

Chun's paper restart analysis

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```
## Warning: use rgdal::readOGR or sf::st_read  
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```

Introduction

This is a rewrite of the paper to tackle the issues that are still remaining.

Here is the general approach proposed:

1. Run a regression model on the tree cover data (mixed model): $Tree_{cover} \sim time(years) + AR1(error)$.
The H_0 would be that the tree cover has not changed in time. This model would also more clearly identify those years where change in tree cover is likely (but cannot confirm this).
2. Run a regression model that removes the variation in monthly rainfall and tests the significance of a “tree_cover” variable. This model also includes the monthly rainfall averaged over the Murray Darling Basin, which might mean that variables such as “season” is no longer needed.
 $Rainfall MonthlyMDBRain + SST + trend_{treecover} + trend_{time} + AR1(error)$
3. Calculate monthly rainfall residuals using a regression model (based on the above model, but dropping the tree cover trend term): $RainfallResiduals = Rainfall - MonthlyMDBRain - SST - trend_{time}$
4. Running Mann-Whitney or Pettitt tests on the rainfall residuals. However, Serinaldi et al argue that the MK and Pettitt tests are equivalent on timeseries data (give very similar results).

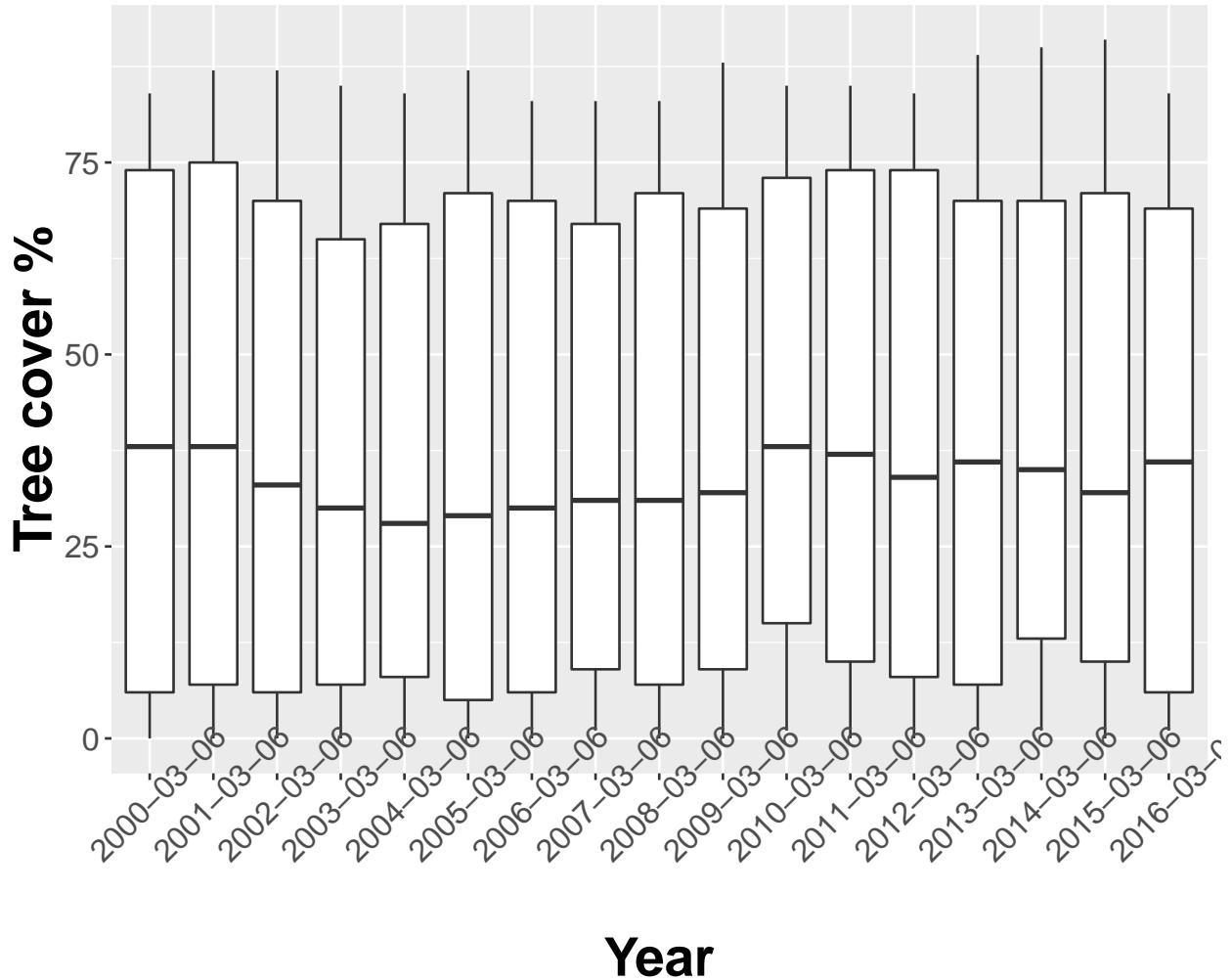
Step 1, Tree cover change

First we load the data, using the older code

plot for NSW

```
NSW_data <- as.tibble(rasterToPoints(mod_tc_r22))  
colnames(NSW_data)[3:19] <- as.character(tm)  
  
NSWdata <- NSW_data %>%  
  gather(key="Year", value="Tree_cover", `2000-03-06`:`2016-03-06`) %>%  
  filter(Tree_cover < 200)  
NSWdata %>%  
  ggplot(aes(as.factor(Year),Tree_cover)) + geom_boxplot() +  
  xlab("Year") + ylab("Tree cover %") +  
  ggtitle("Percent tree cover change NSW") +  
  theme(axis.text.x = element_text(angle=45, size=rel(1.5)),  
        axis.text.y = element_text(size=rel(1.5)),  
        axis.title = element_text(size=rel(2), face = "bold"))
```

Percent tree cover change NSW



Year

```
mod_NSW <- lmer(Tree_cover ~ as.factor(Year) + (1|Year),
                   data = NSWdata)
summary(mod_NSW)

## Linear mixed model fit by REML ['lmerMod']
## Formula: Tree_cover ~ as.factor(Year) + (1 | Year)
##   Data: NSWdata
##
## REML criterion at convergence: 76701693
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max 
## -1.3835 -1.0151 -0.1761  1.0686  1.7326 
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   Year     (Intercept) 2.809   1.676  
##   Residual           890.626 29.843 
##   Number of obs: 7965027, groups: Year, 17
##
```

```

## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)            39.7071   1.6765 23.685
## as.factor(Year)2001-03-06  0.2582   2.3709  0.109
## as.factor(Year)2002-03-06 -1.6376   2.3709 -0.691
## as.factor(Year)2003-03-06 -4.0957   2.3709 -1.727
## as.factor(Year)2004-03-06 -4.0084   2.3709 -1.691
## as.factor(Year)2005-03-06 -2.5105   2.3709 -1.059
## as.factor(Year)2006-03-06 -2.3561   2.3709 -0.994
## as.factor(Year)2007-03-06 -2.3186   2.3709 -0.978
## as.factor(Year)2008-03-06 -1.6609   2.3709 -0.701
## as.factor(Year)2009-03-06 -1.4513   2.3709 -0.612
## as.factor(Year)2010-03-06  2.5808   2.3709  1.089
## as.factor(Year)2011-03-06  1.0589   2.3709  0.447
## as.factor(Year)2012-03-06 -0.5032   2.3709 -0.212
## as.factor(Year)2013-03-06 -1.5163   2.3709 -0.640
## as.factor(Year)2014-03-06  0.4014   2.3709  0.169
## as.factor(Year)2015-03-06 -0.4125   2.3709 -0.174
## as.factor(Year)2016-03-06 -1.3335   2.3709 -0.562

##
## Correlation matrix not shown by default, as p = 17 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)      if you need it

```

This shows that in NSW the years 2003 and 2004 were likely to be different from the mean at $p < 0.10$, and they were less than the mean. all the other years had higher p values (and are thus less likely to be different from the mean). These would coincide with the bushfire.

plot for QLD

```

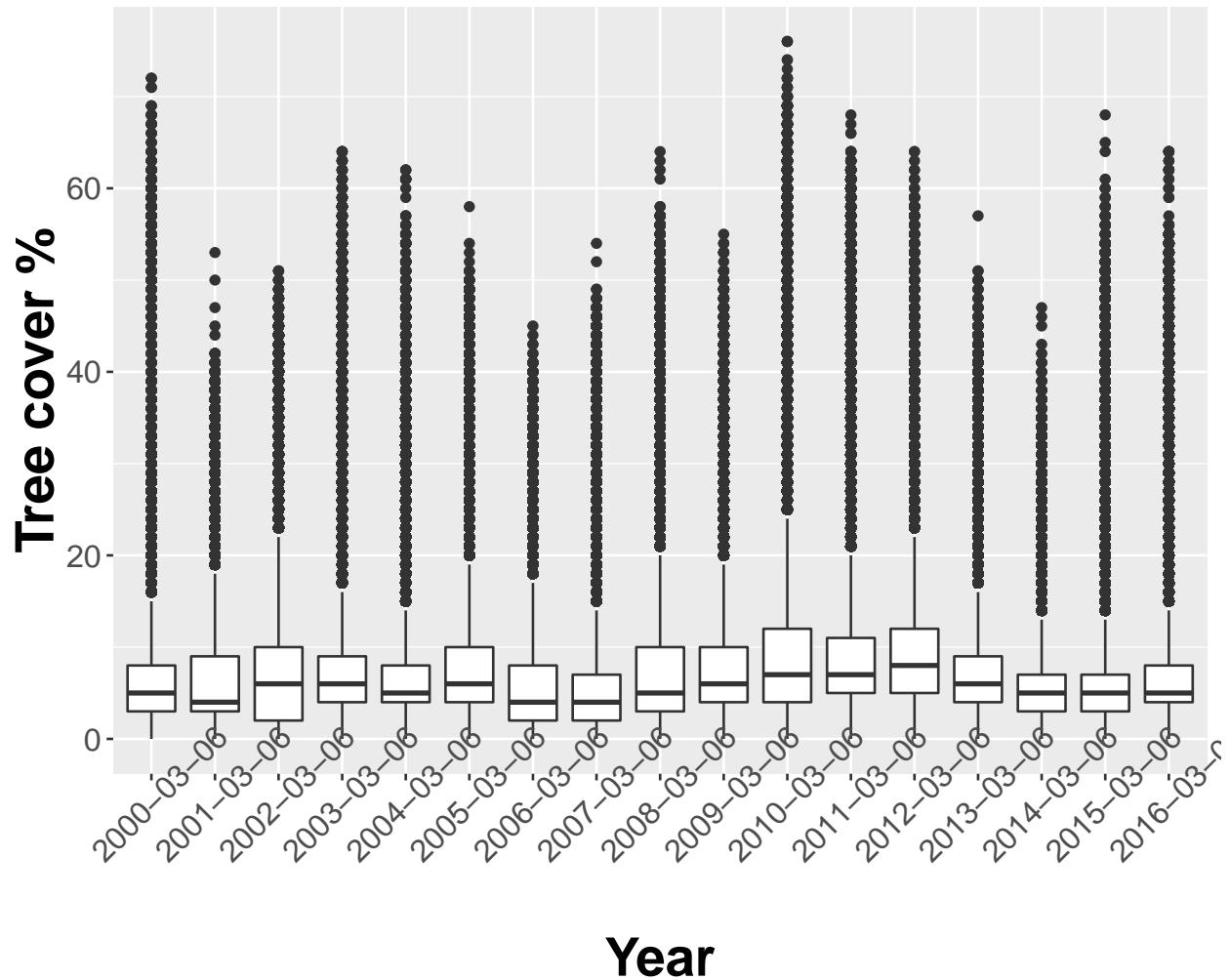
QLD_data <- as.tibble(rasterToPoints(mod_tc_r11))
colnames(QLD_data)[3:19] <- as.character(tm)

QLDdata <- QLD_data %>%
  gather(key="Year", value="Tree_cover", `2000-03-06`:`2016-03-06`) %>%
  mutate(Tree_cover = replace(Tree_cover, Tree_cover == 200, NA))
QLDdata %>%
  ggplot(aes(as.factor(Year),Tree_cover)) + geom_boxplot() +
  xlab("Year") + ylab("Tree cover %") +
  ggtitle("Percent tree cover change QLD") +
  theme(axis.text.x = element_text(angle=45, size=rel(1.5)),
        axis.text.y = element_text(size=rel(1.5)),
        axis.title = element_text(size=rel(2), face = "bold"))

## Warning: Removed 3111 rows containing non-finite values (stat_boxplot).

