Harrigan et al. (2017) re-submission of manuscript with final point-by-point response

Dear QJ,

Thank you for inviting us to revise our paper. We attach i.) our revised abstract, ii.) our revised manuscript, iii.) a final point-by-point response to all reviewers and editor comments with where changes have been made in the revised manuscript, and a marked-up version of the manuscript as required (combined in this pdf), and iv.) revised supplementary tables and figures.

We thank all reviewers again for their time and constructive comments which have helped to greatly improve the quality of the manuscript.

Kind regards,

Shaun.

Response to editor comment

The referees have made very thorough and constructive reviews - Thank you!

The authors' responses to the review comments are well considered. Please go ahead and revise the paper.

I note the discussion on the definition of lead times. I tend to follow the convention of the seasonal climate forecasting community, and would encourage you to do the same. Please find the attached slide of mine, which defines target period and lead-time. For example, a forecast issued at the start of January for the target period of January to March has a lead time of zero, while a forecast issued at the start of January for the target period of February to April has a lead time of one month.

Thank you for your slide which very nicely defines forecast target period and lead time. We agree this definition of lead time is indeed common and distinguishing between target period and lead time in this manor has its advantages. However, we would prefer to keep our current definition of lead time which is consistent with what is being used operationally within the UK Hydrological Outlooks (HOUK, Prudhomme et al., 2017), as this paper forms the skill evaluation of one of three of the methods used within HOUK. As per our response to R#1-4 and R#3-3 we made this clearer on Pg6; L11-14 in the revised manuscript: “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”. We hope this avoids any confusion, but can revert to your suggestion of zero lead time with n-day/month target period if you feel strongly about this.

Final response to reviewers

Reviewer 1 comments are labelled consecutively, for example, comment 1 is R#1-1, with our responses to reviewers given in blue text.

General Comments:

R#1-1. Overall the paper is well written and makes a positive contribution to the scientific literature within this field. It is well balanced, set out clearly and has a good range of figures. The authors need to address whether they are referring to ‘forecasts’ or ‘projections’. Without conditioning ESP results according to forecast large scale

climatic influences i.e. NAO then the results should be termed 'projections' not 'forecasts'. I recommend than with minor revisions the paper should be accepted.

We thank the reviewer for their positive and constructive review. We have made the majority of your suggestions and clarify any points raised below. We address your comment about referring to ESP as a forecast below.

Specific Comments:

R#1-2. 1. The paper on many occasions refers to 'ESP forecasts', however as this method is not driven by a meteorological forecast it would be better to refer to these as 'ESP Projections'.

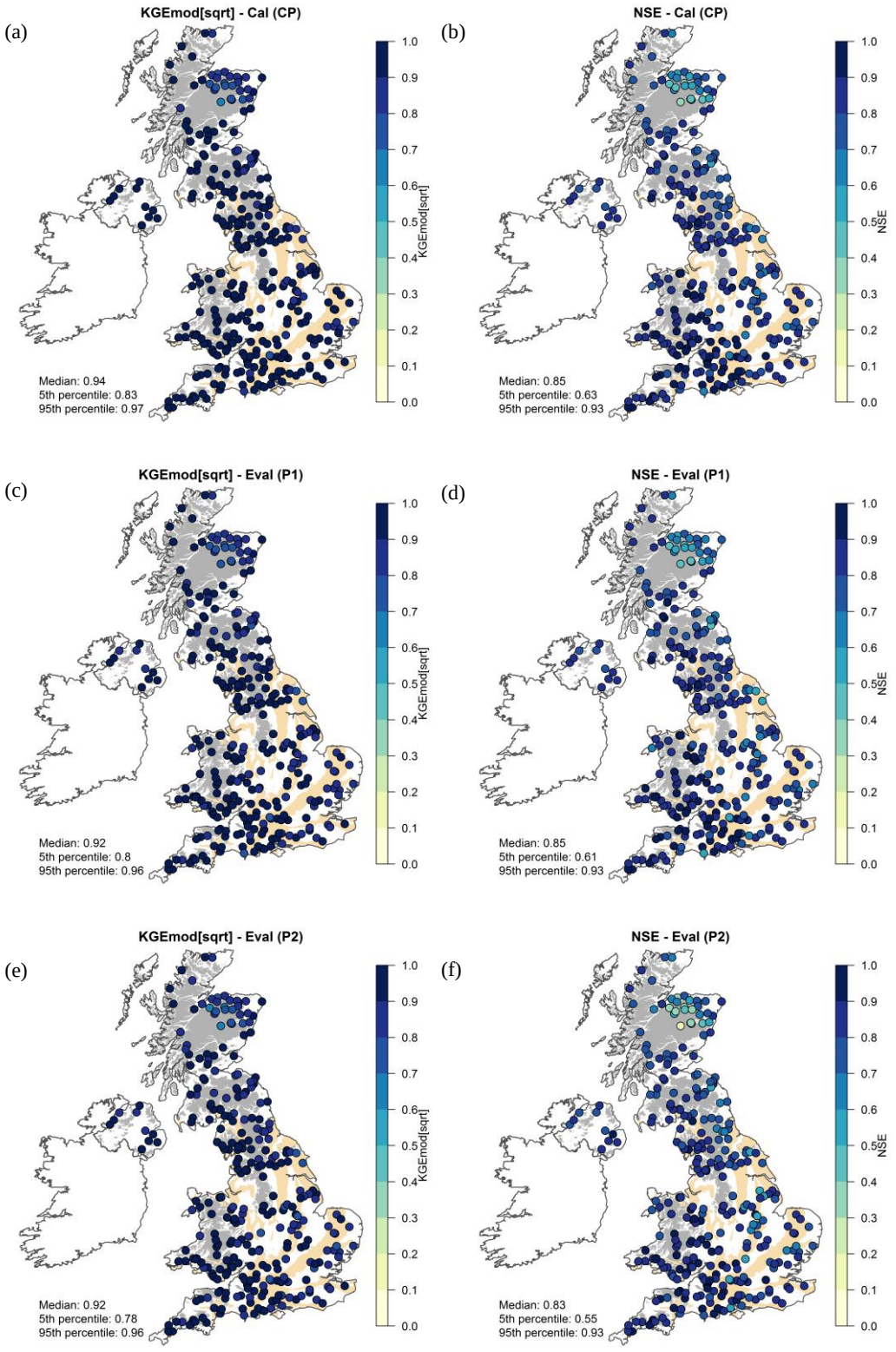
Whilst it is true that ESP does not contain any information about future atmosphere dynamics, it is now standard practice to describe its application in terms of a forecast (e.g., wood et al. (2016), as well as papers within this special issue: e.g., Beckers et al. (2016), Crochemore et al. (2017), and Arnal et al. (2017)). We would like to keep our terminology consistent with these papers but could change it if deemed necessary by the editor.

R#1-3. 2. Page 5 lines 11-17: There needs to be greater in depth discussion as to the results presented in Table 2 in the context of other studies. Are the calibration results better than other models/studies?

The main focus of the paper is not on the hydrological modelling component, it is instead to show that the GR4J model used here could reasonably simulate river flow observations in a wide range of catchments across the UK and could be deemed a viable model for catchment-scale ESP forecasting. The particular focus was on calibration and evaluation of medium range flows metrics (hence why the modified Kling-Gupta efficiency applied to root transformed flows KGE_{mod}[sqrt] was used (i.e. Pg5; L3 in the original manuscript), and not low (e.g. using log transformed flows) or high flow (e.g. using Nash-Sutcliffe Efficacy (NSE)), as the hydrological simulation aims to provide ESP forecasts across the full range of the flow regime.

However, we acknowledge that it would be useful to know how our modelling results compare to other models/studies. The most universally used metric for hydrological model calibration/evaluation is the NSE. We have therefore also calculated the NSE for all 314 catchments and provided a summary of results in **supplementary Fig. S1** (see below) and have added individual catchment NSE scores for the calibration and evaluation periods, along with KGE_{mod}[sqrt], in **supplementary Table S1** so that others can make more detailed comparisons.

We have also inserted the following text to address this comment on Pg5; L25-31 in the revised manuscript: "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. 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 KGEmod[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)".



Supplementary Figure 1: Spatial distribution of GR4J model performance for 314 catchments over the calibration (Cal CP [WY1983-2014], top row), and two evaluation periods (Eval P1 [WY1983-1998], middle row and Eval P2 [WY1999-2014], bottom row) for the modified Kling-Gupta efficiency applied to root squared transformed flows (KGEmod[sqrt]) and Nash-Sutcliffe efficiency (NSE) model performance metrics. UK-wide Summary statistics are given in the bottom left for the median and 5th and 95th percentiles.

R#1-4. 3. Page 6 Section 3.4: a. Please can the authors clarify what river flow metric are the skill scores being applied to? Is it the skill in comparing the mean daily river flow on a future day 1 day/3day/1 week/2 week etc ahead? Or is it the volume of discharge over the next day/3 days, 1 week/2 weeks,…12 months? b. Did the authors consider using RoC scores to assess skill? Please indicate in the discussion why these were not used.

a.) We thank the reviewer for highlighting needs for clarification (also queried by R#3-3). The evaluation metrics are calculated on time series equivalent to the volume of water which flowed from the first day (forecast initialisation date) to the last day of the forecast. For simplification, it is expressed in the manuscript in equivalent average daily streamflow (evaluation results are identical for both). We have inserted the following text in Pg6; L11-14 for clarification: "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".

b.) The choice of score to evaluate forecast skill is always a difficult subject; in Wilks (2011), the forecast verification chapter on the plethora of available scores/metrics is nearly 100 pages long. The main aim of our work was to investigate the overall performance of the ESP method; as rightly pointed out in R#3-7, ESP is an ensemble forecasting method, so focus should be on probabilistic scores – we've used one of the most common metrics, the Continuous Ranked Probability Score (CRPS, and skill score) which has the advantage of defaulting to the Mean Absolute Error (MAE) for a deterministic forecast, so is easy to interpret. The ROC diagram and the area under the ROC curve are indeed another way to evaluate the probabilistic forecast performance, but we chose CRPSS for the above reasons.

