North Carolina

Cate Jaffe

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Setup

```
##### Library #####
library(tidyverse)
library(ggplot2)
library(scales)
library(auk) # eBird Package
library(agricolae)
library(lubridate)
library(corrplot)
library(colormap)
library(ggridges)
library(RColorBrewer)
library(cowplot)


# set working directory for knitting
knitr::opts_knit$set( root.dir =
  "/Users/Kate/Documents/1.Spring 2021/JaffeWellbaumFrear_ENV872_EDA_FinalProject",
                  tidy.opts = list(width.cutoff = 60),
                  tidy = TRUE)
# check wd
#getwd()

# set ggplot theme
mytheme <- theme_light( base_size = 14) +
  theme( axis.text = element_text( color = "#222222ff"),
         legend.position = "top",
         # margins (top,right,bottom,left)
         axis.title.x = element_text( color = "black",
                                      margin = margin(20,0,0,0)),
```

```r
        axis.title.y = element_text( color = "black",
                                    margin = margin(0,20,0,0)))
theme_set(mytheme)
```

Import Data

```r
# import bird data
# eBird data is in text format, package "auk" used to convert to dataframe
woodduck <- read_ebd(
  "./Data/Raw/NorthCarolina/ebd_US-NC_wooduc_relFeb-2021/ebd_US-NC_wooduc_relFeb-2021.tx
rwbbird <- read_ebd(
  "./Data/Raw/NorthCarolina/ebd_US-NC_rewbla_relMar-2021/ebd_US-NC_rewbla_relMar-2021.tx
osprey <- read_ebd(
  "./Data/Raw/NorthCarolina/ebd_US-NC_osprey_relFeb-2021/ebd_US-NC_osprey_relFeb-2021.tx

# import temperature data
temp <- read.csv("./Data/Raw/NorthCarolina/NCTemperature20102021.csv") %>% unique()
```

Data Cleaning

```
##      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
##     0.000      0.015      0.036      0.659      0.111 13333.333
```

```r
#  create temperature dataset grouped by month & year
temp_YM <- temp %>%
  # omit NAs
  na.omit() %>%
  # make Year-Month column
  mutate( Year_Month = ydm((paste0(Year,"-01-",Month)))) %>%
  group_by(Year_Month) %>%
  # take statewide average
  summarise(AvgMonthlyTemp_Statewide = mean(AvgMonthlyTemp)) %>%
  # re-add month and year columns
  mutate(Month = month(Year_Month),
         Year = year(Year_Month))
```

Data Exploration

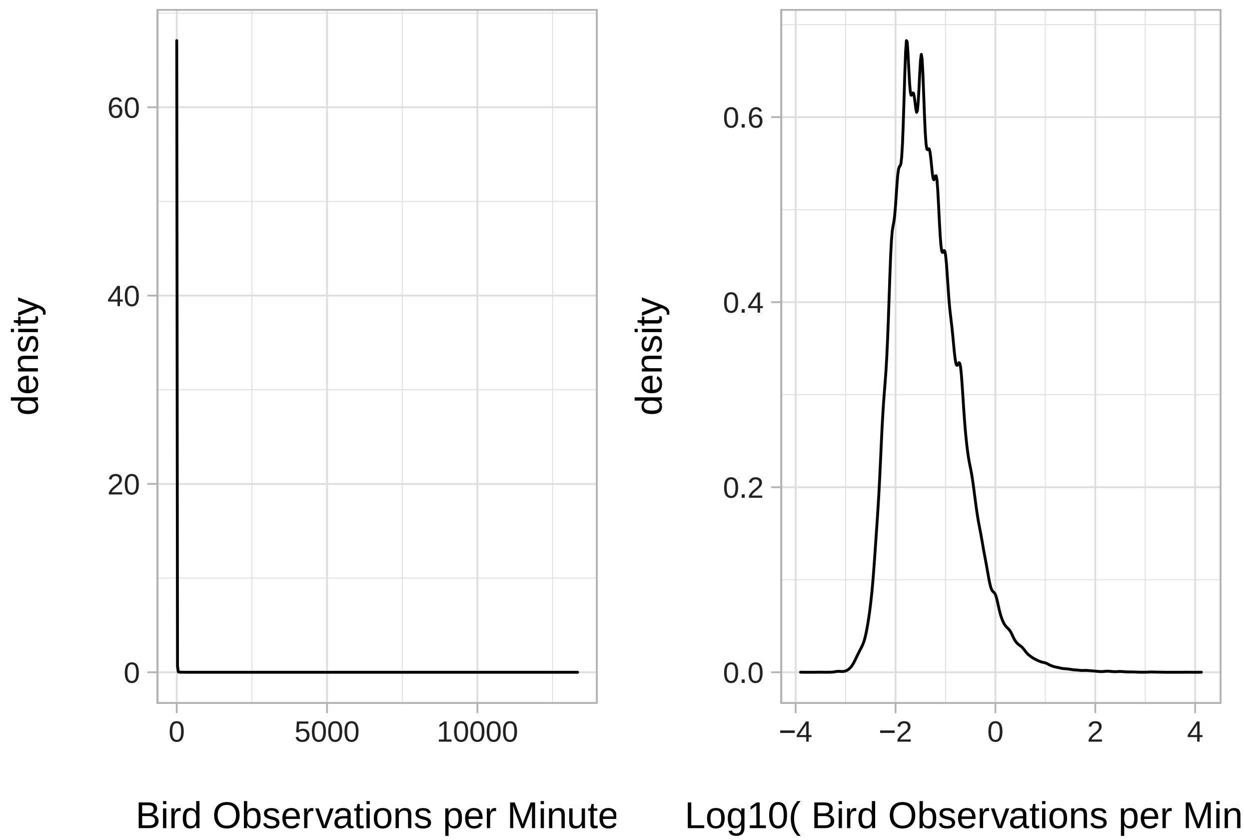


Figure 1: A comparison of Bird observations, raw data (left) and log transformed (right). Log transformed data have a more normal distribution

