Characteristics of Inherent Coupling Structure of Model Climates

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ABSTRACT: This work proposes a framework to examine interactions of climate modes that are identified as leading EOF modes; their coupling structure is unveiled through correlation analysis and helps in constructing a regression model, whose performance is compared across GCMs, thereby providing a quantitative overview of model performances in simulating mode interaction. As a demonstration surface temperature is analyzed for five CMIP5 preindustrial control (PiControl) simulations. Along with the seasonal land and ocean modes, four interannual modes are identified: the tropical mode (TM) associated with the Hadley circulation, the tropical Pacific mode (TPM) characterizing a zonal temperature contrast between the eastern tropical Pacific and the Atlantic/Indian Oceans, and two annular modes, the Arctic mode (AM) and Antarctic mode (AAM). All GCMs converge on the following points: 1) TM strongly couples with seasonal signals of the previous year; 2) TPM leads TM by 1 year, and thus a weaker zonal temperature contrast in the tropics contributes to warming in the entire tropical band 1 year later; and 3) AM weakly couples to TM at a 1-yr lead, suggesting that a colder North Pole may contribute to colder tropics. In addition, all GCMs do not support a linear coupling between AAM and TM. The above-learned coupling structure is incorporated to construct an optimum regression model that demonstrates considerable predictive power. The proposed approach may both serve as a useful tool for dynamical analysis and lend insight into GCM differences. Its merit is demonstrated by the finding that different representations of the mean seasonal cycle in GCMs may account for the GCM dependence of relative contributions of seasonal and interannual modes to TM variability.

KEYWORDS: Annular mode; ENSO; Hadley circulation; Climate variability; Surface temperature; Climate models; Interannual variability; Seasonal cycle; Tropical variability

1. Introduction

Global warming is drawing increasing attention largely due to a growing media coverage that often associates disastrous impacts of climate extremes with anthropogenic warming. Prior to such an attribution task, an essential step that has to be undertaken is to separate anthropogenically forced climate signals from natural variability, which is by no means an easy task (Hasselmann 1993; Hegerl and Zwiers 2011; Santer et al. 2011; Lee and Ouarda 2012; Frankcombe et al. 2015). Along the way general circulation models (GCMs) become a powerful tool with increasing importance, but also pose enormous challenges. This concerns model construction, validation, and projection, not only in the technical sense, since it requires knowledge of computer science, mathematics, and climate physics, but also in the scientific sense, namely, how faithfully GCMs represent key processes governing the climate system.

On the one hand, GCM performances have been extensively evaluated regarding how key climate modes and processes are reproduced, which include among many others the Hadley

cell (HC) (e.g., Hu et al. 2013; Grise and Davis 2020), the Asian monsoon system (e.g., Mishra et al. 2018; Preethi et al. 2019), ENSO (e.g., Guilyardi 2006; Chen et al. 2017; Lu et al. 2018), the Atlantic multidecadal oscillation, and the Atlantic meridional overturning circulation (Zhu et al. 2006; Drijfhout et al. 2011; Weaver et al. 2012; Zhang and Wang 2013). On the other hand, model comparison has seldom touched how well the interaction between climate modes is reproduced, despite a large collection of observational and model evidence suggesting a climate variability continuum (Huybers and Curry 2006; Dommenges and Latif 2008; Fraedrich et al. 2009; Lovejoy 2018), which essentially characterizes cross-scale linkages.

Take the Hadley cell as an example. Some of its basic features remain challenging for GCMs. For instance, the thermodynamic structure of the HC shows significant discrepancies between models and reanalysis data (e.g., Mitas and Clement 2006). Although there is a broad agreement between models and observations that the tropics are expanding in the recent decades, no consensus has been reached on the exact magnitude (e.g., Johanson and Fu 2009; Hu et al. 2013; Grise and Davis 2020) and the cause of such a forced expansion (e.g., Nguyen et al. 2015; Allen and Kovilakam 2017; Amaya et al. 2018). In addition, abundant studies reveal that the HC closely interacts with the annual cycle (e.g., Bowman and Cohen 1997; Kang and Lu 2012; Baker et al. 2018), ENSO (e.g., Oort and Yienger 1996; Quan et al. 2004), and the annular modes from both hemispheres (e.g., Previdi and Liepert 2007). Moreover, the HC's response to global warming may be highly sensitive to

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the thermal forcing's meridional structure: when the thermal forcing is confined to a narrow region around the equator, the HC contracts, which resembles its response to El Niño events, whereas a forcing with wider meridional extent produces global warming-like HC expansion (e.g., Tandon et al. 2013; Baker et al. 2018).

All these studies suggest that GCM climates that differ in details of simulated internal climate variability and model dynamics may account for their different responses to global warming (Shepherd 2014; Staten et al. 2018). However, model-intrinsic coupling/interactions on their own (i.e., irrespective of the variation of the external forcing) have seldom been discussed, although a deep understanding about the former is prerequisite for learning about the latter, because forced responses are often projected onto the leading intrinsic modes of the climate system (e.g., Hurrell 1995; Branstator and Selten 2009; Zhu et al. 2016).

This study attempts to develop a framework devoted to examining interactions of the most influential climate modes in a given climate as such that it will aid model comparison, particularly regarding how mode interaction is represented. Within this framework, the following goals are addressed: 1) to identify those climate modes that are most fundamental and active in undisturbed GCM climates, 2) to explore how these inherent climate modes couple with each other globally, and 3) to find out whether, and how, the identified coupling structure differs from one GCM to another. The focus is on inherent climate modes that are identified in global surface temperature fields through the EOF analysis, and their interactions are assessed by lead-lag correlation. Based on the identified coupling structure, a suitable regression model is introduced and applied as a model intercomparison tool to provide quantitative measures of mode interaction. A companion analysis on the coupling structure in forced simulations will be discussed separately.

