A Preliminary Attempt On Decadal Prediction of The East Asian Summer Monsoon

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A Preliminary Attempt on Decadal Prediction of the East Asian Summer Monsoon

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ABSTRACT

The East Asian summer monsoon (EASM) is one of the major synoptic systems that affect the summer climate in China. The anomaly of the EASM is closely related to the occurrence of droughts and floods in China. Decadal prediction of the EASM is of great significance, yet few attempts have been made by far. This study represents a preliminary attempt that uses the decadal increment (DI) method to predict the decadal variability of the EASM. The 3-year increment of the decadal variability is used as the predictand, and predictors are selected from the previous circulation and external forcing. The predicted increment is combined with the observation three years ago to get the final prediction result. The results of cross validation and independent hindcast show that the decadal increment method can well predict decadal variability of the EASM during the recent century. In particular, the decadal regime shifts of the EASM are accurately captured. The decadal variability of the EASM in 2021 is further predicted with two previous predictors of the leading 4-year summer DI of the South Indian Ocean and the DI of the East Siberian Sea sea ice cover. The real-time prediction results show that the chance for the occurrence of strong decadal EASM would be rare in 2021 and 2022. The method developed in the present study provides a new approach for decadal prediction of the EASM.

Keywords  East Asian summer monsoon; Decadal prediction; Decadal increment method
Declarations

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Availability of data and material

Sea ice concentration data from the Met Office Hadley are available at https://www.metoffice.gov.uk/hadobs/hadisst/data/download.html; The National Oceanic and Atmospheric Administration (NOAA) Extended Reconstructed SST v3b dataset are from https://psl.noaa.gov/data/gridded/data.noaa.ersst.v3.html; The fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis (ERA5) are obtained at https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5. The Twentieth Century Reanalysis Product v3 dataset can be downloaded at https://psl.noaa.gov/data/gridded/data.20thC_ReanV3.pressure.html.

Code availability

All the codes are programmed by NCAR Command Language and MATLAB. The codes are available and maintained by author.

Conflicts of interest /Competing interests

The authors declare no conflicts of interest or competing interests.

Authors’ contributions

Conceptualization: D.W.Q., Y.Y.H. and H.J.W.; Methodology: Y.Y.H.; Formal analysis and software: D.W.Q.; Writing - original draft preparation: D.W.Q.; Writing - review and editing: D.W.Q., Y.Y.H. and H.J.W. All authors have read and agreed to the published version of the manuscript.
1. Introduction

The East Asian summer monsoon (EASM) refers to the southerly winds that prevail in East Asia in summer. As a unique component of the Asian climate system, the EASM demonstrates special spatiotemporal structure and dominates climate and climate change in East Asia (Tao et al. 1987; Ding et al. 1994; Huang et al. 2004). Due to its interactions with the climate system on multiple time scales, the EASM shows large variations from intraseasonal to interdecadal scale. The interaction between the EASM and the climate system often leads to anomalies of the EASM, which can subsequently cause heavy droughts and floods in China. Such kinds of meteorological disasters impose serious impacts on people's lives and economic activities in East Asia. Therefore, reliable prediction of the EASM changes is of great significance (Huang et al. 2007; Ha et al. 2012). On the intraseasonal scale, the EASM often demonstrates 10–20-day and 30–60-day oscillation patterns (Chen et al. 2001; Mao and Chan 2005; Guan and Johnny 2006). On the interannual scale, 2-year and 4-year oscillations account for a large part of the EASM variability. These intraseasonal and interannual variabilities of the EASM have remarkable impacts on summer rainfall in China and large-scale circulation in East Asia (Meehl and Arblaster 2002; Wu et al. 2008; Ding et al. 2013). Decadal climate change is defined as changes on the time scale of 10–30 year in the future. In the 20th century, the EASM has undergone significant decadal changes. The weakening of the EASM that occurred at the end of the 1970s (Wang 2001; Xue 2001; Wang 2002; Huang et al. 2004; Ding et al. 2008) was characterized by weaker than normal southwesterly winds in the surface level and at 850hPa and a weakened easterly jet in the upper troposphere (Hu 1997; Xu et al. 2006; Ding et al. 2008; Zhou et al. 2009). Meanwhile, the western Pacific subtropical high retreated to the east (Huang et al. 2015; Huang and Li 2015; Tong et al. 2020). At the beginning of the 1990s, the EASM started to intensify (Liu et al. 2012; Ding et al. 2013).
Corresponding to the aforementioned decadal changes in the EASM, summer precipitation in China has also experienced significant decadal changes. From the middle of the 1960s to the end of the 1970s, the rainbelts in eastern China were located in North China and South China, while the Jianghuai and Yangtze river basins had less than normal precipitation. The spatial distribution of rainfall anomaly displayed a “positive-negative-positive” pattern (“+ − +” meridional pattern) along the meridional direction. In the late 1970s, following the EASM weakening, the rainfall zone shifted to the Yangtze River basin, while precipitation in North China and South China decreased. Precipitation anomaly presented a “negative-positive-negative” pattern (“− + −” pattern) along the meridional direction. By the early 1990s, with the intensification of the summer monsoon, the main rainfall zone moved northward again, and a dipole-type of rainfall pattern prevailed in eastern China with floods in the north and droughts in the south (Wang 2001; Ding et al. 2008; Si et al. 2009; Zhu et al. 2010; Huang et al. 2011; Lü et al. 2014; Ding et al. 2018).

