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Key Points:

- Regional climate models may slightly improve cloud climatology estimations but do not capture decreasing trend
- Regional models produce higher annual total cloud cover in the Mediterranean when compared with that simulated by the driving global models
- Total cloud cover from regional models is stable, in contradiction with decreasing trend that is observed and reproduced by global models

Supporting Information:

- Supporting Information S1

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Discrepancies in the Climatology and Trends of Cloud Cover in Global and Regional Climate Models for the Mediterranean Region

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Abstract The present study aims at comparing total cloud cover (TCC) as simulated by regional climate models (RCM) from CORDEX project with the same variable as simulated by the driving global climate models (GCM), which are part of the fifth phase of the Climate Model Intercomparison Project ensemble. The comparison is performed for the Mediterranean region, and for the 1971–2005 period, when results from the "historical" scenario can also be compared with two data sets of ground-based cloud observations. We work with 14 modeling results (resolution, 0.11° × 0.11°), which are a combination of five GCMs and five RCMs. In general, RCMs improve only very slightly the climatic estimation of TCC when compared with observations. Indeed, not all RCMs behave the same, and some indicators (monthly evolution of the relative bias) show an enhancement, while other indices (overall mean bias and annual range difference) improve only very slightly with respect to GCMs. Changes in the estimate of TCC in summer might be the most relevant value added by RCMs, as these should describe in a more proper way several mesoscale processes, which play a more relevant role in summer. Noticeably, RCMs are unable to capture the observed decadal trend in TCC. Thus, TCC simulated by RCMs is almost stable, in contradiction with observations and GCMs, which both show statistically significant decreasing trends in the Mediterranean area. This result is somewhat unsatisfactory, as if RCMs cannot reproduce past trends in TCC, their skill in projecting TCC into the future may be questioned.

1. Introduction

Clouds play an important role in the water balance of the atmosphere, and their interaction with longwave and shortwave radiation implies that cloudiness is an important regulator of the climate. Currently, the scientific community keeps working in constraining the response and feedbacks of clouds in relation with anthropogenic forcing of climate (Flato et al., 2013; Zelinka et al., 2016). Similarly, research is undergoing to reduce the uncertainty of recent trends in cloudiness (Hartmann et al., 2013; Norris et al., 2016). Difficulties with understanding all cloud-climate interactions exist because of the difficulty in observing clouds with sufficient spatial and temporal resolution, and also because of limitations in representing and describing cloud phenomena in climate models. Of course this has strong influence when performing climate projections and estimating the climate sensitivity (Bony et al., 2015) so efforts are under way to try to address these issues (Webb et al., 2016).

Global climate models (GCMs) are the main tool devoted to simulate past and future climate, so in particular, to perform climate projections into the future. One limitation of GCMs is their spatial resolution, which even in the most recent models is coarser than about 100 km. Indeed, most models within the ensemble of GCMs that took part in the fifth phase of the Climate Model Intercomparison Project (CMIP5), results of which were the basis of the last Intergovernmental Panel for Climate Change report, use grid sizes greater than 1° of latitude and longitude (Taylor et al., 2012). With this resolution, all cloud processes are parameterized and many orographic features are much smoothed. Therefore, it is understandable that total cloud cover (TCC) as simulated by GCMs shows large differences with observations (Klein et al., 2013; Lacagnina & Selten, 2014; Lauer & Hamilton, 2013). In particular, for the Mediterranean region, a general underestimation of TCC is found (Enriquez-Alonso et al., 2016), although the decreasing decadal trend seems to be quite correctly captured (Sanchez-Lorenzo et al., 2017).

Climate impact assessment and the development of regional to local-scale adaptation strategies require the availability of high-resolution climate change scenarios (Jacob et al., 2014). In this sense, results of GCMs are "downscaled" to higher resolution fields by means of several techniques, namely, statistical approaches or dynamical methods. Roughly speaking, dynamical downscaling involves nesting a regional climate model (RCM), which is run at resolutions of some tens of kilometers, into a global climate model (GCM). So the RCM inherits the main patterns and trends from the GCM but adds more detail in the climate projection, since it uses finer orography and physical parameterizations that may reproduce better the smaller scale processes. Several efforts in downscaling climate projections have been carried out in recent years. The European projects PRUDENCE (Christensen, Carter, et al., 2007) and ENSEMBLES (Hewitt & Griggs, 2004) are to be highlighted, while currently, a much more ambitious project, CORDEX, is underway. CORDEX, the Coordinated Regional Climate Downscaling Experiment, is a project sponsored by the World Meteorological Organization through its World Climate Research Programme that coordinates the use of RCMs in different regions around the world (Giorgi et al., 2009).

In the present study, we focus on the Mediterranean region because several studies point to this region as a climate "hot spot," as it is a region where climate change may have a big impact on biodiversity and socioeconomic activities (Diffenbaugh et al., 2007; Giorgi, 2006; Schneider et al., 2007). Both subprojects MED-CORDEX (Ruti et al., 2016) and EURO-CORDEX (Jacob et al., 2014) have carried out climate simulations that cover the Mediterranean area with several RCMs driven by different GCMs. Specifically, there are a number of runs at 50 km (0.44°) resolution and other runs at 12.5 km (0.11°) resolution.

There are in the scientific literature several studies that compare results from RCMs with results from the associated GCMs and discuss the added value of the former in comparison with the latter (Feser et al., 2011; Paeth & Mannig, 2013; Rummukainen, 2016). For cloudiness properties in general and for TCC in particular, there are no studies (to our knowledge) centered in comparing results from GCMs with results from RCMs and with observations. Bartók et al. (2016), however, compared GCMs with RCMs regarding the variable surface solar radiation (SSR) in Europe and found that while GCMs capture the recent solar brightening (which is also detected in observations), RCMs do not produce in general a significant positive trend. This was partly explained by discrepancies in the trends of cloudiness. This result is in line with the contradiction between GCMs and RCMs regarding future evolution of solar radiation: while Wild et al. (2015) found projected increases in SSR with GCMs, Jerez et al. (2015) found a general future decrease in SSR when using RCM projections.

The main goal of the present study is to compare TCC as simulated by RCMs from CORDEX project with the same variable as simulated by the corresponding driving GCMs. The comparison will be performed for the Mediterranean region, and for the period when results from RCMs and GCMs can also be compared with an available data set of ground-based cloud observations (section 2). The outputs of both types of models will be compared between them and with observations from a climatic point of view (i.e., averaging for the whole period, section 3.1) and also considering the temporal evolution (including long-term trends, section 3.2). Further discussion and conclusions of this study are presented in section 4.

