

Research papers

Leveraging GCM-based forecasts for enhanced seasonal streamflow prediction in diverse hydrological regimes

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A B S T R A C T

Seasonal hydrological forecasts are vital for managing water resources and adapting to climate change, aiding in diverse planning and decision-making processes. Currently it is unknown how different forecasting methods, considering initial hydrological conditions and dynamic meteorological forcing, perform across the Swedish river systems, despite the significant socio-economic implications. Here we explore the drivers that mostly impact streamflow predictions and attribute the added quality of these predictions to local hydrological regimes. We compare the accuracy of seasonal streamflow forecasts driven by dynamic GCM-based meteorological forecasts with those generated by the Ensemble Streamflow Prediction (ESP) method. The analysis spans across about 39,500 sub-catchments in Sweden encompassing various climatic, geographical and human-influenced factors. Results show that the streamflow predictability varies in space due to the country's diverse hydrological regimes. Regardless of the regime, updating the models to achieve the best possible initial conditions is crucial for enhancing forecast skill across all seasons for up to 4 months. GCM-based meteorological forcing notably improves short-term streamflow accuracy, showing significant impact particularly up to 4–8 weeks lead time depending on the local hydrological regime. In the snow-driven northern regions, ESP demonstrates superior performance over GCM-based streamflow forecasts in winter. Conversely, in the southern regions, where conditions are predominantly influenced by rainfall, GCM-based forecasts show higher performance up to 4–6 weeks ahead, regardless of the season. In river systems with high human influences, streamflow climatology outperforms ESP and GCM-based forecasts underscoring the challenges of accurately modelling artificial reservoir management and the need for better access to management data. These insights guide the development of an advanced national seasonal hydrological forecasting service, and highlight the need for region-specific forecasting strategies indicating areas where predictability is enhanced by improved monitoring, hence initial conditions, and/or meteorological forcings. Finally, we discuss the applicability of these forecasting methods to other regions worldwide, thereby placing our new insights within a global context.

Plain Language Summary: Our research focuses on improving streamflow predictability in Sweden, especially looking ahead to the coming weeks to seasons. We compare the Ensemble Streamflow Predictions (ESP) method that uses historical weather data to predict future streamflows, and a dynamic forecasting method based on bias-adjusted ECMWF SEAS5 system that considers current weather conditions and predicts how climate evolves. We cover all river systems across Sweden, each with unique climatic and physiographic characteristics. Streamflow predictions based on SEAS5 are generally more accurate than ESP in the short term, regardless of the season; however, for longer time horizons, ESP often becomes just as good, if not better, especially in winter. We show that one single forecasting method may not work best for all areas depending on the regional hydrological regime and the season. ESP is more effective in handling the variability caused by snow and rain, which is crucial in determining streamflow in the northern mountainous areas. In southern Sweden, where streamflow is more influenced by rainfall than snow, SEAS5 generates more accurate streamflow in the short term for up to 6 weeks ahead. In regions with large rivers controlled by human interventions, neither method consistently outperforms the other, even in the short term.

1. Introduction

Hydrological forecasts are essential for diverse purposes, playing a pivotal role in water resource management, disaster preparedness, and environmental planning. These forecasts offer crucial insights into expected river flows, reservoir levels, and groundwater conditions, serving as vital tools for efficiently managing water resources to sustain agricultural, industrial and domestic needs (Boucher et al., 2012; Samaniego et al., 2019; Crochemore et al., 2024). As climate change intensifies,

hydrological forecasts become increasingly critical, helping to understand and adapt to shifts in precipitation patterns and other hydrological processes influenced by climate variability (Xu et al., 2005). In this broader context, seasonal hydrological forecasts emerge as valuable tools for planning and management across diverse activities requiring long-term foresight, such as water reservoir operation and optimization, among others (Crochemore et al., 2021; Hurkmans et al., 2023; White et al., 2022). These forecasts provide valuable insights into the seasonal trends of the systems, enhancing their role in effective decision-making

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amid changing climatic conditions (Du et al., 2023; Jackson-Blake et al., 2022; Winsemius et al., 2014).

Starting from simple approaches based on climatological data, the methods for predicting the future states of hydro-meteorological fluxes have evolved with increasing complexity and improved capabilities, resulting in enhanced forecast accuracy, resolution and lead time (Mendoza et al., 2017). In particular, understanding and effectively integrating the sources of predictability is key for enhancing the accuracy and utility of seasonal hydrological forecasts, especially in the context of climate variability and change (Lavers et al., 2020; Papa-charalampous et al., 2022). Among these sources of predictability are the climate forcings, the initial hydrological conditions and the model performances, which reflect the capacity of the model to reproduce the natural catchment behaviour as well as its anthropogenic influences. Current methods allow, for instance, assimilating different types of data, considering variations in initial conditions, and occasionally model parameterizations and structures, more comprehensively reflecting the drivers in predicting the hydro-meteorological dynamics (Dasgupta et al., 2023; Musuuza et al., 2023).

A widely-used seasonal forecasting method is the Ensemble Streamflow Prediction (ESP) (Day, 1985), which makes use of historical meteorological data to generate ensemble streamflow forecasts. ESP is a useful tool that has been widely used due to its methodological simplicity and ease of use in operational settings (Wang et al., 2011; Wood & Lettenmaier, 2006). The strength of ESP lies in its ability to use the correct initial hydrological conditions (IHC) updated for the forecast issue date and to account for uncertainties inherent in meteorological forcing (MF). ESP offers a robust seasonal forecasting framework in comparison to, for instance, streamflow climatology, whose performance is subject to uncertainties from both MF and IHC. However, ESP is limited by the information contained in the historical meteorological forcing, and falls short in predicting streamflow due to extreme weather that has not been previously recorded (Monhart et al., 2019).

Other seasonal forecasting methods are based on Global Climate Models (GCMs), which dynamically represent the climate system (Yuan et al., 2015). GCMs overcome the static nature of climatology in anticipating unprecedented weather events by depicting the interactions between the atmosphere, oceans and land surface, and dynamically incorporating ongoing climate changes, including rising temperatures and shifting precipitation patterns. Moreover, unlike climatology, GCM-based MF integrates real-time observations, enhancing the responsiveness to current atmospheric conditions, and thus the predictive accuracy, particularly of extreme weather events. Despite the significant challenges posed by uncertainties in the atmosphere's initial and boundary conditions, GCM-based forecasts are impeded by systematic biases due to hypotheses on the modelled processes (Pechlivanidis et al., 2020). These biases need to be addressed prior to impact assessments, as they can further deteriorate the accuracy of the seasonal hydrological forecasts (Crochemore et al., 2016; Lan et al., 2020; Lee et al., 2023).

