

The forced response of the El Niño– Southern Oscillation-Indian monsoon teleconnection in ensembles of Earth System Models

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1	The forced response of the El Niño–Southern Oscillation-Indian monsoon teleconnection in
2	ensembles of Earth System Models
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17	
18	Abstract
19	
20	We study the teleconnection between the El Niño-Southern Oscillation (ENSO) and the
21	Indian summer monsoon (IM) in large ensemble simulations, the Max Planck Institute Earth
22	System Model (MPI-ESM) and the Community Earth System Model (CESM1). We
23	characterize ENSO by the JJA Niño 3 box-average SST and the IM by the JJAS average

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24 precipitation over India, and define their teleconnection in a changing climate as an ensemble-25 wise correlation. To test robustness, we also consider somewhat different variables that can characterize ENSO and the IM. We utilize ensembles converged to the system's snapshot 26 27 attractor for analyzing possible changes in the teleconnection. Our main finding is that the 28 teleconnection strength is typically increasing on the long term in view of appropriately 29 revised ensemble-wise indices. Indices involving a more western part of the Pacific reveal, 30 furthermore, a short-term but rather strong increase in strength followed by some decrease at 31 the turn of the century. Using the station-based SOI as opposed to area-based indices leads to 32 the identification of somewhat more erratic trends, but the turn-of-the-century "bump" is well-33 detectable with it. All this is in contrast, if not in contradiction, with the discussion in the literature of a weakening teleconnection in the late 20th century. We show here that this 34 35 discrepancy can be due to any of three reasons: ensemble-wise and temporal correlation 36 coefficients used in the literature are different quantities; the temporal moving correlation has 37 a high statistical variability but possibly also persistence; MPI-ESM does not represent the 38 Earth system faithfully.

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40 **1. Introduction**

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Probably the most important teleconnection phenomena are those of the El Niño–Southern Oscillation (ENSO) (Trenberth, 1976; Trenberth, 1984; Bjerknes, 1969; Neelin, 1998). ENSO is a natural, irregular fluctuation phenomenon in the tropical Pacific region (Timmermann et al., 2018), and mostly affects the tropical and the subtropical regions; however, it has an impact on the global climate system as well. A crucial and open question that has challenged scientists for decades is how ENSO would change as a result of the increasing radiative forcing due to the increasing greenhouse gas concentrations. The IPCC has low confidence in 49 what would exactly happen to ENSO in the future, even though they have high confidence 50 that ENSO itself would continue (Christensen et al., 2013). There have been several studies 51 (e.g. Guilyardi et al., 2009; Collins et al., 2010; Vecchi and Wittenberg, 2010; Cai et al., 2015) 52 that aimed to reveal how ENSO might respond to greenhouse-gas forcing. However, most of 53 the applied methods have a common drawback: they evalute averages and further statistical 54 quantifiers (including variances, correlations, etc.) with respect to time in a time-dependent 55 dynamical system, i.e., in our changing climate, or in simplified models thereof.

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In a changing climate, where one or more relevant parameters are changing in time, there can 57 58 be no stationarity by definition, whereas stationarity is crucial for the applicability of temporal 59 averages, as illustrated by Drótos et al. (2015) in a toy model. In realistic GCMs globally 60 averaged quantities seem to behave better, but the problem proves to be significant for local 61 quantities and teleconnections (Herein et al., 2016, Herein et al., 2017). Since the ENSO 62 events are identified by temperatures that are warmer or cooler than average, and 63 teleconnections are defined as correlations between such anomalies, it is important to have a 64 firmly established notion of averages when climatic means are shifting, as also pointed out by 65 L'Heureux et al. (2013, 2017) and Lindsey et al. (2013).

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To properly address the problem of evaluating averages in a changing climate, in this study we turn to a gradually strengthening view according to which the relevant quantities of the climate system are the statistics taken over an ensemble of possible realizations evolved from various initial conditions (see e.g. Bódai et al., 2011; Bódai and Tél, 2012; Deser et al., 2012; Daron and Stainforth, 2015; Kay et al., 2015; Stevens, 2015; Bittner et al., 2016; Herein et al., 2016; Herein et al., 2017; Drótos et al., 2017; Hedemann et al., 2017; Lucarini et al., 2017; Suárez-Gutiérrez et al., 2017; Li et al., 2018; Maher, 2019). We can trace back this view to 74 Leith (1978), which was recently revived (Branstator & Teng 2010) and rediscovered 75 independently also by others. In contrast to weather forecast, one focuses here on long-term properties, independent of initial conditions, in order to characterize the internal variability, as 76 77 well as the forced response of the climate. The mathematical concept that provides an 78 appropriate framework is that of snapshot (Romeiras et al., 1990; Drótos et al., 2015) or 79 pullback attractors (Arnold, 1998; Ghil et al., 2008; Chekroun et al., 2011); and the concept's 80 applicability has also been demonstrated in laboratory experiments (Vincze et al., 2017) as 81 well as to tipping dynamics (Kaszás, 2019).

82

83 Qualitatively speaking, a snapshot attractor is a unique object in the phase space of dissipative 84 systems with arbitrary, non-periodic forcing, to which an ensemble of trajectories converges within a basin of attraction. In the climatic context, the ensemble members can be regarded as 85 86 Earth systems evolving in *parallel*, all of which are controlled by the *same* physics and are 87 subject to the same external forcing (Leith 1978; Herein et al., 2017). If the dynamics is 88 chaotic, convergence implies that the initial condition of the ensemble is "forgotten": after 89 some time (the convergence time) the evolution of the particular ensemble becomes 90 independent of how it was initialized; instead, the distribution of its members, at any time 91 instant, becomes determined by the natural probability distribution of the attractor. This 92 means that the ensemble members, in the given time instant, characterize the plethora of all 93 possible weather situations permitted in the Earth system in a probabilistically correct way 94 (Drótos et al., 2017). The snapshot attractor and its natural distribution depend on time in 95 general, and their time evolution is determined uniquely by the forcing scenario of the system. 96 Note that ensemble statistics are instantaneous by construction.

