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Key Points:

- Precipitation over Africa is assessed by means of a large ensemble of reanalysis, gauge-based, and satellite-based products
- Southern Africa and the Atlas region show the largest agreement amongst different products for most of the precipitation characteristics
- Similarly large ensembles of regional models are able to reproduce daily precipitation characteristics as well as the observations

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What Can We Know About Recent Past Precipitation Over Africa? Daily Characteristics of African Precipitation From a Large Ensemble of Observational Products for Model Evaluation

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Abstract We assess the daily characteristics of recent past precipitation over Africa by means of a large ensemble of observational products, including reanalysis, gauge-based, and satellite-based products. The spatial distribution of seasonal mean precipitation varies considerably amongst products especially over areas where gauge networks are sparse. Large uncertainties in the annual precipitation cycle are visible in particular over the Ethiopian Highlands, the eastern Sahel, the coasts of the Gulf of Guinea, and the Horn of Africa. Interannual variability shows large differences especially amongst reanalysis data sets whereas satellite and gauge-based products usually show more consistent results.

Plain Language Summary Southern Africa and the Atlas region show the largest agreement amongst different products for most of the precipitation characteristics, including annual time series and trends, spatial and temporal correlations, and indices of mean and extreme events. Over other regions, discrepancies amongst different products are larger, especially for indices based on short time scales, in particular, over the regions affected by the monsoon (the Sahel, the coasts of the Gulf of Guinea, and Central Africa). Observed precipitation characteristics have been compared to the results of state-of-the-art regional climate models (RCMs). Given the impossibility to select a single “best” observation data set for a realistic representation of all precipitation characteristics, our results show that comparing model results to a very limited set of observations is not only pointless, but it can be even misleading. When similarly large ensembles of model results and observations are compared, our findings show that RCMs are able to reproduce daily precipitation characteristics as well as the observations.

1. Introduction

Over the past decades, Africa has been affected by significant rainfall anomalies: for instance, both the Horn of Africa and West Africa suffered severe droughts during the 1970s and 1980s (e.g., Williams et al., 2012) and, recently, the City of Cape Town in South Africa was hit by one of the worst multi-year droughts in decades (Otto et al., 2018). On the other hand, severe floods have affected countries located in dry areas, such as Algeria, Tunisia, Egypt, and Somalia (Niang et al., 2014).

The analysis and the understanding of precipitation trends and variability rely on the availability of observational records (e.g., Sun et al., 2018). Reliable observational data sets are also of paramount importance in the evaluation of climate models (e.g., Maidment et al., 2015; Tapiador et al., 2017). In fact, both general circulation models (GCMs) and regional climate models (RCMs) still show limitations in simulating various aspects of the African precipitation (e.g., Akinsanola et al., 2018; Dosio et al., 2015; Gbobiye et al., 2014; Gibba et al., 2018; Kim et al., 2014; Kitembe et al., 2019; Nikulin et al., 2012; Panitz et al., 2014; Sow et al., 2020; Tamoffo et al., 2020, 2021) and large uncertainties still remain over the projected precipitation change, in particular over West and Central Africa (Dosio & Panitz, 2016; Dosio et al., 2019, 2020; Klutse et al., 2018; Mba et al., 2018; Monerie et al., 2017; Tamoffo et al., 2019). The models ability at reproducing the physical processes and drivers of the African climate is a task even more challenging when available observational data sets are scarce and incomplete. In the past decade, several observational data sets have

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become available, including reanalysis, station (gauge) based, and satellite-based products, covering different time and spatial scales. Recent works that compile and compare different data sets at global scale include Sun et al. (2018), Roca et al. (2019), Tapiador et al. (2017), Gehne et al. (2016), Beck et al. (2017), Masunaga et al. (2019), Alexander et al. (2020), and Bador et al. (2020). They found that although global precipitation characteristics are generally consistent across the products, large discrepancies amongst data sets exist especially in the tropics, and, in particular, for precipitation extremes (Bador et al., 2020; Herold et al., 2017; Masunaga et al., 2019). Focusing over specific regions in Africa, Williams et al. (2012) examined observed precipitation trends in the Greater Horn of Africa and Sahel, Diaconescu et al. (2015) compared three satellite-estimated products and four reanalysis products with those of two RCMs over West Africa, Nkrumah et al. (2019) examine recent trends in extreme rainfall in Southern West Africa based on station data, Ayugi et al. (2019) compared four satellites derived precipitation estimates over Kenya, Hua et al. (2019) compared seven reanalysis data sets to a gauge based data set over central equatorial Africa, Odoulami and Akinsanola (2018) analyzed the trends in the summer monsoon rainfall over West Africa using two gridded products, Dinku et al. (2018) compared three satellite products to gauge station data over Ethiopia, Kenya, and Tanzania, and Gebrechorkos et al. (2019) evaluated several products (satellite-based estimates, reanalysis, and RCMs) against station data over Ethiopia, Kenya, and Tanzania.

At (sub-) continental scale, Maidment et al. (2015) compared GCM results to three gauge-based and five satellite-based precipitation data, Nicholson et al. (2018) analyzed the precipitation variability over the last century and a half using a data set containing a large number of rain stations, and Harrison et al. (2019) compared multiple daily gridded gauge and satellite products over Sub-Saharan Africa.

Generally, all these works point out that differences between the data sets are often very large, especially in regions where station networks are sparse, with for example, some products showing systematic biases and unrealistic trends. As a result, it is not possible to select a single “best” data set, and model evaluation must rather make use of several, diverse observational products (e.g., Alexander et al., 2020; Bador et al., 2020; Gehne et al., 2016; Herold et al., 2017). However, model (RCM) evaluation studies over Africa have rarely made use of more than a few of them (Diaconescu et al., 2015; Dosio et al., 2015; Kim et al., 2014; Nikulin et al., 2012; Panitz et al., 2014; Sylla et al., 2013).

For the first time to our knowledge, here we assess the daily characteristics of recent past precipitation over Africa by means of a large (20) ensemble of observational products, including reanalysis, gauge-based, and satellite-based products. We compare them with the results from a similarly large ensemble of high-resolution RCM runs from the Coordinated Regional-climate Downscaling Experiment (CORDEX; Giorgi & Gutowski, 2015) and evaluate the uncertainty ranges of the two ensembles.

The study is structured as follows: the data (observational products and model runs) used in the analysis are described in Section 2; the main characteristics of observed African daily precipitation are analyzed in Section 3, from seasonal means and trends to monsoon onset and retrieval dates, spatial and temporal correlations, and so on, and compared to the results of the CORDEX runs. Finally, the summary and concluding remarks are discussed in Section 4.

2. Data and Methods

2.1. Observational Data Sets

Table 1 presents the 20 observational data sets included in the evaluation. In this study, we consider only data sets that provide daily precipitation estimates (excluding, therefore, popular products such as CRU and UDEL) and that are available for at least 20 years. As in Sun et al. (2018) and Roca et al. (2019) products have been classified in three broad categories: reanalyses, satellite-based, and gauge-based. A detailed description of the various techniques and an in-depth analysis of the advantages and drawbacks of each specific data set is provided in the above-mentioned works and Tapiador et al., 2012, 2017). Therefore, here we give only a brief overview of the main characteristics of the products categories.

Reanalysis products assimilate observed meteorological fields (such as temperature, wind, pressure, and humidity) into a weather forecast model to produce four-dimensional, physically consistent fields of meteorological variables including precipitation. Being a modeled quantity, precipitation from reanalysis can

Table 1
List of Observational Products

Acronym	Full name	Resolution	Period	Type	References
20CR	NOAA-CIRES-DOE Twentieth-century reanalysis	2°	1974–2014	Reanalysis	Compo et al. (2011)
ERAINT	ECMWF ERA-Interim	0.75°	1979–2018	Reanalysis	Dee et al. (2011)
NCEP-2	NCEP-DOE reanalysis 2	1,875°	1979–2018	Reanalysis	Kanamitsu et al. (2002)
WATCH_WFDEI-CRU	Water and global change (WATCH) forcing data methodology applied to ERA Interim reanalysis data	0.5°	1979–2018	Reanalysis	Weedon et al. (2014)
WATCH_WFDEI-GPCC	Water and global change (WATCH) forcing data methodology applied to ERA interim reanalysis data	0.5°	1979–2018	Reanalysis	Weedon et al. (2014)
JRA-55	Japanese 55-year reanalysis	0.5625°	1979–2018	Reanalysis	Kobayashi et al. (2015)
CFSR	NCEP climate forecastSystem version 2	38 km	1979–2010	Reanalysis	Saha et al. (2014)
MERRA-2	Modern-era retrospective analysis for research and applications, version 2	0.5 × 0.625°	1979–2018	Reanalysis	Gelaro et al. (2017)
CMORPH	CPC Morphing technique (CMOPRH) global precipitation analysis	0.25°	2003–2016	Infrared, microwave.	Joyce et al. (2004)
CMORPH_ADJ	CPC Morphing technique (CMOPRH) globalPrecipitation analysis	0.25°	1998–2018	Infrared, microwave. Adjusted with daily CPC (land) and GPCP data (ocean).	Xie et al. (2017)
TRMM 3B42	NASA/JAXA tropicalRainfall measuring mission multi-satellite precipitation analysis version 7	0.25°	1998–2018	Infrared, microwave, precipitation radar. Scaled to GPCP monthly satellite-gauge data.	Huffman et al. (2007)
Tamsat	Tropical applications of Meteorology using SATellite data and ground-based observations	4 km	1983–2017	Geostationary thermal infrared images and on ground-based observations.	Maidment et al. (2017)
ARC2	NOAA NCEP CPC FEWS African rainfall climatology from the famine early warning system	0.1°	1983–2018	Geostationary infrared and rainfall accumulation records from the gauge database.	ftp.cpc.ncep.noaa.gov/fews/AFR_CLIM/ARC2/
CHIRPS	Climate hazards group infraRed precipitation with station data (CHIRPS)	0.05°	1981–2018	Gauge data, infrared, TRMM-T3B42 and CFSR.	Funk et al. (2015)
GPCP_1DD	Global precipitation climatology project	1°	1997–2014	Infrared, microwave. Scaled to GPCP monthly satellite-gauge data.	Huffman et al. (2001)
PERSIANN CDR	Precipitation estimation from remotely sensed information using artificial neural networks-climate data record	0.25°	1983–2018	Infrared, artificial neural network trained on gauge and radar data. Scaled to GPCP monthly satellite-gauge data.	Ashouri et al. (2015)
MSWEP	Multi-source weighted-ensemble precipitation (MSWEP)	0.5°	1979–2016	Rain gauge measurements, satellite observations, and estimates from atmospheric models.	Beck et al. (2019)
CPC	Unified gauge-based analysis of global daily precipitation	0.5°	1979–2018	Gauge data	Xie et al. (2010)
GPCC_FDD	Global precipitation climatology center full data daily V2018	1°	1982–2016	Gauge data	Ziese et al. (2018)
REGEN ALL	Rainfall Estimates on a Gridded Network V1-2019	1°	1979–2016	Gauge data	Contractor et al. (2019)

Table 2
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	RACMO22 E	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

Note. Simulations are those available through the Earth System Grid Federation (ESGF) server. GCM, general circulation models; RCM, regional climate models.

suffer the same issues as those of weather and climate models, with a tendency to overestimate light precipitation events (e.g., Sun et al., 2018). In addition, physic parameterizations such as convection can have a large influence on the reanalysis performance, especially in the tropics (Gehne et al., 2016). Some reanalysis products incorporate also gauge data: to assess the impact of this approach, as an example in this study, we use two versions of the WATCH-WFDEI data set, one calibrated by means of the CRU data set and the other one by GPCC.

