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**The expectation of future precipitation change over the  
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1 **The expectation of future precipitation change over the**  
2 **Mediterranean region is different from what we observe**

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8 In this study we assess the role of anthropogenic forcing (Greenhouse gases and  
9 Sulphate aerosols, GS) in recently observed precipitation trends over the Mediter-  
10 ranean region. We investigate whether the observed precipitation trends (1966-2005  
11 and 1979-2008) are consistent with what 22 models project as response of precipi-  
12 tation to GS forcing. Significance is estimated using 9,000-year control runs derived  
13 from the CMIP3 archive. The results indicate that externally forced changes are de-  
14 tectable in observed precipitation trends in winter, late summer and in autumn. Nat-  
15 ural internal climate variability cannot explain these changes. However, the observed  
16 trends (derived from 3 sources) are markedly inconsistent with expected changes due  
17 to GS forcing. While the influence of GS signal is detectable in winter and early  
18 spring, observed changes are several times larger than the projected response to GS  
19 forcing. The most striking inconsistency, however, is the contradiction between pro-  
20 jected drying and the observed increase in precipitation in late summer and autumn,  
21 irrespective of the data set used. Natural (internal) variability as estimated from the  
22 models cannot account for these inconsistencies, which are already present in the  
23 large scale circulation patterns (Geopotential height at 500 hPa). The obtained results  
24 are robust to the removal of the fingerprint of the North Atlantic Oscillation. The de-  
25 tection of an outright sign mismatch of observed and projected trends in autumn and  
26 late summer, leads us to conclude that the recently observed trends can not be used as

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27 an illustration of plausible future expected change in the Mediterranean region. These  
28 significant shortcomings in our understanding of recent observed changes complicate  
29 communication of future expected changes in Mediterranean precipitation.

## 30 1 Introduction

31 The issue of future climate change in general is an issue of broad interest - satisfying  
32 a general intellectual curiosity but also having much to do with practical managerial  
33 decisions about how to plan, design and shape our future on global to local scales.  
34 In this study, we examine to what extent the present climate change “is on the way”  
35 towards conditions described by the climate change scenarios at the end of this cen-  
36 tury. We have earlier determined that observed recent (1980-2009) warming over the  
37 Mediterranean region has very likely an anthropogenic origin and thus will likely  
38 continue to rise, albeit not in a monotonous manner (Barkhordarian et al., 2012).

39 The high natural variability of Mediterranean climate in both space and time,  
40 which leads to low signal-to-noise ratio of externally forced changes compared to  
41 internal variability, makes both the detection of climate change and attribution of  
42 its causes very difficult, significantly for non-temperature parameters such as pre-  
43 cipitation, for which the response to the forcing is weak relative to the background  
44 variability (Hegerl and Zwiers, 2011). Nonetheless, observations suggest that climate  
45 may already be changing in the region, with long-term trends in near-surface temper-  
46 ature (Barkhordarian et al., 2012), mean sea level pressure (Barkhordarian, 2012) and  
47 surface specific humidity (Barkhordarian et al., submitted) that cannot be explained  
48 by long-term natural variability (in some seasons).

49 At the global scale, there is evidence for a detectable influence of both short-  
50 wave (primarily natural) forcing on observed precipitation trends and also long-wave  
51 greenhouse gas (GHG) forcing. It has been shown by Zhang et al. (2007) that an-  
52 thropogenic forcing contributed significantly to observed increases in zonal mean  
53 land precipitation in the Northern Hemisphere mid-latitudes and drying in the North-  
54 ern Hemisphere subtropics and tropics. Internal climate variability or natural forcing  
55 cannot explain these changes. The CMIP3 simulations, however, underestimate the  
56 observed change. A more recent study by Min et al. (2011) found that human-induced  
57 increases in GHGs have contributed to the observed intensification of heavy precip-  
58 itation events over two-thirds of the data-covered parts of northern hemisphere land  
59 areas. As with mean precipitation, they also found that models underestimate the  
60 observed precipitation change.

61 On the other hand, the studies by Lambert et al. (2004) and Lambert et al. (2005),  
62 indicate that short-wave forcing of the climate system such as changes in volcanic  
63 aerosols or solar irradiance has a larger effect on global precipitation than GHG long-  
64 wave forcing. Lambert et al. (2004) detect a response to combined anthropogenic  
65 and natural forcing in the observed record from 1944-1997 (and more weakly so  
66 from 1908-1997). They suggest that natural forcing, in particular the response to  
67 stratospheric aerosols due to volcanic activity, is the dominant forcing in the 20<sup>th</sup>  
68 century precipitation record. This supports the findings of Gillett et al. (2004), who  
69 were able to formally attribute the observed global land precipitation changes over

70 the 20<sup>th</sup> century to volcanic forcing, but not to anthropogenic GHGs and sulphates or  
71 solar forcings.

72 At smaller spatial scales, however, there is critical uncertainty in the attribution  
73 of regional observed precipitation changes (Hegerl and Zwiers, 2011). Analysis of  
74 the CMIP3 ensemble of models shows that the Mediterranean region is one of the  
75 most prominent climate change hotspots, i.e. one of the most responsive regions to  
76 global warming (Giorgi, 2006). Study by Gao and Giorgi (2008) indicates that under  
77 the greenhouse gas forcing by the end of the 21st century the Mediterranean region  
78 might experience a substantial increase and northward extension of arid regimes. This  
79 is mostly because of a large decrease of precipitation during the spring and summer  
80 seasons (Giorgi and Bi, 2005).

81 The method used in this study has been earlier applied to near-surface tempera-  
82 ture (Barkhordarian et al., 2012) and mean sea level pressure (Barkhordarian, 2012).  
83 Here we analyze precipitation trends and investigate whether the observed changes  
84 are likely to have been due to natural (internal) variability alone, and if not, whether  
85 they are consistent with what models simulate as response of precipitation to an-  
86 thropogenic (GS) forcing. Therefore, we compare trends in observed precipitation  
87 with the response to GS forcing derived from the set of global climate model simula-  
88 tions provided through the World Climate Research Programme's (WCRP) Coupled  
89 Model Intercomparison Project 3 (CMIP3 Meehl et al., 2007). Consistency of ob-  
90 served trends with climate change projections would point to the plausibility that  
91 the recent trend will continue into the future - based on the understanding that the  
92 recent trend is related to anthropogenic forcing (GS), which will continue in the fu-  
93 ture (Bhend and von Storch, 2008). For the first time this method is being applied to  
94 Mediterranean precipitation. While recent studies have often focused on winter and  
95 summer only, here we analyze trends in sliding 3-month windows.

## 96 **2 Observations and model data**

97 The Mediterranean area is defined here as the region from 25°N to 50°N and 10°W  
98 to 40°E (See Fig.3). Observations are subject to uncertainty; in this study this un-  
99 certainty is addressed by using three independently developed observed data sets.  
100 We use land-only rain gauge data from the latest version of the Climatic Research  
101 Unit's (CRU) gridded high-resolution ( 0.5° by 0.5°) dataset CRU TS 3.10 (Mitchell  
102 and Jones , 2005, referred to as CRU3.1 in the following). The station records of the  
103 CRU3.1 dataset are quality controlled and homogenized, using an automated method  
104 developed from the GHCN method (Easterling and Peterson, 1995).

105 We also use version 5 of the "Full Data Reanalysis Product" of the Global Precip-  
106 itation Climatology Centre (GPCC Rudolf et al., 2005). These data include quality  
107 controlled rain gauge data from 1901-2009 that have been interpolated to a 0.5° by  
108 0.5° grid using the SPHEREMAP method (Willmott et al., 1985).

109 Furthermore, we use monthly mean precipitation over land and sea areas from  
110 the Global Precipitation Climatology Project (GPCP Adler et al., 2003). The GPCP  
111 dataset provides rain gauge-satellite merged data in 2.5° by 2.5° grids over the period

112 1979 to 2008. Rain-gauge data are quality controlled to contribute to the analysis over  
113 land.

114 CRU has advised the users of CRU TS2.1 that it is not suitable for detection and  
115 attribution, as the effect of urban development and land use changes are potentially  
116 present in the data, however, there is no published study exploring this issue further.  
117 The main difference between CRU TS2.1 and CRU TS3.1 version is that no new  
118 homogenization is explicitly performed on the latter. Existing homogenizations in  
119 the underlying datasets, and those additionally performed by national meteorological  
120 agencies prior to releasing their station data, are incorporated. Thus, the station series  
121 of CRU TS3.1 might still be affected by urban development and land use changes.  
122 In addition the rain-gauge data of GPCC5 and GPCP data sets are quality controlled,  
123 which does remove outliers, but does not ensure homogeneity. Thus, our results must  
124 be interpreted with the caveat of potential inhomogeneity of the currently available  
125 gridded precipitation data sets. However, we expect that most of the in-homogeneities  
126 are not systematic.

127 For all datasets, trends have been calculated using ordinary least squares linear  
128 regression and the units are mm/season/decade (season = 3 months). To describe ex-  
129 pected anthropogenic trends, we use global projections based on the IPCC SRES  
130 A1B (A2) scenario, ending with a CO<sub>2</sub> concentration of 720 (850) ppm by the year  
131 2100, obtained from 22 (18) global Atmosphere-Ocean General Circulation Models  
132 (AOGCMs). The simulations are included in the CMIP3 multi-model dataset (Meehl  
133 et al., 2007). Previous to the analysis, the model data are interpolated to a latitude-  
134 longitude grid with a resolution of 0.5° (or in case of GPCP, 2.5°) using conservative  
135 remapping (Jones, 1999). We mask grid cells in the monthly data according to the  
136 missing value mask in the observed record.

### 137 3 Methodology

138 We follow the same approach as presented in Barkhordarian et al. (2012). In the first  
139 step, we investigate whether the observed changes are derived from an undisturbed  
140 stationary climate. This is handled by testing the null hypothesis  $H_0$ : *zero trend*. To  
141 test the null hypothesis, annual and seasonal observed precipitation trends are com-  
142 pared with estimated natural (internal) variability, derived from control integrations  
143 of CMIP3 climate models. Control integrations are experiments with all external forc-  
144 ings fixed to the values attained in 1850 reflecting pre-industrial conditions.

145 Estimating natural (internal) variability from long control simulations has been  
146 a popular method, since the experiment setup is sound and long simulations (and  
147 thus precise estimates) are possible (Stone et al., 2009). However, the verification  
148 of variability of global climate models is difficult since the instrumental record for  
149 precipitation is not long enough (100-year) to give a reliable estimate of internal  
150 variability, while paleoclimatic data are sparse and often of limited quality (see e.g.  
151 Hegerl et al. (1996)).

152 From 9,000 simulated years of control runs that are sufficiently long to resolve  
153 variability on all relevant timescales, we draw 285 non-overlapping 30-year seg-  
154 ments (or 213 non-overlapping 40-year segments) to estimate internal variability, i.e.

155 stochastic variability that would be present irrespective of any external influence on  
 156 the climate system (Hegerl and Zwiers, 2011). In order to remove the potential drift  
 157 in coupled atmosphere-ocean models, a de-trending treatment is applied to the control  
 158 simulations. Independent control run segments are calculated in such a way as to  
 159 mimic the observations using the same observation mask to account for the effects of  
 160 missing data. A list of the climate models and the number of years used from control  
 161 integrations to estimate the internal variability is given in Table 1.

