Analysis

An analysis using LiDAR data to detect moose browsing effects, with ground truthing

```r
library(readr)
library(ggplot2)
library(glmmTMB)
```

Get compiled dataset (see compile.R)

```r
dat <- read_csv("../data/compiledDataset.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   locality_and_treatment = col_character(),
##   LocalityCode = col_character(),
##   LocalityName = col_character(),
##   Treatment = col_character(),
##   resolution_m = col_character(),
##   region = col_character()
## )

## See spec(...) for full column specifications.
```

```r
head(dat)
```

```
## # A tibble: 6 x 27
##   locality_and_tr~ LocalityCode LocalityName Treatment Longitude Latitude
##   <chr>            <chr>        <chr>        <chr>         <dbl>    <dbl>
## 1 bratsberg_b      BRB          Bratsberg    B              10.5     63.4
## 2 bratsberg_ub     BRUB         Bratsberg    UB             10.5     63.4
## 3 didrik_holmsen_b DHB          Didrik Holm~ B              11.4     59.9
## 4 didrik_holmsen_~ DHUB         Didrik Holm~ UB             11.4     59.9
## 5 drangedal1_b     1DRB         Drangedal1   B               9.15    59.1
## 6 drangedal1_ub    1DRUB        Drangedal1   UB              9.15    59.1
## # ... with 21 more variables: Clear.cut <dbl>, Year.initiated <dbl>,
## #   LiDAR.data.from.year <dbl>, plot_density_m2 <dbl>, resolution_m <chr>,
## #   region <chr>, Moose2015 <dbl>, Reddeer2015 <dbl>, Roedeer2015 <dbl>,
## #   YrsSinceExclosure <dbl>, field_mean <dbl>, field_median <dbl>, mn <dbl>,
## #   md <dbl>, sd <dbl>, min <dbl>, max <dbl>, first_qu.25. <dbl>,
## #   third_qu.75. <dbl>, mad <dbl>, prod <dbl>
```

A quick data check

```r
table(dat$Treatment, dat$Clear.cut)
```

```
##
##      2000 2002 2003 2004 2005 2006 2007 2008 2009
##   B     1    4    3    7    8    4   10    7    1
##   UB    1    4    3    7    8    4   10    7    1
```

```r
table(dat$Year.initiated, dat$LiDAR.data.from.year)
```

```
##
##        2010 2011 2013 2015 2016 2017 2018 2019
##   2007    0    0    0    0    0    0    0    6
##   2008    4    4    0   18    2    2    0    0
##   2009    0    0    0    0    4   24    0    0
##   2010    0    0    0    0    4    4    4    0
##   2011    0    0    2    0    4    0    0    8
```

```r
table(dat$plot_density_m2, dat$resolution_m)
```

```
##
##     0,25 0,5
##   2    2  54
##   5   32   2
```

Something odd there…

```r
table(dat$region, dat$Treatment)
```

```
##
##              B UB
##   Hedmark   16 16
##   Telemark  14 14
##   Trondelag 15 15
```

```r
table(dat$LocalityName, dat$Treatment)
```

```
##
##                         B UB
##   Bratsberg             1  1
##   Didrik Holmsen        1  1
##   Drangedal1            1  1
##   Drangedal3            1  1
##   Drangedal4            1  1
##   Eidskog               1  1
##   Fet 3                 1  1
##   Fritsoe1              1  1
##   Fritsoe2              1  1
```

```
##   Furesdal              1  1
##   Halvard Pramhus       1  1
##   Hi_tydal              1  1
##   Kongsvinger 1         1  1
##   Kongsvinger 2         1  1
##   Kviteseid1            1  1
##   Kviteseid2            1  1
##   Kviteseid3            1  1
##   Maarud 1              1  1
##   Maarud 2              1  1
##   Maarud 3              1  1
##   Malvik                1  1
##   namdalseid_1kub       1  1
##   Nes 1                 1  1
##   Nes 2                 1  1
##   Nome_Cappelen1        1  1
##   Nome_Cappelen2        1  1
##   Notodden3             1  1
##   Notodden5             1  1
##   Notodden6             1  1
##   Nsb_Verdal            1  1
##   Selbu_Flub            1  1
##   Selbu_kl              1  1
##   Selbu_Sl              1  1
##   Singsaas              1  1
##   Sl_Tydal              1  1
##   Soerum                1  1
##   Stangeskovene Aurskog 1  1
##   Stangeskovene Eidskog 1  1
##   steinkjer_1BBb        1  1
##   steinkjer_2BBb        1  1
##   Stig Dahlen           1  1
##   Sub_Namdalseid        1  1
##   Truls Holm            1  1
##   verdal_1vb            1  1
##   verdal_2VB            1  1
```

Looks good.

Canopy growth per year

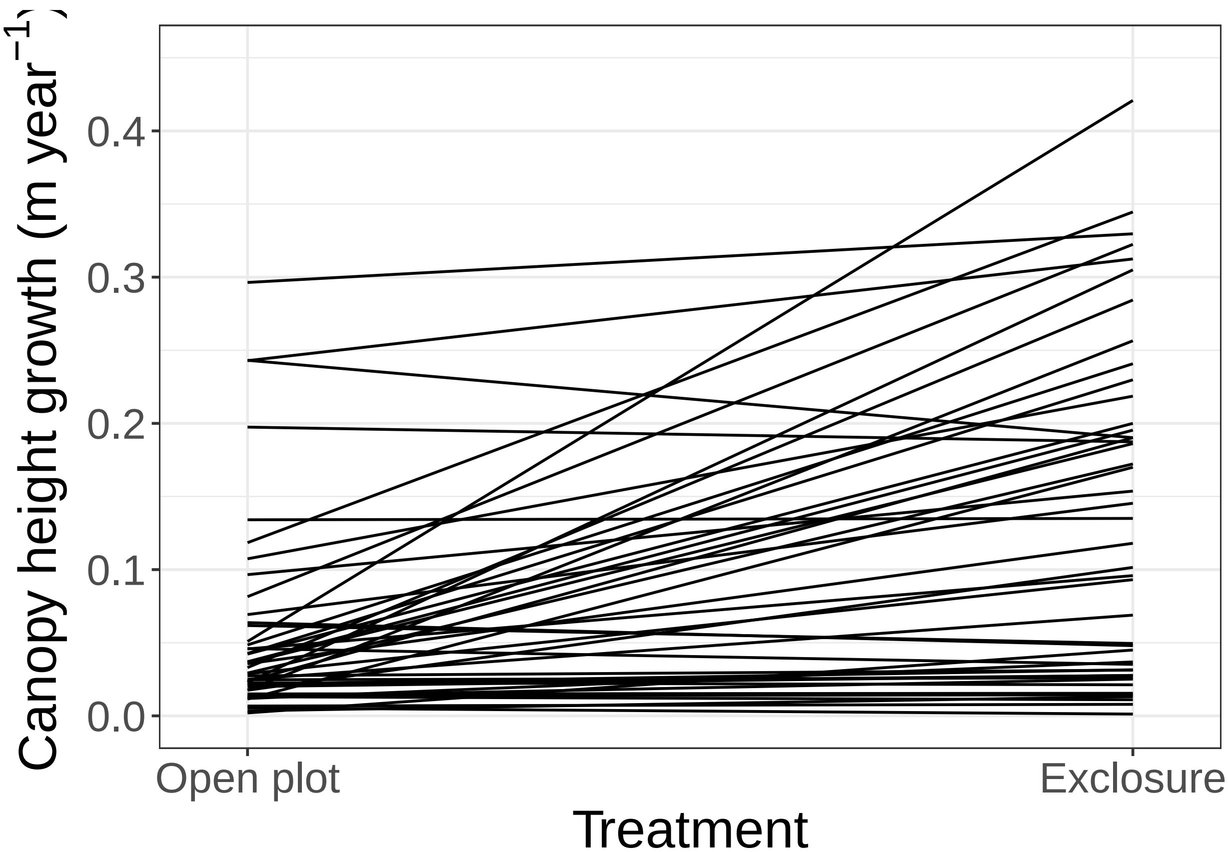
Lets first compute canopy growth per year since exclosure

```r
dat$canopygrowth <- dat$md/dat$YrsSinceExclosure
summary(dat$canopygrowth)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## 0.001214 0.022698 0.045375 0.096275 0.165922 0.420857
```

The numbers are in meters I'm pretty sure

```r
dat$Treatment <- as.factor(dat$Treatment)
levels(dat$Treatment) <- c('Open plot','Exclosure')
(chg_treat <- ggplot(dat, aes(x=Treatment, y=canopygrowth, group=LocalityName))+
  geom_line()+
  labs(y=expression(paste('Canopy height growth (m year'^'-1', ')')), x='Treatment')+
  scale_linetype_manual(breaks = c("Exclosure", "Open plot"),
                        labels = c("Open plots", "Exclosures"), values=c(1,2))+
  scale_x_discrete(limits = c('Open plot', 'Exclosure'),
                   breaks = c('Open plot', 'Exclosure'), expand = c(0.1,0))+
  theme_bw()+
  theme(text = element_text(size = 20))+
  ylim(0, 0.45))
```



Remove sites with top productivity and plot the interaction Treatment X Productivity

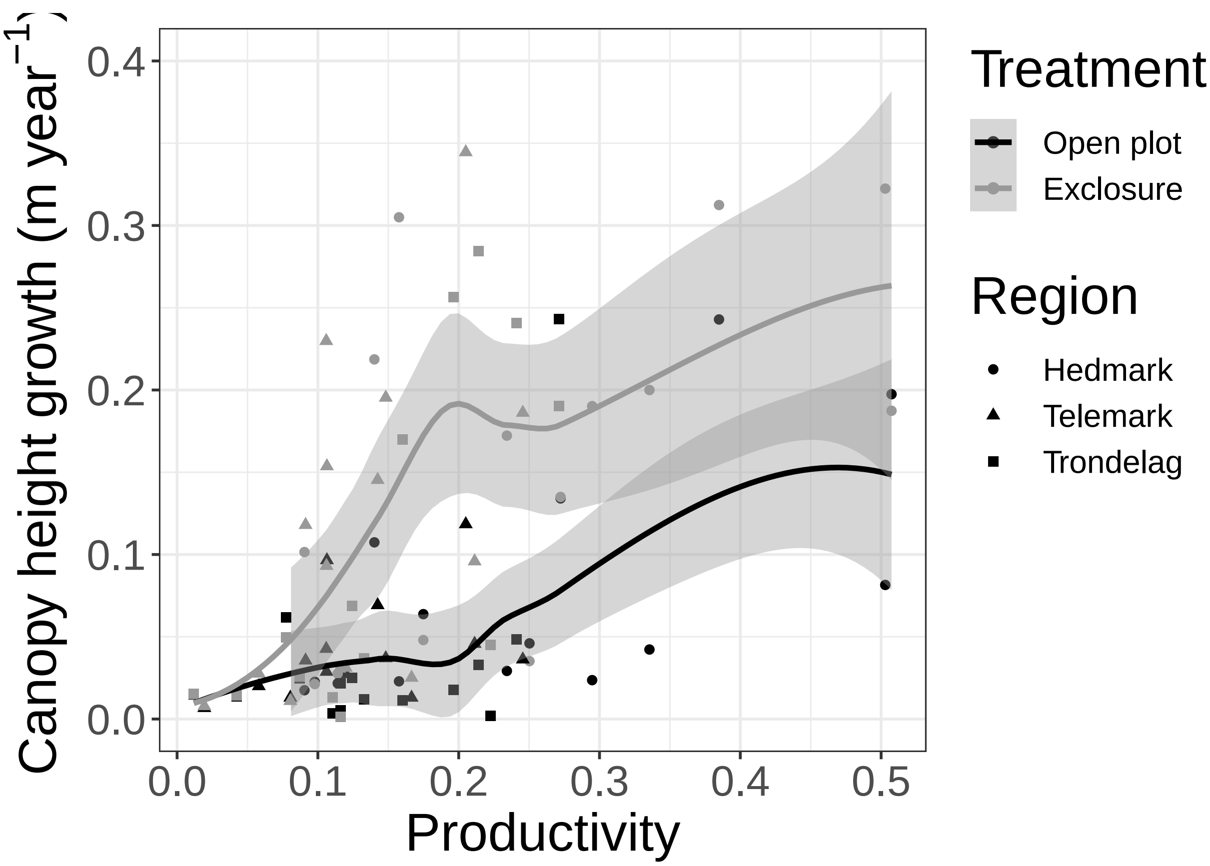
```r
dat2 <- dat[dat$prod<0.8,]
dim(dat2)
```

```
## [1] 86 28
```

