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Separation methods of the internal climate variability and externally forced response, and their applications to the decadal climate variability in the tropical ocean-atmosphere.

(外部強制応答と内部気候変動の分離手法とその熱帯大気海洋系における 10 年周期気候変動への応用)

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Abstract

The present study performed inter-comparisons of methods to remove the externally forced response (EFR) from the observed records by examining remaining decadal anomalies over the Indo-Pacific sector as the internal climate variability (ICV). A warming trend of sea surface temperature (SST) in recent decades is quite pronounced in the Indian Ocean than in the other tropical basins. Therefore, the EFR and the ICV over the Indian Ocean have comparable variances and mixed in the observed SST records. While the previous studies attempted to obtain the cross-basin relationship of the decadal SST variability between over the Pacific and over the Indian Ocean, those results depended on separating treatments of the ICV and the EFR. Here, the present study compared the methods of the ICV and EFR in the observations.

Three methods were applied as follows. (i) MG method utilized the multi-model ensemble mean of global mean surface temperature (MG) as a representative index of the externally forced component, and then removed the regressed components of each variable at each grid point onto the MG. (ii) LT method is a conventional detrend method by which a linear trend on each variable at each grid point is removed. (iii) ML method calculate time series of the multi-model ensemble mean on each variable at each grid point based on the selected simulations, and then remove its time series from the observed records at the same grid points.

While the Empirical Orthogonal Function (EOF) analyses of remaining SST and sea level pressure (SLP) anomalies over the Pacific did not make much difference among the three methods, MG method was most likely to successfully remove the global warming signal contained in the observed records over the Indian Ocean. As a result, the leading EOFs and their associated PCs represented the background physics of the large-scale air–sea interactions in any analysis domain by MG method. In addition, since the most

coherent pattern of the cross-basin interaction between the Pacific and Indian Ocean was obtained by MG method, these results mean the advantage of MG method.

Inter-comparisons of the methods based on the 50-member historical simulations from Model for Interdisciplinary Research on Climate version 6 (MIROC6) indicate that MG method largely suppressed ICVs contained in each member by estimating EFRs via the MG. Whereas, the ensemble mean at local grid insufficiently suppressed ICVs contained in each member. When analyzing large ensemble data of at least less than 172 members, it is recommended to employ the ensemble mean among the EFRs estimated by MG method at each member, to estimate the impact of external forcing.

An analysis onto the extracted ICV in the observed records by MG method showed positive correlation of decadal temperature anomalies over the upper Indian Ocean and the Interdecadal Pacific Oscillation (IPO) index. In the positive (negative) phase of the IPO, intensification (weakening) of the surface ocean circulation over the Indian Ocean had a significant contribution in forming positive (negative) temperature anomalies of upper layers. Such advection effect associated with the enhanced (reduced) surface winds over the Indian Ocean overwhelmed the damping effect of surface heat flux on local SST. Whereas the dominant effects of atmospheric processes often observed in the climate variabilities on inter-annual time scales, the present study indicates the relative importance of oceanic processes in decadal variabilities.

List of abbreviations

CEC: Cross-equatorial cell

CMIP: Coupled Model Intercomparison Project

ER: Estimation error rate

EFR: Externally forced response

EM: Ensemble mean

EOF: Empirical Orthogonal Function

EOF1: Spatial loadings of the leading mode

ERA: European Re-Analysis

ESTOC: Evaluation of the applicability of the Estimated State of the Global Ocean for
Climate Research

ETP: Eastern Tropical Pacific

GECCO2: Second German contribution to Estimating the Circulation and Climate of
the Ocean

GISST: Global sea-ice and SST

GMST: Global mean surface temperature

ICV: Internal climate variability

IPO: Interdecadal Pacific Oscillation

JRA: Japanese Reanalysis

LEM: Large ensemble mean

LT: Linear trend

MG: Multi-model ensemble mean of global mean surface temperature

MIROC6: Model for Interdisciplinary Research on Climate version 6

ML: Multi-model ensemble mean at local grid point

MME: Multi-model ensemble mean

NCEP: National Center for Environmental Prediction

NE: Non-extracted

OFES: Ocean GCM for the Earth Simulator

OISST: Optimum Interpolation SST

ORAS4: Ocean Reanalysis System version 4

PC1: Principal component of the leading mode

RMSE: Root mean squared error

SAT: Surface air temperature

SCC: Spatial correlation coefficient

SD: Standard deviation

SHF: Sea surface heat flux

SLP: Sea level pressure

SODA: Simple Ocean Data Assimilation

SSH: Sea surface height

SST: Sea surface temperature

STC: Subtropical cell

TCC: Temporal correlation coefficient

TIO: Tropical Indian Ocean

TP: Tropical Pacific

WIP: Whole Indo–Pacific sector

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Chapter 1 General introduction

1.1 The externally forced response and internal climate variability

Since the Industrial Revolution, increased anthropogenic greenhouse gases have raised the global mean surface temperature (GMST) (Hegerl et al. 2007). The GMST increase accelerated during the 1980s and 1990s but has slowed or paused since 2000 (Easterling and Wehner 2009). Then, this global warming hiatus is commonly recognised to have ended around 2012 (Medhaug et al., 2017). These decadal modulations in the increase rate of GMST are largely attributed to the internal climate variability (ICV) of the ocean-atmosphere rather than to modulations in radiative forcing (Kosaka and Xie 2016). Hence, the observed long-term climate variations contain both the ICV and an externally forced response (EFR).

1.2 The internal climate variability over the Indo-Pacific sector

Several studies have linked the slowdown of the global warming trend to increased ocean heat uptake (Chen and Tung 2014, Meehl et al. 2011). The increased ocean heat uptake over the tropical Pacific (TP) is associated with a transition to the negative phase of the Interdecadal Pacific Oscillation (IPO), which significantly contributes to the slowdown of global warming (Kosaka and Xie 2013, England et al. 2014). The uptaken heat at the TP has been advected through the Indonesia archipelago and stored in the surface layers of the Indian Ocean (Lee et al. 2015, Maher et al. 2018). Whereas the Pacific climate variability is dominated by ICVs such as the IPO, the long-term climate variability over the Indian Ocean is predominantly affected by external forcing (Han et al. 2014a). Under global warming conditions, the sea surface temperature (SST) over the

Indian Ocean has warmed more rapidly than the global average SST (Du and Xie 2008). This trend has influenced the long-term climate variability over the Pacific by modulating the atmospheric Walker circulation (Luo et al. 2012). Thus, an excess heat exchange between the Pacific and Indian Ocean is found in both the upper ocean and troposphere. Elucidating the background mechanism of this heat exchange is essential for understanding future climate change and its decadal modulation over the Indo-Pacific region.

1.3 Isolating methods of the internal climate variability and externally forced response

Based on the existing records, estimating the relative contributions of the EFR and the ICV of the ocean–atmosphere system to the long-term climate variability is a challenging task, because external forcing causes a non-uniform effect on the tropical ocean and is a nonlinear function of the increase rate of external radiative forcing. As the ICV is difficult to extract from the observed records, the trans-basin internal decadal variability between over the Pacific and over the Indian Ocean remains incompletely understood.

Han et al. (2014b) attempted to extract the ICV from the observed SST records by removing the linear trends at individual grid points. They found a positive correlation between the IPO index and the decadal SST variability over the Indian Ocean during the early period (1900–1984), but a negative correlation during the latest years (1984–2008). However, Han et al. (2014b) did not discuss the primary reasons for the sign change of the correlation. Dong and McPhaden (2017) attempted a different extraction of the ICV from the observed SST records, and discussed whether the sign change of the correlation was a truly observed finding or an aliasing artefact caused by inappropriate statistical treatment. After removing the multi-model ensemble mean (MME) of the historical

simulations of the Coupled Model Intercomparison Project 5 (CMIP5) from the observed SST records at individual grid points, they found that the IPO index was positively correlated with the decadal SST variability over the Indian Ocean throughout the analysed span (1900–2012).

1.4 Objectives of this study

Assuming that the MME truly represents the nonlinear effect of external forcing at any location, a linear detrending treatment is expected to generate artificial ICV. To discuss the background mechanism of the ICV over the Indo-Pacific region, an appropriate statistical analysis of all observed climate variables in the ocean and atmosphere as well as the SST is required. Thus, the present study compares the results of different procedures in EFR estimation and seeks the most appropriate procedure for extracting the decadal ICV over the Indo-Pacific sector from the observed records. In addition, based on the appropriately extracted ICV, the background mechanism of the cross-basin interaction between the Pacific and the Indian Ocean is investigated.

This paper describes three themes. In Chapter 2, the present study compares and evaluate methods for extracting ICV from the observed records. In Chapter 3, utilizing large ensemble historical simulations, the present study compares methods for separating the EFR and the ICV in model data and discusses the differences between the methods presented in Chapter 2. In Chapter 4, by analyzing ICV properly extracted from the observed data, the present study discusses the impact of IPO on SST in the Indian Ocean and its background mechanisms. Findings of the present study are summarised in Chapter 5.

Chapter 2 Inter-comparisons of methods for extracting the internal climate variability from the observed records over the Indo– Pacific sector

2.1 Introduction

Besides the methods introduced in the previous chapter that use linear trends (Han et al. 2014) and subtract MMEs from historical simulations (Dong and McPhaden 2017), other methods have been used to separate external forcing response and internal variability components from the observed data. Dai et al. (2015) obtained ICV by regressing observed surface temperature data at each grid point onto the MME of the GMST in a historical simulation and subtracting the component synchronized with the multi-model ensemble mean of global mean surface temperature (MG) from the observed data as the EFR. Hereafter, GMST of the MME is referred to as MG. This chapter compares these three methods. A more detailed description of the methods is provided in Section 2.2.3.

Xu and Hu (2018) compared methods for extracting ICV from SST data in historical simulations as a preliminary analysis to analyze IPO expressed in climate models. They showed that ICV can be extracted appropriately by subtracting the MME at each grid point. When a linear trend was subtracted from the SST at each grid point, remaining anomalies were still influenced by external forcing. However, it is not clear that the same procedure would work properly when extracting ICV from the observed records. In addition, although Xu and Hu (2018) compared methods for extracting ICV in SST, it is necessary to extract ICVs in other climate variables as well in order to investigate the background mechanisms of IPO and other SST internal variability. Therefore, this chapter compares the ICVs extracted from observed SST and sea level pressures (SLP) data by

different methods and attempt to present the most appropriate method.

In the tropical ocean–atmosphere, SST and SLP anomalies are known to be coupled by the Bjerknes feedback (Bjerknes 1969). Based on the Bjerknes feedback, the dominant variability of SST and SLP in ICV is expected to correlate with each other. Therefore, this study attempted to obtain the leading modes of the remaining anomalies of SST and SLP, where the EFR is removed from the observed records by each method. By employing the Empirical Orthogonal Function (EOF) analysis (see Section 2.2.4 for details) for each method, we evaluate those methods based on their correlation coefficients between the leading mode of SST and that of SLP. A statistically significant SST–SLP correlation can be evaluated as leading modes of remaining anomalies adequately represent the large-scale ocean–atmosphere interaction in the tropics, as ICV. In this way, each method for extracting ICV from observed records is evaluated in this chapter.

2.2 Data and methods

2.2.1 Observations

The observation data were three pairs of monthly SSTs and SLPs collected from 1958 to 2017 inclusive. These pairs are referred to as (1) Japanese Reanalysis (JRA), (2) the National Center for Environmental Prediction (NCEP) and (3) the European Re-Analysis (ERA) project (see Table 1). The SLP data were extracted from atmospheric reanalysis datasets and the SST data were the lower boundary conditions of these reanalysis datasets (see references in Table 1). To lengthen the records, the global (sea) Ice and SST (GISST) and Optimum Interpolation SST (OISST) were combined as consecutive SST records for the NCEP SST. Similarly, ERA-40 and ERA-interim data as the ERA SLPs were combined. To avoid atmospheric variability over the land, only the SLP data over the ocean were analyzed. To standardise the different spatial resolutions of the individual

datasets, all SST and SLP data were regridded at a horizontal resolution of 2° longitude $\times 2^\circ$ latitude by using bilinear interpolation. Monthly anomalies were obtained by removing the monthly climatologies averaged over the 1958–2017 period from the original monthly records and then passing those monthly anomalies through an 8-year lowpass filter to extract the decadal variations.

Each of the SST datasets was reconstructed from different instrumental measurements using different spatial-smoothing and temporal-interpolation methods (Yasunaka and Hanawa 2011). Likewise, each of the atmospheric reanalysis datasets was produced by assimilating different observations with different numerical models (Zhang et al. 2016). Thus, the individual datasets may include systematic errors in the 50-year records. To obtain the common features of the long-term signals in those datasets, the three SST (SLP) datasets were merged into a virtually single SST (SLP) field for the EOF analysis. The EOF analysis (see Section 2.2.4 for details) provided the solid observed evidence that is independent of the dataset selection.

2.2.2 Multi-model data

The present study utilized multi-model climate simulations in the CMIP5 (Taylor et al. 2012) to evaluate the EFR contained in the observed datasets. The present study employed the SST, SLP and surface air temperature (SAT) data of 1958–2005 for the historical runs and the RCP4.5 runs for 2006–2017. Following the previous studies (Dong and McPhaden 2017), the RCP4.5 runs were selected among several runs of future projection because the number of the climate models with ensemble members was largest under the RCP4.5 scenario than in other scenarios. Thus, twelve climate models with three ensemble members were selected (see Table 2) to suppress the ICVs in the MMEs that were calculated from 36 and 30 simulations over the 1958–2005 and 2006–2017 periods,

respectively. Note that the scenario selection is unlikely to affect the following results because the GMST spread among the future projections of different scenarios was reasonably small during the 2006–2017 period.

As described for the observations, the simulated GPVs were regridded onto a horizontal resolution of 2° longitude $\times$ 2° latitude and passed through an 8-year lowpass filter.

2.2.3 Methods for extracting the internal climate variability from the observed records

Long-term observed records of ocean and atmospheric variables tend to contain both ICVs in the ocean–atmosphere system and EFRs introduced by anthropogenic and natural radiative forcing. To investigate the remote effect of the internal IPO on the climate variations in other tropical basins, the ICV must be accurately extracted from the observed records by isolating the EFR. In most of the previous studies, a linear trend estimated by the least-squares method was removed from the observed record, and the remaining signal was treated as the ICV. This linear detrending method is easy and simple, but whether the ICVs are properly represented in the linearly detrended signal is doubtful. As introduced in the previous section, Dong and McPhaden (2017) report that a 21-year running window correlation of the decadal SST variability between the Indian and Pacific Ocean undergoes a dramatic transformation around 1985 with a change in the sign, when the linear detrend is applied in isolating the ICVs. Meanwhile this inter-basin correlation shows the sustained sign over several decades when the ICVs are calculated by removing the MME of the historical simulations from the observed records.

Based on observations, the present study here investigate the cross-basin relationship of the decadal SST variability between over the Indian Ocean and over the TP. To discuss

the likely background mechanism of the cross-basin relationship, the present study statistically analysed the observed records and attempted to accurately obtain the ICV of both the SST records and the other ocean and atmosphere variables.

In later sections, an inter-comparison of three methods is performed for estimating the EFR and ICV of each variable. First method utilizes the MG as a representative index of the EFR (hereafter MG method, see next paragraph for details). Second method applies the conventional detrending method to each variable at each grid point (hereafter LT method). Third method (hereafter ML method) first calculate the MMEs at local grid points for each variable based on the selected 36 simulations. The ICVs are expected to be suppressed in that MME time series because the ICVs among individual simulations tend to be temporally uncorrelated. Thus, these MME time series from the observed records at the same grid points are removed in order to extract the ICVs in the observed records. ML method follows Dong and McPhaden (2017) but is here extended to all variables (not the SST alone).

MG method assumes that the EFR of each variable at each grid point is synchronised with the time series of the MG. In Dai et al. (2015), this assumption is applied only to the SAT, but is here applied to all climate variables.

Let t be time steps and e be assigned numbers of simulated ensemble members. $MG(t)$ is calculated from 36 $GMST(t, e)$ as

$$MG(t) = \frac{1}{36} \sum_{e=1}^{36} GMST(t, e). \quad (1)$$

where $GMST(t, e)$ is time series of an area-average of SAT over the globe in the individual ensemble members. Since the ICVs in 36 time series of $GMST$ are assumed to be uncorrelated each other, the $MG(t)$ is expected to reflect only the external forcing. Therefore, the EFR of the observed variable at each grid point n can be calculated as

$$X_{EFR}(t, n) = \alpha_X(n) \times MG(t) + \beta(n), \quad (2)$$

where $X_{\text{EFR}}(t, n)$ is the EFR of observed variable $X(t, n)$, $\alpha_X(t, n)$ is the regression coefficient of the observed X onto the MG, and $\beta(n)$ denotes the constant residuals. Consequently, the ICV (X_{ICV}) is determined as

$$X_{\text{ICV}}(t, n) = X(t, n) - X_{\text{EFR}}(t, n). \quad (3)$$

Given a large number of the ensemble members as in Watanabe et al. (2021) who employed 220 members in total based on a combined set of large ensembles only from four different climate models, the EFR of each variable at each grid point is expected to be appropriately evaluated by ML method. In contrast, MG method is expected to properly remove the ICV from the GMST time series because it performs spatial averaging over the globe and also averages over the 36 simulations, thus suppressing the ICV in the surface temperature time series.

Figure 1 denotes spatial patterns of the EFRs for MG, LT and ML method. We note that unit of α_{SST} by MG method (Fig. 1a) is K/K, and unit of SST trend for LT method (Fig. 1b) and ML method (Fig. 1c) is K/60years. The spatial pattern of α_{SST} indicates that SST responds strongly to external forcing in the Indian Ocean and the western tropical Pacific and weakly in the central to eastern tropical Pacific (Fig. 1a). A similar east-west contrast in the tropics also exists in the observed linear SST trend (Fig. 1b). However, such east-west contrasts are absent in the MME trends (Fig. 1c). These differences between observations and models can lead to a poor representation of the changes in the Walker circulation when estimating the EFR and ICV by ML method.

The present study further compared MG, LT and ML methods against an analysis of non-extracted anomalies that retains both the EFR and ICV (hereafter NE).

