Proximity to Urbanised Regions has a Significant Effect on the Morphology of Endemic Hawaiian Forest Birds

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Keywords

Morphology, Wing length, Mass, Culmen length, Anthropogenic effects, Urban population centres, Selection, Linear mixed model, Model averaging

Abstract

Employing linear mixed models, anthropogenic variables were identified to affect the wing length, culmen length, and mass of eight Hawaiian birds. Notably, the distance to a United States military installation – Pohakuloa Training Area – showed a significant effect on all three traits. Other variables, such as distance to an urban space – Waimea – and time in years only had a significant effect on wing length and mass. We suspect that changes in habitat as well as anthropogenic disturbance could lead to changes in foraging behaviour and food availability, thereby influencing the morphology of these birds.

Introduction

Identifying the drivers of morphological adaptations is a key challenge for evolutionary biologists. Ever since Darwin's case study on the morphological adaptation and rapid speciation of Galapagos Island finches, identifying and understanding the selective forces that shape phenotypic adaptations has been considered the principal goal in the field of ecology and evolutionary biology. This goal, however, is not merely theoretical, but bears immediate and physical consequences concerning the way we choose to interact with the natural world. Given how rapidly living organisms adapt to natural processes, the question of how much human-induced disturbance can influence the adaptive traits of living organisms is a timely one to answer (Sullivan et al 2017). Moreover, the rising trend of urbanisation and our increased encroachment into the natural habitat of local fauna have both raised the importance and urgency of answering this important question (Sullivan et al 2017). In particular, studies on birds in particular have started being done to address these questions. For instance, long-term studies show that human influence has impacted morphological changes in songbirds due to a redistribution in the landscape of natural habitats (Desrochers 2010). Similarly, bill morphology has adapted to urbanised settings for house finches over a hypothesised long-period of fine-tuning selection (Hutton and McGraw 2016).

Though long-term studies provide evidence of human-induced morphological changes in birds, such studies fail to formally identify how the specific factor of spatial proximity to human settlements contributes to morphological changes in birds. In addition, short-term studies examining the morphological changes as a result of bird adaptations to human disturbance are largely missing from the literature as well. As such, the potential for continued avian morphological adaptation to the proximity of human settlements over short passages of time has not been thoroughly investigated. Examining the simple variable of distance to human settlements as a driver of morphological variance could permit us to compound complex factors that may be involved under the label of “human disturbance” to quickly obtain a working idea of how much disturbance is induced by various human settlements. Additionally, examining the impact of proximity to human settlements will allow us to understand the strength of selection placed upon our surroundings. With the ever growing fragmentation of natural habitats, it is important to formally quantify the short-term effects that the factor of proximal distance to human settlements might have on its local avian community.

To bridge these gaps in the literature, we will examine the effect that the proximity to human settlements have on the general morphology of bird fauna local to the region in this project. In particular, we will examine the extent that the proximity to several main human settlements (military bases, cities, etc.) has on the morphology of forest bird species endemic to the island of Hawaii in the Hawaiian Islands archipelago. We will examine three measurements of bird morphology in this project; wing length, culmen length, and mass. These are the standard measurements of bird morphology that we will use for our analyses due to their availability in the datasets examined as part of this project.

Wing length is a standard measure of bird morphology and is defined as the distance of the wing chord, the distance between the leading and trailing edge of the wing, when unflattened (Paxton et al 2016). Wing length could indicate several ecological functions of a specimen, such as its flying and foraging behaviour (Lank et al 2017). Secondly, the mass of a bird could indicate several aspects of its general ecology as well. For one, a drastic change in a bird’s mass could indicate a change in diet or an attempt from birds to respond to fluctuations in climatic conditions by losing excess fat (Hall et al 2021, Jirinec et al 2021). Lastly, culmen length is a measure of the length of the upper ridge of a bird's bill from its apical tip to its point of insertion into the skull (Paxton et al 2016). Culmen length is a standard measurement of bird morphology because it shows the least stochastic variation among other beak-related measurements. The measurement of culmen could give us insight into the ecology of birds with regard to their diet since changes in beak length has been proven to indicate an adaptation to different food sources (Hall et al 2021, Grenier and Greenberg 2007).

Collectively, this project will fill a gap in the literature by examining the specific extent that the proximity to different types of human settlements have on the morphological characteristics of a group of birds in Hawaii. Moreover, this project could also provide insight as to which morphological characteristics, and their corresponding ecological function, in birds are the most evolutionary sensitive to anthropogenic-induced disturbances. This could facilitate future efforts to conserve bird biodiversity by pinpointing which morphological characteristics are the clearest markers for human-induced adaptations. As such, and more broadly, this project could shed light on the extent that different human settlements have on their surrounding biodiversity at large. This study could thus inform our efforts to implement meaningful policies to protect local fauna. All things considered, this project will add valuable insight into the eco-evolutionary dynamics of an ever-changing, every-urbanising world.

Hypothesis

We will use a statistical analysis to attempt to investigate the relationship between bird morphology and proximity to human populations in a relatively short time span. Our hypothesis is as thus:

> Alternate hypothesis (HA): Proximity to human population centres or structures has a significant effect on the morphology of Hawaiian bird species over a short time span.
>
> Null hypothesis (H0): Proximity to human population centres or structures does not have a significant effect on the morphology of Hawaiian bird species over a short time span.

We can construct several general predictions related to our hypothesis as to the directions of the effects human population centres have on bird morphology:

1. There would be a positive correlation between wing length and proximity to urban centres. One possible mechanism for this correlation is that the foraging behaviour of birds would be altered due to either loss of natural habitat near human population centres, or increased disturbance due to human activity. Birds would be forced to fly longer distances and more often to seek out suitable food sources. This may lead to an increase in wing length correlating with closer proximity to human population centres, as selection favours longer wing lengths to facilitate increased flight time and distance during foraging (Nowakowski et. al. 2014).
2. There would be a change in culmen length as a result of proximity to urban centres, perhaps due to changes in food availability due to anthropogenic effects. While there is some evidence of human presence influencing beak morphology in Galapagos finches (De León et. al., 2011), we are unsure as to if or how this change would be seen in endemic Hawaiian birds.
3. There would be a change in mass correlating with proximity to urban centres. Again, the direction of this change is difficult to predict. Anthropogenic effects can affect mass in different ways, and while it is possible that mass would correlate with wing length (Nowakowski et. al. 2014) and increase with proximity to human population centres, it is also possible that the decrease in food due to loss of habitat would result in decreased mass. Further, it is also possible that an increase in heat production from human settlements could cause birds to respond by decreasing their average mass in order to adapt to these fluctuations in climatic conditions (Jirinec et al 2021).

Methods

Data Description

We used an open-source dataset that included morphological characteristics of birds endemic to Hawaii. The data was collected by E. H. Paxton and E. C. Abraham (2022) and uploaded to the US Geological Survey (USGS) online database. This survey data was initially collected across the avian annual cycle, over a span of 26 years (from 1994 to 2020), from multiple locations on the island of Hawaii in the Hawaiian Islands archipelago, in an effort to evaluate molt patterns and to establish criteria for the assignment of age and sex in native bird species. The data includes trapping sites in UTM coordinates, the collection date of each specimen , the sex of each specimen, and morphological measurements for eight endemic forest bird species. These birds are of the following species: ‘Ōma‘o (*Myadestes obscurus*), ‘Apapane (*Himatione sanguinea*), ‘I‘iwi (*Drepanis coccinea*), Hawai‘i ‘amakihi (*Chlorodrepanis virens*), ‘Akiapola‘au (*Hemignathus munroi*), Hawai‘i ‘elepaio (*Chasiempis sandwichensis*), Hawai‘i creeper (*Oreomystis mana*), Hawai‘i ‘akepa (*Loxops coccineus*). These species represent a good collection of mid-size forest birds, all endemic to Hawaii.

Data Analysis

Anthropogenic effects on the Island of Hawaii were classified into two main categories: urbanised centres and United States military bases. To elucidate trends in bird morphology, we constructed three linear mixed effect models with urbanised spaces and military bases as our predictor variables, with morphological trait as the dependent variable. These two predictors were selected based on Hawaii's unique characteristic of having 21% military-owned land (US Department of Defense 1998). Private individuals in urbanised spaces only own around 1/3 of total land available (Hawaii State Department). This dichotomy in land-ownership provides a clear distinction between land-use patterns on Hawaii Island, yielding two major anthropogenic variables.

To account for habitat variation, we considered three random variables in our models: mountains, active volcanoes, and shoreline distance. These random variables were selected based on prior research highlighting significant morphological changes due to elevation and water-based geographical gradients. Specifically, a Central European study on wing morphology identified a reduction in wing length with increasing elevation gradients (Mikitová et al. 2022). Moreover, changes to feeding activity have been correlated with shoreline proximity, mainly due to diet and vegetation differences (Chukwuka et al. 2022). As such, the proximity of each sampling site to the highest point of elevation of mountains and volcanoes, and proximity to the shore was considered.

Selection of each predictor focused on elucidating the greatest anthropogenic effect. We selected the top 3 urbanised population centres by population and all major military bases (2) on the island. For each random variable, we accounted for all mountains and active volcanoes present (see Appendix 2 for list). We used the function "geocode" from package ggmap to identify the longitude and latitude coordinates of each variable (v 3.0.1, Kahle 2022). This was done in R version 4.2.1. For testing within the mixed effect model, we calculated the distance – in km – of each sampling site to each variable using the function "spDistsN1" from package spatial points (v 1.5-1, Pebesma 2022). This function calculates Euclidean distances using the Pythagorean theorem (Liberti et al. 2014). Finally, we calculated the distance from each sampling site to the shoreline using coast data from Open Street Map (OSM 2015). Employing the package geosphere, we first drew a bounding box around each sampling site using the function "getbb". Then the "dist2Line" function was used to calculate the distance between the coastline and each sampling site (v 1.5-18, Hijmans). Since linear model random effects must be categorical, we binned the distances into three categories – near, middle, far – using the “discretize” function in package arules (v 1.7-5, Hahsler). Finally, we merged all calculated distances with the bird morphology dataset.

Our linear mixed effect models were performed using a stepwise method. Using the “lmer” function in package lme4, (v 1.1-31, Bolker), we performed individual mixed models for the three morphologies sampled: wing length, culmen length, and mass. The base models included all anthropogenic predictors and all habitat-based random effects (see Appendix 2 for full formula). The base models indicated possible significant results for wing length, albeit using coarse calculations.

