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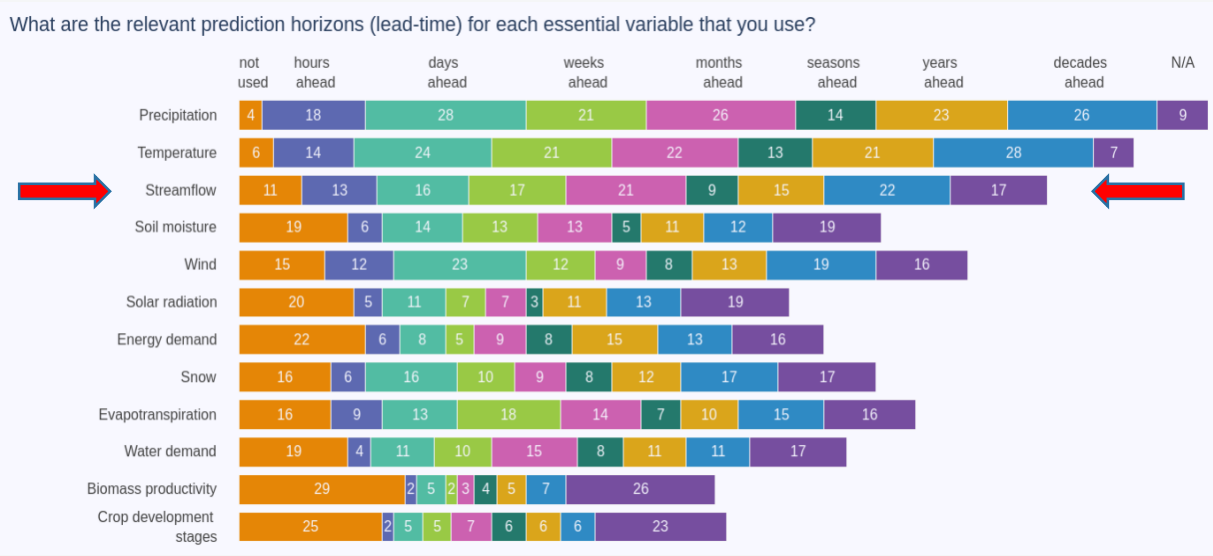
Understanding the drivers controlling the seasonal predictability of floods and droughts over Europe

Yiheng Du, Ilaria Clemenzi, Ilias G. Pechlivanidis





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Objectives:

1. Assess the predictability of floods (90th percentile) and hydrological droughts (10th percentile)
2. Compare the predictabilities for different lead times and at different river systems
3. Understand the drivers leading to the difference in predictability

Data and models:

Hydro model:	E-HYPE (35408 subbasins)
Reference forcing:	HydroGFD product v2.0
Meteo forcing:	Bias-adjusted ECMWF SEAS5
Period:	1993-2015
Ensemble:	25 members
Initialization:	Every month
Max lead time:	30 lead weeks

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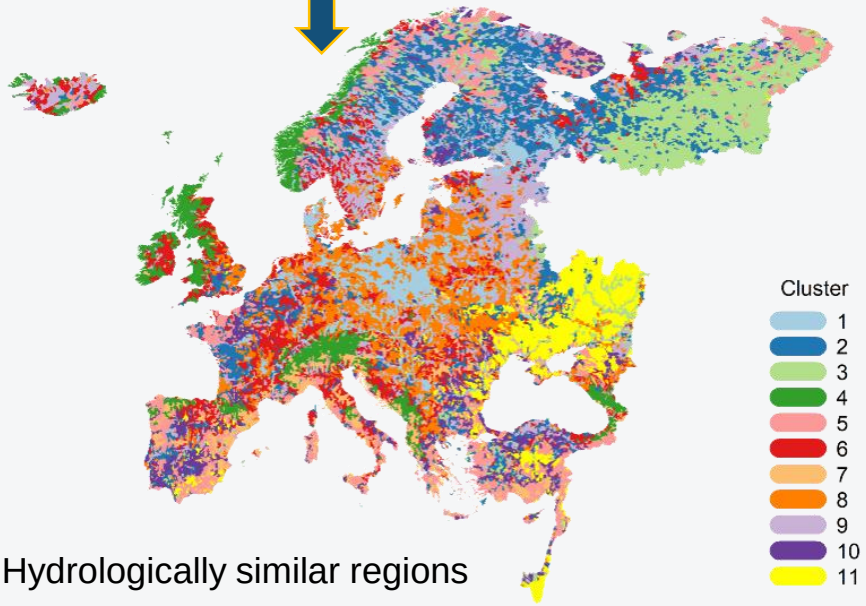
Background - Hydrologically similar river systems over Europe
- first application of AI/ML

