



What can we know about future precipitation in Africa? Robustness, significance and added value of projections from a large ensemble of regional climate models

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Abstract

We employ a large ensemble of Regional Climate Models (RCMs) from the COordinated Regional-climate Downscaling EXperiment to explore two questions: (1) what can we know about the future precipitation characteristics over Africa? and (2) does this information differ from that derived from the driving Global Climate Models (GCMs)? By taking into account both the statistical significance of the change and the models' agreement on its sign, we identify regions where the projected climate change signal is robust, suggesting confidence that the precipitation characteristics will change, and those where changes in the precipitation statistics are non-significant. Results show that, when spatially averaged, the RCMs median change is usually in agreement with that of the GCMs ensemble: even though the change in seasonal mean precipitation may differ, in some cases, other precipitation characteristics (e.g., intensity, frequency, and duration of dry and wet spells) show the same tendency. When the robust change (i.e., the value of the change averaged only over the land points where it is robust) is compared between the GCMs and RCMs, similarities are striking, indicating that, although with some uncertainty on the geographical extent, GCMs and RCMs project a consistent future. Potential added value of downscaling future climate projections (i.e., non-negligible fine-scale information that is absent in the lower resolution simulations) is found for instance over the Ethiopian highlands, where the RCM ensemble shows a robust decrease in mean precipitation in contrast with the GCMs results. This discrepancy may be associated with the better representation of topographical details that are missing in the large scale GCMs. The impact of the heterogeneity of the GCM–RCM matrix on the results has been also investigated; we found that, for most regions and indices, where results are robust or non-significant, they are so independently on the choice of the RCM or GCM. However, there are cases, especially over Central Africa and parts of West Africa, where results are uncertain, i.e. most of the RCMs project a statistically significant change but they do not agree on its sign. In these cases, especially where results are clearly clustered according to the RCM, there is not a simple way of subsampling the model ensemble in order to reduce the uncertainty or to infer a more robust result.

Keywords CORDEX-Africa · RCMs · GCMs · Added value

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1 Introduction

Africa, the second-largest continent on Earth and with the fastest population growth, is most vulnerable to weather and climate variability (Niang et al. 2014). For instance, over the past century, West Africa has been affected by significant climate anomalies, which have led to the severe droughts of the 1970s and 1980s. Other areas, such as the Horn of Africa, have also suffered serious droughts, particularly since the end of the 1960s. The city of Cape Town in South Africa has recently suffered, during 2015–2017, one of the worst multi-year droughts in decades (Otto et al. 2018). On

the other hand, severe floods, which can result in substantial economic and human losses in both rural and urban areas (e.g., Tarhule 2005; Douglas et al. 2008) have even affected countries located in dry areas, such as Algeria, Tunisia, Egypt and Somalia (Niang et al. 2014).

As future climate change and low adaptive capacity are likely to lead to even more severe impacts on many vital sectors (Niang et al. 2014), Africa was selected as the first target region for the World Climate Research Programme CORDEX (COordinated Regional-climate Downscaling EXperiment, Giorgi et al. 2009). CORDEX aims at fostering international collaboration to generate high-resolution historical and future climate projections, relevant to applications at regional scale, by downscaling the global climate models (GCMs) participating in the Coupled Model Inter-comparison Project (e.g. CMIP5, Taylor et al. 2012).

Since then, much research has evaluated the ability of the CORDEX Regional Climate Models (RCMs), forced either by the ERA-Interim reanalysis (Dee et al. 2011) or GCMs, to reproduce present African climatology (e.g., Nikulin et al. 2012; Endris et al. 2013; Kalognomou et al. 2013; Kim et al. 2013; Krähenmann et al. 2013; Gbobaniyi et al. 2014; Panitz et al. 2014; Dosio et al. 2015; Favre et al. 2016; Endris et al. 2016; Klutse et al. 2016). This shows that RCMs simulate the precipitation seasonal mean and annual cycle quite accurately, but large differences and biases exist amongst models in some regions and seasons. In addition, although RCMs are not always able to improve the simulation skills of the driving GCMs, especially for the general characteristics of the mean climatology, added value is found especially in the fine scales and in the ability of the RCMs to simulate extreme events (e.g., Giorgi et al. 2014; Dosio et al. 2015).

Future climate projections have been analyzed in several studies (Laprise et al. 2013; Haensler et al. 2013; Teichmann et al. 2013; Vizy et al. 2013; Giorgi et al. 2014; Buontempo et al. 2014; Mariotti et al. 2014; Vizy et al. 2015; Dosio and Panitz 2016; Pinto et al. 2016; Diallo et al. 2016; Fotso-Nguemo et al. 2017; Akinsanola and Zhou 2018; Endris et al. 2018), although most of these are based on the results of a single RCMs downscaling an ensemble of GCMs, or on a small ensemble of RCMs downscaling a small ensemble of GCMs. Projections based on large ensembles of CORDEX-Africa RCMs are presented by e.g., Dosio (2017) for temperature extremes and heat waves at the end of the century, Abiodun et al. (2017) for extreme precipitation over four coastal cities. More recently, a series of studies investigated the effect of climate change under 1.5 °C and 2 °C global warming levels over specific African regions (Déqué et al. 2017; Abiodun et al. 2018; Klutse et al. 2018; Lennard et al. 2018; Maure et al. 2018; Muthige et al. 2018; Nikulin et al. 2018; Osima et al. 2018; Parkes et al. 2018; Pokam Mba et al. 2018; Tamoffo et al. 2019b).

It is important to note that discrepancies have been found when comparing the results of a single RCM to those of the driving GCMs (e.g. Mariotti et al. 2014; Laprise et al. 2013; Teichmann et al. 2013; Bouagila and Sushama 2013; Coppola et al. 2014; Buontempo et al. 2014) including projected future precipitation changes in the RCMs having opposite sign to that of their driving GCMs (Saeed et al. 2013; Teichmann et al. 2013; Dosio and Panitz 2016).

In addition, it is also worth noting that even when using a single RCM, the impact on the results of different parameterizations (e.g. convection), land surface schemes and internal variability can be as large as that of the boundary condition (driving GCM) (Crétat et al. 2011a, b; Crétat and Pohl 2012; Ramarohetra et al. 2015).

Here, for the first time to our knowledge, we employ the large CORDEX-Africa RCM ensemble to investigate, at pan-Africa level, if and where the change projected by the RCMs at the end of the century is consistent with that inherited through the boundary conditions, and where differences are more striking.

In particular, we assess the robustness and statistical significance of the change projected by the RCM and GCM ensembles to specifically address two questions:

1. What are the future characteristics of precipitation over Africa as projected by a large ensemble of RCMs?
2. Does this information differ from that derived from the driving GCMs?

The paper is structured as follows: Sect. 2 describes the data used and the statistical analysis performed; in Sect. 3 results are shown and discussed; an analysis of the impact of the heterogeneity of the GCM–RCM matrix is performed in Sect. 4; concluding remarks are presented in Sect. 5.

2 Data and methods

2.1 Climate data

Daily precipitation data for the period 1981–2100 was obtained from a large ensemble of models listed in Table 1. Five different RCMs were used to downscale the results of ten CMIP5 GCMs for a total of 23 simulations. All RCMs were run over the same numerical domain covering continental Africa at a resolution of 0.44° following the CORDEX protocol (http://www.cordex.org/wp-content/uploads/2017/10/cordex_general_instructions.pdf). Historical simulations, forced by observed natural and anthropogenic atmospheric composition, covered the period until 2005; in order to maximize the projected climate change signal, only the projections (2006–2100) forced by the Representative

Table 1 List of RCMs and driving GCMs used in this study

Institute	RCM	Driving GCM
CLMcom	CCLM4.8-17	CNRM-CM5
		EC-EARTH
		HadGEM2-ES
		MPI-ESM-LR
DMI	HIRHAM5	EC-EARTH
		Nor-ESM1-M
GERICS	REMO	HadGEM2-ES
		IPSL-CM5A-MR
		MIROC5
MPI-M	REMO	EC-EARTH
		MPI-ESM-LR
KNMI	RACMO22E	EC-EARTH
		HadGEM2-ES
SMHI	RCA4	CanESM2
		CNRM-CM5
		CSIRO-MK3
		GFDL-ESM2M
		EC-EARTH
		HadGEM2-ES
		IPSL-CM5A-MR
		MIROC5
		MPI-ESM-LR
		Nor-ESM1-M

Simulations are those available through the Earth System Grid Federation (ESGF) server at the time of this study

Concentration Pathways 8.5 (RCP8.5, Van Vuuren et al. 2011) are analyzed in this study.

2.2 ETCCDI indices

Several indices (Table 2) from the Expert Team on Climate Change Detection and Indices (ETCCDI, Zhang et al. 2011) were calculated on every land point of each model along with seasonal mean precipitation. These include precipitation intensity (simple daily intensity, SDII, and maximum daily precipitation, RX1 day) and frequency (number of wet days, RR1), the duration of wet and dry spells (number of consecutive wet and dry days, CWD and CDD), and two heavy precipitation indices (total number of days with precipitation greater than 10 mm and 20 mm, R10 mm and R20 mm).

2.3 Statistical analysis

The robustness of the change of an index, on the basis of the models' ensemble, is assessed with a methodology similar to that proposed by Tebaldi et al. (2011) and applied to Europe by Dosio and Fischer (2018). First, for each land grid box and for each model run, we test the statistical significance of the change between the reference period (1981–2010) and the end of the century (2070–2099), by means of a two-sample Kolmogorov–Smirnov test with the null hypothesis that the discrepancies between the two distributions are only due to sampling error. A significance level of 5% indicates that the null hypothesis can be rejected statistically.

Second, we classify the change as follows:

- the change is considered robust if more than 50% of the runs show a statistically significant change and, at the same time, more than 80% of them agree on its sign,
- the change is considered uncertain, or unreliable, if more than 50% of the runs show a statistically significant change but less than 80% of them agree on its sign.

Table 2 List of climate change indices analyzed in this study

Acronym	Name	Description	Units
ETCCDI precipitation indices			
SM	Seasonal mean	Average over the season	mm/day
SDII	Simple day intensity	Mean daily precipitation over wet days (i.e., when precipitation > 1 mm)	mm/day
RX1 day	Max 1 day precipitation (maximum precipitation intensity)	Maximum daily precipitation in a given period	mm/day
RR1	Number of wet days	Total number of days when precipitation > 1 mm	Days/season
CWD	Consecutive wet days (dry spells)	Largest number of consecutive days where precipitation > 1 mm	Days/season
CDD	Consecutive dry days (wet spells)	Largest number of consecutive days where precipitation < 1 mm	Days/season
R10 mm	Heavy precipitation days	Total number of days when precipitation > 10 mm	Days/season
R20 mm	Very heavy precipitation days	Total number of days when precipitation > 20 mm	Days/season

For a complete list and definitions, see e.g., Zhang et al. (2011). Note that SM (seasonal mean) is not an ETCCDI index. Here, the indices are calculated on a seasonal basis, and the reference period is defined as 1981–2010

In addition to these two classes, and in accordance with e.g., Knutti and Sedláček (2012), we also distinguish the case where more than 80% of models' runs show a non-significant change (independently of the agreement on the sign): this is a meaningful and useful information, often overlooked, as it indicates areas where there is a robust indication that any apparent change simulated by most of the models is small compared to the variability, i.e. non-significant.

Many different methods exist to define the robustness of the climate change signal (see, e.g., Collins et al. 2013). For instance, Donnelly et al. (2017) compared the value of the ensemble mean change to the standard deviation of the changes of the individual models. However, in the case of very small changes (as may happen for precipitation) if models give very similar results (so that the standard deviation is smaller than the mean change) this criterion may be fulfilled even if the change is non-significant. Haensler et al. (2013) investigated the change of precipitation over central Africa defining the robustness of the signal based on the agreement on the sign of change for at least 66% of models; however, this method alone is not sufficient, as it does not take into account the magnitude of change. As a result, they consider also a "likely range" that is defined as a range of 66% around the median projected change.

Note that all definitions of robustness (ours included) are subjective; in particular, none of these methods attempt to link the projected change (hence its robustness) to its dynamic and thermodynamic drivers.