Both methodologies (i.e., ESP and GCM-based seasonal hydrological forecasts) are currently being operationally used in different settings around the globe to inform water resource management and readiness (Bell et al., 2017; Bennett et al., 2017; Demargne et al., 2014; Thielen et al., 2009). In Sweden, seasonal hydrological forecasting holds significant importance for water resource management, energy production, and disaster preparedness (Cantone et al., 2023; Olsson et al., 2016). The Swedish Meteorological and Hydrological Institute (SMHI) plays a central role in providing forecasts that aid municipalities, county boards and the Swedish Civil Contingencies Agency. Two different hydrological models, i.e. the HBV model (Bergström, 1976) and the more recently developed S-HYPE model (Strömqvist et al., 2012), contribute to accurate streamflow predictions. However, in recent years, research and development efforts have primarily shifted to S-HYPE as the model offers a more integrated, high-resolution representation of Sweden's hydrological systems, making it better suited for nationwide forecasting (Pechlivanidis et al., 2014). These forecasts are crucial for efficiently

managing water resources, optimising hydropower production, and preparing for extreme events. However, in addition to the aforementioned limitations of the different seasonal hydrological forecasting methods, the complexities of Sweden's hydrological systems, influenced by diverse factors, such as topography, land use and changing climatic patterns, pose additional challenges to achieving precise seasonal forecasts (Girons Lopez et al., 2021; Pechlivanidis et al., 2020). Thus, while seasonal hydrological forecasts offer invaluable insights, ongoing efforts are necessary to improve their precision in addressing Sweden's evolving hydrological challenges.

Here, for the first time to our knowledge, we assess the performance of seasonal streamflow forecasts from different methods across all Swedish river systems accounting for the two sources of predictability (IHC and GCM-based forcing). This investigation leads to identifying the drivers that mostly impact streamflow predictions, and further attributing the potential added quality of the forecasting method to the local hydrological regimes. From the perspective of an operational user-centric hydrological service, we aim to provide recommendations on when to use which seasonal streamflow prediction system resulting in profound socio-economic implications to multiple water-dependent sectors (e.g. agriculture, hydropower, drinking water etc.). We pose the following questions, which are not only scientifically relevant, but also guide the developments in the national state-of-the-art hydrological forecasting service: (1) *Which driver (IHC or GCM-based forcing) has the highest influence on the streamflow forecasting skill over the Swedish river systems?* (2) *When and where is there a performance gain from using GCM-based forecasts instead of ESP?* and (3) *Can the gain in streamflow predictability from GCM-based forecasts or historical meteorological records be attributed to local hydrological regimes?* To address these questions, we compare the performance from different seasonal streamflow forecasting methods for different time horizons and seasons, and across Sweden's hydro-climatic gradient. We then explore emerging links between the method-dependent forecasting skill and the hydrological regimes.

2. Models and data

2.1. Hydrological model

Here we used the HYPE hydrological model (Lindström et al., 2010), and more specifically its operational implementation for Sweden, known as S-HYPE (Strömqvist et al., 2012). HYPE is a semi-distributed process-based model that includes routines for simulating both water quantity and quality. In addition to the natural hydrological processes, a number of anthropogenic processes, such as reservoir operation, water extraction and irrigation, are also accounted for in the S-HYPE setup. Model parameters are dependent on soil and land-use classes. Many Swedish river systems are regulated, mainly for hydropower production, and therefore general regulation regimes or, depending on data availability, case-specific reservoir operating/rule curves are provided in S-HYPE for a number of reservoirs. They can be represented by either a constant or a seasonally varying sine-wave shape or a combination of both depending on the reservoir level or, sometimes, the date. The Swedish and transboundary river catchments (shared with Norway and Finland) are divided into 39,493 sub-catchments with an average size of 10 km². S-HYPE has a high model performance, with a median Kling-Gupta Efficiency of 0.79 for the period 1981–2016 at daily time step at about 540 hydrological stations (a value of 1 indicates perfect accuracy; Gupta et al. (2009)). This performance level indicates the adequate representation of hydrological processes over most of the domain. More information about the S-HYPE model can be found in Girons Lopez et al. (2021).

2.2. Meteorological and hydrological observations

Historical meteorological information is available from Sweden's

observational meteorological dataset, named PTHBV (Johansson, 2002). This product consists of 4x4 km gridded temperature and precipitation data based on an optimal interpolation of station measurements that aims to generate a spatially continuous and accurate representation of the meteorological patterns. This dataset is available from 1961 onwards at a daily temporal resolution. The PTHBV optimal interpolation scheme uses a background field that incorporates factors such as elevation and wind speed and direction for various regions of Sweden ensuring that the interpolated data accurately capture the spatial variability and distribution patterns of the meteorological observations (Johansson, 2002; Johansson and Chen, 2003). PTHBV represents the state-of-the-art historical forcing dataset for the S-HYPE model and is an essential part to forecasting and generating hydroclimatic projections. Extensive validation processes have therefore been conducted, both internally at SMHI and through peer-reviewed studies, to assess point estimates of the dataset's variables and of streamflow derived from it, primarily in combination with the HBV model (Johansson, 2000; Johansson and Chen, 2005). Furthermore, Giron Lopez et al. (2021) previously conducted streamflow validation specifically using the S-HYPE model. In addition, we used SMHI's hydrological observation network providing daily data of streamflow and water level from about 540 stations to correct the S-HYPE model states prior to producing the forecasts (see Section 3.1 for further details).

2.3. Bias-adjusted seasonal meteorological forecasts

The GCM-based seasonal forecasts of precipitation and temperature were obtained from the ECMWF SEAS5 forecasting system (Johnson et al., 2019). More specifically, we used the SEAS5 re-forecast (hindcast) dataset which consists of 25 ensemble members and which is available for the period 1981–2016 at a grid of approximately 36 km. The forecasts are issued every month and provide information up to seven months ahead. Despite the wide application of the ECMWF SEAS5 forecasts (Emerton et al., 2018; Macian-Sorribes et al., 2020), the GCM model outputs are subject to regional biases, which are further propagated into the hydrological predictions (Pechlivanidis et al., 2020). To address these biases, a quantile-mapping method capable of accounting for drifting and derived from the Distribution Based Scaling (DBS) method (Yang et al., 2010) was applied to the re-forecasts. The PTHBV observational dataset was used as reference. The parameters of the method were conditioned on the lead month and the initialisation date, using the whole period 1981–2016 as a calibration period.

3. Methods

3.1. Hydrological forecast initialisation

S-HYPE was initially forced with the PTHBV meteorological data to generate the initial model states on the forecast issue date; that is the 1st day of each month. The operational S-HYPE version that is used here includes a correction of the model outputs (streamflow and water level) for those stations and times for which observations are available. When observations are no longer available, an autoregressive correction method allows correcting model outputs based on the last available observation until corrected outputs converge with the non-corrected simulation results (Lindström & Carlsson, 2000; Pechlivanidis et al., 2014). More details can be found in Giron Lopez et al. (2021).

3.2. Seasonal hydrological forecasting

Here, we used three different approaches to generate seasonal forecasts of streamflow. Depending on the approach, different sources of uncertainty, i.e. initial hydrological conditions (IHC) and meteorological forcing (MF), contribute (or not) to the seasonal hydrological predictability. In catchments with or downstream from observations, where the autoregressive correction method is applied, the seasonal

streamflow predictability is expected to be linked to historical model performance at least for the first lead times where initial conditions are important. This is relevant for catchments with low model performance where observed and simulated streamflow values can significantly deviate.

Streamflow climatology: This is generated for each initialisation month by randomly selecting streamflow time series from historical data for the sub-catchment of interest. Candidate time series start on the same day as the initialisation date in all available historical years, excluding the forecast year and a window of 3 years around it. The purpose of leaving out 3 years is to only select members that are independent from the forecast year. Streamflow climatology is commonly used as a benchmark in sensitivity analyses since there is uncertainty in both the IHC and MF.