```

Percent tree cover change QLD



Year

```

mod_QLD <- lmer(Tree_cover ~ as.factor(Year) + (1|Year),
                  data = QLDdata)
summary(mod_QLD)

## Linear mixed model fit by REML ['lmerMod']
## Formula: Tree_cover ~ as.factor(Year) + (1 | Year)
##   Data: QLDdata
##
## REML criterion at convergence: 127080868
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max 
## -1.4978 -0.6171 -0.3170  0.2179  9.7587 
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   Year     (Intercept) 1.74     1.319  
##   Residual           46.41     6.813  
##   Number of obs: 19036889, groups: Year, 17
##

```

```

## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                 6.4105   1.3190  4.860
## as.factor(Year)2001-03-06   0.8362   1.8654  0.448
## as.factor(Year)2002-03-06   2.1741   1.8654  1.166
## as.factor(Year)2003-03-06   1.5035   1.8654  0.806
## as.factor(Year)2004-03-06   0.2507   1.8654  0.134
## as.factor(Year)2005-03-06   2.0967   1.8654  1.124
## as.factor(Year)2006-03-06  -0.2603   1.8654 -0.140
## as.factor(Year)2007-03-06  -0.8951   1.8654 -0.480
## as.factor(Year)2008-03-06   1.5336   1.8654  0.822
## as.factor(Year)2009-03-06   2.0880   1.8654  1.119
## as.factor(Year)2010-03-06   3.1047   1.8654  1.664
## as.factor(Year)2011-03-06   2.7495   1.8654  1.474
## as.factor(Year)2012-03-06   3.7937   1.8654  2.034
## as.factor(Year)2013-03-06   2.1646   1.8654  1.160
## as.factor(Year)2014-03-06  -0.7962   1.8654 -0.427
## as.factor(Year)2015-03-06   0.8636   1.8654  0.463
## as.factor(Year)2016-03-06   0.8631   1.8654  0.463

##
## Correlation matrix not shown by default, as p = 17 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)      if you need it

```

For Qld only the years 2010 and 2012 are likely to be different from the mean ($p < 0.10$) and were consistently higher than the mean in % cover, they were also two very wet years.

Step 2 Rainfall regression model

This mainly repeats the analysis that has been done in the earlier versions of the paper. But there are some changes:

- the correlation analysis is done in another script “CorrelationClimateRainfall2018.Rmd”
- We have decided to use SILO data as the ANUCLIM (finer grid data) only extends to 2014 and therefore we cannot capture 2016

load the data

All the older climate index data

```

## Parsed with column specification:
## cols(
##   Year = col_integer(),
##   Jan = col_double(),
##   Feb = col_double(),
##   Mar = col_double(),
##   Apr = col_double(),
##   May = col_double(),
##   Jun = col_double(),
##   Jul = col_double(),
##   Aug = col_double(),

```

```

##   Sep = col_double(),
##   Oct = col_double(),
##   Nov = col_double(),
##   Dec = col_double()
## )

## Parsed with column specification:
## cols(
##   YEAR = col_character(),
##   JAN = col_double(),
##   FEB = col_double(),
##   MAR = col_double(),
##   APR = col_double(),
##   MAY = col_double(),
##   JUN = col_double(),
##   JUL = col_double(),
##   AUG = col_double(),
##   SEP = col_double(),
##   OCT = col_double(),
##   NOV = col_double(),
##   DEC = col_double()
## )

## Parsed with column specification:
## cols(
##   Date = col_character(),
##   West = col_double(),
##   East = col_double(),
##   `DMI(=West-East)` = col_double()
## )

```

Rainfall

Downloading from SILO. Can be replaced by ANUCLIM if the data to 2016 becomes available

```

# SILO data

## -----extract_Silo-----
years <- seq(1979,2016,by=1)

SIL0data <- list()

# run a loop
for (i in 1:length(years)) {
  # url <- paste("https://s3-ap-southeast-2.amazonaws.com/silo-open-data/annual/monthly_rain/",
  #             years[i],
  #             ".monthly_rain.nc",sep="")
  # curl_download(url,
  #               paste("data/monthly_rainfall_",years[i],".nc",sep ""))
  SIL0data[[i]] <- brick(paste("data/monthly_rainfall_",years[i],".nc",
                                sep=""),varname="monthly_rain")
}

SIL0data__b <- do.call(stack, SIL0data)

```

```

#crop to extents
e111 <- extent(c(145.825, 148.625, -28.075, -25.575))
e222 <- extent(c(147.075, 148.925, -36.675, -35.075))

# NSW
SIL0data.NSW <- crop(SIL0data__b, extent(e222))

#QLD
SIL0data.QLD <- crop(SIL0data__b, extent(e111))

# MDB
mdb_reg <- readShapePoly("data/Geo\\MDB\\mdb_boundary.shp",
                           proj4string=CRS("+proj=lcc +lat_1=-18 +lat_2=-36 +lat_0=-27 +lon_0=132 +"))

## Warning: use rgdal::readOGR or sf::st_read
SIL0data.MDB <- crop(SIL0data__b, extent(mdb_reg))

aus_reg <- readShapePoly("data/Geo\\aus_state2011\\STE11aAust.shp",
                           proj4string=CRS("+proj=lcc +lat_1=-18 +lat_2=-36"))

## Warning: use rgdal::readOGR or sf::st_read

# remove orig
rm(SIL0data)
rm(SIL0data__b)

# test -----
# require(rasterVis)
# gplot(SIL0data.NSW[[1]]) + geom_tile(aes(fill = value)) + coord_equal() +
#   facet_wrap(~variable) + scale_fill_gradient(low="darksalmon", high="blue",
#                                                 guide="colorbar",na.value="white") +
#   xlab("Longitude") + ylab("Latitude")
# ----

# rewrite as a monthly dataframe
# NSW
rainNSW_t <- as.tibble(data.frame(Date = seq.Date(as.Date("1979-01-01"),
                                                    as.Date("2016-12-31"), by="month"),
                               rain=t(SIL0data.NSW@data@values)))

# calculate mean by row
nsw_mean <- rainNSW_t %>%
  mutate(Means = rowMeans(.[, -1], na.rm = T)) %>%
  dplyr::select(Date, Means)

rm(SIL0data.NSW)

# Qld
rainQld_t <- as.tibble(data.frame(Date = seq.Date(as.Date("1979-01-01"),
                                                    as.Date("2016-12-31"), by="month"),
                               rain=t(SIL0data.QLD@data@values)))

# calculate mean by row
qld_mean <- rainQld_t %>%
  mutate(Means = rowMeans(.[, -1], na.rm = T)) %>%
  dplyr::select(Date, Means)

```

```

rm(SIL0data.QLD)

# MDB
rainMDB_t <- as.tibble(data.frame(Date = seq.Date(as.Date("1979-01-01"),
                                                 as.Date("2016-12-31"), by="month"),
                                                 rain=t(SIL0data.MDB@data@values)))

# calculate mean by row
MDB_mean <- rainMDB_t %>%
  mutate(MDBrain = rowMeans(.[, -1], na.rm = T)) %>%
  dplyr::select(Date, MDBrain)

rm(SIL0data.MDB)

```

Regression model

This regression model now includes the mean monthly MDB rainfall as an additional variable to take out the seasonal trend and the overall possible long term trends.

```

## predicting model: land cover is category variable
rain.trend <- function(x,y,var.data) {
  # add a very small number to take out 0 values
  var.data$rain <- as.vector(unlist(y[x]))[1:nrow(var.data)]+0.0001

  rain_fit <- gam(rain ~ MDB
                  + s(SOI, k=3, bs="cs")
                  + s(IOD, k=3, bs="cs")
                  #+ s(PDO, k=3, bs="cs")
                  + s(NIN03.4, k=3, bs="cs")
                  + s(NIN04, k=3, bs="cs")
                  + cover
                  + trd
                  , data=var.data, #family=Gamma(link=log),
                  na.action = na.omit)
  #
  return(rain_fit)
}

## generate variables for the model
trd <- seq(1:456)

LC <- c(rep("tree",288),rep("clear",168))
# different QLD scenarios
LC_qld1 <- c(rep("tree",294),rep("clear",162)) ## after-change: from Jun 2003
LC_qld2 <- c(rep("tree",300),rep("clear",156)) ## after- : from Jan 2004
LC_qld3 <- c(rep("tree",306),rep("clear",150)) ## after- : from Jun 2004
LC_qld4 <- c(rep("tree",312),rep("clear",144)) ## after- : from Jan 2005

# NSW
var.data <- data.frame(trd, MDB = MDB_mean$MDBrain,
                       SOI = SOI_37Y$SOI,

```

```

    IOD = IOD_37Y$IOD,
    PDO = PDO_37Y$PDO,
    NINO3.4 = SST34_37Y$$SST34,
    NINO4 = SST4_37Y$$SST4,
    cover = LC)

# QLD
# test different scenarios
#
var.qld2 <- data.frame(trd, MDB = MDB_mean$MDBrain,
                        SOI = SOI_37Y$SOI,
                        IOD = IOD_37Y$IOD,
                        PDO = PDO_37Y$PDO,
                        NINO3.4 = SST34_37Y$$SST34,
                        NINO4 = SST4_37Y$$SST4,
                        cover = LC_qld2)

var.qld4 <- data.frame(trd, MDB = MDB_mean$MDBrain,
                        SOI = SOI_37Y$SOI,
                        IOD = IOD_37Y$IOD,
                        PDO = PDO_37Y$PDO,
                        NINO3.4 = SST34_37Y$$SST34,
                        NINO4 = SST4_37Y$$SST4,
                        cover = LC_qld4)

## run model for all periods
## QLD
coef.rain30.qld2 <- lapply(2:ncol(rainQld_t),
                           function(x) rain.trend(x,rainQld_t,var.qld2))
coef.rain30.qld4 <- lapply(2:ncol(rainQld_t),
                           function(x) rain.trend(x,rainQld_t,var.qld4))
# NSW/VIC
coef.rain30.nswvic <- lapply(2:ncol(rainNSW_t),
                           function(x) rain.trend(x,rainNSW_t,var.data))

```

Extract the sign and significance of the MDB variable. This is just to show that this variable is significant and has a consistent value across the area

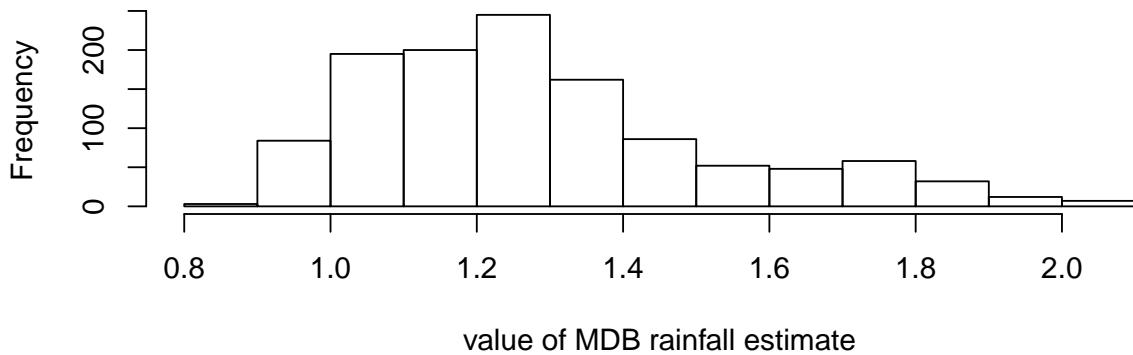
```

## extract sign of MDB, which is assumed to have a linear relationship with
## the rainfall in the area
# Qld
MDB_qld <- unlist(lapply(1:length(coef.rain30.qld4),function(x) ifelse(summary(coef.rain30.qld4)[x,2]==
# NSW/VIC
MDB_nswvic <- unlist(lapply(1:length(coef.rain30.nswvic),function(x) ifelse(summary(coef.rain30.nswvic)

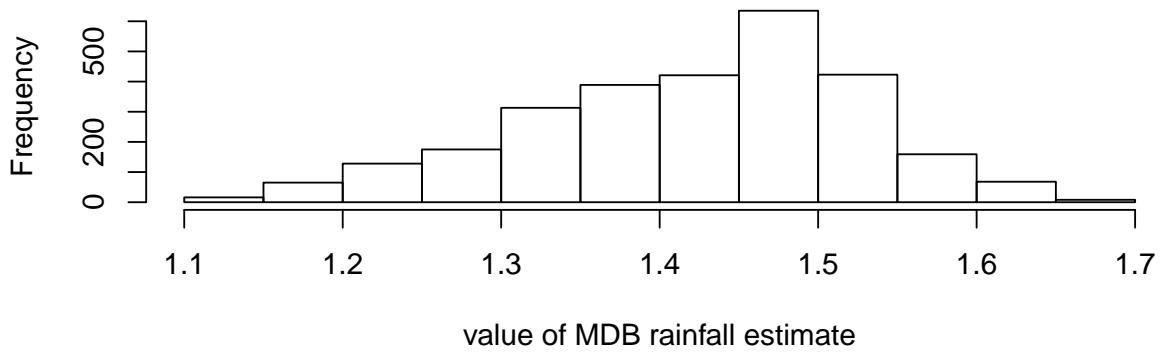
par(mfrow=c(2,1))
hist(MDB_nswvic, xlab = "value of MDB rainfall estimate", main="NSW full data period")
hist(MDB_qld, xlab = "value of MDB rainfall estimate", main="Qld full data period")

