Migratory Mismatch

Contents

long versus short distance migrants (calendar vs weather birds): - long distance will have no idea of what going on far (use internal clocks), but also, short distance that are in the equator don't have a lot of variation on day length or environmental conditions to follow - internal rhythms initiate, photo-period and environment adjusts speed (fine-tune). - when long distance leave, is not only to get good quality in the breeding grounds, but also leaving before conditions get harsh - a tricky timing challenge to find the right balance between flexibly adjusting migration to the current environment on the one hand, and keeping track of seasonally appropriate behavior on the other - bad conditions on a site make birds move, not 'predicting' good ones in the future

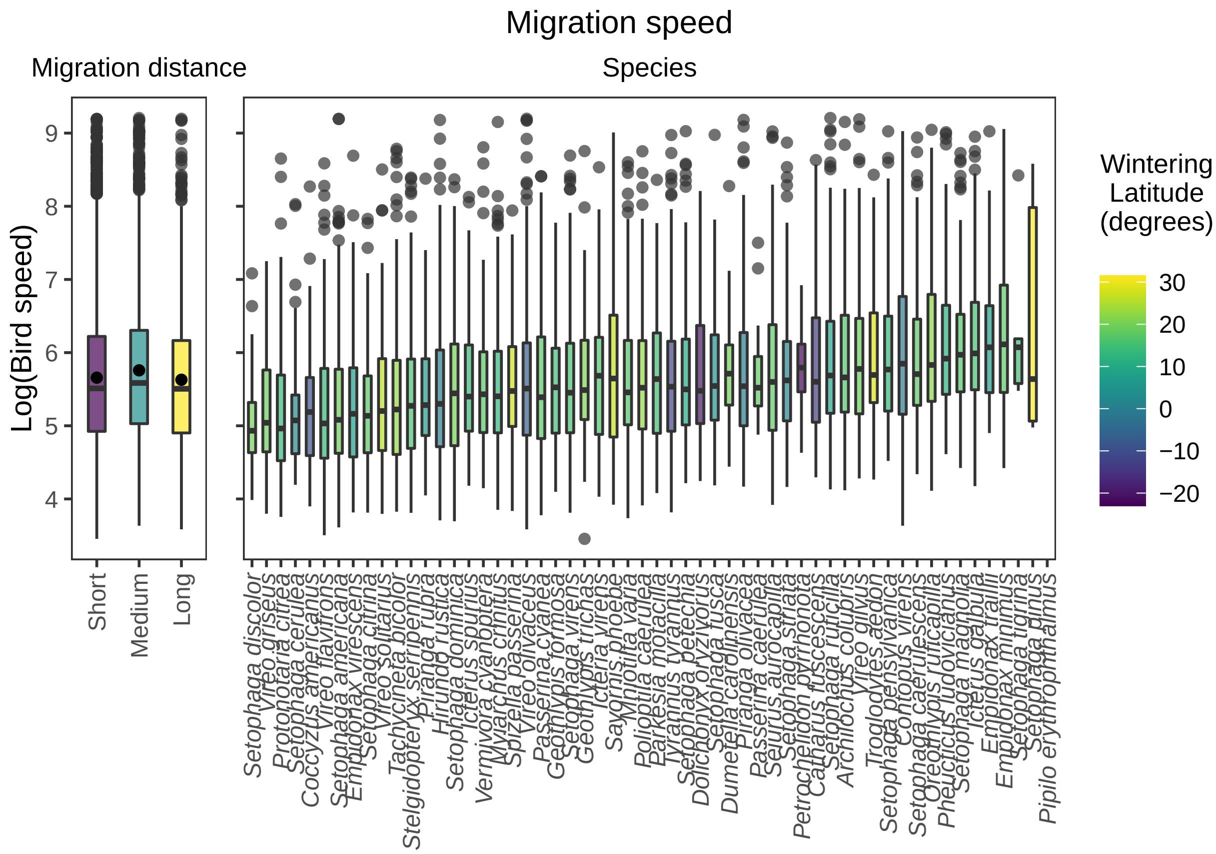
Paper: - long: less synchrony, arrive later, move quicker, inflexible - short: more synchrony, arrive earlier, move slower, flexible

1 BIRD TRAITS ——————————————-

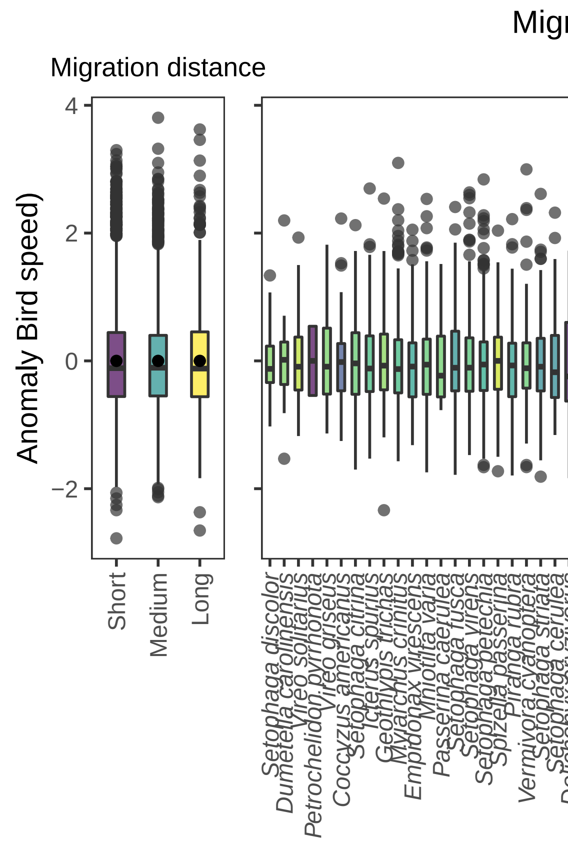
1.1 Winter latitude

1.1.1 - bird speed and winter range

Which species are fast and slow? how does how far south they come from influences speed?


Migration speed
Migration distance
Species
Log(Bird speed)
Short
Medium
Long
Wintering Latitude (degrees)
30
20
10
0
−10
−20

1.1.2 - speed anomaly and winter range



How is anomaly in bird speed affected by how further north they come from?

```
modb_1 <- lmer(data = final2, AnomVArr ~ winlat + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modb_2 <- lmer(data = final2, AnomVArr ~ winlatcat + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modb_3 <- lmer(data = final2, AnomVArr ~ winlat + (1|cell_lat) + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modb_4 <- lmer(data = final2, AnomVArr ~ winlatcat + (1|cell_lat) + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
head(taicb <- AIC(modb_1,modb_2, modb_3, modb_4
                  ) %>% arrange(AIC))
```

```
## Warning in AIC.default(modb_1, modb_2, modb_3, modb_4): models are not all
## fitted to the same number of observations
```

```
##        df      AIC
## modb_3  6 15468.67
## modb_4  7 15470.53
## modb_1  5 15745.28
## modb_2  6 15747.28
```

```
#summary(moda_1)
sjPlot::tab_model(
  get(rownames(taicb)[1]),
  #moda_1,
  show.re.var= TRUE, digits = 3)
```

AnomVArr

Predictors

Estimates

CI

p

(Intercept)

