Masticated Fuels Analyses

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Contents

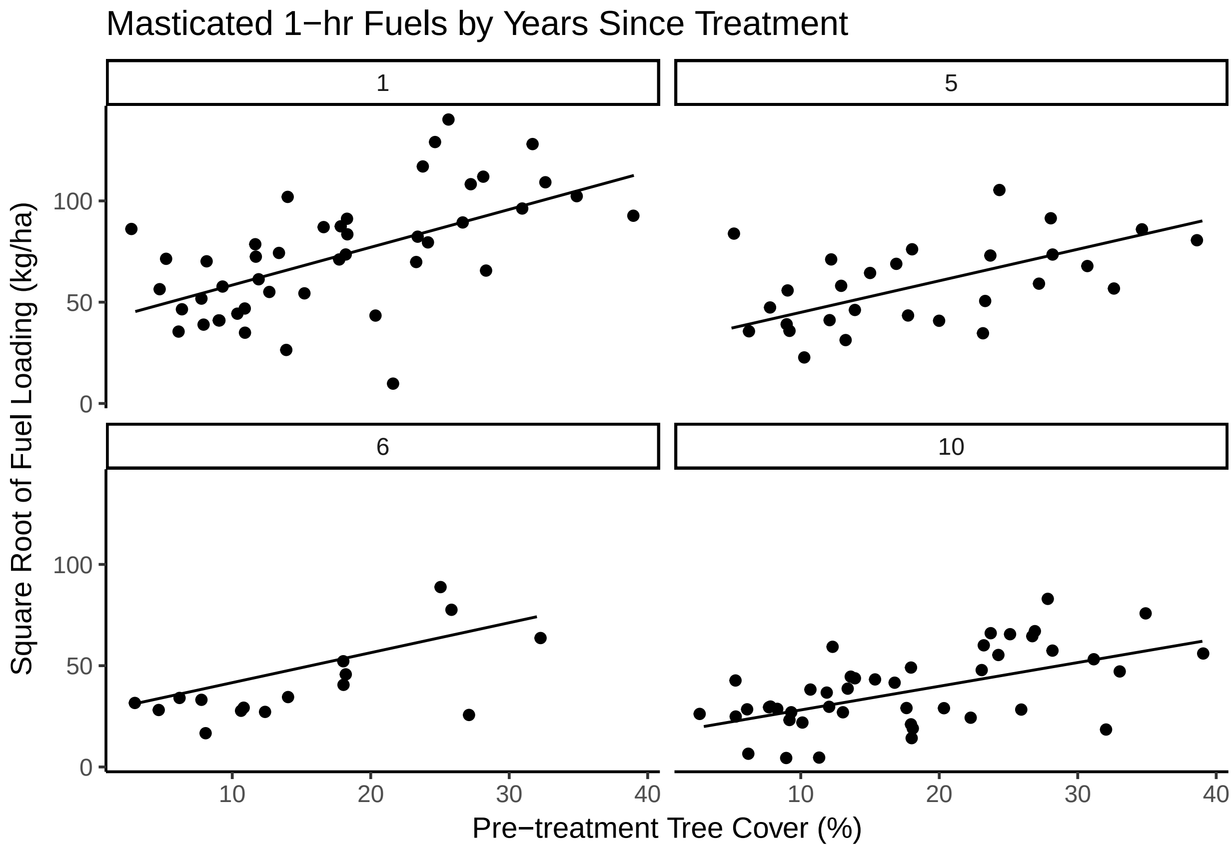
Masticated 1-hr fuels

pre_tree_cvr = pre-treatment tree cover (%)

yst = years since treatment; 0 represents pre-treatment; yst is a factor for masticated fuels

Model

```
m <- lmer(sqrt(dwd_1hr) ~ pre_tree_cvr + yst + pre_tree_cvr:yst + (1|site), data = d)
```



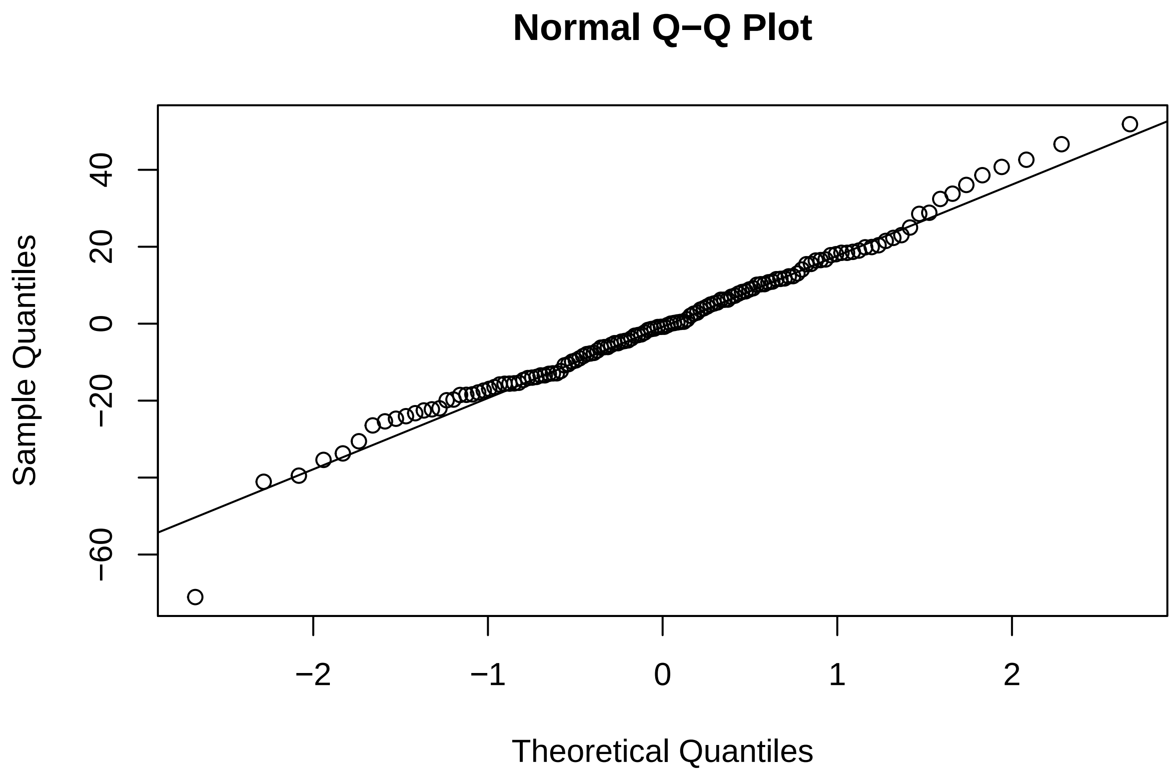
Inferences

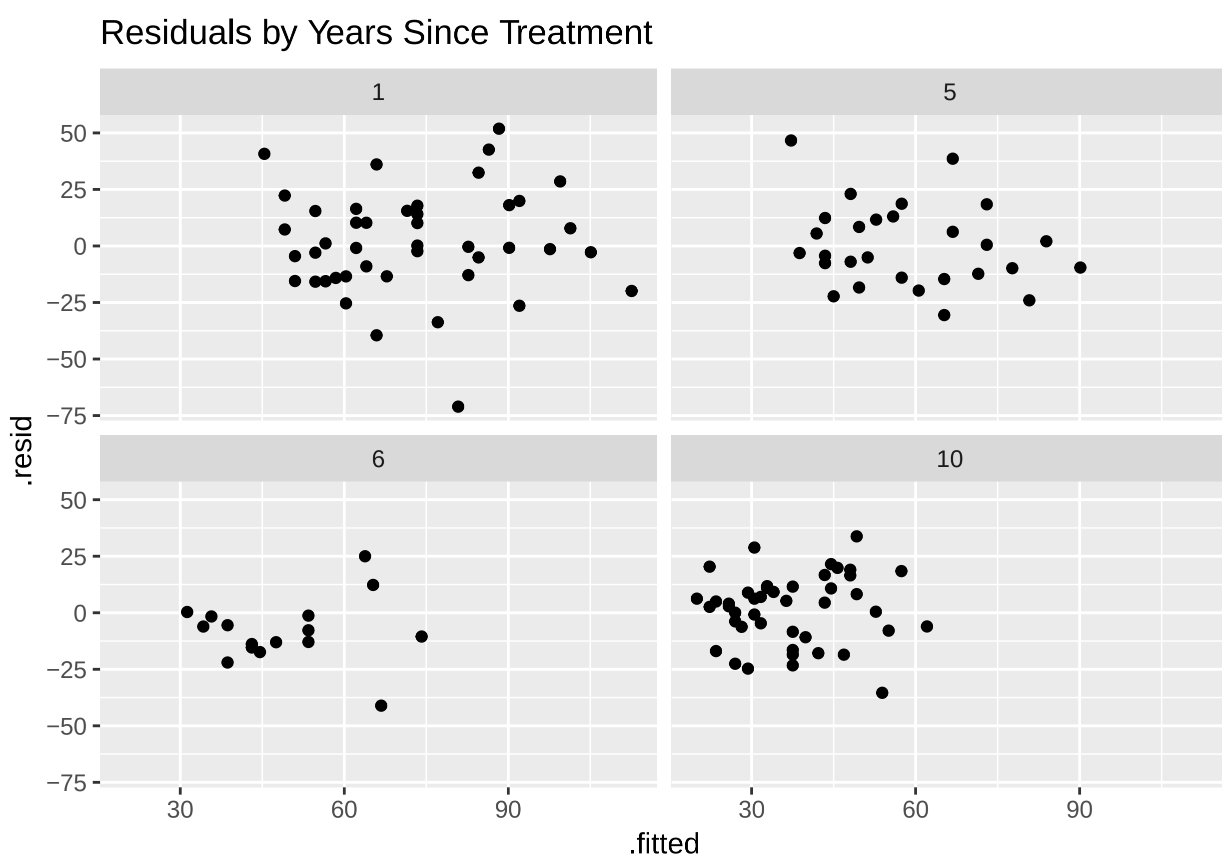
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(dwd_1hr) ~ pre_tree_cvr + yst + pre_tree_cvr:yst + (1 |
##     site)
##    Data: d
##
## REML criterion at convergence: 1169
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.725 -0.698 -0.042  0.610  2.719
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  site     (Intercept)   0       0.0
##  Residual             364      19.1
## Number of obs: 134, groups:  site, 3
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       42.3811     6.3976    6.62
## pre_tree_cvr       1.9438     0.3240    6.00
## yst               -2.5929     0.9697   -2.67
## pre_tree_cvr:yst  -0.0774     0.0493   -1.57
```

```
##
## Correlation of Fixed Effects:
##             (Intr) pr_tr_ yst
## pre_tre_cvr -0.888
## yst         -0.829  0.737
## pr_tr_cvr:y  0.735 -0.828 -0.888
```

```
##                  estimate     se  lower   upper tvalue  df   pvalue
## (Intercept)       42.3811 6.3976 29.842 54.9201   6.62 Inf 3.48e-11
## pre_tree_cvr       1.9438 0.3240  1.309  2.5788   6.00 Inf 1.98e-09
## yst               -2.5929 0.9697 -4.494 -0.6923  -2.67 Inf 7.50e-03
## pre_tree_cvr:yst  -0.0774 0.0493 -0.174  0.0191  -1.57 Inf 1.16e-01
```

Plotted Residuals





Masticated 10-hr fuels

pre_tree_cvr = pre-treatment tree cover (%)

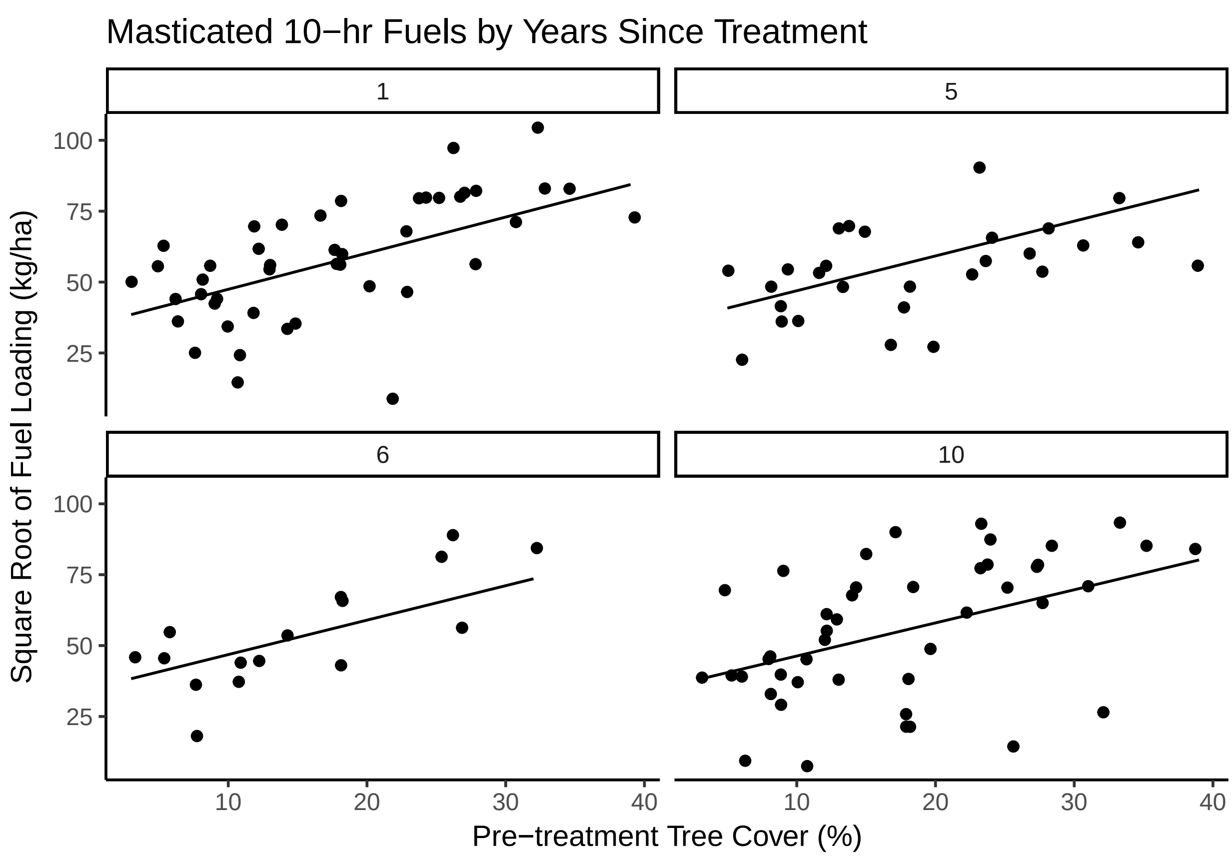
yst = years since treatment; 0 represents pre-treatment

Model

```
m <- lmer(sqrt(dwd_10hr) ~ pre_tree_cvr + yst + pre_tree_cvr:yst + (1|site) + (1|subplot_id), data = d)
```

```
#Response averaged across sites
d$yhat10 <- predict(m, re.form = NA)

p <- ggplot(data = d, aes(x = pre_tree_cvr, y = sqrt(dwd_10hr)))
p <- p + geom_jitter()
p <- p + geom_line(aes(y = yhat10))
p <- p + theme_classic()
p <- p + labs(title = 'Masticated 10-hr Fuels by Years Since Treatment',
              x = 'Pre-treatment Tree Cover (%)',
              y = 'Square Root of Fuel Loading (kg/ha)')
p <- p + facet_wrap(~yst)
plot(p)
```



Inferences

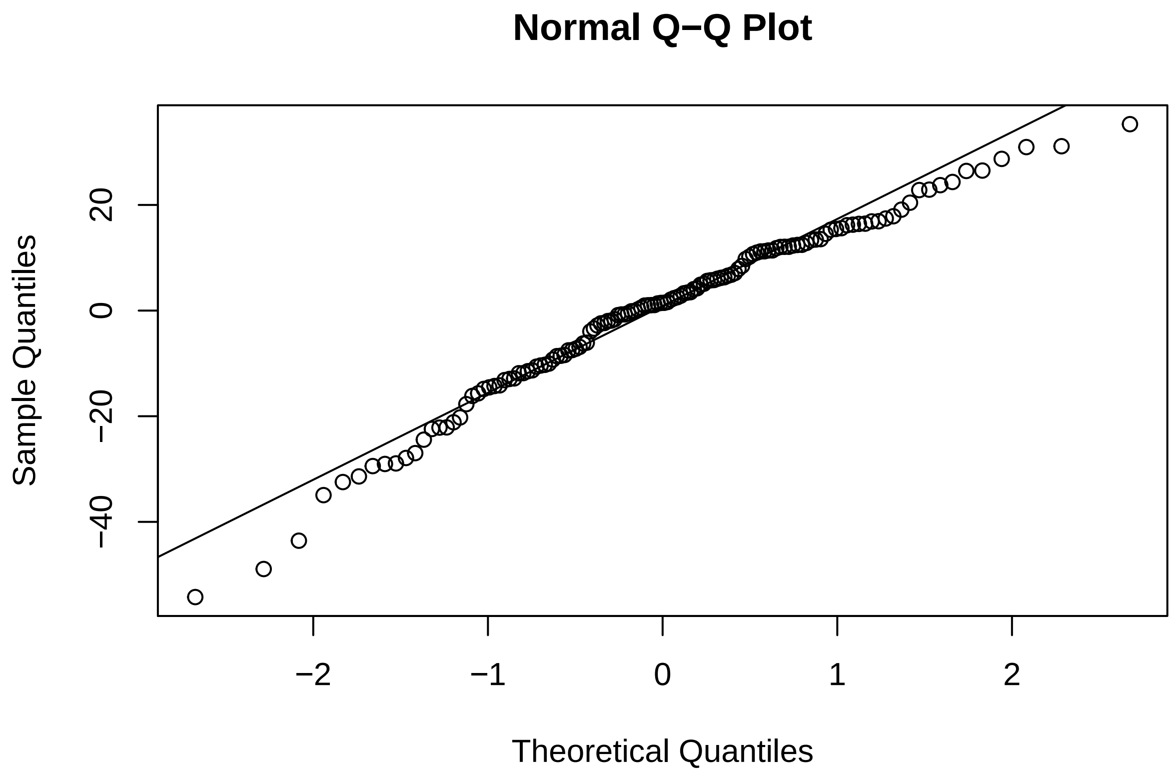
```r
summary(m)
```

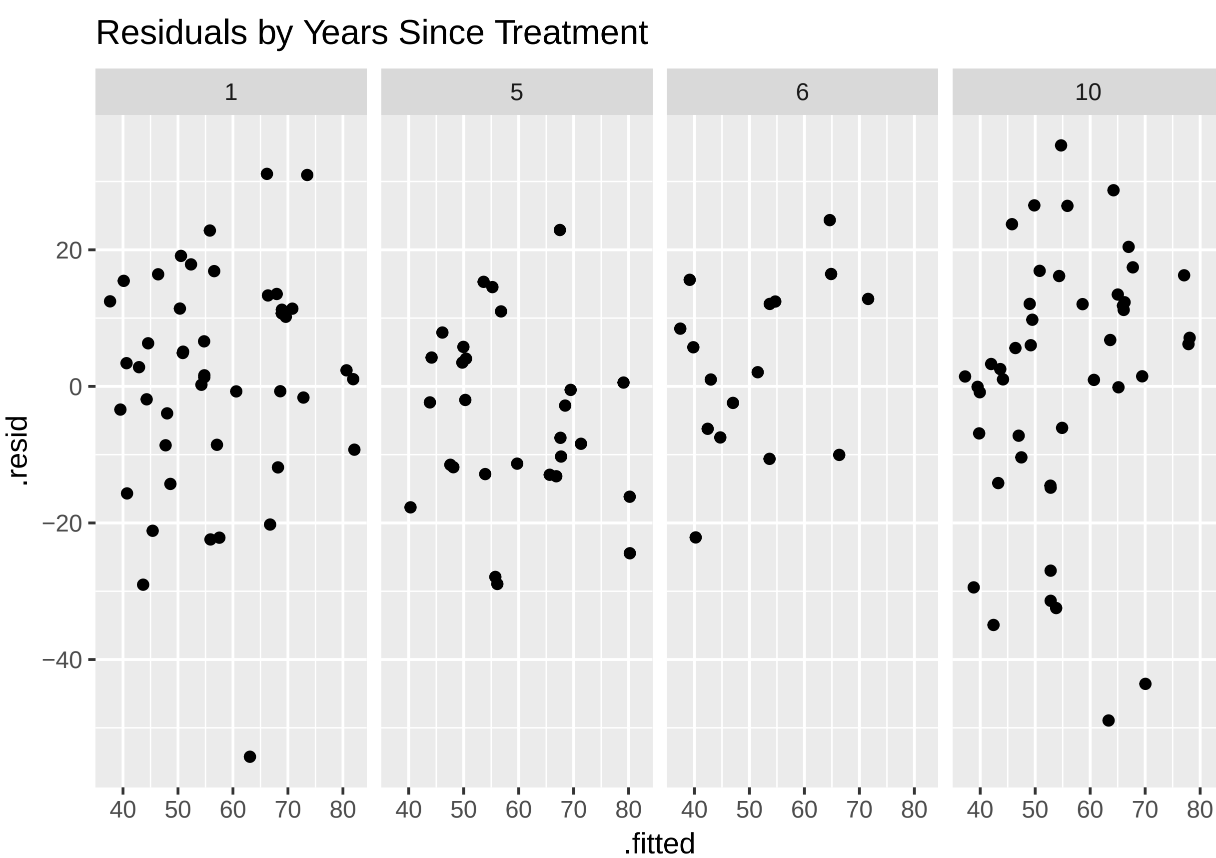
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(dwd_10hr) ~ pre_tree_cvr + yst + pre_tree_cvr:yst + (1 |
##     site) + (1 | subplot_id)
##    Data: d
##
## REML criterion at convergence: 1149
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.169 -0.597  0.085  0.700  2.062
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  subplot_id (Intercept)  14.3     3.79
##  site       (Intercept)  11.4     3.38
##  Residual               292.9    17.11
## Number of obs: 134, groups:  subplot_id, 45; site, 3
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)      34.71709    6.20197    5.60
## pre_tree_cvr      1.28575    0.29844    4.31
## yst              -0.00824    0.87023   -0.01
## pre_tree_cvr:yst -0.01174    0.04420   -0.27
##
## Correlation of Fixed Effects:
##             (Intr) pr_tr_ yst
## pre_tre_cvr -0.844
## yst         -0.766  0.717
## pr_tr_cvr:y  0.680 -0.806 -0.888
```

```r
lincon(m)
```

```
##                  estimate     se   lower   upper   tvalue  df   pvalue
## (Intercept)      34.71709 6.2020 22.5615 46.8727  5.59775 Inf 2.17e-08
## pre_tree_cvr      1.28575 0.2984  0.7008  1.8707  4.30828 Inf 1.65e-05
## yst              -0.00824 0.8702 -1.7139  1.6974 -0.00947 Inf 9.92e-01
## pre_tree_cvr:yst -0.01174 0.0442 -0.0984  0.0749 -0.26565 Inf 7.91e-01
```

