# Dynamical downscaling of climate projections in the tropics

Shuchang Liu<sup>1</sup>, Christian Zeman<sup>2</sup>, and Christoph Schär<sup>3</sup>

<sup>1</sup>IAC ETHz <sup>2</sup>IAC ETHZ <sup>3</sup>ETH Zurich

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# Abstract

The long-existing double-ITCZ problem in Global Climate Models (GCMs) hampers accurate climate simulation. Using a regional climate model (RCM) over the tropical and sub-tropical Atlantic with a horizontal resolution of 12 km and explicit convection, we develop a bias-correction downscaling methodology to remove GCM biases. The methodology is adapted from the pseudo-global warming (PGW) approach, typically used to exert the climate-change signal to a reanalysis-driven RCM simulation. We show that the double ITCZ problem persists with conventional dynamical downscaling, but with our bias-corrected downscaling, the double ITCZ problem is removed. Detailed analysis attributes the main cause of the double ITCZ problem of the selected GCM to the sea surface temperature (SST) bias. Compared to the GCM's AMIP simulations, RCMs with higher resolution allow explicit deep convection and enable a better simulation of tropical convection and clouds. The developed methodology is promising for constraining climate sensitivity by removing double-ITCZ biases.









220 230 240 250 260 270 280 290 W/m<sup>2</sup>

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 $^1 \mathrm{Institute}$  for Atmospheric and Climate Science, ETH Zürich

# 5 Key Points:

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6	•	Downscaling of GCM results with RCMs in the tropics is problematic, as conven-
7		tional downscaling replicates the driving model's ITCZ bias.
8	•	A bias-corrected downscaling approach is proposed and tested. It enables a cred-
9		ible simulation of the ITCZ without the double-ITCZ bias.
10	•	For the tested GCM, the double-ITCZ bias is mainly attributed to the SST bias.

Corresponding author: Shuchang Liu, Shuchang.liu@env.ethz.ch

#### 11 Abstract

The long-existing double-ITCZ problem in Global Climate Models (GCMs) hampers ac-12 curate climate simulation. Using a regional climate model (RCM) over the tropical and 13 sub-tropical Atlantic with a horizontal resolution of 12 km and explicit convection, we 14 develop a bias-correction downscaling methodology to remove GCM biases. The method-15 ology is adapted from the pseudo-global warming (PGW) approach, typically used to 16 exert the climate-change signal to a reanalysis-driven RCM simulation. We show that 17 the double ITCZ problem persists with conventional dynamical downscaling, but with 18 our bias-corrected downscaling, the double ITCZ problem is removed. Detailed analy-19 sis attributes the main cause of the double ITCZ problem of the selected GCM to the 20 sea surface temperature (SST) bias. Compared to the GCM's AMIP simulations, RCMs 21 with higher resolution allow explicit deep convection and enable a better simulation of 22 tropical convection and clouds. The developed methodology is promising for constrain-23 ing climate sensitivity by removing double-ITCZ biases. 24

# <sup>25</sup> Plain Language Summary

The Global Climate Models (GCMs) have a problem in simulating the Intertrop-26 ical Convergence Zone (ITCZ), which makes it hard to accurately simulate the climate. 27 To tackle this, we developed a method to first remove the large-scale biases in the GCM 28 and then conduct downscaling with a regional climate model (RCM). Our results show 29 that conventional downscaling carries the double-ITCZ bias from the GCM. But with 30 our bias-corrected method, the problem is solved. We found that the main cause of the 31 double-ITCZ problem is related to the bias in sea surface temperatures (SST). By us-32 ing the RCM with higher resolution, we were able to get better simulations of tropical 33 convection and clouds compared to the GCM. This new method shows promise in im-34 proving the accuracy of climate change projections by addressing the double-ITCZ bi-35 ases in GCMs. 36

# 37 1 Introduction

<sup>38</sup> Dynamical downscaling – i.e. the spatial refinement of low-resolution global climate <sup>39</sup> models (GCMs) using limited-area regional climate models (RCMs) – is mainstay in climate-<sup>40</sup> change impact assessment and in the planning of local adaptation measures (Senior et <sup>41</sup> al., 2021). It has successfully been used in the extratropics for many decades. For instance, <sup>42</sup> over Europe a large set of simulations is currently available at resolutions from 12 km <sup>43</sup> (Jacob et al., 2014; Sørland et al., 2021) to 3 km (Ban et al., 2021; Pichelli et al., 2021).

Downscaling relies on the consistency between the synoptic-scale fields of the driv-44 ing GCM and the driven RCM (Jones et al., 1995). Large differences in circulations are 45 undesirable since they inevitably lead to inconsistencies near the lateral boundaries. It 46 then follows that significant large-scale biases of the driving GCM are problematic, since 47 in general one would expect the same biases in the RCM. In the tropics, significant bi-48 ases are common, indeed the representation of the Intertropical Convergence Zone (ITCZ) 49 is fraught with difficulties. These large-scale biases lead to challenges with downscaling 50 methodologies (Nobre et al., 2001; Sun et al., 2005; Tang et al., 2019; de Medeiros et al., 51 2020). 52

The Intertropical Convergence Zone (ITCZ), which exists due to the convergence of the trade winds, plays an important role in the tropical climate (Waliser & Jiang, 2015). The ITCZ locates mainly in the Northern hemisphere throughout the year except for boreal spring. During this period, the ITCZ reaches its southernmost location due to solar heating, when the observations show a strong precipitation band north of the equator and a secondary precipitation band south of the equator in the Western Pacific, and a single band straddling the equator over the tropical Atlantic. However, global climate models (GCMs) have difficulty simulating asymmetric precipitation distribution. In boreal spring, they produce too strong precipitation within the secondary band over the
Pacific and a miss-placed band over Tropical Atlantic, which is too far in the south (G. J. Zhang
et al., 2019). The annual mean precipitation projected by GCMs thus shows two distinctive bands on both sides of the equator instead of producing a single northern band indicated by the observation, which is called the double ITCZ problem.

The erroneous ITCZ representation in GCMs is not only related to the inaccurate 66 simulation of the current climate (Richter & Xie, 2008; Bellucci et al., 2010; Richter et 67 al., 2014; Li & Xie, 2014; Shonk et al., 2019), but also affects the climate sensitivity pre-68 dicted by GCMs, in the sense that GCMs with larger double-ITCZ problem tend to pro-69 duce lower values of climate sensitivity (Tian, 2015; Webb & Lock, 2020). Despite the 70 efforts devoted to reducing the double ITCZ bias, the problem persists from the Cou-71 pled Model Intercomparison Project Phase 3 to Phase 6 (Lin, 2007; de Szoeke & Xie, 72 2008; Bellucci et al., 2010; X. Zhang et al., 2015; Adam et al., 2018; Woelfle et al., 2019; 73 Tian & Dong, 2020; Boucher et al., 2020). 74

The double ITCZ bias is more distinctive among coupled ocean-atmosphere mod-75 els compared with those models forced with observed sea surface temperature (SST) (F. Song 76 & Zhang, 2016, 2017). The coupled models typically produce warmer SST in the east 77 of the tropical Pacific and Atlantic near the coast and colder SST in the west of the trop-78 ical Atlantic and middle of the Pacific. On the one hand, SST is closely related to the 79 convective activity over tropical oceans by affecting the surface flux of heat and mois-80 ture (Hirota et al., 2011). On the other hand, the SST gradients also impacts lower-level 81 wind convergence (Back & Bretherton, 2009), thereby affecting the simulation of the ITCZ. 82

