Accurate Attribution and Seasonal Prediction of Climatic Anomalies Using Causal Inference Theory

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ABSTRACT: Using features based on correlation or noncausal dependence metrics can lead to false conclusions. However, recent research has shown that applying causal inference theory in conjunction with Bayesian networks to large-sample-size data can accurately attribute synoptic anomalies. Focusing on the East Asian summer monsoon (EASM), this study adopts a causal inference approach with model averaging to investigate causation of interannual climate variability. We attribute the EASM variability to five winter climate phenomena; our result shows that the eastern Pacific El Niño–Southern Oscillation has the largest causal effect. We also show that the causal precursors of the EASM variability are interpretable in terms of physics. Using linear regression, these precursors can predict the EASM one season ahead, outperforming correlation-based empirical models and three climate models. This study shows that even without large-sample-size data and substantial human intervention, even laymen can implement the causal inference approach to investigate the causes of climatic anomalies and construct reliable empirical models for prediction.

SIGNIFICANCE STATEMENT: We use causal inference theory to redesign the attribution procedure fundamentally and adjust a causal inference approach to commonly used climate research data. Our study shows that the causal inference approach can exhaustively reveal the causes of climatic anomalies with little human intervention, which is impossible for correlation-based studies. According to this attribution, one can construct models with a better predictive performance than the climate and correlation-based empirical models. Therefore, our causal inference approach will tremendously help both meteorologists and laymen (e.g., stakeholders and policymakers) accurately predict climate phenomena and reveal their interpretable causes. We recommend that it become a standard practice in attribution studies and operational prediction.

KEYWORDS: Monsoons; Climate prediction; Climate variability

1. Introduction

The East Asian summer monsoon (EASM), as a vital component in Earth’s climate system, shows large interannual variability in atmospheric circulation and rainfall that stretches from the Yangtze River basin to the Korean Peninsula and Japan (Ding and Chan 2005; Wang et al. 2008). In 1998, the EASM circulation was unusually weak, characterized by a westward extension of the western North Pacific subtropical high (WNPSH) and severe Yangtze Valley flash floods (Bell et al. 1999; Xue et al. 2018). In 2018, a significantly stronger EASM was accompanied by a northward shift of the WNPSH; consequently, tropical cyclones continually struck the Shanghai area and extreme heatwaves affected Northeast Asia (Blunden and Arndt 2019). If accurate predictions of the EASM were available, we could have mitigated some impacts of these natural catastrophes.

Both dynamic and correlation-based empirical approaches have been applied to predict climatic anomalies. The understanding of climate variability helps researchers construct correlation-based empirical models, which may predict the EASM (Wu et al. 2016; Wu and Yu 2016; Wu et al. 2009). For instance, El Niño–Southern Oscillation (ENSO) induces sustained WNPSH anomalies, thus greatly influencing the EASM (Rong et al. 2010; Xie et al. 2009). The North Atlantic Oscillation (Wu et al. 2009), Eurasian snow cover (Lu et al. 2020), and the Pacific decadal oscillation (Feng et al. 2014), among others, are also identified as the drivers of EASM variability. Recently, using correlation-based features as input, various artificial intelligence techniques have been used to predict the EASM, thereby enhancing the prediction performances (Dai et al. 2020; Wei et al. 2020; Xing et al. 2020). Dynamic approaches are also capable of simulating the climate system, including the EASM features, and provide skillful predictions (Martin et al. 2020; Ren et al. 2019; Wang et al. 2015). These approaches have made numerous attribution results and prediction products available, which meet the needs of various stakeholders (IPCC 2014; Zhou et al. 2020).

