# SOSH GAMLSS

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Goal: demonstrate improved quality of seabird distribution models by incorporating individual tracking data Method: Locations from tracked sooty shearwaters have been aggregated into kernel density estimates. These utilization distributions will be used in conjunction with more commonly used variables to create distribution models. The model of choice is GAMLSS, for its ability to handle non-linear relationships and errors.

#### Load packages

```
library(gamlss)
library(dplyr)
library(foreach)
library(doParallel)
library(MASS)
library(ggplot2)
```

#### 2. Load data

```
SOSHcount Binarea Month Latitude DistCoast Dist200
                                                          DepCI SSTmean STD_SST MEAN_Beaufort L10CHLproxy
##
                          7 45.74943 90.730011 39.84471 0.3441763 15.10290 0.1543211
## 1
           0 0.6070346
                                                                                             3 -0.13471743
## 2
           0 1.0199987 7 45.75098 31.043267 11.65864 0.1656442 14.72605 0.5041291
                                                                                            3 -0.09102068
                         7 45.75140 24.261040 17.33907 0.1140940 15.30328 0.1757790
## 3
           0 1.0199989
                                                                                            3 0.00484971
                         7 45.75116 17.711237 22.74802 0.2592593 15.38545 0.2115198
## 4
         0 1.0164059
                                                                                           3 0.07141375
                          7 45.75159 11.183655 28.56728 0.2884615 15.70420 0.1791671
## 5
           0 1.0199985
                                                                                     3 0.16948388
                          7 45.75038 4.532045 34.69352 0.6710526 15.70320 0.1887719
           0 1.0199988
## 6
                                                                                            3 0.31959755
    STD CHL log10 Watermass L10CHLsurvey CHLsurvanom L10CHLsurvclim
##
                                                                    FCPI
## 1
       0.02840480
                         3 -0.7665744 -1.2941501
                                                     -0.2932137 0.1824324
## 2
       0.06258219
                             0.3587903 -1.5384094 0.6951271 0.2905405
## 3
       0.02031565
                             0.4023360 -1.5200367
                                                     0.7013794 0.2770270
## 4
       0.05416992
                             0.2798753 -1.5658311
                                                     0.7424677 0.2567568
## 5
       0.02248318
                         2
                             0.5573132 -0.8559388 0.8132451 0.2905405
## 6
       0.04746003
                         2
                             0.5720522 -0.3275567
                                                      0.7162526 0.2364865
```

