

LETTER • OPEN ACCESS

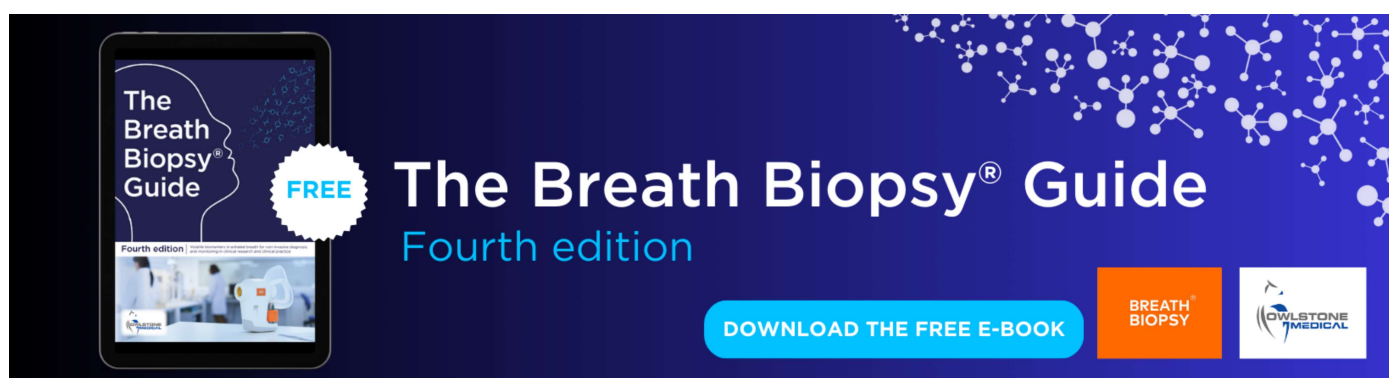
Hydrological regimes explain the seasonal predictability of streamflow extremes

To cite this article: Yiheng Du *et al* 2023 *Environ. Res. Lett.* **18** 094060

View the [article online](#) for updates and enhancements.

You may also like

- [Optimizing Parameters of Artificial Intelligence Deep Convolutional Neural Networks \(CNN\) to improve Prediction Performance of Load Forecasting System](#)
F M Butt, L Hussain, S H M Jafri et al.
- [A Statistical out-of-Sample Forecast to Estimate Lithium-Ion Parameters That Determine State of Charge](#)
Asadullah Khalid, Aditya Sundararajan and Arif Sarwat
- [Configuration of Bayesian Model Averaging Training Window to Improve Seasonal Rainfall Ensemble Prediction](#)
R Muharsyah, T W Hadi and S W Indratno



The Breath Biopsy® Guide
Fourth edition

FREE

DOWNLOAD THE FREE E-BOOK

BREATH BIOPSY

DOWLSTONE MEDICAL

ENVIRONMENTAL RESEARCH
LETTERS

LETTER

OPEN ACCESS

RECEIVED

15 March 2023

REVISED

10 July 2023

ACCEPTED FOR PUBLICATION

4 September 2023

PUBLISHED

18 September 2023

Original content from
this work may be used
under the terms of the
[Creative Commons
Attribution 4.0 licence](#).

Any further distribution
of this work must
maintain attribution to
the author(s) and the title
of the work, journal
citation and DOI.

Hydrological regimes explain the seasonal predictability of
streamflow extremesYiheng Du^{*} , Ilaria Clemenzi and Ilias G Pechlivanidis

Swedish Meteorological and Hydrological Institute, 601 76 Norrköping, Sweden

^{*} Author to whom any correspondence should be addressed.E-mail: Yiheng.du@smhi.se**Keywords:** hydrological extremes, seasonal predictability, comparative analysis, performance attribution, pan-European scale, large-scale hydrological models

Abstract

Advances in hydrological modeling and numerical weather forecasting have allowed hydro-climate services to provide accurate impact simulations and skillful forecasts that can drive decisions at the local scale. To enhance early warnings and long-term risk reduction actions, it is imperative to better understand the hydrological extremes and explore the drivers for their predictability. Here, we investigate the seasonal forecast skill of streamflow extremes over the pan-European domain, and further attribute the discrepancy in their predictability to the local river system memory as described by the hydrological regimes. Streamflow forecasts at about 35 400 basins, generated from the E-HYPE hydrological model driven with bias-adjusted ECMWF SEAS5 meteorological forcing input, are explored. Overall the results show adequate predictability for both hydrological extremes over Europe, despite the spatial variability in skill. The skill of high streamflow extreme deteriorates faster as a function of lead time than that of low extreme, with a positive skill persisting up to 12 and 20 weeks ahead for high and low extremes, respectively. A strong link between the predictability of extremes and the underlying local hydrological regime is identified through comparative analysis, indicating that systems of analogous river memory, e.g. fast or slow response to rainfall, can similarly predict the high and low streamflow extremes. The results improve our understanding of the geographical areas and periods, where the seasonal forecasts can timely provide information on very high and low streamflow conditions, including the drivers controlling their predictability. This consequently benefits regional and national organizations to embrace seasonal prediction systems and improve the capacity to act in order to reduce disaster risk and support climate adaptation.

1. Introduction

In the 21st century, an increased frequency of hydrological extremes, both droughts and floods, has been observed over Europe, posing immediate socio-economic threats (Cammalleri *et al* 2020, Rakovec *et al* 2022). Early warning systems can reduce the societal vulnerability to these hydrological extremes, but demand for high-quality hydrological forecasts (Wanders and Wood 2016, De Perez *et al* 2017). Against increasingly extreme weather and climate change, the United Nations initiated the 'Early Warnings for All' action plan 2023–2027 to boost the power of predictions and build the capacity to act to reduce disaster risk and

support climate adaptation. With a time horizon of two weeks ahead, short- to medium-range forecasts are the principal tools in daily operations (Pechlivanidis *et al* 2014, Bruno Soares and Dessai 2015), while long-range forecasts addressing the sub-seasonal to seasonal time horizons can support strategic planning leading also to timely mitigation of natural climate-induced hazards (Wanders *et al* 2016, Crochemore *et al* 2021, Brunner and Slater 2022a, White *et al* 2022). The seasonal planning in sectors, i.e. energy production, agriculture, water management, disaster mitigation and health, usually falls into the long-range time horizons (van den Hurk *et al* 2016, Hewitt *et al* 2020, Cantone *et al* 2023).

Scientific efforts have been devoted to assessing the sub-seasonal to seasonal hydrological forecasts, including extremes, providing information for better understanding their predictability under different local conditions. However, the majority of assessments on seasonal hydrological forecasts were conducted targeting the overall forecast assessments (Arnal *et al* 2018, Greuell *et al* 2018, Harrigan *et al* 2018), or tackling independently the high or low streamflow extremes (Madrigal *et al* 2018, Kompore *et al* 2020, Siqueira *et al* 2020, Sutanto *et al* 2020). It is not necessary that river systems with high forecast quality for floods would perform equally well for droughts (and vice versa), due to the physical and/or human induced processes that can filter the meteorological signal. Moreover, this solo approach has not allowed the development of diagnostics to uncover the origins of the discrepancies in flood and drought predictability over space and forecast time, which can further feed in the evolution of early warning and climate services.

Although recent efforts aimed at understanding the key drivers that influence the hydrological predictability (Harrigan *et al* 2018, Beer *et al* 2014, Girons Lopez *et al* 2021), the insights regarding hydrological extremes still remain insufficient. Hydrological forecasts over long lead times (weeks, months or seasons) are produced on the basis of firstly initialing the hydrological conditions at the onset of a forecast, and secondly forcing the hydrological model(s) with (bias-adjusted) meteorological forecasts; thus these two sources drive the hydrological forecast quality (Yossef *et al* 2013, Yuan *et al* 2015, Greuell *et al* 2019, Patterson *et al* 2022). Sensitivity analysis methods can exploit the (relative) importance of these sources of predictability, which are also well connected to the local hydrological processes (Wood and Lettenmaier 2008, Wood *et al* 2016, Arnal *et al* 2017).

Moreover, the majority of previous studies on seasonal hydrological forecasting have been carried out in a limited number of basins to further allow comparative analyses. Even investigations that were conducted at the large scale, lack of synthesis of knowledge across geographical locations and hydro-climatic regimes (Kumar *et al* 2013, Pechlivanidis and Arheimer 2015, Gudmundsson *et al* 2019). Recently, studies explored the link of overall hydrological forecast quality to physical drivers concluding river memory as a key controller of the predictability (Pechlivanidis *et al* 2014, Sutanto and van Lanen 2022).