Lost 4 rows, i.e two localities

Lets use loess as it makes less assumptions about the shape of the relationship:

```r
(chg_prod <- ggplot(data = dat2,
                    aes(x = prod, y = canopygrowth))+
  geom_point(aes(colour= Treatment, shape=region))+
   geom_smooth(aes(colour= Treatment),
               method = "loess", formula =  'y ~ x')+
  labs(y=expression(paste('Canopy height growth (m year'^'-1', ')')), x='Productivity')+
  theme_bw()+
  scale_color_manual(values = c("gray0", "gray60"))+
  labs(colour="Treatment", shape="Region")+
  theme(text = element_text(size = 20))+
  ylim(0, 0.4)+
  theme(legend.position = 'right',
                              legend.justification = c("left", "top"),
                              legend.box.just = "left",
                              #legend.margin = margin(5, 5, 5, 5),
                              legend.text = element_text(size=12))
)
```



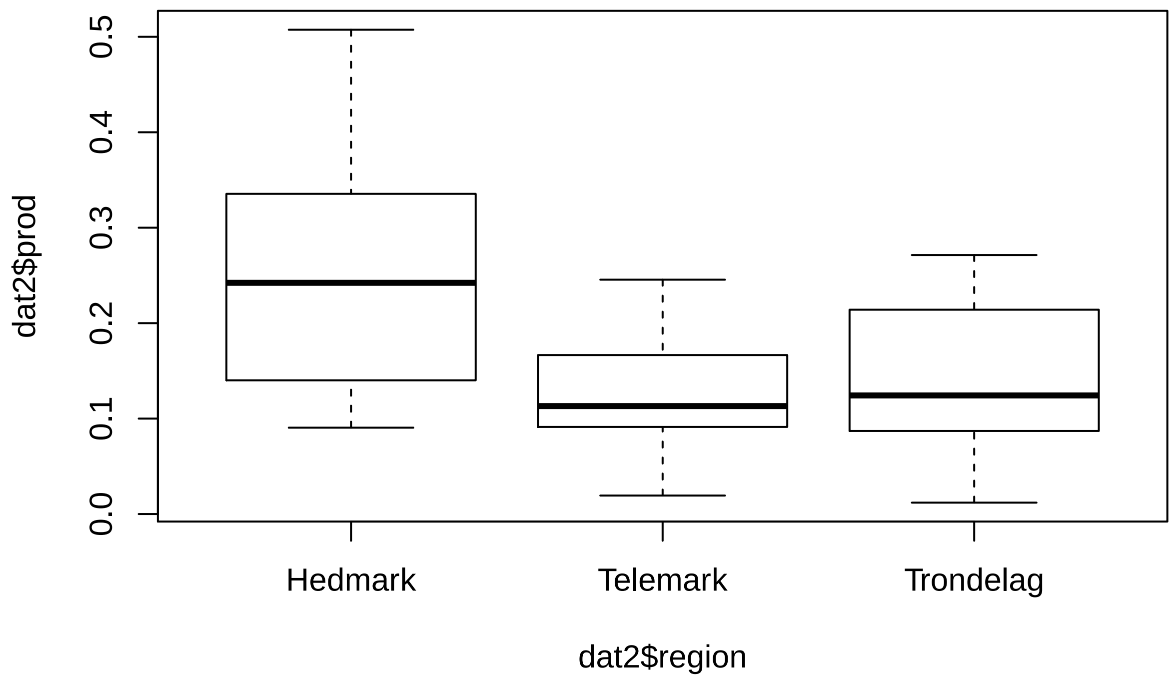
There's a relationship there it seems like, but perhaps not linear. Also note that all the really productive sites are in Hedmark:

```r
table(round(dat$prod, 1), dat$region)
```

```
##
##       Hedmark Telemark Trondelag
##   0         0        2         4
```

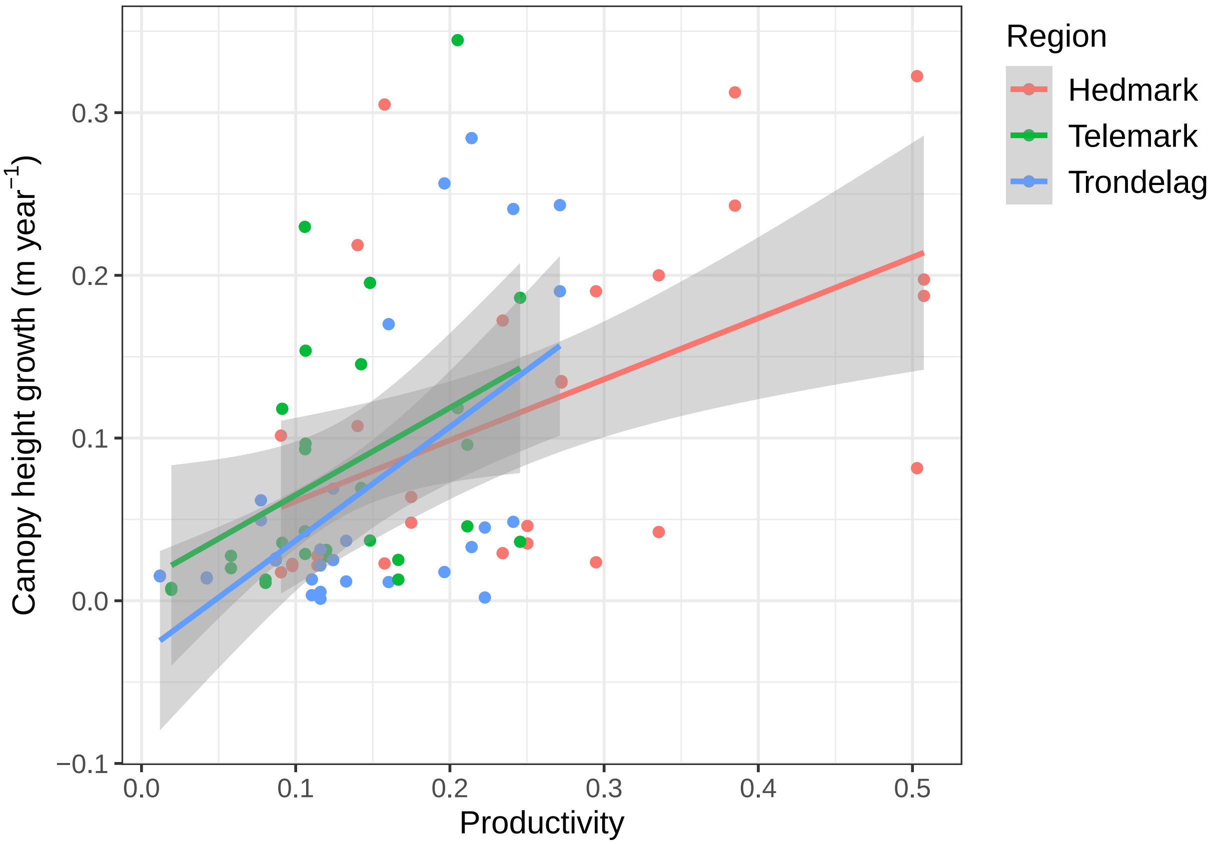
```
##    0.1         8        18         14
##    0.2         6         8         10
##    0.3         8         0          2
##    0.4         2         0          0
##    0.5         4         0          0
##    1           4         0          0
```

```
boxplot(dat2$prod~dat2$region)
```



Lets investigate the effect of region a bit more.

```
ggplot(data = dat2,
  aes(x = prod, y = canopygrowth, colour = region))+
  geom_point()+
  geom_smooth(method = "lm")+
  labs(y=expression(paste('Canopy height growth (m year'^'-1', ')')), x='Productivity')+
  theme_bw()+
  #scale_color_manual(values = c("gray0", "gray50", "grey100"))+
  labs(colour="Region")+
  theme(text = element_text(size = 12))+
  #ylim(0, 0.4)+
  theme(legend.position = 'right',
                             legend.justification = c("left", "top"),
                             legend.box.just = "left",
                             #legend.margin = margin(5, 5, 5, 5),
                             legend.text = element_text(size=12))
```



This plot tells us there is no justification for a random slope model.

