data wrangling and plots

Maggie Slein

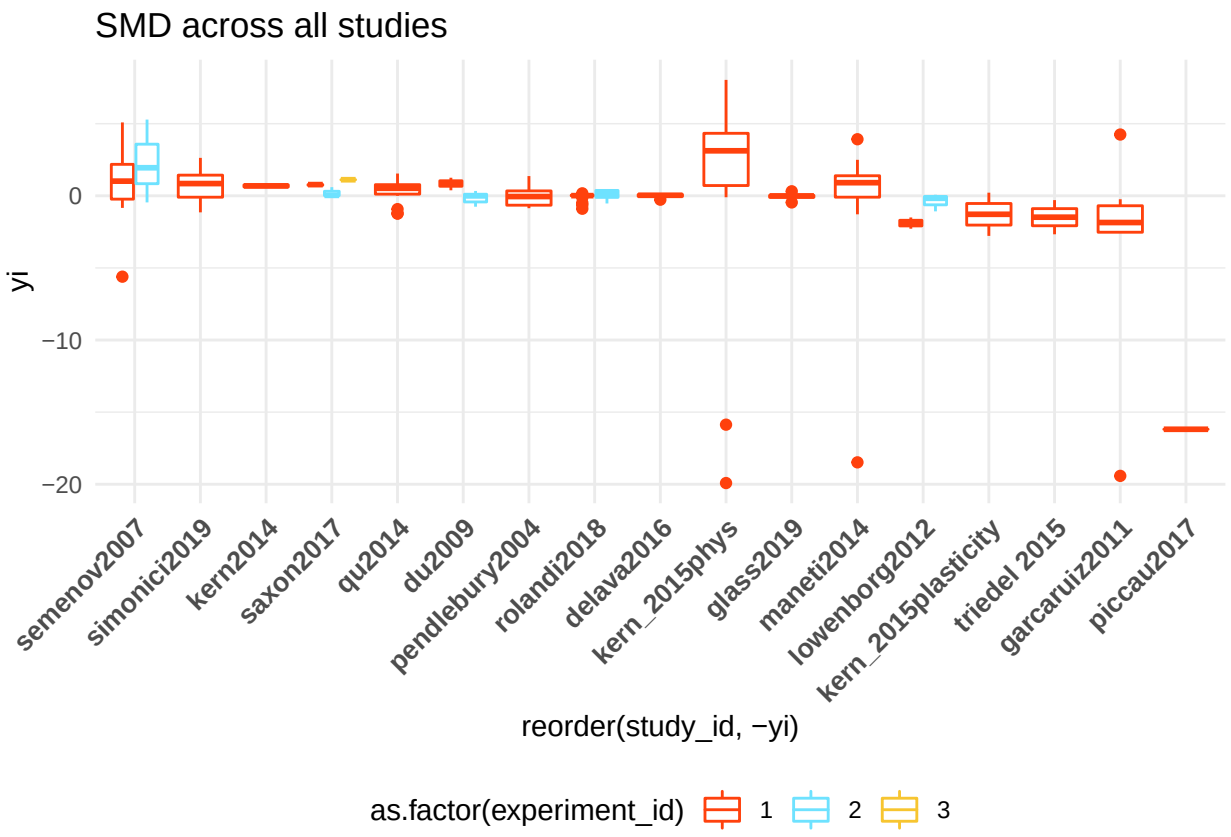
2/22/2021

Plots

Question: How does response compare across studies and experiments?

Figure 1.

```
#SMD across all studies
ggplot(normalized, aes(x=reorder(study_id, -yi), y=yi, color = as.factor(experiment_id)))+
  geom_boxplot()+
  scale_color_tron()+
  theme_minimal()+
  theme(axis.text.x = element_text(face = "bold",
                                   size = 10, angle = 45,hjust = 1),
        legend.position = "bottom")+
  ggtitle("SMD across all studies")
```




```
#corresponding random effects model
fig1 <- rma.mv(yi, vi, data=dat_MA_ES,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig1
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                  factor
## sigma^2.1   0.0000  0.0009      3     no           experiment_id
## sigma^2.2  10.3073  3.2105     25     no  experiment_id/study_id
##
## Test for Heterogeneity:
## Q(df = 209) = 5733.4320, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.6056  0.6438  -0.9406  0.3469  -1.8674  0.6563
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#trying out mixed effects model
fig1me <- rma(yi, vi, data=dat_MA_ES, mods = ~study_id,
              method="FE")
fig1me
```

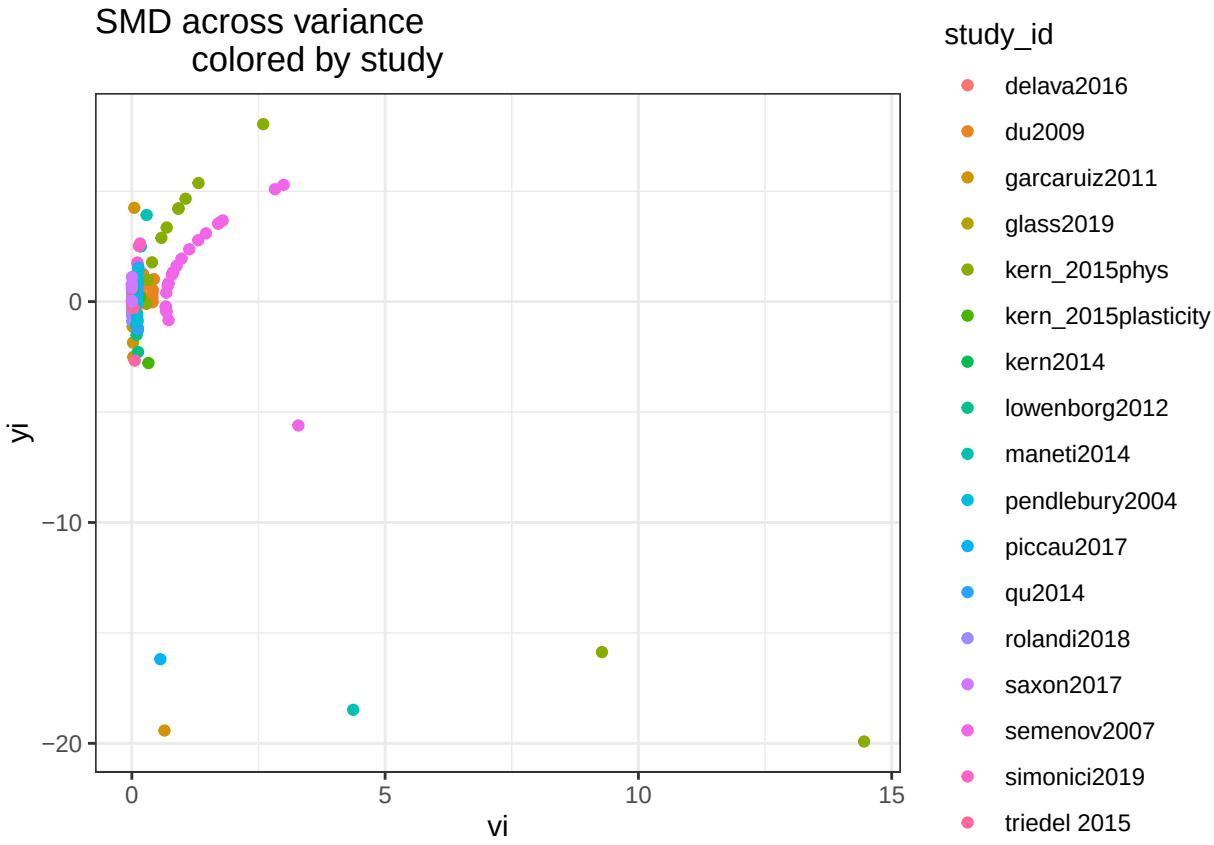
```
##
## Fixed-Effects with Moderators Model (k = 210)
##
## I^2 (residual heterogeneity / unaccounted variability): 95.10%
## H^2 (unaccounted variability / sampling variability):   20.41
##
## Test for Residual Heterogeneity:
## QE(df = 193) = 3938.4753, p-val < .0001
##
## Test of Moderators (coefficients 2:17):
## QM(df = 16) = 1794.9567, p-val < .0001
##
## Model Results:
##
##                              estimate      se      zval    pval     ci.lb
## intrcpt                        0.0006  0.0448    0.0127  0.9899   -0.0872
## study_iddu2009                 0.1754  0.0782    2.2433  0.0249    0.0222
## study_idgarcaruiz2011         -1.0855  0.0792  -13.7139  <.0001   -1.2407
## study_idglass2019             -0.0359  0.0636   -0.5638  0.5729   -0.1606
## study_idkern_2015phys          1.0833  0.2297    4.7170  <.0001    0.6332
## study_idkern_2015plasticity   -1.0742  0.2347   -4.5766  <.0001   -1.5343
## study_idkern2014               0.5837  0.1132    5.1571  <.0001    0.3618
## study_idlowenborg2012         -0.8458  0.1396   -6.0565  <.0001   -1.1195
## study_idmaneti2014             0.7240  0.1146    6.3198  <.0001    0.4995
## study_idpendlebury2004        -0.0100  0.1239   -0.0807  0.9357   -0.2529
## study_idpiccau2017           -16.1904  0.7515  -21.5444  <.0001  -17.6633
## study_idqu2014                 0.3173  0.0858    3.6992  0.0002    0.1492
## study_idrolandi2018            0.0200  0.0467    0.4283  0.6684   -0.0716
## study_idsaxon2017              0.4966  0.0470   10.5578  <.0001    0.4044
## study_idsemenov2007            0.9931  0.2096    4.7384  <.0001    0.5823
## study_idsimonici2019           0.5785  0.0932    6.2079  <.0001    0.3958
## study_idtriedel 2015          -1.1246  0.1483   -7.5818  <.0001   -1.4153
##                                ci.ub
## intrcpt                       0.0883
## study_iddu2009                0.3287    *
## study_idgarcaruiz2011        -0.9304  ***
## study_idglass2019             0.0888
## study_idkern_2015phys         1.5334  ***
## study_idkern_2015plasticity  -0.6142  ***
## study_idkern2014              0.8055  ***
## study_idlowenborg2012        -0.5721  ***
## study_idmaneti2014            0.9485  ***
## study_idpendlebury2004        0.2329
## study_idpiccau2017          -14.7175  ***
## study_idqu2014                0.4854  ***
## study_idrolandi2018           0.1116
## study_idsaxon2017             0.5888  ***
## study_idsemenov2007           1.4039  ***
```

```
## study_idsimonici2019           0.7611  ***
## study_idtriedel 2015          -0.8339  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#basic linear model
simple1<-lm(yi ~ study_id, data = dat_MA_ES)
summary(fig1)
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
##     logLik    Deviance         AIC         BIC        AICc
## -1696.2751   3392.5502   3398.5502   3408.5772   3398.6673
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                  factor
## sigma^2.1   0.0000  0.0009      3     no           experiment_id
## sigma^2.2  10.3073  3.2105     25     no  experiment_id/study_id
##
## Test for Heterogeneity:
## Q(df = 209) = 5733.4320, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.6056  0.6438  -0.9406  0.3469  -1.8674  0.6563
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 2.

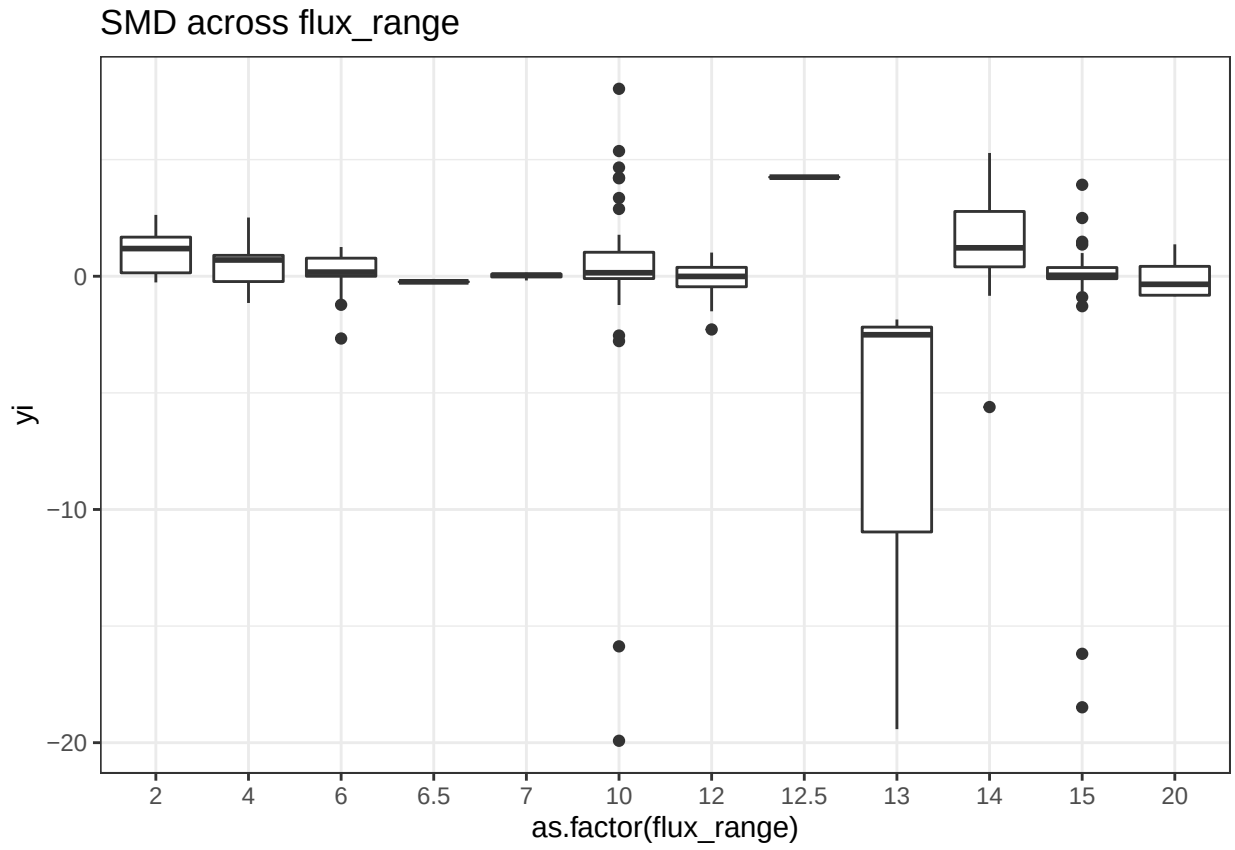



