# Covariate data for Scripps's Murrelet egg size model

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```
knitr::opts_chunk$set(echo = TRUE)

## load libraries
library(here)
library(tidyverse)
library(janitor)
library(ggplot2)
library(lubridate)
library(viridis)
library(Hmisc)
library(stats)
library(faraway)
library(sjPlot)
library(corrplot)
```

This is v.2021-10-23

## Introduction

This document details steps taken to compile and clean covariate data for a linear mixed model on Scripps's Murrelet (*Synthliboramphus scrippsi*) egg size at Santa Barbara Island within Channel Islands National Park from 2009-2017. Oceanographic indices were pulled from NOAA'S California Current Integrated Ecosystem Assessment Program (CCIEA); data descriptions are provided by CCIEA. Covariates are grouped by spatial scale: local, regional, and international. We also tested for correlation among predictors. Given the differences in spatial and temporal extent of oceanographic variables and their impacts on seabirds, we tested all environmental covariates for the Scripps's Murrelet egg size model (see SCMU_model.Rmd) under four scenarios:
1. Monthly averages for January to June in year $t$ (6 months) to encompass pre-breeding and breeding season ("half").
2. Monthly averages for July in year $t-1$ to June in year $t$ (12 months) to encompass the entire post-breeding, pre-breeding, and breeding season ("full").
3. Monthly averages for January to June in year $t-1$ (6 months) to encompass pre-breeding and breeding season in the previous year ("half_lag").
4. Monthly averages for July in year $t-2$ to June in year $t-1$ (12 months) to encompass the entire post-breeding, pre-breeding, and breeding season in the previous year ("full_lag").

We tested 6 covariates:
1. Larval Anchovy (ANCHL)
2. Biologically Effective Upwelling Transport Index (BEUTI)
3. Sea Surface Temperature (SST)
4. North Pacific Gyre Oscillation Index (NPGO)

5. Pacific Decadal Oscillation Index (PDO)
6. Oceanic Nino Index (ONI)

```
## load egg size data
egg <- read.csv(here("data", "SCMU_egg_data.csv"))%>%
  filter(TrueOrder == TRUE) %>% # select eggs with order known only
  dplyr::select(Year, Observer, Plot, Size, EggOrder)
```

# Oceanographic Indices

## Local indices

### Sea Surface Temperature

Sea surface temperature was provided by NOAA buoy station 46025. The data description can be found here.

```
SSTraw <- read_csv(here("data", "covariates", "cciea_OC_SST3_91cf_d165_213f-46025.csv"))
```

```
## Rows: 449 Columns: 2

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (2): time, SST

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
## are there NAs in the data?
sum(is.na(SSTraw$SST))
```

```
## [1] 0
```

```
## Scenario 1: "half" dataset from Jan-June in time t
SST_half <- SSTraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(sst = as.numeric(SST)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  group_by(Year) %>%
  summarise(SST = mean(sst, na.rm = TRUE)) %>%
  dplyr::select(Year, SST) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(SST_half = scale(SST)) %>%
  arrange(Year) %>%
  dplyr::select(Year, SST_half)

## Scenario 2: "full" dataset from July in time t-1 to June in time t
SST_full <- SSTraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(sst = as.numeric(SST),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month =
                             Year + 1, Year)) %>%
```

```r
  rename(Year = split_year, true_year = Year) %>%
  group_by(Year) %>%
  summarise(SST = mean(sst, na.rm = TRUE)) %>%
  dplyr::select(Year, SST) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(SST_full = scale(SST)) %>%
  arrange(Year) %>%
  dplyr::select(Year, SST_full)

## Scenario 3: "half_lag" dataset from Jan-June in time t-1
SST_half_lag <- SSTraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(sst = as.numeric(SST)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(SST = mean(sst, na.rm = TRUE)) %>%
  dplyr::select(Year, SST) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(SST_half_lag = scale(SST)) %>%
  arrange(Year) %>%
  dplyr::select(Year, SST_half_lag)

## Scenario 4: "full_lag" dataset from July in time t-2 to June in time t-1
SST_full_lag <- SSTraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(sst = as.numeric(SST),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(SST = mean(sst, na.rm = TRUE)) %>%
  dplyr::select(Year, SST) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(SST_full_lag = scale(SST)) %>%
  arrange(Year) %>%
  dplyr::select(Year, SST_full_lag)

