North Pacific Fisheries Commission

NPFC-2023-SSC PS12-WP03

Simulation of climate indices for process error in Pacific Saury assessment

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Background and objective

The interim Pacific Saury MSE will use an operating model built upon the current BSSPM stock assessment. In order to test management procedures and harvest control rules, projections of future conditions will have to be made. In the current Pacific Saury assessment there are fairly large process errors. Some of these process errors may be related to environmental considerations (e.g. reduced ecosystem productivity under some climate regimes). In order to make and test projections, this process error needs to be simulated. One way to do this is to draw future scenarios from the current process error distribution.

If however, the thought is that the environment is controlling or mitigating Pacific Saury productivity, then process errors may take on some of the characteristics of environmental conditions. This might be seen in the level of autocorrelation in the process errors and the magnitude of the variance.

The objective of this project was to build out a function that could simulate future conditions for environmental indices by calculating the autocorrelation function and variance (here standard deviation) of some common environmental covariates. These could then be used as an alternative to sampling from the historical distribution of process errors from the stock assessment. Instead process errors could be chosen from a distribution that "looked like" environmental variables thought to be controlling stock productivity.

Here are figures for six large scale environmental covariates that have been linked to fish productivity in the North Pacific Ocean through a number of studies. The six variables are the Pacific Decadal Oscillation, Kuroshio Current Extension (link provided by Dr. Hiroomi Miyamoto), the North Pacific Gyre Oscillation Index, the North Pacific Index, The Aleutian Low Pressure Index and the Arctic Oscillation Index. With the exception of the Kuroshio Current Extension and the Aleutian Low Pressure Index these indices were compiled using the PACea package from NOAA's National Centers for Environmental Information (NCEI).

Environmental covariates

Pacific decadal oscillation (PDO)