We have undertaken additional assessment on the use of different forecast evaluation metrics based on suggestions from Reviewer #3 and have taken on board their recommendation to concentrate on the CRPSS instead of the MSESS in the revised manuscript (please see our responses to R#3).

Technical Corrections:

R#1-5. Page 2 line 10: The Environment Agency implemented operational ESP groundwater level projections in March 2012.

This has been inserted in Pg2; L13-14 in the revised manuscript: i.e., "…and also feeds into the Environment Agency's monthly 'Water Situation Report for England' (operational for groundwater levels in March 2012)".

R#1-6. Page 3 line 28: 'NHMP 2017' is the wrong font size

Changed.

R#1-7. Page 4 line 9: 'hydro climatic regions' – how have these been defined and by whom? please include the reference for their designation.

The hydroclimatic regions used in the manuscript were defined based on merging contiguous UK hydrometric areas, which are integral river catchments having topographical similarity with outlets to the sea/estuaries (National River Flow Archive, 2014), into regions that reflect broad hydrological and climatological patterns in the UK. The approach was based on expert judgment and guided by the Met Office UK regional precipitation regions (HadUKP: https://www.metoffice.gov.uk/hadobs/hadukp/). For example, the division between North-west England & North Wales (NWENW) and South-west England & South Wales (SWESW).

Note that these UK Hydroclimate Regions were designed to facilitate the analysis and interpretation of the results, and in particular to investigate if any ESP skill patterns emerged in contrasting hydroclimatic regions. They have, however, no impact on the individual forecast performance. We have edited the revised manuscript on Pg4; L19-21 for clarity by inserting the following text: "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 UK Hydroclimate Region shapefile, together with metadata, is openly available from the Centre for Ecology & Hydrology (CEH), Wallingford, UK, and we also highlight this under Sect. 7 – Data availability.

R#1-8. Page 4 line 13: There are no major sandstone aquifers in Southern England.

We thank the reviewer spotting this. We have removed reference to sandstone.

R#1-9. Page 4 line 16:' highly productive' – please can you provide an explanation to this term

Highly productive refers to highly permeable aquifers (e.g. Chalk). We agree that this does not fit well here as we are referring to a 'Chalk river', and not specifically the aquifer underneath the catchment so will remove 'highly productive' and change the sentence "in catchments with productive aquifers" in P12; L22 in the revised manuscript to "in catchments with highly permeable aquifers".

When we refer to a catchment with a large groundwater influence on streamflow, we say the catchment is 'slow responding'.

R#1-10. Page 5 line 7: need to define a UK water year (starting 1st October in year in question)

This was mentioned on Pg4; L3, but have modified in the revised manuscript to make clearer (Pg4; L11-12): "Q was retrieved from the NRFA over the longest possible period of observed Q across the 314 stations, 32 water years from 1983 to 2014 (water year from 1 October to 30 September referred to by the calendar year in which it ends)".

R#1-11. Page 8 lines 14-15, Page 10 lines 28-29 Page 13 lines 9 and 10: There is generally little variation in monthly rainfall across the year – spring and summer are not necessarily significantly drier. It's the greater evaporative demands in the spring and summer which drives the transition referred to.

We thank the reviewer for highlighting the need for clarification regarding the transition between these two half year periods being not significant in terms of precipitation but in increased evaporative demand. This is summarised better in terms of Soil Moisture Deficits (SMDs). We have edited the text to "April, which in the UK is a transition month between winter months with lowest soil moisture deficits (SMDs) and summer months with highest SMDs" in the revised manuscript, i.e. Pg9; L10-12 & Pg12-13; L10 & Pg14; L12-13).

R#1-12. Page 11 line 8: The location of the Mole at Kinnersley Manor will not be known by most readers .It would be better to include the location of all sites mentioned in the text on Figure 1 rather than the insert to Figure 2 which does not include the Mole at Kinnersley Manor.

This is a good suggestion and we have labelled the 5 catchments mentioned in Figure 2, along with the Mole at Kinnerley Manor, in Figure 1 in the revised manuscript.

R#1-13. Figure 1: Include names of sites referred to in the text and Figure 2.

This is done as per R#1-12, thanks.

R#1-14. Figure 3: Consider a non linear x axis scale to allow readers to view sub monthly skill results – this is not possible with a linear scale.

We believe the linear scale shows the high rate of skill decay and prefer to keep the linear scale. However, we agree that sub-monthly results are too difficult to see. We have therefore redrawn Figure 3 to include results for short (1- and 3-days) and extended (1- and 2-weeks) lead times. Note: figure 3 in the revised manuscript is now based only on CRPSS based on R#3 comments on most appropriate choice of skill score.

R#1-15. Figure 8: axis labels are absent on all x and y axis – is this because they are dimensionless, if not please can these be included on the figure?

Figure 8 has now been modified based on R#2-5. X1 (mm) and X3 (mm) are now combined as catchment storage capacity (X1 + X3 in mm) but log transformed (using the natural log) because of the large skew in the values (as was done in the original manuscript). Therefore the units are 'log mm'. BFI and CRPSS are dimensionless '[-]'. Axis labels have now been included.

References

Arnal, L., Cloke, H. L., Stephens, E., Wetterhall, F., Prudhomme, C., Neumann, J., Krzeminski, B. and Pappenberger, F.: Skilful seasonal forecasts of streamflow over Europe?, Hydrol. Earth Syst. Sci. Discuss., 2017, 1–27, doi:10.5194/hess-2017-610, 2017.

Beckers, J. V. L., Weerts, A. H., Tijdeman, E. and Welles, E.: ENSO-conditioned weather resampling method for seasonal ensemble streamflow prediction, Hydrol. Earth Syst. Sci., 20(8), 3277–3287, doi:10.5194/hess-20-3277-2016, 2016.

Crochemore, L., Ramos, M.-H., Pappenberger, F. and Perrin, C.: Seasonal streamflow forecasting by conditioning climatology with precipitation indices, Hydrol. Earth Syst. Sci., 21(3), 1573–1591, doi:10.5194/hess-21-1573-2017, 2017.

Crooks, S. M., Kay, A. L. and Reynard, N. S.: Regionalised Impacts of Climate Change on Flood Flows: Hydrological Models, Catchments and Calibration, Centre for Ecology & Hydrology, Environment Agency, Defra, London., 2009.

National River Flow Archive: Integrated Hydrological Units of the United Kingdom: Hydrometric Areas with Coastline, NERC Environmental Information Data Centre, Available from: https://doi.org/10.5285/1957166d-7523-44f4-b279-aa5314163237, 2014.

Poncelet, C., Merz, R., Merz, B., Parajka, J., Oudin, L., Andréassian, V. and Perrin, C.: Process-based interpretation of conceptual hydrological model performance using a multinational catchment set, Water Resour. Res., 53(8), 7247–7268, doi:10.1002/2016WR019991, 2017.

Wood, A. W., Hopson, T., Newman, A., Brekke, L., Arnold, J. and Clark, M.: Quantifying Streamflow Forecast Skill Elasticity to Initial Condition and Climate Prediction Skill, J. Hydrometeor., 17(2), 651–668, doi:10.1175/JHM-D-14-0213.1, 2016.

Reviewer 2 (Guillaume Thirel') comments are labelled consecutively, for example, comment 1 is R#2-1, with our responses to his comments given in blue text.

R#2-1. This manuscript presents an evaluation of ESP over the UK. The ensemble forecasts are based on the lumped conceptual GR4J model and past P and PET observations that were resampled as used as input to GR4J. These forecasts are compared to proxy observations (GR4J streamflows using P and PET observations) and a benchmark (resampling of these GR4J streamflows).

This paper is generally well written, very clear, and it makes a significant contribution to the HESS journal. However, I of course have some remarks that would deserve some attention from the authors, some of them not being minor. I am convinced that the authors will be able to handle that efficiently and allow the paper to be published.

We thank Guillaume Thirel very much for his supportive comments and constructive feedback that has helped us refine our paper, particularly his insights on hydrological modelling components.

Major comments:

R#2-2. The way ESP is thought of in this manuscript is a bit old fashioned in my opinion. It is true that first ESPs were using IHCs and past data, but this is not really the standard nowadays. Indeed, the standard is more what is called in the article NWS ESP. These forecasts are now a well-established method and are the reference, especially up to a month of lead time. I would advise the authors using a more modern terminology in the abstract and article or at least being more specific. Moreover, the justification of the choice of this method should be given.

We fully recognise that ESP, in its traditional form as used here, is a very simple method, and that alternative more sophisticated ensemble hydrological forecasting techniques are becoming increasingly used. We believe, however, there is still a need for benchmarking the skill of such simpler methods, as traditional ESP is still considered a good alternative forecasting technique, in the absence of for example expensive seasonal climate forecasts. The choice of evaluating the forecast performance of a simple method like traditional ESP was motivated for three main reasons: 1) to provide a benchmark against which more complex methods could be evaluated for a range of lead times, up to 365 days - this is rarely done (nor possible with more computationally expensive techniques); 2) to identify when/where traditional ESP does not contain sufficient information to generate a skilful hydrological forecast, and henceforth where more complex methods, including use of dynamic atmospheric forecasts, are therefore essential for generating skilful hydrological forecasts; and 3) to formalise the skill of the hydrological seasonal forecasting systems currently used operationally in the UK (within the Hydrological Outlooks UK: http://www.hydoutuk.net/), through a national-scale analysis – the first time this has been done.