## join datasets together
SST1 <- full_join(SST_half, SST_full, by = "Year")
SST2 <- full_join(SST1, SST_half_lag, by = "Year")
SST3 <- full_join(SST2, SST_full_lag, by = "Year")

## join with egg size data
SST_df <- left_join(egg, SST3, by = "Year")
```

```
## run models
SST_half_mod <- lm(Size ~ SST_half, data = SST_df)
SST_full_mod <- lm(Size ~ SST_full, data = SST_df)
SST_half_lag_mod <- lm(Size ~ SST_half_lag, data = SST_df)
SST_full_lag_mod <- lm(Size ~ SST_full_lag, data = SST_df)

## Model selection table
SST_AIC <- matrix(NA, nrow = 4, ncol = 3) # 4 rows for 6 top models
SST_AIC[1,1] <- AIC(SST_half_mod)
SST_AIC[2,1] <- AIC(SST_full_mod)
SST_AIC[3,1] <- AIC(SST_half_lag_mod)
SST_AIC[4,1] <- AIC(SST_full_lag_mod)
SST_AIC[,2] <- SST_AIC[,1] - min(SST_AIC[,1]) # calculate delta AIC
SST_AIC[,3] <- exp(-0.5*SST_AIC[,2])/(sum(exp(-0.5*SST_AIC[,2]))) # calculate model weights
colnames(SST_AIC) <- c("AIC", "deltaAIC", "model_weights")
rownames(SST_AIC) <- c("half", "full", "half_lag", "full_lag")
print(SST_AIC)
```

```
##               AIC deltaAIC model_weights
## half     10724.84 0.000000    0.66899301
## full     10729.84 5.000953    0.05488812
## half_lag 10727.50 2.653379    0.17752012
## full_lag 10728.67 3.829430    0.09859875
```

The half SST model has more support.

## Regional indices

### Larval Anchovy (ANCHL)

Derived from spring California Cooperative Oceanic Fisheries Investigations (CalCOFI) surveys. Larval fish data summed across all stations of the CalCOFI survey in spring (units are in number under 10 sq. m of surface area; ln(abundance+1); CalCOFI lines 76.7 - 93.3; stations 28.0 - 120.0). Sampling data is only available at a yearly sampling interval. Therefore, we tested this variable under two scenarios: 1) yearly value in time $t$, and 2) yearly value in time $t-1$.

```
## load data
ANCHLraw  <- read.csv(here("data", "covariates", "cciea_EI_FBS_2020_a29e_1fd0_409d.csv"), na.strings =

## are there NAs in the data?
sum(is.na(ANCHLraw$relative_abundance))
```

```
## [1] 0
```

```
## create dataset from 2009-2017 for values in year t
ANCHL_full <- ANCHLraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time)) %>%
  mutate(ANCHL = as.numeric(relative_abundance)) %>%
  arrange(Year) %>%
  dplyr::select(Year, ANCHL) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(ANCHL_full = scale(ANCHL)) %>%
  dplyr::select(Year, ANCHL_full)
```

```r
## create dataset from 2008-2016 for values in year t-1
ANCHL_full_lag <- ANCHLraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time)) %>%
  mutate(ANCHL = as.numeric(relative_abundance)) %>%
  arrange(Year) %>%
  dplyr::select(Year, ANCHL) %>%
  filter(Year >= 2008 & Year <= 2016) %>%
  mutate(TrueYear = Year,
         Year = TrueYear + 1,
         ANCHL_full_lag = scale(ANCHL)) %>%
  dplyr::select(Year, ANCHL_full_lag)

## join no-lag and lag datasets
ANCHL1 <- full_join(ANCHL_full, ANCHL_full_lag, by = "Year")

## join with egg size data
ANCHLdf1 <- left_join(egg, ANCHL1, by = "Year")

## run models
ANCHL_full_mod <- lm(Size ~ ANCHL_full , data = ANCHLdf1)
ANCHL_full_lag_mod <- lm(Size ~ ANCHL_full_lag, data = ANCHLdf1)

## Model selection table
ANHCL_AIC <- matrix(NA, nrow = 2, ncol = 3)
ANHCL_AIC[1,1] <- AIC(ANCHL_full_mod)
ANHCL_AIC[2,1] <- AIC(ANCHL_full_lag_mod)
ANHCL_AIC[,2] <- ANHCL_AIC[,1] - min(ANHCL_AIC[,1]) # calculate delta AIC
ANHCL_AIC[,3] <- exp(-0.5*ANHCL_AIC[,2])/(sum(exp(-0.5*ANHCL_AIC[,2]))) # calculate model weights
colnames(ANHCL_AIC) <- c("AIC", "deltaAIC", "model_weights")
rownames(ANHCL_AIC) <- c("full", "full_lag")
print(ANHCL_AIC)
```

