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Assessing current and future trends of climate extremes across Brazil based on reanalyses and earth system model projections

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Abstract
Brazil experiences extreme weather and climate events that cause numerous economic and social losses, and according to climate change projections, these events will increase in intensity and frequency over this century.This study adds to the body of research on Brazil's climate change by analyzing the historical patterns and projected changes in temperature and precipitation extremes across Brazil using the World Climate Research Program's Expert Team on Climate Change Detection and Indices framework. This novel approach analyzes climate extreme events over the past four decades (1980–2016) using multiple gridded observation and reanalysis datasets. Furthermore, future changes in climate extremes are analyzed from 20 downscaled Earth System Models (ESMs) at high horizontal resolution (0.25° of latitude/longitude), under two representative concentration pathway scenarios (RCP4.5 and RCP8.5). Projected changes in the extreme indices are analyzed over mid-twenty-first century (2046–2065) and end-of-twenty-first century (2081–2100) relative to the reference period 1986–2005. Results show consistent warming patterns with increasing (decreasing) trends in warm (cold) extremes in the historical datasets. A similar but more intense warm pattern is projected in the mid and end of the twenty-first century. For precipitation indices, observations show an increase in consecutive dry days and a reduction of consecutive wet days over almost all Brazil. The frequency and intensity of extremely wet days over Brazil are expected to increase according to future scenarios. Designing effective adaptation and mitigation measures in response to changes in climate extremes events depends on this improved understanding of how conditions have and are likely to change in the future at regional scales.

Keywords Climate trends · CMIP5 models · Downscaling · ETCCDI · Hydrological basins · Scenarios

1 Introduction

Previous studies have shown how global temperatures have increased, leading to changes in atmospheric patterns that intensify and increase the frequency of extreme precipitation and heat waves (Zhang et al. 2007; IPCC 2018; Giorgi et al. 2019). Moreover, Earth System Models (ESMs) project a continued upward trend in extreme temperature and precipitation events over the majority of land regions throughout the twenty-first century (Sillmann et al. 2013; Donat et al. 2016; Marelle et al. 2018; Bador et al. 2018; Mora et al. 2018).

Natural hazards such as floods, landslides, and droughts caused damage on the order of the R$182.7 billion (about US $56.0 billion) in Brazil between 1995 and 2014 (CEPED-UFSC 2016). Climate projections reveal increasing mean temperatures and decreasing precipitation, suggesting more frequent/intense episodes of droughts over northern and northeastern Brazil, with a large increase in the length of the most prolonged period of consecutive dry days (Sillmann et al. 2013; Marengo et al. 2017; Betts et al. 2018). In addition, Debortoli et al. (2017) indicate that Brazil has many regions that are highly vulnerable to natural disasters including flash flooding and landslides. Moreover, Almagro et al. (2017) reveals that future projections show an increase

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in rainfall-induced erosion potential across the southern regions, which can affect agricultural production in this area.

In Brazil, studies of climate extremes developed over the last few decades (e.g., the 1990s and 2000s) have encountered some limitations in both evaluating observations and validating climate models, mainly due to the lack of reliable and continuous to meteorological data (e.g., Marengo et al. 2009; Rusticucci et al. 2010). Presently, many researchers have used weather stations in specific areas to investigate climate extremes in present climate and found an increase of extreme temperature and precipitation events in the recent past (Dufek and Ambrizzi 2008; Skansi et al. 2013; Silva Dias et al. 2013; Carvalho et al. 2014; Oliveira et al. 2014, 2017; Rosso et al. 2015; Ávila et al. 2016; Zilli et al. 2017; Murara et al. 2018; Bezerra et al. 2019; Xavier et al. 2020). Studies using climate model projections indicate additional increases in future climate extremes over South America, although ESMs with coarser resolutions (100–300 km) are not appropriate for climate change studies at local/regional scales (Marengo et al. 2009; Dereczynski et al. 2013; Sillmann et al. 2013; Silva et al. 2014; Valverde and Marengo 2014; Natividade et al. 2017; Nguyen et al. 2017). In addition, Lyra et al. (2018) used climate projections from an Eta regional model at 5-km horizontal resolution and found that maximum temperatures are projected to increase by 9 °C in three metropolitan regions of southeast Brazil, where the annual precipitation could decrease by approximately 40–50% by the end of the century in the RCP8.5 scenario relative to 1961–1990 period.

A more detailed study about historical and future climate extreme variability on local/regional scales using the most recent high resolution climate datasets over Brazil has not yet been carried out. Hence, the following is a comprehensive evaluation using new sources (e.g., reanalysis and downscaled climate projections) that provide relevant information for climate processes and natural hazards monitoring. In order to expand previous work and improve our understanding of climate extremes events in Brazil, historical (1980–2016) and projected (2046–2100) changes in temperature and precipitation extremes are analyzed using the guidance defined by the Expert Team on Climate Change Detection and Indices (ETCCDI). To characterize the historical climate, datasets comprised of observations, reanalysis, and other merged products from 1980 to 2016 are used. Observational uncertainty is also analyzed. Furthermore, we evaluate the future climate changes using the National Aeronautics Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) for the period 1950–2005 (historical simulations) and 2006–2100 (climate projections). Section 2 describes the climate indices, data, and methods used in this investigation. Section 3 depicts observations and performance evaluations, historical trends, and future changes based on RCP4.5 and 8.5 scenarios. Finally, Sect. 4 provides a summary of the main results and discussion concerning how changes to extreme climate indices impact various aspects of the Brazilian population.

2 Data and methodology

2.1 Extreme climate indices

Sixteen extreme climate indices defined by ETCCDI (Zhang et al. 2004; Zhang et al. 2011; https://etccdi.pacificclimate.org/list_27_indices.shtml) were selected for this study, eight each related to daily air temperature and rainfall (Table 1). Selected extreme temperature indices comprise absolute (associated with the maximum (TX) or minimum (TN) magnitudes within a year) and percentile-based indices (related to the frequency of hot or cold extreme events). Absolute indices include hottest day (TXx), coldest night (TNn), and diurnal temperature range (DTR). Percentile-based indices include cold nights (TN10p), warm nights (TN90p), cold days (TX10p), and warm days (TX90p) indices. Additionally, warm spell duration index (WSDI) describing the annual count of days with at least 6 consecutive days when the maximum temperature is above the 90th percentile was calculated.

The eight precipitation-related extreme indices characterize intensity, frequency, and duration of precipitation (PR) events. The total wet-day precipitation (PRCPTOT), maximum 1-day precipitation (RX1day), maximum 5-day precipitation (RX5day), very wet days (R95p), and simple daily intensity (SDII) are used to characterize the intensity of rainfall events. The number of very heavy precipitation days (R20mm) expresses the frequency of extreme precipitation. Finally, consecutive dry days (CDD) and consecutive wet days (CWD) describe persistent drier and wetter conditions, respectively.

The selected climate indices have been calculated on an annual scale to improve knowledge and understanding of inter-annual extreme temperature and precipitation variability in Brazil. Furthermore, the indices chosen were based on their relevance to the study area and ability to compare with evaluations in different parts of the world (Sillmann et al. 2013; Skansi et al. 2013; Alexander 2016; Alexander and Arblaster 2017; Giorgi et al. 2019; Avila et al. 2019; Loaiza et al. 2020). Several studies have used ETCCDI indices to validate reanalyses and ESMs in simulating observed climate extremes (Dufek and Ambrizzi 2008; Zhou et al. 2014; Nguyen et al. 2017; de Lima and Alcântara 2019; Ongoma et al. 2019; Dosio et al. 2019). Similar to Aerenson et al. (2018), we do not include a seasonal evaluation of ETCCDI extreme climate indices here as many of the indices are more meaningful on an annual scale.

Table 1 Extreme climate indices employed in this study as recommended by ETCCDI

Index—Indicator name	Description[a]	Unit
1. TXx—hottest day	Annual maximum value of daily maximum temperature	ºC
2. TNn—coldest night	Annual minimum value of daily minimum temperature	ºC
3. DTR – Diurnal temperature range	Annual mean difference between daily max and min temperature	ºC
4 TN10p—cold nights	Percentage of days when TN < 10th percentile	%
5. TN90p—warm nights	Percentage of days when TN > 90th percentile	%
6. TX10p—cold days	Percentage of days when TX < 10th percentile	%
7. TX90p—warm days	Percentage of days when TX > 90th percentile	%
8. WSDI—warm spell duration indicator	Annual count of days with at least 6 consecutive days when TX > 90th percentile	Days
9. PRCPTOT—annual total wet-day precipitation	Annual total precipitation (PR) in wet days (PR ≥ 1 mm)	mm
10. RX1day—max 1-day precipitation amount	Annual maximum 1-day precipitation	mm
11. RX5day—max 5-day precipitation amount	Annual maximum consecutive 5-day precipitation	mm
12. R95p—very wet days	Annual total precipitation from days > 95th percentile	mm
13. SDII—simple daily intensity index	The ratio of annual total precipitation to the number of wet days (≥ 1 mm)	mm/day
14. R20mm—number of very heavy precipitation days	Annual count of days when PR ≥ 20 mm	Days
15. CWD—consecutive wet days	Maximum number of consecutive days with daily PR ≥ 1 mm	Days
16. CDD—consecutive dry days	Maximum number of consecutive days with daily PR < 1 mm	Days

[a]The full list of indices and precise definitions are provided at https://etccdi.pacificclimate.org/list_27_indices.shtml. Abbreviations are as follows: TX (TN), daily maximum (minimum) temperature. A wet (dry) day is defined when precipitation ≥ 1 mm (PR < 1 mm)

2.2 Observation and reanalysis datasets

We selected four datasets to study the complexity of climate extremes at a high horizontal spatial resolution (Table 2) over the 1980–2016 period. We chose one gridded observation dataset, one reanalysis, and two merged products that combine satellite precipitation, reanalysis estimates, and in-situ records and offer prolonged periods of daily records of meteorological variables (e.g., TX, TN, and PR). The year of 1980 was chosen as the beginning of our evaluation for the purpose of intercomparing datasets, and for the fact that reanalyses and merged products have improved since the early 1980s as more climate datasets have become available, the understanding of the climate system has advanced, and numerical weather prediction techniques have improved (Sheffield et al. 2006; Dee et al. 2014; Beck et al. 2019a). The daily outputs were obtained from the following data projects:

I. A gridded observational dataset (OBS-BR) produced by Xavier et al. (2015, 2017) available for Brazil with a horizontal resolution of 0.25° latitude/longitude (~ 25 km × 25 km) over the period 1980–2016, taken as our reference. The temperature and precipitation fields are based on an interpolation of 735 and 9259 observations sites, respectively.
II. The fifth European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis—ERA5

Table 2 Characteristics of (a) gridded observations, (b) reanalyses, and (c) merged datasets

	Variables	Period	Resolution; spatial coverage
(a) Gridded observation			
OBS-BR https://utexas.app.box.com/v/Xavier-etal-IJOC-DATA	TX, TN, PR	1980–2016	0.25° (~ 28 km); Brazil
(b) Reanalysis product			
ECMWF ERA5 Reanalysis (ERA5) https://cds.climate.copernicus.eu/	TX, TN, PR	1979–2018	0.25° (~ 28 km); Global
Global Meteorological Forcing Dataset for Land Surface Modeling (GMFD) https://hydrology.princeton.edu/data.pgf.php	TX, TN, PR	1948–2016	0.25° (~ 28 km) Global
(c) Merging of different data sources (gauge, satellite, and reanalysis)			
Multi-Source Weighted-Ensemble Precipitation (MSWEP) Version 2.2 https://www.gloh2o.org/	PR	1979–2017	0.1° (~ 10 km); Global

Variables are precipitation (PR), maximum temperature (TX) and minimum temperature (TN)

(Dee et al. 2011; Hersbach et al. 2018). ERA5 is a global high-resolution (0.25°) reanalysis, available for the period between 1979 and the near-present.

