Authors' response to referees

We have structured our response in this document as follows. First, we share our point-by-point response to Reviewer 1 (RC1 response), followed by our point-by-point response to Reviewer 2 (RC2 response). Following this there is a combined response to both reviewers (which we call the supplement). The final section is the marked-up version of our manuscript.

RC1 response

Review of the study "Improving sub-seasonal forecast skill of meteorological drought: a weather pattern approach" by Richardson et al. This study aims at analysing the predictability of meteorological droughts over UK and the potential interest of using predictors based on weather patterns. The authors conclude about the improvement of the forecasts by using this approach, and depending the seasons and regions, they provide recommendations to forecasters. This study is well documented, the figures and the text are clear and the statistics are robusts. After a careful reading, I recommend to publish this study that bring innovative and interesting results after substantial revisions.

Response: We thank the referee for their detailed review of our manuscript and hope to satisfactorily address their comments and concerns, as detailed below.

Please note there is a supplement to this document.

Major comments

Comment: *To clarify the different forecasts, I suggest to add a schema of the different forecast systems. The assignment procedure (from the forecasted WP to precipitation) is not clear enough and part of it should be moved from the Sup. Mat. to the main document.*

Response: We agree that adding a schematic of the different forecast systems and expanding on the WP-to-precipitation detail in the main document would be useful to the reader.

Changes to manuscript: We have created a schematic for the four precipitation/drought forecast systems (Fig 2 in the supplement). We tested graphical schematics, but the number of graphics needed (many of which look similar – MSLP anomaly fields, for example) resulted in them being difficult to interpret. Therefore, we created a textual schematic. Table 2 is no longer required so we have removed it.

We have removed the assignment procedure from the Sup. Mat. To Section 3.2 of the manuscript.

Comment: *Figures 4, 5 and 6: Since the scores are depending the regions, I would suggest to plot maps (with one value per region) instead of radar-plots. That will also provide more accurate information about the spatial variability of the scores.*

Response: We chose the radar plots to reduce the number of sub-plots per figure. However, we accept the arguments from both referees that maps would be easier to interpret for a variety of reasons, not least for those with less familiarity of the UK regions used in our study.

Changes to manuscript: We have changed these figures to maps (see Figs. 4, 5, 6, 7, S1 and S2 in the supplement). This has enabled us to label the regions on each plot. Fig. 2 is therefore redundant and we have removed it.

Comment: *It is quite surprising to use the same WPs for all the year long since there is a strong seasonal cycle. What are the results when splitting the year in 2 or 4 seasons? The use of several classification could improve the predictions, for instance in Spring and Summer (L289, Fig. 6b and c, Fig. 7b and c).*

Response: There are several choices that must be made when deriving WP classifications, such as the domain, the spatial and temporal resolution of the data, the number of WPs etc., each of which is a trade-off. Whether to derive separate classifications for each season is also a choice. Classifying on each season might yield WPs that are more representative of the changes in MSLP that occur seasonally, but at the expense of reducing the sample size (which can be critical for machine learning methods such as the simulated annealing procedure used here), and having to find ways to deal with changes in the classification over the year. For example, a forecast issued in one season and ending in the next must deal with a jump in classification. There are methods for doing so (such as appending months to the traditional three-month seasons in the classification derivation), but these are again choices. Furthermore, the classification we used here, MO30, has strong seasonality despite being derived on an annual scale (Neal et al., 2016; Richardson et al., 2018), hence a decision not to apply the classification procedure to individual seasons.

In addition, we focussed on MO30 alone because its relationship with historical UK drought has already been analysed (Richardson et al., 2018) and is used operationally by the UK Met Office and Environment Agency Flood Forecasting Centre for coastal flooding applications (Neal et al., 2018). Therefore, there is interest in exploring further applications using this classification specifically.

Changes to manuscript: We have added details of the frequencies of occurrence of each WP to Fig.1 (see the supplement) to highlight the strong seasonality exhibited by WPs in MO30. We have also added the following sentences in Section 2 highlighting the differences between the frequencies of the ERA-Interim WPs used here and the original WPs used to derive the classification and determine how the WPs were numbered (i.e. their ordering according to historical frequency):

"A consequence of assigning WPs using ERA-Interim compared to the EMULATE data set used in the original derivation of MO30 is that the historical frequencies of occurrence of the WPs differ. The same strongly seasonal behaviour is retained (lower-numbered WPs occurring more often in summer than higher-numbered WPs, and vice versa), but the annual frequencies are more evenly distributed across the WPs - there is no clear decrease in annual frequency as the WP number is increased."

Detailed comments:

l102: *it is not clear if there is a post-processing of the reforecasts. Do you observe any drift with lead time? Is there a bias between the distribution of assigned WP for short and long lead time?*

Response: As mentioned in Section 2 L102-104, the only post-processing is the removal of a MSLP climatology from the MSLP reforecasts to generate the anomalies. This climatology is the same as that used in the derivation of the WP classification (Neal et al., 2016), which is a

reanalysis data set (EMULATE MSLP). We did not remove a lead-time dependent bias from the forecast model as the distribution of assigned WPs for our chosen lead times does not change particularly, as we show in Figure 1 here.

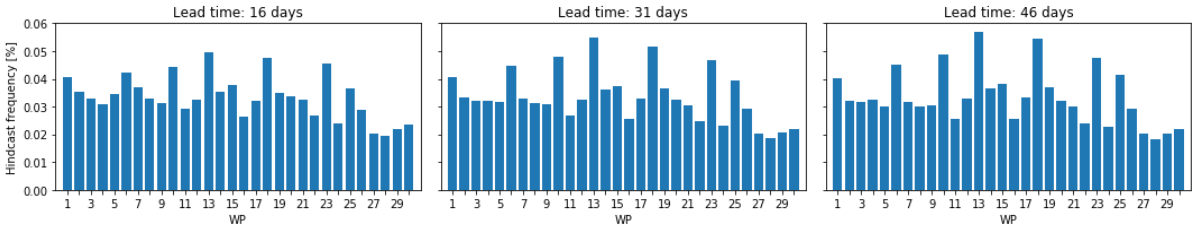

Figure 1: Frequency of forecast WP by the ECMWF EPS at lead times of 16, 31 and 46 days.

Changes to manuscript: None.

l111: *same question for the forecasted precipitation. Is there a correction/post- processing applied?*

Response: We did not apply any post-processing to precipitation. In hindsight, this does not provide a fair assessment of the skill of ECMWF precipitation forecasts (EPS-P) due to systematic model bias, and the fact that we are comparing to WP-based models that sample from the same observational precipitation data set that is used as the 'truth' in the forecast verification. As we frame the paper around the potential usefulness of WP methods compared to model precipitation, we feel that it is important to apply some post-processing to EPS-P.

We have now applied a 3-monthly-mean bias correction to these forecasts and regenerated the skill scores. Unsurprisingly, this increases the skill of EPS-P overall, and weakens the advantages that EPS-WP had over EPS-P as described in the original manuscript.

We thank the referee for highlighting to us that a calibration of EPS-P would make for a much fairer model comparison.

Changes to manuscript: We have added in a sentence to Section 2 to clarify that we have applied a bias correction to the precipitation forecasts. The results section has significantly changed as a result of this, in particular the section describing the forecast accuracy (RPSS and BSS results. The ROC and reliability scores are less affected). The modifications to the results section of the manuscript are too long to put here, we ask the reader to refer to the supplement that contains the new results sections.

Furthermore, we have removed some text (L367-385) from the conclusions recommending models to forecasters as the skill is now too similar to provide a clear choice, and changed the sentence on L352-353 to read:

"We compared two levels of drought: mild drought, when the total precipitation over the lead-time (16, 31 or 46 days) was below the 30.9th percentile climatology, and moderate drought, when the total precipitation over the lead-time was below the 15.9th percentile. Overall, forecast models were found to be more skilful during winter and autumn, particular for longer lead-times. The Markov model tended to be the least skilful, especially when predicting drought. Differences in skill between EPS-P and EPS-WP were typically small, with RPSS, BSS and ROC results not highlighting a clear winner."

4.1 *I think the improvement of forecast with lead time deserves more attention. This result should be better analyzed. The classification of WP is done with reanalysis, correct? The sentences, "the observation and the forecasts tend towards climatology at longer lead time' and 'As the lead-time is increased, the observations become noisier …' sound weirds to me. There is no 'lead time' for the observations. Please clarify.*

Response: The skill of EPS-WP does not change much with lead-time – the JSD remains near 0.2 for all months and lead-times. The skill of the Markov model, however, increases significantly with lead-time. This is a consequence of using the JSD, which is a way of measuring the distance between the probability distribution of the observed WP frequencies of occurrence and the probability distribution of the forecasted WP frequencies of occurrence. The number of WPs in our classification is 30 and therefore these two probability distributions consist of 30 points, each reflecting how often every WP has occurred in the forecast or corresponding observed period. It is important to bear in mind that the length of the observed period is the same length as the forecast, so for forecast of 16 days, the observed period is also 16 days, while for 46-day forecasts, we compare with observations over 46 days.

For shorter lead-times, the probability distribution of observed WPs will be far noisier than the corresponding distribution from the Markov-predicted WPs, as different realisations of the Markov model (i.e. its ensemble members) diverge from each other very quickly. For longer periods, more WPs are likely to have occurred, resulting in a less noisy observed distribution. This is what we mean by "noise" in the observations for longer lead-times. The apparent increase in skill with longer lead-times for Markov, then, is a result of the distance in probability between the two distributions decreasing because of a smoothing of the observed WP frequencies distribution. That is, Markov is better at predicting the long-term average than the short-term.

In summary, for EPS-WP the distribution of forecast WPs looks as similar to the distribution of the observed WPs for shorter and for longer leads. For Markov, the distribution of predicted WPs looks far more like the distribution of observed WPs at longer leads than at shorter leads.

The reason we did not use typical verification metrics here, such as a Brier Score measuring the models' ability to predict WPs at each lead independently (through hits and misses), is that we are considering the total precipitation over multiple weeks. Therefore, we are not interested particularly in whether the models correctly predict the timing of a WP, only that they capture the general distribution over each forecast period.

Changes to manuscript: We have modified the second paragraph of Section 4.1 to be clearer as to the above explanation. Following a comment by the other referee, we have added some text to highlight the fact that the JSD might not be a particularly useful verification metric in the traditional (operational) sense. The second and third paragraphs of Section 4.1 now read:

"An interesting result is how JSD scores for Markov decrease as the lead-time increases (Fig. 3), suggesting an improvement in skill with lead-time. This is the opposite of the expected (and usual) effect. The Markov model predicts WPs using the one-day transition probabilities, and its ensemble members therefore diverge very quickly, resulting in a distribution of predicted WPs that looks similar to the climatological WP distribution for all

lead-times. For a 16-day forecast, the observed WP distribution of the corresponding 16 days will generally be less similar to the climatological WP distribution than for 31-day forecasts, and less similar still than for 46-day forecasts. For instance, at a 16-day lead, only 16 unique WPs could form the observed distribution, whereas Markov is capable of predicting all possible WPs across its 1000 members at this lead. As the JSD measures the distance between these probability distributions, it tends to score the differences between these distributions as more similar (a smaller divergence) for longer lead-times. This means the JSD is perhaps not appropriate as a verification metric in an operational sense, but is noteworthy for highlighting the behaviour of the Markov model.

We could have assessed model skill in predicting the WPs using more common metrics such as the BS, which could measure the hit/miss ratio for each WP at each lead-time. However, the focus of this paper is on multi-week precipitation (and drought) totals, so we are not particularly interested in the models' ability to predict the timing of a WP, only whether they are able to capture the distribution of the WP frequencies of occurrence. It is likely that using the BS would show that EPS-WP and Markov skill decreases with lead-time, as was the case for a WP classification derived from MO30 by Neal *et al.* (2016)."

L238 *How do the authors explain the fact that EPS-WP outperforms Perfect-WP in summer? That could reflect a bias in the forecasted WP compared to the observed ones.*

Response: There are no cases where EPS-WP outperforms Perfect-WP in Fig. 4 (or elsewhere). Perhaps the referee has mistaken the EPS-P results for EPS-WP in this case?

Changes to manuscript: None.

L250 *"The difference in skill . . . for northern and western regions..." this will be more visible if the authors use maps instead of radar-plots.*

Response: This has been implemented as explained previously.

L265 *Maybe the sentences are a bit too optimistic. Indeed, for several regions, the differences between EPS-WP and EPS-P do not look significant (ES, NEE, SEE in winter for different lead times). The potential benefit of the use of WP (perfect-WP) could be also discussed since if the WP are not well forecasted and if the processes between WP and precipitation is well represented in the model, that means the main mistake of the model is the same when using forecasted WP and precipitation. That could limit the interest of using such predictors. This should be discussed.*

Response: We agree that these sentences are a little optimistic, particularly since we corrected the bias of EPS-P, reducing the difference in skill between this model and EPS-WP. We also agree with the referee regarding the limitations of WPs as predictors given the difficulty EPS-WP has in predicting them.

Changes to manuscript: As mentioned in a previous comment regarding precipitation post-processing, we have updated the results section (see supplement) and removed some recommendations to forecasters from the conclusions. We have also expanded on our discussion of potential improvements to increase the predictability of the WPs by adding the following sentences to the last paragraph of the conclusions section:

"The skill of this model during winter and autumn suggest that the processes between the WPs are precipitation are well represented in these seasons. The lesser skill of EPS-WP and Markov, then, is a result of poor prediction of the WPs. A focus on improving the skill of the WP forecasts could be the most useful route to improving precipitation and drought predicting skill."

L266 *Does "simple statistical WP prediction" mean Markov here? I suggest to keep the same name of the experience.*

Response: Yes, we were referring to Markov.

Changes to manuscript: In the new results section (see supplement), this phrase is no longer used.

L279 and Fig 6: *Please remind to the readers that mild droughts mean here. Also I am a bit confused about the definition of droughts with lead time d-46. Droughts are calculated with 30-d cumulated periods. Since the authors used the Extended ensemble, how they calculated droughts with 16 and 46-d lead time? Please clarify.*

Response: Droughts are not calculated with 30-day cumulated periods. As stated in Section 3.4 L168-170, they are calculated on cumulated periods of length equal to the forecast lead-time i.e. over 16, 31 or 46 days. However, we noticed that Table 2 had the incorrect heading of "30-day precipitation sums".

Changes to manuscript: We have reminded readers of the definitions for mild and moderate drought at the beginning of Section 4.3.1 and in the figure captions, as suggested. We have also added clarification when originally defining the types of drought to stress that droughts are defined according to climatological percentiles derived separately for each lead. We have also modified Table 2 – both the incorrect heading and to add a row indicating the max precipitation intervals, as suggested in RC2. See the supplement.

L284 (and elsewhere): *Because of the radar-plots it is quite complicated to locate the regions (here Scotland). That requires constantly back and forth to the UK map (Fig. 2).*

Response: See earlier regarding new map plots.

L292 *It is not clear why the authors conclude "... but not for more severe droughts." since these results are not shown nor discussed previously. Does it mean the same results with severe droughts provide negative BSS? These results could be discussed and added in Sup Mat.*

Response: Thank you for pointing out this error. We were referring to moderate drought, not to a more severe class.

Changes to the manuscript: This phrase is no longer in the results section since it has been updated (see supplement).

L313 *"EPS-WP is the most reliable forecast model" The authors should clarified that perfect-WP is the most reliable but not a real forecast.*

Response: Ok, thanks for the suggestion.

Changes to manuscript: The relevant sentence now reads:

"EPS-WP is the most reliable forecast model (i.e. excluding Perfect-WP)…"

L325 *"... forecasts from EPS-WP are more reliable than from Perfect-WP. . ." According to several figures, I am not convinced with that conclusions (Fig. 9c, 9g, 10a, 10c, 10g)*

Response: We drew this conclusion based on the fact that the results for EPS-WP lie closer to the diagonal than for Perfect-WP. We think that this conclusion is fair, although only for drought forecasts issued with a probability below a certain level (80% for mild drought and 60% for moderate drought). We think this is an important clarification to add to the paper.

Changes to manuscript: We have added to the sentence on L325-326, which now reads:

"An interesting result is that forecasts from EPS-WP are more reliable than from Perfect-WP when the predicted drought probabilities are below 80% for mild drought (Fig. 9) and 60% for moderate drought (except in spring; Fig. 10), despite having lower accuracy (e.g. Fig. 6)"

And a sentence on L328: "However, for drought forecasts issued with higher probabilities, EPS-WP is the less reliable model, under- or over-forecasting drought (depending on the season) more than Perfect-WP."

Discussion section: *In the recommendation section, the authors should redefine their drought definition. Also these conclusions could be different if they change the definition of WP (by splitting the year in 2 or 4 seasons).*

Response: We think it is a good idea to redefine our drought definitions here. We agree that the conclusions could be different if the WP classification was derived separately for each season. They could also be different if we made other choices when defining the classification e.g. domain size, number of WPs etc. See our response to the previous comment (L46-79 of this document).

Changes to manuscript: We have redefined drought definitions in this section, as suggested.

References:

Neal, R., Dankers, R., Saulter, A., Lane, A., Millard, J., Robbins, G., Price, D., 2018. Use of probabilistic medium- to long-range weather-pattern forecasts for identifying periods with an increased likelihood of coastal flooding around the UK. Meteorol. Appl. 25, 534–547. https://doi.org/doi:10.1002/met.1719

Neal, R., Fereday, D., Crocker, R., Comer, R.E., 2016. A flexible approach to defining weather patterns and their application in weather forecasting over Europe. Meteorol. Appl. 23, 389–400. https://doi.org/10.1002/met.1563

Richardson, D., Fowler, H.J., Kilsby, C.G., Neal, R., 2018. A new precipitation and drought climatology based on weather patterns. Int. J. Climatol. 38, 630–648. https://doi.org/10.1002/joc.5199

RC2 response

Dear authors

I read your work integrating weather patterns in the process of generating sub-seasonal forecasts of meteorological drought.

A graphical abstract would help in understanding the methodology.

The presented data and analyses are a good contribution and I have some minor requests and suggestions in the attached supplement.

From my point of view it would be desirable to present the results also in form of spatial maps and the addition of other lead times might suit to better identify the potential for end users.

I also ask you to clearly stat all along the manuscript that only meteorological drought is evaluated. From section 3.4 on you generalize to "drought" in many occasions.

Response: We thank the referee for their review of our manuscript. We have responded to the suggested changes by replying to their comments provided in the next section). For some material, we ask the reader to refer to our RC1 response (above), which contains new text for the results section and the updated figure.

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Improving sub-seasonal forecast skill of meteorological drought: a weather pattern approach

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Abstract. Dynamical model skill in forecasting extratropical precipitation is limited beyond the medium-range (around 15 days), but such models are often more skilful at predicting atmospheric variables. We explore the potential benefits of using weather pattern (WP) predictions as an intermediary step in forecasting UK precipitation and meteorological drought on sub-seasonal time scales. [illegible] forecasts from the ECMWF ensemble prediction system (ECMWF-EPS) are post-processed into probabilistic WP predictions. Then we derive precipitation estimates and dichotomous drought event probabilities by sampling from the conditional distributions of precipitation given the WPs. We compare this model to the direct precipitation and drought forecasts from ECMWF-EPS and to a baseline Markov chain WP method. A perfect-prognosis model is also tested to illustrate the potential of WPs in forecasting. Using a range of skill diagnostics, we find that for 31- and 46-day lead-times, dynamical, and to a lesser extent Markov, model forecasts using WPs can achieve higher skill scores that the non-WP method, particularly for precipitation. Forecast skill scores are generally modest (rarely above 0.4), although those for the perfect-prognosis model highlight the potential predictability of precipitation and drought using WPs, with certain situations yielding skill scores of almost 0.8, and drought event hit and false alarm rates of 70% and 30%, respectively.

1 Introduction

Droughts are a recurrent climatic feature in the UK. Severe events, such as those in 1975-76, 1995 and 2010-12, had significant implications for many sectors, including agriculture, water resources and the economy, as well as for ecosystems and natural habitats (Marsh, 1995; Marsh *et al.*, 2007; Rodda and Marsh, 2011; Kendon *et al.*, 2013). To mitigate the effects of drought, it is crucial that relevant sectors plan ahead, and drought forecasts have an important role in designing these strategies. Despite this, there is very little published research on UK drought prediction, and studies have predominantly focussed on hydrological drought (Wedgbrow *et al.*, 2002; Wedgbrow *et al.*, 2005; Hannaford *et al.*, 2011).

Meteorological drought is challenging to predict using dynamical ensemble prediction systems (Yoon *et al.*, 2012; Dutra *et al.*, 2013; Yuan and Wood, 2013; Mwangi *et al.*, 2014; Lavaysse *et al.*, 2015). This is primarily due to the complex processes involved in precipitation formation, making it a difficult variable to forecast beyond short lead-times (Golding, 2000; Cuo *et al.*, 2011; Smith *et al.*, 2012; Saha *et al.*, 2014). At longer lead-times, dynamical model skill in predicting atmospheric variables tends to be much higher (Saha *et al.*, 2014; Scaife *et al.*, 2014; Vitart, 2014; Baker *et al.*, 2018). This has led researchers to investigate the potential of using atmospheric forecasts as a precursor to predicting precipitation-related hazards (Lavers *et al.*, 2014; Lavers *et al.*, 2016; Baker *et al.*, 2018).

Weather pattern (WP; also called weather types, circulation patterns and circulation types) classifications are a candidate for such an application. A WP classification consists of a number of individual WPs, which are typically defined by an atmospheric variable and represent the broad-scale atmospheric circulation over a given domain (Huth *et al.*, 2008). They can be used to make general predictions of local-scale variables such as wind speed, temperature and precipitation and are a tool for reducing atmospheric variability to a few discrete states. WP classifications have mainly been studied in the context of extreme hydro-meteorological events (Hay *et al.*, 1991; Wilby, 1998; Bárdossy and Filiz, 2005; Richardson *et al.*, 2018a; Richardson *et al.*,

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Natural Hazards and Earth System Sciences
Discussions

2018b), and as a tool for analysing historical and future changes in atmospheric circulation patterns (Hay *et al.*, 1992; Wilby, 1994; Brigode *et al.*, 2018). See Huth *et al.* (2008) for a comprehensive review of WP classifications.

Until recently, the capability of dynamical models to predict WP occurrences had been little researched. Ferranti *et al.* (2015) evaluated the forecast skill of the medium-range European Centre for Medium-Range Weather Forecasts ensemble prediction system (ECMWF-EPS) (Buizza *et al.*, 2007; Vitart *et al.*, 2008) using WPs. They objectively defined four WPs according to daily 500 hPa geopotential heights over the North Atlantic – European sector. Model forecasts of this variable for October through April between 2007 and 2012 were then assigned to the closest matching WP using the root-mean-square difference. Verification scores indicated that there was superior skill for predictions initialised during negative phases of the North Atlantic Oscillation (NAO) (Walker and Bliss, 1932). Similarly, WPs were used to evaluate the skill of the Antarctic Mesoscale Prediction System by Nigro *et al.* (2011).

To support weather forecasting in the UK in the medium- to long range, the Met Office use a WP classification, MO30, in a post-processing system named "Decider" (Neal *et al.*, 2016). Using a range of ensemble prediction systems, forecast mean sea-level pressure (MSLP) fields over Europe and the North Atlantic Ocean are assigned to the best-matching WP according to the sum-of-squared differences between the forecast MSLP anomaly and WP MSLP anomaly fields. Decider therefore produces a probabilistic prediction of WP occurrences for each day in the forecast lead-time. Decider has various operational applications: predicting the possibility of flow transporting volcanic ash originating in Iceland into UK airspace, highlighting potential periods of coastal flood risk around the British Isles (Neal *et al.*, 2018) and as an early-forecast system for fluvial flooding (Richardson *et al.*, in review).

For Japan, Vuillaume and Herath (2017) defined a set of WPs according to MSLP. These WPs were used to refine bias-correction procedures, via regression modelling, of precipitation from two global ensemble forecast systems. The authors found that improvements from the bias-correction method using WPs was strongly dependent on the WP, but overall superior to the global (non-WP) method. Relevant to this study, Lavaysse *et al.* (2018) predicted monthly drought in Europe using a WP-based method. They aggregated ECMWF-EPS daily reforecasts of WPs to predict monthly frequency anomalies of each WP. For each 1° grid cell, the predictor was chosen to be the WP that corresponded to the maximum absolute temporal correlation between the monthly WP frequency of occurrence anomaly and the monthly Standardised Precipitation Index (SPI) (McKee *et al.*, 1993). Using this relationship, the model predicted drought in a grid cell when 40% of the ECMWF-EPS ensemble members forecast a Standardised Precipitation Index (SPI; McKee *et al.*, 1993) value below -1. Compared to direct ECMWF-EPS drought forecasts, the WP-based model was more skilful in north-eastern Europe during winter, but less skilful for central and eastern Europe during spring and summer. Over the UK, the WP model appeared to be superior for north-western regions in winter, but inferior in summer, although scores for the latter were of low magnitude.

The aforementioned studies have all considered daily WPs. An example of WPs defined on the seasonal time-scale was presented by Baker *et al.* (2018). The authors analysed reforecasts of UK regional winter precipitation between the winters of 1992-93 and 2011-12 using GloSea5, which has little raw skill in forecasting this variable (MacLachlan *et al.*, 2015). GloSea5 has, however, been shown to skilfully forecast the winter NAO (Scaife *et al.*, 2014). Baker *et al.* (2018) exploited this by constructing two winter MSLP indices over Europe and the North Atlantic, and reforecasts of these indices were derived from the raw MSLP fields. A simple regression model then related these indices to regional precipitation and produced more skilful forecasts than the raw model output.

In this study, we shall explore the potential for utilising a WP classification (specifically MO30) in UK meteorological drought prediction. We shall predict WPs using two models, ECMWF-EPS and a Markov chain, from which precipitation and drought forecasts will be derived. These models will be compared to direct precipitation and drought forecasts from ECMWF-EPS. We also run an idealised, perfect prognosis model that uses WP observations rather than forecasts as an 'upper benchmark' to

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Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

assess the upper limit of the usefulness of the WP classification. Section 2 contains details of the data sets used, including describing the creation of a WP reforecast data set. Section 3 describes the models in detail and the forecast verification procedure. In Sect. 4, we shall present the results and in Sect. 5, we draw some conclusions and make recommendations for future work.

