Benchmarking Ensemble Streamflow Prediction skill in the UK

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Abstract. Skilful hydrological forecasts at sub-seasonal to seasonal lead times would be extremely beneficial for decision-making in water resources management, hydropower operations, and agriculture, especially during drought conditions. 10 Ensemble Streamflow Prediction (ESP) is a well-established method for generating an ensemble of streamflow forecasts in the absence of skilful future meteorological predictions, instead using Initial Hydrological Conditions (IHCs), such as soil moisture, groundwater, and snow, as the source of skill. We benchmark when and where the ESP method is skilful across a diverse sample of 314 catchments in the UK and explore the relationship between catchment storage and ESP skill. The GR4J hydrological model was forced with historic climate sequences to produce a 51-member ensemble of streamflow hindcasts. 15 We evaluated forecast skill seamlessly from lead times of 1-day to 12-months initialised at the first of each month over a 50-year hindcast period from 1965-2015. Results showed ESP was skilful against a climatology benchmark forecast in the majority of catchments across all lead times up to a year ahead, but the degree of skill was strongly conditional on lead time, forecast initialisation month, and individual catchment location and storage properties. UK-wide mean ESP skill decayed exponentially as a function of lead time with continuous ranked probability skill scores across the year of 0.75, 0.20, and 0.11 20 for 1-day, 1-month, and 3-month lead times, respectively. However, skill was not uniform across all initialisation months. For lead times up to 1-month, ESP skill was higher than average when initialised in summer and lower in winter months, whereas for longer seasonal and annual lead times skill was higher when initialised in autumn and winter months and lowest in spring. ESP was most skilful in the south and east of the UK, where slower responding catchments with higher soil moisture and groundwater storage are mainly located; correlation between catchment Base Flow Index (BFI) and ESP skill was very strong 25 (Spearman's rank correlation coefficient = 0.90 at 1-month lead time). This was in contrast to the more highly responsive catchments in the north and west which were generally not skilful at seasonal lead times. Overall, this work provides a scientifically defensible justification for when and where use of such a relatively simple forecasting approach is appropriate in the UK and creates a low cost benchmark against which potential skill improvements from more sophisticated hydro-meteorological ensemble prediction systems can be judged.

1 Introduction

Skilful hydrological forecasts at sub-seasonal to seasonal lead times would provide a valuable tool for improved decision making for wide range of sectors such as water resources management (Anghileri et al., 2016), hydropower operations (Hamlet et al., 2002), and agriculture (Letcher et al., 2004), particularly in times of slow onset events such as drought (Simpson et al., 2016). One of the earliest operational hydrological forecasting methods is Ensemble Streamflow Prediction (ESP). ESP was pioneered in the US at the National Weather Service (NWS) during the 1970s and 1980s as a means of providing ensemble forecasts of streamflow for a variety of lead times from 1-day to seasonal and beyond (Day, 1985; Twedt et al., 1977; originally stood for Extended Streamflow Prediction). Two years of severe drought in California in 1976 and 1977 provided the motivation for such hydrological forecasting developments at the time (Wood et al., 2016b). In the UK, the 2010-2012 drought in England and Wales provided the impetus for the establishment of the first operational seasonal hydrological forecasting service, the Hydrological Outlook UK (HOUK), that went live in June 2013 (Prudhomme et al., 2017 ; forecasts available at: http://www.hydoutuk.net/). ESP is used as one of three hydrological forecasting methods in HOUK and also feeds into the Environment Agency's monthly 'Water Situation Report for England' (operational for groundwater levels in March 2012), providing forward look ESP forecasts of streamflow for 29 catchments out to a 12-month lead time (https://www.gov.uk/government/collections/water-situation-reports-for-england).

In the traditional formulation of ESP, as used in this paper, historical sequences of climate data (precipitation, potential evapotranspiration, and/or temperature) at the time of forecast are used as forcing to hydrological models, providing a plausible range of representations of the future streamflow states. The source of ESP skill is therefore due to Initial Hydrologic Conditions (IHCs) from antecedent stores of soil moisture, groundwater, snowpack, and channel streamflow itself (Wood et al., 2016a; Wood and Lettenmaier, 2008) which can be detectable up to a year ahead (Staudinger and Seibert, 2014), rather than from skilful atmospheric forecasts. The original operational concept of the NWS ESP forecasting system was that it was flexible, easy to use, and could be run efficiently using simple conceptual hydrological models (Day, 1985). Traditional ESP, while simple, is still widely used today in operational seasonal hydrological forecasting (e.g. US NWS and HOUK) and as a low cost forecast against which to benchmark potential skill improvements from more sophisticated hydro-meteorological ensemble prediction systems (e.g. Arnal et al., 2017; Crochemore et al., 2017; Pappenberger et al., 2015; Thober et al., 2015; Wood et al., 2005).

Several studies have established the skill of the ESP method for catchments in particular regions based on carefully constructed hindcast experiments. For example, in the western US, Franz et al. (2003) found ESP forecasts in 14 snow dominated catchments were, on average, skilful (compared to benchmark climatology forecasts) with a lead time up to 7-months, particularly when initialised early in the spring snowmelt season. Wood and Lettenmaier (2008) found that information about IHCs was more important than climate information during the transition between wet and dry seasons in two western US catchments up to a 5-month lead time. For non-snow dominated catchments in the south east of the US, Li et al. (2009) showed that harnessing the long memory of soil moisture and groundwater stores can provide skilful ESP forecasts, as the

impact of anomalous dry or wet conditions can take weeks or months to dissipate. Wang et al. (2011) found simple conceptual rainfall-runoff models were able to reliably estimate conditional catchment IHCs in two east Australian catchments, subsequently producing ESP forecasts of comparable skill to the current operational Bayesian Joint Probability statistical forecast system (BJP, Wang et al., 2009) at 1- and 3-month lead times. More recently, Singh (2016) assessed the potential for long-range ESP forecasting for integrated water management in four catchments (two rainfall dominated and two snowfall dominated) in South Island New Zealand and found ESP to be skilful out to a 3-month lead time, with greatest improvements over climatology forecasts in summer. The previous studies demonstrate that the traditional ESP method is skilful at both short and long lead times in many regions around the world and given its relative ease of application and low computational cost remains a valuable ensemble hydrological forecasting approach. Although ESP is being used operationally within the UK, its skill has not yet been investigated at the catchment-scale within a rigorous hindcast experiment and is therefore the focus of this paper.

By definition, a forecast can only be considered *skilful* if it is more accurate against observations than some simpler and/or cheaper reference or *benchmark* forecast (Jolliffe and Stephenson, 2003; Wilks, 2011). Pappenberger et al. (2015) identified three classes of benchmark forecasts commonly used in hydrological forecasting: (i) climatology, used for seasonal forecasting, (ii) persistence, used for short range forecasting, and (iii) simplified hydrology models, for testing whether more complex models provide useful skill gains. We define the process of *benchmarking* as establishing the skill of a forecasting system (here ESP) against a simpler benchmark forecast across various lead times, forecast initialisation months, and for a large sample of diverse catchments within the study domain. Consequently, the aim of this paper is to establish the skill of the traditional ESP method for forecasting streamflow in the UK at the catchment-scale using (streamflow) climatology as the benchmark forecast within a rigorous 50-year hindcast study design. Three key research questions emerge:

1. When is ESP skilful, in terms of a wide range of lead times and forecast initialisation months?
2. Where is ESP skilful, in terms of spatial distribution of skilful forecasts both regionally and at the individual catchment-scale across the UK?
3. Why is ESP skilful, in terms of individual catchment storage capacity?

Section 2 describes the hydroclimatic data used and the selection of catchments, Sect. 3 outlines the methods leading to the generation of ESP hindcasts. Results are presented in Sect. 4 and discussed in Sect. 5, before key conclusions and avenues for further work are offered in Sect. 6. Details about how to access the ESP hindcast archive used in this study as well as supplementary data and figures are given in Sect. 7.

2 Data

We selected a set of 314 catchments for our ESP evaluation from the UK National River Flow Archive (NRFA; http://nrfa.ceh.ac.uk/) chosen to be representative of the range of UK hydroclimatic conditions and ensuring good spatial coverage (Fig. 1). These catchments include those used for routinely assessing the current and future UK hydrological status

(e.g. National Hydrological Monitoring Programme, 2017) as well as 128 catchments that are part of the new version of the UK Benchmark Network (UKBN2; Harrigan et al., 2017) that can be considered relatively free from human disturbances such as water abstractions, urbanisation, and reservoir impacts. Individual details of all 314 catchments are given in supplementary Table S1.

5   Observed catchment average daily mean streamflow Q (m^3 s^{-1}), daily precipitation P (mm d^{-1}), and daily potential evapotranspiration ET_p (mm d^{-1}) were extracted for each catchment and are needed for three tasks: i) as input to the hydrological model calibration (Q, P, and ET_p; Sect. 3.1); ii) to generate historic climate sequences (P and ET_p, Sect. 3.2) used as forcing to the ESP method; and iii) as forcing to the reference simulation (P and ET_p; i.e. proxy observations in Section 3.3).

Q was retrieved from the NRFA over the longest possible period of observed Q across the 314 stations, 32 water years

10   from 1983 to 2014 (water year from 1 October to 30 September referred to by the calendar year in which it ends). P was retrieved from the 1 km gridded CEH-GEAR dataset (Keller et al., 2015; Tanguy et al., 2016) between 1961 and 2015 for the UK. ET_p according to Penman-Monteith for FAO-defined well-watered grass was retrieved from the 1 km gridded CHESS-PE dataset (Robinson et al., 2016, 2017) between 1961 and 2015 for catchments in Great Britain. CHESS-PE does not cover Northern Ireland, so an alternative 5 km ET_p dataset for the UK based on the temperature-based McGuinness-Bordne equation

15   was used instead for these 10 catchments (Tanguy et al., 2017).

