Growth Resilience

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```
library("tidyverse")
library("dplR")
library("stringr")
library("knitr")
library('gtable')
library('grid')
library('gridExtra')
library('pander')
library('broom')
library('effects')
library('devtools')
# devtools::install_github("ajpelu/auxiliar")
library('car')
library('auxiliar')
library('WRS2')
library('MASS')
library('rcompanion')
```

Resilience

- Calcularemos las métricas resiliencia de (Lloret et al. 2011) 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.
```

```r
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

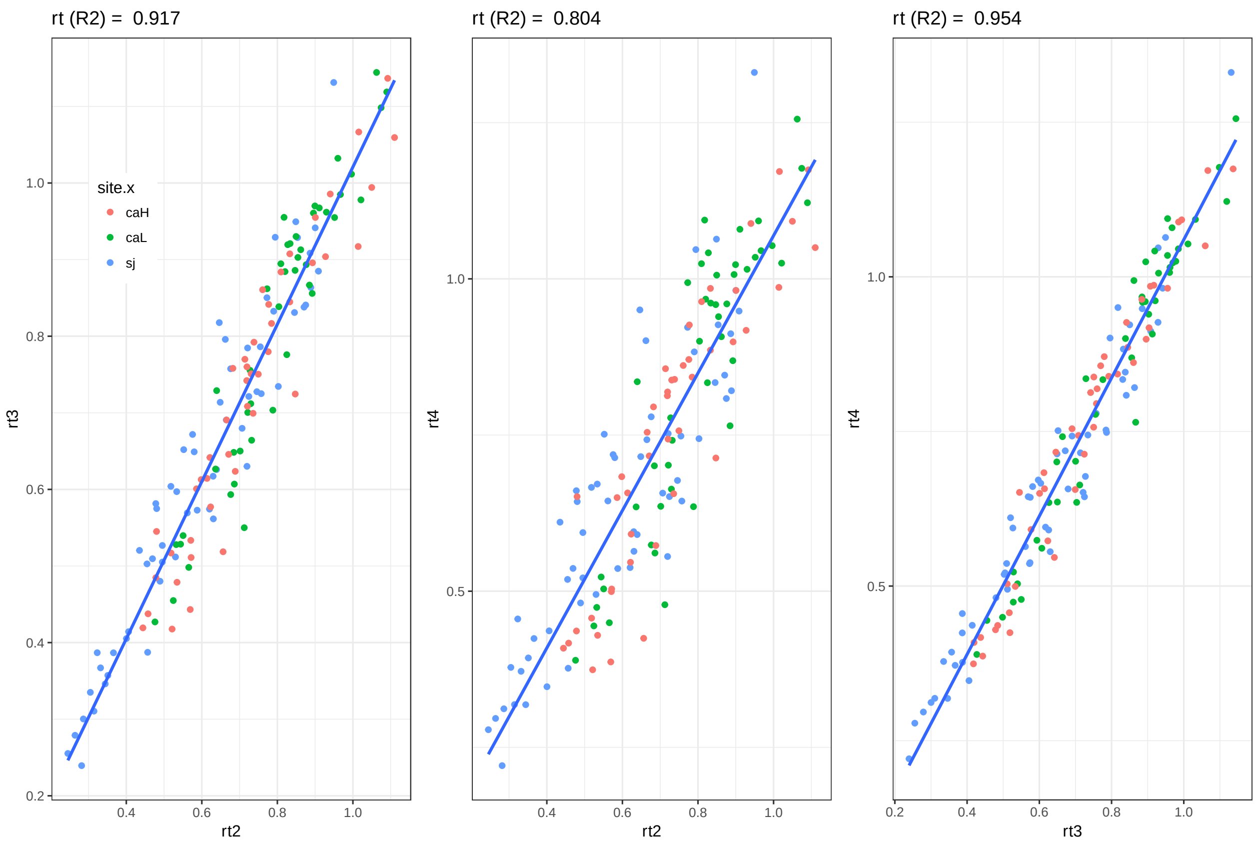
- Computar métricas de resiliencia BAI para los tres sitios.
- Computar tres eventos climáticos: 1995, 2005, 2012
- Computar dos ventanas temporales: 2 y 3

```
# 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

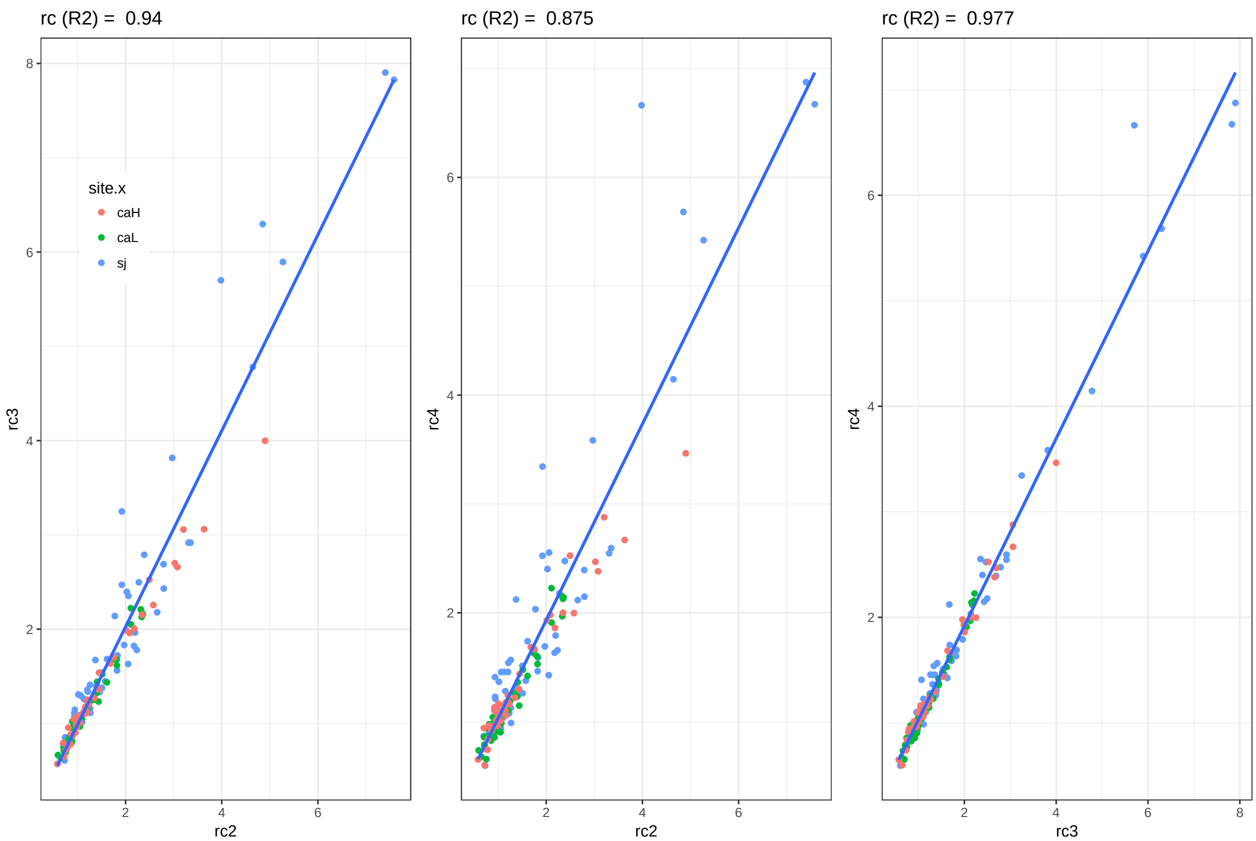
```
# Vector with objects name
obj <- c('res_2_sj', 'res_3_sj', 'res_4_sj',
         'res_2_caL', 'res_3_caL', 'res_4_caL',
         'res_2_caH', 'res_3_caH', 'res_4_caH')

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]_", '')) %>%
    dplyr::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"]] %>% dplyr::select(-ws) %>% mutate(ind = row_number())
cor3 <- correla[["ws_3"]] %>% dplyr::select(-ws) %>% mutate(ind = row_number())
cor4 <- correla[["ws_4"]] %>% dplyr::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')
```

```r
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)
```



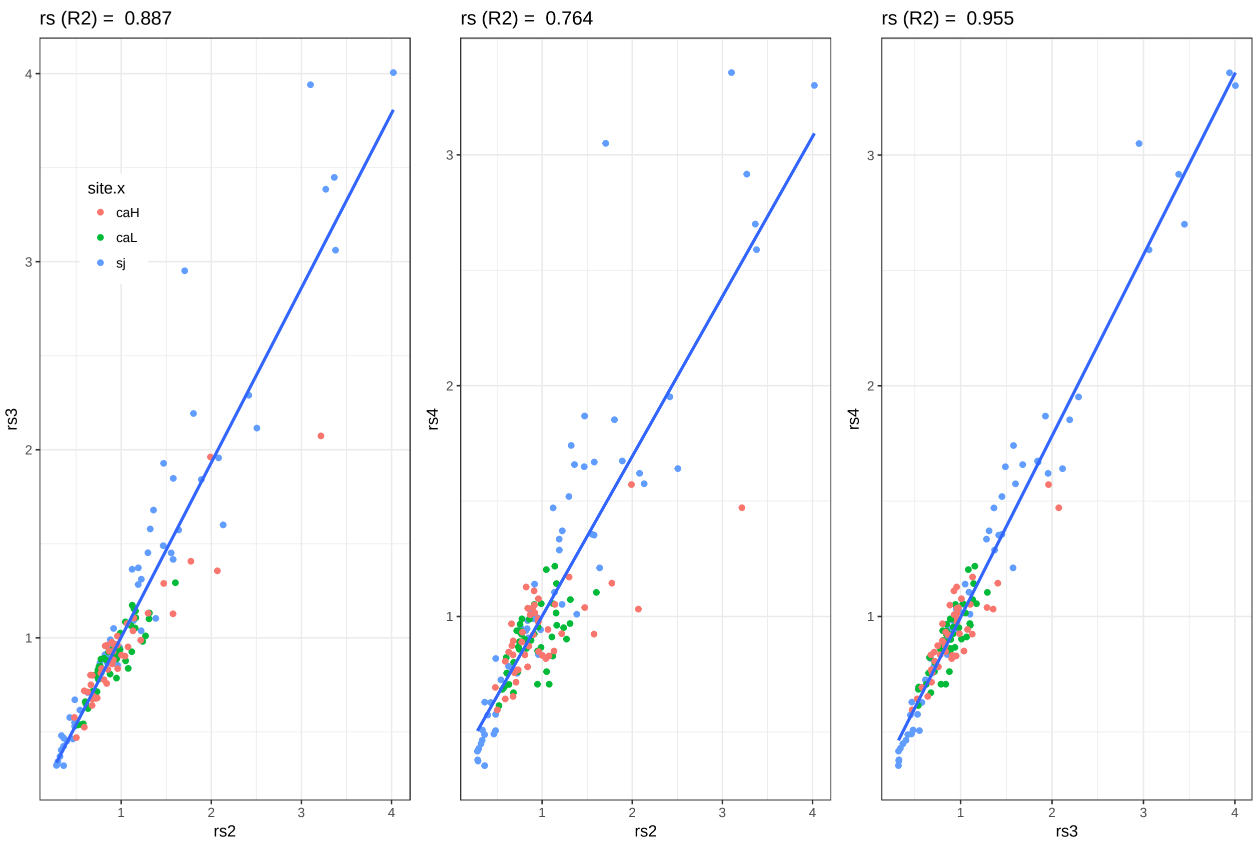

```r
# Recovery
model <- lm(rc2~rc3, data=correlations)
p_rc23 <- correlations %>% ggplot(aes(rc2, rc3)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rc (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = c(.2, .75))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



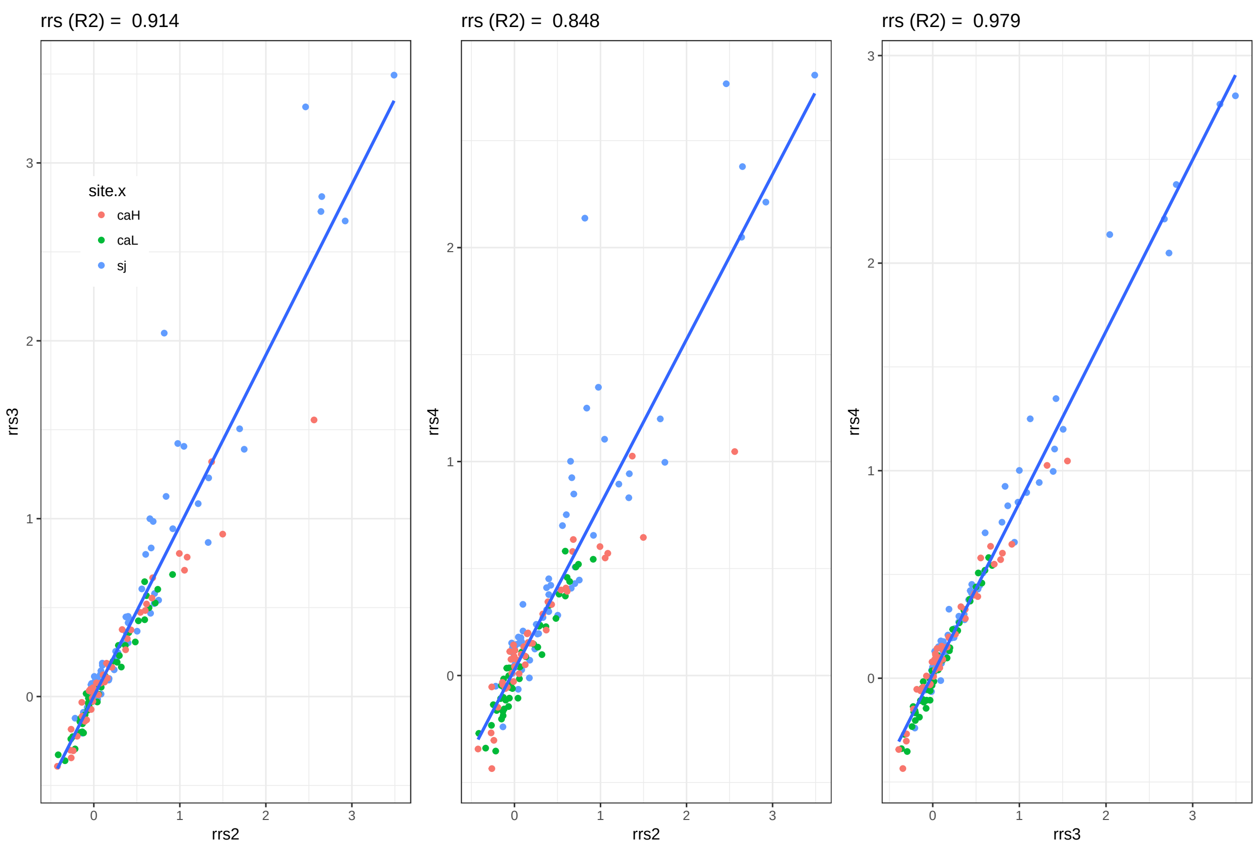

