What do large-scale patterns teach us about extreme precipitation over the Mediterranean at medium- and extended-range forecasts?

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Abstract
Extreme precipitation events (EPEs) can have devastating consequences, such as floods and landslides, posing a great threat to society and economy. Predicting such events long in advance can support the mitigation of negative impacts. Here, we focus on EPEs over the Mediterranean, a region that is frequently affected by such hazards. Previous work identified strong connections between localized EPEs and large-scale atmospheric flow patterns, affecting weather over the entire Mediterranean. We analyse the predictive skill of these patterns in the European Centre for Medium-Range Weather Forecasts (ECMWF) extended range forecasts and assess if and where these patterns can be used for indirect predictions of EPEs, using the Brier skill score. The results show that the ECMWF model provides skilful predictions of the Mediterranean patterns up to 2 weeks in advance. Moreover, using the forecasted patterns for indirect predictability of EPEs outperforms the reference score up to $\sim 10$ days lead time for many locations. For high orography locations or coastal areas in particular, like parts of western Turkey, western Balkans, Iberian Peninsula, and Morocco, this limit extends to 11–14 days lead time. This study demonstrates that the connections between localized EPEs and large-scale patterns over the Mediterranean extend the forecasting horizon of the model by over 3 days in many locations, in comparison with forecasting based on the predicted precipitation. Thus, it is beneficial to use the predicted patterns rather than the predicted precipitation at longer lead times for EPE forecasting. The model’s performance is also assessed from a user perspective, showing that the EPE forecasting based on the patterns increases the economic benefits at medium/extended range lead times. Such information could support higher confidence in the decision-making of various users; for example, the agricultural sector and (re)insurance companies.

KEYWORDS
extreme precipitation, forecasting, large-scale circulation patterns, Mediterranean, sub-seasonal, weather regimes

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### 1 INTRODUCTION

Extreme precipitation events (EPEs) pose a great threat to society, the economy, and the environment, with consequences like landslides and floods (Jonkman, 2005). Especially for locations in the Mediterranean, this threat is one of the most crucial and frequent natural hazards, resulting in high economic losses, injuries, and casualties (Llasat et al., 2010; Llasat et al., 2013). Being able to better predict when and where such events are expected to occur can support the mitigation of their negative impacts. This is becoming more crucial in the light of non-stationary climate (e.g., Hannaford et al., 2021) and ongoing climate change, resulting in the intensification of the frequency and magnitude of such extremes in many locations (e.g., Kostopoulou and Jones, 2005; Alexander et al., 2006; Toreti et al., 2013; Papalexiou and Montanari, 2019; Cardell et al., 2020). This outcome can be attributed to the increased temperatures of the planet, which lead, in agreement with the Clausius–Clapeyron relationship, to increased water vapour (Douville and John, 2020) and, therefore, to increased precipitation.

Recently, there has been an ever increasing scientific and operational interest in sub-seasonal predictability of atmospheric variability and weather extremes, meaning from 10–15 days up to 2–3 months in advance. Such interest is driven not only by the needs of various sectors and users (e.g., agriculture, (re)insurance companies, emergency response units; White et al., 2017), but also by advances in numerical weather prediction (NWP) models and related research (Magnusson and Källén, 2013), providing skilful information about the atmospheric variability at longer lead times. An example is the skill of models in predicting atmospheric variability in the middle troposphere over the Northern Hemisphere, which has increased by about 1 day per decade (Bauer et al., 2015). The European Centre for Medium-Range Weather Forecasts (ECMWF) model, for example, is now predicting weather variability 10 days in advance as well as it was predicting this variability 7 days in advance 30 years ago (relevant plot available at https://www.ecmwf.int/en/forecasts/charts/catalogue/plwww_m_hr_ccaf_adrian_ts).

Nevertheless, challenges remain at the sub-seasonal predictability of weather conditions, especially for surface extremes at fine spatiotemporal resolutions. Thus, there is ongoing interest in assessing and quantifying if and how other variables of higher forecasting reliability can be used for indirectly informing about (extreme) surface conditions at medium- and extended-range forecasts (Magnusson, 2019). Such a variable of reliable forecasting skill at the sub-seasonal scale is the atmospheric flow variability in the lower and middle troposphere, usually depicted by large-scale patterns over extended domains (Vitart, 2014; Lavaysse et al., 2018). Many recent studies have analysed these interactions between surface conditions and such atmospheric variables (e.g., cold spells and geopotential height at 500 hPa: Ferranti et al., 2018; wind power and geopotential height at 500 hPa: Grams et al., 2017; wind extremes and geopotential height at 500 hPa: Thomas et al., 2021; precipitation and weather patterns generated from multiple variables: Hoy et al., 2014; precipitation and sea-surface temperature: Rieger et al., 2021).