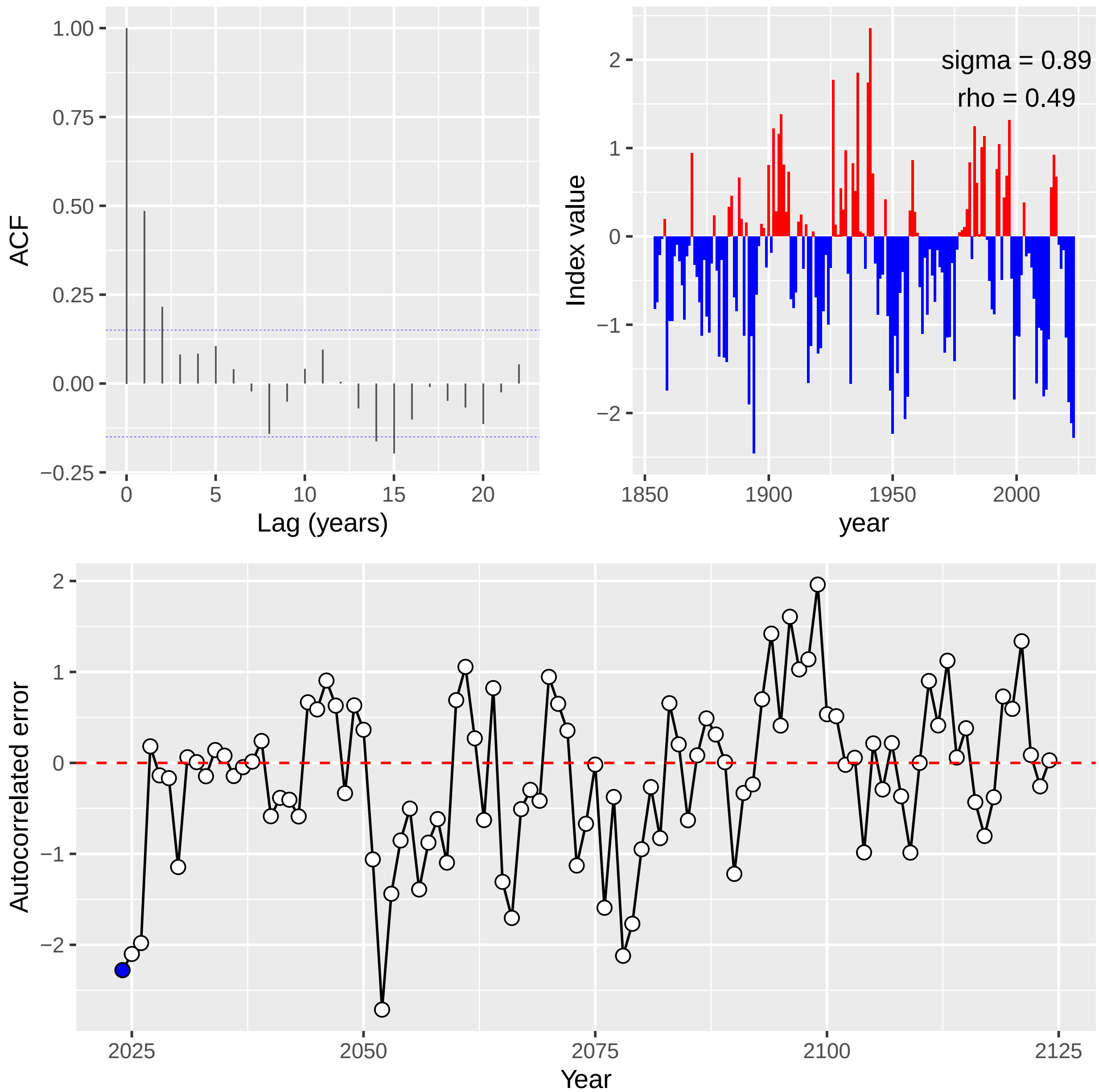

Figure 1: Autocorrelation function, time series and simulated future time series for the Pacific Decadal Oscillation (PDO). Blue point indicates the most recent value.

