**Decadal Variation of Predictability of the Indian Ocean Dipole during 1880–2017 Using an Ensemble Prediction System**

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**ABSTRACT:** In this study, we investigate both the decadal variation of the Indian Ocean dipole (IOD) prediction skill and possible sources of this decadal variation. We use an ensemble long-term retrospective forecast experiment covering 1880–2017 that utilizes the Community Earth System Model (CESM). We find that the decadal variation of the IOD prediction skill is significant and that it varies with the lead time. We also find that the decadal variation of the IOD prediction skill for the target season of boreal autumn determines that for all initial conditions, regardless of the lead months. For short lead times, the decadal variations of the IOD strength and of the IOD precursor in the initial month of July are the major factors influencing the IOD prediction skill. This occurs because the IOD events are in the developmental phase, and the stronger IOD signal in the initial conditions leads to better predictions. For long lead times, the decadal variation of remote forcing by El Niño–Southern Oscillation (ENSO) and the ENSO precursor signal in the IOD influence the IOD prediction skill more significantly than the strengths of the ENSO or the IOD. In addition, the analysis also indicated that the period with a low ENSO–IOD relationship has low predictability, not only because the ENSO little influence on IOD but also because the model biasedly overestimates the ENSO–IOD relationship.

**SIGNIFICANCE STATEMENT:** The Indian Ocean dipole (IOD) has strong climatic effects, both around the Indian Ocean and globally, which have strong impacts on human life and economic development. It is important to be able to predict IOD events accurately to mitigate those impacts. Here, we conducted a 138-yr prediction experiment using a state-of-the-art climate model to confirm the existence of a decadal variation in IOD predictability and to identify factors that influence the IOD prediction skill. The most important factors that influence the decadal variation of IOD prediction skill differ for 3-month and 6-month lead times, and additional studies will be necessary to clarify the specific factors responsible for these differences.

**KEYWORDS:** Forecast verification/skill; Hindcasts; Decadal variability; Indian Ocean

1. **Introduction**

The Indian Ocean dipole (IOD) is the strongest interannual climate variation in the boreal autumn in the Indian Ocean (Saji et al. 1999). The major feature of the IOD is the gradient of the sea surface temperature anomaly (SSTA) between the equatorial western Indian Ocean (WO) 50°–70°E, 10°S–10°N and the southeastern Indian Ocean (EIO) 90°–110°E, 10°S–0°N (Saji and Yamagata 2003a; Saji et al. 1999). Through the atmospheric bridge, the IOD has strong climate impacts not only around the Indian Ocean but also all over the world, including southern China, Europe, and North and South America (Ashok and Saji 2007; Black 2005; Jourdain et al. 2013; Saji and Yamagata 2003b; Xiao et al. 2015; Xie et al. 2009). The strongest positive IOD event in the satellite era occurred in late 2019, and it is considered to be the major factor affecting the extreme Australian drought in 2019 (Zhang et al. 2021) and the enhanced mei-yu rainfall in early summer 2020 (Takaya et al. 2020), both of which impacted human life and hindered economic development. Thus, it is important to predict IOD events accurately in order to provide a basis for action by the decision-making departments.

The current IOD prediction skill extends about one season ahead with the anomaly correlation coefficient (ACC) of 0.5 (Liu et al. 2017; Luo et al. 2005 2007; Shi et al. 2012; Wu and Tang 2019; Zhao and Hendon 2009). However, several studies have shown that the upper limit of the IOD prediction skill—as measured by the potential predictability of the IOD—is much higher than the actual prediction skill (Liu et al. 2017; Wu and Tang 2019), suggesting a large scope for improvement in IOD prediction.