Many scientists have conducted research to explore the mechanisms for the decadal variability of the EASM. At the end of the 1970s, it was found that a persistent interdecadal scale cooling occurred in the upper troposphere and lower stratosphere. On the one hand, it affected the cyclonic circulation anomaly in the upper levels and promoted the strengthening of the westerly winds to the south of the East Asian jet axis. On the other hand, it influenced the anticyclonic circulation anomaly in the lower levels and weakened the EASM (Yu et al. 2004, 2007). Based on results of numerical experiments, Li et al. (2008) demonstrated that the decadal weakening of the EASM is attributed to the decadal change in the tropical sea surface temperature (SST). Changes in the SST over the tropical central and eastern Pacific led to tropospheric warming above the tropical ocean in the late 1970s. At the same time, temperature in the temperate zone of continental East Asia decreased. As a result, the thermal contrast between the ocean and the land reduced, which subsequently weakened the EASM. Yu (2013)
believed that the negative correlation between the phases of the Pacific Decadal Oscillation (PDO) and the EASM is the reason for the decadal weakening of the EASM since the late 1970s. The phase change of the PDO caused SST variation in the Pacific and Indian oceans, which affected the intensity of the western Pacific subtropical high and led to the anticyclone anomaly over the western Pacific. As a result, the EASM was weakened (Gong and Ho 2002; Dong and Xue 2016). In addition, Ding et al. (2008, 2009) found that the weakening of the atmospheric heating over the Tibet Plateau since the late 1970s has effectively reduced sensible heat flux transfer from the surface to the atmosphere, leading to increased snowfall in the previous winter and spring. Larger than normal snow cover in the Tibet Plateau delayed the formation of monsoon temperature gradient, and thereby weakened the EASM. Other factors such as North Atlantic SST tripole and North Pacific Gyre Oscillation can also affect the decadal variability of the EASM (Zuo et al. 2013; Ye et al. 2016).

In recent years, extensive attention has been focused on decadal climate prediction, which potentially has great impacts on economic and social development (Meehl et al. 2014; Zhou et al. 2017). Decadal climate prediction at present mainly relies on the initialized climate models, yet the initial shock is still a problem in the model initialization that hasn’t been fully solved (Meehl et al. 2014; Zhou et al. 2017). Compared with that in the North Pacific, the initialization in decadal prediction over the North Atlantic has been remarkably improved (Doblas-Reyes et al. 2013; Kirtman et al. 2013). Most of the current models have demonstrated satisfactory skills for prediction of the Atlantic Multidecadal Oscillation (AMO), whereas the model skills for PDO prediction are generally low (Kim et al. 2012). In addition, the model performance for the prediction of land surface temperature in the northern hemisphere remains poor. Compared with the uninitialized prediction skills, the model performance shows no obvious improvement after implementing initialization strategies (Doblas-Reyes et al. 2013; Wu et al. 2019). Also, decadal prediction of precipitation by climate models still has problems. The models only show
prediction skills over some areas, and the improvements are quite limited even after the
initialization strategy is implemented (Kirtman et al. 2013; Meehl et al. 2014; Wang et al.
2018). Therefore, decadal climate prediction by current climate models still remains a
challenging issue.

Based on the interannual increment approach (Fan et al. 2008; Wang et al. 2012), Huang
and Wang (2020a, b) proposed a decadal increment method to address climate prediction. In
this method, decadal signals are first obtained from moving averages of the raw data, and the
decadal increments are then used to identify the predictors to build the forecast model. Finally,
the predicted increment is combined with the previous observations to get the final prediction
result. This method helps to increase the effective samples and obtain more useful decadal
signals of the climate system from previous observations. Great progress has been made in the
predictions of PDO and decadal variability of summer precipitation in North China using the
decadal increment method. The regime shifts can also be effectively captured. Taking into
account the close relationship between the EASM and the summer climate in China and the
limited predictive skills of current climate models for precipitation and land surface
temperature, this study attempts to predict decadal variability of the EASM using the decadal
increment method.

The rest of this article is organized as follows. Section 2 describes the datasets and method.
Section 3 introduces how to use the decadal increment to build a statistical model. The hindcast
skills of the statistical model based on the decadal incremental method are presented in Section
4. Section 5 uses this method to build a real-time prediction model to predict EASM. The
discussion is given in Section 6. Finally, Section 7 presents the summary.

2. Data and methods

Monthly mean reanalysis datasets used in this study include the following:
1) Horizontal wind components (U and V) and geopotential height are extracted from the Twentieth Century Reanalysis Product v3 with a horizontal resolution of $1^\circ \times 1^\circ$ and cover the period from 1901–2012 (Compo et al. 2011);

2) Sea surface temperature (SST) data with a horizontal resolution of $2^\circ \times 2^\circ$ are from the National Oceanic and Atmospheric Administration (NOAA) Extended Reconstructed SST v3b dataset and covers the period from 1901–2010 (Smith et al. 2008);

3) Sea ice cover (SIC) data are from the Met Office Hadley Centre with a horizontal resolution of $1^\circ \times 1^\circ$ and covers the period from 1901–2010 (Rayner et al. 2003).