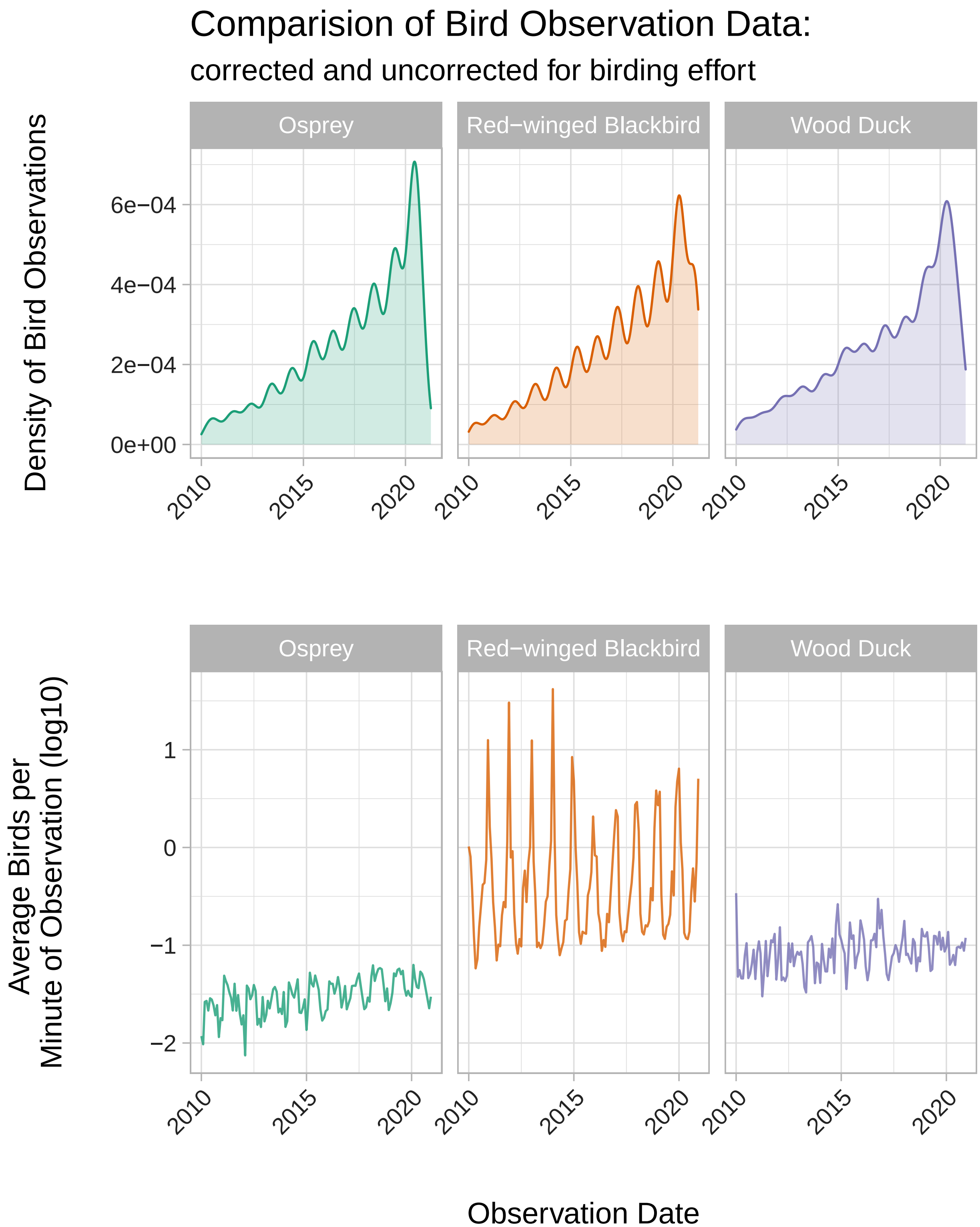


Figure 2: The top plot is raw bird observation data the bottom plot is observations per minute of observation

```r
# Temperature trends by year-month groups
ggplot(temp_YM %>% filter(Year != 2021),
       aes(x = Year_Month, y = AvgMonthlyTemp_Statewide,
           color = AvgMonthlyTemp_Statewide)) +
  geom_point(alpha = .4) +
  geom_line(alpha = .8) +
  scale_x_date(breaks = "6 months",
               date_labels = "%b %Y") +
  theme(axis.text.x = element_text(angle = 45,
                                   hjust = 1),
        legend.position = "none") +
  scale_color_colormap(colormap = "plasma") +
  labs(y = "Average Monthly Temperature (F)",
       x = "Date")
```

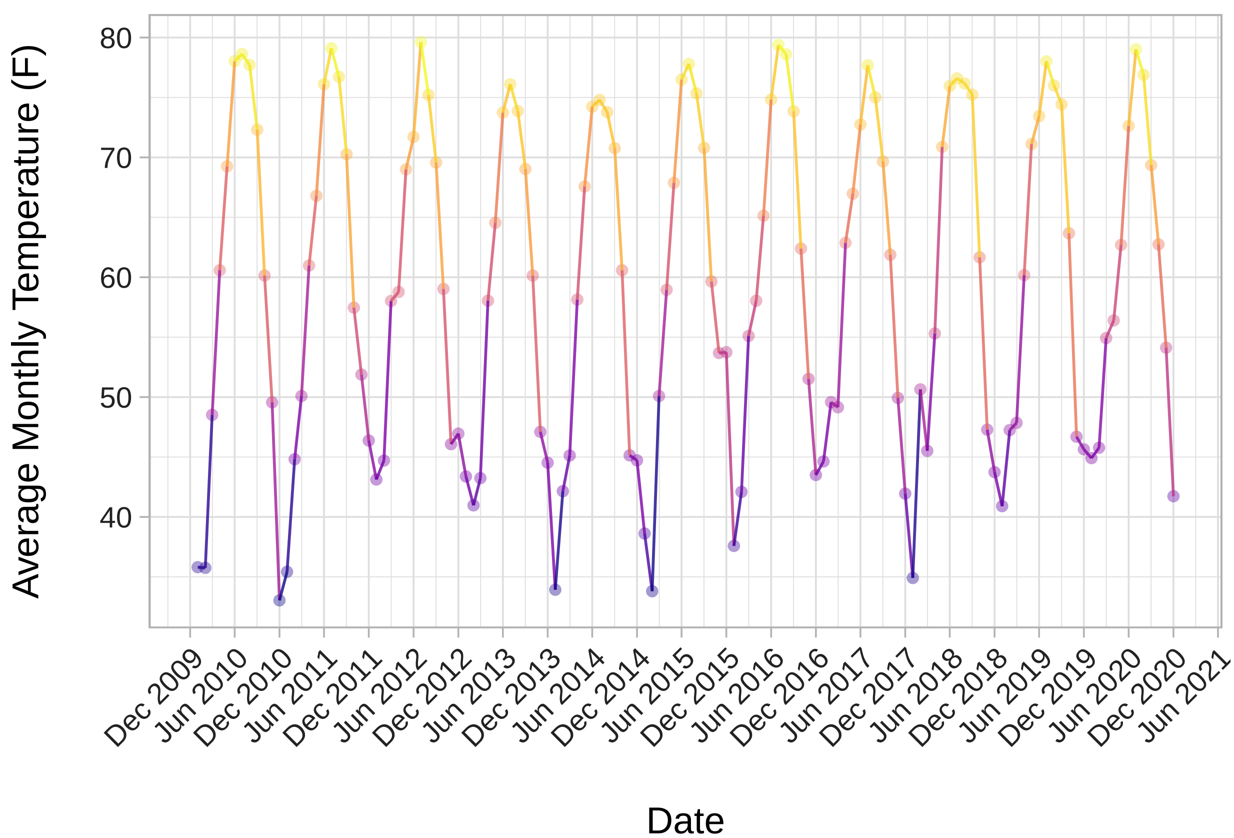


Figure 3: Average Monthly Temperature for the Study Period: 2010-2020

Join Bird and Temperature Data

```
birdsTemp_YM <- full_join(allBirds_YMgrouped, temp_YM,
                             by = "Year_Month")
```

