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Skill-informed seamless communication of European S2S
hydrological forecastsIlias G Pechlivanidis^{1,*}  and Louise Crochemore²¹ Swedish Meteorological and Hydrological Institute, 601 76 Norrköping, Sweden² University Grenoble Alpes, CNRS, INRAE, IRD, Grenoble INP (Institute of Engineering and Management University Grenoble Alpes), IGE, 38000 Grenoble, France

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E-mail: ilias.pechlivanidis@smhi.se**Keywords:** S2S forecasts, seamless communication, hydro-climate services, forecast evaluation, European river systems

Abstract

Sub-seasonal to seasonal (S2S) information holds significant socio-economic value for decision-makers relying on climate variability. While significant advancements have been made in S2S meteorological forecasting, skill variability among prediction systems persists due to differences in physical process representation and technical characteristics of the predictive systems. Traditionally, sub-seasonal systems are considered more informative than seasonal systems within their time horizons, leading to seamless communication approaches that combine systems at fixed horizons, overlooking tailored solutions to optimize forecast skill. This study investigates S2S streamflow forecasting skill across Europe's diverse hydrological regimes, identifying optimal combination horizons for skill-informed seamless communication. Using bias-adjusted forecasts from ECMWF's sub-seasonal (ENS-ER) and seasonal (SEAS5) systems, we evaluate streamflow forecasts to uncover spatiotemporal complementarities between the two systems. The results reveal that most European basins benefit from sub-seasonal forecasts up to 3–6 weeks ahead, while steep, snow-dominated mountain ranges, high-precipitation basins, and elevated Mediterranean areas exhibit shorter horizons of 2–4 weeks. Gains in meteorological forecast skill at short lead times (1–3 weeks) are amplified when translated into hydrological processes, extending predictability up to 6 weeks. ENS-ER-based forecasts demonstrate greater spatial homogeneity in skill during shorter lead times, while SEAS5-based forecasts excel at extended horizons. These findings highlight the potential for tailored seamless products to enhance S2S forecast utility. By integrating complementary S2S prediction systems with this diagnostic, region-dependent strategy tailored to diverse hydrological regimes, hydro-climate services can seamlessly deliver accurate, actionable, and operationally relevant information to water- and climate-dependent sectors.

1. Introduction

Hydro-climate services are now providing observations, predictions and projections to practitioners and decision-makers operating at the national, continental and/or global scales. Within these services, sub-seasonal to seasonal (S2S) forecasts have received particular interest and shown potential for user groups that are affected by variations in the climate and hydrological fluxes and that could manage such variations to their advantage through better predictions (Bruno Soares *et al* 2018, Vitart and Robertson 2018). Sectors sensitive to meteorological and climate variations, and more particularly at S2S

time scales, include the water management, energy, tourism, insurance, transport, health and agriculture sectors. Due to insufficient meteorological skill over some areas of the globe for dynamic forecasts provided by different prediction systems, such forecasts have traditionally been based on historical climatology (Harrigan *et al* 2018, Girons Lopez *et al* 2021). In particular, there has been relatively little uptake of S2S forecasts by users for decision making in Europe compared to Africa, the USA and Australia, probably due to the limited and, in many regions, still insufficient skill of precipitation forecasts over the domain (Hansen *et al* 2011, Bruno Soares and Dessai 2016, Ceglar and Toreti 2021, Kondal *et al* 2024).

However, recent advances in our understanding and forecasting of meteorology and climate have resulted in skillful and useful meteorological predictions, and further in the development of operational services capable of making the S2S information available to users and of addressing their needs (Wood and Lettenmaier 2006, van den Hurk *et al* 2016, Cantone *et al* 2023).

Seamless integration of S2S forecasts has become an important focus within hydro-climate services, driven by the need to provide users with continuous predictions across different time horizons (Hewitt *et al* 2017, Crochemore *et al* 2021, White *et al* 2022). Traditionally, the merging of sub-seasonal and seasonal forecasts has been achieved through overlapping time horizons, where the short-range sub-seasonal system is used for the initial weeks (up to 6 weeks ahead), and the long-range seasonal system takes over for subsequent periods (Wetterhall and Di Giuseppe 2018, Soret *et al* 2019, Paxian *et al* 2023). This approach often overlooks potential differences in skill between the systems. Recognizing and addressing these differences is crucial to developing tailored, science-informed seamless forecasts that optimize forecast performance based on regional and temporal variability. By doing so, hydro-climate services can better serve user needs, particularly in regions where skill differences between systems may have significant socio-economic implications (Giuliani *et al* 2020, Crochemore *et al* 2024).

The variability in S2S forecasting skill arises from intrinsic properties of the prediction systems, including differences in physical process representation, initialization frequency, spatial resolution, and ensemble size (Vitart *et al* 2017, Fröhlich *et al* 2021, Vitart and Takaya 2021). These factors lead to notable spatiotemporal differences in forecast performance across prediction systems, regions and time horizons (Arnal *et al* 2018, Greuell *et al* 2018, Crochemore *et al* 2020). For instance, sub-seasonal systems often demonstrate higher skill in predicting shorter-term atmospheric phenomena, while seasonal systems excel in capturing large-scale climate drivers such as ENSO or long-term trends (Beckers *et al* 2016, Dalelane *et al* 2020). However, these strengths are not uniform and depend heavily on the hydro-climate characteristics of the target region (Pechlivanidis *et al* 2020, Sutanto and Van Lanen 2022, Du *et al* 2023, Girons Lopez *et al* 2025). This variability underscores the need for an evidence-based approach to seamlessly combine the systems, moving beyond traditional blending techniques. Consequently, there is a need for introducing a diagnostic framework that leverages performance criteria to optimize the combination of sub-seasonal and seasonal forecasts, offering a more adaptive solution to meet user needs.