This work is organized as follows: section 2 introduces the data and analysis method, section 3 presents the complete analysis of the undisturbed simulation of MPI-ESM-MR (PiControl), which serves to guide the construction and selection of regression models in section 4; section 5 presents analyses of PiControl simulations of four additional GCMs and discusses the possible GCM dependence of the coupling structure; the main results are summarized in section 6; and section 7 presents discussion and conclusions.

2. Data and method

Surface temperature (ST) fields of PiControl simulations (forced by preindustrial conditions) from five CMIP5 climate models (listed in Table 1) are analyzed. First, monthly ST time series of year i and month m , $X_{i,m}$, with $i = 1, \dots, Y$, $m = 1, \dots, 12$, undergo a time-scale decomposition in a mathematical sense, $X_{i,m} = \bar{X}_i + X'_{i,m}$, where annual means $\bar{X}_i$ describe variations on interannual scales and monthly deviations $X'_{i,m}$ predominantly reflect the seasonal cycle and its possible change on longer time scales. Hereafter they are referred to as interannual and seasonal components, respectively.

Subsequently, these two components of the global ST fields are subjected to the correlation matrix-based EOF analysis (with area weighting considered).

The correlation matrix-based EOF analysis is applied because, in comparison to the covariance matrix-based alternative, it is less influenced by variables with stronger variability. For instance, it is well known that temperature records in polar regions have larger variances than those in lower latitudes, which is referred to as “polar amplification” in the case of global warming (e.g., Smith et al. 2019). A covariance matrix-based EOF is expected to capture such a *contrast in genuine variability* in the first place, which is greatly mitigated by the normalization procedure (temporal anomaly divided by local standard deviation) prior to the correlation matrix-based EOF. It is expected that, through the normalization, the correlation-based EOF analysis is able to capture structures that are otherwise hidden behind the genuine structure of variances.

3. An exploratory analysis

This section first introduces EOF results of the interannual and seasonal components (IAC and SC, respectively) in the PiControl simulation of MPI-ESM-MR. The first leading EOF mode of the IAC is selected to showcase how the coupling structure (CS) between climate modes is identified.

a. Interannual component

The first interannual component (IAC) EOF mode (16.2% of the total variance) shows strong loadings predominantly in the tropical band and, in particular, over the tropical ocean; meanwhile, anomalies with an opposite sign occur in the midlatitude oceans (Fig. 1a). Hereafter it is referred to as the tropical mode (TM). The second and third modes (7.5% and 7.2% of the total variance), in contrast to the first mode that accentuates the lower latitudes, are characterized by strong temperature anomalies in either polar region (Figs. 1b,c) and referred to as the Arctic mode (AM) and the Antarctic mode (AAM), respectively. The fourth mode (5% of the total variance) (Fig. 1d) is characterized on the one side by warm anomalies over the Eurasian continent and cold anomalies over the Arctic and Canadian Archipelago and, on the other side, by transbasin temperature gradients with negative anomalies over the Maritime Continent and the tropic Atlantic and warm anomalies over the eastern tropical Pacific. As will soon be shown, only the transbasin temperature gradients in the tropics interact with TM, which forms the focus of this study. Thus, it is referred to as the tropical Pacific mode (TPM).

The significance of these four EOF modes is inspected with a Monte Carlo test. Specifically, 50 subsets of 300-yr ST fields are randomly selected from the entire 1000-yr ST fields; each subset is subjected to the EOF analysis. It is expected that physically meaningful modes would be persistent and robust and thus retain their rank in the hierarchy. It is found that 1) the match between the EOFs of the Monte Carlo subsets

TABLE 1. Five PiControl GCM simulations.

PiControl	MPI-ESM-MR	NCAR_CCSM4	IPSL-CM5A-LR	MRI-CGCM3	GISS-E2-R
Duration (yr)	1000	1051	1000	500	550

and their counterparts in Figs. 1a and 1d is evidenced by a spatial correlation of at least 0.75 in 75% of the 50 subsets (bottom edge of boxes in Fig. S1a in the online supplemental material); 2) while TM (TPM) always remains on its first (fourth) place in ranking, AM and AAM switch their ranking positions in some of the subsets, which is consistent with their explained variance being almost equal; and 3) more importantly, taking this into account, the relative ranking of the four leading modes is well kept in all Monte Carlo subsets (Fig. S1b).

FIG. 1. MPI-ESM-MR. (a)–(d) The leading four IAC EOF modes of surface temperature: TM (IAC1), AM (IAC2), AAM (IAC3), and TPM (IAC4) (unit: std of IAC; explained variances: 16.2%, 7.5%, 7.2%, 5.0%). (e)–(h) Correlation coefficients between the corresponding principal components (PCs) and sea level pressure (SLP) (shading indicates significant values at the 5% level). Also shown are composites (color shading) of (i),(j) mass streamfunction (unit: 10^9 kg s^{-1}), (k),(l) surface temperature (unit: K), and (m),(n) velocity potential at 200 hPa (unit: $10^6 \text{ m}^2 \text{ s}^{-1}$) for TM and TPM, respectively (positive minus negative); climatological fields are contoured.

PHYSICAL EMBEDDING OF IAC MODES

The TM describes two essential aspects of the tropical circulation, the Walker cell and the Hadley cell. It characterizes a zonal contrast in sea level pressure (SLP) between the Indo-Pacific warm pool and the central and eastern tropical Pacific and depicts a negative phase of the Walker cell with sinking motion over the Maritime Continent (Fig. 1e). Meanwhile, its high loadings occur off the equator (being around 10°S and 10°N in the eastern tropical Pacific; Fig. 1a) and correspond to the equinoctial pattern of the HC (Fig. 1i) as has been depicted in Dima and Wallace (2003). Such an equatorially symmetric structure forms a strong contrast with the seasonally reversing solstitial pattern that associates with the monsoons (see their Figs. 3–6). Stronger TM (warmer tropics) is linked with a strengthening and contraction of the HC (Fig. 1i), which resembles the HC response to a narrow forcing centered at the equator [termed El Niño-like HC contraction in Tandon et al. (2013)], in contrast to the global warming-like HC expansion. The latter occurs when the thermal forcing with wider meridional extent is applied (Tandon et al. 2013) and has been simulated by most CMIP GCMs under global warming (Lu et al. 2008; Lucas et al. 2014; Vallis et al. 2015).

