

Climate Water Loss Experiment - Capture Hydration Analysis

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Contents

Packages	2
Background and Goals	2
Load Data	2
Check Weather ~ Date Distribution	4
Clean Data	4
LMMs	5
By Date	5
Hematocrit	7
Models	7
Selection	10
LM Conditions	11
Export	14
Osmolality	15
Models	15
Selection	20
LM Conditions	21
Export	24
CEWL	26
Models	26
Selection	43
LM Conditions	44
Export	47
Group Model Export	51
Figures	52
Custom Colors	52
Hct ~ SMI	53
Hct ~ VPD at Capture	54
Hct ~ Wind Speed at Capture	55
Hct ~ Solar Radiation at Capture	56
Osmolality ~ SVL	57
Osmolality ~ SMI	59
Osmolality ~ VPD at Capture	60
Osmolality ~ Solar Radiation at Capture	61
Osmolality ~ Date	62
CEWL ~ Cloacal Temperature	64
CEWL ~ Plasma Osmolality	65
Add SLR	66

CEWL ~ Temperature at Measurement	67
CEWL ~ VPD at Measurement	68
CEWL ~ VPD at Capture	69
CEWL ~ Wind at Capture	70
CEWL ~ Date	71
Figure Arrangements	73

Packages

```

if (!require("tidyverse")) install.packages("tidyverse")
library("tidyverse") # workflow and plots
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.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
if (!require("AICcmodavg")) install.packages("AICcmodavg")
library("AICcmodavg") # model selection
if (!require("RColorBrewer")) install.packages("RColorBrewer")
library("RColorBrewer") # color

```

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 then acclimated to 4 different climate treatments. **This R file analyzes the state and variation of osmotic balance and regulation at the time of capture.** Please refer to the published scientific journal article for full details.

Load Data

```

dat <- read_rds("./data/analysis_data_capture.RDS")
summary(dat)

```

```

## individual_ID      mass_g      hematocrit_percent      SVL_mm
## 201      : 1  Min.      : 8.80  Min.      :27.00  Min.      :60.00
## 202      : 1  1st Qu.:10.60  1st Qu.:34.25  1st Qu.:66.00
## 203      : 1  Median :11.65  Median :39.00  Median :67.00
## 204      : 1  Mean   :11.73  Mean   :38.93  Mean   :67.71
## 205      : 1  3rd Qu.:12.70  3rd Qu.:43.00  3rd Qu.:70.00
## 206      : 1  Max.   :17.40  Max.   :52.00  Max.   :77.00
## (Other):132

```

```

##      capture_date      osmolality_mmol_kg_mean CEWL_g_m2h_mean  msmt_temp_C
## Min.      :2021-06-16  Min.      :305.0          Min.      : 7.152  Min.      :25.90
## 1st Qu.   :2021-06-26  1st Qu.   :334.3          1st Qu.   :17.255  1st Qu.   :26.72
## Median    :2021-07-20  Median    :344.6          Median    :21.030  Median    :26.96
## Mean      :2021-07-16  Mean      :348.3          Mean      :20.760  Mean      :27.20
## 3rd Qu.   :2021-08-08  3rd Qu.   :361.9          3rd Qu.   :24.416  3rd Qu.   :27.50
## Max.      :2021-08-22  Max.      :395.0          Max.      :34.660  Max.      :29.20
##
## msmt_RH_percent cloacal_temp_C      date_time
## Min.      :25.52  Min.      :25.00  Min.      :2021-06-16 09:54:00.00
## 1st Qu.   :45.77  1st Qu.   :26.00  1st Qu.   :2021-06-26 12:59:30.00
## Median    :47.09  Median    :26.00  Median    :2021-07-20 13:17:00.00
## Mean      :44.08  Mean      :26.45  Mean      :2021-07-17 06:56:12.60
## 3rd Qu.   :48.44  3rd Qu.   :27.00  3rd Qu.   :2021-08-08 13:39:00.00
## Max.      :53.15  Max.      :30.00  Max.      :2021-08-22 15:19:00.00
##
##      msmt_temp_K      e_s_kPa_m      e_a_kPa_m      msmt_VPD_kPa
## Min.      :299.1  Min.      :3.441  Min.      :0.9894  Min.      :1.612
## 1st Qu.   :299.9  1st Qu.   :3.616  1st Qu.   :1.6913  1st Qu.   :1.846
## Median    :300.1  Median    :3.669  Median    :1.7342  Median    :1.942
## Mean      :300.3  Mean      :3.724  Mean      :1.6312  Mean      :2.093
## 3rd Qu.   :300.6  3rd Qu.   :3.790  3rd Qu.   :1.7865  3rd Qu.   :2.053
## Max.      :302.4  Max.      :4.194  Max.      :1.8502  Max.      :3.021
##
##      SMI      capture_date_time      hold_time_sec
## Min.      : 9.122  Min.      :2021-06-16 08:28:00.00  Length:138
## 1st Qu.   :10.926  1st Qu.   :2021-06-26 09:44:45.00  Class :difftime
## Median    :11.687  Median    :2021-07-20 09:52:00.00  Mode  :numeric
## Mean      :11.690  Mean      :2021-07-14 14:50:11.13
## 3rd Qu.   :12.347  3rd Qu.   :2021-08-08 09:56:45.00
## Max.      :14.263  Max.      :2021-08-22 13:25:00.00
##
##      hold_time_min      hold_time_hr      temp_C_interpol RH_percent_interpol
## Length:138      Length:138      Min.      :15.11  Min.      : 19.73
## Class :difftime      Class :difftime      1st Qu.   :19.91  1st Qu.   : 59.20
## Mode  :numeric      Mode  :numeric      Median    :21.91  Median    : 69.33
##
##      Mean      :23.41  Mean      : 62.27
##      3rd Qu.   :23.91  3rd Qu.   : 77.29
##      Max.      :35.83  Max.      :100.00
##      NA's      :14      NA's      :14
##
##      VPD_kPa_int      wind_mph_interpol      solar_rad_W_sqm_interpol
## Min.      :0.0000  Min.      : 0.100  Min.      : 294.7
## 1st Qu.   :0.5420  1st Qu.   : 2.025  1st Qu.   : 682.9
## Median    :0.8284  Median    : 3.100  Median    : 759.9
## Mean      :1.4295  Mean      : 4.406  Mean      : 762.9
## 3rd Qu.   :1.2321  3rd Qu.   : 5.880  3rd Qu.   : 873.2
## Max.      :4.9400  Max.      :12.720  Max.      :1007.0
## NA's      :14      NA's      :14      NA's      :14

```

```
mean(dat$hold_time_hr, na.rm=T)
```

```
## Time difference of 2.959005 secs
```

note IDs I do not have data for (and shouldn't): 254, 284, 304

Check Weather ~ Date Distribution

```
dat %>%
  group_by(capture_date) %>%
  summarise(min(VPD_kPa_int, na.rm = T),
            max(VPD_kPa_int, na.rm = T),
            min(wind_mph_interpol, na.rm = T),
            max(wind_mph_interpol, na.rm = T),
            min(temp_C_interpol, na.rm = T),
            max(temp_C_interpol, na.rm = T),
            min(solar_rad_W_sqm_interpol, na.rm = T),
            max(solar_rad_W_sqm_interpol, na.rm = T))

## # A tibble: 5 x 9
##   capture_date min(VPD~1 max(V~2 min(w~3 max(w~4 min(t~5 max(t~6 min(s~7 max(s~8
##   <date>          <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 2021-06-16      2.93    4.94    9.1    12.7    27.6    35.8    295.    962.
## 2 2021-06-26      0.481   0.924   3.43    6.42    19.4    22.4    598.   1007.
## 3 2021-07-20      0.339   1.54    2       4.18    18.6    25.8    612.    943.
## 4 2021-08-08      0       1.21    0.1     5.63    15.1    23.8    513.   1007.
## 5 2021-08-22      0.279   0.966   0.1     3.93    18.4    23.1    492.    960.
## # ... with abbreviated variable names 1: `min(VPD_kPa_int, na.rm = T)`,
## #   2: `max(VPD_kPa_int, na.rm = T)`, 3: `min(wind_mph_interpol, na.rm = T)`,
## #   4: `max(wind_mph_interpol, na.rm = T)`,
## #   5: `min(temp_C_interpol, na.rm = T)`, 6: `max(temp_C_interpol, na.rm = T)`,
## #   7: `min(solar_rad_W_sqm_interpol, na.rm = T)`,
## #   8: `max(solar_rad_W_sqm_interpol, na.rm = T)`
```

Temp, wind speed, and VPD were all exceptionally higher for the June 16 capture date compared to the other capture dates. We could either relativize the data, or remove the data for that date. Since I want the models to have intuitive results, I will remove the data for that capture date since it would skew our results.

Clean Data

```
dat_reduced <- dat %>%
  dplyr::filter(capture_date != as.Date("2021-06-16"))
summary(dat_reduced)
```

```
##   individual_ID      mass_g      hematocrit_percent      SVL_mm
## 227      : 1   Min.      : 8.8   Min.      :27.00   Min.      :60.00
## 228      : 1   1st Qu.:10.5   1st Qu.:34.00   1st Qu.:65.00
## 229      : 1   Median :11.6   Median :38.00   Median :67.00
## 230      : 1   Mean    :11.7   Mean    :38.33   Mean    :67.29
## 231      : 1   3rd Qu.:12.7   3rd Qu.:43.00   3rd Qu.:69.25
## 232      : 1   Max.     :17.4   Max.     :52.00   Max.     :77.00
## (Other):106
##   capture_date      osmolality_mmol_kg_mean CEWL_g_m2h_mean  msmt_temp_C
## Min.      :2021-06-26   Min.      :305.0   Min.      :13.90   Min.      :25.90
## 1st Qu.:2021-06-26   1st Qu.:336.0   1st Qu.:19.23   1st Qu.:26.62
## Median :2021-07-20   Median :347.2   Median :22.11   Median :26.91
## Mean      :2021-07-23   Mean      :350.5   Mean      :22.38   Mean      :26.94
## 3rd Qu.:2021-08-08   3rd Qu.:365.2   3rd Qu.:25.37   3rd Qu.:27.30
## Max.      :2021-08-22   Max.      :395.0   Max.      :34.66   Max.      :27.78
##
##   msmt_RH_percent cloacal_temp_C      date_time
```

```
## Min. :45.30 Min. :25.00 Min. :2021-06-26 12:08:00.00
## 1st Qu.:46.18 1st Qu.:26.00 1st Qu.:2021-06-26 17:53:00.00
## Median :47.71 Median :26.00 Median :2021-07-20 14:55:30.00
## Mean :47.94 Mean :26.23 Mean :2021-07-24 10:07:25.71
## 3rd Qu.:49.21 3rd Qu.:27.00 3rd Qu.:2021-08-08 14:35:30.00
## Max. :53.15 Max. :28.00 Max. :2021-08-22 15:19:00.00
##
## msmt_temp_K e_s_kPa_m e_a_kPa_m msmt_VPD_kPa
## Min. :299.1 Min. :3.441 Min. :1.672 Min. :1.612
## 1st Qu.:299.8 1st Qu.:3.595 1st Qu.:1.714 1st Qu.:1.827
## Median :300.1 Median :3.658 Median :1.747 Median :1.903
## Mean :300.1 Mean :3.666 Mean :1.757 Mean :1.910
## 3rd Qu.:300.4 3rd Qu.:3.744 3rd Qu.:1.795 3rd Qu.:2.014
## Max. :300.9 Max. :3.854 Max. :1.850 Max. :2.098
##
## SMI capture_date_time hold_time_sec
## Min. : 9.122 Min. :2021-06-26 09:20:00.00 Length:112
## 1st Qu.:11.185 1st Qu.:2021-06-26 14:23:15.00 Class :difftime
## Median :11.790 Median :2021-07-20 10:29:30.00 Mode :numeric
## Mean :11.844 Mean :2021-07-22 01:59:40.41
## 3rd Qu.:12.554 3rd Qu.:2021-08-08 10:23:00.00
## Max. :14.263 Max. :2021-08-22 13:25:00.00
## NA's :14
## hold_time_min hold_time_hr temp_C_interpol RH_percent_interpol
## Length:112 Length:112 Min. :15.11 Min. : 54.84
## Class :difftime Class :difftime 1st Qu.:19.71 1st Qu.: 67.82
## Mode :numeric Mode :numeric Median :20.74 Median : 74.28
## Mean :20.94 Mean : 73.19
## 3rd Qu.:22.18 3rd Qu.: 78.00
## Max. :25.79 Max. :100.00
## NA's :14 NA's :14
## VPD_kPa_int wind_mph_interpol solar_rad_W_sqm_interpol
## Min. :0.0000 Min. :0.1000 Min. : 492.4
## 1st Qu.:0.5170 1st Qu.:0.1083 1st Qu.: 687.0
## Median :0.6438 Median :2.2000 Median : 765.9
## Mean :0.7103 Mean :2.6514 Mean : 773.9
## 3rd Qu.:0.8779 3rd Qu.:4.6333 3rd Qu.: 855.5
## Max. :1.5441 Max. :6.4200 Max. :1007.0
## NA's :14 NA's :14 NA's :14
```

LMMs

By Date

Check whether our dependent or weather-predictor variables of interest are significantly different across capture dates.

```
anova(lm(data = dat_reduced,
          hematocrit_percent ~ as.factor(capture_date)))
```

```
## Analysis of Variance Table
##
## Response: hematocrit_percent
##           Df Sum Sq Mean Sq F value Pr(>F)
```

```

## as.factor(capture_date)  3 240.96 80.319 3.173 0.02718 *
## Residuals                108 2733.82 25.313
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(lm(data = dat_reduced,
          osmolality_mmol_kg_mean ~ as.factor(capture_date)))

## Analysis of Variance Table
##
## Response: osmolality_mmol_kg_mean
##              Df Sum Sq Mean Sq F value    Pr(>F)
## as.factor(capture_date)  3 23099 7699.7 41.657 < 2.2e-16 ***
## Residuals                108 19962 184.8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(lm(data = dat_reduced,
          CEWL_g_m2h_mean ~ as.factor(capture_date)))

## Analysis of Variance Table
##
## Response: CEWL_g_m2h_mean
##              Df Sum Sq Mean Sq F value    Pr(>F)
## as.factor(capture_date)  3  509.02 169.673 11.477 1.366e-06 ***
## Residuals                108 1596.64 14.784
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(lm(data = dat_reduced,
          temp_C_interpol ~ as.factor(capture_date)))

## Analysis of Variance Table
##
## Response: temp_C_interpol
##              Df Sum Sq Mean Sq F value    Pr(>F)
## as.factor(capture_date)  3  44.41 14.8029 4.3126 0.006776 **
## Residuals                94 322.65 3.4325
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(lm(data = dat_reduced,
          VPD_kPa_int ~ as.factor(capture_date)))

## Analysis of Variance Table
##
## Response: VPD_kPa_int
##              Df Sum Sq Mean Sq F value    Pr(>F)
## as.factor(capture_date)  3  0.8854 0.295124 3.4804 0.01897 *
## Residuals                94 7.9708 0.084796
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(lm(data = dat_reduced,
          wind_mph_interpol ~ as.factor(capture_date)))

## Analysis of Variance Table
##

```

```
## Response: wind_mph_interpol
##               Df Sum Sq Mean Sq F value    Pr(>F)
## as.factor(capture_date) 3 305.956  101.98  107.38 < 2.2e-16 ***
## Residuals              94  89.276    0.95
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(lm(data = dat_reduced,
          solar_rad_W_sqm_interpol ~ as.factor(capture_date)))
```

```
## Analysis of Variance Table
##
## Response: solar_rad_W_sqm_interpol
##               Df Sum Sq Mean Sq F value Pr(>F)
## as.factor(capture_date) 3  77839  25946  1.8722 0.1396
## Residuals              94 1302683  13858
```

Our variables of interest are still significantly different across capture dates, for hct, osml, and CEWL. So, we can include capture date as a random effect. Weather is significantly different across date for 3/4 of the variables, which is to be expected because the dates were spaced out across the season. We are primarily interested in within-day variability, and the ranges of the variables were similar across dates (after June 16 was removed), so this should not be an issue for what we're interested in.

Hematocrit

Models

First, start with a full model, then check for multicollinearity.

```
hct_mod1 <- lm(data = dat_reduced,
               # response variable
               hematocrit_percent ~
               # body size options
               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))
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
hct_mod1_VIFs

##               VIF
## VPD_kPa_int      434.186709
## temp_C_interpol:VPD_kPa_int 221.430576
## mass_g           164.858051
## SVL_mm           145.805705
## SMI              71.083734
## temp_C_interpol   66.551079
## solar_rad_W_sqm_interpol  3.712395
## wind_mph_interpol  1.359344
```

remove VPD*temp interaction:

```

hct_mod2 <- lm(data = dat_reduced,
               # 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          158.251131
## SVL_mm          139.418643
## SMI              67.901185
## temp_C_interpol  42.314642
## VPD_kPa_int      39.100371
## solar_rad_W_sqm_interpol  3.672885
## wind_mph_interpol  1.354287

```

drop mass

```

hct_mod3 <- lm(data = dat_reduced,
               # response variable
               hematocrit_percent ~
               # body size
               SVL_mm + 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  42.281327
## VPD_kPa_int      38.942435
## solar_rad_W_sqm_interpol  3.259818
## wind_mph_interpol  1.277896
## SMI              1.100727
## SVL_mm           1.096165

```

drop temperature:

```

hct_mod4 <- lm(data = dat_reduced,
               # response variable
               hematocrit_percent ~
               # body size
               SVL_mm + 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
## solar_rad_W_sqm_interpol 3.031552
## VPD_kPa_int              2.620763
## wind_mph_interpol        1.274442
## SVL_mm                   1.095692
## SMI                      1.094870

drop1(hct_mod4)

## Single term deletions
##
## Model:
## hematocrit_percent ~ SVL_mm + SMI + VPD_kPa_int + wind_mph_interpol +
##   solar_rad_W_sqm_interpol
##               Df Sum of Sq    RSS    AIC
## <none>                                2164.4 315.31
## SVL_mm              1      0.330 2164.8 313.32
## SMI                  1   185.846 2350.3 321.38
## VPD_kPa_int          1     1.992 2166.4 313.40
## wind_mph_interpol    1   243.674 2408.1 323.76
## solar_rad_W_sqm_interpol 1    14.594 2179.1 313.96
```

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

Drop SVL first:

```
hct_mod5 <- lm(data = dat_reduced,
               # 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>                                2164.8 313.32
## SMI              1   191.896 2356.7 319.64
## VPD_kPa_int      1     2.065 2166.8 311.41
## wind_mph_interpol 1   245.057 2409.8 321.83
## solar_rad_W_sqm_interpol 1    15.226 2180.0 312.01
```

Drop VPD:

```
hct_mod6 <- lm(data = dat_reduced,
               # 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>                2166.8 311.41
## SMI                1   189.962 2356.8 317.65
## wind_mph_interpol    1   250.253 2417.1 320.12
## solar_rad_W_sqm_interpol 1    18.752 2185.6 310.26
```

Drop solar:

```
hct_mod7 <- lm(data = dat_reduced,
               # 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>                2185.6 310.26
## SMI                1   182.35 2367.9 316.11
## wind_mph_interpol    1   390.27 2575.9 324.36
```

Drop SMI:

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

Finally, null model:

```
hct_mod_null <- lm(data = dat_reduced,
                  # 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, SVL',
                  '(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
## 4      (model 7) ~ Wind-C, SMI 4 590.8005    0.000000
## 3      (model 6) ~ Wind-C, SMI, Solar-C 5 592.1782    1.377632
## 2      (model 5) ~ Wind-C, SMI, Solar-C, VPD-C 6 594.3556    3.555105
## 5      (model 8) ~ Wind-C 3 596.4788    5.678263
## 1 (model 4) ~ Wind-C, SMI, Solar-C, VPD-C, SVL 7 596.6621    5.861554
## 6      null model 2 689.2480   98.447433
##      ModellLik      AICcWt      LL      Cum.Wt
## 4 1.000000e+00 5.608356e-01 -291.1852 0.5608356
## 3 5.021703e-01 2.816350e-01 -290.7630 0.8424706
## 2 1.690514e-01 9.481006e-02 -290.7163 0.9372806
## 5 5.847644e-02 3.279567e-02 -295.1117 0.9700763
## 1 5.335556e-02 2.992370e-02 -290.7088 1.0000000
## 6 4.191905e-22 2.350970e-22 -342.5689 1.0000000

```

The best model is 7 with wind and SMI as predictors. Model 6 with Wind, SMI, and solar is equally as good.