```
# Resilience
model <- lm(rs2~rs3, data=correlations)
p_rs23 <- correlations %>% ggplot(aes(rs2, rs3)) +
  geom_point(aes(colour=site.x)) + theme_bw() + geom_smooth(method = 'lm', se=FALSE) +
  ggtitle(paste('rs (R2) = ', round(summary(model)$r.squared, 3))) +
  theme(legend.position = c(.2, .75))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




```
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)
```

```
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

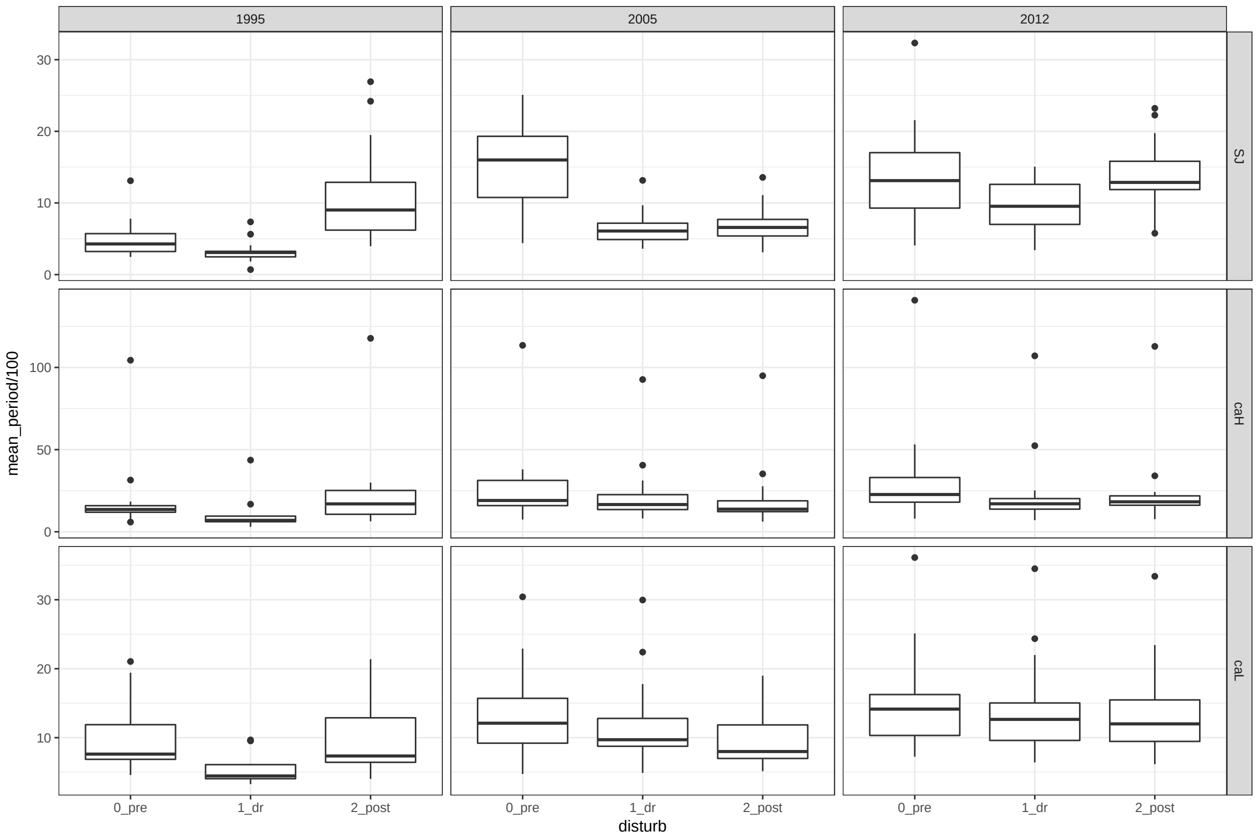
var	window_size	r2
rc	2-4	0.875357103621433
rc	3-4	0.977309191655523
rs	2-3	0.887274876125786
rs	2-4	0.764147394080222
rs	3-4	0.955085073886915
rrs	2-3	0.914381250472491
rrs	2-4	0.848277808345292
rrs	3-4	0.978980936308473

Nos quedamos con 3 años de ventana temporal.

Plots Crecimiento

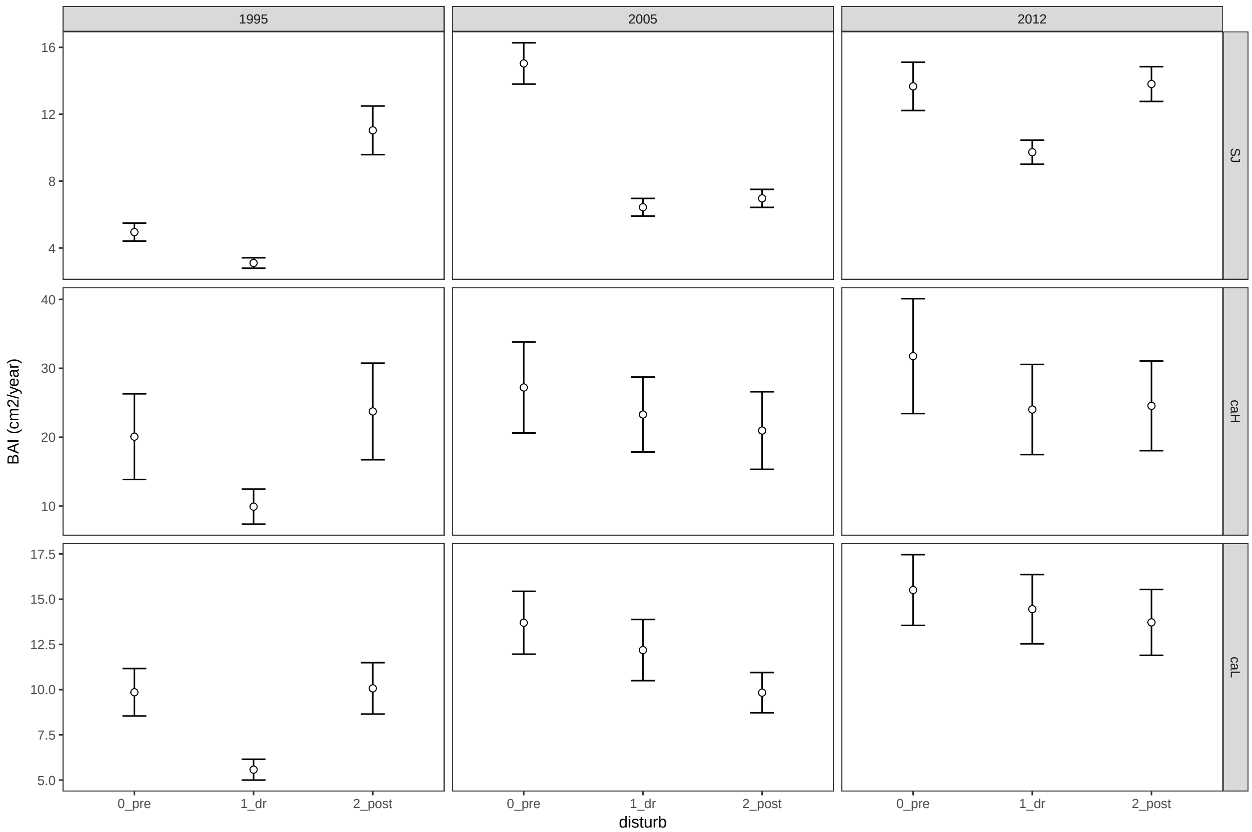
Boxplot with outliers

```
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 = dplyr::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()
```

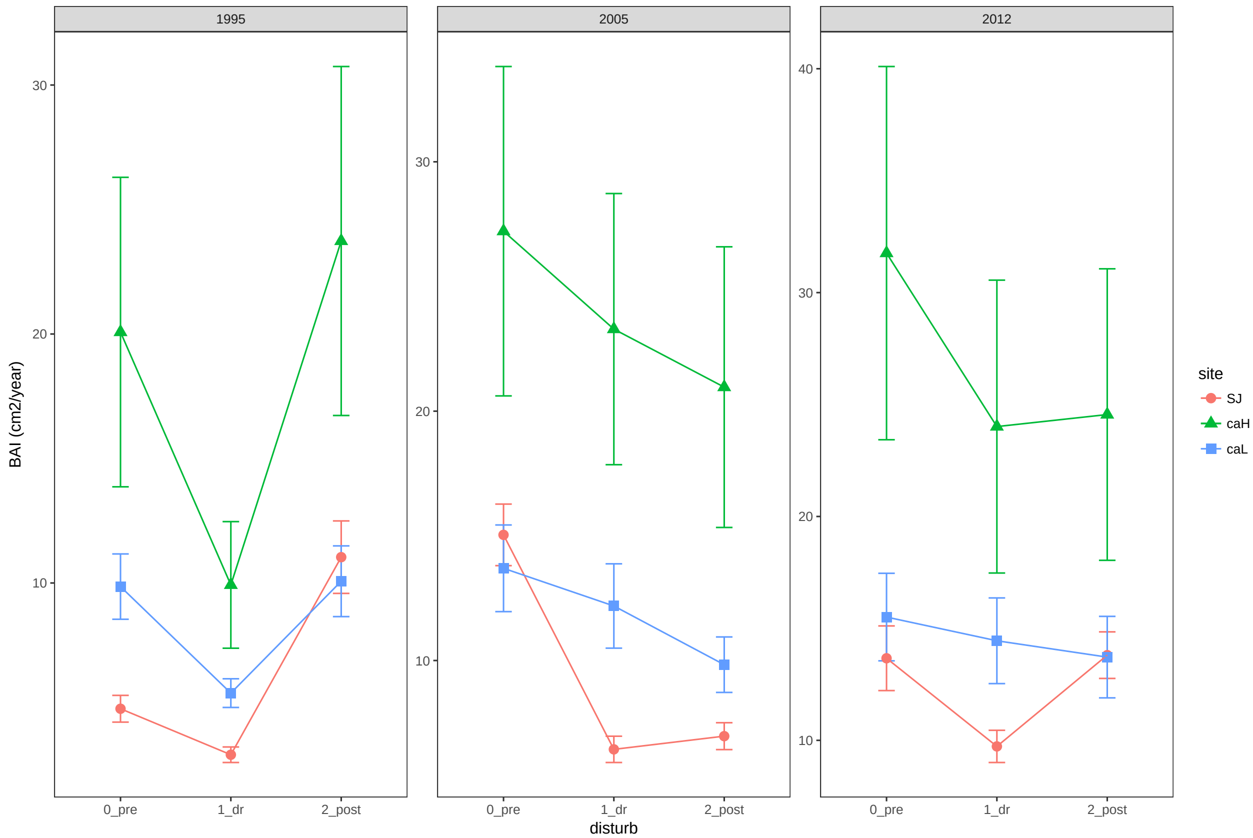


Mean + se

```
g %>%
  mutate(disturb = dplyr::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 = dplyr::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) +
  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
```




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

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

site	disturb_year	disturb	mean	sd	se
SJ	1995	0_pre	4.949	2.402	0.5371
SJ	1995	1_dr	3.102	1.395	0.3119
SJ	1995	2_post	11.04	6.508	1.455
SJ	2005	0_pre	15.04	5.522	1.235
SJ	2005	1_dr	6.437	2.358	0.5273
SJ	2005	2_post	6.967	2.41	0.5388
SJ	2012	0_pre	13.67	6.458	1.444
SJ	2012	1_dr	9.729	3.218	0.7196
SJ	2012	2_post	13.8	4.651	1.04
caH	1995	0_pre	20.08	24.07	6.215
caH	1995	1_dr	9.923	9.846	2.542
caH	1995	2_post	23.74	27.14	7.008
caH	2005	0_pre	27.22	25.58	6.605
caH	2005	1_dr	23.29	21.06	5.437
caH	2005	2_post	20.96	21.79	5.627
caH	2012	0_pre	31.76	32.29	8.336

site	disturb_year	disturb	mean	sd	se
caH	2012	1_dr	24.02	25.33	6.541
caH	2012	2_post	24.55	25.22	6.511
caL	1995	0_pre	9.855	5.081	1.312
caL	1995	1_dr	5.577	2.23	0.5757
caL	1995	2_post	10.07	5.501	1.42
caL	2005	0_pre	13.7	6.73	1.738
caL	2005	1_dr	12.19	6.549	1.691
caL	2005	2_post	9.832	4.308	1.112
caL	2012	0_pre	15.51	7.572	1.955
caL	2012	1_dr	14.45	7.411	1.914
caL	2012	2_post	13.72	7.05	1.82

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)
```

Asumptions

- Explorar si se cumplen los supuestos de normalidad y homocedasticidad. Tenemos que comprobar que cada uno de los grupos son normales (1995,2005,2012; site: SJ, CaH, CaL; e interactions)

```
shapirosNormal <- function(df, resp_var, factor_vars) {
  rv <- enquo(resp_var)
  out <- df %>%
    group_by_(.dots=factor_vars) %>%
    summarise(statistic = round(shapiro.test(!!rv)$statistic,5),
              p_value = round(shapiro.test(!!rv)$p.value,5)) %>%
    data.frame()

  return(out)
}

homogetest <- function(resp_var, factores, df){

  out_factores <- c()

  for (f in factores){
    hv <- c()
    myformula <- as.formula(paste0(resp_var, "~", f))
```

```r
    #tests
    fk <- fligner.test(myformula, data = df)
    lv <- leveneTest(myformula, data = df)
    # out
    hv$fk_stat <- fk$statistic
    hv$fk_pvalue <- fk$p.value
    hv$lev_stat <- lv$`F value`[1]
    hv$lev_pvalue <- lv$`Pr(>F)`[1]
    hv$factor <- f
    hv <- as.data.frame(hv)
    row.names(hv) <- NULL

    out_factores <- rbind(out_factores, hv)}
  return(out_factores)

}
```

Normalidad

```r
# See auxiliar::shapirosNormal
### Resilience

nrsA <- shapirosNormal(re, resp_var = rs, 'disturb_year')
nrsA$var <- 'rs'
nrsB <- shapirosNormal(re, resp_var = rs, 'site')
nrsB$var <- 'rs'
nrsAB <- shapirosNormal(re, resp_var = rs, c('disturb_year','site'))
nrsAB$var <- 'rs'

### Recovery
nrcA <- shapirosNormal(re, resp_var = rc, 'disturb_year')
nrcA$var <- 'rc'
nrcB <- shapirosNormal(re, resp_var = rc, 'site')
nrcB$var <- 'rc'
nrcAB <- shapirosNormal(re, resp_var = rc, c('disturb_year','site'))
nrcAB$var <- 'rc'

### Resistance
nrtA <- shapirosNormal(re, resp_var = rt, 'disturb_year')
nrtA$var <- 'rt'
nrtB <- shapirosNormal(re, resp_var = rt, 'site')
nrtB$var <- 'rt'
nrtAB <- shapirosNormal(re, resp_var = rt, c('disturb_year','site'))
nrtAB$var <- 'rt'


### Relative Resilience
nrrsA <- shapirosNormal(re, resp_var = rrs, 'disturb_year')
nrrsA$var <- 'rrs'
nrrsB <- shapirosNormal(re, resp_var = rrs, 'site')
nrrsB$var <- 'rrs'
nrrsAB <- shapirosNormal(re, resp_var = rrs, c('disturb_year','site'))
```

```r
nrrsAB$var <- 'rrs'
```

```r
normtestAB <- rbind(nrcAB, nrtAB, nrsAB, nrrsAB)
normtestAB %>% pander()
```

disturb_year	site	statistic	p_value	var
1995	SJ	0.7989	0.00083	rc
1995	caH	0.9388	0.3676	rc
1995	caL	0.8746	0.03943	rc
2005	SJ	0.9849	0.9806	rc
2005	caH	0.958	0.658	rc
2005	caL	0.928	0.2543	rc
2012	SJ	0.945	0.2979	rc
2012	caH	0.8691	0.03275	rc
2012	caL	0.9628	0.7418	rc
1995	SJ	0.9583	0.5109	rt
1995	caH	0.919	0.1861	rt
1995	caL	0.9581	0.6587	rt
2005	SJ	0.9286	0.1453	rt
2005	caH	0.9733	0.9033	rt
2005	caL	0.9632	0.7472	rt
2012	SJ	0.9597	0.5371	rt
2012	caH	0.9797	0.9676	rt
2012	caL	0.8614	0.02526	rt
1995	SJ	0.8921	0.02936	rs
1995	caH	0.8123	0.00531	rs
1995	caL	0.9826	0.9844	rs
2005	SJ	0.9191	0.09531	rs
2005	caH	0.9316	0.2887	rs
2005	caL	0.9163	0.1689	rs
2012	SJ	0.8959	0.0345	rs
2012	caH	0.9512	0.5435	rs
2012	caL	0.9275	0.2502	rs
1995	SJ	0.8511	0.00556	rrs
1995	caH	0.8753	0.04041	rrs
1995	caL	0.9468	0.4759	rrs
2005	SJ	0.9638	0.6222	rrs
2005	caH	0.9517	0.551	rrs
2005	caL	0.9489	0.5077	rrs
2012	SJ	0.9657	0.6639	rrs
2012	caH	0.7872	0.00253	rrs
2012	caL	0.9734	0.9052	rrs

```r
write.csv(normtestAB,
          file=paste0(di, '/out/anovas_resilience/normo_disturb_year_site.csv'), row.names = F)
```

```r
rm(nrcA, nrcB, nrcAB,
   nrsA, nrsB, nrsAB,
   nrrsA, nrrsB, nrrsAB,
   nrtA, nrtB, nrtAB)
```