To further substantiate the close connection of TM with warming or cooling over the *entire tropical band*, tropical mean surface temperature (TMT; averaged between 20°S and 20°N) is correlated to the TM principal component and a linear correlation of almost 1 is obtained. Next, their causal relation is examined following Liang (2014). The information flow from TMT to TM is -0.36 and that from TM to TMT is 0.54 (nats per unit time), which indicates that knowledge of TM provides *noise* (positive information flow) to TMT (and thus increases its uncertainty), whereas knowledge of TMT decreases TM's uncertainty and thereby increases its predictability. Considering their close-to-1 correlation coefficient, TMT as the temperature indicator of the entire tropical band is a *defining feature* of TM. In this sense, TM should be viewed as the manifestation of the Hadley circulation on surface temperature.

Both AM and AAM are characterized by a weaker pressure gradient between middle and high latitudes (Figs. 1f,g) and thus correspond to negative phases of the northern and southern annular modes, respectively (Marshall 2003; Gillett et al. 2006). One interesting feature worth noting is that AM features cold high pressure anomalies over the Arctic, whereas AAM features warm high pressure anomalies over the Antarctic.

In comparison to TM, TPM also features a similar zonal contrast in SLP in the tropics (Fig. 1h), but its expression in the meridional mass streamfunction is considerably weaker (Fig. 1j). Meanwhile, its strong loadings in high latitudes (Fig. 1d) suggest a possible signal mixture, which more likely occurs to lower-ranked EOF modes, because the lower the rank of one eigenvalue, the more modes that are required to be orthogonal, and the more likely its pattern is to be dictated by mathematical constraints rather than by physical or dynamical causes.

To explore what is more essential for the TPM, its loading in high latitudes or the zonal temperature/SLP gradients in the tropics, the EOF analysis is applied to ST fields taken from two subdomains: north of 40°N and the tropical band between 30°S and 30°N. The first leading EOF mode of the two subdomain analyses shows high spatial similarity to AM and TM, respectively, with spatial and temporal correlations of almost 1. The second mode in both cases corresponds well to TPM spatially (spatial correlation coefficients: 0.9 and 0.96) and also temporally (both with a temporal correlation of 0.69). Therefore, they jointly capture the spatial features of TPM in high and low latitudes (Fig. 1d). Their principal components are correlated to that of TM. As will be discussed in section 3c, TPM leads TM by 1 year with a strong positive correlation coefficient, which, as an indication of mode interaction, is unambiguously captured *only* by the TPM features in the tropics (Fig. S2). Therefore, it is the transbasin temperature/SLP gradient in the tropics that is engaged in the interaction between TPM and TM.

Although TM and TPM both show a similar zonal contrast in SLP in the tropical Pacific (Figs. 1e,h), a discernible characteristic marks their difference: TM is characterized by an overall warming/cooling of the entire tropical band, being the weakest near the Maritime Continent. In contrast, TPM emphasizes a zonal seesaw pattern with warming (cooling) in the central and eastern tropical Pacific and cooling (warming) in the Atlantic and Indian Oceans (Figs. 1a,d,k,l), which is still visible in the upper troposphere (Figs. 1m,n). Such a seesaw pattern in ST and SLP between the tropical Pacific and the Atlantic/Indian Oceans has been recognized as part of the natural variability in a prediction system and can be considerably better predicted than ENSO (Chikamoto et al. 2015; Kosaka 2018).

b. Seasonal component

The first two seasonal component (SC) EOF modes account for 74.1% and 14.6% of the total variance (not shown). To seek a decomposition that further eases physical understanding, factor analysis is performed to rotate these two EOFs ("rotatefactors" in Matlab). Two patterns with almost equal contributions to the total variance (45% and 44%) are obtained, both showing clear interhemispheric temperature contrast. The first mode has strong loadings prevailing over land, while the second one shows strong loadings mainly over the ocean (Figs. 2a,b); hereafter they are referred to as the land mode (LM) and the ocean mode (OM), respectively.

In the course of a year, the LM peaks in July and reaches its low in January, while approximately 1 month later the OM reaches its high (low) in August–September (February–March) (Fig. 2c). This 1–2-month delay results from the large difference in effective heat capacity between the ocean and the land.

The typical monsoon regimes deserve some special consideration here. The interplay between the two SC modes indicated by their phase difference (Fig. 2c) demonstrates vividly how the LM and OM work with and against each other in different months of the seasonal evolution. For instance, the

FIG. 2. MPI-ESM-MR. The leading two EOF modes of the seasonal component (SC) of surface temperature: (a) land mode (SC-land) and (b) ocean mode (SC-ocean) (unit: std of SC; explained variances are 45% and 44%, respectively), and (c) their seasonal courses. Monthly ranges are shadowed.

earliest Asian monsoon onset (withdrawal) is reported to occur in May (September) over the Indian Peninsula and the Indo-China Peninsula (Wang and LinHo 2002). Figure 2c suggests that the early occurrence of monsoon signals in these regions may mainly result from the LM, which increases its contribution considerably in May (compared with its almost zero contribution in April); in June–August, the dominance of control shifts from the LM to OM while both are still sharing the same sign and further enhance the monsoon. The subsequent withdrawal in September mainly reflects the sharp decrease of the LM from August to September while the OM remains more or less stable. The reconstructed climatological monthly ST field is presented in the supplemental material (Fig. S3a).

c. Coupling structure

The focus of this section is to examine how the first leading IAC mode (TM) interacts with both SC modes and IAC modes by calculating the lead-lag correlation between the corresponding principal components. Therefore, the analysis here is restricted to linear relationships.