```
##
## Call:
## lm(formula = yi ~ vi, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -45.310  -0.925  -0.509   0.453  21.707
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.9134     0.3404   2.683  0.00788 **
## vi           -2.9429     0.2091 -14.076  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.719 on 208 degrees of freedom
## Multiple R-squared:  0.4879, Adjusted R-squared:  0.4854
## F-statistic: 198.1 on 1 and 208 DF,  p-value: < 2.2e-16
```

Question: How does fluctuation amplitude affect response variables?

Figure 3.

```
# boxplots of how fluctuation range influences SMD
ggplot(normalized, aes(x=as.factor(flux_range), y=yi))+
  geom_boxplot()+
  theme_bw()+
  ggtitle("SMD across flux_range")
```




```
#random effects model including org_level as a random variable
fig7 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~flux_range,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig7
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                  factor
## sigma^2.1   0.0000  0.0011      3     no           experiment_id
## sigma^2.2  10.0491  3.1700     25     no  experiment_id/study_id
```

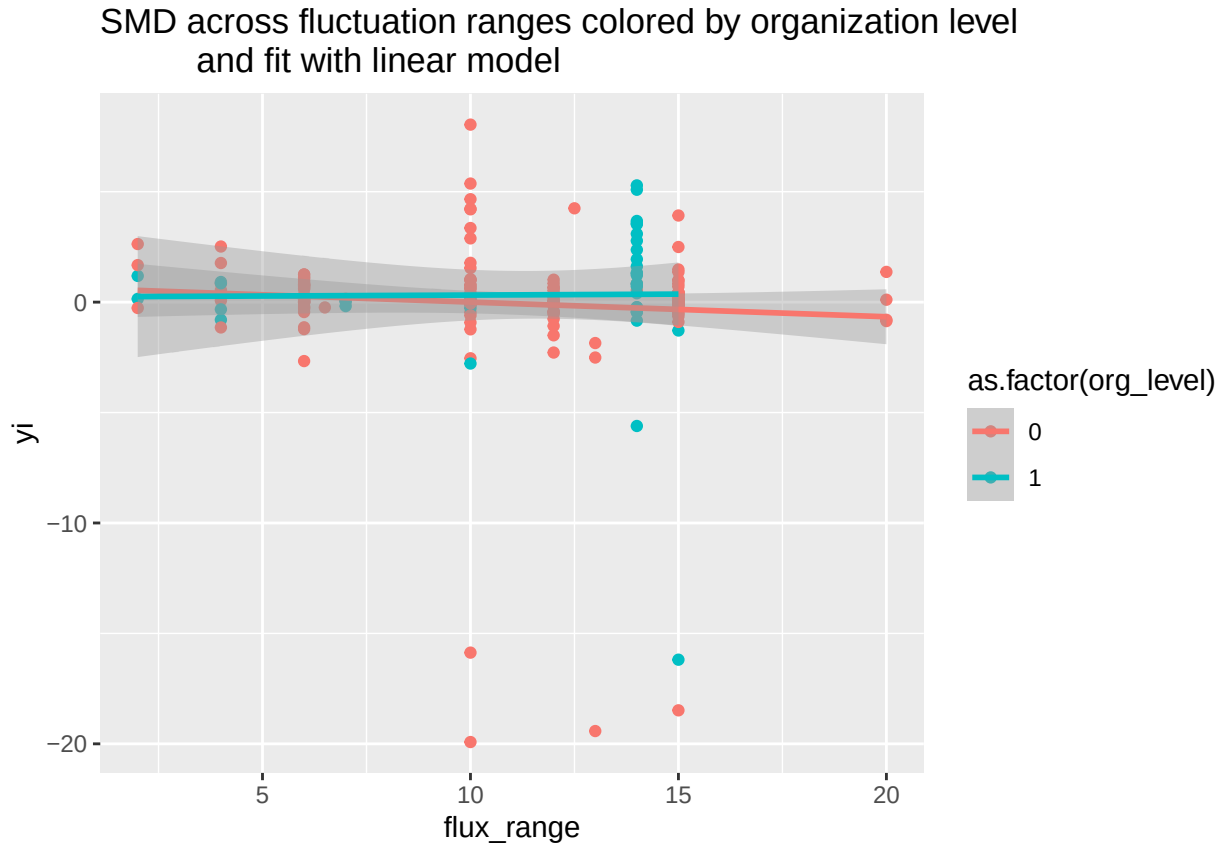
```
##
## Test for Residual Heterogeneity:
## QE(df = 208) = 5240.3845, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 18.3592, p-val < .0001
##
## Model Results:
##
##             estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt      -0.1098  0.6462  -0.1699  0.8651  -1.3762   1.1566
## flux_range   -0.0466  0.0109  -4.2848  <.0001  -0.0680  -0.0253  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how flux_range affects yi
simple7<-lm(yi~flux_range, data =dat_MA_ES)
summary(simple7)
```

```
##
## Call:
## lm(formula = yi ~ flux_range, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -82.218   0.109   0.696   1.255   8.423
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.6215     1.3262   0.469    0.640
## flux_range   -0.1007     0.1138  -0.885    0.377
##
## Residual standard error: 6.582 on 208 degrees of freedom
## Multiple R-squared:  0.003751,   Adjusted R-squared:  -0.001039
## F-statistic: 0.7831 on 1 and 208 DF,  p-value: 0.3772
```

Figure 4.