-0.078

-0.166 – 0.011

0.085

winlat

0.000

-0.002 – 0.002

0.679

Random Effects

2

0.66

00 species

0.00

00 cell_lat

0.00

00 year

0.02

N cell_lat

32

N species

55

N year

15

Observations

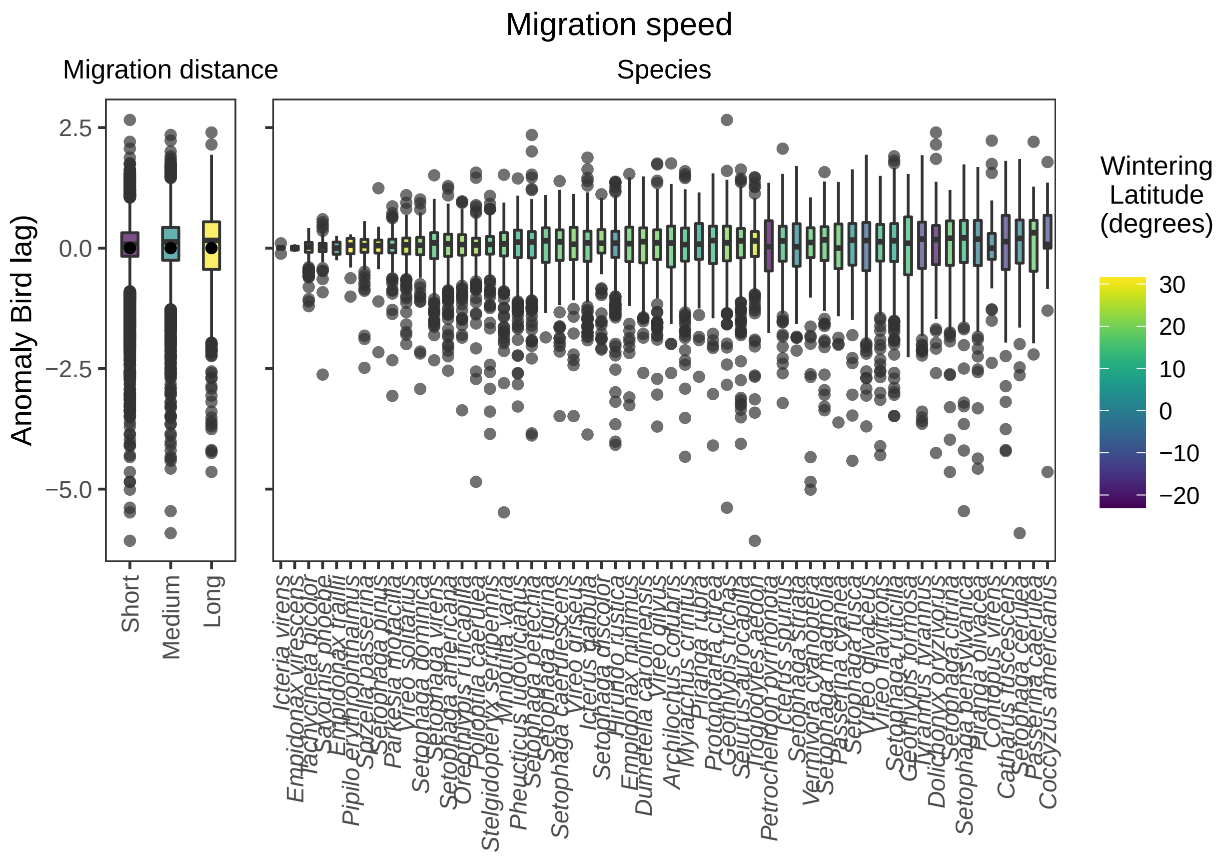
6341

Marginal R2 / Conditional R2

0.000 / NA

1.1.3 - !!! lag and winter range

how are species that come from further south tracking green up - looking at lag!




```
modc_1 <- lmer(data = final2, AnomLag ~ winlat + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modc_2 <- lmer(data = final2, AnomLag ~ winlatcat + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modc_3 <- lmer(data = final2, AnomLag ~ winlat + (1|cell_lat) + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modc_4 <- lmer(data = final2, AnomLag ~ winlatcat + (1|cell_lat) + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```
modc_5 <- lmer(data = final2, AnomLag ~ winlat + poly(winlat,2) + (1|species) + (1|year))
```

```
## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## boundary (singular) fit: see ?isSingular
```

```
head(taicc <- AIC(modc_1,modc_2, modc_3, modc_4, modc_5
                  ) %>% arrange(AIC))
```

```
##        df      AIC
## modc_5  6 21145.98
## modc_1  5 21147.92
## modc_3  6 21149.92
## modc_2  6 21151.16
## modc_4  7 21153.16
```

```
#summary(moda_1)
sjPlot::tab_model(
  get(rownames(taicc)[1]),
  #moda_1,
  show.re.var= TRUE, digits = 3)
```

AnomLag

Predictors

Estimates

CI

p

(Intercept)

-0.051

-0.182 – 0.079

0.443

winlat

0.002

0.000 – 0.003

0.007

winlat [2nd degree]

1.222

-0.239 – 2.683

0.101

Random Effects

2

0.40

00 species

0.00

00 year

0.07

N species

56

N year

16

Observations

10934

Marginal R2 / Conditional R2

0.001 / NA

```
modc_1g <- gam(data = final2 %>% mutate(species = as.factor(species)),
               AnomLag ~ winlat + s(species, bs = 're') + s(year, bs = 're'))

modc_2g <- gam(data = final2 %>% mutate(species = as.factor(species)),
               AnomLag ~ winlatcat + s(species, bs = 're') + s(year, bs = 're'))

modc_3g <- gam(data = final2 %>% mutate(species = as.factor(species)),
               AnomLag ~ winlat + s(cell_lat, bs = 're') + s(species, bs = 're') + s(year, bs = 're'))

modc_4g <- gam(data = final2 %>% mutate(species = as.factor(species)),
               AnomLag ~ winlatcat + s(cell_lat, bs = 're') + s(species, bs = 're') + s(year, bs = 're'

head(taiccg <- AIC(modc_1g,modc_2g, modc_3g, modc_4g
                  ) %>% arrange(AIC))
```

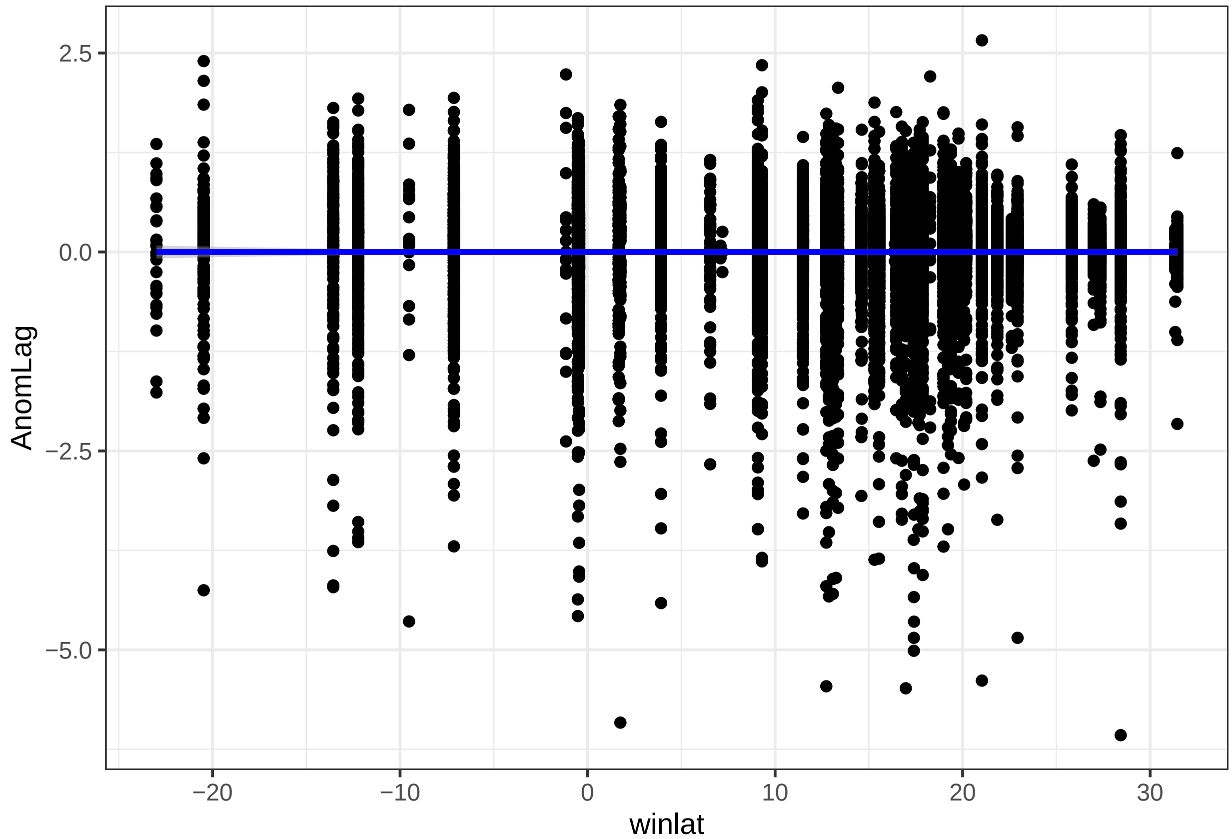
```
##         df      AIC
## modc_3g  3 22783.27
## modc_1g  3 22783.27
## modc_4g  4 22785.27
## modc_2g  4 22785.27
```

```
summary(get(rownames(taiccg)[1]))
```