98 In this paper we directly construct the snapshot attractor and its natural probability 99 distribution, following Herein et al. (2017) (see also Sec. 4), and apply our methodology -100 foreseen already by Leith (1978) - to the teleconnection of ENSO and the Indian summer 101 monsoon. To our knowledge, it is the first time that the snapshot approach (taking care of the 102 convergence) is used in the context of the ENSO-Indian monsoon teleconnection. Although an 103 externally forced system is almost surely nonstationary, in a finite ensemble this signal might 104 not show up. Here we will resort to statistical tests against the null-hypothesis of stationarity 105 in order to "detect nonstationarity" and learn about its nature. 106 107 108 109

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111 **2.** Subjects of the study

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Our investigations concern ensemble simulations from two state-of-the-art climate models:
the Community Earth System Model (CESM, Hurrell et al. (2012)) and the Max Planck
Institute Earth System Model (MPI-ESM, Giorgetta et al. (2013)).

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The CMIP5 versions of these models were already studied regarding how reliable their ENSO characteristics are. It is known that both models underestimate the ENSO asymmetry, but all of the CMIP5 models suffer from this problem (Zhang and Sun, 2014). Generally, however, both models show relatively good ENSO characteristics compared to observations (Bellenger et al., 2014; Capotondi, 2013). The pattern of the monsoon precipitation is quite realistic in both models (see also our analysis in Sec. 6.1), however, the future projections for the Indian region generally have a moderate confidence (Freychet et al., 2015). In the recent study of Ramu et al. (2018), the strength of the ENSO–IM teleconnection has been found to be considerably underestimated in both models compared to observations. We must note, however, that Ramu et al. (2018) calculate the correlation coefficient with respect to time in a historically forced single run, so that the resulting values are possibly unreliable, cf. Section 6.1.

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130 We consider five ensembles in total. The CESM community designed the CESM Large 131 Ensemble ('CESM-LE') with the explicit goal of enabling assessment of climate change in 132 the presence of internal climate variability (Kay et al., 2015). All realizations use a single model version (CESM with the Community Atmosphere Model, version 5) at a resolution of 133 192×288 in latitudinal and longitudinal directions, with 30 atmospheric levels. The MPI-134 135 ESM (Giorgetta et al., 2013) was also used to produce ensembles (called together the 'Grand 136 Ensemble', 'MPI-GE') to explore internal variability in a changing climate (Stevens, 2015; 137 Bittner et al., 2016; Maher et al. 2019). The single configuration applied to this purpose is 138 model version MPI-ESM1.1 in low-resolution (LR) mode, which corresponds to a horizontal resolution of T63 with 47 vertical levels in the atmosphere, and to 1.5-degree horizontal 139 140 resolution with 40 vertical levels in the ocean.

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The CESM Large Ensemble ('CESM-LE') consists of 35 comparable members and covers the time span of 1920-2100. Between 1920 and 2005, historical climate forcing (Lamarque et al., 2010) is used, and the RCP8.5 (van Vuuren et al., 2011) is applied afterwards, reaching a nominal radiative forcing of Q = 8.3 W/m² by 2100. The MPI-ESM historical ensemble ('MPI-HE' in what follows) has 63 members unaffected by spin-up artifacts in the ocean (Maher et al., 2019), and runs from 1850 to 2005 under historical climate forcing (Lamarque

et al., 2010). The nominal radiative forcing becomes thus $Q = 2.1 \text{ W/m}^2$ by 2005 (similarly as 148 149 in the CESM-LE). The MPI-ESM RCP2.6 and RCP8.5 ensembles (which we shall call 'MPI-150 RCP2.6E' and 'MPI-RCP8.5E') continue the previous runs between 2006 and 2099 under the 151 RCP2.6 and the RCP8.5, respectively (van Vuuren et al., 2011): the former provides 152 information about the effects of a pathway peaking in the early 21st century, while the latter 153 assumes further growth in the anthropogenic emission. Finally, the MPI-ESM one-percent 154 ensemble ('MPI-1pctE' in what follows), having 43 members of reliable output, starts in 1850 155 with the same (pre-industrial-like) external conditions as the MPI-HE. Being an idealized experiment, the CO₂ concentration is increased in this case by 1 percent per year until 1999, 156 157 while the concentrations of other greenhouse gases and radiative agents are kept constant. The 158 nominal radiative forcing (calculated via the logarithmic response (Ramaswamy et al., 2001)) 159 reached by 1999 is $Q = 8.3 \text{ W/m}^2$.

160

Fig. 1 gives an overview (Meinshausen et al., 2011) of the forcing scenarios, interpreted in terms of the nominal radiative forcing Q, in the time spans of our particular investigations (beginning in 1890, see later). Note that the nominal radiative forcing Q is *not* a parameter of the system, so that its time dependence is *not* a forcing from a dynamical point of view. Instead, we treat it as a proxy for the aggregated effect of all different forcing agents (which include different tracers in the atmosphere, as well as the varying solar activity and land use — except for the MPI-1pctE).

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In order to ensure memory loss (i.e., convergence to the snapshot attractor (Drótos et al., 2015; Herein et al., 2016; Drótos et al., 2017)), in most cases we discard the first 40 years of the simulations (the only exceptions are the simulations forced by the RCP scenarios, which are continuations of the historical simulation). We emphasize that, in principle, a detailed and dedicated investigation should be carried out in both models to determine the time scale of the convergence, as advocated in Drótos et al. (2017). Due to technical limitations, however, this is far beyond the scope of the present study, which we believe to nevertheless provide with reliable results with the assumption of maximum 40 years for the convergence time, see Part I of the Supplementary Material.

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179 We note that our estimates for the convergence time correspond to the convergence properties 180 that are determined by the atmosphere and the upper ocean with timescales of a few decades, 181 and not those that characterize the deep ocean and its abyssal circulation, which has time 182 scales of thousands of years. According to this time-scale separation, we conjecture that the 183 adjustment of the slow climate variables corresponding to the abyssal circulation does not 184 influence substantially the statistical properties investigated here. Note that, otherwise, all the 185 studies on the 21st-century climate change performed by looking at the properties of an 186 ensemble of simulations would be hopeless. The details of this time-scale separation in the 187 climate system and its particular implications remain the topic of future research.

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189 3. Characterizing ENSO in a changing climate

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The phases of ENSO are traditionally characterized by looking at carefully constructed climate indices, which surrogate the dominant features of the behavior of the fields of interest of the climate system. Most directly – and commonly – the sea surface temperature (SST) is considered to characterize ENSO, which is given rise in part by oceanic Kelvin waves closely confined to the Equator (Dijkstra 2005). Indices of ENSO, the so-called Niño indices (Trenberth, 1997), are defined as the average SST in various rectangular regions stretched along the Equator, minus the temporal mean of that, then divided by its temporal standard deviation, but traditionally involving some smoothing as well. Thereby, anomalously high and low values of the Niño index are considered as "episodes" or phases of the fluctuation phenomenon, called El Niño and La Niña, respectively (Trenberth 1997). Here we are not concerned with episodes, nevertheless, we will naturally end up with using anomalies in our context (Sec. 4).