summary(sosh.data)

```
##
      SOSHcount
                          Binarea
                                        Month
                                                     Latitude
                                                                    DistCoast
                                                                                        Dist200
                                                                                                             DepCI
##
    Min.
           : 0.000
                      Min.
                              :0.0122
                                        6:512
                                                 Min.
                                                         :39.25
                                                                  Min.
                                                                         : 1.974
                                                                                     Min.
                                                                                            : 0.01411
                                                                                                        Min.
                                                                                                                :0.01885
                                                                                    1st Qu.: 7.87697
    1st Qu.: 0.000
                      1st Qu.:0.5100
                                        7:561
                                                 1st Qu.:41.25
                                                                  1st Qu.: 11.506
                                                                                                        1st Qu.:0.23184
##
    Median : 0.000
                                                 Median :44.00
                                                                  Median : 22.894
##
                      Median :1.0200
                                        9:569
                                                                                     Median :17.27896
                                                                                                        Median :0.33641
    Mean
          : 3.879
                      Mean
                             :0.8249
                                        10:538
                                                 Mean
                                                         :43.59
                                                                  Mean
                                                                        : 33.173
                                                                                     Mean
                                                                                            :19.79308
                                                                                                        Mean
                                                                                                                :0.42077
##
                                                                                     3rd Qu.:29.18043
    3rd Ou.: 0.000
                       3rd Ou.:1.0200
                                                  3rd Ou.:45.55
                                                                  3rd Ou.: 50.999
                                                                                                         3rd Ou.:0.57890
           :595.000
                                                         :47.05
##
    Max.
                      Max.
                              :1.0200
                                                 Max.
                                                                  Max.
                                                                         :125.649
                                                                                     Max.
                                                                                            :80.15171
                                                                                                        Max.
                                                                                                                :1.00000
                        STD SST
                                                        L10CHLproxy
                                                                           STD CHL log10
##
       SSTmean
                                       MEAN Beaufort
                                                                                                Watermass
##
    Min.
           : 8.371
                     Min.
                             :0.0000
                                       Min.
                                              :0.000
                                                       Min.
                                                               :-0.60703
                                                                           Min.
                                                                                   :0.00000
                                                                                              Min.
                                                                                                     :1.000
                     1st Qu.:0.1609
    1st Qu.:12.785
                                       1st Qu.:2.000
                                                        1st Qu.:-0.04165
                                                                           1st Qu.:0.02528
                                                                                              1st Qu.:1.000
    Median :13.956
                     Median :0.1940
                                       Median :2.729
                                                        Median : 0.17588
                                                                           Median :0.04042
                                                                                              Median :3.000
##
    Mean
           :13.705
                             :0.2534
                                              :2.575
                                                              : 0.14823
                                                                                   :0.05143
                                                                                                     :2.444
##
                     Mean
                                       Mean
                                                        Mean
                                                                           Mean
                                                                                              Mean
    3rd Qu.:14.861
                     3rd Qu.:0.2822
                                       3rd Qu.:3.037
                                                        3rd Qu.: 0.32251
                                                                            3rd Qu.:0.06532
                                                                                              3rd Qu.:3.000
##
    Max.
           :16.916
                     Max.
                             :1.3345
                                               :6.000
                                                        Max.
                                                               : 1.06842
                                                                           Max.
                                                                                   :0.39497
                                                                                                     :4.000
##
                                       Max.
                                                                                              Max.
                                                                  FCPI
##
     L10CHLsurvey
                       CHLsurvanom
                                         L10CHLsurvclim
    Min.
           :-0.7825
                              :-2.2561
                                         Min.
                                                :-0.53229
                                                             Min.
                                                                    :0.03378
##
                      Min.
    1st Qu.:-0.1748
                                         1st Qu.:-0.00885
                      1st Qu.:-0.8558
                                                             1st Qu.:0.17568
##
    Median : 0.1007
                      Median :-0.3395
                                         Median : 0.32011
                                                             Median :0.21622
##
    Mean
          : 0.1674
                            :-0.3365
                                               : 0.32061
                                                             Mean
                                                                    :0.21730
##
                      Mean
                                         Mean
                                         3rd Qu.: 0.64963
    3rd Ou.: 0.4927
                      3rd Ou.: 0.2051
                                                             3rd Ou.:0.25676
##
    Max.
           : 1.4523
                      Max.
                              : 1.8245
                                         Max.
                                              : 1.13857
                                                             Max.
                                                                    :0.31757
```

3. Set up parallel processing

```
nCores <- detectCores()
gamlssCl <- makeCluster(nCores)
registerDoParallel(gamlssCl)</pre>
```

4. Create geographic and oceanographic models by month using canonical discrete distributions WITHOUT home range variable:

```
# Wrapper for gamlss. Error handling and refitting.
N_REFIT <- 5
try.fit <- function(formula, data, family, n_refit = N_REFIT) {
    # Try to fit model
    model <- try(gamlss(formula, data = data, family = family))
    fitAttempts <- 1</pre>
```

```
# Keep refitting model until...
                                     # ... we run out of attempts,
  while(fitAttempts <= n refit &&</pre>
        class(model) != 'try-error' &&
                                           # get an error,
        !getElement(model, 'converged')) {  # or model converges
    model <- try(refit(model))</pre>
    fitAttempts <- fitAttempts + 1</pre>
  # Return fitting results. Hopefully it's a fitted model, may be a try-error
  model
}
# Create models using canonical discrete distributions.
# SOSHcount as function of FCPI, Dist200, SSTmean (all three cubic splines) with Month as random variable
# and log(Binarea) as offset
# Create models using canonical discrete distributions for each month.
# Geographic + oceanographic models
# geo = SOSHcount ~ cs(Latitude)+cs(DistCoast)+cs(Dist200)+cs(DepCI) + offset(Log(Binarea))
# ocean = SOSHcount ~ cs(SSTmean)+cs(STD SST)+cs(MEAN Beaufort)+cs(L10CHLproxy)+cs(STD CHL Log10)+Watermass+cs(L10CHLsurv
ey)+
# cs(CHLsurvanom)+cs(L10CHLsurvclim)+cs(FCPI) + offset(log(Binarea))
discrete.dist <- c('PO', 'NBI', 'NBII', 'DEL', 'PIG', 'SI', 'SICHEL', 'ZIP', 'ZIP2')
months \leftarrow c(6, 7, 9, 10)
# For each discrete distribution...
monthly.geo.ocean.models <- foreach(dist = discrete.dist,</pre>
                                     .packages = c('foreach',
                                                   'doParallel',
                                                   'gamlss',
                                                   'dplyr')) %dopar% {
  # For each month's survey...
  foreach(month = months) %do% {
    print(sprintf('Distribution %s, month %i', dist, month))
    # Filter SOSH data to the month of interest
    month.data <- filter(sosh.data, Month == month)</pre>
    if(nrow(month.data) == 0) stop(sprintf('No data in month %i', month))
    # Fit geographic model
    print('Fitting geographic model')
```

```
geo.model <- try.fit(SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) + cs(DepCI) + offset(log(Binarea)),</pre>
                         data = month.data,
                         family = get('dist'))
   # Fit oceanographic model
   print('Fitting oceanographic model')
    ocean.model <- try.fit(SOSHcount ~ cs(SSTmean) + cs(STD SST) + cs(MEAN Beaufort) + cs(L10CHLproxy) +
                                cs(STD_CHL_log10) + as.factor(Watermass) + cs(L10CHLsurvey) + cs(CHLsurvanom) +
                                cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                           data = month.data,
                           family = get('dist'))
   list(dist = dist,
         month = month,
         geo.model = geo.model,
         ocean.model = ocean.model)
 }
stopCluster(gamlssCl)
```