To determine the possible factors and mechanisms that influence the actual prediction skill, a widely used strategy is to conduct retrospective forecast experiments using a dynamic model (Chen et al. 2004; Deng and Tang 2009; Song et al. 2018a; Tang et al. 2008; Zheng et al. 2016). For IOD predictability studies, retrospective forecast experiments performed using coupled general circulation models (CGCMs) usually

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cover periods of about 40 years because of the lack of long-term observations and huge computation costs (Liu et al. 2017; Luo et al. 2007; Shi et al. 2012; Wu and Tang 2019). This relatively short period contains only a few IOD cycles, which are insufficient to yield statistically robust conclusions about IOD predictability. Song et al. (2018a) first used a tropical intermediate-coupled model (TICM; Song et al. 2018b) to perform a 136-yr retrospective forecast experiment from 1881 to 2016. They found that the decadal variation of IOD predictability is significant and that the signal induced by El Niño–Southern Oscillation (ENSO) in the Indian Ocean plays an important role in modulating IOD predictability.

However, previous studies have shown that the IOD prediction skill varies from model to model (Liu et al. 2017; Wu and Tang 2019). Thus, it is challenging to determine whether the features and impact factors of IOD predictability derived from the TICM—a highly simplified coupled model—are consistent with those obtained from other complex coupled models. In other words, are the decadal variations of IOD predictability and the mechanisms influencing the IOD predictability model dependent? Recently, we completed a long-term ensemble retrospective forecast experiment using the Community Earth System Model (CESM) from 1880 to 2017 and investigated the general features of IOD predictability (Song et al. 2022b). In this paper, we examine the decadal variation of IOD predictability in this ensemble-forecast product, and investigate the factors that may influence IOD predictability. We consider two main questions: 1) Does the decadal variation of IOD predictability appear in this ensemble-forecast system? 2) What causes the decadal variation of IOD predictability, and how does it influence this variation?

This paper is organized as follows: section 2 briefly describes the construction of this long-term ensemble retrospective forecast experiment. Section 3 considers the features of the decadal variation of IOD prediction skill in this retrospective forecast. Section 4 discusses mechanisms that may be responsible for the decadal variation of IOD predictability for different lead times. Our conclusions and some discussions are presented in section 5.

2. Long-term ensemble retrospective forecast

The model used in this paper is the CESM version 1.2.1, which was developed by the National Center for Atmosphere Research. The CESM supports various component sets with different resolutions and configurations. The oceanic component used in this paper is the Parallel Ocean Program 2 (POP2) model, which has a horizontal resolution of about 1.1° × (0.54°–1°). There are 60 layers in the vertical direction, with 33 layers in the top 500 m. The atmospheric component is the Community Atmosphere Model 4, which has a horizontal resolution of 0.9° × 1.25° and a 26-layer hybrid sigma-pressure vertical coordinate. Other components include the land model CLM (Community Land Model), the sea ice model CICE (the Los Alamos National Laboratory Sea Ice Model), the land-ice model CISM (Community Ice Sheet Model), and the river model RTM (River Transport Model). Previous studies show that this configuration can represent well the major feature of IOD events, including the period, phase locking, and amplitude (Yao et al. 2016).

To construct a long-term ensemble retrospective forecast, we used a nudging method to incorporate the reanalysis datasets of the ocean temperature and low-level wind components into the model for prediction initialization. For the oceanic component, the nudging coefficient for the ocean temperature varies with depth from about (10 days)⁻¹ at the surface to about (140 days)⁻¹ at 500 m (the 33rd layer). The nudging coefficients for the wind components are uniformly (6 h⁻¹) below 500 hPa and 0 above 500 hPa. More details of this nudging scheme can be found in Song et al. (2022a).

Considering the different timespans of the reanalysis data, we used two different sets of oceanic and atmospheric reanalysis data to construct the long-term retrospective forecast. For 1880–1982, we used the monthly ocean temperatures from the Simple Ocean Data Assimilation, version 2.2.4 (SODA 2.2.4) (Carton and Giese 2008) and the wind components from the ERA-20C dataset (Stickler et al. 2014), whereas for 1983–2017 we used the ocean temperatures from the Global Ocean Data Assimilation System (GODAS; Behringer and Xue 2004) and the wind components from the ERA-interim dataset (Berrisford et al. 2011). In addition, we used the sea level pressure anomalies (SLPA) from ERA-20C and ERA-interim to investigate the possible sources of the IOD prediction skills.