```
# scatterplot of standardized mean response vs flux range colored and lm fit by org level
ggplot(normalized, aes(x=flux_range, y=yi, color = as.factor(org_level)))+
  geom_point()+
  geom_smooth(method="lm", formula = y~x)+
  ggtitle("SMD across fluctuation ranges colored by organization level
          and fit with linear model")
```




```
#random effects model including org_level as a random variable
fig8 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~flux_range + org_level,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig8
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.0000  0.0004      3     no           experiment_id
## sigma^2.2  9.7057  3.1154     25     no  experiment_id/study_id
##
## Test for Residual Heterogeneity:
## QE(df = 207) = 5180.8169, p-val < .0001
##
## Test of Moderators (coefficients 2:3):
## QM(df = 2) = 45.4076, p-val < .0001
##
## Model Results:
##
##             estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt      -0.0161  0.6357  -0.0253  0.9798  -1.2620   1.2298
## flux_range   -0.0467  0.0109  -4.2904  <.0001  -0.0680  -0.0254  ***
```

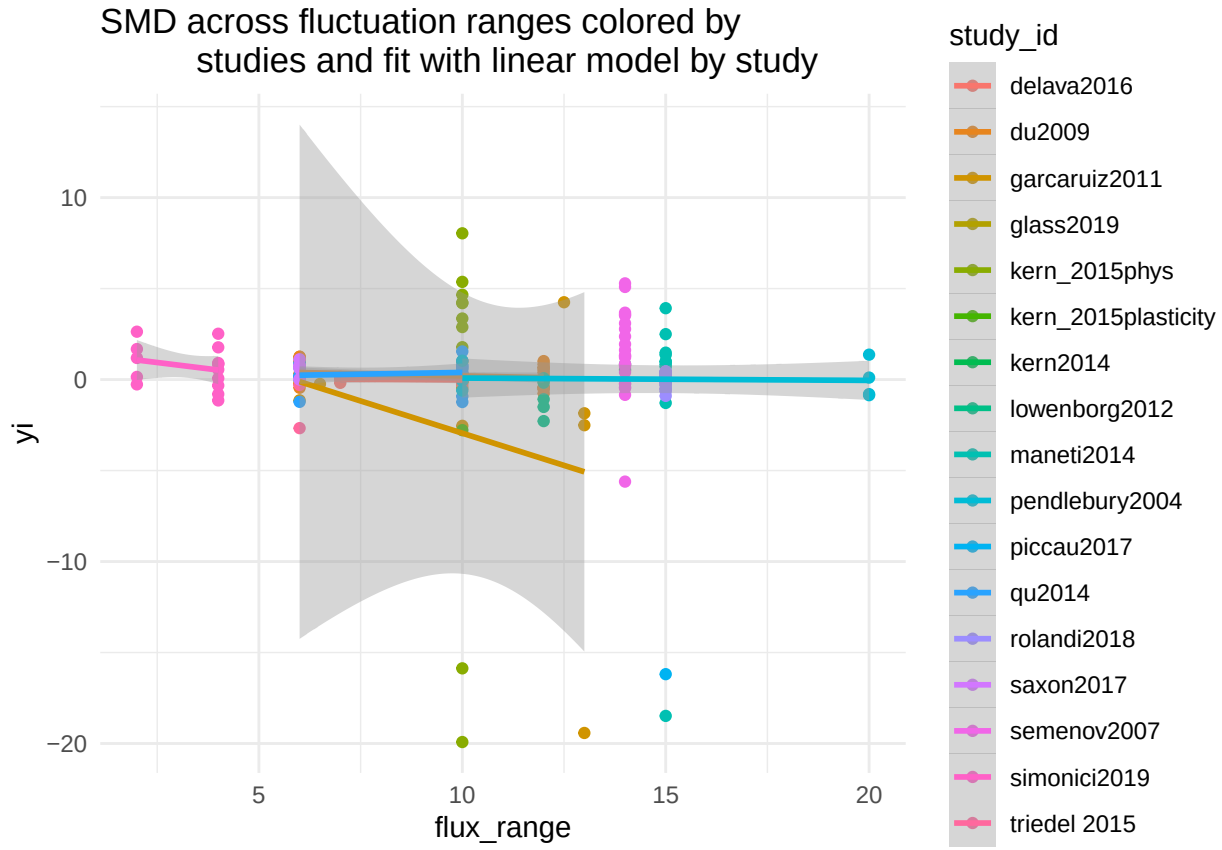
```
## org_level    -0.4314  0.0830  -5.1989  <.0001  -0.5940  -0.2688  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how flux_range and org_level affect yi
simple8<-lm(yi~flux_range*org_level, data =dat_MA_ES)
summary(simple8)
```

```
##
## Call:
## lm(formula = yi ~ flux_range * org_level, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -81.939   0.018   0.815   1.372   8.597
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.7952     1.4711   0.541    0.589
## flux_range             -0.1355     0.1275  -1.062    0.289
## org_level              -0.5607     3.4529  -0.162    0.871
## flux_range:org_level    0.1440     0.2870   0.502    0.616
##
## Residual standard error: 6.596 on 206 degrees of freedom
## Multiple R-squared:  0.009051,   Adjusted R-squared:  -0.005381
## F-statistic: 0.6271 on 3 and 206 DF,  p-value: 0.5982
```

Figure 5.

```
#scatterplot of standardized mean difference across flux range colored by study fit with lm
ggplot(normalized, aes(x=flux_range, y=yi, color = study_id))+
  geom_point()+
  geom_smooth(method="lm", formula = y~x)+
  theme_minimal()+
  ggtitle("SMD across fluctuation ranges colored by
          studies and fit with linear model by study")
```




```
#random effects model including org_level as a random variable
fig9 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~flux_range + study_id,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig9
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.0000  0.0002      3     no           experiment_id
## sigma^2.2  0.5371  0.7329     25     no  experiment_id/study_id
##
## Test for Residual Heterogeneity:
## QE(df = 192) = 3921.4651, p-val < .0001
##
## Test of Moderators (coefficients 2:18):
## QM(df = 17) = 274.8153, p-val < .0001
##
## Model Results:
##
##                              estimate      se      zval    pval     ci.lb
## intrcpt                        0.3911  0.7401    0.5285  0.5971   -1.0593
## flux_range                    -0.0460  0.0109   -4.2140  <.0001   -0.0673
```

```
## study_iddu2009                 0.3321  0.9012    0.3685  0.7125   -1.4341
## study_idgarcaruiz2011         -1.0411  1.0395   -1.0015  0.3166   -3.0785
## study_idglass2019              0.0331  1.0385    0.0319  0.9746   -2.0023
## study_idkern_2015phys          1.1522  1.0617    1.0853  0.2778   -0.9286
## study_idkern_2015plasticity   -0.9959  0.9279   -1.0732  0.2832   -2.8146
## study_idkern2014               0.0107  0.9279    0.0116  0.9908   -1.8080
## study_idlowenborg2012         -0.9247  0.9104   -1.0158  0.3097   -2.7091
## study_idmaneti2014             1.0227  1.0451    0.9786  0.3278   -1.0257
## study_idpendlebury2004         0.2830  1.0461    0.2705  0.7868   -1.7674
## study_idpiccau2017           -15.8916  1.2822  -12.3944  <.0001  -18.4046
## study_idqu2014                 0.2923  1.0400    0.2811  0.7787   -1.7460
## study_idrolandi2018            0.3189  0.9016    0.3537  0.7236   -1.4482
## study_idsaxon2017              0.5726  0.8482    0.6751  0.4996   -1.0898
## study_idsemenov2007            1.3452  0.9253    1.4538  0.1460   -0.4684
## study_idsimonici2019           0.3429  1.0421    0.3290  0.7421   -1.6996
## study_idtriedel 2015          -1.2394  1.0473   -1.1834  0.2366   -3.2922
##                                ci.ub
## intrcpt                       1.8416
## flux_range                   -0.0246  ***
## study_iddu2009                2.0983
## study_idgarcaruiz2011         0.9963
## study_idglass2019             2.0685
## study_idkern_2015phys         3.2331
## study_idkern_2015plasticity   0.8229
## study_idkern2014              1.8295
## study_idlowenborg2012         0.8596
## study_idmaneti2014            3.0712
## study_idpendlebury2004        2.3333
## study_idpiccau2017          -13.3786  ***
## study_idqu2014                2.3306
## study_idrolandi2018           2.0859
## study_idsaxon2017             2.2351
## study_idsemenov2007           3.1589
## study_idsimonici2019          2.3854
## study_idtriedel 2015          0.8133
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