Here, we simultaneously investigate, for the first time to our knowledge, the seasonal forecast skill of streamflow extremes (very high and low conditions), over the pan-European domain and further attribute the difference in their predictability to the local hydrological signatures across all river systems. We gain new insights by posing the following

questions that not only add scientific value but also guide development in hydrological early warning systems and climate services: (1) *How does the skill of seasonal streamflow forecasts on high and low extremes vary over the European river systems?* and (2) *Can the predictability of the high and low streamflow extremes, including their discrepancy, be attributed to the hydrological regimes?* To address these questions, we: (a) assess the forecast skill (up to 30 weeks ahead) of streamflow extremes across Europe's hydro-climatic gradient, (b) analyze the forecast skill for each hydrological regime to understand emerging links between them, and (c) identify the regimes in which high and low streamflow predictability is experiencing similar ranges.

2. Models and data

2.1. Hydrological model description

The E-HYPE model v.3.1.3 covering the pan-European domain (8.8 million km²) was used. E-HYPE is a semi-distributed process-based model operating at a fine spatial resolution with 35 408 sub-basins and an average spatial resolution of 215 km² (Hundecha *et al* 2016). The HYPE model code is available from the HYPEweb portal (SMHI 2022). Details about the model can be found in the [appendix](#).

2.2. Meteorological historical data and forecasts

In this study we used the HydroGFD v2.0 (Hydrological Global Forcing Data version 2.0) product, an observation-corrected reanalysis dataset providing historical meteorological information of precipitation and mean temperature at a 0.5° gridded resolution (Berg *et al* 2018). The HydroGFD was used to force the E-HYPE hydrological model to generate the reference simulation (here considered as 'observations'; pseudo-observations) and to generate the initial hydrological conditions at the beginning of each month.

Seasonal forecasts of daily mean precipitation and temperature were available for the period 1993–2015 (re-forecasts/ hindcasts) from the fifth-generation seasonal forecasting system of the European Centre for Medium-Range Weather Forecasts, ECMWF SEAS5 (Johnson *et al* 2019), which are freely accessible from the Copernicus Climate Data Store (CDS 2023). SEAS5 re-forecasts are initialized at the beginning of each month and extend 215 d ahead with 25 ensemble members. Seasonal forecasts of daily mean precipitation and temperature were bias-adjusted to the reference dataset (HydroGFD) and used to force the E-HYPE model for seasonal streamflow forecasts. Details about the bias-adjustment method are in the [appendix](#).

2.3. Hydrological forecasting

The initial hydrological states (i.e. snow, water levels in reservoirs /lakes and /wetlands, soil moisture, and

streamflow) for the 1st day of every month during the 1993–2015 period were generated by forcing E-HYPE with the HydroGFD v2.0 meteorological data (reference simulation). Seasonal forecasts were then obtained by running the model with the bias-adjusted SEAS5 re-forecasts and the HydroGFD-based climatological data as forcing input at the start of each month with a seven-month lead time. Real-time seasonal forecasts obtained through E-HYPE are openly available on the HYPEweb portal (SMHI 2023). Modeled streamflow was extracted in all ~35 400 sub-basins to assess the model's predictive skill at seasonal time scales. The hydrological model was run at a daily time scale and the generated forecasts were then aggregated to weekly means.

3. Methodology

3.1. Evaluation of hydrological forecast extremes

Seasonal streamflow forecasts are evaluated with respect to their forecast performance against the reference simulation (pseudo-observations), which allows inter-comparison between sub-basins and limits the impact of the model's structural and parametric inadequacies to represent reality. The evaluation of streamflow forecasts is performed on weekly values (i.e. daily streamflow averaged over 7 d) for the period 1993–2015, with lead week 0 denoting the first week of the forecast and so forth.

Here, we assess the predictability of hydrological droughts and floods in terms of low and high streamflow using the 10th and 90th percentiles of the available 23 years climatology, respectively. The target periods are defined for each sub-basin for low and high streamflow (figure 1(a)) to consider the intra-annual variability of the hydrological response between sub-basins, given Europe's strong hydro-climatic gradient. The target period of each sub-basin is identified by the terciles from the streamflow climatology in the reference simulation, and the weeks with streamflow higher (lower) than the 66th (33rd) percentile are considered as high (low) streamflow weeks. The start and end month of the streamflow extreme periods for each sub-basin are shown in figure 1(b). Note that the start and end months illustrated here only cover the longest consecutive months, since sub-basins can have discontinuous extreme weeks depending on their hydro-climatic properties (figures 2(b) and (c)).

The seasonal forecast performance is assessed using the Brier Score (BS; Brier 1950) on both high (90th percentile) and low (10th percentile) streamflow extremes for each sub-basin, target week and lead time. BS follows a strictly proper scoring rule to measure the accuracy of the probabilistic forecasts. The performance for the target weeks from different initializations are then pooled and analyzed for different lead weeks in each sub-basin separately. The forecast skill (BSS) is further calculated to indicate

the degree of improvement of the seasonal forecasts (BS_{fst}) using simulated streamflow climatology as a benchmark system (BS_{ben}):

$$BSS = 1 - BS_{fst}/BS_{ben}. \quad (1)$$

BSS can range from $-\infty$ to 1, with 1 indicating perfect skill and negative values indicating superiority of the benchmark (Wanders and Wood 2016). The benchmark system (simulated streamflow climatology) is constructed by sampling 20 years from the historical time series for the same target weeks as the forecast excluding the forecasted year.

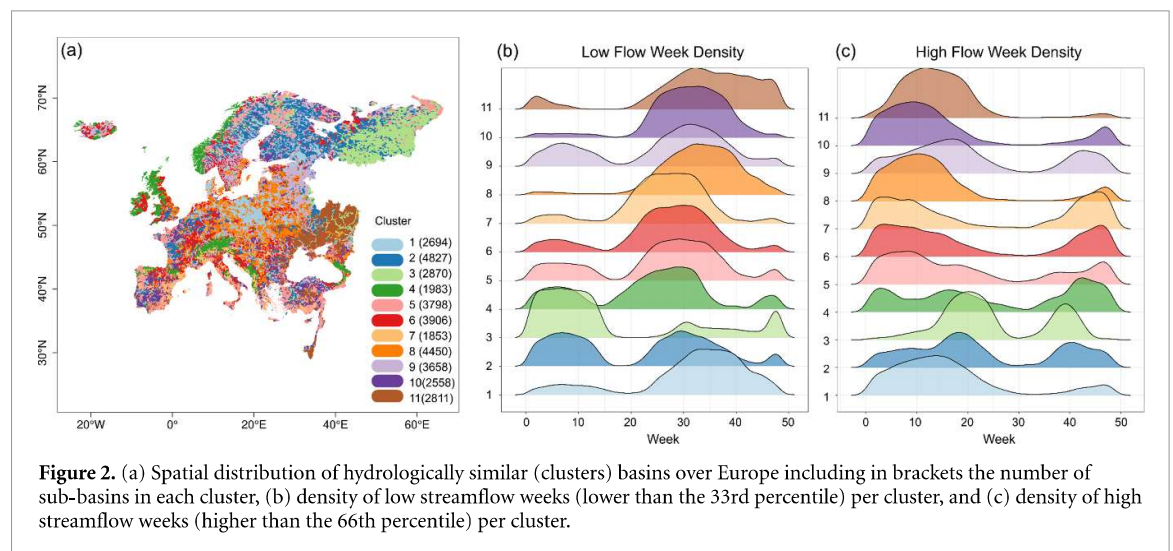
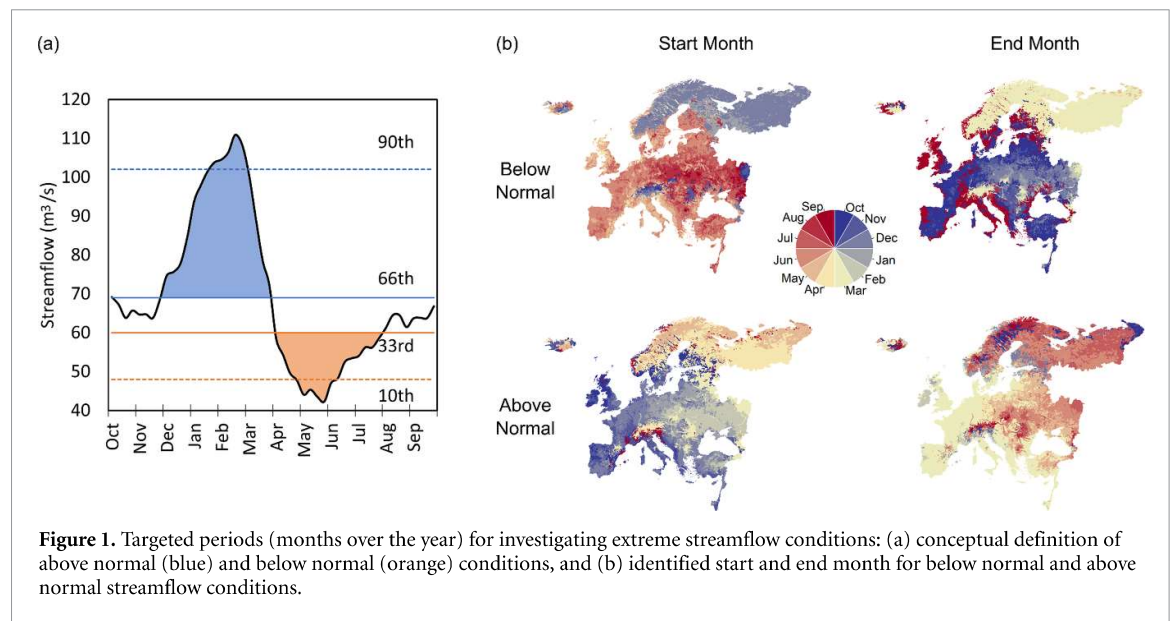
As a measure of the relative predictability of low and high streamflow extremes, we use a modified index based on the difference between BSS10 and BSS90 (denoted as ΔBSS), and standardized by the perfect forecast (BSS equals 1) (Pechlivanidis *et al* 2014). Positive (negative) ΔBSS values indicate superiority of the low (high) streamflow predictability, while 0 indicates equal predictability for the two types of extremes:

$$\Delta BSS = (BSS10 - BSS90) / (1 - BSS90). \quad (2)$$

3.2. Extreme forecast predictability—identifying controlling hydrological systems

The link between the predictability of streamflow extremes and hydrological regimes is investigated using the hydrological clusters that were previously generated by Pechlivanidis *et al* (2014) based on 15 hydrological signatures. The European river systems lie on a strong hydro-climatic gradient and were hence divided into 11 clusters, where basins in the same cluster were identified as hydrologically similar (figure 2(a)). Various river systems (i.e. in Poland and Denmark) are baseflow dominated and experience large river memory with streamflow being dampened from large water channels and water bodies (cluster 1). Other river systems are very responsive to rainfall, yet the hydrograph is characterized by long recessions (cluster 6). Human influence is also observed in the hydrological response, with for instance basins characterized by low runoff coefficient and relatively high intra-annual variability influenced by irrigation (cluster 11). More information about the hydrological similarity over Europe can be found in Pechlivanidis *et al* (2014). The distinct hydrological characteristics of each cluster are also reflected in their extreme periods, as evidenced by the density ridgeline of extreme streamflow weeks in figures 2(b) and (c).

Following the skill assessment of streamflow forecast extremes, a k-means clustering method (Jin and Han 2010) is applied to further categorize the clusters based on their common discrepancy profile in the predictability of hydrological extremes. This step allows a numerical identification (and not visual which could introduce subjectivity) of the basins that share common dominant hydrological regimes and



forecast skill patterns of high and low streamflow extremes.

4. Results

4.1. Assessment of seasonal hydrological forecast extremes

We firstly explore the spatial-temporal variability of predictability for each of the hydrological extremes. Results show that the forecasts across the pan-European domain achieve high predictability for both streamflow extremes (as described by BSS) in the first lead week, with a median skill over 0.9 in both extreme types (left column in figures 3(a) and (b)). Thereafter, the skills deteriorate along the increasing lead weeks, where a faster deterioration is observed in the skills for high streamflow extremes. After approximately 12 weeks, and until the furthest forecast horizon (lead week 29), the seasonal forecasts of high streamflow extremes provide, in general, no added value with respect to streamflow climatology.

In particular, a rapid decrease in skill of the high streamflow extremes in the first forecast month is observed, while the skill decline is smoother, and still positive, after lead week 6. In contrast, forecasts of low streamflow extremes maintain skill up to 20 weeks ahead.

The observed patterns of skill deterioration of the streamflow extremes are connected to the impact that initial hydrological conditions and meteorological forcing have on hydrological forecasts. It is apparent that the persistence of initial hydrological conditions is relatively short during the high streamflow period, while the skill in high streamflow extremes is shortly after driven by the meteorological forcing, which is known to have low skill at long lead times. However, the persistence of the initial hydrological conditions is longer during the low streamflow period, which results in slow decline in the forecast skill of low streamflow extremes. Moreover, the variations in the skill of low streamflow extremes are larger compared to those of high streamflow extremes, as depicted by the