We used the climatically relevant singular-vectors method (CSV) (Tang et al. 2006) to generate an ensemble prediction with a total of 20 members. The CSV modes describe the fastest-growing modes of the errors, and they are obtained by perturbing the ocean temperatures of the upper 200 m of the tropical oceans (30°S–30°N) on the first days of January, April, July, and October for each year. We found that the leading CSV spatial patterns are not very sensitive to the initial conditions, unlike the growth rate. This is consistent with earlier findings using intermediate models (Cheng et al. 2010). We used the first three CSV modes to construct the ensemble retrospective forecast, with a total of 20 members. We obtained the first six ensemble members by perturbing the initial conditions of the sea temperature above 200 m with positive and negative values of the first three CSV modes. We obtained the last 14 ensemble members by perturbing the initial conditions of the sea temperature above 200 m with a linear combination of a random number multiplied by one of the first three CSV modes.

By using the initialized method mentioned above, we first assimilated the reanalysis datasets to obtain initial conditions for the period of 1870–2017. Then we perturbed the initial conditions on 1 January, 1 April, 1 July, and 1 October, respectively, to conduct 20-member ensemble predictions from 1880 to 2017. All ensemble retrospective forecasts were run for 12 months.

The anomalies were calculated by subtracting the corresponding climatology of the running 20-yr window at each lead month. In this paper, the predicted ensemble mean is investigated. Following Zhao and Hendon (2009), we defined a lead time of one month as a forecast initialized on the first day of the given month that is valid for that month.

We adopted several common indices to represent the ENSO and the IOD. For the ENSO, we used the Niño-3
index, which is the surface temperature anomaly averaged over the eastern Pacific (150°–90°W, 5°S–5°N). For the IOD, we used the dipole-mode index (DMI), which is defined as the difference between the WIO and EIO (Saji et al. 1999). The correlation and regression methods are used to investigate the relationship between the decadal variation of IOD prediction skill and its possible sources. However, neither the decadal variation of IOD prediction skill nor its possible sources are completely independent in time. Thus, the persistent effect should be considered for statistically significant tests (Trenberth 1984; Bretherton et al. 1999). In this paper, we adopted the effective degrees of freedom mentioned in Bretherton et al. (1999) and Zheng et al. (2016) for significance tests:

$$T_{XY}^* = \frac{T}{\sum_{r=(T-1)}^{T-1} \left(1 - \frac{|r|}{T}\right) \rho_X^r \rho_Y^r},$$

where $X$ and $Y$ are the time series used calculating the correlation, and $\rho_X^r$ and $\rho_Y^r$ are the corresponding autocorrelation at time $\tau$, $T$ is the unadjusted degrees of freedom, while $T_{XY}^*$ is the effective degrees of freedom used in significant tests (Zheng et al. 2016).

3. Decadal variation of IOD prediction skill

We first calculated the IOD prediction skill for all 138 years (the black lines in Fig. 1). If a skillful prediction is defined as one with an ACC larger than 0.5 (Liu et al. 2017), then the IOD can be predicted skillfully about one season ahead. If the prediction skill is evaluated based on a shorter period of 1982–2010, the ACC can reach 0.54 at a 4-month lead time (not shown). This prediction skill of IOD is comparable with some state-of-the-art models in the North American Multimodel Ensemble (Kirtman et al. 2014; Wu and Tang 2019), suggesting a reliable hindcast product for studying the IOD predictability.

Figure 1 also shows the IOD prediction skills for seven consecutive 20-yr windows in this 138-yr period, and it shows that the IOD prediction skill varies from decade to decade. For example, the lead time for a skillful IOD prediction for the period 1940–59 is less than 2 months, whereas for the period 1980–90 a skillful prediction can be made 5 months ahead. Thus, consistent with previous results obtained using the intermediate-coupled model (Song et al. 2018a), the IOD prediction skill has a significant decadal variation in the CESM. The decadal variation of the normalized root-mean-square error (NRMSE) resembles that of the ACC (Fig. 1b). In the remainder of this study, we, therefore, use only the ACC as the measure of prediction skill.