162 Rejecting the null hypothesis  $H_0$ : *zero trend*, indicates that the observed changes  
 163 can not be explained by internal variability alone and externally forced changes are  
 164 detectable. Once it is found that external forcings must be invoked (are detectable)  
 165 for explaining recent trends, in the second step we assess whether the observed sig-  
 166 nificant trends are within the range of expected changes due to anthropogenic forc-  
 167 ing (Greenhouse gases and Sulphate aerosols, GS) generated by 22 climate models  
 168 (Sect. 3.1). To this end, we compare area-mean changes of observed precipitation in  
 169 three-month windows over the period 1966-2005 (over land) and 1978-2009 (over  
 170 land and sea) with what climate models project as response of precipitation to an-  
 171 thropogenic (GS) forcing. We consider a large number of A1B (22) and A2 (18)  
 172 simulations. If the recent observed trends reside in this range of possible and plausi-  
 173 ble changes due to increasing greenhouse gas and sulfate aerosol concentrations, we  
 174 call the observed change consistent with GS forcing.

175 In order to take the spatial pattern of change into account, we use regression  
 176 indices as a pattern similarity statistic (R, Eq. 1).

$$R(O, P) = \frac{\sum_{i=1}^n P_i \cdot O_i}{\sum_{i=1}^n P_i^2} \quad (1)$$

177 The index subscript  $i = 1, \dots, n$  counts the spatial points,  $O_i$  and  $P_i$  refer to the ob-  
 178 served and simulated pattern of change, respectively.

179 The distribution of the regression indices is assessed from fits of the regression  
 180 model (Eq. 1) to non-overlapping control run segments derived from long control  
 181 simulations. We use the combination of the quantiles of control run trends and the fit  
 182 to the observations to test the null hypothesis that the uncertainty range of regression  
 183 indices does not include “0”, indicating that the influence of GS signal is detectable  
 184 in the observed record (see Fig. 4). To examine if anthropogenic (GS) forcing is a  
 185 plausible explanation for the observed change, we evaluate the hypothesis  $H_d$  that  
 186 the regression of the observed trend on the GS signal does not include “0” but in-  
 187 cludes “1” (Hegerl et al., 1997). When there is insufficient evidence to reject  $H_d$ , we  
 188 claim that the observed change is consistent with climate change projections. If re-  
 189 cent trends and scenarios are inconsistent, however, we conclude that the observed  
 190 recent change cannot be interpreted as a harbinger of future change.

### 191 3.1 Anthropogenic climate change signal estimates

192 In this study, two methods are used to estimate the anthropogenic (GS) signal. On  
 193 the one hand, we use time-slice experiments and define the anthropogenic climate

194 change signal as the difference between the last decades of the 21st century (2071-  
 195 2100) and the reference climatology (1961-1990). We assume a linear development  
 196 from 1961-2100 and the resulting signal is scaled to change per year (Bhend and  
 197 von Storch, 2008). The linearity assumption is supported by the study of Raisanen  
 198 et al. (2004) and Cubasch et al. (2001). Using well-separated time slices, 110 years  
 199 in this study, has the advantage of increasing the signal-to-noise ratio and avoiding  
 200 the need to average multiple models to get clear signal patterns. A list of the climate  
 201 models and the number of ensemble members of the individual models, is given in  
 202 Table 1. For each model, these ensemble members differ only in the initial conditions  
 203 and thus represent different realizations of internal variability. Therefore, by aver-  
 204 aging over an ensemble of runs the signal to noise ratio of externally forced changes  
 205 compared to internal variability is further increased. The multi-model CMIP3 archive  
 206 offers unique opportunities. A key opportunity is that the archive contains informa-  
 207 tion from models with different resolution, physics, parameterizations and forcings.  
 208 This method allows us to best exploit this wealth of information by explicitly dealing  
 209 with individual models separately.

210 On the other hand, we estimate the anthropogenic signal from transient model  
 211 simulations, forced with historical anthropogenic forcing only (ANT, greenhouse  
 212 gases and sulphate aerosols), over the time period 1979-2008 and 1966-2005. The  
 213 multi-model ensemble mean is used here to get model simulated response patterns  
 214 with high signal-to-noise ratio of externally forced changes compared to internal  
 215 variability (Gillett et al., 2002). Here we use the multi-model ensemble mean of 10  
 216 models (18 ANT simulations) derived from the CMIP3 archive. The models used  
 217 are, BCCR-BCM2.0 (1 run), CNRM-CM3 (1 run), CSIRO-MK3.0 (1 run), CSIRO-  
 218 MK3.5 (1 run), GISS-AOM (2 runs), INGV-ECHAM4 (1 run), ECHAM5/MPI-OM  
 219 (4 runs), CCCMA-CGCM3.1 (5 runs), CCCMA-CGCM3.1-T63 (1 run) and UKMO-  
 220 HadGEM1 (1 run). The strategy used to compute multi-model mean is based on giv-  
 221 ing each model equal weight. Thus, the multi-model mean response is not dominated  
 222 by responses of models with many simulations. The formula to compute effective  
 223 number of models with equal weighting of the individual models is:  $n = \frac{m^2}{\sum_{i=1}^m \frac{1}{l_i}}$ ,  
 224 where  $m$  is the number of models and  $l$  is the ensemble size (Allen and Tett, 1999).  
 225 The final internal variance is then just  $1/n$  the internal variance. Thus, by using the  
 226 multi-model mean of 10 models (18 ANT simulations), the internal variability de-  
 227 creases by more than 90% compared to using an individual simulation, which in-  
 228 creases the signal-to-noise ratio in estimated anthropogenic patterns considerably.

229 Since the 20th century simulations generally finished in 1999 (2000), it was nec-  
 230 essary to use outputs from SRES A1B scenario for the last 8 (5) years of the simu-  
 231 lation period. Thus, we combine the 20<sup>th</sup> century historical runs with the projections  
 232 for the 21<sup>st</sup> century driven by anthropogenic (GS) forcings according to the SRES  
 233 A1B emission scenario. The A1B runs provide a reasonable estimate of GHG forc-  
 234 ings over 2000 to 2010 (Santer et al., 2011), but it is not clear how realistically they  
 235 represent the true net aerosol forcing over this period (Santer et al., 2011), thus splic-  
 236 ing together output from the 20th century and A1B simulations can introduce forcing  
 237 discontinuities (Arblaster et al., 2011).

**Table 1** The twenty-two coupled ocean-atmosphere models used in this study along with the number of twentieth century runs per model, and the number of years and independent segments of the control runs used in this study to estimate natural (internal) variability.

	Models (number of runs)	Number of years used from control integrations
1	bccr-bcm2.0 (1)	250 (8 segments of 30-year or 6 segments of 40-year)
2	cccma-cgcm3.1 (5)	1000(33 segments of 30-year or 26 segments of 40-year)
3	cccma-cgcm3.1-T63 (1)	350 (11 segments of 30-year or 8 segments of 40-year)
4	cnrm-cm3 (1)	500 (16 segments of 30-year or 12 segments of 40-year)
5	csiro-mk3.0 (1)	350 (11 segments of 30-year or 9 segments of 40-year)
6	csiro-mk3.5 (1)	1000 (33 segments of 30-year or 26 segments of 40-year)
7	gfdl-cm2.0 (1)	500 (16 segments of 30-year or 12 segments of 40-year)
8	gfdl-cm2.1 (1)	500 (16 segments of 30-year or 12 segments of 40-year)
9	giss-aom (2)	250 (8 segments of 30-year or 6 segments of 40-year)
10	giss-model-e-h (3)	380 (12 segments of 30-year or 9 segments of 40-year)
11	ingv-echam4 (1)	100 (3 segments of 30-year or 2 segments of 40-year)
12	inmcm3.0 (1)	350 (11 segments of 30-year or 8 segments of 40-year)
13	ipsl-cm4 (1)	500 (16 segments of 30-year or 12 segments of 40-year)
18	miroc3.2-hires (1)	100 (3 segments of 30-year or 2 segments of 40-year)
15	miroc3.2-medres (3)	500 (16 segments of 30-year or 12 segments of 40-year)
16	miub-echo-g (3)	350 (11 segments of 30-year or 8 segments of 40-year)
17	mpi-echam5 (4)	500 (16 segments of 30-year or 12 segments of 40-year)
18	mri-cgcm2.3-2a (5)	350 (11 segments of 30-year or 8 segments of 40-year)
19	ncar-ccsm3.0 (7)	230 (7 segments of 30-year or 5 segments of 40-year)
20	ncar-pcm1 (4)	350 (11 segments of 30-year or 8 segments of 40-year)
21	ukmo-hadcm3 (1)	350 (11 segments of 30-year or 8 segments of 40-year)
22	ukmo-hadgem1 (1)	160 (5 segments of 30-year or 4 segments of 40-year)
		Total: 285 non-overlapping 30-year segments
		Total: 213 non-overlapping 40-year segments

## 238 4 Results

### 239 4.1 Detection of externally forced changes

240 Fig. 1 shows observed area-mean changes of precipitation over land in three-month  
 241 windows for the period from 1966 to 2005 based on the CRU3.1 and GPCC5 datasets.  
 242 The grey bars represent the mean value of CRU3.1 and GPCC5, with trends from  
 243 each dataset corresponding to the brown bars. The datasets generally agree well, with  
 244 notable differences in JJA, JAS, ASO and NDJ. Both datasets suggest that the area  
 245 mean precipitation decreases in all sliding 3-month windows from December to Au-  
 246 gust (DJF, JFM, ..., JJA). The general drought conditions in the wet season since  
 247 the 1960s over large part of the Mediterranean region is a consistent finding among  
 248 other studies (e.g. Xoplaki et al. 2004, Mariotti 2010, Hoerling et al. 2012). In late  
 249 summer and autumn, however, the observations suggest an increase in the amount of  
 250 precipitation in JAS, ASO, SON and OND over the 1966-2005 period.

251 Here we assess whether externally forced changes have a detectable influence on  
 252 the observed trends by comparing observed trends with those calculated from pre-  
 253 industrial control simulations (see Sect. 3). We analyze 9,000 years of control inte-  
 254 grations and derive 213 non-overlapping 40-year trends in an undisturbed stationary  
 255 climate (Table 1). The observed trend is likely not due to natural (internal) variability



256 alone in cases for which the 90% uncertainty range about the observed trends (red  
257 whiskers in Figs. 1 and 2) excludes zero. In DJF, JFM and FMA, the observed trends  
258 are highly unlikely due to internal variability alone, noting that no single sample of  
259 213 segments yield a negative trend of precipitation as strong as that observed.

260 Also in autumn (SON and OND) the uncertainty range of observed trends derived  
261 from control runs does not include zero with both CRU3.1 and GPCC5. This indicates  
262 that the observed positive trends in the amount of precipitation in SON and OND  
263 intervals deviate significantly (at 5% level, one-sided test) from natural (internal)  
264 variability. In ASO the mean value of both datasets are significantly different from  
265 internal variability, and also GPCC5 displays a significantly greater than zero positive  
266 trend, however the observed trend derived from CRU3.1 is not significant (Fig. 1).  
267 Therefore, we conclude that it is unlikely that the observed negative trends in winter  
268 and positive trends in autumn can be attributed to natural (internal) variability alone  
269 and externally forced changes are significantly detectable.