One of the most challenging variables is precipitation, not only regarding its accurate forecasting (Sukovich et al., 2014), but also in terms of correct spatial representation of the observational data (e.g., Khairul et al., 2018; Mastrantonas et al., 2019). This variable is of immense importance for many applications and users. In this regard, previous studies demonstrate the strong association of large-scale atmospheric flow patterns to precipitation and localized EPEs. Such diagnostic studies are, for example, conducted for locations in the Mediterranean, India, and the United Kingdom (Xoplaki et al., 2004; Toreti et al., 2010; Xoplaki et al., 2012; Merino et al., 2016; Toreti et al., 2016; Richardson et al., 2018; Grazzini et al., 2020; Neal et al., 2020). These patterns can be used as a prognostic tool for extremes and provide skilful predictions of surface weather variability at longer lead times. In a recent study, it was shown that UK-specific large-scale patterns can support the predictability of extreme rainfall at medium-range forecasts (Richardson et al., 2020b). The same patterns have also been used to infer information about the likelihood of coastal flooding (Neal et al., 2018) and of droughts (Richardson et al., 2020a) at medium- and extended-range lead times. In a similar concept, weather analogues of atmospheric variability over Europe have been used to infer information about precipitation (and temperature) at sub-seasonal scales (Yiou and Déandréis, 2019; Krouma et al., 2021).

We build upon previous research that quantified the EPE connections over the Mediterranean to large-scale atmospheric flow patterns, specifically designed over the domain (Mastrantonas et al., 2021). These patterns, presented in Figure 1, are significantly associated with localized EPEs, with each of them being the preferential pattern for EPEs at different regional subdomains. The patterns represent distinct atmospheric variability over the domain, and some of them highly resemble patterns derived using self-organized maps for a larger domain centred over the Mediterranean (Rousi et al., 2014), demonstrating their robustness. They indicate negative anomalies over the western Mediterranean (Atlantic/Biscay/Iberian Low), central Mediterranean (Sicilian Low), and the eastern Mediterranean (Balkan/Black Sea Low), positive anomalies over the whole domain (Mediterranean
FIGURE 1 The nine Mediterranean patterns (Mastrantonas et al., 2021). (a)–(i) Composites of the 9 clusters derived with K-means clustering on the principal components’ projections of sea-level pressure (SLP) and geopotential height at 500 hPa (Z500) anomalies. The anomalies are derived after subtracting the 1979–2019 ERA5 5-day smoothed daily climatology. Colour shading refers to SLP anomalies (hPa) and contoursto Z500 anomalies (dam). Percentages indicate the climatological frequencies of each cluster. This figure incorporates the modifications introduced in the current study (Section 3). The differences from the original patterns and their frequencies (Figure 5 in Mastrantonas et al., 2021) are negligible [Colour figure can be viewed at wileyonlinelibrary.com]
Mediterranean (Mastrantonas et al., 2021). Thus, given its global coverage and consistency throughout the domain studied, it can be considered an informative source for this study. For SLP and Z500, the selected horizontal resolution was $1^\circ \times 1^\circ$; the domain covered the area $26^\circ$–$50^\circ$N and $-11^\circ$–$41^\circ$E, so that the analysis captures the influence of adjacent areas to the Mediterranean (e.g., Atlantic Ocean and Alps) – analysis and reasoning for the selection of this domain are available in Mastrantonas et al. (2021).

The forecasting data used are produced by the ECMWF extended range model (Owens and Hewson, 2018), which provides information from 0 up to 46 days' lead time. The model runs twice per week, and the data produced are available every Monday and Thursday. We used all available data derived with cycle 46r1, with the initiation dates extending between June 11, 2019, and June 30, 2020 (110 initiation dates in total), to provide consistency in model physics and parametrization schemes. As we were interested in long-term statistical analysis, we made use of the reforecasts of these dates. Each reforecast provides ensemble data of one control and 10 perturbed members for the same day–month as the actual forecasts, but for the past 20 years (e.g., a reforecast associated with the actual forecast of June 11, 2019, has data initiated at June 11, 2018, 2017, ..., 1999). Thus, the total dataset used consisted of 2,200 initiation dates per lead time (20 years of reforecasts $\times$ 110 initiation dates), with each date having 11 ensemble members. For the remaining sections, the term “forecasts” is used to refer to the ECMWF reforecasts. The selected horizontal resolutions and domains of the three variables are the same as with ERA5. As we used the forecast data stored internally at ECMWF, their raw horizontal resolution is equal/finer to the resolution used in this study, thus the regridding, where needed, was only for upscaling purposes. The daily values used for the analysis were derived by considering two time steps: the 0000 UTC of the date of interest, and 0000 UTC of the following date. This mismatch in the derivation of daily data between ERA5 and forecasts (hourly vs. 0000 UTC only) is due to operation constraints (forecast data do not have hourly values for all lead days). Nevertheless, when performing the analysis based on 0000 UTC ERA5 data only, the results are similar. Using all hourly data for ERA5, though, is preferred, as, when considering the diurnal variations, the strength of the disturbances in the atmosphere is more accurately represented.

