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Changes in future synoptic circulation patterns: consequences for extreme event attribution

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Abstract: Anthropogenic emissions can modify the frequency and intensity of extreme weather events such as cold-spells, heat-waves and heavy precipitations. A major challenge is to detect changes in the atmospheric circulation patterns associated to those extreme events. The emergence of patterns depends on the chaotic behavior of the atmospheric flow and can also be modified by anthropogenic emissions. By embedding the circulation patterns observed during selected extremes into historical climate simulations and projections based on emission scenarios, we find major changes in probability, predictability and persistence of atmospheric patterns observed during extreme events using an analog based method. The results highlight the need to take into account the role of atmospheric circulation in attribution studies as future

16 **extremes will be associated to modified circulation patterns.**

17 **Significance**

18 Weather extreme events greatly impact agricultural, social and economic activities. In a chang-
19 ing climate, it seems primordial to ask how anthropogenic emissions impact the frequency and
20 intensity of extreme events. Attribution studies focus on this issue, often assuming that the
21 atmospheric circulation associated to extreme events is not itself affected by climate changes.
22 Here we show that the synoptic patterns associated to extreme events will be greatly affected
23 by anthropogenic forcing. These results warn that such changes must be taken into account in
24 future research to perform meaningful attribution studies

25 **Introduction**

26 Understanding to what extent an extreme weather event is caused or modified by anthropogenic
27 climate change is a challenging scientific question. One of the outcomes of extreme event
28 attribution (EEA) is an estimate of how the probability of an event is altered with climate change
29 (1, 2). Many local or regional extremes of temperature or precipitation are driven by features of
30 the synoptic circulation (3, 4). Focusing on the relations between extremes and the circulation is
31 part of a general "storyline" approach to EEA (5). Assessing changes in the synoptic circulation
32 was deemed as a major scientific challenge (6–8). One of the difficulties has a statistical nature
33 due to the rarity of the multivariate features of the circulation leading to extremes. The other
34 major difficulty is of physical nature, related to the chaotic behavior of the atmosphere (9)
35 and the complexity introduced by other components of the climate system (oceans, vegetation,
36 sea and continental ice, volcanoes). This generates an intrinsic variability on a wide range of
37 spatial and temporal scales which can affect the occurrence and intensity of extreme events.
38 On top of this, the climate system is never on a stationary state: external forcings, both natural

39 (solar activity, volcanic eruptions, orbital parameters) and anthropogenic (greenhouse gases
40 emissions, land use cover changes) change continuously on a wide range of temporal scales (10,
41 11). This non stationarity is difficult to tackle from both statistical and physical perspectives.
42 Here, we develop a new paradigm to treat this challenge of estimating shifts in rare atmospheric
43 patterns.

44 Previous studies have focused on detecting significant global and average shifts in the at-
45 mospheric circulation pattern under anthropogenic forcing (6, 12–16). At this point, there is no
46 general consensus on the existence and direction of a potential shift. In contrast, little attention
47 has been devoted to the evolution of circulation patterns related to specific observed weather
48 events (17–19). The originality of this article is to use the framework of dynamical systems
49 theory applied to these specific observed circulation patterns. We aim to understand how likely,
50 persistent and predictable those patterns will be under different greenhouse gases emissions
51 scenarios. We build our studies on the analogs theory and the results presented in (20, 21).
52 The main idea is to follow the atmospheric flow in its full phase space, avoiding to project it
53 onto specific and empirical indices (such as North Atlantic Oscillation (NAO), Arctic Oscillation
54 (AO)) and compute the recurrences (analogs) properties of the circulation patterns associated to
55 extreme events. Indeed, (21) have shown that robust changes of atmospheric circulation patterns
56 under anthropogenic emissions can be identified with this methodology.

57 We test our methodology on recent observed examples of different classes of extreme events
58 in Europe (cold spells, heatwaves and extreme precipitations) and their associated circulation
59 patterns and we detect their changes using global coupled climate models from the CMIP5
60 (Coupled models inter-comparison project) ensemble.

61 **Methodology**

62 We select 12 different extreme events: 4 cold spells, 4 heatwaves and 4 extreme precipitations
63 (see Table 1 for event descriptions). The selection of these events is based on their socio-
64 economic impacts and is detailed in the Supplementary Material. All these events affected one
65 or more European countries and they are associated to specific circulation patterns. We define
66 the circulation on a region corresponding to the North Atlantic basin and Europe [22.5N-70N,
67 80W-50E]. This region has been already used in studies based on analogs (18), and on weather
68 patterns (22–24). We use geopotential height at 500mb (hereafter Z500), issued from the NCEP
69 reanalysis as proxy for atmospheric circulation.

70
71 We extract the daily Z500 fields corresponding to the selected extreme event (average Z500
72 maps anomalies during the events are shown in Figure 1). We then embed these observed tra-
73 jectories into historical simulations (1951–2000), and projections (2051–2100) under a medium
74 (RCP4.5) and high (RCP 8.5) emissions scenarios (25) of the CMIP5 models given in Table S1.
75 Data are regridded to the NCEP spatial resolution. When we embed the portion of Z500 trajec-
76 tories corresponding to extreme events, we assume that the circulation patterns associated to the
77 extreme event are observed in the climate model simulations. Given that the models have biased
78 representation of the geopotential heights, we apply a statistical bias correction — allowing to
79 account for climate change (26) — on the Z500 fields, before the analysis. Since there is a trend
80 on Z500 fields directly related to the surface temperature, we present the results for a bias cor-
81 rection on the raw Z500 field as well as for a bias correction on detrended Z500 fields. Details
82 about the bias correction and detrending procedures are given in the Supplementary Material.

83
84 For each extreme event, we compute the analogs of the observed synoptic patterns in each set

85 of model simulations, and determine their properties. For each daily Z500 field observed during
86 extreme events, we select the closest 2% of daily Z500 fields using Euclidean distance. This
87 defines our analogs ensemble. Note that the results do not crucially depend on this percentage
88 provided that it is in the range of 0.5 to 3%. The values of the Euclidean distance allow to
89 determine how well the circulation patterns associated to extreme events fit in the simulations.
90 In addition to this metric (hereafter called analogs quality and precisely defined as the average of
91 the Euclidian distance of the 2% closest fields), we compute the predictability d and persistence
92 θ^{-1} metrics (20) (see Supplementary material). Those parameters describe the recurrences of a
93 system around a state in phase space. In our case, the state is the Z500 map for a given extreme
94 event. Values of d and θ^{-1} are obtained for every day in the dataset of interest. d provides
95 information on the number of pathways the system can take to reach and leave a state, and it
96 acts as a proxy for the systems active number of degrees of freedom around the state of interest.
97 θ^{-1} describes the persistence of an atmospheric circulation state in time, i.e. how long the
98 system typically stays around the state of interest. A very persistent state (i.e., with a large θ^{-1})
99 is highly stable (and therefore also highly predictable), while a very unstable state yields low
100 persistence.

101 By repeating this procedure for all models and scenario runs, we can detect changes in the
102 atmospheric circulation observed during extreme events. A change in the analogs quality will
103 tell us whether the atmospheric configuration is more or less likely in the historical than in the
104 scenario experiments. A change in the dynamical indices will inform us on the change of pre-
105 dictability and persistence of the circulation pattern associated to the extreme event.

106

107 **Results**

108 Figure 2 shows the change in the atmospheric circulation associated to climate change in terms
109 of relative changes $(x_{\text{RCP}} - x_{\text{HIST}})/x_{\text{HIST}}$ where x is alternatively the analogs quality, the pre-
110 dictability d and the persistence θ^{-1} for each of the events considered in this study. Individual
111 results for each event are displayed in Figure S1–S12 in the Supplementary material. As an
112 indicator of significance of the results, we use the number of models yielding changes of the
113 same sign for the analogs quality (size of the circles in Figure 2). Panels a) and b) (respectively
114 c) and d)) corresponds to non-detrended (respectively detrended) bias correction for RCP 4.5
115 Scenario (a) and c) and RCP 8.5 Scenario (b) and (d). Figure 3 shows the same results with a
116 bar representation for RCP 4.5 (a) and RCP 8.5 scenario (b).

117
118 We first begin with the results for the non-detrended results shown in Figure 2-a,b and bars
119 with blue edges in Figure 3. We note that different classes of extreme events have similar re-
120 sponses: all heatwaves yield better analogs in RCP4.5 and RCP 8.5 than in the historical periods
121 (i.e., negative change in the average Euclidean distance), although more slightly for RCP8.5.
122 We also remark that the model agreement on the sign of changes is very low for the RCP8.5
123 scenario, possibly meaning that the circulation deviates too much from the observed patterns to
124 be observed under very large greenhouse gases forcing. All the heatwaves suffer of a decrease
125 in predictability (5-10%) and a decrease in the persistence (10–15%). Cold spells become less
126 likely in the RCP 4.5 ($\approx 5\%$ less) and RCP 8.5 (10–15% less) scenarios. They all become more
127 persistent but interestingly, the predictability depends on the event considered. For the patterns
128 connected to precipitation events, results strongly depend on the event considered. Overall, we
129 find that the changes in the patterns associated to the extreme events are most of the time sig-
130 nificant: there is a large agreement among different models on the sign of these changes. The

131 intensity of the changes is approximately of 10% and therefore not negligible.

132

133 We analyse the effect of detrending (Figure 2-c,d and bars with red edges in Figure 3). In
134 general, detrending reduces the magnitude of changes for the three indicators because we are
135 looking at residuals. Those residuals between detrended and non-detrended analysis can be in-
136 terpreted as the part of changes not directly linked to the thermodynamic trend on Z500, since
137 the trend in Z500 are a direct consequence of anthropogenic emissions. For some events, the
138 changes in the detrended data have an opposite sign, e.g. the analogs quality for heatwave events
139 which decreases in the RCP 8.5 scenario. This implies that the circulation patterns associated
140 to the examined heatwaves are less probable in a RCP 8.5 scenario than in present climate. This
141 does not mean that there will be no heatwaves – as it has been shown by numerous studies that
142 anthropogenic climate change has led and will lead to more heatwaves (27) – but rather that
143 there will be other kinds (or even unprecedented) heatwave events.

144

145 **Discussion**

146 We have provided a framework for attributing to climate change synoptic circulations associated
147 to extreme events. Our analysis provides a range of indicators, which inform on the likelihood
148 of observing those circulation patterns in future emission scenarios, and estimate their changes
149 in predictability and persistence. Different extreme events have different responses to climate
150 change. We however found similarities within each class of extremes. Performing a detrended
151 or not detrended bias correction also affects the results and allows to separate the thermody-
152 namic effect in the increase of the geopotential height from the residual anomalies.

