

# *Evaluation of the HadGEM3-A simulations in view of detection and attribution of human influence on extreme events in Europe*

Article

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1 **Evaluation of the HadGEM3-A simulations in view of**  
2 **detection and attribution of human influence on extreme**  
3 **events in Europe**

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21

## 22 Abstract

23

24 A detailed analysis is carried out to assess the HadGEM3-A global atmospheric model skill in simulating  
25 extreme temperatures, precipitation and storm surges in Europe in the view of their attribution to  
26 human influence. The analysis is performed based on an ensemble of 15 atmospheric simulations  
27 forced with observed Sea Surface Temperature of the 54 year period 1960–2013. These simulations,  
28 together with dual simulations without human influence in the forcing, are intended to be used in  
29 weather and climate event attribution. The analysis investigates the main processes leading to extreme  
30 events, including atmospheric circulation patterns, their links with temperature extremes, land-  
31 atmosphere and troposphere-stratosphere interactions. It also compares observed and simulated  
32 variability, trends and generalized extreme value theory parameters for temperature and precipitation.

33 One of the most striking findings is the ability of the model to capture North-Atlantic atmospheric  
34 weather regimes as obtained from a cluster analysis of sea level pressure fields. The model also  
35 reproduces the main observed weather patterns responsible for temperature and precipitation  
36 extreme events. However, biases are found in many physical processes. Slightly excessive drying may  
37 be the cause of an overestimated summer interannual variability and too intense heat waves, especially  
38 in central/northern Europe. However, this does not seem to hinder proper simulation of summer  
39 temperature trends. Cold extremes appear well simulated, as well as the underlying blocking frequency  
40 and stratosphere-troposphere interactions. Extreme precipitation amounts are overestimated and too  
41 variable. The atmospheric conditions leading to storm surges were also examined in the Baltics region.  
42 There, simulated weather conditions appear not to be leading to strong enough storm surges, but  
43 winds were found in very good agreement with reanalyses. The performance in reproducing  
44 atmospheric weather patterns indicates that biases mainly originate from local and regional physical  
45 processes. This makes local bias adjustment meaningful for climate change attribution.

46

47

## 48 1. Introduction

49

50 In recent years attribution of changing likelihood of weather events has motivated an outstanding  
51 effort of the climate science community (Stott et al., 2016). While detecting trends in odds of extreme  
52 events (eg. as characterized by the exceedance of a threshold) can draw solely on observational data,  
53 formal attribution to human activities requires comparing statistics in a “current climate” world and in  
54 a world where human activities have not occurred. This requires model simulations with different sets  
55 of assumptions concerning external forcing. This also requires that the models used are able to  
56 simulate the changes in likelihood of extremes by comparing with observations, which is often difficult  
57 in practice due to the short length and lack of homogeneity of observational data sets. A simplification  
58 is often made with the assumption that the anthropogenic effect is included in surface variables such  
59 as SST, sea ice (Pall et al., 2011) or soil moisture (Hauser et al., 2016), and in atmospheric composition,  
60 and that extreme events respond to this influence through processes linking surface and atmosphere.  
61 In contrast, attribution of observed trends to causes relies on analysis of the observed change with the  
62 help of climate models, hence is more directly anchored to the observed change (see NAS report, 2016;  
63 Hegerl and Zwiers, 2011). In practice, anthropogenic forcing influence on temperature-related variables  
64 is such that changes are found with a high consistency using both approaches for trends in mean and  
65 extremes (Bindoff et al., 2013).

66 Attribution makes one unavoidable assumption: that dynamical and physical processes are correctly  
67 represented in the climate model used for attribution. If all processes are well accounted for,  
68 sensitivities to forcing changes should be realistic. Attribution of weather events therefore requires a  
69 careful evaluation of processes involved in the build-up of the events. Evaluation also requires  
70 examination of extreme events statistics, and if possible their change with increasing greenhouse gases  
71 and other human-driven changes (Bellprat and Doblas-Reyes, 2016; Lott and Stott, 2016; Sippel et al.,  
72 2016).

73 This study examines how the newly upgraded Hadley Centre Global Environmental Model version 3-  
74 Atmosphere (HadGEM3-A) atmospheric model performs in view of event attribution in Europe, with a  
75 focus on processes leading to extreme events. The earlier, lower resolution, version of the model was  
76 employed in several attribution studies of extreme events including consecutive cold winters in the UK,  
77 the Moscow heatwave in July 2010 (Christidis et al., 2013a), the severe East African drought of 2011  
78 (Lott et al., 2013), the Eastern Australia floods of 2011 (Christidis et al., 2013b) and the cold spring of  
79 2013 in the UK (Christidis et al., 2014). These analyses quantified the effect of anthropogenic influence  
80 on the likelihood of the events as well as the associated uncertainty from limited number of available  
81 simulations. Moreover, simple evaluation assessments were carried out to demonstrate that the model  
82 was fit for purpose and able to realistically represent the type of extremes under consideration in the  
83 region of interest. Angelil et al. (2016) compared the simulated extreme events with reanalyses  
84 datasets at relatively high resolution and found mismatches among all sets (models and reanalyses and  
85 among reanalyses themselves). This highlights observational difficulties when comparing sub-regional  
86 trends using reanalyses, and emphasizes the need to not only evaluate statistical properties but also  
87 physical mechanisms involved in the trends.

88 Here, the new ensemble of simulations is evaluated through comparison with available observations.  
89 These simulations are now used in several attribution studies (e.g. Eden et al, 2016; van Oldenborgh et  
90 al., 2017, in preparation; Philip et al., 2017, Hauser et al, 2017, Klehmet et al, 2017, in preparation,  
91 Eden et al, 2017, Christiansen et al, 2017, in preparation, Wilcox et al., 2017), where evaluation is  
92 carried out for the local case study. However, an overall evaluation of the model for Europe is necessary  
93 in order to assess confidence in attribution results derived from this model.

94 This article addresses three main questions: (i) are the simulations correctly representing the statistics  
95 of events for the historical period 1960-2013? (ii) Are the simulations correctly representing long-term  
96 changes in extreme events and dynamics along the reference period? (iii) Are the simulations correctly  
97 representing the key processes driving to extreme events?

98 The first and last issues are covered in detail in this document. The second one is a more difficult  
99 question to address with 54-year long simulations. Trends, especially in extremes, have regional  
100 patterns of response to human activities that are fairly uncertain due to long-term atmospheric  
101 variability. Hence a single-realization observation is not expected to agree completely with model  
102 simulations.

103 A last issue concerning the model ensemble is also whether the overall ensemble also captures the  
104 natural variability well. This will however not be considered here to keep focus on processes. This  
105 question was addressed in a theoretical framework to show that the consistency of the ensemble  
106 spread can be measured by the notion of reliability (Bellprat and Doblas-Reyes, 2016; Lott and Stott,  
107 2016). Ensemble reliability measures whether the probability to exceed a threshold (e.g. an extreme  
108 event or a large model quantile) agrees with the frequencies of the same threshold in an observed  
109 record. Correct reliability is therefore a necessary condition for the ensemble probabilities used in  
110 event attribution studies not to be biased. A bias in ensemble reliability systematically affects the  
111 fraction of attributable risk (Bellprat and Doblas-Reyes, 2016).

112 We focus here on a few types of events and processes to give an overview of the performance of the  
113 HadGEM3-A system in Europe. The evaluation does not pretend to be exhaustive, as event-specific  
114 evaluation will always be necessary. The selected events types are: heat waves, cold spells, droughts,  
115 heavy precipitation events, and wind events leading to storm surges. These generally have a daily to  
116 seasonal time scale. They were selected because the underlying weather variables have long  
117 observational records.

118 In Section 2, we briefly describe the simulations. A more detailed description is given in a separate  
119 article (Ciavarella et al., 2017, in preparation). We also describe the data sets used. Section 3 is devoted  
120 to an overall assessment of the main biases in mean state, variability and extremes, as well as a  
121 comparison between simulated and observed trends. In Section 4, an extreme value analysis is carried  
122 out in order to investigate distribution tails. Section 5 is dedicated to an analysis of a few key processes

123 driving the extreme events. A final conclusion and discussion follow (Section 6) where tentative  
124 conclusions for attribution are given.

## 125 **2. Simulations and observations**

### 126 **2.1 The HadGEM3-A simulations**

127 The simulations used in this work were generated by the Hadley Centre event attribution system  
128 (Christidis et al., 2013a) that has facilitated numerous studies of different types of high-impact extreme  
129 events. A typical attribution study involves pairs of large ensemble experiments with and without  
130 anthropogenic forcings, from which the changing likelihood of extreme events under climate change  
131 can be determined (Stott et al., 2016). The Hadley Centre system is built on the HadGEM3-A model  
132 that was recently upgraded within the EUropean CLimate Event Interpretation and Attribution  
133 (EUCLEIA) project (<http://eucleia.eu/>) and now features one of the highest resolution global models  
134 used in global event attribution research. The model runs at N216 horizontal resolution, equivalent to  
135 about 60 km at mid-latitudes, and comprises 85 vertical levels. The upgraded model also benefits from  
136 a new atmospheric science package with an improved dynamical core, which leads to better numerical  
137 stability (Williams et al., 2015).

138 An ensemble of 15 atmospheric simulations of the historical climate during the period 1960-2013 was  
139 produced with the new model and is the basis of the evaluation assessments discussed in this paper. A  
140 second ensemble of model runs without the effect of anthropogenic forcings was also generated and  
141 employed in attribution analyses (Christidis et al., 2016; Burke et al., 2016; Wilcox et al., 2017), but is  
142 not used here. The historical forcings in the model simulations include anthropogenic greenhouse gas,  
143 aerosols, tropospheric and stratospheric ozone emissions, changing land use, as well as natural changes  
144 in the solar output and volcanic aerosols (Jones et al., 2011). Ensemble members are generated by  
145 implementing random parameter perturbations as well as a stochastic kinetic energy backscatter  
146 scheme that accounts for energy sources on sub-grid scales (Christidis et al., 2013a). Monthly  
147 observations of the sea surface temperature (SST) and sea-ice from the Hadley Centre Sea Ice and Sea



148 Surface Temperature (HadISST) v1 dataset (Rayner et al., 2003) provide boundary conditions for the  
149 simulations of the historical climate. Building on the multi-decadal simulations, an operational  
150 attribution system is currently being developed by firstly extending the model runs and increasing the  
151 ensemble size and then by continuing to extend the simulations on a seasonal timescale in a similar  
152 fashion to seasonal forecasting systems.

## 153 **2.2 Observations**

154 In this paper we use a number of observational data sets for the model simulations evaluation. In  
155 general, the NCEP/NCAR 20<sup>th</sup> Century reanalysis 20CR re-analyses of sea level pressure have been used  
156 for characterizing atmospheric circulations. Surface temperatures and precipitation are either taken  
157 from CRUTS3.2 or from E-OBS data sets. Specific data sets have been used to study the land-  
158 atmosphere interactions, described in Table 1.

## 159 **3. Model climatology, trends and variability**

### 160 **3.1 Mean states and trends**

161 In this section we review the main statistics of the model climate and compare it to observations. The  
162 mean state, time evolution, and interannual variability of metrics of mean and daily extremes in the  
163 15-member HadGEM3-A N216 ensemble are compared to a variety of observational datasets (primarily  
164 CRUTS3.23 and E-OBS) for the June to August (JJA) and December to February (DJF) seasonal means.  
165 Spatial patterns have been considered over the European domain, and time series have been  
166 considered over three regions: Europe (35–70°N, 10°W–40°E); Northern Europe (50–60°N, 10°W–  
167 25°E); and Southern Europe (35–45°N, 10°W–25°E). Where regional means are considered, they only  
168 include model grid cells with a land fraction over 75%, as observations are only available over land.

169 In general, HadGEM3-A represents the spatial pattern of mean near-surface temperature well, but does  
170 not reproduce the regional pattern of the trends. In summer, the model underestimates warming in  
171 southern Europe (in line with coupled models, van Oldenborgh et al, 2009; Kirtman and Power, 2013,

172 Box 11.2), and overestimates it in northern and eastern Europe (Figure 1a-b,e-f). Such trend  
173 discrepancies are not due to atmospheric internal long-term variability as they are found in most  
174 members (Figure 1f). However, when averaging over Europe, the model trend of  $0.36\pm 0.05\text{K/decade}$  is  
175 compatible with the linear trends from CRUTS3.24 ( $0.33\pm 0.08\text{K/decade}$ ), E-OBS v14.0  
176 ( $0.35\pm 0.08\text{K/decade}$ ), and CRUTEM4.5 ( $0.32\pm 0.08\text{K/decade}$ ). In the above numbers, the 95% confidence  
177 interval is provided. The histogram of the rank of the observations in the ensemble also shows an  
178 overall reliability of simulated temperatures at the continental scale (Figure 1i, see van Oldenborgh et  
179 al., 2013 for the reliability rank histograms calculations). When averaged over Northern Europe, the  
180 model slightly overestimates the positive trend in near-surface temperature ( $0.36\pm 0.05\text{K/decade}$   
181 compared to  $0.28\text{-}0.31\text{K/decade}$  in observations), and underestimates the positive trend when  
182 averaged over Southern Europe ( $0.36\pm 0.06\text{K/decade}$  compared to  $0.41\text{-}0.44\text{K/decade}$  in observations).  
183 Similar findings are obtained for the trends in daily minimal and maximal temperatures ( $T_{min}$  and  $T_{max}$ ),  
184 yearly maximum of daily maxima and minima (TXx and TNx) (not shown). Least squares linear trends,  
185 as calculated above, were taken for the period 1960-2013, and should be interpreted with a degree of  
186 caution, due to the nonlinear nature of the time series evolution (see also Figure 3).

187 HadGEM3-A also represents the spatial pattern of mean summer precipitation, and trend patterns  
188 match the observed dipole, with some discrepancies (Figure 1c-d,g-h), and a general underestimation  
189 of precipitation trend in the ensemble members (Figure 1h). Positive precipitation trends over  
190 Scandinavia and negative trends over France and Eastern Europe are found. However, the model fails  
191 to capture the observed increase in precipitation over the UK and drying over Spain, and does not  
192 simulate drying over the full longitudinal extent of the Alps, as is seen in observations. The imbalance  
193 toward systematic trend underestimation is also shown in the rank histograms when considering the  
194 whole continent (Fig. 1j). The simulated trend over southern Europe is  $-0.023\pm 0.021\text{mm/day/decade}$ ,  
195 while it is  $-0.042$  and  $-0.034\text{mm/day/decade}$  in E-OBS v14 and CRUTS3.23 respectively. In Northern  
196 Europe, trends are found in observations ( $0.052$  and  $0.046\text{ mm/day/decade}$ ) however they are not  
197 significant. HadGEM3-A also shows no significant trend here (see also van Haren et al., 2013).