Here, we investigate the hydrological forecasting skill from a sub-seasonal and a seasonal prediction system (the sub-seasonal forecasts ENS-ER and the

seasonal forecast SEAS5 from the European Centre for Medium-Range Weather Forecasts, ECMWF) across Europe, a region where forecast performance varies significantly due to contrast climate and topographic conditions. We identify optimal combination horizons (OCHs) for these systems defined as the horizon when a switch from S2S forecasts yields the highest skill throughout the upcoming season. Based on these, we propose a skill-informed adaptive approach to seamlessly communicate S2S streamflow forecasts from the corresponding prediction systems. We gain innovative insights by posing the following questions that not only add scientific value but also guide development in seamless S2S hydro-climate services: (1) *What is the streamflow forecasting skill at S2S horizons?* (2) *When is the optimal combination time for skill-informed seamless communication of S2S streamflow forecasts?* and (3) *How does the optimal combination time vary across Europe's hydro-climatic gradient and why?* To address these questions, we: (a) assess the streamflow forecast skill (up to 6 and 10 weeks ahead for the ENS-ER and SEAS5 systems respectively) across Europe's diverse river systems, (b) analyze the OCHs for 35 408 European sub-basins to understand emerging spatial links between them, and (c) identify the hydrological regimes in which the OCHs experience similar ranges.

2. Methods

2.1. Meteorological historical data and S2S forecasts

The HydroGFD v2.0 (Hydrological Global Forcing Data version 2.0) is an observation corrected reanalysis dataset that provides historical meteorological information of precipitation and mean temperature at a 0.5° gridded resolution (Berg *et al* 2018). The meteorological (precipitation and temperature) re-forecasts (also called hindcasts) of the sub-seasonal and seasonal prediction systems from ECMWF, known as ENS-ER and SEAS5 respectively, were used. ENS-ER re-forecasts were available for the period 1999–2015 (hindcast), are issued twice a week (Monday and Thursday; though only the Monday initialisations were considered in this study) and extend up to 46 d ahead. During the hindcast period, each ENS-ER forecast ensemble comes with 11 members. The seasonal SEAS5 re-forecasts were available for the period 1993–2015, are initialized at the beginning of each month and extend 215 d ahead with 25 ensemble members (Johnson *et al* 2019).

Both the sub-seasonal and seasonal meteorological forecasts were bias-adjusted against the reference dataset (HydroGDF) at 0.5-degree resolution. The distribution based scaling (DBS) method was used to bias-adjust both ENS-ER and SEAS5 meteorological forecasts (Yang *et al* 2010). DBS is a quantile-mapping method and the adjustment is conducted on all members of the prediction systems using

HydroGFD as reference. After bias-adjustment, the cumulative distributions of daily precipitation and temperature values closely follow that of the reference dataset. For ENS-ER, a 3 week moving window was used in the adjustment and the estimated DBS parameters were applied in the middle week of the window (see figure A1 in the appendix). The biases prior and after the bias-adjustment of precipitation and temperature are presented in figure A2 in the appendix. For SEAS5, the bias-adjustment was applied for every month, with the results available in Pechlivanidis *et al* (2020).

2.2. Hydrological modeling and forecasting

The European setup of the Hydrological Predictions for the Environment model (E-HYPE v.3.1.3) hydrological model was used to simulate streamflow across the pan-European domain (approximately 8.8 million km²). E-HYPE is a semi-distributed, process-based model that operates at an average spatial resolution of 215 km², partitioning the region into 35 408 sub-basins (Hundecha *et al* 2016). The model achieved a median Nash-Sutcliffe Efficiency (Nash and Sutcliffe 1970) of 0.54 and 0.53 for independent calibration and verification streamflow stations, based on more than 500 stations across Europe. Additionally, the model exhibits a median volume error of −1.6% and 1.3% for calibration and verification stations, respectively. This performance confirms that E-HYPE is capable of producing reliable hydrological outputs over the European domain. Further details regarding the model setup and performance can be found in Hundecha *et al* (2020, 2016).

The hydrological states of the E-HYPE model (e.g. lake levels, soil water content, snowpack) are initialized prior to each forecast run by forcing the model with the HydroGFD reanalysis up to the forecast issue date (also known as pseudo-observations, which represents the ‘observations’ one aims to forecast; see Greuell *et al* 2018). Streamflow forecasts are then obtained for each forecast run based on the corresponding initial states and by forcing E-HYPE with the ECMWF ENS-ER and SEAS5 bias-adjusted precipitation and temperature re-forecasts. Following the forecast specifications, the hydrological runs based on ENS-ER forecasts are run only once a week with a 6-week lead time (46 d), while the hydrological runs based on the SEAS5 forecasts are initialized at the start of each month with a 7 month lead time (yet here we only focus up to 10 weeks lead time). Streamflow was forecasted in all 35 408 sub-basins to assess the forecast skill at S2S time scales. E-HYPE was run at a daily time scale and the generated sub-seasonal and seasonal forecasts were then aggregated to weekly means.

2.3. Evaluation of hydrological forecasts

S2S forecasts based on ENS-ER and SEAS5 are evaluated against a historical reference simulation (pseudo-observations) for each sub-basin,

initialization time and lead time. This reference was chosen to allow inter-comparison between sub-basins and to minimize the impact of the model’s structural and parametric limitations in representing reality. E-HYPE is run at a daily timescale, with the ENS-ER and SEAS5 forecasts evaluated on weekly averages (i.e., daily values averaged over seven days) for the period 1999–2015. Lead week 0 refers to the first week of the forecast, with subsequent weeks numbered accordingly.

Forecast performance is assessed using the continuous ranked probability score (CRPS; Hersbach, 2000), a probabilistic metric that accounts for biases, over- and under-confidence by penalizing deviations from the observed distribution. To ensure comparability between prediction systems with different ensemble sizes, we apply the fair version of CRPS (Ferro 2014, Siegert *et al* 2020), and for simplicity, we refer to the fair CRPS as CRPS throughout the manuscript. The CRPS ranges between 0 (optimum) and infinity. The CRPS performance of the two forecast systems is compared to the CRPS performance of a benchmark—here the simulated climatology. The benchmark is generated by sampling 17 years from the historical time series for the same target weeks as the forecast, excluding the year to forecast. To quantify the forecast systems’ skill relative to this benchmark, the continuous ranked probability skill score (CRPSS) is calculated by dividing the forecast system’s CRPS by the benchmark’s CRPS and comparing this ratio to 1. The CRPSS ranges from minus infinity to 1, where a value of 1 indicates a perfect forecast, 0 denotes equal performance between the forecast system and the benchmark, and negative values indicate that the forecast system performs worse than the benchmark.