Figure 2 shows the decadal variation of the ACC for the DMI index using a running 20-yr window for 3- and 6-month lead times. For the 3-month lead time, the ACC between the observed and forecast DMI index is relatively high before the 1910s and after the 1960s, with an ACC value larger than 0.6. For the periods around the 1930s, however, the ACC is relatively low (smaller than 0.3). The ACC difference between the high- and low-predictability periods is thus as large as 0.3. For the 6-month lead time, the decadal variation of the ACC is similar to that of the 3-month lead in some periods, such as the low-predictability period of the 1930s and with high predictability before the 1900s. However, after the 1970s, the ACC for the 6-month lead decays from almost 0.5 in the 1970s to near 0.3 in the 2000s; in contrast, the ACC continues to increase for the 3-month lead. The correlation coefficient between the ACC decadal variation for the 3- and 6-month lead times after the 1970s is only −0.29, which does not exceed the confidence level of 90%. This suggests a significant difference in the ACC decadal variation between the 3- and 6-month lead times. The difference in the ACC decadal variation between these two lead times implies that the factors that influence the decadal variation of the IOD prediction skill at different lead times may be different.
We further calculated the decadal variations of the ACC for the target season SON (September–November) for 3- and 6-month lead times (the red lines in Fig. 2). For the 3-month lead time, the predictions were initialized in July, whereas for the 6-month lead time the predictions were initialized in April. They show that the decadal variation of the IOD prediction skill for the boreal autumn target season is consistent with that for all initial conditions. The correlation coefficients are as high as 0.89 and 0.91 for the 3- and 6-month lead times, respectively. For 3- and 6-month lead times, the decadal variations of the IOD prediction skill for the SON target are also different, which is similar to the case for all initial conditions. We also examined the decadal variation of prediction skills for other seasons. The results show that the target season SON has the largest decadal variation in prediction skill, with the features very consistent with that in the ACC of all initial conditions in Fig. 2. Thus, we conclude that the decadal variation of the IOD prediction skill is dominated by the SON prediction skill.

4. Sources of the decadal variation of IOD prediction skills

To investigate the factors that influence the decadal variation of the IOD prediction skill, we consider the main climate factors in the Indo-Pacific Ocean: ENSO and the IOD itself. The strength of the IOD and of ENSO is measured by the standard deviation of the DMI in the boreal autumn and the Niño-3 index in the boreal autumn. In addition, we used the correlation between the DMI for SON and the Niño-3 index for the initial conditions—July for the 3-month lead time and April for the 6-month lead time—as the precursor signal of the ENSO in IOD events. Similarly, we considered the correlation between the DMI for SON and the DMI for the initial conditions as the precursor signal for the IOD itself. Considering the difference in the decadal variation of the IOD prediction skill between the 3- and 6-month lead times discussed in section 3, in this section we explore the sources of the decadal variations at these two lead times to determine the underlying reasons for these differences.

The occurrence of IOD events also has the decadal variation. We defined a positive (negative) IOD event by the SON DMI larger (smaller) than 0.5°C (−0.5°C), and then calculated its decadal variation using a running 20-yr window. It is found that the decadal variation of the IOD occurrence (the summation of the positive and negative IOD event occurrence) is consistent with that of the IOD strength, with their correlation coefficient up to 0.76 (not shown). Namely, the IOD occurrence is equivalent to the IOD signal strength in characterizing the IOD events, both having a consistent relationship to the IOD predictability. Therefore, in this paper, we mainly focus on the effect of the decadal variation of IOD strength on the IOD prediction skill.

a. Lead 3 months

Figure 3a shows the decadal variation of the IOD prediction skill at the 3-month lead time, the IOD strength, and the
IOD precursor signal using a running 20-yr window. It shows that the decadal variations of the IOD strength and the IOD precursor signal have good relationships with that of the IOD prediction skill at the 3-month lead time, with relatively low values in the period 1930–40 and high values after the 1960s. The scatterplots of the IOD prediction skill and the IOD strength/precursor signal shown in Fig. 4a also exhibit a good linear relationship, with a correlation coefficient as high as 0.55/0.66. These correlation coefficients are significant at the 90% confidence level.

**Fig. 3.** (a) Time evolution of the decadal variation of the IOD prediction skill for 3-month lead time (black line), the strength of the IOD (red line), and the IOD precursor signal (blue line) using a 20-yr running window. (b) As in (a), but the red and blue lines here represent the strength of the ENSO and the ENSO precursor signal, respectively.