198 In the winter season (Figure 2), mean states are again well simulated, but regional trend patterns are  
199 not well reproduced either. Over Scandinavia, the pattern of the near-surface temperature mean state  
200 is also well-represented by the model, but the model is too cold (Figure 2a-b). Observed temperature  
201 trends show significant warming over most of Europe at the 5% or 10% level, with the greatest warming  
202 over Scandinavia and the Baltics, but HadGEM3-A generally underestimates the magnitude and  
203 significance of the trends (Fig. 2e-f). However these trends discrepancies can be due to long-term  
204 atmospheric variability, as seen from Fig.2f and the rank histogram of Figure 2i, and no major  
205 incompatibility with the observation is found. HadGEM3-A simulates the pattern of the mean states  
206 and interannual variability in  $T_{min}$ ,  $T_{max}$ ,  $T_{NX}$ , and  $T_{Xx}$  well, but it does not reproduce the observed  
207 trends (not shown).

208 The pattern of the wintertime precipitation mean state is strongly tied to orography in both the model  
209 and observations. However, the model overestimates precipitation over the Pyrenees, Massif Central,  
210 Alps, and Greece, and underestimates it over the UK and Ireland (Figure 2c-d). Observed trends in  
211 precipitation have a strong dipole pattern, with drying in southern Europe, and increasing precipitation  
212 in the north resembling trends associated with a tendency towards positive NAO (see Deser et al.,  
213 2016). There is a hint of this pattern in the ensemble mean model trend, but the magnitude is much  
214 weaker than observed (Figure 3), and the ensemble fails to capture the main contrasts (Figure 2h and  
215 2j). Patterns in the mean state and interannual variability in extreme precipitation values are well  
216 represented in HadGEM3-A. Trends in these quantities are noisy in both the model output and  
217 observations (not shown).

## 218 **3.2 Variability**

219 In general the interannual variability is reasonably well simulated, as seen in Figure 3 from time series  
220 of individual members and superimposed observations. The model overestimates variability in  
221 seasonal mean daily mean and maximal temperatures (Figure 3), for European average, but simulates

222 the variability in daily minimal temperatures fairly well (not shown). The overestimation in daily  
223 maxima is more marked in Northern Europe than in Southern Europe.

224 In winter, HadGEM3-A reproduces the inter-annual standard deviation of near-surface temperature  
225 over Europe as a whole, but shows a larger standard deviation in Southern Europe (Figure 3), and  
226 appears to underestimate it in Northern Europe. Interannual variability in  $T_{max}$  and  $T_{min}$  is well  
227 represented by HadGEM3-A in Europe, despite underestimates in the north, as for near-surface  
228 temperature. In southern Europe, the model overestimates variability in  $T_{max}$  (not shown), but  
229 underestimates it in  $T_{min}$  (Fig. 3). Variability in TNx and TXx is underestimated in all regions (not shown;  
230 see also Section 4). Variability in seasonal precipitation amount, as well as in heavy precipitations (over  
231 10 mm or 20 mm per day) is well represented by HadGEM3-A in general in both seasons (not shown).  
232 However, it should be kept in mind that the model resolution does not allow a proper representation  
233 of convective precipitation events.

### 234 **3.3 In summary**

235 HadGEM3-A generally shows reasonable performance in reproducing the observed mean-state,  
236 variability, and trends in daily means and extremes when considering Europe as a whole. However  
237 observed regional patterns of trends are not always well reproduced. For instance, the model fails to  
238 reproduce the observed JJA and DJF drying in southern Europe. In JJA, the model also locates the  
239 maximum in near-surface temperature trends too far east, so that the amplitude of warming over  
240 southern Europe is underestimated. In winter, temperature variability is high making trends from  
241 simulations and observations almost compatible despite a general tendency for the model to  
242 underestimate warming. The model ensemble fails to reproduce positive trends in temperature  
243 extremes ( $T_{min}$ ,  $T_{max}$ , TNx, and TXx) throughout Europe, and also underestimates interannual variability  
244 in TNx and TXx in winter. The amplitude of the dipole in precipitation trends in DJF is substantially  
245 underestimated by HadGEM3-A in DJF, and to a lesser extent in JJA.

246 The correct simulation of trends in summer implies that their attribution should not be hindered by  
247 model's climatological biases in this season. For temperature this means a realistic mean response to  
248 external forcing and a potential for attributing temperature-related events. The differences in regional  
249 patterns of trends are partly due to the relatively short length of observational data sets combined with  
250 a chaotic atmosphere and weak SST dependence. It is also probably due to uncertainties in underlying  
251 processes (see Section 5). In winter the too weak warming trend may potentially lead to  
252 underestimation of likelihood reduction in winter cold spells. However, this discrepancy may also result  
253 from the large interannual and variability in winter temperatures. Some of the 15 members do show  
254 trends as observed in daily mean winter temperatures.

#### 255 **4. Extreme value analysis**

256 A specific focus is given now on extremes of temperature and precipitation. The evaluation of the  
257 model's representation of extremes was undertaken using extreme value analysis, based on annual  
258 maxima of the historical runs in precipitation (rx1day) and maximum (TXx) and minimum daily  
259 temperature (TNn) discussed above. These were fitted to a stationary generalized extreme value (GEV)  
260 distribution (Coles, 2001). The three parameters of the GEV distribution, namely the location  
261 parameter  $\mu$  (representing the mean values), scale parameter  $\sigma$  (representing the typical range of  
262 values) and shape parameter  $\xi$  (describing whether the distribution is heavy tailed or not), were  
263 evaluated alongside distributions fitted to the same extremes from E-OBS. Non-parametric  
264 bootstrapping (1000 replications) was used to estimate the uncertainty margins. Comparisons are  
265 made using the 0.5° regular grid E-OBS product, which represents the resolution closest to that of the  
266 model.

267 For extreme maximum daily temperature (TXx), the location parameter is significantly under-estimated  
268 in Northern Europe and over-estimated in much of Southern and Eastern Europe. As illustrated in  
269 Figure 4, the model exhibits warm biases in hot events across Central, Eastern and, to a lesser extent,  
270 Southern Europe, explaining the bias in the location parameter. The scale parameter is overestimated

271 somewhat across most of the continent, but underestimated in Britain, and the shape parameter is  
272 overestimated somewhat over most of Northern Europe, indicating too heavy tail potentially related  
273 to unrealistically high drying in summer in this model (see Section 5).

274 For extreme minimum daily temperature (TNn), regions of complex topography (including the Alps and  
275 the western coastline of Scandinavia) are characterized by a clear under-estimation of the location  
276 parameter. The cold bias to the south of the Alps is also apparent in the analysis of cold events in Figure  
277 4, with similar spatial features evident in multiple ensemble members. The scale parameter is  
278 reasonably well represented, but the shape parameter is much too large in Eastern Europe, where the  
279 model simulates too extreme very cold events. By contrast, the shape parameter is too small in much  
280 of Western Europe.

281 For extreme precipitation the broad coastal and topographical precipitation features are well-  
282 reproduced by the model, but both the location and scale parameters are consistently larger than those  
283 of observed extremes (Figure 5): the model generates too much rain in extremes with too much  
284 variability. This is particularly the case in Mediterranean coastal regions and immediately south of the  
285 Alps. This is the opposite of what one would intuitively expect: given the model's coarse resolution,  
286 extremes in the simulated precipitation field should typically be smaller in magnitude than those  
287 events occupying the same point of likelihood in the observed distribution.

## 288 **5. Process analysis**

289

290 **The ability of a model to simulate physical and dynamical processes leading to extremes is key for its**  
291 **capacity to simulate their changes under human activities influence.** Extreme events generally result  
292 from an ensemble of processes involving atmospheric dynamics, large-scale drivers, as well as regional  
293 to local-scale processes which interact with one another. Here, we evaluate whether the model  
294 captures the most important processes leading to extreme events. For the five types of events under  
295 study (heat and cold waves, heavy precipitation events, drought and storm surges) we examine in

296 particular the role of large-scale circulation and a few key regional-to-local scale processes, such as  
297 interaction with land surface.

298 In general, extreme weather events occur under specific types of weather patterns: heat waves,  
299 droughts and cold spells relate to long persisting anticyclones sitting over a large area. In Europe, heavy  
300 precipitation is associated either with summer convective episodes coming after a long warm period  
301 with the arrival of frontal systems with cold air aloft destabilizing the troposphere, or in long-lasting  
302 wintertime cyclonic episodes bringing in recurring storms. In each case typical atmospheric circulation  
303 patterns are found. Then, extreme events also result from amplifying processes, which may dominate  
304 in some cases, such as land-atmosphere interactions in particular in the case of heat waves and  
305 droughts (Seneviratne et al. 2010), and also cold spells through the effect of snow cover (Orsolini et al.  
306 2013). Stratosphere-troposphere interactions have also been shown to be important in the build-up of  
307 cold spells (Baldwin and Dunkerton, 1999). Here we evaluate these processes in HadGEM3-A  
308 simulations.

## 309 **5.1. Atmospheric weather patterns** 310 311

312 One way to evaluate whether the model correctly simulates the atmospheric circulation variability is  
313 through the analysis of *weather regimes*. Weather regimes are usually defined as large typical clusters  
314 of atmospheric flows that are observed. The concept of weather regimes is based on dynamical systems  
315 theory analysis of atmospheric variability: certain phase-space areas may include slow-down of  
316 trajectories, due to the vicinity of stationary solutions (Legras and Ghil, 1985), or quasi-stationary  
317 solutions (Vautard and Legras 1988). Since then, a number of studies (e.g. Michelangeli et al., 1995;  
318 Cassou et al. 2005) have characterized weather regimes using cluster analysis. Over the North-East  
319 Atlantic and Europe, such an analysis usually finds four stable clusters from observations or reanalysis  
320 of sea-level pressure or geopotential height.

321 Here, we compare clusters obtained by a *k*-means algorithm applied to the NCEP/NCAR reanalysis and  
322 the HadGEM3-A simulations carried out over the same period (1960-2013). The same North-Atlantic  
323 domain is used **both for model and observations** [-80°W-50°E, 22.5°N-70°N]. A separate analysis is  
324 done for winter (DJF) and summer (JJA) seasons using sea-level pressure fields.

325 The centroids of the obtained clusters for the NCEP/NCAR reanalysis and the HadGEM3-A model 15  
326 member ensemble, are shown for winter in Figure 6a-h and for summer in figure 6i-p. The HadGEM3-  
327 A model weather regimes centroids are quite similar to the observed ones with slight shifts. For  
328 instance, the “blocking” (BLO) regime is well represented in winter and summer but the “Atlantic ridge”  
329 (AR) regime has differences that can be seen mainly in winter. However, this should not be a major  
330 issue for European extremes of temperature and rain as this latter regime is generally not associated  
331 with extremes. Cold spells are usually characterized in winter by either the negative North Atlantic  
332 oscillation (NAO-) regime, as was the case for the winter of 2009-2010 (Cattiaux et al., 2010), or by the  
333 BLO regime. **Mild** winters with persistent rainfalls over Western Europe are characterized by the “Zonal  
334 flow” (ZO) regime as shown by Schaller et al. (2016).

335 Another important aspect for extremes is the frequency of occurrence of regimes. One expects that to  
336 correctly simulate the statistics of extreme events, a model must simulate correct frequencies in the  
337 weather regimes. **In order to compare similar clusters statistics, we used the NCEP/NCAR cluster**  
338 **centroids SLP anomalies as reference and counted the number of SLP fields for which each centroid is**  
339 **nearest, both for NCEP/NCAR and HadGEM3-A fields for a best comparison. HadGEM3-A weather**  
340 **regime frequencies are well represented with respect to ones in NCEP/NCAR. BLO and NAO- regimes**  
341 **are well represented** in both seasons while ZO (winter) and AL (summer) have slight differences to  
342 NCEP/NCAR (lower and higher frequencies of occurrence respectively).

343 Table 2 shows the frequencies of nearest neighbors calculated in this way. It is quite remarkable how  
344 well the frequencies match between observations and the model. We conclude that the HadGEM3-A



345 model simulates quite well the main weather patterns of the North East Atlantic with mean frequencies  
346 that reproduce faithfully the observations.

## 347 **5.2. Atmospheric circulations associated with hot and cold events**

348  
349 The previous analysis was made for weather patterns independently of extreme events. We now turn  
350 to the evaluation of the capability of HadGEM3-A in representing the specific weather patterns  
351 associated with hot and cold events in Central Europe (defined here as the average over 2°-15°E and  
352 47°N-54°N). This analysis builds on Krueger et al. (2015) and is based on a composite analysis of  
353 temperatures and circulation states (characterized by the geopotential heights at 500 hPa) for hot and  
354 cold events. We show here results for hot extremes and cold events are shown in the supplement. The  
355 temperature data was deseasonalized (using a 10-day filter for calculating the climatology); prior to  
356 detecting hot and cold extremes the linear long-term trends over the analysis period were removed  
357 from each gridpoint.

358 Hot and cold events with a time scale of five days were obtained as consecutive values above the 95<sup>th</sup>  
359 and below the 5<sup>th</sup> daily temperature percentile for summer (JJA) and winter (DJF), respectively. These  
360 moderate extremes should occur under broadly similar circulation conditions to stronger extremes, but  
361 are well sampled (Krueger et al., 2015) and have been found useful (Alexander, 2016). Composites of  
362 all such events were calculated for the 1960-2013 period which yields 143 heat waves and 137 cold  
363 spells from the 20CR v2c in comparison to a range of 149-154 hot spells and 147-150 cold spells for the  
364 model ensemble, respectively (note that the reanalysis shows slightly, but significantly, fewer hot and  
365 cold spells). The associated circulation patterns are calculated as the composites of the 500 hPa  
366 geopotential height found for each occurrence of a cold- or hot temperature event, following Krueger  
367 et al. (2015). In contrast to Krueger et al. (2015), the composite analysis was performed for land-only  
368 temperatures. The analysis for the model was performed for each of the 15 ensemble members  
369 separately, with resulting composites then averaged to provide an ensemble mean value.