Obstacles exist, however, in attributing and predicting climatic anomalies. Specifically, climate models cannot accurately
reproduce certain physical processes responsible for the climatic anomalies (Séférian et al. 2019; Sellar et al. 2019). Additionally, errors in model parameterizations and initial conditions remain (Warner 2010). These factors limit the forecast skill of the EASM as lead time exceeds one season and may lead to conclusions inconsistent with the observations when the model-based precursors of EASM anomalies are analyzed (Liu et al. 2019; Nie and Guo 2019; Yang and Jiang 2014). In addition, the climate models require substantial computing and storage resources (Mizielinski et al. 2014). Alternatively, empirical approaches can be used when expensive climate model simulations are not practical for institutions or individuals with limited computing resources. To date, the empirical models for predicting the EASM variability rely on correlation or noncausal dependence metrics (Wu and Yu 2016; Wu et al. 2009). These metrics are limited by the trade-off between high detection power versus a reliable false positive control (Runge et al. 2019). Despite the skillful prediction of the correlation-based models, these models can incorrectly rely on spurious precursors, thereby reducing generalizability (Li et al. 2020). Confounders, which produce spurious associations between the factors of interest, can also lead to false conclusions (Christensen et al. 2013; Pearl 2009a). Additionally, the empirical models using features based on correlation or noncausal dependence including deep learning do not explain the causal reasons behind the dynamics, thereby reducing generalizability (Li et al. 2020; Reichstein et al. 2019). Causal inference approaches, in contrast, can optimally learn (parts of) the causation by working with Bayesian networks under several assumptions (e.g., not confounded, the Markov condition, and minimality; see section 2c). These networks are probabilistic graphical models that encode the causal structure of variables and their joint distributions into factorized formulas (Pearl et al. 2016). This encoding makes outcomes interpretable and helps determine whether the causation encoded is reasonable (Pearl 2009b, 2019), a result that is otherwise impossible for many other artificial intelligence techniques (Li et al. 2020; Reichstein et al. 2019). In addition, the causal inference approaches beat the correlation and noncausal dependence approaches; they not only distinguish direct effects from indirect effects and common causes (Ebert-Uphoff and Deng 2015; Runge et al. 2019) but also manage the confounders effectively (Pearl 2009a). In this way, they quantify causal effects exhaustively and provide further insights into the dynamics, thereby improving climate predictions.

Causal inference approaches are becoming more widely adopted in the field of geosciences (Ebert-Uphoff and Deng 2015; Runge et al. 2019). For example, they were used to study the causal structure among the stratospheric polar vortex variability and its known drivers (Kretschmer et al. 2016) and to examine synoptic-scale causal structures within the climate models (Nowack et al. 2020). However, few studies employed the causal inference approaches to study seasonal or interannual climate variability due to the small sample size. This study introduces a causal inference framework. The framework is able to produce robust results, even with a low amount of independent data. It learns seasonal- or longer-scale causation, relying on the concept of model averaging to improve robustness (see section 2d), and is used in the context of linear systems. To prevent overfitting, we determine the number of causal precursors based on a forward stepwise selection using the Bayesian information criterion (BIC) score (Schwarz 1978). The framework identifies five winter causal precursors, including ENSO, of the June–August EASM variability. A linear regression model is fitted using the five causal precursors, enabling skillful predictions of the June–August EASM.

2. Datasets and methods

a. Datasets

This study uses the following observational and reanalysis products: 1) monthly 850-hPa zonal wind, 2-m air temperature, and sea level pressure (SLP) data from the National Centers for Environmental Prediction–Department of Energy Reanalysis 2 (Kanamitsu et al. 2002), and 2) monthly sea surface temperature (SST) data from the National Oceanic and Atmospheric Administration Extended Reconstructed Sea Surface Temperature version 5 (Huang et al. 2017). The SST data exclude the areas with sea ice, and the air temperature data exclude the sea surface without sea ice. To assess the relative performance of our causal inference framework, we use the hindcast data issued on 1 March from the CanCM4i and the GEM-NEMO of the North American Multimodel Ensemble project (Kirtman et al. 2014) and those from the CMCC-SPS3, GCF2.0, Météo-France System 7, and SEAS5 of the Copernicus Climate Change Service Seasonal Forecasts project. The hindcast data from the Météo-France System 7 are also issued on the last two Thursdays of February. This study analyzes the ensemble-mean hindcasts of every model. It uses monthly anomalies with linear trends removed. Monthly climatology is calculated based on the period of 1979–2019, except for the climatology for the hindcast, which is based on the period of 1994–2016.