Catchment characteristics are summarised in Table 1 for the UK and nine hydroclimate regions as shown in Fig. 1 inset. The nine UK Hydroclimate Regions were derived by merging contiguous UK hydrometric areas (National River Flow Archive, 2014) that reflect broad hydrological and climatological similarity across the UK and are used for aiding interpretation of results. The distribution of the 314 catchments within the nine regions varies between 10 in Northern Ireland (NI) and 59 in

20   Southern England (SE). Catchment areas range from 4.4 km^2 to 9948 km^2 with a median area of 181 km^2. There is a distinctive hydroclimatic gradient in the UK with wetter more responsive upland catchments in the north and west, and drier lowland catchments in the south and east, many of which drain the principal Chalk and Limestone aquifers. The slow flow contribution from groundwater and other delayed sources, such as lakes, snow, and soil water storage, was characterised using the Base Flow Index (BFI; Gustard et al., 1992) obtained from UK NRFA metadata. BFI ranges between 0 and 1 with values ~0.15-

25   0.35 representative of more responsive rainfall-runoff regimes in the north and west whereas many Chalk rivers in the south east have a BFI ≥ 0.9. Three regions (Severn-Trent (ST), Anglian (ANG) and SE) have median runoff-ratios (RR) < 0.5 meaning more precipitation is lost to evaporation than runoff in the majority of these catchments. Less than 5 % of catchments have a significant amount of snowfall, defined here following Berghuijs et al. (2014) as catchments with a long-term mean fraction of precipitation falling as snow $\bar{F}_s > 0.15$, and are mainly situated in Eastern Scotland (ES). The range of these

30   hydroclimatic characteristics provide a large and diverse set of catchments to benchmark ESP skill.

3 Methods

3.1 Hydrological modelling

The first of four key methodological steps was to calibrate and evaluate the GR4J (Génie Rural à 4 paramètres Journalier) model (Perrin et al., 2003) used for the generation of streamflow series. It is a daily lumped catchment rainfall-runoff model with a parsimonious structure consisting of four free parameters that require calibration against steamflow observations using daily P and ET_p as input. GR4J has been shown to reliably simulate the hydrology of a diverse set of catchments (Perrin et al., 2003) including temporal transition between wet and dry periods (Broderick et al., 2016), and for the generation of ESP forecasts (e.g. Pagano et al., 2010). The GR4J structure includes a soil moisture accounting reservoir (capacity controlled with parameter X1 [mm]) with a water exchange function (rate controlled by parameter X2 [mm d^{-1}]), and a non-linear routing store to represent baseflow (capacity determined by parameter X3 [mm]), with rainfall-runoff time lags (set in days by parameter X4 [d]) controlled by two unit hydrographs.

GR4J was calibrated using the open source 'airGR' package v1.0.2 in R (Coron et al., 2016, 2017) with the inbuilt calibration optimisation algorithm based on a steepest descent local search procedure and default parameter ranges. The modified Kling-Gupta Efficiency (KGE$_{mod}$; Gupta et al., 2009, Kling et al., 2012) applied to root squared transformed flows KGE$_{mod}$[sqrt] was used as the objective function for automatic fitting, thus placing weight on mid-range flows, rather than high or low flows. This was decided given ESP forecasts are made across the year during both dry and wet conditions. A split sample test (Klemeš, 1986) was used by dividing the 32 year complete period (CP; water years 1983-2014) of available streamflow observations into two equal 16 year segments for calibration and evaluation: period 1 (P1; water years 1983-1998) and period 2 (P2; water years 1999-2014). Three calibrated GR4J parameter sets were created for each catchment using data from P1, P2, and CP, thus allowing testing of parameter stability between P1 and P2. Model performance against streamflow observations was evaluated using KGE$_{mod}$[sqrt], the Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970), and percent bias (PBIAS; Gupta et al., 1999) to assess water balance errors.

The UK-wide median (5th and 95th percentile) KGE$_{mod}$[sqrt] is 0.94 (0.83, 0.97) for calibration (CP) and for evaluation 0.92 (0.80, 0.96) and 0.92 (0.78, 0.96) for P1 and P2, respectively (Table 2). Median PBIAS across all catchments over CP is low, -0.1 % (-3.7 %, 0.7 %). Overall, GR4J performs well against streamflow observations and parameter sets remain stable across P1 and P2 with comparable performance to Crochemore et al. (2017) and Poncelet et al. (2017) using GR6J for catchments across France, Germany, and Austria. For completeness and comparison with other works, the NSE was calculated as it is the most universally used metric. Spatial maps and summary statistics for KGE$_{mod}$[sqrt] and NSE are provided in supplementary Fig. S1 and, notwithstanding differences in study design, results for GR4J are on par with other large-sample catchment modelling studies in the UK (e.g. Crooks et al. (2009) using the Probability Distributed Model (PDM; Moore, 2007) for 120 catchments). All streamflow simulations (proxy observations, and benchmark and ESP forecasts) were generated using model parameter sets calibrated over CP and with KGE$_{mod}$[sqrt] as objective function; median and ranges of calibrated parameter

values for GR4J X1,…,X4 across the UK and nine hydroclimate regions are given in Table 2 and for individual catchments in supplementary Table S1 along with respective performance metrics.

3.2 Generation of ESP hindcasts from historic climate data

In step 2, Initial Hydrologic Conditions (IHCs) were estimated for each catchment and forecast initialisation date by forcing the calibrated GR4J model with four years of observed P and ET_p previous to the forecast initialisation date, over the 1961 to 2015 period, thus the first usable forecast date after model spin up is 1 January 1965. Secondly, a 51-member ensemble m of streamflow hindcasts was generated for each forecast initialisation date (first of each month) by forcing GR4J with 51 historic climate sequences (P and ET_p pairs) extracted from 1961 to 2015 out to a 12-month lead time at a daily time-step. Each of the 51 generated hindcast time-series were then temporally aggregated to provide a forecast of mean streamflow over seamless lead times of 1-day to 12-months, resulting in 365 lead times per forecast (leap days were removed). Following convention in the HOUK, lead time (LT) in this paper refers to the streamflow (expressed as mean daily streamflow) over the period from the forecast initialisation date to n days/months ahead in time. So a January ESP forecast with 1-month lead time is the mean daily streamflow from 1 January to the end of January and a January forecast with 2-month lead time is the mean daily streamflow from 1 January to the end of February.

Although it is not possible to create a hindcast experiment under exactly the same conditions experienced in operational mode, effort was made to ensure historic climate sequences did not artificially inflate skill (see Robertson et al., 2016) by using leave-3-years-out cross-validation (L3OCV) whereby the 12-month forecast window and the two succeeding years were not used as climate forcings. This was done to account for persistence from known large-scale climate-streamflow teleconnections such as the North Atlantic Oscillation with influences lasting from several seasons to years (Dunstone et al., 2016). Because this climate information could be an advantage, but is not available in operational forecasting, it was not used in the hindcast experiment. Using the first forecast on 1 January 1965 as an example, 51 sequences of P and ET_p pairs of length 365 days (from 1 January to 31 December) were extracted from observed P and ET_p records between 1961 to 2015, but not for 1965, 1966, or 1967. To keep a 51-member ensemble across all hindcast years, forecasts made in 2013 and 2014 did not have enough data for L3OCV so in these cases climate sequences from 1961, and 1961 and 1962, respectively were instead removed. The skill of ESP was evaluated over a 50-year hindcast period N between 1965 and 2015 for each of 12 initialisation months i (January to December) and all 365 LTs. In total, 600 hindcasts were generated ($N \times i$) with 51 ensemble members each at 365 LTs across 314 catchments resulting in over 3.5×10^9 forecast values of streamflow in the ESP hindcast archive.

3.3 Creation of proxy streamflow observation series

In step 3, a proxy streamflow observation series was produced by forcing the calibrated GR4J model with observed P and ET_p over 1961-2015 with a four year model spin-up. A four year model spin up ensures model states are appropriately stabilised, especially important for slower responding catchments (e.g. in Southern England and Anglian regions). The proxy observation series, the best estimate of streamflow observations given current model and observed meteorological data, is used

to evaluate ESP forecasts against. It is common to use this approach instead of using direct streamflow observations as it has the advantage of isolating loss of skill to IHCs rather than from model errors and biases (e.g. Alfieri et al., 2014; Pappenberger et al., 2015; Wood et al., 2016a; Yossef et al., 2013).

3.4 Evaluation of ESP skill

In step 4, forecast skill is presented as a skill score, which is the improvement over the benchmark forecast using some measure of accuracy A, given generically by Wilks (2011) in Eq. (1):

$$\text{Skill Score} = \frac{A_{fc} - A_{bench}}{A_{perf} - A_{bench}}$$

(1)

where A_{fc} is the accuracy measure of the hydrological forecasting system Q_{fc} (here ESP) against observations Q_{obs*} (here *proxy observations); A_{bench} is the accuracy measure of the benchmark forecast Q_{bench} against Q_{obs*}, and A_{perf} is the value of A in the case of a perfect forecast (typically 1 or 0 depending on metric). For each forecast made over the hindcast period the probabilistic skill of the full ESP 51-member ensemble forecast Q_{fc} was evaluated against a probabilistic climatology benchmark forecast Q_{bench} calculated as the full sample climatological distribution of proxy streamflow observations over 1965-2015 for the forecast period. Similar to the historic climate forcing sequences in Sect. 3.2, the probabilistic climatology benchmark forecast was also created using L3OCV to account for persistence known to occur for several years in streamflow, particularly during drought (Wilby et al., 2015). In testing, we performed the skill evaluation with and without cross-validation of ESP forecasts and streamflow climatology benchmark forecasts. It was found that cross-validation was important as in some cases failing to cross-validate ESP forecasts inflated skill scores whereas failing to cross-validate climatological benchmark forecasts deflated skill scores (i.e. the benchmark forecast was advantaged thereby disadvantaging ESP forecasts), in some cases skill scores were advantaged/disadvantaged by +/-15 %.