2.4. Identifying OCHs

The concept of the OCH, as applied here, refers to the maximum lead time for which sub-seasonal ENS-ER forecasts demonstrate higher skill than seasonal SEAS5-based forecasts. In operational terms, this horizon represents the point up to which sub-seasonal forecasts provide added predictive value compared to seasonal forecasts, while beyond this horizon, seasonal forecasts become more skillful. The OCH marks the transition point in seamless S2S forecasts, where switching from the sub-seasonal to the seasonal system yields the most informative predictions by maximizing forecast skill across the lead weeks. However, since SEAS5 may underperform relative to simulated climatology in some regions or lead times, the OCH is only meaningful where SEAS5 retains skill over climatology; otherwise, climatology should be preferred in an operational setting. SEAS5’s monthly initialization implies that a new forecast is issued shortly after ENS-ER’s week 4 initialization within the month. However, to mimic how available forecasts at a given time would be used, the OCH

applied here does not account for these additional SEAS5 initializations and is thus permitted to range between 1 and 6 weeks ahead, corresponding to the maximum lead time of the ENS-ER system.

2.5. Identifying controlling hydrological regimes

The link between the OCHs and hydrological regimes is investigated using the hydrological clusters that were previously generated by Pechlivanidis *et al* (2020) 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 (see figure 3(a)). In summary, clusters 1, 8, and 9, covering Poland, Denmark, central Europe, Scandinavia, and Russia, are baseflow-dominated with long recessions and minimal precipitation response. Cluster 2 basins, located predominantly in France, Germany, Sweden, southern Finland, and Russia, show frequent peak flows due to regular precipitation despite long recessions. Cluster 3 basins in north-central and north-western Russia are snowmelt-driven, with lakes and wetlands dampening flows. Clusters 4 and 5, in elevated or cool continental regions, display high seasonality from snowmelt, with hydropower regulation affecting winter flows in cluster 4. Clusters 6 and 7 show varied precipitation responses across Europe. Cluster 6 basins have long recessions despite high precipitation sensitivity, while cluster 7 basins, in high-altitude Mediterranean areas, experience high flow variability and low evapotranspiration. Cluster 10 basins, typical of Mediterranean rivers, have low flows and runoff due to high evapotranspiration. Cluster 11 basins, in eastern Ukraine and south-eastern Russia, show low runoff and high variability, influenced by irrigation. More information about the hydrological similarity over Europe can be found in Pechlivanidis *et al* (2020).

3. Results

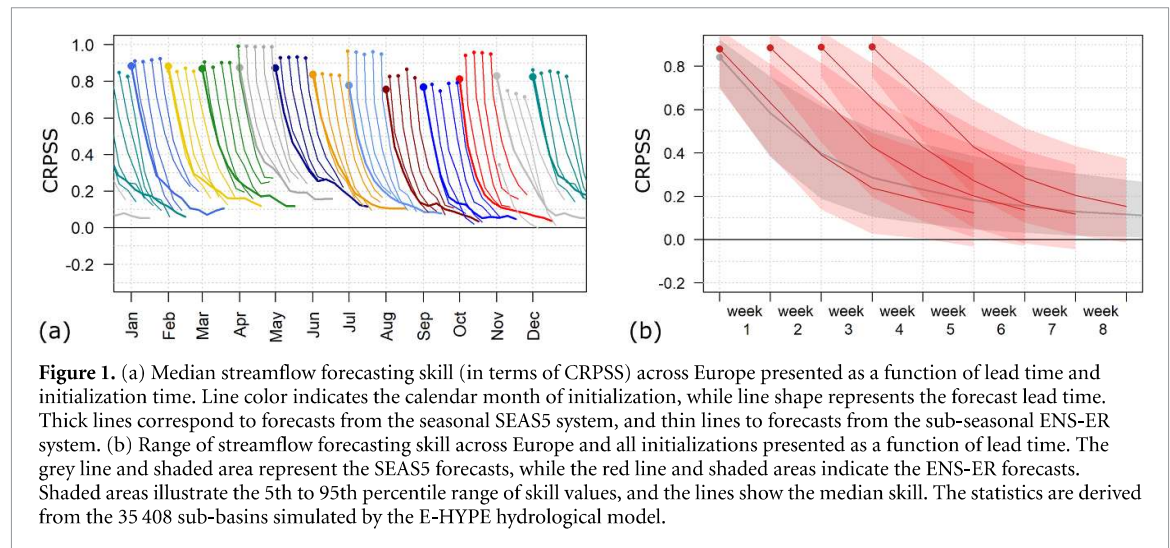
3.1. Initialization frequency strongly affects forecast skill

We firstly explore the temporal variability of the ENS-ER-based and SEAS5-based forecast skill, using simulated climatology as the benchmark, for the entire pan-European domain. Overall, results show that the S2S streamflow forecasts across all initialization times achieve high predictability in the first lead week (figure 1). Although there are no significant intra-annual variations in the overall skill magnitude for the SEAS5-based forecasts, the ENS-ER yields more skillful streamflow forecasts showing notable variations throughout the year (figure 1(a)). In particular, in certain months (April, May, July, August and October), streamflow forecasts based on the sub-seasonal ENS-ER system consistently

outperform those from the seasonal SEAS5 system, achieving higher skill across all lead weeks. This pattern aligns with previous findings showing that sub-seasonal systems often demonstrate enhanced skill during certain times of the year by capturing short-lived atmospheric processes (Vitart and Robertson 2018, Wetterhall and Di Giuseppe 2018). While differences in forecast skill can be linked to the predictive systems' specifications, particularly variations in process representation and initialization frequency, the results presented here primarily reflect the higher skill of ENS-ER compared to SEAS5 in forecasting precipitation (see figure A3 in the appendix). In other months, the skill of the two systems is more comparable, with no consistent advantage observed for either system.