270 We have also analysed the GPCP dataset incorporating precipitation over sea  
271 (Fig. 2). Over the period 1979-2008, GPCP displays a negative trend in all sliding  
272 3-month windows (over land and sea) from November to June (NDJ, DJF, ..., MJJ).  
273 Consistent with CRU3.1 and GPCC5 datasets, GPCP also displays a positive trend in  
274 late summer and autumn (JJA, JAS, ASO and SON). As displayed by the red whiskers  
275 in Fig. 2, the statistical test indicates that the observed trends in winter (NDJ, DJF,  
276 JFM), early spring (FMA), late summer (JAS) and autumn (ASO, SON) are detected  
277 at the 5% level (one-sided test). That is, there is less than a 5% probability of such  
278 a large trend due to natural (internal) variability alone according to 285 segments of  
279 unforced trends (derived from 9,000 years of control simulations).

280 Thus, the merged rain gauge and satellite record according to GPCP along with  
281 the station based records, CRU3.1 and GPCC5, are suggesting that the observed  
282 changes in winter, late summer and autumn exceed the limits of natural (internal)  
283 variability. That is, externally forced changes are detectable (at 5% significant level,  
284 one-sided test). In the following, we assess whether the observed trends, which are  
285 found to be inconsistent with natural (internal) variability, are consistent with climate  
286 change scenarios.

#### 287 4.2 Consistency of observed and projected area-mean changes

288 Here we analyze whether the CMIP3 projections encompass the observed trends the  
289 magnitude of which can not be reconciled with natural (internal) variability alone. To  
290 this end, we compare the observed trends with what climate change scenarios project  
291 as response of precipitation to GS forcing (Fig. 1 and 2). With a few exceptions,  
292 all A1B (A2) scenarios from the 22 (18) models used project negative trends in all  
293 3-month windows. Under increasing GHG concentrations we thus expect drier condi-  
294 tions in the region, with maximum decreases in precipitation in the warm season  
295 and minimum decreases in the cold season. This indicates clearly that warm season  
296 precipitation is expected to be more responsive to GS forcing.

297 Figure 3 shows maps of change for the GPCP and CRU3.1 datasets as well as  
298 the spatial pattern of the anthropogenic climate change signal (GS) derived from the

299 multi-model ensemble mean of 22 models (49 ensemble members). In most simula-  
300 tions, as in the multi-model ensemble mean shown in Fig. 3, wintertime precipitation  
301 is projected to increase in a narrow band in the northern part of the Mediterranean  
302 and is projected to decrease in the remaining area with large reductions in areas at  
303 the western border of the region (southern Spain, northern Algeria and Morocco) and  
304 over Turkey. Giorgi and Lionello (2008) and Mariotti (2010) confirm this meridional  
305 contrast in precipitation change with drying in the south and wettening in the north.  
306 Lionello and Giorgi (2007) suggests that the increase of the winter (DJF) cyclone  
307 activity in future climate scenarios over western Europe is responsible for the larger  
308 precipitation at the northern coast of the Mediterranean, while the reduction of cy-  
309 clone activity inside the Mediterranean region in future scenarios is responsible for  
310 the lower precipitation at the southern coast. Also, such a south-north contrast in Eu-  
311 ropean wintertime (DJF and FJM) precipitation trends is seen with observed records  
312 (Fig. 3). The spatial pattern of precipitation suggested by CRU3.1 and GPCC5 is  
313 characterized by a meridional dipole of increase in the northern Europe and strong  
314 decrease of precipitation over Southern Europe and northern Algeria and Morocco.

315 When comparing the observed and projected area-mean changes as shown in  
316 Fig. 1, the trends derived from the observed record display a negative trend in the  
317 annual amount of precipitation which can be attributed to internal variability alone.  
318 This is in agreement with the study by Zhang et al. (2007), which indicates that there  
319 has been no detected change in the zonal averages of annual land precipitation during  
320 1925-1999 within the extratropical band 30°N to 50°N. The disagreement between  
321 observed and projected changes are considerably worse when 3-monthly means are  
322 considered. The CRU3.1 and GPCC5 datasets show a large negative trend in total  
323 winter precipitation in DJF, JFM and FMA months. These trends are greater than the  
324 central 90% of unforced trends derived from model-based estimates of natural (in-  
325 ternal) variability. In addition, the multi-model ensemble mean projections strongly  
326 underestimate the observed trends by a factor of  $\sim 6$ ,  $\sim 9$  and  $\sim 5$  in DJF, JFM and  
327 FMA respectively (Fig. 1).

328 The wintertime precipitation trends derived from the GPCP dataset are also strongly  
329 and consistently underestimated by the projections (Fig. 2). GPCP displays negative  
330 trends in the NDJ, DJF, JFM and FMA intervals which are significantly (at 5% level,  
331 one-sided test) different than natural (internal) variability and several times larger  
332 than the ensemble mean of the projections.

333 A warm season drying signal over the Mediterranean is a remarkably consistent  
334 feature in the last few generations of global (Giorgi et al. 2001, Giorgi and Bi 2005)  
335 and regional climate change projections (Deque et al. 2005, Somot et al. 2008 and  
336 Gao and Giorgi 2008). As reported in the IPCC AR4 (Christensen et al., 2007), the  
337 risk of summer drought is likely to increase in the Mediterranean area. In spite of  
338 this, we find a notable discrepancy in late summer (JAS) when observations display  
339 a positive trend (+2.8 mm/month per decade) in the amount of precipitation over  
340 the period 1979-2008 according to the GPCP dataset. Natural (internal) variability  
341 cannot explain the observed change. As displayed in Fig.3, precipitation increases  
342 throughout the region in JAS from 1979 to 2008 with a more pronounced increase in  
343 the northern part.

344 This contradiction extends into autumn. In SON we find an important difference,  
345 namely those trends of observed precipitation amounts contradict the projections in  
346 terms of both sign and intensity of the trends. There is a significant (at 5% level)  
347 increase in the precipitation amount in the CRU3.1, GPCC5 and GPCP data sets  
348 (together with an increase in the total number of wet days; not shown). The increase  
349 of precipitation is significant in the northeast and southwest parts of the region, while  
350 decreases of precipitation are seen over parts of the central Mediterranean, which  
351 is pronounced over Italy, north of Algeria and Tunisia (Fig. 3). In contrast to these  
352 upward trends, all climate change projections according to both the A1B and A2  
353 scenarios describe increasingly drier and stable conditions in autumn.

354 As outlined in Sect. 3.1, we further evaluate the robustness of the results against  
355 estimating the anthropogenic signal from transient simulations of 20<sup>th</sup> century cli-  
356 mate solely forced with anthropogenic forcing. As shown in Figs. 1 and 2, climate  
357 models suggest an increase in precipitation in response to GS forcing in winter (DJF  
358 and JFM). The response to GS forcing derived from the transient simulations is  
359 strongly at odds with the observed negative trends in the cold season. In contrast,  
360 trends in the GS response derived from time slices are predominantly negative al-  
361 beit much weaker than the observed decrease in winter. In some 3-month intervals,  
362 the simulated response to GS forcing is almost zero, although this result from the  
363 disagreement of the climate models and the cancelation of trends that have oppo-  
364 site signs. The contradiction is also striking in late summer and autumn, when both  
365 approaches to derive the GS response result in negative trends in the amount of pre-  
366 cipitation, in contrast with the observed increase. Therefore, we conclude that the  
367 inconsistency of observed trend patterns with GS signal patterns in winter and late  
368 summer and autumn are robust against the approach used to estimate the GS response.  
369 However, results must be interpreted with the caveat of forcing discontinuities due to  
370 splicing together output from the 20th century and A1B simulations (Arblaster et al.,  
371 2011).

### 372 4.3 Regression analysis

373 In order to take the spatial pattern of changes into account, we further use regression  
374 indices (Eq. 1) and investigate whether the influence of anthropogenic forcing is de-  
375 tectable in observed changes that cannot be explained by natural (internal) variability  
376 alone.

377 Figure 4 shows the regression indices of observed precipitation changes according  
378 to GPCP dataset over the period 1979-2008 onto the GS signal patterns derived from  
379 22 climate change projections in winter (DJF, JFM, FMA), late summer (JAS) and  
380 autumn (ASO and SON). As outlined in Sect. 3, the distribution of the regression  
381 indices are assessed from fits of the regression model (Eq. 1) to 285 independent  
382 control run segments derived from 9,000 year control simulations. The results of  
383 the regression analysis can be interpreted as follows: The GS forcing is detectable  
384 if the regression indices are significantly greater than zero, that is, the uncertainty  
385 range about the central estimate does not include the zero line. On the other hand,  
386 GS forcing is not detected if the indices are negative or not significantly greater than

387 zero. Consistency of the observed trend patterns with the GS signal pattern is claimed  
388 in cases where the uncertainty range of regression indices dose not include zero but  
389 includes “1”.

390 In DJF, the 95% distribution of regression indices do not include the zero line with  
391 8 out of the 22 models, indicating that the GS signal is detectable (on the 5% level)  
392 with 8 models. However, the uncertainty range does not include unity (except in two  
393 cases out of these 8 cases) and the central estimates of the regression indices are in  
394 the range of [3.8, 8.1], suggesting that while the effect of GS forcing is detectable  
395 in the observed record, these projections strongly underestimate the observed trends.  
396 In JFM the uncertainty range of regression indices does not include zero for 14 out  
397 of the 22 models, indicating that with 14 models the GS signal is found to have a  
398 detectable influence on the observed record. Observed trend patterns, however, are  
399 inconsistent with the GS signal patterns, since climate change projections strongly  
400 underestimate the observed trends (the central estimate of regression indices of these  
401 14 models is in the range of [3.1, 7.2]). In FMA, the GS signal is detectable with  
402 14 out of 22 models, and for 9 out of these 14 models, the observed trend patterns  
403 are found to be consistent with GS signal patterns. In NDJ consistency is detectable  
404 solely with 3 out of 22 models (not-shown). In JAS, ASO and SON, the regression  
405 indices are negative with all 22 models except one model in JAS and one model in  
406 SON, indicating that the observations contradict the climate change projections, in  
407 agreement with results discussed in previous sections.

408 The red bars in Fig. 4 displays the regression of observed trend patterns onto the  
409 transient GS signal patterns as estimated from the multi-model mean of 10 models  
410 (18 ANT simulation). The negative regression indices in all intervals shown in Fig. 4,  
411 points to the inconsistency of observed precipitation changes with what models sim-  
412 ulate as response of precipitation to GS forcing.

## 413 **5 Regionally detailed results**

414 The Mediterranean region is characterized by complex topographical and land-ocean  
415 features. The study by Gao et al (2006) provides evidence that topography can in-  
416 duce fine scale features to the precipitation change signal over the Mediterranean  
417 region. To capture the fine scale structure of the climate change signal, we further  
418 use simulations with the INGV model (Gualdi et al., 2012) to estimate the anthro-  
419 pogenic signal. This model developed within the CIRCE EU-FP6 Project, consists  
420 of a high resolution general circulation model coupled to a high-resolution model of  
421 the Mediterranean Sea with a horizontal resolution of approximately 7 km, which  
422 allow to assess the role of the basin, and in particular of the air-sea feedbacks in the  
423 climate of the region (Gualdi et al., 2012). We use the time slice approach introduced  
424 in Sect. 3.1 to derive GS response patterns. Since the scenario run of INGV is only  
425 till 2070, the GS signal is defined as the difference of 2041-2070 and the reference  
426 climatology (1961-1990).

