Skilful probabilistic predictions of UK floods months ahead using machine learning models trained on multimodel ensemble climate forecasts

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This EarthArXiv original preprint has been submitted to Hydrology and Earth System Science (HESS) and has not been peer-reviewed or edited.

Abstract

Seasonal streamflow forecasts are an important component of flood risk management. Hybrid forecasting methods that predict seasonal streamflow using machine learning models driven by climate model outputs are currently underexplored, yet have some important advantages over traditional approaches using hydrological models. Here we develop a hybrid subseasonal to seasonal streamflow forecasting system to predict the monthly maximum daily streamflow up to four months ahead. We train a random forest machine learning model on dynamical precipitation and temperature forecasts from a multimodel ensemble of 196 members (eight seasonal climate forecast models) from the Copernicus Climate Change Service (C3S) to produce probabilistic hindcasts for 579 stations across the UK for the period 2004-2016, with up to four months lead time. We show that multi-site ML models trained on pooled catchment data together with static catchment attributes are significantly more skilful compared to single-site ML models trained on data from each catchment individually. Considering all initialization months, 60% of stations show positive skill (CRPSS>0) relative to climatological reference forecasts in the first month after initialization. This falls to 41% in the second month, 38% in the third month and 33% in the fourth month.

1 Introduction

Reliable streamflow forecasts weeks to months ahead are vital for managing the impacts of hydrological variability and extremes. Dynamical subseasonal to seasonal (S2S) streamflow forecasts are commonly produced by forcing a conceptual or physics-based hydrological model with the outputs of dynamical seasonal forecasts from climate models, and may also include a subsequent statistical or machine learning post-processing step. This may be achieved either directly or indirectly – e.g., by using dynamical climate prediction information as direct inputs to the hydrological model, or by using the dynamic predictions or empirical information as conditioning factors in a statistical weather generation scheme to create the model's input meteorological forecasts. These systems represent the current standard in S2S streamflow forecasting, underpinning flood forecasting services in Europe (Arheimer et al., 2020; Arnal et al., 2018), the US (Demargne et al., 2014), Australia (Bennett et al., 2017), and globally (Emerton et al., 2018).

The chaotic nature of the atmosphere places a time limit of around 14 days on the predictability of weather from initial atmospheric circulation conditions, although this limit may vary from less than a week to nearly three weeks depending on local climate features and the current weather regime. S2S hydro-meteorological forecasts therefore rely on relatively slowly-varying aspects of the climate system that are more predictable beyond weather time scales, including initial hydro-meteorological conditions and large-scale climate variability modes (Doblas-Reyes et al., 2013; Emerton et al., 2018). . While the skill of seasonal climate forecasts is relatively low in the extra-tropics compared to other parts of the world (Doblas-Reyes et al., 2013), recent progress in forecasting European climate has resulted in skilful seasonal climate forecasts that support various climate services (e.g. Arheimer et al., 2020). For example, the European Flood Awareness System (EFAS) is at the forefront of operational streamflow forecasting in Europe, providing a pan-European service that aims to support preparatory action before major floods. The seasonal component of EFAS uses precipitation, temperature and evaporation from the ECMWF System 5 (SEAS5) seasonal prediction system to drive LISFLOOD, a physics-based distributed hydrological model that estimates hydrological states and fluxes with a daily time step (Arnal et al., 2018). Operationally, EFAS produces seasonal streamflow outlooks for Europe at the beginning of each month up to seven months ahead. Previous work using this setup suggests that skilful forecasts may be obtained for lead times up to one month ahead, but that skill decreases gradually thereafter (Arnal et al., 2018).

The conceptual and physics-based hydrological models used operationally are computationally intensive. Spatial downscaling and bias correction are needed to bridge the gap between the relatively coarse spatial scale of S2S climate prediction systems and the finer resolution inputs needed by hydrological models, introducing a layer of methodological uncertainty to the process-based seasonal hydrologic forecasting process. The hydrological forecast outputs may then require further bias-correction before they can be used (Yuan et al., 2015). In contrast, hybrid methods for seasonal streamflow forecasting overcome many of the shortcomings of dynamical approaches (Slater et al. 2023). Instead of using the downscaled outputs of dynamical seasonal prediction systems to drive a hydrological model, hybrid methods use dynamical climate predictions to drive statistical or machine-learning models to directly predict the target variables of interest – e.g. streamflow quantiles or flood frequency. The dynamical climate predictions provide valuable information on large-scale climate patterns and atmospheric conditions, while the statistical or machine-learning models offer the ability to capture complex nonlinear relationships related to streamflow behaviour. Such hybrid approaches follow from similar concepts used in empirical S2S hydrologic prediction, in which observed climate system variables, reanalyses or indices (but not dynamical climate forecasts) are used in statistical schemes to predict streamflow directly (e.g. Mendoza et al., 2017; Regonda et al., 2006).

By combining the strengths of both dynamical and statistical approaches, hybrid methods have shown promise for improving seasonal streamflow predictions. For example, Tian et al. (2022) developed a hybrid framework that skilfully predicted month-ahead reservoir inflows in two US watersheds (in Colorado and Alabama) using an ML model driven by seasonal climate forecasts, observed large-scale climate indices and satellite-based estimates of antecedent conditions. In Europe, Hauswirth et al. (2023) showed that a hybrid seasonal forecasting system could skilfully predict surface water level up to three months ahead using ML models driven by climate and hydrological inputs from SEAS5. Hybrid methods are unconstrained by the need to conserve the water balance and implicitly handle biases in the climate data (Slater et al., 2023). Further, they are able to exploit relationships between variables at different spatial and temporal resolutions and spatial extents – e.g. relating daily local streamflow quantiles to monthly climate inputs or large-scale climate patterns (Moulds et al., 2023; Tian et al., 2022).

Previous work using observed data has shown that ML models work best when trained on data from multiple catchments (Nearing et al., 2021). While much of the recent literature on this topic focuses on deep learning architectures (e.g. Kratzert et al., 2019), similar results have been found for tree-based models (e.g. Gauch et al., 2021). Multi-site approaches allow the models to learn relationships from a large sample of hydrological variability that encompasses a broad spectrum of catchment characteristics, which they can use effectively to make predictions in individual catchments (e.g. Lees et al., 2021). However, this has not yet been evaluated for seasonal flood prediction using ML models trained on climate forecasts.