The continuous ranked probability score (CRPS) (Hersbach, 2000) accuracy measure A, and corresponding skill score (CRPSS), was used for evaluating the probabilistic skill of ESP. The CRPS penalises biased forecasts and those with low sharpness (Wilks, 2011). The Ferro et al. (2008) ensemble size correction for CRPS was applied to account for differences between the number of members in Q_{fc} (period 1961-2015 → L3OCV → $n = 51$) and Q_{bench} (period 1965-2015 → L3OCV → $n = 47$), as done in evaluation of hydrological ensemble forecasting elsewhere (e.g. Crochemore et al., 2017). Calculation of skill scores was undertaken using the open source 'easyVerification' package v0.4.2 in R (MeteoSwiss, 2017).

The CRPS is one of the most recommended scores for evaluation of overall hydrological ensemble forecast performance (Pappenberger et al., 2015). However, several commonly used metrics were also calculated for evaluation of deterministic ESP performance (using the ESP ensemble mean): Pearson correlation coefficient (Cor.), the mean squared error skill score (MSESS), and the deterministic equivalent to CRPSS, the mean absolute error skill score (MAESS). The pattern of results in terms of where and when ESP is most/least skilful was found to be independent of chosen metric, with virtually identical results between probabilistic (using CRPSS) and deterministic (using MAESS) results (see supplementary Fig. S2), and so for

brevity the remainder of paper is based on CRPSS only. A Skill Score of 1 indicates a perfect forecast, a Skill Score > 0 shows the ESP forecast is more skilful than the benchmark, a Skill Score = 0 shows ESP is only as accurate as the benchmark, and a Skill Score < 0 warns that ESP is inferior to the benchmark forecast. The CRPSS was applied to the 314 catchments for the 12 initialisation months and 365 lead times for each year over the 50-year hindcast period.

4 Results

Results are presented in the following order: First, ESP skill is shown for all 365 lead times (LT), then by forecast initialisation month for a sample of eight representative LTs commonly used in operational hydrological forecasting (i.e. short (1- and 3-days), extended (1- and 2-weeks), monthly (1-month), seasonal (3- and 6-months), and annual (12-months)). Second, the spatial distribution of ESP skill is shown, both averaged across the UK and each of the nine hydroclimate regions, then for individual catchments to explore sub-region heterogeneity. Third, the relationship between catchment storage and ESP skill is assessed.

Reducing accuracy of a forecast to a numeric skill metric value is abstract and difficult to interpret. Throughout the results and discussion sections skill score values are assigned qualitative descriptions according to degree of skill based on the CRPSS: Very High [0.75, 1]; High [0.5, 0.75); Moderate [0.25, 0.5); Low (0, 0.25); No Skill = 0, and Negative Skill < 0; CRPSS values which are near zero, defined between ± 0.05, are regarded as 'neutrally skilful' (after Bennett et al., 2017). Five example 1965-2015 hindcast time-series with skills ranging from very high to negative skill are visualised in Fig. 2 and act as a graphical reference in the remainder of the paper to aid interpretation of skill.

4.1. Timing of ESP skill

4.1.1 Lead time

UK-wide mean ESP skill across all catchments and initialisation months decays exponentially as a function of lead time (Fig. 3). Mean CRPSS values from short (1-day) to extended (2-week) lead times range from 0.75 to 0.30, and across monthly, seasonal (3-month), and annual lead times from 0.20, 0.11, to 0.04, respectively. There is large spread around mean skill scores for any lead time, depicted by the semi-transparent 5th and 95th percentile bands across the 314 catchments in Fig. 3. For example, at a 2-week lead time CRPSS values are bound between 0.11 and 0.71, and for monthly lead times between 0.06 and 0.59. Skill scores for the deterministic ESP ensemble mean (measured by MAESS) are virtually the same as those for probabilistic forecasts (measured by CRPSS) for all lead times and regions (see Fig. S2c and d).

4.1.2 Initialisation month

ESP skill varies depending on forecast initialisation month (IM), and the time-of-year with highest and lowest skill is conditional on lead time. Figure 4 shows skill scores for initialisation months January to December for short and extended lead

times (LTs) as summarised by boxplots across all catchments. Skill scores for these four sample LTs (1-day, 3-day, 1-week, and 2-week) are highest in summer months (June, July, August) with August the most skilful forecast IM on average, whereas skill is lower for winter months (December, January, February) with January the least skilful forecast IM. Skill scores across IMs for the four sample monthly to annual LTs are shown in Fig. 5. Skill is also highest for the 1-month forecasts when initialised in August, however for 3-month, 6-month, and 12-month LTs, forecast skill is generally higher for autumn (September, October, November) and winter IMs, with October the most skilful on average. All four monthly, seasonal, and annual LTs have lowest skill scores when initialised in spring months, particularly April, which in the UK is a transition month between winter months with lowest soil moisture deficits (SMDs) and warmer summer months with highest SMDs.

The decay in skill with LT as shown in Fig. 3 also occurs across all initialisation months (Figs. 4 and 5). Whilst mean ESP skill tends towards zero for longer LTs, there are many catchments with much higher skill scores than average. For example, for 1-month LT ESP forecasts initialised in August the average UK-wide ESP skill is moderate (CRPSS = 0.30), but 36 catchments have high skill (CRPSS ≥ 0.5), and a CRPSS as high as 0.91 is achieved for the Lambourn at Shaw in Southern England.

4.2 Spatial distribution of ESP skill

4.2.1 UK Hydroclimate Regions

Figure 6 shows a heatmap of mean ESP skill across initialisation months for the UK and for nine hydroclimate regions using the CRPSS metric. The same patterns are found for Cor., MSESS, and MAESS (Fig. S2). ESP skill has a prominent spatial pattern across the UK consistent over shorter and longer LTs. Least skilful UK regions are Western Scotland (WS), North-west England & North Wales (NWENW), and Northern Ireland (NI), whereas Severn-Trent (ST), Anglian (ANG), and Southern England (SE) are most skilful. Using a 1-week LT as an example, ESP is over twice as skilful in SE (CRPSS = 0.57) than in WS (CRPSS = 0.25). All regions are, on average, skilful out to 1-month LT, but by 3-month LT WS, NWENW, and NI are only neutrally skilful; at LTs up to 6- and 12-months ST, ANG, and SE are the only regions to remain skilful, as a whole.

4.2.2 Catchment-scale

There is considerable sub-region heterogeneity when skill scores for individual forecasts at the catchment-scale are examined. CRPSS values are mapped in Fig. 7 for all 314 catchment locations for a sample of four LTs (ranging from extended to annual) and three initialisation months (January, April, and August). Although WS is considered a low skill region overall at a 1-week LT in Fig. 6 (i.e. CRPSS = 0.248), moderate to high skill ESP forecasts can be made for some catchments at different times of the year. For example, August 1-week LT forecasts (Fig. 7c) in WS are moderately skilful (CRPSS ≥ 0.25) for over 80 % of the 35 catchments or even highly skilful (CRPSS ≥ 0.5) for 20 % of catchments. In all regions, almost all individual catchments are more skilful than the reference climatological forecast for up to extended LTs (i.e. Fig. 7a-c).

Sub-region heterogeneity is much more apparent for monthly, seasonal, and annual LTs (Fig. 7d-l). As in Fig. 6, skill decays at different rates depending on region and lead time, but also initialisation month. However, the finer spatial information in Fig. 7 shows that skill decays towards zero at vastly different rates for individual catchments even within the same region. For example, despite low average skill of January 12-month LT forecasts in SE (CRPSS = 0.14), nearly 20 % of catchments have modest skill. In April, when UK-wide forecasts at longer LTs are least skilful (i.e. Fig. 5), skilful forecasts can still be made at monthly and seasonal LTs for the majority of catchments in ST, ANG, and SE (Fig. 7e and h). Sub-region heterogeneity is perhaps most prominent for the Thames basin in SE. The April 3-month LT forecast for the Thames at Kingston has low skill (CRPSS = 0.22, size = 9948 km^2), but two of its sub-catchments have contrasting skills; the Lambourn at Shaw is highly skilful (CRPSS = 0.65, size = 234 km^2) whereas the forecast made for the Mole at Kinnersley Manor has effectively no skill (CRPSS = 0.02, size = 142 km^2).

4.3. Relationship between catchment storage and ESP skill

The relationship between the two calibrated GR4J catchment storage parameters, X1 (soil store capacity [mm]) and X3 (groundwater store capacity [mm]), BFI, and ESP skill (CRPSS) for n = 314 individual catchments is shown in the scatterplot matrix in Fig. 8 using the non-parametric Spearman's rank correlation coefficient ρ. It is difficult to link X1 and X3 specifically to soil moisture and groundwater storage capacity, respectively, as GR4J is not a physically-based hydrological model. However, their sum (X1 + X3) can be considered an estimate of total catchment storage (excluding water in the river channel and snowpack). Total catchment storage (X1 + X3) is strongly positively (non-linearly) correlated with BFI (ρ = 0.87); catchments with high BFIs tend to have much higher than average catchment storage capacity. The BFI is also very strongly positively correlated with ESP skill (ρ = 0.90). The 1-month LT forecast skill (based on CRPSS) averaged across all 12 initialisation months is used to demonstrate this, but similar results are found over the range of lead times, individual initialisation months, and skill metrics (not shown). Forecasts in the most responsive catchments (BFI $\leq$ 0.35, 20 % of catchments) have on average low skill (CRPSS = 0.08) whereas the slowest responding catchments (BFI $\geq$ 0.9, 5 % of catchments) have high skill (CRPSS = 0.66).