Satellite-based products make use of different types of sensors (visible/infrared, passive, and active microwave, see e.g. Tapiador et al., 2017) to provide precipitation estimates by means of retrieval algorithms, which, however, can introduce errors and biases (Sun et al., 2018). Many satellite products therefore merge satellite observations with other sources of information: to investigate the effect of such approach here we use both the uncorrected CMORPH v0 data set and the bias-adjusted CMORPH_ADJ, where biases have been removed by comparison with the CPC and GPCP data sets.

Gauge-based products are built by employing rain data from measurement station networks which, however, can be sparse or even non-existent (especially over large areas of Africa, see, e.g., Nikulin et al., 2012), and, where available, heterogeneous in space and time, with the number of gauge stations markedly declining, globally, since the 1980s (e.g., Sun et al., 2018). Besides data scarcity, the performance of gridded gauge products depends critically on the algorithm used to homogenize the data onto the final regular grid (e.g., Tapiador et al., 2017). It must be noted that many of the available data sets used here are not completely independent. In fact, gauge-based products may rely on the same underlying station network. In addition, many products combine different sources of information such as gauge and satellite estimates (CMORPH_ADJ, GPCP-1DD, PERSIANN-CDR, and TRMM_3B42), gauge and reanalysis (WATCH-WFDEI), and gauge, satellite, and reanalysis data (CHIRPS and MSWEP).

For comparison with RCMs results, data have been interpolated bilinearly on the same 0.44° grid used by the models.

Note also that the data sets cover different periods (see Table 1). Long-term mean statistics (e.g., seasonal mean and annual cycles) will scarcely depend on the different lengths of the observational records. Trends, however, are calculated over the period 1983–2010, the longest common period amongst the majority of the data sets. Temporal correlations are calculated over the common period between the pair of data sets considered.

2.2. Regional Climate Models

Modeled daily precipitation data were obtained from a large ensemble of CORDEX RCMs, listed in Table 2. Five different RCMs were used to downscale the results of 10 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). The precipitation time series over the reference period (1981–2010) is constructed using the last 25 years of the historical runs (1981–2005) and the first 5 years (2006–2010) of the scenario runs under the Representative Concentration Pathway RCP8.5, as done for instance in other studies over Africa (e.g., Dosio et al., 2019) and Europe (e.g., Dosio & Fischer, 2018). It is important to note that here we do not evaluate the results of RCMs driven by reanalysis (the so-called evaluation runs, as in e.g., Taguela et al., 2020) but, rather, those of the downscaled GCMs; in these runs, biases are a combination of those inherited through

Table 3
List of Climate Change Indices Analyzed in This Study

Acronym	Name	Description	Units
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
RX1day	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

Note. 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.

the boundary conditions and those resulting from the RCMs parameterizations (e.g., Dosio et al., 2015). Although this may limit the evaluation, as, for instance, modeled trends can be the result of unforced internal variability and, therefore not directly comparable to the observed ones, our scope is not to find the “best” performing RCM, rather, to verify if the GCM-RCM ensemble captures the daily characteristics of the African precipitation within the limits of the observational uncertainty therefore ensuring its fitness for purpose when used for future projections.

2.3. Indices of Precipitation Characteristics

Besides seasonal mean precipitation, several indices (Table 3) from the Expert Team on Climate Change Detection and Indices (ETCCDI; Zhang et al., 2011) were calculated on every land point of each observation product and model. Indices include precipitation intensity (simple daily intensity, SDII, and maximum daily precipitation, RX1day) 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 and 20 mm, R10 mm and R20 mm).

3. Results

Seasonal mean daily precipitation for the different observational products in June-July-August (JJA) is compared in Figure 1. Differences among data sets are remarkable, especially over the Gulf of Guinea, the Sahel, and central Africa, that is, areas where gauge networks are generally sparse (see, e.g., Masunaga et al., 2019). Compared to the multi-data set ensemble mean, the precipitation spatial distribution varies considerably especially amongst reanalysis products, with 20CR showing a wet bias over the West Sahel and a dry bias over the western coasts of the Gulf of Guinea and Central Africa, a pattern that is opposite in sign to that of ERAINT. Smaller differences are found in both the satellite-based and gauge-based products, with notable exceptions being CMORPH, ARC2, and CPC, which show large wet and dry biases up to more than 5 mm/day. The largest uncertainties (measured as multi-data set standard deviation) amongst the products are visible over the coasts of Sierra Leone and Guinea, the mountain ranges of Cameroon and the Ethiopian Highlands, which can be partly due to differences in the spatial resolution of the data sets, but also to the difficulties of satellite-based products in retrieving precipitation over complex topography areas (Sun et al., 2018). It is worth noting that the ensemble mean of the comparably large RCMs ensemble is generally very similar (over land) to that of the observations, although individual model results can vary greatly (e.g.,

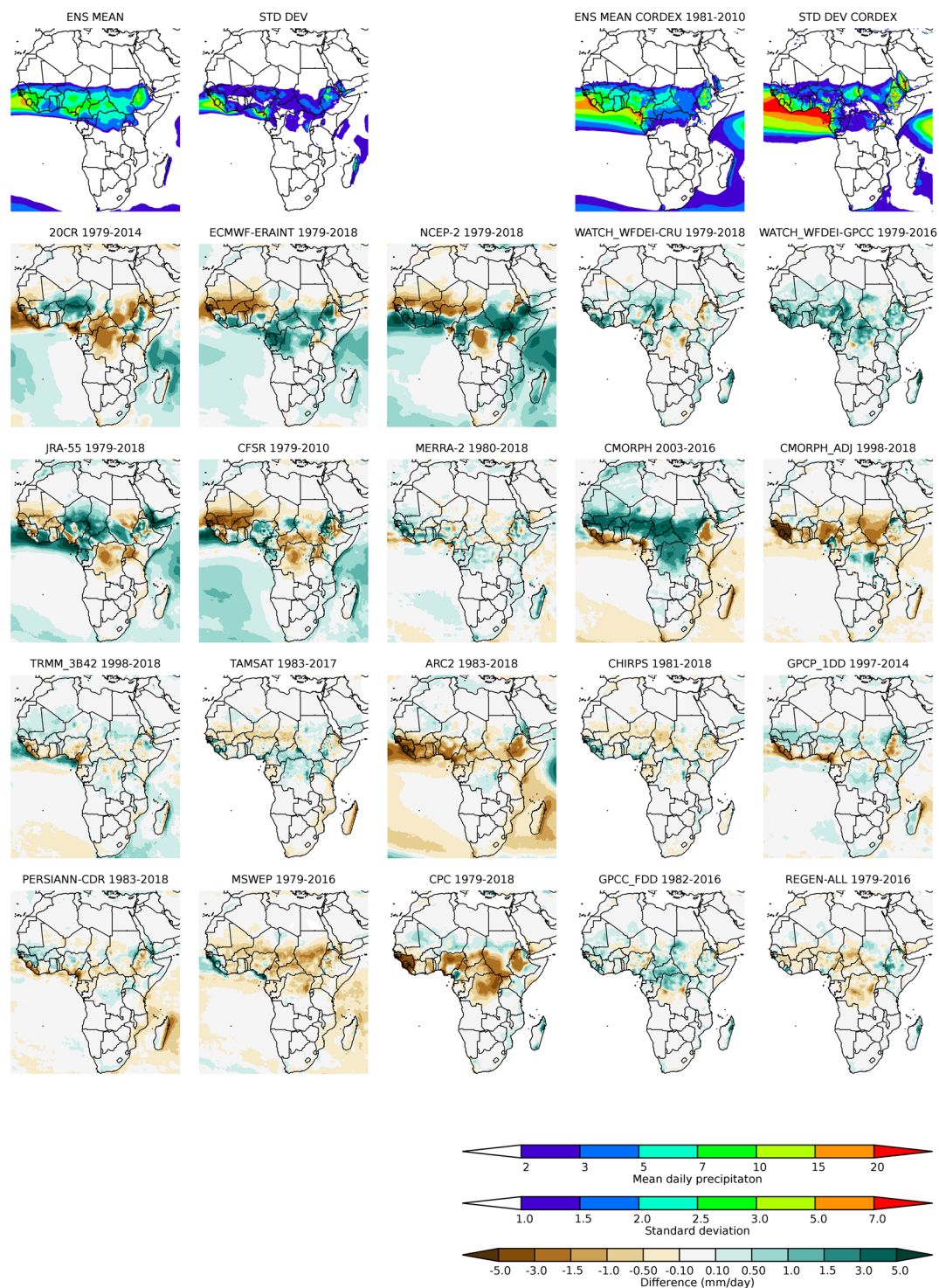


Figure 1. Seasonal mean (JJA) daily precipitation for different observational products. Rows 2–5 show the difference between a selected product and the ensemble mean of the entire ensemble of observational products, shown in the top-left panel. Ensemble mean and standard deviation (top row) are calculated on every grid point from the values of the individual (20 products) long term (1983–2010) JJA seasonal means. For comparison, in the top row (right panels) the CORDEX RCMs ensemble mean and standard deviation are also shown.