2. Data and Methods

We have chosen the 14 data sets provided by EURO-CORDEX project (Jacob et al., 2014) with a spatial resolution of 12.5 × 12.5 km^2 (0.11° × 0.11° approximately) which are a combination of five GCMs from the CMIP5 (CNRM-CM5, EC-EARTH, IPSL-CM5A-MR, HadGEM2-ES, and MPI-ESM-LR) and five RCMs obtained from different research institutions (CLM4-8-17, HIRHAM5, RACMO22E, REMO2009, and RCA4). Our analysis is based upon the monthly data sets provided by the project, for the variable TCC and for the "historical" experiment (i.e., for the runs performed with past—and known—natural and anthropogenic forcings). Despite MED-CORDEX also covers our study area, we could only find results for TCC associated to seven realizations of a single model pair (ALADIN52 nested in CNRM-CM5) in contrast to the 14 combinations in EURO-CORDEX. These latter combinations, used in the present study, are listed in Table 1. Some details for both GCMs and RCMs are given in the next paragraphs.

Results from the driving GCMs have been obtained from the CMIP5 data server, also for the "historical" experiment. Specifically, we could obtain the monthly values of TCC for the first realization (*r1i1p1*) from three models and for two realizations (r1i1p1 and *r2p1i1*) from MPI. TCC data from EC-Earth are not available in the CMIP5 server, but we could access these results from another data server, although only for realization *r12* (it should be noted that three realizations of this model have been used for driving the RCMs). Historical

Table 1
EURO-CORDEX Data Sets Included in This Study

Institute	RCM (short name)	GCM (short name)	Realization
CLMcom	CCLM4-8-17 (CCLM)	CNRM-CM5 (CNRM)	r1i1p1
		EC-EARTH (EC-Earth)	r12i1p1
		HadGEM2-ES (HadGem)	r1i1p1
		MPI-ESM-LR (MPI)	r1i1p1
DMI	HIRHAM5 (HIRHAM)	EC-EARTH	r3i1p1
KNMI	RACMO22E (RACMO)	EC-EARTH	r1i1p1
		HadGEM2-ES	r1i1p1
MPI-CSC	REMO2009 (REMO)	MPI-ESM-LR	r1i1p1
		MPI-ESM-LR	r2i1p1
SMHI	RCA4 (RCA)	CNRM-CM5	r1i1p1
		EC-EARTH	r12i1p1
		HadGEM2-ES	r1i1p1
		IPSL-CM5A-MR (IPSL)	r1i1p1
		MPI-ESM-LR	r1i1p1

simulations with these GCMs are available from 1850 to 2005. Regardless of the original resolution of each GCM, we have used here a resolution of 2° × 2.5° (latitude × longitude) for all models, which has been obtained by interpolation. More details regarding cloud parameterizations included in GCMs may be found in Enriquez-Alonso et al. (2016).

The regional climate model COSMO-CLM (CCLM) (Doms et al., 2011; Doms & Baldauf, 2015) is a nonhydrostatic model developed from the Local Model (LM) of the German Weather Service by the Consortium of Small-scale Modeling (COSMO) and the Climate Limited-area Modeling-Community (CLM-Community). The model used in CORDEX is the current standard version for regional climate applications (CCLM_4.8_clm17). Configuration of the physics parameterizations is identical to that used by the German Weather Service (DWD) for its operational European daily weather forecast with the so called COSMO-EU model until version COSMO_4.10. The model called REMO (REgional MOdel) is a new regional atmospheric model that was set up in a joint effort by DKRZ (Deutsches Klimarechenzentrum), DWD (Deutscher Wetterdienst), and GKSS (Forschungszentrum Geesthacht). This model can be used in weather forecast mode as well as in climate mode. It is based on the Europa-Model (EM), the main weather forecast model of the new numerical weather prediction system of DWD. HIRHAM (Christensen, Drews, et al., 2007) and RACMO (van Meijgaard et al., 2008) use HIRLAM (High Resolution Limited Area Model, Unden et al., 2002) dynamical core. The HIRLAM model is a hydrostatic grid point model, based on a semi-implicit semi-Lagrangian discretization of the multilevel primitive equations, using a hybrid coordinate in the vertical. Optionally, an Eulerian dynamics scheme can be used as well. Finally, RCA4 is the modern version of model RCA which includes several updates, mainly in surface processes (Samuelsson et al., 2011). RCA also uses the numerical weather prediction model HIRLAM (Unden et al., 2002) as dynamical core and the radiation scheme is based on the HIRLAM radiation scheme, too, with some modifications for the treatment of cloud fraction. More details on the physics parameterizations of RCMs (in particular, for cloud-related processes) may be found in Kotlarski et al. (2014) and Bartók et al. (2016).

Regarding surface observations, we have used the *Extended Edited Synoptic Cloud Reports Archive* (EECRA) data set, which is an update of the *Edited Synoptic Cloud Reports Archive* (ECRA) (Hahn et al., 1996). These data sets make use of routine meteorological observations from the ground (or on ships in the ocean). Developers of EECRA applied a strict quality control to the data (Hahn et al., 2009). In the current study we have used a further updated version of EECRA (Eastman & Warren, 2013) that comprises the 1971–2009 period. More precisely, we have used an interpolated data set into a regular grid of 2° × 2.5° (latitude × longitude). For more details, see Enriquez-Alonso et al. (2016). In order to further enhance our comparison with observations, putting emphasis on the differences between resolution of RCMs and GCMs, we have also used cloud observations from more than 100 meteorological stations across the Mediterranean region and located in different countries (Spain, Switzerland, Slovenia, Croatia, Bosnia, Serbia, Bulgaria, and Turkey; see supporting information). The use of a number of sites to assess RCMs in comparison to GCMs is inspired in works such as Bartók et al. (2016).

The region of interest in the present work is the Mediterranean basin. Specifically, we have used the Southern Europe and Mediterranean region (*SEM*) defined elsewhere (30–48°N, 10°W–40°E) as our study area (Figure 1). This region is easily matched by the GCMs and EECRA grids of 2° × 2.5°. RCMs from CORDEX project, however, use a different geographical projection (polar rotated), in such a way that a rectangular grid from the RCMs do not match an area defined by meridians and parallels. Therefore, the original CORDEX results have also been interpolated to a regular nonrotated grid, with a resolution of 0.25° × 0.25°. It should be noted as well that not all grid cells in the *SEM* region contain observational data from the EECRA data set. The *EECRA mask*, therefore, distinguishes those grid cells with observations from those without data. In summary, the whole region *SEM* is used when comparing RCMs with GCMs, while the *EECRA mask* is applied when comparing models with observations. The period under study is 1971–2005, that is from the beginning of EECRA data until the last year simulated by climate models in historical experiments.

