Assessing the Robustness of Future Extreme Precipitation Intensification in the CMIP5 Ensemble

MARGOT BADOR AND MARKUS G. DONAT

Climate Change Research Centre, School of BEES, and Australian Research Council's Centre of Excellence for Climate System Science, University of New South Wales, Sydney, New South Wales, Australia

OLIVIER GEOFFROY

Climate Change Research Centre, School of BEES, University of New South Wales, Sydney, New South Wales, Australia, and Centre National de Recherches Météorologiques, Météo-France/CNRS, Toulouse, France

LISA V. ALEXANDER

Climate Change Research Centre, School of BEES, and Australian Research Council's Centre of Excellence for Climate System Science, University of New South Wales, Sydney, New South Wales, Australia

(Manuscript received 12 October 2017, in final form 23 April 2018)

ABSTRACT

A warming climate is expected to intensify extreme precipitation, and climate models project a general intensification of annual extreme precipitation in most regions of the globe throughout the twenty-first century. We investigate the robustness of this future intensification over land across different models, regions, and seasons and evaluate the role of model interdependencies in the CMIP5 ensemble. Strong similarities in extreme precipitation changes are found between models that share atmospheric physics, turning an ensemble of 27 models into around 14 projections. We find that future annual extreme precipitation intensity increases in the majority of models and in the majority of land grid cells, from the driest to the wettest regions, as defined by each model's precipitation climatology. The intermodel spread is generally larger over wet than over dry regions, smaller in the dry season compared to the wet season and at the annual scale, and largely reduced in extratropical compared to tropical regions and at the global scale. For each model, the future increase in annual and seasonal maximum daily precipitation amounts exceeds the range of simulated internal variability in the majority of land grid cells. At both annual and seasonal scales, however, there are a few regions where the change is still within the background climate noise, but their size and location differ between models. In extratropical regions, the signal-to-noise ratio of projected changes in extreme precipitation is particularly robust across models because of a similar change and background climate noise, whereas projected changes are less robust in the tropics.

1. Introduction

Atmospheric specific humidity is expected to increase with temperature, as expressed by the Clausius–Clapeyron equation, by about $7\% \text{ K}^{-1}$ (under the constraint of constant relative humidity; Allen and Ingram 2002; Trenberth et al. 2003; Held and Soden 2006), and this is expected to

lead to an increase in the magnitude of annual extreme rainfall events (Allan and Soden 2008; Trenberth 2011). While the response of extreme precipitation to global warming is expected to be primarily controlled by the change in total atmospheric moisture availability (Allen and Ingram 2002; Allan and Soden 2008), the response in global mean precipitation is constrained by the radiative cooling of the atmosphere, and therefore, increases in mean precipitation are expected at a lower rate (Allen and Ingram 2002; Pendergrass and Hartmann 2014a). Overall, a general intensification of extreme precipitation is expected over the twenty-first century (Collins et al. 2013) and is shown by climate model projections

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/JCLI-D-17-0683.s1>.

Corresponding author: Margot Bador, m.bador@unsw.edu.au

(Allen and Ingram 2002; Trenberth 2011; O’Gorman and Schneider 2009; Collins et al. 2013; Kharin et al. 2013; Toreti et al. 2013; Sillmann et al. 2013b; Donat et al. 2016). Over land, more increases than decreases in extreme precipitation are observed in the instrumental record (Groisman et al. 2005; Alexander et al. 2006; Westra et al. 2013; Donat et al. 2013, 2016).

The scaling of the extreme precipitation with surface mean temperature varies with space and time, and spatial fluctuations exist, as shown by both observations (e.g., Westra et al. 2013) and climate models (Kharin et al. 2013; O’Gorman 2015). Changes in extreme precipitation can be decomposed into a local contribution associated with thermodynamic changes and with large-scale dynamical changes (Emori and Brown 2005; O’Gorman and Schneider 2009; Pfahl et al. 2017). Although the thermodynamic contribution shows a robust increase in climate models, dynamical changes vary in sign and exhibit strong model dependency in some regions (Pfahl et al. 2017). The dynamical contribution to extreme precipitation changes can amplify or inhibit the thermodynamic increase in extreme precipitation at the regional scale (Pfahl et al. 2017). The competition between both components can vary throughout the year: for instance, between a dry and a wet season. The general expectation of an increase in extreme precipitation can therefore not hold over some regions or during some seasons.

While extreme precipitation appears generally better simulated in climate models from phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) with more intense precipitation and fewer consecutive wet days (Sillmann et al. 2013a), compared to previous model intercomparisons, climate models generally precipitate too often and too lightly (Stephens et al. 2010; Dai 2006). Numerous studies conclude that climate models cannot reliably simulate extreme precipitation in the tropics (O’Gorman and Schneider 2009; Kharin et al. 2013; Toreti et al. 2013; O’Gorman 2015). This is partly explained by differences in the parameterization of the convective processes, resulting in a biased representation of the precipitation frequency and intensity (Wilcox and Donner 2007) and interannual variability (Allan and Soden 2008), and by a wide range of changes in vertical velocities across the models (O’Gorman and Schneider 2009).

The Intergovernmental Panel on Climate Change (IPCC) recommends investigating future climatic changes using a multimodel framework along with projection uncertainties. However, in most previous literature, model interdependencies are often not accounted for when studying extreme precipitation changes. CMIP models share common representations of some physical phenomena,

codes, or even model components (Masson and Knutti 2011; Knutti et al. 2013; Flato et al. 2013). For instance, Alexander and Arblaster (2017) show that changes in extreme precipitation are more closely related to climate model physics than to spatial resolution over Australia. These interdependencies are often not taken into account in multimodel-based studies.

Most of the studies investigating future changes in extreme precipitation generally assess the significance of the change with regard to the statistical difference in the probability distribution between a present-day and future period of 20–30 years. However, over 2–3 decades, only a limited sampling of climate internal variability can be estimated. Internal variability can be defined by all variations that the different components of the climate system (e.g., ocean, atmosphere, cryosphere) experience under fixed external radiative forcings (i.e., in a stationary climate) over different spatial and temporal scales. These natural fluctuations of the climate range from high-frequency variability at local or subregional scales to multidecadal and centennial variations over large-scale regions. Thus, a change statistically different from internal variability corresponds to an unprecedented change. The respective role of the natural radiative forcings compared to anthropogenic forcings in observed trends and changes in mean and extreme precipitation has also been investigated. Evidences of a human-induced intensification of the water cycle are found, (Polson et al. 2013) and the observed increase in extreme precipitation amounts has been attributed to the increase in anthropogenic greenhouse gases (GHGs; Min et al. 2011). Such studies, however, use a set of simulations where the different radiative forcings of the climate system are prescribed individually, and the realism of such idealized simulations of a “world that might have been” is debatable.

In this study, we investigate the robustness of the CMIP5 ensemble in simulating future increases in extreme precipitation amounts from the driest to the wettest land regions, as defined by each model’s precipitation climatology. We use an ensemble of 27 climate models and first assess how different the projected changes are among models sharing atmospheric physics. Then, we investigate model uncertainties in annual and seasonal future changes over the globe and the tropical and extratropical regions separately. The significance of the anthropogenic-induced changes in extremes is assessed against the range of changes that could be naturally driven by internal variability. The final objective is to highlight common features among the CMIP5 models from which a better characterization of the robustness of the projected increase in extreme precipitation amounts could be gained.

TABLE 1. Groups of models, atmospheric components, reference papers, and the length of simulation in each model control simulation. More details on the other model components (i.e., land, ocean, ice) can be found in Table 1 of Sanderson et al. (2015).