153 This study comes with some caveats. Models have biases in synoptic patterns associated
154 to extreme events as they are marked by blocking, strong gradients of even cut-offs in the

155 Z500 fields. They also have different mean global and local temperatures and this affects the
156 average height of Z500 data. This motivated our need for performing a bias correction. Another
157 caveat comes from the stationarity hypothesis on 50 years periods used to pick up the analogs
158 field. Detrending partly answers this problem and allows to compute the residual changes.
159 Another limitation is the use of the Z500 field as a proxy of the synoptic circulation. It does
160 not completely capture the synoptic circulation of the atmosphere. The time and spatial scale
161 of the Z500 field may affect the results. The sensitivity of our analysis in the choice of the
162 domain analyzed is reflected in the different quality of the results for heatwaves/coldspells with
163 respect to flood events. Indeed the synoptic patterns leading to high precipitation yield a smaller
164 scale, as shown in (19, 28)). The role of convection for these events could also be taken into
165 account (29).

166 The method presented has the advantage of being a very flexible and fast tool that could
167 be applied in real time to observed (and potentially forecasted) extreme weather events. This
168 would be a way to complete extreme event attribution diagnostics on the role of anthropogenic
169 as well as natural climate change on the synoptic circulation leading to the observed event (30).
170 The evaluation of which extreme events are and will become more or less predictable could
171 be useful to improve weather forecast and climate projections (31). While previous studies
172 mostly focus on single extreme events attribution our method is completely general and can be
173 potentially applied to all possible class of extreme events. Our results also express the need of
174 including the role of atmospheric circulation in attribution studies (32). Further developments
175 of this tool could include the recent extensions of dynamical system techniques to take into
176 account multiple variables (33), that can be used for studying compound events (34).

177

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230 Modelling, which is responsible for CMIP, and we thank the climate modeling groups (listed in
231 the Supplementary Table 1) for producing and making available their model output. For CMIP
232 the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison
233 provides coordinating support and led development of software infrastructure in partnership
234 with the Global Organization for Earth System Science Portals

Event	Type	Region Affected	Starting Date	Ending Date
CS1956-SE	Cold Spell	Southern and Central Europe	01/02/1956	20/02/1956
CS2012-SE	Cold Spell	Italy & the Balkans	05/02/2012	15/02/2012
CS2013-WE	Cold Spell	Western and Central Europe	10/03/2013	16/03/2013
CS2017-SE	Cold Spell	Italy & Greece	05/01/2017	08/01/2017
FL2014-BK	Flood	The Balkans	31/08/2014	06/09/2014
FL2016-FR	Flood	France	28/05/2016	31/05/2016
FL2018-06-FR	Flood	France	11/06/2018	12/06/2018
FL2018-10-FR	Flood	France	14/10/2018	15/10/2018
HW2003-EU	Heatwave	Central, Western Europe	01/08/2003	15/08/2003
HW2010-RU	Heatwave	Eastern Europe & Russia	01/07/2010	18/07/2010
HW2017-SE	Heatwave	Southern Europe	01/08/2017	10/07/2017
HW2018-NE	Heatwave	Northern Europe	15/07/2018	02/08/2018

Table 1: Description of the extreme events analyzed in this study. More details in the Supplementary Material.

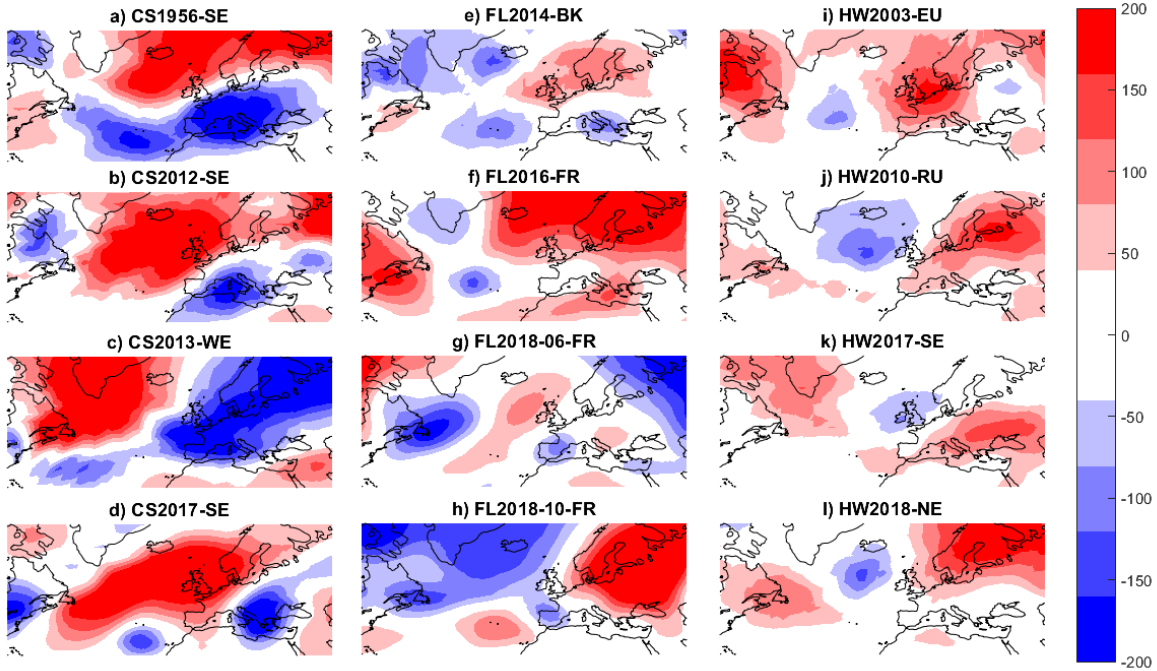


Figure 1: NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly climatology from the average Z500 field of the event. a-d) cold spell events, e-h) extreme precipitations, i-l) heatwaves. Details reported in Table 1. See Supplemental material for a description of the events.

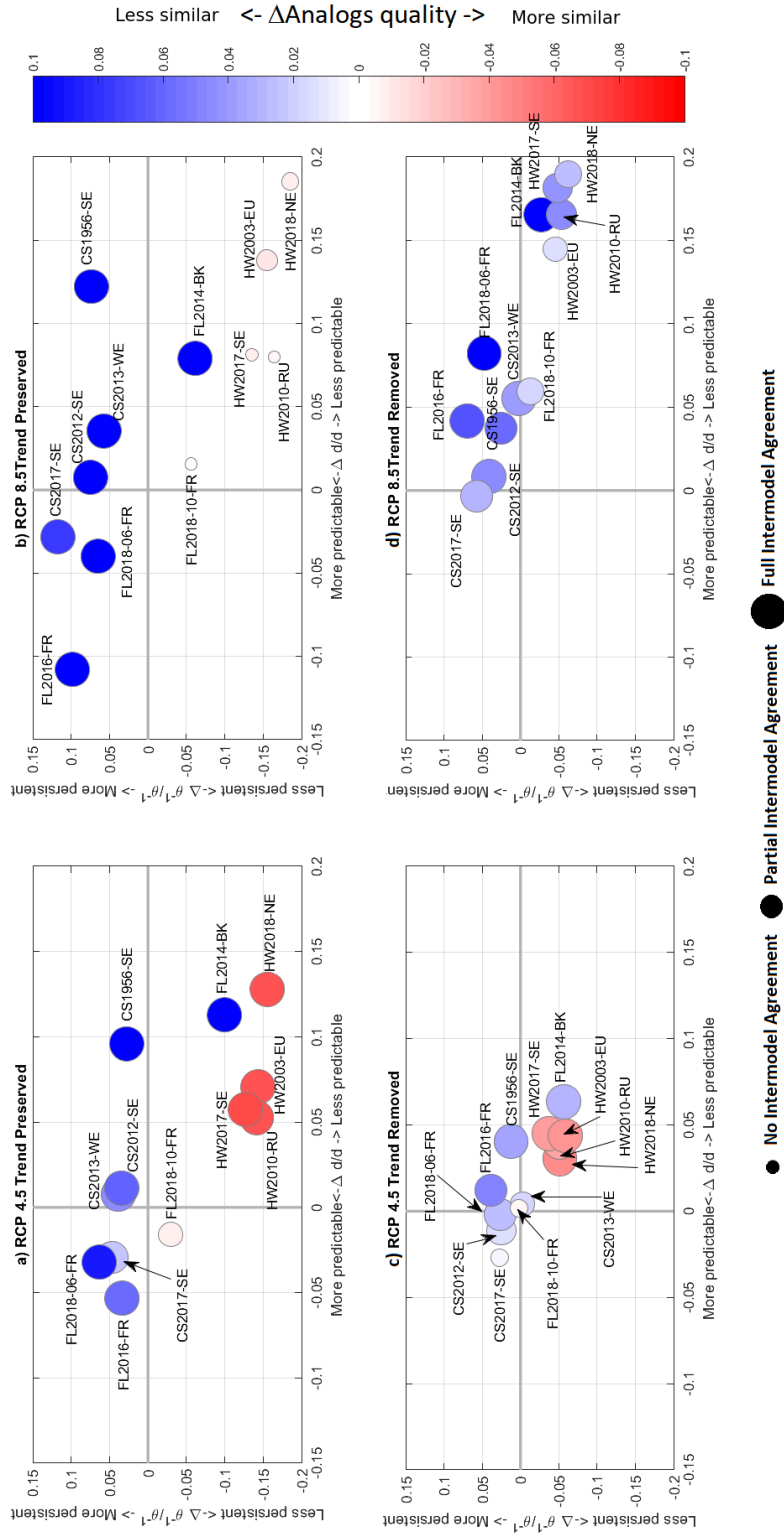


Figure 2: Relative changes in predictability (x-axis), persistence (y-axis) and analogs quality (color-scale) for the RCP 4.5 (a,c) and RCP 8.5 (b,d) scenarios. The size of the ball indicates the sign agreement among models (full data in Supplementary figures). Trend preserving bias correction (a,b). Trend removed bias correction (c,d). Details regarding the extreme events analyzed are reported in Table 1.