LM Conditions

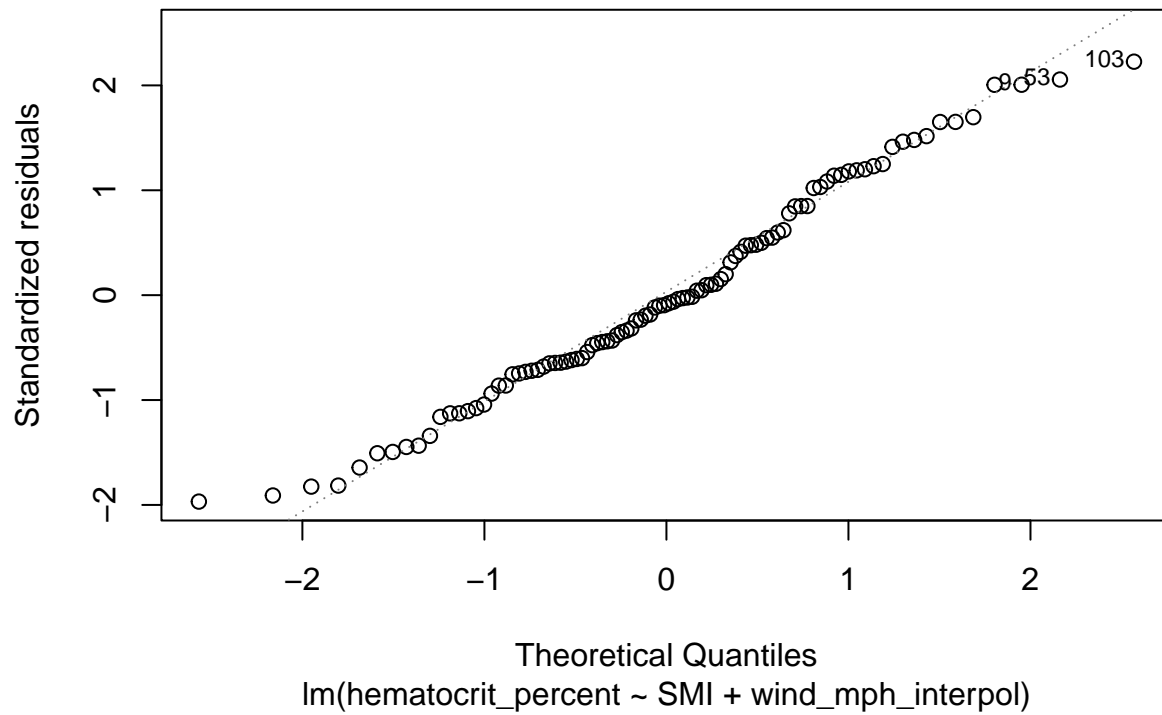
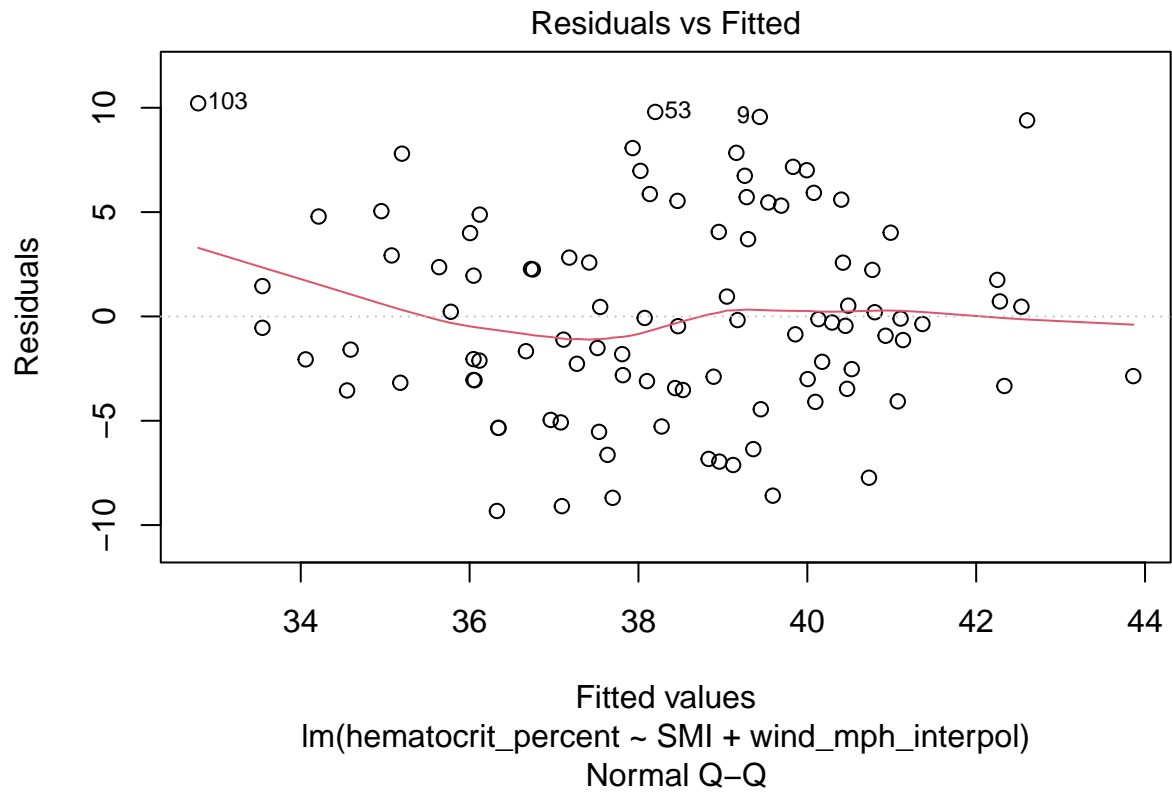
Check that the best model meets the criteria for linear regression and has no collinearity.

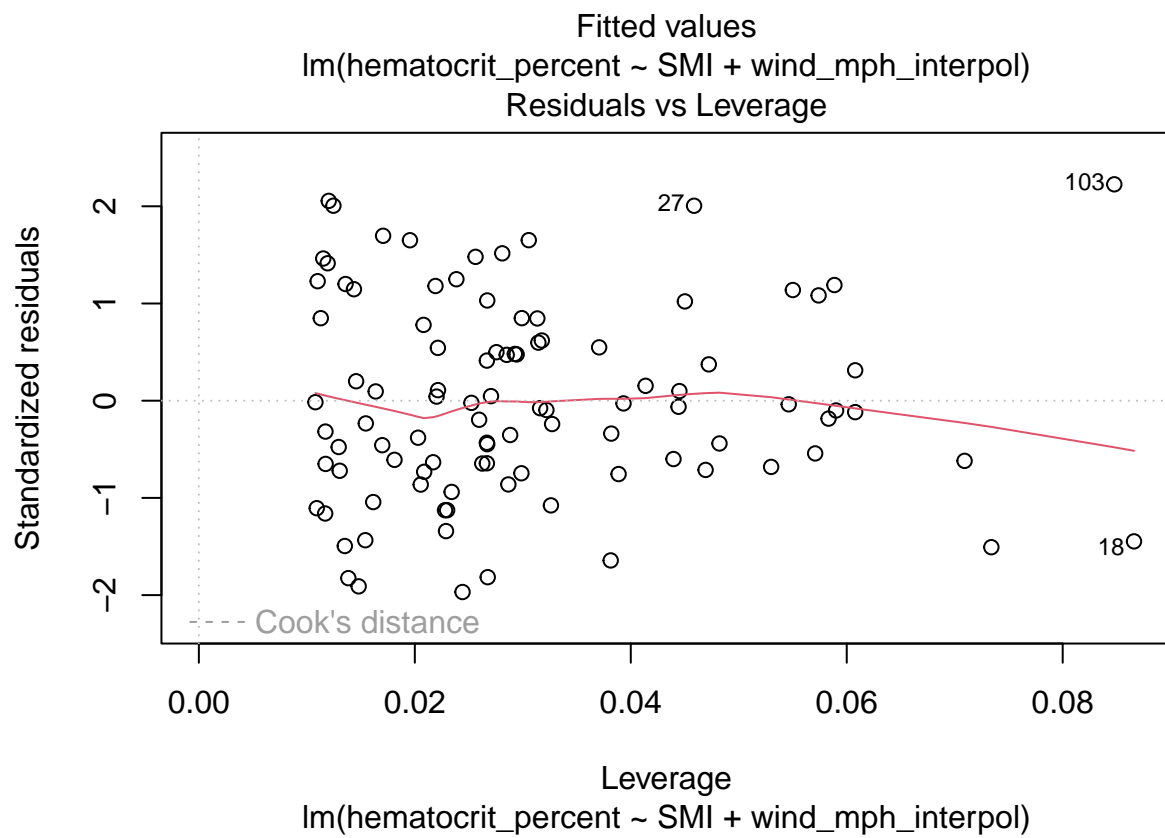
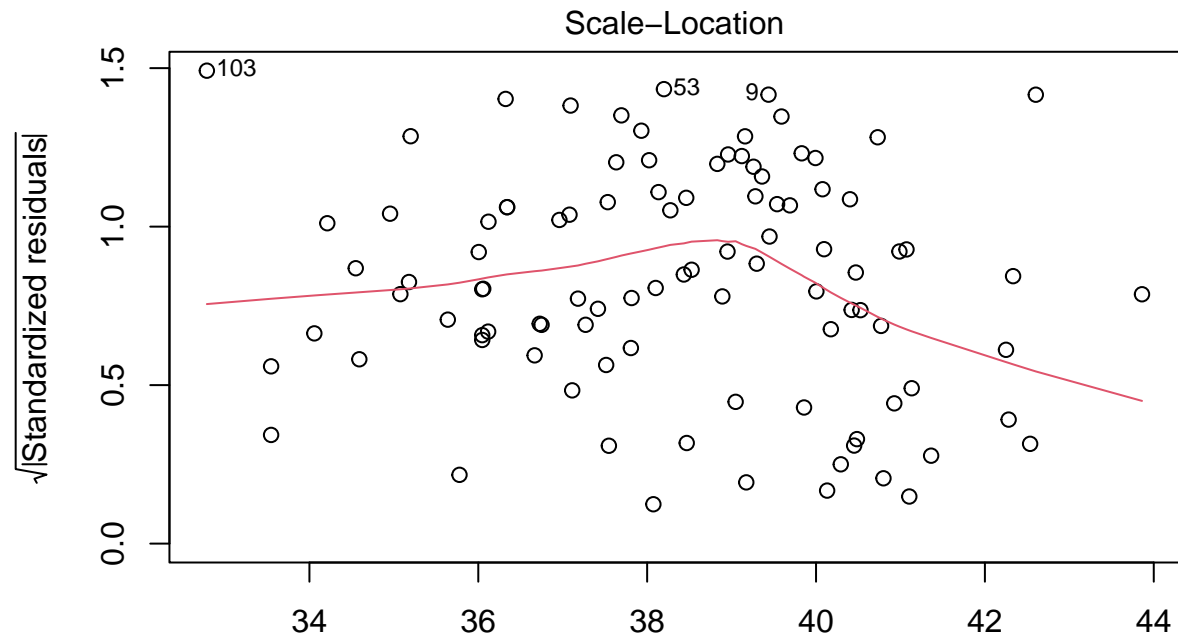
```

vif(hct_mod7)

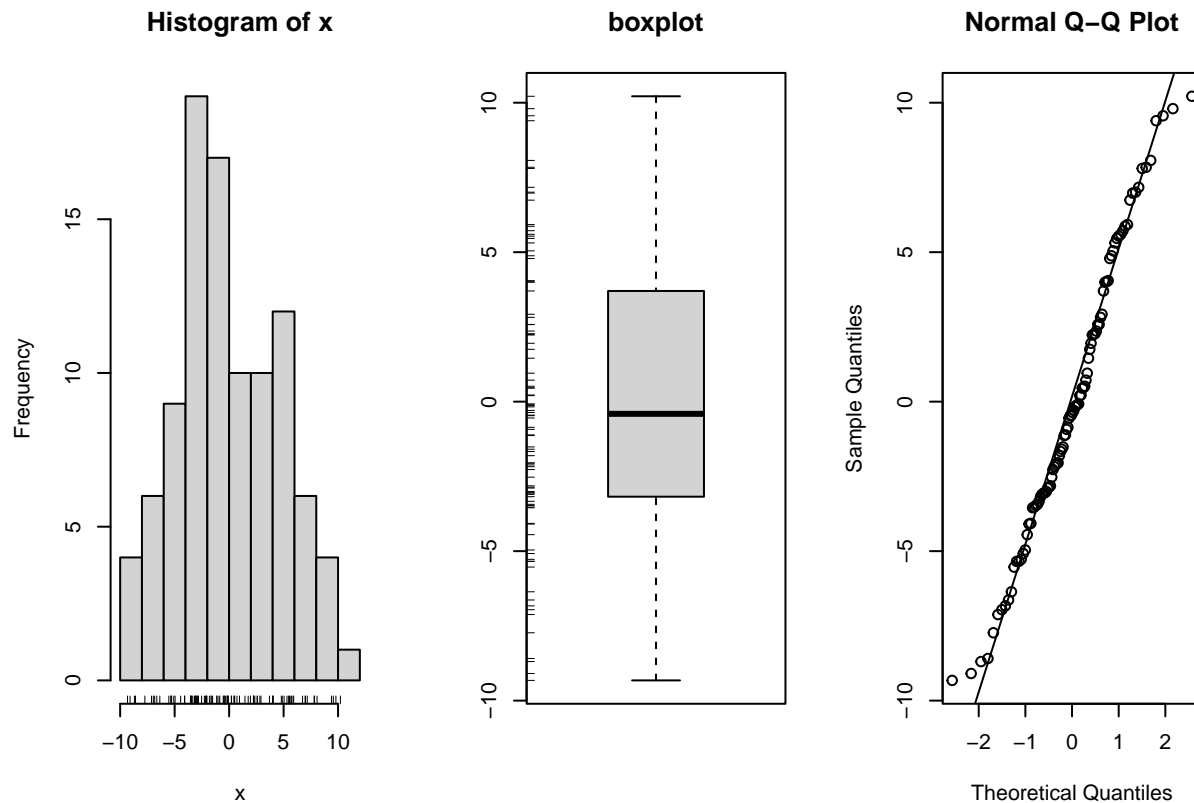
##               SMI wind_mph_interpol
##      1.017682      1.017682
plot(hct_mod7)

```





```
simple.eda(residuals(hct_mod7))
```



```
shapiro.test(residuals(hct_mod7))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(hct_mod7)
## W = 0.98052, p-value = 0.155
```

LINE is almost perfect.

Export

```
hct_mod7p <- lm(data = dat_reduced,
                # response variable
                hematocrit_percent ~
                # body size
                SMI +
                # weather at the time of capture
                wind_mph_interpol)
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 within 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 predictor in it, then check for multicollinearity.

```
osml_mod1 <- lme4::lmer(data = dat_reduced,
  # 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      534.605447
## temp_C_interpol:VPD_kPa_int 240.291835
## mass_g           166.612853
## SVL_mm           144.058809
## temp_C_interpol  108.269259
## SMI              71.898047
## solar_rad_W_sqm_interpol    4.898134
## wind_mph_interpol    1.696851
## hematocrit_percent    1.181664
```

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

```
osml_mod2 <- lme4::lmer(data = dat_reduced,
  # 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          162.704391
```

```
## SVL_mm                140.401579
## SMI                    70.036881
## temp_C_interpol       67.050277
## VPD_kPa_int           61.276054
## solar_rad_W_sqm_interpol  4.892261
## wind_mph_interpol      1.612177
## hematocrit_percent     1.181520

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>                812.13
## mass_g                1 811.15
## SVL_mm                1 811.58
## SMI                   1 811.17
## hematocrit_percent    1 810.58
## temp_C_interpol       1 810.75
## VPD_kPa_int           1 810.66
## wind_mph_interpol     1 810.13
## solar_rad_W_sqm_interpol 1 810.79

anova(osml_mod2)

## Analysis of Variance Table
##               npar Sum Sq Mean Sq F value
## mass_g                1 578.42  578.42  3.3010
## SVL_mm                1 455.81  455.81  2.6012
## SMI                   1 171.43  171.43  0.9783
## hematocrit_percent    1 178.94  178.94  1.0212
## temp_C_interpol       1 838.94  838.94  4.7877
## VPD_kPa_int           1 110.38  110.38  0.6299
## wind_mph_interpol     1  17.17   17.17  0.0980
## solar_rad_W_sqm_interpol 1  97.49   97.49  0.5563
```

Drop SMI next, since it's extremely collinear with mass and SVL but explains less variance.

```
osml_mod3 <- lme4::lmer(data = dat_reduced,
  # response variable
  osmolality_mmol_kg_mean ~
  # body size
  mass_g + SVL_mm +
  # 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              66.177503
## VPD_kPa_int                  61.093560
## solar_rad_W_sqm_interpol     4.654746
## SVL_mm                       2.758684
## mass_g                       2.738718
## wind_mph_interpol            1.611989
## hematocrit_percent           1.181310

drop1(osml_mod3)

## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ mass_g + SVL_mm + hematocrit_percent +
##   temp_C_interpol + VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##   (1 | capture_date)
##               npar      AIC
## <none>                811.17
## mass_g                1 809.17
## SVL_mm                1 811.06
## hematocrit_percent    1 809.64
## temp_C_interpol       1 809.62
## VPD_kPa_int           1 809.61
## wind_mph_interpol     1 809.18
## solar_rad_W_sqm_interpol 1 810.28

anova(osml_mod3)
```

```
## Analysis of Variance Table
##               npar Sum Sq Mean Sq F value
## mass_g          1 578.07  578.07  3.3080
## SVL_mm          1 456.36  456.36  2.6115
## hematocrit_percent 1 189.58  189.58  1.0849
## temp_C_interpol  1 776.18  776.18  4.4417
## VPD_kPa_int      1  98.26   98.26  0.5623
## wind_mph_interpol 1  24.54   24.54  0.1404
## solar_rad_W_sqm_interpol 1 166.53  166.53  0.9530
```

Temperature is still introducing a lot of multicollinearity with VPD, but temp has a much higher SS than VPD, so drop VPD:

```
osml_mod4 <- lme4::lmer(data = dat_reduced,
  # response variable
  osmolality_mmol_kg_mean ~
  # body size
  mass_g + SVL_mm +
  # blood sample traits
  hematocrit_percent +
  # weather at the time of capture
  temp_C_interpol +
  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
## solar_rad_W_sqm_interpol 4.578723
## temp_C_interpol         4.054450
## SVL_mm                  2.756996
## mass_g                  2.723423
## wind_mph_interpol       1.597632
## hematocrit_percent      1.149307

anova(osml_mod4)

## Analysis of Variance Table
##                                npar Sum Sq Mean Sq F value
## mass_g                      1 578.09  578.09  3.3294
## SVL_mm                      1 456.33  456.33  2.6282
## hematocrit_percent          1 189.53  189.53  1.0916
## temp_C_interpol             1 776.15  776.15  4.4701
## wind_mph_interpol           1  18.96   18.96  0.1092
## solar_rad_W_sqm_interpol     1 198.94  198.94  1.1458

drop1(osml_mod4)

## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ mass_g + SVL_mm + hematocrit_percent +
##      temp_C_interpol + wind_mph_interpol + solar_rad_W_sqm_interpol +
##      (1 | capture_date)
##                                npar      AIC
## <none>                        809.61
## mass_g                        1 807.61
## SVL_mm                        1 809.45
## hematocrit_percent            1 807.95
## temp_C_interpol               1 807.62
## wind_mph_interpol             1 807.63
## solar_rad_W_sqm_interpol      1 808.91
```

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

Start by dropping wind:

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

drop1(osml_mod5)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ mass_g + SVL_mm + hematocrit_percent +
```

```
##      temp_C_interpol + solar_rad_W_sqm_interpol + (1 | capture_date)
##                                npar    AIC
## <none>                        807.63
## mass_g                        1 805.64
## SVL_mm                       1 807.50
## hematocrit_percent           1 805.95
## temp_C_interpol              1 805.64
## solar_rad_W_sqm_interpol     1 806.96
anova(osml_mod5)
```

```
## Analysis of Variance Table
##                                npar Sum Sq Mean Sq F value
## mass_g                        1 578.20  578.20  3.3648
## SVL_mm                       1 456.16  456.16  2.6546
## hematocrit_percent           1 189.22  189.22  1.1012
## temp_C_interpol              1 776.00  776.00  4.5159
## solar_rad_W_sqm_interpol     1 217.91  217.91  1.2681
```