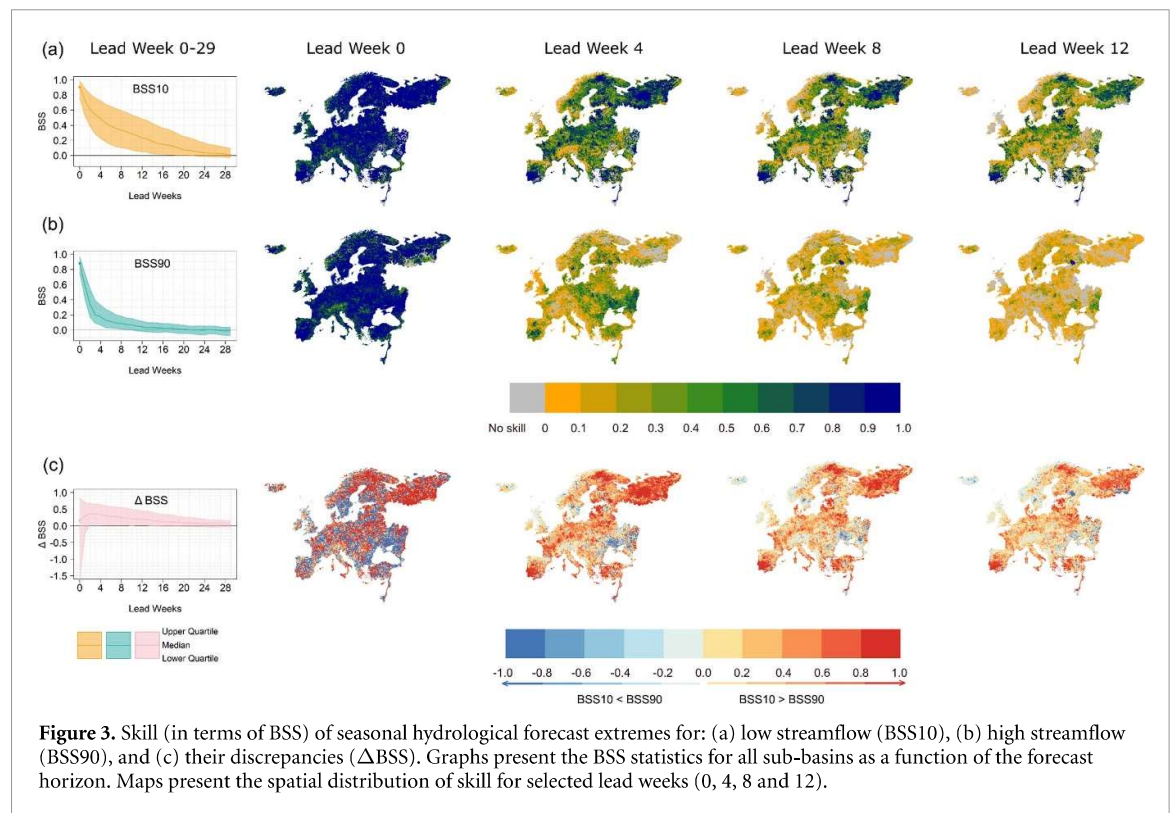


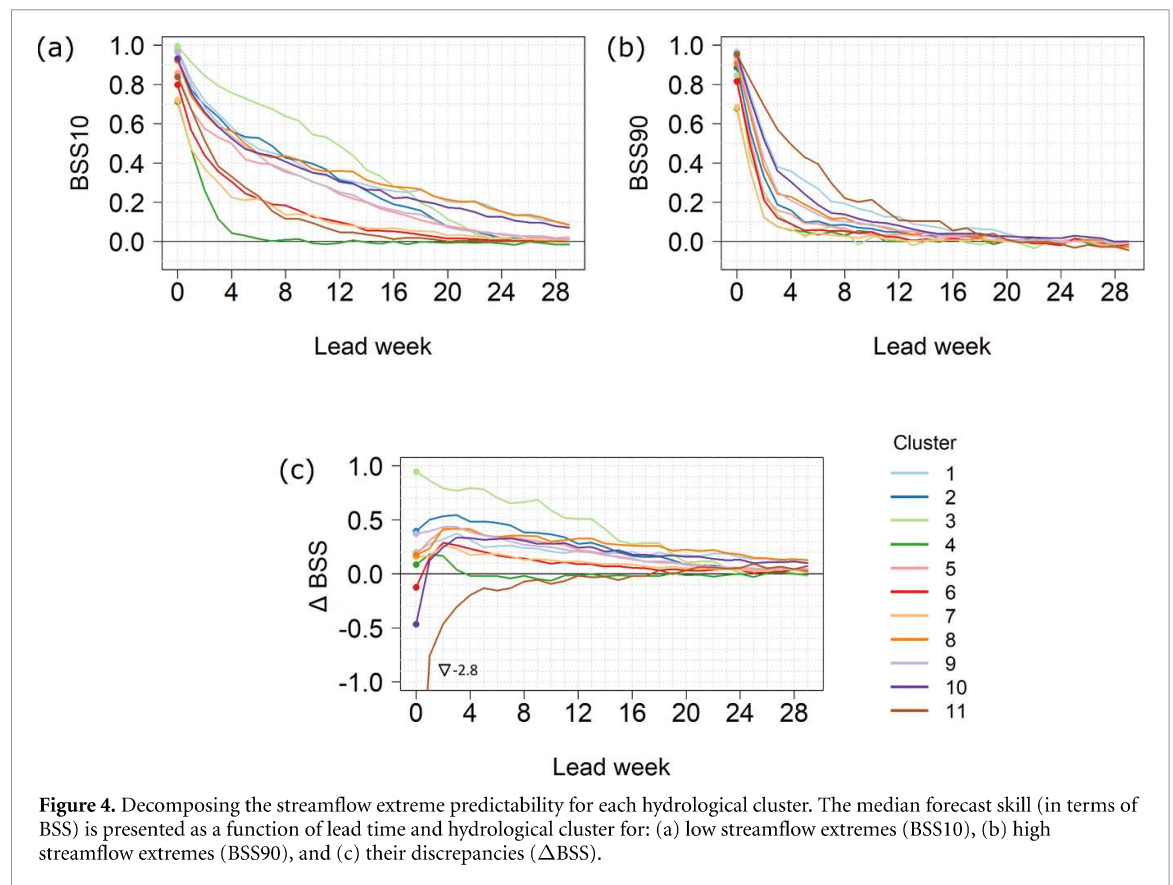
Figure 3. Skill (in terms of BSS) of seasonal hydrological forecast extremes for: (a) low streamflow (BSS10), (b) high streamflow (BSS90), and (c) their discrepancies (ΔBSS). Graphs present the BSS statistics for all sub-basins as a function of the forecast horizon. Maps present the spatial distribution of skill for selected lead weeks (0, 4, 8 and 12).

upper-lower quartiles in figures 3(a) and (b), which could be attributed to the underlying characteristics of the different hydrological regimes.

The skill of both extremes varies geographically with high skill ranges ($BSS > 0.8$) over the entire domain in the first lead week, while in the long lead times the forecast skill drops significantly, as expected, reaching BSS less than 0.2 (maps in figures 3(a) and (b)). Forecast skill for low streamflow is generally high in most parts of Europe (figure 3(a)), with lower skills in the coastal areas, especially in southern Europe. The latter could be related to the relatively small streamflow volumes occurring in the low streamflow months in comparison to the other months. We also note that in the semi-arid regions in southern Europe (southeast Spain, and parts of Greece and Italy), temperature forecasts are more influential affecting the hydrological response. Forecasts for high streamflow extremes can achieve good skills over the main continent, yet with lower skills in the coastal areas in the south and high elevation areas in the north. This variability in forecast skill could be the result of remaining precipitation biases in the forcing meteorological data even after bias adjustment, which were mainly observed in southern Europe, the Mediterranean, and generally in highly elevated regions (Pechlivanidis *et al* 2014). During lead weeks 4–12, the forecast skill overall deteriorates faster for high streamflow extremes than for low streamflow extremes, particularly in northeastern Europe and the coastal areas in the south.

We next assess the relative difference between the predictability of low and high streamflow extremes (ΔBSS) with the results showing a distinct difference in the superiority of low streamflow forecasts (figure 3(c)). However, ΔBSS during the first lead weeks (0–2) is highly variable ranging from less than -1.5 to almost 0.9 (note that these values are the lower and upper quartiles, respectively). This variability indicates that there is a significant number of sub-basins in which flood conditions are better predicted than drought conditions. Generally, in northern Europe, low streamflow extremes show higher predictability than high streamflow extremes (positive ΔBSS), whilst the opposite is observed in the eastern and southern parts of Europe (maps in figure 3(c)). Particularly in Eastern Europe, the skill for high streamflow extremes exceeds that for low streamflow up to lead week 12. Results also show that the skill superiority of low streamflow extremes is generally persistent in time; however, with increased lead time, the level of superiority (ΔBSS value) decreases, reaching a critical time after which ΔBSS could not be considered significant. The distinct behaviors of forecast skills and their discrepancy underscore the necessity for further investigation of potential drivers.

Results for longer lead times (lead weeks 16–28) show that overall the spatial distribution of forecast skill differs across forecast horizons (figure A1 in the appendix), with the low streamflow extremes maintaining their skill in northern Europe up to 16 weeks ahead. However, in central Europe, the skill of low



extremes remains almost to the furthest lead week. Forecast skill of high streamflow extremes generally drops fast in all river systems, with the BSS in some basins having positive values, yet close to 0, whilst in others basins reaching a negative skill.

4.2. Linking skill of forecast extremes to hydrological regimes

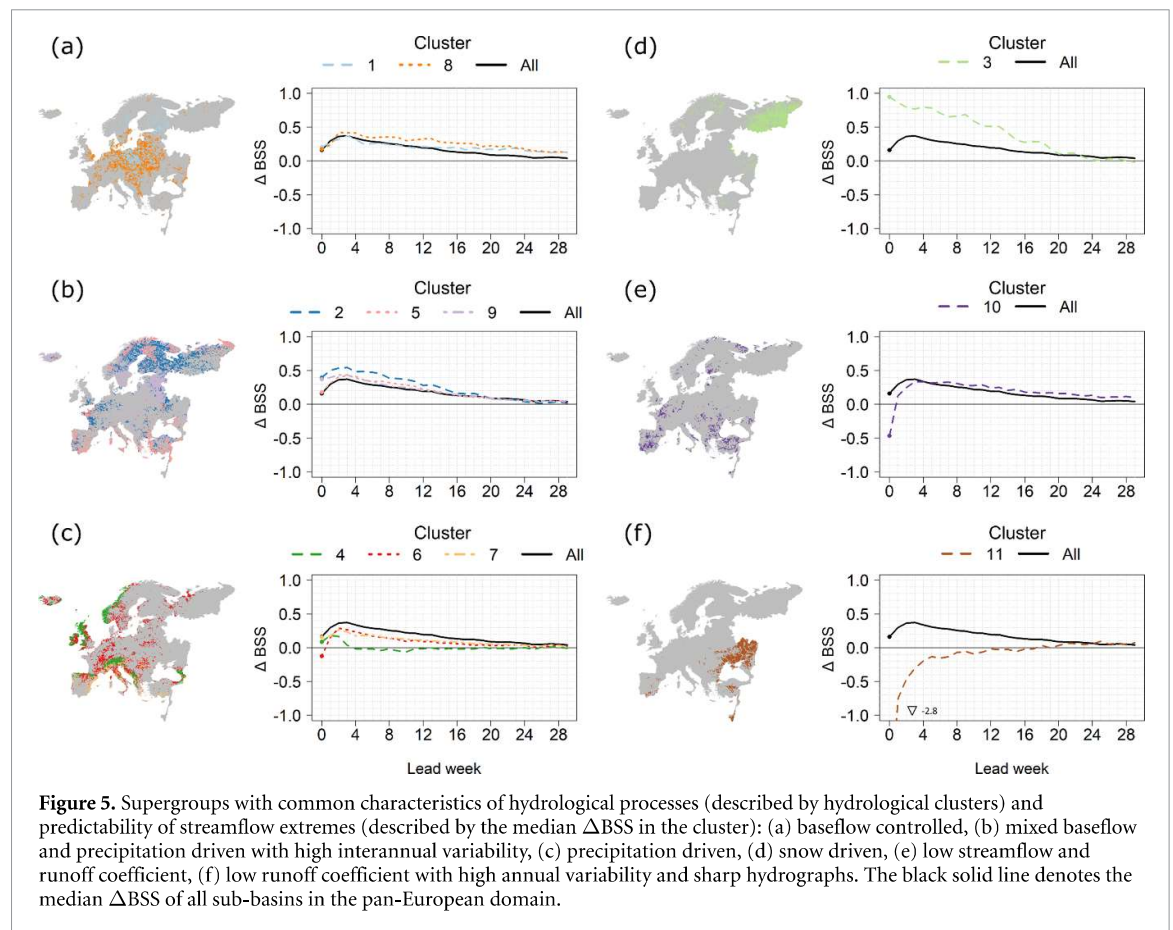
We next analyze the forecast skill for each hydrological cluster across Europe in order to identify emerging patterns in terms of predictability and persistence. The predictability of low and high streamflow extremes as a function of lead time and hydrological cluster is shown in figure 4. The skill for both extremes is overall high (>0.6) during the medium-range time horizons (up to 2 weeks ahead) for all hydrological clusters. Beyond that period the skill exhibits different deteriorating patterns, indicating that the skill (and its temporal distribution) is linked to the hydrological regime.