Plotted residuals





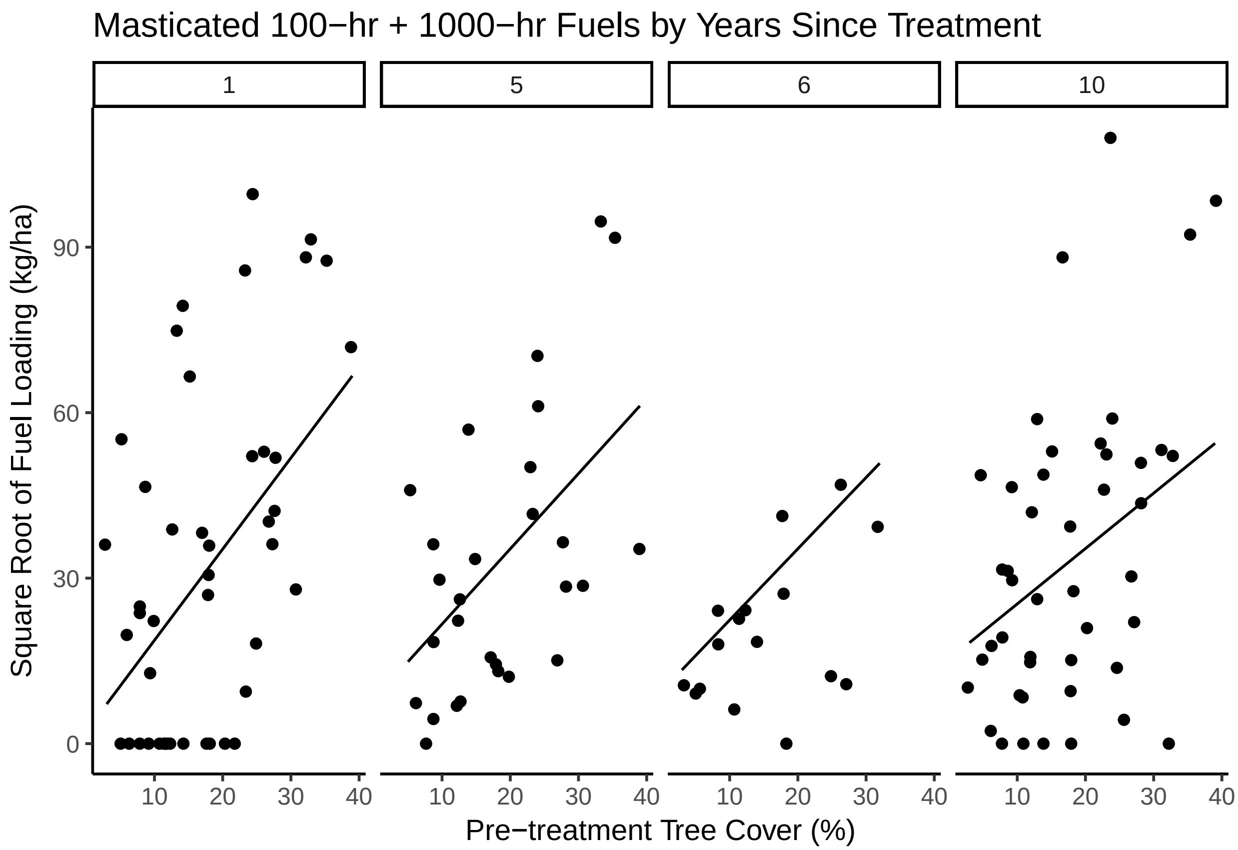
Masticated 100 + 1000-hr fuels

pre_tree_cvr = pre-treatment tree cover (%)

yst = years since treatment; 0 represents pre-treatment

Model

```
m <- lmer(sqrt(dwd_100_1000hr) ~ pre_tree_cvr + yst + pre_tree_cvr:yst + (1 + yst|site), data = d)
```



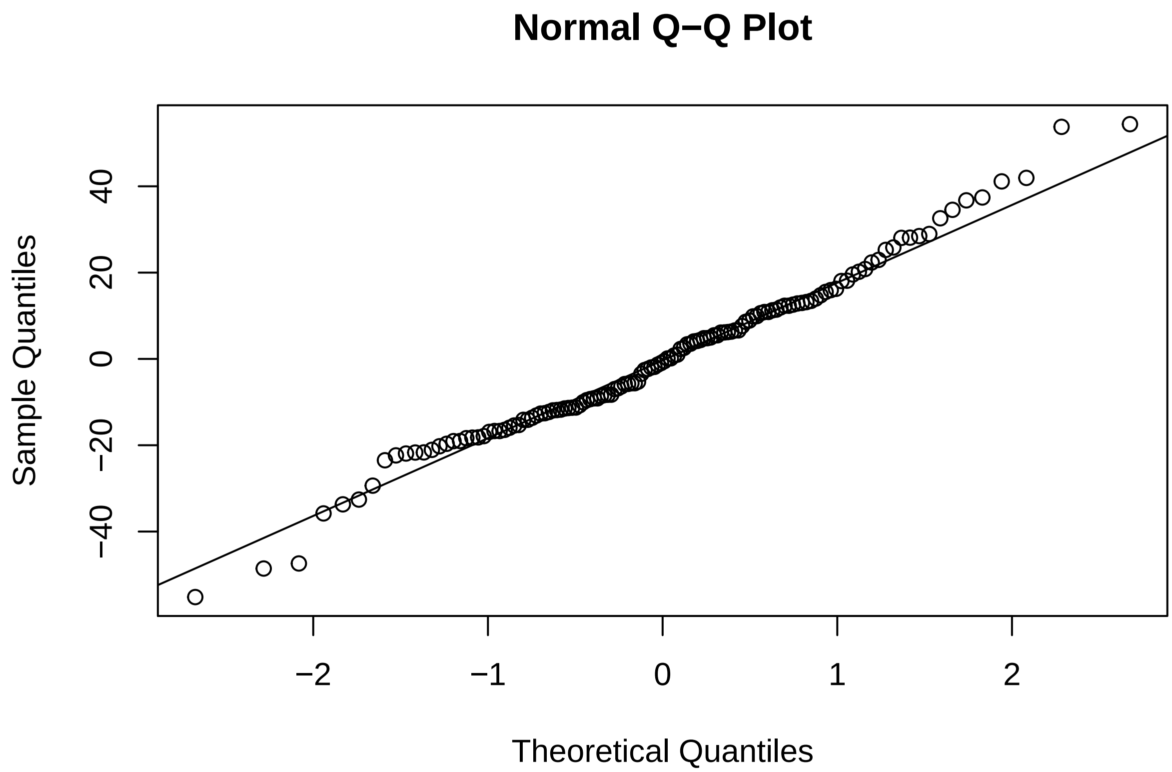
Inferences

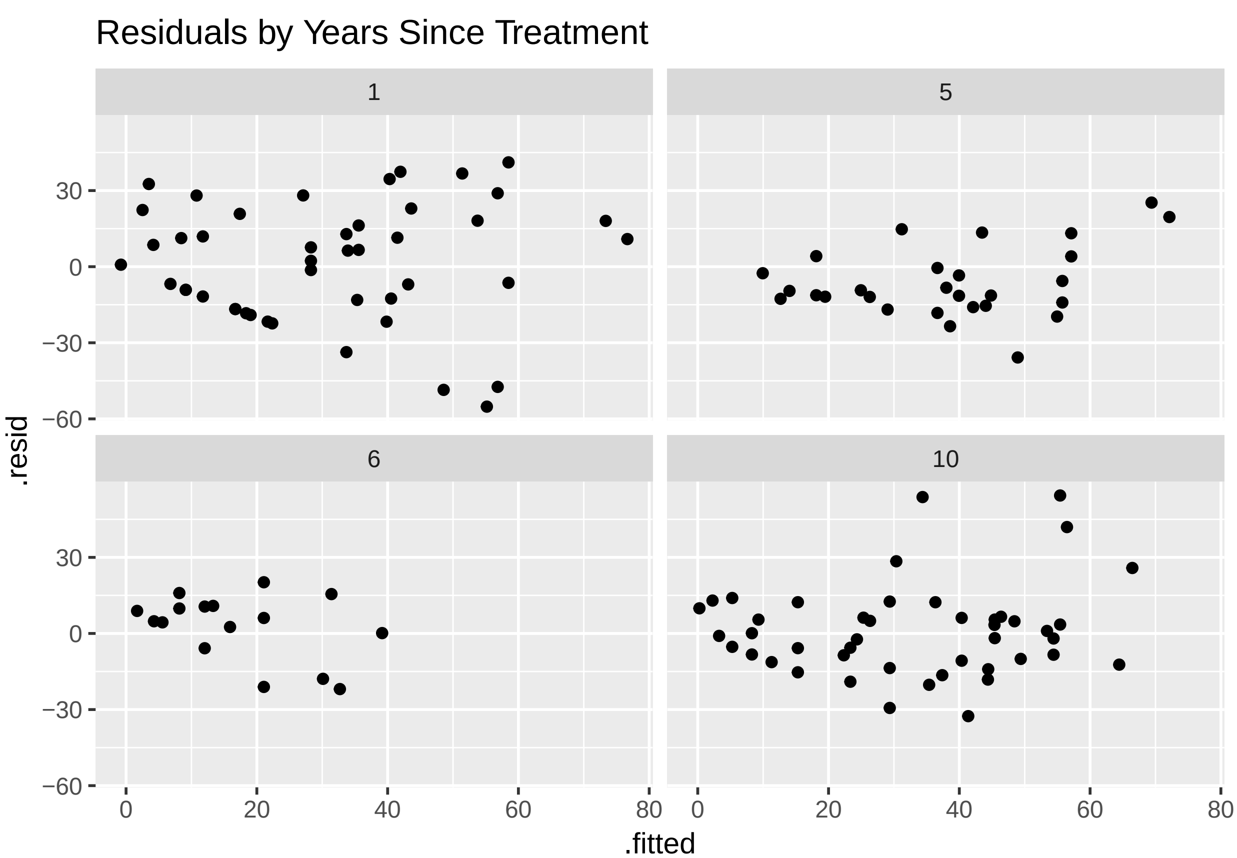
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(dwd_100_1000hr) ~ pre_tree_cvr + yst + pre_tree_cvr:yst +
##     (1 + yst | site)
##    Data: d
##
## REML criterion at convergence: 1186
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8143 -0.6377 -0.0376  0.6017  2.7742
##
## Random effects:
```

```
##  Groups   Name        Variance Std.Dev. Corr
##  site     (Intercept) 271.34   16.47
##           yst           3.19    1.79    -0.47
##  Residual             384.42   19.61
## Number of obs: 134, groups:  site, 3
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)        0.7641    11.6150    0.07
## pre_tree_cvr       1.7247     0.3385    5.09
## yst                1.4532     1.4457    1.01
## pre_tree_cvr:yst  -0.0721     0.0515   -1.40
##
## Correlation of Fixed Effects:
##             (Intr) pr_tr_ yst
## pre_tre_cvr -0.512
## yst         -0.608  0.517
## pr_tr_cvr:y  0.424 -0.827 -0.625
```

```
##                  estimate      se   lower   upper  tvalue  df   pvalue
## (Intercept)        0.7641 11.6150 -22.001 23.5290  0.0658 Inf 9.48e-01
## pre_tree_cvr       1.7247  0.3385   1.061  2.3881  5.0947 Inf 3.49e-07
## yst                1.4532  1.4457  -1.380  4.2866  1.0052 Inf 3.15e-01
## pre_tree_cvr:yst  -0.0721  0.0515  -0.173  0.0288 -1.4007 Inf 1.61e-01
```

Plotted Residuals





Tree Litter + Duff Fuels

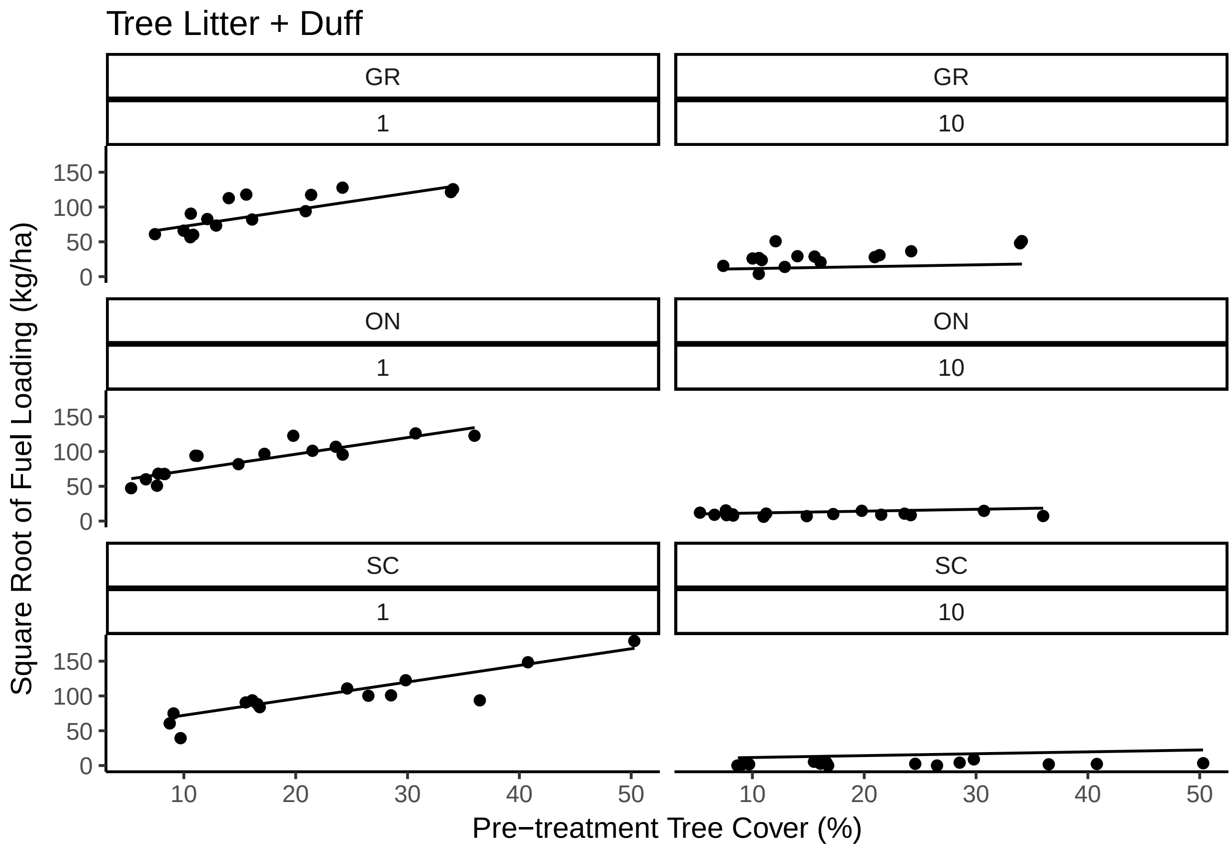
```r
#model, inferences, and residuals
m <- lmer(sqrt(duff) ~ yst + pre_tc + yst:pre_tc + (1 + yst|scode), data = d)
summary(m)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(duff) ~ yst + pre_tc + yst:pre_tc + (1 + yst | scode)
##    Data: d
##
## REML criterion at convergence: 706
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.267 -0.546  0.005  0.396  2.393
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  scode    (Intercept)  10.02    3.16
##           yst           1.16    1.08    1.00
##  Residual             135.92   11.66
## Number of obs: 90, groups:  scode, 3
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  52.6424     4.3859   12.00
## yst          -4.3817     0.8407   -5.21
## pre_tc        2.6266     0.1870   14.05
## yst:pre_tc   -0.2357     0.0266   -8.87
##
## Correlation of Fixed Effects:
##            (Intr) yst    pre_tc
## yst        -0.154
## pre_tc     -0.794  0.443
## yst:pre_tc  0.597 -0.590 -0.753
```

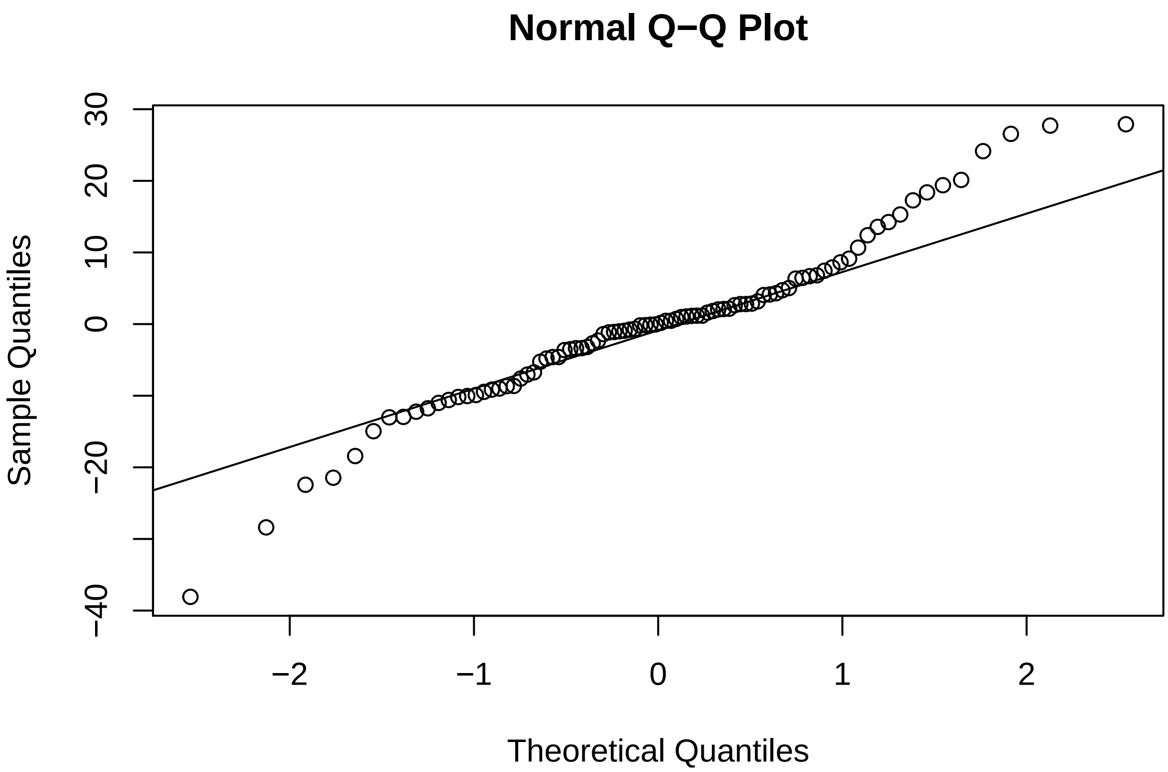
```r
lincon(m)
```