3 | METHODOLOGY

3.1 | Large-scale patterns

The large-scale patterns in this study were derived by Mastrantonas et al. (2021) using the ERA5 data between 1979 and 2019. The analysis was based on the empirical orthogonal function (EOF) and subsequent K-means clustering of the daily SLP and Z500 anomalies. The anomalies are derived after subtracting the 1979–2019 ERA5 5-days smoothed daily climatology. The necessary number of modes (principal components) from EOF analysis that explain at least 90% of the total variance was kept, meaning six and seven for SLP and Z500, respectively. Each day was allocated to one of nine clusters, whose composites represent the nine Mediterranean patterns. The domain and variables used for generating the patterns, as well as the number of clusters, were selected so that the patterns derived have a strong association with localized EPEs over the Mediterranean and exhibit distinct synoptic-scale features over the domain. More information about the exact methodology is available in the relevant paper.

Here, we introduced a small refinement compared with Mastrantonas et al. (2021), so that the patterns can be used for operational purposes, without having ambiguities related to K-means clustering. More specifically, after performing K-means clustering, each day is allocated to one cluster, and by averaging the daily fields belonging to each cluster the nine composites are derived. The additional step is as follows: each day is reallocated to the cluster with the minimum aggregated Euclidian distance from the nine composites, considering the distances of both SLP and Z500. This iterative process ends when all the daily fields are allocated to the same cluster for two consecutive iterations, meaning that the clusters are stable (18 iterations needed in total). This method gave an initial overlap of 97% with the allocations solely based on K-means clustering. The final composites are practically the same in magnitudes and spatial patterns – compare Figure 1 in this article with the relevant figure in Mastrantonas et al. (2021). Both methods provide almost identical results, with this refinement being nevertheless useful for stabilizing the derived
nine clusters and having no ambiguities for operational purposes. Further explaining the methodology, as there are two atmospheric variables used, for each day, there are nine Euclidian distances from the composites based on SLP and nine distances based on Z500. The time series of these distances for all ERA5 daily data between 1979 and 2019 were normalized for each variable by dividing with the mean distance of each variable from the whole dataset. Then, the aggregated Euclidian distance was calculated for each day by averaging the normalized Euclidian distances from the SLP and Z500 composites. It should be noted that similar methods for allocating daily forecasts to predefined patterns based on minimum Euclidian distance is a practice implemented for other weather regimes, too, especially operationally; for example, the four EuroAtlantic regimes at ECMWF (Ferranti et al., 2015), and the 30 regimes used by the Met Office (MO30; Neal et al., 2016).

3.2 Connections of large-scale patterns to extreme precipitation

The connection between patterns and EPEs was quantified with the conditional probability of observing EPEs at each grid cell given each of the nine patterns. We analysed the conditional probabilities of 90th, 95th, and 99th percentile extremes (P90, P95, and P99, respectively) considering full-year statistics for the period 1979–2020. Owing to the high seasonal variation of the pattern frequencies, we also apply half-year statistics, with summer halves referring to 16 April–15 October (including both dates) and winter halves the remaining dates, as these two periods mark a substantial difference in the frequencies of most patterns (Figure 3). Note that EPEs are always derived based on full-year statistics; the only difference is that the conditional probabilities are refined to winter and summer halves in addition to the pattern conditioning, so that they incorporate information about the seasonality of the patterns and the EPEs. Finer subsetting (e.g., seasonal) was not implemented, as the sample size for some patterns became too small and conditional probabilities had high fluctuations (a conclusion derived after implementing bootstrapping).

To assess the discriminatory skill of inferring information about EPEs given the allocated pattern, the Brier score (BS; Wilks, 2011) was used. Each day was assigned an EPE probability at each grid cell equal to the conditional probability of the relevant pattern. The analysis was implemented for both full-year and winter/summer half statistics. This score was compared (Brier skill score; BSS) with a reference score of inferring information about EPEs based on the climatological EPE occurrence. More specifically, we used a seasonal climatology and a 31-day moving-window (centred at the date of interest) climatological occurrence of EPEs. We considered the minimum of both as the reference score. This discriminatory skill informs about if, in which locations, and by how much the use of large-scale patterns for informing about EPEs can outperform the reference score if we had a perfect forecast of the Mediterranean patterns.