427 The INGV model, consistent with the suite of CMIP3 models, projects a negative  
428 trend in all sliding 3-month windows as a response to increasing GHG concentrations  
429 (Fig. 5). The precipitation change signals projected by the INGV model show sea-

430 sonally dependent fine scale topographical detail over the Balkan mountains, Iberian  
431 Plateau, south of Turkey and North African coast lines. A noticeable feature is the  
432 horizontal gradient in precipitation change in DJF and JFM across the Alps with in-  
433 creases (or no changes) in precipitation at higher altitudes and large decreases in the  
434 low-lands (Fig. 3).

435 This topographically-induced structure in the climate change signal is less evi-  
436 dent in warm months, when convection rather than topographic uplift plays a major  
437 role (Gao et al, 2006). However, it is still evident in the JAS interval over the Alps  
438 (Fig. 3). The INGV model projects generally drier and warmer conditions in the re-  
439 gion, with a maximum decrease in precipitation in winter (DJF, JFM) and a minimum  
440 decrease in summer (MJJ, JJA). The main part of the reduction is due to a decrease in  
441 the amount of convective precipitation in all months and snow fall in the cold months,  
442 while the decrease of large-scale precipitation plays only a minor role in the drought  
443 condition projected by the INGV model (Fig. 5).

444 The regression approach reveals that in winter (DJF, JFM and FMA) the anthro-  
445 pogenic signal (GS) is detectable over the 1979-2008 period (at the 5% level, not  
446 shown). The GS signal, however, explains only a part of the observed drying, in-  
447 dicating that other processes likely also contribute. It is notable that the projected  
448 changes in winter in INGV are closer to the observations than trends estimated from  
449 the CMIP3 multi-model ensemble. This may point to the importance of using high  
450 resolution climate models in winter in order to generate the response to the topo-  
451 graphic forcing, however, with the caveat of using just one model. Whereas in sum-  
452 mer (JJA), in agreement with the suite of CMIP models, a strong inconsistency exists  
453 in both sign and intensity of the trends. This contradiction extends into autumn, in  
454 particular in JAS, ASO and SON, when observed trends are of opposite sign and  
455 more than 3 times larger than projected changes (Fig. 5).

## 456 **6 The influence of the NAO**

457 The North Atlantic atmospheric circulation and in particular the North Atlantic Oscil-  
458 lation (NAO Hurrell, 1995) affects the Mediterranean climate (Lionello et al., 2006,  
459 and references therein). The positive phase of the NAO is associated with stronger  
460 surface westerlies across the mid-latitudes and with anomalous northerly flow across  
461 the Mediterranean (Hurrell et al., 2003). Winter precipitation is anti-correlated with  
462 the NAO over most of the western Mediterranean region (Xoplaki, 2002), southern  
463 Spain, and northern Morocco (Matti et al, 2009). This strong link is due to the con-  
464 trol exerted by NAO on the branch of the storm track affecting the Mediterranean,  
465 mainly in its western part (Lionello et al., 2006). The NAO is also considered to be  
466 a key factor influencing the precipitation over the Mediterranean Sea, especially on  
467 decadal time scales (Mariotti and Dell'Aquila, 2011).

468 It is now recognized that models may underestimate the variability of the North  
469 Atlantic Oscillation (Stephenson et al. 2006, Osborn 2004). The study by Gillett  
470 (2005) indicates that the simulated changes of the NAO in climate models are gener-  
471 ally of correct sign but underestimate the magnitude of the observed changes. Under-  
472 estimation of the simulated NAO variability may lead to a spurious detection result,

473 if as a consequence the simulated natural variability is of smaller amplitude than the  
474 real variability. Therefore, in this section, we explore the consequences of subtracting  
475 from the observations that part of the precipitation variability that can be attributed  
476 to the NAO.

477 We use a station based NAO index (Osborn, 2006). The fingerprint of the NAO is  
478 defined as the fraction of the variability in precipitation time series which co-varies  
479 with the NAO index. Thus, we define the fingerprint of the NAO as the slope of the  
480 regression of precipitation time series on the NAO index for each grid box separately.  
481 The NAO signal is removed from the observations by subtracting the product of the  
482 trend in the NAO index times the NAO signal from the trend in the observations.

483 Figure 6 shows the observed trends based on GPCP data for 1979-2008 in com-  
484 parison with the observed trends after the removal of the NAO fingerprint. Statistical  
485 significance of the NAO-removed observed trends is determined using 9,000 years  
486 of control integrations and calculating 285 30-year segments for which the NAO in-  
487 fluence has been removed as well. The fingerprint of the NAO is removed from each  
488 of the 285 control run segments in a manner analogous to what was done with the  
489 observed record, that is, we regress the de-trended precipitation time series on the de-  
490 trended NAO index using ordinary least squares estimation of the parameters of the  
491 linear regression. The slope of the regression is the NAO fingerprint. Black whiskers  
492 in Fig. 6 denote the 90% uncertainty range of NAO-free internal variability.

493 The removal of the NAO signal does not considerably change the observed de-  
494 creasing trend in winter (NDJ, DJF, JFM and FMA). The black whiskers in Fig. 6,  
495 do not include zero in winter, indicating that the residual trends can not be explained  
496 solely by NAO-free internal variability and that externally forced changes are de-  
497 tectable. Thus, a NAO index time series for 1979-2008 fails to exhibit trend-like  
498 behavior analogous to that seen for Mediterranean rainfall. Therefore, we conclude  
499 that the observed Mediterranean drying cannot be attributed to an observed change in  
500 the behavior of the NAO. These results are in line with the study by (Hoerling et al.,  
501 2012), who note that the NAO behavior has not changed in the dramatic manner char-  
502 acterizing the temporal evolution (pre- and post-1970) of observed Mediterranean  
503 rainfall in the cold season (November-April).

504 Recently, a summer NAO manifestation has been shown to impact Mediterranean  
505 precipitation in this season (Folland et al., 2009). Our results also indicate that the  
506 NAO has been associated with approximately 50% of the observed rainfall increase  
507 in JJA, 34% in JAS, 23% in ASO and 41% in SON intervals. As indicated by the black  
508 whiskers in Fig. 6, none of the 285 NAO-free control run segments yield a positive  
509 trend as strong as that observed in JAS and ASO intervals. However, the detection of  
510 externally forced changes in observed precipitation trends in late summer (JAS) and  
511 autumn (ASO) and also the fact that observed positive trends contradict the climate  
512 change projections, are robust against the removal of the NAO signal.

513 Figure 7 displays the regression indices (y axis) of NAO-free observed precipita-  
514 tion changes onto climate change projections and its 95% uncertainty ranges, derived  
515 from NAO-free internal variability. Removing the effect of NAO causes a small reduc-  
516 tion in the regression indices and slightly smaller uncertainty ranges. Thus, analysis  
517 of Fig 7 further illustrates that the obtained results in Sect.4.3 are robust against the  
518 removal of NAO fingerprint.

## 519 7 Changes in large scale circulation

520 In the Mediterranean region during winter, a strong correlation exists between the regional precipitation patterns and upper-air large-scale circulation anomalies (Quadrelli et al., 2001). The winter dryness over the eastern Mediterranean (Greece) during 521 1958-1994 has also found to be connected with the raising of 500 hPa geopotential 522 height and increasing sea level pressure (Xoplaki et al., 2000). Over Europe, van 523 Haren et al. (2012) suggest that modeled atmospheric circulation and sea surface 524 temperature (SST) trends over the past century contain large biases in global climate 525 models and are responsible for a large part of the misrepresentation of precipitation 526 trends over Europe in the CMIP3 climate models. 527

528 In this section, to examine the possibility that the inconsistency of observed precipitation trends with climate change projections may be related to trends in large-scale circulations, we compare observed (NCEP/NCAR reanalysis, Kalnay et al. 529 1996) and projected changes in geopotential height at 500 hPa (referred to as 500 Gph 530 in the following), derived from the ensemble mean of the CMIP3 multi-model dataset 531 (A1B scenario). The time slice experiment (Sect. 3.1) is used to estimate the trends 532 of 500 Gph in response to GS forcing. That is, we define the anthropogenic climate 533 change signal (GS) of 500 Gph as the difference between the last decades of the 534 21st century (2071-2100, SRES A1B scenario) and the reference climatology (1961- 535 1990). We assume a linear development in multi-decadal running means from 1961- 536 2100 and the resulting signal is scaled to change per year. The linearity assumption 537 is supported by the study of Cubasch et al. (2001) who indicates that the global mean 538 response to anthropogenic forcing is as a first approximation linear. Natural (internal) 539 variability of 500 Gph is estimated from long control simulations. As outlined 540 in Sect. 3, we draw 285 independent segments with the same length and spatial coverage 541 as the observations (NCEP reanalysis) from 9000 years of control simulations 542 to estimate the internal variability of 30-year trends of 500 Gph in an undisturbed 543 stationary climate. 544

545 Figure 8 shows the 500 Gph trend patterns in NCEP/NCAR over the period 1979- 546 2008 in DJF, JFM, JAS, ASO and SON, in comparison with what the ensemble mean 547 of 22 models projects as a response of 500 Gph to GS forcing. Using an ensemble 548 mean of 22 models (49 simulations), leads to decreasing the internal variability by 549 more than 90% in the response pattern. 550

551 In winter (DJF and JFM), trends in the NCEP reanalysis data show a tendency towards a ridge that covers a large part of the Mediterranean. The increase in 500 Gph 552 (and also the sea level pressure, not shown) over the region thus enhance atmospheric 553 stability. The anticyclonic circulation and the decrease in the occurrence of convection 554 due to increasing subsidence thus lead to the winter dryness over the region. The 555 response of 500 Gph to GS forcing is also characterized by a monopole pattern, however 556 in terms of magnitude of change, the CMIP3 climate change projections show 557 an uniform increase (Fig. 8) and underestimate the observed increasing trend of up 558 to 16 m/decade, which consequently may lead to an underestimation of the observed 559 decreasing trend in the amount of precipitation. 560

561 Figure 9 shows the area-mean changes of 500 Gph in the NCEP/NCAR reanalysis 562 data in DJF, JFM, FMA, JAS, ASO, and SON along with the respective 95% uncer- 563

564 tainty range due to internal variability (red whiskers in Fig. 9) derived from long con-  
565 trol simulations (outlined in Sect. 3). In the winter months, the NCEP/NCAR reanaly-  
566 sis data suggests a 5.8 m/decade increase of 500 Gph in DJF, 6.8 m/decade increase in  
567 JFM and 6.3 m/decade increase in FMA (Fig. 9). These observed changes are found  
568 to be different from changes due to natural (internal) variability alone (as indicated by  
569 the red whiskers in Fig. 9), whereas they are within the range of changes suggested  
570 by 22 climate change scenarios (black whiskers in Fig. 9). Projected changes derived  
571 from 22 models are in the range of [3.2 to 13] m/decade, [3.4 to 13.6] m/decade,  
572 and [3.7 to 13.3] m/decade in DJF, JFM and FMA, respectively. Lucarini and Russell  
573 (2002) also show a significant positive trend of 500 Gph (almost 6 m/decade) in win-  
574 ter (DJF) with NCEP/NCAR over the period 1960-2000, which is underestimated by  
575 GHG experiments.