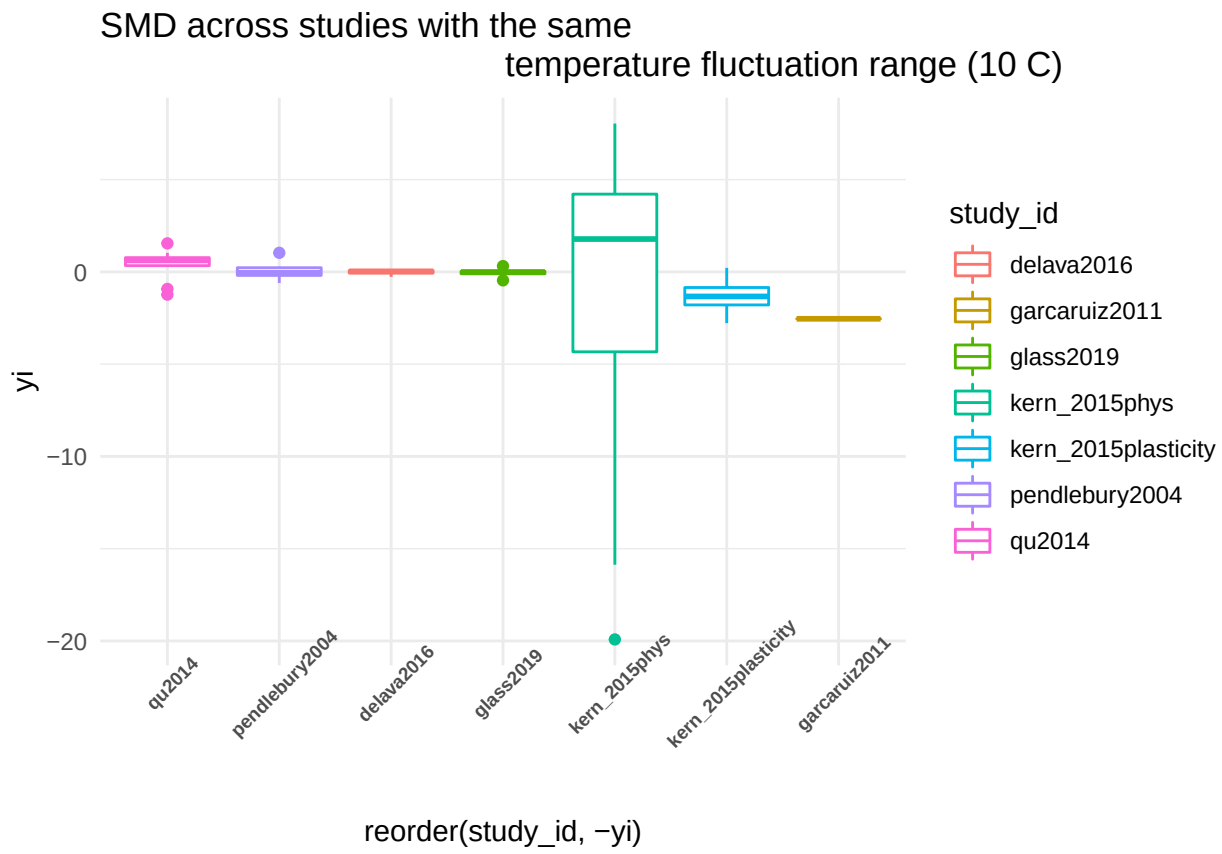
```
#simple linear model looking at how flux_range and study_id affect yi
simple9<-lm(yi~flux_range*study_id, data =dat_MA_ES)
summary(simple9)
```

```
##
## Call:
## lm(formula = yi ~ flux_range * study_id, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -62.646  -0.387   0.036   0.592  22.869
##
## Coefficients: (11 not defined because of singularities)
##                                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         0.091100  12.109848   0.008    0.994
```

```
## flux_range                                -0.010684   1.403009  -0.008    0.994
## study_iddu2009                             0.575435  12.558697   0.046    0.964
## study_idgarcaruiz2011                     22.254823  14.702737   1.514    0.132
## study_idglass2019                         -0.020693   3.645125  -0.006    0.995
## study_idkern_2015phys                     -0.920130   3.349639  -0.275    0.784
## study_idkern_2015plasticity               -1.290924   4.209028  -0.307    0.759
## study_idkern2014                          -1.272987   8.534172  -0.149    0.882
## study_idlowenborg2012                     -0.955077   5.968976  -0.160    0.873
## study_idmaneti2014                        -0.530046   9.515672  -0.056    0.956
## study_idpendlebury2004                     0.119910  13.818039   0.009    0.993
## study_idpiccau2017                       -16.120645  11.091762  -1.453    0.148
## study_idqu2014                            -0.077323  13.295318  -0.006    0.995
## study_idrolandi2018                        0.087188   9.408920   0.009    0.993
## study_idsaxon2017                          0.543332   4.668339   0.116    0.907
## study_idsemenov2007                        1.440235   8.094112   0.178    0.859
## study_idsimonici2019                       1.535025  13.361776   0.115    0.909
## study_idtriedel 2015                      -1.510015   5.869209  -0.257    0.797
## flux_range:study_iddu2009                 -0.035825   1.446189  -0.025    0.980
## flux_range:study_idgarcaruiz2011          -3.266636   1.587083  -2.058    0.041 *
## flux_range:study_idglass2019                    NA         NA      NA       NA
## flux_range:study_idkern_2015phys                NA         NA      NA       NA
## flux_range:study_idkern_2015plasticity          NA         NA      NA       NA
## flux_range:study_idkern2014                     NA         NA      NA       NA
## flux_range:study_idlowenborg2012                NA         NA      NA       NA
## flux_range:study_idmaneti2014                   NA         NA      NA       NA
## flux_range:study_idpendlebury2004         -0.002104   1.464785  -0.001    0.999
## flux_range:study_idpiccau2017                   NA         NA      NA       NA
## flux_range:study_idqu2014                  0.048564   1.552847   0.031    0.975
## flux_range:study_idrolandi2018                  NA         NA      NA       NA
## flux_range:study_idsaxon2017                    NA         NA      NA       NA
## flux_range:study_idsemenov2007                  NA         NA      NA       NA
## flux_range:study_idsimonici2019           -0.264625   2.150773  -0.123    0.902
## flux_range:study_idtriedel 2015                 NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.952 on 187 degrees of freedom
## Multiple R-squared:  0.2675, Adjusted R-squared:  0.1813
## F-statistic: 3.103 on 22 and 187 DF,  p-value: 1.481e-05
```

Figure 6.

```
#looking at yi across studies with the same temperature range (10 C)
ggplot(common_range, aes(y=yi, x=reorder(study_id, -yi), color = study_id))+
  geom_boxplot()+
  theme_minimal()+
  theme(axis.text.x = element_text(face = "bold",
                                   size = 7, angle = 45))+
                                   ggtitle("SMD across studies with the same
                                           temperature fluctuation range (10 C)")
```




```
#random effects model within subset data
fig12 <- rma.mv(yi, vi, data=common_range,
                random = ~1 | experiment_id/ study_id,
                  method="REML")
fig12
```

```
##
## Multivariate Meta-Analysis Model (k = 46; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.0000  0.0003      2     no           experiment_id
## sigma^2.2  1.2206  1.1048      8     no  experiment_id/study_id
##
## Test for Heterogeneity:
## Q(df = 45) = 554.4933, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.3844  0.3974  -0.9673  0.3334  -1.1632  0.3945
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

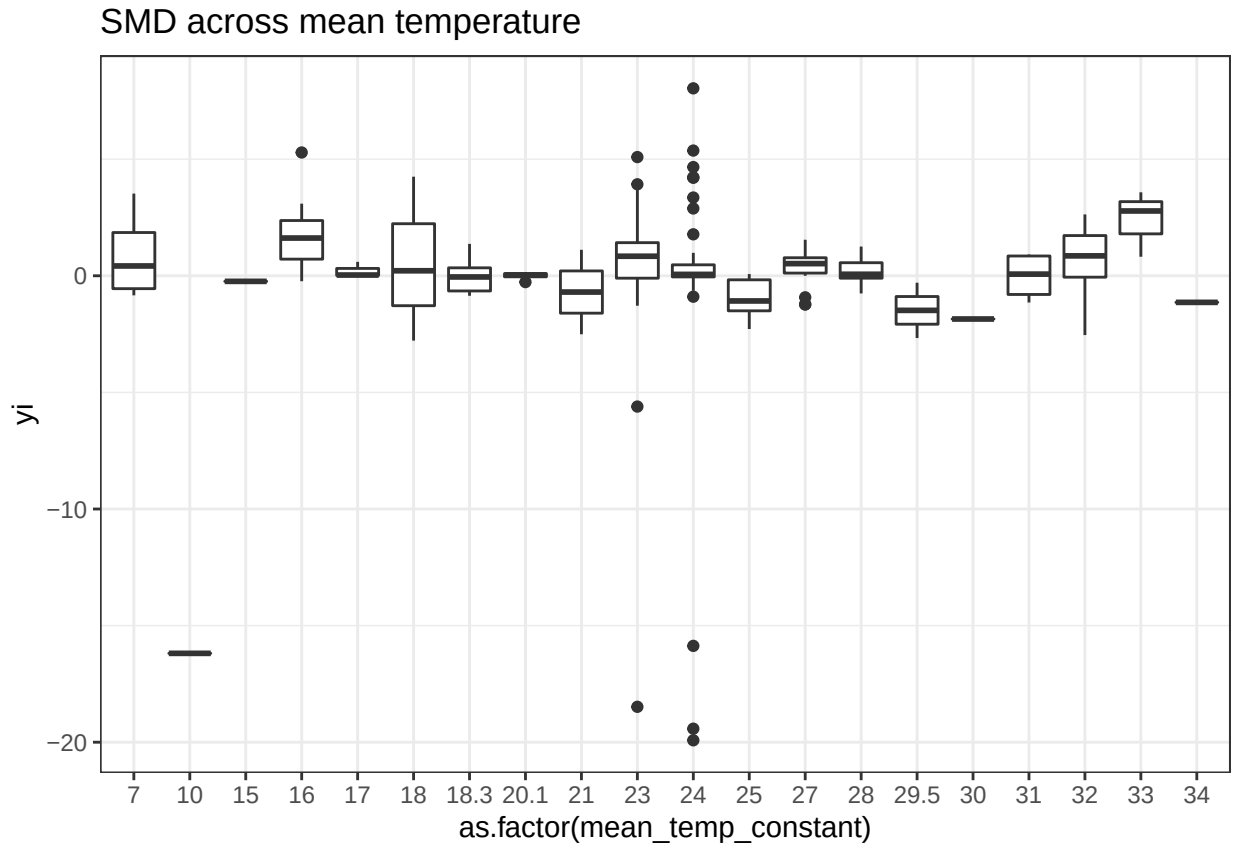
```r
#simple linear model looking at how flux_range affects yi within subset data
simple12<-lm(yi~flux_range, data =common_range)
summary(simple12)
```

```
##
## Call:
## lm(formula = yi ~ flux_range, data = common_range)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.5292  -0.1766   0.4291   1.3201   8.4270
##
## Coefficients: (1 not defined because of singularities)
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.3892     0.6618  -0.588    0.559
## flux_range        NA         NA      NA       NA
##
## Residual standard error: 4.489 on 45 degrees of freedom
```

Question how does mean temperature affect response variables?

Figure 7.