We have however edited the revised manuscript to:

a.) More clearly distinguish that it is ESP in its traditional form we are assessing: Pg2; L16: “In the traditional formulation of ESP as used in this paper,…” & Pg2 23-25: “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”.

b.) Give a stronger justification why the simple ESP method is still used by many others today and indeed why we are examining it within this manuscript on Pg3; L7-11: “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”.

R#2-3. IHCs influence is high for short lead times and low for large lead times. Following the authors' sentence (P. 8, L. 2-4) that would mean that for short lead times, MSESS and CRPSS should be closer than for long lead times. However, we don't see that on Fig. 4, all lead times seem to have a similar difference between both SSs.

This comment and the comments from reviewer #3 sparked our curiosity of the impact of using different skill score metrics. We agree with R#3-6 that comparing MSESS (as the deterministic measure of ensemble mean) and CRPSS (as the probabilistic measure of full ensemble) as originally done in Figure 3, 4, and 5 (and on Pg8; L2-4 in the original manuscript that you are referring to) is misleading as these two scores are not directly comparable. As reviewer #3 points out it is the Mean Absolute Error Skill Score (MAESS) that equals CRPSS for a deterministic forecast (also mentioned in Trinh et al. (2013) as recommend by you), and would have been better to use instead of MSESS. We have therefore changed the analysis to replace MSESS by MAESS, and in fact see virtually the same results for probabilistic (using CRPSS) and deterministic (using MAESS), and as a consequence this section of text has been removed in the revised manuscript. The following text has been added to the revised manuscript on Pg8; L26-27 instead: "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)".

A more detailed response is given in R#3-6 below (relevant here but not repeated for brevity) justifying changing the core analysis to be based on CRPSS instead of MSESS.

R#2-4. Section 4.1.2: this analysis is interesting. However, there is a second possible entry, in addition to the initialisation month, to take into account in my opinion: the lead time month. Indeed, some periods of the period are easier to predict (typically in between seasons are more prone to changing weather, which is difficult to predict sometimes); that may reflect on the scores, and could explain the differences that are highlighted here. Moreover, some scores can be impacted, for instances, by the streamflow characteristics. It is known that Nash-Sutcliffe (not used here) is higher for rivers with strong seasonality, or that CRPS is impacted by the streamflow magnitude (Trinh et al., 2013). I'm wondering to which extent the seasonal analysis (but also the spatial analysis actually!) can be impacted by such issues.

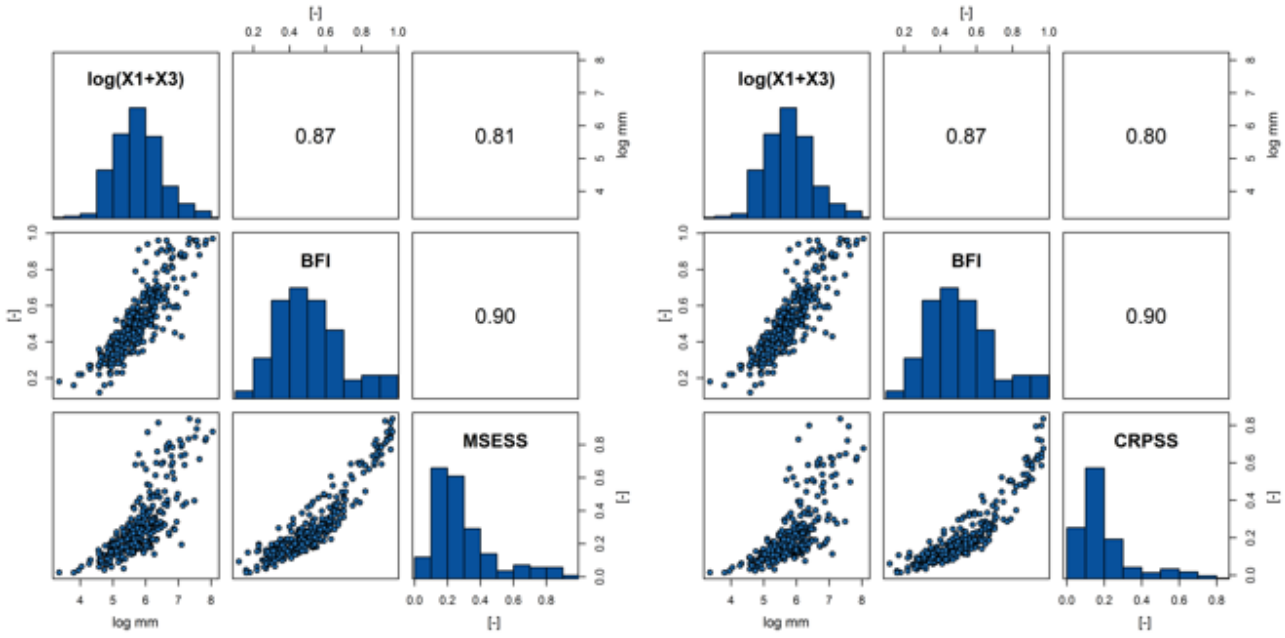
Thanks for these insights and references. First, the issue with CRPS being impacted by streamflow magnitude (as shown in Trinh et al., 2013) is not relevant in our analysis as we are using the CRPS skill score (CRPSS), independent on streamflow magnitude. However, the other issues highlighted could certainly be playing a minor or major role. As explained in our response to R#2-1 the main aim of this work was to perform the first assessment of ESP skill over a range of lead times at the national scale. In order to identify future possible research avenues, we looked if any simple spatial/temporal patterns emerged from the analysis (i.e. Sections 4.1 and 4.2). The attribution of skill (the 'why' in Section 4.3) is meant as a first assessment of the apparent strong relationship between catchment storage and ESP skill.

While we believe a full diagnostic and attribution assessment of the factors responsible for different ESP skills initialised in different times of the year is outside the scope of this paper, as it would require a much more detailed analysis over a complex range of issues, which would lengthen the paper considerably. We have however added a discussion point on the matter and modified the text on Pg 11; L28-32 in the revised manuscript to: "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".

R#2-5. P. 9, L. 21-22: X1 is the production store capacity, and X3 the routing store capacity. It seems difficult to actually link them directly and specifically to soil and groundwater. However, their sum can be considered of the maximum amount of water in the basin (excluding the water in the river and snowpack) and as such it could be of interest including it in Fig. 8.

We agree that it is very difficult directly link X1 and X3 to soil moisture and groundwater, respectively. However, what is really of interest in this first assessment is the more general question of whether catchment storage is in any way related to ESP performance. We have therefore removed specific reference to linking skill directly to individual soil moisture/groundwater storage capacity model parameter values in the revised manuscript, but instead use your suggestion (thank you!). The text on Pg10; L19-23 in the revised manuscript now reads: "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".

We now use total catchment storage capacity (X1 + X3) in Section 4.3 and Figure 8, instead of X1 and X2 individually. Results are shown in the below redrawn Figure 8 (left using MSESS and right using the CRPSS, as suggested by reviewer #3). First is that results are virtually the same independent if MSESS or CRPSS is used. Interestingly, the Spearman's correlation coefficient is higher against MSESS for (X1 + X3) (ρ = 0.81), than for X1 (ρ = 0.73) or X3 (ρ = 0.57) individually, and is also higher against the BFI for (X1 + X3) (ρ = 0.87), than for X1 (ρ = 0.76) or X3 (ρ = 0.74). Therefore, Section 4.3 and Figure 8 has been replaced with the combined catchment storage variable (X1 + X3), instead of X1/X3 individually, and for CRPSS rather than MSESS.



New Figure 8: Redrawn using MSESS for comparison with original manuscript (left), and using the CRPSS as is proposed metric within the revised manuscript.

R#2-6. Section 4.3 aims at finding factors for skill in the model. Did the authors check if the initial states of the model show a correlation with skill? For example, the initial amount of water in the basin, S + R in Fig. 1 of Perrin et al., 2003 (production store + routing store fillings) and the initial snow pack (if a snow model is used) can give good insight (see Singla et al., 2012).

Thank you for this really interesting suggestion. We did not yet explore if initial states show a relationship with skill, but this would certainly be a fruitful avenue for further research into a more detailed attribution of the sources of ESP skill. We feel the revised Figure 8, as outlined in R#2-5, is at a suitable level of detail for the first assessment paper and will certainly pursue this research idea in more detail in our ongoing work, thank you!

Minor comments:

R#2-7. Abstract: there is a mix between present tense and past tense. Line 14: missing S at ensembleS. Also, lines 21-22 there is a mix between lower, lowest, higher and highest. It is not known from the abstract what the rho symbol represents.

Thank you for these suggestions: We have changed this to: "to produce **a** 51-member ensemble of streamflow hindcasts", we have also revised the tenses and now spell out the rho symbol as "Spearman's rank correlation coefficient".

R#2-8. P. 3, L. 21: Section 5 should be Sect. 5 to be consistent with the other occurrences.

Changed.

R#2-9. P. 3, L. 28: please check all fonts sizes

Changed.

R#2-10. P. 6, L. 2: initialisation is misspelled

Changed.

R#2-11. P. 6, L. 3: at p. 5, L. 21, m is the ensemble, not the ensemble size. Also, LT means lead time, it is therefore better not to use LT for designing the number of lead times

We now do not refer to m or LT in this way as per your suggestion.

R#2-12. P. 6, L. 4: no need for volumes, I think that streamflow is enough

Volumes are now not referred to as per your suggestion.

R#2-13. P. 6, L. 15: remove the comma after Wilks

Changed.

R#2-14. Section 4.1.1, P. 7, L. 26 and later on: do we really need such a precision for all the scores?

We agree with the reviewer that the third decimal point in the skill scores/correlations was not necessary and have changed all instances in figures and text throughout the revised manuscript.

R#2-15. P. 9, L. 6: replace "is" with "in" (I think). In this section, percentages sometimes have a space between the figure and the percent sign, sometimes not.