b. The index of climate phenomena

To achieve a comprehensive indication of the EASM features, this study selects the EASM index of Wang and Fan (Wang et al. 2008). It is defined as the difference in June–August 850-hPa zonal wind between 90°–130°E, 5°–15°N and 110°–140°E, 22.5°–32.5°N (Fig. 1). This study also uses the surface air temperature averaged north of 60°N to represent the Arctic temperature. To quantify the central Pacific ENSO intensity, an El Niño Modoki index is defined as $x_1 - 0.5x_2 - 0.5x_3$, where $x_1$ is the SST averaged over 165°E–140°W, 10°S–10°N, $x_2$ is the SST averaged over 110°–70°W, 15°S–5°N, and $x_3$ the SST averaged over 125°–145°E, 10°S–20°N. A Niño-3 index is defined as the SST averaged over 150°–90°W, 5°S–5°N to quantify the eastern Pacific (EP) ENSO intensity.

c. The causal inference approach with Bayesian networks

Analyses (see appendix A) are based on Runge et al.’s framework of causal inference (Runge et al. 2015), which comprises dimension reduction and causal discovery. The causal discovery cannot achieve scalability and theoretical consistency if the number of variables considerably exceeds the number of samples (Guo et al. 2020). Therefore, the first

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step is to apply the varimax-rotated principal component analysis (Kaiser 1958) to every set of the year-around anomaly data. This procedure produces a smaller set of time series, namely rotated modes, representing localized physical processes. The criterion proposed by Vejmelka et al. (2015) is used to select principal components with nonrandom spatial dependence, and thus to decide the number of principal components retained. The presence of spatial dependence (i.e., nonrandom correlations among the time series) increases the eigenvalues of principal components reflecting this dependence and decreases other eigenvalues (Müller et al. 2005). Therefore, provided that the eigenvalues are sorted in a descending order, the values of certain principal components obtained in this study are significantly larger than their corresponding ones from the autoregressive models that replicate the temporal autocorrelation of the data without nonrandom spatial dependence. These components are regarded as the components with nonrandom spatial associations and thereby selected. This study uses the Monte Carlo experiment to estimate the distributions of eigenvalues under the null hypothesis of no spatial dependence. In the Monte Carlo experiment, autoregressive models of up to 30th order are constructed from the time series of every grid point separately, whereas every autoregressive model generates 10 000 time series, according to the method in Schneider and Neumaier (2001) (see appendix B). Subsequently, the principal components retained are rotated based on varimax rotation to obtain the rotated modes.

After reducing the data dimensions, we assume a linear Gaussian model and apply the adjacency search of the PC-stable (named after Peter and Clark) algorithm (Colombo and Maathuis 2014) with linear partial correlation to the time series of the rotated modes. The algorithm is a highly effective way of examining whether causation exists among thousands of variables (Guo et al. 2020). It constructs candidate causal models capable of generating the time series data. Specifically, it efficiently examines whether, given that the state of a second mode is known, the EASM and its every unconditionally dependent rotated mode can become conditionally independent; this removes the spurious association, due to a common cause or an indirect effect, between these unconditionally dependent variables. The remaining associations are then oriented by time order because a cause must come before its effect (see appendix C). In this way, the remaining modes with a particular lead time are considered to be the causal precursors of EASM variability. This procedure examines the time series of the rotated modes in the preceding December–February. Subsequently, to estimate the path coefficients between the EASM and its causal precursors, this study deploys the ordinary least squares regression without a constant (Pearl et al. 2016). Each partial regression coefficient represents a causal effect—specifically, the change induced by the unit-variance change in the causal precursor corresponding to the coefficient given the states of the other precursors. The causal precursors at a particular lead time and the coefficients form a Bayesian network, which serves as a causation-based empirical model.