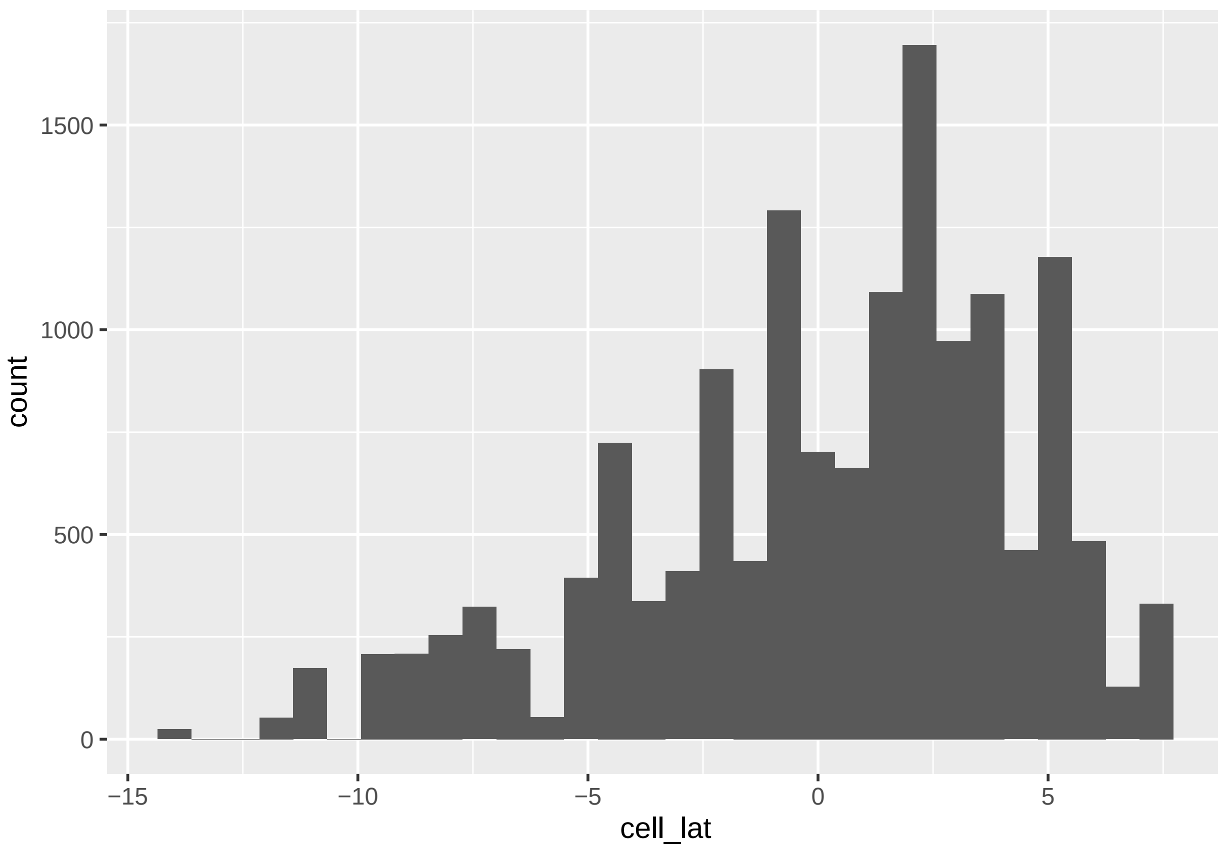
```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## AnomLag ~ winlat + s(cell_lat, bs = "re") + s(species, bs = "re") +
##     s(year, bs = "re")
##
## Parametric coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.704e-13  1.082e-02       0        1
## winlat      -1.301e-18  6.292e-04       0        1
##
## Approximate significance of smooth terms:
##                   edf Ref.df F p-value
## s(cell_lat) 3.897e-09      1 0   1.000
## s(species)  1.445e-08     54 0   1.000
## s(year)     1.447e-13      1 0   0.569
##
## R-sq.(adj) =  -9.15e-05   Deviance explained =    0%
## GCV = 0.47032  Scale est. = 0.47023   n = 10934
```

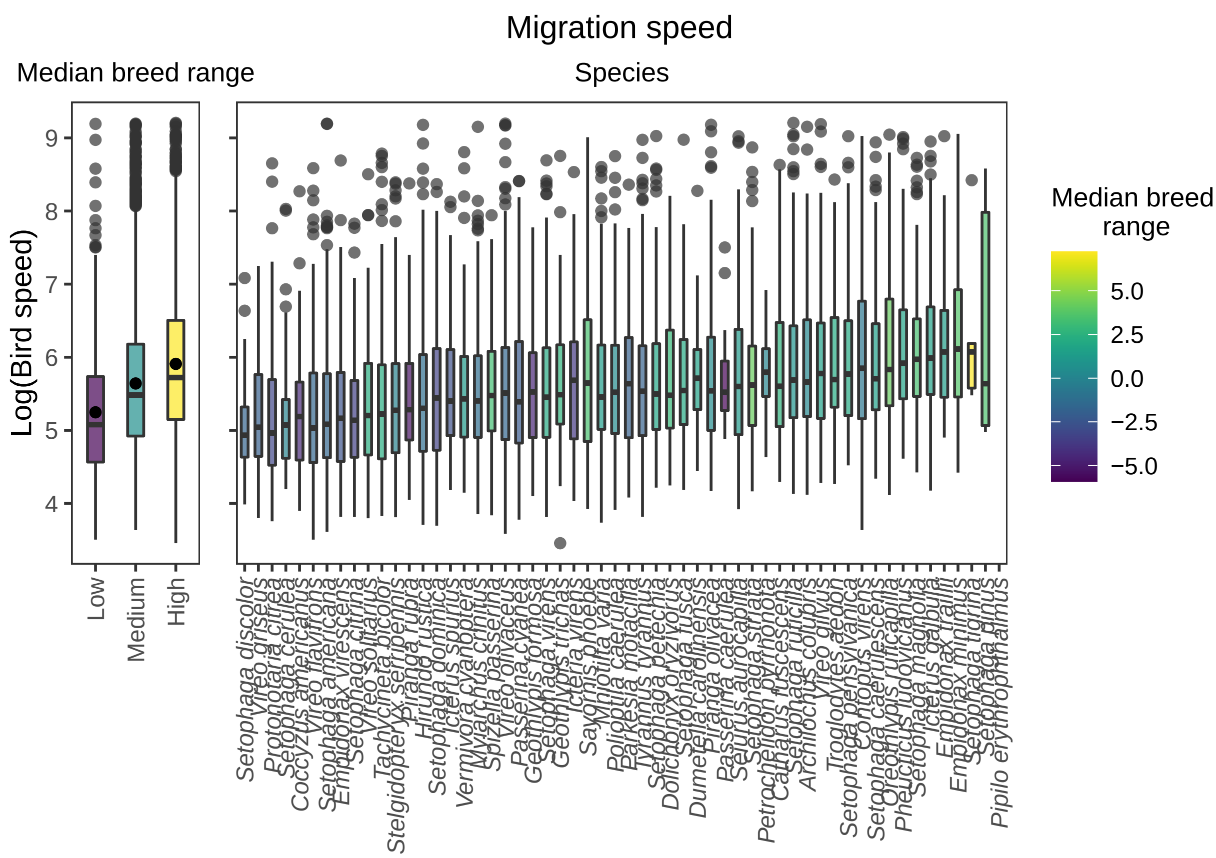
```
ggplot(final2) +
   geom_point(aes(y = AnomLag, x = winlat)) +
   geom_smooth(aes(y = AnomLag, x = winlat), col = "green") +
   geom_smooth(aes(y = AnomLag, x = winlat), method = "lm", col = "red") +
   geom_smooth(aes(y = AnomLag, x = winlat), col = "blue", formula = y ~ x + I(x^2)) +
   theme_bw()
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'

## Warning: Removed 4941 rows containing non-finite values (stat_smooth).

## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 4941 rows containing non-finite values (stat_smooth).

## `geom_smooth()` using method = 'gam'

## Warning: Removed 4941 rows containing non-finite values (stat_smooth).

## Warning: Removed 4941 rows containing missing values (geom_point).
```



ok, maybe it is hard to assess conditions from that far... but what if we use how further north the species need to go? MEAN BREEDING LAT ## Breeding latitude ### - !!! breeding lat and speed


1500
1000
500
0
count
−15
−10
−5
0
5
cell_lat




```r
# only BREEDING CELLS
mod_f1 <- lmer(data = final5, log(vArrMag) ~ (1|cell_lat) + medbree + (1|species) + (1|year))
mod_f2 <- lmer(data = final5, log(vArrMag) ~ cell_lat + medbree + (1|species) + (1|year))

head(taicf1 <- AIC(mod_f1, mod_f2
                  ) %>% arrange(AIC))
```

```
##        df      AIC
## mod_f1  6 16732.12
## mod_f2  6 16875.96
```

```r
sjPlot::tab_model(
  get(rownames(taicf1)[1]),
  #moda_1,
  show.re.var= TRUE, digits = 3)
```

log(vArrMag)

Predictors

Estimates

CI

p

(Intercept)