2.2.4 How to evaluate the methods: Combined EOF analysis

Let N be the number of grid points over the target analysis domain (e.g., the TP) and T

be the number of time steps. Expressing the SST anomalies in the individual dataset as $x(t, n)$, the covariance $v(n1, n2)$ between locations $n1$ and $n2$ is calculated as follows:

$$v(n1, n2) = \frac{1}{T-1} \sum_{t=1}^T x(t, n1)x(t, n2). \quad (4)$$

Recall that the SST anomalies from the three SST datasets (JRA, NCEP and ERA) are combined into a single EOF analysis by concatenating in space. Hence, the $3N \times 3N$ covariance matrix of this combined EOF analysis is given by

$$\begin{aligned} V &= \begin{bmatrix} v(1,1) & \dots & v(1,3N) \\ \vdots & \ddots & \vdots \\ v(3N,1) & \dots & v(3N,3N) \end{bmatrix} \\ &= \begin{bmatrix} V_{\text{JRA,JRA}} & V_{\text{JRA,NCEP}} & V_{\text{JRA,ERA}} \\ V_{\text{NCEP,JRA}} & V_{\text{NCEP,NCEP}} & V_{\text{NCEP,ERA}} \\ V_{\text{ERA,JRA}} & V_{\text{ERA,NCEP}} & V_{\text{ERA,ERA}} \end{bmatrix}. \end{aligned} \quad (5)$$

For example, $V_{\text{JRA,JRA}}$ and $V_{\text{NCEP,JRA}}$ are described by Eqs. (6) and (7), respectively,

$$V_{\text{JRA,JRA}} = \begin{bmatrix} v(1,1) & \dots & v(1,N) \\ \vdots & \ddots & \vdots \\ v(N,1) & \dots & v(N,N) \end{bmatrix}, \quad (6)$$

$$V_{\text{NCEP,JRA}} = \begin{bmatrix} v(N+1,1) & \dots & v(N+1,N) \\ \vdots & \ddots & \vdots \\ v(2N,1) & \dots & v(2N,N) \end{bmatrix}. \quad (7)$$

Here, $V_{\text{JRA,JRA}}$, $V_{\text{NCEP,NCEP}}$ and $V_{\text{ERA,ERA}}$ are the $N \times N$ covariance matrices calculated from the JRA, NCEP and ERA SSTs, respectively. The individual elements in the covariance matrices were calculated from $x(t, n)$ in the same datasets, as done in the conventional EOF analysis. Meanwhile, the matrix elements in $V_{\text{JRA,NCEP}}$, $V_{\text{JRA,ERA}}$ and $V_{\text{NCEP,ERA}}$ and their transposed elements in V are calculated from the $x(t, n)$ of the different datasets. If the SST anomalies of the different datasets are correlated, the leading modes of the matrix V in the combined EOF analysis are expected to emphasise the common signals of decadal climate variability among the datasets.

The combined EOF analysis of these three SST datasets obtains the single principal component of the leading mode with T steps (SST PC1) from the covariance matrix V .

The associated spatial loadings of the leading mode (hereafter denoted by EOF1) are the regressed SST anomalies onto the SST PC1. The regression pattern is presented as the average of the regression patterns of the three individual datasets.

Applying this combined EOF analysis to the remaining SST anomalies extracted by four methods, four types of SST PC1s and their associated SST EOF1s were obtained.

Applying the same analysis to the remaining SLP anomalies extracted by four methods, four types of SLP PC1 and their associated SLP EOF1s were also obtained.

In addition to the above combined EOF analysis by concatenating in space (S-EOF analysis), an alternative combined EOF analysis were also applied by concatenating in time (T-EOF analysis), following Neeti and Eastman (2014). In the T-EOF analysis, the PC1 with $3 \times T$ steps from the $N \times N$ covariance matrix is obtained. Therefore, after separating into the three single PC1s with T steps, those three PC1s are averaged. The PC1 from the S-EOF analysis and the one from the T-EOF analysis are highly correlated each other, for any variable of SST or SLP in any domain, as well as in any four methods. This means that the present study will reach the same conclusion, no matter which method is chosen, S-EOF analysis or T-EOF analysis. For simplicity, the present study will present the results with S-EOF analysis in later sections.

The next section will present temporal correlation coefficients (TCCs) among time series of PC1s, as well as spatial correlation coefficients (SCCs) among spatial pattern of EOF1s. To test significances of those correlation coefficients, a two-tailed significance test were performed based on the Student's t-distribution with eight degrees of freedom. Significant correlation coefficients at 95% confidence level are shown with asterisks in Figs. 2-7 and Tables 3-8.

2.3 Comparison of the methods

2.3.1 Individual domains

The combined EOF analyses of four methods were applied to the remaining anomalies over three domains of the SST field: the TP (120°E–80°W, 20°S–20°N), the tropical Indian Ocean (TIO, 40°E–110°E, 20°S–20°N), and the whole Indo–Pacific sector (WIP, 40°E–80°W, 60°S–60°N). The same procedure was applied to the remaining SLP anomalies. Finally, twelve leading EOFs and their accompanying PCs were obtained for the SST field, along with twelve sets of EOFs and PCs for the SLP field. To simplify the analysis, the EOF1s and PC1s of the remaining SST anomalies are represented as $Method EOF1^{domain_SST}$ and $Method PC1^{domain_SST}$, respectively. For example, the EOF1 and PC1 of MG method in the TP domain are represented by $^{MG}EOF1^{TP_SST}$ and $^{MG}PC1^{TP_SST}$, respectively.

In the present study, the TP rather than the whole Pacific was selected as an analysis domain because the climate variabilities over the Pacific and Indian Ocean are coupled over the tropics (Chikamoto et al. 2015). The TIO domain was adopted for the same reason. However, in an EOF analysis over the whole Pacific, the inter-comparison among for methods led to the same conclusions as the TP analysis (data not shown).

2.3.1.1 Tropical Pacific

Figure 2 shows the patterns of the leading EOFs of the TP obtained by four methods, namely $^{MG}EOF1^{TP_SST}$, $^{LT}EOF1^{TP_SST}$, $^{ML}EOF1^{TP_SST}$ and $^{NE}EOF1^{TP_SST}$, along with their accompanying time series of $^{MG}PC1^{TP_SST}$, $^{LT}PC1^{TP_SST}$, $^{ML}PC1^{TP_SST}$ and $^{NE}PC1^{TP_SST}$. An individual PC1 in Fig. 2 is calculated by projecting SST anomalies of the three datasets at a particular time onto the EOF1 obtained from the combined EOF analysis for SST anomalies over the TP domain. Then, onto this PC1, regressed SST anomalies can be calculated over the whole Indo-Pacific sector rather than only over the TP domain. Since

those regressed SST anomalies are obtained for the three datasets, the average of the three regressed anomalies at a particular grid point is plotted as the spatial pattern as in the left panels in Fig. 2. In all spatial pattern in the later figures, the averages of the three regressions are plotted.

The regressed spatial pattern of $^{MG}EOF1^{TP_SST}$ shows basin-wide positive anomalies in the TP, along with negative anomalies over the mid-latitudes in the North and South Pacific (Fig. 2a). This tripole pattern of SST anomalies over the whole Pacific was characterised as an IPO-like pattern in previous studies (Power et al. 1999, England et al. 2014), although the latitude range of the TP domain in our EOF analysis is narrower than in the earlier studies. Besides, slight positive SST anomalies were widespread over the tropics and subtropics of the Indian Ocean. The temporal evolution of $^{MG}PC1^{TP_SST}$ (Fig. 2b) depicts a negative-to-positive phase transition in the late 1970s and an opposite transition in the late 1990s. Decadal variations such as the climate-regime shift over the Pacific in 1976/1977 (Nitta and Yamada 1989, Trenberth and Hurrell 1994, Deser and Philips 2006) and the persistent negative phase of the IPO after 2000 (Henley 2017) also appeared in the time series.

The decadal SST variations were associated with pronounced decadal SLP variations all over the Pacific. The regressed spatial pattern of $^{MG}EOF1^{TP_SLP}$ (Fig. 3a) appeared as a zonal seesaw over the TP with a positive (negative) centre in the west (east), along with negative anomalies in the North and South Pacific with a centre of action in the mid-latitudes. The decadal variations in the temporal evolution of $^{MG}PC1^{TP_SLP}$ (Fig. 3b) were similar to those in the temporal evolution of $^{MG}PC1^{TP_SST}$.

As revealed in many previous studies, the decadal SST and SLP anomalies over the TP interact through Bjerknes feedback (Bjerknes 1969, Bordbar et al. 2017). As feedback theory has proven valid and dominant in reality, the dominant internal variabilities of the observed SST and SLP should be significantly correlated. Indeed, the TCC between

$^{MG}PC1^{TP_SST}$ and $^{MG}PC1^{TP_SLP}$ was statistically significant (0.984, Figs. 3b and 3b). In the spatial patterns of $^{MG}EOF1^{TP_SST}$ and $^{MG}EOF1^{TP_SLP}$, a zonal SST gradient and a zonal SLP seesaw involved in Bjerknes feedback appeared over the TP. Those SST and SLP spatial patterns in the $^{MG}EOF1^{TP_SST}$ and $^{MG}EOF1^{TP_SLP}$ typify Bjerknes feedback in which weakened (enhanced) easterly trade winds associated with a decreased (increased) zonal gradient of SLP over the equatorial Pacific relax (enhance) the zonal SST gradient over the TP. These gradient changes are fed back to the original SLP gradient (Bordbar et al. 2017, L'Heureux et al. 2013).

The large-scale anomalies in SST and SLP over the TP are accompanied by extratropical anomalies (see Figs. 2a and 3a). Over mid-latitudes in the North Pacific, the negative (positive) SLP anomalies with a centre of action around the Aleutian low enhance (weaken) the westerly surface winds. Negative (positive) SST anomalies in the central North Pacific then arise through the increased (decreased) upward sea surface heat fluxes (SHFs) and southward Ekman advection (Tanimoto et al. 1997, Alexander et al. 2002). The same anomalies occur at mid-latitudes of the South Pacific (Shakun and Shaman 2009), albeit with weaker amplitudes than in the North Pacific. Hence, the spatial patterns of $^{MG}EOF1^{TP_SST}$ and $^{MG}EOF1^{TP_SLP}$ are temporally related. This inference is corroborated by the similarities of $^{MG}PC1^{TP_SST}$ and $^{MG}PC1^{TP_SLP}$. The relationship between these patterns can be physically interpreted in both the TP and the extratropical Pacific, as discussed in the aforementioned studies.

The spatial patterns of $^{LT}EOF1^{TP_SST}$ and $^{LT}EOF1^{TP_SLP}$ (Figs. 2c and 3c, respectively) and the time series of $^{LT}PC1^{TP_SST}$ and $^{LT}PC1^{TP_SLP}$ (Figs. 2d and 3d, respectively) obtained by LT method were similar to those of MG method, implying that $^{LT}PC1^{TP_SST}$ and $^{LT}PC1^{TP_SLP}$ are significantly correlated (TCC = 0.984). Therefore, MG and LT methods obtain the same relationship between the SST and SLP patterns.

After applying ML method, the spatial pattern of $^{ML}EOF1^{TP_SLP}$ (Fig. 3e) and its

associated time series of $^{ML}PC1^{TP_SLP}$ (Fig. 3f) were similar to those of MG and LT methods. However, along the time series of $^{ML}PC1^{TP_SST}$ (Fig. 2f), positive values appeared during the 1960s and weak negative values appeared during the 1970s. The 2000–2017 period was marked by strong negative values. These features differed from those of $^{MG}PC1^{TP_SST}$ and $^{LT}PC1^{TP_SST}$, and led to a smaller TCC between $^{ML}PC1^{TP_SST}$ and $^{ML}PC1^{TP_SLP}$ (0.621) than in MG and LT methods.

The four types of EOFs obtained by the four methods give visually identical fields of SST (Fig. 2a, c, e and g) and SLP (Fig. 3a, c, e and g). However, while the interdecadal variations in the time series of the PCs obtained by MG and LT methods show significant correlations between the SST and SLP anomalies (Fig. 2b, 2d, 3b and 3d), the distinctly descending trend in the SST time series obtained by ML method (Fig. 2f) was also obtained by NE (Fig. 2h), which retained the EFR. These results indicate that ML method does not actually isolate the EFR and ICV.

2.3.1.2 Tropical Indian Ocean

The analytical procedures of the four methods were repeated in the TIO domain (see Figs. 4 and 5). The regressed spatial pattern of $^{MG}EOF1^{TIO_SST}$ (Fig. 4a) shows positive anomalies over the entire TIO, along with the typical tripole pattern of the IPO over the whole Pacific (also found in $^{EOF1^{TP_SST}}$; see Fig. 2a). The time series of $^{MG}PC1^{TIO_SST}$ (Fig. 4b) was mainly similar to that of the TP, with limited deviations during the 1960s. Meanwhile, the spatial pattern of $^{MG}EOF1^{TIO_SLP}$ displays positive anomalies over most of the TIO along with the coherent SLP pattern associated with the IPO (Fig. 5a) (also found in $^{MG}EOF1^{TP_SLP}$; see Fig. 3a). The time series of $^{MG}PC1^{TIO_SLP}$ (Fig. 5b) is also similar to that over the TP apart from a limited mismatch during the 1960s. Consequently, the TCC between $^{MG}PC1^{TIO_SST}$ and $^{MG}PC1^{TIO_SLP}$ is significantly positive (0.701).

The regressed pattern of $^{LT}EOF1^{TIO_SST}$ (Fig. 4c) obtained by LT method captured the positive anomaly over the TIO, but at weaker amplitude than MG method. Over the Pacific, however, the tripole pattern of the IPO was ambiguous. In the spatial pattern of $^{LT}EOF1^{TIO_SLP}$, the coherent SLP pattern associated with the IPO included a dominant zonal SLP seesaw over the TP (Fig. 5c). The corresponding time series of $^{LT}PC1^{TIO_SST}$ (Fig. 4d) and $^{LT}PC1^{TIO_SLP}$ (Fig. 5d) were uncorrelated ($TCC = -0.066$). The TCC differences between MG and LT methods (0.701 versus -0.066) means that MG method was successful in extracting the ocean-atmosphere coupled variability in the TIO as the leading EOFs, but LT method failed.

The spatial pattern of $^{ML}EOF1^{TIO_SST}$ depicted negative and positive anomalies over the eastern and western parts of the TIO, respectively, along with basin-wide positive anomalies over the Pacific (Fig. 4e). The corresponding time series of $^{ML}PC1^{TIO_SST}$ trended obviously downward (Fig. 4f). The spatial pattern of $^{ML}EOF1^{TIO_SLP}$ (Fig. 5e) displayed the same features as the spatial patterns of $^{MG}EOF1^{TIO_SLP}$ and $^{LT}EOF1^{TIO_SLP}$, but the time series of $^{ML}PC1^{TIO_SLP}$ (Fig. 5f) exhibited an upward trend with a quite weak and short negative phase in the 2000s, inconsistent with the time series of $^{ML}PC1^{TIO_SST}$.

As the EFR was not removed in NE, the spatial pattern of $^{NE}EOF1^{TIO_SST}$ shows the geographical intensities of global SST warming (Fig. 4g). Significant positive anomalies over the entire TIO of $^{NE}EOF1^{TIO_SST}$ and the upward trend in $^{NE}PC1^{TIO_SST}$ (Fig. 4h) indicate that SST warming associated with global warming dominates over the TIO. The $^{NE}PC1^{TIO_SLP}$ also contained an upward trend, but this trend was superimposed with interdecadal variations (Fig. 5h). The similarity between $^{ML}PC1^{TIO_SLP}$ and $^{NE}PC1^{TIO_SLP}$ indicates that over the TIO, the EFR is less effectively removed from the observed SLP in ML method than in MG and LT methods.

The upward trends in $^{NE}PC1^{TIO_SST}$ (Fig. 4h) and $^{NE}PC1^{TIO_SLP}$ (Fig. 5h) meant that both time series were positively correlated ($TCC = 0.604$). Conversely, the downward trend in

$^{ML}PC1^{TIO_SST}$ (Fig. 4f) opposed the upward trend in $^{ML}PC1^{TIO_SLP}$ (Fig. f), resulting in a negative TCC (-0.608) between these time series. Thus, in ML Methods and NE, the SST PC1 and SLP PC1 were significantly correlated through the common features in their long-term trends. These results indicate that the EFRs over the TIO were not sufficiently removed by ML method.

2.3.1.3 *Whole Indo-Pacific sector*

In the previous sections, the leading EOFs and corresponding PCs of the remaining SST and SLP anomalies were obtained in the four methods over the TP and TIO. This subsection now repeat the EOF analysis over the WIP sector (Figs. 6 and 7) which covers the whole study domain.

In the regressed spatial pattern of $^{MG}EOF1^{WIP_SST}$ (Fig. 6a), the IPO tripole pattern appeared over the whole Pacific. Positive anomalies appeared over the entire TIO, as observed in both $^{MG}EOF1^{TP_SST}$ (Fig. 2a) and $^{MG}EOF1^{TIO_SST}$ (Fig. 4a). The SLP fields were also similar among $^{MG}EOF1^{WIP_SLP}$ (Fig. 5a), $^{MG}EOF1^{TP_SLP}$ (Fig. 3a), and $^{MG}EOF1^{TIO_SLP}$ (Fig. 5a). The time series of $^{MG}PC1^{WIP_SST}$ (Fig. 6b) and $^{MG}PC1^{WIP_SLP}$ (Fig. 7b) were significantly correlated ($TCC = 0.874$) as observed in MG method analyses of the individual TP and TIO, although the WIP domain is considerably larger than the TP and TIO domains.

The $^{LT}EOF1^{WIP_SST}$ (Fig. 6c) and $^{LT}EOF1^{WIP_SLP}$ (Fig. 7c) obtained by LT method displays a coherent IPO pattern over the whole Pacific, and the associated SLP pattern includes a zonal SLP seesaw over the TP along with negative anomalies over the mid-latitudes of the North and South Pacific. These findings are consistent with MG method over the WIP domain. Also consistent with MG method, the behaviours of $^{LT}PC1^{WIP_SST}$ (Fig. 6d) and $^{LT}PC1^{WIP_SLP}$ (Fig. 7d) were similar and thus the two time series were

significantly correlated ($TCC = 0.866$).

The time series of $^{ML}PC1^{WIP_SST}$ trended obviously downward (Fig. 6f) and the decadal oscillation in the IPO signal found in $^{MG}PC1^{WIP_SST}$ and $^{LT}PC1^{WIP_SST}$ was absent here. Although the spatial pattern of $^{ML}EOF1^{WIP_SST}$ hints at the IPO tripole pattern, the amplitudes of the SST anomalies were larger in the TP and smaller in the mid-latitudes of the North and South Pacific (Fig. 6e) than $^{MG}EOF1^{WIP_SST}$ and $^{LT}EOF1^{WIP_SST}$. As in the EOF analysis over the TIO, the time series of $^{ML}PC1^{WIP_SLP}$ contained an upward trend (Fig. 7f), unlike the $^{MG}PC1^{WIP_SLP}$ and $^{LT}PC1^{WIP_SLP}$. Consequently, the TCC between $^{ML}PC1^{WIP_SST}$ and $^{ML}PC1^{WIP_SLP}$ was negative. However, the result was insignificant ($TCC = -0.470$).

The spatial pattern of $^{NE}EOF1^{WIP_SST}$ must contain the effect of global warming (Fig. 6g). In contrast to the downward trend in $^{ML}PC1^{WIP_SST}$, the $^{NE}PC1^{WIP_SST}$ monotonically increased (Fig. 6h). How the geographical contrast in SLP responds to global SST warming is debatable (Tokinaga et al. 2012), but our $^{NE}EOF1^{WIP_SLP}$ (Fig. 7g) and $^{NE}PC1^{WIP_SLP}$ (Fig. 7h) were mainly identical to the $^{ML}EOF1^{WIP_SLP}$ and $^{ML}PC1^{WIP_SLP}$ pair.

These inter-comparisons between ML method and NE suggest that ML method is not appropriate for removing the EFR from observed records. The high similarities between $^{ML}EOF1^{WIP_SLP}$ and $^{NE}EOF1^{WIP_SLP}$ and between $^{ML}PC1^{WIP_SLP}$ and $^{NE}PC1^{WIP_SLP}$ indicate that the current ML method cannot properly isolate the EFR and ICV. An insufficient number of ensemble members in the employed CMIP5 data may lead to a biased ensemble mean that fails to represent the EFR of each variable at each grid point.