For low streamflow forecasts (figure 4(a)), the skill in cluster 3 (snow dominated regime) emerges for its high and prolonged predictability with an absolute superiority compared to the other clusters up to 16 weeks ahead. Moreover, in cluster 4 (precipitation driven regime), the low streamflow predictability shows a limited persistence in time, with a noticeable skill decrease already within the first lead month. The skill in the other clusters generally has similar deteriorating patterns, however, with distinct tails. In most

clusters, the skill deteriorates to zero before reaching the furthest lead week, whilst in some of the clusters (e.g. cluster 1, 8 and 10), the forecasts remain skillful during all lead times. The different patterns in skill indicate that the persistence of initial hydrological conditions varies among the river systems (i.e. long in snow dominated basins and short in fast responding basins).

The predictability of high streamflow extremes shows in general similar patterns for all clusters (figure 4(b)), with a fast deterioration within the first 2 months. Among the clusters, cluster 11 (basins with high intra-annual variability of the streamflow response and human impacts) shows the highest skill with the longest persistence, followed by cluster 1 (baseflow dominated with hydrographs dampened by large river channels and water bodies) and 10 (characterized by low runoff coefficients and annual streamflow). In clusters 4 and 7 (basins with high runoff coefficients and flashy streamflow response to precipitation) the predictability of high streamflow extremes shows a fast deterioration with the skill almost disappearing within the first lead month. It is also interesting to note that although the skill for low streamflow extremes shows high variability between the clusters, for high streamflow extremes this variability is much less and mainly observed in lead weeks 2–8.

The discrepancy between the forecast skill of low and high streamflow extremes (Δ BSS) strongly



highlights the different patterns among the clusters (figure 4(c)). This discrepancy starts with a wide range (Δ BSS between -2.8 and 1) and converges towards 0 following a unique cluster pace. Cluster 3 emerges with high positive Δ BSS values throughout the forecast horizon, indicating the superior predictability of low streamflow extremes to high streamflow extremes. The opposite is observed in cluster 11, where the high positive skill in high streamflow extremes generates large negative Δ BSS values that gradually approach 0 in lead week 20. Cluster 4 also shows a distinctive pattern with Δ BSS approaching 0 within the first lead month, due to the fast deterioration in both low and high streamflow predictability, as shown in figures 4(a) and (b), respectively. These discrepancies seem from a visual assessment to have a similar pattern for the other clusters; however, this remains a subjective conclusion and a further thorough investigation is needed.

4.3. Attributing predictability to hydrological processes

Following the identified links between skill and hydrological regimes, we next dig deeper and attribute the discrepancy of skills in low and high streamflow extremes to the hydrological processes. Applying the k-means clustering to the discrepancy (Δ BSS) profiles of each hydrological cluster results in six distinct supergroups, whose both Δ BSS profile and

hydrological processes are similar (figure 5). Some supergroups (i.e. (a), (b) and (c)) are merges of 2 or 3 clusters, while the other supergroups have uniquely identified a single cluster. In terms of dominant hydrological processes, we describe these supergroups as: (a) baseflow controlled consisting of clusters 1 and 8; (b) mixed baseflow and precipitation driven with high interannual variability consisting of clusters 2, 5 and 9; (c) precipitation driven consisting of clusters 4, 6 and 7; (d) snow driven which is uniquely defined by cluster 3; (e) basins in cluster 19 with low streamflow during the year and with low runoff coefficients; and (f) basins in cluster 11 with low runoff coefficients, yet with relatively high intra-annual variability and sharp hydrograph (fast response to precipitation and hydrograph recession). The predictability of low and high streamflow extremes including their discrepancies are also visualized separately for each supergroup in figure A2 in the appendix, where details of common characteristics within the supergroup can be observed.

Distinct Δ BSS profiles are revealed between baseflow controlled (group (a)) and precipitation driven river systems (group (c); figures 5(a) and (c)). The positive Δ BSS values suggest a general advantage in forecasting low streamflow extremes for the baseflow controlled river systems (group (a)). In the short lead times, Δ BSS of group (a) remains close to the median Δ BSS of the pan-European domain,

while an exceedance is observed from lead week 4 onwards, highlighting the skill persistence in low streamflow extremes in baseflow controlled systems. Precipitation responsive river systems (clusters 4, 6 and 7 in group (c)) show a relatively higher predictability of high streamflow extremes compared to the median Δ BSS pattern of the pan-European domain. The Δ BSS peak in group (c) occurs in lead week 2, which is one week earlier than Europe's median Δ BSS peak, indicating also a faster deterioration in the forecast skills. Basins in group (b) have varying characteristics in terms of baseflow controlled (cluster 9) or snow/precipitation driven (clusters 2 and 5), yet they all share a common regime of relatively large intra-annual variability in streamflow. These clusters have higher Δ BSS values than Europe's median up to lead week 12, indicating a higher forecast skill of low streamflow extremes up to the seasonal horizon (figure 5(b)).

Groups (d), (e) and (f) consist of a single hydrological cluster each, indicating distinguishable Δ BSS profiles in these clusters. Snow dominated river systems in cluster 3 are identified in group (d), with Δ BSS reflecting superiority in predicting low streamflow extremes over high streamflow extremes (figure 5(d)). This superiority is also observed over Europe's median Δ BSS up to lead week 20. Moreover, group (f) exhibits an almost opposite profile to group (d), where Δ BSS starts from negative values and gradually approaches Europe's median (figure 5(f)). River systems in group (f), characterized by low runoff coefficient and relatively high annual variability influenced by human impacts, have a higher predictability of high streamflow extremes compared to the other river systems. As for group (f), Δ BSS values in group (e) also start with negative values and below Europe's median, which is exceeded in lead week 4 (figure 5(e)). This result indicates a generally high predictability of high streamflow extremes, yet with relatively faster deterioration in those river systems with low streamflow and low runoff coefficients.

5. Discussion

5.1. Understanding the predictability of extremes across hydro-climatic gradients

It has been well demonstrated that knowledge of the initial hydrological conditions and the forecasted meteorological status are two key sources of predictability for seasonal hydrological forecasts, including extremes (Wood and Lettenmaier 2008, Arnal et al 2017). The evaluation in this study digs deeper in this direction, finding that the skill of hydrological forecast extremes, including their differences, can be regionalized based on knowledge of the hydrological regimes, therefore promoting additional physiographic drivers to diagnose their predictability.

Here, the hydrological regimes are based on a model simulation, thus the connection of predictability and the hydrological regime is subject to the model's representation of reality. Although large-scale (e.g. continental, global) hydrological modeling is subject to larger model uncertainty than catchment-scale modeling (Pechlivanidis and Arheimer 2015), the use of the continental model here provides indicative forecasts of streamflow extremes for all European river systems. E-HYPE's evaluation involved a multi-variable, multi-period, and multi-objective approach, covering an adequate number of European basins (Hundecha et al 2020). This ensures that E-HYPE is 'a good model for the right reasons', thereby facilitating scientific insights through model-based assessments.

With the acknowledgements above, our study reveals links between hydrological regimes and the skill of forecasted hydrological extremes, implying that basin-specific outcomes can be regionalized to other geographic locations. This finding is in accordance with conclusions from previous studies exploring key drivers of seasonal hydrological forecast skills (Crochemore et al 2020, Giron Lopez et al 2021, Pechlivanidis et al 2014, Brunner and Fischer 2022b, Musuuza et al 2023). Particularly for European drought forecasting, Sutanto and van Lanen (2022) highlighted the strong link between river memory and seasonal hydrological drought predictability. Our study extends previous investigations by simultaneously focusing on both types of hydrological extremes. In our results, seasonal streamflow forecasts of low extremes possess better predictability in river systems with long memory (i.e. snow or baseflow dominated and/or with long recessions), compared to high streamflow extremes. Meanwhile, in river systems of relatively short memory, for instance, basins that are highly rainfall driven or with low runoff coefficient yet with high intra-annual variability, the forecast skill of high streamflow extremes outperforms the ones of low extremes. Consequently, these results can be regionalized to other regions with similar climatological and hydrological characteristics.

5.2. Practical implications

Climate change is expected to increase the severity and frequency of hydrological hazards (i.e. floods and droughts) in multiple regions across Europe and the globe (Krysanova et al 2017, Pechlivanidis et al 2017, Zhao et al 2023), which raises the concern of having multiple hazards striking a community simultaneously (IPCC 2021). Beyond the severe consequences of individual hazards (Schumacher et al 2022, Mondal et al 2023), the potential for compound and cascading effects further extends their impacts in space and time. To assist societal adaptation aiming to mitigate the effects, flood and drought early warning and

hydro-climatic services are needed to provide accurate information on the impacts of water-related hazards (Merz *et al* 2020, Göber *et al* 2023), and our study contributes towards the evolution of these services.