Ensemble Streamflow Prediction (ESP): This approach assumes that the ensemble of historical meteorological data contains adequate information to predict the future. Therefore, precipitation and temperature data are resampled to force the initialised hydrological model (Wood & Lettenmaier, 2006). An ensemble of streamflow forecasts is generated by initialising the hydrological model for the forecast issue date before forcing it with the resampled precipitation and temperature time series. As for streamflow climatology, we exclude the forecast year and a window of 3 years around it when selecting precipitation and temperature time series. The initialisation of the model states prior to forecasting allows the consideration of the initial conditions as a source of skill, and hence makes the ESP methodology advantageous over other approaches, e.g. streamflow climatology (Pappenberger et al., 2015), provided that the hydrological model performs adequately. Nevertheless, ESP can also lead to forecast overconfidence since the historical meteorological data can limit the ability to capture unprecedented events (Harrigan et al., 2018).

Dynamical Streamflow Prediction (DSP): A dynamical approach based on seasonal meteorological forecasts from a GCM as input to the hydrological model is explored. Here, S-HYPE runs with the bias-adjusted ECMWF SEAS5 re-forecasts (25 members) as forcing input to generate seasonal streamflow forecasts. As for ESP, the model is initialised for the forecast issue date, hence the difference in skill between ESP and GCM-based forecasts is attributed to the dynamic meteorological forcing.

3.3. Forecast performance

The performance of the given forecast is commonly assessed with respect to a reference simulation (also known as “pseudo-observations” or “perfect” forecast), which represents the ‘truth’ one aims to forecast. Here, seasonal streamflow re-forecasts based on SEAS5, ESP and streamflow climatology are evaluated based on their capacity to predict the historical reference simulation for each target season and lead time (van Dijk et al., 2013). The reference simulation follows SMHI's operational setup utilising a combination of observations (for catchments with or downstream from observation points) and model simulations to achieve optimal initial conditions; see Giron Lopez et al. (2021).

In particular, S-HYPE is run at a daily timescale, with the generated forecasts averaged over a week for the 1981–2016 period. To ensure comparability, we used 25 ensemble members across all forecasting methods. Hence, the forecasting experiment includes 39,493 sub-catchments and 32,400 forecast initialisations (1 start date per month $\times$ 12 months $\times$ 36-year re-forecast period (1981–2016) $\times$ 25 members $\times$ 3 forecasting methods (SEAS5, ESP and streamflow climatology)), with results averaged weekly up to 28 weeks ahead. Performance (i.e. the closeness of the forecast to the reference) is here assessed based on the continuous ranked probability score (CRPS; Hersbach (2000)).

3.4. Forecast skill

Once performance is assessed, the skill of a given forecast set is

obtained by comparing its performance to that of a selected “benchmark”; i.e. an alternative forecast upon which one wishes to improve. The choice of the benchmark was here adapted to quantify the contributions to forecast skill of two main factors (IHC and GCM-based forcings), and consequently to know where and when GCM-based forecast products improve performance in hydrological forecasts (see Fig. 1a). For instance, by comparing the performance of ESP against that of the streamflow climatology as a benchmark, we can get an estimate of the influence of initial conditions on the forecast performance. By comparing the performance of SEAS5 against that of the streamflow climatology as a benchmark, we can get an estimate of the combined influence of initial conditions and GCM-based forcings on the forecasts. Consequently, by comparing the performance of SEAS5 against that of ESP as a benchmark, we obtain information on the influence of using GCM-based forcings on the forecasts (Crochemore et al., 2020). Skill is here assessed based on the continuous ranked probability skill score (CRPSS). CRPSS is non-dimensional and ranges between 1 (perfect forecast) and minus infinity, with the positive (negative) values indicating a better (worse) performance of the forecast system than that of the selected benchmark.

3.5. Attribution of forecast skill

Thereafter, we investigated the drivers (IHC and GCM-based MF) that lead to improved streamflow forecast skill for different hydrological regimes. To do so, we used the Giron Lopez et al. (2021) classification of the Swedish river systems based on similarities of catchment functioning (Fig. 1b). This classification was based on a k-means clustering approach applied on 15 hydrological signatures that determine the temporal characteristics of the streamflow response. The hydrological signatures in each cluster are presented in Fig. 1c, while their description is given in Table S1 in the Appendix. The clustering allowed further identification of the dominant streamflow generating processes for specific regions in Sweden. Here, we analysed the seasonal hydrological predictability for each of the clusters as a function of lead time. Specifically, we focus on identifying the regions and understanding the regimes in which GCM-based forecasts can add value to the streamflow forecast skill, and further, the regions in which the ESP approach can still be considered as a robust forecasting system.

4. Results

4.1. Bias-adjustment of GCM-based forecasts

The bias-adjustment of the SEAS5 precipitation and temperature

forecasts was performed using the DBS method with the PTHBV dataset as a reference. Overall, while the DBS method has significantly improved the accuracy of SEAS5 forecasts, particularly for temperature, some challenges remain in accurately forecasting precipitation in summer and autumn, and at longer lead months (see Fig. 2, and Figs. S1, S2 and S3 in the Appendix for precipitation and temperatures at lead months 0 and 3). The raw precipitation SEAS5 forecasts exhibited notable biases, especially across the mountain ranges in Sweden, while other areas showed relatively minor discrepancies. After the DBS-based adjustment, these biases were substantially mitigated, but an underestimation trend in precipitation forecasts persisted for longer lead months. It is important to note that DBS, as a quantile-mapping method, can correct for biases in the quantile distribution, but is not designed to correct for other biases, such as for e.g. underestimation of precipitation frequency in the original seasonal forecast data or wet-spell lengths. Reasons for such a bias might be manifolds, including different resolutions of the seasonal forecast and the reference data, model parameterizations, challenging topography leading to precipitation shading effects, and difficulties to model specific types of precipitation (e.g. convective precipitation). The limitation of the bias-adjustment method to handle those biases highlights the need for further investigations to understand the causes of the residual bias.

In terms of temperature forecasts, the initial raw SEAS5 data predominantly displayed a cold bias regardless of the lead time, and more particularly in the north-western mountainous areas. The application of the DBS method proved effective in mitigating this issue, eliminating the cold bias from the temperature forecasts (see Figs. S2 and S3 in the Appendix). This successful adjustment indicates the robustness of DBS in handling temperature biases, enhancing the reliability of the forecast data, particularly in regions where temperature can significantly influence the hydrological response (i.e. mountainous areas in the north-western parts of the country).