Possible reasons why the MG method can estimates the EFR more appropriately than the ensemble mean at each grid are discussed in Chapter 3.

2.3.2 Cross-domain correlation

2.3.2.1 Temporal correlations obtained by MG method

Thus far, the SST PC1s have been obtained in three different domains (TP, TIO, and WIP). Table 3a is a matrix of the cross-domain TCCs among the three SST PC1s obtained by MG method. All TCCs are significant and exceed 0.733. Table 3b is a similar matrix of cross-domain TCCs of the SLP PC1s obtained by MG method. All values are significant and exceed 0.891. In addition, the cross-domain TCCs between SST PC1 and SLP PC1 by MG method were calculated (Table 3c). The diagonal components in Table 3c are the cross-variable TCCs given in Figs. 2b, 4b and 6b. The significant positive values in this table are unsurprising if the SST and SLP anomalies extracted by MG method represent the true ICV over each domain. These significant cross-domain TCCs indicate that the dominant SST and SLP variabilities in the TP and TIO are well correlated with each other and are closely related to inter-basin air–sea interactions over the WIP.

2.3.2.2 *Spatial correlations obtained by MG method*

In addition to the cross-domain TCCs among the PC1s, the SCCs among the EOF1s (i.e., the cross-domain SCCs) were calculated. Tables 4a and 4b are matrices of the cross-domain SCCs among the SST EOF1s and SLP EOF1s, respectively, obtained by MG method. All SCCs were calculated for the regressed anomalies over the WIP sector (plotted in the (a) panels of Figs. 2–7), although the individual EOF1s were calculated for the SST or SLP anomalies over the individual domains (TP, TIO or WIP). All values in both matrices of MG method are statistically significant (>0.934 for the SST EOF1s and >0.984 for the SLP EOF1s).

The spatial patterns of SLP EOF1 (Figs. 3a, 5a and 7a) and the regressed SLP anomalies onto the SST PC1s were further compared over the three domains (data not shown). In the same way, the spatial patterns of SST EOF1 (Figs. 2a, 4a and 6a) and the regressed

SST anomalies onto the SLP PC1s over the three domains are compared. As summarised in Tables 4c and 4d, all SCCs were statistically significant (>0.894). Together, the TCCs in Table 3 and the SCCs in Table 4 indicate that MG method successfully extracted the dominant ocean–atmosphere coupled internal variability across the Indo–Pacific.

2.3.2.3 Cross-domain correlations by the other methods

Matrices of the cross-domain TCCs and cross-domain SCCs in LT method (Tables 5, 6) and ML method (Tables 7, 8) were additionally compiled. Note that these correlation coefficients were not always statistically significant.

2.3.3 Advantages of MG method

In MG method, the leading PCs and EOFs of the remaining SST and SLP anomalies over the three domains had significantly positive TCCs and SCCs (Tables 3a-b and 4a-b). The cross-variable TCCs and SCCs of the PCs and EOFs by MG method were also significant (Tables 3c and 4c–d). The spatial patterns of these SST and SLP EOFs indicate an inter-basin interaction over the Indo–Pacific sector (Dong and McPhaden 2017) or a portion of the trans-basin variability over the whole tropics (Chikamoto et al. 2015), implying that MG method well isolated the EFR and thereafter reliably extracted the ocean–atmosphere ICV from the observed records.

In contrast to these advantages in MG method, the obtained SST PC1 and the SLP PC1 over the TIO of LT method are uncorrelated (Fig. 4d), implying that LT method failed to extract the dominant ocean–atmosphere coupled variability. In ML method, as shown in the panels (f) of Figs. 2-7, SST PC1s and SLP PC1s over the three analysis domains contained a long-term upward or downward trend. Hence, the TCCs among those PC1s

in ML method are not always statistically significant. These trend-like features indicate that the EFRs are not sufficiently removed by ML method.

In conclusion, the present study recognise that MG method is the most appropriate method for extracting the ICV from the observed records over the Indo–Pacific sector.

2.4 Summary of inter-comparisons of the methods

Applying three statistical procedures, the present study isolated the decadal ICV and the EFR from observed SST and SLP records over the Indo–Pacific sector during the 1958–2017 period. In MG method, the EFR is represented by the MG in historical simulations because the ICV must be negligible when the MG is derived from sufficiently many ensemble members. The regressed anomalies of each variable at each grid point onto the MG are regarded as the EFRs. After removing these regressed anomalies, the remaining anomalies are regarded as the ICVs. LT method is the conventional detrending method that removes the linear trend on each variable at each grid point. In ML method, the time series of the MME of each variable is calculated at each grid point based on selected simulations, and the time series is removed from the observed records at the same grid points. In an EOF analysis of the remaining anomalies obtained by the three methods, the present study demonstrated that in the most appropriate method, the leading EOFs and their associated PCs represent the background physics of the large-scale air–sea interactions in any analysis domain. Although the remaining SST and SLP anomalies were statistically independent, the decadal time series of the leading EOFs of those anomalies were significantly correlated in MG method. However, an EOF analysis of the remaining anomalies by LT and ML methods often yielded peculiar appearances in the spatial patterns and time series, which were attributable to over- or under-removal of the EFR. Therefore, among the tested methods, the present study conclude that MG

method best extracts the decadal ICV from the observed SST and SLP records over the Indo-Pacific sector.

Chapter 3 Evaluation of methods using large ensemble data

3.1 Introduction

In Chapter 2, the present study compared methods for extracting ICV from observed data and demonstrated the reliability of MG method. However, if the climate models reproduce the realistic atmosphere-ocean system, ML method should be able to properly estimate EFR and ICV. The possible reasons why ML method did not work appropriately include the possibility that the MME of 36 member insufficiently suppress the ICV at each grid, and model bias due to systematic errors. However, the analysis in Chapter 2 did not clarify the factors that caused MG method to perform better than ML method.

Recently, advances in computing technology allow us to analyze the results of a large number of simulations. As a result, the observed internal variability, which was not reproduced by the small number of members in CMIP5, can be well reproduced by the large ensemble simulations of CMIP6. Here, the present study attempt to utilize large ensemble simulations to advance the evaluation of methods for separating the EFR and the ICV.

As utilized in Chapter 2, multi-model data contain bias among climate models. In contrast, if a large number of members can be obtained from a single model, it is possible to analyze large ensemble data without (careful treatment, correction) the requirement to account for model bias. An ensemble mean with a sufficient number of members to suppress ICV should represent the proper EFR in the climate model. Therefore, in this chapter, the EFR is estimated for large ensemble data using MG and LT methods used in Chapter 2 and compared to the large ensemble mean (LEM).

3.2 Data and method

3.2.1 Large ensemble data

The present study utilized 50 members of large ensemble simulations by the Model for Interdisciplinary Research on Climate version 6 (MIROC6, Tatebe et al. 2019) from the CMIP6 (Eyring et al. 2016). The present study employed the SST and SAT data of 1958–2013 for the historical runs and the SSP2-4.5 runs for 2014–2017. The analysis period and the selection of future projection scenarios were adapted to Chapter 2. The MG time series used in MG method was obtained from total 36 members by twelve models of CMIP5, as in Chapter 2. Since both MG in CMIP5 and LEM of GMST in MIROC6 reflect only the external forcing, those decadal modulations are almost identical ($TCC = 0.996$).

Monthly anomalies of all data were passed through an 8-year lowpass filter to extract the decadal variations, as in Chapter 2.

3.2.2 Method

In the next Section, the present study estimates the EFRs using MG and LT methods used in Chapter 1. Instead of the observed records used in Chapter 2, 50 different EFRs for each of the 50 members are obtained, using each method. Similarly to Eq. (2) for the observed records, the EFR of the simulated variable XM from member m at each grid point n can be calculated as

$$XM_{EFR}(t, n, m) = \alpha_{XM}(n, m) \times MG(t) + \beta_{XM}(n, m), \quad (8)$$

where $XM_{EFR}(t, n, m)$ is the EFR of simulated variable $XM(t, n, m)$, $\alpha_{XM}(n, m)$ is the regression coefficient of the simulated XM onto the MG, and $\beta(n)$ denotes the constant residuals. Here, MG in this chapter is same as in Chapter 2. Thus, ensemble means and standard deviation of the XM_{EFR} among the 50 members can be obtained.

The time series for each variable and each grid are averaged across 50 members to

obtain the LEM. If the number of members is sufficient to suppress ICVs, the LEM is expected to represent the proper EFR in the MIROC6.

3.3 Results

3.3.1 Comparison of externally forced response estimated by each method

Fig. 8a shows the EFRs contained in the GMST obtained by each method. The red and green lines show the 50-member mean of the EFRs estimated by MG and LT methods, respectively, and black line shows LEM of the GMST. Comparing the three time series, the EFRs obtained by MG method and the LEM show good agreement, while LT method shows a clear difference with the other two time series. These comparisons indicate that MG method could generally reproduce the EFR of the GMST. However, LT method fails to reproduce the modulations in the increase rate of GMST due to EFR, including the cooling years of the 1960s, the slowdown of warming in the 1990s, and the rapid warming thereafter. These modulations in GMST increase are likely related to the large volcanic eruptions of 1963 and 1991(Fujiwara et al. 2020). The eruption of El Chichón also occurred in 1982. Although the change in the increase rate of GMST was small, the effect of that volcanic eruption on the EFR by MG method and LEM can be seen.

The present study next compared EFRs by each method for SSTs over the Eastern Tropical Pacific (180°W – 80°W , 10°S – 10°N) (ETP SST). This area is at the center of the tropical anomaly of the IPO, the first mode of the ICV over the Indo-Pacific (Fig. 5). Therefore, the influence of ICV tends to remain in the ensemble mean. In contrast to the case of GMST, the EFR of ETP SST by the three methods exhibit different characteristics. While the LEM shows long-term variability similar to the EFR by MG method, the time series shows short-period fluctuations.

Short-period fluctuations in the LEM may be due to oscillation in radiative forcing,

such as solar activity (Hansen et al. 2011), or to ICVs in each member that remain in the LEM. To investigate the causes of the short-period fluctuations in the LEM, the spatial patterns of long-term and short-term SST changes in the LEM were compared. Fig. 9a shows the SST difference for the two periods of 1980-1989 and 2000-2009, as shown by the solid purple line in Fig. 8b. It is clear that SST has warmed over almost the entire region during the 20 years. The greater warming in the Northern Hemisphere than in the Southern Hemisphere suggests that Fig. 9a depicts a spatial pattern of SST warming associated with global warming. To depict the spatial pattern of the short-term change of the LEM, Fig. 9b then show the SST difference between the January 2006 and January 2008, as shown by the purple stars in Fig. 8b. This spatial pattern indicates that cooling of ETP SST over 2-year period is caused by La Nina-like SST variability. These results mean that the 50-member ensemble mean insufficiently suppress ENSO-like internal variability and its effect remains in the LEM as the short-period fluctuations. In contrast, since MG method regards the time series synchronized with the MG as the EFR at any grid point, the effect of ICV is not shown (Fig. 8b). Therefore, when estimating EFR based on 50-member large ensemble data, the 50-member mean of EFR obtained by MG method is more appropriate than LEM.

3.3.2 Required number of members for the large ensemble mean

In the previous section, it was shown that a 50-member ensemble average cannot sufficiently suppress the effects of internal variability at each grid point. Therefore, this section discusses how many members can sufficiently suppress the effects of internal variability.

At first, as shown by the blue dotted line in Fig. 8, the time series in which the LEM was again passed through an 8-year lowpass filter were defined as the long-term

component of the LEM (LEM_{Low}), and the difference between this time series and the LEM was considered the short-term component of the LEM. We note that, while the black and red lines in Fig.8 once lowpass filtered, the blue dotted line twice lowpass filtered. The black line in Fig. 10 shows the estimated error of the LEM with reference to LEM_{Low} as a function of the number of members (N). To plot this black line, N (N is from 1 to 50) members were randomly selected from the 50 members of MIROC6, then ensemble mean, $EM(t, N)$, was calculated among those selected members for each N and time step t . Root mean squared error (RMSE) between $EM(t, N)$ and $LEM_{Low}(t)$ was calculated for each N as

$$RMSE(N) = \sqrt{\frac{1}{T} \sum_{t=1}^T \{EM(t, N) - LEM_{Low}(t)\}^2} . \quad (9)$$

The ratio of RMSE to SD of ICV (SD_{ICV}) was determined as the estimation error rate (ER)

$$ER(N) = \frac{RMSE(N)}{SD_{ICV}} , \quad (10)$$

where SD_{ICV} is 50-member mean of SDs of the ICV. Finally, by repeating 50 times random sampling from 50 members and the calculations in Eqs. (9) and (10), the mean value of the 50 patterns of ER is shown as the black line, and the SD of ER is also shown as the gray shading.

The ER decrease with increasing number of members N and is inversely proportional to the root of N . The approximate curve is $ER = 0.821 \frac{1}{\sqrt{N}} + 0.097$ (green dashed line). This equation means that no matter how much the number of members is increased, the short-term component will not become zero, and approximately 10% error will remain between LEM and LEM_{Low} . This remained short-term component is considered to represent the short-term effects of external forcing, such as volcanic eruptions, which

cannot be represented by the LEM_{Low} . The approximately 90% of SD, that will be reduced by increasing the number of members, is considered to represent an error due to the short-term component caused by the internal variability of each member that are insufficiently suppressed by ensemble averaging.

The same calculations as for the LEM were performed for the MG method. Thus, the red solid line indicates the ER by the MG method with reference to LEM_{Low} . The approximate curve is $ER = 0.098 \frac{1}{\sqrt{N}} + 0.152$ (red dashed line). From 1 to 50 members, the SDs from MG method is less than the ones from the short-term component of the LEM, indicating that MG method can better estimate the EFR in this range of the numbers. Such superiority of MG method is also true for 100 members, and the superiority switches when the number of members exceeds 172. These comparisons advantage the LEM over MG method because the LEM_{Low} is used as the reference. Nevertheless, when the number of members is less than 172, the short-term component of the LEM, due to the effect of ICVs, causes a larger error than MG method. Therefore, it is recommended that at least for a number of members below 172, MG method should be used to estimate the EFR and the average among members should be considered the EFR.

The red dotted line in Fig. 10 shows the SD ratio of MG method for one member. Based on this value, the present study discusses the reasons for the validity of MG method in observed data, as shown in Chapter 2. The SD from MG method for one member is equivalent to the one from the LEM for 34 members. This indicates that MG method largely removes the effect of internal variability by estimating EFR via GMST.

Although the MME for ML method in Chapter 2 was calculated from 36 members, MG method worked more appropriately. This is likely due to the fact that 36 members were utilized from 12 models. Since there is no guarantee that the ICV expressed in each model is the same, the MME retains a greater effect of internal variability than the 36 members mean from the same model.

3.3.3 Spatial distribution of estimation error

In the previous section, the ratio of error due to MG method and LEM to the ICV were presented for the ETP SST. This section discusses the spatial distribution of error ratios.

An error ratio by LEM with reference to the 50-member mean of EFR estimated by MG method, $\overline{EFR}_{MG}(i, t)$, at grid point i was calculated as $R_{LEM}(i)$

$$R_{LEM}(i) = \sqrt{\frac{1}{T} \sum_{t=1}^T \{LEM(i, t) - \overline{EFR}_{MG}(i, t)\}^2} / SD_{ICV}. \quad (11)$$

Same calculations were conducted for 50-member mean of EFR estimated by LT method, $\overline{EFR}_{LT}(i, t)$ with reference to MG method as

$$R_{LT}(i) = \sqrt{\frac{1}{T} \sum_{t=1}^T \{\overline{EFR}_{LT}(i, t) - \overline{EFR}_{MG}(i, t)\}^2} / SD_{ICV}. \quad (12)$$

Fig 11 displays the spatial distributions of R_{LEM} and R_{LT} . The R_{LEM} is greater than R_{LT} in most area. This is likely due to a short-term component in LEM caused by the ICVs. The ETP exhibits a relatively smaller R_{LEM} and R_{LT} than other regions. This is due to the fact that the denominator of R , the SD_{ICV} , is quite large in the ETP region.

The R_{LT} is relatively small over the Pacific and large over the Indian Ocean. This is consistent with the fact that in Chapter 2, the difference between MG and LT methods was small for the EOF analysis in TP, and a clear difference appeared with the EOF analysis in TIO. Since the R_{LT} is larger than R_{LEM} over the Northern Atlantic, it is considered that the application of MG method is particularly necessary for the analysis of ICV over the Northern Atlantic.

3.4 Summary

By utilizing the 50-member historical simulations from MIROC6, a comparison of methods for estimating the EFR indicated that MG method largely suppressed ICVs contained in each member by estimating EFRs via the MG. Such advantage of the MG method can be adapted to the results of Chapter 2. While MG method most appropriately estimated the EFR, the ensemble mean at local grid insufficiently suppressed ICVs contained in each member. By employing large ensemble data of at least more than 172 members, the ensemble mean at local grid is expected to represent the EFR more appropriately than the MG method.

Chapter 4 Remote effect of the IPO on the decadal SST variability over the Indian Ocean

4.1 Introduction

In Chapter 2, ICVs extracted from observed SST and SLP by MG method revealed a statistical relationship of coupled ocean–atmosphere climate variabilities over the Indo–Pacific region. This chapter investigate the background mechanism of this relationship.

4.1.1 cross-basin interaction on interannual scale

Remote effects and interactions across the basins of climate variabilities in the tropics had been reported in several studies (Xie et al. 2009, Chikamoto et al. 2015). In particular, the dominant role of El Niño – Southern Oscillation (ENSO) on seasonal to interannual scales and the IPO on decadal to multi decadal scales over the Pacific and its effects on climate systems over the other basins have been under intense investigation (Klein et al. 1999, Dong et al. 2016). Over the Indian Ocean, the seasonally phase locked response of SST to the ENSO are observed (Du et al. 2009, Saji et al. 1999). The ENSO induces changes in surface winds over the Indian Ocean via the Walker circulation. As a result, the observed SST response over the Indian Ocean to ENSO are largely contributed by SHF effect associated with the modulation of the Walker circulation (Ohba and Ueda 2005, Tokinaga and Tanimoto 2004).

4.1.2 cross-basin interaction on decadal scale

In contrast to interannual time scales, mechanisms of SST changes over the Indian

Ocean triggered by the SST variability over the Pacific on decadal time scales are controversial. A modeling study proposed increased (decreased) short-wave radiation associated with reduced (increased) cloud cover and Ekman downwelling (upwelling) induced by anomalous easterly (westerly) wind over the tropical Indian Ocean as the background mechanism of the positive (negative) SST anomalies over the Indian Ocean related to the positive (negative) IPO phase (Dong et al. 2016). However, several studies based on observed data proposed different mechanisms of the decadal SST changes related to the IPO, such as changes in sea surface turbulent heat flux and horizontal circulations in upper Ocean associated with modulated Walker circulation (Srinivasu et al. 2017). Advection effects of Indonesian Throughflow on upper ocean temperature over the South Indian Ocean is also reported although the relationship between IPO and ITF is still under debate (Dong and McPhaden 2016, Jin et al. 2018, Lee et al. 2015, Zhou et al. 2017). These disagreements of the remote effects of the IPO on the decadal SST variabilities over the Indian Ocean seem to be caused by difficulties in treatment of ICV and EFR in the observed records. Li et al. (2018) implied that relative contributions of ICV and EFR to decadal temperature changes over the upper Indian Ocean had changed depending on the periods. Thus, differences in the employed period of the observed datasets may change estimation of the EFR and affect results of studies. Here, the remote effect of the IPO on the decadal SST variabilities over the Indian Ocean is revisited on the basis of the ICV appropriately extracted by MG method.