5 Discussion

Overall, the ESP method is found to be skilful when benchmarked against climatology in the UK, but the degree of skill is dependent on lead time, initialisation month, and individual catchment location and storage properties.

5.1 When is ESP skilful?

UK-wide ESP forecasts for short lead times (out to 3-days) are on average highly skilful (CRPSS $\geq$ 0.5) and for extended lead times (out to 2-weeks) moderately skilful (CRPSS $\geq$ 0.25). Mean ESP skill decays exponentially with increasing lead time so skill is on average much lower for monthly, seasonal, and annual lead times, as expected. However, the magnitude of

skill is not uniform across the 12 forecast initialisation months. ESP skill for short, extended, and monthly lead times is higher than average when initialised in summer months and lower than average for winter months. Svensson (2016) also found higher skill across the UK when initialised in summer (highest also for August forecasts at a 1-month lead time) using the statistical persistence forecasting method. This is consistent with Li et al. (2009) and Shukla and Lettenmaier (2011) who found soil moisture Initial Hydrologic Conditions (IHCs) contributed to greater skill for forecasts initialised in the warmer summer season than the cold winter season in the south east of the US due to drier initial moisture states in summertime, up to a 1-month lead time. Similarly, Staudinger and Seibert (2014) found drier initial soil moisture was connected to longer persistence in all seasons but winter in Switzerland. Soil Moisture Deficits (SMDs) are also highest in summer in the UK, peaking in July, and lowest in winter (based on UK Met Office MORECS dataset (Hough and Jones, 1997) over 1961-2015). This could help explain why up to 1-month LT hydrological forecasts initialised in summer months using IHCs alone (e.g. ESP) are more skilful than if initialised in winter in the UK. Higher summer ESP forecast skill could be capitalised upon operationally given seasonal climate predictability over Northern Europe is notoriously challenging for summer rainfall (e.g. Weisheimer and Palmer, 2014).

In contrast, ESP skill at seasonal to annual lead times is generally higher than average when initialised in winter and autumn months, and lowest in April. However, these higher skills occur in catchments with higher BFIs, suggesting that perhaps groundwater from large slowly responding aquifers is the source of ESP skill at these longer lead times. This is supported by Wood and Lettenmaier (2008) who found that baseflow dominates hydrological persistence in winter in the Rio Grande River in the US. Staudinger and Seibert (2014) also found for simulations initialised in winter, wetter initial conditions lead to longer persistence, although they note it was difficult to separate the relative influences from snow and aquifer memory. Lower longer-range skill for forecasts initialised in spring months was also found by Svensson (2016) for a 3-month LT based on statistical streamflow persistence forecasts. However, there are limited seasonal hydrological hindcast studies for the UK that have also assessed skill at longer than 3-month lead times to compare results. Spring in the UK is characterised as a transition season between lowest (winter) and highest (summer) SMDs, in which groundwater recharge no longer occurs and baseflow begins its recession. Factors that might contribute to lower skilled forecasts initialised in spring, and indeed to differences in skill across all initialisation months, include: potentially higher variability in IHC storage states, changing variability in rainfall across the forecast window (e.g. from late spring to early autumn), and differences in model performance for different months over the year due to the global calibration of GR4J. Given the answer is likely a combination of many of these factors, among others, further work should endeavour to attribute differences in skill during different times of the year but this is outside the scope of this paper.

5.2 Where is ESP skilful?

The skill of ESP is also not uniformly distributed in space. Least skilful hydroclimate regions within the UK are situated in the north and west (WS, NWENW, and NI) whereas the most skilful are situated in the south and east (ST, ANG, and SE) across all lead times studied. This prominent spatial pattern was also noted, among others, by Svensson et al. (2015) and

Svensson (2016) using statistical persistence forecasting and Bell et al. (2017) using a gridded national-scale hydrological model. These space-time patterns are also apparent in skill maps of individual catchments (i.e. Fig. 7), although there is marked sub-region heterogeneity, as demonstrated using the Thames basin: the slow responding Lambourn at Shaw sub-basin (BFI = 0.97) was highly skilful whereas the fast responding Mole at Kinnersley Manor catchment (BFI = 0.39) had virtually no ESP skill.

5.3 Why is ESP skilful?

The most skilful ESP regions of the UK are also those that are underlain by the UK's principal aquifers (Fig. 1). Catchments with larger calibrated soil moisture and groundwater storage capacity parameters in GR4J (i.e. X1 and X3) are also situated in ST, ANG, and SE, and tend to have a higher Base Flow Index (BFI) (Table 2). The BFI is therefore interpreted here broadly as an integrated index of catchment storage capacity and is inferred to be responsible for modulating ESP skill - catchments with higher storage are more skilful with skill decaying at a much slower rate with increasing lead time, compared to catchments with low storage capacity. For example, forecasts for the Lambourn remains on average moderately skilful (i.e. CRPSS ≥ 0.25) until a lead time of 306 days, but the Mole drops below the moderately skilful threshold at a lead time of just 10 days.

These findings are consistent with current physical understanding of sources of ESP skill in non-snow dominated catchments in the literature. Water storage within the soil introduces a memory effect whereby anomalously dry or wet conditions can take weeks or months to be 'forgotten' (Ghannam et al., 2016; Li et al., 2009), and the slow transformation of precipitation to streamflow in catchments with highly permeable aquifers in the south east of the UK leads to temporal streamflow dependence for up to a season ahead, and longer (Chiverton et al., 2015). Although it is encouraging that GR4J storage parameter values (X1 and X3) appear to show some physical realism, a note of caution is needed as GR4J is not a physically-based hydrological model, nor is it guaranteed that these results are directly transferable to any lumped catchment hydrological model. It has also been noted that the BFI in the UK is influenced by many other factors such as lake and snow storage (Parry et al., 2016), therefore a more detailed examination of the physical hydrogeological controls on catchment BFI, such as in Bloomfield et al. (2009) for the Thames, is needed at a national-scale.

The ESP method was originally developed and tested in the snow dominated catchments of the western US with particular strength in forecasting spring snow melt driven streamflow (e.g. Franz et al., 2003; Wood and Lettenmaier, 2008). Because the source of ESP is from IHCs, and because individual catchments will have different relative contributions of IHC sources (e.g. snow, soil moisture, and groundwater), ESP skill must be assessed using a large-sample of diverse catchment types and sizes for each region it is being applied in (e.g. Yossef et al., 2013). The present study adds to the broader international literature on benchmarking ESP skill in non-snow dominated catchments. In particular, results show that IHCs in catchments with large soil moisture and groundwater storage provide skill up to at least a year ahead. It must however be acknowledged that the UK is not completely snow-free. Just under 5 % of catchments studied have a significant snow contribution (i.e. $\bar{F}_s > 0.15$) located mainly in upland areas of Eastern Scotland (ES) (see Fig. 1). In the present experimental set-up, snow accumulation and melt

processes were not represented within the GR4J model. This would explain why ES has the lowest GR4J model performance for the reference simulation of all regions (Table 2). In addition, the worst performing forecast in the entire ESP hindcast archive is the 3-month LT April forecast for the Dee at Park with a negative CRPSS = -0.12 (see Fig 2e). In this instance both the ESP forecast and the proxy streamflow observations (or perfect model) in which the forecast was evaluated against was not a good enough representation of reality.

ESP in its traditional form as used here provides the *lower limit* of streamflow forecasting skill in the absence of skilful atmospheric forecasts (Pagano et al., 2010) or improved hydrological process representation (e.g. snow). As such, ESP assumes near total uncertainty about future rainfall; when there is limited to no influence of IHCs on streamflow prediction (e.g. highly responsive catchments), the ESP ensemble mean and spread defaults to climatology (see Fig. 2d). Given the known influence of the NAO on rainfall and therefore streamflow in the UK, particularly in the north and west for winter (e.g. Svensson et al., 2015), there is potential for an NAO-conditioned ESP method to be developed. This would involve sub-sampling historic climate sequences used to force ESP based on year's most similar to NAO conditions at the time of forecast. Beckers et al. (2016) developed an ENSO-conditioned ESP method for three test sites in the US Pacific Northwest and found skill improvements in the order of 5 to 10 %, and showed the added value of including a weather resampling technique to account for the unavoidable reduction in ensemble size. Overall, low ESP forecast performance and sharpness in highly responsive catchments in the north and west would be expected to improve with incorporation of information that reduces rainfall forcing uncertainty at all lead times but particularly seasonal, whether from ensemble sub-sampling or inclusion of skilful atmospheric forecasts.

6 Conclusions

Ensemble Streamflow Prediction (ESP) has a rich history internationally as a low cost and efficient ensemble hydrological forecasting system used operationally across a range of lead times. The ESP method using simple lumped conceptual hydrological models is currently one of three methods used within the operational UK Hydrological Outlook (HOUK) seasonal hydrological forecasting service and also feeds into the Environment Agency's monthly 'Water Situation Report for England'. However, the skill of ESP at the catchment-scale under a rigorous hindcast experiment for a large-sample of diverse catchments across the UK had not previously been investigated.

We conclude that ESP is skilful against a climatology benchmark forecast in the majority of catchments across all lead times up to a year ahead, but the degree of skill is strongly conditional on lead time, forecast initialisation month, and individual catchment location and storage properties. In summary:

- ESP skill decayed exponentially with increasing lead time but catchments with larger storage capacity decayed at a much slower rate, resulting in the possibility of low to moderate skill forecasts based on Initial Hydrological Conditions (IHCs) alone even at a 12-month lead time for some catchments.

- For short (1- to 3-days), extended (1- to 2-weeks), and monthly forecasts, skill was highest when initialised in summer months and lowest in winter months.

- For seasonal (3- to 6-months) to annual forecasts, skill was highest when initialised in winter and autumn months, but only for catchments with high storage capacity (i.e. high Base Flow Index). Longer range forecast skill was lowest when initialised in spring, particularly April, which is likely due to the complex interplay of hydrological and climatological processes involved during the transition from lower winter to higher summer soil moisture deficit conditions and needs to be explored further.