Group	Model	Atmospheric model	Reference papers	No. of years in control simulation
a	CCSM4	CAM4	Neale et al. (2010); Collins et al. (2004)	156
	CESM1 (BGC)			500
	NorESM1-M	CAM4-Oslo	Bentsen et al. (2013); Collins et al. (2004)	500
	BCC_CSM1.1	BCC_AGCM2.0.1	Wu et al. (2010); Neale et al. (2010);	500
b	BCC_CSM1.1(m)	(CAM3 modified)	Collins et al. (2004)	400
	MPI-ESM-MR	ECHAM6	Stevens et al. (2013); Giorgetta et al. (2013)	1000
	MPI-ESM-LR			1000
	CMCC-CM	ECHAM5	Scoccimarro et al. (2011); Roeckner et al. (2003)	330
c	CMCC-CMS			500
c	MRI-CGCM3	MRI-AGCM3	Yukimoto et al. (2012)	500
	HadGEM2-CC	HadGAM2	Collins et al. (2011); Martin et al. (2011)	240
d	HadGEM2-ES			577
	ACCESS1.0		Bi et al. (2013)	500
	ACCESS1.3	HadGAM2 modified		500
	EC-EARTH	ECMWF IFS version 31r1	Hazeleger et al. (2010)	450
f	IPSL-CM5A-MR	LMDZ5A	Dufresne et al. (2013); Hourdin et al. (2006)	300
	IPSL-CM5A-LR			1000
g	IPSL-CM5B-LR	LMDZ5B	Hourdin et al. (2013)	300
h	MIROC-ESM	MIROC-AGCM	Watanabe et al. (2011)	630
	MIROC-ESM-CHEM			255
i	MIROC5	MIROC-AGCM6	Watanabe et al. (2010)	670
j	GFDL-ESM2G	AM2.1	Dunne et al. (2012); Anderson et al. (2004)	500
	GFDL-ESM2M			500
k	GFDL CM3	AM3	Donner et al. (2011)	800
l	CanESM2	CanAM4	Chylek et al. (2011)	1096
m	CNRM-CM5	ARPEGE-Climat	Voltaire et al. (2013)	850
n	CSIRO Mk3.6.0	Mk3.6	Gordon et al. (2010); Jeffrey et al. (2013)	500

In section 2, we introduce the data and methodology used in this paper. Results are then presented in two subsections: section 3a focuses on changes in extreme precipitation over the globe, and section 3b assesses the significance of the projected changes with regard to internal variability. Finally, we end with a discussion of our results and concluding remarks in section 4.

2. Data and methods

a. Simulated daily precipitation

We study extreme precipitation events derived from the daily output of an ensemble of 27 CMIP5 climate models (see Table 1 for the list of models). Note that we use the maximum number of models that provide daily precipitation rates for the three different types of simulations [preindustrial, historical, and representative concentration pathway 8.5 (RCP8.5), described as follows].

For each model, we consider a pair of simulations to estimate future changes in extreme precipitation: the historical and the continuing future simulations. The historical simulation has observed natural (e.g., solar

activity and volcanic aerosols) and anthropogenic (e.g., GHG and aerosols) forcings, and the future simulation has anthropogenic emissions as prescribed by RCP8.5 (van Vuuren et al. 2011). This scenario of future anthropogenic emissions is usually referred to as a business-as-usual scenario, leading to a total radiative forcing of roughly 8.5 W m^{-2} in 2100.

One simulation per model is used (usually rli1p1, except r2i1p1 for CCSM4), and thus simulations from different models may also differ due to representing different phases with regard to internal variability (Deser et al. 2012; Fischer et al. 2014). In addition, we focus on long-term future change (see section 2b), for which the climate change signal is more important compared to internal variability (Hawkins and Sutton 2009), and we also specifically estimate the range of changes in extreme precipitation that could be driven by internal variability alone (see section 2e) from the control simulation of each model (described below).

For each model, we also consider extreme precipitation from the preindustrial control simulation. This long simulation covers between 156 and 1096 years, depending on the model (see Table 1), with all radiative forcings (natural and anthropogenic) set constant at

their preindustrial 1850 values. These simulations allow an estimation of a range of changes in extreme precipitation driven by internal variability alone, as described in section 2e. These long-term simulations can be affected by nonphysical long-term trends or model drift (Sen Gupta et al. 2013). We focus on land regions, where these spurious trends are negligible for daily precipitation, with 100-yr linear trends lower than $0.001 \text{ mm day}^{-1}$ in all models [see Supplementary Fig. 1 (hereafter Fig. S1) in the online supplemental material], so we do not detrend the simulations.

Model output on the scale of a grid cell is considered to be an areal mean, so to avoid scaling issues between models, we interpolate all model output to the same grid (Chen and Knutson 2008; Gervais et al. 2014). We choose the CanESM2 model grid, as it has the coarsest latitudinal resolution of the ensemble ($\sim 2.8^\circ$). When discussing regional results, it should be noted that we are limited by the resolution of the global models, and our conclusions on regional scales should be considered in that context. We first interpolate the output from each model onto the common grid (with a conservative remapping interpolation scheme) and then calculate extreme precipitation as follows.

b. Changes in extreme precipitation

We define extreme precipitation as the maximum 1-day precipitation amount over a season or year [i.e., the Rx1day (mm) index recommended by the WMO/WCRP/JCOMM ETCCDI; Zhang et al. (2011)]. This index gives information on the magnitude of extreme precipitation events but does not consider possible changes in frequency. First, we calculate annual or seasonal extreme precipitation from two 30-yr periods in the historical (1976–2005) and future (2071–2100) simulations. Then, we calculate the respective 30-yr averages of extreme precipitation. Finally, we consider the relative changes in extreme precipitation between the future and the historical periods, as expressed below:

$$\begin{aligned} & \text{relative change in extreme precipitation (\%)} \\ &= \frac{\overline{\text{Rx1day}}_{\text{future}} - \overline{\text{Rx1day}}_{\text{hist}}}{\overline{\text{Rx1day}}_{\text{hist}}} \times 100, \end{aligned}$$

where $\overline{\text{Rx1day}}_{\text{future}}$ and $\overline{\text{Rx1day}}_{\text{hist}}$ are the 30-yr averages of Rx1day over the future and historical periods, respectively.

We also consider changes in extreme precipitation scaled by simulated global warming. To this end, we divide the relative change in annual or seasonal extreme precipitation of each grid cell by the annual mean global change in surface air temperature between the future

(2071–2100) and historical (1976–2005) periods for each model.

c. Definition of a wet and a dry season

Wet and dry seasons are defined by the 30% wettest and driest days of the year, respectively. The selection of the wettest and driest days of the year is estimated from the daily mean precipitation climatology in the control simulation, over hundreds of years, and no requirement such as a certain number of consecutive days is applied (i.e., days in each respective season do not need to be contiguous in time). The calculation is independently performed for each grid cell and each model. Figure S2 shows an example of the selection of the 30% wettest and driest days from the climatological precipitation amounts in the control simulation for one random grid cell (the same across all models). This illustrates that at the gridcell scale, the dry and wet seasons can be quite different in terms of magnitude and timing from model to model. Over a region or a subregion, some intermodel differences in the annual precipitation cycle will cancel out, although certainly not all of them. Defining a wet and dry season as the 30% wettest and driest days of the year for each model allows us to avoid part of the annual precipitation cycle biases.

d. Partitioning in bins of mean precipitation amounts

To investigate how the changes in annual or seasonal extreme precipitation could affect different regions, we partition grid cells with respect to their annual or seasonal mean precipitation. This follows Donat et al. (2016), who investigated the changes in extreme precipitation in the wet and dry regions of the world as defined by both precipitation totals and extremes. Here, we consider the complete spectrum of mean precipitation, from the lowest (driest) to the highest (wettest) areas, regardless of any geographical location. To this end, we use preset bins of daily mean precipitation climatology equally distributed every 1 mm day^{-1} (e.g., in Fig. 1). The climatological precipitation amount for each grid cell is estimated from the control simulation, over hundreds of years, and for each model individually to obtain a climatological grid-scale precipitation estimate from a large sample of natural climate variations. The radiative forcings in the control simulations have preindustrial values. While we could have estimated mean precipitation rates from the historical simulation (i.e., under present-day forcings), we would have sampled less natural climate variability. Using the control instead of the historical simulation also allows us to define climatological mean precipitation independent of the periods used to define future change.

The global distribution of grid cells is partitioned with regard to the model mean rather than climatological extreme precipitation for a better intermodel comparison

FIG. 1. Changes in Rx1day (relative to the historical period; %) between 2071–2100 (RCP8.5) and 1976–2005 (historical) in 27 CMIP5 climate models (one per panel), grouped with regard to their shared atmospheric components (colors and letters; see also Table 1). The global distribution of grid cells (gray dots) is shown as a function of the climatological annual mean precipitation estimated from each model control simulation and partitioned in preset bins (every 1 mm day^{-1} , as indicated by vertical thin lines). Colored dots refer to the changes in the median estimate in each bin of mean precipitation (with a minimum value of 10 grid cells per bin required). Only land grid cells (60°S – 90°N) are considered.

of the regions of the globe, from the driest to the wettest. Indeed, the intermodel differences are reduced for the climatological annual mean precipitation, compared to the climatological annual maximum daily precipitation,

in terms of spatial distribution and magnitude (see Figs. S3, S4).