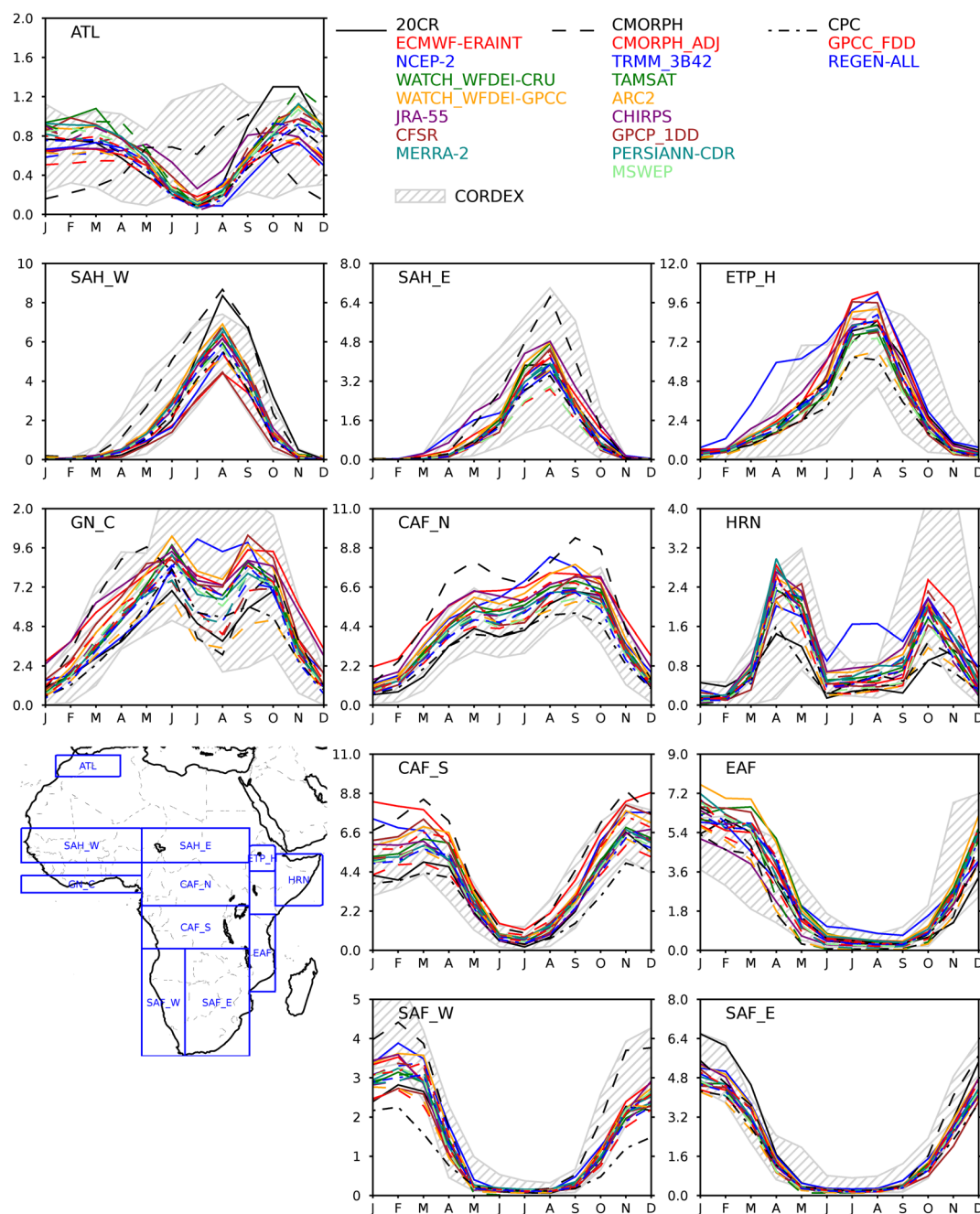


Figure 2. Annual cycle of daily precipitation for the observational products spatially averaged over different sub-regions (blue boxes) shown in the map. Observations are plotted according to their type, namely, reanalysis (continuous line), satellite products (dashed lines), and gauge-based products (dashed-dotted line). The range (min-max) of CORDEX-Africa RCMs is also shown for comparison.

Dosio et al., 2019) as indicated by the RCMs standard deviation, which shows larger values, compared to the observed ones, over southern Chad and the Ethiopian highlands.

The annual cycle of daily precipitation is shown in Figure 2 for selected sub-regions. With few exceptions, all observational data sets show very similar yearly evolution of daily precipitation; however, uncertainties in the peak values are visible over all regions, in particular over the Ethiopian Highlands (ETP_H) in July and August, with the spread reaching nearly 4 mm/day, the eastern Sahel (SAH_E), the coasts of the Gulf of Guinea (GN_C) and the Horn of Africa (HRN). In some cases, some products exhibit values

substantially different from the others, like NCEP-2 over ETP_H, CMORPH over SAH_E, northern Central Africa (CAF_N) and, together with 20CR, the western Sahel (SAH_W) and HRN. Finally, it is noteworthy that in few cases the precipitation peak of some products is misplaced compared to all other data sets, like CMORPH over the Atlas Region (ATL) and NCEP-2 over CGN_C and HRN, where the inability of capturing the biannual precipitation regime is possibly due to the coarse horizontal resolution of the reanalysis. For comparison, the multi-model range of CORDEX RCMs is also shown; it is interesting to note that models are able to capture the annual distribution and peak values very satisfactorily especially in sub-equatorial Africa, with the only exception being the coasts of the Gulf of Guinea where the large spread is due to few models not capturing the biannual regime (see, e.g., Dosio et al., 2015 but also Sow et al., 2020 for GCMs).

A methodology to calculate the timing of precipitation onset and cessation was originally proposed by Dunning et al. (2016) and it is applied here (Figure 3). Satellite and gauge-based data sets usually show very similar results over most regions, notable exception being the Atlas region, where the large spread in the satellite products is due to the anomalous annual cycle by the CMORPH data set as discussed before. Also, the cessation date over western Southern Africa (SAF_W) shows a relatively large discrepancy amongst the satellite products. The spread amongst reanalysis data sets is considerably larger than those of the other products over most of the northern equatorial regions. CORDEX RCMs show the largest uncertainties in the onset and cessation dates, although in median, modeled results lie usually within the range of the observations. CORDEX results are particularly uncertain over the Atlas region and the coasts of the Gulf of Guinea, where the large spread in the value of the first cessation date and the second onset date are due to few models simulating a one-peak precipitation cycle, instead of a biannual regime.

Yearly evolution of seasonal mean daily precipitation is shown in Figure 4. Here, we point out only a few selected aspects worth noting: over SAH_W CMORPH shows the largest values and CFSR the smallest; over ETP_H MERRA-2, CPC and ARC2 show a drop in values in the period 2000–2005 (low skills over Ethiopia by ARC2 are reported also by Dinku et al., 2018), similar to that by MERRA-2 over the same period over CAF_S (see also Hua et al., 2019). Interannual variability (i.e., the standard deviation of the annual times series) varies greatly across regions, with the smallest values (median across all data sets) being over ATL in DJF and the largest over ETP_H in JJA. Large discrepancies between products in the interannual and decadal variations over the Congo basin are reported also by Sun et al. (2018). The largest differences usually occur amongst the reanalysis data set (e.g., over CAF_S, CAF_N, GN_C, etc.) whereas satellite and gauge-based products usually show more consistent results. However, over SAH_E, CAF_N, and ETP_H, the satellite and gauge-based products show values of interannual variability that significantly differ between them (as reported also by Sun et al., 2018 for the Congo basin), so that the ranges of the two ensembles taken separately do not overlap.

CORDEX models show values of interannual variability relatively similar to those of the total set of observations, in median, over ATL, SAH_W, GN_C, HRN, and SAF_W, but smaller values over the other regions. However, the spread of modeled interannual variability is usually similar, if not smaller, than that of the observations in most regions apart from GN_C.

Figure 5 shows the spatial and temporal correlations of seasonal mean daily precipitation across the observational products over the sub-regions. Results show that, in general, the spatial pattern of seasonal mean precipitation is similarly captured by all products especially over Southern Africa, the Atlas region, the Sahel, and East Africa. Also, Diaconescu et al. (2015) found high spatial correlations over West Africa between reanalysis data sets and three sets of observations (ARC2, TRMM, and GPCP) used as reference. Similarly, Sow et al. (2020) found high spatial correlations between TRMM, GPCP, and CHIRPS for the annual cycle of daily precipitation over the Western Sahel and the Guinea regions. As noted by Gehne et al. (2016), high correlations are to be expected amongst products that share the same underlying data, such as GPCP, TRMM_3B42, and PERSIANN-CDR. Lower values of the spatial correlation are found over central Africa and the Horn of Africa, especially for the reanalysis (e.g., NCEP-2, ERAINT, and 20CR, see e.g. also Hua et al., 2019) whereas satellite and gauge-based products have generally higher values of cross-correlation. Dinku et al. (2018) showed that over areas of complex terrain (Ethiopia and Tanzania) the performances of satellite-based products vary considerably, with CHIRPS precipitation distribution comparing better to the gauge data than that of ARC2.

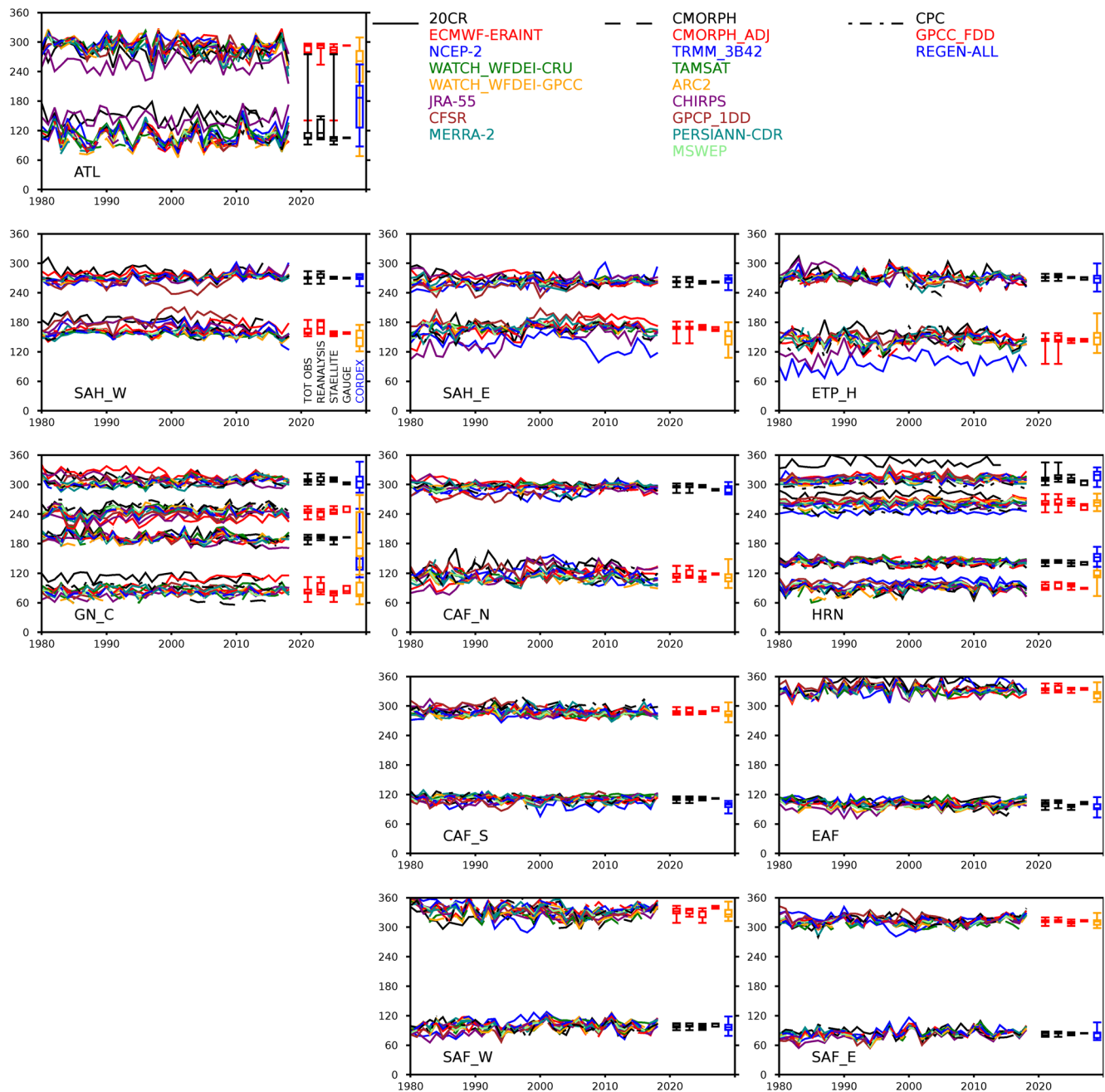


Figure 3. Time series of mean (spatial average) onset and cessation date (day of the year) for the different sub-regions. Onset and cessation dates are calculated according to Dunning et al. (2016). Box and whiskers plots show the range of the mean (temporal average) onset and cessation dates across different groups of observations (total, reanalyses, satellite, and gauge products). Red (observations) and orange (CORDEX) boxes denote onset dates, black (observations) and blue (CORDEX) ones the cessation date.