- ESP is most skilful in the south and east of the UK, where slower responding catchments with higher storage are mainly located. This is in contrast to the more highly responsive catchments in the north and west which are generally not skilful at seasonal lead times. However, substantial sub-region heterogeneity was observed and skilful ESP forecasts are still possible at the individual catchment-scale despite when the region as a whole has low skill.

We show that simple lumped conceptual rainfall-runoff models (here using GR4J) are able to be used to produce skilful ESP forecasts at short to annual lead times in the UK. This hindcast experiment provides a scientifically defensible justification for when (lead time and initialisation month) and where (region and catchment types) use of such a relatively simple forecasting approach is appropriate. Currently, ESP is only used operationally in the UK at seasonal and annual lead times in England and Wales. This skill evaluation has shown that much higher skills are possible for short (1- to 3-days) and extended (1- to 2-weeks) lead times in all regions across the UK and opens the potential for applying ESP as a low cost and efficient catchment-scale ensemble hydrological forecasting system in a wider context.

Finally, most ensemble hydrological forecasting systems are benchmarked against an arguably too simplistic climatology benchmark forecast which is not particularly challenging to beat. Pappenberger et al. (2015) calls this 'naïve skill' and argues that a forecasting system can only be classified as having 'real skill' when it performs better than a 'tough to beat' lower cost benchmark forecast system. The ESP hindcast archive derived and presented here in itself provides such a 'tough to beat' simplified hydrology model benchmark in which the potential value of improvements from more sophisticated forms of ESP (e.g. incorporation of snow processes, sub-sampling historic climate) or more complex and expensive hydro-meteorological ensemble forecasting systems can be judged. When and where ESP cannot provide skilful streamflow forecasts provides an opportunity to benchmark the degree to which recent improvements in seasonal prediction of UK regional rainfall (e.g. Baker et al., 2017, accepted) leads to improvements over using IHCs alone (i.e. our ESP method), and is the focus of future work.

7 Data availability

The ESP hindcast archive (~60 GB) and the 'UK Hydroclimate Regions' shapefile can be requested from the Centre for Ecology & Hydrology (CEH), Wallingford, UK. Supplementary Table S1 includes metadata for all 314 catchments as well as data used to generate Table 1 and 2, and Fig. 8 for others to explore.

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Table 1. Summary statistics of eight catchment characteristics for the UK and nine hydroclimate regions shown in Fig. 1. The median across n catchments within each region is given with the 5th and 95th percentile ranges in brackets. Area, Median elevation, and Base Flow Index (BFI) were retrieved from the UK NRFA. Mean annual Q, P, and ET_P were calculated over water years 1983 to 2014 using data in Sect. 2. RR is the runoff ratio and $\overline{F_s}$* is the long-term (water years 1983-2014) mean fraction of precipitation that has fallen as snow.

Region	n	Area (km²)	Median elevation (m a. s. l.)	BFI (-)	Mean annual Q (mm yr⁻¹)	Mean annual P (mm yr⁻¹)	Mean annual ET_p (mm yr⁻¹)	RR $\overline{Q}/\overline{P}$ (-)	$\overline{\overline{F_s}}$ (-)
UK	314	181 (27, 1844)	179 (60, 437)	0.5 (0.27, 0.89)	595 (162, 1839)	1031 (648, 2202)	504 (400, 542)	0.59 (0.24, 0.87)	0.03 (0.01, 0.14)
WS	35	229 (64, 1745)	268 (146, 468)	0.33 (0.20, 0.61)	1115 (554, 2847)	1460 (998, 3145)	428 (391, 476)	0.74 (0.58, 0.90)	0.06 (0.03, 0.12)
ES	43	289 (70, 2759)	303 (100, 596)	0.51 (0.34, 0.67)	693 (338, 1498)	1040 (783, 1970)	432 (387, 481)	0.63 (0.44, 0.84)	0.09 (0.06, 0.21)
NEE	30	344 (11, 1910)	264 (88, 449)	0.43 (0.26, 0.82)	559 (344, 1054)	1037 (757, 1462)	486 (455, 516)	0.57 (0.44, 0.83)	0.07 (0.04, 0.09)
ST	25	198 (48, 6345)	145 (87, 312)	0.56 (0.41, 0.79)	392 (209, 844)	858 (670, 1311)	511 (493, 528)	0.46 (0.31, 0.68)	0.03 (0.02, 0.05)
ANG	33	99 (23, 1540)	80 (33, 132)	0.56 (0.25, 0.88)	183 (128, 254)	655 (600, 716)	535 (528, 551)	0.27 (0.21, 0.36)	0.03 (0.03, 0.04)
SE	59	134 (18, 1091)	105 (43, 178)	0.64 (0.23, 0.96)	356 (146, 568)	856 (654, 1033)	529 (520, 541)	0.42 (0.20, 0.64)	0.02 (0.01, 0.03)
SWESW	47	174 (29, 915)	207 (77, 377)	0.51 (0.37, 0.67)	979 (507, 1549)	1372 (1002, 1971)	519 (495, 537)	0.69 (0.51, 0.83)	0.01 (0.00, 0.03)
NWENW	32	112 (30, 1094)	210 (108, 360)	0.35 (0.27, 0.58)	1154 (390, 2102)	1529 (884, 2429)	478 (457, 514)	0.75 (0.44, 0.91)	0.04 (0.02, 0.05)
NI	10	230 (68, 1235)	140 (90, 172)	0.38 (0.33, 0.50)	688 (533, 1206)	1111 (917, 1565)	475 (466, 488)	0.63 (0.57, 0.77)	0.01 (0.00, 0.02)

*$\overline{F_s}$ calculated using the CemaNeige snow-accounting module (Valéry et al., 2014) within the airGR package (Coron et al., 2016, 2017) applied to the GR4J model (Perrin et al., 2003).

Table 2. Summary statistics of GR4J calibrated parameters and performance metrics for the UK and nine hydroclimate regions shown in Fig. 1. The median across n catchments within each region is given with the 5th and 95th percentile ranges in brackets. Calibration (Cal) was over the complete period (CP; water years 1983-2014) while evaluation (Eval) for both period 1 (P1; water years 1983-1998) and period 2 (P2; 1999-2014).

Region	n	GR4J X1 (mm)	GR4J X2 (mm d^{-1})	GR4J X3 (mm)	GR4J X4 (d)	Cal (CP) KGE$_{mod}$[sqrt] (-)	Eval (P1) KGE$_{mod}$[sqrt] (-)	Eval (P2) KGE$_{mod}$[sqrt] (-)	Cal (CP) PBIAS (%)
UK	314	250 (78, 955)	-0.1 (-4.2, 0.8)	40 (12, 380)	1.3 (1.0, 2.6)	0.94 (0.83, 0.97)	0.92 (0.80, 0.96)	0.92 (0.78, 0.96)	-0.1 (-3.7, 0.7)
WS	35	130 (46, 438)	0.0 (-0.6, 0.6)	27 (14, 130)	1.2 (1.1, 2.1)	0.93 (0.83, 0.96)	0.92 (0.82, 0.95)	0.91 (0.81, 0.95)	0.1 (-2.2, 1.2)
ES	43	296 (112, 523)	0.0 (-0.7, 0.8)	43 (18, 104)	1.2 (1.1, 1.8)	0.90 (0.74, 0.94)	0.88 (0.74, 0.94)	0.88 (0.71, 0.94)	-0.5 (-2.2, 0.4)
NEE	30	277 (79, 499)	0.0 (-1.1, 0.7)	24 (12, 109)	1.3 (1.1, 2.3)	0.92 (0.87, 0.95)	0.91 (0.83, 0.94)	0.90 (0.78, 0.93)	-0.2 (-7.1, 0.4)
ST	25	345 (142, 1169)	-0.5 (-1.0, 0.5)	44 (18, 153)	1.4 (1.1, 2.7)	0.96 (0.88, 0.97)	0.93 (0.83, 0.96)	0.92 (0.80, 0.96)	0.2 (-1.6, 0.7)
ANG	33	286 (128, 773)	-0.8 (-4.5, -0.1)	28 (5, 371)	1.5 (1.2, 2.7)	0.92 (0.86, 0.95)	0.88 (0.82, 0.94)	0.88 (0.81, 0.94)	-0.2 (-8.7, 1.4)
SE	59	411 (160, 1877)	-0.7 (-17.2, 1.0)	77 (6, 703)	1.4 (1.0, 9.5)	0.95 (0.88, 0.97)	0.92 (0.82, 0.96)	0.92 (0.8, 0.96)	-0.1 (-5.0, 0.4)
SWESW	47	205 (83, 459)	0.1 (-1.0, 0.9)	81 (29, 182)	1.2 (0.9, 2.0)	0.97 (0.94, 0.97)	0.94 (0.86, 0.97)	0.94 (0.85, 0.96)	-0.3 (-1.2, 0.3)
NWENW	32	141 (60, 480)	0.2 (-0.6, 0.8)	36 (19, 134)	1.2 (1.1, 1.8)	0.95 (0.93, 0.97)	0.95 (0.88, 0.96)	0.94 (0.87, 0.96)	0.0 (-0.5, 0.4)
NI	10	146 (70, 244)	0.2 (-0.1, 0.3)	23 (16, 37)	1.4 (1.1, 1.9)	0.93 (0.91, 0.96)	0.93 (0.86, 0.95)	0.93 (0.86, 0.95)	-0.1 (-1.0, 0.9)