A large proportion of grid cells in the first bins of mean precipitation (i.e., the driest ones) belong to Antarctica,

which can partly outweigh other dry regions. Since Antarctica is largely uninhabited, we exclude it from our global domain and only consider grid cells in the latitude range from 60°S to 90°N.

e. Estimates of simulated internal variability

For each model, annual and seasonal extreme precipitation is first calculated in the entire preindustrial control simulation. Then, two blocks of 30 years are randomly chosen across the entire time series of annual and seasonal extremes, and the relative change between these two random periods is calculated (as expressed in section 2b). This operation is repeated 5000 times to estimate a distribution of the possible changes between 30-yr blocks that could occur naturally. Blocks are sampled with replacement and can possibly overlap. From this distribution, the 5th and 95th percentiles are determined, and we finally obtain a 90% interval of the changes in extreme precipitation driven by internal variability alone for each grid cell of each model (see Fig. S5).

f. Grouping of models

We want to test how different the simulated future changes in extreme precipitation are among CMIP5 models sharing atmospheric physics and, in particular, in their treatment of convection. To that end, we classify the climate models according to their similarities in atmospheric physics, that is, with respect to their atmospheric convection schemes based on information found in relevant reference papers. We do not implement a metric to estimate intermodel spread or any comparison with observations over a present-day period; hence, we evaluate neither the interdependency nor the skill, as done in Sanderson et al. (2015), for instance. Our classification of models is not meant to give the “best” subset of CMIP5 models but rather to investigate if, from the 27 models used here, there are similarities in the future extreme precipitation amounts among models sharing atmospheric components. Such duplications in the ensemble could artificially give more weight to a pattern, eventually leading to overly robust results in the multimodel assessment of the change.

The resulting groups of models are presented in Table 1 (see the online supplemental material for more details on the methodology). Different models from the same modeling center can appear in different groups if they contain major differences in their physics and, in particular, in their treatment of convection. This is the case for the models IPSL-CM5B-LR, MIROC5, and GFDL-CM3. The atmospheric components in IPSL-CM5B-LR differ substantially from its previous version, including a new treatment of shallow convection, major modifications in the representation of deep convection closure

and triggering, and the addition of a cold pools scheme (Hourdin et al. 2013). MIROC5 differs from MIROC-ESM in the representation of convection (entrainment rate formulation and triggering conditions), large-scale clouds, and large-scale precipitation (Watanabe et al. 2010). The atmospheric component in GFDL-CM3 incorporates deep and shallow convection schemes that differ from the previous version (Donner et al. 2011). In these cases, different model versions were considered as different groups, whereas in other cases (e.g., CAM3/CAM4, ECHAM5/ECHAM6) where changes between versions are less substantial, model versions are treated as the same group.

Different models within the same group can differ in other than atmospheric components. For instance, oceanic components differ between models in group j, and land components differ between models in group d. Other model groups can also exhibit differences in spatial resolution (e.g., between MPI-ESM-MR and MPI-ESM-LR), the representation of chemistry (e.g., between MIROC-ESM and MIROC-ESM-CHEM), aerosols and aerosol–cloud interactions (e.g., NorESM1-M compared to CCSM4 and CESM1-M), or minor changes related to their atmospheric physics. From ECHAM5 to ECHAM6 (i.e., models in group b), changes concern aerosols, minor changes in the representation of convective processes, vertical discretization within the troposphere, and some model parameters (Stevens et al. 2013). The atmospheric component of ACCESS1.0 is that of HadGEM2, and differences between ACCESS1.0 and ACCESS1.3 atmospheric components are minor (models in group d; Bi et al. 2013). The BCC_AGCM2.0.1 convection scheme differs slightly from that of CAM3 (i.e., models in group a), with changes in CAPE closure formulation and the inclusion of a triggering threshold depending on relative humidity (Zhang and Mu 2005; Wu et al. 2010). Note that the model grouping is not fully objective and also depends on the results. For instance, the differences between atmospheric convection schemes in models in group a could have been a reason to split this group in two, but projections within this group do not present substantial differences.

3. Results

a. Future changes in extreme precipitation

We first investigate simulated changes in annual extreme precipitation in different regions according to their climatological annual mean precipitation across the 27 CMIP5 models (Fig. 1). Projected changes in extreme precipitation between the end of the twentieth and the end of the twenty-first centuries range from

about -50% to $+100\%$ across the spectrum of mean precipitation, indicating grid cells associated with a drying and grid cells associated with an intensification of precipitation extremes (gray dots in Fig. 1). Some models indicate larger changes, especially in some of the driest locations (leftmost bins). The majority of models also have a larger spread of extreme precipitation changes in the driest grid cells than in the wettest grid cells, in agreement with Donat et al. (2016). Overall, the CMIP5 models predominantly show an intensification of the annual extreme precipitation in most grid cells across the entire spectrum of climatological annual precipitation amounts.

We then estimate the median change in extreme precipitation in every bin of mean precipitation (colored dots in Fig. 1). Note the median, rather than the mean, estimate is considered to avoid biasing the results with outliers from the tails of the distribution (especially in bins associated with a small number of grid cells). The median estimates from all 27 models indicate an intensification of extreme precipitation across the entire spectrum of mean precipitation, except two models: MIROC-ESM and MIROC-ESM-CHEM (model group h). These two models show the largest intensification of extreme precipitation across the models for the driest bins and a very small positive change (or even no change) for the wettest bins. MIROC5 (model i), another model from the same modeling center (see Table 1) but with differences in the atmospheric physics, shows different results with relatively constant positive median changes across all bins. Similarly, the median estimates of the changes from IPSL-CM5B-LR (model g) are different from those of both IPSL-CM5A-LR and IPSL-CM5A-MR (model group f). More generally, relatively consistent results are reflected in the models clustered in the same groups (e.g., the projections given by the five models in group a or in groups b, d, f, h, and j). The grouping of models clearly shows that from an initial set of 27 climate models, we more reasonably have no more than 14 different estimates.

There are considerable intermodel differences in the projected changes in annual extreme precipitation across the entire spectrum of mean precipitation. Our aim here is not to assess the best multimodel estimate of projected change but rather to better assess the uncertainties given by the model differences (structural uncertainties), so we consider all individual models. Note that only one simulation per model is considered; therefore, part of the intermodel differences could also be due to internal variability (see section 2a). The median estimates of the changes given by the 27 models (shown in Fig. 1) are shown together in Fig. 2a, and other panels in Fig. 2 show different spatial or seasonal

aggregations. The intermodel spread is larger for the wettest than for the driest bins of mean precipitation (Fig. 2a). For dry regions associated with annual mean precipitation ranging from 0 to 2 mm day^{-1} , the CMIP5 ensemble shows a positive change in extreme precipitation amounts from 10% to 50%, whereas for the wettest regions, the changes range from -5% to $+55\%$.

The changes in extreme precipitation projected by the CMIP5 ensemble and the associated intermodel uncertainties are further investigated at the seasonal scale. We focus on the dry and wet seasons, respectively, defined by the 30% driest and wettest days of the year (see section 2c). At the seasonal scale, similarly to the annual scale, the large majority of models show an intensification of extreme precipitation over most of the globe. The projected intermodel spread of changes in the wet season are similar in magnitude to the annual results, but the values cover a larger range of mean precipitation bins (Fig. 2b), reflecting the high precipitation amounts in the wet season. On the other hand, the projected changes in the dry season indicate somewhat smaller intermodel spread, compared to annual extreme precipitation (Fig. 2c). Models agree on a future intensification of dry season extreme precipitation for the complete spectrum of mean precipitation (except the $4\text{--}5 \text{ mm day}^{-1}$ bin of mean precipitation, which is composed of fewer grid cells, where only the MIROC-ESM models do not show increasing intensity of extreme precipitation).