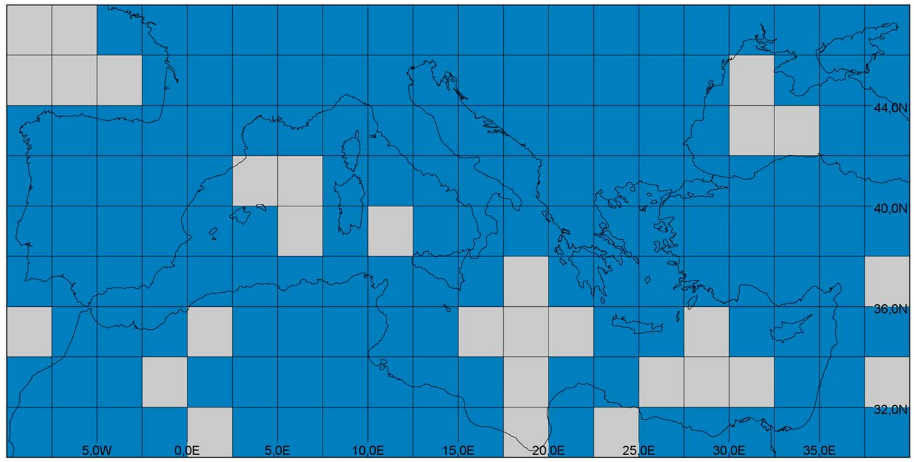

Figure 1. Region SEM used in this paper, with the gridding corresponding to the resolution of interpolated CGMs and EECRA values (2° × 2.5°). Grey indicates cells with no EECRA data, so when the EECRA mask is applied, the average is performed using blue cells only.

Two metrics are applied to quantify differences between RCMs and GCMs and also to assess differences between RCMs (or GCMs) and observations, from the climatic point of view. These are mean bias (MB) and annual range difference (ARD). MB is defined as the difference between mean TCC (for the whole period) from two data sets and can be computed for each cell, or for the whole domain, and for different temporal basis (annual or seasonal). ARD is the difference between the annual ranges (AR) produced by two data sets and is applied here only to the average for the whole domain. AR is the difference between mean TCC in winter (December, January, and February (DJF)) and summer (June, July, and August (JJA)). To give an overall picture of regional and global models, multimodel means will be computed (for the 14 RCMs and the 5 GCMs) and named MRM and MGM, respectively. Following the methods applied by Jerez et al. (2015) and Tobin et al. (2015, 2016), significance of differences is assessed by means of Student's *t* test applied to the series of annual values, while when at least 75% of RCM-GCM combinations (11 out of 14) are consistent in the sign, the overall result is labeled as "robust."

Regarding the temporal evolution of TCC, we use the coefficient of variation (CV) and the long-term linear trend to characterize the simulated and observed series. In both cases, series are built as the TCC annual means for each cell or for the region, so seasonal effects are removed. CV accounts for interannual variability and is defined as the ratio of standard deviation of a series to the mean of the same series. Trends are computed by least squares linear regression; significance is assessed by applying a *t* test.

3. Results

3.1. Climatology

In this section we focus on comparing the TCC climate as given by RCMs with that given by the driving GCMs, using as complement the observational data. In this context, "climate" means the temporal average for the whole analyzed period (1971–2005). First of all, as a summary of previous published results (Enriquez-Alonso et al., 2016) Table 2 shows several characteristics and the main indexes (MB and ARD) regarding GCMs included in the present study. It is clear that all GCMs greatly underestimate the mean TCC for the whole Mediterranean region (48%TCC from EECRA), while most of them overestimate the annual range (26%TCC from EECRA), as a result of too low TCC in summer time. Possible causes of this differences are suggested in Enriquez-Alonso et al. (2016).

Table 3 shows the differences of RCMs against the driving GCMs, and the same indexes for RCMs against EECRA. It should be noted that the MB with respect to EECRA for the MRM is −6.5%TCC (compare with the MB for the MGM, −8.1%TCC). Therefore, the overall effect of RCMs is to reduce the MB by increasing the annual mean TCC. In particular, CCLM and RACMO produce a mean TCC that is closer to the observations, although in general, they still underestimate the EECRA values (only two combinations, CCLM-CNRM and

Table 2
Climatic (Mean TCC and AR) and Temporal Behavior (CV and Trend) for the Driving GCMs, and Metrics MB and ARD Versus EECRA and MB Versus the Data Set of Meteorological Stations From Several Countries

	SEM region				EECRA mask		Stations data set
GCM	TCC (%TCC)	AR (%TCC)	CV (%)	Trend (%TCC/decade) [*p* value][a]	MB (%TCC)	ARD (%TCC)	MB (%TCC)
CNRM	36.4	24.3	3.8	−0.36 [<0.15]	−11.8	−2.3	−5.9
EC-Earth[b]	42.4	33.7	3.4	0.02	−5.4	7.0	2.3
HadGem	39.3	32.1	3.6	−0.41 [<0.1]	−9.1	6.8	−5.1
IPSL	36.9	37.5	5.1	−0.54 [<0.1]	−11.6	12.5	−7.2
MPI[b]	45.1	29.5	3.6	−0.26 [<0.4]	−2.8	3.7	4.8
MGM	40.0	31.4		−0.31 [<0.05]	−8.1	5.5	−2.2

[a]The *p* values >0.1 imply low statistical significance, but if they are <0.33 the corresponding trend may be considered "likely," and if <0.5, "more likely than not"; *p* values >0.5 are not given. [b]Values for r12 for EC-Earth and for r1 for MPI.

CCLM-MPI produce positive MB). HIRHAM and REMO result in values of MB about −9%TCC, which are higher (in absolute value) than the bias of the corresponding driving GCMs (EC-Earth and MPI). RCA produces relative large values of MB, regardless of the driving GCM. In three cases, the RCA result is worse than that of the driving GCM, while in the other two cases, the MB is only slightly improved. Therefore, based on MB, these later three regional models do not improve the global model results. In other words, RCMs do not produce a robust improvement of TCC in the Mediterranean, as some of them produce the desired increase but other combinations result in lowered cloudiness (see Table 3, third column).