4) Horizontal wind components (U and V), sea surface temperature (SST) and sea ice cover (SIC) are derived from the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis (ERA5, Hersbach et al. 2020) with a horizontal resolution of $1^\circ \times 1^\circ$ and cover the period from 1980–2020.

The EASM index (EASMI) is defined as the area-mean ($110^\circ–125^\circ$E, $20^\circ$N–$40^\circ$N) wind speed at 850hPa in summer (June–July–August) (Wang 2002). Based on the decadal increment method proposed by Huang and Wang (2020a, b), the statistical model is established. First, decadal EASM is obtained from the 5-year running mean of the original EASMI and marked as EASMI in the middle year of the five years. Decadal increment (DI) of the EASMI (DI_EASMI) is then calculated from decadal EASM, that is, the decadal EASM of the current year minus the decadal EASM three years ago will be treated as DI_EASMI of the current year (Eq. 1). Finally, predictors are identified based on DI_EASMI and a prediction model is built using these predictors. The final predicted EASMI is the predicted DI_EASMI plus the observed EASMI three years ago (Eq. 2). For example, the predicted DI_EASMI in 1924 is added to the observed EASMI in 1921 to get the final predicted EASMI in 1924. Similar to the DI of the predictand, the DI of the predictor is obtained by performing the 5-year running mean
first and then calculating the 3-year increment. To avoid possible containing of the information
of the prediction period in the predictors, the predictors have to lead the predictand by at least
three years. For example, the summer DI_SST from 1918 to 2007 and the DI_EASMI from
1921 to 2010 are used for correlation analysis to find key predictors, and so on.

\[ DI_{-EASMI_i} = EASMI_i - EASMI_{i-3} \]  
(1)

\[ EASMI_i = EASMI_{i-3}^{obs} + EASMI_i^{pre} \]  
(2)

In order to judge whether climate variables follow normal distribution, the skewness
coefficient (g1) and kurtosis coefficient (g2) are calculated.

\[ g1 = \sqrt{\frac{1}{6n} \sum_{i=1}^{n} \left( \frac{x_i - \bar{x}}{s} \right)^3 } \]  
(3)

\[ g2 = \sqrt{\frac{n}{24} \left[ \frac{1}{n} \sum_{i=1}^{n} \left( \frac{x_i - \bar{x}}{s} \right)^4 \right] - 3 } \]  
(4)

Where n is the number of the sample, \( \bar{x} \) and s are the mean and standard deviation of the
sample. The skewness coefficient characterizes the degree to which the peak of the curve
deviates from the mean value. A positive g1 indicates that the mean is to the left of the peak,
and a negative g1 indicates that the mean is to the right of the peak. The kurtosis coefficient
characterizes the convexity of the peak of the distribution pattern and measures the degree of
concentration of the frequency distribution. A positive g2 indicates that the frequency
distribution is more concentrated than the normal distribution, and the average is more
representative, and a negative g2 is the opposite.

Cross validation and independent hindcast are used to verify the predictive skill of the
established empirical statistical model. In the cross validation, the EASM observational data
for the period 1921–2010 and the predicted EASM data three/four/five years ahead of the
observation time are selected first, and the 5-year data centered on the target year are excluded. The data in the remaining years are then used to build the model to predict the EASM in the target year. This process is repeated for each target year. The first and last three years of the data are verified by leaving the first and last five years of data out. The independent hindcast uses the same observational data. To avoid using the information of the prediction period, the data from the starting year to three years ahead of the target year are used as the training samples to establish the empirical statistical model to predict the situation in the target year. The aforementioned process is repeated for 1980–2010. For example, if the target year is 1990 (1991), the data from 1921–1987 (1921–1988) is used to build the prediction model.

The moving t-test (MTT) with a 10-year moving window is used to detect regime transitions of decadal variation of the EASM, and the significance of the correlation coefficient is tested by Student’s t-test. The effective sample size $N^*$ is computed (Bretherton et al. 1999):

$$N^* = N \frac{1 - r_x r_y}{1 + r_x r_y}$$ (5)

Where $N$ is the number of available time steps, and $r_x$ and $r_y$ are the autocorrelation coefficients of the two correlated variables lagging one step behind.

The mean square skill score (MSSS) is used to test the predictive skill of the model (Murphy, 1988; Goddard et al. 2012). The MSSS algorithm is written as:

$$MSSS = 1 - \frac{MSE}{MSE_c}$$ (6)

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (f_i - o_i)^2$$ (7)

$$MSE_c = \frac{1}{n} \sum_{i=1}^{n} (o_i - \bar{o})^2$$ (8)
Where $f_i$ and $o_i$ represent the time series of observations and forecasts, respectively. MSSS reflects the percentage reduction of the mean square error (MSE) predicted by the statistical model, and $\text{MSE}_c$ is the MSE of the "climatological forecast". A positive MSSS indicates that the statistical model prediction is better than that of the "climatological forecast", and a negative MSSS indicates that the model forecast is inferior to the "climatological forecast".