```r
# boxplots of how mean temperature influences SMD
ggplot(normalized, aes(x=as.factor(mean_temp_constant), y=yi))+
  geom_boxplot()+
  theme_bw()+
  ggtitle("SMD across mean temperature")
```




```
#random effects model including org_level as a random variable
fig6 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~mean_temp_constant,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig6
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                  factor
## sigma^2.1   0.0000  0.0010      3     no           experiment_id
## sigma^2.2  11.9104  3.4511     25     no  experiment_id/study_id
##
## Test for Residual Heterogeneity:
## QE(df = 208) = 5706.0015, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 112.0552, p-val < .0001
##
## Model Results:
##
##                     estimate      se      zval    pval    ci.lb    ci.ub
## intrcpt               1.3636  0.7165    1.9032  0.0570  -0.0407   2.7680    .
## mean_temp_constant   -0.0861  0.0081  -10.5856  <.0001  -0.1021  -0.0702  ***
```

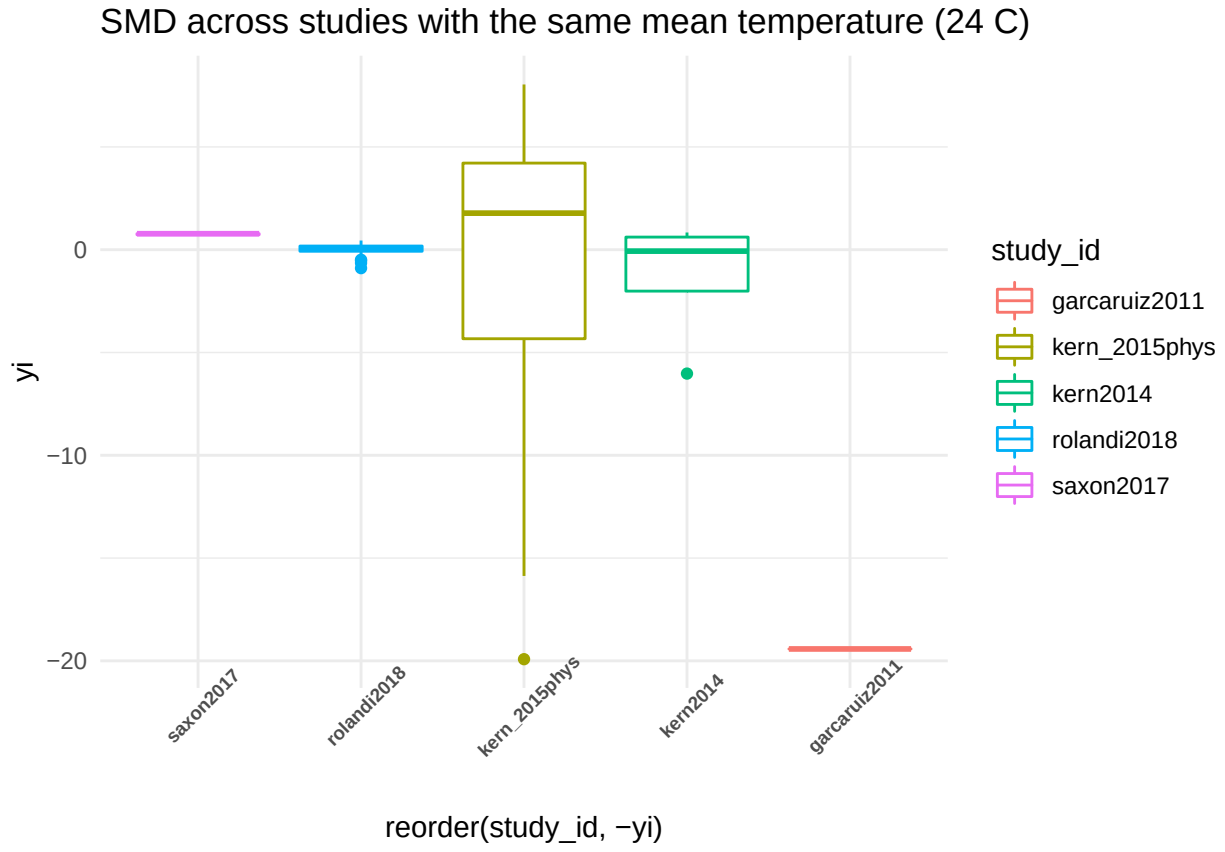
```
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how mean_temp_constant affects yi
simple6<-lm(yi~mean_temp_constant, data =dat_MA_ES)
summary(simple6)
```

```
##
## Call:
## lm(formula = yi ~ mean_temp_constant, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -82.412   0.214   0.574   1.313   8.517
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        -0.371344   2.336504  -0.159    0.874
## mean_temp_constant -0.004495   0.093830  -0.048    0.962
##
## Residual standard error: 6.594 on 208 degrees of freedom
## Multiple R-squared:  1.103e-05,  Adjusted R-squared:  -0.004797
## F-statistic: 0.002295 on 1 and 208 DF,  p-value: 0.9618
```

Figure 8.

```
#looking at yi across studies with the same mean temperature (24 C)
ggplot(common_temp, aes(y=yi, x=reorder(study_id, -yi), color = study_id))+
  geom_boxplot()+
  theme_minimal()+
  theme(axis.text.x = element_text(face = "bold",
                                   size = 7, angle = 45))+
  ggtitle("SMD across studies with the same mean temperature (24 C)")
```




```
#random effects model within subset data
fig13 <- rma.mv(yi, vi, data=common_temp,
                random = ~1 | experiment_id/ study_id,
                  method="REML")
fig13
```

```
##
## Multivariate Meta-Analysis Model (k = 61; method: REML)
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed                 factor
## sigma^2.1   0.0000  0.0018      2     no           experiment_id
## sigma^2.2  54.6053  7.3895      7     no  experiment_id/study_id
##
## Test for Heterogeneity:
## Q(df = 60) = 2244.2008, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -2.6001  2.7964  -0.9298  0.3525  -8.0808  2.8807
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

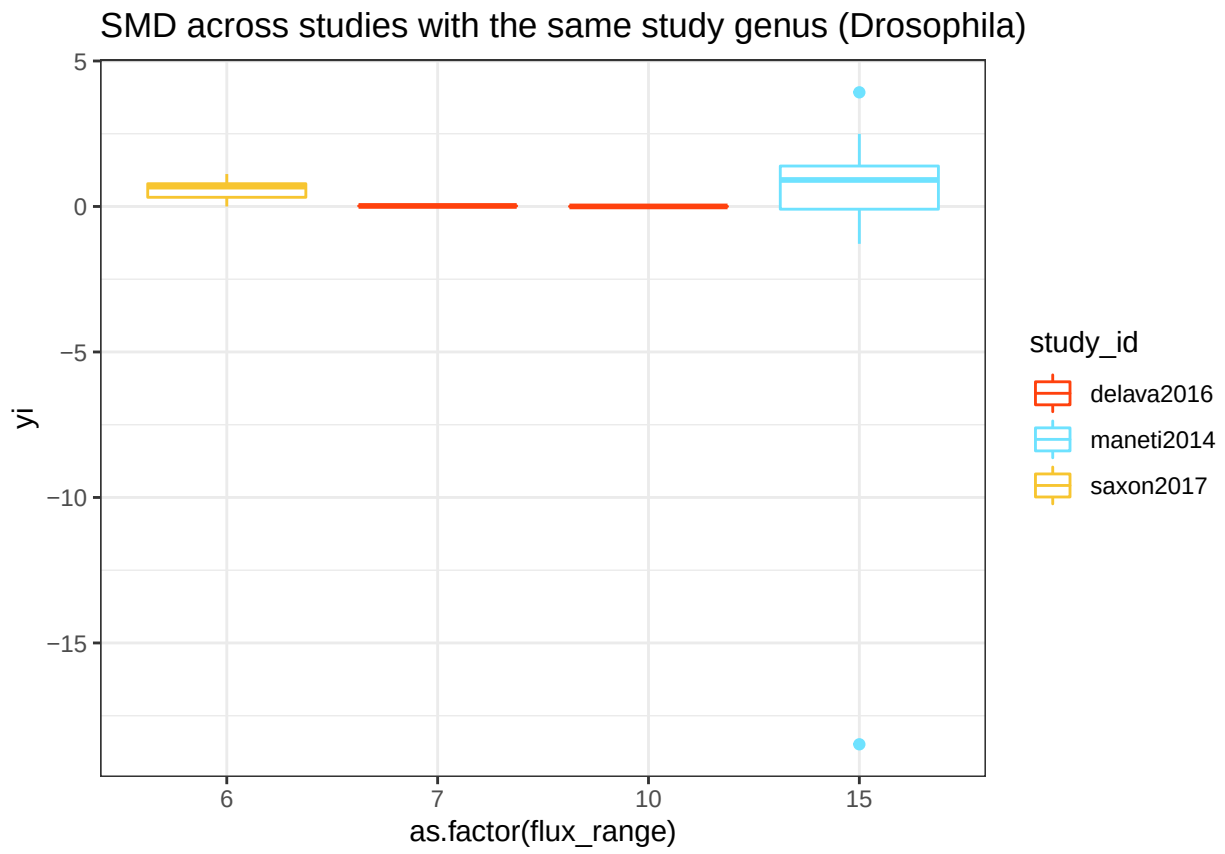
```r
#simple linear model looking at how flux_range affects yi within subset data
simple13<-lm(yi~mean_temp_constant, data =common_temp)
summary(simple13)
```

```
##
## Call:
## lm(formula = yi ~ mean_temp_constant, data = common_temp)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.3306   0.4578   0.6406   1.0274   8.6256
##
## Coefficients: (1 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -0.5877     0.5925  -0.992    0.325
## mean_temp_constant       NA         NA      NA       NA
##
## Residual standard error: 4.627 on 60 degrees of freedom
```

Question: How does genus affect response?