Analysis: Bird Observations & Temperature

```r
#  observations per minute to overtime, by temperature
ggplot(birdsTemp_YM %>% filter(Year != 2021),
       aes(x = Year_Month, y = log10(observation_per_min_avg),
           color = AvgMonthlyTemp_Statewide)) +
  geom_line(lwd = .8) +
  facet_wrap(vars(common_name), nrow = 3, scale = "free") +
  theme(legend.position = "right") +
  scale_color_colormap(colormap = "plasma") +
  scale_x_date(date_breaks = "1 year", date_labels = "%Y") +
  labs(y = "Average Birds per Minute of Observation (log10)",
       x = "Year",
       color = "Average Monthly \nTemperature (F)",
       title = "Bird Observations in North Carolina",
       subtitle = "2010 - 2020")
```

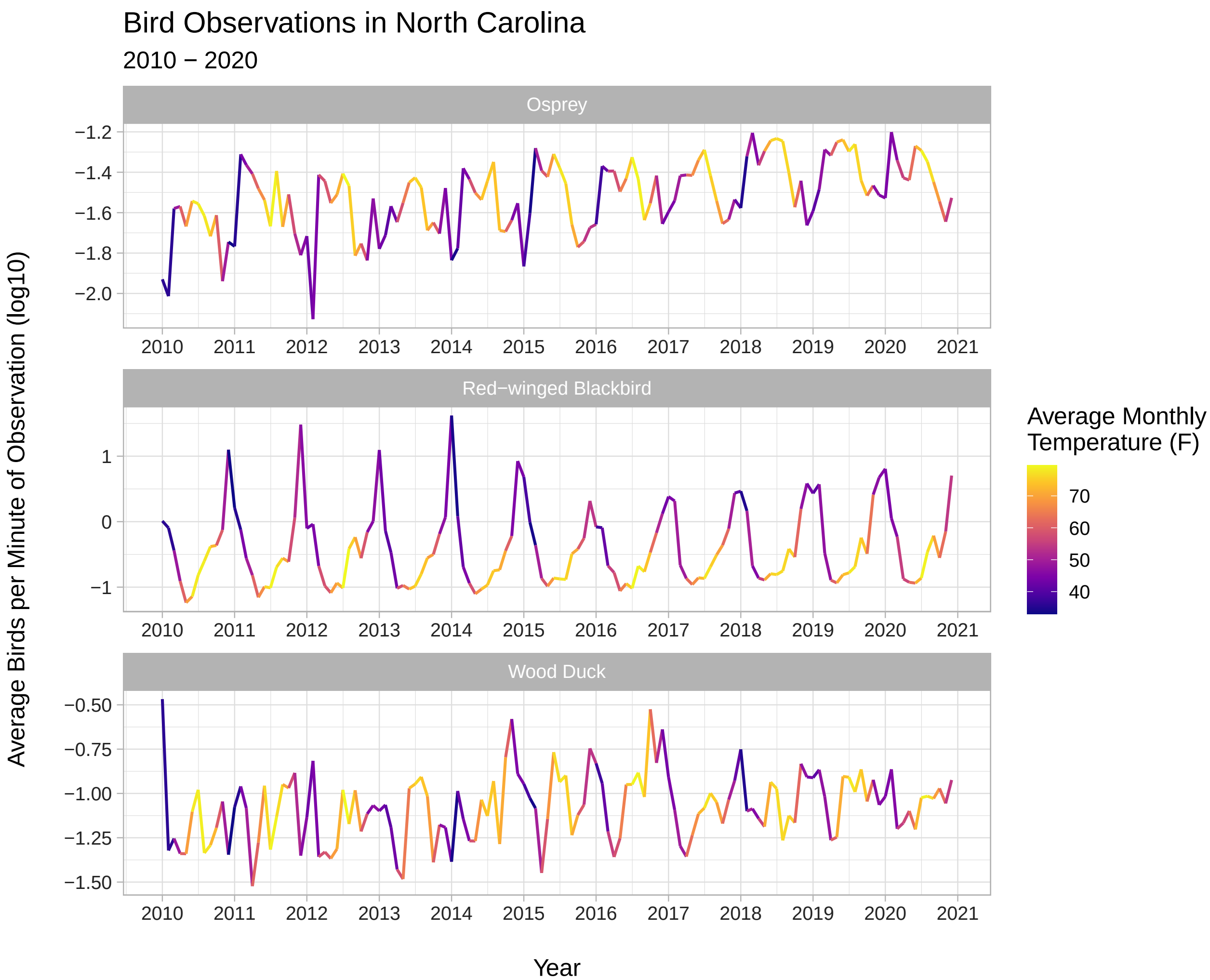


Figure 4: Bird Observations by Temperature in North Carolina

Linear Regression

```r
### Osprey ###########
# Observations per minute vs. Temperature, Year, and Month
# as an lm()
lm_osprey <- lm(data = birdsTemp_YM %>% filter(common_name == "Osprey"),
                observation_per_min_avg ~ AvgMonthlyTemp_Statewide +
                  # have to convert month and year to factors
                  as.factor(Year) + as.factor(Month))
# summarize output
summary(lm_osprey)
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ AvgMonthlyTemp_Statewide +
##     as.factor(Year) + as.factor(Month), data = birdsTemp_YM %>%
##     filter(common_name == "Osprey"))
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0182578 -0.0044408  0.0000751  0.0034037  0.0240445
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)              0.0014202  0.0083056   0.171 0.864545
## AvgMonthlyTemp_Statewide 0.0001840  0.0002039   0.902 0.368933
## as.factor(Year)2011      0.0088992  0.0028450   3.128 0.002253 **
## as.factor(Year)2012      0.0047090  0.0028565   1.649 0.102094
## as.factor(Year)2013      0.0055760  0.0028320   1.969 0.051474 .
## as.factor(Year)2014      0.0078695  0.0028345   2.776 0.006462 **
## as.factor(Year)2015      0.0100104  0.0028465   3.517 0.000636 ***
## as.factor(Year)2016      0.0129689  0.0028570   4.539 1.45e-05 ***
## as.factor(Year)2017      0.0128259  0.0028571   4.489 1.77e-05 ***
## as.factor(Year)2018      0.0228491  0.0028417   8.041 1.11e-12 ***
## as.factor(Year)2019      0.0211754  0.0028648   7.392 3.02e-11 ***
## as.factor(Year)2020      0.0186843  0.0028551   6.544 1.96e-09 ***
## as.factor(Year)2021      0.0181480  0.0054667   3.320 0.001223 **
## as.factor(Month)2        0.0103753  0.0029355   3.534 0.000599 ***
## as.factor(Month)3        0.0205126  0.0036007   5.697 1.03e-07 ***
## as.factor(Month)4        0.0135575  0.0049270   2.752 0.006936 **
## as.factor(Month)5        0.0105254  0.0064065   1.643 0.103252
## as.factor(Month)6        0.0146578  0.0077221   1.898 0.060295 .
## as.factor(Month)7        0.0148735  0.0083585   1.779 0.077928 .
```

```
## as.factor(Month)8         0.0135240  0.0079874   1.693 0.093255 .
## as.factor(Month)9        -0.0003171  0.0071321  -0.044 0.964621
## as.factor(Month)10        0.0003866  0.0052466   0.074 0.941396
## as.factor(Month)11        0.0018421  0.0035510   0.519 0.604966
## as.factor(Month)12        0.0043840  0.0030775   1.425 0.157123
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.006934 on 110 degrees of freedom
## Multiple R-squared:  0.7363, Adjusted R-squared:  0.6812
## F-statistic: 13.35 on 23 and 110 DF,  p-value: < 2.2e-16
```

```
# stepwise selection of most parsimonious model
step(lm_osprey)
```

```
## Start:  AIC=-1310.75
## observation_per_min_avg ~ AvgMonthlyTemp_Statewide + as.factor(Year) +
##     as.factor(Month)
##
##                            Df Sum of Sq       RSS     AIC
## - AvgMonthlyTemp_Statewide  1 0.0000391 0.0053282 -1311.8
## <none>                                  0.0052891 -1310.8
## - as.factor(Month)         11 0.0056056 0.0108947 -1235.9
## - as.factor(Year)          11 0.0060664 0.0113555 -1230.4
##
## Step:  AIC=-1311.77
## observation_per_min_avg ~ as.factor(Year) + as.factor(Month)
##
##                    Df Sum of Sq       RSS     AIC
## <none>                          0.0053282 -1311.8
## - as.factor(Year)  11 0.0064252 0.0117535 -1227.8
## - as.factor(Month) 11 0.0083842 0.0137124 -1207.1
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ as.factor(Year) + as.factor(Month),
##     data = birdsTemp_YM %>% filter(common_name == "Osprey"))
##
## Coefficients:
##         (Intercept)  as.factor(Year)2011  as.factor(Year)2012
##            0.008475             0.009155             0.005053
## as.factor(Year)2013  as.factor(Year)2014  as.factor(Year)2015
##            0.005505             0.007741             0.010279
## as.factor(Year)2016  as.factor(Year)2017  as.factor(Year)2018
```

```
##            0.013317            0.013174            0.023073
## as.factor(Year)2019 as.factor(Year)2020 as.factor(Year)2021
##            0.021572            0.019019            0.018259
##   as.factor(Month)2   as.factor(Month)3   as.factor(Month)4
##            0.011076            0.022406            0.017134
##   as.factor(Month)5   as.factor(Month)6   as.factor(Month)7
##            0.015667            0.021105            0.021937
##   as.factor(Month)8   as.factor(Month)9  as.factor(Month)10
##            0.020229            0.005551            0.004316
##  as.factor(Month)11  as.factor(Month)12
##            0.003658            0.005245
```