370 Figure 7 shows the temperature composites of hot events, and Figure 8 the circulation associated with  
371 it. The differences between circulation composites are relatively large in both summer and winter even  
372 though these are aggregated over events occurring over 54 years in each case. Larger differences  
373 between the ensemble members are found for summer. For the circulation associated with extreme  
374 hot events, there is high variability across the ensemble members while for the ensemble mean the  
375 geopotential pattern resembles a classic omega blocking in 20CR with the eastern, negative center of  
376 the blocking suppressed or moved in the average circulation of HadGEM3-A. The location of low  
377 pressure anomalies and their magnitude varies across ensemble members for this 54 year average. The  
378 spatial extent and intensity of heat waves varies across ensemble members consistent with the subtle  
379 variations in circulation (for example, compare middle of the second to bottom left panel for figures 7  
380 and 8). The observations lie within that large variability.

381 Results for cold events are similar (Supplementary Figure 1 and 2), with a strong pressure gradient  
382 between a high and low in NW and SE Europe, respectively, causing cold spells, whose average intensity  
383 and extent varies depending on the tilt of the pressure gradient, again exemplifying the important role  
384 of atmospheric variability even on the long timescales averaged across here.

### 385 **5.3 Land-atmosphere interactions**

386

387 Land-atmosphere interactions are major processes in the development of many extremes and must  
388 therefore be well represented in view of attribution studies. This is particularly important for heat  
389 waves, which are expected to become more frequent with greenhouse gases increase (Seneviratne et  
390 al. 2012), with potential severe impacts on society and economy (Rosenzweig et al. 2001, Corti et al.  
391 2009, Blauhut et al. 2015, Zhao et al., 2016). The uncertainty of projections of future temperatures and  
392 associated hot extremes is especially large in regions where a shift of the evapotranspiration regime is  
393 expected, i.e. where evapotranspiration is radiation-limited in today's climate but will become soil-  
394 moisture-limited in future climate. This is due to a large uncertainty in the representation of the land-  
395 atmosphere coupling across state-of-the-art Earth System Models (ESMs) in present and future climate

396 (Seneviratne et al. 2016), and resulting fluxes (Stegehuis et al., 2013). This problem needs to be  
397 addressed by validating and evaluating the involved modelled processes in present climate conditions  
398 against observations. Thanks to recent advances in the development of reference datasets for land key  
399 variables such as soil moisture (Orth and Seneviratne 2015) and evapotranspiration (Mueller et al.  
400 2013), a comprehensive evaluation of the modelled land-atmosphere coupling became feasible.

401 We assess and evaluate the land-atmosphere coupling in the HadGEM3-A model in Europe by  
402 considering all parts of the overall coupling separately (see Figure 9 of Seneviratne et al. 2010). In  
403 particular we focus on (i) the coupling between soil moisture and evapotranspiration, (ii) the coupling  
404 between evapotranspiration and temperature (extremes), and (iii) the (resulting) coupling between  
405 precipitation and temperature (extremes). In terms of temperature we will focus on monthly mean  
406 temperature, and to represent hot extremes we use TXx.

407 The relationship between the variables involved in each part modelled by HadGEM3-A is compared  
408 with the corresponding observed interplay using state-of-the-art reference datasets of the  
409 corresponding variables (Table 1). Here we focus on the time period 1960-2013, however, due to  
410 limited availability of the reference datasets, the evaluation of evapotranspiration-related couplings is  
411 constrained to 1989-2005, and the evaluation of soil moisture-related couplings is restricted to 1984-  
412 2013. Note furthermore the different spatial resolutions between the employed reference datasets  
413 (see Table 1), and of the HadGEM3-A output data. Model output has been masked whenever the  
414 reference data was not available to ensure the same spatial and temporal basis of the analyses.

415 In order to focus on the highest coupling strengths, we perform all computations with monthly data  
416 using only the hottest month of each year. In the case of soil moisture and precipitation we use the  
417 previous month to capture their influence on subsequent temperature or evapotranspiration. For the  
418 estimation of the considered coupling strengths we consider 3 European subregions, (i) Northern  
419 Europe (NEU), (ii) Central Europe (CEU), and (iii) the Mediterranean (MED) as defined in Seneviratne et  
420 al. (2012). For the Mediterranean region, however, we focus on latitudes between 35°N-45°N instead

421 of 30°N-45°N as in Seneviratne et al (2012) due to limited spatial availability of the reference datasets  
422 (region hence denoted as MED\*). Coupling strengths are expressed as monthly correlations.  
423 Furthermore, we compare modelled versus reference distributions of the considered variables in the  
424 considered months.

425 **Soil moisture - Evapotranspiration Coupling:** The HadGEM3-A coupling between preceding soil  
426 moisture and evapotranspiration in the hottest month is compared with reference data in Figure 9.  
427 Apart from the apparent bias in evapotranspiration in NEU and CEU, HadGEM3-A captures the  
428 observed coupling well. Overall strength and the spatial pattern of the correlation between soil  
429 moisture and evapotranspiration are also well represented. With few exceptions the HadGEM3-A  
430 ensemble captures the observed coupling strength in all European regions. Only over the Iberian  
431 Peninsula (underestimation) and in Ireland (no coupling) the model results do not agree with the  
432 correlations across the reference datasets. Note the large spread of correlations between the individual  
433 ensemble members suggesting strong variability of the modelled coupling.

434 **Evapotranspiration - Temperature Coupling:** The HadGEM3-A coupling between evapotranspiration  
435 and temperature in the hottest month is compared with reference data in Figures 10 and 11. While the  
436 overall strength and the north-south gradient in the correlation are represented in the model, its  
437 simulated spatial coupling pattern agrees only partially with the reference datasets. The transition zone  
438 with zero coupling strength between the positive coupling in NEU and the negative coupling in MED\*  
439 is too wide in the model, and it is shifted northward as compared to the reference datasets. This  
440 contributes to the overestimation of hot temperature extremes by the HadGEM3-A model found in  
441 Section 4. The underestimation of the evapotranspiration-temperature coupling between 50°N-65N°  
442 also explains why the observed correlation is not contained in the HadGEM3-A ensemble in large parts  
443 of this region. This occurs even though the spread of correlations between the ensemble members of  
444 HadGEM3-A is large, as for the previous coupling (Figure 9 of Seneviratne et al., 2010). Results also  
445 show a Northward extension of coupling region, potentially creating too warm hot periods, in

446 agreement with the extreme value analysis of Section 4. We find comparable results for mean and  
447 extreme temperatures indicating almost no change of this coupling in heat waves.

448 We find a large spread of coupling strengths between the ensemble member simulations (not shown)  
449 indicating large variability of the coupling. It remains unclear if this is a model-specific feature. This  
450 could be tested by comparing the temporal variability of the coupling strength in the reference data  
451 and in the model output using temporal subsets of the available data. However, this is beyond the  
452 scope of this article. We note, however, that this variability could help to explain the offset in the spatial  
453 patterns of coupling strengths between the reference datasets and the model.

454 **Spring preconditioning of heat waves:** We next investigate to what extent spring preconditioning of  
455 soil matters for individual heat wave metrics (see e.g. Vautard et al., 2007; Hirschi et al., 2011). A metric  
456 of European heat waves that targets impacts is used, based on maximum and minimum temperatures  
457 exceeding the 90<sup>th</sup> percentile threshold for at least 3 days and 2 nights (Pezza et al., 2012; Cowan et al.  
458 2017). This approach should be considered analogous to approaches using Excess Heat Factor (e.g.  
459 Perkins et al., 2012) or hottest daily maximum temperature of the year (Hauser et al., 2016) and hence  
460 relates to the index considered above. We tested the sensitivity of summer heat waves to preceding  
461 wet and dry springs for different European sub-regions in E-OBS v14.0, and whether the HadGEM3-A  
462 can capture this sensitivity. Heat wave composites were calculated over summers following the top  
463 20% driest and wettest springs (i.e. for E-OBS this is equivalent to the 14 driest and 14 wettest springs,  
464 for HadGEM3-A this corresponds to the 11 driest and 11 wettest springs per ensemble member) based  
465 on 3-month Standardized Precipitation Index (SPI; McKee et al., 1993) for spring ending in May,  
466 averaged over each region of interest (bounded regions in Figure 12). A non-parametric two-sample  
467 Wilcoxon sign-ranked test (Hollander and Wolfe, 1999) was used in order to determine if the summer  
468 heat wave metrics are distinguishably different between dry and wet spring cases at the 95%  
469 confidence level (e.g. Cowan et al., 2017).

470 Figure 12 shows the composite patterns following the wet and dry springs for the heat wave duration  
471 (HWD), which describes the longest seasonal heat wave. The model composites are based on 11 springs  
472 each from the 15 historical ensemble members (165 springs in total). The patterns from E-OBS show  
473 that dry springs across southern Europe are systemically followed by longer summer heat waves  
474 compared to wet springs (Figure 12, left panels), with many Mediterranean regions exceeding 5.5 days  
475 on average. This is consistent with the results for coupling strength shown above (Figure 10). Further  
476 north into central and eastern continental Europe, this observed tendency becomes much weaker and  
477 less significant. Across southern England and northern France, despite the lack of significance there is  
478 a small increase in HWD following dry springs compared to wet springs. For western Scandinavia, longer  
479 summer heat waves tend to emerge following wetter springs, consistent with a positive  
480 evapotranspiration temperature coupling, which suggests that antecedent soil moisture conditions,  
481 based on the SPI, are not a significant predictor of summer-time heat wave activity.

482 In general, HadGEM3-A shows a smaller effect of dry springs on HWDs across the western  
483 Mediterranean, however, it captures the significant differences compared to the wet spring composites  
484 (Figure 12; right panels). The model also appears to overestimate the dry-spring HWDs over the far  
485 eastern Mediterranean including Romania. Further north, the model simulates a much weaker spring  
486 SPI - summer HWD relationship, with strong positive biases over most of Scandinavia (compared to E-  
487 OBS). Across southeastern England and northern France, the model suggests that spring drying has  
488 significant control over heat wave activity (also seen in the simulated heat wave amplitude; not shown);  
489 this signal is more pronounced in the model if upper layer soil moisture is used instead of the SPI (not  
490 shown). Despite model biases, the patterns across southern Europe imply that dry springs and winters  
491 do exert a strong influence on summer heat wave activity, confirming earlier observational studies  
492 (Quesada et al., 2012, Vautard et al., 2007) and consistent with results for coupling strength shown  
493 above (Figure 10). For central Europe, Scandinavia and the Baltic states, there is only a weak association  
494 to spring conditions in both model and observations, although the model captures the strong spring  
495 pre-conditioning across Eastern Europe. This is in agreement with a northward shift of the negative

496 coupling region as found above (Figure 10), and as such, the model appears to have a stronger response  
497 to dry spring anomalies in Eastern Europe compared with observations. The results for both E-OBS and  
498 HadGEM3-A are affected by sampling uncertainty, particularly for observations, and the fact that the  
499 SPI is averaged over large domains with many different climates; thus care must be taken in interpreting  
500 the spring-summer coupling. Furthermore, the SPI may not fully represent variations in the simulated  
501 upper soil moisture over northern latitudes (e.g. Scandinavia), given low correlations ( $\sim 0.1$ ) in the  
502 model, compared to 0.93 over western Mediterranean.

## 503 **5.4 Stratosphere-troposphere interactions**

504

505 A key process in cold spells development is the interaction between stratosphere and troposphere,  
506 which must also be well represented in view of cold spell events attribution. In the extra-tropical NH  
507 winter there is a tendency for anomalies to propagate from the stratosphere to the troposphere where  
508 they disturb the NAO and the weather related to this dominating mode of variability. In particular, weak  
509 stratospheric vortex events are followed by an increased probability of cold temperatures and cold  
510 extremes in Europe. Although this coupling between the stratosphere and the troposphere on intra-  
511 seasonal time-scales has been known for more than a decade (Baldwin and Dunkerton, 1999;  
512 Christiansen, 2001) there still remain unanswered questions about how to represent the stratospheric  
513 variability in order to optimally catch the coupling. Here, we evaluate the HadGEM3-A model's ability  
514 to reproduce the observed connection between the stratosphere and the troposphere.

515 The downward propagation from the stratosphere to the troposphere can be demonstrated by lagged  
516 correlations between zonal mean wind at 60°N, 10 hPa (a measure of the stratospheric vortex) and the  
517 zonal mean wind at other vertical levels at 60°N.

518 Unfortunately, only monthly averaged stratospheric model data have been saved in the model  
519 experiments while daily should be used. To partly overcome this we have interpolated the monthly  
520 averages to daily values. To evaluate the soundness of this approach we compare them with  
521 observations sub-sampled to monthly values and then interpolated back to daily values. In daily

522 observations the downward propagation is clearly seen with maximum correlations at the surface  
523 lagging those in the stratosphere with about 2 weeks. In the model there is a similar connection  
524 between the stratosphere and the troposphere but it appears less lagged. This is at least partly due to  
525 the smoothing effect of dealing with monthly data (as seen in the top left panel of Fig. 13).

526 The fact that the stratosphere is leading the troposphere also in the model is more clearly seen in Fig.  
527 13 which shows the correlations between the stratospheric vortex (zonal mean wind at 60°N 10 hPa)  
528 and the NAO. The effect of a weak NAO on European temperatures are well known (Hurrell et al., 2003),  
529 thus Figure 14d shows the model skill to simulate a key connection between stratosphere and the  
530 circulation pattern present during cold spells occurrences.

531 Finally, Figure 14 shows the correlation between the anomaly of the stratospheric vortex, defined as  
532 above, and surface temperatures, for observations and five model ensemble members. For the  
533 observations we find a pattern that is consistent with the impact of the NAO: positive correlations in  
534 the middle and Northern Europe and negative correlations in Southern Europe (although these  
535 correlations are not statistically significant). For the model we find that the ensemble members agree  
536 on the general pattern, as revealed by ensemble mean correlations although there are considerable  
537 differences between ensemble members.

## 538 **5.5 Processes involved in storm surges**

539

540 Storm surges can occur in numerous places in Europe and driving processes are essentially the  
541 interaction between winds, low pressure systems, seas dynamics, and waves. It would be a tremendous  
542 task, well beyond the scope of this article, to assess the model's capacity to simulate weather  
543 conditions conducive to storm surges everywhere in Europe. Only a case study is developed here as an  
544 example, in the Baltic sea, a region that is known for witnessing severe surges due to the geometry of  
545 the sea and weather conditions. These occur in particular when strong winds develop after the passage  
546 of cyclones over the Baltic Sea, potentially inducing extreme variations in sea level resulting in storm



547 surges e.g. along the German Coast in the southwestern Baltic Sea region (Sztobryn et al., 2005;  
548 Hünicke et al., 2015). During strong onshore winds, the sea level rises due to wind set-up.