III. The Global Meteorological Forcing Dataset with a horizontal resolution of 0.25° covering the period from 1948 to 2016 was also used (GMFD; Sheffield et al. 2006). GMFD dataset is based on Climatic Research Unit (CRU) Version 3.24.01 (monthly precipitation and temperature observations in a horizontal resolution of 0.5° × 0.5°; Harris et al. 2014), Global Precipitation Climatology Project—GPCC (daily precipitation in a 1° × 1° horizontal resolution; Huffman et al. 2001), Tropical Rainfall Measuring Mission—TRMM (3 hourly precipitation data in 0.25° of latitude/longitude; Huffman et al. 2007, 2010) and National Centers for Environmental Prediction/National Center for Atmospheric Research reanalysis—NCEP/NCAR reanalysis (3 hourly meteorological data in a ~ 2° × 2° horizontal resolution; Kalnay et al. 1996).

IV. The Multi-Source Weighted-Ensemble Precipitation (MSWEP) Version 2, another merged product consisting of satellite data, reanalysis and rain gauges provides reliable precipitation estimates on a daily world scale (Beck et al. 2017b, 2019a), which is available on a horizontal resolution of 0.1° for the period from 1979 to 2017.

It is noteworthy to mention that OBS-BR, ERA5, GMFD, and MSWEP datasets have not been assessed regarding their temporal-spatial patterns of climate extremes over Brazil. Dufek et al. (2008) evaluated the performance of NCEP/NCAR in capturing the extreme temperature and precipitation indices over Brazil from 28 weather stations during the period 1961–1990. They found that NCEP/NCAR reanalysis agrees well with observed climate extremes. However, we do not compare our results with Dufek et al. (2008) as their period and station network differ from the present study (1980–2016).

For intercomparison purposes, all datasets were regridded to a common 0.25° horizontal resolution grid using a bilinear interpolation algorithm, following analogous studies (Chaney et al. 2014; Zhou et al. 2014; Fotso-Nguemo et al. 2018; Beck et al. 2019a).

2.3 Climate change projections

Climate change projections used in this study were produced by the NASA Earth Exchange Global Daily Downscale Projection—NEX-GDDP (Thrasher et al. 2012). This product was derived from ESM experiments of the Coupled Model Intercomparison Project Phase 5 (CMIP5). We used the ensemble from 20 CMIP5 ESMs statistically downscaled to a horizontal resolution of 0.25° of latitude/longitude under two future emission scenarios: RCP 4.5 and RCP 8.5 (Table S1). According to Avila-Diaz et al. (2020), the observed climate extreme indices are generally well represented by the multi-model ensemble compared to individual ESMs from the NEX-GDDP dataset over Brazil during the 1980–2005 period. The NEX-GDDP dataset is prepared by the Climate Analytics Group and NASA Ames Research Center using the NASA Earth Exchange, and distributed by the NASA Center for Climate Simulation (NCCS), which is available at https://cds.nccs.nasa.gov/nex-gddp/. The NEX-GDDP produces three daily variables, TX, TN, and PR, over the periods 1950–2005 (historical) and 2006–2100 (projections under RCP 4.5 and RCP 8.5 scenarios). The Bias-Correction Spatial Disaggregation (BCSD) method was used to downscale each CMIP5 ESM output (Thrasher et al. 2012).

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (IPCC AR5) based their conclusions on projected changes in climate extreme events using the CMIP5 models for the time-slices 2046–2065 (mid-twenty-first century) and 2081–2100 (end-twenty-first century), relative to the reference period 1986–2005 (Hoegh-Guldberg et al. 2018; Collins et al. 2013). We used the same intervals to facilitate a comparative analysis with other studies in other locations throughout the world (Fischer et al. 2013; Sillmann et al. 2013; Alexander and Arblaster 2017; Ongoma et al. 2018; Liao et al. 2019; Santos et al. 2019).

To evaluate changes in extreme climate extreme indices, we applied a multi-model ensemble approach (Parker 2013; Gulizia and Camilloni 2015) adapted from Tebaldi et al. (2011) that ensures robust results. This methodology has been widely adopted in climate change and extreme events studies to address the significance of the change between two periods and the signal agreement among the models (Sillmann et al. 2013; Alexander and Arblaster 2017; Almazroui et al. 2017; Zhou et al. 2019; Dosio et al. 2019). For this purpose, we filled all grid cells with the mean multi-model relative change through a color pattern. To assess the significance of projected changes in annual climate extremes, we performed a Student's t-test between the historical (reference) and future (RCP4.5 and RCP8.5) scenarios. We stippled all grid cells where more than 66 percent of the models agreed on the change signal and more the 50% of the models showed a significant change (t test, p-value < 0.05).

The relative change between the future and the historical periods in each climate extreme index (CEI) was calculated using Eq. (1) adapted from Bador et al. (2018):

$$\text{Relative change in CEI} = \frac{\overline{\text{CEI}}_{\text{future}} - \overline{\text{CEI}}_{\text{his}}}{\overline{\text{CEI}}_{\text{his}}} \tag{1}$$

where $\overline{CEI}_{future}$ and $\overline{CEI}_{his}$ are 20-yr averages in a given CEI over the future (2046–2065 or 2081–2100) and historical (1986–2005) periods, respectively.

2.4 Performance and trend analysis

This study employed four metrics to evaluate the performance of different datasets in reproducing the observed climate indices from 1980–2016 over the eight largest Brazilian hydrological basins (Fig. 1). These basins are defined largely by their climate, precipitation and runoff intensity and seasonality, topography, and latitudinal position (Rocha and Santos 2018; and references therein). According to the Brazilian National Water Agency (the Portuguese acronym is ANA), the country is divided in the following zones: Amazon River (AMZ), Tocantins River (TOC), North Atlantic Region (NAR), São Francisco River (SFR), Central Atlantic Region (CAR), Parana River (PAR), Uruguay River (URU), and South Atlantic Region (SAR).

The performance metrics include Percent Bias (PBIAS), RMSE-observations standard deviation ratio (RSR; Moriasi et al. (2007)), refined index of agreement (d_{r}), and Pearson correlation coefficient (CORR). PBIAS indicates whether a given dataset overestimates or underestimates the observational information. The closer PBIAS and RSR are to 0,

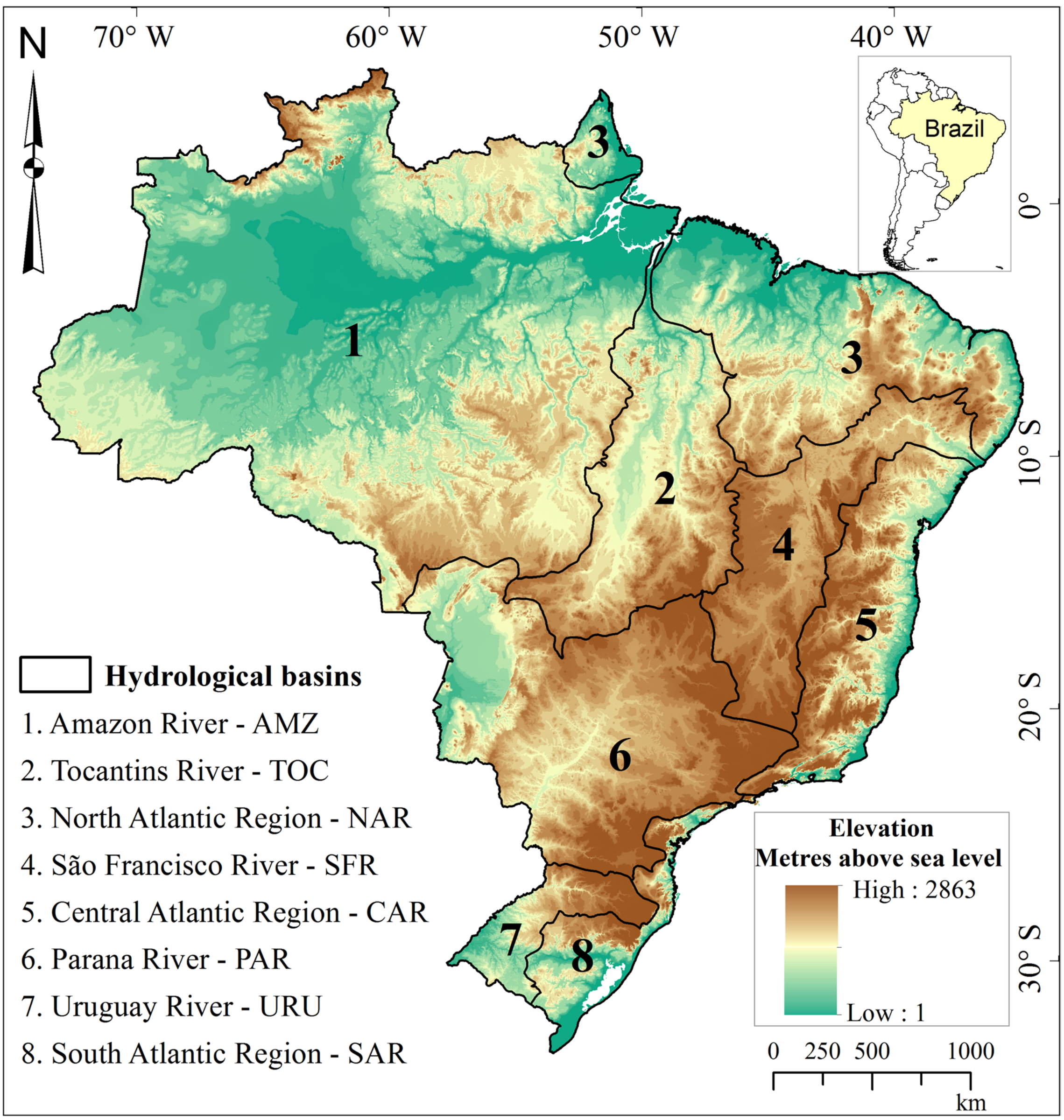

Fig. 1 Hydrological basins in Brazil according to the Brazilian National Water Authority (ANA)

the better the model performs. Furthermore, the d_r varies between − 1 and 1, 1 being the perfect agreement (Willmott et al. 2012). Finally, the value of CORR 1 (− 1) indicates a stronger positive (negative) relationship between the two variables; meanwhile, 0 value indicates the absence of a relationship.

To detect trends in extreme climate indices, we used the Theil-Sen's slope estimator (Sen 1968). The significance of trends is calculated at the confidence level of 95% ($\alpha = 0.05$) using a Mann–Kendall test (Mann 1945; Kendall 1975). More details can be found in Yue et al. (2002). These non-parametric tests are often used to detect trends in extreme climate indices, but also because this approach is less sensitive to outliers than parametric methods such as the ordinary least squares regression method (Cornes and Jones 2013; Donat et al. 2013a, 2016; Skansi et al. 2013).

3 Results and analysis

To reduce the quantity of similar results (climatologies and spatial trends) for different extreme climate indices in each dataset, we only present selected indices (two each for temperature and precipitation, respectively) for each subsection. Additional figures can be found in the Supplementary Material.

3.1 Metrics analysis of datasets performance

3.1.1 Temperature indices

Climatologies of temperature indices from two climate datasets (ERA5 and GMFD) were compared to gridded observations (OBS-BR) over Brazil for 1980–2016 using different performance metrics (Figs. 2 and 3). Observations and ERA5 climatologies are similar (Fig. 2). ERA5 reflects similar climatologies to OBS-BR for all variables except diurnal temperature range (DTR; Fig. 2b, c). For the DTR index, GMFD has similar magnitudes as the gridded observational dataset with values of PBIAS close to zero (Fig. 2).