4.2. Temporal distribution of forecast skill

The effect of the initial hydrological conditions on forecast performance is obtained by assessing the ESP forecast performance with respect to streamflow climatology (Fig. 3; top row). ESP demonstrates a distinct added value over streamflow climatology in the first 2–4 months, varying with the target season. However, this added value diminishes roughly beyond 12 lead weeks for summer, autumn and winter, after which the differences between ESP-based and climatology-based streamflow forecasts become minimal. Notably, the ESP-based forecast skill exhibits greater variability during winter and spring in the short lead weeks (up to 6 weeks), which is likely attributable to the

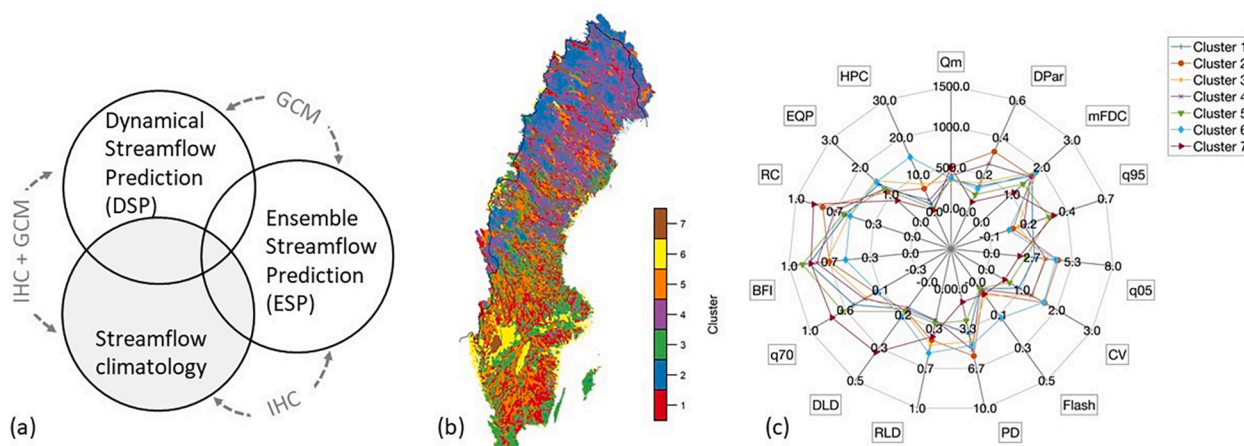


Fig. 1. (a) An illustration of the forecasting systems and the corresponding evaluation framework used to address the scientific objectives. (b) Spatial distribution of the 7 hydrological clusters across Sweden (source: Giron Lopez et al. (2021)). (c) Radar chart of the hydrological signatures (median value) in each cluster.

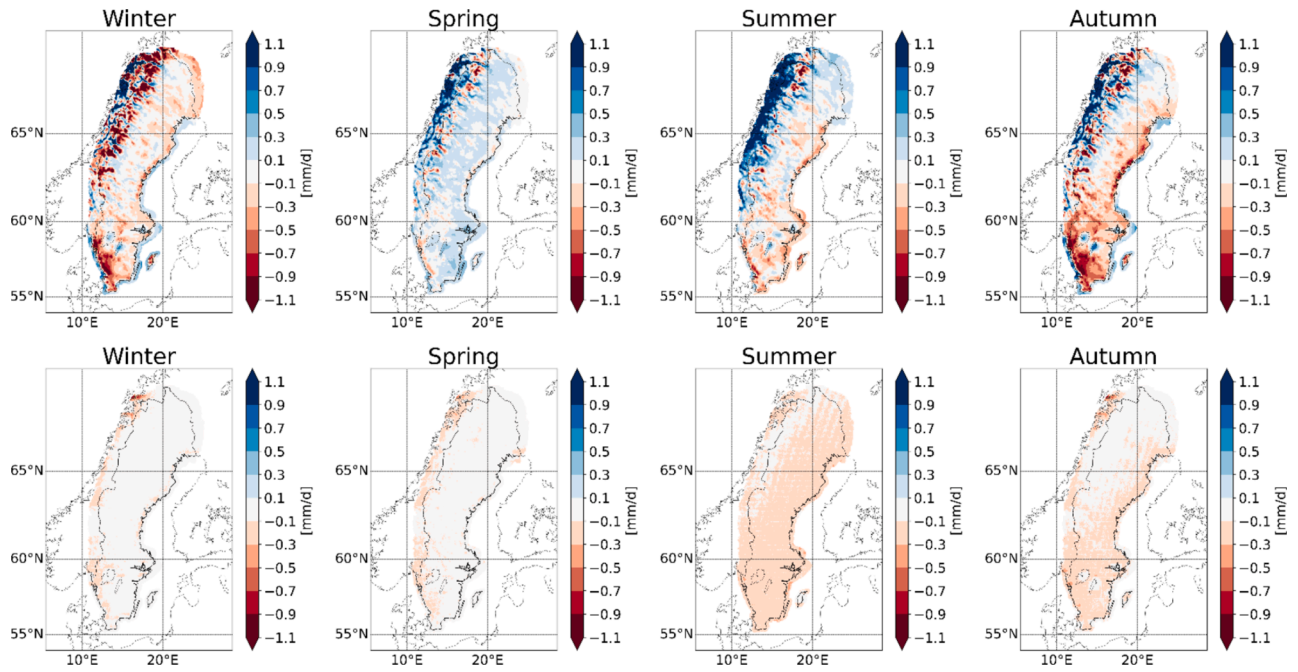


Fig. 2. Mean precipitation forecast bias for lead month 0 in raw (top row) and bias-adjusted (bottom row) forecasts for winter (DJF), spring (MAM), summer (JJA) and autumn (SON).

