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

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Summary

Over the past ~40 years, the distribution of silver hake (SH) on the Northeast U.S. shelf is found to be closely related to changes in the latitude of the Gulf Stream (GS) path. The correlation coefficient between the fall GS position (GS hereafter) and the center of biomass (COB) of spring SH (SH hereafter) reaches 0.75 when the GS leads the SH for 0.5 year. Based on this lead-lag relationship and the low-frequency variability of GS position with a dominant period of ~9-10 years, the GS path index is used as a predictor for the COB of SH in linear autoregressive (AR) models. The goal of this study is then to optimize the AR models for the prediction of SH based on the observed changes in GS position. Fall GS position is first predicted out to 5 years using a 5th order AR model and the observed GS position in preceding years. We then use this predicted GS position to predict the COB of SH in subsequent spring. The predicted SH 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.

Introduction

Silver hake (SH) is a semi-pelagic fish prolific in Northeast U.S. shelf. Nye et al. (2011) reported that changes in spatial distribution of SH over the past forty years demonstrate a high correlation with the latitude of the Gulf Stream (GS) path. These changes are in direct response to changes in the Atlantic Meridional Overturning Circulation (AMOC), which drive shifts in bottom temperature on the outer continental shelf. The correlation between GS position and SH spatial distribution is characterized by a phase lag with the GS leading the SH by 0.5 year (Figure 1). This lagged correlation offers some potential predictability of SH using GS data. Based on the GS path index as defined in Joyce et al. (2009) and the Silver hake data collected by the NOAA Northeast Fisheries Science Center (NEFSC) trawl survey on the Northeast U.S. shelf, we optimize autoregressive models for the prediction of the GS, which is then used to predict the SH spatial variability.

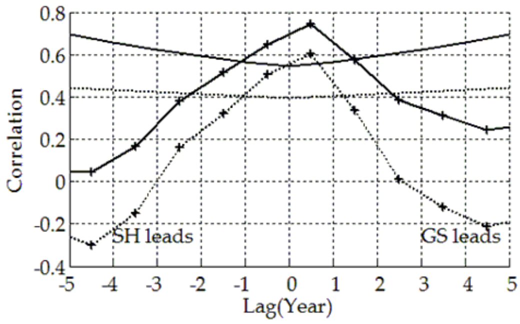

Figure. 1 The cross correlations between the latitude of fall GS and the COB of spring SH. The solid (dotted) lines with plus signs are cross correlations between the observed data with (without) their trends. The solid (dotted) lines without plus signs mark the significance at 95% level for the correlations with (without) trends respectively.

Materials and Methods

Silver hake data are collected by the NOAA Northeast Fisheries Science Center (NEFSC) trawl survey on the Northeast U.S. shelf. The data used are the COB of the southern SH as calculated in Nye et al. (2009) as an overall distance from the Cape Hatteras, North Carolina. There are two measurements in each year: one in spring, the other in fall. The spring SH data were collected from 1968 to 2008 and the fall SH data start 5 years earlier, i.e., from 1963 to 2008. GS path index data used representing coherent north-south shift of the current in 55°-75°W is based on the historical subsurface temperature data at 200 m depth (Joyce et al. 2009). The GS data are available from 1954 to 2008, which has four data points in each year, one in each season. Here we define the spring and fall GS path index by simply averaging the first two data points and last two data points of the GS path index in each year, respectively. The autocorrelation function shows the GS variability has a dominant frequency of ~ 9 years. Therefore, we optimize Autoregressive (AR) models for the prediction of GS path in future 5 years and then predict the SH based on their close relationship. An AR5 is determined for the fall GS prediction based on the Schwartz's Bayesian (SBC) Criterion (Schwartz 1978). To optimize the AR parameters, we develop a combined prediction skill and test its use and robustness through AR models from order 2 to 5.

Results and Discussion

It is found that the correlation between the prediction of the GS and the observation using AR5 can be as high as 0.83 for the 1st year and ~ 0.6 for the 2nd to 5th year. We then made the prediction of the spring SH based on the fall GS prediction through the linear relationship between the fall GS and spring SH. Another method of the prediction of spring SH is also performed by adding the prediction of the 'residual' also using AR5 model to the predicted SH based on GS. The 'residual' here is the difference between observed and the predicted spring SH for the 1st year, which is based on the linear regression between the fall GS and spring SH. By comparison, the prediction of the spring SH with 'residual' demonstrates better prediction skill with the correlation coefficients as high as 0.83 (Figure 2) for the 1st year prediction and all others above 0.6 for the future 5 years' prediction. This 'residual' may represent biological aspects of the SH and does not have a dominant frequency significantly based on its autocorrelation. Since the SH's preferred bottom-water temperature range (7-10˚ C, Nye et al. 2011) is mainly responsible for the close correlation between GS and SH, the 'residual' could also be due to temperature changes affecting SH that are unrelated to GS path variations.

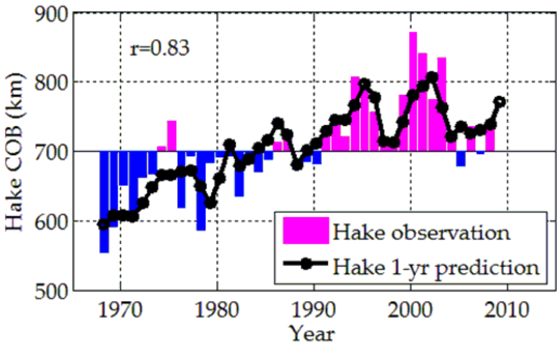

Figure. 2 The 1st year prediction of the spring SH based on the fall GS prediction and the 'residual'. The magenta and blue bars are the observed spring SH and the black lines with dots are the predicted time series.

Based on our prediction, the GS path shifted toward its northerly position after 2010 and the COB of southern spring SH migrated northward (Figure 2). This prediction of the GS path is in agreement with the satellite observations (Pérez-Hernández and Joyce 2014). There are many biological and anthropogenic factors that can contribute to the variability of SH which are not the subject of interest in this study. By considering the impact of physical environment represented by GS alone and using a simple optimized AR model, the 1st year prediction of SH can explain as much as ~ 69% of the observed variance of SH. The result suggests the dominant role of the physical environment in the SH variability and the effectiveness of the AR model for this type of study. The successful prediction of biological production and distribution is critical for the fishery management and planning. Our results here offer a valuable basis for current efforts in the prediction of biological variability based on climate indices.

References

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