```
##             estimate     se  lower  upper tvalue  df   pvalue
## (Intercept)   52.642 4.3859 44.046 61.239  12.00 Inf 3.44e-33
## yst           -4.382 0.8407 -6.029 -2.734  -5.21 Inf 1.87e-07
## pre_tc         2.627 0.1870  2.260  2.993  14.05 Inf 8.02e-45
## yst:pre_tc    -0.236 0.0266 -0.288 -0.184  -8.87 Inf 7.44e-19
```

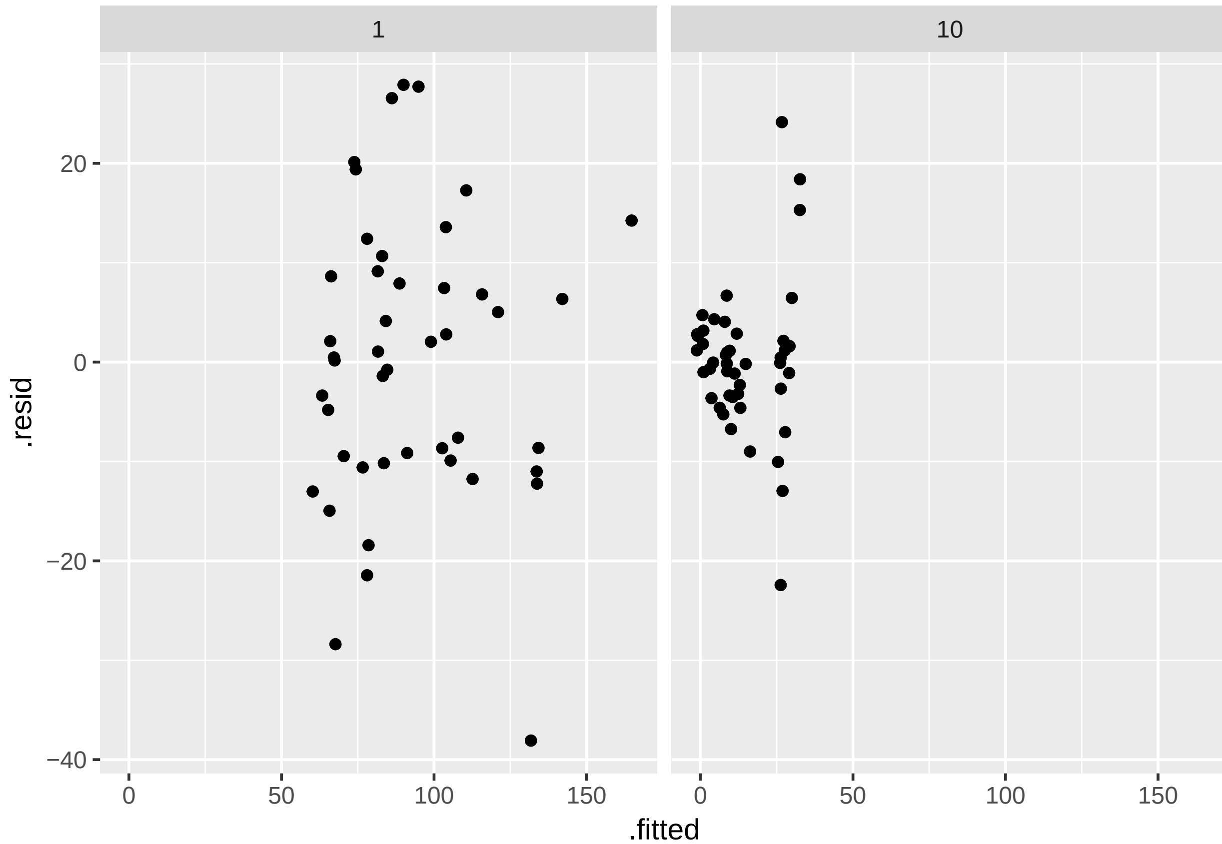
```r
#by yst
d$yhat_duff <- predict(m, re.form = NA)
p <- ggplot(data = d, aes(x = pre_tc, y = sqrt(duff)))
p <- p + geom_jitter()
p <- p + geom_line(aes(y = yhat_duff))
p <- p + theme_classic() + facet_wrap(scode~yst, ncol = 2)
p <- p + labs(title = 'Tree Litter + Duff',
              x = 'Pre-treatment Tree Cover (%)',
              y = 'Square Root of Fuel Loading (kg/ha)')
plot(p)
```



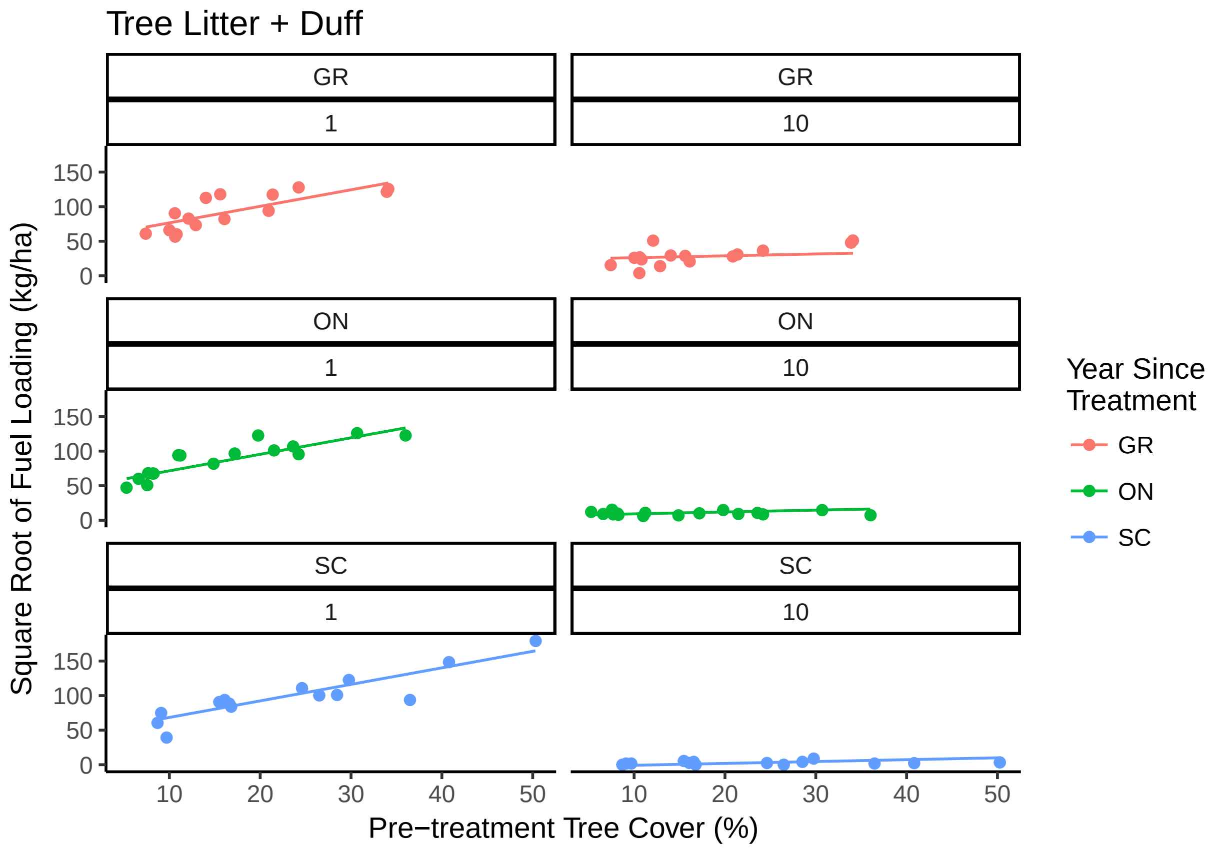

```
qqnorm(resid(m)); qqline(resid(m))
```



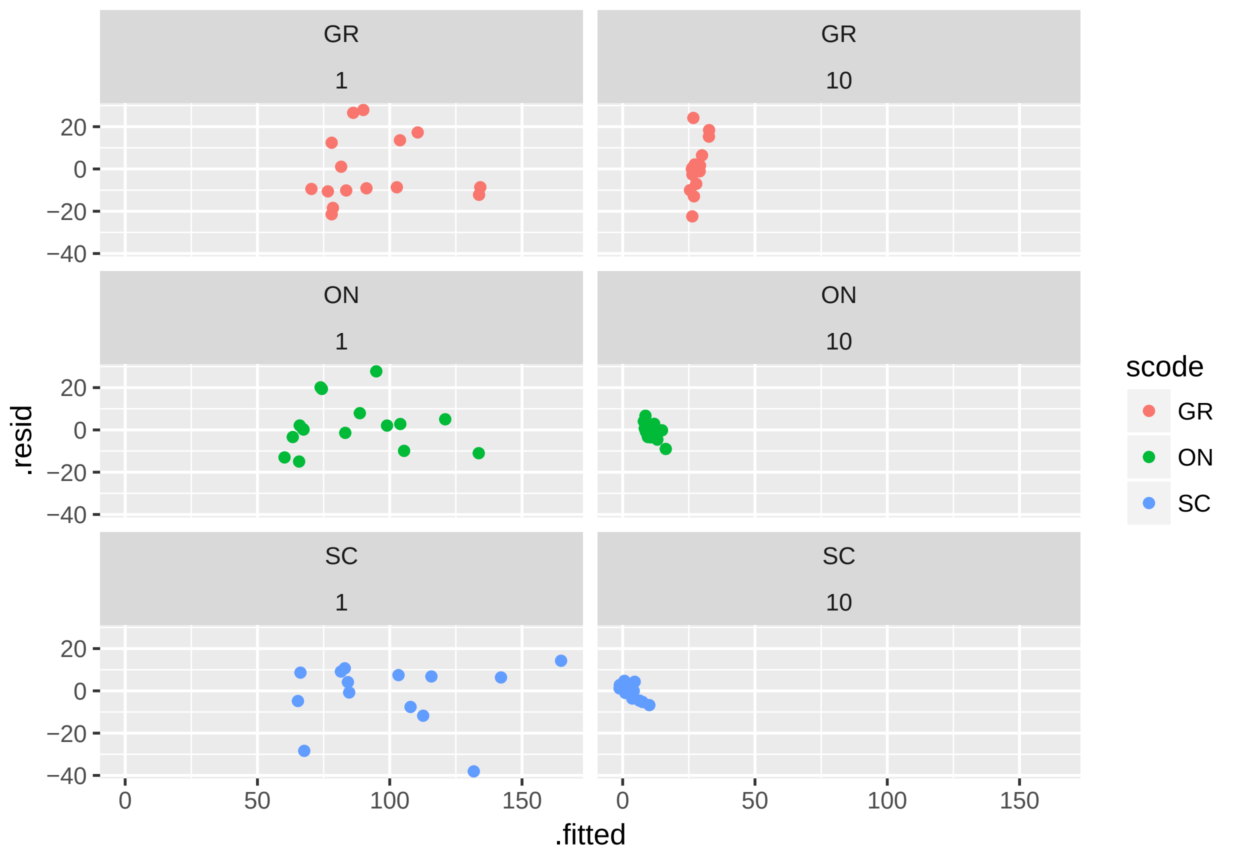

```r
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```r
#by yst and site
d$yhat_duff <- predict(m)
p <- ggplot(data = d, aes(x = pre_tc, y = sqrt(duff), color = scode))
p <- p + geom_jitter()
p <- p + geom_line(aes(y = yhat_duff))
p <- p + theme_classic() + facet_wrap(scode~yst, ncol = 2)
p <- p + labs(title = 'Tree Litter + Duff',
               x = 'Pre-treatment Tree Cover (%)',
               y = 'Square Root of Fuel Loading (kg/ha)',
               color = 'Year Since \nTreatment')
plot(p)
```




```r
ggplot(m, aes(x = .fitted, y = .resid, color = scode)) +
  geom_point() + facet_wrap(scode~yst, nrow = 3)
```



For shrub and Herbaceous biomass and cover, use tree dominance index (TDI) instead of pre-treatment tree cover.

Tree Dominance Index (TDI) = (pre-treatment tree cover)/(pre-treatment tree cover + grass cover + shrub cover)

Herbaceous Fuels

yst = years since treatment

scode = site

herb_ttl = herbaceous fuel loading

**Investigate value of zero at Onaqui, yst = 10

```
m <- lmer(sqrt(herb_ttl) ~ TDI + yst + yst:TDI + (1 + yst|scode), data = l)
#m <- lmer(herb_ttl ~ TDI + yst + yst:TDI + (1 + yst|scode) + (1|OJprecip), data = l)
summary(m)
```

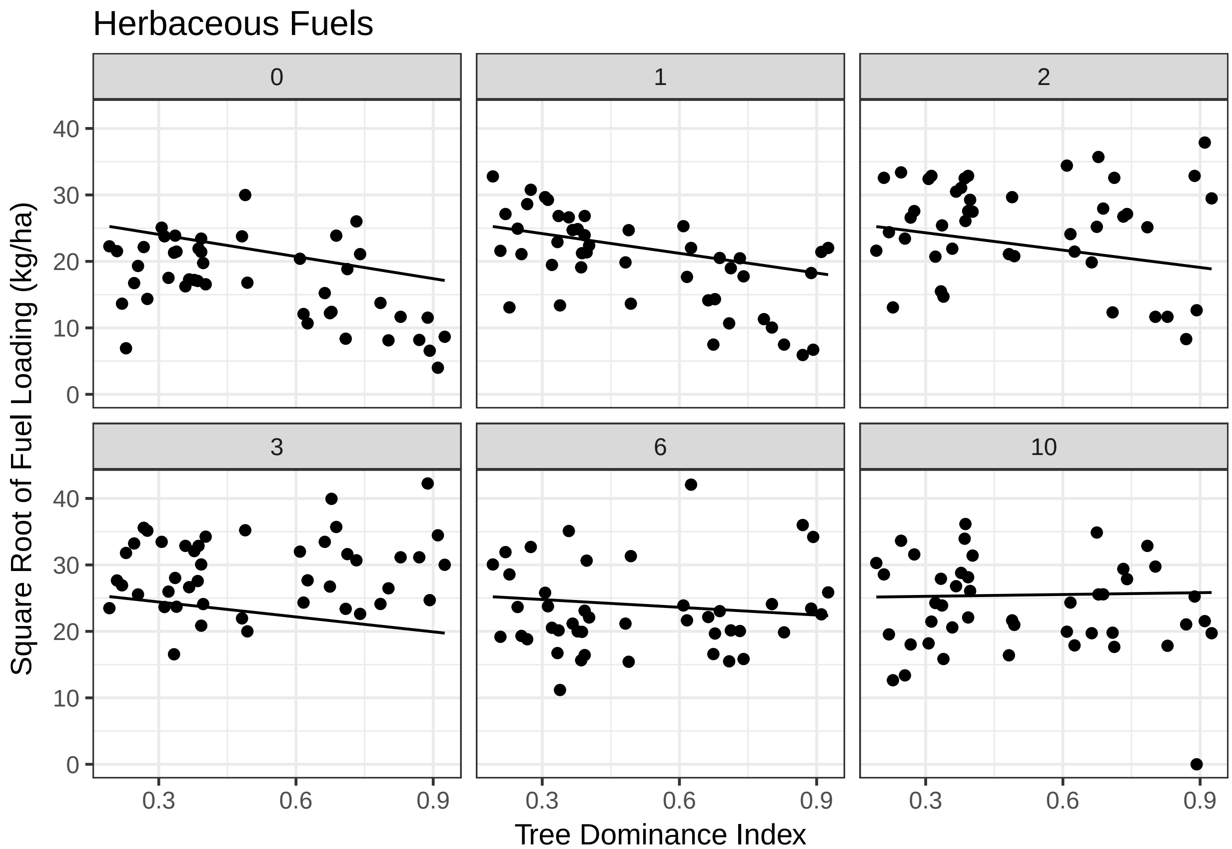
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(herb_ttl) ~ TDI + yst + yst:TDI + (1 + yst | scode)
##    Data: l
##
```

```
## REML criterion at convergence: 1810
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.624 -0.766 -0.072  0.722  3.004
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  scode    (Intercept)  9.3175  3.052
##           yst          0.0944  0.307    -0.91
##  Residual             48.9327  6.995
## Number of obs: 269, groups:  scode, 3
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   27.388      2.357   11.62
## TDI          -11.091      2.787   -3.98
## yst           -0.239      0.359   -0.67
## TDI:yst        1.201      0.557    2.16
##
## Correlation of Fixed Effects:
##         (Intr) TDI    yst
## TDI     -0.609
## yst     -0.759  0.584
## TDI:yst  0.445 -0.732 -0.796
```

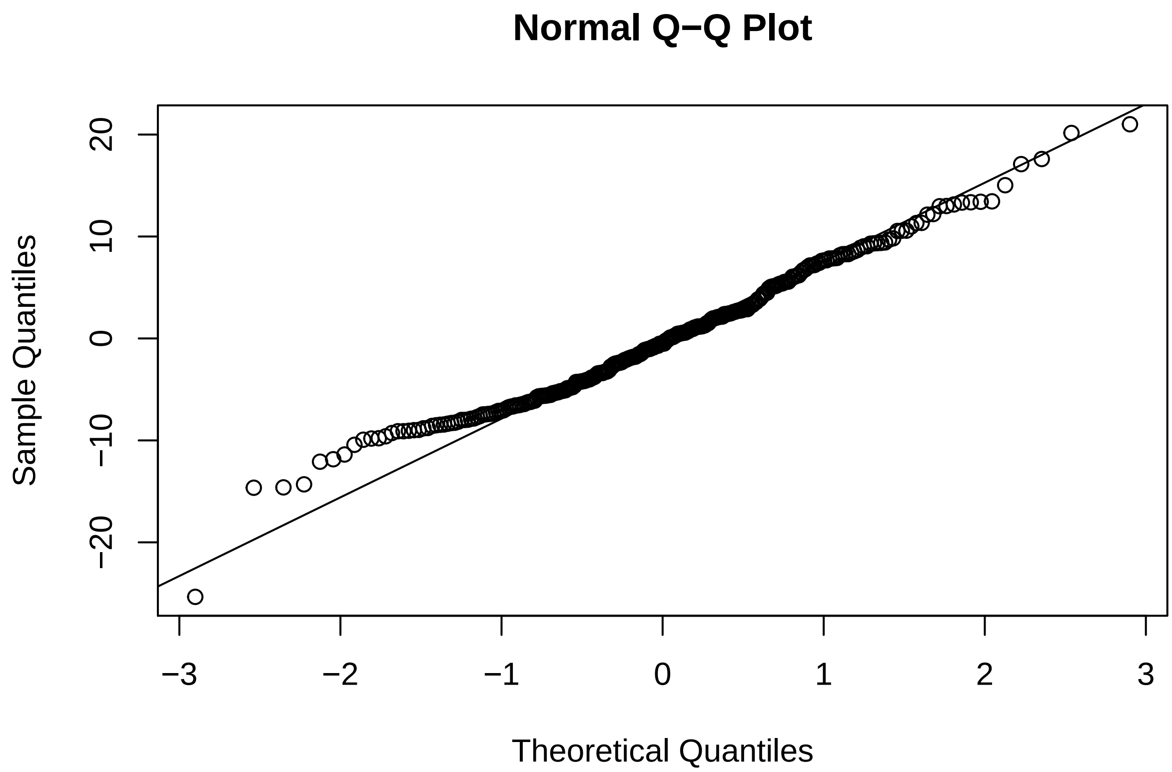
```r
lincon(m)
```

```
##             estimate    se   lower  upper tvalue  df   pvalue
## (Intercept)   27.388 2.357  22.768 32.008 11.618 Inf 3.32e-31
## TDI          -11.091 2.787 -16.554 -5.629 -3.980 Inf 6.90e-05
## yst           -0.239 0.359  -0.943  0.465 -0.666 Inf 5.05e-01
## TDI:yst        1.201 0.557   0.110  2.292  2.157 Inf 3.10e-02
```

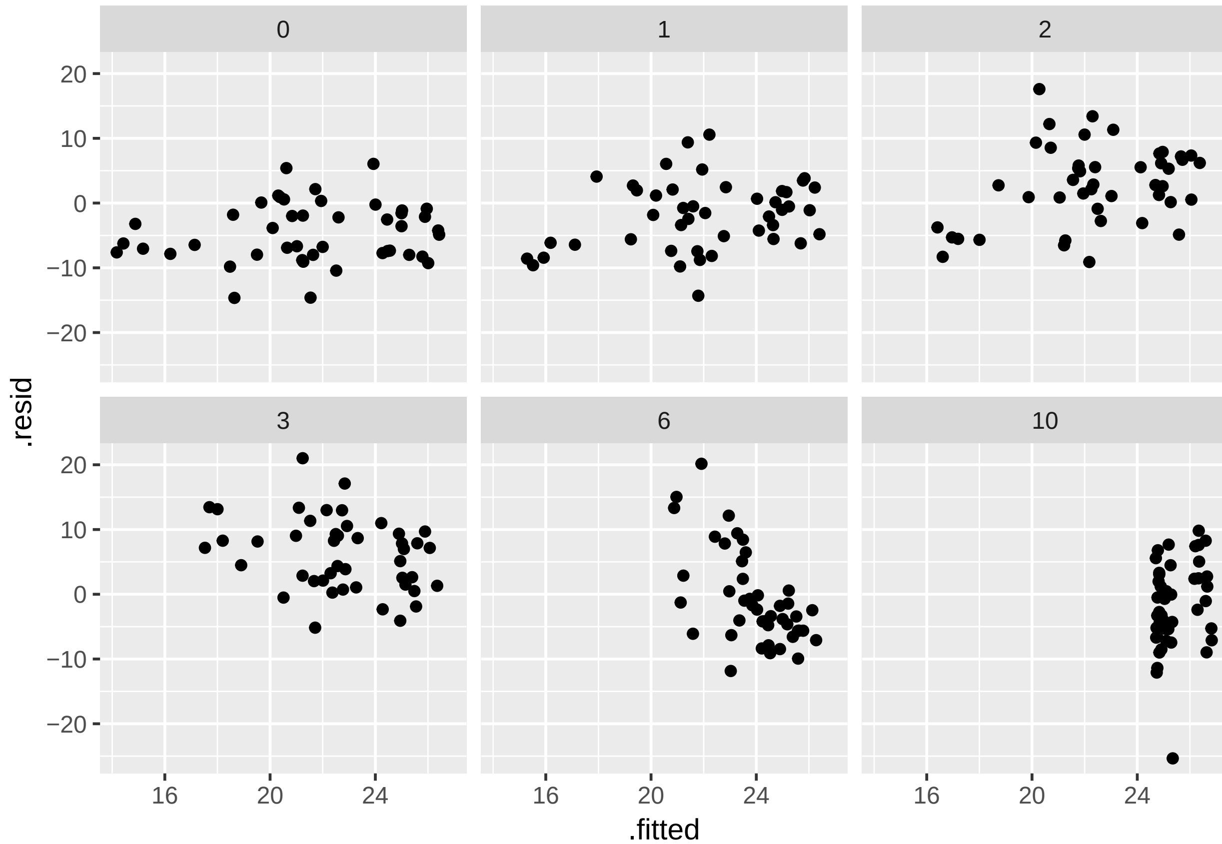
```r
#by yst
l$yhat_herb <- predict(m, re.form = NA)
p <- ggplot(data = l, aes(x = TDI, y = sqrt(herb_ttl)))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_herb))
p <- p + theme_bw()
p <- p + labs(title = 'Herbaceous Fuels',
                x = 'Tree Dominance Index',
                y = 'Square Root of Fuel Loading (kg/ha)')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(~yst, ncol = 3)
plot(p)
```