4.2 Data

4.2.1 Ocean reanalysis data

Three SST data were analyzed (Table 1) as employed in Chapter 2. In addition to the SLP data employed in Chapter 2, zonal and meridional 10-m wind velocity and 10-m

scalar wind speed were used from three atmospheric reanalysis data sets.

For ocean temperature fields, the present study employed four different ocean reanalysis data sets: (1) Evaluation of the applicability of the Estimated State of the Global Ocean for Climate Research version 03a (ESTOC; 1° latitude $\times$ 1° longitude $\times$ 46 levels; Osafune et al. 2015) for 1958-2014, (2) Second German contribution to Estimating the Circulation and Climate of the Ocean (GECCO2: 1° latitude $\times$ 1° longitude $\times$ 50 levels; Köhl 2015) for 1958-2016, (3) ECMWF Ocean Reanalysis System, version 4 (ORAS4: 1° latitude $\times$ 1° longitude $\times$ 42 levels; Balmaseda et al. 2013) for 1958-2017 and (4) Simple Ocean Data Assimilation version 2.2.4(SODA; 0.5° latitude $\times$ 0.5° longitude $\times$ 40 levels; Carton and Giese 2008) for 1958-2010.

All data were regridded onto a horizontal resolution of 2° longitude $\times$ 2° latitude and passed through an 8-year lowpass filter as in Chapter 2.

4.2.2 OFES hindcast data

For further analysis to investigate oceanic processes associated with the IPO, the present study employed ocean temperature fields, zonal, horizontal and vertical velocity fields, sea surface height (SSH) and net SHF from the ocean GCM for the Earth Simulator (OFES; Sasaki et al. 2008) hindcast. The model resolution is 0.1° latitude $\times$ 0.1° longitude with 54 vertical levels. Temporal variations in the OFES are always calculated on a basis of dynamical equation in the numerical model, whereas temporal variations in reanalysis data are not always consistent with the theory of physical process because of the assimilations of observed records. Thus, the OFES hindcast were analyzed to explore the mechanisms of temperature variabilities corresponding to the IPO.

4.2.3 Extraction method of the internal climate variability

Based on the discussion of the methods in Chapters 2 and 3, MG method was here adopted to extract the ICVs for each variable. Later, the same analysis of the ICV estimated by LT method and NE are conducted to validate the dependency of the analysis results of the extracting method.

4.2.4 IPO index

Following previous studies (Dong and McPhaden 2017), IPO index was defined as SST PC1 over the whole Pacific by conducting combined EOF analysis for three SST data, after extracting ICV from the observed records.

4.3 Results

4.3.1 Temperature variability over the upper Indian Ocean associated with the IPO

This section investigate remote effects of the IPO onto the SST variability over the Indian Ocean. The spatial pattern of the regressed SST onto the IPO index is shown in Fig. 12a. The typical pattern of the positive phase of the IPO over the Pacific and the broad positive anomalies over the Indian Ocean, which indicate the positive correlation between the IPO and SST over the Indian Ocean as shown in Section 2.3.2. This relationship was also shown in Dong and McPhaden (2017). To investigate the vertical structure of the temperature anomalies over the upper Indian Ocean, regressed temperatures onto the IPO index are shown in Fig. 13 by using ocean reanalysis data sets. Positive temperature anomalies are shown between the surface and around 150m depth over the equatorial and the northern Indian Ocean regardless of datasets (Fig. 13a-d) and

the mean regressed temperature anomalies among the four datasets (Fig. 13e). The maximum of positive temperature anomalies is located around 100m depth. Furthermore, averaged temperature anomalies between the surface and 150m depth are positive over most of the equatorial and the northern Indian Ocean (Fig. 14a). Since positive anomalies extend deeper than the thermocline, these results indicate that not only atmospheric process at the surface but also oceanic process over the upper ocean contribute to the positive SST anomalies over the equatorial and the northern Indian Ocean associated with the IPO. Around 10°S, while SST shows positive anomalies, negative temperature anomalies are shown at the thermocline depth (Fig. 12a, Fig. 13 e). These results indicate that the main process which contribute to the temperature anomalies at the surface and at the thermocline depth are different. As noted above, the temperature anomalies at upper ocean layer over the tropical and the northern Indian Ocean are shown regardless of datasets, although the temperature anomalies are not identical among the datasets in the south part of the Indian Ocean (Fig. 13a-d).

The positive correlation between the IPO and the SST anomalies over the Indian Ocean is not shown clearly in the ICV estimated by LT method and NE which contain both ICV and EFR (Fig. 12b, c). The regressed SST onto the IPO index shows negative anomalies over the entire Indian Ocean in NE. LT method shows weaker positive SST anomalies associated with the positive IPO (Fig. 12 b) than results of MG method (Fig. 12a), which indicated that the EFR are not well removed by LT method over the Indian Ocean. The negative anomalies in NE and weak positive anomalies by LT method are distributed between the surface layers over the tropical and northern Indian Ocean (Fig. 13f, g). Since the external forcing significantly influences on temperatures between the surface and around 100m depth over the Indian Ocean, temperature anomalies associated with the IPO seem to depend on the methods to extract ICV. Thus, the positive correlation between the IPO and the temperature anomalies over the upper Indian Ocean is shown clearly only

when the ICV is extracted by MG method.

4.3.2 The effects of the IPO on the surface Indian Ocean via the atmosphere

To investigate the process which induced the positive temperature anomaly over the upper Indian Ocean associated with the positive phase of the IPO, the OFES hindcast were analyzed in addition to the reanalysis data sets of ocean and atmosphere. MG method were applied to extract the ICV contained in the OFES hindcast. Vertical and horizontal distributions of temperature anomalies over the Indian Ocean associated with the IPO in OFES hindcast are shown in Fig. 13h and 14b, which are similar to the results of ocean reanalysis data sets (Figs. 13e, 14a). The positive anomalies near the equator and around 20°S and negative anomalies around 10°S are shown in the results of the OFES hindcast as in the ocean reanalysis data sets. However, a significant difference between the OFES hindcast and the ocean reanalysis data sets are shown over the south part of the Arabian Sea. Hence, the OFES hindcast should be analyzed, with careful treatment over the south part of the Arabian Sea.

On seasonal-interannual time scales, the SST variability over the tropical Pacific induces the changes in surface winds over the Indian Ocean via the Walker circulation, which cause changes in the SHF and fluctuations of thermocline depth due to vertical processes (Tokinaga and Tanimoto 2004, Xie et al. 2002, Ohba and Ueda 2005). These oceanic and atmospheric processes result in the SST variability over the Indian Ocean. In our analysis on decadal time scales, regressed surface wind speed onto the IPO index show positive anomalies over the entire Indian Ocean except for the equatorial region (Fig. 15a). The intensification (weakening) of surface wind is expected to contribute to an increased (decreased) release of the SHF from ocean and an intensification

(weakening) of wind-driven ocean circulations.

Net SHF anomalies from ocean corresponds to the distribution of upper ocean temperature anomalies associated with the IPO (Fig. 15b). Positive SHF anomalies are located near the equator where positive temperature anomalies are exhibited, and negative SHF anomalies are located around 10°N and 10°S where negative temperature anomalies are exhibited (Fig. 12d). These results indicate the damping effect of SHF on local SST. It is inferred that anomalous warm (cold) SST results in increase (decrease) of upward turbulent heat and longwave radiation from ocean.

The regression coefficients of averaged ocean current speed between the surface and 150m depth onto the IPO index (Fig. 15c) exhibit positive anomalies over the large part of the Indian Ocean, implying an intensification (weakening) of wind-driven circulations over the Indian Ocean corresponding to the positive (negative) IPO. The intensification (weakening) of wind-driven circulation is expected to cause changes in temperature advection, and thereby contribute to water temperature anomalies.

4.3.3 Temperature advection effects associated with the IPO

To examine the effect of the changes in the wind-driven circulations onto the thermal structure over the upper Indian Ocean, temperature advectons were calculated in the OFES hindcast as follows:

$$Adv_x = -U \frac{\partial T}{\partial x}$$

$$Adv_y = -V \frac{\partial T}{\partial y}$$

$$Adv_z = -W \frac{\partial T}{\partial z}$$

where Adv_x , Adv_y and Adv_z are the zonal, meridional and vertical components of the temperature advection, U , V and W are the zonal, meridional and vertical velocity, T is the temperature. Note that the temporal evolution of the temperature advection was first calculated for monthly mean data and then climatologies averaged over the 1958–2017 and anomalies are calculated. After that, the 8-year low-pass filter was applied to monthly anomalies, and finally ICV of the temperature advection was extracted.

Temperature advection over the upper Indian Ocean in the climatological mean state is primarily dominated by positive meridional temperature advection (Fig. 16c), associated with southward currents over the entire Indian Ocean (Fig. 17c). These mean southward currents are branch of the meridional overturning circulation which consist of the cross-equatorial cell (CEC) and the subtropical cell (STC) (Han et al. 2014a). The north Indian Ocean gains heat via SHF and this heat gain is transported across the equator to the south by the southward mean currents, resulting in the basin-wide warming effect of the meridional temperature advection. While the upwelling region of the CEC near the coasts of Somali and Oman is ambiguous due to the horizontal resolution of the figure, the upwelling region of the STC is apparent at the equator to 10°S (Fig. 17e). Along the two meridional overturning circulations, surface water subducts south of 15°S. Those upwelling (downwelling) cause cooling (warming) effect of the vertical temperature advection (Fig. 16e). These vertical process with STC predominate the mean temperature field in the upper southern Indian Ocean (Fig. 18), causing the shoaling (deepening) of thermocline in the upwelling (downwelling) region. (See contours in Fig. 13h). Since any low temperature regions associated with equatorial upwelling were not observed, the cooling effect of upwelling is considered to be overwhelmed by the effect of the horizontal temperature advection and SHF.

Associated with the summer/winter Asian monsoons, the surface circulations and the temperature fields in the Northern Indian Ocean dramatically change through the seasons

(Han et al. 2014a). Thus, zonal temperature advection in the mean state, as shown in Fig. 16a, is not always consistent with mean temperature fields (Fig. 18) and mean zonal currents (Fig. 17a). Near the equator, although the eastward mean temperature gradient and eastward mean current are expected to cause a cooling effect, mean zonal temperature advections show a warming effect (Fig. 16a). This inconsistency is considered to be resulted from the fact that the zonal current at the equator reverses during a year.

Fig 16b, d, and f show the regression coefficients of 3-dimensional components of the temperature advection over the upper Indian Ocean onto the IPO index. The zonal advection anomalies exhibit the warming (cooling) effect near the equator and the cooling (warming) effect around 10°N and 10°S associated with the positive (negative) IPO (Fig. 16b), which are consistent with the spatial pattern of the regressed temperature onto the IPO index (Fig. 14b). Thus, it is indicated that the zonal advection effects largely contribute to the distributions of temperature anomalies associated with the IPO. In the mean state over the tropical Indian Ocean, upper ocean temperatures are relatively low in the west and high in the east (Fig. 18). Thus, anomalous westward (eastward) current (Fig. 17b) result in the warming (cooling) effect near the equator, and anomalous eastward (westward) current result in the cooling (warming) effect at $5\text{--}10^{\circ}\text{S}$ and $5\text{--}10^{\circ}\text{N}$ during the positive (negative) IPO. Anomalous zonal current at $5\text{--}10^{\circ}\text{S}$ and $5\text{--}10^{\circ}\text{N}$ can be interpreted as geostrophic flow caused by the meridional distribution of SSH anomalies (Fig. 15d). As seen in Fig. 15d and Fig. 17, positive (negative) temperature anomalies increase (decrease) SSH. With the positive (negative) temperature anomalies near the equator, negative (positive) temperature anomalies at $5\text{--}10^{\circ}\text{S}$ and $5\text{--}10^{\circ}\text{N}$ enhance (weaken) an equatorward pressure gradient during the positive (negative) IPO, which cause anomalous eastward (westward) currents on both sides of the equator. These anomalous eastward (westward) currents can contribute to the negative (positive) temperature anomalies at $5\text{--}10^{\circ}\text{S}$ and $5\text{--}10^{\circ}\text{N}$ by the temperature advection effect.

Therefore, the negative (positive) temperature anomalies at 5–10°S and 5–10°N are considered to maintain themselves by the zonal temperature advection of the anomalous eastward (westward) geostrophic flow during the positive (negative) IPO.

Regression coefficients of meridional velocity onto the IPO index depicts anomalous equatorward current at 40–80°E (Fig. 17d). This convergence of the meridional current is considered to contribute to the positive SSH anomalies near the equator (Fig. 15d). The anomalous southward (northward) currents during the positive (negative) IPO also contribute to the warming (cooling) over the upper Indian Ocean by enhancing (weakening) the southward warm water transport (Fig. 16d).

The cooling (warming) effect of vertical advection associated with positive (negative) IPO (Fig. 16f) is corresponding to enhanced (weakened) upwelling (Fig. 17f), which acts to suppress positive (negative) temperature anomalies in the equatorial upper Indian Ocean. The anomalous strong upwelling over the northern and tropical Indian Ocean partly reflects the intensification of CEC and STC.

In summary, the relative contributions of temperature advection and SHF to temperature anomalies associated with the IPO are compared (Fig. 19). The contribution of SHF onto temperature change was calculated as $-Q_{Net}/(\rho C_p H)$, where Q_{Net} is net SHF from ocean to atmosphere, ρ is the seawater density, C_p is the heat capacity of the seawater, and H is thickness (=150m).

The red line shows the damping effect of SHF on temperature anomalies associated with the IPO (black line) as shown in Fig. 15b. Intensified (weakened) CEC and STC could enhance (weaken) the southward warm water transport in the surface layer associated with the positive (negative) IPO. Therefore, meridional advection (blue line) largely contributes to temperature anomaly near the equator. Due to the enhanced (weakened) upwelling associated with intensified (weakened) CEC and STC, vertical advection (green line) exhibits a cooling (warming) effect over the TIO during the

positive (negative) IPO. Vertical advection shows the largest contribution to the temperature anomalies around 10°S . Zonal advection (light blue) shows a significant contribution to the temperature anomalies at the equator and at 10°N .

The horizontal temperature advection effect in the upper Indian Ocean temperature due to changes in ocean circulation associated with IPO are different from the background mechanism of the Indian Ocean SST variability associated with ENSO, which are mainly driven by SHF, on seasonal-interannual time scales. Thus, our analysis indicates the relative importance of oceanic processes in decadal climate variabilities.

4.4 Summary

Based on the remaining anomalies extracted by MG method from observed records, positive (negative) temperature anomalies are exhibited at 150 m depth from the sea surface in the tropical and the northern Indian Ocean associated with the positive (negative) IPO, indicating that the Indo-Pacific coupled ocean–atmosphere variability extends from the troposphere to the upper Indian Ocean, not just to the ocean surface layer. The remaining anomalies extracted by LT method did not clearly show such coupled ocean–atmosphere variability across the Indo-Pacific.

While previous studies showed that the SHF largely contributes to the SST variability over the Indian Ocean related to the ENSO on seasonal-interannual time scales, the present study showed substantial contributions of advection effects which overwhelm the damping effect of SHF on SST anomalies over the Indian Ocean associated with the IPO on decadal time scales. Enhanced (reduced) surface winds over the Indian Ocean corresponding to the positive (negative) IPO induced intensification (weakened) of the wind-driven circulation. Thus, enhanced (reduced) advection effects showed significant contribution in forming temperature anomalies in the Indian Ocean surface layer associated with the positive (negative) IPO.

Chapter 5 Conclusion

Applying three statistical procedures, the present study isolated the decadal ICV and the EFR from observed SST and SLP records over the Indo–Pacific sector during the 1958–2017 period. In MG method, the EFR is represented by the MG in historical simulations because the ICV must be negligible when the MG is derived from sufficiently many ensemble members. The regressed anomalies of each variable at each grid point onto the MG are regarded as the EFRs. After removing these regressed anomalies, the remaining anomalies are regarded as the ICVs. LT method is the conventional detrending method that removes the linear trend on each variable at each grid point. In ML method, the time series of the MME of each variable is calculated at each grid point based on selected simulations, and the time series is removed from the observed records at the same grid points. In an EOF analysis of the remaining anomalies obtained by the three methods, the present study demonstrated that in the most appropriate method, the leading EOFs and their associated PCs represent the background physics of the large-scale air–sea interactions in any analysis domain. Although the remaining SST and SLP anomalies were statistically independent, the decadal time series of the leading EOFs of those anomalies were significantly correlated in MG method. However, an EOF analysis of the remaining anomalies by LT method and ML method often yielded peculiar appearances in the spatial patterns and time series, which were attributable to inappropriate removal of EFRs. Therefore, among the examined methods, the present study conclude that MG method best extracts the decadal ICV from the observed SST and SLP records over the Indo–Pacific sector.

A comparison of the methods based on the 50-member historical simulations from MIROC6 indicated that MG method largely suppressed ICVs contained in each member by estimating EFRs via the MG, thus successfully extracted ICVs from the observed

records or historical simulations. While the ensemble mean of 50-member EFRs obtained by MG method most appropriately estimated the impact of external forcing, the ensemble mean at local grid insufficiently suppressed ICVs contained in each member. When analyzing large ensemble data of at least less than 172 members over the ETP region, it is recommended to employ the ensemble average of the EFRs estimated by MG method to estimate the impact of external forcing.

ICVs extracted from observed records by MG method exhibited positive (negative) temperature anomalies at 150 m depth from the sea surface in the tropical and the northern Indian Ocean associated with the positive (negative) IPO, indicating that the Indo-Pacific coupled ocean–atmosphere variability extends from the troposphere to the upper Indian Ocean, not just to the ocean surface layer. ICV extracted by LT method did not clearly show such coupled ocean–atmosphere variability across the Indo-Pacific.

While previous studies showed that the SHF largely contributes to the SST variability over the Indian Ocean related to the ENSO on seasonal-interannual time scales, the present study showed substantial contributions of advection effects which overwhelms the damping effect of SHF on SST anomalies over the Indian Ocean associated with the IPO on decadal time scales. Enhanced (reduced) surface winds over the Indian Ocean corresponding to the positive (negative) IPO induced intensification (weakened) of the wind-driven circulation. Thus, enhanced (reduced) advection effects showed significant contribution in forming temperature anomalies over the Indian Ocean related to the positive (negative) IPO. The present study conclude that the advection effect largely contributes to the positive correlation between the decadal SST variability over the Indian Ocean and the IPO.

While the present study showed that intensification (weakened) of the wind-driven circulation in the mean state contributes to positive (negative) temperature anomalies in the upper Indian Ocean, the surface currents in the equatorial Indian Ocean reverse during

a year with the summer/winter Asian monsoons (Han et al. 2014a). Therefore, surface wind anomalies and changes in surface circulation over the Indian Ocean associated with the IPO are also considered to depend on the season. Investigating the remote effects of IPO at each season is expected to further clarify the background mechanisms of the Indo-Pacific coupled ocean–atmosphere variability. For this purpose, the seasonal separation of EFR and ICV may also work effectively.