549 In this section we assess the ability of using HadGEM3-A as atmospheric forcing data to drive the  
550 regional ocean model TRIM-NP (Kapitza, 2008) for calculating water level of the Baltic Sea in 12.8km  
551 spatial resolution. Results are summarized here as a parallel study assesses the attribution of these  
552 events to climate change (Klehmet et al., 2017, in preparation). Dynamical downscaling of HadGEM3-  
553 A data has been done with 7 ensemble members only (due to computing costs) for 1971-2010. To  
554 obtain a gridded reference data for the evaluation, one model reconstruction of water level of TRIM-  
555 NP has been performed using the CoastDat2 data (Geyer, 2014) as atmospheric forcing. CoastDat2 is a  
556 regional atmospheric hindcast simulation for the European continent for 1948 to 2012 obtained with  
557 the regional climate model COSMO-CLM (Rockel et al., 2008) using the global reanalysis data of NCEP-  
558 R1 (Kalnay et al., 1996; Kistler et al., 2001) as forcing data. We then first directly compare the outputs  
559 of HadGEM3A-TRIM-data with those of CoastDat-TRIM.

560 Maximal November water level anomalies for selected grid boxes representing locations co-located to  
561 cities along the German coast (here : Warnemünde, Travemünde) for 1971-2010 relative to the 1971-  
562 2010 mean of the HadGEM3A-TRIM-data underestimate extreme water levels as compared with  
563 CoastDat-TRIM (Figure 15). The high water levels of both storm surge events in 1995 and 2006 shown  
564 by CoastDat-TRIM, used as reference data, are not found in the time series of historical HadGEM3A-  
565 TRIM ensemble simulations that represent actual climate with anthropogenic forcing.

566 However, extreme winds in the area are properly reproduced by the model. We compared the  
567 simulated distribution of three simple wind indicators with ERA-Interim surface winds: the wind speed  
568 itself, the wind speed conditional on winds in the North-East Quadrant, and the North-Easterly  
569 component of the daily wind field calculated as  $NEW = -U - V$ , U and V being respectively the zonal and  
570 meridional wind components. All indices were averaged over the area (10°E-18°E; 54°N-56°N), which  
571 encompasses the South-Western Baltic Sea. Distributions are fairly well represented as shown in Figure

572 16, despite a minor wind underestimation by HadGEM3-A relative to ERA-Interim. This  
573 underestimation is quite homogeneous irrespective of the wind speed, and reaches about 6% in the  
574 extreme values, but cannot explain the too low water levels of storm surges in Figure 15. However,  
575 ERA-Interim winds may themselves have biases and one should be prudent in the interpretation of  
576 these results. Comparisons with winds over sea remains difficult as observation data are largely  
577 missing. Therefore, at least for this Baltic Sea, we could not find any major HadGEM3-A simulation bias  
578 hindering the attribution of storm surges.

## 579 **6. Conclusion and discussion**

580

581 In view of attribution of change of likelihood of extreme events to human activity, we have presented  
582 a number of comparisons between an ensemble of 15 atmospheric simulations from the HadGEM3-A  
583 model and various observations over Europe. We have presented an analysis of model mean and  
584 extreme statistics, and an assessment of its capacity to simulate key processes involved in a few  
585 extreme events development. Results presented here show that HadGEM3-A simulates the  
586 atmospheric mean, variability and extremes in Europe fairly realistically. As for any climate model,  
587 some biases are found but (i) the major regional patterns of the climatology of the main variables is  
588 well simulated and (ii) dynamical weather patterns are faithfully simulated by the model. This provides  
589 confidence in use for attribution. Concerning extreme values, too strong heat extremes and heavy  
590 precipitation are found, but the parameters of distributions do not exhibit qualitatively different  
591 behavior than in observations. However, simulations do not well capture the observed patterns and  
592 amplitudes of trends in temperature and precipitation, which is partly due to a trend in circulation that  
593 is different from the observed one and from other climate models. While for temperature our trend  
594 analysis shows that these discrepancies can be due to internal atmospheric variability (especially in  
595 winter), precipitation trends have slight, but systematic, biases across the ensemble, which remain  
596 unexplained.

597 We then have examined some key atmospheric processes but found no major deficiencies. The  
598 variability of circulation types is well simulated, both in terms of spatial patterns and occurrence  
599 frequencies. Physical processes behind these statistics consistently demonstrate the ability of the  
600 model to simulate extreme events. Here are the main consequences that could be drawn for each of  
601 the five types of extremes that we considered in this study.

## 602 **Heat Waves**

603 Simulated weather patterns associated with hot events compare favorably with those shown in the  
604 reanalysis, however, with significant internal variability in the representation of events between model  
605 ensemble members. However, heat build-up is also amplified by land-atmosphere feedbacks. We  
606 found that HadGEM3-A captures land-atmosphere interactions in present-day climate reasonably well.  
607 We assessed the different parts of this coupling and find that especially the soil moisture-  
608 evapotranspiration coupling is well represented, while the evapotranspiration-temperature coupling is  
609 underestimated in regions between 50°N-65N°. The overall coupling is investigated by correlating  
610 preceding precipitation with temperature in the hottest month where the correlations of the model  
611 output and between the reference datasets are similar, but the spatial patterns are not entirely  
612 captured. Consistently, observed heat wave metrics following wet springs are significantly different  
613 from those following dry springs, particularly in Southern Europe and this process is reasonably well  
614 captured in the model.

615 Too strong drying is taking place in the model with exaggerated evapotranspiration, in central and  
616 northern Europe in the hottest month, a probable reason for too many and strong heat waves.  
617 Simulated summer temperatures actually exhibit a too large interannual variability in these regions.  
618 Whether all these phenomena are linked remains to be confirmed with further analyses, however, our  
619 results are suggestive of a bias towards a too fast transition towards a soil-moisture limited regime in  
620 Central/ Northern areas as found in many other models (Fischer et al., 2012, Bellprat et al., 2014). This  
621 may explain the biases found in the shape and location parameters for hot extremes. The role of spring

622 preconditioning on heat wave metrics appears reasonably simulated, although findings are consistent  
623 with the biases discussed above.

624 The consequences for attribution of these results remain difficult to evaluate. The overestimated  
625 interannual variability, together with evapotranspiration overestimation in large parts of Europe  
626 suggests that heat waves responses to atmospheric composition changes may be too large. However,  
627 observed trends in summer temperatures themselves do not show evidence of such oversensitivity.  
628 This indicates that biases may not have a major influence on the skill of the model to simulate the  
629 overall change in odds of heat waves **or that some of the model errors compensate for current climate.**

### 630 **Droughts**

631 Droughts have not been investigated in detail. However, several remarks can be made. The above  
632 results for temperatures and evapotranspiration should in principle translate in the model simulating  
633 too strong summer droughts. In addition, interannual precipitation variability appears to be slightly  
634 overestimated in summer, potentially leading to both drier and wetter summers. However a deeper  
635 investigation is required to better understand biases of the model and whether these biases are  
636 hindering attribution of drought in Europe. It should be noted that climate models have large  
637 differences in trends in droughts in Central Europe.

### 638 **Cold spells**

639 The circulation associated with cold events in Central Europe is well captured by the model and  
640 individual model ensemble members again show long-term variations in the extent and intensity of  
641 average cold spells linked to atmospheric internal variability. Extreme value analysis of extreme cold  
642 winter temperatures show a fairly good agreement between simulated and observed values. However,  
643 the simulations are not free of biases in the frequency of cold spells. Weather regimes such as blocking  
644 or negative NAO, which usually drive cold spells in Europe, are well simulated, although their trend  
645 does not necessary match that in the model. Interactions and lagged correlations between the  
646 stratospheric vortex and tropospheric NAO and European temperatures are similar in model and

647 observations. Therefore, we did not find any major process hindering the representation of cold spells.  
648 However, the trends in circulation and temperature are not well-simulated. Due to high natural  
649 variability it cannot be assessed how this translates to trends in cold extremes.

### 650 **Extreme precipitation**

651 Extreme daily precipitation are in large parts of Europe due to convective phenomena and thus local  
652 by nature. Global climate models usually have difficulties in simulating such phenomena given their  
653 coarse spatial resolution. HadGEM3-A has a wet bias in these extremes, associated with a too-large  
654 variability, especially around the Mediterranean sea. **In this area we expect daily precipitation patterns**  
655 **to have a smaller scale than the model resolution calling for prudence in attribution interpretation from**  
656 **this model. However, it is noteworthy that** the spatial pattern of extreme precipitation distributions is  
657 quite similar to observed. **Also, despite the biases, the simulations exhibit GEV parameters that are**  
658 **quite consistent with observations, which could make the simulations** eligible for attribution of  
659 precipitation extremes once the bias has been corrected.

### 660 **Storm surges**

661 Results for storm surges indicate an underestimation of the events amplitude when a regional ocean  
662 model is driven by HadGEM3-A as compared to a regional atmospheric hindcast obtained by  
663 downscaling the NCEP-R1 reanalysis. Comparisons of simulated winds with ERA-Interim reanalysis  
664 show a good performance of the model for strong winds or strong North-Easterlies in the South-  
665 Western Baltic Sea region where storm surges occur in Northern Germany, indicating that winds in the  
666 investigated domain are actually not the main factor of underestimation. Thus HadGEM3-A model  
667 simulations can a priori be used for storm surge attribution.

668

669

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671

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887 **Figure Captions**

888

889 **Figure 1:** JJA mean near-surface temperature: (a) mean state (1960-2013) from CRUTS3.23; (b) mean  
890 state (1960-2013) from HadGEM3-A; (c) linear trends (1960-2013) from CRUTS3.23; (d) the number of  
891 HadGEM3-A ensemble members simulating a trend smaller than observed; (e) rank histogram over all  
892 land grid points counting the probability of the observations falling in each bin between the ranked  
893 simulated values. (c), (d), (g), (h), (j) are the equivalent plots for precipitation. Hatching in panels (e)  
894 and (g) indicates where trends are significant at the 10% level ( $p < 0.1$ ); cross-hatching indicates  
895 significance at the 5% level ( $p < 0.05$ ).

896 **Figure 2:** Same as Figure 1 but for the winter season (DJF).

897 **Figure 3:** Left, middle and right panels: Evolution of seasonal mean daily mean temperatures in Europe,  
898 Southern Europe and Northern Europe; First row: JJA daily mean temperatures; Second row: JJA daily  
899 max temperatures; Third row: DJF daily mean temperatures; Fourth row: daily min temperatures.

900 **Figure 4:** Three left columns: parameters of the GEV distribution fitted to observations (left panels) and  
901 the model simulations (center panels for the distribution of annual maxima in daily temperature (TXx)).  
902  $\mu$  refers to the location parameter which is related to the mean value,  $\sigma$  the scale parameter, related to  
903 the range, and  $\zeta$  the shape parameter, diagnosing if the distribution is heavy-tailed (large value of  $\zeta$ ).  
904 The differences between the parameters of the observed and simulated GEV fits are shown in the right  
905 column of panels. For  $\mu$  and  $\xi$  the difference is expressed in absolute terms;  $\sigma$  the difference is  
906 expressed as a ratio. Stippling indicates areas where the observed-simulated difference is larger than  
907 the 95% confidence intervals. Three right columns: same as left columns for the GEV distributions of  
908 the minimal temperatures Tnn.

909 **Figure 5:** As Figure 4 but for the distribution of annual maxima in daily precipitation. The fourth row of  
910 panel shows the ratio of the scale parameter  $\sigma$  and location parameter  $\mu$ , with the difference again  
911 expressed as a ratio.

912 **Figure 6:** Centroids of the four weather regimes sea-level pressure anomalies as obtained from the  
913 NCEP/NCAR re-analyses (a-d for winter, i-l for summer) and HadGEM3-A (Ensemble of 15 members, e-  
914 h for winter, m-p for summer). First column: Atlantic Ridge (AR) regime, second column: Blocking (BLO)  
915 regime, third column: Negative NAO (NAO-) regime and fourth column: Zonal (ZO) regime for winter  
916 (d, h) and Atlantic Low (AL) regime for summer (l, p).

917 **Figure 7:** JJA Composites of the standardized near-surface temperature for hot summer events over  
918 Central Europe in Had-GEM3-N216 historical forcing ensemble members 1-15 ( lines 1-3), ensemble  
919 mean (line 4, left) and and 20CR ensemble mean ( line 4, right). The composites have been derived  
920 from all cases where the area-averaged and 5-day averaged temperature over Central Europe is larger  
921 than its 95th seasonal percentile in JJA.

922 **Figure 8:** as figure 7, but showing composites of the standardized near-surface geopotential height at  
923 500mb during hot summer events from Figure 7 over Central Europe.

924 **Figure 9:** Relationship between July evapotranspiration and June soil moisture averaged across  
925 European subregions (left panels), in observations (gray) and HadGEM3-A (black). The considered time  
926 period is 1989-2005. Correlation between July evapotranspiration and June soil moisture (right panels)  
927 in observations (top) and HadGEM3-A ensemble median (middle). Bottom plot indicates whether or  
928 not HadGEM3-A ensemble captures observed coupling strength. Considered time period is 1989-2005.

929 **Figure 10:** Relationship between temperature and evapotranspiration in July averaged across European  
930 subregions, in observations (gray) and HadGEM3-A ensemble median (black). The considered time  
931 period is 1989-2005. The range of correlations across HadGEM3-A ensemble members is shown in red  
932 if the observed correlation is not contained.

933 **Figure 11:** Correlation between temperature and evapotranspiration in July in observations (top) and  
934 HadGEM3-A ensemble median (middle). Bottom plot indicates whether or not HadGEM3-A ensemble  
935 captures observed coupling strength. Considered time period is 1989-2005.

936 **Figure 12:** Composite of average duration (HWD) of the *longest* summer heat wave following the (top)  
937 20% driest, and (bottom) 20% wettest springs for (left) E-OBS (1950-2015) and for (right) fifteen  
938 HadGEM3-A historical members (1960-2013), based on Standardised Precipitation Index (SPI) averaged  
939 over each bounded region (i.e. each regions' HWD pattern is composited based on its own wet and dry  
940 spring ranking). Stippling indicates points that show a statistically significant difference at the 95% level  
941 between dry and wet spring composites, based on a two sample Wilcoxon signed-rank test (Hollander  
942 and Wolfe 1999). Significant differences are only marked on the dry-spring composite maps. HWD  
943 values for regions without heat waves are set to zero. Each composite consists of 14 and 165 springs  
944 for E-OBS and HadGEM3-A (i.e. 11 springs  $\times$  15 ensemble members), respectively.