Let's get some summary stats.

```
m <- tapply(dat2$canopygrowth, dat2$Treatment, FUN = mean)
# And standard error:
source('se.R')
s <- tapply(dat2$canopygrowth, dat2$Treatment, FUN = se)
(sumStats <- data.frame("mean canopy growth per year" = round(m, 3),
                        "standard error of the mean" = round(s, 3)))
```

```
##            mean.canopy.growth.per.year standard.error.of.the.mean
## Open plot                        0.051                      0.009
## Exclosure                        0.125                      0.016
```

We need a model to describe the interaction between treatment and productivity. The response is continous and both positive and negative variable can occur, so a gaussian familiy would be appropriate.

```
library(glmmTMB) # using this package even though I dont need all its finesse...
dat2$region <- as.factor(dat2$region)
mod1 <- glmmTMB(canopygrowth ~ Treatment * prod + (1|region),
  data = dat2,  family = gaussian)
```

```
mod2 <- glmmTMB(canopygrowth ~ Treatment * prod ,
  data = dat2,  family = gaussian)
```

```r
AIC(mod1, mod2)
```

```
##      df       AIC
## mod1  6 -211.5329
## mod2  5 -213.5329
```

Model 2 is slightly better, suggesting we drop the random intercept. What does ANOVA say about this?

```r
anova(mod1, mod2)
```

```
## Data: dat2
## Models:
## mod2: canopygrowth ~ Treatment * prod, zi=~0, disp=~1
## mod1: canopygrowth ~ Treatment * prod + (1 | region), zi=~0, disp=~1
##      Df     AIC     BIC logLik deviance Chisq Chi Df Pr(>Chisq)
## mod2  5 -213.53 -201.26 111.77  -223.53
## mod1  6 -211.53 -196.81 111.77  -223.53     0      1          1
```

They are not different, so we can drop the random intercept. The only reason for keeping it is if we want to argue it's part of the design, which it is. However, I don't think that's more important than having a parsimoinous model.

```r
summary(mod2)
```

```
##  Family: gaussian  ( identity )
## Formula:          canopygrowth ~ Treatment * prod
## Data: dat2
##
##      AIC      BIC   logLik deviance df.resid
##   -213.5   -201.3    111.8   -223.5       81
##
##
## Dispersion estimate for gaussian family (sigma^2): 0.00435
##
## Conditional model:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -0.003533   0.018914  -0.187 0.851835
## TreatmentExclosure      0.029838   0.026749   1.115 0.264644
## prod                    0.311650   0.091980   3.388 0.000703 ***
## TreatmentExclosure:prod  0.256527   0.130079   1.972 0.048601 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

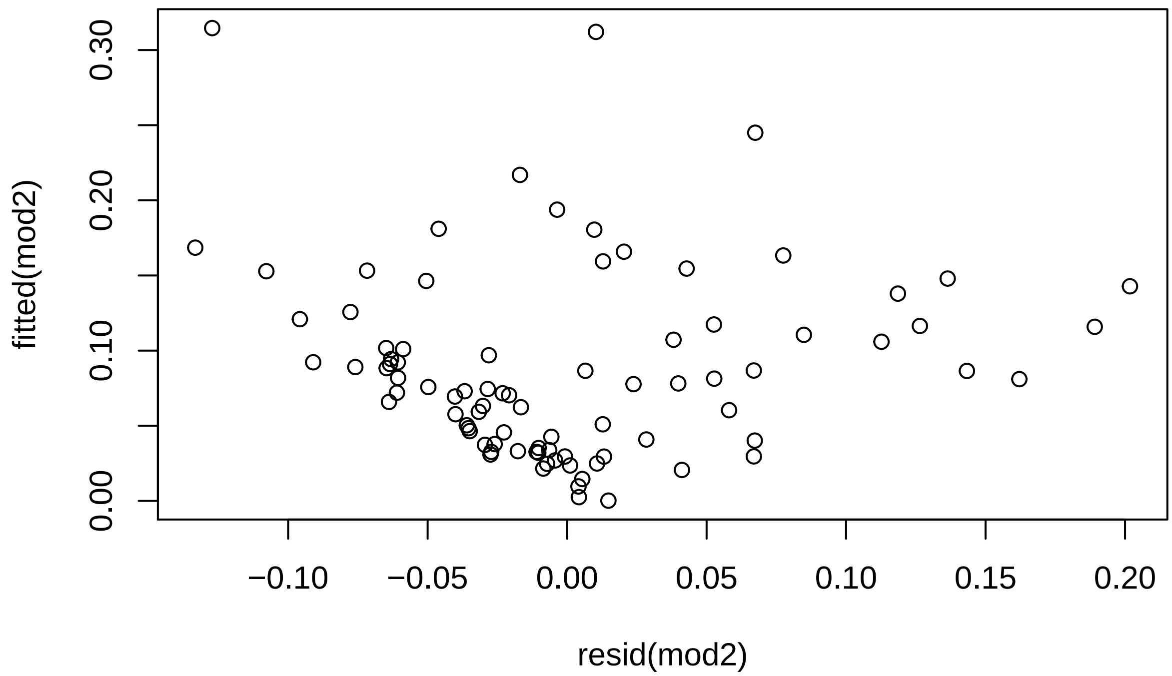
Significant interaction term, so we're keeping this full model. We can also see what the random effect would've give us:

```r
ranef(mod1)
```

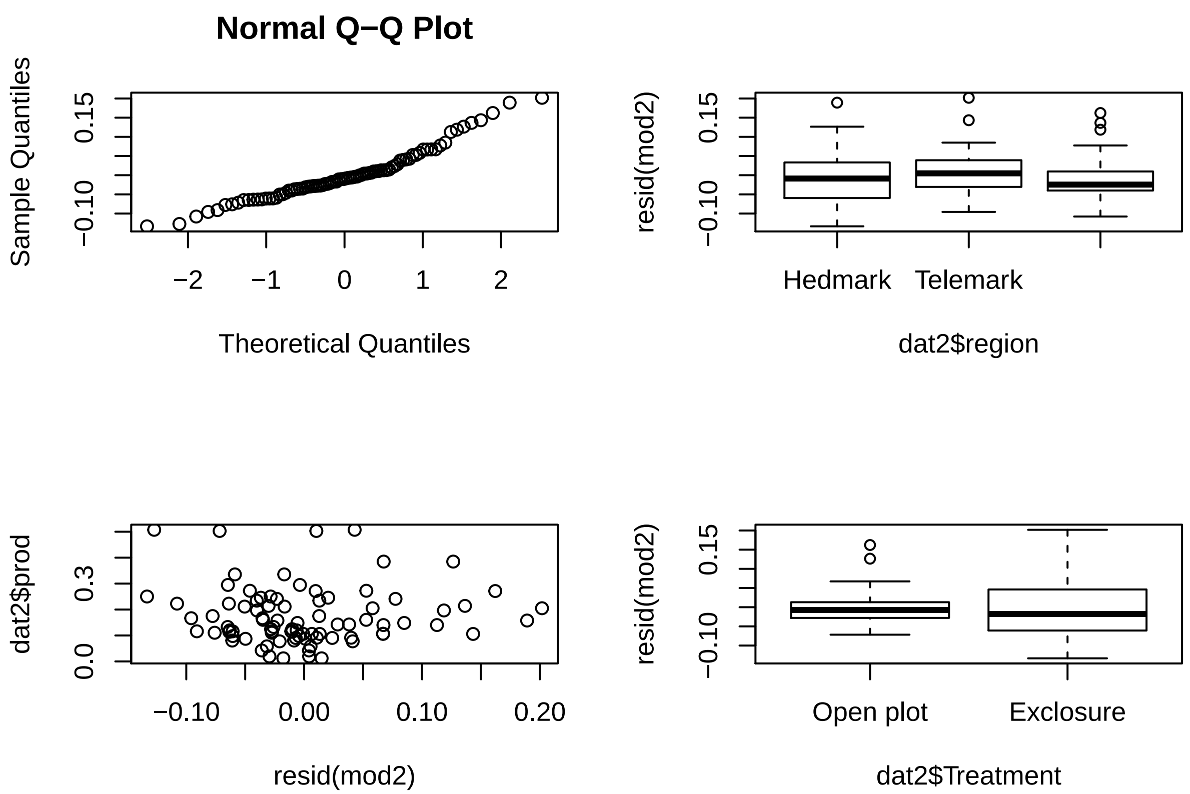
```
## $region
##             (Intercept)
## Hedmark   -6.689350e-11
## Telemark   1.955132e-10
## Trondelag -1.286198e-10
```

, and it's not very much.

```r
plot(resid(mod2), fitted(mod2))
```

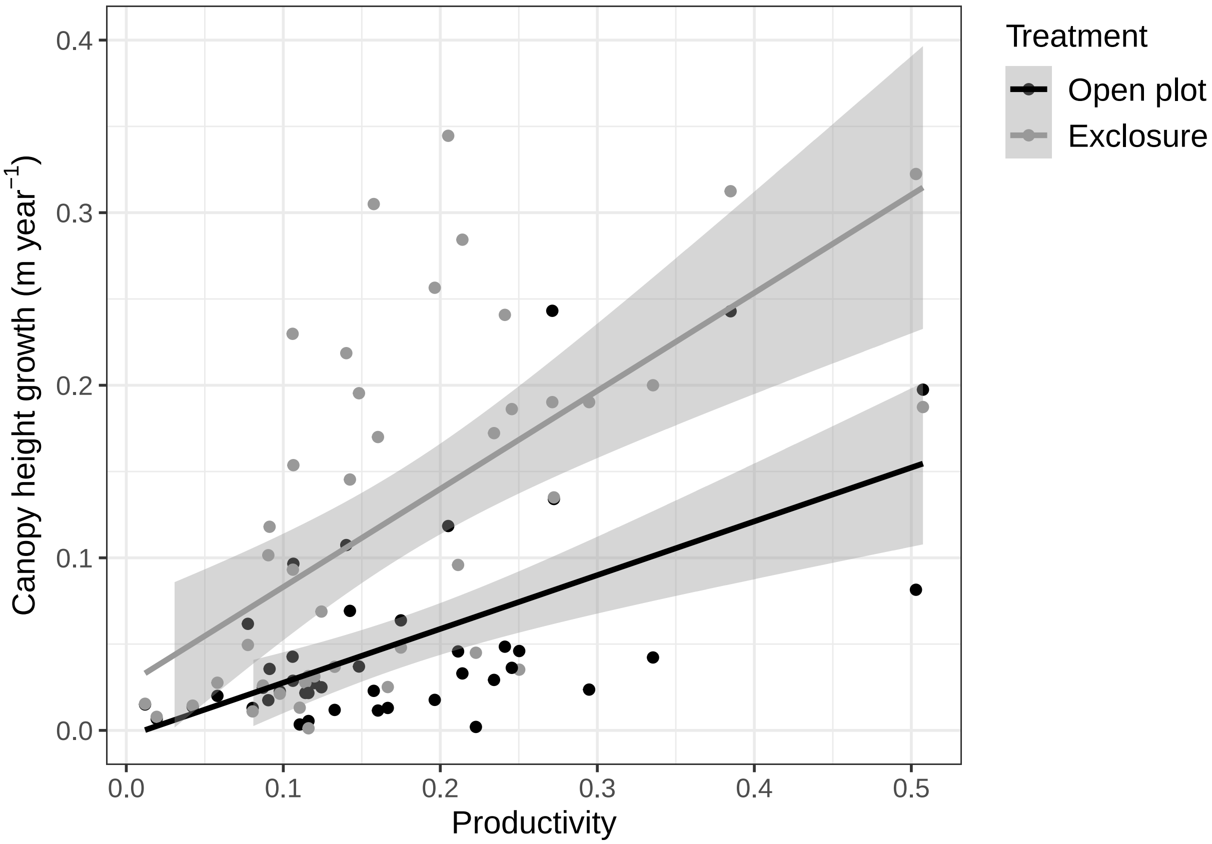



```r
par(mfrow=c(2,2))
qqnorm(resid(mod2))
plot(resid(mod2)~ dat2$region)
plot(resid(mod2), dat2$prod)
plot(resid(mod2)~ dat2$Treatment)
```



Looks like everything is in order.

```
(intPlot <- ggplot(data = dat2,
                        aes(x = prod, y = canopygrowth, colour= Treatment))+
  geom_point()+
   geom_smooth(method = "lm")+
  labs(y=expression(paste('Canopy height growth (m year'^'-1', ')')), x='Productivity')+
  theme_bw()+
  scale_color_manual(values = c("gray0", "gray60"))+
  labs(colour="Treatment")+
  theme(text = element_text(size = 12))+
  ylim(0, 0.4)+
  theme(legend.position = 'right',
                             legend.justification = c("left", "top"),
                             legend.box.just = "left",
                             #legend.margin = margin(5, 5, 5, 5),
                             legend.text = element_text(size=12))
)
```



So here we're modelling a linear function of productivity. We could try adding a quadratic term.