Figure 2 (top) gives spatial detail regarding the MB of the TCC as simulated by RCMs. Specifically, the behavior of MB for MRM versus EECRA is shown. As expected (since the average MB for the whole region is negative, as above commented) there is a general underestimation of the simulated TCC, both in land areas and in maritime areas. There are, however, some exceptions to this general behavior: in one hand, areas of the Atlantic Ocean (west of the Iberian Peninsula) and areas of the Mediterranean Sea (south of Sicily and by the Nile

Table 3
Mean TCC and AR for RCMs Compared With That of the Driving GCMs, Temporal Behavior (CV and Trend, the Latter Also Compared With That of the GCM), and Metrics MB and ARD Versus EECRA and MB Versus the Data Set of Meteorological Stations From Several Countries

		SEM region					EECRA mask		Stations data set
RCM	GCM	$TCC_{RCM} - TCC_{GCM}$ (%TCC)[a]	$AR_{RCM} - AR_{GCM}$ (%TCC)	CV (%)	Trend (%TCC/decade) [*p*-value][b]	$Trend_{RCM} - Trend_{GCM}$ (%TCC/decade)	MB (%TCC)	ARD (%TCC)	MB (%TCC)
CCLM	CNRM	15.5	−7.0	2.1	−0.03	0.33	4.4	−9.4	13.4
	EC-Earth	3.0	−11.2	3.4	0.10	0.08	−2.4	−4.6	5.4
	HadGem	4.1	−1.2	3.5	−0.17	0.25	−4.2	4.1	2.3
	MPI	5.2	−5.1	3.0	−0.24 [<0.4]	0.02	2.5	−2.3	10.6
HIRHAM	EC-Earth	−2.5	−14.9	2.3	−0.32 [<0.1]	−0.34	−9.1	−7.7	−8.8
RACMO	EC-Earth	0.7	−5.4	3.6	−0.26 [<0.4]	−0.28	−5.9	0.8	−4.0
	HadGem	3.0	0.1	3.2	−0.08	0.34	−6.6	5.1	−5.4
RCA	CNRM	3.0	−4.5	2.1	0.00	0.35	−9.5	−6.1	−10.8
	EC-Earth	−5.7	−15.0	2.7	0.01	−0.01	−12.3	−7.1	−14.1
	HadGem	−4.0	−8.4	3.5	−0.13 [<0.5]	0.29	−13.7	−2.0	−16.3
	IPSL	2.0	−14.4	4.5	0.02	0.56	−10.0	−2.6	−10.8
	MPI	−3.5	−9.2	2.8	−0.02	0.23	−7.4	−5.0	−9.0
REMO	MPI (*r1*)	−4.9	−7.9	2.6	−0.01	0.25	−8.7	−4.4	−9.2
	MPI (*r2*)	−4.7	−8.2	3.0	0.03	0.13	−8.6	−4.7	−9.6
MRM	MGM	2.1	−8.3		−0.08	0.24	−6.5	−3.3	−4.7

[a]All differences between the mean TCC for RCMs and for GCMs are significant at 99% level, except for the pair RACMO / EC-Earth, which is significant at 90% level. [b]The *p* values >0.1 imply low statistical significance, but if they are <0.5 the corresponding trend may be considered "more likely than not"; *p* values >0.5 are not given.

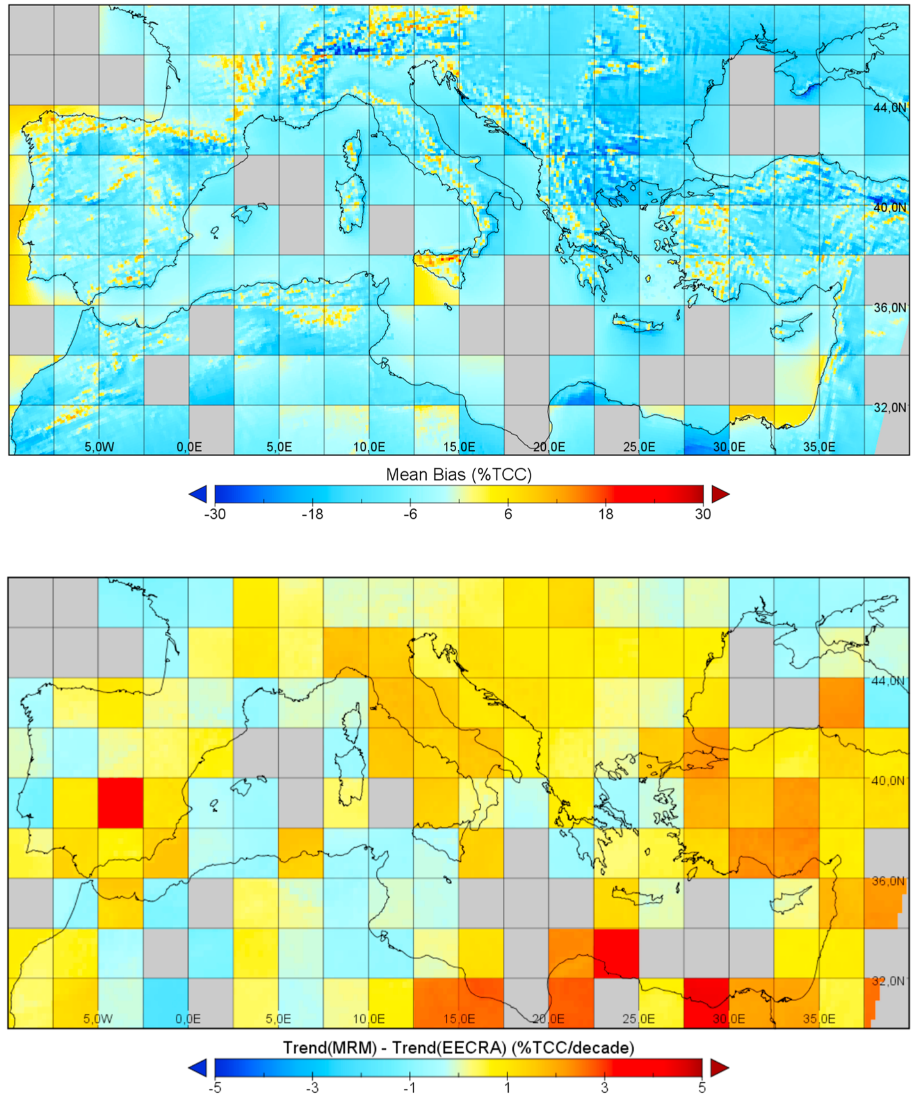

Figure 2. (top) MB (%TCC) and differences (bottom) between trends (%TCC/decade) for the MRM against EECRA. There is one EECRA value in each 2.5° × 2.0° cell (except in those shown in grey).

Delta) and on the other hand, and more interesting, in most mountainous areas of the region (e.g., Pyrenees, Alps, Apennines, Balkans, and Atlas) there are pixels with a slight overestimation. These results show that the high resolution of regional models would help in representing local differences in TCC produced by the sea-land interface or by the orography (it should be recalled that comparison is performed against the low-resolution EECRA gridded data set). In particular, it is clearly shown the enhanced cloudiness variability due to orographic effects.

Regarding the ARD for the RCMs against EECRA (Table 3), it should be noted that in average for all RCMs is −3.3%TCC, while the average for all the driving GCMs is 5.5%TCC (Table 2). This means that the seasonal variation given by RCMs is slightly lower than observations, while for GCMs it is greater than observations. Indeed, all RCMs (except the combination RACMO-HadGem) clearly reduce the AR given by the driving GCM and the result is that all RCMs, except RACMO and CCLM driven by HadGem, show a negative ARD. We will show below that this is due to a general increase in TCC in summer (and a decrease in winter) when using RCMs. The robust reduction of AR does not result in a general improvement of the ARD as in several cases the (negative) ARD for a RCM is greater (in absolute value) than the (positive) ARD of the driving GCM.