What we need to decide about is the Equatorial Pacific *region* of interest. We choose the box [5°N-5°S, 150°W-90°W] which defines the Niño 3 index, that is, we consider the average SST, T_{N3} , in this box. This is so because we wish to check the consistency of our findings in the ESM with a previous report on observational data analysis (Krishna Kumar et al. 1999) which considers the the Niño 3 index.

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210 To demonstrate the robustness of the detected changes in the ENSO-IM teleconnection in the 211 MPI-ESM, or the lack of that, we also consider the difference, denoted by p_{diff} , between the seasonal mean of the sea level pressure at Tahiti and at Darwin ($p_{\text{diff}} = p_{\text{Tahiti}} - p_{\text{Darvin}}$). The 212 213 difference p_{diff} is the basis of the Southern Oscillation Index (SOI) as defined by the Bureau of 214 Meteorology of the Australian Government, and measures the strength of the Walker circulation. This version, not involving statistical preprocessing of the time series of the sea-215 216 level pressure before taking their difference, is also called the Troup SOI. An anomalously 217 low (high) value of p_{diff}, and so that of the SOI, indicates an El Niño (La Niña) phase (Troup, 218 1965), and, therefore, the SOI (p_{diff}) is negatively correlated with the Niño 3 (T_{N3}).

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In the Supplementary Material (Part II), we recall from Herein et al. (2017) that climate indices should be treated carefully in a changing climate. In particular, long-term temporal averaging has to be avoided in their definition, and should be replaced by averaging with

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223 respect to the ensemble (after convergence has occurred). In the following whenever we 224 mention Niño 3 or SOI, we mean the revised ensemble-wise index/anomaly when needed: we subtract the ensemble mean from the quantity in question, and divide the result by the 225 226 ensemble standard deviation. Indices or any anomalies defined in this proper way do not carry 227 information about temporal shifts in the climatic mean of the corresponding original 228 quantities (like T_{N3} or p_{diff}). Therefore, investigations of shifts in climatic means have to be 229 and can be carried out separately from those targeting the internal variability as represented by 230 anomalies only. We do not investigate the shift of means here, but it can be found in (Herein 231 et al., 2018) for a setting somewhat different from here.

232

4. The ENSO-IM teleconnection in a changing climate of the MPI-ESM: a forced
response of internal variability

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236 **4.1 Conceptual considerations**

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238 A special aspect of internal variability is the presence of teleconnections: for certain variables 239 characterizing geographically distant regions, anomalies with respect to their climatic mean 240 do not occur independently in a statistical sense. As an example, in the case of ENSO, if T_{N3} 241 (p_{diff}) is anomalously low (high) during the summer months, there is a good chance that the 242 precipitation of the Indian monsoon is anomalously high, and vice-versa (Trenberth, 1997). 243 Although, Roy et al. (2019) reports that the teleconnection strength can be very different 244 when filtering for canonical, Modoki or mixed ENSO events. Note that we will primarily consider the JJA average of T_{N3} and p_{diff} and the JJAS (monsoon season) average of the 245 246 precipitation P to conform to traditional definitions and because the truly instantaneous quantities would have much lower correlation. We will nevertheless use exactly one data pointfrom each year, which is the time period within which these quantities are defined.

249

250 The simplest way to quantify the strength of the (tele-) connection between two given 251 variables is via Pearson's correlation coefficient r (Rogers and Nicewander, 1988). Note that 252 the correlation coefficient is obtained, by definition, as the average of the product of the 253 anomalies (as defined by subtracting the average and dividing by the standard deviation, cf. 254 the previous section) of the corresponding quantities. Consequently, a correlation coefficient between anomalies is the same as that between the original quantities. Therefore, in our 255 256 context of the teleconnection we can speak interchangeably about T_{N3} and Niño 3, on the one hand, and p_{diff} and SOI, on the other hand. We underline that Pearson's correlation coefficient 257 258 is limited to detect a linear correlation between the two quantities of interest; nonetheless, it is 259 useful for having a first order picture of the existing correlations in the fields.

260

261 In Herein et al. (2017) it has been demonstrated that the traditional evaluation of correlation 262 coefficients, carried out via averaging over time, provides with grossly incorrect results under a changing climate. It is thus important to evaluate correlation coefficients with respect to the 263 264 ensemble: in nonautonomous systems with explicit time dependence the two operations are not equivalent. As evaluation over the ensemble can be done at any "instant" of time (after 265 convergence), it also enables one to monitor the temporal evolution of the strength of the 266 267 teleconnection during a climate change. This temporal evolution is one aspect of the response 268 of internal variability to an external forcing. This is what we shall investigate in this Section 269 for the teleconnection between ENSO and the Indian monsoon.

270

In particular, we numerically evaluate the ensemble-based correlation coefficient between the "instantaneous" JJA averages of the SST (T_{N3}) – or the sea level pressure difference (p_{diff}) between (gridpoints closest to) Tahiti (17°31' S, 21°26' E) and Darwin (12°28' S, 130°50' E) – and the "instantaneous" JJAS seasonal average precipitation (P) over India (except for a few states in order to keep to the AISMR data set being our reference; see Fig. 1 of (Parthasarathy et al. 1994)); with the "option" of p_{diff} it reads as:

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$$r = \frac{p_{diff} P - p_{diff} P}{\sqrt{\left(p_{diff}^2 - p_{diff}^2\right)\left(P^2 - P^2\right)}}$$

where <...> denotes averaging with respect to the ensemble. The time *t* here, concerning the ENSO-IM teleconnection, is discrete with yearly increments, as explained above; this is why we write "instantaneous" using quotation marks.

281

Our choice corresponds to investigating the direct, i.e., non-lagged influence of ENSO on the IM. There also exists an indirect influence (Wu et al., 2012) between the beginning of a given ENSO period (from December to February) and the consecutive Indian summer monsoon. Interestingly, the sign of the correlation coefficient between the ENSO characteristic and the IM precipitation is opposite in this case. Beyond these influences, Wu et al. (2012) also identify a "coherent" influence, with origins in both seasons. These alternatives are, however, out of the scope of the present paper.