3. Prediction model

Based on the definition of the EASMI, decadal EASMI is calculated. The time series of EASMI for the period 1918–2010 is displayed in Fig. 1a, which shows that the EASMI was in a positive phase from 1920 to the mid-1930s and then switched to a negative phase from the mid-1930s to the mid-1940s. The EASMI was relatively strong during the period from the 1950s to the 1970s, but it suddenly weakened at the end of the 1970s. This result is consistent with studies of Wang (2001), Guo et al. (2003), Huang et al. (2004) and Ding et al. (2008). In the early 1990s, the EASM began to intensify again. This phenomenon is also found in Liu et al. (2012) and Ding et al. (2013).

The basic assumption of climate statistics analysis is that the climate variables follow a normal distribution. When the skewness coefficient ($g_1$) and kurtosis coefficient ($g_2$) of the data are both less than 1.96, the data can be treated as following normal distribution at the 95% confidence level. For the decadal EASMI (Fig. 2), both the skewness coefficient and the kurtosis coefficient are higher than 1.96, which means right shifting skewness distribution than normal distribution and steeper kurtosis distribution. The 1-year and 2-year increments of decadal EASMI are also not satisfy the normal distribution. Interestingly, the 3-year increment follows normal distribution at the 95% confidence level (Fig. 2). Therefore, the 3-year increment is selected for further analysis. Time series of 3-year increment is shown in Fig. 1b.
This paper implements the decadal increment method and uses the predictors in the decadal increment form to establish the empirical statistical model for DI_EASMI prediction. First, based on findings of previous studies, potential predictors are identified from SST, SIC and circulation fields, etc. To avoid possible containing of the information during the prediction period in the predictors, the predictors need to lead the DI_EASMI by at least three years. The stepwise regression method is then used to select the predictors that are significantly related to DI_EASMI and are independent of each other. The finally built prediction model is expressed by:

\[
DI_{EASMI} = 0.50 \times DI_{SSTI} + 0.41 \times DI_{BH} + 0.30 \times DI_{SIC} \quad (9)
\]

DI_SSTI, DI_BH and DI_SIC explain 25%, 17%, and 9% of the DI_EASMI variance, respectively.

The first predictor selected in this paper is the tropical ocean temperature signal in summer that leads DI_EASMI by three years. Fig. 3a shows the spatial pattern of the correlation coefficient between DI_SST and DI_EASMI for the period 1921–2010. The colder equatorial western Pacific and the warmer equatorial central and eastern Pacific are conducive to the enhancement of DI_EASMI. Physically, the equatorial central and eastern Pacific warming is favorable for the EASM intensification because anomalous ascending motions develop above the equatorial central-eastern Pacific while descending motions occur over the subtropical western Pacific. The above circulation is the so-called “quasi-Walker circulation” (Ying and Sun 2000; Wu et al. 2003; He et al. 2015). Additionally, the western Pacific cooling can strengthen the EASM through changing in-situ precipitation and further triggering descending atmospheric Rossby waves (Zhang et al. 1999; Wang et al. 2000; Wang et al. 2013; Huang et al. 2018). To quantify this characteristic relationship, area-weighted regionally averaged DI_SST in these two regions (multiplied by -1 in the negative region) is defined as the sea
surface temperature index (DI_SSTI). The ranges of positive and negative regions are (10°S–4°N, 170°E–160°W) and (0°–16°N, 129°E–155°E), respectively.

The second predictor is the leading 4-year autumn Bonin high (32°N–50°N, 130°E–165°E), which is an anticyclone over Japan (Fig. 3b). As a possible descending branch of the Hadley cell, the Bonin high can induce a meridional overturning and PJ pattern is established (Enomoto et al. 2003; Hsu and Lin 2007; He et al. 2018). There is an anomalous strong westward flow on the south of the Bonin high, which makes humid in East Asia and the EASM increases accordingly (Wakabayashi and Kawamura 2004; Yasunaka and Hanawa 2006; Ming et al. 2019).

The third predictor is the leading 5-year Kara Sea SIC (77°N–80°N, 70°E–90°E) in summer (Fig. 4a). The changes of SIC are highly correlated with the variability of the EASM (Zhao et al. 2004; Wu et al. 2009a, b; Guo et al. 2013; Li et al. 2018; Lin and Li 2018). The SIC anomaly is closely related to changes in the extent of Eurasia snow cover (Fig. 4b) (Cohen et al. 2012; Li et al. 2018), which has an impact on EASM (Wu et al. 2009c) through affecting the soil moisture (Zhang and Zuo 2011). The reduction in SIC over the Kara Sea also may trigger an anomalous high in summer (Fig. 4c) through the European land surface acting as a “bridge”. The EASM is prevented from moving northward by the anomalous high and weakens (Zhao et al. 2004).

Fig. 5 shows time series of DI for each predictor and DI_EASMI. The correlation coefficients of DI_EASMI with DI_SIC, DI_SSTI and DI_BH are 0.67, 0.47 and 0.59, respectively, all of which are significant at the 99% confidence level. Due to the long study period, the correlation between each predictor and DI_EASMI may present decadal changes. The correlation between the Bonin high and the EASMI changed abruptly at the end of the 1950s, and a weak correlation remained until the end of the 1970s (Fig. 6a). In addition to the weak correlation between DI_SSTI and DI_SIC occurred around 1980, the correlation...
remained stable in other years (Fig. 6b, c). Therefore, on the whole, the three predictors are stably and significantly correlated with DI_EASMI across the study period.

