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Prediction of silver hake distribution on the Northeast U.S. shelf based on the Gulf Stream path index

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ABSTRACT

Over the past ~40 years, the distribution of silver hake on the Northeast U.S. shelf is found to be significantly correlated with changes in the latitude of Gulf Stream path. The correlation coefficient between the fall Gulf Stream position and the center of biomass of spring silver hake reaches 0.75 when the Gulf Stream leads the silver hake for 6 months. Based on this lead-lag relationship and low-frequency variability of Gulf Stream position with a dominant periodicity of ~9–10 years, the Gulf Stream position is used as a predictor for the center of biomass of silver hake in linear autoregressive (AR) models. The goal of this study is then to optimize the AR model for the prediction of silver hake based on the observed changes in Gulf Stream position. Fall Gulf Stream position is first predicted out to 5 years using a 5th order AR model and the observed Gulf Stream position in preceding years. An optimization process is proposed to choose best AR coefficients based on a newly proposed combined skill parameter. Furthermore, the robustness of our Gulf Stream prediction is verified by comparing the observed Gulf Stream path index data from 2009 to 2012, which are not used for optimizing the AR model, and the predicted Gulf Stream path values for the same time period. We then use this predicted Gulf Stream position to further predict the center of biomass of silver hake in the subsequent spring. Three different methods are used and compared for the silver hake prediction. The predicted silver hake time series can explain as much as 69% of the variance of the observation for the 1st year prediction and 41% for the 5th year prediction. Our results indicate that including Gulf Stream as a predictor produces better prediction skills of silver hake center of biomass than the AR model prediction solely based on the observed silver hake time series.

1. Introduction

Recent studies continue to reveal that the large-scale climate variability and change can lead to a reorganization of the biology in the ocean. For example, Nye et al. (2009) showed changes in spatial distribution of marine fish on the Northeast U.S. continental shelf in response to the climate change. Similar findings are reported by the various studies in other regions of the world ocean (e.g. Dulvy et al., 2008; Mueter and Litzow, 2008; Pinksy et al., 2013). Climate indices, such as North Atlantic Oscillation (NAO), Atlantic Multidecadal Oscillation (AMO) in the North Atlantic and El Niño-Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO) in the Pacific, represent large-scale variations of the ocean and atmosphere and have been found to be closely tied to the variability of the distribution and productivity of certain biological species (Mantua et al., 1997; Hatun et al., 2009; Nye et al., 2011, 2014; Pershing et al., 2015).

In some cases, attention has been directed towards exploring biophysical relationships driven by individual components of the climate system, e.g. ocean western boundary currents such as Gulf Stream. The abundance of biological and physical data in the western North Atlantic has motivated numerous investigations of the relationships between the two (Lohrenz et al., 1993; Hitchcock et al., 1993; Anderson et al., 2000; Anderson and Robinson, 2001; Ottersen et al., 2000; Nye et al., 2011). The open ocean frontal regions such as the Gulf Stream have been observed to enhance the biological growth associated with their meandering, mesoscale eddies and upwelling (Hitchcock et al., 1993; Lohrenz et al., 1993; McGillicuddy et al., 2007). The mesoscale processes associated with the Gulf Stream are also shown to be important for the local biology, based on various physical-biological modeling (Anderson et al., 2000; Anderson and Robinson, 2001; Anderson et al., 2011).

Furthermore, the north-south shift of the Gulf Stream reflects the large scale change in the North Atlantic and has been found to be linked to the changes in temperature and zooplankton abundance (Taylor and Stephens, 1980; Taylor et al., 1992; Taylor, 1996) as well as the spatial distribution of the fish biomass (Nye et al., 2011). In

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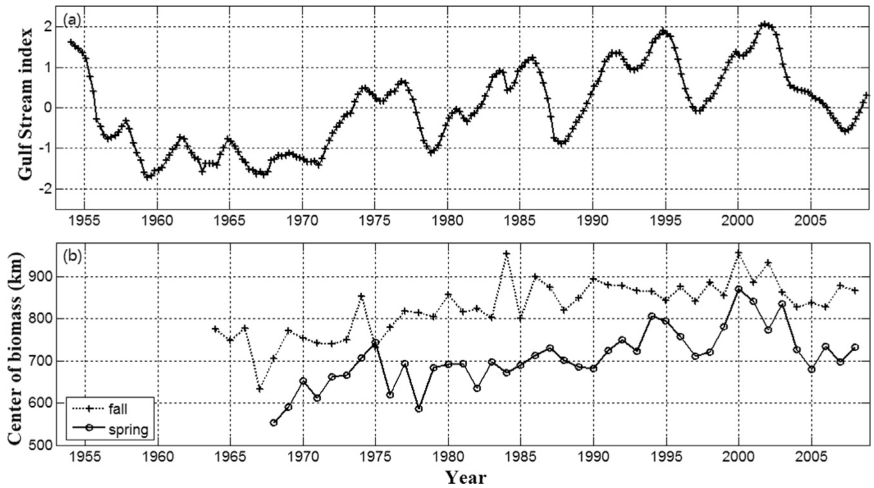

Fig. 1. The time series of the (a) Gulf Stream path index and (b) silver hake spatial distribution: In (a), the Gulf Stream index time series is in seasonal resolution, positive values represent northward displacement of the Gulf Stream. In (b), the distance (km) of the center of biomass of the spring and fall southern silver hake from the Cape Hatteras North Carolina is in yearly resolution. Larger distances indicate a northward position generally.

particular, Nye et al. (2011) reported that changes in spatial distribution of silver hake, *Merluccius bilinearis*, a commercially important, semi-pelagic fish prolific in Northeast U.S. shelf, over the past forty years demonstrates a high correlation with the latitude of the Gulf Stream path. They suggested that these changes are indirect response to changes in the Atlantic Meridional Overturning Circulation (AMOC), which drive shifts in bottom temperature on the outer continental shelf (Peña-Molino and Joyce, 2008; Joyce and Zhang, 2010). The north (south) shift of the Gulf Stream is correlated with the warming (cooling) of the bottom temperature over the shelf of order 1 °C (Nye et al., 2011). Meanwhile the silver hake prefers the water temperature range of 7–10 °C (Nye et al., 2011). When Gulf Stream was in its northern position, the bottom temperature in the southern area increased to be warmer than 10 °C so that the silver hake moved northward to be in the Gulf of Maine where the bottom temperature was within the range of 7–10 °C. Note that the changes in the Gulf Stream path are also associated with NAO (Joyce et al., 2000; Frankignoul et al., 2001) through both wind-driven gyre adjustment and AMOC changes (Marshall et al., 2001; Kwon et al., 2010).

Nye et al. (2011) further pointed out that the correlation between Gulf Stream position and silver hake is characterized by a phase lag with the Gulf Stream leading the silver hake by 0.5 or 1 year, which implies some potential predictability of silver hake using Gulf Stream data. The impact of the physical environment on the commercially important fish stocks in the North Atlantic (e.g., Nye et al., 2009, 2011; Friedland et al., 2013 ; Pinksy et al., 2013; Pershing et al., 2015) has indeed motivated the prediction studies of parameters of the physical environment. For example, Ottersen et al. (2000) developed the prediction of the Barents Sea's temperature using a statistical analysis method. Based on the combination of a first order autoregressive (AR) model, local advection and large-scale air-sea interaction terms, their 1st year prediction explained 50% of the total historical temperature variability.

Our study builds on these works and advances application of an AR model in conjunction with Gulf Stream path record to provide a predictive tool for Gulf Stream variability and associated biological variability. More specifically, we examine the potential predictability of silver hake distribution using Gulf Stream path record based on the AR models. The AR model is a group of linear prediction formulae that attempt to predict an output of a system based on the previous values. In climate studies, previous works have demonstrated the utility of AR models in simulating trends in global indicators such as sea surface temperature anomalies in the Pacific (Reynolds, 1978) and global atmospheric temperature (Seidel and Lanzante, 2004; Mahajan et al., 2011). Some efforts have also demonstrated the effectiveness of AR models in identifying and forecasting impacts of climate shifts on some elements of the global ecosystem, such as changes of salmon production in the Northeast Pacific Ocean (Hare and Francis, 1994) and sediment transport rates of rivers in the United Kingdom (Augustin et al., 2008). Unlike complicated general circulation models, the predictability characteristics of AR models can often be derived without the computational expense of ensemble integrations (Schneider and Griffies, 1999). Also notable is that dynamical predictions have had little success in this region thus far – likely due to coarse resolution of the detailed shelf processes (Stock et al., 2015). Further motivation in this approach is derived from the fact that an AR model is based on the linear combination of its own previous values. This is highly suitable in the case of the Gulf Stream, since the Gulf Stream path demonstrates low-frequency variability in the near-decadal (7–10 years) band (Gangopadhyay et al., 2016). Coupled with this is the existence of a strong correlation between Gulf Stream path and silver hake time series.

The paper is organized as follows. In Section 2.1, we first describe the data that we will use. The basics of AR models and the criteria for our prediction comprise Section 2.2. In Section 2.3, we detail the methodology we developed for the application of the AR model to the prediction of the Gulf Stream and silver hake. We report our results based on this methodology in Section 3. Finally we discuss our results in Section 4 and conclude in Section 5.