In the following, results are presented either as maps of the RCMs' ensemble median, or as aggregated statistics over sub-regions (Fig. 1), defined as North-Africa (NAF, which includes also the Arabian peninsula), West-Africa (WAF), Central Africa (CAF), East-Africa (EAF) and Southern-Africa (SAF), similar to those in the IPCC atlas of global and regional climate projections (IPCC 2013). Seasons are defined as December–January–February (DJF), March–April–May (MAM), June–July–August (JJA) and September–October–November (SON).

As an example, Fig. 1 shows the various steps of the methodology applied to the seasonal mean precipitation change in SON. We note that, for instance, over SAF most models project a reduction in precipitation, including areas such as Zimbabwe where more than 90% agree on the sign of the change (Fig. 1, top-left). In contrast, over part of EAF (Somalia) and WAF (e.g., Cote d'Ivoire) more than 80% of projections are for an increase in seasonal precipitation (Fig. 1, top-left). This change, however, is not always statistically significant, such as over Cote d'Ivoire, where less than 40% of models show significant change (Fig. 1, top-right). As a result, the projected positive (negative) change over Somalia (Zimbabwe) is considered robust, but that over Cote d'Ivoire is not. With the same

methodology we can highlight regions where the multi-model signal is non-significant (e.g. Sahara) or uncertain (e.g. Gabon). Regions that are neither 'uncertain' nor marked by hatching represent areas where evidence for change is limited (see also Knutti and Sedláček 2012).

It must be noted, however, that a robust change does not necessarily mean that the inter-model variability (as measured by e.g. the inter-quartile range) is small (whereas this is true by definition for the regions where the signal is non-significant). Over Somalia, for instance, the inter-quartile range can be as large as the models' median (Fig. 1, bottom row): this means that although the signal is robust (i.e. statistically significant and equal in sign for most of the runs), its value can vary greatly amongst different models.

3 Results

3.1 Evaluation of present mean climatology

CORDEX-Africa RCMs have been extensively evaluated in the past not only for mean climatology, but also for extreme events (temperature and precipitation), land–atmosphere coupling, circulation patterns, and added value of downscaling. Several previous works investigated the ERA-interim driven runs (e.g., Nikulin et al. 2012; Dosio et al. 2015 and references therein; Akinsanola et al. 2015; Shongwe et al. 2015; Sarr et al. 2015; Klutse et al. 2016; Favre et al. 2016; Kitembe et al. 2018; Careto et al. 2018; Warnatzsch and Reay 2019), as well as GCM-driven runs (e.g., Laprise et al. 2013; Teichmann et al. 2013; Dosio et al. 2015; Endris et al. 2016; Pinto et al. 2016; Dosio 2017; Fotso-Nguemo et al. 2017; Gibba et al. 2018; Pinto et al. 2018; Tamoffo et al. 2019a).

As a consequence, here, we perform only a basic evaluation of the RCMs performances in simulating present day precipitation climatology. Results are shown in Fig. 2, where model biases are averaged according to the RCM. Previous works (e.g. Dosio et al. 2015; Fotso-Nguemo et al. 2017) showed that when analyzing precipitation characteristics over Africa, the effect of the errors inherited through the boundary conditions (e.g., position of the high seasonal rainfall band simulated by the driving GCM) is small compared to the structural bias of the downscaling RCM, as local effects and model parameterization are the main drivers of the simulated precipitation. This is confirmed by our analysis that shows that the bias of the RCM is scarcely affected by the lateral boundary conditions for all seasons and over most of the continent, even when a large number of GCMs is downscaled; for instance, RCA-RACMO shows a consistent (i.e. independent of the driving GCM) dry bias over equatorial Africa, whereas CCLM shows a dry bias over the eastern coast of the Guinea Gulf.

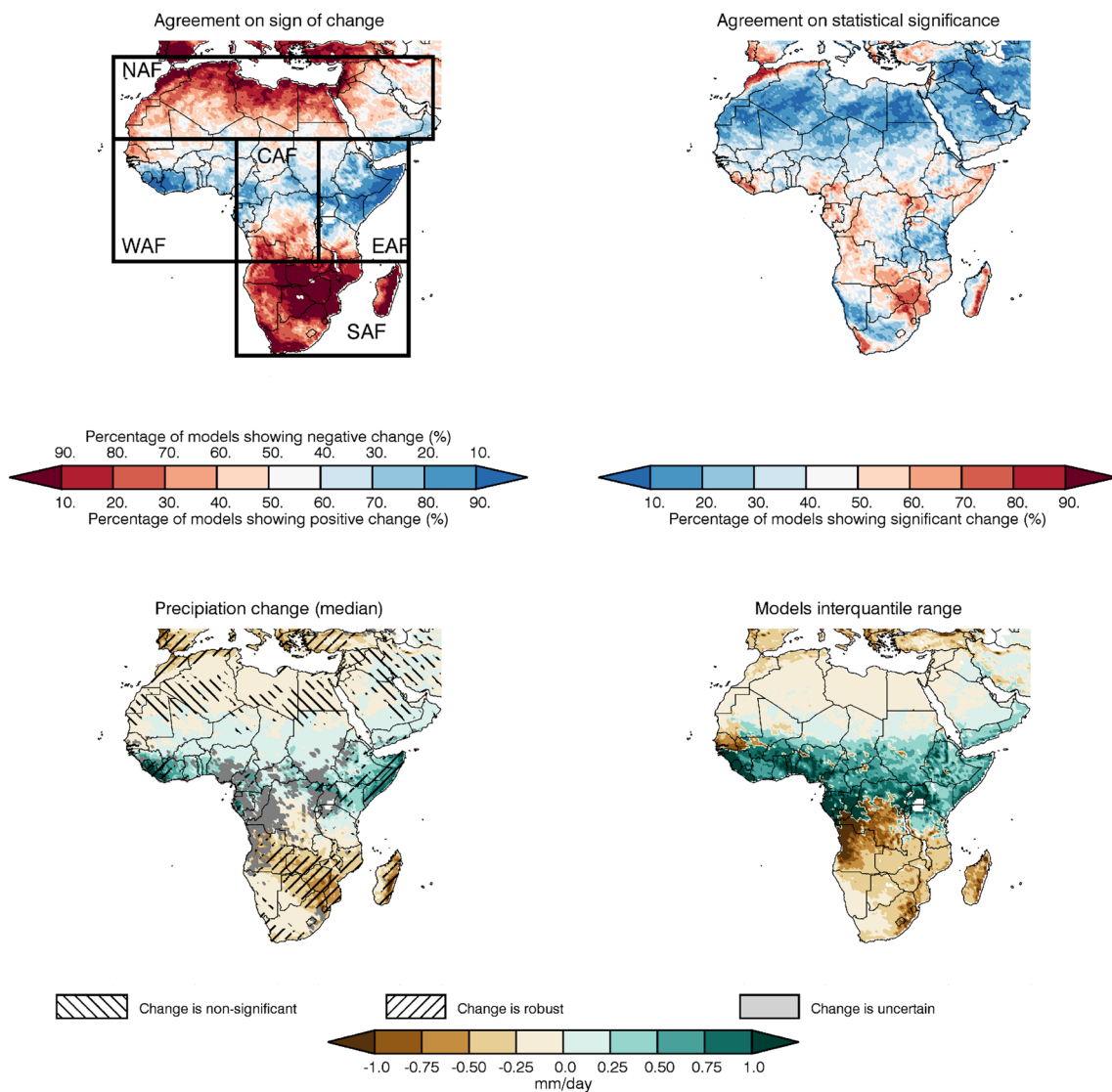


Fig. 1 Example of the methodology used to define robustness, non-significance, and uncertainty in the climate signal of the RCMs' ensemble. Top left panel: percentage of models showing the same positive (negative) sign in the precipitation signal (left panel). Top right panel: percentage of models showing a statistical significant

change. Bottom left: models' median seasonal mean precipitation change (mm/day). Areas where the change is non-significant, robust and uncertain are highlighted. Bottom right: uncertainty in the precipitation signal as represented by the models' interquartile range (mm/day)

Although large differences exist amongst RCMs in the simulated position, extension and intensity of the band of high rainfall, it is interesting to note that a wet (dry) bias on the present climate does not necessarily imply a tendency towards wetter (drier) future precipitation characteristics (discussed later), making any attempt to select a 'best-performing' RCM, or even linking future projections to simulation skills over the present climate, very challenging.

3.2 RCMs-based projections

Figures 3 and 4 show the projected change in mean precipitation (SM) and ETCCDI indices at both annual and seasonal scales.

Models results show a robust increase in both annual and seasonal mean precipitation over part of EAF, especially Kenya in DJF and Somalia in SOM (up to more than 1 mm/day), whereas a robust decrease in precipitation is projected over the Atlas region (through all year), over the western coasts of SAF in MAM (and at annual time scale), and a large fraction of southern Africa, including Madagascar, in JJA and SON. Apart from the Sahara desert, a

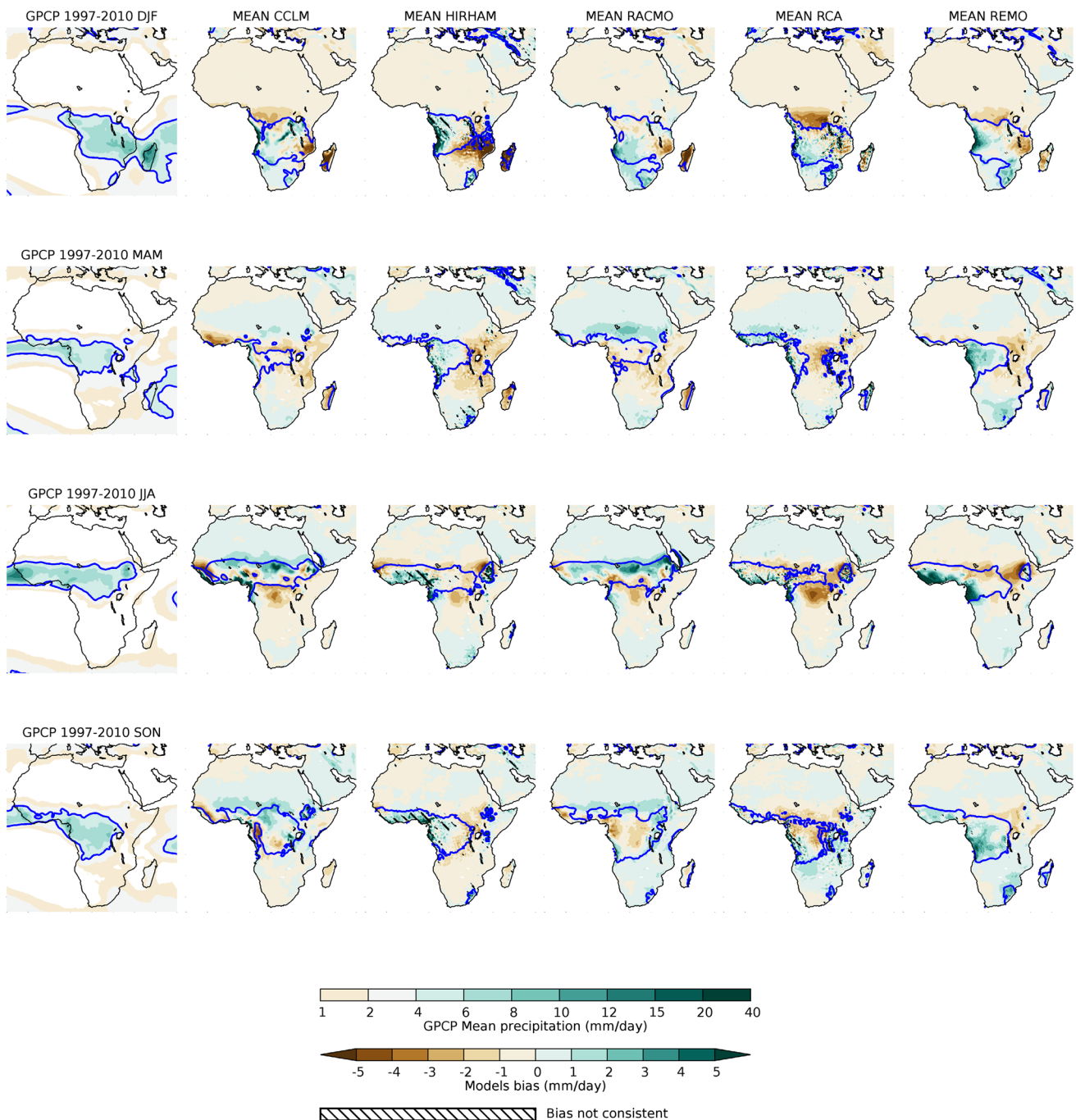


Fig. 2 Evaluation of seasonal mean precipitation over the reference period (1981–2010) for the CORDEX RCM simulations. For each RCM, the bias against observed precipitation (GPCP, 1997–2010) is shown as average of the respective GCM driven runs. The blue line shows high seasonal rainfall band defined as precipitation >4 mm/day. For each RCM, regions where the standard deviation (across