Clustering (K-means) using these 15 hydrological signatures



Hydrologically similar regions

Hydrological signatures		
Qm	Mean annual specific runoff	mm/year
q05	Normalized high streamflow	--
q95	Normalized low streamflow	--
q70	Normalized relatively low streamflow	--
mFDC	Slope of streamflow duration curve	%/%
Dpar	Range of Pardé coefficient	--
CV	Coefficient of variation	--
Flash	Flashiness	--
PD	Normalized peak distribution	--
RLD	Rising limb density	--
DLD	Declining limb density	--
BFI	Baseflow index	--
RC	Runoff coefficient	--
EQP	Streamflow elasticity	--
HPC	High pulse count	--

Pechlivanidis et al. (2020). Water Resources Research
https://doi.org/10.1029/2019WR026987

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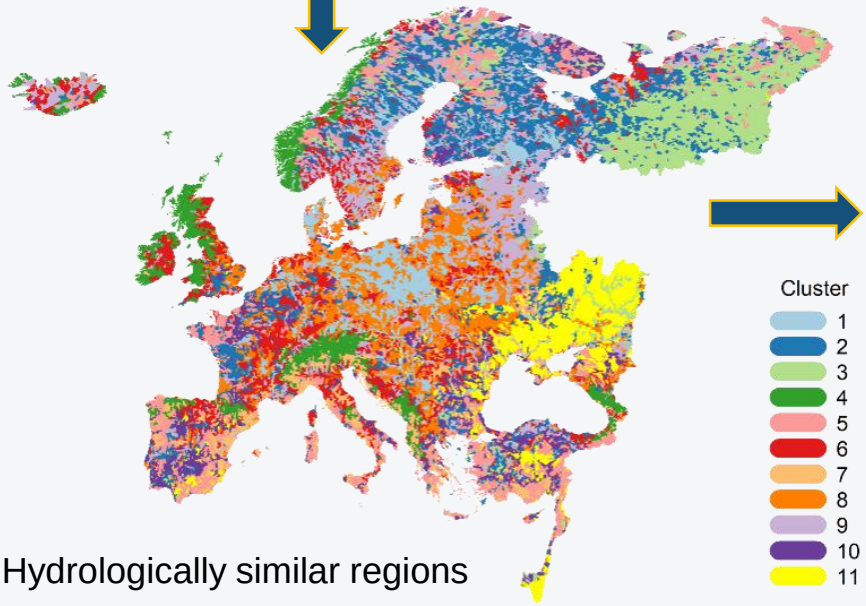

Hydrologically similar regions

Hydrological clusters	
1	Mainly **baseflow controlled**, snow driven
2	**Precipitation driven**
3	Snow dominated, dampening due to **lakes/wetlands**
4	Responsive to precipitation, regulated in winter
5	**Snow melting** driven, precipitation driven
6	Quickly responsive to precipitation, **long recession**
7	**Flashy response** to precipitation
8	**Baseflow dominated** with sharp rising limbs
9	Highly baseflow dominated
10	Low streamflow, low runoff coefficients
11	Low runoff coefficients, **irrigation**

Pechlivanidis et al. (2020). Water Resources Research
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What are the predictabilities of hydrological extremes in the pan-European region?