While the double-ITCZ problem is less severe among GCMs with prescribed sea 83 surface temperature, it still exists (Richter & Xie, 2008; Xiang et al., 2017; Zhou et al., 84 2022). Convection and boundary layer parameterization of the GCMs is believed to play 85 one of the most important roles in the misrepresentation of the ITCZ (Bellucci et al., 86 2010; Hirota et al., 2011; Landu et al., 2014). Many studies have been working on im-87 proving the convection schemes to alleviate the double ITCZ problem (X. Song & Zhang, 88 2009; Möbis & Stevens, 2012; X. Song & Zhang, 2018). Nolan et al. (2016) found that 89 aquaplanet simulations with explicit instead of parameterized convection would smooth 90 out the double ITCZ structures due to a better representation of squall lines. Therefore, 91 using km-scale models with explicit convection can reduce the double ITCZ bias and en-92 able a better representation of the tropical climate and quantification of climate sensi-93 tivity (Tian, 2015). 94

As mentioned above, the double-ITCZ bias represents a major challenge to dynamical downscaling. In this context, Heim et al. (2023) explored the pseudo-global warming (PGW, see Brogli et al. (2023)) approach to this challenge. They showed that the approach is highly successful and enables a credible representation of the tropical climate change without double-ITCZ bias (Heim & Schär, 2023).

The PGW approach uses a reanalysis-driven control simulation and therefor is un-100 affected by GCM control biases. A potential disadvantage of the PGW approach is the 101 neglect of changes in short-term synoptic climatology. Another approach is to adjust the 102 bias of the driving fields before conducting the dynamical downscaling (Misra & Kana-103 mitsu, 2004). Previous studies mainly focus on extratropics (Colette et al., 2012; Prein 104 et al., 2017; C. Liu et al., 2017; Musselman et al., 2018; Hernández-Díaz et al., 2019). 105 Here we thus try to assess the potential of conventional downscaling approaches over the 106 tropics. 107

In this study, we use the Consortium for Small-Scale Modeling (COSMO) in climate mode with explicit deep convection combined with a bias-correction method to downscale the GCM MPI-ESM1-2-HR model results over tropical Atlantic to investigate whether the double-ITCZ problem could be removed through such kind of downscaling and thus provide a possibility for constraining the climate sensitivity.

# <sup>113</sup> 2 Materials and Methods

## 114 2.1 Model and Set-Up

We use the fully compressible non-hydrostatic limited-area COSMO model (Baldauf 115 et al., 2011; Rockel et al., 2008) version 6 to conduct the dynamical downscaling. This 116 version of COSMO exploits Graphics Processing Units which speeds up the simulation 117 and enables experiments with high computational demand (Leutwyler et al., 2016). Rayleigh 118 damping is applied for the upper boundary following Durran and Klemp (1983). The com-119 putation of radiative fluxes follows the  $\delta$ -two-stream approach after (Ritter & Geleyn, 120 1992). For the computation of subgrid-scale vertical turbulent flux, we employ a 1D TKE-121 based model (Raschendorfer, 2001). The Tiedtke scheme (Tiedtke, 1989) is applied as 122 123 convection parameterization, but in some simulations we switch off this parameterization, or only switch on the shallow convection scheme (Vergara-Temprado et al., 2020; 124 Zeman et al., 2021). Over the ocean, the sea-surface temperature is prescribed. 125

All simulations are run with 60 vertical levels and a horizontal grid spacing of 12 km. To determine the parameter settings and the convection parameterization scheme, we applied the systematic calibration developed by S. Liu et al. (2022) based on the work of Bellprat et al. (2012, 2016). The calibration and downscaling simulations are performed over the tropical and sub-tropical Atlantic with a size of 867x658 grid columns (green domain in Figure 1). Details about the model calibration can be found in the Supporting Information .

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# 2.2 Conventional Downscaling

Dynamical downscaling is applied to the result of the CMIP6 historical simulation 134 of the MPI-ESM1-2-HR model (von Storch et al., 2017; Max Planck Institute for Me-135 teorology, 2020), following a recent study (Christoph Heim et al., 2022). The MPI-ESM1-136 2-HR input for the COSMO model has a horizontal resolution of around 100 km and 95 137 vertical levels. The boundary condition is updated 6-hourly. 2D surface pressure, skin 138 temperature, 3D temperature, wind and specific humidity are included as the lateral-139 boundary conditions. SST is prescribed based on the MPI-ESM1-2-HR result. The GCM 140 results are downscaled to 12 km using the calibrated parameters as described in the Sup-141 porting Information. 142

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# 2.3 Bias-Corrected Downscaling

We use a bias-corrected downscaling methodology, where the GCM data is corrected using the European Center for Medium-Range Weather Forecast (ECMWF) Re-Analysis (ERA5) data (Hersbach et al., 2020) to make it essentially bias free. To remove the biases, we use a methodology that is derived from the pseudo-global warming (PGW) approach (Brogli et al., 2023).

The PGW method is normally used to study regional climate change in response to global warming (Schär et al., 1996; Adachi et al., 2012; Brogli et al., 2023). In this case, the PGW methodology imposes the large-scale climate-change signal from a GCM onto a historical climate simulation by modifying the lateral and lower boundary conditions (including all atmospheric variables used to drive an RCM, i.e. temperature, geopotential height, wind, humidity, etc., as well as sea-surface temperature). More specifically, the climate change signal is defined as

$$\Delta = SCEN - HIST,\tag{1}$$

where *HIST* and *SCEN* represent historical (control) and scenario climate conditions taken from a GCM. Both *HIST* and *SCEN* periods must be chosen long enough to reduce the effects of internal variability (e.g. averages of 30 years). The climate deltas  $\Delta = \Delta(x, y, p, t_m)$  represent the set of 2D and 3D fields used to drive an RCM, but here merely the mean-seasonal cycle is provided with monthly resolution (i.e., m=1-12). The control RCM simulation is driven by some reanalysis (referred to as  $ERA_{BC}$  where the subscript *BC* stands for boundary conditions), while the scenario simulation is driven by

$$SCEN_{BC} = ERA_{BC} + \Delta.$$
 (2)

Here  $ERA_{BC}$  has the full temporal resolution, while  $\Delta$  is slowly varying (in our case it is linearly interpolated from monthly means). The so derived fields must undergo a pressure adjustment to restore hydrostatic balance (Brogli et al., 2023). This will also ensure that the hydrostatic and thermal wind balance are maintained, as both *SCEN* and *HIST*, and thus  $\Delta$ , approximately maintain the thermal wind balance by design.