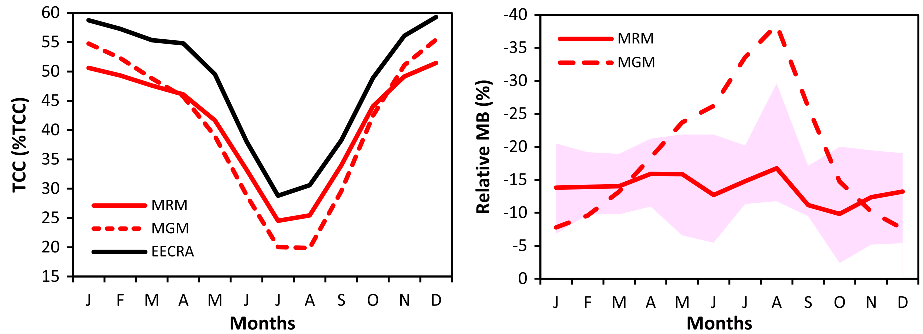

Figure 3. (left) Mean monthly TCC for 1971–2005 period as observed by EECRA, and simulated by the regional models (MRM) and global models (MGM). (right) Monthly relative MB (%) for MRM and MGM versus EECRA. Shaded region means the range (percentiles 25 and 75) of relative MB for individual RCMs. It should be noted that *y* axis is inverted (all bias are negative). All values represented here correspond to the EECRA mask.

Thus, Figure 3 (left) shows the annual cycle of TCC in the Mediterranean region. EECRA observations show a strong seasonal cycle, with maximum TCC in winter (next to 60%TCC) and minimum in summer (less than 30%TCC in July). MGM follows this evolution more or less parallel and always with lower values, although the difference is about −5%TCC in winter months and reaches −10%TCC in some spring and summer months. This reflects the already mentioned underestimation of TCC and overestimation of the annual range (negative MB and positive ARD, Table 2). The MRM also somewhat parallels the observed evolution, but in this case, differences are greater in winter (about −8%TCC) and much lower in some summer and autumn months (about −4%TCC). This produces a lower underestimation of TCC and also an underestimation of the annual range (negative MB and negative ARD, Table 3). Figure 3 (right) shows more clearly the seasonal differences between RCMs and GCMs. In this plot, the relative mean bias in shown (i.e., the MB as above defined divided by the EECRA mean value). Relative MB for MRM is more or less constant through the whole year, between 10 and 15% (in absolute value), with lowest values in fall and highest values in spring. Contrarily, for MGM the relative MB steadily increases from winter values as low as 7% (in absolute value) to summer values as high as 40%. The shadowed area confirms that most individual RCMs behave similarly; that is, most RCMs tend to reduce TCC in winter and increase TCC in summer. This result is consistent with the above findings and suggests that the main improvement from using RCMs (regarding description of cloudiness) has to do with mesoscale phenomena, that is, with clouds generated by orography and local convection, which are much more usual in summer given the enhanced instability due to greater solar input. It is not easy to find an explanation for the reduced winter cloudiness from RCMs. In any case, it should be noted that in the Mediterranean region there exists a high spatial diversity of intra-annual cloudiness variability and that in particular in winter a given synoptic condition produces very different cloudiness on different areas within the region (Ioannidis et al., 2017; Lolis, 2009).

A more detailed analysis of each model configuration may be addressed from the plots in Figure 4 where the TCC differences between each RCM and the corresponding driving GCM are shown for annual and summer. Summer has been chosen given the differences that we have commented above. In several cases, RCMs tend to reduce annual TCC from the values produced by the associated GCM over continental areas, while most RCMs increase TCC (with respect to the corresponding GCM) over maritime areas. This is quite clear for HIRHAM, RCA, and REMO, and less obvious (or even opposite behavior) for RACMO and CCLM. Regarding summer season, the overall behavior is similar, but there are more model combinations that produce TCC increases even over continental areas and in particular over mountainous regions.

Specifically, CCLM produces notable increases in the TCC given by the driving GCM over most of the domain, especially when it is driven by CNRM. Only in some maritime areas (Eastern Mediterranean) this RCM tends to slightly decrease the TCC; when CCLM is driven by HadGem, the lowered TCC extends across the whole sea. In summer, these characteristics are further enhanced. Contrarily, RCA, whatever is the driving GCM, tends to produce less TCC over continental areas, and somewhat more TCC over oceanic areas. This is especially noticeable for the summer season when RCA is driven by EC-Earth. Interestingly, the only case that uses