- No se cumplen los requisitos de normalidad

Heterocedasticidad

```
## See auxiliar::homogetest
factores <- c('disturb_year', 'site', 'interaction(disturb_year, site)')
responses <- c('rs', 'rc', 'rt', 'rrs')
homo <- c()


for (i in responses){
  ht <- homogetest(resp_var = i, factores = factores, df = re)
  ht <- ht %>% mutate(response = i)
  homo <- rbind(homo, ht)
}

homo %>% pander()
```

fk_stat	fk_pvalue	lev_stat	lev_pvalue	factor	response
35.03	2.472e-08	16.5	3.436e-07	disturb_year	rs
44.13	2.613e-10	19.31	3.573e-08	site	rs
41.88	1.425e-06	9.072	5.231e-10	interaction(disturb_year, site)	rs
35.96	1.557e-08	14.78	1.414e-06	disturb_year	rc
12.41	0.002015	5.564	0.004685	site	rc
62.94	1.232e-10	8.321	3.315e-09	interaction(disturb_year, site)	rc
25.59	2.778e-06	15.59	7.267e-07	disturb_year	rt
0.6251	0.7316	0.3586	0.6993	site	rt
14.53	0.06902	1.782	0.08539	interaction(disturb_year, site)	rt
40.59	1.537e-09	17.16	2.003e-07	disturb_year	rrs
13.99	0.0009147	7.446	0.0008313	site	rrs
54.08	6.67e-09	9.558	1.618e-10	interaction(disturb_year, site)	rrs

```
write.csv(homo,
          file=paste0(di, '/out/anovas_resilience/homocedasticidad.csv'), row.names = F)
```

- Tampoco se cumplen los requisitos de homogeneidad de varianzas entre grupos
- Probamos a transformar los datos con log y reanalizar los supuestos de homocedasticidad

```
factores <- c('disturb_year', 'site', 'interaction(disturb_year, site)')
responses <- c('logrs', 'logrc', 'logrt', 'logrrs')
homo_log <- c()

re <- re %>%
  mutate(
    logrs = log(rs),
    logrc = log(rc),
    logrt = log(rc),
    logrrs = log(rrs)
)
```

```r
for (i in responses){
  ht <- homogetest(resp_var = i, factores = factores, df = re)
  ht <- ht %>% mutate(response = i)
  homo_log <- rbind(homo_log, ht)
}

homo_log %>% pander()
```

fk_stat	fk_pvalue	lev_stat	lev_pvalue	factor	response
18.09	0.000118	9.431	0.0001401	disturb_year	logrs
41.3	1.077e-09	30.45	8.633e-12	site	logrs
22.44	0.004155	3.336	0.001586	interaction(disturb_year, site)	logrs
8.671	0.01309	6.408	0.002147	disturb_year	logrc
5.079	0.0789	2.769	0.06602	site	logrc
25.48	0.001286	4.143	0.0001806	interaction(disturb_year, site)	logrc
8.671	0.01309	6.408	0.002147	disturb_year	logrt
5.079	0.0789	2.769	0.06602	site	logrt
25.48	0.001286	4.143	0.0001806	interaction(disturb_year, site)	logrt
2.434	0.2961	1.511	0.2256	disturb_year	logrrs
2.644	0.2666	0.9344	0.3961	site	logrrs
5.803	0.6692	0.694	0.696	interaction(disturb_year, site)	logrrs

```r
write.csv(homo_log,
          file=paste0(di, '/out/anovas_resilience/homocedasticidad_log.csv'), row.names = F)
```

- Tampoco se cumplen

Custom functions

```r
# 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 = '*')))

  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)
```

```r
  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 = "bon")

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

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

  # interaction
  ph_i <- lsmeans(mymodel, pairwise ~ disturb_year:site, adjust = "bon")
  cld_i <- cld(ph_i, alpha   = 0.01,
                 Letters = letters,
                 adjust  = "bon")

  # 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)
  return(list(aux_ph_site, aux_ph_event, aux_ph_i, cld_site, cld_event, cld_i))
}
```

OJO SOLO 2005 y 2012

```
# Only 2005 and 2012
re <- re %>% filter(disturb_year != 1995) %>% as.data.frame()
vars <- c('disturb_year','site')
re$disturb_year <- factor(re$disturb_year)
```

Recovery

```
# Variable
resp_var <- 'rc'

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

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 6: ANOVA table: rc

term	df	sumsq	meansq	statistic	p.value
disturb_year	1	1.316	1.316	32.78	**0**
site	2	2.847	1.424	35.45	**0**
disturb_year:site	2	0.1961	0.09805	2.442	**0.09253**
Residuals	94	3.775	0.04016		

```
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}","AIC
rownames(gm) <- "Statistic"
pander(t(gm))
```

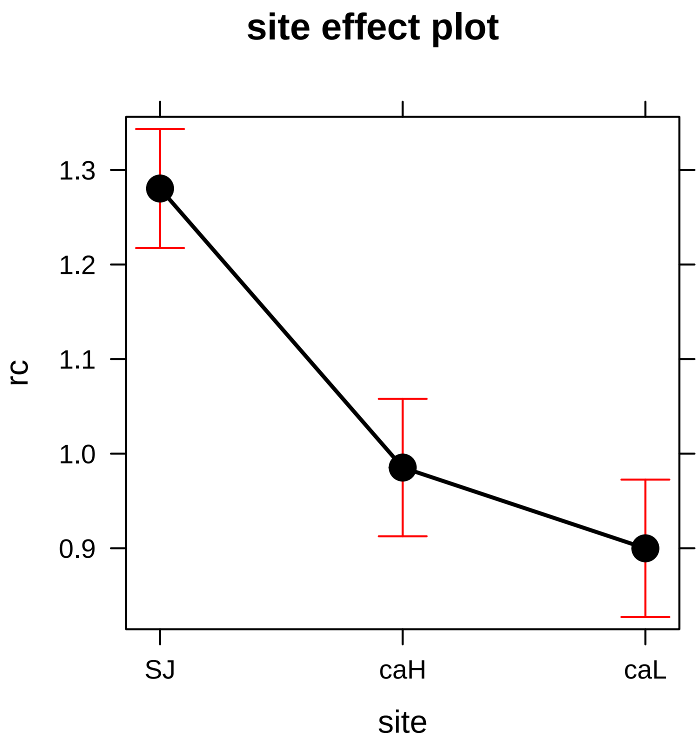
	Statistic
R^2	0.54
$\mathrm{adj}R^2$	0.51
σ_e	0.20
F	21.71
p	0.00
df_m	6.00
logLik	21.95
AIC	-29.89
BIC	-11.66
dev	3.77
df_e	94.00

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

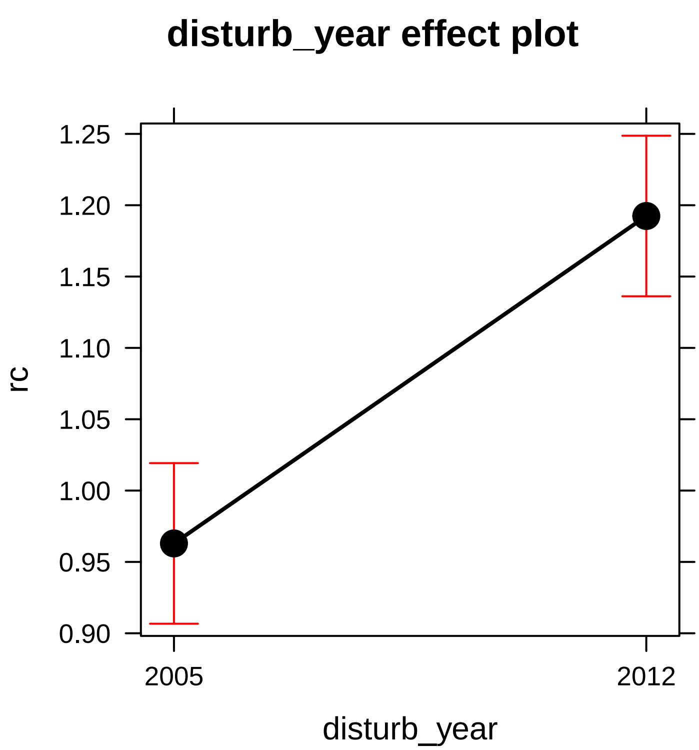
```
##
## ### Event ###
## $lsmeans
##  disturb_year    lsmean         SE df  lower.CL upper.CL
##  2005         0.9460722 0.02860151 94 0.8892832 1.002861
##  2012         1.1643064 0.02860151 94 1.1075175 1.221095
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate         SE df t.ratio p.value
##  2005 - 2012 -0.2182343 0.04044865 94  -5.395  <.0001
##
## Results are averaged over the levels of: site
##
##  disturb_year    lsmean         SE df  lower.CL upper.CL .group
##  2005         0.9460722 0.02860151 94 0.8809216 1.011223  a
##  2012         1.1643064 0.02860151 94 1.0991558 1.229457   b
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 2 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
## $lsmeans
##  site    lsmean         SE df  lower.CL  upper.CL
##  SJ   1.2803536 0.03168543 94 1.2174414 1.3432657
##  caH  0.9853013 0.03658718 94 0.9126566 1.0579460
##  caL  0.8999131 0.03658718 94 0.8272684 0.9725578
##
## 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  0.29505228 0.04840029 94   6.096  <.0001
##  SJ - caL  0.38044051 0.04840029 94   7.860  <.0001
##  caH - caL 0.08538823 0.05174209 94   1.650  0.3067
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: bonferroni method for 3 tests
##
##  site    lsmean         SE df  lower.CL  upper.CL .group
##  caL  0.8999131 0.03658718 94 0.8107290 0.9890971  a
##  caH  0.9853013 0.03658718 94 0.8961172 1.0744854  a
##  SJ   1.2803536 0.03168543 94 1.2031179 1.3575893   b
##
## Results are averaged over the levels of: disturb_year
```

```
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 3 estimates
## P value adjustment: bonferroni method for 3 tests
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site    lsmean         SE df  lower.CL  upper.CL
##  2005         SJ   1.1150292 0.04480996 94 1.0260579 1.2040004
##  2012         SJ   1.4456780 0.04480996 94 1.3567068 1.5346492
##  2005         caH  0.8836738 0.05174209 94 0.7809387 0.9864089
##  2012         caH  1.0869288 0.05174209 94 0.9841937 1.1896639
##  2005         caL  0.8395136 0.05174209 94 0.7367785 0.9422487
##  2012         caL  0.9603126 0.05174209 94 0.8575774 1.0630477
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate         SE df t.ratio p.value
##  2005,SJ - 2012,SJ   -0.33064881 0.06337085 94  -5.218  <.0001
##  2005,SJ - 2005,caH   0.23135538 0.06844835 94   3.380  0.0159
##  2005,SJ - 2012,caH   0.02810037 0.06844835 94   0.411  1.0000
##  2005,SJ - 2005,caL   0.27551559 0.06844835 94   4.025  0.0017
##  2005,SJ - 2012,caL   0.15471662 0.06844835 94   2.260  0.3916
##  2012,SJ - 2005,caH   0.56200419 0.06844835 94   8.211  <.0001
##  2012,SJ - 2012,caH   0.35874918 0.06844835 94   5.241  <.0001
##  2012,SJ - 2005,caL   0.60616440 0.06844835 94   8.856  <.0001
##  2012,SJ - 2012,caL   0.48536543 0.06844835 94   7.091  <.0001
##  2005,caH - 2012,caH -0.20325501 0.07317436 94  -2.778  0.0991
##  2005,caH - 2005,caL  0.04416021 0.07317436 94   0.603  1.0000
##  2005,caH - 2012,caL -0.07663876 0.07317436 94  -1.047  1.0000
##  2012,caH - 2005,caL  0.24741522 0.07317436 94   3.381  0.0158
##  2012,caH - 2012,caL  0.12661625 0.07317436 94   1.730  1.0000
##  2005,caL - 2012,caL -0.12079897 0.07317436 94  -1.651  1.0000
##
## P value adjustment: bonferroni method for 15 tests
```

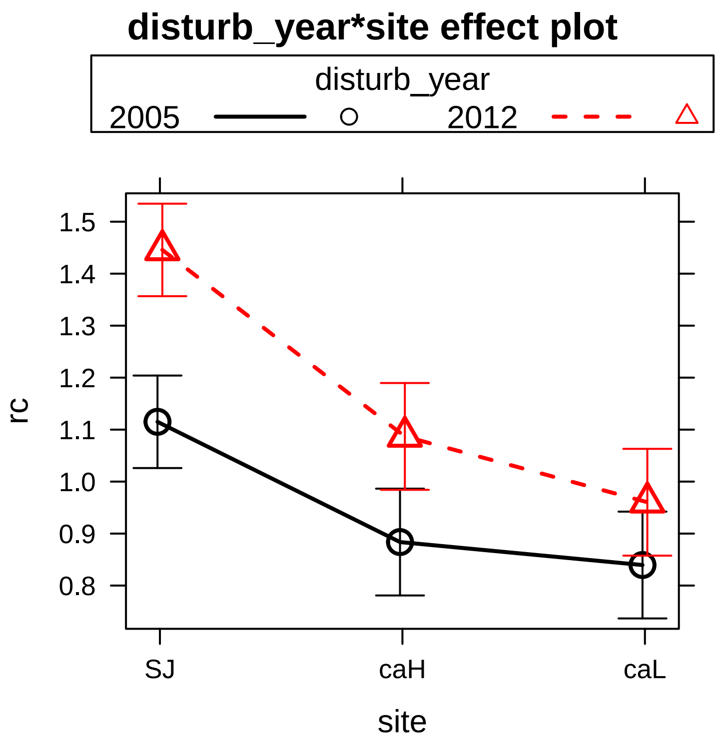
```
ps
```



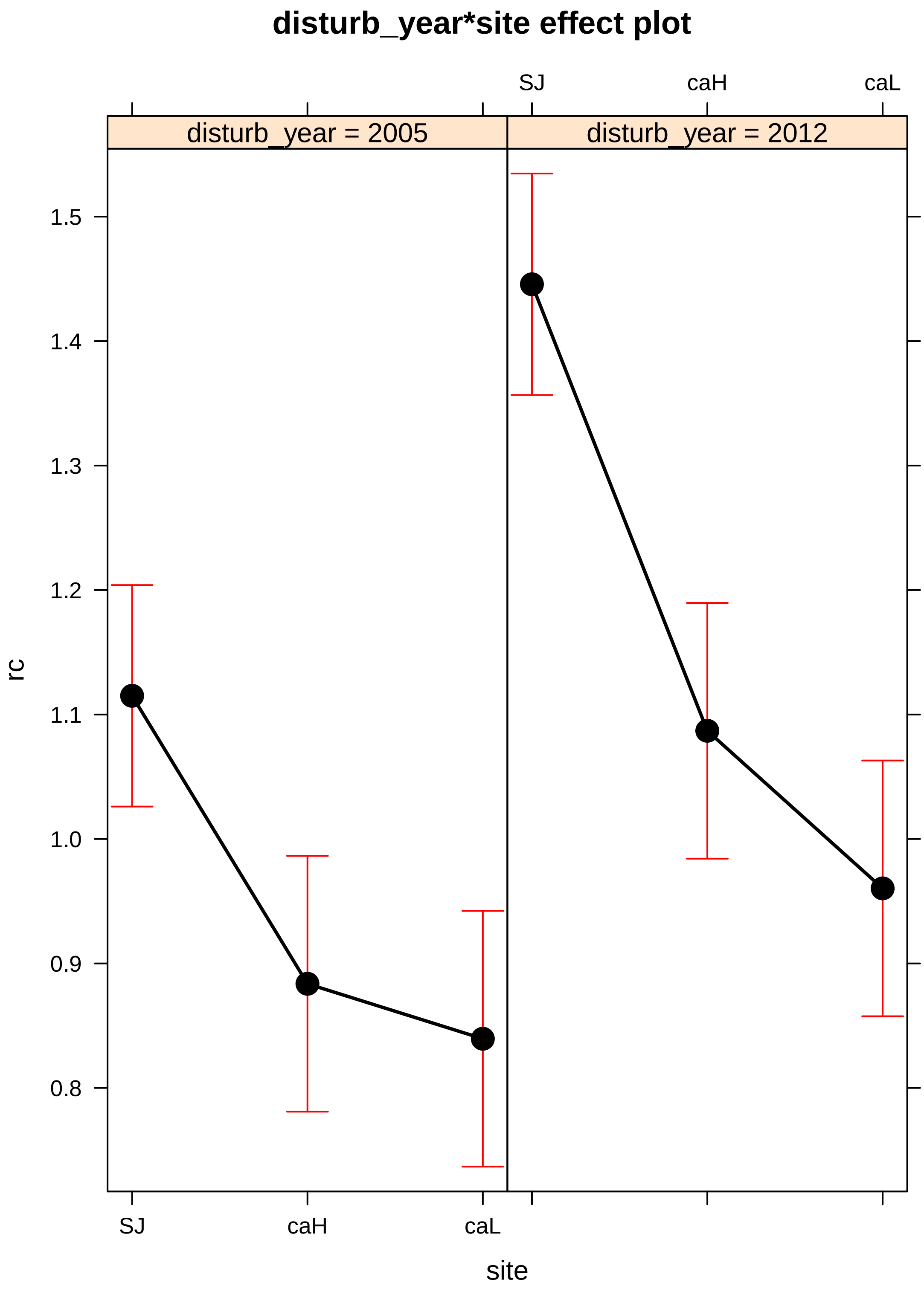