d. Model averaging and selection

To construct the causation-based empirical model with high confidence, this study resamples the data using bootstrap, obtains a set of causal precursors from every set of bootstrapped samples, and forms an averaged model with the precursors that emerge most frequently (see appendix A). The process described above is known as the model averaging (Nagarajan et al. 2013) and is described in more detail below. In the dimension reduction, the nonparametric bootstrap (Efron 1979) is used to reduce the bias resulting from the small sample size of the monthly data. This study derives the time series of bootstrapped rotated modes from the original samples. The nonparametric bootstrap described above generates 250 sets of samples in the implementation of dimension reduction; thus, we obtain 250 sets of nonparametric-bootstrap rotated modes. In the causal discovery after the dimension reduction, this study employs the block bootstrap (Carlstein 1986) to retain the causal structure when reducing the bias. Every block comprises the June–August EASM index of a certain year and one set of the bootstrapped time series in the preceding December–February. The block bootstrap and adjacency search of the PC-stable algorithm are applied successively 250 times to every set of the nonparametric-bootstrap modes, ultimately producing 62 500 sets of bootstrapped causal precursors of the EASM. In addition, this study uses the Hungarian algorithm (Munkres 1957) to match the spatial patterns between the original and bootstrapped rotated modes according to the absolute values of their normalized dot products (see appendix D). Every matching pair of the modes is considered equivalent. In this way, the more frequently the bootstrapped counterparts of one original rotated mode emerge in the bootstrapped causal precursors in the causal discovery, the more likely this original mode is to be the causal precursor of EASM variability. These frequencies are considered to be the degree of confidence that a particular directed dependence is present in the true Bayesian network describing the causation of climate system under the modeling assumptions. Subsequently, the original modes are represented by the averages of their bootstrapped counterparts. Using the ordinary least
squares regression and the averages of counterparts, the path coefficients are estimated, and causation-based empirical models are constructed from the most frequent modes.

The forward stepwise selection is used to determine the number of the averaged modes retained. It selects the most frequent mode to add at each step. We select the model with the lowest BIC score (Schwarz 1978). This criterion is an increasing function of the unexplained variation in the dependent variable, and penalizes the complexity of the model. In this way, it limits false-positive findings and prevents overfitting. The BIC score is calculated as follows:

\[
\text{BIC} = -2 \ln l + K \ln n,
\]

where \( l \) is the estimated maximum likelihood of the model, \( K \) is the number of parameters, and \( n \) is the sample size.

e. Correlation-based empirical models

We use two correlation-based empirical models to compare with our causation-based empirical model. The first model of Wu and Yu (2016) is a partial least squares regression model with two components. It is fitted to the preceding December–February SST anomalies in 40°S–40°N, 40°E–0°. The second model of Jin and Huo (2018) is an ordinary least squares regression model. It is fitted to the preceding April–May North Atlantic Oscillation index, the March–May tropical Atlantic index, the December–February Niño-3.4 index, and the difference in Niño-3.4 index between the preceding April–May and the preceding February–March.

f. Cross-validation

To hindcast the EASM, this study employs 10-fold cross-validation, and performs it 25 times in the regression process of both the causation-based and correlation-based empirical models after having selected the predictors. For every implementation, the data from 1979 to 2019 are randomly split into 10 subsets of equal size. The predictor data of every subset are used in turn to hindcast the EASM based on the regression model fitted to the remaining subsets. Additionally, the 10-consecutive-fold cross-validation, which splits the data from 1979 to 2019 into 10 consecutive subsets, is applied to the entire modeling of the causation-based empirical model. This study then analyzes the hindcasted EASM time series from 1994 to 2016 or their ensemble mean.

g. Statistics

The 95% confidence level is used throughout this study. To estimate the relationship between the observations and hindcasts, this study uses the Gaussian process regression with a sum kernel comprised of a dot-product kernel and a white noise kernel (Rasmussen and Williams 2005). The prior mean is assumed to be the data’s mean.