Yes, have changed and made spacing consistent throughout.

R#2-16. P. 9, L. 13: is “E” actually “SE”?

Yes, good spot, changed.

R#2-17. P. 12, L. 4-6: yes, that definitely has an impact in some basins!

Indeed, while we show that it is only a very small fraction of basins studied that have a significant fraction of snow, and usually only for winter months, it is nonetheless an important consideration within ongoing work and this is acknowledged in the text.

R#2-18. Ghannam et al. reference has some misspelling in the authors’ list

Changed.

R#2-19. Table 1 caption: I would add “R package (Coron et al., 2016, 2017)” after “airGR” and “(Perrin et al., 2003)” at the end of the caption

Have now also cited these sources in the caption: “* $\overline{F_S}$ 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)”.

R#2-20. Table 2 caption: please remind the GR4J calibration period for the parameters that are given here.

The Table 2 caption now reads in the revised manuscript: “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)”.

R#2-21. Figure 3: I think that “short”, “extended”, “monthly”, “seasonal” and “annual” should indicating more precisely what they refer to. Maybe use some arrows for this.

These terms refer directly to text on Pg7; L12-13 in the original manuscript and Figure 3 has now been redrawn as per R#1-14 in the revised manuscript so we believe it is less cluttered and easier to see the vertical lines these terms directly relate to. This is also clearer in the revised figure 3 caption.

References:

Singla, S., Céron, J.P., Martin, E., Regimbeau, F., Déqué, M., Habets, F., Vidal, J.-P. Predictability of soil moisture and river flows over France for the spring season (2012) Hydrology and Earth System Sciences, 16 (1), pp. 201-216.

Trinh, B.N., Thielen-del Pozo, J., Thirel, G. The reduction continuous rank probability score for evaluating discharge forecasts from hydrological ensemble prediction systems
(2013) Atmospheric Science Letters, 14 (2), pp. 61-65.

Reviewer 3 comments are labelled consecutively, for example, comment 1 is R#3-1, with our responses to reviewers given in blue text.

R#3-1. This paper investigates the performance of the ESP forecast method in the United Kingdom. The authors investigate when, where and why the ESP is skillful, based on a set of 314 catchments and 50 years of hindcasts generated with the GR6J model and data from the UK National River Flow Archive. The forecasts are evaluated with a deterministic and a probabilistic criterion, and compared to modelled streamflow climatology. The authors conclude that the skill decreases exponentially with lead time. Higher skill are observed in forecasts initialized in summer months for lead times up to one month, and in winter and autumn months for seasonal and annual lead times. Higher skill is observed in slow responding catchments with high soil moisture and groundwater reservoirs and less skillful in highly responsive catchments.

General comment

I think that this paper is very well-written and of great quality. The objectives and methods are clearly defined, and therefore easy to read and to follow the scope of the paper. The length of the article and the number of figures were appropriate and the content was always relevant. In addition, this paper fits nicely in the Subseasonal-to-seasonal special issue. This study provides a useful diagnostic of ESP over the UK. I particularly enjoyed how the authors made the link between the spatial and temporal skill patterns and catchment characteristics and seasonal features. I listed some comments and questions below, most of them dealing with methodological aspects, and none of them being major.

We thank the reviewer for very supportive comments on our manuscript. The comments and questions around the methodological issues have been assessed and we have decided to take on board your suggestion about focusing on CRPSS and so have changed the figures and text throughout the revised manuscript. We discuss the impact this has had on the revised manuscript below.

Major comments and general questions

R#3-2. In both Twedt et al. (1977) and Day (1985), the abbreviation ESP actually stands for “Extended Streamflow Prediction”. It is true that “Ensemble Streamflow Prediction” is widely used, but I think that the original term better conveys the purpose of the method and should be used instead.

We acknowledge the terminology associated with ESP has changed over the years, and recognise that we did not quote appropriately Twedt et al. (1977) and Day (1985). We have edited the text on Pg2; L7-8 to “(Day, 1985; Twedt et al., 1977; originally stood for Extended Streamflow Prediction)”.

As per R#1-2, it is now common practice to describe the traditional ESP approach as ‘Ensemble Streamflow Prediction’ (see response). As per R#2-2, we have now made it clearer that we are talking about the ‘traditional formulation of ESP’ whereby historic meteorological sequences are resampled. We would like to keep our terminology consistent with these papers but could change it if deemed necessary by the editor.

R#3-3. P5 L24-25 : “Each of the 51 generated hindcast time-series were then temporally aggregated to provide a forecast of streamflow volume with seamless lead times of 1-day to 12-months, resulting in 365 lead times LT per forecast (leap days were removed).” Do I understand correctly that the streamflow volume for 30 days is obtained by aggregating daily forecasts from day 1 to day 30, and that the streamflow volume for the year aggregates all daily forecasts from day 1 to day 365? If not, could you please clarify? If so, I was confused by the word “lead time” and the analysis involves more factors than just the lead time. Rather than an analysis on lead times, it is an analysis on both aggregation periods and lead times that can be argued to be between 0 days and the last day of the aggregation period. I don’t believe this to be real issue, but maybe the authors could be more careful in the way they used the term “lead time”. To be more specific, it is the occurrence of “lead times” in Figures 3, 4 and 5 and Section 3.1.1 that triggered this comment.

We thank the reviewer for pointing out that this needs more clarification in the manuscript, and answered in R#1-4a (not repeated here for brevity).

R#3-4. P5 L28 : Regarding the implementation of the L3OCV method, I was wondering why the authors excluded the subsequent two years but not the preceding two. My guess would be that, operationally, the preceding two years are always available, in any case, while the succeeding two are still missing on the day of the forecast, and adding them will add missing and non-independent information to the calibration-validation procedure. Could the authors say a bit more on that?

Yes, this is correct. Operationally we have meteorological forcing data to drive ESP up until the forecast initialisation date. In the hindcast experimental design, we will never have exactly the same conditions as the operational case, because we are driving the ESP in the hindcast (e.g. 1965) with precipitation and PET sequences from 'future' periods (e.g. 1967), which clearly we would not have operationally. To make sure the hindcast experiment is as close to operational conditions as practically possible we do not use the current or two succeeding years (i.e. L3OCV), as large-scale climate phenomenon such as the NAO has shown to have multi-season/year persistence in some parts of the UK. We were motivated by an insightful HEPEX blog post by Robertson et al. (2016) which we also cited in the original manuscript: https://hepex.irstea.fr/how-good-is-my-forecasting-method-some-thoughts-on-forecast-evaluation-using-cross-validation-based-on-australian-experiences/.

We have modified this section of text (now at Pg6; L15-21) to: "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.

R#3-5. P6 L25-27 : "It was found in testing that ESP skill was artificially advantaged (disadvantaged) if cross-validation was not carried out in historic climate forcings (benchmark forecasts), in some cases by +/-15 %." Could you please clarify this sentence?

This sentence also relates to a point made in the Robertson et al. (2016) HEPEX blog post "Forgetting to cross-validate reference forecasts can unfairly *disadvantage* your forecast method. Remembering to cross-validate the reference forecast (e.g. streamflow climatology used here) is just as important as cross-validating ESP forecasts".

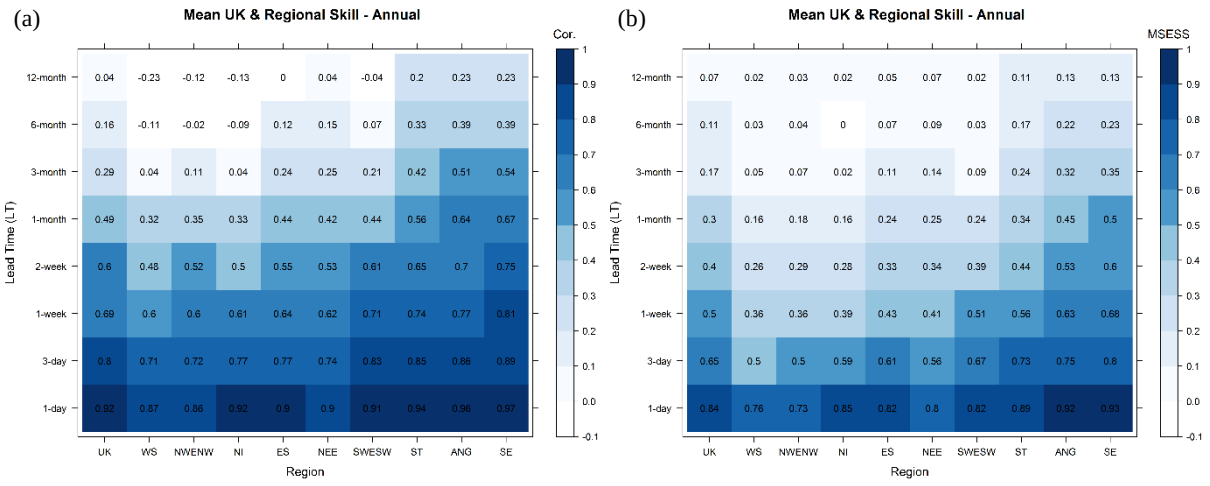
We have replaced the text on P7; L15-19 with: "In testing, we performed the skill evaluation with and without cross-validation of ESP forecasts and streamflow climatology benchmark forecasts. It was found that cross-validation was important as in some cases failing to cross-validate ESP forecasts inflated 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 %".