2. Data, model and methodology

2.1. Data

2.1.1. Gulf Stream path index data

Gulf Stream path index representing coherent north-south shift of the current in 55°–75°W is based on the historical subsurface temperature data at 200 m depth essentially from the World Ocean Database (WOD2015) at the National Oceanographic Data Center (NODC), and the detailed definition can be found in Joyce et al. (2000, 2009) and Nye et al. (2011). The Gulf Stream path index has four data points in each year, one in each season (Fig. 1a). Since the variability of the center of biomass of the silver hake during spring and fall seasons are very different (solid and dotted lines in Fig. 1b), we will next define the spring and fall Gulf Stream path indices to examine the relationship of the center of the biomass of the silver hake and Gulf Stream indices during spring and fall seasons. Specifically, we define the spring and fall Gulf Stream path indices by simply averaging the first two data points and last two data points of the Gulf Stream path index in each year, respectively. The Gulf Stream data shown (Fig. 1a) are from 1954 to 2008. The data during 1967 and 2008 are used for prediction in this study to match the overlapping time period of the available spring silver hake data, which will be described next. More recent Gulf Stream path index data from 2009 to 2012 are later used as an independent comparison to the prediction based on 1967–2008 data.

2.1.2. Silver hake data

Silver hake biomass (mean-stratified weight per tow) data are collected by the NOAA Northeast Fisheries Science Center (NEFSC) trawl survey on the Northeast U.S. shelf. The center of biomass is a metric commonly used to describe the overall spatial distribution of organisms which usually links to climate variability and climate change. The center of biomass of the southern silver hake (simply silver hake hereafter) used here was calculated as an overall distance from the Cape Hatteras, North Carolina (35.3°N, 75.5°W) as described in Nye et al. (2009) (Fig. 1b). There are two measurements in each year: one in spring, the other in fall. The spring silver hake data were collected from 1968 to 2008 and the fall silver hake data started 5 years earlier, i.e., from 1963 to 2008 (Fig. 1b). More details about these data can be found in Azarovitz (1981) and Nye et al. (2009).

2.1.3. The relationship between the Gulf Stream and Silver Hake

As detailed in later Section 3.1, the 4 pairs of cross correlations between Gulf Stream path index and the silver hake center of biomass in spring and fall seasons, is calculated and analyzed. Considering the maximum correlation and corresponding lead-lag relationship, a pair of time series is chosen for the model construction and prediction study shown in later sections.

2.2. Model

2.2.1. AR modeling

The AR model is a group of linear prediction formulae that attempts to predict an output Y(t) of a system based on the previous values Y(t-1), Y(t-2)...Y(*t*-p) such that

$$Y(t) = A_1 Y(t-1) + A_2 Y(t-2) + \ldots + A_p Y(t-p) + n_t \tag{1}$$

for AR(p) model. Where A1, A2, ...Ap are the coefficients of AR model; Y(t-1), Y(t-2) ... Y(*t*-p) are the values of the time series Y at time step t-1, t-2, ... t-p; p is the order of the AR model and nt stands for white noise with a mean value of zero. Deriving the AR(p) prediction model for a time series Y(t) involves determining the parameters A1, A2, ...Ap and nt in the Eq. (1). These parameters are estimated for fall Gulf Stream and spring silver hake time series using the stepwise least square algorithm by Neumaier and Schneider (2001). The confidence levels of the model parameters and the adequacy of the order are also calculated and evaluated as detailed in the following subsections and Appendix.

2.2.2. AR model order selection

The autocorrelation function of the fall Gulf Stream path index shows a 9-year periodicity (Fig. 2a) significant at 80% confidence level, which suggests the AR model can be a good tool for the prediction of the fall Gulf Stream path based on the assumption that the fall Gulf Stream path index is stationary. The significance threshold (80%) here is calculated following Mitchell et al. (1966), in which the serial correlation check was recommended, i.e., when the autocorrelation coefficients of different lag times, calculated for a time series, are outside the threshold confidence level, the observations in this time series can be accepted as being dependent on each other. Similarly, this serial correlation check can be used for two time series when their correlations are calculated. Eq. (1), which is also called the Yule-Walker equation, can be used for the AR model of any order. However, increasing the model order after a certain extent will result in over-fitting of the model and does not improve the data representation much. Increasing the AR model order also means increasing the number of previous data points needed for the prediction.

There are various criteria for evaluating the 'optimum' order of autoregressive processes, such as the Schwartz's Bayesian Criterion, SBC (Schwartz, 1978; SAS, 1988a), the logarithm of Akaike's (1969) Final Prediction Error and the Akaike Information Criteria (Akaike, 1974). The comparison between the SBC and other order selection criteria was made in a simulation study by Lütkepohl (1985) and the author concluded that by applying SBC criteria, the smallest mean-squared prediction error of the fitted AR models was achieved on the average and the correct model order was chosen mostly. Hence, we choose SBC criterion for our study here. For the same length of the time series, a smaller value of SBC indicates a better choice of the model order. Given a lower bound and an upper bound on the model order, the optimum order of an AR model for a given time series can be selected according to the SBC criterion (Schneider and Neumaier, 2001). In our study, we calculated the SBC values of the AR models for fall Gulf Stream time series from order 1–10 (Fig. 2b) and found that SBC for order 5 has the smallest values. Therefore we choose 5th order for the fall Gulf Stream prediction. We also assessed the adequacy of the fitted AR5 model for representing the fall Gulf Stream time series based on the hypothesis by Li and Mcleod (1981) and concluded that it is sufficient since the residuals are uncorrelated.

2.3. Application of AR model to Gulf Stream and silver hake data

Based on the lead-lag relationship and the maximum correlation between Gulf Stream and silver hake during spring and fall seasons as detailed in later Section 3.1, we choose to use fall Gulf Stream as the predictor of the spring silver hake. We next describe the methodology we use for the prediction of the fall Gulf Stream path and spring silver hake.

2.3.1. Prediction of fall Gulf Stream path using the optimized AR5 model

To use the AR model as a tool for prediction, we first fit the AR5 model to the observed fall Gulf Stream path index time series by calculating the model coefficients A1, A2 ... A5 and the ranges with 95% confidence level for each coefficient following Neumaier and Schneider (2001). While the calculated coefficients guarantee the best prediction skill for the first year prediction using only the observed values, the same does not hold for the predictions beyond the 1st year when the predicted as well as observed values are used as input. Therefore, we need to further optimize the model coefficients A1, A2, ...A5 within their 95% confidence range for each prediction beyond the 1st year to ensure the best prediction. We here define a "combined prediction skill Pcombo" (as detailed in the Appendix A), through which the optimization of AR model coefficients can be achieved as detailed in Appendix B. Here we test the AR model from second to fifth order and compare their optimum prediction skills for fall Gulf Stream (Fig. 3). It is clear that for all five years of predictions, the higher the order of AR model, the smaller the root mean square error (RMSE), the larger the skill coefficient (ρ), the larger the percentage of the explained variance (PEV), hence the smaller the Pcombo (where the RMSE, ρ and PEV are defined in Appendix A). In other words, the AR5 has the best prediction skills as expected based on SBC criterion. Note that the prediction is made based on the detrended fall Gulf Stream first, then the trend is added back to the predicted time series. With this best prediction of fall Gulf Stream up to 5 years, we then predict the spring silver hake time series based on the linear regression coefficient between observed Gulf Stream and silver hake.

2.3.2. Prediction of spring silver hake

Three methods are used for the prediction of the silver hake, two of

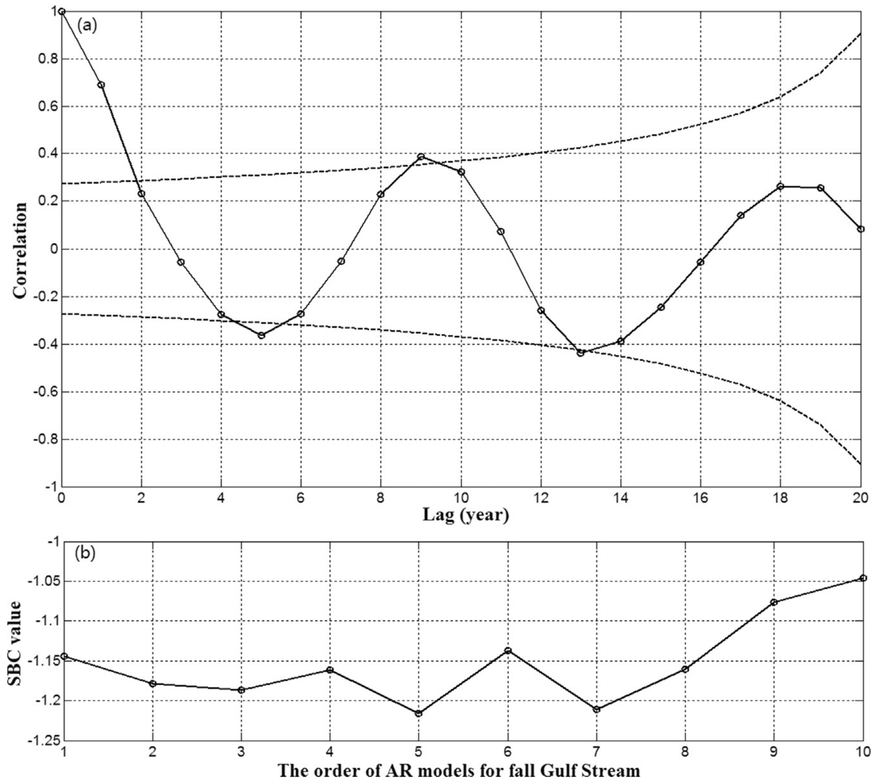

Fig. 2. (a) The autocorrelation function of the detrended fall Gulf Stream for 1967–2008. The auto correlation is significant at 80% level when it lies outside the dashed lines. Significance threshold (dashed line) is calculated by considering serial correlation following Mitchell et al. (1966). (b) The Schwartz's Bayesian Criterion (SBC) values as a function of the order of auto-regressive (AR) models for the detrended fall Gulf Stream from order 1–10.