PBIAS in the warmest daily temperature index (TXx; Figs. 2, 3a, b) reflects cooler (warmer) than observed conditions in ERA5 (GMFD) for all hydrological basins. Overall, performance suffers over the Amazon, Tocantins, and Parana basins, with PBIAS overestimated by up to 14% (3 °C) compared to observations. ERA5 overestimates the coldest daily minimum temperature (TNn; Figs. 2, 3c, d) for all basins, except for Uruguay and South Atlantic basins. GMFD reflects PBIAS of TNn (− 13%) over the Uruguay River.

ERA5 performs well compared to gridded observations for percentile indices (TN10p, TN90p, TX10p, TX90p, and WSDI; Fig. 2). GMFD underestimates the warm spell duration index (WSDI) for all hydrological basins. The highest values of PBIAS (> 80%) are found across the north (Amazon basin) and northeast regions (e.g., Tocantins, North Atlantic, and São Francisco basins).

Importantly, our analysis shows that ERA5 and GMFD do not compare well with observations over the Amazon basin. There are likely two important facets to this weaker performance over the Amazon. First, Betts et al. (2009) indicate that cloud cover parameterizations are a persistent challenge in reanalysis models (ERA-40 and ERA-Interim), which implies a substantial underestimation of temperature indices (e.g., TXx, DTR, and TN90p) over the Amazon basin (Fig. 1a). Secondly, land surface properties contribute greatly to the performance of models. Land surface models and overlying boundary layer parameterizations vary in their sophistication and representation of temperature and moisture fluxes, albedo, and near-surface turbulence, all of which have varying impacts on atmospheric temperature. Proper parameterizations of the land/soil/vegetation processes are challenges for modelers, especially within a complex biome such as the Amazon rainforest (Marengo 2005; Karam and Bras 2008; Fersch and Kunstmann 2014).

3.1.2 Precipitation indices

Figures 4 and 5 show the precipitation results for all datasets and hydrological basins. All datasets are consistent with observations for total precipitation of wet days index (PRCPTOT). PBIAS and RSR are low, and d_r and CORRs are close to 1. Intensity indices vary; however, PBIAS is quite large across all basins for RX1day, RX5day, and R95p, especially over the Amazon basin (Fig. 4). RSR and d_r are generally lower for GMFD and MSWEP compared to ERA5 (Figs. 4 and 5).

The ERA5 and GMFD show strong ability to estimate the number of consecutive dry days (CDD; Figs. 4a, b, 5c, d). However, the GMFD dataset exhibits the weakest performance for all intensity precipitation indices (e.g. RX1day and RX5day) compared to observations. The analysis suggests that ERA5 may be useful as an alternative dataset to study daily temperature and precipitation indices over Brazil. In general, ERA5 outperforms GMFD for temperature-based extreme indices and ERA5 and MSWEP (only for precipitation-based extreme indices) capture spatial patterns of extreme climate indices when compared to observational values.

It should be noted that the GMFD dataset was produced from a combination of observed and reanalysis data since the data sets based on observations have a coarse temporal resolution (Sheffield et al. 2006). A monthly gridded observation-based dataset was resampled to a sub-monthly scale using reanalysis data. GMFD differences with observed climate extremes may stem from the fact that the CRU dataset is based on the collection of data

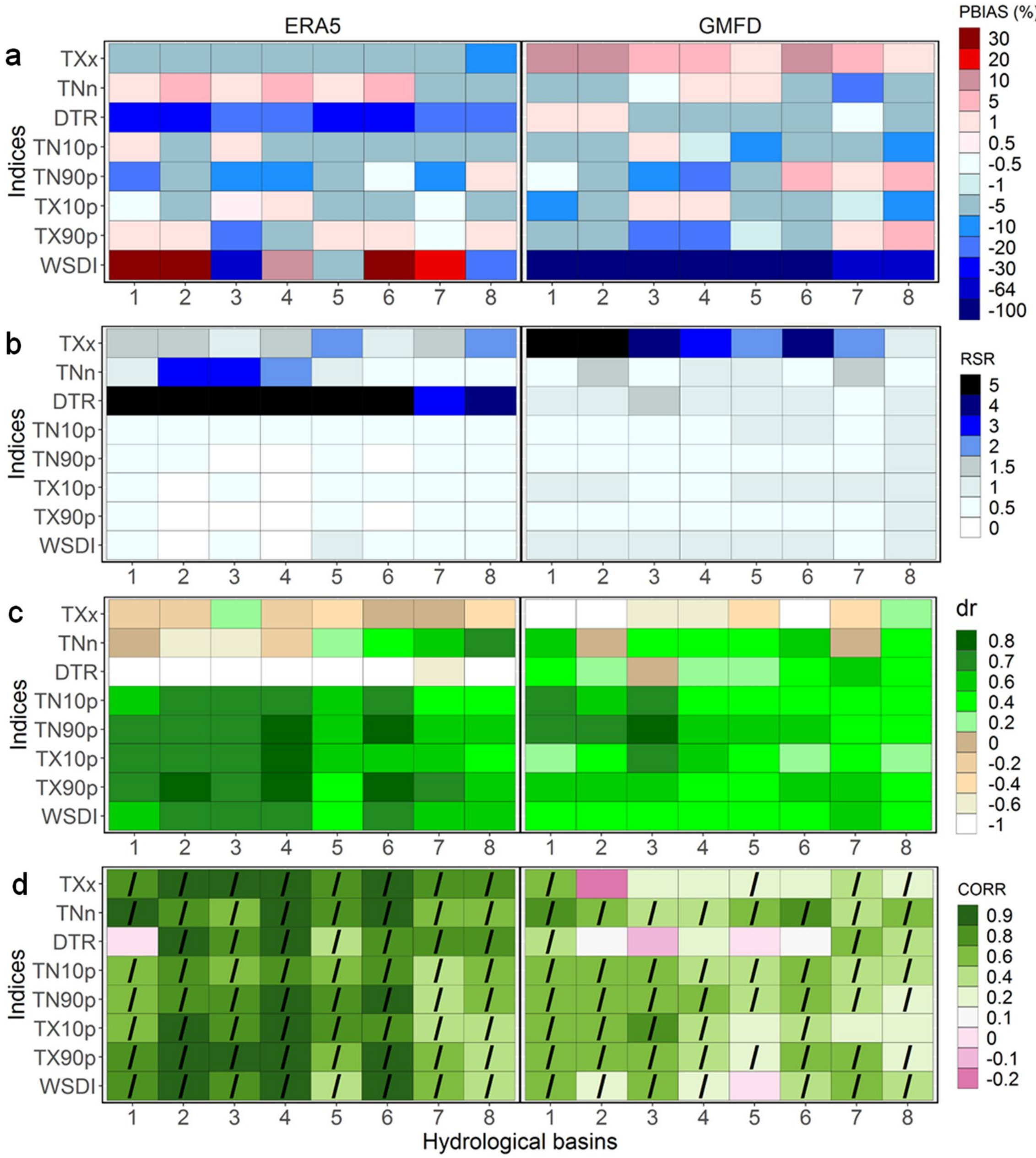

Fig. 2 Evaluation metrics for temperature indices for ERA5 and GMFD with respect to the observational dataset (OBS-BR) from 1980 to 2016 over the eight hydrological basins in Brazil. **a** Bias in percentage (PBIAS); **b** RMSE-observations standard deviation ratio (RSR); **c** refined index of model performance (dr); **d** Pearson correlation coefficients (CORR); diagonal black lines indicate correlation values statistically significant correlations at 95% confidence level

from weather stations worldwide, but the density of stations varies widely (Liebmann and Allured 2006; Rozante et al. 2010; Xavier et al. 2015). Regions with a low density of meteorological stations, such as the Amazon basin, for example, can reduce the quality of the interpolation. Finally, the coarse resolution of NCEP-NCAR reanalysis can be affects the temporal precipitation estimates (Rao et al. 2002; de Lima and Alcântara 2019).

Noteworthy, MSWEP (a merged product) is dependent on the precipitation field of the ERA-Interim reanalysis. Donat et al. (2014) and Beck et al. (2017a) point out that the ECMWF reanalyses (ERA-40 and ERA-Interim) tend to show agreement with the observations. ERA5 has demonstrated many enhancements compared to its predecessor ERA-Interim, most notably increased horizontal and vertical resolution (~79 km/60 levels to ~31 km/137

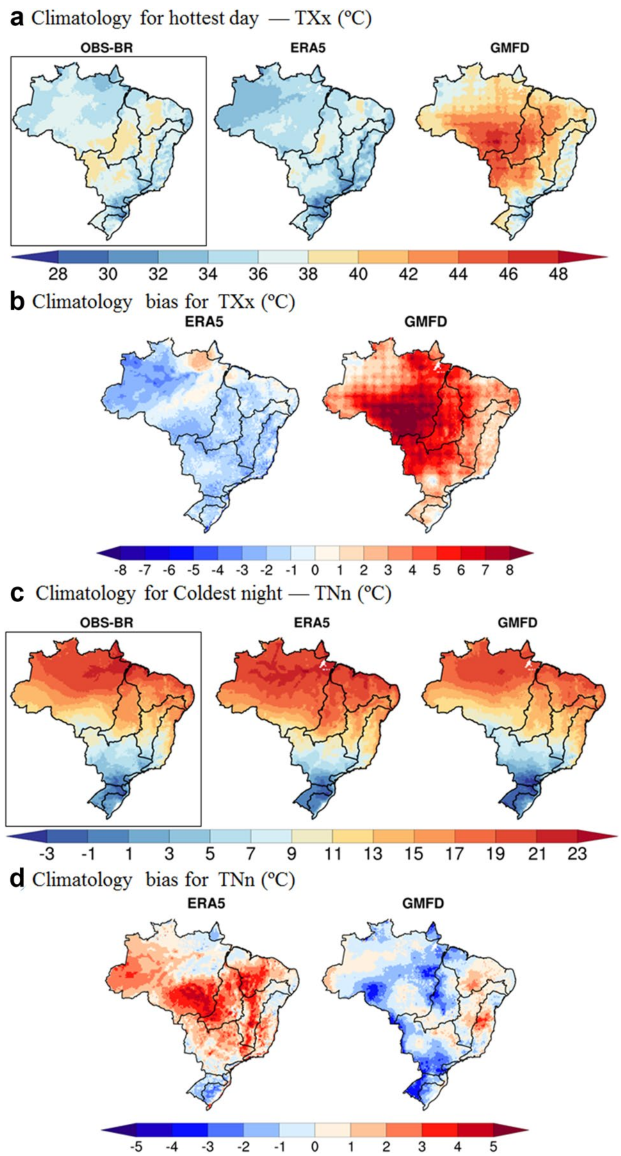

Fig. 3 The 1980–2016 climatology and bias for TXx (**a**, **b**) and TNn (**c**, **d**) for OBS-BR (black rectangle; gridded observations), ERA5, and GMFD. Figures for additional temperature indices are in Supplementary Material

levels; Hoffmann et al. 2019). As suggested by Beck et al. (2019b) and supported by our results, MSWEP can use ERA5 outputs to improve the accuracy of daily precipitation estimates. Therefore, caution is recommended when using reanalyses or merged products as reference datasets to evaluate changes or patterns for daily precipitation indices, especially in regions where station data are sparse (Rozante et al. 2010; Zhang et al. 2011).

3.2 Historical changes in climate extremes

3.2.1 Observed trends in temperature indices

Table 3 and Fig. 6 depict the spatial trends and regional patterns in all three datasets across hydrological basins, respectively. Nearly all datasets show warming trends for cold (TNn, TN10p, TX10p) and warm climate extreme indices (TXx, TN90p, TX90p, and WSDI) across almost all of Brazil from 1980 to 2016. Note that Supplementary Material displays additional trends for all of climate indices mentioned in Sect. 2.1 and Table 1.