5.457

5.308 – 5.606

<0.001

medbree

0.026

0.001 – 0.052

0.043

Random Effects

 2

0.88

 00 species

0.04

 00 cell_lat

0.08

 00 year

0.03

ICC

0.14

N cell_lat

32

N species

54

N year

15

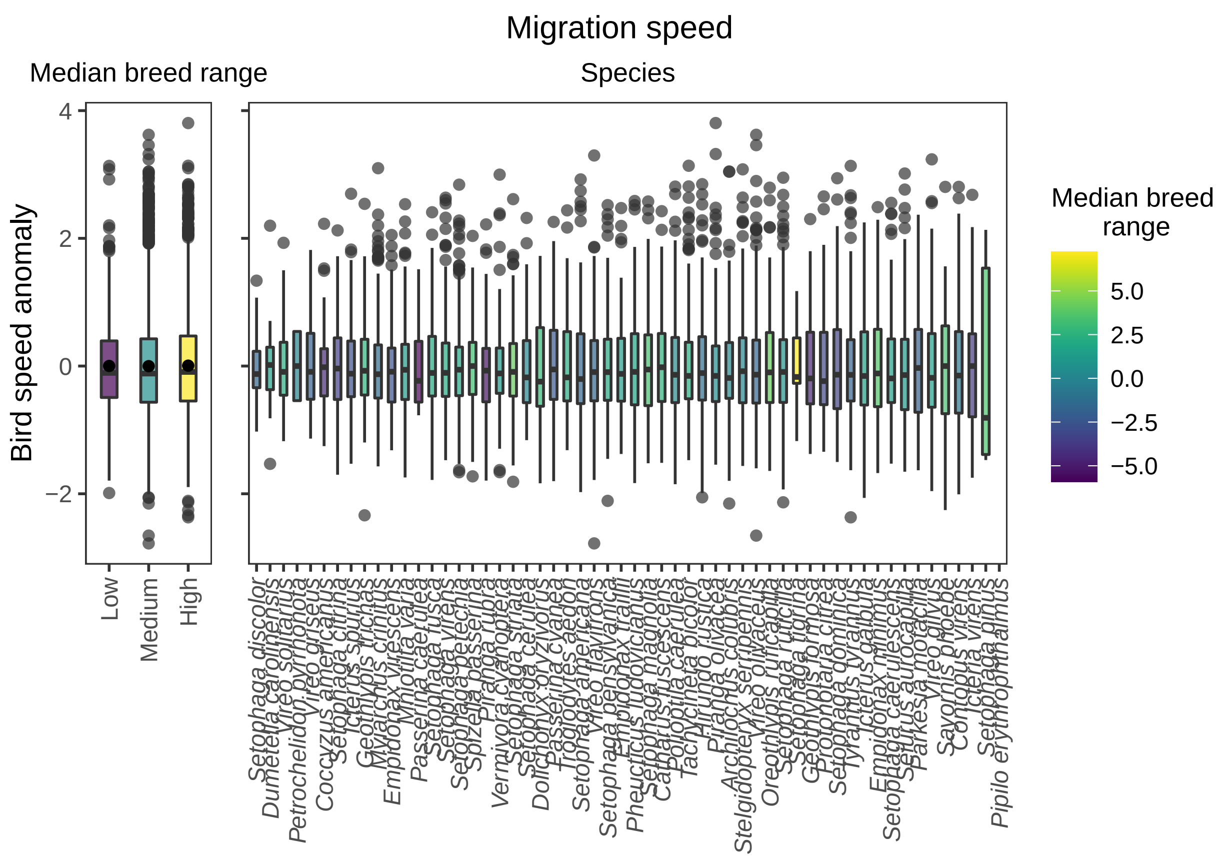
Observations

6082

Marginal R2 / Conditional R2

0.003 / 0.143

1.1.4 - breeding lat and anomaly in speed




```r
# only BREEDING CELLS
mod_f3 <- lmer(data = final5, AnomVArr ~ (1|cell_lat) + medbree + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```r
mod_f4 <- lmer(data = final5, AnomVArr ~ cell_lat + medbree + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```r
head(taicf2 <- AIC(mod_f3, mod_f4
                  ) %>% arrange(AIC))
```

```
##        df      AIC
## mod_f3  6 14885.61
## mod_f4  6 14895.02
```

```r
sjPlot::tab_model(
  get(rownames(taicf2)[1]),
  #moda_1,
  show.re.var= TRUE, digits = 3)
```

AnomVArr

Predictors

Estimates

CI

p

(Intercept)

-0.072

-0.156 – 0.012

0.093

medbree

0.004

-0.005 – 0.014

0.380

Random Effects

2

0.67

00 species

0.00

00 cell_lat

0.00

00 year

0.02

N cell_lat

32

N species

54

N year

15

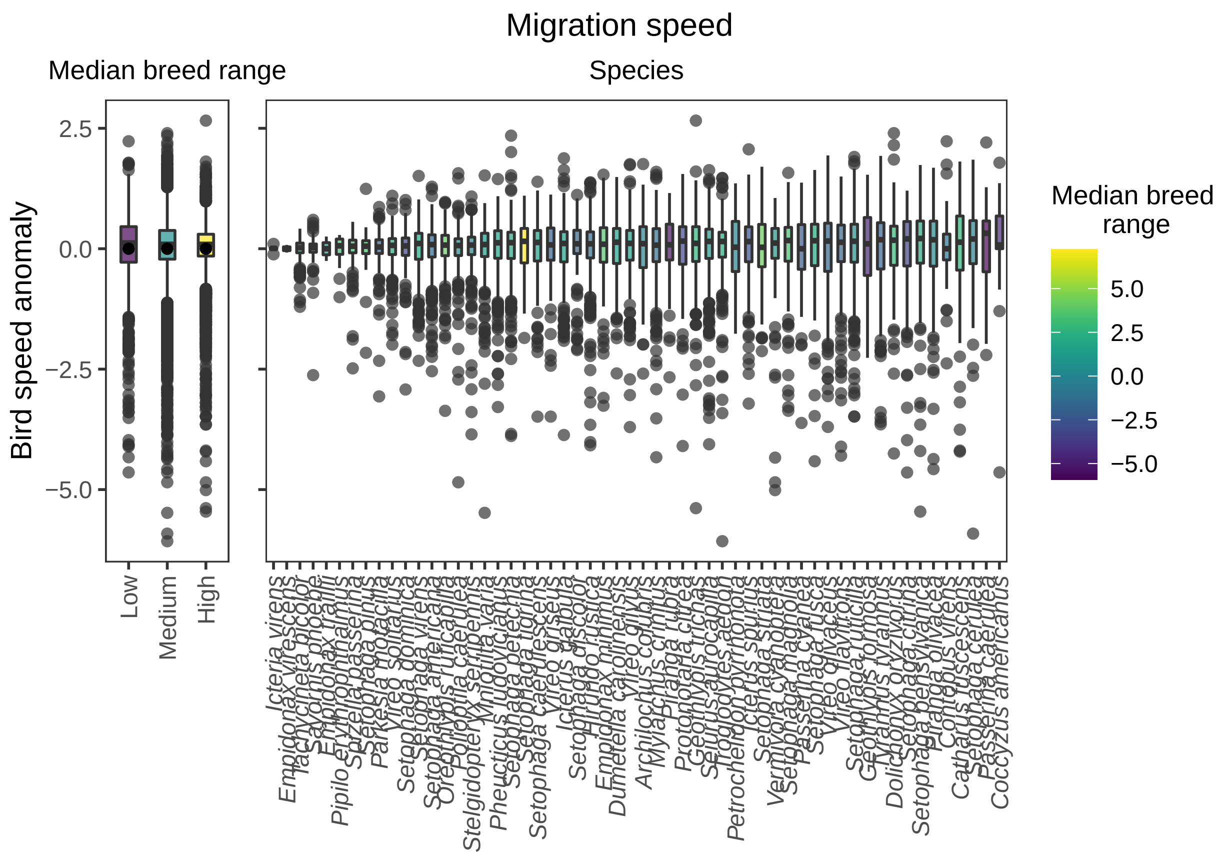
Observations

6082

Marginal R2 / Conditional R2

0.000 / NA

1.1.5 - breeding lat and lag




```r
# only BREEDING CELLS
mod_f5 <- lmer(data = final5, AnomLag ~ (1|cell_lat) + medbree + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```r
mod_f6 <- lmer(data = final5, AnomLag ~ cell_lat + medbree + (1|species) + (1|year))
```

```
## boundary (singular) fit: see ?isSingular
```

```r
head(taicf3 <- AIC(mod_f5, mod_f6
                 ) %>% arrange(AIC))
```

```
##         df      AIC
## mod_f5  6 20303.95
## mod_f6  6 20314.32
```

```r
sjPlot::tab_model(
  get(rownames(taicf3)[1]),
  #moda_1,
  show.re.var= TRUE, digits = 3)
```

AnomLag

Predictors

Estimates

CI

p

(Intercept)