which are based on the best prediction of the fall Gulf Stream path. The third one is based on the spring silver hake itself. In the first method, the best predicted fall Gulf Stream (without trend) is used to predict the spring silver hake (without trend) based on their linear regression at the 0.5 year lag, then we add the trend of the spring silver hake back to the predicted spring silver hake without trend. The flow diagram I (Fig. 4a) summarizes this prediction procedure for the spring silver hake. In the second method, we consider an additional prediction of

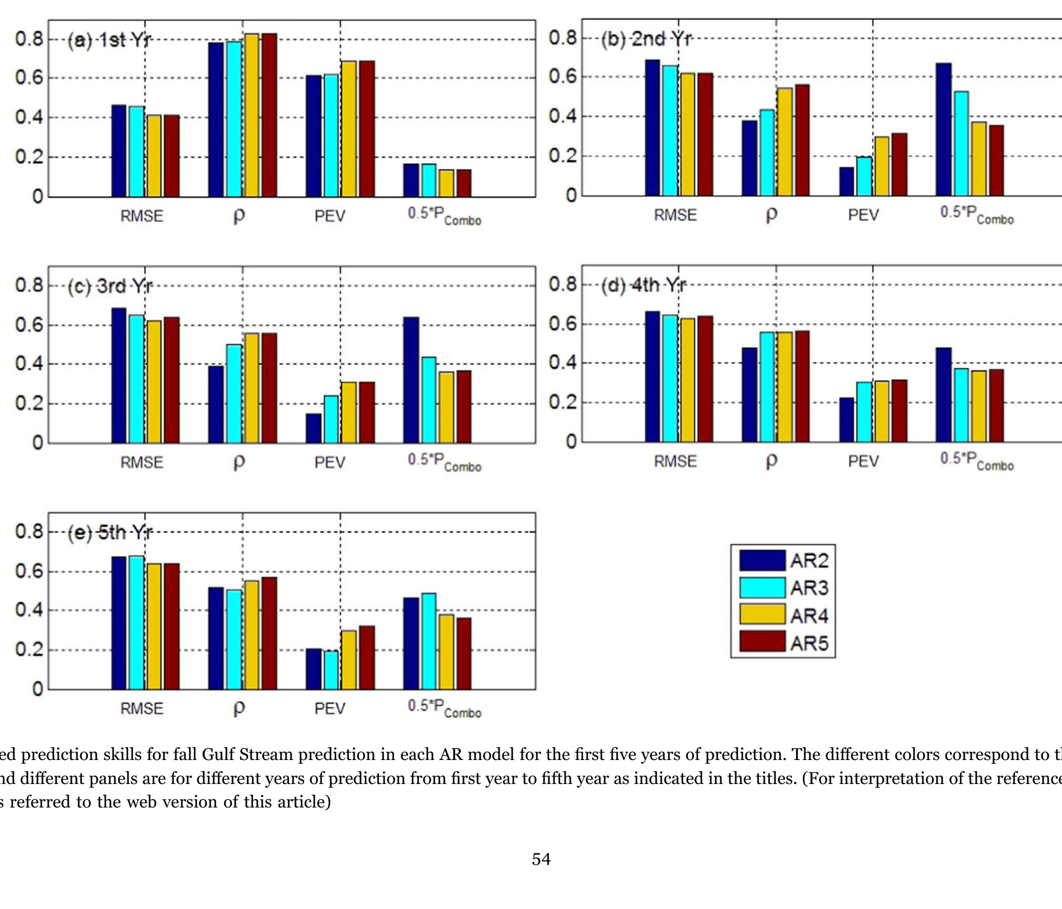

Fig. 3. The optimized prediction skills for fall Gulf Stream prediction in each AR model for the first five years of prediction. The different colors correspond to the different AR models (shown in legend) and different panels are for different years of prediction from first year to fifth year as indicated in the titles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

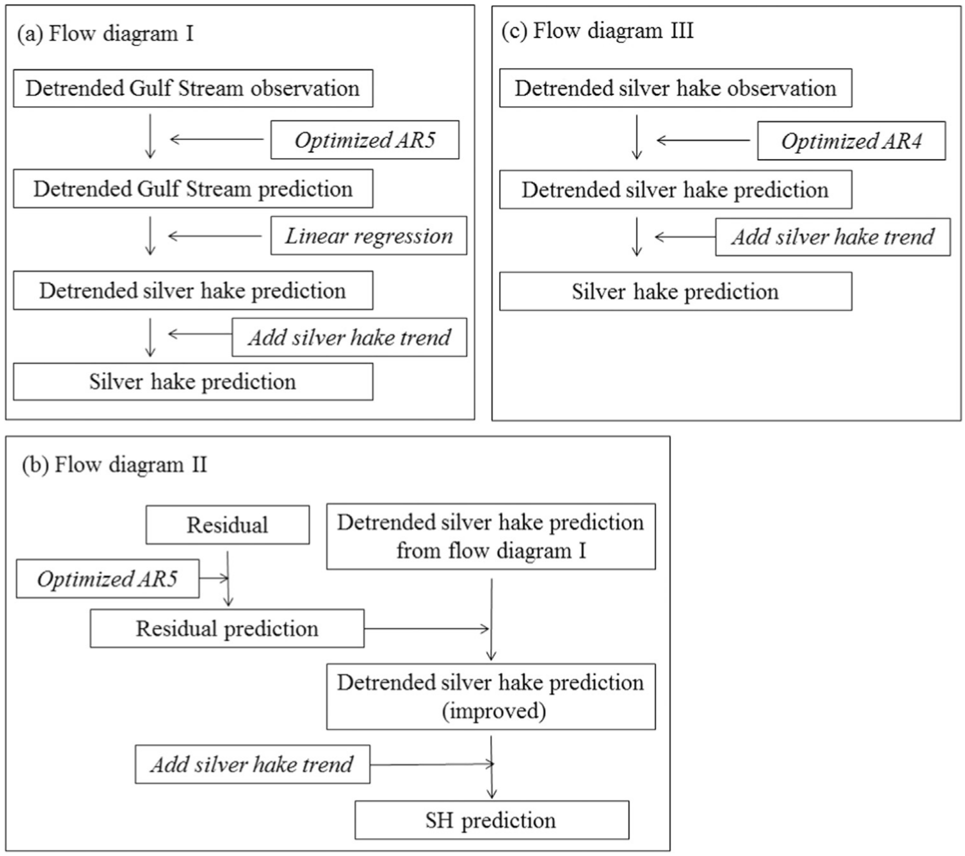

Fig. 4. The flow diagrams for illustrating the procedure of spring silver hake prediction using three different methods. (a) Flow diagram I: the procedure for predicting spring silver hake based on optimum Gulf Stream prediction using AR5; (b) Flow diagram II: the procedure for predicting spring silver hake based on the optimum Gulf Stream and 'residual' predictions both using AR5; (c) Flow diagram III: the procedure for predicting spring silver hake based on optimum silver hake prediction using AR4.

the residual time series, i.e. observed silver hake minus predicted, in an attempt to further improve the silver hake prediction. To have a fair comparison, AR5 is chosen for the residual prediction based on the Pcombo criterion and we use the same methodology as that for the prediction of fall Gulf Stream to find the best prediction of the residual time series. Then we add this prediction of residual from year 1 to year 5 to the original prediction of the spring silver hake at each year based on fall Gulf Stream prediction before adding back the linear trend of silver hake. The specific procedure for this prediction is shown in the flow diagram II (Fig. 4b). Since the observed silver hake also exhibits some low-frequency oscillation, it would also be possible to construct the AR prediction solely based on the observed silver hake time series. So in the third method, we fit an AR model directly to the spring silver hake time series (using the same optimization as that for the Gulf Stream) to make the prediction and compare it with the prediction based on the fall Gulf Stream. Using the same optimization method described in Section 2.3.1 for Gulf Stream prediction, we find that AR4 and AR5 have best and comparable prediction skills based on Pcombo for the spring silver hake. Compared to AR5, AR4 requires one less previous value for prediction (4 vs 5), i.e., it has the advantage of producing a prediction of the silver hake with one extra year value. Thus the AR4 is used for the silver hake prediction here. The specific procedure is similarly shown in the flow diagram III (Fig. 4c).

3. Results

3.1. The relationship between the Gulf Stream and silver hake

The Gulf Stream path index (normalized to have a standard deviation of unity) and the center of biomass of silver hake have a similar trend and variability (Fig. 1). The correlations between annual mean Gulf Stream index and center of biomass of the spring silver hake and fall silver hake are 0.73 and 0.61 respectively during their overlapping time period. Generally, when Gulf Stream index is positive and larger, i.e. Gulf Stream is in its northerly position, the distance of the center of biomass of the silver hake from Cape Hatteras is larger, i.e. the center of biomass of the silver hake is more northerly. This relationship between the Gulf Stream path and the silver hake distribution can be seen clearly by comparing the time periods when Gulf Stream was in its most northern (represented by the years when Gulf Stream index was greater than 0.7, Fig. 5) and southern positions (represented by the years when Gulf Stream index was smaller than −0.7, Fig. 5). The center of biomass of the spring silver hake shown in Fig. 5 includes effects of both the long-term trend and the interannual-to-decadal variability. Here we use the southern spring silver hake as an example since the spring silver hake is the main subject of the study as detailed next in this section. Gulf Stream path index values of ± 0.7 are chosen as the thresholds to represent the time periods of the most northern (large peaks in Fig. 1a corresponding to Gulf Stream path index > 0.7) and southern positions (large troughs in Fig. 1a corresponding to Gulf Stream path index < −0.7) to illustrate clearly the relationship of the Gulf Stream position and the center of biomass of the spring silver hake. However, the result is not sensitive to the exact threshold values. Note that the southern spring silver hake area extends from southern Georges Banks to Cape Hatteras along the Northeast U.S. shelf. The large spring silver hake biomass was concentrated in the Gulf of Maine and northern Mid-Atlantic Bight when Gulf Stream was in its northerly positions (Fig. 5a) and the large concentration of spring silver hake was mainly along the outer shelf of southern Mid-Atlantic Bight when Gulf Stream was in its southerly position (Fig. 5b).