GCM driven runs) of the bias is larger than its mean, are marked as ‘inconsistent’ (shown, for clarity, only where the bias is larger than 1 mm/day). This means that, over non hatched regions, the intrinsic bias of the RCM is scarcely affected by the lateral boundary condition (driving GCM)

non-significant change in precipitation is projected over the Gulf of Guinea in DJF (which is a dry season), and part of Zimbabwe and Mozambique both in DJF and MAM (notably, both countries receive the largest amount of rainfall

between December and March). These findings are consistent with those of e.g., Niang et al. (2014), showing a non-significant change in mean precipitation during October–March over Southern Africa, under RCP4.5, and Maure

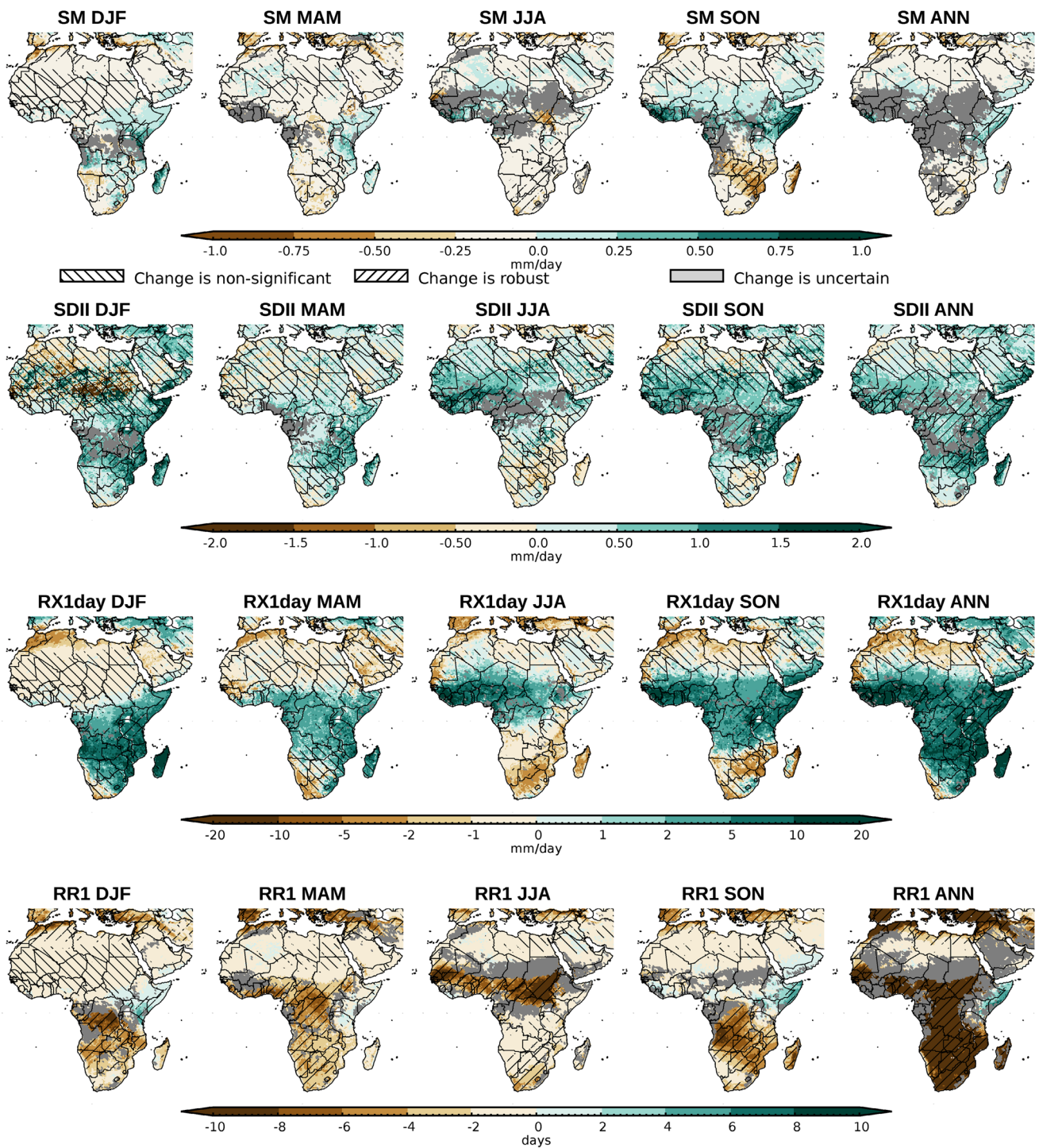


Fig. 3 Projected RCMs ensemble median seasonal change of some ETCCDI indices. Areas where the change is robust, non-significant and uncertain, as defined in the methodology, are highlighted

et al. (2018) showing similar results for DJF under 1.5 °C and 2 °C warming. It is worth remembering that, according to our methodology, non-significant change means that the large majority (80% or more) of projections exhibit this property. This is remarkable considering that, under the most

extreme emission scenario (RCP8.5), one would expect a substantial change in many climate statistics at the end of the century: under these conditions, for instance, Engelbrecht et al. (2015) and Dosio (2017) showed that RCMs project warming of more than 3.5 °C in DJF over most of the

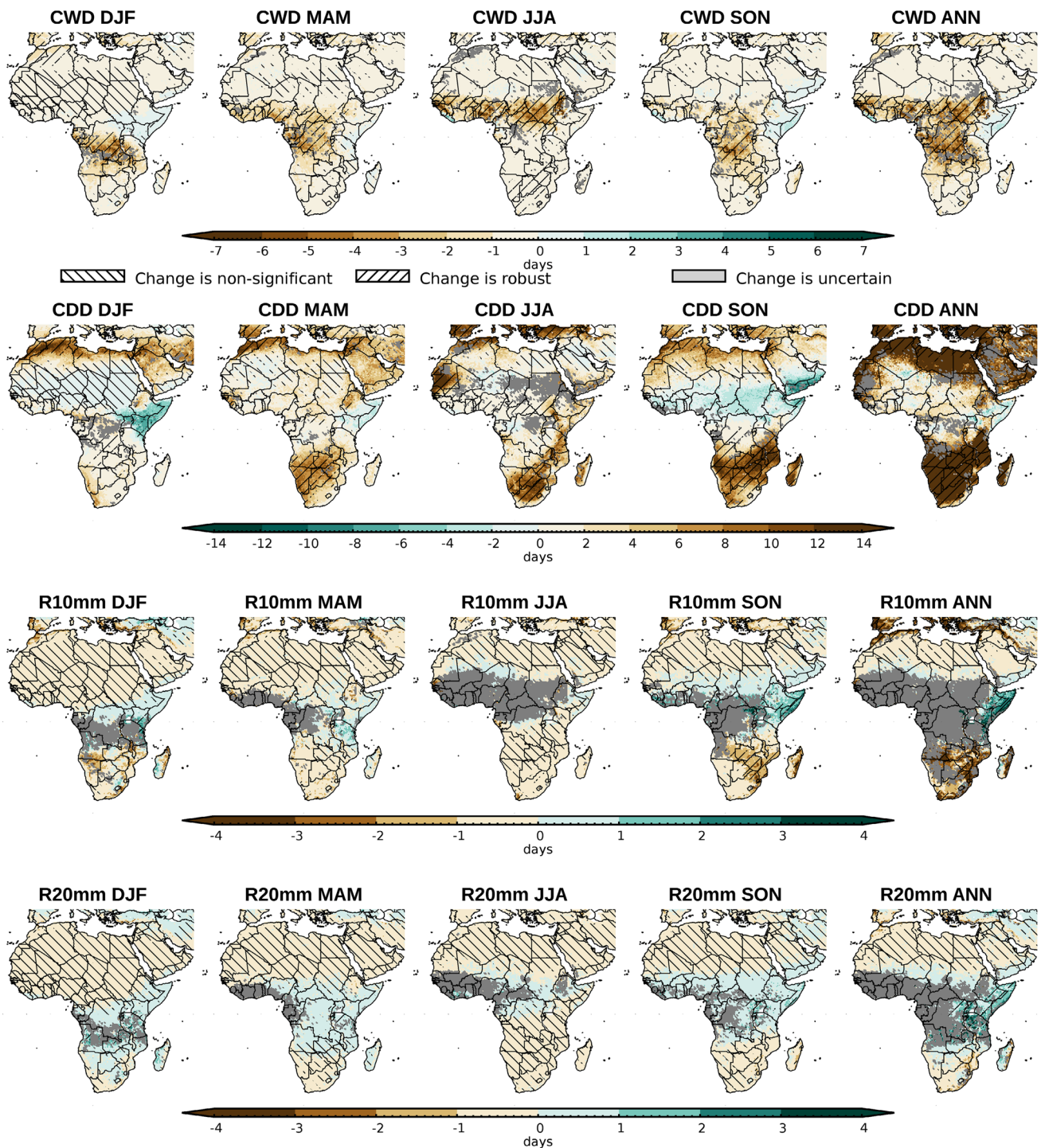


Fig. 4 Similar to Fig. 3 for ETCCDI indices related to the duration of wet and dry spells, and frequency of extreme precipitation events

continent, and up to more than 5 °C over parts of Southern Africa.

Finally, the annual mean change over most of central and West Africa is uncertain, as is the seasonal mean change over parts of central Africa in DJF, the Gulf of

Guinea in MAM and SON, and a large fraction of north-equatorial Africa in JJA. Crucially, these are the areas affected by the passage of the West African Monsoon (see e.g., Panitz et al. 2014). Our results show that over these regions, most of the models show a statistically significant

change in precipitation, but they do not always agree on its sign.

By comparing the different ETCCDI indices, we can analyze the change in several characteristics of the projected precipitation. Some illustrative examples are listed below:

1. Although the change in annual and seasonal (SON) mean precipitation over Democratic Republic of Congo is not robust, the changes in both frequency (RR1) and daily mean intensity (SDII) are, with a tendency towards less frequent but more intense precipitation.
2. Over Botswana, Zimbabwe and Mozambique, in SON, RCMs project a robust decrease in both mean precipitation and frequency (RR1), with a consequent increase in the number of consecutive dry days (CDD) up to more than 12 days/season; however, both the mean and maximum precipitation intensity (RR1 and RX1 day) are projected to not change significantly.
3. Over the Horn of Africa (Somalia), a robust increase in annual and SON mean precipitation is accompanied by an increase in both maximum daily intensity (RX1 day) and frequency of extreme events (R10 mm).
4. Although the change in annual and seasonal (JJA) mean precipitation over the Gulf of Guinea is uncertain, the change in other indices is not; for instance, a robust increase in precipitation intensity (SDII) is accompanied by a robust reduction in its frequency (RR1) and wet spell duration (CWD, up to 5 days/season), and a slight increase in the length of dry spells.