-0.029

-0.159 – 0.101

0.664

medbree

0.004

-0.002 – 0.010

0.174

Random Effects

2

0.40

00 species

0.00

00 cell_lat

0.00

00 year

0.07

N cell_lat

42

N species

56

N year

16

Observations

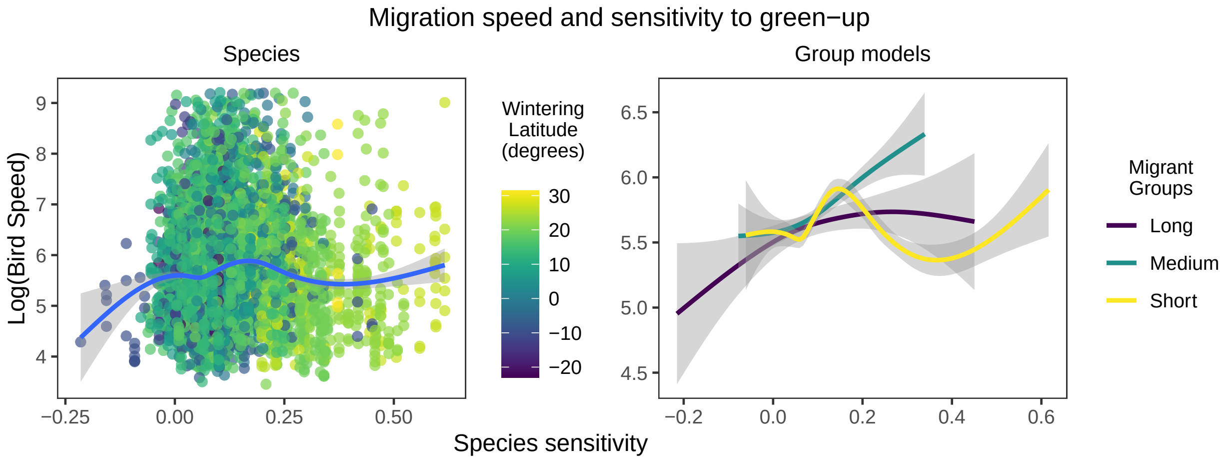
10526

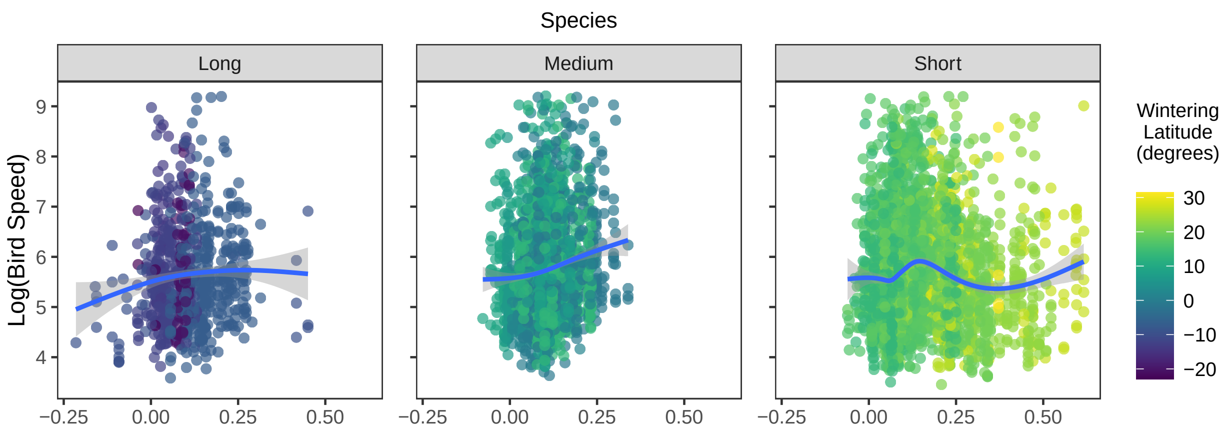
Marginal R2 / Conditional R2

0.000 / NA

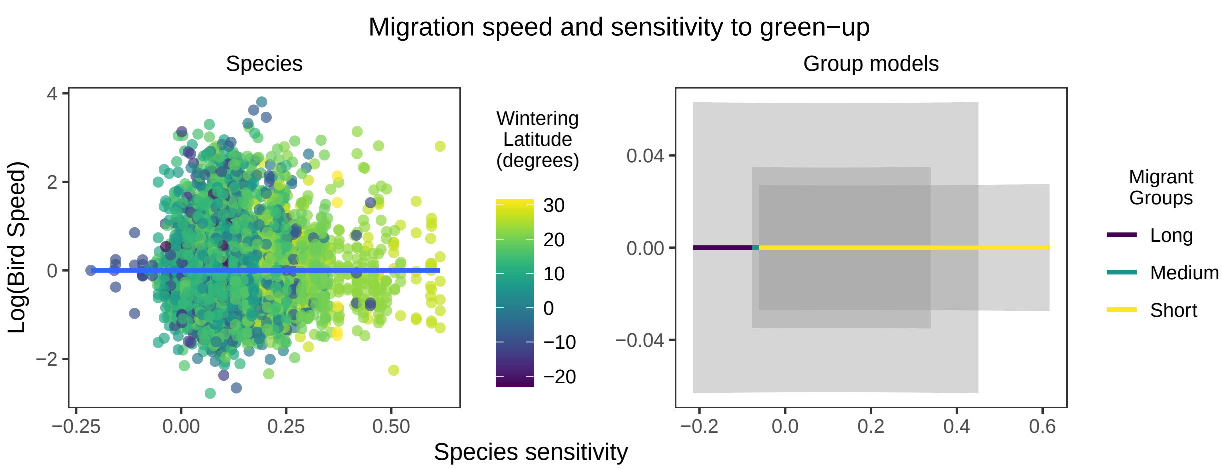
2 SENSITIVITY

are sensitive birds faster? or more flexible? ## Sensitivity and speed ### - winter distance groups

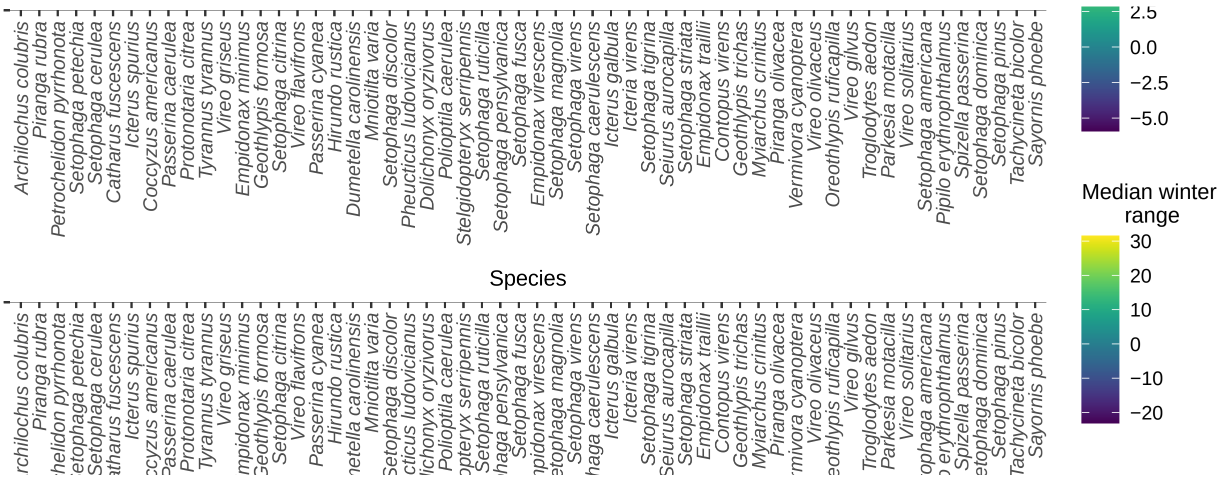


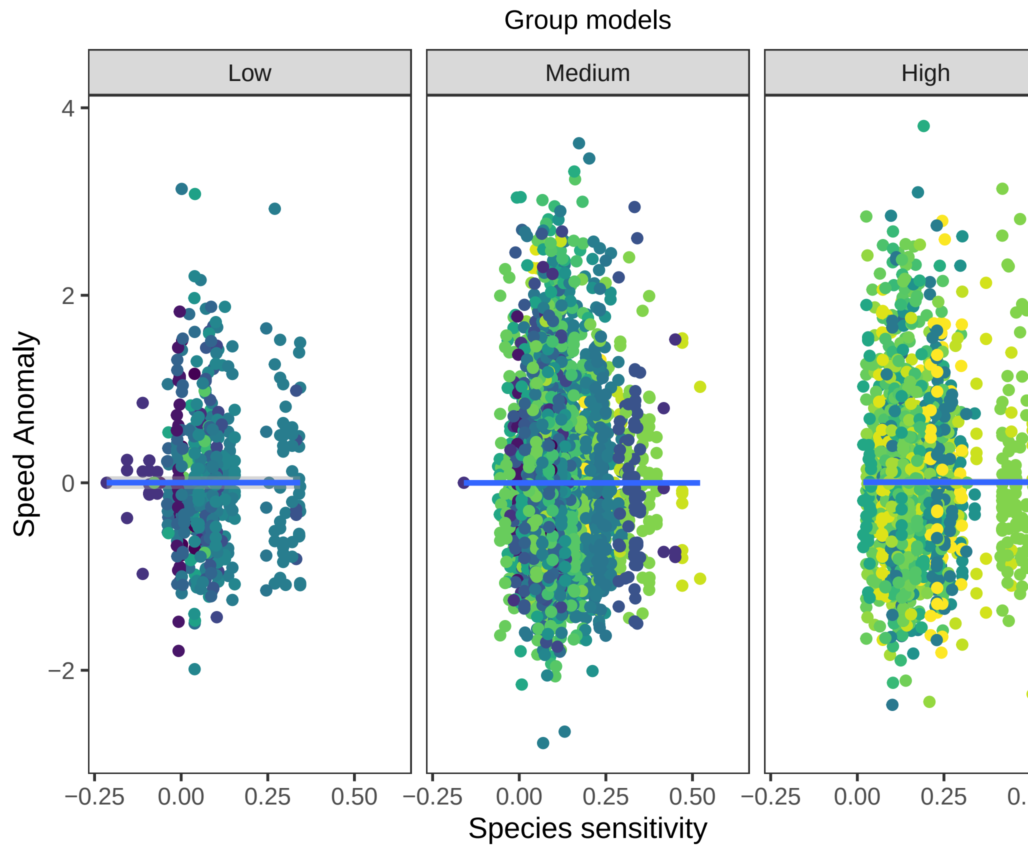


2.0.1 - breeding latitude



2.0.2 - species (groups - breeding and winter)