To examine the relationship between Gulf Stream and silver hake in

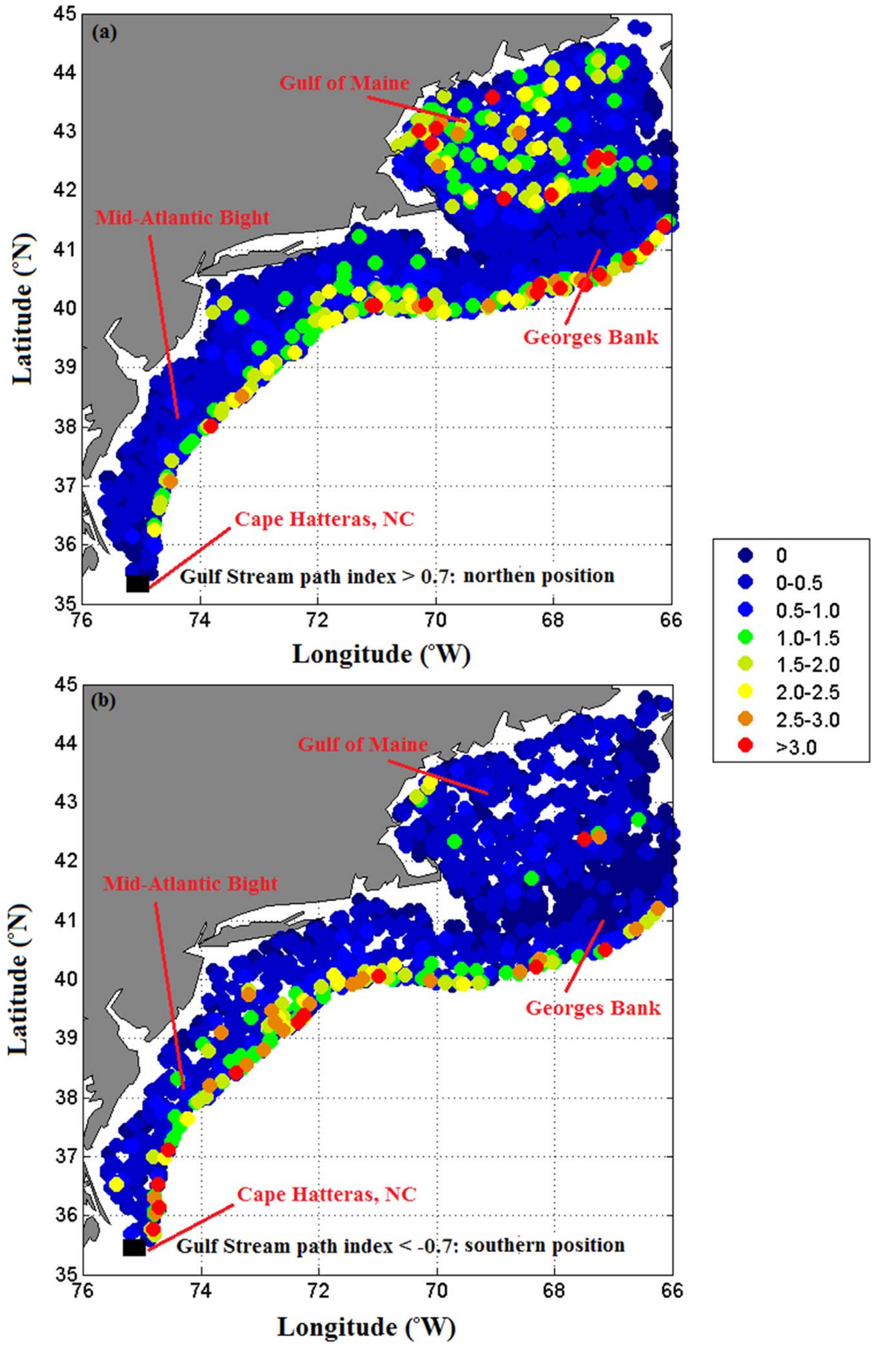

Fig. 5. The spatial distribution of the spring silver hake biomass (in color dots, unit: log weight (kg) per tow). (a) when Gulf Stream was in its northerly position and (b) when Gulf Stream was in its southerly position. The northerly (southerly) position years here are defined as the years when Gulf Stream path index is greater (smaller) than 0.7 (−0.7). The location of the Cape Hatteras is marked by black rectangle. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

spring and fall seasons, the correlation between the Gulf Stream and silver hake is calculated based on the four pairs of fall and spring time series (Fig. 6). The maximum correlation coefficients (Fig. 6 and Table 1), from high to low, are 0.75 between fall Gulf Stream and following spring silver hake with 0.5 year lag (Gulf Stream leads the silver hake), 0.74 between spring Gulf Stream and spring silver hake without any lag, 0.71 between fall Gulf Stream and fall silver hake with 1 year lag (Gulf Stream leads the silver hake) and 0.69 between spring Gulf Stream and fall silver hake with 0.5 year lag (Gulf Stream leads the silver hake). After the linear trends are removed, their correlations become lower, ranging from 0.44 to 0.61 (dotted lines with plus signs in Fig. 6). All the above coefficients are statistically significant at 95% confidence level (solid and dashed lines without plus signs in Fig. 6) regardless of the trend removal. Three out of four correlations mentioned above show that Gulf Stream variability leads the silver hake variability: fall Gulf Stream leading the following spring silver hake by 0.5 year (Fig. 6a), spring Gulf Stream leading fall silver hake by 0.5 year (Fig. 6b), and the fall Gulf Stream leading the fall silver hake by 1 year (Fig. 6c). Note that the removal of the linear trend does not affect the lead-lag relationship.

Considering the maximum correlation coefficient (i.e., 0.75) between the fall Gulf Stream and the spring silver hake and that the fall Gulf Stream leads the spring silver hake 0.5 year (Table 1), we choose to use fall Gulf Stream and spring silver hake for the prediction study here. The fact that fall Gulf Stream leads the following spring silver hake for 0.5 year (i.e., the high correlation corresponding to the offset

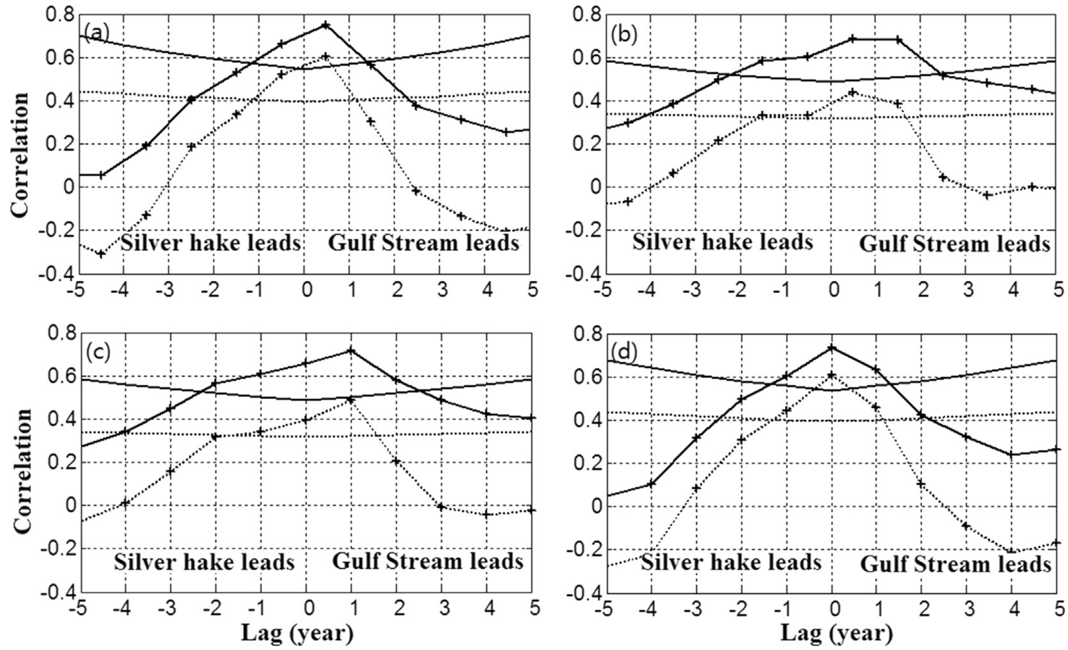

Fig. 6. The cross correlations between Gulf Stream and silver hake. (a) the fall Gulf Stream and spring silver hake (b) the spring Gulf Stream and fall silver hake (c) the fall Gulf Stream and fall silver hake and (d) the spring Gulf Stream and spring silver hake. The solid (dotted) lines with plus signs are cross correlations between the observed data with (without) their trends. The solid (dotted) lines without plus signs mark the significance at 95% level for the correlations with (without) trends, respectively. Significance threshold is calculated by considering serial correlation following Mitchell et al. (1966).

