Growth Resilience

*AJ Perez-Luque ((**???**))*

2017 June

```r
library("tidyverse")
library("dplR")
library("stringr")
library("knitr")
library('gtable')
library('grid')
library('gridExtra')
library('pander')
library('broom')
library('effects')
```

Resilience

- Calcularemos las métricas resiliencia de (**???**) sobre el crecimiento.
- Vamos a calcularlas sobre el BAI de cada árbol.
- Utilizaremos tres sitios: SJ, CAH y CAL (ver ./analysis/analysis_chronologies.md)

Prepare data

- Leer datos `rwl` de SJ y CA
- Leer datos de diametros de los focal tree

```
## There does not appear to be a header in the rwl file
## There are 48 series
## 1        SNA0101      1947    2016   0.01
## 2        SNA0102      1947    2016   0.01
## 3        SNA0201      1946    2016   0.01
## 4        SNA0202      1948    2016   0.01
## 5        SNA0301      1949    2016   0.01
## 6        SNA0302      1948    2016   0.01
## 7        SNA0401      1947    2016   0.01
## 8        SNA0402      1947    2016   0.01
## 9        SNA0501      1953    2016   0.01
## 10       SNA0502      1948    2016   0.01
## 11       SNA0601      1948    2016   0.01
## 12       SNA0602      1957    2016   0.01
## 13       SNA0603      1947    2012   0.01
## 14       SNA0701      1954    2016   0.01
## 15       SNA0702      1947    2016   0.01
## 16       SNA0801      1949    2016   0.01
## 17       SNA0802      1951    2016   0.01
## 18       SNA0901      1947    2016   0.01
## 19       SNA0902      1947    2016   0.01
## 20       SNA0903      1947    2002   0.01
## 21       SNA1001      1950    2016   0.01
```

```
## 22       SNA1002      1953    2016   0.01
## 23       SNA1003      1948    2008   0.01
## 24       SNA1101      1940    2016   0.01
## 25       SNA1102      1929    2016   0.01
## 26       SNA1103      1942    1994   0.01
## 27       SNA1201      1929    2016   0.01
## 28       SNA1202      1929    2016   0.01
## 29       SNA1203      1927    1983   0.01
## 30       SNA1301      1960    2016   0.01
## 31       SNA1302      1949    2016   0.01
## 32       SNA1303      1949    2011   0.01
## 33       SNA1401      1930    2016   0.01
## 34       SNA1402      1949    2016   0.01
## 35       SNA1501      1952    2016   0.01
## 36       SNA1502      1948    2016   0.01
## 37       SNA1601      1959    2016   0.01
## 38       SNA1602      1927    2016   0.01
## 39       SNA1701      1926    2016   0.01
## 40       SNA1702      1930    2016   0.01
## 41       SNA1703      1931    2016   0.01
## 42       SNA1801      1937    2016   0.01
## 43       SNA1802      1936    2016   0.01
## 44       SNA1901      1921    2016   0.01
## 45       SNA1902      1924    2016   0.01
## 46       SNA2001      1932    2016   0.01
## 47       SNA2003      1932    2016   0.01
## 48       SNA2002      1934    2016   0.01
```

```
## There does not appear to be a header in the rwl file
## There are 60 series
## 1        SNB0101      1899    2016   0.01
## 2        SNB0102      1902    2016   0.01
## 3        SNB0201      1916    2016   0.01
## 4        SNB0202      1876    2016   0.01
## 5        SNB0301      1862    2016   0.01
## 6        SNB0302      1862    2016   0.01
## 7        SNB0401      1870    2016   0.01
## 8        SNB0402      1866    2016   0.01
## 9        SNB0501      1864    2016   0.01
## 10       SNB0502g     1867    2016   0.01
## 11       SNB0601      1860    2016   0.01
## 12       SNB0602      1873    2016   0.01
## 13       SNB0701      1851    2016   0.01
## 14       SNB0702g     1861    2016   0.01
## 15       SNB0801g     1851    2016   0.01
## 16       SNB0802g     1853    2016   0.01
## 17       SNB0901g     1836    2016   0.01
## 18       SNB0902      1844    2016   0.01
## 19       SNB1001      1868    2016   0.01
## 20       SNB1002      1870    2016   0.01
## 21       SNB1101      1949    2016   0.01
## 22       SNB1102      1893    2016   0.01
## 23       SNB1201      1867    2016   0.01
## 24       SNB1202      1834    2016   0.01
```

```
## 25       SNB1301     1865    2016   0.01
## 26       SNB1302     1874    2016   0.01
## 27       SNB1401     1843    2016   0.01
## 28       SNB1402     1848    2016   0.01
## 29       SNB1501     1898    2016   0.01
## 30       SNB1502     1927    2016   0.01
## 31       SNB1601     1846    2016   0.01
## 32       SNB1602     1857    2016   0.01
## 33       SNB1701     1856    2016   0.01
## 34       SNB1702     1853    2016   0.01
## 35       SNB1801     1827    2016   0.01
## 36       SNB1802     1843    2016   0.01
## 37       SNB1901     1888    2016   0.01
## 38       SNB1902     1901    2016   0.01
## 39       SNB2001     1830    2016   0.01
## 40       SNB2002g    1837    2016   0.01
## 41       SNB2101     1863    2016   0.01
## 42       SNB2102     1858    2016   0.01
## 43       SNB2201g    1819    2016   0.01
## 44       SNB2202g    1822    2016   0.01
## 45       SNB2301g    1832    2016   0.01
## 46       SNB2302     1819    2016   0.01
## 47       SNB2401     1829    2016   0.01
## 48       SNB2402     1831    2016   0.01
## 49       SNB2501     1831    2016   0.01
## 50       SNB2502     1839    2016   0.01
## 51       SNB2601     1872    2016   0.01
## 52       SNB2602     1867    2016   0.01
## 53       SNB2701     1865    2016   0.01
## 54       SNB2702g    1863    2016   0.01
## 55       SNB2801     1860    2016   0.01
## 56       SNB2802     1866    2016   0.01
## 57       SNB2901     1877    2016   0.01
## 58       SNB2902     1892    2016   0.01
## 59       SNB3001     1867    2016   0.01
## 60       SNB3002     1874    2016   0.01
```

```r
source(paste0(di, 'script/R/rw_byTree.R'))
source(paste0(di, 'script/R/bai_piovesan.R'))
source(paste0(di, 'script/R/baiResilience.R'))
```

- Crear dataframes `rwl` por cada sitio CA_High, CA_Low, SJ_High. SJ_Low

```r
# Replace SNA by SJ and SNB by CA
names(ca) <- stringr::str_replace(names(ca), "SNB", "CA")
names(sj) <- stringr::str_replace(names(sj), "SNA", "SJ")

# Remove g in name of some cores of CA.
names(ca) <- stringr::str_replace(names(ca), "g", "")
```

```r
# Create subset to compare between sites
caL <- ca[,c("CA0101","CA0102","CA0201","CA0202","CA0301","CA0302","CA0401","CA0402","CA0501","CA0502",
             "CA0601","CA0602","CA0701","CA0702","CA0801","CA0802","CA0901","CA0902","CA1001","CA1002",
             "CA2601","CA2602","CA2701","CA2702","CA2801","CA2802","CA2901","CA2902","CA3001","CA3002")]
caH <- ca[, c("CA1101","CA1102","CA1201","CA1202","CA1301","CA1302","CA1401","CA1402","CA1501","CA1502"
```

```
              "CA1601","CA1602","CA1701","CA1702","CA1801","CA1802","CA1901","CA1902","CA2001","CA2002"
              "CA2101","CA2102","CA2201","CA2202","CA2301","CA2302","CA2401","CA2402","CA2501","CA2502")
```

- Lectura y preparación de datos de diámetro

```r
# Prepare Diameter data

# Compute diameter (mm)
compete <- compete %>%
  mutate(dn_mm = (perim_mm / pi))

# Change name focal according to loc
compete <- compete %>%
  mutate(id_focalLoc = stringr::str_replace_all(id_focal, c("A" = "SJ", "B" = "CA")))


# Get only focal trees, and only selected variables
ft <- compete %>%
  filter(sp=='Focal') %>%
  filter(id_focal!='Fresno') %>%
  dplyr::select(id_focal, id_focalLoc, loc, dn_mm, height_cm)

# Set levels of eleveation
ca_lowcode <- c(paste0('CA', str_pad(1:10, 2, pad='0')),
             paste0('CA', 26:30))
ca_highcode <- paste0('CA', 11:25)

ft <- ft %>%
  mutate(site = as.factor(
    ifelse(id_focalLoc %in% ca_lowcode, 'CAL',
           ifelse(id_focalLoc %in% ca_highcode, 'CAH', 'SJ'))))
```

Aggregate RW by tree

- Agregar valores medios de RW por site (obtenemos sj_tree / caL_tree, caH_tree)
- ver fun rw_byTree o utilizar treeMean (dplR)

```r
# Remember snc = structure of core name SJ0101 (site | tree | core)
sj_tree <- rw_byTree(sj, snc =c(2,2,2), locname = 'SJ')
caL_tree <- rw_byTree(caL, snc =c(2,2,2), locname = 'CA')
caH_tree <- rw_byTree(caH, snc =c(2,2,2), locname = 'CA')
```

- Crear diferentes dataset de diametro por sitio

```r
diam <- ft %>%
  mutate(diameter = dn_mm,
         id = id_focalLoc) %>%
  dplyr::select(id, diameter, site) %>%
  split(.$site)


d_caH <- diam$CAH[,c('id','diameter')]
d_caL <- diam$CAL[,c('id','diameter')]
d_sj <- diam$SJ[,c('id','diameter')]
```

Cómputo del BAI por site

- He construido una funcion para el computo del BAI, teniendo en cuenta la aproximación de (Piovesa et al. 2008). Es similar a `bai.out`

```
bai_sj <- bai_piovesan(rwdf = sj_tree, diam_df = d_sj)
bai_caH <- bai_piovesan(rwdf = caH_tree, diam_df = d_caH)
bai_caL <- bai_piovesan(rwdf = caL_tree, diam_df = d_caL)

# Set class to bai object
# Esto es para que funcionen algunas otras funciones de dplR
bais <- c('bai_sj', 'bai_caH', 'bai_caL')

for (i in bais){
  aux <- get(i)

  class(aux) <- c('rwl', 'data.frame')

  assign(i, aux)
}
```

Resilience

- Computar métricas de resiliencia BAI para los tres sitios.
- Computar tres eventos climáticos: 1995, 2005, 2012
- Computar dos ventanas temporales: 2 y 3

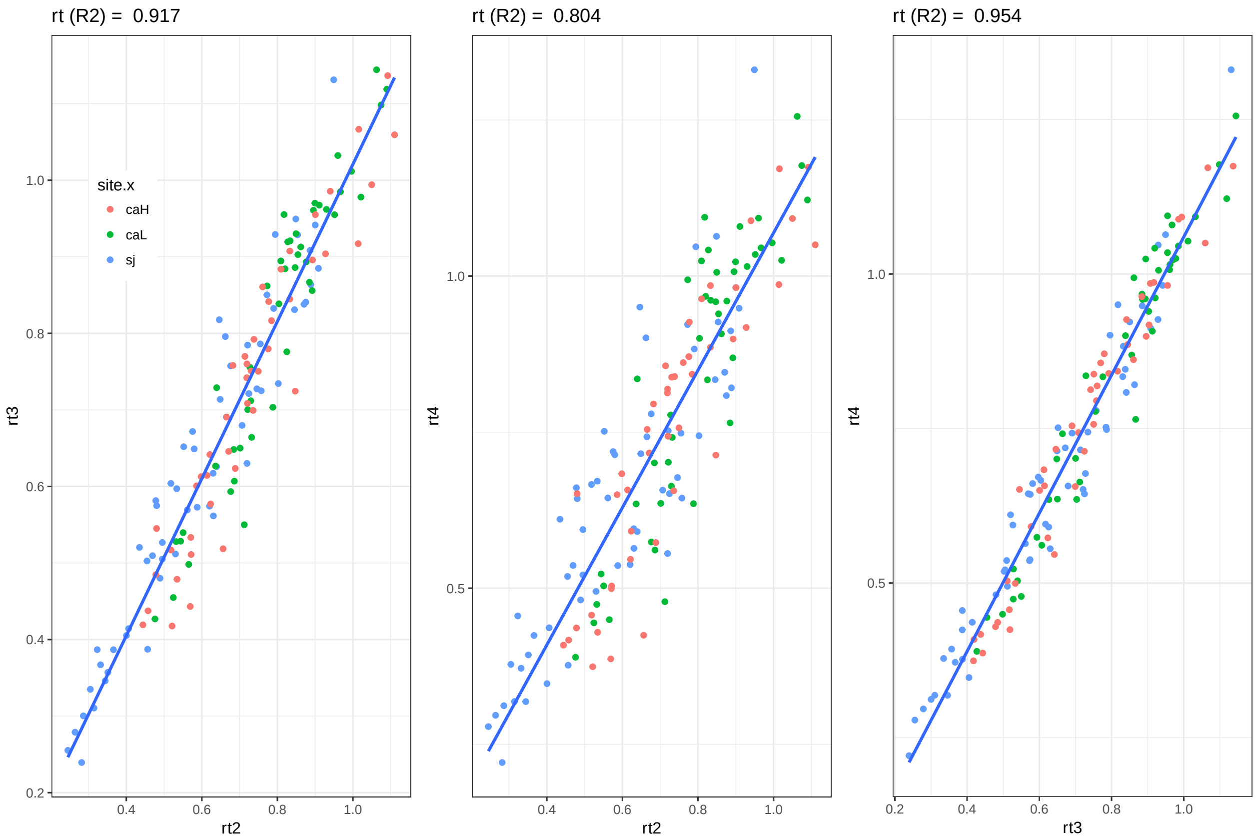
```
# Drought years
dyears <- c(1995, 2005, 2012)

# SJ
res_4_sj <- baiResilience(bai_sj, event_years = dyears, window = 4)
res_3_sj <- baiResilience(bai_sj, event_years = dyears, window = 3)
res_2_sj <- baiResilience(bai_sj, event_years = dyears, window = 2)

# caL
res_4_caL <- baiResilience(bai_caL, event_years = dyears, window = 4)
res_3_caL <- baiResilience(bai_caL, event_years = dyears, window = 3)
res_2_caL <- baiResilience(bai_caL, event_years = dyears, window = 2)

# caH
res_4_caH <- baiResilience(bai_caH, event_years = dyears, window = 4)
res_3_caH <- baiResilience(bai_caH, event_years = dyears, window = 3)
res_2_caH <- baiResilience(bai_caH, event_years = dyears, window = 2)
```

Computar correlaciones ventanas temporales

```
# Vector with objects name
obj <- c('res_2_sj', 'res_3_sj', 'res_4_sj',
         'res_2_caL', 'res_3_caL', 'res_4_caL',
         'res_2_caH', 'res_3_caH', 'res_4_caH')
```