576 In contrast to the situation in winter, in late summer (JAS), the NCEP/NCAR re-  
577 analysis data shows an area of decreasing geopotential height (-5 m/decade), and thus  
578 increasing cyclonic circulation over the north and northwest of the Mediterranean  
579 and an area of increasing geopotential height (+6 m/decade) in the south (Fig. 8).  
580 This dipole mode portrays northward migration of storm tracks. The same dipole  
581 structure is also observed in ASO and SON intervals, when a cyclonic circulation  
582 is observed over the northwest of the region with a -9 m/decade decreasing trend in  
583 500 Gph, and an anticyclonic circulation over the south with +8 m/decade increas-  
584 ing trend of 500 Gph. This results in a blocking-like pattern in autumn that tends to  
585 deflect storms northward. Furthermore, the areas of lower pressure tend to result in  
586 an increase in the occurrence of convection. Thus, the corresponding changes in the  
587 storm track favour an increase in late summer and autumn precipitation over the north  
588 and north-west of the Mediterranean area.

589 As shown in Fig. 8 (right column), the projected 500 Gph change pattern in late  
590 summer and autumn is strikingly inconsistent with changes in the NCEP/NCAR re-  
591 analysis data over the 1979-2008 period. The CMIP3 models project changes towards  
592 more anticyclonic conditions over the Mediterranean. The projections also show an  
593 upward trend in mean sea level pressure (not shown). Increasing pressure and anti-  
594 cyclonic conditions go along with less rain, which is at odds with the observed  
595 significant positive trends in the amount of precipitation in late summer and autumn.  
596 When comparing the area- mean changes, NCEP/NCAR is suggesting a very small  
597 and not significantly different than natural (internal) variability change in JAS, ASO  
598 and SON (Fig. 9), though the dipole structure of trend patterns causes the cancellation  
599 of 500 Gph changes that have opposite sign (see Fig. 8).

600 We further use regression (Eq. 1) as a pattern similarity measure. Figure 10 dis-  
601 plays the regression coefficients of observed 500 Gph changes against changes in  
602 response to GS forcing derived from the multi-model ensembles mean of 22 mod-  
603 els. The 95% distribution of regression indices are assessed by calculating regression  
604 indices of 285 non-overlapping control run segments on the GS signal patterns. In  
605 winter and early spring (DJF, JFM and FMA), the uncertainty range of regression  
606 indices does not include “zero” but includes “1” (Fig. 10). This indicates that the GS  
607 signal is detectable in the NCEP/NCAR reanalysis data over the 1979-2008 period  
608 and anthropogenic forcing is a plausible explanation for observed positive trends of  
609 500 Gph in winter and spring (with less than 5% risk level). In contrast to winter and



610 spring, the regression indices are almost zero in JAS, ASO and SON, indicating the  
611 inconsistency of observed trends of 500 Gph with climate change projections.

612 Therefore, we conclude that it is – at least to some extent – the inconsistency of  
613 the description of ongoing changes in circulation in the simulated possible futures,  
614 which leads to the inconsistency with observed precipitation trends in late summer  
615 and autumn. The mismatch between simulated and observed precipitation in late sum-  
616 mer and autumn is already present in the atmospheric circulation.

## 617 **8 Dependence on trend period**

618 We further analyze how strongly our results depend on the exact time period under  
619 analysis. Figure 11 shows moving 40-year trends in CRU3.1 and GPCC5 over the  
620 time period from 1901 to 2009. The CRU3.1 and GPCC5 observed records exhibit  
621 strong disagreement during the early decades. This is probably related to sparse data  
622 coverage during the 1900-1960 period (not shown) and differences in the treatment of  
623 data-sparse areas in the different datasets. However, after 1960 the two datasets come  
624 to a relatively good agreement. The observed trends are likely not due to internal  
625 variability alone in cases for which the trend is beyond the 5-95% distribution of 213  
626 control run segments (as denoted by the horizontal dashed lines in Fig. 11).

627 In winter (DJF, JFM), both datasets show developing drought conditions towards  
628 the end of the 20<sup>th</sup> century. The observed trends in winter months become signif-  
629 icantly different from internal variability in the early 1990s, with strongest drying  
630 during 1960-2000 in JFM with about -2.8 mm/decade decrease in the amount of pre-  
631 cipitation. There is indication of a slight decrease in the strong drying in the 21<sup>st</sup>  
632 century. In spring and summer (MJJ, JJA, JAS) in contrast, the observed trends are  
633 hardly distinguishable from unforced trends and externally forced changes are not  
634 detectable. In late summer and autumn (ASO, SON and OND), both datasets show a  
635 period with increasing precipitation over the Mediterranean after the 1960s (40-year  
636 trends ending in the late 1990s), which contrast mostly negative trends during prior  
637 decades. The rate of change towards wetter conditions increases with time and ex-  
638 ceeds the limits of natural (internal) variability for trends ending in the 21<sup>st</sup> century.  
639 Evidence for the presence of an external driving factor is clearly detectable in SON  
640 and OND at 5% significant level.

641 In the following, we assess to what extent the observed moving 40-year trends  
642 over the 1901-2009 period are consistent with what the ensemble mean of 22 mod-  
643 els projects as human-induced climate change. Figure 12 shows seasonal regression  
644 indices of observed moving 40-year trends based on CRU3.1 onto the multi-model  
645 mean GS signal. The gray shaded area indicates the 95% uncertainty range of regres-  
646 sion indices, derived from fits of the regression model (Eq. 1) to 213 non-overlapping  
647 control run segments onto the GS signal patterns. Detection of GS forcing is claimed  
648 where the gray shaded area in Fig. 12 excludes “0” and consistency is claimed in  
649 cases where the gray shaded area does not include “0” but includes “1”.

650 In DJF, JFM and FMA, the gray shaded area does not (with a few exceptions) in-  
651 clude the zero line after 1990, indicating the emergence of a detectable anthropogenic  
652 (GS) influence in the late 20<sup>th</sup> century. While the influence of GS signal is detectable,

653 the gray shaded area clearly does not include 1 in FMA (and to a lesser extent in JFM  
654 and DJF), indicating that the climate change projections underestimate the observed  
655 trends.

656 In ASO, SON and OND, the detection of an outright sign mismatch of observed  
657 and projected trends is obvious with negative regression indices of 40-year trends  
658 ending in 1990 and later on. The negative regression indices in SON and OND be-  
659 come significantly beyond the range of regression indices of unforced trends with GS  
660 signal patterns in the late 20<sup>th</sup> century. This result points either to the presence of an  
661 alternative driver of precipitation change not included in the models or to gross mis-  
662 representation of the precipitation response to GS forcing in the CMIP3 simulations.

## 663 9 Conclusion

664 In this study, we examine to what extent the present climate change “is on the way”  
665 towards conditions described by the climate change scenarios at the end of this cen-  
666 tury. To this end, we determine if the observed trends in precipitation over the period  
667 1966-2005 (over land) and 1979-2008 (over land and sea), are consistent with the  
668 expected change due to GS forcing. Our analysis demonstrates that externally forced  
669 changes are detectable (at the 5% level) in observed precipitation trends in winter,  
670 late summer and in autumn. Natural (internal) climate variability cannot explain these  
671 changes. In contrast, we do not find evidence for the presence of an external driving  
672 factor in the observed precipitation trends in spring and early summer. In addition,  
673 we show that the observed trends (derived from 3 sources) are markedly inconsis-  
674 tent with expected changes due to GS forcing. While the influence of GS forcing is  
675 detectable (at the 5% level) with 8 out of 22 models in DJF, 14 models in JFM and  
676 14 models in FMA, observed changes are several times larger than the projected re-  
677 sponse to GS forcing in these models. The most striking inconsistency, however, is  
678 the contradiction between projected drying and the observed increase in precipitation  
679 in late summer and autumn. Our analysis thus points to the presence of an external  
680 forcing which is in contrast to the expected response to GS forcing. The inconsis-  
681 tency of observed trend patterns with GS signal patterns in winter, late summer and  
682 autumn are robust against the approach used to estimate the GS response and are also  
683 robust against estimating the GS signal from a high resolution climate model (INGV).  
684 The results are furthermore insensitive to the removal of the fingerprint of the North  
685 Atlantic Oscillation.

686 Analysis of changes in large scale circulation patterns reveals that the influence  
687 of GS forcing is detectable in the observed (NCEP/NCAR reanalysis) 500 Gph in  
688 winter (DJF, JFM) and spring (FMA, MAM, AMJ). The observed positive trends of  
689 500 Gph are consistent with the ensemble mean of 22 climate change projections.  
690 However, in late summer (JAS) and autumn (ASO, SON) the observed dipole pat-  
691 tern of 500 Gph contradicts the uniform increase pattern of 500 Gph projected by  
692 CMIP3 models. This indicates that inconsistencies in the simulated circulation re-  
693 sponse could account for at least some of the inconsistencies between simulated and  
694 observed precipitation changes in the Mediterranean. Our analysis clearly shows that  
695 projections of future regional precipitation change, an important factor for the es-

696 timation of future agricultural and hydrological resources, are not consistent with  
697 observed recent changes. We note that our results must be interpreted with the caveat  
698 of potential inhomogeneity in the observed gridded precipitation data sets. Another  
699 caveat is the coarse horizontal resolution of the climate models used in this study.

700 Candidates to explain the observed inconsistency are manifold and we will high-  
701 light the most important ones. Careful analysis of the potential sources for inconsis-  
702 tency, however, is beyond the scope of this manuscript. First, natural internal vari-  
703 ability could be much stronger than simulated. Observed variability of changes in  
704 the NAO - an important indicator of circulation variability in the region - has been  
705 found to exceed simulated variability (Gillett, 2005). Our conclusions, however, are  
706 insensitive to a potential underestimate of NAO-related variability in the models.

707 Second, changing atmospheric greenhouse gas and sulfate concentrations are not  
708 the dominant forcing for precipitation changes in the Mediterranean region. Previous  
709 studies conclude that global precipitation changes are more sensitive to short-wave  
710 forcing such as changes in stratospheric aerosol concentrations due to explosive vol-  
711 canic eruptions than low-frequency GHG forcing (Lambert et al., 2004). This is in  
712 contrast to global land temperature anomalies, which are dominated by the response  
713 to GHG forcing (e.g., Stott et al. 2000). Furthermore, there are additional anthro-  
714 pogenic forcing agents which potentially have a large effect on regional scale pre-  
715 cipitation and which are missing in current climate models such as the emission of  
716 aerosols related to traffic and industry and/or forcing from land-use changes such  
717 as deforestation. Whether the inconsistency of observed and simulated precipitation  
718 changes might be resolved taking into account additional forcing mechanisms could  
719 be assessed with the next generation of climate models that include a more complete  
720 set of processes relevant for precipitation formation (CMIP5 Taylor et al., 2012).