4. Prediction effect

To evaluate the performance of the established statistical model, cross validation and independent hindcast are conducted in the present study. Results of the cross validation are displayed in Fig. 7a, which shows that the correlation coefficient between the predicted DI_EASMI and the observation for the period 1921–2010 is 0.81, which is significant at the 99% confidence level. MSSS is 0.65. The predicted DI_EASMI well captures the variability shown in observations during the study period except for the mid-1950s and the 1970s, when decadal variability of the related relationships occurred. This result indicates that the empirical statistical model developed in the present study has a high predictive skill. The DI_EASMI predicted by the empirical statistical model is added to the leading 3-year observed EASMI to obtain predicted decadal EASMI. Except for the inconsistency that existed in the mid-1950s and the 1970s, the predicted EASMI realistically reproduces the positive phase over the period from the 1920s to the 1930s, the negative phase from around the late 1930s to the 1940s, the positive phase since the 1960s, the weaker EASM in the 1980s, and the intensification of the EASM in the early 1990s. The amplitude of the EASM oscillation is also quite consistent with observations. Furthermore, the correlation coefficient between the observed and predicted EASMI is 0.90 and MSSS is 0.78 (Fig. 7b and Table 1). In addition, the predicted EASMI well captures the regime shifts of the EASM due to its intensification in the 1940s and its weakening in the 1960s and 1970s as well as its intensification in the early 1990s. The prediction errors for these regime shifts all are less than three years (Fig. 7c). The above results show that the decadal increment method has a high hindcast skill.
The hindcast skill is further verified based on the independent hindcast of the DI_EASMI from 1980 to 2010. Fig. 7d shows that the variability displayed in observations is accurately grasped, and the correlation coefficient between the observed and the predicted DI_EASMI is 0.91, which is above the 99% confidence level. MSSS is 0.81. The variability and amplitude of the predicted EASMI are quite consistent with observations, including the transition from negative to positive EASMI in the early 1990s. The correlation coefficient between the observations and predictions of the EASMI is 0.87, and MSSS is 0.72 (Fig. 7e and Table 1). In addition, the predicted EASMI accurately captures the regime shift of the EASM in the early 1990s (Fig. 7f). Therefore, results of cross validation and independent hindcast indicate that the empirical statistical model combined with the decadal incremental method has a high skill of prediction for decadal variability of the EASM. The decadal regime shifts of the EASM can also be well captured.

5. The real-time prediction for EASM in 2021

Through the above analysis, it is found that the decadal increment method can effectively predict the EASM. Therefore, this method is further used to predict the EASM in 2021. Considering the study period has changed and the relationships between predictand and predictors may have decadal variations, the new prediction model is rebuilt by using the training period from 1985 to 2020 based on ERA5 data.

\[
DI_{-EASMI} = -0.85 \times DI_{-SIC} - 0.37 \times DI_{-SST}
\]

The leading 4-year summer East Siberian Sea sea ice cover (71°–76°N, 150°–178°E) (Fig. 8a) and leading 4-year summer South Indian Ocean (SIO) sea surface temperature (35°–44°S, 70°–110°E) by removing the effect of East Siberian Sea sea ice cover (Fig. 9) are selected as predictors, which explain 72% and 14% of the DI_EASMI variance, respectively. The correlation coefficients of DI_EASMI with DI_SIC and DI_SST are 0.85 and 0.37,
respectively, both of which are significant at the 95% confidence level. Their relationships have
remained steady during most of the study period except DI_SST was inconsistent during 1996-
2002 (Fig. 10), so they are selected as predictors.

Physically, the Arctic SIC is contributed to the EASM as previously discussed. As shown
in Fig. 8b, the anomaly of sea ice in the East Siberian Sea possibly impacts SST anomalous in
the North Pacific by affecting atmospheric circulation, which can persist into summer and
influence the EASM circulation and precipitation (Guo et al. 2014). In addition, the SIO SST
anomaly has an important impact on the interdecadal changes of the EASM at the end of the
20th century (Xue 2001; Zhang et al. 2017). The decadal cooling in the SIO may lead to
anomalous mid-tropospheric descents over the western SIO and anomalous ascents over the
eastern SIO and the tropical Indian Ocean. The upper-level divergent flows converge over
tropical East Asia, an anomalous low-level anticyclone is observed over the South China Sea-
Philippines, thereby enhancing the EASM (Zhang et al. 2017).

In the cross validation, the correlation coefficient between the predicted DI_EASMI and
the observation for the period 1990–2018 is 0.90 and MSSS is 0.81 (Fig. 11a). The predicted
DI_EASMI is added to the leading 3-year observed EASMI to obtain predicted EASMI. The
correlation coefficient between the observed and predicted EASMI is 0.90 and MSSS is 0.78
(Fig. 11b). In addition, the predicted EASMI well captures the regime shift of the EASM in the
early 2000s (Fig. 11c). In the independent hindcast, the correlation coefficient between the
observed and the predicted DI_EASMI is 0.90 during 2011–2018, and MSSS is 0.79 (Fig.
11d). The correlation skill of the final predicted EASMI is 0.94, along with an MSSS of 0.87
(Fig. 11e).