Figures 3b and 4b show the relationship between the decadal variation of the IOD prediction and the remote ENSO influence in IOD events, as represented by the strength of the ENSO and the ENSO precursor signal. Clearly, the decadal variations of the ENSO influence and those of the IOD prediction skill do not coincide with each other. The correlation coefficient between the decadal variation of the IOD prediction and the ENSO strength is only 0.53, and the corresponding correlation with the ENSO precursor signal is only 0.51,

**Fig. 4.** (a) Scatterplots of the strength of the IOD (red triangles) and of the IOD precursor signal (blue dots) against the IOD prediction skill for a 3-month lead time. (b) As in (a), but for the strength of the ENSO (red triangles) and the ENSO precursor signal (blue dots). Dotted lines represent the corresponding linear fits. The r values denote the corresponding correlation coefficients, and the r values with asterisks mean that the correlation coefficients exceed the 90% confidence level.
both insignificant at the 90% confidence level. Therefore, the influence of the ENSO on the decadal variation of the IOD prediction skill is not significant.

In summary, for a short lead time (i.e., the 3-month lead time), the decadal variations of the IOD strength and the IOD precursor signal in IOD events are important factors in the decadal variation of the IOD prediction skill. This occurs mainly because the IOD is in the developing phase in the initial month of July. Stronger IOD precursor signals in July result in stronger IOD events, which thus lead to higher IOD prediction skills.

b. Lead 6 months

For a lead time of 6 months with the initial month of April, the decadal variations of the strengths of the ENSO and the IOD—together with their precursor signals in the initial conditions, as well as the decadal variations of IOD prediction skills—are shown in Fig. 5. These plots show that the decadal variation of the IOD strength and the IOD precursor signal are both different from that of the IOD prediction skill, with few significant correlation coefficients (Fig. 6a). In particular, for the period after the 1970s, the decadal variations of IOD strength and the IOD precursor signal in the initial conditions are inversely related to the decadal variation of the IOD prediction skill. Thus, they cannot explain the decay of the IOD prediction skill for the period after the 1970s, suggesting that the local signal in the Indian Ocean has little influence on the IOD prediction skill for a 6-month lead time.

We also investigated the influence of the ENSO on the decadal variation of the IOD prediction skill. Figures 5b and 6b show the relationship between the decadal variation of the IOD prediction at the 6-month lead time and the ENSO
influence, including the ENSO strength and the ENSO precursor signal in the initial month of April. This shows that the decadal variation of the ENSO strength does not coincide with that of the IOD prediction skill. The correlation coefficient between them is only 0.43, which is insignificant at the 90% confidence level. However, the decadal variation of the ENSO precursor signal in the initial conditions is closely related to the decadal variation of the IOD prediction skill, with a correlation coefficient as high as 0.72. This is consistent with the conclusion of our previous study (Song et al. 2018a), which found that the ENSO-induced signal in the IOD—instead of the ENSO signal itself—is the main factor that influences the IOD prediction skill.

It should be noticed that we attempt to identify uniform factors that can influence the decadal variation of IOD prediction skills for the entire period. The factors considered in this work are not independent of each other. For instance, multiple factors can cause the low prediction skill in the 1940s, including the low IOD strength and the low ENSO–IOD connection. However, for the 1980s–90s, the larger IOD strength cannot fully explain the reduced IOD prediction skill. Thus, we conclude that the ENSO precursor signal, rather than the IOD strength, is a consistent factor that dominates the IOD predictability for the entire 138 years.

Since there are two poles of the IOD, it is interesting to explore the modulation of ENSO with regard to the WIO and EIO. Similar to the DMI, we used the correlation between the SON EIO (WIO) index with the Niño-3 index of the initial conditions (April) as the precursor signal, calculated using a 20-yr running window. As shown in Fig. 7, the precursor signal of ENSO–EIO has a strong negative relationship with the decadal variation of IOD prediction skill, with a correlation coefficient of −0.76. The decadal fluctuation of the precursor signal of ENSO–EIO is similar to that of the ENSO–DMI, suggesting that the modulation of ENSO on EIO is important in the ENSO–IOD relationship and has a significant impact on the IOD prediction skill. On the other hand, the role of ENSO–WIO is relatively small in explaining IOD prediction skill.