Drop hematocrit:

```
osml_mod6 <- lme4::lmer(data = dat_reduced,
                        # response variable
                        osmolality_mmol_kg_mean ~
                        # body size
                        mass_g + SVL_mm +
                        # weather at the time of capture
                        temp_C_interpol +
                        solar_rad_W_sqm_interpol +
                        (1|capture_date))
drop1(osml_mod6)
```

```
## Single term deletions
##
## Model:
## osmolality_mmol_kg_mean ~ mass_g + SVL_mm + temp_C_interpol +
##      solar_rad_W_sqm_interpol + (1 | capture_date)
##                                npar    AIC
## <none>                        805.95
## mass_g                        1 803.96
## SVL_mm                       1 805.55
## temp_C_interpol              1 803.96
## solar_rad_W_sqm_interpol     1 805.43
anova(osml_mod6)
```

```
## Analysis of Variance Table
##                                npar Sum Sq Mean Sq F value
## mass_g                        1 578.28  578.28  3.3887
## SVL_mm                       1 456.04  456.04  2.6724
## temp_C_interpol              1 884.15  884.15  5.1811
## solar_rad_W_sqm_interpol     1 243.89  243.89  1.4292
```

Drop solar:

```
osml_mod7 <- lme4::lmer(data = dat_reduced,
                        # response variable
                        osmolality_mmol_kg_mean ~
```

```

# body size
mass_g + SVL_mm +
# weather at the time of capture
temp_C_interpol +
(1|capture_date))

anova(osml_mod7)

```

```

## Analysis of Variance Table
##              npar Sum Sq Mean Sq F value
## mass_g        1 578.33  578.33  3.3727
## SVL_mm        1 455.95  455.95  2.6590
## temp_C_interpol 1 884.02  884.02  5.1554

```

Drop SVL:

```

osml_mod8 <- lme4::lmer(data = dat_reduced,
# response variable
osmolality_mmol_kg_mean ~
# body size
mass_g +
# weather at the time of capture
temp_C_interpol +
(1|capture_date))

anova(osml_mod8)

```

```

## Analysis of Variance Table
##              npar Sum Sq Mean Sq F value
## mass_g        1 578.56  578.56  3.3217
## temp_C_interpol 1 929.39  929.39  5.3359

```

Drop mass:

```

osml_mod9 <- lme4::lmer(data = dat_reduced,
osmolality_mmol_kg_mean ~
temp_C_interpol +
(1|capture_date))

```

Lastly, compute null model:

```

osml_mod_null <- lme4::lmer(data = dat_reduced,
osmolality_mmol_kg_mean ~ 1 +
(1|capture_date))

```

Selection

Compare models 4-9 and null.

```

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) ~ Temp-C, Mass, SVL, Solar-C, Hct, Wind-C',
'(model 5) ~ Temp-C, Mass, SVL, Solar-C, Hct',
'(model 6) ~ Temp-C, Mass, SVL, Solar-C',
'(model 7) ~ Temp-C, Mass, SVL',
'(model 8) ~ Temp-C, Mass',
'(model 9) ~ Temp-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
osml_AICc

##
##          Modnames K      AICc Delta_AICc
## 4          (model 7) ~ Temp-C, Mass, SVL 6 796.7726  0.000000
## 5          (model 8) ~ Temp-C, Mass 5 797.7816  1.008955
## 6          (model 9) ~ Temp-C 4 799.7813  3.008714
## 3          (model 6) ~ Temp-C, Mass, SVL, Solar-C 7 803.3533  6.580653
## 1 (model 4) ~ Temp-C, Mass, SVL, Solar-C, Hct, Wind-C 9 805.6466  8.873971
## 2          (model 5) ~ Temp-C, Mass, SVL, Solar-C, Hct 8 806.1201  9.347462
## 7          null model 3 916.7643 119.991730
##      Modellik      AICcWt    Res.LL    Cum.Wt
## 4 1.000000e+00 5.306753e-01 -391.9248 0.5306753
## 5 6.038209e-01 3.204328e-01 -393.5647 0.8511081
## 6 2.221601e-01 1.178949e-01 -395.6756 0.9690029
## 3 3.724168e-02 1.976324e-02 -394.0544 0.9887662
## 1 1.183155e-02 6.278711e-03 -392.8006 0.9950449
## 2 9.337367e-03 4.955110e-03 -394.2510 1.0000000
## 7 8.792793e-27 4.666118e-27 -455.2711 1.0000000

```

LM Conditions

Check residual plots and VIFs

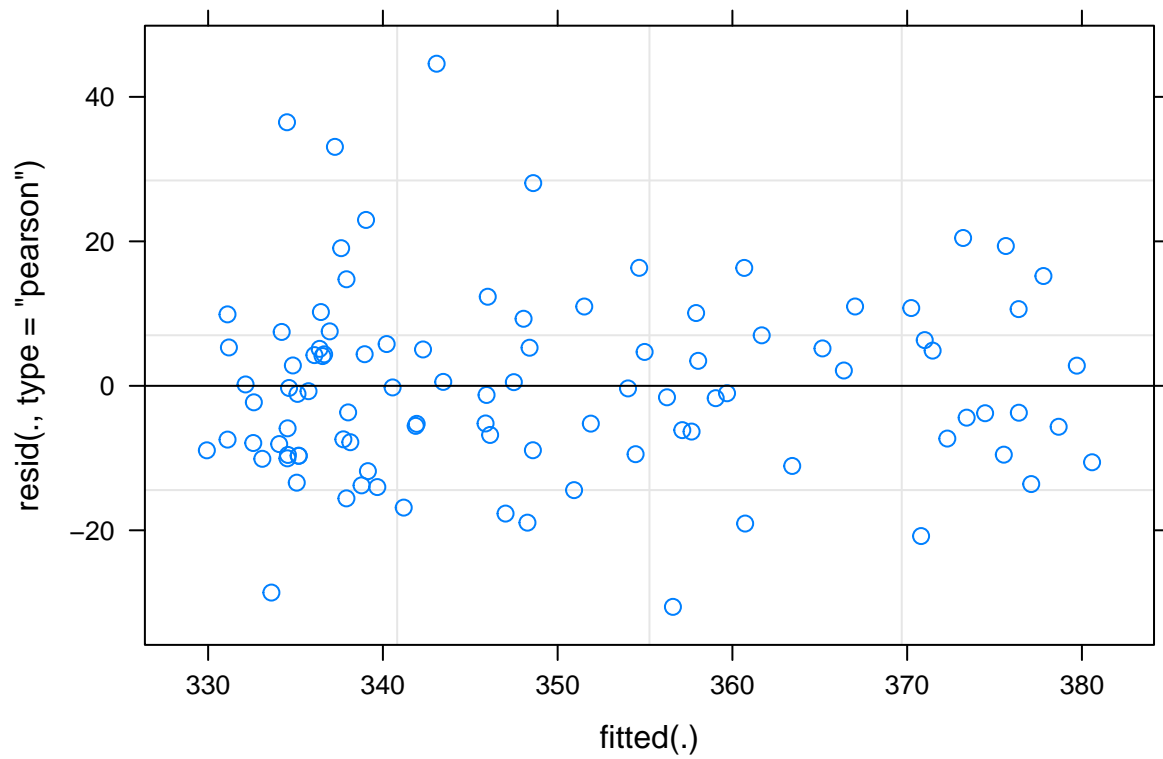
```

vif(osml_mod8)

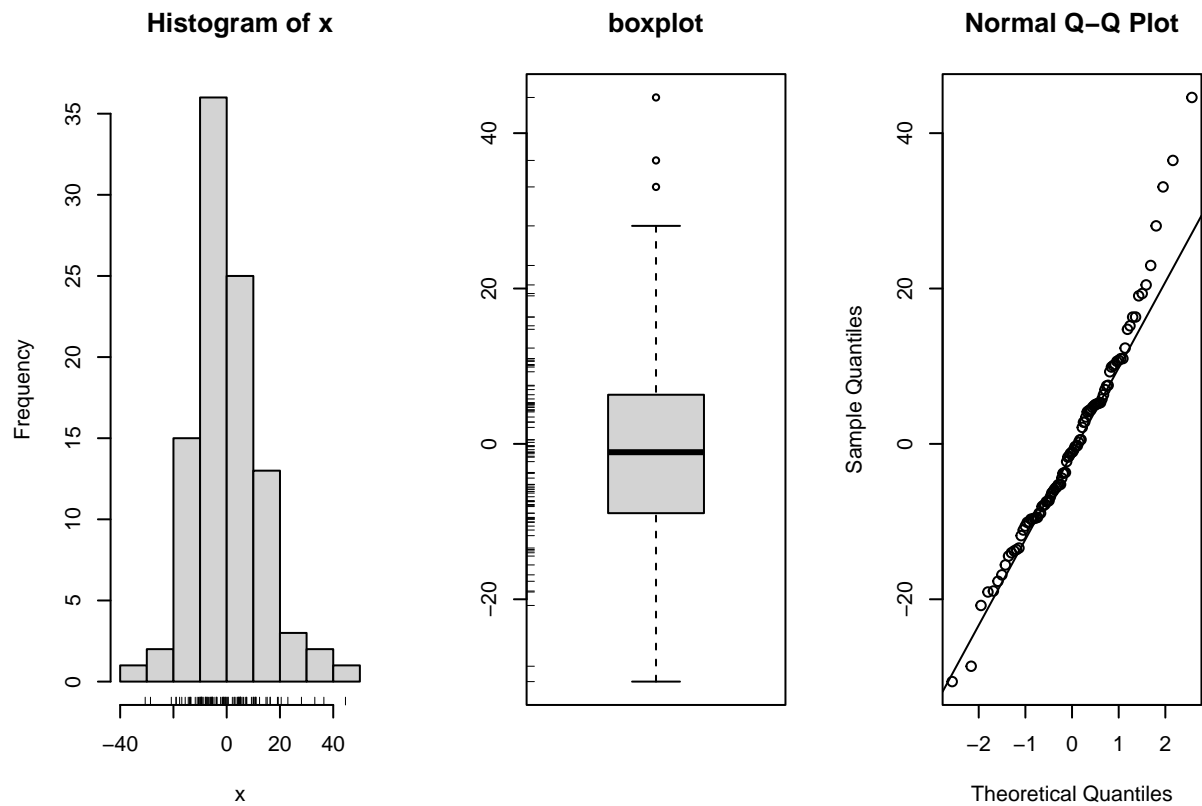
##          mass_g temp_C_interpol
##          1.003613          1.003613

plot(osml_mod8)

```



```
simple.eda(residuals(osml_mod8))
```



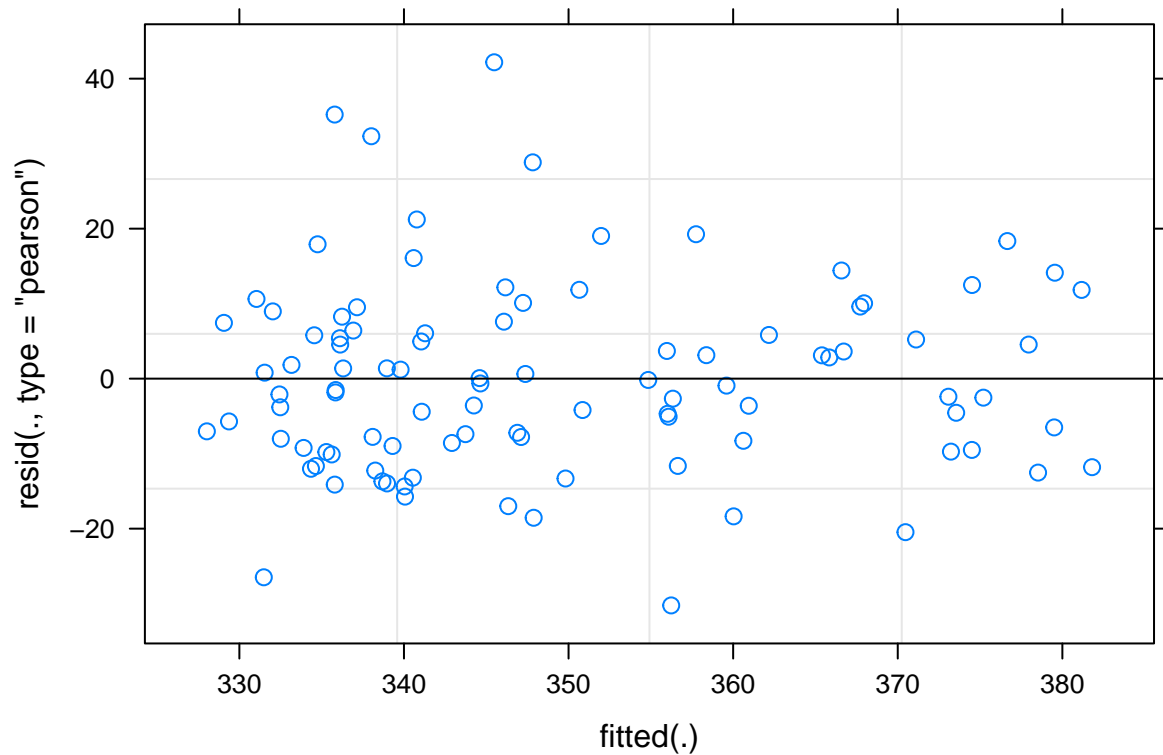
```
shapiro.test(residuals(osml_mod8))
```

```
##  
##  Shapiro-Wilk normality test  
##  
## data:  residuals(osml_mod8)  
## W = 0.96742, p-value = 0.01556
```

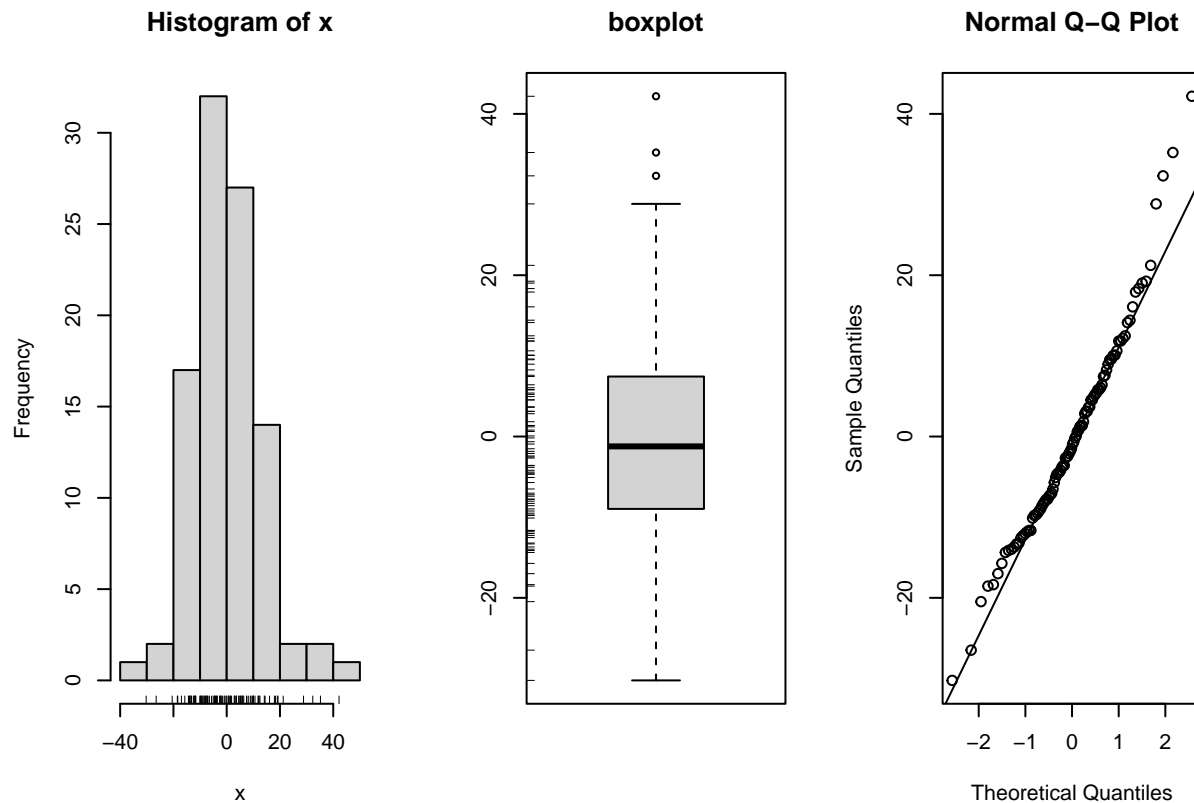
```
vif(osml_mod7)
```

```
##          mass_g          SVL_mm temp_C_interpol  
##          2.441360          2.444388          1.004961
```

```
plot(osml_mod7)
```



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



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

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(osml_mod7)
## W = 0.97314, p-value = 0.04202
```

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:

```
osml_mod7p <- lmerTest::lmer(data = dat_reduced,
  # response variable
  osmolality_mmol_kg_mean ~
  # body size
  mass_g + SVL_mm +
  # weather at the time of capture
  temp_C_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 ~ mass_g + SVL_mm + temp_C_interpol +
##          (1 | capture_date)
```



```

## Data: dat_reduced
##
## REML criterion at convergence: 783.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.3090 -0.6778 -0.0935  0.5484  3.2214
##
## Random effects:
##   Groups             Name             Variance Std.Dev.
## capture_date (Intercept) 332.8       18.24
## Residual                171.5       13.09
## Number of obs: 98, groups: capture_date, 4
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)   255.1285    36.1334   90.3787   7.061 3.29e-10 ***
## mass_g        -0.1263     1.2522   91.0388  -0.101  0.9199
## SVL_mm         0.9678     0.6259   91.1381   1.546  0.1255
## temp_C_interpol 1.6567     0.7296   91.5357   2.271  0.0255 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) mass_g SVL_mm
## mass_g       0.493
## SVL_mm      -0.839 -0.767
## tmp_C_ntrpl -0.374 -0.010 -0.037
osml_mod8p <- lmerTest::lmer(data = dat_reduced,
                             # response variable
                             osmolality_mmol_kg_mean ~
                             # body size
                             mass_g +
                             # weather at the time of capture
                             temp_C_interpol +
                             (1|capture_date))
summary(osml_mod8p)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## osmolality_mmol_kg_mean ~ mass_g + temp_C_interpol + (1 | capture_date)
## Data: dat_reduced
##
## REML criterion at convergence: 787.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.3183 -0.6595 -0.0811  0.4692  3.3788
##
## Random effects:
##   Groups             Name             Variance Std.Dev.
## capture_date (Intercept) 326.0       18.06
## Residual                174.2       13.20

```

```
## Number of obs: 98, groups:  capture_date, 4
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)   302.0031    19.7479   44.8291  15.293   <2e-16 ***
## mass_g        1.3600     0.8092   92.0863   1.681    0.0962 .
## temp_C_interpol 1.6974     0.7348   92.5674   2.310    0.0231 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) mass_g
## mass_g       -0.433
## tmp_C_ntrpl -0.747 -0.060
```

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

There are differences in CEWL across dates, and based on cloacal temp, capture temp, capture VPD, capture wind, and capture solar radiation.

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 = dat_reduced,
# 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 +
# time between capture and measurements)
```

```

        hold_time_hr +
        (1|capture_date))

## Warning: Some predictor variables are on very different scales: consider
## rescaling
CEWL_mod1_VIFs <- data.frame(VIF = car::vif(CEWL_mod1)) %>%
  arrange(desc(VIF))
CEWL_mod1_VIFs

##              VIF
## VPD_kPa_int      591.145170
## temp_C_interpol:VPD_kPa_int 263.841659
## mass_g           171.980542
## SVL_mm           149.295495
## temp_C_interpol  112.024099
## SMI              74.001162
## msmt_VPD_kPa     16.587718
## msmt_temp_C      12.171098
## solar_rad_W_sqm_interpol  5.079626
## hold_time_hr     3.006195
## wind_mph_interpol 2.349485
## hematocrit_percent 1.216280
## osmolality_mmol_kg_mean 1.186450
## cloacal_temp_C    1.150555
drop1(CEWL_mod1)

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

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

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

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

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

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

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

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

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

```

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

## 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 +
##      hold_time_hr + (1 | capture_date)
##
##               npar      AIC
## <none>                515.80
## cloacal_temp_C        1 514.18
## mass_g                 1 515.34
## SVL_mm                 1 515.28
## SMI                    1 515.44
## osmolality_mmol_kg_mean 1 521.12
## hematocrit_percent      1 514.09
## msmt_temp_C             1 527.22
## msmt_VPD_kPa            1 520.63
## wind_mph_interpol       1 517.74
## solar_rad_W_sqm_interpol 1 514.03
## hold_time_hr            1 521.61
## temp_C_interpol:VPD_kPa_int 1 513.90
```

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

