Climate Water Loss Experiment - Capture Hydration Analysis

Savannah Weaver

2021

Contents

Packages

```
if (!require("tidyverse")) install.packages("tidyverse")
library("tidyverse") # workflow and plots
if (!require("zoo")) install.packages("zoo")
library("zoo") # interpolation using na.approx
if (!require("weathermetrics")) install.packages("weathermetrics")
library("weathermetrics") # F to C conversion
if (!require("lme4")) install.packages("lme4")
library("lme4") # for LMMs
if (!require("lmerTest")) install.packages("lmerTest")
library("lmerTest") # for p-values
if (!require("UsingR")) install.packages("UsingR")
library("UsingR") # simple.eda model assumption checker
if (!require("ggpubr")) install.packages("ggpubr")
library("ggpubr") # for multi-ggplot figs
if (!require("broom")) install.packages("broom")
library("broom") # lmer model export
if (!require("broom.mixed")) install.packages("broom.mixed")
library("broom.mixed") # lmer model export
if (!require("AICcmodavg")) install.packages("AICcmodavg")
library("AICcmodavg") # model selection
if (!require("car")) install.packages("car")
library("car") # VIFs
```

Background and Goals

This data was collected June - August by Master's student Savannah Weaver, advisor Dr. Emily Taylor, and research assistants Tess McIntyre and Taylor Van Rossum. Adult male *Sceloporus occidentalis* were caught across the Cal Poly campus and in Poly Canyon. This R file analyzes the state and variation of osmotic balance and regulation at the time of capture. Please refer to **doi:** for the published scientific journal article and full details.

Data

Load

Read-in and attach all data. Details described later.

```
        # mass and hematocrit data
full_dat <- read.csv("./data/mass_hct_notes.csv", # filename
                             na.strings=c("","NA") # fix empty cells
                             ) %>%
        # format date to enable joining by date
  mutate(measurement_date = as.character(as.Date(measurement_date,
                                          format = "%m/%d/%y"))
         ) %>%
        # join plasma osmolality data
  left_join(read.csv("./data/osml_means_clean.csv", # filename
                             na.strings=c("","NA") # fix empty cells
            ), by = c("individual_ID",
                      "measurement_date" = "date_blood_drawn")
            ) %>%
        # join CEWL data
  left_join(read.csv("./data/CEWL_dat_all_clean.csv", # filename
                             na.strings=c("","NA") # fix empty cells
            ), by = c("individual_ID",
                      "measurement_date" = "date")
            ) %>%
        # select variables of interest only
  dplyr::select(measurement_date,
                time_captured,
                time_processed,
                time_c_temp,
                type, day,
                individual_ID,
                mass_g,
                hemolyzed,
                hematocrit_percent,
                osmolality_mmol_kg_mean,
                CEWL_g_m2h_mean = CEWL_g_m2h,
                msmt_temp_C,
                msmt_RH_percent,
                cloacal_temp_C
                ) %>%
          # format date-time-related variables
  mutate(measurement_date = as.Date(measurement_date,
                                    format = "%Y-%m-%d"),
         # compute vapor pressure deficit
         msmt_temp_K = msmt_temp_C + 273.15,
         # find saturation level first
         e_s_kPa_m = 0.611*exp((2500000/461.5)*
                               ((1/273)-(1/msmt_temp_K))),
         # actual vapor pressure
         e_a_kPa_m = e_s_kPa_m * (msmt_RH_percent/100),
         # VPD
         msmt_VPD_kPa = e_s_kPa_m - e_a_kPa_m
         ) %>%
```

```r
  group_by(individual_ID) %>%
          # for each individual, extract capture date
  mutate(capture_date = min(measurement_date),
         day_n = as.numeric(measurement_date - capture_date))

summary(full_dat)
```

```
##  measurement_date     time_captured      time_processed     time_c_temp       
##  Min.   :2021-06-16   Length:957         Length:957         Length:957        
##  1st Qu.:2021-06-30   Class :character   Class :character   Class :character  
##  Median :2021-07-25   Mode  :character   Mode  :character   Mode  :character  
##  Mean   :2021-07-22                                                            
##  3rd Qu.:2021-08-14                                                            
##  Max.   :2021-09-01                                                            
##                                                                                
##      type               day            individual_ID       mass_g     
##  Length:957         Length:957         Min.   :201.0   Min.   : 7.00  
##  Class :character   Class :character   1st Qu.:236.0   1st Qu.: 9.50  
##  Mode  :character   Mode  :character   Median :271.0   Median :10.60  
##                                        Mean   :271.3   Mean   :10.62  
##                                        3rd Qu.:307.0   3rd Qu.:11.60  
##                                        Max.   :341.0   Max.   :17.40  
##                                                                       
##   hemolyzed         hematocrit_percent osmolality_mmol_kg_mean CEWL_g_m2h_mean
##  Length:957         Min.   :13.00      Min.   :295.3           Min.   : 7.152 
##  Class :character   1st Qu.:26.00      1st Qu.:336.3           1st Qu.:19.727 
##  Mode  :character   Median :32.00      Median :352.0           Median :24.152 
##                     Mean   :32.09      Mean   :358.1           Mean   :24.909 
##                     3rd Qu.:38.00      3rd Qu.:371.0           3rd Qu.:28.486 
##                     Max.   :52.00      Max.   :576.0           Max.   :79.267 
##                     NA's   :417        NA's   :414             NA's   :684    
##   msmt_temp_C    msmt_RH_percent cloacal_temp_C   msmt_temp_K   
##  Min.   :24.80   Min.   :25.52   Min.   :23.00   Min.   :297.9  
##  1st Qu.:26.27   1st Qu.:46.07   1st Qu.:25.00   1st Qu.:299.4  
##  Median :26.75   Median :47.80   Median :26.00   Median :299.9  
##  Mean   :26.73   Mean   :46.67   Mean   :25.93   Mean   :299.9  
##  3rd Qu.:27.12   3rd Qu.:50.48   3rd Qu.:27.00   3rd Qu.:300.3  
##  Max.   :29.20   Max.   :56.16   Max.   :30.00   Max.   :302.4  
##  NA's   :684     NA's   :684     NA's   :684     NA's   :684    
##    e_s_kPa_m       e_a_kPa_m       msmt_VPD_kPa    capture_date       
##  Min.   :3.219   Min.   :0.9894   Min.   :1.486   Min.   :2021-06-16  
##  1st Qu.:3.518   1st Qu.:1.6467   1st Qu.:1.784   1st Qu.:2021-06-26  
##  Median :3.623   Median :1.7394   Median :1.854   Median :2021-07-20  
##  Mean   :3.623   Mean   :1.6818   Mean   :1.941   Mean   :2021-07-17  
##  3rd Qu.:3.704   3rd Qu.:1.7986   3rd Qu.:2.017   3rd Qu.:2021-08-08  
##  Max.   :4.194   Max.   :1.9326   Max.   :3.021   Max.   :2021-08-22  
##  NA's   :684     NA's   :684      NA's   :684                         
##      day_n       
##  Min.   : 0.000  
##  1st Qu.: 4.000  
##  Median : 6.000  
##  Mean   : 5.658  
##  3rd Qu.: 8.000  
##  Max.   :10.000  
```

```
##
```

```r
# check
unique(full_dat$capture_date)
```

```
## [1] "2021-06-16" "2021-06-26" "2021-07-20" "2021-08-08" "2021-08-22"
```

Export

Export full_dat to be used in 'experiment_analysis'.

```r
write.csv(full_dat, "./data/full_exp_data.csv")
```

Format

Extract only the data from capture day (1 row of observations for each individual) and format the data classes properly for analysis.

```r
capture_dat <- full_dat %>%
          # select only data from capture days
  dplyr::filter(day_n == 0) %>%
  left_join(read.csv("./data/tmt_assignments.csv"),
            by = "individual_ID") %>%
          # put date and time together
  mutate(capture_date_time = (paste(capture_date, time_captured)),
         capture_date_time = as.POSIXct(capture_date_time,
                                        format = "%Y-%m-%d %H:%M"),
          # correctly format time-only variables
         time_captured = as.POSIXct(time_captured,
                                     format = "%H:%M"),
         time_processed = as.POSIXct(time_processed,
                                      format = "%H:%M"),
         time_c_temp = as.POSIXct(substr(time_c_temp, 12, 16),
                                  format = "%H:%M"),
          # set categorical variables as factors
         type = as.factor(type),
         day = as.factor(day),
         individual_ID = as.factor(individual_ID),
         hemolyzed = as.factor(hemolyzed),
          # set numeric measurements as numeric
         mass_g = as.numeric(mass_g),
         hematocrit_percent = as.numeric(hematocrit_percent),
         osmolality_mmol_kg_mean = as.numeric(osmolality_mmol_kg_mean),
         CEWL_g_m2h_mean = as.numeric(CEWL_g_m2h_mean),
         cloacal_temp_C = as.numeric(cloacal_temp_C)
              ) %>%
  # make sure only complete data included
  # this removes the data for individuals 304 (recapture) & 254 (escapee)
  dplyr::filter(complete.cases(osmolality_mmol_kg_mean,
                               CEWL_g_m2h_mean, cloacal_temp_C)) %>%
  # remove experiment variables not relevant to capture analysis
  dplyr::select(-trial_number, -temp_tmt, -humidity_tmt,
                -conclusion, -notes,
                -shed, -tail_broken, -died)
summary(capture_dat)
```

```
##  measurement_date     time_captured
##  Min.   :2021-06-16   Min.   :2022-01-13 08:28:00
##  1st Qu.:2021-06-26   1st Qu.:2022-01-13 10:00:00
##  Median :2021-07-20   Median :2022-01-13 10:40:00
##  Mean   :2021-07-16   Mean   :2022-01-13 11:09:32
##  3rd Qu.:2021-08-08   3rd Qu.:2022-01-13 11:56:15
##  Max.   :2021-08-22   Max.   :2022-01-13 15:54:00
##                       NA's   :14
##  time_processed                time_c_temp                   type
##  Min.   :2022-01-13 11:00:00   Min.   :2022-01-13 09:54:00   exp:138
##  1st Qu.:2022-01-13 12:08:45   1st Qu.:2022-01-13 12:53:00
##  Median :2022-01-13 13:05:30   Median :2022-01-13 14:01:30
##  Mean   :2022-01-13 13:34:40   Mean   :2022-01-13 14:04:02
##  3rd Qu.:2022-01-13 14:19:30   3rd Qu.:2022-01-13 15:12:30
##  Max.   :2022-01-13 17:52:00   Max.   :2022-01-13 18:09:00
##
##       day      individual_ID     mass_g      hemolyzed hematocrit_percent
##  capture:138   201    :  1   Min.   : 8.80   N:127     Min.   :27.00
##                202    :  1   1st Qu.:10.60   Y: 11     1st Qu.:34.25
##                203    :  1   Median :11.65             Median :39.00
##                204    :  1   Mean   :11.73             Mean   :38.93
##                205    :  1   3rd Qu.:12.70             3rd Qu.:43.00
##                206    :  1   Max.   :17.40             Max.   :52.00
##                (Other):132
##  osmolality_mmol_kg_mean CEWL_g_m2h_mean   msmt_temp_C    msmt_RH_percent
##  Min.   :305.0           Min.   : 7.152   Min.   :25.90   Min.   :25.52
##  1st Qu.:334.3           1st Qu.:17.255   1st Qu.:26.72   1st Qu.:45.77
##  Median :344.6           Median :21.030   Median :26.96   Median :47.09
##  Mean   :348.3           Mean   :20.760   Mean   :27.20   Mean   :44.08
##  3rd Qu.:361.9           3rd Qu.:24.416   3rd Qu.:27.50   3rd Qu.:48.44
##  Max.   :395.0           Max.   :34.660   Max.   :29.20   Max.   :53.15
##
##  cloacal_temp_C   msmt_temp_K      e_s_kPa_m       e_a_kPa_m
##  Min.   :25.00   Min.   :299.1   Min.   :3.441   Min.   :0.9894
##  1st Qu.:26.00   1st Qu.:299.9   1st Qu.:3.616   1st Qu.:1.6913
##  Median :26.00   Median :300.1   Median :3.669   Median :1.7342
##  Mean   :26.45   Mean   :300.3   Mean   :3.724   Mean   :1.6312
##  3rd Qu.:27.00   3rd Qu.:300.6   3rd Qu.:3.790   3rd Qu.:1.7865
##  Max.   :30.00   Max.   :302.4   Max.   :4.194   Max.   :1.8502
##
##   msmt_VPD_kPa    capture_date            day_n       SVL_mm
##  Min.   :1.612   Min.   :2021-06-16   Min.   :0   Min.   :60.00
##  1st Qu.:1.846   1st Qu.:2021-06-26   1st Qu.:0   1st Qu.:66.00
##  Median :1.942   Median :2021-07-20   Median :0   Median :67.00
##  Mean   :2.093   Mean   :2021-07-16   Mean   :0   Mean   :67.71
##  3rd Qu.:2.053   3rd Qu.:2021-08-08   3rd Qu.:0   3rd Qu.:70.00
##  Max.   :3.021   Max.   :2021-08-22   Max.   :0   Max.   :77.00
##
##  capture_date_time
##  Min.   :2021-06-16 08:28:00
##  1st Qu.:2021-06-26 09:44:45
##  Median :2021-07-20 09:52:00
##  Mean   :2021-07-14 14:50:11
##  3rd Qu.:2021-08-08 09:56:45
```

```
## Max.   :2021-08-22 13:25:00
## NA's   :14
```

Variable Summary

- measurement_date = date measurements were taken, including capture day
- collection/capture time for each lizard
- time_processed = when mass and blood draw were recorded
- time_c_temp = the time when cloacal temperature was recorded, immediately after CEWL measurements
- type = whether measurements were during experiment (exp) or after rehydration (post-rehab). For this R script/analysis, I'm only going to use capture day data, which is listed as "exp"
- day = whether measurements are from capture day or post-experiment, which was recorded in relation to CEWL & cloacal temp data. All observations used for this analysis will be from capture day
- individual ID for each lizard
- mass in grams
- hemolyzed = whether or not red blood cells burst and contaminated plasma
- hematocrit_percent = percent of blood that's red blood cells (measured in CRITOCAP microhematocrit capillary tubes)
- osmolality_mmol_kg_mean = the mean of 1-3 technical replicates of plasma osmolality measurements taken from plasma extracted from our blood samples and run on a VAPRO vapor pressure osmometer
- CEWL_g_m2h_mean = the mean of 3-5 technical replicates, after outliers were omitted, of CEWL measurements taken in the same area of the dorsum
- cloacal_temp_C = cloacal temperature recorded immediately after CEWL measurements
- capture_date = date of capture. For this dataset, it should be the same as measurement date
- day_n = numeric day of measurement. In this dataset, it should always be zero
- capture_date_time = combination of capture date and time
- SVL_mm = snout-to-vent length in mm

Weather Data

This data was obtained from http://www.itrc.org/databases/precip/ (Adcon Server Data) to test the effect of ambient conditions on CEWL.

Load and format:

```r
weather <- read.csv("./data/weather.csv", sep = ';') %>%
         # add a variable for combined date-time
  mutate(capture_date_time = as.POSIXct(paste(date, time),
                               format = "%m/%d/%y %I:%M %p"))
```

The weather data is only every 15 minutes, but I want to match it to any minute measurement, so I need to interpolate the values for each minute.

First, make a separate dataframe with every minute on each capture day.

```r
all_times <- data.frame(capture_date_time = c(
                           # June 16
                           seq(from = as.POSIXct("2021-06-16 07:00"),
                               to = as.POSIXct("2021-06-16 19:00"),
                               by="min"),
                           # June 26
                           seq(from = as.POSIXct("2021-06-26 07:00"),
                               to = as.POSIXct("2021-06-26 19:00"),
                               by="min"),
                           # July 20
```

```
                            seq(from = as.POSIXct("2021-07-20 07:00"),
                                to = as.POSIXct("2021-07-20 19:00"),
                                by="min"),
                            # August 8
                            seq(from = as.POSIXct("2021-08-08 07:00"),
                                to = as.POSIXct("2021-08-08 19:00"),
                                by="min"),
                            # August 22
                            seq(from = as.POSIXct("2021-08-22 07:00"),
                                to = as.POSIXct("2021-08-22 19:00"),
                                by="min")
                            ))
```

Next, merge the weather data into the times dataframe and interpolate the temperature and humidity between measurements.

```
weather_every_minute <- all_times %>% # time only dataframe
  # add weather measurements based on matching date-time
  left_join(weather, by = 'capture_date_time') %>%
         # convert temperature units F->C
  mutate(temp_C = fahrenheit.to.celsius(temperature_F, round = 2),
         # interpolate temperatures
         temp_C_interpol = na.approx(temp_C),
         # also get temperature C-> K
         temp_K_interpol = temp_C_interpol + 273.15,
         # interpolate humidities
         RH_percent_interpol = na.approx(relative_humidity_percent),
         # interpolate Wind Speeds
         wind_mph_interpol = na.approx(wind_speed_mph),
         # interpolate solar radiation
         solar_rad_W_sqm_interpol = na.approx(solar_radiation_W_sqm),
         # compute vapor pressure deficit
         # find saturation level first
         e_s_kPa_int = 0.611*exp((2500000/461.5)*
                            ((1/273)-(1/temp_K_interpol))),
         # actual vapor pressure
         e_a_kPa_int = e_s_kPa_int * (RH_percent_interpol/100),
         # VPD
         VPD_kPa_int = e_s_kPa_int - e_a_kPa_int
         ) %>%
  # keep only the relevant variables
  dplyr::select(capture_date_time,
                temp_C_interpol,
                RH_percent_interpol,
                VPD_kPa_int,
                wind_mph_interpol,
                solar_rad_W_sqm_interpol)
summary(weather_every_minute)
```

```
##  capture_date_time              temp_C_interpol RH_percent_interpol
##  Min.   :2021-06-16 07:00:00   Min.   :12.50   Min.   : 16.50
##  1st Qu.:2021-06-26 10:00:00   1st Qu.:20.04   1st Qu.: 56.83
##  Median :2021-07-20 13:00:00   Median :22.35   Median : 67.10
##  Mean   :2021-07-19 08:12:00   Mean   :23.22   Mean   : 63.15
```

```
##  3rd Qu.:2021-08-08 16:00:00   3rd Qu.:25.17   3rd Qu.: 76.13
##  Max.   :2021-08-22 19:00:00   Max.   :38.33   Max.   :100.00
##   VPD_kPa_int     wind_mph_interpol solar_rad_W_sqm_interpol
##  Min.   :0.0000   Min.   : 0.100    Min.   :  13.6
##  1st Qu.:0.5724   1st Qu.: 2.800    1st Qu.: 370.0
##  Median :0.9074   Median : 4.700    Median : 699.6
##  Mean   :1.4591   Mean   : 4.820    Mean   : 624.2
##  3rd Qu.:1.4235   3rd Qu.: 5.833    3rd Qu.: 902.6
##  Max.   :5.8841   Max.   :13.600    Max.   :1011.7
```

I will add the weather data in when I add the scaled mass index (computed next) to the dataframe.

Compute Scaled Mass Index

This is also known as the body condition index, or log-log residuals.

I calculate as described by: Peig, J., & Green, A. J. (2009). New perspectives for estimating body condition from mass/length data: The scaled mass index as an alternative method. Oikos, 118(12), 1883–1891. https://doi.org/10.1111/j.1600-0706.2009.17643.x

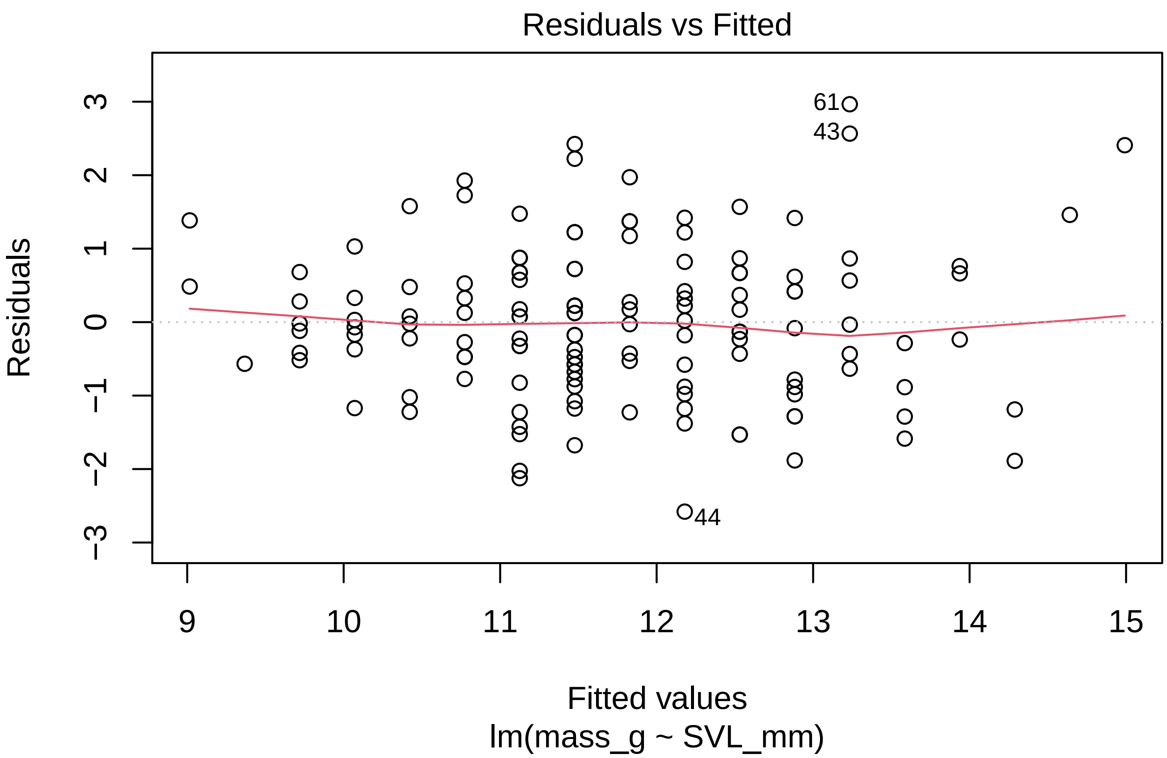
Step 1: Simple Linear Regression

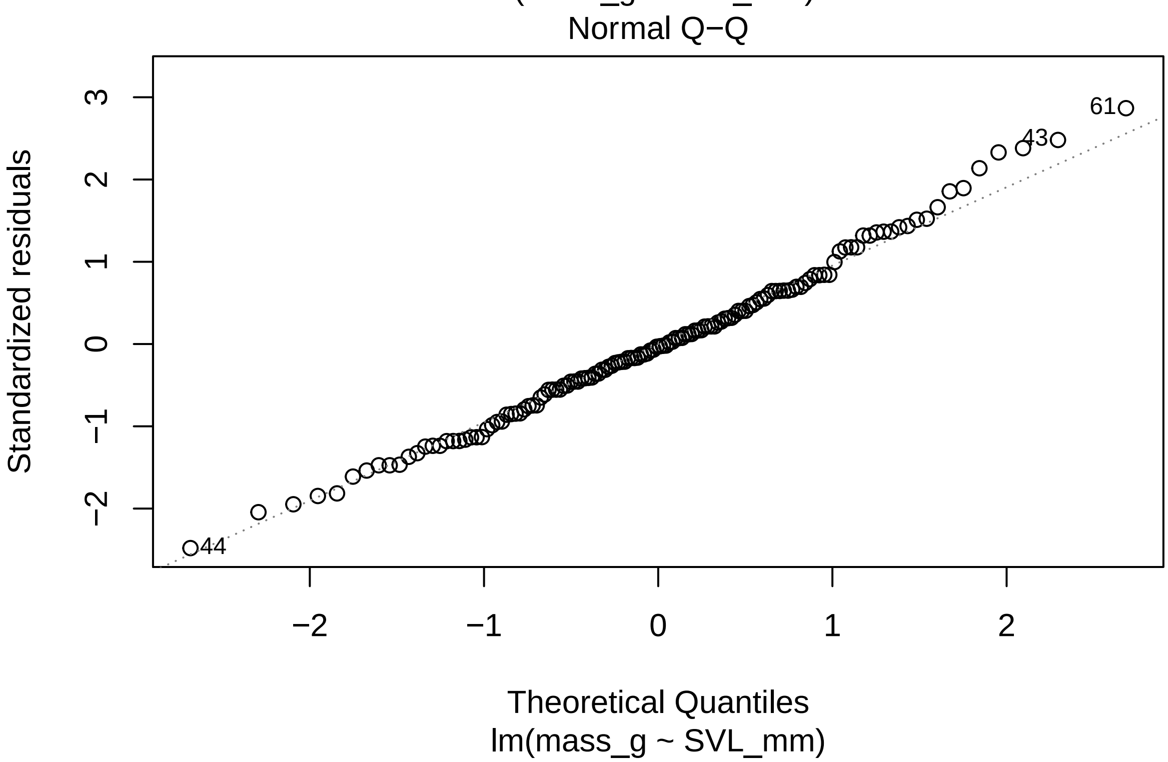
```
mass_SVL_SLR <- lm(data = capture_dat, mass_g ~ SVL_mm)
summary(mass_SVL_SLR)
```

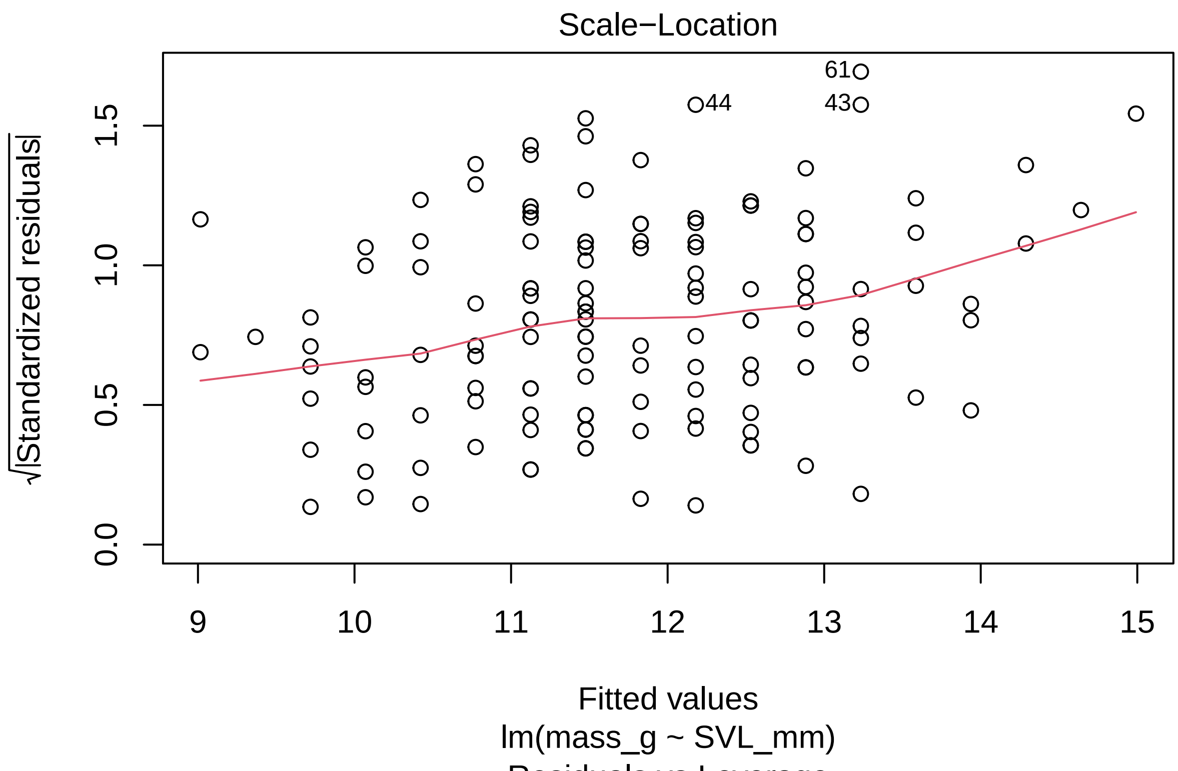
```
##
## Call:
## lm(formula = mass_g ~ SVL_mm, data = capture_dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.57951 -0.66586 -0.03104  0.66743  2.96590
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -12.07614    1.78776  -6.755 3.82e-10 ***
## SVL_mm        0.35153    0.02637  13.330  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.044 on 136 degrees of freedom
## Multiple R-squared:  0.5665, Adjusted R-squared:  0.5633
## F-statistic: 177.7 on 1 and 136 DF,  p-value: < 2.2e-16
```

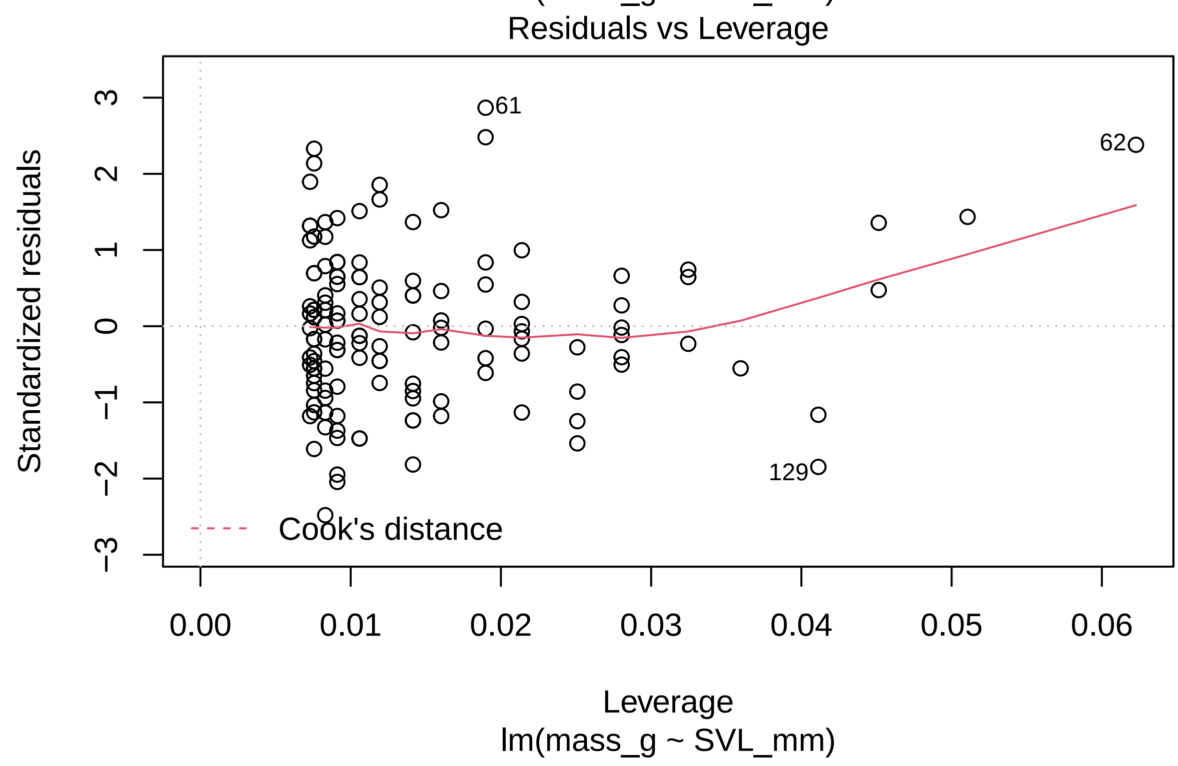
Step 2: Identify Outliers

```
plot(mass_SVL_SLR)
```


Residuals vs Fitted
Residuals
Fitted values
lm(mass_g ~ SVL_mm)
61
43
44

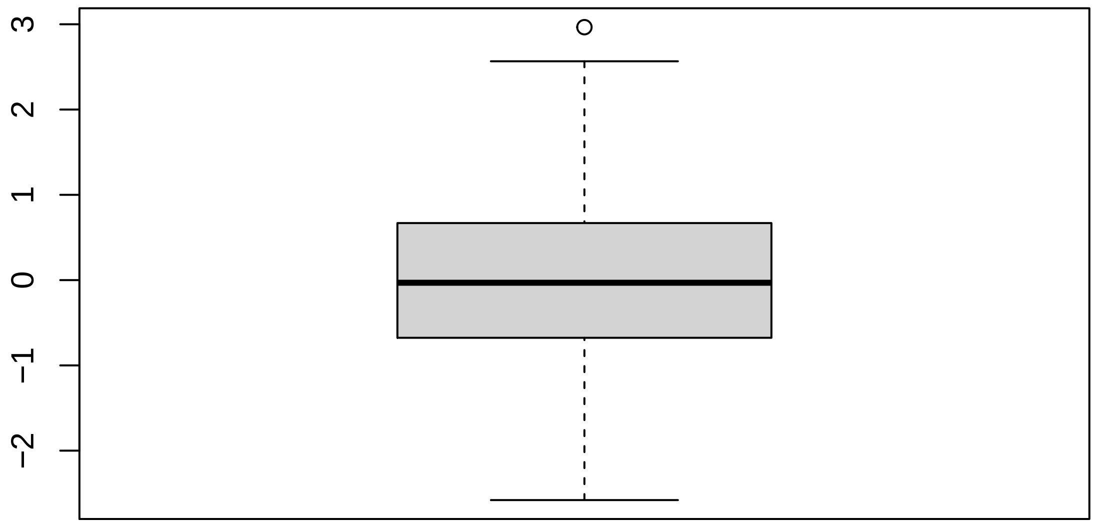

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(mass_g ~ SVL_mm)
61
43
44



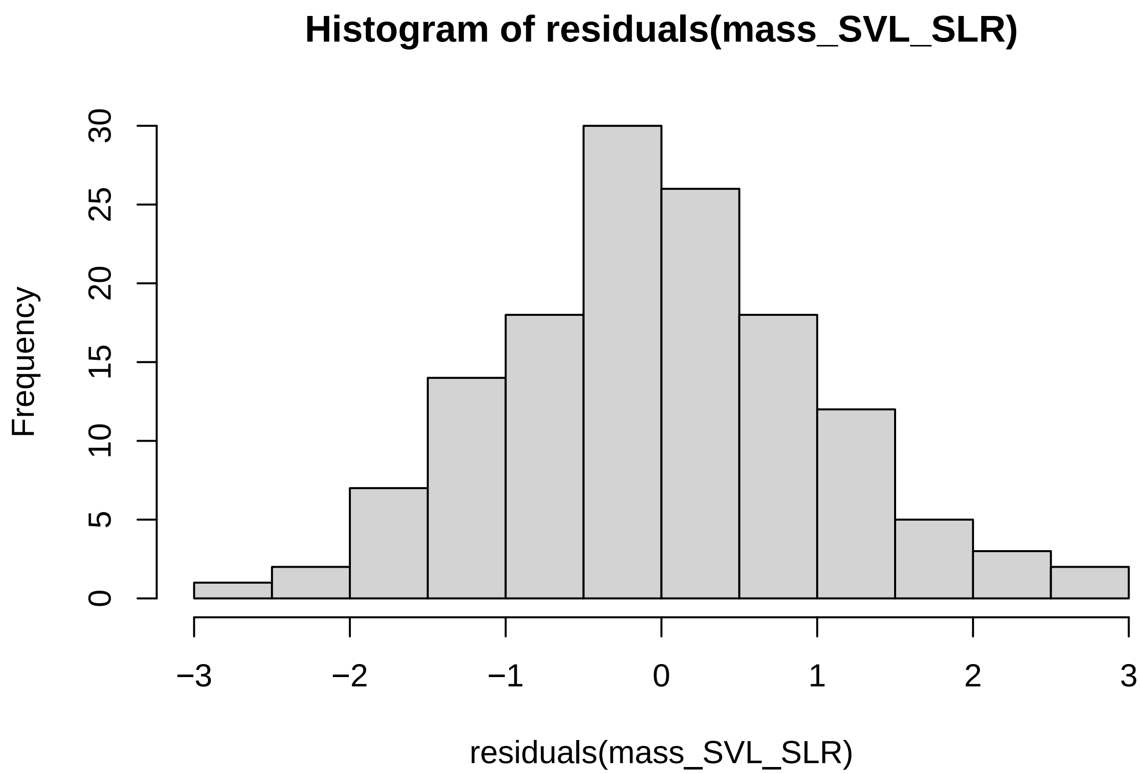


The conditions of linearity, equal error variance, and normality are all satisfied. It doesn't look like any residuals are >3 or <-3.

```
boxplot(residuals(mass_SVL_SLR))
```




```r
hist(residuals(mass_SVL_SLR))
```



From the boxplot, there is one individual with a much higher residual than the rest of the distribution. The histogram looks fine, and incredibly normally distributed.

Check average residual value:

```r
mean(residuals(mass_SVL_SLR))
```

```
## [1] -4.331781e-17
```

```r
median(residuals(mass_SVL_SLR))
```

```
## [1] -0.03104232
```

The mean is basically zero and the median is pretty close to zero, which is very good.

Check for high leverage points:

```
# compute values for observations
high_leverage <- data.frame(H = hatvalues(mass_SVL_SLR)) %>%
  mutate(row = row_number())

# compute cutoff value
h_bar <- (3*sum(high_leverage$H))/nrow(high_leverage)

# add to original dataframe
# see which observations have extremely high leverage (if any)
high_leverage_dat <- capture_dat %>%
  mutate(row = row_number()) %>%
  left_join(., high_leverage, by = "row") %>%
  dplyr::filter(H > h_bar)
high_leverage_dat
```

```
## # A tibble: 0 x 25
## # Groups:   individual_ID [0]
## # ... with 25 variables: measurement_date <date>, time_captured <dttm>,
## #   time_processed <dttm>, time_c_temp <dttm>, type <fct>, day <fct>,
## #   individual_ID <fct>, mass_g <dbl>, hemolyzed <fct>,
## #   hematocrit_percent <dbl>, osmolality_mmol_kg_mean <dbl>,
## #   CEWL_g_m2h_mean <dbl>, msmt_temp_C <dbl>, msmt_RH_percent <dbl>,
## #   cloacal_temp_C <dbl>, msmt_temp_K <dbl>, e_s_kPa_m <dbl>, e_a_kPa_m <dbl>,
## #   msmt_VPD_kPa <dbl>, capture_date <date>, day_n <dbl>, SVL_mm <int>,
## #   capture_date_time <dttm>, row <int>, H <dbl>
```

No points are considered high leverage, which is fantastic.