```
mod3 <- glmmTMB(canopygrowth ~ Treatment * prod + I(prod^2),
  data = dat2,  family = gaussian)
```

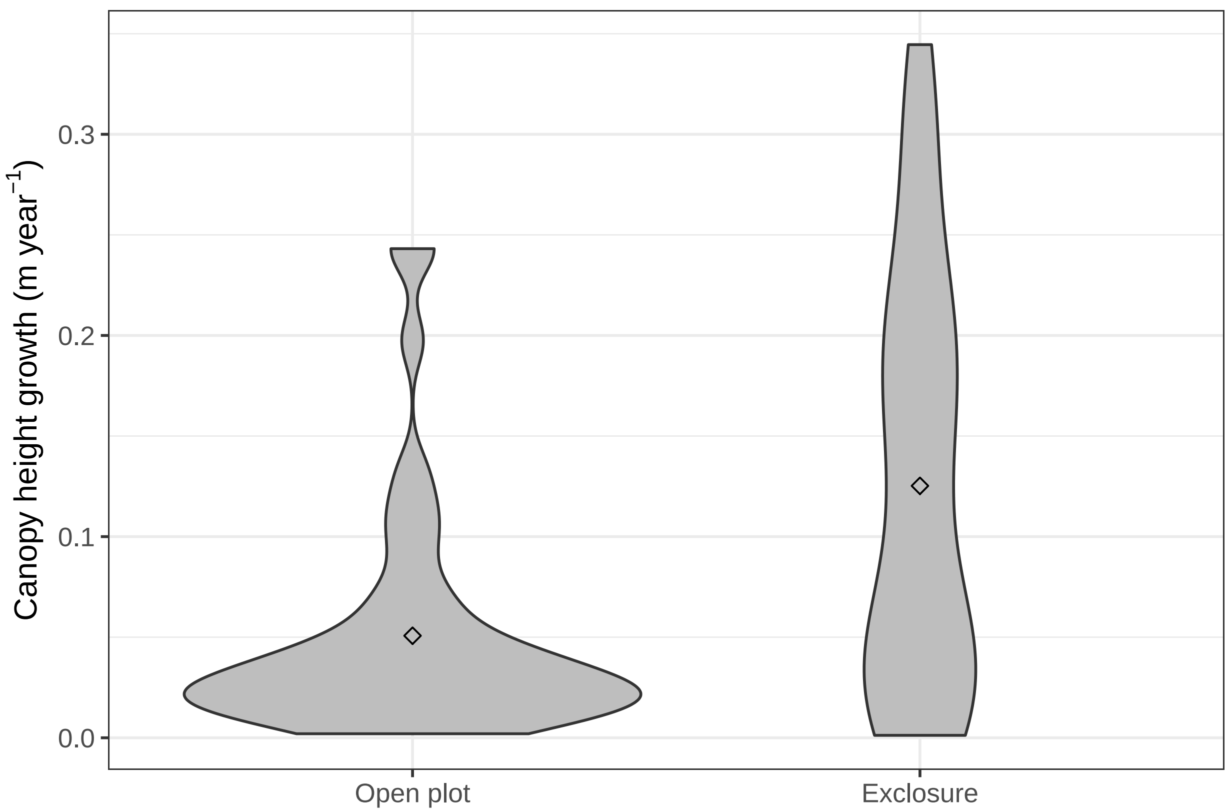
```
AIC(mod2, mod3)
```

```
##      df       AIC
## mod2  5 -213.5329
## mod3  6 -212.8157
```

This gave no improvement.

We can also make these nice violin plots, even though the main pot should show the interaction effect like the plot above does.

```
(viol <- ggplot(data = dat2, aes(x = Treatment, y = canopygrowth))+
  geom_violin(fill = "grey")+
  theme_bw()+
  theme(text = element_text(size = 12))+
  labs(y=expression(paste('Canopy height growth (m year'^'-1', ')')), x='')+
  stat_summary(fun.y=mean, geom="point", shape=23, size=2))
```



Compare LiDAR and field data

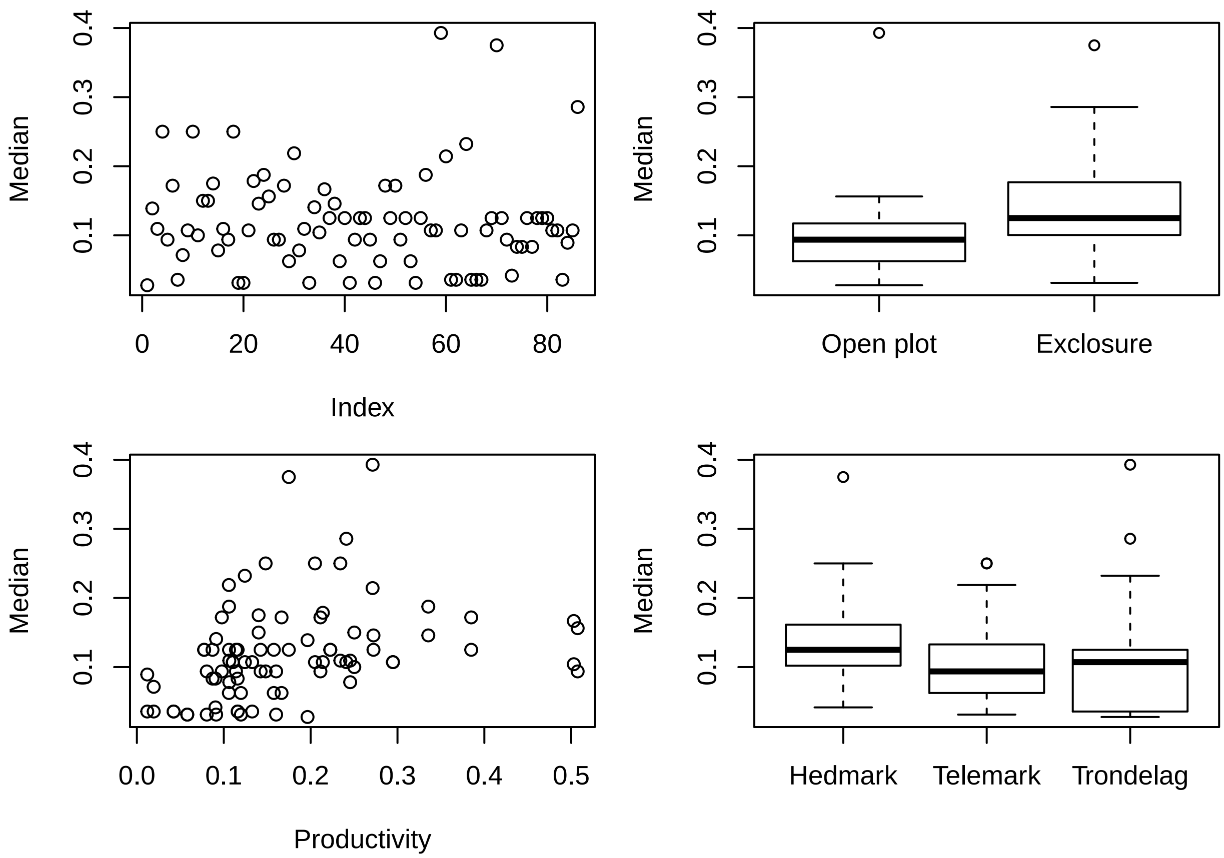
First, let's calculate canopy growth as we did for the LiDAR data

```
dat2$canopygrowth_f <- dat2$field_median/dat2$YrsSinceExclosure
```

```
summary(dat2$canopygrowth_f)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.02778 0.07943 0.10714 0.11947 0.14583 0.39286
```

```
par(mfrow=c(2,2), mar=c(4,4,1,1))
plot(dat2$canopygrowth_f, ylab="Median")
plot(dat2$canopygrowth_f~dat2$Treatment, xlab="", ylab="Median")
plot(dat2$canopygrowth_f~dat2$prod, xlab="Productivity", ylab="Median")
plot(dat2$canopygrowth_f~dat2$region, xlab="", ylab="Median")
```



Appears the annual median tree growth of a site (median of the median of a circle) is around 0.1, or precisely:

```
median(dat2$canopygrowth_f)
```

```
## [1] 0.1071429
```

Also, it is greater in exclosures and increases with productivity, and is highest in Hedmark. Very similar to the LiDAR data.

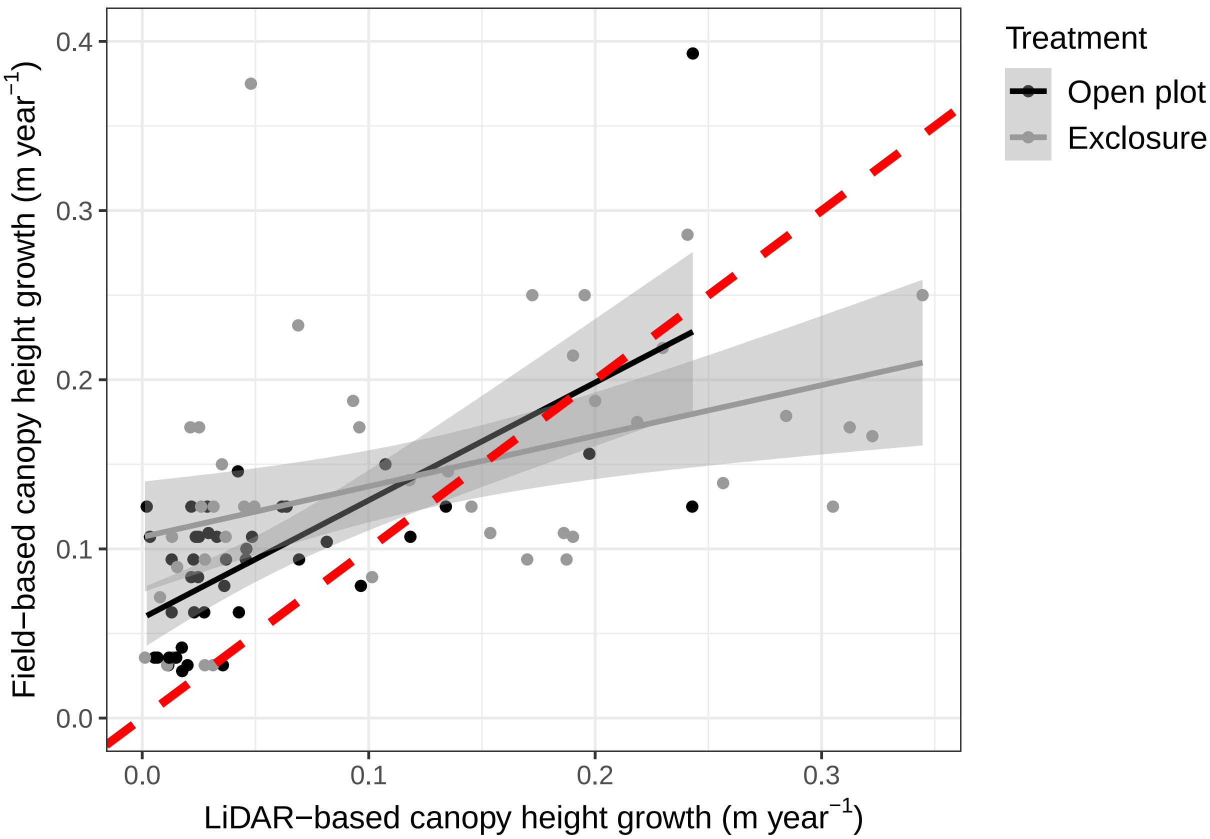
```
m2 <- tapply(dat2$canopygrowth_f, dat2$Treatment, FUN = mean)
s2 <- tapply(dat2$canopygrowth_f, dat2$Treatment, FUN = se)
(sumStats <- data.frame("mean canopy growth per year" = round(m2, 3),
                        "standard error of the mean" = round(s2, 3)))
```