```

NSW full data period



Qld full data period



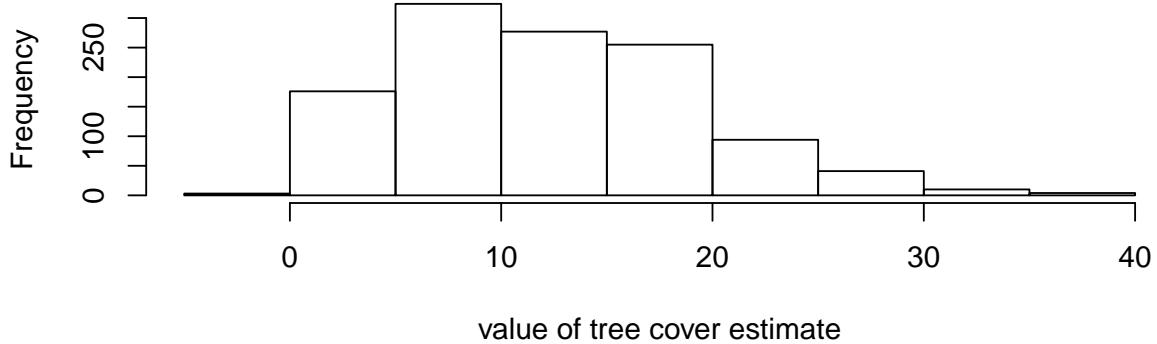
The value of the linear effect of the MDB rainfall is all positive and ranges from 0.8 - 2. Interestingly, in both locations, the rainfall is generally above the average monthly MDB rainfall.

Extract the sign of C, which is the tree cover effect.

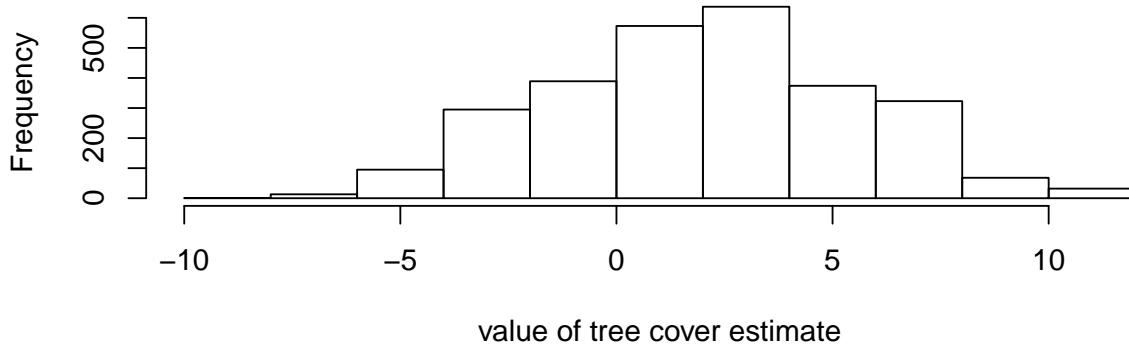
```
## extract sign of C (the tree cover effect)
C30_qld <- unlist(lapply(1:length(coef.rain30.qld4), function(x) ifelse(summary(coef.rain30.qld4)[x,2]==
# NSW/VIC
C30_nswvic <- unlist(lapply(1:length(coef.rain30.nswvic), function(x) ifelse(summary(coef.rain30.nswvic)
# NSW/VIC 7 year (includes 2009)
# C30_nswvic7 <- unlist(lapply(1:length(coef.rain30.nswvic7), function(x) ifelse(summary(coef.rain30.nswvic7)[x,2]==
# # NSW/VIC 8 year (includes 2010)
# C30_nswvic8 <- unlist(lapply(1:length(coef.rain30.nswvic8), function(x) ifelse(summary(coef.rain30.nswvic8)[x,2]==

par(mfrow=c(2,1))
hist(unlist(lapply(1:length(coef.rain30.nswvic), function(x) ifelse(summary(coef.rain30.nswvic)[x,2]=="g
hist(unlist(lapply(1:length(coef.rain30.qld4), function(x) ifelse(summary(coef.rain30.qld4)[x,2]=="gam",
```

NSW full data period



Qld full data period



Tree cover effect values are quite significant on a linear relationship, but they are not all significant (see below). For NSW/VIC they are all positive, but for QLD they are centered around 0. What does it mean when they are positive? It is categorical variable, which is ranked alphabetically, so “clear” = 1 and “tree” = 2. This means that a positive coefficient (on a linear scale) means there is more rainfall with tree cover and less when it is “clear”.

```
# p-value of the linear variables
pvalues_qld4 <- lapply(1:length(coef.rain30.qld4),
  function(x) summary(coef.rain30.qld4[[x]])$p.pv[2:4])

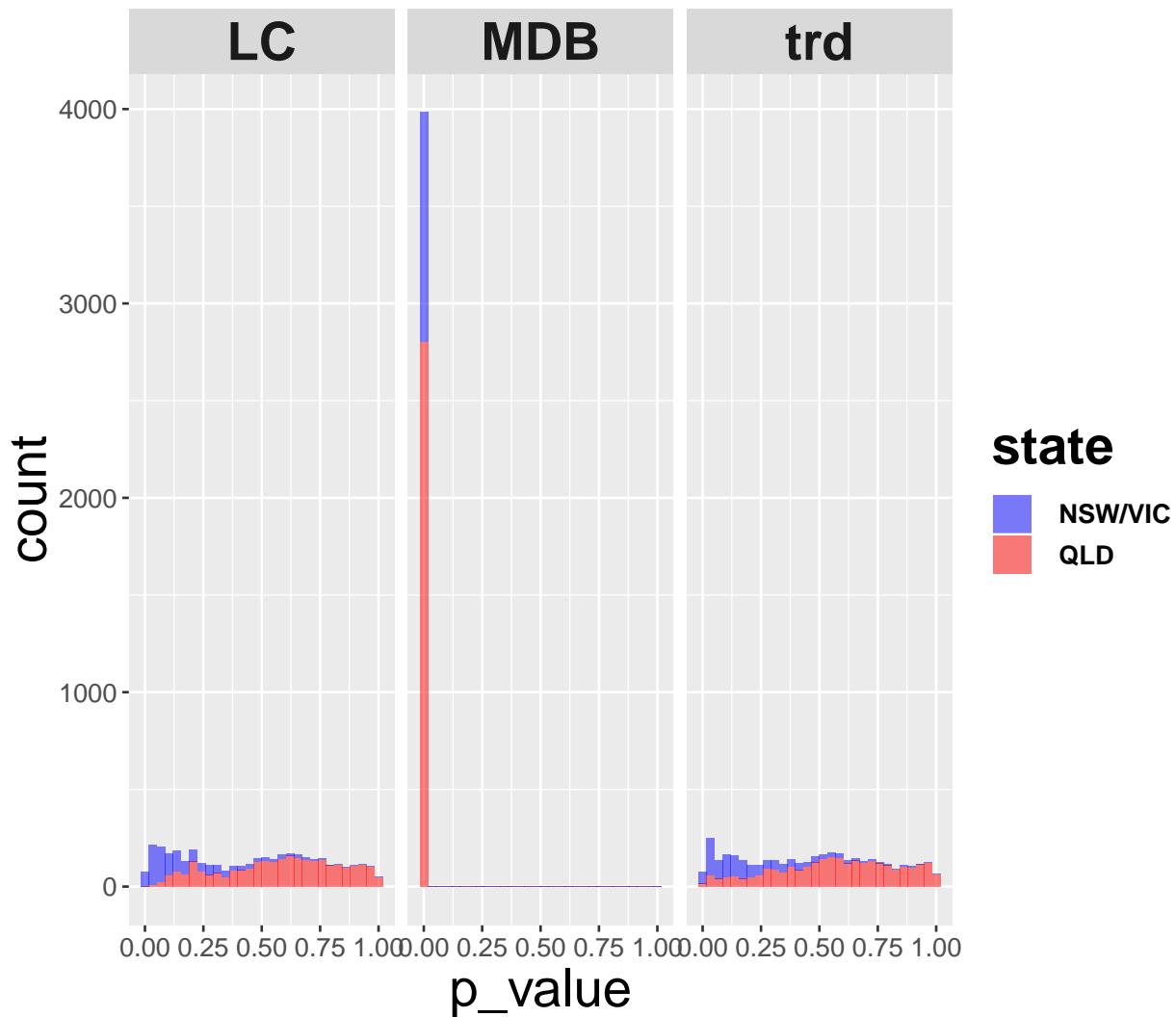
plinear_qld <- as.tibble(do.call(rbind,pvalues_qld4))
colnames(plinear_qld) = c("MDB", "LC", "trd")
plinear_qld$state <- "QLD"

# NSW all data
pvalues_nswvic <- lapply(1:length(coef.rain30.nswvic),
  function(x) summary(coef.rain30.nswvic[[x]])$p.pv[2:4])

plinear_nsw <- as.tibble(do.call(rbind,pvalues_nswvic))
colnames(plinear_nsw) = c("MDB", "LC", "trd")
plinear_nsw$state <- "NSW/VIC"
```

```
# plotting
p_plot_df <- rbind(plinear_qld, plinear_nsw)
p_plot_df %>%
  gather(key="Variable", value="p_value", MDB:trd) %>%
  ggplot(aes(p_value, fill=state)) + geom_histogram(alpha=0.5) +
  facet_wrap(~Variable) +
  scale_fill_manual(values = c("blue","red")) +
  theme(axis.title = element_text(size = rel(2)),
        axis.text = element_text(size=rel(1)),
        strip.text = element_text(face="bold", size= rel(2)),
        legend.text = element_text(face="bold", size= rel(1)),
        legend.title = element_text(face="bold", size= rel(2)))
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.



```
# produce also as jpeg
jpeg("figures/pvalues_linear_fullmodel.jpg", height=960, width=960)
p_plot_df %>%
  gather(key="Variable", value="p_value", MDB:trd) %>%
```

```

ggplot(aes(p_value,fill=state)) + geom_histogram(alpha=0.5) +
  facet_wrap(~Variable) +
  scale_fill_manual(values = c("blue","red")) +
  theme(axis.title = element_text(size = rel(2)),
        axis.text = element_text(size=rel(1)),
        strip.text = element_text(face="bold", size= rel(2)),
        legend.text = element_text(face="bold", size= rel(1)),
        legend.title = element_text(face="bold", size= rel(2)))

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
dev.off()

## pdf
## 2
rm(p_plot_df)

## p value of seasons and climate indices
p_qld <- do.call(rbind,
  lapply(1:length(coef.rain30.qld4), function(x) {
    ifelse(summary(coef.rain30.qld4)[x,2]=="gam",
           return(summary(coef.rain30.qld4[[x]])$s.pv),
           return(rep(NA,6))))))

p_qld <- as.tibble(p_qld)
colnames(p_qld) = c("SOI", "IOD", "NINO3.4", "NINO4")
p_qld$state <- "QLD"

p_nsw <- do.call(rbind,
  lapply(1:length(coef.rain30.nswvic), function(x) {
    ifelse(summary(coef.rain30.nswvic)[x,2]=="gam",
           return(summary(coef.rain30.nswvic[[x]])$s.pv),
           return(rep(NA,6))))))