To refine the wing mixed model, we used the function “dredge” from package MuMIn (v1.47.1, Bartoń 2022) to perform a dredge of each of the three base linear mixed models. This allows us to construct a list of models, each with a different combination of our selected fixed effects. These models are ranked based on corrected Akaike information criterion (AICc). The model with the lowest AICc is ranked as the best explanation for the data. We selected the models with the lowest AICc values, that is ΔAICc <=2 (see Appendix 1 Table A. 1), and we used the function “model.avg” from package MuMIn (v1.47.1, Bartoń 2022) to obtain estimated coefficients for the fixed effects based on a weighted average of the selected models.

Results

Estimates of the coefficients of the terms described by the fixed effects in the linear mixed models (“Estimate”), as well as the corresponding z-statistics (z) and p-values (p) were obtained from the results of the averaged linear mixed models for each of the three morphological traits (Table 1). Out of the fixed effects, we found that distance to Pohakuloa has a significant negative effect on all three traits, i.e. wing length (Estimate = -0.259, z = 5.241, p = 2e-07), culmen length (Estimate = -0.159, z = 3.705, p = 0.000211), and mass (Estimate = -0.142, z = 3.515, p = 0.00044). We also found that distance to Waimea has a positive effect on only two of the traits, i.e. wing length (Estimate = 0.0955, z = 2.694, p = 0.00707) and mass (Estimate = 0.0612, z = 2.025, p = 0.04287). We also saw that the covariate year has a significant negative effect on two of our traits, i.e. wing length (Estimate = -0.237, z = 2.311, p = 0.02082), and mass (Estimate = -0.178, z = 2.038, p = 0.04158).

Table 1: Summarized results of three linear mixed model averages. Models with AICc <= 2 were selected from a linear mixed model dredge with one of the three morphological traits as dependent variable and distance to urban locations as fixed effects. Distance to natural locations and shoreline were included as random effects while year was included as a covariate. These models were averaged to obtain the full model-averaged intercepts and coefficeints, as well as corresponding *z* -statistic and *p* -values. Significant *p* -values are bolded and marked with asterisk (*) on the right.

Fixed effects	Morphological Traits											
	wing length				culmen length				mass			
	Estimate	*z*	*p*		Estimate	*z*	*p*		Estimate	*z*	*p*	
Intercept	78.302721	43.668	**< 2.00E-16**	*	19.280376	10.166	**< 2.00E-16**	*	20.734522	13.062	**< 2.00E-16**	*
Distance to location												
Pohakuloa	-0.259061	5.241	**2.00E-07**	*	-0.159236	3.705	**0.000211**	*	-0.141718	3.515	**0.00044**	*
Waimea	0.095545	2.694	**0.00707**	*	0.041576	1.012	0.311511		0.0611804	2.025	**0.04287**	*
Kona	-0.001607	0.164	0.87002		-0.001618	0.234	0.815095		0.0020213	0.217	0.82817	
Hilo	0.00304	0.236	0.81319		0.325823	0.557	0.577453		-0.000592	0.064	0.94872	
Army Reserve	0.003251	0.244	0.80698		-0.321657	0.546	0.584975		-0.000617	0.066	0.94758	
Covariate												
Year	-0.236927	2.311	**0.02082**	*	0.017436	0.372	0.71001		-0.177722	2.038	**0.04158**	*

Discussion

Our results seemed to support our hypothesis, at least in part. While there is support for the significant effect of at least one of our urban sites on the morphology of the selected bird species, the direction of the effect is far from consistent; in fact, many of our chosen fixed effects did not produce a significant effect on bird morphology. This shows that anthropogenic effects can be distinct to specific locations and environmental conditions, and are not generalised across the island. Below, we present a few theories on why this is the case.

Effect of proximity to Pohakuloa Training Area

The Pohakuloa Training Area was the only site that significantly impacted all 3 morphological traits. This is likely due to both geographical and functional features of the site. The training area is located centrally on the island of Hawaii, which makes it closer in proximity to many of the locations where the birds were found. This proximity allows the training area to affect a great number of the birds found on the island, including affecting their morphological traits. Functionally, there is an airfield within the training area (the Bradshaw Army Airfield). Airfields are highly disruptive to birds as the planes are loud, scary, and alter flight patterns. There is evidence to suggest that air traffic reduces avian foraging and feeding duration , due to the increased visual alert and scanning behaviour (Klett-Mingo et. al. 2016). There is also the effect of training area activity and physical building structures on the surrounding area. Loud noises caused by firearms and destruction of the physical area, along with the previously mentioned geographical and functional features make the area surrounding Pohakuloa an unfit habitat for the birds.

Our estimates suggest that mass and wing length increase with closer proximity to Pohakuloa. We believe this is due to impacts of the training area on the surrounding resource availability, forcing the birds to fly further away to reach them. Research suggests that longer wing length in birds is correlated with fitness ability and dispersal distance (Claramunt 2021). Increased mass is also correlated with increased flight distance (Mølller. 2008). This supports the idea that birds with these larger sizes from Pohakuloa travel further for resources. Mass of the birds does not decrease due to the lack of resources around Pohakuloa because the birds have already adapted to flying further for resources, thus mass is maintained.

While the Pohakuloa training area was highly impactful on the morphological traits, the other army reserve had little effect on any of the traits. We suspect that this is also due to the differences in the geographical and functional features of the 2 sites. The army reserve is located near the coast, making it further in proximity from the island birds. The further distance decreases the site's opportunity to affect the bird's morphological traits, as compared to Pohakuloa. Also, the army reserve does not have an airfield, making its presence less disruptive to birds.

Effect of proximity to Waimea

In regards to urban areas, Waimea significantly affected wing length and mass. The other two urban areas did not have a significant effect. We suspect the difference in site elevation as the primary cause. Waimea has an elevation of 814 metres, while the other two urbanised spaces have elevations of 18m and 2.18m. This difference in elevation caused a difference in habitat between Waimea and the other 2 cities. The effect of an urban area therefore might differ on the 2 types of habitats.

Also important to the effect of the Waimea habitat is its non-native flora. Based on this area's lack of significant effect on culmen length, we suspect that the birds have not adapted to the new food sources around them.We hypothesise, based on our coefficient directions, that effect on mass is a possible result of the large non-native habitat, which provides less food sources. Thus, closer proximity to Waimea correlates with lower body mass. The correlation between wing length and mass may also be in effect, i.e. smaller body correlating with smaller wings. Thus, we see a similar trend of closer proximity to Waimea correlating with shorter wing length (Nowakowski et. al. 2014). Flight ability and distance may not have as great an effect on mass as predicted, and certainly warrants further research.

Effect of Year as a covariate on morphology

Year is also included in our model because it is a covariant, and we found that it had a significant effect on wing length and mass. This is because morphological change takes time to occur, and this effect of time is shown through the year covariable. Year could also be linked to other factors such as climate change, which increases average temperature over the years.Prior research has shown temperature changes to have an effect on the avian morphological traits (Jirinec et. al. 2021).

Random effects

The random effects in our model include mountains, volcanoes, and the shoreline. According to the linear mixed models that included all the fixed and random effects, none of these random effects had a significant impact on the morphological traits in our model, specifically for wing length and mass. The random effects also explained very little of the variance for the culmen length linear mixed model. Our rationale for this result is based on the fact that both the endemic bird species and the natural features of the island have coexisted for a very long time. Thus, adaptations to these natural features likely happened long before our data was collected. Therefore, no effect is represented in our dataset, and sequentially our model/tests.

Conclusion

Our original hypothesis highlights that human-originating factors can affect the morphological traits of the endemic Hawaiian birds over a relatively short period of time. Our results indicate that some anthropogenic factors did have an effect on morphology. Standout results include the Pohakuloa site having a significant effect on all three morphological traits, and the Waimea site having an effect on two of the three traits. Year as a covariable impacted the morphological traits as well. These results lead us to reject the null hypothesis of human-originating factors not significantly affecting morphological traits of the Hawaiian birds. Moreover, these results support the alternative hypothesis of human-originating factors significantly affecting the morphological traits of endemic Hawaiian birds over a relatively short period of time.

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Appendix 1

Table A. 1: Lists of models estimating morphogical trait values with the lowest AICc values, which were used for model averaging. Combination of fixed effects pertaining to each model, degrees of freedom, log-likelihood values, AICc, ΔAICc, and model weight are included.

Table A. 1(i): List of models estimating wing length.

Fixed effects[+]	df	logLiK	AICc	ΔAICc	weight
Pohakuloa + Waimea + Year*	10	-9603.494	19227.1	0.00	0.207
Army Reserve + Pohakuloa + Waimea + Year*	11	-9603.291	19228.7	1.61	0.092
Hilo + Pohakuloa + Waimea + Year*	11	-9603.305	19228.7	1.64	0.091
Kona + Pohakuloa + Waimea + Year*	11	-9603.406	19228.9	1.84	0.082

Table A. 1(ii): List of models estimating culmen length.

Fixed effects[+]	df	logLiK	AICc	ΔAICc	weight
Pohakuloa + Waimea	9	-8149.430	16316.9	0.00	0.103
Army Reserve + Hilo + Pohakuloa	10	-8148.552	16317.2	0.26	0.091
Pohakuloa + Waimea + Year*	10	-8148.831	16317.7	0.82	0.068
Hilo + Pohakuloa + Waimea	10	-8149.078	16318.2	1.31	0.053
Army Reserve + Hilo + Pohakuloa + Year*	11	-8148.093	16318.3	1.36	0.052
Kona + Pohakuloa + Waimea	10	-8149.106	16318.3	1.37	0.052
Army Reserve + Pohakuloa + Waimea	10	-8149.109	16318.3	1.37	0.052
Pohakuloa	8	-8151.158	16318.4	1.44	0.050

Table A. 1(iii): List of models estimating mass.

Fixed effects[+]	df	logLiK	AICc	ΔAICc	weight
Pohakuloa + Waimea + Year*	10	-9208.314	18436.7	0.00	0.132
Kona + Pohakuloa + Waimea + Year*	11	-9208.165	18438.4	1.72	0.056
Army Reserve + Pohakuloa + Waimea + Year*	11	-9208.301	18438.7	1.99	0.049
Hilo + Pohakuloa + Waimea + Year*	11	-9208.302	18438.7	1.99	0.049

df = degrees of freedom, logLiK = log-likelihood value, AICc = corrected Alkaike Information Criteron score, ΔAICc = difference in AICc compared to lowest AICc model, weight = model weight

[+]All fixed effects location names are abbreviations of "Distance from [location]".

*Although year is a covariate, it is included as a fixed effect in function "lmer" (package lme4), thus is included here.