```
##            mean.canopy.growth.per.year standard.error.of.the.mean
## Open plot                        0.094                      0.009
## Exclosure                        0.145                      0.011
```

We don't want to analyse the field data alone, or by itself. That we have done in other papers and with more data. Here we are only interested in 'ground-truthing' the LiDAR data. So..:

```
(corPlot <- ggplot(data = dat2,
                   aes(x = canopygrowth, y = canopygrowth_f, colour= Treatment))+
  geom_point()+
```

```
  geom_smooth(method = "lm")+
  labs(y=expression(paste('Field-based canopy height growth (m year'^'-1', ')')), x=expression(paste('Li
  theme_bw()+
  scale_color_manual(values = c("gray0", "gray60"))+
  labs(colour="Treatment")+
  theme(text = element_text(size = 12))+
  ylim(0, 0.4)+
  theme(legend.position = 'right',
                           legend.justification = c("left", "top"),
                           legend.box.just = "left",
                           #legend.margin = margin(5, 5, 5, 5),
                           legend.text = element_text(size=12))+
   geom_abline(intercept = 0, slope = 1, color="red",
              linetype="dashed", size=1.5)
)
```

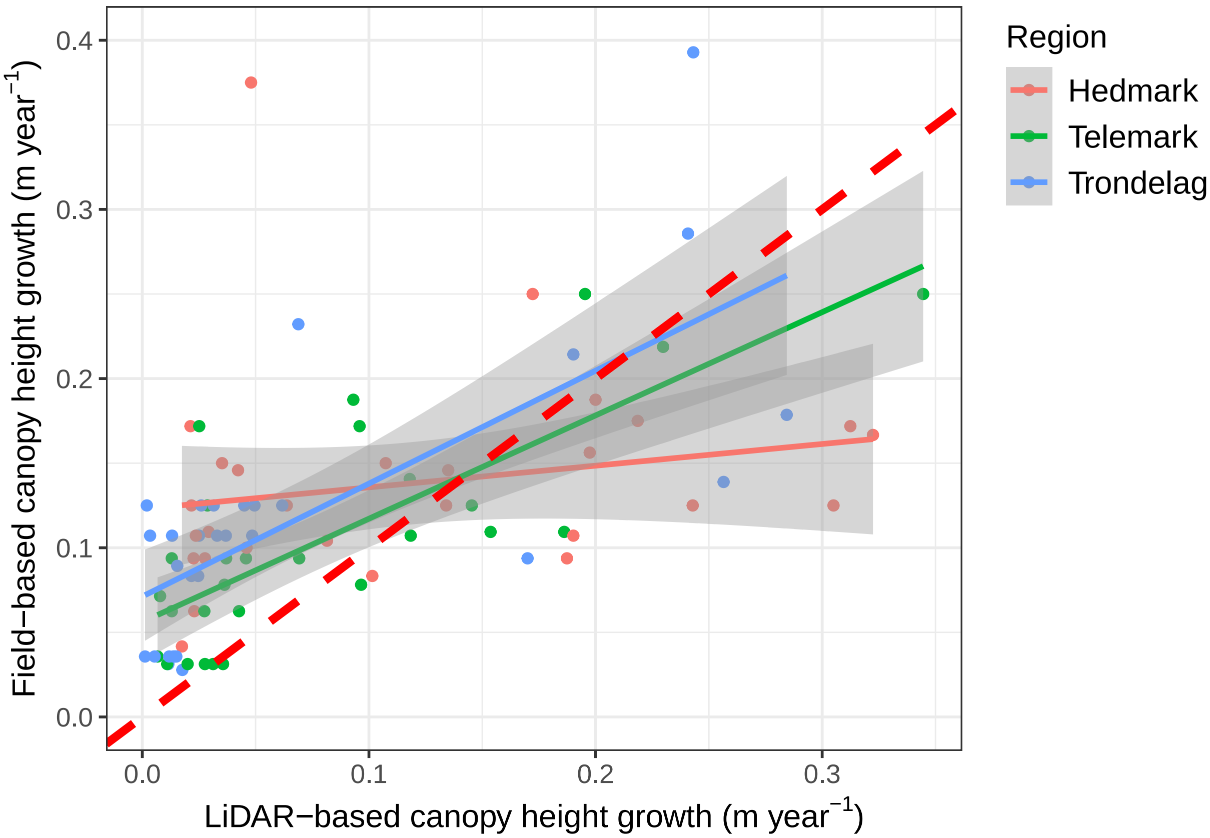


Perhaps the correation strength differes between treatment, but not very much.

```
ggplot(data = dat2,
                    aes(x = canopygrowth, y = canopygrowth_f, colour= region))+
  geom_point()+
   geom_smooth(method = "lm")+
  labs(y=expression(paste('Field-based canopy height growth (m year'^'-1', ')')), x=expression(paste('Li
  theme_bw()+

  labs(colour="Region")+
```

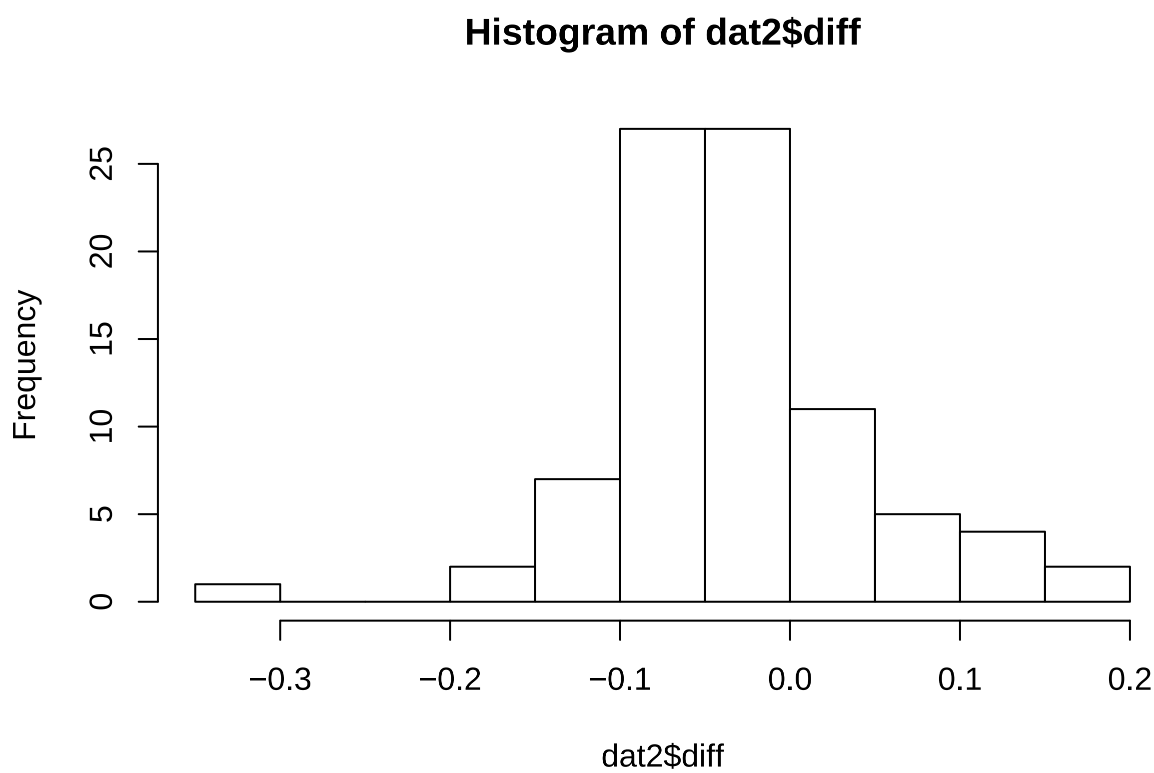
```
  theme(text = element_text(size = 12))+
  ylim(0, 0.4)+
  theme(legend.position = 'right',
                                legend.justification = c("left", "top"),
                                legend.box.just = "left",
                                #legend.margin = margin(5, 5, 5, 5),
                                legend.text = element_text(size=12))+
   geom_abline(intercept = 0, slope = 1, color="red",
                   linetype="dashed", size=1.5)
```



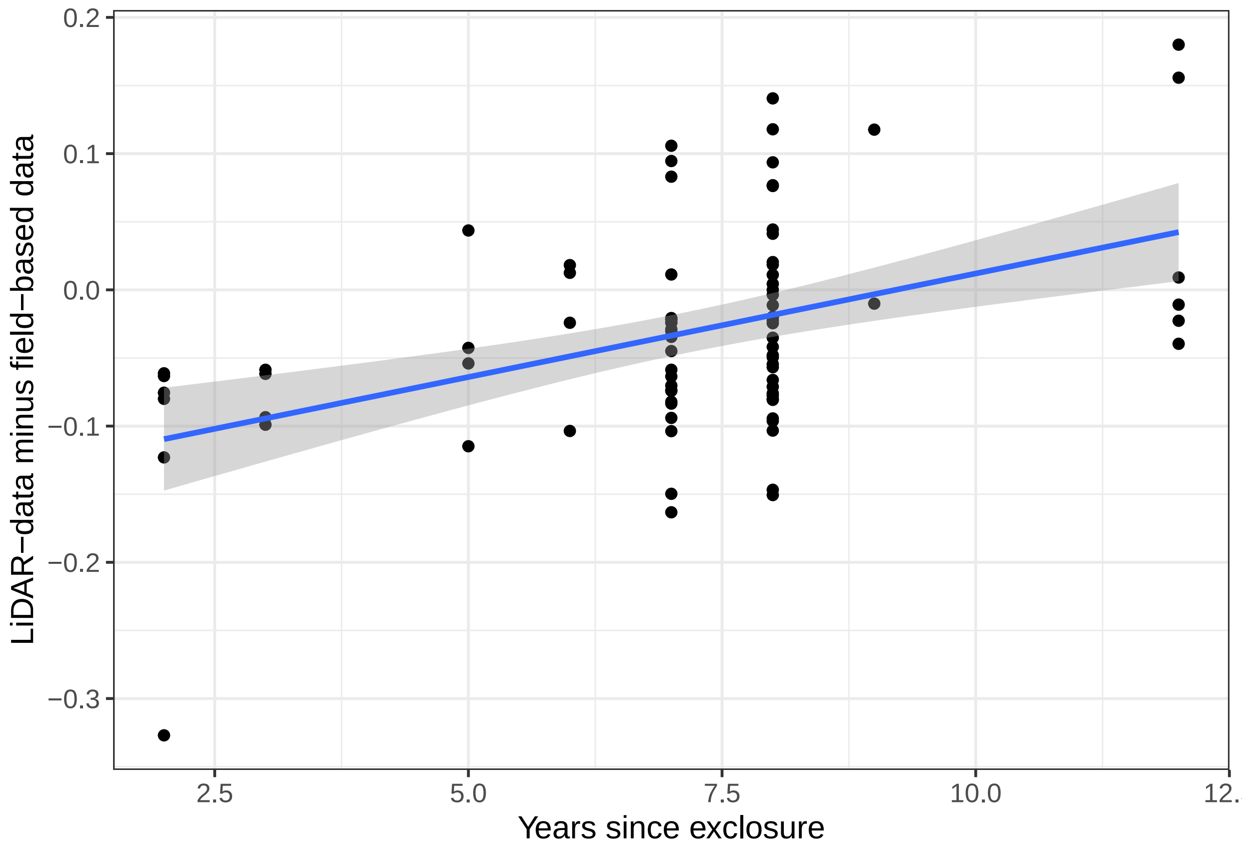
Also it differs a bit between region.

Also, we can look at the effect that experimental duratio has had on the correlation:

```
dat2$diff <- dat2$canopygrowth-dat2$canopygrowth_f
hist(dat2$diff)
```




```
ggplot(data = dat2,
        aes(x = YrsSinceExclosure, y = diff))+
  geom_point()+
  geom_smooth(method = "lm")+
  labs(y="LiDAR-data minus field-based data",
         x="Years since exclosure")+
  theme_bw()+
  theme(text = element_text(size = 12))+
  #ylim(0, 0.4)+
  theme(legend.position = 'right',
                            legend.justification = c("left", "top"),
                            legend.box.just = "left",
                            #legend.margin = margin(5, 5, 5, 5),
                            legend.text = element_text(size=12))+
   geom_abline(intercept = 0, slope = 1, color="red",
                linetype="dashed", size=1.5)
```



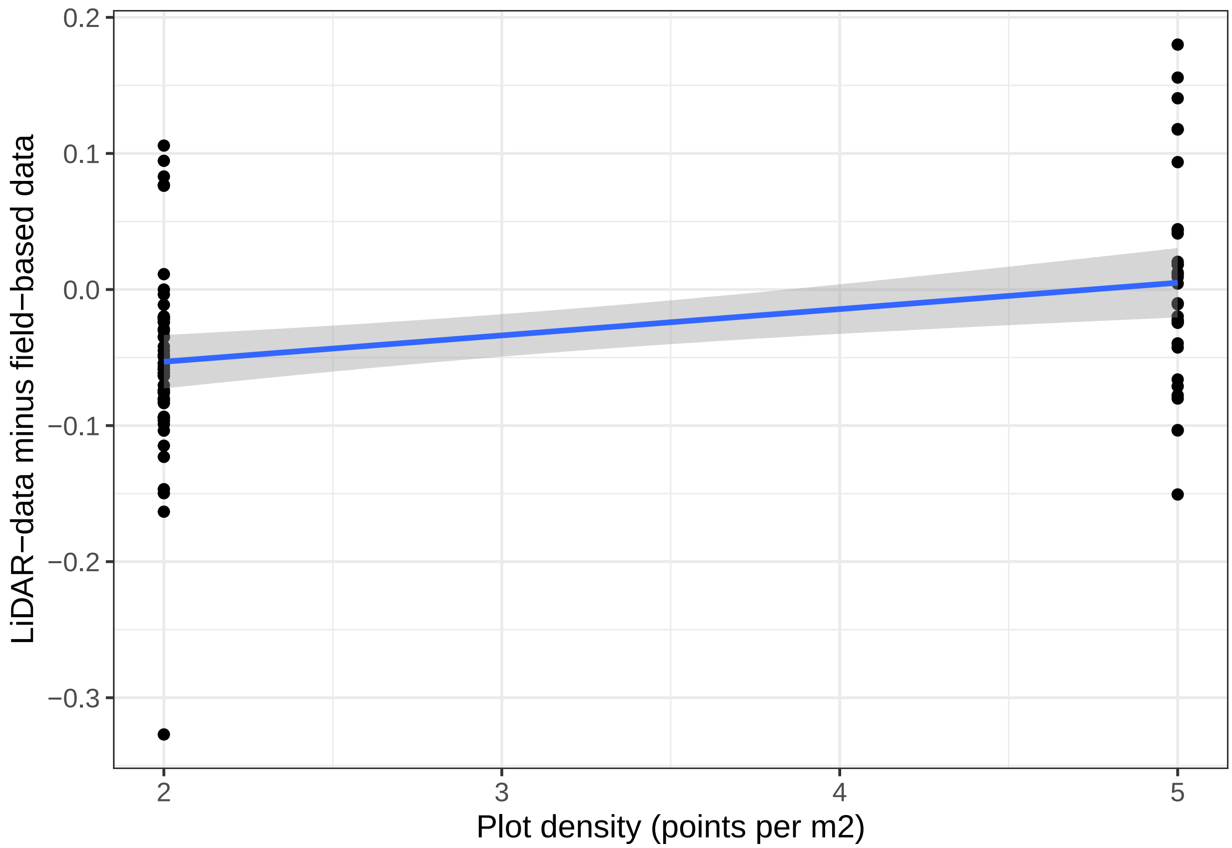
It looks like older difference between LiDAR and field-based data.

I would like to see if the correlation depends on LiDAR resolution, but then we should figure out what this is about:

```
table(dat2$plot_density_m2, dat2$resolution_m)
```

```
##
##      0,25 0,5
##   2     2  52
##   5    30   2
```

It's not clear which is derived from which, but I think its plot density that is the original.



No big difference.

Note that we are not seein if the slope is close to 1 or not. We assume it will be. It's correlation strength that matters.

```
cor(dat2$canopygrowth, dat2$canopygrowth_f)
```

```
## [1] 0.5693676
```

And it's not very high. We can use a more sophisticated model to see where the field-based data is better or worse at predicting LiDAR results.

```
moddiff <- glmmTMB(canopygrowth~canopygrowth_f
                   +region+canopygrowth_f:region
                   +YrsSinceExclosure+YrsSinceExclosure:canopygrowth_f
                   +plot_density_m2+plot_density_m2:canopygrowth_f
                   +Treatment+Treatment:canopygrowth_f,
                   family=gaussian,
                   data=dat2)
summary(moddiff)
```

```
##  Family: gaussian  ( identity )
## Formula:
## canopygrowth ~ canopygrowth_f + region + canopygrowth_f:region +
##     YrsSinceExclosure + YrsSinceExclosure:canopygrowth_f + plot_density_m2 +
##     plot_density_m2:canopygrowth_f + Treatment + Treatment:canopygrowth_f
```

```
## Data: dat2
##
##      AIC      BIC   logLik deviance df.resid
##   -216.8   -184.9    121.4   -242.8       73
##
##
## Dispersion estimate for gaussian family (sigma^2): 0.00348
##
## Conditional model:
##                                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         0.028696   0.067070   0.428    0.669
## canopygrowth_f                     -0.501168   0.437962  -1.144    0.252
## regionTelemark                     -0.021372   0.050695  -0.422    0.673
## regionTrondelag                    -0.027782   0.052147  -0.533    0.594
## YrsSinceExclosure                  -0.004944   0.010008  -0.494    0.621
## plot_density_m2                     0.004487   0.014719   0.305    0.760
## TreatmentExclosure                  0.021574   0.029502   0.731    0.465
## canopygrowth_f:regionTelemark       0.166680   0.400241   0.416    0.677
## canopygrowth_f:regionTrondelag      0.245282   0.404599   0.606    0.544
## canopygrowth_f:YrsSinceExclosure    0.109693   0.076821   1.428    0.153
## canopygrowth_f:plot_density_m2      0.077693   0.121632   0.639    0.523
## canopygrowth_f:TreatmentExclosure   0.141096   0.233017   0.606    0.545
```

Nothing significant. Applying dredge:

```r
library(MuMIn)
dredge(moddiff, beta="none", rank = "AICc")
```

```
## Fixed terms are "cond((Int))" and "disp((Int))"
```

```
## Global model call: glmmTMB(formula = canopygrowth ~ canopygrowth_f + region + canopygrowth_f:region +
##     YrsSinceExclosure + YrsSinceExclosure:canopygrowth_f + plot_density_m2 +
##     plot_density_m2:canopygrowth_f + Treatment + Treatment:canopygrowth_f,
##     data = dat2, family = gaussian, ziformula = ~0, dispformula = ~1)
## ---
## Model selection table
##     cnd((Int)) dsp((Int)) cnd(cnp_f) cnd(plt_dns_m2) cnd(rgn) cnd(Trt)
## 284  0.0023810          +   -0.25930       0.0132300                 +
## 412  0.0120600          +   -0.34500       0.0132000                 +
## 316  0.0069280          +   -0.29720       0.0097240                 +
## 282  0.0143100          +   -0.23430                                 +
## 444  0.0157800          +   -0.37570       0.0099600                 +
## 288  0.0019960          +   -0.25810       0.0131900        +        +
## 276  0.0154100          +   -0.21890       0.0126900
## 308  0.0258100          +   -0.31440       0.0041080
## 410  0.0248900          +   -0.32840                                 +
## 286  0.0490300          +   -0.32760                        +        +
## 416  0.0127300          +   -0.34760       0.0130200        +        +
## 28  -0.1254000          +    0.66090       0.0133100                 +
## 320  0.0042720          +   -0.29230       0.0098010        +        +
## 60  -0.0913100          +    0.39650       0.0003423                 +
## 274  0.0263900          +   -0.19630
## 414  0.0623100          +   -0.44350                        +        +
```