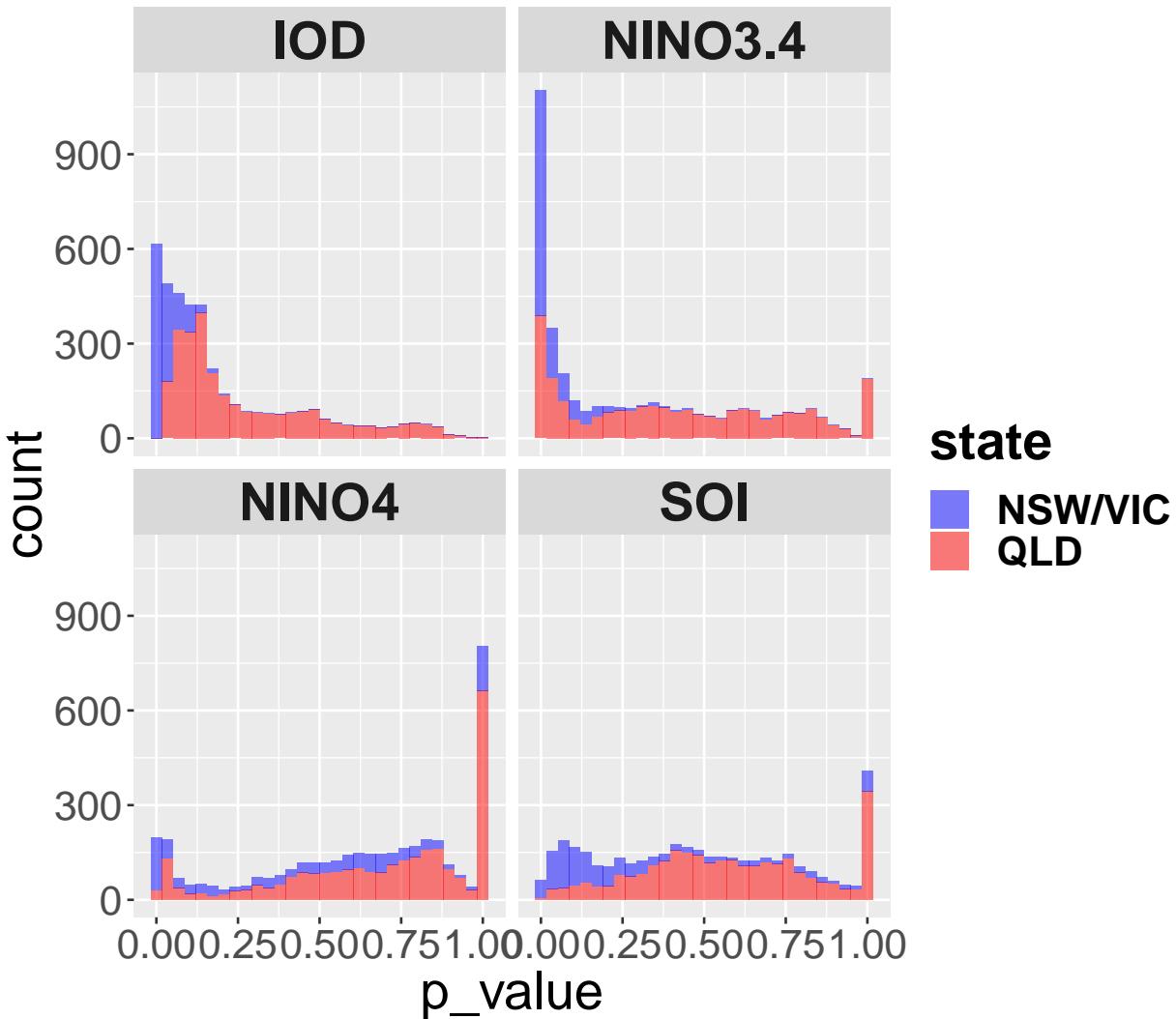
p_nsw <- as.tibble(p_nsw)
colnames(p_nsw) = c("SOI", "IOD", "NINO3.4", "NINO4")
p_nsw$state <- "NSW/VIC"

p_plot_df <- rbind(p_qld,p_nsw)

p_plot_df %>%
  gather(key="Variable", value="p_value", SOI:NINO4) %>%
  ggplot(aes(p_value,fill=state)) + geom_histogram(alpha=0.5) +
  facet_wrap(~Variable) +
  scale_fill_manual(values = c("blue","red")) +
  theme(axis.title = element_text(size = rel(2)),
        axis.text = element_text(size=rel(1.5)),
        strip.text = element_text(face="bold", size= rel(2)),
        legend.text = element_text(face="bold", size= rel(1.5)),
        legend.title = element_text(face="bold", size= rel(2)))

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

```



```
# produce also as jpg
jpeg("figures/pvalues_fullmodel.jpg", height=960, width=960)
p_plot_df %>%
  gather(key="Variable", value="p_value", SOI:NINO4) %>%
  ggplot(aes(p_value, fill=state)) + geom_histogram(alpha=0.5) +
  facet_wrap(~Variable) +
  scale_fill_manual(values = c("blue", "red")) +
  theme(axis.title = element_text(size = rel(2)),
        axis.text = element_text(size=rel(1.5)),
        strip.text = element_text(face="bold", size= rel(2)),
        legend.text = element_text(face="bold", size= rel(1.5)),
        legend.title = element_text(face="bold", size= rel(2)))

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
#dev.off()
rm(p_plot_df)
```

Clearly the MDB data is highly significant and takes out a lot of the variation in the model. This takes out quite a bit of variation out of the model for the climate indices, but at some locations these are still significant. It is also clear that the average MDB rainfall explains more of the variation in rainfall in QLD

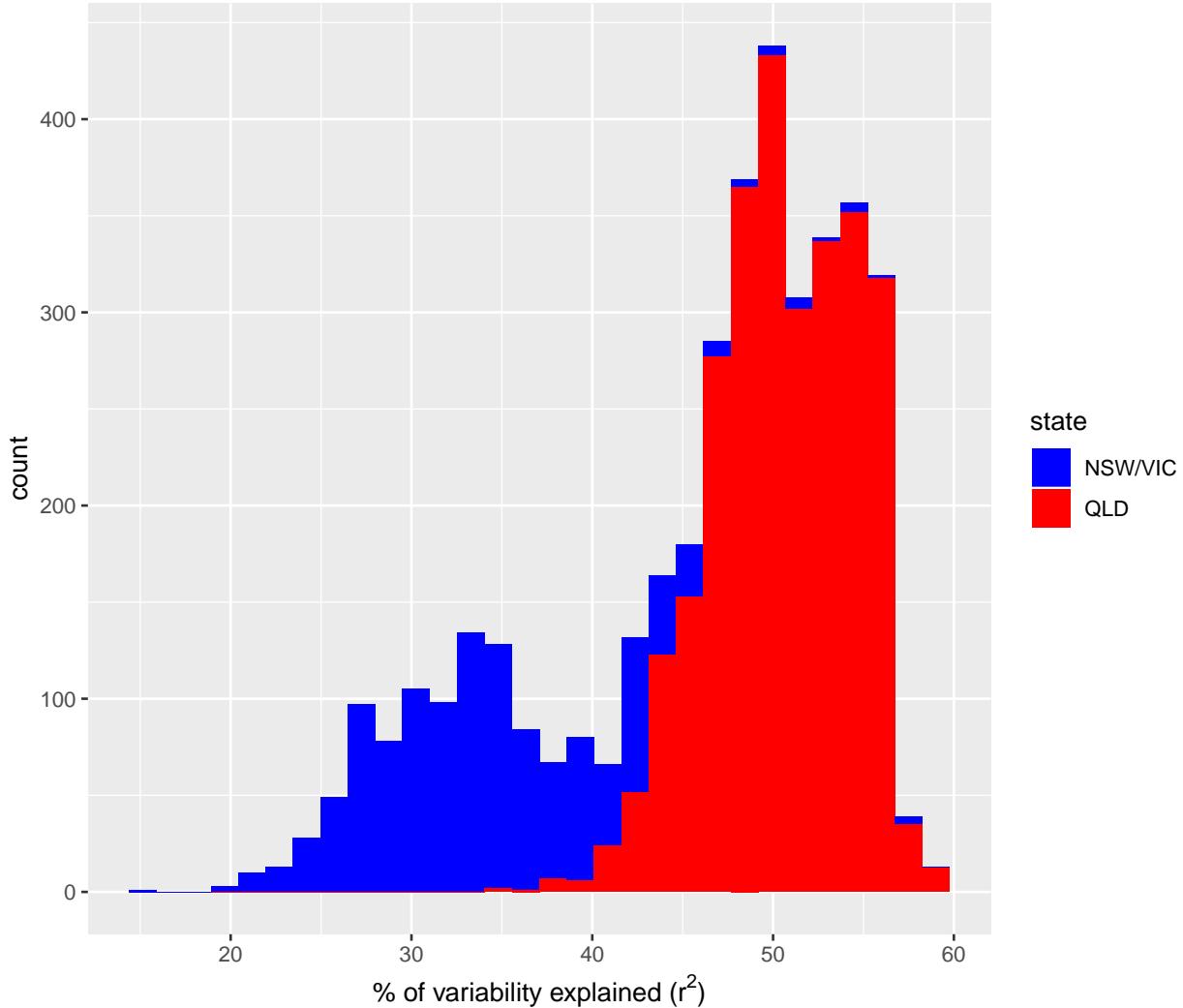
then it does in NSW/VIC. This is particularly clear in the significance of the other variables, which have much less significance in QLD.

```
## extract r.sq of the model
rsq_qld <- unlist(lapply(1:length(coef.rain30.qld4),
    function(x) ifelse(summary(coef.rain30.qld4)[x,2]=="gam",
        summary(coef.rain30.qld4[[x]])$r.sq,NA)))
rsq_nsw <- unlist(lapply(1:length(coef.rain30.nswvic),
    function(x) ifelse(summary(coef.rain30.nswvic)[x,2]=="gam",
        summary(coef.rain30.nswvic[[x]])$r.sq,NA)))

# show histogram
plot_df <- data_frame(`r.squared` = c(rsq_qld,rsq_nsw),
    state = c(rep("QLD", length(rsq_qld)),
        rep("NSW/VIC", length(rsq_nsw)))) 

#jpeg("../figures/rsq_fullmodel.jpg", height=480, width=480)
plot_df %>%
    ggplot(aes(`r.squared`*100, fill=state)) + geom_histogram() +
    scale_fill_manual(values = c("blue","red")) +
    xlab(expression(paste("% of variability explained (",r^2,")")))

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
#dev.off()

plot_df %>%
  group_by(state) %>%
  summarise(mean_rsq = mean(`r.squared`))

## # A tibble: 2 x 2
##   state   mean_rsq
##   <chr>     <dbl>
## 1 NSW/VIC  0.343
## 2 QLD      0.506

## frame of the two regions (100 years data)
qld_tif <- raster("Data\\BoM\\rainfall\\AWAP\\from1900_FVG\\r19000101_qld.tif")
nsw_tif <- raster("Data\\BoM\\rainfall\\AWAP\\from1900_FVG\\r19000101_nsw.tif")

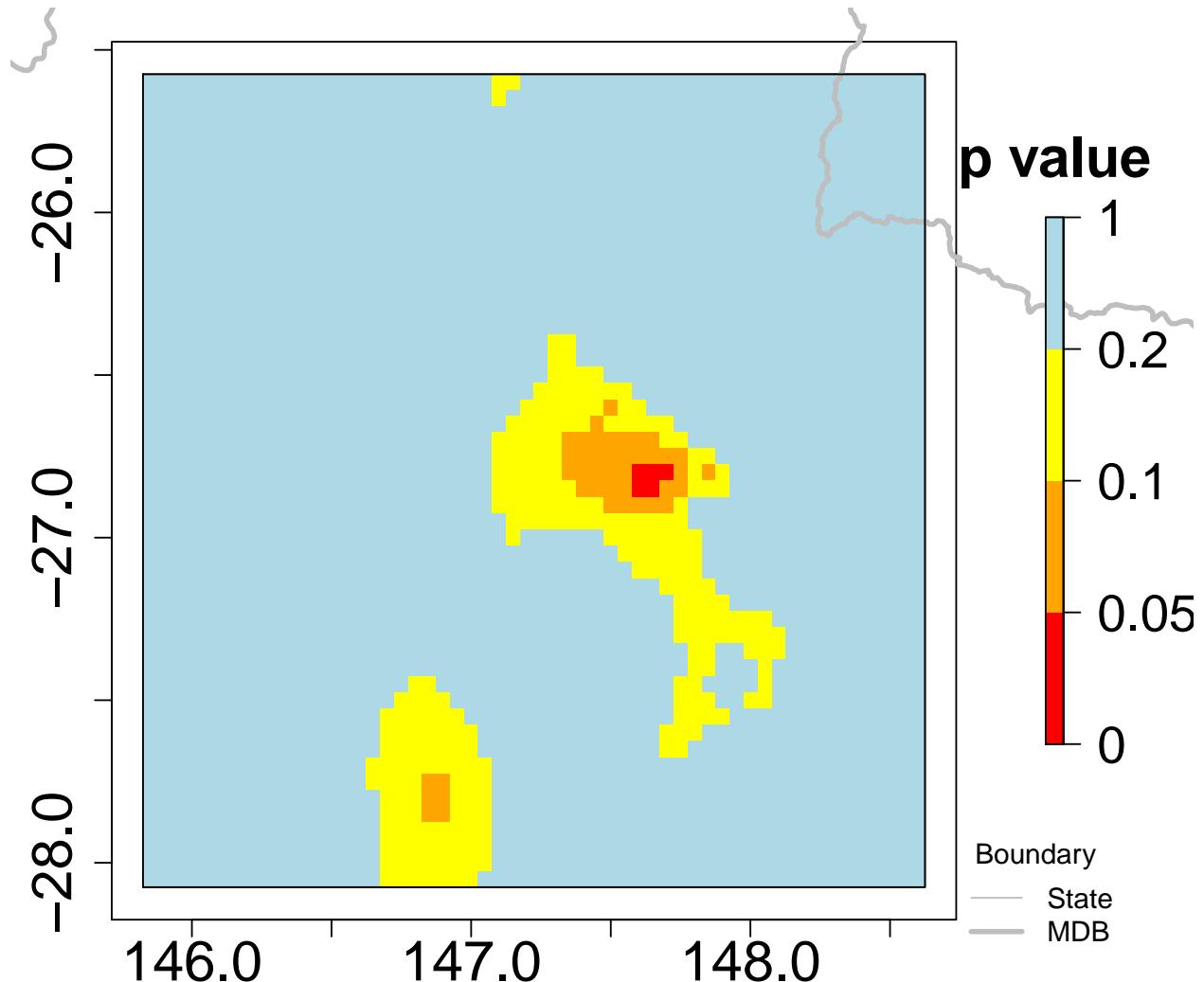
dist_Cp30_qld4 <- raster(qld_tif)
dist_Cp30_qld4[] <- plinear_qld$LC