5. Summarize model results for ranking (parameters, convergence, EDF, AIC)

##		Distribution	Month	GeoConverged	GeoEDF	GeoAIC	OceanConverged	OceanEDF	OceanAIC
##	1	PO	6	_		14429.1667	_		8720.4084
##		PO	7		17.22401				2206.1990
##	3	PO	9	NA	NA	NA			2401.9413
##	4	PO	10	NA	NA	NA	TRUE	40.00109	1943.9565
##	5	NBI	6	TRUE	19.76089	1597.5923	TRUE	41.00034	1559.7594
##	6	NBI	7	TRUE	19.64882	854.0322	TRUE	41.11919	877.4572
##	7	NBI	9	NA	NA	NA	TRUE	41.00053	1373.9162
##	8	NBI	10	TRUE	19.58401	909.4861	TRUE	41.00000	893.7608
##	9	NBII	6	TRUE	19.57903	1641.2317	TRUE	41.00221	1630.9974
##	10	NBII	7	TRUE	19.35685	912.5372	TRUE	40.99794	952.9774
##	11	NBII	9	TRUE	20.09472	1389.9298	TRUE	41.00057	1431.6700
##	12	NBII	10	TRUE	19.07953	933.8088	TRUE	40.99842	942.9446
##	13	DEL	6	NA	NA	NA	NA	NA	NA
##	14	DEL	7	TRUE	19.65512	805.9848	TRUE	42.00058	848.9592
##	15	DEL	9	TRUE	20.45498	1317.7136	TRUE	41.99937	1371.0198
##	16	DEL	10	TRUE	19.89557	864.0192	TRUE	42.00111	872.7358
##	17	PIG	6	TRUE	19.54640	1578.3406	TRUE	41.00224	1547.9482
##	18	PIG	7	TRUE	19.31741	812.3070	TRUE	40.99844	846.7177
##	19	PIG	9	TRUE	19.86607	1306.4611	TRUE	41.00071	1356.8089
##	20	PIG	10	TRUE	18.99260	866.9973	TRUE	40.99824	876.4088
##	21	SI	6	TRUE	20.52629	1580.0869	TRUE	41.99769	1546.8304
##	22	SI	7	TRUE	20.37716	797.8217	TRUE	41.99955	844.9290
##	23	SI	9	TRUE	21.06846	1307.0433	TRUE	41.99905	1357.4700
##	24	SI	10	TRUE	20.06931	867.2903	TRUE	42.00210	882.2266
##	25	SICHEL	6	TRUE	20.54553	1580.4882	TRUE	41.99817	1546.7936
##	26	SICHEL	7	TRUE	20.36798	797.8504	TRUE	41.99945	845.1267
##	27	SICHEL	9	TRUE	21.07391	1307.0165	TRUE	41.99906	1357.5018
##	28	SICHEL	10	TRUE	20.07979	866.9274	TRUE	42.00003	879.3872
##		ZIP	6	NA	NA	NA	NA	NA	NA
##	30	ZIP	7	NA	NA	NA	NA	NA	NA
##	31	ZIP	9	NA	NA	NA	TRUE	41.00300	2205.6094
##	32	ZIP	10	NA	NA	NA	NA	NA	NA
##	33	ZIP2	6	NA	NA	NA	NA	NA	NA
##	34	ZIP2	7	NA	NA	NA	NA	NA	NA
##	35	ZIP2	9	NA	NA	NA	NA	NA	NA
##	36	ZIP2	10	NA	NA	NA	NA	NA	NA