To investigate further the physical processes that affect the IOD prediction skill of 6-month leads, we chose two representative periods: 1965–85 to represent the high-prediction-skill period and 1930–50 to represent the low-prediction-skill period. Figures 8a–c show the spatial patterns of the SSTA, the subsurface temperature anomaly at 90 m (Tsub), SLPA, and wind components anomaly at 850 hPa (UV850) in the initial month of April regressed to the SON DMI index for the period 1965–85, which indicates the precursor signals of IOD events in the ocean–atmosphere system. This shows that the precursor signal in the ocean appears only in the central tropical Pacific and includes both surface and subsurface warming. In the atmosphere, the precursor signals SLPA and UV850 are significant in the Indian Ocean and western Pacific. There are high SLP anomalies in the Maritime Continent, the Australian continent,
and the Indian peninsula, and low SLP anomalies in the tropical North Pacific. The high SLP anomalies in the Maritime Continent and Australia indicate that the upwelling branch of the Walker circulation is suppressed, resulting in equatorial easterly anomalies in the tropical central Indian Ocean and westerly anomalies in the western Pacific. The persistent easterly anomalies in the tropical central Indian Ocean ultimately lead to a positive IOD event.

Figures 8d–f show the spatial patterns of the SSTA, Tsub, SLP, and UV850 in the initial month of April regressed to the April Niño-3 index to explore the response of the climate system caused by the ENSO in April. In the tropical Pacific, a Gill-type response appears, forced by the ENSO, with high anomalies in the northwest and southwest Pacific and westerly anomalies in the equatorial western Pacific. The influence of ENSO in April also extends to the Maritime Continent and the northern Indian Ocean, with high anomalies in the Indian peninsula and easterly anomalies in the tropical central Indian Ocean. This is similar to the IOD precursor signals in April (Figs. 8a–c), and this suggests that the ENSO has a significant influence on the IOD precursor signal in April through the role of the atmospheric bridge.

Figures 9a–c show the regression coefficients between the observed equatorial SSTA, Tsub, SLP, and UV850 in different calendar months and the DMI index in the boreal autumn. This shows that the IOD precursor signal first appears in February and March with the warming in the tropical Pacific, easterly anomalies in the central Indian Ocean, and suppressed Walker circulation, while the precursor signal is insignificant for the surface and subsurface of the Indian Ocean. With the development of ENSO, the easterly anomalies in the central Indian Ocean persist until the boreal summer, resulting in subsurface cooling in the eastern Indian Ocean. Finally, the IOD occurs through Bjerknes feedback in the Indian Ocean. This shows that ENSO not only influences the IOD precursor signal in the initial conditions but also plays an important role in the maintenance of the IOD precursor signal, which leads to the high IOD prediction skill.

Figures 9d–f show the regression coefficients between the predicted variables for the different calendar months initialized in April and the predicted SON DMI index, which we use to explore the source of the predicted IOD events. Although the forecast overestimates the cooling SST in the eastern Indian Ocean, it represents the coherent variation of the ENSO and the IOD in the observations, including the maintenance of the precursor signal in the atmosphere and the ocean subsurface. Thus, the predicted IOD has relatively high skill.

For the low-prediction-skill period 1930–50, neither the IOD precursor signal in the tropical Indian Ocean nor that in the tropical Pacific is significant (Figs. 10a–c). The influence of the ENSO on the Indian Ocean can be observed on the surface as an Indian-basin mode, but the easterly anomalies in response to the ENSO in the central Indian Ocean are not significant (Figs. 10d–f). This indicates that the precursor signals of IOD events in April are independent of the ENSO, which leads to the low prediction skill for this period.