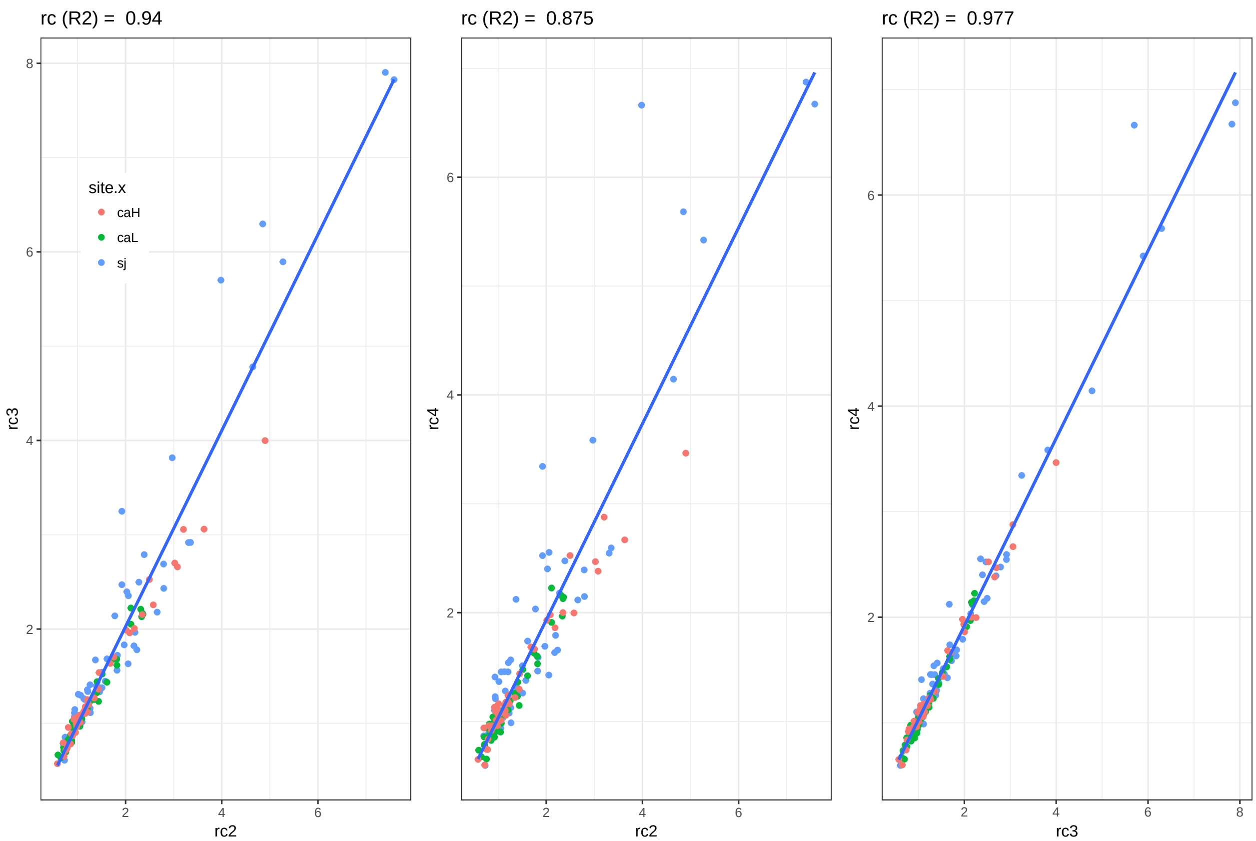
```
correla_ws <- c()

for (i in obj){
  x <- get(i)
  xres <- x$resilience
  out <- xres %>%
    mutate(ws = paste0('ws_', as.character(str_extract(i, "([0-9])"))),
           site = str_replace(i, "res_[0-9]_", '')) %>%
    select(-disturb_year, -tree)

  correla_ws <- bind_rows(correla_ws, out)

}

# Split by window size
correla <- correla_ws %>% split(.$ws)

# Change names
names(correla[["ws_2"]])[1:4] <- paste0(names(correla[["ws_2"]])[1:4], '2')
names(correla[["ws_3"]])[1:4] <- paste0(names(correla[["ws_3"]])[1:4], '3')
names(correla[["ws_4"]])[1:4] <- paste0(names(correla[["ws_4"]])[1:4], '4')

cor2 <- correla[["ws_2"]] %>% select(-ws) %>% mutate(ind = row_number())
cor3 <- correla[["ws_3"]] %>% select(-ws) %>% mutate(ind = row_number())
cor4 <- correla[["ws_4"]] %>% select(-ws) %>% mutate(ind = row_number())


correlations <- inner_join(cor2, cor3, by='ind') %>% inner_join(cor4, by='ind')


# Resistance
aux_coefs <- c()

model <- lm(rt2~rt3, data=correlations)
p_rt23 <- correlations %>% ggplot(aes(rt2, rt3)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rt (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = c(.2, .75))
aux <- as.data.frame(cbind('rt','2-3', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

model <- lm(rt2~rt4, data=correlations)
p_rt24 <- correlations %>% ggplot(aes(rt2, rt4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rt (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rt','2-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

model <- lm(rt3~rt4, data=correlations)
p_rt34 <- correlations %>% ggplot(aes(rt3, rt4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rt (R2) = ', round(summary(model)$r.squared, 3))) +
```

```
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rt','3-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

grid.arrange(p_rt23, p_rt24, p_rt34,ncol=3)
```



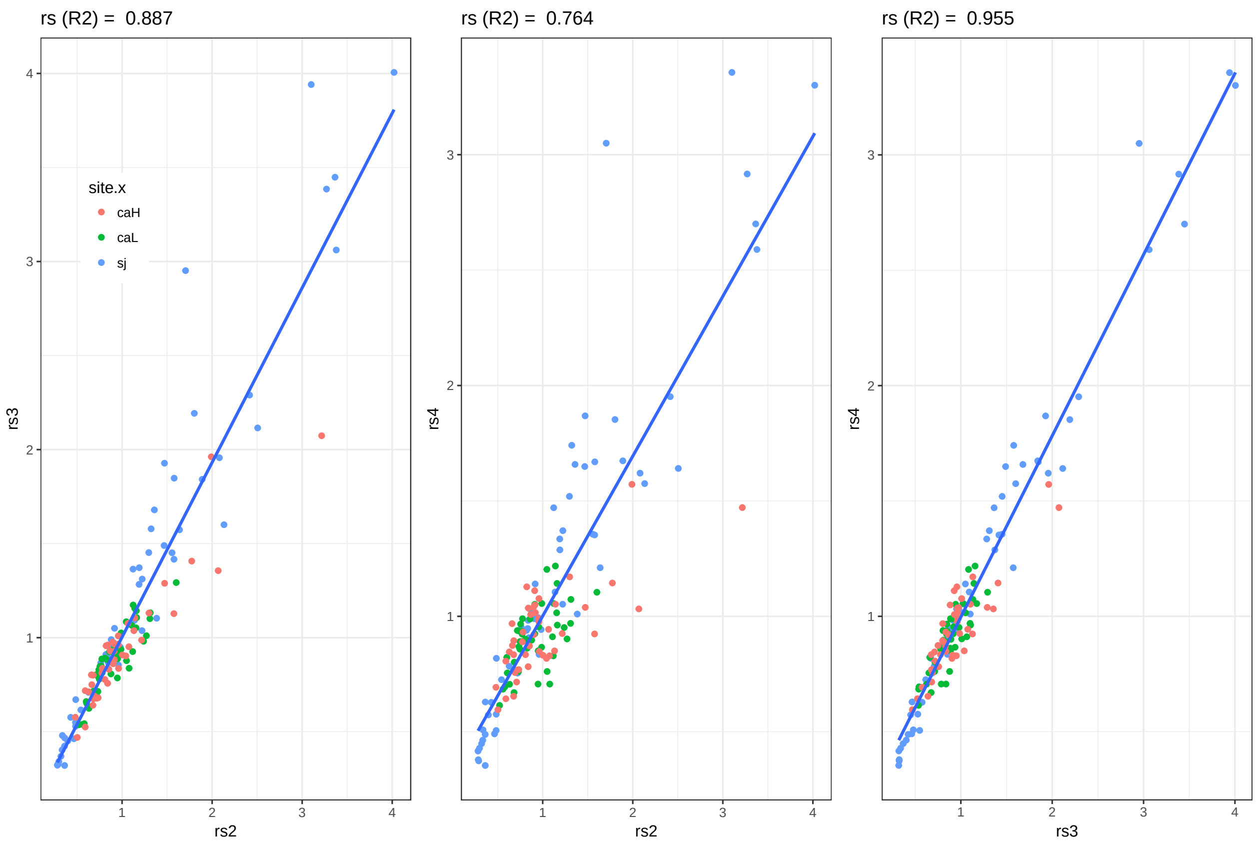

```
# Recovery
model <- lm(rc2~rc3, data=correlations)
p_rc23 <- correlations %>% ggplot(aes(rc2, rc3)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rc (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = c(.2, .75))
aux <- as.data.frame(cbind('rc','2-3', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)


model <- lm(rc2~rc4, data=correlations)
p_rc24 <- correlations %>% ggplot(aes(rc2, rc4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rc (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rc','2-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)


model <- lm(rc3~rc4, data=correlations)
p_rc34 <- correlations %>% ggplot(aes(rc3, rc4)) +
```

```
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rc (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rc','3-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)


grid.arrange(p_rc23, p_rc24, p_rc34,ncol=3)
```



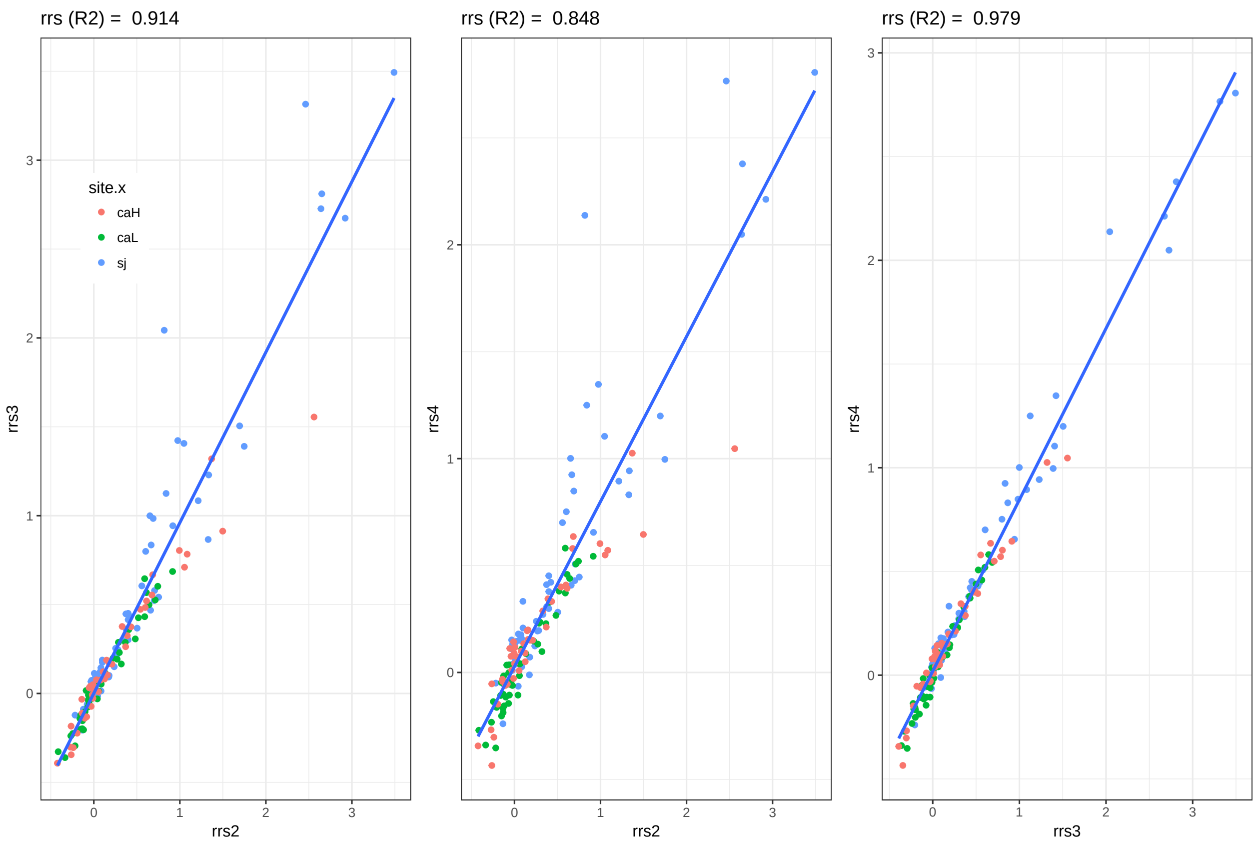

```
# Resilience
model <- lm(rs2~rs3, data=correlations)
p_rs23 <- correlations %>% ggplot(aes(rs2, rs3)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = c(.2, .75))
aux <- as.data.frame(cbind('rs','2-3', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

model <- lm(rs2~rs4, data=correlations)
p_rs24 <- correlations %>% ggplot(aes(rs2, rs4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rs','2-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

model <- lm(rs3~rs4, data=correlations)
```

```
p_rs34 <- correlations %>% ggplot(aes(rs3, rs4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rs','3-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

grid.arrange(p_rs23, p_rs24, p_rs34,ncol=3)
```




```
# Relative Resilience
model <- lm(rrs2~rrs3, data=correlations)
p_rrs23 <- correlations %>% ggplot(aes(rrs2, rrs3)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rrs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = c(.2, .75))
aux <- as.data.frame(cbind('rrs','2-3', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

model <- lm(rrs2~rrs4, data=correlations)
p_rrs24 <- correlations %>% ggplot(aes(rrs2, rrs4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rrs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rrs','2-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

model <- lm(rrs3~rrs4, data=correlations)
```

```r
p_rrs34 <- correlations %>% ggplot(aes(rrs3, rrs4)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rrs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = 'none')
aux <- as.data.frame(cbind('rrs','3-4', as.numeric(summary(model)$r.squared)))
aux_coefs <- rbind(aux_coefs, aux)

grid.arrange(p_rrs23, p_rrs24, p_rrs34,ncol=3)
```




```r
names(aux_coefs) <- c('var', 'window_size', 'r2')

write.csv(aux_coefs, file=paste0(di, '/out/correla_resilience/correla_window_size.csv'), row.names = F)
```

```r
aux_coefs %>% pander()
```

var	window_size	r2
rt	2-3	0.916882284149449
rt	2-4	0.804404303544226
rt	3-4	0.954056995082479
rc	2-3	0.940435462578806
rc	2-4	0.875357103621433
rc	3-4	0.977309191655523
rs	2-3	0.887274876125786
rs	2-4	0.764147394080222
rs	3-4	0.955085073886915
rrs	2-3	0.914381250472491
rrs	2-4	0.848277808345292

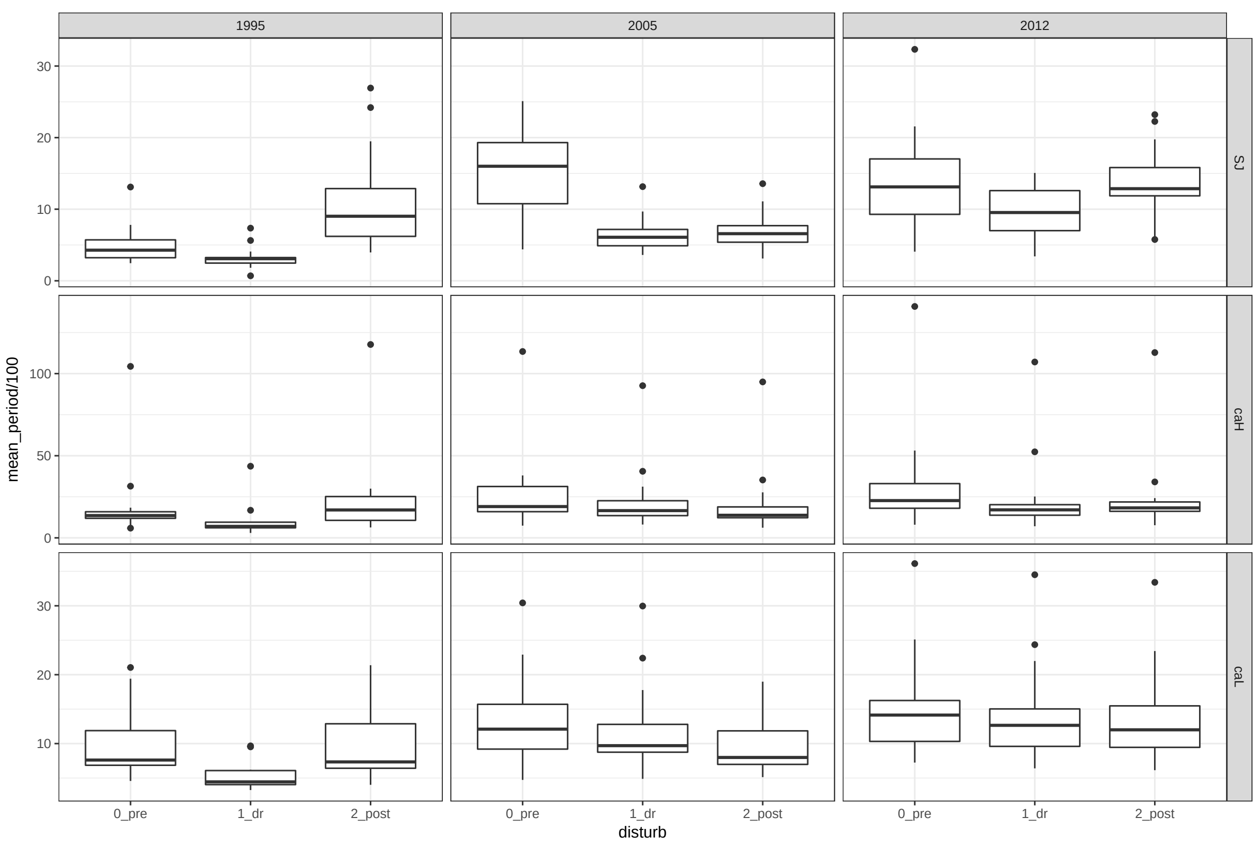
var	window_size	r2
rrs	3-4	0.978980936308473

Nos quedamos con 3 años de ventana temporal.