The skill patterns within each month reveals more pronounced differences (figure 1(b)). The higher initialization frequency of the sub-seasonal ENS-ER system results in median CRPSS exceeding 0.8 as early as the second issue week of each month. The impact of initialization becomes more apparent later in the month, when sub-seasonal forecasts continue to provide updated conditions, whereas the seasonal SEAS5 system, initialized once at the beginning of the month, remains static. Consequently, the sub-seasonal system's more frequent updates enhance its ability to capture evolving hydrological conditions, particularly in rapidly changing river systems. However, in certain months, such as January, February and September, the seasonal SEAS5 system maintains skill for longer lead times compared to the sub-seasonal system (see figure 1(a)). This slower skill decay is likely linked to the underlying specification differences between the two systems. Although both SEAS5 and ENS-ER are based on ECMWF's Integrated Forecasting System and include atmosphere–ocean–land coupling, SEAS5 is designed specifically for long-range predictions, featuring a larger hindcast ensemble and a modeling strategy that emphasizes the representation of slow-evolving oceanic and atmospheric states and large-scale teleconnections (Johnson *et al* 2019). In contrast, ENS-ER is initialized more frequently and runs at higher resolution, optimizing it for shorter-term weather forecasts rather than for capturing low-frequency climate drivers. Similar persistence of skill at long lead times has also been observed in other seasonal prediction systems, such as those in the North American Multi-Model Ensemble (NMME), which maintain forecast skill due to their ability to represent large-scale, slowly evolving teleconnections (Balan-Sarajini *et al* 2024, Kirtman *et al* 2014).

To better understand the S2S streamflow forecast skill, we additionally explored the S2S skill of the meteorological variables, i.e. temperature and precipitation (figure A3 in the appendix). In particular, the ENS-ER and SEAS5 temperature forecasts remained



comparable across all initialization times; however, as with the other variables, ENS-ER's frequent initialization contributed to the high CRPSS values during the first lead week. As expected, precipitation forecasts exhibited lower skill than temperature forecasts, particularly during the summer months (June–August), while ENS-ER consistently outperformed SEAS5 at shorter lead times. It is interesting to note that, for both temperature and precipitation, the ENS-ER skill declined more rapidly with increasing lead time compared to SEAS5 skill. This fast degradation of ENS-ER skill is shown by the negative CRPSS values at longer lead times (from week 4 onwards), whereas SEAS5 forecasts remain equivalent to the climatological benchmark at longer lead times.

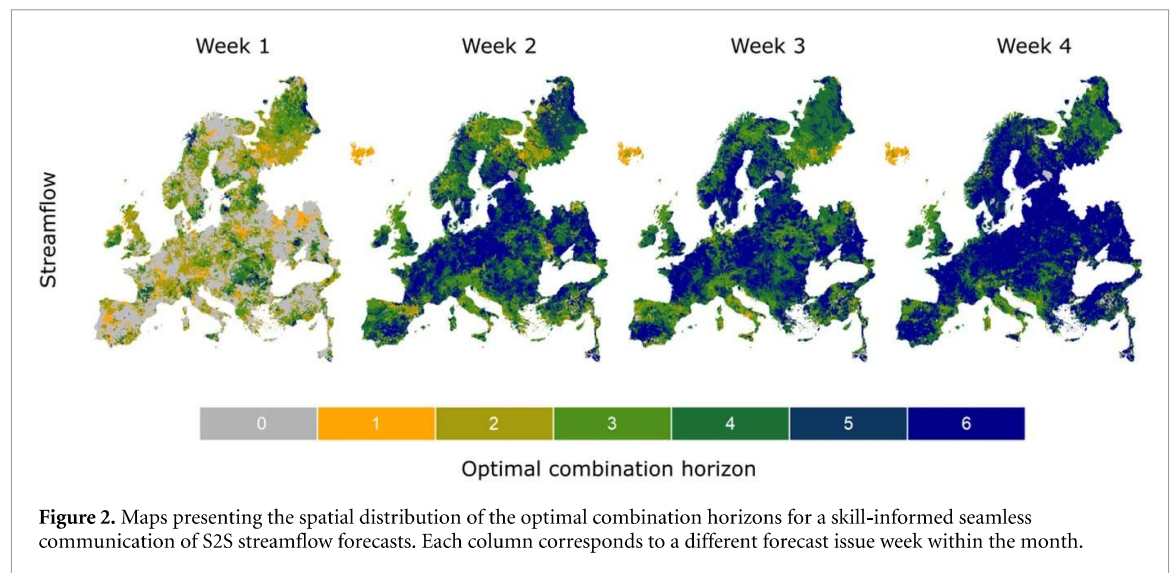
3.2. Optimal S2S combination horizon varies across Europe

We next explore the spatial variability of the OCH values across all 35 408 sub-basins. Note that since both systems retain positive skill at longer lead times (figure 1(a)), the OCH does not signify a loss of predictability but rather the lead time at which the seasonal forecast becomes more skillful than the sub-seasonal one. As expected, OCH results show that a skill-informed seamless communication of S2S streamflow forecasts depends on the forecast issue dates and location (figure 2). Overall, the OCH increases with the forecast issue week within the month across all locations. Particularly, in the first week of the month, ENS-ER-based streamflow forecasts already provide higher skill in comparison to the SEAS5-based forecasts, with most regions attaining OCH values between 1 and 3 weeks ahead. Some well-defined regions, for instance in France, Romania and the Saint Petersburg area, already benefit from sub-seasonal forecasts up to 6 weeks ahead, already from the first week of initialization. We note here that in the first week of initialization the streamflow forecasts from both S2S predictive systems have shown a very

high skill ($\text{CRPSS} > 0.7$), since predictability is driven by the initial hydrological conditions. Therefore, the regions shown to have an OCH of 0 week correspond to regions where ENS-ER-based and SEAS5-based streamflow forecasts perform similarly, with only marginal differences in skill; yet both demonstrating positive skill relative to the simulated climatology benchmark. Moving towards initializations at the end of the month (week 4), the OCH values show a spatial dominance of values ranging between 4 and 6 weeks depending on the geographical location. In particular, regions with long OCH values, indicating a persistent higher skill from sub-seasonal in comparison to seasonal streamflow forecasts, are identified for example in central Europe, along the western coast of the Black Sea and along the coasts of the Baltic Sea. In these regions, the OCH can extend up to 6 weeks as early as for the second issue week in the month.

Specific regions in Europe consistently exhibit shorter OCH ranging from 3 to 4 weeks, particularly between the second and fourth issue weeks. These regions, including the Alps, Norway, parts of Spain and Italy, the western part of the Balkans and north-western UK, receive relatively higher annual precipitation volumes compared to the rest of the domain. Interestingly, the observed OCH values for streamflow in these areas do not align with the OCH values observed for temperature and precipitation forecasts (see figure A4 in the appendix), suggesting that land processes and water storage dynamics (e.g. soil moisture variability, snowpack dynamics, lakes and reservoirs) play a significant role in modulating the meteorological signal and influencing streamflow forecasts.