Here we develop and test a hybrid system to predict the monthly maximum daily flow values (Q_{max}) at lead times up to four months for 579 catchments in the UK. We train a machine learning model to predict Q_{max} using seasonal forecasts of precipitation and temperature from the C3S multimodel as well as antecedent conditions and catchment characteristics. We focus on monthly maximum daily streamflow rather than other common S2S hydrologic predictands (e.g., monthly or seasonal average flow) because it serves as an indicator of future flood hazards at S2S lead times, recognizing that individual flood events (timing and magnitude) cannot be skilfully predicted beyond weather time scales. We address two main research questions: (i) How skilfully can we predict monthly maximum daily flow with up to four months lead time using uncorrected monthly dynamical climate forecasts and antecedent conditions? (ii) To what extent can we improve the skill of S2S streamflow predictions at individual sites by developing a multi-site machine learning model that leverages static catchment attributes to learn the hydrological behaviour at individual sites?

2 Materials and methods

2.1 Data

For the prediction target and observational validation dataset we used daily streamflow observations for Great Britain taken from the National River Flow Archive (NRFA, 2024). We first selected stations that had streamflow records between 1994 and 2016 to match the hindcast period of the climate models, before discarding stations with less than 95% data availability in any given year. We also discarded stations that are not included in the CAMELS-GB dataset (Coxon et al., 2020), leaving a total of 579 stations. We computed specific discharge (mm day^{-1}) by dividing the daily streamflow values by the catchment area, then calculated the monthly maximum daily specific discharge for all months and stations.

Monthly predictions of precipitation and temperature were obtained from the Copernicus Climate Change (C3S) multimodel seasonal forecasting system. We took seasonal reforecasts ("hindcasts") of precipitation and temperature for the period 1994-2016 from eight seasonal prediction systems, resulting in a large multimodel ensemble of 196 members (Table S1). We computed the multimodel ensemble mean values of precipitation and temperature. We found that including quantiles (0.05, 0.25, 0.5, 0.75, 0.95) drawn from the precipitation and temperature ensemble as additional covariates in the ML models did not improve skill (results not shown). All C3S forecasting systems are assigned a nominal start date of the first day of each month such that no members are initialized using observations later than this date, although the initialization method varies across the individual systems. In the text we refer to the predictions for the month immediately following initialization as having a lead time of zero (e.g. for a forecast initialized on August 1st, the zeroth lead time prediction covers August 1-31st). The C3S forecasting system predicts climate up to a minimum of 6 months ahead, but we focus on the first 4 months following initialization as we are unlikely to observe substantial skill for monthly predictands thereafter (e.g. Arnal et al., 2018; Harrigan et al., 2018). We computed the climate inputs for each catchment by taking the area-weighted average monthly value for each variable.

We used antecedent mean monthly streamflow as a proxy indicator of initial catchment soil moisture conditions, an important driver of seasonal hydrologic predictability (Arnal et al., 2018; Bierkens & Van Beek, 2009). We used the monthly mean specific discharge in the three months prior to the forecast initialization to create three predictor variables describing the mean specific discharge over one month, two months and three months prior to the nominal forecast initialization date, respectively. We also included estimates of antecedent precipitation using ERA5 reanalysis data, creating variables to represent the average precipitation over one month, two months and three months prior to the initialization time. Antecedent precipitation and streamflow both estimate initial hydrologic condition predictability, and are likely to be colinear predictors, to a degree. However, as random forests are robust to multicollinearity we chose to keep both predictors.

Multi-site ML models can benefit from additional information about the catchment characteristics (e.g. Lees et al., 2021, Slater et al., 2024). We added static catchment descriptors from the CAMELS-GB dataset (Table S3; Coxon et al., 2020) to our ML model. We also tried including streamflow signatures that describe the hydrologic behaviour of each catchment, including the baseflow index, slope of the flow duration curve, the 5th and 95th percentile of daily streamflow, and the mean daily streamflow. These were computed using data up to the start of the test period (2004) of our hybrid models, to avoid data contamination (i.e., the situation where a statistical or ML model is inadvertently trained on the same data it will later be tested on). However, although the signature predictors assumed high importance in the QRF model, they did not increase Q_{max} forecasting skill, suggesting that the model can learn these hydrological characteristics from the static catchment attributes alone. We therefore left out the streamflow signatures from the final multi-site model.

2.2 Methods

We employ quantile regression forests (QRF; Meinshausen, 2006) to predict the monthly maximum of mean daily streamflow (Q_{max}) using dynamic and static predictor variables. QRFs are a generalisation of random forests (Breiman, 2001) that estimate conditional quantiles from predictor variables, enabling probabilistic predictions of the dependent variable. Like traditional random forests, QRFs are adept at exploiting nonlinear relationships between dependent and independent variables and require relatively little tuning because their performance is less sensitive to the values of hyperparameters than can be the case with other ML methods (Tyralis et al., 2019). QRFs can also be interrogated to establish the relative importance of predictor variables.

We train the model directly on the climate forecast outputs to avoid introducing additional uncertainty by performing further post-processing of the dynamical climate forecasts. Similar to other forms of regression, the ML model implicitly performs bias correction by relating the raw climate inputs to observed streamflow (e.g. Slater et al. 2023; Slater and Villarini 2018). We compared three model structures to predict Q_{max} in each catchment (Table 1). First, we trained QRF models on each streamflow time series independently, giving a site-specific model for every catchment. We compared the single-site models with a multi-site QRF model that was trained on all (n=579) available streamflow time series data at once. To assess the extent to which the multi-site model learns from catchment attributes, we also include a multi-site model with the catchment ID as the only static attribute. Owing to the inherent robustness of random forest to potentially irrelevant predictors, whereby unimportant features are automatically assigned low weights, we do not perform predictor variable selection or screening.

In both single-site and multi-site approaches, a separate QRF model is trained for each lead time using all months from the training period. This is because the biases in the climate forecasts often change over time from initialization, so a model trained on climate forecasts with a lead time of one month would be unsuitable to make predictions using climate forecasts with a lead time of two months. We note that a similar approach is used for bias correcting seasonal climate forecasts (Crochemore et al., 2016). Thus, for each training period we obtain four models, trained on climate predictions with lead times of one, two, three and four months ahead, respectively. Dataset stratification choices are important in S2S prediction because predictability and prediction system biases typically vary seasonally and with lead time. There are strong geophysical reasons to tailor a statistical or empirical model using both factors, but each stratification dimension reduces the sample size available for training and testing, thus a trade-off is often adopted (e.g. Lehner et al., 2017). Here we do not stratify by initialization date (i.e., season). We construct an ensemble forecast by using the QRF model to predict the conditional quantiles of Q_{max} corresponding to probabilities between 0.01 and 0.99, with an interval of 0.02.