721 Third, the inconsistency could also be due the misrepresentation of the precipita-  
722 tion response to GS forcing in the CMIP3 models. The good model agreement on the  
723 forced response (e.g. Figs. 1 and 2) suggests, however, that this is a valid explanation  
724 only if all of the CMIP3 models misrepresent the GS response. Furthermore, it has  
725 been suggested that sea surface temperature (SST) forcing likely played an important  
726 role in the observed Mediterranean wintertime drying (Hoerling et al., 2012). The  
727 CMIP3 models have biases in their SST response to GHG forcing, especially over  
728 the tropical Pacific (Vecchi et al., 2008). Our results indicate that the CMIP3 models  
729 simulate a relatively uniform increase in 500 Gph in response to anthropogenic forc-  
730 ing (Fig. 8). The CMIP3 models also simulate a uniform pattern of SST change in  
731 response to anthropogenic forcing. The observed change in tropical SSTs, however,  
732 involves a stronger zonal SST gradient across the Indian and Pacific Ocean than sim-  
733 ulated in CMIP3 models (Hoerling et al., 2012). Thus, it is suggested by Hoerling et  
734 al. (2012) that the amplitude of the CMIP3 drying signal in winter (November-April)  
735 over the Mediterranean is weak owing to biases in the coupled model's global SST  
736 response.

737 Overall, communication of future expected change of precipitation is complicated  
738 by the fact that the expected future changes are inconsistent with observed changes,  
739 irrespective of the data sets used. We have earlier determined that the ongoing trends  
740 in temperature in the Mediterranean region are consistent with climate change projec-  
741 tions (Barkhordarian et al., 2012). Therefore, recently observed warming is a plausi-

742 ble illustration of future expected warming in the region. In terms of precipitation, the  
743 detection of an outright sign-reversal in the observed and projected trends, which is  
744 a newly documented phenomenon, provides strong evidence that the recent observed  
745 changes cannot be used to illustrate the future expected changes of precipitation. The  
746 societal significance of our analysis is in the answer of the often-asked question in  
747 the public: Is the recent trend a harbinger of the future? In the case of precipitation,  
748 in the Mediterranean region: quite probably not.

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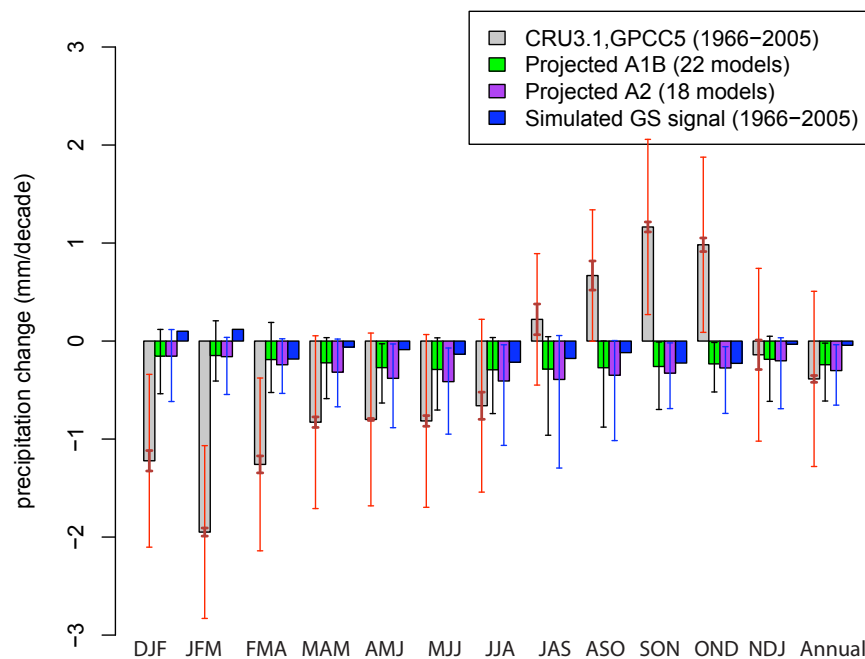
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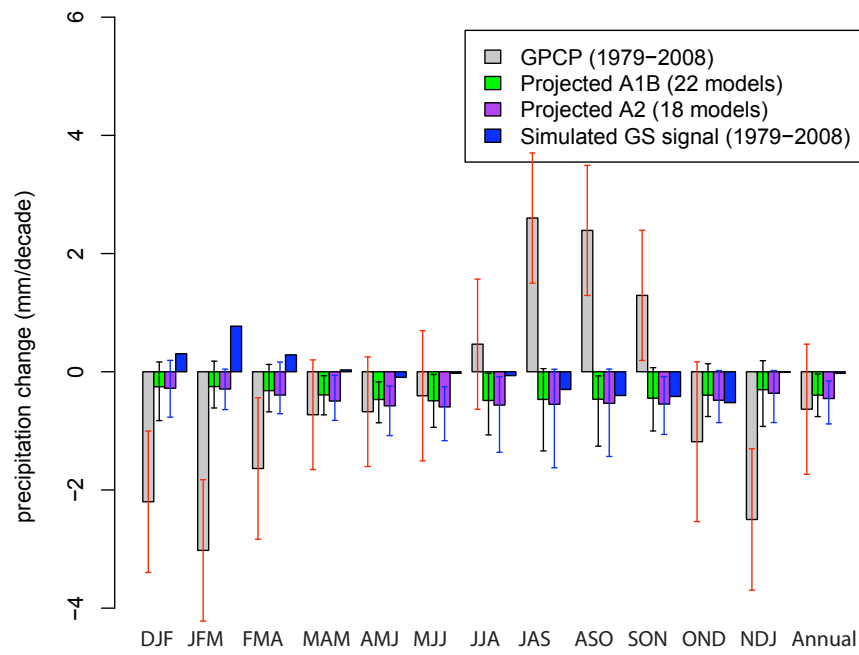
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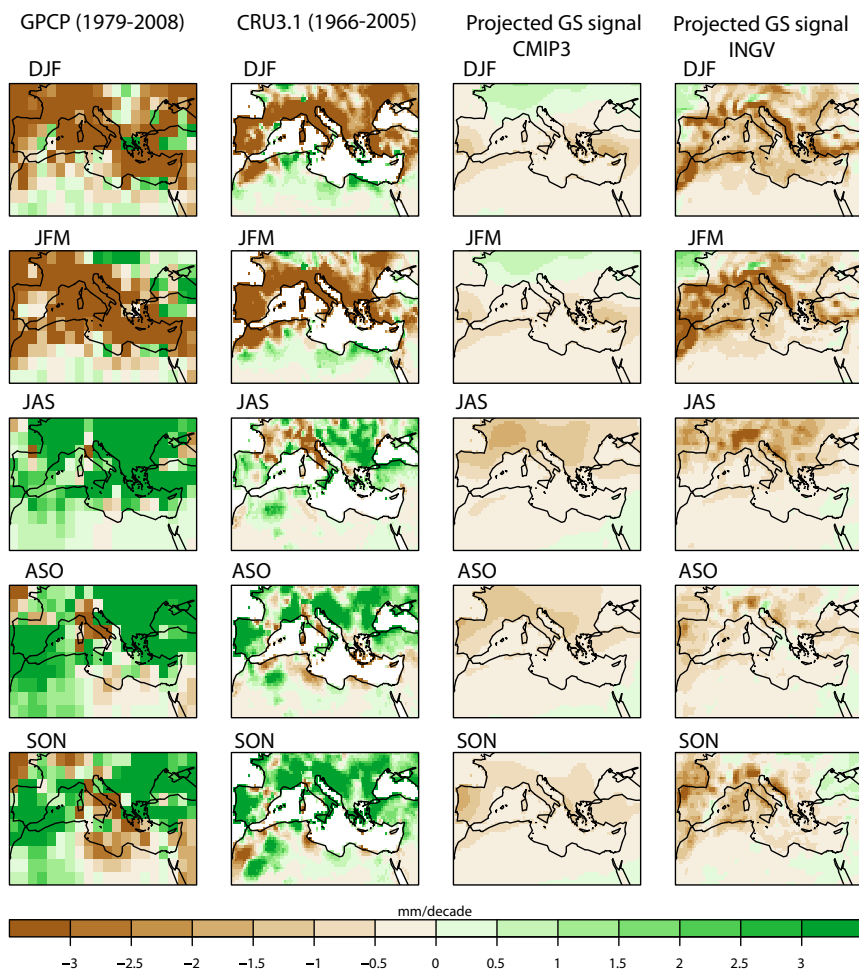
**Fig. 1** Observed trends in precipitation over land in the Mediterranean from 1966 to 2005 (in mm/decade) for sliding 3-month windows (grey bars) in comparison with the anthropogenic (GS) signal estimated from CMIP3 simulations. The GS signal has been derived from time slices of simulations according to the A1B (green bars) and A2 (purple bars) scenarios and from the multi-model mean of transient simulations from 10 CMIP3 models with anthropogenic forcing only (blue bars). The brown whiskers denote the spread of trends of the two observational datasets (CRUv3, GPCC5). The black and blue whiskers show the spread of trends of 22 A1B and 18 A2 climate change projections. The red whiskers indicate the 90% confidence interval of observed trends, derived from model-based estimates of natural (internal) variability (213 non-overlapping 40-year segments derived from 9'000 years of control integration)

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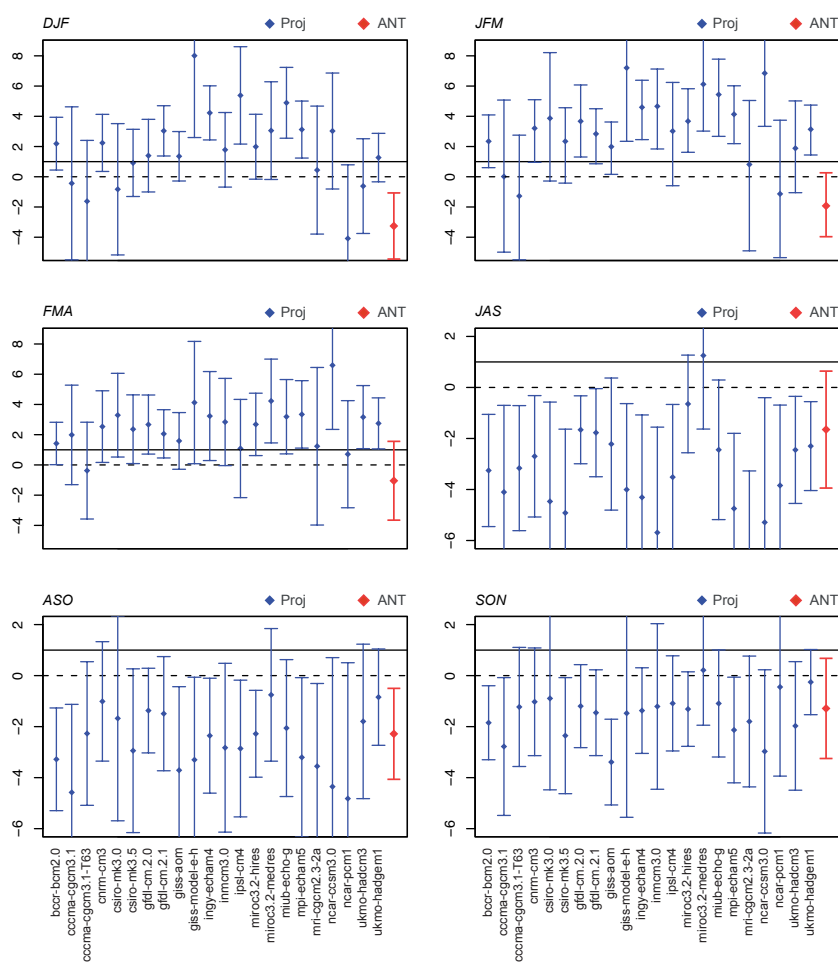