When compared to streamflow, temperature and precipitation forecasts demonstrate shorter OCH, typically reaching up to 4 weeks. For ENS-ER precipitation forecasts, poor skill beyond 3 lead weeks results in OCH values mostly limited to 2 weeks, with only occasional extensions to 3 weeks depending



on the issue week. Temperature forecasts exhibit OCH values of approximately 3 weeks, although these are reduced by 1 week in regions such as the Mediterranean and eastern Europe. However, the identified OCH is only meaningful if SEAS5 demonstrates skill relative to simulated climatology at that lead time; otherwise, climatology should be used instead. These differences between the OCH values of meteorological variables (temperature and precipitation) and streamflow emphasize the non-linearity of the processes linking atmospheric and hydrological variables. Gains of up to 3 weeks in meteorological forecast skill can translate into gains of up to 6 weeks in streamflow forecasts. This extended skill horizon arises from the persistence of hydrological storages, and the cumulative impact of upstream precipitation on downstream streamflow responses (Crochemore *et al* 2020, Girons Lopez *et al* 2025).

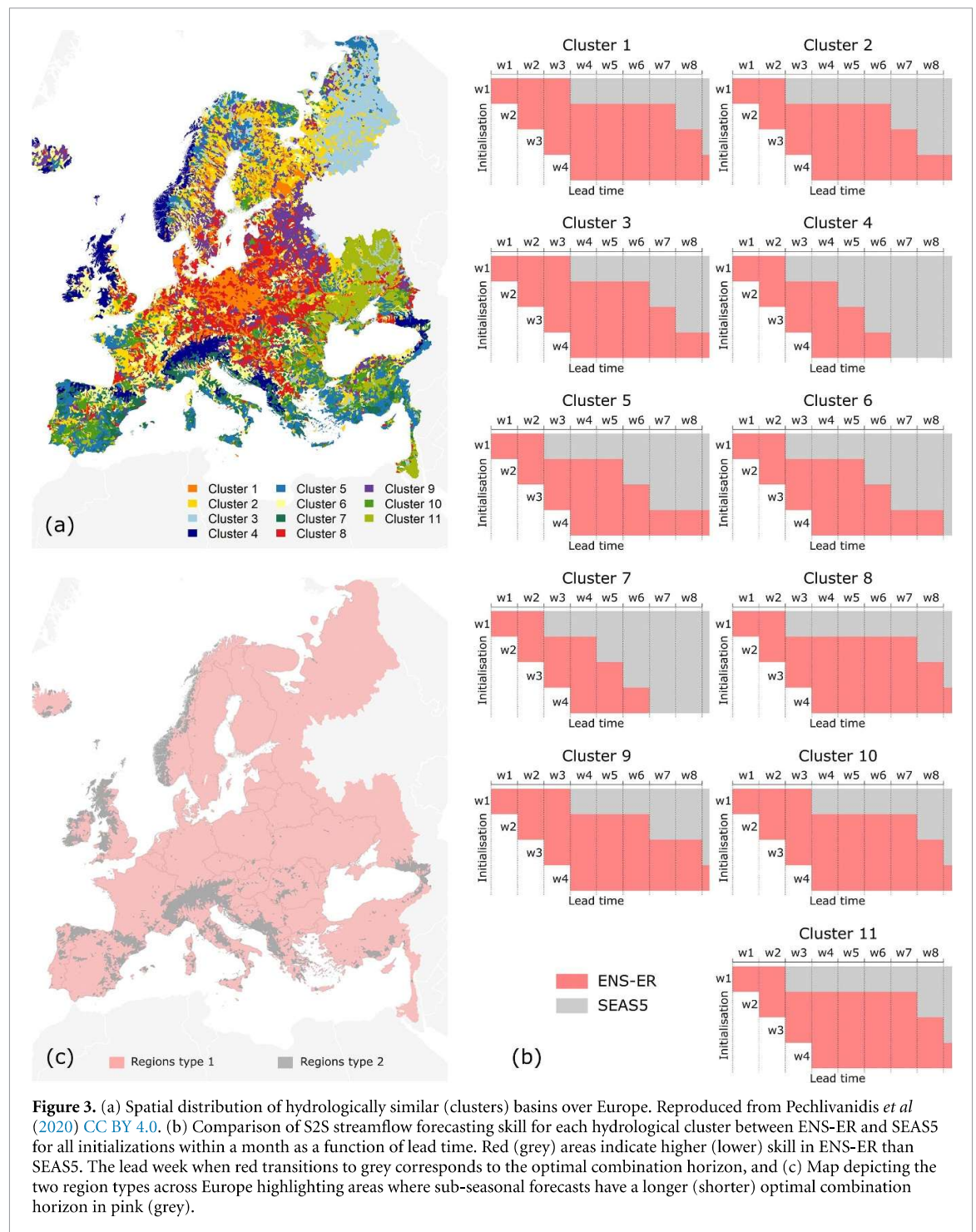
3.3. Hydrological regimes explain the optimal S2S combination horizon across Europe

Here we investigate the potential attribution of the OCH ranges to the hydrological regimes of the European river systems. Using the hydrological classification of the river systems established by Pechlivanidis *et al* (2020), we examine the S2S streamflow forecast skill for each hydrological cluster, comparing the performance of ENS-ER and SEAS5 forecasts across all initialization times within a month and as a function of lead time (figure 3). As concluded above, results reveal that ENS-ER-based streamflow forecasts generally exhibit higher skill during short lead weeks across all clusters and initialization times (figure 3(b)). However, the OCH varies among clusters, reflecting regional hydrological characteristics. These variations allow the identification of two primary types of regions across Europe, differentiated by their OCH patterns.