945 **Figure 13:** Correlations of winter zonal mean zonal wind anomalies at 60N with that at 10 hPa as  
946 function of pressure and time lag. Positive lags mean that the stratosphere leads. Light and dark  
947 shading identify regions where the correlations are significantly different from zero at the 5% and 1%  
948 levels as estimated with a Monte-Carlo method that takes serial correlations into account. Top left:  
949 NCEP daily. Top right: NCEP monthly. Bottom left: A typical member from HadGEM3-A ensemble.  
950 Bottom right: correlations between the stratospheric vortex (zonal mean wind at 60 N, 10 hPa) and the  
951 NAO as function of lag (positive lags mean that the stratosphere leads). Annual cycle has been  
952 removed. Winter (DJF). NCEP (green), a typical HadGEM-3A ensemble member (blue), NCEP  
953 interpolated from monthly values (green, dashed). The NAO is calculated as the leading principal  
954 component of sea-level pressure.

955 **Figure 14:** Correlations between the stratospheric vortex and surface temperatures. Annual cycle has  
956 been removed. Winter months (DJF). Large dots indicate correlations that have been estimated to be  
957 significantly different from zero (5 % level) as estimated with a Monte-Carlo method that takes serial  
958 correlations into account. Upper left panel: Observations (E-Obs for surface temperature, NCEP for  
959 stratospheric vortex). Other panels: Different members from HadGEM-3A ensemble.

960 **Figure 15.** November anomalies of maximum water level [m] for 1971-2010 based on reconstructed  
961 model data (Coastdat-TRIM) and historical HadGEM3-A-TRIM (hist) ensemble members 1-7. Selected  
962 grid boxes represent locations co-located with German cities of Travemünde (left) and Warnemünde  
963 (right).

964 **Figure 16:** Quantile-quantile plots of the distributions of the three ERA-Interim vs. HadGEM3-A derived  
965 indices of wind in the South-West Baltic sea (see main text for definitions of the indicators). All wind  
966 values or wind speeds are expressed as  $\text{ms}^{-1}$ .

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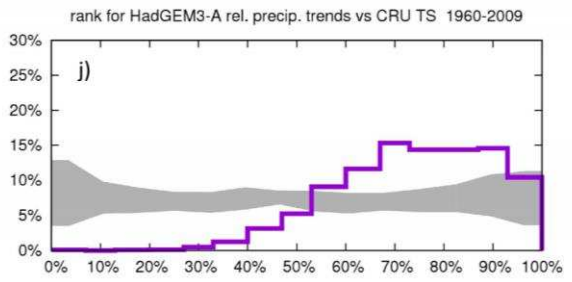
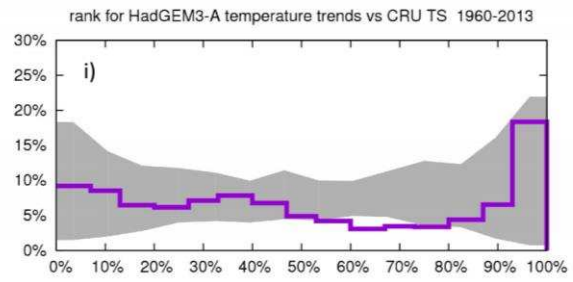
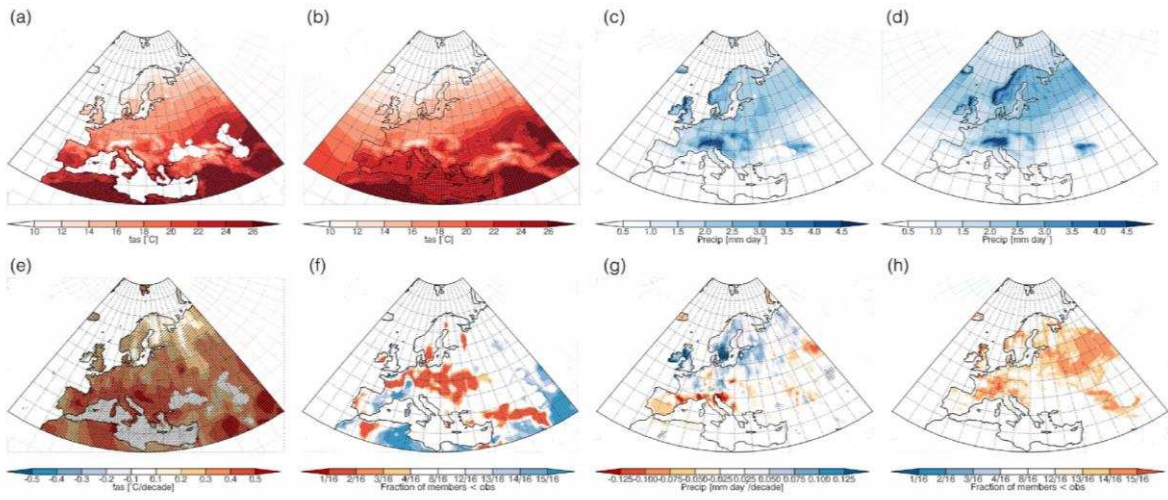
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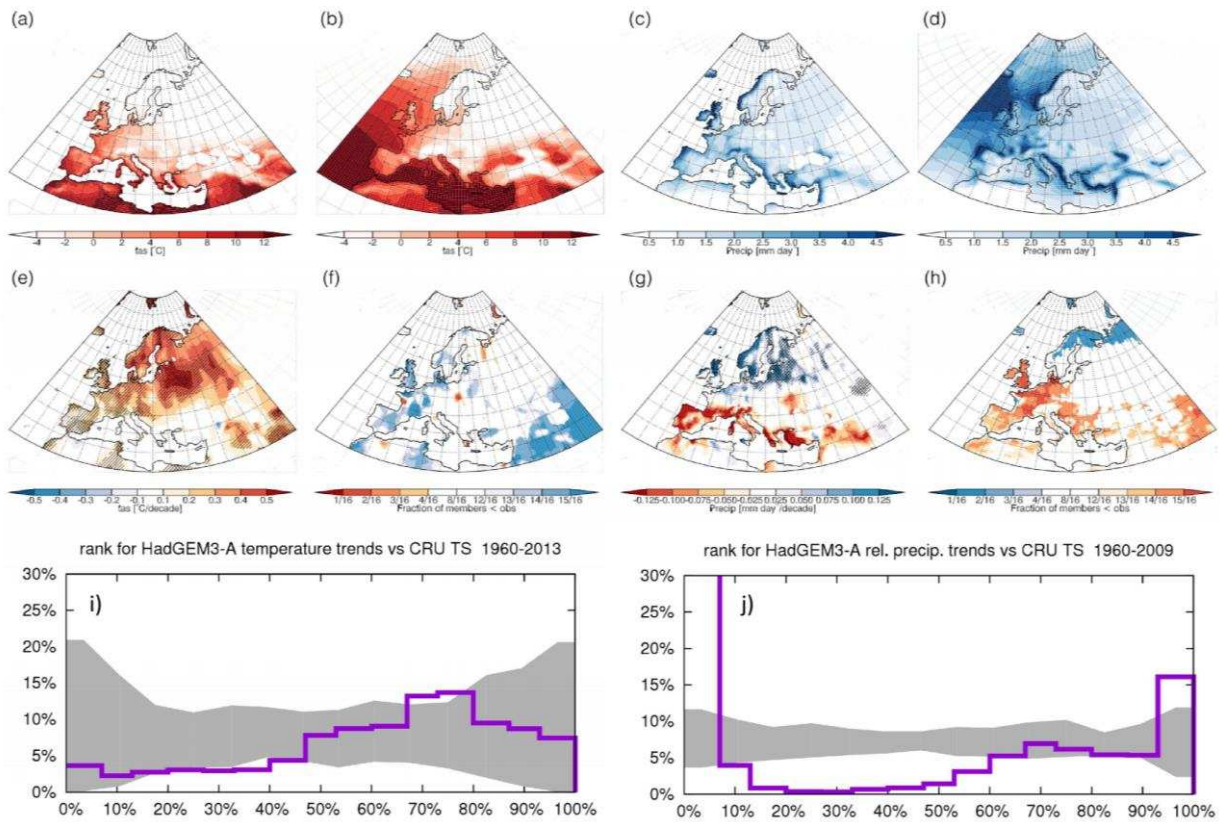
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Figure 1



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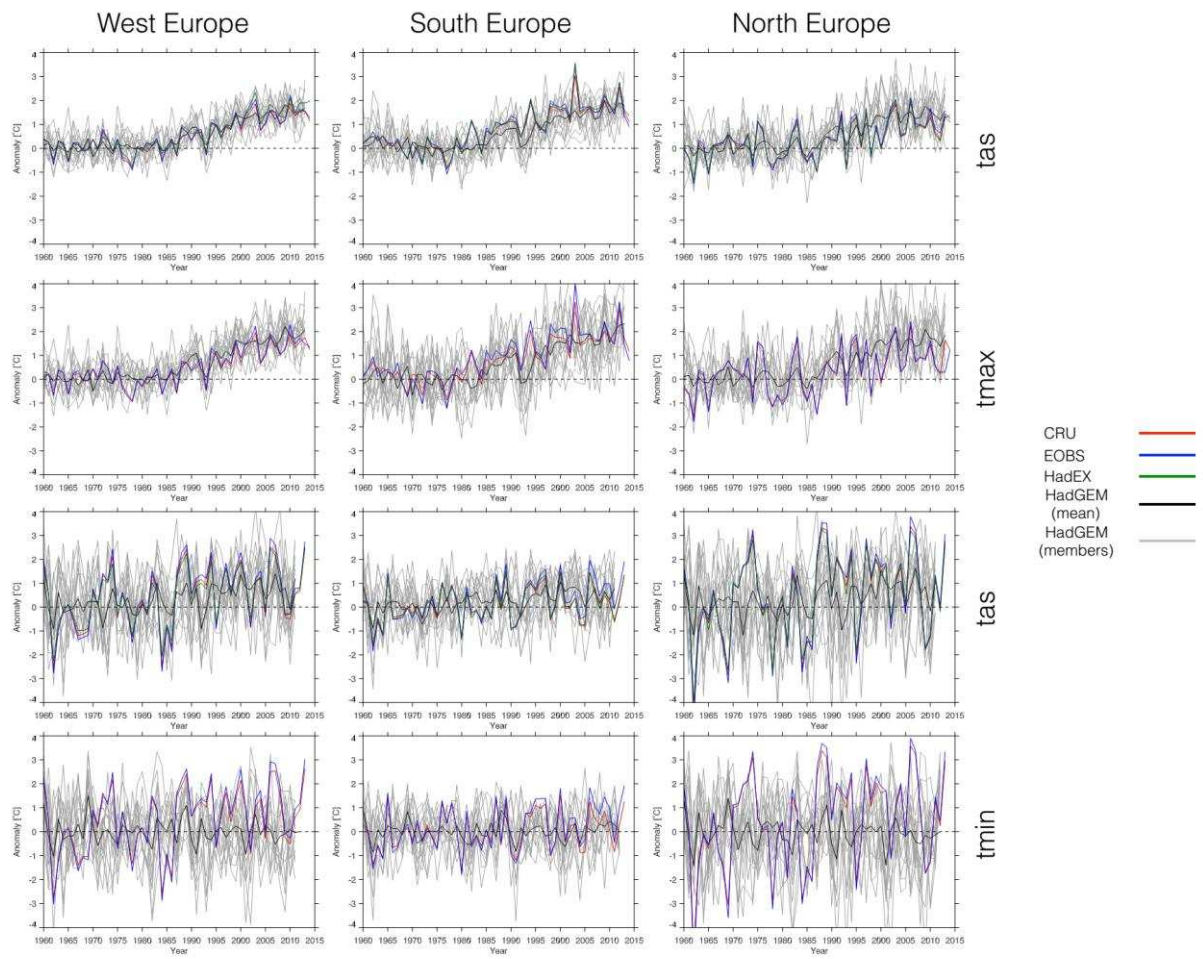
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983 Figure 2