Lower values are generally found for the temporal correlation, as reported also by Gehne et al. (2016), especially over central Africa and the Ethiopian highlands, with few cases where the correlation across data sets shows negative values. Again, this may be due to spurious values in some years discussed previously for some products. Harrison et al. (2019) noted that over sub-Saharan Africa satellite-based products perform well for precipitation totals, with CHIRPS and PERSIANN showing the highest correlation values against REGEN (used as reference), whereas CPC and ARC2 show less satisfactory results.

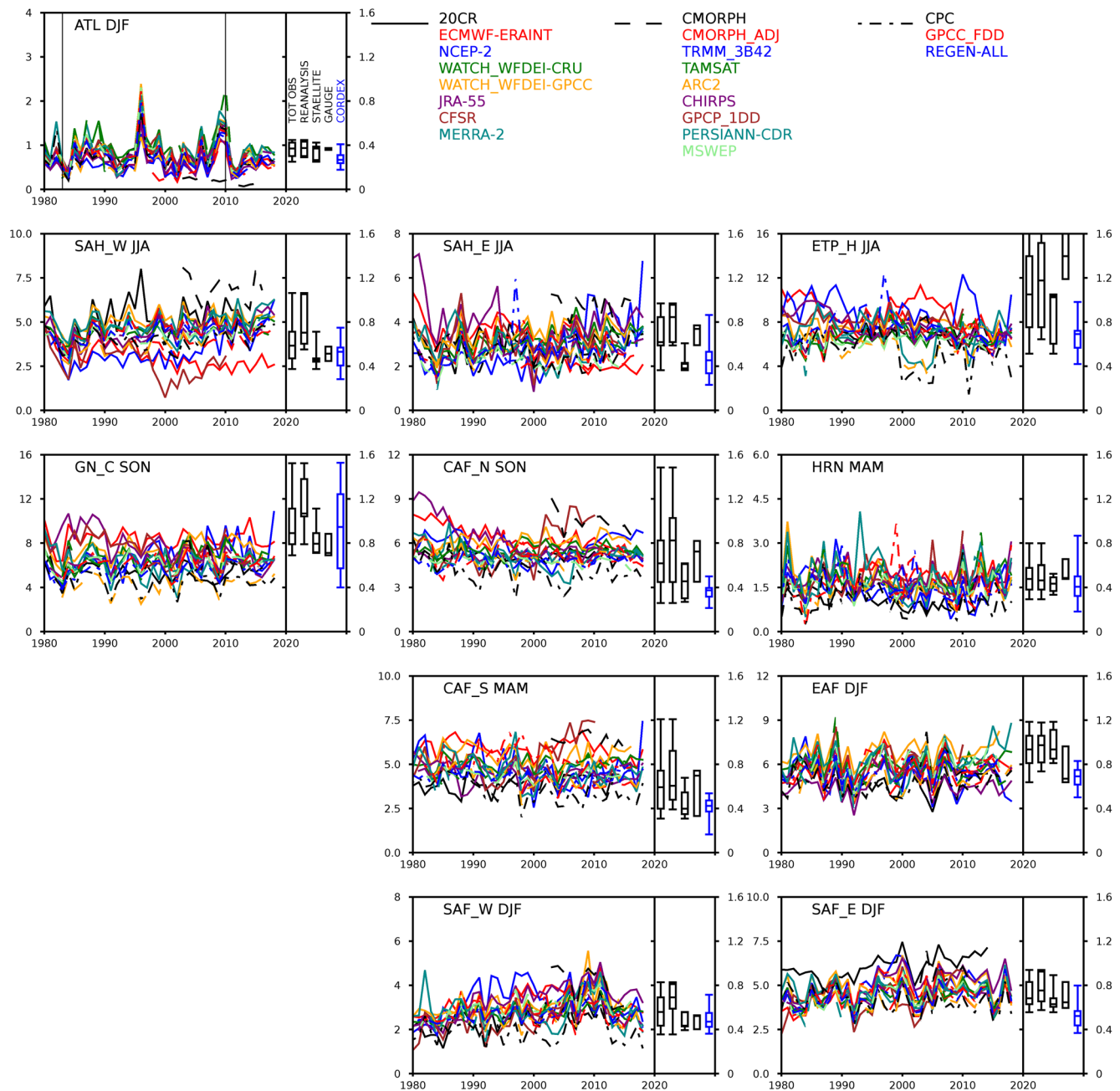


Figure 4. Yearly evolution of daily mean precipitation (units, mm/day) for the observational products spatially averaged over different sub-regions during the wet season (which depends on the region, see Figure 2). The box and whisker plots show the range of the interannual variability across different groups of observations (total, reanalyses, satellite, and gauge products). Interannual variability is defined as the standard deviation of the time (yearly) series. Interannual variability across CORDEX RCMs is also shown in blue.

Figures 6 and 7 show annual time series and interannual variability for the precipitation intensity on rainy days (SDII) and the maximum daily precipitation index (RX1day), respectively. By comparing these results with those of Figure 4, we note that differences amongst products are larger, both in the annual time series and the interannual variability, even over regions where the uncertainty in mean precipitation was relatively small (e.g., Atlas region and Southern Africa).

Larger uncertainties for indices of extreme precipitation (RX1day) are reported also by other works (e.g., Masunaga et al., 2019). In particular, Sun et al. (2018) reported that over eastern Africa satellite-based

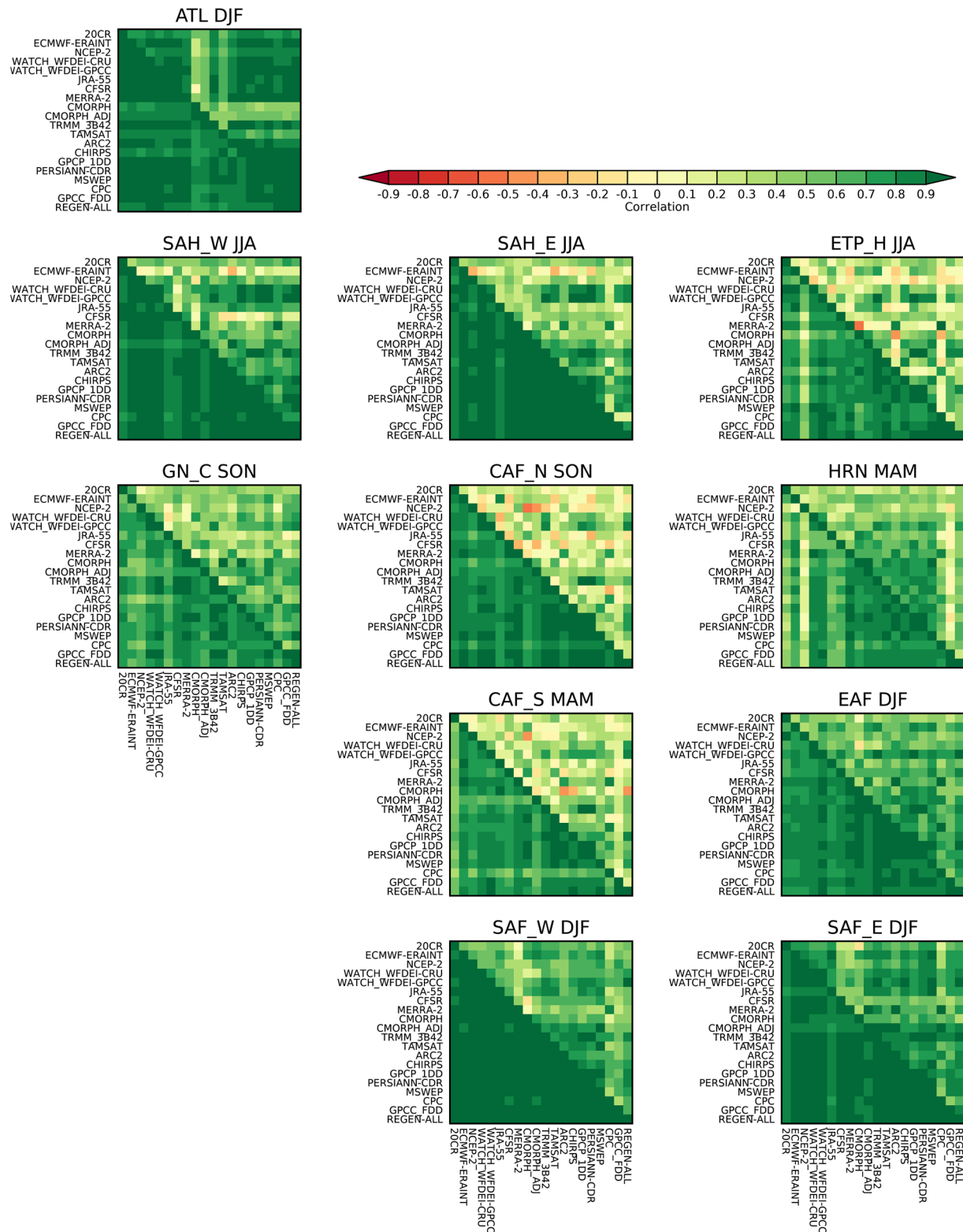


Figure 5. Correlation of seasonal mean daily precipitation across the observational products for the sub-regions. Values above the diagonal line represent the temporal correlation of the yearly time series shown in Figure 3; values below the diagonal line are the spatial correlation of the seasonal mean daily precipitation pattern (shown for instance in Figure 1 for JJA), over the sub-regions.