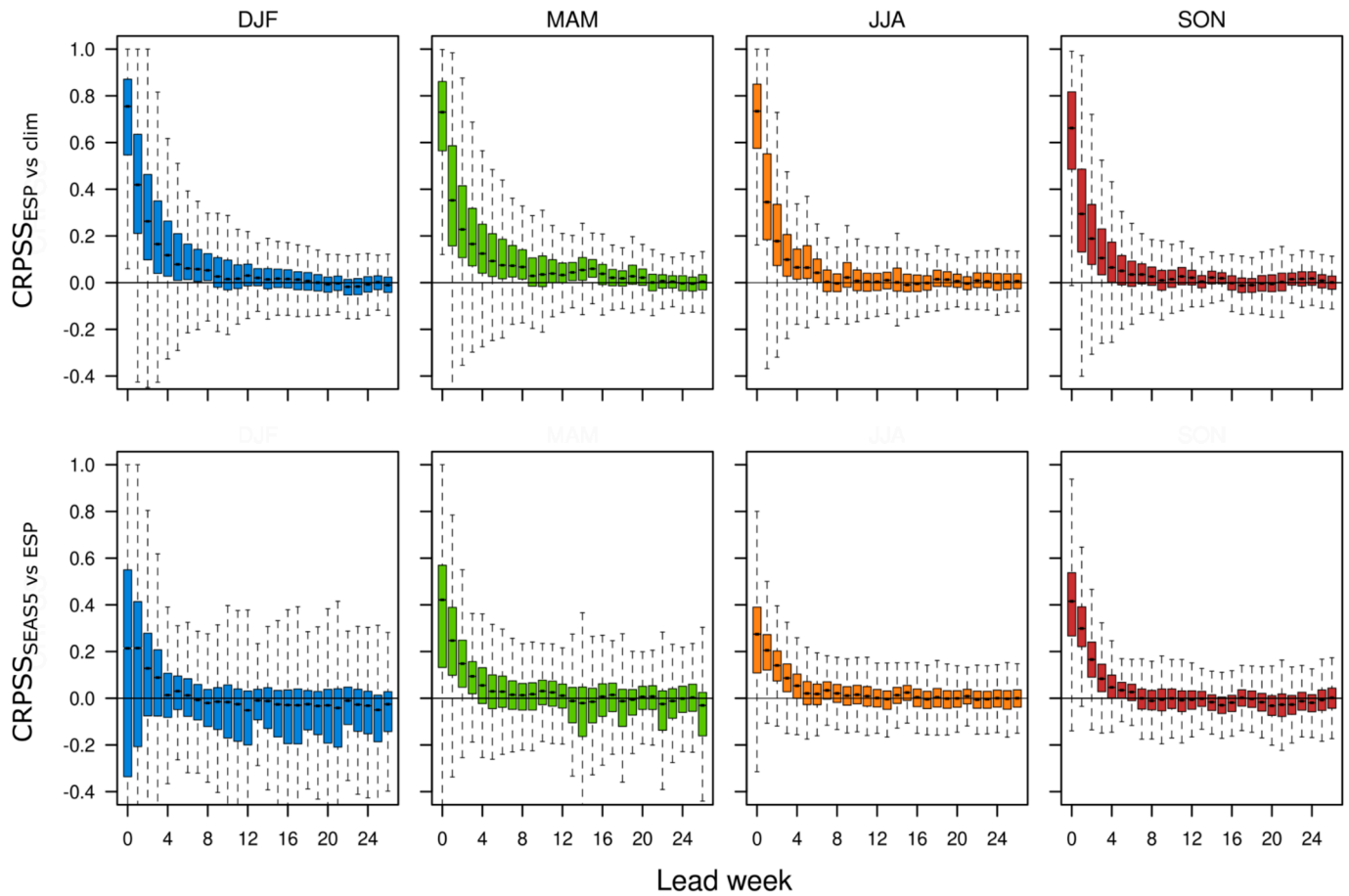


Fig. 3. Streamflow forecast skill (in terms of CRPSS) averaged over each target season as a function of lead time (in weeks) for the ESP approach with respect to climatology (top row) and the dynamic SEAS5 system with respect to ESP (bottom row). The boxes and whiskers represent the variability amongst the catchments.

rainfall- and snow-driven hydrological responses which vary in space; for instance, snow accumulation is dominant in the northern part of the country during winter. In contrast, there is a relatively higher skill observed in longer lead times during spring, as opposed to other seasons, which is linked to the snow-melting, subsequently resulting in the onset of the high streamflow season (May-July).

Furthermore, while the forecast skill generally decreases as a function of lead time across all seasons, this decline is more gradual in summer and autumn, particularly during the first lead month. This pattern can be explained by the snow accumulation and melting processes, which result in longer catchment response times, as opposed to

the sharper declines observed in summer and autumn due to the rainfall-driven responses. These insights highlight the seasonally dependent nature of ESP forecast performance, emphasising the critical role of initial conditions in shaping streamflow forecast accuracy over varying temporal scales.

We also evaluate the impact of incorporating dynamic GCM-based MF by comparing the SEAS5-based streamflow forecasts with respect to ESP (Fig. 3; bottom row). Overall, GCM-based streamflow forecasts demonstrate a higher skill than ESP in short lead weeks (up to 6–10 weeks) across the target seasons. The skill diminishes over longer time horizons, with minimal differences between ESP and SEAS5 observed in

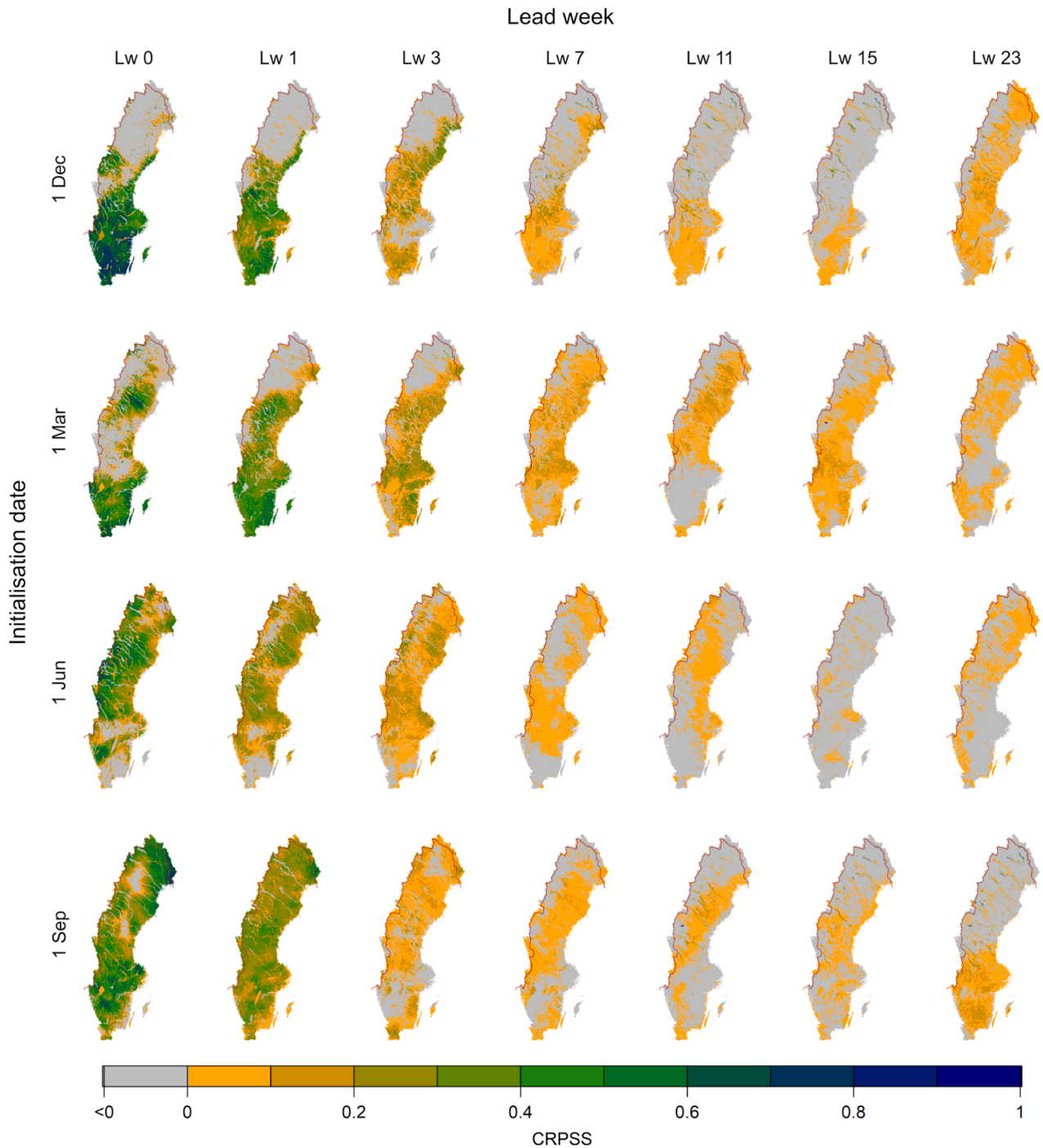


Fig. 4. Spatial distribution of SEAS5-based streamflow forecast skill with respect to ESP (in terms of CRPSS) for selected initialisation dates (rows) and forecast time horizons (columns).

most seasons, while in all seasons and beyond 3 months ahead, ESP surpasses SEAS5-based streamflow forecast performance. In winter, the advantage of GCM-based forecasts over ESP is less pronounced, while, for 20–40 % of the catchments, ESP exhibits higher performance compared to GCM-based forecasts even in short lead weeks. During long lead times (spanning beyond 12 weeks ahead) in winter and spring, SEAS5 forecasts display high variability, with the spread in SEAS5-based forecast skill between catchments widening notably. Note that in many of these catchments, the performance of SEAS5 falls below that of streamflow climatology. An intriguing observation is that during long lead times in winter and spring, no skill is discernible from the GCM-based forecasts in most catchments, which is also accompanied by high variability in skill. This suggests that during these seasons, GCM-based forecasts may become disinformative, highlighting the season-specific limitations and uncertainties inherent in dynamic prediction systems. Similar conclusions are drawn for summer and autumn, however with lower variability in skill during long lead times than the other two seasons.