Table 1
The maximum cross correlations and corresponding time lags between Gulf Stream and silver hake time series.

Gulf Stream & Silver hake Correlation (r)	With trend	Without trend	Years led by Gulf Stream
Fall Gulf Stream vs. following Spring silver hake	0.75	0.60	0.5 year
Spring Gulf Stream vs. Spring silver hake	0.74	0.61	0 year
Fall Gulf Stream vs. Fall silver hake	0.71	0.49	1 year
Spring Gulf Stream vs. Fall silver hake	0.69	0.44	0.5 year

of 0.5 year between fall Gulf Stream and the coming spring silver hake) enhances the use of fall Gulf Stream as a predictor.

3.2. Prediction of fall Gulf Stream path using the optimized AR5 model

Based on the optimum set of AR5 coefficients corresponding to the smallest positive Pcombo, the first 5 years prediction of fall Gulf Stream is shown together with the observed fall Gulf Stream time series (Fig. 7). The 1st year prediction is solely based on the previous 5 years of observation (Fig. 7a). The predicted Gulf Stream time series reproduce not only the low frequency (~9 years) variations of the Gulf Stream but also the higher frequency (~2–5 years) variability, such as the double positive peaks around 1977, 1986, 1994 and 2002. The correlation coefficient is as high as 0.83 between the predicted and observed fall Gulf Stream time series for the overlapping period, 1973–2008. The 2nd year prediction, which uses four previous observations and one prediction from the 1st year prediction, still exhibits the low frequency features but with little indications of the higher frequency signals (Fig. 7b). The correlation coefficient for the 2nd year prediction is a 0.56, which shows a significant decrease compared to the 1st year prediction. Similarly, the 3rd, 4th and 5th year results predict the low frequency well but not the high frequency features of the observed Gulf Stream with similar correlation coefficients between the predicted and observed fall Gulf Stream index (Fig. 7c, d and e). As mentioned earlier, for the 2nd year to 5th year prediction, the prediction is based on the combination of the observed and predicted values for previous years, which may explain the noticeable decrease in the correlation coefficient compared to that of the 1st year prediction.

3.3. Prediction of spring silver hake

3.3.1. Prediction of spring silver hake based on optimum Gulf Stream prediction

Given the observed strong correlation between the fall Gulf Stream and spring silver hake with 0.5 year lag (Table 1), we use the optimum fall Gulf Stream prediction from the Section 3.2 to predict the spring silver hake (i.e., using the first method described in Section 2.3.2 and the flow diagram I in Fig. 4a). The 1.5, 2.5, 3.5 and 4.5 year prediction of silver hake (Fig. 8b-e) are resulting from the 1st, 2nd, 3rd and 4th year prediction of Gulf Stream, respectively, according to the 0.5 year lag between Gulf Stream and silver hake. Note that the 0.5 year prediction of spring silver hake is achieved solely based on the observed fall Gulf Stream using the maximum detrended regression between the observed fall Gulf Stream and spring silver hake at 0.5 year lag (Fig. 8a). To be brief, we hereafter call the 0.5, 1.5, 2.5, 3.5 and 4.5 year prediction of silver hake as the 1st, 2nd, 3rd, 4th and 5th prediction of silver hake (Fig. 8a-e). The correlation between predicted (for the 1st year prediction) and observed spring silver hake is 0.81 (Fig. 8a), comparable to the 1st year prediction of fall Gulf Stream index based on AR5 (Fig. 7a). Note that this correlation coefficient of 0.81 is larger than the observed correlation between fall Gulf Stream and spring silver hake as shown in Fig. 6a and Table 1, which is not contradictory, since here the predicted spring silver hake has the same trend as that of the observed spring silver hake. Correlation without the trends between the predicted and observed spring silver hake is 0.60 (Table 2), which is identical to the observed correlation (Fig. 6a and Table 1). This indicates the advantage of the detrending for the prediction, which optimizes the prediction of the detrended time series as the first step instead of focusing on predicting both the linear trend and the detrended data. Based on the fall Gulf Stream prediction, the

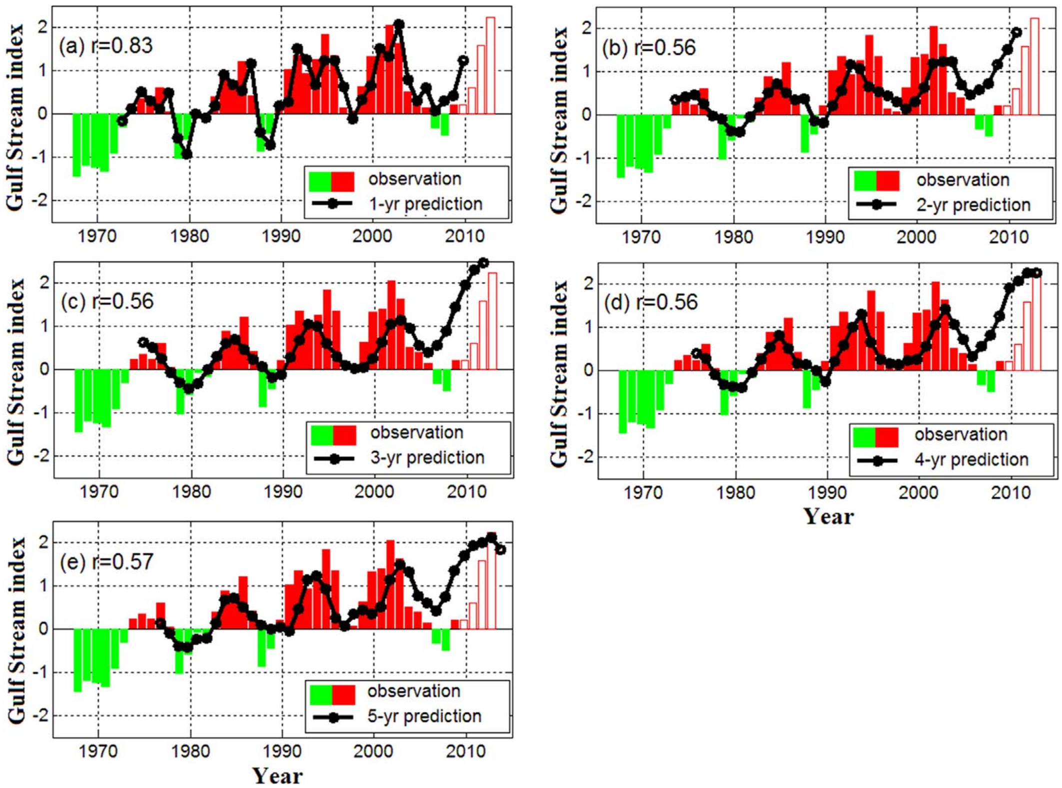

Fig. 7. The prediction of the fall Gulf Stream index based on the optimized AR5 model for the (a) 1st year, (b) 2nd year, (c) 3rd year, (d) 4th year and (e) 5th year prediction, respectively. The observed fall Gulf Stream position index is represented by red (positive values) and green (negative values) bars. The filled bars are the observed Gulf Stream fall position index from 1968 to 2008 that are used for the prediction. Further, more recent (2009–2012) observed Gulf Stream fall position index is also plotted (open bars) for independent comparison with prediction. The correlation coefficients (r) between the observation and the prediction are shown on the upper left corner of each panel. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

predicted spring silver hake has a correlation coefficient as high as 0.67 for the 2nd year prediction and around 0.6 for predictions during the 3rd, 4th and 5th year (Fig. 8b-e).

3.3.2. Improving the spring silver hake prediction by considering the residual prediction

Though based on observed fall Gulf Stream alone the correlation coefficient between the predicted and observed time series of spring silver hake is as high as 0.81, there remains ~36% variance, which is not explained by the predicted time series. The residual here (Fig. 9f) is simply the difference between the observed and the predicted spring silver hake for the 1st year, which is based on the linear regression between the observed fall Gulf Stream and spring silver hake (i.e., the difference between the time series plotted in bar and line in Fig. 8a). By adding the prediction of the residual (i.e., using the second method detailed in Section 2.3.2 and the flow diagram II in Fig. 4b), the predicted spring silver hake improved slightly for all five years of prediction (Fig. 9 and Table 2), the correlation coefficients range from 0.62 to 0.83. The largest improvement is for the 4th year prediction as the correlation coefficient between the predicted and observed values increased from 0.59 to 0.66 (Fig. 8d vs. 9d). The predicted time series with residual prediction exhibits higher frequency variations than that without residual prediction, which is especially clear for the 3rd, 4th and 5th year predictions.

3.3.3. The prediction of spring silver hake based on the observed silver hake only

In this section, we use the third method described in Section 2.3.2 and optimized the AR models by fitting directly to the spring silver hake data. The prediction using the spring silver hake itself and the optimized AR model shows that the skill correlation for the 1st year is 0.68, a significant drop compared to the previous two methods with r=0.83 and 0.81, using fall Gulf Stream (Fig. 8a, 9a, vs. Fig. 10a). The 2nd year prediction is not either as good as the other two methods, i.e. r=0.64 comparing to 0.67 and 0.70 (Figs. 8b, 9b and 10b). For the 3rd year and longer predictions, the all three methods produce comparable prediction skills (Figs. 8c-e, 9c-e and 10c-e).

In Table 2, we summarized the prediction of the spring silver hake using the three methods that we described in the Section 2.3.2. In addition to what is shown in Figs. 8, 9 and 10, the skill correlations between the detrended prediction and the observation are also included.