3. Attribution of the EASM and the effects of its winter causal precursors

We first reduce the dimensions of monthly 2-m air temperature, SLP, and SST data with the varimax-rotated principal component analysis to obtain a smaller set of the time series representing the localized processes (see sections 2a and 2c). In analyzing spatial associations, we examine whether the eigenvalues from the SST anomalies are significantly greater than their corresponding eigenvalues from the autoregressive models. The \( p \) value of the 21st eigenvalue is 0.0001, whereas that of the 22nd eigenvalue is 0.5632 (Fig. 2a). According to these \( p \) values, the first 21 principal modes are retained, with nonrandom spatial associations. These components explain 68% of the variance in the SST anomaly data. As for the 2-m air temperature (SLP) anomaly data, the \( p \) value of the 58th (53rd) eigenvalue is 0.0586 (0.0092), whereas that of the 59th (54th) eigenvalue is 1.0000 (1.0000) (Fig. 2c for 2-m air temperature, Fig. 2e for SLP). Therefore, the first 58 (53) components are retained, explaining 74% (85%) of the variance in the 2-m air temperature (SLP) data.

The right panels of Fig. 2 show the spatial patterns of the averages of equivalent bootstrapped rotated modes. These modes are numbered in a descending order according to the eigenvalues of their original modes. Notably, these modes represent most climate phenomena. Several primary modes and their relevant phenomena are listed next. ENSO is one of the dominant phenomena. Mode number 3 (No. 3) resembles the SST anomalies of the EP ENSO (Kao and Yu 2009) with a contrast between the eastern equatorial Pacific and western tropical Pacific, whereas mode No. 81 resembles the EP ENSO SLP change over the eastern tropical Pacific. Mode No. 2 resembles the Indian Ocean basin mode with basinwide SST anomalies in the tropical Indian Ocean, whereas mode No. 11 resembles the Indian Ocean dipole mode with marked SST anomalies in the eastern Indian Ocean south of Indonesia. Another tropical phenomenon is the WNPSH, which determines the East Asian climate. Mode No. 86 shows the SLP change over the western subtropical Pacific, representing the change in the WNPSH. For the extratropics, mode No. 90 shows the change in the Icelandic low, and mode No. 94 that in the Azores high. These two modes represent the north–south dipole of the North Atlantic Oscillation. Additionally, mode No. 9 is related to the North Atlantic Oscillation, resembling the North Atlantic tripole with marked SST anomalies in the eastern subtropical Atlantic.

To attribute the EASM variability to particular winter climate phenomena with high confidence, we apply the causal discovery and model averaging to the time series of the bootstrapped rotated modes (see sections 2c and 2d). The causation-based empirical model formed from the five most frequent modes shows the lowest BIC score of 158.4 (Fig. 3; see section 2d). As the model includes additional modes, the BIC score increases owing to the penalty term for model complexity (Fig. 3); that is, this model is likely to include false-positive findings despite offering a better model fit. In addition, the models formed from fewer than five modes show high BIC scores because of the goodness-of-fit term (Fig. 3): namely, the five-mode model offers a better fit to the time series of the EASM index and limits false-positive findings. According to these BIC scores, the five most frequent modes at a particular lead time are regarded as the causal precursors (Figs. 4a–e). Among them, mode No. 102 in February is the most likely causal precursor according to its frequency in the 62,500 sets of bootstrapped precursors (Fig. 4a). These results
show that the EASM is independent of the other modes conditional on one of the five modes; all or part of the five modes mediate the indirect causal effects of the modes that can affect the EASM or, as the common causes, induce spurious associations between the EASM and other modes (Pearl et al. 2016).

In addition to the modes regarded as the causal precursors of EASM variability, the causal discovery produces the path coefficients, by which the effect of every causal precursor on the EASM is estimated (see section 2c). Both the causal precursors at a particular lead time and their coefficients compose the Bayesian network, encoding the causal structure (Fig. 4f; see appendix E). Notably, the network is standardized so that it is possible to compare different coefficients with each other. The effect on the EASM of mode No. 102 in February is 0.237; namely, an increase of 1 unit in the mode can cause an increase of 0.237 units in the EASM. Additionally, mode No. 33 in December, mode No. 73 in December, and mode No. 132 in February are 0.296, 0.255, and 0.208, respectively.

