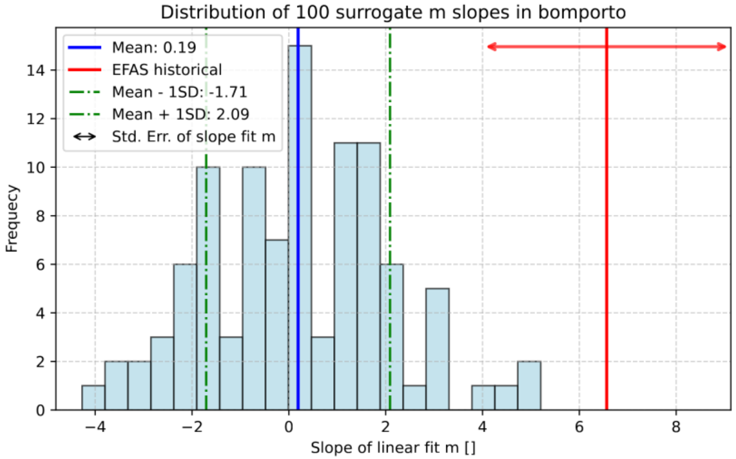
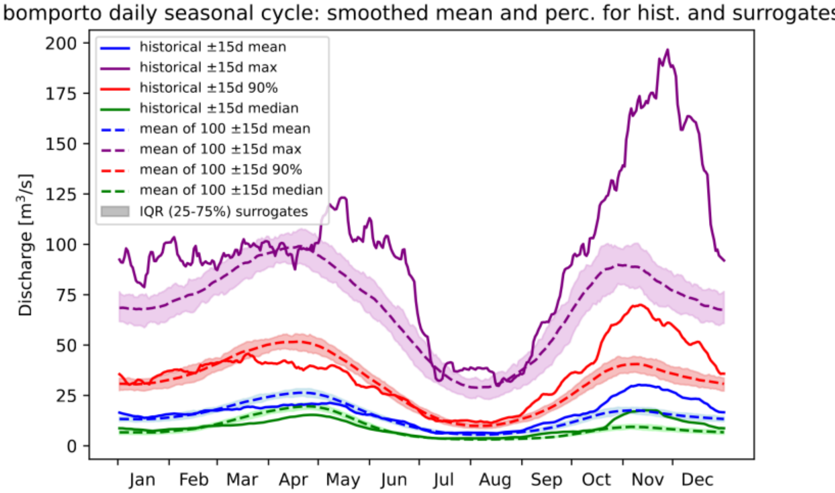
Lastly, the seasonal-cycle is much better than before, with some overestimation in Nov and some underestimation in May and June.



For comparison: the initial version of RD annual max statistic for the original surrogates







Summary and outlook:

1) The EFAS RD surrogate timeseries fail describing the RD Annual Maxima variability and trends of the historical EFAS timeseries (outlier?).
   While synoptic conditions leading to RD extremes (from ERA5) are well represented in SEAS5, the local rain has a dry bias with respect to EMO1, particularly in Autumn and near the Appenines. The resulting bias in the surrogates RD affects the ensemble ability to diagnose the relative roles of internal and forced trends of RD annual maxima.

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2) However, a CNN trained on the historical data can successfully correct the seasonal-dependent RD bias induced by the SEAS5 precipitation biases. A statistical correction of the 100 EFAS surrogate timeseries (0.92 million of days) improved things (e.g. the distribution tail of extreme RDs), and the new distribution of slopes includes the historical one, which now can be attributed to internal climate variability, with ~13% of forced changes.

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3) Need for inflation implies that not all physical processes are correctly captured, warning caution on quantitative assessments, particularly whether climate-change trends in Autumn precipitation are underestimated. It would be useful to investigate whether similar results can be observed in other catchments, especially small- to medium-sized watersheds located in areas with complex orography.

