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The Impact of Parameterized Convection on Climatological Precipitation in Atmospheric Global Climate Models

Penelope Maher¹*, Geoffrey K. Vallis¹, Steven C. Sherwood², Mark J. Webb³, and Philip G. Sansom ¹.

5	¹ Department of Mathematics, University of Exeter, Exeter, UK
6	² University of New South Wales (UNSW), Sydney, New South Wales, Australia and ARC Centre of Excellence for Climate
7	Extremes
8	³ Met Office Hadley Centre, Exeter, UK

Climatological precipitation patterns with and without parameterized convection schemes are surprisingly similar. Daily precipitation extremes are too strong without convective schemes, but in contrast, tropical wave activity is more realistic. Tropical ocean rainfall, double ITCZ, and SH storm-track moist biases all persist without the schemes.

^{*}Penelope Maher, Department of Mathematics, Laver Building room 925, University of Exeter, Exeter, UK.

Corresponding author: Penelope Maher, p.maher@exeter.ac.uk

16 Abstract

Convective parameterizations are widely believed to be essential for realistic simulations of 17 the atmosphere. However, their deficiencies also result in model biases. The role of convec-18 tion schemes in modern atmospheric models is examined using Selected Process On/Off Klima 19 Intercomparison Experiment (SPOOKIE) simulations without parameterized convection and 20 forced with observed sea surface temperatures. Convection schemes are not required for rea-21 sonable climatological precipitation. However, they are essential for reasonable daily precip-22 itation and restraining extreme daily precipitation that otherwise develops. Systematic effects 23 on lapse rate and humidity are likewise modest compared with the inter-model spread. With-24 out parameterized convection Kelvin waves are more realistic. An unexpectedly large moist 25 Southern Hemisphere storm track bias is identified. This storm track bias persists without con-26 vection schemes, as does the double intertropical convergence zone and excessive ocean pre-27 cipitation biases. This suggests that model biases originate from processes other than convec-28 tion or that convection schemes are missing key processes. 29

30 1 Introduction

The parameterization of convection was borne out of necessity. In the 1960s the primitiveequation moist atmospheric models required a convection scheme for stable time integrations [*Kasahara*, 1993]. The moist adjustment scheme of *Manabe et al.* [1965] was one of the first, and simplest, convection schemes implemented into a radiative-convective equilibrium model. The scheme successfully prevented grid-scale convection which previously caused the model to quickly deteriorate [*Manabe et al.*, 1965, see references within] and become numerically unstable.

Fifty years after *Manabe et al.* [1965], convective parameterizations are still implicitly 38 assumed to be an important component of global climate models (GCM), as they are used at 39 all the major modeling centers and in the models submitted to the CMIP5 archive. More re-40 cently, model runs were performed without parameterized convection by Frierson [2007] in 41 developing a simplified convection scheme, and Lin et al. [2008] in testing the sensitivity of 42 convective equatorial waves to convection schemes. The first organised collection of atmosphere-43 only models run without parameterized convection is the Selected Process On/Off Klima In-44 tercomparison Experiment (SPOOKIE) by Webb et al. [2015]. The motivation for SPOOKIE 45 was to test if convection schemes are a leading source of inter-model spread in cloud feed-46 backs, which is known to be important for model equilibrium climate sensitivity. Webb et al. 47

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[2015] found the range of cloud feedbacks were similar with and without parameterized con vection suggesting that the convective parameterizations are not a leading-order source of inter model spread.

The SPOOKIE simulations also disprove a second commonly held assumption namely 51 that convection parameterizations are still required for numerical stability in modern GCMs. 52 This is likely due to the improved numerical schemes and much higher horizontal and verti-53 cal resolution. The question that remains unanswered, and is the aim of this study, is what im-54 pact does parameterized convection have on climatological precipitation? A first step in a sys-55 tematic approach to improving convection parameterizations is to establish what impact the 56 schemes have on model climatology and the distribution of daily rain rates. In this way we 57 hope to provide guidance for modelling centers on what biases are a direct result of the con-58 vection schemes. 59

60 2 Methods and Data

SPOOKIE consists of ten global atmospheric models, identical to the standard 'AMIP'
configuration except without parameterized convection, herein 'ConvOff', [*von Salzen et al.*,
2013; *Neale et al.*, 2012; *Voldoire et al.*, 2013; *Anderson et al.*, 2004; *Zhao et al.*, 2009; *Mar- tin et al.*, 2011; *Dufresne et al.*, 2013; *Watanabe et al.*, 2010; *Giorgetta et al.*, 2012; *Yukimoto et al.*, 2012]. See supplementary Table 1 for models, resolutions, and time periods. See acknowledgement for data storage locations.

