Skilful seasonal predictions of Summer European rainfall

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Key Points:

- First evidence for skilful seasonal predictions of Summer Northern European rainfall
- Model convective rainfall variability is the primary source of skill, whilst dynamical circulation is still poorly predicted
- Large ensembles are required to achieve skilful rainfall forecasts

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Abstract

Year-to-year variability in Northern European summer rainfall has profound societal and economic impacts; however current seasonal forecast systems show no significant forecast skill. Here we show skilful predictions are possible (r~0.5, p<0.001) using the latest high-resolution Met Office near-term prediction system over 1960-2017. The model predictions capture both low-frequency changes (e.g. wet summers 2007-2012) and some of the large individual events (e.g. dry summer 1976). Skill is linked to predictable North Atlantic sea surface temperature variability changing the supply of water vapour into Northern Europe and so modulating convective rainfall. However, dynamical circulation variability is not well predicted in general – although some interannual skill is found. Due to the weak amplitude of the forced model signal (likely caused by missing or weak model responses) very large ensembles (>80 members) are required for skilful predictions. This work is promising for the development of European summer rainfall climate services.

1 Introduction

European summer rainfall anomalies are often persistent for weeks to months and spatially coherent over large areas. For example, the dry summers of 1976 and 2003 spanned June-August leading to increased water shortages (Rodda & Marsh, 2007), fire hazards (Fink et al., 2004) and crop failure (Ciais et al, 2003) both in the UK and across much of Northern Europe. Equally, the succession of wet summers over 2007-2012 (Marsh & Hannaford, 2007; Blackburn et al., 2008; Parry et al., 2013) caused widespread flooding.

There are a number of potential drivers of European summer rainfall variability, including: variability in the behaviour of the North Atlantic jet (i.e. storm track; Folland et al., 2009; O'Reilly et al., 2017), preconditioning of soil moisture anomalies (Schär et al., 1999; Seneviratne et al., 2006) , or changes in moisture availability due to varying sea surface temperatures (SSTs; Knight et al., 2006; Årthun et al., 2017). However, the relative contribution of each process to European summer rainfall variability, their inherent predictability and the skill of current seasonal prediction systems to represent and predict them are still poorly understood.

The Summer North Atlantic Oscillation (SNAO; Folland et al., 2009) is the mode of circulation variability associated with latitudinal shifts in summer North Atlantic jet position. A positive/negative phase of the SNAO gives a north/south shifted jet position resulting in drier/wetter conditions for Northern Europe. Previous studies, however, estimate that the SNAO explains only a relatively small proportion (22%) of the total regional summer mean sea level pressure variance (for comparison, in winter the NAO explains 37%) and only ~25% of Northern European summer rainfall variability (Folland et al., 2009). To date, no skill has been reported for predicting the SNAO in seasonal forecast systems.

Soil moisture can be an important source of persistence (Koster et al., 2003) which can then amplify or dampen summer European rainfall anomalies (Ferranti & Viterbo, 2006).

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Initialisation of soil moisture has been shown to give modest improvement in seasonal forecasts for some extreme European summers (such as 2003) but not in general (Prodhomme et al. 2016).

On longer, multi-decadal timescales, variations in European summer rainfall have been linked to changes in North Atlantic SSTs, with wet periods linked to warm phases of the Atlantic multi-decadal variability (AMV) such as in the 1950-60s and 1990-2000s and dry periods linked to cool AMV phases such as in the 1970-80s (Sutton & Hodson, 2005; Knight et al., 2006; Sutton & Dong, 2012). Decadal predictions show skilful hindcasts (retrospective forecasts) for predicting AMV (Smith et al., 2010, Hermanson et al., 2014), likely linked to persistence, ocean dynamics (Robson et al., 2012) and changes in aerosol forcings over the past century (Booth et al., 2012). Climate models can simulate a robust increase in summer European rainfall in response to North Atlantic warming, but only when very long model simulations are run (Knight et al., 2006), or for decadal prediction case studies when very large lagged ensembles (~100 members) are used (Robson et al., 2013). For the standard operational hindcast ensemble sizes (~10-20 members), typically used in current seasonal forecast systems, there is no statistically significant skill for predicting Northern European summer rainfall variability (for example, ECMWF S4 and Met Office GloSea5 models both show no significant skill: $r<0.3$, $p>0.1$). We return to the need for large ensembles later. Finally, empirical statistical forecast models of European summer rainfall have also been constructed using lagged predictors of North Atlantic SSTs (Colman & Davey, 1999, Osso et al, 2017). Whilst good skill was found in hindcasts, a decade of real-time seasonal forecasts in the former study showed relatively poor skill (A. Colman, personal communication).