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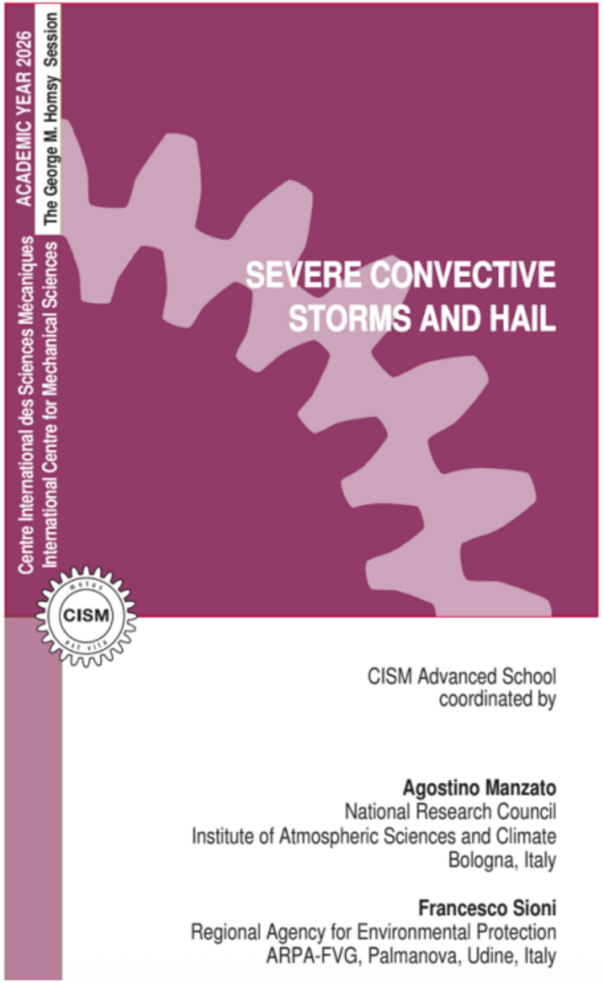
For info: *a.manzato@isac.cnr.it*

THANKS!

Course on Severe Convective Storms and Hail



Udine (Italy), 20-24 July 2026

https://cism.it/en/activities/courses/C2611/

Matthew Kumjian - Pennsylvania State University, USA
Hail microphysics; Dual-polarization radar variables

Michael Kunz - Karlsruhe Institute of Technology, Germany
Hailstorm damage patterns across Europe; Modeling hail risk for insurance applications; Hail hazard in a changing climate

Kelly Lombardo - Pennsylvania State University, USA
Gravity waves and bores in convection initiation; Impact of mountains on organized convection

Agostino Manzato - CNR-ISAC Bologna, Italy
Thermodynamics of moist air; Thermodynamic diagrams; Instability indices

Mario Marcello Miglietta - CNR-ISAC Padua, Italy
Tornadoes in Mediterranean region; Hailstorms over northeastern Italy; Intense orographic precipitation in the Mediterranean region; Mediterranean tropical-like cyclones

Mateusz Taszarek - Adam Mickiewicz University Poznan, Poland
Convective parameters; Environments associated with severe storms in the world; Storm modes