```
CEWL_mod2 <- lme4::lmer(data = dat_reduced,
  # 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 +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

```
CEWL_mod2_VIFs <- data.frame(VIF = car::vif(CEWL_mod2)) %>%
  arrange(desc(VIF))
CEWL_mod2_VIFs
```

```
##
##               VIF
## mass_g          166.809922
## SVL_mm          144.677469
```

```
## SMI                                71.683760
## temp_C_interpol                    66.121829
## VPD_kPa_int                        60.765502
## msmt_VPD_kPa                       15.019831
## msmt_temp_C                        11.161314
## solar_rad_W_sqm_interpol           5.052952
## hold_time_hr                       2.846373
## wind_mph_interpol                  2.105251
## hematocrit_percent                  1.216311
## osmolality_mmol_kg_mean             1.182713
## cloacal_temp_C                      1.149812
```

```
drop1(CEWL_mod2)
```

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

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

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

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

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

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

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

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

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

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

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

```
## 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 +
##   hold_time_hr + (1 | capture_date)
##               npar      AIC
```

```
## <none> 513.90
## cloacal_temp_C 1 512.29
## mass_g 1 513.35
## SVL_mm 1 513.29
## SMI 1 513.45
## osmolality_mmol_kg_mean 1 519.14
## hematocrit_percent 1 512.20
## msmt_temp_C 1 525.69
## msmt_VPD_kPa 1 518.91
## temp_C_interpol 1 515.64
## VPD_kPa_int 1 515.68
## wind_mph_interpol 1 515.76
## solar_rad_W_sqm_interpol 1 512.10
## hold_time_hr 1 519.78
```

```
anova(CEWL_mod2)
```

```
## Analysis of Variance Table
```

	npair	Sum Sq	Mean Sq	F value
## cloacal_temp_C	1	0.000	0.000	0.0000
## mass_g	1	1.589	1.589	0.1903
## SVL_mm	1	0.539	0.539	0.0646
## SMI	1	19.988	19.988	2.3937
## osmolality_mmol_kg_mean	1	148.068	148.068	17.7319
## hematocrit_percent	1	1.102	1.102	0.1319
## msmt_temp_C	1	214.609	214.609	25.7006
## msmt_VPD_kPa	1	7.697	7.697	0.9218
## temp_C_interpol	1	2.826	2.826	0.3384
## VPD_kPa_int	1	34.665	34.665	4.1513
## wind_mph_interpol	1	2.236	2.236	0.2677
## solar_rad_W_sqm_interpol	1	5.014	5.014	0.6005
## hold_time_hr	1	71.685	71.685	8.5846

MUCH better. Drop SVL next:

```
CEWL_mod3 <- lme4::lmer(data = dat_reduced,
  # 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 +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

```
CEWL_mod3_VIFs <- data.frame(VIF = car::vif(CEWL_mod3)) %>%
  arrange(desc(VIF))
CEWL_mod3_VIFs
```

```
##              VIF
## temp_C_interpol 64.855258
## VPD_kPa_int     60.436264
## msmt_VPD_kPa    14.892342
## msmt_temp_C     11.077925
## solar_rad_W_sqm_interpol 4.786136
## hold_time_hr    2.814224
## wind_mph_interpol 2.095149
## mass_g          1.454014
## SMI             1.407215
## hematocrit_percent 1.214980
## osmolality_mmol_kg_mean 1.160822
## cloacal_temp_C  1.145507
```

```
drop1(CEWL_mod3)
```

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

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

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

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

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

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

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

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

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

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

```
## 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 +
##      hold_time_hr + (1 | capture_date)
##              npar      AIC
## <none>              513.29
## cloacal_temp_C      1 511.61
## mass_g              1 511.39
## SMI                 1 511.58
## osmolality_mmol_kg_mean 1 519.37
## hematocrit_percent  1 511.55
## msmt_temp_C         1 524.85
## msmt_VPD_kPa        1 518.16
## temp_C_interpol     1 514.56
## VPD_kPa_int         1 514.83
## wind_mph_interpol   1 514.88
## solar_rad_W_sqm_interpol 1 511.57
## hold_time_hr        1 518.87
```

```
anova(CEWL_mod3)
```

```
## Analysis of Variance Table
```

```
##              npar  Sum Sq Mean Sq F value
## cloacal_temp_C      1    0.000    0.000  0.0000
## mass_g              1    1.578    1.578  0.1882
## SMI                 1    0.014    0.014  0.0017
## osmolality_mmol_kg_mean 1 160.255 160.255 19.1170
## hematocrit_percent  1    1.027    1.027  0.1225
## msmt_temp_C         1 214.976 214.976 25.6447
## msmt_VPD_kPa        1    8.686    8.686  1.0362
## temp_C_interpol     1    1.965    1.965  0.2344
## VPD_kPa_int         1   33.295   33.295  3.9718
## wind_mph_interpol   1    2.713    2.713  0.3236
## solar_rad_W_sqm_interpol 1    8.381    8.381  0.9998
## hold_time_hr        1   67.190   67.190  8.0152
```

Next drop temperature at the time of capture:

```
CEWL_mod4 <- lme4::lmer(data = dat_reduced,
  # 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 +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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



```
CEWL_mod4_VIFs <- data.frame(VIF = car::vif(CEWL_mod4)) %>%
  arrange(desc(VIF))
CEWL_mod4_VIFs
```

```
##              VIF
## msmt_VPD_kPa    15.782551
## msmt_temp_C     11.751231
## solar_rad_W_sqm_interpol  4.366620
## VPD_kPa_int     4.079054
## hold_time_hr    2.875139
## wind_mph_interpol  2.080781
## mass_g          1.437998
## SMI             1.406587
## hematocrit_percent  1.188771
## osmolality_mmol_kg_mean  1.152509
## cloacal_temp_C   1.133914
```

```
drop1(CEWL_mod4)
```

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

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

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

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

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

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

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

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

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

```
## 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 + hold_time_hr +
##   (1 | capture_date)
```

```
##              npar      AIC
```

```
## <none>              514.56
```

```
## cloacal_temp_C      1 512.64
## mass_g              1 513.08
## SMI                 1 513.09
## osmolality_mmol_kg_mean 1 523.32
## hematocrit_percent  1 512.62
## msmt_temp_C         1 525.09
## msmt_VPD_kPa        1 519.24
## VPD_kPa_int         1 512.83
## wind_mph_interpol   1 515.16
## solar_rad_W_sqm_interpol 1 515.72
## hold_time_hr        1 521.67
```

```
anova(CEWL_mod4)
```

```
## Analysis of Variance Table
```

	np	Sum Sq	Mean Sq	F value	Pr(>F)
cloacal_temp_C	1	0.001	0.001	0.0001	0.9999
mass_g	1	1.667	1.667	0.1979	0.6591
SMI	1	0.010	0.010	0.0012	0.9598
osmolality_mmol_kg_mean	1	159.853	159.853	18.9819	0.0001
hematocrit_percent	1	0.962	0.962	0.1142	0.7341
msmt_temp_C	1	213.312	213.312	25.3299	0.0001
msmt_VPD_kPa	1	8.703	8.703	1.0334	0.3141
VPD_kPa_int	1	0.204	0.204	0.0242	0.8801
wind_mph_interpol	1	2.364	2.364	0.2807	0.6021
solar_rad_W_sqm_interpol	1	21.200	21.200	2.5174	0.1161
hold_time_hr	1	71.162	71.162	8.4501	0.0041

Drop hct:

```
CEWL_mod5 <- lme4::lmer(data = dat_reduced,
  # response variable
  CEWL_g_m2h_mean ~
  # essential covariate
  cloacal_temp_C +
  # body size
  mass_g + SMI +
  # 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 +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

```
drop1(CEWL_mod5)
```

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

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

```

## rescaling

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

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

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

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

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

## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ cloacal_temp_C + mass_g + SMI + osmolality_mmol_kg_mean +
##      msmt_temp_C + msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol +
##      solar_rad_W_sqm_interpol + hold_time_hr + (1 | capture_date)
##
##               npar      AIC
## <none>                512.62
## cloacal_temp_C        1 510.73
## mass_g                 1 511.16
## SMI                    1 511.29
## osmolality_mmol_kg_mean 1 521.49
## msmt_temp_C           1 523.17
## msmt_VPD_kPa          1 517.30
## VPD_kPa_int           1 510.89
## wind_mph_interpol     1 513.34
## solar_rad_W_sqm_interpol 1 513.77
## hold_time_hr          1 519.68
anova(CEWL_mod5)

## Analysis of Variance Table
##
##               npar  Sum Sq Mean Sq F value
## cloacal_temp_C      1    0.001    0.001  0.0002
## mass_g              1    1.670    1.670  0.2006
## SMI                  1    0.010    0.010  0.0012
## osmolality_mmol_kg_mean 1 159.839 159.839 19.1937
## msmt_temp_C         1 214.180 214.180 25.7190
## msmt_VPD_kPa        1   8.725   8.725  1.0477
## VPD_kPa_int         1   0.211   0.211  0.0253
## wind_mph_interpol   1   2.254   2.254  0.2707
## solar_rad_W_sqm_interpol 1 21.233 21.233  2.5497
## hold_time_hr        1  70.706  70.706  8.4905

next drop cloacal temperature:

```

```

CEWL_mod6 <- lme4::lmer(data = dat_reduced,
  # response variable
  CEWL_g_m2h_mean ~
  # body size
  mass_g + SMI +
  # 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 +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))

## Warning: Some predictor variables are on very different scales: consider
## rescaling
drop1(CEWL_mod6)

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

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

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

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

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

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

## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ mass_g + SMI + osmolality_mmol_kg_mean + msmt_temp_C +
##      msmt_VPD_kPa + VPD_kPa_int + wind_mph_interpol + solar_rad_W_sqm_interpol +
##      hold_time_hr + (1 | capture_date)
##               npar      AIC
## <none>                510.73
## mass_g                1 509.21
## SMI                   1 509.39
## osmolality_mmol_kg_mean 1 519.74
## msmt_temp_C            1 521.30
## msmt_VPD_kPa           1 515.30

```

```
## VPD_kPa_int          1 509.03
## wind_mph_interpol    1 511.51
## solar_rad_W_sqm_interpol 1 512.02
## hold_time_hr         1 518.15
```

```
anova(CEWL_mod6)
```

```
## Analysis of Variance Table
```

```
##              npar  Sum Sq Mean Sq F value
## mass_g          1   1.661   1.661  0.2017
## SMI              1   0.010   0.010  0.0012
## osmolality_mmol_kg_mean 1 159.818 159.818 19.4125
## msmt_temp_C      1 212.484 212.484 25.8097
## msmt_VPD_kPa     1   6.653   6.653  0.8081
## VPD_kPa_int      1   0.064   0.064  0.0077
## wind_mph_interpol 1   2.563   2.563  0.3114
## solar_rad_W_sqm_interpol 1 22.027 22.027 2.6756
## hold_time_hr     1  72.908  72.908  8.8559
```

```
next drop SMI:
```

```
CEWL_mod7 <- lme4::lmer(data = dat_reduced,
  # 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 +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

```
drop1(CEWL_mod7)
```

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

```
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```

```
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## rescaling
```

```
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## rescaling
```

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

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

## 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 +
##      hold_time_hr + (1 | capture_date)
##               npar      AIC
## <none>                509.39
## mass_g                1 507.53
## osmolality_mmol_kg_mean 1 517.86
## msmt_temp_C            1 520.28
## msmt_VPD_kPa           1 514.29
## VPD_kPa_int            1 507.57
## wind_mph_interpol      1 510.55
## solar_rad_W_sqm_interpol 1 510.21
## hold_time_hr           1 517.17
```

```
anova(CEWL_mod7)
```

```
## Analysis of Variance Table
```

```
##               npar  Sum Sq Mean Sq F value
## mass_g          1   1.632    1.632  0.1983
## osmolality_mmol_kg_mean 1 157.089 157.089 19.0851
## msmt_temp_C      1 210.473 210.473 25.5708
## msmt_VPD_kPa     1   6.562   6.562  0.7972
## VPD_kPa_int      1   0.082   0.082  0.0099
## wind_mph_interpol 1   2.924   2.924  0.3552
## solar_rad_W_sqm_interpol 1 17.483 17.483 2.1240
## hold_time_hr     1  76.358  76.358  9.2769
```

```
next drop VPD at capture:
```

```
CEWL_mod8 <- lme4::lmer(data = dat_reduced,
  # 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
  wind_mph_interpol + solar_rad_W_sqm_interpol +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

```
drop1(CEWL_mod8)
```

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

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

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

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

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

## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ mass_g + osmolality_mmol_kg_mean + msmt_temp_C +
##      msmt_VPD_kPa + wind_mph_interpol + solar_rad_W_sqm_interpol +
##      hold_time_hr + (1 | capture_date)
##
##               npar      AIC
## <none>                507.57
## mass_g                1 505.72
## osmolality_mmol_kg_mean 1 515.88
## msmt_temp_C            1 519.50
## msmt_VPD_kPa           1 513.47
## wind_mph_interpol      1 508.86
## solar_rad_W_sqm_interpol 1 509.42
## hold_time_hr           1 516.60
anova(CEWL_mod8)
```

```
## Analysis of Variance Table
##
##               npar  Sum Sq Mean Sq F value
## mass_g           1   1.636    1.636  0.2007
## osmolality_mmol_kg_mean 1 157.067 157.067 19.2669
## msmt_temp_C       1 210.423 210.423 25.8119
## msmt_VPD_kPa      1   6.567   6.567  0.8055
## wind_mph_interpol 1   2.708   2.708  0.3322
## solar_rad_W_sqm_interpol 1  5.408   5.408  0.6634
## hold_time_hr      1  87.330  87.330 10.7125
```

9 next drop mass:

```
CEWL_mod9 <- lme4::lmer(data = dat_reduced,
  # 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 + solar_rad_W_sqm_interpol +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

```
drop1(CEWL_mod9)
```

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

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

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

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

```
## Single term deletions
```

```
##
```

```
## Model:
```

```
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##      wind_mph_interpol + solar_rad_W_sqm_interpol + hold_time_hr +
##      (1 | capture_date)
```

	npars	AIC
<none>		505.72
osmolality_mmol_kg_mean	1	513.90
msmt_temp_C	1	517.52
msmt_VPD_kPa	1	511.49
wind_mph_interpol	1	507.08
solar_rad_W_sqm_interpol	1	507.56
hold_time_hr	1	515.17

```
anova(CEWL_mod9)
```

```
## Analysis of Variance Table
```

	npars	Sum Sq	Mean Sq	F value
osmolality_mmol_kg_mean	1	146.735	146.735	18.1173
msmt_temp_C	1	220.371	220.371	27.2091
msmt_VPD_kPa	1	4.813	4.813	0.5943
wind_mph_interpol	1	2.297	2.297	0.2836
solar_rad_W_sqm_interpol	1	4.934	4.934	0.6092
hold_time_hr	1	90.671	90.671	11.1951

10 next drop wind:

```
CEWL_mod10 <- lme4::lmer(data = dat_reduced,
  # 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
  solar_rad_W_sqm_interpol +
  # time between capture and measurements
  hold_time_hr +
```



```

(1|capture_date))

## Warning: Some predictor variables are on very different scales: consider
## rescaling
drop1(CEWL_mod10)

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

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

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

## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + msmt_VPD_kPa +
##      solar_rad_W_sqm_interpol + hold_time_hr + (1 | capture_date)
##
##               npar      AIC
## <none>                507.08
## osmolality_mmol_kg_mean      1 515.84
## msmt_temp_C                  1 515.79
## msmt_VPD_kPa                 1 509.93
## solar_rad_W_sqm_interpol      1 511.56
## hold_time_hr                 1 513.28
anova(CEWL_mod10)

## Analysis of Variance Table
##
##               npar  Sum Sq Mean Sq F value
## osmolality_mmol_kg_mean      1 145.748 145.748 17.9459
## msmt_temp_C                  1 219.014 219.014 26.9672
## msmt_VPD_kPa                 1   4.758   4.758  0.5858
## solar_rad_W_sqm_interpol      1   6.511   6.511  0.8017
## hold_time_hr                 1  72.937  72.937  8.9807

drop VPD at msmt
CEWL_mod11 <- lme4::lmer(data = dat_reduced,
  # response variable
  CEWL_g_m2h_mean ~
  # blood
  osmolality_mmol_kg_mean +
  # microclimate at the time of msmt
  msmt_temp_C +
  # weather at the time of capture
  solar_rad_W_sqm_interpol +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
drop1(CEWL_mod11)

## Single term deletions
##

```

```
## Model:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + solar_rad_W_sqm_interpol +
##   hold_time_hr + (1 | capture_date)
##               npar    AIC
## <none>                509.93
## osmolality_mmol_kg_mean    1 520.44
## msmt_temp_C                1 517.86
## solar_rad_W_sqm_interpol    1 511.29
## hold_time_hr              1 512.01
```

```
anova(CEWL_mod11)
```

```
## Analysis of Variance Table
```

```
##               npar  Sum Sq Mean Sq F value
## osmolality_mmol_kg_mean    1 147.027 147.027 17.0643
## msmt_temp_C                1 220.784 220.784 25.6248
## solar_rad_W_sqm_interpol    1   6.259   6.259  0.7265
## hold_time_hr              1  34.659  34.659  4.0226
```

```
drop solar:
```

```
dat_reduced2 <- dat_reduced %>%
  dplyr::filter(complete.cases(osmolality_mmol_kg_mean, msmt_temp_C, hold_time_hr))
CEWL_mod12 <- lme4::lmer(data = dat_reduced2,
  # response variable
  CEWL_g_m2h_mean ~
  # blood
  osmolality_mmol_kg_mean +
  # microclimate at the time of msmt
  msmt_temp_C +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

```
drop1(CEWL_mod12)
```

12

```
## Single term deletions
```

```
##
## Model:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + hold_time_hr +
##   (1 | capture_date)
##               npar    AIC
## <none>                511.29
## osmolality_mmol_kg_mean    1 525.77
## msmt_temp_C                1 529.48
## hold_time_hr              1 510.82
```

```
anova(CEWL_mod12)
```

```
## Analysis of Variance Table
```

```
##               npar  Sum Sq Mean Sq F value
## osmolality_mmol_kg_mean    1 146.819 146.819 16.6920
## msmt_temp_C                1 220.489 220.489 25.0676
## hold_time_hr              1  13.644  13.644  1.5512
```

drop hold time:

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

drop1(CEWL_mod13)

## Single term deletions
##
## Model:
## CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean + msmt_temp_C + (1 |
##   capture_date)
##               npar      AIC
## <none>                614.84
## osmolality_mmol_kg_mean    1 623.51
## msmt_temp_C                1 627.42

anova(CEWL_mod13)
```

```
## Analysis of Variance Table
##               npar Sum Sq Mean Sq F value
## osmolality_mmol_kg_mean    1 126.26  126.26  10.165
## msmt_temp_C                1 184.75  184.75   14.873
```

drop osml:

```
CEWL_mod14 <- lme4::lmer(data = dat_reduced,
  # response variable
  CEWL_g_m2h_mean ~
  # microclimate at the time of msmt
  msmt_temp_C +
  (1|capture_date))
```

And finally, null model:

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

Selection

compare models 4-14 and the null

```
CEWL_models <- list(CEWL_mod4, CEWL_mod5, CEWL_mod6, CEWL_mod7,
  CEWL_mod8, CEWL_mod9, CEWL_mod10, CEWL_mod11,
  CEWL_mod12, CEWL_mod13, CEWL_mod14, CEWL_mod_null)
```

#specify model names

```
CEWL_mod_names <- c('(model 4) ~ Temp-M, Osml, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C, SMI, Clo',
  '(model 5) ~ Temp-M, Osml, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C, SMI, Clo',
  '(model 6) ~ Temp-M, Osml, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C, SMI',
  '(model 7) ~ Temp-M, Osml, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C',
```

```

      '(model 8) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C, Mass',
      '(model 9) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C',
      '(model 10) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M',
      '(model 11) ~ Temp-M, Osm1, Hold Time, Solar-C',
      '(model 12) ~ Temp-M, Osm1, Hold Time',
      '(model 13) ~ Temp-M, Osm1',
      '(model 14) ~ 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
CEWL_AICc