Check for influential points based on Cook's distance:

```
# get Cook's distance
cooks <- data.frame(c = cooks.distance(mass_SVL_SLR)) %>%
  mutate(row = row_number())

# add to original dataframe
influential <- capture_dat %>%
  mutate(row = row_number()) %>%
  left_join(., cooks, by = "row")

# see moderately influential points
cook_mod_inf <- influential %>%
  dplyr::filter(c>0.5)
cook_mod_inf
```

```
## # A tibble: 0 x 25
## # Groups:   individual_ID [0]
## # ... with 25 variables: measurement_date <date>, time_captured <dttm>,
## #   time_processed <dttm>, time_c_temp <dttm>, type <fct>, day <fct>,
## #   individual_ID <fct>, mass_g <dbl>, hemolyzed <fct>,
## #   hematocrit_percent <dbl>, osmolality_mmol_kg_mean <dbl>,
## #   CEWL_g_m2h_mean <dbl>, msmt_temp_C <dbl>, msmt_RH_percent <dbl>,
## #   cloacal_temp_C <dbl>, msmt_temp_K <dbl>, e_s_kPa_m <dbl>, e_a_kPa_m <dbl>,
## #   msmt_VPD_kPa <dbl>, capture_date <date>, day_n <dbl>, SVL_mm <int>,
## #   capture_date_time <dttm>, row <int>, c <dbl>
```

There are no infuential points based on Cook's distance, so there's nothing to potentially remove.

We could remove the one outlier found using the boxplot, but it's the only one, so we will leave it in the dataset. No points were indicated to be outliers based on residuals or a histogram, and there were no high leverage or influential points. Thus I can create a log-log model using the data as-is. Observation omissions are unlikely to increase generalizability.

Step 3: log-log Regression

```
log_mass_SVL_SLR <- lm(data = capture_dat,
                       log(mass_g) ~ log(SVL_mm))
summary(log_mass_SVL_SLR)
```

```
##
## Call:
## lm(formula = log(mass_g) ~ log(SVL_mm), data = capture_dat)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.231524 -0.059318 -0.000981  0.055085  0.206551
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -5.9803     0.6283  -9.519   <2e-16 ***
## log(SVL_mm)   2.0013     0.1491  13.424   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.08708 on 136 degrees of freedom
## Multiple R-squared:  0.5699, Adjusted R-squared:  0.5667
## F-statistic: 180.2 on 1 and 136 DF,  p-value: < 2.2e-16
```

Step 4: Extract Values

compute standardized major axis using the log-log regression equation:

```
r <- sqrt(0.5699) # Pearson's correlection coefficient (sqrt of R-squared)
b_OLS <- 2.0013 # regression slope
b_SMA <- b_OLS/r
```

mean length in capture data:

```
L0 <- mean(capture_dat$SVL_mm)
```

Step 5: Calculate Scaled Mass Index

(And join weather data.)

```
capture_dat_plus <- capture_dat %>%
  # compute SMI
  mutate(SMI = mass_g * ((L0/SVL_mm) ^ b_SMA)) %>%
  # join weather data
  left_join(weather_every_minute, by = c("capture_date_time")) %>%
  # clean up the dataframe
  dplyr::select(capture_date, capture_date_time, individual_ID, # basics
                mass_g, SVL_mm, SMI, # lizard size
                hemolyzed, hematocrit_percent, osmolality_mmol_kg_mean, # blood
```

```
                CEWL_g_m2h_mean, msmt_temp_C, msmt_VPD_kPa, cloacal_temp_C, # CEWL
                temp_C_interpol, VPD_kPa_int, wind_mph_interpol, solar_rad_W_sqm_interpol # weather
                )
summary(capture_dat_plus)
```

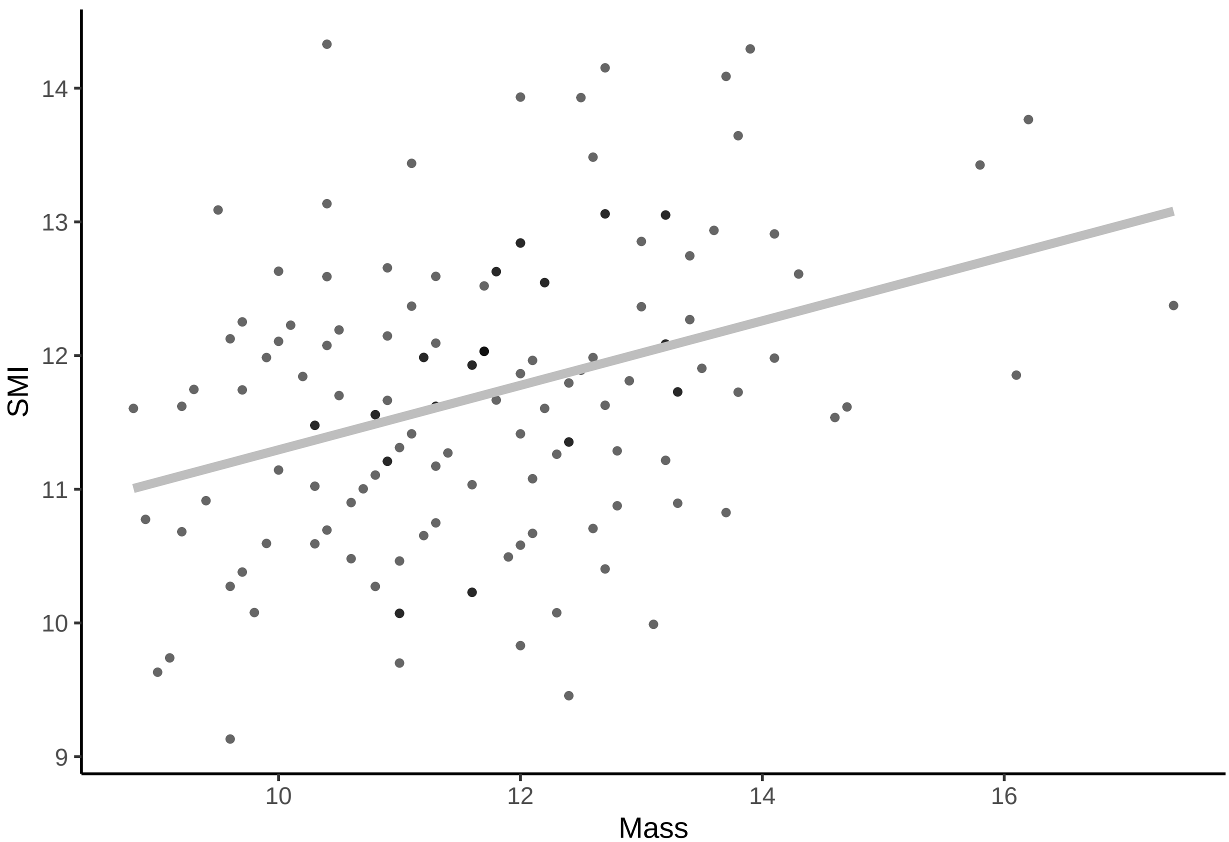
```
##   capture_date        capture_date_time              individual_ID
##  Min.   :2021-06-16   Min.   :2021-06-16 08:28:00   201    :  1
##  1st Qu.:2021-06-26   1st Qu.:2021-06-26 09:44:45   202    :  1
##  Median :2021-07-20   Median :2021-07-20 09:52:00   203    :  1
##  Mean   :2021-07-16   Mean   :2021-07-14 14:50:11   204    :  1
##  3rd Qu.:2021-08-08   3rd Qu.:2021-08-08 09:56:45   205    :  1
##  Max.   :2021-08-22   Max.   :2021-08-22 13:25:00   206    :  1
##                       NA's   :14                    (Other):132
##      mass_g          SVL_mm           SMI          hemolyzed hematocrit_percent
##  Min.   : 8.80   Min.   :60.00   Min.   : 9.132   N:127     Min.   :27.00
##  1st Qu.:10.60   1st Qu.:66.00   1st Qu.:10.937   Y: 11     1st Qu.:34.25
##  Median :11.65   Median :67.00   Median :11.727             Median :39.00
##  Mean   :11.73   Mean   :67.71   Mean   :11.712             Mean   :38.93
##  3rd Qu.:12.70   3rd Qu.:70.00   3rd Qu.:12.369             3rd Qu.:43.00
##  Max.   :17.40   Max.   :77.00   Max.   :14.329             Max.   :52.00
##
##  osmolality_mmol_kg_mean CEWL_g_m2h_mean   msmt_temp_C     msmt_VPD_kPa
##  Min.   :305.0           Min.   : 7.152   Min.   :25.90   Min.   :1.612
##  1st Qu.:334.3           1st Qu.:17.255   1st Qu.:26.72   1st Qu.:1.846
##  Median :344.6           Median :21.030   Median :26.96   Median :1.942
##  Mean   :348.3           Mean   :20.760   Mean   :27.20   Mean   :2.093
##  3rd Qu.:361.9           3rd Qu.:24.416   3rd Qu.:27.50   3rd Qu.:2.053
##  Max.   :395.0           Max.   :34.660   Max.   :29.20   Max.   :3.021
##
##  cloacal_temp_C  temp_C_interpol  VPD_kPa_int     wind_mph_interpol
##  Min.   :25.00   Min.   :15.11   Min.   :0.0000   Min.   : 0.100
##  1st Qu.:26.00   1st Qu.:19.91   1st Qu.:0.5420   1st Qu.: 2.025
##  Median :26.00   Median :21.91   Median :0.8284   Median : 3.100
##  Mean   :26.45   Mean   :23.41   Mean   :1.4295   Mean   : 4.406
##  3rd Qu.:27.00   3rd Qu.:23.91   3rd Qu.:1.2321   3rd Qu.: 5.880
##  Max.   :30.00   Max.   :35.83   Max.   :4.9400   Max.   :12.720
##                  NA's   :14      NA's   :14       NA's   :14
##  solar_rad_W_sqm_interpol
##  Min.   : 294.7
##  1st Qu.: 682.9
##  Median : 759.9
##  Mean   : 762.9
##  3rd Qu.: 873.2
##  Max.   :1007.0
##  NA's   :14
```

Check

Look at the difference between regular mass and SMI:

```
capture_dat_plus %>%
  ggplot(data = .) +
  geom_point(aes(x = mass_g,
                 y = SMI,
```

```
            ),
          size = 1,
          alpha = 0.6) +
  stat_smooth(aes(x = mass_g,
                  y = SMI,
                  ),
           formula = y ~ x,
           method = "lm",
           color = "gray",
           se = F,
           size = 1.6,
           alpha = 1 ) +
  theme_classic() +
  xlab("Mass") +
  ylab("SMI")
```

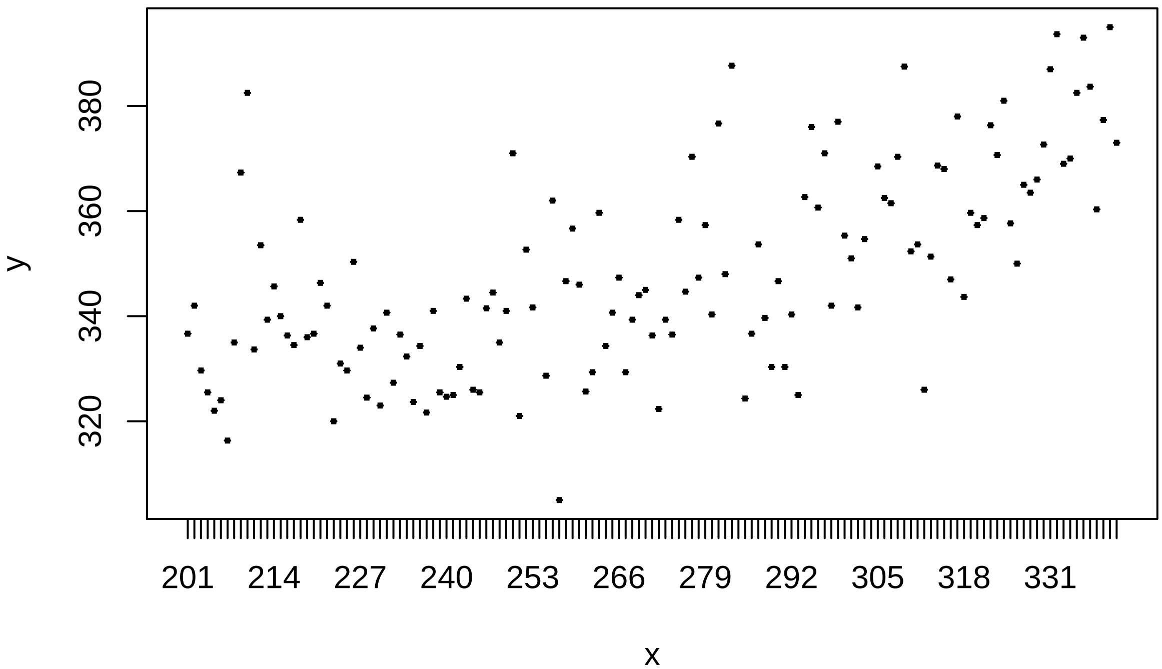


Quick Plots

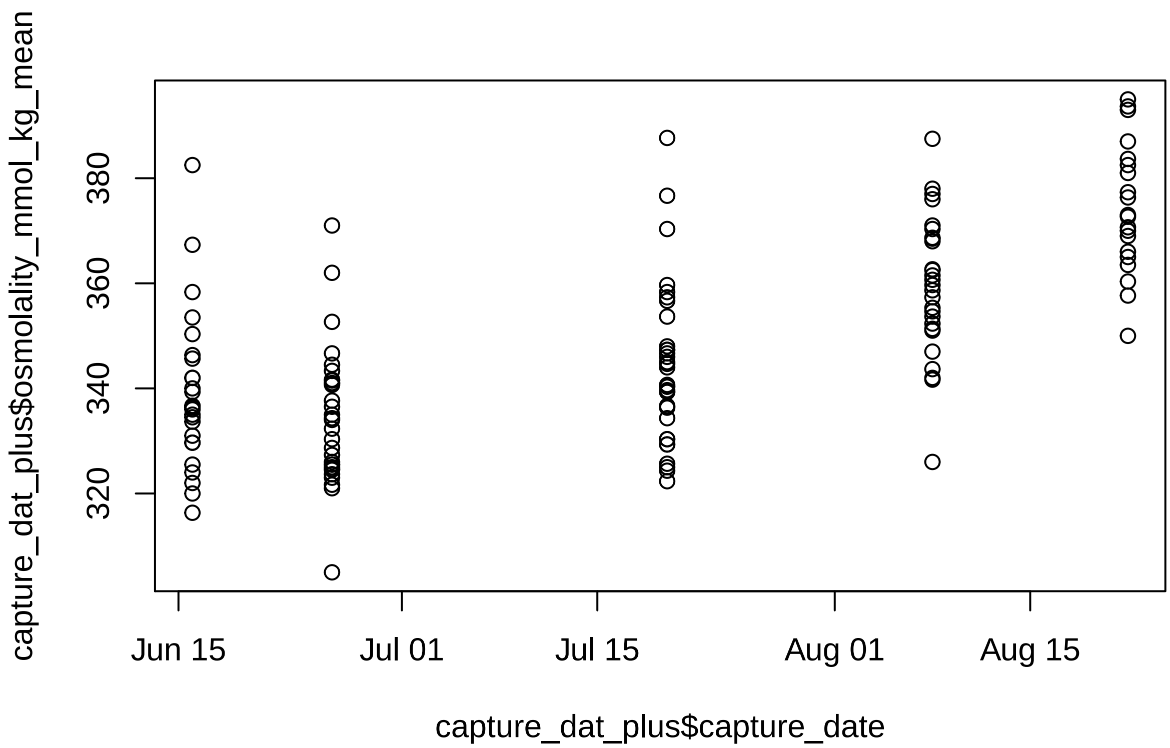
Plot very basic graphs to get an idea of what variables to incorporate into models and how.

Osmolality

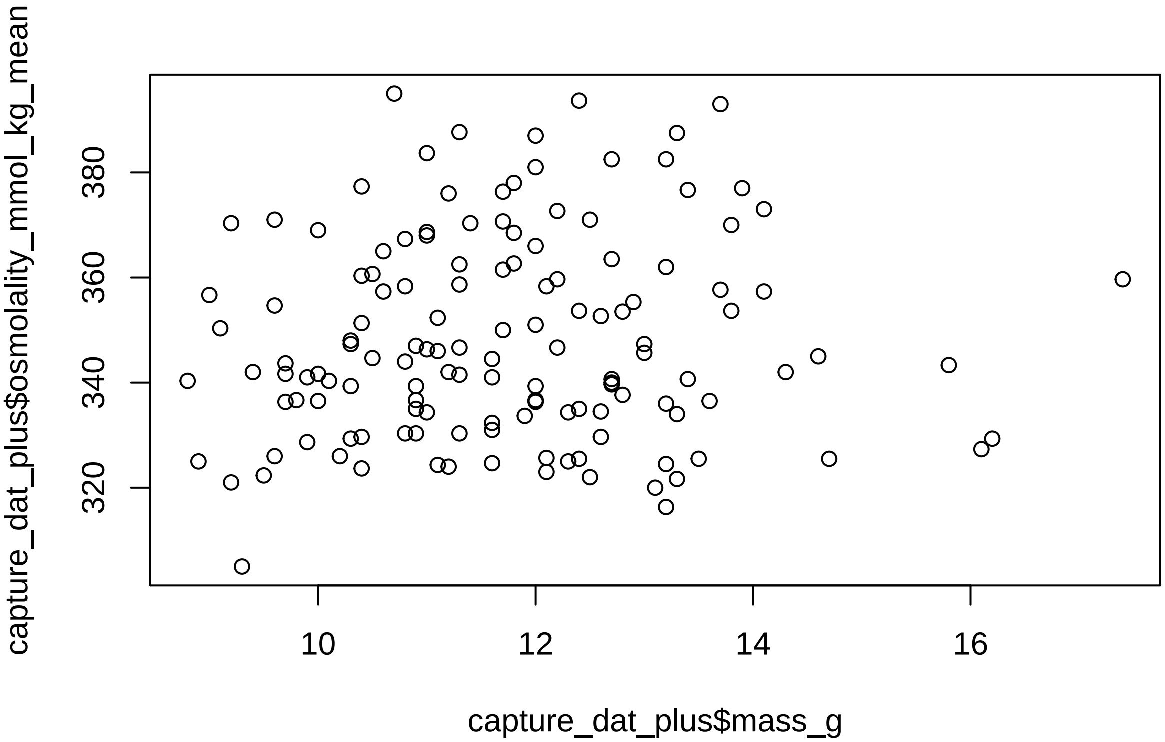
```
plot(capture_dat_plus$individual_ID,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



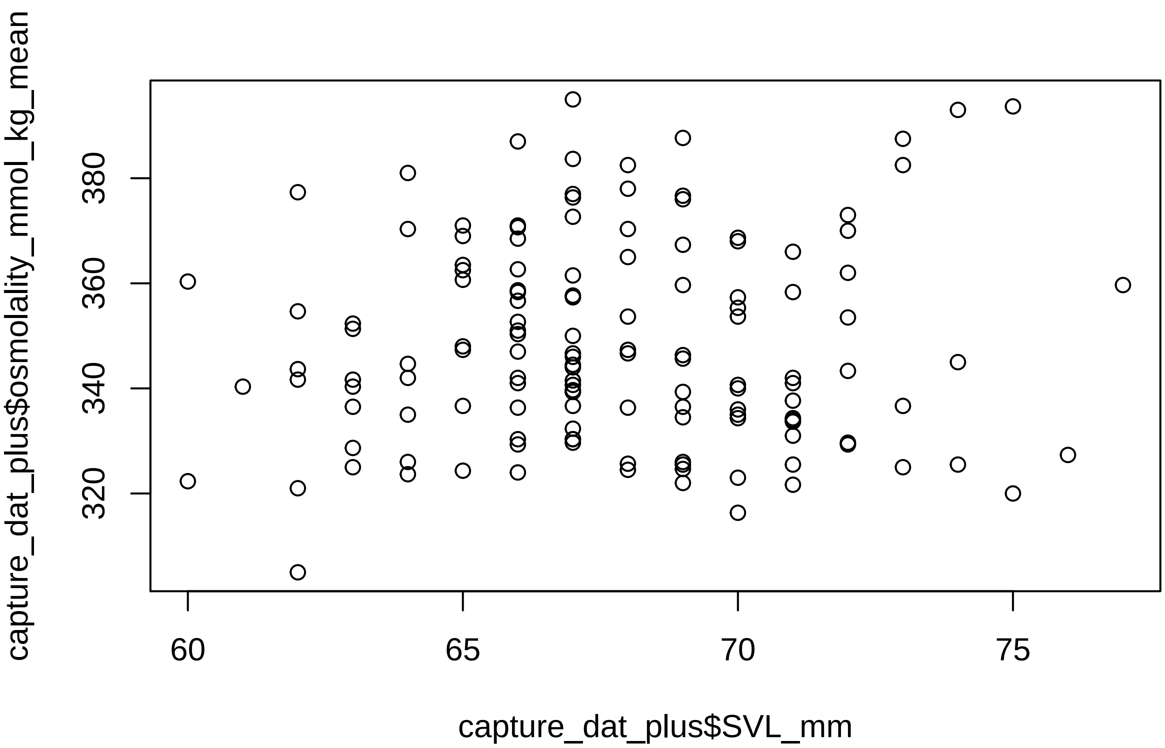

```
plot(capture_dat_plus$capture_date,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



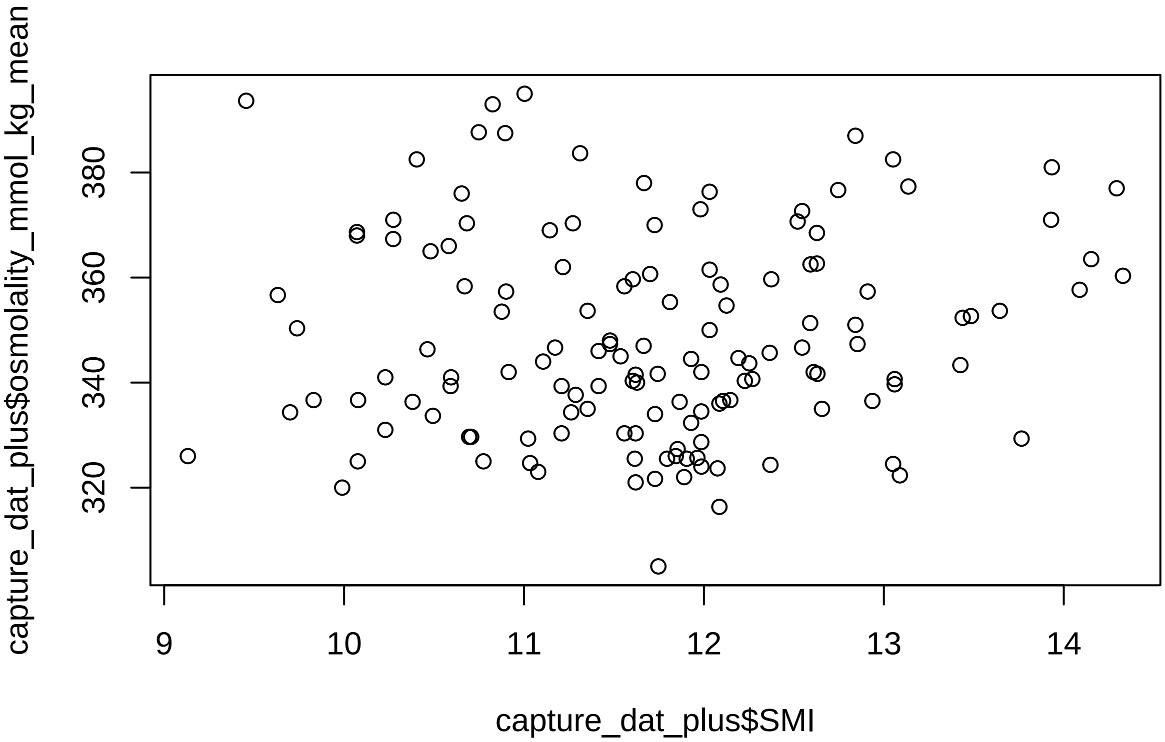

```
plot(capture_dat_plus$mass_g,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



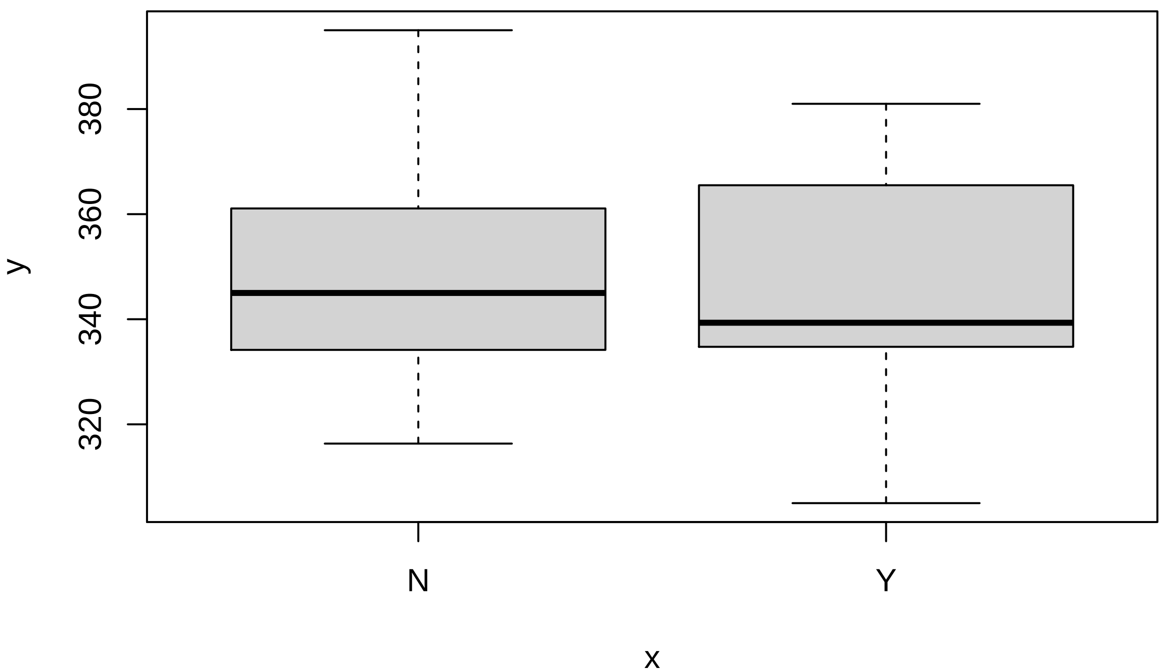

```r
plot(capture_dat_plus$SVL_mm,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



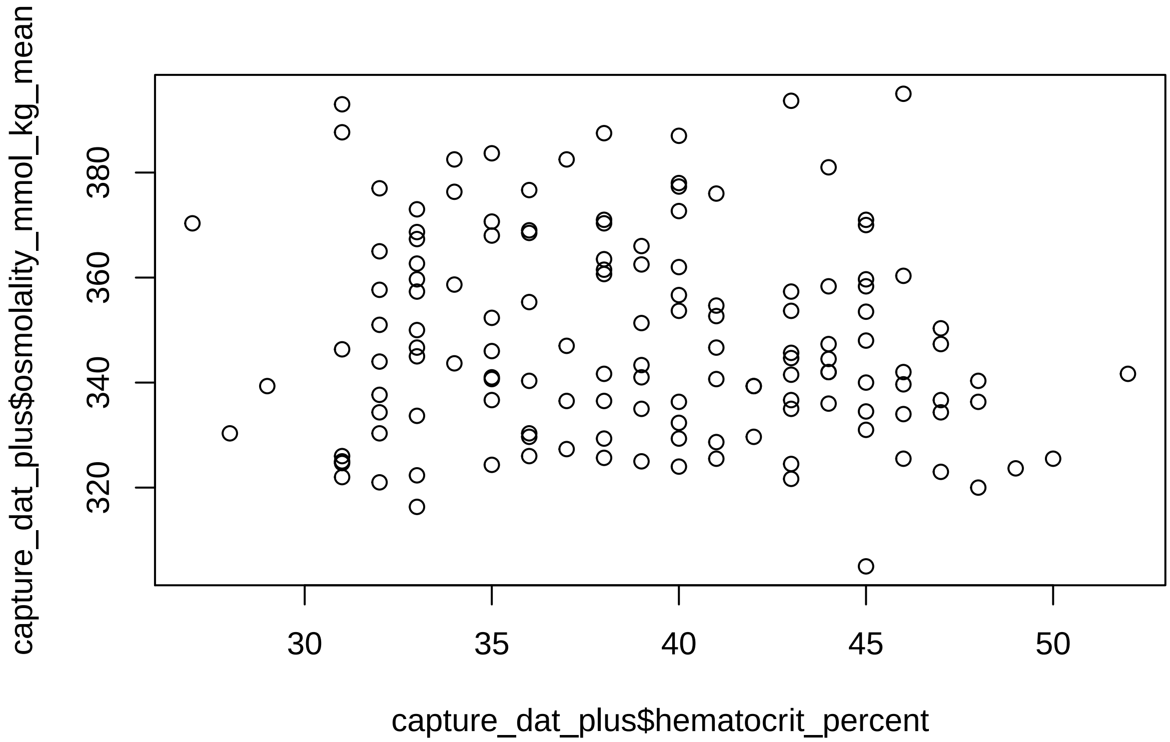

```r
plot(capture_dat_plus$SMI,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



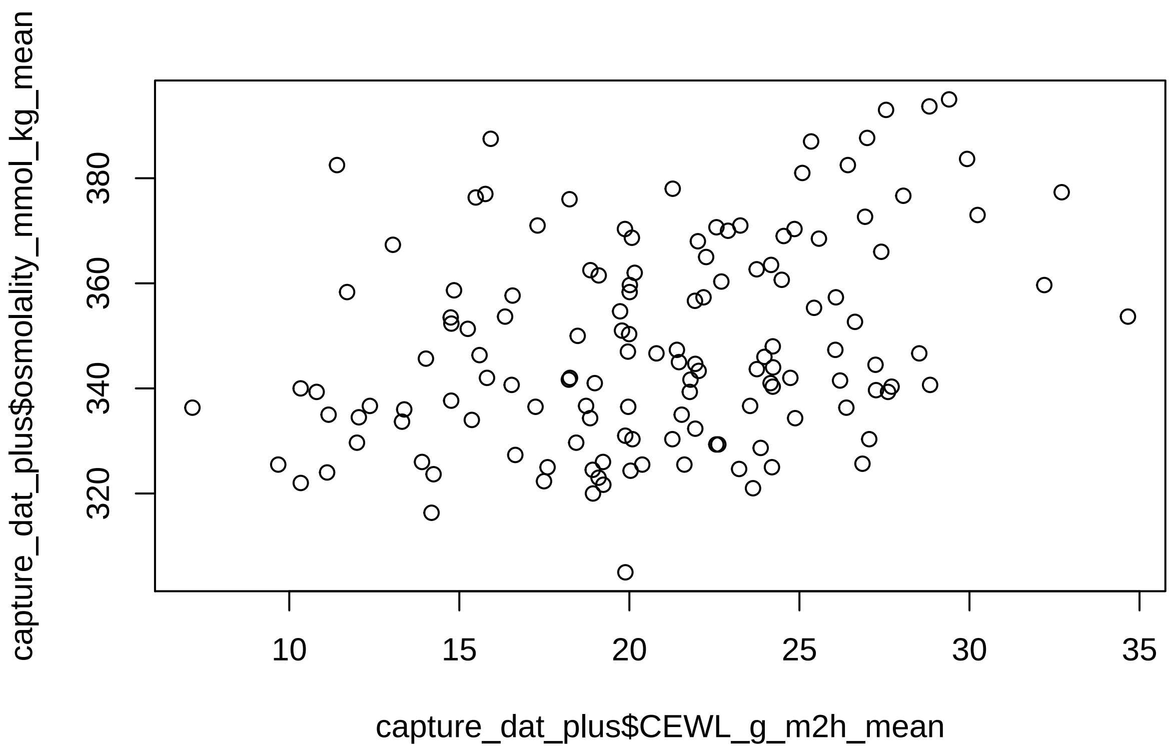

```r
plot(capture_dat_plus$hemolyzed,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



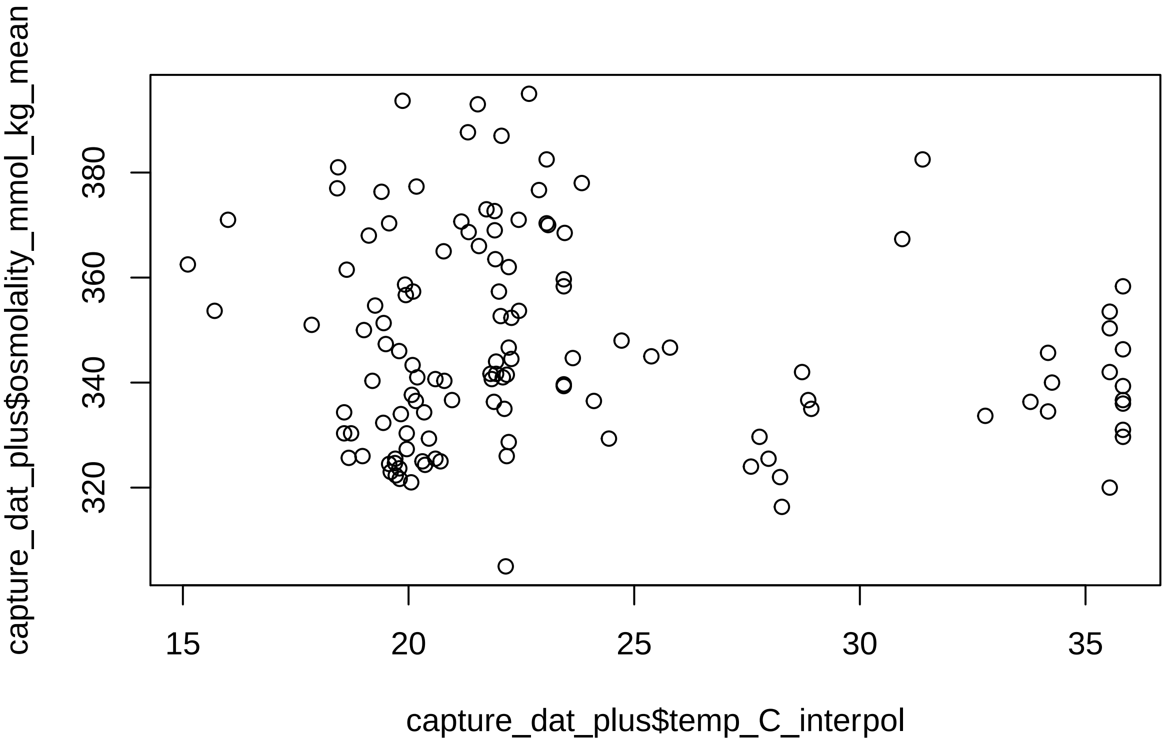

```r
plot(capture_dat_plus$hematocrit_percent,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



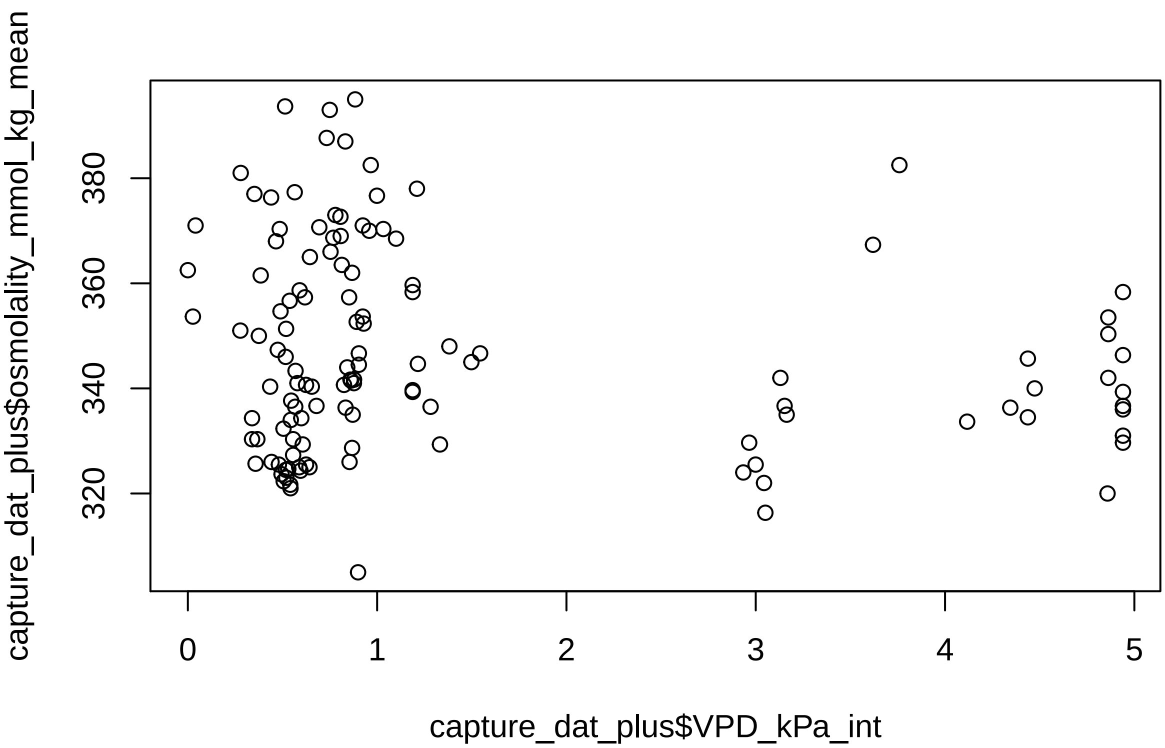