3.3 Skill of the ECMWF model

The model anomalies were derived after subtracting the lead-time-dependent model climatology. These anomalies were used to allocate each day to one of the nine Mediterranean patterns, based on the minimum aggregated Euclidian distance, as in ERA5. The SLP and Z500 Euclidian distances of the forecasts were normalized by dividing with the previously calculated ERA5 1979–2019 mean distance of each variable. As each forecast day is allocated to one of the nine patterns, the BS was used to assess the performance of the model in predicting the patterns (dichotomous event of occurrence/non-occurrence of each pattern at each time step). The results were compared with the minimum of two reference scores; the BS based on 91-day moving-window climatology (centred at the date of interest) and the BS based on half-year transition probabilities (Markov chain). Moreover, the long-term frequencies of the patterns for each lead time were compared with the frequencies of these dates based on ERA5 data for assessing possible biases in pattern allocations of the ECMWF model. To assess the results’ significance, we used bootstrapping of 1,000 resamples with replacement, each of
them having 2,200 dates (as the size of actual sample). We considered a 90% two-tailed confidence interval for the frequencies and a 90% one-tailed confidence interval for BSS. We also performed the analysis independently for winter and summer halves. Block-bootstrapping was not used, although it is of importance due to the high temporal correlation of the atmospheric variables. This is because the ECMWF extended-range forecasts are produced twice per week, not daily.

The skill of the model in predicting EPEs (P90, P95, P99) was also assessed based on BS. We calculated the direct BS for EPEs when considering the model-predicted precipitation, and the indirect BS when using the model-predicted patterns and their connections to EPEs. The latter was derived by substituting each predicted pattern with the relevant conditional probabilities for EPEs at each grid cell. As each forecast has 11 members, the final conditional probabilities used for the indirect BS were the average of all 11 members at each grid cell. Thus, the maximum forecast probability that can be provided with the indirect method is the maximum conditional probability of EPEs, which occurs when all ensemble members indicate the most preferential pattern for EPEs at a specific grid cell. Note that the conditional probabilities of EPEs given the patterns (and the climatological occurrences) were derived based on the overall 1979–2020 ERA5 data. As with the previous section, the reference score was based on climatological information. It was the minimum of the seasonal climatology and a 31-day moving-window (centred at the date of interest) climatological occurrence of EPEs. To assess the significance of the results (BSS > 0), we used bootstrapping of 1,000 resamples with replacement and considered a 90% one-tailed confidence interval. To obtain a larger sample of data at each bootstrap (the actual set had 2,200 at each lead time), and to respect the full-year statistics that EPEs are based on, each resample had 3,000 dates, with a climatologically stable number of winter, spring, summer, and autumn days (741, 756, 756, and 747 days, respectively). For each resample, we finally calculated the BS for EPEs, given a perfect forecast of the patterns, so we could assess the statistical significance of the discriminatory skill presented in the previous section of the methodology.

3.4 | Relative economic value of forecasts

One way to look at the forecasts’ skill from a user perspective is to calculate the relative economic value (EV) of the forecasts. This indicator informs users about the economic benefits that could be obtained by basing the decision on the outputs of a forecasting system rather than on climatological information and is relative to the benefits derived from a perfect forecast. It is a function of the frequency of the event studied o, its cost/loss ratio a, the false-alarm rate F, and the hit rate H, with the latter two referring to the skill of the forecasting model. The EV is calculated for all possible cost/loss ratios of a preventing action, ranging from 0 to 1, so that any user can assess the usefulness of the system for their operational needs and constraints. For an ensemble model, this value is not unique, but changes based on the selected probability threshold for converting the probabilistic forecast to a dichotomous one (event vs. non-event), which consequently alters the false-alarm and hit rates. Thus, we made use of the maximum potential relative economic value. This value is derived when making optimal use of the model and selecting the most appropriate probability threshold for converting to deterministic outputs. This threshold depends on the cost/loss ratio, and thus varies for different actions and users. Richardson (2000) provided a comprehensive analysis of the complete sets of formulas and explanations for deriving this indicator. Here, we present the main two formulas:

\[
EV = \frac{EV_{climatology} - EV_{forecast}}{EV_{climatology} - EV_{perfect}}
\]

and

\[
EV = \min(o, a) - F \min(1-o) + H \min(1-o) - a
\]

where all the terms and relevant variables have already been described herein.

EV follows the logic of a skill score, with positive values indicating that the forecast brings larger economic benefits compared with climatology. The upper limit is 1 and is achieved with a perfect knowledge of the future. This formula was used for understanding the economic benefits of EPE forecasting based on the ECMWF model: either direct forecasts, when considering the forecasted precipitation, or indirect forecasts, when considering the forecasted patterns and their connections to EPEs.

4 | RESULTS

Here, we present the results of the P95 EPEs, as they correspond to a good trade-off between extremity and sample size. See the supplementary data for results on P90 and P99 EPEs.