Regardless of cross validation or independent hindcast, the prediction model shows almost
consistent results with observations, which increases our confidence in predicting future
changes of EASM. According to the results of independent hindcast, EASM is relatively weak
in 2019 and 2020, but it is likely to be a weak positive phase in 2021 (Fig. 11e). To explore whether 2021 will be a decadal regime shift, EASM in 2022 is further calculated. Different from the previous method, we consider using the predicted DI_EASMI from the statistical model added to the prediction of EASMI three years ago from decadal increment method to get the re-predicted EASMI in 2022. This method is tested and the results show that the correlation coefficient between the re-predicted EASMI and the observation is 0.78 and MSSS is 0.51, and the variability of the predicted value is relatively consistent with observations (Fig. 12). Therefore, EASM in 2022 is predicted by this method and it may return to a negative phase (Fig. 11e and Fig. 12), which means the chance of a decadal regime shift is relatively rare.

6. Discussion

To compare with the decadal increments method, the empirical statistical model in the original form is established, and the predictors are selected over the same areas as that selected for the decadal increment model (Eq. 9).

\[ EASMI = 0.41 \times SSTI + 0.39 \times BH + 0.48 \times SIC \]  

(11)

The correlation coefficients of decadal EASMI during the period 1921–2010 with the SIC, BH and SSTI are 0.51, 0.37, and 0.66, respectively, all of which are significant at the 90% confidence level. Results of the cross validation show that the correlation coefficient between observations and predictions of the EASMI by the empirical statistical model in the original form is 0.67 and MSSS is 0.43 (Fig. 13a and Table 1), both of which are lower than that between observations and forecast of the empirical statistical model for decadal increment prediction (correlation coefficient and MSSS are 0.90 and 0.78 respectively). The empirical statistical model in the original form fails to capture the EASM variability, although it reproduces the negative phase around 1940, the positive phase in the early 1960s, the negative phase in the 1980s and the positive phase in the early 1990s (Fig. 13a). The model also cannot
effectively capture the decadal regime shifts of the EASM (Fig. 13b). In the independent
hindcast, the correlation coefficient between the predicted and the observed EASM from 1980
to 2010 is 0.76 (Fig. 13c and Table 1) and the decadal regime shift in the early 1990s is
accurately grasped (Fig. 13d). However, the negative phase that began in the mid-1990s was
mistakenly predicted as a positive phase, and MSSS is -1.39 (Table 1). This result indicates
that the hindcast skill of the statistical model is quite limited. Therefore, using the decadal
increment method to build a statistical model is helpful to improve the skill for the EASM
prediction.

Moreover, it is noticed that there is a correlation between observed DI_EASMI and EASMI
by comparing Fig. 11a and b. The cross-correlation for DI_EASMI at a 2-year ahead and
EASMI is 0.85, and the variability and amplitude are relatively consistent (Fig. 14). Therefore,
it may be possible to predict the variability of EASMI based on changes in DI_EASMI. As for
the reasons for the relationship between them, the research needs to be further explored.

7. Summary

Based on previous research of decadal changes in the EASM and analysis of the
relationship between the DI of predictors and DI_EASMI, the present study develops the
empirical statistical prediction model that is combined with the decadal increment method to
predict decadal variability of the EASM.

The statistical model is established as illustrated in Fig. 15. First, based on the 5-year
running mean EASMI, the 3-year decadal DI_EASMI is calculated, that is, the running mean
EASMI of the current year minus the EASMI three years ago. The leading 3-year summer
DI_SSTI over the equatorial Pacific, the leading 4-year DI_BH in autumn and the leading 5-
year summer DI_SIC over the Kara Sea are then selected as predictors. Note that these
predictors remain independent of each other. Compared with the method of selecting the
original variables directly, the incremental method increases effective samples in the correlation analysis and obtains more useful decadal signals in the climate system from previous observations. Finally, the selected predictors are used to build the statistical model, and the final predicted EASMI is the predicted DI_EASMI plus the observed EASMI three years ago. Results of cross validation from 1921 to 2010 indicate that the variability and amplitude of the predicted EASMI are quite consistent with the observed EASMI. Their correlation coefficient is 0.90, and MSSS is 0.78. The independent hindcast during the period 1980 to 2010 also shows that the variability and amplitude of the predicted EASMI are consistent with the observed EASMI. Their correlation coefficient is 0.87, and MSSS is 0.72. In addition, the predicted EASMI accurately captures the decadal regime shifts. The above results indicate that the decadal incremental method can well reproduce the characteristics of decadal variability of the EASM. Compared with the statistical model in the original form, the prediction skills of the model developed in this study are also improved, which makes it a great tool for future prediction of decadal changes in the EASM.

Therefore, this method is further used to build a real-time prediction model to predict the EASM in 2021 and 2022, the leading 4-year summer DI of the South Indian Ocean (SIO) sea surface temperature and the leading 4-year summer DI of the East Siberian Sea sea ice cover are selected as predictors. The results show that EASM is in a negative phase in 2019 and 2020, but it may be in a weak positive phase in 2021 and will go back to a negative phase in 2022.