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290 4.2 Numerical results

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Since the temporal character of the forcing is quite different in certain ensembles, the results are more easily compared if we plot them as a function of the radiative forcing Q instead of time. One should keep in mind, however, that the response is always expected to exhibit some

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delay (Herein et al., 2016), and that the nominal radiative forcing Q is just a proxy for the aggregated effects of different forcing agents (see Section 2; this can also be formulated in a rather rigorous way using the formalism of response theory, see discussion in (Lucarini et al., 2017)).

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300 The results are shown in this representation in Fig. 2 (a,b) for all ensembles considered. Due 301 to the moderate size of the ensembles, especially for the CESM-LE, but also strongly 302 affecting the MPI-ESM ensembles, the numerical fluctuation of the signals is considerable, so 303 much that one cannot read off meaningful coefficients for particular years (corresponding to 304 individual data points in our representation). The structure of the time-dependence thus remains hidden. What might be identified, however, from our plots are main trends or their 305 306 absence, with approximate values on a coarse-grained temporal resolution. Had our ensembles 307 been of infinite size and, thus, able to accurately describe the distribution supported by the 308 snapshot attractor, we would be able to have information at all time scales.

309

310 As shown in Fig. 2 the MPI-ESM ensembles seem to give a rather constant value, $|\mathbf{r}|\approx 0.5$, for the coefficient (both with Niño 3 (T_{N3}) and SOI (p_{diff})), both when plotted as a function of Q 311 312 (panels (a,b)) and when plotted as a function of the time t (panels (c,d)). By a visual 313 inspection, no trends can be identified with "confidence" even for the MPI-RCP8.5E or the 314 MPI-1pctE. The magnitude and the sign of the correlation coefficients are in harmony with the observations (Walker and Bliss, 1937; Parthasarathy and Pant, 1985; Yun and 315 316 Timmermann, 2018). At the same time, the CESM shows very little correlation. Such a large 317 discrepancy is unexpected. For this reason we do not examine the CESM here any further. 318 Note that the underestimation of the strength of the teleconnection by the CESM agrees with 319 Ramu et al. (2018).

321 After the visual inspection, we take to formally testing if we can reject with high confidence 322 the hypothesis that the correlation coefficient is constant during the timespan of the MPI-ESM 323 simulations, or in any (sub)intervals. Our test is based on the fact that the distribution of the 324 Fisher-transform (Fisher, 1915; 1921) of an estimate of a given correlation coefficient r (i.e., 325 its area-hyperbolic tangent, which we shall denote by z) calculated from a sample (in our case, 326 an ensemble) of given size N follows a known distribution to a very good approximation: a Gaussian with a standard deviation of $1/\sqrt{N-3}$, provided that the original quantities also 327 328 follow Gaussian distributions (Fisher, 1936). Should the latter conditions be met, the sampling 329 distribution of z would be the same in each year of a given ensemble simulation with the only 330 possible difference appearing in the mean of this distribution. Since calculations described in 331 Part III of the Supplementary Material support that different years are independent for this 332 exceptional, single variable, the setup would become suited for a Mann-Kendall test (Mann, 333 1945; Kendall, 1975) for the presence of a monotonic trend in the time series of z, whereby 334 stationarity would become rejectable. (Note that non-monotonic time dependence is out of the 335 scope of a single Mann-Kendall test, but testing in different intervals may reveal non-336 monotonicity, as discussed below.) To keep simplicity, we evaluate Mann-Kendall tests for z337 calculated from the original variables in the main text, and give support for the negligible 338 effect of their non-Gaussianity in Part IV of the Supplementary Material.

339

We present values of the test statistic (Z_{MK}) to indicate the certainty of the presence of trends and also the sign of detected trends (and show the more commonly used p-values in Part V of the Supplementary Material). We carry out the test in all possible subintervals of our time series (of annual data points) in order to gain some insight into the possible inner structure of the simulations. Note that this representation suffers from the so-called multiple hypothesis 345 testing problem enhanced by correlation between neighboring data points of the plot (Wilks, 346 2016), i.e., even larger seemingly significant patches may be false detections. However, the point-by-point values of the test statistic are not corrupted, so that the probabilities associated 347 348 to these values are correct and can be interpreted in the usual way. Results for Z_{MK} in the 349 MPI-HE and the MPI-RCP8.5E stitched together can be seen in panels (a) and (b) of Fig. 3. 350 Such a diagram could indicate if a trend is *linear* in time, because in that case a stratification 351 of the color chart would be parallel to the diagonal or the hypotenause of the right triangle of 352 color. In contrast with this, a "hockey-stick"-like time dependence would instead result in a 353 horizontal contour of low p-values, in association with the start year of the steep change. A 354 further relevant pattern will be a "dipole" of Z_{MK} with an axis parallel to the diagonal, corresponding to the emergence and the subsequent reversal of a trend (a "bump" or a 355 "ditch"). Note that these features are *temporal*, as opposed to a possible relationship with the 356 357 forcing (which might be represented e.g. by the radiative forcing Q, which is not a linear function of time according to Fig. 1). 358

359

360 A steady increase in the teleconnection strength is an attribute more so when Niño 3 characterizes ENSO (as in panel (a)) as opposed to the SOI (panel (b)). In fact, with the SOI a 361 362 change is not even detected under the RCP8.5 scenario alone, only if the historical period is included. A very certain trend begins within the historical period, in the late 20th century, and 363 can be detected almost irrespectively of the starting point of the interval, like a "hockey 364 stick". This is unexpected, as the historical forcing is the weaker one. It is even more 365 366 interesting to notice a trend with an opposite sign a few decades later: as indicated by the "dipole" structure, the teleconnection first becomes stronger, then loses strength. Note the 367 368 contrast with the Niño 3-based characterization for which hard significant trends are traced out only in the late 21st century: trends in the late 21st century are practically absent when
using the SOI.

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To support the reliability of our methodology, we present analogous results obtained with an independent hypothesis testing technique in Part V of the Supplementary Material. In a completely different approach, the slopes of linear fits displayed in similar diagrams also trace out the same structure as that of panels (a) and (b) of Figs. 3, see panels (c) and (d) of the same figure. Even a small-scale organization of the diagrams along vertical and horizontal lines proves to be the same, which suggests that this organization is not an artifact of the methodologies, but is presumably due to the influence of the more outlying values of *z*.

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The diagrams of the slopes in Figs. 3(c) and (d) also give us a first estimate for the strength of assumed monotonic trends. Of course, these are very unreliable along the main diagonal (cf. the high absolute values of Z_{MK} in Figs. 3(a) and (b)), but, in statistically significant areas of the plots, show how sudden the increase and the drop in the teleconnection strength is for the SOI, and that the strengthening is particularly fast in the late 21st century for Niño 3.