```
##               AIC deltaAIC model_weights
## full     10719.99 0.000000    0.91359752
## full_lag 10724.71 4.716747    0.08640248
```

There is support to use the ANCHL data in year $t$ since the lagged data is delta AIC > 2.

### Biologically Effective Upwelling Transport Index (BEUTI)

Summary: BEUTI is a new upwelling index that leverages state-of-the-art ocean models as well as satellite and in situ data to improve upon historically available upwelling indices for the U.S. west coast. BEUTI provides estimates of vertical nitrate flux near the coast (i.e., the amount of nitrate upwelled/downwelled), which may be more relevant than upwelling strength when considering some biological responses. See Jacox, M. G., C. A. Edwards, E. L. Hazen, and S. J. Bograd (2018) Coastal upwelling revisited: Ekman, Bakun, and improved upwelling indices for the U.S. west coast. Journal of Geophysical Research, doi:10.1029/2018JC014187.

```r
BEUTIraw <- read_csv(here("data", "covariates", "cciea_OC_BEUTI_784c_ef9f_af6f.csv"))
```

```
## Rows: 389 Columns: 3
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (3): time, beuti, latitude
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
## are there NAs in the data?
sum(is.na(BEUTIraw$beuti))
```

```
## [1] 0
```

```
## Scenario 1: "half" dataset from Jan-June in time t
BEUTI_half <- BEUTIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(beuti = as.numeric(beuti)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  group_by(Year) %>%
  summarise(BEUTI = mean(beuti, na.rm = TRUE)) %>%
  dplyr::select(Year, BEUTI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(BEUTI_half = scale(BEUTI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, BEUTI_half)

## Scenario 2: "full" dataset from July in time t-1 to June in time t
BEUTI_full <- BEUTIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(beuti = as.numeric(beuti),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  group_by(Year) %>%
  summarise(BEUTI = mean(beuti, na.rm = TRUE)) %>%
  dplyr::select(Year, BEUTI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(BEUTI_full = scale(BEUTI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, BEUTI_full)

## Scenario 3: "half_lag" dataset from Jan-June in time t-1
BEUTI_half_lag <- BEUTIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(beuti = as.numeric(beuti)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(BEUTI = mean(beuti, na.rm = TRUE)) %>%
  dplyr::select(Year, BEUTI) %>%
```

```r
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(BEUTI_half_lag = scale(BEUTI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, BEUTI_half_lag)

## Scenario 4: "full_lag" dataset from July in time t-2 to June in time t-1
BEUTI_full_lag <- BEUTIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(beuti = as.numeric(beuti),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(BEUTI = mean(beuti, na.rm = TRUE)) %>%
  dplyr::select(Year, BEUTI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(BEUTI_full_lag = scale(BEUTI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, BEUTI_full_lag)

## join datasets together
BEUTI1 <- full_join(BEUTI_half, BEUTI_full, by = "Year")
BEUTI2 <- full_join(BEUTI1, BEUTI_half_lag, by = "Year")
BEUTI3 <- full_join(BEUTI2, BEUTI_full_lag, by = "Year")

## join with egg size data
BEUTI_df <- left_join(egg, BEUTI3, by = "Year")

## run models
BEUTI_half_mod <- lm(Size ~ BEUTI_half, data = BEUTI_df)
BEUTI_full_mod <- lm(Size ~ BEUTI_full, data = BEUTI_df)
BEUTI_half_lag_mod <- lm(Size ~ BEUTI_half_lag, data = BEUTI_df)
BEUTI_full_lag_mod <- lm(Size ~ BEUTI_full_lag, data = BEUTI_df)

## Model selection table
BEUTI_AIC <- matrix(NA, nrow = 4, ncol = 3) # 4 rows for 6 top models
BEUTI_AIC[1,1] <- AIC(BEUTI_half_mod)
BEUTI_AIC[2,1] <- AIC(BEUTI_full_mod)
BEUTI_AIC[3,1] <- AIC(BEUTI_half_lag_mod)
BEUTI_AIC[4,1] <- AIC(BEUTI_full_lag_mod)
BEUTI_AIC[,2] <- BEUTI_AIC[,1] - min(BEUTI_AIC[,1]) # calculate delta AIC
BEUTI_AIC[,3] <- exp(-0.5*BEUTI_AIC[,2])/(sum(exp(-0.5*BEUTI_AIC[,2]))) # calculate model weights
colnames(BEUTI_AIC) <- c("AIC", "deltaAIC", "model_weights")
rownames(BEUTI_AIC) <- c("half", "full", "half_lag", "full_lag")
print(BEUTI_AIC)
```