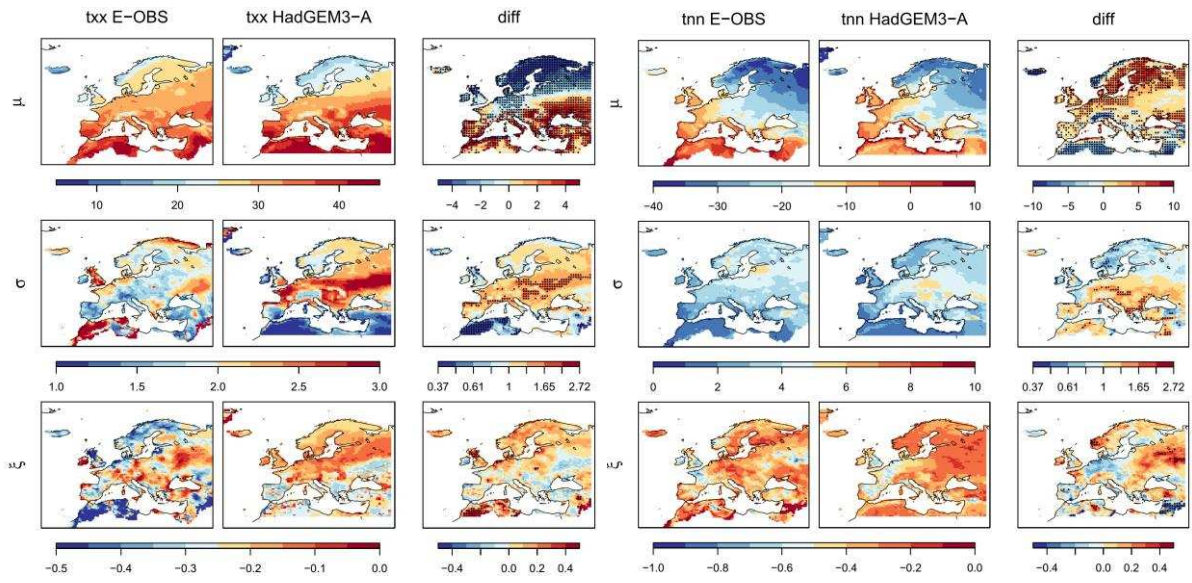


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986 Figure3

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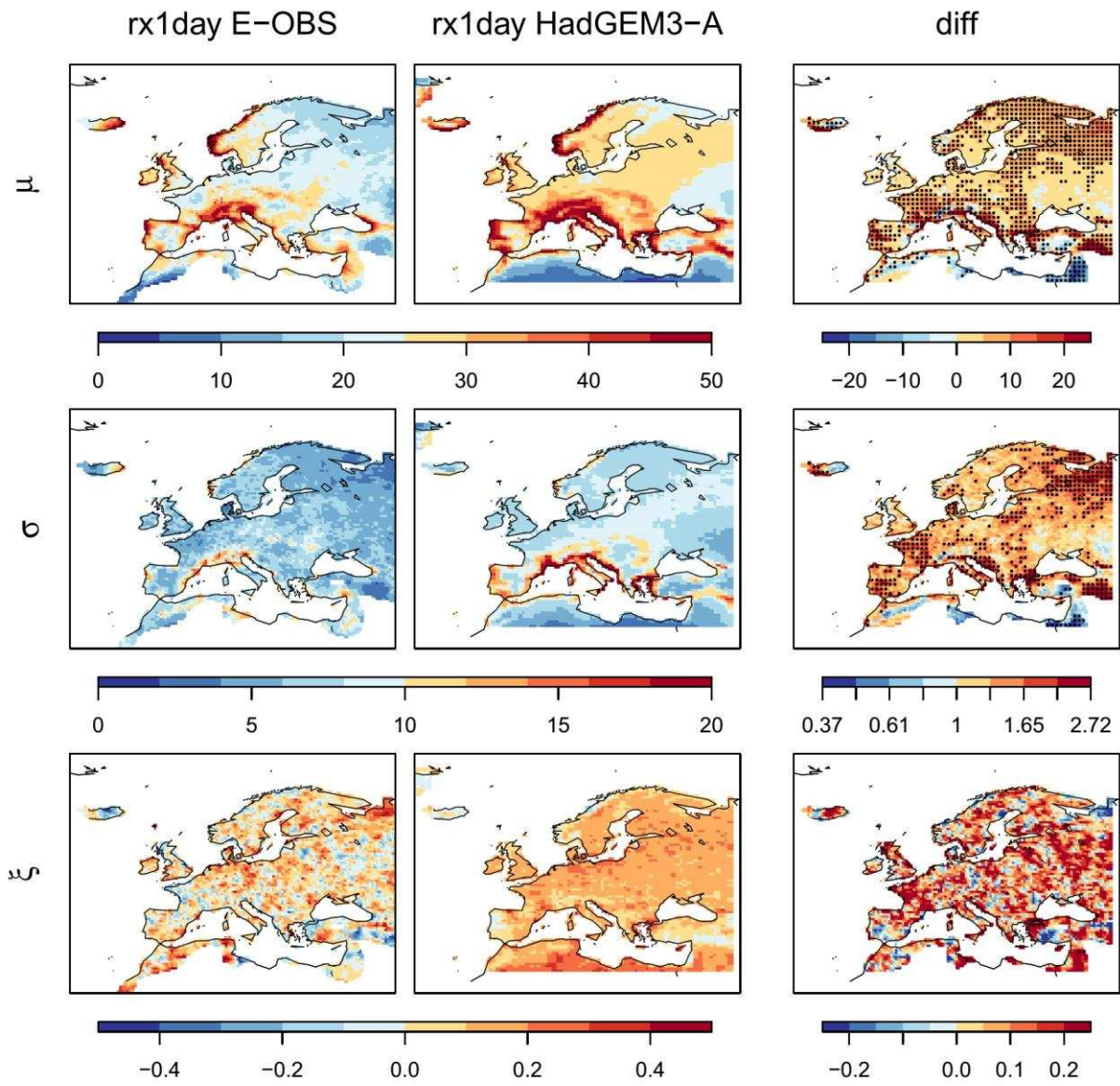
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991 Figure 4

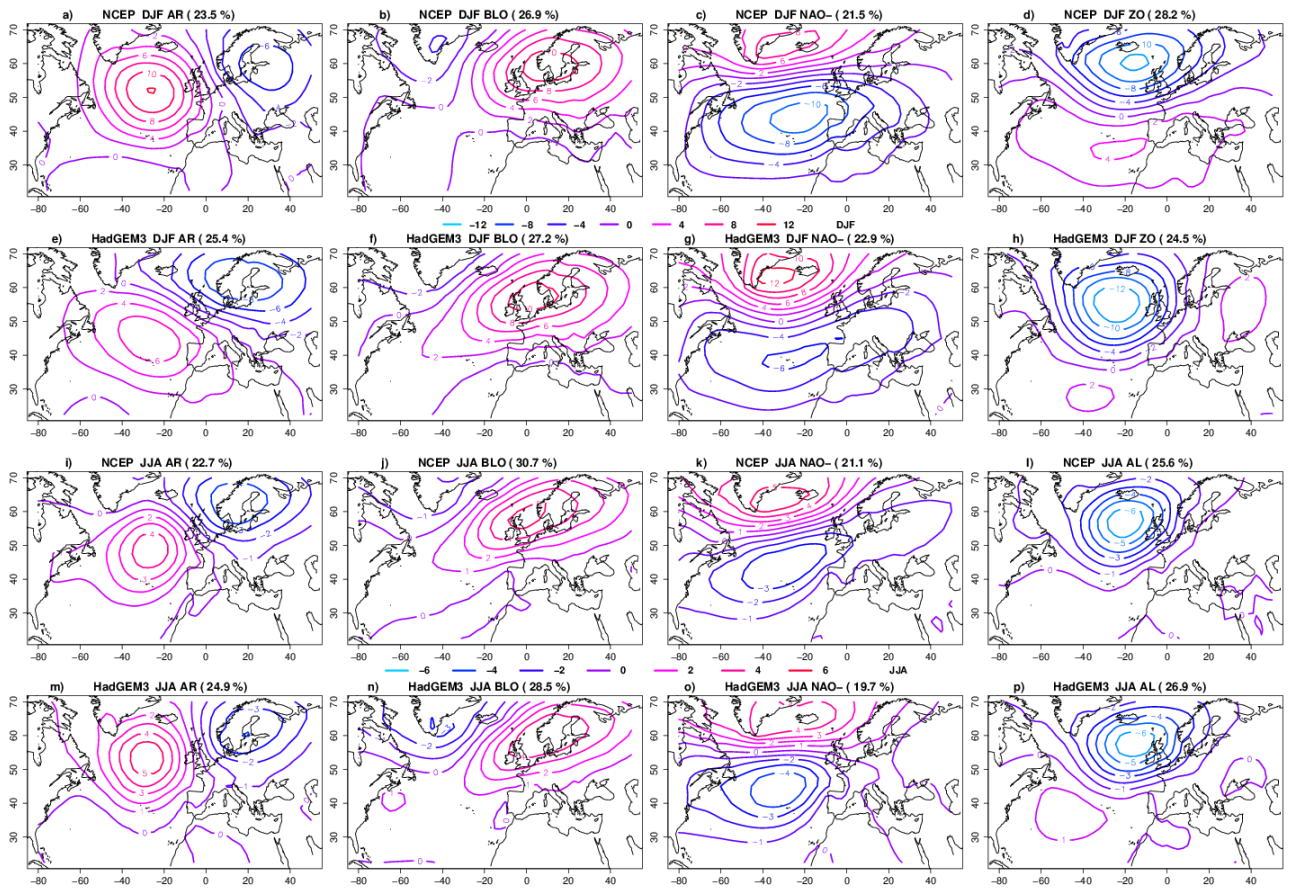
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994 Figure 5

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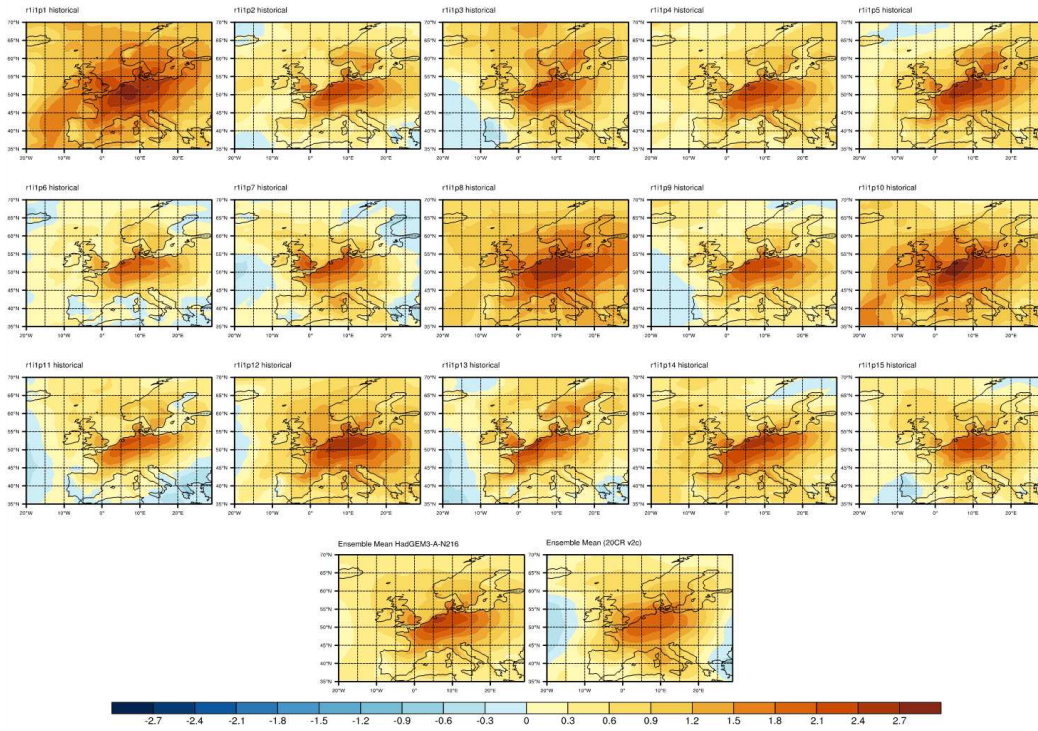


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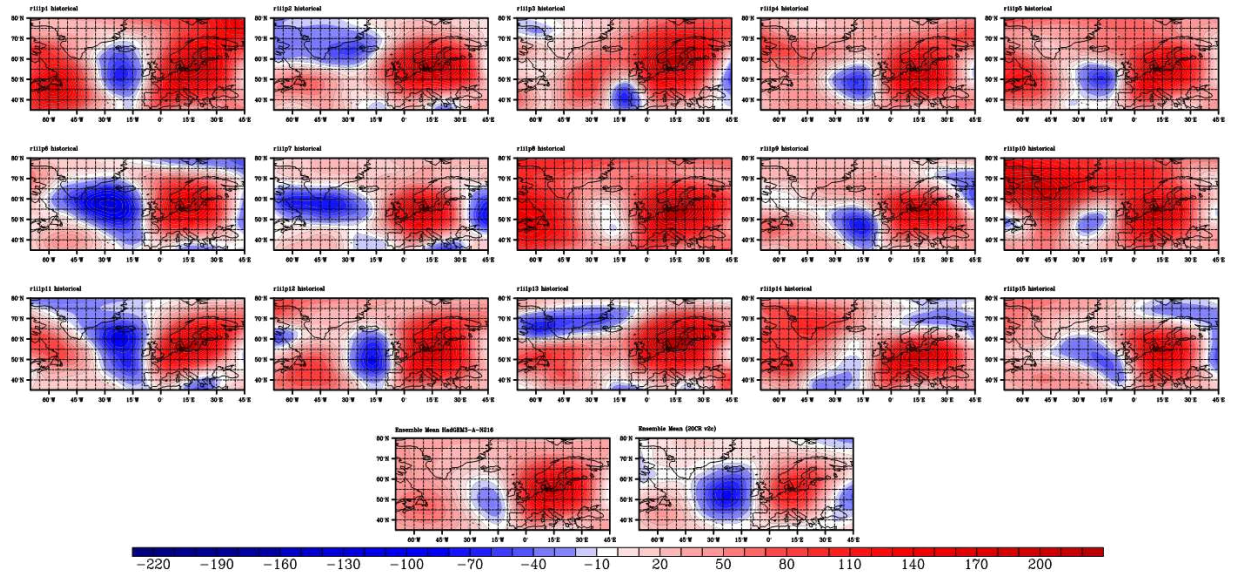
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999 Figure 6



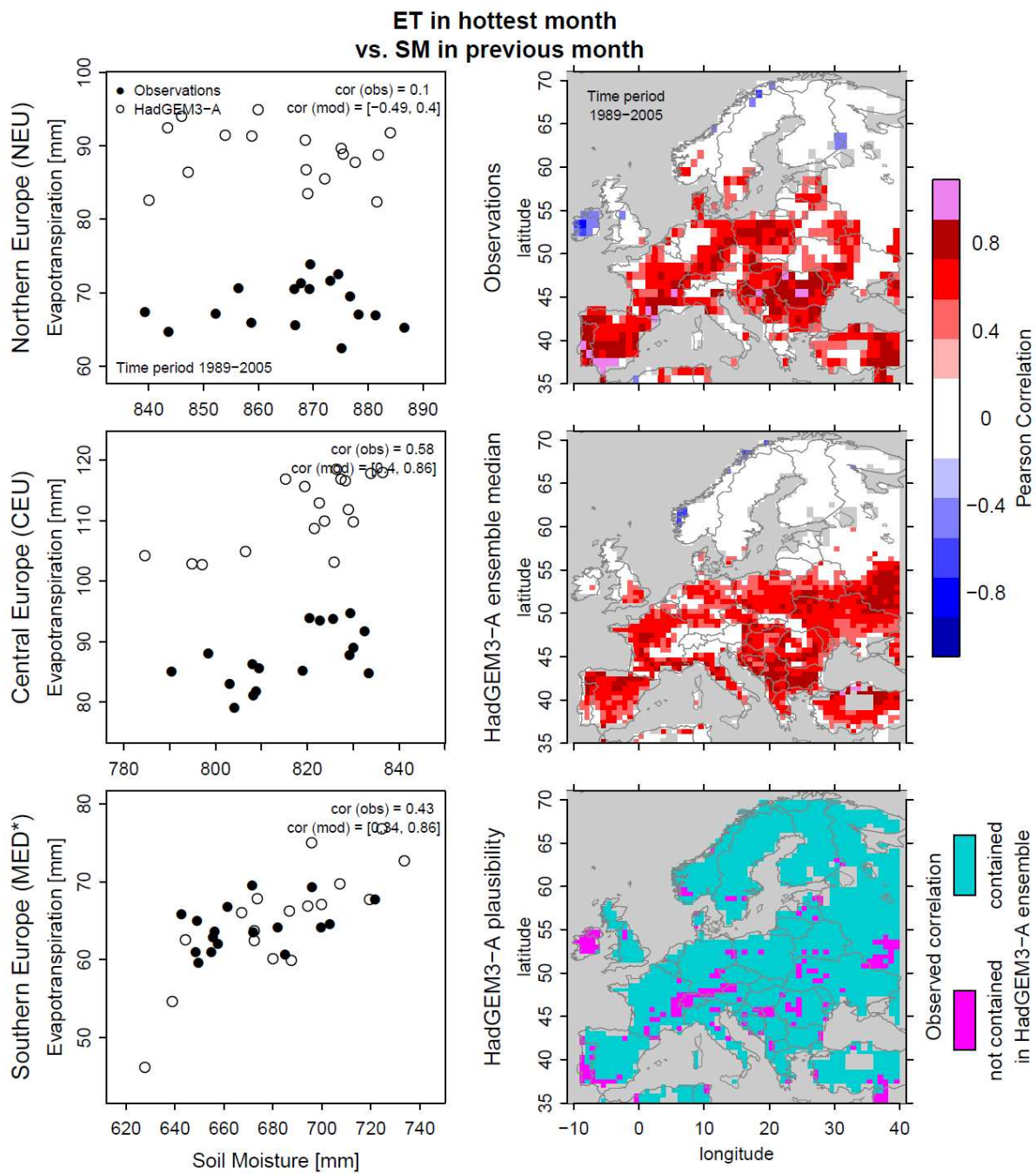
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Figure 7