Plots Crecimiento

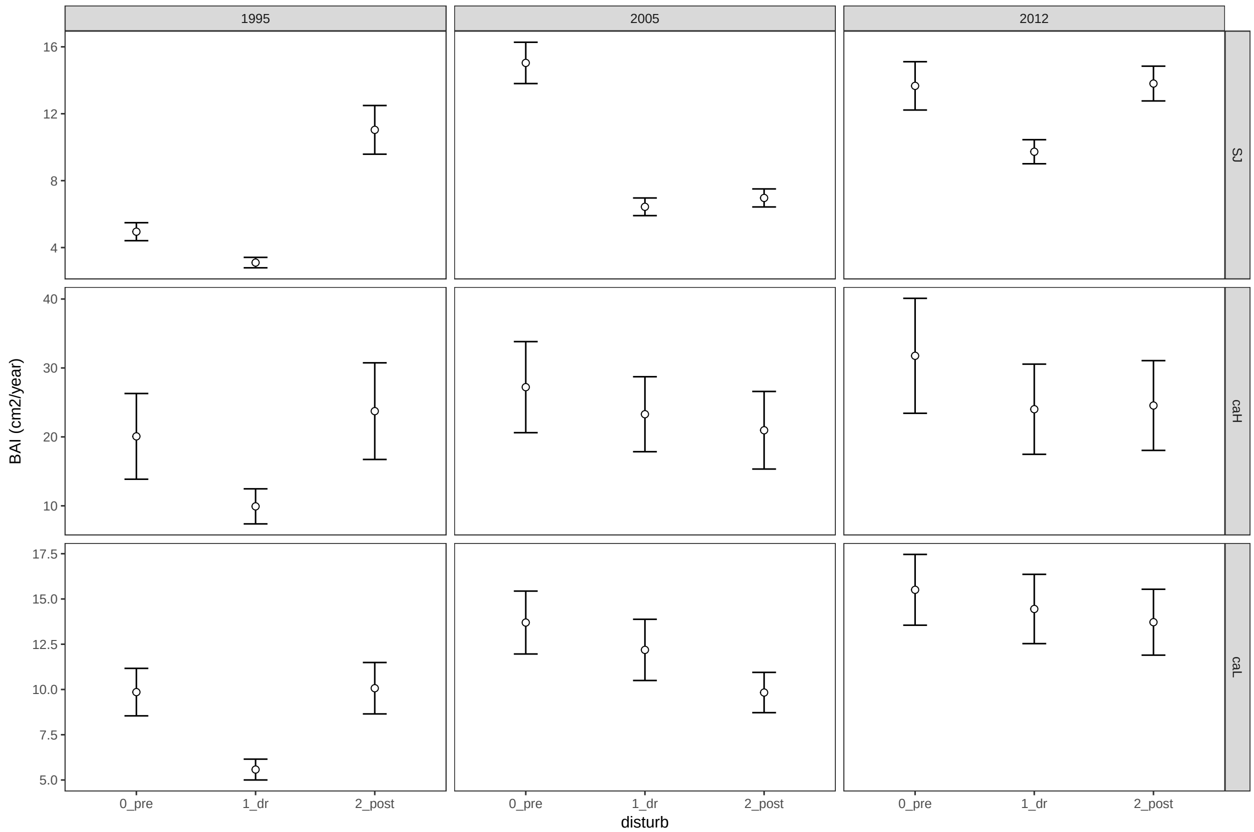
Boxplot with outliers

```
gsj <- res_3_sj$growth %>% mutate(site='SJ')
gcaL <- res_3_caL$growth %>% mutate(site='caL')
gcaH <- res_3_caH$growth %>% mutate(site='caH')

g <- bind_rows(gsj, gcaL, gcaH)

# Export csv
write.csv(g, file=paste0(di, 'data/resilience/crecimientos_drought.csv'), row.names = FALSE)

g %>% mutate(disturb = recode(disturb,
                              dr = '1_dr', pre = '0_pre', post = '2_post')) %>%
  ggplot(aes(y=mean_period/100, x=disturb)) +
  geom_boxplot() +
  facet_grid(site~disturb_year, scales='free_y') +
  theme_bw()
```



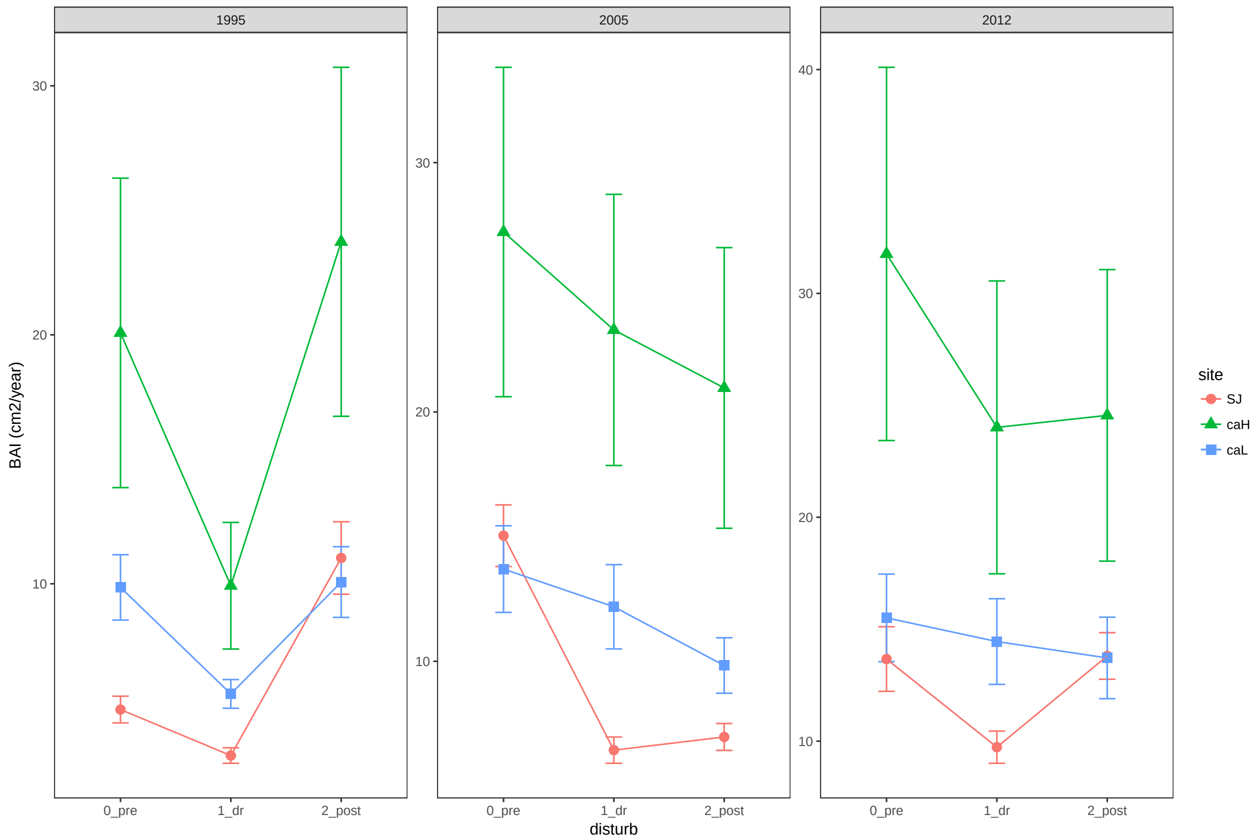
Mean + se

```
g %>%
  mutate(disturb = recode(disturb, dr = '1_dr', pre = '0_pre', post = '2_post')) %>%
  group_by(disturb, disturb_year, site) %>%
  summarise(mean = mean(mean_period),
            sd = sd(mean_period),
            se = sd/sqrt(length(mean_period))) %>%
  ggplot(aes(y=mean/100, x=disturb)) +
  geom_errorbar(aes(ymin=mean/100 - se/100,
                    ymax=mean/100 + se/100),
                width = 0.2) +
  geom_point(size=2, shape=21, fill='white') +
  facet_grid(site~disturb_year, scales='free_y') +
  theme_bw() + ylab('BAI (cm2/year)') +
  theme(panel.grid = element_blank())
```




```
pgrowht <- g %>%
  mutate(disturb = recode(disturb, dr = '1_dr', pre = '0_pre', post = '2_post')) %>%
  group_by(disturb, disturb_year, site) %>%
  summarise(mean = mean(mean_period),
            sd = sd(mean_period),
            se = sd/sqrt(length(mean_period))) %>%
  ggplot(aes(y=mean/100, x=disturb, colour=site)) +
  geom_errorbar(aes(ymin=mean/100 - se/100,
                    ymax=mean/100 + se/100),
                width = 0.15) +
```

```r
  geom_point(size=3, aes(shape=site), fill='white') +
  geom_line(aes(group=site))+
  facet_wrap(~disturb_year, scales='free_y') +
  theme_bw() + ylab('BAI (cm2/year)') +
  theme(panel.grid = element_blank())

pgrowht
```




```r
ggsave(plot=pgrowht, width=8, height = 4,
       filename=paste0(di, 'out/fig/resilience/bai_events.pdf'))
```

```r
g %>%
  mutate(disturb = recode(disturb, dr = '1_dr', pre = '0_pre', post = '2_post')) %>%
  group_by(site, disturb_year, disturb) %>%
  summarise(mean = mean(mean_period/100),
            sd = sd(mean_period/100),
            se = sd/sqrt(length(mean_period/100))) %>% pander()
```

site	disturb_year	disturb	mean	sd	se
SJ	1995	0_pre	4.949360	2.401841	0.5370680
SJ	1995	1_dr	3.102071	1.394718	0.3118683
SJ	1995	2_post	11.037538	6.507541	1.4551304
SJ	2005	0_pre	15.038941	5.521582	1.2346633
SJ	2005	1_dr	6.437153	2.358030	0.5272715
SJ	2005	2_post	6.966562	2.409606	0.5388042
SJ	2012	0_pre	13.666405	6.457739	1.4439943
SJ	2012	1_dr	9.729436	3.218183	0.7196077

site	disturb_year	disturb	mean	sd	se
SJ	2012	2_post	13.804918	4.651000	1.0399953
caH	1995	0_pre	20.078179	24.072135	6.2153984
caH	1995	1_dr	9.923127	9.845728	2.5421560
caH	1995	2_post	23.735572	27.143508	7.0084236
caH	2005	0_pre	27.216860	25.581156	6.6050261
caH	2005	1_dr	23.290311	21.057950	5.4371394
caH	2005	2_post	20.963604	21.794923	5.6274250
caH	2012	0_pre	31.763565	32.285075	8.3359704
caH	2012	1_dr	24.015379	25.334862	6.5414332
caH	2012	2_post	24.552089	25.215397	6.5105875
caL	1995	0_pre	9.855063	5.080906	1.3118843
caL	1995	1_dr	5.577226	2.229862	0.5757479
caL	1995	2_post	10.070205	5.500586	1.4202452
caL	2005	0_pre	13.698045	6.730193	1.7377283
caL	2005	1_dr	12.187221	6.548989	1.6909416
caL	2005	2_post	9.832373	4.307852	1.1122825
caL	2012	0_pre	15.506432	7.571946	1.9550681
caL	2012	1_dr	14.447602	7.411388	1.9136121
caL	2012	2_post	13.717155	7.050255	1.8203679

Anovas Resiliencia

```
# Prepara data
rsj <- res_3_sj$resilience %>% mutate(site='SJ')
rcaL<- res_3_caL$resilience %>% mutate(site='caL')
rcaH <- res_3_caH$resilience %>% mutate(site='caH')

re <- bind_rows(rsj, rcaL, rcaH)
re$disturb_year <- as.factor(re$disturb_year)
re$site <- as.factor(re$site)

# Export csv
write.csv(re, file=paste0(di, 'data/resilience/resilience_bai.csv'), row.names = FALSE)
```

Custom functions

```
# Custom Function to compute ANOVAS
aovas <- function(df, vars, resp_var){
  require('dplyr')
  require('broom')

  # Create subset
  dfsel <- df %>% dplyr::select_(.dots=c(vars, resp_var))


  # Model
  myformula <- as.formula(paste0(resp_var,  " ~ ",
                                 paste(vars, collapse = '*')))
```

```r
  mymodel <- aov(myformula, data=dfsel)

  # Output model Summary http://my.ilstu.edu/~wjschne/444/ANOVA.html#(1)
  model_coeff <- broom::tidy(mymodel)
  model_summary <- broom::glance(mymodel)

  out <- c()
  out$model_coeff <- model_coeff
  out$model_summary <- model_summary
  out$mymodel <- mymodel

  return(out)
}


# Post-Hoc comparison
phc <- function(mymodel, resp_var){
  require(lsmeans)

  # Disturb Event
  ph_event <- lsmeans(mymodel, pairwise ~ disturb_year, adjust = "tukey")

  # differences letters
  cld_event <- cld(ph_event, alpha   = 0.01,
                   Letters = letters,
                   adjust  = "tukey")

  # Site
  ph_site <- lsmeans(mymodel, pairwise ~ site, adjust = "tukey")
  cld_site <- cld(ph_site, alpha   = 0.01,
                  Letters = letters,
                  adjust  = "tukey")

  # interaction
  ph_i <- lsmeans(mymodel, pairwise ~ disturb_year:site, adjust = "tukey")

  # Objets for plot
  aux_ph_site <- as.data.frame(summary(ph_site$lsmeans))
  aux_ph_site <- aux_ph_site %>% mutate(var = resp_var)
  aux_ph_event <- as.data.frame(summary(ph_event$lsmeans))
  aux_ph_event <- aux_ph_event %>% mutate(var = resp_var)
  aux_ph_i <- as.data.frame(summary(ph_i$lsmeans))
  aux_ph_i <- aux_ph_i %>% mutate(var = resp_var)

  # Return objects
  cat('\n### Event ###\n')
  print(ph_event)
  print(cld_event)
  cat('\n### Clu pop ###\n')
  print(ph_site)
  print(cld_site)
  cat('\n### Event:Clu pop ###\n')
  print(ph_i)
```

```r
  return(list(aux_ph_site, aux_ph_event, aux_ph_i))
}
```

```r
vars <- c('disturb_year','site')
```

Recovery

```r
# Variable
resp_var <- 'rc'

# AOV
aov_rc <- aovas(re, vars=vars, resp_var = resp_var)
```

```r
mc <- aov_rc$model_coeff

pander(mc, round=5,
       caption = paste0("ANOVA table: ", resp_var), missing = '',
       emphasize.strong.cells =
         which(mc < 0.1 & mc == mc$p.value, arr.ind = T))
```

Table 3: ANOVA table: rc

term	df	sumsq	meansq	statistic	p.value
disturb_year	2	91.04	45.52	77.14	**0**
site	2	24.64	12.32	20.88	**0**
disturb_year:site	4	17.02	4.255	7.211	**3e-05**
Residuals	141	83.21	0.5901		

```r
gm <- aov_rc$model_summary

gm <- apply(gm, 1, formatC, digits = 2, format = "f") %>% t()
colnames(gm) <- paste0("$",c("R^2","\\mathrm{adj}R^2","\\sigma_e","F","p","df_m","\\mathrm{logLik}","AI
rownames(gm) <- "Statistic"
pander(t(gm))
```

	Statistic
R^2	0.61
$\mathrm{adj}R^2$	0.59
σ_e	0.77
F	28.11
p	0.00
df_m	9.00
logLik	-168.65
AIC	357.29
BIC	387.40
dev	83.21
df_e	141.00

Post hoc comparison

```r
# Post hoc Define model
mymodel <- aov_rc$mymodel
postH_rc <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year    lsmean        SE  df  lower.CL upper.CL
##  1995         2.6025795 0.1096419 141 2.3858250 2.819334
##  2005         0.9460722 0.1096419 141 0.7293177 1.162827
##  2012         1.1643064 0.1096419 141 0.9475520 1.381061
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate       SE  df t.ratio p.value
##  1995 - 2005  1.6565073 0.155057 141  10.683  <.0001
##  1995 - 2012  1.4382730 0.155057 141   9.276  <.0001
##  2005 - 2012 -0.2182343 0.155057 141  -1.407  0.3398
##
## Results are averaged over the levels of: site
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  disturb_year    lsmean        SE  df  lower.CL upper.CL .group
##  2005         0.9460722 0.1096419 141 0.6811300 1.211014  a
##  2012         1.1643064 0.1096419 141 0.8993643 1.429249  a
##  1995         2.6025795 0.1096419 141 2.3376373 2.867522   b
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
## $lsmeans
##  site   lsmean         SE  df  lower.CL upper.CL
##  SJ   2.107125 0.09917481 141 1.9110632 2.303187
##  caH  1.425855 0.11451720 141 1.1994624 1.652248
##  caL  1.179978 0.11451720 141 0.9535853 1.406371
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast   estimate        SE  df t.ratio p.value
##  SJ - caH  0.6812699 0.1514920 141   4.497  <.0001
##  SJ - caL  0.9271470 0.1514920 141   6.120  <.0001
##  caH - caL 0.2458771 0.1619518 141   1.518  0.2855
##
## Results are averaged over the levels of: disturb_year
```