##                               Modnames
## 7                               (model 10) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M
## 6                               (model 9) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C
## 9                               (model 12) ~ Temp-M, Osm1, Hold Time
## 4                               (model 7) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C
## 5                               (model 8) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C, Mass
## 3                               (model 6) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C, SMI
## 2                               (model 5) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C, SMI, Clo-Temp
## 8                               (model 11) ~ Temp-M, Osm1, Hold Time, Solar-C
## 1 (model 4) ~ Temp-M, Osm1, Hold Time, Solar-C, VPD-M, Wind-C, Mass, VPD-C, SMI, Clo-Temp, Hct
## 10                              (model 13) ~ Temp-M, Osm1
## 11                              (model 14) ~ Temp-M
## 12                              null model

##      K      AICc  Delta_AICc  Modellik      AICcWt  Res.LL  Cum.Wt
## 7      8 512.9138  0.00000000 1.000000e+00 3.415404e-01 -247.6479 0.3415404
## 6      9 512.9609  0.04708532 9.767323e-01 3.335936e-01 -246.4577 0.6751340
## 9      6 514.4008  1.48707439 4.754293e-01 1.623783e-01 -250.7389 0.8375123
## 4     11 515.8847  2.97089223 2.264013e-01 7.732520e-02 -245.4074 0.9148375
## 5     10 516.7440  3.83018403 1.473283e-01 5.031856e-02 -247.1076 0.9651560
## 3     12 518.1977  5.28391185 7.122183e-02 2.432513e-02 -245.2635 0.9894812
## 2     13 520.3973  7.48357832 2.371164e-02 8.098484e-03 -245.0320 0.9975797
## 8      7 523.1163 10.20250039 6.089129e-03 2.079684e-03 -253.9359 0.9996593
## 1     14 526.7344 13.82065943 9.974289e-04 3.406623e-04 -246.8371 1.0000000
## 10     5 617.4886 104.57486082 1.958202e-23 6.688051e-24 -303.4613 1.0000000
## 11     4 619.5792 106.66547486 6.884722e-24 2.351411e-24 -305.6027 1.0000000
## 12     3 632.2994 119.38565830 1.190512e-26 4.066079e-27 -313.0386 1.0000000

```

The best models are 10, 9, then 12.

LM Conditions

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

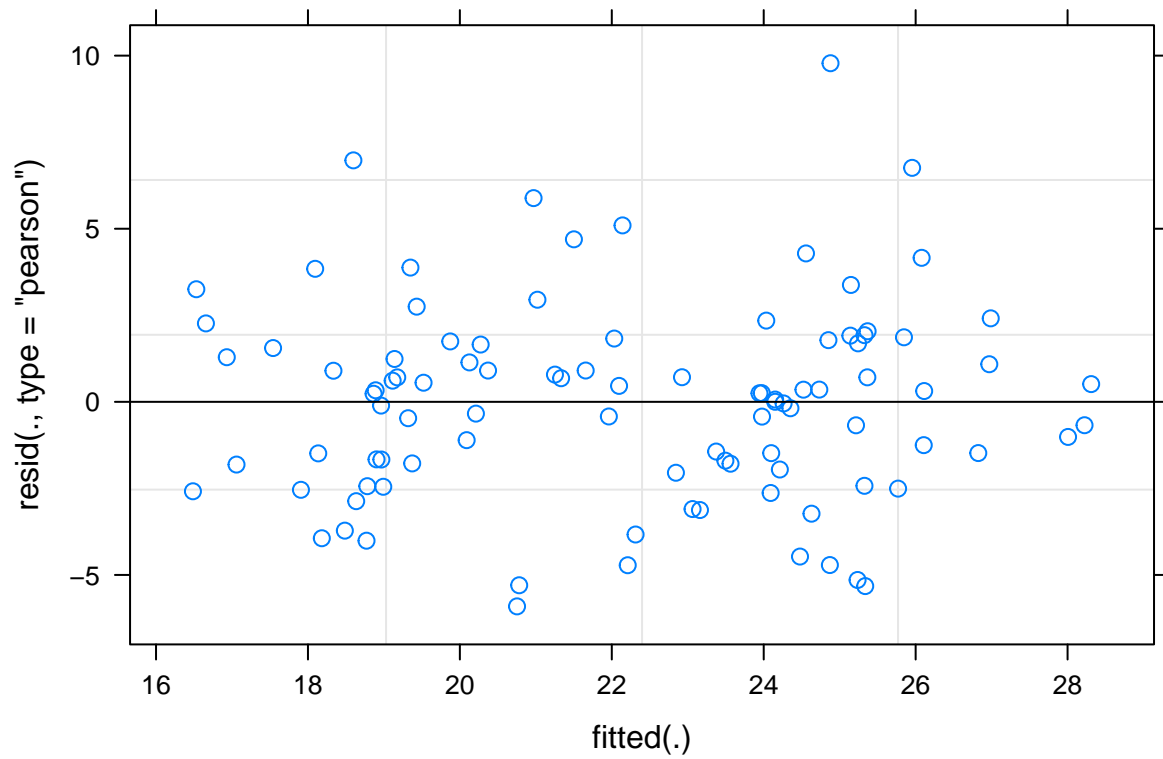
```

vif(CEWL_mod12)

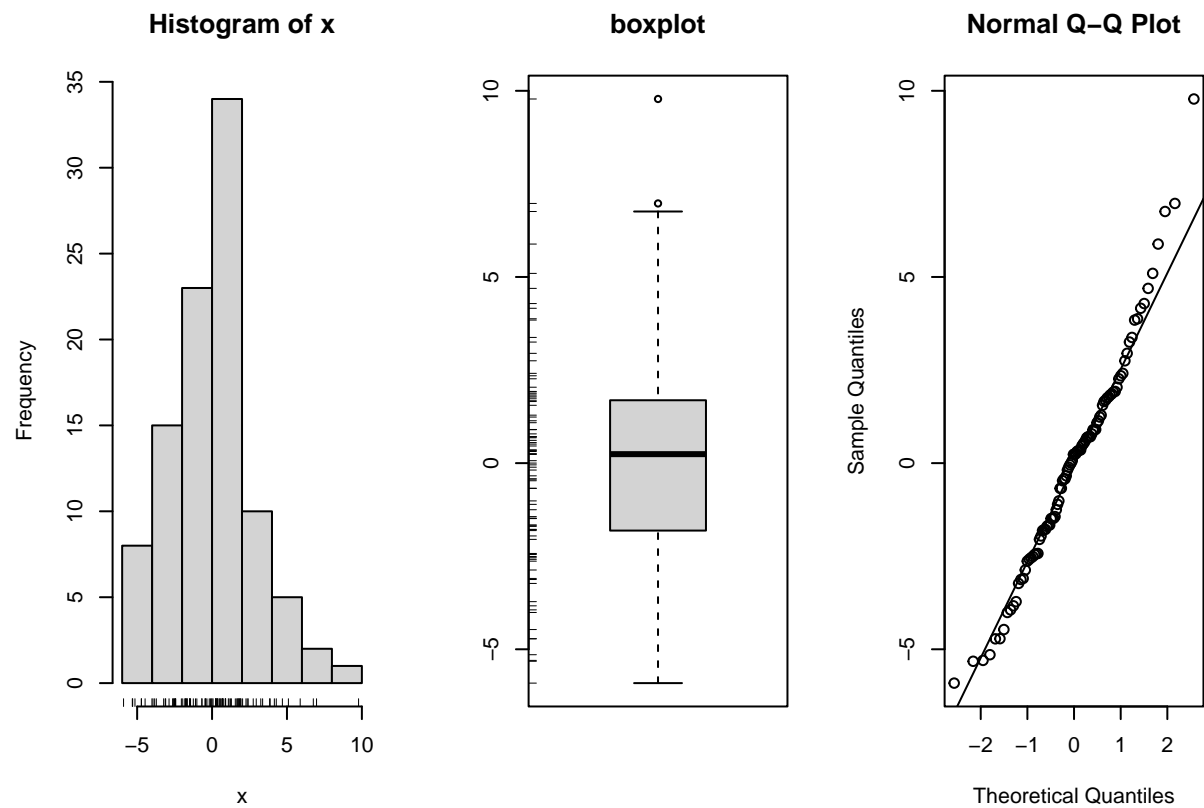
## osmolality_mmol_kg_mean      msmt_temp_C      hold_time_hr
##                1.012546                1.044161                1.055785

```

```
plot(CEWL_mod12)
```



```
simple.eda(residuals(CEWL_mod12))
```



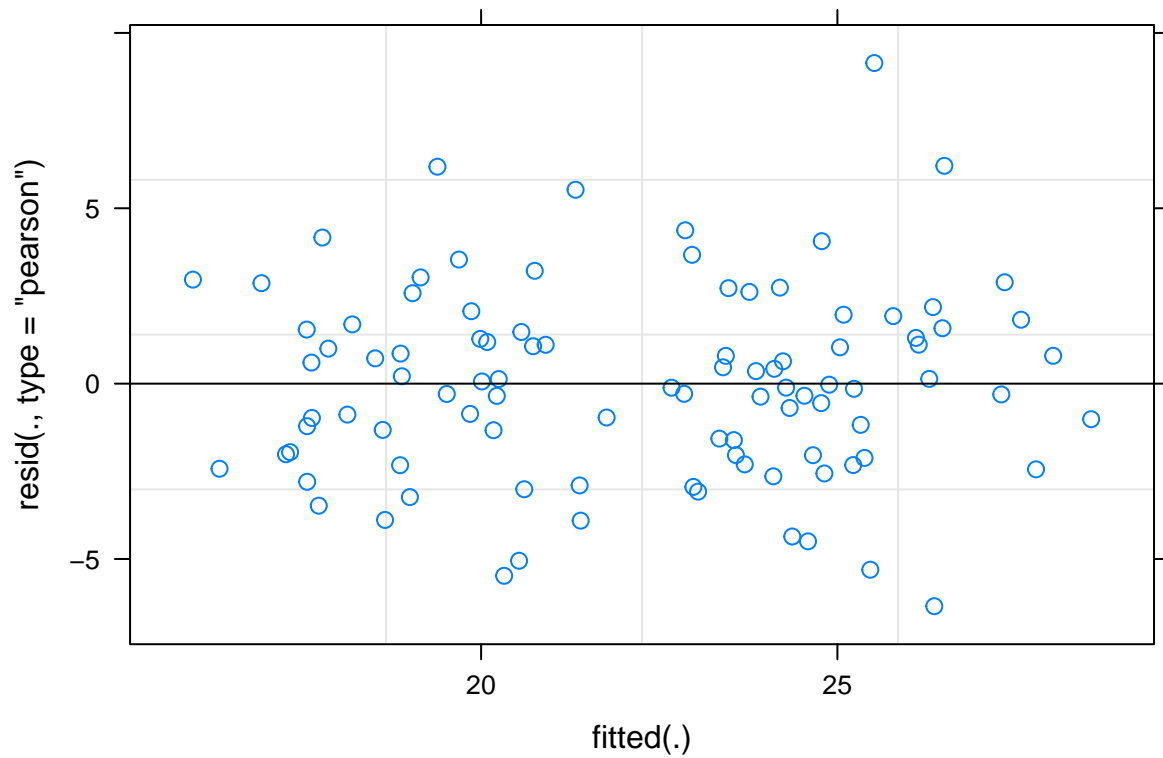
```
shapiro.test(residuals(CEWL_mod12))
```

```
##  
##  Shapiro-Wilk normality test  
##  
## data:  residuals(CEWL_mod12)  
## W = 0.97999, p-value = 0.1411
```

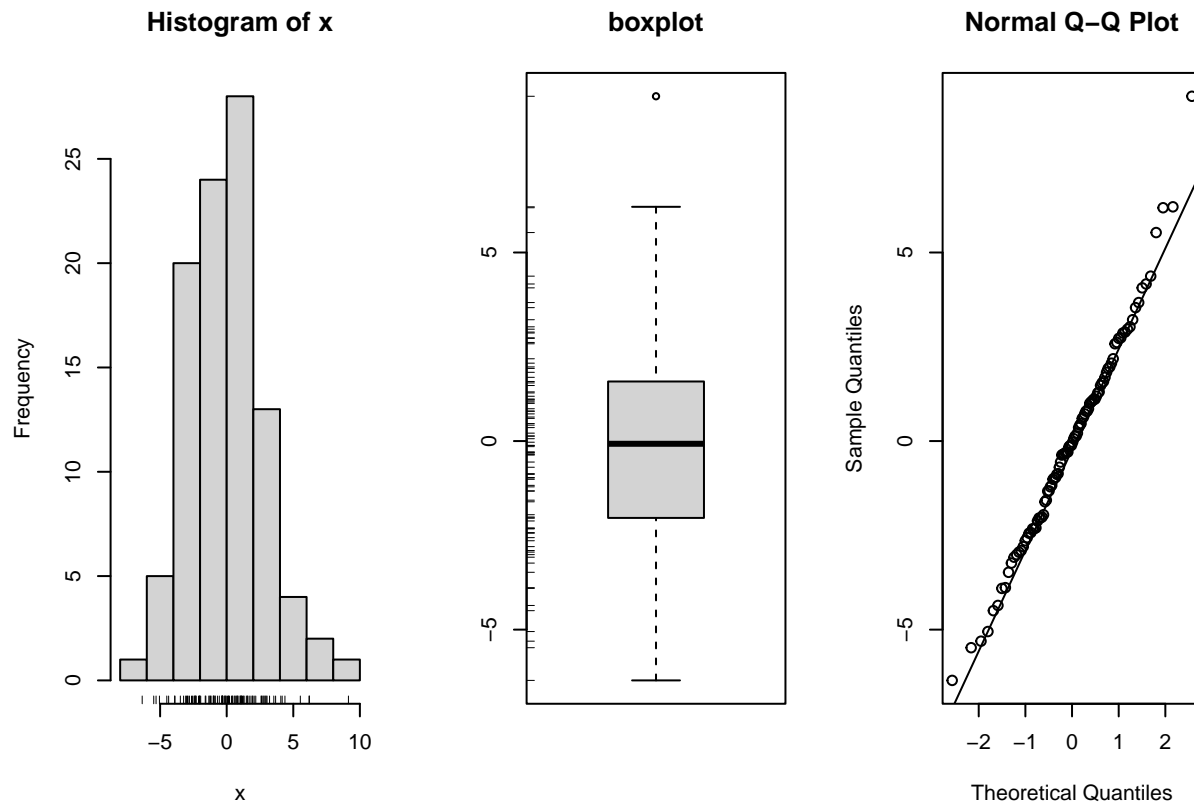
```
vif(CEWL_mod10)
```

```
##  osmolality_mmol_kg_mean      msmt_temp_C      msmt_VPD_kPa  
##           1.099571           10.426915           12.752686  
##  solar_rad_W_sqm_interpol    hold_time_hr  
##           2.083057           2.071252
```

```
plot(CEWL_mod10)
```



```
simple.eda(residuals(CEWL_mod10))
```



```
shapiro.test(residuals(CEWL_mod10))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(CEWL_mod10)
## W = 0.9894, p-value = 0.6305
```

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_mod10p <- lmerTest::lmer(data = dat_reduced,
  # 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
  solar_rad_W_sqm_interpol +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
```

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

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

summary(CEWL_mod10p)

## 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 +
##      solar_rad_W_sqm_interpol + hold_time_hr + (1 | capture_date)
##      Data: dat_reduced
##
## REML criterion at convergence: 495.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.2268 -0.7131 -0.0253  0.5510  3.2079
##
## Random effects:
##      Groups          Name          Variance Std.Dev.
## capture_date (Intercept) 11.730    3.425
## Residual                8.122    2.850
## Number of obs: 98, groups: capture_date, 4
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)    -2.657e+02  6.919e+01  3.782e+01  -3.840 0.000455 ***
## osmolality_mmol_kg_mean  7.691e-02  2.215e-02  9.199e+01   3.472 0.000789 ***
## msmt_temp_C      1.225e+01  3.667e+00  3.398e+01   3.340 0.002045 **
## msmt_VPD_kPa    -4.194e+01  1.804e+01  2.610e+01  -2.324 0.028155 *
## solar_rad_W_sqm_interpol  9.237e-03  3.601e-03  9.086e+01   2.565 0.011946 *
## hold_time_hr     1.064e+00  3.551e-01  8.194e+01   2.997 0.003610 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) osm___ msm__C m_VPD_ s__W__
## osmlly_m__ -0.116
## msmt_temp_C -0.980 -0.007
## msmt_VPD_kP  0.850  0.051 -0.929
## slr_rd_W_s_ -0.095 -0.274  0.189 -0.392
## hold_tim_hr -0.294 -0.074  0.370 -0.540  0.622
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling

CEWL_mod9p <- lmerTest::lmer(data = dat_reduced,
  # 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 + solar_rad_W_sqm_interpol +
```



```

# time between capture and measurements
hold_time_hr +
(1|capture_date))

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

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

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 +
##   wind_mph_interpol + solar_rad_W_sqm_interpol + hold_time_hr +
##   (1 | capture_date)
## Data: dat_reduced
##
## REML criterion at convergence: 492.9
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.1898 -0.6676 -0.0043  0.5059  3.2327
##
## Random effects:
##   Groups             Name             Variance Std.Dev.
##   capture_date (Intercept) 7.425         2.725
##   Residual                8.099         2.846
## Number of obs: 98, groups:  capture_date, 4
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)    -2.780e+02  6.757e+01  3.074e+01  -4.115 0.000269 ***
## osmolality_mmol_kg_mean  7.404e-02  2.196e-02  9.048e+01   3.371 0.001103 **
## msmt_temp_C      1.327e+01  3.635e+00  2.893e+01   3.650 0.001028 **
## msmt_VPD_kPa     -5.000e+01  1.846e+01  2.258e+01  -2.709 0.012634 *
## wind_mph_interpol  6.472e-01  3.999e-01  6.578e+01   1.618 0.110342
## solar_rad_W_sqm_interpol  7.806e-03  3.637e-03  8.857e+01   2.146 0.034571 *
## hold_time_hr      1.318e+00  3.939e-01  7.458e+01   3.346 0.001287 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr)  osm___  msm__C  m_VPD_  wnd_m_  s__W__
## osmllty_m__ -0.076
## msmt_temp_C -0.978 -0.052
## msmt_VPD_kP  0.840  0.098 -0.927
## wnd_mph_ntr -0.245 -0.018  0.308 -0.411
## slr_rd_W_s_ -0.017 -0.279  0.091 -0.252 -0.210
## hold_tim_hr -0.336 -0.094  0.428 -0.608  0.470  0.431
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling

```

```
CEWL_mod12p <- lmerTest::lmer(data = dat_reduced,
  # response variable
  CEWL_g_m2h_mean ~
  # blood
  osmolality_mmol_kg_mean +
  # microclimate at the time of msmt
  msmt_temp_C +
  # time between capture and measurements
  hold_time_hr +
  (1|capture_date))
summary(CEWL_mod12p)

## 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 + hold_time_hr +
## (1 | capture_date)
## Data: dat_reduced
##
## REML criterion at convergence: 501.5
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.9922 -0.6088  0.0812  0.5665  3.2978
##
## Random effects:
##   Groups             Name             Variance Std.Dev.
##   capture_date (Intercept) 7.816       2.796
##   Residual                8.796       2.966
## Number of obs: 98, groups:  capture_date, 4
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)    -160.08883   32.67718   91.96036  -4.899 4.11e-06 ***
## osmolality_mmol_kg_mean    0.09049    0.02189   91.77382   4.134 7.86e-05 ***
## msmt_temp_C         5.54375    1.19362   90.92988   4.644 1.15e-05 ***
## hold_time_hr         0.32839    0.26367   91.53552   1.245  0.216
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) osm___ msm__C
## osmllty_m__ -0.205
## msmt_temp_C -0.970 -0.035
## hold_tim_hr  0.150  0.111 -0.205

anova(CEWL_mod10p, type = "1", ddf = "Kenward-Roger")

## Type I Analysis of Variance Table with Kenward-Roger's method
##              Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## osmolality_mmol_kg_mean  88.474   88.474     1  23.941 10.8938 0.0030143 **
## msmt_temp_C             97.809   97.809     1  86.923 12.0432 0.0008115 ***
## msmt_VPD_kPa           19.824   19.824     1  27.753  2.4409 0.1295401
## solar_rad_W_sqm_interpol 11.171   11.171     1  91.295  1.3755 0.2439215
```

```
## hold_time_hr          66.273  66.273      1 82.266  8.1602 0.0054202 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(CEWL_mod9p, type = "1", ddf = "Kenward-Roger")
```