4. Discussion

Based on our prediction, the Gulf Stream path will shift toward its northerly position after 2010 (Fig. 7) and the center of biomass of southern silver hake will migrate northward as well (Figs. 8–10). Though the most recent silver hake data calculated in a consistent fashion are not available for a comparison with our prediction, the prediction of the Gulf Stream is in agreement with the recent observations (unfilled bars in Fig. 7), a validation of our prediction for the Gulf Stream path. This recent northward shift of the Gulf Stream has also been reported in other observational studies (Gawarkiewicz et al., 2012; Pérez-Hernández and Joyce, 2014). Based on an AR model, Mahajan et al. (2011) predicted a weakening trend of AMOC over the time period between 2010 and 2015, which also supports the AR model prediction of a northerly position of the Gulf Stream path. As discussed earlier, it is mainly the changes of bottom temperature on the Northeast U.S. Shelf corresponding to the Gulf Stream shifts that alters the shift of the silver hake center of biomass, as the northward shift of the Gulf Stream indicates a warming of the bottom temperature. In other regions, this relation between the bottom temperature and fish abundance has also been documented, for

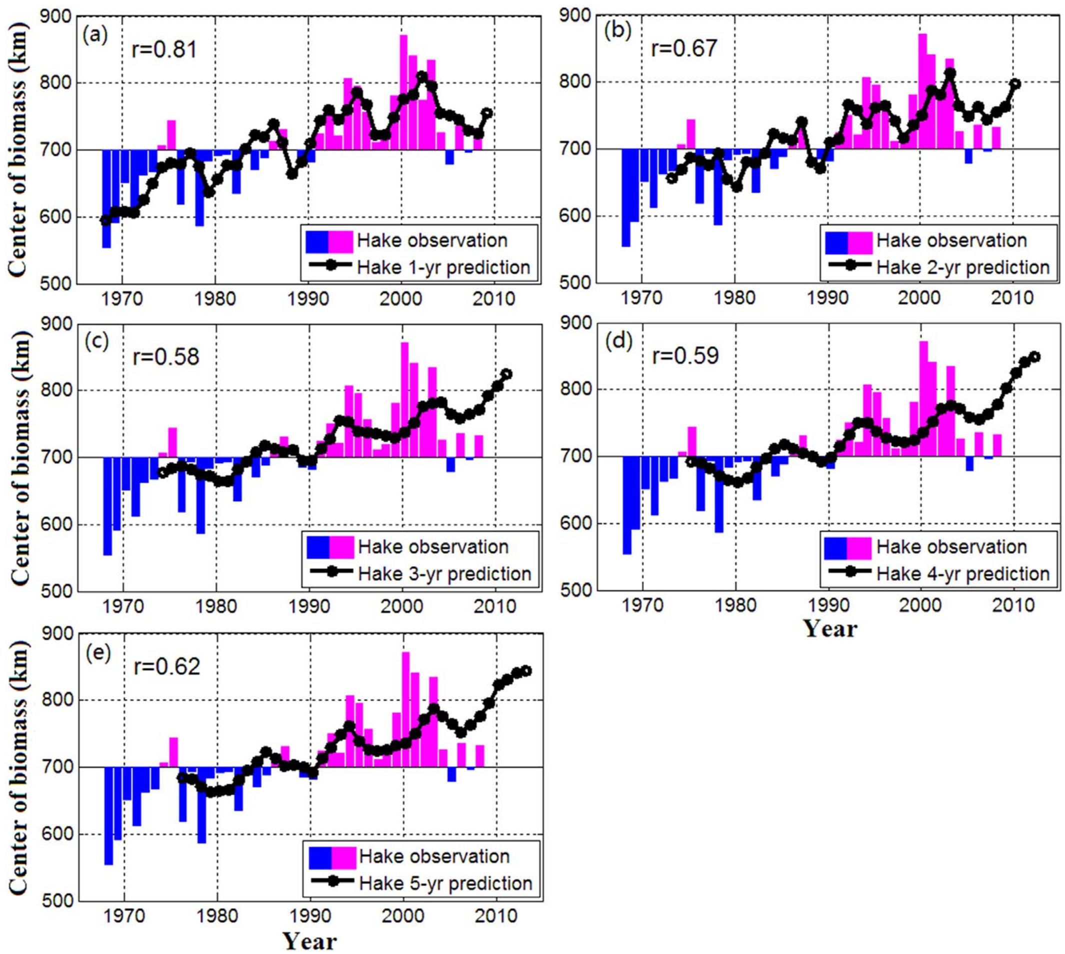

Fig. 8. The prediction of the center of biomass of the spring silver hake (black lines with dots) based on the fall Gulf Stream prediction. Note that in (a) the 1st year prediction of spring silver hake is based on the observed fall Gulf Stream and the observed detrended linear regression between fall Gulf Stream and spring silver hake, as explained in Section 3.3.1. In (b), (c), (d) and (e), the predictions are based on the corresponding Gulf Stream prediction shown in the Fig. 7a-d, but without the trend. The observed spring silver hake is represented by magenta (positive values) and blue (negative values) bars. The correlation coefficients (r) between the observation and the prediction are shown on the upper left corners of each panel. The prediction procedure is summarized in the flow diagram I in Fig. 4a. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

example, the northward shift of the North Sea bottom-dwelling fishes in response to the warming of the European shelf bottom water is reported by Dulvy et al. (2008) and their study further suggests that the latitude indicator may be more suitable for the north-south oriented shelf seas like the Northeast U.S. coastal region.

Our approach for the silver hake prediction could be expanded for predictions of the other fish specifies on the Northeast U.S. shelf, which have been shown to exhibit significant correlations with the changes in the Gulf Stream path. Lucey and Nye (2010) reported that practically the entire fish and macroinvertebrate assemblage respond to changes in water mass properties as indicated by the Gulf Stream path index even when taking into account the impacts of fishing. The effectiveness of this approach may be sensitive to multiple factors, including the preferred depth range of each species. For example, this approach may work better for the bottom dwellers, such as the silver hake (Nye et al., 2011) or cod (Pershing et al., 2015), considering the link through the preferred temperature range of the adult fish as emphasized already. In addition to this physiological aspect of the adult fish which controls the upper trophic level distribution, there could also be a link between the Gulf Stream path changes and the fish distribution through the changes in the nutrient regimes (Greene et al., 2013), which may impact the lower trophic levels. For example, Saba et al. (2015) suggest that the Gulf Stream index is associated with phytoplankton biomass on the shelf break, slope, and specific coastal regions of the Mid-Atlantic

Table 2
Summary of the correlation coefficients between the observed and predicted time series of spring silver hake based on three main methods as shown in Figs. 8, 9 and 10.

Correlation between Prediction & Observation	Based on Gulf Stream prediction (AR5) (**after**/before adding back hake trend) *As shown in Fig. 4a, and Fig. 8*	Based on Gulf Stream prediction (AR5) + silver hake residual prediction (AR5) (**after**/before adding back hake trend) *As shown in Fig. 4b, and Fig. 9*	Based on silver hake prediction (AR4) (**after**/before adding back hake trend) *As shown in Fig. 4c, and Fig. 10*
1st year prediction	**0.81**/0.60	**0.83**/0.64	**0.68**/0.45
2nd year prediction	**0.67**/0.45	**0.70**/0.53	**0.64**/0.39
3rd year prediction	**0.58**/0.25	**0.62**/0.53	**0.62**/0.37
4th year prediction	**0.59**/0.25	**0.66**/0.33	**0.64**/0.36
5th year prediction	**0.62**/0.21	**0.64**/0.36	**0.64**/0.25