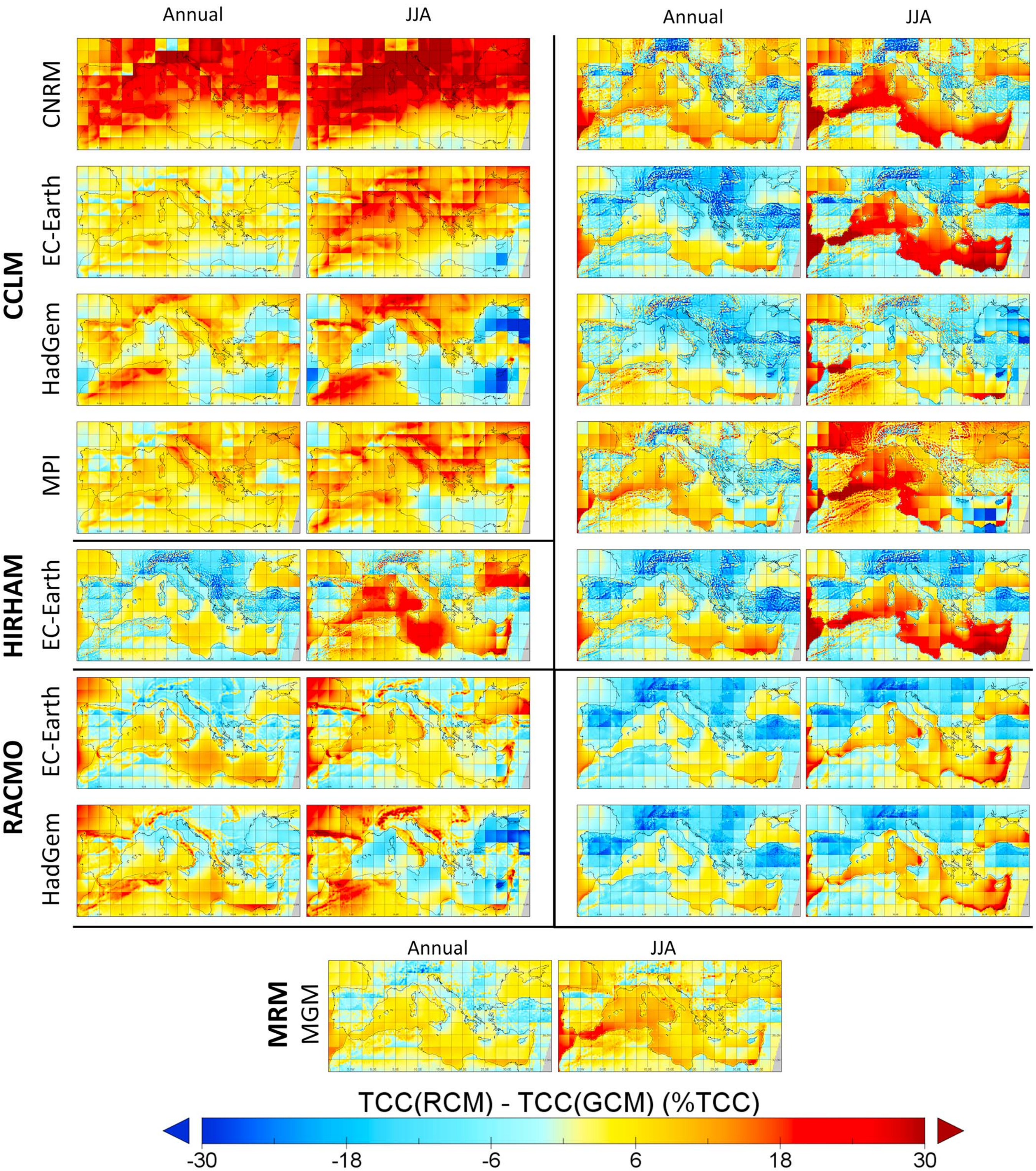

Figure 4. Annual and summer (JJA) difference of mean TCC (%TCC) between RCMs and GCMs, for the period 1971–2005. It should be noted that GCM results are interpolated into a regular grid (2° × 2.5°).

HIRHAM (driven also by EC-Earth) produces quite similar results. In addition, these two RCMs share a characteristic with RACMO: TCC is remarkably affected by orography, as in all these cases and particularly in summer the high-resolution results clearly show large TCC spatial variability in mountainous areas (Pyrenees, Alps, Apennines, and Carpathian mountains). Finally, the two REMO results are very similar, as they are both driven by MPI. Here TCC is lowered over continental areas and slightly increased over the Mediterranean and Caspian seas (especially in summer).

As above mentioned, modeling results have also been compared with observations at particular meteorological stations. Detailed results (i.e., differences for each RCM and GCM and for each station) are given as supporting information. A synthesis of these results, namely, the MB for the whole data set of stations, is given in the last column of both Table 2 (for GCMs) and Table 3 (for RCMs). Based on this comparison, GCMs perform better than RCMs: the range of MB for GCMs is [−7.9, 2.3] %TCC, while for RCMs the range is [−16.3, 13.4] %TCC. All CCLM simulations give positive bias, while the other regional models produce negative bias. In most cases, MB for each RCM is worse (i.e., greater in absolute value) than the corresponding MB when using EECRA gridded data as reference, and also worse than the MB of the driving GCM. We think that this is a consequence of the different behavior of models over land and sea. For example, as above mentioned, CCLM tends to increase TCC especially in continental areas (so it produces large positive MB when the comparison is restricted to stations, obviously located inland). Contrarily, RCA produces larger negative MB when compared with stations than when compared with EECRA data. In addition, it is true that meteorological stations considered here do not cover the whole domain (e.g., there are no data for North Africa and Middle East). Also, the specific behavior of RCMs in some particular regions may also influence the result. For example, all Swiss stations present positive bias with GCMs and negative differences for RCMs.

3.2. Temporal Variability and Trends

In this section we analyze the results of the same climate models as far as temporal evolution is concerned. First, Figure 5 (top) shows the evolution of TCC for the driving GCMs and the MGM, along with the observed evolution (EECRA data set). Several facts can be highlighted from this figure: one, the above mentioned underestimation of TCC as given by the GCMs. Two, an apparent similar interannual variability; indeed, the coefficient of variation is 3.4%TCC for EECRA and is in the range [3.4, 5.1] %TCC for the GCMs (Table 2). Obviously, the variability of the MGM is lower, as the MGM results from averaging TCC given by the five GCMs, which are not correlated. Three, EECRA values show a slight decreasing tendency; this is confirmed by the trend derived from the linear regression, which is -0.63%TCC decade^{-1} ($p < 0.05$) (Sanchez-Lorenzo et al., 2017). Trends of each GCM, however, do not fully agree with observations. Indeed, Table 2 shows the values of the trends for the GCMs, and we can see that only two of them (IPSL, HadGem) are significant ($p < 0.1$) but with absolute values lower than the observed. Two other GCMs (CNRM and MPI) produce also negative slopes but with a very low statistical significance; EC-Earth, finally, does not give any trend for the analyzed period. Trend of the MGM is -0.31%TCC decade^{-1} ($p < 0.05$), so the group of these five GCMs capture half of the observed trend, similarly to what Sanchez-Lorenzo et al. (2017) reported for the full ensemble of the CMIP5 models.

An equivalent plot, but for the evolution of TCC as simulated by the RCMs (as well as MRM and EECRA observations), is given in Figure 5 (bottom). As expected, the general underestimation is again clearly observable, but there are two simulations (with CCLM) above the observations, and MRM is closer to EECRA than MGM. At the other end, RCA is confirmed as the RCM that produces in general the lowest TCC. Interannual variability of TCC given by RCMs (see CV in Table 3, the range is [2.1, 4.5] %TCC) is somewhat lower than that given by the driving GCMs (and therefore is in general lower than the observed variability).