Using the decadal increment method, preliminary attempts have been made to predict decadal variability in the EASM, and satisfactory results have been achieved. This study provides a new solution for the prediction of decadal variability. In the future, this method can be applied for the prediction of other climatic phenomena such as decadal variability of drought in North China. Since the predictive effect of the decadal increment method is better than that
of the original form, it can also be applied for decadal prediction in climate dynamic models, which may further improve the predictive skill of climate models.
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Table 1: The predictive skill of the statistical model combined with the increment method for the DI_EASMI and EASMI.
Fig. 1  
(a) Decadal EASMI during 1918–2010 and (b) DI_EASMI during 1921–2010

Fig. 2  
Skewness coefficient (red bar) and kurtosis coefficient (blue bar) of decadal EASMI and DI_EASMI. “0” represents decadal EASMI, “1”, “2”, and “3” represent 1-year, 2-year, and 3-year increment of decadal EASMI, respectively

Fig. 3  
Correlation coefficients between DI_EASMI during 1921–2010 and the leading DI of predictors (a 3-year leading sea surface temperature in summer (June to August); b 4-year leading Bonin high in Autumn (September to November). Dotted areas indicate values significant at the 95% confidence level by the student’s t-test, and the boxes indicate the key areas of the predictors, including DI_SSTI (10°S–4°N, 170°E–160°W) and (0°–16°N, 129°E–155°E), DI_BH (32°N–50°N, 130°E–165°E)

Fig. 4  
(a) Correlation coefficient between DI_EASMI during 1921–2010 and the leading 5-year DI of sea ice concentration in summer (June to August). The box indicates the key area of the predictor, and area-weighted regionally averaged DI_SIC (77°S–80°N, 70°E–90°E) is used as a predictor. Correlation coefficient of the summer DI_SIC during 1916–2005 with b the spring (March to May) DI of snow cover during 1921–2010 and c the summer DI of 850hPa geopotential height during 1921–2010. Dotted areas indicate values significant at the 95% confidence level by the student’s t-test

Fig. 5  
Time series of DI_EASMI during 1921–2010 (black line) and 3-year leading DI_SSTI (blue line), 4-year leading DI_BH (green line) and 5-year leading DI_SIC (red line)

Fig. 6  
25-year running correlation between DI_EASMI during 1921–2010 and leading DI of predictors (a BH, b SSTI, c SIC). The dotted line is at the 90% confidence level by the student’s t-test, and the effective sample numbers are 21, 21, and 22, respectively

Fig. 7  
Predictions of a, d DI_EASMI and b,e EASMI and c, f the results of the moving t-test with a 10-year moving window of EASMI (a, b, c results of the cross validation during 1921–2010; d, e, f results of independent hindcast during 1980–2010; the light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions; the thin solid lines in c and f are significant at the 95% confidence levels)

Fig. 8  
(a) Correlation coefficient between DI_EASMI during 1990–2018 and the leading 4-year summer (June to August) DI of sea ice cover removing the effect of the DI of SIO sea surface temperature. The box indicates the key area of the predictor, and area-weighted regionally averaged DI_SIC (71°–76°N, 150°–178°E) is used as a predictor. b Correlation coefficient between summer DI_SIC during 1986–2014 and the spring (March to May) DI of sea surface temperature during 1990–2018. Dotted areas indicate values significant at the 95% confidence level by the student’s t-test
Fig. 9 Correlation coefficient between DI_EASMI during 1990–2018 and the 4-year leading DI of sea surface temperature in summer (June to August). Dotted areas indicate values significant at the 95% confidence level by the student’s t-test, and the box indicates the key area of the predictor, including DI_SST (35°S–44°S, 70°E–110°E).

Fig. 10 Time series of DI_EASMI during 1990–2018 (black line) and 4-year leading DI_SST (blue line) and DI_SIC (red line) during 1990–2022.

Fig. 11 Predictions of a, d DI_EASMI and b, e EASMI and c the results of the moving t-test with a 9-year moving window of EASMI (a, b, c results of the cross validation during 1990–2018; d, e results of independent hindcast during 2011–2022; the light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions; the thin solid lines in c are significant at the 95% confidence levels).

Fig. 12 Re-predictions of EASMI during 1993–2022, which is obtained by adding the predicted DI_EASMI from statistical model to the EASMI prediction result three years ago from decadal increment (left of the dotted line: results of the cross validation during 1993–2013; right of the dotted line: results of the independent hindcast during 2014–2022). The light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions.

Fig. 13 Direct predictions of EASMI a, c based on statistical prediction model in the original form and b, d the results of the moving t-test with a 10-year moving window (a, c results of the cross validation during 1921–2010; b, d results of independent hindcast during 1980–2010; the light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions; the thin solid lines in b and d are significant at the 95% confidence levels).

Fig. 14 Time series of DI_EASMI at a 2-year ahead (red line) and EASMI (black line) during 1992–2018.

Fig. 15 Schematic diagram illustrating the process of predicting EASM using the decadal increment method.
### Table 1: The predictive skill of the statistical model combined with the increment method for the DI_EASMI and EASMI.