To illustrate, the annual maximum temperature (TXx) shows significantly increasing trends at rates of 0.07 to 0.64 °C/decade across much of the country (Table 3 and Fig. 6a). ERA5 and GMFD show weak regional cooling in southern parts of the Uruguay and South Atlantic basins; however, the trend is not statically significant. The frequency of the warm nights (TN90p; 0.58–6.2 percent of days/decade) has increased greater than the frequency of warm days (TX90p; 0.17–4.63 percent of days/decade) in almost all basins, except in the South Atlantic basin for OBS-BR (Table 3). The warm spell duration indicator index (WSDI) has increased consistently across the country, with regional increases between 0.03 and 3.13 days/decade. The largest positive trends are found throughout many areas of northwest Amazon and Parana River basins (Fig. S3). Central Atlantic and South Atlantic basins show insignificant decreasing trends for WSDI. Our results are consistent with previous studies, with increasing trends across northern Brazil and smaller increases across southern portions of the country (Gloor et al. 2015; Geirinhas et al. 2018; Feron et al. 2019). Additionally, we find the largest positive trends throughout many areas of northwest Amazon and central Parana River basins for DTR (Fig. S3a), TN90p (Fig. S3b), and WSDI (Fig. S3d). This widening between maximum and minimum temperatures is in response to a reduction in water vapor (i.e. drier air), as warming temperatures and land use changes transition parts of the Amazon to arid savannas (Marengo et al. 2018). Drier air warms and cools more efficiently than during periods of increased atmospheric moisture and cloud cover (Dai et al. 1999; He et al. 2015).

Cold extremes are warming as well. The coldest night of the year (TNn) has increased 0.07 to 0.54 °C/decade over the recent past in several parts of the country (Fig. 6b). On the other hand, gridded observations for Uruguay and South Atlantic basins show statically significant cooling trends of − 0.74 and − 0.46 °C/decade, respectively. Finally, cold nights (TN10p; Fig. 6b) and cold days (TX10p Fig. S3c) display warming trends over Brazil, but decreasing trends are found over Uruguay and South Atlantic basins.

Results of extreme temperature indices reveal significant warming trends and are broadly similar across all datasets

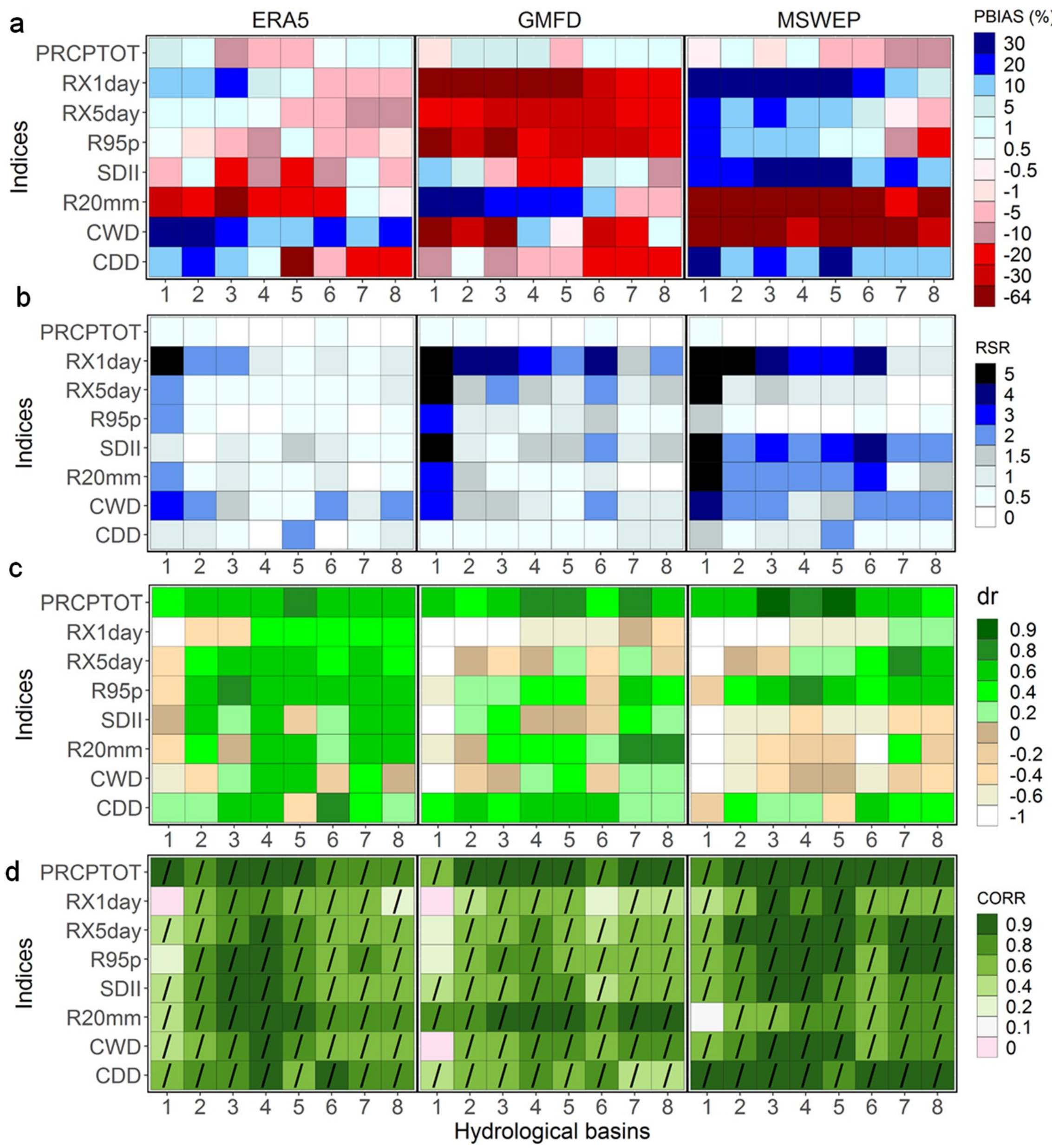

Fig. 4 Evaluation metrics for precipitation indices for ERA5 and GMFD with respect to the observational dataset (OBS-BR) from 1980 to 2016 over the eight hydrological basins in Brazil. **a** Bias in percentage (PBIAS); **b** RMSE-observations standard deviation ratio (RSR); **c** refined index of model performance (dr); **d** Pearson correlation coefficients (CORR); diagonal black lines indicate correlation values statistically significant correlations at the 95% confidence level

and with other global and regional studies (Donat et al. 2013a, b; Skansi et al. 2013; Rosso et al. 2015; Almeida et al. 2017; Natividade et al. 2017; Soares et al. 2017; Marengo et al. 2018; da Silva et al. 2019). However, there are some differences in the Uruguay and South Atlantic basins. In these regions, ERA5 and GMFD display warming trends while OBS-BR indicates a cooling trend. Also, over the same hydrological basins, GMFD differs with OBS-BR for the diurnal temperature range (DTR; Fig. S3). The interaction between complex topography and regional climate systems plays an essential role in the regulation of inter-annual variability over the Uruguay River and South Atlantic basins (Fig. 1), which are not well represented by ERA5 and GMFD. In this sense, Gao et al. (2012) and Cornes and Jones (2013) indicated that the high-elevation terrain still poses a challenge for reanalyses, principally because the model topography used by reanalyses does not have sufficient resolution to resolve the climate interaction at small scales. To help solve the topography-dependent problems, a topographic correction of reanalysis data is necessary to

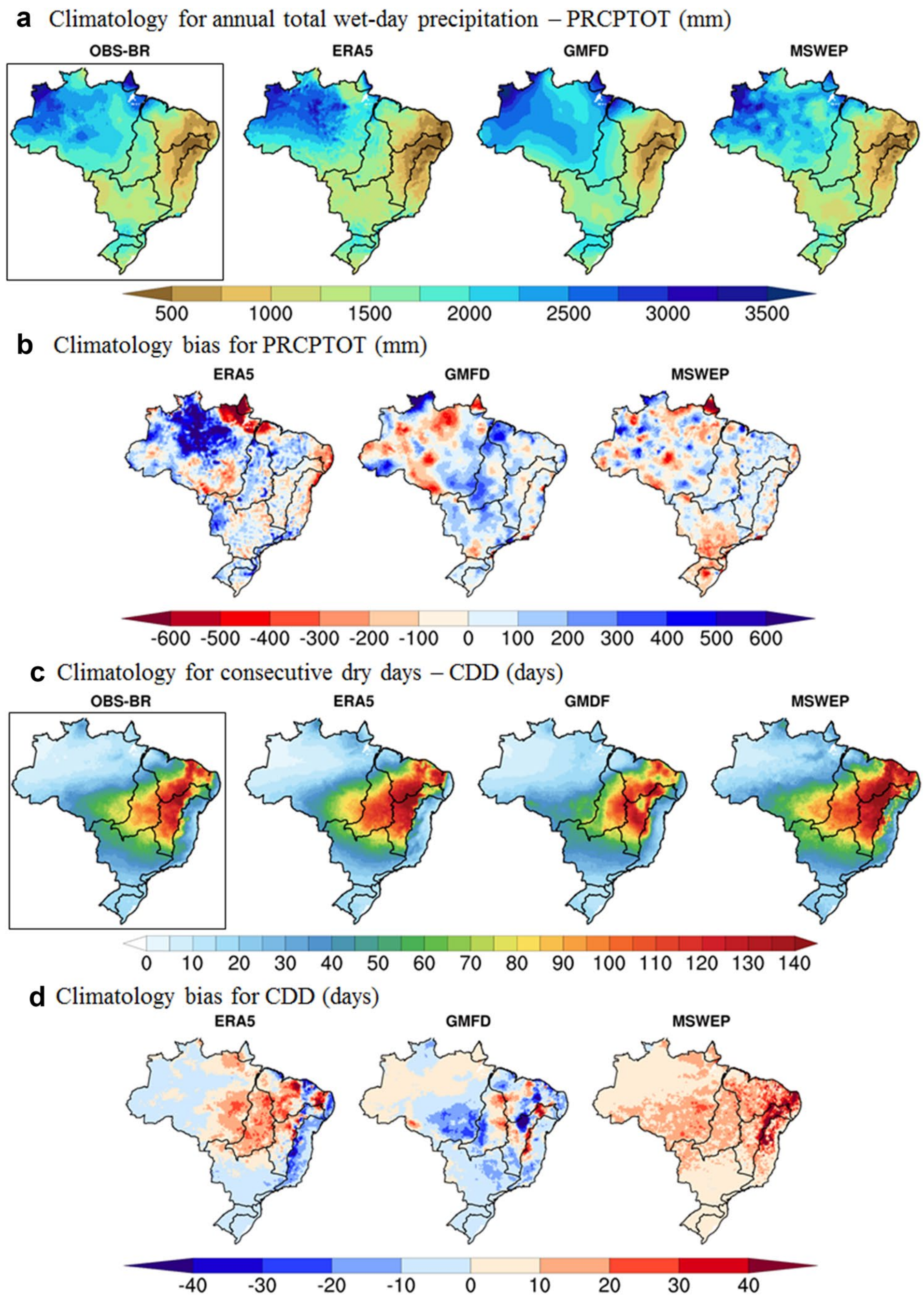

Fig. 5 The 1980–2016 climatology and bias for PRCPTOT (**a**, **b**) and CDD (**c**, **d**) for OBS-BR (black rectangle; gridded observations), ERA5, and GMFD. Figures for additional precipitation indices are in Supplementary Material

reduce the bias between the estimated and observed values (Gao et al. 2012; Luo et al. 2019).