# jpeg("../figures/Cp_30yrs_qld.jpg", width=1440, height=720)
```

```

# par(mfrow=c(1,2))
par(mar=c(3,3,1,7),xpd=T)
plot(e111,xlab="",ylab="", cex.lab = 2,
     cex.axis=2)
image(dist_Cp30_qld4,col=c("red","orange","yellow","light blue"),breaks=c(0,0.05,0.1,0.2,1),legend=F,
      plot(aus_reg, border="grey",add=T)
plot(mdb_reg, border="grey",lwd=3,add=T)
plot(e111,add=T)
image.plot(zlim=c(0,4),breaks=c(0,1,2,3,4),lab.breaks=c(0,0.05,0.1,0.2,1),legend.only=T,horizontal=F,
legend(148.7,-27.9,c("State","MDB"),col=c("grey","grey"),lwd=c(1,3),bty="n",title="Boundary",cex=1)

```



```

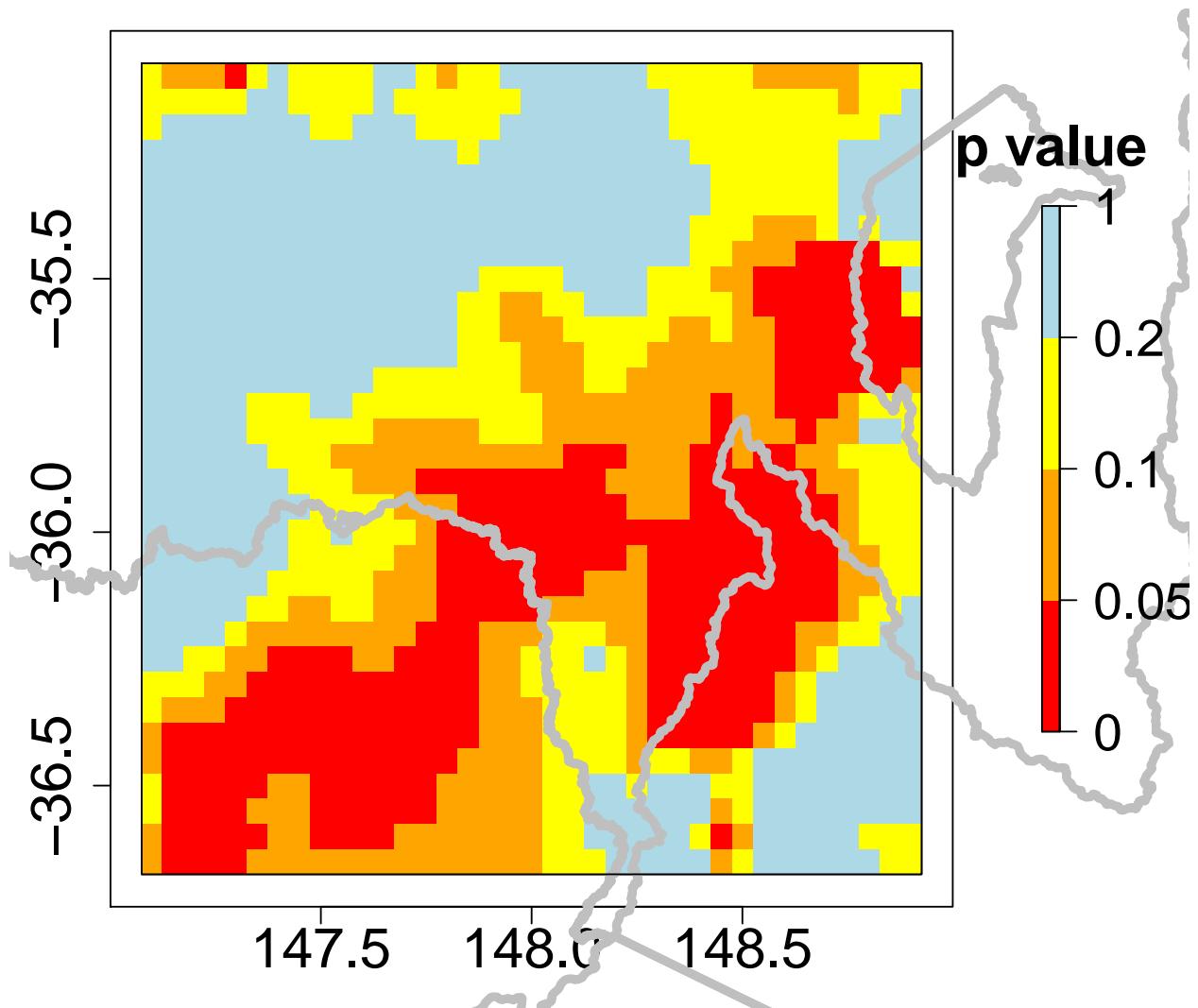
dist_Cp30_nsw <- raster(nsw_tif)
dist_Cp30_nsw[] <- plinear_nsw$LC
#
# jpeg("../figures/Cp_30yrs_nsuvic.jpg", width=1440, height=720)
# par(mfrow=c(1,3))
par(mar=c(3,3,1,7),xpd=T)
plot(e222,xlab="",ylab="", cex.lab = 2,
     cex.axis=2) #,border="white")

```

```

image(dist_Cp30_nsw,col=c("red","orange","yellow","light blue"),breaks=c(0,0.05,0.1,0.2,1),legend=F,add=T)
plot(aus_reg,border="grey75",lwd=5,add=T)
plot(mdb_reg,border="grey75",lwd=5,add=T)
plot(e222,add=T)
image.plot(zlim=c(0,4),breaks=c(0,1,2,3,4),lab.breaks=c(0,0.05,0.1,0.2,1),legend.only=T,horizontal=F,

```



```
#dev.off()
```

```

# Now make the final plot for the paper with both sites all data
# jpeg("../figures/Cp_30yrs.jpg", width=1440, height=1440)
par(mfrow=c(2,1))
# NSW first
par(mar=c(3,3,1,9),xpd=T)
plot(e222,xlab="",ylab="", cex.lab = 2,
      cex.axis=2, #,border="white")
image(dist_Cp30_nsw,col=c("red","orange","yellow","light blue"),breaks=c(0,0.05,0.1,0.2,1),legend=F,add=T)
plot(aus_reg,border="grey75",lwd=5,add=T)
plot(mdb_reg,border="grey75",lwd=5,add=T)

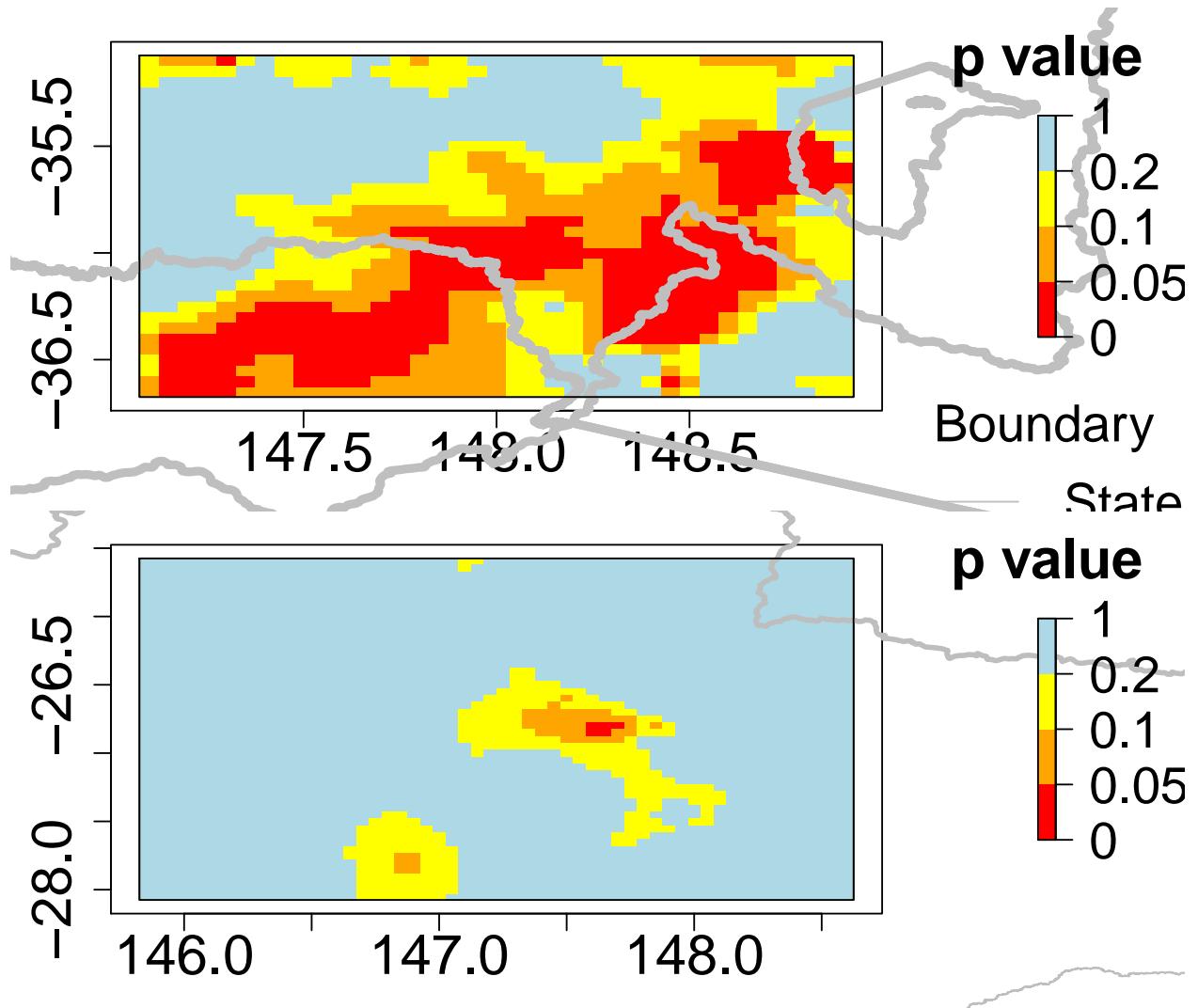
```

```

plot(e222,add=T)
image.plot(zlim=c(0,4),breaks=c(0,1,2,3,4),lab.breaks=c(0,0.05,0.1,0.2,1),legend.only=T,horizontal=F,
legend(149,-36.6,c("State","MDB"),col=c("grey","grey"),
lwd=c(1,3),bty="n",title="Boundary",cex=1.8)
#dev.off()