```r
plot(capture_dat_plus$CEWL_g_m2h_mean,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



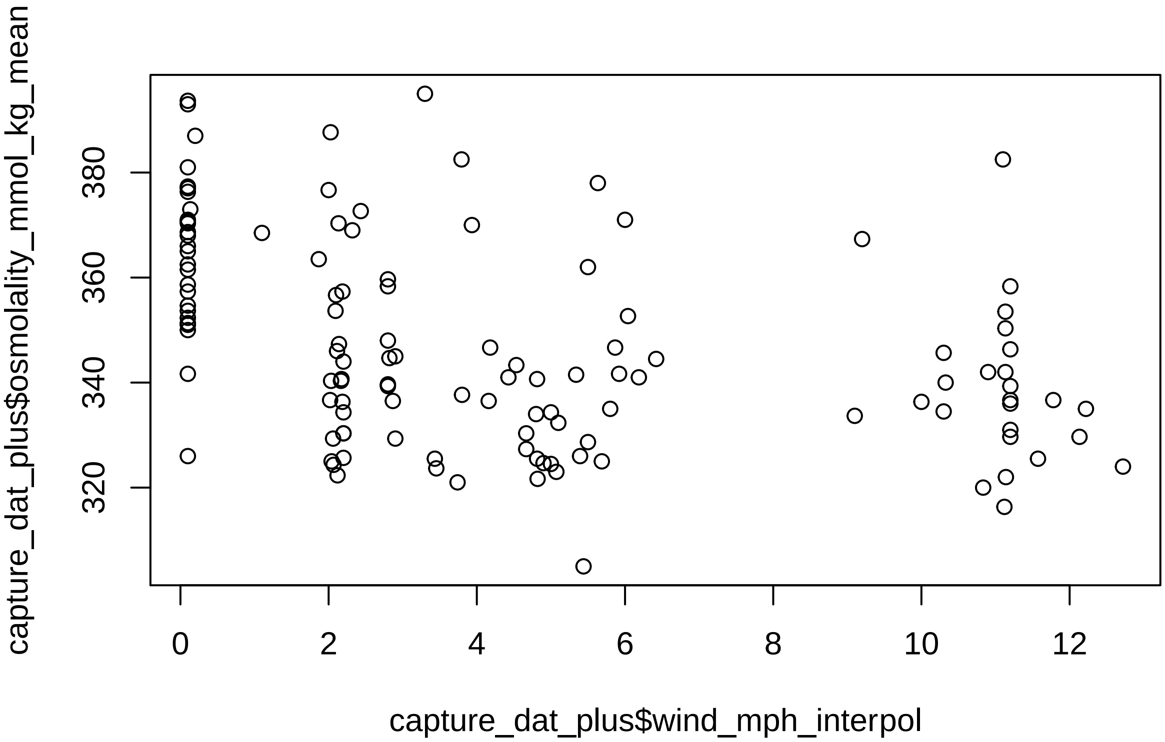

```r
plot(capture_dat_plus$temp_C_interpol,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



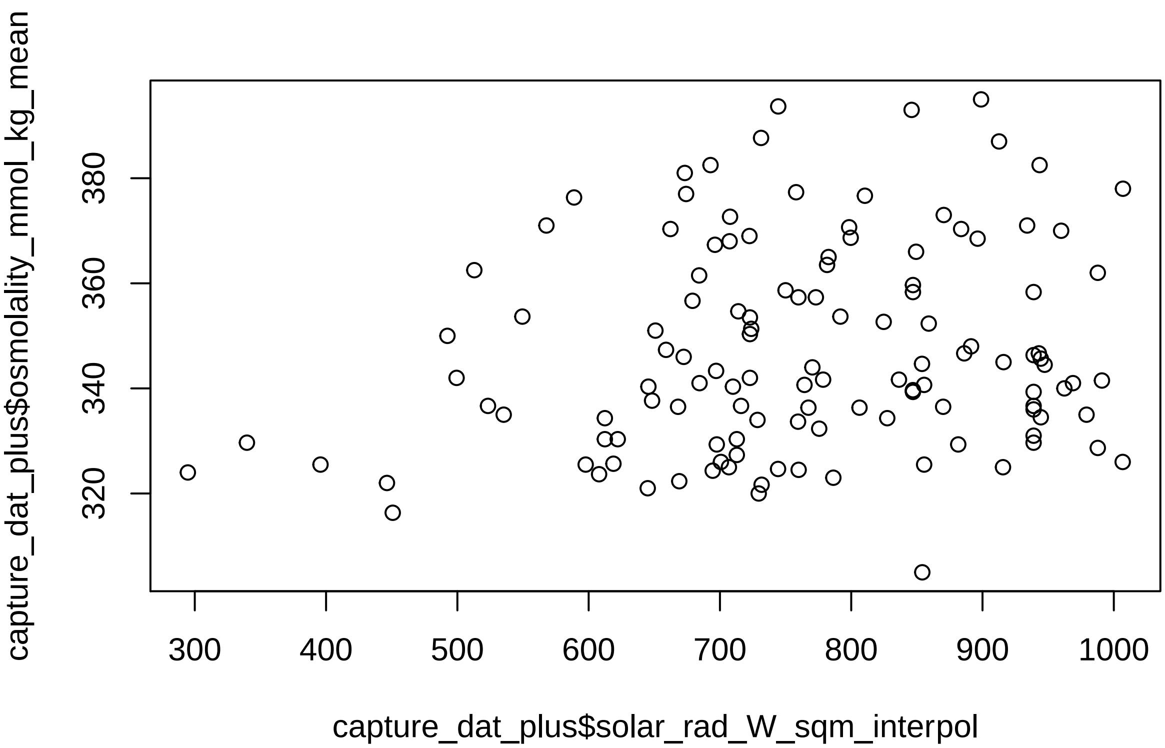

```
plot(capture_dat_plus$VPD_kPa_int,
     capture_dat_plus$osmolality_mmol_kg_mean)
```




```
plot(capture_dat_plus$wind_mph_interpol,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



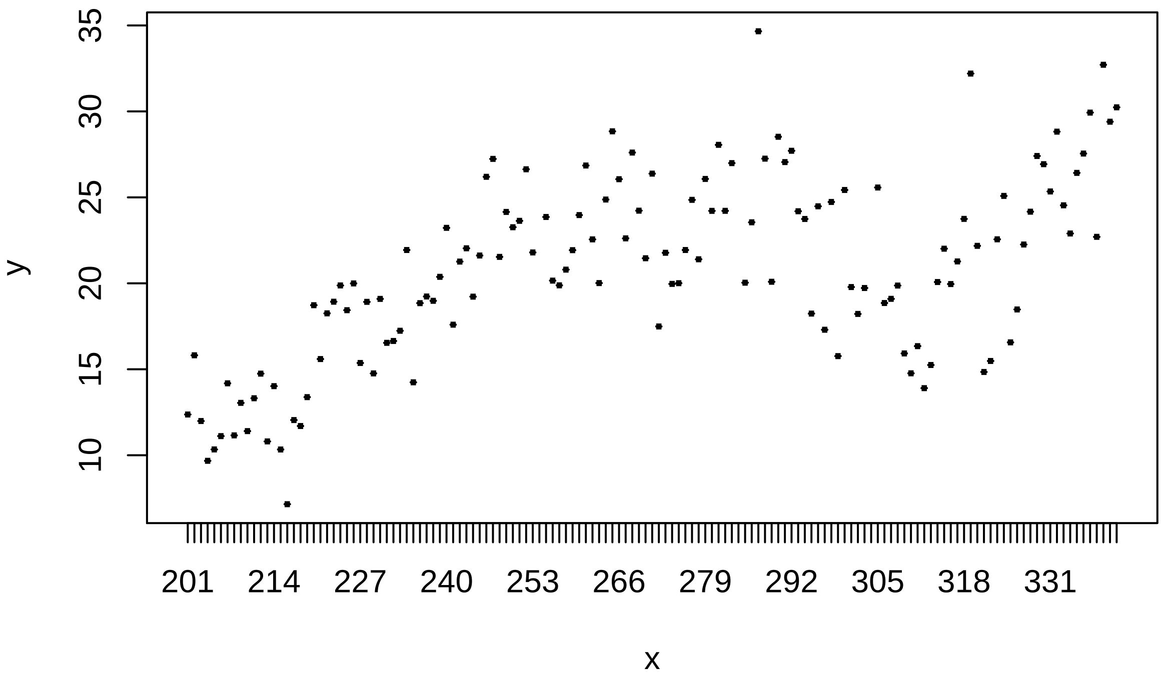

```
plot(capture_dat_plus$solar_rad_W_sqm_interpol,
     capture_dat_plus$osmolality_mmol_kg_mean)
```



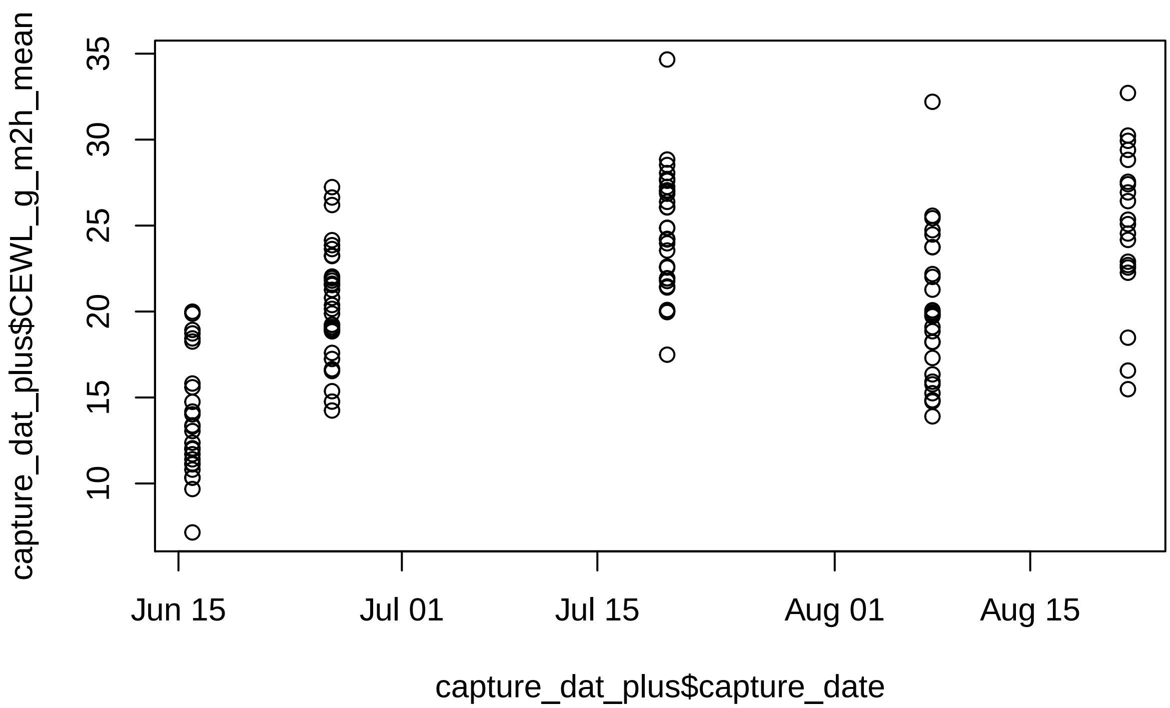
There does not appear to be a meaningful visual trend for any predictors of plasma osmolality, so it will be interesting to see how the model selection process goes… There is definitely an increase in osmolality over the course of the season, though.

CEWL

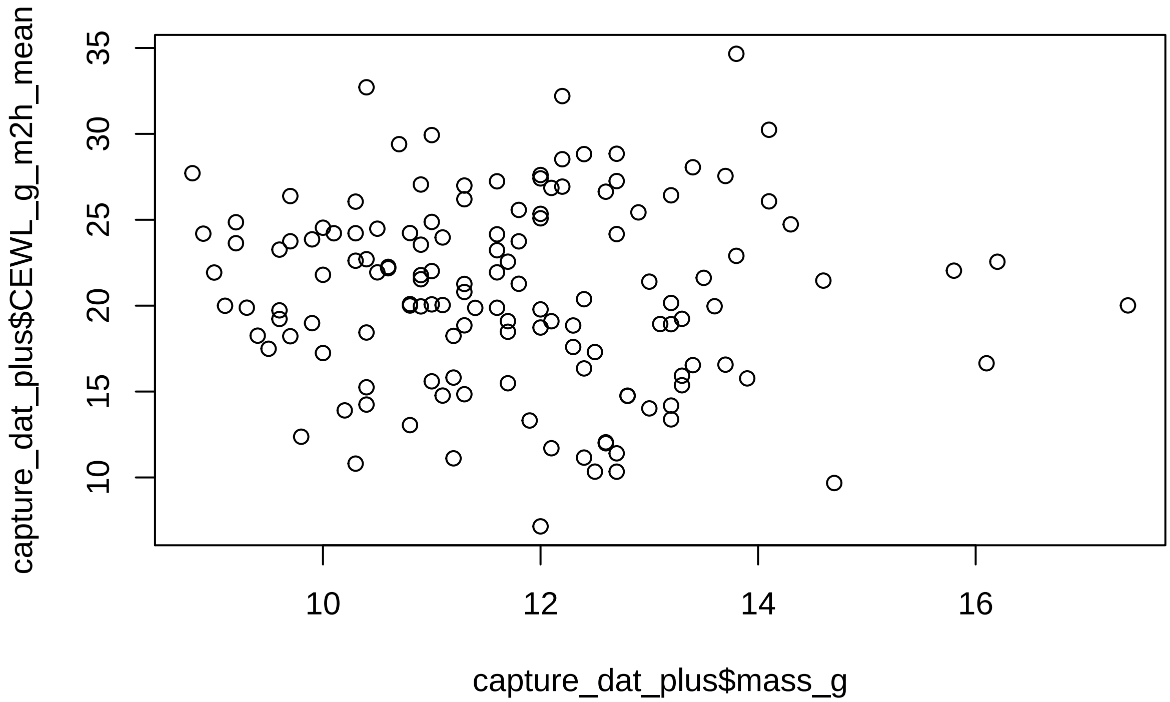
```r
plot(capture_dat_plus$individual_ID,
     capture_dat_plus$CEWL_g_m2h_mean)
```



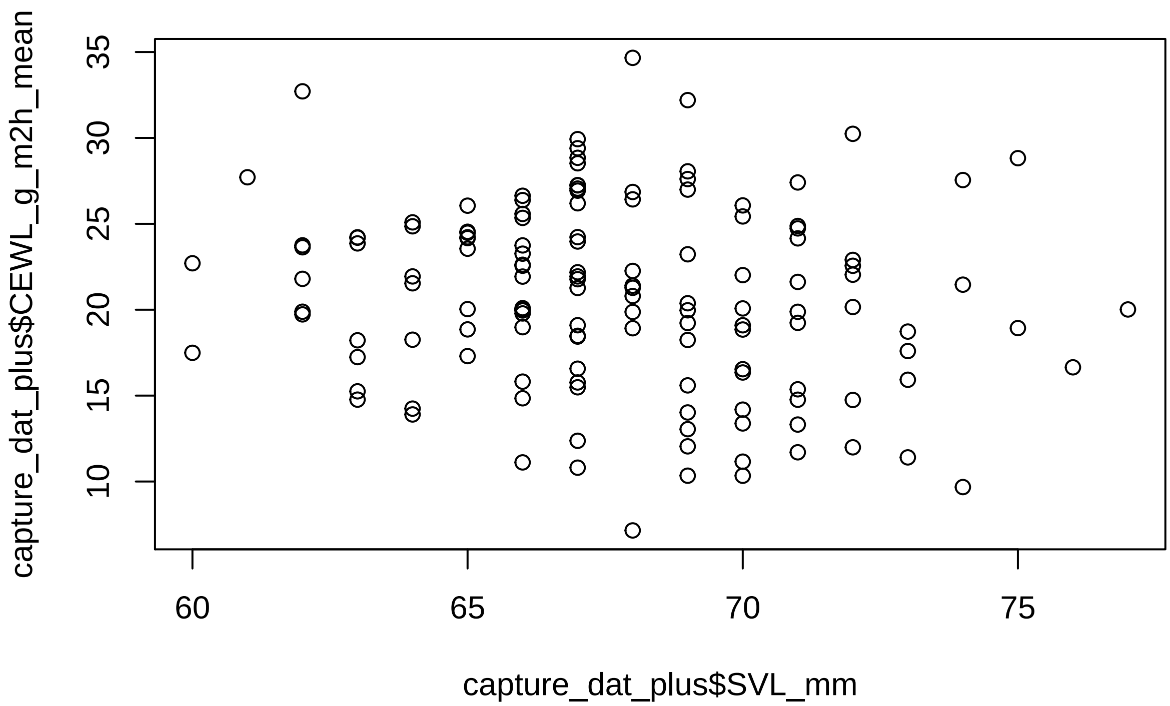

```r
plot(capture_dat_plus$capture_date,
     capture_dat_plus$CEWL_g_m2h_mean)
```



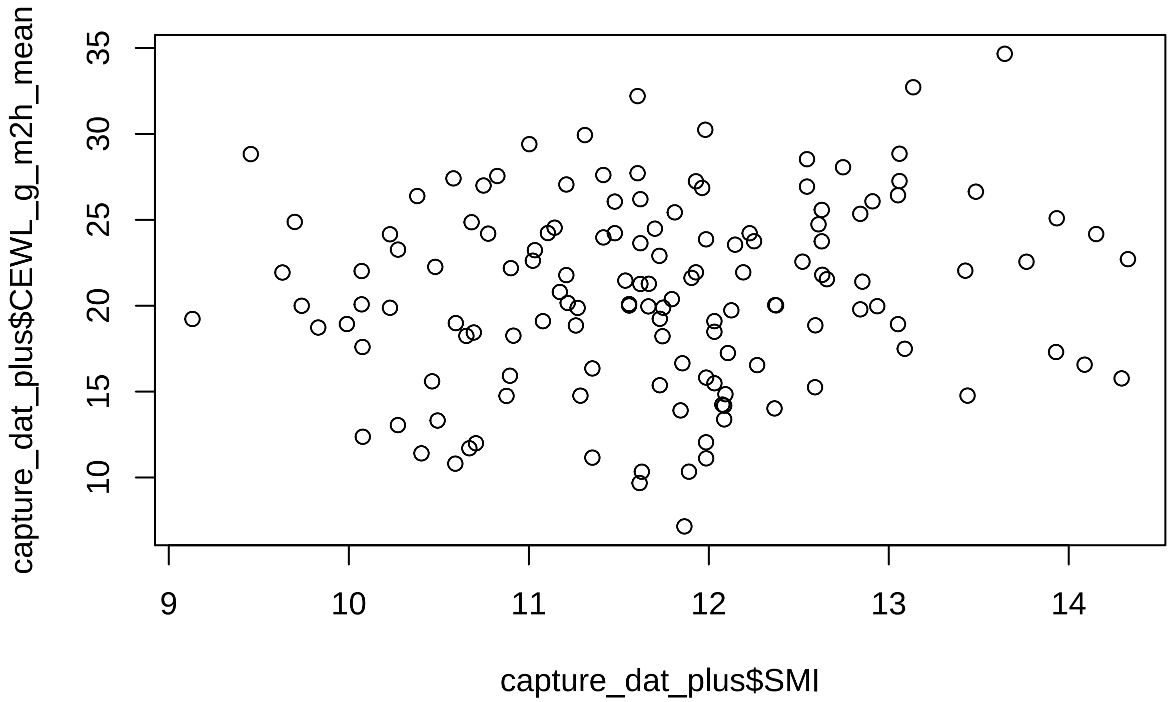

```r
plot(capture_dat_plus$mass_g,
     capture_dat_plus$CEWL_g_m2h_mean)
```



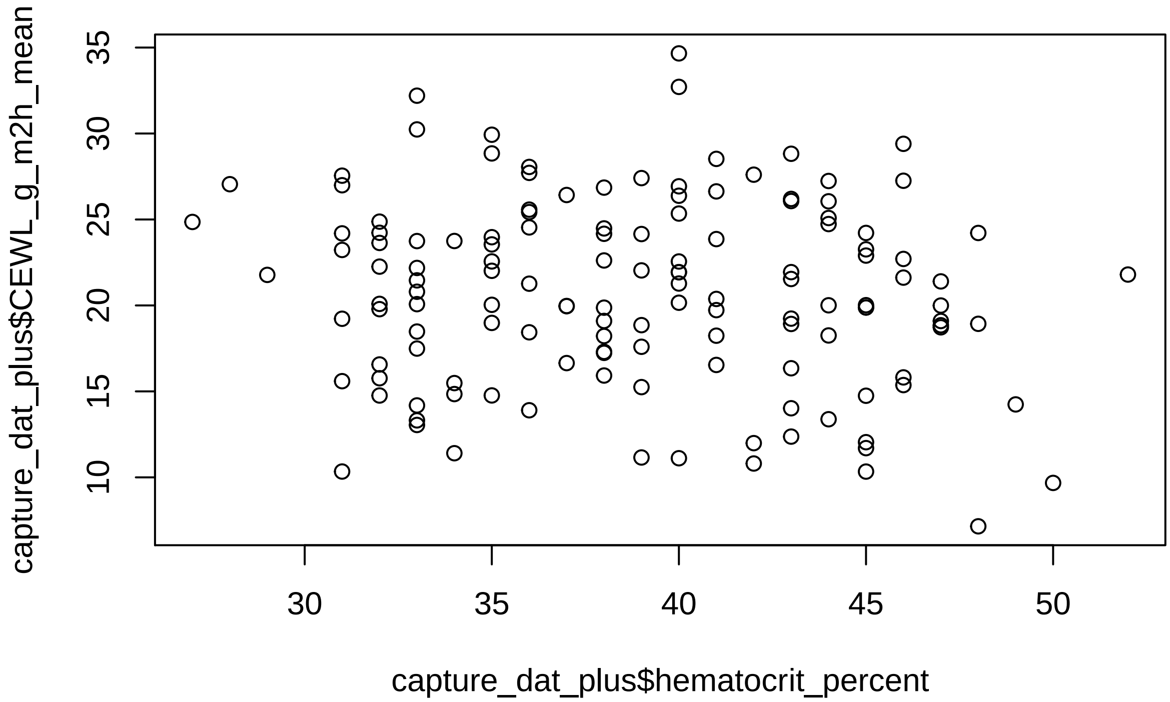

```r
plot(capture_dat_plus$SVL_mm,
     capture_dat_plus$CEWL_g_m2h_mean)
```



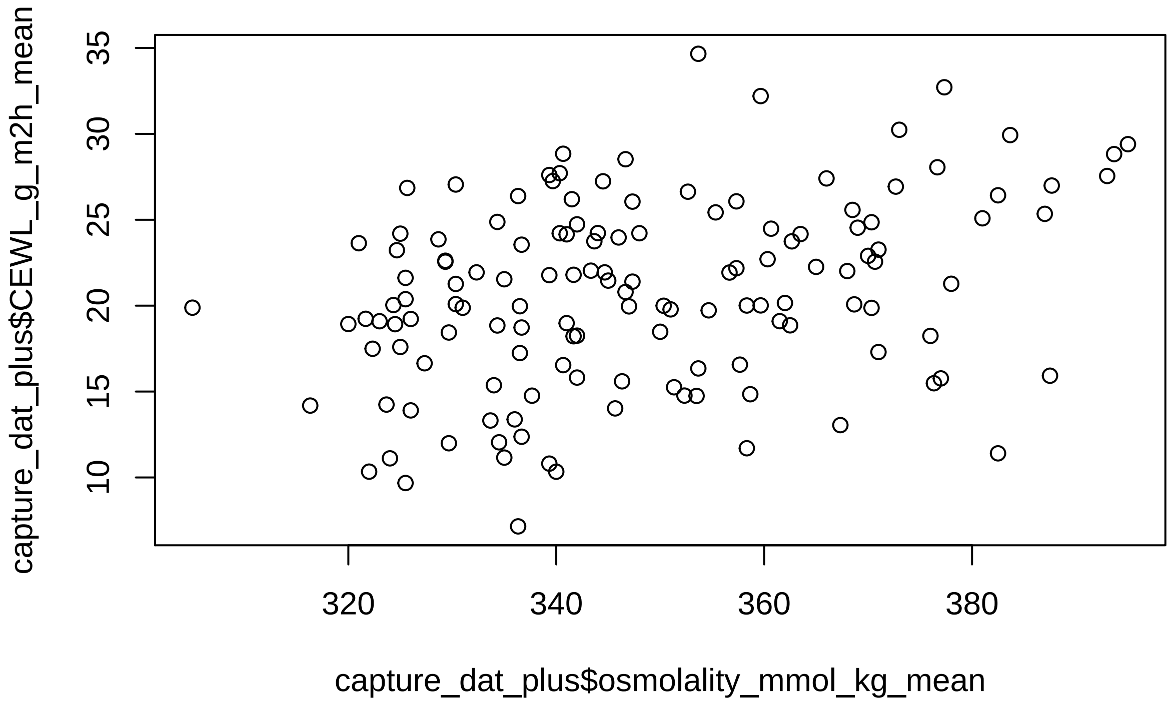

```r
plot(capture_dat_plus$SMI,
     capture_dat_plus$CEWL_g_m2h_mean)
```



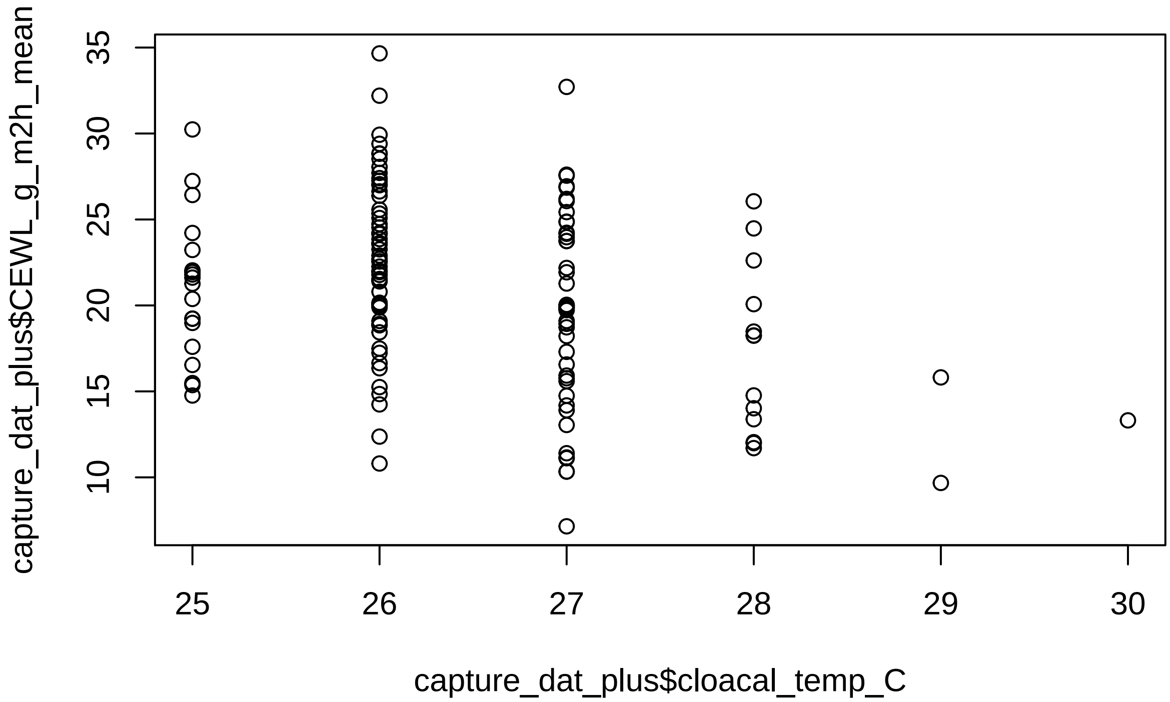

```
plot(capture_dat_plus$hematocrit_percent,
     capture_dat_plus$CEWL_g_m2h_mean)
```



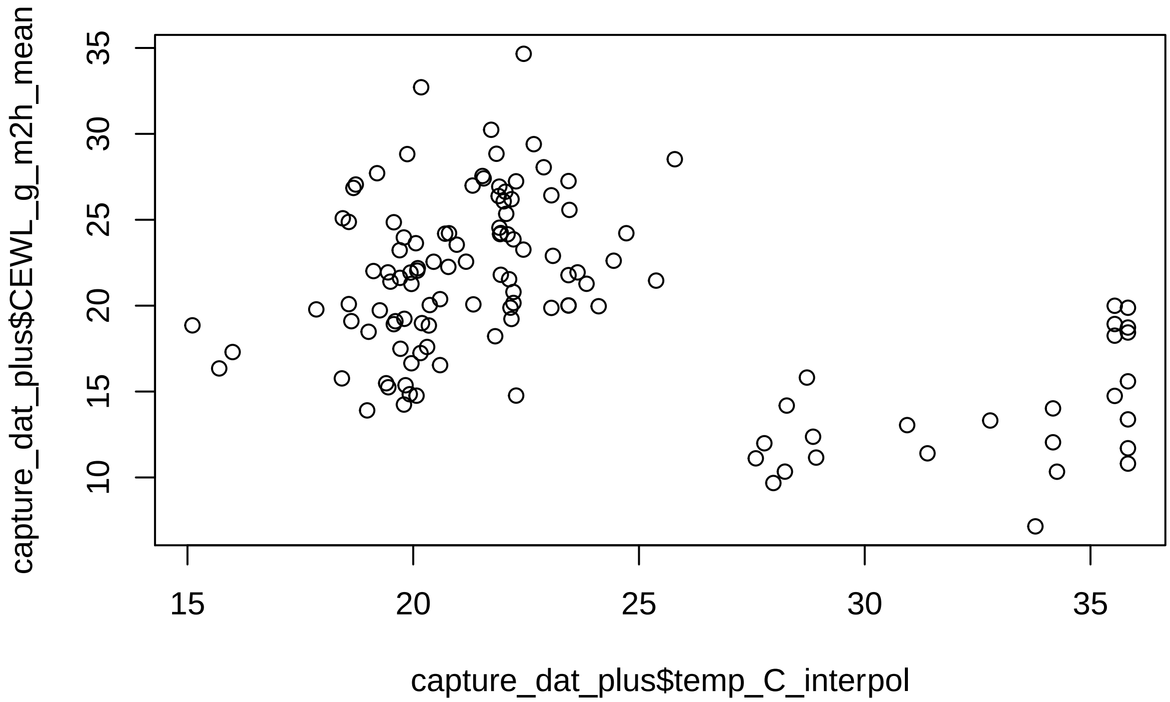

```
plot(capture_dat_plus$osmolality_mmol_kg_mean,
     capture_dat_plus$CEWL_g_m2h_mean)
```



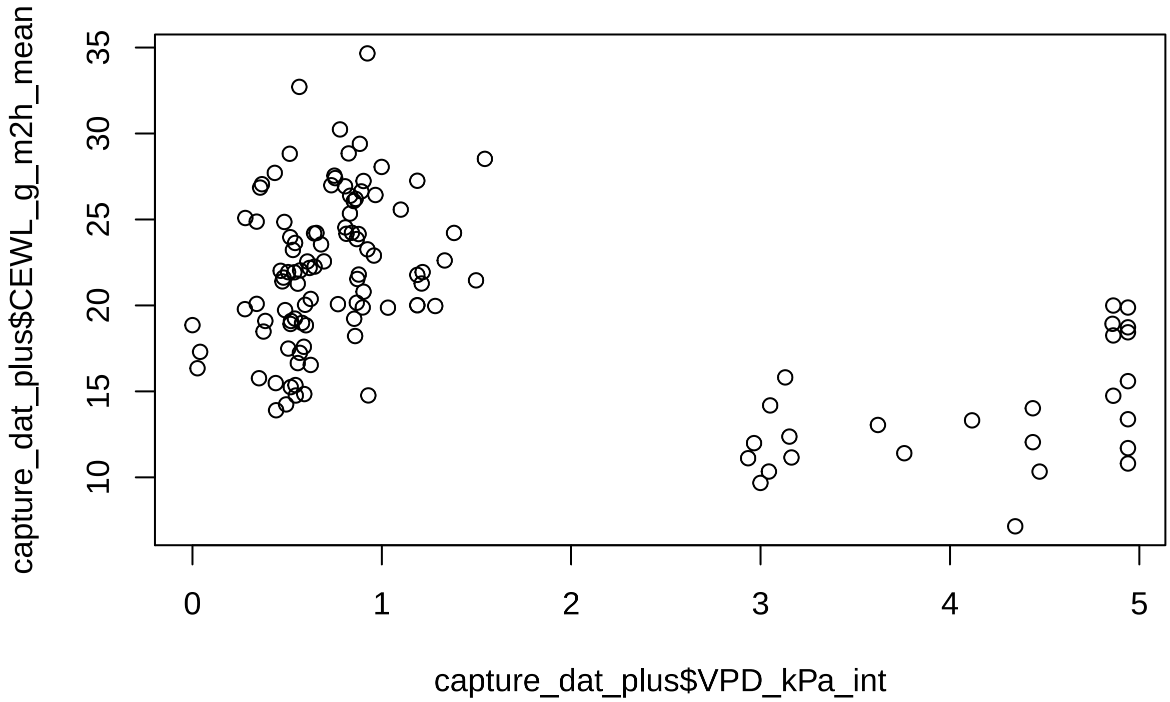

```r
plot(capture_dat_plus$cloacal_temp_C,
     capture_dat_plus$CEWL_g_m2h_mean)
```



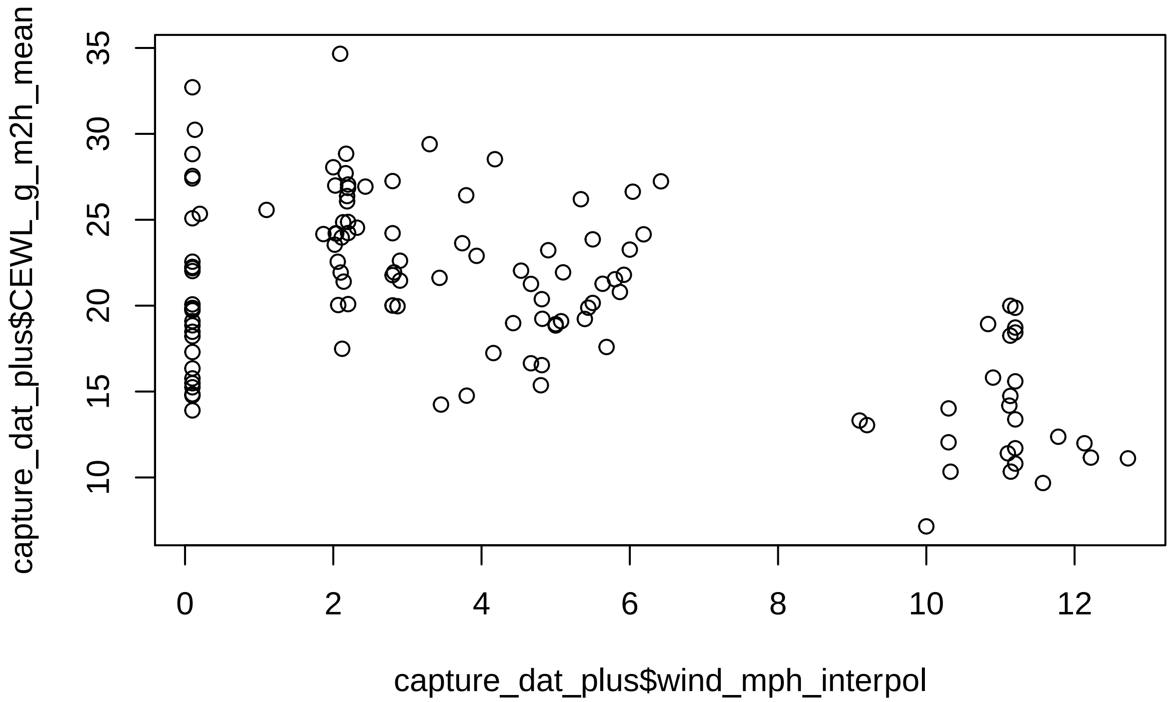

```r
plot(capture_dat_plus$temp_C_interpol,
     capture_dat_plus$CEWL_g_m2h_mean)
```



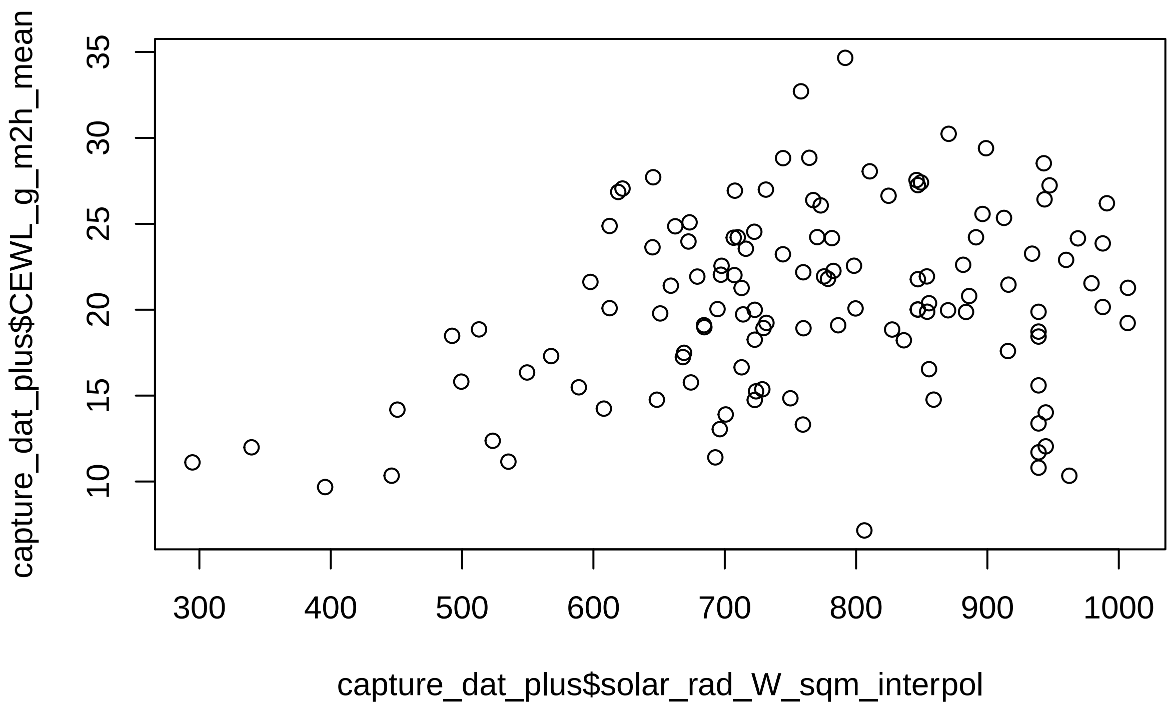

```
plot(capture_dat_plus$VPD_kPa_int,
     capture_dat_plus$CEWL_g_m2h_mean)
```




```
plot(capture_dat_plus$wind_mph_interpol,
     capture_dat_plus$CEWL_g_m2h_mean)
```




```
plot(capture_dat_plus$solar_rad_W_sqm_interpol,
     capture_dat_plus$CEWL_g_m2h_mean)
```



It looks like there are meaningful differences in CEWL across individuals/dates (probably confounded), and based on cloacal temp, capture temp, capture VPD, capture wind, and capture solar radiation.