Although the GCMs downscaled in this analysis represent only a fraction of the entire CMIP5 ensemble, the analysis by e.g. Sonkoué et al. (2018), shows that our results over Central Africa are consistent with those from the large CMIP5 ensemble, projecting a tendency for less frequent but more intense rainfall, longer dry spells and shorter wet spells. The wetting of the Horn of Africa is also consistent with CMIP5 results (e.g. Otieno and Anyah 2013; Tierney et al. 2015) as is the drying of Southern Africa (Sillmann et al. 2013; Hoegh-Guldberg et al. 2018). Although large uncertainties in CMIP5 results exist (e.g., Sillmann et al. 2013; Seth et al. 2013), works based on both GCMs and RCMs (Vizy et al. 2013; Cook and Vizy 2015; Hoegh-Guldberg et al. 2018; Klutse et al. 2018) project an increase in rainfall intensity especially over the Sahel in July–September accompanied, however, by longer dry spells, qualitatively consistent with our results. Note that the intensification of hydrological extremes, with increasing mean intensity and higher frequency of heavy rainfall, has also been observed in the past decades (e.g., Taylor et al. 2017; Panthou et al. 2018).

Figure 5 shows, for each sub-region and season, the fraction of land projected to face robust, non-significant,

and uncertain change in the selected ETCCDI indices. As explained earlier, the confidence for change over the remaining fraction (white) is limited.

Over NAF, most of the indices show a non-significant change over large parts of the region, although smaller fractions (usually between 5 and 25%), mostly located over the Atlas region (see Figs. 2, 3) are projected to face a robust reduction in seasonal mean precipitation and its frequency (RR1), with consequent reduction in CWD and increase in CDD.

Over WAF, the change in all precipitation indices is projected to be non-significant for about 80% of the land in DJF. During MAM a robust decrease in RR1 and CWD is projected over more than 20% of the land; this fraction becomes substantial in JJA, with neatly 70% facing a robust reduction in RR1, around 45% a reduction in CWD, and more than 30% an increase in CDD. However, although the precipitation frequency is projected to decrease (with consequent change in the length of dry and wet spells), its mean intensity (SDII) is projected to increase over more than 50% of the land. We also note that the change in mean precipitation and frequency of extreme events is uncertain over more than 50% of land. Finally, in SON, there is a low evidence for the change of all the precipitation indices over most of the land.

Central Africa shows a consistent decrease in precipitation frequency throughout all seasons, together with increasing dry spell and decreasing wet spell durations. However, part of CAF (between 8% in MAM and 34% in SON) is projected to face an increase in mean precipitation intensity, and, over smaller fractions of land, a robust increase of maximum daily precipitation intensity, and frequency of extreme events (R20 mm, in DJF and SON).

Between 10 and 20% of East Africa in DJF and SON is projected to face a robust increase in precipitation frequency and intensity, including extreme events (especially over Somalia, see Figs. 2, 3). However, most of the precipitation indices show a robust negative change in JJA, with more than 20% of the land affected by less frequent precipitation, longer dry spells and shorter wet spells.

Southern Africa is the region showing the largest (in terms of fraction of land affected) and more consistent (a part from SDII in DJF) trend towards drier future conditions, with around 40% of the land projected to face a robust reduction in mean precipitation in JJA and SON, and up to nearly 80% affected by less frequent rain and longer dry spells in JJA. Given the severe drought that part of South Africa has recently suffered during 2015–2017 (see e.g. Otto et al. 2018), this may have profound and worrying implications.

The expected robust change in precipitation characteristics is shown in Fig. 6. Here, i.e., for each index, only the land points where the change is robust are used to compute the spatial average.

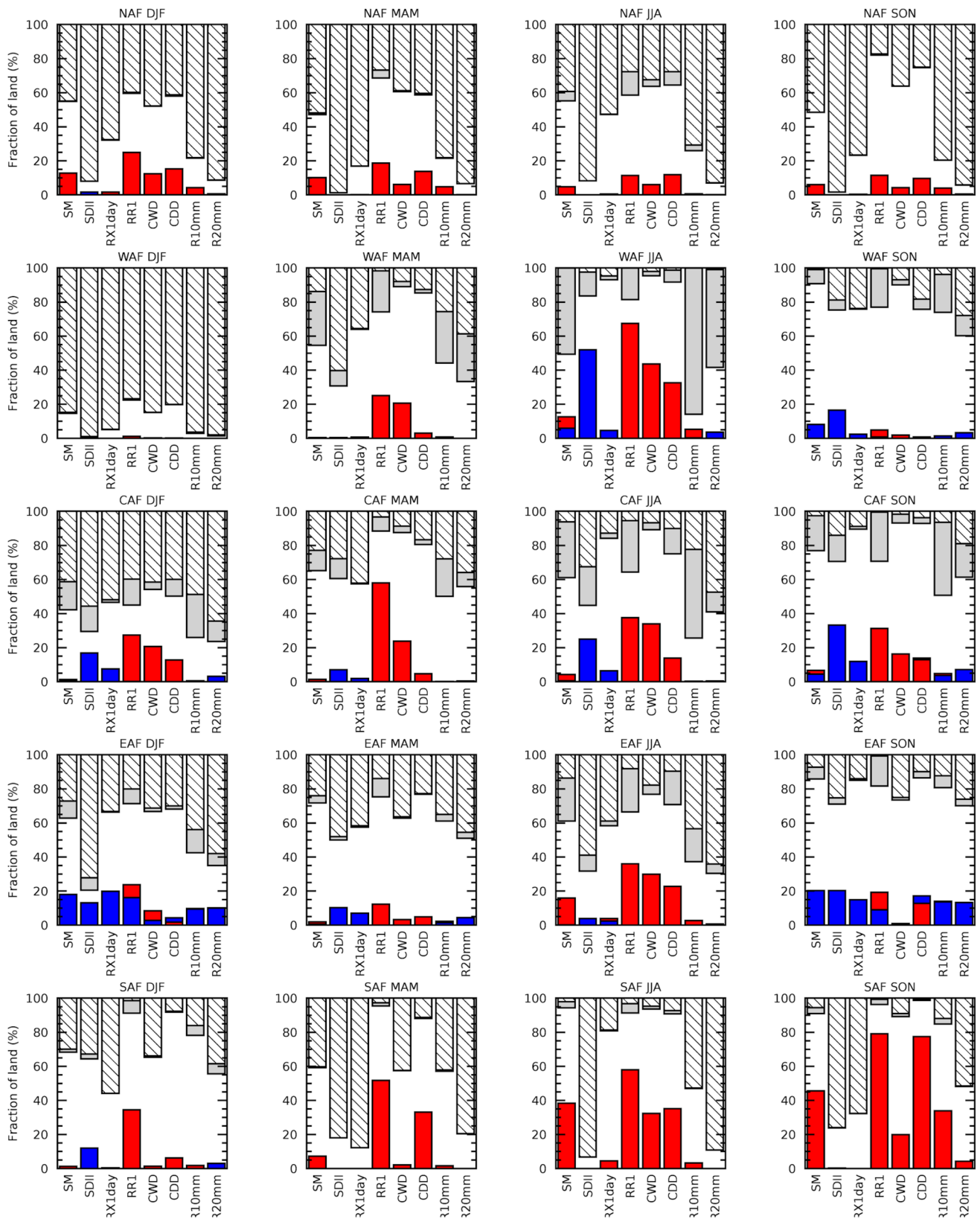


Fig. 5 Fraction (%) of land area affected by robust (colored), non-significant (hatched) and uncertain (gray) change. Blue color indicate positive change and red color negative, apart from CDD, where red

color indicates robust increase and blue decrease. White areas represent the fraction of land where the evidence of change in the index is low

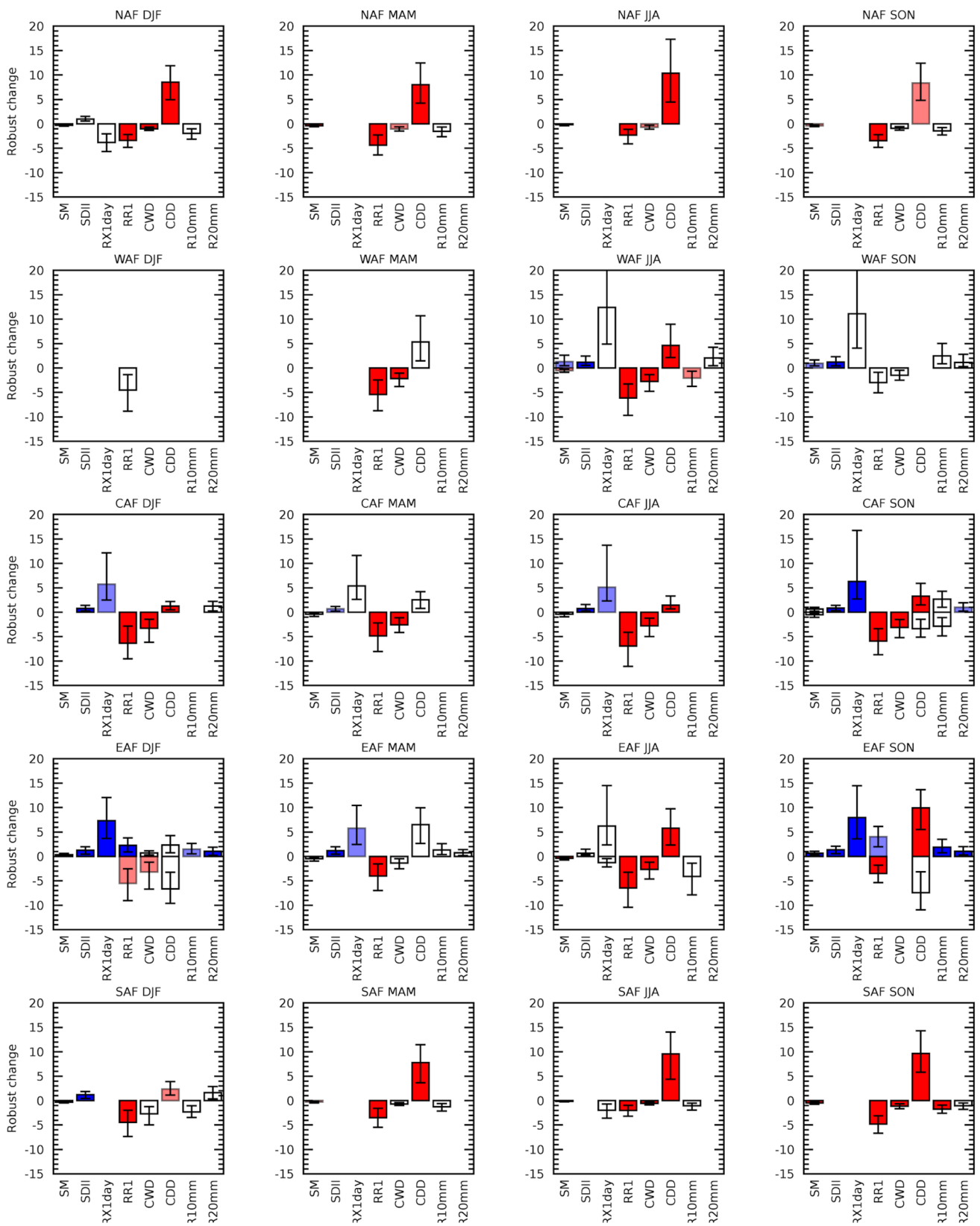
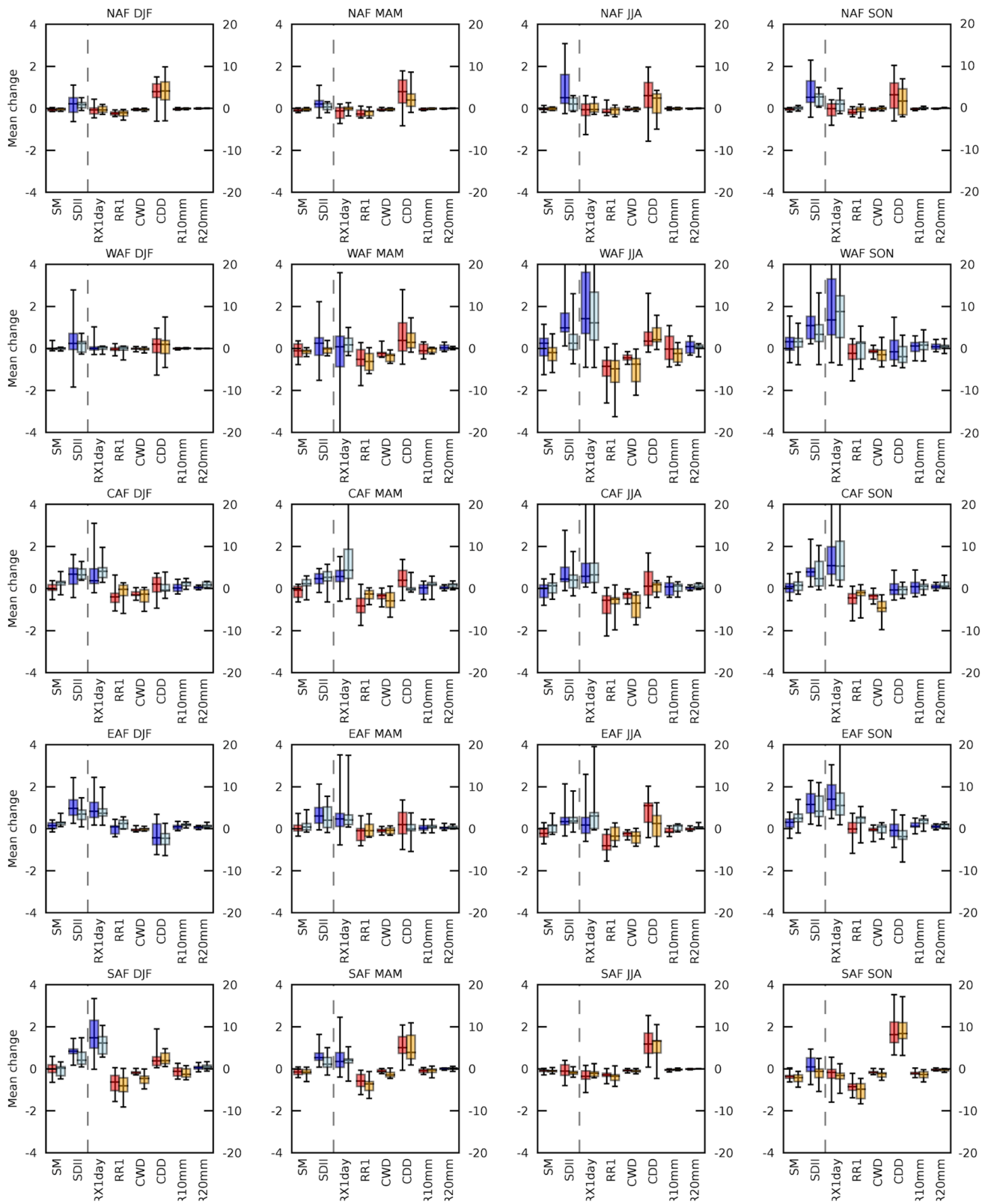