```
## Type I Analysis of Variance Table with Kenward-Roger's method
##              Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## osmolality_mmol_kg_mean 64.722  64.722      1 12.137   7.9912 0.015118 *
## msmt_temp_C            44.571  44.571      1 55.237   5.5032 0.022599 *
## msmt_VPD_kPa           9.805   9.805      1 14.473   1.2106 0.289180
## wind_mph_interpol      11.809  11.809      1 60.208   1.4580 0.231967
## solar_rad_W_sqm_interpol 8.186   8.186      1 90.903   1.0107 0.317397
## hold_time_hr          79.630  79.630      1 75.092   9.8318 0.002448 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(CEWL_mod12p, type = "1", ddf = "Kenward-Roger")
```

```
## Type I Analysis of Variance Table with Kenward-Roger's method
##              Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## osmolality_mmol_kg_mean 103.74  103.74      1 91.079 11.7939 0.0008963 ***
## msmt_temp_C            198.40  198.40      1 90.586 22.5558 7.615e-06 ***
## hold_time_hr           13.60   13.60      1 91.409   1.5462 0.2168747
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Save the best CEWL model output.

```
#write.csv(broom.mixed::tidy(CEWL_mod9p),
#          "./results_statistics/capture_CEWL_best_model1.csv")
#write.csv(broom.mixed::tidy(CEWL_mod10p),
#          "./results_statistics/capture_CEWL_best_model2.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.

Group Model Export

```
# model rankings
all_mod_ranks <- CEWL_AICc %>%
  rbind(osml_AICc) %>%
  dplyr::rename(LL = Res.LL) %>%
  rbind(hct_AICc) %>%
  mutate(var = c(rep("CEWL", nrow(CEWL_AICc)),
                  rep("osml", nrow(osml_AICc)),
                  rep("hct", nrow(hct_AICc))),
         AICc = round(AICc, digits = 2),
         Delta_AICc = round(Delta_AICc, digits = 2),
         Modellik = round(ModelLik, digits = 2),
         AICcWt = round(AICcWt, digits = 2),
         LL = round(LL, digits = 2),
```

```

Cum.Wt = round(Cum.Wt, digits = 2))

write.csv(all_mod_ranks, "./results_statistics/capture_ALL_mod_rankings.csv")

# calculate F & p-values
anova_tables <- data.frame(anova(CEWL_mod12p,
                                type = "1",
                                ddf = "Kenward-Roger"))) %>%
rbind(data.frame(anova(osml_mod8p,
                        type = "1",
                        ddf = "Kenward-Roger")))) %>%
rbind(data.frame(anova(hct_mod7p) %>%
mutate(NumDF = 1, DenDF = 95) %>%
dplyr::select(-Df))) %>%
mutate(df = paste((NumDF), round(DenDF, 0), sep = ", "),
Sum.Sq = round(Sum.Sq, 0),
F.value = round(F.value, 2),
term = rownames(.)) %>%
dplyr::select(term,
seq_sum_of_squares = Sum.Sq,
df,
F_statistic = F.value,
p_value = Pr..F.) %>%
dplyr::filter(term != "Residuals")

# models
all_top_mods <- broom.mixed::tidy(CEWL_mod12p) %>% # chose the least-variable one
rbind(broom.mixed::tidy(osml_mod8p)) %>% # chose the least-variable one
rbind((broom.mixed::tidy(hct_mod7p) %>%
mutate(effect = NA,
group = NA,
df = NA))) %>%
mutate(var = c(rep("CEWL", 6),
rep("osml", 5),
rep("hct", 3)),
estimate = round(estimate, digits = 2),
std.error = round(std.error, digits = 2)) %>%
dplyr::select(var, effect, group, term, estimate, std.error) %>%
left_join(anova_tables, by = 'term')

write.csv(all_top_mods, "./results_statistics/capture_ALL_best_mods.csv")

```

Figures

Custom Colors

```

lizard_color = "turquoise"
VPD_color = "blue"
temp_color = "gray"
solar_color = "orange"
wind_color = "orange"
date_color = "gray"

```

```
osml_color <- c(brewer.pal(11, "Spectral")[c(10)])
```

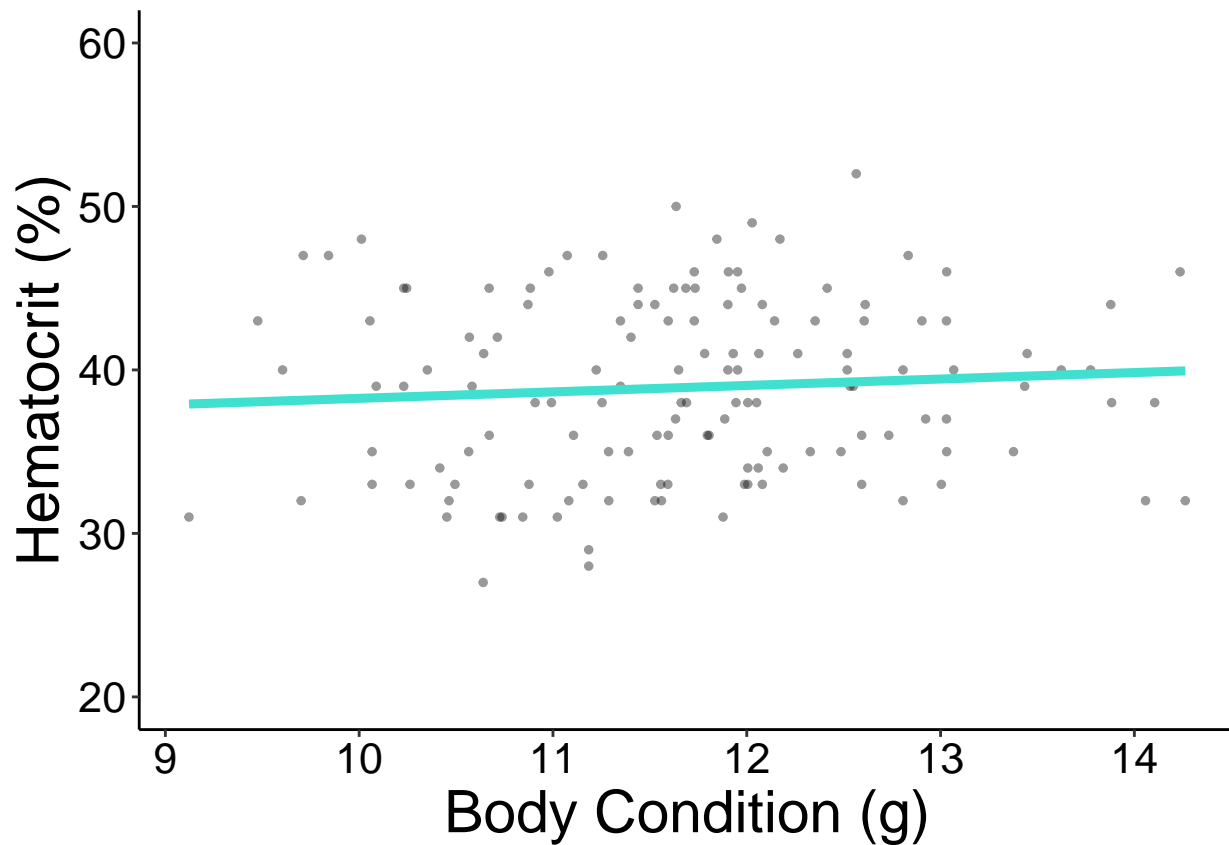
Hct ~ SMI

```
ggplot(dat) +  
  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
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
```

```
## i Please use `linewidth` instead.
```

```
cap_hct_SMI_fig
```



Hct ~ VPD at Capture

```
ggplot(dat) +
  aes(x = VPD_kPa_int,
       y = hematocrit_percent,
       color = as.factor(capture_date)) +
  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),
```

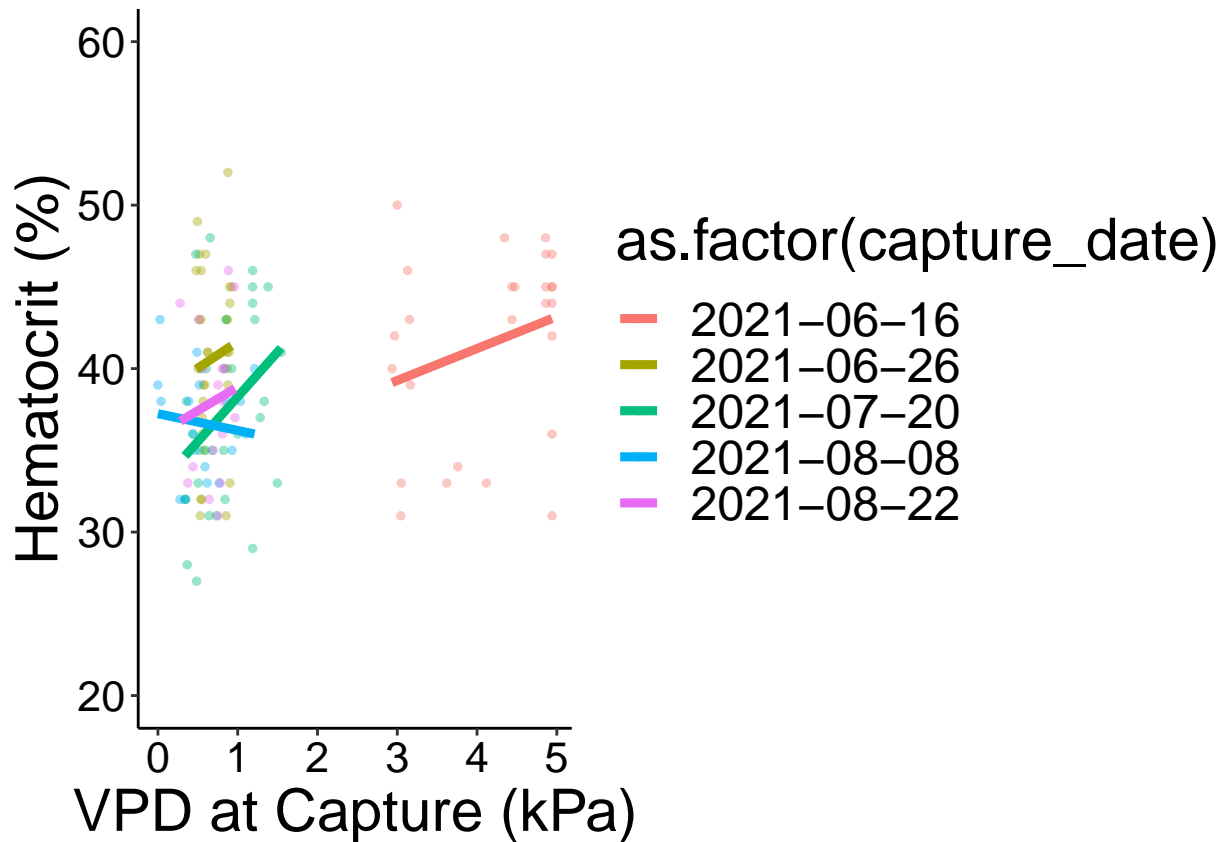
```

    #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(dat) +
  aes(x = wind_mph_interpol,
      y = hematocrit_percent,
      color = as.factor(capture_date))+
  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("") +

```

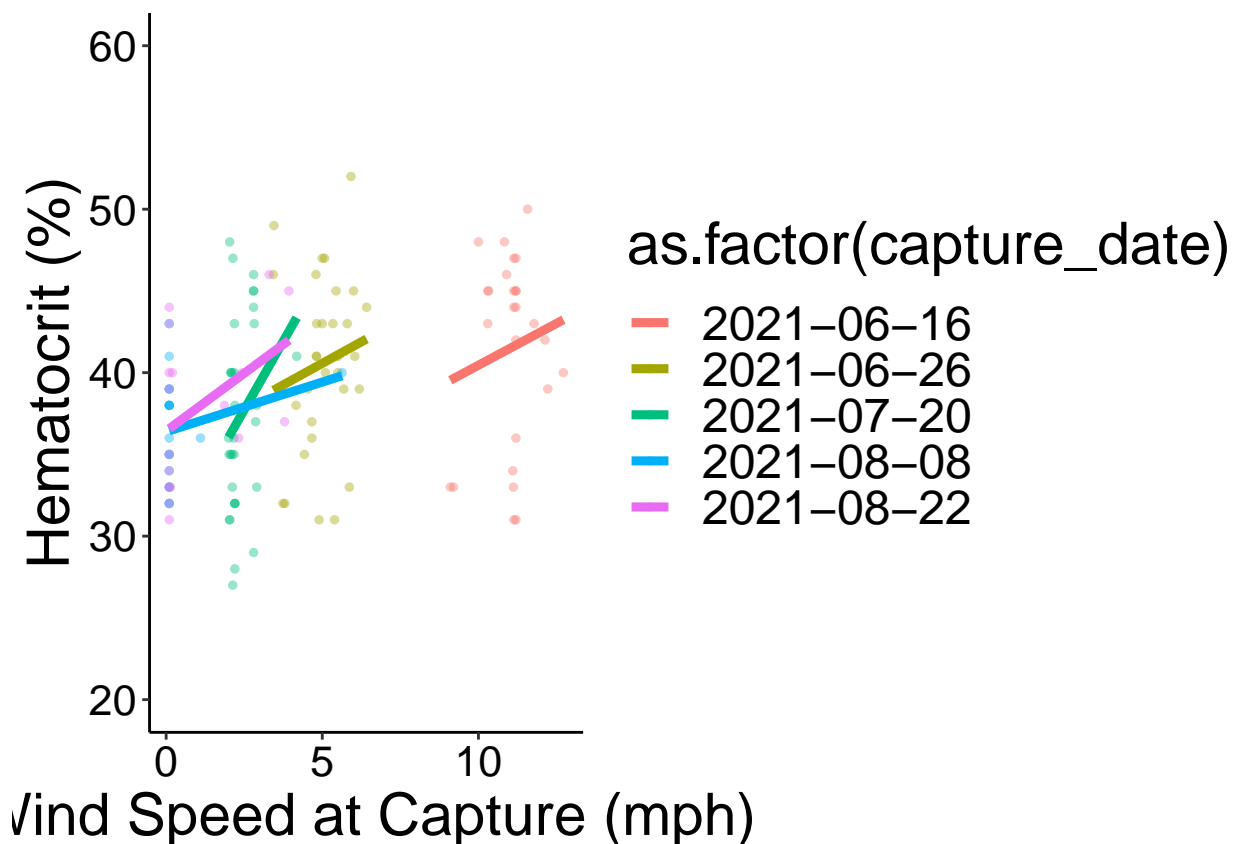
```

#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(dat) +
  aes(x = solar_rad_W_sqm_interpol,
      y = hematocrit_percent,
      color = as.factor(capture_date)) +
  geom_point(size = 1,
            alpha = 0.4) +
  stat_smooth(formula = y ~ x,
            method = "lm",

```



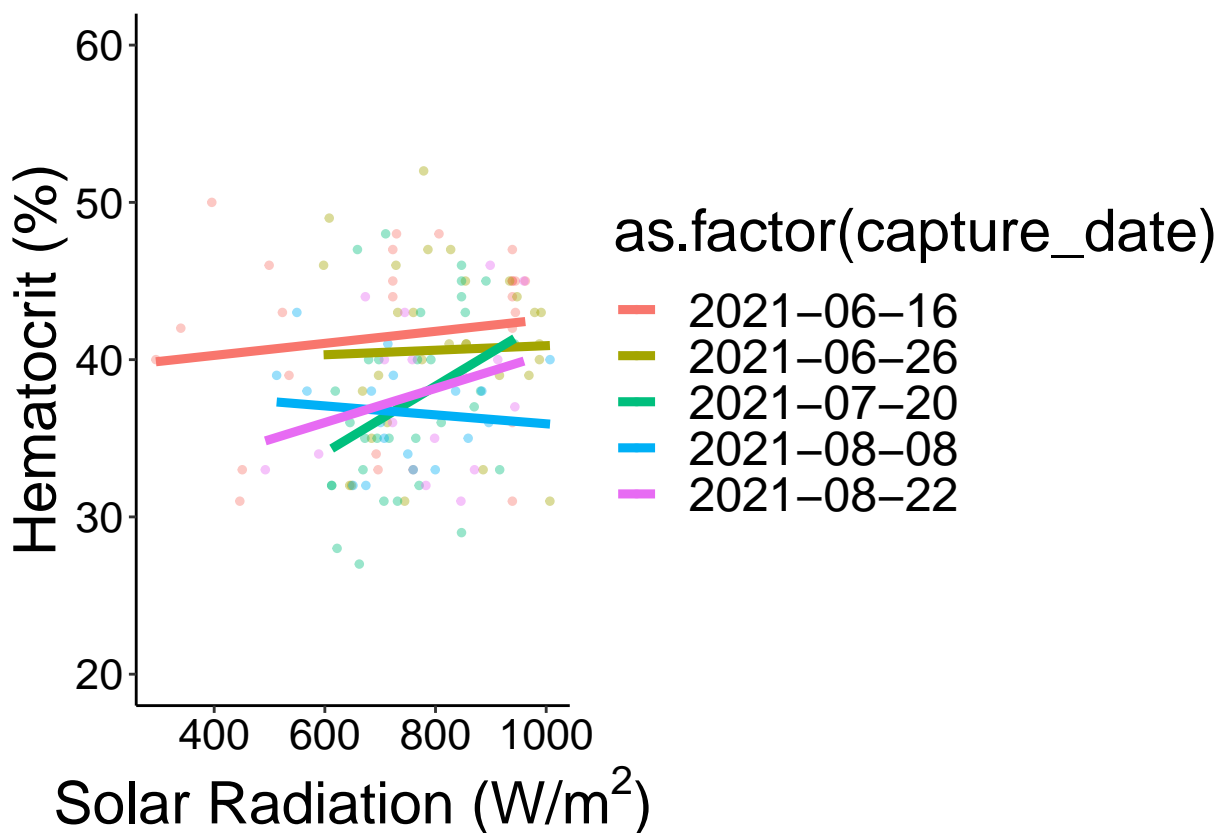
```

      se = F,
      #color = solar_color,
      size = 1.6,
      alpha = 1 ) +
theme_classic() +
xlab(bquote('Solar Radiation (W/*m2*)')) +
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()``).