Appendix 2

R code

Here we include the R code used to perform our data manipulation and clean-up, linear mixed model dredges and model averaging. This code is presented as a full R notebook, which begins on the next page.

EEB313 Project: Complete cleaned-up code

2022-12-08

##Setup: required libraries

```
## Warning: package 'rgdal' was built under R version 4.2.2

## Warning: package 'mapproj' was built under R version 4.2.2

## Warning: package 'usethis' was built under R version 4.2.2

## Warning: package 'ggmap' was built under R version 4.2.2

## Warning: package 'mapview' was built under R version 4.2.2

## Warning: package 'arules' was built under R version 4.2.2

## Warning: package 'report' was built under R version 4.2.2

## Warning: package 'geosphere' was built under R version 4.2.2

## Warning: package 'osmdata' was built under R version 4.2.2

## Warning: package 'arsenal' was built under R version 4.2.2
```

##Input data

```
morph <- read.csv("Morphology_metadata2.csv")
```

##PCA

```
morph_means <- morph %>%
  group_by(Species) %>%
  filter(!is.na(Wing) & !is.na(Culmen) & !is.na(Mass)) %>%
  summarize(mean(Wing), mean(Culmen), mean(Mass))
```

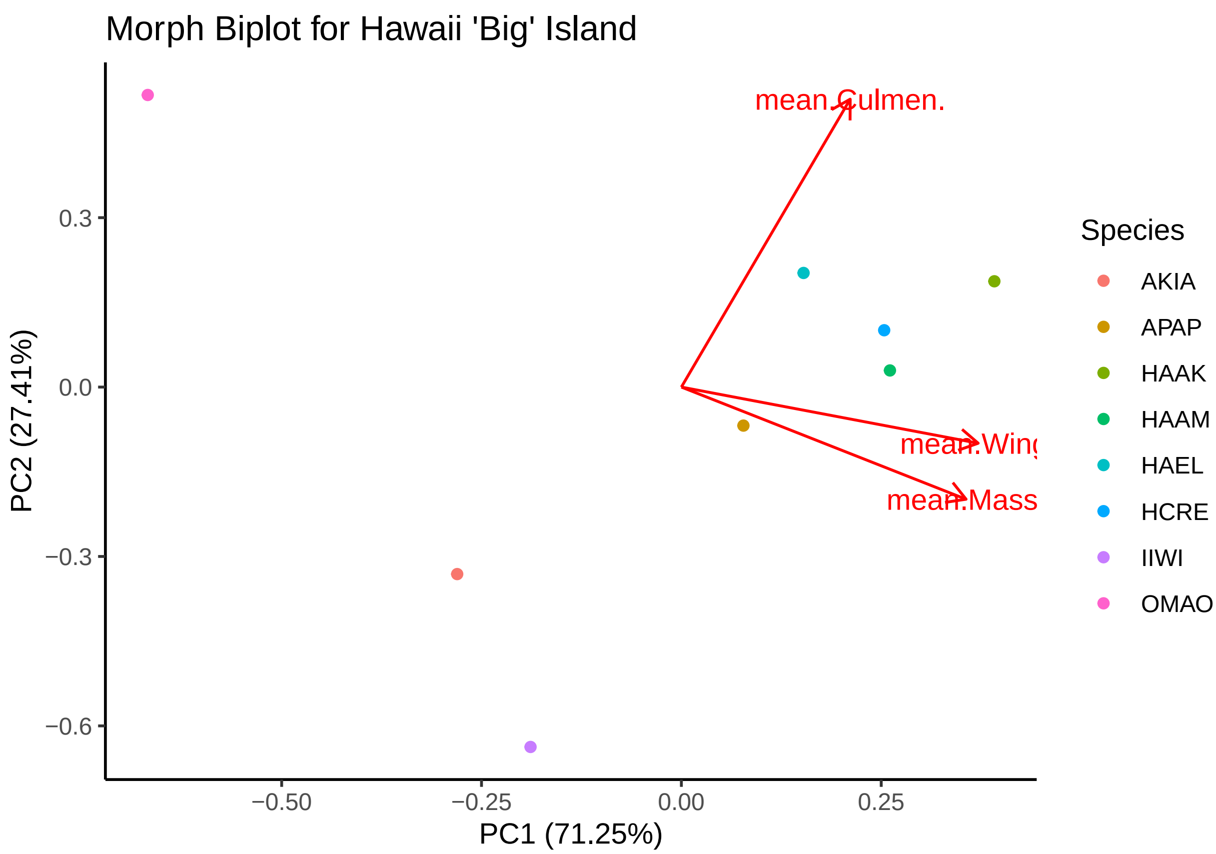
```
df <- data.frame(morph_means[,-1])

morph_pc <- prcomp(df, scale = TRUE, center = TRUE, retx = T)
summary(morph_pc)
```

```
## Importance of components:
##                           PC1    PC2     PC3
## Standard deviation     1.4620 0.9069 0.20055
## Proportion of Variance 0.7125 0.2741 0.01341
## Cumulative Proportion  0.7125 0.9866 1.00000
```

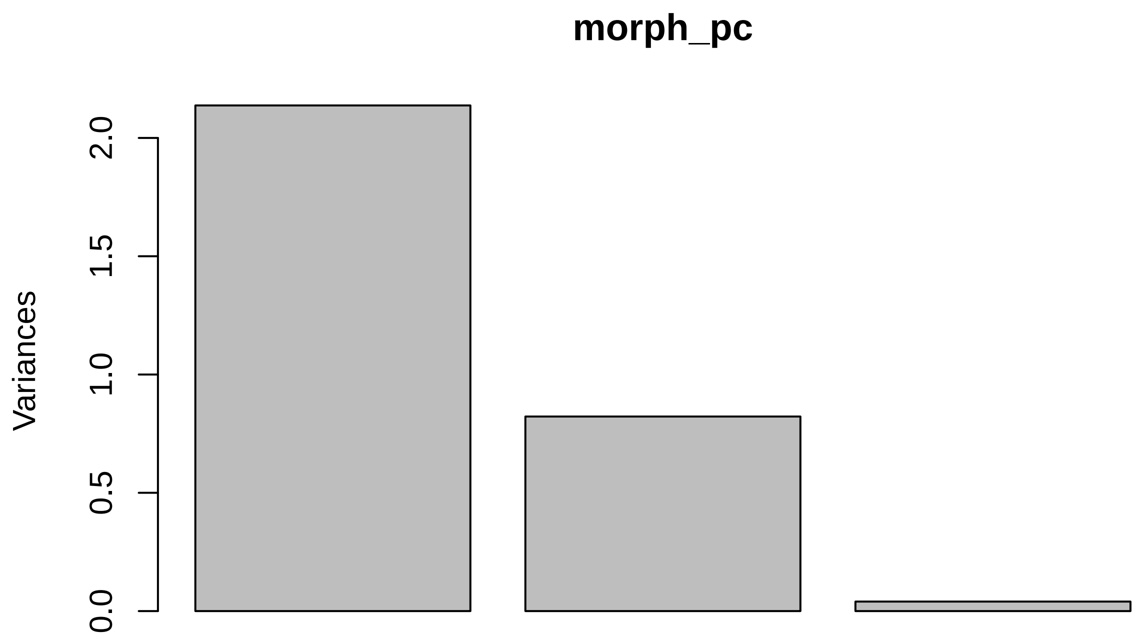
```
morph_pc$rotation <- -1*morph_pc$rotation
morph_pc$rotation
```

```
##                   PC1        PC2        PC3
## mean.Wing.   0.6676279 -0.1788466  0.7226942
## mean.Culmen. 0.3797288  0.9167602 -0.1239225
## mean.Mass.   0.6403741 -0.3571619 -0.6799679
```

```
autoplot(morph_pc, data = morph_means, colour = 'Species', loadings = TRUE,
         loadings.label = TRUE) +
labs(title = "Morph Biplot for Hawaii 'Big' Island") +
theme_classic()
```




```
plot(morph_pc)
```



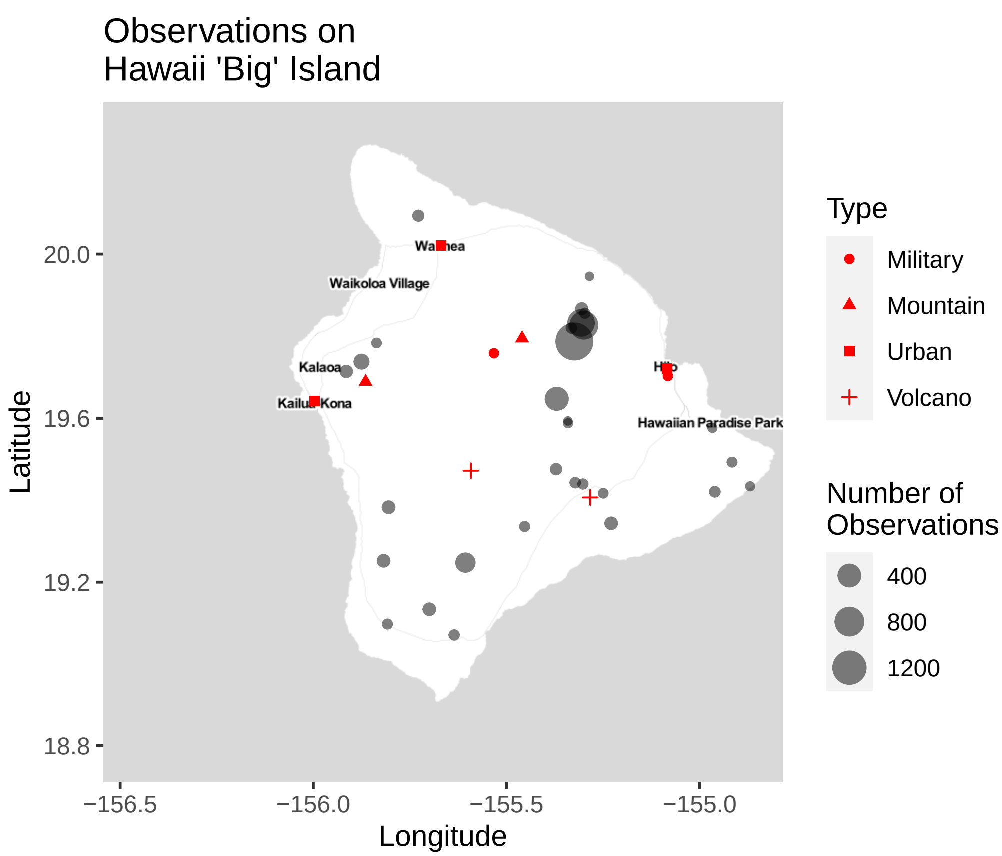
##Conversion to lat-long and adding landmarks

```
# Identifies ESPG as 6334.
morph_sf <- st_as_sf(morph, coords = c("UTM_X", "UTM_Y"), crs = 6334)

# Transforms coordinates to standard lat-lon format.
morph_wgs84 <- st_transform(morph_sf, crs = 4326)

# Converts geometry class into separate lat-lon columns.
morph <- morph_wgs84 %>%
  extract(geometry, c('lon', 'lat'), '\\((.*), (.*)\\)', convert = TRUE) %>%
  as.data.frame()

# Selects for relavent columns.
morph_spa <- morph %>%
  select(Species, Date, Sex, Wing, Culmen, Mass, lat, lon)

# Previews the data.
#head(morph_spa)

# Uses ggmap to extract map of Hawaii.
register_google(key = "AIzaSyCAOX4U9l7oFpljVfFnF1U-IW-0ve92QTk")
map_hi <- get_map(location = 'Island of Hawaii', zoom = 9, source = "stamen",
                  maptype = "toner-lite")

# List of natural and anthropogenic effects that can be analyzed.
```

```r
effects <- list(Mauna_Loa = c(geocode("Mauna Loa"), Type = "Volcano"),
                Kīlauea = c(geocode("Kīlauea"), Type = "Volcano"),
                Hilo = c(geocode("Hilo"), Type = "Urban"),
                Waimea = c(geocode("Waimea"), Type = "Urban"),
                Kona = c(geocode("Kona"), Type = "Urban"),
                Hualalai = c(geocode("Hualalai"), Type = "Mountain"),
                Mauna_Kea = c(geocode("Mauna Kea Access Rd, Hilo, HI 96720, United States"),
                              Type = "Mountain"),
                Pohakuloa = c(geocode("Pohakuloa Training Area"), Type = "Military"),
                Army_Reserve = c(geocode("470 W Lanikaula St, Hilo, HI 96720, United States"),
                                 Type = "Military"))
```

```
## Warning: "Kona" not uniquely geocoded, using "kailua-kona, hi, usa"
```

```r
# Formats list as a dataframe.
effects <- as.data.frame(bind_rows(effects, .id = "Name"))

# Plots the data.

ggmap(map_hi) +
  geom_count(data = morph_spa, aes(x = lon, y = lat), alpha = 0.5) +
  labs(title = "Observations on \nHawaii 'Big' Island", x = "Longitude", y = "Latitude",
       size = "Number of \nObservations") +
  geom_point(data = effects, aes(x = lon, y = lat, shape = Type), color = "Red")
```