Figures

Figure 1: Location of 314 gauging stations (red dots) and catchment boundaries (black lines) with upland areas (shaded in grey) and principal aquifers (shaded in pale yellow). UK Hydroclimate Regions, derived from grouping smaller UK hydrometric areas, are shown inset.
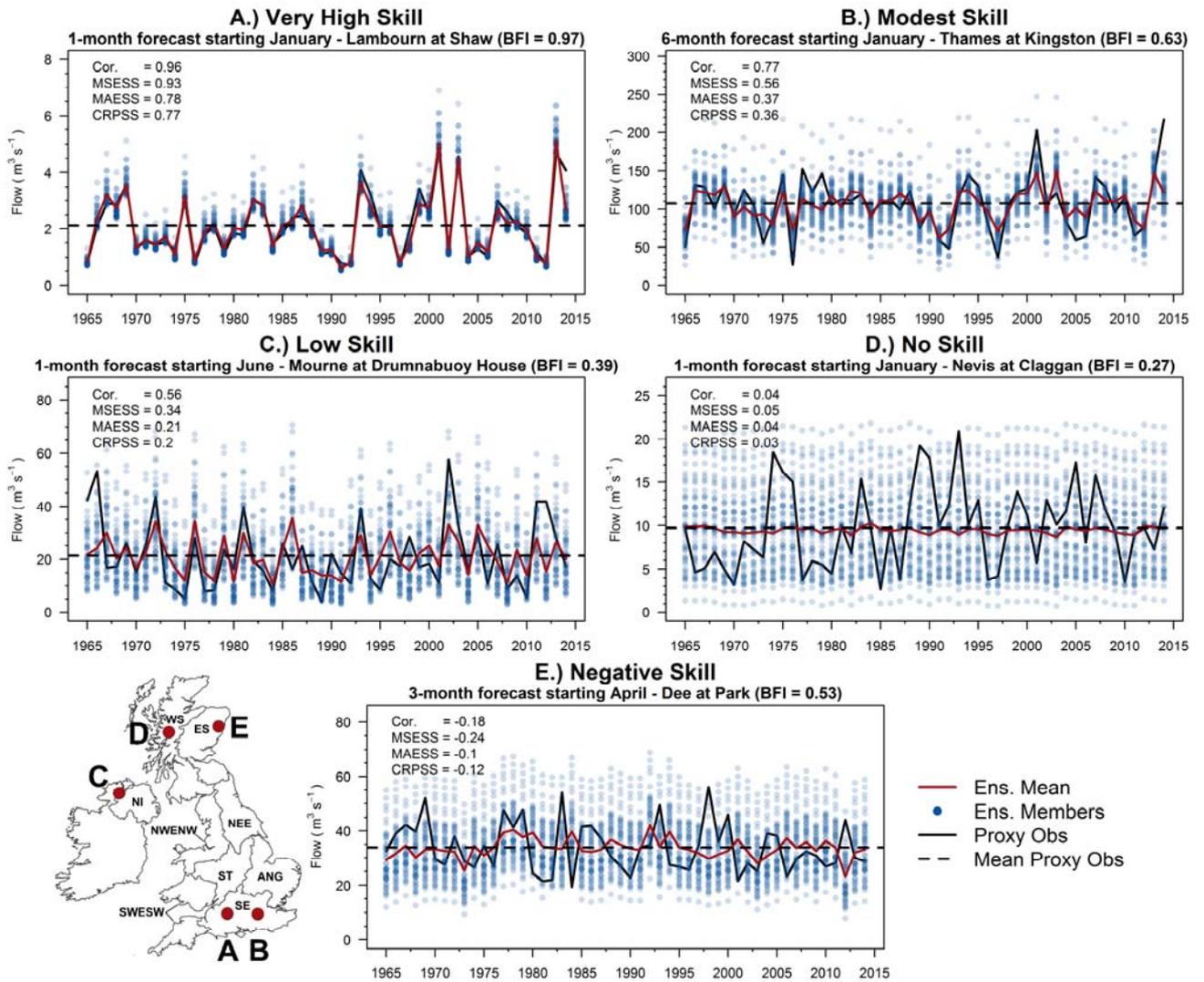
Figure 2: Five example 1965-2015 hindcast time-series in which skill metrics range from very high (a) to negative skill (e). The red line is the 51-member ESP ensemble mean, black line the proxy observed streamflow (also known as a perfect forecast), semi-transparent blue dots show the ensemble spread for each forecast year, and the dashed horizontal black line mean proxy observed streamflow (analogous to a deterministic climatology benchmark forecast, although not cross-validated here as was done in calculation of skill scores (i.e. simply the same value repeated each year)).
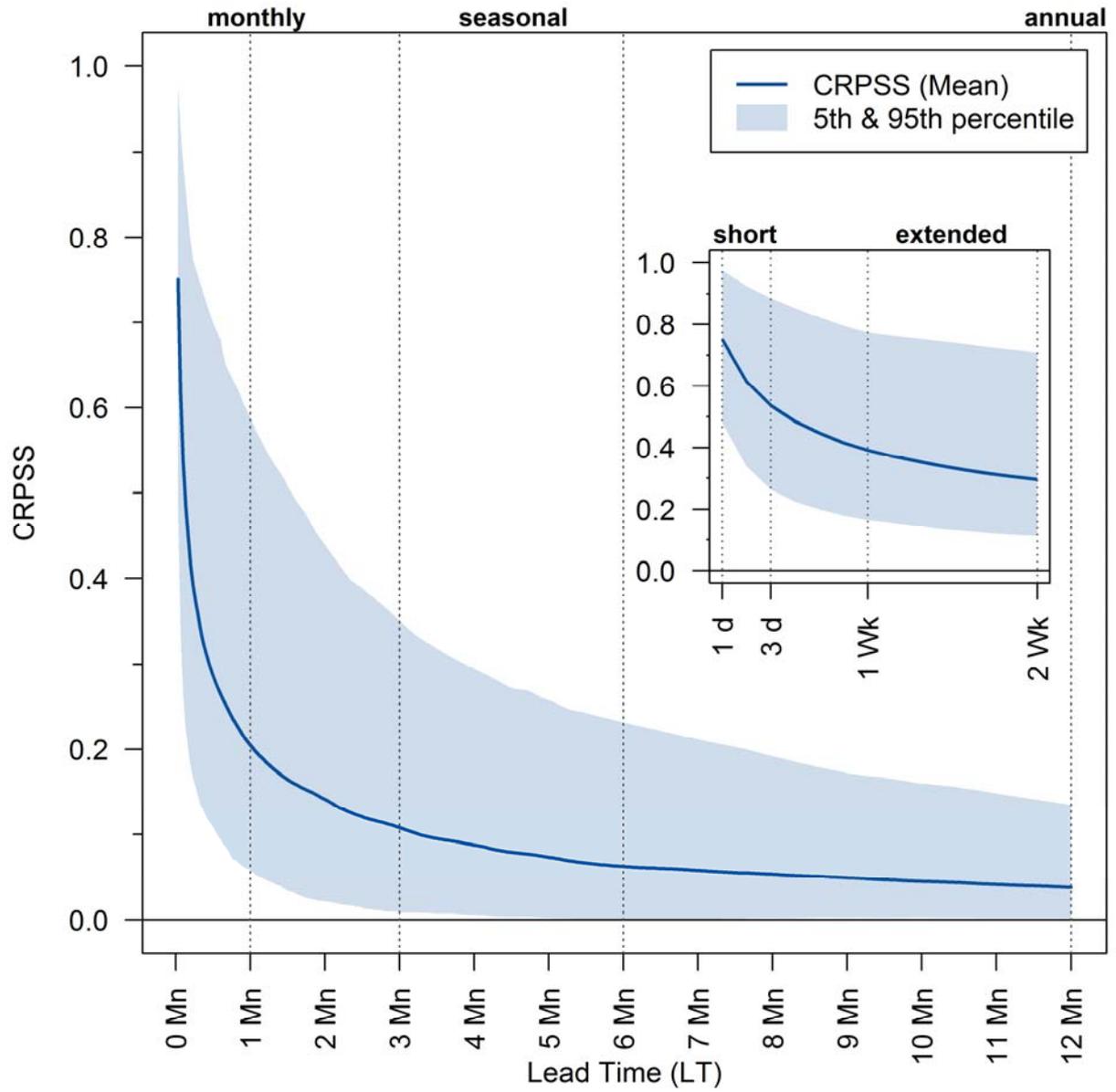
Figure 3: UK-wide mean ESP CRPSS values across all 314 catchments and 12 forecast initialisation months for all 365 lead times (LTs) with short and extended lead times also shown inset for