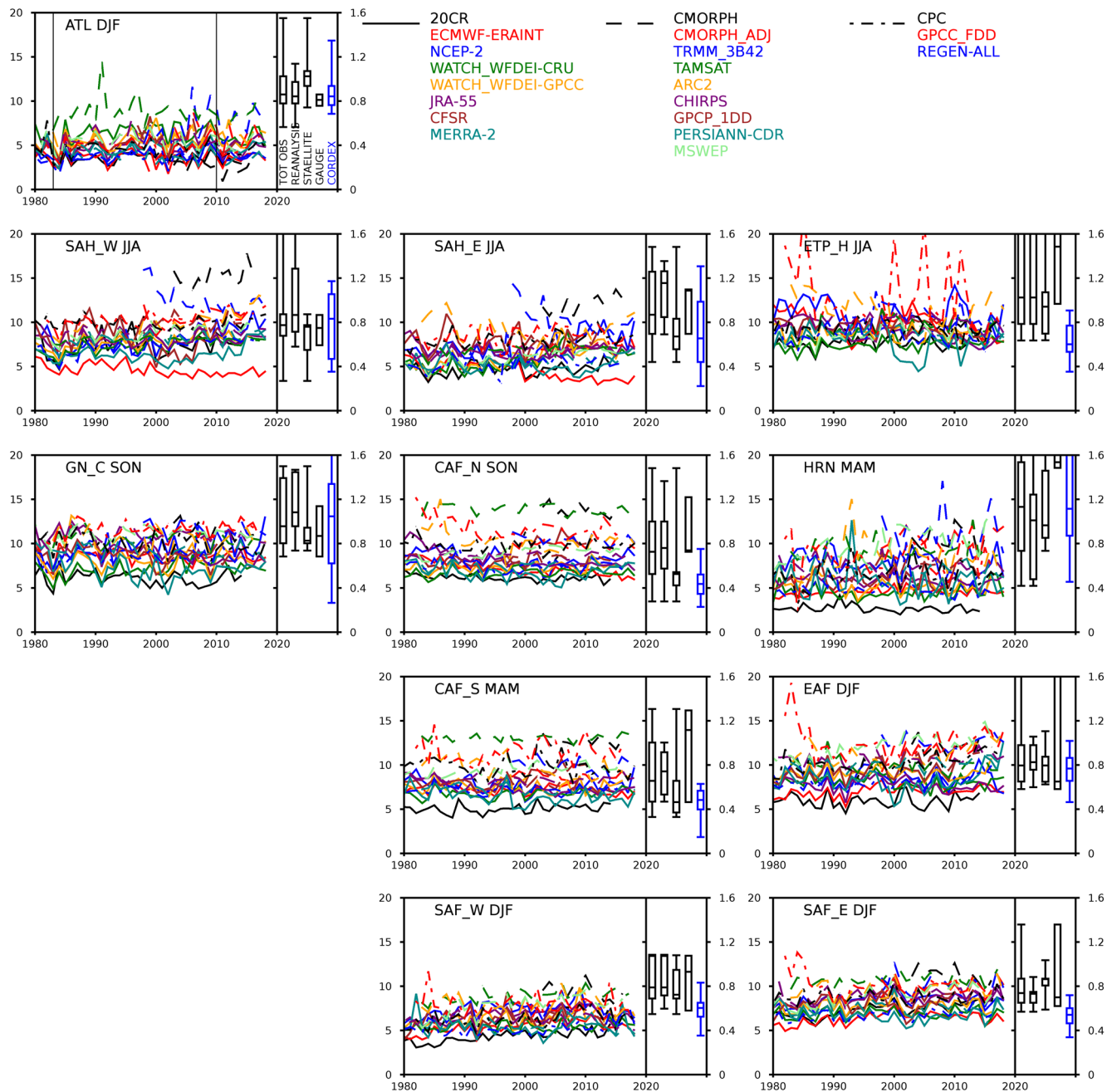


Figure 6. As Figure 3 for the simple precipitation intensity index (SDII, units mm/day), that is, the mean precipitation on wet days.

products tend to underestimate heavy precipitation amounts; Herold et al. (2017) found that the inter-product spread of daily precipitation indices such as CWD, Rx1day, and SDII becomes significant at spatial resolution finer than 1° , with TRMM_3B42 showing the highest and PERSIANN-CDR the lowest maximum values of Rx1day, respectively; Harrison et al. (2019) claim that satellite products are less accurate for precipitation intensity and indices based on short accumulation periods like Rx1day; Sow et al. (2020) claim that over the Sahel and the Gulf of Guinea, CHIRPS, TRMM, and GPCP tend to disagree on the frequency of wet days, the 95th percentile of precipitation and CWD. The representation of indices of extreme precipitation is influenced by the spatial resolution (e.g., in the reanalysis) and interpolation procedures (in gauge-based products; Sun et al., 2018) that can result in an underestimation of heavy precipitation events. Our results show indeed that inter-product uncertainty is generally very large, with 20CR (and in general

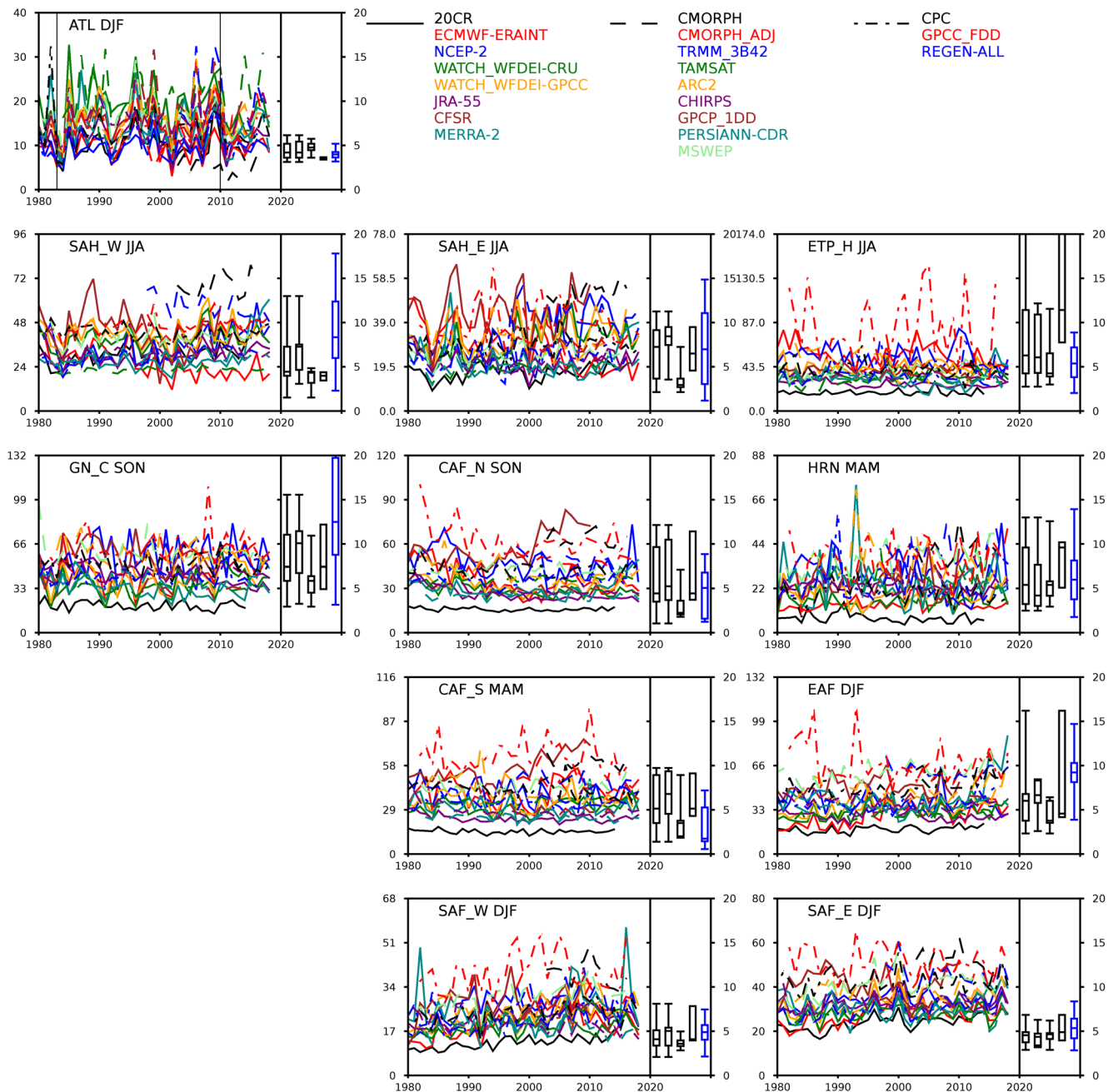


Figure 7. As Figure 3 for the maximum daily precipitation index (RX1day, units mm/day).

reanalyses) showing the lowest values of both SDII and RX1day in most regions, especially sub-Saharan Africa. Interannual variability shows the closest agreement amongst products in SAF_W for SDII and the Atlas region and Southern Africa for RX1day, where it also displays the lowest values. Over the regions affected by the monsoon (the Sahel, the coasts of the Gulf of Guinea and Central Africa), discrepancies are larger for both indices, especially between reanalyses and satellite products.

CORDEX models show heterogeneous results, with regions where interannual variability is similar, in median and spread, to that of the observations, (Atlas, SAH_E), regions where uncertainty is smaller (central and southern Africa for SDII) and regions where it is much larger (Guinea coast). However, in general, model results are not too dissimilar from the observed ones, given the large discrepancies between observational products.

To better investigate how precipitation intensity is represented by the different observational products, Figure 8 shows the frequency distribution (empirical probability distribution function) of daily precipitation intensities over the sub-regions during the wet season. Precipitation intensities are grouped into four classes, namely: light, moderate, intense, and extreme precipitation. Results show large uncertainties in the precipitation intensity distribution for most of the regions, especially for light and moderate events. For instance over GN_C in SON, the frequency of light events ranges between 20% and 55%, and that of moderate events between 15% and 60%, but results are similar over other regions. Uncertainty for intense events frequency is also large especially over central Africa (ranging from nearly 0% to 10%) the west Sahel, the Ethiopian Highlands, east Africa, and the coasts of the Gulf of Guinea.

In general, reanalysis products tend to show higher numbers of light and moderate precipitation events, compared to both satellite and gauge-based products, and a lower number of intense and extreme events, especially CR20. On the contrary, CMORPH shows the largest frequency of intense events especially over the Sahel, central and southern Africa. As explained, being a modeled quantity, precipitation in reanalysis products is greatly influenced by parameterizations such as convection: as for climate models, reanalyses tend to overestimate light precipitation events (e.g., Sun et al., 2018). On the other hand, extreme precipitation in gauge and satellite-based products is influenced by the spatial resolution and interpolation schemes.

Figure 9 shows the seasonal mean values of the various ETCCDI indices, for each sub-region, according to each observational product. First, we note that, as mentioned previously, inter-product spread is the largest for SDII, RR1, and RX1day, where the uncertainty is as large as the index mean value (and sometimes even larger) over most regions. In particular, the number of wet days (RR1) is usually overestimated, compared to the other products, by most of the reanalyses (see, e.g., GN_C and central Africa), which consequently, also overestimate the length of wet spells (CWD) and underestimate SDII. Bador et al. (2020) claim that reanalysis products show the largest spread in RX1day while in situ-based data show the smallest.