LMMs

Hematocrit

Models

First, start with a full model with every probable potential predictor in it, then check for multicollinearity.

Hematocrit did not vary by capture day, so we are using simple linear models rather than linear mixed-effects models.

```
hct_mod1 <- lm(data = capture_dat_plus,
                          # response variable
                          hematocrit_percent ~
                          # body size
                          mass_g + SVL_mm + SMI +
                          # weather at the time of capture
                          temp_C_interpol * VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol
                            )
hct_mod1_VIFs <- data.frame(VIF = car::vif(hct_mod1)) %>%
  arrange(desc(VIF))
hct_mod1_VIFs
```

```
##                                    VIF
## VPD_kPa_int                 776.757637
## temp_C_interpol:VPD_kPa_int 259.553383
## temp_C_interpol             180.892477
## mass_g                      144.335588
## SVL_mm                      138.619872
## SMI                          69.489069
## wind_mph_interpol             5.204263
## solar_rad_W_sqm_interpol      3.987365
```

remove VPD*temp interaction:

```
hct_mod2 <- lm(data = capture_dat_plus,
                          # response variable
                          hematocrit_percent ~
                          # body size
                          mass_g + SVL_mm + SMI +
                          # weather at the time of capture
                          temp_C_interpol + VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol
                            )
hct_mod2_VIFs <- data.frame(VIF = car::vif(hct_mod2)) %>%
  arrange(desc(VIF))
hct_mod2_VIFs
```

```
##                                 VIF
## mass_g                   142.040733
## SVL_mm                   136.131895
## temp_C_interpol           89.600299
## VPD_kPa_int               88.738603
## SMI                       68.200398
## wind_mph_interpol          4.087720
## solar_rad_W_sqm_interpol   2.293567
```

```r
drop1(hct_mod2)
```

```
## Single term deletions
##
## Model:
## hematocrit_percent ~ mass_g + SVL_mm + SMI + temp_C_interpol +
##     VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol
##                          Df Sum of Sq    RSS    AIC
## <none>                                2998.1 410.99
## mass_g                    1     0.756 2998.8 409.03
## SVL_mm                    1     0.503 2998.6 409.02
## SMI                       1     0.927 2999.0 409.03
## temp_C_interpol           1     4.223 3002.3 409.17
## VPD_kPa_int               1     1.547 2999.6 409.06
## wind_mph_interpol         1   250.753 3248.8 418.96
## solar_rad_W_sqm_interpol  1    77.163 3075.2 412.15
```

drop SVL:

```r
hct_mod3 <- lm(data = capture_dat_plus,
                          # response variable
                          hematocrit_percent ~
                          # body size
                          mass_g + SMI +
                          # weather at the time of capture
                          temp_C_interpol + VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol
                            )
hct_mod3_VIFs <- data.frame(VIF = car::vif(hct_mod3)) %>%
  arrange(desc(VIF))
hct_mod3_VIFs
```

```
##                                VIF
## temp_C_interpol          84.912303
## VPD_kPa_int              83.182330
## wind_mph_interpol         4.052541
## solar_rad_W_sqm_interpol  2.215162
## SMI                       1.382672
## mass_g                    1.222359
```

```r
drop1(hct_mod3)
```

```
## Single term deletions
##
## Model:
## hematocrit_percent ~ mass_g + SMI + temp_C_interpol + VPD_kPa_int +
##     wind_mph_interpol + solar_rad_W_sqm_interpol
##                          Df Sum of Sq    RSS    AIC
## <none>                                2998.6 409.02
## mass_g                    1     3.084 3001.7 407.14
## SMI                       1   136.794 3135.4 412.55
## temp_C_interpol           1     3.781 3002.4 407.17
## VPD_kPa_int               1     1.213 2999.8 407.07
## wind_mph_interpol         1   255.037 3253.6 417.14
## solar_rad_W_sqm_interpol  1    77.526 3076.1 410.18
```

drop temperature:

```
hct_mod4 <- lm(data = capture_dat_plus,
                         # response variable
                         hematocrit_percent ~
                         # body size
                         mass_g + SMI +
                         # weather at the time of capture
                         VPD_kPa_int +
                         wind_mph_interpol + solar_rad_W_sqm_interpol
                           )
hct_mod4_VIFs <- data.frame(VIF = car::vif(hct_mod4)) %>%
  arrange(desc(VIF))
hct_mod4_VIFs
```

```
##                               VIF
## wind_mph_interpol        4.040106
## VPD_kPa_int              4.010513
## SMI                      1.379849
## mass_g                   1.222097
## solar_rad_W_sqm_interpol 1.068149
```

```
drop1(hct_mod4)
```

```
## Single term deletions
##
## Model:
## hematocrit_percent ~ mass_g + SMI + VPD_kPa_int + wind_mph_interpol +
##     solar_rad_W_sqm_interpol
##                          Df Sum of Sq    RSS    AIC
## <none>                                3002.4 407.17
## mass_g                    1     2.986 3005.3 405.30
## SMI                       1   135.022 3137.4 410.63
## VPD_kPa_int               1    13.125 3015.5 405.71
## wind_mph_interpol         1   252.383 3254.7 415.18
## solar_rad_W_sqm_interpol  1   113.739 3116.1 409.78
```

VIFs are all below 5 now, so start backwards selection.

Drop mass first:

```
hct_mod5 <- lm(data = capture_dat_plus,
                         # response variable
                         hematocrit_percent ~
                         # body size
                         SMI +
                         # weather at the time of capture
                         VPD_kPa_int +
                         wind_mph_interpol + solar_rad_W_sqm_interpol
                           )
drop1(hct_mod5)
```

```
## Single term deletions
##
## Model:
## hematocrit_percent ~ SMI + VPD_kPa_int + wind_mph_interpol +
##     solar_rad_W_sqm_interpol
```

```
##                           Df Sum of Sq    RSS    AIC
## <none>                                 3005.3 405.30
## SMI                        1   185.240 3190.6 410.71
## VPD_kPa_int                1    13.248 3018.6 403.84
## wind_mph_interpol          1   263.098 3268.4 413.70
## solar_rad_W_sqm_interpol   1   116.371 3121.7 408.01
```

Drop VPD:

```r
hct_mod6 <- lm(data = capture_dat_plus,
                          # response variable
                          hematocrit_percent ~
                          # body size
                          SMI +
                          # weather at the time of capture
                          wind_mph_interpol + solar_rad_W_sqm_interpol
                            )
drop1(hct_mod6)
```

```
## Single term deletions
##
## Model:
## hematocrit_percent ~ SMI + wind_mph_interpol + solar_rad_W_sqm_interpol
##                           Df Sum of Sq    RSS    AIC
## <none>                                 3018.6 403.84
## SMI                        1    194.22 3212.8 409.57
## wind_mph_interpol          1    612.60 3631.2 424.75
## solar_rad_W_sqm_interpol   1    104.56 3123.2 406.06
```

Drop solar:

```r
hct_mod7 <- lm(data = capture_dat_plus,
                          # response variable
                          hematocrit_percent ~
                          # body size
                          SMI +
                          # weather at the time of capture
                          wind_mph_interpol
                            )
drop1(hct_mod7)
```

```
## Single term deletions
##
## Model:
## hematocrit_percent ~ SMI + wind_mph_interpol
##                    Df Sum of Sq    RSS    AIC
## <none>                          3123.2 406.06
## SMI                 1    170.48 3293.6 410.65
## wind_mph_interpol   1    594.70 3717.9 425.68
```

Drop SMI:

```r
hct_mod8 <- lm(data = capture_dat_plus,
                          # response variable
                          hematocrit_percent ~
                          # weather at the time of capture
                          wind_mph_interpol
```

```
                            )
```

Finally, null model:

```
hct_mod_null <- lm(data = capture_dat_plus,
                         # response variable
                         hematocrit_percent ~ 1)
```

Selection

Compare models 4-8 and the null model.

```
hct_models <- list(hct_mod4, hct_mod5, hct_mod6, hct_mod7,
                   hct_mod8, hct_mod_null)

#specify model names
hct_mod_names <- c('(model 4) ~ Wind-C, SMI, Solar-C, VPD-C, Mass',
                       '(model 5) ~ Wind-C, SMI, Solar-C, VPD-C',
                       '(model 6) ~ Wind-C, SMI, Solar-C',
                       '(model 7) ~ Wind-C, SMI',
                       '(model 8) ~ Wind-C',
                       'null model')
#calculate AIC of each model
hct_AICc <- data.frame(aictab(cand.set = hct_models,
                              modnames = hct_mod_names))
hct_AICc
```

```
##                                        Modnames K     AICc Delta_AICc
## 3              (model 6) ~ Wind-C, SMI, Solar-C 5 758.2459   0.000000
## 2       (model 5) ~ Wind-C, SMI, Solar-C, VPD-C 6 759.9099   1.664044
## 4                       (model 7) ~ Wind-C, SMI 4 760.2962   2.050306
## 1 (model 4) ~ Wind-C, SMI, Solar-C, VPD-C, Mass 7 762.0342   3.788370
## 5                            (model 8) ~ Wind-C 3 764.7505   6.504613
## 6                                    null model 2 861.5454 103.299575
##       ModelLik       AICcWt        LL    Cum.Wt
## 3 1.000000e+00 5.042773e-01 -373.8687 0.5042773
## 2 4.351684e-01 2.194456e-01 -373.5960 0.7237229
## 4 3.587416e-01 1.809053e-01 -375.9800 0.9046282
## 1 1.504409e-01 7.586393e-02 -373.5344 0.9804921
## 5 3.868489e-02 1.950791e-02 -379.2752 1.0000000
## 6 3.704950e-23 1.868322e-23 -428.7283 1.0000000
```

The best models are models 6 and 5.

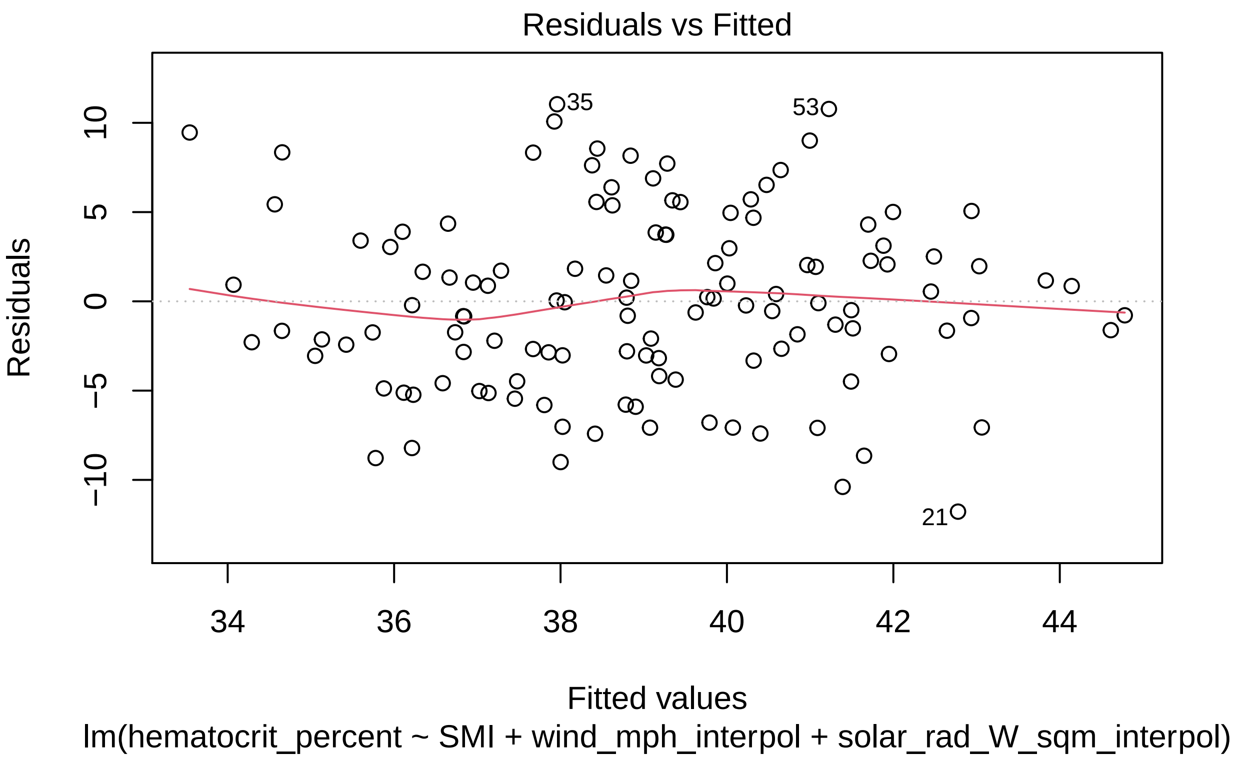
LM Conditions

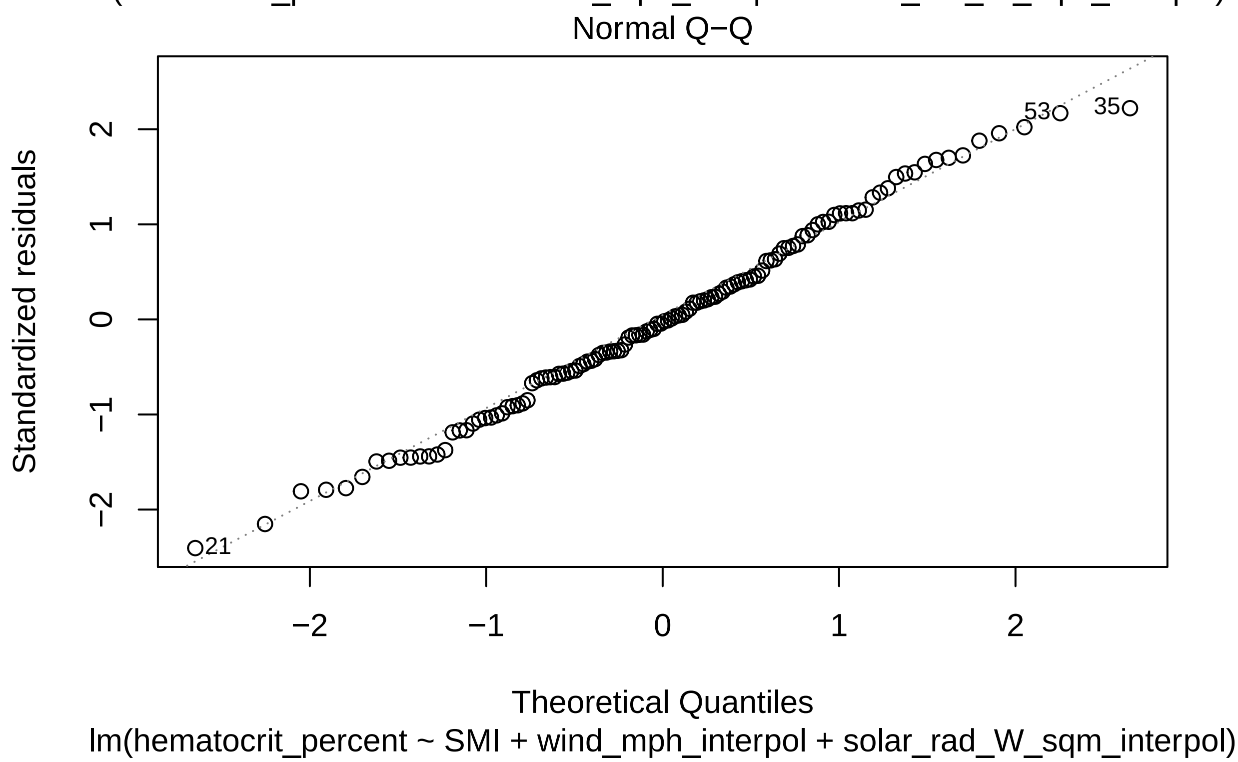
Check that the best model meets the criteria for linear regression and has no collinearity.

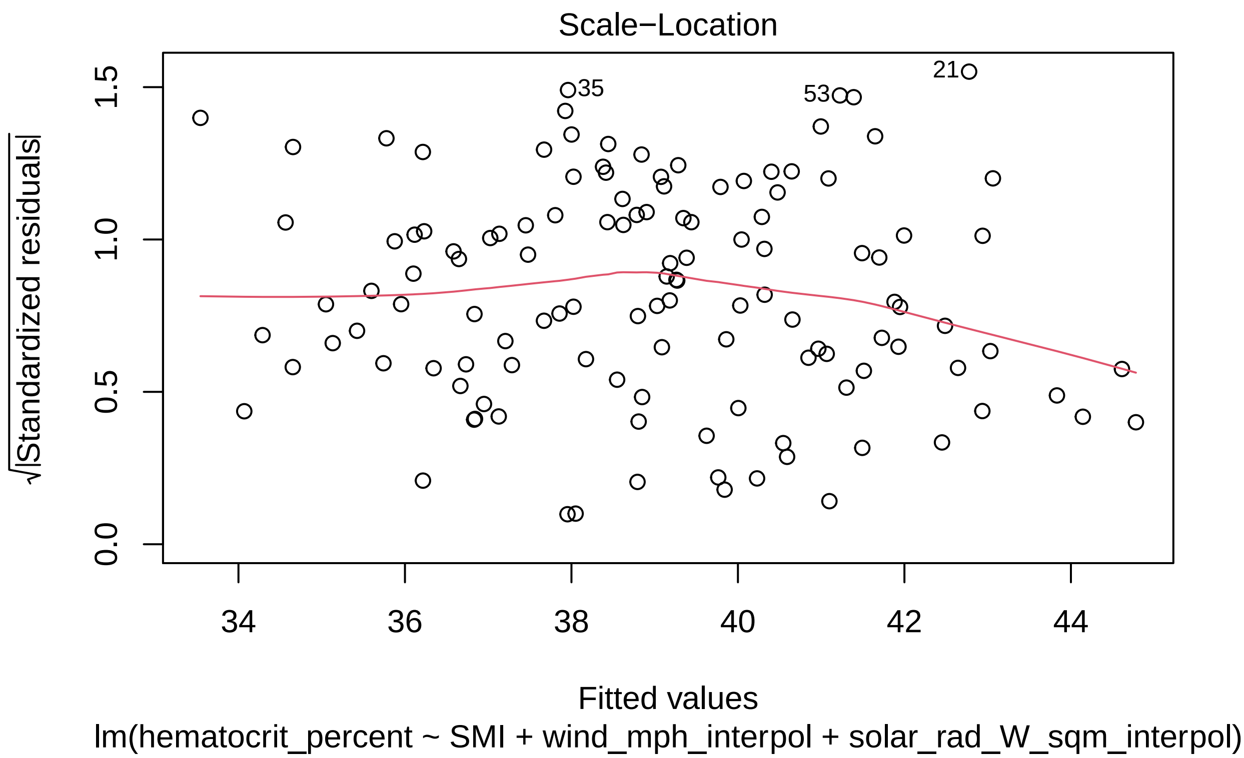
```
vif(hct_mod6)
```

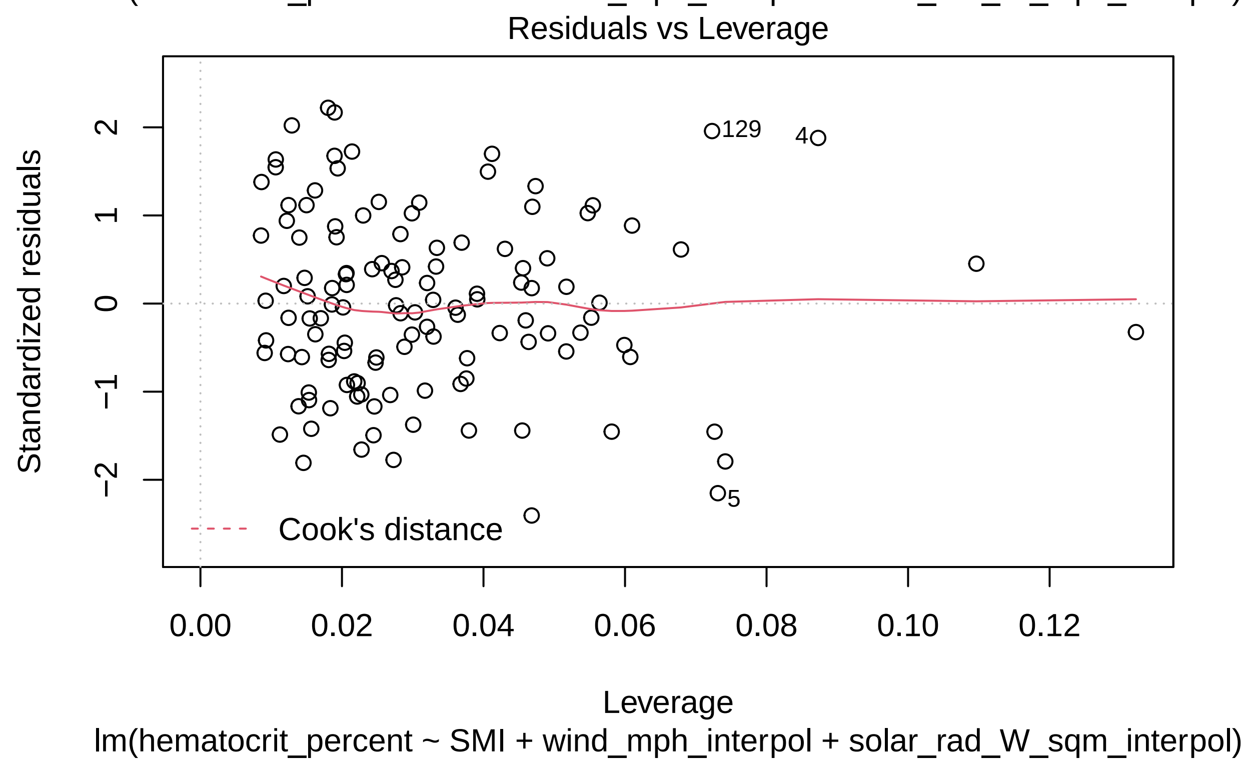
```
##                   SMI        wind_mph_interpol solar_rad_W_sqm_interpol
##              1.128678                 1.120821                 1.008470
```

```
plot(hct_mod6)
```

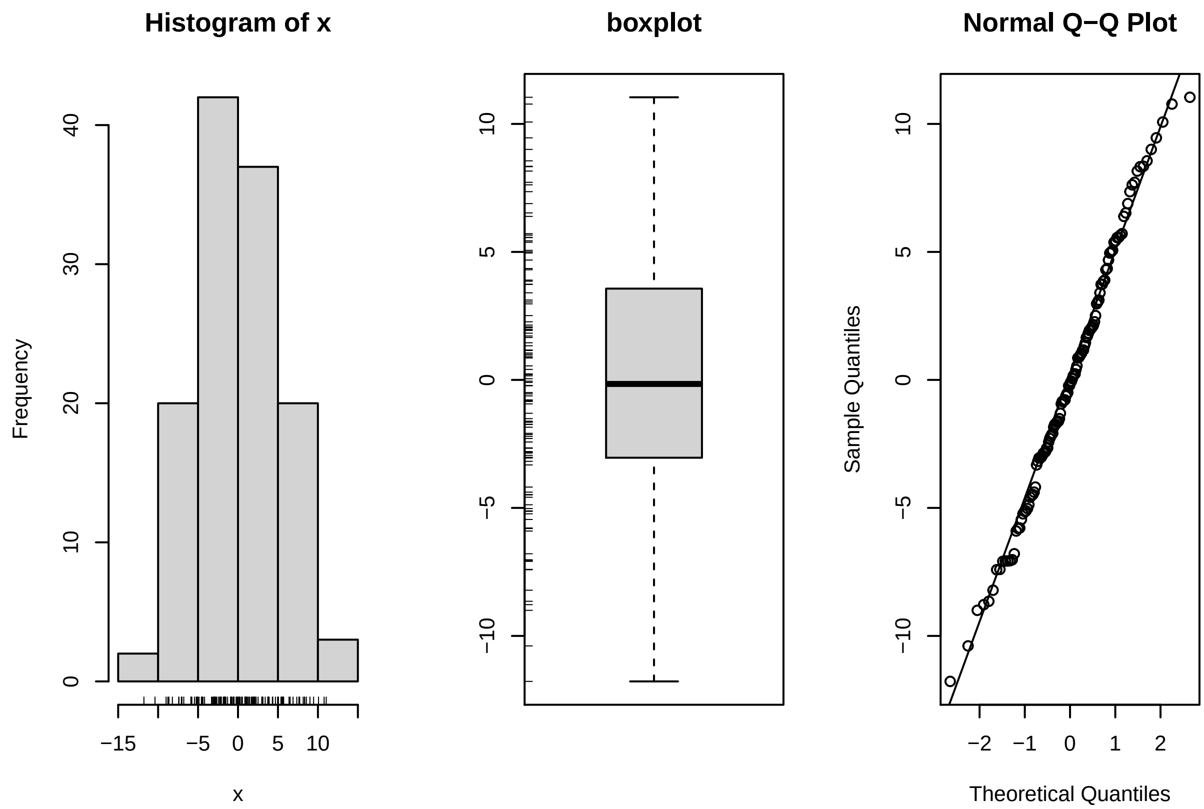

Residuals vs Fitted
Residuals
10
5
0
−5
−10
35
53
21
34
36
38
40
42
44
Fitted values
lm(hematocrit_percent ~ SMI + wind_mph_interpol + solar_rad_W_sqm_interpol)


Normal Q−Q
Standardized residuals
2
1
0
−1
−2
53
35
21
−2
−1
0
1
2
Theoretical Quantiles
lm(hematocrit_percent ~ SMI + wind_mph_interpol + solar_rad_W_sqm_interpol)






```
simple.eda(residuals(hct_mod6))
```



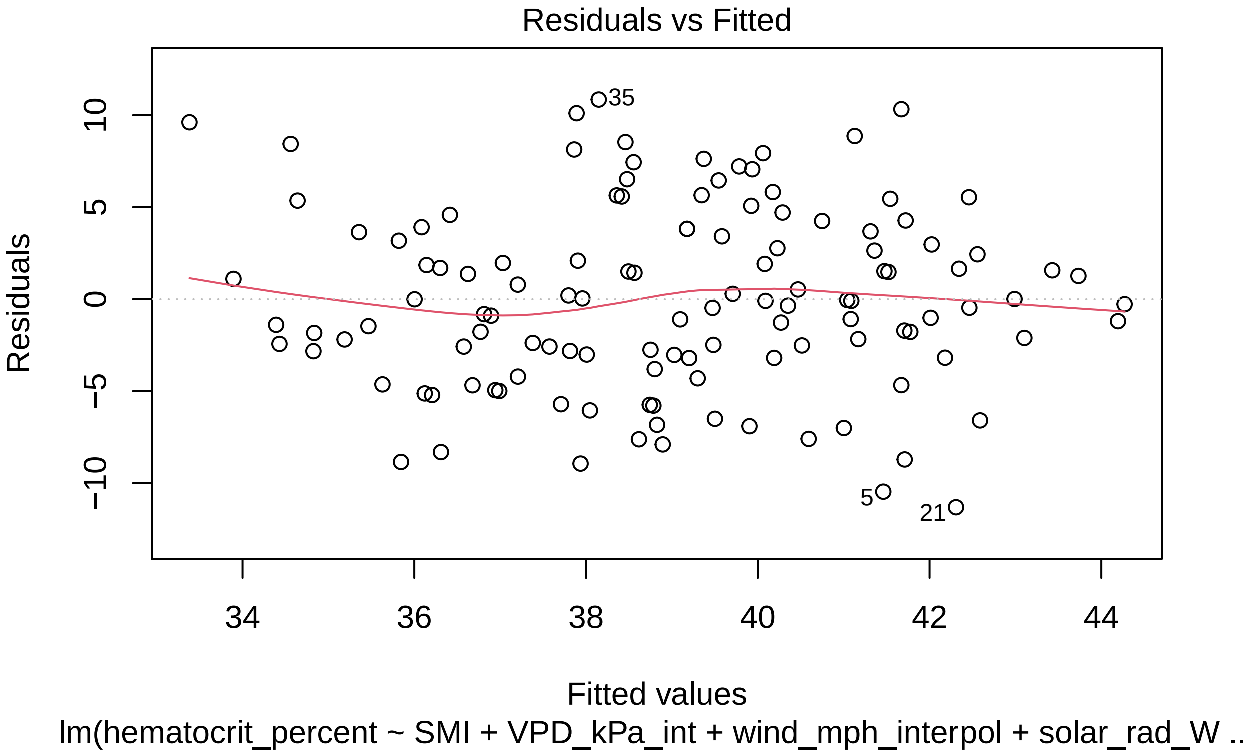

```r
shapiro.test(residuals(hct_mod6))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(hct_mod6)
## W = 0.99121, p-value = 0.6227
```

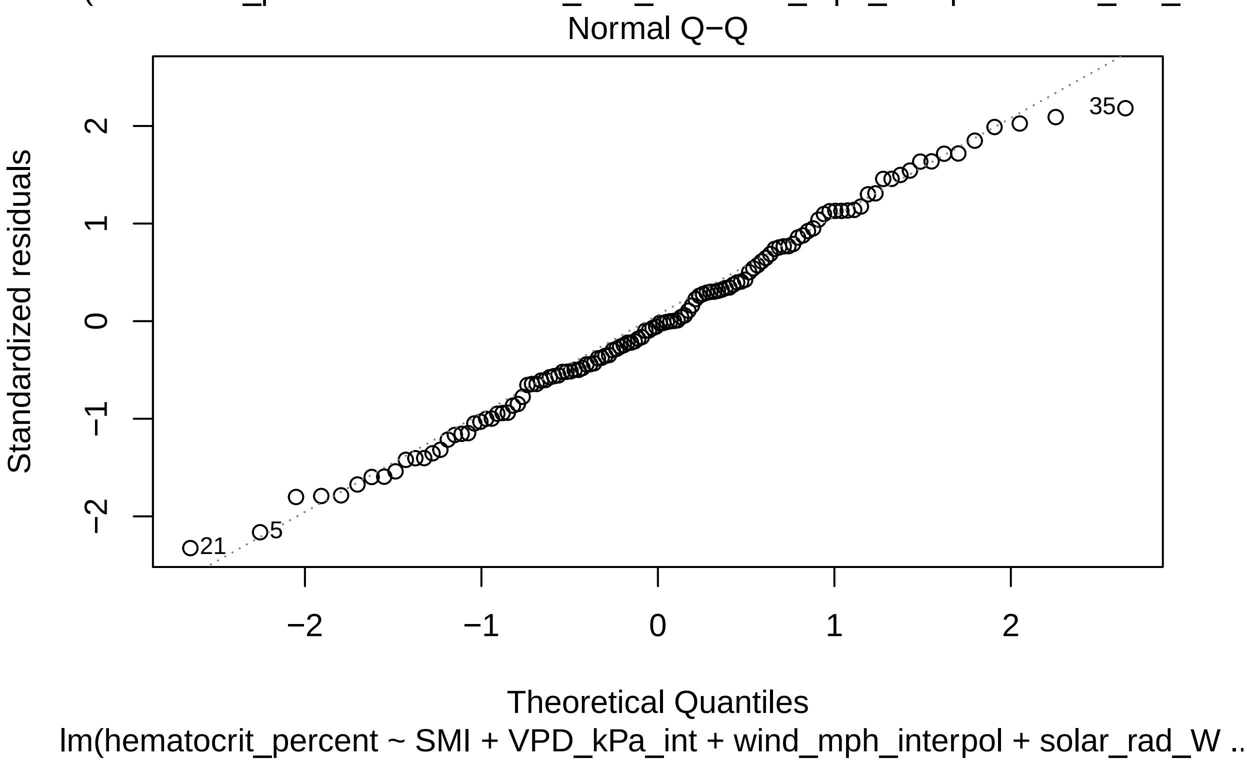
```r
vif(hct_mod5)
```

```
##                    SMI            VPD_kPa_int         wind_mph_interpol
##               1.135566               4.010134                  3.979500
## solar_rad_W_sqm_interpol
##               1.064326
```

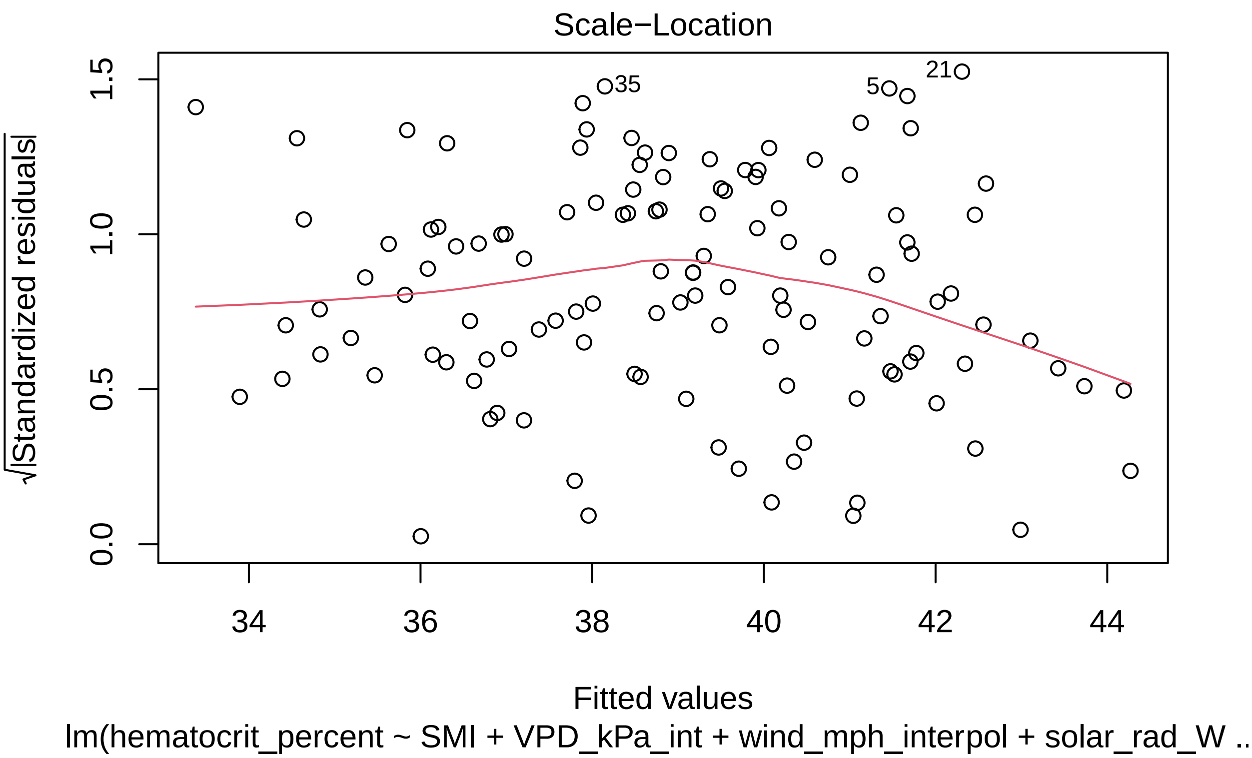
```r
plot(hct_mod5)
```

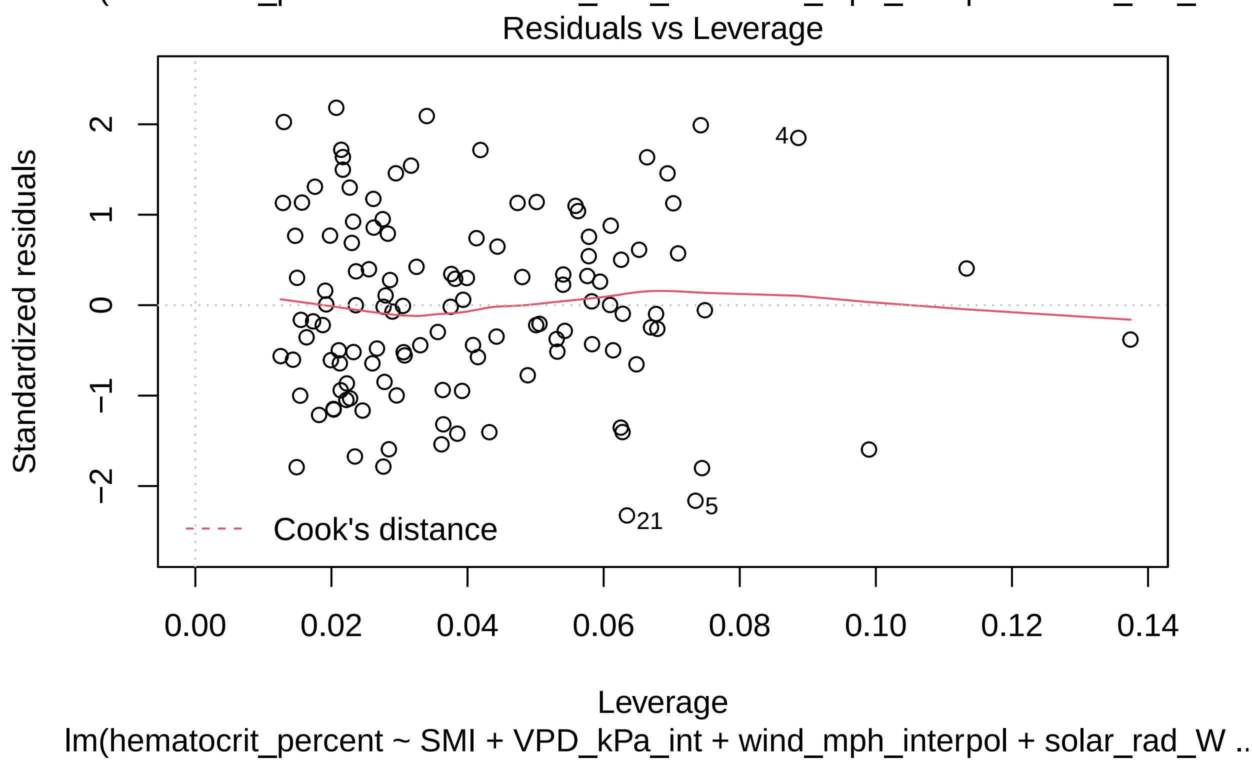


Residuals vs Fitted
Residuals
Fitted values
lm(hematocrit_percent ~ SMI + VPD_kPa_int + wind_mph_interpol + solar_rad_W ..
35
5
21

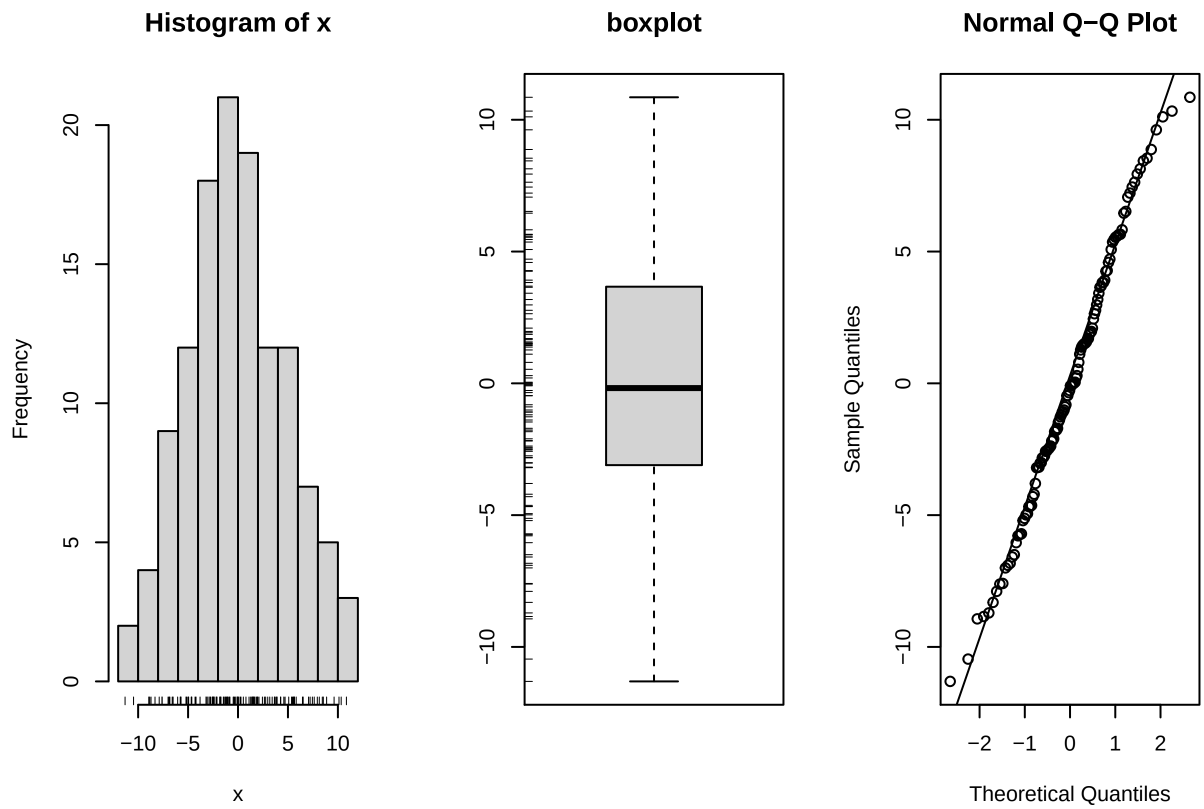


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(hematocrit_percent ~ SMI + VPD_kPa_int + wind_mph_interpol + solar_rad_W ..
35
21
5






```
simple.eda(residuals(hct_mod5))
```




```
shapiro.test(residuals(hct_mod5))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(hct_mod5)
## W = 0.99023, p-value = 0.5302
```

Everything is almost perfect.