Francesco Sioni – ARPA FVG, Italy
Weather Briefings

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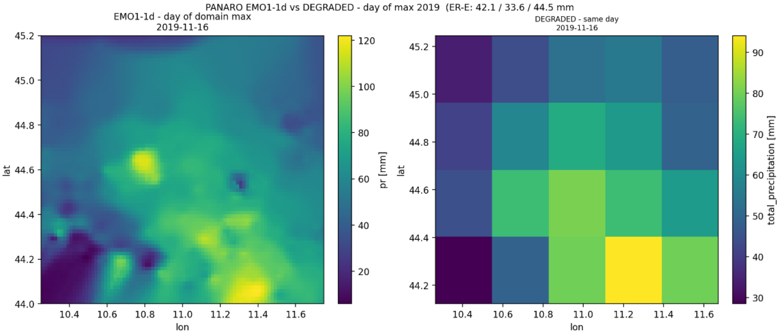
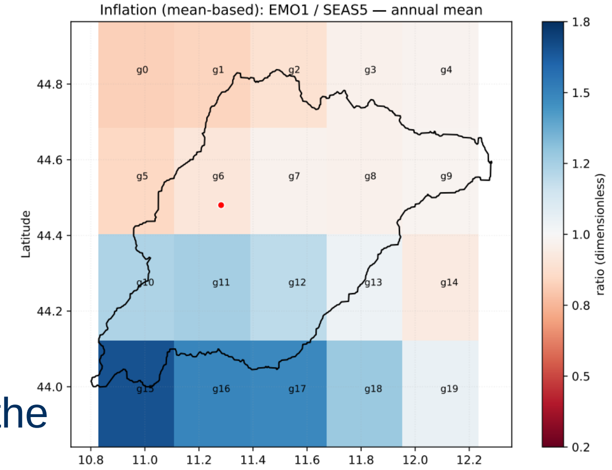
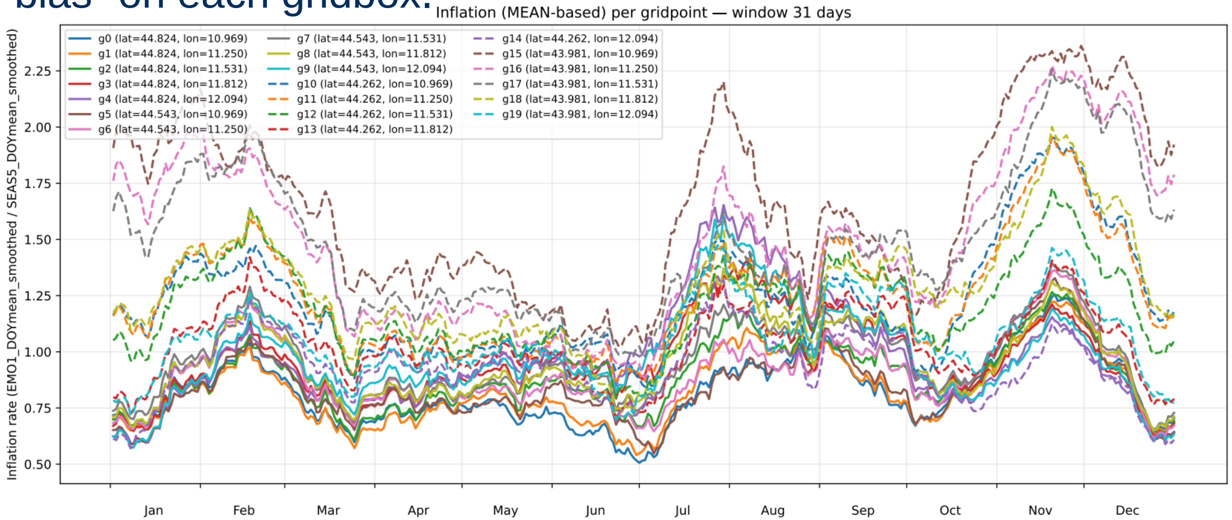
Spatial and temporal analysis of the mean EMO1 and SEAS5 local rain: Casalecchio



1. We downgraded the 2000-2022 rain of EMO1 on the SEAS5 grid and computed the "rain bias" on each gridbox.



2. EMO1 mean rain has a peculiar spatial climatology, with larger mean max rain toward the SW corner (mountains), while SEAS5 rain is more homogeneous. Thus the map of mean-rain bias (blu-red map) has a spatial distribution, similar to the EMO1 climatology.



3. If we compute a day-of-year bias-correction for mean rain it is different both for the day of year as for each of 20 gridpoints, varying from 0.5 to 2.3.

*Can we use this **rain-bias** correction to correct the **RD bias**?*

Of course, RD is not a linear function of rain...