We use a forward-chain cross-validation approach whereby the models are trained on reforecasts from the previous *n* years and tested on the current year. For example, to predict all months in 2004, the first training period was taken as January 1994 to December 2003. For 2005, we then extended the training period by one year to December 2004, and continued adding one year until 2016, the final year in the test period, at which point the training period for the QRF models was January 1994 to December 2015.

We evaluated predictive skill using the continuous ranked probability score (CRPS) and associated skill score (CRPSS). The CRPS represents the error between the forecast and observed cumulative distribution functions (Wilks, 2019). It ranges between zero and infinity and is negatively oriented (i.e. smaller values are better), similar in concept to other common error terms (e.g., mean absolute error). We evaluated our forecasts against an observation-based ensemble climatological forecast consisting of the observed monthly streamflow values from the previous 20 years (e.g. Hauswirth et al., 2023). We used the CRPSS to evaluate the skill of our ML forecasts against the reference ensemble climatology. The CRPSS ranges between negative infinity and 1, where 1 indicates perfect skill and 0 or below indicates no skill compared to the reference forecast. We computed the CRPS of the forecast and reference for each month in the test period (2004-2016) and took the mean across individual months to compute the CRPSS.

We complemented the CRPS (CRPSS) with the anomaly correlation coefficient (ACC) and reliability index (RI). The ACC varies between -1 and 1, with a score of 1 representing perfect correlation between observed and forecast streamflow values. The RI is a probabilistic measure of the extent to which the forecast ensemble spread represents the uncertainty in observations. It varies between 0 and 1, with 1 denoting a perfectly reliable forecast. Like the CRPSS, we calculate the ACC and RI for every month and lead time separately. Lastly, we assessed the relative importance of the predictor variables using the Gini index, which measures the importance of individual variables in tree-based ML models. Specifically, the Gini index quantifies the extent to which a variable contributes to making homogeneous groups, where outcomes are similar and predictions are more reliable, while reducing impurity, indicating mixed groups with less predictable outcomes.

Table 1: Formulation of the three ML models used in the analysis. Precipitation and temperature are the monthly ensemble mean values from the C3S multimodel system. Antecedent precipitation is the forecasted precipitation from the month prior to the target month, with lead time varying between 1 and 3 months (i.e. to make a prediction in lead time 4 the antecedent precipitation would be taken from lead time 3). Antecedent streamflow is the mean daily observed streamflow prior to the forecast initialization. Catchment attributes are listed in Table S1.

Model name	**Configuration**	**Model description**
Single-site	Single-site	Precipitation, temperature, antecedent streamflow and precipitation
Multi-site with ID	Multi-site	Precipitation, temperature, antecedent streamflow and precipitation, catchment ID
Multi-site with attributes	Multi-site	As for single-site model , plus 15 static catchment attributes

3 Results

The multi-site model with catchment attributes significantly outperforms the multi-site model with the catchment ID alone (Figure 1a). This suggests that including static catchment attributes enables the model to better reproduce the hydrologic behaviour of different catchments, aligning with previous research for the UK on ML applied to daily streamflow simulation using observed climate inputs (e.g. Slater et al., 2024). Considering the skill scores for each lead time and combining all initialization months, the multi-site model with catchment attributes narrowly but significantly outperforms the single-site models at lead times of one to three months, with a similar average performance between the multi-site and single-site model for the zeroth lead time (Figure 1b). However, the relative performance of the multi-site model with attributes and the single-site model varies by forecast month and lead time (Figure S2). For the zeroth lead time, the multi-site model tends to outperform the single-site model in the months where the highest skill is observed (i.e. December, January, June, July).