1) TM STATISTICS

The quantile–quantile plot (QQ plot) suggests that TM exhibits no systematic deviation from the normal distribution (Fig. 3a), which is also supported by various statistical tests for normality at 5% significance level (e.g., the Jaque–Bera test

and the Anderson–Darling test, hereafter referred to as the JB and AD tests).

2) CROSS-CORRELATIONS

(i) TM–IACs coupling

The strongest correlation is found between TM and TPM [the fourth interannual component (IAC) mode] when the latter leads the former by 1 year (Fig. 3b). A further cross-spectrum analysis reveals strong coherence between the two at frequency of around 4, 5, and 7 years that is characteristic of ENSO periodicity (not shown). Therefore, TM and TPM jointly describe the tropical circulation that is strongly imprinted by ENSO dynamics. In comparison, the correlation between TM and the other two modes (AM and AAM) is much weaker; in particular, the TM–AAM correlation hardly exceeds the 95% confidence levels.

(ii) TM–SCs coupling

The cross-correlation between TM and seasonal component (SC) modes at lag -1 (SC modes lead TM by 1 year) is distinctly different from that at lag 0 and 1. The following details are noted:

- (i) The LM- and OM–TM correlations at lag -1 follow approximately a monotonic evolution with comparable magnitudes; that is, the OM–TM correlation evolves from

FIG. 3. MPI-ESM-MR. (a) QQ plots of the TM (IAC1) principal component: (top) normal QQ plot and (bottom) residual QQ plot. Also shown are cross-correlations between PCs of TM (IAC1) and (b) other IAC modes (IAC2: AM, IAC3: AAM, IAC4: TPM) and (c) two seasonal modes. In (b), horizontal dashed lines mark the 95% confidence intervals; in (c) coefficients with $p < 0.01$ are marked with squares; lag = -1 corresponds to seasonal modes leading TM by 1 year. The climatological monthly cycle of two seasonal modes (blue: LM, SC-land; brown: OM, SC-ocean) follows the right axis.

positive to negative values and has its positive (negative) extrema in January (December), while the LM–TM correlation shows a similar pathway but with opposite signs.

- (ii) The TM–OM correlations at lag 0 and 1 are oscillatory, swinging from its negative to positive phase. The intensity extrema occur around April and October and not at the beginning and end of the year, as noted for lag = -1 when it varies monotonically with time.
- (iii) The TM–LM correlation decreases monotonically (from positive to negative) at lag 1 and almost mirrors the pattern at lag = -1, whereas at lag 0 positive correlation is found near the middle of the year (around June) and weak negative correlation in September–October. Another noteworthy feature is that the LM–TM correlation at lag 0 is considerably weaker than that of the OM, but both are of comparable magnitude at other lags.

The coupling of TM with SC modes and IAC modes at lag = -1 (when they lead TM by 1 year) guides us to use this information to introduce a regression model diagnostic for TM, which is presented in the next section.

4. Regression model and its predictive quality

This section sets out in search of a combination of variables (principal components of the four IAC modes and two SC modes) to construct a regression model of TM with the highest explanatory power measured by Bayesian information criterion (BIC); the adjusted r -squared is calculated as a complementary measure.

It is worth pointing out that BIC is selected because it measures goodness of fit, whereas another information measure, the Akaike information criterion (AIC), which is originally derived from a predictive viewpoint, is more suitable for measuring predictive accuracy of a model to predict new data. For an in-depth explanation on the differences between AIC and BIC, readers are referred to [Sober \(2002\)](#) and [Shmueli \(2010\)](#).

a. Regression model

The regression model of TM is expressed as follows:

$$TM(t) = c + IAC^+(t-1) + SC^+(t-1, m) + \epsilon, \quad (1)$$

in which c is a constant, ϵ is white noise with zero mean, IAC^+ denotes the principal components of interannual modes, and SC^+ denotes those of the seasonal modes in month m of year $t-1$. Written in full expansion one obtains

$$IAC^+(t-1) = a_1 \times TM(t-1) + a_2 \times AM(t-1) + a_3 \times AAM(t-1) + a_4 \times TPM(t-1), \quad (2)$$

$$SC^+(t-1, m) = b_1 \times LM(t-1, m) + b_2 \times OM(t-1, m). \quad (3)$$

If only the first term on the right side of Eq. (2) is considered and the SC^+ term set to zero, Eq. (1) represents an AR(1) model of TM.

The task here is to find out a combination of various (or all) modes that appear in Eqs. (2) and (3) to achieve the maximum explanatory power. The BIC serves as the selection criterion for the best regression model; the adjusted r -squared is also calculated as a supplementary check. Two SC modes are regarded as being inseparable because only the two together can closely capture the full seasonal cycle.

The regression model selection is conducted in two steps:

Step 1 is to examine the relative contribution of seasonal and interannual variability to the variability of TM [keeping only SC^+ or only IAC^+ in Eq. (1) in their full expansion as in Eqs. (2) and (3)]. For comparison, the full regression model (SC^+ plus IAC^+ in full expansion) is also assessed. When only SC^+ is considered, the model performance is examined for each month, only the month with top performance is presented, which turns out to be December (thus $m = 12$); this also applies to the full model.

FIG. 4. MPI-ESM-MR. Performance of candidate statistical models in terms of BIC (left axis) and r -squared (right axis) assessed in two steps; the top performer at each step is marked in gray. (a) Three regression models: SCs-only, IAC(1–4)-only, and SCs + IAC(1–4) (the full model). (b) Eight regression models, all including both SCs and TM(IAC1) but with different combinations of the other three IAC modes (IACs 2, 3, and 4). The optimum regression model turns to be SCs + IAC(1–2, 4). All candidate models comprising both SCs show their lowest BIC in December, thus $m = 12$.