Export

```
write.csv(hct_AICc, "./results_statistics/capture_hct_mod_rankings.csv")
write.csv(broom.mixed::tidy(hct_mod6),
          "./results_statistics/capture_hct_best_mod1.csv")
write.csv(broom.mixed::tidy(hct_mod5),
          "./results_statistics/capture_hct_best_mod2.csv")
```

Osmolality

Models

Since there are large differences in osmolality by date, but we are interested in what's different among dates, rather than the capture date itself, we will include that as a random effect in the model.

We would also include whether or not a blood sample is hemolyzed as a random effect, but only 11 of the almost 150 samples were hemolyzed, so we will assume that any potential effects will be undetectable and/or overshadowed. We do not have concern about using those points.

First, start with a full model with every probable potential predictor in it, then check for multicollinearity.

```r
osml_mod1 <- lme4::lmer(data = capture_dat_plus,
                         # response variable
                         osmolality_mmol_kg_mean ~
                         # body size
                         mass_g + SVL_mm + SMI +
                         # blood sample traits
                         hematocrit_percent +
                         # weather at the time of capture
                         temp_C_interpol * VPD_kPa_int +
                         wind_mph_interpol + solar_rad_W_sqm_interpol +
                         (1|capture_date))
osml_mod1_VIFs <- data.frame(VIF = car::vif(osml_mod1)) %>%
  arrange(desc(VIF))
osml_mod1_VIFs
```

```
##                                    VIF
## VPD_kPa_int                 230.849814
## mass_g                      154.460607
## SVL_mm                      135.742089
## temp_C_interpol:VPD_kPa_int  74.811657
## temp_C_interpol              74.180625
## SMI                          67.415865
## solar_rad_W_sqm_interpol      4.985336
## wind_mph_interpol             1.733325
## hematocrit_percent            1.144684
```

VPD and temperature introduce a lot of collinearity, so start by dropping their interaction:

```r
osml_mod2 <- lme4::lmer(data = capture_dat_plus,
                         # response variable
                         osmolality_mmol_kg_mean ~
                         # body size
                         mass_g + SVL_mm + SMI +
                         # blood sample traits
                         hematocrit_percent +
                         # weather at the time of capture
                         temp_C_interpol + VPD_kPa_int +
                         wind_mph_interpol + solar_rad_W_sqm_interpol +
                         (1|capture_date))
osml_mod2_VIFs <- data.frame(VIF = car::vif(osml_mod2)) %>%
  arrange(desc(VIF))
osml_mod2_VIFs
```

```
##                                 VIF
## mass_g                   154.065312
## SVL_mm                   135.248546
## SMI                       67.183598
## temp_C_interpol           25.018043
## VPD_kPa_int               17.521684
## solar_rad_W_sqm_interpol   3.793826
## wind_mph_interpol          1.286763
## hematocrit_percent         1.135251
```

```r
drop1(osml_mod2)
```

```
## Single term deletions
```

```
##
## Model:
## osmolality_mmol_kg_mean ~ mass_g + SVL_mm + SMI + hematocrit_percent +
##     temp_C_interpol + VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        1026.7
## mass_g                      1 1025.3
## SVL_mm                      1 1025.5
## SMI                         1 1025.2
## hematocrit_percent          1 1024.7
## temp_C_interpol             1 1026.0
## VPD_kPa_int                 1 1026.6
## wind_mph_interpol           1 1025.0
## solar_rad_W_sqm_interpol    1 1026.5
```

Drop mass next, since it's extremely collinear and we get slightly better AIC by dropping mass compared to SVL:

```
osml_mod3 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # body size
                          SVL_mm + SMI +
                          # blood sample traits
                          hematocrit_percent +
                          # weather at the time of capture
                          temp_C_interpol + VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
osml_mod3_VIFs <- data.frame(VIF = car::vif(osml_mod3)) %>%
  arrange(desc(VIF))
osml_mod3_VIFs
```

```
##                                VIF
## temp_C_interpol          24.144245
## VPD_kPa_int              17.159217
## solar_rad_W_sqm_interpol  3.673653
## wind_mph_interpol         1.277519
## SMI                       1.153357
## hematocrit_percent        1.135222
## SVL_mm                    1.076835
```

```
drop1(osml_mod3)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ SVL_mm + SMI + hematocrit_percent +
##     temp_C_interpol + VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        1025.3
## SVL_mm                      1 1026.5
## SMI                         1 1023.5
## hematocrit_percent          1 1023.3
```

```
## temp_C_interpol              1 1024.3
## VPD_kPa_int                  1 1025.0
## wind_mph_interpol            1 1023.6
## solar_rad_W_sqm_interpol     1 1025.7
```

Temperature is still introducing a lot of multicollinearity, so drop:

```r
osml_mod4 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # body size
                          SVL_mm + SMI +
                          # blood sample traits
                          hematocrit_percent +
                          # weather at the time of capture
                          VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
osml_mod4_VIFs <- data.frame(VIF = car::vif(osml_mod4)) %>%
  arrange(desc(VIF))
osml_mod4_VIFs
```

```
##                               VIF
## VPD_kPa_int              2.679147
## solar_rad_W_sqm_interpol 2.423227
## wind_mph_interpol        1.190630
## SMI                      1.149874
## hematocrit_percent       1.133518
## SVL_mm                   1.075327
```

```r
summary(osml_mod4)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: osmolality_mmol_kg_mean ~ SVL_mm + SMI + hematocrit_percent +
##     VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1000.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3277 -0.6763 -0.0915  0.6145  3.1713
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 290.4    17.04
##  Residual                 179.4    13.39
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error t value
## (Intercept)              288.19862   34.80574   8.280
## SVL_mm                     0.66892    0.39175   1.708
## SMI                       -0.49716    1.27078  -0.391
## hematocrit_percent         0.04681    0.24780   0.189
```

```
## VPD_kPa_int               -3.55130    3.96947  -0.895
## wind_mph_interpol         -0.15535    1.19310  -0.130
## solar_rad_W_sqm_interpol   0.03473    0.01316   2.639
##
## Correlation of Fixed Effects:
##             (Intr) SVL_mm SMI    hmtcr_ VPD_P_ wnd_m_
## SVL_mm      -0.840
## SMI         -0.567  0.243
## hmtcrt_prcn -0.109 -0.030 -0.245
## VPD_kPa_int  0.054  0.044  0.084 -0.104
## wnd_mph_ntr -0.058 -0.034  0.012 -0.145 -0.290
## slr_rd_W_s_ -0.135 -0.071  0.021 -0.014 -0.742  0.093
```

```r
drop1(osml_mod4)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ SVL_mm + SMI + hematocrit_percent +
##     VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        1024.3
## SVL_mm                      1 1025.4
## SMI                         1 1022.5
## hematocrit_percent          1 1022.4
## VPD_kPa_int                 1 1023.2
## wind_mph_interpol           1 1022.4
## solar_rad_W_sqm_interpol    1 1029.8
```

Great, VIFs are well-within acceptable ranges. Now we can start backwards model selection.

Start by dropping wind:

```r
osml_mod5 <- lme4::lmer(data = capture_dat_plus,
                         # response variable
                         osmolality_mmol_kg_mean ~
                         # body size
                         SVL_mm + SMI +
                         # blood sample traits
                         hematocrit_percent +
                         # weather at the time of capture
                         VPD_kPa_int + solar_rad_W_sqm_interpol +
                         (1|capture_date))
summary(osml_mod5)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: osmolality_mmol_kg_mean ~ SVL_mm + SMI + hematocrit_percent +
##     VPD_kPa_int + solar_rad_W_sqm_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1003
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3331 -0.6846 -0.1049  0.6265  3.1859
```

```
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 285.8    16.91
##  Residual                 178.0    13.34
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error t value
## (Intercept)              287.93394   34.59973   8.322
## SVL_mm                     0.66717    0.38992   1.711
## SMI                       -0.49475    1.26553  -0.391
## hematocrit_percent         0.04203    0.24418   0.172
## VPD_kPa_int               -3.70269    3.77643  -0.980
## solar_rad_W_sqm_interpol   0.03489    0.01303   2.677
##
## Correlation of Fixed Effects:
##             (Intr) SVL_mm SMI    hmtcr_ VPD_P_
## SVL_mm      -0.844
## SMI         -0.567  0.244
## hmtcrt_prcn -0.119 -0.035 -0.246
## VPD_kPa_int  0.039  0.036  0.092 -0.154
## slr_rd_W_s_ -0.130 -0.068  0.020  0.000 -0.749
```

```
drop1(osml_mod5)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ SVL_mm + SMI + hematocrit_percent +
##     VPD_kPa_int + solar_rad_W_sqm_interpol + (1 | capture_date)
##                          npar    AIC
## <none>                        1022.4
## SVL_mm                      1 1023.4
## SMI                         1 1020.6
## hematocrit_percent          1 1020.5
## VPD_kPa_int                 1 1021.6
## solar_rad_W_sqm_interpol    1 1027.9
```

Drop hematocrit:

```
osml_mod6 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # body size
                          SVL_mm + SMI +
                          # weather at the time of capture
                          VPD_kPa_int + solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(osml_mod6)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## osmolality_mmol_kg_mean ~ SVL_mm + SMI + VPD_kPa_int + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##    Data: capture_dat_plus
```

```
##
## REML criterion at convergence: 1002
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3427 -0.6857 -0.0986  0.6211  3.1838
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 284.0    16.85
##  Residual                 176.5    13.29
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error t value
## (Intercept)              288.64070   34.21616   8.436
## SVL_mm                     0.66955    0.38808   1.725
## SMI                       -0.44133    1.22173  -0.361
## VPD_kPa_int               -3.60215    3.71763  -0.969
## solar_rad_W_sqm_interpol   0.03489    0.01298   2.687
##
## Correlation of Fixed Effects:
##             (Intr) SVL_mm SMI    VPD_P_
## SVL_mm      -0.855
## SMI         -0.619  0.243
## VPD_kPa_int  0.021  0.031  0.056
## slr_rd_W_s_ -0.131 -0.068  0.021 -0.758
```

```r
drop1(osml_mod6)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ SVL_mm + SMI + VPD_kPa_int + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        1020.5
## SVL_mm                      1 1021.5
## SMI                         1 1018.6
## VPD_kPa_int                 1 1019.6
## solar_rad_W_sqm_interpol    1 1025.9
```

Drop SMI:

```r
osml_mod7 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # body size
                          SVL_mm +
                          # weather at the time of capture
                          VPD_kPa_int + solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(osml_mod7)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
```

```
## osmolality_mmol_kg_mean ~ SVL_mm + VPD_kPa_int + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1004.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3370 -0.6953 -0.0963  0.6058  3.2280
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 282.0    16.79
##  Residual                 175.2    13.24
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)             280.98723   26.77002  10.496
## SVL_mm                    0.70358    0.37510   1.876
## VPD_kPa_int              -3.52647    3.69840  -0.954
## solar_rad_W_sqm_interpol   0.03499    0.01293   2.705
##
## Correlation of Fixed Effects:
##             (Intr) SVL_mm VPD_P_
## SVL_mm      -0.925
## VPD_kPa_int  0.072  0.018
## slr_rd_W_s_ -0.151 -0.075 -0.761
```

```r
drop1(osml_mod7)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ SVL_mm + VPD_kPa_int + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        1018.6
## SVL_mm                      1 1020.1
## VPD_kPa_int                 1 1017.7
## solar_rad_W_sqm_interpol    1 1024.1
```

Drop VPD:

```r
osml_mod8 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # body size
                          SVL_mm +
                          # weather at the time of capture
                          solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(osml_mod8)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: osmolality_mmol_kg_mean ~ SVL_mm + solar_rad_W_sqm_interpol +
```

```
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1009.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3259 -0.6885 -0.0971  0.5530  3.2419
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 288.1    16.97
##  Residual                 175.0    13.23
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)             2.828e+02  2.671e+01  10.589
## SVL_mm                  7.103e-01  3.748e-01   1.895
## solar_rad_W_sqm_interpol 2.560e-02  8.387e-03   3.053
##
## Correlation of Fixed Effects:
##             (Intr) SVL_mm
## SVL_mm      -0.928
## slr_rd_W_s_ -0.148 -0.095
```

Drop SVL:

```
osml_mod9 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # weather at the time of capture
                          solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(osml_mod9)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## osmolality_mmol_kg_mean ~ solar_rad_W_sqm_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1013.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4085 -0.6875 -0.1434  0.5776  3.3124
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 277.1    16.65
##  Residual                 179.0    13.38
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
```

```
## (Intercept)              3.297e+02  9.915e+00  33.256
## solar_rad_W_sqm_interpol 2.712e-02  8.444e-03   3.212
##
## Correlation of Fixed Effects:
##             (Intr)
## slr_rd_W_s_ -0.648
```

Lastly, compute null model:

```r
osml_mod_null <- lme4::lmer(data = capture_dat_plus,
                         osmolality_mmol_kg_mean ~ 1 +
                         (1|capture_date))
summary(osml_mod_null)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: osmolality_mmol_kg_mean ~ 1 + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1127.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4072 -0.6642 -0.1005  0.5332  3.1645
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 262.1    16.19
##  Residual                 190.9    13.82
## Number of obs: 138, groups:  capture_date, 5
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  350.168      7.338   47.72
```

Selection

Compare models 4-9 and null.

```r
osml_models <- list(osml_mod4, osml_mod5, osml_mod6,
                    osml_mod7, osml_mod8, osml_mod9,
                    osml_mod_null)
#specify model names
osml_mod_names <- c('(model 4) ~ Solar-C, SVL, VPD-C, SMI, Hct, Wind-C',
                       '(model 5) ~ Solar-C, SVL, VPD-C, SMI, Hct',
                       '(model 6) ~ Solar-C, SVL, VPD-C, SMI',
                       '(model 7) ~ Solar-C, SVL, VPD-C',
                       '(model 8) ~ Solar-C, SVL',
                       '(model 9) ~ Solar-C',
                       'null model')
#calculate AIC of each model
osml_AICc <- data.frame(aictab(cand.set = osml_models,
                               modnames = osml_mod_names))
```

```
## Warning in aictab.AIClmerMod(cand.set = osml_models, modnames = osml_mod_names):
## Model selection for fixed effects is only appropriate with ML estimation:
## REML (default) should only be used to select random effects for a constant set of fixed effects
```

```r
osml_AICc
```

```
##                                             Modnames K     AICc  Delta_AICc
## 3              (model 6) ~ Solar-C, SVL, VPD-C, SMI 7 1016.984   0.0000000
## 4                   (model 7) ~ Solar-C, SVL, VPD-C 6 1017.103   0.1181748
## 2         (model 5) ~ Solar-C, SVL, VPD-C, SMI, Hct 8 1020.227   3.2428699
## 5                          (model 8) ~ Solar-C, SVL 5 1020.255   3.2705424
## 1 (model 4) ~ Solar-C, SVL, VPD-C, SMI, Hct, Wind-C 9 1020.350   3.3659221
## 6                               (model 9) ~ Solar-C 4 1021.516   4.5311041
## 7                                        null model 3 1133.960 116.9754918
##       ModelLik       AICcWt    Res.LL    Cum.Wt
## 3 1.000000e+00 3.809909e-01 -501.0094 0.3809909
## 4 9.426244e-01 3.591313e-01 -502.1923 0.7401222
## 2 1.976149e-01 7.528949e-02 -501.4876 0.8154117
## 5 1.948995e-01 7.425494e-02 -504.8732 0.8896667
## 1 1.858229e-01 7.079685e-02 -500.3857 0.9604635
## 6 1.037727e-01 3.953647e-02 -506.5897 1.0000000
## 7 3.972782e-26 1.513594e-26 -563.8904 1.0000000
```

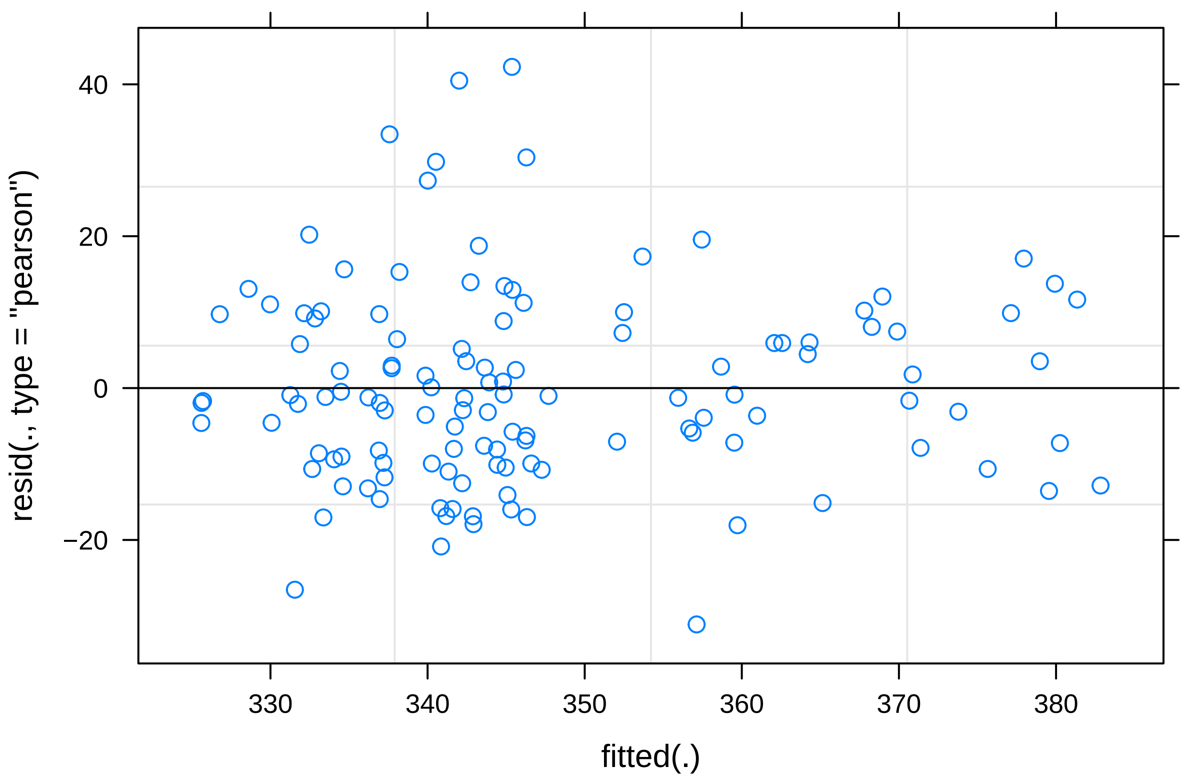
LM Conditions

Check residual plots and VIFs

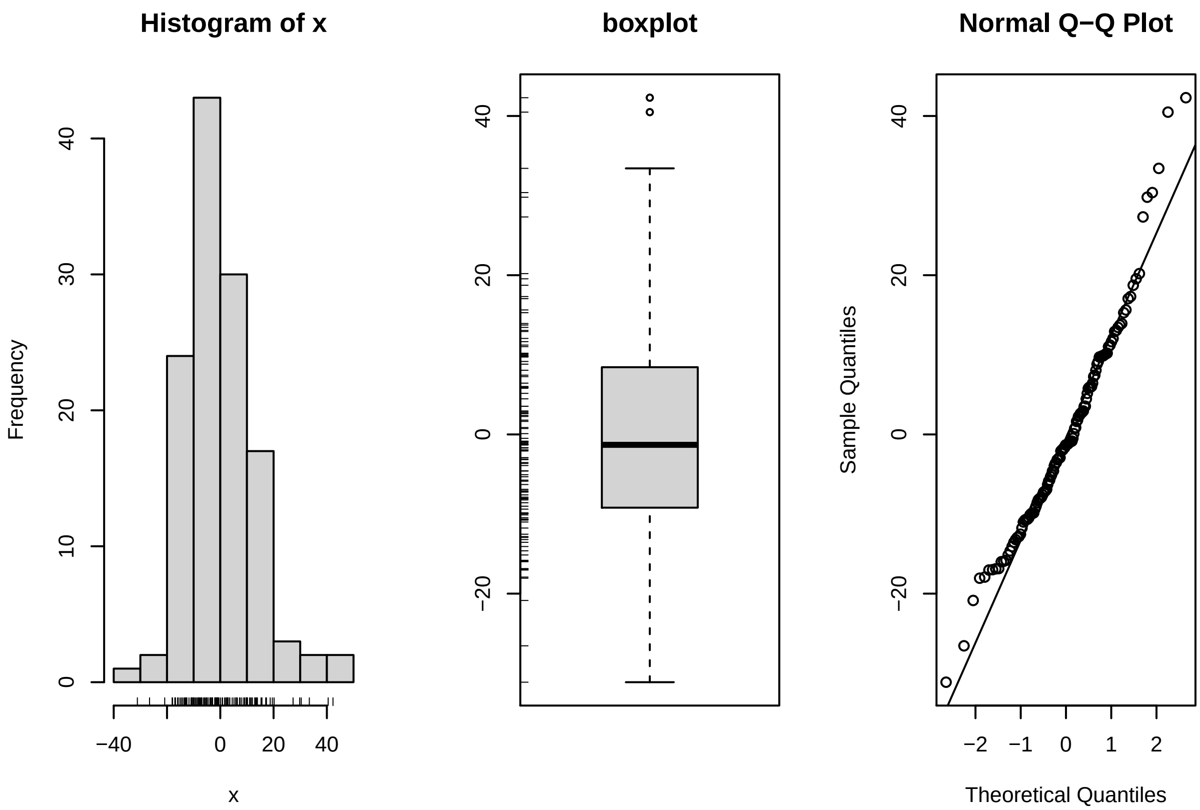
```r
vif(osml_mod6)
```

```
##                   SVL_mm                      SMI              VPD_kPa_int
##                 1.072726                 1.080392                 2.391457
## solar_rad_W_sqm_interpol
##                 2.397798
```

```r
plot(osml_mod6)
```



```r
simple.eda(residuals(osml_mod6))
```



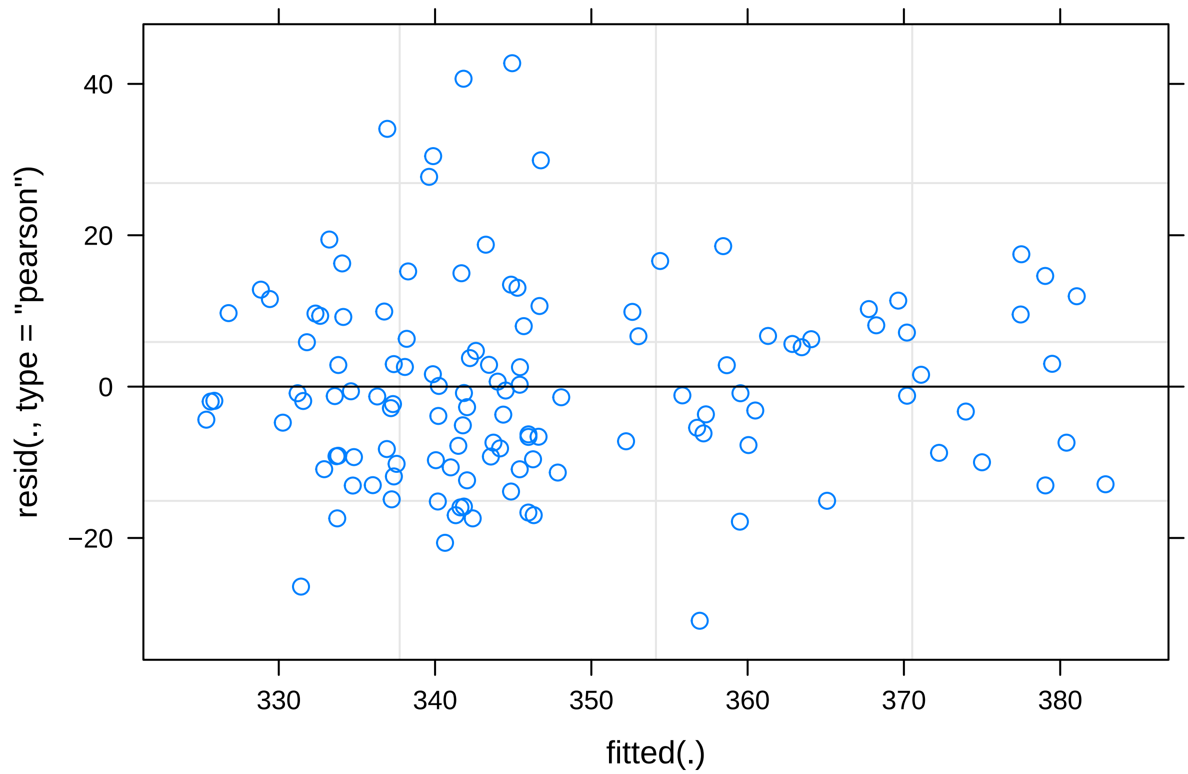

```r
shapiro.test(residuals(osml_mod6))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(osml_mod6)
## W = 0.96769, p-value = 0.004552
```

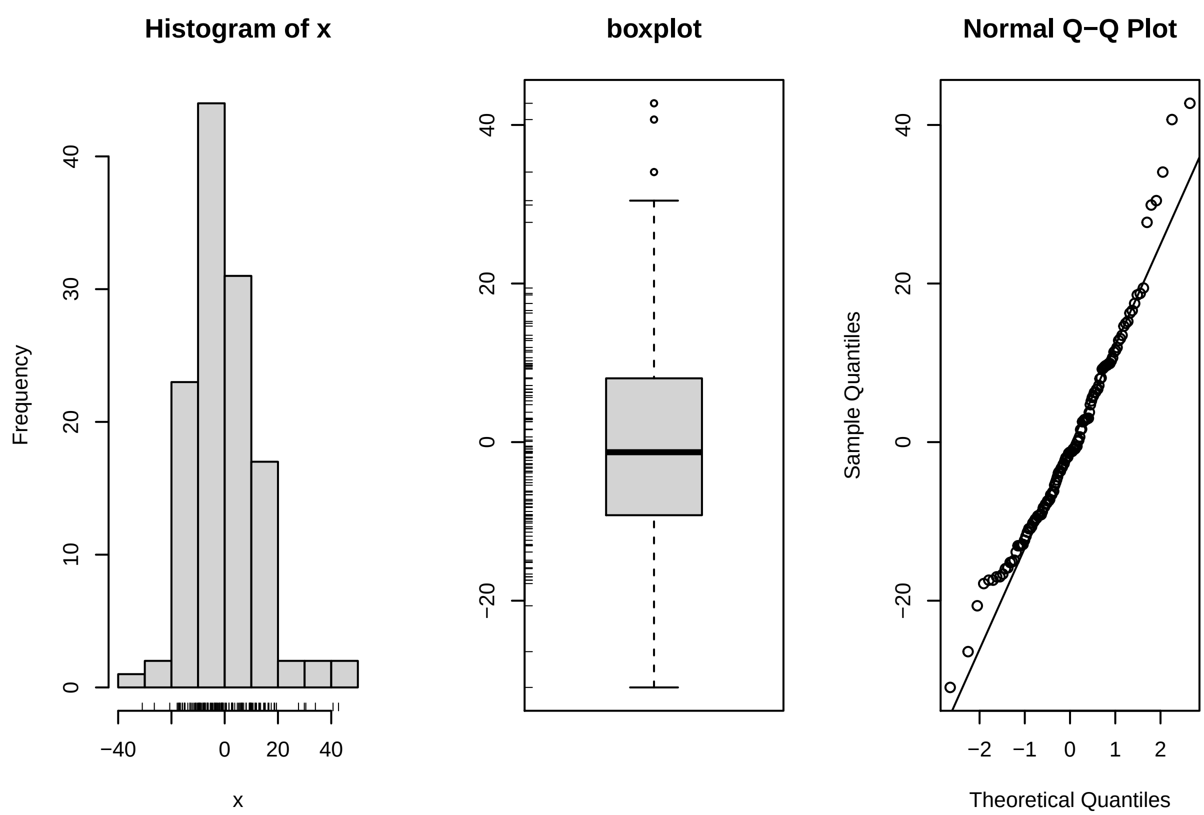
```r
vif(osml_mod7)
```

```
##                  SVL_mm              VPD_kPa_int solar_rad_W_sqm_interpol
##                1.009504                 2.383988                 2.396868
```

```r
plot(osml_mod7)
```




```r
simple.eda(residuals(osml_mod7))
```



```r
shapiro.test(residuals(osml_mod7))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(osml_mod7)
## W = 0.96557, p-value = 0.002973
```

There is no clear pattern in the residuals ~ fitted plot, so linearity seems satisfied. slight fanning, but equal error variance seems fine. Normality seems fine, even though the Shapiro-Wilk normality test is significant. VIFs essentially negligible.

Export

First, re-run for p-values:

```r
osml_mod6p <- lmerTest::lmer(data = capture_dat_plus,
                          # response variable
                          osmolality_mmol_kg_mean ~
                          # body size
                          SVL_mm + SMI +
                          # weather at the time of capture
                          VPD_kPa_int + solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(osml_mod6p)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## osmolality_mmol_kg_mean ~ SVL_mm + SMI + VPD_kPa_int + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1002
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3427 -0.6857 -0.0986  0.6211  3.1838
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 284.0    16.85
##  Residual                 176.5    13.29
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)              288.64070   34.21616 117.25661   8.436 9.89e-14 ***
## SVL_mm                     0.66955    0.38808 116.53034   1.725   0.0871 .
## SMI                       -0.44133    1.22173 115.79100  -0.361   0.7186
## VPD_kPa_int               -3.60215    3.71763  15.08348  -0.969   0.3479
## solar_rad_W_sqm_interpol   0.03489    0.01298  34.46737   2.687   0.0110 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Correlation of Fixed Effects:
##              (Intr) SVL_mm SMI    VPD_P_
## SVL_mm       -0.855
## SMI          -0.619  0.243
## VPD_kPa_int   0.021  0.031  0.056
## slr_rd_W_s_ -0.131 -0.068  0.021 -0.758
```

```
osml_mod7p <- lmerTest::lmer(data = capture_dat_plus,
                             # response variable
                             osmolality_mmol_kg_mean ~
                             # body size
                             SVL_mm +
                             # weather at the time of capture
                             VPD_kPa_int + solar_rad_W_sqm_interpol +
                             (1|capture_date))
summary(osml_mod7p)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## osmolality_mmol_kg_mean ~ SVL_mm + VPD_kPa_int + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 1004.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3370 -0.6953 -0.0963  0.6058  3.2280
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 282.0    16.79
##  Residual                 175.2    13.24
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)              280.98723   26.77002 109.79195  10.496   <2e-16 ***
## SVL_mm                     0.70358    0.37510 117.63142   1.876   0.0632 .
## VPD_kPa_int               -3.52647    3.69840  14.98489  -0.954   0.3555
## solar_rad_W_sqm_interpol   0.03499    0.01293  34.53408   2.705   0.0105 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) SVL_mm VPD_P_
## SVL_mm       -0.925
## VPD_kPa_int   0.072  0.018
## slr_rd_W_s_ -0.151 -0.075 -0.761
```

Save the model output.

```
write.csv(broom.mixed::tidy(osml_mod6p),
          "./results_statistics/capture_osml_best_model1.csv")
write.csv(broom.mixed::tidy(osml_mod7p),
```

```
          "./results_statistics/capture_osml_best_model2.csv")
write.csv(osml_AICc, "./results_statistics/capture_osml_mod_rankings.csv")
```

To report in paper:

The best models to predict the variation in baseline plasma osmolality included SVL, SMI, VPD, and solar radiation at the time of capture as fixed effects. Date was included as a random effect. The final model had acceptable LM conditions. The full model included mass, SVL, SMI, percent hematocrit, and temperature, VPD, wind speed, and solar radiation at the time of capture, with date as a random effect.

CEWL

It looks like there are meaningful differences in CEWL across individuals/dates (probably confounded), and based on cloacal temp, capture temp, capture VPD, capture wind, and capture solar radiation.

I didn't calculate holding time!!!!!!!!!!!!!!!!!!!

Models

Start with the full model of all potential predictor variables. We will again include date as a random effect. Individual ID is not included as a random effect bc each lizard only has one set of capture observations.