Fig. 6 Absolute value of the change over land points where it is robust. For each index, the figure shows the RCMs ensemble median and the inter-quartile range. As in Fig. 5, red colors indicate negative changes and blue positive ones, a part for CDD, where the colors

are inverted. Full colors indicate that fraction of area undergoing the change is larger than 10%, shaded colors between 5% and 10%, and white less than 5% (see Fig. 5). Units depend on the index



Over NAF, substantial changes throughout all year are projected for CDD (with increase up to 10 days/season in JJA) and RR1, projected to decrease up to 4 days/season in

MAM. Other indices show either smaller values, or, as for RX1 day in DJF, the area where they are robust is relatively modest (less than 5%, see Fig. 5).

Fig. 7 Comparison of RCMs and GCMs changes of ETCCDI indices. Results show the median (horizontal line), inter-quartile range (colored box) and minimum–maximum range (vertical bar) of the RCMs and GCMs' runs. Values are calculated as spatial average over the entire sub-region, independently of the robustness of the change. Red blue color represent RCMs' results, yellow and light blue the GCMs' ones. Red/yellow colors indicate a negative median change, blue colors a positive one (the opposite for CDD). The vertical dashed line separates the indices according to the plotting scale: SM and SDII range between -4 and 4 mm/day, whereas all other indices range between -20 and 20 (units depend on the index)

RCMs' results for WAF show a robust reduction in precipitation frequency up to 7 days/season in both MAM and JJA, accompanied by longer dry spell (up to 5 days/season) and shorter wet spells (3 days/season); as discussed previously (Fig. 4) these changes in JJA are projected to affect a substantial fraction of land, up to nearly 70% for RR1. Mean precipitation and its intensity (SDII) are projected to increase slightly more than 1 mm/day in JJA and SON. Finally, although the change in RX1 day is substantial (more than 10 mm/day both in JJA and SON), the area where this change is robust is very small and, in addition, the model's inter-quartile range is very large.

Over CAF, both precipitation frequency and wet spell duration are projected to significantly decrease in all seasons (both over large fraction of land areas, see Fig. 5); however, precipitation mean and maximum intensity are projected to increase (up to 7 (3–12) mm/day for RX1 day in SON).

Results over East Africa show a consistent increase throughout all year in precipitation intensity, especially the daily maximum (RX1 day), with changes up to 8 (3–15) mm/day in SON. DJF and SON are characterized by areas showing a robust increase in precipitation frequency and extreme events, and, at the same time, areas where RR1 decrease, with a consequent increase in CDD (up to 10 (5–14) days/season in SON).

Finally, southern Africa is projected to face less frequent precipitation (up to 5 days/season in both DJF and SON), shorter wet spells and longer dry spells (up to 10 days/season in both JJA and SON); however, in DJF some areas (around 12% of land see Fig. 5) will be affected by a slight increase (around 1 mm/day) in precipitation intensity (SDII).

3.3 Comparison with driving GCMs

As mentioned, due to their coarse resolution, GCMs are unable to simulate fine-scale climate variations, especially in regions of complex topography or coastlines, or with heterogeneous land cover. On the other hand, the downscaled climate is a combination of that inherited through lateral boundary conditions, and that generated by the RCM by means of dynamical processes (especially over such a large domain) and small scale processes (e.g., convection) and

physical parameterizations (e.g. Hong and Kanamitsu 2014; Dosio and Panitz 2016).

It is therefore interesting to compare the results of the RCM ensemble to those of the driving GCMs to investigate whether or not the downscaled climate change signal is similar to the forcing one, and to highlight if and where substantial differences exist.

Figure 7 shows the comparison of the ETCCDI indices as simulated by the RCM and GCM ensembles. For each sub-region, results are spatially averaged over all land points, i.e., regardless of the significance and robustness of the change. We first note that the RCM ensemble median projected tendency towards either a drier or a wetter climate is in agreement with that of the GCM ensemble in two-thirds of the region-season permutations. There are, however, some differences: the projected median change from the RCM and GCM ensembles is, respectively a decrease/increase over CAF (in DJF and MAM), EAF (in MAM and JJA), and SAF (in DJF). The opposite is seen over WAF in JJA. However, in all these cases the ranges of spatially averaged precipitation change overlap considerably and include zero change. Also, even though the median change in seasonal mean precipitation differs between RCMs and GCMs, most of other indices show the same tendency; for instance, over WAF in JJA both RCMs and GCMs project an increase in mean and maximum precipitation intensity, but a reduction in its frequency, with consequent increase in the length of dry spells and reduction in the length of wet spells.

Occasional discrepancies in the sign of change between RCMs and GCMs exist for other indices (e.g., CDD over CAF in DJF and MAM or RR1 over WAF in SON, RX1 day over WAF in SON, SDII over WAF in SON) but, again, the difference between the two ensemble median values is small (usually around 1 day/season for CDD) and always much smaller than the models' inter-quartile range.

Larger differences are found, however, in the range of projected change: as would be expected given the RCM ensemble includes multiple downscalings of some of the GCM ensemble members (Table 1) and as demonstrated for a single GCM being downscaled by a several RCMs (Dosio 2017). However, there are cases where this difference is extremely marked, especially for SDII and RX1 day (particularly over WAF but also over CAF in DJF); although part of the difference is related to the different GCM and RCM ensemble sizes, the fact that some RCMs projects a much larger change (either positive or negative) in precipitation mean and maximum intensity may be also an effect of small scale processes (such as convection) being resolved differently by GCMs and RCMs. In contrast, there are also a few cases where the range of projections changes in the RCM ensemble is less than that of the driving GCMs, namely RX1 day over CAF in MAM and over EAF in SON. Also, Haensler et al. (2013) found a smaller range in a 4-member