6. SI, SICHEL, and PIG distributions perform the best (which makes sense, they're all closely related), but only SI and SICHEL are in each month's top 4 distributions for both geographic and oceanographic models. SI has the slightly greater mean AIC weight than SICHEL, so we'll proceed using SI.

```
# Utility function for calculating AIC weight. vAIC is a vector of AIC values
calcAICw <- function(vAIC) {</pre>
  deltaAIC <- vAIC - min(vAIC, na.rm = TRUE)</pre>
  relLikelihood <- exp(-0.5 * deltaAIC)
  normalizingFactor <- sum(relLikelihood, na.rm = TRUE)</pre>
  relLikelihood / normalizingFactor
}
# Sort models by month and quality of fit
monthly.geo.ranks <- model.rankings %>%
  group_by(Month) %>%
  mutate(GeoDeltaAIC = GeoAIC - min(GeoAIC, na.rm = TRUE),
         GeoAICw = calcAICw(GeoAIC) %>% round(3)) %>%
  arrange(-GeoAICw) %>%
  slice(1:4) %>%
  ungroup %>%
  select(Distribution:GeoAICw)
monthly.ocean.ranks <- model.rankings %>%
  group by(Month) %>%
  mutate(OceanDeltaAIC = OceanAIC - min(OceanAIC, na.rm = TRUE),
         OceanAICw = calcAICw(OceanAIC) %>% round(3)) %>%
  arrange(-OceanAICw) %>%
  slice(1:4) %>%
  ungroup %>%
  select(Distribution, Month, OceanConverged:OceanAICw)
# Identify best available distribution by product of AIC weight across months
monthly.geo.ranks %>%
  group by(Distribution) %>%
  summarize(N = n(),
            meanAICw = mean(GeoAICw)) %>%
  ungroup %>%
  arrange(-N, -meanAICw)
```

```
## # A tibble: 5 x 3
     Distribution
##
                      N meanAICw
           <fctr> <int>
                             <dbl>
##
               SI
                      4 0.2880000
## 1
           SICHEL
## 2
                      4 0.2822500
## 3
              PIG
                      3 0.3676667
## 4
              DEL
                      3 0.2046667
## 5
               P0
                      2 0.0000000
```

```
## # A tibble: 6 x 3
##
     Distribution
                      N meanAICw
##
          <fctr> <int>
                           <dbl>
                      4 0.27425
## 1
               SI
          SICHEL
                      4 0.27100
## 2
                      4 0.23300
## 3
              PIG
              DEL
                      2 0.44250
## 4
## 5
              NBI
                      1 0.00100
## 6
              P0
                      1 0.00000
```