```
# post analysis Tukey Test, only run with categorical explanatory variables.
# this post analysis test will reveal which groups of years and/or
# months had similar observations of birds

# make aov for tukey test
aov_osprey <- aov(data = birdsTemp_YM %>% filter(common_name == "Osprey"),
                observation_per_min_avg ~
                  as.factor(Year) + as.factor(Month))

# create and print group labels - for Month
osprey.groups.yr <-
  HSD.test(aov_osprey, "as.factor(Year)", group = TRUE)
osprey.groups.yr$groups
```

```
##      observation_per_min_avg groups
## 2018              0.04390803      a
## 2019              0.04240748     ab
## 2020              0.03985486    abc
## 2016              0.03415242    bcd
## 2017              0.03400990    bcd
## 2021              0.03227183   bcde
## 2015              0.03111446    cde
## 2011              0.02999051     de
## 2014              0.02857630     de
## 2013              0.02634011     de
## 2012              0.02588886     de
## 2010              0.02083548      e
```

```
# create and print group labels - for Year
osprey.groups.month <-
  HSD.test(aov_osprey, "as.factor(Month)", group = TRUE)
osprey.groups.month$groups
```

```
##    observation_per_min_avg groups
## 3               0.04250742      a
## 7               0.04203857      a
## 6               0.04120636     ab
## 8               0.04033054     ab
## 4               0.03723535     ab
## 5               0.03576862     ab
## 2               0.03172998     bc
## 9               0.02565231     cd
## 12              0.02534643     cd
## 10              0.02441694     cd
## 11              0.02375897     cd
## 1               0.02065403      d
```

```
### Red winged Blackbird ###########
lm_rwbb <- lm(data = birdsTemp_YM %>% filter(common_name == "Red-winged Blackbird"),
                observation_per_min_avg ~ AvgMonthlyTemp_Statewide +
                as.factor(Year) + as.factor(Month))

summary(lm_rwbb)
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ AvgMonthlyTemp_Statewide +
##     as.factor(Year) + as.factor(Month), data = birdsTemp_YM %>%
##     filter(common_name == "Red-winged Blackbird"))
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.988 -1.384  0.231  0.694 31.649
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)              10.15604    5.09522   1.993  0.04869 *
## AvgMonthlyTemp_Statewide -0.09020    0.12536  -0.719  0.47336
## as.factor(Year)2011       1.65246    1.75286   0.943  0.34787
## as.factor(Year)2012      -0.80818    1.75988  -0.459  0.64697
## as.factor(Year)2013      -0.07711    1.74484  -0.044  0.96483
## as.factor(Year)2014       2.96019    1.74637   1.695  0.09287 .
## as.factor(Year)2015      -0.43233    1.75374  -0.247  0.80573
## as.factor(Year)2016      -0.82571    1.76022  -0.469  0.63992
## as.factor(Year)2017      -0.43772    1.76026  -0.249  0.80408
## as.factor(Year)2018      -0.35463    1.75080  -0.203  0.83986
## as.factor(Year)2019       0.09076    1.76497   0.051  0.95908
```

```
## as.factor(Year)2020       0.05109    1.75905   0.029  0.97688
## as.factor(Year)2021      -1.52446    2.83887  -0.537  0.59234
## as.factor(Month)2        -4.94836    1.80832  -2.736  0.00723 **
## as.factor(Month)3        -5.36088    2.18781  -2.450  0.01583 *
## as.factor(Month)4        -4.87605    3.03564  -1.606  0.11106
## as.factor(Month)5        -4.14219    3.94630  -1.050  0.29616
## as.factor(Month)6        -3.48072    4.75558  -0.732  0.46576
## as.factor(Month)7        -3.17058    5.14699  -0.616  0.53915
## as.factor(Month)8        -3.24959    4.91878  -0.661  0.51021
## as.factor(Month)9        -3.50882    4.39268  -0.799  0.42612
## as.factor(Month)10       -4.49868    3.23243  -1.392  0.16679
## as.factor(Month)11       -4.89397    2.18681  -2.238  0.02722 *
## as.factor(Month)12        0.32407    1.89283   0.171  0.86437
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.272 on 111 degrees of freedom
## Multiple R-squared:  0.3189, Adjusted R-squared:  0.1777
## F-statistic: 2.259 on 23 and 111 DF,  p-value: 0.002624
```

```
step(lm_rwbb)
```

```
## Start:  AIC=413.66
## observation_per_min_avg ~ AvgMonthlyTemp_Statewide + as.factor(Year) +
##     as.factor(Month)
##
##                            Df Sum of Sq    RSS    AIC
## - as.factor(Year)          11    159.45 2185.5 401.88
## - AvgMonthlyTemp_Statewide  1      9.45 2035.5 412.28
## <none>                                  2026.0 413.66
## - as.factor(Month)         11    409.42 2435.5 416.50
##
## Step:  AIC=401.88
## observation_per_min_avg ~ AvgMonthlyTemp_Statewide + as.factor(Month)
##
##                            Df Sum of Sq    RSS    AIC
## - AvgMonthlyTemp_Statewide  1     29.89 2215.4 401.72
## <none>                                  2185.5 401.88
## - as.factor(Month)         11    414.79 2600.3 403.34
##
## Step:  AIC=401.72
## observation_per_min_avg ~ as.factor(Month)
##
##                    Df Sum of Sq    RSS    AIC
```

```