4. Dynamics of the five precursors

To explore the possible subsequent dynamics of every precursor regarded as the winter cause of EASM variability conditional on the other precursors, we regress the SST anomalies onto the time series of the causal precursors using the ordinary least squares with standardized data. Mode No. 102 in February represents the change in the western North Atlantic subtropical high (Fig. 4a). This mode is positively correlated with the positive phase of the North Atlantic tripole in spring (Fig. 5a). The anomalous high off the east coast of the United States in February can strengthen the trade winds over the tropical North Atlantic and displace the tropical warm humid air poleward. Consequently,
SSTs increase off the east coast and decrease in the tropical North Atlantic. These SST changes induce the North Atlantic Oscillation in February (Cassou et al. 2004) and thus develop into the North Atlantic tripole in spring (Cui et al. 2015; Wu et al. 2009). This tripole persists until summer and strengthens the EASM via a downstream wave train (Zuo et al. 2013). Mode No. 33 in December represents the Arctic air temperature anomalies (Fig. 4b). Its simultaneous Pearson correlation coefficient with the Arctic temperature anomalies is 0.82, whereas the $p$ value of the coefficient is less than 0.001. The Arctic warming can cause a wave train and thus SST anomalies in the North Pacific (Guo et al. 2014; Kug et al. 2015). These SST anomalies persist until summer and thereby intensify the EASM. In December, mode No. 73 is positively correlated with the SST anomalies of the central Pacific El Niño in the mature phase (Kao and Yu 2009) (Fig. 5b). Its simultaneous Pearson correlation coefficient with the El Niño Modoki index is 0.41, whereas the $p$ value of the coefficient is 0.008. Note that mode No. 73 may represent these SST anomalies because none of the rotated modes represents the anomalies. Therefore, the impact of mode No. 73 on the EASM may resemble that of the central Pacific ENSO (Yuan and Yang 2012).

As described previously, mode No. 81 in January represents the EP ENSO-related SLP change in the mature phase (Fig. 4d). It shows a simultaneous Pearson correlation coefficient of $-0.76$ with the Niño-3 index, whereas the $p$ value of the coefficient is less

![Fig. 3](image)

**Fig. 3.** BIC scores of the causation-based empirical models, varying with the number of predictor modes.

![Fig. 4](image)

**Fig. 4.** (a)–(e) Spatial patterns of the averages of equivalent bootstrapped rotated modes regarded as the winter causal precursors of EASM variability and (f) the graphical model representing the causal effects of the modes on the EASM. The modes are presented in a descending order of their frequencies, whereas the numbers, variable names, and lead time of the modes are shown above each panel. In (f), arrows from causes to effects indicate the causation and standardized path coefficients.
5. Predicting EASM

To examine the performance of the causation-based empirical model constructed, we use the 10-fold cross-validation in the regression process to compare the hindcasts from this empirical model with those from the correlation-based empirical models, the North American Multimodel Ensemble project, and the Copernicus Climate Change Service (see sections 2a, 2e, and 2f). The EASM time series between the causation-based empirical model with a cross-validated regression process and the reanalysis products show a root-mean-square error (RMSE) of 1.50, whereas their Pearson correlation coefficient is 0.75 (the point labeled “1” in Fig. 6). In addition to the 10-fold cross-validation (see section 2f), other cross-validations (2-, 4-, 5-, and 20-fold) show similar RMSEs and Pearson correlation coefficients. These figures show the stable performance of this empirical model. Figure 6 indicates that despite a minor underestimate of EASM variability, the causation-based model with cross-validated regression most accurately hindcasts the EASM time series among the nine models and the multimodel mean (MMM) of the climate models. In contrast, the empirical model of Wu and Yu (2016) and the CanCM4i are the least accurate prediction models. The low correlations of the GEM-NEMO and CMCC-SPS3 with the reanalysis reduce the accuracy of these models’ predictions, whereas the major underestimates of EASM variability in the GCFS2.0 and Météo-France System 7 reduce the accuracy of predictions. Notably, although the empirical model of Jin and Huo (2018) includes March–May predictors, it shows a BIC score of 165.4 and an RMSE of 1.65, larger than those of the causation-based model with cross-validated regression.