Both deep and shallow convection parameterizations (if they exist) are deactivated in ConvOff. Large-scale precipitation is generated in the microphysics scheme, where precipitation results from grid-scale condensation. The boundary-layer scheme and large-scale dynamics are still free to remove instability and to transport heat and moisture vertically; see *Webb et al.* [2015] for further details. SPOOKIE output is also available with +4K and $4 \times CO_2$ forcings and aquaplanet configurations; however, none of these are used in this study.

Daily and monthly data are interpolated, using bilinear interpolation, for each model to
a common resolution of 2.5°×2.5°, although daily data is only available for four out of the
ten models. A cross-validation approach was used to check for outlier models that could strongly
influence the multi-model mean precipitation; see supplementary Fig. 1. No outlier models were
found and all models are included in the multi-model means.

Modelled precipitation is compared to observed Global Precipitation Combined Precip-78 itation (GPCP) data for the 30-year period from 1979 to 2008 (monthly, GPCP v2.3, Adler 79 et al. [2003]) and the 20-year period from 1996 to 2015 (daily, GPCP v1.2, Huffman et al. [2001]). 80 Monthly ERA-Interim reanalysis [Dee et al., 2011] is used for the 30-year period from 1979 81 to 2008. In calculating relative humidity, ERA-Interim uses a weighted ice- and liquid-water 82 saturation vapor pressures between -23° C and 0° C following Simmons et al. [1999]. We con-83 vert ERA-Interim relative humidity data using pressure with respect to ice below 0° C rather 84 than apply the weighting of Simmons et al. [1999] to AMIP and ConvOff, see supplementary 85 for details. 86

The Southern ITCZ bias metric [*Bellucci et al.*, 2010] is used to measure the double ITCZ, defined as the climatological precipitation model minus observations in the $20^{\circ}S-0S^{\circ}$ and $210^{\circ}-260^{\circ}$ domain. The edge of the ITCZ is measured using the moisture ITCZ definition [*Byrne and Schneider*, 2016] where the edge is defined as the latitude where evaporation dominates over precipitation.

92 **3 Results**

Climatological precipitation for GPCP and the multi-model means of AMIP and Con-93 vOff are shown in Fig. 1a-c, together with their differences in Fig. 1d-f. AMIP precipitation 94 is generally similar to the satellite-derived GPCP, though enhanced AMIP precipitation exists 95 in each of the tropical ocean basins, in particular the western Indian Ocean and off-equatorial 96 bands in the western and central Pacific Oceans (Fig. 1d). These AMIP biases are also present 97 in the CMIP5 coupled models in the 2013 IPCC report [Flato et al., 2014, see their Fig. 9.4b], 98 hence the biases originate from the atmospheric models, noting that they include about fifty 99 models and a slightly shorter time period but these differences are not expected to affect cli-100 matological biases. The enhanced AMIP precipitation bias over the ocean, compared to GPCP 101 observations, persists and is worse without parameterized convection (Fig. 1e). In addition to 102 amplifying the excessive precipitation over the Indian and western Pacific Oceans, ConvOff 103 has more precipitation in the equatorial western Atlantic and eastern Pacific oceans. In the zonal 104 mean these differences are small, AMIP and ConvOff are similar at all latitudes (supplemen-105 tary Fig. 5). 106

The most striking similarities occur between AMIP and ConvOff in Fig. 1f (see also supplementary Fig. 8 and Fig. 10). The multi-model precipitation differences over the ocean are

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much smaller in magnitude and spatial extent than differences between GPCP and AMIP and
 are largest in regions of strongest precipitation. In the Northern Hemisphere eastern Pacific
 there is a poleward shift in the ITCZ in ConvOff. Over tropical land there is reduced precip itation which does not occur in AMIP.