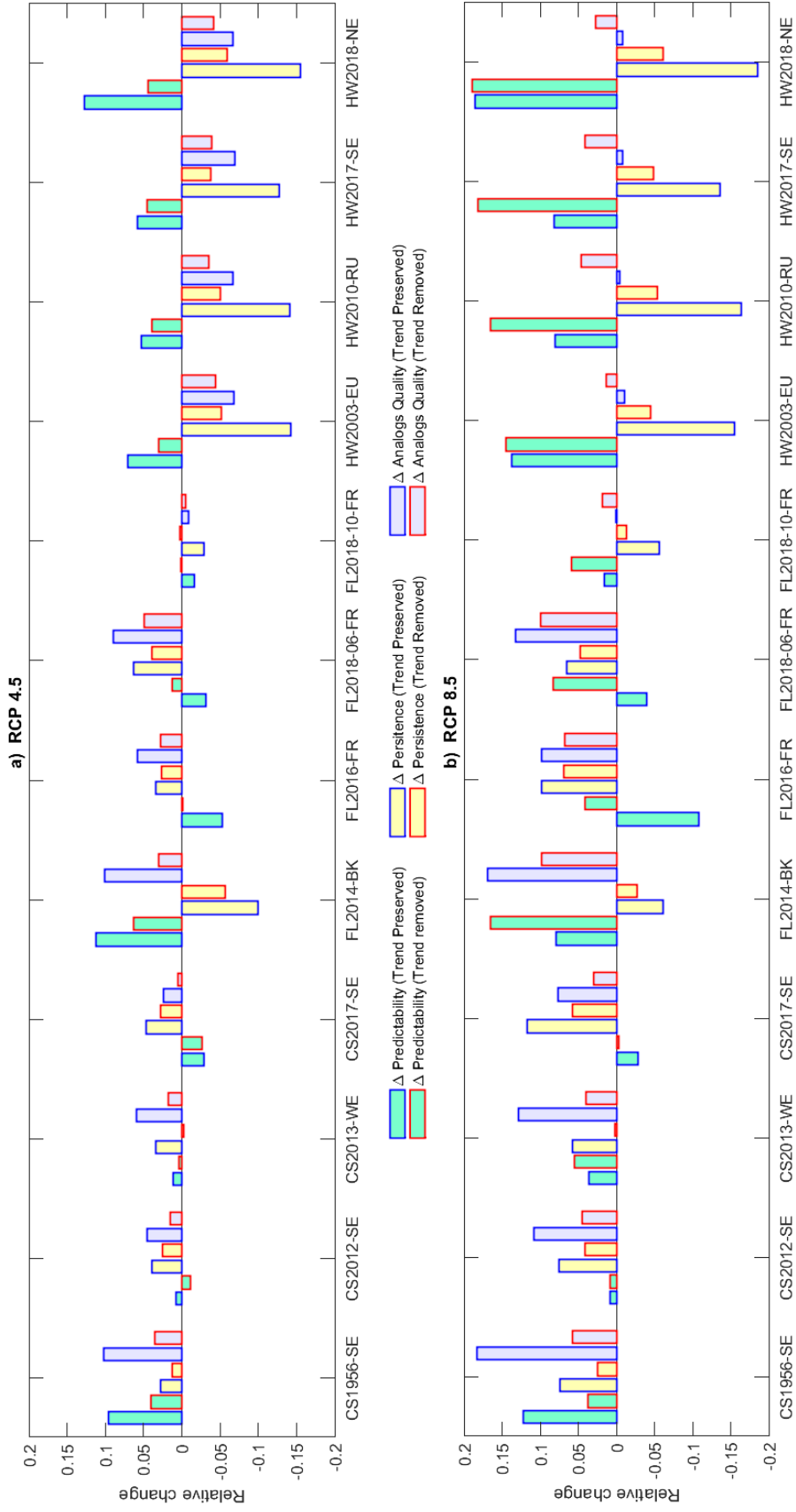


Figure 3: Relative changes in predictability (light green), persistence (yellow) and analogs quality (lavanda) for the RCP 4.5 (a) and RCP 8.5 (b) scenarios. Trend preserving bias correction (blue bar edges) and trend removed bias correction (red bar edges) are shown. Details regarding the extreme events analyzed are reported in Table 1.

Supplementary Material - Changes in future synoptic circulation patterns: consequences for extreme event attribution

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Materials and Methods

Extreme Events Analyzed

We provide here some characteristics of the extreme events analyzed in this study. They have been selected based on their social and economical impact, as an illustration of the method.

1956 Southern Europe Cold spell (CS1956-SE). The cold spells events we analyze are all characterized by the presence of heavy snowfalls over large populated areas. The 1956 cold spell (Supplementary Figure 1) was one of the coldest and snowiest of the 20th century, especially over Italy and Serbia (*I*). Federico Fellini in *Amarcord* reproduces scenes of Rimini, a town at sea level height in Emilia Romagna region, blocked by snow walls over 1 meter high. Locations such as Marseilles, Rome, Naples and Palermo recorded important snowfall amounts.

16 The duration of this event was very long with cold conditions persisting for about 20 days and
17 severe effects on vegetation (2).

18 **2012 Southern Europe Cold spell (CS2012-SE).** The 2012 cold spell (Supplementary Figure
19 2) struck Western and Southern Europe with remarkable effects on the Adriatic sea region (3).
20 In Bologna, over 45 cm of fresh snow fell in one night for a total over one meter during the
21 whole event. Even Rome was covered by 15 cm of snow. The snow caused interruptions at
22 London Heathrow airport where 10cm of snow were measured. Snow fell in Mallorca for the
23 first time since 1956. Finally the snow reached 111 cm height in Sarajevo and 5 people died for
24 cold-related causes.

25 **2013 Western Europe Cold spell (CS2013-WE).** The 2013 cold spell (Supplementary Fig-
26 ure 3) was marked by an unusual cold and snowy weather especially in the United Kingdom and
27 in France. The snowfall affected Scotland, Ireland but also southern England and Normandy (4).
28 In Normandy, nuclear power plants had to reduce their operations for few days.

29 **2017 Southern Europe Cold spell (CS2017-SE).** The beginning of January 2017 (Supple-
30 mentary Figure 4) was extremely cold in central, eastern and southern Europe. The Danube
31 froze in Romania. Snowstorms affected, among other locations, Istanbul, Rome, Athens, San-
32 torini and Majorca (5).

33 **2014 Balkan floods (FL2014-BK).** A series of storms (Supplementary Figure 5) occurred
34 between the Adriatic regions of Italy and the Balkans (especially Croatia, Albania and Greece)
35 at the beginning of September 2014. Extreme precipitations associated to hail, heavy rain and
36 tornados were reported in Puglia as well as in Costal Croatia. One station in Puglia (Falcare)
37 reported over 700 mm rainy in 48h (6).

38 **2016 French floods (FL2016-FR).** Continued heavy rain fell between 28 May to 31 May
39 2016 and caused major flooding in several departments including Seine-et Marne and Loiret
40 (7,8) (Supplementary Figure 6). 155 mm of rain were recorded in Melleroy, Loiret Department,
41 which is the equivalent of 2 to 3 months of rain. The level of the Loing river at Nemours broke
42 a 100-year record by reaching 4.63 meters. The Seine river overflowed its banks and reached a
43 level of 6.10 meters at the Paris Austerlitz reference gauge. (9) performed an attribution study
44 of the event and showed that anthropogenic climate change has increased the likelihood of such
45 an event by about a factor of 2 on the Seine and Loire rivers.

46 **June 2018 French floods (FL2018-06-FR).** A serie of storms (Supplementary Figure 7) oc-
47 curred in France from mid-May to mid-June 2018. In particular, between 11 and 12 June 2018
48 heavy rainfall struck the regions, Ile de France, Pays de Loire, Normandy, Brittany, Centre-Val
49 de Loire and Grand Est (10). Records were broken in Ile de France and in Brittany. For in-
50 stance, according to Météo-France, 75mm of precipitation fell in 24 hours in Orly and 71 mm
51 of precipitation fell in 24 hours in Nantes. The heavy rainfall also caused flooding, especially
52 in the South of Paris, Brittany, Normandy and in Southwestern France.

53 **October 2018 French floods (FL2018-10-FR).** Heavy rainfall (Supplementary Figure 8) fell
54 in the South of France on October 14-15 (11). The event was particularly extreme in Aude
55 department. For instance, 295 mm of rain fell in Trèbes and the level of the Aude River in this
56 town increased by 7 meters overnight. Heavy rainfall were also recorded at the same time in the
57 Mediterranean islands of Corsica (France) and Sardinia (Italy).

58 **2003 European heatwave (HW2003-EU).** The 2003 European heatwave (Supplementary
59 Figure 9) broke records of mean temperature in Western Europe in the past five centuries (12).
60 Numerous studies have shown that climate change increased the probability of occurrence of

61 such a heatwave (e.g. (13, 14)). The maximal temperature anomaly was centered over West-
62 ern in the first half of August (15), hence the choice of the dates for our study (see Table 1).
63 The very low soil moisture exacerbated the intensity of the heatwave (16, 17). (13) evaluated
64 that anthropogenic climate change increased the probability of this event at least 10 times since
65 the preindustrial era. (18) evaluated that a trend in the atmospheric circulation that lead to that
66 event.

67 **2010 Russian heatwave (HW2010-RU).** The 2010 Russian heatwave (Supplementary Figure
68 10) is also one of the most extreme heatwaves recorded in Europe (19, 20). Climate change also
69 seemed to increase the probability of occurrence of such an event (21, 22). Low soil moisture
70 and atmospheric circulation both played a role, as analyzed in (23). In (22) a threefold increase
71 of the probability of such an event was shown. In (24) it was observed that there was no trend
72 in the atmospheric circulation that lead to that event.

73 **2017 Southern Europe heatwave (HW2017-SE).** Western Europe and the Euro-Mediterranean
74 region experienced long spells of heat in the Summer of 2017 (Supplementary Figure 11).
75 Madrid (Retiro) reached 40.6C on July 13, equaling the 2012 record. Heat episodes contin-
76 ued into August, extending to many areas in southern Europe (25). The heatwave in early
77 August was described as the worst heat wave since 2003 (BBC 2017) in southern Europe, with
78 local maximum temperatures in Italy and the Balkans exceeding 40C for several days. Records
79 were broken in southern France (e.g. 4 August, Nmes-Courbessac, 41.6C), and nighttime tem-
80 peratures exceeded 30C in Corsica and Croatia. Anthropogenic climate change has increased
81 the odds of such an event at least threefold since 1950.

82 **Northern Europe heatwave 2018 (HW2018-NE).** A heatwave struck northern Europe in
83 the summer of 2018 (Supplementary Figure 12). Daily temperature anomalies reached 14K in

84 Scandinavia, the Netherlands and Belgium, where records of temperature were broken. This
85 heatwave was exacerbated by a drought caused by a persisting circulation anomaly. The heat-
86 wave and drought favored unprecedented forest fires in Scandinavia. This corresponds to the
87 Scandinavian cluster type of heatwave identified by (16).

88 **Data and models used**

89 In this study we use geopotential height (Z500) as a proxy to describe the North Atlantic circu-
90 lation. A wealth of atmospheric features, ranging from teleconnection patterns to storm track
91 activity to atmospheric blocking can be diagnosed from the Z500 field and this field appears
92 to be the most relevant to perform atmospheric circulation extreme event attribution. We base
93 our study on NCEP/NCAR reanalysis data (26) over the period 1948–2018, with a horizontal
94 resolution of 2.5° . The region of interest is $(22.5^\circ N - 70^\circ N$ and $80^\circ W - 50^\circ E$. We ana-
95 lyze daily output of the Coupled Model Intercomparison Project phase 5 (CMIP5) (27) for:
96 16 historical simulations (Supplementary Table 1), 16 RCP4.5/8.5 projections. The histori-
97 cal simulations cover the period 1950–2000; the forcings are consistent with observations and
98 include changes in: atmospheric composition due to anthropogenic and volcanic influences,
99 solar forcing, emissions or concentrations of short-lived species and natural and anthropogenic
100 aerosols or their precursors, as well as land use. RCP4.5 and RCP8.5 projections are projections
101 of future climates (2051–2100) forced by two representative concentration pathway scenarios
102 (RCPs). These result in a radiative forcing of 4.5 Wm^{-2} and 8.5 Wm^{-2} respectively in year
103 2100, relative to pre-industrial conditions.