The use of the PGW methodology for bias-corrected downscaling has been pioneered by Misra and Kanamitsu (2004) and it has been further applied in some recent studies (Colette et al., 2012; Prein et al., 2017; C. Liu et al., 2017; Musselman et al., 2018; Hernández-Díaz et al., 2019). The basic idea is to use

$$\Delta = OBS - HIST,\tag{3}$$

instead of Equation (1). Here *OBS* denotes observations (in our case the ERA5 reanalysis). The bias-corrected control simulation is then driven by

$$CTRL_{BC} = HIST + \Delta. \tag{4}$$

By design, the procedure using (3-4) yields monthly-mean fields  $CTRL_{BC}$  which are essentially identical to OBS. This means that the large-scale monthly-mean biases of the driving GCM CTRL are removed. However, there will still be some remaining biases. In particular, the short-term variations are taken from the GCM, and the statistics of synoptic systems may still deviate from reality. In analogy to (4), the scenario simulation would be driven by

$$SCEN_{BC} = SCEN + \Delta,$$
 (5)

180 but this will not be used in the current study.

We first get the 30-year-mean difference (1985-2014) between the ERA5 reanaly-181 sis data and the MPI-ESM1-2-HR historical simulation following (3). Then we use (3-182 4) to remove the climatological bias of the MPI-ESM1-2-HR. The considered fields are 183 the same as the study of Christoph Heim et al. (2022), which includes near-surface fields 184 such as surface humidity, skin temperature, sea-surface temperature, and surface pres-185 sure, as well as the three-dimensional fields of temperature, humidity, velocity and geopo-186 tential. The bias-corrected MPI-ESM1-2-HR fields are then used to drive the COSMO 187 model (named "bias-corrected downscaling in the following context). 188

## 2.4 SST-Corrected Downscaling

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To see how much the bias originates from the GCM's SST bias, we will also conduct additional simulations with only the SST bias corrected. The MPI-ESM1-2-HR simulation significantly overestimates SST in an area stretching from the African to the Brazilian coast (Figure 2), especially to the south of the equator and in boreal spring. When using SST-corrected fields from the MPI-ESM1-2-HR results for downscaling, this will be referred to as "SST-corrected downscaling". All downscalings are conducted for 10 years ranging from 1995 to 2004 with a 6-month spin-up.

# 197 **3 Results**

In the following we compare the representation of the ITCZ in reanalysis data (ERA5), 198 satellite observations (GPCP, CERES), GCM simulations (MPI-ESM1-2-HR using cou-199 pled AOGCM and atmospheric AGCM simulations), and limited-area simulations with 200 the COSMO model using different downscaling procedures. Figure 3 shows the merid-201 ional cross section of the 10-year-mean precipitation and vertical mass flux over domain 202 analysis\_D1 (see Figure 1). The ERA5 reanalysis produces quite good results compared 203 to the GPCP observation (see red and black curves with the scale to the right of the pan-204 els). However, the coupled MPI-ESM1-2-HR shows a distinct double-ITCZ, which is mainly 205 due to a misplaced ITCZ in boreal spring. In comparison, the AMIP simulation of the 206 MPI-ESM1-2-HR model, which uses prescribed SST, produces stronger subsidence be-207 tween 20°S and 10°S and much weaker updrafts as seen from the vertical mass flux (Fig-208 ure 3c). The double-ITCZ bias is less severe, indicating that the atmosphere-ocean cou-209 pling enhances the ITCZ biases, as discussed in the introduction. 210

With conventional downscaling, one would like to find out whether the ITCZ bias 211 is due to the large-scale forcing, or due to fine-scale processes that are better resolved 212 in the higher-resolution RCM simulation. Results (Figure 3d) show that with conven-213 tional downscaling there are qualitatively similar results as with the driving GCM (MPI-214 ESM-2-HR). In comparison to the latter, the double-ITCZ bias is somewhat reduced in 215 amplitude, but it remains a dominant feature of the response. Minor differences in com-216 parison to the GCM simulation include the somewhat stronger subsidence south of the 217 equator, and enhanced updrafts between  $10^{\circ}$ S to the  $0^{\circ}$ . 218

With the bias-corrected downscaling (Figure 3e), the large-scale biases of the driving GCM are removed from the downscaled simulation (see section 2.3 for details of the bias correction). In response, the double-ITCZ bias disappears. The differences between the bias-corrected and the conventional downscaling simulations mainly happen during boreal spring. There is stronger subsidence south of the equator in the bias-corrected case. In boreal summer, the vertical mass flux and precipitation in the conventional and bias-corrected downscaling simulations are similar.

To identify the responsible element of the bias, we also present results of SST-corrected downscaling. The bias correction is done similarly as in the fully bias-corrected case, but only applied to the SST field. Results are similar as in the bias-corrected version, indicating that the double-ITCZ problem of the conventional downscaling results primarily originates from the SST bias.

The time series of precipitation (Figure 4) further confirms this point. The over-231 estimation of precipitation is highly related to the warm SST bias, as seen in the con-232 ventional downscaling case. As the SST warm bias is removed, the precipitation over-233 estimation south of the equator mostly disappears. However, a slightly misplaced ITCZ 234 is still present in both the bias-corrected and SST-corrected cases. For example, the bias 235 pattern in June-September during the years 1995, 1996 and 2002 indicates an ITCZ po-236 sition too far north, while in the years 1997 and 2004, the ITCZ is too far south. The 237 ITCZ bias pattern is highly correlated with the SST bias as shown by the green lines in 238 Figure 4. When the SST is colder, the ITCZ moves further north and vice versa. 239

An important element of the double-ITCZ bias are the differences in outgoing long-240 wave radiation in particular during the February-April period (OLR, see Figure 5, sec-241 ond row). In comparison to CERES and ERA5, the MPI model has substantially weaker 242 OLR over the southern trades (south of the ITCZ), and stronger OLR over the north-243 ern trades. However, it is not clear whether this is a reason for or consequence of the double-244 ITCZ bias. On the one hand, the MPI bias in OLR will weaken subsidence over the south-245 ern trades (and strengthen it over the northern trades), potentially affecting the posi-246 tion of the ITCZ. On the other hand, a too southward position of the ITCZ will lead to 247

changes in high clouds, which can explain the OLR biases. The characteristic OLR bias 248 has also been noted in a previous study (Heim et al., 2023). 249

Regarding the downscaled COSMO simulations: it is evident that the main OLR 250 bias of the MPI model is also present under conventional downscaling (Figure 5e) with 251 comparable amplitude. However, both the bias-corrected and the SST-corrected down-252 scaling largely reduce the OLR bias. Results show that the bias-corrected downscaling 253 has a smaller bias than the SST-corrected downscaling, suggesting that factors beyond 254 the SST bias contribute to the biases seen in the MPI model. 255

#### 4 Conclusions 256

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Motivated by the uncertainties in sub-tropical and tropical clouds and the central 257 role of cloud feedbacks for climate-change, there is a large interest to apply high-resolution 258 limited-area convection-resolving models to the tropics. One critical challenge is the oc-259 currence of the double-ITCZ bias in GCMs. Such large-scale biases cannot be corrected 260 by high-resolution alone, i.e. downscaling current GCMs at high resolution will in gen-261 eral replicate the double-ITCZ bias. Currently there are two approaches to conduct down-262 scaling studies that circumvent these difficulties: 263

1. First, one can apply the pseudo-global warming (PGW) approach. Recent stud-264 ies have shown that PGW is a attractive and viable pathway toward climate-change 265 downscaling simulations in the tropics (Heim et al., 2023; Heim & Schär, 2023). 266

2. Second, one can try to debias the GCM output. The methodology uses the raw high-frequency output of a GCM, but corrects the data for large-scale deficiencies occurring in the control climate. The approach has successfully been applied in the extratropics (Misra & Kanamitsu, 2004), and was here explored for the first time in the tropics.