3.2.2 Observed trends in precipitation indices

Extreme precipitation trends show less agreement among the observational trends (OBS-BR) and those estimated by ERA5, GMFD, and MSWEP (Table 4 and Fig. 7). The spatial and regional precipitation trends vary considerably compared to the temperature trends across the different datasets. PRCPTOT increases from 4.43 to 12.94 mm/decade for the Amazon and South Atlantic regions (Table 4). However, negative trends are found over the northwestern and southeastern Amazon basin in OBS-BR, ERA5, and MSWEP (Fig. 7a). Tocantins, North Atlantic, São Francisco, and Central Atlantic basins show a decrease (not statistically significant) for all four datasets. The dry patterns, especially over the southeastern Amazon and Tocantins basins, are consistent with Gloor et al. (2015).

Mixed trends are demonstrated in the intensity indices (Table 4). Similar to previous studies, RX1day, RX5day, and R95p indices show increased extreme rainfall events

Table 3 Decadal trends in temperature indices over the period 1980–2016

Basin	Dataset	TXx	TNn	DTR	TN10p	TN90p	TX10p	TX90p	WSDI
		ºC/decade			% / decade				days/decade
Amazon River	OBS-BR	**0.54**	**0.53**	**-0.04**	**-5.61**	**6.20**	**-2.09**	**4.63**	**2.57**
	ERA5	**0.62**	**0.34**	**0.10**	**-2.23**	**2.94**	**-1.08**	**3.41**	**1.41**
	GMFD	**0.40**	**0.41**	0.01	**-3.39**	**5.01**	**-3.99**	**2.30**	**0.51**
Tocantins River	OBS-BR	**0.59**	**0.26**	**0.13**	**-3.22**	**4.62**	**-2.50**	**3.63**	**1.55**
	ERA5	**0.51**	**0.21**	**0.12**	**-3.32**	**2.79**	**-2.52**	**2.79**	**1.39**
	GMFD	**-0.21**	**0.54**	0.00	**-3.17**	**4.12**	**-3.41**	**1.93**	**0.53**
North Atlantic	OBS-BR	**0.64**	**0.21**	**0.13**	**-3.94**	**4.97**	**-3.23**	**4.31**	**1.89**
	ERA5	**0.34**	**0.11**	**0.04**	**-2.69**	**2.67**	**-1.69**	**2.60**	**1.07**
	GMFD	**0.07**	**0.14**	**0.00**	**-2.75**	**3.54**	**-2.20**	**1.77**	**0.87**
São Francisco	OBS-BR	**0.56**	**0.11**	**0.16**	**-2.27**	**3.47**	**-2.62**	**2.70**	**1.46**
	ERA5	**0.43**	**0.10**	**0.11**	**-2.33**	**2.60**	**-2.09**	**2.32**	**2.01**
	GMFD	-0.04	**0.17**	0.00	**-2.12**	**2.56**	**-1.68**	**1.02**	**0.42**
Central Atlantic	OBS-BR	**0.32**	**0.19**	**-0.12**	**-1.24**	**2.12**	**-0.58**	-0.17	-0.20
	ERA5	**0.59**	0.06	**0.18**	**-1.13**	**1.83**	**-1.87**	**2.56**	**1.37**
	GMFD	**0.12**	**0.21**	0.00	**-1.38**	**1.54**	**-1.15**	**0.52**	0.03
Parana River	OBS-BR	**0.64**	0.07	**0.15**	**-0.39**	**2.74**	**-0.79**	**3.25**	**2.89**
	ERA5	**0.59**	**0.39**	**0.13**	**-1.51**	**2.31**	**-1.60**	**2.87**	**3.13**
	GMFD	-0.08	**0.53**	**-0.01**	**-1.79**	**3.55**	**-2.16**	**1.90**	**0.74**
Uruguay River	OBS-BR	**0.53**	**-0.74**	0.00	**0.88**	**1.13**	0.22	0.38	0.05
	ERA5	**0.18**	**0.10**	0.01	**-0.70**	**0.58**	**-0.81**	0.17	0.07
	GMFD	-0.12	0.10	**-0.09**	**-0.96**	**1.97**	**-0.62**	**0.51**	-0.03
South Atlantic	OBS-BR	**0.26**	**-0.46**	**-0.10**	**1.02**	-0.06	**0.96**	**-0.55**	-0.27
	ERA5	**0.14**	-0.02	0.00	**-0.52**	**0.67**	**-0.82**	0.32	0.26
	GMFD	0.03	0.08	**-0.04**	**-1.34**	**1.77**	**-1.07**	**1.01**	0.00

Values in bold indicate trends are significant at the 95% confidence level. Colors signify cooling (blue), warming (red), or no trend (white)

for the North Atlantic, Central Atlantic, Parana, Uruguay, and South Atlantic basins (Haylock et al. 2006; Skansi et al. 2013; Ávila et al. 2016; Zilli et al. 2017; Murara et al. 2018). With regard to the frequency index R20mm, our results show a positive trend over parts of northern and southern Brazil (Amazon, Uruguay, and South Atlantics basins). However, the northeastern part of the county (São Francisco and Central Atlantic basins) exhibit dominantly drying trends.

Changes in duration indices (CDD and CWD; Table 4 and Fig. 7d) demonstrate mostly non-significant drying trends, with good agreement among the reanalyses and merged datasets (Table 4). Our results of CDD agree well with Valverde and Marengo (2014) who used historical rainfall stations in their assessment. The regionally-specific decadal trends of CWD show increasing tendencies for all basins and only differ from the OBS-BR product for the Amazon (statistically significant rate of 2.08 mm/decade), Parana, and South Atlantic basins (trends not significant in these regions). Signal differences between these datasets may arise due to the scarcity of long-term observations of daily rainfall stations for Amazon basins in both spatial and temporal coverage (Xavier et al. 2015).

In general, precipitation changes show non-significant trends, although the ERA5, MSWEP, and OBS-BR exhibit reasonable spatial coherency. Results indicate increasing trends in annual total wet-day precipitation in northern and southern basins and dry patterns in north and central Basins. Northern and central hydrological regions, such as the North Atlantic region, São Francisco, Central Atlantic, and central part of the Parana basin, show increasing trends in the more extreme precipitation events (RX1day) during the last four decades. Though the magnitudes are small and not statistically significant, these results are consistent with global changes in extreme precipitation events and storm intensity (Wasko et al. 2016; Norris et al. 2019; Myhre et al. 2019) and may be tied to changes in jet stream position over South America (Pena-Ortiz et al. 2013). Southern basins (e.g., Parana, Uruguay, South Atlantic basins) reveal increasing trends in events related to intensity and frequency. Duration indices exhibit a reduction of CWD; meanwhile, the CDD index shows positive trends over the majority of Brazil.

3.3 Future projections in climate extremes

3.3.1 Changes in future temperature indices

Figures 8 and 9 illustrate the regional and spatial changes in temperature indices for the period 2046–2065 relative to the baseline period (1986–2005). Note that Fig. 8 displays the regional projected changes summarized in box-and-whisker

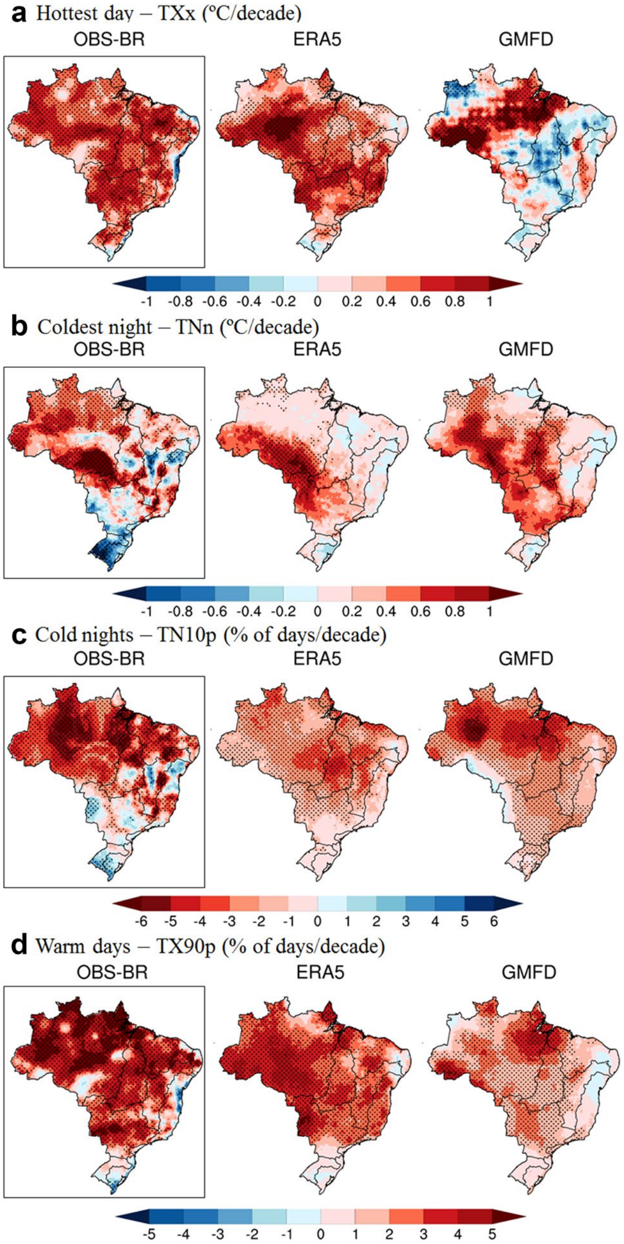

Fig. 6 Decadal trends in TXx (**a**), TNn (**b**), TN10p (**c**), and TX90p (**d**) during the period 1980–2016 for OBS-BR (black rectangle; gridded observations), ERA5, and GMFD. Hatching indicates where trends are significant at the 95% confidence level. Trends for additional temperature indices are in Supplementary Material

plots and presented per hydrological basins, under the representative concentration pathway (RCP) scenarios 4.5 and 8.5. Mean projected changes for 2081–2100 period (end-twenty-first century) are in Supplementary Material (Figs. S6 and S7).

The multi-model ensemble (MME) mean projects significant warming in annual maximum temperature (TXx; Figs. 8a, b, 9a, i) and annual minimum temperature (TNn; Figs. 8c, d, 9b, j). The magnitudes of these indices across the different basins vary between 1.4and 2.3 °C in RCP4.5 and 1.9–3.1 °C in RCP8.5 by mid-twenty-first century. By the end of the twenty-first century, these magnitude ranges increase to 1.6–3.0 °C in RCP4.5 and 3.7–5.9 °C in RCP8.5 scenarios. Figures 8 and 9 show that the maximum warming is predominantly found over the Amazon, Tocantins, and Parana Rivers basins. Similar results for the end of the twenty-first century are noted by Sillmann et al. (2013b) and López-Franca et al. (2016).

There are similar patterns of increasing frequency of warm extremes (TX90p and TN90p) and reduction of cold extremes (TN10p and TX10p) by the middle end of the twenty-first century over Brazil (Figs. 8, 9 and S5). Projected changes in warm indices are more pronounced than those for cold indices. Increases in the occurrence of TX90p and TN90p vary between 20 and 63% under the scenario RCP4.5, and 28–69% in RCP8.5 in the mid-century projections. Also, by the end of the twenty-first century mean changes are 6–15% higher compared to the projected increases for mid-century under both scenarios.