2 Data

We use a Met Office WP classification called MO30 (Neal *et al.*, 2016). WPs in MO30 were defined by clustering 154 years (1850-2003) of daily MSLP anomaly fields into 30 distinct states. The data were extracted from the European and North Atlantic daily to multidecadal climate variability (EMULATE) data set (Ansell *et al.*, 2006) in the domain 30° W-20° E; 35°-70° N, with a spatial resolution of 5° latitude and longitude. These 30 WPs are therefore representative of the 30 most common patterns of daily atmospheric circulation over Europe and the North Atlantic), and they are ordered such that WP1 is the most frequently occurring WP annually, while WP30 is the least freque nsequence of the clustering process and ordering is that the lower-numbered WPs have lower-magnitude MSLP anomalies and are more common in the summer than in the winter, and vice versa for the higher-numbered WPs (Richardson *et al.*, 2018a)(Neal *et al.*, 2016).

For this analysis, we have created a 20-year daily WP probabilistic reforecast data set. We use the sub-seasonal to seasonal (S2S) project (Vitart *et al.*, 2017) data archive, which, through ECMWF, hosts reforecast data for a multitude of variables and by a range of models from around the globe. In particular, we use ECMWF-EPS, which is a coupled atmosphere-ocean-sea-ice model with a lead-time of 46 days. The horizontal atmospheric resolution is roughly 16 km up to day 15 and 32 km beyond this. The model is run at 00Z, twice weekly (Mondays and Thursdays) and has 11 ensemble members for the reforecasts (compared to 51 members for the real-time forecasts). For further details, refer to the model webpage (ECMWF, 2017). We use daily reforecasts of MSLP between 02 January 1997 and 28 December 2016, inclusive, with the same domain and resolution as MO30. These fields are converted to anomalies by removing a smoothed climatology and subsequently assigned to the closest matching MO30 WP via minimising the sum-of-squared differences. Both the MSLP climatology and the WP definitions are the same as those used by Neal *et al.* (2016) to ensure consistency. We compare this against an observed WP time series to measure forecast skill. For this, WPs are assigned from 00Z SLP fields from the ERA-Interim reanalysis data set (Dee *et al.*, 2011) to align with the ECMWF-EPS forecast times.

As observed precipitation, we use the Met Office Hadley Centre UK Precipitation (HadUKP) data set (Alexander and Jones, 2000). For nine regions covering the UK (Fig. 2), we use daily precipitation series from 1979 to 2017. We discretise the data into precipitation intervals ("bins") defined in Table 1; see the supporting material for further information. The large region sizes in HadUKP are suitab th for analyses of drought, which is typically considered a regional rather than localised event, and for MO30 because they correspond to the large-scale circulati tterns that the WPs represent. From the S2S archive, we extract ECMWF-EPS precipitation reforecasts for the same dates as the WP reforecast data set. The data have a resolution of 0.5° latitude and longitude; grid cells are assigned to whichever of the nine HadUKP regions the cell centres lie in and by taking the daily mean of all cells over each region, we produce a probabilistic reforecast data set of precipitation for each of the HadUKP regions. These data are discretised in the same way as the HadUKP data.

3 Methods

3.1 Weather pattern forecast models and verification procedure

For WP forecasts, we compare two models. The first is ECMWF-EPS, which we shall refer to as EPS-WP (in practice this is the WP reforecast data set discussed in the previous subsection). The second model is a 1000-member, first-order, nonhomogeneous Markov chain, with separate transition matrices for each month. This is similar to the Markov model used

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

for a simulation study by Richardson *et al.* (2018b), who found it was able to reasonably replicate the observed frequencies of occurrences of the MO30 WPs. Full details of the Markov model are given in the supporting material.

To evaluate WP forecast skill we use the Jensen-Shannon divergence (JSD), suitable for measuring the distance between two probability distributions (Lin, 1991). It is based on information entropy, which is used to measure uncertainty. An information-theoretic approach to verification is not widespread, although there is some published research on the topic (Leung and North, 1990; Kleeman, 2002; Roulston and Smith, 2002; Ahrens and Walser, 2008; Weijs *et al.*, 2010; Weijs and Giesen, 2011). The JSD will be used to measure the forecast performance by quantifying the distance between distributions of the observed and forecast WP frequencies. The JSD is based on the Kullback-Leibler divergence (KLD) (Kullback and Leibler, 1951). Let P and Q be two discrete probability distributions. The KLD from Q to P is given by:

$$D_{KL}(P||Q) = -\sum_{i=1}^{I} P_i \log_2 \frac{Q_i}{P_i},$$

Equation 1

measured in bits (i.e. a binary unit of information). In our application $I = 30$, the number of WPs and $P = (p_{f,1}, \dots, p_{f,30})$ and $Q = (q_{f,1}, \dots, q_{f,30})$ are the vectors of observed and forecast WP relative frequencies, respectively. (Because these are relative frequencies, $\sum P = 1$ and $\sum Q = 1$.) As there would inevitably be some cases where the model predicts no occurrences of some WPs (i.e. when Q contains zeros), $D_{KL}(P||Q)$ will be undefined at times. Using the JSD avoids this problem; it is defined as:

$$D_{JSD}(P||Q) = \frac{1}{2} D_{KL}(P||M) + \frac{1}{2} D_{KL}(Q||M),$$

Equation 2

where $M = (P + Q)/2$. Unlike the KLD, the JSD is symmetric i.e. $D_{JSD}(P||Q) \equiv D_{JSD}(Q||P)$. Also, $0 \leq D_{JSD}(P||Q) \leq 1$, with a score of zero indicating P and Q are the same (a perfect forecast). Equation 2 gives the JSD for a single forecast-event pair; to obtain the average JSD for all forecasts we take the mean of all forecast-event pairs. Skill is evaluated separately for each month, with the middle date of each forecast period used to assign the month. We calculate forecast skill for lead-times of 16, 31 and 46 days. We use the JSD to compare WP forecast skill of EPS-WP and the Markov model, considering each lead-time separately.

3.2 Precipitation and drought forecast models

We compare four models (Table 2), three of which are forecast models, while one model is a perfect prognosis model. All models are considered at the same lead-times as the WP predictions. Two of the forecast models are driven first by a WP component: EPS-WP and the Markov model described above. The perfect prognosis model, Perfect-WP, is used as an 'upper benchmark' with (future) observed WPs as input, rather than forecast WPs. It is an idealised model that cannot be used operationally, but it allows us to assess the potential usefulness of WPs in precipitation and drought forecasting. Precipitation is estimated from the WP predictions (or observations in the case of Perfect-WP) by sampling from the conditional distributions of precipitation given each WP. As we discretised the precipitation, these conditional distributions reflect the observed relative frequencies of each precipitation interval occurring. The sampling procedure is done for each ensemble member and each day in the forecast lead-time, with the results summed across all members and days to provide probabilistic forecasts of summed precipitation intervals (Table 1). A full description of this method is detailed in the supporting information. The fourth model (the third forecast model) is the direct ECMWF-EPS precipitation forecasts (EPS-P), processed to provide probabilistic predictions of regional precipitation intervals as described earlier.

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

3.3 Precipitation forecast verification

To evaluate precipitation forecast performance we use the ranked probability score (RPS) (Epstein, 1969; Murphy, 1971). We express the RPS as the ranked probability skill score (RPSS) using

$$\mathrm{RPSS} = 1 - \frac{\mathrm{RPS}}{\mathrm{RPS}_{\mathrm{ref}}},$$

Equation 3

Where $\mathrm{RPS}_{\mathrm{ref}}$ is the score of a climatological forecast, which in our case is the climatological event category (i.e. precipitation interval) relative frequencies (PC). A perfect score is achieved when $\mathrm{RPSS} = 1$, which is also the upper limit. Negative (positive) values indicate the forecast is performing worse (better) than $\mathrm{RPS}_{\mathrm{ref}}$.

3.4 Drought forecast verification

We evaluate model performance in predicting dichotomous drought/non-drought events. We define two classes of drought severity. The first class, mild drought, is when precipitation sums (over the length of the considered lead-time) are below the 30.9$^{\mathrm{th}}$ percentile of the summed precipitation distribution. The second class is moderate drought, with such sums being below the 15.9$^{\mathrm{th}}$ percentile. These percentiles are calculated for each region and month using the whole data set from 1979 through 2017, and are chosen as they correspond to SPI values of -0.5 and -1, respectively.

3.4.1 The Brier Skill Score

We use three verification techniques to assess skill in predicting droughts. The first is the Brier Skill Score (BSS). The BSS is based on the Brier Score (BS) (Brier, 1950), which measures the mean-square error of probability forecasts for a dichotomous event, in this case the occurrence or non-occurrence of drought. The BS is converted to a relative measure, or skill score, by setting

$$\mathrm{BSS} = 1 - \frac{\mathrm{BS}}{\mathrm{BS}_{\mathrm{ref}}},$$

Equation 4

where $\mathrm{BS}_{\mathrm{ref}}$ is the score of a reference forecast given by the quantiles associated with each drought threshold, 0.309 for mild drought and 0.159 for moderate drought. As with the RPSS, a perfect score is achieved when $\mathrm{BSS} = 1$ and negative (positive) values indicate the forecast is performing worse (better) than $\mathrm{BS}_{\mathrm{ref}}$.

3.4.2 Reliability diagrams – forecast reliability, resolution and sharpness

The BS can be decomposed into reliability, resolution and uncertainty terms (Murphy, 1973):

$$\mathrm{BS} = \mathrm{reliability} - \mathrm{resolution} + \mathrm{uncertainty},$$

Equation 5

enabling a more in-depth assessment of forecast model performance. Reliability diagrams offer a convenient way of visualising the first two of these terms (Wilks, 2011). These diagrams consist of two parts, which together show the full joint distribution of forecasts and observations. The first element is the calibration function, $g(o_1|p_i)$, for $i = 1, \ldots n$, where o_1 indicates the event (here, a drought) occurring and the p_i are the forecast probabilities. The calibration function is visualised by plotting the event relative frequencies against the forecast probabilities and indicates how well calibrated the forecasts are. We split the forecast probabilities into 10 bins (subsamples) of 10% probability and the mean of all forecast probabilities in each bin is the

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

value plotted on the diagrams (Bröcker and Smith, 2007). Points along the 1:1 line represent a well-calibrated, *reliable*, forecast, as event probabilities are equal to the forecast probabilities and suggest that we can interpret our forecasts at 'face value'. If the points are to the right (left) of the diagonal, the model is over-forecasting (under-forecasting) the number of drought events.

The forecast *resolution* can also be deduced from the calibration function. For a forecast with poor resolution, the event relative frequencies $g(o_1|p_i)$ only weakly depend on the forecast probabilities. This is reflected by a smaller difference between the calibration function and the horizontal line of the climatological event frequencies and suggests that the forecast is unable to resolve when a drought is more or less likely to occur than the climatological probability. Good resolution, on the other hand, means that the forecasts are able to distinguish different subsets of forecast occasions for which the subsequent event outcomes are different to each other.

The second element of reliability diagrams is the refinement distribution, $g(p_i)$. This expresses how confident the forecast models are by counting the number of times a forecast is issued in each probability bin. This feature is also called *sharpness*. A low-sharpness model would overwhelmingly predict drought at the climatological frequency, while a high-sharpness model would forecast drought at extreme high and low probabilities, reflecting its level of certainty with which a drought will or will not occur, independent of whether a drought actually does subsequently occur or not.

3.4.3 Relative operating characteristics

As a final diagnostic we use the relative operating characteristic (ROC) curve (Mason, 1982; Wilks, 2011), which visualises a model's ability to discriminate between events and non-events. Conditioned on the observations, the ROC curve may be considered a measure of potential usefulness – it essentially asks what the forecast is, given that a drought has occurred. The ROC curve plots the hit rate (when the model forecasts a drought and a drought subsequently occurs) against the false alarm rate (when the model forecasts a drought but a drought does not then occur). We compute the hit rate and false alarm rate for cumulative probabilities between 0% and 100% at intervals of 10%. A skilful forecast model will have a hit rate greater than a false alarm rate, and the ROC curve would therefore bow towards the top-left corner of the plot. The ROC curve of a forecast system with no skill would lie along the diagonal, as the hit rate and false alarm rate would be equal, meaning the forecast is no better than a random guess. The area under the ROC curve (AUC) is a useful scalar summary. AUC ranges between zero and one, with higher scores indicating greater skill.

4 Results

To reduce information overload, we do not show results for every combination of region, lead-time and drought class. Key results not shown will be conveyed via the text. We aggregate the precipitation results from monthly to three-month seasons for visual clarity and combine regional results for the ROC and reliability diagrams for the same reason.

4.1 WP forecasts

We find that EPS-WP is more skilful at predicting the WPs than the Markov model for every month and every lead-time, although the difference in skill between the two models decreases as the lead-time increases. The skill difference between models is much larger for a lead-time of 16 days compared to a lead-time of 46 days. For a 46-day lead-time, the difference in skill is negligible for May through October. In fact, these months have the smallest differences in JSD for all lead-times. This is presumably because the summer months are associated with fewer WPs compared to winter (Richardson *et al.*, 2018a), resulting in a more skilful Markov model due to higher transition probabilities.

An interesting result is how JSD scores for both models, especially for Markov, decrease as the lead-time increases (Fig. 3), suggesting an improvement in skill with lead-time. This is the opposite of the expected (and usual) effect and is probably

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

because both the observations and the forecasts tend towards climatology at longer lead-times. The JSD measures the distance between probability distributions, and at the shorter lead-times, the forecast relative frequency distribution tends to be much noisier compared to the observed relative frequency distribution i.e. a greater number of different WPs are predicted than observed. As the lead-time is increased, the observations become noisier and as a result the JSD tends to score the differences between these distributions as more similar (a smaller divergence).

4.2 Precipitation forecasts

During summer and spring, all three forecast models are well matched, although for a 16-day lead-time Markov is the least skilful. For this lead-time, EPS-P mostly scores similarly to EPS-WP, although it has higher skill for some regions (Figs. 4b and 4c) and even outperforms Perfect-WP for several regions in summer (Fig. 4c). At lead-times of 31 and 46 days, there is little difference in forecast model skill during spring and summer, although in summer NI and SWE appear to benefit from dynamical WP predictions (i.e. EPS-WP), as do the four eastern regions from any kind of WP forecast (EPS-WP and Markov; Fig. 5). On the other hand, using WP predictions is to the detriment of precipitation forecast skill in spring for SEE, as shown by the superior performance of EPS-P (Fig. 5). This split between the east and west is also found by Lavaysse *et al.* (2015), who used ECMWF-EPS to predict meteorological drought with a one month lead-time.

For winter and autumn, EPS-WP is the most skilful forecast model except when considering a 16-day lead-time, for which EPS-P is often the best performer. Scotland benefits most from the use of EPS-WP, as even at the shortest lead-time this model is superior (Figs. 4a and 4d). Note that the skill of the WP forecasts matter, as Markov is associated with poor precipitation skill at this lead-time, which corresponds to its low skill in forecasting the WPs compared to EPS-WP (Fig. 3). EPS-WP is the most skilful model for 31- and 46-day lead-times; EPS-P and Markov score fairly evenly overall for a 31-day lead-time, with the former model the least skilful for a 46-day lead-time (Fig. 5). The difference in skill between EPS-WP and Markov is much larger for northern and western regions, particularly in winter. Therefore the improvement in skill by predicting the WPs with a dynamical model, rather than Markov (Fig. 3), translates to a spatially non-uniform gain in skill for precipitation, with western and northern regions the principal beneficiaries. However, it is difficult to say why this is the case, as from the JSD scores alone we do not know whether EPS-WP is better at predicting all WPs, or just some of them. Similarly, as the RPSS is for all forecast dates, we can't be sure whether the improvement in precipitation forecast skill comes from an improvement over all periods or if the gain is made for predictions of dry or wet periods; drought forecast analysis results in the next subsection will go some way to answering this.

Unsurprisingly, Perfect-WP is uniformly the most skilful precipitation 'forecast' model for all regions, seasons and lead-times, except for some regions and seasons with a 16-day lead-time. At this shortest lead-time, Perfect-WP is the most skilful in all cases during winter (Fig. 4a) and in all cases except NS during spring (Fig. 4b) and NEE during autumn (Fig. 4d), for which EPS-P is the most skilful. The only season in which Perfect-WP does not have the most skill for most regions is during summer, when EPS-P is superior (Fig. 4c). For lead-times of 31 and 46 days, perfectly predicting WPs would enable by far the most skilful precipitation estimates of any model, for all regions and seasons (Fig. 5). This model is obviously not practical, but the results serve to show that WPs are a potentially useful tool in medium-range precipitation forecasting.

The key conclusions from this subsection are that, for winter and autumn, precipitation forecasts are notably more skilful when derived from dynamical predictions of WPs compared to either simple statistical WP predictions or direct precipitation forecasts from a dynamical model. Furthermore, the relative gain in skill is greater for longer lead-times, mainly as a result of ...able drop in skill for EPS-P when comparing a 31-day to a 46-day lead-time, whereas other forecast models' score changes are less severe. For spring and summer, EPS-P is marginally the most skilful model at a 16-day lead-time, with little to choose between all three forecast models at the longer lead-times. A potential reason for the lower skill of WP-based models compared to EPS-P in summer is that the WPs associated with this season tend to be less clear-cut in terms of being associated with dry

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

or wet conditions (Richardson *et al.*, 2018a), possibly as a result of their higher intra-WP variability compared to winter WPs (Richardson *et al.*, 2018b). Only WP6, WP8 and WP9 are distinctly dry or wet and so precipitation estimates from summer WPs may not be appropriate for periods of non-normal precipitation.

4.3 Drought forecasts

4.3.1 Forecast accuracy

Forecast accuracy for mild and moderate drought is qualitatively similar to those of general precipitation in terms of regional and lead-time differences. EPS-WP is overall the most skilful model, although this is less the case for a 16-day lead-time, for the three regions in East England and for most regions in spring and summer. Only the results for predicting moderate drought at the 46-day lead-time are presented (Fig. 6). This is because the results for mild drought are more similar to the RPSS results than those of moderate drought, those for the 16-day lead-time are the least useful for drought prediction (which tends to be focussed on longer-range forecasts) and those for the 31-day lead-time are qualitatively similar to the 46-day lead-time.

For the shortest lead-time, EPS-P has the highest accuracy for predicting winter and autumn drought of both classes, except in land, for which EPS-WP has the highest skill. Indeed, EPS-WP has the highest skill for the other lead-times during these seasons (Fig. 6). However, a key difference is that eastern England droughts are at least as accurately predicted by EPS-P as by EPS-WP for the two longer lead-times (Fig. 6), whereas for precipitation forecasting the latter tend to be more accurate (Fig. 5). Difference in model skill is lower for spring and summer drought forecasts, particularly for moderate drought (Fig. 6). In fact, for this drought class, there is very little or no gain in skill by using WPs at 31- and 46-day lead-times for spring and summer compared to EPS-P (Fig. 6). Furthermore, at these lead-times both models are less skilful than issuing climatological drought probabilities (shown by their negative BSS), except for spring predictions of eastern and southern droughts. This suggests that, during spring and summer, deriving precipitation from predicted WPs may be useful if forecasting mild drought, but not for more severe droughts.

4.3.2 Relative operating characteristics

All models are better able to discriminate between drought and non-drought events than random chance, with Perfect-WP the most able and Markov the least able, subject to similar caveats regarding lead-time and season as for the BSS and RPSS results. During summer and spring, EPS-P has the highest AUC of any of the three forecast models (Figs. 7 and 8), and for a 16-day lead-time scores similarly to Perfect-WP (not shown). On the other hand, EPS-WP has the highest skill during winter and autumn at the other lead-times, particularly for mild drought. Markov is consistently the least suitable model for predicting drought according to the ROC curve, although still represents a better method of doing so than random chance.

A use of the ROC curve is to provide end-users with information on how to apply the considered forecast models. As the plotted points on each curve indicate the hit rate and false alarm rate associated with predicting droughts at each probability interval, they can be used to make an informed decision in selecting a probability threshold for issuing a drought forecast. For example, should a forecaster choose to issue a mild drought warning in winter at a 20% probability level and 46-day lead-time (Fig. 7), then they would expect EPS-WP to achieve a hit rate roughly double that of the false alarm rate (60% and 30%, respectively). EPS-P, meanwhile, shows a slightly higher hit rate but at the expense of a higher false alarm rate (65% and 40%). The idealised benchmark model (Perfect-WP) achieves an outstanding score – roughly a 75% hit rate compared to a 10% false alarm rate. For mild drought, a 20% probability threshold for EPS-WP and EPS-P achieves at least 60% hit rates at all lead-times, whereas for moderate drought, this threshold will only achieve such rates at a 16-day lead-time and during autumn for all lead-times. In general, it appears that these low probability thresholds yield the best compromise between hits and false alarms, although in practice, the costs (e.g. financial) associated with false alarms and missed events will determine how responders use these probabilities.

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

4.3.3 Forecast reliability, resolution and sharpness

EPS-WP is the most reliable forecast model, and while all three WP-driven forecast models tend to under-forecast droughts, EPS-P only does so for lower probability thresholds, with the higher thresholds resulting in this model over-forecasting. This is particularly true for shorter lead-times and during winter, although is still clear for 31-day lead-times in some seasons (Figs. 9 and 10). Sometimes EPS-WP follows the same pattern as EPS-P and over-forecasts drought occurrence for higher predicted probabilities (e.g. Figs. 9c, e, g and 10c). However, the total number of forecasts issued in these intervals is generally smaller than for EPS-P, as the refinement distributions show most clearly for mild drought (Fig. 9). This means the corresponding points of the calibration function are less reliable for EPS-WP (and Markov) due to smaller sample sizes (Bröcker and Smith, 2007). In fact, all three WP-based models have occasions when there are no issued forecasts with certain probabilities. These are high probabilities for Perfect-WP and EPS-WP (Figs. 10c and e) but can be as low as between 30% and 40% for Markov (Figs. 10e and g). As such, although EPS-WP appears the most reliable model from looking only at the calibration function, there is less certainty of this fact for moderate drought and for higher forecast probabilities. This erratic behaviour of the conditional event relative frequencies is most obvious in Fig. 10c and is explained by the very low sample sizes of forecasts issued with anything but a small probability (Fig. 10e) (Wilks, 1995). An interesting result is that forecasts from EPS-WP are more reliable than from Perfect-WP (Figs. 9 and 10), despite having lower accuracy (e.g. Fig. 6). As a more skilful BSS is composed of smaller reliability and larger resolution terms (Eq. 5), it follows that the resolution of Perfect-WP is sufficiently large to overcome the larger reliability term compared to EPS-WP and yield an overall more accurate forecast model. These under- or over-forecasting biases must be taken into account by an operational forecaster using these models.

A key difference apparent from the calibration function relates to the ability of the models to identify subsets of forecast situations where the subsequent event relative frequencies are different, i.e. the forecast resolution. An almost completely consistent feature across all lead-times and drought classes is the poorer resolution of EPS-P, particularly obvious in autumn (Figs. 9g and 10g), with the conditional event relative frequencies quite clearly closer to the climatological average compared to the other models. This should be considered in conjunction with the sharpness of the forecast, which is relatively high for this model as shown by the numbers of issued extreme probabilities, particularly those in the upper-tail (Figs. 9h and 10h). This combination of poor resolution and high sharpness indicates "overconfidence" (Wilks, 2011) – on the occasions that EPS-P issues a forecast indicating the likelihood of a drought is very high, the actual likelihood of a drought subsequently occurring is lower. To compensate for this overconfidence, a user would adjust the probabilities to be less extreme to make the forecasts more reliable.

We can compare these refinement distributions to those of the Markov model, which exhibits low sharpness, overwhelmingly predicting droughts at the climatological frequency (second column of Figs. 9 and 10). This means that the Markov model is not a useful operational tool in these situations, as similar forecasts could be obtained simply by using the climatological drought frequency. The refinement distributions for EPS-WP show that for mild drought in winter and spring and for moderate drought in all seasons, the model predicts droughts with low probabilities the majority of the time (Figs. 9b, d and 10b, d, f, h). For mild drought in summer and autumn, however, this model mostly issues forecasts close to the climatological frequency, although not nearly as regularly as the Markov model (Fig. 9f, h). As with adjusting for bias, a forecaster can use model resolution and sharpness when assessing drought forecast probabilities output by a model.

5 Discussion and conclusions

We have compared the performance of a dynamical forecast system (EPS-WP) and a first-order Markov model in predicting WP occurrences over a range of lead-times, showing that the dynamical model is always more skilful, although the difference in skill reduces with lead-time. From these WP predictions, we derived precipitation forecasts and compared them to direct precipitation predictions from the dynamical system (EPS-P). EPS-P has the highest overall skill in precipitation and drought

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

forecasts for a 16-day lead-time, whereas EPS-WP predictions provided the greatest skill for longer 31- and 46-day lead-times. We also demonstrated the potential in improving WP forecasts further by showing that an idealised, perfect prognosis model (Perfect-WP) would provide much more skilful precipitation and drought forecasts, with high hit rates and low false alarm rates.

From assessing reliability diagrams we found that WP-based models only issue binary drought forecasts with either very low probabilities or probabilities close to the climatological average. In particular, there is little to gain in using the Markov model in mild drought prediction over the climatological frequency, as it tends to issue drought forecasts with this probability anyway. EPS-P has the highest sharpness, predicting drought occurrence with a wide range of probabilities. In particular, it issues greater numbers of high-probability drought forecasts compared to WP-based methods. However, this model also has poor resolution, indicating it is an overconfident forecast model. Overall, drought forecasts issued by EPS-WP are the most reliable, i.e. the forecast probabilities are most similar to the subsequent event probabilities (they "mean what they say") (Wilks, 2011). Perfect-WP tends to under-forecast the number of drought events, while EPS-P over-forecasts drought events, particularly for moderate drought. These reliability diagrams are therefore useful to aid users in adjusting for an over- or under-forecasting bias.

Given the results presented here, we would recommend the use of EPS-WP for the following drought forecast situations.