Table 3 also contains the trends of the annual TCC for all data sets of EURO-CORDEX. RCMs are far from describing the observed decreasing trend. This is a robust result, as only one RCM (HIRHAM) gives a significant negative trend, which is, however, lower (in absolute value) than that from the EECRA data set. Other four simulations give negative trends lower than -0.10%TCC decade^{-1}, but with very low statistical significance. The other nine combinations of RCMs/GCMs give stationary TCC for the period. As a result of these values, the trend for the MRM is also very close to null and nonsignificant. In other words, RCMs tend to counteract GCMs, in the sense that most trends for RCMs are less negative that those for GCMs. The only exception

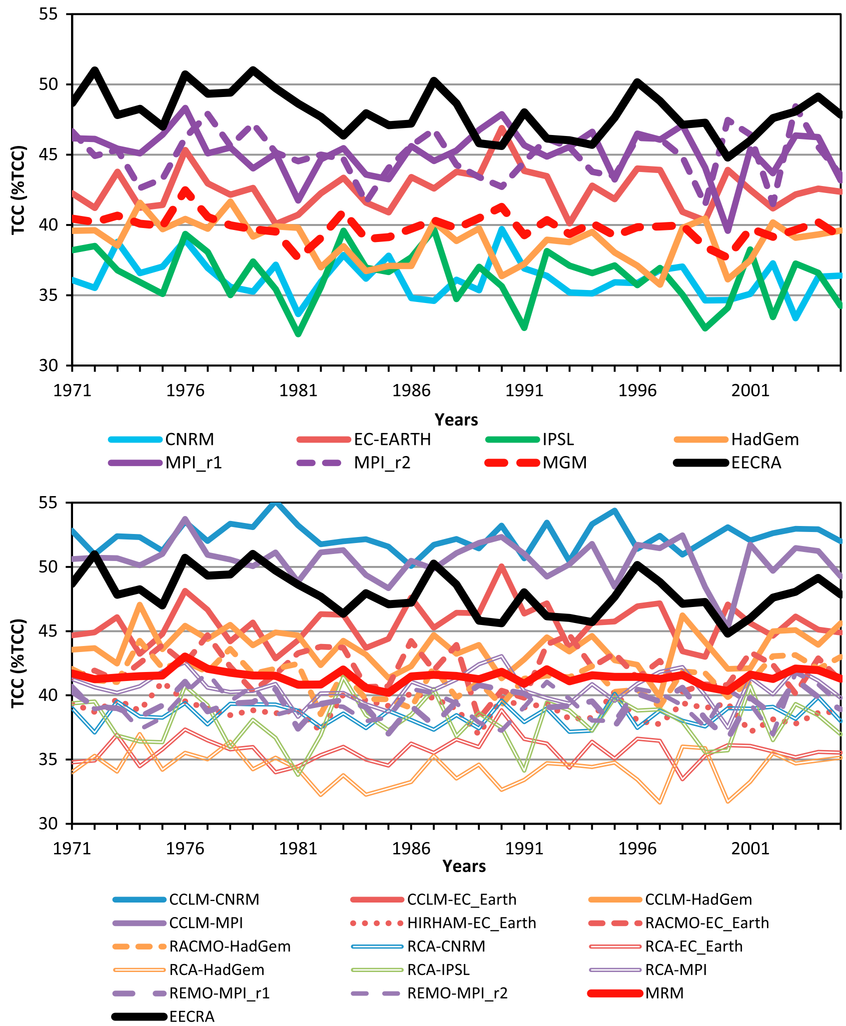

Figure 5. (top) TCC for the GCMs, MGM, and EECRA data set. (bottom) TCC for the 14 data sets of EURO-CORDEX, MRM, and EECRA. 1971–2005 period.

to this general behavior is for EC-Earth, which in two cases (CCLM and RCA) trends are almost not modified, while in the other two (HIRHAM and RACMO) trends become more negative.

Figure 6 shows the spatial variability of these trend differences between the RCMs and the corresponding driving GCMs. It is difficult to find any common pattern among all combinations, although the map of differences between MRM and MGM seems to indicate that RCMs have a tendency to increase the trends in both extremes of the domain (west and east) while they do not vary (or slightly decrease) the trends in the central Mediterranean and the central part of North African coast. Both RACMO and HIRHAM reduce trends with respect to EC-Earth, except in the westernmost part of the domain. The increase in the trends in this area is also produced by both CCLM and RCA when driven by CNRM. Figure 2 (bottom) shows the spatial differences between the trends from the MRM and those from EECRA. As commented, most differences are positive, which corresponds with the absence of an overall trend in the MRM and the existence of a negative trend in the observations. It is also evident that EECRA trend values may be quite different in adjacent cells. This is due to the fact that despite working on a gridded data set, some cells may include information of a single (with a particular behavior) site, while other cells may be the result of averaging several sites. This has a relatively minor effect on the mean TCC but is clearly visible in the trends map (Sanchez-Lorenzo et al., 2017). It should be noted, in addition, that many trends at individual grid cells, in the RCMs, GCMs, and also in EECRA, might be nonsignificant.