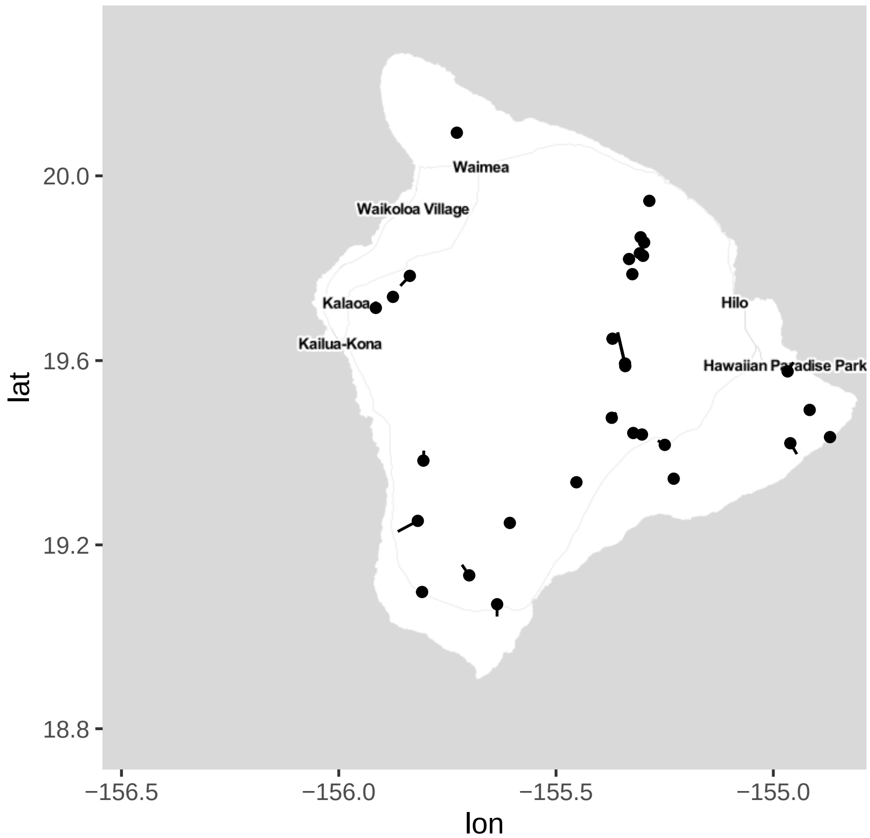


##Distance to landmarks calculation

```
#extract points lat-long data into a matrix
points <- as.matrix(morph_spa[,7:8])

#names of the distance columns in a list
name_loc <- c("dist_mau_loa","dist_kil","dist_hil","dist_wai","dist_kon",
              "dist_hua","dist_mau_kea","dist_poh","dist_arm_res")

#Distance calculation for loop
for(i in 1:9){
  loc <- as.numeric(c(effects[i,3], effects[i,2]))
  dist_x <-  as.data.frame(spDistsN1(points,loc,longlat=T))
  colnames(dist_x) <- name_loc[i]
  morph_spa <- cbind(morph_spa,dist_x)
}
```

##Distance to shoreline calculation

```
# Uses the previously created sf_object to identify unique sample sites.
morph_wgs84_distinct <- morph_wgs84 %>%
  distinct(geometry)



# Creates a bounding box of Hawaii coastline data.
osm_box <- getbb(place_name = "Hawaii") %>%
  opq() %>%
  add_osm_feature("natural", "coastline") %>%
  osmdata_sf()


# Uses the dist2line function in geosphere.
dist_coast <- geosphere::dist2Line(p = st_coordinates(morph_wgs84_distinct),
                        line = st_coordinates(osm_box$osm_lines)[,1:2])

# Creates a lat lon version of unique sampling sites.
morph_spa_distinct <- morph_spa %>%
  distinct(lat, lon)

# Combine initial data with distance to coastline.
morph_spa_coast.distance <- cbind(morph_spa_distinct %>%
                                    rename(y = lat, x = lon), dist_coast) %>%
                                    mutate(kilometers = distance/1000)

# Plot distances
ggmap(map_hi) +
  geom_point(data = morph_spa_distinct,
             aes(x = lon, y = lat)) +
  geom_segment(data = morph_spa_coast.distance,
               aes(x = x,
                   y = y,
                   xend = lon,
                   yend = lat))
```




```
morph_spa_coast.binned <- morph_spa_coast.distance %>%
  mutate(shr_bin = discretize(kilometers, method="interval", breaks=3,
                              labels=c("near","middle","far")))
```

```
morph_spa <- left_join(morph_spa, morph_spa_coast.binned %>%
                         select(y, shr_bin),
                       by = c("lat" = "y"))
morph_spa$shr_bin <- as.character(morph_spa$shr_bin)
```

##Filtering out N/A values

```
#Filter out NAs
morph_spa_noNA <- morph_spa %>%
  filter(!is.na(Wing) & !is.na(Culmen) & !is.na(Mass))
```

##Binning distance to random effects

```
#Sort Natural Landmarks (random effect) into categories
morph_spa_bins <- morph_spa_noNA %>%
  mutate(mau_loa_bins = discretize(dist_mau_loa, method="interval", breaks=3,
                                   labels=c("near","middle","far"))) %>%
  mutate(kil_bins = discretize(dist_kil, method="interval", breaks=3,
                               labels=c("near","middle","far"))) %>%
  mutate(hua_bins = discretize(dist_hua, method="interval", breaks=3,
```

```r
                                labels=c("near","middle","far"))) %>%
  mutate(mau_kea_bins = discretize(dist_mau_kea, method="interval", breaks=3,
                                    labels=c("near","middle","far")))
```

##Numericise Year

```r
#Extract last 2 digits -- Years as numeric variable
morph_spa_bins <- morph_spa_bins %>%
  mutate(Year=as.numeric(str_sub(morph_spa_bins$Date,-2,-1)))
```

##Base Linerar Mixed Models

Here are the base linear mixed models, one for each of the morphological traits. Note that all fixed effects, random effects and covariate (year) are included.

```r
#Mixed model for Wing
wing_lmer <- lmer(Wing~Year+dist_hil+dist_wai+dist_kon+dist_poh+dist_arm_res+
                    (1|mau_loa_bins)+(1|kil_bins)+(1|hua_bins)+(1|mau_kea_bins)+
                    (1|shr_bin),data=morph_spa_bins,REML=F)
```

```
## boundary (singular) fit: see help('isSingular')
```

```r
summary(wing_lmer)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## Wing ~ Year + dist_hil + dist_wai + dist_kon + dist_poh + dist_arm_res +
##     (1 | mau_loa_bins) + (1 | kil_bins) + (1 | hua_bins) + (1 |
##     mau_kea_bins) + (1 | shr_bin)
##    Data: morph_spa_bins
##
##      AIC      BIC   logLik deviance df.resid
##  19231.8  19308.0  -9602.9  19205.8     2600
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.2325 -0.7888 -0.1196  0.5708  3.6110
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  mau_loa_bins (Intercept)  0.00    0.000
##  kil_bins     (Intercept)  0.00    0.000
##  hua_bins     (Intercept)  0.00    0.000
##  mau_kea_bins (Intercept)  0.00    0.000
##  shr_bin      (Intercept)  0.00    0.000
##  Residual                 91.12    9.546
## Number of obs: 2613, groups:
## mau_loa_bins, 3; kil_bins, 3; hua_bins, 3; mau_kea_bins, 3; shr_bin, 3
##
## Fixed effects:
##                Estimate Std. Error         df t value Pr(>|t|)
```

```
## (Intercept)    72.66206    6.78137 2613.00000  10.715  < 2e-16 ***
## Year           -0.21921    0.11851 2613.00000  -1.850 0.064459 .
## dist_hil       -0.59539    0.86858 2613.00000  -0.685 0.493102
## dist_wai        0.13930    0.06592 2613.00000   2.113 0.034688 *
## dist_kon        0.03917    0.07079 2613.00000   0.553 0.580087
## dist_poh       -0.34452    0.10245 2613.00000  -3.363 0.000783 ***
## dist_arm_res    0.66755    0.88408 2613.00000   0.755 0.450270
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Year   dst_hl dist_w dst_kn dst_ph
## Year        -0.348
## dist_hil     0.456 -0.423
## dist_wai    -0.418  0.190 -0.823
## dist_kon    -0.831 -0.019  0.061 -0.045
## dist_poh     0.790  0.005  0.326 -0.531 -0.724
## dist_arm_rs -0.530  0.409 -0.995  0.828  0.029 -0.405
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