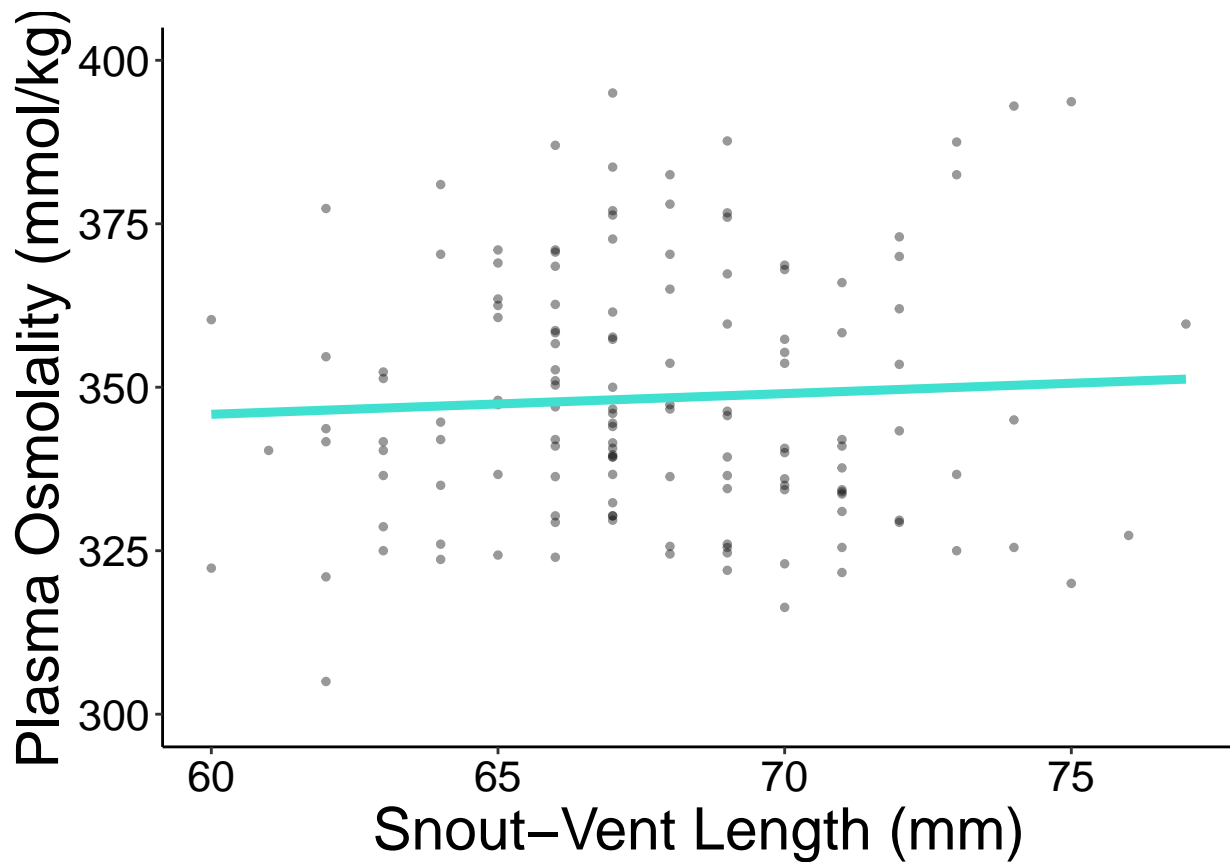


Osmolality ~ SVL

```

ggplot(dat) +
  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

```



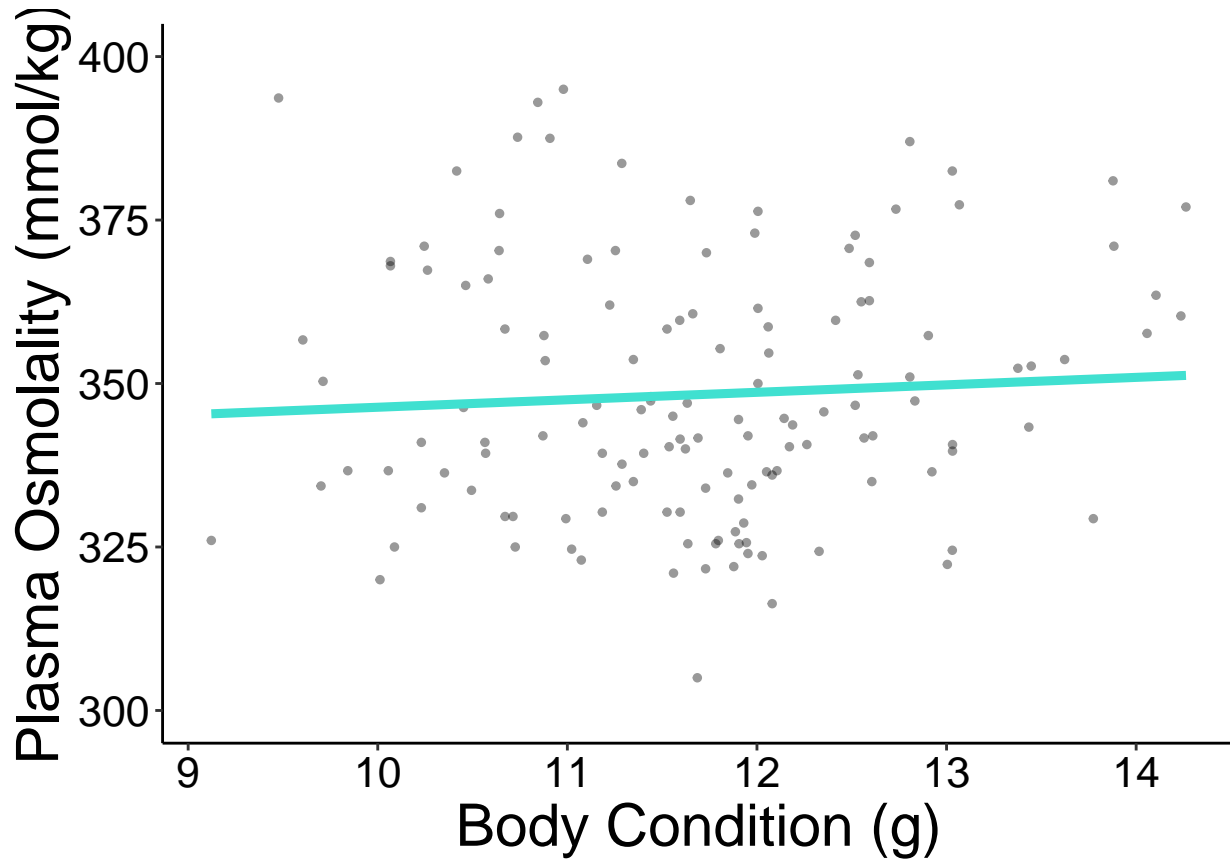
Osmolality ~ SMI

```
ggplot(dat) +
  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(dat_reduced) +
  aes(x = VPD_kPa_int,
      y = osmolality_mmol_kg_mean,
      color = as.factor(capture_date))
  ) +
  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) +

```

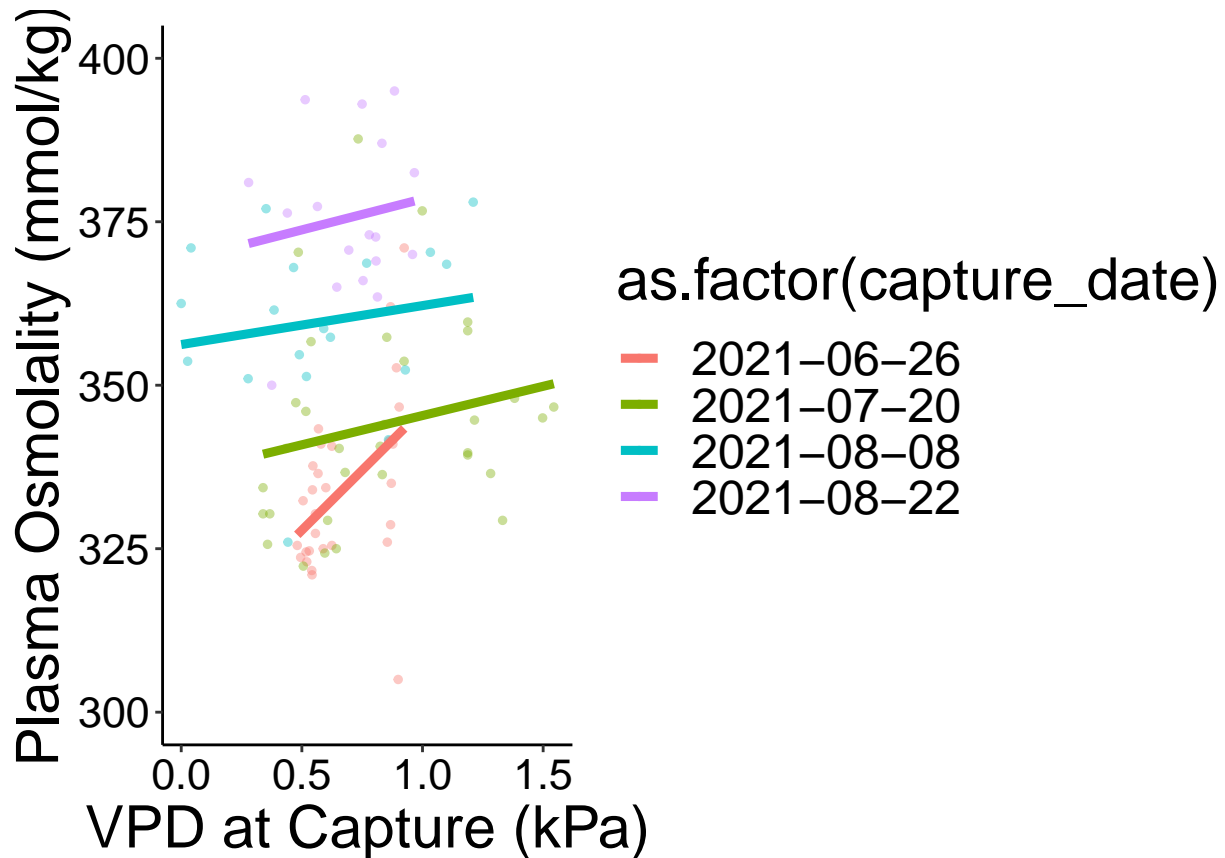
```

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(dat) +
  aes(x = solar_rad_W_sqm_interpol,
      y = osmolality_mmol_kg_mean,
      color = as.factor(capture_date)) +
  geom_point(size = 1,
            alpha = 0.4) +
  stat_smooth(formula = y ~ x,
            method = "lm",
            se = F,

```

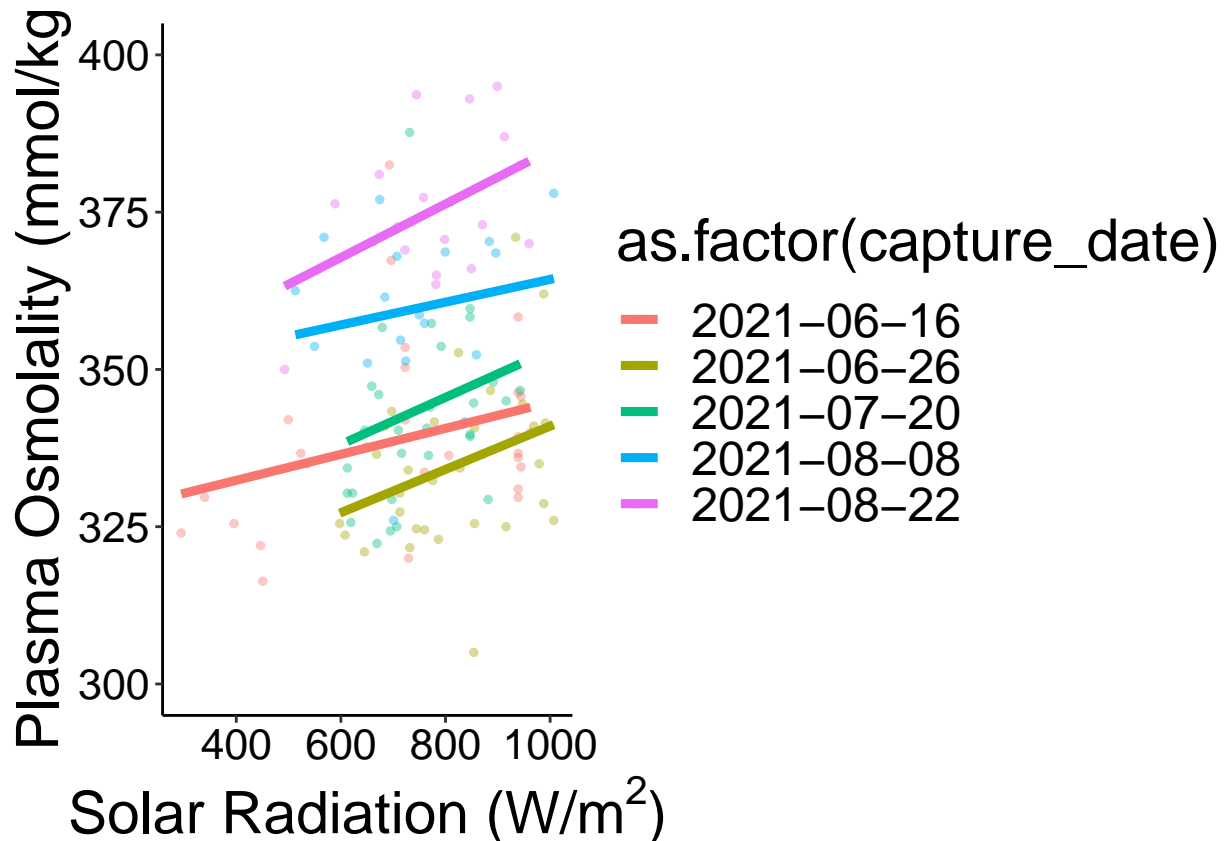
```

      #color = solar_color,
      size = 1.6,
      alpha = 1 ) +
theme_classic() +
xlab(bquote('Solar Radiation (W/'*m2*)')) +
ylab("Plasma Osmolality (mmol/kg)") +
#ylab("") +
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_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

```

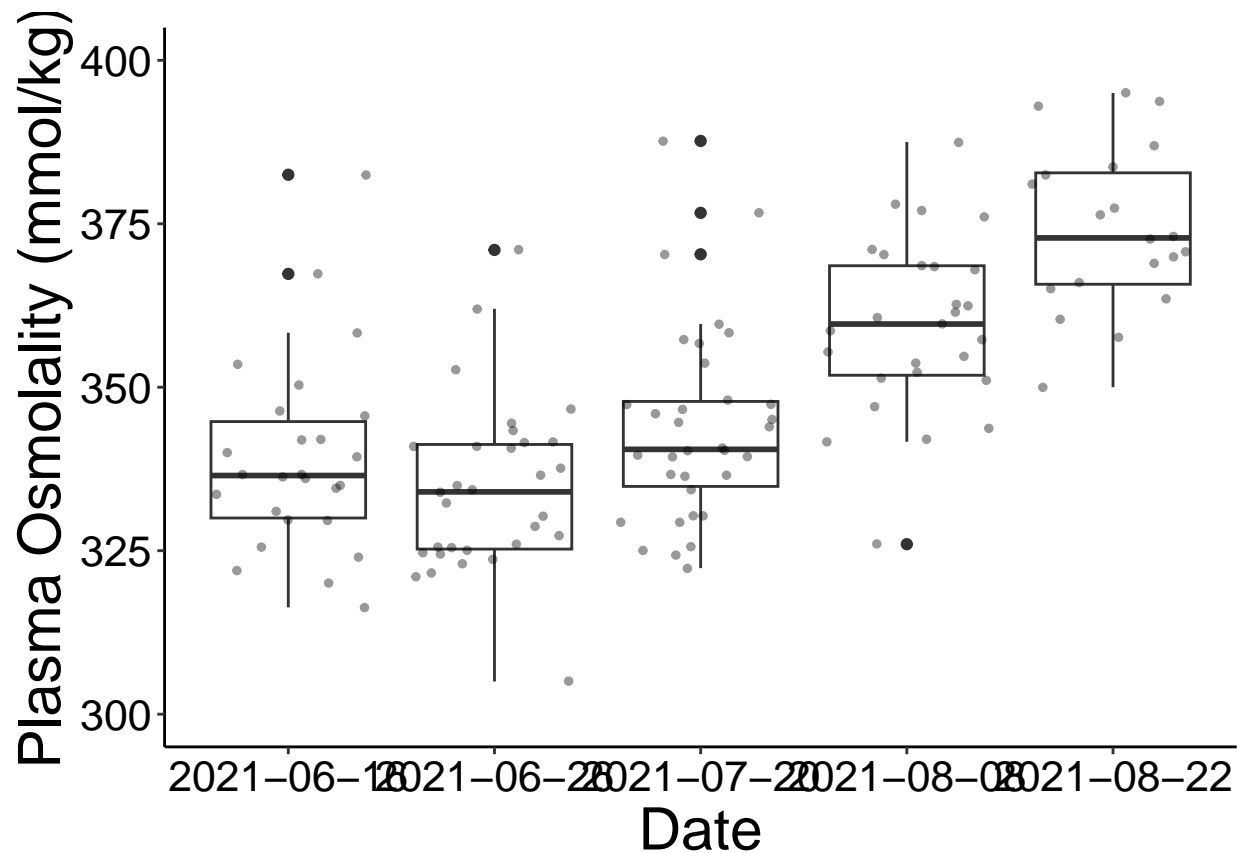
ggplot(dat) +
  aes(x = as.factor(capture_date),

```

```

    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

```

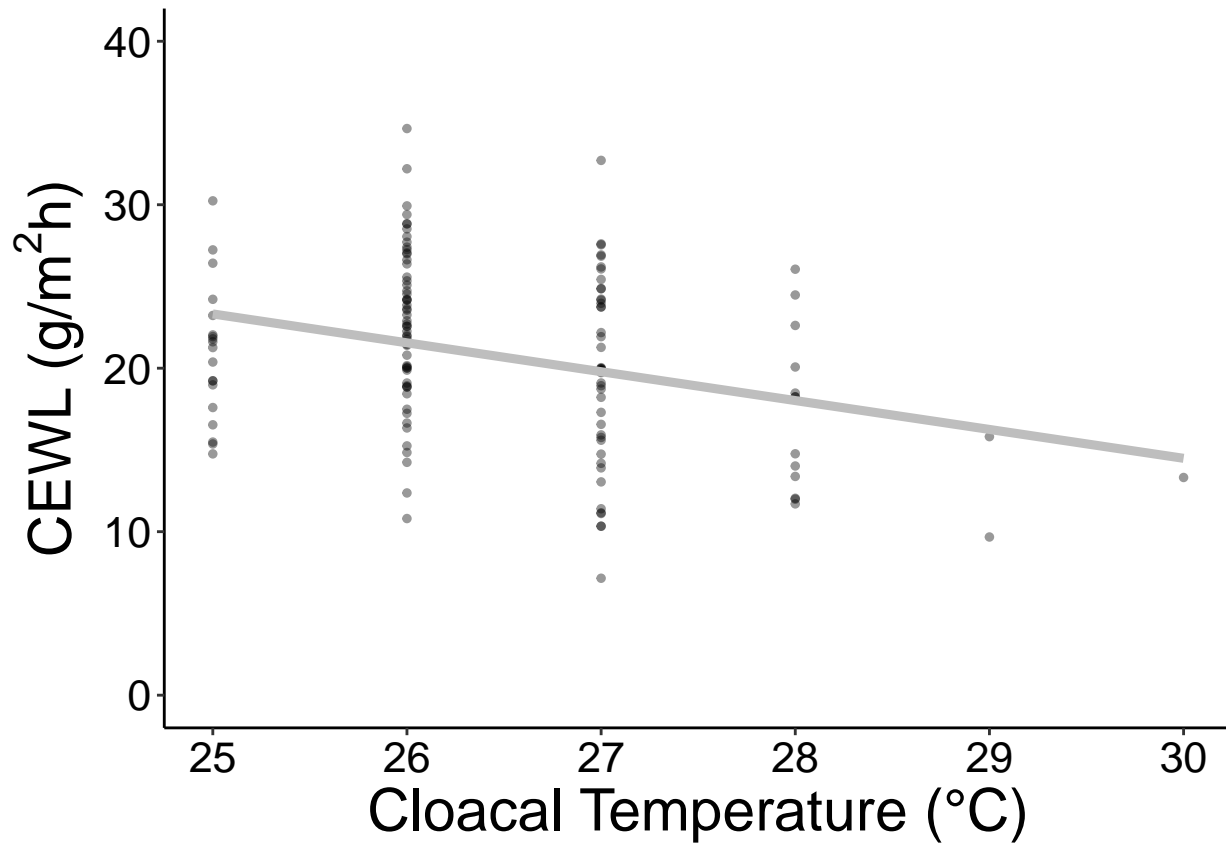


CEWL ~ Cloacal Temperature

```
ggplot(dat) +
  aes(x = cloacal_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("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
```



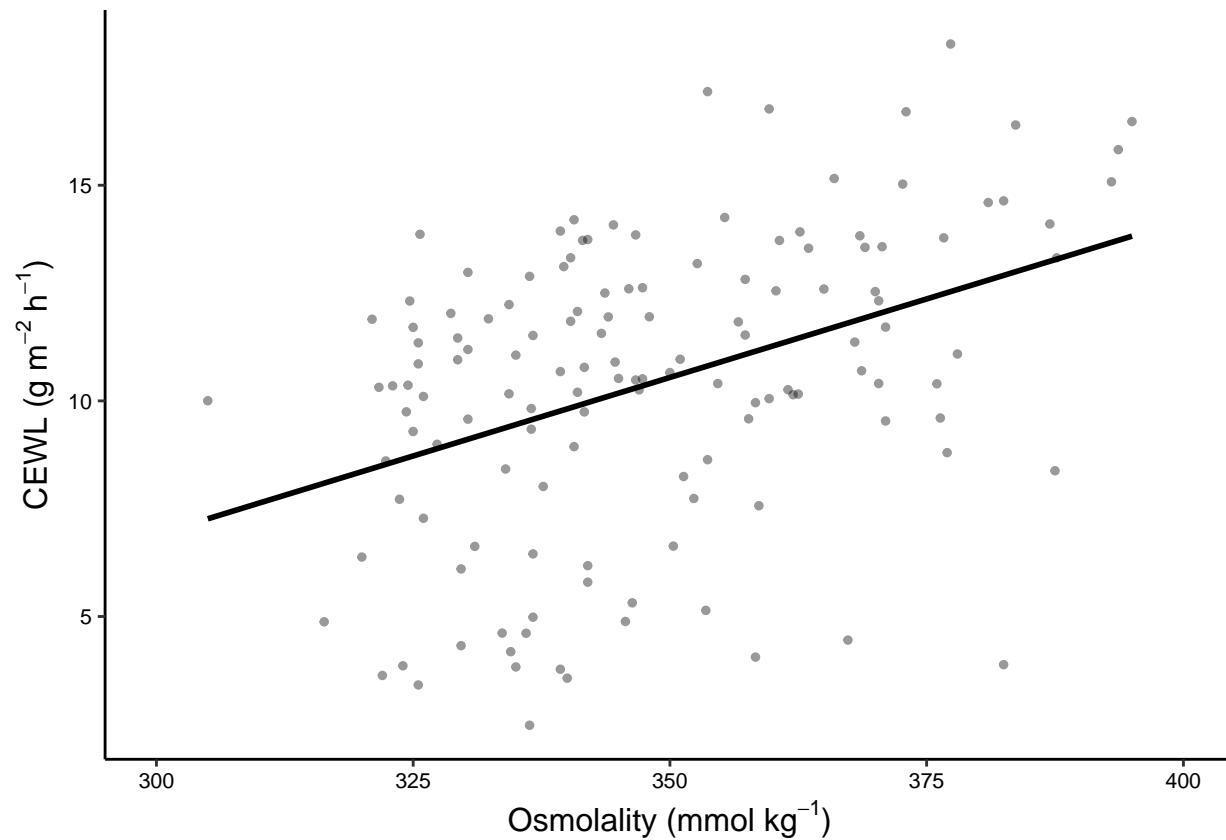
CEWL ~ Plasma Osmolality