Annual and seasonal changes in extreme precipitation are further investigated within a tropical ($30^{\circ}\text{S}\text{--}30^{\circ}\text{N}$) and an extratropical band (all land grid cells north of 30°N and between 30° and 60°S). On both annual and seasonal scales, the intermodel spread of the projected changes in extreme precipitation is smaller in extratropical regions (Figs. 2d–f) and larger in tropical regions (Figs. 2g–i), compared to the global domain (Figs. 2a–c). In the extratropics (mostly Northern Hemisphere regions), all models show a clear and consistent increase in extreme precipitation amount in both seasons, from about $+10\%$ to $+50\%$. In most models, the intensification of extratropical extreme precipitation is slightly stronger in the dry season (Fig. 2f) compared to the wet season (Fig. 2e) and at the annual scale (Fig. 2d), with stronger relative increases in the dry compared to the wet regions. The response to human-induced emissions is much more uncertain in the tropics (Figs. 2g–i), in agreement with O’Gorman (2012). In particular, at the annual scale and in the wet season, changes range from -30% to more than $+50\%$, with the largest intermodel uncertainties in the driest regions (Figs. 2g,h), in agreement with Donat et al. (2016). A larger proportion of models show more positive than negative changes across the different tropical regions,

FIG. 2. Median estimates of changes in annual and seasonal maximum daily precipitation (%) in each bin of climatological mean precipitation (mm day^{-1}). We consider (left) annual, (center) wet season, and (right) dry season extreme and mean precipitation over the (a)–(c) globe and (d)–(f) extratropical and (g)–(i) tropical (30°S – 30°N) regions. The median estimates from the 27 CMIP5 climate models shown in Fig. 1 are combined in (a) (see Fig. 1 for the color–model relation).

but the spread remains important. The intermodel spread in the tropics is slightly smaller in the dry season (Fig. 2i) compared to the wet season and at the annual scale (Fig. 2g). In the dry season, the models seem to indicate a drying of the extremes in the driest tropical regions (mean daily precipitation amount lower than 2 mm day^{-1}) and an intensification of the extremes in more wet regions. But similar to the wet season, in the dry season, these results must be nuanced given the large uncertainties between CMIP5 models in the tropics contrasted with smaller uncertainties in the extratropics. Finally, global, extratropical, and tropical CMIP5 projections during the wet season are more similar to annual projections (albeit covering a larger range of mean precipitation bins; first two columns of Fig. 2) compared to dry season projections (last column of Fig. 2). This is expected from the fact that annual extreme events are more likely to occur during the wet season.

Extreme precipitation intensity is expected to increase with global warming (Allen and Ingram 2002; Trenberth et al. 2003). However, the amount of

simulated warming over the twenty-first century can substantially differ between models. We investigate how this may affect the CMIP5 intermodel differences in projected extreme precipitation intensities discussed above. To this end, we scale the future changes in extreme precipitation by the annual mean global change in temperature (see section 2a) for each model (Fig. 3). The same qualitative results are found: the intermodel spread is generally larger over the wet regions compared to the dry regions of the globe, smaller in the dry season compared to the wet season and at the annual scale, and largely reduced in extratropical compared to tropical regions and at the global scale. In the following section, we thus consider the relative changes in extreme precipitation without taking into account the different amounts of warming in the CMIP5 ensemble. Donat et al. (2016) showed that part of the CMIP5 intermodel spread in extreme precipitation changes over dry regions could be explained by the spread in global temperature changes and that this relationship was not found over wet regions. The comparison between

FIG. 3. As in Fig. 2, but with changes in annual and seasonal maximum daily precipitation ($\% \text{ K}^{-1}$). For each model, the relative change in extreme precipitation (%) of each land grid cell is divided by the annual mean global change in surface air temperature (K) between 2071 and 2100 (RCP8.5) and between 1976 and 2005 (historical).

changes in percent per kelvin (Fig. 3) and changes in percent (Fig. 2) is in agreement with their findings, with a slight reduction of the spread in the first bin of mean precipitation (i.e., in the driest grid cells of each model) for global and extratropical changes (first and second rows of Figs. 2 and 3, respectively), but no clear reduction of the spread is found for the wettest grid cells or for tropical regions. In the tropics, in addition to a larger influence of internal variability (Deser et al. 2012), the sensitivity of the response of extreme precipitation to warming is more uncertain (O’Gorman 2012), and intermodel differences are probably more linked to differences in simulated vertical motions (O’Gorman and Schneider 2009) and more generally to differences in the parameterization of convection (Wilcox and Donner 2007).

b. Comparison to changes driven by internal variability alone

In addition to estimating the intermodel uncertainties of the projected changes in extreme precipitation, another important aspect is to assess the significance of

those changes. In most studies, the significance of the future changes is evaluated with regard to the statistical difference between future and present-day climatologies. Here, we assess the significance of the changes with regard to internal variability [as in Bador et al. (2016), who assessed future changes in record-breaking temperatures]. We test if the projected change at the gridcell scale is large enough to exceed the 90% interval of the changes in extreme precipitation driven by internal variability alone. This interval gives an indication of a range of changes that could occur naturally through climatic variations over different spatiotemporal scales. This can also be interpreted as the climatic background noise that the signal (the change between the future and the historical periods) has to exceed to be significant.

In all 27 climate models, there are at least some regions where future changes in annual extreme precipitation are still within the interval (red stippling in Fig. 4). However, the size and location of such regions depend on model. Some models project significant changes over most of the globe (e.g., model i, MIROC5) whereas others show much fewer significant changes

FIG. 4. Changes in Rx1day (relative to the historical period; %) between 2071–2100 (RCP8.5) and 1976–2005 (historical) for the 27 CMIP5 models (one per panel) grouped with regard to their shared atmospheric components (colors and letters; see also Table 1). Red stippling indicates grid cells where the change is within the 90% interval of the changes in annual maximum daily precipitation driven by internal variability alone. Internal variability intervals are estimated in each model control simulation based on 5000 bootstrap realizations of changes between two 30-yr random periods (see section 2e).

(e.g., model g, IPSL-CMB-LR). Within each model, the majority of the significant changes indicate an intensification of annual extreme precipitation. Most of the drying is seen in subtropical regions and is not significant (e.g., model groups a, c, e, h, i, j, k, and m), but models g and l indicate a drying in South America with a portion of significant results, and models from groups b, f, and n indicate a drying in North Africa with a fraction of significant results. Models differ over the Sahara region. Australia also illustrates the diversity in model projections in terms of both the sign and significance of the change. Some models indicate a significant drying (e.g., model n, CSIRO Mk3.6.0) or a significant intensification (e.g., models j and l, GFDL-ESM2G) over the entire region, while others show mostly non-significant changes (e.g., models k, l, and m). Alexander and Arblaster (2017) associate weak confidence with extreme precipitation projections in Australia also because of poor agreement between different observational datasets. On the contrary, extratropical regions of the Northern Hemisphere are generally associated with more significant changes compared to the rest of the globe, especially in northeast Asia, yet with discrepancies between models at subregional scales.

Seasonal projections have common features compared to annual projections. For instance, all 27 models show that by the end of the twenty-first century, changes in extreme precipitation in the dry and wet seasons remain within the interval over some regions of the world (red stippling in Figs. 5, 6, respectively). Similar to annual projections, the size and location of such regions associated with nonsignificant changes in seasonal extreme precipitation differ from one CMIP5 model to another. However, there are also some seasonal results that contrast the annual-scale results. For instance, in the tropical band, there are more models showing a drying in the dry season, with a portion of grid cells in these regions associated with significant changes (Fig. 5), compared to the annual projections (Fig. 4). As previously highlighted in Fig. 2i, this suggests a reduced intensity of extreme precipitation in some tropical regions in the dry season in the future. However, the intermodel uncertainties remain important (Fig. 5). Figure 2i indicates a drying in the driest tropical areas (i.e., in the subtropics) in each model in the dry season, but there is no clear agreement between the models on the precise regions where such a drying could happen (Fig. 5). Some models highlight northern parts of South America (e.g., models b, c, g, h, j, k, and l) as regions where dry season extremes become less intense, and others highlight the northern (e.g., models b, f, and g) or southern part of Africa (e.g., models d, g, h, j, l, and n) or some parts of Australia (e.g., models d, m, and n), while

others do not show any significant reduction of dry season extreme precipitation (e.g., models a, e, and i). In contrast, it is interesting to note that in the extratropics, there is a projected intensification of dry season extreme precipitation amounts (Fig. 5). This intensification (relative to historical climatology) in the dry season is larger and more significant than indicated at the annual scale by the majority of models (Fig. 4), especially over northeast Asia. As previously highlighted in Fig. 2e, the CMIP5 ensemble tends to agree on an intensification of wet season extreme precipitation. Here, we further show that very few models indicate a significant drying at the regional scale in the wet season (Fig. 6). In the tropical band, the changes in extreme precipitation in the wet season are contrasted between models, with regard to the sign, magnitude, and significance of change (Fig. 2h), and no clear agreement between the models can be drawn out at the regional scale (Fig. 6).