Without a convection scheme each models precipitation response is similar in spatial struc-113 ture (supplementary Fig. 10) and in each case AMIP is closer to GPCP than ConvOff, with 114 errors quantified in a Taylor diagram (supplementary Fig. 3). There is some evidence to sug-115 gest that higher resolution models have smaller differences between AMIP and ConvOff pre-116 cipitation, which have lower root mean square errors, however the sample size (number of mod-117 els) is too small to draw any quantitative conclusions (supplementary Fig. 2). There is no ev-118 idence to suggest that AMIP models have a dependence on resolution for the ratio of convec-119 tive to large-scale precipitation. 120

Known CMIP5 precipitation biases also persist in ConvOff. These include deficient pre-121 cipitation over the Amazon region, India and its surrounding ocean, southern Africa, and South 122 China Sea. The double ITCZ bias also persists and appears somewhat worse with a broader 123 South Pacific convergence zone and more precipitation. However the double ITCZ bias, as mea-124 sured by the Southern ITCZ bias metric of Bellucci et al. [2010], is very similar for the multi-125 model mean AMIP and ConvOff runs (supplementary Fig. 4). Some models have an improved 126 double ITCZ bias and some worsen with individual models having similar magnitude biases 127 to coupled CMIP3-5 models [Tian, 2015, see their Fig. 1b]. The multi-model mean width of 128 the ITCZ is narrower in ConvOff (14°) compared to AMIP (17°). The ITCZ is expected to 129 narrow with global warming and so understanding the sensitivity of the width is important. 130 In this study, the model agreement on the size and sign of the change is limited and it is un-131 clear what impact running models without parameterized convection has on the width of the 132 ITCZ. 133

Daily precipitation histograms in Fig. 2 reveal larger differences between ConvOff and AMIP than seen in climatologies (supplementary Fig. 6). Over land GPCP has 55% of its grid cells without precipitation, defined as $P \le 1.0$ mm day⁻¹, fewer in AMIP (50%) and more in ConvOff (70%). Over the ocean GPCP has 60% of its grid cells without precipitation, less for AMIP (40%) and ConvOff (55%). There are more non-precipitating grid cells in ConvOff than AMIP, too many dry land grid cells compared to GPCP but an improvement in dry ocean grid cells which are known to produce too much drizzle [*Stephens et al.*, 2010]. The distribu-

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tion of precipitating grid cells, over land Fig. 2b) and ocean Fig. 2d), highlights that there are
fewer ConvOff grid cells with light-to-medium rain rates and more grid cells with extreme precipitation, i.e., biases that are worse in ConvOff than in AMIP, compared to GPCP. The extreme rain rates in ConvOff are almost twice as large as GPCP and AMIP and somewhat worse
over the ocean.

The more intense precipitation and increased number of non-precipitating grid cells in 146 ConvOff can also be seen in daily snapshots of precipitation (supplementary Fig. 7). Daily snap-147 shots also indicate that precipitation is more organised and intensely clustered into grid cell 148 storms while AMIP is more uniform, consistent with Becker et al. [2017] who show more ag-149 gregation in a GCM without parameterized convection in radiative convective equilibrium. The 150 increased organisation in ConvOff is also present in the multi-model mean wave-frequency plots 151 in Fig. 3 (supplementary Fig. 15-16). ConvOff actually has a more realistic Kelvin wave power 152 spectra than AMIP. This enhancement in the Kelvin waves occurs in each of the four mod-153 els, especially in IPSL for lower wave numbers. Only minor differences occur in the equato-154 rial Rossby wave response and, perhaps surprisingly, in the MJO region. There is some ev-155 idence to suggest that the IPSL model has improved variability at MJO wave numbers but closer 156 investigate is required to determine if the signal is MJO-like. 157

Differences in ConvOff temperature and moisture response compared to AMIP are shown 158 in Fig. 4 (also supplementary Fig. 9, 11-14). As expected with fixed-SST model runs, the near-159 surface temperature and moisture differences are small (Fig. 4). Farther aloft, AMIP and Con-160 vOff are both cooler than ERA-Interim, especially in the Southern Hemisphere polar region. 161 In the middle and upper subtropical troposphere, ConvOff is cooler than AMIP (Fig. 4c). Trop-162 ical cooling also occurs in the middle and upper troposphere, however the response is not ro-163 bust between models, see supplementary Fig. 14, hence the temperature response appears as 164 two subtropical lobes. 165