## <none>                             2215.4 401.72
## - as.factor(Month) 11    759.09 2974.5 419.49
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ as.factor(Month), data = birdsTemp_YM %>%
##     filter(common_name == "Red-winged Blackbird"))
##
## Coefficients:
##        (Intercept)   as.factor(Month)2   as.factor(Month)3   as.factor(Month)4
##            6.62255            -5.29185            -6.31114            -6.49269
##  as.factor(Month)5   as.factor(Month)6   as.factor(Month)7   as.factor(Month)8
##           -6.52626            -6.50477            -6.49687            -6.40010
##  as.factor(Month)9  as.factor(Month)10  as.factor(Month)11  as.factor(Month)12
##           -6.24891            -6.28816            -5.64729             0.03865
```

```
# stepwise selection suggests a model with only month is the most parsimonious
lm_rwbb_monthOnly <- lm(data = birdsTemp_YM %>% filter(common_name == "Red-winged Blackb
                observation_per_min_avg ~ as.factor(Month))

summary(lm_rwbb_monthOnly)
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ as.factor(Month), data = birdsTemp_YM %>%
##     filter(common_name == "Red-winged Blackbird"))
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -5.833 -0.192 -0.018  0.026 35.083
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         6.62255    1.22513   5.406 3.22e-07 ***
## as.factor(Month)2  -5.29185    1.73259  -3.054 0.002766 **
## as.factor(Month)3  -6.31114    1.73259  -3.643 0.000396 ***
## as.factor(Month)4  -6.49269    1.77153  -3.665 0.000366 ***
## as.factor(Month)5  -6.52626    1.77153  -3.684 0.000343 ***
## as.factor(Month)6  -6.50477    1.77153  -3.672 0.000358 ***
## as.factor(Month)7  -6.49687    1.77153  -3.667 0.000363 ***
## as.factor(Month)8  -6.40010    1.77153  -3.613 0.000440 ***
## as.factor(Month)9  -6.24891    1.77153  -3.527 0.000591 ***
## as.factor(Month)10 -6.28816    1.77153  -3.550 0.000547 ***
## as.factor(Month)11 -5.64729    1.77153  -3.188 0.001818 **
```

```
## as.factor(Month)12  0.03865    1.77153   0.022 0.982631
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.244 on 123 degrees of freedom
## Multiple R-squared:  0.2552, Adjusted R-squared:  0.1886
## F-statistic: 3.831 on 11 and 123 DF,  p-value: 9.415e-05
```

```
# post analysis Tukey Test, only run with categorical explanatory variables.
# this post analysis test will reveal which groups of years and/or
# months had similar observations of birds

aov_rwbb <- aov(data = birdsTemp_YM %>% filter(common_name == "Red-winged Blackbird"),
                observation_per_min_avg ~ as.factor(Month))

# create and print group labels - for Month
rwbb.groups.month <-
  HSD.test(aov_osprey, "as.factor(Month)", group = TRUE)
rwbb.groups.month$groups
```

```
##    observation_per_min_avg groups
## 3               0.04250742      a
## 7               0.04203857      a
## 6               0.04120636     ab
## 8               0.04033054     ab
## 4               0.03723535     ab
## 5               0.03576862     ab
## 2               0.03172998     bc
## 9               0.02565231     cd
## 12              0.02534643     cd
## 10              0.02441694     cd
## 11              0.02375897     cd
## 1               0.02065403      d
```

```
### Wood Duck ##########
lm_duck <- lm(data = birdsTemp_YM %>% filter(common_name == "Wood Duck"),
                observation_per_min_avg ~ AvgMonthlyTemp_Statewide + Year + Month)

summary(lm_duck)
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ AvgMonthlyTemp_Statewide +
```

```
##     Year + Month, data = birdsTemp_YM %>% filter(common_name ==
##     "Wood Duck"))
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.070410 -0.030131 -0.008806  0.024946  0.255294
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -4.1484198  2.4889519  -1.667   0.0980 .
## AvgMonthlyTemp_Statewide -0.0007204  0.0002990  -2.409   0.0174 *
## Year                      0.0021180  0.0012351   1.715   0.0887 .
## Month                     0.0025514  0.0011854   2.152   0.0332 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04602 on 130 degrees of freedom
## Multiple R-squared:  0.07764,    Adjusted R-squared:  0.05636
## F-statistic: 3.648 on 3 and 130 DF,  p-value: 0.01445
```

```
step(lm_duck)
```

```
## Start:  AIC=-821.12
## observation_per_min_avg ~ AvgMonthlyTemp_Statewide + Year + Month
##
##                            Df Sum of Sq     RSS     AIC
## <none>                                  0.27537 -821.12
## - Year                      1 0.0062293 0.28159 -820.13
## - Month                     1 0.0098127 0.28518 -818.43
## - AvgMonthlyTemp_Statewide  1 0.0122926 0.28766 -817.27
```

```
##
## Call:
## lm(formula = observation_per_min_avg ~ AvgMonthlyTemp_Statewide +
##     Year + Month, data = birdsTemp_YM %>% filter(common_name ==
##     "Wood Duck"))
##
## Coefficients:
##              (Intercept)  AvgMonthlyTemp_Statewide                      Year
##               -4.1484198                -0.0007204                 0.0021180
##                    Month
##                0.0025514
```

```
# stepwise selection indicates no variables should be removed from model
# No Tukey HSD is run for this model because it includes a continuous numerical variab
```