The top performance (with the lowest BIC value) among the three regression models evaluated here turns out to be the full regression model (gray bar in Fig. 4a). One also learns that the IACs-only regression model, in comparison to the SCs-only option, has a higher r -squared value and a lower BIC (BIC: 2403 vs 2702; r^2 : 37% vs 15%), suggesting a higher contribution of interannual modes to TM variability.

Step 2 is to find the most relevant IAC modes for the regression model. Both SC modes and TM itself [term 1 in Eq. (2)] are included by default; subsequently, all possible combinations of the remaining three IACs are added into the default model and their performances are compared. Note that the full model (SC^+ plus IAC^+ in full expansion) is listed in the last column of Fig. 4b (and as well in Fig. 4a).

The best performance is delivered by the regression model that excludes AAM (gray bar in Fig. 4b), which is consistent with the weak and insignificant AAM-TM correlation in Fig. 3b. This final optimum model, in comparison to the full regression model, has a further reduced BIC value (by 12), whereas the adjusted r -squared values of both options are almost identical and do not help distinguish them further.

b. Predictive quality

A statistical model with high explanatory power is often assumed to show reasonable prediction quality, although it should be emphasized that the regression model being selected in the previous section is because of its high *explanatory power* (measured by BIC), not due to its *prediction skill*, which is better measured by AIC. In fact, when using AIC as the

selection criterion, the top performance regression model would be instead the full model [SC^+ plus IAC^+ in full expansion in Eq. (2), last column in Figs. 4a,b], because AIC tends to select more general models when n is large (here $n = 1000$) (Burnham and Anderson 2004).

To assess the prediction quality, the 1000-yr data are divided into two equal parts, the first 500 years as the training data and the second half as holdout/validation data. Model parameters are determined from the training data (see Table 2) and kept constant for predicting the second 500 years.

The parameters determined from the training period approximate closely to those estimated from the entire period and are well within the 95% confidence intervals. The prediction shows a correlation of 0.74 with the target holdout data (Fig. 5), which lies well above 0.47 that is achieved by an AR(1) model of TM.

5. GCM dependence

To explore whether the coupling structure (CS) revealed above is GCM dependent, this section is devoted to analyzing ST fields of PiControl simulations of additional four GCMs listed in Table 1. Given that the four IAC modes in MPI-ESM-MR (Figs. 1a–d) correspond well to well-known climate processes with their characteristic spatial domains, they are used as orthogonal bases, onto which (compressed) ST fields from these four GCMs are projected, which allows *only* the information of these physically meaningful modes to be extracted; the resulting temporal loadings are then treated as principal components, from which the explained variances are calculated.

Prior to the projection, monthly ST fields are first interpolated onto the T63 grid employed in MPI-ESM-MR; their interannual parts are compressed (or filtered) by keeping only the first k EOF modes, where k is the effective number of spatial degrees of freedom, estimated following Fraedrich et al. (1995) and Bretherton et al. (1999). The reconstructed fields with the leading k modes are then considered for projection. A brief summary on variance reduction that ensues from data compression and projection is presented in Fig. S4.

The following results are noted:

- 1) **Normality test:** The null hypothesis that TM follows a normal distribution is rejected in NCAR-CCSM4 and GISS-E2-R (Figs. 6a,j) but not in IPSL-CM5A-LR and MRI-CGCM3 (Figs. 6d,g) at a 5% significance level ($p < 0.01$, in the AD and JB tests).
- 2) **TM–IACs coupling:** The TM–TPM coupling at lag 1 that is observed in MPI-ESM-MR (positive correlation when TPM leads; Fig. 3b) is found in all GCMs (yellow line, Figs. 6b,e,h,k) but is the weakest in IPSL-CM5A-LR (close to 0.2); the TM–AM coupling that is manifested as negative correlation at lag 1 in MPI-ESM-MR (blue line, Fig. 3b) is also found in all GCMs but barely exceeding the 95% confidence levels in MRI-CGCM3 and GISS-E2-R (blue line, Figs. 6b,e,h,k); the TM–AAM correlation differs from GCM to GCM being in general rather weak (red lines, Figs. 6b,e,h,k).

TABLE 2. Parameters of the optimum regression model (AAM excluded, thus $a_3 = 0$) for the PiControl simulation of MPI-ESM-MR; LM and OM are taken from December ($m = 12$). Numbers in parentheses denote the 95% confidence intervals. Parameters estimated from the entire 1000-yr data are listed for comparison.

MPI-ESM-MR optimum model	b_1 (LM)	b_2 (OM)	a_1 (TM)	a_2 (AM)	a_4 (TPM)
Entire 1000 years	2.01 (1.19, 2.84)	−6.42 (−7.38, −5.45)	0.55 (0.50, 0.59)	−0.10 (−0.14, −0.06)	0.26 (0.21, 0.30)
First 500 years	1.70 (0.55, 2.84)	−6.12 (−7.49, −4.76)	0.54 (0.48, 0.61)	−0.10 (−0.17, −0.04)	0.23 (0.17, 0.30)

3) **TM-SCs coupling:** MRI-CGCM3 differs greatly from the other three GCMs and is discussed separately shortly afterward. The other three GCMs share with MPI-ESM-MR the following common features: 1) TM closely correlates to the seasonal LM (OM) that increases (decreases) monotonously at lag -1 (when SC modes lead by 1 year) with maximum intensity in December. 2) The evolution pattern at lag -1 is mirrored at lag 1, in particular in the case of the seasonal LM. 3) At lag 0, the correlation between TM and the seasonal LM is generally weaker than that with the seasonal OM; furthermore, the TM-OM correlation at lag 0 and lag 1 distinguishes itself from that in the preceding year with an oscillatory behavior, with maximum intensity in early spring and September–October (instead of in December).