- Winter and autumn 31- and 46-day forecasts.
- Winter and autumn 16-day forecasts for Scotland (ES, NS and SS).
- Spring and summer 16-day forecasts for ES.
- Summer 31- and 46-day forecasts of mild drought for eastern and southern regions.

EPS-P is recommended for:

- Winter and autumn 16-day forecasts for all regions except those in Scotland.
- Spring and summer 16-day forecasts for all regions except ES
- Spring 31- and 46-day forecasts for all regions except those in Scotland.

Otherwise, the use of climatological drought frequencies represents the most parsimonious (in terms of skill versus model complexity) choice for:

- Summer 31- and 46-day forecasts for mild drought in northern and western regions and moderate drought in all regions.
- Spring 31- and 46-day forecasts for Scotland.

Focussing on the 31- and 46-day lead-times (that are more useful for drought prediction than 16-day forecasts), winter and autumn are clear-cut, with EPS-WP recommended for every region. Summer is more complex. Mild droughts are best predicted by EPS-WP for the eastern and southern regions, but drought climatological frequencies are suggested over the forecast models for western and northern regions and more severe droughts for all regions. In spring, climatology is also recommended for Scotland, with the use of EPS-P for the remaining regions.

The higher skill of EPS-WP during winter (and possibly autumn) is probably due to the typically higher skill that medium- to long-range dynamical forecast systems have in predicting atmospheric variables in this season compared to other seasons (Scaife *et al.*, 2014; MacLachlan *et al.*, 2015; Neal *et al.*, 2016). In fact, by forecasting a set of eight WPs derived from MO30, Neal *et al.* (2016) found that ECMWF-EPS exhibited greater skill in winter than summer. Furthermore, the relationship between the NAO (which is the primary mode of North Atlantic/European atmospheric circulation) and precipitation is stronger in this season (Hurrell and Deser, 2009; Lavers *et al.*, 2010; Svensson *et al.*, 2015). This is particularly true for western

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

regions (Jones *et al.*, 2013; Svensson *et al.*, 2015; van Oldenborgh *et al.*, 2015; Hall and Hanna, 2018), which potentially explains the greater difference in precipitation and drought forecast skill between EPS-WP and EPS-P in these seasons. The skill of precipitation forecasting using observed WPs (Perfect-WP) is also lower for eastern regions than western regions in winter, implying that MO30 is not as suited for representing precipitation in the east. Perhaps this is because the WPs are more closely related to the NAO in this season, compared to other teleconnection patterns. As Hall and Hanna (2018) showed, the NAO is not the only important teleconnection pattern influencing UK precipitation. However, in general forecast skill is lower for eastern regions independent of the model.

By analysing the skill of an idealised 'forecast' model that assumes perfect WP predictions, we have demonstrated the potential for using WP forecasts to derive precipitation and drought predictions. Currently, dynamical models such as the ECMWF system used here represent the best method of predicting WPs. Moreover, the ECMWF reforecast data used here had 11 ensemble members, whereas the live forecasts are run with 51 members. Therefore, an operationalised version of the models might improve forecast skill or better represent uncertainty. A useful piece of further research would be to assess the forecast skill of other models, and even multi-model ensembles, at predicting MO30 WPs or other WP classification systems. Another potential method to improve precipitation and drought forecast skill would be to alter the process by which precipitation is derived from the WPs. Here we have sampled from the entire conditional distribution of precipitation given the WP and season, but this may not be the optimal way of estimation. It is possible that other factors influence the precipitation from WPs, such as slowly-varying atmospheric and oceanic processes. For example, it would be interesting to see if conditioning the distributions further on the state of the NAO index, or some North Atlantic SST index, and sampling precipitation from these, would improve forecast skill. This is potentially most useful in predicting more severe forms of drought (D2 in this study), for which skill from current models is lower than for mild drought.

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Natural Hazards and Earth System Sciences
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Preprint. Discussion started: 16 July 2019

Natural Hazards and Earth System Sciences
Discussions

Daily precipitation		30-day precipitation sums	
p_b	Range of precipitation, x (mm)	s_c	Range of summed precipitation, y (mm)
p_1	0	s_1	$0 \leq y < 10$
p_2	$0 < x \leq 1$	s_2	$10 < y \leq 20$
…	Intervals of 1mm	…	Intervals of 10mm
p_{11}	$9 < x \leq 10$	s_{25}	$240 < y \leq 250$
p_{12}	$10 < x \leq 15$	s_{26}	$250 < y \leq 300$
p_{13}	$15 < x \leq 20$	…	Intervals of 50mm
p_{14}	$20 < x \leq 30$		
…	Intervals of 10mm		

Table 1: Range of daily precipitation, x, for each bin p_b and of 30-day precipitations sums, y, for each bin s_c.

Model	WP component	Precipitation component
Markov	Predicted using a first-order Markov chain	Estimated by sampling from conditional distributions of precipitation given the WPs.
EPS-WP	Predicted by assignment of forecast SLP fields from ECMWF-EPS	
Perfect-WP	Observed WPs	
EPS-P	-	Forecast by ECMWF-EPS

Table 2: Details of the four models. Markov, EPS-WP and EPS-P are forecast models and Perfect-WP is a perfect prognosis model that cannot be used for forecasting.

https://doi.org/10.5194/nhess-2019-221
Preprint. Discussion started: 16 July 2019

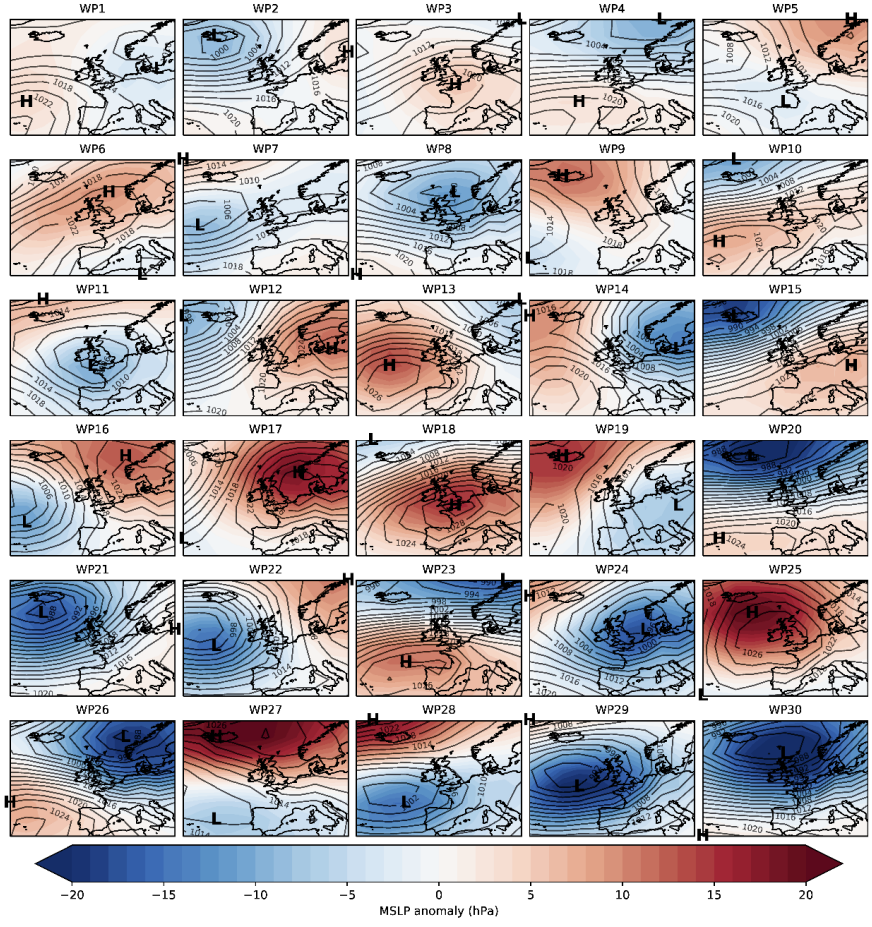

Figure 1: Weather pattern (WP) definitions according to mean sea-level pressure (MSLP) anomalies (hPa). The black contours are isobars showing the absolute MSLP values associated with each weather pattern, with the centres of high and low pressure also indicated. From Richardson *et al.* (2018b).

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Preprint. Discussion started: 16 July 2019

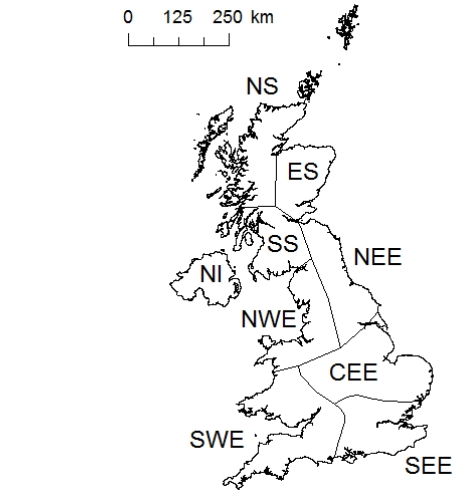

Figure 2: HadUKP regions: northeast England (NEE), central and east England (CEE), southeast England (SEE), southwest England and southern Wales (SWE), northwest England and northern Wales (NWE), Northern Ireland (NI), southwest Scotland (SS), northern Scotland (NS) and eastern Scotland (ES).

Figure 3: Jensen-Shannon Divergence scores for EPS-WP and Markov models for three lead-times.

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Preprint. Discussion started: 16 July 2019

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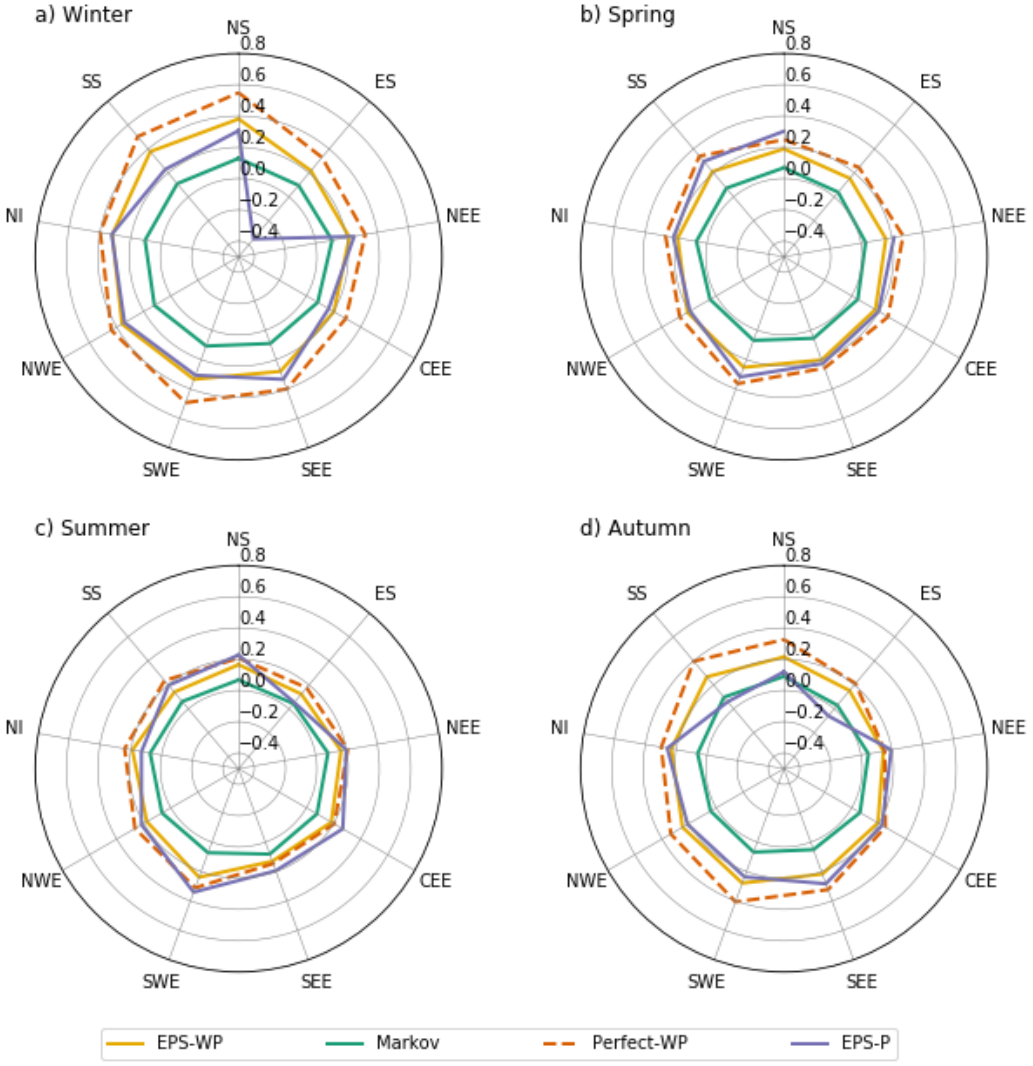

Figure 4: Ranked Probability Skill Scores by region and season for the three forecast models (EPS-WP, Markov and EPS-P) and the idealised model (Perfect-WP). Lead-time is 16 days. Scores lower than -0.5 are omitted for visual clarity. The omitted scores are for EPS-P in ES during spring (-0.54).

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Preprint. Discussion started: 16 July 2019

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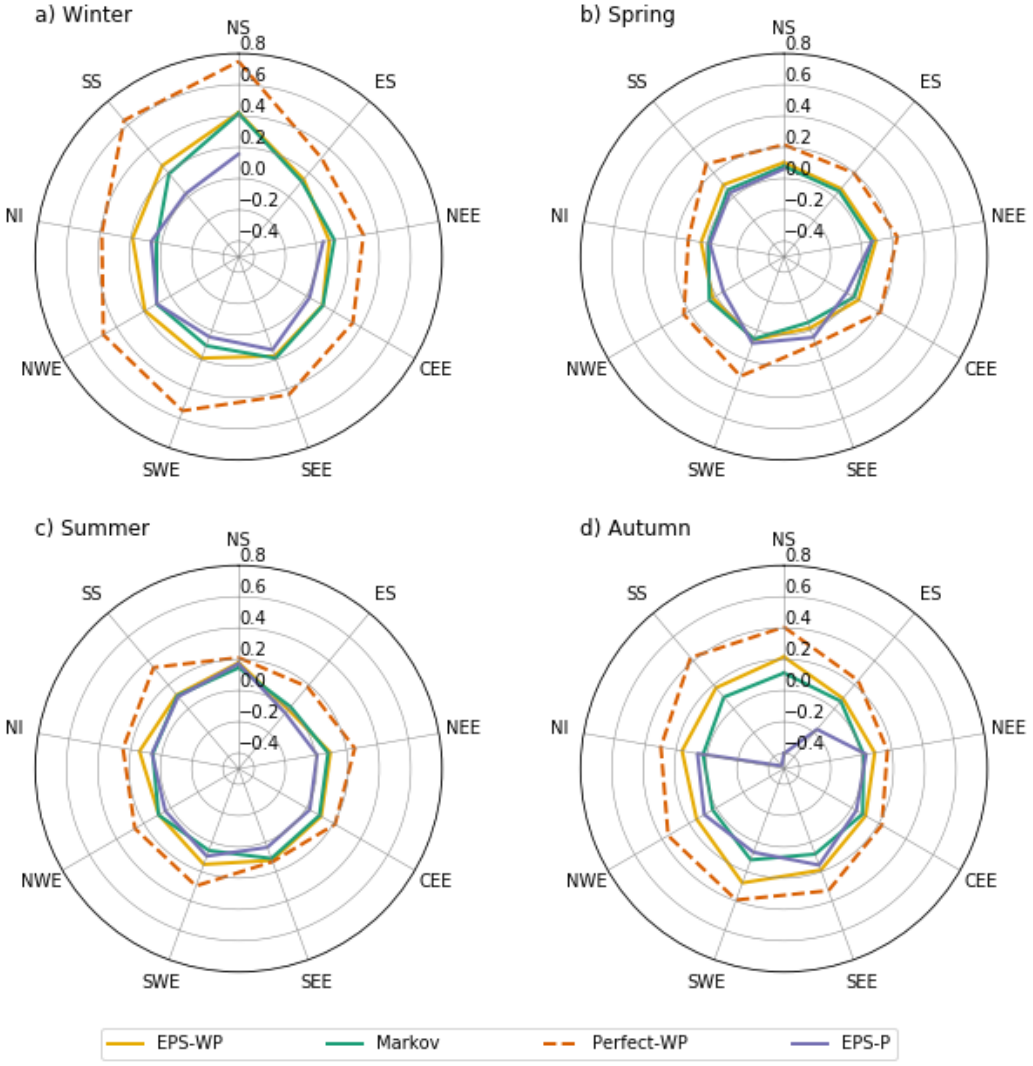

Figure 5: As Fig. 4 but for a lead-time of 46 days. The omitted scores are for EPS-P in ES during winter (-1.15) and spring (-1.37).

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Preprint. Discussion started: 16 July 2019

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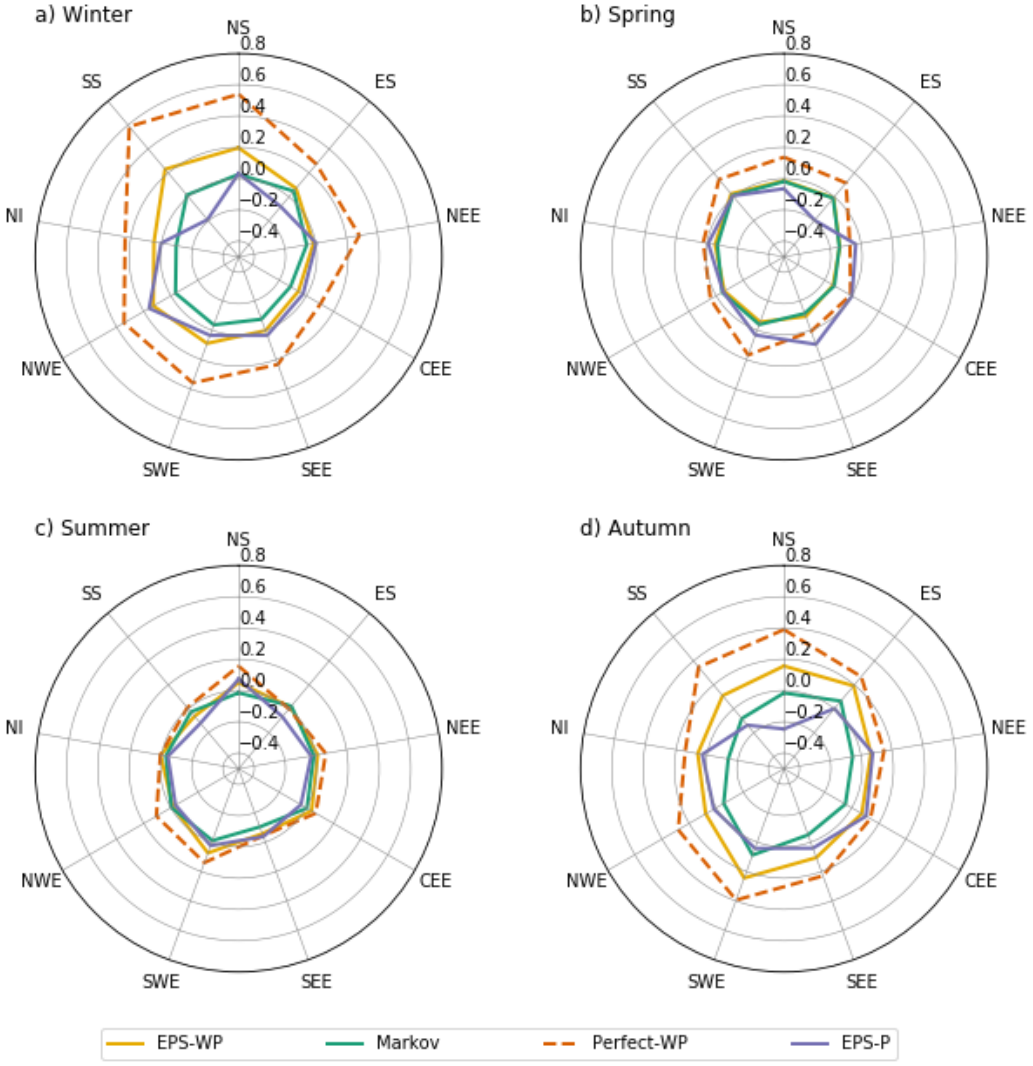

Figure 6: Brier Skill Score (BSS) by region and season for moderate drought for the three forecast models (EPS-WP, Markov and EPS-P) and the idealised model (Perfect-WP). Lead-time is 46 days.

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Preprint. Discussion started: 16 July 2019

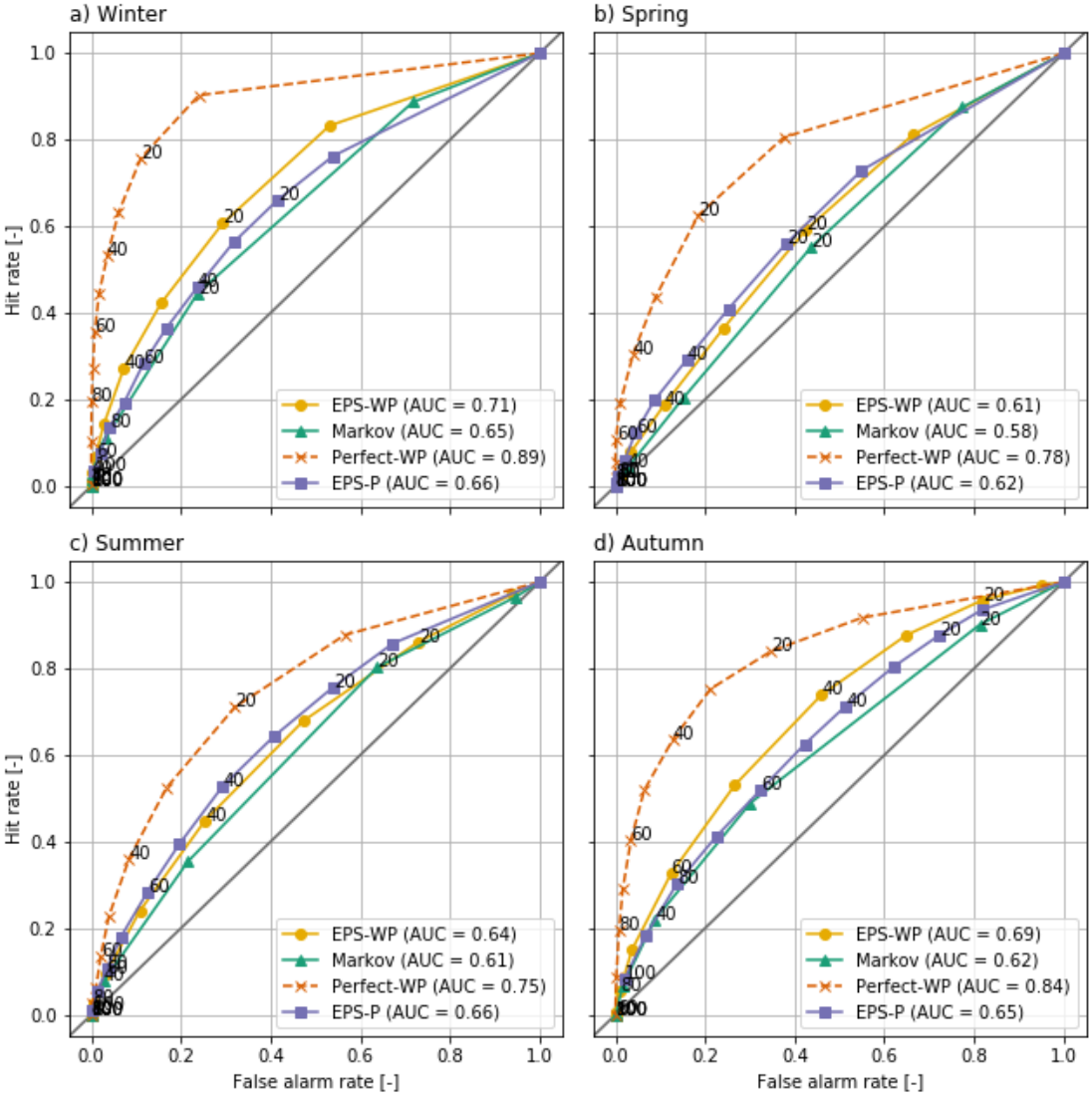

Figure 7: Relative operating characteristics (ROC) curves and area under ROC curve (AUC) for mild drought with a 46-day lead-time. Annotated values indicate drought forecast probability thresholds.