# Then qld
par(mar=c(3,3,1,9),xpd=T)
plot(e111,xlab="",ylab="", cex.lab = 2,
cex.axis=2)
image(dist_Cp30_qld4,col=c("red","orange","yellow","light blue"),breaks=c(0,0.05,0.1,0.2,1),legend=F,
plot(aus_reg,border="grey",add=T)
plot(mdb_reg,border="grey",lwd=3,add=T)
plot(e111,add=T)
image.plot(zlim=c(0,4),breaks=c(0,1,2,3,4),lab.breaks=c(0,0.05,0.1,0.2,1),legend.only=T,horizontal=F,

```



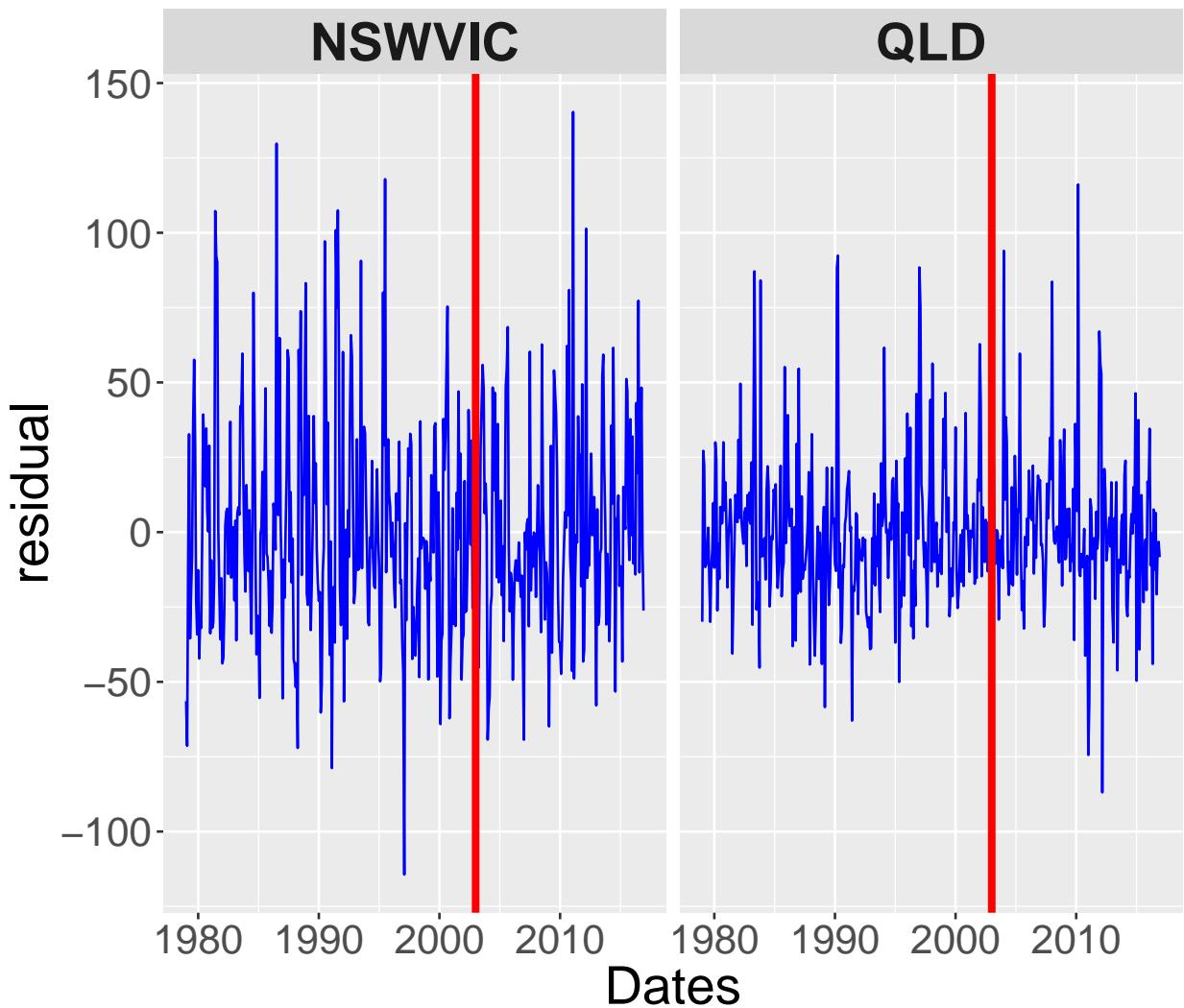
Overall, more of the variation in the rainfall is explained in QLD compared to NSW/VIC by the model. The NSW/VIC model shows an almost bimodal distribution of the r-squared.

In terms of the spatial distribution of the significance of the tree cover (LC) effect, there is little evidence of a

consistent change in the rainfall due to tree cover in QLD. However across the NSW/VIC area there is a significant area of change, and as indicated earlier, this change is all positive, suggesting more rainfall with tree cover.

Rainfall model residuals

```
#  
resid_qld <- lapply(1:length(coef.rain30.qld4), function(x) if(summary(coef.rain30.qld4)[x,2]=="gam") {  
  
# ## calculate mean residual  
test <- do.call(cbind,resid_qld)  
qld.resid.mean <- apply(test,1, mean,na.rm=T)  
residuals <- data_frame(Dates = seq.Date(as.Date("1979-01-01"),  
length = length(qld.resid.mean),  
by = "month"),  
QLD = qld.resid.mean)  
  
#  
resid_nswvic <- lapply(1:length(coef.rain30.nswvic),  
function(x) if(summary(coef.rain30.nswvic)[x,2]=="gam")  
{residuals(coef.rain30.nswvic[[x]])} else{NA})  
  
## calculate mean residual  
test <- do.call(cbind,resid_nswvic)  
nswvic.resid.mean <- apply(test,1, mean,na.rm=T)  
residuals$NSWVIC <- nswvic.resid.mean  
  
## plots  
residuals %>%  
gather(key="State", value="residual", QLD, NSWVIC) %>%  
ggplot(aes(Dates,residual)) + geom_line(colour="blue") +  
geom_vline(xintercept=as.numeric(as.Date("2003-01-01")), colour="red",  
size=1.5) +  
facet_wrap(~State) +  
theme(axis.text = element_text(size=rel(1.5)),  
axis.title = element_text(size=rel(2)),  
strip.text = element_text(size=rel(2), face = "bold"))
```



```

jpeg("figures/GAMresidualTime.jpeg", height=960, width=960)
residuals %>%
  gather(key="State", value="residual", QLD, NSWVIC) %>%
  ggplot(aes(Dates,residual)) + geom_line(colour="blue") +
  geom_vline(xintercept=as.numeric(as.Date("2003-01-01")), colour="red",
             size=1.5) +
  facet_wrap(~State) +
  theme(axis.text = element_text(size=rel(1.5)),
        axis.title = element_text(size=rel(2)),
        strip.text = element_text(size=rel(2), face = "bold"))
dev.off()

## pdf
## 2
#
#
## plot gam.check
jpeg("figures/gam_check.jpg", width=720, height=960)
par(mfrow=c(4,2))
gam.check(coef.rain30.qld4[[1]])

```

```

##  

## Method: GCV Optimizer: magic  

## Smoothing parameter selection converged after 16 iterations.  

## The RMS GCV score gradient at convergence was 4.824291e-05 .  

## The Hessian was positive definite.  

## Model rank = 12 / 12  

##  

## Basis dimension (k) checking results. Low p-value (k-index<1) may  

## indicate that k is too low, especially if edf is close to k'.  

##  

##          k'      edf k-index p-value  

## s(SOI)    2.00e+00 1.22e-10   0.99    0.40  

## s(IOD)    2.00e+00 3.12e-10   1.00    0.49  

## s(NIN03.4) 2.00e+00 8.29e-11   1.03    0.76  

## s(NIN04)   2.00e+00 9.78e-11   0.95    0.14  

  gam.check(coef.rain30.nswvic[[1]])  

##  

## Method: GCV Optimizer: magic  

## Smoothing parameter selection converged after 16 iterations.  

## The RMS GCV score gradient at convergence was 1.876017e-05 .  

## The Hessian was positive definite.  

## Model rank = 12 / 12  

##  

## Basis dimension (k) checking results. Low p-value (k-index<1) may  

## indicate that k is too low, especially if edf is close to k'.  

##  

##          k'      edf k-index p-value  

## s(SOI)    2.00e+00 3.10e-10   1.01    0.66  

## s(IOD)    2.00e+00 1.79e+00   0.99    0.36  

## s(NIN03.4) 2.00e+00 1.66e+00   0.99    0.40  

## s(NIN04)   2.00e+00 9.20e-11   1.00    0.43  

  dev.off()  

## pdf  

## 2

```

Step 3 Residual trend analysis for model without tree cover

This is the same model as above, but we have removed the tree cover variable.

```

## predicting model: land cover is category variable
rain.trend3 <- function(x,y,var.data) {
  # add a very small number to take out 0 values
  var.data$rain <- as.vector(unlist(y[x]))[1:nrow(var.data)]+0.0001

  rain_fit <- gam(rain ~ MDB
                  + s(SOI, k=3, bs="cs")
                  + s(IOD, k=3, bs="cs")
                  #+ s(PDO, k=3, bs="cs")
                  + s(NIN03.4, k=3, bs="cs"))

```

```

+ s(NIN04, k=3, bs="cs")
+ trd
, data=var.data, #family=Gamma(link=log),
na.action = na.omit)
#
return(rain_fit)

}

## run model for 37 years
mod_rain_qld4 <- lapply(2:ncol(rainQld_t),
                         function(x) rain.trend3(x, rainQld_t, var.qld4))
mod_rain_qld2 <- lapply(2:ncol(rainQld_t),
                         function(x) rain.trend3(x, rainQld_t, var.qld2))
## QLD
rsq_qld <- unlist(lapply(1:length(mod_rain_qld4),
                           function(x) summary(mod_rain_qld4[[x]])$r.sq))
#
#
## extract residual
residual_qld <- lapply(1:length(mod_rain_qld4),
                       function(x) {mod_rain_qld4[[x]]$y-fitted(mod_rain_qld4[[x]])})

residual_qld2 <- lapply(1:length(mod_rain_qld2),
                        function(x) {mod_rain_qld2[[x]]$y-fitted(mod_rain_qld2[[x]])})

#
# ## NSW/VIC
#
#NSW/VIC
mod_rain_nswvic <- lapply(2:ncol(rainNSW_t),
                           function(x) rain.trend3(x, rainNSW_t, var.data))

## explaining power of the partial model
rsq_nswvic <- unlist(lapply(1:length(mod_rain_nswvic),
                            function(x) summary(mod_rain_nswvic[[x]])$r.sq))
#
#
# extract residual
residual_nswvic <- lapply(1:length(mod_rain_nswvic),
                           function(x) {mod_rain_nswvic[[x]]$y-fitted(mod_rain_nswvic[[x]])})

```

partial r-sq

We can now analyse the residuals and the models. First we look at the partial explaining power of the climate indices in the model

```

# histogram of partial model rsq
qld_df <- data.frame(rsq = rsq_qld*100,
                      state = "Qld")
nsw_df <- data.frame(rsq = rsq_nswvic*100,
                      state = "NSW/VIC")

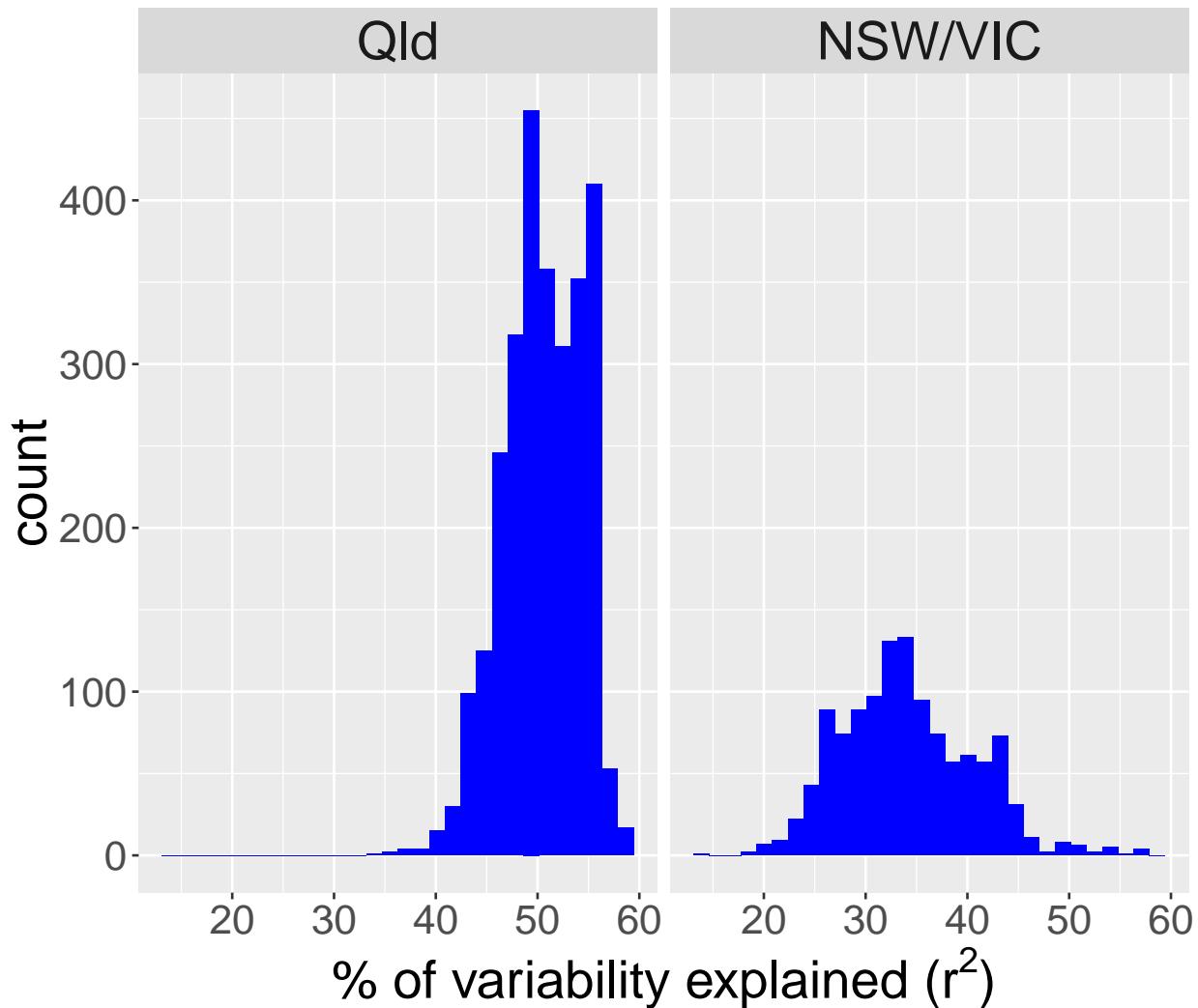
```

```

plot_df <- rbind(qld_df, nsw_df)
#jpeg("../figures/pmodel_explHistogram.jpg")
plot_df %>%
  ggplot(aes(rsq)) + geom_histogram(fill="blue") +
  facet_wrap(~state) +
  xlab(expression(paste("% of variability explained (",r^2,")"))) +
  theme(axis.text = element_text(size=rel(1.5)),
        strip.text = element_text(size=rel(2)),
        axis.title = element_text(size=rel(2)))