Figure 4 presents the pattern that corresponds to the highest conditional probability of P95 EPEs for each grid cell of the area studied. The results refer to the full-year statistics (first column), and winter- and summer-half sub-settings (second and third columns, respectively). As mentioned in the Section 3, EPEs are always derived based on full-year statistics; the only difference is that the conditional probabilities are refined to winter and summer halves in addition to the pattern conditioning for the
two latter columns. This temporal subsetting is in fact supported by previous studies demonstrating that there are different precipitation processes active in summer versus winter (e.g., Grazzini et al., 2021). In general, each pattern is preferentially associated with EPEs in different subdomains. For example, the Biscay Low is the main EPE pattern in parts of Morocco, Iberian Peninsula, France, Italy, and western Balkans, whereas the Black Sea Low mainly affects locations in Turkey. These results can be explained by the air flow and subsequent moisture flow associated with each pattern’s composites (Figure 1). The results between the three temporal subsets do not vary much; the main differences are identified in the Middle East. These differences though are not that crucial for EPEs, as the associated probabilities are very low for these locations and temporal subsets (Figure 4, second row), meaning that EPEs are generally not expected in these periods and grid cells (in fact most EPEs over the domain occur in winter-halves; Mastrantonas et al., 2021). In general, the conditional probabilities of EPEs, given the most preferential pattern at each grid cell, are about three times higher than the climatological ones (5% for P95 EPEs). Especially for locations of high orography and coastal areas (Figure 2), this ratio is even higher (around five times). The half-year subsetting drives an increase of the conditional probabilities, as it takes into consideration the temporal occurrence of EPEs. For most of the domain, the majority of EPEs occurs in winter-half years. Thus, the conditional probabilities are higher for this period. The summer half is the preferential period for EPEs in the north Balkans and Alps; thus, the conditional probabilities are higher for that period for these two regions. Similar conclusions can be extracted for the P90 and P99 EPEs (Figures S1, S2 in Appendix S1).

When using these nine patterns for inferring information about EPEs, the discriminatory skill that can be derived for long-term EPEs analysis is more interesting (Figure 5 for the P95 EPEs). Figure 5a presents the BSS when using full-year conditional probabilities. The results are masked and only present locations where the discriminatory skill outperforms the reference score. In general, conditioning based on the patterns beats the reference score in most locations except for the southeastern Mediterranean, where EPEs are very seasonal. When further refining the conditional probabilities, based on half-year temporal subsetting (Figure 5b), the use of patterns outperforms the reference score almost everywhere; for most locations there is a more than 2.5% increase in BSS. This is the best possible improvement given a perfect forecast of the Mediterranean patterns. As with Figure 4, locations of high orography and coastal areas have increased performance (over 7% skill increase). This can be explained by the strong influence of topography in the EPE generation; a topography that can be considered a “passive
mechanism of forced convection”. The latter makes it more common to observe EPEs under specific patterns and large-scale flows that direct air and moisture perpendicularly to orography. This is not true for locations over the sea and northern Africa, where topography is generally smooth over large areas (except for the Atlas Mountains). Northern Africa, moreover, lies under the sinking air masses of the Hadley cell, which largely minimizes the formation of large-scale unstable conditions. Thus, EPEs in these regions mostly show more localized drivers compared with the northern Mediterranean. For the Middle East, the conditioning does not bring many benefits, as none of the nine patterns is strongly related with EPEs over that domain. One reason is that the Cyprus Low circulation that drives many of the EPEs in that region (Toreti et al., 2010) is not identified by the nine patterns, due to its lower spatial extent on the domain studied, as this configuration mainly affects only the eastern Mediterranean. Similar conclusions can be extracted for the P90 and P99 EPEs (Figures S3, S4 in Appendix S1). These figures show that the discriminatory skill decreases with higher thresholds, which can be explained as follows: convective EPEs, which can be of high magnitude and are thus very rare, are not substantially affected by large-scale weather variability but, rather, are driven mainly by localized characteristics.