104 **Bias Correction procedures**

105 The statistical bias correction method applied is the Cumulative Distribution Function - trans-
106 form (CDF-t) method, developed in (28). This approach links the cumulative distribution func-

107 tion (CDF) of a climate variable (here Z500) from GCM simulations to be corrected, to the
 108 CDF of this variable from a reference dataset, here the NCEP/NCAR reanalysis dataset (29).
 109 A mathematical transformation T is performed on the simulations CDF to define a new CDF
 110 as close as possible to the reference CDF. Let F_{Gh} and F_{Rh} denote respectively the CDFs of
 111 the variable of interest from the GCM and from the reference over a historical time period
 112 (here 1950-2005). We assume that, whatever the value x of the variable to be corrected, the
 113 transformation T allows to go from F_{Gh} to F_{Rh} :

$$T(F_{Gh}(x)) = F_{Rh}(x). \quad (1)$$

114 Therefore, by noting that x can be written as $F_{Gh}^{-1}(p)$, with p a probability value in $[0, 1]$, the
 115 transformation T can be expressed as

$$T(p) = F_{Rh}(F_{Gh}^{-1}(p)). \quad (2)$$

116 Then, Eq. (2) is assumed to stay valid under evolving climate conditions. This means that if
 117 the GCM CDF F_{Gh} for the historical period becomes F_{Gf} in a future time period, it is assumed
 118 that T enables us to estimate F_{Rf} , the target reference CDF for the future time period, through
 119 $F_{Rf}(x) = T(F_{Gf}(x))$, which is thus formulated as

$$F_{Rf}(x) = F_{Rh}(F_{Gh}^{-1}(F_{Gf}(x))). \quad (3)$$

120 Then, this future corrected CDF F_{Rf} allows us to perform a quantile-mapping approach (30–32)
 121 between F_{Gf} and F_{Rf} to generate values out of F_{Rf} , respecting the GCM rank chronology.
 122 Hence, CDF-t can be considered as a variant of the empirical quantile-mapping method but
 123 within the appropriate target (here future) time period and therefore accounts for changes of
 124 CDF from the calibration period to the projection one.

125 This bias correction method is applied in two different ways. First, CDF-t is applied on a
 126 monthly basis to the raw NCEP/NCAR reanalyses and CMIP5 GCM simulations. The results

127 are the non-detrended bias corrections. Secondly, CDF-t is applied, still on a monthly basis,
128 to NCEP/NCAR reanalyses and GCM simulations from which a spatial and seasonal trend is
129 removed. To do so, for each day, the Z500 spatial average is calculated. Next, for each calendar
130 day (e.g., each January, 1) over the period of interest (1951-2000 or 2051-2100), a linear fit
131 of the daily Z500 spatial average as a function of time is estimated. This spatial trend is then
132 removed from each Z500 grid-cell value for the specific calendar day, and the spatial average
133 value estimated by the model for the year 2006 for the calendar day is added. This ensures
134 that a seasonality (that estimated for 2006) is preserved, with no trend in the resulting Z500
135 data. Those seasonally and spatially detrended data are the inputs of CDF-t, therefore providing
136 adjusted values hereafter and in the main text referred to as detrended bias corrections.

137 In the present study, all bias corrections have been made through the CDF-t R package
138 (freely available on www.r-project.org/). More theoretical and technical details, as well as first
139 validations and comparisons can be found in (33). Various applications of CDF-t can be found
140 in (34–37), among others.

141 **Dynamical systems metrics**

142 The attractor of a dynamical system is a geometric object defined in the space hosting all the
143 possible states of the system (phase-space). Each point ζ on the attractor can be characterized
144 by two dynamical indicators: the local dimension d , which indicates the number of degrees of
145 freedom active locally around ζ , and the persistence θ^{-1} , a measure of the mean residence time
146 of the system around ζ (38). To determine d , we exploit recent results from the application of
147 extreme value theory to Poincaré recurrences in dynamical systems. This approach considers
148 long trajectories of a system — in our case successions of daily SLP latitude–longitude maps —
149 corresponding to a sequence of states on the attractor. For a given point ζ in phase space (e.g.,
150 a given SLP map), we compute the probability that the system returns within a ball of radius ϵ

151 centered on the point ζ . The Freitas et al. (39) theorem, modified by Lucarini et al. (40), states
 152 that logarithmic returns:

$$g(x(t)) = -\log(\text{dist}(x(t), \zeta)) \quad (4)$$

153 yield a probability distribution such that:

$$\Pr(z > s(q)) \simeq \exp \left[-\vartheta(\zeta) \left(\frac{z - \mu(\zeta)}{\sigma(\zeta)} \right) \right] \quad (5)$$

154 where $z = g(x(t))$ and s is a high threshold associated to a quantile q of the series $g(x(t))$.
 155 Requiring that the orbit falls within a ball of radius ϵ around the point ζ is equivalent to asking
 156 that the series $g(x(t))$ is over the threshold s ; therefore, the ball radius ϵ is simply $e^{-s(q)}$. The
 157 resulting distribution is the exponential member of the Generalized Pareto Distribution family.
 158 The parameters μ and σ , namely the location and the scale parameter of the distribution, depend
 159 on the point ζ in phase space. $\mu(\zeta)$ corresponds to the threshold $s(q)$ while the local dimension
 160 $d(\zeta)$ can be obtained via the relation $\sigma = 1/d(\zeta)$.

161 When $x(t)$ contains all the variables of the system, the estimation of d based on extreme
 162 value theory has a number of advantages over traditional methods (e.g. the box counting algo-
 163 rithm (41, 42)). First, it does not require to estimate the volume of different sets in scale-space:
 164 the selection of $s(q)$ based on the quantile provides a selection of different scales s which de-
 165 pends on the recurrence rate around the point ζ . Moreover, it does not require the a priori
 166 selection of the maximum embedding dimension as the observable g is always a univariate
 167 time-series.

168 The persistence of the state ζ is measured via the extremal index $0 < \vartheta(\zeta) < 1$, an adi-
 169 mensional parameter, from which we extract $\theta(\zeta) = \vartheta(\zeta)/\Delta t$. $\theta(\zeta)$ is therefore the inverse of
 170 the average residence time of trajectories around ζ and it has unit of a frequency (in this study
 171 1/days). If ζ is a fixed point of the attractor $\theta(\zeta) = 0$. For a trajectory that leaves the neighbor-

Supplementary Table 1: List of CMIP5 Models Analysed. The resolution refers to the average horizontal resolution.

No.	Model	Institution/ID	Country	Reolution
01	BCC-CSM1-M	Beijing Climate Center	China	1.125×1.125
02	BCC-CSM1-1	Beijing Climate Center	China	2.81×2.79
03	BNU-ESM	Beijing Normal University Earth System Model	China	2.81×2.81
04	CANESM2	Canadian Centre for Climate Modelling and Analysis	Canada	2.81×2.81
05	CMCC-CMS	Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	1.87×1.87
06	CNRM-CM5	CNRM-CERFACS	France	1.40×1.40
07	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, NOAA	USA	2.5×2.02
08	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, NOAA	USA	2.5×2.02
09	HadGEM2-CC	MetOffice-Hadley Centre	UK	1.87×1.25
10	IPSL-CM5A-MR	Institute Pierre Simon Laplace, IPSL	France	2.5×1.26
11	IPSL-CM5B-LR	Institute Pierre Simon Laplace, IPSL	France	3.75×1.89
12	MIROC-ESM-CHEM	MIROC	Japan	2.81×2.79
13	MPI-ESM-LR	Max Planck Institute for Meteorology, MPI	Germany	1.87×1.87
14	MPI-ESM-MR	Max Planck Institute for Meteorology, MPI	Germany	1.87×1.87
15	MRI-CGCM3	Meteorological Research Institute, MRI	Japan	$1.125 \times 1.$
16	NorESM1-M	Norwegian Climate Center	Norway	2.5×1.89

hood of ζ at the next time iteration, $\theta = 1$. To estimate θ , we adopt the Süveges estimator (43).

For further details on the the extremal index, see (44).