In addition to stronger warming, warm spell duration index (WSDI) increases significantly for 2046–2065 (Fig. 9) and 2081–2100 (Fig S6) under the RCPs scenarios. The significant increase in WSDI is projected in all basins with mean changes greater than 39 (56) days by the middle and end of the twenty-first century under RCP4.5 (8.5) scenario. Consistent with the warming patterns, fewer cold nights (TN10p) and cold days (TX10p) are projected. The TN10p (TX10p) index decreases from about 6.2% (6.6%) in 2046–2065 to 6.4% (7.1%) under RCP4.5 (8.5) scenario, with slightly negative trends by the end of the century. The regional changes in percentile indices by middle and end of the century are consistent with previous studies over South America (Marengo et al. 2009; Sillmann et al. 2013; López-Franca et al. 2016; Feron et al. 2019). These results are in agreement with other regions throughout the globe (Zhou et al. 2014; Lelieveld et al. 2016; Schoof and Robeson 2016; Alexander and Arblaster 2017).

In summary, the most significant increases (decreases) in warm (cold) extremes occur in the Amazon, Tocantins, and North Atlantic basins. However, the smallest changes in the ensemble mean temperature extremes are projected in the Uruguay River and South Atlantic basins. The findings are in agreement with the results by Sillmann et al. (2013b), who used CMIP5 models to project extreme climate indices over South America.

3.3.2 Changes in future precipitation indices

Changes in precipitation indices relative to the 1986–2005 reference period are presented in Figs. 10 and 11. For comparison purposes with other studies (e.g., Sillmann et al. (2013)), relative changes (see Eq. 1) are expressed in

Table 4 Decadal trends in precipitation indices over the period 1980–2016

Basin	Dataset	PRCPTOT	RX1day	RX5day	R95p	SDII	R20mm	CWD	CDD
		mm/decade				mm.day^{-1}/10yr	days/decade		
Amazon River	OBS-BR	4.43	-0.05	0.64	2.38	-0.004	0.19	**2.08**	0.62
	ERA5	8.94	**6.76**	**8.32**	**84.94**	**0.31**	**2.53**	**-5.17**	**3.67**
	GMFD	14.55	0.08	-0.15	-3.18	0.15	-0.29	-0.16	**1.26**
	MSWEP	**62.72**	**2.06**	**4.05**	**38.32**	**0.24**	**1.43**	0.23	0.44
Tocantins River	OBS-BR	-34.32	-0.11	-1.83	-11.94	-0.08	-0.72	-1.64	**4.13**
	ERA5	**-90.88**	-1.13	-4.90	-2.49	-0.07	-0.20	**-5.11**	**7.97**
	GMFD	-4.99	**2.25**	2.88	16.02	0.18	0.50	**-1.78**	0.85
	MSWEP	17.63	2.03	0.98	25.01	**0.35**	0.74	**-1.39**	3.46
North Atlantic	OBS-BR	-19.60	1.34	0.33	5.27	0.06	0.07	-1.67	1.80
	ERA5	-39.83	2.75	1.27	16.41	-0.08	0.12	**-4.49**	1.30
	GMFD	21.76	0.69	-0.08	5.78	0.26	0.21	-1.27	**-5.11**
	MSWEP	-23.20	1.96	-1.37	3.83	0.13	-0.24	**-1.21**	2.98
São Francisco	OBS-BR	-39.52	0.75	-1.32	-5.17	0.06	-0.48	**-1.33**	2.80
	ERA5	**-73.49**	-0.62	-2.35	-14.73	-0.16	-0.82	**-2.06**	4.93
	GMFD	-24.90	1.28	-1.02	2.65	0.05	-0.06	**-1.23**	-2.91
	MSWEP	-32.75	1.86	0.57	2.24	0.29	-0.25	**-1.10**	4.16
Central Atlantic	OBS-BR	-35.26	1.73	3.14	7.07	0.14	-0.12	**-1.19**	1.22
	ERA5	**-62.87**	0.32	0.22	-12.69	-0.05	-0.71	**-1.47**	**1.75**
	GMFD	-37.05	0.08	-1.50	-8.11	-0.03	-0.29	-0.45	0.86
	MSWEP	-26.64	**5.17**	7.37	**30.54**	**0.63**	0.15	**-0.82**	**4.67**
Parana River	OBS-BR	-5.32	0.54	0.60	1.13	-0.02	-0.14	0.03	2.14
	ERA5	-51.13	0.57	0.71	1.13	0.00	-0.28	**-1.31**	**4.26**
	GMFD	29.29	1.09	**3.09**	**23.25**	**0.47**	**0.93**	**-1.13**	1.28
	MSWEP	32.27	**2.53**	**4.24**	**32.19**	**0.44**	**1.07**	**-0.63**	1.78
Uruguay River	OBS-BR	-7.05	0.45	3.50	15.96	-0.01	0.28	-0.13	0.48
	ERA5	-48.99	-0.15	-2.38	-6.90	-0.19	-1.10	-0.36	0.55
	GMFD	-1.30	2.74	-0.14	24.41	0.41	1.23	-0.27	0.31
	MSWEP	30.77	**4.54**	6.20	**43.09**	**0.57**	0.92	-0.33	0.20
South Atlantic	OBS-BR	12.94	1.02	2.97	16.19	0.01	0.29	0.02	-0.01
	ERA5	-25.78	-0.96	-1.89	-12.09	-0.15	-0.55	-0.16	0.33
	GMFD	14.68	**2.79**	**4.32**	**40.85**	**0.39**	1.23	-0.42	0.58
	MSWEP	21.65	**3.17**	**4.64**	29.23	**0.43**	0.86	**-0.38**	0.26

Values in bold indicate trends are significant at 95% confidence level. Colors signify wetting (blue), drying (yellow), or no trend (white)

percentage. Mean projected changes for 2081–2100 period (end-twenty-first century) are in the Supplementary Material (Figs. S8 and S9).

The ensemble mean of PRCPTOT reflects a reduction over Amazon, Tocantins, North Atlantic, São Francisco, and Central Atlantic basins (Figs. 10a, b, 11a, and i). At the same time, the CDD projections indicate an increase across most regions of Brazil for RCP4.5 (8.5) scenario, ranging from 1 to 18% (3–27%) by the mid-century and ranging from 1 to 22% (3–61%) by the end of twenty-first century (Fig. 10c, d). CWD shows a pattern opposite to that of CDD (Figs. 10g, h and 11g, h, o, p). Small trends in PRCPTOT, CDD, and CWD are projected over southern Brazil (URU and SAR) in the ensemble mean. In general, future projections show a reduction in PRCPTOT and CWD and increases in CDD. This trend toward a drier future climate is consistent with previous findings (Amorim et al. 2014; Chou et al. 2014; Marengo et al. 2017; Lyra et al. 2018).

For rainfall intensity extremes (RX1day, RX5day, R95p, and SDII), increasing trends are projected over most of Brazil under both scenarios, more pronounced by the end of the century (Figs. 10, 11). The largest increases of R95p index, on the order of 4–18% (6–29%), are expected for the mid-century in the RCP4.5 (8.5) scenario. By the end of the twenty-first century, the R95p mean increases most in the RCP8.5 scenario (16–45%). In general, projections of intensity indices indicate the weakest trends over the Central Atlantic basin, whereas the most significant changes are generally found in the Tocantins, São Francisco, and South Atlantic basins (Fig. 11). The signal of change in intensity indices such as RX1day is consistent with those obtained by Valverde and Marengo (2014) and Bador et al. (2018), and

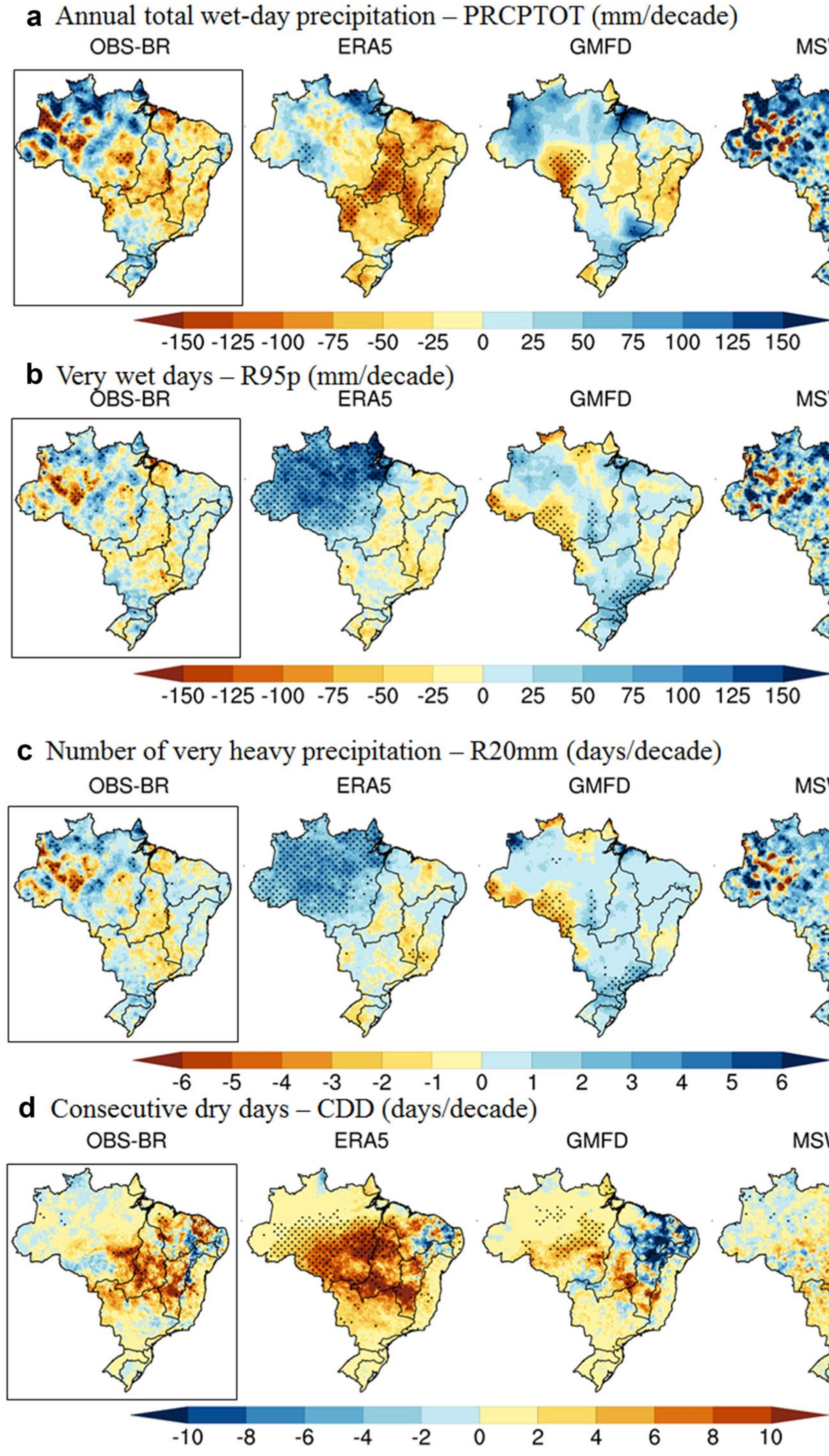

Fig. 7 Decadal trends in PRCPTOT (**a**), R95p (**b**), R20mm (**c**), and CDD (**d**) during the period 1980–2016 for OBS-BR (black rectangle; gridded observations), ERA5, GMFD, and MSWEP. Stippling indicates where trends are significant at the 95% confidence level. Trends for additional precipitation indices are in Supplementary Material

projected increases in R20mm index over southern Brazil are evident over Uruguay and South Atlantic basins. These results are in agreement with that of Sillmann et al. (2013) and Lyra et al. (2018), who reported the reduction in the number of heavy precipitation days.