The first region, encompassing most European basins, benefits from sub-seasonal forecasts with

OCH values ranging from 3 to 6 weeks ahead (regions type 1 in figure 3(c)). These basins, which lie in all clusters at the exception of clusters 4 and 7, exhibit a variety of hydrological characteristics. For instance, basins in clusters 1 and 8 are baseflow-dominated, featuring long persistence in streamflow due to extensive water storage in water bodies. Other basins, such as those in cluster 6, respond rapidly to precipitation but exhibit long hydrograph recessions. Human influences, such as irrigation, are evident in basins within cluster 11, where low runoff coefficients and high intra-annual variability shape the streamflow regime. Snow-driven processes dominate cluster 3, where snowmelt contributes significantly to streamflow seasonality. In contrast, the second region, which includes mountainous and rain-driven basins receiving relatively high annual precipitation volumes, exhibits shorter OCH, typically ranging from 2 to 4 weeks (regions type 2 in figure 3(c)). These basins belong to clusters 4 and 7. High seasonality from snowmelt and/or precipitation characterizes cluster 4 basins, located in highly elevated snow dominated regions and regions receiving large amounts of precipitation. Additionally, hydropower regulation during winter alters their natural streamflow regimes. Cluster 7 basins, situated in warm and temperate Mediterranean climates but at high altitudes, experience highly variable streamflow. The response of the basins in these two clusters is highly sensitive to precipitation, driven by precipitation climatology, while evapotranspiration remains low.

These findings emphasize that hydrological regimes play a critical role in explaining OCH variability across Europe. The differences in hydrological processes from snowmelt and baseflow dominance to rapid precipitation responses highlight the need for region-specific considerations when optimizing a seamless communication of S2S forecasts. For example, basins with longer OCH benefit from the prolonged persistence of hydrological processes, such



as baseflow and snow accumulation, which extend the predictability window beyond atmospheric timescales. Conversely, shorter OCH in clusters 4 and 7 reflect the dominance of rapid hydrological responses and higher precipitation or precipitation and temperature sensitivity for snow accumulation and snowmelt; in cluster 4, mountainous regions with steep slopes exhibit a strong sensitivity to temperature, accelerating snowmelt, while precipitation significantly influences snow accumulation dynamics. This distinction underscores the importance of tailoring S2S forecasting strategies to the unique hydrological

characteristics of each region to maximize their utility for water resource management and decision-making.

4. Discussion—enhancing hydro-climate services through skill-informed seamless communication of S2S forecasts

Enhancing hydro-climate services through skill-informed seamless communication of S2S streamflow forecasts requires embedding a deeper understanding of forecast skill, hydrological regimes,

and region-specific requirements into operational frameworks. Leveraging the complementarity of S2S predictive systems (e.g. ENS-ER and SEAS5) is essential for enhancing their utility across diverse socio-economic contexts. Skill-informed seamless S2S communication, tailored to the unique needs of different hydrological regimes, can transform hydro-climate services, providing actionable and effective support for decision-making in water resource management, agriculture, and disaster risk reduction. These improvements are not only technically significant but also operationally valuable, as they align with the real-world constraints and priorities of operational agencies (Pechlivanidis *et al* 2025).

Developing predictive systems with increased initialization frequency, such as the enhanced ENS-ER updates and the new SEAS6 system from ECMWF, is a critical step forward. Frequent initialization provides more timely and accurate sub-seasonal forecasts, improving the responsiveness of hydro-climate services to evolving conditions, particularly in regions with high precipitation sensitivity and rapid hydrological response. ENS-ER's frequent initialization and accuracy at short-term horizons offer actionable insights for early response planning, while SEAS5's capacity to capture slow-evolving climate phenomena supports long-term strategies such as reservoir management and drought mitigation. These complementary strengths highlight the potential for a seamless forecasting approach that ensures continuous and reliable information flow across lead times.

The spatial variability of OCH values underscores the necessity of tailoring forecasts to regional hydrological regimes. Basins with longer OCH benefit from extended predictability driven by the prolonged persistence of hydrological processes, which enhances water resource management strategies such as optimizing irrigation schemes, improving reservoir operations, and strengthening flood control planning. Conversely, regions with shorter OCH, such as steep, snow-dominated mountain ranges, high-precipitation basins, and elevated Mediterranean areas, require frequent updates from sub-seasonal systems to address rapid hydrological responses and high precipitation sensitivity. We note that the OCH should only be relied upon where the seasonal forecasts maintain skill over climatology; otherwise, operational services may be better served by reverting to climatological benchmarks. These insights not only clarify the scientific basis for region-dependent forecast strategies, but also demonstrate operational advantages: tailoring forecast integration based on OCH variability has the potential to outperform conventional, fixed-horizon methods, as it maximizes usable skill for each specific setting. While a full skill-to-value analysis is outside the scope of this paper, our findings provide the evidence base needed to

assess cost-benefit trade-offs in future implementations (Giuliani *et al* 2020, Rougé *et al* 2023).

Finally, we propose a paradigm shift in how sub-seasonal and seasonal forecasts are merged within hydro-climate services. The traditional approach of overlapping time horizons—where sub-seasonal systems cover the initial weeks and seasonal systems take over subsequently—fails to leverage the full potential of these systems. Instead, we recommend a diagnostic, region-dependent and skill-informed transition methodology based on specific hydrological regimes and user applications. By ensuring that the hydro-climatic services seamlessly communicate the outputs of the two systems based on skill analysis, such as that presented here, forecast skill can be optimized across lead times, effectively addressing the needs of decision-makers. Moreover, our seamless communication approach is well-positioned to evolve alongside advances in computational power, modeling capabilities and analytical tools—including artificial intelligence, hybrid modeling frameworks, and optimally weighted ensemble combinations (Chang *et al* 2023, Slater *et al* 2023, Du and Pechlivanidis 2025). As these technologies continue to mature, they are expected to enhance model accuracy and integration flexibility, making the adaptive transition framework proposed here increasingly powerful and scalable.

5. Conclusions

As sub-seasonal forecast products become increasingly available, offering improved skill for the month ahead, the need for efficient and optimal integration with seasonal products has become evident. This study has demonstrated the importance of skill-informed seamless communication in enhancing S2S hydro-climate services. By leveraging complementary S2S prediction systems like ECMWF ENS-ER and SEAS5, tailoring forecast communication strategies to diverse hydrological regimes across Europe, and transitioning from traditional integration approaches to more diagnostic, region-dependent methodologies, hydro-climate services can provide accurate and effective information to the water- and climate-dependent sectors. This approach maximizes the utility of S2S forecasts by aligning transitions from S2S forecast systems with skill analyses, enhancing their operational relevance.