On the one hand, improvements in accurately forecasting high-risk extreme events is critical for disaster risk reduction, which can be achieved through the application of new methods (e.g. machine learning, hybrid approaches, data assimilation) on the basis of better understanding the predictability (Troin *et al* 2021, van der Wiel *et al* 2021, Gordon *et al* 2022, Papacharalampous *et al* 2022, Torelló-Sentelles and Franzke 2022, Hauswirth *et al* 2023). Our study presents insights into the limitations of predictability for both floods and droughts and their discrepancies, including their spatial patterns and temporal deterioration. This provides an essential perspective in the context of potential compound/cascading scenarios (van den Hurk *et al* 2023), which can be further improved through post-processing.

On the other hand, the transferability of knowledge and seasonal forecasting techniques for identifying solutions across local studies is crucial to maximize the global efficacy (Jackson-Blake *et al* 2022, Dasgupta *et al* 2023, Göber *et al* 2023). Our study highlights the significance of attributing predictability to local hydrological characteristics and enables the knowledge to be regionalized and transferred to other (ungauged) geographical locations. This provides a scientific basis for implementing knowledge and services from pilot studies to a wider use case, particularly in vulnerable areas with limited resources, hence aiding effective risk reduction actions in those areas.

6. Conclusions

Herein, we investigate the seasonal forecast skill of streamflow extremes over the pan-European domain, and further attribute the discrepancy in their predictability to the local hydrological signatures. An evaluation of the seasonal predictability of both high and low streamflow extremes is conducted over about 35 400 European basins, which lie along a strong gradient in terms of climatology, scale, physiography, and hydrological regime. A link is established between the forecast skill of hydrological extremes and hydrological regimes, which leads towards attributing predictability to dominant physical processes. The insights bring hydrological science towards the potential to regionalize the predictability of extremes, which is of high added value to disaster risk reduction and hydro-climate services.

The main conclusions from this study are as follows:

- The seasonal forecast skill of streamflow extremes varies geographically and deteriorates with

increased lead time. High forecast skill is shown in northern Europe in the short lead weeks in terms of low streamflow extremes, and in eastern and southern Europe in terms of high streamflow extremes. After approximately 12 weeks, the seasonal forecasts of high streamflow extremes provide, in general, no added value with respect to streamflow climatology, while forecasts of low streamflow extremes maintain skill up to 20 weeks ahead.

- Comparing the predictability in high and low streamflow extremes, the skill persistence for low streamflow extremes is longer than the high streamflow extremes. In northern Europe the predictability for low streamflow extremes is higher than for high streamflow extremes. Opposite behavior is observed in eastern and southern parts of the continent, where the predictability of high streamflow extremes exceeds the one of low streamflow extremes up to lead week 12.
- A decomposition of the streamflow extreme predictability for the hydrological clusters allowed identification of distinct patterns in terms of skill and its persistence. Analysis of the skill discrepancy between low and high streamflow extremes results in 6 supergroups over Europe that share common characteristics of hydrological processes and predictability of streamflow extremes. Overall, dominant processes, i.e. baseflow, dampening, interannual variability, snow and runoff coefficient, could explain the supergroups across Europe.
- The seasonal predictability of streamflow extremes is attributed to the local hydrological processes with distinguishable patterns for different hydrological regimes. The forecast skill for low streamflow extremes is higher than for high streamflow extremes in river systems with generally long memory (i.e. snow-related processes, dampening from lakes or large channels, and long recessions). In systems with low runoff coefficient and relatively high annual variability influenced by human impacts (i.e. irrigation), the predictability of high streamflow extremes is higher than of low streamflow extremes.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgments

This study was funded by the EU Horizon 2020 project I-CISK (Innovating climate services through integrating scientific and local knowledge) under Grant Agreement 101037293, and by the EU Horizon

2020 project CLINT (Climate Intelligence: Extreme events detection, attribution and adaptation design using machine learning) under Grant Agreement 101003876. Funding was also received from the project ‘The role of hydropower as a regulating resource in a renewable energy system with climate impact and increased internationalization of electricity markets’ granted by the Swedish Energy Agency (Grant No. 52095-1).

Conflict of interest

The authors of this work declare no conflict of interest. Our funders had no role in the choice of research project; design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Author contributions

Y D contributed to the basic idea, study design, code development, model runs, result analysis and figures, interpretation of results, and writing of the manuscript. I C contributed to the interpretation of results, and writing of the manuscript. I G P was responsible for the project management and funding acquisition and contributed to the basic idea, study design, result analysis and figures, interpretation of results, and writing of the manuscript.

Appendix

Here, we present a detailed description of the EHYPE model and bias-adjustment method, which are referenced in sections 2.1 and 2.2, and two additional figures, which are referenced in sections 4.1

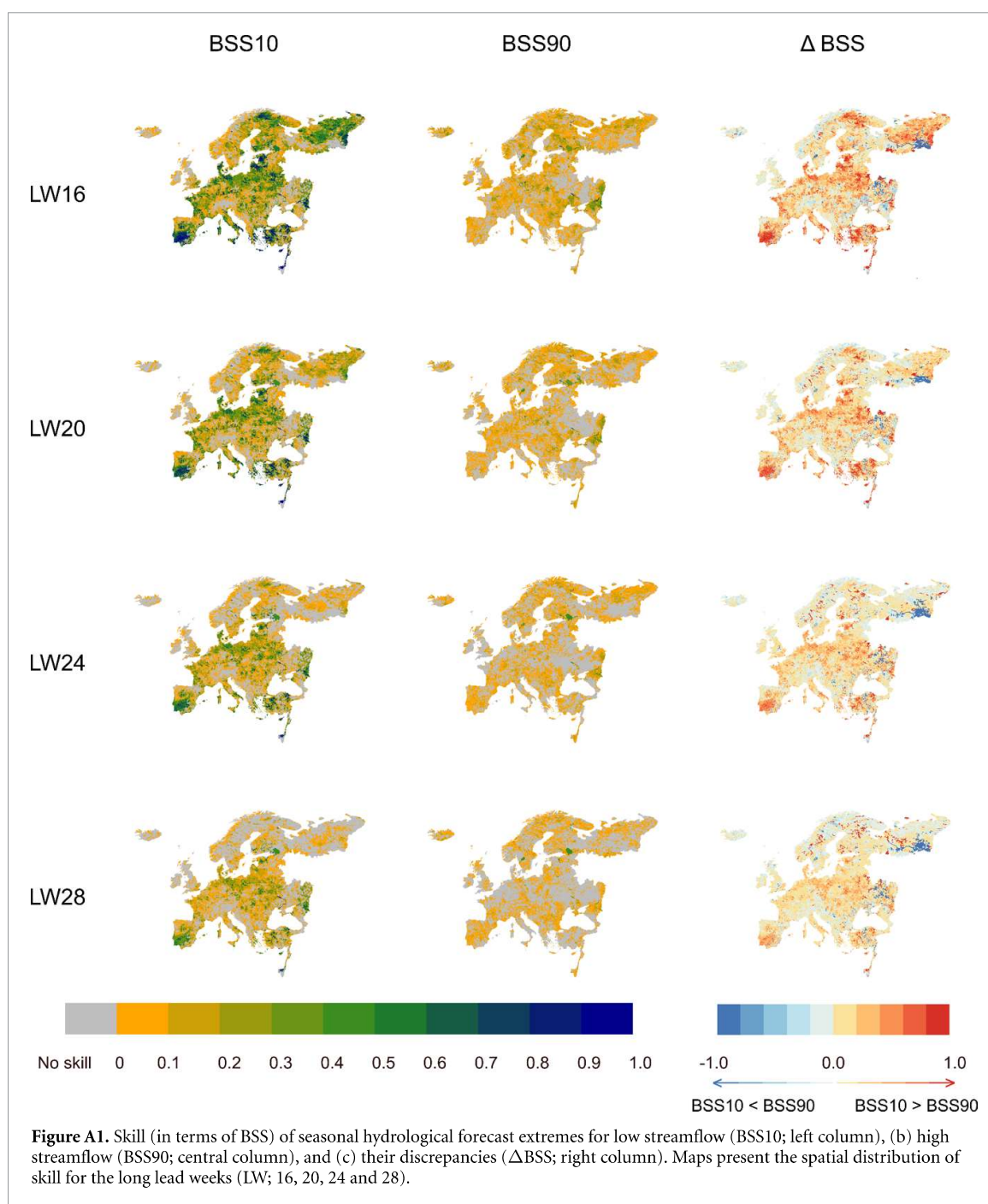
and 4.3. The figures are introduced to provide detailed information of the predictability of streamflow extremes in long lead time and at individual hydrological clusters, which complement our conclusions.