We further aim to bring out common features from the CMIP5 ensemble, and to this end, we investigate the significance of the projected changes in extreme precipitation by partitioning the global distribution of grid cells as a function of their mean precipitation (Fig. 7). Indeed, as described above, it can be difficult to conclude and bring out regions or subregions of clear significant results because of intermodel uncertainties (and also by internal variability to a lesser extent, as only one simulation per model is used; see section 2a). Previously, we showed that this is partly explained by a wide range of changes in extreme precipitation (i.e., the signal). One would then also compare the 90% interval of the changes in extreme precipitation driven by internal variability alone (i.e., the noise), against which the significance of the future change is evaluated. Indeed, contrasted estimates of the significant changes between models could also be linked to a different representation of noise. The top panels of Fig. 7 show that all models but two (GFDL-ESM2G and GFDL-ESM2M; models j1 and j2, respectively) indicate a larger mean estimate of the 90% interval in the driest than in the wettest bins of mean precipitation. These two models (from group j) show larger noise amplitude for the driest bin of mean precipitation compared to the other bins except the very last, but this last bin is composed of fewer grid cells compared to the other bins. Overall, CMIP5 models thus agree on a larger estimate of the noise over dry regions, compared to wet regions (when considering relative changes). It is worth noting that the CMIP5 models actually have quite similar spatial distribution of the relative dry and wet regions over the globe [see Fig. S3 and Donat et al. (2016)]. Apart from this common feature, there are still some discrepancies in the amplitude of the 90% interval, in particular over the wettest bins of mean

FIG. 5. As in Fig. 4, but for the changes in dry season maximum daily precipitation.

FIG. 6. As in Fig. 4, but for the changes in wet season maximum daily precipitation.

FIG. 7. Each top panel shows mean estimates (gray bars; %) of the 90% interval of the changes in annual maximum daily precipitation driven by internal variability alone (see section 2e), for all global land grid cells partitioned in bins of climatological annual mean precipitation (every 1 mm day⁻¹, as indicated by vertical thin lines), and for each of the 27 CMIP5 models (one per panel), grouped with regard to their shared atmospheric components (colors and letters; see also Table 1). Mean estimates correspond to the averaged value of the interval lower and upper limits (5th and 95th percentiles; brown and blue horizontal lines, respectively) across all grid cells in each bin. The number of years used to estimate the interval from the control simulation is indicated in the boxes (see section 2e). Each bottom panel shows the proportion (%) of the changes in annual maximum daily precipitation within the interval (gray shading), below the interval lower limit (brown shading), or above the interval upper limit (blue shading). The proportion of the changes is assessed across all grid cells in a bin of climatological annual mean precipitation (mm day⁻¹) for each of the 27 CMIP5 models. In each bin of climatological annual mean precipitation, the brown-, gray-, and blue-shaded bars are stacked so they add up to 100%. By construction of the interval, under the hypothesis of a change only driven by internal variability, 5% of the changes would be below the interval lower limit (brown horizontal line), 5% would be above the interval upper limit (blue horizontal line), and 90% would be within the interval.

FIG. 8. As in Fig. 7, but considering only grid cells from extratropical regions.

precipitation (top panels of Fig. 7), with some models showing larger estimates of the noise (e.g., models j and m) than others (e.g., models d, i, and n). These panels illustrate once more the similarities across models from the same group, which show a very similar distribution of the noise magnitude against the mean precipitation.

It is striking to see that the estimation of noise over the extratropical and tropical regions separately show that intermodel uncertainties on the global scale mostly come from the tropical regions (Figs. 8, 9, respectively). The CMIP5 models have a very similar representation of the range of changes induced by internal variability

alone in the extratropics, in terms of both magnitude and distribution. Again, larger relative noise amplitude is found in the driest than in the wettest regions, with maximum noise amplitude of $\pm 20\%$ (top panels of Fig. 8). Hence, in extratropical regions, the significance of changes in extreme precipitation is robust because of a similar representation of internal variability across models, as well as a similar representation of the changes themselves in the CMIP5 ensemble (Figs. 2d–f). In tropical regions, the CMIP5 ensemble similarly features larger noise amplitude in the driest than in the wettest regions, but the magnitude of this

FIG. 9. As in Fig. 7, but considering only grid cells from tropical regions.

estimated noise is larger than in the extratropical and global regions. The noise amplitude in tropical regions can also be quite different from one model to another, with the interval in some models ranging from -30% to $+40\%$ (and above) in the driest bins and only from -20% to $+30\%$ in other models (top panels of Fig. 9). In tropical regions, the CMIP5 estimate of the noise is larger and less robust across models, in addition to a large intermodel range of changes in extreme precipitation (Figs. 2g–i). Hence, both signal and noise are less robust in the CMIP5 ensemble, which gives a lower signal-to-noise ratio and a lower robustness of

change estimates in the tropics compared to the extratropics.

Overall, Fig. 4 shows spatially organized patterns of significant (or nonsignificant) changes in extreme precipitation. To verify that the results are not significant by chance, we evaluate the proportion of grid cells in each bin of mean precipitation showing a future change above the upper limit of the 90% interval of the changes in extreme precipitation driven by internal variability alone (significant intensification) and below the lower limit of this interval (significant drying; blue and brown horizontal bars in the top panels of Fig. 7, respectively)

or within this interval (nonsignificant change). Under the hypothesis of a change in extreme precipitation driven by internal variability alone, one would expect 5% of the total number of grid cells to be above the interval, 5% below the interval (blue and brown bars in the bottom panels of Fig. 7, respectively), and 90% within the interval (gray bars in the bottom panels of Fig. 7; note that in each bin of annual mean precipitation, the brown, gray, and blue bars are stacked so they add up to 100%). Overall, the majority of the CMIP5 models indicate a much higher proportion of significant intensification compared to the 5% expected (blue bars in the bottom panels of Fig. 7) and for the entire spectrum of mean precipitation. Aggregating the spatial information into bins of mean precipitation demonstrates a clear intensification of extreme precipitation in the majority of the CMIP5 models. The majority of the CMIP5 model groups also indicate a larger proportion of nonsignificant change in the first bins of mean precipitation (bottom panels of Fig. 7), which could be expected from the larger noise magnitude in the driest regions (top panels of Fig. 7). Out of the 14 different groups of models, two (i.e., model group h and n) show a different result. These models share a significant intensification of extreme precipitation in the driest regions, but they differ in the wettest, with a large fraction of grid cells showing significant drying. Hence, differently from all the other models, these models (in particular, model group h) indicate a lower median estimate of the changes in extreme precipitation in the wettest regions (see Fig. 1), which is here assessed to be significant.

Analyzing the significance of the changes in extreme precipitation in bins of mean precipitation separately for the extratropical and tropical regions shows again striking results (bottom panels of Figs. 8, 9, respectively). Over the extratropics, all models (including the previous outliers at the global scale) project a significant intensification of extreme precipitation for the entire spectrum of mean precipitation (Fig. 7). Over tropical regions, however, there is mainly a significant intensification, but significant drying is also found, especially in the first bins of mean precipitation. The model groups h and n again appear as outliers with both a significant decrease and a significant increase in extreme precipitation intensity indicated for the most of the bins.

4. Discussion and conclusions

We have investigated changes in extreme precipitation between the end of the twentieth and the end of the twenty-first centuries, as simulated by an ensemble of 27 CMIP5 climate models. Overall, we have shown

that the CMIP5 ensemble indicates a general intensification of annual extreme precipitation from the driest to the wettest regions of the globe (as defined by each model's precipitation climatology), and we have further investigated the robustness of this future increase in extreme precipitation amounts.

First, we have investigated the robustness of the CMIP5 projections based on their similarities by grouping models according to their common atmospheric components. This grouping clearly shows that models that share the same atmospheric physics have similarities in their projected changes. This means that from the ensemble of 27 models used here, we cannot reasonably consider 27 different projections. Important caveats can thus be associated with the widespread “one model one vote” methodology used to estimate a multimodel mean of extreme precipitation change from an ensemble with duplications. Here, we find that the ensemble size is realistically reduced from 27 to 14. However, we do not assess the intermodel distance using a statistical metric, nor do we estimate model skill against observations. These two steps are usually done to estimate a corrected or weighted multimodel mean of the change from a selected subset of models presenting reduced codependencies (e.g., Abramowitz and Bishop 2015; Sanderson et al. 2015; Knutti et al. 2017; Herger et al. 2018). This is particularly important for studies interested in assessing the “best” possible multimodel mean estimate of a change (e.g., for downscaling). We have shown here that extreme precipitation is particularly affected by such model dependence issues. For such extreme events, we therefore recommend considering model interdependencies in the CMIP5 ensemble.

The robustness of the CMIP5 projections has then been evaluated based on the intermodel uncertainties of future changes and also based on the significance of the future projected changes relative to changes due to internal variability in long preindustrial control runs. At the gridcell scale, we have compared future change (i.e., the signal) to a range of changes that could be driven by internal variability alone (i.e., background climate noise), as simulated by each individual model. The robustness of the changes in annual extreme precipitation over the globe has further been investigated during a dry and a wet season and by considering the tropical and extratropical regions separately.