Kuroshio current extension

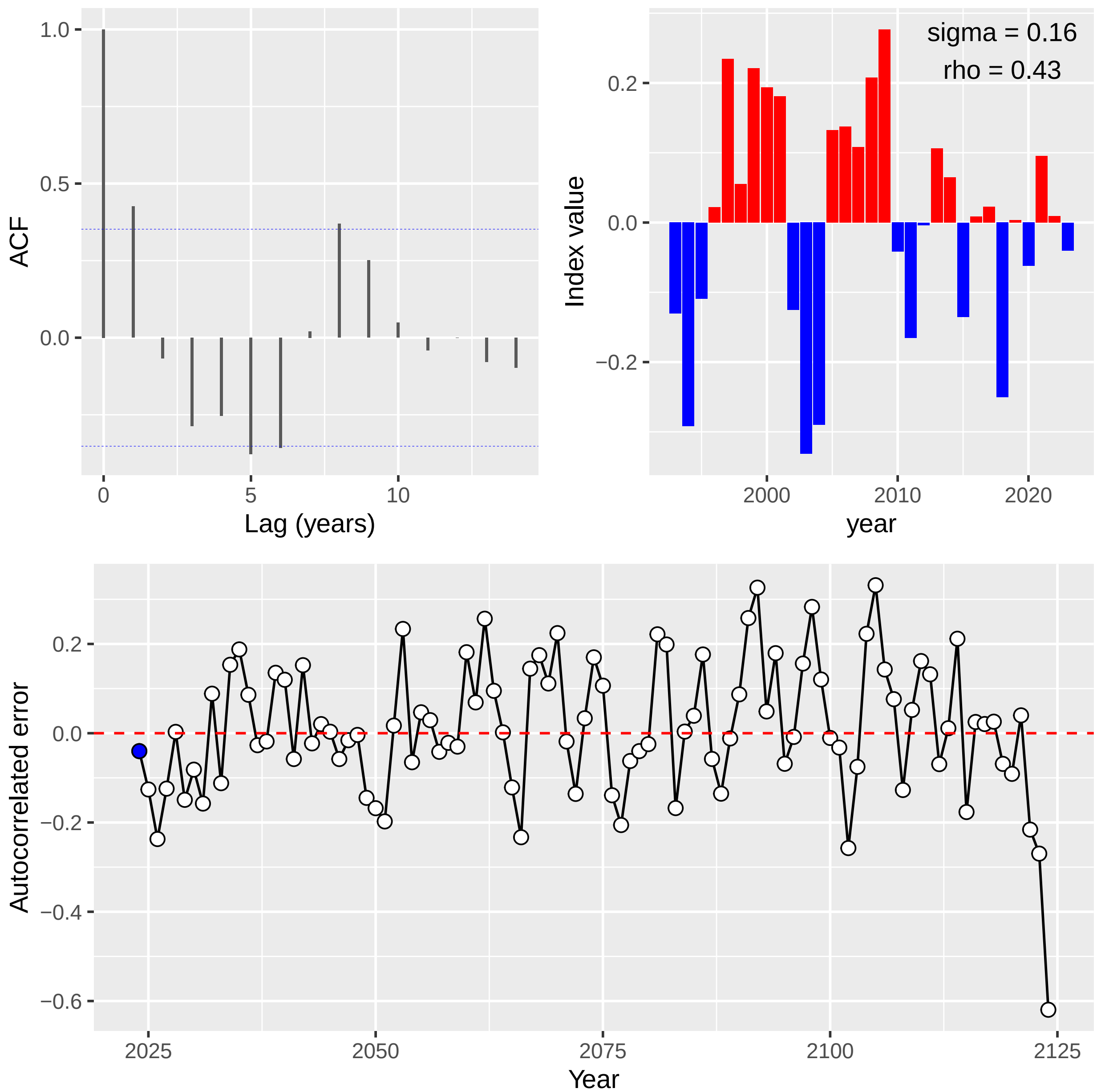

Figure 2: Autocorrelation function, time series and simulated future time series for the Kuroshio Current Extension. Blue point indicates the most recent value.

North Pacific Gyre Oscillation (NPGO)

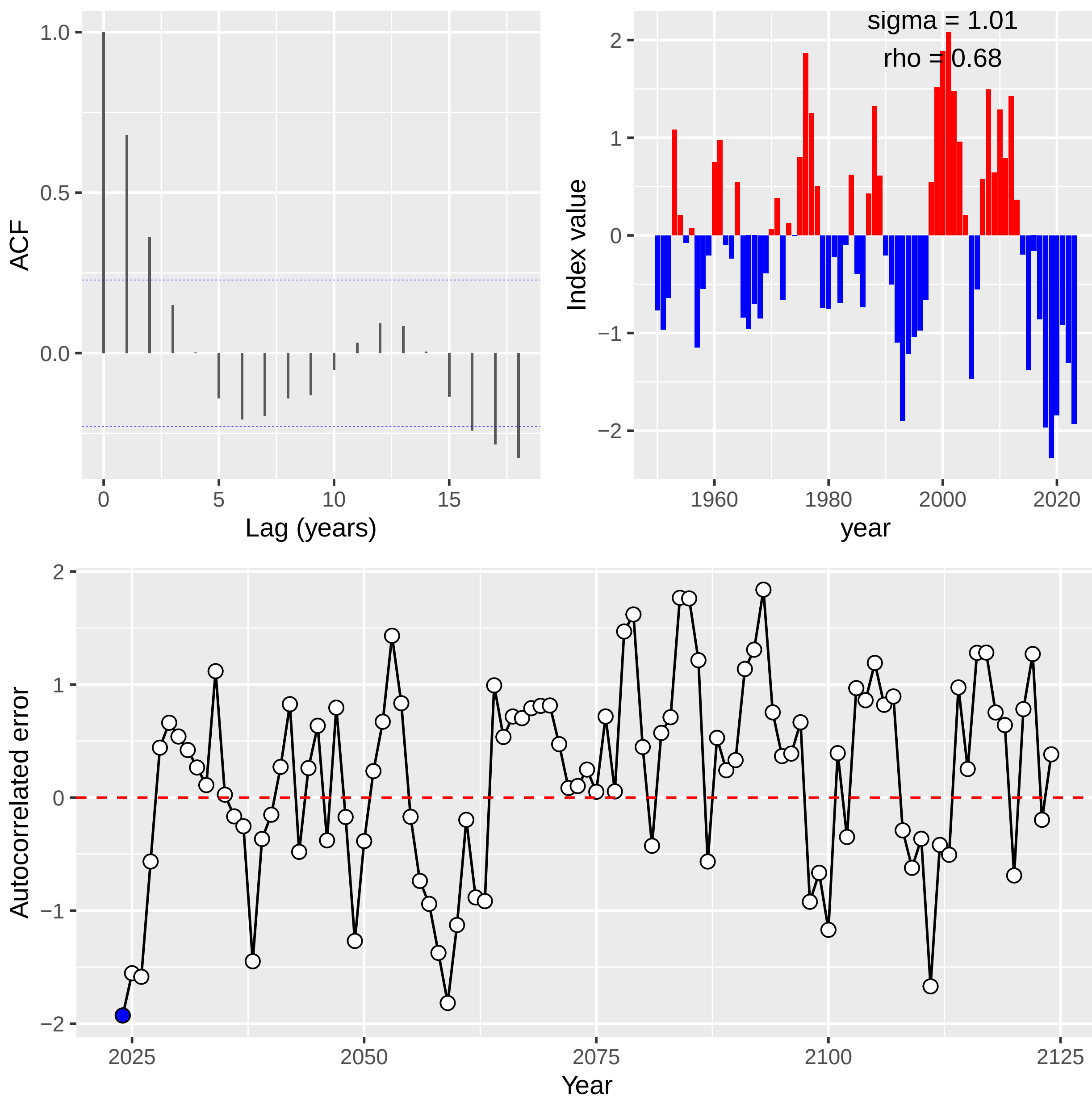

Figure 3: Autocorrelation function, time series and simulated future time series for the North Pacific Gyre Oscillation (NPGO). Blue point indicates the most recent value.