When we have this many variables, it's extremely important to start with checking for multicollinearity.

```
CEWL_mod1 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # essential covariate
                          cloacal_temp_C +
                          # body size
                          mass_g + SVL_mm + SMI +
                          # blood
                          osmolality_mmol_kg_mean + hematocrit_percent +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          temp_C_interpol * VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
CEWL_mod1_VIFs <- data.frame(VIF = car::vif(CEWL_mod1)) %>%
  arrange(desc(VIF))
CEWL_mod1_VIFs
```

```
##                                    VIF
## VPD_kPa_int                 783.440465
## temp_C_interpol:VPD_kPa_int 245.669675
## temp_C_interpol             162.888530
## mass_g                      155.683993
## SVL_mm                      138.059473
## SMI                          68.418373
## msmt_VPD_kPa                 27.311890
## msmt_temp_C                  12.309096
## solar_rad_W_sqm_interpol      4.931287
## wind_mph_interpol             3.105989
## hematocrit_percent            1.217811
## osmolality_mmol_kg_mean       1.175932
```

```
## cloacal_temp_C                1.120234
```

```
drop1(CEWL_mod1)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + SVL_mm + SMI + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + temp_C_interpol *
##     VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                              npar    AIC
## <none>                            658.07
## cloacal_temp_C                  1 656.54
## mass_g                          1 658.30
## SVL_mm                          1 658.07
## SMI                             1 657.98
## osmolality_mmol_kg_mean         1 666.82
## hematocrit_percent              1 656.24
## msmt_temp_C                     1 668.77
## msmt_VPD_kPa                    1 659.05
## wind_mph_interpol               1 659.57
## solar_rad_W_sqm_interpol        1 657.70
## temp_C_interpol:VPD_kPa_int     1 656.17
```

Just as for osmolality, VPD and temperature introduce a lot of collinearity. Start with dropping their interaction:

```
CEWL_mod2 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # essential covariate
                          cloacal_temp_C +
                          # body size
                          mass_g + SVL_mm + SMI +
                          # blood
                          osmolality_mmol_kg_mean + hematocrit_percent +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          temp_C_interpol + VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
CEWL_mod2_VIFs <- data.frame(VIF = car::vif(CEWL_mod2)) %>%
  arrange(desc(VIF))
CEWL_mod2_VIFs
```

```
##                                 VIF
## mass_g                   155.583829
## SVL_mm                   137.939177
## SMI                       68.362502
## temp_C_interpol           33.288867
## VPD_kPa_int               30.165485
## msmt_VPD_kPa              10.479774
## msmt_temp_C                4.921924
## solar_rad_W_sqm_interpol   4.620922
```

```
## wind_mph_interpol          3.151631
## hematocrit_percent         1.211977
## osmolality_mmol_kg_mean    1.177108
## cloacal_temp_C             1.087846
```

```r
drop1(CEWL_mod2)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + SVL_mm + SMI + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + temp_C_interpol +
##     VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        656.17
## cloacal_temp_C              1 654.71
## mass_g                      1 656.35
## SVL_mm                      1 656.12
## SMI                         1 656.02
## osmolality_mmol_kg_mean     1 664.82
## hematocrit_percent          1 654.32
## msmt_temp_C                 1 683.91
## msmt_VPD_kPa                1 663.04
## temp_C_interpol             1 660.42
## VPD_kPa_int                 1 663.25
## wind_mph_interpol           1 657.57
## solar_rad_W_sqm_interpol    1 655.72
```

MUCH better. Drop SVL next:

```r
CEWL_mod3 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # essential covariate
                          cloacal_temp_C +
                          # body size
                          mass_g + SMI +
                          # blood
                          osmolality_mmol_kg_mean + hematocrit_percent +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          temp_C_interpol + VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
CEWL_mod3_VIFs <- data.frame(VIF = car::vif(CEWL_mod3)) %>%
  arrange(desc(VIF))
CEWL_mod3_VIFs
```

```
##                                VIF
## temp_C_interpol          31.568736
## VPD_kPa_int              28.958335
## msmt_VPD_kPa             10.095248
## msmt_temp_C               4.887108
## solar_rad_W_sqm_interpol  4.466726
```

```
## wind_mph_interpol         3.068351
## SMI                       1.338973
## mass_g                    1.262001
## hematocrit_percent        1.211178
## osmolality_mmol_kg_mean   1.162251
## cloacal_temp_C            1.077536
```

```r
drop1(CEWL_mod3)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + SMI + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + temp_C_interpol +
##     VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        656.12
## cloacal_temp_C              1 654.48
## mass_g                      1 655.03
## SMI                         1 654.14
## osmolality_mmol_kg_mean     1 665.72
## hematocrit_percent          1 654.26
## msmt_temp_C                 1 682.98
## msmt_VPD_kPa                1 662.35
## temp_C_interpol             1 659.19
## VPD_kPa_int                 1 662.06
## wind_mph_interpol           1 657.37
## solar_rad_W_sqm_interpol    1 655.08
```

Next drop temperature at the time of capture:

```r
CEWL_mod4 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # essential covariate
                          cloacal_temp_C +
                          # body size
                          mass_g + SMI +
                          # blood
                          osmolality_mmol_kg_mean + hematocrit_percent +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
CEWL_mod4_VIFs <- data.frame(VIF = car::vif(CEWL_mod4)) %>%
  arrange(desc(VIF))
CEWL_mod4_VIFs
```

```
##                               VIF
## msmt_VPD_kPa             8.198253
## VPD_kPa_int              4.875379
## msmt_temp_C              4.751222
## solar_rad_W_sqm_interpol 3.194119
```

```
## wind_mph_interpol        2.499711
## SMI                      1.328391
## mass_g                   1.259718
## hematocrit_percent       1.203086
## osmolality_mmol_kg_mean  1.146825
## cloacal_temp_C           1.043984
```

```r
summary(CEWL_mod4)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + SMI + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int +
##     wind_mph_interpol + solar_rad_W_sqm_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 647.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9878 -0.6407 -0.0218  0.5908  3.6003
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.834    2.199
##  Residual                 9.612    3.100
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                            Estimate Std. Error t value
## (Intercept)              -1.740e+02  3.544e+01  -4.909
## cloacal_temp_C           -5.662e-02  3.967e-01  -0.143
## mass_g                   -2.240e-01  1.972e-01  -1.136
## SMI                       3.024e-02  3.151e-01   0.096
## osmolality_mmol_kg_mean   6.928e-02  2.098e-02   3.302
## hematocrit_percent        1.858e-02  5.889e-02   0.315
## msmt_temp_C               7.599e+00  1.496e+00   5.078
## msmt_VPD_kPa             -1.643e+01  6.190e+00  -2.655
## VPD_kPa_int              -1.912e+00  1.052e+00  -1.817
## wind_mph_interpol         5.751e-01  3.158e-01   1.821
## solar_rad_W_sqm_interpol  1.850e-03  3.493e-03   0.530
##
## Correlation of Fixed Effects:
##             (Intr) clc__C mass_g SMI    osm___ hmtcr_ msm__C m_VPD_ VPD_P_
## clocl_tmp_C -0.351
## mass_g      -0.051  0.022
## SMI         -0.091 -0.044 -0.418
## osmllty_m__ -0.309  0.022 -0.140  0.123
## hmtcrt_prcn  0.031 -0.005 -0.020 -0.206 -0.016
## msmt_temp_C -0.898  0.085  0.051  0.008  0.106 -0.124
## msmt_VPD_kP  0.533 -0.131 -0.005  0.001 -0.044  0.231 -0.757
## VPD_kPa_int  0.108 -0.020 -0.025  0.053  0.016 -0.200  0.089 -0.515
## wnd_mph_ntr -0.417  0.106 -0.042  0.049  0.095 -0.238  0.508 -0.604 -0.038
## slr_rd_W_s_  0.348  0.008 -0.012  0.021 -0.225  0.092 -0.504  0.622 -0.658
##             wnd_m_
```

```
## clocl_tmp_C
## mass_g
## SMI
## osmllty_m__
## hmtcrt_prcn
## msmt_temp_C
## msmt_VPD_kP
## VPD_kPa_int
## wnd_mph_ntr
## slr_rd_W_s_ -0.224
```

```
drop1(CEWL_mod4)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + SMI + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int +
##     wind_mph_interpol + solar_rad_W_sqm_interpol + (1 | capture_date)
##                          npar    AIC
## <none>                        659.19
## cloacal_temp_C              1 657.23
## mass_g                      1 658.45
## SMI                         1 657.19
## osmolality_mmol_kg_mean     1 669.07
## hematocrit_percent          1 657.27
## msmt_temp_C                 1 682.43
## msmt_VPD_kPa                1 665.35
## VPD_kPa_int                 1 660.61
## wind_mph_interpol           1 661.33
## solar_rad_W_sqm_interpol    1 657.38
```

Great, VIFs are minimal and we're ready to start backwards selection!

Start with dropping SMI:

```
CEWL_mod5 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # essential covariate
                          cloacal_temp_C +
                          # body size
                          mass_g +
                          # blood
                          osmolality_mmol_kg_mean + hematocrit_percent +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(CEWL_mod5)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int +
```

```
##     wind_mph_interpol + solar_rad_W_sqm_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 647.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9914 -0.6396 -0.0157  0.5957  3.6281
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.817    2.195
##  Residual                 9.527    3.087
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                             Estimate Std. Error t value
## (Intercept)               -1.737e+02  3.515e+01  -4.941
## cloacal_temp_C            -5.478e-02  3.945e-01  -0.139
## mass_g                    -2.161e-01  1.784e-01  -1.212
## osmolality_mmol_kg_mean    6.902e-02  2.073e-02   3.330
## hematocrit_percent         1.976e-02  5.738e-02   0.344
## msmt_temp_C                7.596e+00  1.490e+00   5.097
## msmt_VPD_kPa              -1.643e+01  6.165e+00  -2.665
## VPD_kPa_int               -1.917e+00  1.046e+00  -1.833
## wind_mph_interpol          5.733e-01  3.141e-01   1.825
## solar_rad_W_sqm_interpol  1.845e-03  3.477e-03   0.531
##
## Correlation of Fixed Effects:
##             (Intr) clc__C mass_g osm___ hmtcr_ msm__C m_VPD_ VPD_P_ wnd_m_
## clocl_tmp_C -0.356
## mass_g      -0.098  0.004
## osmllty_m__ -0.301  0.028 -0.098
## hmtcrt_prcn  0.012 -0.014 -0.119  0.009
## msmt_temp_C -0.901  0.086  0.060  0.106 -0.125
## msmt_VPD_kP  0.535 -0.131 -0.005 -0.045  0.236 -0.758
## VPD_kPa_int  0.114 -0.017 -0.003  0.010 -0.193  0.088 -0.515
## wnd_mph_ntr -0.415  0.108 -0.023  0.090 -0.233  0.508 -0.604 -0.041
## slr_rd_W_s_  0.352  0.009 -0.004 -0.230  0.099 -0.504  0.622 -0.660 -0.225
```

```r
drop1(CEWL_mod5)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + osmolality_mmol_kg_mean +
##     hematocrit_percent + msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int +
##     wind_mph_interpol + solar_rad_W_sqm_interpol + (1 | capture_date)
##                         npar    AIC
## <none>                       657.19
## cloacal_temp_C             1 655.24
## mass_g                     1 656.64
## osmolality_mmol_kg_mean    1 667.18
## hematocrit_percent         1 655.29
## msmt_temp_C                1 680.43
```

```
## msmt_VPD_kPa               1 663.36
## VPD_kPa_int                1 658.64
## wind_mph_interpol          1 659.33
## solar_rad_W_sqm_interpol   1 655.38
```

next drop cloacal temperature (What?!):

```r
CEWL_mod6 <- lme4::lmer(data = capture_dat_plus,
                        # response variable
                        CEWL_g_m2h_mean ~
                        # body size
                        mass_g +
                        # blood
                        osmolality_mmol_kg_mean + hematocrit_percent +
                        # microclimate at the time of msmt
                        msmt_temp_C + msmt_VPD_kPa +
                        # weather at the time of capture
                        VPD_kPa_int +
                        wind_mph_interpol + solar_rad_W_sqm_interpol +
                        (1|capture_date))
summary(CEWL_mod6)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + hematocrit_percent +
##     msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol +
##     solar_rad_W_sqm_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 647.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9923 -0.6336 -0.0171  0.5743  3.6500
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.835    2.199
##  Residual                 9.443    3.073
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error t value
## (Intercept)             -1.754e+02  3.271e+01  -5.361
## mass_g                  -2.161e-01  1.776e-01  -1.217
## osmolality_mmol_kg_mean   6.909e-02  2.064e-02   3.348
## hematocrit_percent        1.968e-02  5.712e-02   0.344
## msmt_temp_C               7.611e+00  1.479e+00   5.145
## msmt_VPD_kPa            -1.653e+01  6.090e+00  -2.714
## VPD_kPa_int             -1.921e+00  1.042e+00  -1.843
## wind_mph_interpol         5.772e-01  3.111e-01   1.855
## solar_rad_W_sqm_interpol  1.855e-03  3.462e-03   0.536
##
## Correlation of Fixed Effects:
##             (Intr) mass_g osm___ hmtcr_ msm__C m_VPD_ VPD_P_ wnd_m_
```

```
## mass_g      -0.104
## osmllty_m__ -0.312 -0.098
## hmtcrt_prcn  0.008 -0.119  0.010
## msmt_temp_C -0.935  0.059  0.104 -0.124
## msmt_VPD_kP  0.528 -0.005 -0.042  0.236 -0.756
## VPD_kPa_int  0.115 -0.003  0.011 -0.193  0.089 -0.520
## wnd_mph_ntr -0.405 -0.024  0.087 -0.233  0.502 -0.598 -0.040
## slr_rd_W_s_  0.379 -0.004 -0.230  0.099 -0.506  0.627 -0.660 -0.227
```

```r
drop1(CEWL_mod6)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + hematocrit_percent +
##     msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol +
##     solar_rad_W_sqm_interpol + (1 | capture_date)
##                          npar    AIC
## <none>                        655.24
## mass_g                      1 654.68
## osmolality_mmol_kg_mean     1 665.23
## hematocrit_percent          1 653.34
## msmt_temp_C                 1 678.49
## msmt_VPD_kPa                1 661.60
## VPD_kPa_int                 1 656.72
## wind_mph_interpol           1 657.48
## solar_rad_W_sqm_interpol    1 653.43
```

next drop hematocrit:

```r
CEWL_mod7 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # body size
                          mass_g +
                          # blood
                          osmolality_mmol_kg_mean +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          VPD_kPa_int +
                          wind_mph_interpol + solar_rad_W_sqm_interpol +
                          (1|capture_date))
summary(CEWL_mod7)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + msmt_temp_C +
##     msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 643.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9521 -0.6473  0.0034  0.5975  3.6786
```

```
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.769    2.184
##  Residual                 9.373    3.062
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                             Estimate Std. Error t value
## (Intercept)               -1.755e+02  3.258e+01  -5.386
## mass_g                    -2.088e-01  1.757e-01  -1.189
## osmolality_mmol_kg_mean    6.903e-02  2.056e-02   3.358
## msmt_temp_C                7.676e+00  1.462e+00   5.251
## msmt_VPD_kPa              -1.703e+01  5.893e+00  -2.890
## VPD_kPa_int               -1.851e+00  1.018e+00  -1.818
## wind_mph_interpol          6.025e-01  3.013e-01   1.999
## solar_rad_W_sqm_interpol  1.734e-03  3.432e-03   0.505
##
## Correlation of Fixed Effects:
##             (Intr) mass_g osm___ msm__C m_VPD_ VPD_P_ wnd_m_
## mass_g      -0.104
## osmllty_m__ -0.312 -0.098
## msmt_temp_C -0.942  0.045  0.106
## msmt_VPD_kP  0.541  0.024 -0.045 -0.753
## VPD_kPa_int  0.119 -0.026  0.013  0.067 -0.499
## wnd_mph_ntr -0.414 -0.053  0.092  0.491 -0.575 -0.089
## slr_rd_W_s_  0.381  0.008 -0.232 -0.501  0.625 -0.656 -0.211
```

```
drop1(CEWL_mod7)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + msmt_temp_C +
##     msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##     (1 | capture_date)
##                          npar    AIC
## <none>                        653.34
## mass_g                      1 652.71
## osmolality_mmol_kg_mean     1 663.31
## msmt_temp_C                 1 677.16
## msmt_VPD_kPa                1 660.63
## VPD_kPa_int                 1 654.73
## wind_mph_interpol           1 656.16
## solar_rad_W_sqm_interpol    1 651.50
```

next drop solar radiation:

```
CEWL_mod8 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # body size
                          mass_g +
                          # blood
                          osmolality_mmol_kg_mean +
                          # microclimate at the time of msmt
```

```r
                           msmt_temp_C + msmt_VPD_kPa +
                           # weather at the time of capture
                           VPD_kPa_int +
                           wind_mph_interpol +
                           (1|capture_date))
summary(CEWL_mod8)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + msmt_temp_C +
##     msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 634.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0039 -0.6474 -0.0118  0.6191  3.7046
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.472    2.115
##  Residual                 9.325    3.054
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                           Estimate Std. Error t value
## (Intercept)             -181.96381   29.95050  -6.075
## mass_g                    -0.20909    0.17523  -1.193
## osmolality_mmol_kg_mean    0.07145    0.01991   3.588
## msmt_temp_C                8.05676    1.25485   6.420
## msmt_VPD_kPa             -18.94173    4.54187  -4.170
## VPD_kPa_int               -1.51446    0.76479  -1.980
## wind_mph_interpol          0.63844    0.29280   2.180
##
## Correlation of Fixed Effects:
##             (Intr) mass_g osm___ msm__C m_VPD_ VPD_P_
## mass_g      -0.116
## osmllty_m__ -0.250 -0.098
## msmt_temp_C -0.938  0.057 -0.012
## msmt_VPD_kP  0.416  0.024  0.134 -0.648
## VPD_kPa_int  0.527 -0.028 -0.193 -0.398 -0.158
## wnd_mph_ntr -0.372 -0.053  0.048  0.458 -0.585 -0.308
```

```r
drop1(CEWL_mod8)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + msmt_temp_C +
##     msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol + (1 | capture_date)
##                         npar    AIC
## <none>                       651.50
## mass_g                     1 650.87
## osmolality_mmol_kg_mean    1 662.74
```

```
## msmt_temp_C                  1 676.59
## msmt_VPD_kPa                 1 663.49
## VPD_kPa_int                  1 653.75
## wind_mph_interpol            1 655.10
```

next drop mass:

```
CEWL_mod9 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # blood
                          osmolality_mmol_kg_mean +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          VPD_kPa_int +
                          wind_mph_interpol +
                          (1|capture_date))
summary(CEWL_mod9)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##     VPD_kPa_int + wind_mph_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 634.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0096 -0.6635 -0.0026  0.6022  3.5571
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.278    2.068
##  Residual                 9.368    3.061
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)            -186.28515   29.73743  -6.264
## osmolality_mmol_kg_mean    0.06913    0.01984   3.484
## msmt_temp_C                8.15246    1.24977   6.523
## msmt_VPD_kPa             -18.85585    4.51353  -4.178
## VPD_kPa_int               -1.54131    0.76511  -2.014
## wind_mph_interpol          0.62313    0.29218   2.133
##
## Correlation of Fixed Effects:
##             (Intr) osm___ msm__C m_VPD_ VPD_P_
## osmllty_m__ -0.265
## msmt_temp_C -0.940 -0.007
## msmt_VPD_kP  0.419  0.138 -0.647
## VPD_kPa_int  0.526 -0.198 -0.395 -0.165
## wnd_mph_ntr -0.383  0.046  0.464 -0.587 -0.310
```

```r
drop1(CEWL_mod9)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##     VPD_kPa_int + wind_mph_interpol + (1 | capture_date)
##                         npar    AIC
## <none>                       650.87
## osmolality_mmol_kg_mean    1 661.35
## msmt_temp_C                1 675.91
## msmt_VPD_kPa               1 662.73
## VPD_kPa_int                1 653.24
## wind_mph_interpol          1 654.25
```

next drop VPD:

```r
CEWL_mod10 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # blood
                          osmolality_mmol_kg_mean +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          # weather at the time of capture
                          wind_mph_interpol +
                          (1|capture_date))
summary(CEWL_mod10)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##     wind_mph_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 639.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.2054 -0.6820  0.0294  0.6981  3.4495
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.840    2.200
##  Residual                 9.587    3.096
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)             -154.16542   25.66838  -6.006
## osmolality_mmol_kg_mean    0.06132    0.01973   3.108
## msmt_temp_C                7.12092    1.17029   6.085
## msmt_VPD_kPa             -20.14789    4.59168  -4.388
## wind_mph_interpol          0.43374    0.28273   1.534
##
```

```
## Correlation of Fixed Effects:
##             (Intr) osm___ msm__C m_VPD_
## osmllty_m__ -0.192
## msmt_temp_C -0.936 -0.094
## msmt_VPD_kP  0.602  0.109 -0.788
## wnd_mph_ntr -0.267 -0.021  0.386 -0.668
```

```
# can't test drop1 bc of NA's
```

based on t-values, wind should be dropped next:

```
CEWL_mod11 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # blood
                          osmolality_mmol_kg_mean +
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          (1|capture_date))
summary(CEWL_mod11)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##     (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 740.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0076 -0.6511 -0.0032  0.6792  3.4191
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept)  2.828   1.682
##  Residual                 12.064   3.473
## Number of obs: 138, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)            -137.99713   26.31861  -5.243
## osmolality_mmol_kg_mean    0.05162    0.02061   2.505
## msmt_temp_C                6.44585    1.11981   5.756
## msmt_VPD_kPa             -16.51862    2.96126  -5.578
##
## Correlation of Fixed Effects:
##             (Intr) osm___ msm__C
## osmllty_m__ -0.195
## msmt_temp_C -0.944 -0.102
## msmt_VPD_kP  0.624  0.169 -0.783
```

```
drop1(CEWL_mod11)
```

```
## Single term deletions
##
```

```
## Model:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##     (1 | capture_date)
##                         npar    AIC
## <none>                       752.61
## osmolality_mmol_kg_mean    1 756.56
## msmt_temp_C                1 775.13
## msmt_VPD_kPa               1 764.23
```

drop osmolality:

```
CEWL_mod12 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # microclimate at the time of msmt
                          msmt_temp_C + msmt_VPD_kPa +
                          (1|capture_date))
summary(CEWL_mod12)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CEWL_g_m2h_mean ~ msmt_temp_C + msmt_VPD_kPa + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 740.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1447 -0.6565 -0.0485  0.6256  3.3559
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept)  2.385   1.544
##  Residual                 12.581   3.547
## Number of obs: 138, groups:  capture_date, 5
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  -125.832     26.094  -4.822
## msmt_temp_C     6.769      1.119   6.048
## msmt_VPD_kPa  -17.893      2.795  -6.401
##
## Correlation of Fixed Effects:
##             (Intr) msm__C
## msmt_temp_C -0.990
## msmt_VPD_kP  0.692 -0.786
```

```
drop1(CEWL_mod12)
```

```
## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ msmt_temp_C + msmt_VPD_kPa + (1 | capture_date)
##              npar    AIC
## <none>            756.56
## msmt_temp_C     1 779.51
## msmt_VPD_kPa    1 768.96
```

drop VPD at the time of msmt:

```r
CEWL_mod13 <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~
                          # microclimate at the time of msmt
                          msmt_temp_C +
                          (1|capture_date))
summary(CEWL_mod13)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CEWL_g_m2h_mean ~ msmt_temp_C + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 755.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1664 -0.6915 -0.0549  0.5410  3.2942
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 39.63    6.295
##  Residual                 12.55    3.543
## Number of obs: 138, groups:  capture_date, 5
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept) -72.3114    22.5292  -3.210
## msmt_temp_C   3.4235     0.8222   4.164
##
## Correlation of Fixed Effects:
##             (Intr)
## msmt_temp_C -0.992
```

And finally, null model:

```r
CEWL_mod_null <- lme4::lmer(data = capture_dat_plus,
                          # response variable
                          CEWL_g_m2h_mean ~ 1 +
                          (1|capture_date))
summary(CEWL_mod_null)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CEWL_g_m2h_mean ~ 1 + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 772.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4713 -0.6736 -0.0596  0.7187  3.1910
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 19.32    4.396
```

```
##  Residual                 14.29    3.780
## Number of obs: 138, groups:  capture_date, 5
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   20.746      1.993   10.41
```

Selection

compare models 4-13 and the null

```r
CEWL_models <- list(CEWL_mod4, CEWL_mod5, CEWL_mod6, CEWL_mod7,
                    CEWL_mod8, CEWL_mod9, CEWL_mod10, CEWL_mod11,
                    CEWL_mod12, CEWL_mod13, CEWL_mod_null)

#specify model names
CEWL_mod_names <- c('(model 4) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C, Hct, Temp-Clo, SMI'
                    '(model 5) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C, Hct, Temp-Clo',
                    '(model 6) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C, Hct',
                       '(model 7) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C',
                       '(model 8) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass',
                       '(model 9) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C',
                       '(model 10) ~ Temp-M, VPD-M, Osml, Wind-C',
                       '(model 11) ~ Temp-M, VPD-M, Osml',
                      '(model 12) ~ Temp-M, VPD-M',
                      '(model 13) ~ Temp-M',
                      'null model')
#calculate AIC of each model
CEWL_AICc <- data.frame(aictab(cand.set = CEWL_models,
                                 modnames = CEWL_mod_names))
```

```
## Warning in aictab.AIClmerMod(cand.set = CEWL_models, modnames = CEWL_mod_names):
## Model selection for fixed effects is only appropriate with ML estimation:
## REML (default) should only be used to select random effects for a constant set of fixed effects
```

```r
CEWL_AICc
```

```
##                                                                                      Modnames
## 6                                     (model 9) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C
## 5                               (model 8) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass
## 7                                            (model 10) ~ Temp-M, VPD-M, Osml, Wind-C
## 4                      (model 7) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C
## 3                 (model 6) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C, Hct
## 2       (model 5) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C, Hct, Temp-Clo
## 1  (model 4) ~ Temp-M, VPD-M, Osml, Wind-C, VPD-C, Mass, Solar-C, Hct, Temp-Clo, SMI
## 9                                                          (model 12) ~ Temp-M, VPD-M
## 8                                                    (model 11) ~ Temp-M, VPD-M, Osml
## 10                                                               (model 13) ~ Temp-M
## 11                                                                        null model
##     K     AICc Delta_AICc     ModelLik       AICcWt    Res.LL    Cum.Wt
## 6   8 651.4532   0.000000 1.000000e+00 6.664557e-01 -317.1005 0.6664557
## 5   9 654.0051   2.551909 2.791643e-01 1.860507e-01 -317.2131 0.8525064
## 7   7 654.4776   3.024382 2.204265e-01 1.469045e-01 -319.7560 0.9994109
## 4  10 665.6353  14.182157 8.324992e-04 5.548239e-04 -321.8442 0.9999657
## 3  11 671.8177  20.364510 3.783579e-05 2.521588e-05 -323.7303 0.9999910
## 2  12 674.2787  22.825508 1.105360e-05 7.366738e-06 -323.7339 0.9999983
```

```
## 1  13 677.2440  25.790851 2.509504e-06 1.672473e-06 -323.9675 1.0000000
## 9   5 751.3494  99.896229 2.031466e-22 1.353882e-22 -370.4474 1.0000000
## 8   6 753.3335 101.880269 7.533219e-23 5.020557e-23 -370.3461 1.0000000
## 10  4 764.0328 112.579607 3.578071e-25 2.384626e-25 -377.8660 1.0000000
## 11  3 778.7422 127.289039 2.288424e-28 1.525133e-28 -386.2816 1.0000000
```

The single best model is model 9, which included Temp-M, VPD-M, Osml, Wind-C, VPD-C.

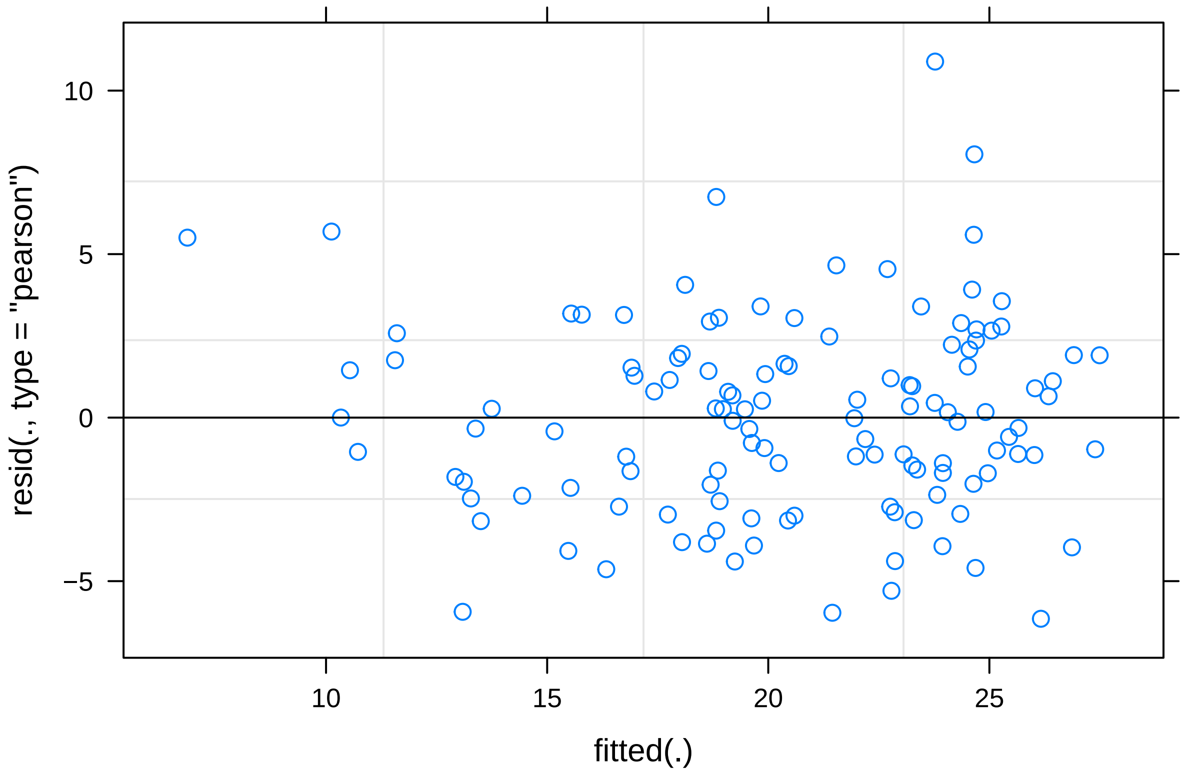
LM Conditions

Check that the best model meets the criteria for linear regression and has no collinearity.

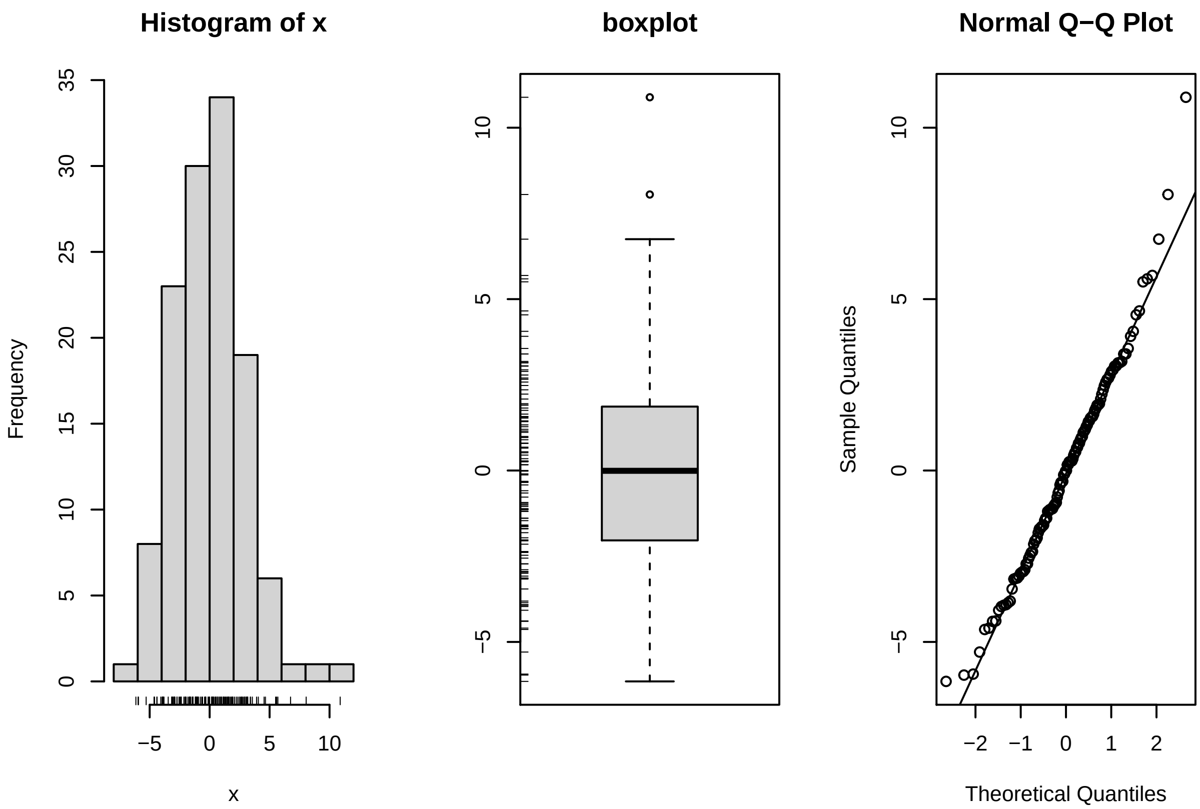
```
vif(CEWL_mod9)
```

```
## osmolality_mmol_kg_mean              msmt_temp_C             msmt_VPD_kPa
##                1.060239                 3.453048                 4.772639
##             VPD_kPa_int        wind_mph_interpol
##                2.747889                 2.308771
```

```
plot(CEWL_mod9)
```




```
simple.eda(residuals(CEWL_mod9))
```




```
shapiro.test(residuals(CEWL_mod9))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(CEWL_mod9)
## W = 0.9832, p-value = 0.1271
```

There is some slight fanning in the residuals ~ fitted plot, suggesting equal error variance is not perfect, but overall, all LNE conditions appear to be met and VIFs are very low.

Export

First, re-run the best model using lmerTest for p-values.

```
CEWL_mod9p <- lmerTest::lmer(data = capture_dat_plus,
                             # response variable
                             CEWL_g_m2h_mean ~
                             # blood
                             osmolality_mmol_kg_mean +
                             # microclimate at the time of msmt
                             msmt_temp_C + msmt_VPD_kPa +
                             # weather at the time of capture
                             VPD_kPa_int +
                             wind_mph_interpol +
                             (1|capture_date))
summary(CEWL_mod9p)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
```

```
## Formula:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##     VPD_kPa_int + wind_mph_interpol + (1 | capture_date)
##    Data: capture_dat_plus
##
## REML criterion at convergence: 634.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0096 -0.6635 -0.0026  0.6022  3.5571
##
## Random effects:
##  Groups       Name        Variance Std.Dev.
##  capture_date (Intercept) 4.278    2.068
##  Residual                 9.368    3.061
## Number of obs: 124, groups:  capture_date, 5
##
## Fixed effects:
##                          Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)             -186.28515   29.73743   84.19375  -6.264 1.52e-08 ***
## osmolality_mmol_kg_mean    0.06913    0.01984  112.99431   3.484 0.000703 ***
## msmt_temp_C                8.15246    1.24977   47.59406   6.523 4.11e-08 ***
## msmt_VPD_kPa             -18.85585    4.51353   19.40683  -4.178 0.000491 ***
## VPD_kPa_int               -1.54131    0.76511  109.38127  -2.014 0.046413 *
## wind_mph_interpol          0.62313    0.29218   75.84397   2.133 0.036184 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) osm___ msm__C m_VPD_ VPD_P_
## osmllty_m__ -0.265
## msmt_temp_C -0.940 -0.007
## msmt_VPD_kP  0.419  0.138 -0.647
## VPD_kPa_int  0.526 -0.198 -0.395 -0.165
## wnd_mph_ntr -0.383  0.046  0.464 -0.587 -0.310
```

Save the best CEWL model output.

```
write.csv(broom.mixed::tidy(CEWL_mod9p),
          "./results_statistics/capture_CEWL_best_model.csv")
write.csv(CEWL_AICc,
          "./results_statistics/capture_CEWL_mod_rankings.csv")
```

To report in paper:

The best model to predict CEWL included plasma osmolality, temperature and VPD at the time of measurement, and VPD and wind at the time of capture. The final model met all linear regression conditions for linearity, normality, and equal error variance, and there was no multicollinearity.