Caution must be given when interpreting the results of these precipitation indices. Unlike temperature indices, most models disagree with the signal of change, with fewer than half of the models showing a significant change. For example, our results point out the model agreement increase in both RCP4.5 and RCP8.5 scenarios compared to the historical (e.g., PRCPTOT, R95p, and CDD). This is in concert with previous studies showing similar lower confidence for precipitation indices over other parts of the world (e.g., Sillmann et al. (2013); Alexander and Arblaster (2017)). In this sense, Lin et al. (2018) indicated

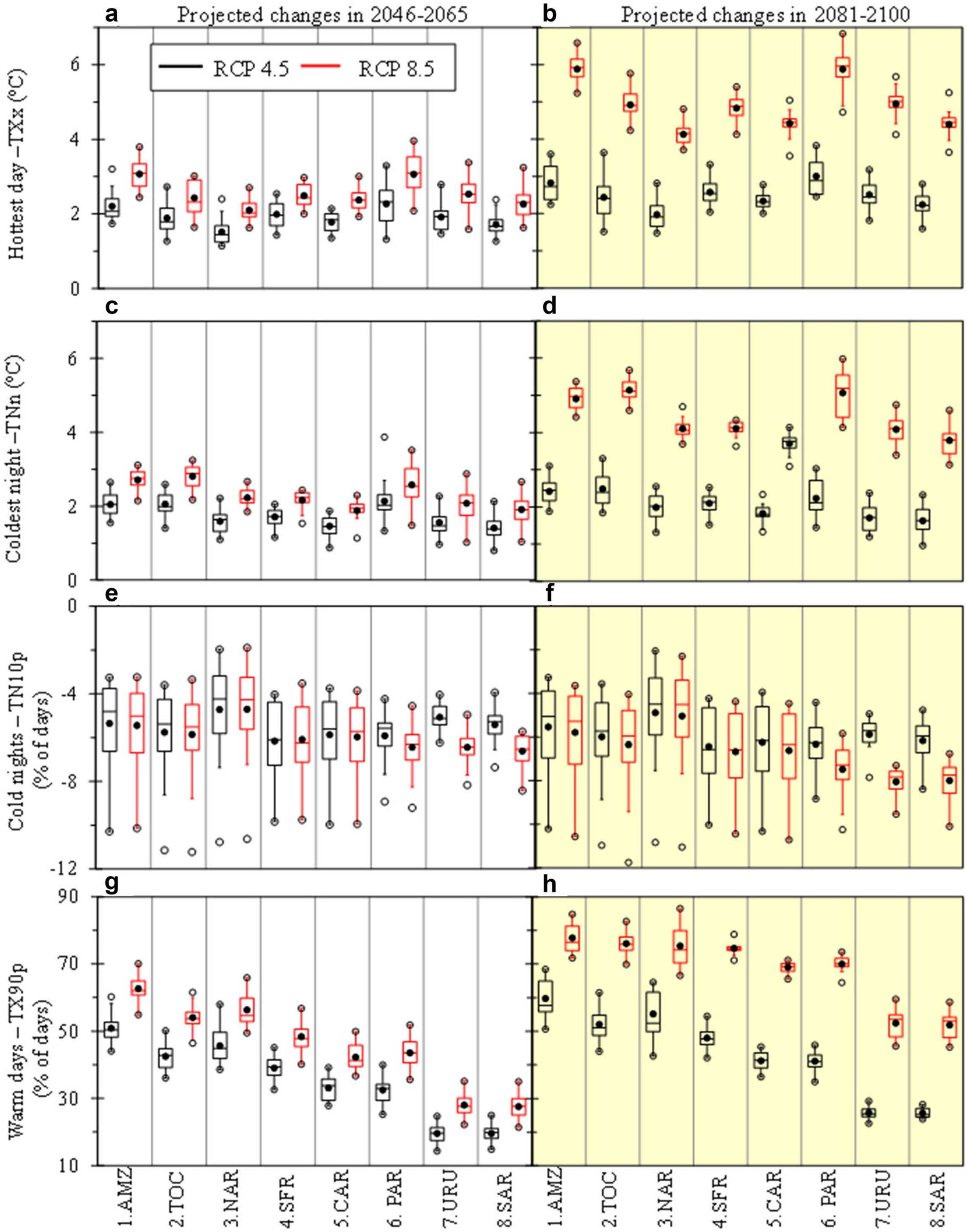

Fig. 8 Projected changes in the hottest day–TXx (**a**, **b**), coldest night–TNn (**c**, **d**), cold nights—TN10p (**e**, **f**) and warm days—TX90p (**g**, **h**) over the period 2046–2065 (white zone) and 2081–2100 (yellow zone) relative to the reference period (1986–2005) for RCP4.5 (black line) and RCP8.5 (red line) scenarios. Regional mean changes are shown for each hydrological regions; the acronyms are defined in Fig. 1. The boxes indicate the variability of the ensemble of the downscaled models—MME (Table S1), which include the interquartile range (25th–75th percentiles), median (horizontal line), mean (black dots), maximum and minimum values (black circles)

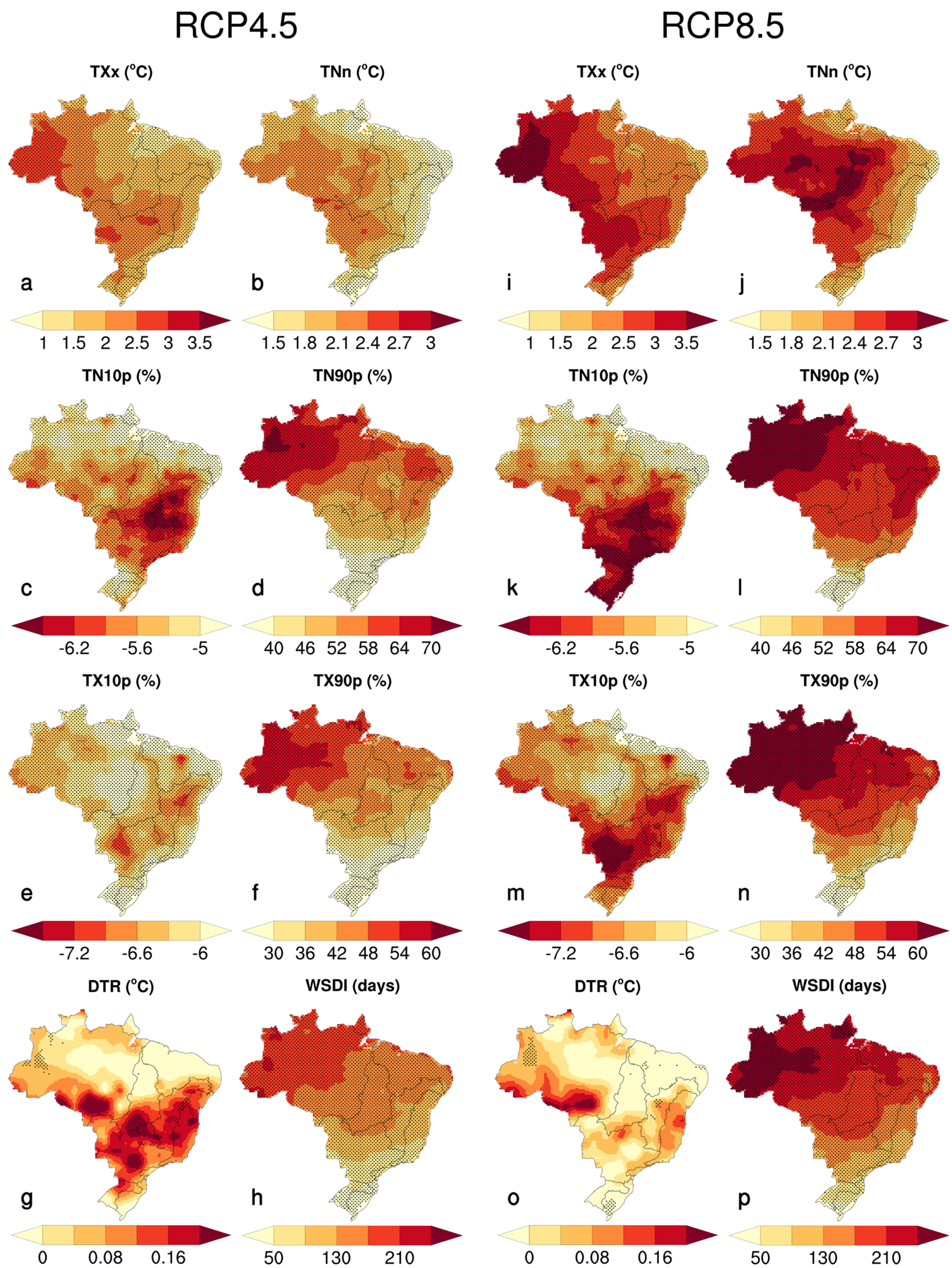

Fig. 9 Future changes of multi-model ensemble in temperature extremes indices under the **a**–**h** RCP4.5 and **i**–**p** RCP8.5 scenarios for the period 2046–2065 relative to the reference period (1986–2005). Stippling indicates grid-points where more than 66% of the models agreed in change signal and in which more than 50% of the models show a significant change

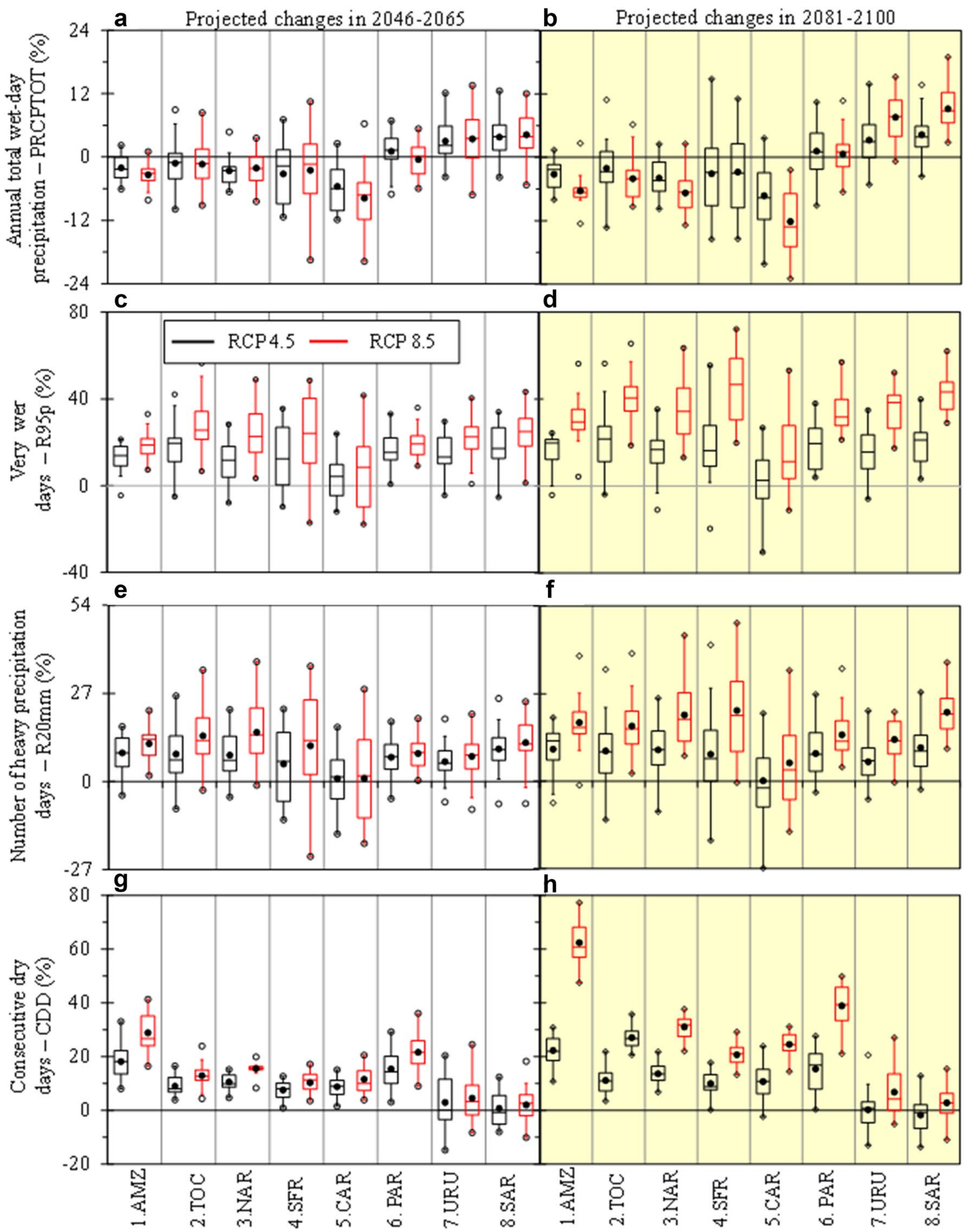

Fig. 10 As Fig. 7 but for the annual total wet-day precipitation—PRCPTOT (**a**, **b**), very wet days–R95p (**c**, **d**), Number of heavy precipitation days–R20mm (**e**, **f**), and consecutive dry days–CDD (**h**–**g**)

that the CMIP5 multimodel ensemble shows a significant sensitivity of precipitation extremes to aerosol forcing on the large-scale rainfall processes, which may be influencing the confidence in the agreement of climate projections across most of Brazil. To resolve the low confidence in the long-term projections of MMEs, Guyennon et al. (2013) and Yhang et al. (2017) concluded that the combination of dynamical and statistical downscaling of ESMs produced a better representation of regional precipitation, which can