For accurate decadal climate predictions, we must understand the background mechanisms of the ICV and the effect of external forcing, and properly express these effects in climate models. By clarifying the importance of isolating the ICV and EFR in each climate variable on each region, we expect to stimulate further investigations of the mechanism underlying the decadal ICV and evaluations of climate model performances, thereby improving future climate projections over decades and centuries.

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Tables

Table 1: Datasets of observed SST and SLP

	Variable	Data set	Period	Resolution (latitude $\times$ longitude)
(1) JRA	SST	COBE-SST 2 (Hirahara et al. 2014)	1958–2017	$1^\circ \times 1^\circ$
	SLP	JRA-55 (Kobayashi et al. 2015)	1958–2017	$1.25^\circ \times 1.25^\circ$
(2) NCEP	SST	GISST 2.3b (Rayner et al. 1996)	1958–1981	$1^\circ \times 1^\circ$
		OISST v2 (Reynolds et al. 2007)	1982–2017	$0.25^\circ \times 0.25^\circ$
	SLP	NCEP/NCAR Reanalysis 1 (Kalnay et al. 1996)	1958–2017	$2.5^\circ \times 2.5^\circ$
(3) ERA	SST	HadISST 1 (Rayner et al. 2003)	1958–1978	$1^\circ \times 1^\circ$
		ERA-interim (Dee et al. 2011)	1979–2017	$0.75^\circ \times 0.75^\circ$
	SLP	ERA-40 (Uppala et al. 2005)	1958–1978	$2.5^\circ \times 2.5^\circ$
		ERA-interim	1979–2017	$0.75^\circ \times 0.75^\circ$

Table 2: CMIP5 models and numbers of ensemble members used in this study

Model Name	historical	RCP4.5
CanESM2	3	3
CCSM4	3	3
CNRM-CM5	3	1
CSIRO-Mk3L-1-2	3	3
GFDL-CM3	3	3
GISS-E2-H	3	3
HadGEM2-ES	3	3
IPSL-CM5A-LR	3	3
MIROC5	3	3
MPI-ESM-LR	3	3
MRI-CGCM3	3	1
NorESM1-M	3	1

Table 3: Cross-domain temporal correlation coefficients (TCCs) between the time series of (a) SST PC1 and (b) SLP PC1 over the tropical Pacific (TP, 120°E–80°W, 20°S–20°N), the tropical Indian Ocean (TIO, 40°E–110°E, 20°S–20°N), and the whole Indo–Pacific sector (WIP, 40°E–80°W, 60°S–60°N) based on the ICVs obtained by MG method. Part (c) lists the cross-variable TCCs between the SST PC1 and SLP PC1. Significance for each TCCs is tested by a two-tailed test based on the Student’s t-distribution. TCCs with asterisks are statistically significant at 95 % confidence level with eight degrees of freedom.

(a) Cross-domain TCCs of SST PC1

MG Method	TP SST	TIO SST	WIP SST
TP SST	1.000 *	-	-
TIO SST	0.733 *	1.000 *	-
WIP SST	0.980 *	0.805 *	1.000 *

(b) Cross-domain TCCs of SLP PC1

MG Method	TP SLP	TIO SLP	WIP SLP
TP SLP	1.000 *	-	-
TIO SLP	0.891 *	1.000 *	-
WIP SLP	0.900 *	0.970 *	1.000 *

(c) Cross-domain TCCs of SST PC1 vs. SLP PC1

MG Method	TP SLP	TIO SLP	WIP SLP
TP SST	0.984 *	0.823 *	0.831 *
TIO SST	0.720 *	0.701 *	0.668 *
WIP SST	0.975 *	0.860 *	0.874 *

Table 4: Cross-domain spatial correlation coefficients (SCCs) between the leading patterns of the combined EOF1 of (a) SST and (b) SLP over the TP, TIO, and WIP (see Table 3 caption for details) based on the ICVs obtained by MG method. Part (c) lists the SCCs between the leading pattern of SLP EOF1 and the regressed pattern of SLP onto the SST PC1 and (d) lists the SCCs between the leading pattern of SST EOF1 and the regressed pattern of SST onto the SLP PC1. Significance for each TCCs is tested by two-tailed test based on the Student's t-distribution. TCCs with asterisks are statistically significant at 95 % confidence level with eight degrees of freedom.

(a) Cross-domain SCCs of SST EOF1

MG Method	TP SST	TIO SST	WIP SST
TP SST	1.000 *	-	-
TIO SST	0.934 *	1.000 *	-
WIP SST	0.996 *	0.950 *	1.000 *

(b) Cross-domain SCCs of SLP EOF1

MG Method	TP SLP	TIO SLP	WIP SLP
TP SLP	1.000 *	-	-
TIO SLP	0.984 *	1.000 *	-
WIP SLP	0.987 *	0.998 *	1.000 *

(c) Cross-domain SCCs of SLP EOF1 vs. regressed SLP on SST PC1

MG Method	TP SLP	TIO SLP	WIP SLP
TP SST	0.997 *	0.949 *	0.998 *
TIO SST	0.966 *	0.935 *	0.978 *
WIP SST	0.969 *	0.932 *	0.981 *

(d) Cross-domain SCCs of SST EOF1 vs. regressed SST on SLP PC1

MG Method	TP SST	TIO SST	WIP SST
TP SLP	0.996 *	0.948 *	0.949 *
TIO SLP	0.928 *	0.901 *	0.894 *
WIP SLP	0.997 *	0.965 *	0.966 *

Table 5: As for Table 3, but based on the ICVs obtained by LT method

(a) Cross-domain TCCs of SST PC1

LT Method	TP SST	TIO SST	WIP SST
TP SST	1.000 *	-	-
TIO SST	0.224	1.000 *	-
WIP SST	0.980 *	0.251	1.000 *

(b) Cross-domain TCCs of SLP PC1

LT Method	TP SLP	TIO SLP	WIP SLP
TP SLP	1.000 *	-	-
TIO SLP	0.889 *	1.000 *	-
WIP SLP	0.890 *	0.954 *	1.000 *

(c) Cross-domain TCCs of SST PC1 vs. SLP PC1

LT Method	TP SLP	TIO SLP	WIP SLP
TP SST	0.984 *	0.820 *	0.817 *
TIO SST	0.161	-0.066	-0.072
WIP SST	0.981 *	0.856 *	0.866 *

Table 6: As for Table 4, but based on the ICVs obtained by LT method

(a) Cross-domain SCCs of SST EOF1

LT Method	TP SST	TIO SST	WIP SST
TP SST	1.000 *	-	-
TIO SST	0.459	1.000 *	-
WIP SST	0.996 *	0.443	1.000 *

(b) Cross-domain SCCs of SLP EOF1

LT Method	TP SLP	TIO SLP	WIP SLP
TP SLP	1.000 *	-	-
TIO SLP	0.979 *	1.000 *	-
WIP SLP	0.982 *	0.996 *	1.000 *

(c) Cross-domain SCCs of SLP EOF1 vs. regressed SLP on SST PC1

LT Method	TP SLP	TIO SLP	WIP SLP
TP SST	0.996 *	0.122	0.999 *
TIO SST	0.958 *	-0.032	0.973 *
WIP SST	0.960 *	-0.019	0.975 *

(d) Cross-domain SCCs of SST EOF1 vs. regressed SST on SLP PC1

LT Method	TP SST	TIO SST	WIP SST
TP SLP	0.996 *	0.945 *	0.943 *
TIO SLP	0.412	0.245	0.244
WIP SLP	0.998 *	0.964 *	0.963 *

Table 7: Same as Table 3, but based on the ICVs obtained by ML method

(a) Cross-domain TCCs of SST PC1

ML Method	TP SST	TIO SST	WIP SST
TP SST	1.000 *	-	-
TIO SST	0.445	1.000 *	-
WIP SST	0.922 *	0.707 *	1.000 *

(b) Cross-domain TCCs of SLP PC1

ML Method	TP SLP	TIO SLP	WIP SLP
TP SLP	1.000 *	-	-
TIO SLP	0.718 *	1.000 *	-
WIP SLP	0.622	0.962 *	1.000 *

(c) Cross-domain TCCs of SST PC1 vs. SLP PC1

ML Method	TP SLP	TIO SLP	WIP SLP
TP SST	0.621	-0.043	-0.203
TIO SST	-0.246	-0.608	-0.682 *
WIP SST	0.336	-0.315	-0.470

Table 8: As for Table 4, but based on the ICVs obtained by ML method

(a) Cross-domain SCCs of SST EOF1

ML Method	TP SST	TIO SST	WIP SST
TP SST	1.000 *	-	-
TIO SST	0.531 *	1.000 *	-
WIP SST	0.947 *	0.762 *	1.000 *

(b) Cross-domain SCCs of SLP EOF1

ML Method	TP SLP	TIO SLP	WIP SLP
TP SLP	1.000 *	-	-
TIO SLP	0.886 *	1.000 *	-
WIP SLP	0.849 *	0.996 *	1.000 *

(c) Cross-domain SCCs of SLP EOF1 vs. Regressed SLP on SST PC1

ML Method	TP SLP	TIO SLP	WIP SLP
TP SST	0.311	-0.580	-0.096
TIO SST	-0.196	-0.858 *	-0.564
WIP SST	-0.276	-0.892 *	-0.632 *

(d) Cross-domain SCCs of SST EOF1 vs. Regressed SST on SLP PC1

ML Method	TP SST	TIO SST	WIP SST
TP SLP	0.663 *	-0.053	-0.218
TIO SLP	-0.217	-0.759 *	-0.839 *
WIP SLP	0.405	-0.339	-0.493

Figures

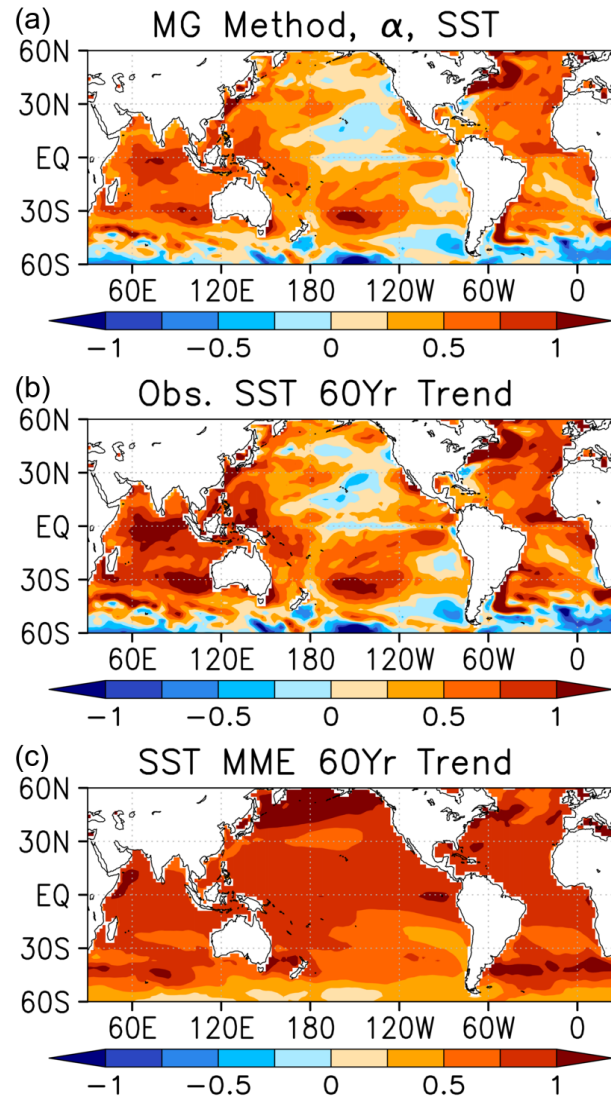


Figure 1 The spatial distributions of (a) regression coefficients of observed SST onto the MG (in K/K), (b) 60-yr linear trend of mean SST among three observed datasets (in K/60yr) and (c) 60-yr linear trend of multi-model ensemble mean of SST from CMIP5 36 members (in K/60yr).

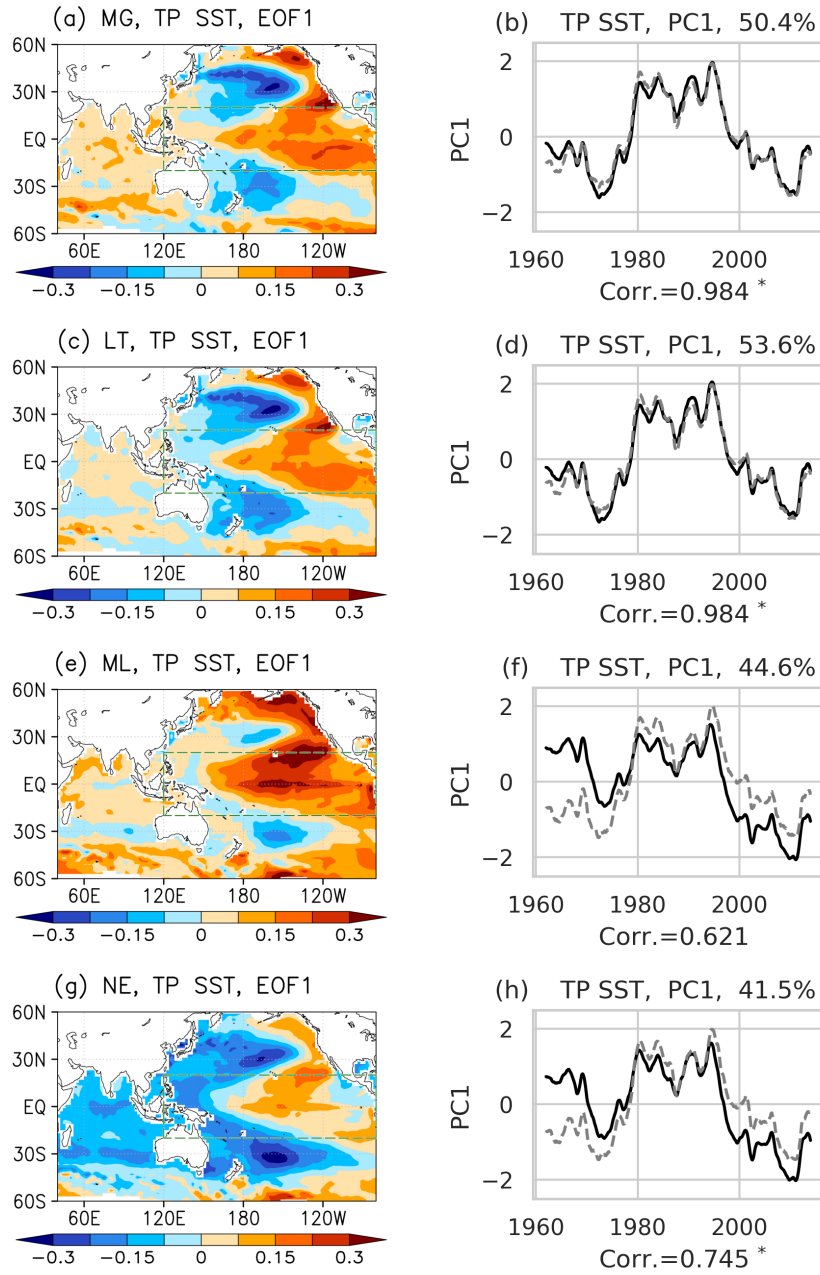


Figure 2 Regressed anomalies of EOF1 (left panels) and time series of PC1 (right panels) in the combined EOF analysis of SST (in K) across the three datasets over the tropical Pacific (TP, 120°E–80°W, 20°S–20°N). Rows show the extraction methods of ICVs, which are MG, LT and ML method and NE. Gray dashed lines in the right panels denote the SLP PC1s over the TP obtained by the same method. All time series are standardized. The top right and bottom center of each panel state the percentage of the explained variance and the temporal correlation coefficients between the SST PC1 and the SLP PC1, respectively. The correlation coefficients with asterisks are statistically significant at 95 % confidence level with eight degrees of freedom on the basis of two-tailed Student's t-test. The boxes (dashed line) in the left panels enclose the TP domain.

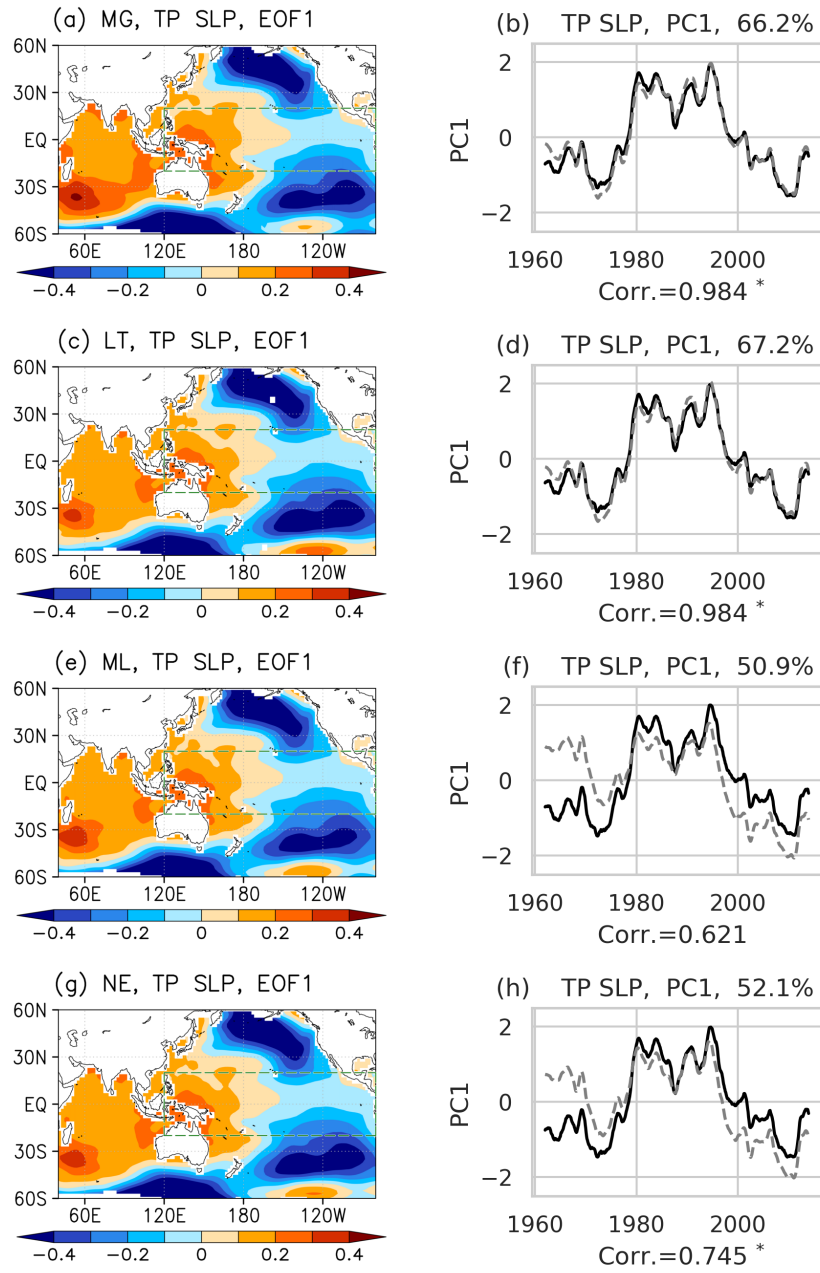


Figure 3 As for Fig. 2 but showing the SLP (in hPa) over the tropical Pacific (TP, 120°E–80°W, 20°S–20°N). Gray dashed lines in the right panels denote the SST PC1s over the TP obtained by the same method.