```
## 156 -0.1305000          +    0.71430       0.0133400                   +
## 280  0.0104300          +   -0.20820       0.0132600          +
## 448  0.0141100          +   -0.37280       0.0099740          +        +
## 352  0.0023030          +   -0.25990       0.0132000          +        +
## 188 -0.0963300          +    0.44790       0.0004675                   +
## 26  -0.1139000          +    0.69000                                  +
## 312  0.0156200          +   -0.29840       0.0046700          +
## 278  0.0577500          +   -0.27790                          +
## 32  -0.1396000          +    0.66930       0.0150800          +        +
## 128 -0.0150200          +   -0.22430      -0.0066400          +        +
## 52  -0.0729000          +    0.38360      -0.0053750
## 350  0.0488400          +   -0.32790                          +        +
## 64  -0.1080000          +    0.38900       0.0019180          +        +
## 384  0.0089170          +   -0.33540       0.0059390          +        +
## 480  0.0178600          +   -0.38730       0.0130500          +        +
## 20  -0.1200000          +    0.76830       0.0127300
## 12  -0.0691400          +    0.60820       0.0200400                   +
## 154 -0.1186000          +    0.73910                                  +
## 96  -0.0886500          +    0.36830       0.0148200          +        +
## 160 -0.1447000          +    0.72150       0.0151700          +        +
## 256  0.0042250          +   -0.38600      -0.0081080          +        +
## 44  -0.0347000          +    0.34000       0.0068610                   +
## 478  0.0669800          +   -0.48090                          +        +
## 344  0.0079830          +   -0.19860       0.0131300          +
## 30  -0.0963700          +    0.66200                          +        +
## 192 -0.1130000          +    0.43950       0.0020680          +        +
## 512  0.0287000          +   -0.50120       0.0044870          +        +
## 112  0.0487800          +   -0.39710      -0.0034510          +        +
## 140 -0.0742200          +    0.66110       0.0200700                   +
## 120 -0.0043950          +   -0.22100      -0.0111400          +
## 56  -0.0953200          +    0.37400      -0.0030300          +
## 18  -0.1092000          +    0.79260
## 342  0.0542400          +   -0.26640                          +
## 224 -0.0867100          +    0.35180       0.0148000          +        +
## 172 -0.0396500          +    0.39070       0.0069860                   +
## 94  -0.0449900          +    0.35430                          +        +
## 376  0.0188000          +   -0.32810       0.0009479          +
## 24  -0.1391000          +    0.77930       0.0152800          +
## 158 -0.1003000          +    0.70400                          +        +
## 240  0.0721600          +   -0.60100      -0.0054010          +        +
## 16  -0.0847000          +    0.62560       0.0219500          +        +
## 80  -0.0275100          +    0.24610       0.0206500          +        +
## 48  -0.0524300          +    0.33570       0.0082540          +        +
## 36  -0.0119100          +    0.32310       0.0010820
## 222 -0.0412500          +    0.32180                          +        +
## 104  0.0633800          +   -0.40290      -0.0080030          +
## 4   -0.0598100          +    0.71960       0.0198400
## 88  -0.0948500          +    0.52380       0.0149600          +
## 22  -0.0953200          +    0.77290                          +
## 144 -0.0910700          +    0.68790       0.0220200          +        +
## 208 -0.0227600          +    0.20430       0.0205900          +        +
## 176 -0.0586600          +    0.39640       0.0084080          +        +
## 40  -0.0367100          +    0.31750       0.0032860          +
## 86  -0.0508100          +    0.51060                          +
```

```
## 8   -0.0813200          +    0.73960       0.0225100        +
## 72  -0.0292200          +    0.40180       0.0212600        +
## 78   0.0733100          +    0.16150                        +        +
## 10  -0.0083050          +    0.62530                                 +
## 14   0.0147400          +    0.59190                        +        +
## 206  0.0818300          +    0.08194                        +        +
## 138 -0.0125000          +    0.66970                                 +
## 142  0.0098830          +    0.64200                        +        +
## 2    0.0002539          +    0.73440
## 70   0.0746500          +    0.32050                        +
## 6    0.0209200          +    0.70950                        +
## 27  -0.0478900          +                  0.0168800                 +
## 11  -0.0150500          +                  0.0211100                 +
## 31  -0.0347200          +                  0.0139000        +        +
## 15  -0.0004760          +                  0.0188500        +        +
## 25  -0.0288100          +                                            +
## 29   0.0040740          +                                   +        +
## 13   0.0816700          +                                   +        +
## 9    0.0507400          +                                            +
## 3    0.0222000          +                  0.0211100
## 19  -0.0106400          +                  0.0168800
## 17   0.0084420          +
## 23   0.0025320          +                  0.0139000        +
## 7    0.0367800          +                  0.0188500        +
## 21   0.0413300          +                                   +
## 5    0.1189000          +                                   +
## 1    0.0879900          +
##       cnd(YSE) cnd(cnp_f:plt_dns_m2) cnd(cnp_f:rgn) cnd(cnp_f:Trt)
## 284 -0.008476
## 412 -0.009152                                                   +
## 316 -0.007803               0.02881
## 282 -0.004758
## 444 -0.008496               0.02662                             +
## 288 -0.008367
## 276 -0.009101
## 308 -0.007411               0.07081
## 410 -0.005509                                                   +
## 286 -0.007004
## 416 -0.009045                                                   +
## 28   0.010120
## 320 -0.007587               0.03016
## 60   0.010090               0.10650
## 274 -0.005506
## 414 -0.007912                                                   +
## 156  0.010120                                                   +
## 280 -0.008948
## 448 -0.008296               0.02726                             +
## 352 -0.008277                                    +
## 188  0.010090               0.10570                             +
## 26   0.013940
## 312 -0.006928               0.07650
## 278 -0.007579
## 32   0.010450
## 128  0.008615               0.18660              +
```

```
## 52   0.010600              0.14930
## 350 -0.007214                                    +
## 64   0.010360              0.11460
## 384 -0.004749              0.06617               +
## 480 -0.008953                                    +              +
## 20   0.010720
## 12
## 154  0.013950                                                   +
## 96   0.009280                                    +
## 160  0.010410                                                   +
## 256  0.008477              0.19830               +              +
## 44                         0.10810
## 478 -0.008046                                    +              +
## 344 -0.009819                                    +
## 30   0.013500
## 192  0.010330              0.11400                              +
## 512 -0.004944              0.07769               +              +
## 112                        0.20550               +
## 140                                                             +
## 120  0.009058              0.22670               +
## 56   0.010770              0.15910
## 18   0.014360
## 342 -0.008757                                    +
## 224  0.009267                                    +              +
## 172                        0.10730                              +
## 94   0.012250                                    +
## 376 -0.003828              0.11100               +
## 24   0.010960
## 158  0.013480                                                   +
## 240                        0.22020               +              +
## 16
## 80                                               +
## 48                         0.11870
## 36                         0.15410
## 222  0.012220                                    +              +
## 104                        0.24870               +
## 4
## 88   0.009977                                    +
## 22   0.014060
## 144                                                             +
## 208                                              +              +
## 176                        0.11800                              +
## 40                         0.16590
## 86   0.012980                                    +
## 8
## 72                                               +
## 78                                               +
## 10
## 14
## 206                                              +              +
## 138                                                             +
## 142                                                             +
## 2
## 70                                               +
```

```
## 6
## 27   0.006445
## 11
## 31   0.007302
## 15
## 25   0.011140
## 29   0.010150
## 13
## 9
## 3
## 19   0.006445
## 17   0.011140
## 23   0.007302
## 7
## 21   0.010150
## 5
## 1
##     cnd(cnp_f:YSE) df  logLik   AICc delta weight
## 284         0.1402  7 121.087 -226.7  0.00  0.436
## 412         0.1453  8 121.176 -224.5  2.26  0.141
## 316         0.1351  8 121.147 -224.4  2.31  0.137
## 282         0.1408  6 117.585 -222.1  4.63  0.043
## 444         0.1403  9 121.227 -222.1  4.65  0.043
## 288         0.1400  9 121.089 -221.8  4.93  0.037
## 276         0.1491  6 117.381 -221.7  5.04  0.035
## 308         0.1359  7 117.730 -220.0  6.71  0.015
## 410         0.1464  7 117.684 -219.9  6.81  0.015
## 286         0.1495  8 118.812 -219.8  6.98  0.013
## 416         0.1453 10 121.182 -219.4  7.31  0.011
## 28                  6 116.223 -219.4  7.35  0.011
## 320         0.1340 10 121.152 -219.4  7.37  0.011
## 60                  7 117.052 -218.7  8.07  0.008
## 274         0.1493  5 114.402 -218.1  8.68  0.006
## 414         0.1563  9 118.963 -217.6  9.18  0.004
## 156                 7 116.312 -217.2  9.55  0.004
## 280         0.1479  8 117.392 -216.9  9.82  0.003
## 448         0.1396 11 121.233 -216.9  9.84  0.003
## 352         0.1391 11 121.091 -216.6 10.12  0.003
## 188                 8 117.130 -216.4 10.35  0.002
## 26                  5 113.046 -215.3 11.40  0.001
## 312         0.1322  9 117.783 -215.2 11.54  0.001
## 278         0.1575  7 115.275 -215.1 11.62  0.001
## 32                  8 116.409 -214.9 11.79  0.001
## 128                11 120.246 -214.9 11.81  0.001
## 52                  6 113.889 -214.7 12.02  0.001
## 350         0.1514 10 118.814 -214.7 12.04  0.001
## 64                  9 117.352 -214.3 12.40  0.001
## 384         0.1093 12 121.242 -214.2 12.53  0.001
## 480         0.1438 12 121.221 -214.2 12.57  0.001
## 20                  5 112.323 -213.9 12.84  0.001
## 12                  5 112.018 -213.3 13.45  0.001
## 154                 6 113.116 -213.2 13.57  0.000
## 96                 10 117.977 -213.0 13.72  0.000
## 160                 9 116.492 -212.6 14.12  0.000
```

```
## 256                 12 120.417 -212.6 14.18  0.000
## 44                   6 112.792 -212.5 14.22  0.000
## 478          0.1569 11 118.994 -212.4 14.32  0.000
## 344          0.1562 10 117.489 -212.0 14.69  0.000
## 30                   7 113.722 -212.0 14.73  0.000
## 192                 10 117.427 -211.9 14.82  0.000
## 512          0.1097 13 121.425 -211.8 14.94  0.000
## 112                 10 117.282 -211.6 15.11  0.000
## 140                  6 112.097 -211.1 15.61  0.000
## 120                 10 117.029 -211.1 15.61  0.000
## 56                   8 114.349 -210.8 15.91  0.000
## 18                   4 109.649 -210.8 15.93  0.000
## 342          0.1684  9 115.413 -210.5 16.28  0.000
## 224                 11 117.980 -210.4 16.35  0.000
## 172                  7 112.860 -210.3 16.45  0.000
## 94                   9 115.292 -210.2 16.52  0.000
## 376          0.1054 11 117.888 -210.2 16.53  0.000
## 24                   7 112.587 -209.7 17.00  0.000
## 158                  8 113.773 -209.7 17.06  0.000
## 240                 11 117.546 -209.5 17.21  0.000
## 16                   7 112.298 -209.2 17.58  0.000
## 80                   9 114.700 -209.0 17.71  0.000
## 48                   8 113.219 -208.6 18.17  0.000
## 36                   5 109.513 -208.3 18.46  0.000
## 222                 10 115.303 -207.7 19.06  0.000
## 104                  9 113.983 -207.6 19.14  0.000
## 4                    4 108.005 -207.5 19.22  0.000
## 88                   9 113.850 -207.3 19.41  0.000
## 22                   6 110.060 -207.1 19.68  0.000
## 144                  8 112.406 -206.9 19.80  0.000
## 208                 10 114.718 -206.5 20.23  0.000
## 176                  9 113.316 -206.3 20.47  0.000
## 40                   7 110.176 -204.9 21.82  0.000
## 86                   8 111.359 -204.8 21.89  0.000
## 8                    6 108.436 -203.8 22.93  0.000
## 72                   8 110.400 -202.9 23.81  0.000
## 78                   8 109.344 -200.8 25.92  0.000
## 10                   4 104.362 -200.2 26.51  0.000
## 14                   6 106.547 -200.0 26.71  0.000
## 206                  9 109.403 -198.4 28.30  0.000
## 138                  5 104.409 -198.1 28.67  0.000
## 142                  7 106.608 -197.8 28.96  0.000
## 2                    3 101.104 -195.9 30.82  0.000
## 70                   7 105.244 -195.1 31.69  0.000
## 6                    5 102.886 -195.0 31.72  0.000
## 27                   5  99.725 -188.7 38.04  0.000
## 11                   4  98.486 -188.5 38.26  0.000
## 31                   7 100.058 -184.7 42.06  0.000
## 15                   6  98.612 -184.2 42.58  0.000
## 25                   4  96.213 -183.9 42.80  0.000
## 29                   6  98.475 -183.9 42.85  0.000
## 13                   5  95.407 -180.1 46.67  0.000
## 9                    3  92.174 -178.1 48.68  0.000
## 3                    3  89.439 -172.6 54.15  0.000
```