Additionally, we use the 10-consecutive-fold cross-validation in the entire modeling of the causation-based empirical model (see section 2f). In every implementation of cross-validation, not all five rotated modes obtained in section 3 are regarded as the causal precursors of EASM variability. The causation-based empirical model with entirely cross-validated modeling shows an RMSE of 1.65 and a Pearson correlation coefficient of 0.69 (the point labeled “2” in Fig. 6). Its predictive performance is comparable to that of the SEAS5 and better than the performances of the correlation-based empirical models and three climate models (i.e., the CanCM4i, GEM-NEMO, and CMCC-SPS3) (Fig. 6). Notably, although the predictors are selected without cross-validation in the empirical model of Jin and Huo (2018), this model underperforms the causation-based model with entire cross-validation.

To provide further information on prediction performances, we explore the joint distributions of hindcasts and observations (Fig. 7). The averages of predictive distributions from the Gaussian process regression model show linear relationships between the observed EASM time series and hindcast ones (Fig. 7; see section 2g). These averages are further compared with the perfect predictions. The results show minor overestimates of the EASM anomalies in the hindcasts of the causation-based empirical models (Figs. 7a,b), whereas the hindcasts of MMM are unbiased (Fig. 7e). In contrast, the hindcasts of Wu and Yu’s (2016) model and CanCM4i show major overestimates of the anomalies (cf. Figs. 7c,f). The hindcasts of the GCFS2.0 and Météo-France

![Figure 5. The ordinary least squares regressions of (a),(c) March–May SST anomalies and (b) December SST anomalies onto the five most frequent modes.](image_url)
System 7 show underestimated anomalies (cf. Figs. 7i,j). As for the unconditional distributions of hindcasts, the causation-based empirical model predicts several extreme anomalies (Figs. 7a,b); indeed, it has the potential to predict a wide range of anomalies. Similarly, the hindcasts of Wu and Yu’s (2016) model, CanCM4i, and CMCC-SPS3 show sharpness (cf. Figs. 7c,f,h) but with larger biases, which reduce the accuracy of predictions. In contrast, the unconditional distributions of the GCFS2.0 and Météo-France System 7 are narrow, and thus show low sharpness of their hindcasts (Figs. 7i,j). In short, the causation-based model with entire cross-validation accurately predicts the EASM owing to both the minor conditional biases and the high sharpness, thus outperforming five of the other models.

6. Conclusions and discussion

We introduce the causal inference framework integrated with model averaging to attribute and predict climatic anomalies. The framework identifies five winter causal precursors for EASM variability, whose effects on the monsoon are mediated by the oceans. This finding shows that within the selected variables and period, the five rotated modes are the most relevant among the possible winter impacts on the EASM. It also suggests a primary role of air–sea interactions in the winter impacts on the EASM. As implied in the examination of dynamic features, the framework offers outcomes that are interpretable in terms of physical processes. Furthermore, despite the small sample size of the monthly data, the model averaging offers high confidence in the causal precursors. In addition, the framework quantifies the impacts of the precursors. This result suggests that major effects on the EASM come from the EP ENSO and Arctic temperature anomalies, while other climate factors worldwide exert relatively minor effects on the monsoon. Among the five winter precursors, the change in the western North Atlantic subtropical high is the most likely causal precursor of the EASM according to the frequency of equivalent bootstrapped mode in the bootstrapped precursors in the causal discovery, although its causal effect is the second smallest. Bootstrap estimates can assess temporal variability in an attribute (Wang et al. 2014). Therefore, the high likelihood of being the causal precursor estimated by the bootstrap may be due to the strong stationarity of the effect of the subtropical high anomalies on the EASM (namely, the high possibility that the anomalies can be regarded as the causal precursor at different periods).