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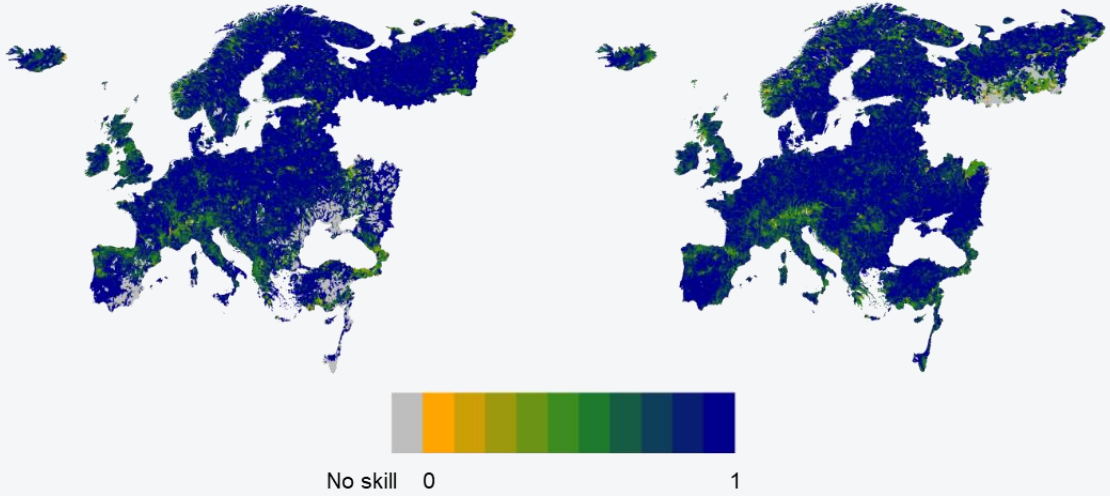
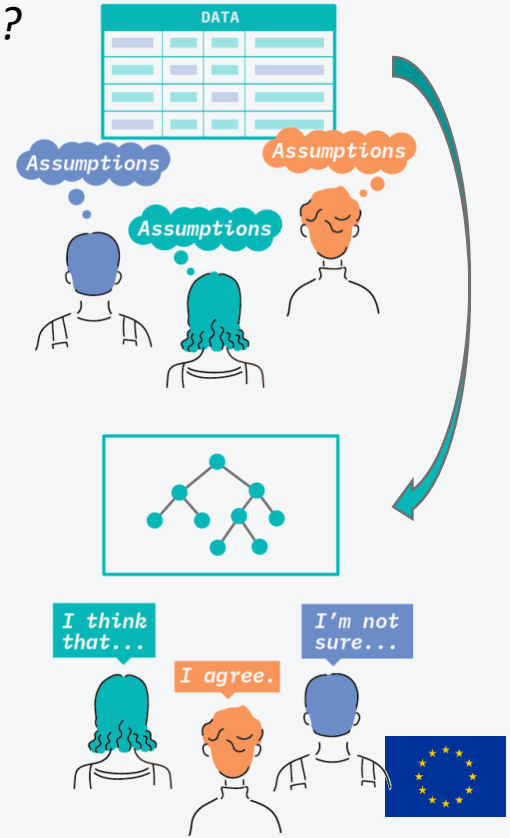
Lead week 0

Drought predictability

Flood predictability



Can the spatial predictability be explained ?



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What are the predictabilities of hydrological extremes across different river systems?