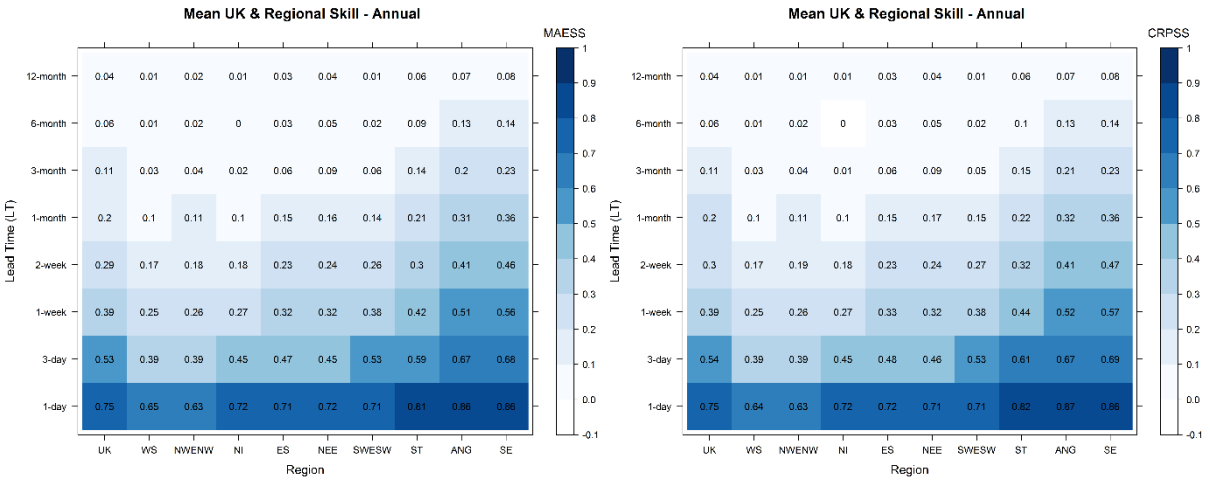
R#3-6. I was wondering about the authors' choice to use the MSE as deterministic score in this case. If the purpose of the two scores is simply to distinguish between deterministic and probabilistic performances, I would recommend using the Mean Absolute Error (the CRPS value of a deterministic forecast is MAE, Hersbach, 2000) so that, when comparing both scores (e.g. Figure 3), the difference in value is solely due to considering the probabilistic side of the forecast.

We thank the reviewer for their recommendation and have implemented the suggestion in the revised manuscript. There is not yet consensus within the hydrological forecasting community on which is the 'best' skill score/combination of scores to use. We originally decided on MSESS for the deterministic evaluation purely as it has been widely applied and recommended elsewhere. It also has the advantage to being analogous the Nash-Sutcliffe Efficacy (NSE) metric used very widely in hydrological modelling. However, after consideration of your comment and in testing with the MAESS it became clear that the way MSESS and CRPSS were represented in Figures 3, 4, and 5 could be confusing as they are not directly comparable – as you point out for any single ESP you cannot conclude that the ensemble mean (deterministic) is more skilful than the full ensemble (probabilistic) if the MSESS value is higher than the CRPSS value – a point responded to R#2-3.

We have further tested four of the most common used metrics for assessing hydrological forecasts: Pearson's correlation coefficient (not a skill score: x = ensemble mean, y = proxy obs), MSESS (deterministic), MAESS (deterministic), and the CRPSS (probabilistic). Results from this analysis show that scores from the MAESS and CRPSS are very similar (see the new **supplementary figure S2 below**), and that there is virtually no difference between the skill ensemble mean and full ensemble across lead times or regions (Figure S2 c and d). The results for correlation (Figure S2a) and MSESS (Figure S2b and same as Figure 6 in the original manuscript) are systematically higher than MAESS and CRPSS, not due to IHC influence etc. but simply due to the different formulation of these metrics. Their values on a 0 to 1 scale are not directly comparable. However, it must be made clear that it is only the ***magnitude*** of values that is different – the results/interpretation of ESP skill remain largely the same no matter which metric is used (so most/least skilful region, skill across initialisation months etc.).

We have now concentrated on CRPSS (instead of MSESS originally) in the revised manuscript, as ESP is a probabilistic method. Given results are so similar between the full ensemble (CRPSS) and deterministic ESP forecasts using MAESS, in the revised manuscript we have only used CRPSS in Figures 3, 4, 5, 6, 7, and 8. Therefore, we have added the following text on Pg 7; L26- Pg 8; L2: "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 (from 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".





Supplementary Figure 2: 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 a.) Pearson correlation coefficient (Cor.), b.) Mean Squared Error Skill Score (MSESS), c.) Mean Absolute Error Skill Score (MAESS), and d.) Continuous Ranked Probability Skill Score (CRPSS). Darker (lighter) shades showing higher (lower) skill; individual mean skill values are shown within each cell.

R#3-7. Still on the evaluation criteria, given that ESP is a probabilistic ensemble that translates the uncertainty from climatology, I would have liked the authors to focus more on the CRPS than on the MSE, e.g. in Figures 6, 7 and, possibly, 8). Was there a reason to focus on MSE instead?

As per our response to R#3-6 above, we have now redrawn figures 3-8 using CRPSS but this do not change the conclusions of the paper in terms of ESP skill. Note that the now reported skill magnitudes using CRPSS are lower than previous MSESS. This highlights that the qualitative threshold of what is a 'highly skilful' forecast is strongly metric dependent. For example, the CRPSS for the 6-month January ESP forecast in the Thames is 0.36 with the Pearson correlation coefficient is 0.77 (new Figure 2b in the revised manuscript). Sect. 3.4 has been modified to reflect this change. Also, we have revisited Figure 7 and added a new threshold in grey (between +/- 0.05) called 'neutrally skilful' after Bennett et al. (2017) to show the difference between CRPSS values near zero. The text on qualitative thresholds has been modified on Pg 8; L13-18 in line with the above changes:

"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 $\pm$ 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".

R#3-8. P7 L17-21 : Is the scale defined for MSESS values or CRPSS values? In the interpretation of Figure 6, it also seems that the threshold value for "Very Low" has shifted to (0, 0.1).

Figure 6 does not discuss these qualitative skill categories but rather shows skill per lead time and hydroclimate region having sequential increments at 0.1.

R#3-9. Figure 4 and Table 2: To which extent does the performance of GR4J for each month of the year explains the results obtained for short to medium lead times and presented in Figure 4?

This is a good point, also brought up by R#2-4. This has been revised - see response to R#2-4 - to include reference here to the potential performance of GR4J throughout the year. This is an interesting point but is outside the scope of the paper.

R#3-10. Figure 7: Here, I would have liked to see the maps for November which is cited earlier in the analysis.

The aim of Figure 7 is to demonstrate the value of mapping skill scores at the individual catchment scale to highlight the high degree of sub-region heterogeneity. To do this we needed to select a sample of lead times (here, four: 1-week, 1-month, 3-month, and 12-month) and a sample initialisation months (here, January, April, and July in the original manuscript). The choice of three interesting initialisation months was mainly guided by results from Sect. 4.1.2. January as being an interesting month representative of months when soil moisture deficits (SMDs) are low, April representative of spring SMD transition conditions, where ESP skills have shown to be lowest in the UK, and August which is now the most skilful month, on average, for lead times up to 1-month using the CRPSS (was July using MSESS in the original manuscript). We could add another initialisation month (e.g. November as you suggested) but there is little additional information and results for January are largely representative, see the below figure for November also. We would prefer to keep just three initialisation months for simplicity and to save space, but could change Figure 7 to the below if deemed preferable by the editor.

Both versions of the Figures are below: three initialisation months (January, April, and August) and four initialisation months are one per mid-season (i.e. January, April, July, and November).

Figure 7 – 3 x 4 (as in the revised manuscript):