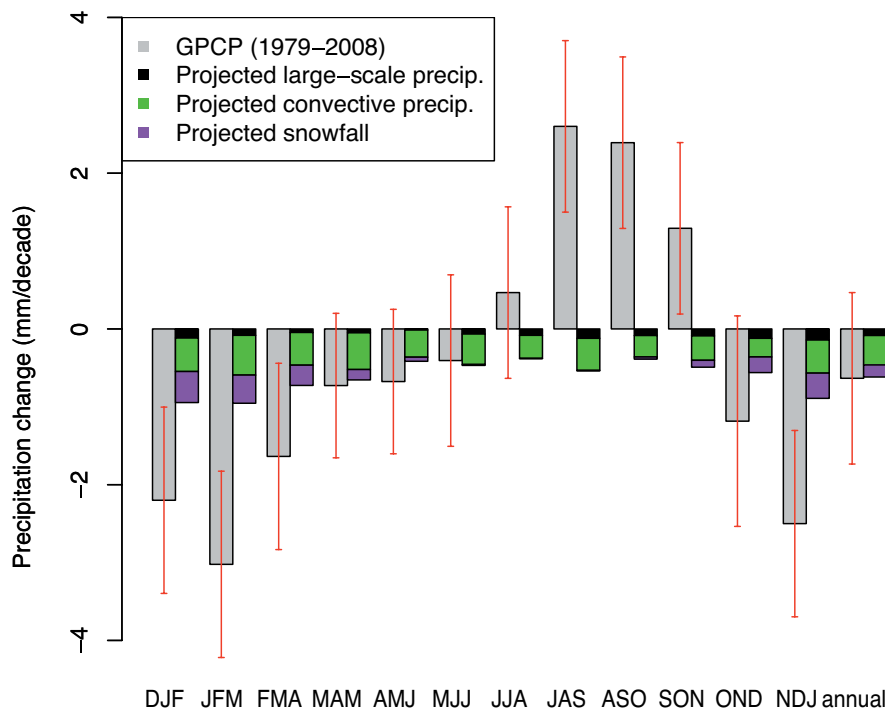
**Fig. 2** According to Fig. 1 but for observed trend in precipitation over land and sea from 1979 to 2008 according to the GPCP dataset. The red whiskers indicate the 90% confidence interval of observed trends, derived from model-based estimates of natural (internal) variability (285 non-overlapping 30-year segments derived from 9'000 years of control integration)



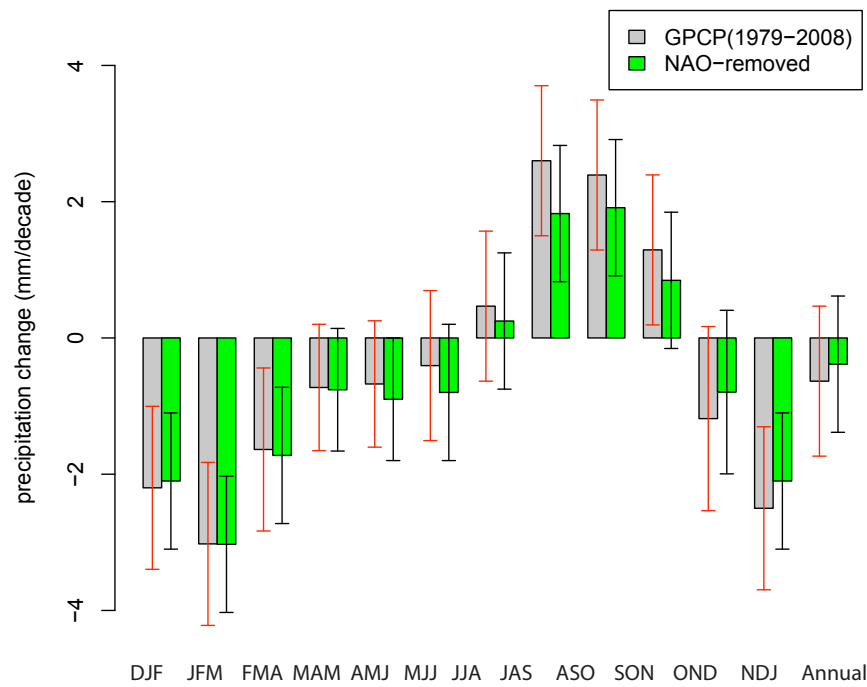
**Fig. 3** From left to right: Seasonal observed pattern of precipitation change over the period 1979-2008 based on GPCP, observed precipitation change over the period 1966-2005 based on CRU3.1, ensemble mean anthropogenic (GS) signal pattern derived from 22 models, and the anthropogenic (GS) signal pattern derived from the INGV coupled regional model, according to SRES A1B scenario.



**Fig. 4** Regression coefficients of observed precipitation change in DJF, JFM, FMA, JAS, ASO and SON from 1979-2008 according to the GPCP dataset on model simulated GS signal patterns. *Blue*: GS signal patterns for 22 individual models estimated from time slices of climate projections based on the SRES A1B scenario. *Red*: Regression against the multi-model ensemble mean of transient simulations with anthropogenic forcing with 10 models (18 simulations) for the period from 1979 to 2008. The bars show the 95% uncertainty range of the regression coefficients derived from model-based estimates of natural (internal) variability (285 non-overlapping 30-year segments derived from 9'000 years of control simulation). The solid lines mark regression coefficients equal to unity.



**Fig. 5** Observed sliding 3-month window trends of precipitation over the land and sea of Mediterranean derived from GPCP dataset over the period from 1979 to 2008 (gray bars) in comparison with anthropogenic signals (GS) derived from INGV model (2041-2070 minus 1961-1990 mean scaled to change per decade). The vertical axes show area mean changes of precipitation (mm per decade). The red whiskers indicate the 90% confidence interval of observed trends, derived from model-based estimate of internal (natural) variability. The black bars are projected large-scale precipitation; the green bars projected convective precipitation and the purple bars indicate projected snowfall.



**Fig. 6** Observed sliding 3-month window trends of precipitation over the land and the sea area of the Mediterranean region in the time period from 1979 to 2008 (grey bars) in comparison with trends after the removal of the fingerprint of the NAO (green bars). The red whiskers indicate the 90% uncertainty range of observed trends, derived from model-based estimates of natural (internal) variability. The black whiskers denote the 90% uncertainty range of observed trends based on NAO-free internal variability (see Sect. 6)

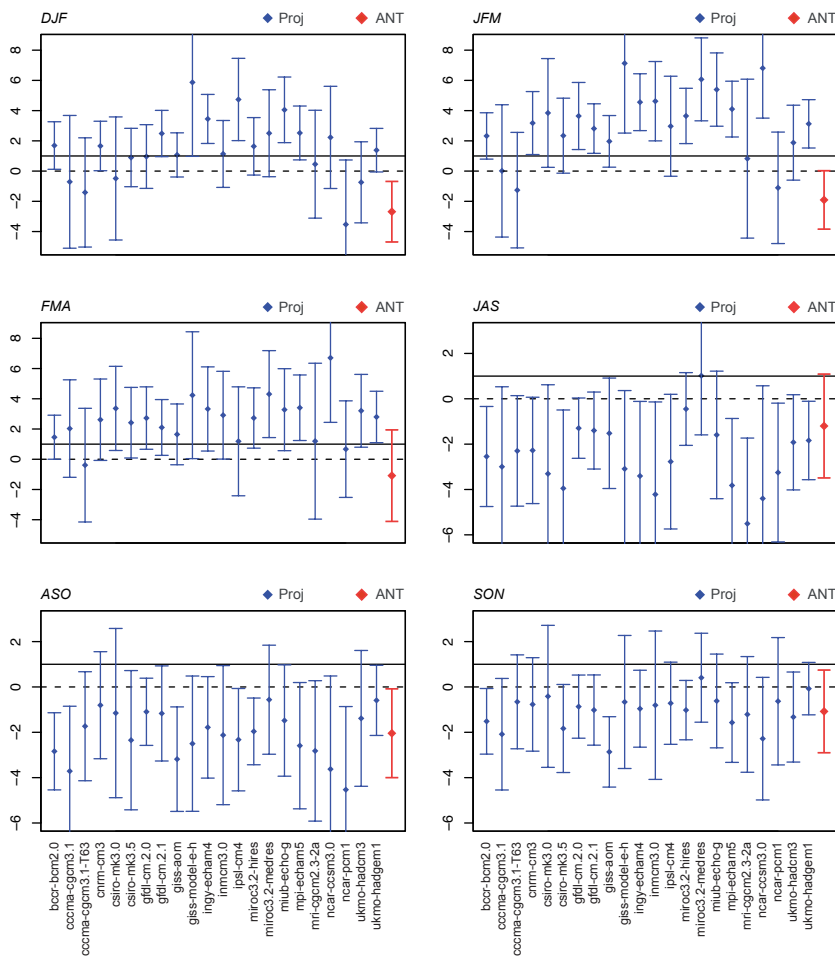
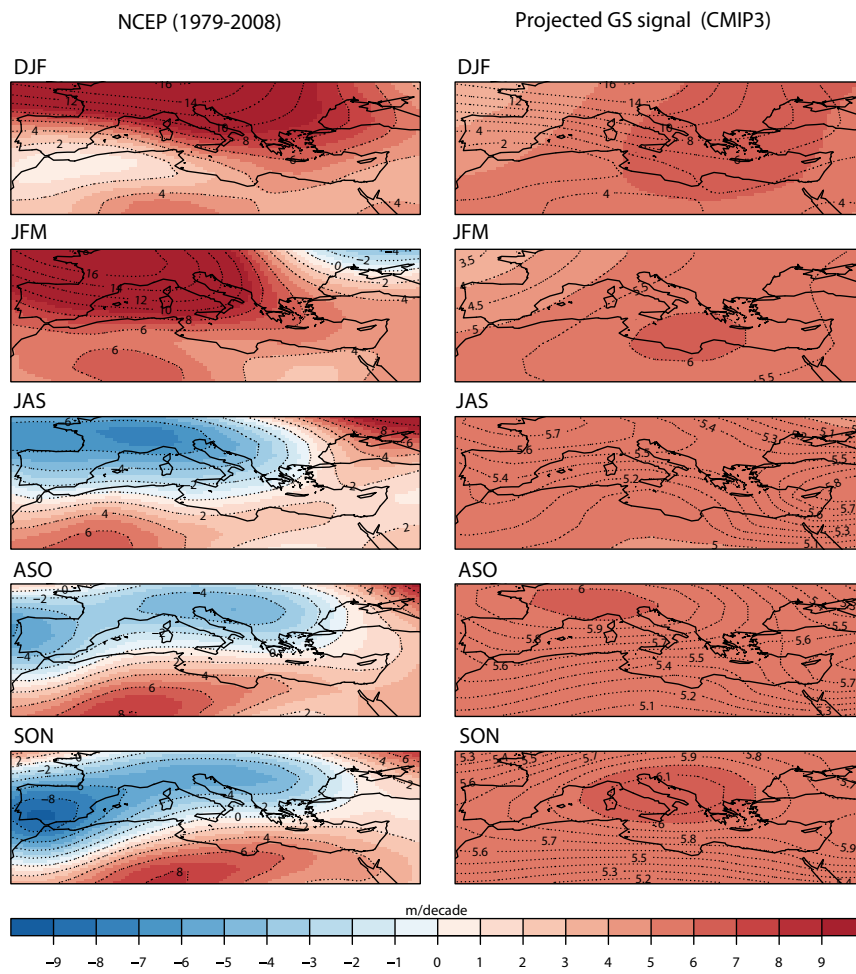
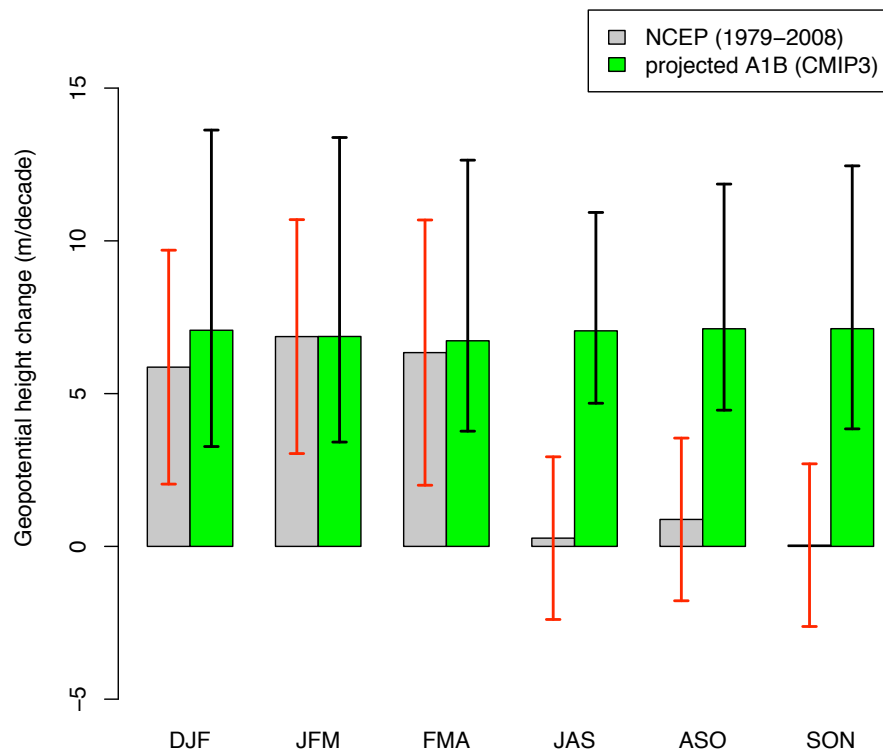