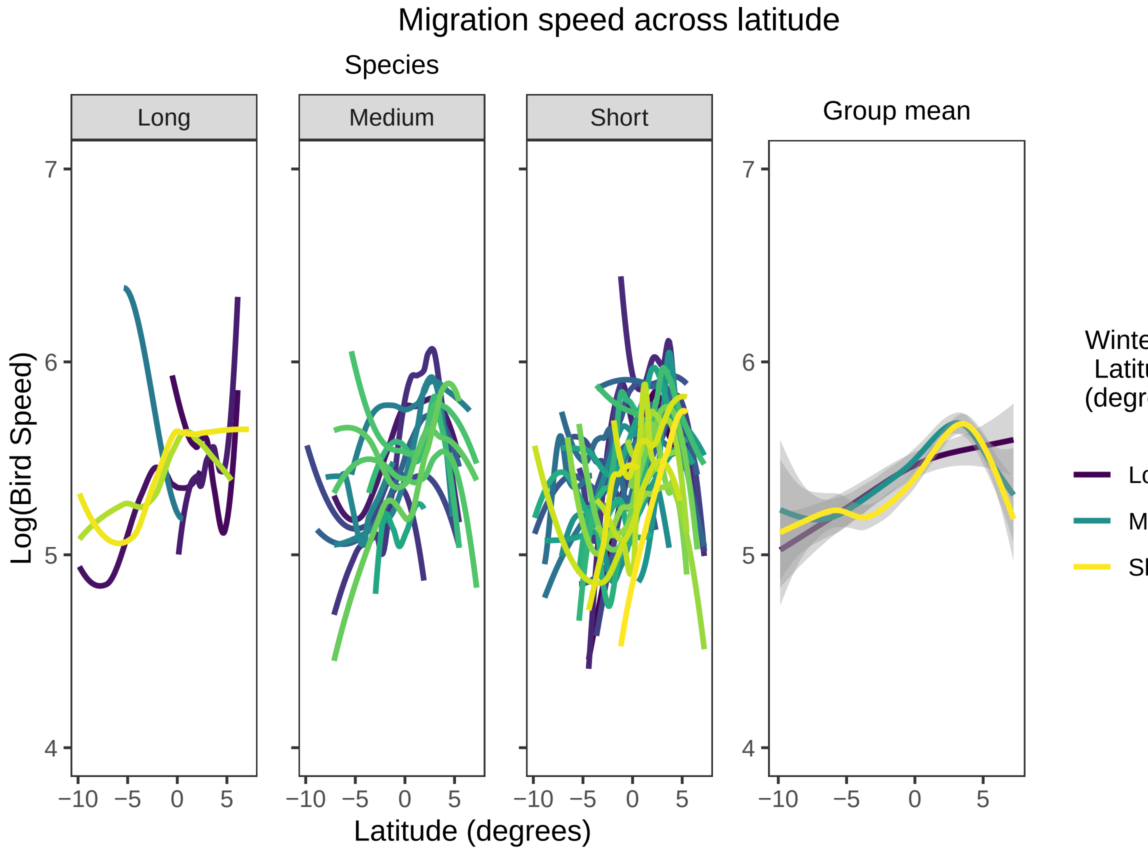




##speed variability and sensitivity

3 LATITUDE

how speed is changing across latitude? - does anomaly goes up with latitude (adapting more)? - does than lag

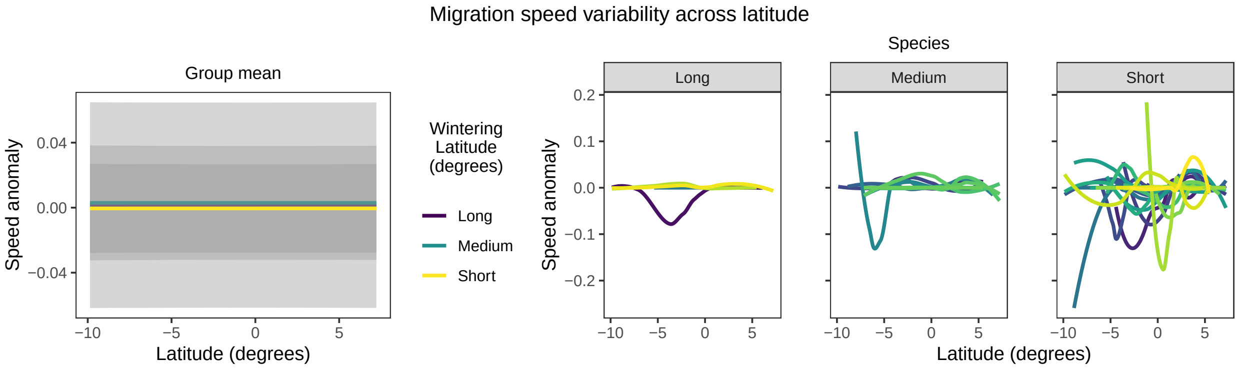


goes downwith latitude?
speed increasing with latitude, but it does not appear to vary with groups

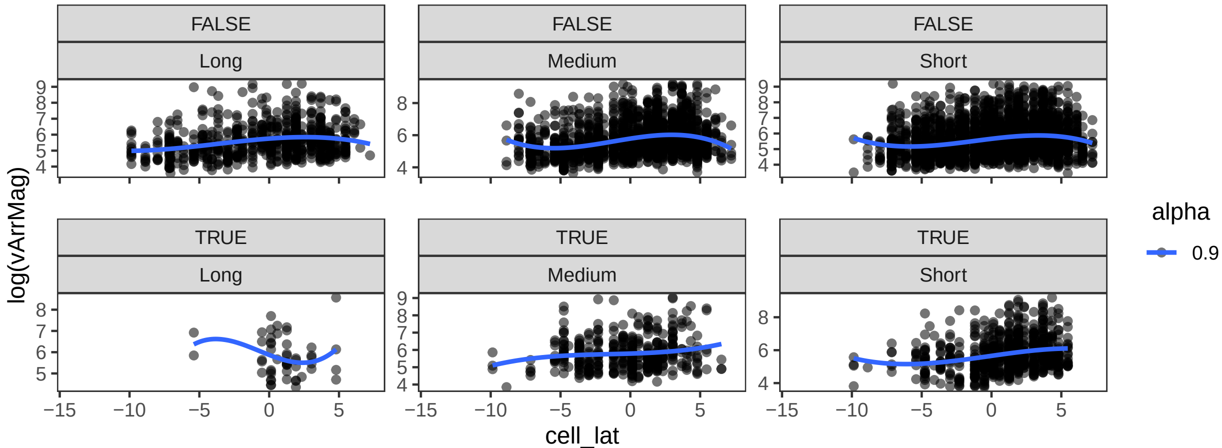
##Test the differences between species and groups:

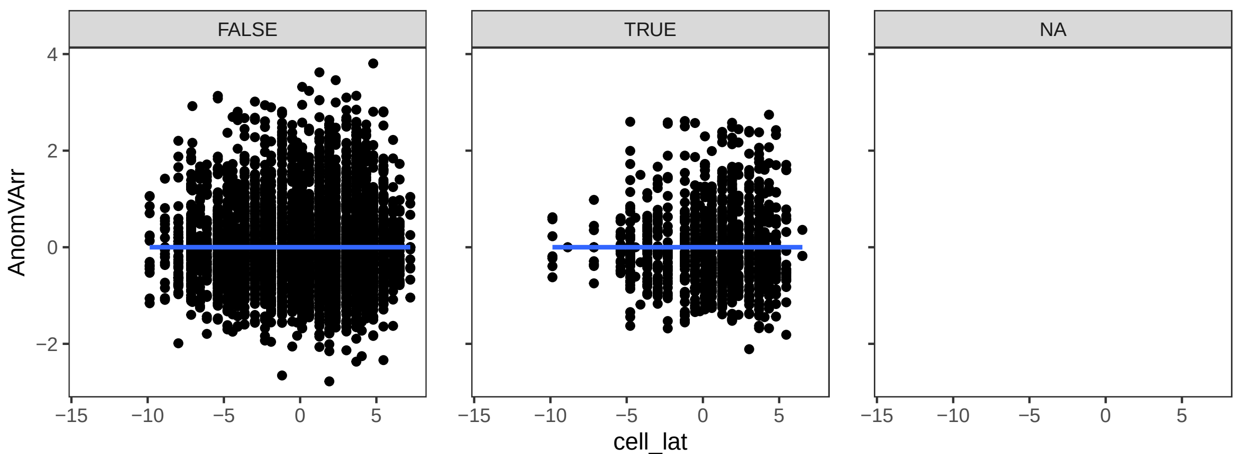
Latitude is affecting bird speed, wintering latitude is not