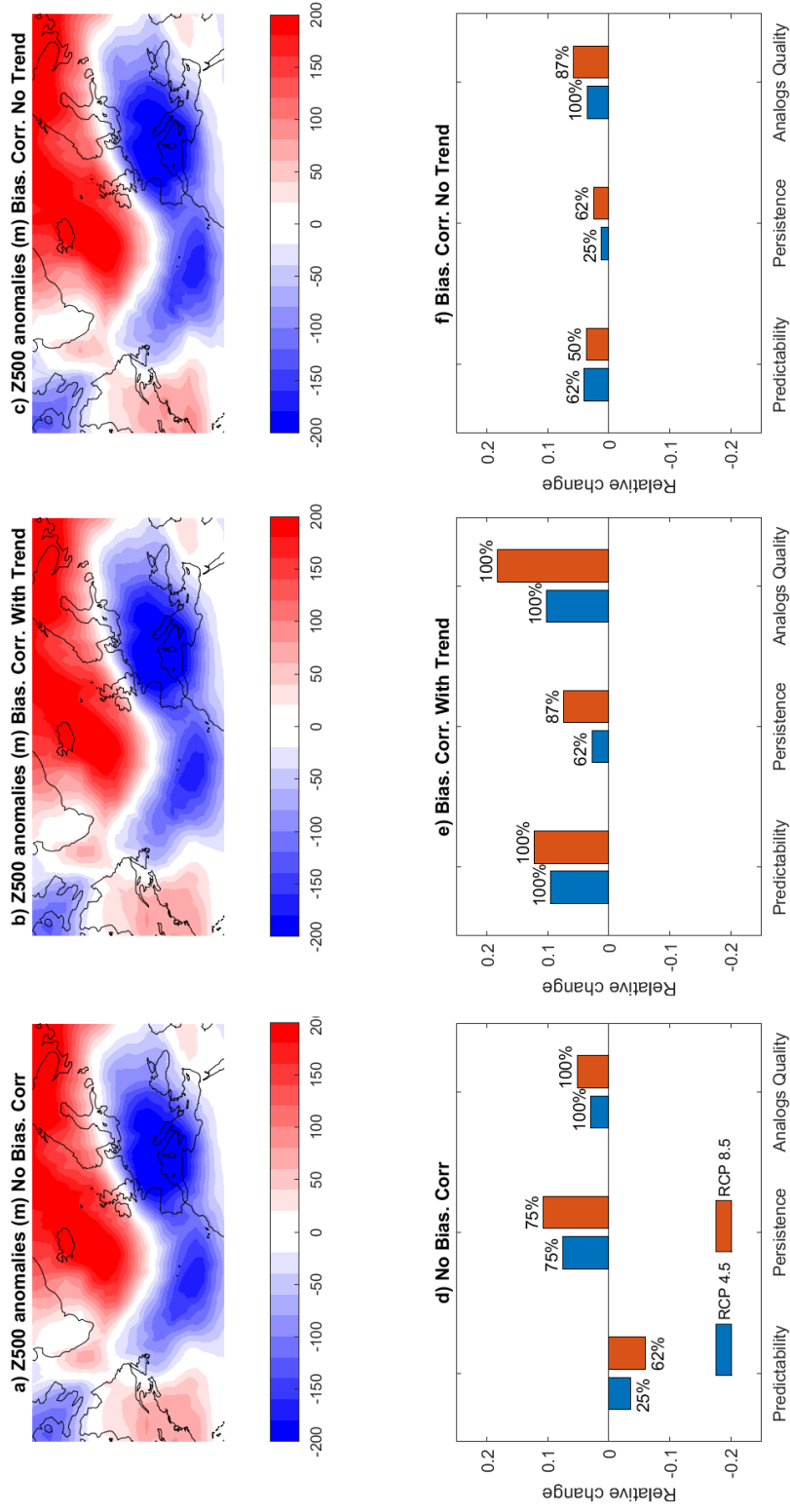
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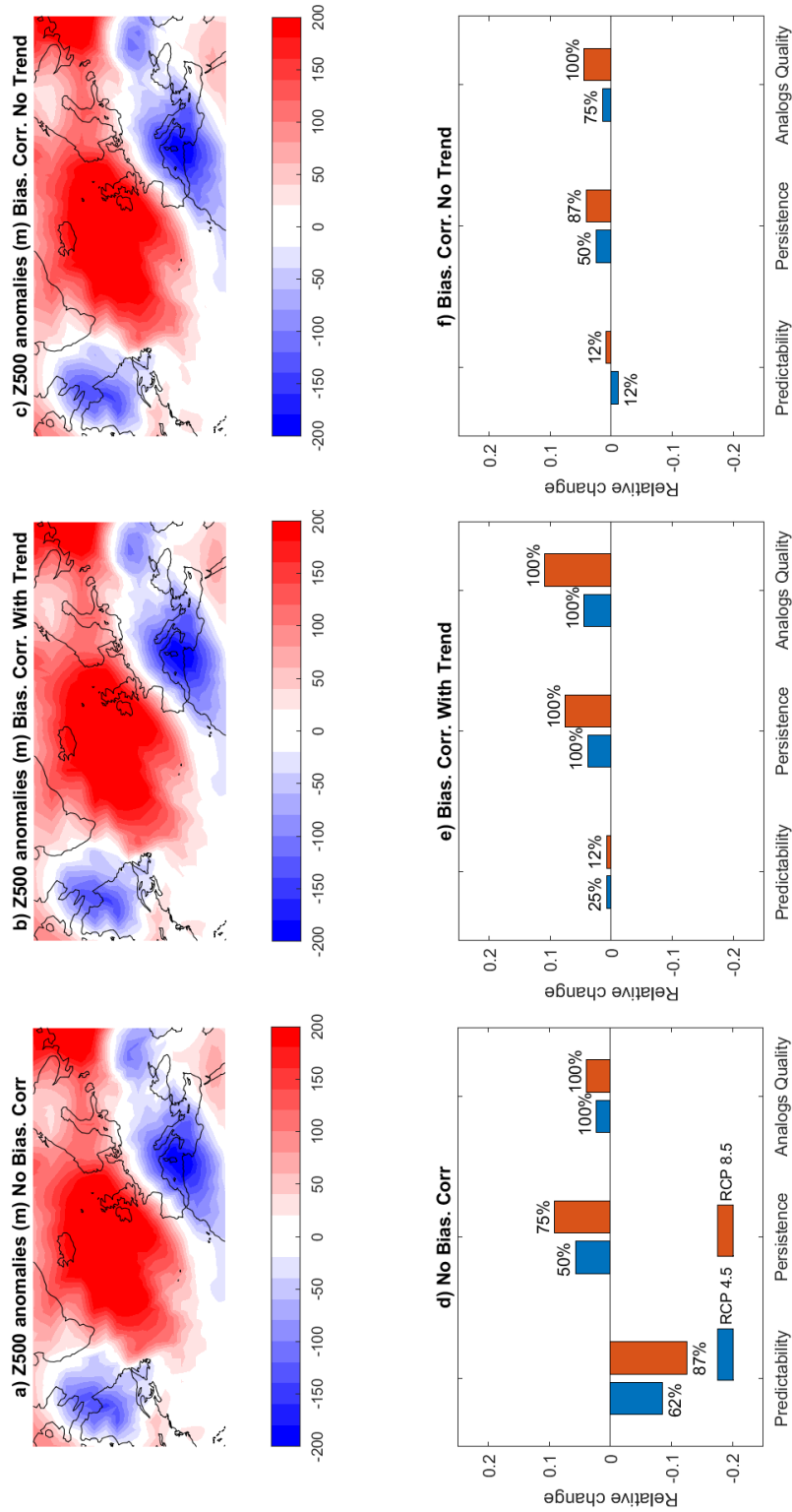
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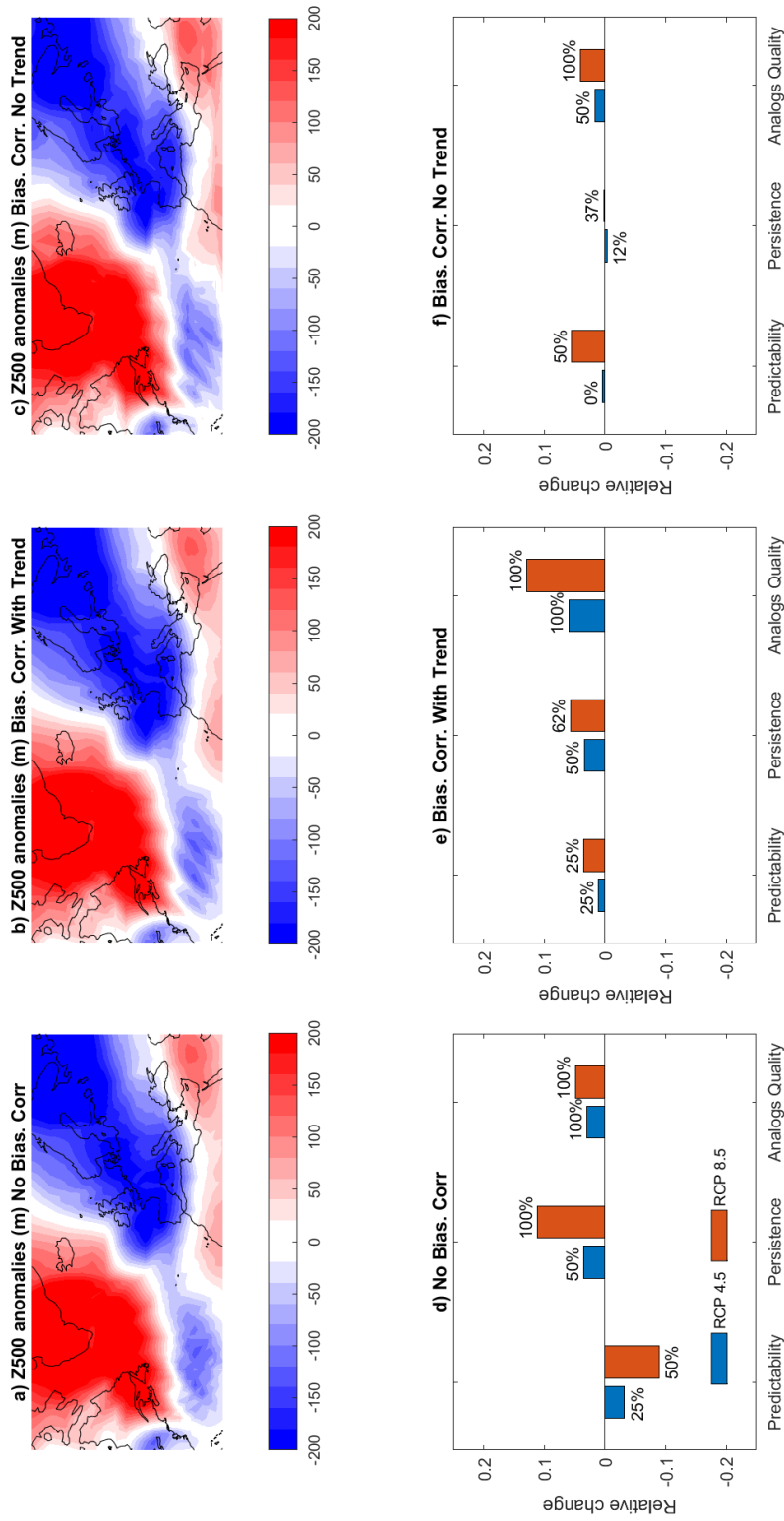
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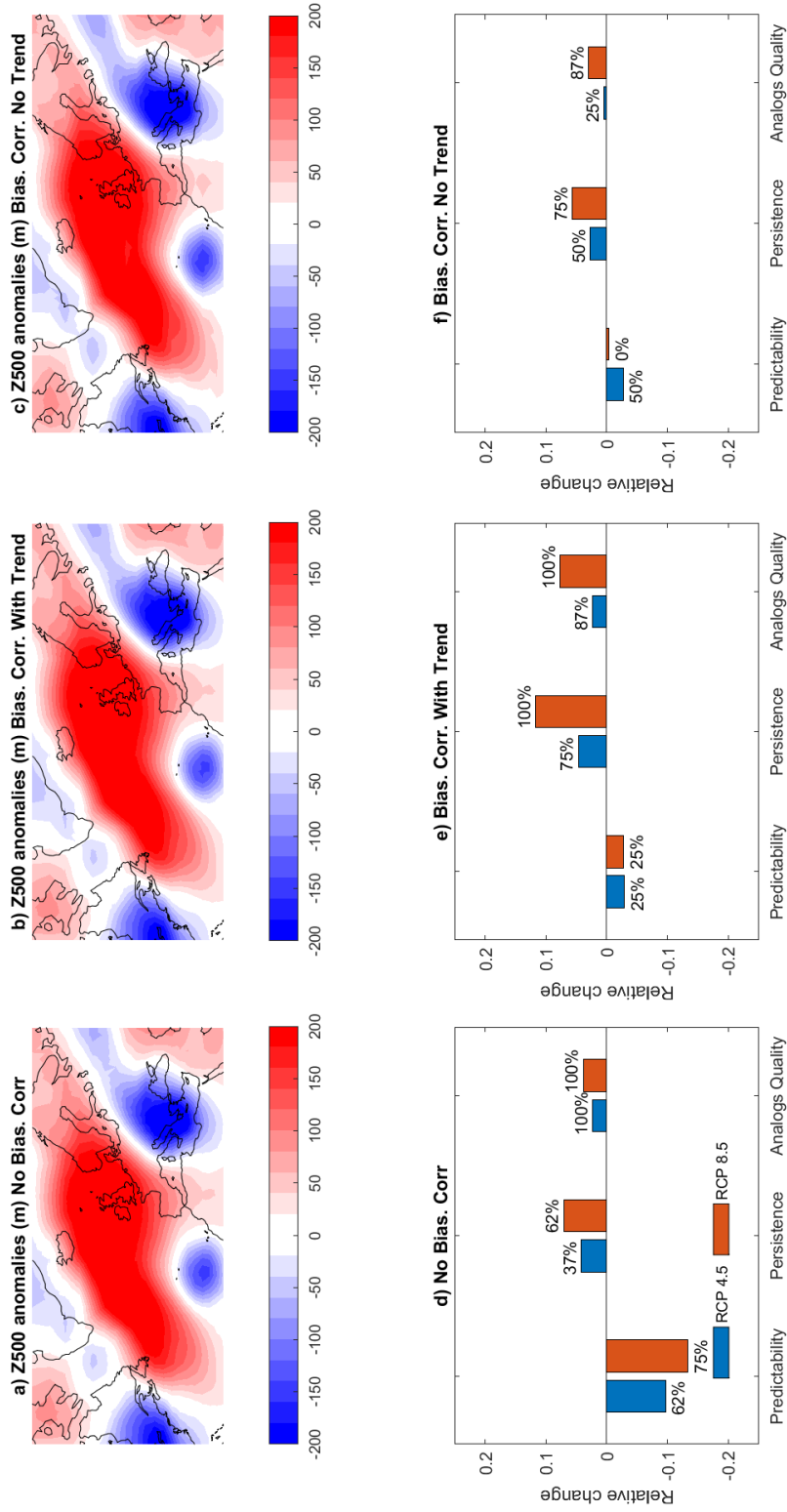
Supplementary Figure 1: Analysis for the 1956 cold spell (CS1956-SE). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