```
#Mixed model for Culmen
cul_lmer <- lmer(Culmen~Year+dist_hil+dist_wai+dist_kon+dist_poh+dist_arm_res+
                   (1|mau_loa_bins)+(1|kil_bins)+(1|hua_bins)+(1|mau_kea_bins)+
                   (1|shr_bin),data=morph_spa_bins,REML=F)
```

```
## boundary (singular) fit: see help('isSingular')
```

```
summary(cul_lmer)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## Culmen ~ Year + dist_hil + dist_wai + dist_kon + dist_poh + dist_arm_res +
##     (1 | mau_loa_bins) + (1 | kil_bins) + (1 | hua_bins) + (1 |
##     mau_kea_bins) + (1 | shr_bin)
##    Data: morph_spa_bins
##
##      AIC      BIC   logLik deviance df.resid
##  16321.8  16398.1  -8147.9  16295.8     2600
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9587 -0.7670 -0.3508  1.0416  2.5514
##
## Random effects:
##  Groups       Name        Variance  Std.Dev.
##  mau_loa_bins (Intercept) 3.160e-08 0.0001778
##  kil_bins     (Intercept) 3.559e+00 1.8865553
##  hua_bins     (Intercept) 0.000e+00 0.0000000
##  mau_kea_bins (Intercept) 0.000e+00 0.0000000
##  shr_bin      (Intercept) 0.000e+00 0.0000000
##  Residual                 2.979e+01 5.4579038
```

```
## Number of obs: 2613, groups:
## mau_loa_bins, 3; kil_bins, 3; hua_bins, 3; mau_kea_bins, 3; shr_bin, 3
##
## Fixed effects:
##                Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)    21.32011    4.33784  226.43137   4.915  1.7e-06 ***
## Year            0.07541    0.07310 2255.96598   1.032   0.3024
## dist_hil        0.94917    0.71718 1113.29140   1.323   0.1860
## dist_wai        0.02247    0.04951  197.63578   0.454   0.6505
## dist_kon       -0.01714    0.04271 1217.45699  -0.401   0.6882
## dist_poh       -0.14580    0.06900  253.55074  -2.113   0.0356 *
## dist_arm_res   -0.97412    0.72710 1112.86812  -1.340   0.1806
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Year   dst_hl dist_w dst_kn dst_ph
## Year        -0.256
## dist_hil     0.437 -0.020
## dist_wai    -0.525  0.069 -0.717
## dist_kon    -0.813  0.003 -0.009  0.155
## dist_poh     0.764 -0.062  0.207 -0.624 -0.749
## dist_arm_rs -0.487  0.014 -0.998  0.725  0.071 -0.260
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

```
#Mixed model for Mass
mas_lmer <- lmer(Mass~Year+dist_hil+dist_wai+dist_kon+dist_poh+dist_arm_res+
                   (1|mau_loa_bins)+(1|kil_bins)+(1|hua_bins)+(1|mau_kea_bins)+
                   (1|shr_bin),data=morph_spa_bins,REML=F)
```

```
## boundary (singular) fit: see help('isSingular')
```

```
summary(mas_lmer)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## Mass ~ Year + dist_hil + dist_wai + dist_kon + dist_poh + dist_arm_res +
##     (1 | mau_loa_bins) + (1 | kil_bins) + (1 | hua_bins) + (1 |
##     mau_kea_bins) + (1 | shr_bin)
##    Data: morph_spa_bins
##
##      AIC      BIC   logLik deviance df.resid
##  18441.0  18517.2  -9207.5  18415.0     2600
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0267 -0.4783 -0.2540  0.0876  4.8573
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  mau_loa_bins (Intercept)  0.00    0.000
```

```
##  kil_bins     (Intercept)  0.00    0.000
##  hua_bins     (Intercept)  0.00    0.000
##  mau_kea_bins (Intercept)  0.00    0.000
##  shr_bin      (Intercept)  0.00    0.000
##  Residual                 67.33    8.205
## Number of obs: 2613, groups:
## mau_loa_bins, 3; kil_bins, 3; hua_bins, 3; mau_kea_bins, 3; shr_bin, 3
##
## Fixed effects:
##                 Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)     15.07076    5.82909 2613.00000   2.585  0.00978 **
## Year            -0.18504    0.10186 2613.00000  -1.817  0.06940 .
## dist_hil         0.14581    0.74661 2613.00000   0.195  0.84517
## dist_wai         0.05237    0.05666 2613.00000   0.924  0.35546
## dist_kon         0.07763    0.06085 2613.00000   1.276  0.20219
## dist_poh        -0.21687    0.08806 2613.00000  -2.463  0.01386 *
## dist_arm_res    -0.06444    0.75994 2613.00000  -0.085  0.93243
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) Year   dst_hl dist_w dst_kn dst_ph
## Year         -0.348
## dist_hil      0.456 -0.423
## dist_wai     -0.418  0.190 -0.823
## dist_kon     -0.831 -0.019  0.061 -0.045
## dist_poh      0.790  0.005  0.326 -0.531 -0.724
## dist_arm_rs -0.530  0.409 -0.995  0.828  0.029 -0.405
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

##Model Dredging

Model Dredging using MuMIn function dredge()

```
wing_lmer_full <- lmer(Wing~Year+dist_hil+dist_wai+dist_kon+dist_poh+dist_arm_res+
                         (1|mau_loa_bins)+(1|kil_bins)+(1|hua_bins)+(1|mau_kea_bins)+
                         (1|shr_bin),data=morph_spa_bins,REML=F, na.action="na.fail")
```

```
## boundary (singular) fit: see help('isSingular')
```

```
wing_dredge <- dredge(wing_lmer_full, rank=AICc)
```

```
## Fixed term is "(Intercept)"
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
```

```
## boundary (singular) fit: see help('isSingular')
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## boundary (singular) fit: see help('isSingular')
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```
wing_dredge
```

```
## Global model call: lmer(formula = Wing ~ Year + dist_hil + dist_wai + dist_kon + 
##     dist_poh + dist_arm_res + (1 | mau_loa_bins) + (1 | kil_bins) + 
##     (1 | hua_bins) + (1 | mau_kea_bins) + (1 | shr_bin), data = morph_spa_bins, 
##     REML = F, na.action = "na.fail")
## ---
## Model selection table 
##    (Int) dst_arm_res    dst_hil   dst_kon   dst_poh    dst_wai     Yer df
## 57 78.06                                  -0.246400  0.0898200 -0.2200 10
## 58 78.26    0.016640                      -0.276000  0.1019000 -0.2541 11
## 59 78.32              0.0157700           -0.274300  0.1005000 -0.2539 11
## 61 78.95                        -0.009222 -0.255000  0.0973300 -0.2415 11
## 25 74.62                                  -0.273100  0.0988500          9
## 60 75.78    0.653300 -0.6249000           -0.303400  0.1409000 -0.2180 12
## 62 74.78    0.064270             0.042150 -0.321600  0.1021000 -0.2536 12
## 63 75.38              0.0574800  0.037610 -0.313200  0.0980800 -0.2558 12
## 28 71.24    1.319000 -1.3000000           -0.305000  0.1639000         11
## 26 74.37    0.008321                      -0.290200  0.1065000         10
## 27 74.40              0.0078020           -0.289200  0.1057000         10
## 29 74.72                        -0.002038 -0.275700  0.1010000         10
## 8  89.48   -1.937000  1.7430000 -0.182700                              10
## 64 72.66    0.667600 -0.5954000  0.039170 -0.344500  0.1393000 -0.2192 13
## 40 90.96   -1.823000  1.6460000 -0.167400                      -0.1818 11
## 41 79.96                                  -0.171000            -0.2196  9
## 54 88.92   -0.183000            -0.184500            0.0708700 -0.1927 11
## 44 79.98   -1.563000  1.5570000           -0.191800            -0.2028 11
## 55 88.71             -0.1850000 -0.190200            0.0796900 -0.1823 11
## 9  76.13                                  -0.179000                     8
## 30 71.45    0.048000             0.036050 -0.327600  0.1061000         11
## 12 77.07   -1.693000  1.6810000           -0.204000                    10
## 31 71.83              0.0436000  0.032600 -0.323200  0.1042000         11
## 22 86.58   -0.195000            -0.191000            0.0689300         10
## 23 85.96             -0.1929000 -0.187300            0.0750500         10
## 16 87.67   -1.939000  1.7740000 -0.155000 -0.035000                    11
## 42 80.34   -0.018600                      -0.153400            -0.2157 10
## 24 89.55   -2.078000  1.8860000 -0.178600           -0.0087950         11
## 45 79.10                         0.016230 -0.170100            -0.2217 10
## 38 88.31   -0.147000            -0.134800                      -0.1880 10
## 43 80.32             -0.0176100           -0.154000            -0.2165 10
## 48 88.68   -1.823000  1.6840000 -0.131800 -0.046570            -0.1837 12
## 6  86.31   -0.159700            -0.147200                               9
## 56 90.96   -1.829000  1.6520000 -0.167300           -0.0003261 -0.1817 12
## 39 87.76             -0.1418000 -0.128100                      -0.1922 10
## 10 77.09   -0.025640                      -0.161800                     9
## 11 77.04             -0.0243600           -0.162300                     9
## 7  85.66             -0.1542000 -0.140500                               9
## 13 75.40                         0.019800 -0.185800                     9
## 36 77.35   -1.647000  1.5270000                                -0.2086 10
## 32 85.81   -1.632000  1.4890000 -0.137700 -0.068050  0.0189400         12
## 46 86.06   -0.112100            -0.099140 -0.040720            -0.1929 11
## 47 79.14             -0.0005375  0.015750 -0.169600            -0.2215 11
```