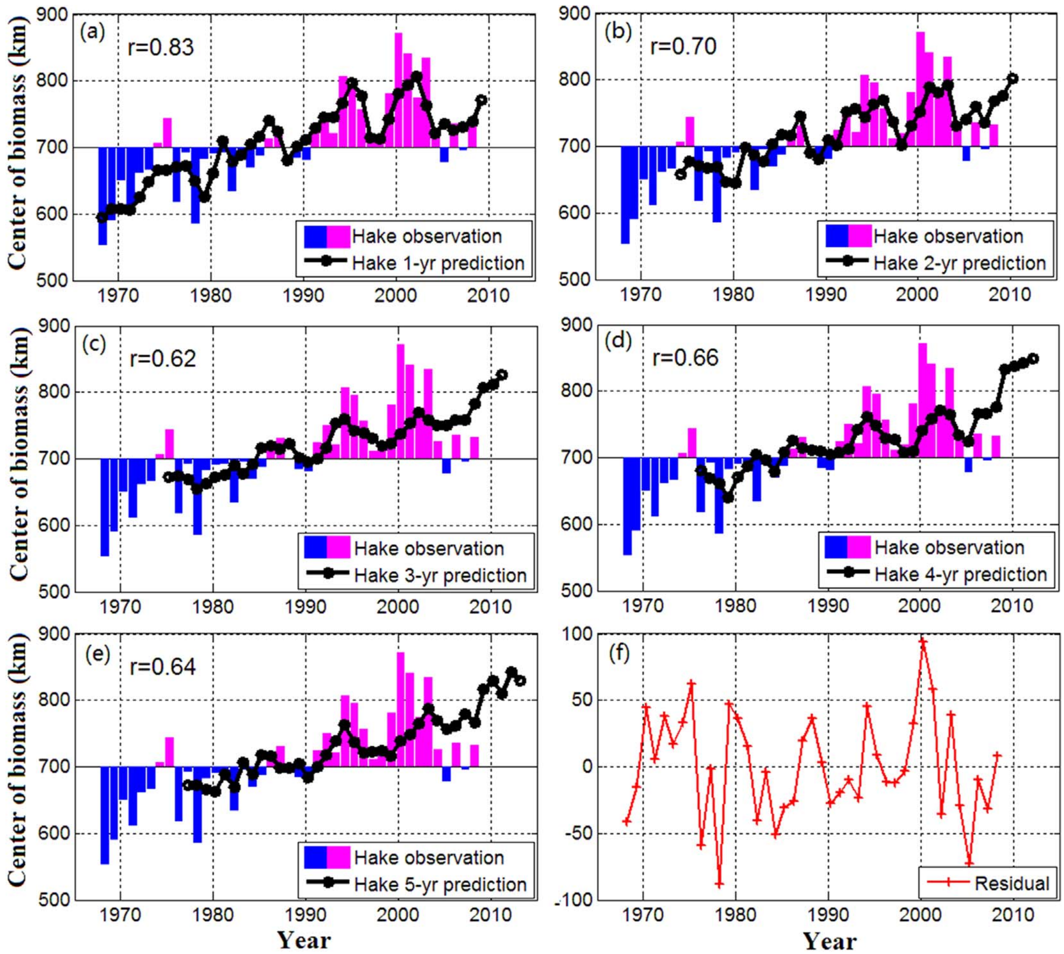

Fig. 9. (a)-(e) are similar to that shown in Fig. 8 except the prediction of the spring silver hake is based on the fall Gulf Stream prediction plus the residual silver hake prediction as described in Section 3.3.2. (f) Residual (red line with plus signs) is the difference between observed and the 1st year prediction of spring silver hake. The prediction procedure shown in (a)-(e) is summarized in flow diagram II in Fig. 4b. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

Bight.

The strong relationship between the Gulf Stream and fish species on the Northeast U.S. Shelf has been recognized as a critical information for the fisheries management (e.g. Ecosystem Assessment Program, 2012). Furthermore, there have been attempts to incorporate the Gulf Stream index into the stock assessment model used by the fisheries managers, e.g. Nye et al. (2010) for the silver hake and Xu et al. (2017) for yellowtail flounder. In addition to these efforts to incorporate the past and current Gulf Stream index values, our approach opens up an intriguing new possibility for using future predicted values of the Gulf Stream index in the fisheries management models. For the operational use of our approach, a further research should be conducted to better understand the uncertainty and to make the best choices of data source and parameters for the operational purpose. In this study, we have assumed the Gulf Stream index and its relationship with silver hake to be stationary when optimizing the AR models, which is a reasonable assumption given the limited record lengths of the observations. However, climate variability is often suggested to be nonstationary. For example, Li et al. (2014) hinted a nonstationary relationship between the basin-scale North Atlantic Oscillation and interannual variability of the alongshore wind in Gulf of Maine and Nova Scotian Shelf. Another aspect to consider is the sensitivity to the choice of the index. In our study, we used the Gulf Stream index based on the subsurface temperature at 200 m, while there are other Gulf Stream indices used in various studies based on the SST (Taylor, 1996) or sea-surface height (Peña-Molino and Joyce, 2008; Pérez-Hernández and Joyce, 2014). It should be verified whether the findings in this study are equally applicable to these other Gulf Stream indices. Furthermore, it should be determined which index would work best for the operational purpose.

The complexity of the coastal environment has made it one of the most challenging aspects for the general circulation model-based dynamical prediction effort in seasonal-to-interannual and decadal time scales as well as the long-term climate change projections. This nature is due to the complex interactions among the deep and shallow ocean, atmosphere, river run-off, and topography in the coastal environment (e.g. Stock et al., 2015). A recent study by Saba et al. (2015) implied that high-resolution general circulation models could improve the prediction and climate projection of the coastal environment. Assuming that the large-scale variability could potentially be more reliably predicted and projected by the general circulation models, an alternative (perhaps more cost effective) approach could be based on statistical relationship between the large-scale variability and the coastal environment. A good example is the Northeast U.S. Shelf bottom temperature (using Gulf Stream as a proxy) and silver hake relationship shown in this study and Nye et al. (2011). Besides the Gulf Stream path, a few other large-scale indices of variability have been shown to be highly correlated with the Northeast U.S. Shelf environment. For example, Xu et al. (2015) showed that the SST associated with the North Atlantic Oscillation propagates from Labrador Shelf to Gulf of Maine over 4 years. Pershing et al. (2015) reported the Pacific Decadal Oscillation to be highly correlated with the summer SST in the Gulf of Maine, although the dynamical link is yet to be understood. Therefore, a better understanding of the dynamical link

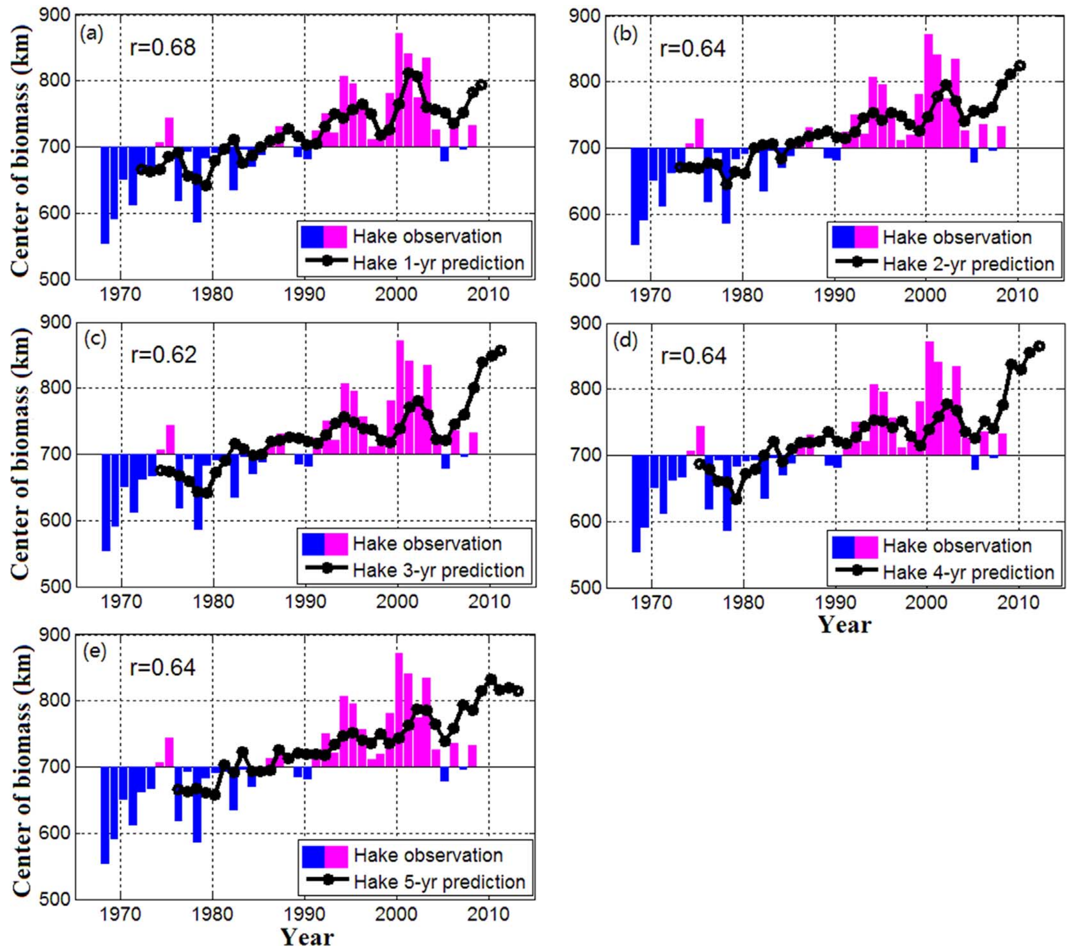

Fig. 10. The prediction of the spring silver hake (the black lines with dots) based on the optimized AR4 model for the silver hake data (a) 1st year, (b) 2nd year, (c) 3rd year, (d) 4th year and (e) 5th year prediction as described in Section 3.3.3. The observed spring silver hake is represented by magenta (positive values) and blue (negative values) bars. The correlation coefficients (r) between the observation and the prediction are shown on the upper left corners of each panel. The prediction procedure is also summarized in flow diagram III in Fig. 4c. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

between the large-scale variability and the coastal environment combined with an improved understanding on the predictable components of the large-scale variability could lead to a significant improvement in the prediction and projection of coastal environment including the Northeast U.S. Shelf in various time scales.

5. Conclusion

During the past 50+ years, the Gulf Stream variability has shown a dominant frequency of ~9 years. The variability of the Gulf Stream is closely related to the change of the bottom temperature on the outer continental shelf (Nye et al., 2011) and the center of biomass of the silver hake are modulated consequently since the silver hake prefers the water temperature range of 7–10 °C (Nye et al., 2011). This physical link between the Gulf Stream and the silver hake time series is reflected quantitatively in the high correlations between them when the Gulf Stream leads, with or without their trends. Based on this, the fall Gulf Stream path time series is chosen as a predictor of the spring silver hake for the future 5 years using linear AR models. The number of years of prediction (i.e., 5 years) is chosen based on the decadal oscillation of the Gulf Stream and the fishery resource management time scales of 5–10 years (Nye et al., 2013). It is found that the correlation between the prediction of the Gulf Stream and the observation using AR5 can be as high as 0.83 for the 1st year and around 0.6 for the 2nd to 5th year. The high correlation (prediction skill) for the 1st year can be detected in the high frequency variations (double peaks with 2–3 year frequency) in the predicted time series, which are not present in predictions beyond the 1st year. The inclusion of the predicted value in the predictions beyond the 1st year may be the cause that the 2–3 year high-frequency variability is not adequately captured in the extended forecasts.