4.3. Spatial distribution of forecast skill driven by GCM

In summary Girons Lopez et al. (2021) shows that the spatial variability of ESP skill with respect to streamflow climatology displays substantial regional differences across Sweden (see also Fig. S4 in the Appendix). ESP performs well in the northern regions where initial hydrological conditions, such as snowpack and soil moisture, enhance streamflow predictability. However, it underperforms in catchments with flashy hydrological response and low river memory, such as agricultural and coastal areas primarily located in southern and central Sweden. More details about the ESP spatiotemporal skill can be found in Girons Lopez et al. (2021).

Building on this analysis, we here investigate the spatial variability of the added forecast performance due to adopting a DSP approach (GCM-based MF) rather than historical meteorological forcings (ESP); ESP is hence used as a benchmark here. The spatial distribution of streamflow forecast skill differs significantly across initialisation months and lead time horizons (Fig. 4). Overall, streamflow forecasts produced using SEAS5 forcing data were generally skillful with respect to ESP for a high proportion of the catchments, for all initialisation months and even in the long lead times. However, large season-dependent spatial variations can be observed, while the regional differences between the north and south of the country highlight the necessity for region-specific forecasting strategies, considering the unique hydro-meteorological dynamics of each area.

In particular, in the mountainous northern regions, GCM-based streamflow forecasts initiated in both winter (December) and spring (March) consistently exhibit a lack of skill (cf. clusters 2 and 4 in Section 4.4). This reflects the complexities in accurately predicting precipitation and, to a lesser extent, temperature (Johnson et al., 2019); see Figs. S5 and S6 in the Appendix. The spatial variability of the skill of actual evapotranspiration, snow and soil moisture with reference to their ESP-based forecasts is also calculated and can be found in Figs. S7–S9 in the Appendix, respectively. Results indicate a very low (and even lack of) skill in the mountainous northern regions, which consequently conditions the accuracy of streamflow predictions in these challenging terrains. The large regulated rivers in this area demonstrate low added forecast skill during summer (June) and autumn (September), while their skill contrasts with most of the northern domain (see the grey lines that present the skill in the main rivers which extend from west to east and outflow in the Baltic sea). However, a sustained yet modest skill is observed in the December and March initialisations, suggesting a seasonal variation in predictability, likely influenced by snowmelt patterns and reservoir management. In winter initialisations (December), the initial lead weeks reveal no forecast skill for this region, including the large rivers and lakes. Nonetheless, a marginal improvement in skill is noted as lead times extend beyond 7 weeks ahead, although this tends to

decrease in other areas. The difficulties in forecasting low streamflow conditions during winter, driven by snow-dominated hydrological regimes and reservoir usage for energy needs, present a contrast to other regions.

Southern Sweden exhibits the highest GCM-driven added streamflow forecast skill in December, particularly in the first lead weeks (cf. clusters 1, 3, 5 and 6 in Section 4.4). This high GCM-driven predictability during early winter is likely due to the region's simpler terrain and less complex hydrological processes. Furthermore, in spring initialisations (March), the southern region demonstrates high added skill from GCM-driven streamflow forecasts in the short lead weeks. Unlike the northern areas, the southern and coastal regions benefit from higher short-term predictability, attributed to their rainfall-dominated hydrological systems.

4.4. Attribution of forecast skill to hydrological behaviour

Here, we investigate the potential attribution of streamflow predictability driven by either GCM-based forecasts or ESP to the hydrological regimes (Fig. 5). This assessment can assist in diagnosing the areas over which a dynamic GCM-driven streamflow forecasting system could add performance over ESP, which has already been shown to be a tough benchmark to overcome (Arnal et al., 2018). Bias-adjusted SEAS5-based streamflow forecasts generally exhibit greater skill than ESP across most hydrological regimes and seasons, notably within short lead times of up to 6 weeks ahead. This trend, however, reverses in longer lead times, where ESP outperforms GCM-based forecasts. Notably, from lead week 16 onwards, especially during summer, autumn and winter, streamflow climatology demonstrates higher performance than both methods. These findings highlight the significant role of both IHC and MF in the predictability of seasonal streamflow in Sweden for lead times shorter than 16 weeks.

In the highland catchments of northern Sweden (cluster 2), which experience high precipitation and a clear contrast between snow accumulation and melting, ESP maintains its superiority over GCM-driven forecasts in winter across all lead times. However, this difference seems to increase for forecasts extending 10 weeks ahead and beyond. The limited winter precipitation, contributing to snowpack, and minimal streamflow response suggest that small inaccuracies in dynamic GCM-based precipitation predictions can lead to substantial discrepancies in streamflow forecasts. A similar pattern is observed for the boreal forest catchments in northern Sweden (cluster 4); however, ESP's advantage over SEAS5 during winter (and also the other seasons) is less marked. Both catchment systems perform similarly in the intermediate lead weeks (8–12 weeks), with ESP gaining superiority in the longer lead times. This pattern indicates a more balanced forecast skill between the two methods in these catchments.

In clusters 1 and 5, characterised by high river memory and low intra-annual variability, GCM-driven forecasts consistently outperform ESP for all seasons up to 12 weeks ahead; though after lead week 8 both systems seem to perform similarly. Beyond lead week 17 in autumn and winter (and beyond lead week 22 in spring), streamflow climatology becomes the most accurate method. This trend suggests a robust persistence of GCM-driven forecast superiority in these specific hydrological regimes, with the skill of GCM forecasts contributing slowly and over long time periods to the skill of hydrology forecasts. Conversely, the rainfall-driven catchments in southern Sweden (clusters 3 and 6) exhibit a shorter period of GCM-based forecasts superiority lasting only 4–6 weeks regardless of the season, and highlighting a limitation of GCM-based meteorological forecasts over long time horizons. Beyond the short lead weeks, both systems perform similarly until streamflow climatology starts outperforming them, depending on the season.