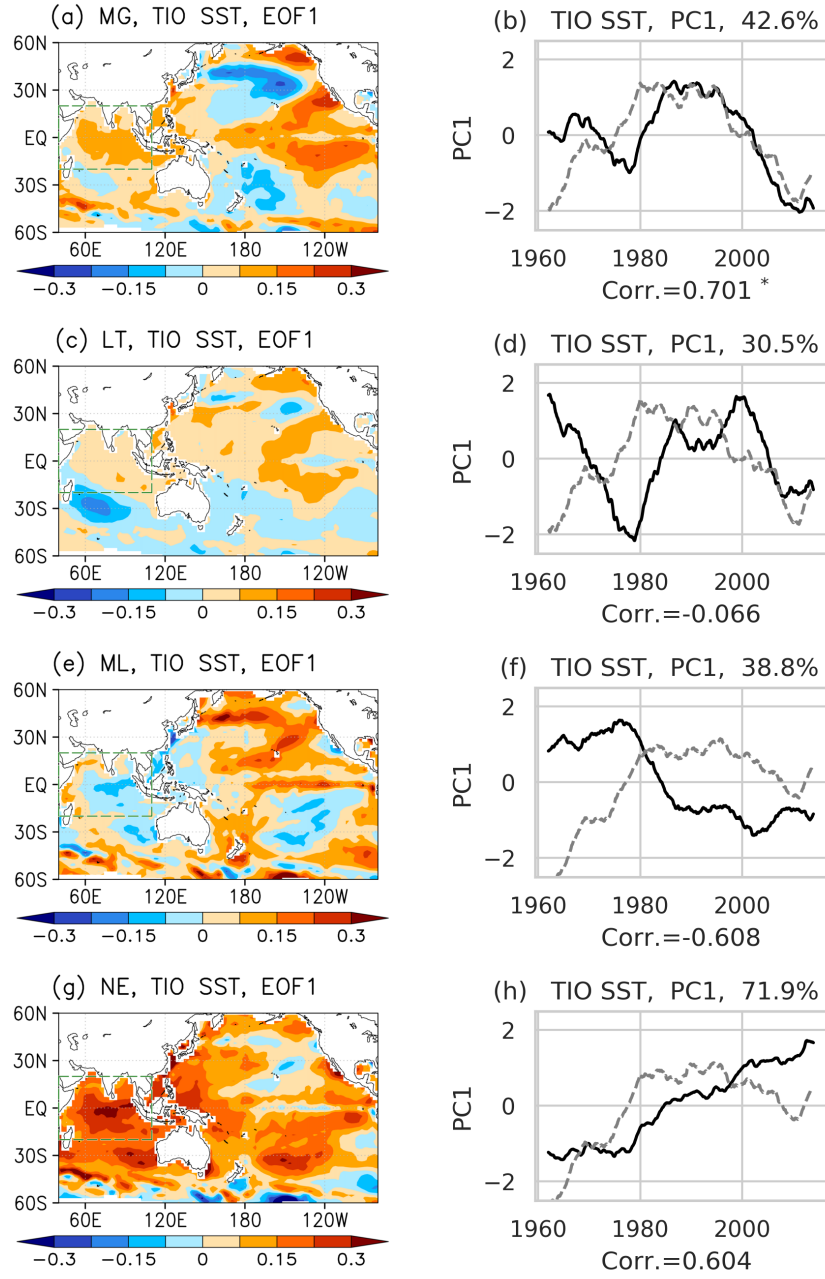


Figure 4 As for Fig. 2 but showing the SST (in K) over the tropical Indian Ocean (TIO, 40°E–110°E, 20°S–20°N). Grey dashed lines in the right panels denote the SLP PC1s over the TIO obtained by the same method. The boxes (dashed line) in the left panels enclose the TIO domain.

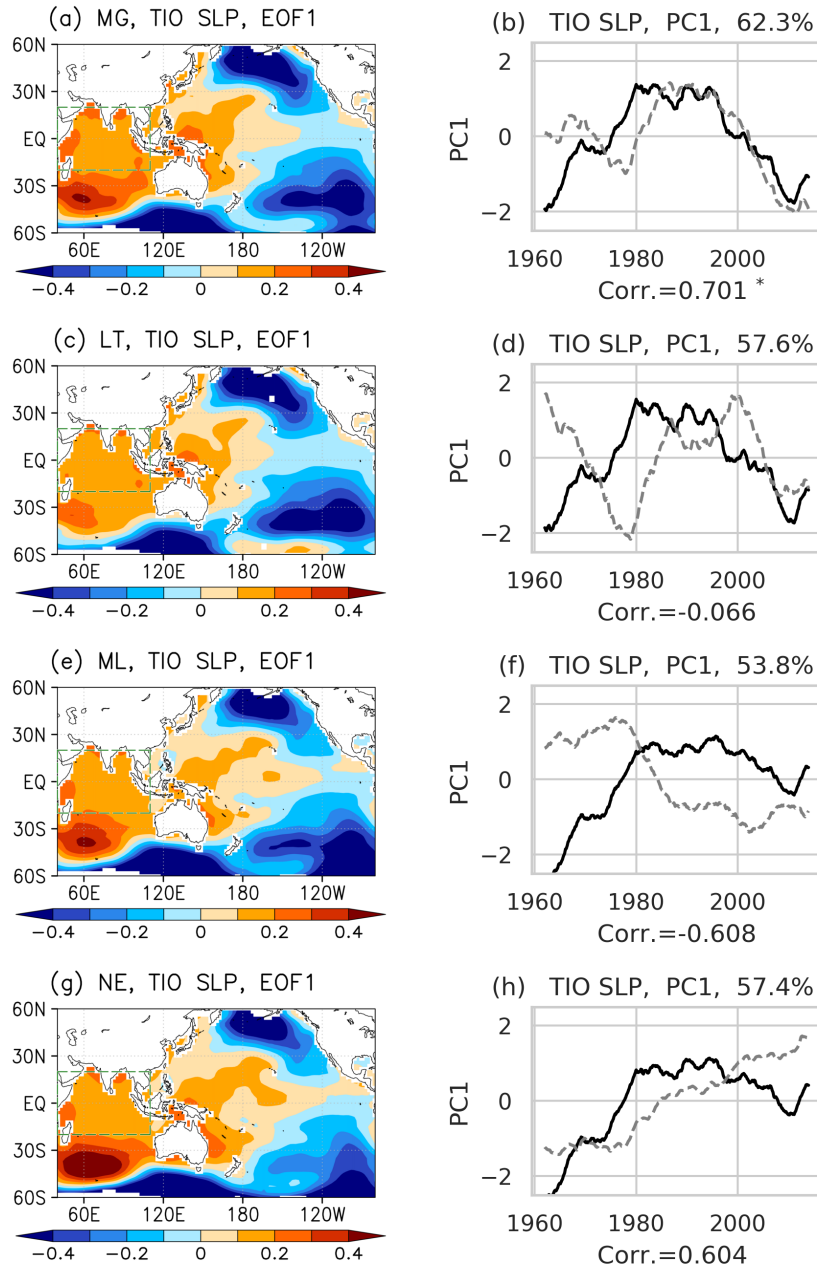


Figure 5 As for Fig. 2 but showing the SLP (in hPa) over the tropical Indian Ocean (TIO, 40°E–110°E, 20°S–20°N). Grey dashed lines in the right panels denote SST PC1s over the TIO obtained by same method. The boxes (dashed line) in the left panels enclose the TIO domain.

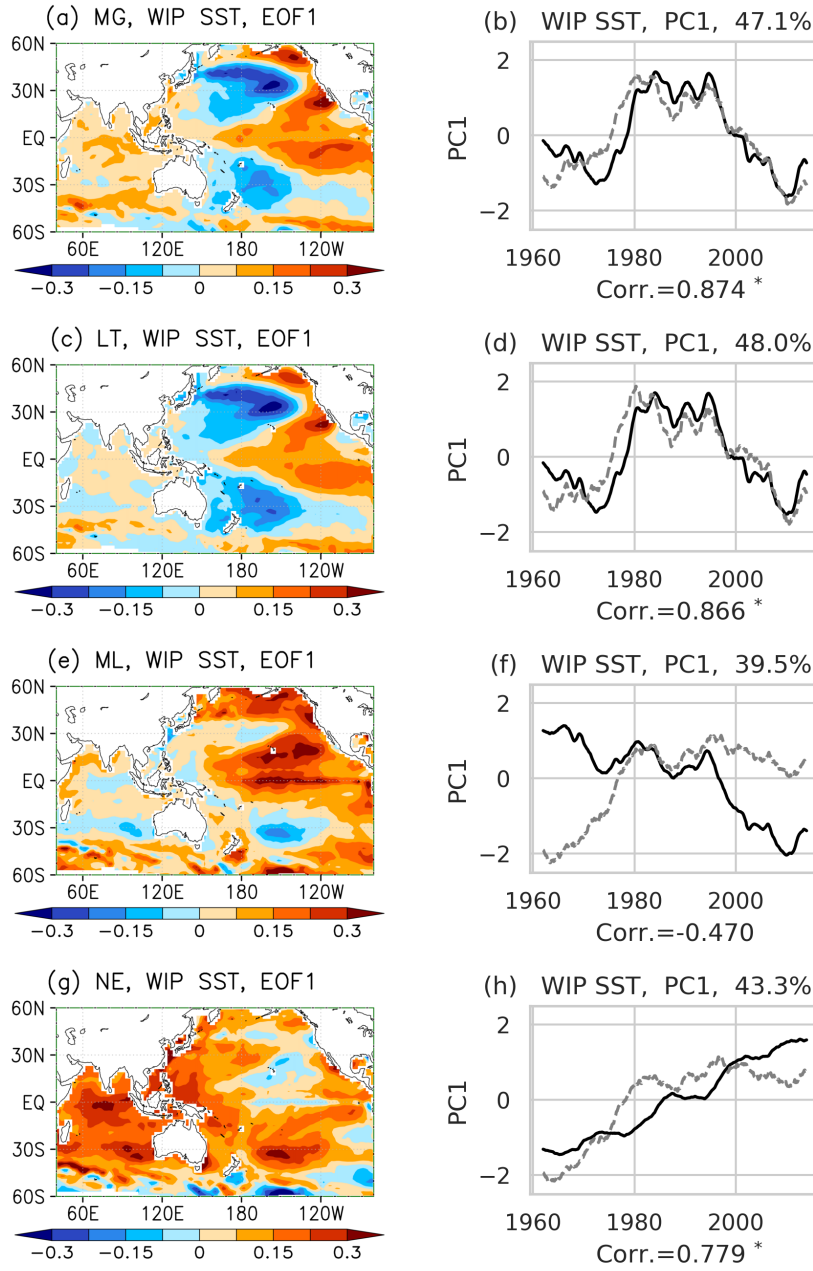


Figure 6 As for Fig. 2 but showing the SST (in K) over the whole Indo-Pacific sector (WIP, 40°E–80°W, 60°S–60°N). Grey dashed lines in the right panels denote the SLP PC1s over the WIP obtained by the same method. The boxes (dashed line) in the left panels enclose the WIP domain.

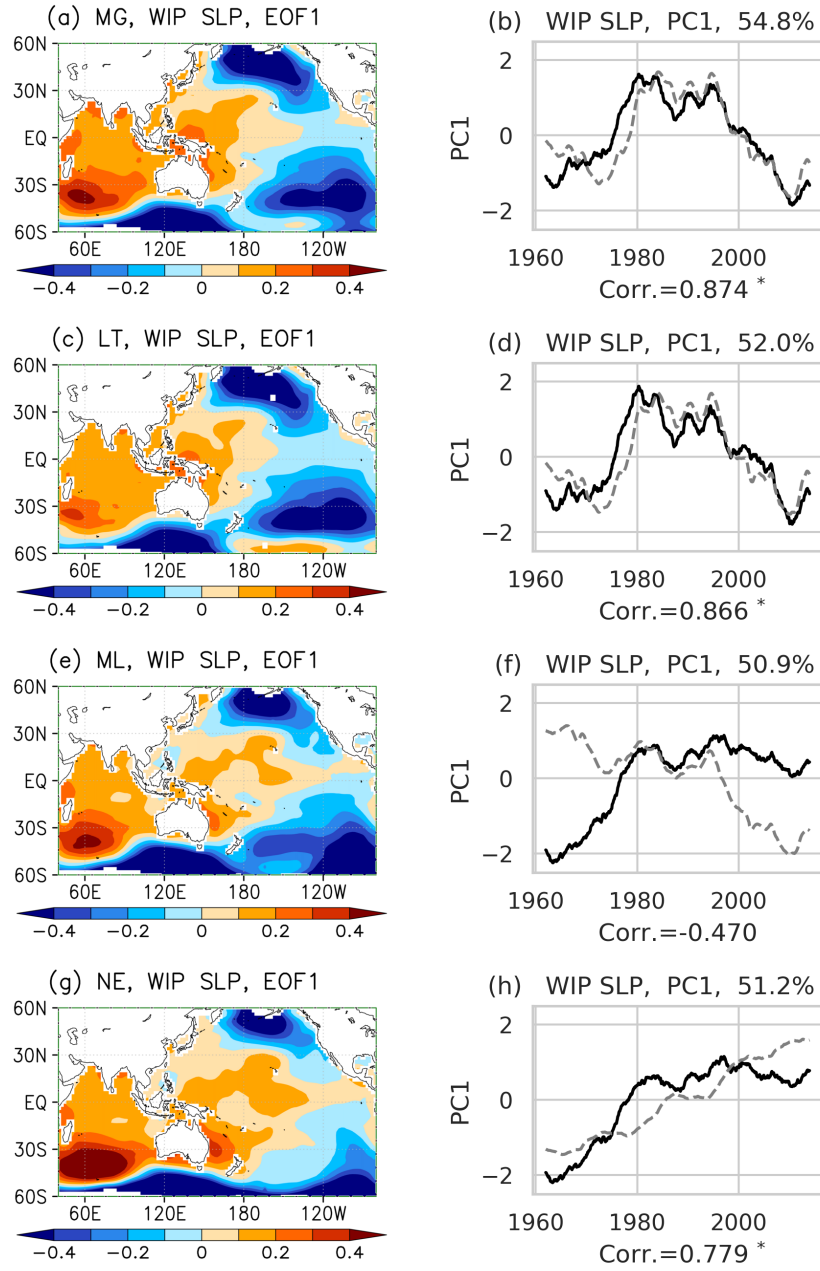


Figure 7 As for Fig. 2 but showing the SLP (in hPa) over the whole Indo-Pacific sector (WIP, 40°E–80°W, 60°S–60°N). Grey dashed lines in the right panels denote the SST PC1s over the WIP obtained by the same method. The boxes (dashed line) in the left panels enclose the WIP domain.

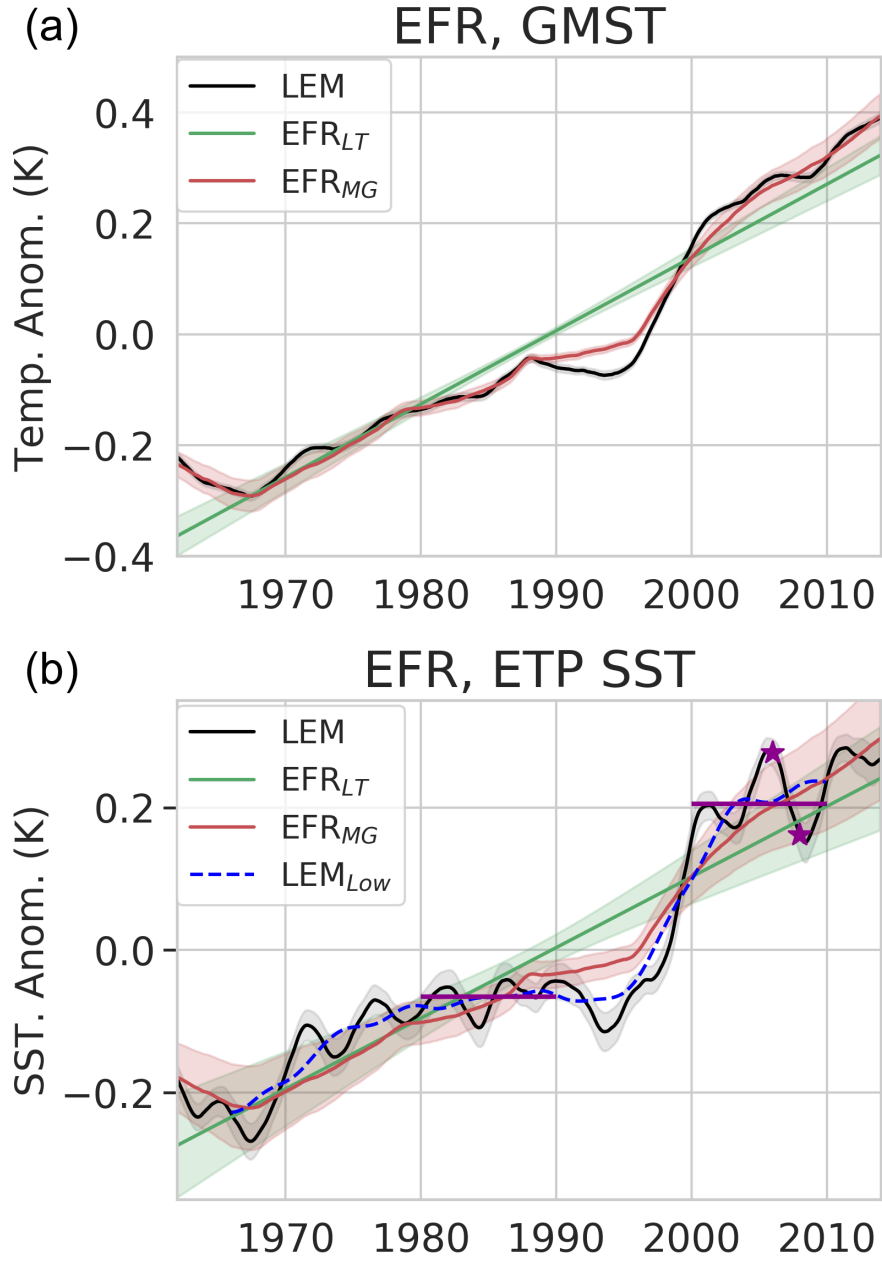
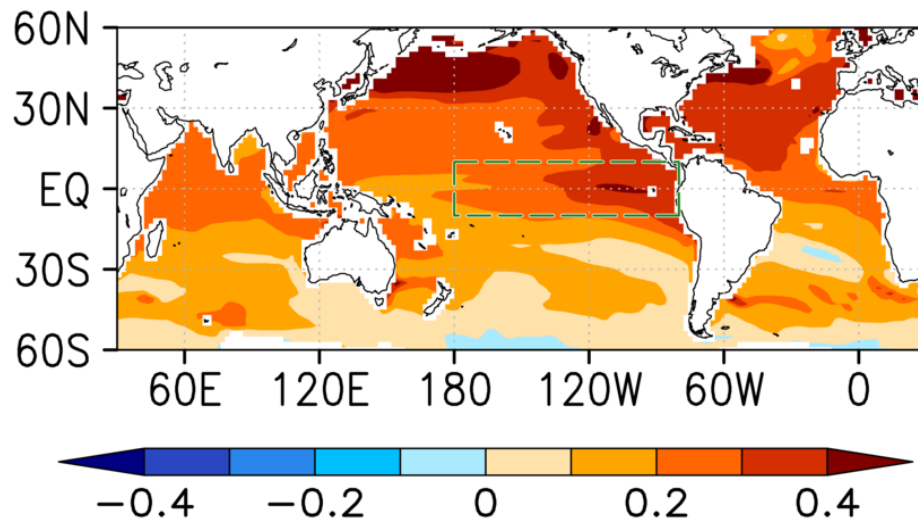


Figure 8 The time series of EFRs of (a) global mean surface temperature and (b) SST over the eastern tropical Pacific (180°W – 80°W , 10°S – 10°N). Solid lines denote large-ensemble mean (LEM, black line) and averaged EFR by MG method (red line) and LT method (green line) among 50 members. Shadings surrounding solid lines denote range of standard deviations among 50 members. In (b), long-term component of LEM time series is shown as blue dashed line. Horizontal purple lines show averaged LEM for the two periods 1980-1989 and 2000-2009, and purple stars show values of LEM in January 2006 and January 2008.