readability. The range of skill scores across catchments at each LT is shown by the semi-transparent 5th and 95th percentile band. Vertical lines represent eight commonly used operational forecasting LTs from short (1- and 3-days), extended (1- and 2-weeks), monthly (1-month), seasonal (3- and 6-months), to annual (12-months).
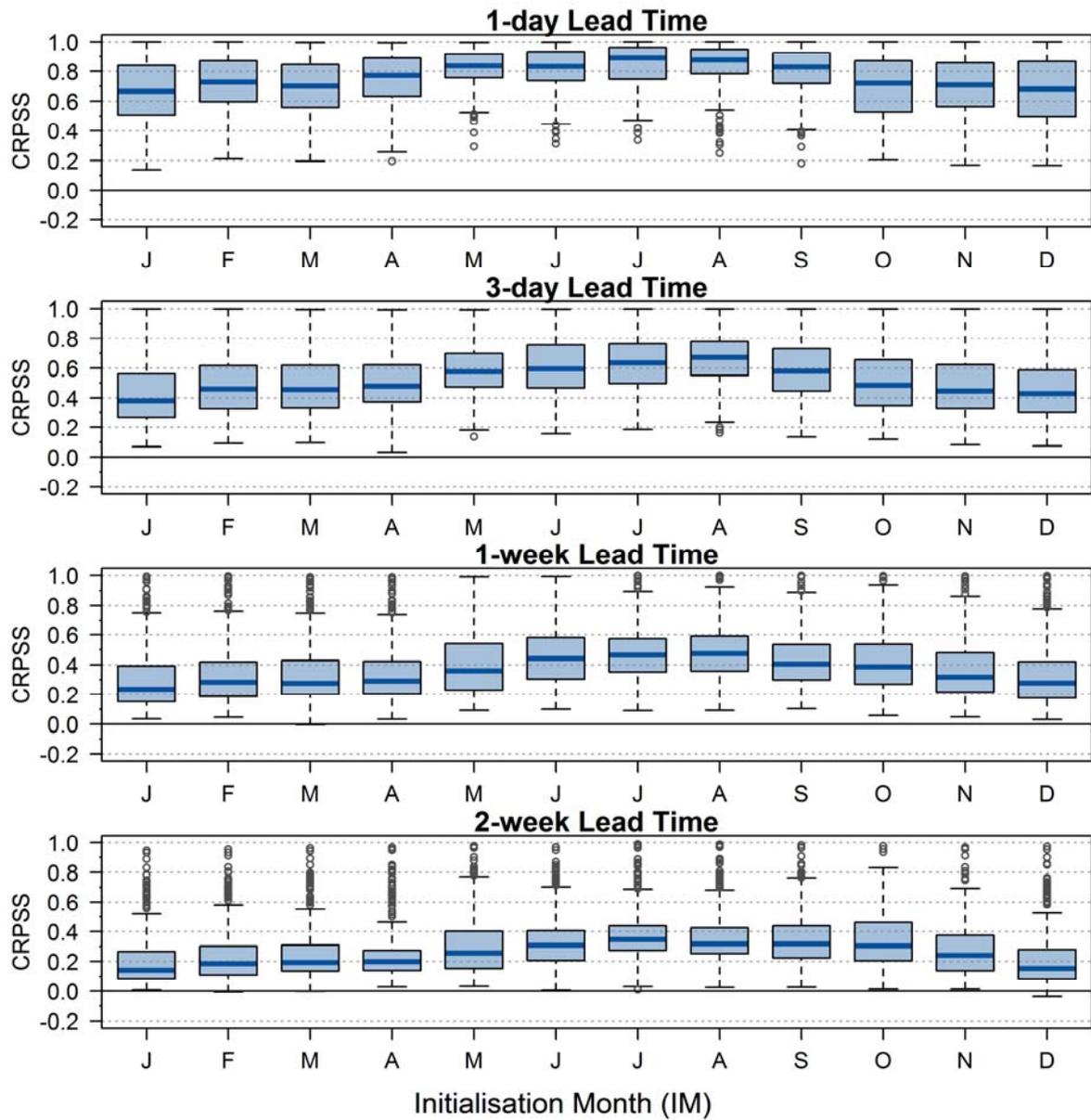
Figure 4: UK-wide ESP skill scores across 314 catchments for each of the 12 forecast initialisation months for four short and extended lead times. Blue boxplots summarise CRPSS values with the black line representing the median, and boxes the interquartile range (IQR); whiskers extend to the most extreme data point, which is no more than 1.5 times the IQR from the box, and grey circles are outliers beyond this range.
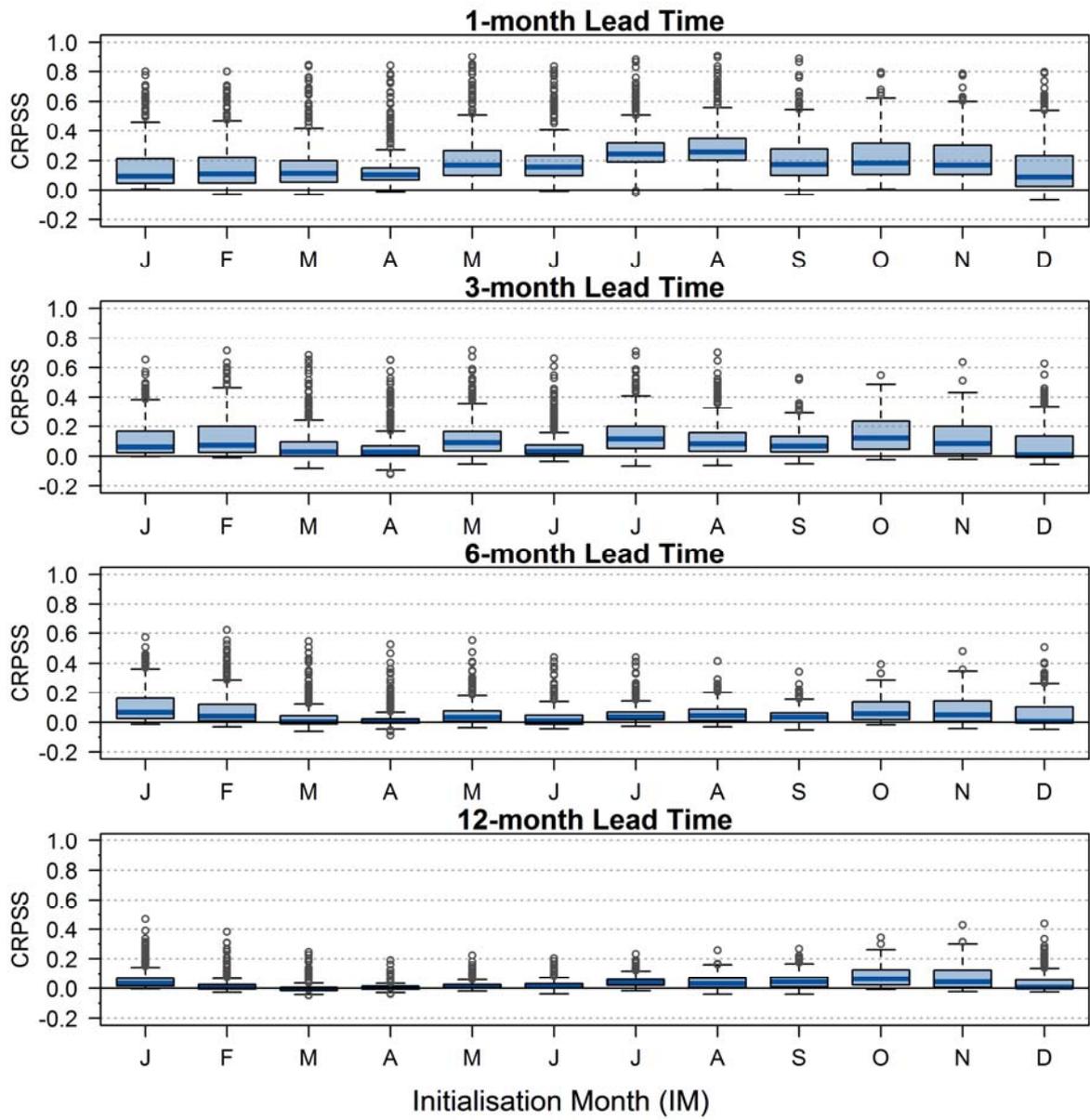
Figure 5: As in Fig. 4 but for four monthly, seasonal, and annual lead times.
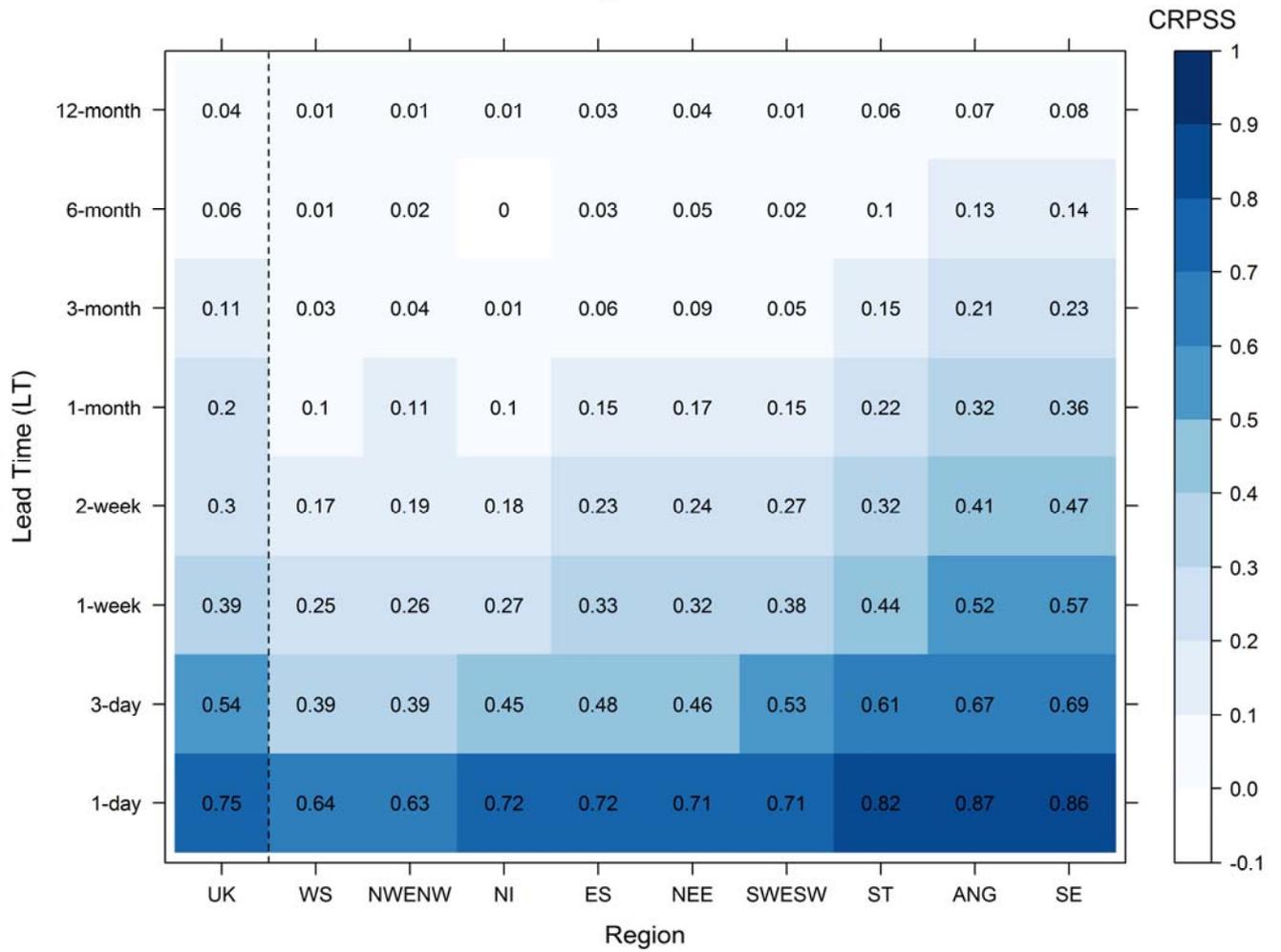
Figure 6: Mean ESP skill across all 12 forecast initialisation months for the UK and for each of the nine hydroclimate regions ordered from least to most skilful (horizontal axis) at eight