Discussion of Linear Regressions:

Osprey: The most parisimonious model for the Osprey observations (corrected for effort) included year and month as explanatory variables, but not temperature. This model explained **68%** of the variation in Osprey observations. Like the Blackbird, the spring and summar months had similar observations (Group ab: April, May, June, August) which were statistically different than the mean of observations in fall and winter months (Group cd: September, October, November, December).

Red-Winged Blackbird: The most parisimonious model for the Blackbird observations (corrected for effort) included only month as an explanatory variable. This model explained only 18.9% of the variation in Blackbird observations. Like the Osprey, the spring and summar months had similar observations of Blackbird (Group ab: April, May, June, August) which were statistically different than the mean of observations in fall and winter months (Group cd: September, October, November, December).

Wood Duck: The most parisimonious model for the Wood Duck observations (corrected for effort) included temperature, year and month as explanatory variables. Together, these variables explain only 5.6% of the variation in wood duck observations. For every 1 degree *increase* in temperature (with month and year held constant) we would expect the observations of wood ducks (per minute of observation) to *decrease* by .00072 duck per minute observation. There is likely some other variable, not measured here, explaining the variation in wood duck observations in North Carolina between 2010 and 2020.

Overall, the Wood Duck appears to be the only bird of the three examined in this study for which average monthly temperature has a statistically significant relationship with bird abundance (corrected for observation effort). The Month of the Year was included in the final model for all three birds, and observations tended to be most similar in non-migratory periods (namely late spring to summer and late fall to winter).

Since the linear regression revealed that across species, month tended to have a strong relationship with bird observation - and that the mean observations per month tended to be similar between seasonal groups of months (for instance, spring months grouped together in group ab of the Tukey test), we visualized how bird observations might vary by "season" and temperature.

```r
# add "seasonal" dummy variable to dataset and summarize temperature.
birdsTemp_season <- birdsTemp_YM %>%
  mutate( season =
            if_else( Month %in% c(3, 4, 5), "spring",
                     if_else(Month %in% c(6,7,8), "summer",
                             if_else( Month %in% c(9,10,11), "fall",
                                      if_else( Month %in% c(12, 1, 2), "winter", "NA")))


# PLot
ggplot(birdsTemp_season,
       aes(x = AvgMonthlyTemp_Statewide, y = log10(observation_per_min_avg), color = sea
  geom_point(alpha = .8) +
  stat_ellipse(alpha = .4) +
  facet_wrap(vars(common_name), nrow = 1, scales = "free") +
  scale_color_manual(values=c('#e75f2dff', '#008066ff', '#ffd42bff', '#0b6ca8ff'))  +
  theme(legend.title = element_blank(), legend.position = "bottom",
        axis.title.x = element_text(vjust = -1),
        axis.title.y = element_text(vjust = 3)) +
  labs(y = "Average Birds per \nMinute of Observation (log10)",
       x = "Average Monthly Temperature (F)",
       title = "Bird Observations vs. Temperature, \nby Season in North Carolina",
       subtitle = "2010 - 2020")
```