```
## 14 86.46   -0.161900            -0.149500  0.002526                      10
## 52 80.50   -2.196000  2.0900000                      -0.0511300 -0.2424 11
## 15 82.19             -0.1030000 -0.087050 -0.061340                      10
## 4  74.23   -1.199000  1.0750000                                           9
## 20 78.71   -3.091000  2.9700000                      -0.0869100          10
## 2  73.44   -0.097490                                                      8
## 34 76.34   -0.092420                                            -0.1783  9
## 35 76.32             -0.0896600                                 -0.1817  9
## 3  73.40             -0.0953900                                           8
## 18 71.17   -0.109700                                  0.0369400           9
## 50 76.87   -0.087980                                 -0.0083180 -0.1851 10
## 19 70.98             -0.1057000                       0.0376400           9
## 51 77.01             -0.0845400                      -0.0107700 -0.1913 10
## 33 71.78                                                        -0.2303  8
## 49 66.47                                              0.0559100 -0.1635  9
## 1  67.51                                                                  7
## 17 64.17                                              0.0477400           8
## 37 72.14                        -0.005008                       -0.2325  9
## 53 68.80                        -0.035170             0.0644500 -0.1966 10
## 5  68.11                        -0.010950                                 8
## 21 64.60                        -0.007891             0.0491900           9
##       logLik    AICc delta weight
## 57 -9603.494 19227.1  0.00  0.207
## 58 -9603.291 19228.7  1.61  0.092
## 59 -9603.305 19228.7  1.64  0.091
## 61 -9603.406 19228.9  1.84  0.082
## 25 -9605.790 19229.6  2.58  0.057
## 60 -9603.031 19230.2  3.11  0.044
## 62 -9603.113 19230.3  3.27  0.040
## 63 -9603.163 19230.4  3.37  0.038
## 28 -9604.722 19231.5  4.47  0.022
## 26 -9605.752 19231.6  4.52  0.022
## 27 -9605.756 19231.6  4.53  0.022
## 29 -9605.787 19231.7  4.59  0.021
## 8  -9605.905 19231.9  4.82  0.019
## 64 -9602.878 19231.9  4.82  0.019
## 40 -9604.966 19232.0  4.96  0.017
## 41 -9607.123 19232.3  5.24  0.015
## 54 -9605.330 19232.8  5.69  0.012
## 44 -9605.468 19233.0  5.96  0.010
## 55 -9605.505 19233.1  6.04  0.010
## 9  -9608.536 19233.1  6.06  0.010
## 30 -9605.624 19233.3  6.28  0.009
## 12 -9606.641 19233.4  6.29  0.009
## 31 -9605.651 19233.4  6.33  0.009
## 22 -9606.710 19233.5  6.43  0.008
## 23 -9606.860 19233.8  6.73  0.007
## 16 -9605.876 19233.9  6.78  0.007
## 42 -9606.899 19233.9  6.81  0.007
## 24 -9605.898 19233.9  6.82  0.007
## 45 -9606.914 19233.9  6.84  0.007
## 38 -9606.916 19233.9  6.85  0.007
## 43 -9606.929 19233.9  6.87  0.007
## 48 -9604.916 19234.0  6.88  0.007
```

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## 6  -9607.947 19234.0  6.89  0.007
## 56 -9604.966 19234.1  6.98  0.006
## 39 -9607.219 19234.5  7.45  0.005
## 10 -9608.240 19234.5  7.48  0.005
## 11 -9608.284 19234.6  7.57  0.005
## 7  -9608.295 19234.7  7.59  0.005
## 13 -9608.317 19234.7  7.63  0.005
## 36 -9607.732 19235.5  8.48  0.003
## 32 -9605.866 19235.9  8.78  0.003
## 46 -9606.893 19235.9  8.82  0.003
## 47 -9606.914 19235.9  8.86  0.002
## 14 -9607.947 19236.0  8.91  0.002
## 52 -9607.059 19236.2  9.15  0.002
## 15 -9608.241 19236.6  9.49  0.002
## 4  -9609.374 19236.8  9.75  0.002
## 20 -9608.648 19237.4 10.31  0.001
## 2  -9611.269 19238.6 11.52  0.001
## 34 -9610.267 19238.6 11.53  0.001
## 35 -9610.453 19239.0 11.90  0.001
## 3  -9611.510 19239.1 12.00  0.001
## 18 -9611.053 19240.2 13.10  0.000
## 50 -9610.260 19240.6 13.53  0.000
## 19 -9611.342 19240.8 13.68  0.000
## 51 -9610.433 19241.0 13.88  0.000
## 33 -9613.300 19242.7 15.58  0.000
## 49 -9612.822 19243.7 16.64  0.000
## 1  -9614.910 19243.9 16.79  0.000
## 17 -9614.130 19244.3 17.24  0.000
## 37 -9613.290 19244.6 17.58  0.000
## 53 -9612.466 19245.0 17.94  0.000
## 5  -9615.050 19246.2 19.08  0.000
## 21 -9614.110 19246.3 19.22  0.000
## Models ranked by AICc(x)
## Random terms (all models):
##   1 | mau_loa_bins, 1 | kil_bins, 1 | hua_bins, 1 | mau_kea_bins, 1 | shr_bin
```

```
cul_lmer_full <- lmer(Culmen~Year+dist_hil+dist_wai+dist_kon+dist_poh+dist_arm_res+
                        (1|mau_loa_bins)+(1|kil_bins)+(1|hua_bins)+(1|mau_kea_bins)+
                        (1|shr_bin),data=morph_spa_bins,REML=F, na.action="na.fail")
```

```
## boundary (singular) fit: see help('isSingular')
```

```
cul_dredge <- dredge(cul_lmer_full, rank=AICc)
```

```
## Fixed term is "(Intercept)"
## boundary (singular) fit: see help('isSingular')
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## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
```

```
cul_dredge
```

```
## Global model call: lmer(formula = Culmen ~ Year + dist_hil + dist_wai + dist_kon +
##     dist_poh + dist_arm_res + (1 | mau_loa_bins) + (1 | kil_bins) +
##     (1 | hua_bins) + (1 | mau_kea_bins) + (1 | shr_bin), data = morph_spa_bins,
##     REML = F, na.action = "na.fail")
## ---
## Model selection table
##    (Int) dst_arm_res   dst_hil   dst_kon  dst_poh   dst_wai     Yer df
## 25 18.79                                 -0.16360  0.062100          9
## 12 21.42   -1.162000  1.163000           -0.14680                   10
## 57 17.53                                 -0.17660  0.068390 0.07845 10
## 27 18.06              0.022770           -0.18710  0.068630         10
## 44 20.61   -1.219000  1.214000           -0.14900           0.07128 11
## 29 19.56                       -0.016240 -0.16190  0.064370         10
## 26 18.02    0.022330                     -0.18650  0.069300         10
## 9  19.73                                 -0.09892                    8
## 28 20.55   -0.898000  0.903800           -0.16430  0.023470         11
## 16 23.28   -1.154000  1.128000 -0.020300 -0.12330                   11
## 59 17.09              0.017850           -0.19080  0.071620 0.06800 11
## 61 18.24                       -0.012740 -0.17160  0.068650 0.06964 11
## 58 17.07    0.017100                     -0.19000  0.072040 0.06854 11
## 41 18.86                                 -0.10340           0.05739  9
## 60 19.67   -0.937600  0.935900           -0.16810  0.025880 0.07370 12
## 48 22.35   -1.211000  1.180000 -0.020190 -0.12610           0.07298 12
## 13 20.18                       -0.008341 -0.09827                    9
## 31 18.51              0.016420 -0.005279 -0.18030  0.067830         11
## 11 19.54              0.006989           -0.10490                    9
## 30 18.82    0.011350           -0.008863 -0.17460  0.067320         11
## 10 19.60    0.004912                     -0.10320                    9
## 32 21.92   -0.928600  0.915700 -0.014120 -0.14560  0.020210         12
## 63 17.62              0.010320 -0.006160 -0.18280  0.070650 0.06821 12
## 62 17.98    0.004220           -0.010150 -0.17620  0.069670 0.06904 12
## 45 19.23                       -0.006369 -0.10170           0.05279 10
## 43 18.77              0.003796           -0.10590           0.05500 10
## 14 22.26   -0.030680           -0.032460 -0.06982                   10
## 42 18.82    0.001370                     -0.10420           0.05653 10
## 6  26.41   -0.095500           -0.085220                             9
## 64 21.32   -0.974100  0.949200 -0.017140 -0.14580  0.022470 0.07541 13
## 15 21.58             -0.021030 -0.024610 -0.07835                   10
## 8  28.71   -0.732500  0.613200 -0.102000                            10
## 7  26.00             -0.091250 -0.082170                             9
## 24 28.98   -1.303000  1.199000 -0.082870          -0.041630         11
## 46 21.50   -0.034790           -0.033340 -0.07002           0.05817 11
## 38 25.67   -0.099740           -0.086250                    0.05761 10
## 40 28.20   -0.840200  0.712900 -0.108000                    0.06849 11
## 47 20.82             -0.024750 -0.025280 -0.07863           0.05619 11
## 22 26.83   -0.103900           -0.092450           0.008941         10
## 39 25.27             -0.095140 -0.083080                    0.05537 10
## 23 26.54             -0.102200 -0.091780           0.012030         10
## 56 28.33   -1.352000  1.242000 -0.086390          -0.040820 0.06490 12
```

```
## 54 26.11   -0.109100           -0.094180           0.009861 0.05901 11
## 55 25.83             -0.107200 -0.093450           0.013060 0.05733 11
## 20 24.41   -2.220000  2.180000                    -0.126600         10
## 52 23.70   -2.268000  2.223000                    -0.127800 0.05769 11
## 5  17.23                       -0.028480                              8
## 4  15.02   -1.490000  1.489000                                        9
## 1  15.51                                                              7
## 36 13.74   -1.622000  1.616000                              0.08354 10
## 18 20.27   -0.029240                              -0.045660          9
## 19 20.20             -0.028520                    -0.045000          9
## 17 18.32                                          -0.045750          8
## 21 18.26                       -0.025390          -0.019800          9
## 37 16.59                       -0.027620                    0.03212  9
## 33 14.62                                                    0.04750  8
## 2  16.11   -0.009352                                                 8
## 3  16.04             -0.008256                                       8
## 50 19.70   -0.031510                              -0.046030 0.03978 10
## 51 19.64             -0.030680                    -0.045300 0.03856 10
## 49 17.45                                          -0.040320 0.02961  9
## 53 17.59                       -0.025020          -0.017630 0.02802 10
## 34 15.28   -0.012270                                        0.05461  9
## 35 15.22             -0.011040                              0.05353  9
##        logLik    AICc delta weight
## 25 -8149.430 16316.9  0.00  0.103
## 12 -8148.552 16317.2  0.26  0.091
## 57 -8148.831 16317.7  0.82  0.068
## 27 -8149.078 16318.2  1.31  0.053
## 44 -8148.093 16318.3  1.36  0.052
## 29 -8149.106 16318.3  1.37  0.052
## 26 -8149.109 16318.3  1.37  0.052
## 9  -8151.158 16318.4  1.44  0.050
## 28 -8148.442 16319.0  2.06  0.037
## 16 -8148.481 16319.1  2.13  0.035
## 59 -8148.661 16319.4  2.49  0.030
## 61 -8148.665 16319.4  2.50  0.029
## 58 -8148.687 16319.5  2.55  0.029
## 41 -8150.838 16319.7  2.81  0.025
## 60 -8147.957 16320.0  3.10  0.022
## 48 -8147.994 16320.1  3.18  0.021
## 13 -8151.027 16320.1  3.19  0.021
## 31 -8149.071 16320.2  3.31  0.020
## 11 -8151.102 16320.3  3.34  0.019
## 30 -8149.091 16320.3  3.35  0.019
## 10 -8151.129 16320.3  3.40  0.019
## 32 -8148.403 16320.9  4.00  0.014
## 63 -8148.652 16321.4  4.49  0.011
## 62 -8148.663 16321.4  4.52  0.011
## 45 -8150.768 16321.6  4.69  0.010
## 43 -8150.824 16321.7  4.80  0.009
## 14 -8150.828 16321.7  4.81  0.009
## 42 -8150.836 16321.8  4.83  0.009
## 6  -8151.866 16321.8  4.87  0.009
## 64 -8147.892 16321.9  4.99  0.008
## 15 -8150.939 16322.0  5.03  0.008
```

```
## 8  -8151.034 16322.2  5.22  0.008
## 7  -8152.149 16322.4  5.44  0.007
## 24 -8150.476 16323.1  6.12  0.005
## 46 -8150.517 16323.1  6.21  0.005
## 38 -8151.561 16323.2  6.28  0.004
## 40 -8150.622 16323.3  6.42  0.004
## 47 -8150.649 16323.4  6.47  0.004
## 22 -8151.795 16323.7  6.74  0.004
## 39 -8151.867 16323.8  6.89  0.003
## 23 -8152.030 16324.1  7.21  0.003
## 56 -8150.099 16324.3  7.39  0.003
## 54 -8151.476 16325.1  8.12  0.002
## 55 -8151.729 16325.6  8.63  0.001
## 20 -8153.533 16327.2 10.22  0.001
## 52 -8153.228 16328.6 11.63  0.000
## 5  -8157.945 16331.9 15.02  0.000
## 4  -8157.009 16332.1 15.16  0.000
## 1  -8159.130 16332.3 15.37  0.000
## 36 -8156.379 16332.8 15.91  0.000
## 18 -8157.393 16332.9 15.92  0.000
## 19 -8157.484 16333.0 16.11  0.000
## 17 -8158.590 16333.2 16.31  0.000
## 21 -8157.827 16333.7 16.79  0.000
## 37 -8157.849 16333.8 16.84  0.000
## 33 -8158.918 16333.9 16.96  0.000
## 2  -8159.054 16334.2 17.23  0.000
## 3  -8159.077 16334.2 17.28  0.000
## 50 -8157.248 16334.6 17.65  0.000
## 51 -8157.347 16334.8 17.85  0.000
## 49 -8158.515 16335.1 18.17  0.000
## 53 -8157.756 16335.6 18.67  0.000
## 34 -8158.783 16335.6 18.70  0.000
## 35 -8158.816 16335.7 18.77  0.000
## Models ranked by AICc(x)
## Random terms (all models):
##   1 | mau_loa_bins, 1 | kil_bins, 1 | hua_bins, 1 | mau_kea_bins, 1 | shr_bin
```

```r
mass_lmer_full <- lmer(Mass~Year+dist_hil+dist_wai+dist_kon+dist_poh+dist_arm_res+
                          (1|mau_loa_bins)+(1|kil_bins)+(1|hua_bins)+(1|mau_kea_bins)+
                          (1|shr_bin),data=morph_spa_bins,REML=F, na.action="na.fail")
```

```
## boundary (singular) fit: see help('isSingular')
```

```r
mass_dredge <- dredge(mass_lmer_full, rank=AICc)
```

```
## Fixed term is "(Intercept)"
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
```