During this low-prediction-skill period, the easterly anomalies in the equatorial central Indian Ocean and the subsurface cold anomalies in the eastern Indian Ocean only appear from June and July (Figs. 11a–c), and these IOD precursor signals are independent of the tropical Pacific. That is, the IOD events during this period are mostly “pure IOD” events. The triggers of these IOD events are mainly the high-frequency atmospheric and oceanic variations in the tropical Indian Ocean itself. Therefore, the relatively low IOD prediction skill for
the initial month of April in this period occurs because of the insignificant IOD precursor signals and the absence of an ENSO influence in the initial conditions.

We also performed the same analysis to explore the possible sources of forecasted IOD events in the period 1930–50 (Figs. 11d–f). It shows similar results for the high-prediction-skill period—namely, that the variation of the forecasted IOD events is coherent with the ENSO for this low-prediction-skill period. However, this is inconsistent with the observations, suggesting that the forecasted ENSO influence on the IOD is overestimated, which leads to large model biases in forecasting IOD events. Therefore, the low IOD prediction skill in this period occurs not only because of the absence of IOD precursor signals in the initial conditions but also because of model biases in the forecast model.
5. Discussion and conclusions

In this study, a long-term IOD retrospective forecast was conducted using CESM to investigate the decadal variation of the IOD prediction skill. It is found that the decadal variation of the IOD prediction skill is significant and that it varies with the lead time. For a short lead time (i.e., the 3-month lead time), the IOD prediction skill is relatively high before the 1910s and after the 1960s, with ACC larger than 0.6, and it is low in the 1930s, with ACC smaller than 0.3. For a long lead time (i.e., the 6-month lead time), the decadal variation of the IOD prediction skill is similar to that for the 3-month lead time before the 1960s, but it differs after the 1960s. Further, we found that the decadal variation of the IOD prediction skill for the target season in the boreal autumn dominates the decadal variation for all initial conditions, regardless of the lead months.

We also investigated the sources of the decadal variation of the IOD prediction skill. For predictions initialized in July with a lead time of 3 months, the decadal variations of the IOD strength and of the IOD precursor in the initial month of July have good relationships with the decadal variation of the IOD prediction skill, suggesting that the local signal strength plays an important role in the IOD prediction skill. This occurs because the IOD events usually start to develop in July when the prediction is initialized, and the local Bjerknes feedback has been established (Saji et al. 1999). Thus, the stronger IOD signal in the initial conditions leads to more predictable information and the remote forcing from the Pacific influences little (Luo et al. 2010). For predictions with a lead time of 6 months initialized in April, the decadal variation of the IOD prediction skill is controlled significantly by the ENSO precursor signal rather than by the strength of the ENSO or the IOD. This suggests that for the long lead time, remote forcing by the ENSO is more important than the local signal in determining the IOD prediction skill. Additionally, an analysis of the IOD source in the retrospective forecast shows that the forecasted IOD events are always correlated with the forecasted ENSO in the Pacific, regardless of the high or low prediction period. This implies that—for a period with a low ENSO–IOD relationship—both the absence of an ENSO influence on the IOD in the initial conditions and systematic biases in an overestimated ENSO–IOD relationship contribute to the low IOD prediction skills. Our results are consistent with previous literature that the ENSO affects the IOD prediction skill mostly for the long lead times (Luo et al. 2010; Zhao et al. 2019) and it is important to represent the realistic ENSO–IOD relationship in coupled models to achieve a reliable IOD prediction (Shi et al. 2012).

Besides the variation of IOD and ENSO, we have also examined the decadal variation of the mean state of SST in the Pacific Ocean and the Indian Ocean using a running 20-yr window. For the Pacific Ocean, the decadal variation of both the Niño-3 SSTA index and the PDO index (from https://www.ncei.noaa.gov/access/monitoring/pdo/) have insignificant relationships with that of the IOD prediction skill, with the correlation of 3-month prediction skill, against the Niño-3 SSTA index and PDO index, of 0.05 and −0.04, respectively. For the Indian Ocean, the relationship between the decadal variation of the DMI index [i.e., the mean gradient between WIO and EIO known as the decadal IOD as in Tozuka et al. (2007) and Ashok et al. (2004a)] and IOD prediction skill is also insignificant. The insignificant relationship between the SST mean state over the Indo-Pacific and the IOD predictability suggests that the decadal variation of the mean state may not be the major source of the decadal variation of IOD.
predictability. In other words, the decadal variation of the variance, rather than the mean state, influences the decadal variation of IOD predictability.