North Pacific Index (NPI)

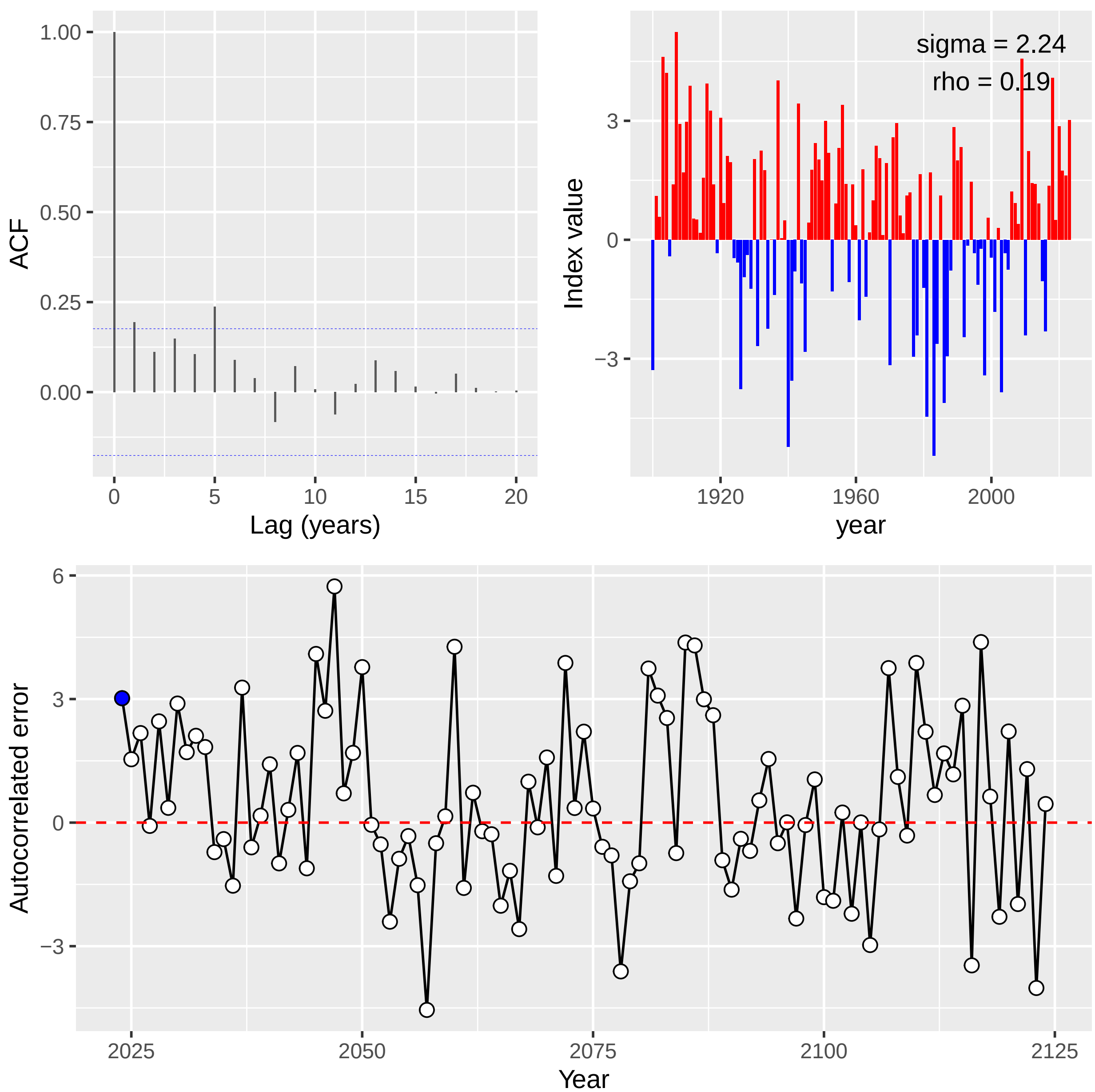

Figure 4: Autocorrelation function, time series and simulated future time series for the North Pacific Index (NPI). Blue point indicates the most recent value.