```
##                AIC  deltaAIC model_weights
## half     10733.29 11.613474   0.002660237
## full     10731.98 10.297204   0.005137416
## half_lag 10725.89  4.213694   0.107587579
```

```
## full_lag 10721.68  0.000000   0.884614768
```

The BEUTI full_lag model has more support.

# International indices

### North Pacific Gyre Oscillation Index (NPGO)

Summary: The NPGO is calculated from an Empirical Orthogonal Function analysis of sea-surface height in the Northeast Pacific. The NPGO is the second dominant mode.

```
NPGOraw <- read_csv(here("data", "covariates", "cciea_OC_NPGO_712b_5843_9069.csv"))
```

```
## Rows: 836 Columns: 2

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): time
## dbl (1): NPGO

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
## are there NAs in the data?
sum(is.na(NPGOraw$NPGO)) # only the first row, which does not contain data
```

```
## [1] 1
```

```
## Scenario 1: "half" dataset from Jan-June in time t
NPGO_half <- NPGOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(npgo = as.numeric(NPGO)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  group_by(Year) %>%
  summarise(NPGO = mean(npgo, na.rm = TRUE)) %>%
  dplyr::select(Year, NPGO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(NPGO_half = scale(NPGO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, NPGO_half)

## Scenario 2: "full" dataset from July in time t-1 to June in time t
NPGO_full <- NPGOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(npgo = as.numeric(NPGO),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  group_by(Year) %>%
  summarise(NPGO = mean(npgo, na.rm = TRUE)) %>%
```

```
  dplyr::select(Year, NPGO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(NPGO_full = scale(NPGO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, NPGO_full)

## Scenario 3: "half_lag" dataset from Jan-June in time t-1
NPGO_half_lag <- NPGOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(npgo = as.numeric(NPGO)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(NPGO = mean(npgo, na.rm = TRUE)) %>%
  dplyr::select(Year, NPGO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(NPGO_half_lag = scale(NPGO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, NPGO_half_lag)

## Scenario 4: "full_lag" dataset from July in time t-2 to June in time t-1
NPGO_full_lag <- NPGOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(npgo = as.numeric(NPGO),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month =
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(NPGO = mean(npgo, na.rm = TRUE)) %>%
  dplyr::select(Year, NPGO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(NPGO_full_lag = scale(NPGO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, NPGO_full_lag)

## join datasets together
NPGO1 <- full_join(NPGO_half, NPGO_full, by = "Year")
NPGO2 <- full_join(NPGO1, NPGO_half_lag, by = "Year")
NPGO3 <- full_join(NPGO2, NPGO_full_lag, by = "Year")

## join with egg size data
NPGO_df <- left_join(egg, NPGO3, by = "Year")

## run models
NPGO_half_mod <- lm(Size ~ NPGO_half, data = NPGO_df)
NPGO_full_mod <- lm(Size ~ NPGO_full, data = NPGO_df)
```

```r
NPGO_half_lag_mod <- lm(Size ~ NPGO_half_lag, data = NPGO_df)
NPGO_full_lag_mod <- lm(Size ~ NPGO_full_lag, data = NPGO_df)

## Model selection table
NPGO_AIC <- matrix(NA, nrow = 4, ncol = 3) # 4 rows for 6 top models
NPGO_AIC[1,1] <- AIC(NPGO_half_mod)
NPGO_AIC[2,1] <- AIC(NPGO_full_mod)
NPGO_AIC[3,1] <- AIC(NPGO_half_lag_mod)
NPGO_AIC[4,1] <- AIC(NPGO_full_lag_mod)
NPGO_AIC[,2] <- NPGO_AIC[,1] - min(NPGO_AIC[,1]) # calculate delta AIC
NPGO_AIC[,3] <- exp(-0.5*NPGO_AIC[,2])/(sum(exp(-0.5*NPGO_AIC[,2]))) # calculate model weights
colnames(NPGO_AIC) <- c("AIC", "deltaAIC", "model_weights")
rownames(NPGO_AIC) <- c("half", "full", "half_lag", "full_lag")
print(NPGO_AIC)
```

```
##               AIC  deltaAIC model_weights
## half     10710.26  0.000000  9.696585e-01
## full     10718.03  7.770044  1.992394e-02
## half_lag 10731.24 20.983985  2.691562e-05
## full_lag 10719.33  9.072072  1.039066e-02
```

The half NPGO model has the most support.

### Pacific Decadal Oscillation Index (PDO)

Summary: The PDO is calculated from an Empirical Orthogonal analysis of sea surface temperature anomalies in the North Pacific. The PDO is the first dominant mode.