385

As a test of robustness, we carry out the same evaluation but exclude September from the monsoon season. The diagrams of the test statistic Z_{MK} (informing about the certainty of the presence of a trend by being normally distributed in the absence of a monotonic trend) and the slopes of linear fits are displayed in Fig. 4. We conclude that the general structure of the changes in the correlation coefficient is robust, even if the detectability of change in some specific intervals is not robust.

393 In order to link what is seen when using Niño 3 and the SOI, we extend our analysis to two 394 further ENSO characteristics: the Niño 3.4 index, considering the SST further west in the Equatorial Pacific (in the box [5°N-5°S, 170°W-120°W]; Ashok et al., 2007), and the box-395 396 SOI, extending the box concept to the atmospheric sea level pressure difference (replacing Tahiti and Darwin by the boxes [5°N-5°S, 80°E-160°E] and [5°N-5°S, 160°W-80°W], 397 respectively; Power and Kociuba, 2010). The results for these two choices, shown in Fig. 5, 398 399 are surprisingly similar to each other, and, furthermore, exhibit the main features of both of 400 the original choices: a gradual increase in the teleconnection strength with an enhancement in 401 the late 21st century (Niño 3) and a "bump" at the turn of the century (SOI). It is thus obvious 402 that both Niño 3.4 and the box-SOI are some kind of intermediate representation of the ENSO phase between Niño 3 and the SOI from the point of view of the teleconnection with the 403 404 Indian monsoon.

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We further extend our analysis by performing the same evaluation for the MPI-1pctE and for 406 407 the combination of the MPI-HE and the MPI-RCP2.6E, see Figs. 6 and 7, respectively. When 408 using Niño 3, a long-term increase in the teleconnection strength is seen under any forcing. It 409 is remarkable that the strength of the teleconnection keeps increasing even after the peak in 410 the radiative forcing of the RCP2.6 (Fig. 7). When following the RCP2.6 after the historical period, the SOI-based characterization, surprisingly, also "sees" this increasing teleconnection 411 strength in the late 21st century very well, unlike for the RCP8.5 (Fig. 3). Finally, the MPI-412 lpctE is completely different from the SOI point of view: the "dipole" pattern indicates a 413 414 weakening followed by a strengthening.

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418 **5. The ENSO-IM teleconnection in view of observational data**

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420 In the context of observations, one is provided with a single historical realization, and 421 therefore no ensemble-wise statistics can be evaluated. The obvious way to check a change in 422 time is to compare statistics belonging to nonoverlapping time windows. A time series can 423 even be obtained by a moving window statistics. There are two approaches to calculating moving cross-correlations. One is a direct approach, calculating Pearson's correlation 424 425 coefficient in any given time window. This way the segment of the time series is "normalized" 426 naturally by the average and standard deviation of this segment. Because of the removal of the 427 mean, this is sometimes viewed as detrending, beside a filtering out of low-frequency variability. Yun & Timmermann (2018) (YT18 in the following) present their result in their 428 429 Fig. 1 (b) following this approach. Alternatively, Krishna Kumar et al. (1999) (KK99 in the 430 following) preprocesses the time series, before applying the direct method, by subtracting a 431 smoothed running mean in a centred window. We note that with the latter approach, the 432 resulting moving correlation time series is shorter by a window size.

433

We apply both of these algorithms here, employing a 21-year window, as did KK99 and YT18. Although, we use a centred window for evaluating the correlation itself, unlike YT18 (and probably also KK99) did without justification. Stages and the result of this are shown in Fig. 8, where we used the ERSST v5 (Huang et al., 2017) and the AISMR (Parthasarathy et al., 1994; Mooley et al., 2016) observational data products for the SST and Indian summer monsoon rainfall, respectively.

440

441 Our results do more or less reproduce that of KK99, except perhaps that we see more 442 variability before 1980. (On the weakening of the teleconnection in the late 20th century see

also (Kinter et al., 2002; Sarkar et al. 2004; Boschat et al., 2012).) It turns out also that the
direct method (YT18) results in approximately the same time series in this scenario, except
that r is most typically, but not always, larger.

446

447 Nevertheless, we examine the robustness of the "significance" of the weakening of the 448 running correlation. Prompted by the diversity of variables used in the literature, we "perturb" 449 both the precipitation and SST variable to be correlated with one another, whose results are 450 shown in panel (a) and (b) of Fig. 9, respectively. By "perturbation" we mean considering 451 alternatives either to the data product or the area over which we calculate the mean.

452

To start with, instead of the AISMR data, we use the CRU PRE v4.03 (Harris, 2019) data 453 454 (available only over land), masked with the AISMR regions for an exact match in this respect. 455 The different data product does make a difference with respect to the "significance" of 456 weakening, indicating less of it in view of the CRU PRE data. It also matters if instead of a 457 mask given by the shape of India (except for a few states; see Fig. 1 of (Parthasarathy et al. 458 1994)) we take the mean in the box $[5^{\circ}N-25^{\circ}N, 70^{\circ}E-90^{\circ}E]$ (Yun & Timmermann, 2018): 459 there is less (more) weakening after 1980 (around 1950). Furthermore, excluding the 460 monsoon rain in September also results in more weakening around 1950. Otherwise, the little difference after 1980 prompts that in this period the monsoon season became shorter. 461

462

Using other data products for the SST, on the other hand, namely, ERSST v4 (Huang et al. 2015) (as also used by (Yun & Timmermann, 2018)) and HadISST1 (Rayner et al., 2013), makes a difference only before 1940. Finally, considering only the eastern half of the Niño 3 box sees again less weakening after 1980, but leaves the period around 1950 largely unaffected. (We have checked that the subtraction of a smoothed running mean before

468 calculating the running correlation (KK99) brings about minuscule difference in all cases;469 results not shown.)

470

471 6. Discussion

472

473 **6.1 Possible reasons for the apparent discrepancy between model and observations**

474

The contrast between the ensemble-wise (Sec. 4) and temporal (Sec. 5) results obtained for the MPI-ESM and observations, respectively, is constituted by the opposite sign of the change in the strength of the ENSO-IM teleconnection. This disagreement may have different reasons:

- 479 1. The ensemble-wise and temporal correlation coefficients do not quantify the same480 thing.
- 4812. The temporal single-realisation result features so much internal variability that it does482 not actually allow for detecting nonstationarity.
- 483 3. The model is not truthful to the real climate.