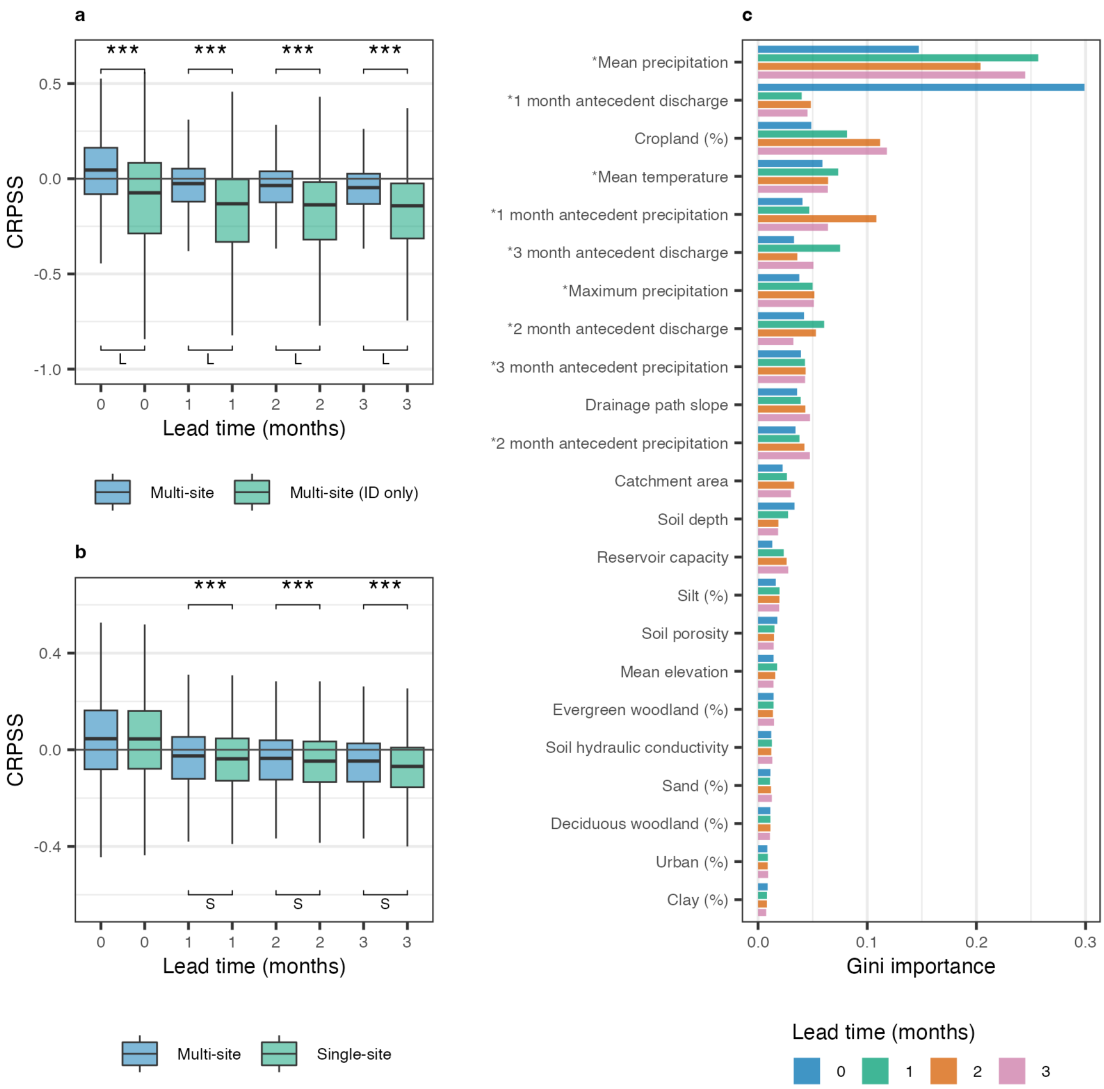

Figure 1: Analysis of model performance. **a.** Comparison of multi-site models with catchment attributes and with the catchment ID only. We used a two-sided Wilcoxon signed rank test to assess whether differences in skill scores between the models were significant (*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$). The effect size r is indicated at the bottom of each plot (S = small effect $0.10 \leq r < 0.3$; M = moderate effect $0.3 \leq r < 0.5$; L = large effect $r \geq 0.5$). **b**. Comparison of single-site model with multi-site model with catchment attributes. **c.** Relative importance of predictor variables in the multi-site model with catchment attributes for each lead time. Time-varying predictors are marked with an asterisk (e.g. *Mean precipitation).

We used the Gini index to assess the importance of each predictor variable to the multi-site model with catchment attributes at each lead time (Figure 1c). Monthly precipitation forecasts have high importance across lead times, while mean temperature forecasts have moderate importance. We included antecedent conditions from observed streamflow and forecast precipitation. Antecedent streamflow is the most important variable at one-month lead time but decreases with importance at later lead times. This is because we are limited to providing antecedent conditions prior to forecast initialization, which has decreasing relevance as the lead time increases, reflecting our general understanding of the influence of initial versus boundary conditions in S2S hydrologic forecasting (e.g. Wood et al., 2016).

We assessed skill by computing the monthly CRPSS using a climatological prediction as a reference. We find that there is significant variability in skill during the different months of the year (Figure 2), especially at shorter lead times. For lead time 0, we observed the highest skill in extended winter (DJFM) and late summer (JJAS), with lower skill during spring and autumn. In December and July more than 80% of stations have positive skill in lead time 0 (Table 2). In most months, the skill decreases sharply over time, whereas for other months (e.g. March) the skill remains relatively consistent as lead time increases. The variation in skill likely reflects the varying importance of antecedent conditions during the year, as well as the varying skill of the climate forecasts.

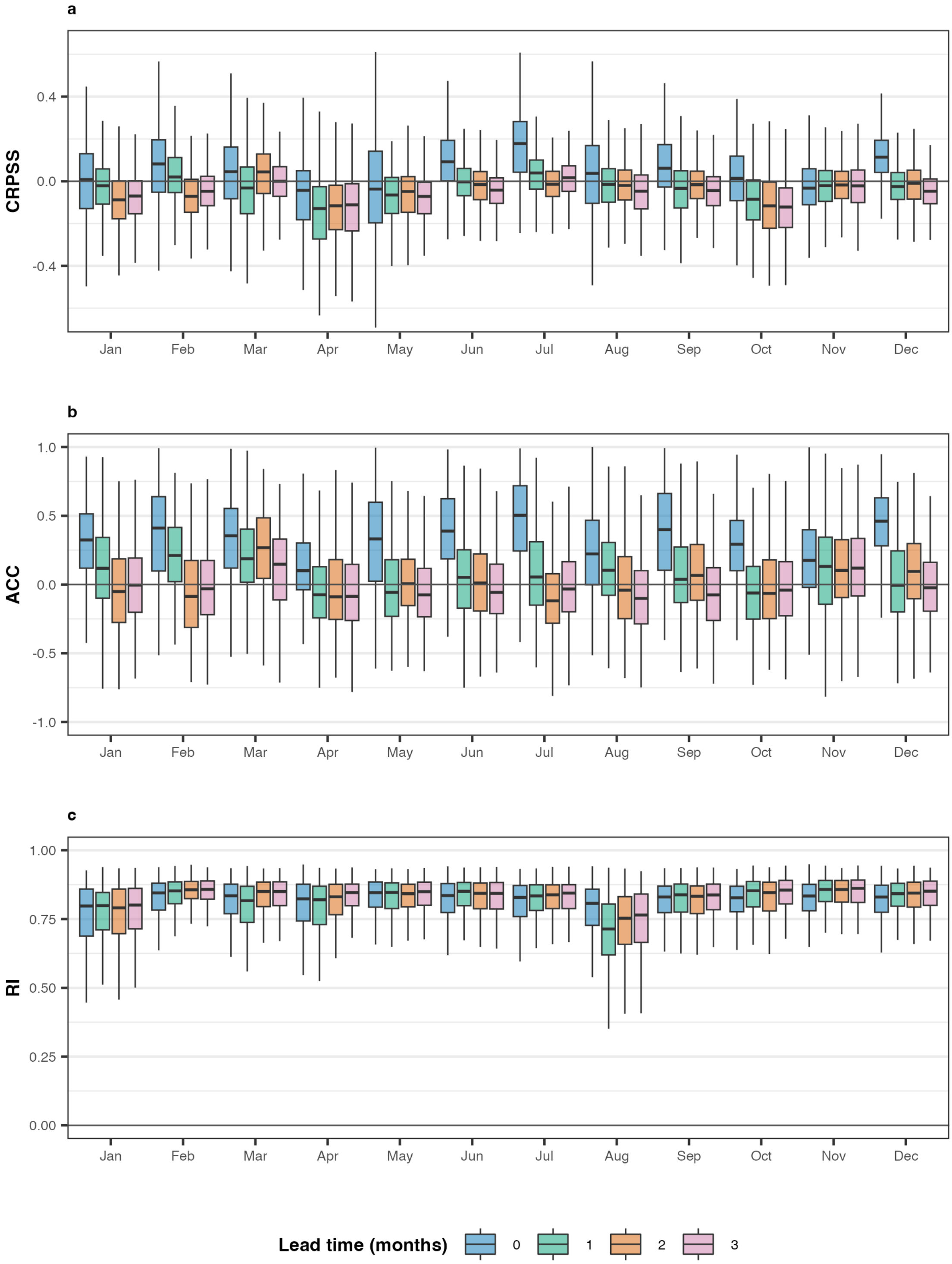

Figure 2: Performance assessment of the multisite model with catchment attributes for each forecast month and lead time. **a.** Continuous ranked probability skill score (CRPSS). We use climatological forecast as the reference forecast, which is computed separately for each test year in the simulation. **b.** Anomaly correlation coefficient (ACC). **c.** Reliability index (RI). The four lead times are shown with different colours.