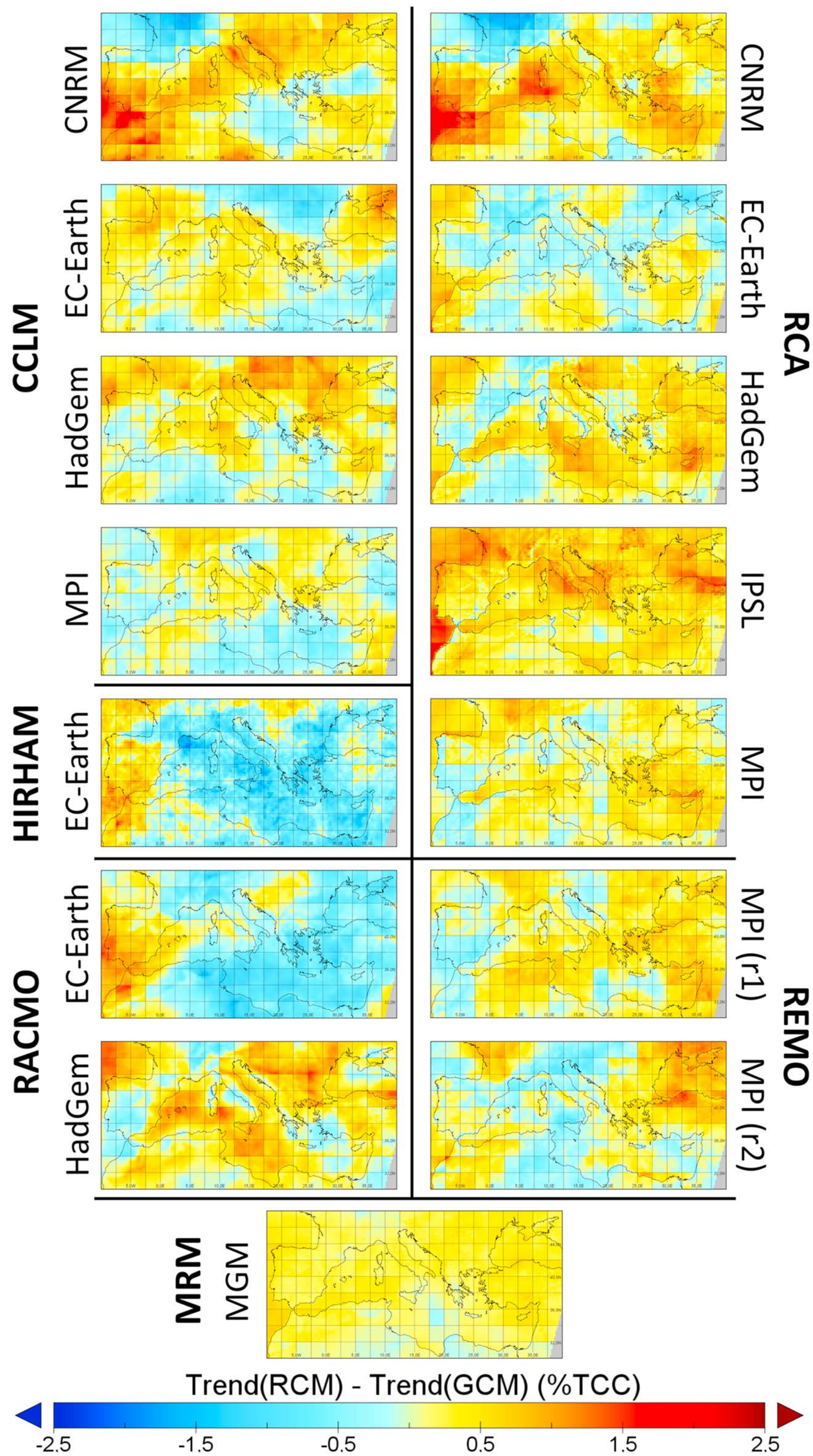

Figure 6. Difference between the trends for the 1971–2005 period from RCMs and those from GCMs. It should be noted that both RCM and GCM results are interpolated into regular grids (0.25° × 0.25° and 2° × 2.5°, respectively).

4. Conclusions and Discussion

RCMs from EURO-CORDEX at 0.11° resolution and driven by several GCMs from CMIP5 improve very slightly the climatic estimation of total cloud cover (TCC) when compared with EECRA observations for the Mediterranean area. Improvement is hardly relevant, because (a) not all RCMs behave in the same manner and (b) some indicators may show a better agreement, while other indicators do not. Indeed, RCMs reduce in general the underestimation in TCC resulting from GCMs; that is, RCMs produce higher annual mean TCC taking the Mediterranean region as a whole. However, RCMs reduce in excess the annual range in TCC; that is, they produce too low differences between the winter maximum and the summer minimum. More specifically, some combinations of the five RCMs with the five GCMs (in particular, CCLM and RACMO with HadGem, MPI, and EC-Earth) show a clear better agreement (lower MB and ARD) than other pairs, and also better results than those from the driving GCMs. Other combinations do not produce so clear improvements, or the improvement is restricted to ARD, while MB is equal (or even worse) than those from the driving GCMs. In addition, when a set of more than 100 meteorological stations located in seven Mediterranean countries are used as reference, RCMs do not show any bias improvement relative to the driving GCMs.

In any case, there are noticeable spatial and temporal patterns in this general behavior. For example, if we analyze the monthly means of TCC from GCMs and compare them with the monthly means from RCMs, it is clear that the latter behave better than the former, as the relative bias is much more constant throughout the year (GCMs produce a very high relative bias in summer). Thus, changes in estimation of TCC in summer might be the most relevant value added by RCMs representation of clouds. This must be due to the fact that RCMs describe in a more proper way several mesoscale processes (free convection, orographic effects), which play a more relevant role in summer. Several previous studies already pointed in this direction (Klein et al., 2013; Lauer & Hamilton, 2013; Randall, 2013). Moreover, the effect of the finer grid is confirmed by the spatial texture of TCC results from RCMs, as in general the main mountain chains are clearly reflected. Nevertheless, it should be noted that surprisingly enough, some RCMs increase TCC (with respect to that from the associated GCM) over the sea and not over continental areas.

Despite the slight improvement in describing the TCC seasonal behavior for the whole period, RCMs are unable to capture the observed decadal trend in TCC. Indeed, TCC simulated by RCMs is almost stable during the 35 year period. This contradicts observations, which show a statistically significant decreasing trend in the Mediterranean area, and opposes the trend obtained by GCMs, which is lower in absolute value but still significantly negative (Sanchez-Lorenzo et al., 2017). This result is unexpected and a bit disappointing, as if RCMs cannot reproduce past trends in TCC, their skill in projecting TCC evolution into the future may be questioned.

We must comment that the current study has some limitations. First, although we always refer to the Mediterranean region, the area considered to perform the spatial averages is not strictly always the same. Thus, when comparing GCMs with RCMs, the whole SEM region has been used, while when the comparison involves gridded observations, we use the *EECRA mask*. Area covered by EECRA mask is more than 80% of SEM but has a certain bias towards continental areas as there are fewer observations over the sea. Second, the EECRA data used here has a low resolution, and this may affect some differences found between RCMs and observations. Indeed, the use of cloudiness observations from a number of meteorological stations has resulted in somewhat different results (partly explained by the continental bias of the stations). However, it should be recalled that the focus of the present study is on the differences between RCMs and GCMs. Third, we must also recall that only one realization of EC-Earth has been used when comparing results, while in fact three realizations are used to drive different RCMs. This should not affect our conclusions, as different realizations of the same model use the same dynamical core and physics parameterizations, so they are practically identical from the climatic point of view.

The 14 combinations of RCMs-GCMs explored here should be enough to give an idea of the problems and advantages of RCMs in capturing TCC behavior and trends in the Mediterranean, but different models exhibit so different results that a general behavior can hardly be defined. Nevertheless, the above results are consistent with some similar studies that have been performed recently. For example, Bartók et al. (2016) analyzed surface solar radiation (which is inversely correlated to cloudiness) in Europe and obtained also important differences between trends given by GCMs (increase in SSR) and trends produced by RCMs (decrease).

They also found that the main differences between RCMs and GCMs correspond to the warm part of the year. The same study (Bartók et al., 2016) suggests that changes in cloudiness representation by RCMs and GCMs may partly explain the different trends in SSR (change in water vapor column is another potential cause). That study covered all Europe including also the Mediterranean region, but only eight sites in Italy and Austria were considered in the assessment, while in the current research we have used more than 100 sites covering both western and eastern Mediterranean areas.

Finally, we must stress that the goal of the present paper is on presenting similarities (and differences) between GCMs and RCMS, regarding the variable total cloudiness. We have found some remarkable results, such as increasing TCC in several RCMs compared to the driving GCMs over the continental areas and not over the sea, but vice versa in other cases, or a bias improvement during the summertime in RCMs but larger bias in wintertime. We could speculate that these apparently inconsistent results are a consequence of the different approaches considered by different RCMs when representing microphysics, convection, and cloud cover estimation. For example, HIRHAM, RACMO, and RCA are based on HIRLAM, and their results are relatively similar, but totally different from results from CCLM, which has a different dynamical core and physics parameterizations (Kotlarski et al., 2014). However, finding physical explanations for all results described here is beyond the scope of this current research; we think that this is a challenge that must be undertaken by the modeling community.

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