The main conclusions from this study are as follows:

- Most basins benefit from sub-seasonal forecasts up to 3–6 weeks ahead, while steep, snow-dominated mountain ranges, high-precipitation basins, and elevated Mediterranean areas typically see shorter benefits ranging from 2 to 4 weeks. Beyond these horizons, seasonal forecasts show higher skill than

sub-seasonal forecasts. The frequent initialization of sub-seasonal forecasts provides a clear advantage in terms of streamflow predictability, with benefits regionalized across Europe. This allows hydro-climate services to better respond to rapid changes in meteorological and hydrological conditions, particularly in regions prone to high precipitation sensitivity and rapid hydrological response.

- Sub-seasonal precipitation and temperature forecasts generally show comparable skill to seasonal forecasts in most months. The primary value of sub-seasonal forecasts lies in their frequent initialization rather than significantly higher skill in meteorological variables. Precipitation forecasts are generally more skillful than seasonal forecasts up to 2 weeks ahead, while temperature forecasts are more skillful up to 3–4 weeks.
- OCHs, defined as the lead times when switching from the sub-seasonal forecast system to the seasonal forecast system maximizes skill, vary significantly across Europe, influenced by issue dates and regional hydrological regimes. Regions such as central Europe, the western coast of the Black Sea, and the coasts of the Baltic Sea exhibit longer horizons. Tailoring forecast strategies to these regimes, such as snowmelt-driven or baseflow-dominated systems, ensures that forecasts align with the unique needs and challenges of each region.
- Gains in meteorological skill from sub-seasonal forecasts (1–3 weeks) are amplified when considering hydrological processes. The non-linearity and persistence of these processes, such as snowmelt, baseflow contributions and lakes and reservoir regulations, extends predictability up to 6 weeks.
- Sub-seasonal forecasts issued late in the month exhibit longer OCHs. This underscores the importance of aligning forecast strategies with initialization timing to maximize skill and usability for decision-makers.

Data availability statement

The data that support the findings of this study are openly available. The ECMWF sub-seasonal (ENS-ER) meteorological forecasts were downloaded from the S2S Prediction Project Database hosted by ECMWF and the International Research Institute for Climate and Society (IRI) (www.ecmwf.int/en/forecasts/dataset/sub-seasonal-seasonal-prediction). The ECMWF seasonal (SEAS5) meteorological forecasts are freely accessible from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>). The HYPE model code is available from the

HYPEweb portal (<https://hypeweb.smhi.se/model-water/>).

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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

IGP and LC contributed to the basic idea, study design, code development, model runs, result analysis and figures, interpretation of results, and writing of the manuscript. IGP was also responsible for the project management and funding acquisition. The authors would finally like to express their sincere gratitude to Thomas Bosshard who contributed with the bias-adjustment of the sub-seasonal and seasonal meteorological forecasts.

Appendix

Here, we present additional figures, which are referenced in sections 2.1, 3.1 and 3.2. The figures are introduced to provide detailed information on the bias-adjustment of the ENS-ER meteorological forecasts, ENS-ER-based and SEAS5-based forecasting skill of additional hydro-meteorological variables for different initialization times, and finally, their corresponding optimal combination horizons across Europe. These results are introduced here to complement our process understanding and support the conclusions from this investigation.

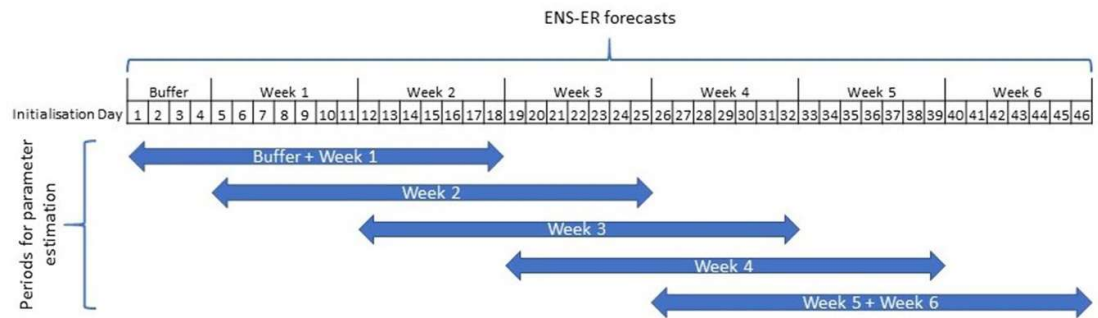


Figure A1. Procedure followed for bias-adjusting the ECMWF ENS-ER forecasts with the estimated distribution-based scaling (DBS) parameters being applied in the middle week of the 3 week window.