We also compared our results to monthly Q_{max} drawn from daily EFAS predictions for a subset of the stations included in this study (n=188) that overlapped with the EFAS reference dataset. We bias corrected the EFAS outputs using a quantile mapping approach so that they could be compared with observations. As EFAS outputs daily streamflow estimates we took the maximum daily streamflow prediction from each month and used this value as the reference forecast to estimate CRPSS. Our results are skilful compared to EFAS (Figure S1), and this high relative skill, coupled with the general lack of positive skill of QRF forecast for lead times 1-3 months compared to a climatological reference, indicated that the EFAS predictions were poorer than expected as a benchmark for this particular monthly extreme predictand. We note that our model is specifically trained to predict Q_{max}, while EFAS seasonal forecasts are developed for more general purposes, such as supporting tercile probability forecasts for monthly or seasonal mean conditions, a common S2S hydrological product (e.g. Arnal et al., 2018).

As with the CRPSS, the ACC varies by forecast month and lead time (Figure 2b), with the monthly variability in ACC following a similar pattern to that of the CRPSS. In lead time 0, the ACC is positive in >75% of stations across all months. During lead time 1, the ACC is positive in >50% of stations in all months except April, May, and October. Compared to the CRPSS and the ACC the RI is more consistent across months and lead times (Figure 2c). Overall, our ensemble hindcasts have high reliability, with the mean RI across all stations exceeding 0.8 in all months except August.

Table 2: Percentage of stations (n=579) that are skilful (CRPSS>0) at each lead time and forecast month for the multi-site model with catchment attributes.

Forecast month	**Lead time**			
	0	**1**	**2**	**3**
January	51.7	42.2	25.3	26.3
February	66.1	59.2	28.0	29.4
March	58.8	42.2	62.3	50
April	38.4	19.2	22.0	20.8
May	46.0	29.8	33.6	24.4
June	76.1	48.3	44.3	31.0

July	81.1	64.5	41.7	59.3
August	56.4	44.3	42.6	33.6
September	67.1	38.2	43.8	31.7
October	53.8	26.6	23.5	18.9
November	40.1	41.3	42.2	42.2
December	83.4	40.0	45.5	28.2

We examined the spatial variability in model skill by averaging the monthly skill scores for the multisite model with catchment attributes within each season (Figure 3). At lead time 0 we observe skill in catchments across the UK, while at later lead times, skilful catchments tend to cluster in southern England. This could be related to the location of catchments with relatively slower responding catchments with greater subsurface storage in south-east UK. However, we found relatively weak correlation between ACC and the baseflow index (R=0.33, 0.31, 0.27, 0.25 for the four lead times). We observe a tendency for the QRF models to underestimate the observed Q_{max}, especially the more extreme values (Figure 4). The underestimation is more pronounced as lead time increases, likely due to greater noise in the seasonal climate forecasts at longer lead times.

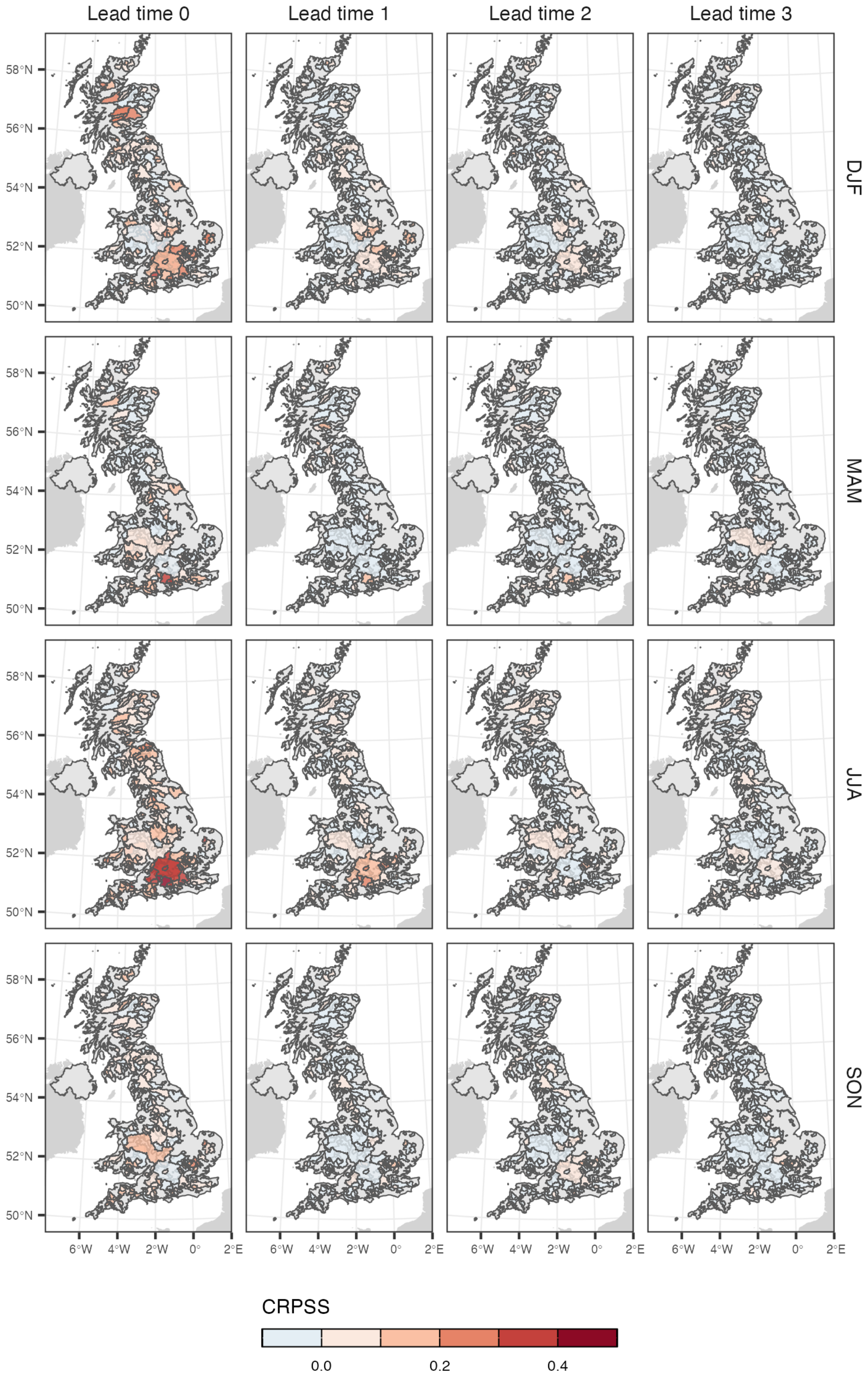

Figure 3: Average seasonal skill in every catchment by lead time. We calculate the CRPSS per month and catchment, then compute the seasonal average (DJF, MAM, JJA, SON).