```
pd
```




```
picollapse
```


disturb_year*site effect plot
disturb_year
2005
2012
rc
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
SJ
caH
caL
site

```
pi
```


disturb_year*site effect plot
disturb_year = 2005
disturb_year = 2012
SJ
caH
caL
rc
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
site

Resistance

Table 8: ANOVA table: rt

term	df	sumsq	meansq	statistic	p.value
disturb_year	1	0.2122	0.2122	9.867	**0.00225**
site	2	1.666	0.833	38.74	**0**
disturb_year:site	2	0.8604	0.4302	20.01	**0**
Residuals	94	2.021	0.0215		

	Statistic
R^2	0.58
adjR^2	0.55
σ_e	0.15
F	25.47
p	0.00
df_m	6.00
logLik	53.18
AIC	-92.35
BIC	-74.11
dev	2.02
df_e	94.00

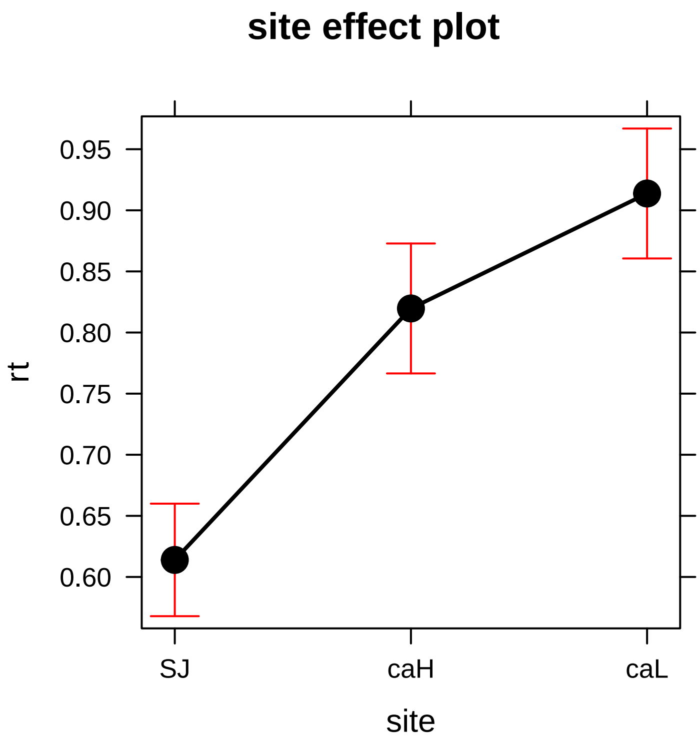
```
# Post hoc Define model
mymodel <- aov_rt$mymodel
postH_rt <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year    lsmean         SE df  lower.CL  upper.CL
##  2005         0.7483129 0.02092964 94 0.7067567 0.7898692
##  2012         0.8166033 0.02092964 94 0.7750470 0.8581596
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast       estimate         SE df t.ratio p.value
##  2005 - 2012 -0.06829036 0.02959898 94  -2.307  0.0232
##
## Results are averaged over the levels of: site
##
##  disturb_year    lsmean         SE df  lower.CL  upper.CL .group
##  2005         0.7483129 0.02092964 94 0.7006379 0.7959880  a
##  2012         0.8166033 0.02092964 94 0.7689282 0.8642784  a
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 2 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
```

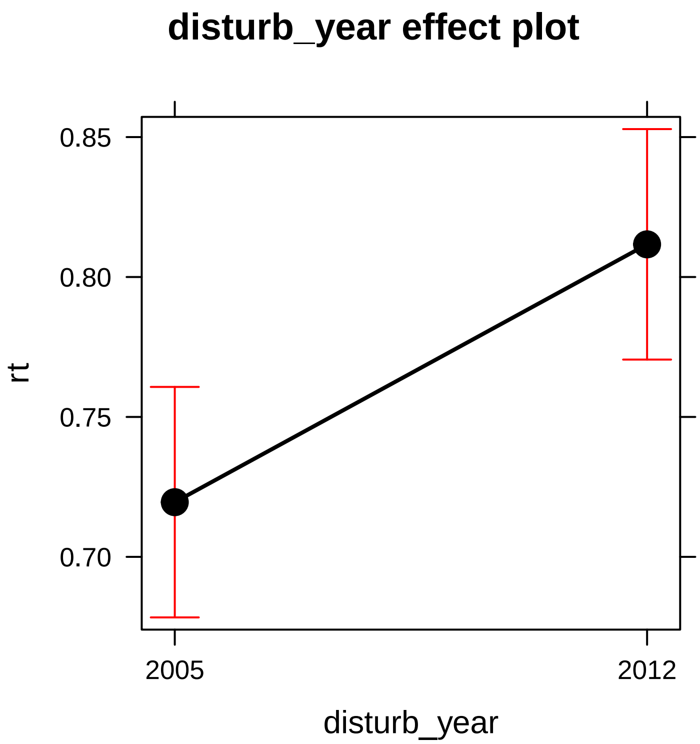
```
## $lsmeans
##  site    lsmean         SE df  lower.CL  upper.CL
##  SJ   0.6139485 0.02318635 94 0.5679114 0.6599855
##  caH  0.8196809 0.02677329 94 0.7665219 0.8728399
##  caL  0.9137450 0.02677329 94 0.8605860 0.9669040
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast     estimate         SE df t.ratio p.value
##  SJ - caH  -0.20573248 0.03541773 94  -5.809  <.0001
##  SJ - caL  -0.29979653 0.03541773 94  -8.465  <.0001
##  caH - caL -0.09406405 0.03786314 94  -2.484  0.0442
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: bonferroni method for 3 tests
##
##  site    lsmean         SE df  lower.CL  upper.CL .group
##  SJ   0.6139485 0.02318635 94 0.5574299 0.6704670  a
##  caH  0.8196809 0.02677329 94 0.7544190 0.8849429   b
##  caL  0.9137450 0.02677329 94 0.8484830 0.9790069   b
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 3 estimates
## P value adjustment: bonferroni method for 3 tests
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site    lsmean         SE df  lower.CL  upper.CL
##  2005         SJ   0.4606116 0.03279045 94 0.3955054 0.5257178
##  2012         SJ   0.7672853 0.03279045 94 0.7021791 0.8323915
##  2005         caH  0.8845609 0.03786314 94 0.8093827 0.9597391
##  2012         caH  0.7548010 0.03786314 94 0.6796228 0.8299791
##  2005         caL  0.8997663 0.03786314 94 0.8245881 0.9749444
##  2012         caL  0.9277237 0.03786314 94 0.8525455 1.0029018
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate         SE df t.ratio p.value
##  2005,SJ - 2012,SJ   -0.30667361 0.04637269 94  -6.613  <.0001
##  2005,SJ - 2005,caH  -0.42394925 0.05008823 94  -8.464  <.0001
##  2005,SJ - 2012,caH  -0.29418931 0.05008823 94  -5.873  <.0001
##  2005,SJ - 2005,caL  -0.43915464 0.05008823 94  -8.768  <.0001
##  2005,SJ - 2012,caL  -0.46711203 0.05008823 94  -9.326  <.0001
##  2012,SJ - 2005,caH  -0.11727564 0.05008823 94  -2.341  0.3199
##  2012,SJ - 2012,caH   0.01248430 0.05008823 94   0.249  1.0000
##  2012,SJ - 2005,caL  -0.13248102 0.05008823 94  -2.645  0.1436
##  2012,SJ - 2012,caL  -0.16043842 0.05008823 94  -3.203  0.0278
##  2005,caH - 2012,caH  0.12975994 0.05354657 94   2.423  0.2594
##  2005,caH - 2005,caL -0.01520539 0.05354657 94  -0.284  1.0000
```

```
##  2005,caH - 2012,caL -0.04316278 0.05354657 94  -0.806  1.0000
##  2012,caH - 2005,caL -0.14496533 0.05354657 94  -2.707  0.1209
##  2012,caH - 2012,caL -0.17292272 0.05354657 94  -3.229  0.0256
##  2005,caL - 2012,caL -0.02795739 0.05354657 94  -0.522  1.0000
##
## P value adjustment: bonferroni method for 15 tests
```

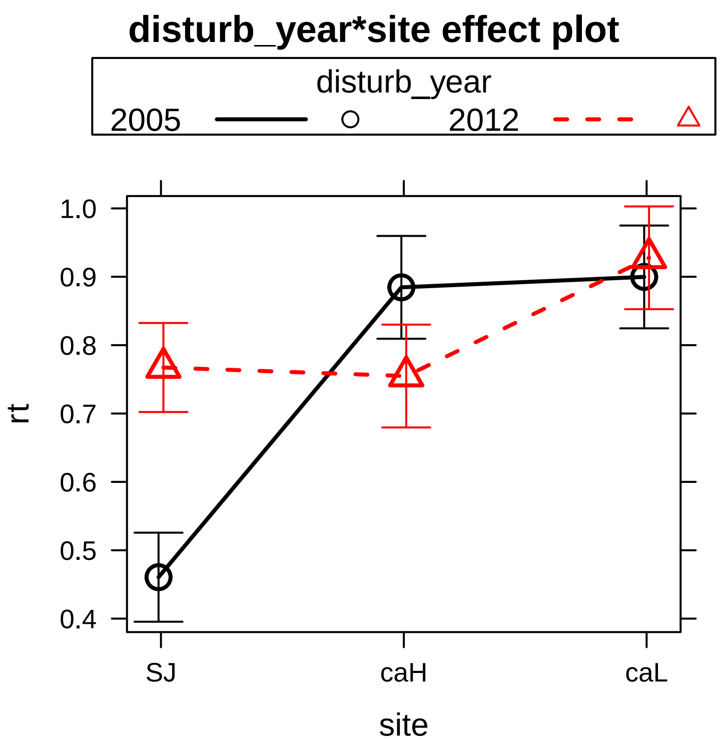
```
ps
```



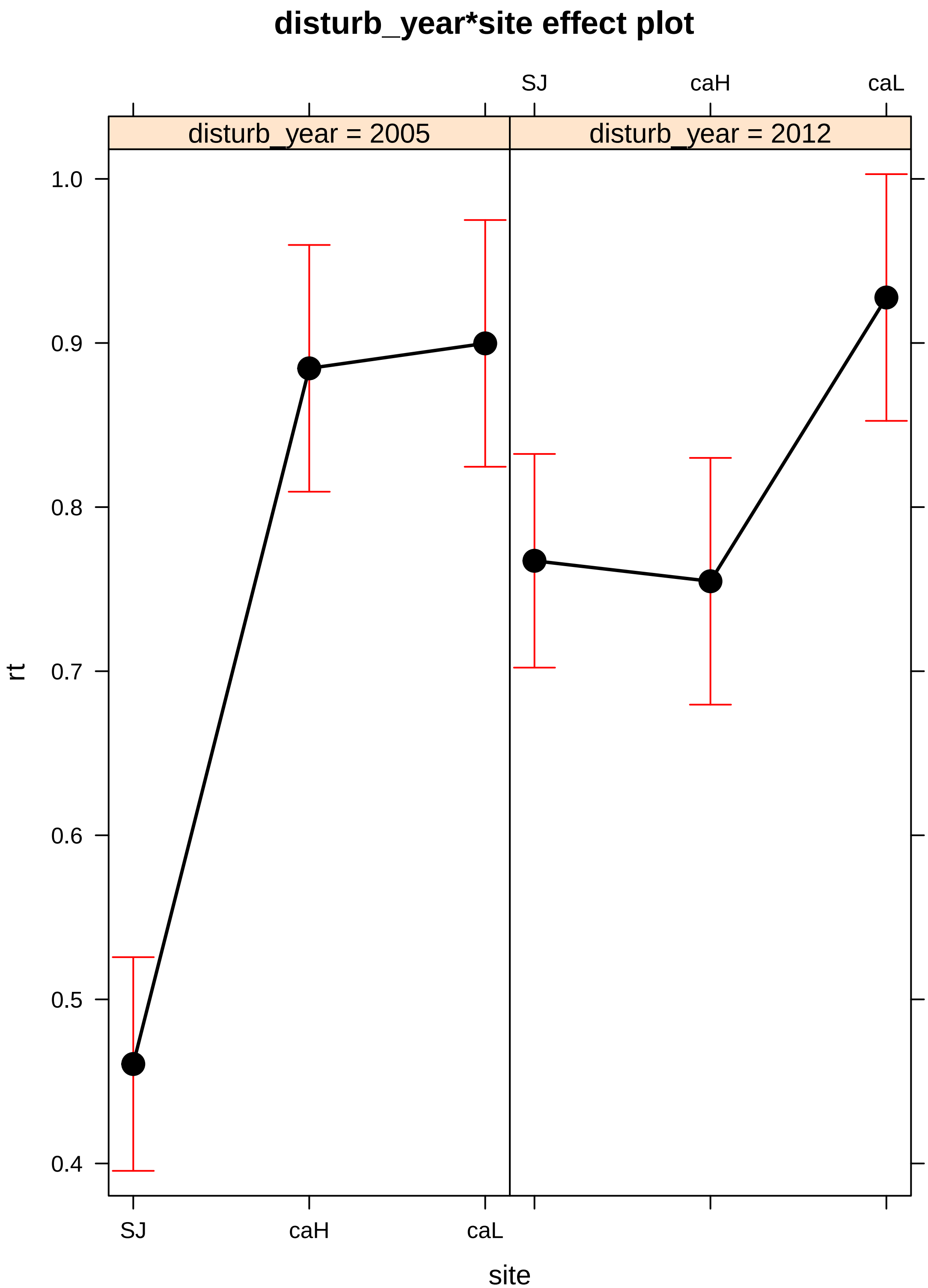

