Supplementary Information: Paleoclimate Modeling

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Last Updated: 2017-03-24

Introduction

In this two-part analysis we first compare temporal patterns of temperature and precipitation, derived from a transient paleoclimate simulation, at three points in the west Mediterranean. Then we analyze the spatial pattern of climate change from the LGM to the Mid Holocene using an ensemble of downscaled equilibrium paleoclimate simulations.

Setup

Load all the packages needed for this analysis.

```
library(ncdf4) # import GCM data
library(rgdal) # read GCM data
library(raster) # process GCM data
library(rasterVis) # plotting GCM data
library(tidyverse) # data management and plotting
library(magrittr) # pipes for code readability
library(EMD) # calculate trends in the data
library(dismo) # for latitudinally weighted samples
library(mgcv) # fit GAM for downscaling
```

Temporal Patterns: TraCE-21k

Sample Locations

Create a matrix with the coordinates for the three locations of interest in the west Mediterranean.

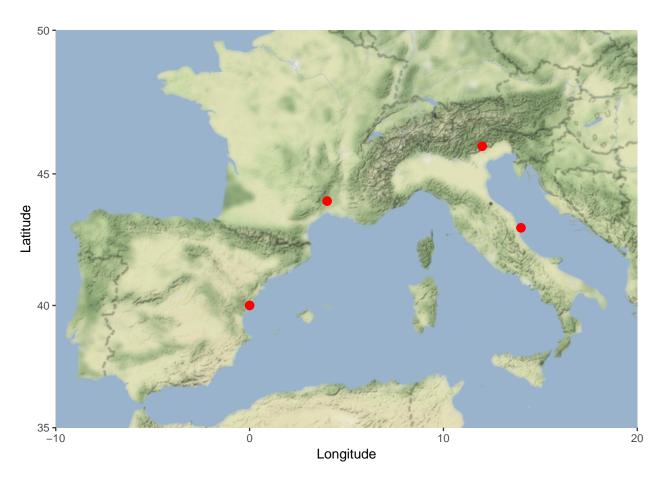
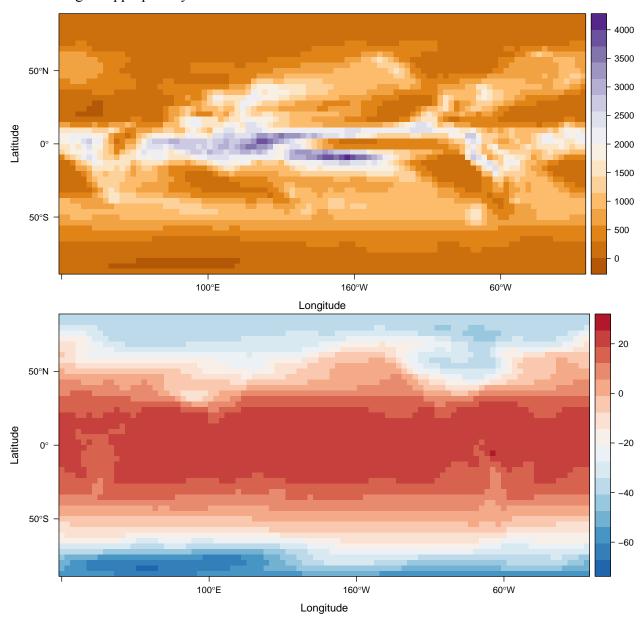


Figure 1: Locations of 3 sample points.

TraCE-21k Import and Preprocessing

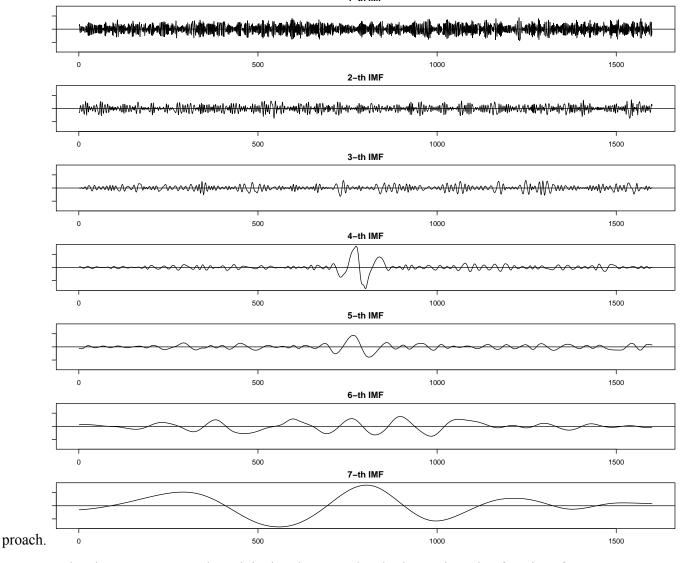
First, import data from the TraCE-21k paleoclimate simulation. Then extract temperature and precipitation values at three locations in the west Mediterranean. Use the *brick* function from **raster** to import decadal averages from the simulation. Put the coordinates for the three locations in a matrix, and use that matrix to and **raster's** *extract* function to get the values from the climate model brick. Convert the precipitation values to mm/year and temperature values to degrees Celsius. Finally, name the columns for each region appropriately.