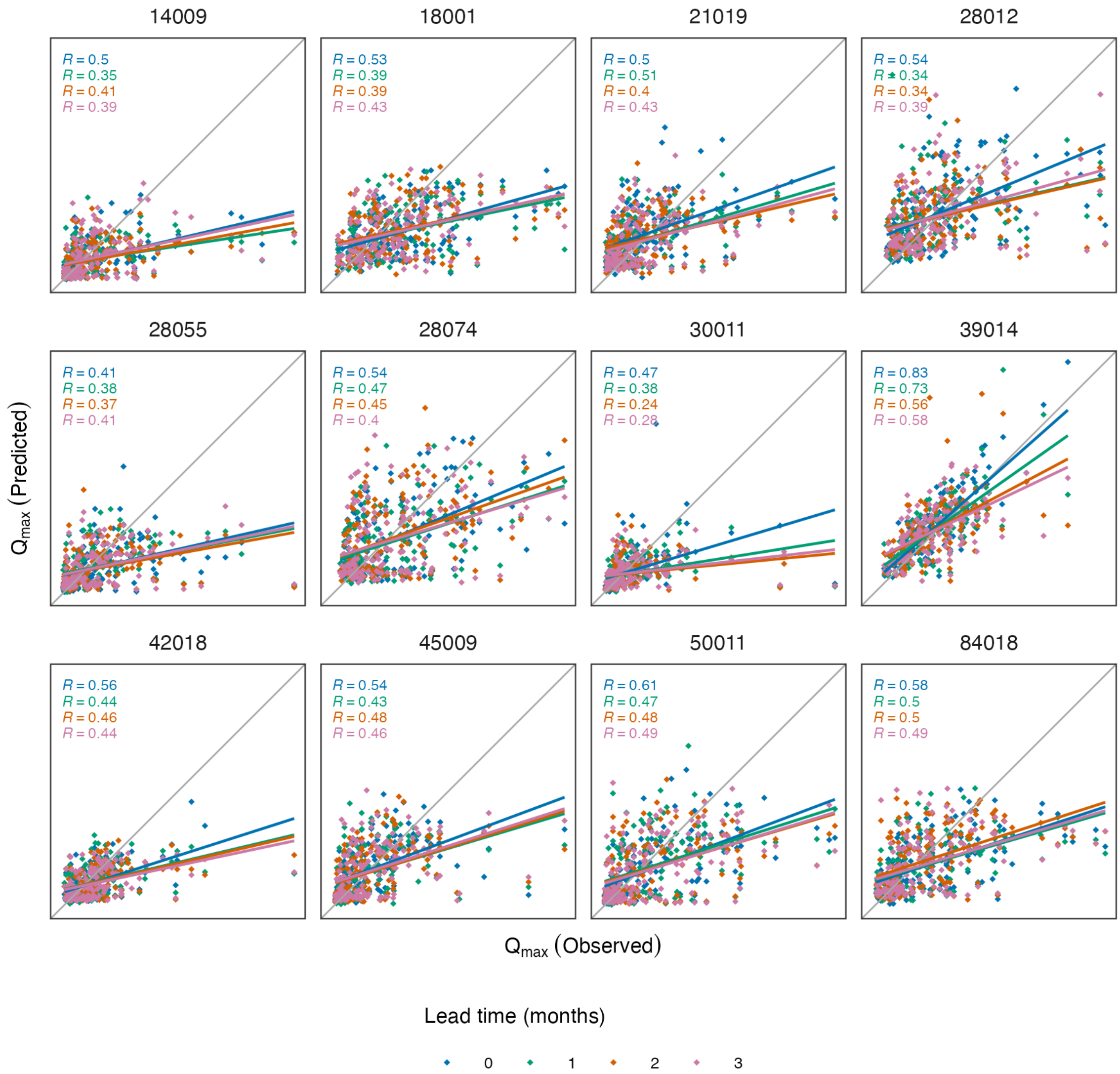

Figure 4: Comparison of observed and predicted Q_{max} across all months for 12 randomly selected catchments, by lead time.

4 Discussion

We developed a hybrid forecasting approach for UK flood risk prediction at subseasonal-to-seasonal time scales using a large multimodel ensemble of climate predictions. We found that S2S flood predictions are generally skilful (CRPSS>0) up to 1 month following initialization, although skill declines thereafter. However, 90 stations out of 579 retained positive skill in at least three months of the year for all four lead times. Across all initialization times, 60% of stations show positive skill compared to the climatological benchmark in the first month after initialization. This drops to 41% in the second month, 38% in the third month and 33% in the fourth month. The level of skill varies within the year, with some months generally more skilful than others. This is likely due to a combination of varying climate predictability and the varying importance of antecedent conditions to flood magnitude and frequency during the year. The underlying seasonal forecasts of precipitation and temperature are also most skilful at shorter lead times, although they retain some information at longer lead times.

Our work provides guidance on how to build hybrid streamflow prediction systems that combine ML with dynamical climate models. The key finding of our work is the outcome that a multi-site forecast, in which an ML model is trained on data from all catchments at once, tends to outperform single-site model forecasts across all lead times, which aligns with previous work on ML based modelling in hydrology (e.g. Kratzert et al., 2019). However, our work specifically looks at forecasting months ahead, whereas previous work has studied out-of-sample simulation or short-term prediction using observed meteorological or weather forecast inputs. This approach enables the ML model to combine information across time and space into a single model that is trained to discriminate a range of hydrological behaviours. The inclusion of static catchment attributes enables the model to learn the different rainfall-runoff behaviours across the catchments. This is especially important when using ML to predict extremes when training data is limited in time as it means the multi-site model will remain realistic over a larger range of conditions.