The CMIP5 ensemble indicates a generally significant intensification of annual and seasonal extreme precipitation over the extratropical regions of the globe throughout the entire spectrum, from the driest to the wettest regions. However, climate models also indicate regions associated with future changes in extreme precipitation intensity (usually an increase) consistent with

changes driven by internal variability alone. The location and size of such regions, however, differ between models, but our results show that the driest regions are more affected than the wettest regions because of a larger influence of internal variability. On the contrary, northeastern Asia and the northern part of North America (to a lesser extent) have been highlighted as regions associated with a robust significant intensification of extreme precipitation across models, in agreement with Fischer et al. (2014), and we show that this intensification is particularly strong during the dry season. Overall, we have shown the robust response of the CMIP5 models to global warming, particularly in extratropical regions. This can be primarily explained by reduced intermodel uncertainties related to future changes (as shown in other studies; e.g., Sillmann et al. 2013b; O’Gorman 2015) due to strong control of changes in the thermodynamic response to global warming over these mid-to-high-latitude land regions (Emori and Brown 2005; O’Gorman and Schneider 2009; O’Gorman 2015; Pfahl et al. 2017). We have further shown that this is also explained by the similar representation of background climate noise across models, which implies a similar signal-to-noise ratio and thus a robust response in the CMIP5 ensemble. Note that CMIP5 intensification of extreme precipitation in response to global warming over the extratropics could yet be underestimated compared to observations (Min et al. 2011; Flato et al. 2013), in particular in the dry regions (Donat et al. 2016). The sensitivity to global warming is not reliable either over extratropical mountainous regions because climate models do not correctly resolve the mechanisms driving extreme precipitation events due to coarse resolution (Shi and Durran 2016).

Over tropical regions, we have shown much less robust future changes in extreme precipitation simulated by the CMIP5 ensemble. This is first explained by a large range of changes (from negative to positive) in both dry and wet seasons and at the annual scale. More regions show an increase than a decrease in extreme precipitation intensity, but the magnitude of the change can strongly differ between models. In addition, there is a wider range of the changes driven by internal variability. This noise magnitude is associated with larger intermodel differences compared to the extratropics. Overall, from the driest to the wettest regions of the tropical band, the CMIP5 models mainly project a significant intensification of extreme precipitation. However, some models also indicate regions with a significant drying. Such a reduction of extreme precipitation intensity is particularly seen in subtropical regions. This is similar to previous studies (e.g., Kharin et al. 2013; Christensen

et al. 2013; Pfahl et al. 2017) that showed a future drying of the annual extreme precipitation in subtropical regions but is, however, found not to be statistically significant in the CMIP5 multimodel mean. Such drying could be related to a change in atmospheric upward motion in many subtropical regions (Emori and Brown 2005; Pfahl et al. 2017). We have further shown that this drying in subtropical regions is more pronounced in the dry season compared to the annual scale. However, because of differences between models, it is difficult to extract with confidence the precise regions or subregions associated with a robust projected drying of extreme precipitation in the dry season or at the annual scale. This could be further investigated by developing regional constraints based on the main dynamical drivers and how models compare to real-world changes, as done by O’Gorman (2012) for tropical precipitation extremes, for instance.

Our results suggest that the different treatments of convection in the CMIP5 ensemble can explain part of the intermodel uncertainties in the tropics. Indeed, changes in annual extreme precipitation and noise estimates across models from the same group are mostly similar, but they vary substantially among the 14 model groups. Extreme precipitation changes depend strongly on the tight coupling between (parameterized) moist processes and the large-scale circulation, in particular in the tropics (Stevens and Bony 2013; Pfahl et al. 2017). Pendergrass and Hartmann (2014b) show that some climate models project future changes in the highest percentiles of precipitation that cannot be fully explained by transformations of the distribution of precipitation (the increase or shift modes). These results may be related to model artifacts associated with stratiform precipitation. Their so-called “extreme mode” explains a large part of the intermodel differences, especially in the tropics, and could be linked to a changing organization of the convection in response to global warming (Pendergrass et al. 2016). Thus, evaluating the respective contribution of stratiform and convective precipitation extremes in both future change and background climate noise for each model could help to understand some of the intermodel differences in the signal-to-noise ratio over tropical regions. Such evaluation could support motivation for future high-resolution modeling.

The robustness of the CMIP5 future intensification in extreme precipitation could be further investigated with regard to temperature dependence. We have compared future changes in extreme precipitation with future changes scaled by annual mean global change in temperature. The same qualitative results are found between scaled and unscaled changes, with largely reduced

intermodel spread over extratropical regions compared to tropical regions and the global scale, and smaller intermodel spread during the dry season compared to the wet season and the annual scale. Lin et al. (2017) showed that correcting simulated future warming by present-day temperature bias narrows the CMIP5 intermodel spread of future warming and also largely modifies the projected change in both temperature and precipitation over the central United States. Such correction could bring further information on future changes in extreme precipitation, especially over the driest parts of extratropical regions, which present the strongest temperature dependence (Donat et al. 2016). Furthermore, similar climate sensitivity (see Table 9.5 of Flato et al. 2013) is generally found among models clustered in the same group, as defined by our classification. Differences in atmospheric physics and, in particular, in convective parameterizations were suggested as the dominant source of spread for climate sensitivity (Medeiros et al. 2008; Ringer et al. 2014; Sherwood et al. 2014). Hence, a better account of the different climate sensitivities in the CMIP5 ensemble might help to understand model uncertainties of future changes in extreme precipitation.

Our work gives more insight into the robustness of the CMIP5 simulated future intensification of annual and seasonal extreme precipitation from the driest to the wettest regions of the globe. Aggregating the global distribution of grid cells according to their precipitation climatology overcomes some regional intermodel differences. The combined evaluation of future changes in extreme precipitation intensity and the range of changes that could be driven by internal variability alone in each model highlight a generally higher robustness in extratropical regions compared to tropical regions in the CMIP5 ensemble. Finally, strong similarities in future changes and climatic noise estimates are found between models that share atmospheric physics, reducing an ensemble of 27 models into around 14 projections.

Acknowledgments. We thank the anonymous reviewers for their helpful and constructive comments, which have improved this manuscript. We acknowledge the modeling groups for providing the CMIP5 simulation data and NCI and the Computational Modelling Systems Team for data access. All analyses and graphics have been done using the NCAR Command Language (NCL 2013). MB and LVA are supported by the Australian Research Council (ARC) Discovery Grant DP160103439 and the ARC Centre of Excellence for Climate System Science Grant CE110001028. MGD received funding from ARC Grant DE150100456. OG is supported by ARC Grant DP140101104.

REFERENCES

- Abramowitz, G., and C. H. Bishop, 2015: Climate model dependence and the ensemble dependence transformation of CMIP projections. *J. Climate*, **28**, 2332–2348, <https://doi.org/10.1175/JCLI-D-14-00364.1>.
- Alexander, L. V., and J. M. Arblaster, 2017: Historical and projected trends in temperature and precipitation extremes in Australia in observations and CMIP5. *Wea. Climate Extremes*, **15**, 34–56, <https://doi.org/10.1016/j.wace.2017.02.001>.
- , and Coauthors, 2006: Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res.*, **111**, D05109, <https://doi.org/10.1029/2005JD006290>.
- Allan, R. P., and B. J. Soden, 2008: Atmospheric warming and the amplification of precipitation extremes. *Science*, **321**, 1481–1484, <https://doi.org/10.1126/science.1160787>.
- Allen, M. R., and W. J. Ingram, 2002: Constraints on future changes in climate and the hydrologic cycle. *Nature*, **419**, 224–232, <https://doi.org/10.1038/nature01092>.
- Anderson, J. L., and Coauthors, 2004: The new GFDL global atmosphere and land model AM2-LM2: Evaluation with prescribed SST simulations. *J. Climate*, **17**, 4641–4673, <https://doi.org/10.1175/JCLI-3223.1>.
- Bador, M., L. Terray, and J. Boé, 2016: Emergence of human influence on summer record-breaking temperatures over Europe. *Geophys. Res. Lett.*, **43**, 404–412, <https://doi.org/10.1002/2015GL066560>.
- Bentsen, M., and Coauthors, 2013: The Norwegian Earth System Model, NorESM1-M—Part 1: Description and basic evaluation of the physical climate. *Geosci. Model Dev.*, **6**, 687–720, <https://doi.org/10.5194/gmd-6-687-2013>.
- Bi, D., and Coauthors, 2013: The ACCESS coupled model: Description, control climate and evaluation. *Aust. Meteor. Oceanogr. J.*, **63**, 41–64, <https://doi.org/10.22499/2.6301.004>.
- Chen, C. T., and T. Knutson, 2008: On the verification and comparison of extreme rainfall indices from climate models. *J. Climate*, **21**, 1605–1621, <https://doi.org/10.1175/2007JCLI1494.1>.
- Christensen, J. H., and Coauthors, 2013: Climate phenomena and their relevance for future regional climate change. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 1217–1308.
- Chylek, P., J. Li, M. K. Dubey, M. Wang, and G. Lesins, 2011: Observed and model simulated 20th century Arctic temperature variability: Canadian Earth System Model CanESM2. *Atmos. Chem. Phys. Discuss.*, **11**, 22 893–22 907, <https://doi.org/10.5194/acpd-11-22893-2011>.
- Collins, M., and Coauthors, 2013: Long-term climate change: Projections, commitments and irreversibility. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 1029–1136.
- Collins, W. D., and Coauthors, 2004: Description of the NCAR Community Atmosphere Model (CAM 3.0). NCAR Tech. Note NCAR/TN-464+STR, 226 pp.
- Collins, W. J., and Coauthors, 2011: Development and evaluation of an Earth-System model—HadGEM2. *Geosci. Model Dev.*, **4**, 1051–1075, <https://doi.org/10.5194/gmd-4-1051-2011>.
- Dai, A., 2006: Precipitation characteristics in eighteen coupled climate models. *J. Climate*, **19**, 4605–4630, <https://doi.org/10.1175/JCLI3884.1>.
- Deser, C., R. Knutti, S. Solomon, and A. S. Phillips, 2012: Communication of the role of natural variability in future North American climate. *Nat. Climate Change*, **2**, 775–779, <https://doi.org/10.1038/nclimate1562>.