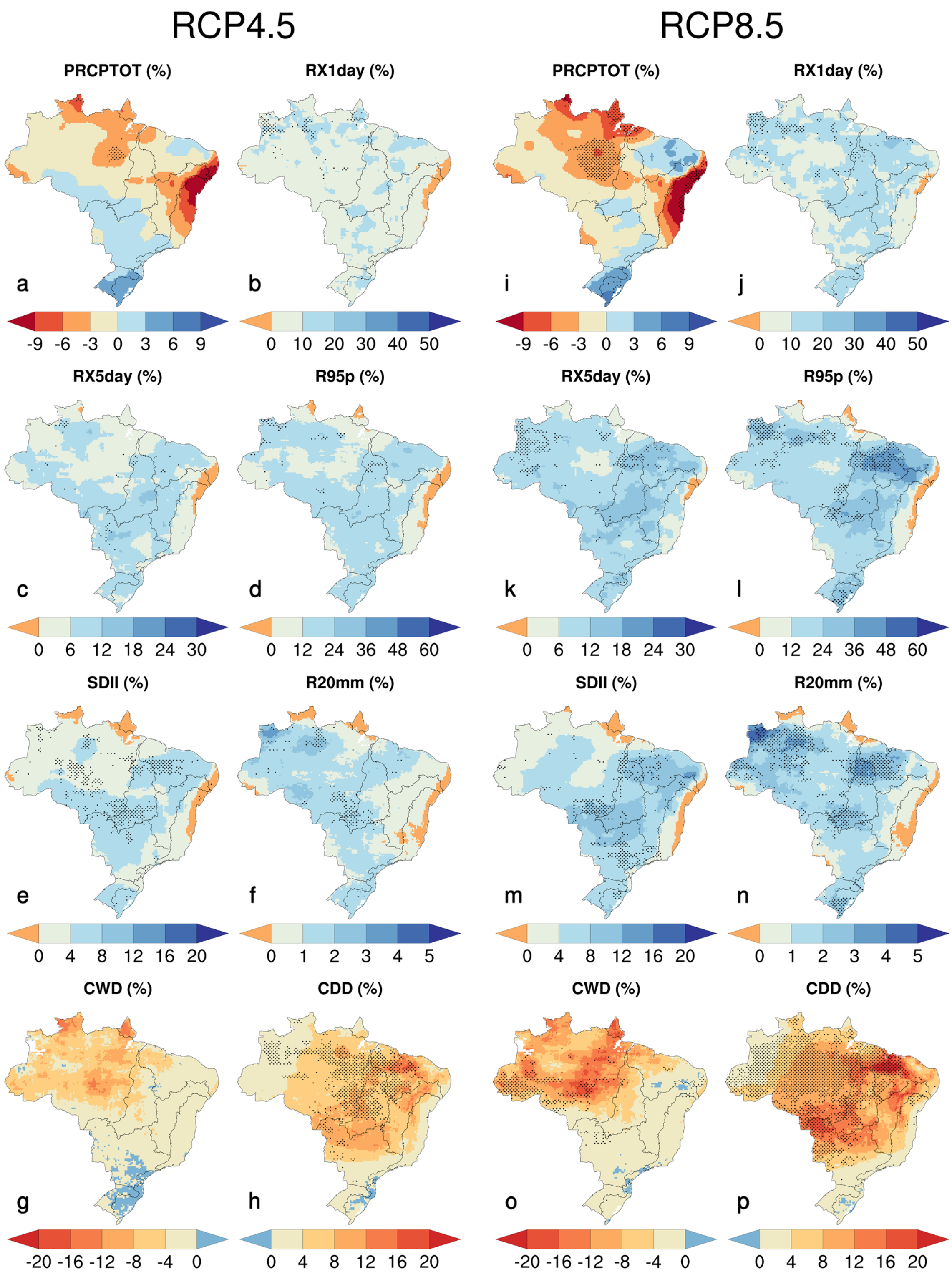

Fig. 11 Future changes of multi-model ensemble in precipitation extremes indices under the **a**–**h** RCP4.5 and **i**–**p** RCP8.5 scenarios for the period 2046–2065 relative to the reference period (1986–2005). Stippling indicates grid-points where more than 66% of the models agreed in change signal and in which more than 50% of the models show a significant change

be resulted in much improved in simulations and increased in the agreement of multi-model projections.

4 Discussion and concluding remarks

We investigated the changes in temperature and precipitation extremes in historical observations from 1980–2016 in Brazil by comparing multiple gridded datasets (ERA5, GMFD, and MSWEP) that use various techniques and station networks to calculate daily gridded fields. Additionally, we analyzed projected changes in climate extremes produced by an ensemble of 20 downscaled ESMs under RCP4.5 and RCP 8.5 scenarios over the periods of 2046–2065 and 2081–2100 relative to the reference period 1986–2005.

ERA5 performs well compared to observations (GMFD and MSWEP less so) in capturing the spatio-temporal patterns of historical climate extremes. In general, the performance over 1980–2016 shows that all datasets have a greater ability to capture temperature extremes compared to precipitation extremes. Moreover, almost all precipitation indices have large uncertainties over the Amazon basin. This study emphasizes the need to properly identify the most reliable datasets when estimating extreme climate events. This ensures that future hydrological studies and beneficial strategies to prevent the negative impacts of hydrological hazards (e.g., floods, droughts, landslides, and heat waves) are informed by the best possible scientific data.

Historical gridded datasets (observations, reanalysis, and merged datasets) analyzed during the last four decades (1980–2016) show statistically significant warming patterns for both warm (TXx, TX90, TN90, and WSDI) and cold (TNn, TX10, and TN10) extreme indices over almost all areas in Brazil. These datasets also indicate a reduction in consecutive wet days (CWD) and an increase in consecutive dry days (CDD) since the 1980s in almost all areas of the study domain. Analysis of annual total precipitation shows negative trends over the Tocantins, North Atlantic, São Francisco, and Central Atlantic basins. Multi-model climate projections reveal intensified warming patterns under future radiative forcing scenarios (RCP4.5 and RCP8.5). Mid-century (end-of-century) maximum and minimum temperatures exceed 1.4 °C (1.6 °C) in RCP4.5 and 1.9 °C (3.2 °C) in RCP8.5 scenarios. Simultaneously, the frequency of warm days/nights increases (TX90p/TN10p) more than cold days/nights (TX10p/TN10p), and heat wave duration (greater than 56 days) is expected to increase in all basins over the twenty-first century.

These observed and projected changes point to a myriad of regional impacts beyond just an increase in drought over much of Brazil (Dai 2011a, b, 2013). An increasing number of CDD affects economic activity over the Parana River Basin for instance, since it is an important region for agriculture production and energy generation (Abou Rafee et al. 2020). Furthermore, the Amazon basin (e.g., Mato Grosso State), Tocantins, North Atlantic Region, and São Francisco basins most affected by changes in climate extremes are in the forefront of Brazilian agricultural production. Studies have evaluated the impact of changes in weather patterns and demonstrated that major crops such as maize, soybeans, beans and sugarcane have been affected and will be very likely in the future (Costa et al. 2009; Justino et al. 2013; Pires et al. 2016). Thus, continued changes in maximum and minimum temperatures as shown here will continue to compromise major crop production areas in Brazil.

Observed warm extremes and an increase in CDD exacerbate impactful events like the 2014–2015 water crisis in the Southeastern region (Nobre et al. 2016) and the recurrent dry spells in Northeast region (Marengo et al. 2017). Northeastern Brazil (parts of Central Atlantic, São Francisco, and North Atlantic basins) are getting drier and the frequency of extreme precipitation events has been increasing since the 1980s. The frequency of hot days has been decreasing near the coast. Annual precipitation amounts have been reducing in this region overall, as well as the extreme rainfall event frequency. However, the northeastern region is the driest and poorest region of Brazil, and projections point to the largest reduction of total precipitation there, threatening the survival of millions of people due to water scarcity and social vulnerability (Darela-Filho et al. 2016; Marengo et al. 2017).

Urban centers across Brazil are vulnerable as well. The intensification of temperature warm extreme events may increase the incidence of respiratory and cardiovascular diseases (Son et al. 2016) and increase heat stress vulnerability (Souza et al. 2020) in Brazilian capitals (Lapola et al. 2019). Future changes show a reduction in the total amount precipitation, CWD, and the number of very heavy rainfall (R20mm) for most of the hydrological basins, except for Uruguay and South Atlantic basins. The extreme precipitation intensity indices (RX1day, RX5day, R95p, and SDII) are projected to increase under future scenarios in a majority of areas. While total precipitation decreases, more intense events over spatially-limited areas are expected to increase. This elevates the risk of flash floods and landslides, which are the most common hydrological hazards over Southern and Southeastern Brazil (CEPED-UFSC 2013; Ávila et al. 2016; Debortoli et al. 2017; Marengo et al. 2020). Again, these are densely populated and economically susceptible areas of the country. Future trends may bring conflicts of water rights and irrigation for food production in heavily agricultural areas (parts of Parana and Tocantins), negative impacts on water availability, greatly affecting the population that depends on hydroelectricity in northern and northeastern basins of Brazil (Marengo et al. 2017; Jong et al. 2018; Llopart et al. 2020).

In other areas, like the southern part of Amazon and Tocantins basins, similar reductions in annual precipitation and increases in CDD since the 1980s are likely to continue throughout the twenty-first century. These drier conditions could fuel additional drought events and enhance the risk of forest fires (Aragão et al. 2007). Ultimately, all of these changes in climate extremes impact the people of Brazil in unique ways. Understanding the perceptions and the challenges in responding to these changing climate conditions is vital for resilience, from heavily populated cities to local indigenous communities (Funatsu et al. 2019).

Thus, understanding how temperature and precipitation extremes in Brazil have changed in the past and are likely to evolve over the current century improves our current lack of understanding with regard economic and social impacts throughout the country. Designing adequate adaptation and mitigation strategies related to climate change impacts hinges on improving this knowledge and limiting the many barriers that still exist (Di Giulio et al. 2019). Still, future climate projections must be interpreted with caution as changing climate increases the variability of climate extreme and the uncertainty associated with downscaled ESMs, especially for rainfall extremes.

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