In comparison, the TM-SCs correlation is not well established in MRI-CGCM3 at all three time lags (Fig. 6i), suggesting a rather limited role of seasonal components in influencing TM variability in this GCM. In NCAR-CCSM4 and GISS-E2-R the TM-SCs correlation at lag 1 (SC modes leading by 1 year) is much stronger (~ 0.6 for TM-OM and 0.4 for TM-LM in December) than that in IPSL-CM5A-LR, which hints at a larger contribution of the seasonal modes in these two model climates.

The results above are further confirmed in the regression model selection process. 1) In IPSL-CM5A-LR and MRI-CGCM3, regression models that comprise only SC modes as explanatory variables (SCs) have lower r -squared values and larger BIC than those comprising only IAC modes [IAC(1–4)] (Figs. 7b,c), suggesting a dominant contribution of IAC modes to TM variability. 2) In contrast, in NCAR-CCSM4, these two regression models [SCs and IAC(1–4)] have almost equal BIC and r -squared values, and thus they make comparable contributions. 3) In GISS-E2-R, however, seasonal modes (SCs) make considerably larger contributions than IAC modes to

TM variability. Predictions made by these selected models are presented in Fig. S5.

What is common among all GCM climates is that the third IAC mode (AAM) does not help to explain TM variability, at least not in linear terms with a 1-yr lead. In all GCMs except GISS-E2-R, the optimum regression models all comprise the first, second, and fourth IAC modes (TM, AM, and TPM), whereas in GISS-E2-R only TM and TPM are included.

6. Summary

This study has proposed an approach to identify mode interaction, which in a way looks for common characteristics from different GCM climates in undisturbed PiControl simulations. Climate modes are identified by means of the EOF analysis that is applied to the interannual and monthly components of the ST field (IAC and SC), respectively. The lead-lag correlation between these modes serves as an indicator of mode interaction and subsequently helps to develop a regression model hierarchy that describes their interaction in a linear format. The systematic selection process for the optimum regression model not only provides an objective perspective for understanding climate dynamics but also makes it possible to quantitatively compare the coupling structure in different GCMs, thereby providing hints for model improvements.

The correlation matrix-based EOF has been employed to capture patterns that are otherwise hidden behind the genuine variance contrast that is characteristic of Earth's climate, namely that 1) on interannual time scales, large ST variation in high latitudes contrasts weak variability in the tropics, and the central and eastern tropical Pacific is loaded with considerably stronger variability than the surrounding oceans (Fig. S3b); and 2) on a seasonal scale, the temperature variability over high-latitude continents is much stronger than the rest of the world,

FIG. 5. MPI-ESM-MR. Cross-validation of the optimum regression model for the PiControl simulation, with parameters determined from the first 500 years of TM's PC (listed in Table 2), while the remaining 500-yr data serve as the target holdout data (black), with respect to which predictions (red) are compared. Correlation between the holdout data and predictions is 0.74.

FIG. 6. Multimodels. As in Fig. 3, but for (a)–(c) NCAR-CCSM4, (d)–(f) IPSL-CM5A-R, (g)–(i) MRI-CGCM3, and (j)–(l) GISS-E2-R. Only residual QQ plots are shown. The null hypothesis that TM follows normal distribution is rejected in (a) and (j) ($p < 0.01$, in both the AD test and JB test).

particularly in the Northern Hemisphere (Fig. S3c). Owing to the correlation matrix–based EOF analysis, the leading four IAC EOF modes capture intrinsic climate modes that essentially manifest the equator-to-pole temperature gradient of the Earth climate (TM, AM, and AAM) and the zonal thermal contrast in the tropics (TPM). These modes correspond closely to well-known climate processes. TM characterizes a weaker (stronger) Walker cell and a stronger (weaker) Hadley circulation on interannual time scales. Being nearly symmetric

about the equator, TM differs greatly from the cross-equatorial pattern of the Hadley circulation that associates with the monsoon systems (e.g., Dima and Wallace 2003). AM and AAM correspond to the northern and southern annular modes, respectively; and TPM emphasizes the seesaw pattern between the eastern tropical Pacific and the Atlantic/Indian Oceans, for which the signals in the tropical Atlantic are essential. Such a pattern closely resembles the pan-tropical dipole-like SST variability that is induced by temperature anomalies in the

FIG. 7. Multimodels. As in Fig. 4a, but including the optimum regression model in the last column (gray). All regression models comprising seasonal components as explanatory variables have their best performances in December ($m = 12$).

Atlantic (Li et al. 2016) and exhibits higher predictability than ENSO (Chikamoto et al. 2015; Kosaka 2018).

It is worth stressing that it should not be taken for granted that this set of modes necessarily comes out so clearly—it would certainly not be the case if the covariance matrix–based EOF had been used. Therefore, *being able to identify these most fundamental climate modes at once* is a vivid demonstration of the capability and usability of the proposed analysis approach. It is simple but powerful and this merit should be acknowledged accordingly.

Since these four interannual modes in the MPI-ESM climate are (geographically) cleanly separated, they serve as orthogonal bases onto which the ST fields of other GCM simulations are projected. Such a projection allows *only* the information of the corresponding *physical* modes to be extracted so that the resulting interaction is less contaminated by mode mixing.

Factor analysis in combination with the EOF analysis captures a stable pair of seasonal modes (LM and OM), with almost equal contributions to the seasonal cycle. The 1–2-month phase lag of OM behind LM results from the seasonal variation of the incoming solar radiation and the difference in effective heat capacity between land and sea. Unlike the typical assumption of being stable and self-repeating, the seasonal cycle captured by SC modes is not constant in time (gray spread in Fig. 2c) and thus suggest a modulated seasonal cycle even in undisturbed climates, which has proven to be essential for ENSO's seasonal phase locking (Wu et al. 2008; Hamlington et al. 2019).