We mainly focused on the SSTA variation over the eastern Pacific, named EP El Niño. In recent decades, a new type of El Niño whose center locates in the central Pacific (CP El Niño) is active. However, the interaction between CP El Niño and IOD is more complicated. On one hand, the extreme IOD events can affect the western Pacific through Walker circulation and generate CP El Niño events (Chen 2011; Luo et al. 2010). On the other hand, some studies have suggested that the occurrence of an extreme IOD event is associated with the CP El Niño in the tropical Pacific (Wang and Wang 2014; Zhang et al. 2015), and the CP El Niño would lead to long skillful IOD prediction (Doi et al. 2020). Therefore, under the circumstance that the CP El Niño events frequently occur, more studies should be conducted to better understand the relationship between CP El Niño and IOD events.

Previous studies using an intermediate coupled model have reported that there are decadal variations of IOD prediction skills over the past century (Song et al. 2018a) and—using CGCMs—over the most recent 50 years (Liu et al. 2017). Our results show some features that are similar to those found in previous studies. For example, for short lead times, a relatively high IOD prediction skill appears before the 1910s and after the 1960s, whereas it is relatively low around the 1940s. This suggests that the decadal variations of IOD prediction skills are inherent characteristics and are independent of the models. However, there are also some different features. For example, for the period of the 1920s, the prediction skill in the CESM ensemble prediction system is lower than that in the TICM. Some factors that may be responsible for this difference include different assimilation methods, different assimilated variables, model biases in this period, and uncertainties in the reanalyzed dataset.

It is revealed that the decadal variation of the IOD prediction skill is affected by the decadal variation of the ENSO–IOD relationship. The source of decadal variation of the ENSO–IOD relationship has been investigated in several literatures, including the decadal variation of the upwelling branch of the Walker circulation over the Maritime Continent, the lower-tropospheric anomalous anticyclone over the western North Pacific, and the Indonesian throughflow (Cai et al. 2005; Yuan and Li 2008; Feng et al. 2018; Li et al. 2018). It is expected that improving the simulation ability of these processes can help coupled models better capture the ENSO–IOD relationship, thereby enhancing the IOD prediction skill.

We emphasized the effect of ENSO, the most predictable phenomenon in the tropical climate system, on the IOD predictability in this study. On the other hand, the monsoon is also an important phenomenon in the tropics. The interaction among monsoons, ENSO, and IOD is an important feature of the tropical climate system, and they impact one another (Ashok et al. 2001, 2004b; Ashok and Saji 2007; Krishnamurthy and Goswami 2000). Most studies, however, have focused on the effects of IOD on monsoon, and how the monsoon in turn impacts the IOD, and in particular IOD prediction, is still unclear. Simulating and predicting monsoons is also a big challenge for current state-of-art CGCMs (Pillai et al. 2018). It has been reported that the errors in simulating monsoons could lead to the IOD-like biases (Li et al. 2015), implying that improving the representation of monsoons may improve the simulation and prediction of IOD events. Thus, it is of great interest to investigate the monsoon decadal predictability, especially its relationship with the IOD decadal predictability using this long-term hindcast product, which will be pursued in the near future.

In this paper, we attempt to identify the major sources of the decadal variation of IOD predictability based on an overall statistical analysis. However, significant differences in the causal factors of IOD predictability may occur among different IOD events. Many previous studies have reported a diversity of dominant factors responsible for IOD development and prediction (Rao et al. 2009; Rao and Yamagata 2004; Du et al. 2020). For example, Endo and Tozuka (2016) discovered varied impacts of ENSO on IOD events. Tanizaki et al. (2017) examined the different contributions of adiabatic vertical mixing and sea surface advection to IOD development. It is also reported that the feature of IOD events can change from period to period (Du et al. 2013). Thus, the statistical analysis may not be able to fully capture the causes of decadal predictability of IOD events. A case-by-case study may help probe in depth the underlying causes of IOD decadal predictability; this is expected to be conducted in the future.

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