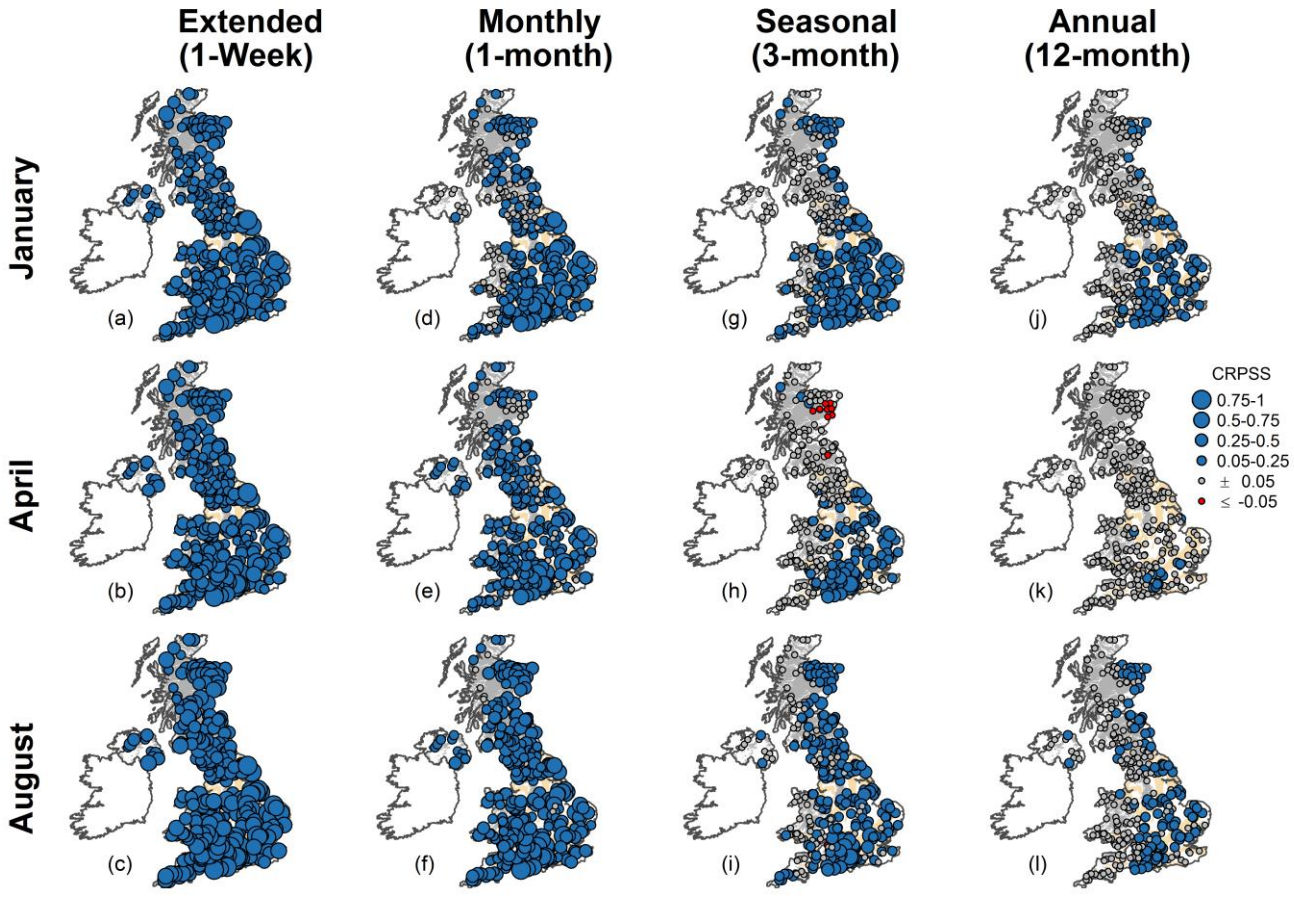
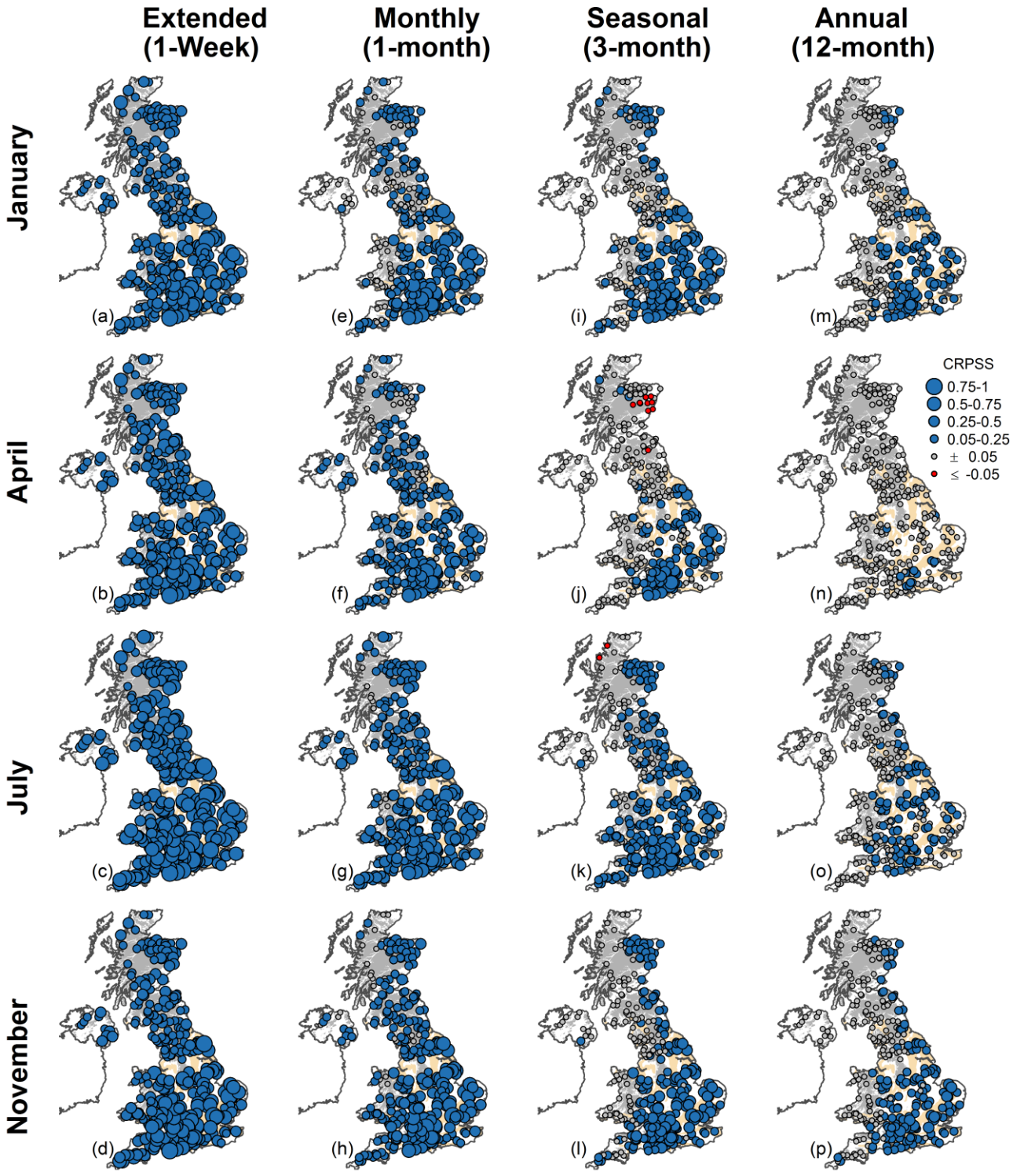


Figure 7 – 4 x 4 (could change to this version if necessary):



Minor comments

R#3-11. P2 L27 : Please change “out to at a least 7-month lead time” to “out to at least a 7-month lead time”

Modified, thanks.

R#3-12. P3 L28 : “132 catchments that are part the new version” to “132 catchments that are part of the new version”

Thank you this has been changed. We also note that the number of UK benchmark catchment is 128, not 132. This error has been corrected in the revised manuscript.

R#3-13. P6 L2: Please change “initilisation” to “initialisation”

Changed.

References

Bennett, J. C., Wang, Q. J., Robertson, D. E., Schepen, A., Li, M., and Michael, K.: Assessment of an ensemble seasonal streamflow forecasting system for Australia, Hydrol. Earth Syst. Sci., 21, 6007-6030, https://doi.org/10.5194/hess-21-6007-2017, 2017.

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. 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. 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 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 (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.

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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

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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

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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.

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 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 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 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 ~0.15-0.35 representative of more responsive rainfall-runoff regimes in the north and west whereas many Chalk rivers in the south east have a BFI $\geq$ 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 hydroclimatic characteristics provide a large and diverse set of catchments to benchmark ESP skill.

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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;

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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

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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):

$$\text{Skill Score} = \frac{A_{fc} - A_{bench}}{A_{perf} - A_{bench}} \quad (1)$$

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

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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).

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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

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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 ≤ 0.35, 20 % of catchments) have on average low skill (CRPSS = 0.08) whereas the slowest responding catchments (BFI ≥ 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.

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5.1 When is ESP skilful?

UK-wide ESP forecasts for short lead times (out to 3-days) are on average highly skilful (CRPSS ≥ 0.5) and for extended lead times (out to 2-weeks) moderately skilful (CRPSS ≥ 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.

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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

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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.

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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.

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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 (km^2)	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).

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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)

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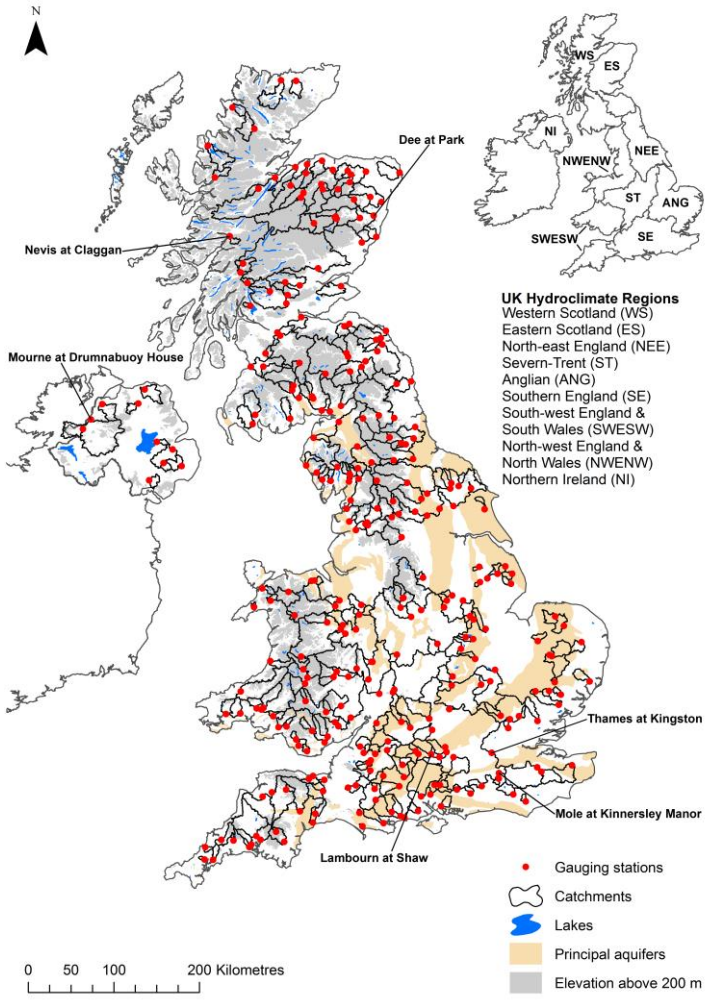

Figure 1: Location of 314 gauging stations (red dots) and catchment boundaries (black lines) with upland areas (shaded in grey) and principal aquifers (shaded in pale yellow). UK Hydroclimate Regions, derived from grouping smaller UK hydrometric areas, are shown inset.