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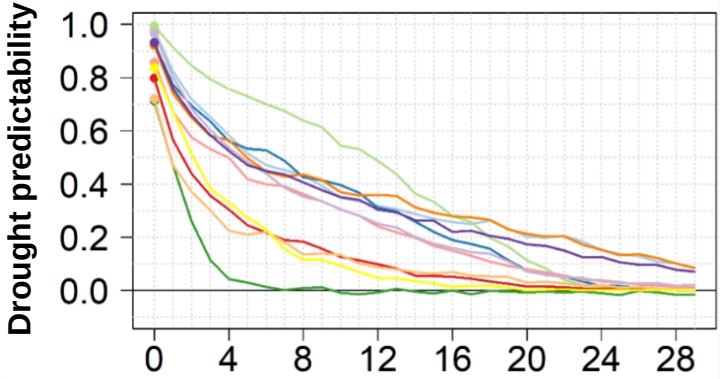
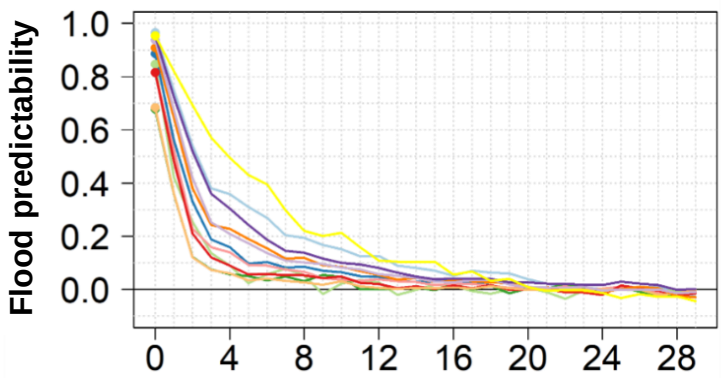
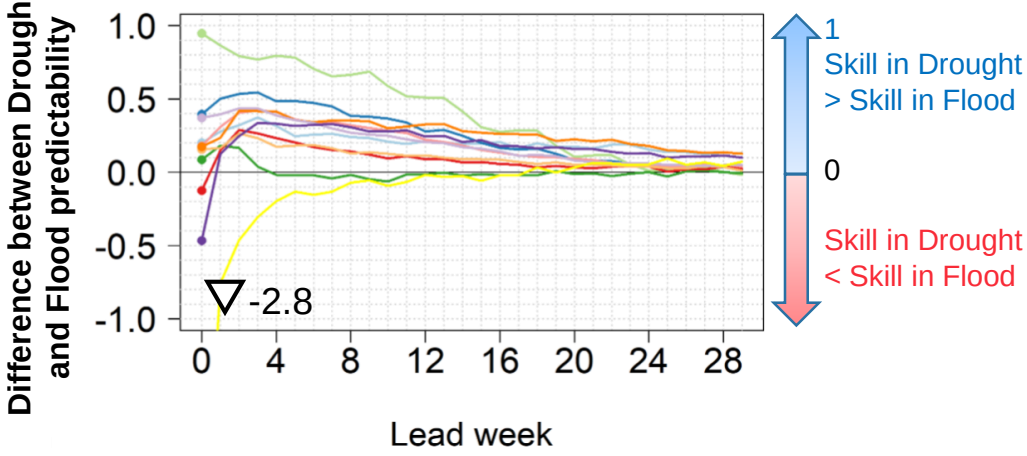




1 - Perfect skill

0

< 0 - No skill



1
Skill in Drought > Skill in Flood

0

Skill in Drought < Skill in Flood

Clusters and catchment properties

1 - Mainly **baseflow controlled**, snow driven
2 - **Frequent peak** streamflows, yet **long recession**
3 - Snow dominated, dampening due to **lakes/wetlands**
4 - Responsive to precipitation, regulated in winter
5 - **Snow melting** driven, precipitation driven
6 - Quickly responsive to precipitation, **long recession**
7 - **Flashy response** to precipitation
8 - **Baseflow dominated** with sharp rising limbs
9 - **Highly baseflow** dominated
10 - Low streamflow during the year, low runoff coefficient
11 - Low runoff coefficients, **irrigation**

What are the drivers leading to different predictabilities of hydrological extremes?

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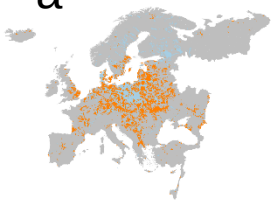
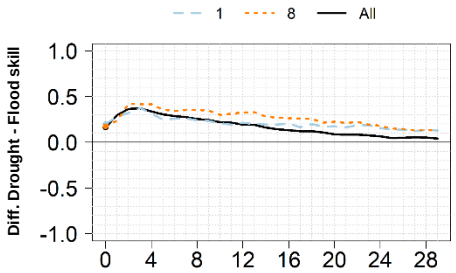
a