Finally, the large and highly regulated rivers in northern Sweden (cluster 7) present a complex interplay between ESP and GCM superiority. In these catchments, no definitive conclusions can be drawn, as both ESP and GCM-based methods perform less accurately than

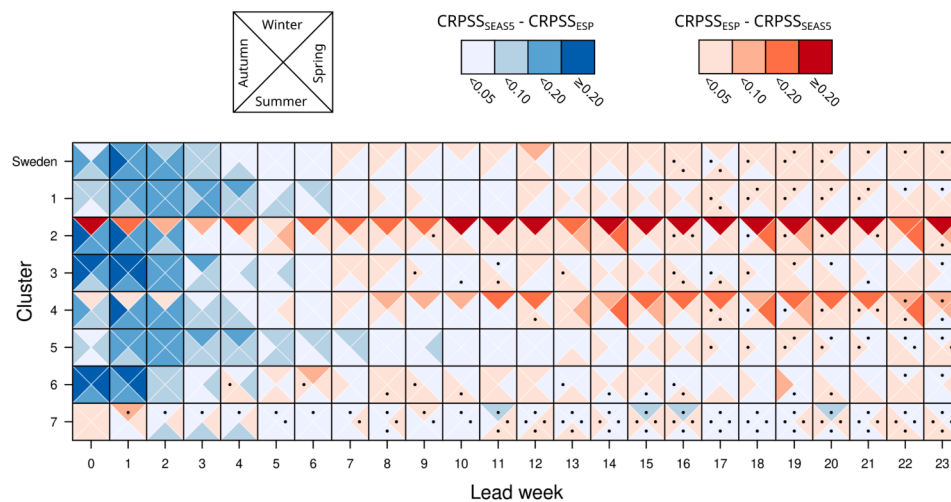


Fig. 5. Comparison of median seasonal streamflow forecasting skill with respect to streamflow climatology between ECMWF SEAS5 and ESP for all target seasons as a function of lead time. Each row aggregates the results for each hydrological cluster, while the top row aggregates the results for the entire domain. Blue (red) triangles indicate higher (lower) skill in SEAS5 than ESP. Triangles with a dot indicate higher accuracy of streamflow climatology than SEAS5 and/or ESP.

streamflow climatology even in the short lead times. The impact of anthropogenic regulations in these areas appears to mask the forecasting skill driven by either initial hydrological conditions and/or meteorological forcing. We additionally note the (lack of) model performance that drives the streamflow forecasting skill; if the hydrological model cannot reproduce the catchment behaviour, including the anthropogenic influences, correctly, streamflow climatology (which occasionally accounts for the correction of the model outputs; see Section 3.1) can outperform both model-based ESP and DSP approaches.

Overall, these diverse patterns across different hydrological clusters in Sweden underscore the geographical complexity that seasonal streamflow forecasting meets and the need for tailored approaches depending on local hydrological and climatic conditions. The results show that the initial hydrological conditions are a strong source of predictability, adding skill in the large majority of catchments till 4 months ahead and for all seasons. The impact of GCM-based meteorological forcings is apparent at lead times up to 4–8 weeks, with variations depending on the hydrological regime. These results can guide future efforts on improving hydrological monitoring networks for more accurate model initialisations and/or enhancing the meteorological forcing systems for accurate precipitation and temperature forecasts.

5. Discussion

5.1. Evolving the national seasonal hydro-meteorological forecasting service

In the realm of operational seasonal hydrological predictions at the Swedish national scale, a significant transition is proposed from the ESP method to GCM-based streamflow forecasting, primarily stemming from GCMs' superior accuracy for the months ahead for streamflow applications (Arnal et al., 2018; Crochemore et al., 2016; Prudhomme et al., 2017). GCM systems have also indicated adaptability to climate variability, particularly in simulating large-scale atmospheric patterns like the North Atlantic Oscillation (NAO), the Arctic Oscillation (AO) and the Scandinavian Pattern (SCAND), which have been concluded to drive meteorological responses over the country (Uvo et al., 2021). GCM-based methods show enhanced performance in lead times at least up to 6 weeks ahead; however, their efficacy reduces over longer time horizons. In shorter time horizons, as noted by Arnal et al. (2018), the streamflow performance (Fig. 4) hardly correlates with the skill in precipitation, which is generally observed up to about a week, with the temperature skill extending up to 2 weeks, or with the persistence in

streamflow up to 4–8 weeks. In some catchments, the streamflow forecast performance appears to be influenced by the non-linear propagation of meteorological forecast errors (Figs. S5 and S6 in the Appendix) when estimating intermediate hydrological states, such as actual evapotranspiration, soil moisture and snow (Figs. S7–S9 in the Appendix). In other catchments, however, the streamflow forecast performance at longer lead times seems to result from the persistence in hydrological storages, including soil moisture, snow and streamflow persistence (Figs. S4, S8 and S9 in the Appendix). In the longer lead times, ESP's reliance on historical data sometimes yields better results, especially in winter, also highlighted by Arnal et al. (2018) as a challenging season to predict, or in specific catchments. This requires region-specific strategies tailored to diverse hydro-meteorological dynamics.

Implementing GCM-based forecasting in operational settings involves complex challenges, including, for instance, the need for aligning model outputs with observed (or reanalysis) meteorological data through bias adjustment, which demands advanced computational infrastructure and sophisticated data integration techniques (Zhao et al., 2017). The variability in GCM-based streamflow forecast performance across different seasons and hydrological regimes further amplifies these challenges. In relation to this variability in performance, critical lead time at which systems should seamlessly transit from GCM-based to ESP can be identified. This challenge could be addressed by embracing a multi-model approach, aiming to enhance forecast accuracy by balancing the benefits of GCM with ESP in space and time (Wanders & Wood, 2016). While this integration improves the overall forecast performance (including forecast reliability and robustness), it introduces computational challenges and needs for computational resources, especially in managing diverse datasets and calibrating different models' outputs.

The socio-economic implications of these advancements are profound, highlighting the potential role of seasonal forecasts in promoting sustainable water resources and economic stability (Bruno Soares et al., 2018; Crochemore et al., 2021). Even slight improvements in forecast accuracy lead to better water resource management, crucial for all water-dependent sectors like agriculture, energy production, transportation and drinking water (Boucher et al., 2012; Cantone et al., 2023; Giuliani et al., 2020; Peñuela et al., 2020). Accurate predictions aid in mitigating the impacts of floods and droughts, protecting communities and reducing disaster-related costs (Shyrokaya et al., 2023, 2024).

5.2. Global relevance of Swedish forecasting insights

It is important to firstly note that Swedish rivers share significant hydrological similarities with other river systems around the world, particularly those located in high-latitude regions, such as Canada, where snowmelt is a major contributor to streamflow during the spring and early summer (Knoben et al., 2018). Additionally, the hydrological response in many Swedish river systems is influenced by the presence of numerous lakes and relatively steep gradients, features that are also characteristic of regions like Norway, the Rocky Mountains in North America, and the Southern Alps in New Zealand. In regions with temperate climates, particularly in central and southern Sweden, the hydrological regime is shaped by a combination of snowmelt and rainfall, resulting in more stable and consistent flow patterns throughout the year. This pattern is similar to river systems in parts of northern Europe, such as Germany and the UK (Harrigan et al., 2018; Pechlivanidis et al., 2020), as well as in temperate regions of the north-eastern United States (Knoben et al., 2018), where seasonal variations in precipitation and moderate temperatures drive river dynamics. Therefore, we argue that the insights from the present investigation are likely to be valid and applicable in regions exhibiting similar hydrological behaviour, making them relevant beyond the specific context of Sweden.