```
pd
```




```
picollapse
```




```
pi
```



Relative Resilience

Table 10: ANOVA table: rrs

term	df	sumsq	meansq	statistic	p.value
disturb_year	1	0.93	0.93	47.8	**0**
site	2	1.39	0.6952	35.73	**0**
disturb_year:site	2	0.145	0.07252	3.727	**0.02769**
Residuals	94	1.829	0.01946		

	Statistic
R^2	0.57
adjR^2	0.55
σ_e	0.14
F	25.34
p	0.00
df_m	6.00
logLik	58.18
AIC	-102.35
BIC	-84.12
dev	1.83
df_e	94.00

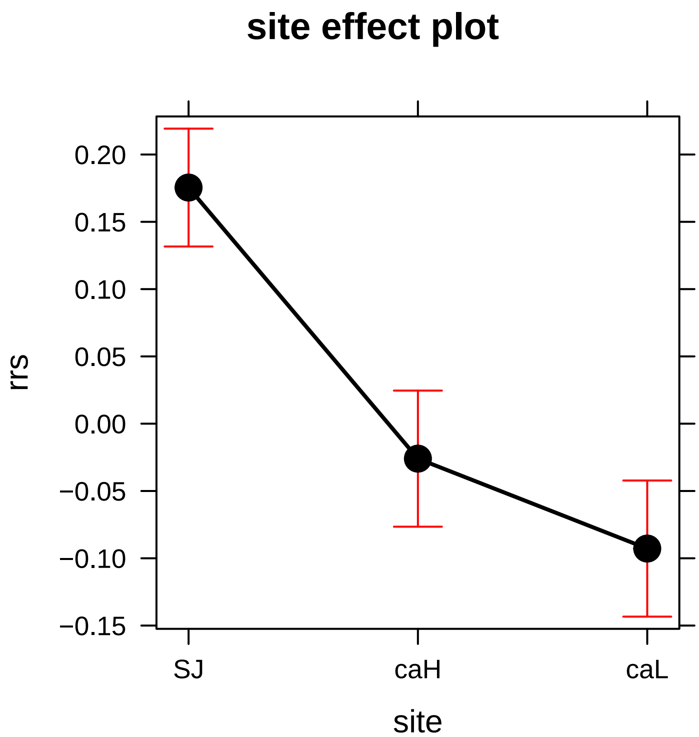
```
# Post hoc Define model
mymodel <- aov_rrs$mymodel
postH_rrs <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year      lsmean         SE df    lower.CL    upper.CL
##  2005         -0.07268135 0.01990865 94 -0.11221043 -0.03315226
##  2012          0.11047515 0.01990865 94  0.07094607  0.15000424
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate         SE df t.ratio p.value
##  2005 - 2012 -0.1831565 0.02815508 94  -6.505  <.0001
##
## Results are averaged over the levels of: site
##
##  disturb_year      lsmean         SE df    lower.CL    upper.CL .group
##  2005         -0.07268135 0.01990865 94 -0.11803071 -0.02733199  a
##  2012          0.11047515 0.01990865 94  0.06512579  0.15582451   b
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 2 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
```

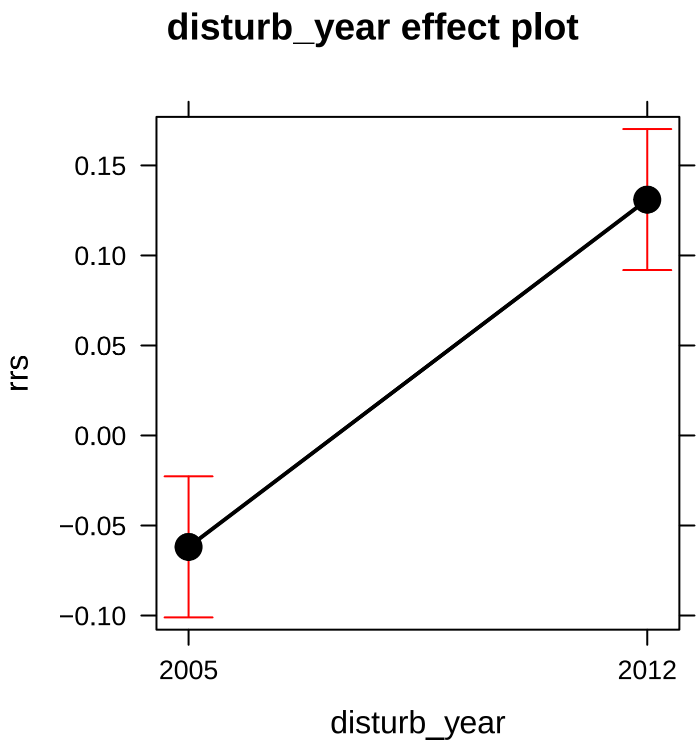
```
## $lsmeans
##  site      lsmean         SE df    lower.CL    upper.CL
##  SJ    0.17544720 0.02205526 94  0.13165595  0.21923844
##  caH  -0.02596381 0.02546723 94 -0.07652958  0.02460197
##  caL  -0.09279268 0.02546723 94 -0.14335846 -0.04222691
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast    estimate         SE df t.ratio p.value
##  SJ - caH  0.20141101 0.03368997 94   5.978  <.0001
##  SJ - caL  0.26823988 0.03368997 94   7.962  <.0001
##  caH - caL 0.06682887 0.03601610 94   1.856  0.2000
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: bonferroni method for 3 tests
##
##  site      lsmean         SE df    lower.CL    upper.CL .group
##  caL  -0.09279268 0.02546723 94 -0.15487101 -0.03071435  a
##  caH  -0.02596381 0.02546723 94 -0.08804214  0.03611452  a
##  SJ    0.17544720 0.02205526 94  0.12168579  0.22920861   b
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 3 estimates
## P value adjustment: bonferroni method for 3 tests
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site      lsmean         SE df    lower.CL    upper.CL
##  2005         SJ    0.03528048 0.03119085 94 -0.02664969  0.09721065
##  2012         SJ    0.31561391 0.03119085 94  0.25368374  0.37754408
##  2005         caH  -0.11035142 0.03601610 94 -0.18186223 -0.03884062
##  2012         caH   0.05842381 0.03601610 94 -0.01308700  0.12993461
##  2005         caL  -0.14297310 0.03601610 94 -0.21448390 -0.07146230
##  2012         caL  -0.04261226 0.03601610 94 -0.11412307  0.02889854
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate         SE df t.ratio p.value
##  2005,SJ - 2012,SJ   -0.28033343 0.04411053 94  -6.355  <.0001
##  2005,SJ - 2005,caH   0.14563191 0.04764482 94   3.057  0.0437
##  2005,SJ - 2012,caH  -0.02314333 0.04764482 94  -0.486  1.0000
##  2005,SJ - 2005,caL   0.17825358 0.04764482 94   3.741  0.0047
##  2005,SJ - 2012,caL   0.07789274 0.04764482 94   1.635  1.0000
##  2012,SJ - 2005,caH   0.42596534 0.04764482 94   8.940  <.0001
##  2012,SJ - 2012,caH   0.25719010 0.04764482 94   5.398  <.0001
##  2012,SJ - 2005,caL   0.45858701 0.04764482 94   9.625  <.0001
##  2012,SJ - 2012,caL   0.35822618 0.04764482 94   7.519  <.0001
##  2005,caH - 2012,caH -0.16877523 0.05093445 94  -3.314  0.0196
##  2005,caH - 2005,caL  0.03262167 0.05093445 94   0.640  1.0000
```

```
##  2005,caH - 2012,caL -0.06773916 0.05093445 94  -1.330  1.0000
##  2012,caH - 2005,caL  0.20139691 0.05093445 94   3.954  0.0022
##  2012,caH - 2012,caL  0.10103607 0.05093445 94   1.984  0.7532
##  2005,caL - 2012,caL -0.10036083 0.05093445 94  -1.970  0.7760
##
## P value adjustment: bonferroni method for 15 tests
```

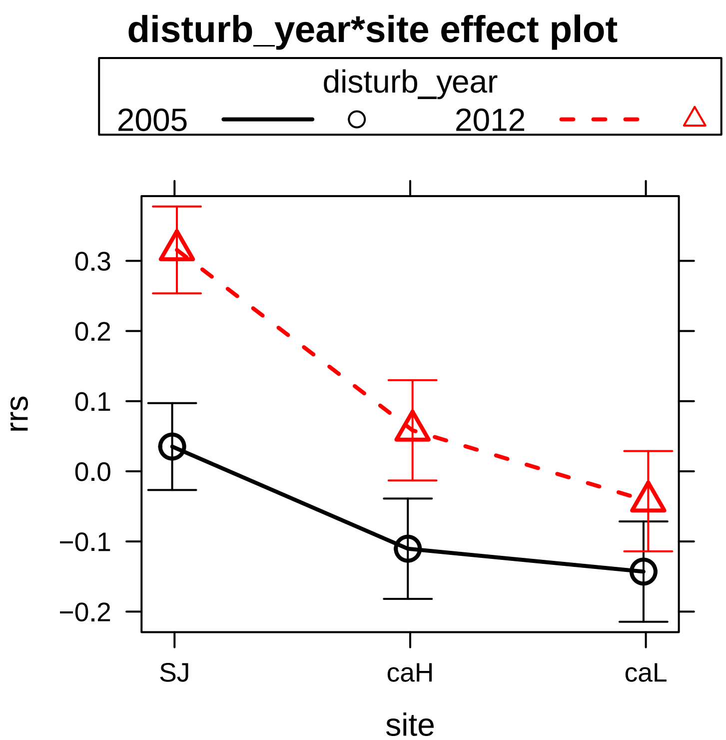
```r
ps
```



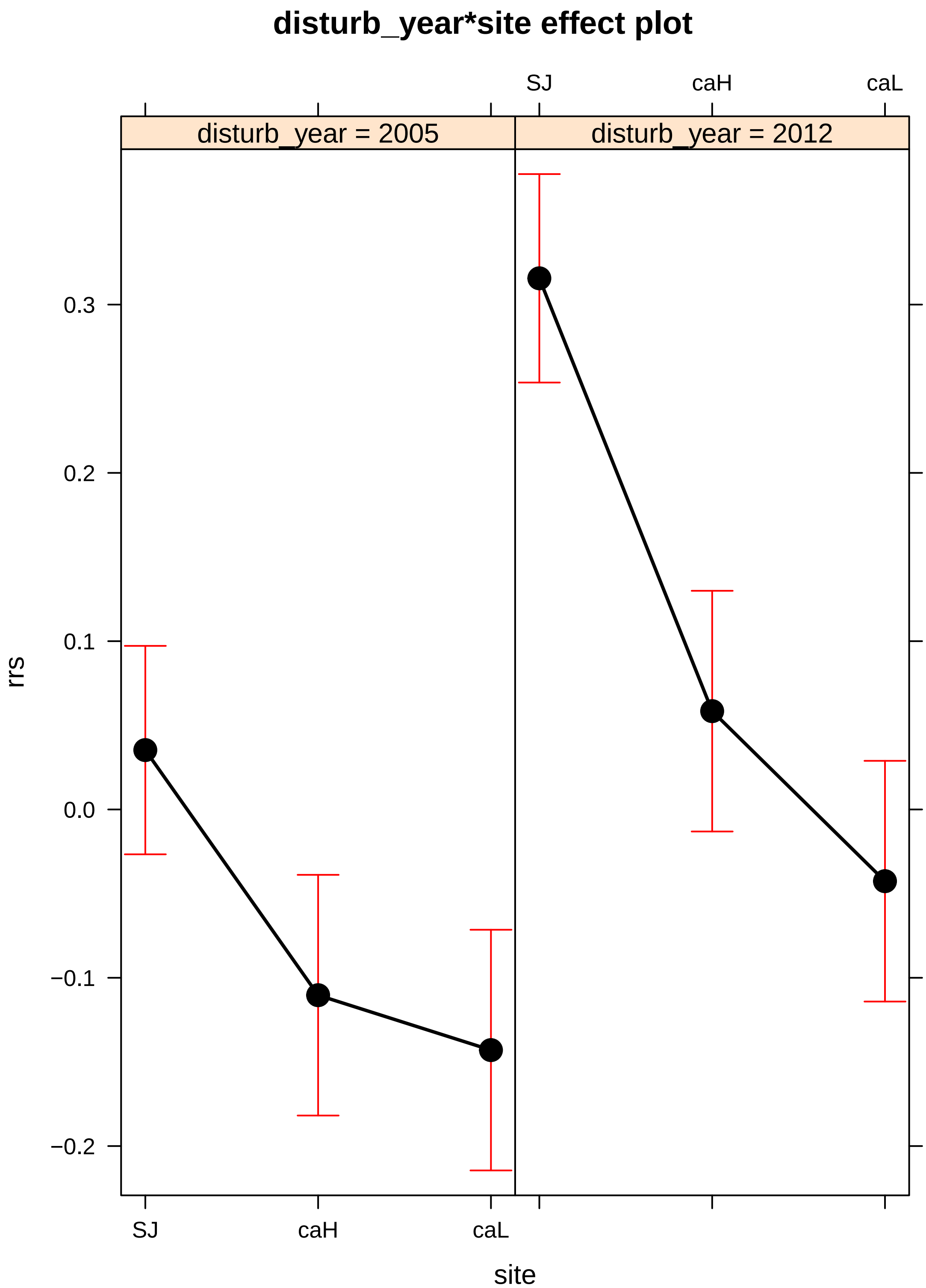

```r
pd
```




```
picollapse
```




```
pi
```


disturb_year*site effect plot
disturb_year = 2005
disturb_year = 2012
SJ
caH
caL
0.3
0.2
0.1
0.0
−0.1
−0.2
rrs
site

Resilience

Table 12: ANOVA table: rs

term	df	sumsq	meansq	statistic	p.value
disturb_year	1	2.031	2.031	66.58	**0**
site	2	0.01885	0.00942	0.309	0.7349
disturb_year:site	2	1.55	0.775	25.41	**0**
Residuals	94	2.867	0.0305		

	Statistic
R^2	0.56
adjR^2	0.53
σ_e	0.17
F	23.60
p	0.00
df_m	6.00
logLik	35.70
AIC	-57.41
BIC	-39.17
dev	2.87
df_e	94.00

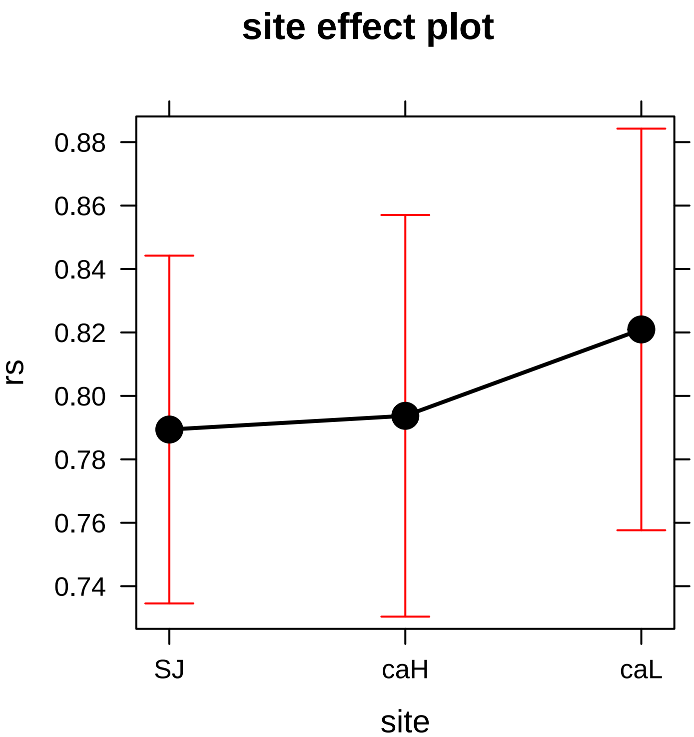
```
# Post hoc Define model
mymodel <- aov_rs$mymodel
postH_rs <- phc(mymodel = mymodel, resp_var = resp_var)
```