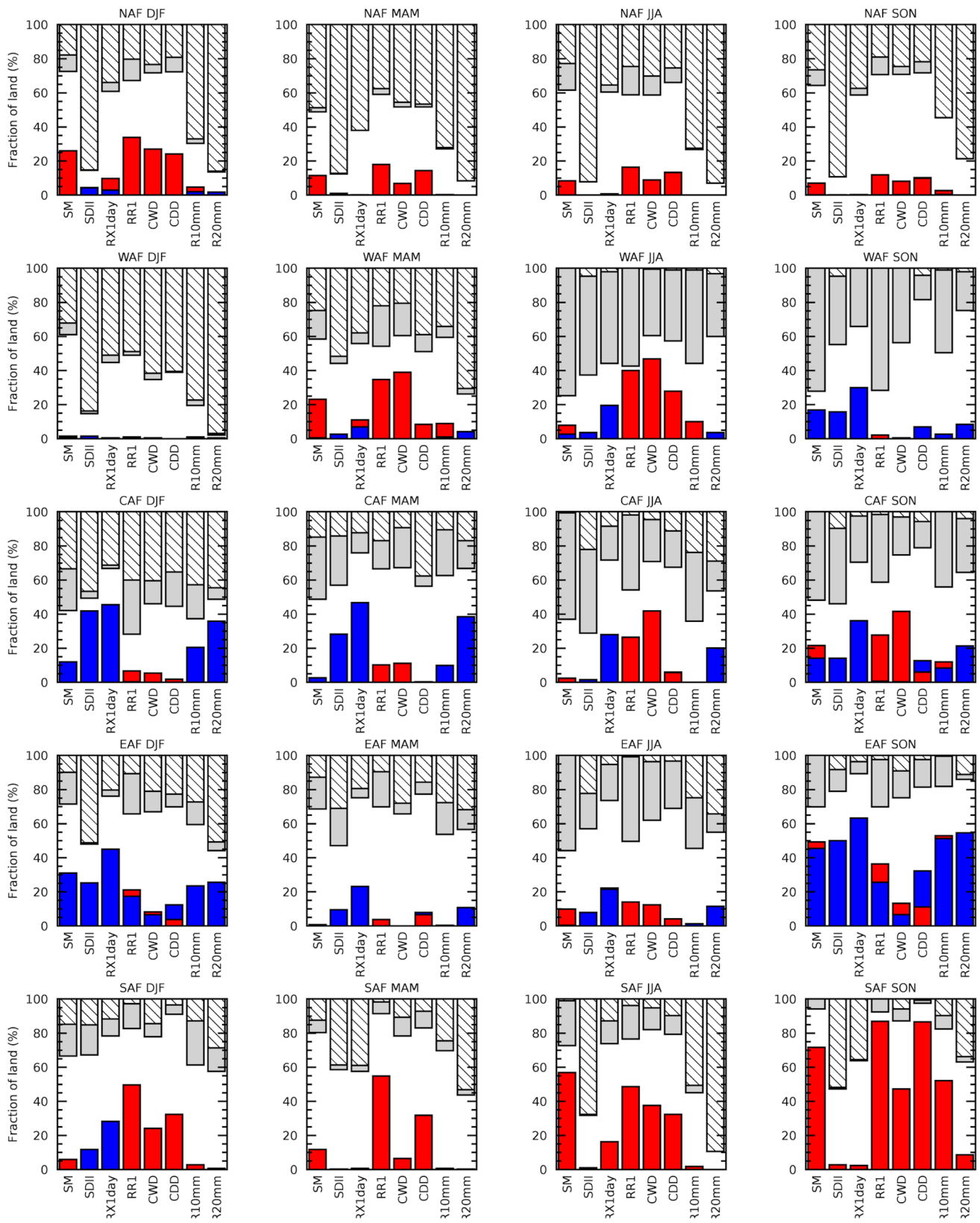


Fig. 8 As Fig. 5 but for GCMs' results

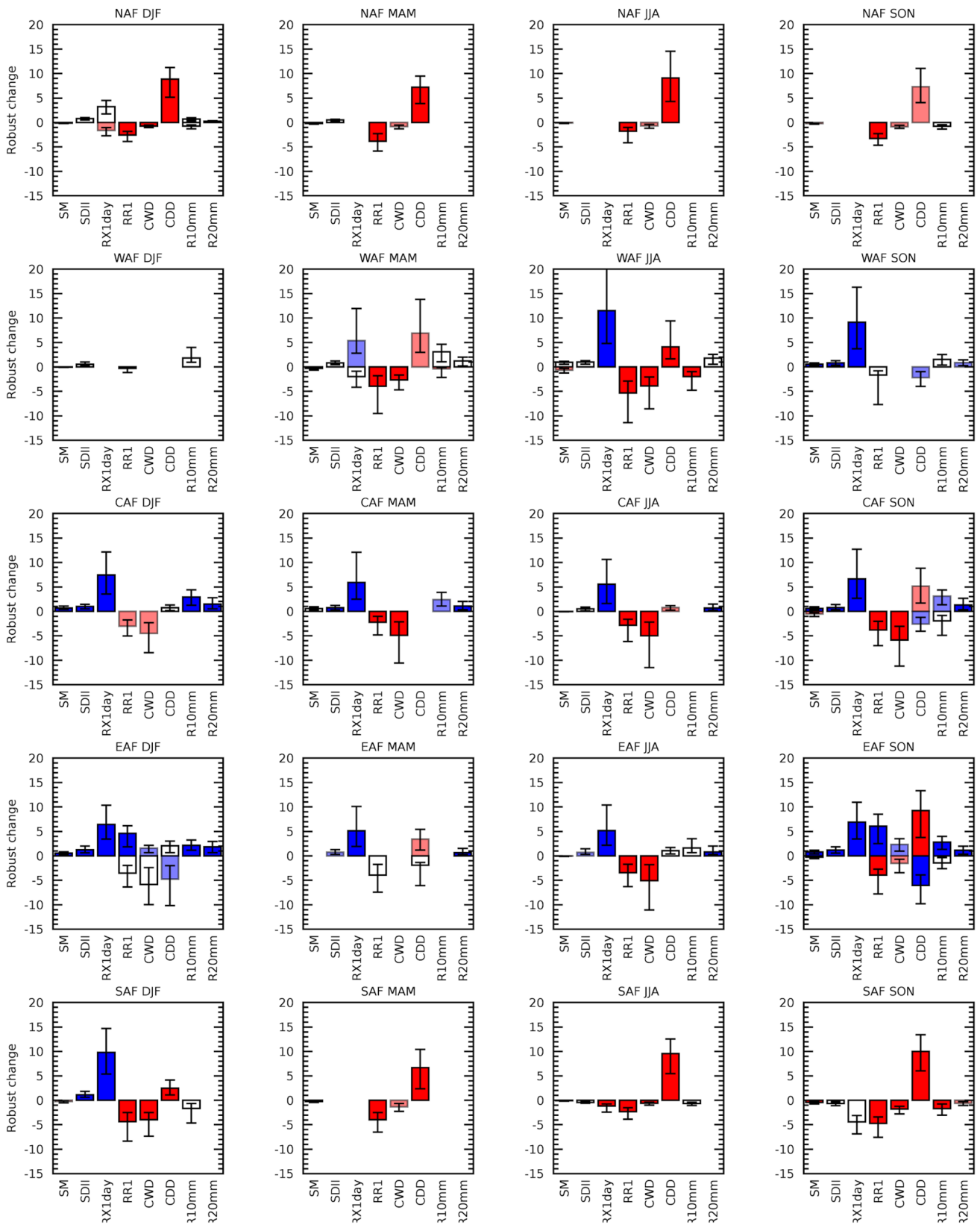


Fig. 9 As Fig. 6 but for GCMs' results

RCM ensemble compared to a 10-member GCM ensemble for both total precipitation and intensity of heavy rainfall over (part of) CAF. Note also that only a subset of the possible GCMs are being considered here, so the RCMs range is likely to underestimate the true uncertainty.

Similarly as in RCMs analysis, Figs. 8 and 9 show the land area fraction projected by the GCMs to face, respectively, a robust, non-significant, and uncertain change, and the value of the change where it is robust. As mentioned a direct, quantitative comparison between GCMs' and RCMs' results is not possible as, by definition, robustness critically depends on the models' ensemble size. However, some qualitative observations can be made.

First, we note that a striking difference between results from the RCMs and GCMs is visible over WAF in JJA and SON, where the fraction of land over which the change is uncertain as simulated by the GCMs (between 40 and 70% in JJA depending on the index) is much larger than the RCMs' one (apart for the extreme events frequency, R10 mm and R20 mm). In particular, the RCMs project a robust positive change in SDII in JJA over more than 50% of the land, compared to less than 5% for the GCMs, whereas the area where the change is uncertain is less than 15% for the RCMs but nearly 60% for the GCMs. This may be partly a consequence of the different ensemble sizes, as the smaller GCM ensemble (10 runs) makes the robustness criteria much more sensitive to outliers (i.e., dependent on the results of a single model), but it is interesting that the larger RCM ensemble, in this case, is able to reduce the uncertainty of the driving GCMs. In addition, Fig. 7 showed that, if averaged over all land points, i.e., independently on the robustness of the signal, the uncertainty range of the RCM ensemble is much larger than that of the GCM. We argue that the analysis of the area averaged climate change signal, without an evaluation of its significance and robustness, may be misleading. We also argue that, when averaging over large regions, the added-value from RCMs, which occurs mainly at much smaller spatial scales (e.g. over topography), may be reduced or lost.

Over other regions and seasons, however, the situation is the opposite, with the GCM ensemble projecting a much larger fraction of land where the change is robust, compared to the RCM (e.g., EAF in SON). Generally, however, both RCMs and GCMs projection are similar, such as over SA in SON, where all precipitation indices suggest future drier conditions over large parts of the region.

When the robust change (i.e., the value of the change averaged only over the points where it is robust) is compared between the GCMs (Fig. 9) and RCMs (Fig. 6) similarities are striking. Although the fraction of land where the change is robust may be different between the two ensembles, usually both the magnitude and the sign of this change are very similar between RCMs and GCMs (with only very

few exceptions, such as RX1 day over WAF in MAM, and RX1 day over SAF in DJF). This indicates that, although with some uncertainty in the geographical extent, GCMs and RCMs project a consistent future.

The question of how much 'added value' can be gained by using RCMs to dynamically downscale low resolution GCMs has been thoroughly investigated in the past (e.g., Di Luca et al. 2012; Diallo et al. 2012; Paeth and Mannig 2012; Diaconescu and Laprise 2013; Cr  tat et al. 2013; Laprise et al. 2013; Lee and Hong 2013; Giorgi et al. 2014; Dosio et al. 2015). These studies demonstrated the ability of RCMs to better simulate present-day, observed fine scale details and precipitation higher order statistics. On the other hand, the issue of quantifying (and even properly defining) the potential added value of projected climate change signal is more controversial, and very few studies addressed it (e.g. Di Luca et al. 2013; Torma et al. 2015; Rummukainen 2016; Fotso-Nguemo et al. 2017). The main outcomes of these studies are that added value in future projections must consist of non-negligible fine-scale information that is absent in the lower resolution ones, and that the added value has to appear when there is a physical context for it, i.e., physical mechanisms that can modify the climate change signal simulated by the GCMs.

Here, we describe only some selected examples where differences between RCMs and GCMs are most evident. Following Di Luca et al. (2013) and Torma et al. (2015) we compare the RCMs (and GCMs) results to those of "virtual GCMs" (V_GCM). For each RCM, the daily precipitation fields (at 0.44 ) have been first aggregated (area averaged) on a 1.32  grid (i.e., upscaled), similar to that used by the GCMs. Note however, that the term 'virtual GCM' means simply an upscaling of RCM results on the GCM grid, without implying any similarities between e.g. GCM and 'virtual GCM' dynamics or physics.

Subsequently, the ETCCDI indices have been calculated and the robustness of the projected climate signal has been evaluated. Results are shown in Fig. 10. As pointed out by Torma et al. (2015), the comparison between downscaled and upscaled results may highlight whether the added value is indeed related to a better representation of fine scale processes, rather than being the result of the disaggregation of the large scale field.

First we note that there are cases, such as seasonal mean precipitation in SON over SAF, where RCMs, V_GCMs and GCMs give similar results, with a robust decrease in precipitation over most of the North-East regions (with the highest values over southern Mozambique and the East coast of Madagascar) and smaller but robust decrease over the Southern and Western coast of South Africa. Finer spatial variations are visible in the RCMs results, for instance over Zimbabwe and Zambia, but, overall, the downscaled field is very consistent to that of the driving GCMs.

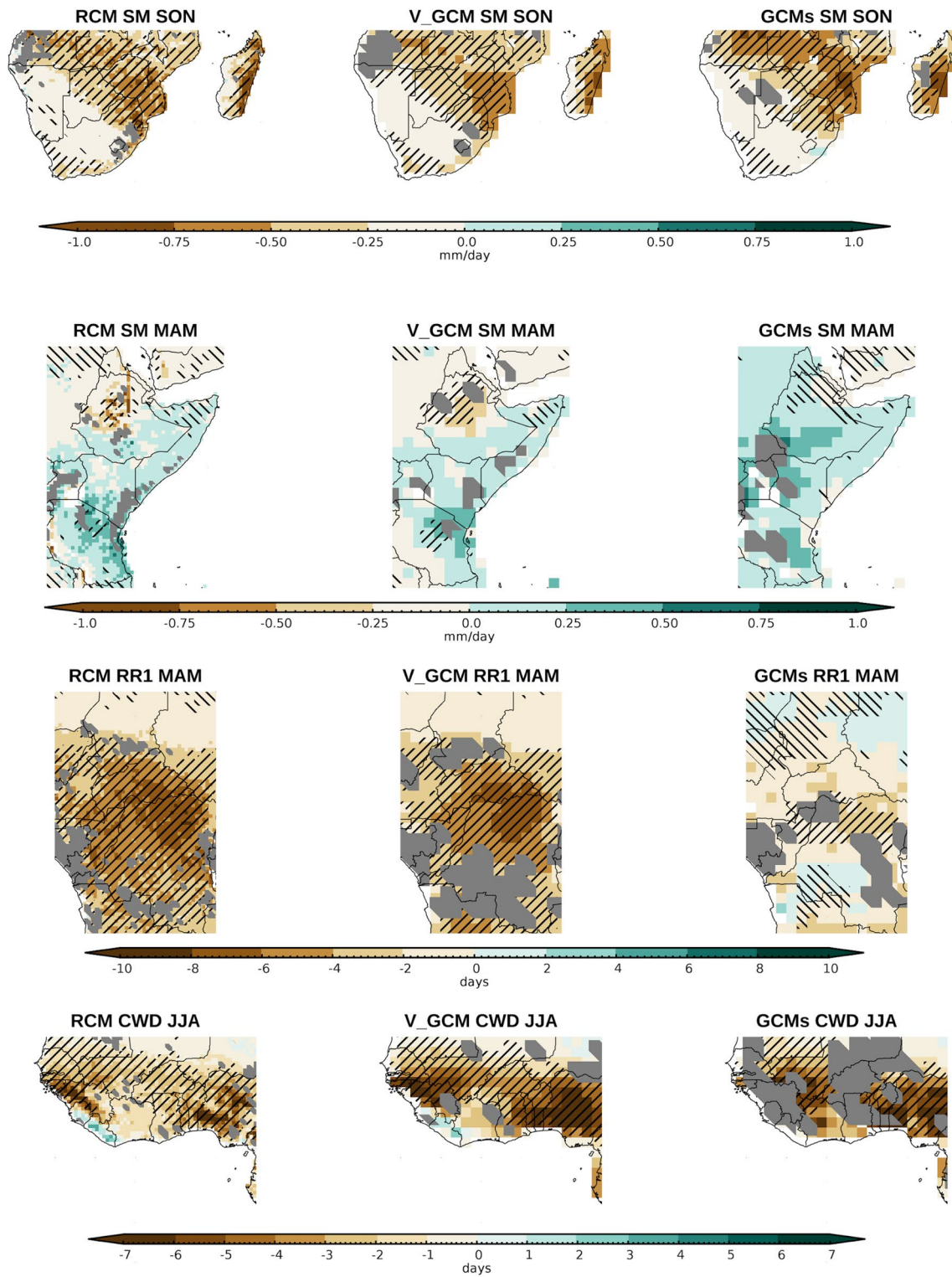


Fig. 10 Comparison of RCMs' and GCMs' results for selected indices and regions. The results of the virtual GCM (V_GCM) is obtained by upscaling the original RCMs' daily precipitation field

on a lower resolution grid (1.32°) common to all GCMs, and, subsequently, computing the ETCCDI indices