sample lead times (vertical axis). Skill is given by the CRPSS with darker (lighter) shades showing higher (lower) skill; mean skill score values are shown within each cell.
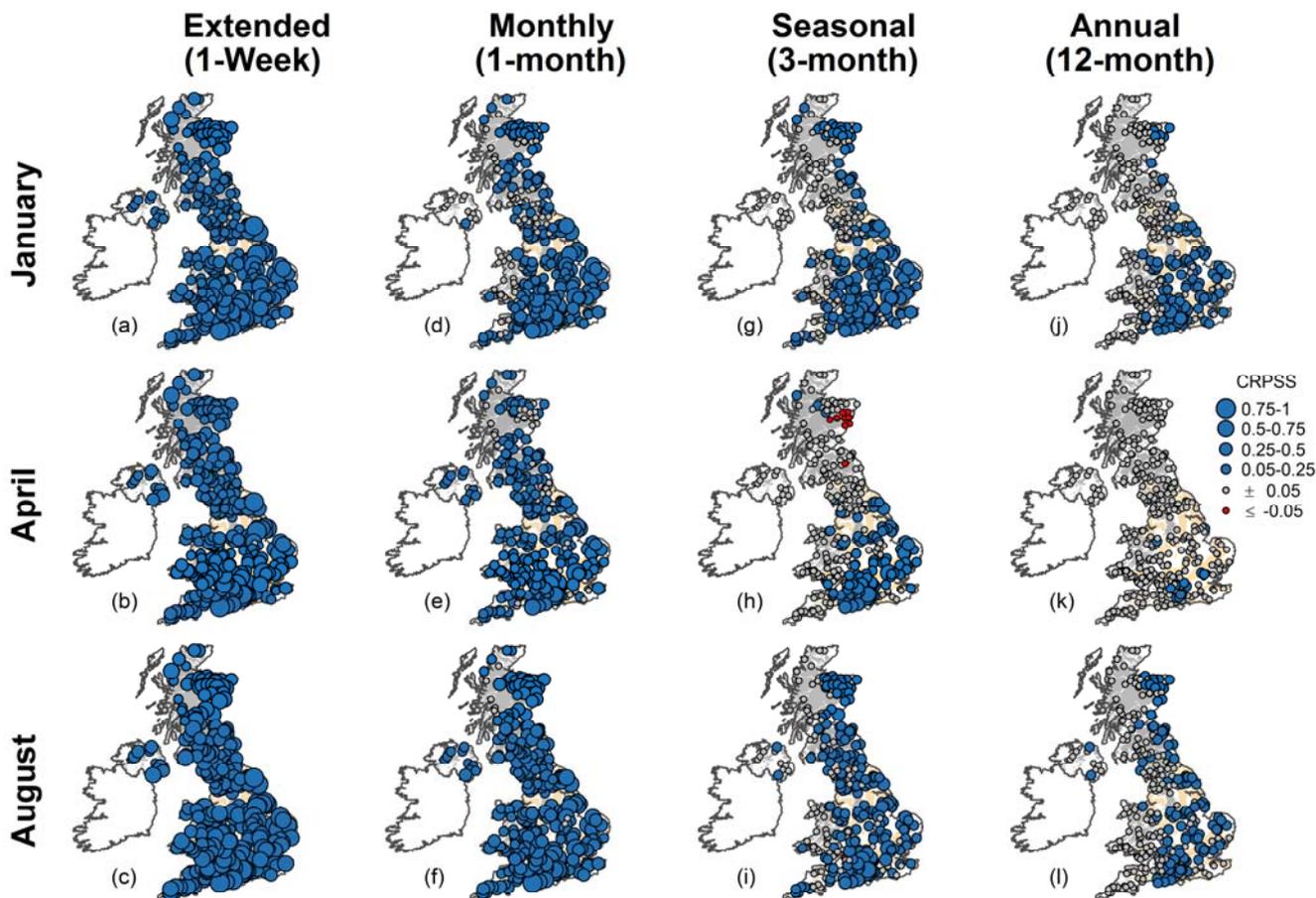
Figure 7: ESP skill for individual forecasts made at each of the 314 catchment locations for four sample lead times (columns) and three initialisation months (rows). Larger (smaller) circles represent higher (lower) skill from CRPSS with blue circles when ESP is more skilful than benchmark climatology and red when ESP has no skill. Grey circles represent neutrally skilful forecasts (i.e. CRPSS values between ± 0.05).
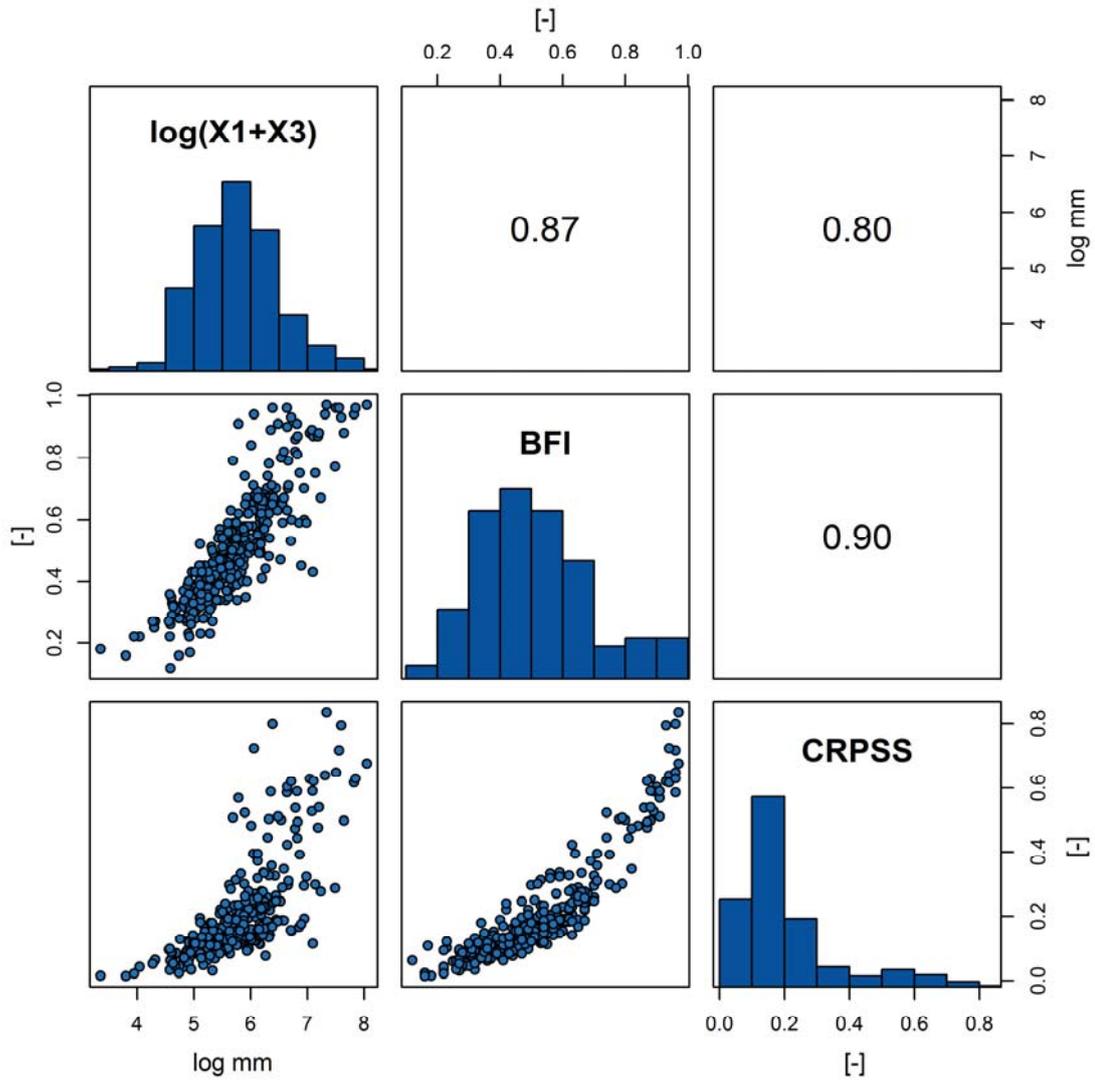
Figure 8: Scatterplot matrix between catchment storage capacity (X1 soil store capacity [mm] + X3 groundwater store capacity [mm]), BFI, and ESP skill (CRPSS) with n = 314 using the non-parametric Spearman's rank correlation coefficient ρ. Skill is the 1-month CRPSS skill score magnitude averaged across all 12 initialisation months. Catchment storage capacity (X1 + X3) was re-expressed by taking the natural log as raw values are heavily positively skewed.