Hybrid prediction systems require training and testing partitions to evaluate the model performance, and different approaches exist to do this. We implemented a forward-chaining cross validation approach such that the model is never trained on data more recent than the test partition. This reproduces an operational setup as far as possible, where the model is never exposed to information from the future. However, one limitation of this approach for hindcast studies is that the relatively short hindcast period of the C3S multimodel ensemble (i.e. 1994-2016) means the smallest training partition may contain as few as 10 years of monthly data. Nevertheless, during model development we found that increasing the length of the training period by focusing on the predictions from the SEAS5 system, which has an extended hindcast period of 1981-2016, did not significantly enhance the performance of the QRF models (results not shown). Moreover, using a multi-site approach reduces the impact of the relatively short reforecast period by pooling data from many catchments to create a much larger training dataset than is used by single-site models (i.e. swapping space for time).

Our hybrid seasonal flood forecasts based on eight models from the C3S multimodel ensemble exhibit relatively low skill, as is also the case with traditional (i.e. process-based hydrological model) flood forecasting systems driven by C3S (e.g. Arnal et al., 2018). These findings suggest that the primary constraint on enhanced skill lies in the seasonal climate forecasts. Increasing the skill of climate forecasts is therefore a priority to achieve more useful seasonal streamflow forecasts. One area for further research is to develop ways of identifying ensemble members that are likely to be more skilful over a given time period. Selecting members based on their ability to reproduce large-scale climate patterns such as the NAO is one potential option that has proved successful in other applications (e.g. Dobrynin et al., 2022). Observed climate states, teleconnections and indices (e.g., describing El Nino, the Southern Oscillation, and other climate modes) may be similarly exploited in regions where they exert an influence on weather patterns. These patterns have been deployed in empirical hydrologic forecast systems for many years, while the operational outputs from climate forecast models remain a relatively less-explored source of predictability in hybrid approaches.

Operational services for seasonal streamflow forecasts have existed for over a century, offering highly skilled predictions in many parts of the world, and particularly when and where predictors with long persistence are present – such as snowpack or groundwater – as well as strong climate seasonality. Despite their successes, there is growing demand from stakeholders for improved seasonal flow prediction skill at times and in places where it has been more difficult to achieve, usually due to data limitations or hydroclimate considerations. This study illustrates that that a hybrid forecasting approach which is trained over a large-sample collections of watersheds may offer benefits for monthly to seasonal predictions of streamflow. In particular, our approach affords users significant flexibility to define target variables of interest (e.g. Q_{max}). We use static catchment attributes as predictor variables to allow the QRF model to learn the different relationships between hydroclimate input data and monthly maximum daily streamflow, demonstrating an ability to produce skilful seasonal forecasts of monthly flood risk up to four months ahead in a moderate fraction of the catchments studied. The use of a multi-site ML model that is trained on data from multiple catchments at once may help to alleviate the long-standing problem of small sample sizes when training seasonal predictions on individual sites alone.

Acknowledgements

SM and LJS were supported by UKRI FLF grant MR/V022008/1. LJS was additionally supported by NERC grant NE/S015728/1. AW was supported by the United States Army Corps of Engineers Climate Preparedness and Resilience Program and the United States Bureau of Reclamation Science and Technology Program. The authors would like to acknowledge the use of the University of Oxford Advanced Research Computing (ARC) facility in carrying out this work (http://dx.doi.org/10.5281/zenodo.22558) and the UK National River Flow Archive (NRFA) for providing historical daily streamflow time series across Great Britain. We are grateful to Christel Prudhomme, Shaun Harrigan and Michel Wortmann at ECMWF for sharing the latest EFAS reforecasts.

Data availability statement

The input data and scripts that are needed to reproduce the results of this study will be uploaded to a research data repository under an MIT license upon acceptance for publication. They can be made available to reviewers upon request.

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Supplementary materials for

Skilful probabilistic predictions of UK floods months ahead using machine learning models trained on multimodel ensemble climate forecasts

This file contains 2 figures (Figure S1—2) and 3 tables (Tables S1—S3)

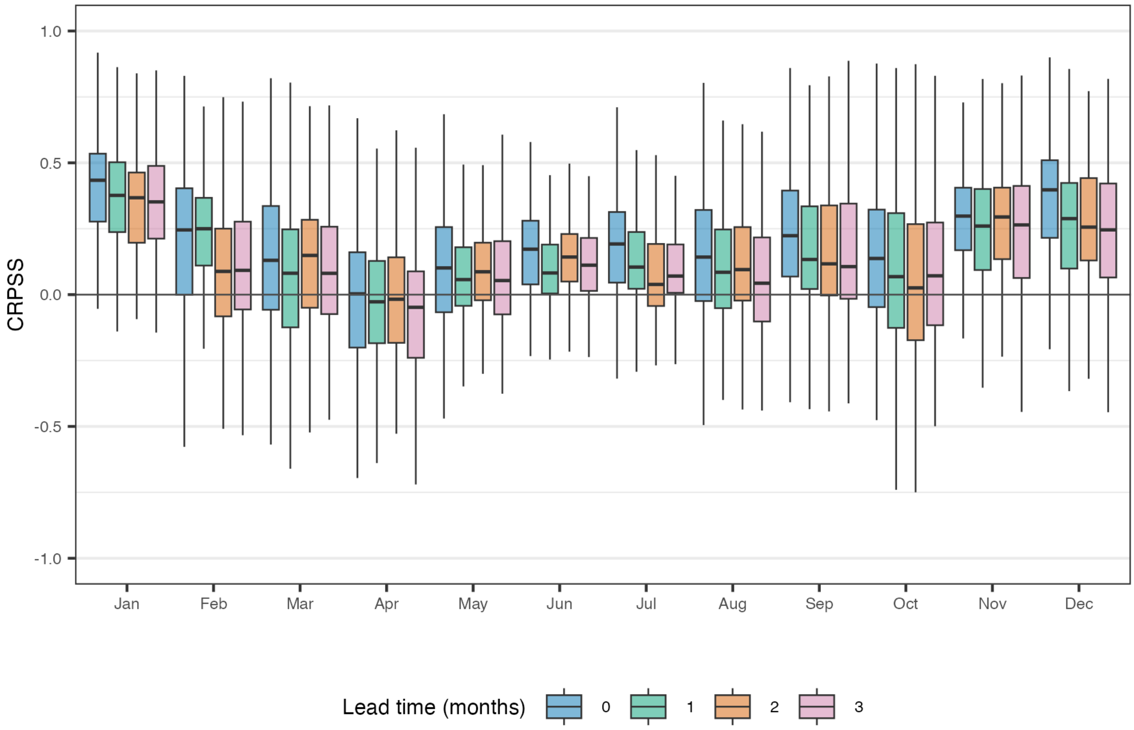

Figure S1: Continuous rank probability skill score of the multisite model with catchment attributes using bias-corrected EFAS hindcasts as a benchmark.