2 New large ensembles of high-resolution initialised seasonal predictions

We re-examine seasonal European summer rainfall skill using the latest high-resolution version of the initialised Met Office Decadal Climate Prediction System (DePreSys3, Dunstone et al., 2016). This system uses the HadGEM3-GC2 coupled climate model (Williams et al., 2015) with N216 (~60km) atmospheric and 0.25° ocean resolution (see Supplementary Information, S1). DePreSys3 has already shown very promising hindcast skill for seasonal to interannual predictions of the winter NAO when large ensembles are used (Dunstone et al., 2016). Here we use an 80 member ensemble, over a 58 year hindcast period (1960-2017) and find highly significant skill (Fig. 1a, $r=0.47$, $p<0.001$ using a 2-sided Student's T-test) for predicting Northern European summer rainfall variability when assessed against the European land surface rainfall dataset (E-OBS v16e, Haylock et al., 2008). For Northern Europe we use a previously defined box (Fig. 1b, Sutton & Dong, 2012) but combine this with a mask based on the first Empirical Orthogonal Function (EOF) of E-OBS observed summer rainfall (Fig. S1). This provides a more physically based definition for Northern Europe rainfall variability as this mask removes the far north Norwegian coast which primarily varies in anti-phase (Fig. S1). However, we note that similar significant skill is achieved ($r=0.45$, $p<0.001$) if this mask is not used and that the skill is also robust if the lower resolution Global Precipitation Climatology Centre (GPCC) observational product is used instead ($r=0.45$, $p<0.001$).

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The model predictions capture much of the observed variability including the transition from wetter summers in the early 1960s to drier conditions in the 1970s and 80s, the particularly wet summers in the late 2000s and the following drier summers (Fig. 1a). In addition to this low-frequency variability the model hindcasts simulate some of the extreme summers such as 1976 – the driest summer in both the observed and model timeseries. Overall, the sign of the rainfall anomaly is correctly forecast in two thirds of summers.

Analysis on a grid-point basis (E-OBS 0.25° grid) reveals significant local rainfall skill in parts of the UK, Scandinavia and Central Europe (Fig. 1b). In addition to the skill of the box average, the model captures some aspects of the large-scale patterns associated with extreme dry and wet years (Fig. 2), along with weaker but significant rainfall skill for Southern Europe (r=0.34, p=0.008, Fig. S2). The 80 member DePreSys3 hindcast ensemble is the combination of two 40 member ensembles initialised in November (8-10 month lead) and May (2-4 month lead). Intriguingly, despite the difference in lead time, both show similar levels of skill when considered individually (r~0.37, p<0.01, Fig. S3). This is consistent with a slowly varying predictable driver of summer rainfall skill and also that skill is strongly dependent on ensemble size - we explore these possibilities in Sections 4 and 5 respectively.

3 Skilful predictions of convective rainfall

We first probe the model skill using the Japanese 55-year Reanalysis (JRA-55, Kobayashi et al., 2015). This covers the entire 58 year period of our hindcasts and has a largely faithful reproduction of observed Northern European rainfall variability when compared to the gridded E-OBS station based observational dataset (Fig. S4a, r=0.92). However, using the reanalysis, rainfall can be split into two components: ‘large-scale’ (frontal rain) and ‘convective’ (from the convective parameterisation scheme). While this is an imperfect split, as in reality much of the convective rainfall is embedded within large-scale frontal systems, it does provide the opportunity to probe the drivers of model rainfall skill on a process level. We also note that the exact partitioning is likely to depend on the model used in the reanalysis. Large-scale JRA-55 rainfall shows strong correlations with the total observed Northern European rainfall (Fig. 3a, r=0.87, p<0.001) and clearly exhibits a north-south dipole related to the position of the North Atlantic jet (and hence SNAO phase). However, the convective rainfall also correlates strongly with total Northern European rainfall (Fig. 3b, r=0.56, p<0.001). It has less of a dipole structure and the cross-correlation with large-scale rainfall is quite low (r=0.26, p=0.05). This suggests that observed summer European rainfall is not solely influenced by the dynamical behaviour of the summer North Atlantic jet, but also likely from thermodynamic processes that contribute to convective rainfall variability.

The model hindcast rainfall data can also be split into convective and large-scale components with a similar partitioning to that in JRA-55 (Fig. S4b-g). To assess how well the model captures the JRA-55 variability, we calculate the model skill at each gridpoint, for each component (Fig. 3c,d). This reveals that the model skilfully predicts much of the JRA-55 convective rainfall variability, especially over the UK and Scandinavia (regions identified as

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skilful in Fig. 1b). However, the model has little large-scale rainfall skill, except weakly over parts of Central Europe.