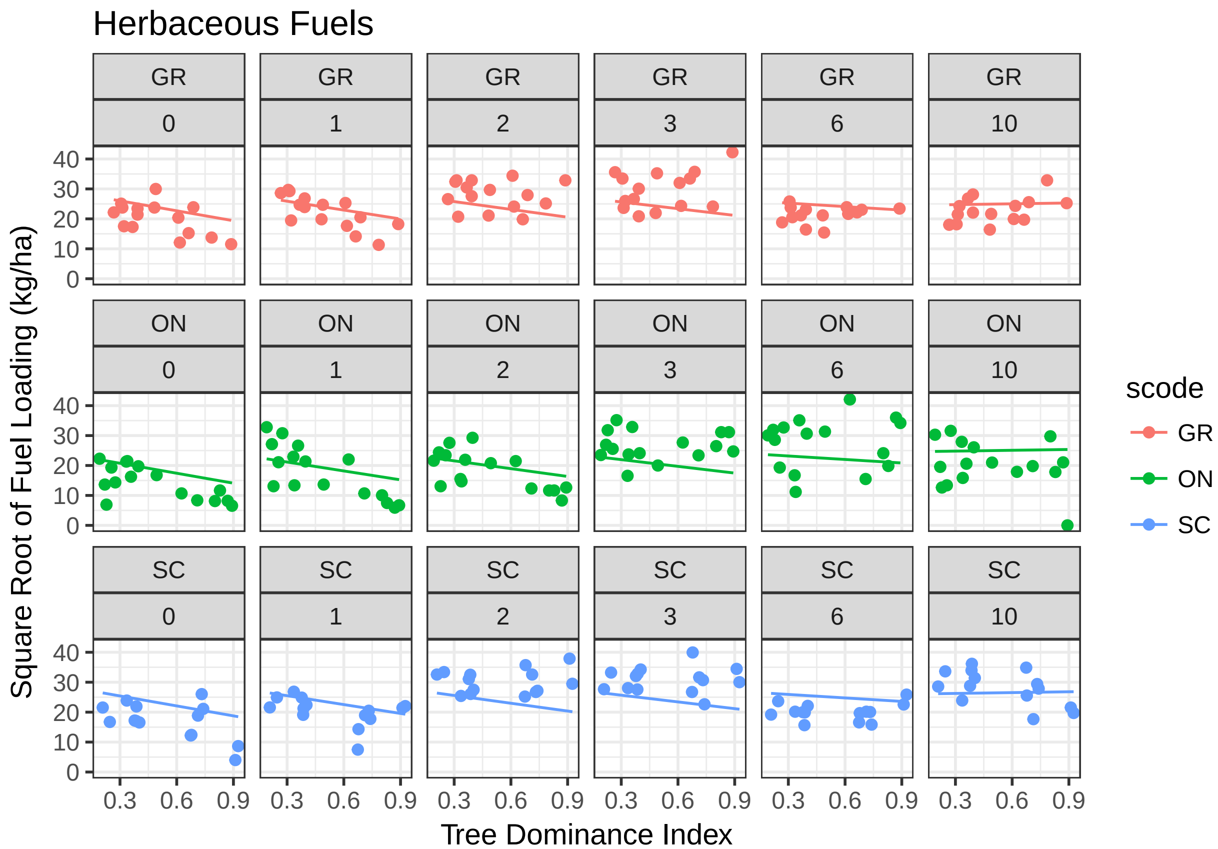

```
qqnorm(resid(m)); qqline(resid(m))
```



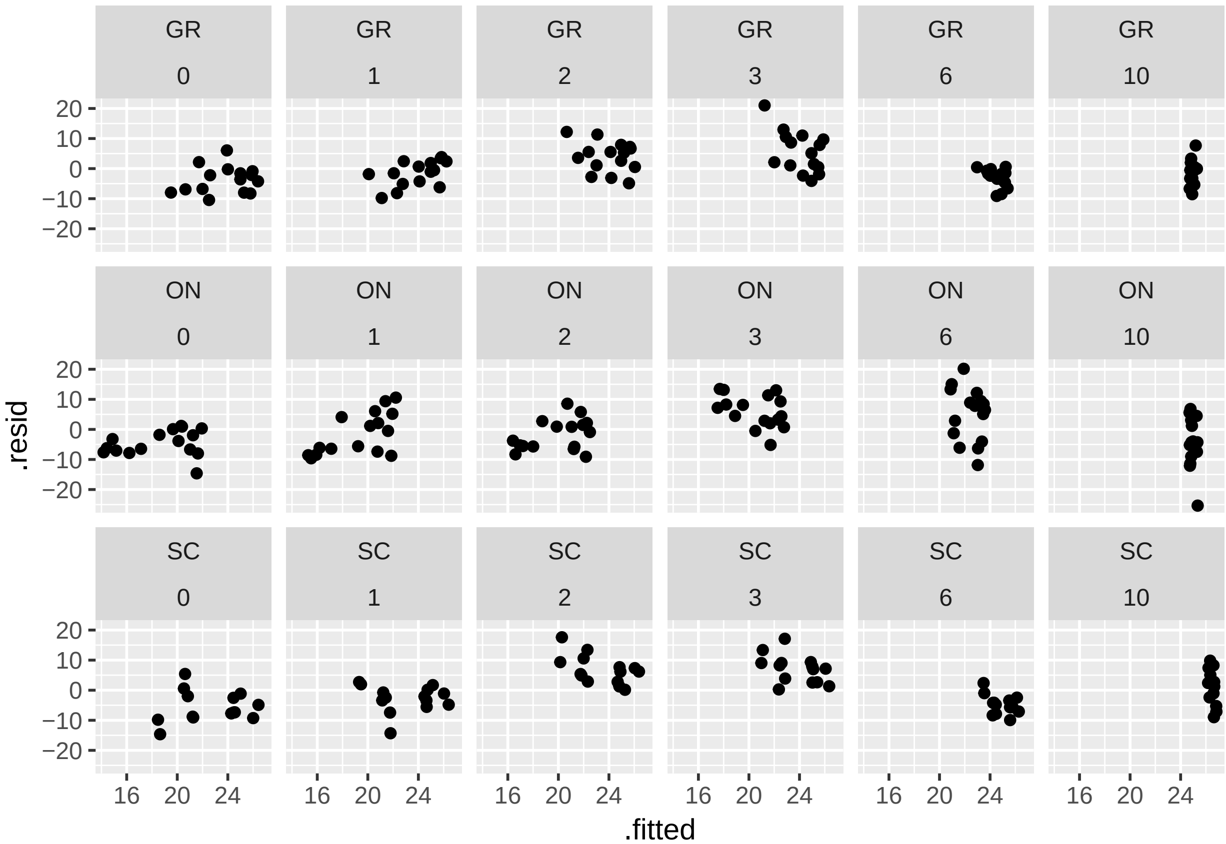

```
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```
#by yst and site
l$yhat_herb <- predict(m)
p <- ggplot(data = l, aes(x = TDI, y = sqrt(herb_ttl), color = scode))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_herb))
p <- p + theme_bw()
p <- p + labs(title = 'Herbaceous Fuels',
                x = 'Tree Dominance Index',
                y = 'Square Root of Fuel Loading (kg/ha)')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(scode~yst, ncol = 6, nrow = 3)
plot(p)
```




```
ggplot(m, aes(x = .fitted, y = .resid)) +
  geom_point() +
  facet_wrap(scode~yst, nrow = 3, ncol = 6)
```



Shrub Fuels

**Data errors: Onaqui year 6, zero values are incorrect (JP-ON-GC-006, JP-ON-GC-010 have high shrub volumes but zero biomass)

**Missing data: no shrub data for Onaqui when YST = 0 (calendar year = 2006)

shrub_fuel = shrub fuel loading

TDI = tree dominance index

yst = years since treatment

scode = site

```
l$shrub_fuel <- abs(l$shrub_bio_ttl)

l$shrub_fuel[l$scode == 'ON' & l$yst == 0] <- NA

l2 <- subset(l, !is.na(shrub_fuel))
l2$scode <- factor(l2$scode, levels = c('GR', 'SC', 'ON'))

m <- lmer(sqrt(shrub_fuel) ~ TDI + yst + yst:TDI + (1 + yst|scode), data = l2)
summary(m)
```

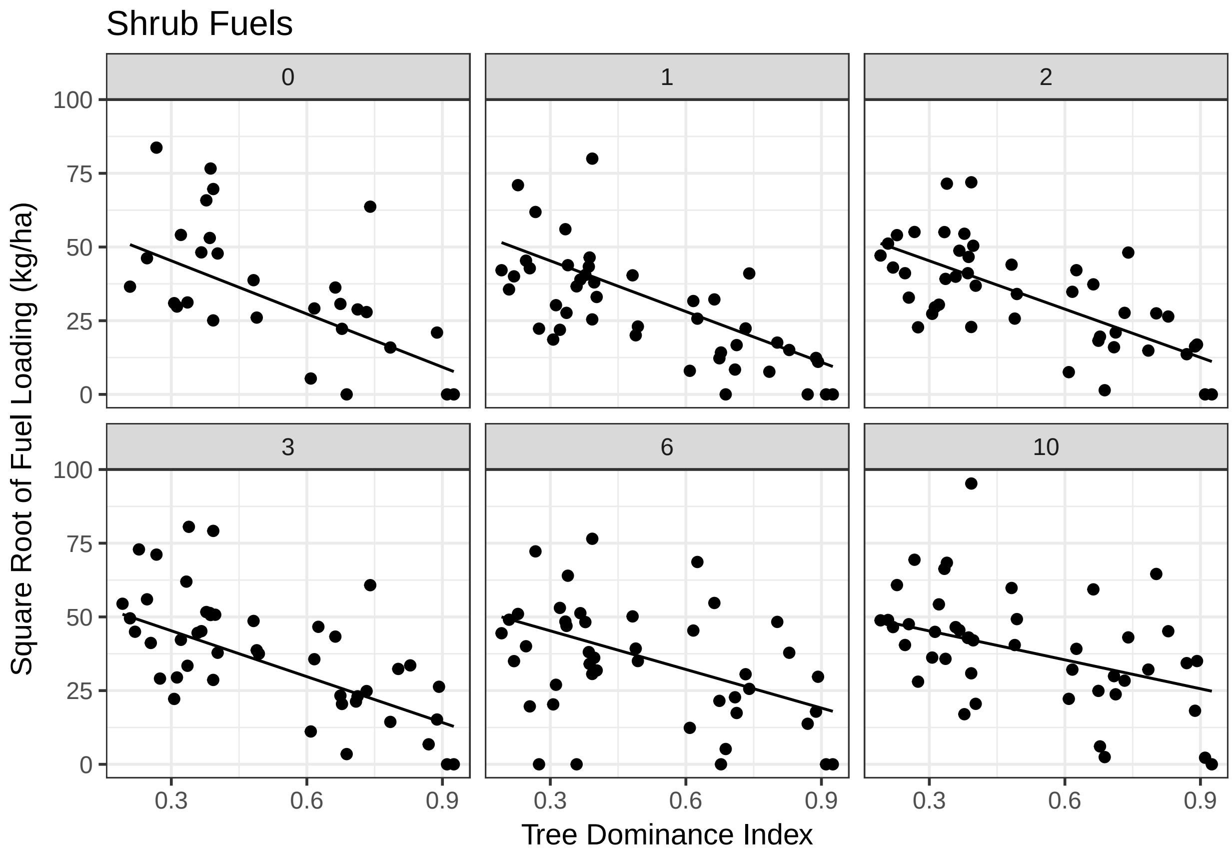
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(shrub_fuel) ~ TDI + yst + yst:TDI + (1 + yst | scode)
```

```
##    Data: l2
##
## REML criterion at convergence: 2096
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.165 -0.722 -0.025  0.558  3.173
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  scode    (Intercept)   7.62    2.76
##           yst           1.34    1.16    -1.00
##  Residual             239.26   15.47
## Number of obs: 253, groups:  scode, 3
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   63.364      4.085   15.51
## TDI          -60.122      6.683   -9.00
## yst           -0.833      0.986   -0.84
## TDI:yst        2.745      1.293    2.12
##
## Correlation of Fixed Effects:
##         (Intr) TDI    yst
## TDI     -0.846
## yst     -0.780  0.516
## TDI:yst  0.642 -0.760 -0.676
```

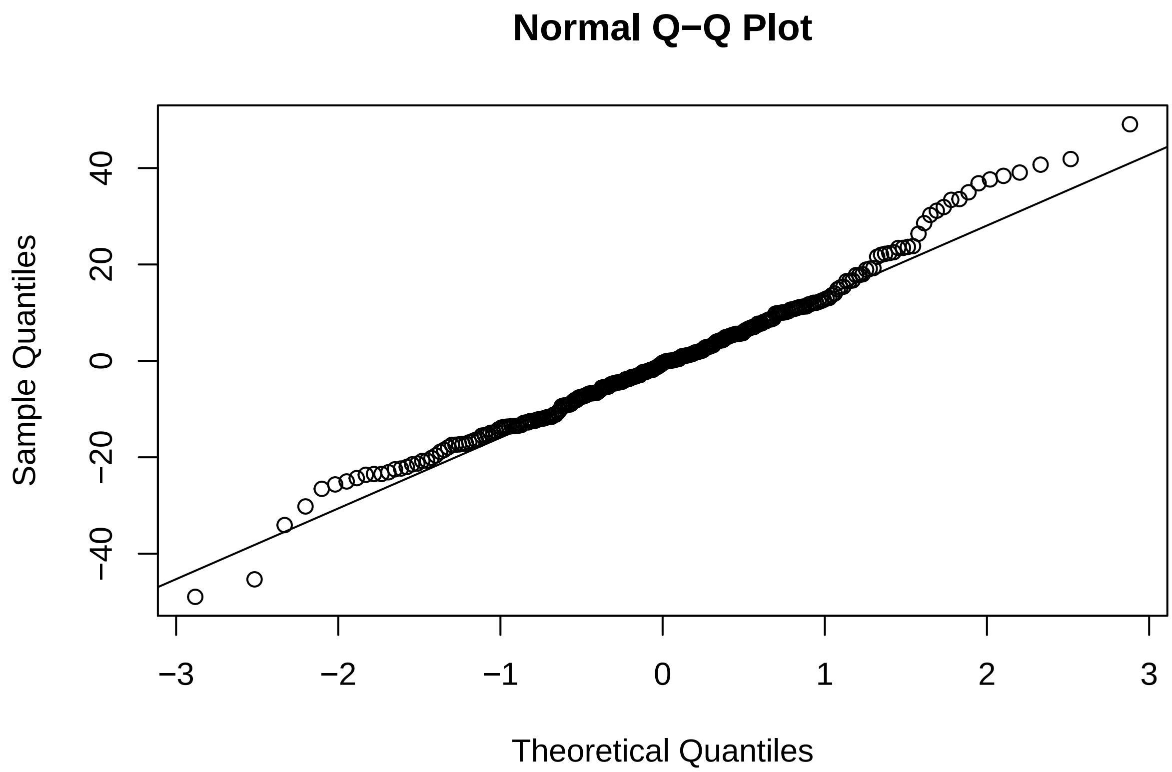
```r
lincon(m)
```

```
##             estimate    se  lower  upper tvalue  df   pvalue
## (Intercept)   63.364 4.085  55.36  71.37 15.512 Inf 2.86e-54
## TDI          -60.122 6.683 -73.22 -47.02 -8.996 Inf 2.34e-19
## yst           -0.833 0.986  -2.77   1.10 -0.844 Inf 3.99e-01
## TDI:yst        2.745 1.293   0.21   5.28  2.122 Inf 3.38e-02
```

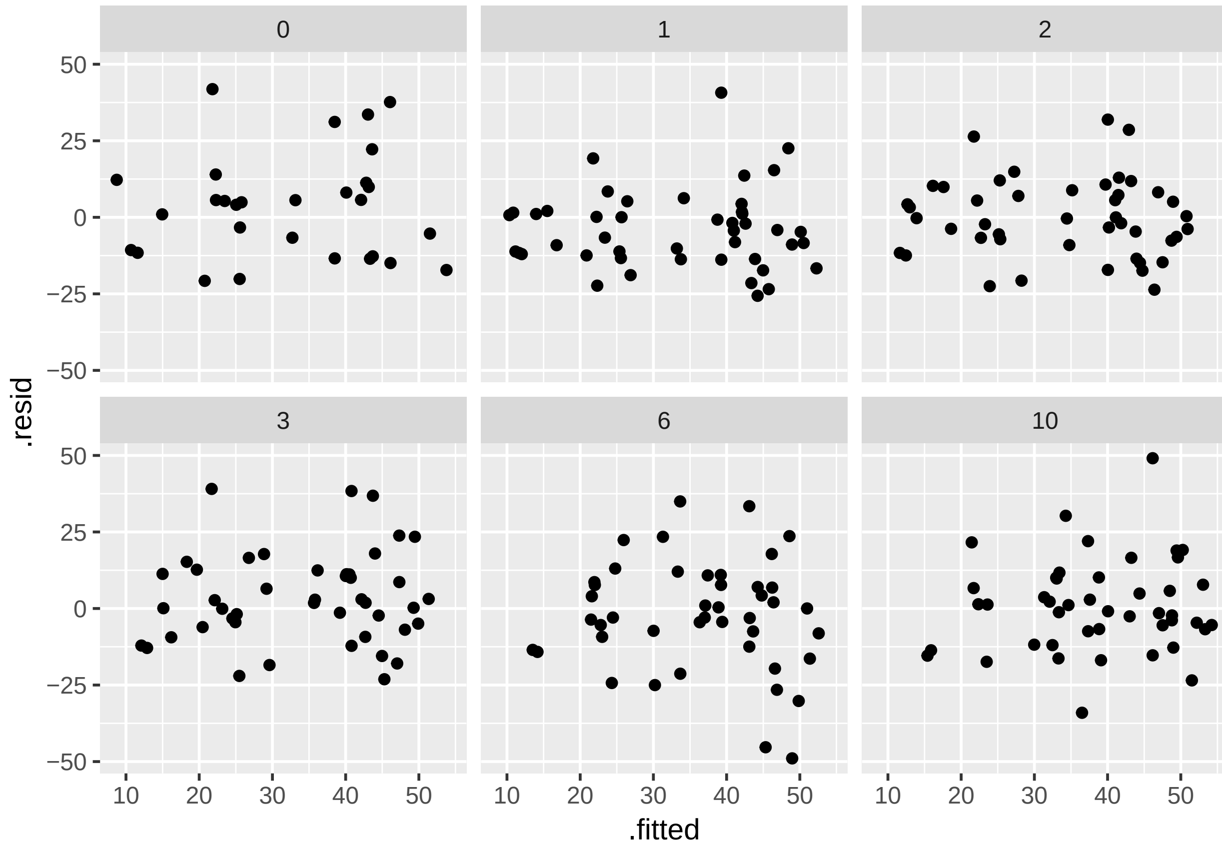
```r
#by yst
l2$yhat_shrub <- predict(m, re.form = NA)
p <- ggplot(data = l2, aes(x = TDI, y = sqrt(shrub_fuel)))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_shrub))
p <- p + theme_bw()
p <- p + labs(title = 'Shrub Fuels',
                x = 'Tree Dominance Index',
                y = 'Square Root of Fuel Loading (kg/ha)')
p <- p + scale_x_continuous(breaks = seq(0,1, by = .3))
p <- p + facet_wrap(~yst, ncol = 3)
plot(p)
```



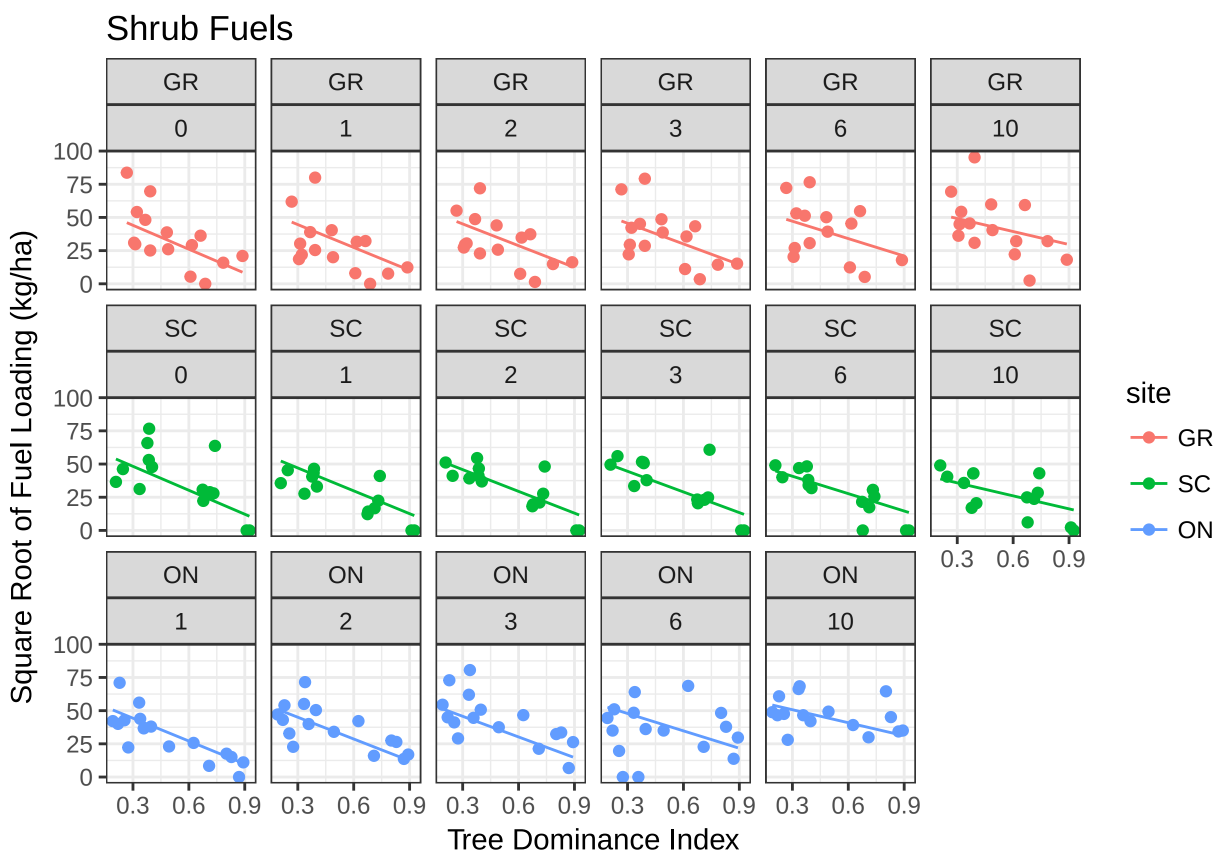