Baseflow controlled



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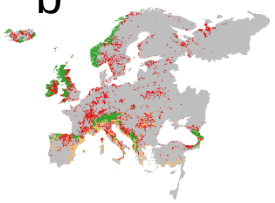
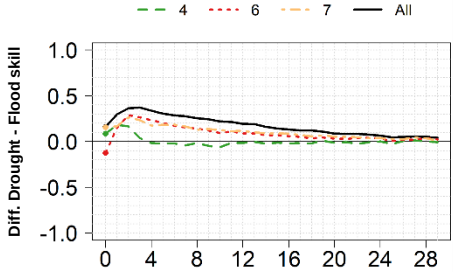


Responsive to precipitation



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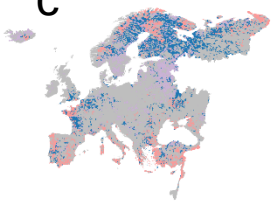
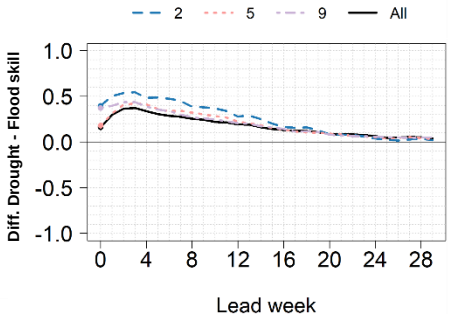


Snow melting, baseflow, long recession



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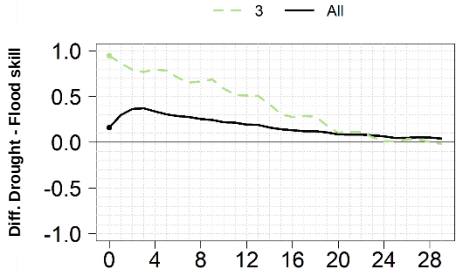
Lakes/wetlands



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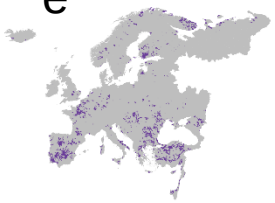
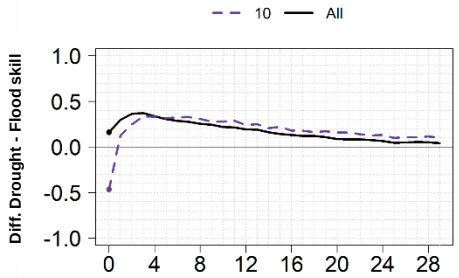


Low streamflow



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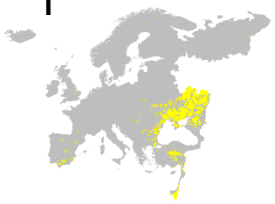
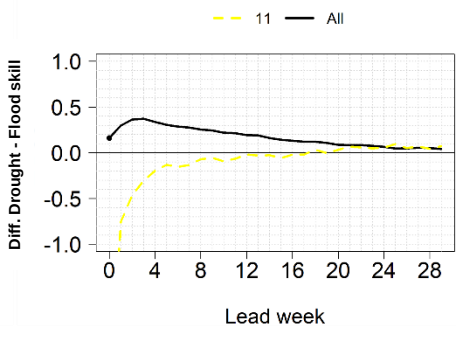


Irrigation



Conclusions

With the assistance of AI/ML, we show that the predictability of the seasonal streamflow extremes (floods and droughts) :

1. varies geographically, and deteriorates with increased lead time
    - the deterioration depends on the dominant streamflow generation processes.

2. has a link to hydrological similarity
    - results can be regionalized based on a priori knowledge of the local hydrological characteristics.

Additional Notes

The insights are valid not only for the European river systems but results can be upscaled to other non-European river systems that has similar hydrological characteristics with those explored here.

Machine learning tools and the big data availability (35408 sub-basins) **allowed the detection of spatial patterns** linking further predictability to local physiographic and hydro-met properties.

Thanks for sharing your insights with us!

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