- Donat, M. G., and Coauthors, 2013: Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The HadEX2 dataset. *J. Geophys. Res. Atmos.*, **118**, 2098–2118, <https://doi.org/10.1002/jgrd.50150>.
- , A. L. Lowry, L. V. Alexander, P. A. O’Gorman, and N. Maher, 2016: More extreme precipitation in the world’s dry and wet regions. *Nat. Climate Change*, **6**, 508–513, <https://doi.org/10.1038/nclimate2941>.
- Donner, L. J., and Coauthors, 2011: The dynamical core, physical parameterizations, and basic simulation characteristics of the atmospheric component AM3 of the GFDL global coupled model CM3. *J. Climate*, **24**, 3484–3519, <https://doi.org/10.1175/2011JCLI3955.1>.
- Dufresne, J. L., and Coauthors, 2013: Climate change projections using the IPSL-CM5 Earth System Model: From CMIP3 to CMIP5. *Climate Dyn.*, **40**, 2123–2165, <https://doi.org/10.1007/s00382-012-1636-1>.
- Dunne, J. P., and Coauthors, 2012: GFDL’s ESM2 global coupled climate–carbon Earth system models. Part I: Physical formulation and baseline simulation characteristics. *J. Climate*, **25**, 6646–6665, <https://doi.org/10.1175/JCLI-D-11-00560.1>.
- Emori, S., and S. J. Brown, 2005: Dynamic and thermodynamic changes in mean and extreme precipitation under changed climate. *Geophys. Res. Lett.*, **32**, L17706, <https://doi.org/10.1029/2005GL023272>.
- Fischer, E. M., J. Sedláček, E. Hawkins, and R. Knutti, 2014: Models agree on forced response pattern of precipitation and temperature extremes. *Geophys. Res. Lett.*, **41**, 8554–8562, <https://doi.org/10.1002/2014GL062018>.
- Flato, G., and Coauthors, 2013: Evaluation of climate models. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 741–866.
- Gervais, M., L. B. Tremblay, J. R. Gyakum, and E. Atallah, 2014: Representing extremes in a daily gridded precipitation analysis over the United States: Impacts of station density, resolution, and gridding methods. *J. Climate*, **27**, 5201–5218, <https://doi.org/10.1175/JCLI-D-13-00319.1>.
- Giorgetta, M. A., and Coauthors, 2013: Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the Coupled Model Intercomparison Project phase 5. *J. Adv. Model. Earth Syst.*, **5**, 572–597, <https://doi.org/10.1002/jame.20038>.
- Gordon, H. B., S. O’Farrell, M. Collier, M. Dix, L. Rotstayn, E. Kowalczyk, T. Hirst, and I. Watterson, 2010: The CSIRO Mk3.5 climate model. CSIRO and Bureau of Meteorology Rep., 74 pp., http://www.cawcr.gov.au/technical-reports/CTR_021.pdf.
- Groisman, P. Y., R. W. Knight, D. R. Easterling, T. R. Karl, G. C. Hegerl, and V. N. Razuvaev, 2005: Trends in intense precipitation in the climate record. *J. Climate*, **18**, 1326–1350, <https://doi.org/10.1175/JCLI3339.1>.
- Hawkins, E., and R. Sutton, 2009: The potential to narrow uncertainty in regional climate predictions. *Bull. Amer. Meteor. Soc.*, **90**, 1095–1108, <https://doi.org/10.1175/2009BAMS2607.1>.
- Hazeleger, W., and Coauthors, 2010: EC-Earth: A seamless Earth-system prediction approach in action. *Bull. Amer. Meteor. Soc.*, **91**, 1357–1364, <https://doi.org/10.1175/2010BAMS2877.1>.
- Held, I. M., and B. J. Soden, 2006: Robust responses of the hydrologic cycle to global warming. *J. Climate*, **19**, 5686–5699, <https://doi.org/10.1175/JCLI3990.1>.
- Herger, N., G. Abramowitz, R. Knutti, O. Angéil, K. Lehmann, and B. M. Sanderson, 2018: Selecting a climate model subset to optimise key ensemble properties. *Earth Syst. Dynam.*, **9**, 135–151, <https://doi.org/10.5194/esd-9-135-2018>.
- Hourdin, F., and Coauthors, 2006: The LMDZ4 general circulation model: Climate performance and sensitivity to parametrized physics with emphasis on tropical convection. *Climate Dyn.*, **27**, 787–813, <https://doi.org/10.1007/s00382-006-0158-0>.
- , and Coauthors, 2013: LMDZ5B: The atmospheric component of the IPSL climate model with revisited parameterizations for clouds and convection. *Climate Dyn.*, **40**, 2193–2222, <https://doi.org/10.1007/s00382-012-1343-y>.
- Jeffrey, M., L. Rotstayn, M. Collier, S. Dravitzki, C. Hamalainen, C. Moeseneder, K. Wong, and J. Syktus, 2013: Australia’s CMIP5 submission using the CSIRO-Mk3.6 model. *Aust. Meteor. Oceanogr. J.*, **63**, 1–13, <https://doi.org/10.22499/2.6301.001>.
- Kharin, V. V., F. W. Zwiers, X. Zhang, and M. Wehner, 2013: Changes in temperature and precipitation extremes in the CMIP5 ensemble. *Climatic Change*, **119**, 345–357, <https://doi.org/10.1007/s10584-013-0705-8>.
- Knutti, R., D. Masson, and A. Gettelman, 2013: Climate model genealogy: Generation CMIP5 and how we got there. *Geophys. Res. Lett.*, **40**, 1194–1199, <https://doi.org/10.1002/grl.50256>.
- , J. Sedláček, B. M. Sanderson, R. Lorenz, E. M. Fischer, and V. Eyring, 2017: A climate model projection weighting scheme accounting for performance and interdependence. *Geophys. Res. Lett.*, **44**, 1909–1918, <https://doi.org/10.1002/2016GL072012>.
- Lin, Y., W. Dong, M. Zhang, Y. Xie, W. Xue, J. Huang, and Y. Luo, 2017: Causes of model dry and warm bias over central U.S. and impact on climate projections. *Nat. Commun.*, **8**, 881, <https://doi.org/10.1038/s41467-017-01040-2>.
- Martin, G. M., and Coauthors, 2011: The HadGEM2 family of Met Office Unified Model climate configurations. *Geosci. Model Dev.*, **4**, 723–757, <https://doi.org/10.5194/gmd-4-723-2011>.
- Masson, D., and R. Knutti, 2011: Climate model genealogy. *Geophys. Res. Lett.*, **38**, L08703, <https://doi.org/10.1029/2011GL046864>.
- Medeiros, B., B. Stevens, I. M. Held, M. Zhao, D. L. Williamson, J. G. Olson, and C. S. Bretherton, 2008: Aquaplanets, climate sensitivity, and low clouds. *J. Climate*, **21**, 4974–4991, <https://doi.org/10.1175/2008JCLI1995.1>.
- Min, S.-K., X. Zhang, F. W. Zwiers, and G. C. Hegerl, 2011: Human contribution to more-intense precipitation extremes. *Nature*, **470**, 378–381, <https://doi.org/10.1038/nature09763>.
- Neale, R. B., and Coauthors, 2010: Description of the NCAR Community Atmosphere Model (CAM 4.0). NCAR Tech. Rep. NCAR/TN-485+STR, 224 pp.
- O’Gorman, P. A., 2012: Sensitivity of tropical precipitation extremes to climate change. *Nat. Geosci.*, **5**, 697–700, <https://doi.org/10.1038/ngeo1568>.
- , 2015: Precipitation extremes under climate change. *Curr. Climate Change Rep.*, **1**, 49–59, <https://doi.org/10.1007/s40641-015-0009-3>.
- , and T. Schneider, 2009: The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. *Proc. Natl. Acad. Sci. USA*, **106**, 14 773–14 777, <https://doi.org/10.1073/pnas.0907610106>.
- Pendergrass, A. G., and D. L. Hartmann, 2014a: The atmospheric energy constraint on global-mean precipitation change. *J. Climate*, **27**, 757–768, <https://doi.org/10.1175/JCLI-D-13-00163.1>.
- , and —, 2014b: Changes in the distribution of rain frequency and intensity in response to global warming. *J. Climate*, **27**, 8372–8383, <https://doi.org/10.1175/JCLI-D-14-00183.1>.
- , K. A. Reed, and B. Medeiros, 2016: The link between extreme precipitation and convective organization in a warming climate: Global radiative-convective equilibrium simulations.