## 7. Model culling

```
# We see SI and SICHEL are the only two distributions to show up in both models' top 4 across months
# SI has the slightly higher mean AIC weight, so we'll go with that.

# Cull models using selected distribution (SI)

# Recursively drop parameters by largest decrease in AIC until model degrades
cull.model <- function(model) {
   aic <- extractAIC(model)[2]</pre>
```

```
# Re-fit model to n-1 terms
  model.terms <- model %>% formula %>% terms
  term.labels <- attr(model.terms, 'term.labels')</pre>
  submodels <- foreach(i = seq(term.labels)) %do% {</pre>
    dropped <- term.labels[i]</pre>
    submodel <- try(update(model, reformulate(sprintf('. - %s', dropped))))</pre>
    list(dropped = dropped,
         submodel = submodel)
  }
  # Which submodels converged? Which submodel has the greatest decrease in AIC?
  drop.results <- foreach(i = seq(submodels), .combine = rbind) %do% {</pre>
    tryCatch(with(submodels[[i]], data.frame(dropped = dropped,
                                               converged = submodel$converged,
                                               AIC = extractAIC(submodel)[2],
                                               deltaAIC = extractAIC(submodel)[2] - aic)),
             error = function(e) data.frame(dropped = NA,
                                              i = NA,
                                              converged = NA,
                                              AIC = NA,
                                              deltaAIC = NA))
  } %>%
    filter(converged) %>%
    arrange(deltaAIC)
  # If no submodels converge or if no submodels are an improvement, return the original model
  if(nrow(drop.results) == 0 || min(drop.results$deltaAIC, na.rm = TRUE) > 0) {
    return(model)
  } else {
    # Otherwise, repeat the process on the best submodel
    best.submodel <- submodels[[drop.results$i[1]]]$submodel</pre>
    return(cull.model(best.submodel))
}
```

```
month6 <- filter(sosh.data, Month == 6)</pre>
# Geo
geo6global <- gamlss(SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) + cs(DepCI) + offset(log(Binarea)),</pre>
                      data = month6,
                     family = SI,
                      control = gamlss.control(n.cyc = 100))
geo6dropterm <- dropterm(geo6global, test = 'Chisq')</pre>
geo6culled <- cull.model(geo6global)</pre>
geo6dropped <- setdiff(terms(geo6global) %>% attr('term.labels'), terms(geo6culled) %>% attr('term.labels'))
# Ocean
ocean6global <- gamlss(SOSHcount ~ cs(SSTmean) + cs(STD SST) + cs(MEAN Beaufort) + cs(L10CHLproxy) +
                          cs(STD CHL log10) + as.factor(Watermass) + cs(L10CHLsurvey) + cs(CHLsurvanom) +
                          cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                        data = month6,
                        family = SI,
                        control = gamlss.control(n.cyc = 100))
ocean6dropterm <- dropterm(ocean6global, test = 'Chisq')</pre>
```

```
## Warning in RS(): Algorithm RS has not yet converged
```

```
ocean6culled <- cull.model(ocean6global)
```

```
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
```

```
ocean6dropped <- setdiff(terms(ocean6global) %>% attr('term.labels'), terms(ocean6culled) %>% attr('term.labels'))
# Month 7
month7 <- filter(sosh.data, Month == 7)</pre>
# Geo
geo7global <- gamlss(SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) + cs(DepCI) + offset(log(Binarea)),</pre>
                      data = month7,
                     family = SI,
                     control = gamlss.control(n.cyc = 100))
geo7dropterm <- dropterm(geo7global, test = 'Chisq')</pre>
geo7culled <- cull.model(geo7global)</pre>
geo7dropped <- setdiff(terms(geo7global) %>% attr('term.labels'), terms(geo7culled) %>% attr('term.labels'))
# Ocean
ocean7global <- try(gamlss(SOSHcount ~ cs(SSTmean) + cs(STD_SST) + cs(MEAN_Beaufort) + cs(L10CHLproxy) +
                              cs(STD_CHL_log10) + as.factor(Watermass) + cs(L10CHLsurvey) + cs(CHLsurvanom) +
                              cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                            data = month7,
                            family = SI,
                            control = gamlss.control(n.cyc = 100)))
ocean7dropterm <- dropterm(ocean7global, test = 'Chisq')</pre>
ocean7culled <- cull.model(ocean7global)</pre>
```

```
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
ocean7dropped <- setdiff(terms(ocean7global) %>% attr('term.labels'), terms(ocean7culled) %>% attr('term.labels'))
# Month 9
month9 <- filter(sosh.data, Month == 9)</pre>
# Geo
# For some reason month 9 geo model doesn't converge reliably
```

```
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not ## obtained in 30 iterations
```

geo9global <- try.fit(SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) + cs(DepCI) + offset(log(Binarea)),</pre>

data = month9, family = SI)

```
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
```

```
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
```

```
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
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## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
```

```
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
## Warning in additive.fit(x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
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## obtained in 30 iterations
## Warning in additive.fit (x = X, y = wv, w = wt * w, s = s, who = who, smooth.frame, : additive.fit convergence not
## obtained in 30 iterations
```