```
##
## ### Event ###
## $lsmeans
##  disturb_year    lsmean         SE df  lower.CL  upper.CL
##  2005         0.6756316 0.02492546 94 0.6261415 0.7251217
##  2012         0.9270785 0.02492546 94 0.8775884 0.9765685
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate         SE df t.ratio p.value
##  2005 - 2012 -0.2514469 0.03524992 94  -7.133  <.0001
##
## Results are averaged over the levels of: site
##
##  disturb_year    lsmean         SE df  lower.CL  upper.CL .group
##  2005         0.6756316 0.02492546 94 0.6188546 0.7324086  a
##  2012         0.9270785 0.02492546 94 0.8703014 0.9838555   b
##
## Results are averaged over the levels of: site
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 2 estimates
## significance level used: alpha = 0.01
##
## ### Clu pop ###
```

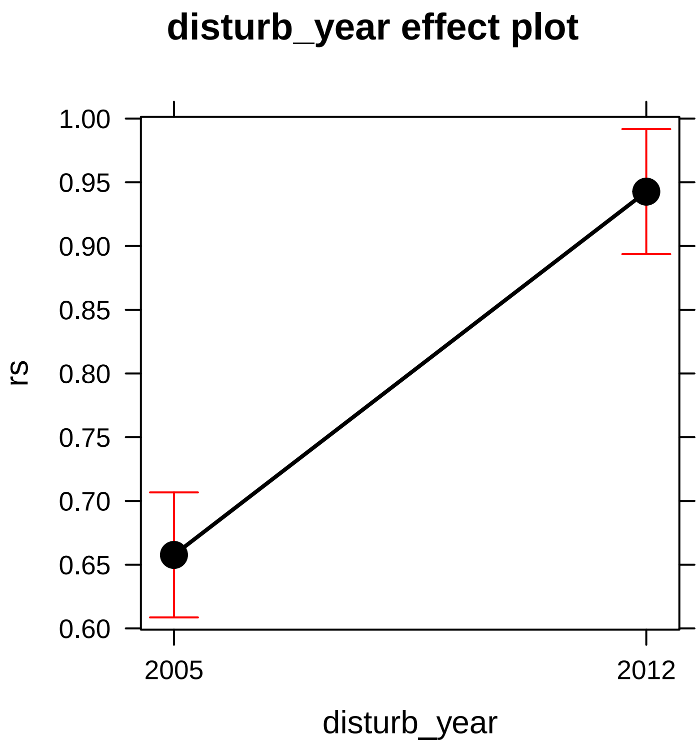
```
## $lsmeans
##  site    lsmean         SE df  lower.CL  upper.CL
##  SJ   0.7893957 0.02761300 94 0.7345694 0.8442219
##  caH  0.7937171 0.03188475 94 0.7304092 0.8570250
##  caL  0.8209523 0.03188475 94 0.7576444 0.8842602
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
##
## $contrasts
##  contrast      estimate         SE df t.ratio p.value
##  SJ - caH  -0.004321471 0.04217956 94  -0.102  1.0000
##  SJ - caL  -0.031556651 0.04217956 94  -0.748  1.0000
##  caH - caL -0.027235180 0.04509185 94  -0.604  1.0000
##
## Results are averaged over the levels of: disturb_year
## P value adjustment: bonferroni method for 3 tests
##
##  site    lsmean         SE df  lower.CL  upper.CL .group
##  SJ   0.7893957 0.02761300 94 0.7220868 0.8567045  a
##  caH  0.7937171 0.03188475 94 0.7159956 0.8714387  a
##  caL  0.8209523 0.03188475 94 0.7432308 0.8986738  a
##
## Results are averaged over the levels of: disturb_year
## Confidence level used: 0.95
## Conf-level adjustment: bonferroni method for 3 estimates
## P value adjustment: bonferroni method for 3 tests
## significance level used: alpha = 0.01
##
## ### Event:Clu pop ###
## $lsmeans
##  disturb_year site    lsmean         SE df  lower.CL  upper.CL
##  2005         SJ   0.4958921 0.03905068 94 0.4183561 0.5734282
##  2012         SJ   1.0828992 0.03905068 94 1.0053631 1.1604352
##  2005         caH  0.7742095 0.04509185 94 0.6846786 0.8637404
##  2012         caH  0.8132248 0.04509185 94 0.7236938 0.9027557
##  2005         caL  0.7567932 0.04509185 94 0.6672623 0.8463241
##  2012         caL  0.8851114 0.04509185 94 0.7955805 0.9746423
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast               estimate         SE df t.ratio p.value
##  2005,SJ - 2012,SJ   -0.58700705 0.05522601 94 -10.629  <.0001
##  2005,SJ - 2005,caH  -0.27831735 0.05965091 94  -4.666  0.0002
##  2005,SJ - 2012,caH  -0.31733264 0.05965091 94  -5.320  <.0001
##  2005,SJ - 2005,caL  -0.26090106 0.05965091 94  -4.374  0.0005
##  2005,SJ - 2012,caL  -0.38921929 0.05965091 94  -6.525  <.0001
##  2012,SJ - 2005,caH   0.30868970 0.05965091 94   5.175  <.0001
##  2012,SJ - 2012,caH   0.26967441 0.05965091 94   4.521  0.0003
##  2012,SJ - 2005,caL   0.32610599 0.05965091 94   5.467  <.0001
##  2012,SJ - 2012,caL   0.19778776 0.05965091 94   3.316  0.0195
##  2005,caH - 2012,caH -0.03901529 0.06376950 94  -0.612  1.0000
##  2005,caH - 2005,caL  0.01741629 0.06376950 94   0.273  1.0000
```

```
##  2005,caH - 2012,caL -0.11090194 0.06376950 94  -1.739  1.0000
##  2012,caH - 2005,caL  0.05643158 0.06376950 94   0.885  1.0000
##  2012,caH - 2012,caL -0.07188665 0.06376950 94  -1.127  1.0000
##  2005,caL - 2012,caL -0.12831823 0.06376950 94  -2.012  0.7059
##
## P value adjustment: bonferroni method for 15 tests
```

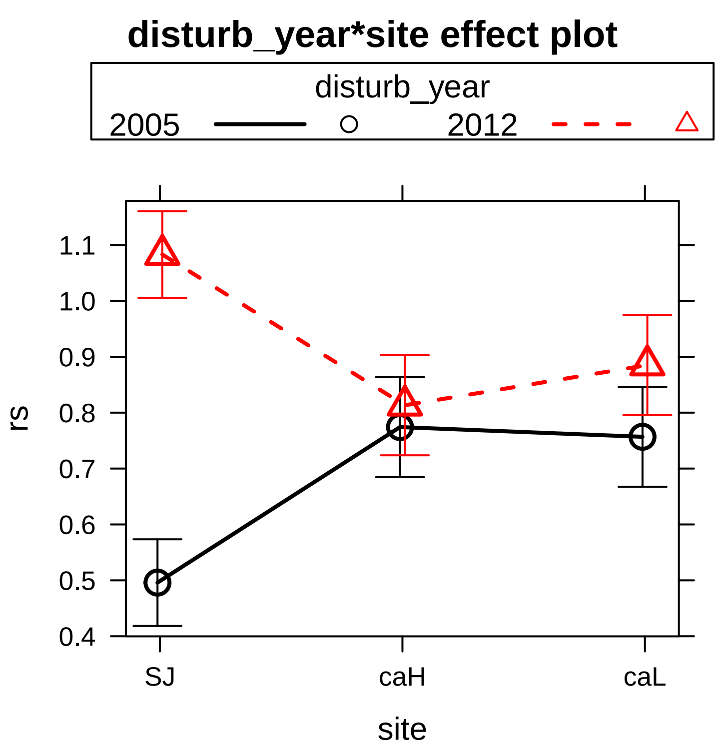
```
ps
```



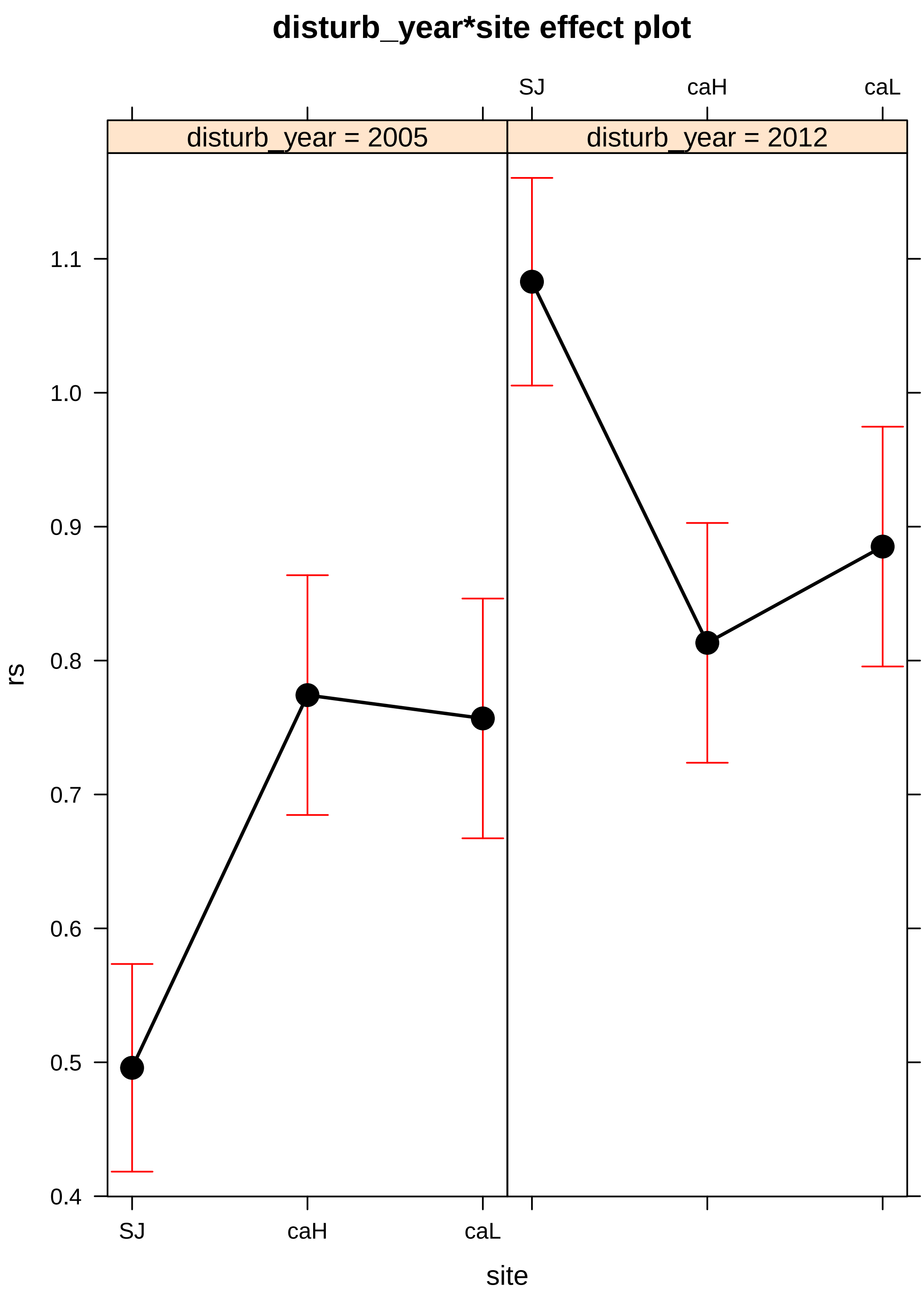

```
pd
```




```
picollapse
```




```
pi
```




```
plot_mds <- means_distub_site %>%
  ggplot(aes(x=site, y=lsmean, group=disturb_year, colour=disturb_year)) +
  geom_point(aes(shape=disturb_year), size=3) +
  geom_line() +
  theme_bw() + xlab('') + ylab('') +
  facet_wrap(~var, scales='free_y', ncol = 1) +
```

```r
  geom_text(aes(y=lsmean+SE, label=letras), nudge_x = 0.15)+
  theme(strip.background = element_rect(colour = "black", fill = "white"),
        legend.position = c(0.8, 0.93),
        legend.background = element_blank()) +
  scale_colour_manual(values = c(micolor, "red"))


plot_mdsSE <- plot_mds + geom_errorbar(mierrorbarSE, size=.5, width=.15)
plot_mdsCI <- plot_mds + geom_errorbar(mierrorbar, size=.5, width=.15)
```

```r
pdf(paste0(di, 'out/fig/resilience/interaction_plotsSE.pdf'), width=9, height = 9)
grid.arrange(plot_mdSE, plot_msSE, plot_mdsSE, ncol=3)
dev.off()
```

```
## pdf
##   2
```

```r
pdf(paste0(di, 'out/fig/resilience/interaction_plotsCI.pdf'), width=9, height = 9)
grid.arrange(plot_mdCI, plot_msCI, plot_mdsCI, ncol=3)
dev.off()
```

```
## pdf
##   2
```

```r
aovas_coeff <- aov_rc$model_coeff %>% mutate(var = 'rc') %>%
  bind_rows(aov_rt$model_coeff %>% mutate(var = 'rt')) %>%
  bind_rows(aov_rs$model_coeff %>% mutate(var = 'rs')) %>%
  bind_rows(aov_rrs$model_coeff%>% mutate(var = 'rrs'))

write.csv(aovas_coeff, file=paste0(di, '/out/anovas_resilience/anovas_statistics.csv'), row.names = F)

aovas_coeff %>% pander()
```

term	df	sumsq	meansq	statistic	p.value	var
disturb_year	1	1.316	1.316	32.78	1.228e-07	rc
site	2	2.847	1.424	35.45	3.373e-12	rc
disturb_year:site	2	0.1961	0.09805	2.442	0.09253	rc
Residuals	94	3.775	0.04016	NA	NA	rc
disturb_year	1	0.2122	0.2122	9.867	0.00225	rt
site	2	1.666	0.833	38.74	5.363e-13	rt
disturb_year:site	2	0.8604	0.4302	20.01	5.77e-08	rt
Residuals	94	2.021	0.0215	NA	NA	rt
disturb_year	1	2.031	2.031	66.58	1.474e-12	rs
site	2	0.01885	0.009425	0.309	0.7349	rs
disturb_year:site	2	1.55	0.775	25.41	1.506e-09	rs
Residuals	94	2.867	0.0305	NA	NA	rs
disturb_year	1	0.93	0.93	47.8	5.63e-10	rrs
site	2	1.39	0.6952	35.73	2.874e-12	rrs
disturb_year:site	2	0.145	0.07252	3.727	0.02769	rrs
Residuals	94	1.829	0.01946	NA	NA	rrs

```r
aovas_model_summary <- aov_rc$model_summary %>% mutate(var = 'rc') %>%
  bind_rows(aov_rt$model_summary %>% mutate(var = 'rt')) %>%
  bind_rows(aov_rs$model_summary %>% mutate(var = 'rs')) %>%
```

```
  bind_rows(aov_rrs$model_summary%>% mutate(var = 'rrs'))

write.csv(aovas_model_summary,
          file=paste0(di, '/out/anovas_resilience/anovas_summary_modelos.csv'), row.names = F)


gm <- apply(aovas_model_summary, 1, formatC, digits = 2, format = "f")
rownames(gm) <- paste0("$",c("R^2","\\mathrm{adj}R^2","\\sigma_e","F","p","df_m","\\mathrm{logLik}","AI
colnames(gm) <- c("rc", "rt", "rs", "rrs")

pander(gm)
```

	rc	rt	rs	rrs
R^2	0.5359434	0.5753458	0.5566473	0.5741044
$\mathrm{adj}R^2$	0.5112596	0.5527578	0.5330647	0.5514503
σ_e	0.2003962	0.1466433	0.1746400	0.1394897
F	21.71230	25.47131	23.60416	25.34227
p	2.166716e-14	3.707920e-16	2.678847e-15	4.239928e-16
df_m	6	6	6	6
logLik	21.94579	53.17511	35.70279	58.17634
AIC	-29.89157	-92.35023	-57.40558	-102.35268
BIC	-11.65538	-74.11404	-39.16939	-84.11649
dev	3.774913	2.021401	2.866917	1.828994
df_e	94	94	94	94
$variable$	rc	rt	rs	rrs

ROBUST ANOVA

- Ver Wilcox (2005, 2012)
- Vamos a realizar un Robust factorial ANOVA. En concreto:
- Two-way robust factorial ANOVA on M-estimator
- pkg WRS2

```
robustANOVA <- function(df, resp_var, factores,
         alpha, nboot, treshold) {
  # alpha: alpha ci for huber m-estimation
  # nboot: numer of iterations
  # treshoold for letter (posthoc)
  # See http://rcompanion.org/rcompanion/d_08a.html

  # Create interaction
  df$interaction <- interaction(df$disturb_year, df$site)

  # Formulas
  formulaFull <- as.formula(paste0(resp_var,  " ~ ",
                                paste(factores, collapse = '+')))

  formula_A <- as.formula(paste0(resp_var,  " ~ ", factores[1]))
  formula_B <- as.formula(paste0(resp_var,  " ~ ", factores[2]))
  formula_AB <- as.formula(paste0(resp_var,  " ~ interaction"))
```

```r
  # Produce Huber M-estimators and confidence intervals by group
  mest <- groupwiseHuber(formulaFull, data = df, ci.type = 'wald', conf.level = alpha)
  mest_a <- groupwiseHuber(formula_A, data = df, ci.type = 'wald', conf.level = alpha)
  mest_b <- groupwiseHuber(formula_B, data = df, ci.type = 'wald', conf.level = alpha)