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## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
```

```
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
## boundary (singular) fit: see help('isSingular')
```

```
mass_dredge
```

```
## Global model call: lmer(formula = Mass ~ Year + dist_hil + dist_wai + dist_kon +
##     dist_poh + dist_arm_res + (1 | mau_loa_bins) + (1 | kil_bins) +
##     (1 | hua_bins) + (1 | mau_kea_bins) + (1 | shr_bin), data = morph_spa_bins,
##     REML = F, na.action = "na.fail")
## ---
## Model selection table
##    (Int) dst_arm_res   dst_hil   dst_kon  dst_poh   dst_wai     Yer df
## 57 20.95                                  -0.14580  0.063680 -0.1850 10
## 61 19.95                         0.010320 -0.13610  0.055260 -0.1609 11
## 58 20.90   -0.003613                      -0.13930  0.061050 -0.1776 11
## 59 20.89             -0.003466            -0.13960  0.061330 -0.1775 11
## 63 14.81              0.082790  0.077780 -0.21990  0.056350 -0.1815 12
## 62 14.55    0.083300            0.076900 -0.22250  0.061470 -0.1766 12
## 13 17.13                        0.035130 -0.09373                     9
## 45 19.34                        0.026240 -0.08635           -0.1149 10
## 29 16.94                        0.026390 -0.13100  0.039040          10
## 44 23.86   -0.712200  0.689200           -0.08672           -0.2016 11
## 48 17.32   -0.646000  0.713500  0.080140 -0.17370           -0.2029 12
## 41 22.34                                  -0.09327           -0.1716  9
## 25 18.75                                  -0.16060  0.058990           9
## 47 14.42              0.079110  0.091000 -0.16550           -0.1337 11
## 10 20.04   -0.036610                      -0.06022                     9
## 42 21.63   -0.025150                      -0.06344           -0.1238 10
## 27 18.98             -0.024930            -0.11210  0.043460          10
## 26 19.06   -0.025210                      -0.11150  0.042000          10
## 11 19.98             -0.035650            -0.06008                     9
## 15 13.20              0.058880  0.084410 -0.15350                    10
## 43 21.60             -0.023740            -0.06440           -0.1240 10
## 14 13.73    0.050070            0.076710 -0.14270                    10
## 60 21.25   -0.092690  0.087430           -0.13550  0.055590 -0.1826 12
## 46 15.39    0.060270            0.075710 -0.14480           -0.1225 11
## 30 12.64    0.062880            0.077840 -0.19580  0.042530          11
## 31 13.17              0.056450  0.073800 -0.18760  0.038360          11
## 64 15.07   -0.064440  0.145800  0.077630 -0.21690  0.052370 -0.1850 13
## 12 20.53   -0.318800  0.280200           -0.06886                    10
## 2  19.26   -0.062060                                                  8
## 3  19.17             -0.060740                                        8
## 28 17.45    0.465200 -0.478100           -0.13680  0.074830          11
## 16 14.08   -0.251000  0.301300  0.078850 -0.15430                    11
## 9  18.79                                  -0.08879                     8
## 34 20.66   -0.052980                                         -0.1113  9
## 32 11.38    0.500000 -0.428500  0.075560 -0.21600  0.071940          12
## 35 20.52             -0.052010                               -0.1070  9
## 38 23.94   -0.074740           -0.033120                     -0.1189 10
## 7  21.85             -0.079210 -0.028090                               9
## 39 23.44             -0.071230 -0.029920                     -0.1126 10
## 18 19.69   -0.059350                                -0.011070          9
## 6  21.81   -0.076500           -0.036560                               9
```

```
## 19 19.51            -0.058540                       -0.008677          9
## 40 26.27   -0.721800  0.639800 -0.056730                      -0.1818 11
## 50 20.89   -0.051520                                 -0.007600 -0.1064 10
## 51 20.71            -0.050820                       -0.005726 -0.1039 10
## 52 23.96   -1.185000  1.138000                       -0.049540 -0.1897 11
## 36 20.46   -0.541900  0.491000                                 -0.1462 10
## 20 20.97   -0.480900  0.417500                       -0.029220         10
## 54 25.19   -0.089570           -0.071600            0.029570 -0.1385 11
## 4  18.43   -0.217000  0.160300                                          9
## 8  22.41   -0.356500  0.273900 -0.043450                               10
## 22 22.46   -0.089030           -0.055640            0.018290         10
## 55 24.94            -0.089410 -0.072640            0.033380 -0.1329 11
## 23 22.39            -0.089900 -0.058230            0.023150         10
## 56 26.23   -0.878400  0.802700 -0.046850           -0.013800 -0.1881 12
## 33 17.48                                                  -0.1443  8
## 24 22.48   -0.294000  0.208700 -0.047960            0.006040         11
## 1  14.86                                                            7
## 37 17.11                      0.008172                      -0.1472  9
## 49 17.04                                          0.005688 -0.1408  9
## 5  13.93                      0.016580                               8
## 17 14.60                                          0.004041          8
## 53 19.44                      0.049540           -0.054290 -0.2059 10
## 21 14.38                      0.021510           -0.011010          9
##       logLik    AICc delta weight
## 57 -9208.314 18436.7  0.00  0.132
## 61 -9208.165 18438.4  1.72  0.056
## 58 -9208.301 18438.7  1.99  0.049
## 59 -9208.302 18438.7  1.99  0.049
## 63 -9207.485 18439.1  2.38  0.040
## 62 -9207.500 18439.1  2.41  0.040
## 13 -9210.540 18439.1  2.44  0.039
## 45 -9209.677 18439.4  2.73  0.034
## 29 -9209.717 18439.5  2.81  0.032
## 44 -9208.776 18439.7  2.94  0.030
## 48 -9207.908 18439.9  3.22  0.026
## 41 -9210.937 18439.9  3.23  0.026
## 25 -9210.988 18440.0  3.33  0.025
## 47 -9209.056 18440.2  3.50  0.023
## 10 -9211.087 18440.2  3.53  0.023
## 42 -9210.095 18440.3  3.56  0.022
## 27 -9210.125 18440.3  3.62  0.022
## 26 -9210.150 18440.4  3.67  0.021
## 11 -9211.164 18440.4  3.68  0.021
## 15 -9210.184 18440.5  3.74  0.020
## 43 -9210.190 18440.5  3.75  0.020
## 14 -9210.291 18440.7  3.95  0.018
## 60 -9208.295 18440.7  4.00  0.018
## 46 -9209.320 18440.7  4.03  0.018
## 30 -9209.330 18440.8  4.05  0.017
## 31 -9209.389 18440.9  4.17  0.016
## 64 -9207.481 18441.1  4.39  0.015
## 12 -9210.804 18441.7  4.98  0.011
## 2  -9212.877 18441.8  5.10  0.010
## 3  -9212.903 18441.9  5.15  0.010
```