The following subsections group multimodel results according to similarities and differences.

a. Similarities

- 1) All five GCMs simulate a stronger TM (warmer tropics, stronger and contracted equinoctial cells of the HC, and a weaker Walker cell) being preceded by a stronger TPM (warmer tropical Pacific and colder Atlantic/Indian Oceans) by 1 year.
- 2) Most GCMs tend to agree on a close but weak association between AM and TM: a stronger AM (colder North Pole) is associated with a weaker TM (colder tropics) 1 year later. This correspondence is also manifested by a negative coefficient for AM ($b_2 < 0$) in statistical models (even though AM is not included into the optimum statistical model in GISS-E2-R in the end).
- 3) AAM does not seem to be important for TM variability in all GCM climates, at least not in a linear format with a 1-yr time lag.
- 4) All GCMs simulate strong coupling between seasonal modes and TM, which shows time-varying features.

When the former leads the latter by 1 year (lag -1), the correlation evolves monotonically in the annual course. Specifically, the OM–TM correlation turns from positive to negative values and has its positive (negative) extrema in January (December), while the LM–TM correlation follows a similar pathway but with opposite signs. The above feature differs completely from that at lag 0 and lag 1, in which the TM–OM correlation evolution is rather oscillatory. Another interesting feature is that

the TM–LM correlation at lag 1 almost mirrors its seasonal evolution at lag -1 .

b. Differences

- 1) TM follows a normal distribution in three out of five models (IPSL-CM5A-LR, MRI-CGCM3, MPI-ESM-MR).
- 2) The relative contribution of the seasonal and interannual modes to TM variability varies greatly from GCM to GCM: in IPSL-CM5A-LR, MRI-CGCM3, and MP-ESM-MR, the SC contributes much less than the IAC to TM variability, while GISS-E2-R simulates the opposite and NCAR-CCSM4 simulates similar contributions from SC and IAC.

7. Discussion and conclusions

This study has focused on identifying the coupling structure that characterizes internal climate dynamics and proposed a quantitative approach to comparing the coupling structure in different GCMs. This approach makes it possible to obtain an overview on whether and how the GCM-simulated coupling structure converges or differs across models. It is unfolded in three steps: first, the most fundamental and active climate modes are identified for model climates by a correlation matrix–based EOF analysis; second, the coupling structure of these climate modes is identified by a lead–lag correlation analysis; third, the revealed correlation relationship is used to develop an optimum regression model that enables a quantitative comparison across models. The thereby gained knowledge may be envisaged as a step toward a follow-on targeted in-depth investigation into the underlying physical processes and the factors that lead to model convergence/dependence.

The results reported in this study are from GCM control simulations under preindustrial conditions. On the other hand, similar analyses of the ERA20C data also reveal the main coupling characteristics reported here (not shown). For instance, after carefully removing the transitional trend from the reanalysis data, TM and TPM as the dominating modes in the tropics, together with AM and AAM, form the first four leading interannual (correlation matrix–based) EOF modes, which account for 16%, 8%, 7%, and 5% of the total variance, respectively (36% in total); TPM shows its highest positive correlation with TM at a 1-yr lead; and the lead–lag correlation between both SCs and TM highly resembles that in Fig. 3c.

Therefore, the fact that all five GCMs simulate a strong TPM–TM coupling on interannual time scales provides an encouraging manifestation of model convergence on tropical dynamics. However, once seasonal variation is brought into discussion, model results tend to diverge owing to the GCMs' high sensitivity to detailed structures of the simulated tropical SST that exerts strong influences on the ENSO–Hadley circulation interaction (Guilyardi 2006; Feng and Li 2013; Guo and Tan 2018 a,b; Feng et al. 2019). In fact, different relative contributions of SC and IAC modes to TM variability may relate to the model-dependent mean state and seasonal cycle (Bellenger et al. 2014), which can be seen in the seasonal statistics of the Niño-3.4 index (Fig. S6). The following features are particularly noteworthy: 1) For MRI-CGCM3, the strongest warming occurs in boreal winter (instead of boreal summer).

2) For IPSL-CM5A-LR, the strongest standard deviation occurs in May–June (instead of in winter months). 3) For all GCMs except MPI-ESM-MR, there exists a temperature minimum in September, which is followed by warming through December. All these features are absent in observations (Magnusson et al. 2013; Tan et al. 2020), pointing to strong model bias in simulating the very basic climatic features in the tropics, which is beyond the current scope and not discussed here. However, it may, in fact, help to explain why the relative contribution of seasonal modes to TM variability in the optimum statistical models varies from GCM to GCM (Figs. 4a and 7a–d).

Note that the two SC modes in Fig. 2 are rotated from the leading two EOFs of the seasonal component. The current decomposition is selected because 1) the interhemispheric thermal contrast that predominates in both modes is consistent with the seasonal change in the solar radiation that is irrespective of ocean or land, and 2) it clearly captures the 1–2-month lag of OM behind LM, which results from the large difference in effective heat capacity between the ocean and the land. It is worth pointing out that the strong correlation of TM with SC modes from December of the previous year (Fig. 3c) does not depend on the eigenvector basis chosen.

The Arctic–tropics linkage that is captured by all five GCMs has already been reported by other modeling studies (e.g., Lin et al. 2002; Jia et al. 2009; Hegyi et al. 2014; Kim and Ahn 2015; L’Heureux et al. 2017), but a clear lead–lag relationship has not yet been deciphered, which, at least partly, has to do with the choices of numerical models (e.g., an atmosphere-only model or atmosphere–ocean coupled GCM) and initial forcing conditions (e.g., idealized forcing for sensitivity studies or forcing directly taken from atmospheric reanalysis data) that greatly differ between studies. The Arctic–tropics interaction has global impacts and likely involves the stratosphere–troposphere coupling and jet dynamics (e.g., Jia et al. 2009; Hegyi et al. 2014; Kim and Ahn 2015).