Figure 9.

```r
#trying to look at drosophila response across studies
ggplot(drosophila, aes(y=yi, x=as.factor(flux_range), color = study_id))+
  geom_boxplot()+
  scale_color_tron()+
  theme_bw()+
  ggtitle("SMD across studies with the same study genus (Drosophila)")
```




```
#random effects model including org_level as a random variable
fig10 <- rma.mv(yi, vi, data=drosophila, mods = ~flux_range + study_id,
                random = ~1 | experiment_id/ study_id,
                  method="REML")
fig10
```

```
##
## Multivariate Meta-Analysis Model (k = 21; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                 factor
## sigma^2.1  0.1034  0.3216      3     no           experiment_id
## sigma^2.2  0.1034  0.3216      5     no  experiment_id/study_id
##
## Test for Residual Heterogeneity:
## QE(df = 17) = 798.4274, p-val < .0001
##
## Test of Moderators (coefficients 2:4):
## QM(df = 3) = 3.2667, p-val = 0.3523
##
## Model Results:
##
##                    estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt              0.0259  0.6614   0.0392  0.9687  -1.2704  1.3223
## flux_range          -0.0055  0.0596  -0.0922  0.9265  -0.1224  0.1114
```

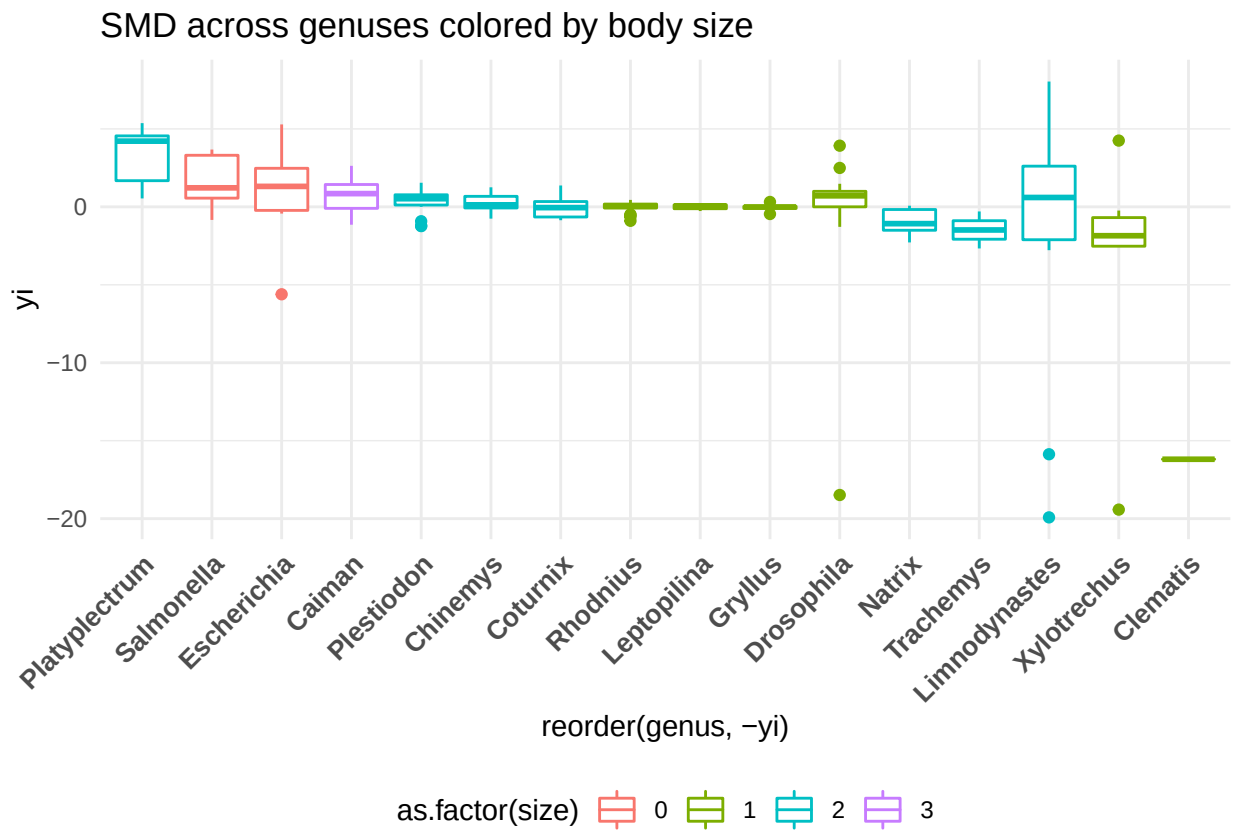
```
## study_idmaneti2014    0.7499  0.6134   1.2226  0.2215  -0.4523  1.9521
## study_idsaxon2017     0.6933  0.4505   1.5389  0.1238  -0.1897  1.5763
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how flux_range and study_id affect yi in drosphila specific studies
simple10<-lm(yi~flux_range + study_id, data =drosophila)
summary(simple10)
```

```
##
## Call:
## lm(formula = yi ~ flux_range + study_id, data = drosophila)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -17.8832   0.0000   0.4773   1.5850   4.5217
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.057126  18.951260   0.003    0.998
## flux_range         -0.005498   2.195634  -0.003    0.998
## study_idmaneti2014 -0.573860  14.708290  -0.039    0.969
## study_idsaxon2017   0.546191   6.638973   0.082    0.935
##
## Residual standard error: 4.658 on 17 degrees of freedom
## Multiple R-squared:  0.01628,    Adjusted R-squared:  -0.1573
## F-statistic: 0.09381 on 3 and 17 DF,  p-value: 0.9624
```

Figure 10.

```
#boxplots of SMD across different genuses colored by body size
ggplot(normalized, aes(y=yi, x= reorder(genus, -yi), color = as.factor(size)))+
  geom_boxplot()+
  theme_minimal()+
  ggtitle("SMD across genuses colored by body size")+
  theme(axis.text.x = element_text(face = "bold",
                                   size = 10, angle = 45,hjust = 1),
        legend.position = "bottom")
```




```
#random effects model including genus as a random variable
fig11 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~genus,
                random = ~1 | experiment_id/ study_id,
                  method="REML")
fig11
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.0000  0.0002      3     no           experiment_id
## sigma^2.2  0.6997  0.8365     25     no  experiment_id/study_id
##
## Test for Residual Heterogeneity:
## QE(df = 194) = 3998.6734, p-val < .0001
##
## Test of Moderators (coefficients 2:16):
## QM(df = 15) = 229.1943, p-val < .0001
##
## Model Results:
##
##                     estimate      se      zval    pval     ci.lb     ci.ub
## intrcpt               0.5791  0.8405    0.6890  0.4908   -1.0682    2.2263
## genusChinemys        -0.2572  1.0299   -0.2498  0.8028   -2.2758    1.7613
```

```
## genusClematis       -16.7689  1.4031  -11.9510  <.0001  -19.5189  -14.0188  ***
## genusCoturnix        -0.5885  1.1914   -0.4939  0.6213   -2.9236    1.7466
## genusDrosophila      -0.0185  0.9205   -0.0201  0.9839   -1.8227    1.7856
## genusEscherichia      0.5628  1.0742    0.5240  0.6003   -1.5425    2.6682
## genusGryllus         -0.6144  1.1866   -0.5177  0.6046   -2.9401    1.7114
## genusLeptopilina     -0.0379  0.9245   -0.0410  0.9673   -1.8499    1.7741
## genusLimnodynastes   -1.5778  0.9512   -1.6588  0.0972   -3.4421    0.2865    .
## genusNatrix          -1.6680  1.0373   -1.6080  0.1078   -3.7011    0.3650
## genusPlatyplectrum   -0.0226  0.9615   -0.0235  0.9813   -1.9071    1.8619
## genusPlestiodon      -0.2612  1.1880   -0.2199  0.8260   -2.5897    2.0673
## genusRhodnius        -0.5584  1.0278   -0.5433  0.5870   -2.5728    1.4561
## genusSalmonella       0.4783  1.0678    0.4480  0.6542   -1.6145    2.5712
## genusTrachemys       -1.7031  1.1942   -1.4262  0.1538   -4.0436    0.6375
## genusXylotrechus     -1.6640  1.1876   -1.4012  0.1612   -3.9916    0.6636
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

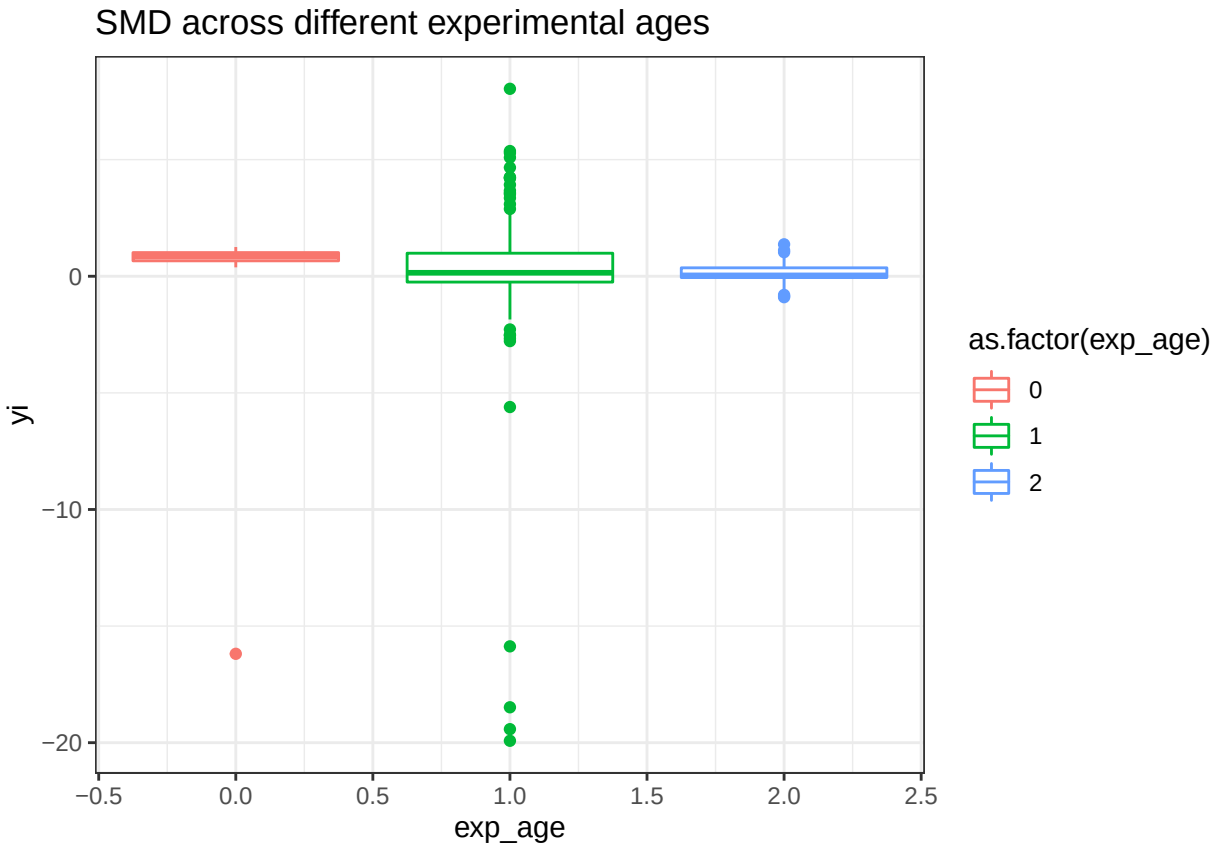
```r
#simple linear model looking at how genus affects yi
simple11<-lm(yi~genus, data =dat_MA_ES)
summary(simple11)
```