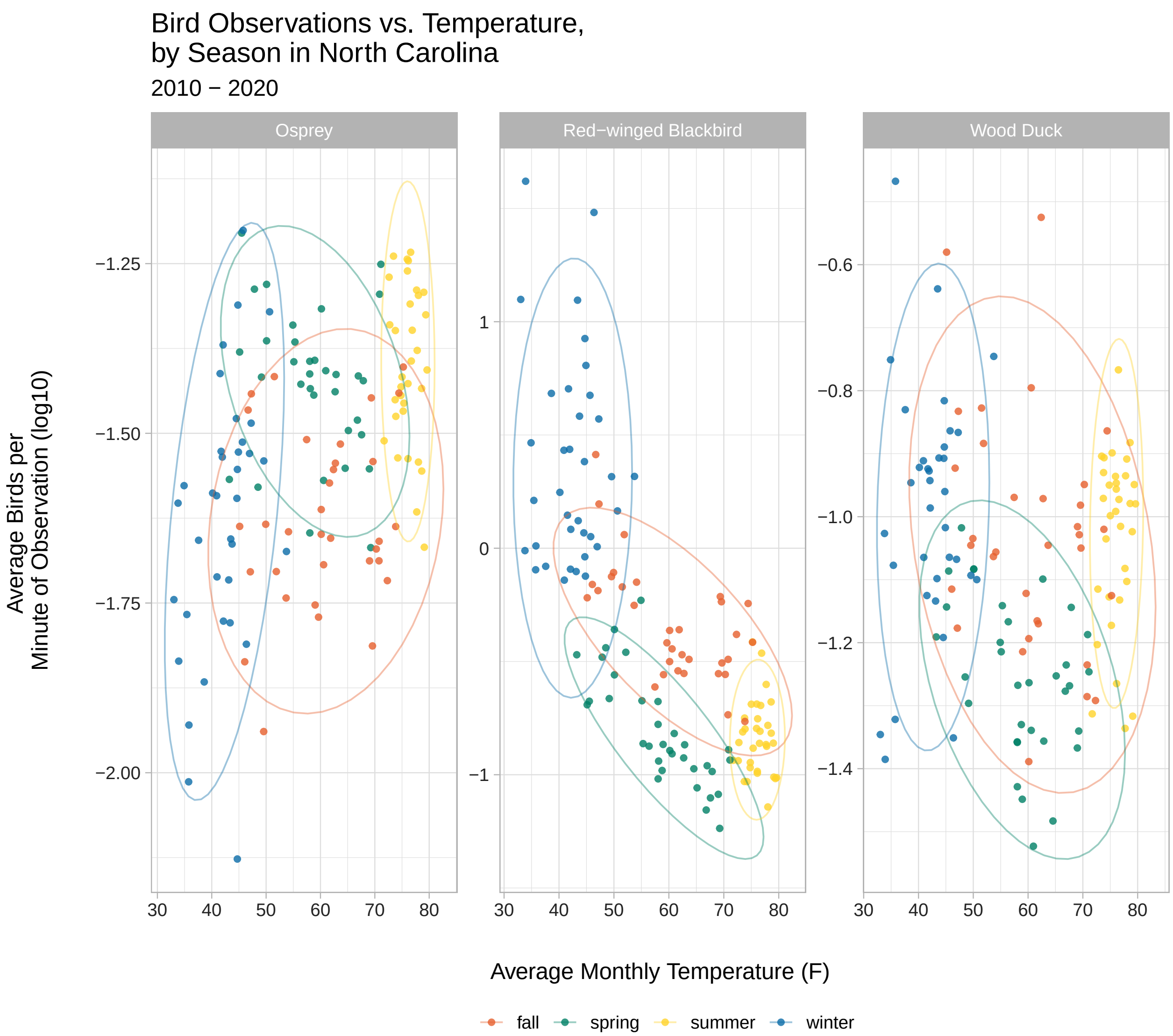


Figure 5: The relationship between bird observations and temperature, broken down by season and bird.

Discussion of Bird Observations and Temperature Relationship

All birds appear to reside in North Carolina year round (Figure 2, Figure 5). Osprey appear most populus in the summer months and least populus in the winter, with populations potentially increasing overtime between 2010 and 2020. The opposite pattern appears to be true for Blackbird, which is more abundant in the summers and less in the winters, and is generally the most populus of the three birds examined here. Wood Duck appears from this plot to be least seasonal, and to be present in constant numbers (at state scale) throughout the year.

To further investigate seasonal *and* long-term (2010-2020) trends in bird observations, we conducted a time-series analysis:

Analysis: Time Series

```r
# Subset data for running time series
birdsTemp_YM_ospr <- birdsTemp_YM %>% filter(common_name == "Osprey" & Year %in% c(2010:

birdsTemp_YM_rwbb <- birdsTemp_YM %>% filter(common_name == "Red-winged Blackbird" & Yea

birdsTemp_YM_wodu <- birdsTemp_YM %>% filter(common_name == "Wood Duck" & Year %in% c(20


## Osprey
osprey.ts <- ts(birdsTemp_YM_ospr$observation_per_min_avg,
                             start = c(2010,1), frequency = 12)
osprey.ts.decomposed <- decompose(osprey.ts, type = "multiplicative")

# Seasonal Mann Kendall
monthly_ospr_trend <- Kendall::SeasonalMannKendall(osprey.ts)
summary(monthly_ospr_trend)
```

```
## Score =  356 , Var(Score) = 1980
## denominator =  660
## tau = 0.539, 2-sided pvalue =1.3323e-15
```

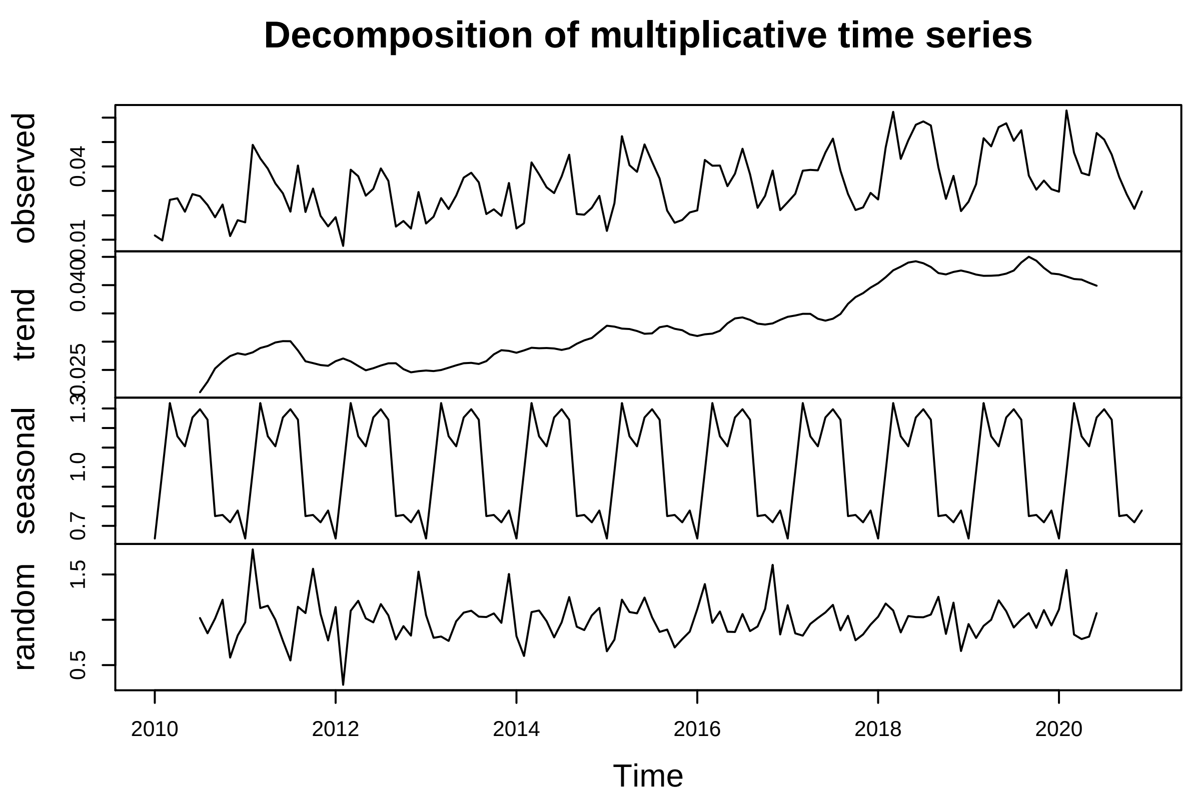
```r
## Red-winged Blackbird
rwbb.ts <- ts(birdsTemp_YM_rwbb$observation_per_min_avg,
                             start = c(2010,1), frequency = 12)
```

```r
rwbb.ts.decomposed <- decompose(rwbb.ts, type = "multiplicative")


monthly_rwbb_trend <- Kendall::SeasonalMannKendall(rwbb.ts)
summary(monthly_rwbb_trend)
```