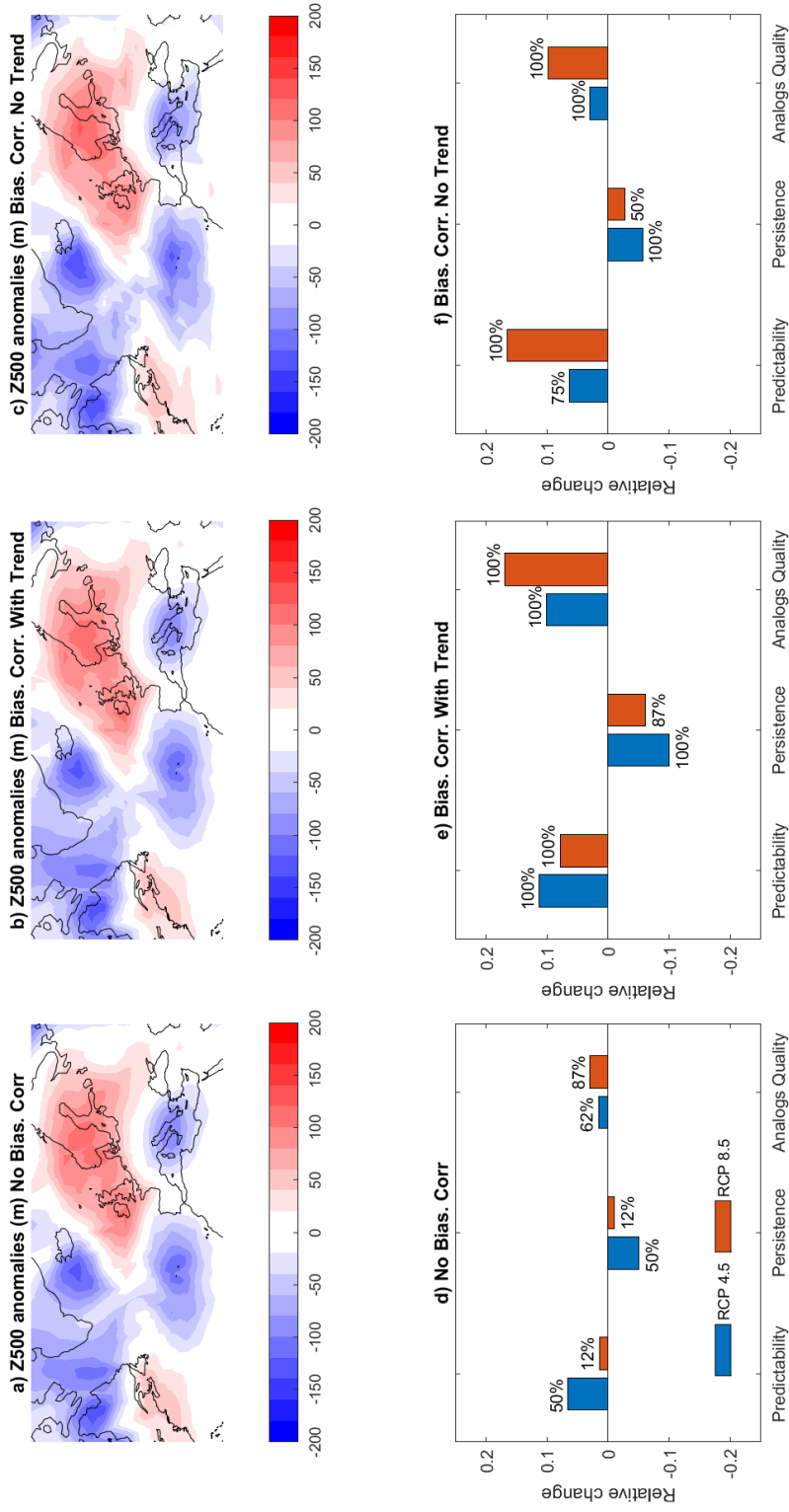
Supplementary Figure 2: Analysis for the 2012 cold spell (CS2012-SE). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



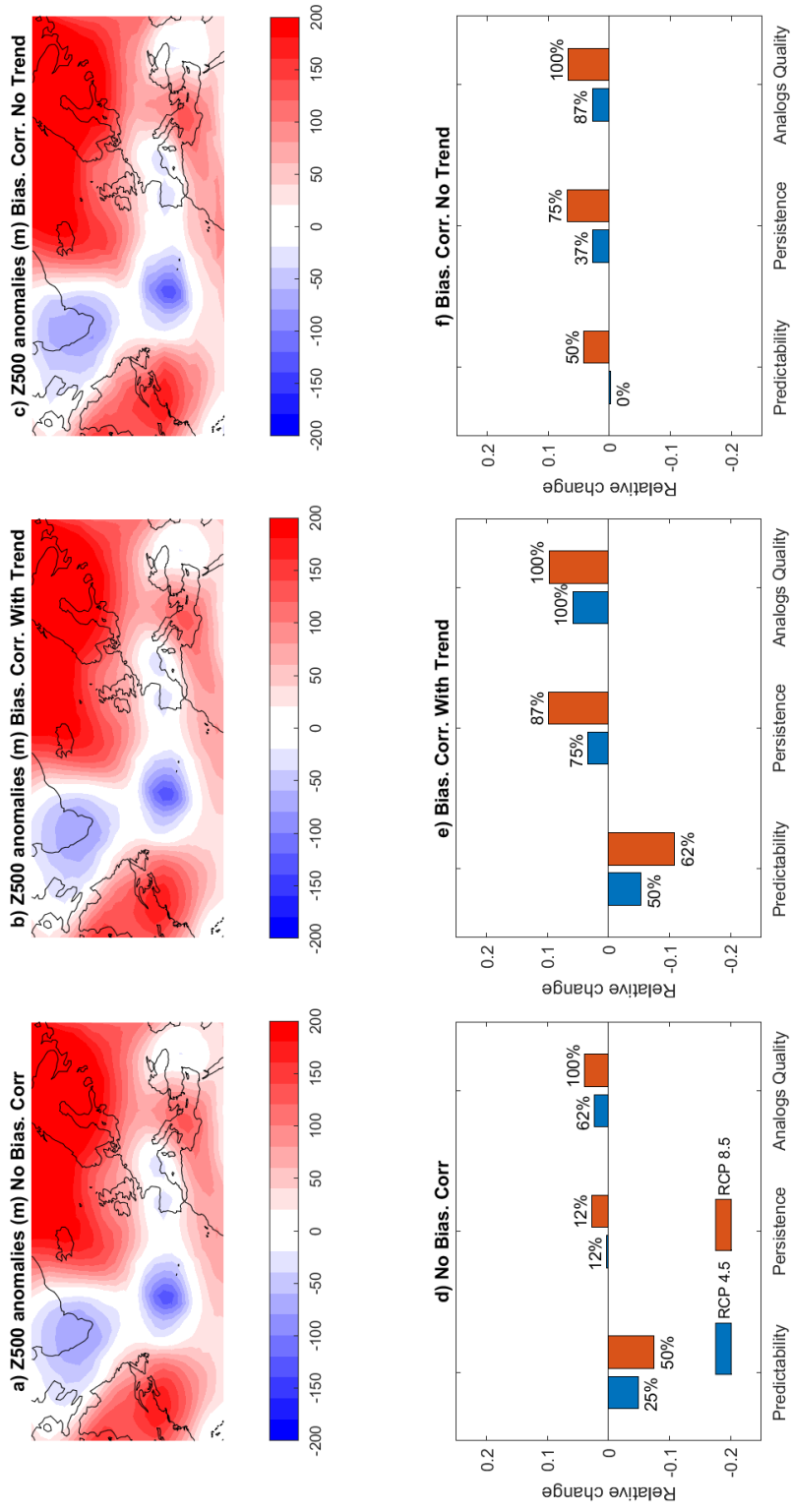
Supplementary Figure 3: Analysis for the 2013 cold spell (CS2013-WE). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



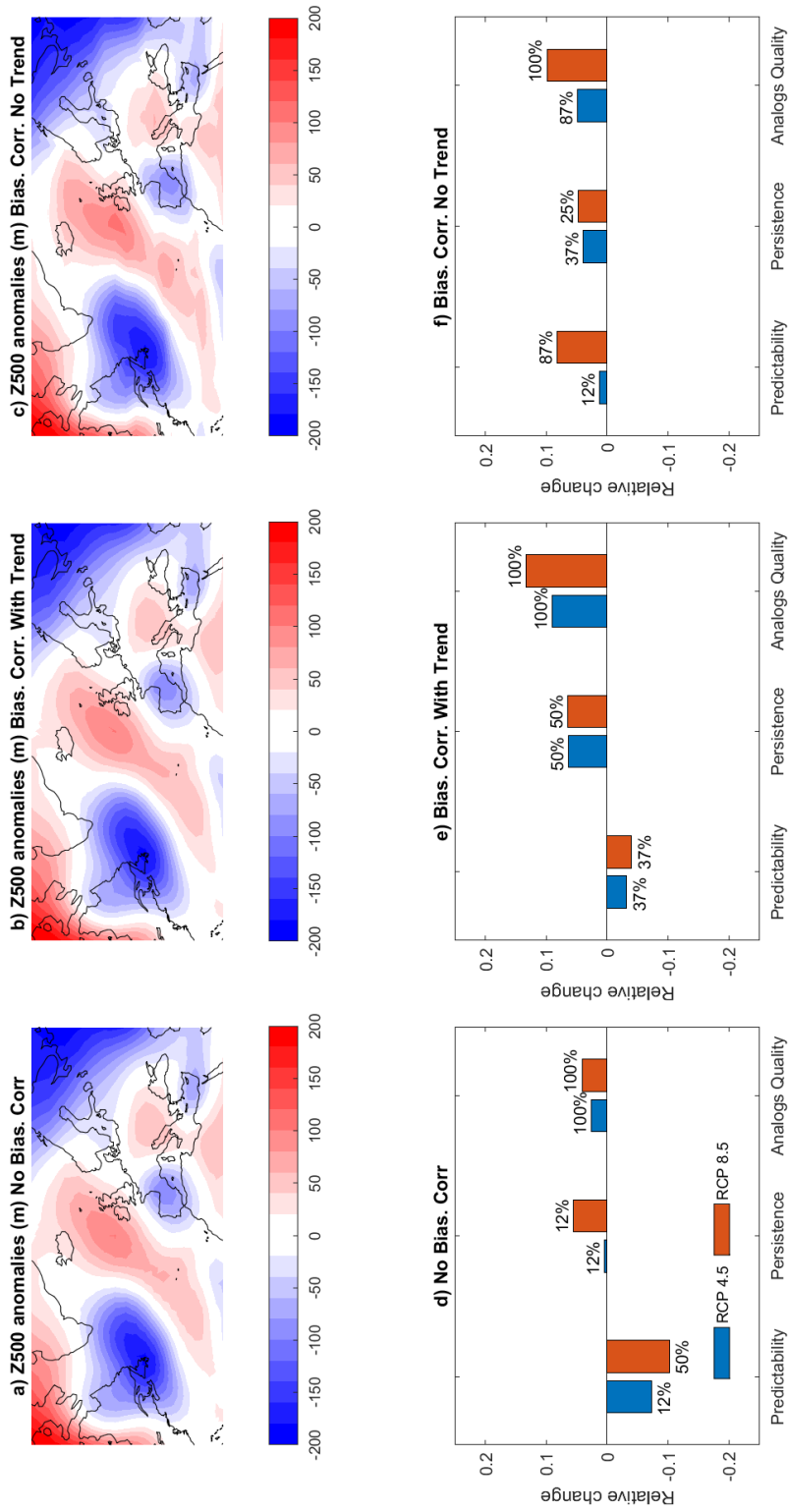
Supplementary Figure 4: Analysis for the 2017 cold spell (CS2017-SE). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