Aleutian Low Pressure Index

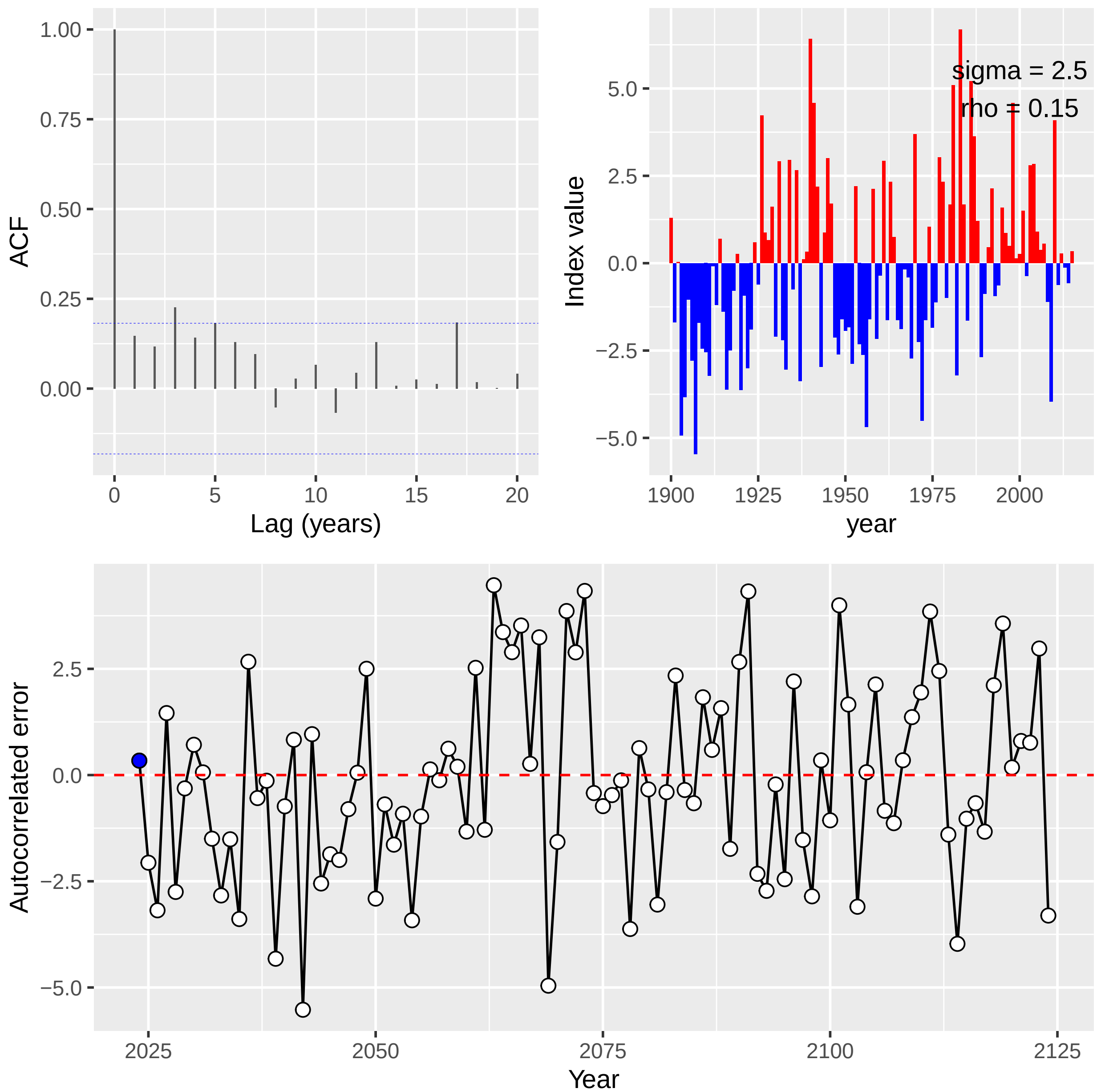

Figure 5: Autocorrelation function, time series and simulated future time series for the Aleutian Low Pressure Index. Blue point indicates the most recent value.