Fig. 7 Same as Fig. 4 but after the removal of the NAO fingerprint

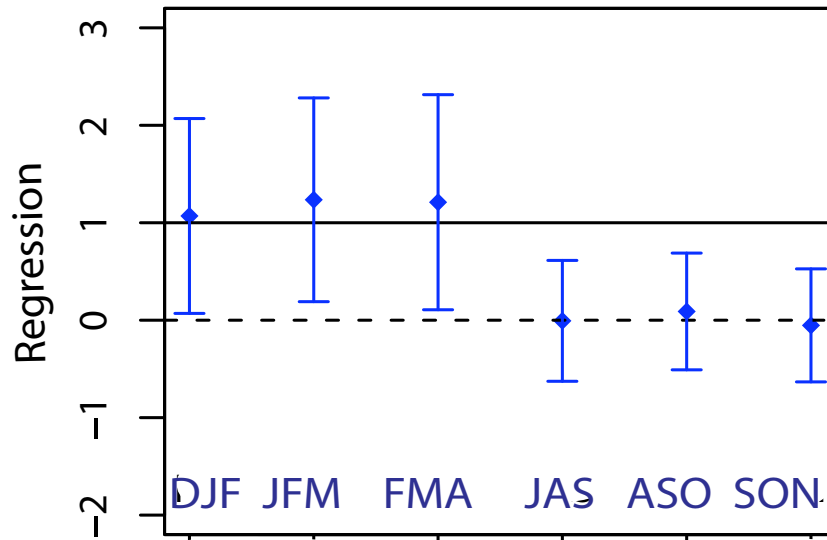


**Fig. 8** Left column: Observed patterns of change in 500 Gph according to the NCEP/NCAR reanalysis over the period 1979-2008 in winter (DJF and JFM), late summer (JAS) and autumn (ASO and SON). Right column: Ensemble mean GS signal patterns estimated from time slices of climate projections from 22 models (2071-2100 minus 1961-1990 mean scaled to change per decade) according to the SRES A1B scenario.

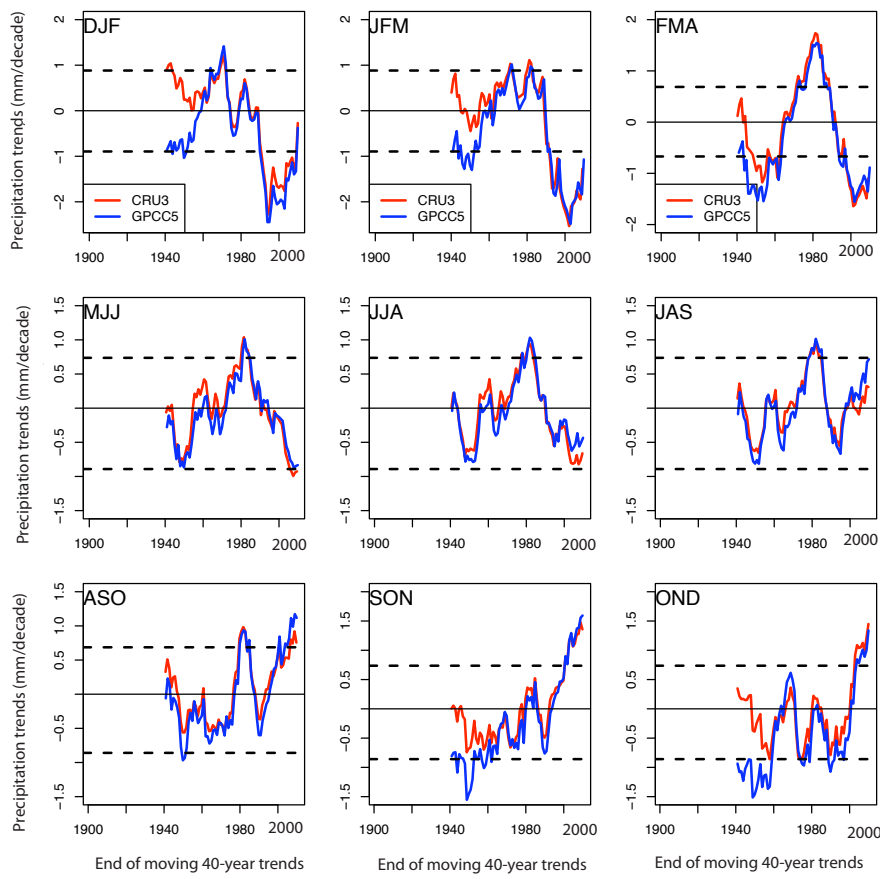


**Fig. 9** Seasonal area mean changes of observed 500 Gph (in m/decade) according to the NCEP/NCAR reanalysis over the period 1979 to 2008 (grey bars) in comparison with the anthropogenic signal (GS) of 500 Gph derived from the multi-model mean of CMIP3 simulations according to the SRES A1B scenario. The black whiskers indicate the spread of trends of the 22 climate change projections. The red whiskers denote the 95% uncertainty range of observed trends derived from long control simulations.

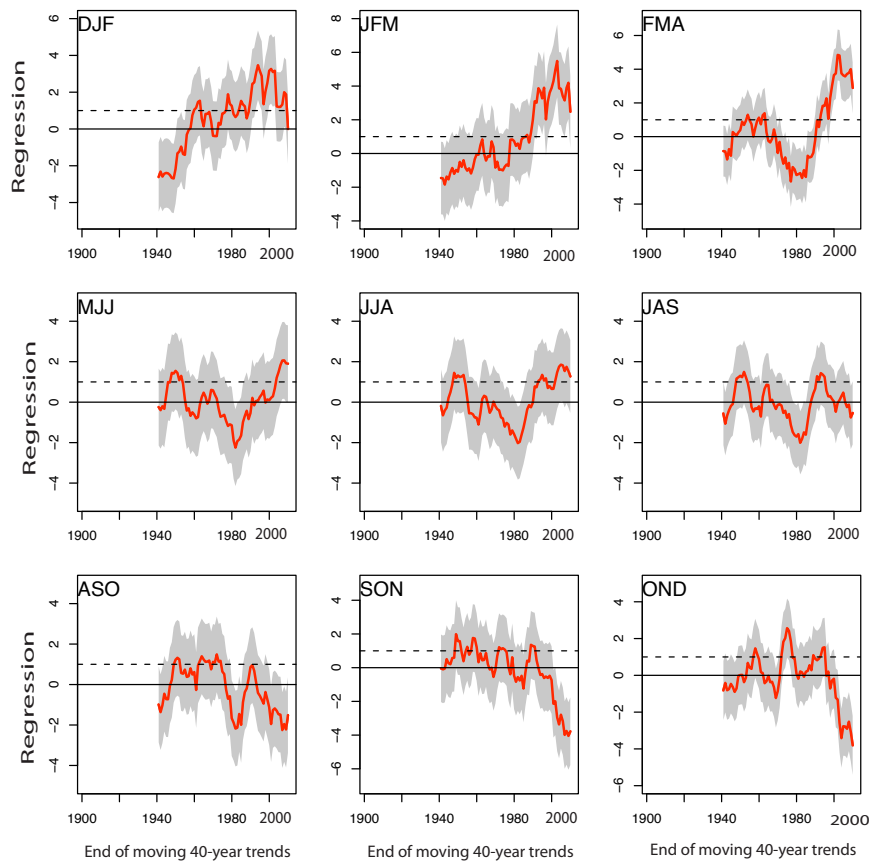




**Fig. 10** Regression coefficients of observed seasonal (DJF, JFM, FMA, JAS, ASO and SON) changes in 500 Gph according to NCEP/NCAR reanalysis over the period 1979-2008 onto projected changes in response to GS forcing, estimated from two well-separated time slices (2071-2100 minus 1961-1990 mean scaled to change per decade, SRES A1B scenario) ensemble mean of 22 models from CMIP3 archive. The bars show the 95% uncertainty ranges of regression indices derived from model based estimates of natural (internal) variability (285 independent 30-year segments). The solid line denotes regression indices equal to unity, indicating consistency with GS forcing.



**Fig. 11** Seasonal moving 40-year observed trends based on CRU3.1 (red curves) and GPCC5 (blue curves) from 1901 to 2009. The vertical axes denote the area mean change of precipitation over the Mediterranean region. The horizontal axes show the end-year of moving 40-year trends. The dotted horizontal lines indicate the 5-95% uncertainty range of observed trends, derived from model-based estimates of natural (internal) variability (213 independent 40-year segments derived from 9'000 years of control simulations).



**Fig. 12** Seasonal regression indices of observed moving 40-year trends, over the period 1901 to 2009, based on CRU3.1 onto the multi-model mean GS signal, estimated from two well-separated time slices (2071-2100 minus 1961-1990 mean scaled to change per decade, A1B scenario) ensemble mean of 22 models from CMIP3 archive. The vertical axes denote the regression indices. The horizontal axes show the end-year of moving 40-year trends. The gray shaded area indicates the 95% range of regression indices in a stationary climate derived from 213 non-overlapping control run segments. The dotted lines mark regression indices equal to zero, and the solid lines mark regression indices equal to unity.