In this paper we have explored approach (2). We use a large computational domain 272 over the tropical and sub-tropical Atlantic with a spatial resolution (grid spacing) of 12 273 km. We used one particular GCM for the experiments (MPI-ESM1-2-HR). The main 274 conclusions of the study are: 275

276	•	When directly driving the RCM with the raw GCM control output (conventional
277		downscaling), the RCM reproduces a double-ITCZ similar as in the driving model.
278		The use of high resolution alone is unable to correct for the double-ITCZ bias.

- When driving the RCM with the bias-corrected GCM fields (bias-corrected down-279 scaling), the RCM credibly reproduces the observed ITCZ, although there are some 280 small differences in the position of the ITCZ in the boreal summer period.
- In order to pinpoint the reasons for the double-ITCZ bias, we have conducted an 282 additional simulation where the bias correction is only applied to the SST field 283 (SST-corrected downscaling). This simulation yields a qualitative realistic sim-284 ulation of the ITCZ, but analysis of the OLR biases shows that it is not as suc-285 cessful as the fully bias-corrected downscaling. Also, this result pertains only to 286 the GCM used, and the role of the SST biases might be smaller in other models. 287

There are several limitations of the current study. First of all, we merely tested one 288 particular GCM in the downscaling approach. Although the GCM considered has a sub-289 stantial double-ITCZ bias, it is not clear whether the current results will carry over to 290 other GCMs. Second, we did not address simulations using future scenario climates, but 291 merely worked with control climates. It is not a priori clear whether the beneficial im-292 pacts of bias-corrected downscaling also apply to the full control / scenario climate-change 293 approach. Currently we are undertaking related simulations and these will feature in a 294 subsequent publication. 295

Nevertheless, in the current study we show that bias-corrected downscaling appears to be a promising methodology, not only in the extratropics as previously shown, but also in the tropics. We have demonstrated the benefits of the approach for the tropical and sub-tropical Atlantic, but we believe that this carries over to other areas. In particular, it appears attractive to use this approach for climate-change impact assessment studies in the Amazon, West Africa or Indonesia – regions that are plagued by biases in the representation of the ITCZ in climate-change assessments.

# 303 5 Open Research

This work complies with the AGU data Policy, the program for bias-corrected downscaling is available on Github: https://github.com/shucliu/bias\_correction\_downscaling.

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 $_{310}$  no conflicts of interest relevant to this study.

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Figure 1. Simulation and analysis domains. The green domain (Simulation) is used for the COSMO calibration and simulations. The red domain (Analysis1) is used for the cross section analysis. The black domain (Analysis2) is used to indicate the SST bias.

Figure 2.SST bias of the MPI-ESM1-2-HR historical simulation (defined as MPI-ESM1-2-HR – ERA5) over a 30 year period (1985-2014) and for the two seasons with
the most southern- and northernmost position of the ITCZ. The black domain (Analysis2) represents the domain with significant SST overestimation; it will be used in some of the analyses.

Figure 3. Meridional cross section of 10-year-mean precipitation and vertical mass 570 flux over domain Analysis1. The panels show the result of different simulations (from 571 top to bottom: ERA5, MPI-ESM1-2-HR historical simulation, MPI-ESM1-2-HR AMIP 572 results, COSMO conventional downscaling, COSMO bias-corrected downscaling and SST-573 corrected downscaling). The first column shows the annual mean result, the second col-574 umn boreal spring average in February–April and the last column shows boreal summer 575 average in July–September. The red and black lines display the zonal mean precipita-576 tion from the data sets and the GPCP satellite observations, respectively (see scale to 577 the right). The coupled MPI simulation shows a distinct double-ITCZ. The double-ITCZ 578 is also visible in the MPI simulations with prescribed SST, and the conventional down-579 scaling with COSMO based on the native MPI simulations. The bias-corrected down-580 scaling as well as the SST corrected downscaling simulations show no double-ITCZ. 581

Figure 4. Time series of the precipitation bias (simulation minus GPCP) in the meridional cross section over the domain Analysis1 (contours), and the SST bias averaged over domain Analysis2 (green line). From top to bottom, the panels show the results of conventional downscaling, bias-corrected downscaling, and SST-corrected downscaling. The misplaced ITCZ is correlated with the SST bias. The bias-corrected downscaling as well as the SST-corrected downscaling remove the reoccurring positive precipitation bias south of the equator in boreal spring.

Figure 5. Outgoing longwave radiation for observations and model results. The 589 panels show (from left to right): CERES observation, ERA5, MPI-ESM1-2-HR histor-590 ical simulation results, MPI-ESM1-2-HR AMIP results, COSMO conventional downscal-591 ing, COSMO bias-corrected downscaling, and COSMO SST-corrected downscaling. The 592 first row shows the annual mean result, the second row shows the boreal spring average 593 (February – April) and the last row the boreal summer average (July – September). As 594 CERES data is only available since March 2000, the plot is calculated based on data from 595 March 2000 to December 2004. 596

Figure 1.



Figure 2.





Figure 3.



Figure 4.



Figure 5.



W/m²

# Dynamical downscaling of climate projections in the tropics

# Shuchang Liu<sup>1</sup>, Christian Zeman<sup>1</sup>, Christoph Schär<sup>1</sup>

 $^1 \mathrm{Institute}$  for Atmospheric and Climate Science, ETH Zürich

# 5 Key Points:

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6	•	Downscaling of GCM results with RCMs in the tropics is problematic, as conven-
7		tional downscaling replicates the driving model's ITCZ bias.
8	•	A bias-corrected downscaling approach is proposed and tested. It enables a cred-
9		ible simulation of the ITCZ without the double-ITCZ bias.
10	•	For the tested GCM, the double-ITCZ bias is mainly attributed to the SST bias.

Corresponding author: Shuchang Liu, Shuchang.liu@env.ethz.ch

#### 11 Abstract

The long-existing double-ITCZ problem in Global Climate Models (GCMs) hampers ac-12 curate climate simulation. Using a regional climate model (RCM) over the tropical and 13 sub-tropical Atlantic with a horizontal resolution of 12 km and explicit convection, we 14 develop a bias-correction downscaling methodology to remove GCM biases. The method-15 ology is adapted from the pseudo-global warming (PGW) approach, typically used to 16 exert the climate-change signal to a reanalysis-driven RCM simulation. We show that 17 the double ITCZ problem persists with conventional dynamical downscaling, but with 18 our bias-corrected downscaling, the double ITCZ problem is removed. Detailed analy-19 sis attributes the main cause of the double ITCZ problem of the selected GCM to the 20 sea surface temperature (SST) bias. Compared to the GCM's AMIP simulations, RCMs 21 with higher resolution allow explicit deep convection and enable a better simulation of 22 tropical convection and clouds. The developed methodology is promising for constrain-23 ing climate sensitivity by removing double-ITCZ biases. 24