Without parameterized convection the middle and upper tropical troposphere are drier (Fig. 4f). In the Southern Hemisphere storm tracks AMIP and ConvOff multi-model means are moister in, compared to ERA-Interim, less so in the Northern Hemisphere. The AMIP moist Southern-Hemisphere storm-track bias and Southern-Hemisphere polar-stratospheric cool bias, compared to ERA-Interim, are broadly consistent with those shown in coupled ocean-atmosphere multi-model means for CMIP3 [*John and Soden*, 2007, see their Fig. 1 rows 1-2] and CMIP5 [*Tian et al.*, 2013, see their Fig. 2-5].

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173 **4 Discussion**

Running a global climate model without parameterized convection is a fairly extreme perturbation, given that most rainfall occurs in convective clouds which are far from being resolved in GCMs. Convection must occur irrespective of whether there is a convection scheme as latent heating is needed to balance radiative cooling.

Without parameterized convection, excessive ocean and deficient land precipitation bi-178 ases occurs. We interpret this response to changes in Convective Available Potential Energy 179 (CAPE). Over land in the afternoon there is a rapid increase in CAPE which can be more eas-180 ily consumed by a convection scheme than resolved convection, hence more AMIP land pre-181 cipitation and presumably less over the ocean in order for moisture conservation in the model. 182 In terms of moisture conservation, the global precipitation amount does not depend on the con-183 vection scheme as differences in the atmospheric temperature, humidity, and total cloud cover 184 do not appear to be large enough to strongly affect global-mean net radiative cooling of the 185 atmosphere. There are statistically significant differences in climatological precipitation in runs 186 with and without convection schemes, however, the magnitude and spatial coverage of these 187 differences are smaller than perhaps expected. Furthermore, AMIP biases compared to GPCP 188 are much larger and cover a greater area than the differences between AMIP and ConvOff. 189

We suspect a key difference between AMIP and ConvOff is how unstable the atmosphere 190 needs to be in order to drive the convection required to transport heat and moisture in a ver-191 tical. By design, parameterized convection initiates before grid-scale saturation occurs. With-192 out parameterized convection, the explicitly resolved motions require more convective insta-193 bility to drive the convective overturning. In order to increase the overturning the atmosphere 194 must presumably be more unstable, hence the lapse rate must increase. This instability could 195 originate from either surface warming (unlikely for fixed SST runs) or cooling of the tropo-196 sphere. Indeed, ConvOff is cooler than AMIP but perhaps surprisingly the difference in tem-197 perature is small and ConvOff is not that much more unstable than AMIP. We do not believe 198 the turbulence schemes alone could explain the cooling response as they do not normally trans-199 port a significant amount of heat except near unstable temperature profiles. 200

Net moistening might have been expected in ConvOff, compared to AMIP, as convec tion is harder to initiate. However, we find net drying in ConvOff and offer two interpretations.
 First, AMIP models can produce shallow convection which has a lower precipitation efficiency
 and moistens the mid-levels, whereas explicitly simulated convection at such coarse resolu-

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tion is mostly deep convection hence has very high precipitation efficiency. Second, convec-

tion is more organized in ConvOff, and more organized convection results in a drier domain

207 [*Tobin et al.*, 2013].

An AMIP Southern Hemisphere storm track moist bias occurs in the mid-lower tropo-208 sphere. This moist bias has previously been identified in coupled CMIP5 models [Tian et al., 2013, see their Fig. 3 and 5 209 and occurs in a region with known cloud biases [Grise and Polvani, 2014, see reference within]. 210 We believe ours is the first study to report this moist bias in AMIP models, indicating the bias 211 arises from the atmospheric models rather than ocean temperature errors in coupled models. 212 The bias may be a consequence of cloud and microphysics schemes [McCoy et al., 2016], their 213 coupling to large-scale circulation or boundary layer schemes. Bodas-Salcedo et al. [2014] has 214 shown that in atmosphere-only GCMs the Southern Hemisphere mid-level clouds are miss-215 ing in the storm track region. Their absence removes a fundamental condensation process which 216 could result in a moist bias, however, further work is needed to test this idea. 217