```
qqnorm(resid(m)); qqline(resid(m))
```



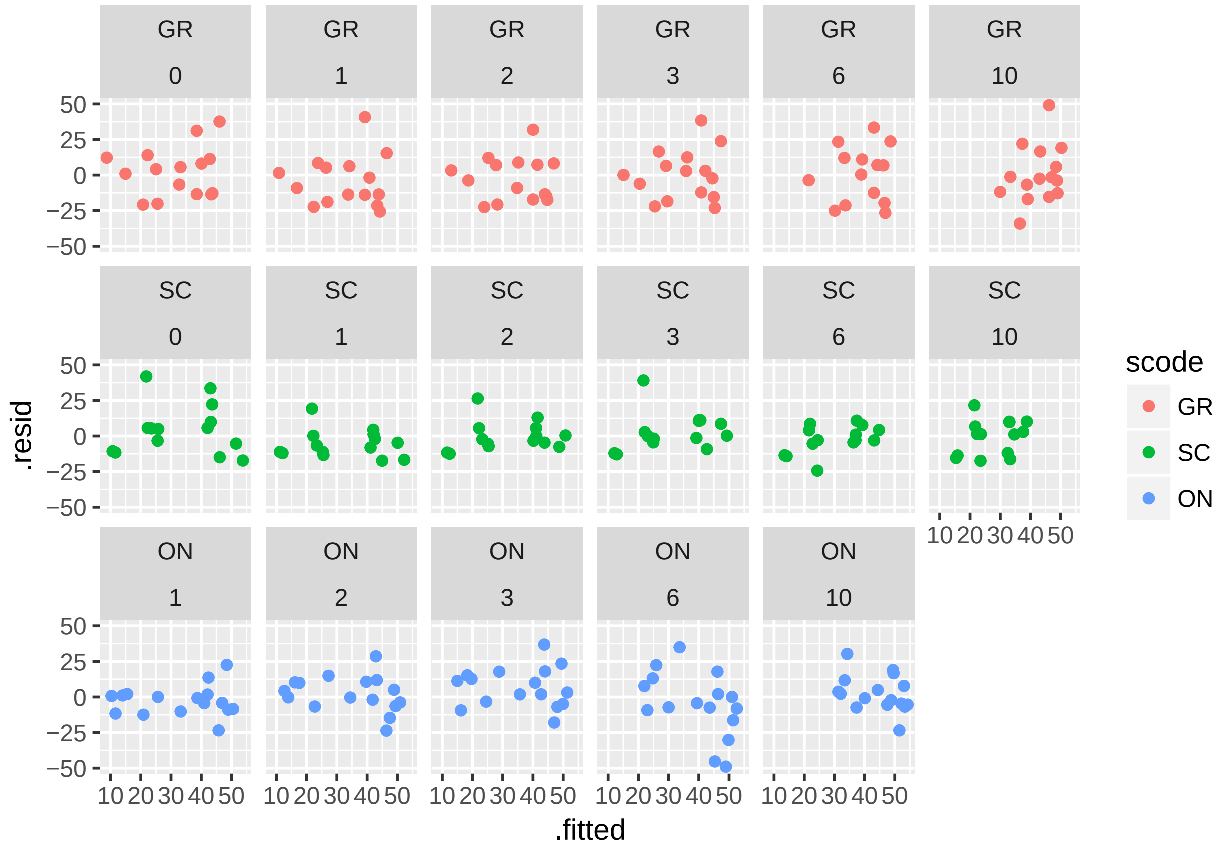

```
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```
#by yst and site
l2$yhat_shrub <- predict(m)
p <- ggplot(data = l2, aes(x = TDI, y = sqrt(shrub_fuel), color = scode))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_shrub))
p <- p + theme_bw()
p <- p + labs(title = 'Shrub Fuels',
              x = 'Tree Dominance Index',
              y = 'Square Root of Fuel Loading (kg/ha)',
              color = 'site')
p <- p + scale_x_continuous(breaks = seq(0,1, by = .3))
p <- p + facet_wrap(scode~yst, ncol = 6, nrow = 3)
plot(p)
```




```
ggplot(m, aes(x = .fitted, y = .resid, color = scode)) +
  geom_point() +
  facet_wrap(scode~yst, ncol = 6, nrow = 3)
```



Shrub Cover

Note: Shrub cover increase when yst = 6 for scode = SC & GR but decrease in herb biomass

```
m <- lmer(can_cover_pt_shrub ~ TDI + yst + yst:TDI + (1 + yst|scode), data = l)
summary(m)
```

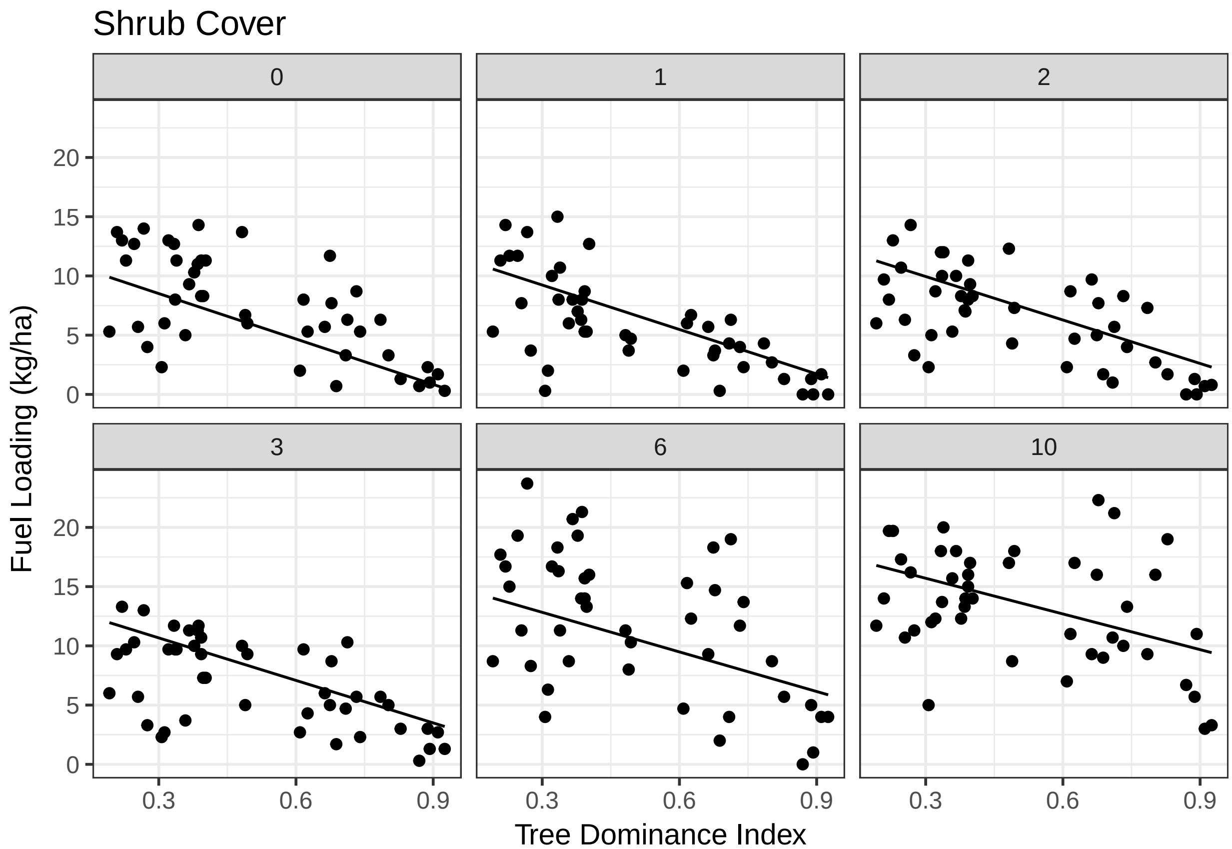
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: can_cover_pt_shrub ~ TDI + yst + yst:TDI + (1 + yst | scode)
##    Data: l
##
## REML criterion at convergence: 1474
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5377 -0.7147 -0.0782  0.6614  3.0501
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  scode    (Intercept)  1.6278  1.276
##           yst          0.0201  0.142    -0.46
##  Residual             13.7350  3.706
## Number of obs: 269, groups:  scode, 3
##
## Fixed effects:
##             Estimate Std. Error t value
```

```
## (Intercept)   12.347      1.109   11.13
## TDI          -12.783      1.476   -8.66
## yst            0.637      0.185    3.45
## TDI:yst        0.274      0.295    0.93
##
## Correlation of Fixed Effects:
##         (Intr) TDI    yst
## TDI     -0.685
## yst     -0.626  0.601
## TDI:yst  0.501 -0.731 -0.821
```

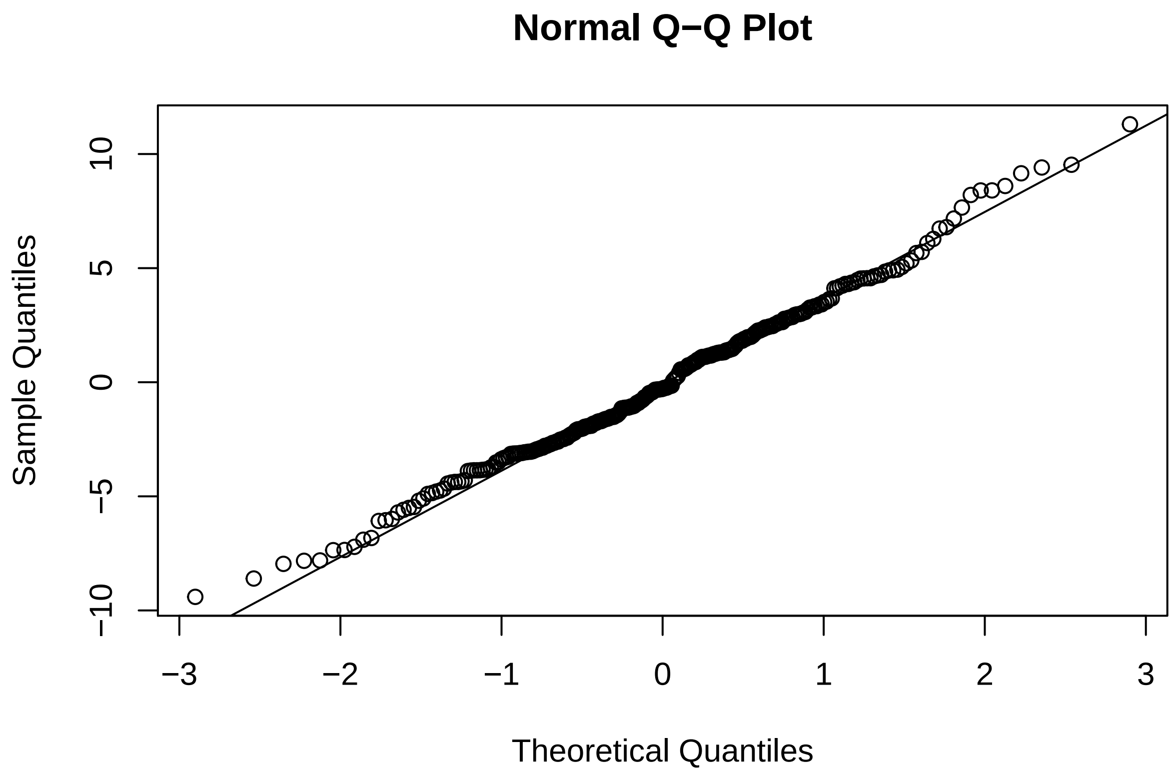
```
lincon(m)
```

```
##             estimate    se   lower  upper tvalue  df   pvalue
## (Intercept)   12.347 1.109  10.173 14.520 11.134 Inf 8.58e-29
## TDI          -12.783 1.476 -15.675 -9.890 -8.661 Inf 4.67e-18
## yst            0.637 0.185   0.275  0.999  3.448 Inf 5.65e-04
## TDI:yst        0.274 0.295  -0.305  0.853  0.928 Inf 3.53e-01
```

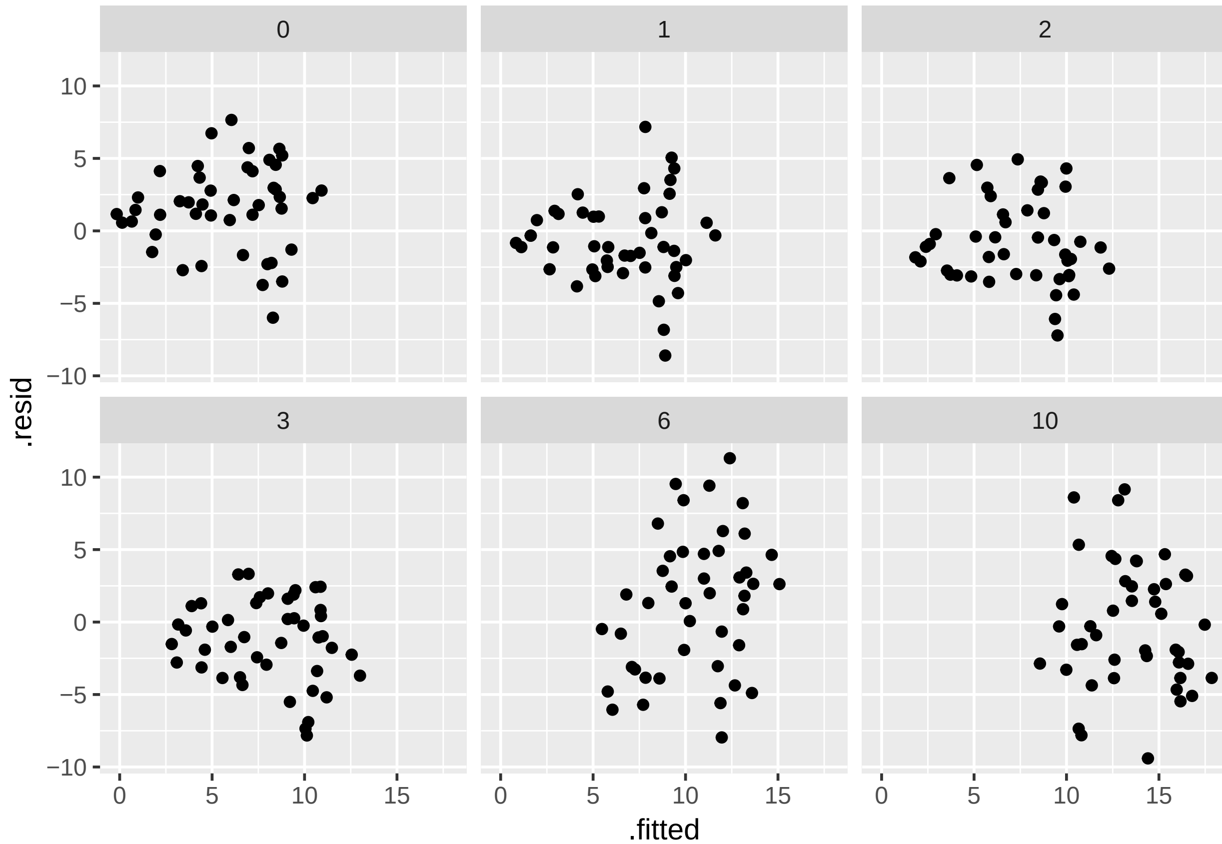
```
#by yst
l$yhat_sh_cvr <- predict(m, re.form = NA)
p <- ggplot(data = l, aes(x = TDI, y = can_cover_pt_shrub))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_sh_cvr))
p <- p + theme_bw()
p <- p + labs(title = 'Shrub Cover',
              x = 'Tree Dominance Index',
              y = 'Fuel Loading (kg/ha)')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(~yst, ncol = 3)
plot(p)
```



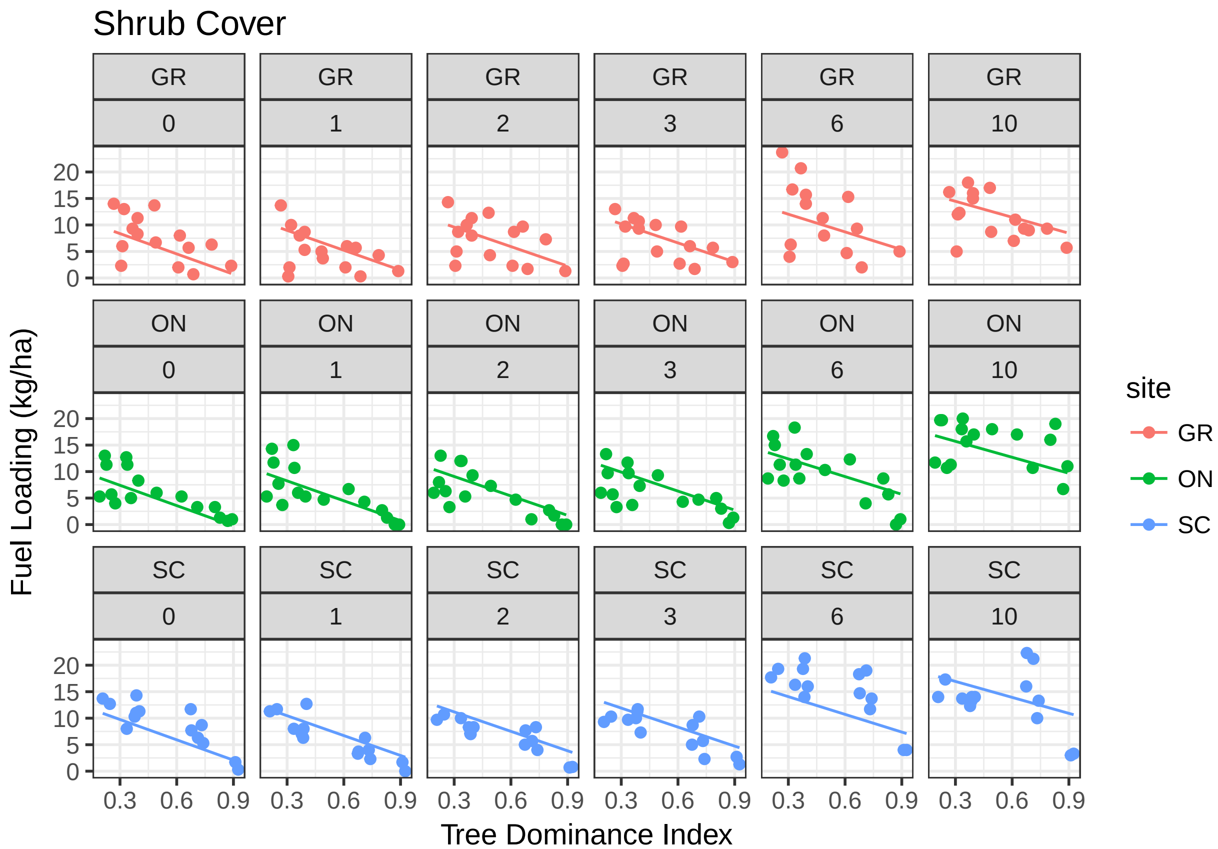

```
qqnorm(resid(m)); qqline(resid(m))
```



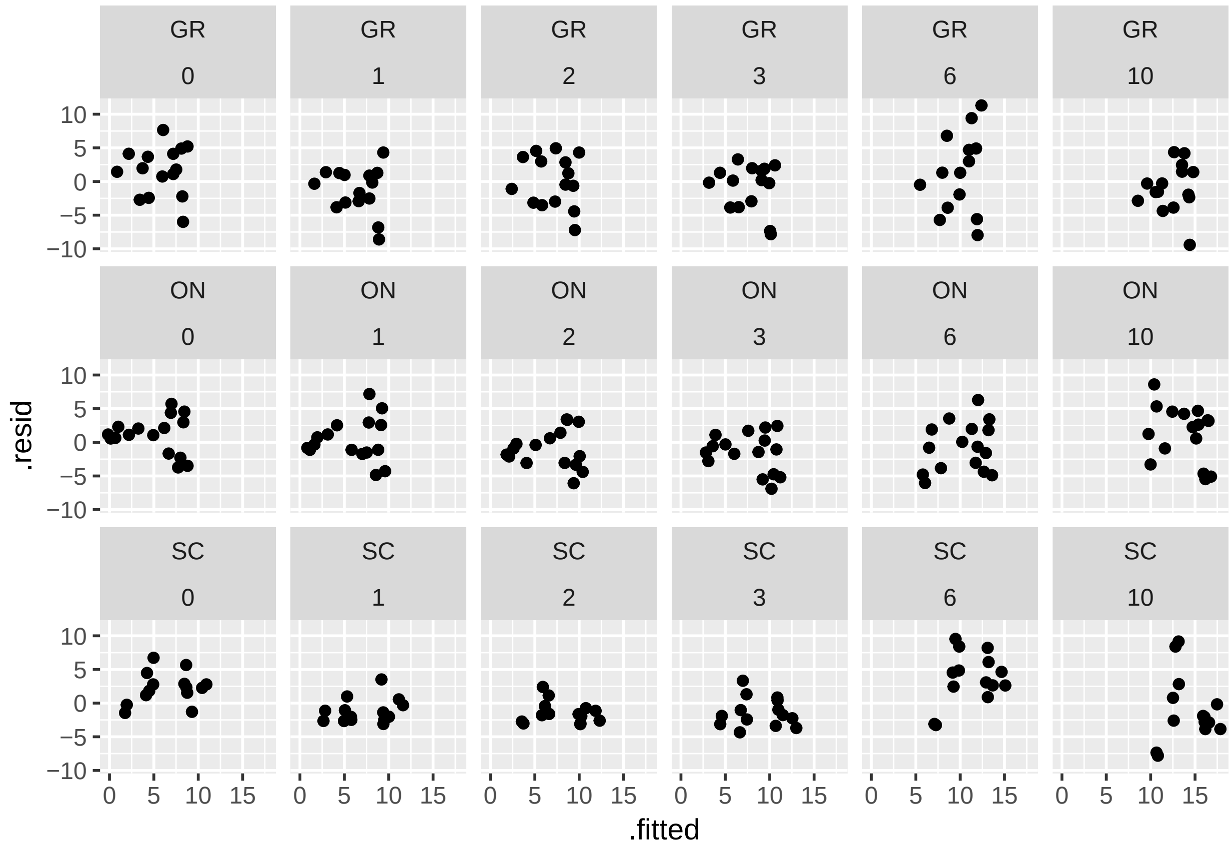

```
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```
#by yst and site
l$yhat_sh_cvr <- predict(m)
p <- ggplot(data = l, aes(x = TDI, y = can_cover_pt_shrub, color = scode))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_sh_cvr))
p <- p + theme_bw()
p <- p + labs(title = 'Shrub Cover',
              x = 'Tree Dominance Index',
              y = 'Fuel Loading (kg/ha)',
              color = 'site')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(scode~yst, ncol = 6, nrow = 3)
plot(p)
```




```r
ggplot(m, aes(x = .fitted, y = .resid)) +
  geom_point() +
  facet_wrap(scode~yst, ncol = 6, nrow = 3)
```