Pub Figures

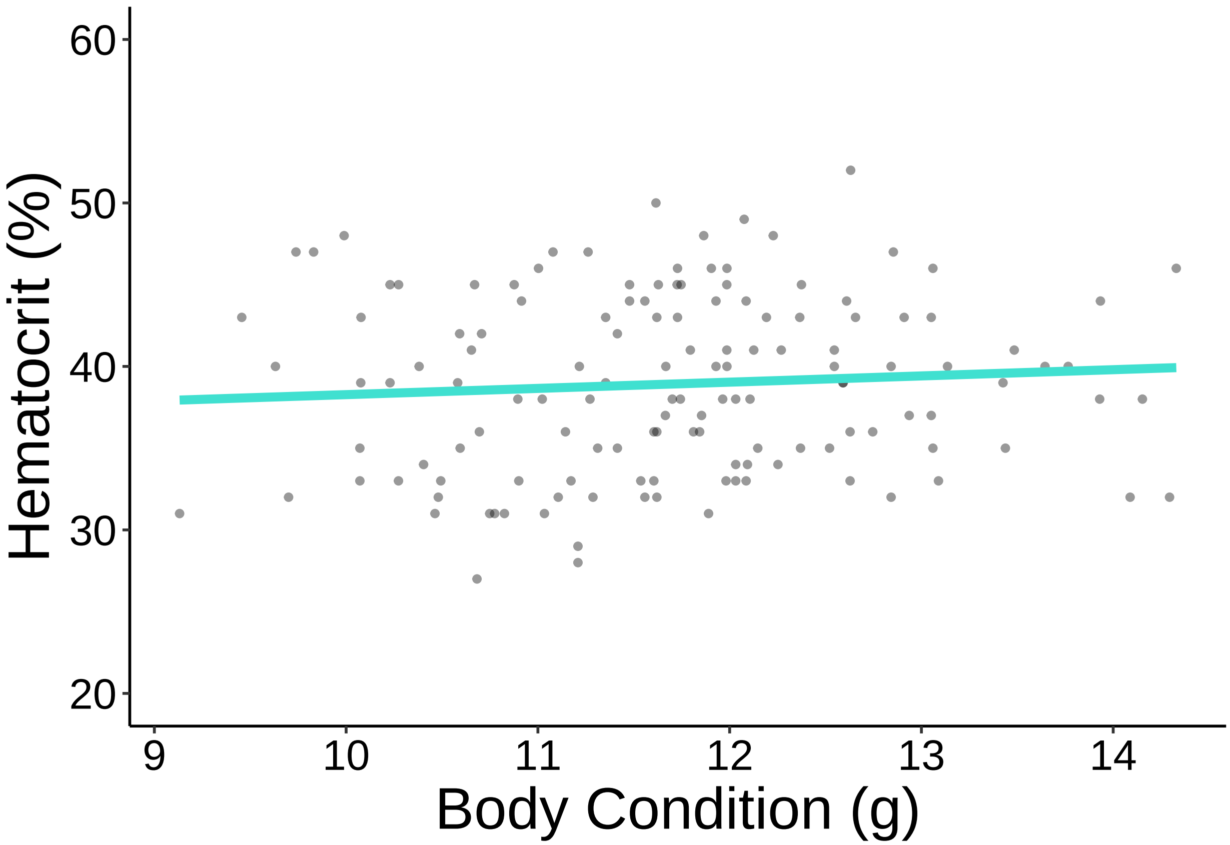
Custom Colors

```
lizard_color = "turquoise"
VPD_color = "blue"
```

```
temp_color = "gray"
solar_color = "orange"
wind_color = "orange"
date_color = "gray"
osml_color = "red"
```

Hct ~ SMI

```
ggplot(capture_dat_plus) +
  aes(x = SMI,
      y = hematocrit_percent) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              size = 1.6,
              color = lizard_color,
              alpha = 1) +
  theme_classic() +
  xlab("Body Condition (g)") +
  ylab("Hematocrit (%)") +
  #ylab("") +
  #xlim() +
  ylim(20,60) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_hct_SMI_fig
cap_hct_SMI_fig
```

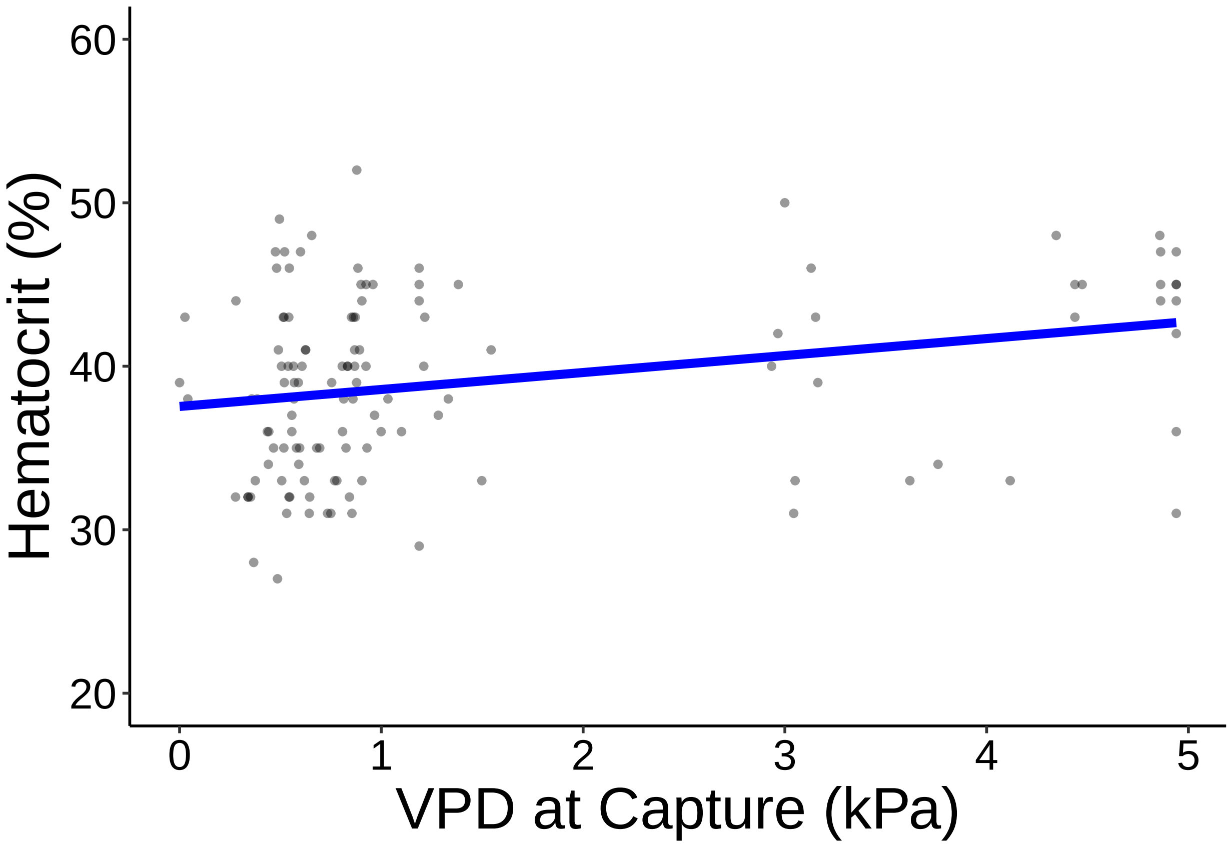


Hct ~ VPD at Capture

```
ggplot(capture_dat_plus) +
  aes(x = VPD_kPa_int,
      y = hematocrit_percent) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = VPD_color,
              size = 1.6,
              alpha = 1 ) +
  theme_classic() +
  xlab("VPD at Capture (kPa)") +
  ylab("Hematocrit (%)") +
  #ylab("") +
  #xlim() +
  ylim(20,60) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
```

```
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_hct_VPD_fig
cap_hct_VPD_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).
```



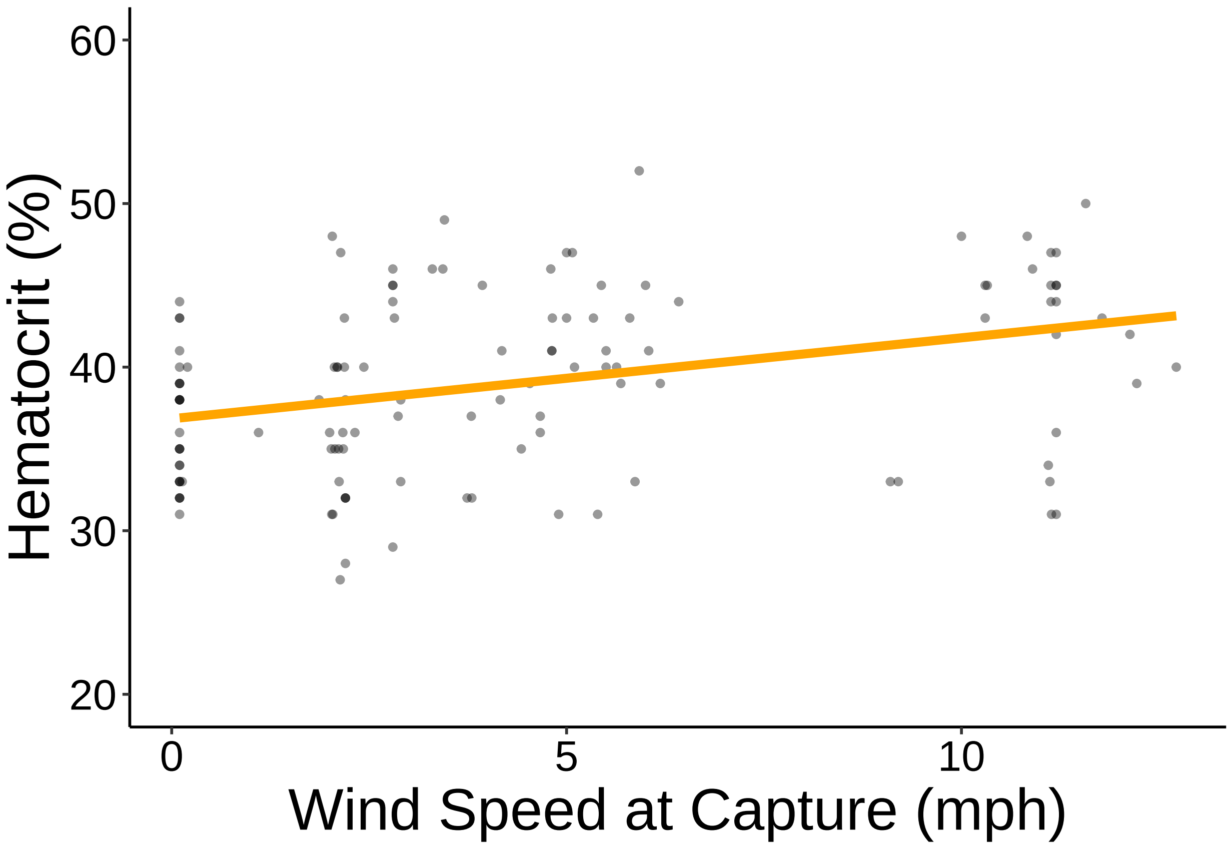
Hct ~ Wind Speed at Capture

```
ggplot(capture_dat_plus) +
  aes(x = wind_mph_interpol,
      y = hematocrit_percent)+
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = wind_color,
              size = 1.6,
              alpha = 1 ) +
  theme_classic() +
  xlab("Wind Speed at Capture (mph)") +
  ylab("Hematocrit (%)") +
  #ylab("") +
  #xlim() +
  ylim(20, 60) +
```

```
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_hct_wind_fig
cap_hct_wind_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 14 rows containing missing values (geom_point).
```



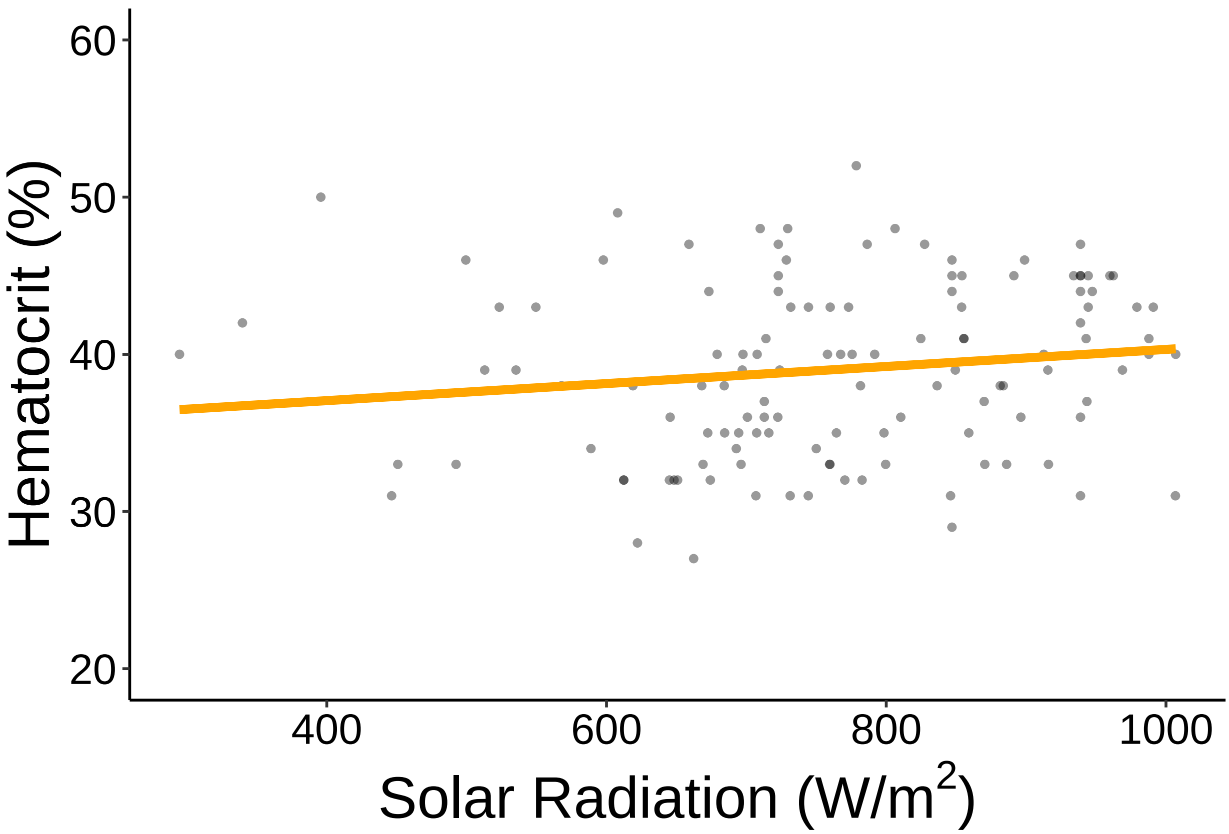
Hct ~ Solar Radiation at Capture

```
ggplot(capture_dat_plus) +
  aes(x = solar_rad_W_sqm_interpol,
      y = hematocrit_percent) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = solar_color,
              size = 1.6,
```

```r
              alpha = 1 ) +
  theme_classic() +
  xlab(bquote('Solar Radiation (W/'*m^2*')')) +
  ylab("Hematocrit (%)") +
  #ylab("") +
  ylim(20, 60) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_hct_sorad_fig
cap_hct_sorad_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).
```

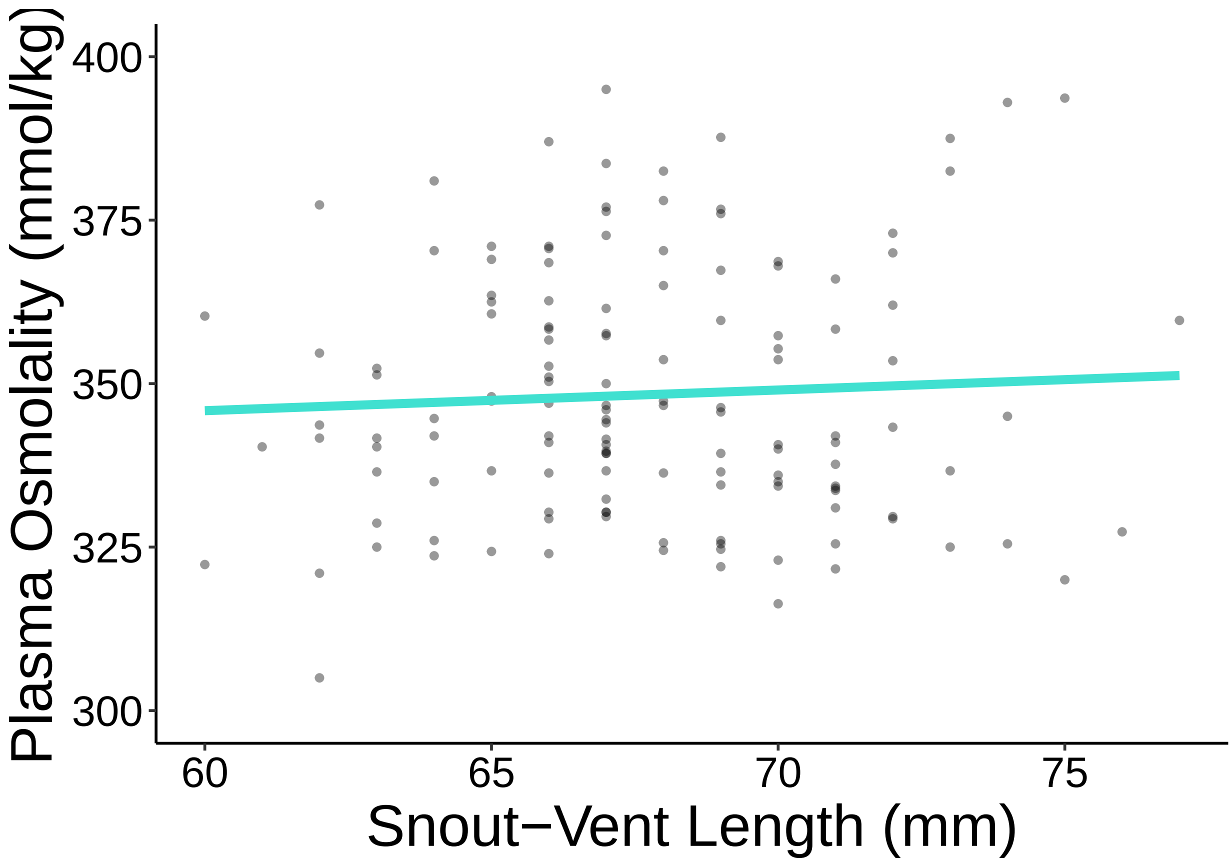
```
## Warning: Removed 14 rows containing missing values (geom_point).
```



Osmolality ~ SVL

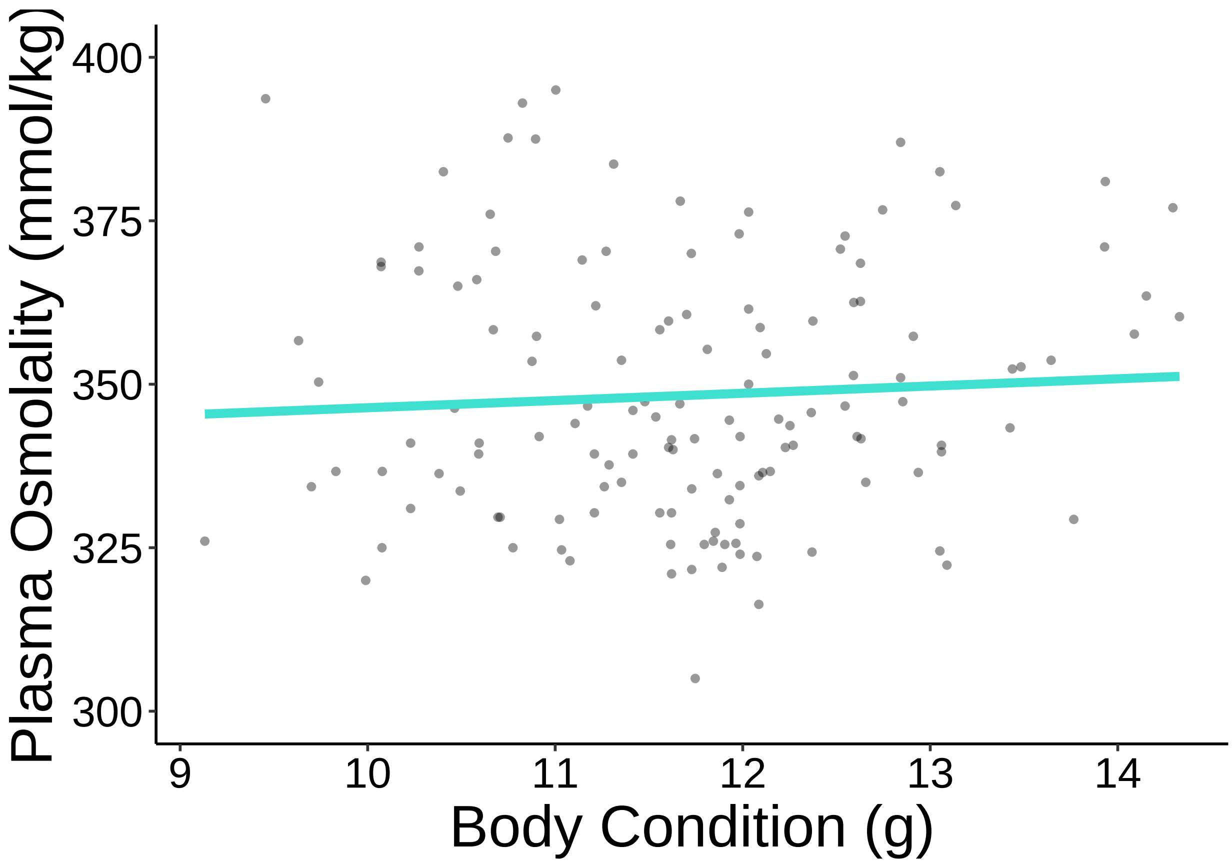
```r
ggplot(capture_dat_plus) +
  aes(x = SVL_mm,
      y = osmolality_mmol_kg_mean) +
  geom_point(size = 1,
```

```
alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              size = 1.6,
              color = lizard_color,
              alpha = 1) +
  theme_classic() +
  xlab("Snout-Vent Length (mm)") +
  ylab("Plasma Osmolality (mmol/kg)") +
  #ylab("") +
  #xlim() +
  ylim(300,400) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_osml_SVL_fig
cap_osml_SVL_fig
```



Osmolality ~ SMI

```r
ggplot(capture_dat_plus) +
  aes(x = SMI,
      y = osmolality_mmol_kg_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              size = 1.6,
              color = lizard_color,
              alpha = 1) +
  theme_classic() +
  xlab("Body Condition (g)") +
  ylab("Plasma Osmolality (mmol/kg)") +
  #ylab("") +
  #xlim() +
  ylim(300,400) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_osml_SMI_fig
cap_osml_SMI_fig
```

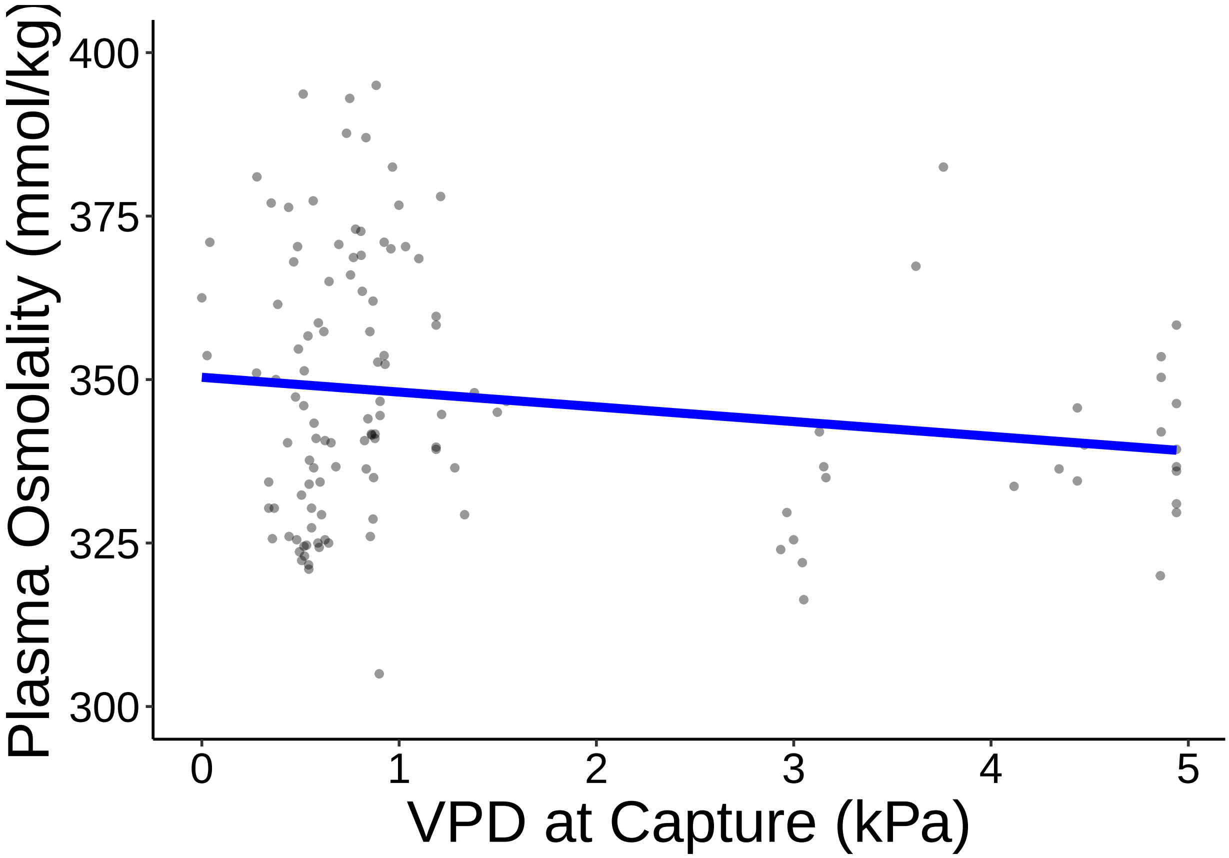


Osmolality ~ VPD at Capture

```
ggplot(capture_dat_plus) +
  aes(x = VPD_kPa_int,
      y = osmolality_mmol_kg_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = VPD_color,
              size = 1.6,
              alpha = 1 ) +
  theme_classic() +
  xlab("VPD at Capture (kPa)") +
  ylab("Plasma Osmolality (mmol/kg)") +
  #ylab("") +
  #xlim() +
  ylim(300,400) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
```

```
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_osml_VPD_fig
cap_osml_VPD_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).
```



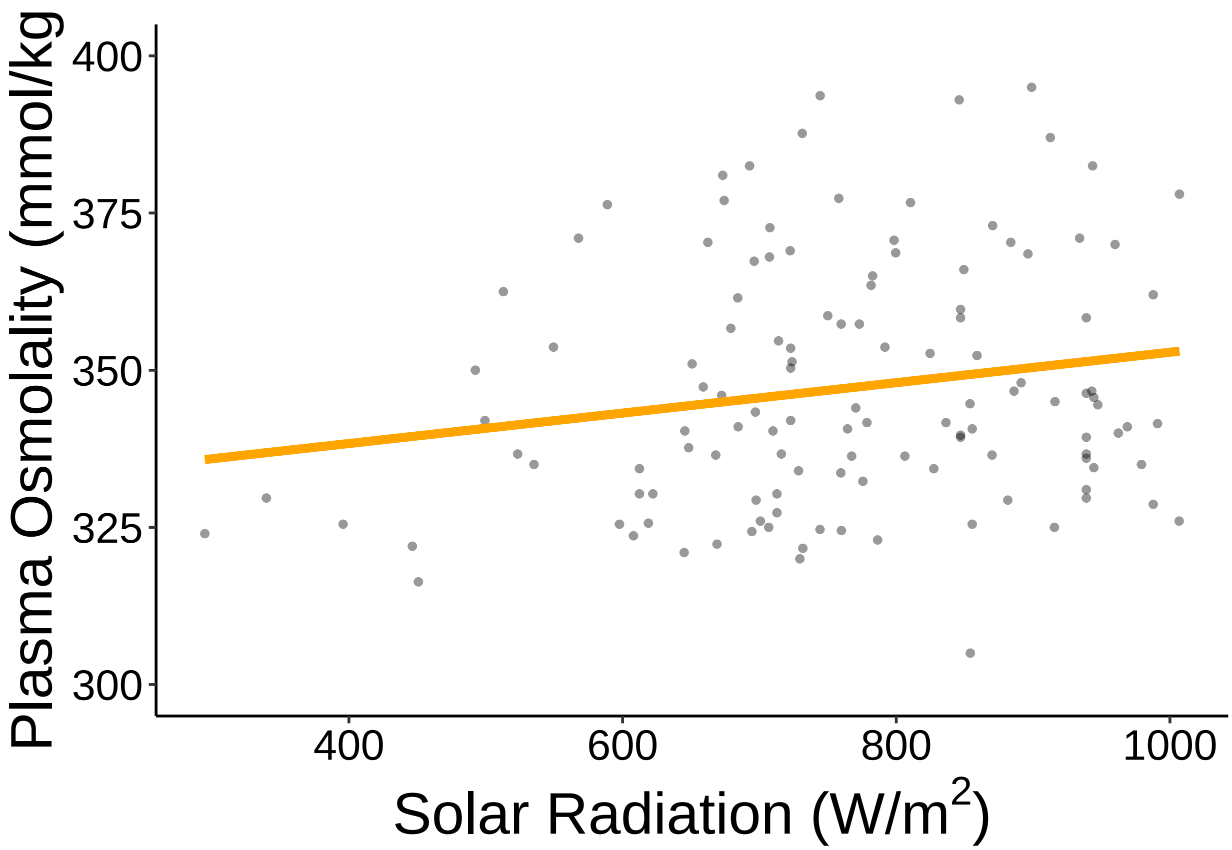
Osmolality ~ Solar Radiation at Capture

```
ggplot(capture_dat_plus) +
  aes(x = solar_rad_W_sqm_interpol,
      y = osmolality_mmol_kg_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = solar_color,
              size = 1.6,
              alpha = 1 ) +
  theme_classic() +
  xlab(bquote('Solar Radiation (W/'*m^2*')')) +
  ylab("Plasma Osmolality (mmol/kg)") +
  #ylab("") +
  ylim(300,400) +
```

```r
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_osml_sorad_fig
cap_osml_sorad_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).
```

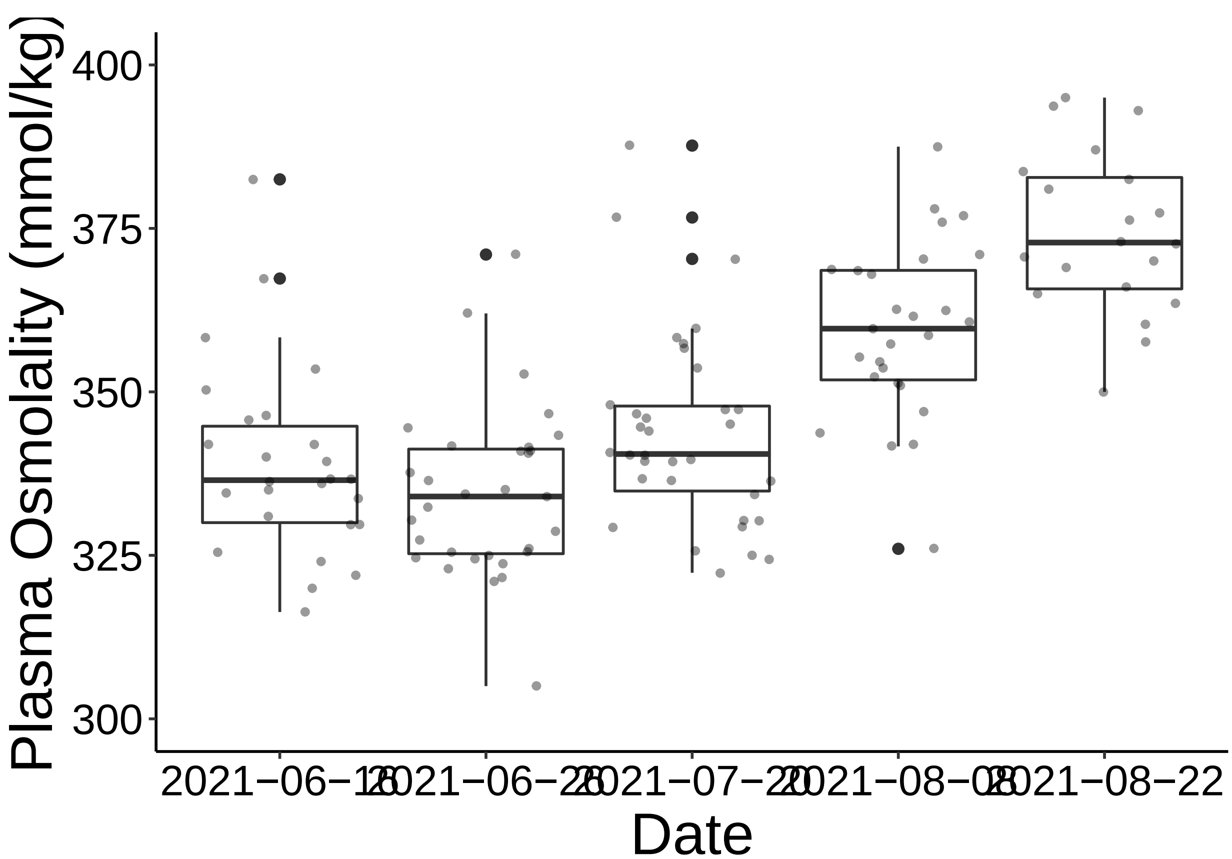
```
## Warning: Removed 14 rows containing missing values (geom_point).
```



Osmolality ~ Date

```r
ggplot(capture_dat_plus) +
  aes(x = as.factor(capture_date),
      y = osmolality_mmol_kg_mean,
      group = as.factor(capture_date)) +
  geom_boxplot() +
  geom_jitter(size = 1,
              alpha = 0.4) +
  theme_classic() +
  xlab("Date") +
  ylab("Plasma Osmolality (mmol/kg)") +
```

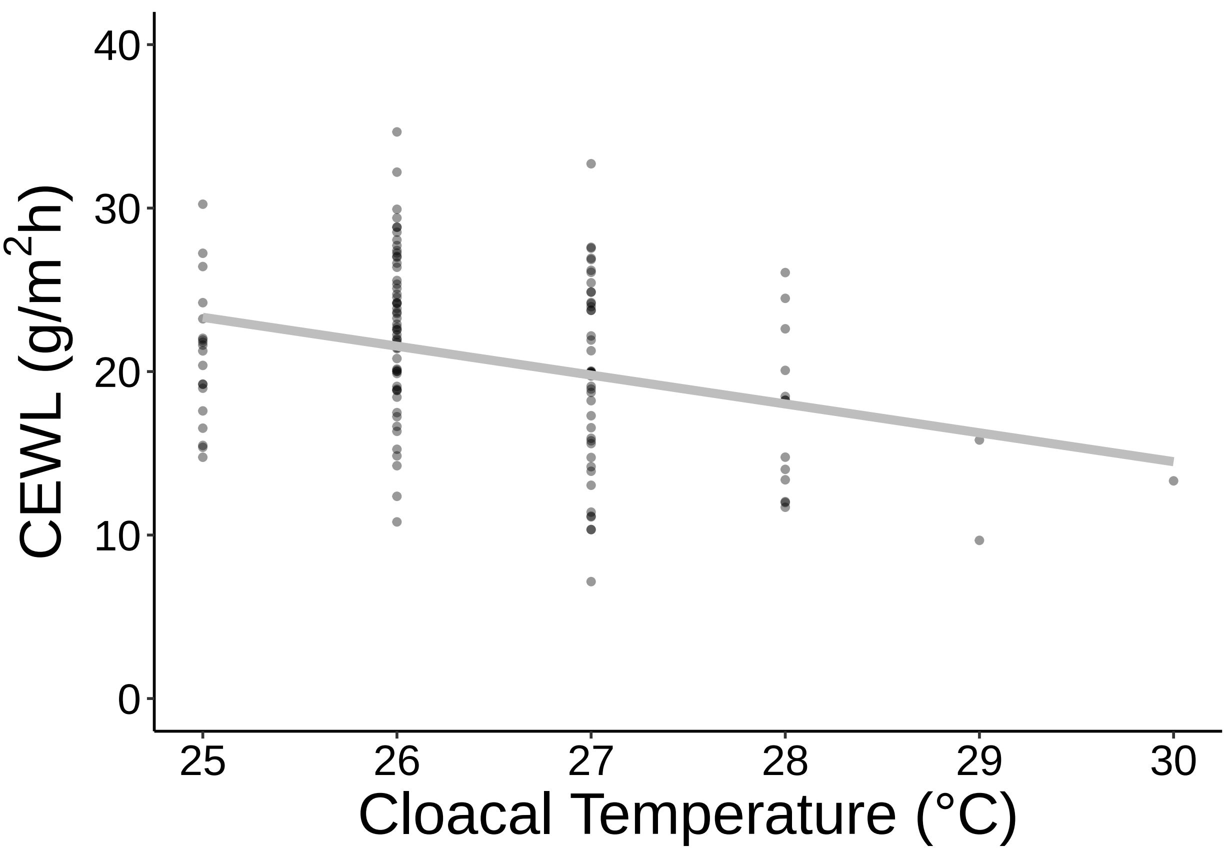
```
  #ylab("") +
  #xlim() +
  ylim(300, 400) +
  #annotate("text", x = , y = ,
   #         label = "paste(italic(R) ^ 2, \" = 0.\")",
    #        parse = TRUE,
     #       size = 6) +
  #annotate("text", x = , y = ,
   #         label = "paste(italic(p), \" < 0.0001\")",
    #        parse = TRUE,
     #       size = 6) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_osml_date_fig
cap_osml_date_fig
```