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Figure 8



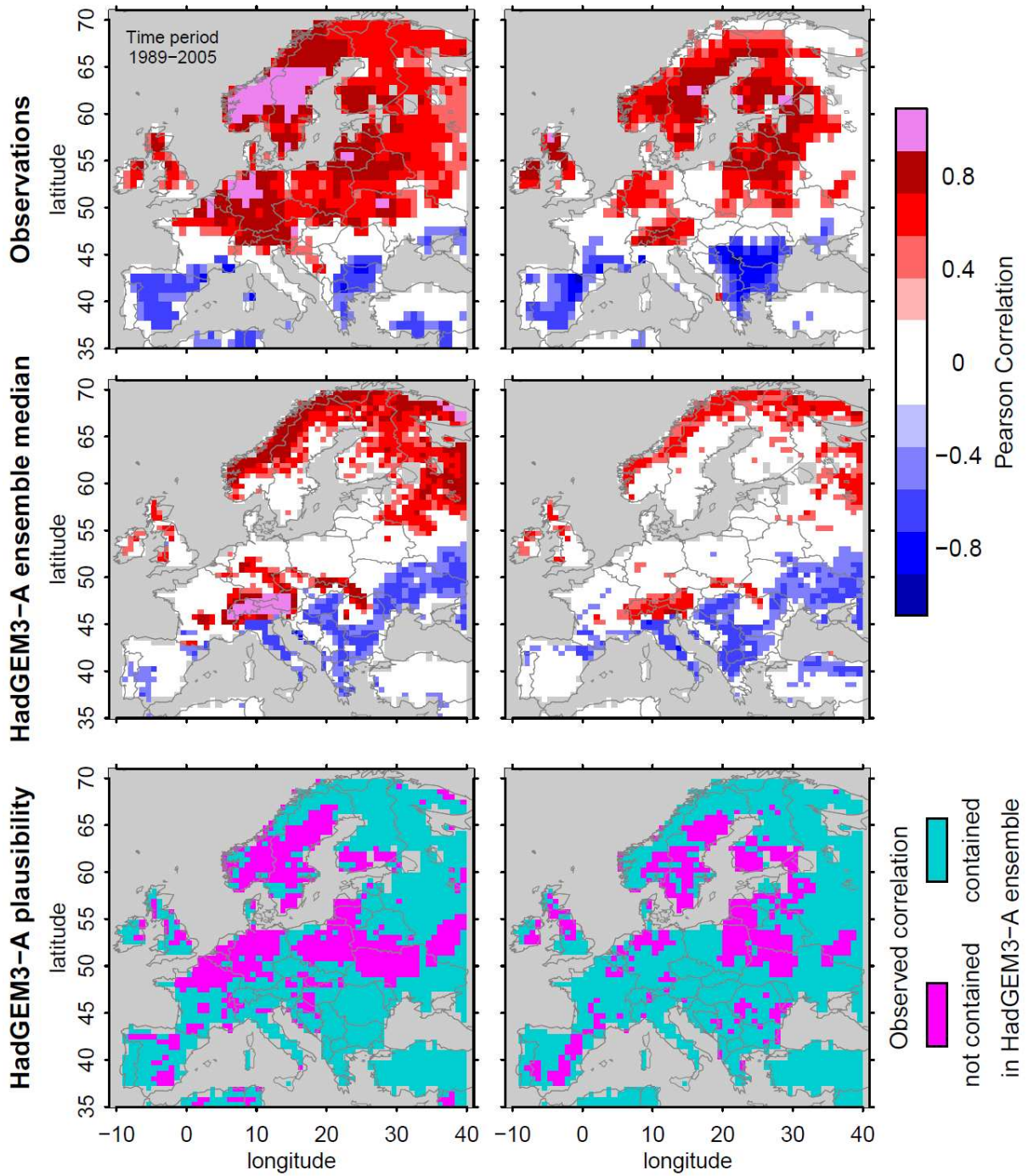
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1009 Figure 9

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monthly mean T in hottest month      TXx in hottest month  
vs. ET in hottest month

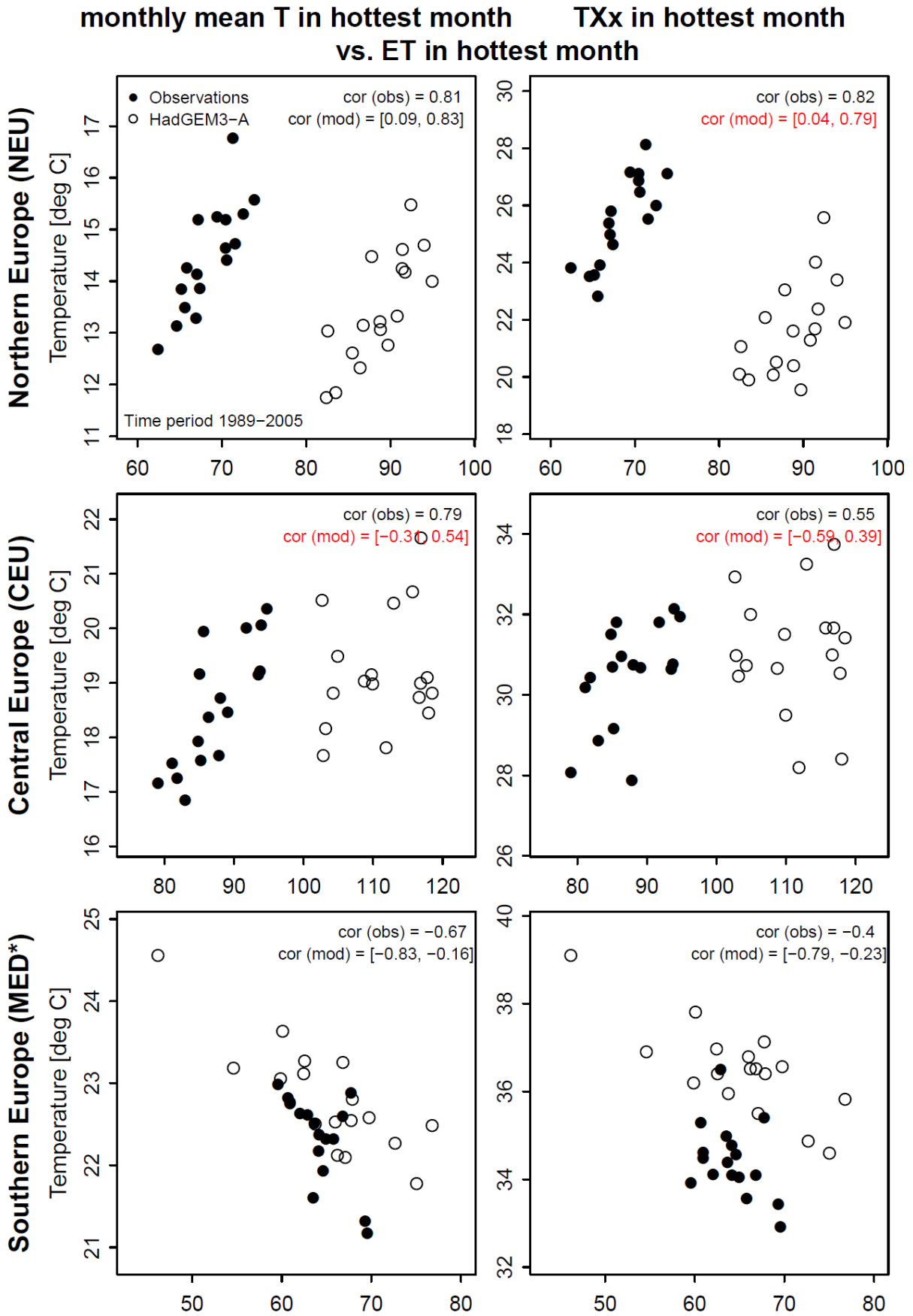


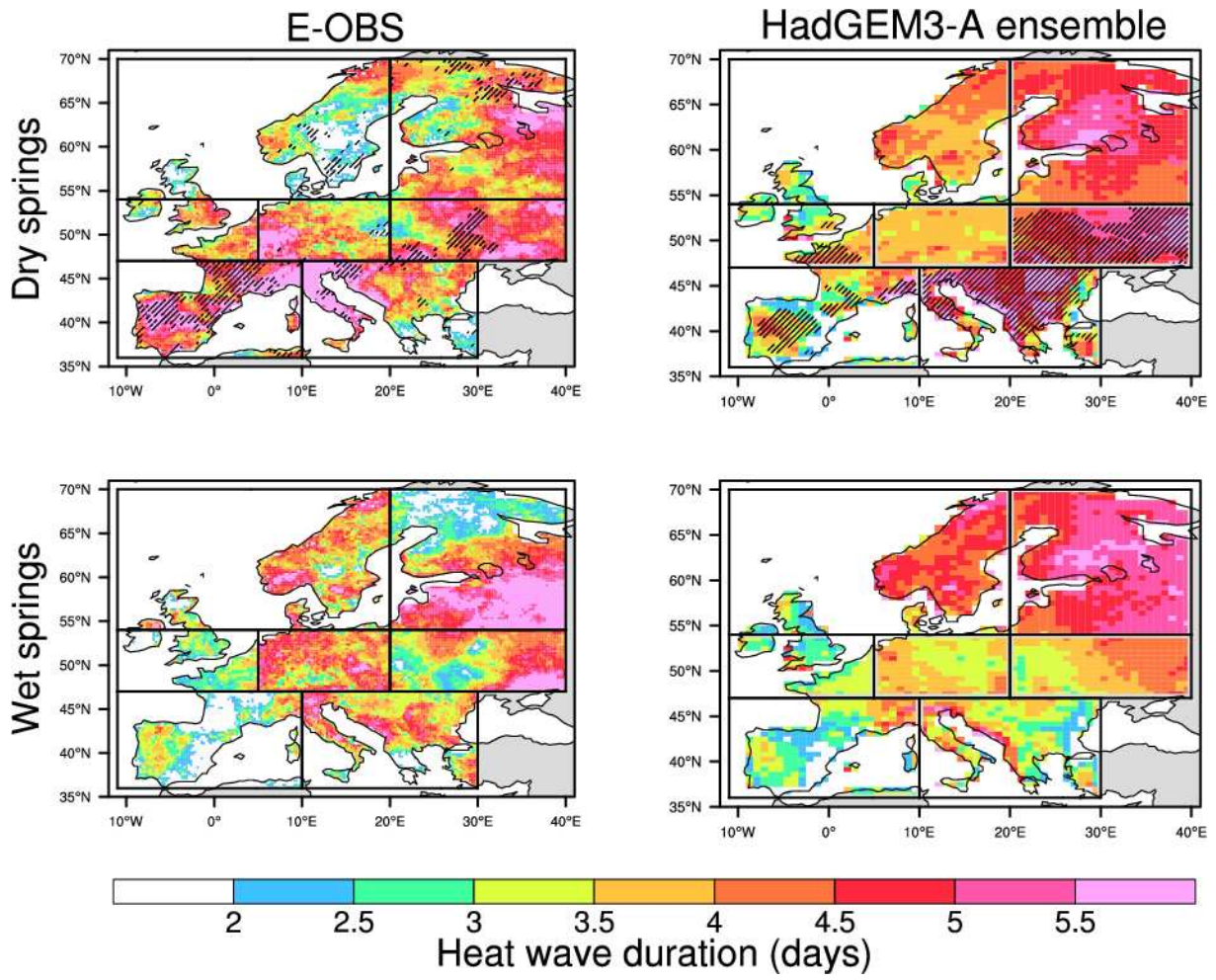
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1012 Figure 10

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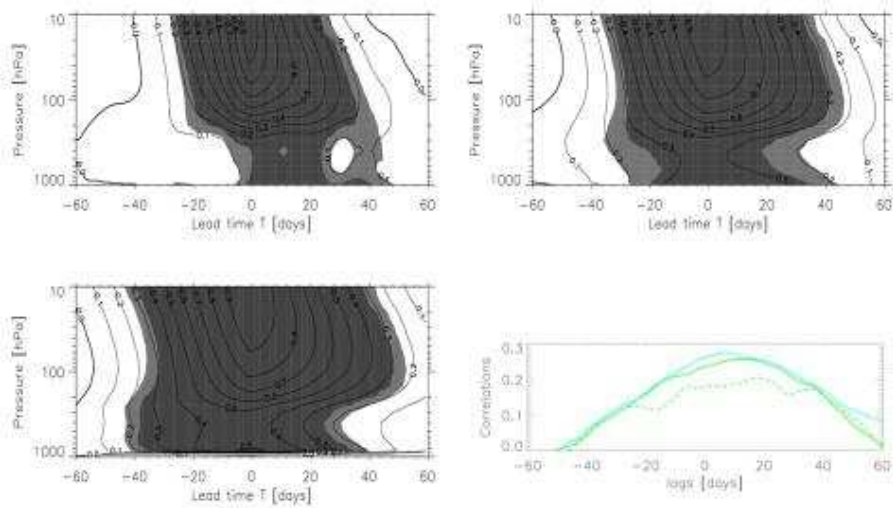