# <sup>25</sup> Plain Language Summary

The Global Climate Models (GCMs) have a problem in simulating the Intertrop-26 ical Convergence Zone (ITCZ), which makes it hard to accurately simulate the climate. 27 To tackle this, we developed a method to first remove the large-scale biases in the GCM 28 and then conduct downscaling with a regional climate model (RCM). Our results show 29 that conventional downscaling carries the double-ITCZ bias from the GCM. But with 30 our bias-corrected method, the problem is solved. We found that the main cause of the 31 double-ITCZ problem is related to the bias in sea surface temperatures (SST). By us-32 ing the RCM with higher resolution, we were able to get better simulations of tropical 33 convection and clouds compared to the GCM. This new method shows promise in im-34 proving the accuracy of climate change projections by addressing the double-ITCZ bi-35 ases in GCMs. 36

# 37 1 Introduction

<sup>38</sup> Dynamical downscaling – i.e. the spatial refinement of low-resolution global climate <sup>39</sup> models (GCMs) using limited-area regional climate models (RCMs) – is mainstay in climate-<sup>40</sup> change impact assessment and in the planning of local adaptation measures (Senior et <sup>41</sup> al., 2021). It has successfully been used in the extratropics for many decades. For instance, <sup>42</sup> over Europe a large set of simulations is currently available at resolutions from 12 km <sup>43</sup> (Jacob et al., 2014; Sørland et al., 2021) to 3 km (Ban et al., 2021; Pichelli et al., 2021).

Downscaling relies on the consistency between the synoptic-scale fields of the driv-44 ing GCM and the driven RCM (Jones et al., 1995). Large differences in circulations are 45 undesirable since they inevitably lead to inconsistencies near the lateral boundaries. It 46 then follows that significant large-scale biases of the driving GCM are problematic, since 47 in general one would expect the same biases in the RCM. In the tropics, significant bi-48 ases are common, indeed the representation of the Intertropical Convergence Zone (ITCZ) 49 is fraught with difficulties. These large-scale biases lead to challenges with downscaling 50 methodologies (Nobre et al., 2001; Sun et al., 2005; Tang et al., 2019; de Medeiros et al., 51 2020). 52

The Intertropical Convergence Zone (ITCZ), which exists due to the convergence of the trade winds, plays an important role in the tropical climate (Waliser & Jiang, 2015). The ITCZ locates mainly in the Northern hemisphere throughout the year except for boreal spring. During this period, the ITCZ reaches its southernmost location due to solar heating, when the observations show a strong precipitation band north of the equator and a secondary precipitation band south of the equator in the Western Pacific, and a single band straddling the equator over the tropical Atlantic. However, global climate models (GCMs) have difficulty simulating asymmetric precipitation distribution. In boreal spring, they produce too strong precipitation within the secondary band over the
Pacific and a miss-placed band over Tropical Atlantic, which is too far in the south (G. J. Zhang
et al., 2019). The annual mean precipitation projected by GCMs thus shows two distinctive bands on both sides of the equator instead of producing a single northern band indicated by the observation, which is called the double ITCZ problem.

The erroneous ITCZ representation in GCMs is not only related to the inaccurate 66 simulation of the current climate (Richter & Xie, 2008; Bellucci et al., 2010; Richter et 67 al., 2014; Li & Xie, 2014; Shonk et al., 2019), but also affects the climate sensitivity pre-68 dicted by GCMs, in the sense that GCMs with larger double-ITCZ problem tend to pro-69 duce lower values of climate sensitivity (Tian, 2015; Webb & Lock, 2020). Despite the 70 efforts devoted to reducing the double ITCZ bias, the problem persists from the Cou-71 pled Model Intercomparison Project Phase 3 to Phase 6 (Lin, 2007; de Szoeke & Xie, 72 2008; Bellucci et al., 2010; X. Zhang et al., 2015; Adam et al., 2018; Woelfle et al., 2019; 73 Tian & Dong, 2020; Boucher et al., 2020). 74

The double ITCZ bias is more distinctive among coupled ocean-atmosphere mod-75 els compared with those models forced with observed sea surface temperature (SST) (F. Song 76 & Zhang, 2016, 2017). The coupled models typically produce warmer SST in the east 77 of the tropical Pacific and Atlantic near the coast and colder SST in the west of the trop-78 ical Atlantic and middle of the Pacific. On the one hand, SST is closely related to the 79 convective activity over tropical oceans by affecting the surface flux of heat and mois-80 ture (Hirota et al., 2011). On the other hand, the SST gradients also impacts lower-level 81 wind convergence (Back & Bretherton, 2009), thereby affecting the simulation of the ITCZ. 82

While the double-ITCZ problem is less severe among GCMs with prescribed sea 83 surface temperature, it still exists (Richter & Xie, 2008; Xiang et al., 2017; Zhou et al., 84 2022). Convection and boundary layer parameterization of the GCMs is believed to play 85 one of the most important roles in the misrepresentation of the ITCZ (Bellucci et al., 86 2010; Hirota et al., 2011; Landu et al., 2014). Many studies have been working on im-87 proving the convection schemes to alleviate the double ITCZ problem (X. Song & Zhang, 88 2009; Möbis & Stevens, 2012; X. Song & Zhang, 2018). Nolan et al. (2016) found that 89 aquaplanet simulations with explicit instead of parameterized convection would smooth 90 out the double ITCZ structures due to a better representation of squall lines. Therefore, 91 using km-scale models with explicit convection can reduce the double ITCZ bias and en-92 able a better representation of the tropical climate and quantification of climate sensi-93 tivity (Tian, 2015). 94

As mentioned above, the double-ITCZ bias represents a major challenge to dynamical downscaling. In this context, Heim et al. (2023) explored the pseudo-global warming (PGW, see Brogli et al. (2023)) approach to this challenge. They showed that the approach is highly successful and enables a credible representation of the tropical climate change without double-ITCZ bias (Heim & Schär, 2023).

The PGW approach uses a reanalysis-driven control simulation and therefor is un-100 affected by GCM control biases. A potential disadvantage of the PGW approach is the 101 neglect of changes in short-term synoptic climatology. Another approach is to adjust the 102 bias of the driving fields before conducting the dynamical downscaling (Misra & Kana-103 mitsu, 2004). Previous studies mainly focus on extratropics (Colette et al., 2012; Prein 104 et al., 2017; C. Liu et al., 2017; Musselman et al., 2018; Hernández-Díaz et al., 2019). 105 Here we thus try to assess the potential of conventional downscaling approaches over the 106 tropics. 107

In this study, we use the Consortium for Small-Scale Modeling (COSMO) in climate mode with explicit deep convection combined with a bias-correction method to downscale the GCM MPI-ESM1-2-HR model results over tropical Atlantic to investigate whether the double-ITCZ problem could be removed through such kind of downscaling and thus provide a possibility for constraining the climate sensitivity.