Results for other indices are more homogeneous amongst products, apart from isolated outliers, depending on the region, index, and season. It is also noteworthy that southern Africa and the Atlas region show the most consistent agreement across the products in all indices, whereas central Africa and the coasts of the gulf of Guinea show the largest discrepancies (see also, e.g., Diaconescu et al., 2015). Over the other regions, inter product uncertainty depends strongly on the index with Harrison et al. (2019) noting that satellite products perform less accurately for CDD, SDII, and RX1day, and gauge networks are affected by large inconsistencies in spatial and temporal densities, as only 15% of sub-Saharan Africa in REGEN is covered by long-term quality data.

CORDEX results are remarkably similar to the observations, when the two ensembles are compared, in both median and interquartile range (which sometimes is even smaller than the observational one), apart from very few exceptions, such as RX1day over the coasts of the Gulf of Guinea and the Sahel region, where the CORDEX uncertainty range is much larger than the observational one. Recently, Onyutha (2020) compared extreme precipitation indices from the large CORDEX-Africa RCM ensemble to those from gauge stations over nine locations in the region around Lake Victoria. They found that the RCM ensemble mean biases in long-term mean indices were smaller than those for trends and that wet spells were simulated better than dry ones. Here, we found that a similarly large ensemble of observations shows the same limitations, with the uncertainty in wet spell duration especially large, particularly due to the spread amongst reanalyses. On the other hand, RCMs show much more consistent results for CWD, and are closer to the values from satellite and gauge-based products.

A more quantitative analysis of the results presented in Figure 9 can be useful to highlight the differences between classes of products. Table 4 reports, for each region, the minimum, mean and maximum value of the ETCCDI indices for the three product classes (reanalysis, satellite, and gauge) separately. Although results are usually consistent across products in terms of both mean and range, in some cases they are clearly dependent on the class of observational products; for instance, over the West Sahel in JJA, SDII ranges between 4.7 and 8.1 mm/day for the reanalysis, but between 8.0 and 15 mm/day (9.1–10.3) for the satellite (gauge) products. This means that all reanalyses underestimate SDII compared to all the other data sets (gauge and satellite). On the other hand, over the coasts of the Gulf of Guinea in SON, the reanalyses show values of CWD larger than any other satellite and gauge products. Over EAF in DJF, most of the reanalyses

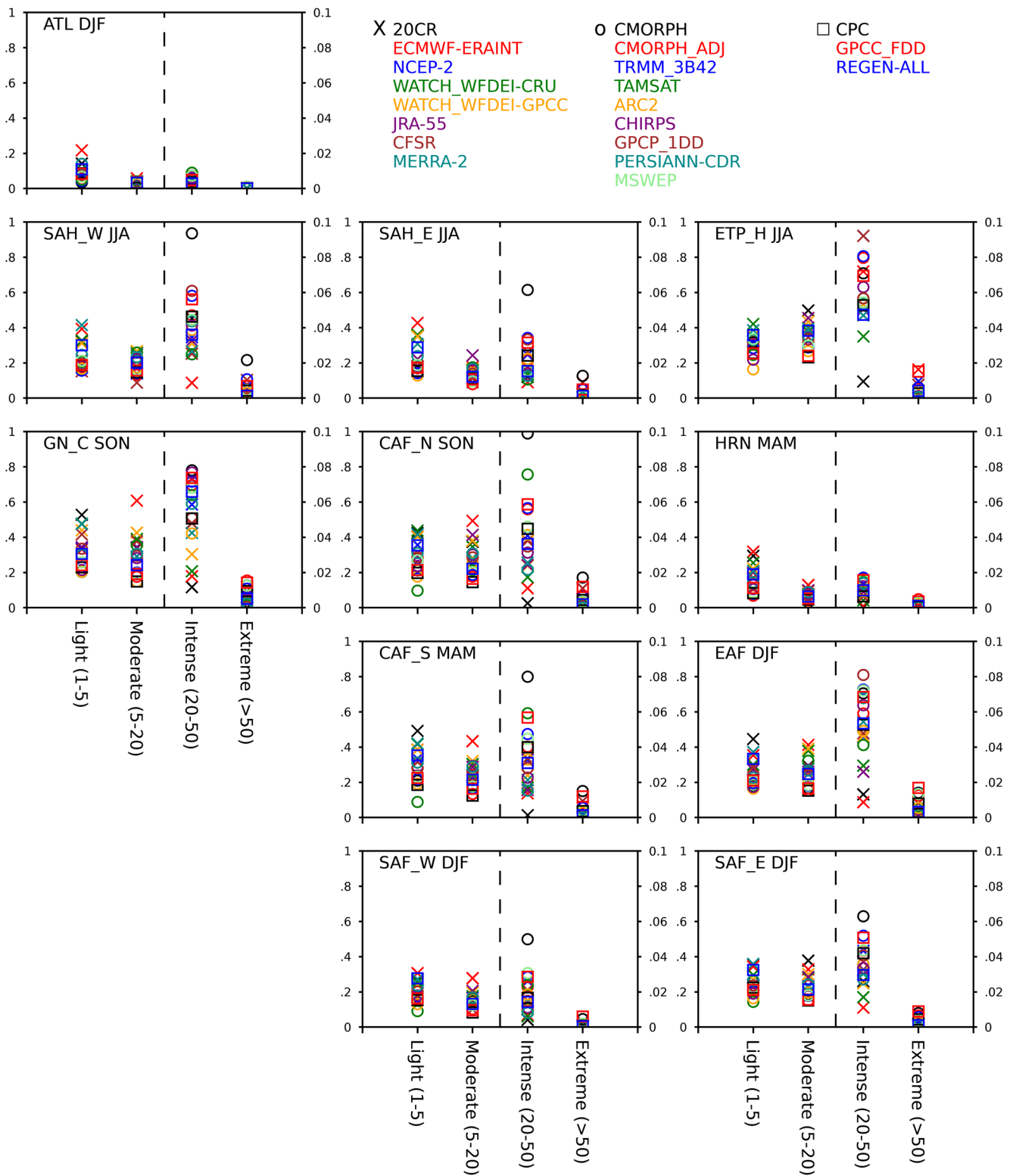


Figure 8. Empirical probability distribution function (frequency distribution) of daily precipitation intensities over the subregions during the season of maximum precipitation. For clarity, intensities are grouped in four classes, namely: Light (up to 5 mm/day), Moderate (5–20 mm/day), Intense (20–50 mm/day), and Extreme precipitation (>50 mm/day). Note that the values for the Intense and Extreme precipitation classes range between 0 and 0.1.

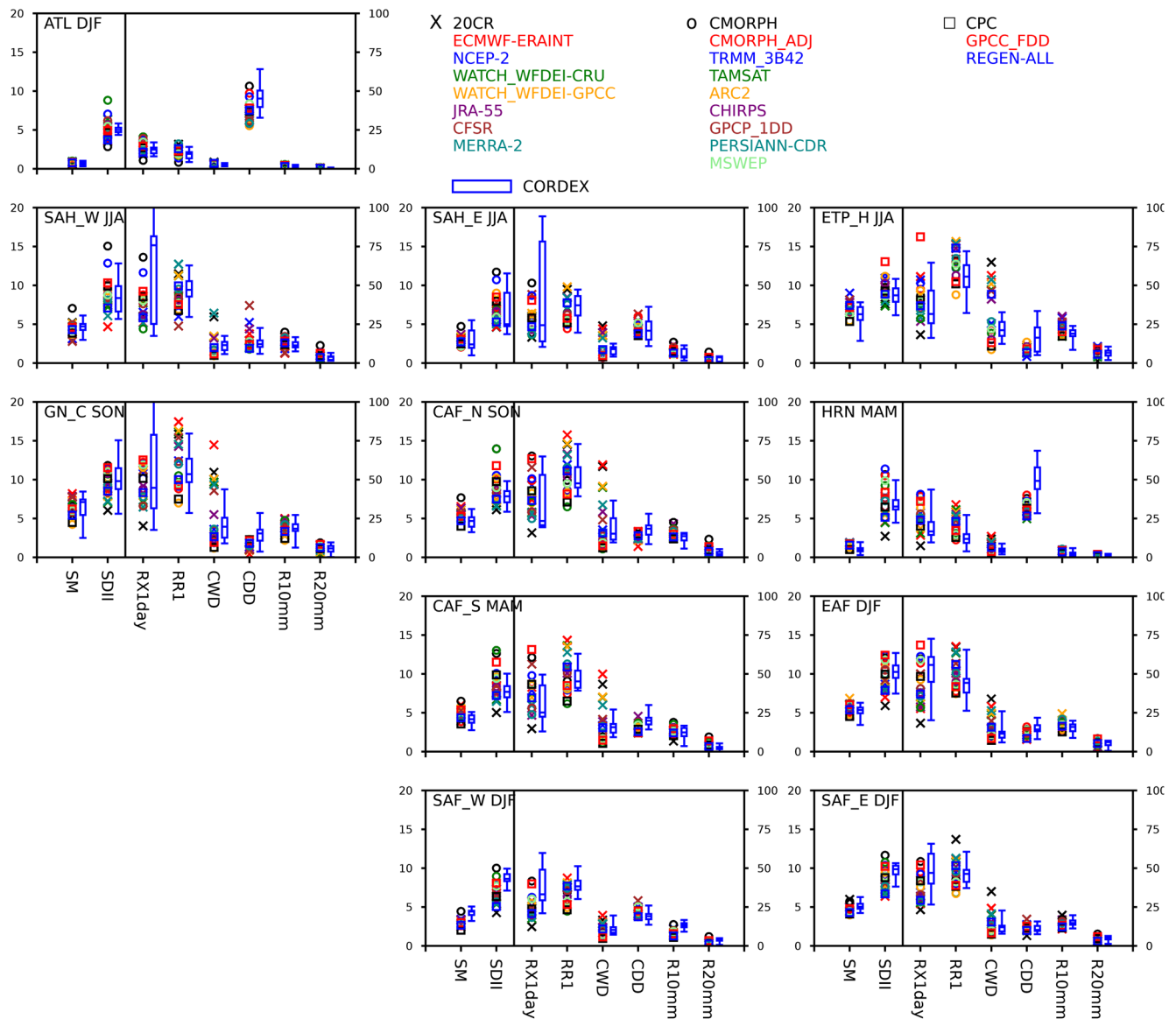


Figure 9. Mean seasonal values of ETCCDI indices over the sub-regions during wet seasons. The vertical lines separate the indices according to the plotting scale: SM and SDII range between 0 and 20 mm/day, whereas all other indices range between 0 and 100 (units depend on the index). The blue box-and-whiskers plot shows CORDEX RCMs results for comparison. Results show mean values over the 1983–2010 period for all products except CMORPH, CMORPH_ADJ, TRMM_3B42, and GPCP_1DD which have a shorter time span (see Table 1).

show smaller values than gauge and satellite products for SDII, RR1, CWD, and R20 mm, whereas over SAF_E in DJF they show larger values of CWD. These results highlight the need for model evaluation to be carried out by means of different classes of data sets, and can be useful to product providers and the research community for further investigating the reasons for such discrepancies.