```r
PDOraw <- read_csv(here("data", "covariates", "cciea_OC_PDO_712b_5843_9069.csv"))
```

```
## Rows: 1445 Columns: 2

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): time
## dbl (1): PDO

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
## are there NAs in the data?
sum(is.na(PDOraw$PDO)) # only the first row, which does not contain data
```

```
## [1] 1
```

```r
## Scenario 1: "half" dataset from Jan-June in time t
PDO_half <- PDOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(pdo = as.numeric(PDO)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  group_by(Year) %>%
  summarise(PDO = mean(pdo, na.rm = TRUE)) %>%
  dplyr::select(Year, PDO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
```

```r
  mutate(PDO_half = scale(PDO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, PDO_half)

## Scenario 2: "full" dataset from July in time t-1 to June in time t
PDO_full <- PDOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(pdo = as.numeric(PDO),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  group_by(Year) %>%
  summarise(PDO = mean(pdo, na.rm = TRUE)) %>%
  dplyr::select(Year, PDO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(PDO_full = scale(PDO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, PDO_full)

## Scenario 3: "half_lag" dataset from Jan-June in time t-1
PDO_half_lag <- PDOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(pdo = as.numeric(PDO)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(PDO = mean(pdo, na.rm = TRUE)) %>%
  dplyr::select(Year, PDO) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(PDO_half_lag = scale(PDO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, PDO_half_lag)

## Scenario 4: "full_lag" dataset from July in time t-2 to June in time t-1
PDO_full_lag <- PDOraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(pdo = as.numeric(PDO),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(PDO = mean(pdo, na.rm = TRUE)) %>%
  dplyr::select(Year, PDO) %>%
```

```r
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(PDO_full_lag = scale(PDO)) %>%
  arrange(Year) %>%
  dplyr::select(Year, PDO_full_lag)

## join datasets together
PDO1 <- full_join(PDO_half, PDO_full, by = "Year")
PDO2 <- full_join(PDO1, PDO_half_lag, by = "Year")
PDO3 <- full_join(PDO2, PDO_full_lag, by = "Year")

## join with egg size data
PDO_df <- left_join(egg, PDO3, by = "Year")

## run models
PDO_half_mod <- lm(Size ~ PDO_half, data = PDO_df)
PDO_full_mod <- lm(Size ~ PDO_full, data = PDO_df)
PDO_half_lag_mod <- lm(Size ~ PDO_half_lag, data = PDO_df)
PDO_full_lag_mod <- lm(Size ~ PDO_full_lag, data = PDO_df)

## Model selection table
PDO_AIC <- matrix(NA, nrow = 4, ncol = 3) # 4 rows for 6 top models
PDO_AIC[1,1] <- AIC(PDO_half_mod)
PDO_AIC[2,1] <- AIC(PDO_full_mod)
PDO_AIC[3,1] <- AIC(PDO_half_lag_mod)
PDO_AIC[4,1] <- AIC(PDO_full_lag_mod)
PDO_AIC[,2] <- PDO_AIC[,1] - min(PDO_AIC[,1]) # calculate delta AIC
PDO_AIC[,3] <- exp(-0.5*PDO_AIC[,2])/(sum(exp(-0.5*PDO_AIC[,2]))) # calculate model weights
colnames(PDO_AIC) <- c("AIC", "deltaAIC", "model_weights")
rownames(PDO_AIC) <- c("half", "full", "half_lag", "full_lag")
print(PDO_AIC)
```

```
##                AIC  deltaAIC model_weights
## half     10729.46 19.158830  6.352108e-05
## full     10728.48 18.178855  1.036852e-04
## half_lag 10710.30  0.000000  9.187661e-01
## full_lag 10715.15  4.855518  8.106673e-02
```

The PDO half_lag has more support.

### Oceanic Nino Index (ONI)

Summary: The ONI is the 3 month running mean of sea surface temperature anomalies in the Nino 3.4 region.