So far, we presented the analysis of connecting EPEs and large-scale patterns based on reanalysis data. The main interest of this work is the usefulness of these connections for medium- and extended-range forecasts. Initially, Figure 6 presents the performance of the ECMWF model (BSS) in predicting the nine patterns (median value of the bootstraps). The points, connected with bold lines, indicate that the model significantly outperforms the reference scores (90% 1-tailed confidence interval). The model's performance is similar for all patterns and both temporal subsets, with a forecasting horizon of about 11 days. The main difference is observed for the winter half and the Mediterranean High and Minor Low patterns. The former has a forecasting horizon of over 2 weeks, whereas the latter is constrained up to 5 days only; a result that we are not yet able to explain. The Biscay Low, a pattern highly associated with EPEs, is also more predictable during the winter half. The higher performance for the Mediterranean High and Biscay Low patterns can be attributed to the high anomalies of these two patterns in a substantial part of the domain studied, giving more confidence in the allocations of the forecasts. The results of this work regarding patterns’ predictability agree with other studies that analyse such predictability over other domains. Büeler et al. (2021), for example, analysed the skill of the ECMWF forecasts in predicting seven weather regimes over Europe and the horizon of skilful predictions was about 14 days. Richardson et al. (2020b) showed that the ECMWF 51-member model has a predictability limit of about 15 days for the eight UK-defined regimes, when analysing the performance based on BS and considering a 1-day flexibility window in the occurrence of the patterns. Increased model skill is also observed in this study when considering a flexibility window in the occurrence of the patterns (not shown). To obtain a more comprehensive understanding about model performance, Figure S5 in Appendix S1 presents the decomposition of the BS. The resolution saturates at about 11 days lead time, whereas the reliability has high fluctuations, especially so in the winter-half and annual statistics. These results also relate to the climatological pattern frequencies (Figure 3), with high impact on the uncertainty component of the BS decomposition.
FIGURE 6  Brier skill score (BSS) for the nine Mediterranean patterns (median value of 1,000 bootstraps), considering the (a) annual, (b) winter-half, and (c) summer-half periods. The points (connected with bold lines) indicate the lead times that the model significantly outperforms the reference score, based on a 90% one-tailed confidence interval. The reference score used was based on climatological information and was the minimum of 91-days moving-window climatology (centred at the date of interest), and the half-year transition probabilities (Markov chain) [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 7 presents the relative biases of the frequencies of the Mediterranean patterns for the ECMWF forecasts (median value of the bootstraps). As with Figure 6, values are presented with points (and connected with bold lines) when biases are statistically significant (90% two-tailed confidence interval this time). The main significant biases observed are an underestimation of the Sicilian Low and an overestimation of the Minor Low. These biases are stable for all lead times and mainly occur in the summer half. The significant negative biases for the first few lead days of the summer half for the Mediterranean High pattern are mainly related to the very low frequency of this pattern during this period (Figure 3). This leads to high differences in percentages, with only a minor difference in the actual occurrences. During the winter half, there is also a consistent overestimation of the Balkan Low and Black Sea Low, mainly significant for most lead times. Nevertheless, most biases (significant and non-significant) lie within the ±10% band, especially for winter. Good representation of the patterns in this period is crucial for indirectly informing about EPEs, as most of the EPEs occur during the winter half.

The forecast performance (median value of the bootstraps) in the predictability of the P95 EPEs is presented in Figure 8 (Figures S6, S7 in Appendix S1 for P90, P99, respectively). The plot shows the performance over selected (large) domains (area-weighted mean of all included grid cells), in terms of BSS for P95 EPEs, based on direct forecasting (using model-predicted precipitation) and indirect forecasting (using the forecasted patterns and their half-year conditional probabilities for EPEs). The direct forecasts have a high skill for short- and medium-range predictions; the skill drops below the reference score (pale-coloured lines) at a lead time of about 8 days. A small spike observed at a lead time of 15 days can be attributed to the change of the horizontal resolution that happens to the ECMWF forecasts at that time, which leads to some errors when resampling the variable from the fine resolution to the coarser one. The indirect EPE forecasting outperforms the reference score over a lead time of 10 days in general, extending the forecasting horizon by about half a week. This extension of the forecasting horizon based on indirect forecasting of EPEs and its convergence to values slightly below zero can be
explained by the nature of this method, which, by construction, is not biased. More specifically, when there are no (or low) biases on the regimes (something that in general applies in this study; Figure 7), the indirect method does not over-/under-forecast EPEs, and that is why the BSS is slightly below zero at longer lead times. On the other hand, the direct forecasting of precipitation is more susceptible to biases, especially so at longer lead times. Note that although for deriving extremes on forecasts we used lead-time-dependent quantiles, meaning that there are no biases in the quantity of EPEs, the model can exhibit biases at shorter temporal resolution and for physical processes. Thus, BSS decreases to below zero after medium-range forecasts. As the discriminatory skill of the patterns nowhere exceeds 20% even for perfect forecasts (Figure 5), the indirect BSS does not exceed 0.2, even at a 1-day lead time. From the selected subregions (subplots b–f), northern Morocco has a better skill. This relates to its small domain and homogeneity, with the mountain ranges forming a barrier that directs the flow and forces moisture to precipitate.