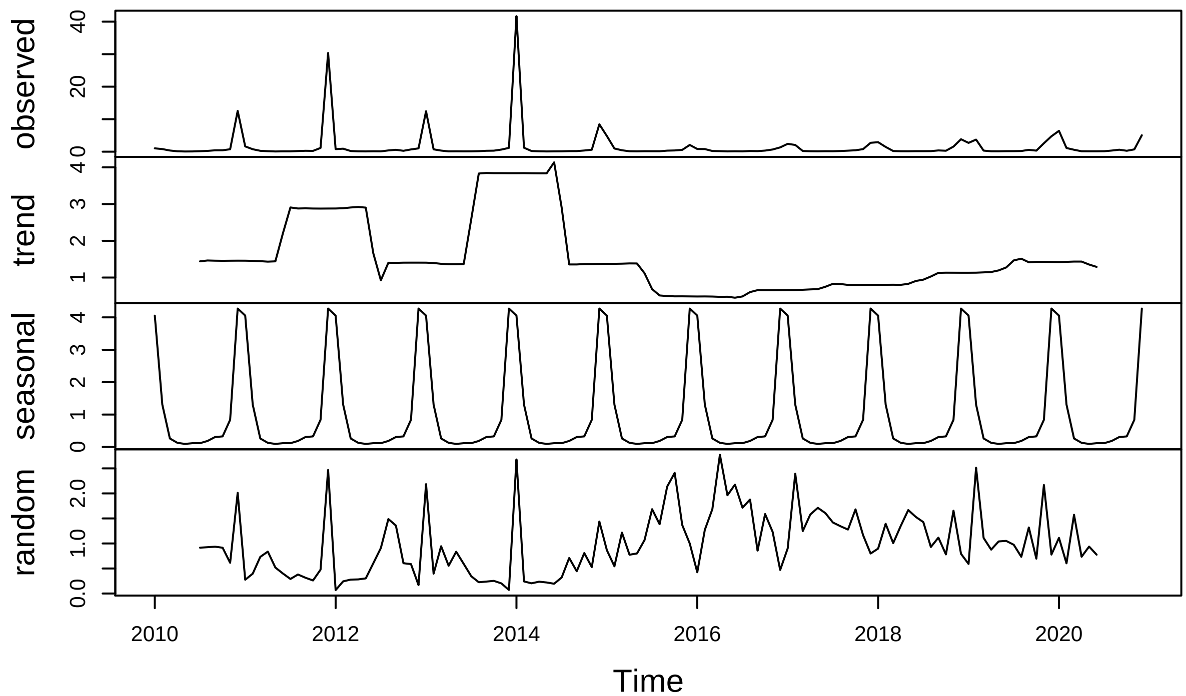
```
## Score =  178 , Var(Score) = 1980
## denominator =  660
## tau = 0.27, 2-sided pvalue =6.3275e-05
```

```r
## Wood Duck

wodu.ts <- ts(birdsTemp_YM_wodu$observation_per_min_avg,
                             start = c(2010,1), frequency = 12)
wodu.ts.decomposed <-  decompose(wodu.ts, type = "multiplicative")


monthly_wodu_trend <- Kendall::SeasonalMannKendall(wodu.ts)
summary(monthly_wodu_trend)
```

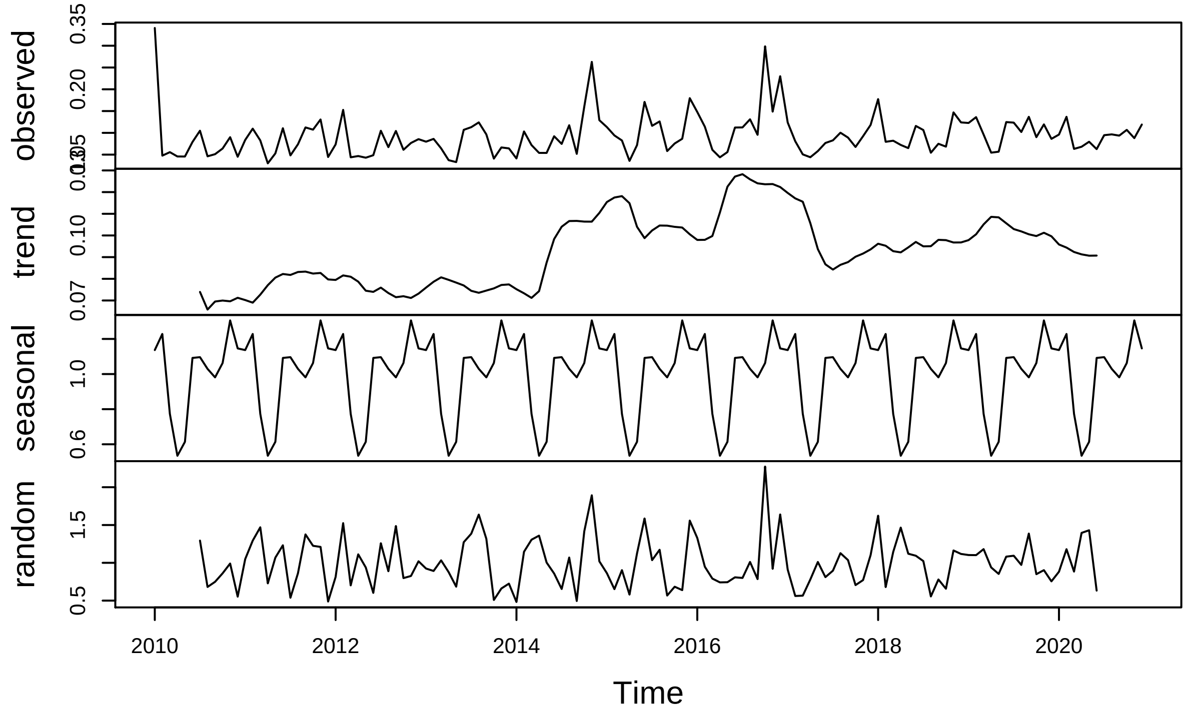
```
## Score =  154 , Var(Score) = 1980
## denominator =  660
## tau = 0.233, 2-sided pvalue =0.00053839
```



Decomposition of multiplicative time series



Decomposition of multiplicative time series



Discussion of Time Series Results:

All three birds have an apparent seasonal trend in obervations. With the seasonal variation in the data removed, Osprey populations tend to generally increase in abundance (upwards monotonic trend) between 2010 and 2020 ($p < .001$). Red-winged Blackbird have notable spikes in population in 2012 and 2014, but appear to sharply decrease in overall abundance in 2015 and remain remain fairly constant in number from 2016 forward. Overall, there appears to be a downward trend in Red-Winged Blackbird observations in NC ($p < .001$). Wood Duck observations in North Carolina were elevated between 2014 and 2017, but sharply decrease in 2017-2018. Overall, Wood Duck observations have increased between 2010 and 2020 ($p < .001$), but this trend is less pronouned than the Blackbird and Osprey trends.