The double ITCZ is a well-known model bias [Zhang et al., 2015], that persists with-218 out parameterized convection. Interestingly, the ConvOff multi-model mean is not qualitatively 219 different to AMIP suggesting that convective schemes are not likely the root cause of the bias. 220 The inter-model response of the double ITCZ is broad (supplementary Fig. 4), some models 221 show a large response and others small. Previous studies have shown that convection schemes 222 play a key role in forming the double ITCZ in aquaplanets [Möbis and Stevens, 2012] and cou-223 pled models [Song and Zhang, 2009]. Our results are not inconsistent with such studies, rather 224 our conclusions differ in that the net impact of the convection schemes in the multi-model mean 225 is smaller than the response in individual models. 226

A second deficiency of GCMs is represent convective organization, self aggregation and 227 the MJO are prime examples. Becker et al. [2017] found that a GCM, in radiative convective 228 equilibrium, has more aggregation without parameterized convection. Furthermore, a differ-229 ence in the MJO might have been expected in ConvOff as the MJO accuracy in GCMs is hin-230 dered by convection parameterizations [Ajayamohan et al., 2013]. Furthermore, it has previ-231 ously been found by *Boyle et al.* [2015], amongst others, that suppressing convection schemes 232 improves the MJO when the entrainment rate was increased. However, in this study we find 233 no robust improvement in the MJO. 234

Unlike the MJO, we find Kelvin waves are more realistic without convective parameterizations. Convection schemes affect the generation of convective coupled waves and so it

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is not surprising that the wave spectra is different in runs with and without parameterized con-237 vection. Fully coupled GCMs in general have less wave activity than is seen in observations, 238 however, the source of the reduced wave activity is difficult to isolate [Kiladis et al., 2009]. 239 Reduced wave activity in GCMs has previously been linked to convective parameterizations, 240 specifically the moisture sensitivity of trigger functions, and to the treatment of stratiform pre-241 cipitation that result in errors in the heating profiles [Kiladis et al., 2009]. The improved wave 242 response in ConvOff may be the results of increased instability, where gravity waves are more 243 easily generated in regions with more stratification, or it may be that parameterized convec-244 tion suppresses gravity wave generation. Further work is needed to isolate why Kelvin waves 245 are more realistic without parameterized convection. 246

A limitation of SPOOKIE the use of fixed SSTs. However, fixed SSTs are necessary to 247 prevent the untuned ConvOff climatology from drifting too far away from AMIP and obser-248 vations. Such a drift would prevent an intercomparison such as this, as it would be almost im-249 possible to interpret the direct impact of the convection schemes. A further limitation is only 250 using one observational and one reanalysis product, however, we believe this is justified as we 251 are primarily focused on the impact of convective schemes on models rather than model eval-252 uation per se. A final limitation is in using daily precipitation data, as exact comparison of mod-253 eled and observed short-term statistics is challenging because of the sampling characteristics 254 of observing systems [e.g. Stephens et al., 2010], but it appears unlikely that observational un-255 certainties are as large as the impact of convective schemes. 256

5 Conclusions

Webb et al. [2015] has previously shown that convection schemes do not contribute to 258 the spread in cloud feedbacks. We build on their study by showing that parameterized con-259 vection does not strongly impact climatological precipitation, temperature or relative humid-260 ity. This contradicts a common expectation that parameterized convection is required for re-261 alistic mean-state climatologies, given realistic sea-surface temperatures. However, there are 262 some interesting differences in runs with and without parameterized convection. Specifically, 263 excessive ocean precipitation biases, deficient land precipitation, a robust 1K cooling in the 264 subtropical mid-upper levels and a robust 5% drying of the equatorial mid-upper levels. 265

At daily time scales the absence of convection parameterizations has a clearer impact where storms are more intense and organized into clustered grid cells. Without the convec-

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tion schemes the most intense tropical storms have daily rate rates almost double observations 268 and AMIP. The convection schemes thus constrain unrealistically large precipitation extremes. 269 There is an improvement in the number of non-precipitating grid-cells over the ocean but this 270 comes at the expense of too many non-precipitating grid cells over land and too fewer light-271 to-medium rain rates. Excessive light rainfall rates is a well known model bias in comprehen-272 sive. Another well known model bias is inhibited organization due to over-active convection 273 schemes, as opposed to suppressed schemes which are harder to initiate. We show that the Kelvin 274 wave power spectra is improved without parameterized convection although no change is found 275 in the MJO. 276