Figure 9 presents similar results to Figure 8, yet now for each grid cell of the domain studied. Subplots (a) and (b) present the forecasting horizon up to when the model beats the reference score for direct and indirect forecasting (statistically significant results based on a 90% one-tailed confidence interval using 1,000 bootstraps). The results of the indirect forecasting are masked to exclude any grid cell that has no significant discriminatory skill for EPEs when conditioning on the patterns (i.e., assuming a perfect pattern forecast). Significance is derived based on the 1,000 bootstraps per lead day (and considering all lead times used for the analysis) with a 90% one-tailed confidence interval. The indirect forecasting outperforms the reference score even for a lead time over 8 days for many regions, especially so for the Iberian Peninsula, southern Balkans, and western Turkey. In contrast, direct forecasting has skillful predictions only for a lead time up to 8 days for most locations. It can be noticed from subplot (c) that indirect forecasting extends the forecasting horizon for EPEs by between 3 and 6 days for many of the locations. This is a substantial increase in lead time, which could support informative decision-making for various domains; for example, (re)insurance companies and the agricultural sector. As the discriminatory skill (Figure 5) of the patterns for inferring EPEs is not very strong, indirect forecasting
FIGURE 8  Brier skill score (BSS) for direct (blue colour) and indirect (orange colour) forecasting of 95th percentile extreme precipitation events (EPEs) for the whole domain (subplot a) and selected subregions (subplots b-f). The reference score for assessing the forecast skills was based on climatological information. It was the minimum of the 31-day moving window (centred at the date of interest) and seasonal climatological frequency of EPEs. The results refer to the area-weighted average of all grid cells within the selected domain, considering the median of 1,000 bootstraps [Colour figure can be viewed at wileyonlinelibrary.com]

is not beneficial at short lead times. This information outperforms the direct forecasting only after the end of week 1 for most locations, as shown in subplot (d).

Summarizing, the results suggest that, up to the end of week 1, it is beneficial to use direct EPE forecasting, whereas for week 2 (extending to week 3 for a few locations), indirect forecasting would be the preferred method. Thereafter, climatological forecasting provides the most informative inputs. The results for the P90 and P99 events are presented in Figures S8 and S9 in Appendix S1. As the EPEs definition becomes stricter, the benefits of indirect forecasting decrease and are confined to smaller areas, mainly related to locations of high orography and coastal domains (Figure 2). One explanation for this has been provided in the discussion of Figure 5. An additional explanation is that P99 EPEs refer to a very small sample of events per domain. Thus, conditional probabilities are not stable and deviate noticeably when using bootstrapping and different subsets. This could be improved by optimizing the probabilities. Yet, significant improvement is not expected, as many events are driven by localized convective activity for high EPEs, which is not substantially affected by large-scale weather variability.

Figure 10 presents the maximum potential relative economic value for 7-, 11-, and 17-day lead-time forecasts for the same regions as Figure 8. The results are calculated from the actual forecasts data (using 105 dates instead of 110, to respect the climatological frequency of seasons), without performing bootstraps due to the computational load. For each of the lead times, the best forecasting method (direct, indirect, reference) for each cost/loss ratio, is selected and coloured accordingly. Figure S10 in Appendix S1 provides an example of how each of the three methods performs for the 7-day lead time. From this plot, the best method at each cost/loss ratio is kept for deriving the 7-day lead-time lines in Figure 10. Note that the reference score has positive values, rather than zero, because it already takes into consideration the seasonality in the occurrence of EPEs, whereas the climatological economic value is based solely on the 5% probability of the EPEs throughout the year. As the EPEs studied are the P95, the maximum economic value is obtained when the cost/loss ratio is equal to the climatological occurrence of the extremes (5%). For high cost/loss ratios, even for extended-range forecasts, the highest benefits are obtained when using model-predicted precipitation. This is because for such high ratios the decisions would be financially viable only if there is high probability and confidence for upcoming EPEs. Direct forecasting is the only method that can deliver high probabilities, as it can even reach 100%, whereas indirect forecasting (or the reference ones) cannot exceed 45% at any location (Figure 3). As for low cost/loss ratios, indirect forecasting brings the highest benefits, already from day 7. The usefulness of this information
FIGURE 9  Forecasting horizon (maximum forecast day) up to when the European Centre for Medium-Range Weather Forecasts model outperforms the reference score (Brier skill score, BSS > 0) in predicting the 95th percentile extreme precipitation events (EPEs), when assessing EPEs based on (a) the forecasted precipitation or (b) the forecasted Mediterranean patterns and their climatological connections to EPEs. (c) Difference of the forecasting horizon between subplot (b) and subplot (a). (d) Minimum lead day from when indirect forecasting of EPEs (based on patterns) outperforms direct forecasting (based on precipitation) [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 10  Maximum potential relative economic value for all cost/loss ratios and three different lead times (7, 11, and 17 days from upper line to lower line) for 95th percentile extreme precipitation events forecasting. The subplots refer to selected subregions (subplot (a) refers to all domain studied). At each cost/loss ratio, the best method among the direct forecasting, indirect forecasting, and reference score are kept and coloured accordingly (blue, orange, and green, respectively) [Colour figure can be viewed at wileyonlinelibrary.com]
becomes wider at a lead time of 11 days, whereas minor benefits can be seen even 17 days ahead. These results further support the previous findings in terms of BSS, translating the usefulness of the forecasts to economic benefits. They demonstrate that there is a wide range of cost/loss ratios that indirect forecasting based on the patterns delivers maximum benefits for decisions regarding EPEs.