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Preprint. Discussion started: 16 July 2019

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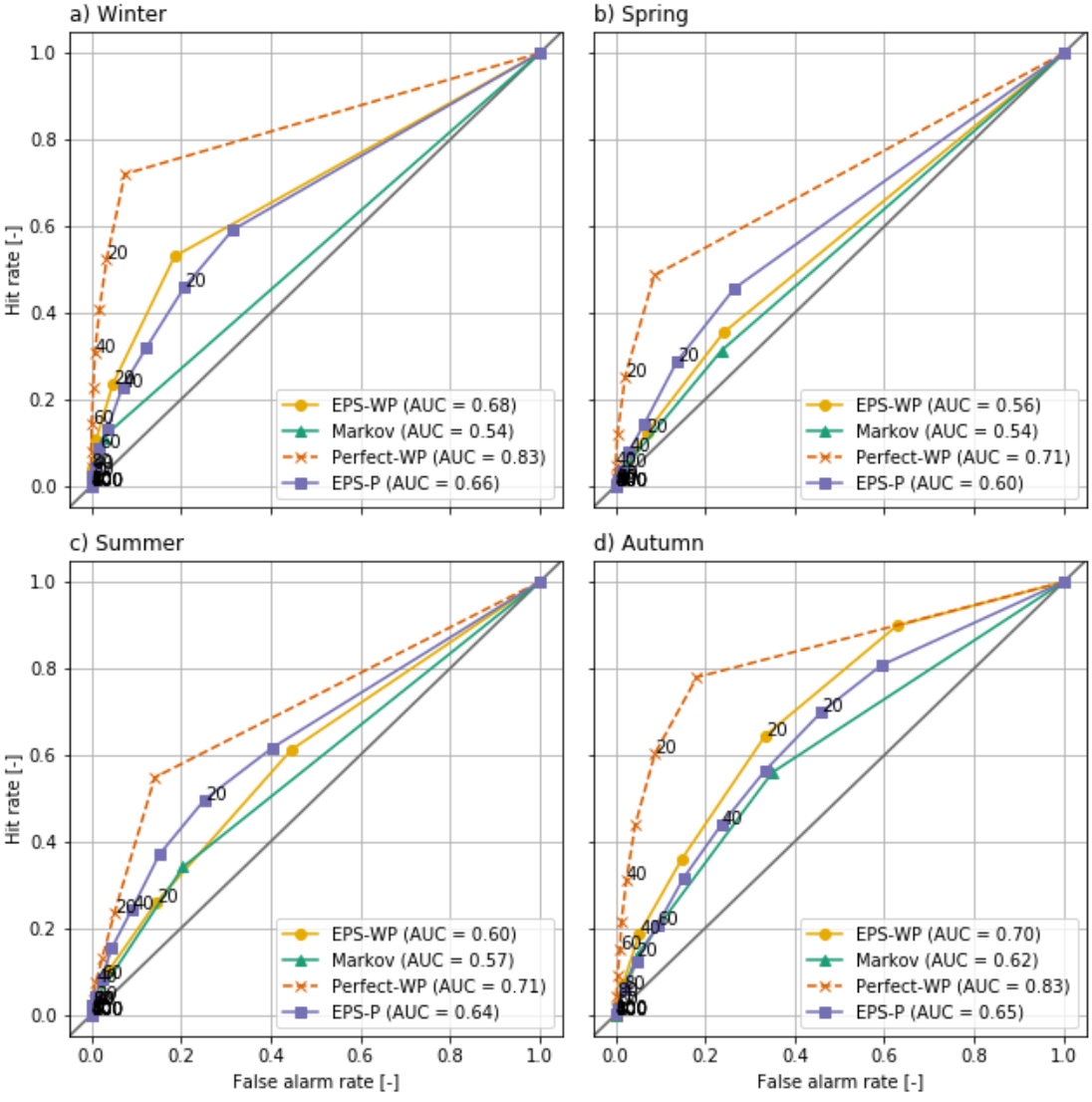

Figure 8: As Fig. 7 but for moderate drought.

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Preprint. Discussion started: 16 July 2019

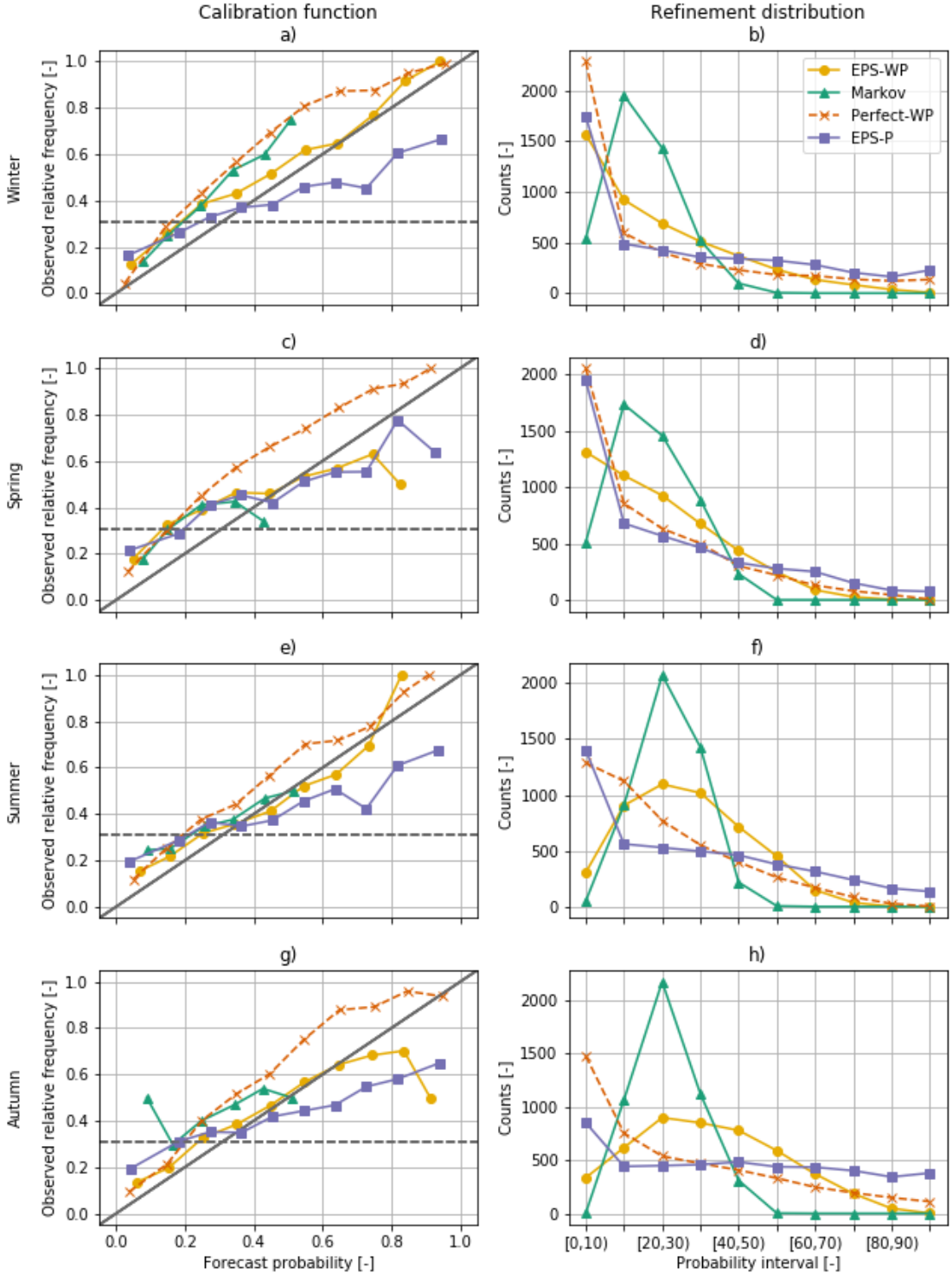

Figure 9: Calibration functions (first column) and refinement distributions (second column) for mild drought with a 31-day lead-time. For the calibration function diagrams, the solid diagonal line indicates perfect reliability and the dashed horizontal line the event relative frequency for mild drought (0.309).

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Preprint. Discussion started: 16 July 2019

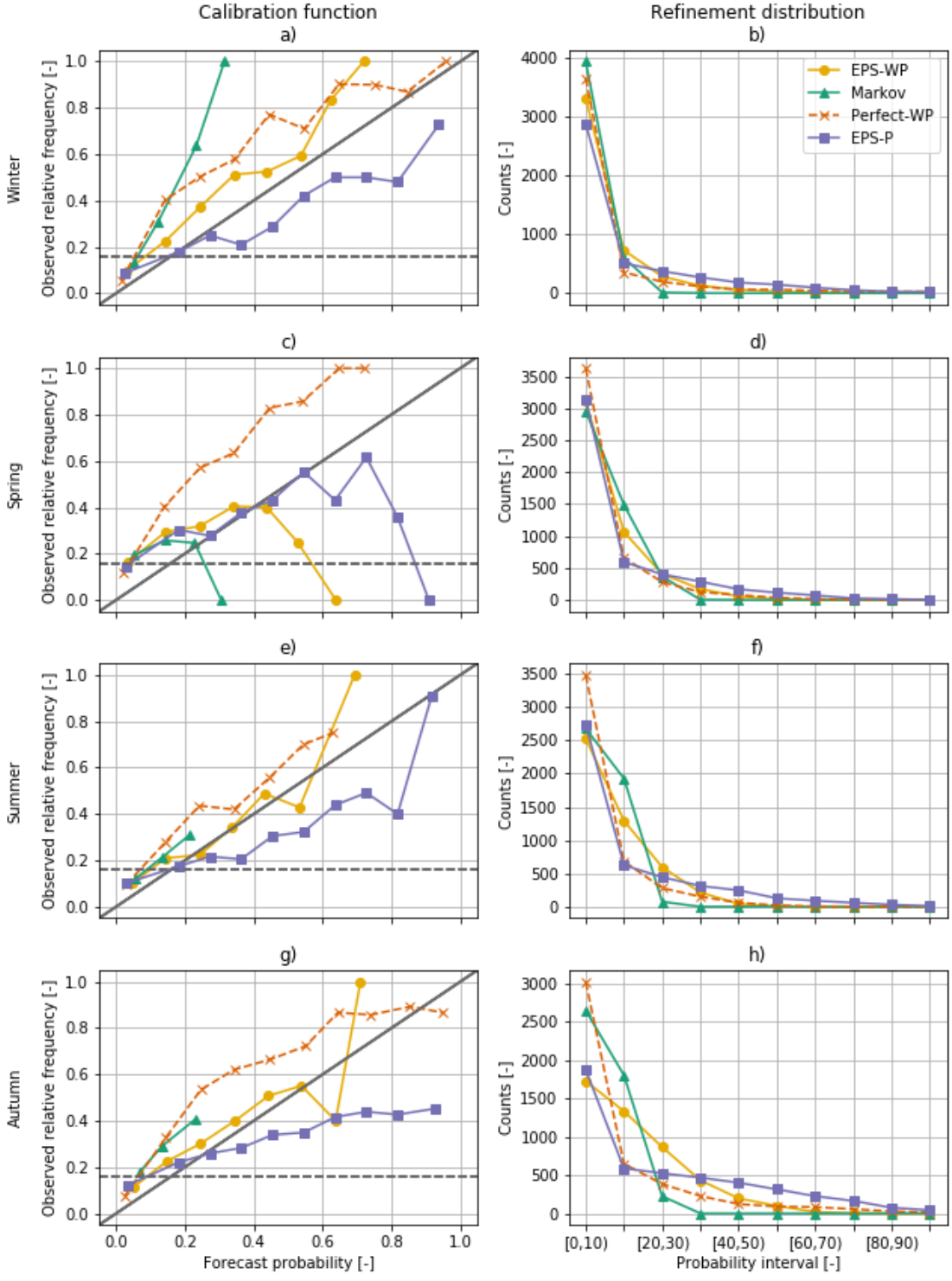

Figure 10: As Fig. 9 but for moderate drought (event relative frequency of 0.159).

Supplement for RC1 and RC2 responses

This supplement contains the new text relating to Sections 4.2 and 4.3.1 of the original submitted manuscript, which have changed as a result of applying a bias-correction to ECMWF EPS precipitation and hence drought forecasts (EPS-P).

We also include all new plots e.g. a new model schematic and updates of the radar plots as map plots. All figures are after the text.

4.2 Precipitation forecasts

We first discuss the skill of the three true forecast models, EPS-WP, EPS-P and Markov. For the most part, all three models are more skilful than climatology independent of season and lead-time, with greater skill in autumn and winter compared to spring and summer (Figs. 4 and 5). For a 16-day lead-time, there is little to choose between EPS-WP and EPS-P, except in ES, for which the latter model is less skilful than climatology in winter and spring (Fig. 4). Markov is the least skilful model at this lead, offering only a marginal improvement on climatology (Fig. 4). The skill of EPS-WP and EPS-P reduces when a 31-day lead is considered, bringing their skill more in line with Markov (Fig. S2). At a 46-day lead the differences are starker, with EPS-P notably less skilful than EPS-WP, Markov and climatology for many regions in summer and, especially, spring (Fig. 5). These results are, however, still only marginally superior to climatology. EPS-WP has greater skill than EPS-P at this lead-time in winter and autumn for NS, NI, CEE and SWE, although the magnitudes of these differences are small (Fig. 5). There is little evidence of coherent regional variability in model skill, except perhaps a tendency for EPS-P to score more highly for western regions in spring and summer at a 16-day lead-time (Fig. 4). Despite low skill relative to climatology at longer lead-times, there is clearly some benefit to using the WP-based models (particularly EPS-WP) for certain regions and seasons.

The potential usefulness of such approaches is highlighted by the performance of Perfect-WP. Unsurprisingly, this model is almost uniformly the most skilful model for all regions, seasons and lead-times (Figs. 4, 5 and S2). The gains in skill for this model over the other three models are most pronounced during winter and autumn and especially for longer lead-times. Skill is greatest for most western regions (NS, NI, NWE and SWE) and lowest for eastern regions ES, NEE and SEE, together with SS (Fig. 5). Perfect-WP is obviously not practical, but the results serve to show that WPs are a potentially useful tool in medium-range precipitation forecasting.

4.3 Drought forecasts

4.3.1 Forecast accuracy

Forecast accuracy is typically lower for mild drought (total precipitation over 16, 31, or 46 days below the 30.9th percentile) than for precipitation, and lower still for moderate drought (total precipitation below the 15.9th percentile). The regional and lead-time differences in precipitation skill are also evident for drought, with higher skill at shorter leads and during winter and autumn (Figs. 6, 7 and S3). Results for mild drought are not shown as they generally lie in-between those for precipitation (Figs. 4, 5 and S2) and moderate drought (Figs. 6, 7 and S3). Markov again has the poorest skill, with a climatology forecast preferable for many combinations of region and lead-time. EPS-P is either equal or more skilful than

EPS-WP at a 16-day lead (Fig. 6), and during spring for longer leads (Figs. 7 and S3). Conversely, EPS-WP outperforms EPS-P during summer at the longer two lead-times, although a climatology forecast would be just as, if not more skilful. As with precipitation forecasts, any gain in skill using EPS-WP over EPS-P in winter and autumn at longer leads is marginal, with both models showing more skill than climatology (Figs 7 and S3).

Skill, where present, is undeniably modest, but the relatively high skill of Perfect-WP in some regions and seasons again shows the potential predictability of drought using WP methods. Compared to precipitation forecasts, skill for Perfect-WP is notably lower for spring and summer, with climatology often a competitive forecast method at a 46-day lead-time (Fig. 7). For winter and autumn, however, the skill is reasonable UK-wide, and particularly high during winter in NS and NI (Fig. 7). The same east-west skill split is present for moderate drought as it was for precipitation, with some western regions benefitting from higher skill than eastern region (Fig. 7).

Daily precipitation		**Total 16-, 31- and 46-day precipitation**	
p_b	**Range of precipitation, x, (mm)**	**s_c**	**Range of summed precipitation, y, (mm)**
p_1	0	s_1	$0 < y \leq 10$
p_2	$0 < x \leq 1$	s_2	$10 < y \leq 20$
…	Intervals of 1 mm	…	Intervals of 10 mm
p_{11}	$9 < x \leq 10$	s_{25}	$240 < y \leq 250$
p_{12}	$10 < x \leq 15$	s_{26}	$250 < y \leq 300$
p_{13}	$15 < x \leq 20$	…	Intervals of 50 mm
p_{14}	$20 < x \leq 30$	s_{30}	$300 < y \leq 450$
…	Intervals of 10 mm		
p_{21}	$90 < x \leq 100$		

Table 1: Range of daily precipitation, x, for each bin p_b and of 16-, 31- and 46-day total precipitation, y, for each bin s_c.

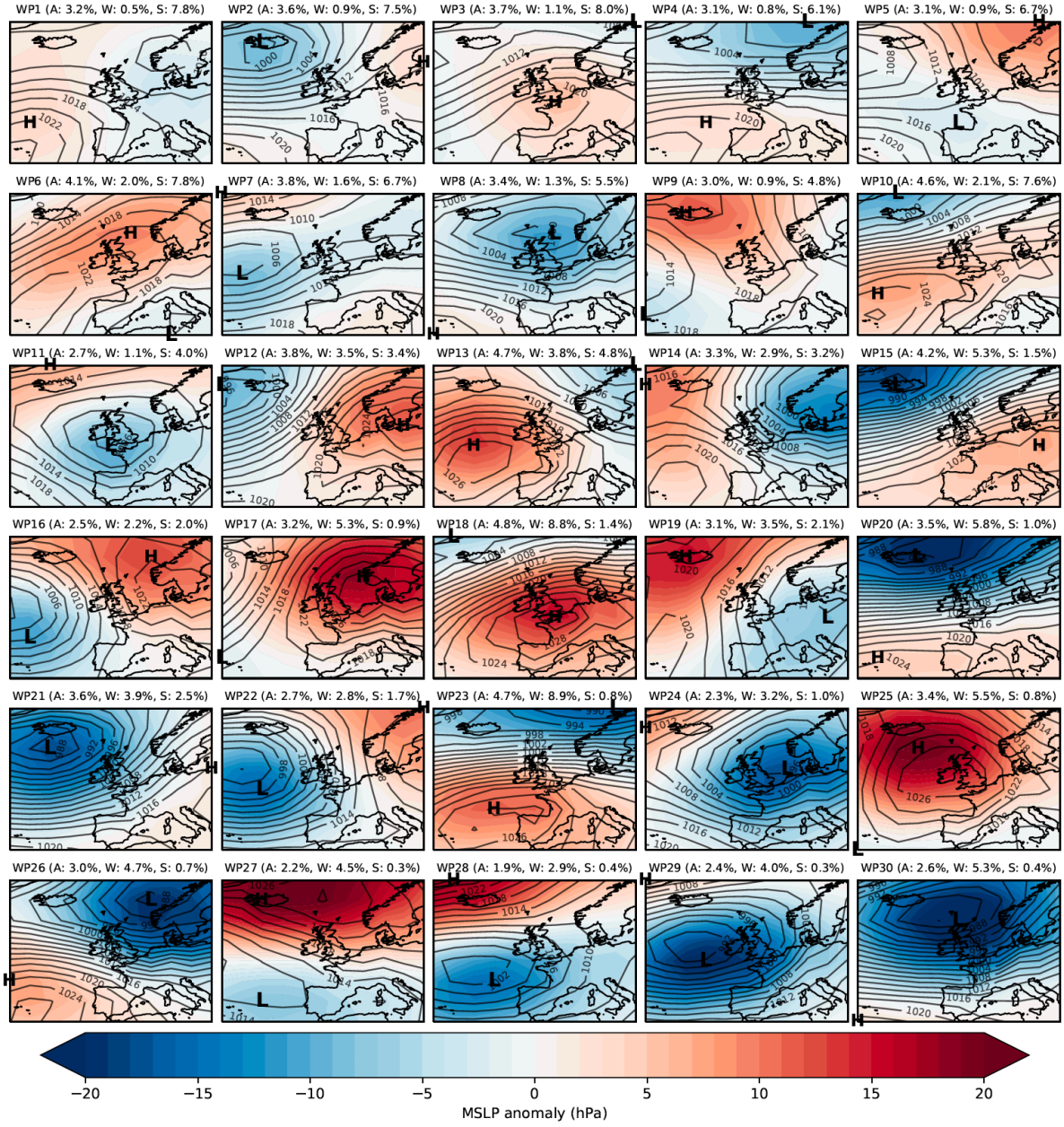

Figure 1: Weather pattern (WP) definitions according to mean sea-level pressure (MSLP) anomalies (hPa). The black contours are isobars showing the absolute MSLP values associated with each weather pattern, with the centres of high and low pressure also indicated. Next to the WP labels are the annual (A), winter (W; DJF) and summer (S; JJA) relative frequencies of occurrences of each WP (%). The frequencies of occurrence data are associated with the WPs based on ERA-Interim between 1979 and 2017, while the WP definitions were generated from a clustering process applied to EMULATE MSLP reanalysis data between 1850 and 2003. See the text for details.

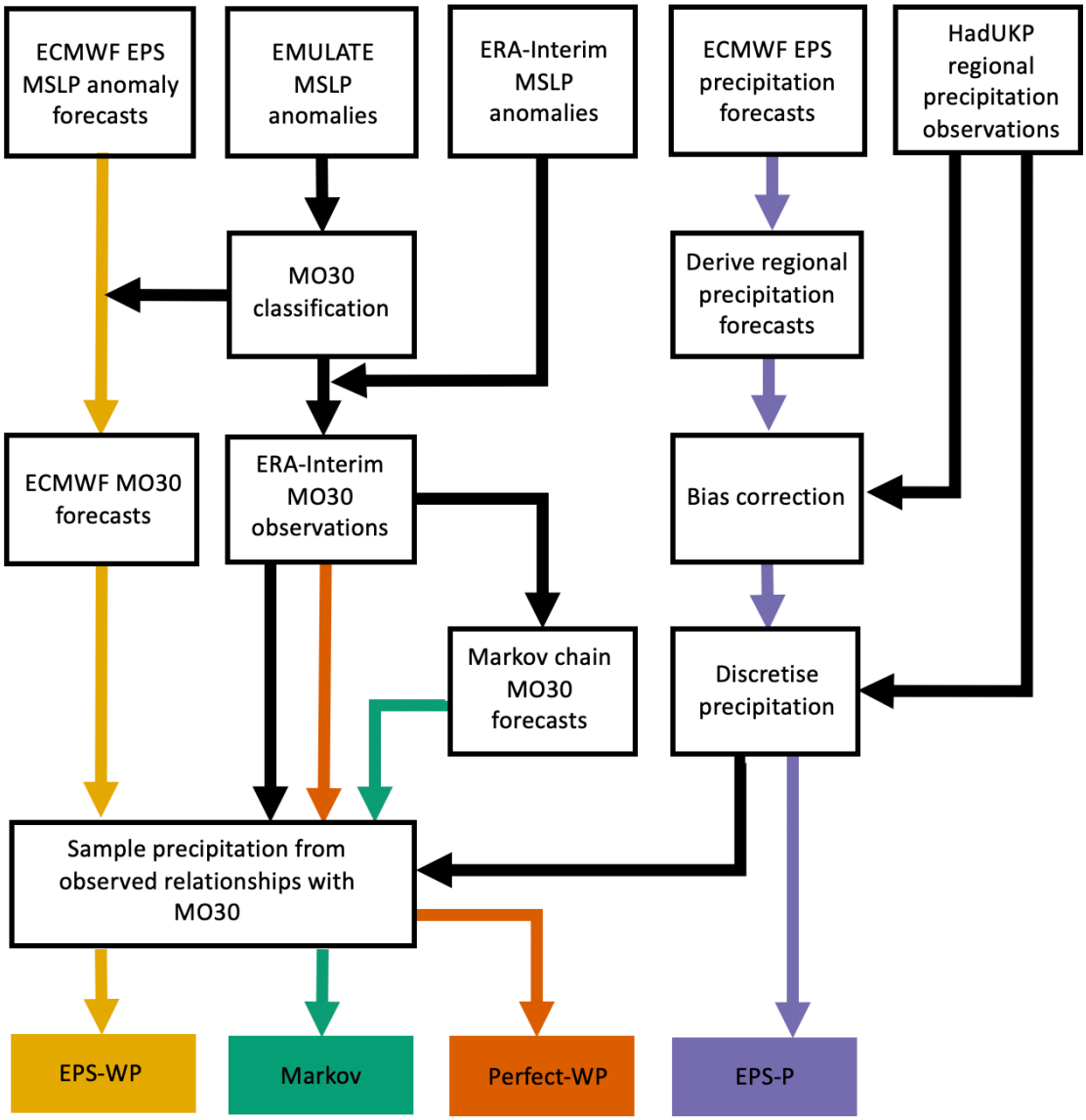

Figure 2: Schematic showing the procedure for the four precipitation forecast models. The top row shows the base data sets used and the bottom row shows the four models. Coloured arrows begin at the first stage for which forecasts are issued: EPS-WP forecasts begin with the ECMWF prediction system MSLP forecasts; Markov forecasts are produced once the ERA-Interim MO30 time series has been derived; Perfect-WP 'forecasts' are observations from the same time series, while EPS-P forecasts are the post-processed data from the ECMWF forecast system.

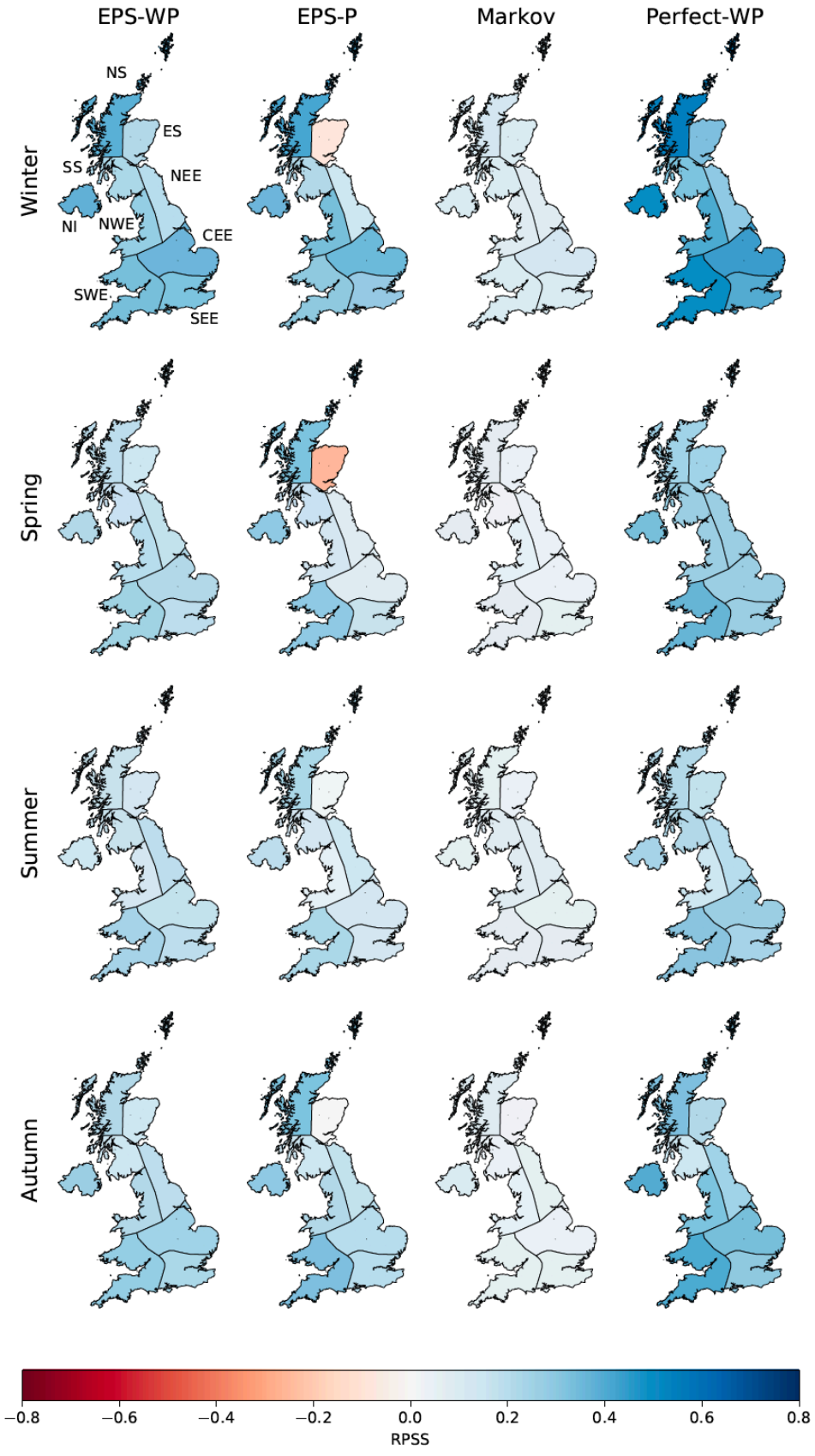

Figure 4: Ranked probability skill scores (RPSS) for precipitation forecasts at a 16-day lead for each model and season.