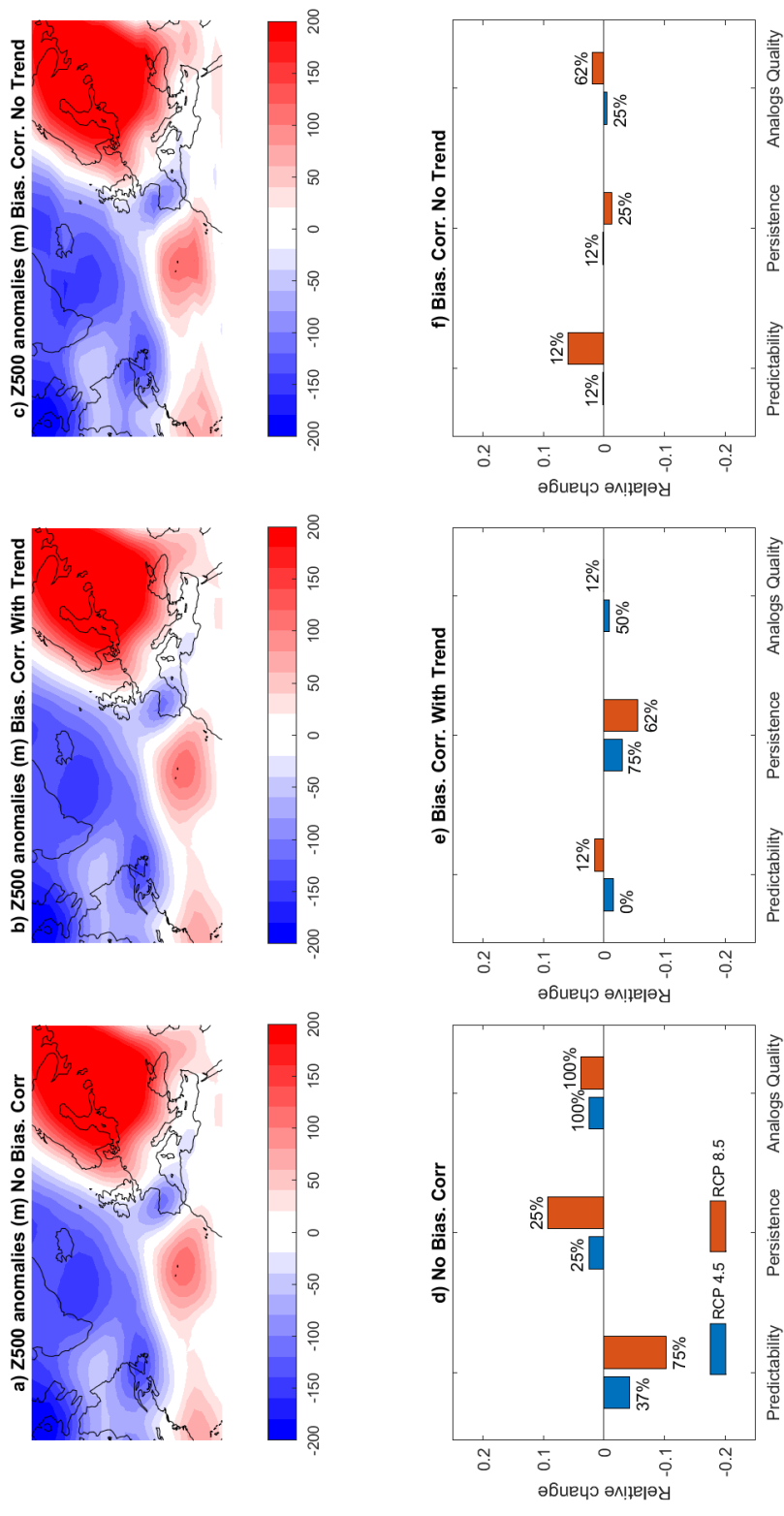
Supplementary Figure 5: Analysis for the 2014 flood (FL2014-BK). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



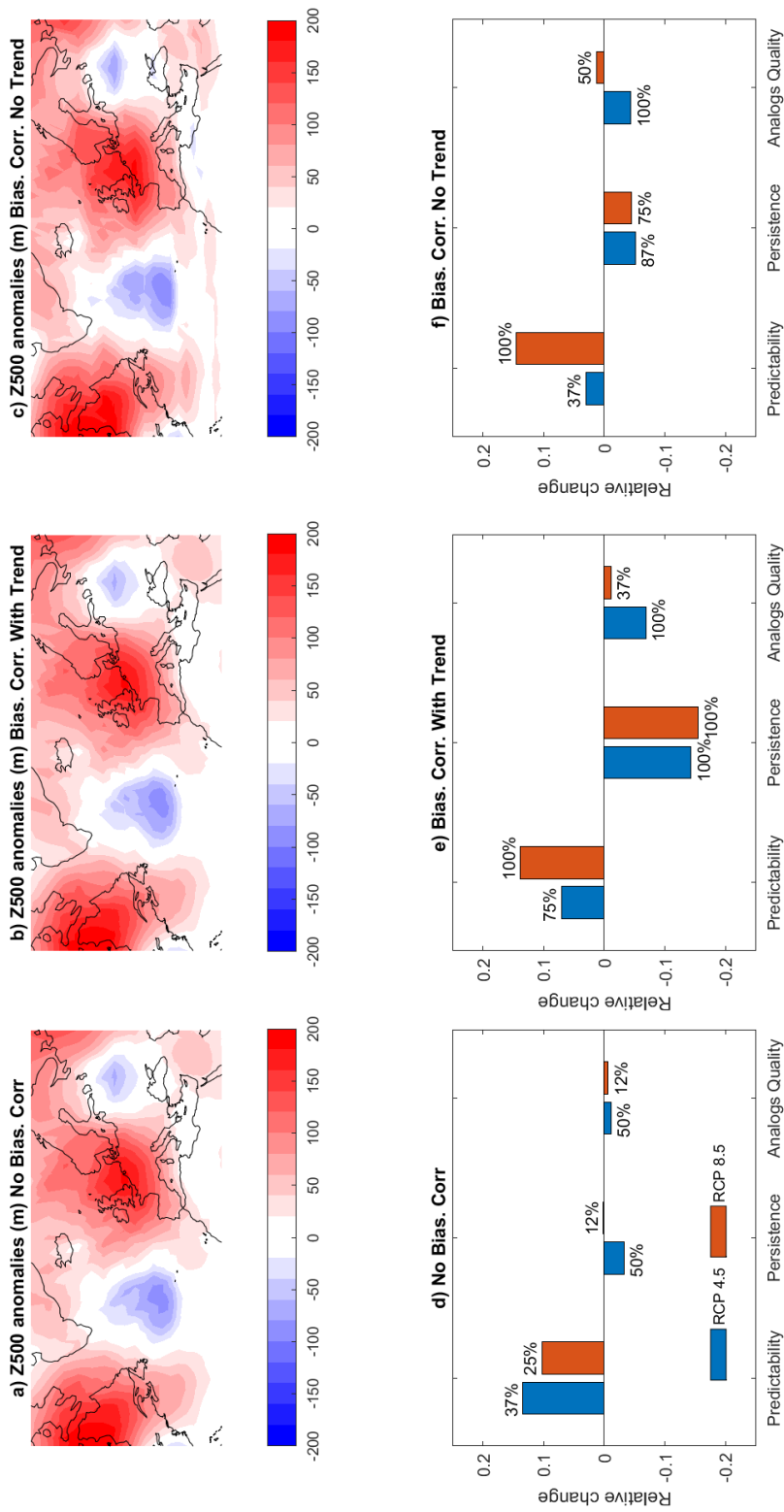
Supplementary Figure 6: Analysis for the 2016 flood (FL2016-FR). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