```
ggplot(dat) +
  aes(x = osmolality_mmol_kg_mean,
       y = (CEWL_g_m2h_mean/msmt_VPD_kPa),
       #color = as.factor(capture_date)
  ) +
  geom_point(size = 1,
             alpha = 0.4) +
  stat_smooth(formula = y ~ x,
             method = "lm",
             se = F,
             color = "black",
             size = 1,
             alpha = 1) +
  theme_classic() +
  xlab(bquote('Osmolality (mmol '*kg-1*)')) +
  ylab(bquote('CEWL (g '*m-2' '*h-1*)')) +
  xlim(300, 400) +
  #ylim(0, 40) +
  theme(text = element_text(color = "black",
                             family = "sans",
```

```

        size = 12),
axis.text = element_text(color = "black",
                          family = "sans",
                          size = 8),
#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

```



```

ggsave(filename = "cap_CEWL_osml_fig.pdf",
plot = cap_CEWL_osml_fig,
path = "./results_figures",
device = "pdf",
dpi = 600,
units = "mm",
width = 80, height = 60)

```

Add SLR

```

CEWL_osml <- lm(data = dat, CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean)
summary(CEWL_osml)

```

```

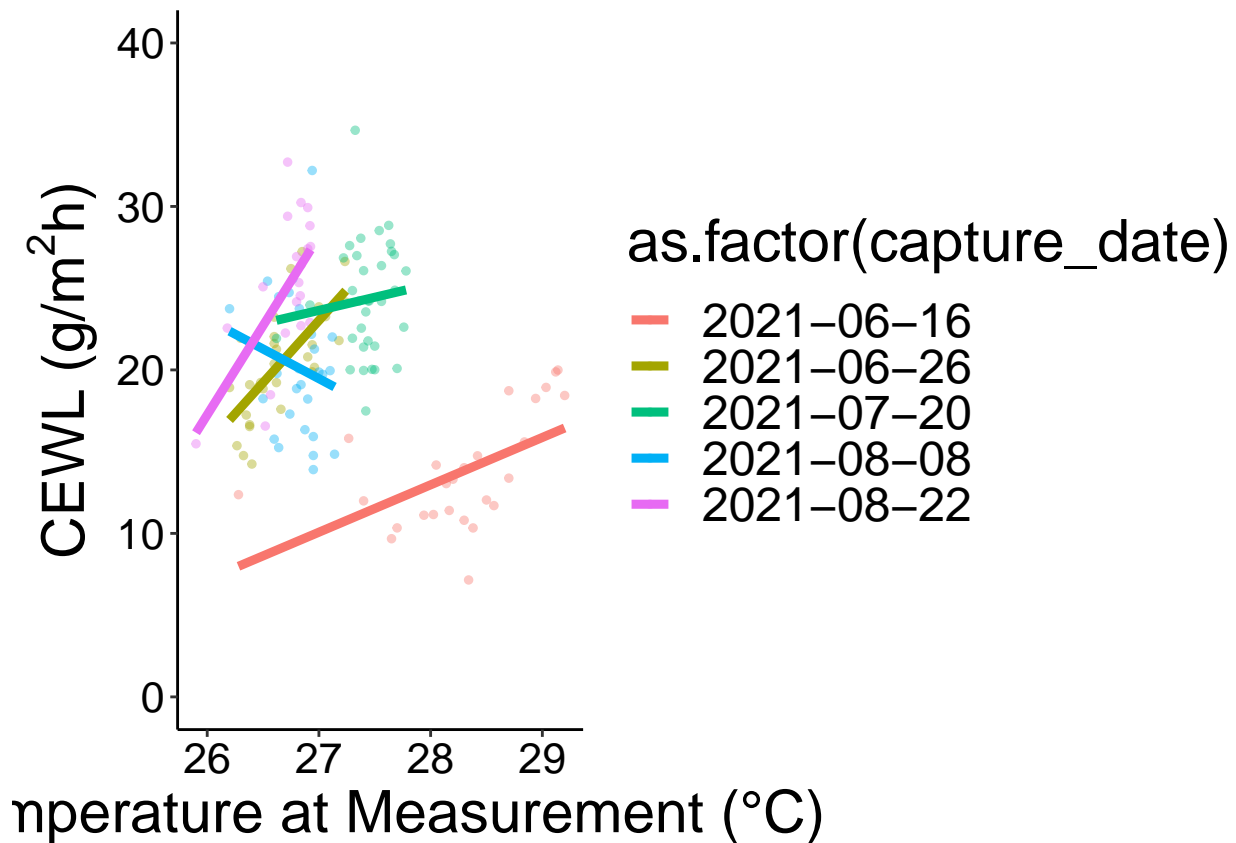
##
## Call:
## lm(formula = CEWL_g_m2h_mean ~ osmolality_mmol_kg_mean, data = dat)
##
## Residuals:

```

```
##      Min      1Q   Median      3Q      Max
## -12.5078 -3.4430  0.6247   3.5847  13.4066
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -11.26104     7.85574  -1.433   0.154
## osmolality_mmol_kg_mean  0.09194     0.02252   4.082 7.57e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.098 on 136 degrees of freedom
## Multiple R-squared:  0.1092, Adjusted R-squared:  0.1026
## F-statistic: 16.67 on 1 and 136 DF,  p-value: 7.565e-05
```

CEWL ~ Temperature at Measurement

```
ggplot(dat) +
  aes(x = msmt_temp_C,
       y = CEWL_g_m2h_mean,
       color = as.factor(capture_date)) +
  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
```



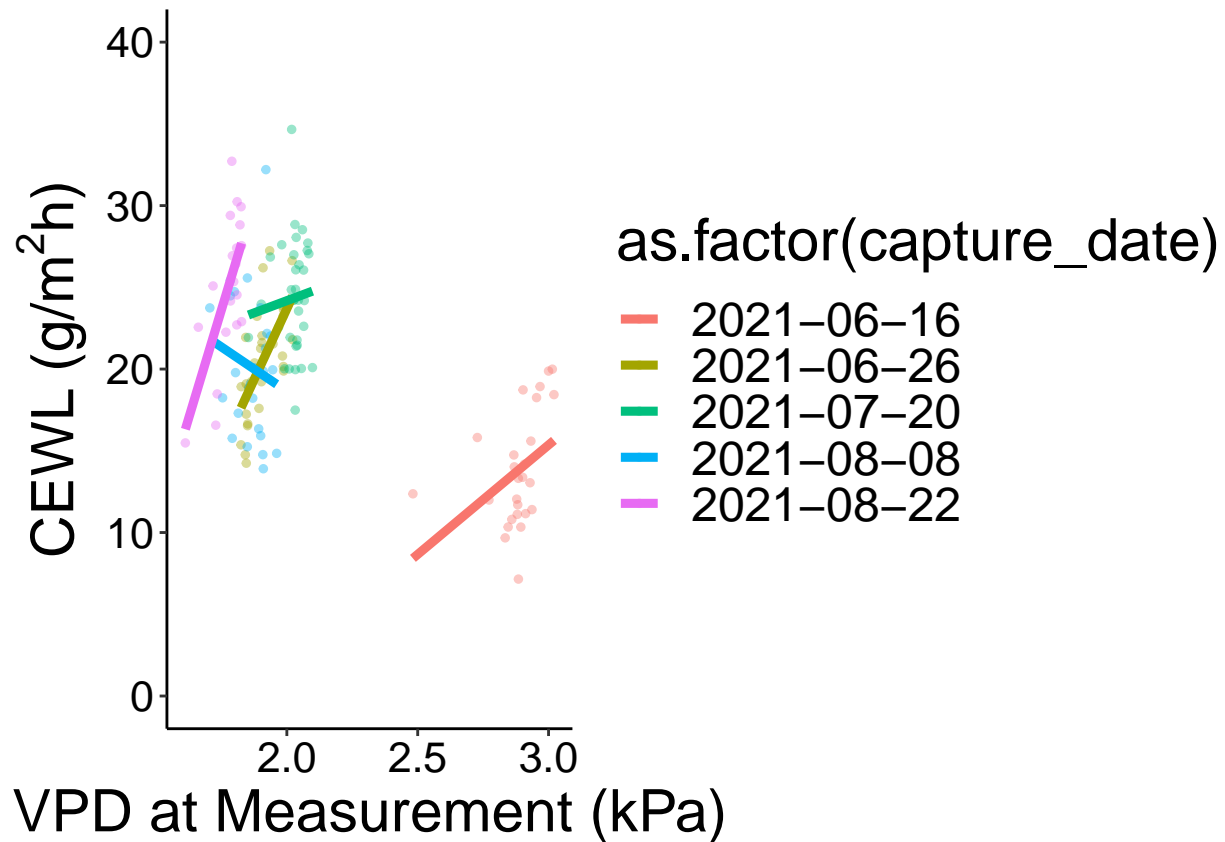
CEWL ~ VPD at Measurement

```
ggplot(dat) +
  aes(x = msmt_VPD_kPa,
       y = CEWL_g_m2h_mean,
       color = as.factor(capture_date)) +
  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(dat) +
  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",

```

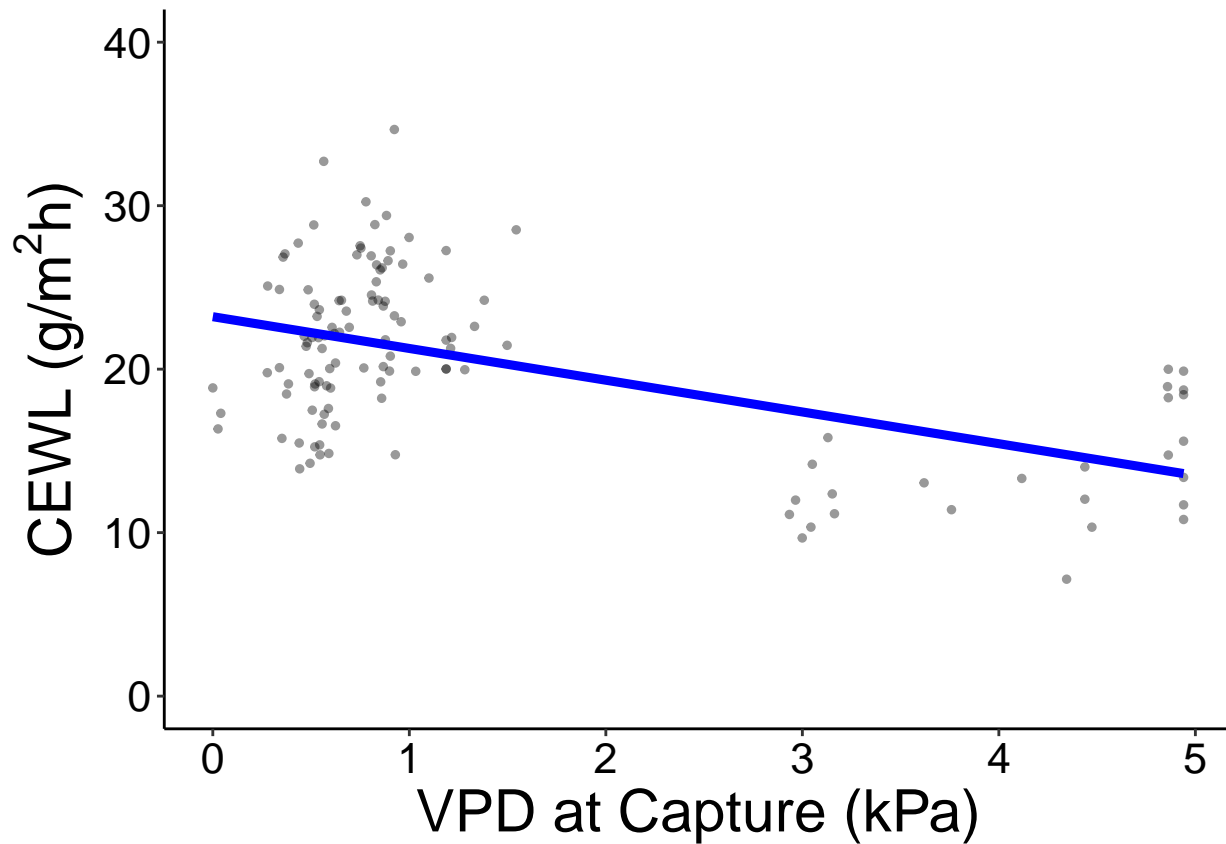
```

        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(dat) +
  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() +

```

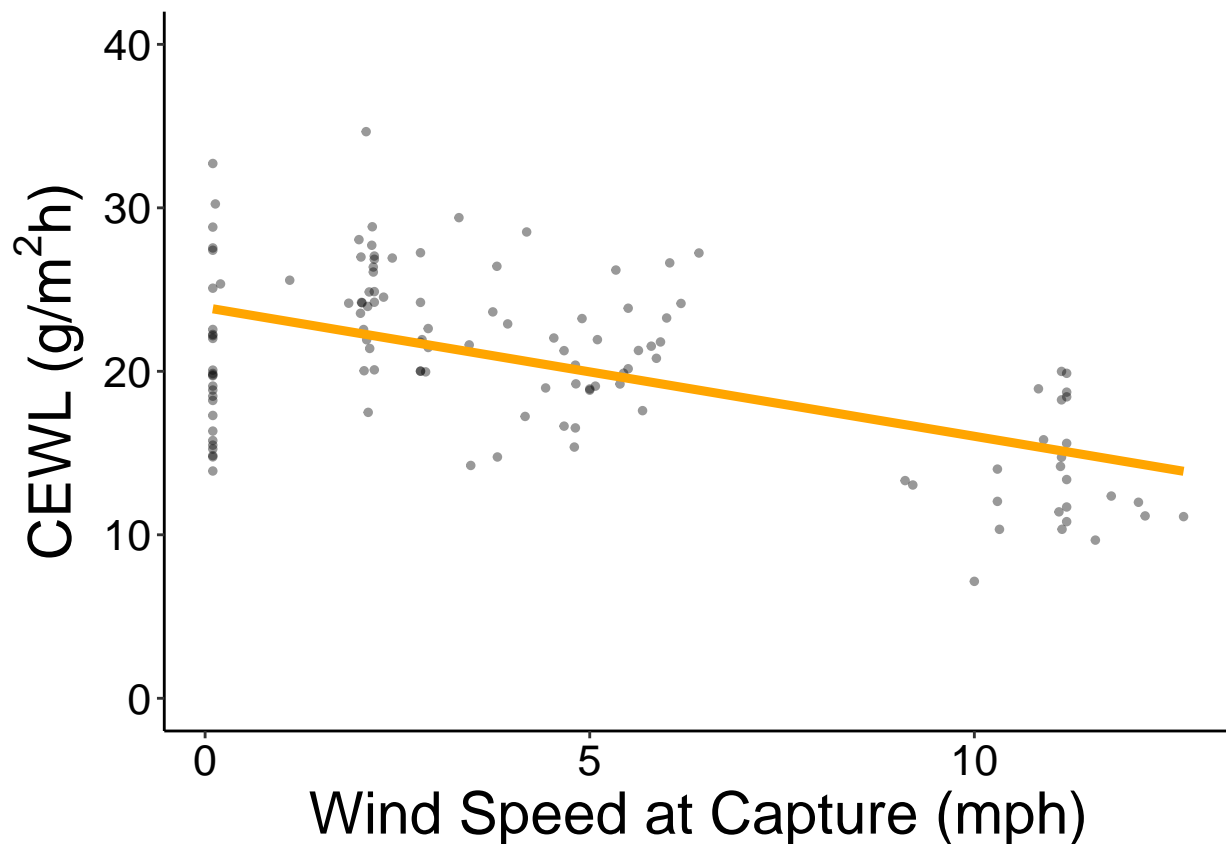
```

xlab("Wind Speed at Capture (mph)") +
ylab(bquote('CEWL (g/'*m2*'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(dat) +
  aes(x = as.factor(capture_date),
       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

```

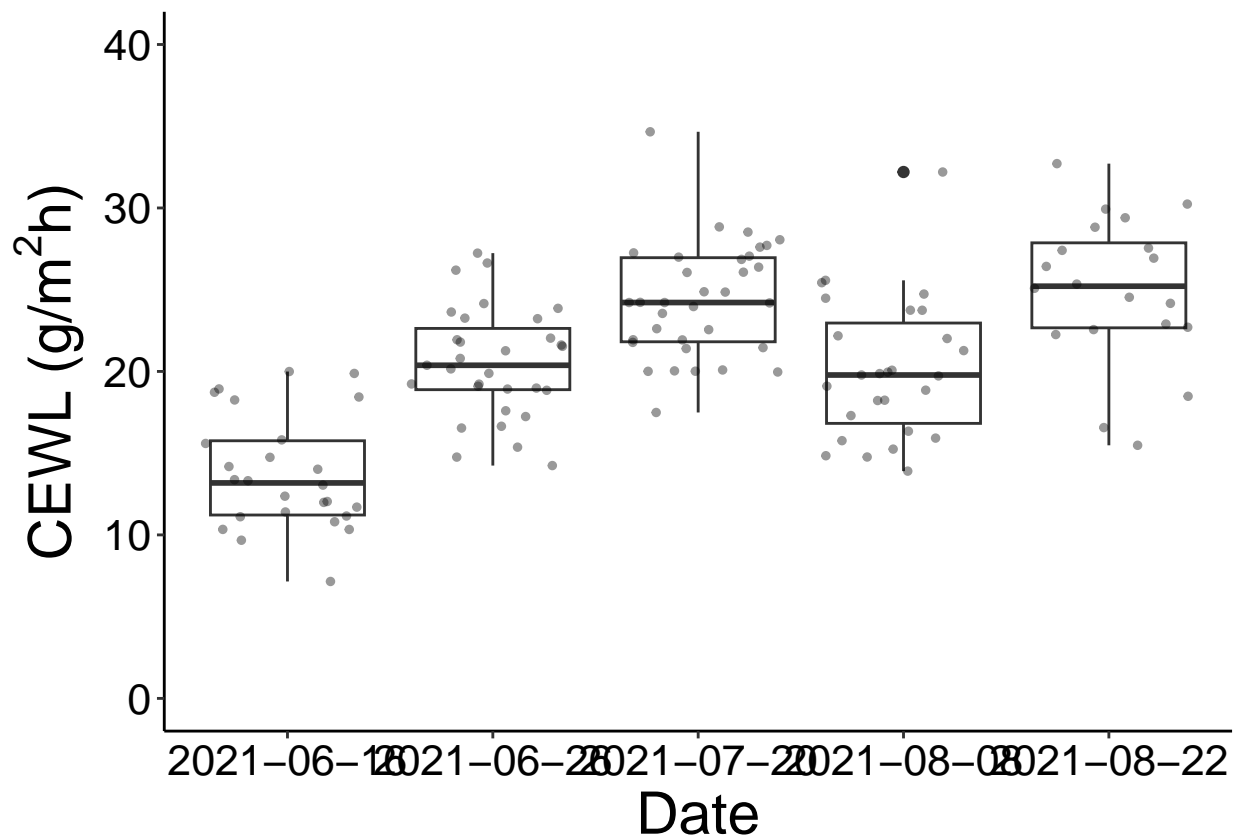


Figure Arrangements

```
# 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()`).
## 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()`).
## 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
# 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
# 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)

```