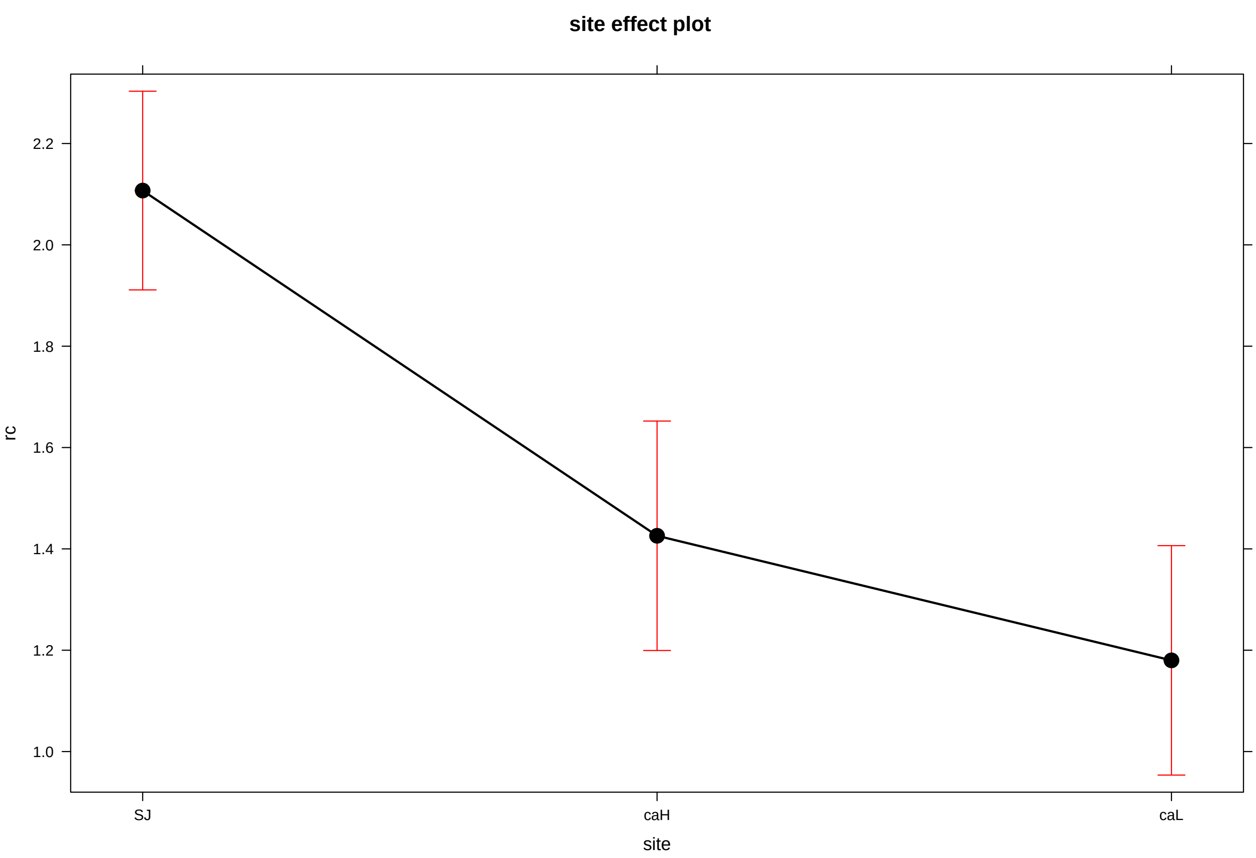
```
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  site   lsmean         SE  df  lower.CL upper.CL .group
##  caL  1.179978 0.11451720 141 0.9032549 1.456701  a
##  caH  1.425855 0.11451720 141 1.1491320 1.702578  a
##  SJ   2.107125 0.09917481 141 1.8674758 2.346774   b
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site    lsmean        SE  df  lower.CL upper.CL
##  1995         SJ   3.7606678 0.1717758 141 3.4210788 4.100257
##  2005         SJ   1.1150292 0.1717758 141 0.7754402 1.454618
##  2012         SJ   1.4456780 0.1717758 141 1.1060890 1.785267
##  1995         caH  2.3069627 0.1983496 141 1.9148391 2.699086
##  2005         caH  0.8836738 0.1983496 141 0.4915502 1.275797
##  2012         caH  1.0869288 0.1983496 141 0.6948052 1.479052
##  1995         caL  1.7401079 0.1983496 141 1.3479843 2.132231
##  2005         caL  0.8395136 0.1983496 141 0.4473900 1.231637
##  2012         caL  0.9603126 0.1983496 141 0.5681890 1.352436
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate        SE  df t.ratio p.value
##  1995,SJ - 2005,SJ    2.64563863 0.2429277 141  10.891  <.0001
##  1995,SJ - 2012,SJ    2.31498982 0.2429277 141   9.530  <.0001
##  1995,SJ - 1995,caH   1.45370507 0.2623919 141   5.540  <.0001
##  1995,SJ - 2005,caH   2.87699401 0.2623919 141  10.964  <.0001
##  1995,SJ - 2012,caH   2.67373900 0.2623919 141  10.190  <.0001
##  1995,SJ - 1995,caL   2.02055992 0.2623919 141   7.701  <.0001
##  1995,SJ - 2005,caL   2.92115422 0.2623919 141  11.133  <.0001
##  1995,SJ - 2012,caL   2.80035525 0.2623919 141  10.672  <.0001
##  2005,SJ - 2012,SJ   -0.33064881 0.2429277 141  -1.361  0.9103
##  2005,SJ - 1995,caH  -1.19193356 0.2623919 141  -4.543  0.0004
##  2005,SJ - 2005,caH   0.23135538 0.2623919 141   0.882  0.9936
##  2005,SJ - 2012,caH   0.02810037 0.2623919 141   0.107  1.0000
##  2005,SJ - 1995,caL  -0.62507870 0.2623919 141  -2.382  0.3019
##  2005,SJ - 2005,caL   0.27551559 0.2623919 141   1.050  0.9800
##  2005,SJ - 2012,caL   0.15471662 0.2623919 141   0.590  0.9996
##  2012,SJ - 1995,caH  -0.86128475 0.2623919 141  -3.282  0.0342
##  2012,SJ - 2005,caH   0.56200419 0.2623919 141   2.142  0.4495
##  2012,SJ - 2012,caH   0.35874918 0.2623919 141   1.367  0.9081
##  2012,SJ - 1995,caL  -0.29442989 0.2623919 141  -1.122  0.9700
##  2012,SJ - 2005,caL   0.60616440 0.2623919 141   2.310  0.3432
##  2012,SJ - 2012,caL   0.48536543 0.2623919 141   1.850  0.6490
##  1995,caH - 2005,caH  1.42328894 0.2805087 141   5.074  <.0001
##  1995,caH - 2012,caH  1.22003393 0.2805087 141   4.349  0.0009
##  1995,caH - 1995,caL  0.56685486 0.2805087 141   2.021  0.5317
```

```
##   1995,caH - 2005,caL  1.46744915 0.2805087 141   5.231  <.0001
##   1995,caH - 2012,caL  1.34665019 0.2805087 141   4.801  0.0001
##   2005,caH - 2012,caH -0.20325501 0.2805087 141  -0.725  0.9984
##   2005,caH - 1995,caL -0.85643409 0.2805087 141  -3.053  0.0654
##   2005,caH - 2005,caL  0.04416021 0.2805087 141   0.157  1.0000
##   2005,caH - 2012,caL -0.07663876 0.2805087 141  -0.273  1.0000
##   2012,caH - 1995,caL -0.65317908 0.2805087 141  -2.329  0.3324
##   2012,caH - 2005,caL  0.24741522 0.2805087 141   0.882  0.9936
##   2012,caH - 2012,caL  0.12661625 0.2805087 141   0.451  1.0000
##   1995,caL - 2005,caL  0.90059430 0.2805087 141   3.211  0.0422
##   1995,caL - 2012,caL  0.77979533 0.2805087 141   2.780  0.1307
##   2005,caL - 2012,caL -0.12079897 0.2805087 141  -0.431  1.0000
##
## P value adjustment: tukey method for comparing a family of 9 estimates
```

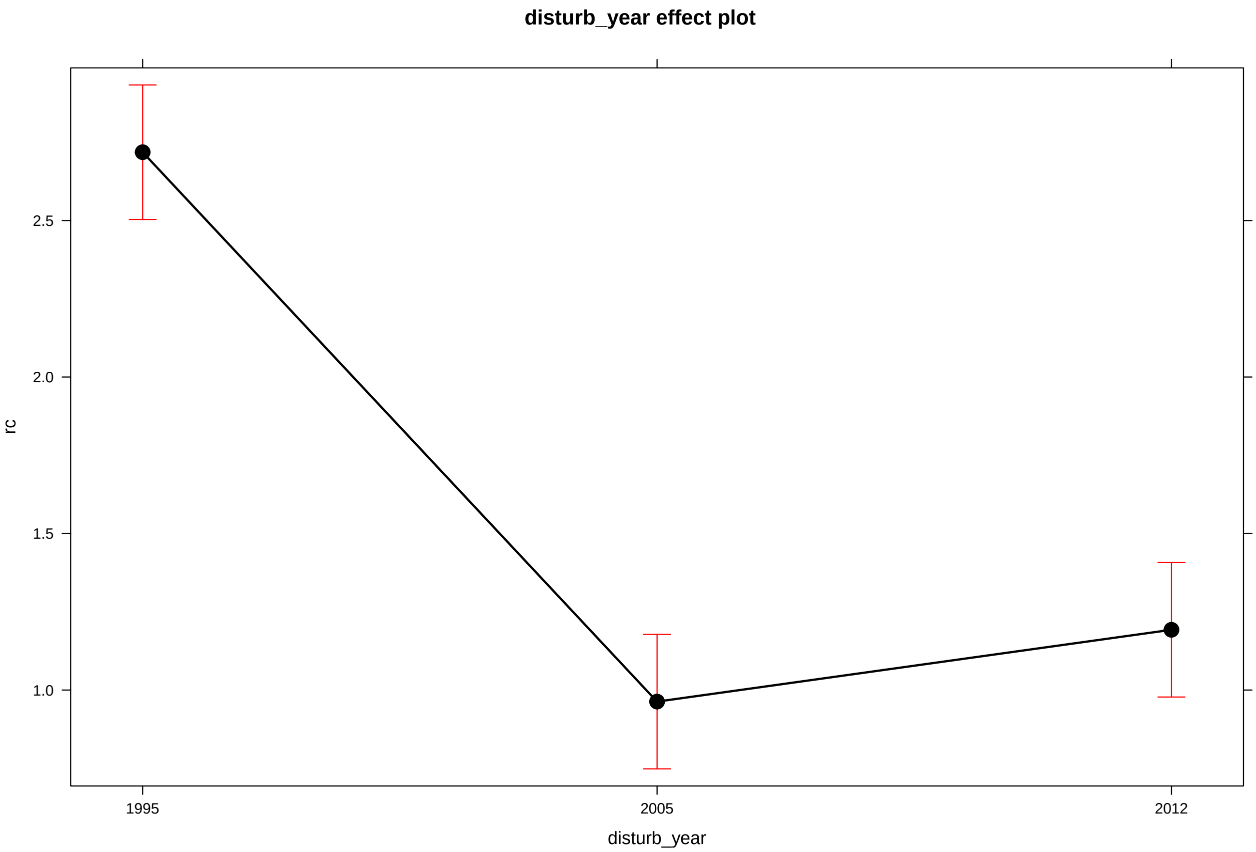
Plots

```r
#### ~ Site
ps <- plot(effect("site",mymodel))
#### ~ Disturb Year
pd <- plot(effect('disturb_year', mymodel))
#### Disturb Year:Site
picollapse <- plot(effect("disturb_year:site",mymodel), multiline = TRUE, ci.style = 'bars')
pi <- plot(effect("disturb_year:site",mymodel), layout=c(3,1))
```

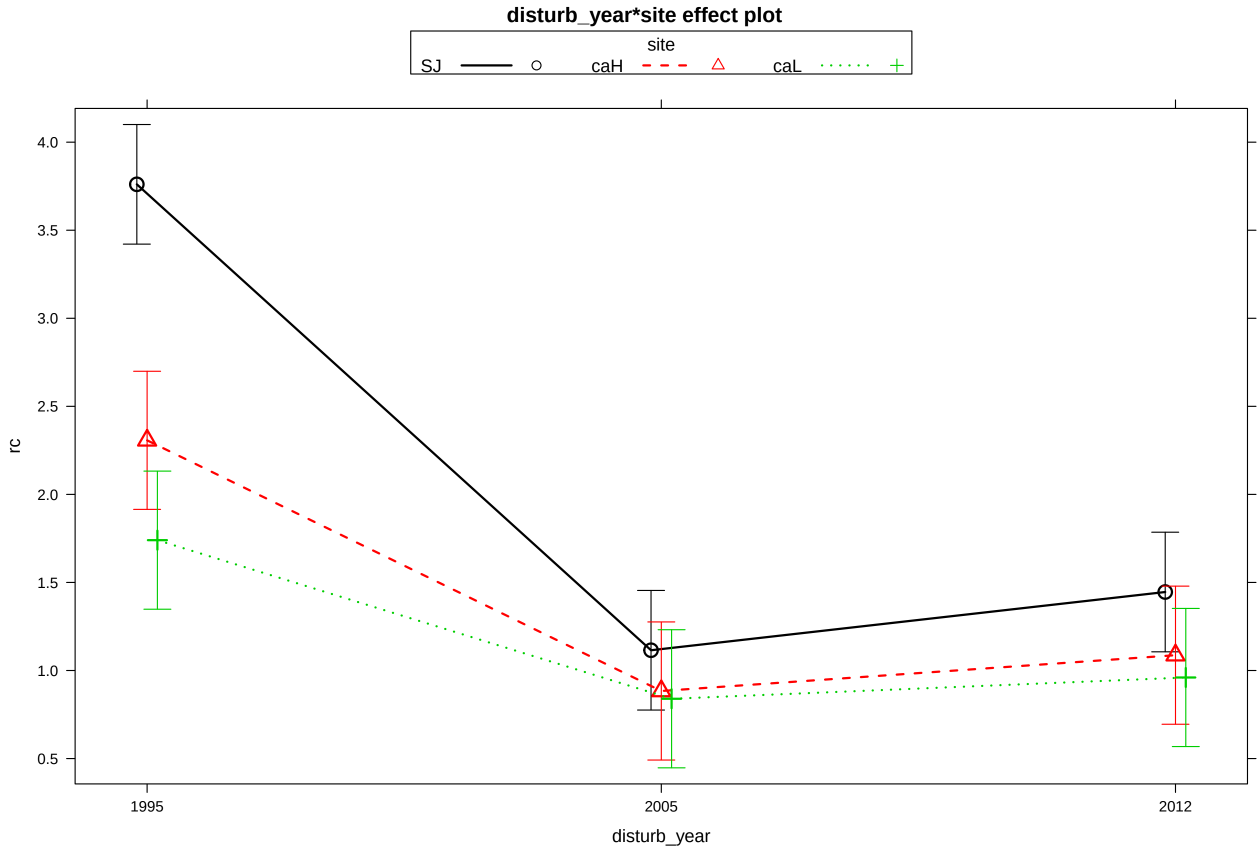
```r
ps
```



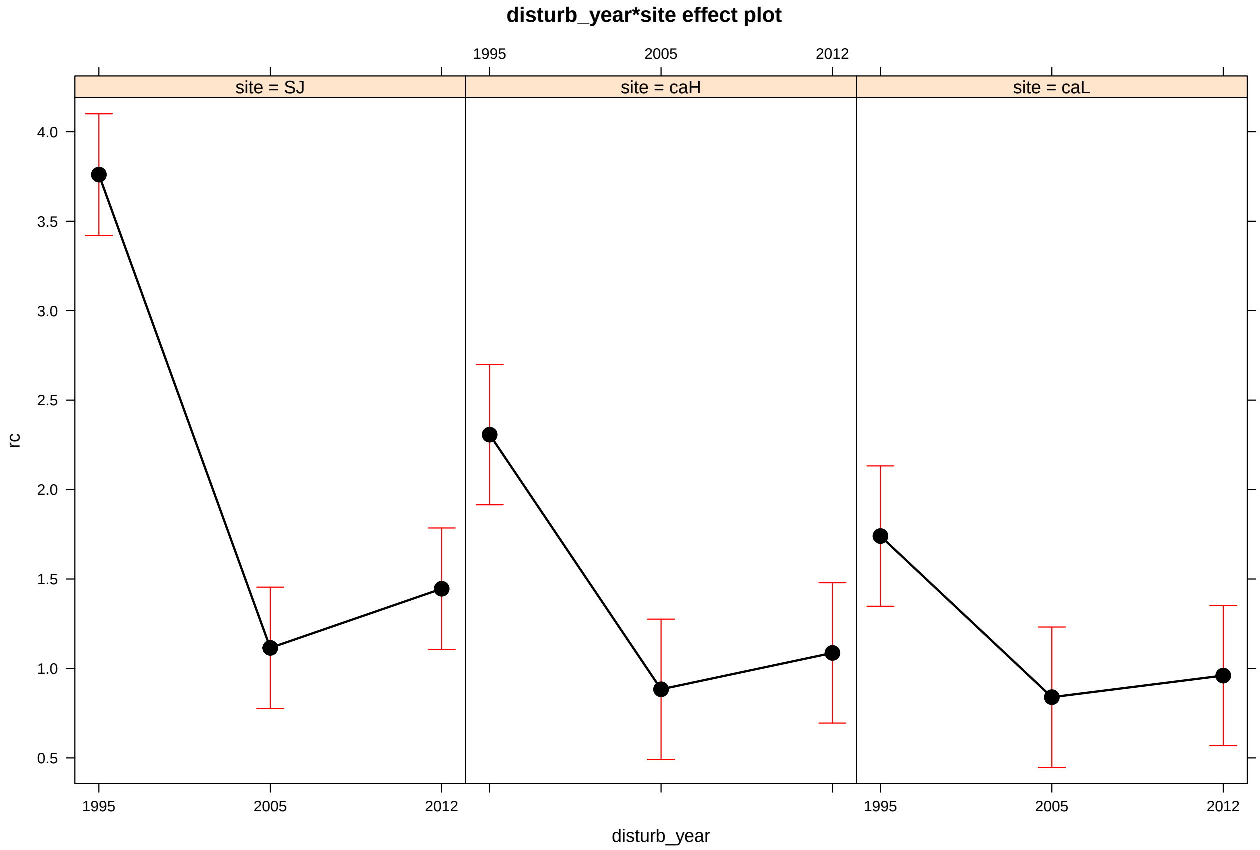
```
pd
```




```
picollapse
```


disturb_year*site effect plot
site
SJ
caH
caL
rc
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1995
2005
2012
disturb_year

```
pi
```