Arctic Oscillation

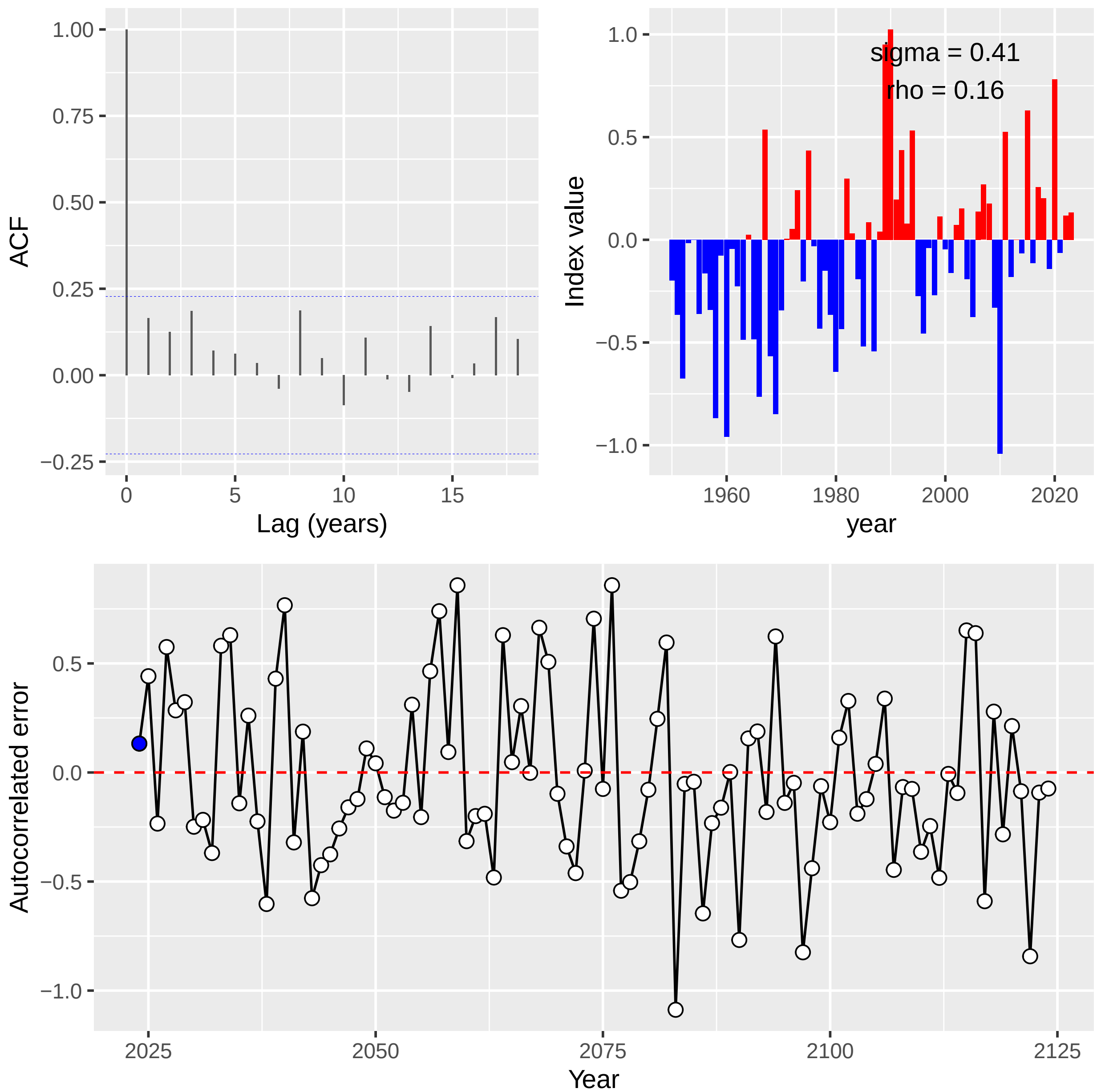

Figure 6: Autocorrelation function, time series and simulated future time series for the Arctic Oscillation. Blue point indicates the most recent value.

Process errors and correlation analysis

The autocorrelation and variance for the median process errors from Base Case 1 of China's BSSPM (NPFC-2023-SSC PS11-WP15) were also examined for patterns from 2003-2023. Then these median values were correlated to the various environmental indices. No time lags were used, but future work will consider appropriate time lags (1-2 years). We also hope to look for potential regime shifts in the climate indices using STARS analysis and compare these to the process errors.

Recommendation

One way to proceed on generating process errors for future predictions would be to use the median of 100 generations of the simulated climate indices (perhaps initially using NPI based on the correlation analysis and some preliminary lagged correlation analysis) scaled to represent the process error.