484

Regarding point 1 we recall that the ensemble-wise correlation coefficient is an "instantaneous" (yearly) quantity while the temporal correlation coefficient is obviously using information from several years. The latter is not really relevant in a changing climate, whereas the probability of the co-occurrence of the anomalies of the two system components (ENSO and IM) is reflected correctly only in the former, as discussed in the Introduction.

490

491 As a further aspect of the difference, the ensemble-wise r, unlike the temporal one, does not 492 exclude correlations of low-frequency variability; in principle it could be the case that the

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493 latter was strengthening in the 20th c. and it dominated over a weakening correlation of
494 higher-frequency variability.

495

496 Regarding point 2 we remark that in Sec. 5 we did not pursue hypothesis testing (like we did 497 in Sec. 4) as the time series of moving correlations has an autocorrelation time determined by 498 the window size, and so it does not satisfy e.g. the assumption of the MK test. While this may be circumvented by restricting the investigation to non-overlapping windows, such a 499 500 technique makes obvious that the autocorrelation introduced by windowing seriously reduces 501 the effective sample size. For instance, even if the original time series of r lacks 502 autocorrelation, a 21-year windowing of a 140-year time series results in an effective sample size of no more than 7, approximately. Nevertheless, it is surprisingly common to see in 503 publications an incorrect report on the significance of e.g. trends despite these aspects. It 504 505 appears to us that KK99 also disregarded these considerations when claimed that the 506 weakening of the teleconnection is significant in a statistical sense. Indeed, if the detection of 507 trends or nonstationarity in this context is already challenging when endowed with a 63-508 member ensemble (Sec. 4), it seems hopeless from a single realization. See also Wunsch (1999), Gershunov et al. (2001), Yun and Timmermann (2018). 509

510

Nevertheless, it would be very valuable to be able to rely on temporal statistics, by which observational climate data could be analyzed. As climate models can represent some aspects of the climate inaccurately, our only chance to gain an understanding of those aspects is by analyzing observational data. Ben Santer advocates (conference contribution) that the great value of ensembles of climate model simulations, like the MPI-GE or CESM-LE, is that they can serve as a test-bed for temporal statistics or algorithms. For example, one can check how well ergodicity is satisfied in some given context, which is known (Drótos et al. 2016) to benot satisfied in a generic nonautonomous case.

519

520 Returning to point 1 in this respect, we can simply evaluate the temporal correlations for all 521 63 converged members of the MPI-GE, and see if they typically feature a weakening teleconnection like KK99 reported. Fig. 10 shows the result with both kinds of "detrending". 522 We see that the ensemble average temporal correlation (a quantity also evaluated by 523 524 Mamalakis et al. (2019)) is rather steadily *increasing* in the historical period, which lets us conclude that the disparate treatment of low-frequency correlations does not bring about a 525 typical opposite trend here. Nevertheless, the different behavior of the ensemble-mean 526 temporal correlation under RCP8.5 - increasing with the indirect method of KK99 and 527 stagnating with the direct method of YT18 - cautions us to keep an open mind about 528 529 unexpected differences.

530

531 The same figure also addresses the possibility of point 2. The variances of the moving 532 correlations are very large, but it is also not very unlikely to have a smaller variance for many 533 decades followed by a drift, i.e., a considerable apparent weakening or strengthening of the 534 teleconnection. We find examples for this among the 63 ensemble members. Actually, it is 535 recognized in many studies (Kinter et al., 2002; Ashrit et al., 2003; Sarkar et al. 2004; Ashrit et al., 2005; Annamalai et al., 2007; Kitoh, 2007; Chowdary et al., 2012; Li and Ting, 2015) 536 that "modulations" and corresponding apparent trends in the studied correlation coefficient, 537 538 when calculated over different time intervals (as done by e.g. Boschat et al. (2012) and Ruiging et al. (2015)) or over moving (sliding) time windows (as done by e.g. Krishna Kumar 539 540 et al. (1999), Ashrit et al. (2001), Kinter et al. (2002), Ashrit et al. (2003), Ashrit et al. (2005), 541 Annamalai et al. (2007), Kitoh (2007), Chowdary et al. (2012), Li and Ting (2015)), can

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542 appear as a result of internal variability. In particular, Li and Ting (2015) conclude that the 543 observed weakening of the teleconnection in the late 20th century would be due to internal 544 variability. Sarkar et al. (2004) go beyond this saying, on the basis of physical arguments, that 545 "the effect of ENSO on Indian precipitation has not decreased but on the contrary it has 546 increased in recent times", aligning, in fact, to our finding in the MPI-GE, but claiming that 547 actual strenghtening was dominated by internal variability seeing a weakening.

548

Finally, we address the possibility of model errors, point 3. We start with presenting maps of global SST trends for the historical period, in Fig. 11, comparing the MPI-ESM and observations. All-year data is used to fit a straight line whose slope represents the trend. As for the model, we show both the ensemble average and standard deviation of the trends.

553

554 Like some earlier version (Collins, 2004), the version of the MPI-ESM used to generate the 555 MPI-GE seems to have a La-Niña-like warming, that is, more warming in the Western 556 Equatorial Pacific versus the Eastern'. Considering the ensemble-wise variance globally, the 557 observed warming (and cooling) trends seem to be consistent with the model. Note that the observed Equatorial Pacific warming, like the ensemble mean in the MPI-GE, is La-Niña-like, 558 559 and it is in disagreement with the report of Lian et al. (2018) on a cooling instead, even if in 560 the Eastern Equatorial Pacific. We do not pursue here rigorously (Wilks, 2016) the question of (in)consistency of these patterns; although it should be clear that it would be just a matter of 561 562 data set size to detect inconsistency.

563

We continue with similar maps of JJAS precipitation climatology over India shown in Fig. 12. It is clear that the model has less rain, possibly partly because of its coarser resolution, so that high mountains that "force" precipitation are not resolved. Increasing model resolution has 567 been plausibly indicated by Anand et al. (2018) to reduce model biases (see their Fig. 6), also 568 over the sea. The latter might be a clue that, due to the conservation of water, negative precipitation bias over high mountains and positive biases nearby over the ocean can be 569 570 related. Considering the ensemble-wise variability too, the discrepancy can be indeed 571 considered a bias, not just a difference by chance or statistical error. However, the patterns 572 between model and observations certainly bear a resemblance. The patterns for the trends, on 573 the other hand, are less similar; see Fig. 13. Furthermore, the magnitude of some local trends 574 in the observation exceeds by far anything in any realization of the model.