Figure 10 shows the least-squares linear trends of annual series of seasonal mean ETCCDI indices between 1983 and 2010 (for all observations but CMORPH, CMORPH_ADJ, TRMM_3B42, and GPCP_1DD). We note that Southern Africa (both SAF_E and SAF_W) is the only region where nearly all data sets show a consistent, statistically significant (at 5%) increase in (DJF) frequency and intensity of mean and extreme precipitation, consistent with the results of Maidment et al. (2015) and Harrison et al. (2019), accompanied by an increase in wet spell (CWD) and a reduction in the dry spell (CDD) durations.

Table 4

Range of Precipitation Indices Over the Subregions During the Season of Maximum Precipitation, Grouped According to Observational Product Classes

	SM mm/day	SDII mm/day	RX1day mm/day	RR1 days/season	CWD days/ season	CDD days/ season	R10 mm days/ season	R20 mm days/season
ATL DJF	(R) 0.6-0.8-1.0	3.5-4.7-6.4	9.5-13.4-19.0	9.7-12.3-15.8	2.7-3.4-4.3	31.1-36.3-38.8	0.9-1.7-2.6	0.1-0.4-0.7
	(S) 0.2-0.7-1.0	2.8-5.6-8.8	5.4-15.5-20.6	4.2-9.2-16.0	1.6-2.5-3.6	27.7-37.5-53.2	0.2-1.7-2.7	0.0-0.6-0.9
	(G) 0.7-0.8-0.8	3.7-4.4-4.9	10.8-13.0-14.7	11.0-11.8-12.9	3.0-3.3-3.6	37.1-38.0-39.2	1.5-1.7-2.0	0.3-0.4-0.5
SAH_W JJA	2.8-4.1-5.2	4.7-7.1-8.1	25.7-33.5-43.1	23.8-47.2-63.6	7.4-18.0-32.1	9.5-18.5-37.0	6.2-11.8-16.7	1.0-3.1- 4.7
	3.7-4.6-7.0	8.0-10.1-15.1	22.0-41.3-68.1	32.8-39.3-47.6	4.7-6.3-8.5	8.9-11.3-14.4	11.2-14.6-19.9	2.7-5.5-11.3
	3.9-4.3-4.6	7.1-9.1-10.3	29.1-39.3-46.2	33.8-40.3-49.6	4.9-7.0-10.0	9.4-11.1-12.1	11.9-13.0-14.1	3.8-4.9-6.2
SAH_E JJA	2.4-3.1-3.7	4.6-5.9-7.8	16.7-28.1-44.1	25.9-41.5-49.1	5.6-16.2-24.0	19.1-23.7-31.6	5.6-7.3-11.6	1.1-1.8-3.3
	2.1-2.9-4.7	5.6-8.0-11.7	18.2-29.8-51.5	22.1-29.5-37.5	3.5-5.1-7.7	18.3-22.9-30.0	5.8-8.5-13.5	1.1-2.7-7.1
	2.5-2.8-3.1	5.3-7.2-8.5	23.3-31.0-40.5	25.9-31.2-38.8	4.0-5.8-8.6	17.6-18.8-20.1	6.5-7.5-8.6	1.7-2.6-3.7
GN_C SON	5.4-6.9-8.2	6.1-8.1-9.6	20.2-40.6-56.3	62.1-76.5-87.2	18.1-45.2-72.4	2.1-5.4-9.3	14.0-19.6-25.0	1.3-4.3-8.1
	4.2- 6.0- 6.8	8.3-10.6-11.8	33.0-49.8-61.2	34.9-49.4-61.6	5.9-11.9-18.2	6.7-9.5-11.6	10.9-18.5-23.8	4.7-7.1-9.4
	4.5-5.4-6.2	8.5-10.1-11.5	41.7-51.8-62.7	37.5-44.7-50.1	6.5-9.8-13.3	8.9-10.3-11.3	12.3-15.5-17.6	5.7-6.8-8.4
ETP_H JJA	6.4-7.7-9.0	7.4-8.9-10.9	18.3-38.0-55.6	66.9-74.9-78.2	25.5-48.2-64.9	4.2-7.4-11.5	17.2-25.0-30.1	1.3-6.4-10.7
	5.4-6.7-7.5	8.6-9.8-11.2	28.5-40.2-51.4	44.0-61.2-67.4	8.7-19.1-26.7	7.1-9.1-13.5	18.2-22.8-24.5	5.6-7.1-9.3
	5.4-6.6-7.4	8.9-1	36.9-52.9-81.2	51.0-59.2-74.1	10.9-22.8-44.2	6.8-8.3-9.2	17.3-20.5-24.0	5.7-6.7-8.6
HRN MAM	1.1-1.7-1.9	2.7-5.3-7.9	7.5-19.8-28.7	16.0-27.1-33.9	5.2-9.7-13.6	24.8-29.4-33.8	0.5-3.3-4.8	0.0-0.7-1.4
	1.3-1.6-1.8	7.3-9.2-11.4	23.5-32.4-40.6	11.2-15.5-22.1	3.3-4.4-6.7	28.3-33.3-40.1	3.1-4.3-5.3	1.1-1.6-1.9
	1.0-1.4-1.7	5.2-6.7-8.4	20.1-26.7-36.1	12.8-17.7-23.1	2.8-4.3-6.4	26.7-29.6-31.6	2.6-3.5-4.4	0.7-1.2-1.9
CAF_N SON	5.0-5.7-6.5	6.1-7.4-8.7	15.8-34.1-57.9	55.5-68.2-78.8	17.6-39.2-59.5	7.0-11.6-16.7	12.1-15.1-21.6	0.3-2.7-4.8
	4.8-5.3-7.7	7.6-10.2-14.0	24.9-40.9-65.2	32.5-46.9-57.8	5.4-10.0-16.1	11.8-13.8-16.7	14.5-17.0-22.5	2.4-5.6-11.7
	4.0-4.7-5.3	7.5- 9.7-11.8	36.5-47.6-63.4	35.6-44.0-55.6	6.1-9.7-15.7	13.9-15.2-16.7	11.8-13.2-14.7	3.8-5.2-6.9
CAF_S MAM	3.9-4.9-6.0	5.0-7.1-8.5	14.7-33.8-56.4	50.5-62.3-71.6	16.9-31.2-49.8	11.9-14.3-22.8	6.8-12.1-14.0	0.2-2.3-4.3
	3.8-4.6-6.5	7.3-9.7-13.0	23.9-39.4-60.6	30.8-43.7-56.4	5.6- 9.4-16.1	12.8-15.8-18.7	10.7-14.7-18.9	1.8-4.6-9.5
	3.6-4.4-5.4	7.2-9.5-11.5	34.6-47.8-65.7	32.5-43.2-54.4	5.2- 9.3-15.4	12.0-13.1-14.4	10.3-12.4-14.8	3.3-4.9-6.9
SAF_W DJF	2.5-3.0-3.4	4.3-5.9-7.3	12.4-21.6-28.7	26.7-37.4-43.7	8.4-13.9-19.7	19.1-22.2-29.1	5.9-8.1-11.1	0.5-1.5-3.0
	2.6-3.0-4.4	5.7-7.6-10.0	18.3-27.1-41.7	22.3-30.3-37.0	5.2-7.5-10.6	18.7-21.5-25.2	7.4-9.4-13.8	1.0-2.6-6.0
	2.0-2.5-3.0	5.1-6.5-8.1	20.9-	23.2-29.4-38.4	4.8-7.1-10.9	18.7-21.2-22.6	5.4-6.5-7.8	1.3-2.2-3.4
SAF_E DJF	4.3-4.8-6.0	6.4-7.5-8.6	23.3-31.2-42.5	40.7-53.5-68.6	13.9-20.6-35.0	6.6-11.0-17.2	10.9-14.5-19.8	1.2-3.1-4.8
	4.0-4.5-5.7	7.7-9.6-11.7	28.2-38.7-54.3	33.7-40.6-47.9	7.0- 9.4-13.1	11.0-12.3-13.0	12.0-14.2-17.3	3.0-4.6-7.6
	4.1-4.4-4.8	6.7-8.6-10.2	29.3-41.1-52.0	38.3-43.0-51.6	7.5-10.4-15.4	9.9-11.4-12.7	11.6-12.4-13.4	3.1-4.5-5.9
EAF DJF	4.6-5.7-6.9	5.9-8.0- 9.2	18.3-33.5-50.0	50.5-60.7-67.7	14.7-23.4-33.9	7.8-9.7-12.3	12.8-17.6-24.4	1.0-3.7-5.6
	4.8-5.7- 6.2	10.0-11.0-12.4	28.3-47.3-61.3	37.3-43.7-50.6	8.7-11.1-15.2	10.5-13.1-16.0	14.0-17.9-20.8	4.1-6.9-8.4
	4.5-5.3-6.0	7.9-10.1-12.4	37.0-51.4-68.7	37.7-45.2-56.1	7.2-10.5-15.8	8.6-11.4-13.0	12.7-15.1-16.3	5.2-6.3-8.1

Note. In each cell, numbers represent the minimum, mean and maximum values (min-mean-max) of the index for the reanalysis (R, first row), satellite (S, second row), and gauge products (G, third row). Bold values represent cases where discrepancies across products are substantial. Cases where a single class is clearly different from the others (if its range does not overlap that of one of the others) are highlighted in italic.

The precipitation recovery and intensification over the Sahel are also broadly consistent amongst all data sets (except ERAINT, which shows negative trends in nearly all indices, in contrast with most of the other products) as documented by several studies (see, e.g., Maidment et al., 2015; Odoulami & Akinsanola, 2018).

A general decline in MAM precipitation is also visible over the Horn of Africa broadly consistent with the results by Sun et al. (2018) and Maidment et al. (2015), although the trend is not always significant, in agreement with Gebrechorkos et al. (2019) who reported that over 1981–2016 the decrease in precipitation