Now pull all the TraCE data into one data frame, with one row per year, and one column per variable/location combination. First *rbind* the two sets of TraCE data and *transpose* the results, turning the 6 rows into 6 columns. Add a column for the Year (in ka BP), and use to select only the entries earlier than 6,000 BP.

Trend Analysis

Let's use the **EMD** package to calculate actual trend lines using the empirical mode decomposition ap-

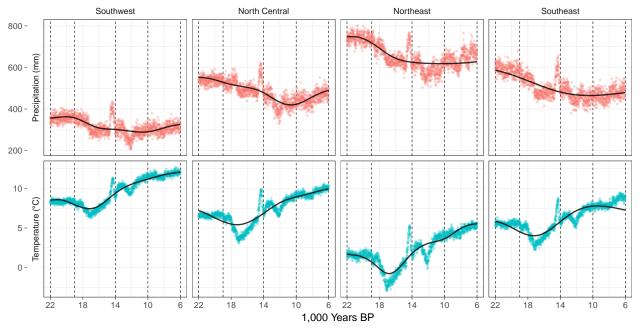


Now organize the temperature and precipitation data to make plotting easier using functions from tidyr.

Plotting

Plot everything with **ggplot2**.

```
ggplot(data = trace.plot, aes(x = Year, y = value)) +
  facet_grid(Variable ~ Region, switch = 'y', scale = 'free_y') +
  geom_vline(xintercept = c(22, 19, 14, 10, 6), lty = 2) +
  geom_point(aes(color = Variable), alpha = .3) +
  geom_line(data = trace.emd, size = 1.2, color = "black", alpha = .8) +
  scale_x_reverse(breaks = seq(6,22,4)) +
  labs(x = '1,000 Years BP', y = ") +
  guides(color = "none") +
  theme_bw(base_size = 20) +
  theme(strip.background = element_blank())
```



Variance

Calculate the detrended variances.

```
emd.dat <- trace.dat %>%
    mutate_at(vars(-Year), emd.res)
```

```
(trace.dat - emd.dat) %>%
  select(-Year) %>%
  cbind(Year = trace.dat$Year, .) %>%
  mutate(Period = cut(Year, c(22, 19, 14, 10, 6))) %>%
  group_by(Period) %>%
  summarise_each(funs(var)) %>%
  select(-Year) %>%
    print(width = Inf)
## # A tibble: 4 × 9
      Period 'tmp, Southwest' 'tmp, North Central' 'tmp, Northeast'
                                           <dbl>
##
      <fctr>
                       <dbl>
                                                            <dbl>
## 1 (6,10]
                  0.08704209
                                       0.0922012
                                                        0.1853124
## 2 (10,14]
                  0.27096878
                                       0.3907428
                                                        0.8121861
## 3 (14,19]
                  0.40989953
                                        1.4185010
                                                        1.3565404
## 4 (19,22]
                  0.10400222
                                       0.2620887
                                                        0.2029233
     'tmp,Southeast' 'prc,Southwest' 'prc,North Central' 'prc,Northeast'
##
##
               <dbl>
                               <dbl>
                                                    <dbl>
                                                                    <dbl>
## 1
           0.4481085
                            488.1919
                                                 778.4795
                                                                1230.0957
                            772.4411
## 2
           0.3543841
                                               1015.4651
                                                                1191.1768
## 3
           0.9364233
                           1317.6964
                                                                1567.4188
                                                1308.8443
## 4
           0.2716865
                            313.4281
                                                 391.5337
                                                                 531.6333
     'prc,Southeast'
##
##
               <dbl>
## 1
            739.1441
## 2
            936.9639
## 3
           2021.5821
## 4
            649.1395
How do these compare to the overall regional variance?
bbox <- extent(c(-10, 20, 35, 47))
trace.reg.avg <- rbind(</pre>
  brick('trace.01-36.22000BP.cam2.TREFHT.22000BP decayg 400BCE.nc') %>%
    raster::extract(bbox, fun = mean) %>%
    subtract(273.15), # convert from kelvin to C
  brick('trace.01-36.22000BP.cam2.PRECT.22000BP_decavg_400BCE.nc') %>%
    raster::extract(bbox, fun = mean) %>%
    multiply_by(3.154e+10)) %>% # convert to mm/year
  t %>% # transpose
  as.data.frame %>%
  set_colnames(c('tmp,StudyArea', 'prc,StudyArea')) %>%
  rownames_to_column('Year') %>%
  mutate(Year = as.numeric(substring(Year, 3))) %>%
```

```
filter(Year > 6)
emd.reg.avg <- trace.reg.avg %>%
 mutate_at(vars(-Year), emd.res)
(trace.dat - emd.dat) %>%
  select(-Year) %>%
  cbind(Year = trace.dat$Year, .) %>%
 mutate(Period = cut(Year, c(22, 19, 14, 10, 6))) %>%
  group_by(Period) %>%
  summarise_each(funs(var)) %>%
  select(-Year) %>%
  subtract(((trace.reg.avg - emd.reg.avg) %>%
  magrittr::extract(c(2,2,2,2,3,3,3,3)) %>%
  cbind(Year = trace.dat$Year, .) %>%
 mutate(Period = cut(Year, c(22, 19, 14, 10, 6))) %>%
  group_by(Period) %>%
  summarise_each(funs(var)) %>%
  select(-Year))) %>%
    print(width = Inf)
## Warning in Ops.factor(left, right): '-' not meaningful for factors
##
    Period tmp, Southwest tmp, North Central tmp, Northeast tmp, Southeast
## 1
        NA -0.03803870
                               -0.03287960
                                              0.06023160
                                                            0.32302766
## 2
        NA -0.16399338
                               -0.04421932
                                              0.37722393 -0.08057806
        NA -0.58309403
## 3
                                0.42550744
                                              0.36354680 -0.05657024
                                0.08987510
                                              0.03070968
## 4
        NA
            -0.06821138
                                                            0.09947292
    prc, Southwest prc, North Central prc, Northeast prc, Southeast
## 1
         127.1965
                           417.4842
                                         869.1004
                                                       378.1488
## 2
         288.8544
                           531.8784
                                         707.5902
                                                       453.3773
## 3
                                                       813.7744
        109.8887
                           101.0366
                                         359.6112
## 4
         102.7977
                           180.9033
                                         321.0029
                                                       438.5091
```