  # Two-way robust analysis
  x <- pbad2way(formulaFull, data = df, est = "mom", nboot = nboot)


  pbad2way(rs ~ disturb_year + site + disturb_year:site, data = df,
           est = "mom", nboot = nboot)

  out_ra <- data.frame(
    term = c(x$varnames[2],
             x$varnames[3],
             paste0(x$varnames[2], ':', x$varnames[3])),
    p_value = c(x$A.p.value, x$B.p.value, x$AB.p.value))

  # post-hoc
  ## factor A
  pha <- pairwiseRobustTest(formula_A, data = df, est = "mom",
                            nboot = nboot, method="bonferroni")

  ## factor B
  phb <- pairwiseRobustTest(formula_B, data = df, est = "mom",
                            nboot = nboot, method="bonferroni")
  ## interaction effect (AB)
  phab <- pairwiseRobustTest(formula_AB, data = df, est = "mom",
                            nboot = nboot, method="bonferroni")

  ph <- rbind(pha, phb, phab)

  phRWS2 <- mcp2a(formulaFull, data=df, est = "mom", nboot = nboot)

  out <- list()
  out$mest <- mest # Huber M-estimators and Confidence Intervals
  out$mest_a <- mest_a
  out$mest_b <- mest_b
  out$ra <- out_ra # Output for Two-way robust analysis (M-estimators)
  out$ph <- ph # posthoc comparison usinng pairwiseRobustTest
  out$pha <- pha
  out$phb <- phb
  out$phab <- phab

  print(out_ra)
  print(phRWS2)

  return(out)
}

  # if (exists('letters_phb')) {
  # letters_phb <- letters_phb} else {
```

```r
  # myerror <- evaluate('cldList(comparison = phb$Comparison,
  #                       p.value = phb$p.adjust, threshold  = treshold)')
  # letters_phb <- as.character(myerror[[2]]$message)}
  #
  # if (exists('letters_pha')) {
  # letters_pha <- letters_pha} else {
  # myerror <- evaluate('cldList(comparison = pha$Comparison,
  #                       p.value = pha$p.adjust, threshold  = treshold)')
  # letters_pha <- as.character(myerror[[2]]$message)}
  #
  # if (exists('letters_phab')) {
  # letters_phab <- letters_phab} else {
  # myerror <- evaluate('cldList(comparison = phab$Comparison,
  #                       p.value = phab$p.adjust, threshold  = treshold)')
  # letters_phab <- as.character(myerror[[2]]$message)}
```

```r
factores = c('disturb_year', 'site', 'disturb_year:site')
```

Resilience

```r
rars <- robustANOVA(df=re, resp_var='rs', factores=factores,
             alpha = 0.95, nboot = 3000, treshold = 0.01)
```

```
## [1] "comparison 1 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
## [1] "comparison 4 ..."
## [1] "comparison 5 ..."
## [1] "comparison 6 ..."
## [1] "comparison 7 ..."
## [1] "comparison 8 ..."
## [1] "comparison 9 ..."
## [1] "comparison 10 ..."
## [1] "comparison 11 ..."
## [1] "comparison 12 ..."
## [1] "comparison 13 ..."
## [1] "comparison 14 ..."
## [1] "comparison 15 ..."
##
##
##                term     p_value
## 1      disturb_year 0.000000000
## 2              site 0.387000000
## 3 disturb_year:site 0.002333333
```

```
## Call:
## mcp2a(formula = formulaFull, data = df, est = "mom", nboot = nboot)
##
##                         psihat ci.lower ci.upper p-value
## disturb_year1       -0.66998 -0.97679 -0.45182 0.00000
## site1               -0.17216 -0.35069  0.14657 0.16933
## site2               -0.13328 -0.34062  0.14250 0.15500
## site3                0.03889 -0.20104  0.19615 0.48900
## disturb_year1:site1 -0.46693 -0.77465 -0.27194 0.00000
## disturb_year1:site2 -0.31564 -0.64915 -0.17700 0.00000
## disturb_year1:site3  0.15129 -0.09442  0.30994 0.12967
```

Rs Letters

```r
x <-rars

cldList(comparison = x$pha$Comparison, p.value = x$pha$p.adjust, threshold  = 0.01)
```

```
##   Group Letter MonoLetter
## 1    25      a          a
## 2   212      b           b
```

```r
cldList(comparison = x$phb$Comparison, p.value = x$phb$p.adjust, threshold  = 0.01)
```

```
## Error: No significant differences.
```

```r
cldList(comparison = x$phab$Comparison, p.value = x$phab$p.adjust, threshold  = 0.01)
```

```
##     Group Letter MonoLetter
## 1   25.SJ      a          a
## 2  212.SJ      b           b
## 3  25.caH      b           b
## 4 212.caH      b           b
## 5  25.caL      b           b
## 6 212.caL      b           b
```

Recovery

```r
rarc <- robustANOVA(df=re, resp_var='rc', factores=factores,
              alpha = 0.95, nboot = 3000, treshold = 0.01)
```

```
## [1] "comparison 1 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
## [1] "comparison 4 ..."
## [1] "comparison 5 ..."
```

```
## [1] "comparison 6 ..."
## [1] "comparison 7 ..."
## [1] "comparison 8 ..."
## [1] "comparison 9 ..."
## [1] "comparison 10 ..."
## [1] "comparison 11 ..."
## [1] "comparison 12 ..."
## [1] "comparison 13 ..."
## [1] "comparison 14 ..."
## [1] "comparison 15 ..."
##
##
##               term   p_value
## 1      disturb_year 0.0000000
## 2              site 0.0000000
## 3 disturb_year:site 0.1103333
## Call:
## mcp2a(formula = formulaFull, data = df, est = "mom", nboot = nboot)
##
##                      psihat ci.lower ci.upper p-value
## disturb_year1       -0.66711 -0.93820 -0.43296 0.00000
## site1                0.55891  0.31706  0.82280 0.00000
## site2                0.77967  0.55622  1.04044 0.00000
## site3                0.22076  0.04039  0.41187 0.00600
## disturb_year1:site1 -0.09620 -0.37858  0.12712 0.16267
## disturb_year1:site2 -0.22864 -0.47713  0.00636 0.02000
## disturb_year1:site3 -0.13244 -0.29751  0.07566 0.10233
```

Rc Letters

```
x <-rarc

cldList(comparison = x$pha$Comparison, p.value = x$pha$p.adjust, threshold  = 0.01)
```

```
##   Group Letter MonoLetter
## 1    25      a          a
## 2   212      b           b
```

```
cldList(comparison = x$phb$Comparison, p.value = x$phb$p.adjust, threshold  = 0.01)
```

```
##   Group Letter MonoLetter
## 1    SJ      a          a
## 2   caH      b           b
## 3   caL      b           b
```

```
cldList(comparison = x$phab$Comparison, p.value = x$phab$p.adjust, threshold  = 0.01)
```

```
##     Group Letter MonoLetter
## 1   25.SJ     ab         ab
## 2  212.SJ      a          a
## 3  25.caH      b           b
## 4 212.caH      b           b
## 5  25.caL      b           b
## 6 212.caL      b           b
```

Resistance

```
rart <- robustANOVA(df=re, resp_var='rt', factores=factores,
              alpha = 0.95, nboot = 3000, treshold = 0.01)
```

```
## [1] "comparison 1 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
## [1] "comparison 4 ..."
## [1] "comparison 5 ..."
## [1] "comparison 6 ..."
## [1] "comparison 7 ..."
## [1] "comparison 8 ..."
## [1] "comparison 9 ..."
## [1] "comparison 10 ..."
## [1] "comparison 11 ..."
## [1] "comparison 12 ..."
## [1] "comparison 13 ..."
## [1] "comparison 14 ..."
## [1] "comparison 15 ..."
##
##
##                term p_value
## 1      disturb_year    0.03
## 2              site    0.00
## 3 disturb_year:site    0.00
## Call:
## mcp2a(formula = formulaFull, data = df, est = "mom", nboot = nboot)
##
##                       psihat ci.lower ci.upper p-value
## disturb_year1       -0.22274 -0.42835 -0.03137 0.01567
## site1               -0.43120 -0.62443 -0.24446 0.00000
## site2               -0.59768 -0.80335 -0.44207 0.00000
## site3               -0.16648 -0.33531 -0.03738 0.00367
## disturb_year1:site1 -0.49622 -0.65830 -0.29071 0.00000
## disturb_year1:site2 -0.31961 -0.50850 -0.14224 0.00067
## disturb_year1:site3  0.17661  0.00272  0.30185 0.01600
```

Rt Letters

```
x <-rart

cldList(comparison = x$pha$Comparison, p.value = x$pha$p.adjust, threshold  = 0.01)
```

```
## Error: No significant differences.
```

```r
cldList(comparison = x$phb$Comparison, p.value = x$phb$p.adjust, threshold  = 0.01)
```

```
##   Group Letter MonoLetter
## 1    SJ      a          a
## 2   caH      b           b
## 3   caL      b           b
```

```r
cldList(comparison = x$phab$Comparison, p.value = x$phab$p.adjust, threshold  = 0.01)
```

```
##     Group Letter MonoLetter
## 1   25.SJ      a         a
## 2  212.SJ     bc         bc
## 3  25.caH     bc         bc
## 4 212.caH      b          b
## 5  25.caL     bc         bc
## 6 212.caL      c           c
```

Relative Resilience

```r
rarrs <- robustANOVA(df=re, resp_var='rrs', factores=factores,
              alpha = 0.95, nboot = 3000, treshold = 0.01)
```

```
## [1] "comparison 1 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
##
##
## [1] "comparison 1 ..."
## [1] "comparison 2 ..."
## [1] "comparison 3 ..."
## [1] "comparison 4 ..."
## [1] "comparison 5 ..."
## [1] "comparison 6 ..."
## [1] "comparison 7 ..."
## [1] "comparison 8 ..."
## [1] "comparison 9 ..."
## [1] "comparison 10 ..."
## [1] "comparison 11 ..."
## [1] "comparison 12 ..."
## [1] "comparison 13 ..."
## [1] "comparison 14 ..."
## [1] "comparison 15 ..."
##
##
##                term   p_value
## 1      disturb_year 0.0000000
## 2              site 0.0000000
## 3 disturb_year:site 0.1073333
## Call:
## mcp2a(formula = formulaFull, data = df, est = "mom", nboot = nboot)
```

```
##
##                         psihat ci.lower ci.upper p-value
## disturb_year1       -0.56395 -0.75068 -0.36376 0.00000
## site1                0.38674  0.20053  0.55708 0.00000
## site2                0.55080  0.40886  0.73211 0.00000
## site3                0.16406  0.01979  0.35071 0.01000
## disturb_year1:site1 -0.07004 -0.28012  0.07136 0.10767
## disturb_year1:site2 -0.16885 -0.35463 -0.02702 0.00400
## disturb_year1:site3 -0.09881 -0.25424  0.08479 0.13767
```

Rt Letters

```
x <-rarrs

cldList(comparison = x$pha$Comparison, p.value = x$pha$p.adjust, threshold  = 0.01)
```

```
##   Group Letter MonoLetter
## 1    25      a          a
## 2   212      b           b
```

```
cldList(comparison = x$phb$Comparison, p.value = x$phb$p.adjust, threshold  = 0.01)
```

```
##   Group Letter MonoLetter
## 1    SJ      a          a
## 2   caH     ab         ab
## 3   caL      b          b
```

```
cldList(comparison = x$phab$Comparison, p.value = x$phab$p.adjust, threshold  = 0.01)
```

```
##     Group Letter MonoLetter
## 1   25.SJ      a          a
## 2  212.SJ      b           b
## 3  25.caH      a          a
## 4 212.caH      a          a
## 5  25.caL      a          a
## 6 212.caL      a          a
```

Estimadores de huber

```
rars$mest$var <- 'rs'
rarc$mest$var <- 'rc'
rart$mest$var <- 'rt'
rarrs$mest$var <- 'rrs'

mhuber <- rbind(rarc$mest, rart$mest, rars$mest, rarrs$mest)
mhuber %>% pander()
```

disturb_year	site	n	M.Huber	lower.ci	upper.ci	var
2005	SJ	20	1.112	1	1.224	rc
2005	caH	15	0.8866	0.8003	0.973	rc
2005	caL	15	0.8321	0.7326	0.9315	rc
2012	SJ	20	1.446	1.322	1.569	rc
2012	caH	15	1.107	1.026	1.188	rc
2012	caL	15	0.952	0.8889	1.015	rc

disturb_year	site	n	M.Huber	lower.ci	upper.ci	var
2005	SJ	20	0.4454	0.3751	0.5158	rt
2005	caH	15	0.8921	0.8091	0.9751	rt
2005	caL	15	0.9012	0.8132	0.9892	rt
2012	SJ	20	0.7687	0.6839	0.8534	rt
2012	caH	15	0.7534	0.6864	0.8204	rt
2012	caL	15	0.9263	0.9001	0.9526	rt
2005	SJ	20	0.4888	0.4213	0.5562	rs
2005	caH	15	0.7895	0.6913	0.8878	rs
2005	caL	15	0.7303	0.6118	0.8489	rs
2012	SJ	20	1.031	0.93	1.132	rs
2012	caH	15	0.8132	0.7413	0.8852	rs
2012	caL	15	0.8761	0.8394	0.9129	rs
2005	SJ	20	0.0426	-0.006558	0.09177	rrs
2005	caH	15	-0.1075	-0.1893	-0.02565	rrs
2005	caL	15	-0.1424	-0.2264	-0.05831	rrs
2012	SJ	20	0.3206	0.229	0.4122	rrs
2012	caH	15	0.08191	0.02746	0.1364	rrs
2012	caL	15	-0.0443	-0.1071	0.01848	rrs

```r
rars$mest_a$var <- 'rs'
rarc$mest_a$var <- 'rc'
rart$mest_a$var <- 'rt'
rarrs$mest_a$var <- 'rrs'

mhuber_a <- rbind(rarc$mest_a, rart$mest_a, rars$mest_a, rarrs$mest_a)
mhuber_a %>% pander()
```

disturb_year	n	M.Huber	lower.ci	upper.ci	var
2005	50	0.9462	0.8794	1.013	rc
2012	50	1.161	1.081	1.24	rc
2005	50	0.721	0.6437	0.7984	rt
2012	50	0.8193	0.7758	0.8628	rt
2005	50	0.653	0.5852	0.7209	rs
2012	50	0.9107	0.8648	0.9567	rs
2005	50	-0.05594	-0.09931	-0.01257	rrs
2012	50	0.1223	0.05958	0.185	rrs

```r
rars$mest_b$var <- 'rs'
rarc$mest_b$var <- 'rc'
rart$mest_b$var <- 'rt'
rarrs$mest_b$var <- 'rrs'

mhuber_b <- rbind(rarc$mest_b, rart$mest_b, rars$mest_b, rarrs$mest_b)
mhuber_b %>% pander()
```

site	n	M.Huber	lower.ci	upper.ci	var
SJ	40	1.282	1.179	1.386	rc
caH	30	0.9962	0.9171	1.075	rc
caL	30	0.8972	0.8431	0.9514	rc

site	n	M.Huber	lower.ci	upper.ci	var
SJ	40	0.6116	0.5387	0.6846	rt
caH	30	0.8157	0.7549	0.8764	rt
caL	30	0.9209	0.8834	0.9584	rt
SJ	40	0.7694	0.6524	0.8864	rs
caH	30	0.7975	0.7439	0.8511	rs
caL	30	0.8172	0.7553	0.8791	rs
SJ	40	0.1656	0.09482	0.2364	rrs
caH	30	-0.006329	-0.06678	0.05412	rrs
caL	30	-0.09387	-0.1455	-0.04226	rrs

Pairwise comparison