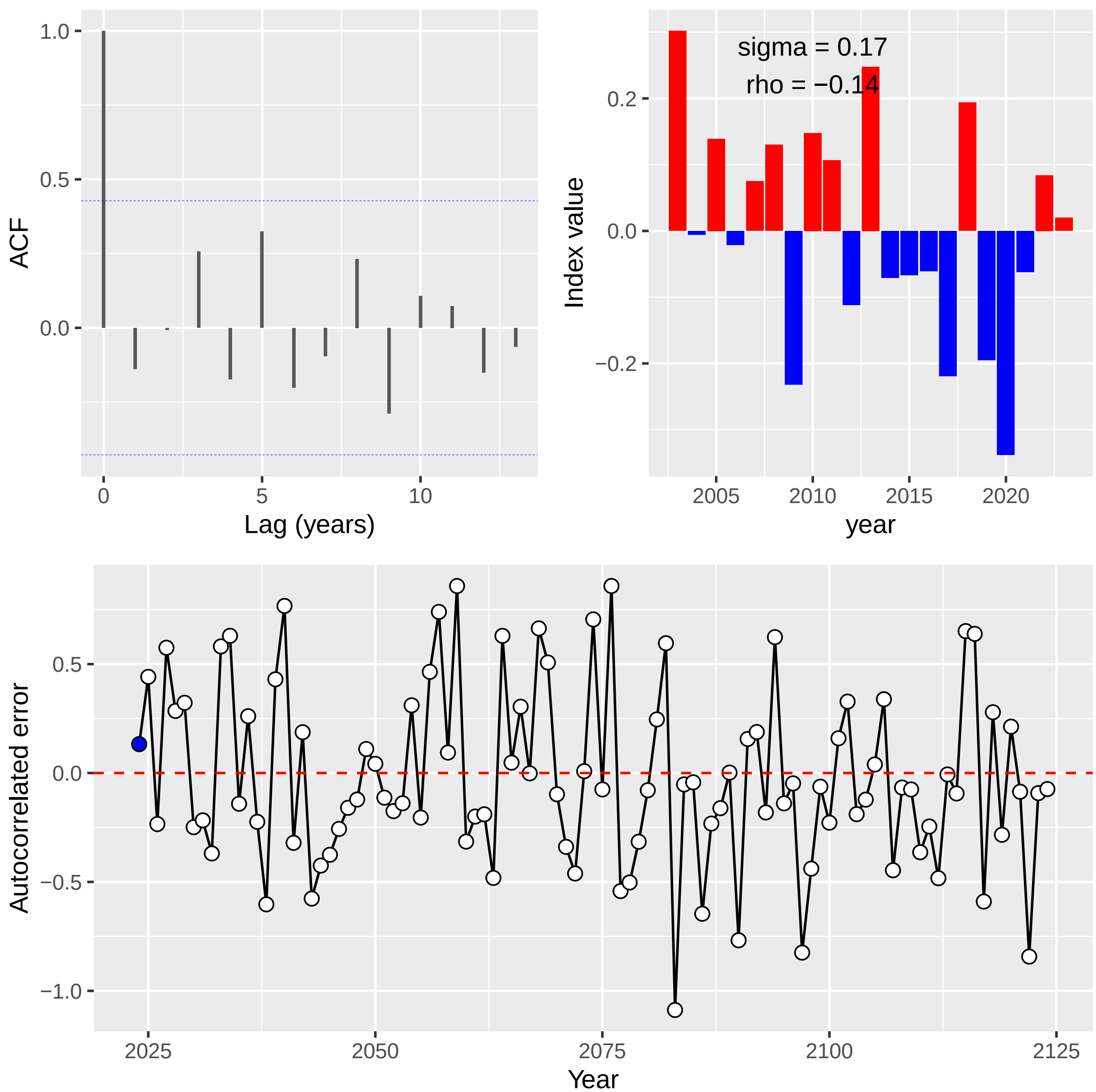

Figure 7: Autocorrelation function, time series and simulated future time series for the process errors from Base Case 1 of China's BSSPM. Blue point indicates the most recent value.