4 Exploring the driving mechanisms on low and high frequencies

We now partition the data into low and high-frequency components, corresponding to five year and interannual timescales (see Supplemary Information, S1), in order to understand the driving mechanisms of rainfall variability (Fig. 4) and whether these are skilfully predicted (Fig. 5). On the low-frequency the model is able to capture much of the observed variability (Fig. 4a) with significant skill (r=0.71, p=0.014, assuming 11 independent datapoints in a Student's t-test). The high-frequency also shows significant skill with a similar level of significance (Fig. 4b, r=0.35, p=0.008). Correlating the low and high-frequency model timeseries with the original, we find that the two timescales contribute almost equally to explaining the total model variance.

To probe the sources of low-frequency skill we correlate model fields with the observed Northern European rainfall timeseries (left column, Fig. 4). In agreement with previous studies (Sutton & Hodson, 2005; Knight et al., 2006; Sutton & Dong 2012), we find a strong positive correlation between Northern European rainfall and North Atlantic SSTs (Fig. 4c). The characteristic 'horseshoe' pattern is that associated with AMV but here has strongest correlations in the North Atlantic sub-polar gyre region. Similarly, we calculate the correlation with the zonal and meridional components of the model moisture flux (at 850hPa) and overplot as vectors (Fig. 4c). These show a strong anti-cyclonic moisture circulation over the North Atlantic that feeds higher moisture air into Northern Europe during wet summer periods. As the moisture flux is a product of wind (mainly u-wind in this case, U 850 hPa) and specific humidity (Q 850 hPa) the wetter years could either be due to an increase in the strength of the prevailing westerlies, an increase in specific humidity, or a combination of both. To determine the prime driver in the model we consider each separately in Figs. 4e & g. We find a strong relationship with specific humidity in the North Atlantic (Fig. 4e) but no significant correlation with zonal wind (Fig. 4g).

In order for these factors to explain forecast skill, they also must be skilfully predicted by the model. Low-frequency North Atlantic SSTs are well predicted by the model (Fig. 5a), as is specific humidity (Fig. 5c) in the regions identified above. However, in agreement with our findings, the low-frequency zonal wind is not skilfully predicted by the model (Fig. 5e) and hence does not drive the skilful part of the low-frequency model rainfall. Consistent with this, the model has no significant skill in forecasting the SNAO (hence North Atlantic jet) on this timescale (not shown). Hence on the low-frequency timescale, the model rainfall skill appears to originate primarily from a thermodynamic response via skilful predictions of North Atlantic SSTs. Warmer SSTs promote more evaporation, leading to increased low-level moisture, which is then advected over Northern Europe by the climatological prevailing westerly winds. The atmospheric moisture content just above the boundary layer is an important determinant of convective efficiency (Derbyshire et al., 2004), as the progression

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of convecting updraughts into the troposphere is retarded by the evaporative cooling of entrained environmental air. The moister the environment, the less evaporative cooling, and so the stronger the upward transport of water and subsequent conversion to precipitation in convecting clouds. Thus, a moister low-level environment leads to increased convective rainfall. In support of this hypothesis, we find in addition that this increased moisture is indeed the dominant contribution to the greater convective instability found in the wettest summers (as shown in Fig. S5).

The interannual timescale appears to be associated with more local SSTs, with Fig. 4d showing a tripole with positive centres to the north of the UK and west of Portugal, with a negative centre to the east of Newfoundland (regions skilfully predicted in Fig. 5b). This SST pattern is similar to previous studies (Gastineau & Frankignoul, 2005, Osso et al 2017) where it is linked to European summer climate variability but further experiments would be needed to establish causality in the model. Positioned near these centres are a cyclonic moisture flux circulation over Northern Europe and an anti-cyclonic circulation over the North-East Atlantic. Together these feed moist air into Northern Europe during wet summers. Again splitting this moisture flux into changes in humidity and winds, we find some very local correlations with humidity over the North Sea (Fig. 4f) which show modest skill (Fig. 5d). However, unlike on the low-frequency timescale, we now see significant correlations in the zonal winds (Fig. 4h) with a skilfully predicted dipole pattern in the North Atlantic jet over Northern Europe (Fig. 5f). We note that this correlation analysis to identify possible drivers does not establish causality and further model experiments are needed to test these conclusions.