The causal precursors and their effects can compose a causation-based empirical model. The low BIC score and the dynamic explanations of the precursors show that the model offers an enough model fit and limits false-positive findings. The model using features based on the causal inference approach outperforms three of the climate models as well as the correlation-based empirical models; it predicts the EASM one season ahead with better accuracy. Compared with the correlation-based empirical approaches, the causal inference approach requires far less human intervention (needing only the selection of variables, lead times, and independence tests), thereby avoiding suboptimal outcomes due to anthropogenic constraints. Therefore, our causal inference framework has great potential to be applied to the studies of climatic anomalies. It will identify their causes with high...
FIG. 7. Scatterplots of the EASM index for observations and hindcasts of different models. The 1:1 diagonal solid line indicates perfect predictions. Dashed line denotes the average of predictive distributions from the Gaussian process regression model, whereas shading is the 95% confidence interval. The histogram in each panel shows the unconditional distribution of the hindcasts. The histogram’s vertical axis is shown to the left of the panel, and the RMSE of each model is given in the top-left corner.
accuracy, facilitate the dynamic explanations, and improve the prediction of anomalies.

A limitation of this study is the linearity assumption of the climate system. Nonlinearity can reduce the performance of the PC-stable algorithm with the Pearson correlation test. Since the climate system is nonlinear (Stuecker et al. 2015; Yeh et al. 2018), further studies could employ the causal inference approach with nonlinear independence tests. Second, the causal inference framework assumes there is no confounding; that is, the variables causing spurious associations are all observed (Pearl 2009a). The rotated modes obtained in this study may exclude some physical processes. Therefore, unobserved confounders can make the associations between the five modes and EASM spurious. Further research examining additional variables can confirm the no confounding. Third, this study does not examine the subseasonal features or nonstationarity of the

Fig. A1. Flowchart of the causal inference framework of this study. A stadium shape represents the start or end point. Arrows show the direction of process flow, and parallelograms represent input or output. A rectangle represents a process; a rhombus indicates a decision.
EASM. The monsoon and its dynamics can vary monthly from June to August and from one year to another (Chiang et al. 2020; Y. H. Ding et al. 2018; Yang et al. 2017). Therefore, when using the causal inference framework adjusted to monthly data, future research could investigate the causal precursors of EASM variability and their effects in different periods.

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APPENDIX A
A Framework for Learning the Seasonal-or-Longer-Scale Causation

Figure A1 shows the flowchart of the causal inference framework introduced in this study.

APPENDIX B
Selection of the Autoregressive Model Order and Simulation of the Autoregressive Process

The stepwise least squares algorithm (Neumaier and Schneider 2001) is employed to evaluate BIC scores of the autoregressive models of different orders and to calculate the model coefficients and noise variance of the optimal order. The order with the lowest BIC score is selected (Fig. B1).

A set of time series samples of the autoregressive process is simulated by replacing the noise term in the autoregressive model with the product of the model's noise standard deviation and a Gaussian white noise variable.

APPENDIX C
Adjacency Search of the PC-Stable Algorithm and Orientation

Given a set of variables, the adjacency search of the PC-stable algorithm starts with a complete undirected graph (Fig. C1a). The first step is to remove all the edges between variables (A, B) if A and B are unconditionally independent (e.g., according to their Pearson correlation coefficients) (Fig. C1b). Subsequently, for each remaining edge between variables (A, B), if the search finds a variable C connected to either A or B right after the first step and a conditional independence between A and B given the value of C (e.g., according to their Pearson partial correlation coefficient), this edge is removed (Fig. C1c). The undirected edges of the resulting graph are then oriented by time order (Fig. C1d).

The aforementioned procedures are illustrated as follows. Suppose we have samples of variables X, Y, Z, and W and the true causal graph is as Fig. C1d. We start with their complete undirected graph (Fig. C1a). In the first step, the
The Causation-Based Empirical Model

The causation-based empirical model formed in section 3 is as follows:

\[ y = 0.237x_1 + 0.296x_2 - 0.255x_3 + 0.343x_4 + 0.208x_5, \]

where \( y \) is the time series of the EASM index; \( x_1, x_2, x_3, x_4, \) and \( x_5 \) are the time series of mode No. 102 in February, mode No. 33 in December, mode No. 73 in December, mode No. 81 in January, and mode No. 132 in February, respectively.

REFERENCES