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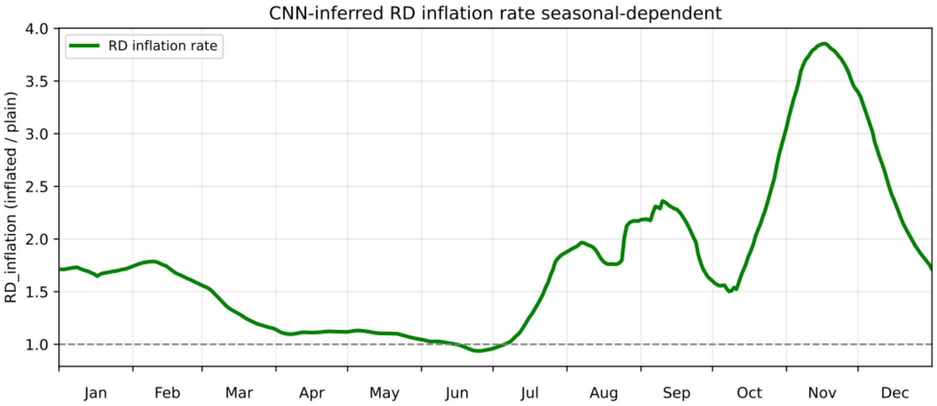
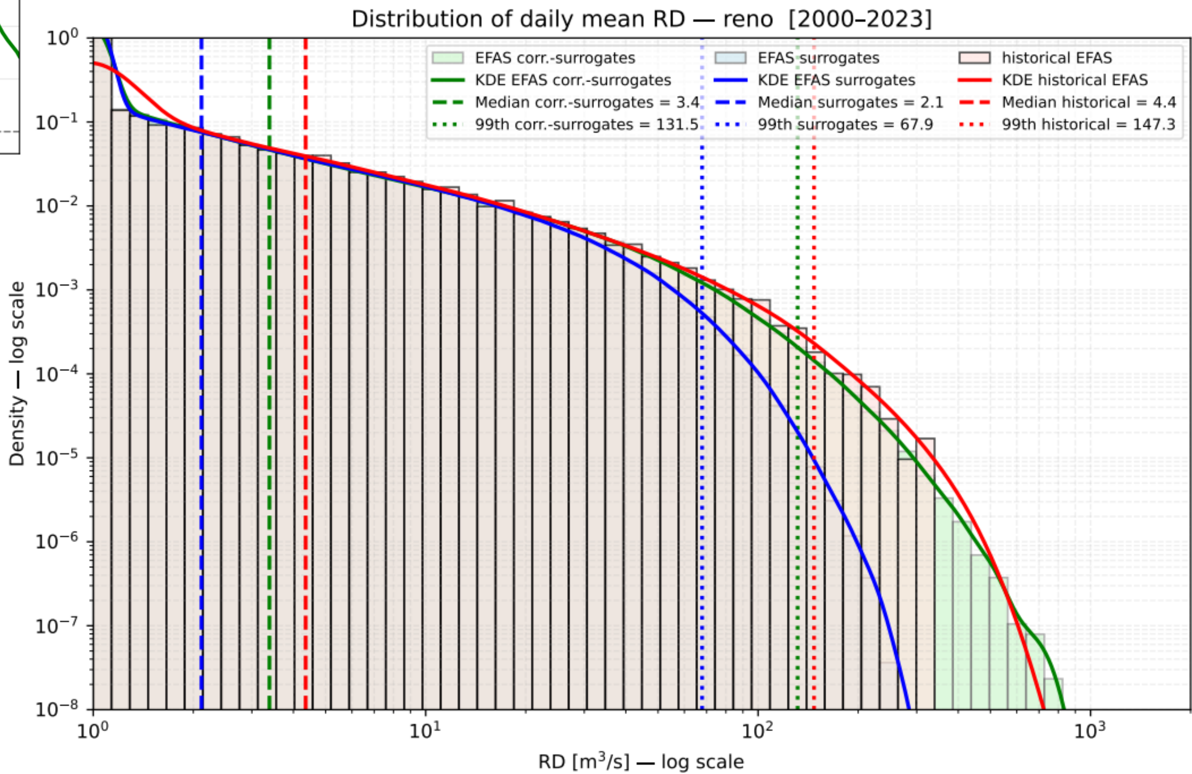
RD results: historical, original and seasonal-dependent bias-corrected surrogates



The seasonal-dependent RD correction (derived from the two different max RD annual cycles) in Casalecchio (Reno) is inflated of about 3.7 times in November.

With this seasonal-dependent correction of RD the **new surrogate** distribution above 40 m^3/s overlap much better with the **historical** EFAS than the **original surrogates**. Note the better estimates of both 50p and 99 percentiles.