In particular, the insights from this investigation on ESP and dynamic forecasting offer an improved understanding on the evolution of seasonal hydrological forecasting services that could be applicable, under certain conditions, to other regions. The effectiveness of ESP in leveraging initial hydrological conditions during the first lead weeks or months is a principle that can be generalised in river systems that are characterised by large river memory (Du et al., 2023; Giron Lopez et al., 2021). However, the persistence of this advantage may vary depending on local hydrological and climatic characteristics (Musuuza et al., 2023). The conclusion that GCM-based forecasts exhibit higher skill than ESP in short lead times across all seasons in most of Sweden, could be extended to other regions, particularly where climate dynamics are dominated by large-scale atmospheric patterns. However, the reduced performance of these models in longer lead times, as seen in Sweden, might also apply elsewhere, emphasising the need for region-specific forecasting strategies. This is especially pertinent in areas with diverse hydro-meteorological dynamics. The decline in GCM forecast performance at longer lead times suggests the potential value of dynamically downscaled RCM (Regional Climate Model) forecasts, particularly in regions like Sweden where local climate processes play a significant role. Previous studies have shown no particular improvement in RCM temperature and precipitation forecasts compared to statistical downscaling (Manzanas et al. 2018, Nikulin et al. 2018). Nevertheless, given recent advances in climate modelling, further studies could explore their potential for hydrological impact modelling.

Furthermore, the observed variations in forecast accuracy between highland and boreal forest catchments versus rainfall-driven catchments in southern Sweden suggest that local geographical and climatic factors significantly influence the performance of both ESP and GCM-based methods. Lastly, streamflow climatology outperformed ESP and DSP forecasts in catchments with high human influences, highlighting the ongoing challenges of representing and predicting artificial reservoir management. Simplified reservoir filling curves often fall short in large-scale seasonal forecasting due to the complexity of human interventions. Improving the representation of reservoirs in models requires better access to management data, which is often restricted for security or financial reasons, as well as more advanced modelling of reservoir dynamics. Studies emphasise the need for incorporating data-driven approaches and improved parameterization to capture the diverse and nuanced management strategies that large-scale models struggle to replicate effectively (Coerver et al., 2018; Hanasaki et al., 2006; Turner et al., 2020; Yassin et al., 2019). Thus, while the overall trends from the Swedish study provide valuable insights, their application to other regions requires careful consideration of local hydrological regimes,

climate variability and anthropogenic influences (Pechlivanidis et al., 2020; Sutanto & Van Lanen, 2022).

6. Conclusions

Herein, we identify key drivers of seasonal streamflow predictability – initial hydrological conditions and GCM-based forcing – and provide a detailed attribution of the added quality of streamflow forecasts to local hydrological regimes across all Swedish river systems, offering valuable recommendations for operational hydrological services with significant socio-economic implications. In particular, we investigate the potential added skill of seasonal streamflow forecasts over Sweden by incorporating GCM-based meteorological forcing (here the bias-adjusted ECMWF SEAS5 forecasts) in comparison to the ESP method that predicts streamflow based on historical meteorological records. We further attribute the streamflow predictability from GCM-based forecasts or historical meteorological records to the local hydrological regimes, allowing the insights to be positioned within a global context. The evaluation of the seasonal streamflow predictability is conducted across all Swedish river systems (about 39,500 sub-catchments), which vary in terms of climatology, scale, physiography, human interventions and hydrological response. Our new insights guide the efforts towards the evolution of the state-of-the-art national seasonal, hydrological forecasting service, while pointing to the areas where predictability is driven by improvements in meteorological forcings and/or initial hydrological conditions, hence enhancements in monitoring and data assimilation techniques.

The main conclusions from this study are as follows:

- The bias-adjustment method (quantile-mapping DBS) has largely enhanced the accuracy of ECMWF SEAS5 temperature forecasts by effectively removing the initial cold-bias, demonstrating the robustness of the method in addressing temperature biases. However, for precipitation forecasts, while the bias-adjustment method has reduced the biases, especially in mountainous regions, it has been unable to fully correct mean biases, leading to a persistent underestimation in longer lead months.
- ESP shows high skill with respect to streamflow climatology in the initial 2–4 lead months depending on the season highlighting the importance of initial hydrological conditions in shaping streamflow forecast accuracy. However, this advantage diminishes in longer lead times, with minimal differences between ESP and streamflow climatology observed beyond 12 lead weeks for summer, autumn and winter.
- GCM-based streamflow forecasts generally exhibit higher skill than ESP in the short lead times (up to 6–10 weeks) across the seasons. This skill is associated with skill in GCM-based precipitation forecasts up to a week or so, and in temperature forecasts up to 2 weeks. However, this advantage reduces over longer time horizons. In winter, the GCM-based forecasts performance is less pronounced, and ESP sometimes outperforms DSP in certain catchments, due to limited skill in other internal fluxes and water storages (actual evapotranspiration, snow and soil moisture). The high variability and reduced skill in the ECMWF SEAS5 forecasts during longer lead times, especially in autumn and winter, suggest limitations in GCM-based predictions. This highlights the need for region-specific forecasting strategies to address the diverse hydro-meteorological dynamics across Sweden.
- Initial hydrological conditions greatly aid predictability in most catchments at least up to 2 months across all seasons, while GCM-based meteorological forcing shows notable impact in early lead times of up to 4–8 weeks. Bias-adjusted SEAS5-based streamflow forecasts generally outperform ESP in the short lead times across most hydrological regimes. However, streamflow climatology shows superior performance to both ESP and DSP from lead week 16 onwards.

- Sweden's diverse hydrological regimes reveal the complexity of seasonal streamflow forecasting, requiring custom approaches based on specific conditions. Particularly, in the highland catchments and boreal forest catchments of northern Sweden, ESP exhibits varying degrees of superiority over DSP, especially in winter, linking to the regional snow-related dynamics. Conversely, in southern Sweden's rainfall-driven catchments, GCM-based forecasts are slightly superior to ESP during the first 4–6 weeks. In the highly regulated northern rivers, neither ESP nor DSP methods consistently outperform streamflow climatology, indicating the significant influence of anthropogenic factors.

Author contributions

IGP was responsible for the project management and funding acquisition and contributed to the basic idea, the study design, clustering analysis and figures, interpretation of the results, and the writing of the manuscript. MGL contributed to the study design, model runs, result analysis and figures, interpretation of the results, and the writing of the manuscript. TB contributed with the bias-adjustment of the ECMWF SEAS5 meteorological forecasts and commenting on the manuscript. LC contributed to the study design, interpretation of the results, and commented on the manuscript.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jhydrol.2024.132504>.

Data availability

The HYPE model code is available from the HYPEweb portal (<https://hypeweb.smhi.se/model-water/>; (SMHI, 2024a)). The meteorological data used for driving the ESP re-forecasts (PTHBV) can be obtained upon contact with SMHI, and the hydrological data used for model correction are available from the Vattenwebb portal (<https://vattenwebb.smhi.se/>; (SMHI, 2024b)). The seasonal meteorological forecasts SEAS5 from the European Centre for Medium-Range Weather Forecasts are freely accessible from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>).

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