```r
ONIraw <- read_csv(here("data", "covariates", "cciea_OC_ONI_712b_5843_9069.csv"))
```

```
## Rows: 844 Columns: 2

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): time
## dbl (1): ONI

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
## are there NAs in the data?
sum(is.na(ONIraw$ONI)) # only the first row, which does not contain data
```

```
## [1] 1
```

```r
## Scenario 1: "half" dataset from Jan-June in time t
ONI_half <- ONIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(oni = as.numeric(ONI)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  group_by(Year) %>%
  summarise(ONI = mean(oni, na.rm = TRUE)) %>%
  dplyr::select(Year, ONI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(ONI_half = scale(ONI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, ONI_half)

## Scenario 2: "full" dataset from July in time t-1 to June in time t
ONI_full <- ONIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(oni = as.numeric(ONI),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month =
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  group_by(Year) %>%
  summarise(ONI = mean(oni, na.rm = TRUE)) %>%
  dplyr::select(Year, ONI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(ONI_full = scale(ONI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, ONI_full)

## Scenario 3: "half_lag" dataset from Jan-June in time t-1
ONI_half_lag <- ONIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(oni = as.numeric(ONI)) %>%
  filter(Month == 1 | Month == 2 | Month == 3 |Month == 4 | Month == 5 | Month == 6) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(ONI = mean(oni, na.rm = TRUE)) %>%
  dplyr::select(Year, ONI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(ONI_half_lag = scale(ONI)) %>%
  arrange(Year) %>%
```

```
  dplyr::select(Year, ONI_half_lag)

## Scenario 4: "full_lag" dataset from July in time t-2 to June in time t-1
ONI_full_lag <- ONIraw %>%
  slice(-1) %>%
  mutate(time = ymd_hms(time)) %>%
  mutate(Year = year(time),
         Month = month(time)) %>%
  mutate(oni = as.numeric(ONI),
         split_year = ifelse(Month == 7 | Month == 8 | Month == 9 | Month == 10 | Month == 11 | Month ==
                             Year + 1, Year)) %>%
  rename(Year = split_year, true_year = Year) %>%
  mutate(Year = Year + 1) %>%
  group_by(Year) %>%
  summarise(ONI = mean(oni, na.rm = TRUE)) %>%
  dplyr::select(Year, ONI) %>%
  filter(Year >= 2009 & Year <= 2017) %>%
  mutate(ONI_full_lag = scale(ONI)) %>%
  arrange(Year) %>%
  dplyr::select(Year, ONI_full_lag)

## join datasets together
ONI1 <- full_join(ONI_half, ONI_full, by = "Year")
ONI2 <- full_join(ONI1, ONI_half_lag, by = "Year")
ONI3 <- full_join(ONI2, ONI_full_lag, by = "Year")

## join with egg size data
ONI_df <- left_join(egg, ONI3, by = "Year")

## run models
ONI_half_mod <- lm(Size ~ ONI_half, data = ONI_df)
ONI_full_mod <- lm(Size ~ ONI_full, data = ONI_df)
ONI_half_lag_mod <- lm(Size ~ ONI_half_lag, data = ONI_df)
ONI_full_lag_mod <- lm(Size ~ ONI_full_lag, data = ONI_df)