Resistance

```
# Variable
resp_var <- 'rt'

# AOV
aov_rt <- aovas(re, vars=vars, resp_var = resp_var)
```

```
mc <- aov_rt$model_coeff

pander(mc, round=5,
       caption = paste0("ANOVA table: ", resp_var), missing = '',
       emphasize.strong.cells =
         which(mc < 0.1 & mc == mc$p.value, arr.ind = T))
```

Table 5: ANOVA table: rt

term	df	sumsq	meansq	statistic	p.value
disturb_year	2	1.143	0.5713	28.49	**0**
site	2	0.8879	0.4439	22.14	**0**
disturb_year:site	4	1.743	0.4358	21.74	**0**
Residuals	141	2.827	0.02005		

```r
gm <- aov_rt$model_summary

gm <- apply(gm, 1, formatC, digits = 2, format = "f") %>% t()
colnames(gm) <- paste0("$",c("R^2","\\mathrm{adj}R^2","\\sigma_e","F","p","df_m","\\mathrm{logLik}","AI
rownames(gm) <- "Statistic"
pander(t(gm))
```

	Statistic
R^2	0.57
$\mathrm{adj}R^2$	0.55
σ_e	0.14
F	23.53
p	0.00
df_m	9.00
logLik	85.01
AIC	-150.03
BIC	-119.92
dev	2.83
df_e	141.00

Post hoc comparison

```r
# Post hoc Define model
mymodel <- aov_rt$mymodel
postH_rc <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year    lsmean         SE  df  lower.CL  upper.CL
##  1995         0.5933021 0.02020965 141 0.5533490 0.6332552
##  2005         0.7483129 0.02020965 141 0.7083599 0.7882660
##  2012         0.8166033 0.02020965 141 0.7766502 0.8565564
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast       estimate         SE  df t.ratio p.value
##  1995 - 2005 -0.15501083 0.02858076 141  -5.424  <.0001
##  1995 - 2012 -0.22330118 0.02858076 141  -7.813  <.0001
##  2005 - 2012 -0.06829036 0.02858076 141  -2.389  0.0475
##
## Results are averaged over the levels of: site
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  disturb_year    lsmean         SE  df  lower.CL  upper.CL .group
##  1995         0.5933021 0.02020965 141 0.5444669 0.6421374  a
##  2005         0.7483129 0.02020965 141 0.6994777 0.7971482   b
##  2012         0.8166033 0.02020965 141 0.7677681 0.8654385   b
##
```

```
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
## $lsmeans
##  site    lsmean         SE  df  lower.CL  upper.CL
##  SJ   0.6245302 0.01828031 141 0.5883913 0.6606691
##  caH  0.7248455 0.02110829 141 0.6831159 0.7665752
##  caL  0.8088426 0.02110829 141 0.7671130 0.8505722
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast     estimate         SE  df t.ratio p.value
##  SJ - caH  -0.10031531 0.02792364 141  -3.592  0.0013
##  SJ - caL  -0.18431239 0.02792364 141  -6.601  <.0001
##  caH - caL -0.08399708 0.02985163 141  -2.814  0.0154
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  site    lsmean         SE  df  lower.CL  upper.CL .group
##  SJ   0.6245302 0.01828031 141 0.5803571 0.6687034  a
##  caH  0.7248455 0.02110829 141 0.6738388 0.7758523   b
##  caL  0.8088426 0.02110829 141 0.7578359 0.8598494   b
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site    lsmean         SE  df  lower.CL  upper.CL
##  1995         SJ   0.6456938 0.03166243 141 0.5830993 0.7082882
##  2005         SJ   0.4606116 0.03166243 141 0.3980172 0.5232061
##  2012         SJ   0.7672853 0.03166243 141 0.7046908 0.8298797
##  1995         caH  0.5351747 0.03656063 141 0.4628969 0.6074526
##  2005         caH  0.8845609 0.03656063 141 0.8122830 0.9568388
##  2012         caH  0.7548010 0.03656063 141 0.6825231 0.8270788
##  1995         caL  0.5990379 0.03656063 141 0.5267600 0.6713157
##  2005         caL  0.8997663 0.03656063 141 0.8274884 0.9720441
##  2012         caL  0.9277237 0.03656063 141 0.8554458 1.0000015
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate         SE  df t.ratio p.value
##  1995,SJ - 2005,SJ    0.18508210 0.04477744 141   4.133  0.0020
```

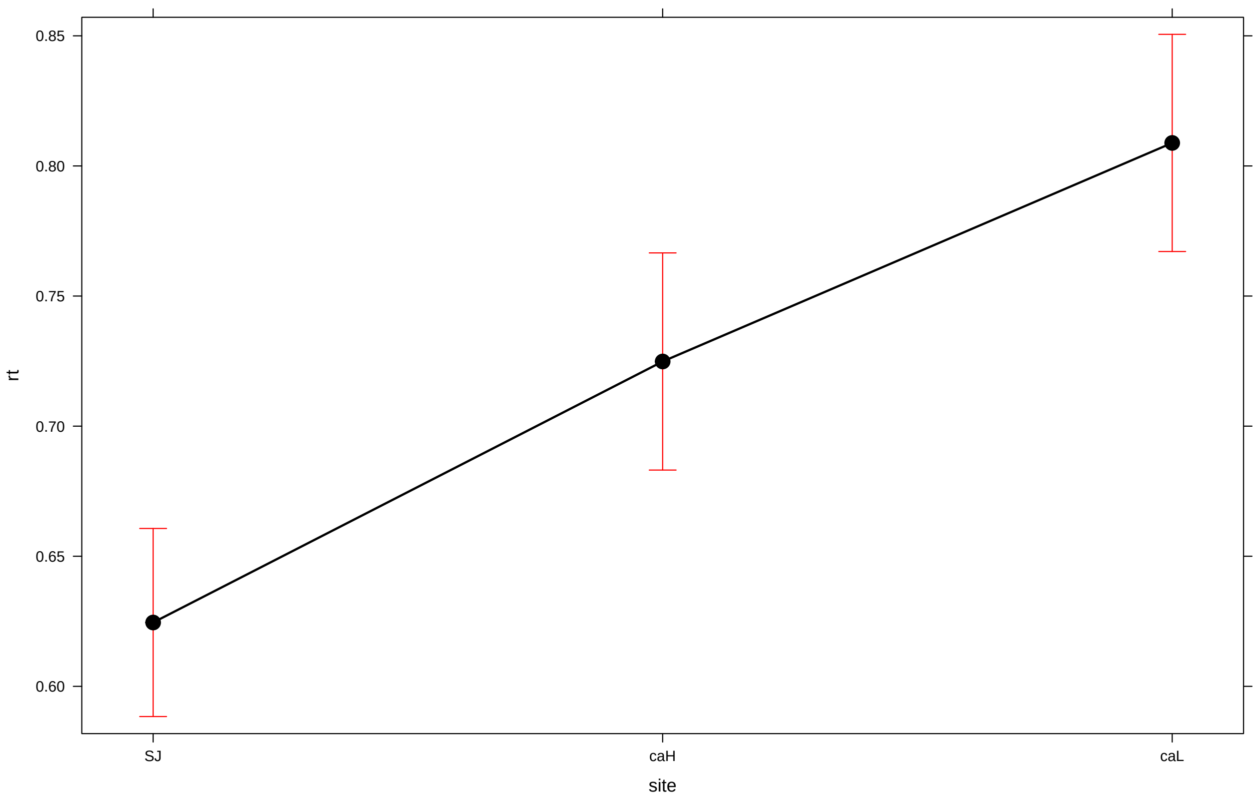
```
##  1995,SJ - 2012,SJ   -0.12159151 0.04477744 141  -2.715  0.1519
##  1995,SJ - 1995,caH   0.11051901 0.04836516 141   2.285  0.3582
##  1995,SJ - 2005,caH  -0.23886715 0.04836516 141  -4.939  0.0001
##  1995,SJ - 2012,caH  -0.10910721 0.04836516 141  -2.256  0.3761
##  1995,SJ - 1995,caL   0.04665589 0.04836516 141   0.965  0.9884
##  1995,SJ - 2005,caL  -0.25407253 0.04836516 141  -5.253  <.0001
##  1995,SJ - 2012,caL  -0.28202993 0.04836516 141  -5.831  <.0001
##  2005,SJ - 2012,SJ   -0.30667361 0.04477744 141  -6.849  <.0001
##  2005,SJ - 1995,caH  -0.07456309 0.04836516 141  -1.542  0.8338
##  2005,SJ - 2005,caH  -0.42394925 0.04836516 141  -8.766  <.0001
##  2005,SJ - 2012,caH  -0.29418931 0.04836516 141  -6.083  <.0001
##  2005,SJ - 1995,caL  -0.13842622 0.04836516 141  -2.862  0.1072
##  2005,SJ - 2005,caL  -0.43915464 0.04836516 141  -9.080  <.0001
##  2005,SJ - 2012,caL  -0.46711203 0.04836516 141  -9.658  <.0001
##  2012,SJ - 1995,caH   0.23211053 0.04836516 141   4.799  0.0001
##  2012,SJ - 2005,caH  -0.11727564 0.04836516 141  -2.425  0.2789
##  2012,SJ - 2012,caH   0.01248430 0.04836516 141   0.258  1.0000
##  2012,SJ - 1995,caL   0.16824740 0.04836516 141   3.479  0.0188
##  2012,SJ - 2005,caL  -0.13248102 0.04836516 141  -2.739  0.1438
##  2012,SJ - 2012,caL  -0.16043842 0.04836516 141  -3.317  0.0308
##  1995,caH - 2005,caH -0.34938616 0.05170453 141  -6.757  <.0001
##  1995,caH - 2012,caH -0.21962622 0.05170453 141  -4.248  0.0013
##  1995,caH - 1995,caL -0.06386313 0.05170453 141  -1.235  0.9473
##  1995,caH - 2005,caL -0.36459155 0.05170453 141  -7.051  <.0001
##  1995,caH - 2012,caL -0.39254894 0.05170453 141  -7.592  <.0001
##  2005,caH - 2012,caH  0.12975994 0.05170453 141   2.510  0.2364
##  2005,caH - 1995,caL  0.28552304 0.05170453 141   5.522  <.0001
##  2005,caH - 2005,caL -0.01520539 0.05170453 141  -0.294  1.0000
##  2005,caH - 2012,caL -0.04316278 0.05170453 141  -0.835  0.9956
##  2012,caH - 1995,caL  0.15576310 0.05170453 141   3.013  0.0729
##  2012,caH - 2005,caL -0.14496533 0.05170453 141  -2.804  0.1235
##  2012,caH - 2012,caL -0.17292272 0.05170453 141  -3.344  0.0284
##  1995,caL - 2005,caL -0.30072842 0.05170453 141  -5.816  <.0001
##  1995,caL - 2012,caL -0.32868582 0.05170453 141  -6.357  <.0001
##  2005,caL - 2012,caL -0.02795739 0.05170453 141  -0.541  0.9998
##
## P value adjustment: tukey method for comparing a family of 9 estimates
```

Plots

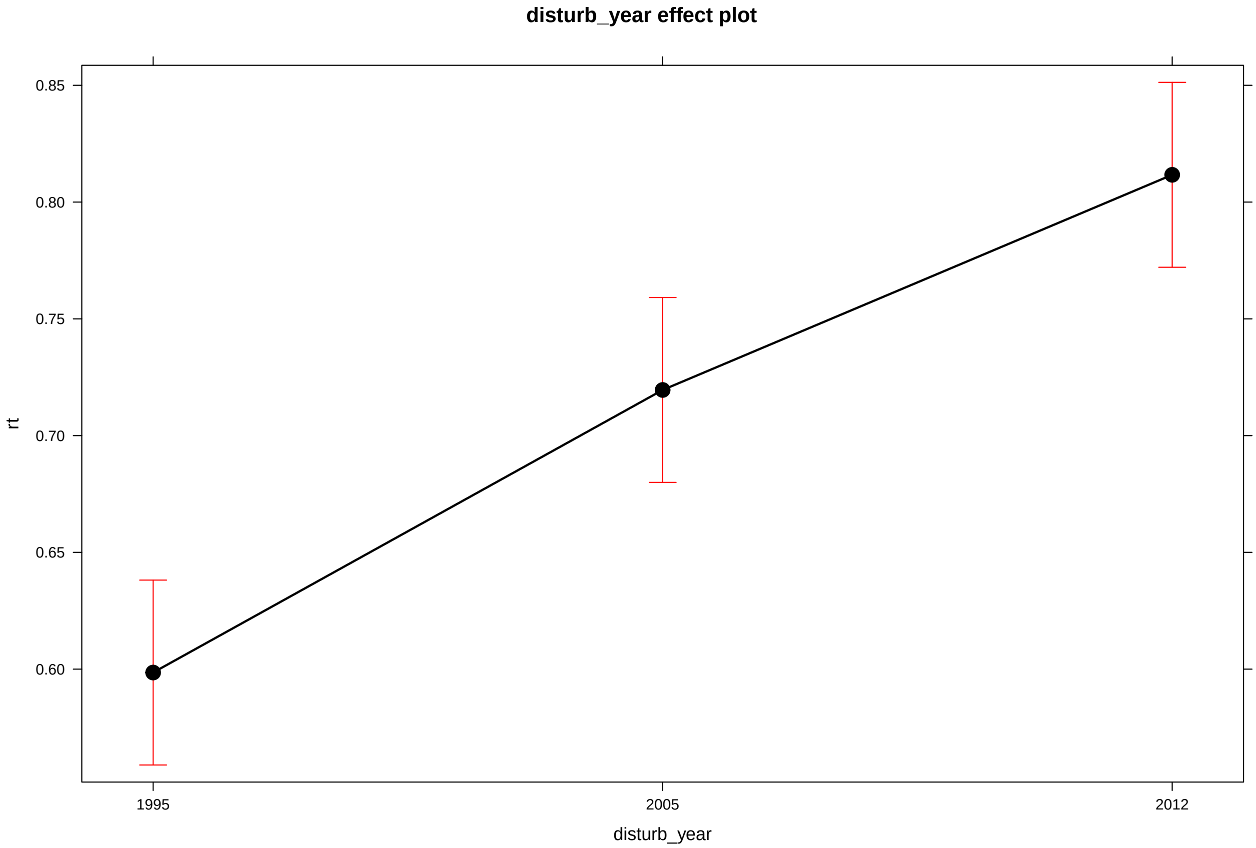
```r
#### ~ Site
ps <- plot(effect("site",mymodel))
#### ~ Disturb Year
pd <- plot(effect('disturb_year', mymodel))
#### Disturb Year:Site
picollapse <- plot(effect("disturb_year:site",mymodel), multiline = TRUE, ci.style = 'bars')
pi <- plot(effect("disturb_year:site",mymodel), layout=c(3,1))
```

```r
ps
```