5 Weak model dynamical signals

The model Northern European summer rainfall skill appears driven partly by dynamical shifts in the position of the Atlantic jet on interannual timescales and partly by low-frequency changes in North Atlantic SSTs that drive changes in European moisture convergence and hence convective precipitation. The relatively weak model dynamical signal, particularly on the low-frequency timescale, raises the question as to the relative role of dynamics and thermodynamics in driving summer European rainfall. Common experience is that a large proportion of the variability is driven by dynamics (O’Reilly et al., 2017; Sutton & Dong, 2012), much of which is caused by shifts in the North Atlantic jet (associated with the SNAO). However, there is also emerging evidence that thermodynamic processes, such as the advection of ocean temperature anomalies in the high latitude North Atlantic and Nordic Seas, can play a significant role in driving North-West Europe temperature and rainfall on multi-year timescales (e.g. Årthun et al., 2017). In Supplementary Information (S2 and Fig. S6) we use three different methods (all using observed mean sea level pressure) in an attempt to partition the role of dynamical and non-dynamical drivers of observed Northern European summer rainfall. The result is a range of correlations between the residual (non-dynamic) and the total observed rainfall: r=0.36-0.74. Hence, there does appear to be significant scope for a non-dynamic component (encompassing the r=0.47 skill), although the relative roles of dynamics and non-dynamical drivers is uncertain.

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The amplitude of ensemble mean rainfall variability is much smaller than that observed (by a factor of ~7, Fig. S7a) and this is explored further in Supplementary Information S3. Hence to extract the forced signal, and enable skilful predictions, a very large ensemble (80 members, Fig. S7b) is required and higher skill is projected for even larger ensembles (Murphy, 1990). A surprising consequence of this is that the model ensemble has higher skill for predicting the observed summer rainfall ($r=0.47$, $p<0.0013$) than it does for predicting itself (Fig. S7b, model-model skill is $r\sim0.1$ and not significant). This large discrepancy clearly illustrates that model members are not interchangeable with the real-world and this can be quantified in the ratio of the predictable components (RPC, Eade et al., 2014). We find an RPC~5 (0.47/0.1), which implies that while the system is not 'over dispersive' (as the model total variance across all ensemble members closely matches that observed, Fig. S7a), the model predictions are 'under confident'. This is opposite to the 'over confident' predictions often associated with tropical seasonal forecasts and so this unusual situation extends the 'signal-to-noise paradox' found recently for winter NAO (RPC>2, Dunstone et al., 2016; Eade et al., 2014; Scaife et al., 2014). Further work is needed to establish the source of these signal-to-noise problems but they may stem from a common model deficiency in the strength of the North Atlantic jet response in both winter and summer. Alternatively, given that model skill appears to originate primarily from convective rainfall, this might point to a deficiency in the model convective rainfall parametrization scheme whereby the sensitivity to large-scale environmental changes is too low. However, this work clearly points to the current need for large ensembles to generate skilful summer European seasonal rainfall forecasts.

6 Conclusions

We have shown the first skilful seasonal predictions of European summer rainfall using a general circulation model. The model successfully captures multi-annual periods of wet Northern European summers (e.g. 2007-2012) and also some extreme dry summers (e.g. 1976 and 2003). Using the JRA-55 reanalysis we find a significant role for convective rainfall in European summer (distinct from large-scale rainfall variability) and that this is the primary source of model skill. The skill originates from skilful predictions of low-frequency variations in North Atlantic SSTs which control moisture availability and hence convective rainfall efficiency over Northern Europe, together with a modest ability to predict high-frequency circulation changes. We stress that the model only explains part of the observed variability and in particular is unable to capture much of the dynamical variability in the position of the North Atlantic jet associated with the SNAO. However, the level of skill appears to be consistent with observed variability that is not associated with dynamical changes. An important issue, also found in winter forecasts, is that the current forecast system exhibits only a very weak rainfall signal and hence very large ensembles (80 members) are required to make skilful forecasts. Nevertheless, our results are very encouraging for the development of climate services to aid preparation for future summer flood and drought events.

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Acknowledgments, Samples, and Data