## Model selection table
ONI_AIC <- matrix(NA, nrow = 4, ncol = 3) # 4 rows for 6 top models
ONI_AIC[1,1] <- AIC(ONI_half_mod)
ONI_AIC[2,1] <- AIC(ONI_full_mod)
ONI_AIC[3,1] <- AIC(ONI_half_lag_mod)
ONI_AIC[4,1] <- AIC(ONI_full_lag_mod)
ONI_AIC[,2] <- ONI_AIC[,1] - min(ONI_AIC[,1]) # calculate delta AIC
ONI_AIC[,3] <- exp(-0.5*ONI_AIC[,2])/(sum(exp(-0.5*ONI_AIC[,2]))) # calculate model weights
colnames(ONI_AIC) <- c("AIC", "deltaAIC", "model_weights")
rownames(ONI_AIC) <- c("half", "full", "half_lag", "full_lag")
print(ONI_AIC)
```

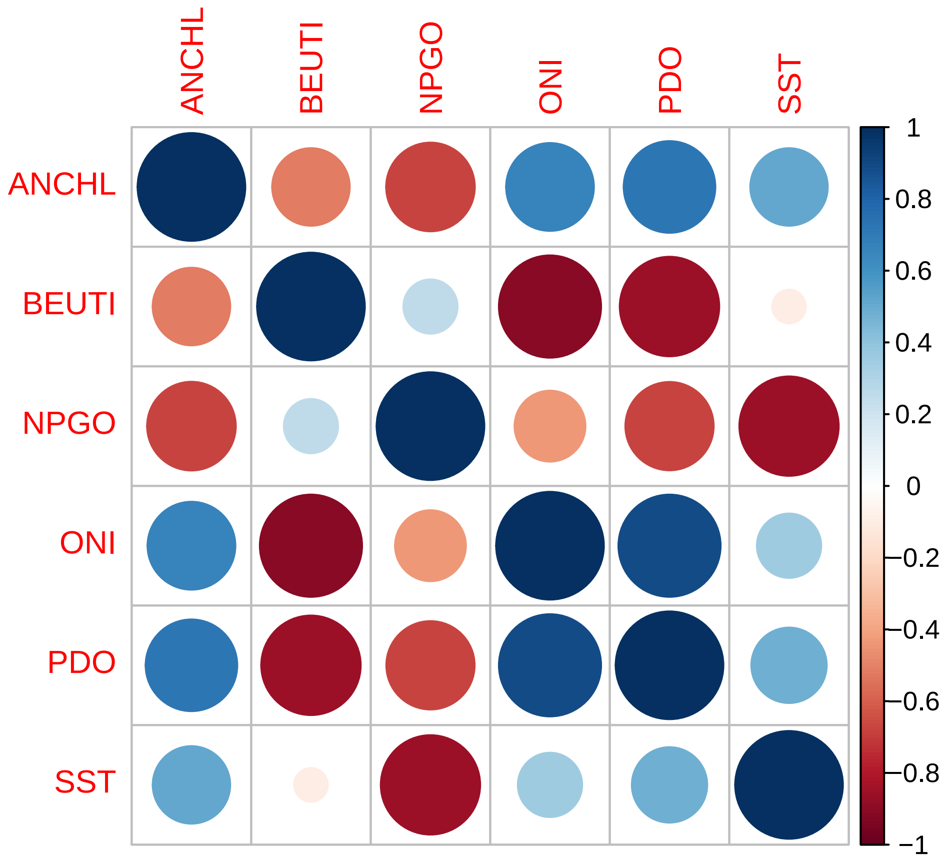
```
##                AIC   deltaAIC model_weights
## half     10733.90 17.2117112  0.0001053966
## full     10733.88 17.1942420  0.0001063212
## half_lag 10716.69  0.0000000  0.5758404504
## full_lag 10717.30  0.6124404  0.4239478318
```

There is equal support for the ONI half_lag (AIC = 10704.14) and full_lag model (AIC = 10705.02).

## Correlation

Check for correlation between the oceanographic indices (absolute value > 0.65).

```
## bind covars
covars <- cbind(ANCHL_full[,2], BEUTI_full_lag[,2], NPGO_half[,2], ONI_half_lag[,2], PDO_half_lag[,2], S
colnames(covars) <- c("ANCHL", "BEUTI", "NPGO", "ONI", "PDO", "SST")

## check for correlation between predictors (cutoff >0.65)
cp <- as.data.frame((round(cor(covars, use="complete.obs"), 2)))

## this function flattens your data in a particular way, used below
flattenCorrMatrix <- function(cormat, pmat) {
  ut <- upper.tri(cormat)
  data.frame(
    row = rownames(cormat)[row(cormat)[ut]],
    column = rownames(cormat)[col(cormat)[ut]],
    cor  =(cormat)[ut],
    p = pmat[ut]
  )
}

cor <- rcorr(as.matrix(covars))