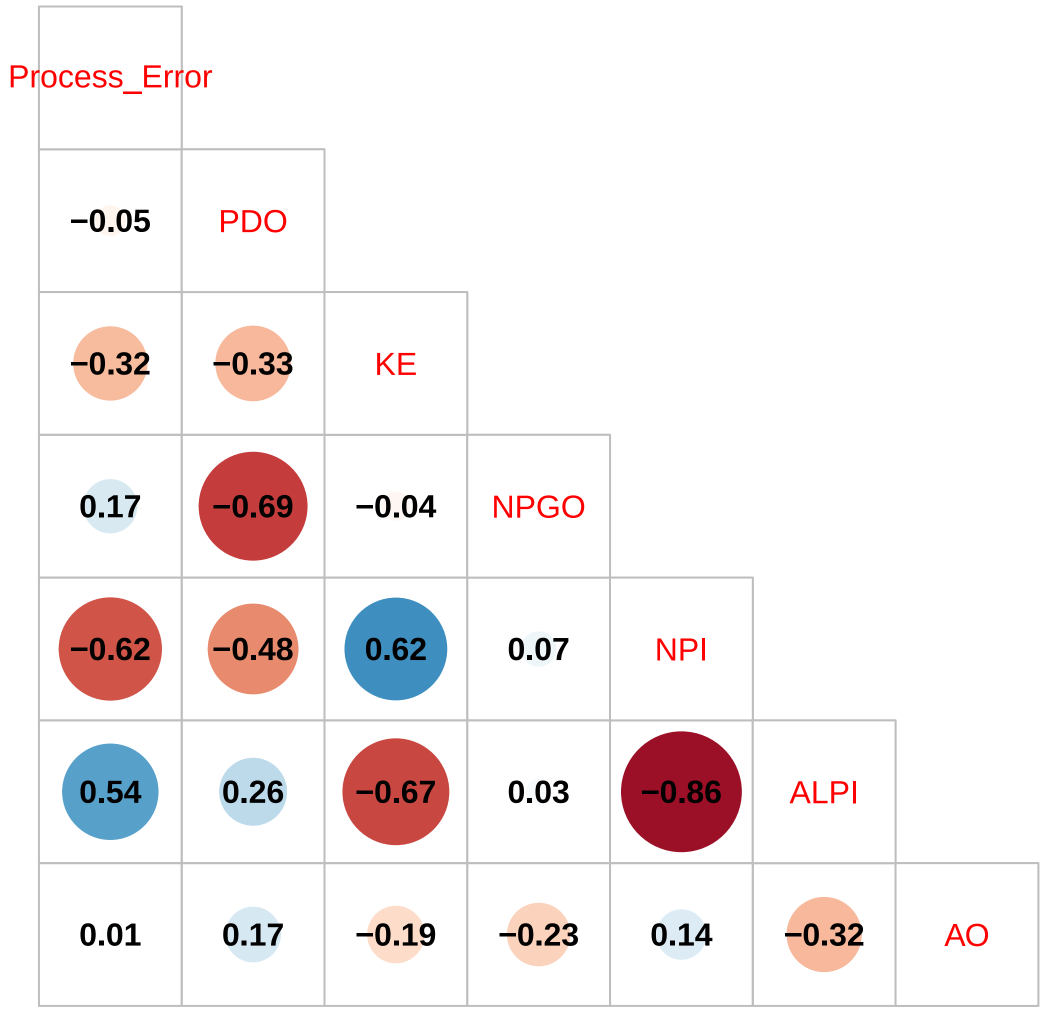

Figure 8: Correlation between environmental indices and process error from BSSPM Base Case 1.

Supplemental Material

```
#Example function use


#Number of years to simulate

years<-100
```

```
#Determine the autocorrelation function of your index data
auto_corr<-acf(data1$annual)

#Determine the standard deviation of your index data
sd_value<-sd(data1$annual)

#Determine a start value for your index (default is a random number from distribution with mean = 0, sd
# the value from the last year of the index time series.
start_value<-data1$anomaly[which.max(data1$year)]

#Run the function
Auto_Sim(auto_corr,sd_value,years,start_value)



#Here is the function code.
Auto_Sim<-function(rho,sigma,yr,start_value=rnorm(1,0,1),plot=TRUE){
  require(ggplot2)
u<-numeric(yr)
v<-numeric(yr)
u[1]<-start_value
v<-rnorm(yr,0,sigma)
for (i in 1:yr) { u[i+1]<-rho*u[i]+sqrt(1-rho^2)*v[i] }
now_year<-as.numeric(format(Sys.Date(),"%Y"))
now_year<-(1:(yr+1))+now_year

rho<-round(rho,2)
sigma<-round(sigma,2)

p1<-ggplot()+geom_line(aes(x=now_year,y=u))+geom_point(aes(x=now_year,y=u),shape=21, colour = "black", 
  ylab("Autocorrelated error")+geom_hline(yintercept=0,color="red",linetype="dashed")+
  annotate("text", x = max(now_year)-15,y=max(u), label = paste0("sigma = ",sigma,"\nrho = ",rho))
```

```
if(plot==TRUE){

print(p1)}


return(list(future_index=data.frame(Year=now_year,Anomaly=u),plot=p1))}
```