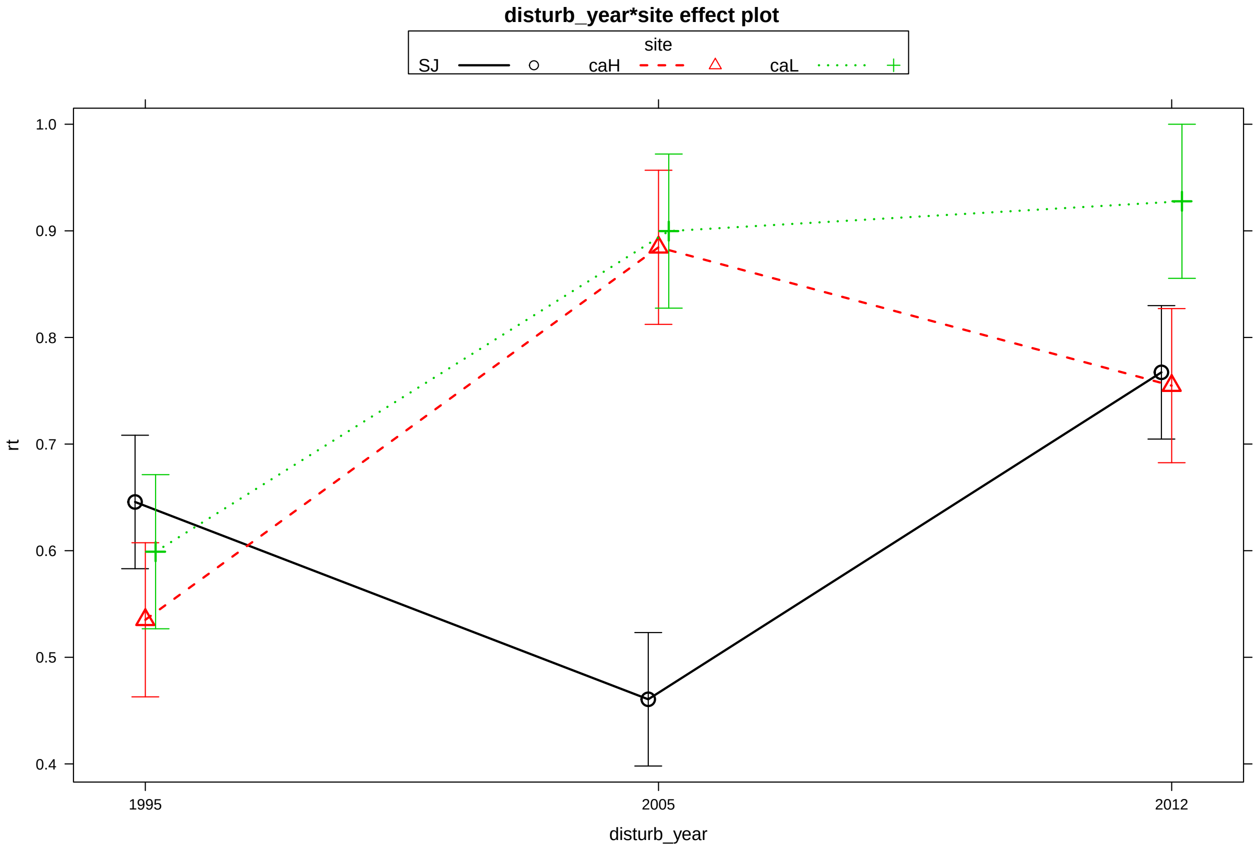
site effect plot




```
pd
```

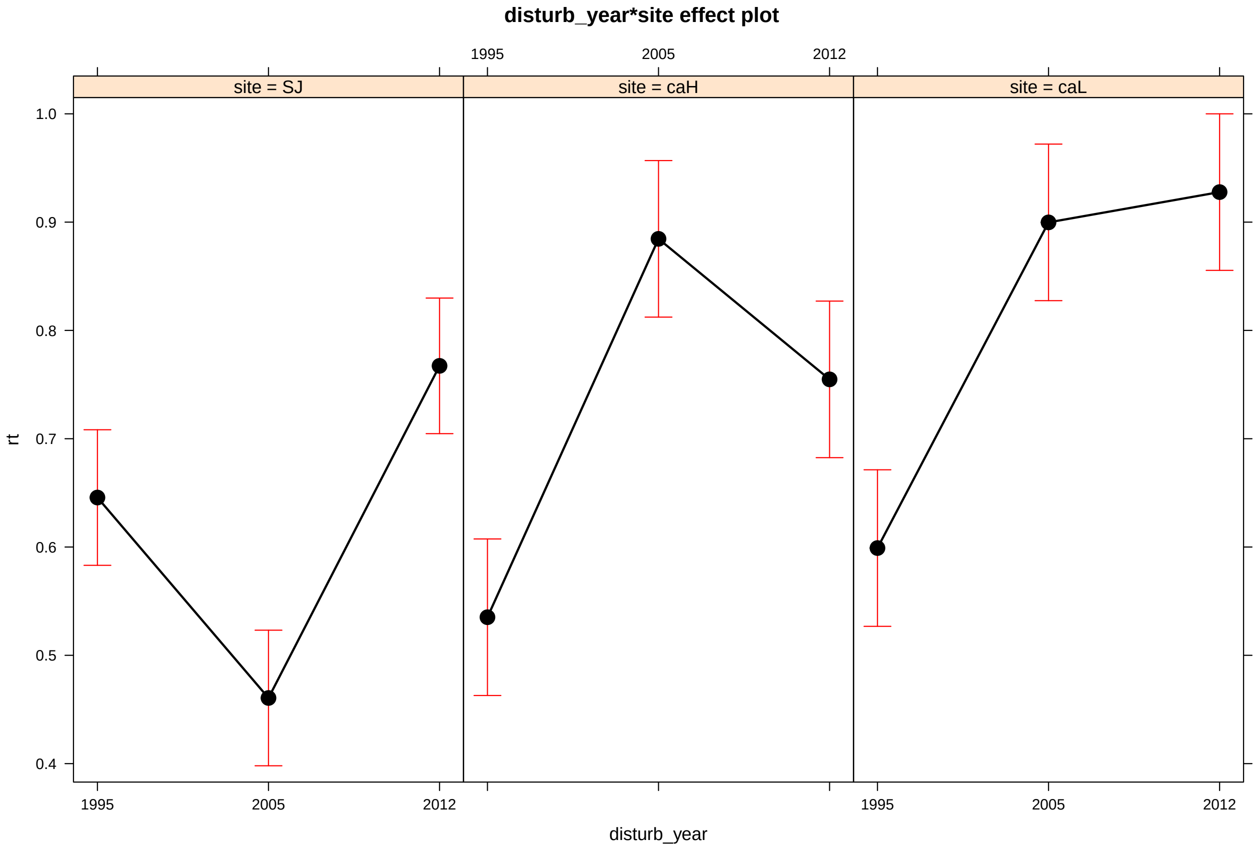

disturb_year effect plot
0.85
0.80
0.75
0.70
0.65
0.60
rt
1995
2005
2012
disturb_year

```
picollapse
```



disturb_year*site effect plot
site
SJ
caH
caL
1.0
0.9
0.8
0.7
0.6
0.5
0.4
rt
1995
2005
2012
disturb_year


```
pi
```



Relative Resilience

```r
# Variable
resp_var <- 'rrs'

# AOV
aov_rrs <- aovas(re, vars=vars, resp_var = resp_var)
```

```r
mc <- aov_rrs$model_coeff

pander(mc, round=5,
       caption = paste0("ANOVA table: ", resp_var), missing = '',
       emphasize.strong.cells =
         which(mc < 0.1 & mc == mc$p.value, arr.ind = T))
```

Table 7: ANOVA table: rrs

term	df	sumsq	meansq	statistic	p.value
disturb_year	2	30.1	15.05	108.7	**0**
site	2	9.83	4.915	35.5	**0**
disturb_year:site	4	5.868	1.467	10.6	**0**
Residuals	141	19.52	0.1384		

```r
gm <- aov_rrs$model_summary

gm <- apply(gm, 1, formatC, digits = 2, format = "f") %>% t()
colnames(gm) <- paste0("$",c("R^2","\\mathrm{adj}R^2","\\sigma_e","F","p","df_m","\\mathrm{logLik}","AI
rownames(gm) <- "Statistic"
pander(t(gm))
```

	Statistic
R^2	0.70
$\mathrm{adj}R^2$	0.68
σ_e	0.37
F	41.35
p	0.00
df_m	9.00
logLik	-59.91
AIC	139.81
BIC	169.92
dev	19.52
df_e	141.00

Post hoc comparison

```r
# Post hoc Define model
mymodel <- aov_rrs$mymodel
postH_rc <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year      lsmean         SE  df     lower.CL  upper.CL
##  1995          0.89895149 0.05310627 141  0.793964043 1.0039389
##  2005         -0.07268135 0.05310627 141 -0.177668799 0.0323061
##  2012          0.11047515 0.05310627 141  0.005487701 0.2154626
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate        SE  df t.ratio p.value
##  1995 - 2005  0.9716328 0.0751036 141  12.937  <.0001
##  1995 - 2012  0.7884763 0.0751036 141  10.499  <.0001
##  2005 - 2012 -0.1831565 0.0751036 141  -2.439  0.0420
##
## Results are averaged over the levels of: site
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  disturb_year      lsmean         SE  df    lower.CL   upper.CL .group
##  2005         -0.07268135 0.05310627 141 -0.20100905 0.05564635  a
##  2012          0.11047515 0.05310627 141 -0.01785255 0.23880285  a
##  1995          0.89895149 0.05310627 141  0.77062379 1.02727919   b
##
```

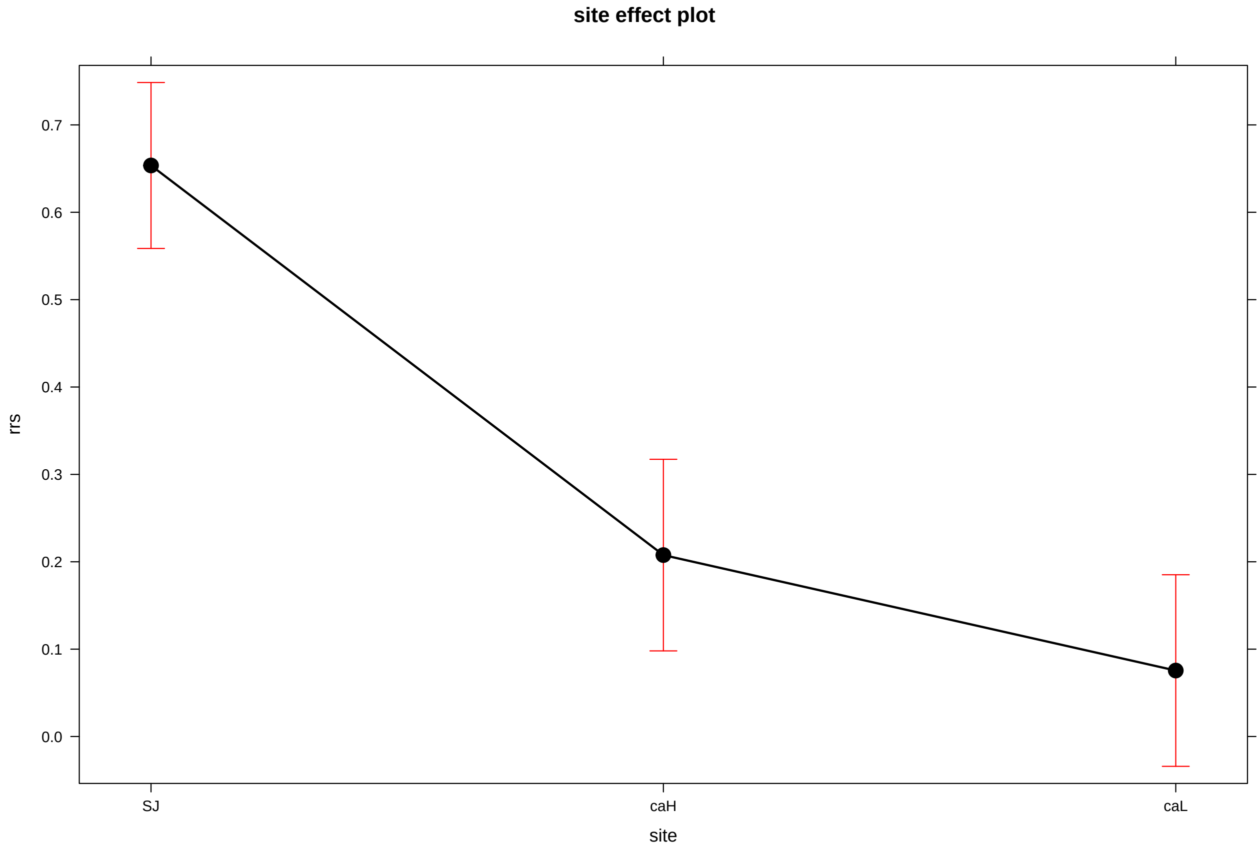
```
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
## $lsmeans
##  site     lsmean         SE  df    lower.CL  upper.CL
##  SJ   0.65357791 0.04803643 141  0.55861318 0.7485426
##  caH  0.20766004 0.05546769 141  0.09800423 0.3173159
##  caL  0.07550735 0.05546769 141 -0.03414847 0.1851632
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast   estimate         SE  df t.ratio p.value
##  SJ - caH  0.4459179 0.07337685 141   6.077  <.0001
##  SJ - caL  0.5780706 0.07337685 141   7.878  <.0001
##  caH - caL 0.1321527 0.07844315 141   1.685  0.2146
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  site     lsmean         SE  df    lower.CL  upper.CL .group
##  caL  0.07550735 0.05546769 141 -0.05852656 0.2095413  a
##  caH  0.20766004 0.05546769 141  0.07362613 0.3416940  a
##  SJ   0.65357791 0.04803643 141  0.53750114 0.7696547   b
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site      lsmean         SE  df   lower.CL   upper.CL
##  1995         SJ    1.60983933 0.08320153 141  1.4453556 1.77432305
##  2005         SJ    0.03528048 0.08320153 141 -0.1292032 0.19976421
##  2012         SJ    0.31561391 0.08320153 141  0.1511302 0.48009764
##  1995         caH   0.67490775 0.09607285 141  0.4849783 0.86483719
##  2005         caH  -0.11035142 0.09607285 141 -0.3002809 0.07957802
##  2012         caH   0.05842381 0.09607285 141 -0.1315056 0.24835325
##  1995         caL   0.41210741 0.09607285 141  0.2221780 0.60203685
##  2005         caL  -0.14297310 0.09607285 141 -0.3329025 0.04695635
##  2012         caL  -0.04261226 0.09607285 141 -0.2325417 0.14731718
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate        SE  df t.ratio p.value
##  1995,SJ - 2005,SJ    1.57455885 0.1176647 141  13.382  <.0001
```

```
##  1995,SJ - 2012,SJ    1.29422542 0.1176647 141  10.999  <.0001
##  1995,SJ - 1995,caH   0.93493158 0.1270924 141   7.356  <.0001
##  1995,SJ - 2005,caH   1.72019075 0.1270924 141  13.535  <.0001
##  1995,SJ - 2012,caH   1.55141552 0.1270924 141  12.207  <.0001
##  1995,SJ - 1995,caL   1.19773192 0.1270924 141   9.424  <.0001
##  1995,SJ - 2005,caL   1.75281243 0.1270924 141  13.792  <.0001
##  1995,SJ - 2012,caL   1.65245159 0.1270924 141  13.002  <.0001
##  2005,SJ - 2012,SJ   -0.28033343 0.1176647 141  -2.382  0.3018
##  2005,SJ - 1995,caH  -0.63962727 0.1270924 141  -5.033  0.0001
##  2005,SJ - 2005,caH   0.14563191 0.1270924 141   1.146  0.9659
##  2005,SJ - 2012,caH  -0.02314333 0.1270924 141  -0.182  1.0000
##  2005,SJ - 1995,caL  -0.37682692 0.1270924 141  -2.965  0.0826
##  2005,SJ - 2005,caL   0.17825358 0.1270924 141   1.403  0.8952
##  2005,SJ - 2012,caL   0.07789274 0.1270924 141   0.613  0.9995
##  2012,SJ - 1995,caH  -0.35929383 0.1270924 141  -2.827  0.1168
##  2012,SJ - 2005,caH   0.42596534 0.1270924 141   3.352  0.0278
##  2012,SJ - 2012,caH   0.25719010 0.1270924 141   2.024  0.5297
##  2012,SJ - 1995,caL  -0.09649349 0.1270924 141  -0.759  0.9977
##  2012,SJ - 2005,caL   0.45858701 0.1270924 141   3.608  0.0124
##  2012,SJ - 2012,caL   0.35822618 0.1270924 141   2.819  0.1192
##  1995,caH - 2005,caH  0.78525917 0.1358675 141   5.780  <.0001
##  1995,caH - 2012,caH  0.61648394 0.1358675 141   4.537  0.0004
##  1995,caH - 1995,caL  0.26280034 0.1358675 141   1.934  0.5914
##  1995,caH - 2005,caL  0.81788085 0.1358675 141   6.020  <.0001
##  1995,caH - 2012,caL  0.71752001 0.1358675 141   5.281  <.0001
##  2005,caH - 2012,caH -0.16877523 0.1358675 141  -1.242  0.9455
##  2005,caH - 1995,caL -0.52245883 0.1358675 141  -3.845  0.0055
##  2005,caH - 2005,caL  0.03262167 0.1358675 141   0.240  1.0000
##  2005,caH - 2012,caL -0.06773916 0.1358675 141  -0.499  0.9999
##  2012,caH - 1995,caL -0.35368360 0.1358675 141  -2.603  0.1947
##  2012,caH - 2005,caL  0.20139691 0.1358675 141   1.482  0.8620
##  2012,caH - 2012,caL  0.10103607 0.1358675 141   0.744  0.9980
##  1995,caL - 2005,caL  0.55508050 0.1358675 141   4.085  0.0023
##  1995,caL - 2012,caL  0.45471967 0.1358675 141   3.347  0.0282
##  2005,caL - 2012,caL -0.10036083 0.1358675 141  -0.739  0.9981
##
## P value adjustment: tukey method for comparing a family of 9 estimates
```