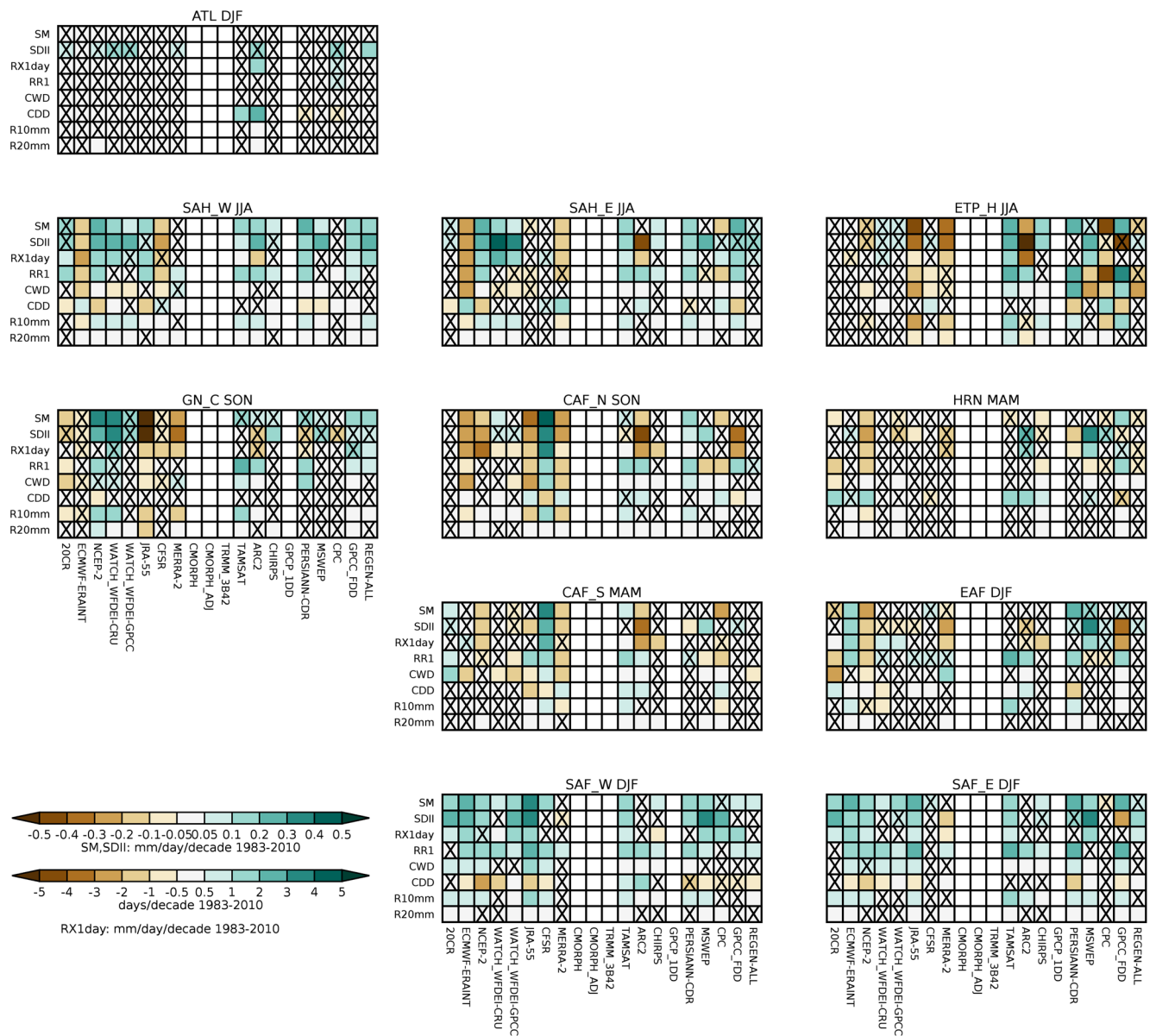


Figure 10. Trends over the period 1983–2010 of ETCCDI indices for each sub-region (during the respective wet season) and product. Crosses indicate non-significant trends (at 5% level). CMORPH, CMORPH_ADJ, TRMM_3B42, and GPCP_1DD are not shown because their periods of available data do not cover entirely 1983–2010.

over the eastern parts of Ethiopia and Kenya is mostly non-significant except for some small areas, and it is accompanied by a (non-significant) increase over the western parts.

Over the other regions, results are more heterogeneous. In general, results amongst reanalysis products vary greatly; for instance, over GN_C JRA-55 shows a significant large decrease in all precipitation indices. Over Central Africa, large discrepancies amongst data sets exist, with products often showing opposite trends, as noted also by Maidment et al. (2015). In particular, Hua et al. (2019) highlighted that discrepancies amongst reanalysis products over central Africa can be explained by differences in the lower-tropospheric and middle-tropospheric circulation. Satellite and gauge-based products show more uniform results; however, ARC-2 and CPC are the only products showing statistically significant negative trends over CAF_S and, especially, ETP_H. As discussed earlier, spurious trends can result from temporal inconsistencies such as the large precipitation anomaly between 2000 and 2005 in some data sets (Harrison et al., 2019; Maidment et al., 2015). Also, the interpolation methods to produce gridded data sets over areas scarcely covered

by gauge stations can affect long-term trends especially of extreme indices (Sun et al., 2018). Unrealistic, amplified SDII trends are reported also by Harrison et al. (2019) for ARC2, whereas discrepancies between REGEN and GPCC_FDD may be related to low-quality gauge data over East Africa and Ethiopia.

Finally, it must be noted that trends sign and statistical significance are strictly related to the period considered. For instance, Nicholson et al. (2018) documented that the period between the 1980s and the early 21st century witnessed a continent-wide, prolonged period of arid conditions, compared to the last century and a half, with changes in the seasonality of rainfall over large parts of Africa. Over Southern Africa, Kruger and Nxumalo (2017) and New et al. (2006) showed that decadal variability can be large and, hence, trends calculated on longer (or different) periods can be significantly different.

4. Summary and Concluding Remarks

For a continent, such as Africa, so profoundly affected by rainfall variability, the analysis of precipitation characteristics is of paramount importance. Many different observational products have become available in the last decade that allows us to investigate recent past precipitation at a range of spatial and temporal scales.

Rain gauges measure precipitation directly, but the spatial density of gauge networks is very heterogeneous, with large areas over Africa scarcely covered, and the number of gauge stations declined significantly in the last decades (e.g., Maidment et al., 2015; Sun et al., 2018). In addition, the quality of gauge-based products is affected by many factors including measuring errors, changes in the temporal and spatial density of the stations, and the interpolation algorithm used to generate the gridded data set, which can impact especially the estimate of precipitation extremes (Bador et al., 2020).

Satellite products can overcome some of the limitations of the gauge-based products as they can cover regions with low gauge density, and provide precipitation data at very high spatial and temporal resolution. However, the satellite estimates are not direct but rely on retrieval algorithms, and the quality of the product depends also on the technology used (e.g., microwave vs. infrared; Herold et al., 2017). As noted by Gehne et al. (2016) satellite estimates perform reasonably well in regions and seasons mostly affected by convective precipitation (such as the tropics), although, for instance, they are less reliable in areas characterized by complex topography or high spatio-temporal variability (Sun et al., 2018).

Finally, reanalyses rely on weather forecast models to produce precipitation estimates from assimilated observed meteorological fields. As such, their quality is strictly linked to that of the underlying model (including parameterizations such as convection) and, generally, they tend to overestimate light precipitation events (e.g., Sun et al., 2018).

When the different observational products are compared over Africa, we note that performances vary greatly according to the region and index. Even for seasonal mean precipitation, the spatial distribution varies considerably amongst reanalysis products, especially over areas where gauge networks are generally sparse. Large uncertainties in the annual precipitation cycle are visible in particular over the Ethiopian Highlands, the eastern Sahel, the coasts of the Gulf of Guinea, and the Horn of Africa. Interannual variability shows large differences especially amongst reanalysis data sets (e.g., over CAF_S, CAF_N, and GN_C) whereas satellite and gauge-based products usually show more consistent results. However, over SAH_E, CAF_N, and ETP_H, the satellite and gauge-based products show values of interannual variability that significantly differ between them. Spatial correlation across products is usually high especially over Southern Africa and the Atlas region, whereas lower values are found over central Africa and the Horn of Africa, especially for the reanalyses.

In general, Southern Africa and the Atlas region show the largest agreement amongst different products (a part from CMORPH over ATL) for most of the precipitation characteristics, including annual time series and trends, spatial and temporal correlations and indices of mean and extreme events, although unrealistic, amplified trends in some products (ARC2 and CPC) are reported by Harrison et al. (2019) over Southern Africa for mean precipitation, frequency, and intensity.

Over other regions, discrepancies amongst different products (or different classes of products) are greater, especially for indices of extreme events or those based on short time scales. In particular, the reanalysis products tend to overestimate the number of wet days and the length of wet spells over the coasts of the Gulf of Guinea and central Africa, and consequently, underestimate SDII. The representation of indices of extreme precipitation is also influenced by the spatial resolution of the product (Herold et al., 2017) and interpolation procedures (in gauge-based products; Sun et al., 2018) that can result in an underestimation of heavy precipitation events. In particular, over the regions affected by the monsoon (the Sahel, the coasts of the Gulf of Guinea and Central Africa), discrepancies are large for both mean and extreme precipitation intensity (SDII and RX1day), especially between reanalyses and satellite products.

Observational products are often a combination of different data sources (e.g. satellite and gauge), sometimes incorporating the same underlying data set (e.g., Gehne et al., 2016); this procedure reduces the errors and increases correlation between different products but, at the same time, makes them not independent. Although assessing the effect of this interdependence across different products on the precipitation indices would be of great value, defining a quantitative approach that would allow selecting or weighting ensemble members is not straightforward. For climate models, for instance, Dosio et al. (2019) showed that RCMs projections over Africa are often robust (or non-significant) regardless of the choice of the specific RCMs or GCMs (i.e., if results were weighted according to the RCM or the GCM). Where the results are uncertain, however, they showed that a simple subsampling based on average according to the RCM and/or the GCM is not able to significantly reduce the uncertainty.

The observed precipitation characteristics have been compared to the results of state-of-the-art RCMs. To the best of our knowledge, this is the first time that such a large ensemble of observational products is compared to model results. Given the impossibility to select a single “best” observation data set (or even a single class of products) for a realistic representation of all precipitation characteristics, from seasonal mean climatology to maximum daily precipitation, dry and wet spell durations, over a vast and climatologically complex region such as Africa (see also e.g., Beck et al., 2017), our results show that a large ensemble of RCMs is able to reproduce these characteristics as well (or, one could say, as badly) as the observations. In particular, results for seasonal mean values of various ETCCDI indices are remarkably similar between the two ensembles over most of the regions, with very few exceptions.

Our findings indicate that comparing model results to a very limited set of observations (or in the extreme case a single observational data set) is not only pointless, but it can be even misleading, in line with other previous works (e.g., Alexander et al., 2020; Bador et al., 2020). Although it is possible to isolate very few cases where models deficiencies are evident, that is, models results are substantially different than most, if not all, observations (e.g. CDD over HRN), in the large majority of cases it is not possible to attempt reducing the biases in the model outcomes when the uncertainty in the observed diagnostic is as large as (if not worse than) the modeled one, at least for precipitation.

Given these large uncertainties and discrepancies in both observed and modeled indices, it can be questioned whether precipitation is indeed an adequate metric for model evaluation (e.g., Tapiador et al., 2019). Similarly to Pendergrass et al. (2020) we argue that evaluating model performances would greatly benefit from the use of process-oriented, regime-oriented, and use-inspired metrics. For instance, process-based model evaluation, that is, the analysis of the underlying drivers and physical processes (e.g., Pinto et al., 2018; Tamoffo et al., 2019, 2021) is a promising approach, but such evaluation relies on reanalysis data sets as reference (given the need of three-dimensional fields of several variables), whose performances over tropical Africa are largely dependent on their representation of the hydrological cycle (Hua et al., 2019).

Finally, given the political and societal relevance of impact assessment studies, there is an increasing demand for bias-adjusted model outputs to be used as input for process-based impact models (e.g., floods). As the reliability of any projection based on bias-adjusted results depends on the observational data set used as reference (Dosio, 2016), the choice of the reference data set may have a substantial effect on the modeled climate change, and, therefore, it needs to be taken into account. This aspect is left for future research.

Data Availability Statement

Observational data used in this study are publicly available through the references listed in Table 1.

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