Perennial Grass Cover

```
m <- lmer(sqrt(can_cover_pt_pgrass) ~ TDI + yst + yst:TDI + (1 + yst|scode), data = l)
summary(m)
```

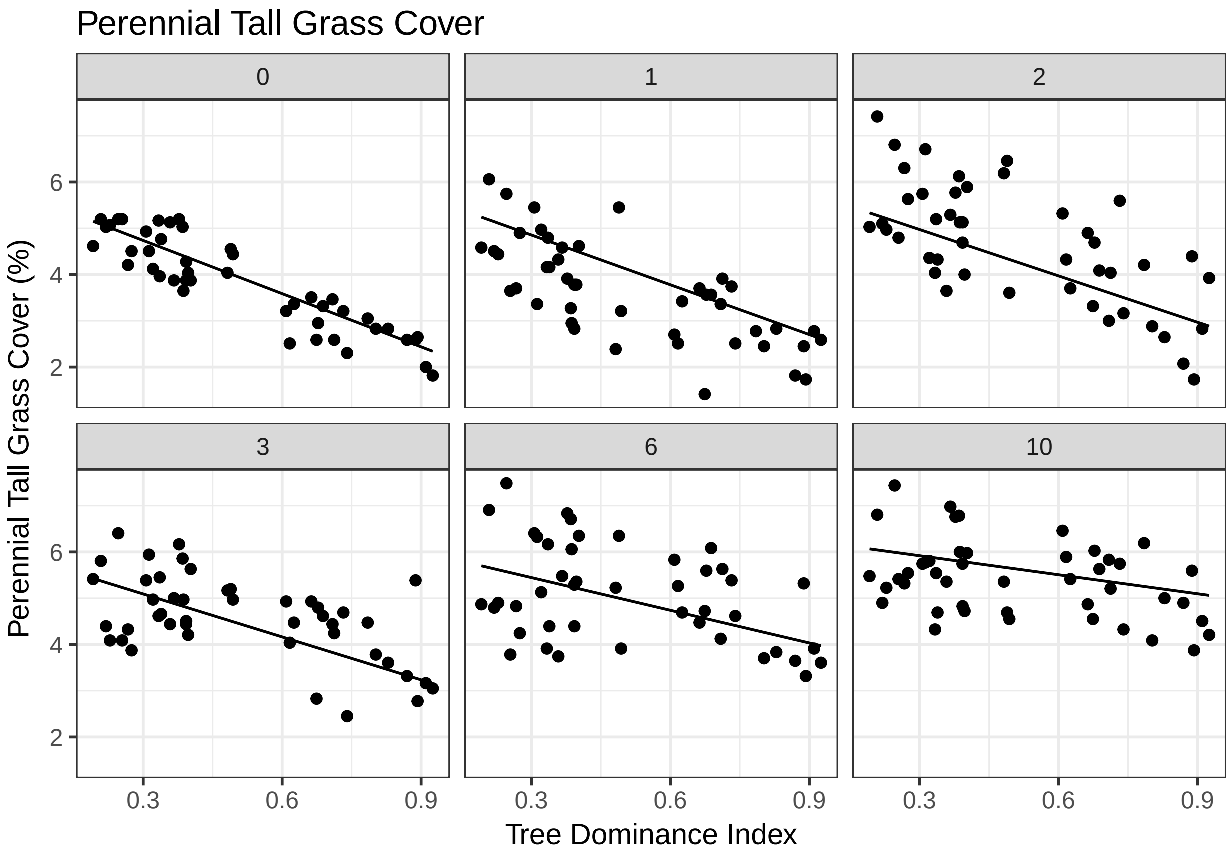
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(can_cover_pt_pgrass) ~ TDI + yst + yst:TDI + (1 + yst |
##     scode)
##    Data: l
##
## REML criterion at convergence: 627
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0533 -0.6140 -0.0251  0.7044  2.6363
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  scode    (Intercept) 0.0502   0.224
##           yst         0.0025   0.050    1.00
##  Residual             0.5616   0.749
## Number of obs: 269, groups:  scode, 3
##
## Fixed effects:
##             Estimate Std. Error t value
```

```
## (Intercept)   5.8865     0.2111   27.89
## TDI          -3.8331     0.2972  -12.90
## yst           0.0442     0.0441    1.00
## TDI:yst       0.2463     0.0595    4.14
##
## Correlation of Fixed Effects:
##         (Intr) TDI    yst
## TDI     -0.723
## yst     -0.035  0.505
## TDI:yst  0.527 -0.729 -0.693
```

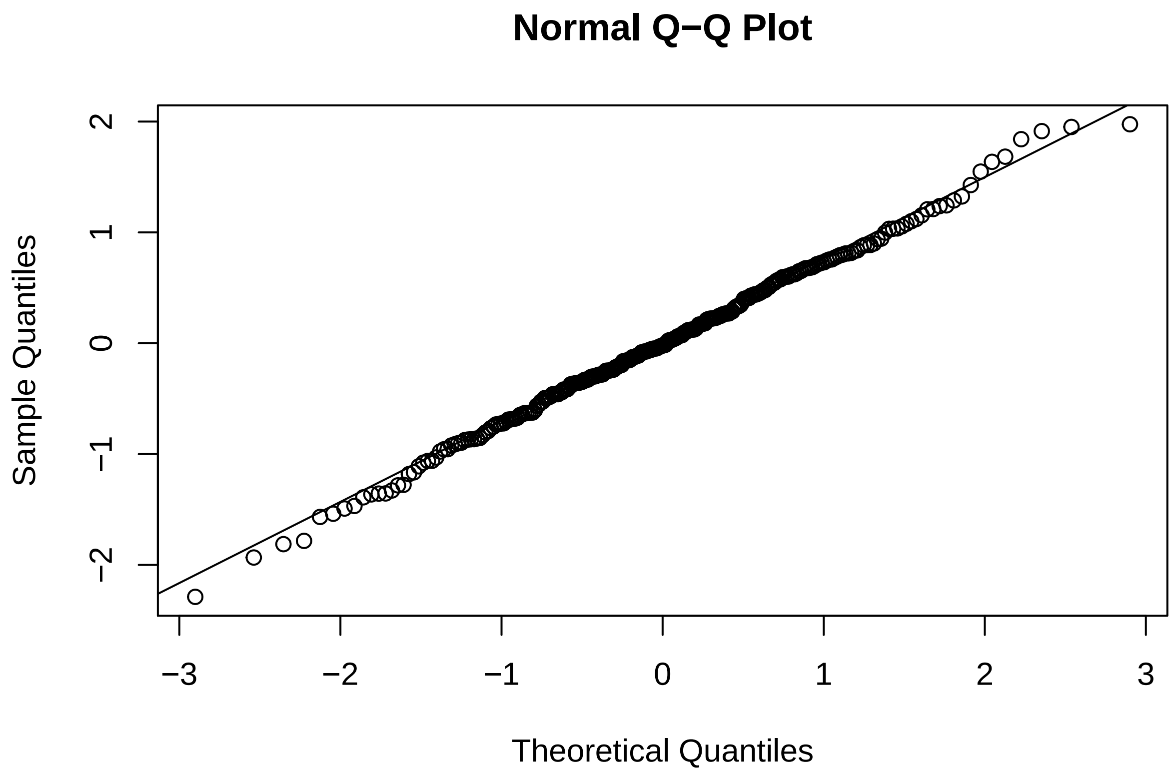
```
lincon(m)
```

```
##             estimate     se   lower  upper tvalue  df    pvalue
## (Intercept)   5.8865 0.2111  5.4728  6.300  27.89 Inf 3.63e-171
## TDI          -3.8331 0.2972 -4.4155 -3.251 -12.90 Inf  4.59e-38
## yst           0.0442 0.0441 -0.0422  0.131   1.00 Inf  3.16e-01
## TDI:yst       0.2463 0.0595  0.1296  0.363   4.14 Inf  3.51e-05
```

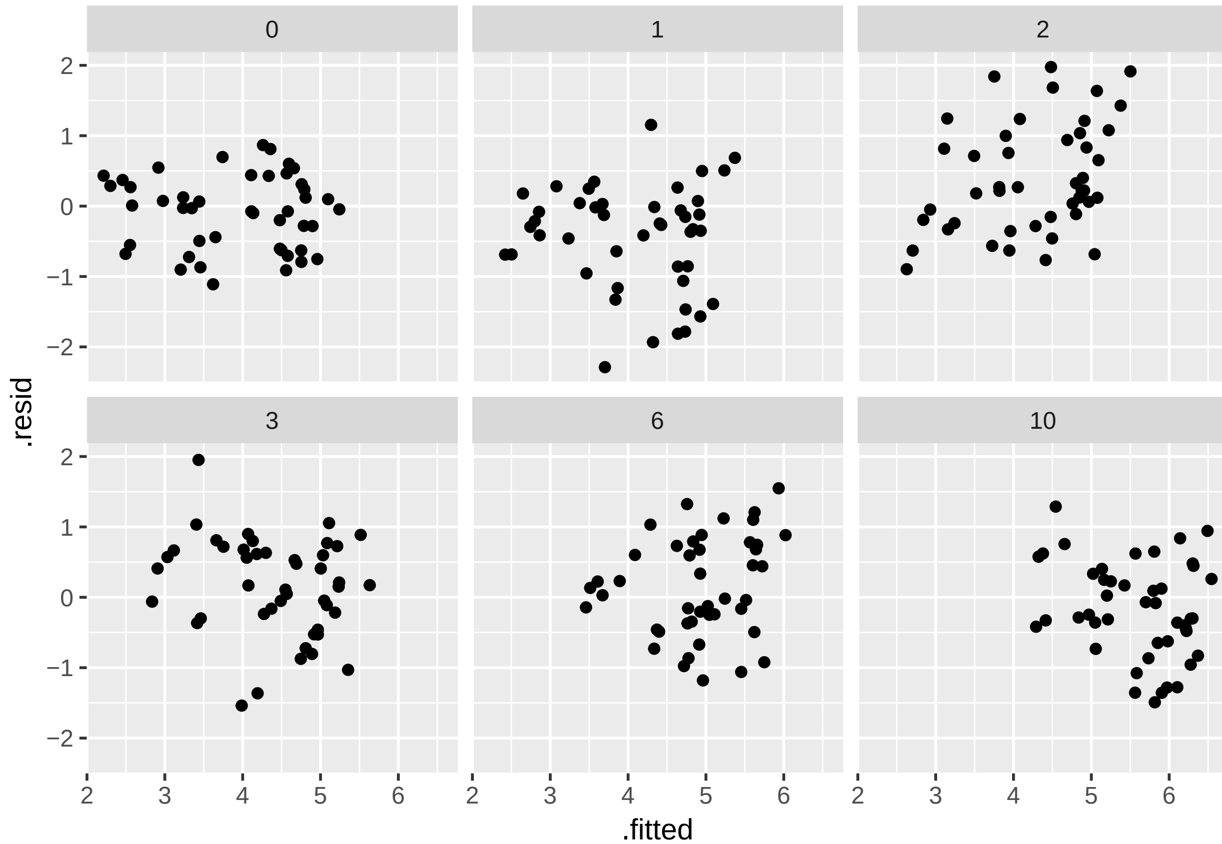
```
#by yst
l$yhat_pgrass_cvr <- predict(m, re.form = NA)
p <- ggplot(data = l, aes(x = TDI, y = sqrt(can_cover_pt_pgrass)))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_pgrass_cvr))
p <- p + theme_bw()
p <- p + labs(title = 'Perennial Tall Grass Cover',
                x = 'Tree Dominance Index',
                y = 'Perennial Tall Grass Cover (%)')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(~yst, ncol = 3)
plot(p)
```



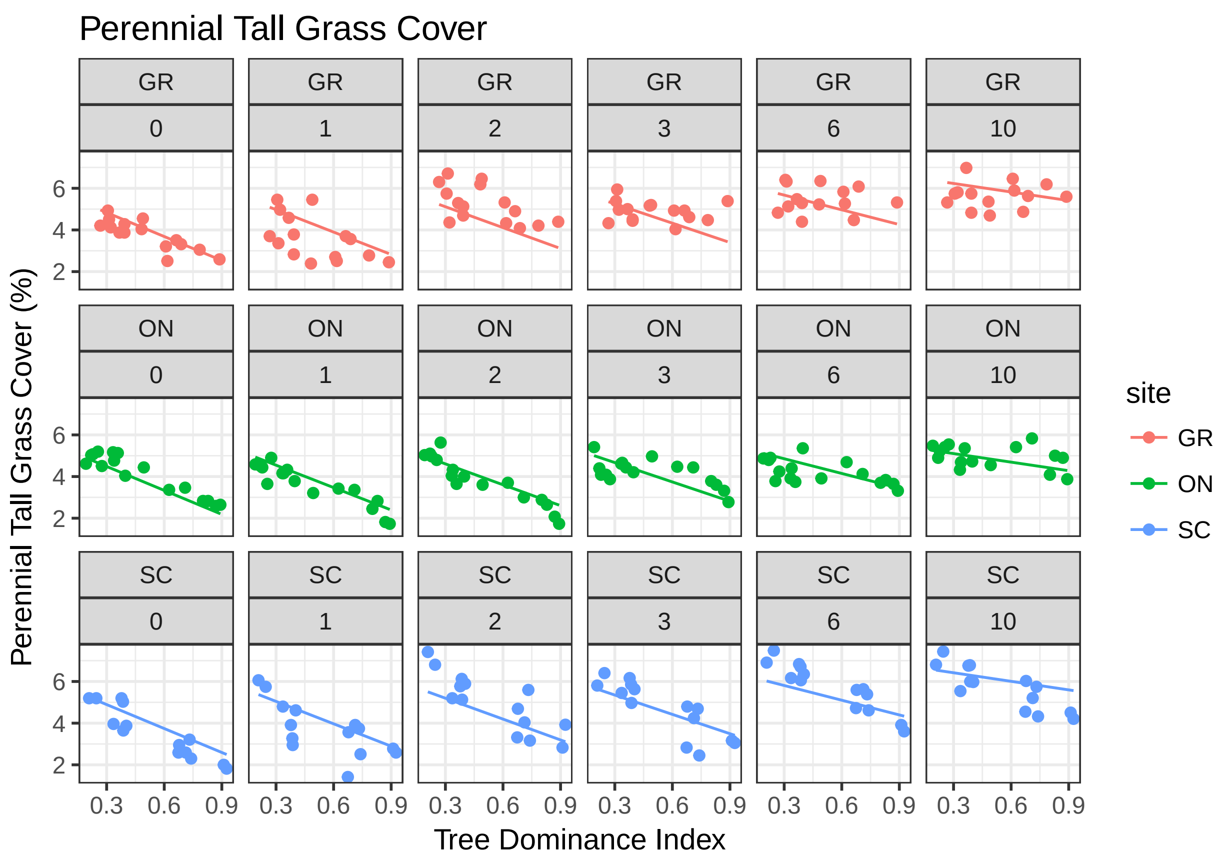

```r
qqnorm(resid(m)); qqline(resid(m))
```



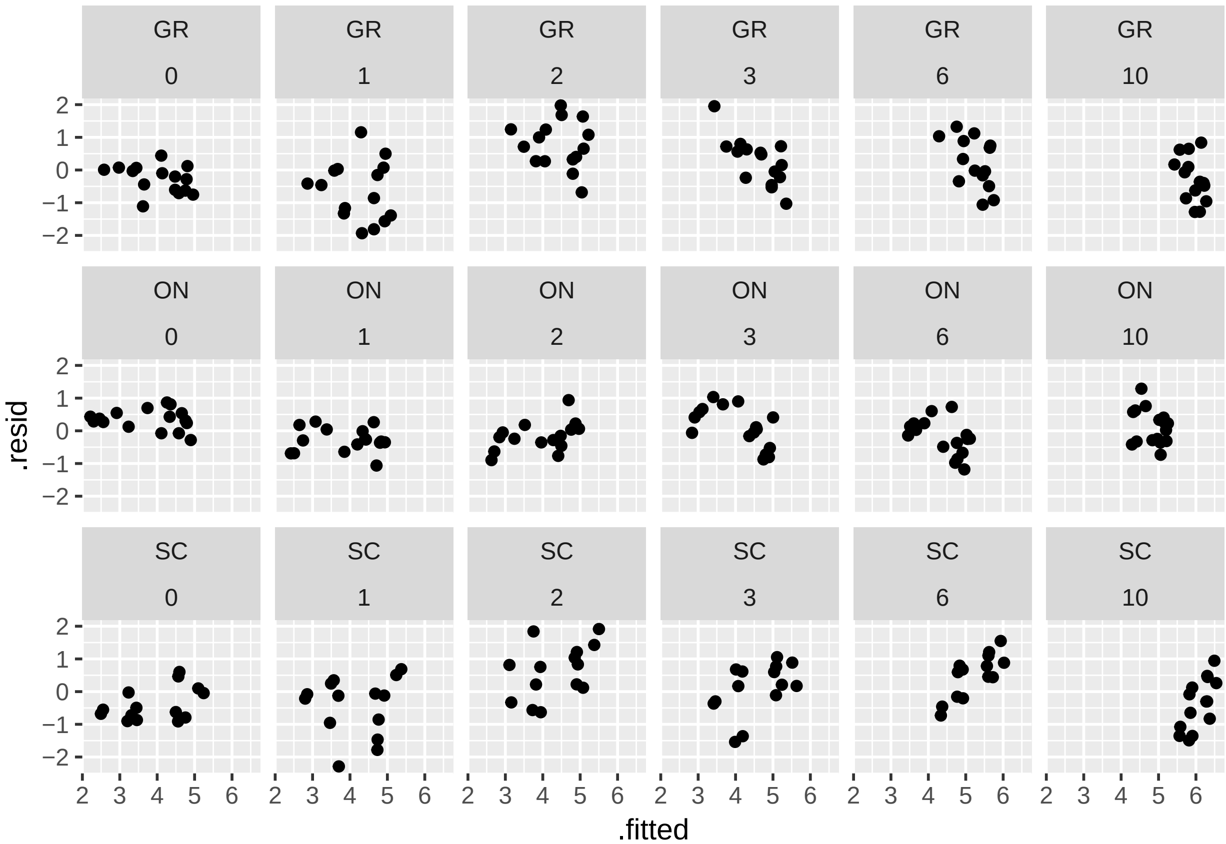

```
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```r
#by yst and site
l$yhat_pgrass_cvr <- predict(m)
p <- ggplot(data = l, aes(x = TDI, y = sqrt(can_cover_pt_pgrass), color = scode))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_pgrass_cvr))
p <- p + theme_bw()
p <- p + labs(title = 'Perennial Tall Grass Cover',
              x = 'Tree Dominance Index',
              y = 'Perennial Tall Grass Cover (%)',
              color = 'site')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(scode~yst, ncol = 6, nrow = 3)
plot(p)
```




```r
ggplot(m, aes(x = .fitted, y = .resid)) +
  geom_point() +
  facet_wrap(scode~yst, ncol = 6, nrow = 3)
```



Annual Grass Cover

Note: what is going on at Scipio in yst = 6,10? Decrease in annual grass cover