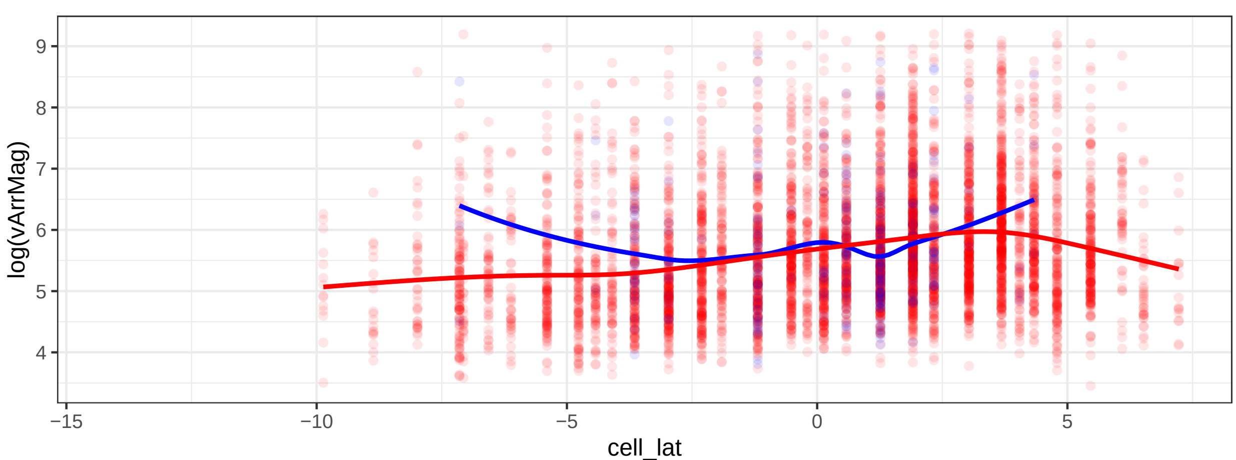
Latitude and groups of birds influencing variability

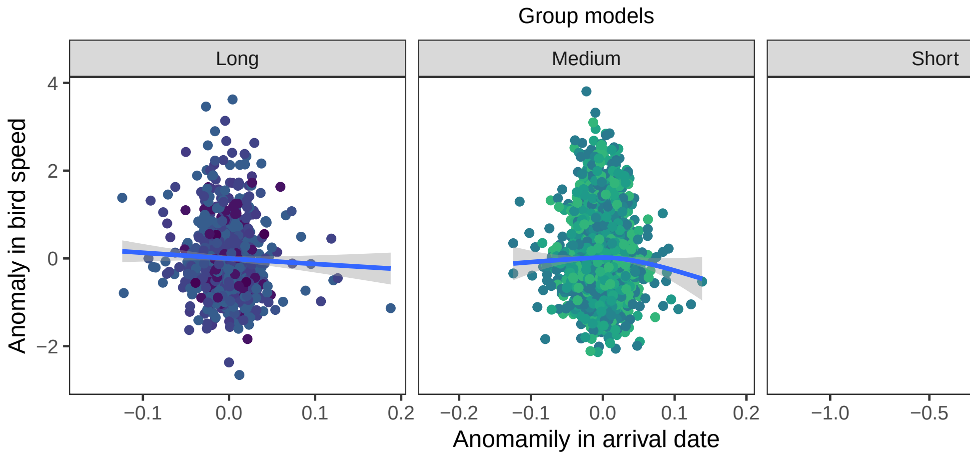


3.1 is it different between migratory and breeding range?