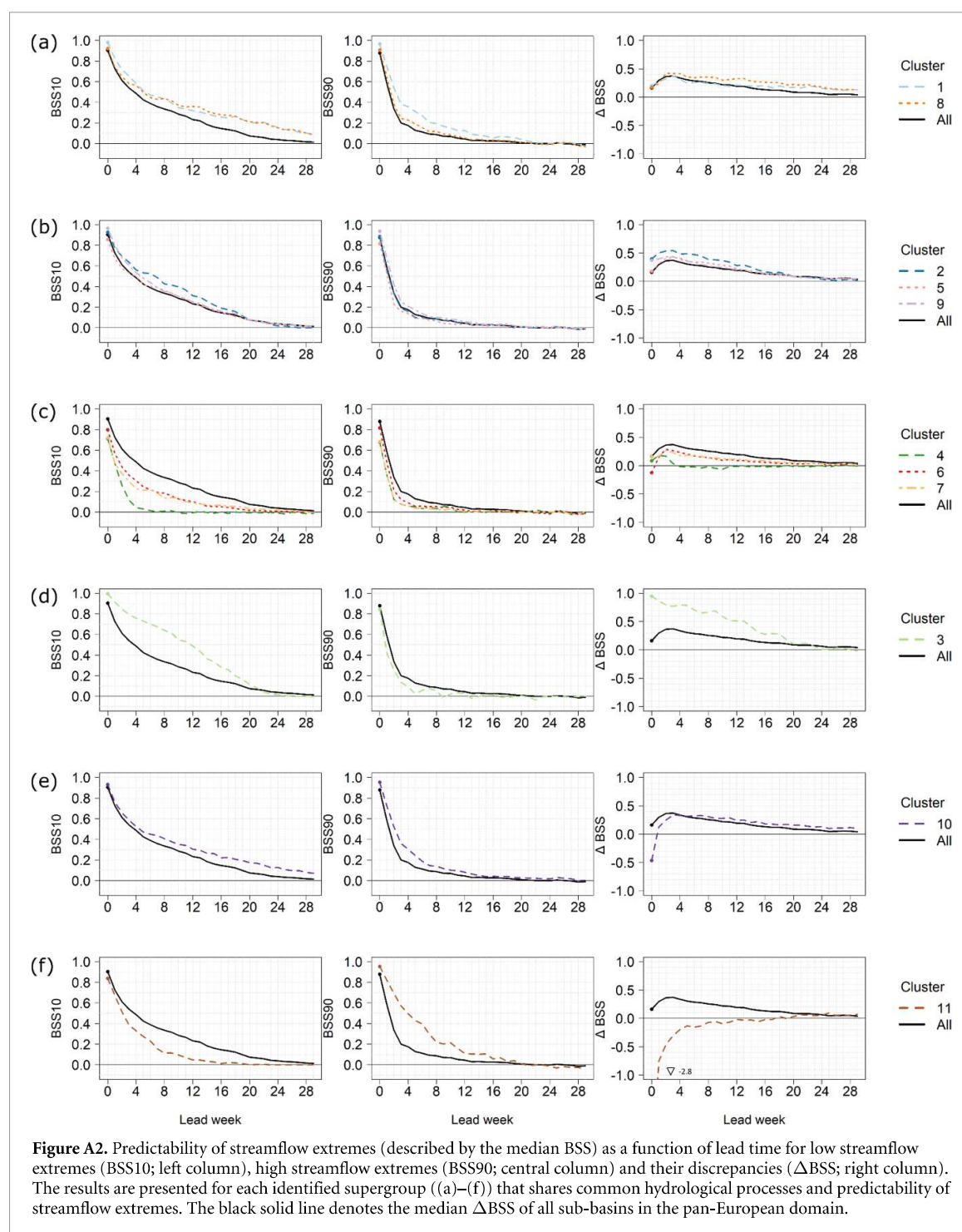
E-HYPE hydrological model description

E-HYPE is a semi-distributed process-based hydrological model of water quantity and quality based on the HYPE (The HYdrological Predictions for the Environment) model structure. The pan-European setup simulates components of the water cycle at daily time steps, i.e. snow accumulation and melting, evapotranspiration, soil moisture, streamflow generation, groundwater recharge, and routing through rivers and lakes. The historical model performance in terms of streamflow reaches a median Nash-Sutcliffe Efficiency of 0.53 over more than 500 streamflow stations across Europe. Details about the model performance and its relation to physiographic-climatic characteristics can be found in Hundecha *et al* (2016).

Bias-adjustment description

The bias-adjustment was performed using a modified version of the distribution based scaling (DBS) method to account for drifting (Yang *et al* 2010). The DBS performs bias-adjustment by fitting a distribution (gamma for precipitation and normal for temperature) to the reference (HydroGFD) and the model (ECMWF SEAS5) data, and maps the model distribution to the reference. After bias-adjustment, the cumulative distribution of the meteorological forecasts closely follows the one of the HydroGFD data.





ORCID iDs

Yiheng Du <https://orcid.org/0000-0002-5176-8111>

Ilaria Clemenzi <https://orcid.org/0000-0001-7140-6647>

Ilias G Pechlivanidis <https://orcid.org/0000-0002-3416-317X>

References

- Arnal L, Cloke H L, Stephens E, Wetterhall F, Prudhomme C, Neumann J, Krzeminski B and Pappenberger F 2018 Skilful seasonal forecasts of streamflow over Europe? *Hydrol. Earth Syst. Sci.* **22** 2057–72
- Arnal L, Wood A W, Stephens E, Cloke H L and Pappenberger F 2017 An efficient approach for estimating streamflow forecast skill elasticity *J. Hydrometeorol.* **18** 1715–29
- Beer M, Au S-K and Hall J W 2014 Vulnerability, uncertainty, and risk: quantification, mitigation, and management *Proc. of the 2nd Int. Conf. on Vulnerability and Risk Analysis and Management (ICVRAM) and the 6th Int. Symp. on Uncertainty Modeling and Analysis (ISUMA)* (Liverpool, United Kingdom, 13–16 July 2014) pp 253–62
- Berg P, Donnelly C and Gustafsson D 2018 Near-real-time adjusted reanalysis forcing data for hydrology *Hydrol. Earth Syst. Sci.* **22** 989–1000
- Brier G W 1950 Verification of forecasts expressed in terms of probability *Mon. Weather Rev.* **78** 1–3