Over East Africa, on the contrary, marked differences exist; whereas the GCMs project an overall increase in mean precipitation in MAM, the change is generally non-robust and, over northern Ethiopia, non-significant. The RCMs, on the other hand, project a robust decrease of mean precipitation over the Ethiopian highlands, which is still visible in the upscaled V_GCM results. This feature may be associated with the better representation of topographical details that are missing in the large scale GCMs. Dosio et al. (2015) show that over the Ethiopian highlands many aspects of precipitation (including extremes, CDD, precipitation PDFs, etc.) are better simulated by a RCM (CCLM) than the driving GCMs (although no detailed evaluation of the dynamical processes involved was performed). A detailed analysis of the ability of CORDEX RCMs to simulate precipitation over the complex topography of northwest Ethiopia has been recently performed by Van Vooren et al. (2018); they claim that low quality in reproducing the orography in some models (including those with smoothed orography) makes their results questionable (although some models with a reasonable representation of the true topography have a too high elevation-precipitation sensitivity and overestimate precipitation). In their analysis over the Alps, Torma et al. (2015) also found that high resolution RCMs can produce, locally, a climate change signal opposite to that of the lower resolution GCMs.

Over central Africa in MAM, the RCM ensemble projects a robust decrease in RR1 whose geographical extension and magnitude are much larger than those of the driving GCMs. Figure 6 showed that CAF is one of the regions where the downscaled climate differs more significantly, with the change in both SM and CDD in MAM being opposite in the two ensembles. In their analysis, both Dosio and Panitz (2016) and Fotso-Nguemo et al. (2017) found that RCMs (CCLM and REMO) produce a precipitation signal over central Africa in striking contrast with that from the driving GCMs. Given the large numerical domain, central Africa is a region where the climate generated by the RCM is scarcely influenced by the lateral boundary conditions, and, consequently, local processes related to the land-atmosphere interaction (soil moisture-precipitation feedback) and convective parameterization may be the most important factors. However, the analysis in this work is not sufficient to indicate which of the GCM or RCM signals is the most credible.

Over West Africa, differences between the projected change in CWD in JJA by the RCM and GCM ensembles are visible especially along the coasts. The robust decrease in wet spell duration over Guinea, is accompanied by an increase (although not robust) over Liberia, which is not visible in the GCM results, which, on the contrary, are uncertain over the region. In addition, the spatial variability of the CWD change related to the topographic details over e.g. Nigeria is missing in both the V_GCMs and GCMs results.

4 Effect of the GCM-RCM matrix heterogeneity and subsampling

In our analysis of the change of ETCCDI indices from the CORDEX RCMs projections, we have applied an approach that can be described as ‘one simulation one vote’, i.e. all simulations were given the same weight in the computation of e.g. ensemble means. This approach has been applied by the vast majority of studies dealing with ensembles of GCM-driven RCMs, over different regions of the world, including the ‘Africa-box’ in the recent IPCC Special Report on 1.5 °C warming (Hoegh-Guldberg et al., 2018); in fact, the issue of dealing with a heterogeneous matrix of GCM-RCM combinations (with e.g. a RCM downscaling a large number of GCMs, and other RCMs relatively few or only one GCM) is far from being settled.

However, model weighting and ensemble subsampling is a topic becoming increasingly debated, and, therefore, the issue of how results depend on the choice (or weight given to) RCMs and GCMs needs further discussion.

In Fig. 11 the change in some selected ETCCDI indices is shown for all GCM-RCM simulations (and not just as box-whisker plot as in Fig. 7). From the analysis of the results some interesting findings are highlighted:

1. First and foremost, we note that, for most regions, seasons, and indices, the results do not depend on the choice of the RCM, GCM or ensemble subsampling. For instance, for Southern Africa (but this is true for other cases e.g., NAF, EAF in JJA, WAF in JJA, etc.) the vast majority of models (and in some cases all of them) project the same tendency, namely less frequent but more intense rainfall, and longer dry spells. As such, the result is robust, and any subsampling of the ensemble would lead to the same qualitative conclusion (although, obviously, the absolute value of the change would change if a subsampling of the ensemble was performed).

2. Similarly, by definition, where the change is non-significant (i.e., for more than 80% of the projections), the results are barely dependent on the GCM or RCM choice.

3. In other cases (e.g., SDII and CDD over WAF in DJF), models results are uncertain; however, this uncertainty is not largely dependent on the choice of the RCM. For instance, both CCLM and RCA show both negative and positive results (depending on the downscaled GCM); here, therefore, the uncertainty in the climate change signal comes from the driving GCM, and mean results are scarcely affected by the choice of the downscaling RCM (assuming the RCM has been used to downscale a reasonable number of GCMs). The impact of the driving GCM is even more evident for instance over EAF in MAM, where the simulations downscaling IPSL-CM5A-MR show the largest increase in SM, SDII and RR1, and the largest decrease in CDD. On

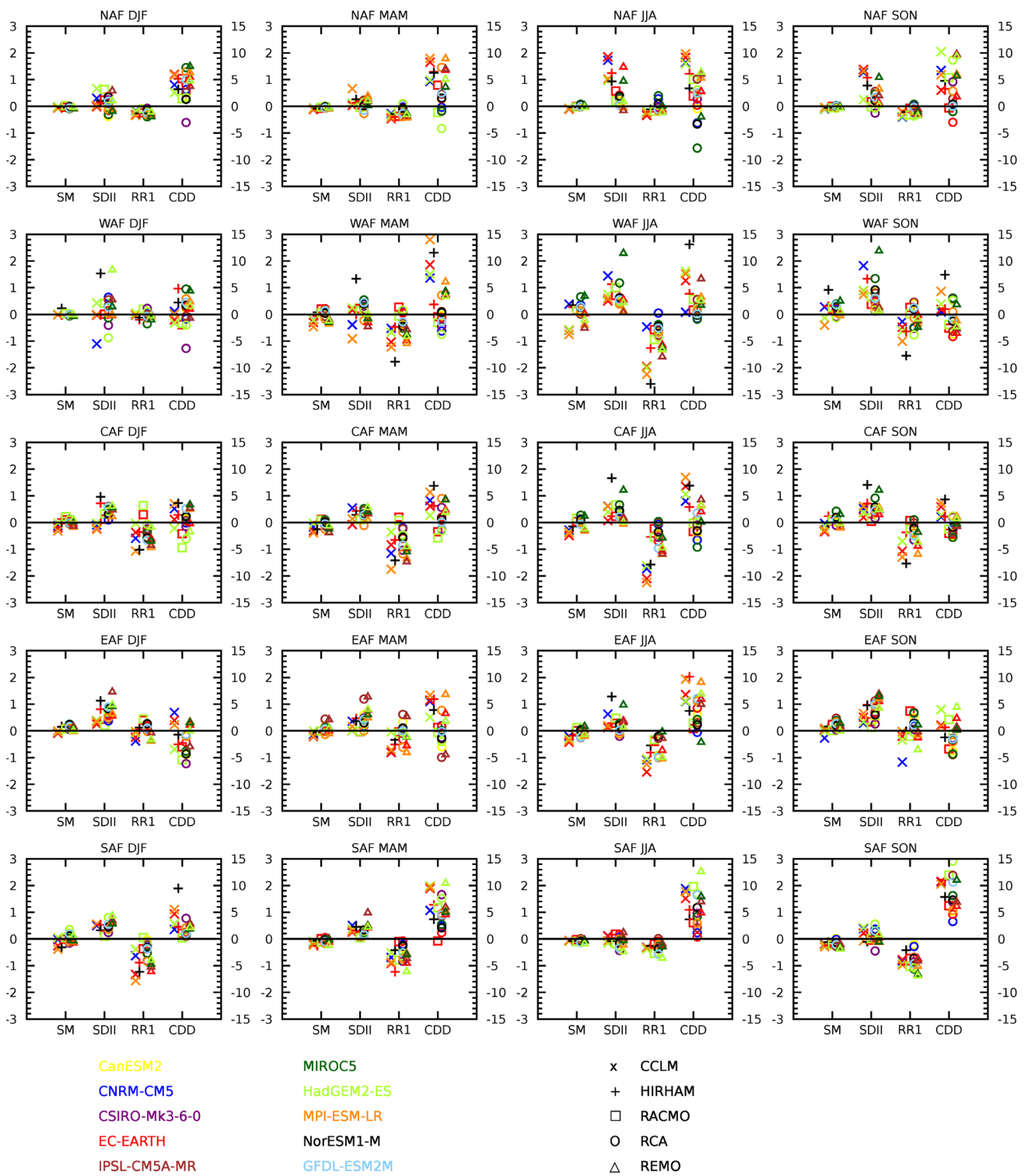


Fig. 11 Changes of selected ETCCDI indices for all GCM–RCM simulations. Results are highlighted according to driving GCM (symbols) and downscaling RCM (colors). Note that results are the

same as those in the box-whisker plot in Fig. 7. SM and SDII range between -3 and 3 mm/day, whereas RR1 and CDD range between -15 and 15 days/season