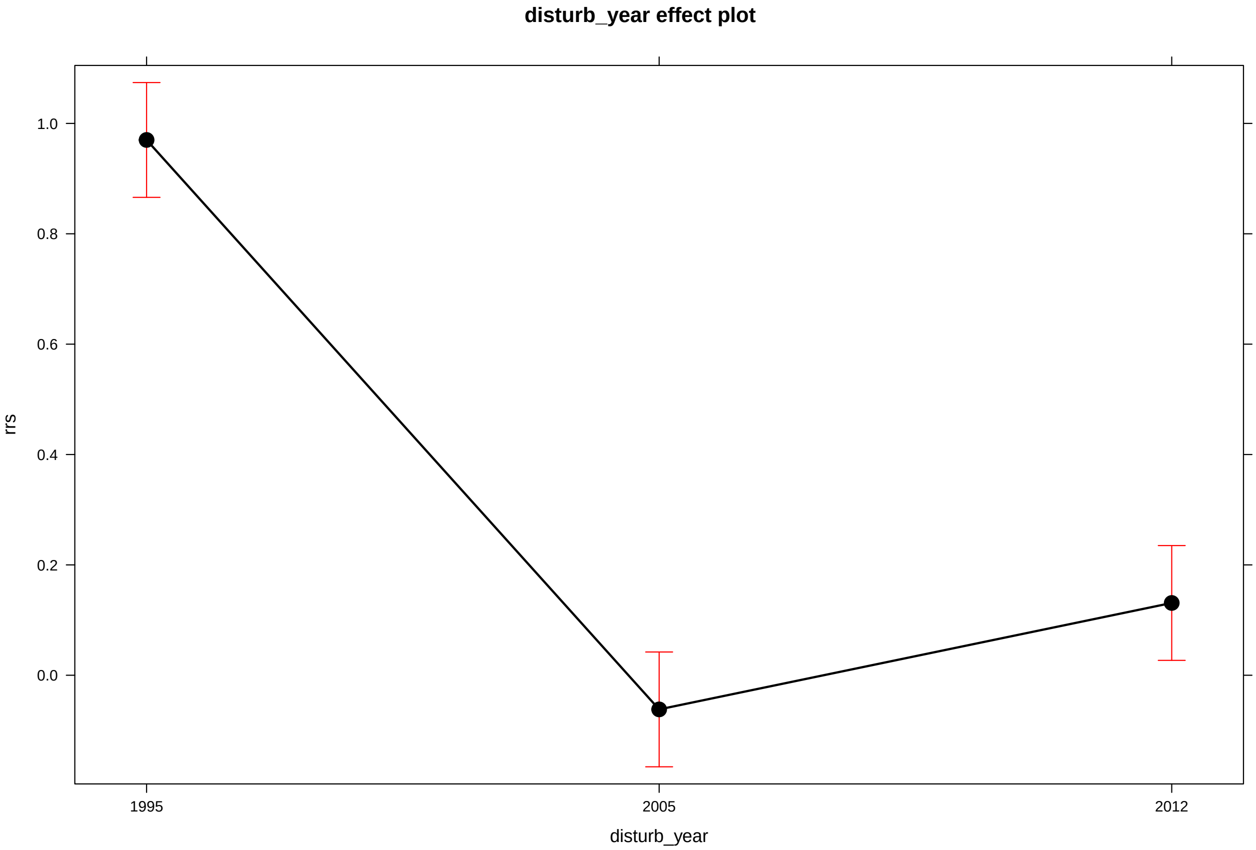
Plots

```r
#### ~ Site
ps <- plot(effect("site",mymodel))
#### ~ Disturb Year
pd <- plot(effect('disturb_year', mymodel))
#### Disturb Year:Site
picollapse <- plot(effect("disturb_year:site",mymodel), multiline = TRUE, ci.style = 'bars')
pi <- plot(effect("disturb_year:site",mymodel), layout=c(3,1))
```

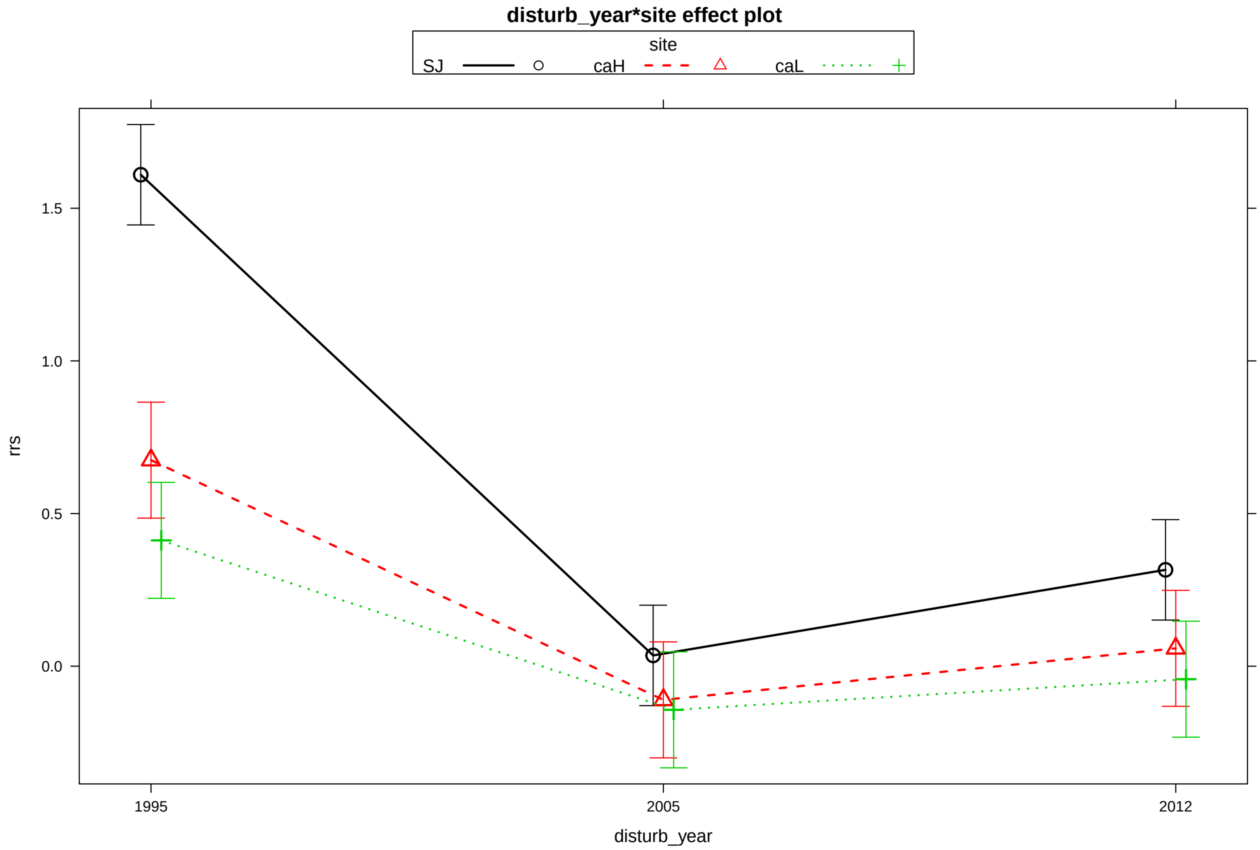
```r
ps
```



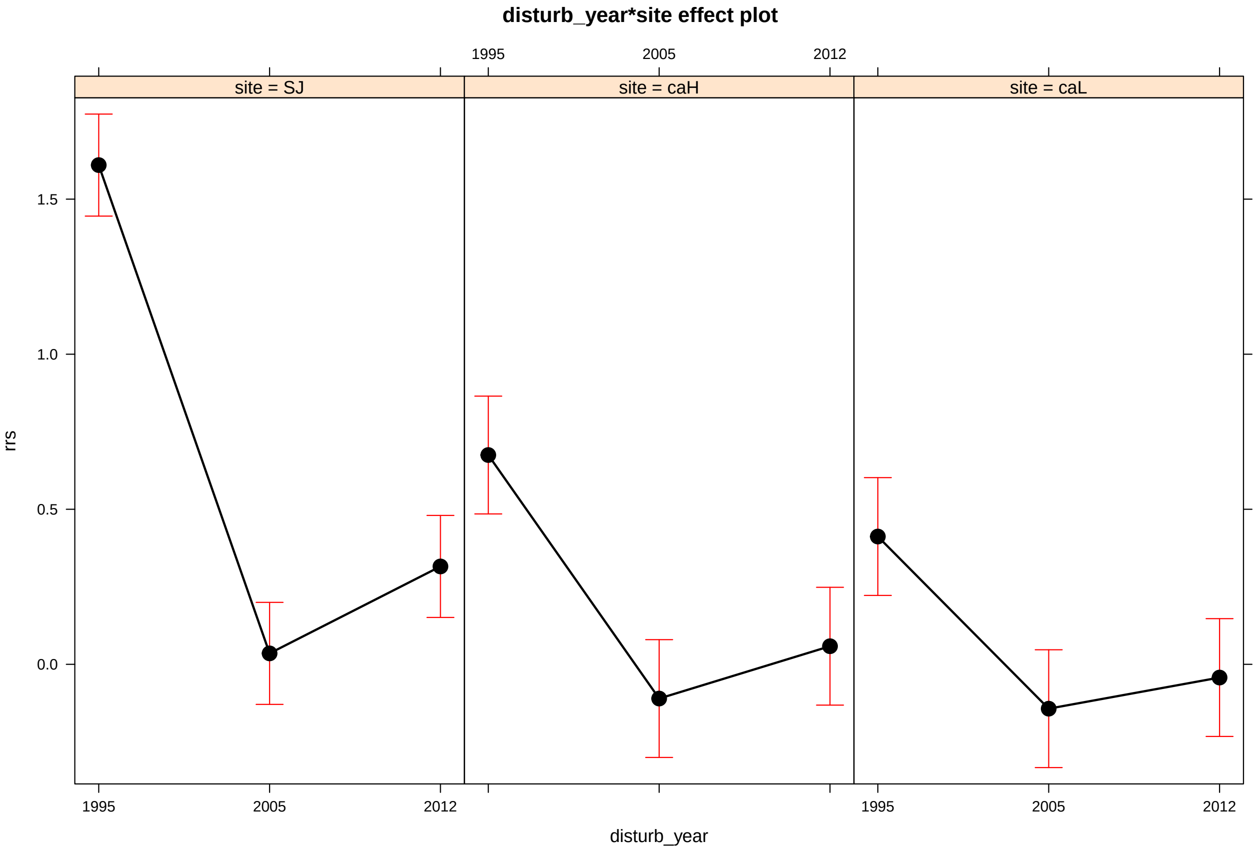

```
pd
```


disturb_year effect plot
1.0
0.8
0.6
0.4
0.2
0.0
rrs
1995
2005
2012
disturb_year

```
picollapse
```


disturb_year*site effect plot
site
SJ
caH
caL
1.5
1.0
0.5
0.0
rrs
1995
2005
2012
disturb_year

```
pi
```



Resilience

```r
# Variable
resp_var <- 'rs'

# AOV
aov_rs <- aovas(re, vars=vars, resp_var = resp_var)
```

```r
mc <- aov_rs$model_coeff

pander(mc, round=5,
       caption = paste0("ANOVA table: ", resp_var), missing = '',
       emphasize.strong.cells =
         which(mc < 0.1 & mc == mc$p.value, arr.ind = T))
```

Table 9: ANOVA table: rs

term	df	sumsq	meansq	statistic	p.value
disturb_year	2	21.71	10.86	76.18	**0**
site	2	4.972	2.486	17.44	**0**
disturb_year:site	4	12.62	3.156	22.14	**0**
Residuals	141	20.09	0.1425		

```r
gm <- aov_rs$model_summary

gm <- apply(gm, 1, formatC, digits = 2, format = "f") %>% t()
colnames(gm) <- paste0("$",c("R^2","\\mathrm{adj}R^2","\\sigma_e","F","p","df_m","\\mathrm{logLik}","AI
rownames(gm) <- "Statistic"
pander(t(gm))
```

	Statistic
R^2	0.66
$\mathrm{adj}R^2$	0.64
σ_e	0.38
F	34.48
p	0.00
df_m	9.00
logLik	-62.08
AIC	144.16
BIC	174.26
dev	20.09
df_e	141.00

Post hoc comparison

```r
# Post hoc Define model
mymodel <- aov_rs$mymodel
postH_rc <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year    lsmean         SE  df  lower.CL  upper.CL
##  1995         1.4922536 0.05388052 141 1.3857355 1.5987717
##  2005         0.6756316 0.05388052 141 0.5691135 0.7821497
##  2012         0.9270785 0.05388052 141 0.8205604 1.0335965
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate         SE  df t.ratio p.value
##  1995 - 2005  0.8166220 0.07619856 141  10.717  <.0001
##  1995 - 2012  0.5651752 0.07619856 141   7.417  <.0001
##  2005 - 2012 -0.2514469 0.07619856 141  -3.300  0.0035
##
## Results are averaged over the levels of: site
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  disturb_year    lsmean         SE  df  lower.CL  upper.CL .group
##  2005         0.6756316 0.05388052 141 0.5454330 0.8058302  a
##  2012         0.9270785 0.05388052 141 0.7968798 1.0572771   b
##  1995         1.4922536 0.05388052 141 1.3620550 1.6224522    c
##
```