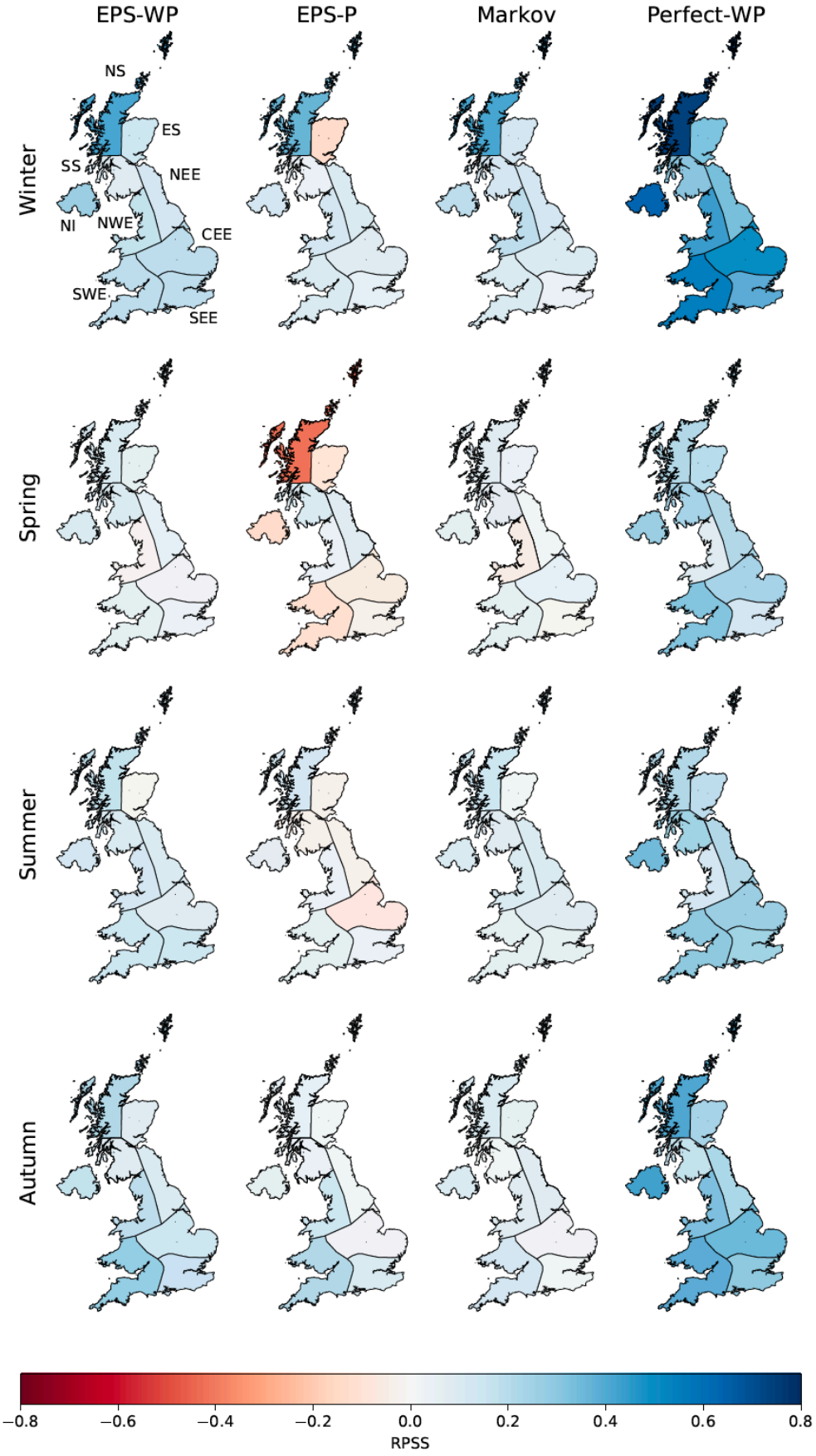

Figure 5: As Figure 4 but for a 46-day lead.

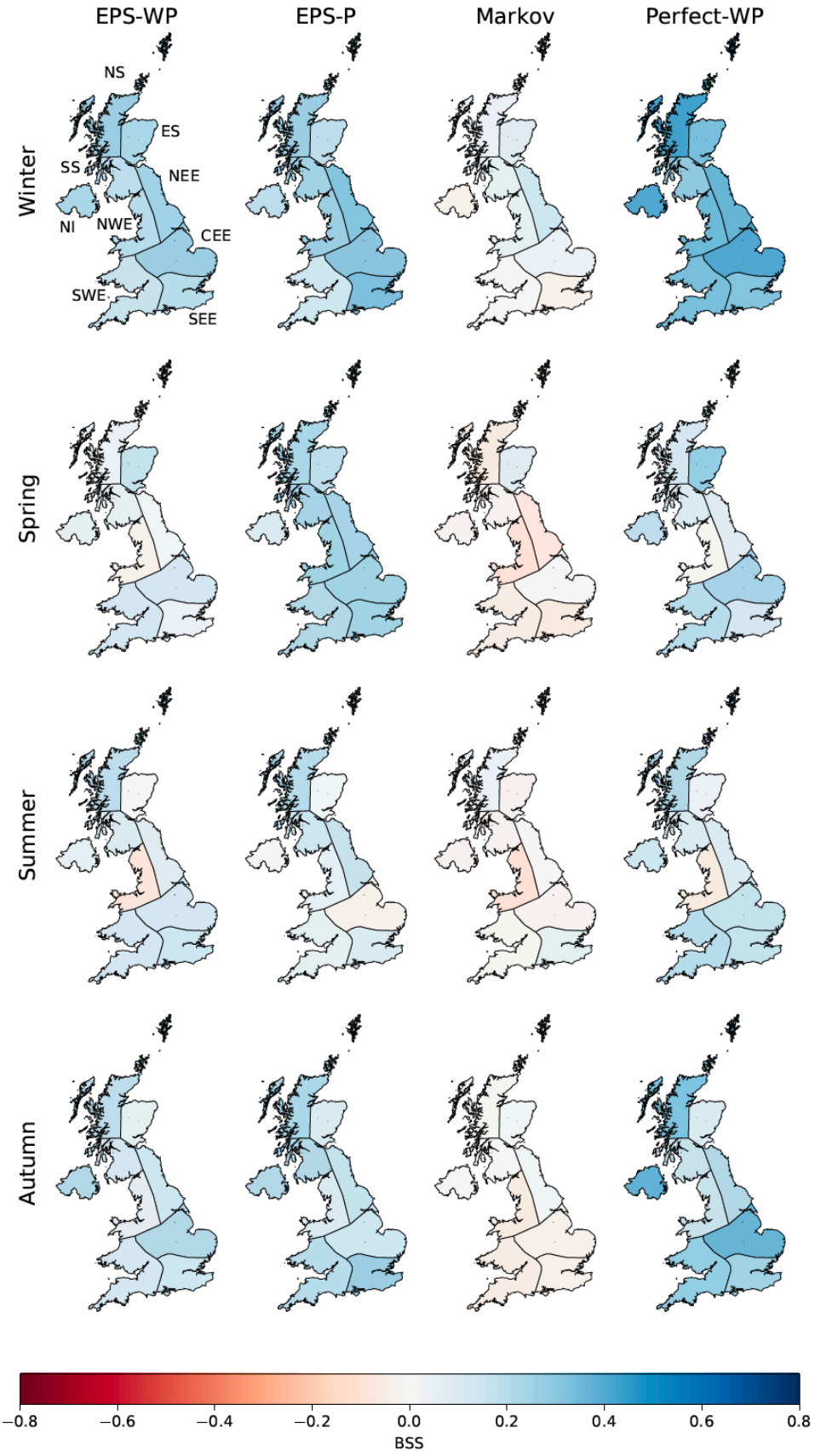

Figure 6: Brier skill scores (BSS) for mild drought (total precipitation below the 30.9th percentile) for a 16-day lead-time for each model and season.

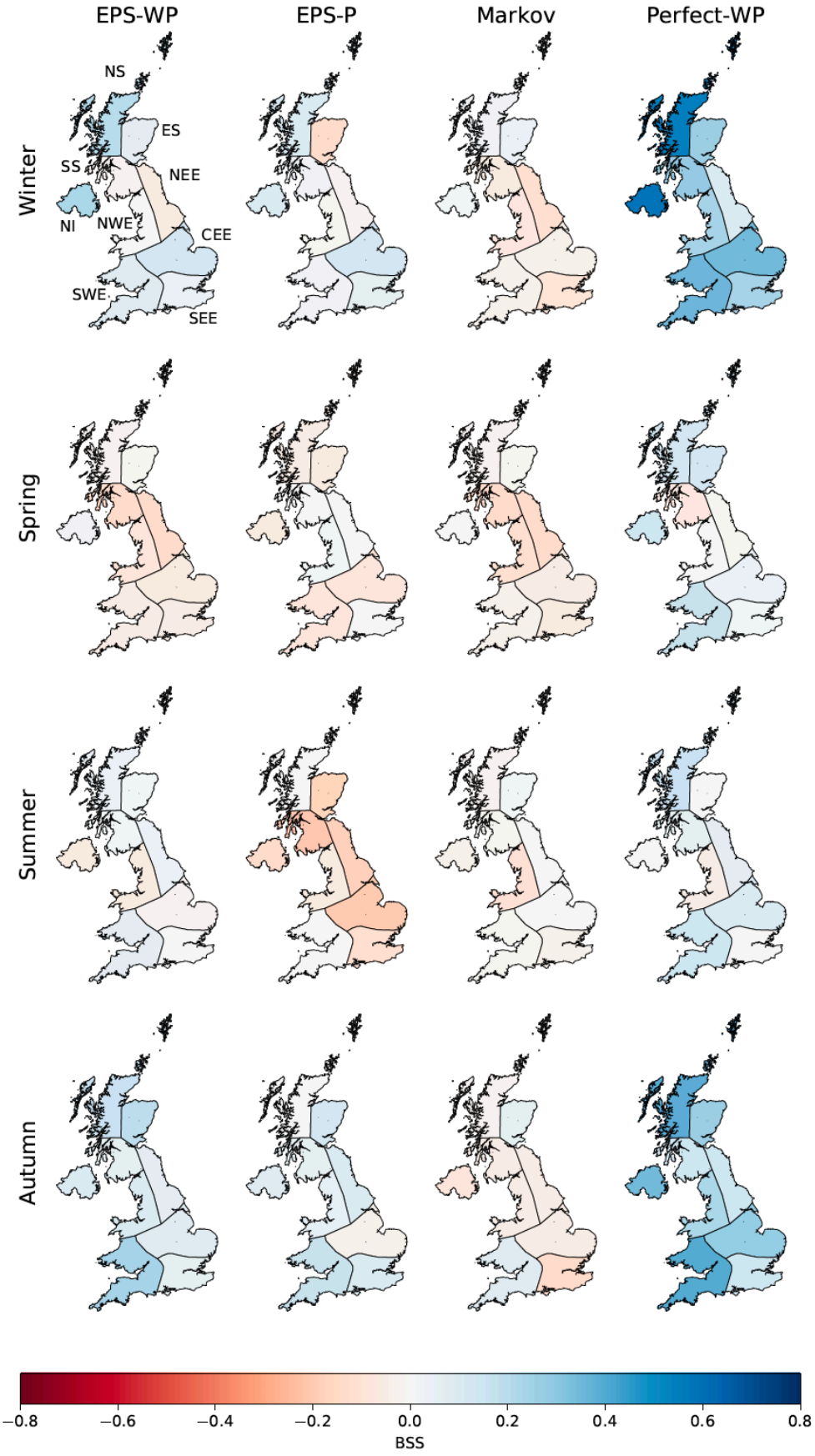

Figure 7: As Figure 6 but for a 46-day lead.

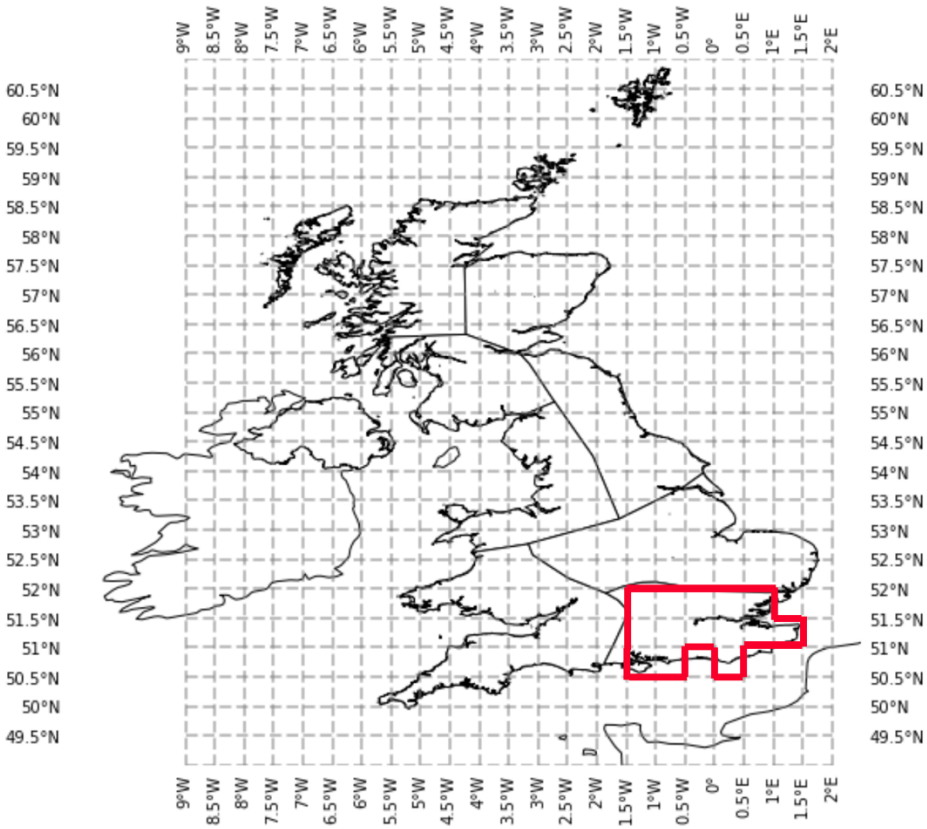

Figure S1: Schematic showing ECMWF-EPS precipitation forecast model grid, over the UK and HadUKP regions. The red box indicates the grid cells assigned to the region SEE using the cell centres.

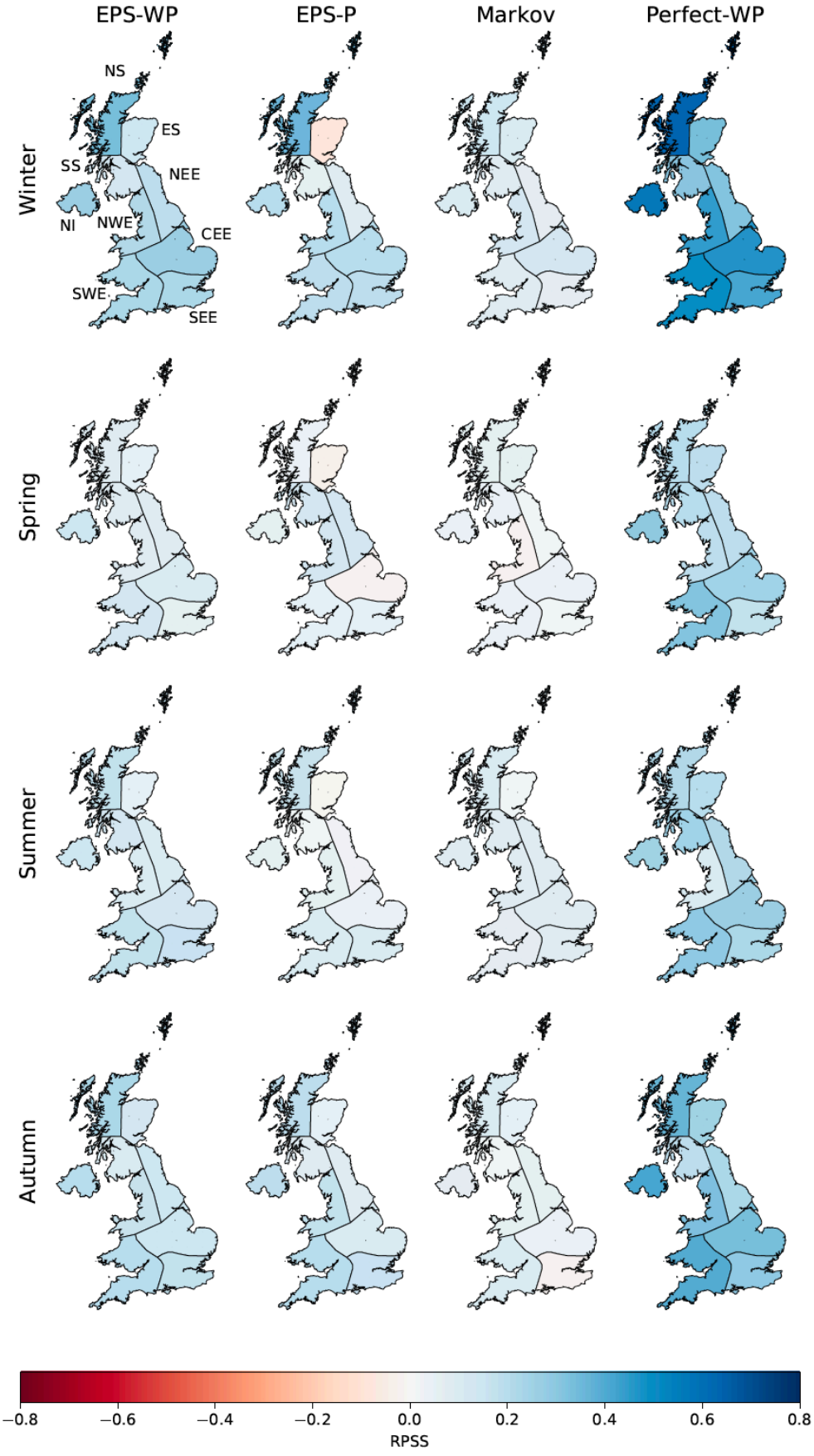

Figure S2: As Figure 4 but for a 31-day lead.

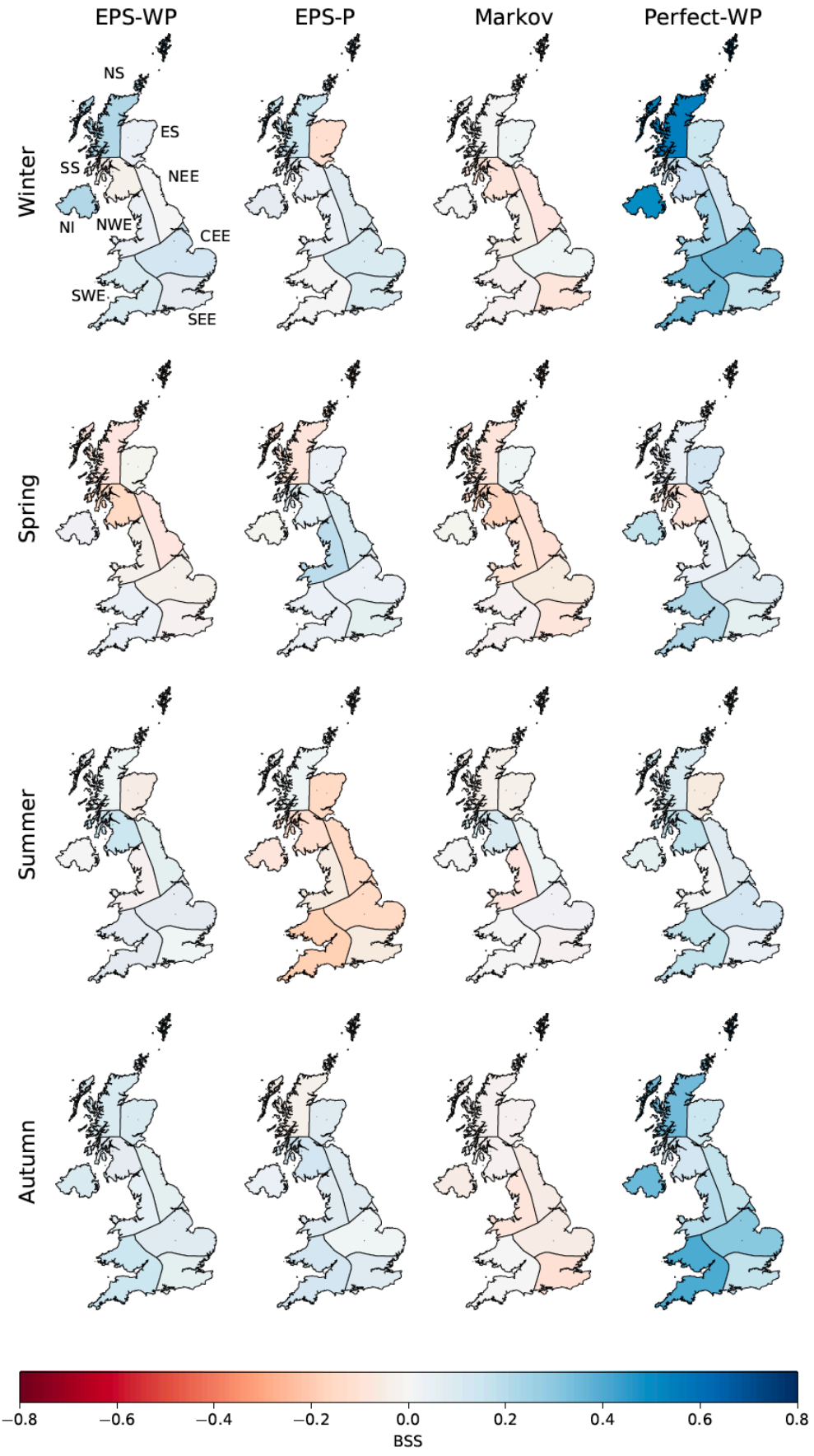

Figure S3: As Figure 6 but for a 31-day lead.

Improving sub-seasonal forecast skill of meteorological drought: a weather pattern approach

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Abstract. Dynamical model skill in forecasting extratropical precipitation is limited beyond the medium-range (around 15 days), but such models are often more skilful at predicting atmospheric variables. We explore the potential benefits of using weather pattern (WP) predictions as an intermediary step in forecasting UK precipitation and meteorological drought on sub-seasonal time scales. Mean sea-level pressure forecasts from the ECMWF ensemble prediction system (ECMWF-EPS) are post-processed into probabilistic WP predictions. Then we derive precipitation estimates and dichotomous drought event probabilities by sampling from the conditional distributions of precipitation given the WPs. We compare this model to the direct precipitation and drought forecasts from ECMWF-EPS and to a baseline Markov chain WP method. A perfect-prognosis model is also tested to illustrate the potential of WPs in forecasting. Using a range of skill diagnostics, we find that the Markov model is the least skilful, while the dynamical WP model and direct precipitation forecasts have similar accuracy independent of lead-time and season. However, drought forecasts are more reliable for the dynamical WP model. Forecast skill scores are generally modest (rarely above 0.4), although those for the perfect-prognosis model highlight the potential predictability of precipitation and drought using WPs, with certain situations yielding skill scores of almost 0.8, and drought event hit and false alarm rates of 70% and 30%, respectively.

1 Introduction

Droughts are a recurrent climatic feature in the UK. Severe events, such as those in 1975-76, 1995 and 2010-12, had significant implications for many sectors, including agriculture, water resources and the economy, as well as for ecosystems and natural habitats (Marsh, 1995; Marsh *et al.*, 2007; Rodda and Marsh, 2011; Kendon *et al.*, 2013). To mitigate the effects of drought, it is crucial that relevant sectors plan ahead, and drought forecasts have an important role in designing these strategies. Despite this, there is very little published research on UK drought prediction, and studies have predominantly focussed on hydrological drought (Wedgbrow *et al.*, 2002; Wedgbrow *et al.*, 2005; Hannaford *et al.*, 2011).

Meteorological drought is challenging to predict using dynamical ensemble prediction systems (Yoon *et al.*, 2012; Dutra *et al.*, 2013; Yuan and Wood, 2013; Mwangi *et al.*, 2014; Lavaysse *et al.*, 2015). This is primarily due to the complex processes involved in precipitation formation, making it a difficult variable to forecast beyond short lead-times (Golding, 2000; Cuo *et al.*, 2011; Smith *et al.*, 2012; Saha *et al.*, 2014). At longer lead-times, dynamical model skill in predicting atmospheric variables tends to be much higher (Saha *et al.*, 2014; Scaife *et al.*, 2014; Vitart, 2014; Baker *et al.*, 2018). This has led researchers to investigate the potential of using atmospheric forecasts as a precursor to predicting precipitation-related hazards (Lavers *et al.*, 2014; Lavers *et al.*, 2016; Baker *et al.*, 2018).