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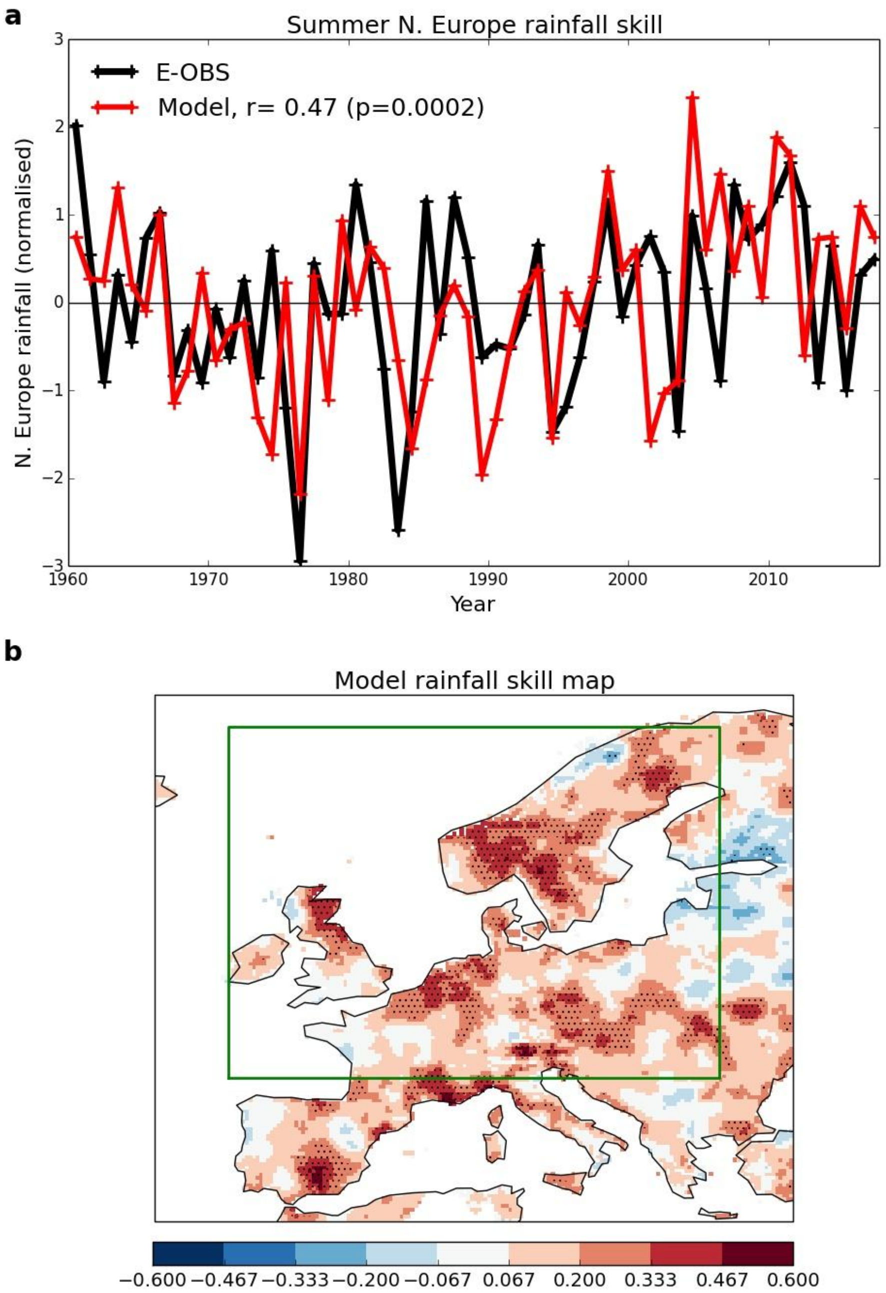

Figure 1: Skilful predictions of European summer rainfall. a, observed (E-OBS) and model ensemble mean predicted timeseries of summer (JJA) Northern European rainfall. **b,** correlation skill map for European rainfall with 95% significant regions stippled (assessed using a 1-sided Student's t-test), the green box shows the Northern European region..

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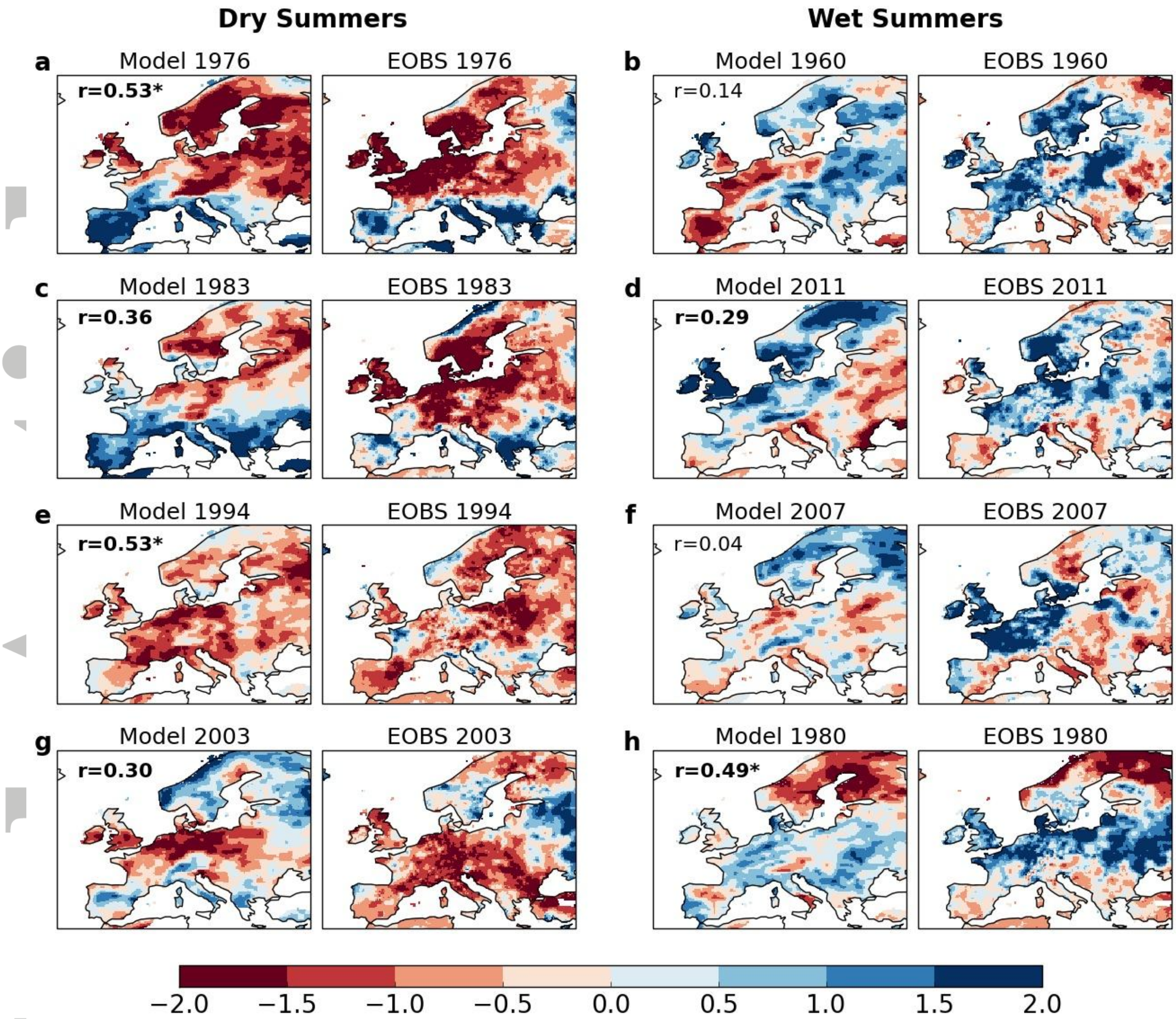