# <sup>113</sup> 2 Materials and Methods

## 114 2.1 Model and Set-Up

We use the fully compressible non-hydrostatic limited-area COSMO model (Baldauf 115 et al., 2011; Rockel et al., 2008) version 6 to conduct the dynamical downscaling. This 116 version of COSMO exploits Graphics Processing Units which speeds up the simulation 117 and enables experiments with high computational demand (Leutwyler et al., 2016). Rayleigh 118 damping is applied for the upper boundary following Durran and Klemp (1983). The com-119 putation of radiative fluxes follows the  $\delta$ -two-stream approach after (Ritter & Geleyn, 120 1992). For the computation of subgrid-scale vertical turbulent flux, we employ a 1D TKE-121 based model (Raschendorfer, 2001). The Tiedtke scheme (Tiedtke, 1989) is applied as 122 123 convection parameterization, but in some simulations we switch off this parameterization, or only switch on the shallow convection scheme (Vergara-Temprado et al., 2020; 124 Zeman et al., 2021). Over the ocean, the sea-surface temperature is prescribed. 125

All simulations are run with 60 vertical levels and a horizontal grid spacing of 12 km. To determine the parameter settings and the convection parameterization scheme, we applied the systematic calibration developed by S. Liu et al. (2022) based on the work of Bellprat et al. (2012, 2016). The calibration and downscaling simulations are performed over the tropical and sub-tropical Atlantic with a size of 867x658 grid columns (green domain in Figure 1). Details about the model calibration can be found in the Supporting Information .

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# 2.2 Conventional Downscaling

Dynamical downscaling is applied to the result of the CMIP6 historical simulation 134 of the MPI-ESM1-2-HR model (von Storch et al., 2017; Max Planck Institute for Me-135 teorology, 2020), following a recent study (Christoph Heim et al., 2022). The MPI-ESM1-136 2-HR input for the COSMO model has a horizontal resolution of around 100 km and 95 137 vertical levels. The boundary condition is updated 6-hourly. 2D surface pressure, skin 138 temperature, 3D temperature, wind and specific humidity are included as the lateral-139 boundary conditions. SST is prescribed based on the MPI-ESM1-2-HR result. The GCM 140 results are downscaled to 12 km using the calibrated parameters as described in the Sup-141 porting Information. 142

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# 2.3 Bias-Corrected Downscaling

We use a bias-corrected downscaling methodology, where the GCM data is corrected using the European Center for Medium-Range Weather Forecast (ECMWF) Re-Analysis (ERA5) data (Hersbach et al., 2020) to make it essentially bias free. To remove the biases, we use a methodology that is derived from the pseudo-global warming (PGW) approach (Brogli et al., 2023).

The PGW method is normally used to study regional climate change in response to global warming (Schär et al., 1996; Adachi et al., 2012; Brogli et al., 2023). In this case, the PGW methodology imposes the large-scale climate-change signal from a GCM onto a historical climate simulation by modifying the lateral and lower boundary conditions (including all atmospheric variables used to drive an RCM, i.e. temperature, geopotential height, wind, humidity, etc., as well as sea-surface temperature). More specifically, the climate change signal is defined as

$$\Delta = SCEN - HIST,\tag{1}$$

where *HIST* and *SCEN* represent historical (control) and scenario climate conditions taken from a GCM. Both *HIST* and *SCEN* periods must be chosen long enough to reduce the effects of internal variability (e.g. averages of 30 years). The climate deltas  $\Delta = \Delta(x, y, p, t_m)$  represent the set of 2D and 3D fields used to drive an RCM, but here merely the mean-seasonal cycle is provided with monthly resolution (i.e., m=1-12). The control RCM simulation is driven by some reanalysis (referred to as  $ERA_{BC}$  where the subscript *BC* stands for boundary conditions), while the scenario simulation is driven by

$$SCEN_{BC} = ERA_{BC} + \Delta.$$
 (2)

Here  $ERA_{BC}$  has the full temporal resolution, while  $\Delta$  is slowly varying (in our case it is linearly interpolated from monthly means). The so derived fields must undergo a pressure adjustment to restore hydrostatic balance (Brogli et al., 2023). This will also ensure that the hydrostatic and thermal wind balance are maintained, as both *SCEN* and *HIST*, and thus  $\Delta$ , approximately maintain the thermal wind balance by design.

The use of the PGW methodology for bias-corrected downscaling has been pioneered by Misra and Kanamitsu (2004) and it has been further applied in some recent studies (Colette et al., 2012; Prein et al., 2017; C. Liu et al., 2017; Musselman et al., 2018; Hernández-Díaz et al., 2019). The basic idea is to use

$$\Delta = OBS - HIST,\tag{3}$$

instead of Equation (1). Here *OBS* denotes observations (in our case the ERA5 reanalysis). The bias-corrected control simulation is then driven by

$$CTRL_{BC} = HIST + \Delta. \tag{4}$$

By design, the procedure using (3-4) yields monthly-mean fields  $CTRL_{BC}$  which are essentially identical to OBS. This means that the large-scale monthly-mean biases of the driving GCM CTRL are removed. However, there will still be some remaining biases. In particular, the short-term variations are taken from the GCM, and the statistics of synoptic systems may still deviate from reality. In analogy to (4), the scenario simulation would be driven by

$$SCEN_{BC} = SCEN + \Delta,$$
 (5)

180 but this will not be used in the current study.

We first get the 30-year-mean difference (1985-2014) between the ERA5 reanaly-181 sis data and the MPI-ESM1-2-HR historical simulation following (3). Then we use (3-182 4) to remove the climatological bias of the MPI-ESM1-2-HR. The considered fields are 183 the same as the study of Christoph Heim et al. (2022), which includes near-surface fields 184 such as surface humidity, skin temperature, sea-surface temperature, and surface pres-185 sure, as well as the three-dimensional fields of temperature, humidity, velocity and geopo-186 tential. The bias-corrected MPI-ESM1-2-HR fields are then used to drive the COSMO 187 model (named "bias-corrected downscaling in the following context). 188

## 2.4 SST-Corrected Downscaling

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To see how much the bias originates from the GCM's SST bias, we will also conduct additional simulations with only the SST bias corrected. The MPI-ESM1-2-HR simulation significantly overestimates SST in an area stretching from the African to the Brazilian coast (Figure 2), especially to the south of the equator and in boreal spring. When using SST-corrected fields from the MPI-ESM1-2-HR results for downscaling, this will be referred to as "SST-corrected downscaling". All downscalings are conducted for 10 years ranging from 1995 to 2004 with a 6-month spin-up.