We then made the prediction of the spring silver hake based on the fall Gulf Stream prediction through the observed linear relationship between the fall Gulf Stream and spring silver hake. Two other methods of the prediction of spring silver hake are also performed. One is by adding the prediction of the 'residual' also using AR5 model to the predicted silver hake based on Gulf Stream, and the other is the prediction based on silver hake itself using the AR4 model. As shown in our study, it is clear that the predictions incorporating the strong environmental variability, i.e., the bottom temperature changes reflected by Gulf Stream path shifts, are better than using the statistical information from the silver hake data alone. Although there are many biological and anthropogenic factors that can contribute to the variability of silver hake, which are beyond the scope of this study, by considering the impact of physical environment represented by Gulf Stream alone and using a simple optimized AR model, the 1st year prediction of silver hake can explain as much as ~ 69% of the observed variance (i.e., $r^2 \approx 0.69$ in Fig. 8a) of silver hake. The result suggests the dominant role of the physical environment in the silver hake variability and the effectiveness of the AR model for this type of study.

Silver hake acts as both prey and predator for many other species and it is thought to play the principal predatory role in the fish communities of the continental shelf in the Northwest Atlantic (Helser et al., 1995). Therefore, it is an important component of the continental shelf marine ecosystems on the Northeast U.S. coast. The shift of the silver hake biomass, the associated food chain alteration, the fishing behavior and fishery management will all continue to change in response to climate forcing; our specific focus here is that aspect of climate change which is tied to shifts in the latitude of the separated Gulf Stream. The successful prediction of biological production and distribution is critical for the fishery management and planning. Our study here provides a simple, statistically-based prediction of the physical parameter (Gulf Stream path) and biological spatial distribution (silver hake center of biomass), thus our results offer a valuable reference for current efforts in the prediction of biological variability based on climate indices using more complex models.

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Appendix A. Combined prediction skill

To seek the best set of AR model coefficients for fall Gulf Stream path prediction, we calculate the following three prediction skills, i.e. root mean square error (RMSE), skill coefficient (ρ) and percentage of explained variance (PEV) between the predicted time series and the observed time series of fall Gulf Stream and the spring silver hake.

Specifically, the RMSE,ρ and PEV are defined as the following:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_{p,i})^2} \tag{A.1}$$

$$\rho = \frac{\mathrm{Cov}(Y, Y_p)}{\sqrt{\mathrm{Var}(Y)\,\mathrm{Var}(Y_p)}} \tag{A.2}$$

$$\mathrm{PEV} = \frac{\mathrm{Var}(Y) - \mathrm{Var}(Y_p - Y)}{\mathrm{Var}(Y)} \tag{A.3}$$

where, Y and Y_p are observed and predicted values, respectively, and n is the number of time steps. $\mathrm{Var}(Y)$is the variance of time series, $\mathrm{Cov}(Y, Y_p)$ is the covariance between Y and Yp. The skill coefficient (ρ) is also often referred to as Brier skill score (von Storch and Zwiers, 2002).

A better prediction corresponds to a smaller RMSE, larger ρ and larger PEV. A certain set of AR parameters corresponds to a certain combination of three prediction skills. We combine the above three skills and define a new combined prediction skill as

$$P_{combo} = RMSE/(\rho + PEV) \tag{A.4}$$

thus the smaller and positive Pcombo indicates a better prediction. The combined prediction skill Pcombo is then introduced and used in this work to determine the optimal set of the AR model coefficients for each prediction beyond the 1st year, which produces the minimum combined prediction skill. P_{combo} is a more robust criterion than using any one of the three skill measures, i.e., RMSE, ρ and PEV as they occasionally do not have their optimum values simultaneously. We have checked the cases when this occurs and it appears that the Pcombo criterion is robust in choosing the optimum AR parameters.

Appendix B. Optimization of AR model coefficients

We demonstrate the optimization process using an AR5 model as an example. At each yearly time step t of the Gulf Stream time series, we make a prediction using AR5 model parameters (A1, A2, A3, A4, A5, nt) based on observed values at previous two time steps t-5, t-4,t-3, t-2 and t-1 for AR5; we call it the 1st year prediction for our yearly Gulf Stream data. The combined prediction skill Pcombo is then assessed by comparing the original time series and the time series of the 1st year prediction. Subsequently, the observed values at time steps t-4, t-3, t-2, t-1 and the 1st year prediction are used with the AR5 to make the 2nd year prediction. In this way, we make the five prediction time series based on the 1–5 year prediction at each time step using AR5, and calculate the Pcombo between these five predicted time series and the actual observed time series of fall Gulf Stream.

As described in earlier, for AR model with order p, AR coefficients A1, A2, ..., Ap are determined using the stepwise least square algorithm with an uncertainty range at 95% confidence level for each parameter (Neumaier and Schneider, 2001). Therefore, these AR coefficients can vary within the range at 95% confidence level as shown in the case of AR5 (Fig. A1), and the predictions and their skills also vary when the AR coefficients vary within this. To achieve the goal of finding the best prediction, we allow the AR coefficients A_i (i=1, 2 ...p) vary within the uncertainty range and calculate the corresponding prediction skills. Specifically, our procedure subsamples the 5 estimates for each coefficient distributed equally across their respective error range. As a result, there are 5^p different sets of possible AR coefficients. We then calculate the prediction skills of the predictions based on 5^p sets of AR parameters and in the end, select the set of AR parameters producing the smallest Pcombo. We have tested the sensitivity of the prediction skills to the choice of the number of different values by allowing the AR parameters have 7 and 9 different values within its range of 95% confidence level. The results indicate that choosing 5 different values is sufficient for our predictions. Note that we find the optimal AR coefficients independently for the predictions with different lead times, i.e. 1st year prediction, 2nd year prediction, etc.

There is one common feature of different order AR models, i.e., the optimal parameters A_i are the same as the default set of A_i for the 1st year prediction, since the default set of A_i is determined with only the observed values, which should be optimal for the year-1 prediction. For later years of predictions, it is not the case, e.g., the optimum choices of AR5 parameters are different for year 1 to year 5 predictions of fall Gulf Stream (Fig. A1). Thus, we use the Pcombo criteria to search for the optimal choice of A_i.

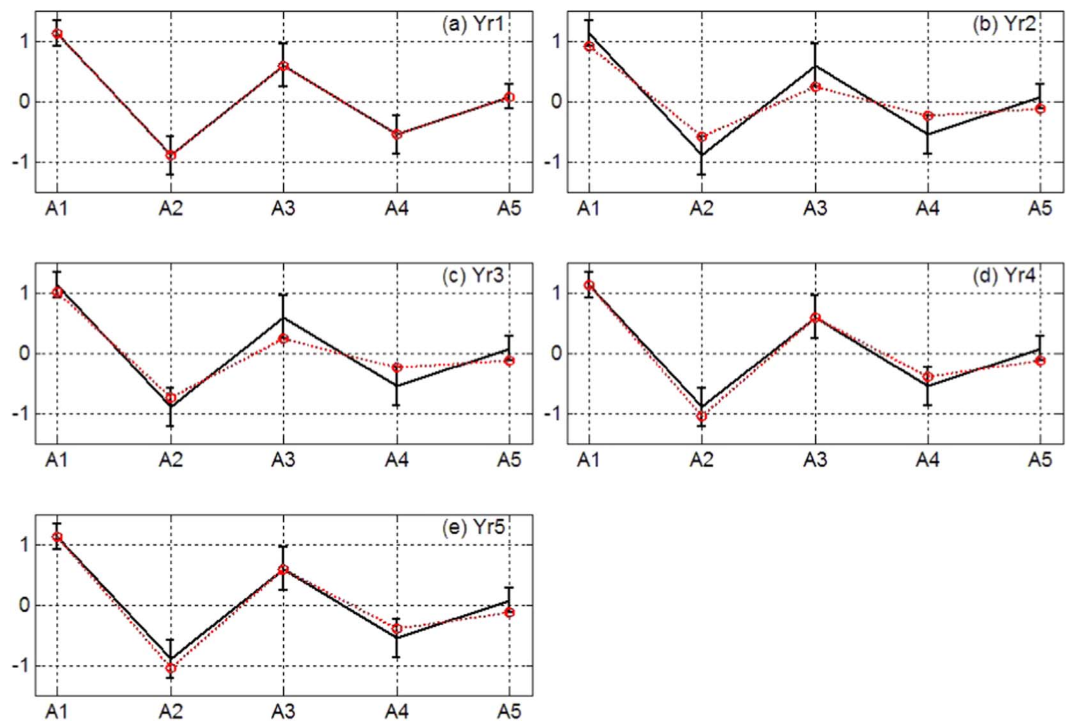

Fig. A 1. The AR5 coefficients (i.e., A_1, A_2, A_3, A_4 and A_5, black line) for the fall Gulf Stream prediction for the (a) 1st (b), 2nd (c) 3rd, (d) 4th and (e) 5th year. The black bars mark the ranges within which the AR5 coefficients can vary with the 95% confidence level. Note that the black lines and bars are identical in all five panels and calculated based on Neumaier and Schneider (2001). The red circles denote the values of AR5 coefficients chosen based on the optimization of AR5 prediction skills as explained in the text. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

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