```
m <- lmer(sqrt(can_cover_pt_agrass) ~ TDI + yst + yst:TDI + (1 + yst|scode), data = l)
summary(m)
```

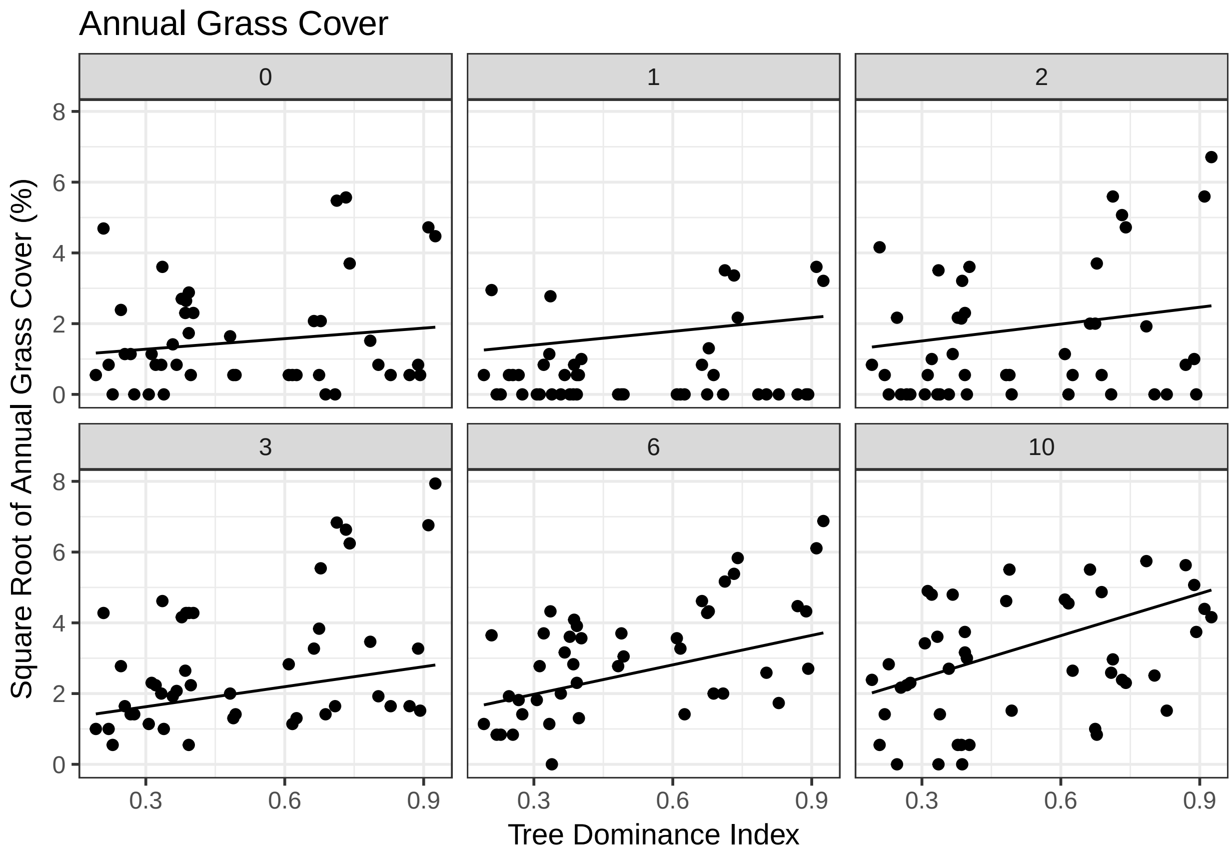
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: sqrt(can_cover_pt_agrass) ~ TDI + yst + yst:TDI + (1 + yst |
##     scode)
##    Data: l
##
## REML criterion at convergence: 876
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.190 -0.602 -0.061  0.695  3.255
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  scode    (Intercept) 3.6176   1.90
##           yst         0.0727   0.27     -0.94
##  Residual             1.3905   1.18
## Number of obs: 269, groups:  scode, 3
##
## Fixed effects:
```

```
##             Estimate Std. Error t value
## (Intercept)   0.9791     1.1295    0.87
## TDI           0.9948     0.4704    2.12
## yst           0.0278     0.1644    0.17
## TDI:yst       0.2972     0.0942    3.16
##
## Correlation of Fixed Effects:
##         (Intr) TDI    yst
## TDI     -0.214
## yst     -0.916  0.216
## TDI:yst  0.157 -0.732 -0.295
```

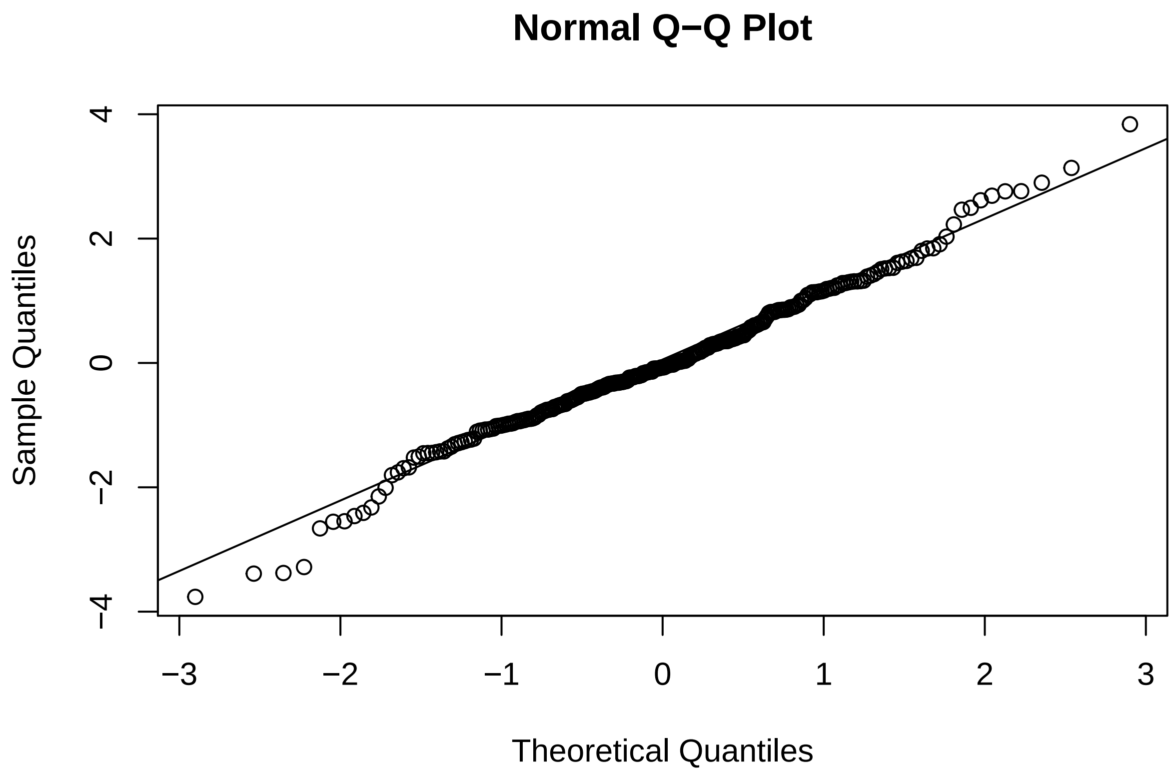
```
lincon(m)
```

```
##             estimate     se   lower upper tvalue  df pvalue
## (Intercept)   0.9791 1.1295 -1.2346 3.193  0.867 Inf 0.3860
## TDI           0.9948 0.4704  0.0729 1.917  2.115 Inf 0.0344
## yst           0.0278 0.1644 -0.2944 0.350  0.169 Inf 0.8659
## TDI:yst       0.2972 0.0942  0.1126 0.482  3.156 Inf 0.0016
```

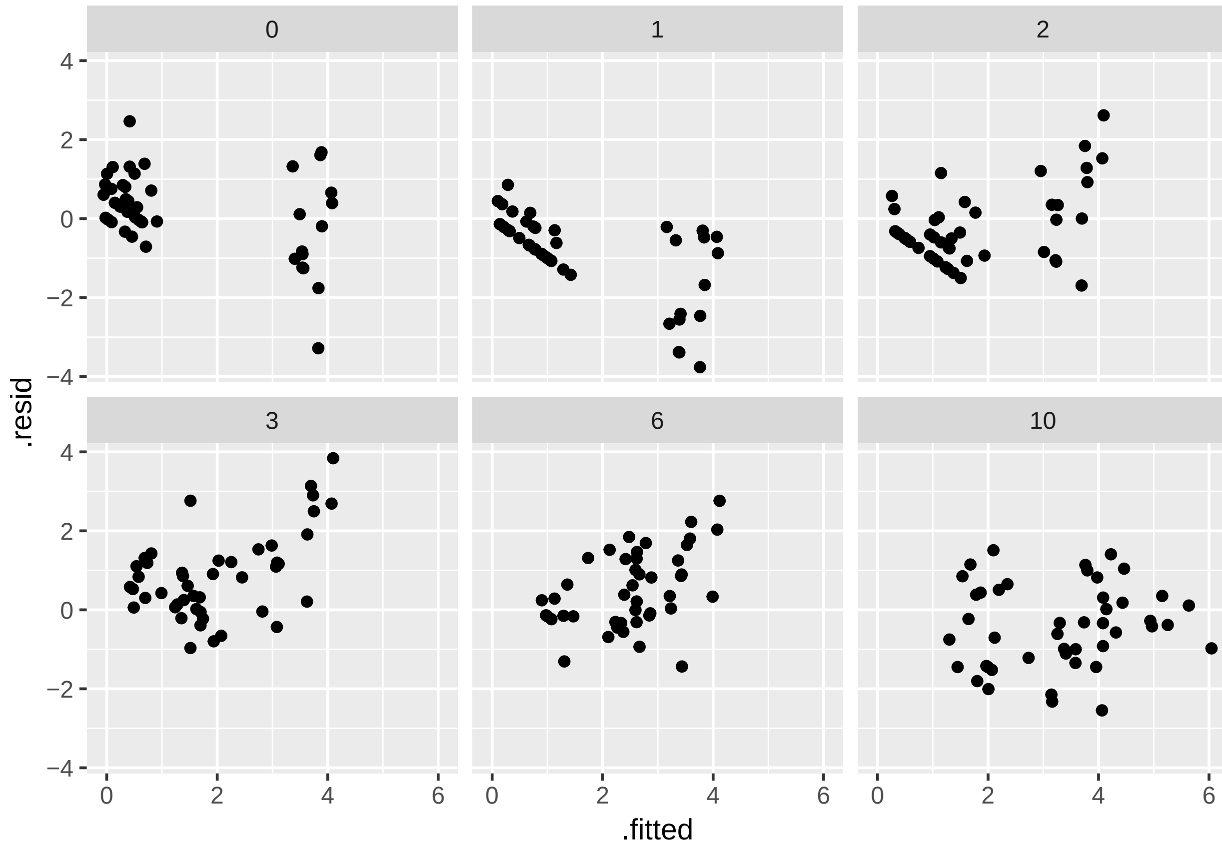
```
#by yst
l$yhat_agrass_cvr <- predict(m, re.form = NA)
p <- ggplot(data = l, aes(x = TDI, y = sqrt(can_cover_pt_agrass)))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_agrass_cvr))
p <- p + theme_bw()
p <- p + labs(title = 'Annual Grass Cover',
              x = 'Tree Dominance Index',
              y = 'Square Root of Annual Grass Cover (%)')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(~yst, ncol = 3)
plot(p)
```



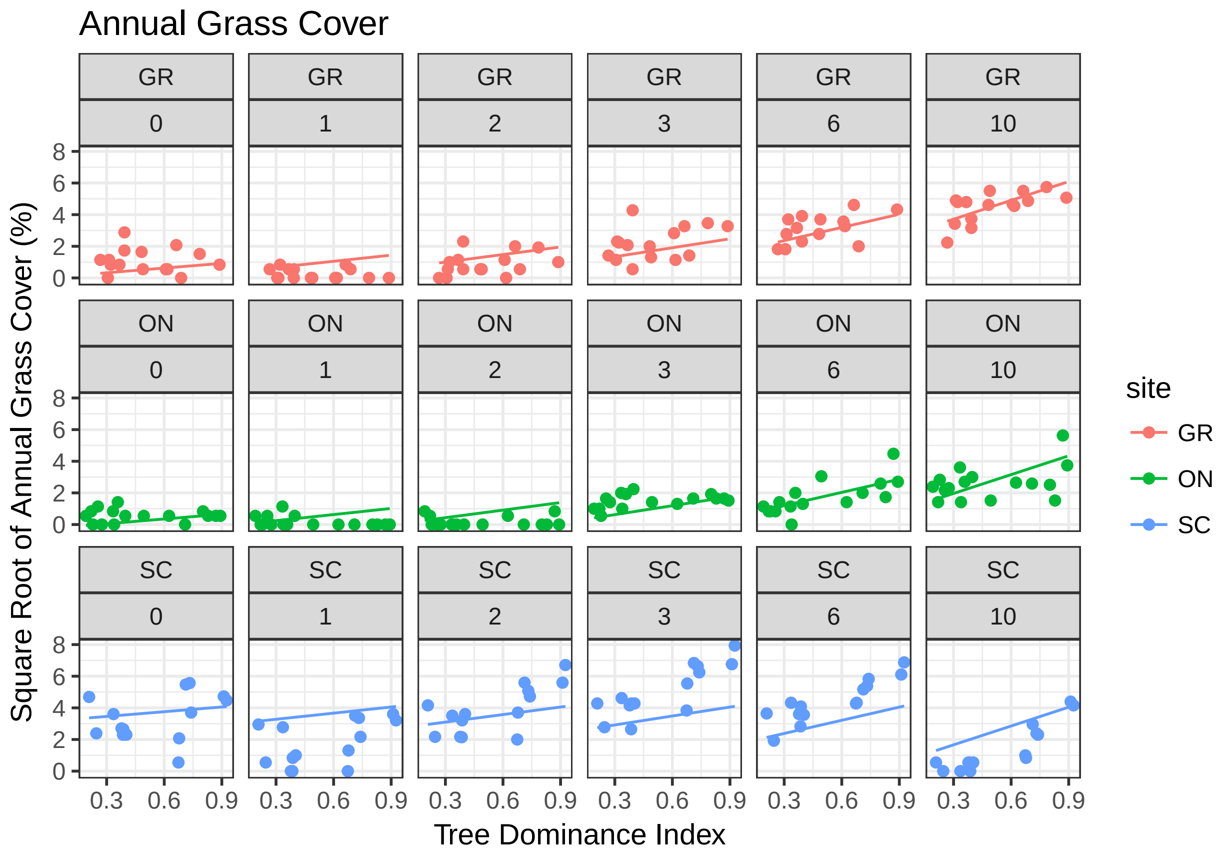

```r
qqnorm(resid(m)); qqline(resid(m))
```



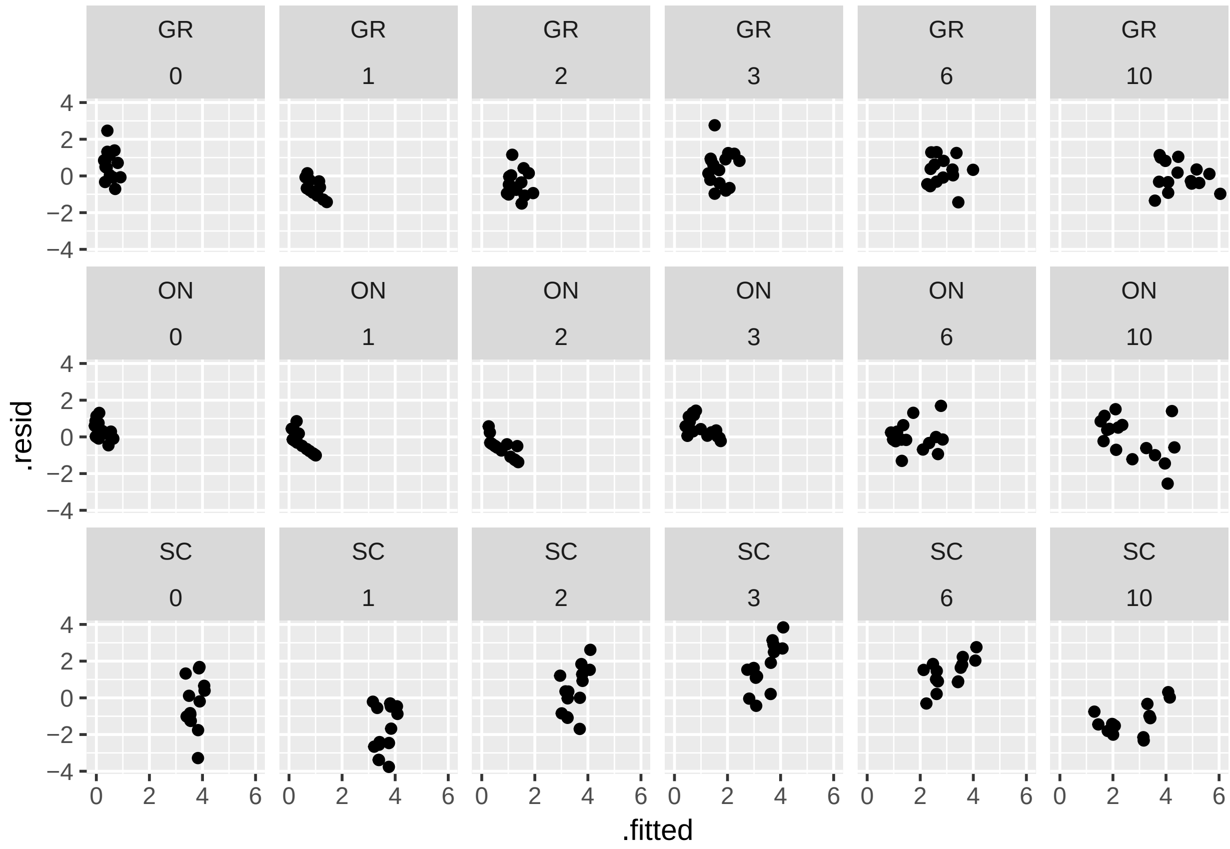

```
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```r
#by yst and site
l$yhat_agrass_cvr <- predict(m)
p <- ggplot(data = l, aes(x = TDI, y = sqrt(can_cover_pt_agrass), color = scode))
p <- p + geom_point()
p <- p + geom_line(aes(y = yhat_agrass_cvr))
p <- p + theme_bw()
p <- p + labs(title = 'Annual Grass Cover',
              x = 'Tree Dominance Index',
              y = 'Square Root of Annual Grass Cover (%)',
              color = 'site')
p <- p + scale_x_continuous(breaks = seq(0,1, by = 0.3))
p <- p + facet_wrap(scode~yst, ncol = 6, nrow = 3)
plot(p)
```




```r
ggplot(m, aes(x = .fitted, y = .resid)) +
  geom_point() +
  facet_wrap(scode~yst, ncol = 6, nrow = 3)
```



Tree Density >5 cm

```
td$tree_density <- td$tree_dns_5_50_JUOS + td$tree_dns_gt50_JUOS + td$tree_dns_5_50_PIED + td$tree_dns_g
td <- filter(td, (yst %in% c(-1,1,2,3,6,10) & scode %in% c('SC', 'GR')) |
               (yst %in% c(0,1,2,3,6,10) & scode == 'ON'))
td$yst[td$yst == -1] <- 0  #so that all pre-treatment years are grouped together
```

MODEL FAILS TO CONVERGE UNLESS I TREAT YST AS FACTOR

```
m <- lmer(sqrt(tree_dns_gt50_JUOS + tree_dns_gt50_PIED) ~
            TC + factor(yst) + factor(yst):TC + (1 + factor(yst)|scode), data = td)
summary(m)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## sqrt(tree_dns_gt50_JUOS + tree_dns_gt50_PIED) ~ TC + factor(yst) +
##     factor(yst):TC + (1 + factor(yst) | scode)
##    Data: td
##
## REML criterion at convergence: 925
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
##  -4.40   0.00   0.00   0.00   3.28
##
```