# 197 **3 Results**

In the following we compare the representation of the ITCZ in reanalysis data (ERA5), 198 satellite observations (GPCP, CERES), GCM simulations (MPI-ESM1-2-HR using cou-199 pled AOGCM and atmospheric AGCM simulations), and limited-area simulations with 200 the COSMO model using different downscaling procedures. Figure 3 shows the merid-201 ional cross section of the 10-year-mean precipitation and vertical mass flux over domain 202 analysis\_D1 (see Figure 1). The ERA5 reanalysis produces quite good results compared 203 to the GPCP observation (see red and black curves with the scale to the right of the pan-204 els). However, the coupled MPI-ESM1-2-HR shows a distinct double-ITCZ, which is mainly 205 due to a misplaced ITCZ in boreal spring. In comparison, the AMIP simulation of the 206 MPI-ESM1-2-HR model, which uses prescribed SST, produces stronger subsidence be-207 tween 20°S and 10°S and much weaker updrafts as seen from the vertical mass flux (Fig-208 ure 3c). The double-ITCZ bias is less severe, indicating that the atmosphere-ocean cou-209 pling enhances the ITCZ biases, as discussed in the introduction. 210

With conventional downscaling, one would like to find out whether the ITCZ bias 211 is due to the large-scale forcing, or due to fine-scale processes that are better resolved 212 in the higher-resolution RCM simulation. Results (Figure 3d) show that with conven-213 tional downscaling there are qualitatively similar results as with the driving GCM (MPI-214 ESM-2-HR). In comparison to the latter, the double-ITCZ bias is somewhat reduced in 215 amplitude, but it remains a dominant feature of the response. Minor differences in com-216 parison to the GCM simulation include the somewhat stronger subsidence south of the 217 equator, and enhanced updrafts between  $10^{\circ}$ S to the  $0^{\circ}$ . 218

With the bias-corrected downscaling (Figure 3e), the large-scale biases of the driving GCM are removed from the downscaled simulation (see section 2.3 for details of the bias correction). In response, the double-ITCZ bias disappears. The differences between the bias-corrected and the conventional downscaling simulations mainly happen during boreal spring. There is stronger subsidence south of the equator in the bias-corrected case. In boreal summer, the vertical mass flux and precipitation in the conventional and bias-corrected downscaling simulations are similar.

To identify the responsible element of the bias, we also present results of SST-corrected downscaling. The bias correction is done similarly as in the fully bias-corrected case, but only applied to the SST field. Results are similar as in the bias-corrected version, indicating that the double-ITCZ problem of the conventional downscaling results primarily originates from the SST bias.

The time series of precipitation (Figure 4) further confirms this point. The over-231 estimation of precipitation is highly related to the warm SST bias, as seen in the con-232 ventional downscaling case. As the SST warm bias is removed, the precipitation over-233 estimation south of the equator mostly disappears. However, a slightly misplaced ITCZ 234 is still present in both the bias-corrected and SST-corrected cases. For example, the bias 235 pattern in June-September during the years 1995, 1996 and 2002 indicates an ITCZ po-236 sition too far north, while in the years 1997 and 2004, the ITCZ is too far south. The 237 ITCZ bias pattern is highly correlated with the SST bias as shown by the green lines in 238 Figure 4. When the SST is colder, the ITCZ moves further north and vice versa. 239

An important element of the double-ITCZ bias are the differences in outgoing long-240 wave radiation in particular during the February-April period (OLR, see Figure 5, sec-241 ond row). In comparison to CERES and ERA5, the MPI model has substantially weaker 242 OLR over the southern trades (south of the ITCZ), and stronger OLR over the north-243 ern trades. However, it is not clear whether this is a reason for or consequence of the double-244 ITCZ bias. On the one hand, the MPI bias in OLR will weaken subsidence over the south-245 ern trades (and strengthen it over the northern trades), potentially affecting the posi-246 tion of the ITCZ. On the other hand, a too southward position of the ITCZ will lead to 247

changes in high clouds, which can explain the OLR biases. The characteristic OLR bias 248 has also been noted in a previous study (Heim et al., 2023). 249

Regarding the downscaled COSMO simulations: it is evident that the main OLR 250 bias of the MPI model is also present under conventional downscaling (Figure 5e) with 251 comparable amplitude. However, both the bias-corrected and the SST-corrected down-252 scaling largely reduce the OLR bias. Results show that the bias-corrected downscaling 253 has a smaller bias than the SST-corrected downscaling, suggesting that factors beyond 254 the SST bias contribute to the biases seen in the MPI model. 255

#### 4 Conclusions 256

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Motivated by the uncertainties in sub-tropical and tropical clouds and the central 257 role of cloud feedbacks for climate-change, there is a large interest to apply high-resolution 258 limited-area convection-resolving models to the tropics. One critical challenge is the oc-259 currence of the double-ITCZ bias in GCMs. Such large-scale biases cannot be corrected 260 by high-resolution alone, i.e. downscaling current GCMs at high resolution will in gen-261 eral replicate the double-ITCZ bias. Currently there are two approaches to conduct down-262 scaling studies that circumvent these difficulties: 263

1. First, one can apply the pseudo-global warming (PGW) approach. Recent stud-264 ies have shown that PGW is a attractive and viable pathway toward climate-change 265 downscaling simulations in the tropics (Heim et al., 2023; Heim & Schär, 2023). 266

2. Second, one can try to debias the GCM output. The methodology uses the raw high-frequency output of a GCM, but corrects the data for large-scale deficiencies occurring in the control climate. The approach has successfully been applied in the extratropics (Misra & Kanamitsu, 2004), and was here explored for the first time in the tropics.

In this paper we have explored approach (2). We use a large computational domain 272 over the tropical and sub-tropical Atlantic with a spatial resolution (grid spacing) of 12 273 km. We used one particular GCM for the experiments (MPI-ESM1-2-HR). The main 274 conclusions of the study are: 275

276	•	When directly driving the RCM with the raw GCM control output (conventional
277		downscaling), the RCM reproduces a double-ITCZ similar as in the driving model.
278		The use of high resolution alone is unable to correct for the double-ITCZ bias.

- When driving the RCM with the bias-corrected GCM fields (bias-corrected down-279 scaling), the RCM credibly reproduces the observed ITCZ, although there are some 280 small differences in the position of the ITCZ in the boreal summer period.
- In order to pinpoint the reasons for the double-ITCZ bias, we have conducted an 282 additional simulation where the bias correction is only applied to the SST field 283 (SST-corrected downscaling). This simulation yields a qualitative realistic sim-284 ulation of the ITCZ, but analysis of the OLR biases shows that it is not as suc-285 cessful as the fully bias-corrected downscaling. Also, this result pertains only to 286 the GCM used, and the role of the SST biases might be smaller in other models. 287

There are several limitations of the current study. First of all, we merely tested one 288 particular GCM in the downscaling approach. Although the GCM considered has a sub-289 stantial double-ITCZ bias, it is not clear whether the current results will carry over to 290 other GCMs. Second, we did not address simulations using future scenario climates, but 291 merely worked with control climates. It is not a priori clear whether the beneficial im-292 pacts of bias-corrected downscaling also apply to the full control / scenario climate-change 293 approach. Currently we are undertaking related simulations and these will feature in a 294 subsequent publication. 295

Nevertheless, in the current study we show that bias-corrected downscaling appears to be a promising methodology, not only in the extratropics as previously shown, but also in the tropics. We have demonstrated the benefits of the approach for the tropical and sub-tropical Atlantic, but we believe that this carries over to other areas. In particular, it appears attractive to use this approach for climate-change impact assessment studies in the Amazon, West Africa or Indonesia – regions that are plagued by biases in the representation of the ITCZ in climate-change assessments.

# 303 5 Open Research

This work complies with the AGU data Policy, the program for bias-corrected downscaling is available on Github: https://github.com/shucliu/bias\_correction\_downscaling.

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Figure 1. Simulation and analysis domains. The green domain (Simulation) is used for the COSMO calibration and simulations. The red domain (Analysis1) is used for the cross section analysis. The black domain (Analysis2) is used to indicate the SST bias.