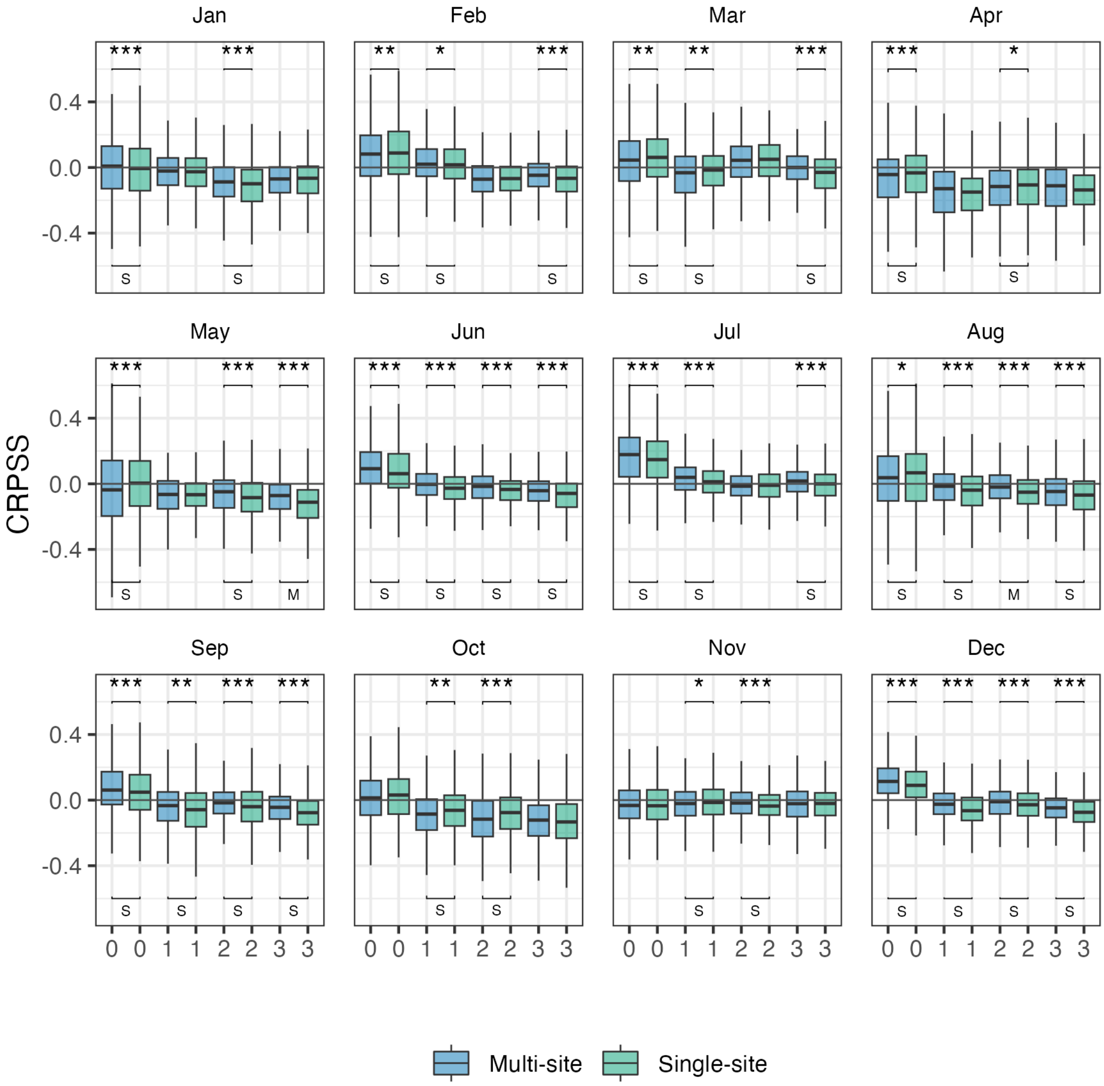

Figure S2: Comparison of CRPSS values for all forecast locations between the single-site model and multi-site model with catchment attributes by month. The skill score used a reference forecast of climatology. We used a one-sided Wilcoxon signed rank test to assess whether differences in skill scores between the models were significant (*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$). The effect size r is indicated at the bottom of each plot (S = small effect $0.10 \leq r < 0.3$; M = moderate effect $0.3 \leq r < 0.5$; L = large effect $r \geq 0.5$).

Table S1: S2S prediction systems used in the analysis.

Forecast centre	Model	Ensemble size
NCEP	CFSv2	28
CMCC	CMCC-CM2	40
DWD	GCFS2.1	30
ECCC	GEM5-NEMO	10
Met Office	HadGEM3	25
ECMWF	SEAS5	28
Météo-France	System8	25
JMA	CPS3	10

Table S2: Dynamical predictor variables used in the ML models.

Variable	Description
Precipitation	Reforecast precipitation (1994-2016)
Temperature	Reforecast temperature (1994-2016)
Antecedent precipitation	Antecedent precipitation, drawn from forecasts of the month prior to the target month
Antecedent streamflow	Antecedent streamflow, drawn from observations of the month prior to forecast initialisation

Table S3: Static catchment descriptors included in the multi-site model with catchment attributes. Median and range are computed from the subset of 580 basins used in our analysis. All indices were drawn from CAMELS-GB (Coxon et al., 2020). Median and range are given for the 579 catchments included in our study.

Variable	**Description**	**Median**	**Range**
area	Catchment area (km2)	157	[2, 9931]
elev_mean	Mean elevation (masl)	177	[32, 682]
dpsbar	Slope of the catchment mean drainage path (m km-1)	86	[11, 488]
sand_perc	Percent sand (%)	43	[19, 86]
silt_perc	Percent silt (%)	30	[9, 42]
clay_perc	Percent clay (%)	23	[4, 50]
porosity_hypres	Soil porosity from hypres pedotransfer function (-)	46	[32, 81]
conductivity_hypres	Soil conductivity from hypres pedotransfer function (cm h-1)	1.39	[0.60, 3.13]
soil_depth_pelletier	Depth to bedrock (m)	1.23	[0.6, 42]
dwood_perc	Percent cover of deciduous woodland (%)	6	[0, 37]
ewood_perc	Percent cover of evergreen woodland (%)	2	[0, 93]
crop_perc	Percent cover of cropland (%)	10	[0, 88]
urban_perc	Percent cover of urban (%)	3	[0, 83]
reservoir_cap	Reservoir capacity (ML)	0	[0, 8×10^7]