(a) SST (2000~09)–(1980~89)



(b) SST (2008JAN)–(2006JAN)

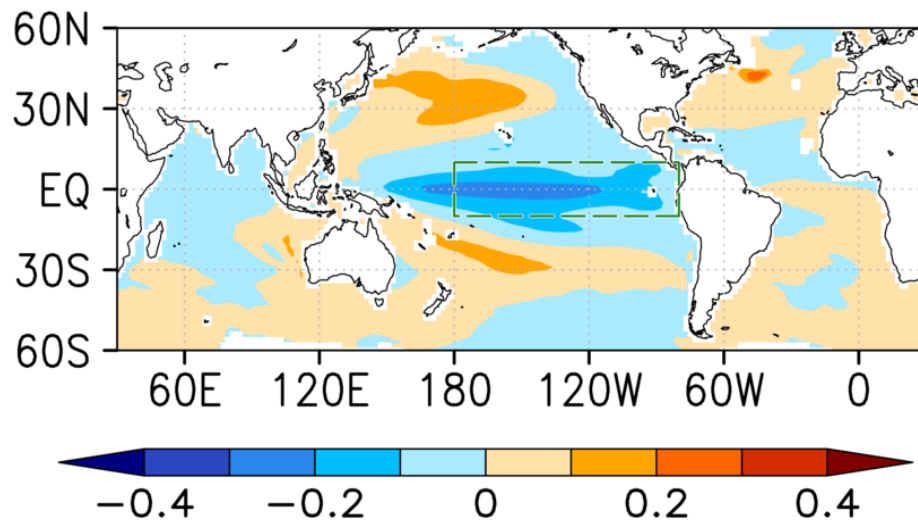


Figure 9 The spatial distribution of SST difference (a) between the two decades of 1980-1989 and 2000-2009 and (b) between two months of January 2006 and January 2008 calculated from LEM among 50 members. The green box encloses the eastern tropical Pacific (180°W–80°W, 10°S–10°N).

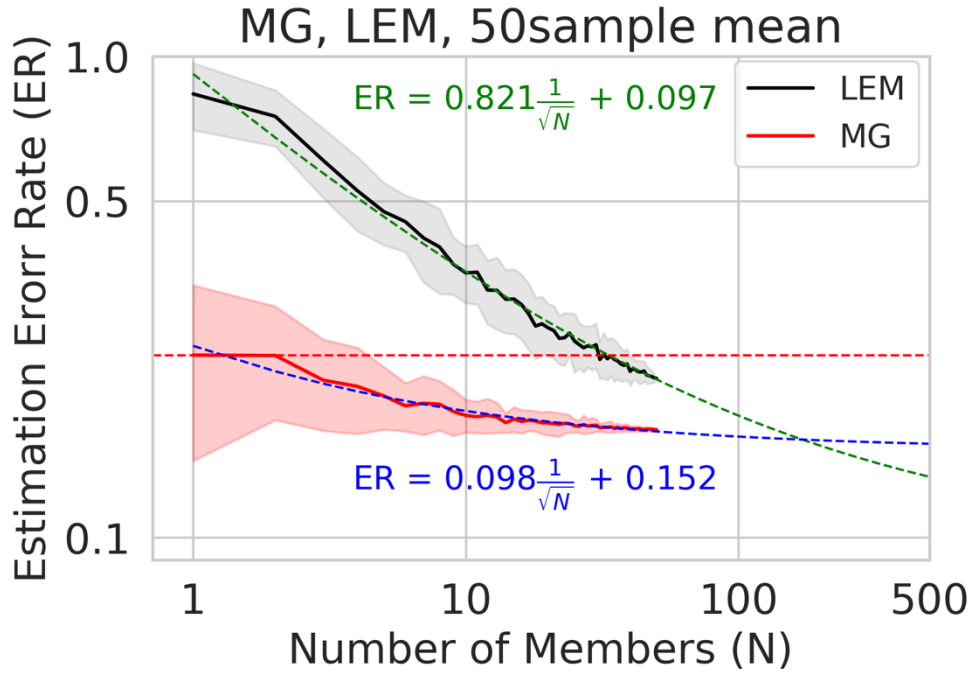


Figure 10 Root mean squared errors (RMSEs) of the the LEM (black line) and EFR estimated by MG method (red line) with reference to the long-term component of the LEM for ETP SST as a function of numbers of averaged members. From 50 times resampling, the solid line shows the mean value, and the shadow shows the standard error. The value on the vertical axis shows the ratio of each RMSE to the standard deviation of the ICVs contained in the ETP SST as ER. Approximate curves for ER of LEM and ER of MG method are shown by green and blue dotted lines. Red dotted line denotes the mean ER of MG method for one member.

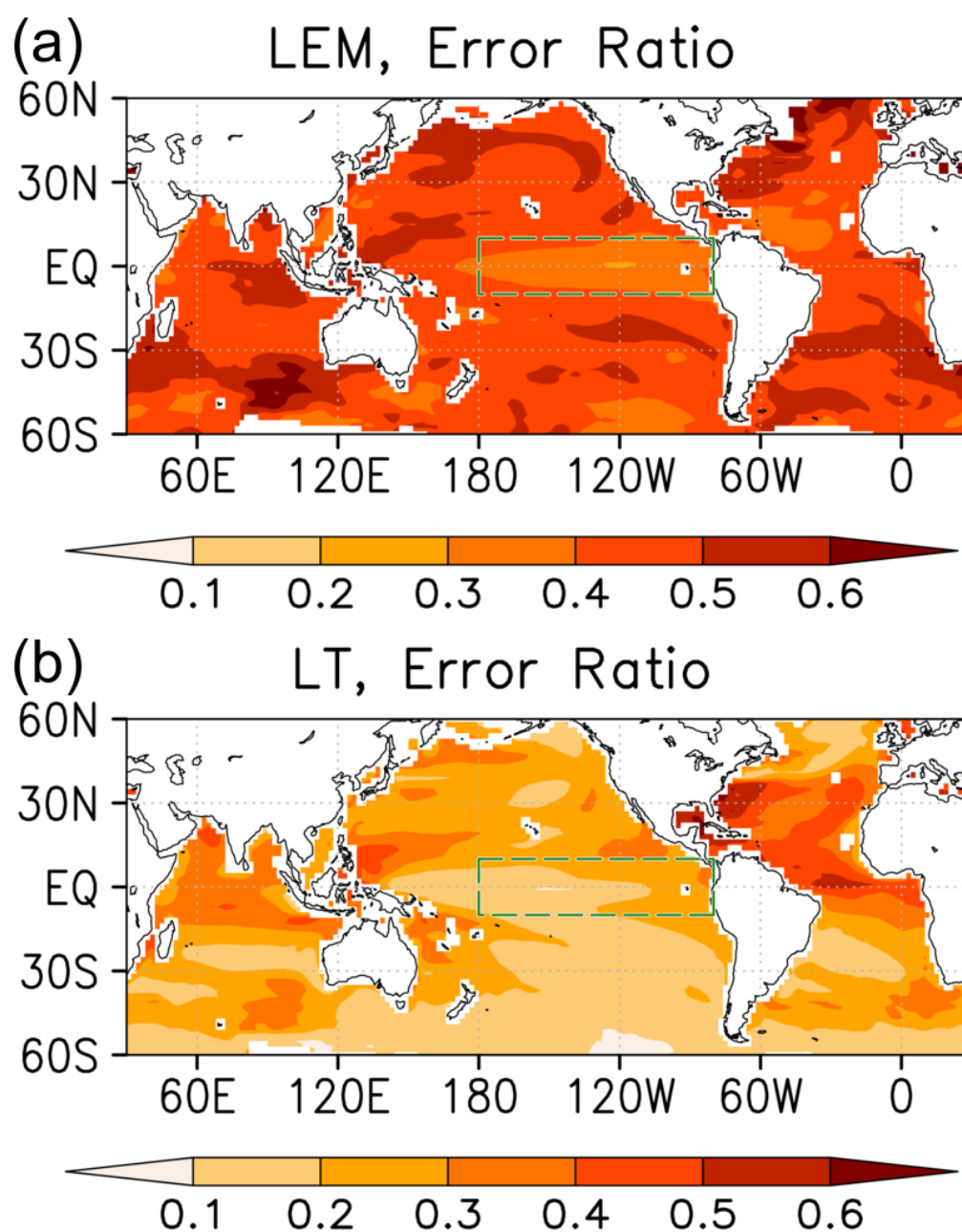


Figure 11 The estimation error ratio (ER) of SST in (a) LEM and (b) LT method to the standard deviation of ICV, with reference to the 50-member mean of the EFR estimated by MG method. The green box encloses the eastern tropical Pacific (180°W – 80°W , 10°S – 10°N).

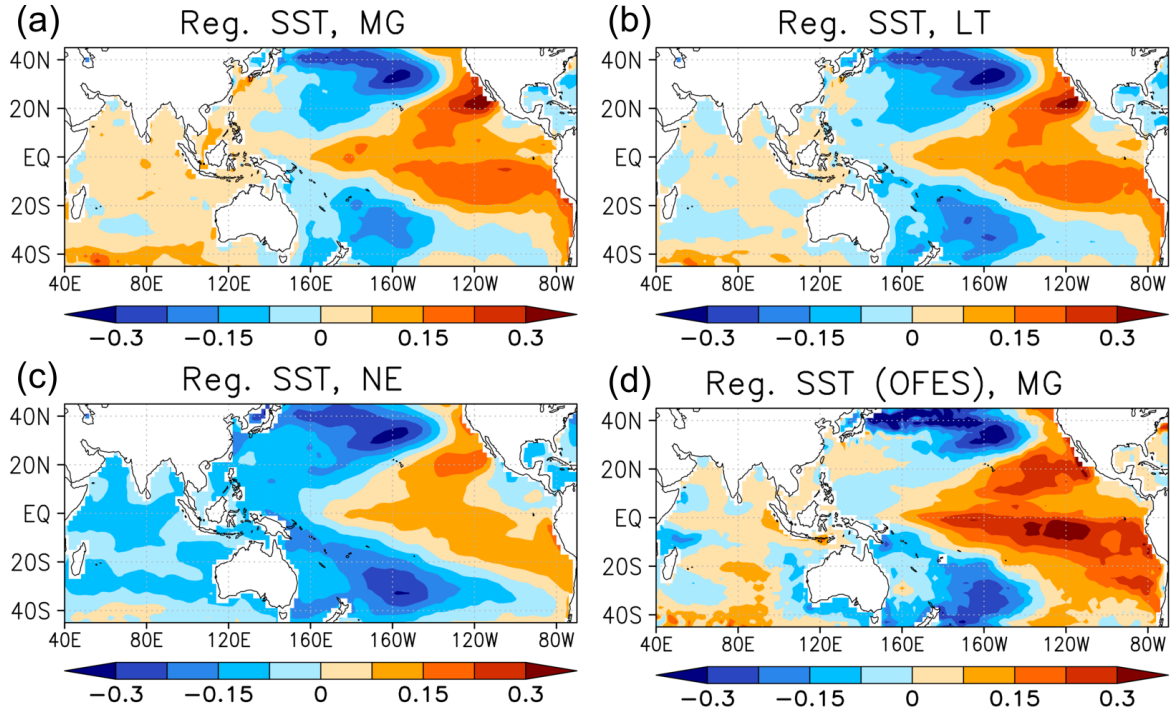


Figure 12 Spatial patterns of regressed SST (in K) onto the IPO index. (a-c) show averaged regression coefficients among three observational data calculated from (a) ICV extracted by MG method, (b) ICV extracted by LT method, (c) NE. In (d), regression coefficients are calculated from ICV extracted from OFES data by MG method.

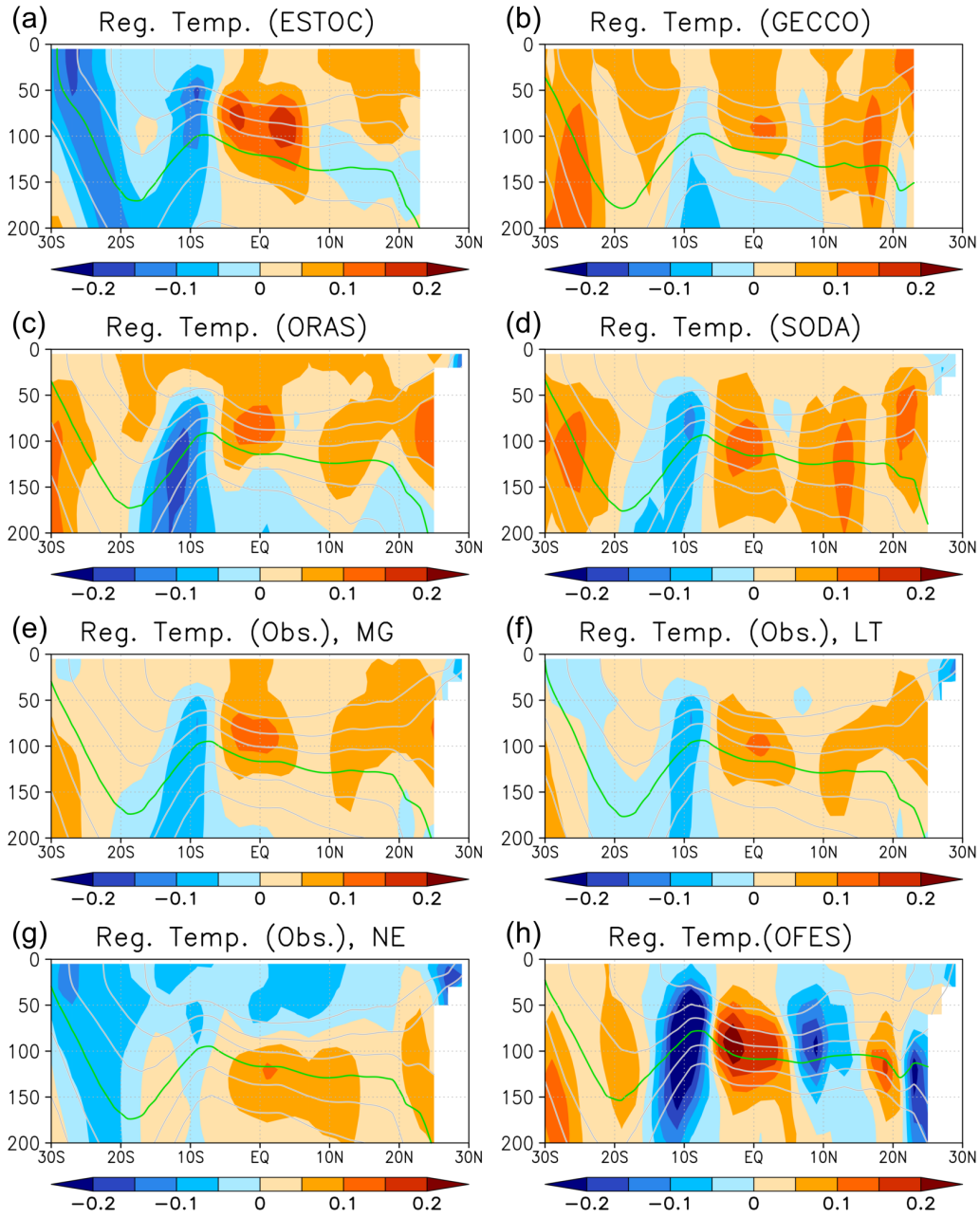


Figure 13 Latitude-depth section of regressed temperatures (in K) onto the IPO index, which are averaged in 40°E-100°E. (a-d) are calculated from four different ocean reanalysis data sets and (h) are calculated from OFES hindcast data, which are averaged in 40°E-100°E. (e-g) shows averaged regression coefficients among four ocean reanalysis data. (a-e) and (h) are based on the ICVs extracted by MG method. (f) is based on the ICV extracted by LT method, and (g) is based on NE. Annual mean temperatures are shown as contour. Contour interval is 2°C. Green contours are 20°C isotherms.

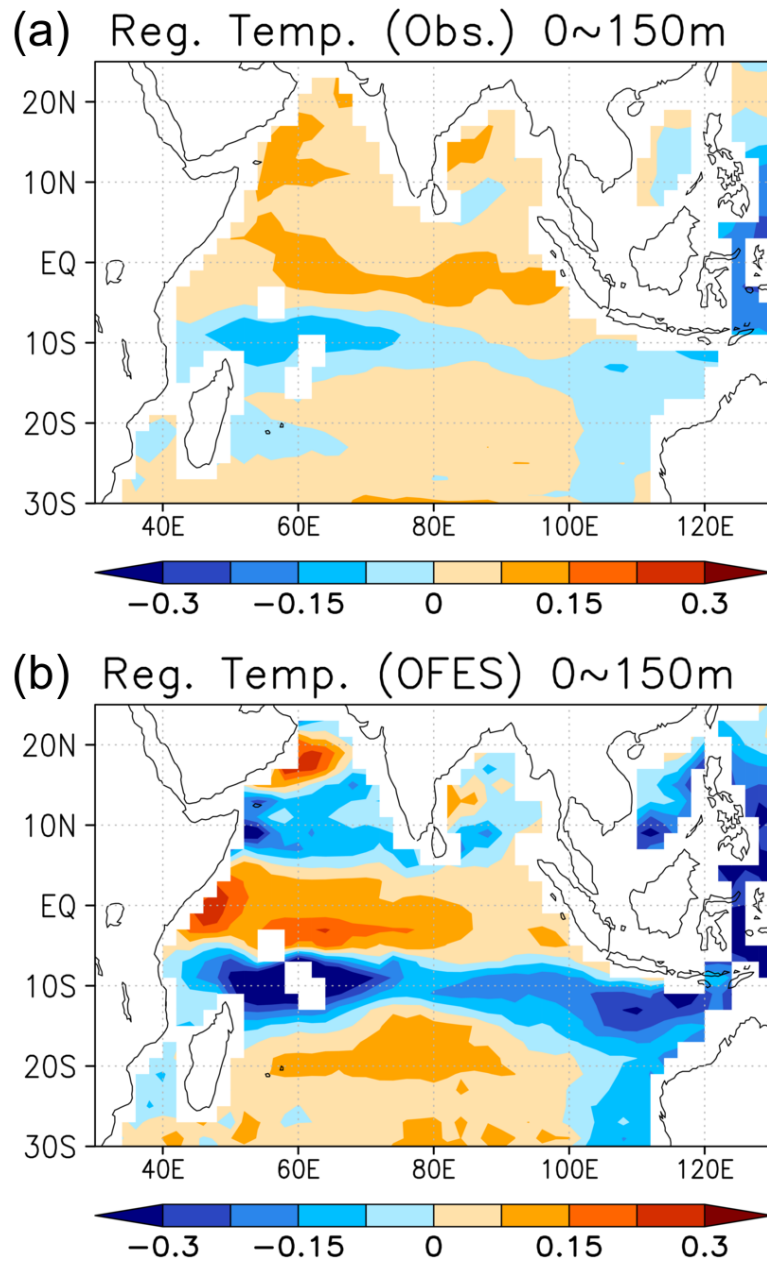


Figure 14 Spatial patterns regression coefficients of averaged temperatures (in K) in 0-150m depth onto the IPO index. (a) is the average among four ocean reanalysis data sets, and (b) is calculated from OFES hindcast.