575

While this might be a clue to the origin of the discrepancy between a possible weakening temporal correlation in observations and a typically strengthening one in the model, we emphasize that a temporal correlation of detrended data is hoped to quantify some relationship between fluctuations rather than forced trends of the climatic mean signal. Nevertheless, in conclusion, if the discrepancy is to do with model errors (point 3), then it is more likely coming from the side of precipitation than SST.

582

However, when regarding the particular quantities at the basis of our analyses of the teleconnection, Fig. 14 (a) shows that the average Indian monsoon rainfall in the model and observations seem to have consistent fluctuation characteristics and perhaps also trend, even though the underestimation of the rainfall by the model is also seen from this angle. The Niño 3 index or T_{N3} , shown in panel (b), can be described very similarly: despite a 2 °C warmer model, the variance and temporal characteristics of the fluctuations seem to closely resemble each other in the model and observations.

590

592 **6.2** The nonlinearity of the response and possible reasons for that

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594 In view of the Niño 3-AISMR correlation (see e.g. the (a) panels of Fig. 3, 4, 6) the possibility 595 that the forced response of the teleconnection would be approximately linear cannot be 596 excluded. However, representing ENSO by the sea surface temperature just in a somewhat 597 more westerly box (Niño 3.4), nonlinearity, what is more, non-monotonicity becomes obvious 598 (see the (b) panels of the same figures). We shall first discuss possible reasons for nonlinearity 599 even if the forcing might be considered relatively weak in all scenarios (from the point of view of response theory (Ruelle, 2009; Lucarini et al., 2017)). Remember that temporal 600 601 linearity has to be distinguished from a linear response to forcing, but non-monotonicity in 602 Fig. 5 excludes both options. We also recall that the teleconnection keeps strengthening even 603 after radiative forcing peaks in the RCP2.6 (see Fig. 7).

604

605 In the slightly different setup of (Herein et al., 2018), considering precipitation only in the 606 northern part of India, from an analysis of the sensitivity of hypothesis tests to stationarity, we 607 concluded that the strength of the teleconnection in view of the SOI cannot respond to the radiative forcing Q instantaneously and linearly, since otherwise those tests would have had to 608 609 detect nonstationarity also in the MPI-RCP8.5E alone and the MPI-1pctE (beyond the MPI-610 HE), which was not the case. Some very strong form of nonlinearity could explain the results 611 in principle. However, another possible explanation lies in the radiative forcing Q not being a dynamical forcing, i.e., a single quantity that appears explicitly in the equations of motion. 612 613 That is, a causal response function might not exist between Q (as predictor) and r (as predictand; Lucarini, 2018). 614

In particular, the strength of the teleconnection may respond in a different way to variations in different forcing agents. Remember that the nominal radiative forcing Q represents the aggregated effects from several different agents, and responses might not be possible to be interpreted in terms of variations in the single quantity Q. The underlying mechanisms might even turn out to be not or not directly related to the increase in the net energy flux.

621

622 In fact, the differentiation of responses with respect to different forcing agents would not be 623 very surprising. As shown by Bódai et al. (2018) by considering a (globally homogeneous) CO_2 forcing alone, while the resulting Q might act as a dynamical forcing with respect to the 624 625 surface temperature, it does not do so e.g. with respect to the temperature at the tropopause (Bódai et al., 2018). The teleconnection of ENSO with the Indian summer monsoon might 626 627 indeed involve a physical mechanism not restricted to the surface, or to observables that 628 would secure the causality of the "response" of the teleconnection to Q. If we add that the 629 response in the climatic mean of the Indian summer monsoon has actually been found by Li et 630 al. (2015; utilizing techniques based on temporal averaging, though) to be governed by 631 different mechanisms under aerosol forcing (related to volcanism, or, indeed, large scale pollution in South and South-East Asia) and greenhouse-gas forcing, we can easily imagine 632 633 that the fluctuations of the Indian summer monsoon respond differently to these two kinds of 634 forcings, causing the teleconnection to respond in a different way, too.

635

Note that volcanism is enhanced in the late 20th century when changes in the strength of the teleconnection are first prominently seen in the MPI-GE. In fact, a hypothesis has been put forward by Maraun and Kurths (2005) that after major volcano eruptions in the Southwest Pacific the "cooling effect could reduce the land/sea temperature gradient and thus make the Monsoon more sensitive to ENSO influence". These authors found more regular oscillatory

641 ENSO dynamics and a phase locking between ENSO and the monsoon in the observed time 642 series after major volcano eruptions in southern Indonesia, which, they claim, should be reflected in an increased correlation, perhaps (see below) consistent with our finding. This 643 644 could also be an indication that a single realization contains already a lot of information about the forced response in terms of a nonlinear quantifier of the teleconnection, as opposed to 645 Pearson's "linear" correlation coefficient. Taking into account that the pure ensemble-based 646 647 description of teleconnections is the statistically most relevant one and is usually more robust 648 than single-realization temporal techniques, it might prove to be extremely fruitful to carry out an ensemble-based analysis but replacing Pearson's correlation coefficient by e.g. 649 650 Spearman's "nonlinear" rank correlation coefficient.

651

652 Nevertheless, Maraun and Kurths (2005) claim to not disagree with KK99 about the decrease 653 of the correlation strength as a forced response. They describe a transition near 1980 from a 1:1 phase locking into a 2:1 phase locking, with the Indian monsoon oscillating twice as fast. 654 655 This connection, they claim, would be "invisible to (linear) correlation analysis", or rather the 656 correlation would be destructed by the additional monsoon peak. Note, however, that nonstationarity is not yet verified for observations (Sec. 6.1), so that the picture might be 657 658 more complicated than sketched by Maraun and Kurths (2005). From this point of view, it 659 could be checked if the MPI-ESM features the same effect in terms of the phase difference analysed by them. 660

661

The above discussion shows many possibilities for a nonlinear response. However, we have also found considerable variations in the results when choosing different characteristics of ENSO. Nevertheless, a long-term increase in the ENSO-IM teleconnection strength is present in *every* scenario when utilizing an area-based index. Furthermore, a "bump" is also rather

666 consistently detected under the combination of the historical and RCP8.5 forcings at the turn 667 of the century if the ENSO characteristic is based on some more western part of the Pacific. It 668 is only for the pressure difference p_{diff} between two gridpoints that a rather erratic behavior is 669 found. Such a quantity should be more sensitive when the spatial patterns playing the main 670 role in the teleconnection phenomenon are not simple and when these patterns change 671 substantially even if the bulk does not.