Indications have been found that seasonal signals are actively involved in the Arctic–tropics connection. Below a brief introduction is presented and a more elaborated discussion is planned for a follow-on report. Specifically, in positive AM years (colder-than-normal Arctic, corresponding to a negative Arctic Oscillation) the seasonal cycle is stronger than normal, which is mainly realized by the intensified land mode (LM) around its peak time, namely, in May–August and November–December, respectively (not shown). As a consequence, the Eurasian continent is anomalously warm (cold) in boreal summer (winter), while in comparison, the AM–ocean mode (OM) correlation is notably weaker. The above feature stems from the fact that AM-related cooling/warming over the Arctic unavoidably alters the thermal contrast between the Arctic and the Eurasian continent and consequently the contrast between continents and oceans (via the strong gearing of LM and OM). Keep in mind that in boreal winter the Siberia–Mongolian high dwells in the cold Eurasia region and dictates the strength of the East Asian winter monsoon (EAWM) by modulating the East Asian trough and the overlying jet stream. Therefore, positive AM enhances the Siberia–Mongolian high by further cooling Eurasia and consequently strengthens the EAWM. This result is consistent with the larger picture that emerges out of

previous studies despite their different perspectives: negative Arctic Oscillation (corresponding to positive AM) being accompanied by a strong Siberian high and strong EAWM (e.g., Gong et al. 2001; Wu and Wang 2002; He et al. 2017), whereby the East Asian trough and the upper-level jet stream make important contributions (Jeong and Ho 2005; Li et al. 2014; Luo and Zhang 2015; Chowdary et al. 2019). Down in the tropics, the anomalously strong EAWM weakens the El Niño-related Walker circulation, thus favoring La Niña conditions (Chen et al. 2000; Ma et al. 2018), which lends support to the negative sign of the AM–TM correlation reported in Fig. 3b.

Along this line, the weak loose TM–AAM connection (Fig. 3b) may relate to the weaker seasonal signals in the Southern Hemisphere owing to the absence of large land-masses like Eurasia. This indirectly supports the vital role the seasonal component plays in the pole–tropics interaction. On the other hand, many important aspects of this coupling are not yet fully understood. For instance, how does EAWM variability interact with ENSO? Where is the key region for the interaction with the Walker circulation, ENSO, and the Hadley circulation to take place? Is it the South China Sea, near the Maritime Continent, or the Indian Ocean (Chen et al. 2000; Wang and Wu 2012)? Another piece of thought-provoking information is that, given the active role of the seasonal signal in the Arctic–tropics connection, a quite common experiment design that involves atmosphere models forced by prescribed surface temperature patterns with a climatological seasonal cycle is doomed to miss the seasonal signal as an active player, as does the resultant mode interaction structure. This aspect should be taken into account when interpreting the results of these sensitivity studies.

One question worth discussing concerns how TM and TPM are related to ENSO. ENSO essentially depicts abnormal conditions in the zonal temperature gradient in the tropical Pacific, where both TM and TPM have considerable loadings (Figs. 1a,d). ENSO indicators that are retrieved locally, including area-averaged sea surface temperature in Niño regions (Trenberth and Stepaniak 2001) and the related leading EOF patterns of temperature in the tropical Pacific sector (e.g., Xu et al. 2017), unavoidably also comprise signals from TM and TPM. How to differentiate between them is rather intricate, if possible at all. For instance, both TM and TPM comprise a zonal seesaw pattern in the tropical Pacific. How to distinguish these patterns from that of ENSO has so far rarely been discussed. Such a discussion requires *unambiguous* definitions of these modes, and it concerns fundamental questions that are more of philosophical nature: what is ENSO? how do we define ENSO? Moreover, TM not only links the tropics and the subtropics via the Hadley circulation but it also connects all tropical oceans through the Walker cell (Figs. 1a,e,i,k,m). Therefore, its spatial scale is much larger than that of ENSO, which by definition prioritizes signals in the tropical Pacific. By focusing only on locally retrieved measures, it is almost impossible to assess to which extent TM exerts its effects on these ENSO indicators, and most likely the detected climate signals end up being *exclusively* attributed to ENSO.

Keeping these complications in mind, it is thus not surprising to obtain large (and statistically significant) correlation

coefficients between TM/TPM and the Niño-3.4 index (not shown). In fact, the first two leading EOFs in Xu et al. (2017), which the authors refer to as the eastern and central Pacific El Niño (EP-El Niño and CP-El Niño), show high spatial resemblance to TM and TPM, respectively. This study suggests that their EP-El Niño pattern may be viewed as a manifestation of a predominant contribution of the HC (TM) within the tropical Pacific; TM mainly represents the equator-to-pole temperature gradient that drives the HC and it is of primary importance for the Earth climate (in comparison to ENSO), which provides a reasonable explanation for the much higher variances of the EP-El Niño type with respect to the CP-El Niño type (e.g., Xu et al. 2017; Freund et al. 2019).

It is worthwhile mentioning that, although all five GCMs analyzed in this study are free of long-term trends, it is not always the case. For this reason, some GCMs are not included in this study (e.g., GFDL CM3). In fact, the coupling structure studied here shows strong sensitivity to the trend removal technique, which, while capturing most of the trend signal, also extracts part of the inherent variability (through overfitting). This aspect will be discussed in a companion study.

In summarizing, this study presents how to obtain a quantitative measure of mode interaction by identifying the model-intrinsic coupling structure and consequently searching the optimum statistical model. Such an approach helps to identify those key processes that are active (or inactive) in model climates. It generates an overview over model capabilities and brings insight into model strengths and weaknesses, which may guide us for tasks like assigning model weights in a multimodel ensemble approach. For instance, MRI-CGCM3 that simulates the weakest coupling between seasonal components and TM, in fact, has a strongly biased mean seasonal cycle in the tropical Pacific which, as a sign of low profile, then justifies a low weight for MRI-CGCM3, at least when seasonal variation in this region is of concern.

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