Weather pattern (WP; also called weather types, circulation patterns and circulation types) classifications are a candidate for such an application. A WP classification consists of a number of individual WPs, which are typically defined by an atmospheric variable and represent the broad-scale atmospheric circulation over a given domain (Huth *et al.*, 2008). They can be used to make general predictions of local-scale variables such as wind speed, temperature and precipitation and are a tool for reducing atmospheric variability to a few discrete states. WP classifications have mainly been studied in the context of extreme hydro-meteorological events (Hay *et al.*, 1991; Wilby, 1998; Bárdossy and Filiz, 2005; Richardson *et al.*, 2018a; Richardson *et al.*,

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2018b), and as a tool for analysing historical and future changes in atmospheric circulation patterns (Hay *et al.*, 1992; Wilby, 1994; Brigode *et al.*, 2018). See Huth *et al.* (2008) for a comprehensive review of WP classifications.

Until recently, the capability of dynamical models to predict WP occurrences had been little researched. Ferranti *et al.* (2015) evaluated the forecast skill of the medium-range European Centre for Medium-Range Weather Forecasts ensemble prediction system (ECMWF-EPS) (Buizza *et al.*, 2007; Vitart *et al.*, 2008) using WPs. They objectively defined four WPs according to daily 500 hPa geopotential heights over the North Atlantic – European sector. Model forecasts of this variable for October through April between 2007 and 2012 were then assigned to the closest matching WP using the root-mean-square difference. Verification scores indicated that there was superior skill for predictions initialised during negative phases of the North Atlantic Oscillation (NAO) (Walker and Bliss, 1932). Similarly, WPs were used to evaluate the skill of the Antarctic Mesoscale Prediction System by Nigro *et al.* (2011).

To support weather forecasting in the UK in the medium- to long range, the Met Office use a WP classification, MO30, in a post-processing system named "Decider" (Neal *et al.*, 2016). Using a range of ensemble prediction systems, forecast mean sea-level pressure (MSLP) fields over Europe and the North Atlantic Ocean are assigned to the best-matching WP according to the sum-of-squared differences between the forecast MSLP anomaly and WP MSLP anomaly fields. Decider therefore produces a probabilistic prediction of WP occurrences for each day in the forecast lead-time. Decider has various operational applications: predicting the possibility of flow transporting volcanic ash originating in Iceland into UK airspace, highlighting potential periods of coastal flood risk around the British Isles (Neal *et al.*, 2018) and as an early-forecast system for fluvial flooding (Richardson *et al.*, in review).

For Japan, Vuillaume and Herath (2017) defined a set of WPs according to MSLP. These WPs were used to refine bias-correction procedures, via regression modelling, of precipitation from two global ensemble forecast systems. The authors found that improvements from the bias-correction method using WPs was strongly dependent on the WP, but overall superior to the global (non-WP) method. Relevant to this study, Lavaysse *et al.* (2018) predicted monthly meteorological drought in Europe using a WP-based method. They aggregated ECMWF-EPS daily reforecasts of WPs to predict monthly frequency anomalies of each WP. For each 1° grid cell, the predictor was chosen to be the WP that corresponded to the maximum absolute temporal correlation between the monthly WP frequency of occurrence anomaly and the monthly Standardised Precipitation Index (SPI) (McKee *et al.*, 1993). Using this relationship, the model predicted drought in a grid cell when 40% of the ECMWF-EPS ensemble members forecast a Standardised Precipitation Index (SPI; McKee *et al.*, 1993) value below -1. Compared to direct ECMWF-EPS drought forecasts, the WP-based model was more skilful in north-eastern Europe during winter, but less skilful for central and eastern Europe during spring and summer. Over the UK, the WP model appeared to be superior for north-western regions in winter, but inferior in summer, although scores for the latter were of low magnitude.

The aforementioned studies have all considered daily WPs. An example of WPs defined on the seasonal time-scale was presented by Baker *et al.* (2018). The authors analysed reforecasts of UK regional winter precipitation between the winters of 1992-93 and 2011-12 using GloSea5, which has little raw skill in forecasting this variable (MacLachlan *et al.*, 2015). GloSea5 has, however, been shown to skilfully forecast the winter NAO (Scaife *et al.*, 2014). Baker *et al.* (2018) exploited this by constructing two winter MSLP indices over Europe and the North Atlantic, and reforecasts of these indices were derived from the raw MSLP fields. A simple regression model then related these indices to regional precipitation and produced more skilful forecasts than the raw model output.

In this study, we shall explore the potential for utilising a WP classification (specifically MO30) in UK meteorological drought prediction. We shall predict WPs using two models, ECMWF-EPS and a Markov chain, from which precipitation and drought forecasts will be derived. These models will be compared to direct precipitation and drought forecasts from ECMWF-EPS. We also run an idealised, perfect prognosis model that uses WP observations rather than forecasts as an 'upper benchmark' to

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assess the upper limit of the usefulness of the WP classification. Section 2 contains details of the data sets used, including describing the creation of a WP reforecast data set. Section 3 describes the models in detail and the forecast verification procedure. In Sect. 4, we shall present the results and in Sect. 5, we draw some conclusions and make recommendations for future work.

2 Data

We use a Met Office WP classification called MO30 (Neal *et al.*, 2016). WPs in MO30 were defined by using simulated annealing to cluster 154 years (1850-2003) of daily MSLP anomaly fields into 30 distinct states. The data were extracted from the European and North Atlantic daily to multidecadal climate variability (EMULATE) data set (Ansell *et al.*, 2006) in the domain 30° W-20° E; 35°-70° N, with a spatial resolution of 5° latitude and longitude. These 30 WPs are therefore representative of the 30 most common patterns of daily atmospheric circulation over Europe and the North Atlantic (Fig. 1), and they were ordered such that WP1 is the most frequently occurring WP annually, while WP30 is the least frequent. A consequence of the clustering process and ordering is that the lower-numbered WPs have lower-magnitude MSLP anomalies and are more common in the summer than in the winter, and vice versa for the higher-numbered WPs (Richardson *et al.*, 2018a)(Neal *et al.*, 2016).

For this analysis, we have created a 20-year daily WP probabilistic reforecast data set. We use the sub-seasonal to seasonal (S2S) project (Vitart *et al.*, 2017) data archive, which, through ECMWF, hosts reforecast data for a multitude of variables and by a range of models from around the globe. In particular, we use ECMWF-EPS, which is a coupled atmosphere-ocean-sea-ice model with a lead-time of 46 days. The horizontal atmospheric resolution is roughly 16 km up to day 15 and 32 km beyond this. The model is run at 00Z, twice weekly (Mondays and Thursdays) and has 11 ensemble members for the reforecasts (compared to 51 members for the real-time forecasts). For further details, refer to the model webpage (ECMWF, 2017). We use daily reforecasts of MSLP between 02 January 1997 and 28 December 2016, inclusive, with the same domain and resolution as MO30. These fields are converted to forecast anomalies by removing a smoothed climatology and subsequently assigned to the closest matching MO30 WP via minimising the sum-of-squared differences. Both the MSLP climatology and the WP definitions are the same as those used by Neal *et al.* (2016) to ensure consistency. We compare this against an 'observed' WP time series to measure forecast skill. For this, WPs are assigned from 00Z SLP fields from the ERA-Interim reanalysis data set (Dee *et al.*, 2011) between 1979 and 2017. A consequence of assigning WPs using ERA-Interim compared to the EMULATE data set used in the original derivation of MO30 is that the historical frequencies of occurrence of the WPs differ. The same strongly seasonal behaviour is retained (lower-numbered WPs occurring more often in summer than higher-numbered WPs, and vice versa), but the annual frequencies are more evenly distributed across the WPs - there is no clear decrease in annual frequency as the WP number is increased (Figure 1).

As observed precipitation, we use the Met Office Hadley Centre UK Precipitation (HadUKP) data set (Alexander and Jones, 2000). For nine regions covering the UK, we use daily precipitation series from 1979 to 2017. We discretise the data into precipitation intervals ("bins") defined in Table 1; see Section 3.2 for further information. The large region sizes in HadUKP are suitable both for analyses of drought, which is typically considered a regional rather than localised event (Marsh *et al.*, 2007), and for MO30 because they correspond to the large-scale circulation patterns that the WPs represent. From the S2S archive, we extract ECMWF-EPS precipitation reforecasts for the same dates as the WP reforecast data set. The data have a resolution of 0.5° latitude and longitude; grid cells are assigned to whichever of the nine HadUKP regions the cell centres lie in (Fig. S1) and by taking the daily mean of all cells over each region, we produce a probabilistic reforecast data set of precipitation for each of the HadUKP regions. Then, we remove the three-monthly-mean bias of the forecasts compared to the observations for each region. The bias correction is done using leave-one-year-out cross validation. Finally, these data are discretised in the same way as the HadUKP data.

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3 Methods

3.1 Weather pattern forecast models and verification procedure

For WP forecasts, we compare two models. The first is ECMWF-EPS, which we shall refer to as EPS-WP (in practice this is the WP reforecast data set discussed in the previous subsection). The second model is a 1000-member, first-order, nonhomogeneous Markov chain, with separate transition matrices for each month. This is similar to the Markov model used for a simulation study by Richardson *et al.* (2018b), who found it was able to reasonably replicate the observed frequencies of occurrences of the MO30 WPs. Full details of the Markov model are given in the supporting material.

To evaluate WP forecast skill we use the Jensen-Shannon divergence (JSD), suitable for measuring the distance between two probability distributions (Lin, 1991). It is based on information entropy, which is used to measure uncertainty. An information-theoretic approach to verification is not widespread, although there is some published research on the topic (Leung and North, 1990; Kleeman, 2002; Roulston and Smith, 2002; Ahrens and Walser, 2008; Weijs *et al.*, 2010; Weijs and Giesen, 2011). The JSD will be used to measure the forecast performance by quantifying the distance between distributions of the observed and forecast WP frequencies. The JSD is based on the Kullback-Leibler divergence (KLD) (Kullback and Leibler, 1951). Let P and Q be two discrete probability distributions. The KLD from Q to P is given by:

$$D_{KL}(P||Q) = -\sum_{i=1}^{I} P_i \log_2 \frac{Q_i}{P_i},$$

Equation 1

measured in bits (i.e. a binary unit of information). In our application $I = 30$, the number of WPs and $P = (p_{f,1}, \dots, p_{f,30})$ and $Q = (q_{f,1}, \dots, q_{f,30})$ are the vectors of observed and forecast WP relative frequencies, respectively. (Because these are relative frequencies, $\sum P = 1$ and $\sum Q = 1$.) As there would inevitably be some cases where the model predicts no occurrences of some WPs (i.e. when Q contains zeros), $D_{KL}(P||Q)$ will be undefined at times. Using the JSD avoids this problem; it is defined as:

$$D_{JSD}(P||Q) = \frac{1}{2} D_{KL}(P||M) + \frac{1}{2} D_{KL}(Q||M),$$

Equation 2

where $M = (P + Q)/2$. Unlike the KLD, the JSD is symmetric i.e. $D_{JSD}(P||Q) \equiv D_{JSD}(Q||P)$. Also, $0 \leq D_{JSD}(P||Q) \leq 1$, with a score of zero indicating P and Q are the same (a perfect forecast). Equation 2 gives the JSD for a single forecast-event pair; to obtain the average JSD for all forecasts we take the mean of all forecast-event pairs. Skill is evaluated separately for each month, with the middle date of each forecast period used to assign the month. We calculate forecast skill for lead-times of 16, 31 and 46 days. We use the JSD to compare WP forecast skill of EPS-WP and the Markov model, considering each lead-time separately.

3.2 Precipitation and drought forecast models

We compare four models, three of which are forecast models, while one model is a perfect prognosis model. Fig. 2 shows a schematic of the procedure involved in generating forecasts from each model. All models are considered at the same lead-times as the WP predictions. Two of the forecast models are driven first by a WP component: EPS-WP and the Markov model described above. The perfect prognosis model, Perfect-WP, is used as an 'upper benchmark' with (future) observed WPs as input, rather than forecast WPs. It is an idealised model that cannot be used operationally, but it allows us to assess the potential

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usefulness of WPs in precipitation and drought forecasting. Note that from here, any reference to drought refers specifically to meteorological drought.

Precipitation is estimated from the WP predictions (or observations in the case of Perfect-WP) by sampling from the conditional distributions of precipitation given each Era-Interim WP between 1979 and 2017. We process the daily HadUKP precipitation data by discretising into v bins with historical probabilities p_b for $b = 1, \dots, v$. Dry days form one bin and bin intervals increase for higher precipitation values (Table 1). This gives a discrete distribution of precipitation interval relative frequencies, $D(z)$, with conditional distributions for each WP given by $D(z|W = i)$, for $i = 1, \dots, 30$. We also define w summed precipitation intervals s_c for $c = 1, \dots, w$. Forecast probabilities of these summed intervals are derived from the WP forecast models as follows:

1. Set the ensemble member $e \in (e_1, \dots, e_N)$, where N_e is the number of ensemble members; time $t = 0$, the first day of the forecast, and then the predicted WP by ensemble member e at time t is $W_e(t) = i$ for $i = 1, \dots 30$.

2. Set $p_0 = 0$, calculate the probabilities $p_1, \dots p_m$ of each of the m daily precipitation bins from the discrete precipitation distribution that is conditional on $W_e(t)$ and on the 91-day windows centred on t (i.e. $t - 45, \dots, t + 45$) from every year except the current year. This last condition is equivalent to a leave-one-year-out cross-validation procedure.

3. Define the maximum value of each bin as $l_{p_b}, b = 1, \dots v$, with $l_{p_0} = 0$. Note that $l_{p_0} = l_{p_1} = 0$, ensuring zero precipitation days can be simulated.

4. Generate u random variables $p_k^* \sim U(0,1)$ for $k = 1, \dots, u$.

5. For each p_k^*, find the index q such that

$$\sum_{j=0}^{q} p_j < p_k^* < \sum_{j=0}^{q+1} p_j .$$

Set $P_q = \sum_{j=0}^{q-1} p_j$ and $P_{q+1} = \sum_{j=0}^{q} p_j$, the cumulative probabilities of the bins adjacent to p_k^*.

6. Define the difference between the adjacent bins as $\alpha = P_{q+1} - P_q$ and the difference between the random number and the lower cumulative probability as $\beta = p_k^* - P_q$.

7. Estimate the precipitation value for each p_k^* as $r_k(t) = l_{p_q} + \frac{\beta}{\alpha}\left(l_{p_{q+1}} - l_{p_q}\right)$. We now have u predicted daily precipitation values at time t, $\boldsymbol{r}(t) = (r_1(t), \dots, r_n(t))$.

8. Set $t = t + 1$ and repeat steps 3 to 6 until the final day of the forecast, $t_{\max}$, is processed.

9. Sum the daily precipitation vectors and divide by the random-sample size $(\sum_\tau \boldsymbol{r}(t))/u$ for $\tau = 0, \dots, t_{\max}$.

10. Discretise according to the w summed precipitation bins $s_1, \dots s_w$ to obtain a distribution of relative frequencies for this ensemble member $\boldsymbol{f_e} = (f_1, \dots, f_w)$.

11. Set a new ensemble member $e^* \in \left(e_1, \dots e_{N_e}\right), e^* \neq e$ and repeat steps 2 to 10 until every ensemble member has been processed.

12. Sum each ensemble member's distribution of summed precipitation relative frequencies and divide by the number of ensemble members to obtain a final forecast probability distribution:

$$\boldsymbol{F} = \left(\sum_e \boldsymbol{f_e}\right) \Big/ N_e .$$

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The number of ensemble members depends on the model. For EPS-WP, $N_e = 11$, i.e. the number of ensemble members of the ECMWF dynamical model. For the Markov model $N_e = 1000$. We set the number of samples drawn from each WP-precipitation conditional distribution as $u = 10{,}000$. The fourth model (the third forecast model) is the direct ECMWF-EPS precipitation forecasts (EPS-P), processed to provide probabilistic predictions of regional precipitation intervals as described earlier.

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3.3 Precipitation forecast verification

To evaluate precipitation forecast performance we use the ranked probability score (RPS) (Epstein, 1969; Murphy, 1971). We express the RPS as the ranked probability skill score (RPSS) using

$$\mathrm{RPSS} = 1 - \frac{\mathrm{RPS}}{\mathrm{RPS}_{\mathrm{ref}}},$$

Equation 3

Where $\mathrm{RPS}_{\mathrm{ref}}$ is the score of a climatological forecast, which in our case is the climatological event category (i.e. precipitation interval) relative frequencies (PC). A perfect score is achieved when $\mathrm{RPSS} = 1$, which is also the upper limit. Negative (positive) values indicate the forecast is performing worse (better) than $\mathrm{RPS}_{\mathrm{ref}}$.

3.4 Drought forecast verification

We evaluate model performance in predicting dichotomous drought/non-drought events. We define two classes of drought severity. The first class, mild drought, is when precipitation sums (over the length of the considered lead-time: either 16, 31 or 46 days) are below the 30.9$^{\mathrm{th}}$ percentile of the summed precipitation distribution. The second class is moderate drought, with such sums being below the 15.9$^{\mathrm{th}}$ percentile. These percentiles are calculated for each region and month using the whole data set from 1979 through 2017, and are chosen as they correspond to SPI values of -0.5 and -1, respectively.

3.4.1 The Brier Skill Score

We use three verification techniques to assess skill in predicting droughts. The first is the Brier Skill Score (BSS). The BSS is based on the Brier Score (BS) (Brier, 1950), which measures the mean-square error of probability forecasts for a dichotomous event, in this case the occurrence or non-occurrence of drought. The BS is converted to a relative measure, or skill score, by setting

$$\mathrm{BSS} = 1 - \frac{\mathrm{BS}}{\mathrm{BS}_{\mathrm{ref}}},$$

Equation 4

where $\mathrm{BS}_{\mathrm{ref}}$ is the score of a reference forecast given by the quantiles associated with each drought threshold, 0.309 for mild drought and 0.159 for moderate drought. As with the RPSS, a perfect score is achieved when $\mathrm{BSS} = 1$ and negative (positive) values indicate the forecast is performing worse (better) than $\mathrm{BS}_{\mathrm{ref}}$.

3.4.2 Reliability diagrams – forecast reliability, resolution and sharpness

The BS can be decomposed into reliability, resolution and uncertainty terms (Murphy, 1973):

$$\mathrm{BS} = \mathrm{reliability} - \mathrm{resolution} + \mathrm{uncertainty},$$

Equation 5

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enabling a more in-depth assessment of forecast model performance. Reliability diagrams offer a convenient way of visualising the first two of these terms (Wilks, 2011). These diagrams consist of two parts, which together show the full joint distribution of forecasts and observations. The first element is the calibration function, $g(o_1|p_i)$, for $i = 1, \dots n$, where o_1 indicates the event (here, a drought) occurring and the p_i are the forecast probabilities. The calibration function is visualised by plotting the event relative frequencies against the forecast probabilities and indicates how well calibrated the forecasts are. We split the forecast probabilities into 10 bins (subsamples) of 10% probability and the mean of all forecast probabilities in each bin is the value plotted on the diagrams (Bröcker and Smith, 2007). Points along the 1:1 line represent a well-calibrated, *reliable*, forecast, as event probabilities are equal to the forecast probabilities and suggest that we can interpret our forecasts at 'face value'. If the points are to the right (left) of the diagonal, the model is over-forecasting (under-forecasting) the number of drought events.

The forecast *resolution* can also be deduced from the calibration function. For a forecast with poor resolution, the event relative frequencies $g(o_1|p_i)$ only weakly depend on the forecast probabilities. This is reflected by a smaller difference between the calibration function and the horizontal line of the climatological event frequencies and suggests that the forecast is unable to resolve when a drought is more or less likely to occur than the climatological probability. Good resolution, on the other hand, means that the forecasts are able to distinguish different subsets of forecast occasions for which the subsequent event outcomes are different to each other.

The second element of reliability diagrams is the refinement distribution, $g(p_i)$. This expresses how confident the forecast models are by counting the number of times a forecast is issued in each probability bin. This feature is also called *sharpness*. A low-sharpness model would overwhelmingly predict drought at the climatological frequency, while a high-sharpness model would forecast drought at extreme high and low probabilities, reflecting its level of certainty with which a drought will or will not occur, independent of whether a drought actually does subsequently occur or not.

3.4.3 Relative operating characteristics

As a final diagnostic we use the relative operating characteristic (ROC) curve (Mason, 1982; Wilks, 2011), which visualises a model's ability to discriminate between events and non-events. Conditioned on the observations, the ROC curve may be considered a measure of potential usefulness – it essentially asks what the forecast is, given that a drought has occurred. The ROC curve plots the hit rate (when the model forecasts a drought and a drought subsequently occurs) against the false alarm rate (when the model forecasts a drought but a drought does not then occur). We compute the hit rate and false alarm rate for cumulative probabilities between 0% and 100% at intervals of 10%. A skilful forecast model will have a hit rate greater than a false alarm rate, and the ROC curve would therefore bow towards the top-left corner of the plot. The ROC curve of a forecast system with no skill would lie along the diagonal, as the hit rate and false alarm rate would be equal, meaning the forecast is no better than a random guess. The area under the ROC curve (AUC) is a useful scalar summary. AUC ranges between zero and one, with higher scores indicating greater skill.

4 Results

To reduce information overload, we do not show results for every combination of region, lead-time and drought class. Key results not shown will be conveyed via the text. We aggregate the precipitation results from monthly to three-month seasons for visual clarity and combine regional results for the ROC and reliability diagrams for the same reason.

4.1 WP forecasts

We find that EPS-WP is more skilful at predicting the WPs than the Markov model for every month and every lead-time, although the difference in skill between the two models decreases as the lead-time increases. The skill difference between models is much larger for a lead-time of 16 days compared to a lead-time of 46 days (Fig. 3). For a 46-day lead-time, the

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difference in skill is negligible for May through October; in fact, these months have the smallest differences in JSD for all lead-times. This is presumably because the summer months are associated with fewer WPs compared to winter (Richardson *et al.*, 2018a), resulting in a more skilful Markov model due to higher transition probabilities.

An interesting result is how JSD scores for Markov decrease as the lead-time increases (Fig. 3), suggesting an improvement in skill with lead-time. This is the opposite of the expected (and usual) effect. The Markov model predicts WPs using the one-day transition probabilities, and its ensemble members therefore diverge very quickly, resulting in a distribution of predicted WPs that looks similar to the climatological WP distribution for all lead-times. For a 16-day forecast, the observed WP distribution of the corresponding 16 days will generally be less similar to the climatological WP distribution than for 31-day forecasts, and less similar still than for 46-day forecasts. For instance, at a 16-day lead, only 16 unique WPs could form the observed distribution, whereas Markov is capable of predicting all possible WPs across its 1000 members at this lead. As the JSD measures the distance between these probability distributions, it tends to score the differences between these distributions as more similar (a smaller divergence) for longer lead-times. This means the JSD is perhaps not appropriate as a verification metric in an operational sense, but is noteworthy for highlighting the behaviour of the Markov model.

We could have assessed model skill in predicting the WPs using more common metrics such as the BS, which could measure the hit/miss ratio for each WP at each lead-time. However, the focus of this paper is on multi-week precipitation (and drought) totals, so we are not particularly interested in the models' ability to predict the timing of a WP, only whether they are able to capture the distribution of the WP frequencies of occurrence. It is likely that using the BS would show that EPS-WP and Markov skill decreases with lead-time, as was the case for a WP classification derived from MO30 by Neal *et al.* (2016).

4.2 Precipitation forecasts

We first discuss the skill of the three true forecast models, EPS-WP, EPS-P and Markov. For the most part, all three models are more skilful than climatology independent of season and lead-time, with greater skill in autumn and winter compared to spring and summer (Figs. 4 and 5). For a 16-day lead-time, there is little to choose between EPS-WP and EPS-P, except in ES, for which the latter model is less skilful than climatology in winter and spring (Fig. 4). Markov is the least skilful model at this lead, offering only a marginal improvement on climatology (Fig. 4). The skill of EPS-WP and EPS-P reduces when a 31-day lead is considered, bringing their skill more in line with Markov (Fig. S2). At a 46-day lead the differences are starker, with EPS-P notably less skilful than EPS-WP, Markov and climatology for many regions in summer and, especially, spring (Fig. 5). These results are, however, still only marginally superior to climatology. EPS-WP has greater skill than EPS-P at this lead-time in winter and autumn for NS, NI, CEE and SWE, although the magnitudes of these differences are small (Fig. 5). There is little evidence of coherent regional variability in model skill, except perhaps a tendency for EPS-P to score more highly for western regions in spring and summer at a 16-day lead-time (Fig. 4). Despite low skill relative to climatology at longer lead-times, there is clearly some benefit to using the WP-based models (particularly EPS-WP) for certain regions and seasons.

The potential usefulness of such approaches is highlighted by the performance of Perfect-WP. Unsurprisingly, this model is almost uniformly the most skilful model for all regions, seasons and lead-times (Figs. 4, 5 and S2). The gains in skill for this model over the other three models are most pronounced during winter and autumn and especially for longer lead-times. Skill is greatest for most western regions (NS, NI, NWE and SWE) and lowest for eastern regions ES, NEE and SEE, together with SS (Fig. 5). Perfect-WP is obviously not practical, but the results serve to show that WPs are a potentially useful tool in medium-range precipitation forecasting.