Figure 2: Individual extreme summers. a-h, the four driest (left) and wettest (right) observed Northern European summers are plotted alongside the model predictions as normalised anomaly rainfall maps. They are shown in order of the driest/wettest summers (top to bottom). Pattern correlations (using an uncentered Pearson's correlation coefficient) are calculated over the displayed region to help illustrate the model performance. Correlations in bold are significant ≥90% level and an asterisk marks significance ≥95%, using bootstrapping with replacement to assess the probability of achieving such correlations by chance.

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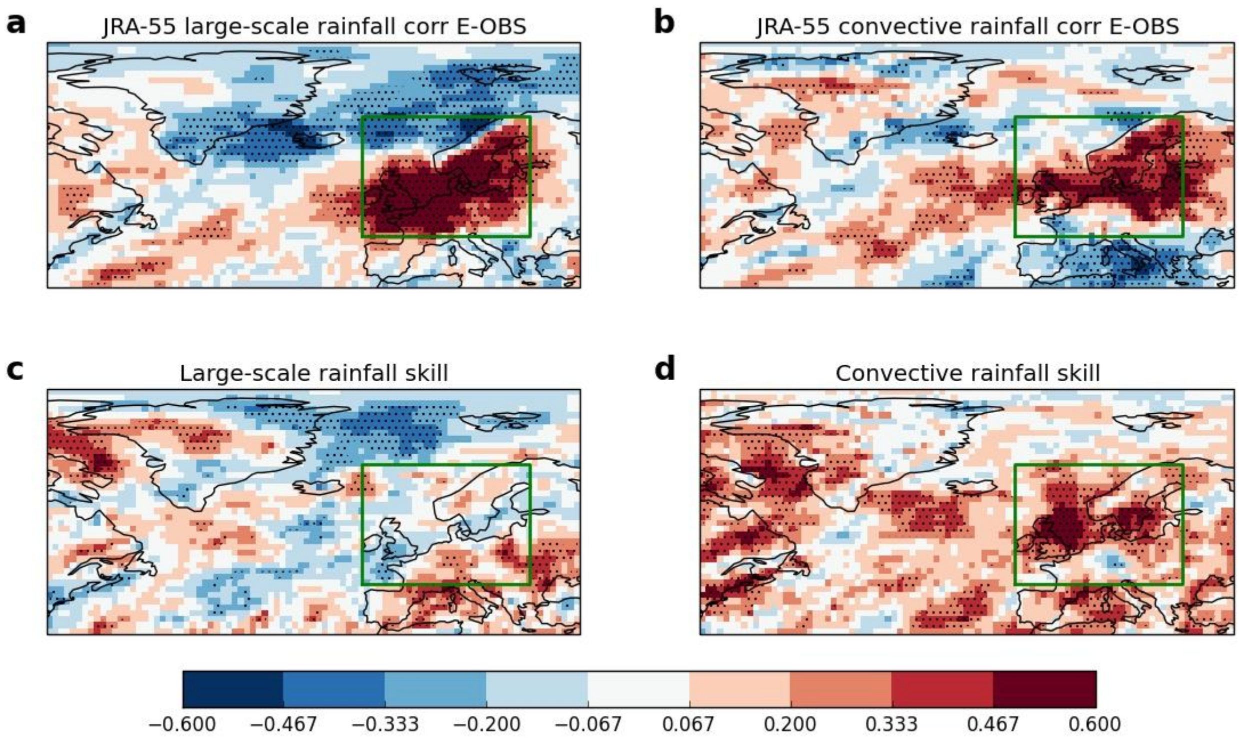