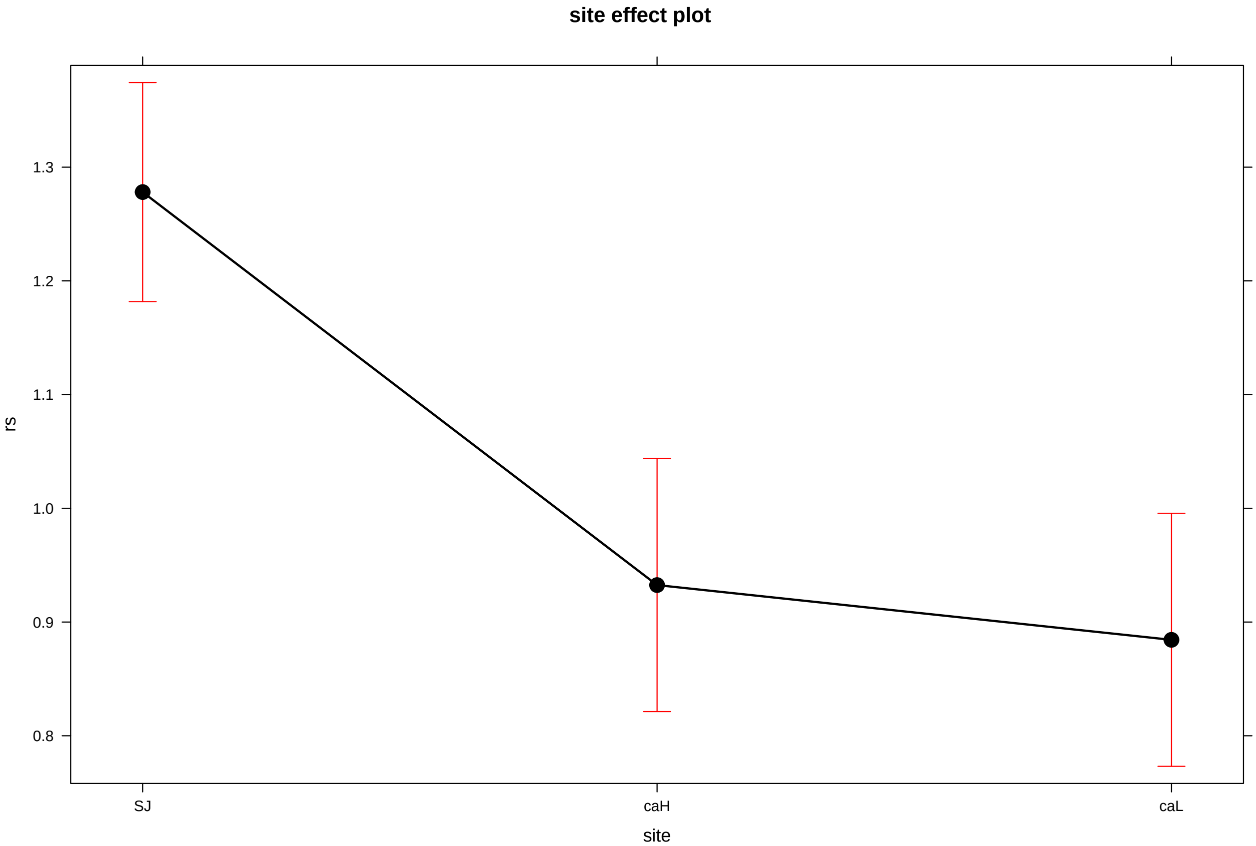
```
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
## $lsmeans
##  site    lsmean         SE  df  lower.CL  upper.CL
##  SJ   1.2781081 0.04873676 141 1.1817589 1.3744574
##  caH  0.9325056 0.05627636 141 0.8212511 1.0437601
##  caL  0.8843500 0.05627636 141 0.7730954 0.9956045
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast    estimate         SE  df t.ratio p.value
##  SJ - caH  0.34560255 0.07444663 141   4.642  <.0001
##  SJ - caL  0.39375817 0.07444663 141   5.289  <.0001
##  caH - caL 0.04815562 0.07958680 141   0.605  0.8176
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: tukey method for comparing a family of 3 estimates
##
##  site    lsmean         SE  df  lower.CL upper.CL .group
##  caL  0.8843500 0.05627636 141 0.7483619 1.020338  a
##  caH  0.9325056 0.05627636 141 0.7965175 1.068494  a
##  SJ   1.2781081 0.04873676 141 1.1603390 1.395877   b
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: sidak method for 3 estimates
## P value adjustment: tukey method for comparing a family of 3 estimates
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site    lsmean         SE  df  lower.CL  upper.CL
##  1995         SJ   2.2555331 0.08441455 141 2.0886513 2.4224149
##  2005         SJ   0.4958921 0.08441455 141 0.3290104 0.6627739
##  2012         SJ   1.0828992 0.08441455 141 0.9160174 1.2497809
##  1995         caH  1.2100825 0.09747352 141 1.0173840 1.4027810
##  2005         caH  0.7742095 0.09747352 141 0.5815110 0.9669080
##  2012         caH  0.8132248 0.09747352 141 0.6205263 1.0059232
##  1995         caL  1.0111453 0.09747352 141 0.8184468 1.2038437
##  2005         caL  0.7567932 0.09747352 141 0.5640947 0.9494917
##  2012         caL  0.8851114 0.09747352 141 0.6924129 1.0778099
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate        SE  df t.ratio p.value
##  1995,SJ - 2005,SJ    1.75964095 0.1193802 141  14.740  <.0001
```

```
##  1995,SJ - 2012,SJ    1.17263391 0.1193802 141   9.823  <.0001
##  1995,SJ - 1995,caH   1.04545060 0.1289454 141   8.108  <.0001
##  1995,SJ - 2005,caH   1.48132360 0.1289454 141  11.488  <.0001
##  1995,SJ - 2012,caH   1.44230831 0.1289454 141  11.185  <.0001
##  1995,SJ - 1995,caL   1.24438781 0.1289454 141   9.651  <.0001
##  1995,SJ - 2005,caL   1.49873989 0.1289454 141  11.623  <.0001
##  1995,SJ - 2012,caL   1.37042166 0.1289454 141  10.628  <.0001
##  2005,SJ - 2012,SJ   -0.58700705 0.1193802 141  -4.917  0.0001
##  2005,SJ - 1995,caH  -0.71419036 0.1289454 141  -5.539  <.0001
##  2005,SJ - 2005,caH  -0.27831735 0.1289454 141  -2.158  0.4386
##  2005,SJ - 2012,caH  -0.31733264 0.1289454 141  -2.461  0.2603
##  2005,SJ - 1995,caL  -0.51525314 0.1289454 141  -3.996  0.0032
##  2005,SJ - 2005,caL  -0.26090106 0.1289454 141  -2.023  0.5299
##  2005,SJ - 2012,caL  -0.38921929 0.1289454 141  -3.018  0.0718
##  2012,SJ - 1995,caH  -0.12718331 0.1289454 141  -0.986  0.9866
##  2012,SJ - 2005,caH   0.30868970 0.1289454 141   2.394  0.2955
##  2012,SJ - 2012,caH   0.26967441 0.1289454 141   2.091  0.4834
##  2012,SJ - 1995,caL   0.07175391 0.1289454 141   0.556  0.9998
##  2012,SJ - 2005,caL   0.32610599 0.1289454 141   2.529  0.2273
##  2012,SJ - 2012,caL   0.19778776 0.1289454 141   1.534  0.8376
##  1995,caH - 2005,caH  0.43587301 0.1378484 141   3.162  0.0484
##  1995,caH - 2012,caH  0.39685772 0.1378484 141   2.879  0.1028
##  1995,caH - 1995,caL  0.19893722 0.1378484 141   1.443  0.8790
##  1995,caH - 2005,caL  0.45328930 0.1378484 141   3.288  0.0336
##  1995,caH - 2012,caL  0.32497107 0.1378484 141   2.357  0.3158
##  2005,caH - 2012,caH -0.03901529 0.1378484 141  -0.283  1.0000
##  2005,caH - 1995,caL -0.23693579 0.1378484 141  -1.719  0.7340
##  2005,caH - 2005,caL  0.01741629 0.1378484 141   0.126  1.0000
##  2005,caH - 2012,caL -0.11090194 0.1378484 141  -0.805  0.9966
##  2012,caH - 1995,caL -0.19792050 0.1378484 141  -1.436  0.8820
##  2012,caH - 2005,caL  0.05643158 0.1378484 141   0.409  1.0000
##  2012,caH - 2012,caL -0.07188665 0.1378484 141  -0.521  0.9999
##  1995,caL - 2005,caL  0.25435208 0.1378484 141   1.845  0.6521
##  1995,caL - 2012,caL  0.12603385 0.1378484 141   0.914  0.9918
##  2005,caL - 2012,caL -0.12831823 0.1378484 141  -0.931  0.9908
##
## P value adjustment: tukey method for comparing a family of 9 estimates
```

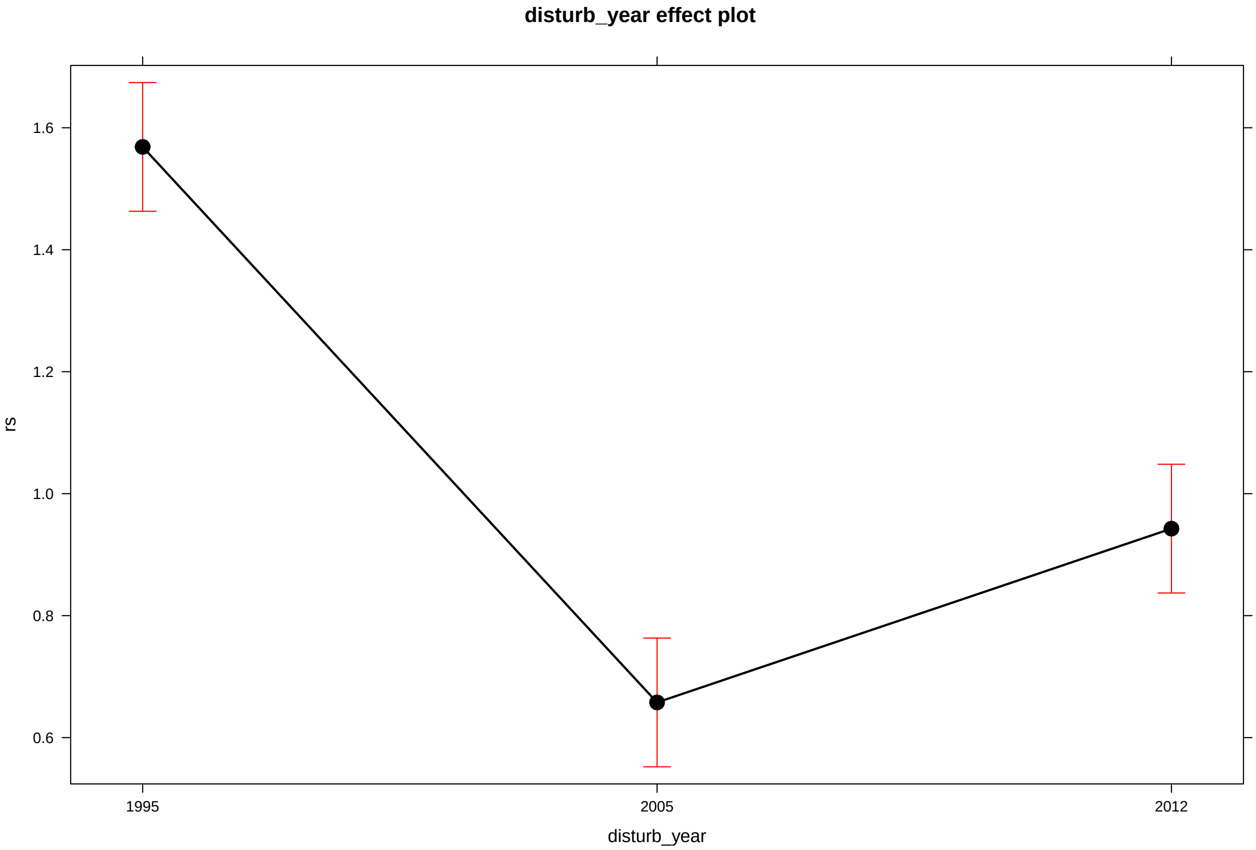
Plots

```r
#### ~ Site
ps <- plot(effect("site",mymodel))
#### ~ Disturb Year
pd <- plot(effect('disturb_year', mymodel))
#### Disturb Year:Site
picollapse <- plot(effect("disturb_year:site",mymodel), multiline = TRUE, ci.style = 'bars')
pi <- plot(effect("disturb_year:site",mymodel), layout=c(3,1))
```

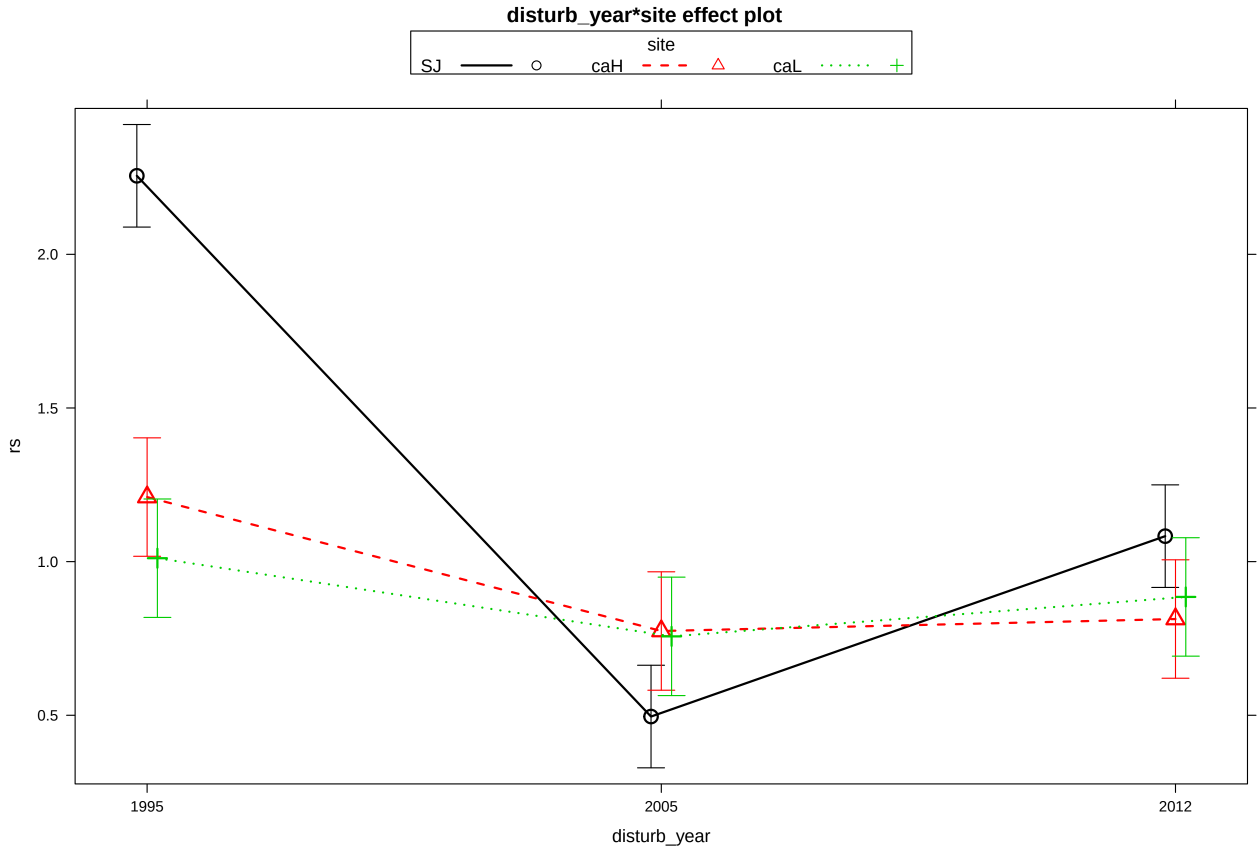
```r
ps
```



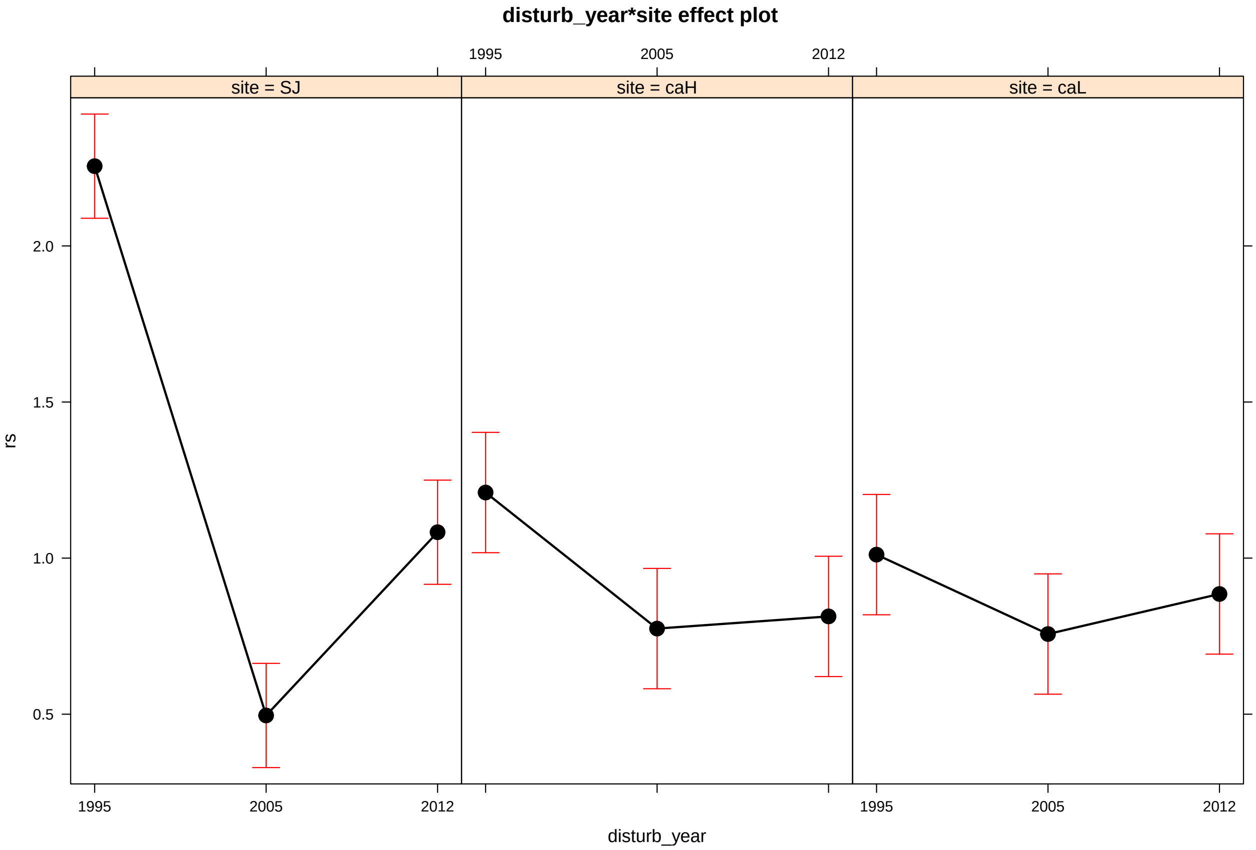

```
pd
```


disturb_year effect plot
1.6
1.4
1.2
1.0
0.8
0.6
rs
1995
2005
2012
disturb_year

```
picollapse
```


disturb_year*site effect plot
site
SJ
caH
caL
rs
2.0
1.5
1.0
0.5
1995
2005
2012
disturb_year

```
pi
```



References

Piovesa, G., F. Biondi, A. D. Filippo, A. Alessandrini, and M. Maugeri. 2008. Drought-driven growth reduction in old beech (fagus sylvatica l.) forests of the central apennines, italy. Global Change Biology 14:1265–1281.