Figure 2.SST bias of the MPI-ESM1-2-HR historical simulation (defined as MPI-ESM1-2-HR – ERA5) over a 30 year period (1985-2014) and for the two seasons with
the most southern- and northernmost position of the ITCZ. The black domain (Analysis2) represents the domain with significant SST overestimation; it will be used in some of the analyses.

Figure 3. Meridional cross section of 10-year-mean precipitation and vertical mass 570 flux over domain Analysis1. The panels show the result of different simulations (from 571 top to bottom: ERA5, MPI-ESM1-2-HR historical simulation, MPI-ESM1-2-HR AMIP 572 results, COSMO conventional downscaling, COSMO bias-corrected downscaling and SST-573 corrected downscaling). The first column shows the annual mean result, the second col-574 umn boreal spring average in February–April and the last column shows boreal summer 575 average in July–September. The red and black lines display the zonal mean precipita-576 tion from the data sets and the GPCP satellite observations, respectively (see scale to 577 the right). The coupled MPI simulation shows a distinct double-ITCZ. The double-ITCZ 578 is also visible in the MPI simulations with prescribed SST, and the conventional down-579 scaling with COSMO based on the native MPI simulations. The bias-corrected down-580 scaling as well as the SST corrected downscaling simulations show no double-ITCZ. 581

Figure 4. Time series of the precipitation bias (simulation minus GPCP) in the meridional cross section over the domain Analysis1 (contours), and the SST bias averaged over domain Analysis2 (green line). From top to bottom, the panels show the results of conventional downscaling, bias-corrected downscaling, and SST-corrected downscaling. The misplaced ITCZ is correlated with the SST bias. The bias-corrected downscaling as well as the SST-corrected downscaling remove the reoccurring positive precipitation bias south of the equator in boreal spring.

Figure 5. Outgoing longwave radiation for observations and model results. The 589 panels show (from left to right): CERES observation, ERA5, MPI-ESM1-2-HR histor-590 ical simulation results, MPI-ESM1-2-HR AMIP results, COSMO conventional downscal-591 ing, COSMO bias-corrected downscaling, and COSMO SST-corrected downscaling. The 592 first row shows the annual mean result, the second row shows the boreal spring average 593 (February – April) and the last row the boreal summer average (July – September). As 594 CERES data is only available since March 2000, the plot is calculated based on data from 595 March 2000 to December 2004. 596



# Supporting information of "Dynamical downscaling of climate projections in the tropics"

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Shuchang Liu<sup>1</sup>, Christian Zeman<sup>1</sup>, Christoph Schär<sup>1</sup>

<sup>1</sup>Institute for Atmospheric and Climate Science, ETH Zürich

Corresponding author: Shuchang Liu, Shuchang.liu@env.ethz.ch

# 5 1 Model Calibration

The calibration of the semi-empirical model parameters is based on the method-6 ology of Bellprat et al. (2012, 2016) The methodology has further been refined and ap-7 plied to the tropics by Liu et al. (2022). It provides an objective calibration of n param-8 eters with an specified plausible parameter range based on expert knowledge. In practice, the methodology requires simulations for the corners of the n-dimensional cube spanned 10 by the parameters. In the interior of the cube a meta-model is used. The performance 11 of the model is optimized using a performance score defined by observational data. In 12 13 our case and following Liu et al. (2022), the observations cover monthly-mean satellite data for outgoing longwave radiation (OLR), outgoing shortwave radiation (OSR) (Loeb 14 et al., 2018) as well as ERA5 data for surface latent heat flux (LHFL) (Hersbach et al., 15 2020). When calculating the performance score, the calibration domain is divided into 16 48 rectangular regions (6 rows and 8 columns with size of  $10^{\circ} \times 10^{\circ}$  each). The calibra-17 tion period covers 4 months (Feb., May, Aug., Nov.) in 2006, each with a 5-day spin-up 18 period. The simulations are driven by ERA5 lateral boundary conditions and ERA5 SST. 19 The validation of the methodology will be presented for an independent period, i.e. the 20 year 2016. 21

While deep convection cannot be fully resolved with 12 km grid spacing, treating it explicitly even at such a relatively coarse resolution can lead to a more realistic model behavior based on previous studies (Vergara-Temprado et al., 2020; Zeman et al., 2021). Therefore we conduct the calibration with three different settings to select the convection scheme for this study, one is with explicit convection, one is with only shallow convection parameterized, and one is with shallow and deep convection all parameterized.

Depending upon the set-up of the convective parameterizations, different param-28 eters are calibrated. For the explicit convection, we calibrate the same 5 parameters as 29 in Liu et al. (2022) (see their Table 1). For the shallow convection parameterization, we 30 use one additional parameter (rat\_mb) to control the strength of the parameterized con-31 vection. This parameter is a scaling factor in determining the massflux at cloud base, 32 it can range from 0 to 1. A value of 0 means that the shallow convection is switched off, 33 while 1 means full strength of the convection scheme. For the deep convection param-34 eterization, thick\_dc is calibrated, which is the threshold of cloud thickness for precip-35 itating deep convection. It can range from 50 hpa to 450 hpa and has a default values 36 of 200 hpa. 37

Figure S1 shows the evaluation of the calibration using an independent validation 38 period. The figure shows the biases before and after calibration (left and right). The field 39 presented are: top-of-atmosphere outgoing longwave radiation (OLR), outgoing short-40 wave radiation (OSR) and surface latent heat flux (LHFL) averaged over 4 months (Feb., 41 May, Aug., Nov.) in the year 2016. Since the default configuration suffers mainly from 42 shortwave radiation biases, the calibration method tends to fix that to obtain a higher 43 performance score. Therefore an improvement in the performance of the OSR can be seen 44 under all three convection scheme choices. It is worth noting that the LHFL has larger 45 uncertainty than the radiation fields, and gets correspondingly less weight than the other 46 fields when evaluating the performance score. 47

<sup>48</sup>Overall, among the three settings with different kinds of convection schemes, the <sup>49</sup>one with only shallow convection parameterization performs the best after the calibra-<sup>50</sup>tion, which is consistent with the studies of Vergara-Temprado et al. (2020) and Zeman <sup>51</sup>et al. (2021). Therefore we choose the corresponding setting for the downscaling simu-<sup>52</sup>lations. For completeness, we here list the COSMO model version 6 and the calibrated <sup>53</sup>parameter values (rlam\_heat: 0.26, rat\_sea: 27.66, rat\_mb: 0.5306, qi0: 4.4300E-6, tur\_len: <sup>54</sup>155, cloud\_num: 4.6E7, clc\_diag: 0.9070).



2016 (bias = COSMO - observations). The panels show the biases for model configurations with shallow and deep convective parameterizations activated (top row), (outgoing shortwave radiation), and surface latent heat flux (LHFL). For all configurations, the calibration leads to significant reductions in overall biases, although with shallow convection activated (middle), and with fully explicit convection (bottom). The three fields considered are OLR (outgoing longwave radiation), OSR Figure S1. Evaluation of the calibrated optimum parameter setting averaged over four months (Feb., May, Aug., Nov.) for the independent validation period some compensations between different fields occur (in particular in the top row, where the biases in OLR and OSR decreases at the expense of increases in the LHFL bias).

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