```
rars$ph$var <- 'rs'
rarc$ph$var <- 'rc'
rart$ph$var <- 'rt'
rarrs$ph$var <- 'rrs'

pairwise <- rbind(rarc$ph, rart$ph, rars$ph, rarrs$ph)
pairwise %>% pander()
```

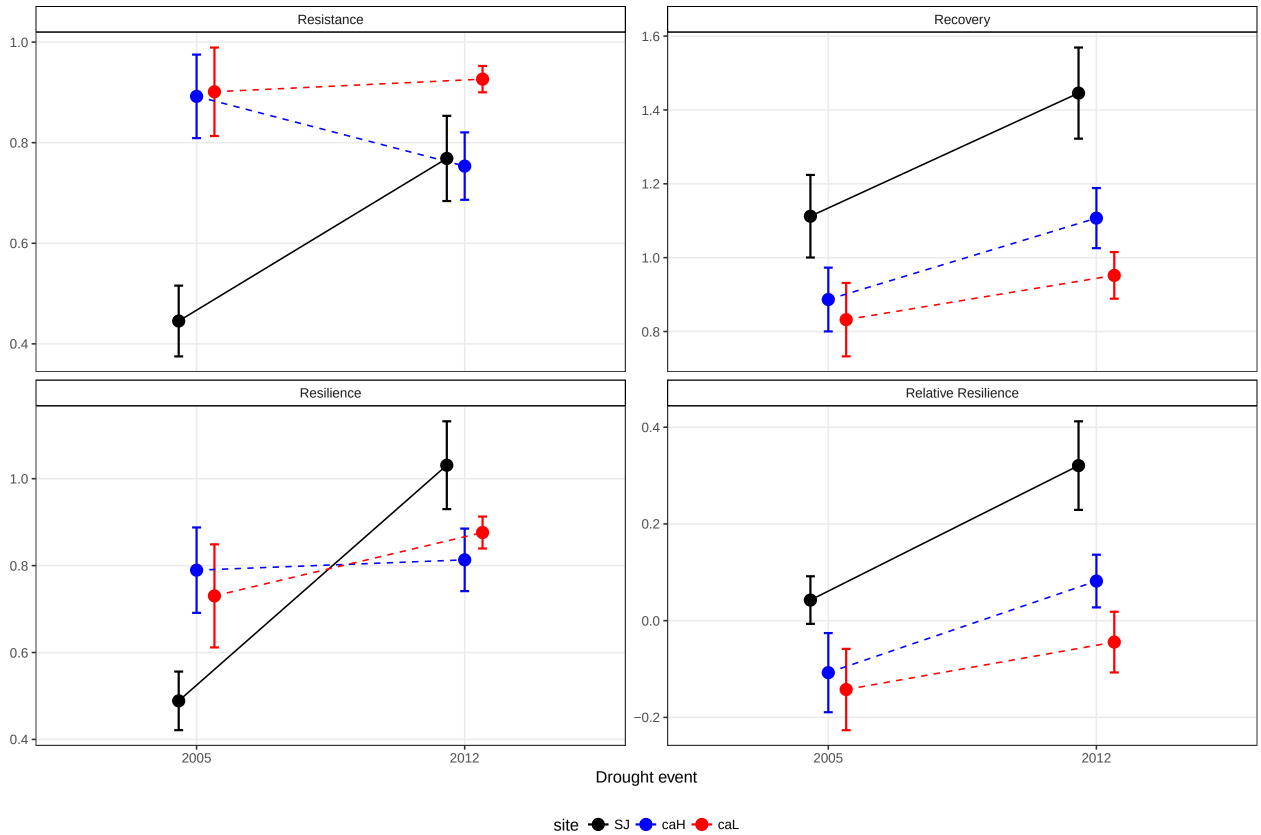
Comparison	Statistic	p.value	p.adjust	var
2005 - 2012 = 0	-0.1672	0.003333	0.003333	rc
SJ - caH = 0	0.2808	0	0	rc
SJ - caL = 0	0.3926	0	0	rc
caH - caL = 0	0.1118	0.02933	0.08799	rc
2005.SJ - 2012.SJ = 0	-0.3306	0.002	0.03	rc
2005.SJ - 2005.caH = 0	0.2314	0.01667	0.25	rc
2005.SJ - 2012.caH = 0	-0.003094	0.8993	1	rc
2005.SJ - 2005.caL = 0	0.2755	0.001333	0.02	rc
2005.SJ - 2012.caL = 0	0.1735	0.02467	0.37	rc
2012.SJ - 2005.caH = 0	0.562	0	0	rc
2012.SJ - 2012.caH = 0	0.3276	0	0	rc
2012.SJ - 2005.caL = 0	0.6062	0	0	rc
2012.SJ - 2012.caL = 0	0.5042	0	0	rc
2005.caH - 2012.caH = 0	-0.2344	0.001333	0.02	rc
2005.caH - 2005.caL = 0	0.04416	0.4007	1	rc
2005.caH - 2012.caL = 0	-0.05785	0.3347	1	rc
2012.caH - 2005.caL = 0	0.2786	0.0006667	0.01	rc
2012.caH - 2012.caL = 0	0.1766	0.005333	0.08	rc
2005.caL - 2012.caL = 0	-0.102	0.05333	0.8	rc
2005 - 2012 = 0	-0.107	0.09533	0.09533	rt
SJ - caH = 0	-0.1948	0.0006667	0.002	rt
SJ - caL = 0	-0.3104	0	0	rt
caH - caL = 0	-0.1156	0.004	0.012	rt
2005.SJ - 2012.SJ = 0	-0.3462	0	0	rt
2005.SJ - 2005.caH = 0	-0.4637	0	0	rt
2005.SJ - 2012.caH = 0	-0.3137	0	0	rt
2005.SJ - 2005.caL = 0	-0.4586	0	0	rt
2005.SJ - 2012.caL = 0	-0.4852	0	0	rt
2012.SJ - 2005.caH = 0	-0.1175	0.1147	1	rt

Comparison	Statistic	p.value	p.adjust	var
2012.SJ - 2012.caH = 0	0.03251	0.6847	1	rt
2012.SJ - 2005.caL = 0	-0.1125	0.07133	1	rt
2012.SJ - 2012.caL = 0	-0.139	0.008667	0.13	rt
2005.caH - 2012.caH = 0	0.15	0.014	0.21	rt
2005.caH - 2005.caL = 0	0.005064	0.8427	1	rt
2005.caH - 2012.caL = 0	-0.02152	0.404	1	rt
2012.caH - 2005.caL = 0	-0.145	0.003333	0.05	rt
2012.caH - 2012.caL = 0	-0.1715	0	0	rt
2005.caL - 2012.caL = 0	-0.02658	0.6593	1	rt
2005 - 2012 = 0	-0.2266	0	0	rs
SJ - caH = 0	-0.004321	0.8107	1	rs
SJ - caL = 0	-0.008101	0.5813	1	rs
caH - caL = 0	-0.00378	0.6033	1	rs
2005.SJ - 2012.SJ = 0	-0.4842	0	0	rs
2005.SJ - 2005.caH = 0	-0.3195	0	0	rs
2005.SJ - 2012.caH = 0	-0.3368	0	0	rs
2005.SJ - 2005.caL = 0	-0.2245	0	0	rs
2005.SJ - 2012.caL = 0	-0.393	0	0	rs
2012.SJ - 2005.caH = 0	0.1646	0.012	0.18	rs
2012.SJ - 2012.caH = 0	0.1474	0.01933	0.29	rs
2012.SJ - 2005.caL = 0	0.2597	0.0006667	0.01	rs
2012.SJ - 2012.caL = 0	0.09118	0.036	0.54	rs
2005.caH - 2012.caH = 0	-0.01725	0.5947	1	rs
2005.caH - 2005.caL = 0	0.09509	0.4887	1	rs
2005.caH - 2012.caL = 0	-0.07345	0.1153	1	rs
2012.caH - 2005.caL = 0	0.1123	0.2473	1	rs
2012.caH - 2012.caL = 0	-0.0562	0.2007	1	rs
2005.caL - 2012.caL = 0	-0.1685	0.02	0.3	rs
2005 - 2012 = 0	-0.1766	0.0006667	0.0006667	rrs
SJ - caH = 0	0.1318	0.012	0.036	rrs
SJ - caL = 0	0.2463	0	0	rrs
caH - caL = 0	0.1145	0.074	0.222	rrs
2005.SJ - 2012.SJ = 0	-0.2676	0	0	rrs
2005.SJ - 2005.caH = 0	0.1584	0.01933	0.29	rrs
2005.SJ - 2012.caH = 0	-0.03922	0.2473	1	rrs
2005.SJ - 2005.caL = 0	0.191	0.002667	0.04	rrs
2005.SJ - 2012.caL = 0	0.09221	0.03133	0.47	rrs
2012.SJ - 2005.caH = 0	0.426	0	0	rrs
2012.SJ - 2012.caH = 0	0.2284	0	0	rrs
2012.SJ - 2005.caL = 0	0.4586	0	0	rrs
2012.SJ - 2012.caL = 0	0.3598	0	0	rrs
2005.caH - 2012.caH = 0	-0.1976	0.0006667	0.01	rrs
2005.caH - 2005.caL = 0	0.03262	0.4713	1	rrs
2005.caH - 2012.caL = 0	-0.06614	0.4153	1	rrs
2012.caH - 2005.caL = 0	0.2302	0.0006667	0.01	rrs
2012.caH - 2012.caL = 0	0.1314	0.003333	0.05	rrs
2005.caL - 2012.caL = 0	-0.09876	0.05333	0.8	rrs

Interaction plot

Response ~ (x=Drought)

```r
mhuber<- mhuber %>%
  mutate(var_sorted = case_when(var == "rc" ~ "1_rc",
                                var == "rt" ~ "0_rt",
                                var == "rs" ~ "2_rs",
                                var == "rrs" ~ "3_rrs"))

pd <- position_dodge(.2)

robust_plot_evi_drought <- ggplot(mhuber, aes(x=disturb_year, y=M.Huber, color = site, group=site, fill=
  geom_errorbar(aes(ymin=lower.ci, ymax=upper.ci),
              width=.1, size=0.7, position=pd) +
  geom_line(aes(group=site,color=site, linetype=site), position=pd) +
  geom_point(shape=21, size=3.5, position=pd) +
  facet_wrap(~var_sorted, nrow = 2, scales = 'free_y',
             labeller=as_labeller(c('0_rt' = 'Resistance',
                                    '1_rc' = 'Recovery',
                                    '2_rs' = 'Resilience',
                                    '3_rrs' = 'Relative Resilience'))) +
  scale_color_manual(values=c('black','blue','red')) +
  scale_fill_manual(values=c('black','blue','red')) + theme_bw() +
  scale_linetype_manual(values=c("solid", "dashed", 'dashed')) +
  theme(panel.grid.minor = element_blank(),
        strip.background = element_rect(colour='black',
                                        fill='white'),
        legend.position="bottom") +
  ylab('') + xlab('Drought event')

robust_plot_evi_drought
```



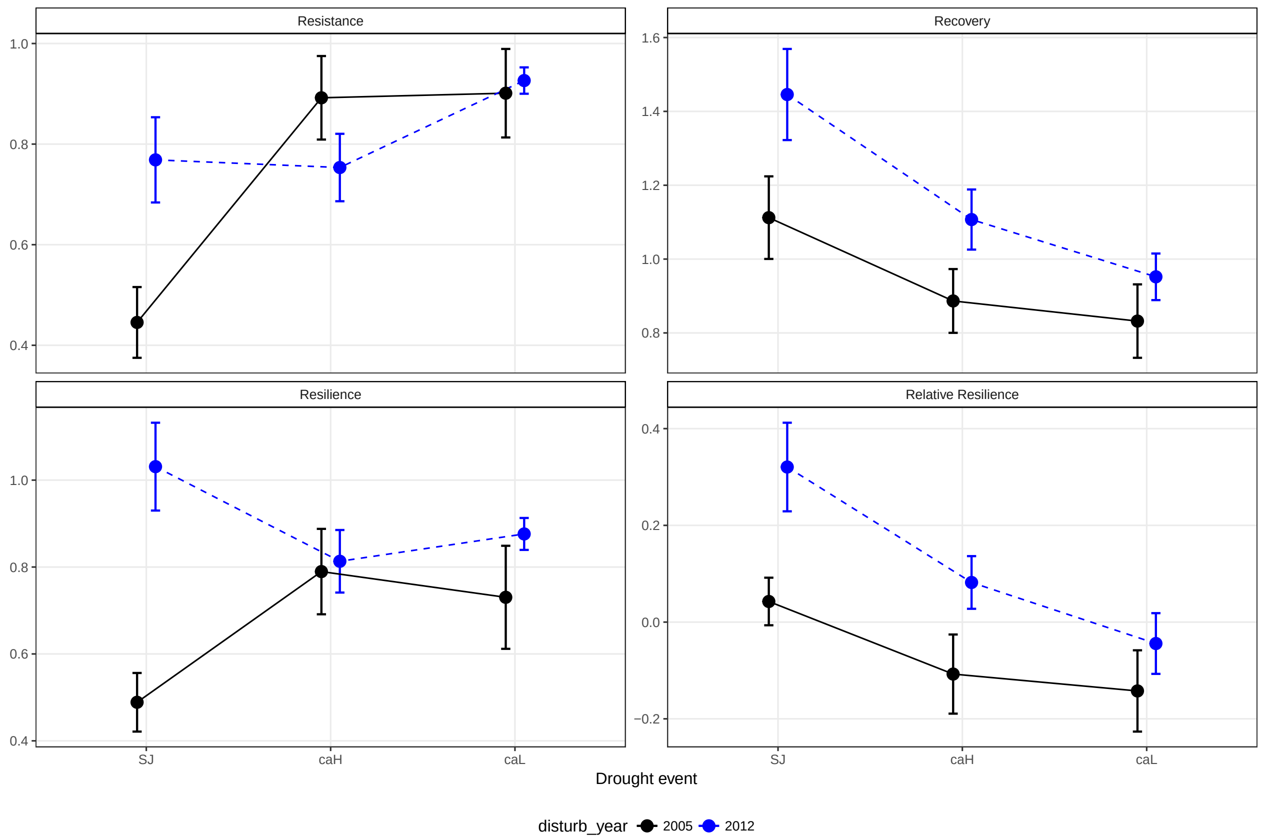

```
pdf(paste0(di, 'out/fig/resilience/robust_plot_evi_drought.pdf'), width=9, height = 9)
robust_plot_evi_drought
dev.off()
```

```
## pdf
##   2
```

Response ~ (x=site)

```
pd <- position_dodge(.2)

robust_plot_evi_site <- ggplot(mhuber, aes(x=site, y=M.Huber, color = disturb_year, group=disturb_year,
  geom_errorbar(aes(ymin=lower.ci, ymax=upper.ci),
                width=.1, size=0.7, position=pd) +
  geom_line(aes(group=disturb_year,color=disturb_year, linetype=disturb_year), position=pd) +
  geom_point(shape=21, size=3.5, position=pd) +
  facet_wrap(~var_sorted, nrow = 2, scales = 'free_y',
             labeller=as_labeller(c('0_rt' = 'Resistance',
                                    '1_rc' = 'Recovery',
                                    '2_rs' = 'Resilience',
                                    '3_rrs' = 'Relative Resilience'))) +
  scale_color_manual(values=c('black','blue')) +
  scale_fill_manual(values=c('black','blue')) + theme_bw() +
  scale_linetype_manual(values=c("solid", "dashed")) +
  theme(panel.grid.minor = element_blank(),
        strip.background = element_rect(colour='black',
```

```
                                                    fill='white'),
        legend.position="bottom") +
  ylab('') + xlab('Drought event')


robust_plot_evi_site
```




```
pdf(paste0(di, 'out/fig/resilience/robust_plot_evi_site.pdf'), width=9, height = 9)
robust_plot_evi_site
dev.off()
```

```
## pdf
##   2
```

```
# Export data
write.csv(mhuber, file=paste0(di, '/out/anovas_resilience/robust_mhuber.csv'), row.names = F)
write.csv(mhuber_a, file=paste0(di, '/out/anovas_resilience/robust_mhuber_a.csv'), row.names = F)
write.csv(mhuber_b, file=paste0(di, '/out/anovas_resilience/robust_mhuber_b.csv'), row.names = F)

write.csv(pairwise, file=paste0(di, '/out/anovas_resilience/robust_pairwise.csv'), row.names = F)
```

References

Lloret, F., E. G. Keeling, and A. Sala. 2011. Components of tree resilience: Effects of successive low-growth episodes in old ponderosa pine forests. Oikos 120:1909–1920.

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.