```
## 28 -9209.900 18441.9  5.19  0.010
## 16 -9209.965 18442.0  5.32  0.009
## 9  -9213.039 18442.1  5.42  0.009
## 34 -9212.074 18442.2  5.50  0.008
## 32 -9209.130 18442.4  5.67  0.008
## 35 -9212.172 18442.4  5.70  0.008
## 38 -9211.303 18442.7  5.98  0.007
## 7  -9212.329 18442.7  6.01  0.007
## 39 -9211.523 18443.1  6.42  0.005
## 18 -9212.723 18443.5  6.80  0.004
## 6  -9212.783 18443.6  6.92  0.004
## 19 -9212.810 18443.7  6.98  0.004
## 40 -9210.880 18443.9  7.15  0.004
## 50 -9212.002 18444.1  7.38  0.003
## 51 -9212.132 18444.3  7.64  0.003
## 52 -9211.335 18444.8  8.06  0.002
## 36 -9212.416 18444.9  8.20  0.002
## 20 -9212.431 18444.9  8.23  0.002
## 54 -9211.448 18445.0  8.28  0.002
## 4  -9213.526 18445.1  8.41  0.002
## 8  -9212.547 18445.2  8.47  0.002
## 22 -9212.591 18445.3  8.55  0.002
## 55 -9211.592 18445.3  8.57  0.002
## 23 -9212.645 18445.4  8.66  0.002
## 56 -9210.841 18445.8  9.09  0.001
## 33 -9215.299 18446.7  9.94  0.001
## 24 -9212.540 18447.2 10.47  0.001
## 1  -9216.599 18447.2 10.53  0.001
## 37 -9215.258 18448.6 11.87  0.000
## 49 -9215.285 18448.6 11.93  0.000
## 5  -9216.386 18448.8 12.11  0.000
## 17 -9216.591 18449.2 12.52  0.000
## 53 -9214.658 18449.4 12.69  0.000
## 21 -9216.349 18450.8 14.05  0.000
## Models ranked by AICc(x)
## Random terms (all models):
##   1 | mau_loa_bins, 1 | kil_bins, 1 | hua_bins, 1 | mau_kea_bins, 1 | shr_bin
```

##Model Averaging (after dredge)

```
top_wing_avg <- model.avg(wing_dredge, subset = delta <=2)
summary(top_wing_avg)
```

```
##
## Call:
## model.avg(object = wing_dredge, subset = delta <= 2)
##
## Component model call:
## lmer(formula = Wing ~ <4 unique rhs>, data = morph_spa_bins, REML = F,
##      na.action = na.fail)
##
## Component models:
##      df   logLik     AICc delta weight
```

```
## 456  10 -9603.49 19227.07  0.00   0.44
## 1456 11 -9603.29 19228.68  1.61   0.20
## 2456 11 -9603.30 19228.71  1.64   0.19
## 3456 11 -9603.41 19228.91  1.84   0.17
##
## Term codes:
## dist_arm_res     dist_hil     dist_kon     dist_poh     dist_wai         Year
##            1            2            3            4            5            6
##
## Model-averaged coefficients:
## (full average)
##               Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)  78.302721   1.792316    1.793124  43.668  < 2e-16 ***
## dist_poh     -0.259061   0.049408    0.049429   5.241    2e-07 ***
## dist_wai      0.095545   0.035454    0.035470   2.694  0.00707 **
## Year         -0.236927   0.102463    0.102510   2.311  0.02082 *
## dist_arm_res  0.003251   0.013302    0.013307   0.244  0.80698
## dist_hil      0.003040   0.012861    0.012865   0.236  0.81319
## dist_kon     -0.001607   0.009817    0.009821   0.164  0.87002
##
## (conditional average)
##               Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)  78.302721   1.792316    1.793124  43.668  < 2e-16 ***
## dist_poh     -0.259061   0.049408    0.049429   5.241    2e-07 ***
## dist_wai      0.095545   0.035454    0.035470   2.694  0.00707 **
## Year         -0.236927   0.102463    0.102510   2.311  0.02082 *
## dist_arm_res  0.016636   0.026130    0.026142   0.636  0.52453
## dist_hil      0.015767   0.025634    0.025646   0.615  0.53869
## dist_kon     -0.009222   0.021973    0.021984   0.419  0.67486
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
top_cul_avg <- model.avg(cul_dredge, subset = delta <=2)
summary(top_cul_avg)
```

```
##
## Call:
## model.avg(object = cul_dredge, subset = delta <= 2)
##
## Component model call:
## lmer(formula = Culmen ~ <8 unique rhs>, data = morph_spa_bins, REML =
##      F, na.action = na.fail)
##
## Component models:
##      df   logLik     AICc delta weight
## 45    9 -8149.43 16316.93  0.00   0.20
## 124  10 -8148.55 16317.19  0.26   0.17
## 456  10 -8148.83 16317.75  0.82   0.13
## 245  10 -8149.08 16318.24  1.31   0.10
## 1246 11 -8148.09 16318.29  1.36   0.10
## 345  10 -8149.11 16318.30  1.37   0.10
## 145  10 -8149.11 16318.30  1.37   0.10
## 4     8 -8151.16 16318.37  1.44   0.10
##
```

```
## Term codes:
## dist_arm_res     dist_hil     dist_kon     dist_poh     dist_wai         Year
##            1            2            3            4            5            6
##
## Model-averaged coefficients:
## (full average)
##              Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)  19.280376   1.896051    1.896501  10.166  < 2e-16 ***
## dist_poh     -0.159236   0.042965    0.042979   3.705 0.000211 ***
## dist_wai      0.041576   0.041073    0.041081   1.012 0.311511
## dist_arm_res -0.321657   0.588920    0.588973   0.546 0.584975
## dist_hil      0.325823   0.584794    0.584847   0.557 0.577453
## Year          0.017436   0.046880    0.046891   0.372 0.710010
## dist_kon     -0.001618   0.006917    0.006919   0.234 0.815095
##
## (conditional average)
##             Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)  19.28038    1.89605     1.89650  10.166  < 2e-16 ***
## dist_poh     -0.15924    0.04297     0.04298   3.705 0.000211 ***
## dist_wai      0.06597    0.03267     0.03269   2.018 0.043590 *
## dist_arm_res -0.86216    0.68090     0.68102   1.266 0.205518
## dist_hil      0.86592    0.66422     0.66434   1.303 0.192430
## Year          0.07534    0.07165     0.07168   1.051 0.293212
## dist_kon     -0.01624    0.01558     0.01559   1.041 0.297648
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
top_mass_avg <- model.avg(mass_dredge, subset = delta <=2)
summary(top_mass_avg)
```

```
##
## Call:
## model.avg(object = mass_dredge, subset = delta <= 2)
##
## Component model call:
## lmer(formula = Mass ~ <4 unique rhs>, data = morph_spa_bins, REML = F,
##      na.action = na.fail)
##
## Component models:
##      df   logLik     AICc delta weight
## 456  10 -9208.31 18436.71  0.00   0.46
## 3456 11 -9208.17 18438.43  1.72   0.20
## 1456 11 -9208.30 18438.70  1.99   0.17
## 2456 11 -9208.30 18438.71  1.99   0.17
##
## Term codes:
## dist_arm_res     dist_hil     dist_kon     dist_poh     dist_wai         Year
##            1            2            3            4            5            6
##
## Model-averaged coefficients:
## (full average)
##               Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)  20.7345217  1.5866660   1.5873604  13.062  < 2e-16 ***
## dist_poh     -0.1417178  0.0402988   0.0403173   3.515  0.00044 ***
```

```
## dist_wai      0.0611804  0.0301997   0.0302136   2.025  0.04287 *
## Year         -0.1777220  0.0871752   0.0872153   2.038  0.04158 *
## dist_kon      0.0020213  0.0093087   0.0093122   0.217  0.82817
## dist_arm_res -0.0006174  0.0093854   0.0093897   0.066  0.94758
## dist_hil     -0.0005920  0.0092006   0.0092048   0.064  0.94872
##
## (conditional average)
##               Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)  20.734522   1.586666    1.587360  13.062  < 2e-16 ***
## dist_poh     -0.141718   0.040299    0.040317   3.515  0.00044 ***
## dist_wai      0.061180   0.030200    0.030214   2.025  0.04287 *
## Year         -0.177722   0.087175    0.087215   2.038  0.04158 *
## dist_kon      0.010320   0.018889    0.018898   0.546  0.58498
## dist_arm_res -0.003613   0.022464    0.022474   0.161  0.87229
## dist_hil     -0.003466   0.022038    0.022048   0.157  0.87508
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
coefTable(top_wing_avg,full=T)
```

```
##                Estimate Std. Error
## (Intercept)  78.3027212     1.7931
## dist_poh     -0.2590612     0.0494
## dist_wai      0.0955451     0.0355
## Year         -0.2369269     0.1025
## dist_arm_res  0.0032513     0.0133
## dist_hil      0.0030401     0.0129
## dist_kon     -0.0016071     0.0098
```

```
coefTable(top_cul_avg,full=T)
```

```
##               Estimate Std. Error
## (Intercept)  19.280376     1.8965
## dist_poh     -0.159236     0.0430
## dist_wai      0.041576     0.0411
## dist_arm_res -0.321657     0.5890
## dist_hil      0.325823     0.5848
## Year          0.017436     0.0469
## dist_kon     -0.001618     0.0069
```

```
coefTable(top_mass_avg,full=T)
```

```
##                 Estimate Std. Error
## (Intercept)  20.73452166     1.5874
## dist_poh     -0.14171783     0.0403
## dist_wai      0.06118039     0.0302
## Year         -0.17772200     0.0872
## dist_kon      0.00202126     0.0093
## dist_arm_res -0.00061737     0.0094
## dist_hil     -0.00059201     0.0092
```

#Appendix A; exporting cleaned-up Dataset

```r
write.csv(morph_spa_bins, "Cleaned_Dataset_final.csv", row.names = FALSE)
```

R package Citations

```r
packs <- c("tidyverse","ggplot2","maps","sp","sf","s2","rgdal","mapproj","ggfortify","usethis",
           "ggmap","mapview","arules","stringr","lme4","lmerTest","nlme","MuMIn","report",
           "geosphere","osmdata","arsenal")
for(i in 1:length(packs)){
  citation(packs[i])
}
```