672

While the analysis of changes in the ENSO pattern (usually investigated by emprical 673 orthogonal functions (EOFs)) may already prove to be informative, the patterns most relevant 674 675 for the teleconnection can be identified by the "maximal covariance analysis" (MCA) or "canonical correlation analysis" (CCA). One can evaluate these also ensemble-wise, similarly 676 to the recently developed snapshot EOF technique (SEOF (Haszpra et al., n.a.); see its 677 678 application to ENSO in (Herein et al., 2019); one may call the new techniques SMCA and 679 SCCA), by which changes in these patterns can be studied or detected. In principle, it may 680 still be that such analyses yield a different picture depending on using the SST or the sea-level 681 pressure to characterize ENSO. We will investigate these matters as future work.

682

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1071	Fig. 1. The nominal radiative forcing Q as a function of time in the particular simulations
1072	within the timespan of our investigation. For the nominal radiative forcing in the CESM-LE,
1073	the MPI-HE, the MPI-RCP8.5E and in the MPI-RCP2.6E, see Meinshausen et al. (2011). The
1074	nominal radiative forcing in the MPI-1pctE has been calculated via the logarithmic response
1075	(Ramaswamy et al., 2001).
1076	
1077	Fig. 2. The correlation coefficient between the All-India summer monsoon rainfall and Niño 3
1078	(a,c) or SOI (b,d) , as a function of the nominal radiative forcing $Q(a,b)$ and time (c,d) in
1079	different ensembles as indicated by the coloring (see Fig. 1). For comparability, $-r$ is plotted
1080	in panels (a) and (c). For visibility, MPI-RCP2.6E is not included in panels (c) and (d).
1081	Consecutive years are connected by lines in all panels.
1082	
1083	Fig. 3. The Z_{MK} values (color coded; $ Z_{MK} > 1.96$ (corresponding to $p_{MK} < 0.05$, shown in
1084	Supplementary Fig. S6): red or blue, according to the sign) and slopes calculated in the MPI-
1085	HE and MPI-RCP8.5 stitched together for all possible subintervals of the whole time span.
1086	ENSO is represented by (a) and (c) Niño 3 and by (b) and (d) SOI.
1087	
1088	Fig. 4. Same as Fig. 3 if September is excluded from the monsoon season.
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1090	Fig. 5. Same as Fig. 3 for Niño 3.4 and the box-SOI.
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1092	Fig. 6. Same as Fig. 3 for the MPI-1pctE. Note the shorter length of the simulation.
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1095 Fig. 7. Same as Fig. 3 for the MPI-RCP2.6E stitched after the MPI-HE. Note that the lower
1096 triangles are identical to those in Fig. 3.

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1098 Fig. 8. Moving temporal correlation coefficient based on observational data (see also the 1099 main text). (a) JJAS All-India summer monsoon rainfall data; (b) JJA mean Niño 3 index 1100 based on the ERSST v5 dataset. In both of these diagrams a 21-year running mean is shown 1101 as well as a smoothing of it obtained by the Savitzky-Golay filter (of order 3 and a window 1102 size of 21 years, applying Matlab's 'sgloayfilt'). This is what is subtracted from the original 1103 data, in ways of detrending, following KK99. (c) "Anomalies" obtained following KK99, 1104 providing visuals of correlation. (d) The correlations coefficient itself, obtained by both the 1105 direct method of YT18 and the method of KK99. 1106 Fig. 9. Moving temporal correlation coefficient, following YT18, based on various 1107 observational variable combinations. Robustness is examined by "perturbing" both the (a) 1108 precipitation and (b) SST variables. The legends indicate the following combinations: #1 -1109 (ERSST v5, AISMR); #2 – (ERSST v5, CRU PRE masked with the AISMR regions); #3 – 1110 (ERSST v5, CRU PRE in the box [5°N–25°N, 70°E–90°E] (Yun & Timmermann, 2018)); #4 – 1111 (ERSST v5, AISMR JJA only); #5 – (HadISST1, AISMR); #6 – (ERSST v4, AISMR); #7 – 1112 (ERSST v5 eastern half of Niño 3 box, AISMR). 1113 1114 Fig. 10. Moving temporal correlation coefficient for all converged members of the MPI-GE in 1115 the historical period continued seamlessly with the RCP8.5 forcing scenario, following both

1116 (a) KK99 and (b) YT18. The thin gray lines show all the realisations while 3 realisations are

- 1117 shown in colour for example. Thick blue lines show the ensemble average of the temporal
- 1118 *correlation, which are blown up in insets to better indicate any trend.*
- 1119

1120	Fig. 11. Climatological SST trend in model and observation. (a) Ensemble-mean and (b)
1121	standard-deviation of the SST trend in the MPI-HE (1880-2005); (c) SST trend in the
1122	ERSST v5 (1880-2016) data set.
1123	
1124	Fig. 12. Climatological JJAS mean precipitation in model and observation. (a) Ensemble-
1125	mean and (b) standard-deviation of the JJAS mean precipitation in the MPI-HE (1880-2005);
1126	(c) JJAS mean precipitation in the CRU PRE (1900-2010) data set (data available only over
1127	land).
1128	Fig. 13. Same as Fig. 12 but for long-term temporal trends of JJAS mean precipitation.
1129	
1130	Fig. 14. Comparison of large-area-averages in model (MPI-ESM) and observation
1131	(precipitation: AISMR magenta; SST: ERSST v5, blue). (a) JJAS precipitation; (b) JJA SST. To
1132	match the AISMR data, precipitation in the model is averaged over the AISMR areas (India,
1133	except for a few states; see main text). The JJA SST is averaged in the Niño 3 box. Thin gray
1134	lines represent all converged members of the MPI-GE, while three coloured lines show
1135	examples of individual members; the thick blue lines show the ensemble mean.
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Fig. 1. The nominal radiative forcing Q as a function of time in the particular simulations within the timespan of our investigation. For the nominal radiative forcing in the CESM-LE, the MPI-HE, the MPI-RCP8.5E and in the MPI-RCP2.6E, see Meinshausen et al. (2011). The nominal radiative forcing in the MPI-1pctE has been calculated via the logarithmic response (Ramaswamy et al., 2001).



Fig. 2. The correlation coefficient between the All-India summer monsoon rainfall and Niño 3 (a,c) or SOI (b,d), as a function of the nominal radiative forcing Q (a,b) and time (c,d) in different ensembles as indicated by the coloring (see Fig. 1). For comparability, -r is plotted in panels (a) and (c). For visibility, MPI-RCP2.6E is not included in panels (c) and (d). Consecutive years are connected by lines in all panels.



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