Figure 3: Using JRA-55 reanalysis to explore convective vs large-scale rainfall. a,b the JRA-55 fields of large-scale and convective rainfall correlated with the E-OBS Northern European timeseries. **c,d** the skill at each gridpoint of the equivalent model fields in predicting the JRA-55 large-scale and convective rainfall. In all panels stippling shows significance at the 95% level according to a 1-sided Student's t-test.

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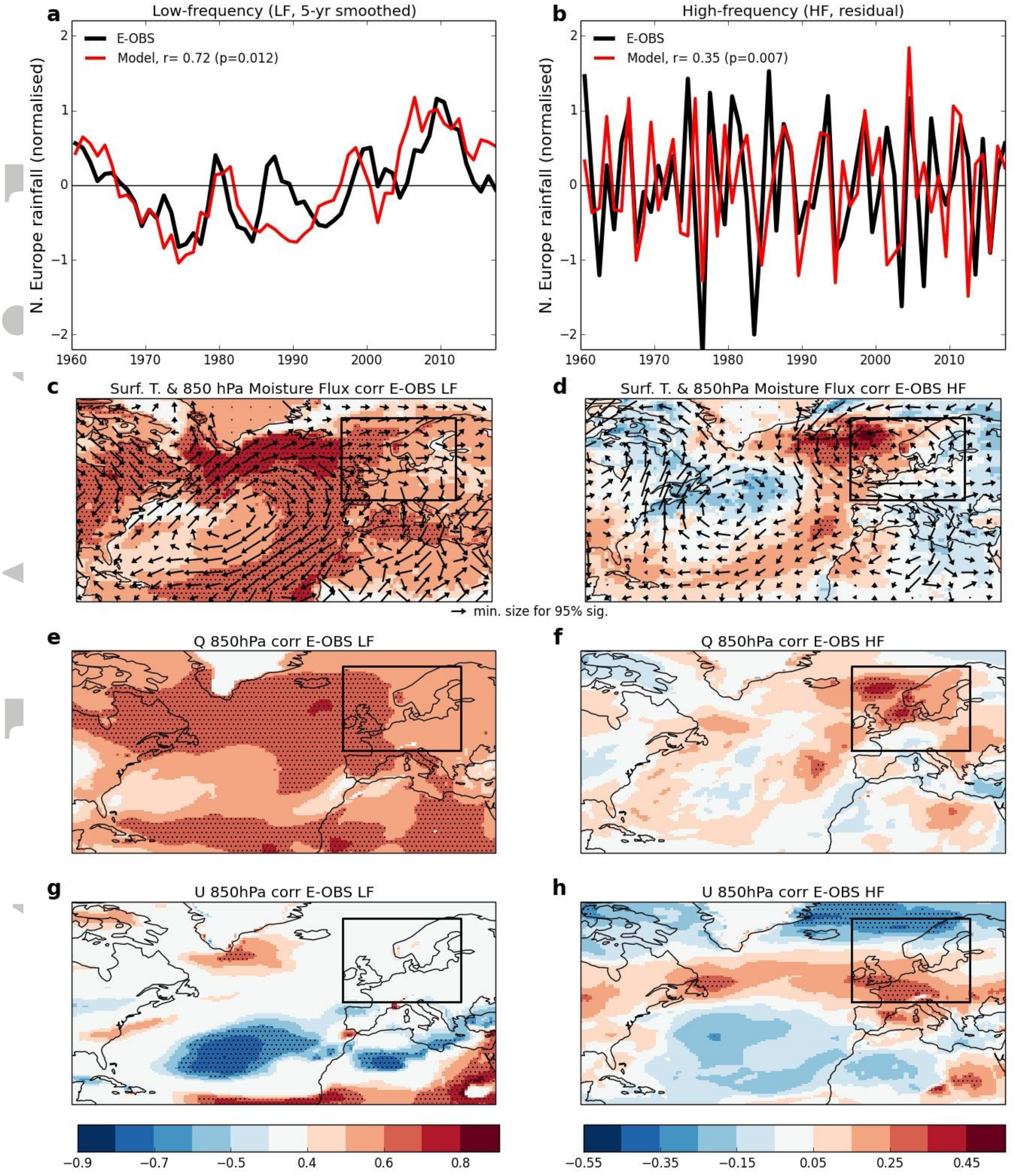