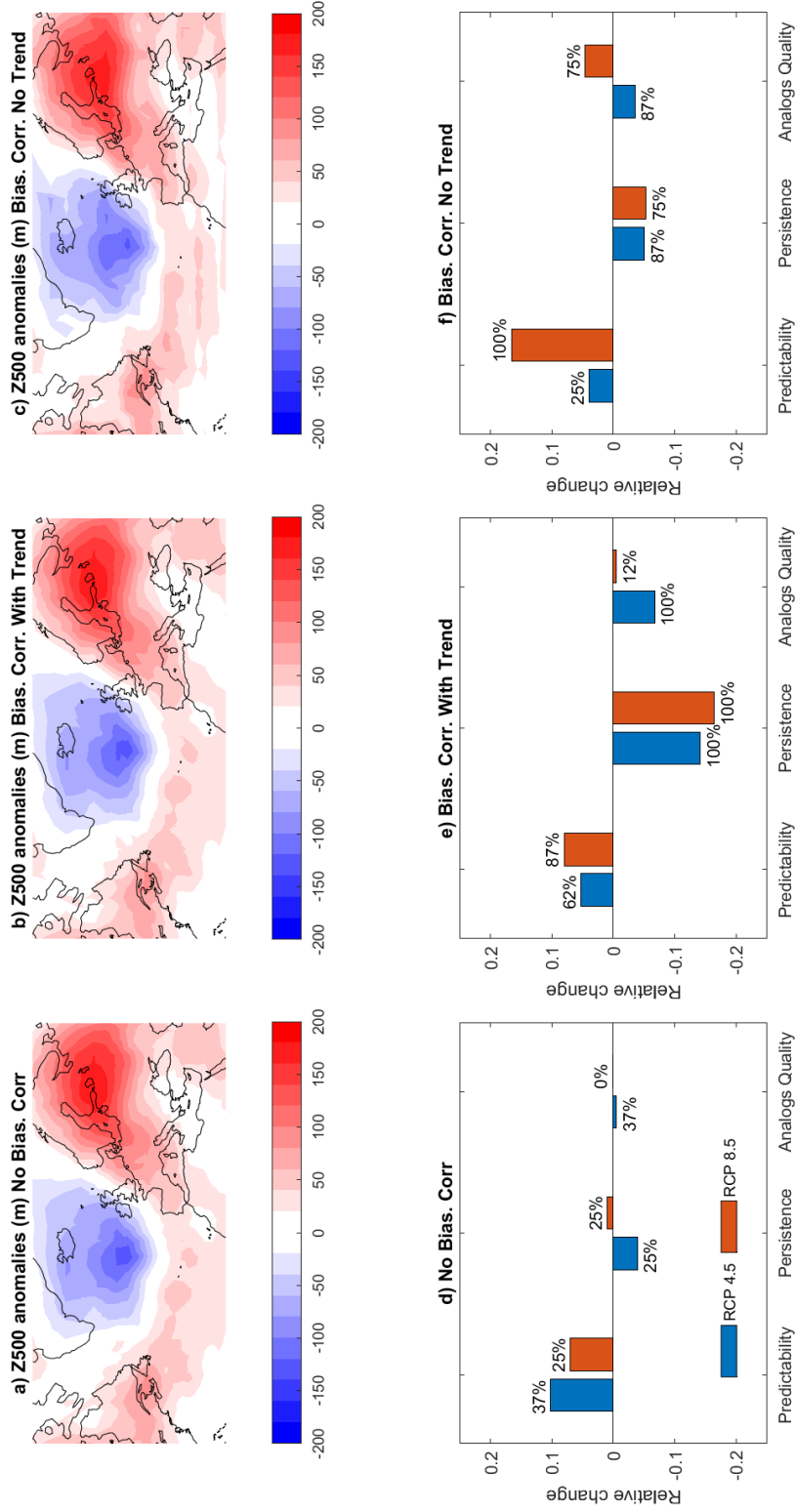
Supplementary Figure 7: Analysis for the June 2018 flood (FL2018-06-FR). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



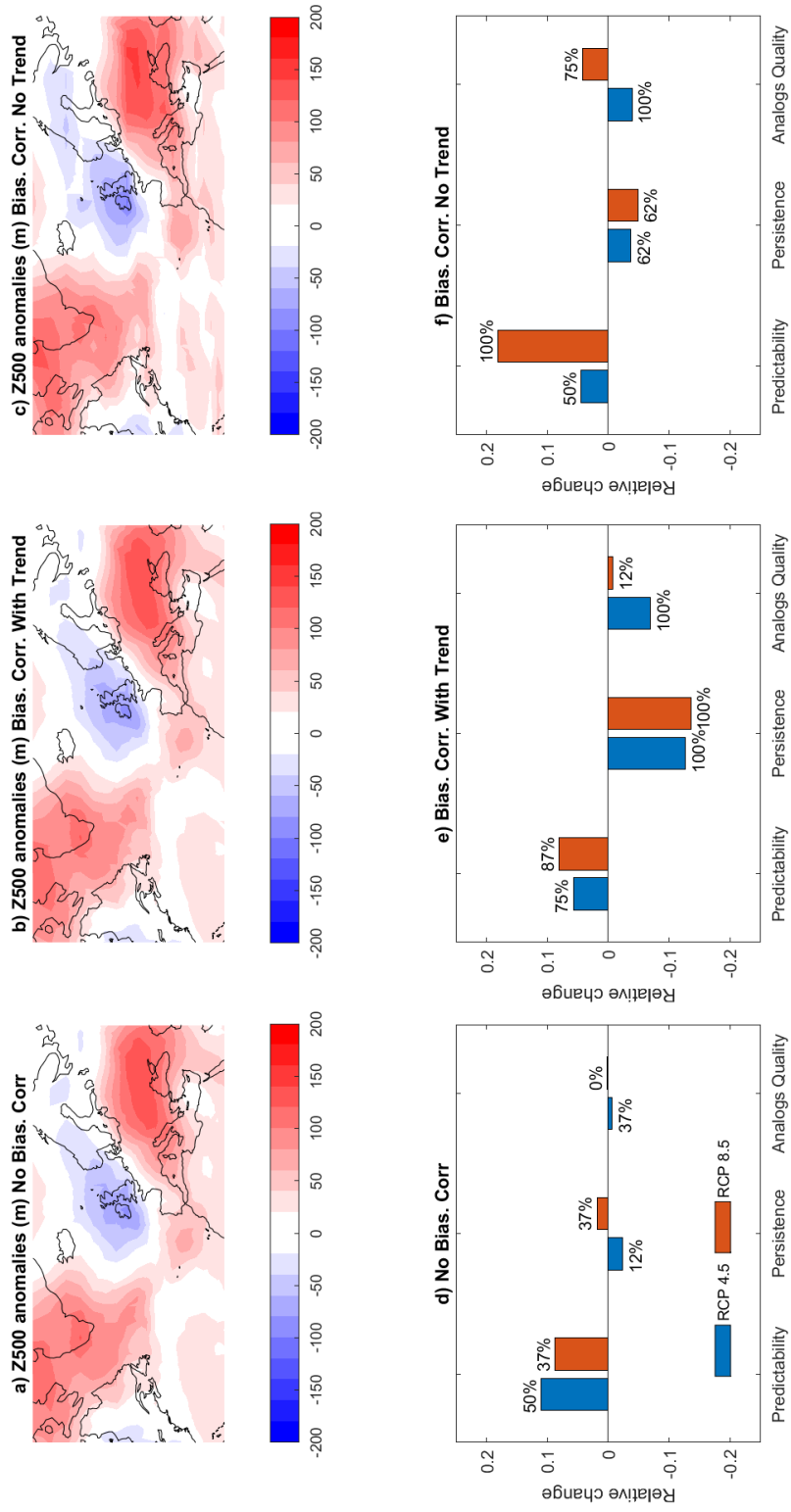
Supplementary Figure 8: **Analysis for the October 2018 flood (FL2018-10-FR)**. a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



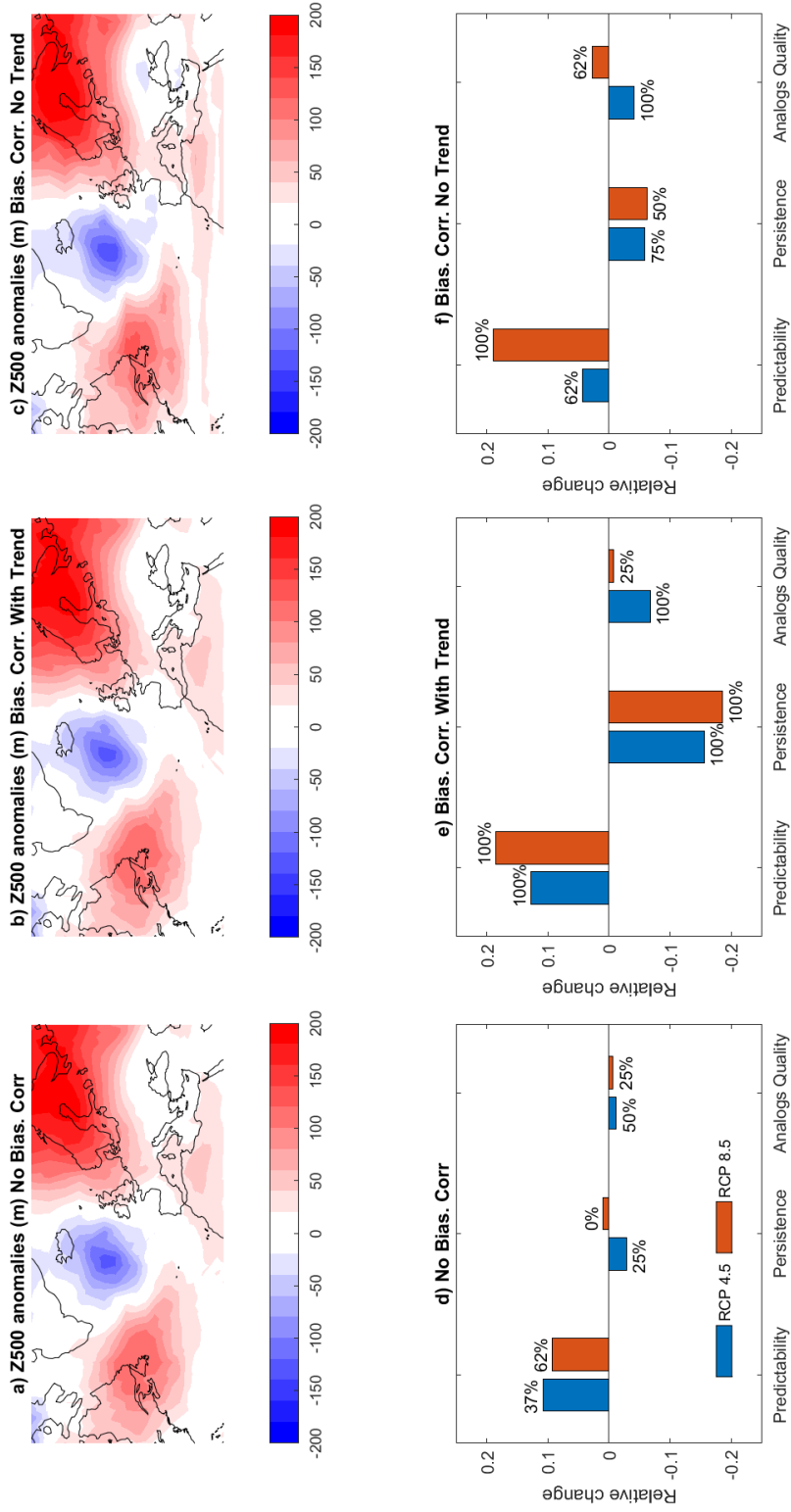
Supplementary Figure 9: Analysis for the 2003 heatwave (HW2003-EU). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



Supplementary Figure 10: **Analysis for the 2010 heatwave (HW2010-RU)**. a, b, c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d, e, f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a, d), with bias correction with trend (b, e) and with trend removed (c, f).



Supplementary Figure 11: **Analysis for the 2017 heatwave (HW2017-SE)**. a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).



Supplementary Figure 12: Analysis for the 2018 heatwave (HW2018-NE). a,b,c) NCEP Geopotential height Z500 anomalies (in meters) computed subtracting the monthly average from the average Z500 field of the event. d,e,f) Relative changes in predictability persistence and analogs quality for the RCP 4.5 (blue) and RCP 8.5 (red) scenarios. The percentage indicates the agreement among different models: 0% means that half of the models have different sign of changes. 100% means that all the models have same sign of changes. Results with no bias correction (a,d), with bias correction with trend (b,e) and with trend removed (c,f).