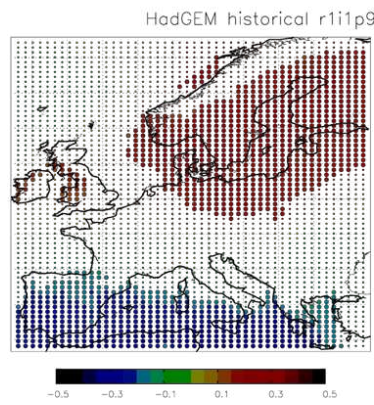
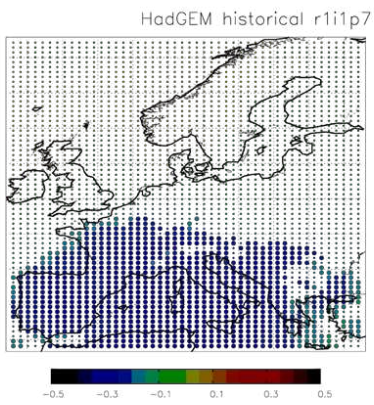
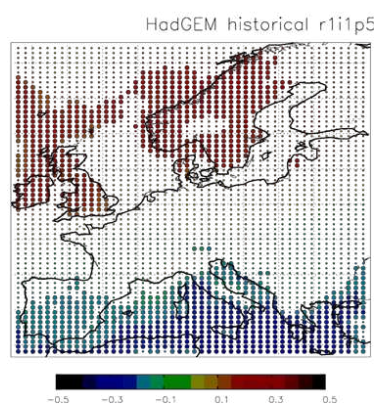
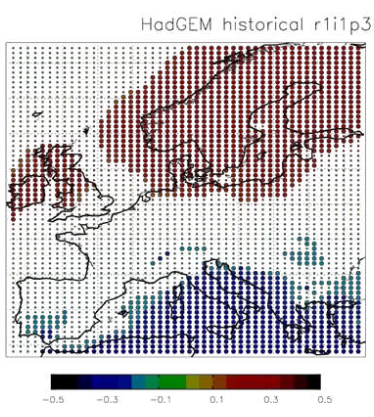
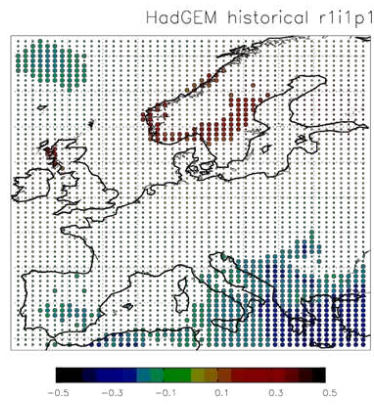
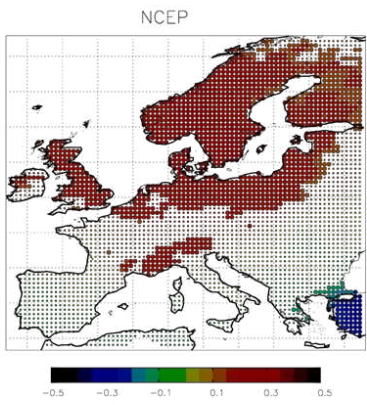
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1018 Figure 12



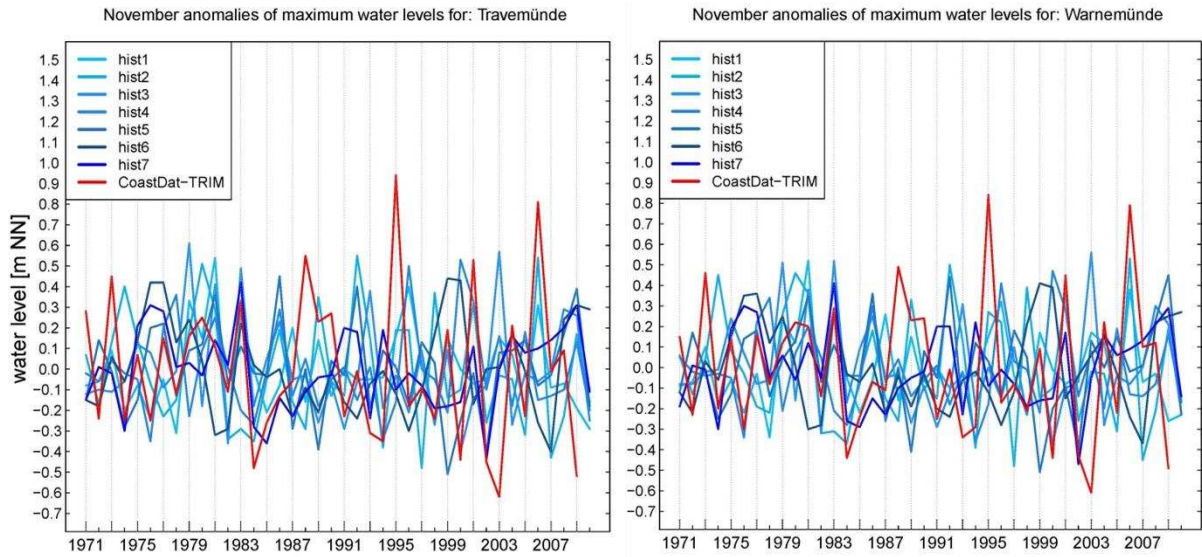
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1020 Figure 13



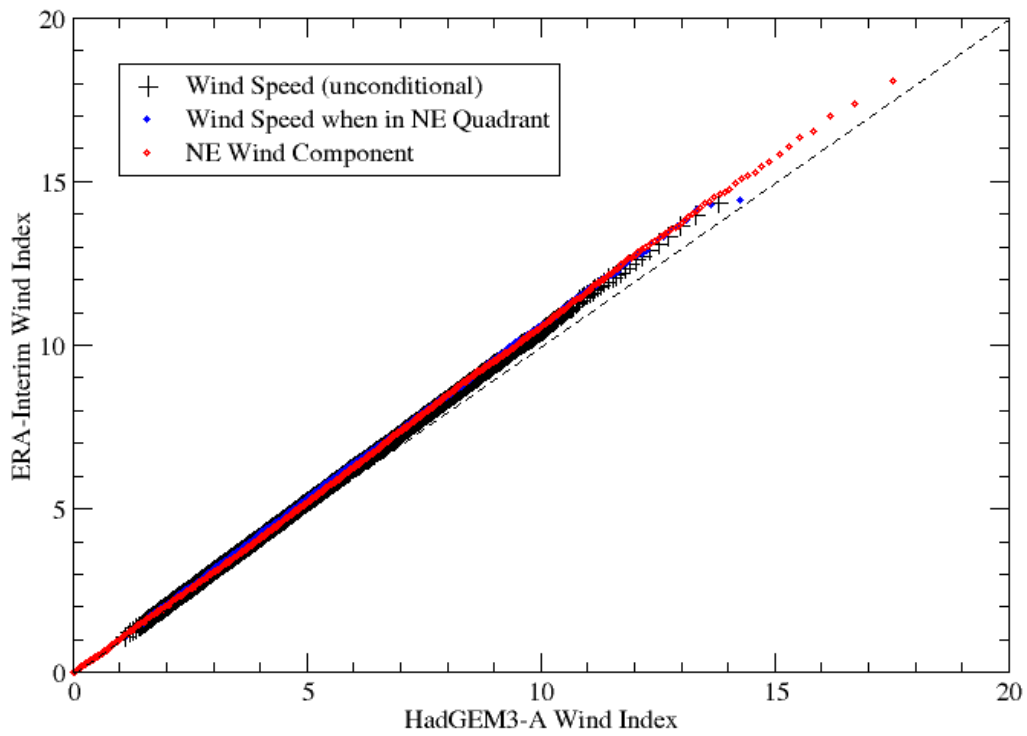
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1022 Figure 14



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1024 Figure 15



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1026 Figure 16

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1028 **Tables**  
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	Dataset	Time period	Spatial Resolution
Temperature	E-OBS v14.0 (Haylock et al. 2008) CRUTS 3.23 (UEA 2015) 20CR reanalysis temperature data, averaged from 6hrly values	1960-2013	0.5°x0.5°
Precipitation	E-OBS v14.0 (Haylock et al. 2008)	1960-2013	0.5°x0.5°
Sea level pressure	NCAR/NCEP reanalyses NOAA 20CR reanalysis, version 2c	1948-2014	2.5°x2.5° 2°x2°
10-m winds	ERA-Interim reanalysis	1979-2013	0.7°x0.7°
Soil Moisture	SWBM Dataset (Orth and Seneviratne 2015)	1984-2013	0.5°x0.5°
Evapotranspiration	LandFlux-EVAL Dataset (Mueller et al. 2013)	1989-2005	1°x1°

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1031 **Table 1:** Overview of employed reference datasets

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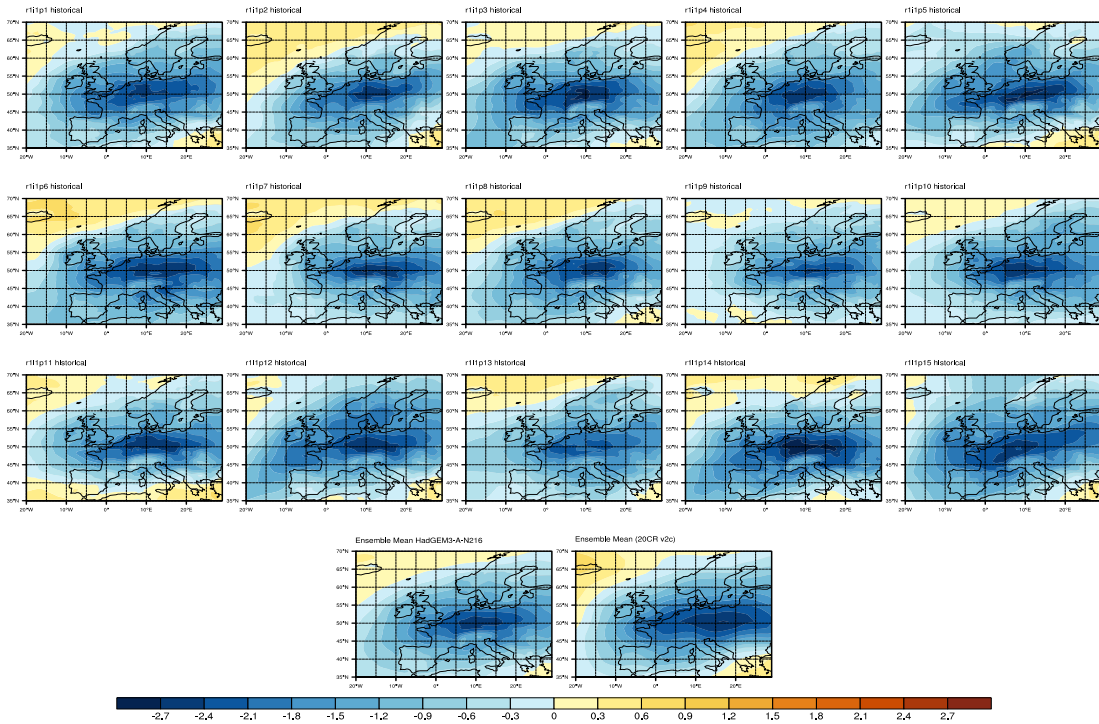
Regime	Winter: AR	Winter: BLO	Winter: NAO-	Winter: ZO	Summer: AL	Summer: BLO	Summer: NAO-	Summer: AR
NCEP/NCAR	24.4%	27.2%	21.0%	27.4%	22.6%	30.1%	21.2%	28.6%
HadGEM3-A (15 members)	23.8%	27.0%	22.5%	26.6%	18.5%	28.4%	24.6%	26.2%

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1034 **Table 2:** Weather regime occupancies (or frequencies) for each cluster, clusters being referenced from  
 1035 the NCEP/NCAR reanalyses, for each season.

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1039 **Supplementary Figure 1:** DJF Composites of the standardized near-surface temperature for cold winter

1040 events over Central Europe in Had-GEM3-N216 historical forcing ensemble members 1-15 (lines 1-3),

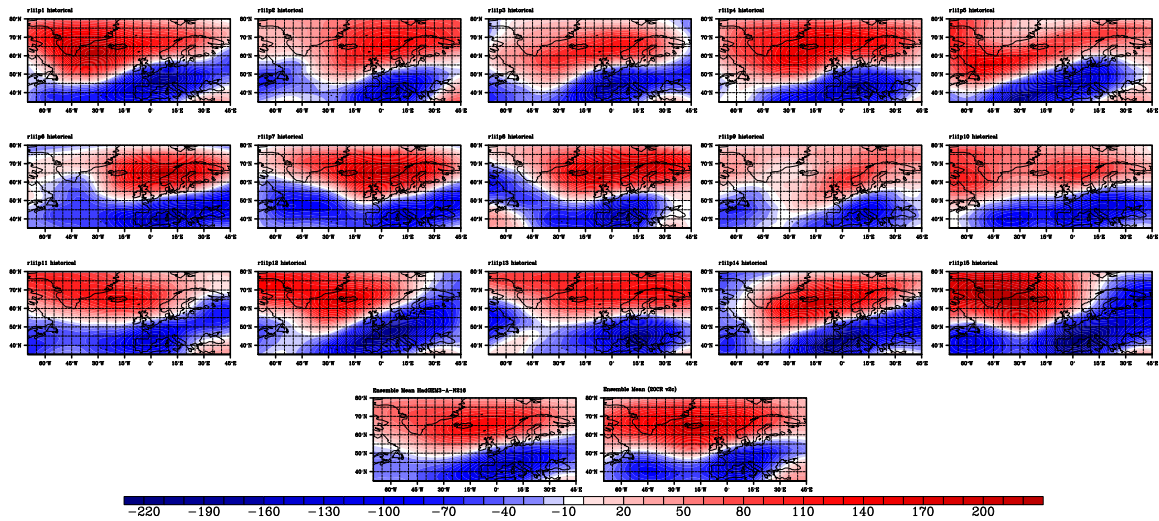
1041 ensemble mean (line 4, left) and and 20CR ensemble mean (line 4, right). The composites have been

1042 derived from all cases where the area-averaged temperature over Central Europe is smaller than its

1043 5th seasonal percentile in DJF.

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1047 **Supplementary Figure 2:** DJF Composites of the standardized geopotential height at 500mb for cold  
1048 winter events over Central Europe in Had-GEM3-N216 ensemble members 1-15 (lines 1-3), ensemble  
1049 mean (line 4, left) and and 20CR ensemble ( line 4, right). The composites have been derived from all  
1050 cases where the area-averaged temperature over Central Europe is lower than the 5th seasonal  
1051 percentile in DJF of the associated temperature.

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