- Brunner M I and Fischer S 2022 Snow-influenced floods are more strongly connected in space than purely rainfall-driven floods *Environ. Res. Lett.* **17** 104038
- Brunner M I and Slater L J 2022 Extreme floods in Europe: going beyond observations using reforecast ensemble pooling *Hydrol. Earth Syst. Sci.* **26** 469–82
- Bruno Soares M and Dessai S 2015 Exploring the use of seasonal climate forecasts in Europe through expert elicitation *Clim. Risk Manage.* **10** 8–16
- Cammalleri C, Naumann G, Mentaschi L, Bisselink B, Gelati E, de Roo A and Feyen L 2020 Diverging hydrological drought traits over Europe with global warming *Hydrol. Earth Syst. Sci.* **24** 5919–35
- Cantone C, Ivars Grape H, El Habash S and Pechlivanidis I G 2023 A co-generation success story: improving drinking water management through hydro-climate services *Clim. Serv.* **31** 100399
- CDS 2023 Copernicus Climate Data Store (available at: <https://cds.climate.copernicus.eu/>) (Accessed 6 September 2023)
- Crochemore L, Cantone C, Pechlivanidis I G and Photiadou C 2021 How does seasonal forecast performance influence decision-making? Insights from a serious game *Bull. Am. Meteorol. Soc.* **102** E1682–99
- Crochemore L, Ramos M-H and Pechlivanidis I G 2020 Can continental models convey useful seasonal hydrologic information at the catchment scale? *Water Resour. Res.* **56** e2019WR025700
- Dasgupta A et al 2023 Connecting hydrological modelling and forecasting from global to local scales: perspectives from an international joint virtual workshop *J. Flood Risk Manage.* **e12880**
- De Perez E C, Stephens E, Bischiniotis K, van Aalst M, van den Hurk B, Mason S, Nissan H and Pappenberger F 2017 Should seasonal rainfall forecasts be used for flood preparedness? *Hydrol. Earth Syst. Sci.* **21** 4517–24
- Girons Lopez M, Crochemore L and Pechlivanidis I G 2021 Benchmarking an operational hydrological model for providing seasonal forecasts in Sweden *Hydrol. Earth Syst. Sci.* **25** 1189–209
- Göber M et al 2023 Enhancing the value of weather and climate services in society—identified gaps and needs as outcomes of the 1st WMO WWRP/SERA “Weather and Society” Conference *Bull. Am. Meteorol. Soc.* **104** E645–51
- Gordon B L, Brooks P D, Krogh S A, Boisrime G F S, Carroll R W H, McNamara J P and Harpold A A 2022 Why does snowmelt-driven streamflow response to warming vary? A data-driven review and predictive framework *Environ. Res. Lett.* **17** 053004
- Greuell W, Franssen W H P, Biemans H and Hutjes R W A 2018 Seasonal streamflow forecasts for Europe—part I: hindcast verification with pseudo- and real observations *Hydrol. Earth Syst. Sci.* **22** 3453–72
- Greuell W, Franssen W H P and Hutjes R W A 2019 Seasonal streamflow forecasts for Europe—part 2: sources of skill *Hydrol. Earth Syst. Sci.* **23** 371–91
- Gudmundsson L, Leonard M, Do H X, Westra S and Seneviratne S I 2019 Observed trends in global indicators of mean and extreme streamflow *Geophys. Res. Lett.* **46** 756–66
- Harrigan S, Prudhomme C, Parry S, Smith K and Tanguy M 2018 Benchmarking ensemble streamflow prediction skill in the UK *Hydrol. Earth Syst. Sci.* **22** 2023–39
- Hauswirth S M, Bierkens M F P, Beijl V and Wanders N 2023 The suitability of a seasonal ensemble hybrid framework including data-driven approaches for hydrological forecasting *Hydrol. Earth Syst. Sci.* **27** 501–17
- Hewitt C D et al 2020 Making society climate resilient: international progress under the global framework for climate services *Bull. Am. Meteorol. Soc.* **101** 227–32
- Hundecha Y, Arheimer B, Berg P, Capell R, Musuza J, Pechlivanidis I and Photiadou C 2020 Effect of model calibration strategy on climate projections of hydrological indicators at a continental scale *Clim. Change* **163** 1287–1306
- Hundecha Y, Arheimer B, Donnelly C and Pechlivanidis I 2016 A regional parameter estimation scheme for a pan-European multi-basin model *J. Hydrol. Reg. Stud.* **6** 90–111
- IPCC 2021 Climate change 2021: the physical science basis *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* ed V Masson-Delmotte et al (Cambridge University Press) (<https://doi.org/10.1017/9781009157896>)
- Jackson-Blake L A et al 2022 Opportunities for seasonal forecasting to support water management outside the tropics *Hydrol. Earth Syst. Sci.* **26** 1389–406
- Jin X and Han J 2010 K-means clustering *Encyclopedia of Machine Learning* ed C Sammut and G I Webb (Springer) pp 563–4
- Johnson S J et al 2019 SEAS5: the new ECMWF seasonal forecast system *Geosci. Model Dev.* **12** 1087–117
- Kompor W, Yoshikawa S and Kanae S 2020 Use of seasonal streamflow forecasts for flood mitigation with adaptive reservoir operation: a case study of the Chao Phraya river basin, Thailand, in 2011 *Water* **12** 1–19
- Krysanova V et al 2017 Intercomparison of regional-scale hydrological models and climate change impacts projected for 12 large river basins worldwide—a synthesis *Environ. Res. Lett.* **12** 105002
- Kumar R, Samaniego L and Attinger S 2013 Implications of distributed hydrologic model parameterization on water fluxes at multiple scales and locations *Water Resour. Res.* **49** 360–79
- Madrigal J, Solera A, Suárez-Almiñana S, Paredes-Arquiola J, Andreu J and Sánchez-Quispe S T 2018 Skill assessment of a seasonal forecast model to predict drought events for water resource systems *J. Hydrol.* **564** 574–87
- Merz B et al 2020 Impact forecasting to support emergency management of natural hazards *Rev. Geophys.* **58** e2020RG000704
- Mondal S, Mishra A K, Leung R and Cook B 2023 Global droughts connected by linkages between drought hubs *Nat. Commun.* **14** 144
- Musuza J, Crochemore L and Pechlivanidis I G 2023 Evaluation of earth observations and in situ data assimilation for seasonal hydrological forecasting *Water Resour. Res.* **59** e2022WR033655
- Papacharalampous G, Tyralis H, Pechlivanidis I G, Grimaldi S and Volpi E 2022 Massive feature extraction for explaining and foretelling hydroclimatic time series forecastability at the global scale *Geosci. Front.* **13** 101349
- Patterson M, Weisheimer A, Befort D J and O'Reilly C H 2022 The strong role of external forcing in seasonal forecasts of European summer temperature *Environ. Res. Lett.* **17** 104033
- Pechlivanidis I G and Arheimer B 2015 Large-scale hydrological modelling by using modified PUB recommendations: the India-HYPE case *Hydrol. Earth Syst. Sci.* **19** 4559–79
- Pechlivanidis I G, Arheimer B, Donnelly C, Hundecha Y, Huang S, Aich V, Samaniego L, Eisner S and Shi P 2017 Analysis of hydrological extremes at different hydro-climatic regimes under present and future conditions *Clim. Change* **141** 467–81
- Pechlivanidis I G, Bosshard T, Spångmyr H, Lindström G, Gustafsson D and Arheimer B 2014 Uncertainty in the Swedish operational hydrological forecasting systems *Vulnerability, Uncertainty, and Risk* pp 253–62
- Rakovec O, Samaniego L, Hari V, Markonis Y, Moravec V, Thober S, Hanel M and Kumar R 2022 The 2018–2020 multi-year drought sets a new benchmark in Europe *Earth's Future* **10** e2021EF002394
- Schumacher D L, Keune J, Dirmeyer P and Miralles D G 2022 Drought self-propagation in drylands due to land-atmosphere feedbacks *Nat. Geosci.* **15** 262–8
- Siqueira V A, Fan F M, de Paiva R C D, Ramos M H and Collischonn W 2020 Potential skill of continental-scale, medium-range ensemble streamflow forecasts for flood prediction in South America *J. Hydrol.* **590** 125430

- SMHI 2022 Model water - download the code and learn how to use hype, HypeWeb (available at: <https://hypeweb.smhi.se/model-water/>) (Accessed 6 September 2023)
- SMHI 2023 Seasonal forecasts Europe, HypeWeb (available at: <https://hypeweb.smhi.se/explore-water/forecasts/seasonal-forecasts-europe/>) (Accessed 6 September 2023)
- Sutanto S J and van Lanen H A J 2022 Catchment memory explains hydrological drought forecast performance *Sci. Rep.* **12** 2689
- Sutanto S J, Wetterhall F and van Lanen H A J 2020 Hydrological drought forecasts outperform meteorological drought forecasts *Environ. Res. Lett.* **15** 084010
- Torelló-Sentelles H and Franzke C L E 2022 Drought impact links to meteorological drought indicators and predictability in Spain *Hydrol. Earth Syst. Sci.* **26** 1821–44
- Troin M, Arsenault R, Wood A W, Brissette F and Martel J-L 2021 Generating ensemble streamflow forecasts: a review of methods and approaches over the past 40 years *Water Resour. Res.* **57** e2020WR028392
- van den Hurk B J J M et al 2016 Improving predictions and management of hydrological extremes through climate services *Clim. Serv.* **1** 6–11
- van den Hurk B J J M, White C J, Ramos A M, Ward P J, Martius O, Olbert I, Roscoe K, Goulart H M D and Zscheischler J 2023 Consideration of compound drivers and impacts in the disaster risk reduction cycle *IScience* **26** 106030
- van der Wiel K, Lenderink G and de Vries H 2021 Physical storylines of future European drought events like 2018 based on ensemble climate modelling *Weather Clim. Extremes* **33** 100350
- Wanders N and Wood E F 2016 Improved sub-seasonal meteorological forecast skill using weighted multi-model ensemble simulations *Environ. Res. Lett.* **11** 094007
- White C J et al 2022 Advances in the application and utility of subseasonal-to-seasonal predictions *Bull. Am. Meteorol. Soc.* **103** E1448–72
- Wood A W, Hopson T, Newman A, Brekke L, Arnold J and Clark M 2016 Quantifying streamflow forecast skill elasticity to initial condition and climate prediction skill *J. Hydrometeorol.* **17** 651–68
- Wood A W and Lettenmaier D P 2008 An ensemble approach for attribution of hydrologic prediction uncertainty *Geophys. Res. Lett.* **35** L14401
- Yang W, Andréasson J, Graham P L, Olsson J, Rosberg J and Wetterhall F 2010 Distribution-based scaling to improve usability of regional climate model projections for hydrological climate change impacts studies *Hydrol. Res.* **41** 211–29
- Yossef N C, Winsemius H, Weerts A, van Beek R and Bierkens M F P 2013 Skill of a global seasonal streamflow forecasting system, relative roles of initial conditions and meteorological forcing *Water Resour. Res.* **49** 4687–99
- Yuan X, Roundy J K, Wood E F and Sheffield J 2015 Seasonal forecasting of global hydrologic extremes: system development and evaluation over GEWEX basins *Bull. Am. Meteorol. Soc.* **96** 1895–912
- Zhao X, Huang G, Li Y and Lu C 2023 Responses of hydroelectricity generation to streamflow drought under climate change *Renew. Sustain. Energy Rev.* **174** 113141