```
## 19                  4  90.440 -172.4 54.35  0.000
## 17                  3  87.588 -168.9 57.85  0.000
## 23                  6  90.708 -168.4 58.38  0.000
## 7                   5  89.542 -168.3 58.40  0.000
## 21                  5  89.431 -168.1 58.63  0.000
## 5                   4  86.928 -165.4 61.38  0.000
## 1                   2  84.256 -164.4 62.37  0.000
## Models ranked by AICc(x)
```

And the best model is…:

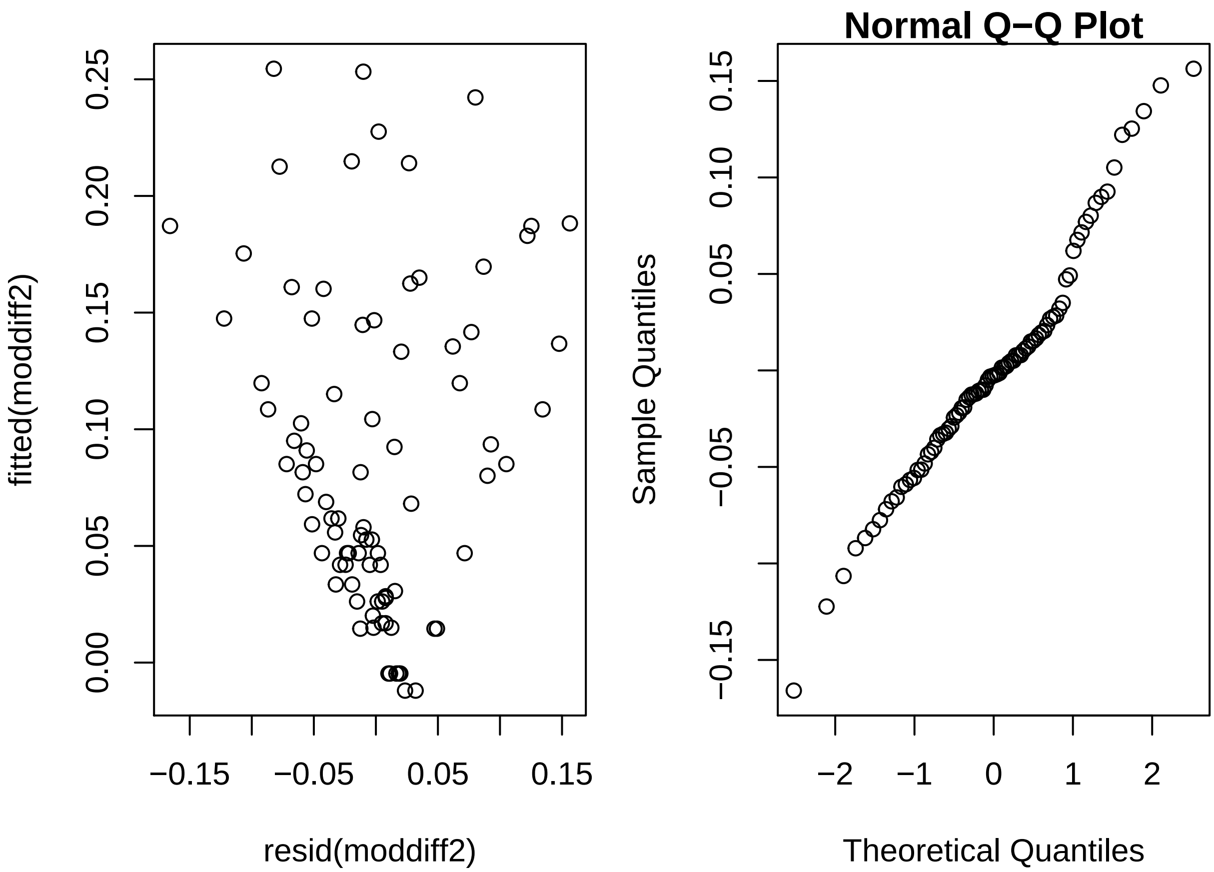
```r
moddiff2 <- glmmTMB(canopygrowth~canopygrowth_f
                   +YrsSinceExclosure+YrsSinceExclosure:canopygrowth_f
                   +plot_density_m2
                   +Treatment,
                   family=gaussian,
                   data=dat2)
summary(moddiff2)
```

```
##  Family: gaussian  ( identity )
## Formula:
## canopygrowth ~ canopygrowth_f + YrsSinceExclosure + YrsSinceExclosure:canopygrowth_f +
##     plot_density_m2 + Treatment
## Data: dat2
##
##      AIC      BIC   logLik deviance df.resid
##   -228.2   -211.0    121.1   -242.2       79
##
##
## Dispersion estimate for gaussian family (sigma^2): 0.0035
##
## Conditional model:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      0.002381   0.047428   0.050  0.95997
## canopygrowth_f                  -0.259305   0.303197  -0.855  0.39242
## YrsSinceExclosure               -0.008476   0.006628  -1.279  0.20100
## plot_density_m2                  0.013229   0.004898   2.701  0.00691 **
## TreatmentExclosure               0.038179   0.013724   2.782  0.00540 **
## canopygrowth_f:YrsSinceExclosure  0.140224   0.043695   3.209  0.00133 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

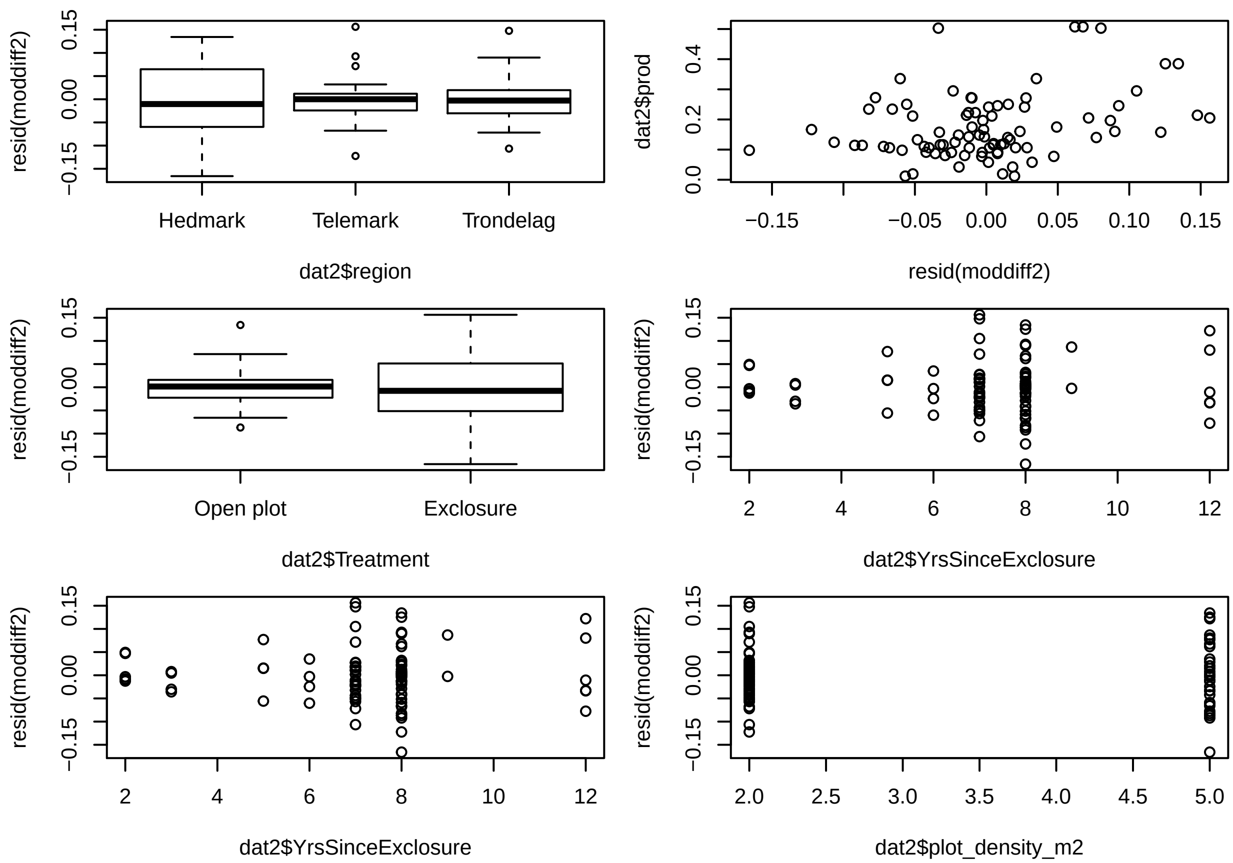
Interpretation: Field-based data have a medium correlation to LiDAR data (0.5ish). The coorelation is dependent on Years since exclosure (probably this could be exchanged with tree height?) and LiDAR data is more likely to underestimate canopy growth at short experimental durations (see figure above). Similarly, lower LiDAR resolution induces underestimates in the same way. Field-based data is also not able to explain the variation induced by the fencing treatemtn. This could be a three way ineraction as well, including years since exclusion. Not sure if it should be included here actually.

Validation

```r
par(mfrow=c(1,2), mar = c(4,4,1,1))
plot(resid(moddiff2), fitted(moddiff2))
qqnorm(resid(moddiff2))
```




```
par(mfrow=c(3,2), mar = c(4,4,1,1))
plot(resid(moddiff2)~ dat2$region)
plot(resid(moddiff2), dat2$prod)
plot(resid(moddiff2)~ dat2$Treatment)
plot(resid(moddiff2)~ dat2$YrsSinceExclosure)
plot(resid(moddiff2)~ dat2$YrsSinceExclosure)
plot(resid(moddiff2)~ dat2$plot_density_m2)
```


resid(moddiff2)
Hedmark
Telemark
Trondelag
dat2$region
dat2$prod
resid(moddiff2)
resid(moddiff2)
Open plot
Exclosure
dat2$Treatment
resid(moddiff2)
dat2$YrsSinceExclosure
resid(moddiff2)
dat2$YrsSinceExclosure
resid(moddiff2)
dat2$plot_density_m2

Looks Ok