CEWL ~ Cloacal Temperature

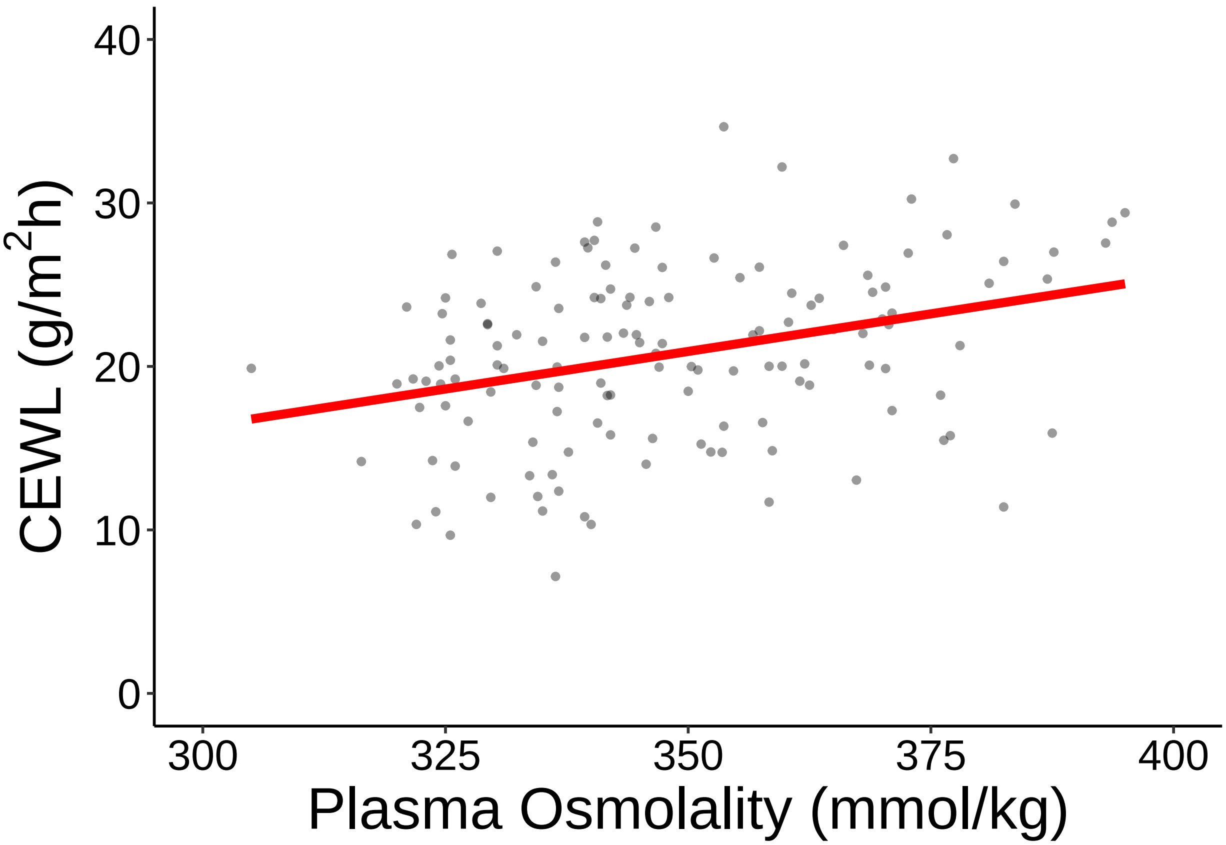
```
ggplot(capture_dat_plus) +
  aes(x = cloacal_temp_C,
```

```r
       y = CEWL_g_m2h_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = temp_color,
              size = 1.6,
              alpha = 1) +
  theme_classic() +
  xlab("Cloacal Temperature (°C)") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  #xlim() +
  ylim(0, 40) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_clotemp_fig
cap_CEWL_clotemp_fig
```



CEWL ~ Plasma Osmolality

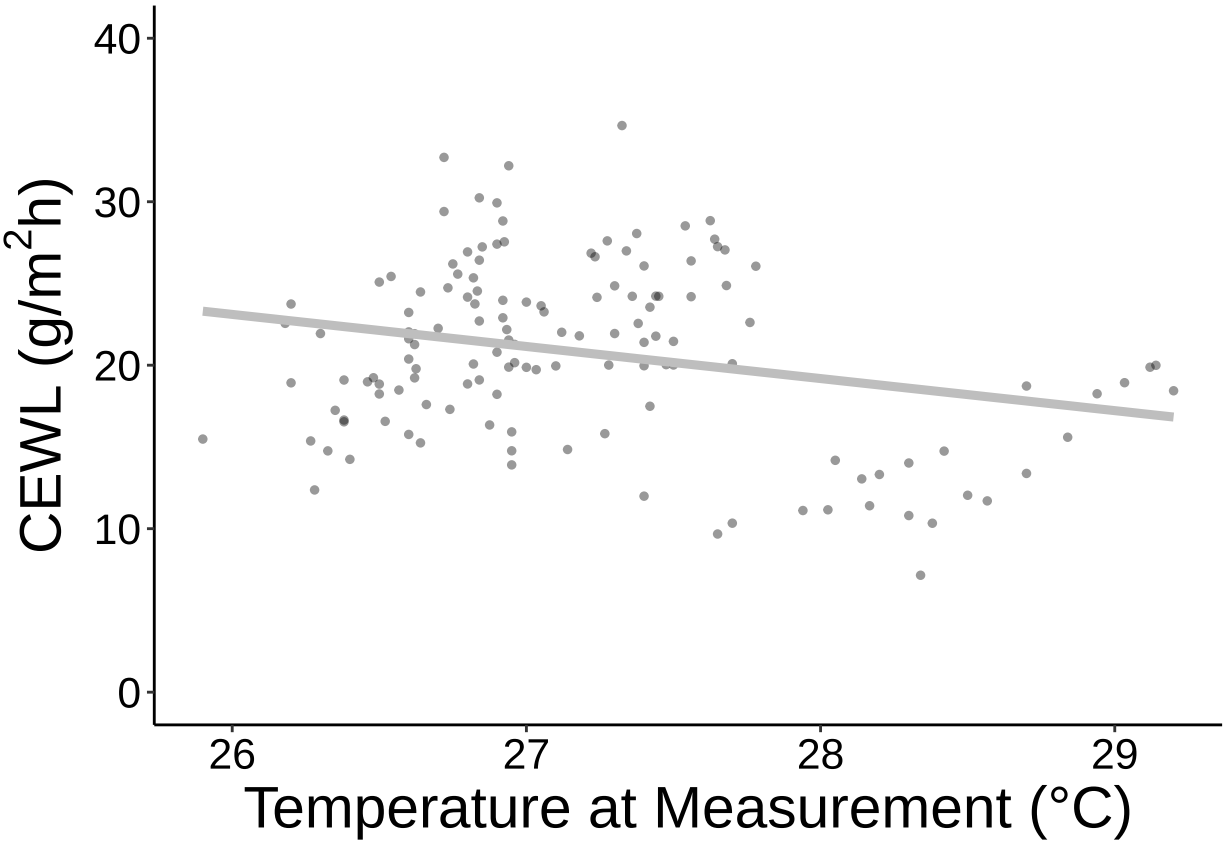
```
ggplot(capture_dat_plus) +
  aes(x = osmolality_mmol_kg_mean,
                y = CEWL_g_m2h_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = osml_color,
              size = 1.6,
              alpha = 1) +
  theme_classic() +
  xlab("Plasma Osmolality (mmol/kg)") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  xlim(300, 400) +
  ylim(0, 40) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_osml_fig
cap_CEWL_osml_fig
```



CEWL ~ Temperature at Measurement

```
ggplot(capture_dat_plus) +
  aes(x = msmt_temp_C,
      y = CEWL_g_m2h_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = temp_color,
              size = 1.6,
              alpha = 1) +
  theme_classic() +
  xlab("Temperature at Measurement (°C)") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  #xlim() +
  ylim(0, 40) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
```

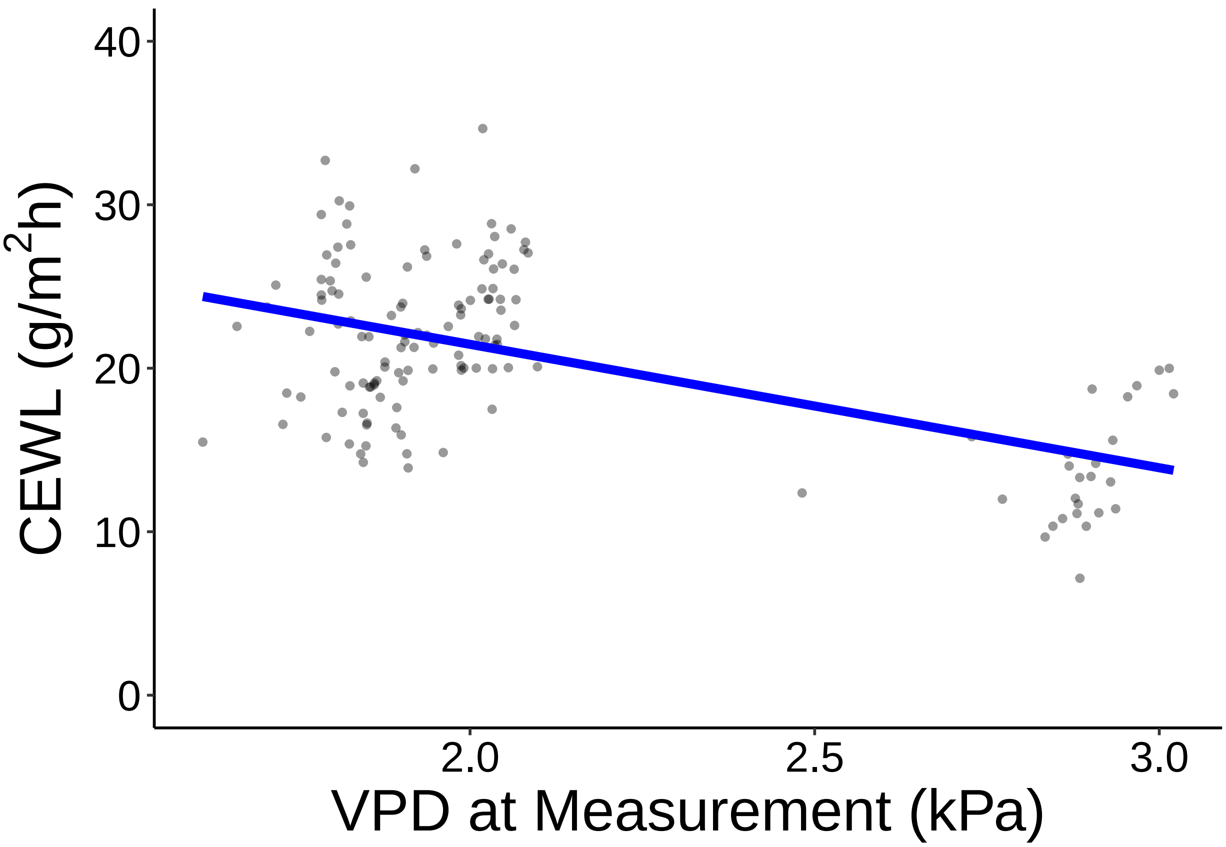
```
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_temp_fig
cap_CEWL_temp_fig
```



CEWL ~ VPD at Measurement

```
ggplot(capture_dat_plus) +
  aes(x = msmt_VPD_kPa,
      y = CEWL_g_m2h_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = VPD_color,
              size = 1.6,
              alpha = 1 ) +
  theme_classic() +
  xlab("VPD at Measurement (kPa)") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  #xlim() +
  ylim(0, 40) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
```

```
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_VPDm_fig
cap_CEWL_VPDm_fig
```



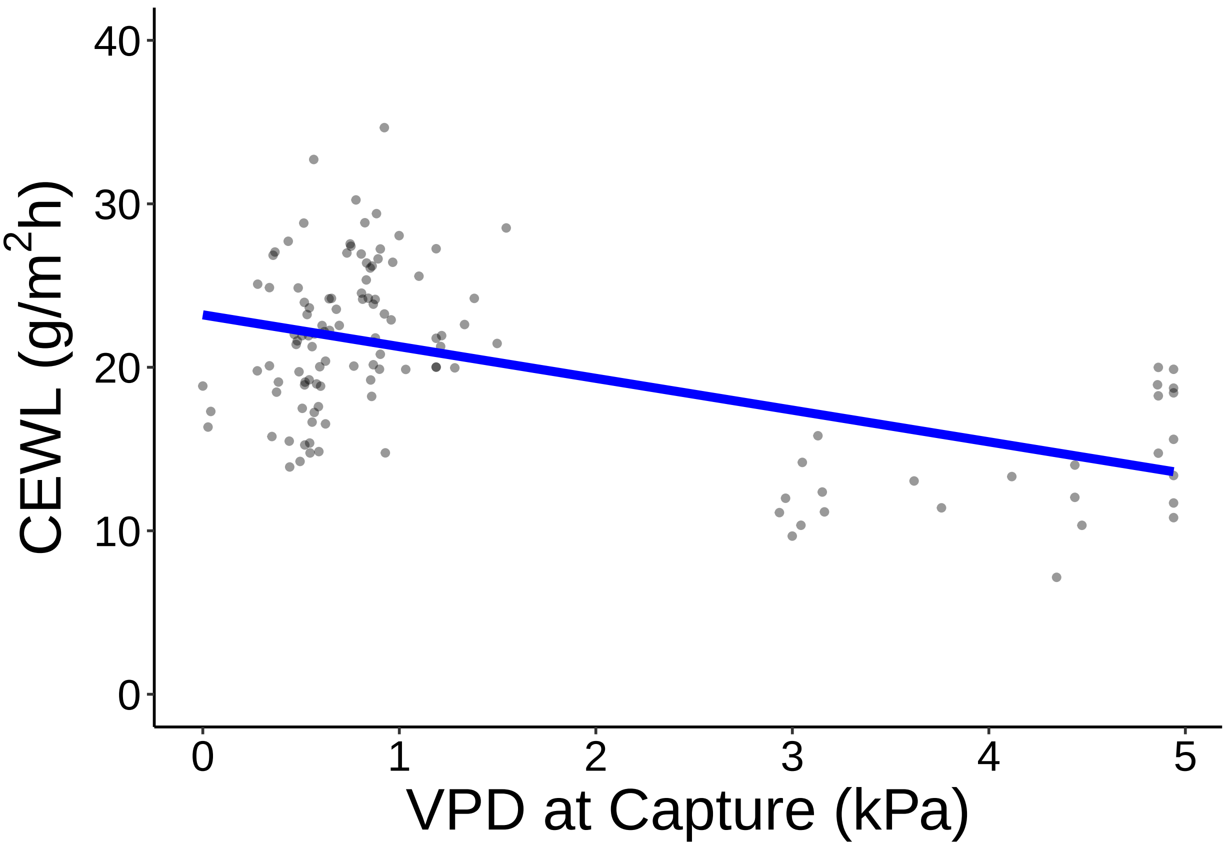
CEWL ~ VPD at Capture

```
ggplot(capture_dat_plus) +
  aes(x = VPD_kPa_int,
      y = CEWL_g_m2h_mean) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = VPD_color,
              size = 1.6,
              alpha = 1 ) +
  theme_classic() +
  xlab("VPD at Capture (kPa)") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  #xlim() +
```

```
  ylim(0, 40) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_VPDc_fig
cap_CEWL_VPDc_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 14 rows containing missing values (geom_point).
```



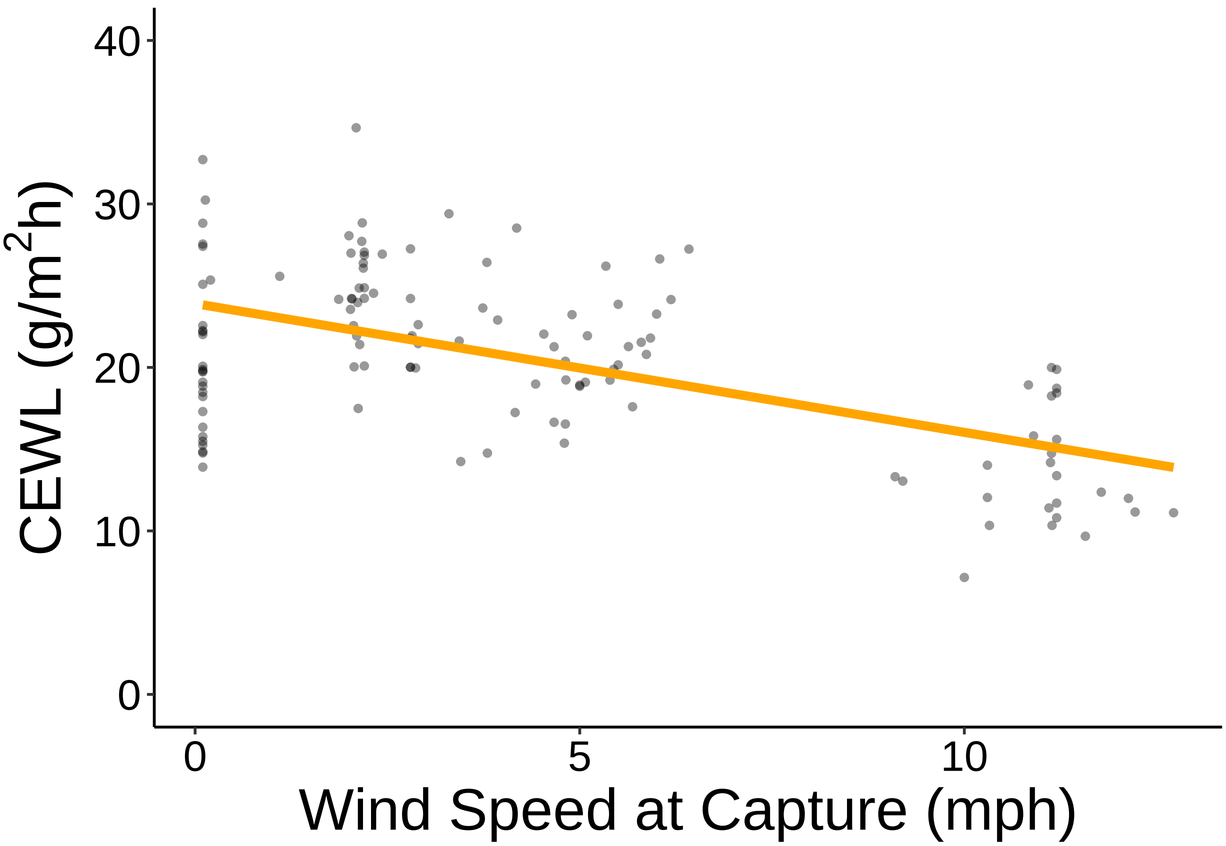
CEWL ~ Wind at Capture

```
ggplot(capture_dat_plus) +
  aes(x = wind_mph_interpol,
      y = CEWL_g_m2h_mean)+
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
              method = "lm",
              se = F,
              color = wind_color,
```

```
                size = 1.6,
                alpha = 1 ) +
  theme_classic() +
  xlab("Wind Speed at Capture (mph)") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  #xlim() +
  ylim(0, 40) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_wind_fig
cap_CEWL_wind_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 14 rows containing missing values (geom_point).
```



CEWL ~ Date

```
ggplot(capture_dat_plus) +
  aes(x = as.factor(capture_date),
```

```r
      y = CEWL_g_m2h_mean,
      group = as.factor(capture_date)) +
  geom_boxplot() +
  geom_jitter(size = 1,
              alpha = 0.4) +
  theme_classic() +
  xlab("Date") +
  ylab(bquote('CEWL (g/'*m^2*'h)')) +
  #ylab("") +
  #xlim() +
  ylim(0, 40) +
  #annotate("text", x = , y = ,
   #        label = "paste(italic(R) ^ 2, \" = 0.\")",
    #       parse = TRUE,
     #      size = 6) +
  #annotate("text", x = , y = ,
   #        label = "paste(italic(p), \" < 0.0001\")",
    #       parse = TRUE,
     #      size = 6) +
  theme(text = element_text(color = "black",
                            family = "sans",
                            size = 22),
        axis.text = element_text(color = "black",
                                 family = "sans",
                                 size = 16),
        #axis.text.y = element_blank(),
        #plot.margin = unit(c(0.1,0,0.1,0.45), "cm")
        ) -> cap_CEWL_date_fig
cap_CEWL_date_fig
```

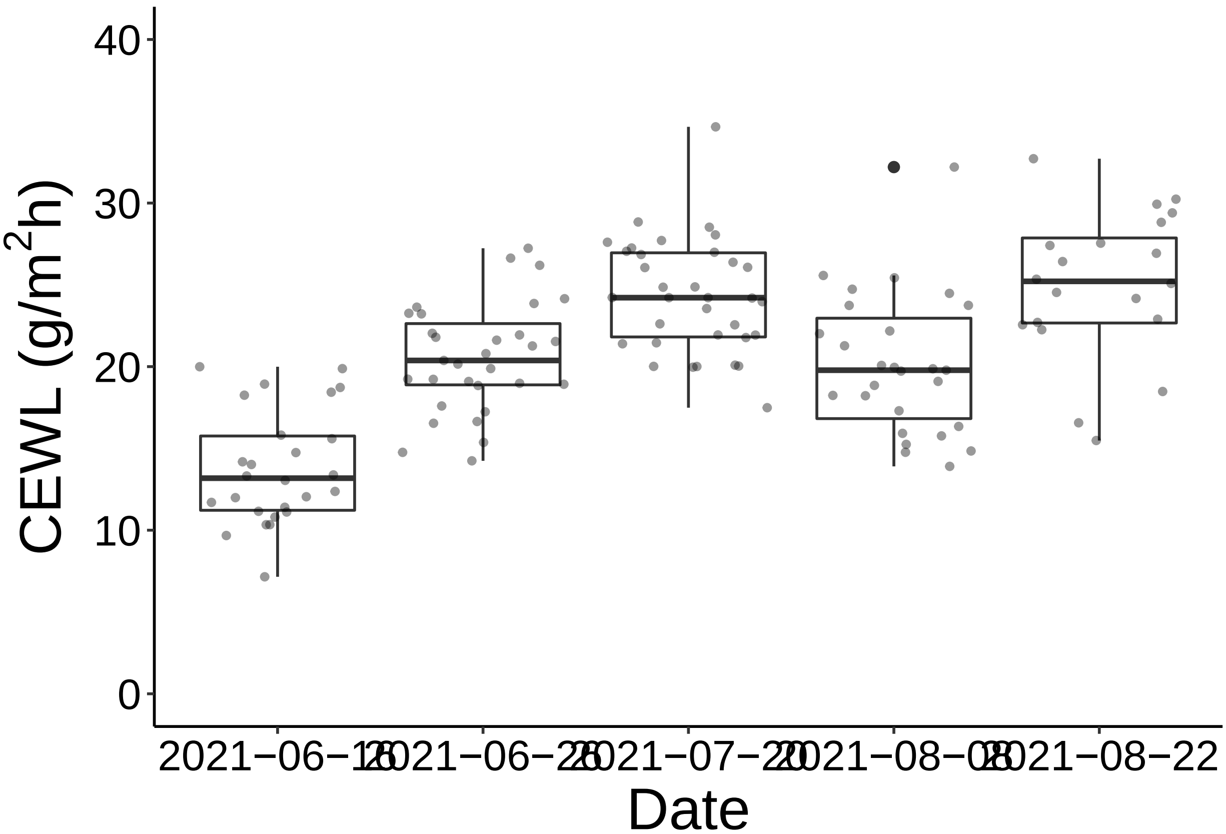
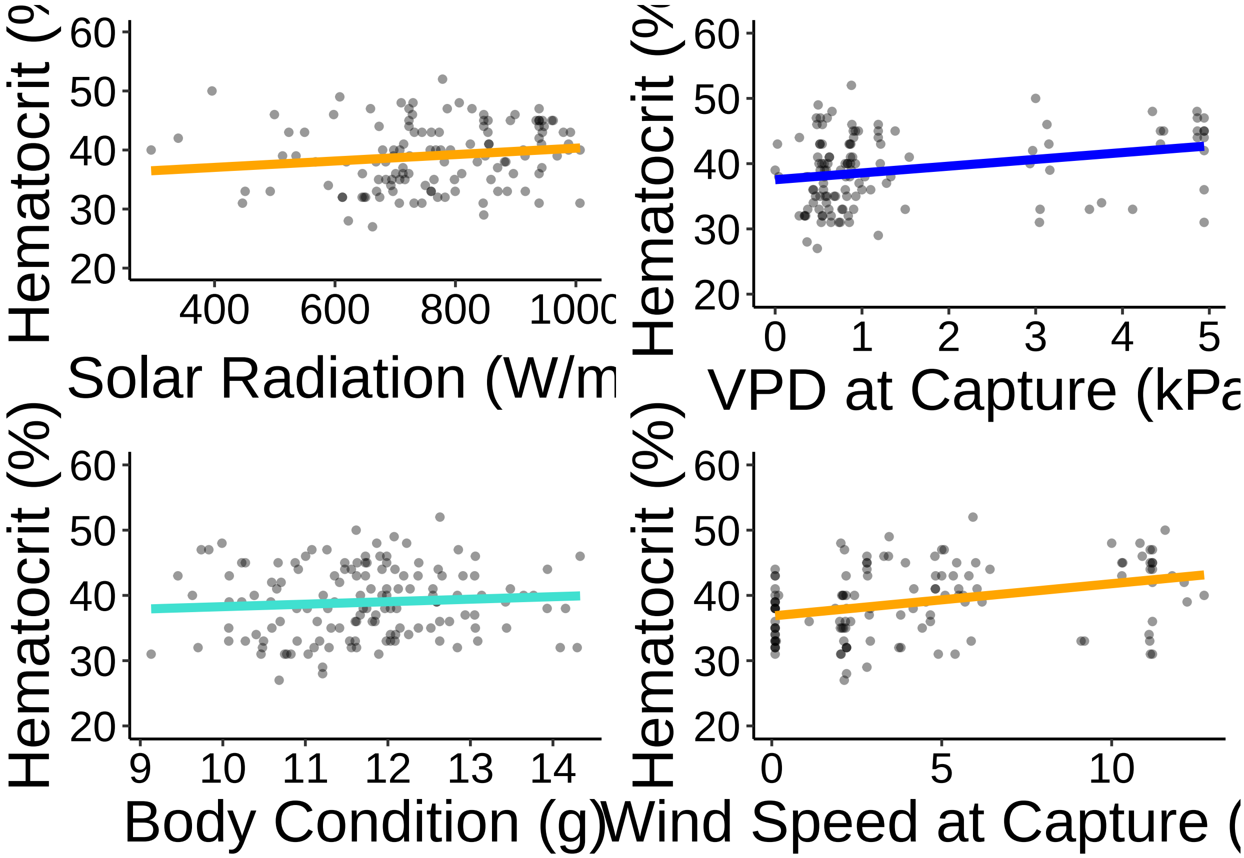


Figure Arrangements

```
# hematocrit
ggarrange(cap_hct_sorad_fig, cap_hct_VPD_fig,
          cap_hct_SMI_fig, cap_hct_wind_fig,
          ncol = 2, nrow = 2,
          legend = "none"
          ) -> cap_hct_multi_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).

## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).

## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).
```

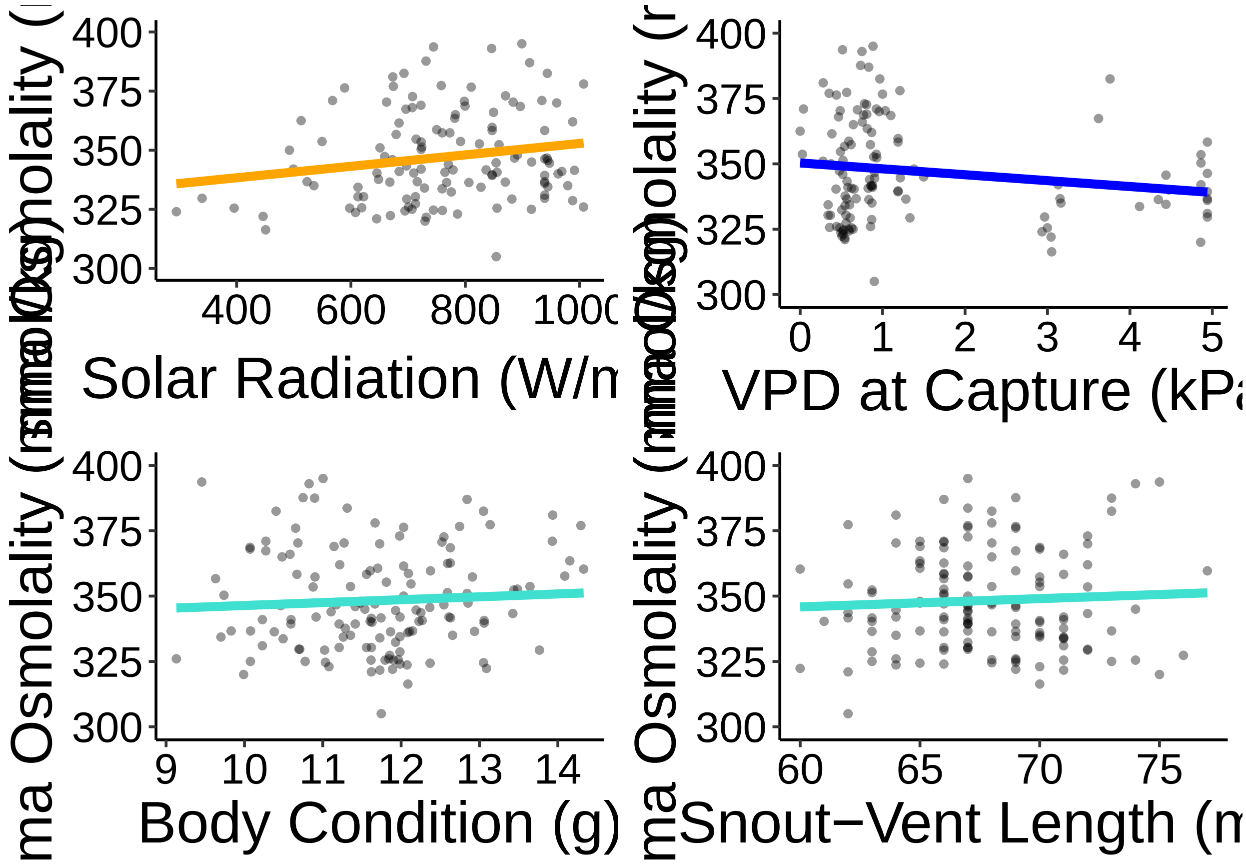
```
cap_hct_multi_fig
```




```
# export figure
ggsave(filename = "cap_hct_multi_fig.jpeg",
       plot = cap_hct_multi_fig,
       path = "./results_figures",
       device = "jpeg",
       dpi = 1200,
       width = 12, height = 8)


# osmolality
ggarrange(cap_osml_sorad_fig, cap_osml_VPD_fig,
          cap_osml_SMI_fig, cap_osml_SVL_fig,
          ncol = 2, nrow = 2,
          legend = "none"
          ) -> cap_osml_multi_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).

## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).
```

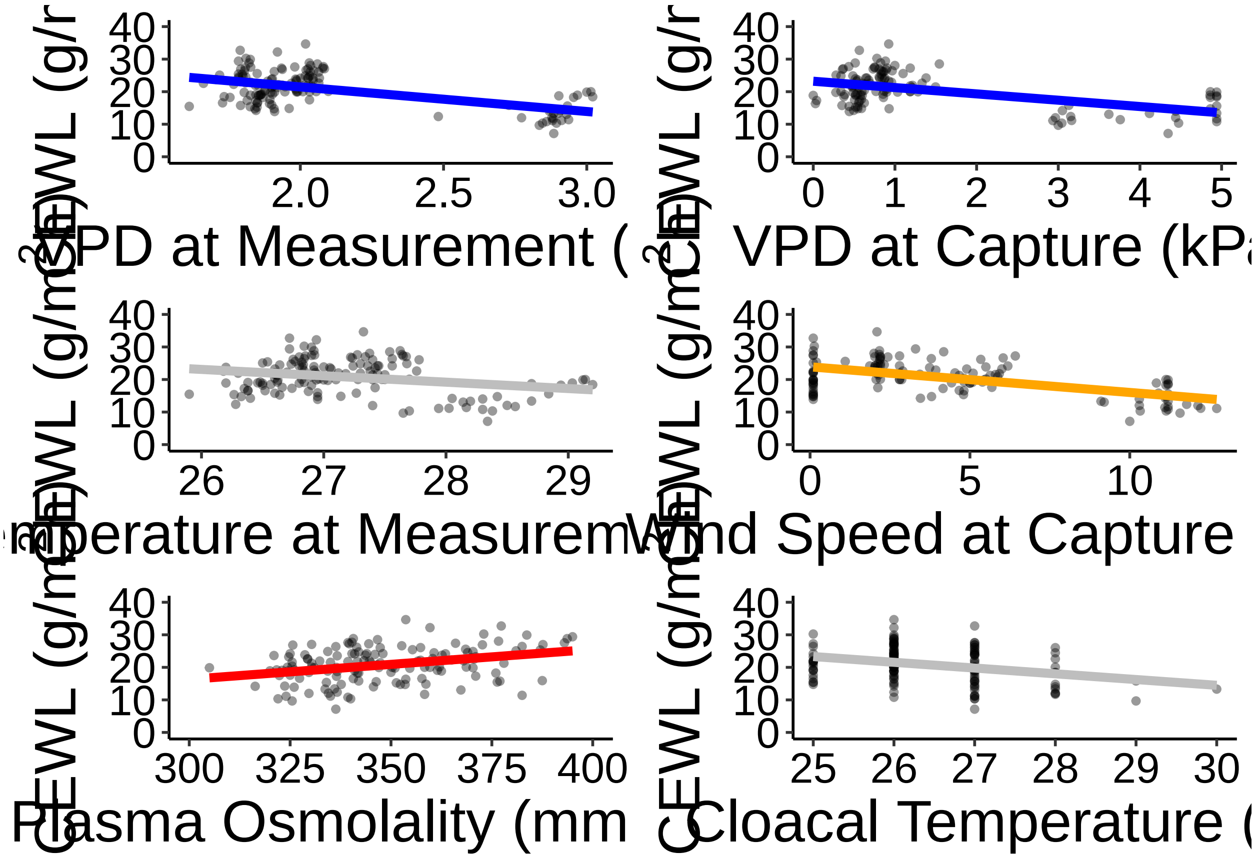
```
cap_osml_multi_fig
```



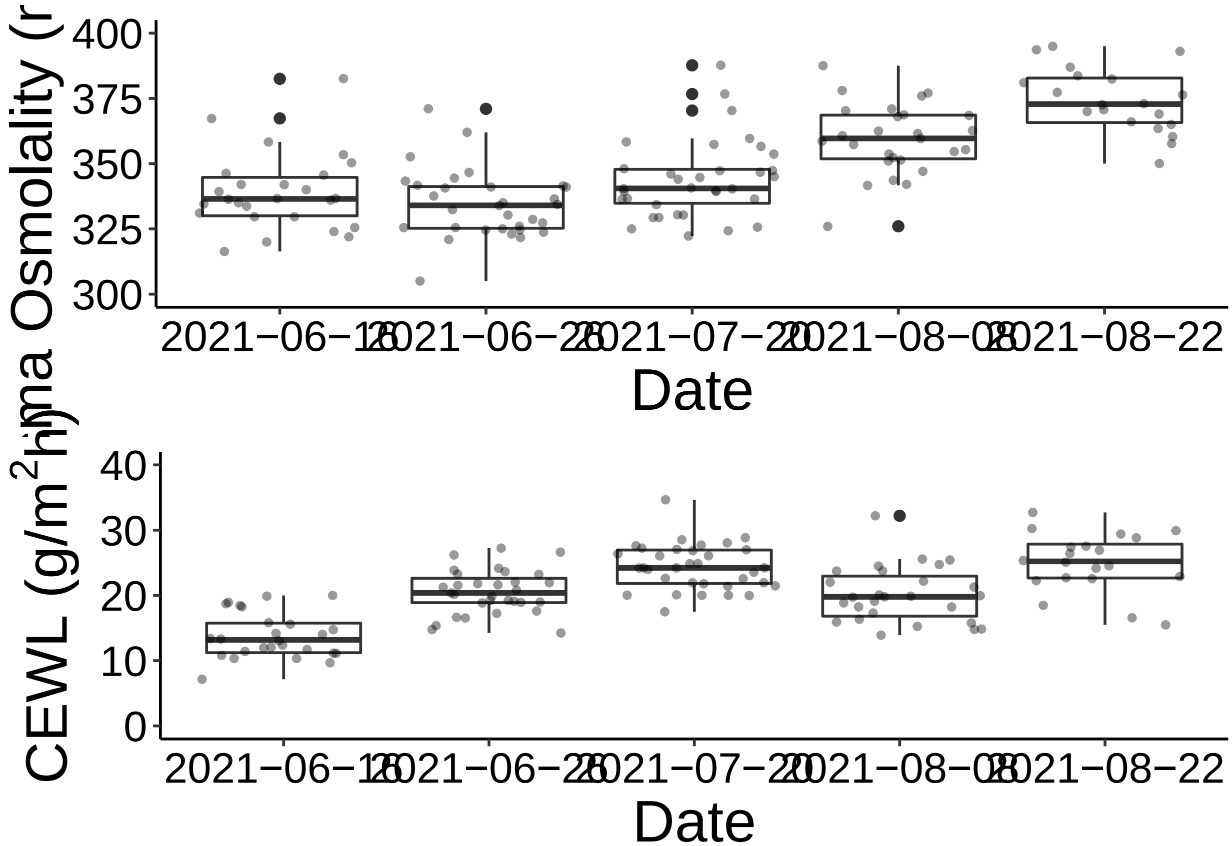

```
# export figure
ggsave(filename = "cap_osml_multi_fig.jpeg",
       plot = cap_osml_multi_fig,
       path = "./results_figures",
       device = "jpeg",
       dpi = 1200,
       width = 12, height = 8)



# CEWL
ggarrange(cap_CEWL_VPDm_fig, cap_CEWL_VPDc_fig,
          cap_CEWL_temp_fig, cap_CEWL_wind_fig,
          cap_CEWL_osml_fig, cap_CEWL_clotemp_fig,
          ncol = 2, nrow = 3,
          legend = "none"
          ) -> cap_CEWL_multi_fig
```

```
## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).

## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).
```

```
cap_CEWL_multi_fig
```




```r
# export figure
ggsave(filename = "cap_CEWL_multi_fig",
       plot = cap_CEWL_multi_fig,
       path = "./results_figures",
       device = "jpeg",
       dpi = 1200,
       width = 12, height = 16)



# date differences
ggarrange(cap_osml_date_fig, cap_CEWL_date_fig,
          ncol = 1, nrow = 2,
          legend = "none"
          ) -> cap_date_diffs_multi_fig
cap_date_diffs_multi_fig
```




```r
# export figure
ggsave(filename = "cap_date_diffs_multi_fig.jpeg",
       plot = cap_date_diffs_multi_fig,
       path = "./results_figures",
       device = "jpeg",
       dpi = 1200,
       width = 6, height = 8)
```