## Warning in RS(): Algorithm RS has not yet converged

## Warning in RS(): Algorithm RS has not yet converged

```
geo9dropterm <- dropterm(geo9global, test = 'Chisq')</pre>
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
geo9culled <- cull.model(geo9global)</pre>
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
## Warning in is.na(data): is.na() applied to non-(list or vector) of type 'closure'
geo9dropped <- setdiff(terms(geo9global) %>% attr('term.labels'), terms(geo9culled) %>% attr('term.labels'))
# Ocean
ocean9global <- gamlss(SOSHcount ~ cs(SSTmean) + cs(STD_SST) + cs(MEAN_Beaufort) + cs(L10CHLproxy) +
                         cs(STD_CHL_log10) + as.factor(Watermass) + cs(L10CHLsurvey) + cs(CHLsurvanom) +
                         cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                       data = month9,
                       family = SI,
                       control = gamlss.control(n.cyc = 100))
ocean9dropterm <- dropterm(ocean9global, test = 'Chisq')</pre>
```

## Warning in RS(): Algorithm RS has not yet converged

```
ocean9culled <- cull.model(ocean9global)
```

```
## Warning in RS(): Algorithm RS has not yet converged
```

```
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
## Warning in RS(): Algorithm RS has not yet converged
```

```
ocean9dropped <- setdiff(terms(ocean9global) %>% attr('term.labels'), terms(ocean9culled) %>% attr('term.labels'))
# Month 10
month10 <- filter(sosh.data, Month == 10)</pre>
# Geo
geo10global <- gamlss(SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) + cs(DepCI) + offset(log(Binarea)),</pre>
                     data = month10,
                     family = SI,
                     control = gamlss.control(n.cyc = 100))
geo10dropterm <- dropterm(geo10global, test = 'Chisq')</pre>
geo10culled <- cull.model(geo10global)</pre>
geo10dropped <- setdiff(terms(geo10global) %>% attr('term.labels'), terms(geo10culled) %>% attr('term.labels'))
# Ocean
ocean10global <- try(gamlss(SOSHcount ~ cs(SSTmean) + cs(STD SST) + cs(MEAN Beaufort) + cs(L10CHLproxy) +
                              cs(STD CHL log10) + as.factor(Watermass) + cs(L10CHLsurvey) + cs(CHLsurvanom) +
                              cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                            data = month10,
                            family = SI,
                            control = gamlss.control(n.cyc = 100)))
ocean10dropterm <- dropterm(ocean10global, test = 'Chisq')</pre>
ocean10culled <- cull.model(ocean10global)</pre>
ocean10dropped <- setdiff(terms(ocean10global) %>% attr('term.labels'), terms(ocean10culled) %>% attr('term.labels'))
```

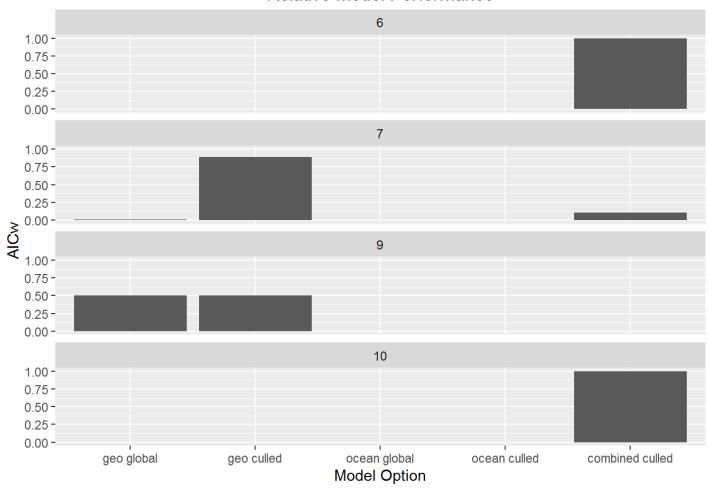
#### 8. Per-month combined models

```
combined6culled <- gamlss(formula = SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) + cs(DepCI) +</pre>
                      cs(SSTmean) + cs(STD SST) + cs(MEAN Beaufort) + cs(L10CHLproxy) +
                      as.factor(Watermass) + cs(L10CHLsurvey) + cs(L10CHLsurvclim) +
                      cs(FCPI) + offset(log(Binarea)),
                    family = SI,
                    data = month6,
                    control = gamlss.control(n.cyc = 100))
combined7culled <- gamlss(formula = SOSHcount ~ cs(Latitude) + cs(DistCoast) +</pre>
                      cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                    family = SI,
                    data = month7,
                    control = gamlss.control(n.cyc = 100))
# Combined model fails for month 9
# combined9culled <- qamlss(formula = SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) +
                        cs(SSTmean) + cs(MEAN_Beaufort) +
#
                        cs(STD_CHL_log10) + cs(CHLsurvanom) + cs(L10CHLsurvclim) +
                        cs(FCPI) + offset(log(Binarea)),
#
#
                      family = SI,
                      data = month9,
                      control = gamlss.control(n.cyc = 100))
combined10culled <- gamlss(formula = SOSHcount ~ cs(Latitude) + cs(DistCoast) + cs(Dist200) +</pre>
                       cs(SSTmean) + cs(STD SST) + cs(L10CHLproxy) +
                       as.factor(Watermass) + cs(L10CHLsurvclim) + cs(FCPI) + offset(log(Binarea)),
                    family = SI,
                    data = month10,
                    control = gamlss.control(n.cyc = 100))
```