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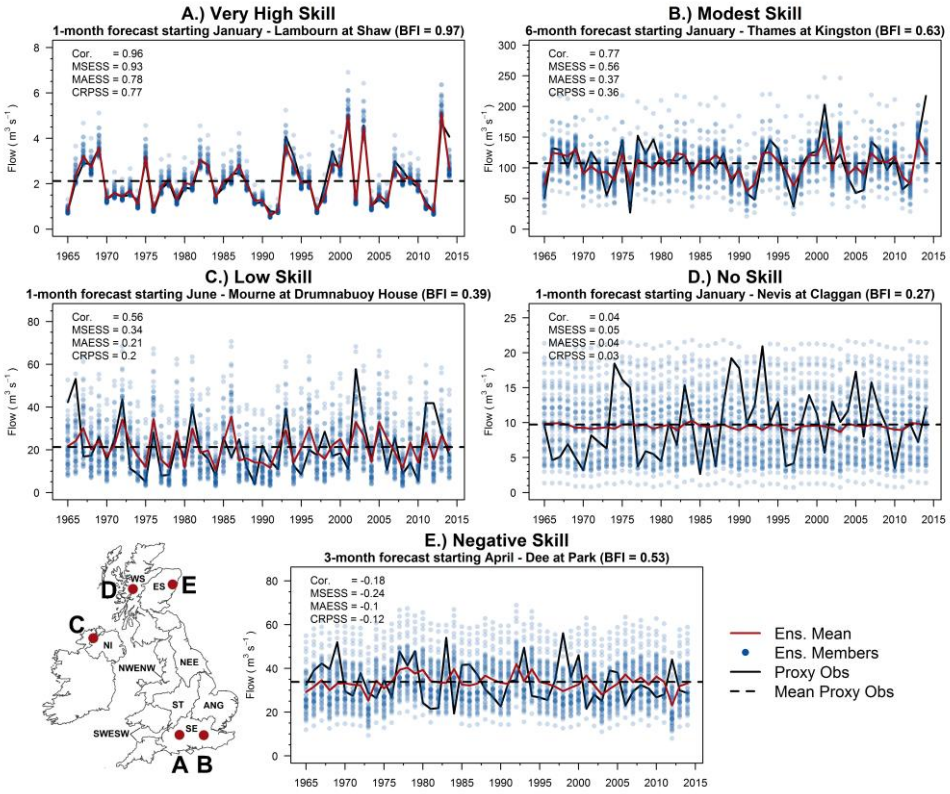

Figure 2: Five example 1965-2015 hindcast time-series in which skill metrics range from very high (a) to negative skill (e). The red line is the 51-member ESP ensemble mean, black line the proxy observed streamflow (also known as a perfect forecast), semi-transparent blue dots show the ensemble spread 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)).

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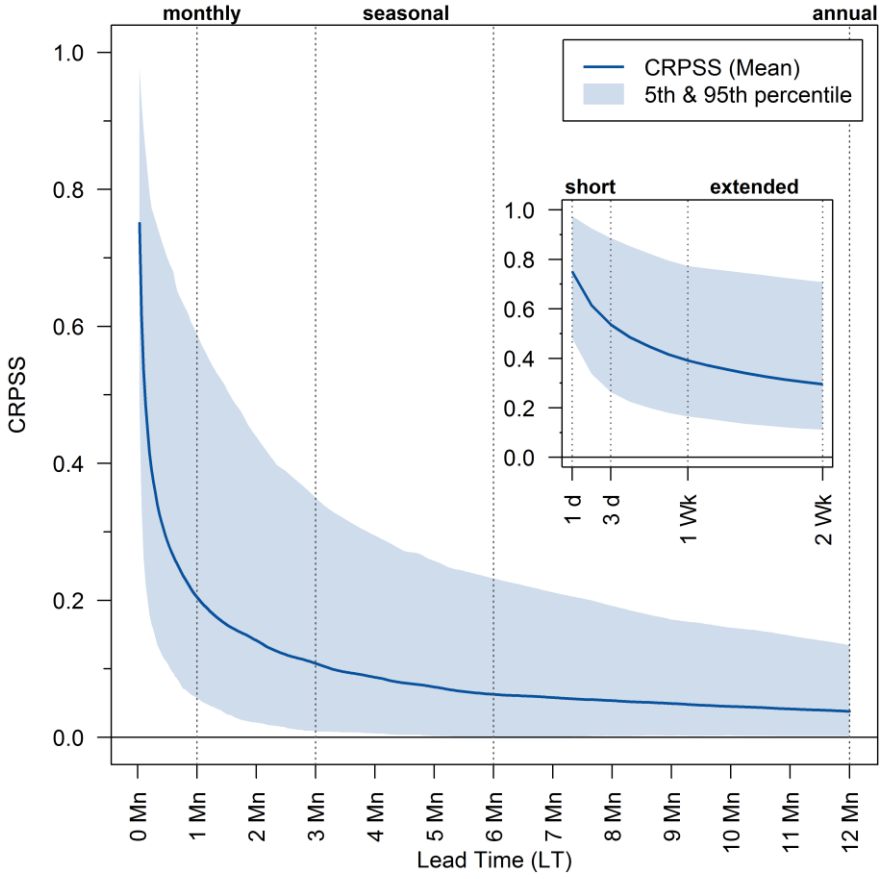

Figure 3: UK-wide mean ESP CRPSS values across all 314 catchments and 12 forecast initialisation months for all 365 lead times (LTs) with short and extended lead times also shown inset for readability. The range of skill scores across catchments at each LT is shown by the semi-transparent 5th and 95th 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).

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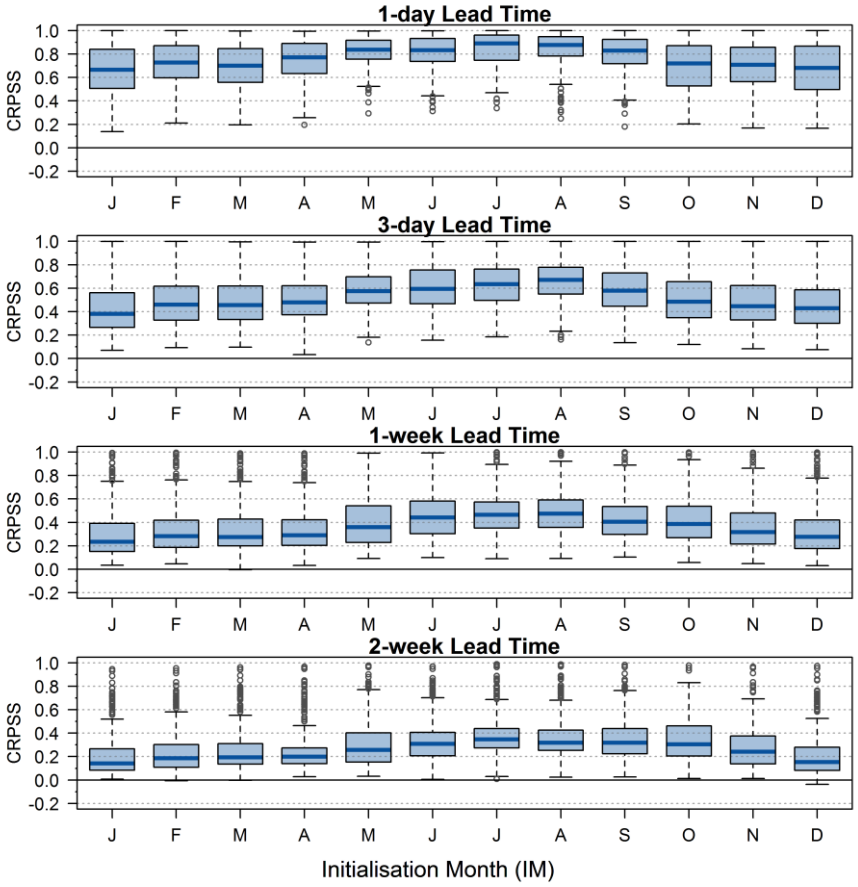

Figure 4: UK-wide ESP skill scores across 314 catchments for each of the 12 forecast initialisation months for four short and extended lead times. Blue boxplots summarise CRPSS values with the black line representing the median, and boxes the interquartile range (IQR); whiskers extend to the most extreme data point, which is no more than 1.5 times the IQR from the box, and grey circles are outliers beyond this range.

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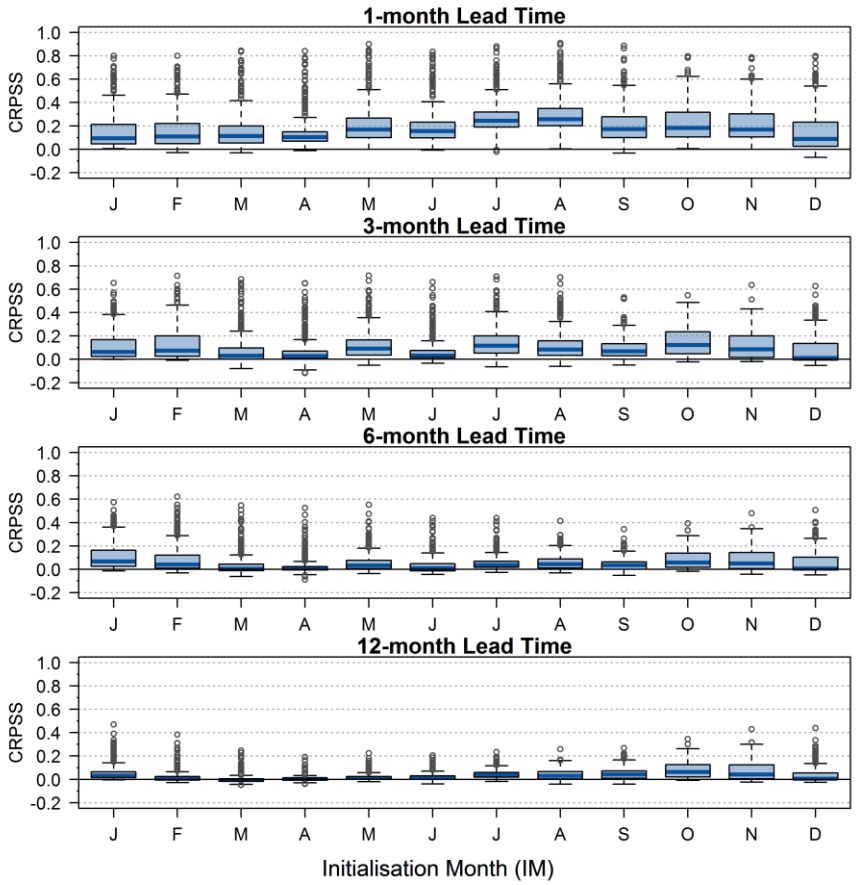

Figure 5: As in Fig. 4 but for four monthly, seasonal, and annual lead times.