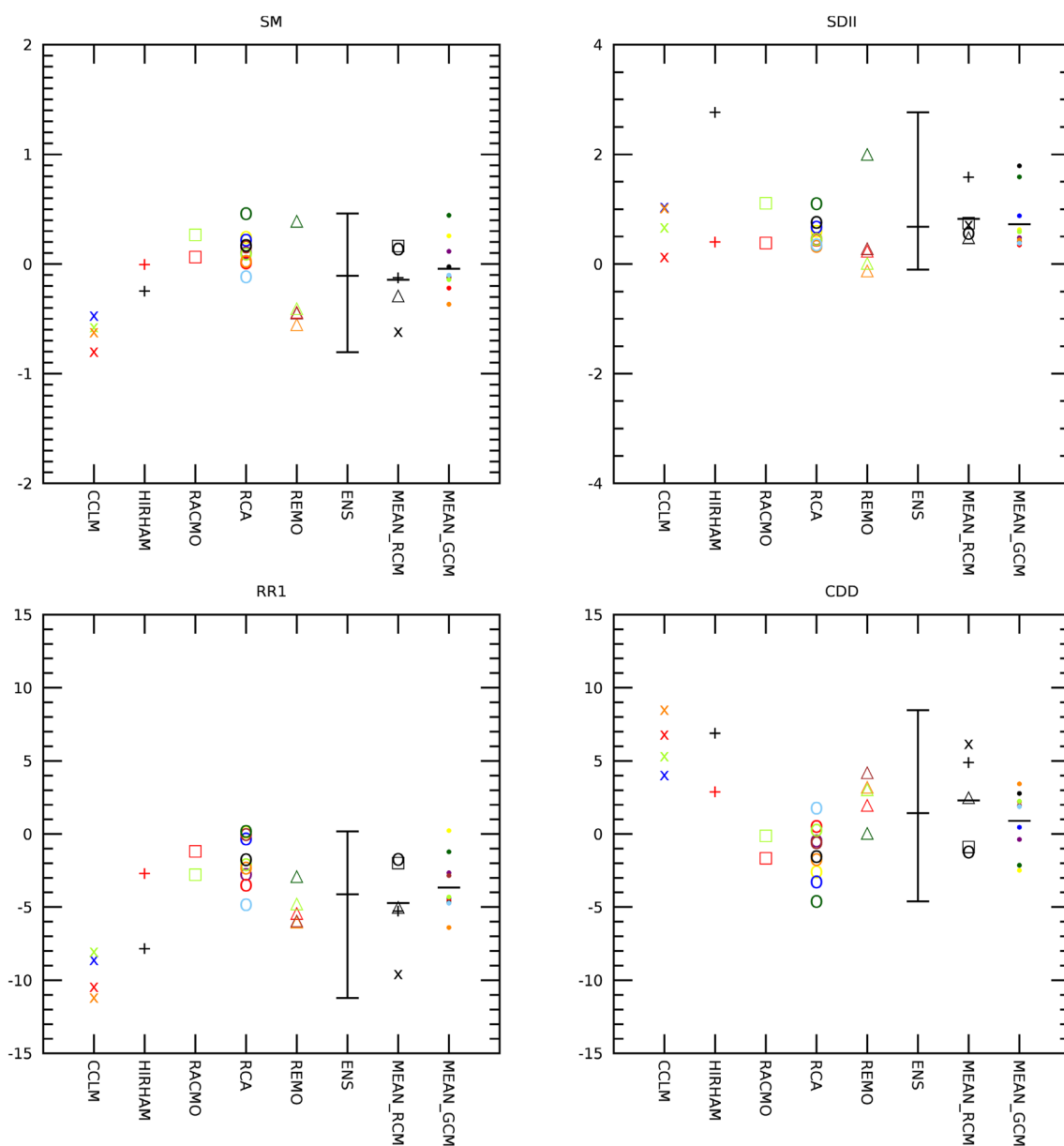


Fig. 12 Changes of selected ETCCDI indices for CAF in JJA. Results for all GCM–RCM simulations are shown according to the downscaling RCM (columns 1–5), with symbols and colors as in Fig. 11. Ensemble mean results and spread are shown in the ‘ENS’ column.

Results are also shown as average according to the RCM (e.g., all 10 GCM-driven runs by RACMO; MEAN_RCM) or driving GCM (i.e., all RCM runs downscaling the same GCM; MEAN_GCM). In these columns, horizontal lines denote the mean of the reduced ensemble

the other hand, the runs downscaling MPI-ESM-LR project a consistently large increase in CDD and reduction of RR1.

4. Finally, however, there are some cases where the results are indeed clearly clustered according to the RCM. These cases are investigated in more detail in Fig. 12 for a selected example, namely CAF in JJA (but similar conclusions can be drawn for other regions and seasons).

In Fig. 12 results are first shown according to the RCMs (similar to Fig. 11), with the addition of the ensemble mean and min–max spread (ENS, as already shown in Fig. 7).

Furthermore, two new set of results are shown; the first one (MEAN-RCM) shows the change in the index computed as average of the single RCM simulations (e.g., the average of the 10 GCM-downscaled runs by RCA); the second one (MEAN_GCM) shows the results when the average is performed according to the driving GCM (i.e., averaging all RCM runs downscaling the same GCM). Looking at the single RCM results, the impact of the RCM choice is clear; for instance, CCLM shows a decrease in SM for all simulations, whereas both RACMO and RCA show mostly an

increase in mean precipitation. Results for the other RCMs are mixed, though. By means of the ‘one simulation one vote’ approach, results are uncertain, with models results generally uniformly spread around an ensemble mean value of nearly zero. However, it is interesting to note that this uncertainty is not substantially reduced if clustering is performed according to either the RCM or the driving GCM (as shown by the columns MEAN-RCM and MEAN_GCM), which show mean values very close to the ensemble mean, and a spread that is not always significantly reduced. Here, even in cases where ensemble mean results are uncertain and single RCM results are clearly clustered together, there is no straightforward way of subsampling the model ensemble to reduce the uncertainty or to infer a more robust result.

It is clear that RCMs can project completely different climate change signals even when downscaling the same GCM, but the investigation on why this happens needs thorough and specifically dedicated research. Here we show that where the results of a large GCM–RCM ensemble (although unbalanced with respect to the combination of GCMs and RCMs) are robust or non-significant, they are so independently of the choice of the GCM and/or RCM. In addition, where results are uncertain, a simple sub-selection of model results based on either GCM or RCM averaging will not reduce the uncertainty significantly, nor change the overall message.

5 Summary and concluding remarks

In this study, for the first time to our knowledge, we employed the large CORDEX-Africa RCMs ensemble to specifically answer two questions:

1. What can we know about the future precipitation characteristics over Africa?
2. Does this information differ from that derived from the driving GCMs?

By employing a definition of robustness that takes into account both the statistical significance of the change and the models’ agreement on its sign, we were able to identify regions where there is confidence that the projected precipitation characteristics will change (i.e., the change is robust) and those where the precipitation statistics are likely to remain unchanged (the change is non-significant). Although results are strongly dependent on the region, season, and precipitation characteristic (ETCCDI indices), from the RCM ensemble some general conclusions can be drawn:

1. Over most of North Africa, precipitation characteristics (especially the precipitation intensity) are projected to not change significantly (Fig. 5); however, over the

Atlas region precipitation frequency is projected to decrease throughout all year (Figs. 3, 4), with a consequent increase in the length of dry spells (up to 10 days/season in JJA).

2. Over most (50%) of West Africa, models do not agree on the changes in mean seasonal precipitation and extreme events, especially in JJA. However, changes in other precipitation characteristic are robust, such as a reduction in precipitation frequency accompanied by longer dry spells and shorter wet spells over nearly 70% of land. At the same time, precipitation intensity is projected to increase over a large fraction of the region up to more than 1 mm/day.
3. Over East Africa, a robust increase in precipitation intensity, frequency and extreme events is projected in both DJF and SON over more than 15% of land, with changes in daily maximum intensity up to 8 mm/day in SON. On the other hand, in JJA, more than 30% of land is projected to face a robust reduction in precipitation frequency, with a consequent increase in CDD and reduction of CWD.
4. Over Central Africa, both precipitation frequency and wet spell duration are projected to significantly decrease in all seasons over a large fraction of land; however, precipitation mean and maximum intensity are projected to increase (up to 7 mm/day for RX1 day in SON over more than 30% of land).
5. Southern Africa is the region showing the largest (in terms of fraction of land affected) and more consistent trend towards drier future conditions, with around 40% of land projected to face a robust reduction in mean precipitation in JJA and SON, and up to nearly 80% of land affected by less frequent rain and longer dry spells in JJA. However, a slight increase (1 mm/day) in precipitation intensity is projected over around 10% of land in DJF.

The RCMs spatially averaged ensemble median change is usually in agreement with that of the GCM ensemble and, when differences exist, the ranges of change overlap considerably and include zero. In addition, even though the median change in seasonal mean precipitation may differ in some cases, most of other indices show the same tendency. Larger differences are found, however, in the range of the projected change: this can be a consequence of several GCMs being downscaled by the same RCM, but also small-scale processes (such as convection) being resolved differently by GCMs and RCMs.

When the robust change (i.e., the value of the change averaged only over the points where it is robust) is compared between the GCMs and RCMs, similarities are striking, indicating that, although with some uncertainty on the

geographical extent, GCMs and RCMs project a consistent future.

The added value of downscaling future climate projections must consist of non-negligible fine-scale information that is absent in the lower resolution ones, and, in addition, it has to be related to physical mechanisms that can modify the climate change signal simulated by the GCMs. By comparing the RCM results not only to those of the GCMs but also those of ‘virtual GCMs’ (i.e., upscaled results), we highlighted regions where the added value is indeed related to a better representation of fine scale processes. A few selected examples were discussed:

1. Over Southern Africa, the downscaled seasonal precipitation change is very consistent with that of the driving GCMs, although finer spatial variations are visible in the RCMs results, for instance over Zimbabwe and Zambia.
2. Over East Africa, the RCMs, project a robust decrease of mean precipitation over the Ethiopian highlands, which is opposite to the GCMs results: this feature may be associated with the better representation of topographical details that are missing in the large scale GCMs.
3. Over Central Africa the downscaled climate differs significantly from the GCMs; the climate generated by the RCM is scarcely influenced by the lateral boundary conditions and local processes, land–atmosphere interaction, and convective parameterization may be the most important factors. For instance, in MAM, the RCMs ensemble projects a robust decrease in precipitation frequency whose geographical extension and magnitude are much larger than those of the driving GCMs.
4. Over West Africa, differences between the RCM and GCM ensembles are visible especially along the coasts; for instance, the spatial variability of the CWD change simulated by the RCMs, related to e.g., the topographic details over Nigeria is missing in both the V_GCMs and GCMs results.

In addition to these general conclusions, however, there are some caveats to our study that need to be mentioned. In particular:

1. As stated, the definition of robustness is sensitive to the ensemble size: in particular, the smaller GCM ensemble (10 members) makes the robustness criteria much more sensitive to outliers (i.e., dependent on the results of a single model); as a result, the comparison between RCM and GCM ensembles can only be qualitative.
2. Although, our study highlighted that, for many regions and seasons, there is high confidence in the projected future characteristics of precipitation, i.e., the RCMs’ projected change is robust (or non-significant) and in agreement with that of the GCMs, there are still cases

where: (a) RCMs results do not agree (i.e. the change is uncertain); (b) the RCM inter-quartile range is very large despite the change being robust; and (c) the down-scaled change differs in sign from that of the driving GCMs. Although some studies have investigated these issues based on the results of a single RCM, a detailed analysis of the causes of the differences based on the large CORDEX-Africa matrix is still missing. Our study can be helpful in identify those regions where future research is most needed.

3. Although it has been shown that a correct representation of topography is needed to realistically reproduce precipitation over e.g., the Ethiopian Highlands, and, hence, that RCMs have the potential to add value to the projected climate, no proof has been provided that the different climate change between RCMs and GCMs is the result of e.g. enhanced mesoscale dynamics. Similarly, for CAF, the differential climate change signals may well stem from different GCM and RCM physics and parameterizations, but whether value has been added is unclear.
4. Our analysis of future precipitation characteristics for Africa is based on mean climatology and selected ETC-CDI indices; however, many other important aspects have been neglected, especially relevant for the monsoon, such as onset, length and end of the rainy season etc. The investigation of monsoon characteristics and its change, especially in West Africa and the Sahel, would require also a thorough analysis of the dynamic and thermodynamic drivers of e.g. moisture transport, low- and mid-tropospheric flows (Easterly Jet) etc., which is outside the scope of this work.
5. Although the results of this study are based on a large ensemble of runs, the CORDEX-Africa RCM–GCM matrix is still incomplete: in particular, only one RCM downscaled all the GCMs, whereas only one GCM (EC-EARTH) has been downscaled by all RCMs (although using different ensemble members). We have shown that the main conclusions of our study, based on ‘one simulation one vote’ approach, hold, and results are often robust (or non-significant) regardless of the choice of the specific RCMs or GCMs. Where the results are uncertain, however, and clearly clustered according to the RCM, we showed that a simple subsampling based on averaging according the RCM and/or the GCM, is not able to reduce significantly the uncertainty nor the value of the mean change.

This adds evidence to the proposition by e.g. Weigel et al. (2010) that, for many applications, equal weighting may be the more transparent way to combine models and is preferable to a weighting that does not appropriately represent the true underlying uncertainties. Weigel et al.

(2010) claim that ‘optimum weighting’ requires both accurate knowledge of the single model skill, and the relative contributions of the joint model error and unpredictable noise: both issues are still open to discussion. In addition, we showed that a simple evaluation of models’ performance for the present climate is not sufficient to single out the ‘best performing’ RCM and, as a consequence, makes it challenging to find a suitable methodology to subsample the ensemble by means of skill based weighting.

This implies that a thorough investigation of models’ performance and their response to external forcing is still required, which needs to be based on the assessment of their ability to reproduce the physical processes and drivers of the African climate. This, clearly, is an important topic for future research.

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