4.3 Meteorological drought forecasts

4.3.1 Forecast accuracy

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Deleted: During summer and spring, all three forecast models are well matched, although for a 16-day lead-time Markov is the least skilful. For this lead-time, EPS-P mostly scores similarly to EPS-WP, although it has higher skill for some regions (Figs. 4b and 4c) and even outperforms Perfect-WP for several regions in summer (Fig. 4c). At lead-times of 31 and 46 days, there is little difference in forecast model skill during spring and summer, although in summer NI and SWE appear to benefit from dynamical WP predictions (i.e. EPS-WP), as do the four eastern regions from any kind of WP forecast (EPS-WP and Markov; Fig. 5). On the other hand, using WP predictions is to the detriment of precipitation forecast skill in spring for SEE, as shown by the superior performance of EPS-P (Fig. 5). This split between the east and west is also found by Lavaysse *et al.* (2015), who used ECMWF-EPS to predict meteorological drought with a one month lead-time.¶
For winter and autumn, EPS-WP is the most skilful forecast model except when considering a 16-day lead-time, for which EPS-P is often the best performer. Scotland benefits most from the use of EPS-WP, as even at the shortest lead-time this model is superior (Figs. 4a and 4d). Note that the skill of the WP forecasts matter, as Markov is associated with poor precipitation skill at this lead-time, which corresponds to its low skill in forecasting the WPs compared to EPS-WP (Fig. 3). EPS-WP is the most skilful model for 31- and 46-day lead-times; EPS-P and Markov score fairly evenly overall for a 31-day lead-time, with the former model the least skilful for a 46-day lead-time (Fig. 5). The difference in skill between EPS-WP and Markov is much larger for northern and western regions, particularly in winter. Therefore the improvement in skill by predicting the WPs with a dynamical model, rather than Markov (Fig. 3), translates to a spatially non-uniform gain in skill for precipitation, with western and northern regions the principal beneficiaries. However, it is difficult to say why this is the case, as from the JSD scores alone we do not know whether EPS-WP is better at predicting all WPs, or [1]

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Forecast accuracy is typically lower for mild drought (total precipitation over 16, 31, or 46 days below the 30.9th percentile) than for precipitation, and lower still for moderate drought (total precipitation below the 15.9th percentile). The regional and lead-time differences in precipitation skill are also evident for drought, with higher skill at shorter leads and during winter and autumn (Figs. 6, 7 and S3). Results for mild drought are not shown as they generally lie in-between those for precipitation (Figs. 4, 5 and S2) and moderate drought (Figs. 6, 7 and S3). Markov again has the poorest skill, with a climatology forecast preferable for many combinations of region and lead-time. EPS-P is either equal or more skilful than EPS-WP at a 16-day lead (Fig. 6), and during spring for longer leads (Figs. 7 and S3). Conversely, EPS-WP outperforms EPS-P during summer at the longer two lead-times, although a climatology forecast would be just as, if not more skilful. As with precipitation forecasts, any gain in skill using EPS-WP over EPS-P in winter and autumn at longer leads is marginal, with both models showing more skill than climatology (Figs 7 and S3).

Skill, where present, is undeniably modest, but the relatively high skill of Perfect-WP in some regions and seasons again shows the potential predictability of drought using WP methods. Compared to precipitation forecasts, skill for Perfect-WP is notably lower for spring and summer, with climatology often a competitive forecast method at a 46-day lead-time (Fig. 7). For winter and autumn, however, the skill is reasonable UK-wide, and particularly high during winter in NS and NI (Fig. 7). The same east-west skill split is present for moderate drought as it was for precipitation, with some western regions benefitting from higher skill than eastern region (Fig. 7).

4.3.2 Relative operating characteristics

All models are better able to discriminate between drought and non-drought events than random chance, with Perfect-WP the most able and Markov the least able, subject to similar caveats regarding lead-time and season as for the BSS and RPSS results. During summer and spring, EPS-P has the highest AUC of any of the three forecast models (Figs. 8 and 9), and for a 16-day lead-time scores similarly to Perfect-WP (not shown). On the other hand, EPS-WP is the best discriminator during winter and autumn at a 46-day lead-time, although the magnitude of the differences is small (Figs. 8 and 9). Markov is consistently the least suitable model for predicting drought according to the ROC curve, although still represents a better method of doing so than random chance.

A use of the ROC curve is to provide end-users with information on how to apply the considered forecast models. As the plotted points on each curve indicate the hit rate and false alarm rate associated with predicting droughts at each probability interval, they can be used to make an informed decision in selecting a probability threshold for issuing a drought forecast. For example, should a forecaster choose to issue a moderate drought warning in winter at a 10% probability level and 46-day lead-time (Fig. 9), then they would expect EPS-WP to achieve a hit rate over double that of the false alarm rate (~55% and ~20%, respectively). EPS-P, meanwhile, shows a slightly lower hit rate and similar false alarm rate (~50% and ~20%). The idealised benchmark model (Perfect-WP) achieves an outstanding score – an over 70% hit rate compared to a <10% false alarm rate. For mild drought, a 20% probability threshold for EPS-WP and EPS-P achieves at least 60% hit rates at all lead-times, whereas for moderate drought, this threshold will only achieve such hit rates at a 16-day lead-time during winter and autumn (EPS-P also achieves this rate for spring and summer; not shown) and during autumn for all lead-times. In general, it appears that these low probability thresholds yield the best compromise between hits and false alarms, although in practice, the costs (e.g. financial) associated with false alarms and missed events will determine how responders use these probabilities.

4.3.3 Forecast reliability, resolution and sharpness

EPS-WP is the most reliable forecast model (i.e. excluding Perfect-WP), and while all three WP-driven forecast models tend to under-forecast droughts, EPS-P only does so for lower probability thresholds, with the higher thresholds resulting in this model over-forecasting. This is particularly true for shorter lead-times and during winter, although is still clear for 31-day

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Deleted: Forecast accuracy for mild and moderate drought is qualitatively similar to those of general precipitation in terms of regional and lead-time differences. EPS-WP is overall the most skilful model, although this is less the case for a 16-day lead-time, for the three regions in East England and for most regions in spring and summer. Only the results for predicting moderate drought at the 46-day lead-time are presented (Fig. 6). This is because the results for mild drought are more similar to the RPSS results than those of moderate drought, those for the 16-day lead-time are the least useful for drought prediction (which tends to be focussed on longer-range forecasts) and those for the 31-day lead-time are qualitatively similar to the 46-day lead-time.¶
For the shortest lead-time, EPS-P has the highest accuracy for predicting winter and autumn drought of both classes, except in Scotland, for which EPS-WP has the highest skill. Indeed, EPS-WP has the highest skill for the other lead-times during these seasons (Fig. 6). However, a key difference is that eastern England droughts are at least as accurately predicted by EPS-P as by EPS-WP for the two longer lead-times (Fig. 6), whereas for precipitation forecasting the latter tend to be more accurate (Fig. 5). Difference in model skill is lower for spring and summer drought forecasts, particularly for moderate drought (Fig. 6). In fact, for this drought class, there is very little or no gain in skill by using WPs at 31- and 46-day lead-times for spring and summer compared to EPS-P (Fig. 6). Furthermore, at these lead-times both models are less skilful than issuing climatological drought probabilities (shown by their negative BSS), except for spring predictions of eastern and southern droughts. This suggests that, during spring and summer, deriving precipitation from predicted WPs may be useful if forecasting mild drought, but not for more severe droughts.¶

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lead-times in some seasons (Figs. 10 and 11). Sometimes EPS-WP follows the same pattern as EPS-P and over-forecasts drought occurrence for higher predicted probabilities (e.g. Figs. 10c, e, g and 11c). However, the total number of forecasts issued in these intervals is generally smaller than for EPS-P, as the refinement distributions show most clearly for mild drought (Fig. 10). This means the corresponding points of the calibration function are less reliable for EPS-WP (and Markov) due to smaller sample sizes (Bröcker and Smith, 2007). In fact, all three WP-based models have occasions when there are no issued forecasts with certain probabilities. These are high probabilities for Perfect-WP and EPS-WP (Figs. 11c and e) but can be as low as between 30% and 40% for Markov (Figs. 11e and g). As such, although EPS-WP appears the most reliable model from looking only at the calibration function, there is less certainty of this fact for moderate drought and for higher forecast probabilities. This erratic behaviour of the conditional event relative frequencies is most obvious in Fig. 11c and is explained by the very low sample sizes of forecasts issued with anything but a small probability (Fig. 11e) (Wilks, 1995). An interesting result is that forecasts from EPS-WP are more reliable than from Perfect-WP when the predicted drought probabilities are below 80% for mild drought (Fig. 10) and 60% for moderate drought (except in spring; Fig. 11), despite having lower accuracy (e.g. Fig. 6). As a more skilful BSS is composed of smaller reliability and larger resolution terms (Kharin and Zwiers, 2003), it follows that the resolution of Perfect-WP is sufficiently large to overcome the larger reliability term compared to EPS-WP and yield an overall more accurate forecast model. However, for drought forecasts issued with higher probabilities, EPS-WP is the less reliable model, under- or over-forecasting drought (depending on the season) more than Perfect-WP. These under- or over-forecasting biases must be taken into account by an operational forecaster using these models.

A key difference apparent from the calibration function relates to the ability of the models to identify subsets of forecast situations where the subsequent event relative frequencies are different, i.e. the forecast resolution. A fairly consistent feature across all lead-times and drought classes is the poorer resolution of EPS-P, particularly obvious in summer (Figs. 10e and 11e), with the conditional event relative frequencies quite clearly closer to the climatological average compared to the other models. This should be considered in conjunction with the sharpness of the forecast, which is relatively high for this model as shown by the numbers of issued extreme probabilities, particularly those in the upper-tail (Figs. 10f and 11f). This combination of poor resolution and high sharpness indicates "overconfidence" (Wilks, 2011) – on the occasions that EPS-P issues a forecast indicating the likelihood of a drought is very high, the actual likelihood of a drought subsequently occurring is lower. To compensate for this overconfidence, a user would adjust the probabilities to be less extreme to make the forecasts more reliable.

We can compare these refinement distributions to those of the Markov model, which exhibits low sharpness, overwhelmingly predicting droughts at the climatological frequency (second column of Figs. 10 and 11). This means that the Markov model is not a useful operational tool in these situations, as similar forecasts could be obtained simply by using the climatological drought frequency. The refinement distributions for EPS-WP show that for mild drought in winter and spring and for moderate drought in all seasons, the model predicts droughts with low probabilities the majority of the time (Figs. 10b, d and 11b, d, f, h). For mild drought in summer and autumn, however, this model mostly issues forecasts close to the climatological frequency, although not nearly as regularly as the Markov model (Fig. 10f, h). As with adjusting for bias, a forecaster can use model resolution and sharpness when assessing drought forecast probabilities output by a model.

5 Discussion and conclusions

We have compared the performance of a dynamical forecast system (EPS-WP) and a first-order Markov model in predicting WP occurrences over a range of lead-times, showing that the dynamical model is always more skilful, although the difference in skill reduces with lead-time. From these WP predictions, we derived precipitation and meteorological drought forecasts and compared them to direct precipitation and drought predictions from the dynamical system (EPS-P). We compared two levels of drought: mild drought, when the total precipitation over the lead-time (16, 31 or 46 days) was below the 30.9th percentile climatology, and moderate drought, when the total precipitation over the lead-time was below the 15.9th percentile. Overall, forecast models were found to be more skilful during winter and autumn, particular for longer lead-times. The Markov model

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tended to be the least skilful, especially when predicting drought. Differences in skill between EPS-P and EPS-WP were typically small, with RPSS, BSS and ROC results not highlighting a clear winner. However, we demonstrated the potential in improving WP forecasts further by showing that an idealised, perfect prognosis model (Perfect-WP) would provide much more skilful precipitation and drought forecasts, with high hit rates and low false alarm rates.

From assessing reliability diagrams, we found that WP-based models only issue binary drought forecasts with either very low probabilities or probabilities close to the climatological average. In particular, there is little to gain in using the Markov model in mild drought prediction over the climatological frequency, as it tends to issue drought forecasts with this probability anyway. EPS-P has the highest sharpness, predicting drought occurrence with a wide range of probabilities. In particular, it issues greater numbers of high-probability drought forecasts compared to WP-based methods. However, this model also has poor resolution, indicating it is an overconfident forecast model. Overall, drought forecasts issued by EPS-WP are the most reliable, i.e. the forecast probabilities are most similar to the subsequent event probabilities (they "mean what they say") (Wilks, 2011). Perfect-WP tends to under-forecast the number of drought events, while EPS-P over-forecasts drought events, particularly for moderate drought. These reliability diagrams are therefore useful to aid users in adjusting for an over- or under-forecasting bias.

The higher skill of EPS-WP during winter (and possibly autumn) is probably due to the typically higher skill that medium- to long-range dynamical forecast systems have in predicting atmospheric variables in this season compared to other seasons (Scaife *et al.*, 2014; MacLachlan *et al.*, 2015; Neal *et al.*, 2016; Arnal *et al.*, 2018). In fact, by forecasting a set of eight WPs derived from MO30, Neal *et al.* (2016) found that ECMWF-EPS exhibited greater skill in winter than summer. Furthermore, the relationship between the NAO (which is the primary mode of North Atlantic/European atmospheric circulation) and precipitation is stronger in this season (Hurrell and Deser, 2009; Lavers *et al.*, 2010; Svensson *et al.*, 2015). This is particularly true for western regions (Jones *et al.*, 2013; Svensson *et al.*, 2015; van Oldenborgh *et al.*, 2015; Hall and Hanna, 2018), which potentially explains the greater skill of precipitation and drought forecasting using observed WPs (Perfect-WP). The regional variations in skill of this model imply that MO30 is not as suited for representing precipitation in the east. Perhaps this is because the WPs are more closely related to the NAO in this season compared to other teleconnection patterns. As Hall and Hanna (2018) showed, the NAO is not the only important teleconnection pattern influencing UK precipitation.

By analysing the skill of an idealised 'forecast' model that assumes perfect WP predictions, we have demonstrated the potential for using WP forecasts to derive precipitation and drought predictions. The skill of this model during winter and autumn suggest that the processes between the WPs and precipitation are well represented in these seasons. The lesser skill of EPS-WP and Markov, then, is a result of poor prediction of the WPs. A focus on improving the skill of the WP forecasts could be the most useful route to improving precipitation and drought predicting skill. Currently, dynamical models such as the ECMWF system used here represent the best method of predicting WPs. Moreover, the ECMWF reforecast data used here had 11 ensemble members, whereas the operational forecasts are run with 51 members. Therefore, an operationalised version of the models might improve forecast skill or better represent uncertainty, although this is also true for precipitation forecasts direct from the model. A useful piece of further research would be to assess the forecast skill of other models, and multi-model ensembles, at predicting MO30 WPs or other WP classification systems. Another potential method to improve precipitation and drought forecast skill would be to alter the process by which precipitation is estimated from the WPs. Here we have sampled from the entire conditional distribution of precipitation given the WP and season, but this may not be the optimal way of estimation. It is possible that other factors influence the precipitation from WPs, such as slowly-varying atmospheric and oceanic processes. For example, it would be interesting to see if conditioning the distributions further on the state of the NAO index, or some North Atlantic SST index, and sampling precipitation from these, would improve forecast skill. This is potentially most useful in predicting moderate drought, for which skill from current models is lower than for mild drought.

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Winter and autumn 31- and 46-day forecasts.¶
Winter and autumn 16-day forecasts for Scotland (ES, NS and SS).¶
Spring and summer 16-day forecasts for ES.¶
Summer 31- and 46-day forecasts of mild drought for eastern and southern regions.¶
EPS-P is recommended for:¶
Winter and autumn 16-day forecasts for all regions except those in Scotland.¶
Spring and summer 16-day forecasts for all regions except ES¶
Spring 31- and 46-day forecasts for all regions except those in Scotland.¶
Otherwise, the use of climatological drought frequencies represents the most parsimonious (in terms of skill versus model complexity) choice for:¶
Summer 31- and 46-day forecasts for mild drought in northern and western regions and moderate drought in all regions.¶
Spring 31- and 46-day forecasts for Scotland.¶
Focussing on the 31- and 46-day lead-times (that are more useful for drought prediction than 16-day forecasts), winter and autumn are clear-cut, with EPS-WP recommended for every region. Summer is more complex. Mild droughts are best predicted by EPS-WP for the eastern and southern regions, but drought climatological frequencies are suggested over the forecast models for western and northern regions and more severe droughts for all regions. In spring, climatology is also recommended for Scotland, with the use of EPS-P for the remaining regions.¶

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Code availability

The code is only available locally with DR. Please contact the corresponding author for any queries regarding sharing the code.

Data availability

Met Office EMULATE MSLP data can be found at https://www.metoffice.gov.uk/hadobs/emslp/; ERA-Interim data at https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim; ECMWF EPS hindcast data at https://apps.ecmwf.int/datasets/data/s2s/ and Met Office HadUKP data at https://www.metoffice.gov.uk/hadobs/hadukp/.

Author contribution

D. Richardson was the primary designer of the experiment, developed the model code, produced the figures and wrote the manuscript. H. Fowler, C. Kilsby, R. Neal and R. Dankers contributed to the design of the experiment and provided input into figure and text editing.

Competing interests

The authors declare that they have no conflict of interest.

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Daily precipitation		Total 16-, 31- and 46-day precipitation	
p_b	Range of precipitation, x, (mm)	s_c	Range of summed precipitation, y, (mm)
p_1	0	s_1	$0 < y \leq 10$
p_2	$0 < x \leq 1$	s_2	$10 < y \leq 20$
…	Intervals of 1 mm	…	Intervals of 10 mm
p_{11}	$9 < x \leq 10$	s_{25}	$240 < y \leq 250$
p_{12}	$10 < x \leq 15$	s_{26}	$250 < y \leq 300$
p_{13}	$15 < x \leq 20$	…	Intervals of 50 mm
p_{14}	$20 < x \leq 30$	s_{30}	$300 < y \leq 450$
…	Intervals of 10 mm		
p_v	$90 < x \leq 100$		

Table 1: Range of daily precipitation, x, for each bin p_b and of 16-, 31- and 46-day total precipitation, y, for each bin s_c

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Daily precipitation	
p_b	Range of precipitation, (mm)
p_1	0
p_2	$0 < x \leq 1$
…	Intervals of 1mm
p_{11}	$9 < x \leq 10$
p_{12}	$10 < x \leq 15$
p_{13}	$15 < x \leq 20$
p_{14}	$20 < x \leq 30$
…	Intervals of 10mm

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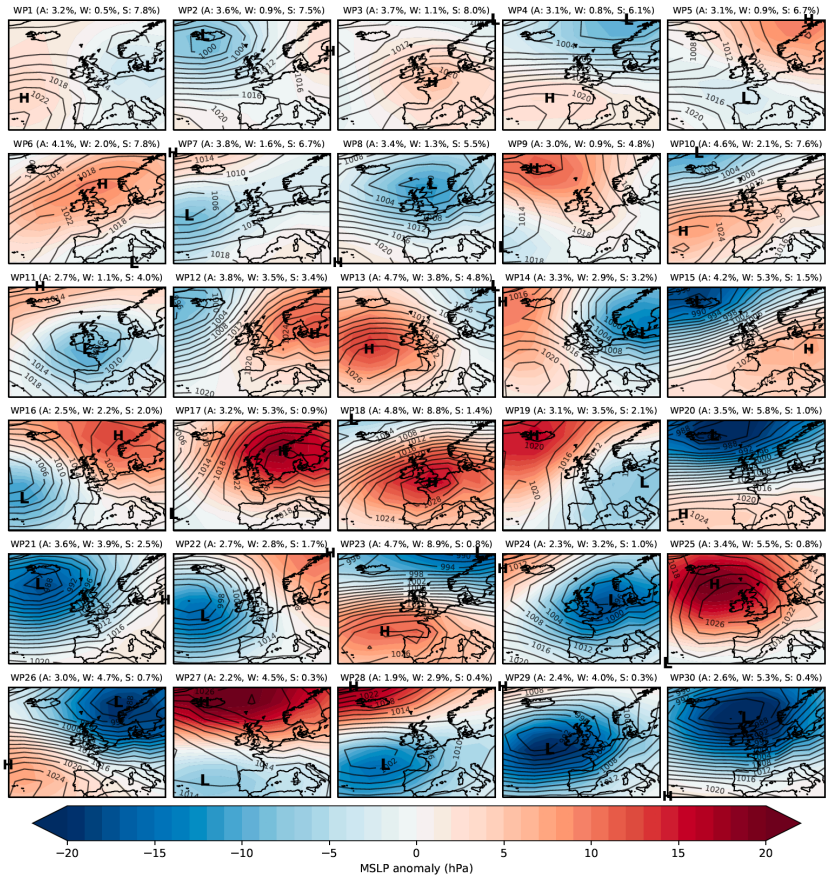

Figure 1: Weather pattern (WP) definitions according to mean sea-level pressure (MSLP) anomalies (hPa). The black contours are isobars showing the absolute MSLP values associated with each weather pattern, with the centres of high and low pressure also indicated. Next to the WP labels are the annual (A), winter (W; DJF) and summer (S; JJA) relative frequencies of occurrences of each WP (%). The frequencies of occurrence data are associated with the WPs based on ERA-Interim between 1979 and 2017, while the WP definitions were generated from a clustering process applied to EMULATE MSLP reanalysis data between 1850 and 2003. See the text for details.

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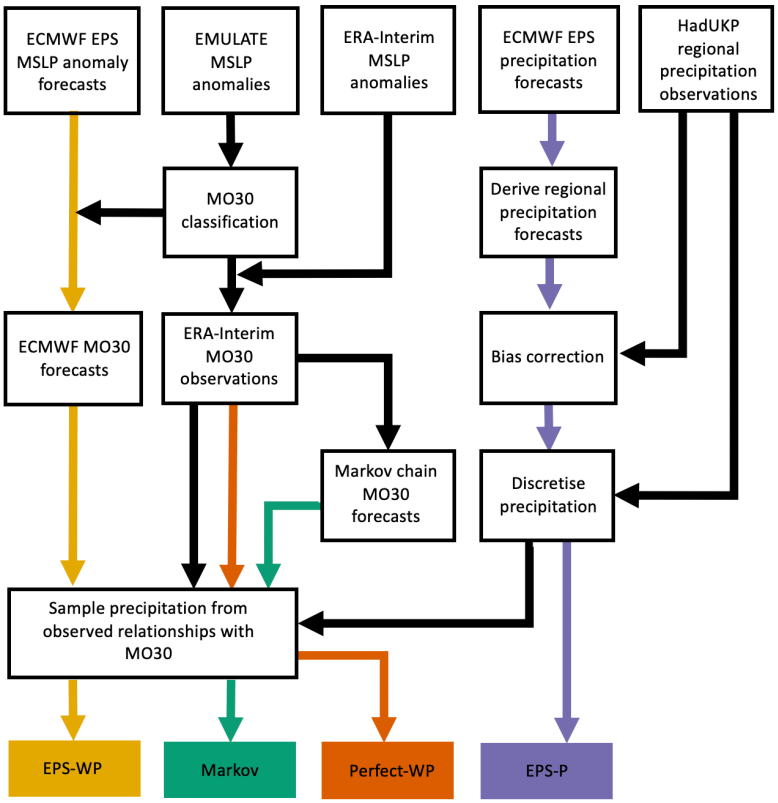

Figure 2: Schematic showing the procedure for the four precipitation forecast models. The top row shows the base data sets used and the bottom row shows the four models. Coloured arrows begin at the first stage for which forecasts are issued: EPS-WP forecasts begin with the ECMWF prediction system MSLP forecasts; Markov forecasts are produced once the ERA-Interim MO30 time series has been derived; Perfect-WP 'forecasts' are observations from the same time series, while EPS-P forecasts are the post-processed data from the ECMWF forecast system.

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Deleted: Figure 1: Weather pattern (WP) definitions according to mean sea-level pressure (MSLP) anomalies (hPa). The black contours are isobars showing the absolute MSLP values associated with each weather pattern, with the centres of high and low pressure also indicated. From Richardson *et al.* (2018b).¶

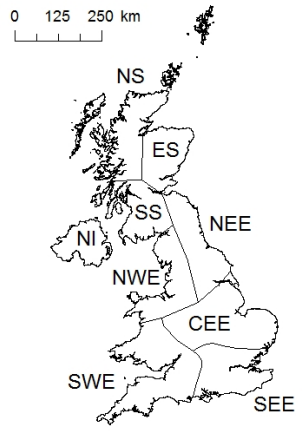

Figure 2: HadUKP regions: northeast England (NEE), central and east England (CEE), southeast England (SEE), southwest England and southern Wales (SWE), northwest England and northern Wales (NWE), Northern Ireland (NI), southwest Scotland (SS), northern Scotland (NS) and eastern Scotland (ES).¶

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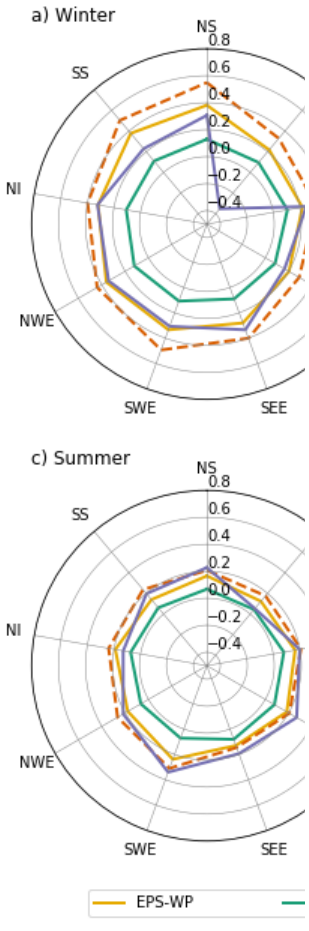
Figure 3: Jensen-Shannon Divergence scores for EPS-WP and Markov models for three lead-times.