5 | CONCLUSIONS

This work analysed if and where large-scale atmospheric flow patterns over the Mediterranean can be used as skilful predictors for localized EPEs at medium- and extended-range forecasts. The nine large-scale patterns selected by Mastrantonas et al. (2021), based on EOF analysis and subsequent K-means clustering of daily anomalies of SLP and Z500, depict distinct atmospheric variability in the lower and middle troposphere over the Mediterranean. The EPEs were derived from the P90, P95, and P99 percentiles of annual daily precipitation at each grid cell. The ERA5 dataset was used as the reference dataset, whereas the ECMWF extended-range reforecasts (cycle 46r1) were used as the forecasting product. Long-term statistics of the product, regarding pattern predictability and indirect EPE predictability, based on the predicted patterns, were assessed with the BSS, considering 2,200 reforecasts at each lead time ranging from 1 to 44 days ahead. Bootstrapping was also implemented to assess the significance of the results.

The results show that the ECMWF model well represents the Mediterranean patterns without remarkable biases of their climatological frequencies – even up to a lead time of 44 days. The model provides skilful predictions of the patterns up to 2 weeks in advance, outperforming results based on climatological frequencies and persistence. Its performance does not show noticeable deviations between the different patterns and the winter-half and summer-half periods. The only differences worth noticing are observed during winter-half years for the Mediterranean High and Minor Low patterns. The former has a forecasting horizon extending up to week 3, whereas the latter is limited to week 1.

Using the forecasted patterns for indirect EPE predictability provides skilful predictions up to ~10 days for many locations in the Mediterranean. Especially for areas with high orography and coastal locations (e.g., parts of the Iberian Peninsula, Morocco, western Italy/Balkans/-Turkey), the use of these patterns outperforms climatological EPE allocations by more than 10 days ahead. In fact, using these patterns, rather than the actual forecasted precipitation fields, extends the EPE forecasting horizon by about half a week for many locations. These benefits also translate to economic value, with the results indicating that the maximum economic benefits for low cost/loss ratios are obtained based on indirect EPE forecasting already from a lead time of 7-days.

Our results demonstrate that using large-scale patterns as predictors can provide useful information for localized extremes at medium-range forecasts, extending up to sub-seasonal scales. Such information can be promising for various users; for example, the agricultural sectors, emergency response units, and (re)insurance companies. To further advance this direction, it would be useful to research additional aspects:

- Are there teleconnections influencing the occurrence of the nine Mediterranean patterns? Such a question can be answered by exploring causal relationships between the patterns and various climatic indices (e.g., Runge et al., 2019; Di Capua et al., 2020; Silini and Masoller, 2021)
- Are there sources of predictability that give higher confidence for the forecasts of the patterns at extended-range lead times?
- What would be the benefits of using more localized large-scale patterns for different subdomains in the Mediterranean, considering, for example, country-wise analysis?
- How skilful is indirect EPE forecasting when using other predictors, such as water vapour flux that is highly related to precipitation (Lavers et al., 2011; Lavers et al., 2014; Lavers et al., 2016a; Lavers et al., 2016b; Lavers et al., 2017; Lavers et al., 2018)?

Answering such questions can provide guidelines about which predictor is beneficial for different spatiotemporal resolutions, locations, and forecasting horizons, making better use of already available NWP model outputs. This can ultimately support the development of new operational products towards seamless predictions of extreme precipitation that will provide higher confidence to decision-makers and users in different sectors. This helps improve forecasting and communication of weather hazards, recognized by the World Meteorological Organization as a priority for international research (Majumdar et al., 2021).

ACKNOWLEDGEMENTS

This work is part of the Climate Advanced Forecasting of sub-seasonal Extremes (CAFE) project; a project funded by the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement no. 813844. We would like to thank the data providers for making the data freely available;
ERA5 is available through the Copernicus Climate Data Store, and ECMWF reforecasts were downloaded via the ECMWF MARS server. NM would like to thank Zied Ben Bouallègue for the discussions regarding forecasts verifications, as well as two anonymous reviewers and David Richardson for providing useful comments that improved the quality of this work. Open Access funding enabled and organized by Projekt DEAL.

AUTHOR CONTRIBUTIONS

Linus Magnusson: Conceptualization; supervision; writing – review and editing. Florian Pappenberger: Supervision; writing – review and editing. Jörg Matschullat: Supervision; writing – review and editing.

DATA AVAILABILITY

The scripts used for this study are publicly available at: https://github.com/ecmwf-lab/med-extreme-prec-atm-patterns

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Mastrantonas, N., Magnusson, L., Pappenberger, F. & Matschullat, J. (2022) What do large-scale patterns teach us about extreme precipitation over the Mediterranean at medium- and extended-range forecasts?. *Quarterly Journal of the Royal Meteorological Society*, 148(743), 875–890. Available from: https://doi.org/10.1002/qj.4236