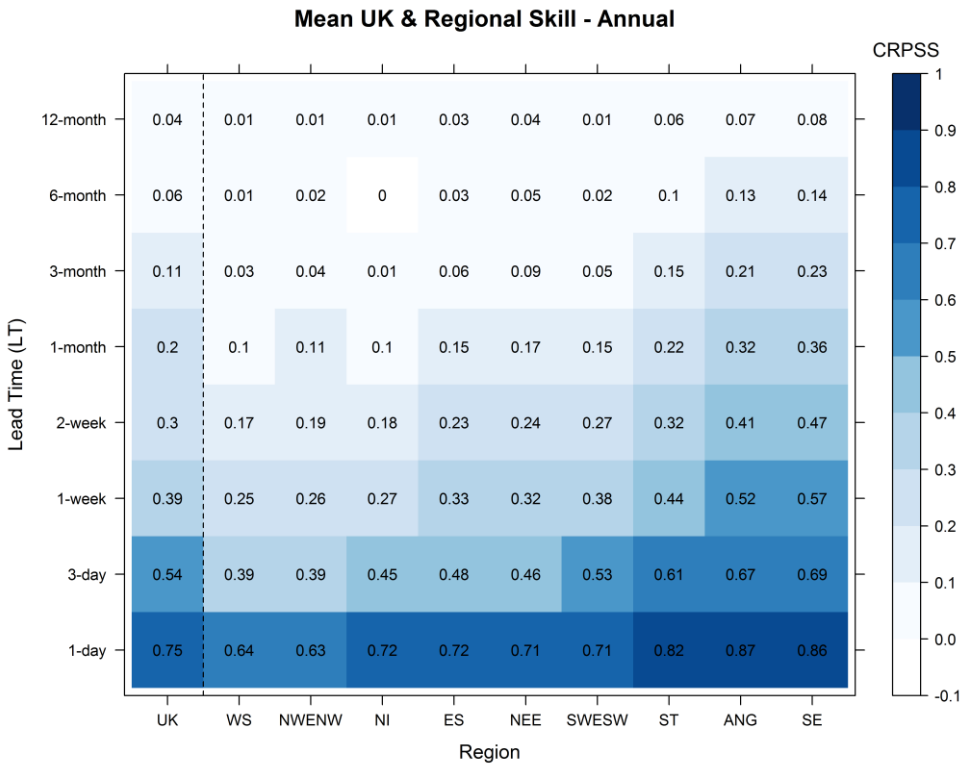

Figure 6: Mean ESP skill across all 12 forecast initialisation months for the UK and for each of the nine hydroclimate regions ordered from least to most skilful (horizontal axis) at eight sample lead times (vertical axis). Skill is given by the CRPSS with darker (lighter) shades showing higher (lower) skill; mean skill score values are shown within each cell.

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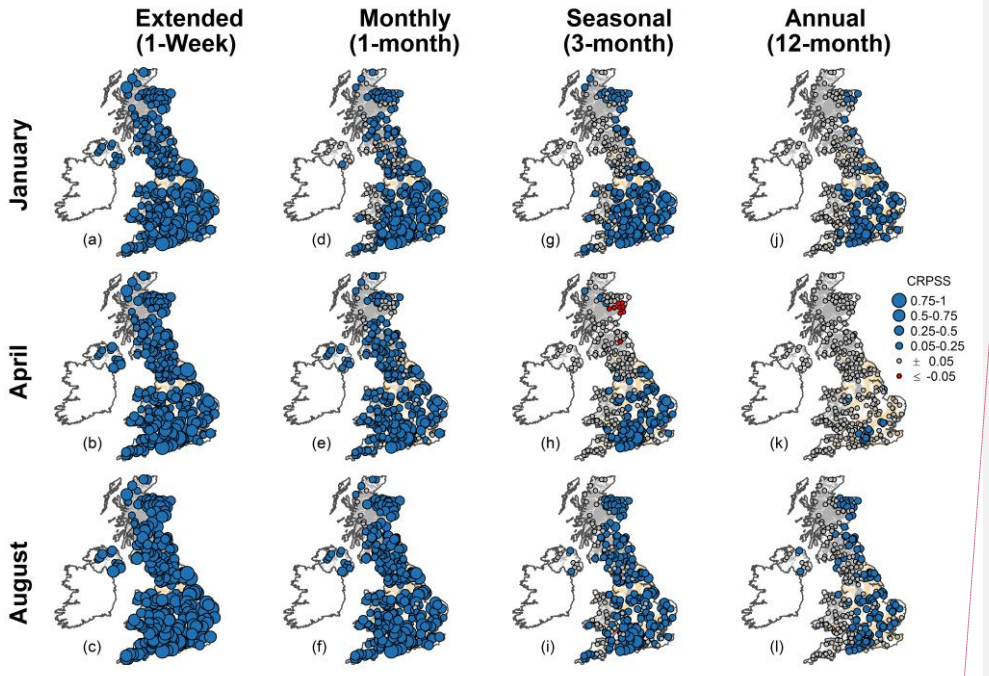

Figure 7: ESP skill for individual forecasts made at each of the 314 catchment locations for four sample lead times (columns) and three initialisation months (rows). Larger (smaller) circles represent higher (lower) skill from CRPSS with blue circles when ESP is more skilful than benchmark climatology and red when ESP has no skill. Grey circles represent neutrally skilful forecasts (i.e. CRPSS values between ± 0.05).

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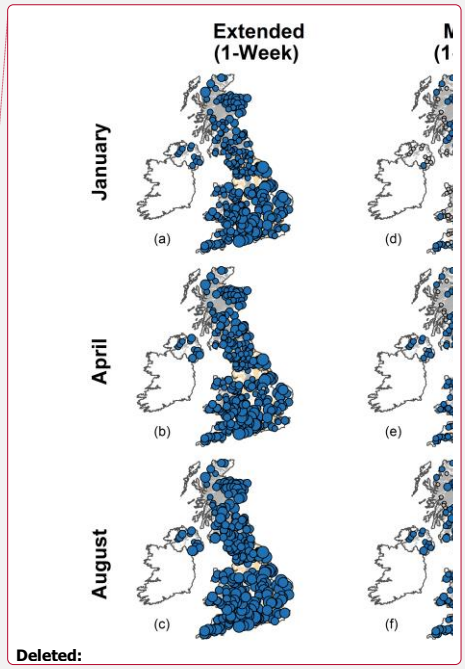

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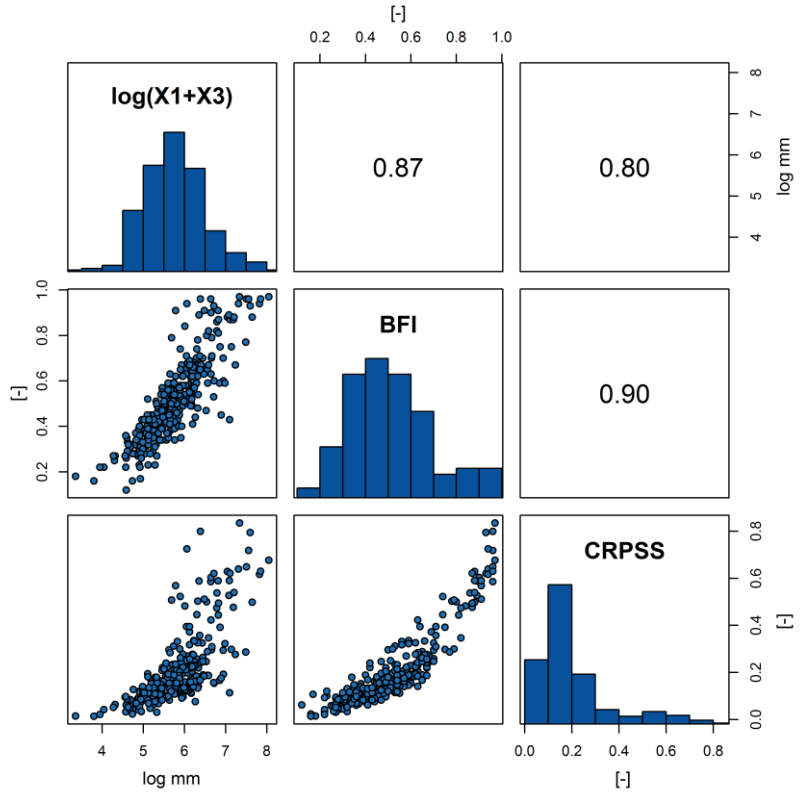

Figure 8: Scatterplot matrix between catchment storage capacity (X1 soil store capacity [mm] + X3 groundwater store capacity [mm]), BFI, and ESP skill (CRPSS) with n = 314 using the non-parametric Spearman's rank correlation coefficient ρ. Skill is the 1-month CRPSS skill score magnitude averaged across all 12 initialisation months. Catchment storage capacity (X1 + X3) was re-expressed by taking the natural log as raw values are heavily positively skewed.

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