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

```



```
# dev.off()
```

Similar to earlier graph, shows that more of the variation is explained in Qld compared to NSW/VIC.

Residual distributions and t-test

We can now analyse the residuals in more detail and look at t-tests

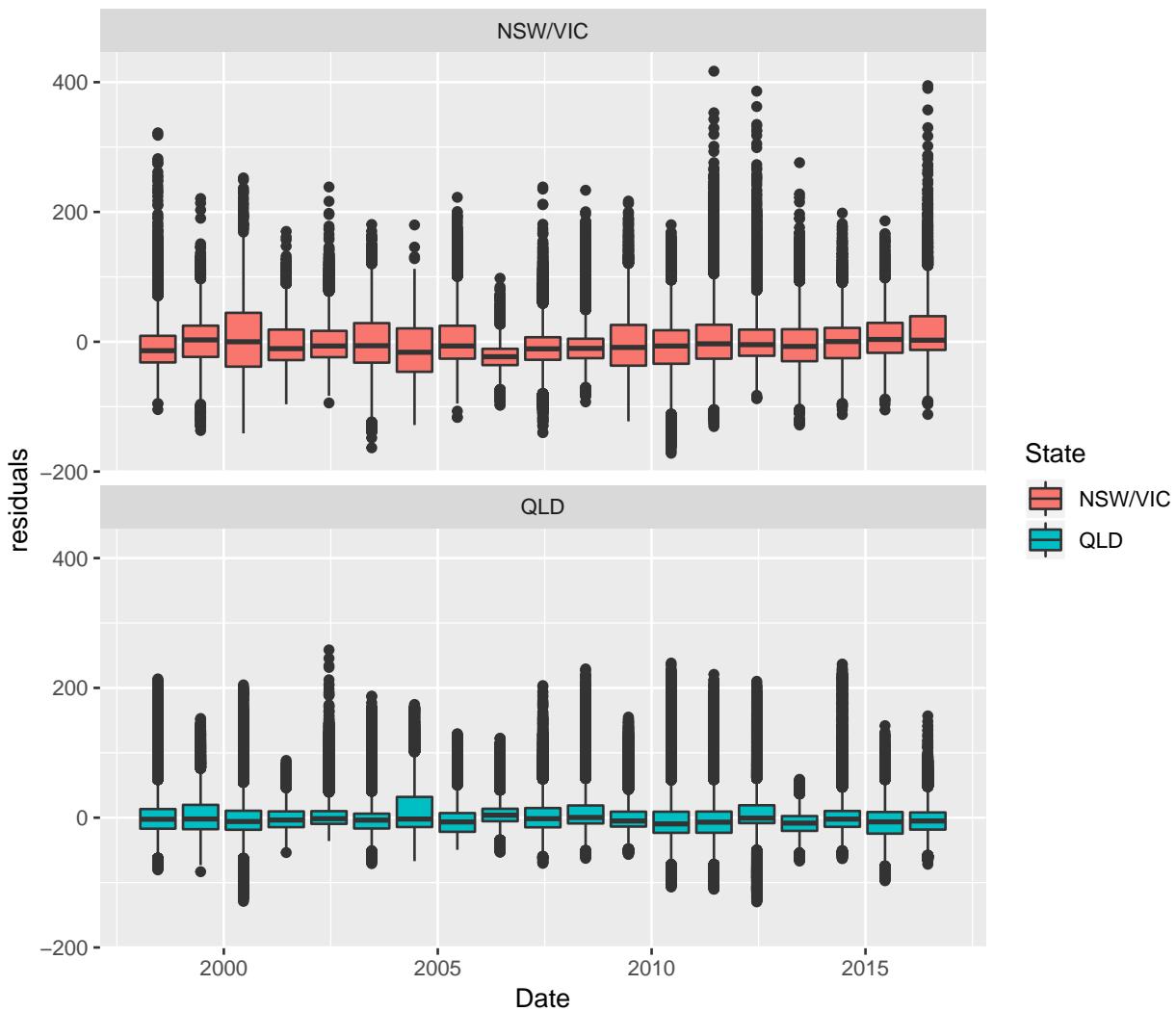
```

# stack the residuals

# create a boxplot with the annual residuals from 1998
resplot_df <- data_frame(Date = rep(ymd(rainNSW_t[[1]]),
                           length(residual_nswvic)+length(residual_qld)),
                           residuals = c(unlist(residual_nswvic),
                           State = c(rep("NSW/VIC",
                                         length(unlist(residual_nswvic))),
                           rep("QLD", length(unlist(residual_qld)))))

resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  ggplot(aes(Date,residuals, fill=State)) +
  geom_boxplot(aes(group=year(Date))) +
  facet_wrap(~State, ncol=1)

```



```

jpeg("figures/ResidualBoxplot.jpg")
resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  ggplot(aes(Date,residuals, fill=State)) +

```

```

geom_boxplot(aes(group=year(Date))) +
  facet_wrap(~State, ncol=1)
dev.off()

## pdf
## 2

# residuals before and after change
#par(mfrow=c(1,2))
jpeg("figures/ResidualBoxplotchange.jpg")
p1 <- resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  mutate(Change = ifelse(year(Date) > 2003, "After", "Before")) %>%
  ggplot(aes(Change,residuals, fill= State)) +
  geom_boxplot(aes(group=Change)) + facet_wrap(~State, ncol=1) +
  guides(fill=FALSE) + ggtitle("whole period")
#dev.off()

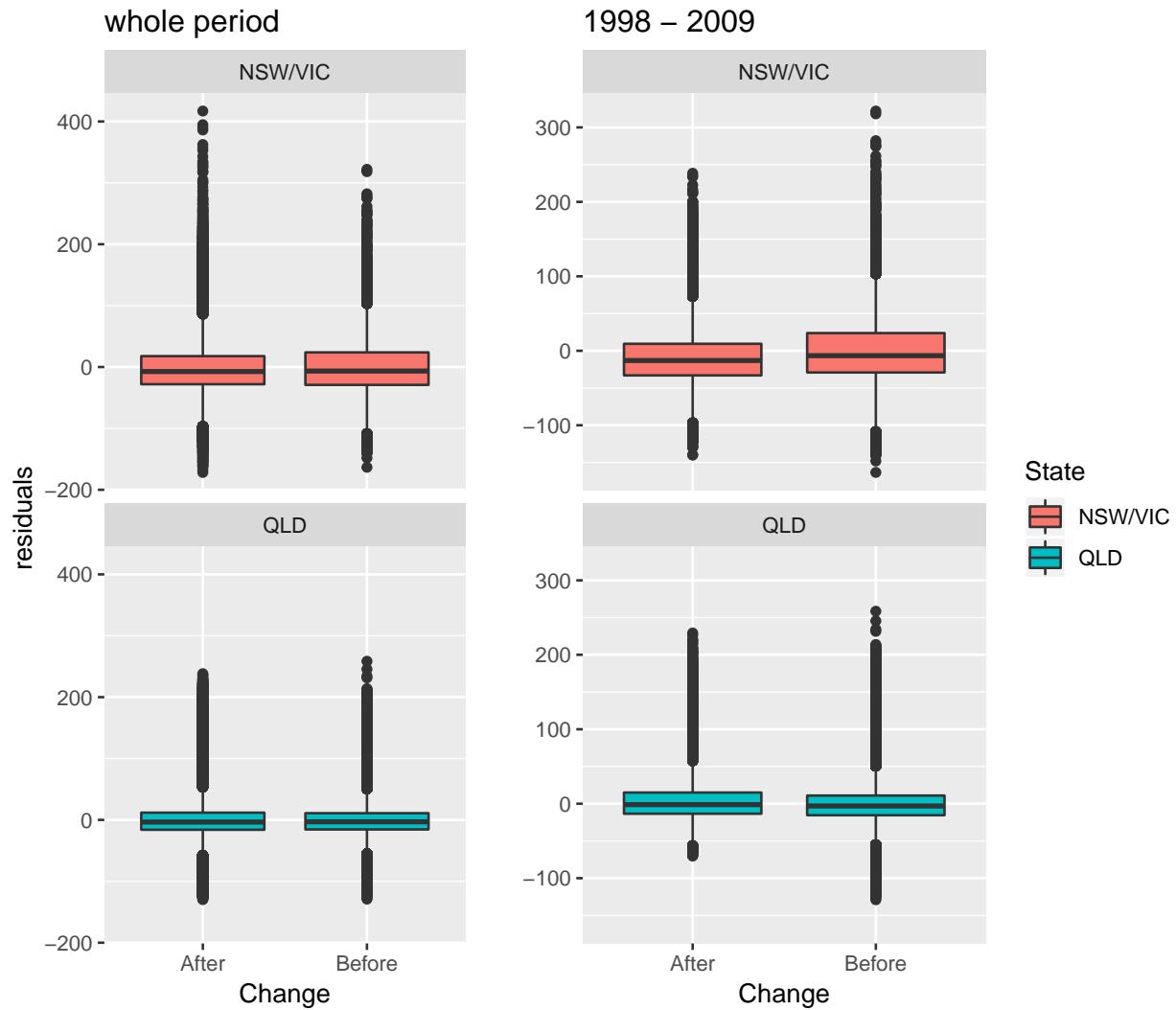
#jpeg("../figures/ResidualBoxplotchange2.jpg")
p2 <- resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  mutate(Change = ifelse(year(Date) > 2003, "After", "Before")) %>%
  filter(year(Date) < 2010) %>%
  ggplot(aes(Change,residuals, fill = State)) +
  geom_boxplot(aes(group=Change)) + facet_wrap(~State, ncol=1) +
  ylab(label="") + ggtitle("1998 - 2009")
lay <- rbind(c(1,1,2,2,2))
grid.arrange(p1,p2, layout_matrix = lay)
dev.off()

## pdf
## 2

p1 <- resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  mutate(Change = ifelse(year(Date) > 2003, "After", "Before")) %>%
  ggplot(aes(Change,residuals, fill= State)) +
  geom_boxplot(aes(group=Change)) + facet_wrap(~State, ncol=1) +
  guides(fill=FALSE) + ggtitle("whole period")
#dev.off()

#jpeg("../figures/ResidualBoxplotchange2.jpg")
p2 <- resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  mutate(Change = ifelse(year(Date) > 2003, "After", "Before")) %>%
  filter(year(Date) < 2010) %>%
  ggplot(aes(Change,residuals, fill = State)) +
  geom_boxplot(aes(group=Change)) + facet_wrap(~State, ncol=1) +
  ylab(label="") + ggtitle("1998 - 2009")
lay <- rbind(c(1,1,2,2,2))
grid.arrange(p1,p2, layout_matrix = lay)

```



```

res2 <- resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  mutate(Change = ifelse(year(Date) > 2003, "After", "Before")) %>%
#filter(year(Date) < 2010) %>%
  filter(State == "QLD")

summary(lm(residuals~Change-1,data=res2))

##
## Call:
## lm(formula = residuals ~ Change - 1, data = res2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -130.247  -16.526   -4.066  10.787  257.426 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## ChangeAfter    0.51053    0.04775   10.69   <2e-16 ***
## ChangeBefore   1.09829    0.07028   15.63   <2e-16 ***

```

```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 31.56 on 638398 degrees of freedom
## Multiple R-squared:  0.0005613, Adjusted R-squared:  0.0005582
## F-statistic: 179.3 on 2 and 638398 DF, p-value: < 2.2e-16
t.test(formula=residuals~Change,data=res2)

##
## Welch Two Sample t-test
##
## data: residuals by Change
## t = -7.3884, df = 463150, p-value = 1.489e-13
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.7436809 -0.4318422
## sample estimates:
## mean in group After mean in group Before
##           0.5105269           1.0982884
# No significant difference if measured to 2010 and slightly less rain (p < 0.05) before if measured to

res2 <- resplot_df %>%
  filter(Date >= ymd("1998-01-01")) %>%
  mutate(Change = ifelse(year(Date) > 2003, "After", "Before")) %>%
  #filter(year(Date) < 2010) %>%
  filter(State != "NSW/VIC")

summary(lm(residuals~Change-1,data=res2))

##
## Call:
## lm(formula = residuals ~ Change - 1, data = res2)
##
## Residuals:
##      Min       1Q     Median       3Q      Max
## -130.247   -16.526    -4.066   10.787  257.426
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## ChangeAfter  0.51053    0.04775   10.69   <2e-16 ***
## ChangeBefore 1.09829    0.07028   15.63   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 31.56 on 638398 degrees of freedom
## Multiple R-squared:  0.0005613, Adjusted R-squared:  0.0005582
## F-statistic: 179.3 on 2 and 638398 DF, p-value: < 2.2e-16
t.test(formula=residuals~Change,data=res2)

##
## Welch Two Sample t-test
##

```

```
## data: residuals by Change
## t = -7.3884, df = 463150, p-value = 1.489e-13
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.7436809 -0.4318422
## sample estimates:
## mean in group After mean in group Before
## 0.5105269 1.0982884
```

This does suggest that the residuals are significantly different before and after the change in landcover

step 4 Analysis of the residuals Mann-Whitney rank-sum statistic

This mainly follows the original paper, except we will go straight for the averaging by 4 cells. The bootstrap analysis is also just run on the HPC, and we only pull in the results here.