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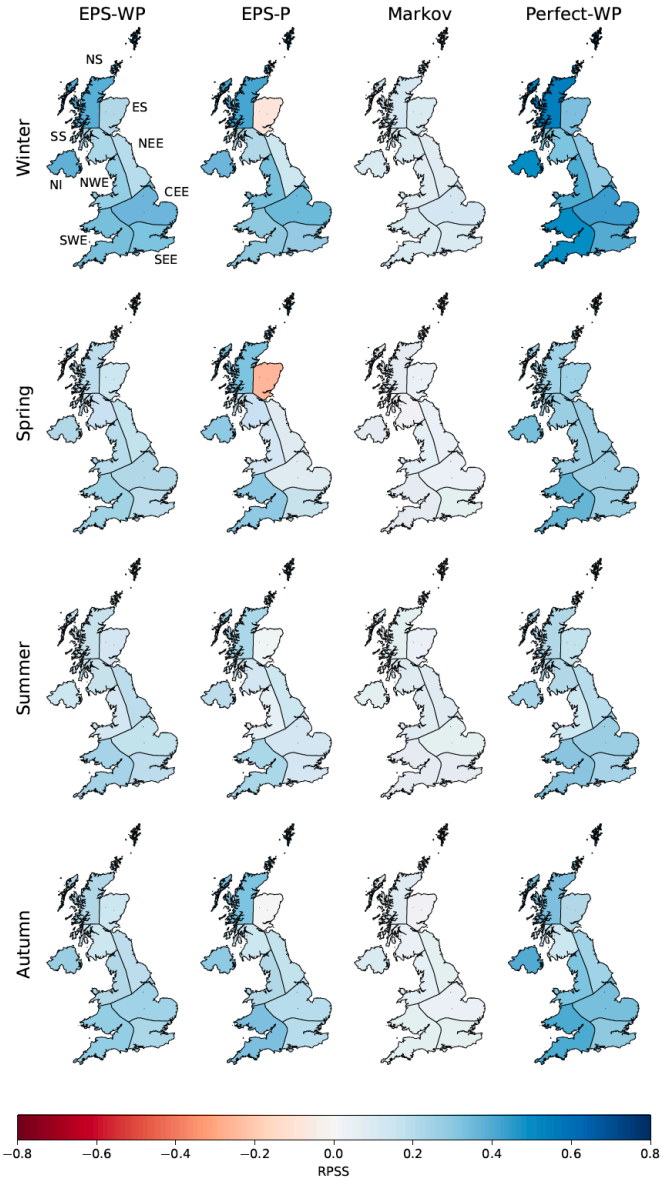

Figure 4: Ranked probability skill scores (RPSS) for precipitation forecasts at a 16-day lead for each model and season.

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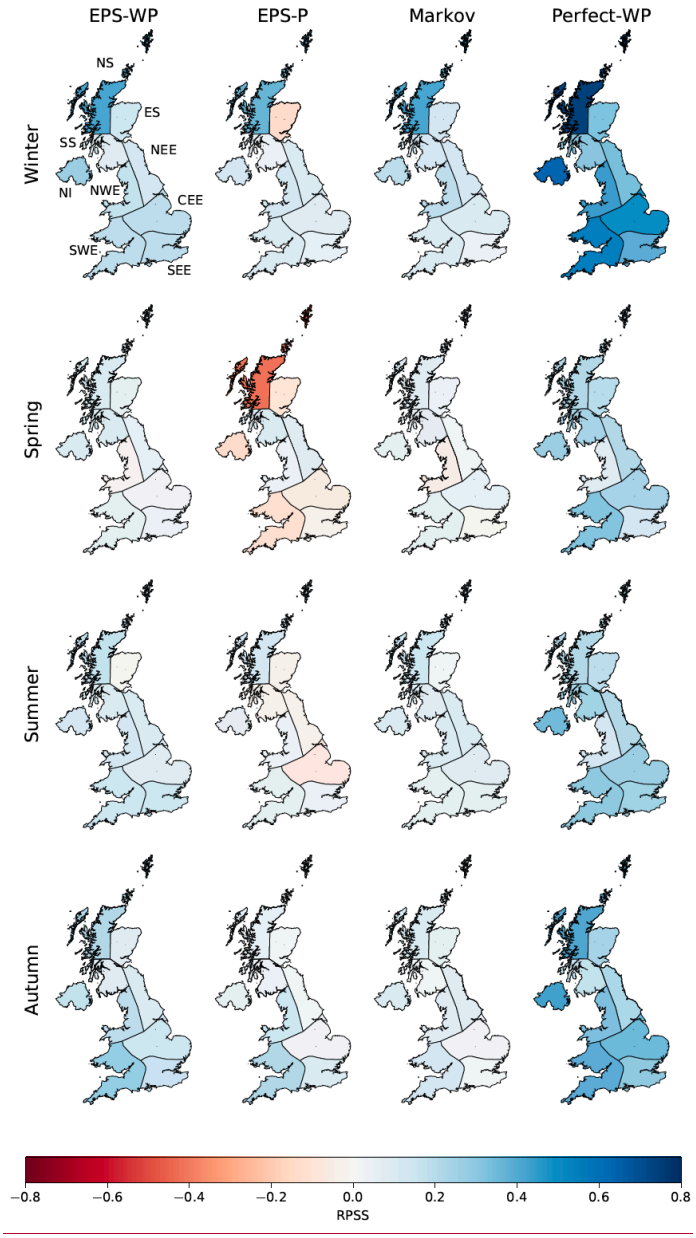

Figure 5: As Figure 4 but for a 46-day lead.

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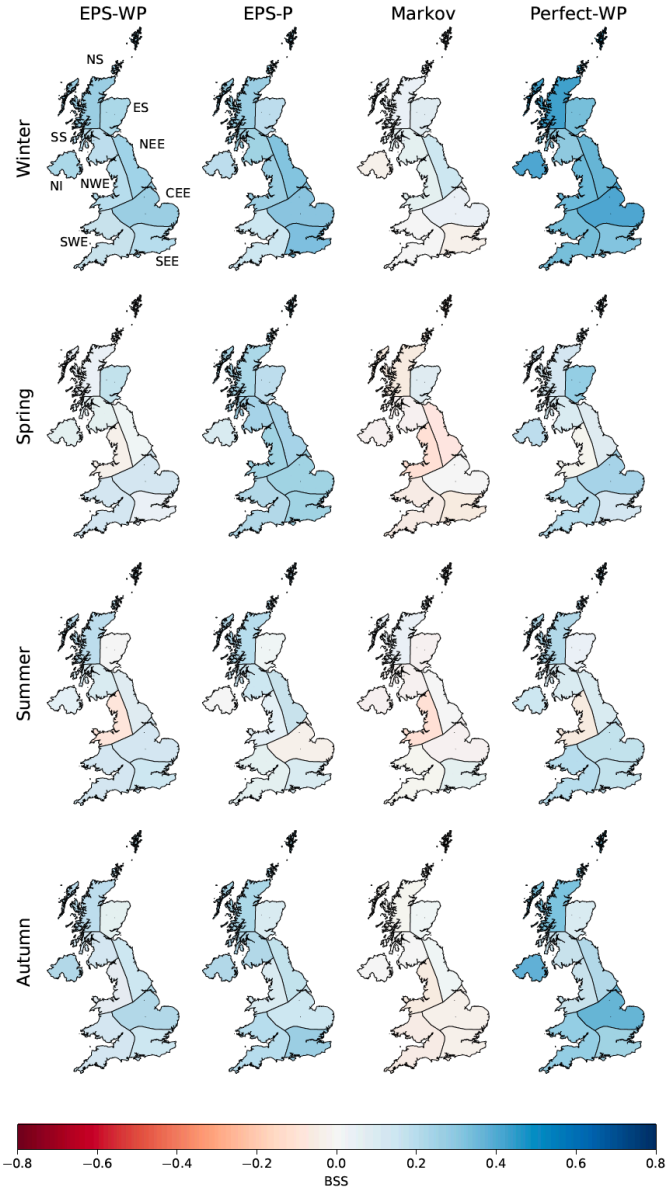

Figure 6: Brier skill scores (BSS) for mild drought (total precipitation below the 30.9th percentile) for a 16-day lead-time for each model and season.

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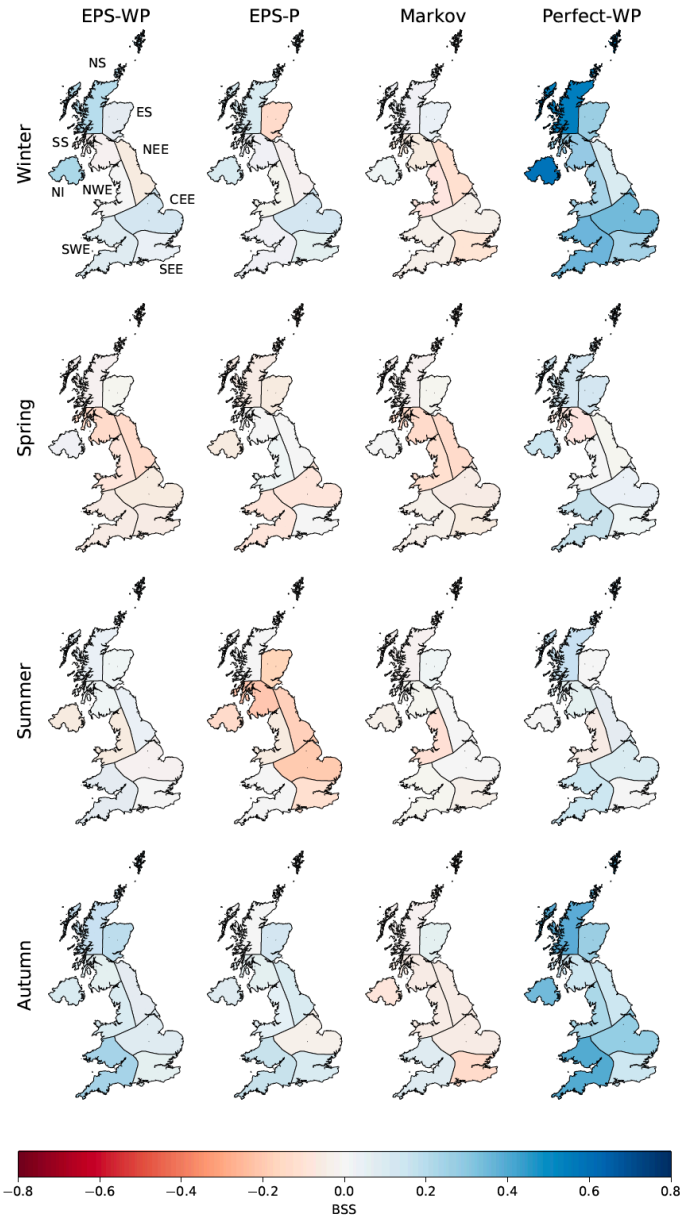

Figure 7: As Figure 6 but for a 46-day lead.

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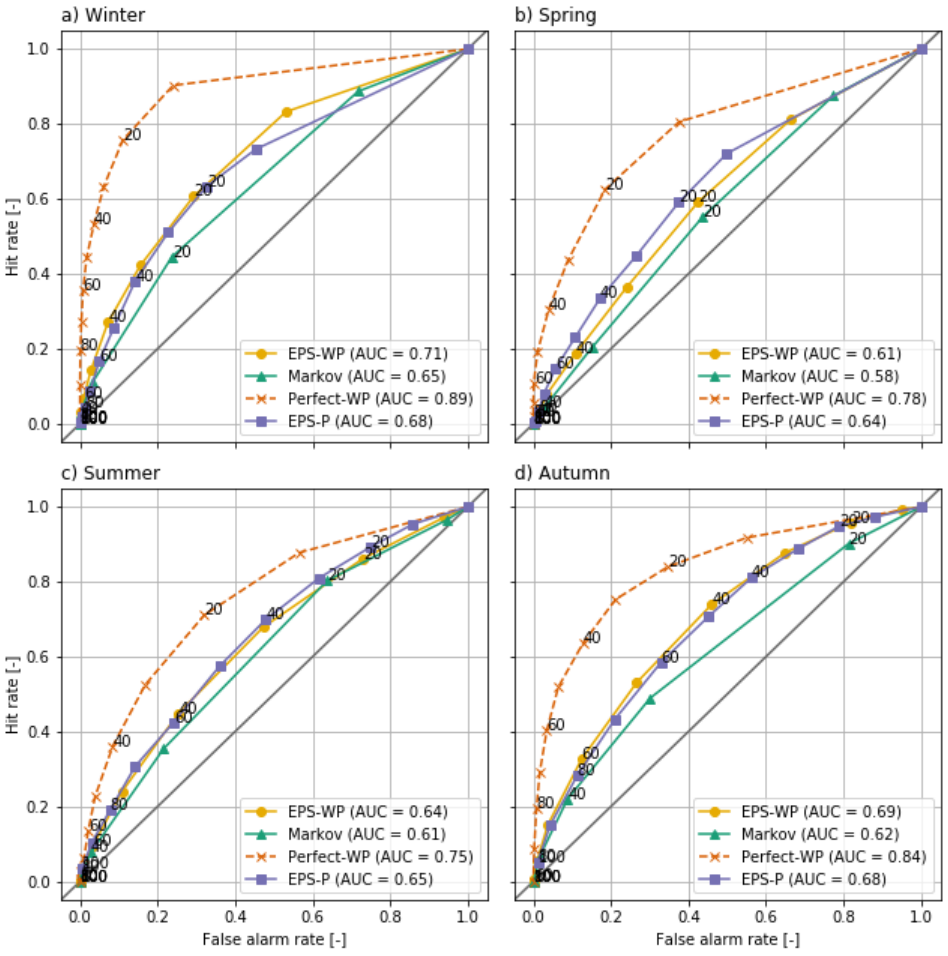

Figure 8: Relative operating characteristics (ROC) curves and area under ROC curve (AUC) for mild drought with a 46-day lead-time. Annotated values indicate drought forecast probability thresholds.

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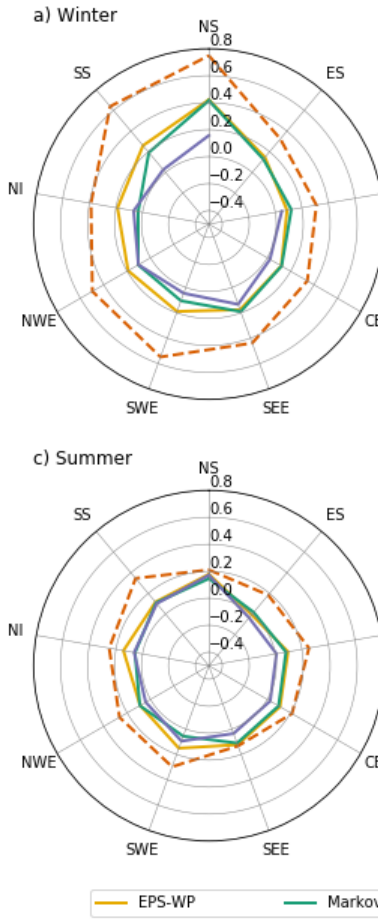

Figure 5: As Fig. 4 but for a lead-time of 46 days. The omitted scores are for EPS-P in ES during winter (-1.15) and spring (-1.37).¶ ... [5]

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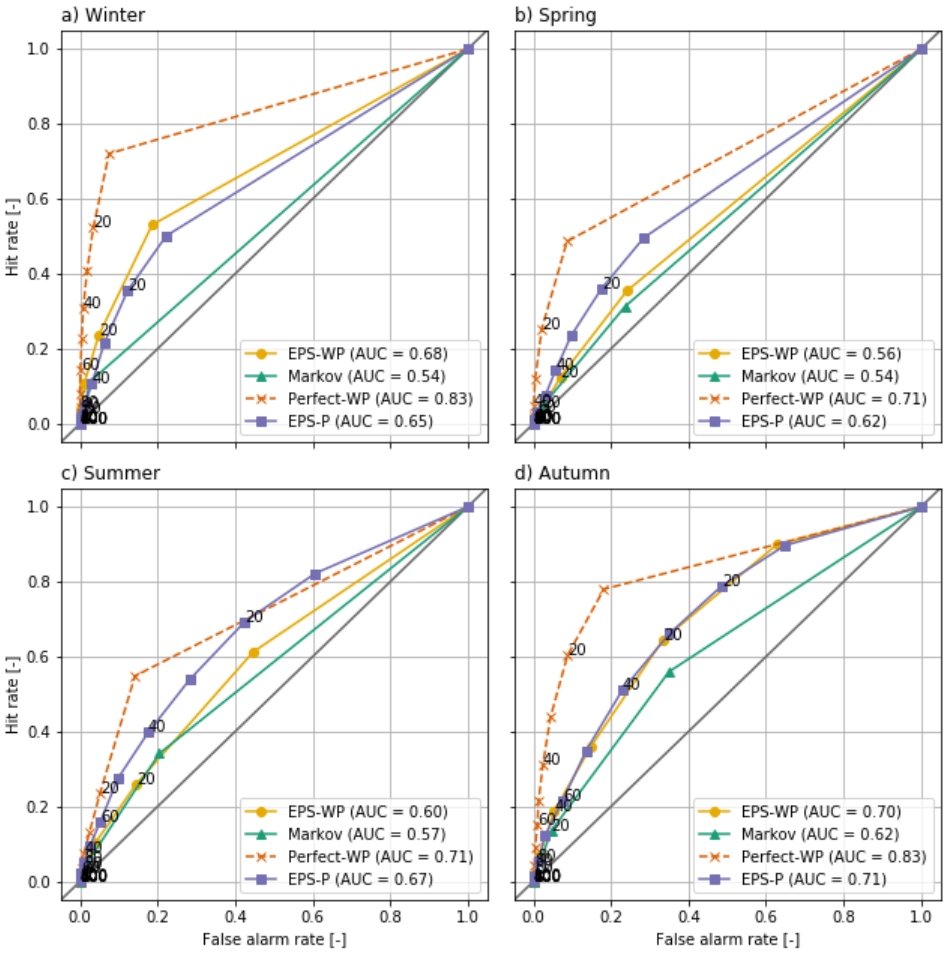

Figure 9: As Fig. 8 but for moderate drought.

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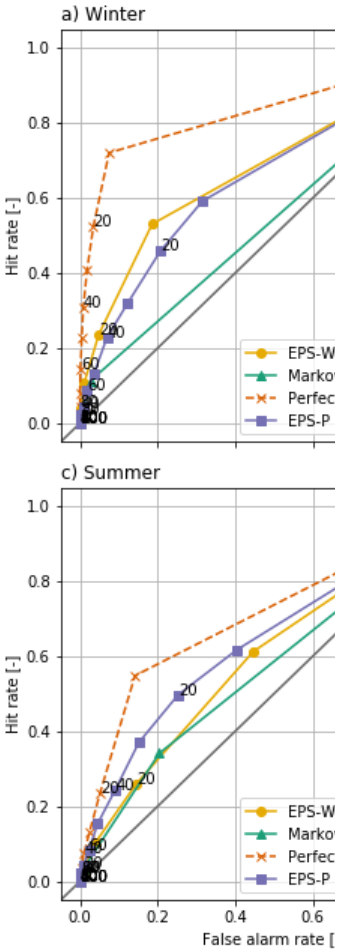

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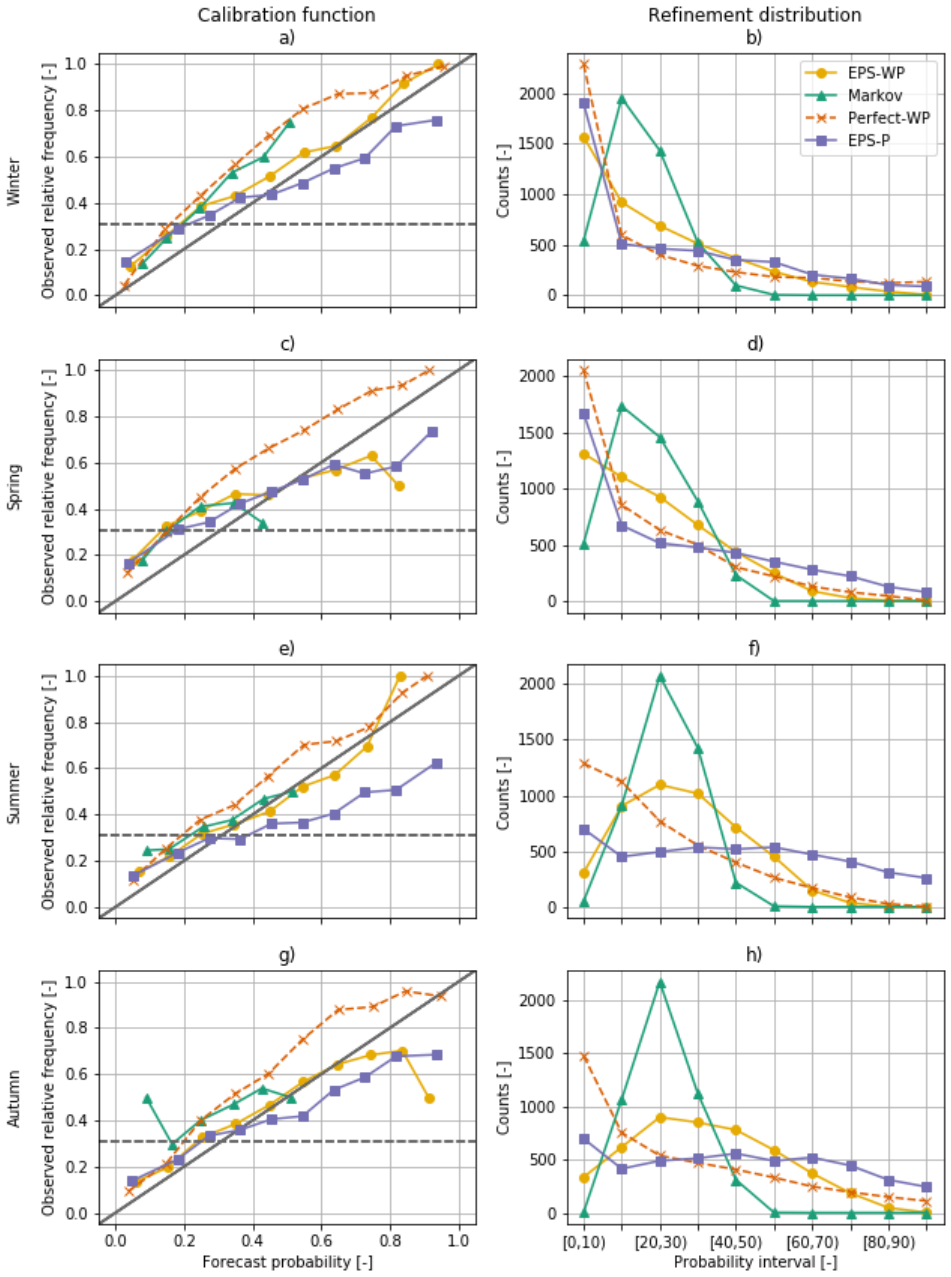

Figure 10: Calibration functions (first column) and refinement distributions (second column) for mild drought with a 31-day lead-time. For the calibration function diagrams, the solid diagonal line indicates perfect reliability and the dashed horizontal line the event relative frequency for mild drought (0.309).

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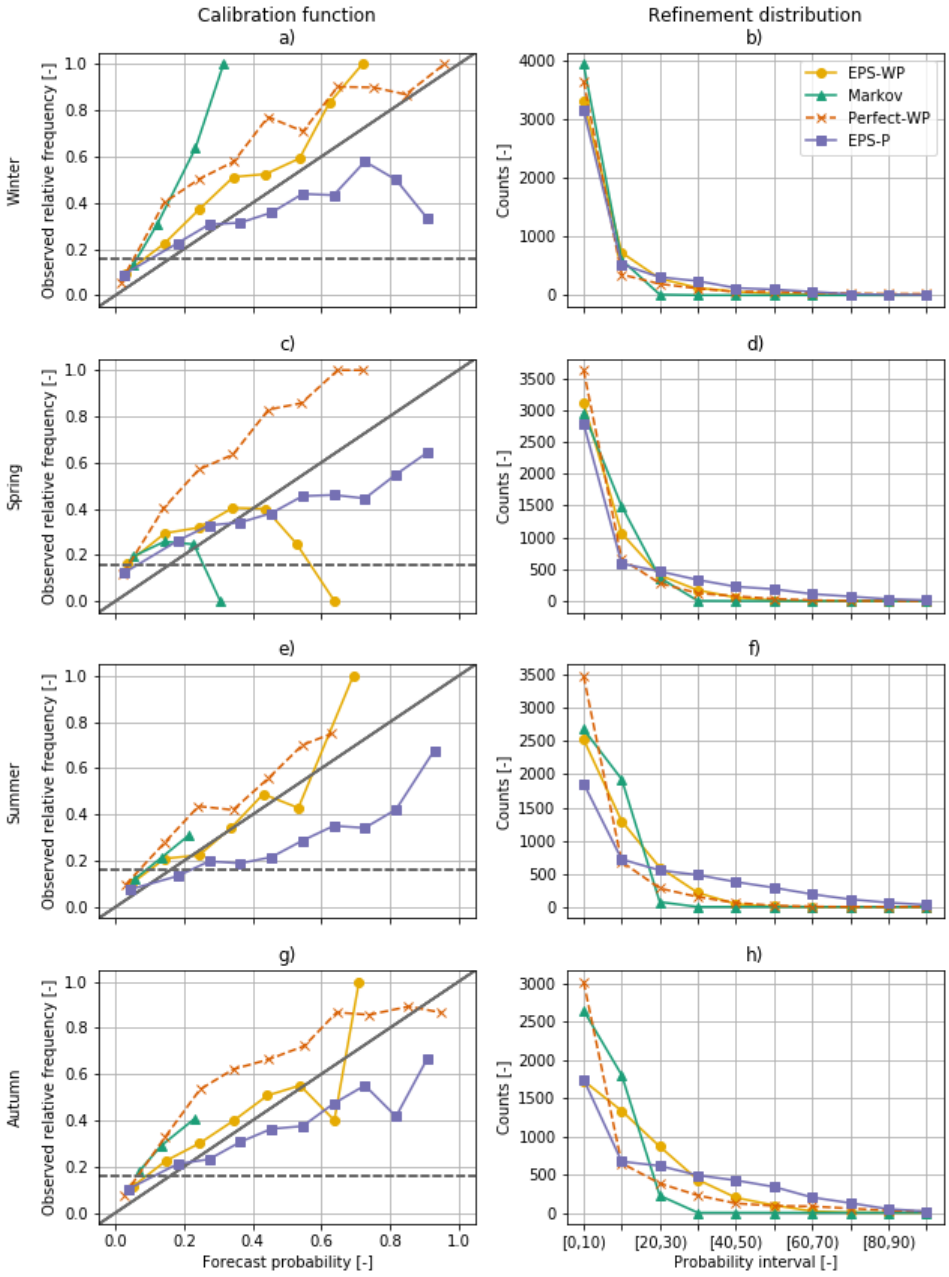

Figure 11: As Fig. 10 but for moderate drought (event relative frequency of 0.159).

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