## create a new formatted df
cor_vals <- flattenCorrMatrix(cor$r, cor$P) %>% arrange(cor)

## plot
corrplot(cor$r)
```



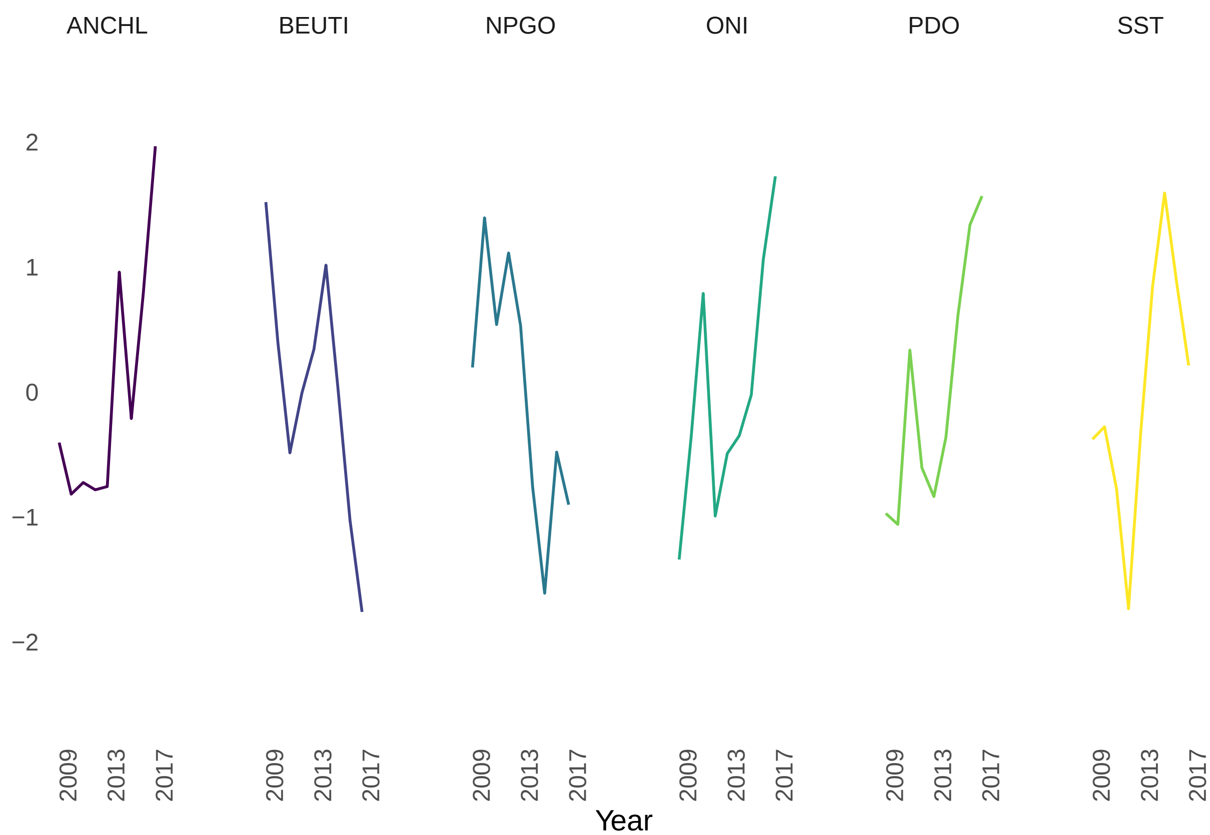

Positive correlations are displayed in blue and negative correlations in red color. Color intensity and the size of the circle are proportional to the correlation coefficients.

We selected +/- 0.65 as our cutoff for correlation. The following covariates should not be in the same model: 1. ANCHL and NPGO (-0.68) 2. ANCHL and ONI (0.66) 3. ANCHL and PDO (0.72) 4. BEUTI and ONI (-0.90) 5. BEUTI and PDO (-0.85) 6. NPGO and PDO (-0.67) 7. NPGO and SST (-0.85) 8. ONI and PDO (0.90)

## Plot

```
covarsplot <- covars %>%
  mutate(year = 2009:2017) %>%
  pivot_longer(cols = 1:6, names_to = "covariate", values_to = "value")

ggplot(data = covarsplot, aes(x = year, y = value, color = covariate)) +
  geom_line() +
  facet_wrap(~covariate, nrow = 1) +
  scale_color_viridis(discrete = TRUE) +
  ylim(c(-2.5, 2.5)) +
  theme_minimal() + xlab("Year") + ylab("") +
  scale_x_discrete(breaks = c(2009, 2013, 2017), limits = c(2009, 2013, 2017)) +
  theme(legend.position = "none",
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.text.x = element_text(angle = 90),
        panel.spacing = unit(2.5, "lines"))
```

```
## Warning: Continuous limits supplied to discrete scale.
## Did you mean `limits = factor(...)` or `scale_*_continuous()`?
```




## Export out

```
finalcovars <- covars %>%
  mutate(Year = 2009:2017) %>%
  select(Year, everything())
#write.csv(x = finalcovars, file = here("data", "covariates", "covars.csv"), row.names = FALSE)
```