```
##
## Call:
## lm(formula = yi ~ genus, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -69.610  -0.326   0.060   0.766  17.544
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.7084     1.5795   0.449  0.65428
## genusChinemys       -0.4605     1.9142  -0.241  0.81015
## genusClematis      -16.8982     6.3179  -2.675  0.00812 **
## genusCoturnix       -0.6892     2.6781  -0.257  0.79718
## genusDrosophila     -0.8597     2.0680  -0.416  0.67807
## genusEscherichia     0.4926     2.3692   0.208  0.83553
## genusGryllus        -0.7449     2.6781  -0.278  0.78121
## genusLeptopilina    -0.7115     2.9549  -0.241  0.80998
## genusLimnodynastes  -3.1279     2.2733  -1.376  0.17042
## genusNatrix         -1.7006     3.1590  -0.538  0.59096
## genusPlatyplectrum   0.3229     2.5793   0.125  0.90049
## genusPlestiodon     -0.3916     2.0895  -0.187  0.85153
## genusRhodnius       -0.6904     1.8654  -0.370  0.71170
## genusSalmonella      0.8706     2.4283   0.359  0.72036
## genusTrachemys      -2.1914     4.6050  -0.476  0.63469
## genusXylotrechus   -14.0034     2.6781  -5.229  4.4e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.117 on 194 degrees of freedom
## Multiple R-squared:  0.1974, Adjusted R-squared:  0.1353
## F-statistic:  3.18 on 15 and 194 DF,  p-value: 0.0001082
```

Question how does scale (life or org level) affect response?

Figure 11.

```
#boxplot
ggplot(normalized, aes(x=exp_age, y=yi, color = as.factor(exp_age)))+
  geom_boxplot()+
  theme_bw()+
  ggtitle("SMD across different experimental ages")
```




```
#random effects model including exp_age as a random variable
fig3 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~exp_age,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig3
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.0000  0.0004      3     no           experiment_id
## sigma^2.2  8.6436  2.9400     25     no  experiment_id/study_id
```

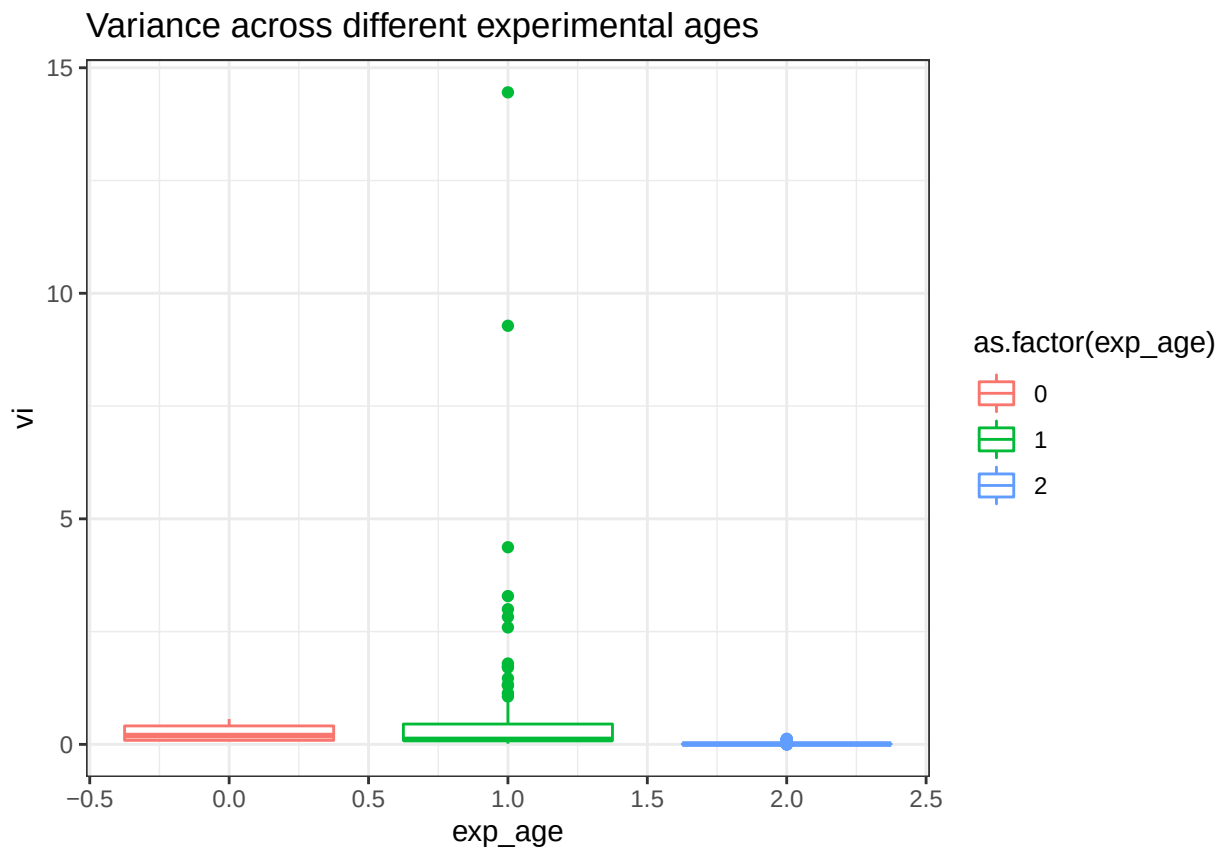
```
##
## Test for Residual Heterogeneity:
## QE(df = 208) = 5631.2445, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 5.6633, p-val = 0.0173
##
## Model Results:
##
##          estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt   -3.6184  1.3989  -2.5866  0.0097  -6.3602  -0.8766  **
## exp_age    2.5946  1.0903   2.3798  0.0173   0.4577   4.7314   *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how exp_age affects yi
simple3<-lm(yi~exp_age, data =dat_MA_ES)
summary(simple3)
```

```
##
## Call:
## lm(formula = yi ~ exp_age, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -82.326   0.071   0.579   1.425   8.617
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.0923     1.1227  -0.973    0.332
## exp_age       0.5134     0.8623   0.595    0.552
##
## Residual standard error: 6.589 on 208 degrees of freedom
## Multiple R-squared:  0.001701,   Adjusted R-squared:  -0.003098
## F-statistic: 0.3545 on 1 and 208 DF,  p-value: 0.5522
```

Figure 12.