Note: The results predicted by the statistical model in the original form are shown in parentheses. CC is the correlation coefficient and MSSS is the mean square skill score.

|       | Cross validation (1921–2010) | Independent hindcast (1980–2010) |
|-------|-----------------------------|----------------------------------|
|       | CC  | MSSS | CC | MSSS |
| DI_EASMI | 0.81 | 0.65 | 0.91 | 0.81 |
| EASMI   | 0.90(0.65) | 0.78(0.42) | 0.87(0.76) | 0.72(-1.39) |
Fig. 1  a Decadal EASMI during 1918–2010 and b DI_EASMI during 1921–2010
Fig. 2 Skewness coefficient (red bar) and kurtosis coefficient (blue bar) of decadal EASMI and DI_EASMI. “0” represents decadal EASMI, “1”, “2”, and “3” represent 1-year, 2-year, and 3-year increment of decadal EASMI, respectively.
Fig. 3 Correlation coefficients between DI_EASMI during 1921–2010 and the leading DI of predictors (a 3-year leading sea surface temperature in summer (June to August); b 4-year leading Bonin high in Autumn (September to November). Dotted areas indicate values significant at the 95% confidence level by the student’s t-test, and the boxes indicate the key areas of the predictors, including DI_SSTI (10°S–4°N, 170°E–160°W) and (0°–16°N, 129°E–155°E), DI_BH (32°N–50°N, 130°E–165°E)
Fig. 4  

**a** Correlation coefficient between DI_EASMI during 1921–2010 and the leading 5-year DI of sea ice concentration in summer (June to August). The box indicates the key area of the predictor, and area-weighted regionally averaged DI_SIC (77°S–80°N, 70°E–90°E) is used as a predictor. Correlation coefficient of the summer DI_SIC during 1916–2005 with **b** the spring (March to May) DI of snow cover during 1921–2010 and **c** the summer DI of 850hPa geopotential height during 1921–2010. Dotted areas indicate values significant at the 95% confidence level by the student’s t-test.
Fig. 5 Time series of DI_EASMI during 1921–2010 (black line) and 3-year leading DI_SSTI (blue line), 4- year leading DI_BH (green line) and 5-year leading DI_SIC (red line)
Fig. 6 25-year running correlation between DI_EASMI during 1921–2010 and leading DI of predictors (a BH, b SSTI, c SIC). The dotted line is at the 90% confidence level by the student’s t-test, and the effective sample numbers are 21, 21, and 22, respectively.
Fig. 7 Predictions of a, d DI_EASMI and b, e EASMI and c, f the results of the moving t-test with a 10-year moving window of EASMI (a, b, c results of the cross validation during 1921–2010; d, e, f results of independent hindcast during 1980–2010; the light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions; the thin solid lines in c and f are significant at the 95% confidence levels)
Correlation coefficient between DI_EASMI during 1990–2018 and the leading 4-year summer (June to August) DI of sea ice cover removing the effect of the DI of SIO sea surface temperature. The box indicates the key area of the predictor, and area-weighted regionally averaged DI_SIC (71°-76°N, 150°-178°E) is used as a predictor. Correlation coefficient between summer DI_SIC during 1986–2014 and the spring (March to May) DI of sea surface temperature during 1990–2018. Dotted areas indicate values significant at the 95% confidence level by the student’s t-test.
Fig. 9 Correlation coefficient between DI_EASMI during 1990–2018 and the 4-year leading DI of sea surface temperature in summer (June to August). Dotted areas indicate values significant at the 95% confidence level by the student’s t-test, and the box indicates the key area of the predictor, including DI_SST (35°S–44°S, 70°E–110°E)
Fig. 10 Time series of DI_EASMI during 1990–2018 (black line) and 4-year leading DI_SST (blues line) and DI_SIC (red line) during 1990–2022
Fig. 11 Predictions of a, d DL_EASMI and b, e EASMI and c the results of the moving t-test with a 9-year moving window of EASMI (a, b, c results of the cross validation during 1990–2018; d, e results of independent hindcast during 2011–2022; the light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions; the thin solid lines in c are significant at the 95% confidence levels)
Fig. 12 Re-predictions of EASMI during 1993–2022, which is obtained by adding the predicted DI_EASMI from statistical model to the EASMI prediction result three years ago from decadal increment (left of the dotted line: results of the cross validation during 1993–2013; right of the dotted line: results of the independent hindcast during 2014–2022). The light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions.
Fig. 13 Direct predictions of EASMI a, c based on statistical prediction model in the original form and b, d the results of the moving t-test with a 10-year moving window (a, c results of the cross validation during 1921–2010; b, d results of independent hindcast during 1980–2010; the light pink shading indicates the 95% confidence interval of the prediction. The value in the upper right corner is the correlation coefficient/MSSS between observations and predictions; the thin solid lines in b and d are significant at the 95% confidence levels)
Fig. 14 Time series of DI_EASMI at a 2-year ahead (red line) and EASMI (black line) during 1992–2018
Fig. 15 Schematic diagram illustrating the process of predicting EASM using the decadal increment method.

Step 1. Decadal EASMI
- 5-year running mean

Step 2. Calculate DI_EASMI
\[ DI_{EASMI_i} = EASMI_i - EASMI_{i-3} \]

Step 3. Predict DI_EASMI
- \[ DI_{EASMI} = 0.50 \times DI_{SST} + 0.41 \times DI_{BH} + 0.3 \times DI_{SIC} \ (1921-2010) \]
- \[ DI_{EASMI} = -0.85 \times DI_{SIC} - 0.37 \times DI_{SST} \ (1985-2020) \]

Step 4. Predict EASMI
\[ EASMI_i = DI_{EASMI_{i}^{\text{prediction}}} + EASMI_{i-3}^{\text{observation}} \]