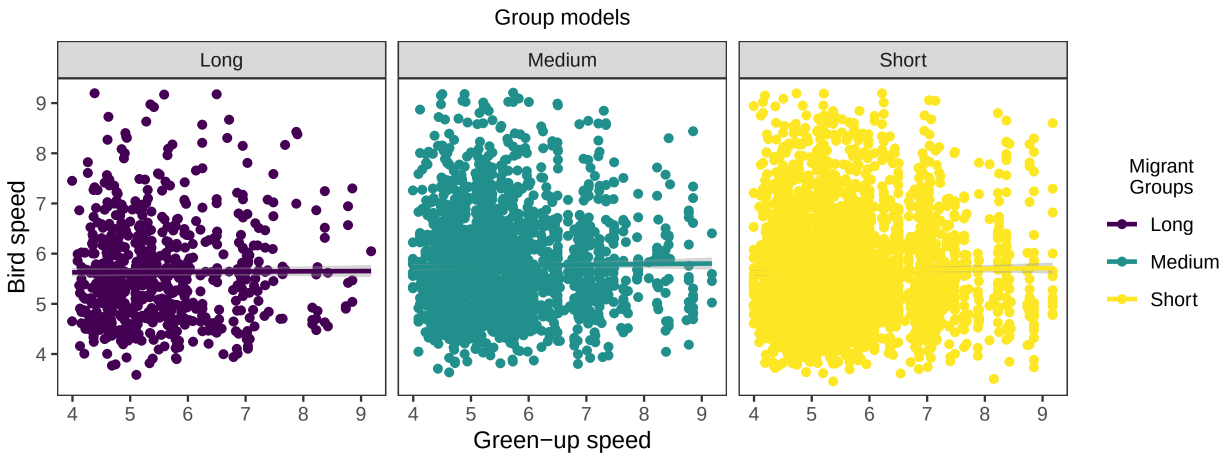


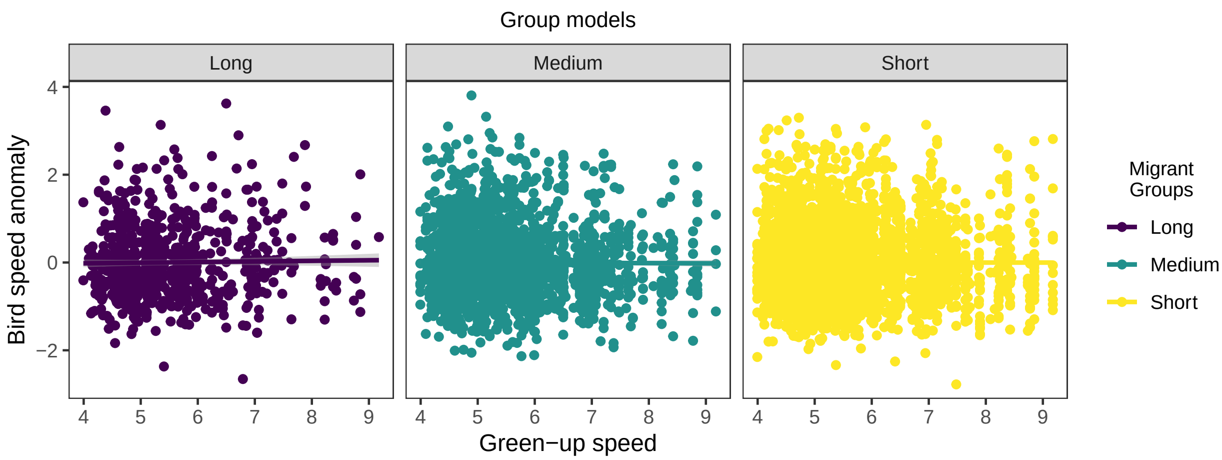


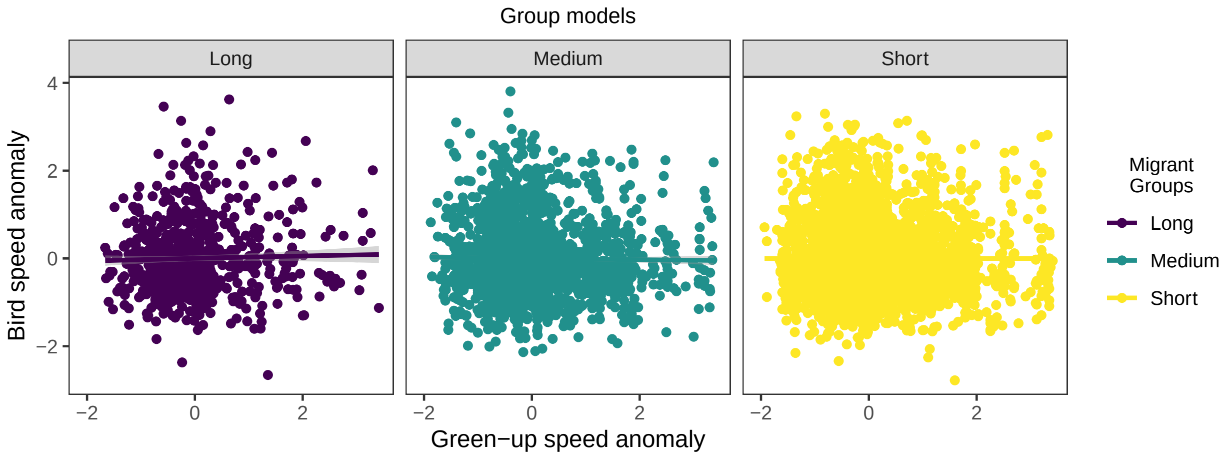


##anomaly on speed and dates on birds

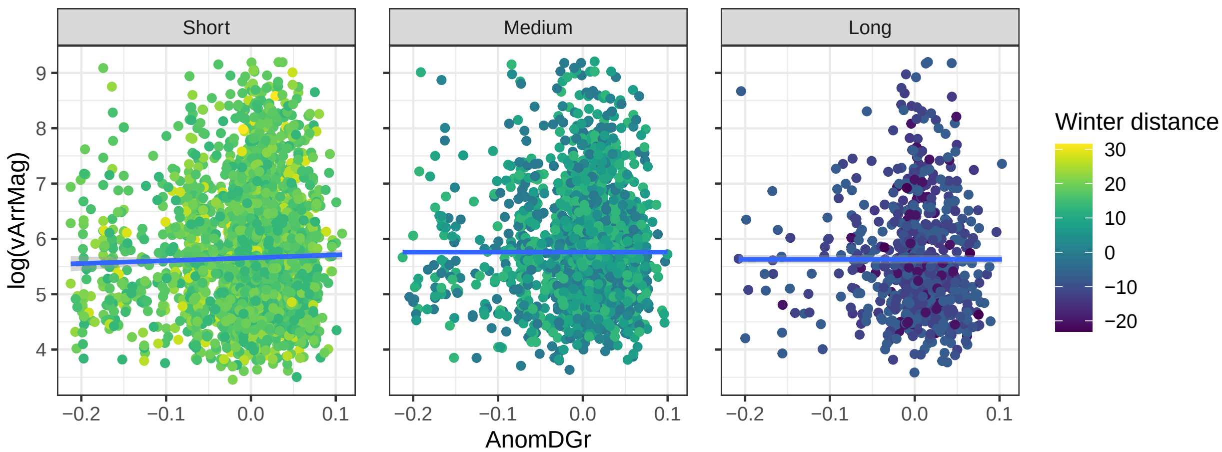
4 green up speed and bird migration speed

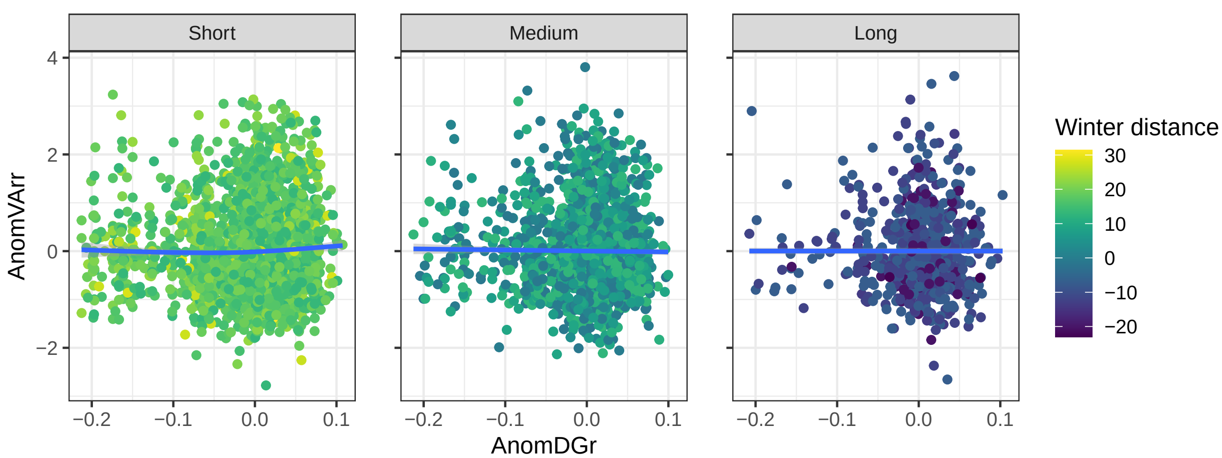






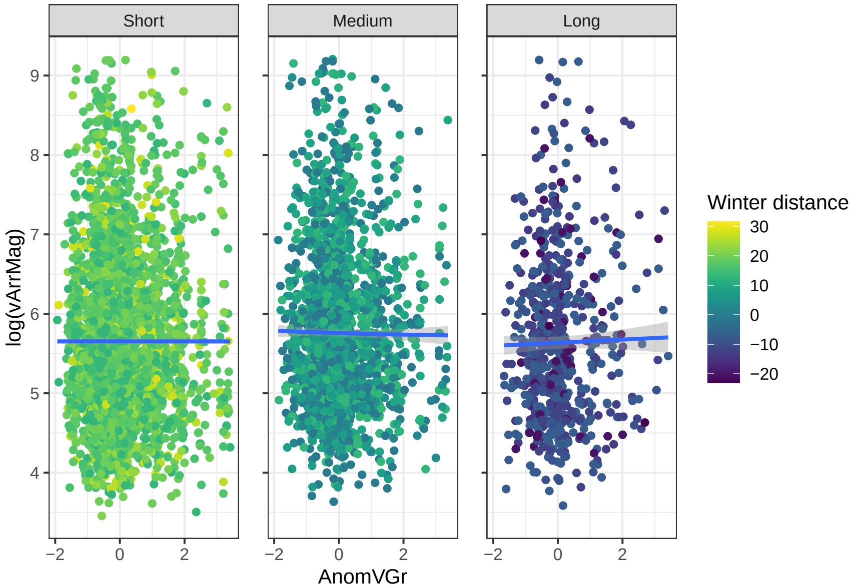
5 abnormal years (green up DATE and bird speed)

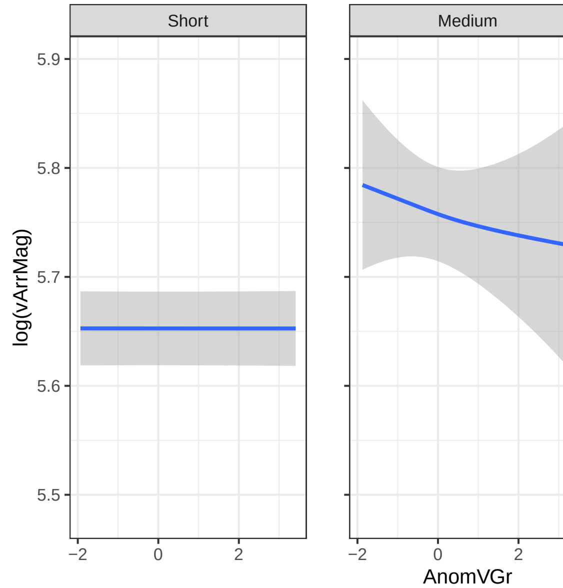


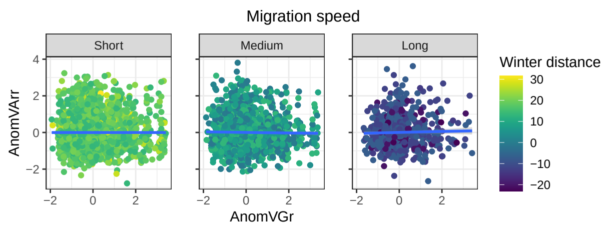


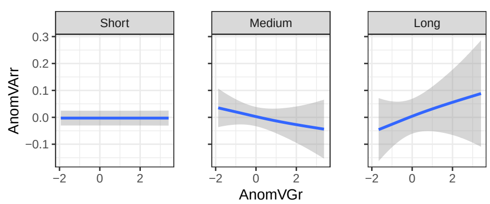
6 abnormal years (green up SPEED and bird speed)

anomaly on green-up speed and bird speed


Short
Medium
Long
log(vArrMag)
AnomVGr
Winter distance
30
20
10
0
−10
−20


Short
Medium
log(vArrMag)
AnomVGr


Migration speed
Short
Medium
Long
AnomVArr
AnomVGr
Winter distance
30
20
10
0
−10
−20


Short
Medium
Long
AnomVArr
AnomVGr