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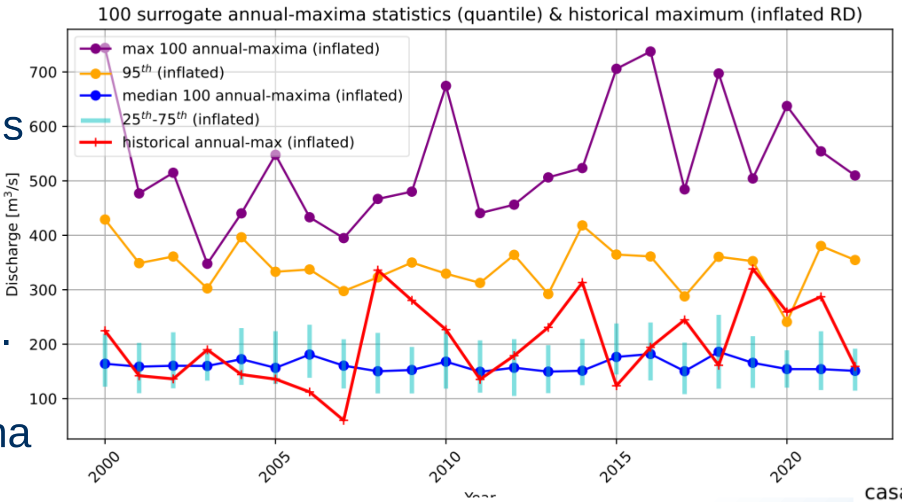
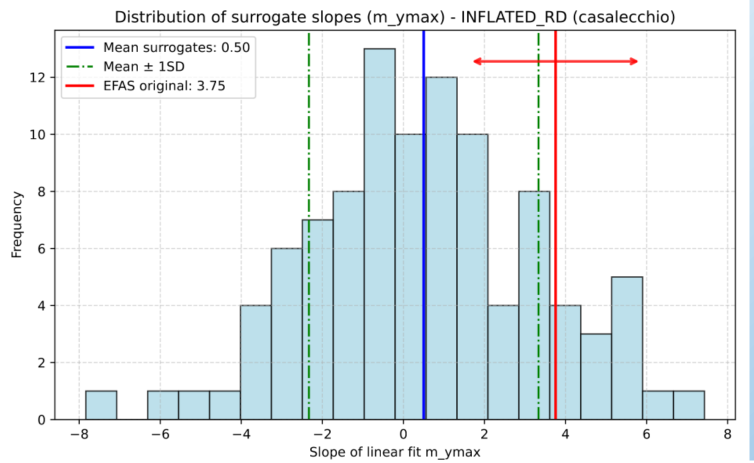
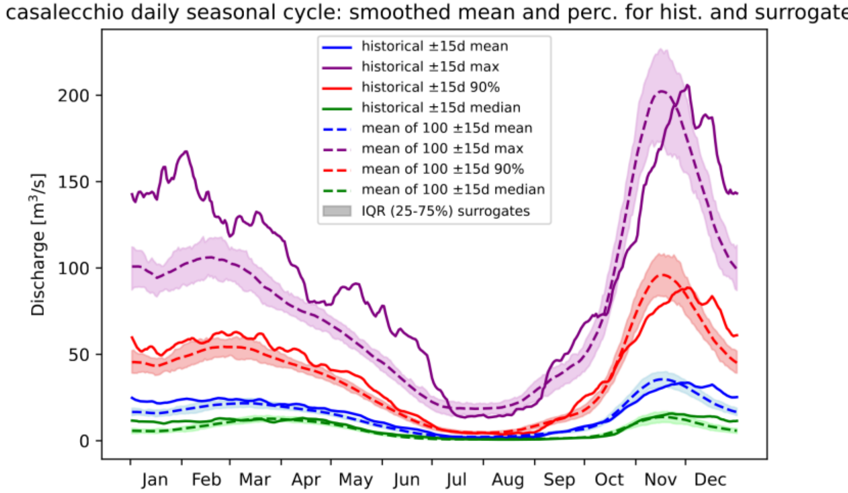




The mean slope of the 100 surrogates (S) increased to 0.50 m³/sy, which is still lower than the positive trends of the historical EFAS (3.8 m³/sy, no more an outlier!). The ensemble spread of slopes is SD=2.8, leading to S/N = 0.18. In this corrected-ensemble there is some external forcing signal emerging from the internal variability.



Lastly, the Casalecchio seasonal-cycle is much better than before, with a not so large underestimation in Jan and Feb.