We find that a number of known GCM biases persist without parameterized convection. Persistent precipitation biases include the double ITCZ, excessive precipitation over the ocean, and deficient precipitation over land. These biases are a little worse without parameterized convection over the ocean but considerably worse over land. Hence, convective parameterizations are reducing biases but not substantially. A large AMIP moist bias is identified, present with and without parameterized convection, over the Southern Hemisphere storm tracks. We suspect this is linked to known cloud biases in the region.

The persistence of modelled precipitation biases without parameterized convection suggests they originate from processes other than convection or that convection schemes are missing key processes and their absence is preventing the schemes from fully ameliorating the biases. Candidate processes include upscale convective momentum transport, convective organization, convective memory, sensitivity to tropospheric humidity, or missing feedbacks.

Our results show that model climatologies are relatively insensitive to convective param-289 eterization for fixed-SST runs. If convection parameterizations are not, to first order, control-290 ling the intensity and spatial distribution of climatological precipitation then what is? Further-291 more, if known precipitation biases persist without convective parameterizations, then where 292 are they generated? We believe these questions warrant further investigation, as well as the 293 deficient land precipitation bias and moist AMIP bias in the Southern Hemisphere storm tracks. 294 These could be addressed in a follow up mechanism-denial type study where other key pro-295 cesses are deactivated. 296

Some of the results presented in this study might have been anticipated by model developers. However the broader community may well be surprised that model climatologies are so similar with and without convective parameterizations. In this study we are not advocat-

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ing abandoning convection parameterization, rather we were motivated to understand what im pact convection schemes have on precipitation and if their impact is as large as commonly ex pected. The results of this study are important for attributing biases in fully coupled climate
 models to model physics, testing long standing expectations about the role of convection schemes
 and in understanding what impact convection schemes have on model climatologies.

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Figure 1. Average precipitation for a) GPCP, the multi-model means of b) AMIP and c) ConvOff. Difference in GPCP with the multi-model means of d) AMIP and e) ConvOff and f) their differences. All plots have the same common resolution of $2.5^{\circ} \times 2.5^{\circ}$. In d-f) differences are only plotted when 90% or more of the models agree on the sign of the multi-model difference and is statistically significant with a two-tailed 95% significance level ($\pm 2\sigma$), where σ is the internal variability of the multi-model mean.



Figure 2. Daily tropical $(15^{\circ} \text{ S}-15^{\circ} \text{ N})$ precipitation for a-b) land and c-d) ocean grid points. Bar plots in a) and c) are the number of grid points with precipitation less than 1 mm day⁻¹ (ie non-precipitating). Histograms in b) and d) are daily precipitation rates from $1 - 130 \text{ mm day}^{-1}$ with a bin width of 1 mm day⁻¹. The percentage of grid points in b) and d) terminates at 0.01%, which for a common $2.5^{\circ} \times 2.5^{\circ}$ grid is 1443 tropical ocean points and 429 tropical land points per time step corresponds to 300-500 points over land and 1000-1600 over ocean (ranging from 20-30 years). The plot includes all available daily data (four of the ten models). The multi-model mean is the average of each models histogram computed on the common grid.



Figure 3. *Wheeler and Kiladis* [1999] diagrams for a) ERA-Interim (1979-2015) b) AMIP (1979-2008) and b) ConvOff (1979-2008) using daily outgoing longwave radiation. The plot includes all available model daily (four out of the ten models). The wave-frequency spectra was computed for each model on its native grid and the resulting wave-frequency values were averaged for the multi-model mean plotted.



Figure 4. Temperature differences between the multi-model mean of a) AMIP and b) ConvOff with ERA-Interim, and c) their differences. Likewise relative humidity differences in d-f). Grey contouring masks orography. Contour lines are a guide for magnitude only. Differences are only plotted when 90% or more of the models agree on the sign of the multi-model mean difference and is statistically significant with a twotailed 95% significance level $(\pm 2\sigma)$, where σ is the internal variability of the multi-model mean. Points which are not significant are set to zero. Each subplot has a common interpolated grid.