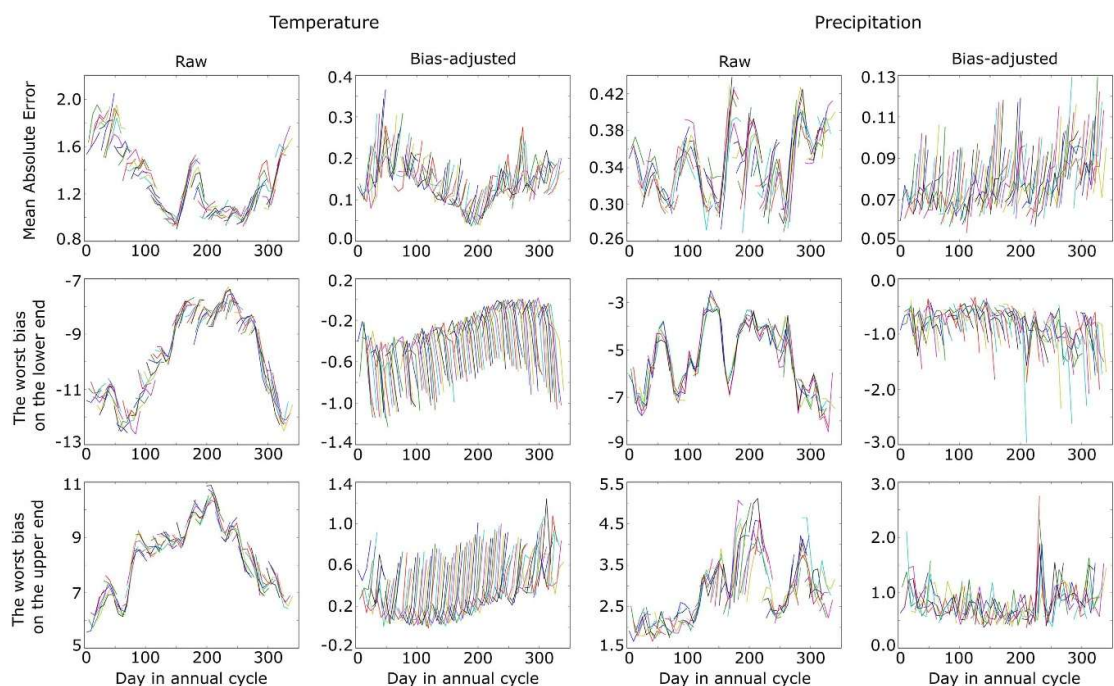


Figure A2. Biases (in terms of mean absolute error, minimum and maximum of all grid points) of the raw and bias-adjusted temperature and precipitation sub-seasonal ECMWF ENS-ER forecasts. HydroGFD was used as reference, while the DBS method was used for bias-adjusting the forecasts. Each color represents a different initialization (twice per week).

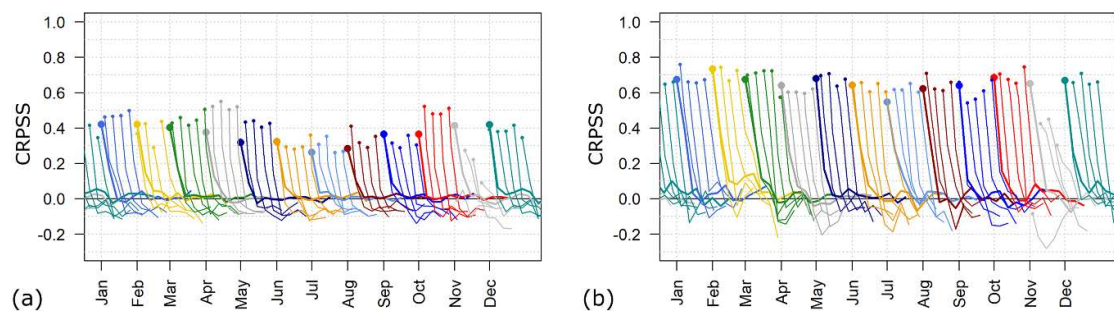
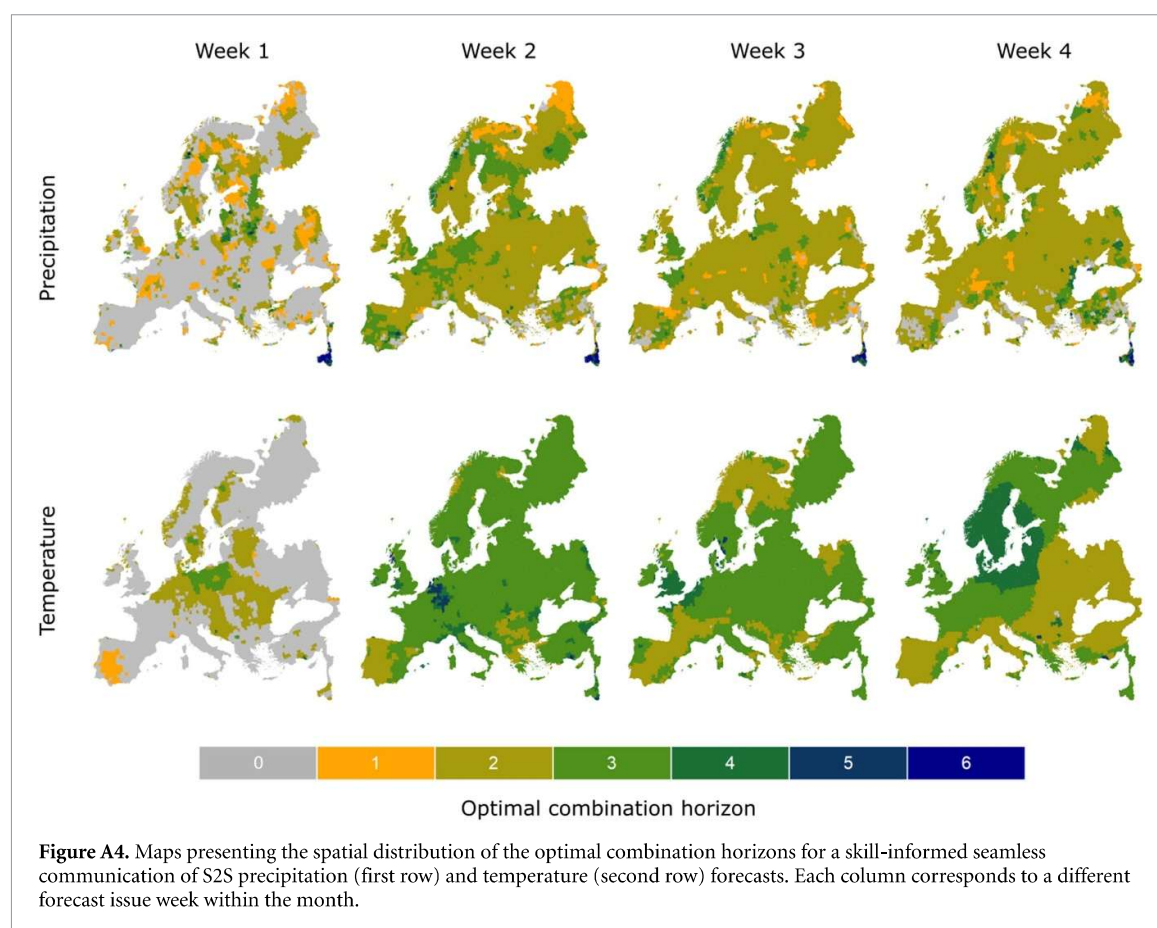


Figure A3. Median forecasting skill (in terms of CRPSS) across Europe presented as a function of lead time and initialization time for: (a) precipitation, and (b) temperature. Line color indicates the calendar month of initialization, while line shape represents the forecast lead time. Thick lines correspond to forecasts from the seasonal SEAS5 system, and thin lines to forecasts from the sub-seasonal ENS-ER system (initialized once per week). The statistics are derived from the 35 408 sub-basins simulated by the E-HYPE hydrological model.



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