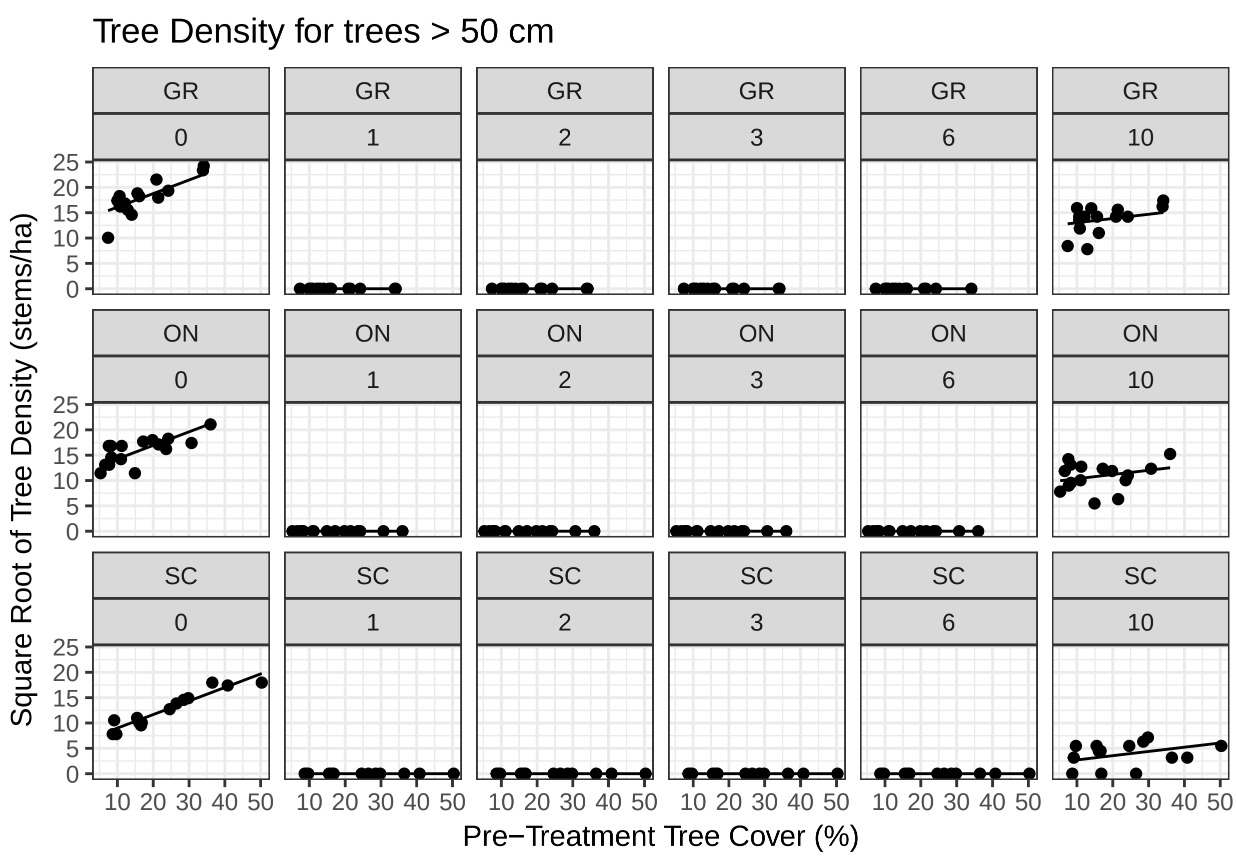
```
## Random effects:
##  Groups   Name          Variance Std.Dev. Corr
##  scode    (Intercept)   13.64    3.69
##           factor(yst)1  13.64    3.69     -1.00
##           factor(yst)2  13.64    3.69     -1.00  1.00
##           factor(yst)3  13.64    3.69     -1.00  1.00  1.00
##           factor(yst)6  13.64    3.69     -1.00  1.00  1.00  1.00
##           factor(yst)10  2.76    1.66      1.00 -1.00 -1.00 -1.00 -1.00
##  Residual                1.53    1.24
## Number of obs: 269, groups:  scode, 3
##
## Fixed effects:
##                  Estimate Std. Error t value
## (Intercept)       10.4426     2.1666    4.82
## TC                 0.2674     0.0181   14.79
## factor(yst)1     -10.4426     2.1994   -4.75
## factor(yst)2     -10.4426     2.1994   -4.75
## factor(yst)3     -10.4426     2.1994   -4.75
## factor(yst)6     -10.4426     2.1999   -4.75
## factor(yst)10     -2.5793     1.0991   -2.35
## TC:factor(yst)1   -0.2674     0.0253  -10.55
## TC:factor(yst)2   -0.2674     0.0253  -10.55
## TC:factor(yst)3   -0.2674     0.0253  -10.55
## TC:factor(yst)6   -0.2674     0.0257  -10.42
## TC:factor(yst)10  -0.1839     0.0252   -7.31
##
## Correlation of Fixed Effects:
##             (Intr) TC     fct()1 fct()2 fct()3 fct()6 fc()10 TC:f()1
## TC          -0.156
## factr(yst)1 -0.985  0.154
## factr(yst)2 -0.985  0.154  0.970
## factr(yst)3 -0.985  0.154  0.970  0.970
## factr(yst)6 -0.985  0.153  0.970  0.970  0.970
## fctr(yst)10  0.800  0.290 -0.788 -0.788 -0.788 -0.788
## TC:fctr(y)1  0.111 -0.713 -0.215 -0.110 -0.110 -0.110 -0.207
## TC:fctr(y)2  0.111 -0.713 -0.110 -0.215 -0.110 -0.110 -0.207  0.509
## TC:fctr(y)3  0.111 -0.713 -0.110 -0.110 -0.215 -0.110 -0.207  0.509
## TC:fctr(y)6  0.110 -0.705 -0.108 -0.108 -0.108 -0.215 -0.204  0.503
## TC:fctr()10  0.106 -0.682 -0.104 -0.104 -0.104 -0.104 -0.426  0.486
##             TC:()2 TC:()3 TC:()6
## TC
## factr(yst)1
## factr(yst)2
## factr(yst)3
## factr(yst)6
## fctr(yst)10
## TC:fctr(y)1
## TC:fctr(y)2
## TC:fctr(y)3  0.509
## TC:fctr(y)6  0.503  0.503
## TC:fctr()10  0.486  0.486  0.480
```

```
lincon(m)
```

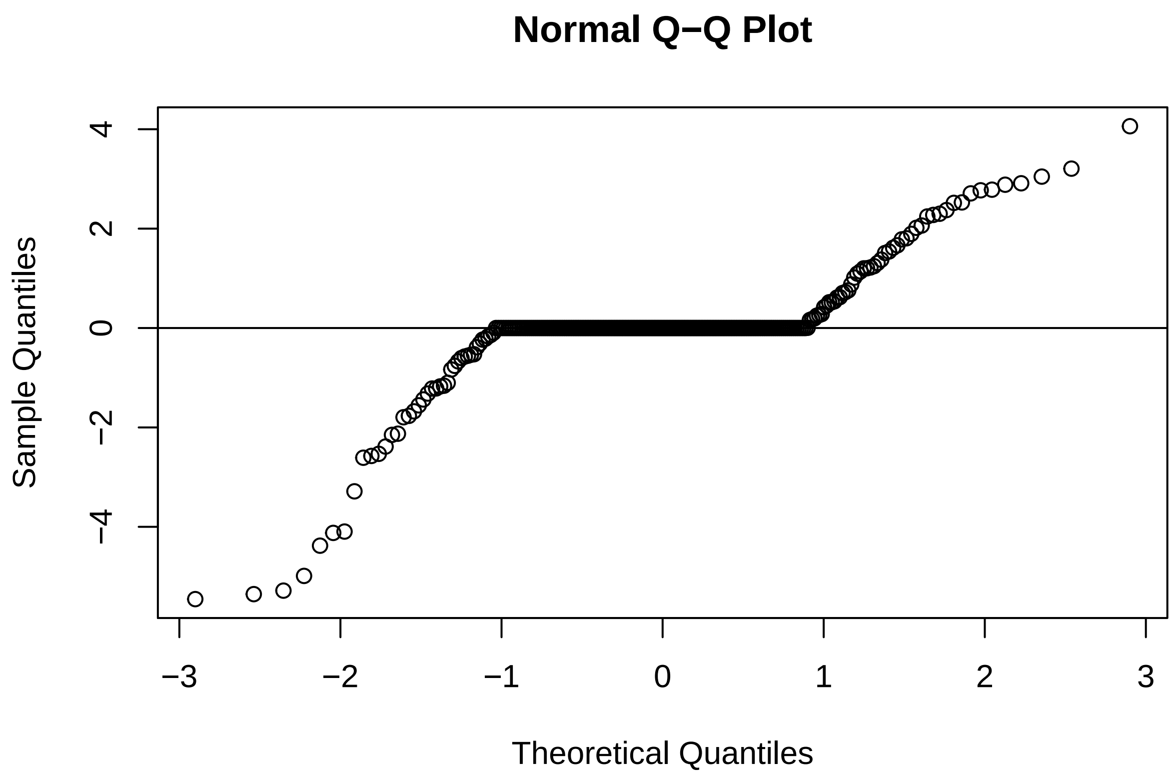
```
##                  estimate     se   lower   upper tvalue  df   pvalue
```

```
## (Intercept)          10.443 2.1666    6.196 14.689    4.82 Inf 1.44e-06
## TC                    0.267 0.0181    0.232  0.303   14.79 Inf 1.67e-49
## factor(yst)1        -10.443 2.1994 -14.753 -6.132   -4.75 Inf 2.06e-06
## factor(yst)2        -10.443 2.1994 -14.753 -6.132   -4.75 Inf 2.06e-06
## factor(yst)3        -10.443 2.1994 -14.753 -6.132   -4.75 Inf 2.06e-06
## factor(yst)6        -10.443 2.1999 -14.754 -6.131   -4.75 Inf 2.07e-06
## factor(yst)10        -2.579 1.0991  -4.733 -0.425   -2.35 Inf 1.89e-02
## TC:factor(yst)1      -0.267 0.0253  -0.317 -0.218 -10.55 Inf 4.92e-26
## TC:factor(yst)2      -0.267 0.0253  -0.317 -0.218 -10.55 Inf 4.92e-26
## TC:factor(yst)3      -0.267 0.0253  -0.317 -0.218 -10.55 Inf 4.92e-26
## TC:factor(yst)6      -0.267 0.0257  -0.318 -0.217 -10.42 Inf 1.97e-25
## TC:factor(yst)10     -0.184 0.0252  -0.233 -0.135  -7.31 Inf 2.63e-13
```

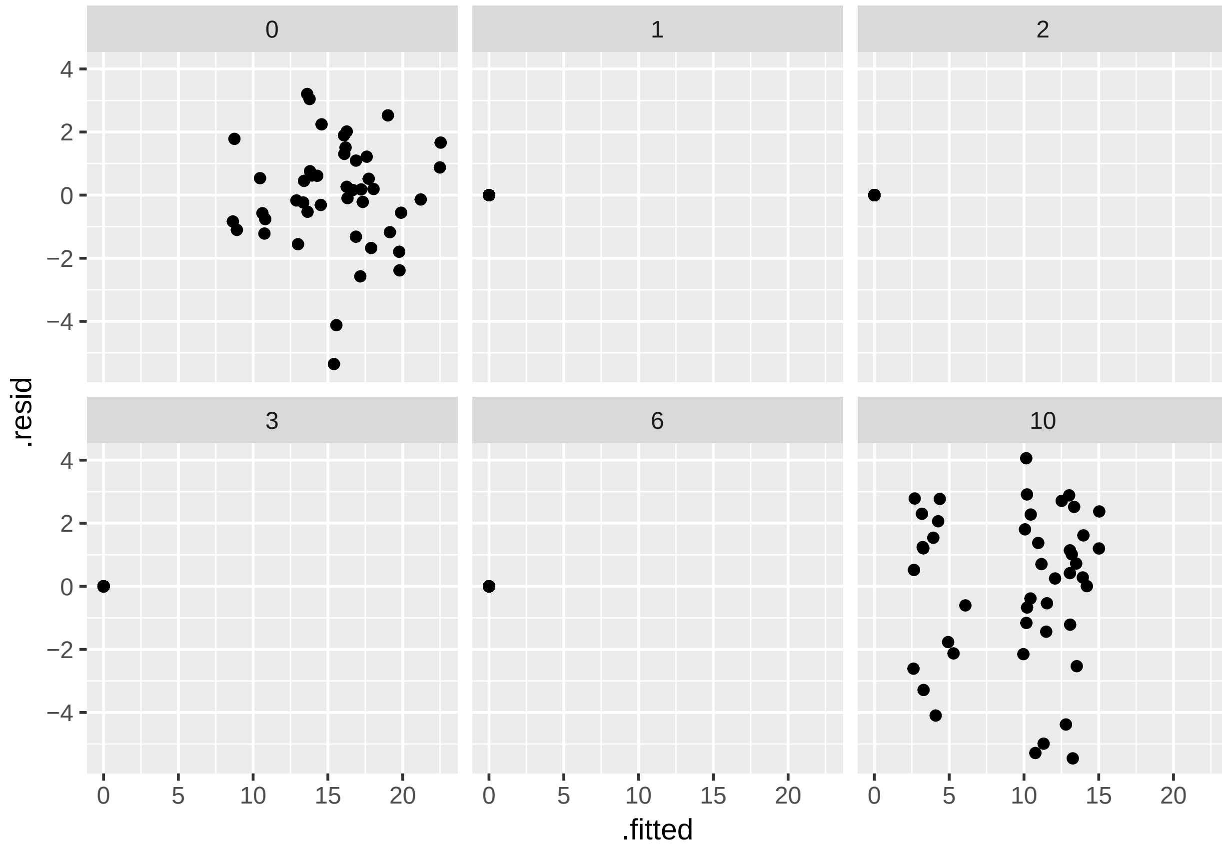
```
#by yst
td$yhat_tree_dens <- predict(m)
p <- ggplot(data = td, aes(x = TC,
                           y = sqrt(tree_dns_gt50_JUOS + tree_dns_gt50_PIED)))
p <- p + geom_point()
p <- p + theme_bw()
p <- p + geom_line(aes(y = yhat_tree_dens))
p <- p + labs(title = 'Tree Density for trees > 50 cm',
              x = 'Pre-Treatment Tree Cover (%)',
              y = 'Square Root of Tree Density (stems/ha)')
#p <- p + scale_x_continuous(breaks = seq(0,10, by = 2))
p <- p + facet_wrap(scode~yst, ncol = 6)
plot(p)
```



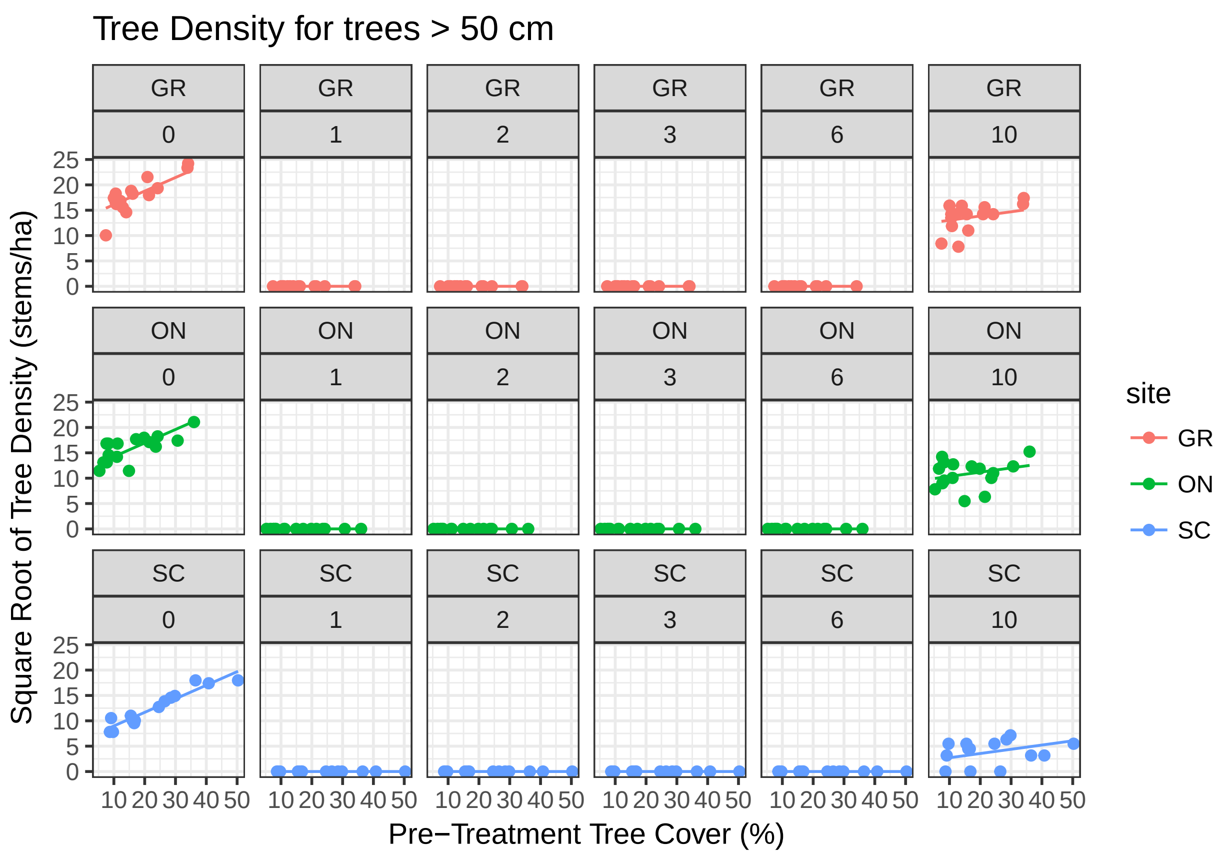
```r
qqnorm(resid(m)); qqline(resid(m))
```



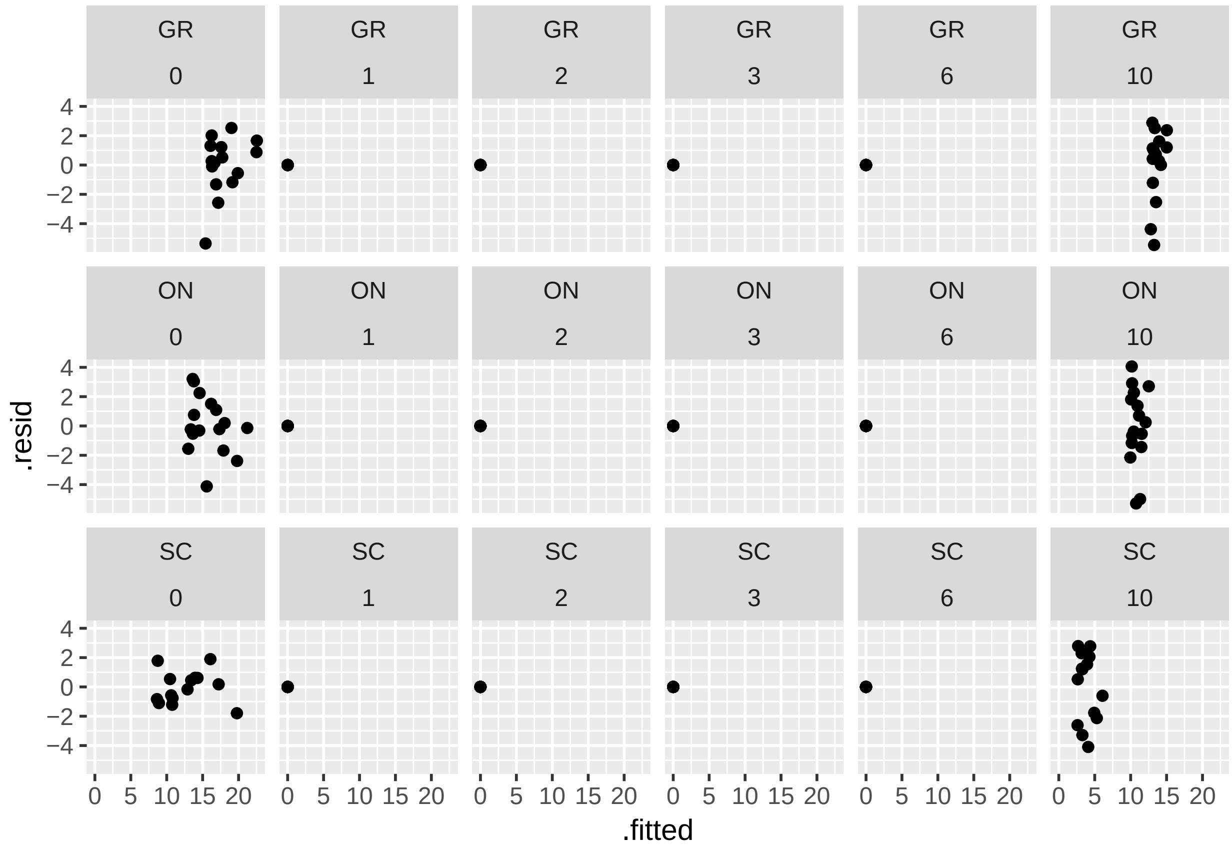

```r
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)
```




```r
#by yst and site
td$yhat_tree_dens <- predict(m)
p <- ggplot(data = td, aes(x = TC,
                           y = sqrt(tree_dns_gt50_JUOS + tree_dns_gt50_PIED),
                           color = scode))
p <- p + geom_point()
p <- p + theme_bw()
p <- p + geom_line(aes(y = yhat_tree_dens))
p <- p + labs(title = 'Tree Density for trees > 50 cm',
              x = 'Pre-Treatment Tree Cover (%)',
              y = 'Square Root of Tree Density (stems/ha)',
              color = 'site')
#p <- p + scale_x_continuous(breaks = seq(0,10, by = 2))
p <- p + facet_wrap(scode~yst, ncol = 6, nrow = 3)
plot(p)
```




```
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(scode~yst, nrow = 3)
```



Tree Cover (trees > 50cm)

```
tcover <- filter(td, scode == 'ON' & year %in% c(6,16)|scode == 'GR' & year %in% c(6,17)|scode == 'SC' &
tcover$tree_cover_ttl[tcover$subplot_id %in% c('JP-SC-GC002', 'JP-SC-GC004', 'JP-SC-GC007') & tcover$yst
tcover$tree_cvr_PIED[tcover$subplot_id %in% c('JP-SC-GC002', 'JP-SC-GC004', 'JP-SC-GC007') & tcover$yst
tcover$tree_cvr_JUOS[tcover$subplot_id %in% c('JP-SC-GC002', 'JP-SC-GC004', 'JP-SC-GC007') & tcover$yst

m <- lmer(sqrt(tree_cover_ttl) ~ TC + yst + yst:TC + (1 + yst|scode), data = tcover)
summary(m)
lincon(m)

#by yst
tcover$yhat_tree_cover <- predict(m)
p <- ggplot(data = tcover, aes(x = TC, y = sqrt(tree_cover_ttl)))
p <- p + geom_jitter()
p <- p + geom_line(aes(y = yhat_tree_cover))
p <- p + theme_bw()
p <- p + labs(title = 'Tree Cover',
              x = 'Pre-Treatment Tree Cover (%)',
              y = 'Square Root of Tree Cover (%)')
#p <- p + scale_x_continuous(breaks = seq(0,60, by = 10))
p <- p + facet_wrap(scode~yst, ncol = 2)
plot(p)
```

```r
qqnorm(resid(m)); qqline(resid(m))
ggplot(m, aes(x = .fitted, y = .resid)) + geom_point() + facet_wrap(~yst)

#by yst and site
tcover$yhat_tree_cover <- predict(m)
p <- ggplot(data = tcover, aes(x = TC, y = sqrt(tree_cover_ttl), color = scode))
p <- p + geom_jitter()
p <- p + geom_line(aes(y = yhat_tree_cover))
p <- p + theme_bw()
p <- p + labs(title = 'Tree Cover',
                x = 'Pre-Treatment Tree Cover (%)',
                y = 'Square Root of Tree Cover (%)')
#p <- p + scale_x_continuous(breaks = seq(0,60, by = 10))
p <- p + facet_wrap(scode~yst, ncol = 2, nrow = 3)
plot(p)

ggplot(m, aes(x = .fitted, y = .resid)) +
  geom_point(aes(color = scode)) +
  facet_wrap(scode~yst, ncol = 2)
```