```

v.1 <- ts(y.1[c(229:length(y.1))],
            start=c(1997,1),frequency=12)
v.2 <- ts(y.2[c(229:length(y.2))],
            start=c(1997,1),frequency=12)
v.3 <- ts(y.3[c(229:length(y.3))],
            start=c(1997,1),frequency=12)
v.4 <- ts(y.4[c(229:length(y.4))],
            start=c(1997,1),frequency=12)
}

## rank by month
for (j in 1:12) {
  assign(paste("r1",j,sep=""),rank(subset(v.1,cycle(v.1)==j)))
  assign(paste("r2",j,sep=""),rank(subset(v.2,cycle(v.2)==j)))
  assign(paste("r3",j,sep=""),rank(subset(v.3,cycle(v.3)==j)))
  assign(paste("r4",j,sep=""),rank(subset(v.4,cycle(v.4)==j)))

}

## mann-whitney rank sum statistic
rlist.1 <- list(r11,r12,r13,r14,r15,r16,r17,r18,r19,r110,r111,r112) ## full year
rlist.2 <- list(r21,r22,r23,r24,r25,r26,r27,r28,r29,r210,r211,r212)
rlist.3 <- list(r31,r32,r33,r34,r35,r36,r37,r38,r39,r310,r311,r312)
rlist.4 <- list(r41,r42,r43,r44,r45,r46,r47,r48,r49,r410,r411,r412)
rlist <- list(unlist(rlist.1),unlist(rlist.2),unlist(rlist.3),unlist(rlist.4))

w.s1 <- 0
w.s2 <- 0
w.s3 <- 0
w.s4 <- 0

for (k in 1:length(rlist.1)) {
  w.s1 <- sum(rlist.1[[k]][1:n1])+w.s1
  w.s2 <- sum(rlist.2[[k]][1:n1])+w.s2
  w.s3 <- sum(rlist.3[[k]][1:n1])+w.s3
  w.s4 <- sum(rlist.4[[k]][1:n1])+w.s4
}
w.s <- sum(w.s1,w.s2,w.s3,w.s4) #,w.s5,w.s6,w.s7,w.s8,w.s9)

## other statistic
# mean for full year
mu <- n1*(n1+n2+1)/2
mu.s <- 12*4*mu

## variance (standard variation). The autocorrelation of the residuals can be assumed to be null (check)
# assume only cross correlation
ss <- n1*n2*(n1+n2+1)/12
ss.s <- 0
for (kk in 1:4) {
  for (kkk in 1:4) {
    #      for (kkkk in 1:12) {
      ss.s <- 12*ss*cor(rlist[[kk]],rlist[[kkk]]) + ss.s
    #
  }
}

```

```

    }

## step trend statistic
z <- (w.s - mu.s)/sqrt(ss.s)

return(z) }

else {return(NA)} }

else {return(NA)}

}

## 30 years
## full year,
## central QLD
qld.z.new <- unlist(lapply(1:(length(residual_qld)-57),function(x) stepTrend2(x,residual_qld,1)))
qld.z.new <- c(qld.z.new,rep(NA,57))
tr_qld.step.new <- raster(qld_tif)
tr_qld.step.new[] <- qld.z.new

## NSW
nswvic.z.new <- unlist(lapply(1:(length(residual_nswvic)-38),function(x) stepTrend2(x,residual_nswvic
nswvic.z.new <- c(nswvic.z.new,rep(NA,38))

tr_nswvic.step.new <- raster(nsw.tif)
tr_nswvic.step.new[] <- nswvic.z.new
plotclt <- rev(brewer.pal(8,"RdYlBu"))

jpeg("figures/step_new.jpg", width=1240, height=960, quality=100)
par(mar=c(3,3,1,9), mfrow=c(2,2), xpd=T)
plot(e222,xlab="",ylab="", cex.axis=2)#,border="white")
image(tr_nswvic.step.new,col=plotclt,breaks=c(-2.3,-1.645,-1.282,-0.842,0,0.842,1.282,1.645,3),legend=F)
plot(mdb_reg2,border="grey",add=T,lwd=3)
plot(aus_reg2,border="grey",add=T)
plot(e222,add=T)
image.plot(zlim=c(-4,4),breaks=c(-4,-3,-2,-1,0,1,2,3,4),lab.breaks=c(0.00,0.05,0.1,0.2,1,0.2,0.1,0.05,0
legend(149,-36.6,c("State","MDB"),col=c("grey","grey"),
lwd=c(1,3),bty="n",title="Boundary",cex=1.8)

# Qld
par(mar=c(3,3,1,9),xpd=T)
plot(e111,xlab="",ylab="", cex.axis=2)#,border="white")
image(tr_qld.step.new,col=plotclt,breaks=c(-3,-1.645,-1.282,-0.842,0,0.842,1.282,1.645,3),legend=F,add=T)
plot(mdb_reg2,border="grey",add=T,lwd=3)
plot(e111,add=T)
image.plot(zlim=c(-4,4),breaks=c(-4,-3,-2,-1,0,1,2,3,4),lab.breaks=c(0.00,0.05,0.1,0.2,1,0.2,0.1,0.05,0

dev.off()

## pdf
## 2

```

```

#ns = 4 results
# positive
qld_origp.new <- length(subset(qld.z.new,qld.z.new>=1.645))/
  length(qld.z.new)
# 0.00034
# negative
qld_origin.new <- length(subset(qld.z.new,qld.z.new<=-1.645))/ 
  length(qld.z.new)
# 0

nsw_origp.z.new <- length(subset(nswvic.z.new,nswvic.z.new>=1.645))/ 
  length(nswvic.z.new)
# 0
nsw_origin.z.new <- length(subset(nswvic.z.new,nswvic.z.new<=-1.645))/ 
  length(nswvic.z.new)
# 0

```

Bootstrap analysis was moved the HPC in January 2019.

Read in results from the HPC bootstrap analysis of the z values.

```

NSW_zvalues <- readRDS("processed data/NSW_zvalues.RDS")
QLD_zvalues <- readRDS("processed data/QLD_zvalues.RDS")

```

Create bootstrap histograms of the results

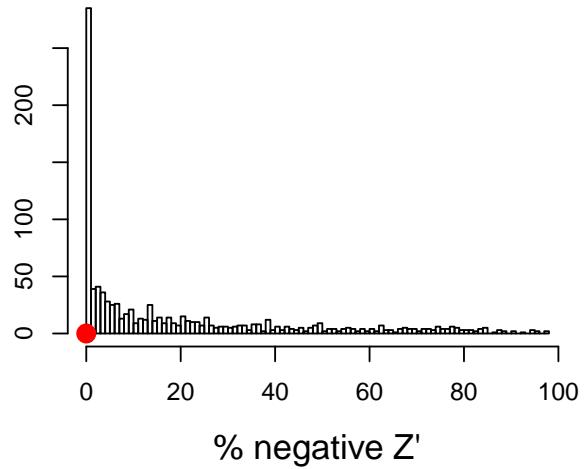
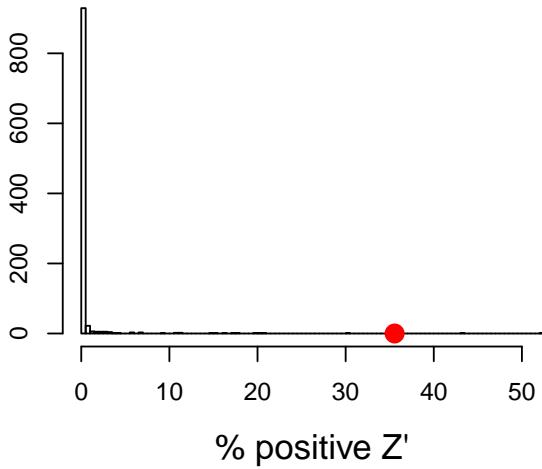
```

bt4_nsdp.values <- NSW_zvalues$zpq.values*100
bt4_nsn.values <- NSW_zvalues$znq.values*100
bt4_qldp.values <- QLD_zvalues$zpq.values*100
bt4_qldn.values <- QLD_zvalues$znq.values*100

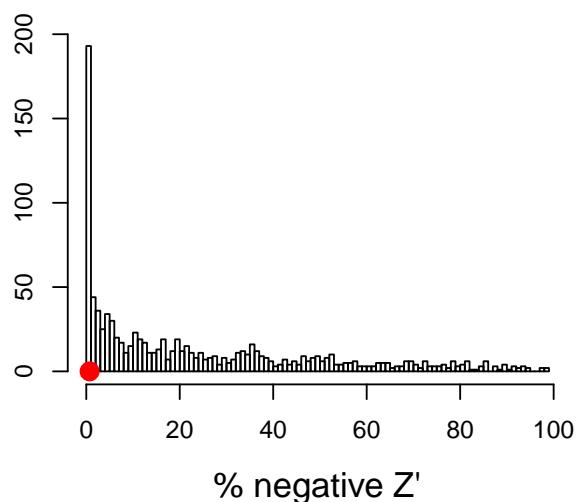
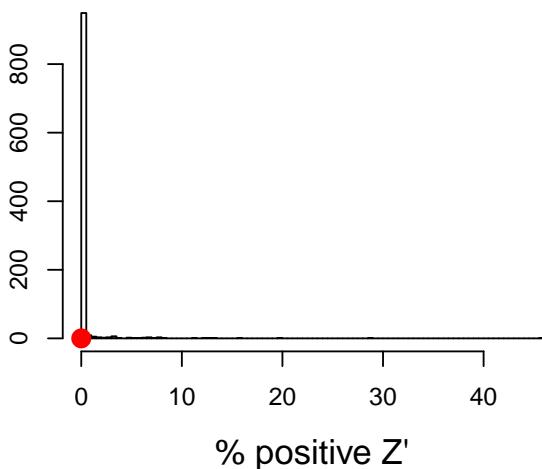
#jpeg("figures/bt4_hist.jpg")
par(mfrow=c(2,2), mar = c(4,3,2,1)+0.1)
# nsw pos
hist(bt4_nsdp.values,nclass=100,
      xlab="% positive Z'",main="NSW/VIC",cex.lab=1.4,cex.main=1.3) #xlim=c(0,20))
points(nsw_origp.z.new*100,0,pch=16,col="red",cex=1.8)
# nsw neg
hist(bt4_nsn.values,nclass=100,
      xlab="% negative Z'",main="",cex.lab=1.4,
      cex.main=1.3) #, xlim=c(0,20))
points(nsw_origin.z.new*100,0,pch=16,col="red",cex=1.8)
#qld pos
hist(bt4_qldp.values,nclass=100,
      xlab="% positive Z'",main="Qld",cex.lab=1.4,cex.main=1.3) #xlim=c(0,20))
points(qld_origp.new*100,0,pch=16,col="red",cex=1.8)
#qld neg
hist(bt4_qldn.values,nclass=100,
      xlab="% negative Z'",main="",cex.lab=1.4,
      cex.main=1.3) #, xlim=c(0,20))
points(qld_origin.new*100,0,pch=16,col="red",cex=1.8)

```

NSW/VIC



QId



#dev.off()