- Geophys. Res. Lett.*, **43**, 11 445–11 452, <https://doi.org/10.1002/2016GL071285>.
- Pfahl, S., P. A. O’Gorman, and E. M. Fischer, 2017: Understanding the regional pattern of projected future changes in extreme precipitation. *Nat. Climate Change*, **7**, 423–427, <https://doi.org/10.1038/nclimate3287>.
- Polson, D., G. C. Hegerl, R. P. Allan, and B. B. Sarojini, 2013: Have greenhouse gases intensified the contrast between wet and dry regions? *Geophys. Res. Lett.*, **40**, 4783–4787, <https://doi.org/10.1002/grl.50923>.
- Ringer, M. A., T. Andrews, and M. J. Webb, 2014: Global-mean radiative feedbacks and forcing in atmosphere-only and coupled atmosphere-ocean climate change experiments. *Geophys. Res. Lett.*, **41**, 4035–4042, <https://doi.org/10.1002/2014GL060347>.
- Roeckner, E., and Coauthors, 2003: The atmospheric general circulation model ECHAM5. Part I: Model description. Max-Planck-Institut für Meteorologie Tech. Rep. 349, 140 pp., http://www.mpimet.mpg.de/fileadmin/models/echam/mpi_report_349.pdf.
- Sanderson, B. M., R. Knutti, and P. Caldwell, 2015: A representative democracy to reduce interdependency in a multimodel ensemble. *J. Climate*, **28**, 5171–5194, <https://doi.org/10.1175/JCLI-D-14-00362.1>.
- Scoccimarro, E., and Coauthors, 2011: Effects of tropical cyclones on ocean heat transport in a high-resolution coupled general circulation model. *J. Climate*, **24**, 4368–4384, <https://doi.org/10.1175/2011JCLI4104.1>.
- Sen Gupta, A., N. C. Jourdain, J. N. Brown, and D. Monselesan, 2013: Climate drift in the CMIP5 models. *J. Climate*, **26**, 8597–8615, <https://doi.org/10.1175/JCLI-D-12-00521.1>.
- Sherwood, S. C., S. Bony, and J. L. Dufresne, 2014: Spread in model climate sensitivity traced to atmospheric convective mixing. *Nature*, **505**, 37–42, <https://doi.org/10.1038/nature12829>.
- Shi, X., and D. Durran, 2016: Sensitivities of extreme precipitation to global warming are lower over mountains than over oceans and plains. *J. Climate*, **29**, 4779–4791, <https://doi.org/10.1175/JCLI-D-15-0576.1>.
- Sillmann, J., V. V. Kharin, X. Zhang, F. W. Zwiers, and D. Bronaugh, 2013a: Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. *J. Geophys. Res. Atmos.*, **118**, 1716–1733, <https://doi.org/10.1002/jgrd.50203>.
- , —, F. W. Zwiers, X. Zhang, and D. Bronaugh, 2013b: Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. *J. Geophys. Res. Atmos.*, **118**, 2473–2493, <https://doi.org/10.1002/jgrd.50188>.
- Stephens, G. L., and Coauthors, 2010: Dreary state of precipitation in global models. *J. Geophys. Res.*, **115**, D24211, <https://doi.org/10.1029/2010JD014532>.
- Stevens, B., and S. Bony, 2013: What are climate models missing? *Science*, **340**, 1053–1054, <https://doi.org/10.1126/science.1237554>.
- , and Coauthors, 2013: Atmospheric component of the MPI-M Earth System Model: ECHAM6. *J. Adv. Model. Earth Syst.*, **5**, 146–172, <https://doi.org/10.1002/jame.20015>.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>.
- Toreti, A., and Coauthors, 2013: Projections of global changes in precipitation extremes from Coupled Model Intercomparison Project phase 5 models. *Geophys. Res. Lett.*, **40**, 4887–4892, <https://doi.org/10.1002/grl.50940>.
- Trenberth, K. E., 2011: Changes in precipitation with climate change. *Climate Res.*, **47**, 123–138, <https://doi.org/10.3354/cr00953>.
- , A. Dai, R. M. Rasmussen, and D. B. Parsons, 2003: The changing character of precipitation. *Bull. Amer. Meteor. Soc.*, **84**, 1205–1218, <https://doi.org/10.1175/BAMS-84-9-1205>.
- van Vuuren, D. P., and Coauthors, 2011: The representative concentration pathways: An overview. *Climatic Change*, **109**, 5–31, <https://doi.org/10.1007/s10584-011-0148-z>.
- Voldoire, A., and Coauthors, 2013: The CNRM-CM5.1 global climate model: Description and basic evaluation. *Climate Dyn.*, **40**, 2091–2121, <https://doi.org/10.1007/s00382-011-1259-y>.
- Watanabe, M., and Coauthors, 2010: Improved climate simulation by MIROC5: Mean states, variability, and climate sensitivity. *J. Climate*, **23**, 6312–6335, <https://doi.org/10.1175/2010JCLI3679.1>.
- Watanabe, S., and Coauthors, 2011: MIROC-ESM 2010: Model description and basic results of CMIP5-20c3m experiments. *Geosci. Model Dev.*, **4**, 845–872, <https://doi.org/10.5194/gmd-4-845-2011>.
- Westra, S., L. V. Alexander, and F. W. Zwiers, 2013: Global increasing trends in annual maximum daily precipitation. *J. Climate*, **26**, 3904–3918, <https://doi.org/10.1175/JCLI-D-12-00502.1>.
- Wilcox, E. M., and L. J. Donner, 2007: The frequency of extreme rain events in satellite rain-rate estimates and an atmospheric general circulation model. *J. Climate*, **20**, 53–69, <https://doi.org/10.1175/JCLI3987.1>.
- Wu, T., and Coauthors, 2010: The Beijing Climate Center atmospheric general circulation model: Description and its performance for the present-day climate. *Climate Dyn.*, **34**, 123–147, <https://doi.org/10.1007/s00382-008-0487-2>.
- Yukimoto, S., and Coauthors, 2012: A new global climate model of the Meteorological Research Institute: MRI-CGCM3—Model description and basic performance. *J. Meteor. Soc. Japan*, **90A**, 23–64, <https://doi.org/10.2151/jmsj.2012-A02>.
- Zhang, G. J., and M. Mu, 2005: Effects of modifications to the Zhang-McFarlane convection parameterization on the simulation of the tropical precipitation in the National Center for Atmospheric Research Community Climate Model, version 3. *J. Geophys. Res.*, **110**, D09109, <https://doi.org/10.1029/2004JD005617>.
- Zhang, X., L. Alexander, G. C. Hegerl, P. Jones, A. K. Tank, T. C. Peterson, B. Trewin, and F. W. Zwiers, 2011: Indices for monitoring changes in extremes based on daily temperature and precipitation data. *Wiley Interdiscip. Rev.: Climate Change*, **2**, 851–870, <https://doi.org/10.1002/wcc.147>.