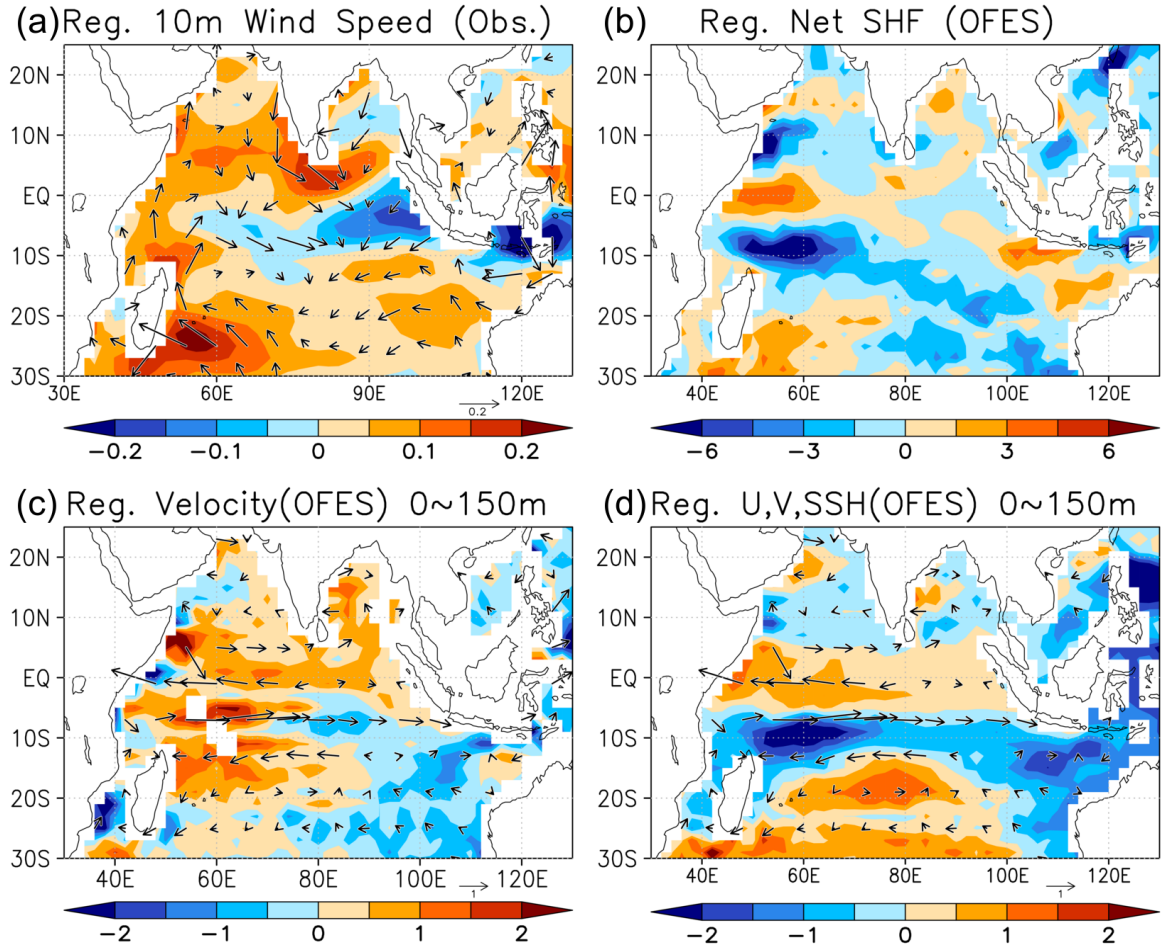


Figure 15 Regression coefficients onto the IPO index of (a) 10m scalar wind speed (in m s^{-1}), (b) net surface heat flux (in W m^{-2}), (c) averaged scalar velocity (in cm s^{-1}) in 0-150m depth and (d) SSH (in cm). (a)Average of the three atmospheric reanalysis data sets. (b)-(d)Results from the OFES hindcast. Zonal and meridional components (vectors) are shown in (a), (c) and (d). The positive (negative) value of surface heat fluxes means upward (downward) flux anomaly.

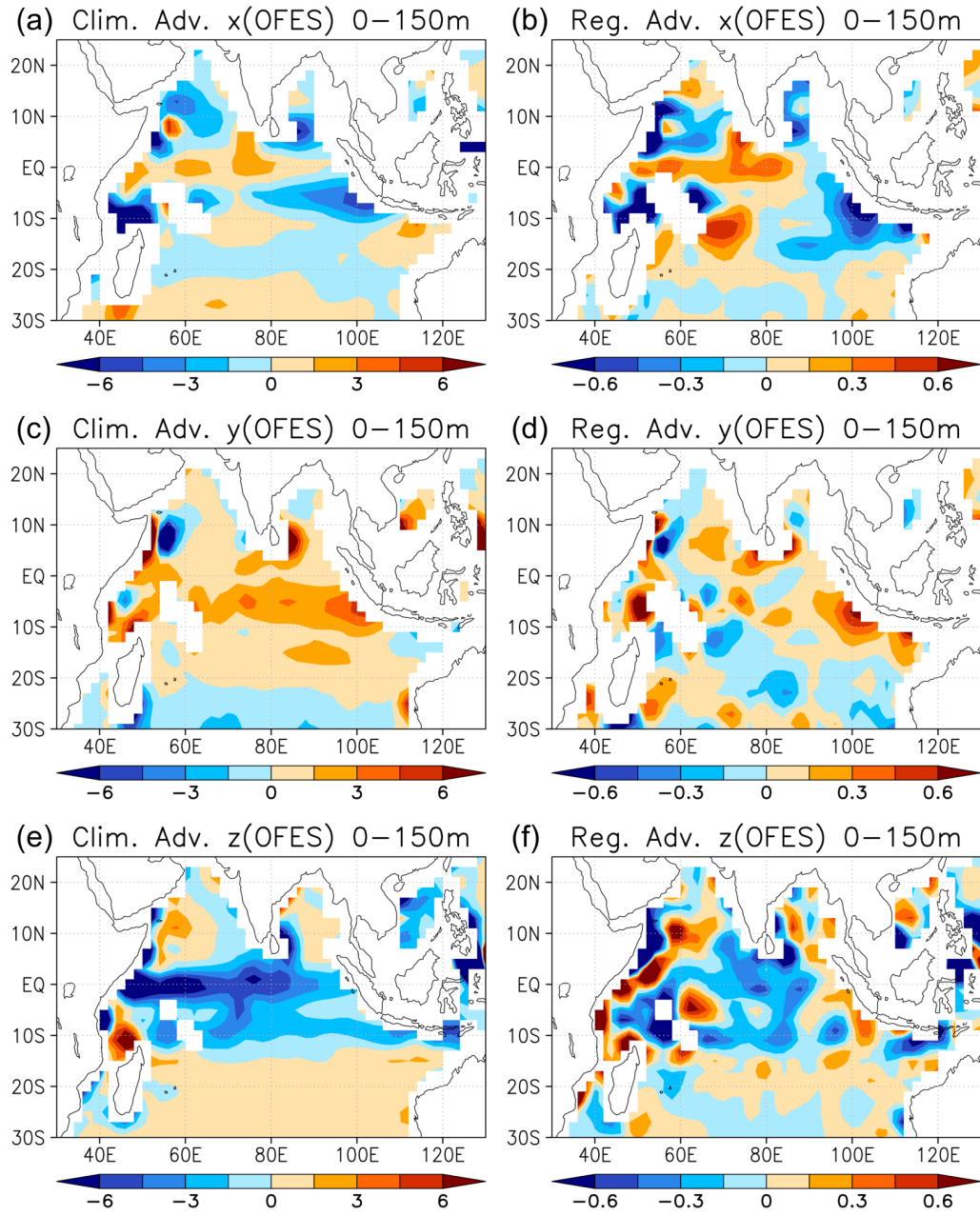


Figure 16 Regression coefficients onto the IPO index (right panels) and climatological mean state (left panels) of (a), (b) zonal temperature advection, (c), (d) meridional temperature advection and (e), (f) vertical temperature advection from the OFES hindcast. Units are K year^{-1} . Each result is averaged in 0-150m depth.

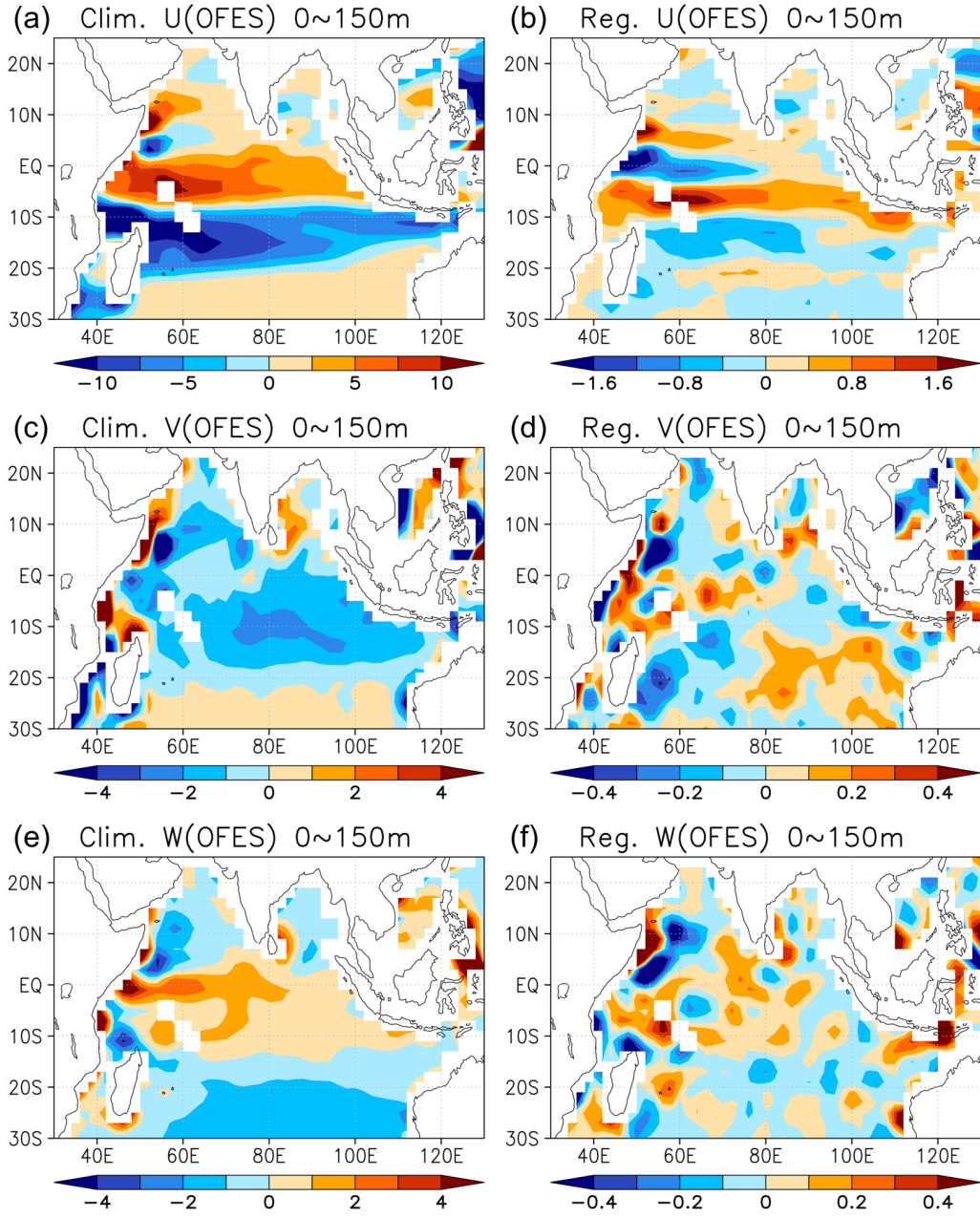


Figure 17 Regression coefficients onto the IPO index (right panels) and climatological mean state (left panels) of (a),(b)zonal velocity, (c),(d)meridional velocity and (e),(f)vertical velocity from the OFES hindcast. Units are cm s⁻¹ for (a)-(d), 10⁻⁴ cm s⁻¹ for (e) and (f). Each result is averaged in 0-150m depth.

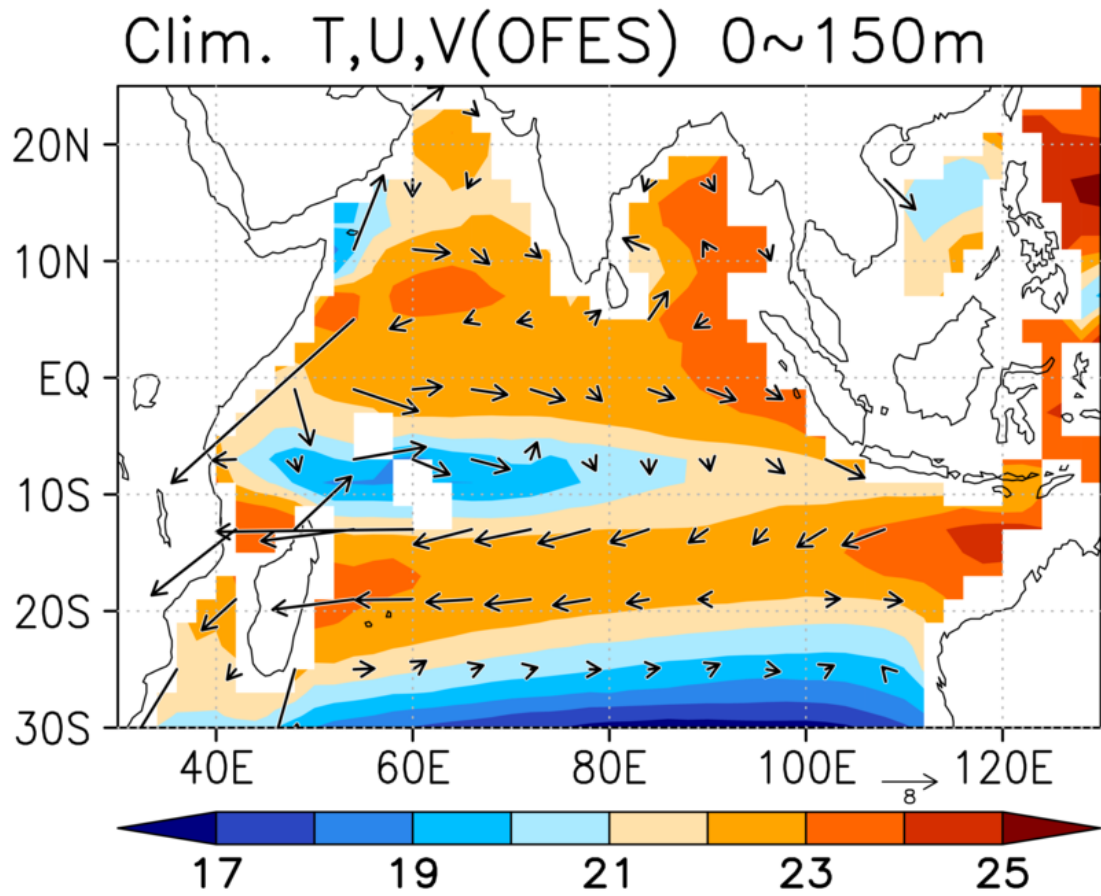


Figure 18 Climatological mean state of averaged temperature (shade, in $^{\circ}\text{C}$) and averaged horizontal velocity (vector, in cm s^{-1}) in 0-150m depth from the OFES hindcast.

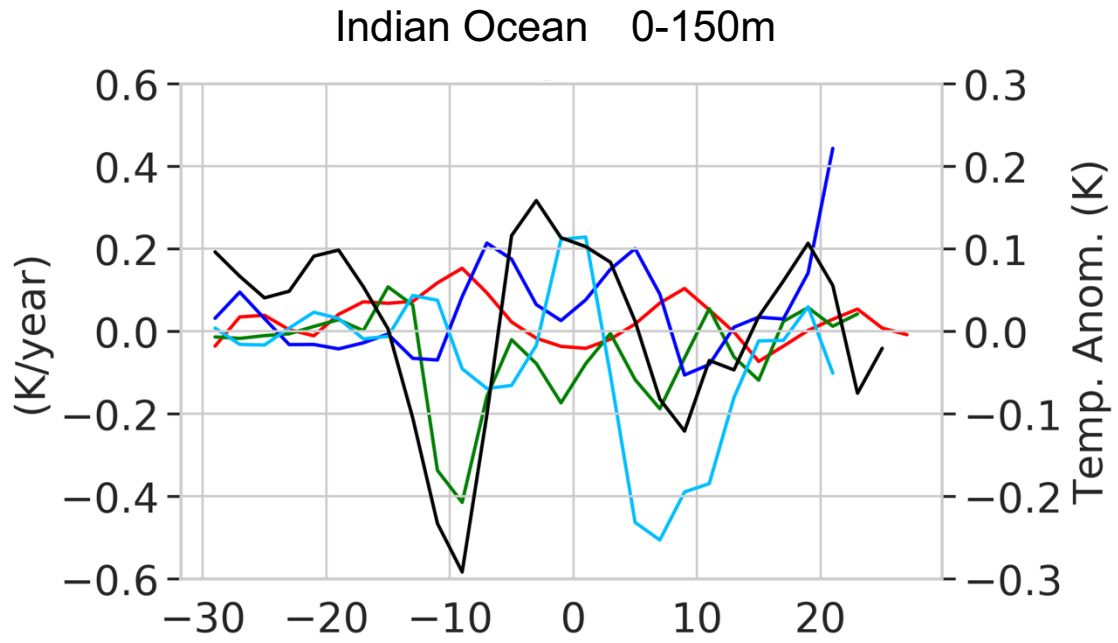


Figure 19 The zonal- and depth-mean regression coefficients of temperature (black, right axis), effect of horizontal temperature advection (light blue, left axis), meridional temperature advection (blue, left axis), vertical temperature advection (green, left axis) and SHF (red, left axis) onto the IPO index for 0-150m depth of the Indian Ocean (50°E-100°E).

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