Figure 4: Mechanisms driving skilful Northern European predictions. Low-frequency (5 year smoothed, left column) and higher frequency (residual, right column) are considered. **a,b** show timeseries of observed and model predictions for the two timescales with significant skill shown (low-frequency p-value has been adjusted to account for reduced number of degrees of freedom). **c,d** show correlation of observed timeseries with model predicted fields of SST and with 850 hPa moisture flux vectors overplotted (arrows). Moisture flux is split into contributions from specific humidity (**e,f**) and zonal wind (**g,h**). In all panels stippling shows regions of significant correlation at the 95% level, according to a 1-sided Student's t-test.

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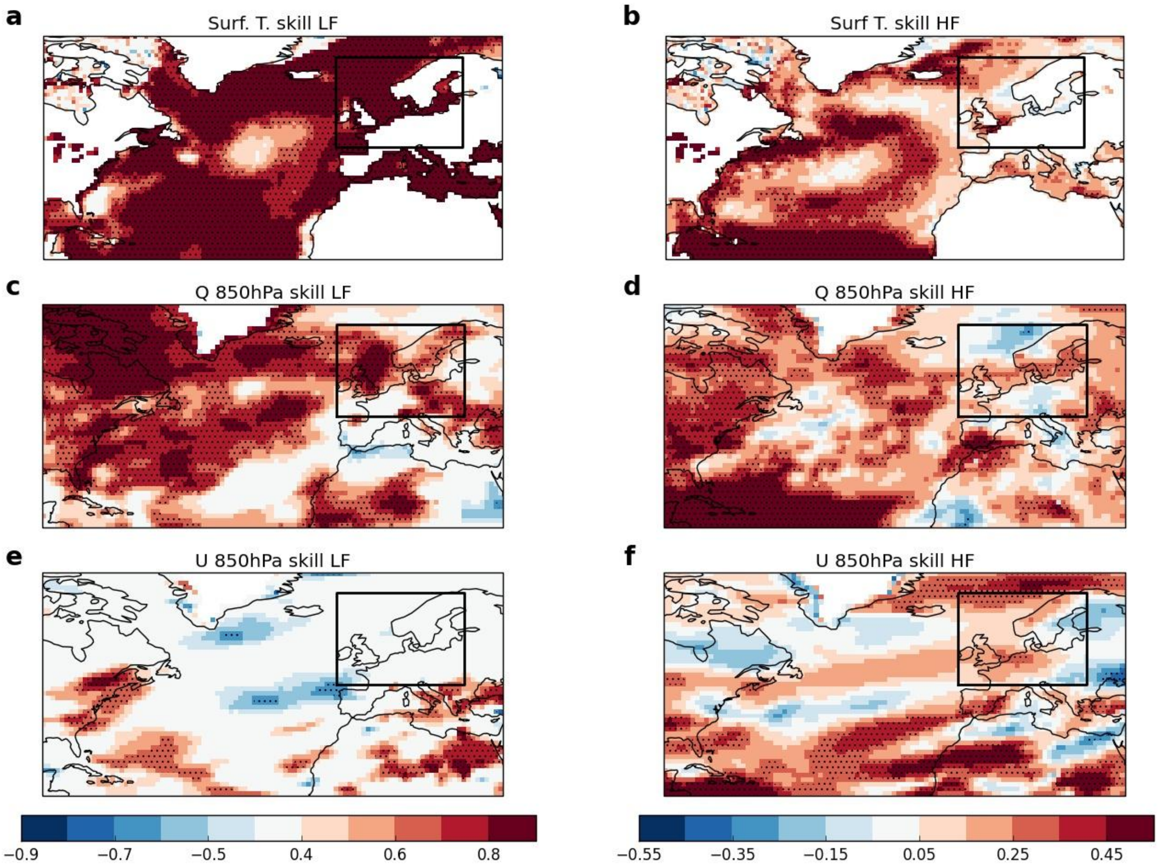

Figure 5: Are the drivers well predicted by the model? As Fig. 4, split into low-frequency (left) and high-frequency (right) variability. Panels show the skill in predicting the drivers identified in Fig. 4 (panels c-g). Skill is plotted for predicting SST in (**a,b**) assessed against the HadISST (Rayner et al., 2003) observational dataset. Specific humidity (**c,d**) and zonal wind (**e,f**) are assessed against the JRA-55 reanalysis. In all panels stippling shows regions of significant correlation at the 95% level, according to a 1-sided Student's t-test.

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