## 9. Model analysis

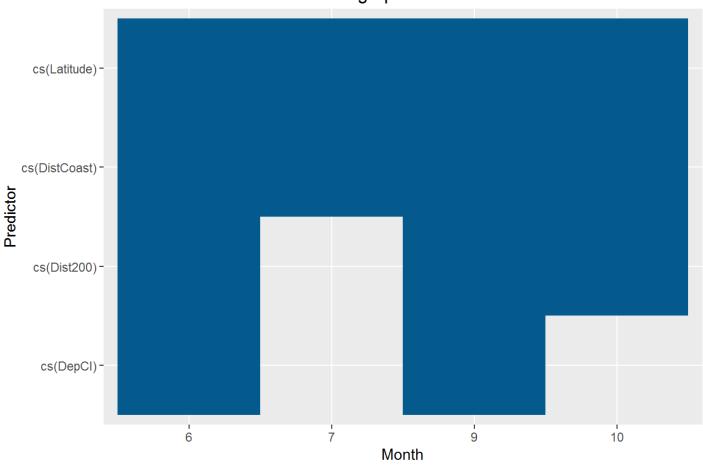
```
model.options <- foreach(type = c('geo', 'ocean', 'combined'), .combine = rbind) %do% {</pre>
  foreach(month = c(6, 7, 9, 10), .combine = rbind) %do% {
    foreach(scope = c('global', 'culled'), .combine = rbind) %do% {
      if(type == 'combined' && scope == 'global')
        return(NULL)
      model <- try(get(paste(type, month, scope, sep = '')))</pre>
      if(class(model)[1] == 'try-error')
        return(NULL)
      aic <- extractAIC(model)[2]</pre>
      predictors <- model %>% formula %>% terms %>% attr('term.labels') %>% paste(collapse = ', ')
      data.frame(type = type,
                 month = month,
                 scope = scope,
                 AIC = aic,
                 predictors = predictors)
} %>%
  group_by(month) %>%
  mutate(AICw = calcAICw(AIC)) %>%
  ungroup %>%
  arrange(month, type, scope)
ggplot(model.options,
       aes(x = paste(type, scope),
           y = AICw)) +
  geom_bar(stat = 'identity') +
  facet_wrap(~ month,
             nrow = 4) +
  scale x discrete('Model Option',
                   limits = c('geo global', 'geo culled',
                               'ocean global', 'ocean culled',
                               'combined culled')) +
  ggtitle('Relative Model Performance')
```

## Relative Model Performance



```
predictor.comparison <- foreach(type = c('geo', 'ocean', 'combined'), .combine = rbind) %do% {</pre>
 foreach(month = c(6, 7, 9, 10), .combine = rbind) %do% {
    foreach(scope = c('global', 'culled'), .combine = rbind) %do% {
      if(type == 'combined' && scope == 'global')
        return(NULL)
     model <- try(get(paste(type, month, scope, sep = '')))</pre>
     if(class(model)[1] == 'try-error')
        return(NULL)
      predictors <- model %>% formula %>% terms %>% attr('term.labels')
      data.frame(type = type,
                 month = month,
                 scope = scope,
                 predictor = predictors)
predictor.comparison %>%
 filter(type == 'geo', scope == 'culled') %>%
  ggplot(aes(x = factor(month),
             y = predictor)) +
  geom_tile(fill = '#045a8d') +
  labs(title = 'Predictor Retention\nGeographic Models',
      x = 'Month',
      y = 'Predictor')
```

## Predictor Retention Geographic Models



## Predictor Retention Oceanographic Models