```
ggplot(normalized, aes(x=exp_age, y=vi, color = as.factor(exp_age)))+
  geom_boxplot()+
  theme_bw()+
  ggtitle("Variance across different experimental ages")
```




```
count(normalized, exp_age)
```

```
##   exp_age   n
## 1       0  13
## 2       1 136
## 3       2  53
```

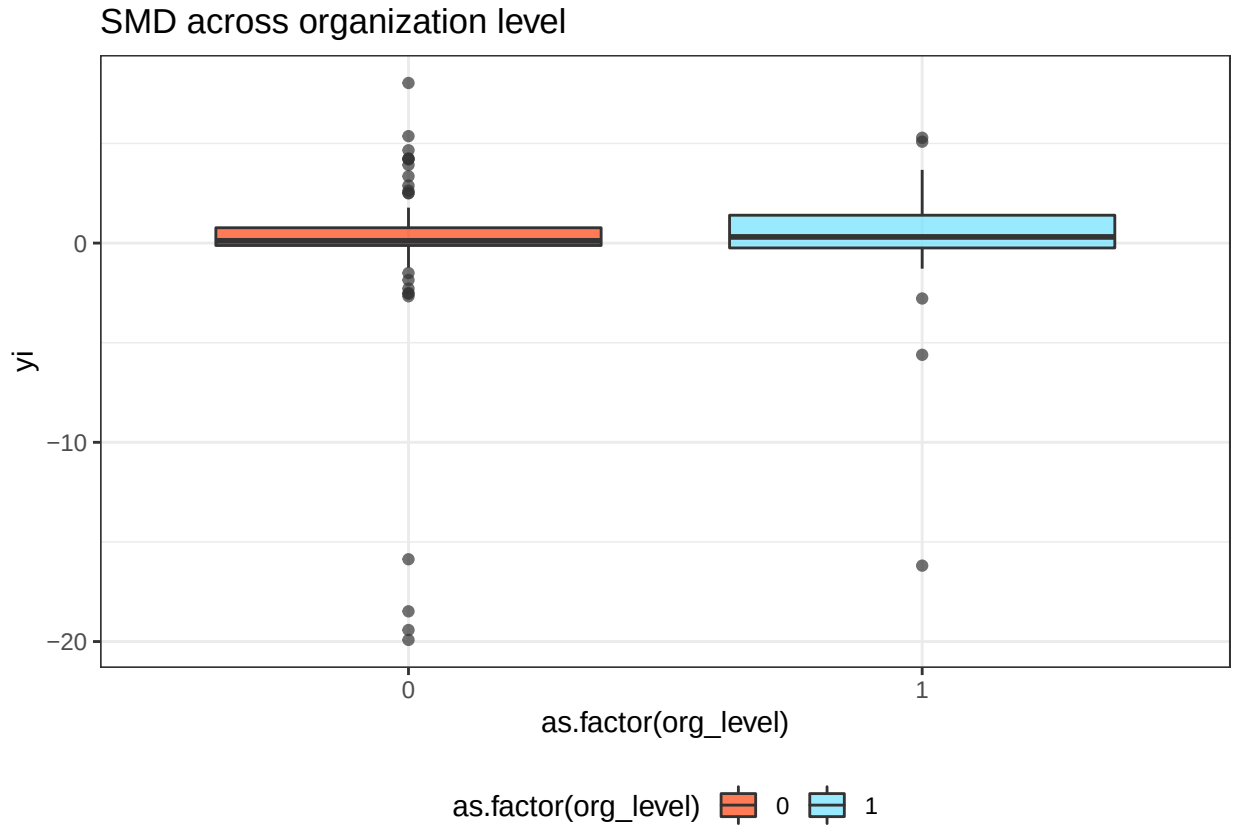
```
#simple linear model looking at how exp_age affects vi
simple4<-lm(vi~ exp_age, data =dat_MA_ES)
summary(simple4)
```

```
##
## Call:
## lm(formula = vi ~ exp_age, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.8121 -0.4538 -0.3402 -0.1517 13.9133
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.8982     0.2648   3.393 0.000829 ***
## exp_age      -0.3565     0.2033  -1.753 0.081083 .
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
##
## Residual standard error: 1.554 on 208 degrees of freedom
## Multiple R-squared:  0.01456,    Adjusted R-squared:  0.009821
## F-statistic: 3.073 on 1 and 208 DF,  p-value: 0.08108
```

Figure 13.

```
#boxplot of SMD across levels of organization
ggplot(normalized, aes(x=as.factor(org_level), y=yi, fill=as.factor(org_level)))+
  geom_boxplot(alpha =0.7)+
  scale_fill_tron()+
  theme_bw()+
  theme(legend.position = "bottom")+
  ggtitle("SMD across organization level")
```




```
#random effects model including org_level as a random variable
fig5 <- rma.mv(yi, vi, data=dat_MA_ES, mods = ~org_level,
               random = ~1 | experiment_id/ study_id,
                 method="REML")
fig5
```

```
##
## Multivariate Meta-Analysis Model (k = 210; method: REML)
```

```
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                 factor
## sigma^2.1  0.0000  0.0001      3     no          experiment_id
## sigma^2.2  9.9527  3.1548     25     no  experiment_id/study_id
##
## Test for Residual Heterogeneity:
## QE(df = 208) = 5704.4015, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 26.9807, p-val < .0001
##
## Model Results:
##
##            estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt     -0.5125  0.6330  -0.8097  0.4181  -1.7531   0.7280
## org_level   -0.4310  0.0830  -5.1943  <.0001  -0.5937  -0.2684  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how org_level affects yi
simple5<-lm(yi~org_level, data =dat_MA_ES)
summary(simple5)
```

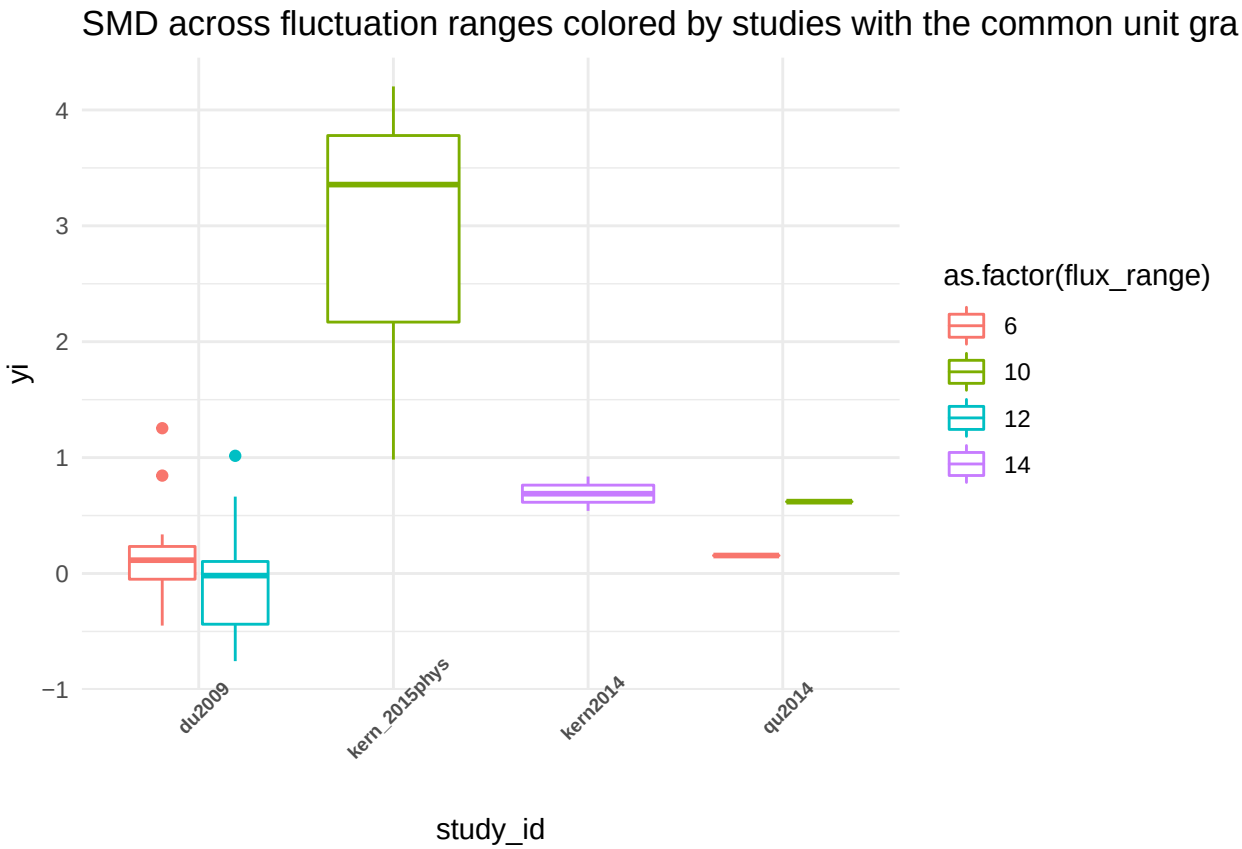
```
##
## Call:
## lm(formula = yi ~ org_level, data = dat_MA_ES)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -82.233   0.152   0.720   1.373   8.710
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.6725     0.5048  -1.332    0.184
## org_level     1.0049     1.1568   0.869    0.386
##
## Residual standard error: 6.582 on 208 degrees of freedom
## Multiple R-squared:  0.003615,   Adjusted R-squared:  -0.001175
## F-statistic: 0.7547 on 1 and 208 DF,  p-value: 0.386
```

Question: How does response variable affect response?

Figure 14.

```
#plot across studies with common response variable body mass
ggplot(common_unit_g, aes(y=yi, color=as.factor(flux_range), x = study_id))+
  geom_boxplot()+
  theme_minimal()+
```

```
  theme(axis.text.x = element_text(face = "bold",
                                   size = 7, angle = 45))+
  ggtitle("SMD across fluctuation ranges colored by studies with the common unit grams")
```




```
#random effects model within subset data
fig14 <- rma.mv(yi, vi, data=common_unit_g,
                random = ~1 | experiment_id/ study_id,
                  method="REML")
fig14
```

```
##
## Multivariate Meta-Analysis Model (k = 31; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed                  factor
## sigma^2.1  0.4301  0.6558      2     no           experiment_id
## sigma^2.2  0.4115  0.6415      5     no  experiment_id/study_id
##
## Test for Heterogeneity:
## Q(df = 30) = 112.7702, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
```

```
##   0.4964  0.5770  0.8603  0.3896  -0.6345  1.6273
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#simple linear model looking at how flux_range affects yi within subset data
simple14<-lm(yi~study_id, data =common_unit_g)
summary(simple14)
```

```
##
## Call:
## lm(formula = yi ~ study_id, data = common_unit_g)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.86411 -0.28023 -0.05915  0.19022  1.35561
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            0.05915    0.13247   0.447    0.659
## study_idkern_2015phys  2.78814    0.39742   7.016 1.53e-07 ***
## study_idkern2014       0.62940    0.47764   1.318    0.199
## study_idqu2014         0.32825    0.47764   0.687    0.498
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.649 on 27 degrees of freedom
## Multiple R-squared:  0.6478, Adjusted R-squared:  0.6087
## F-statistic: 16.56 on 3 and 27 DF,  p-value: 2.655e-06
```