Spatial Patterns: PMIP3 Ensemble

Data Preprocessing

First change the study area to all of Europe and the Mediterranean. Import observed precipitation and temperature normals.

```
bbox <- extent(c(-10, 45, 30, 50))

tmean.obs <- list.files('~/gdrive/Data/MOD11C3v5.0-CHIRPSv2.0_MONTHLY_03m/meantemp', full.names = T) %>%
```

```
stack %>%
    set_names(month.name) %>%
    crop(bbox)
tmean.obs[tmean.obs == -9999] <- NA
p.obs <- list.files('~/gdrive/Data/MOD11C3v5.0-CHIRPSv2.0_MONTHLY_03m/precip', full.names = T) %>%
    stack %>%
    set_names(month.name) %>%
    crop(bbox)
p.obs[p.obs == -9999] <- NA
Import and reproject SRTM DEM.
elev <- raster('~/gdrive/Data/SRTM_1km.tif') %>% projectRaster(p.obs[[1]]) %>% mask(p.obs[[1]])
Use the DEM to calculate a diffusive continentality (DCO) map, with distance to the sea in km.
dco <- elev %>%
  reclassify(c(-Inf, Inf, NA, NA, NA, 1)) %>% # reverse NA and non-NA cells
  distance(doEdge = T) %>% # calculate the distances
  mask(elev) %>% # mask out ocean cells
  divide_by(1000) # convert to km
Import and preprocess of ECMWF-interim reanalysis data, monthly means of daily means, 1979-2010
processECMWF <- function(file, var){</pre>
  brick(paste0('~/gdrive/Data/', file), varname = var) %>%
      stackApply(indices = 1:12, fun = mean) %>%
      rotate %>%
      set_names(month.name) %>% projectRaster(eu.p) %>% mask(eu.p)
}
tcw <- processECMWF('ecmwf_surface.nc', 'tcw')</pre>
msl <- processECMWF('ecmwf surface.nc', 'msl')</pre>
t2m <- processECMWF('ecmwf_surface.nc', 't2m')</pre>
lsp <- processECMWF('ECMWF Precip.nc', 'lsp')</pre>
cp <- processECMWF('ECMWF Precip.nc', 'cp')</pre>
Put all the predictor and response variables together, month by month.
cal.vars <- sapply(1:12, function(x){</pre>
  brick(tmean.obs[[x]], p.obs[[x]], msl[[x]], t2m[[x]], tcw[[x]], lsp[[x]], cp[[x]], elev, dco) %>%
    setNames(c('tmean.obs', 'p.obs', 'msl', 't2m', 'tcw', 'lsp', 'cp', 'elev', 'dco'))
})
Sample the variables at random points, weighting for latitude
cal.data <- lapply(cal.vars, function(x) (raster::extract(x, randomPoints(elev, 20000)) %>% data.frame)) %>%
  do.call(rbind, .)
```

Model Fitting

Use *mgcv* to fit gams to the combined calibration data. Model precipitation occurrence and amounts separately.

Predictions

Write a function to import, process, and generate a monthly average ensemble from PMIP3 data.

```
getEns <- function(period, variable){
  var.dir <- paste0('~/gdrive/Data/PMIP3 Data/', period, '/', variable)
  files.in <- list.files(var.dir, full.names = T)

sapply(files.in, function(x){
  brick(x) %>% rotate %>% projectRaster(elev)
  }) %>% brick %>% stackApply(indices = 1:12, fun = mean)
}
```

Mid Holocene

Use this function to import all the necessary variables. Generate a single prediction set.

```
t2m <- getEns('MH', 'tas')
msl <- getEns('MH', 'psl')
cp <- getEns('MH', 'prc') %>% multiply_by(86.4)
lsp <- (getEns('MH', 'pr') %>% multiply_by(86.4)) - cp
tcw <- getEns('MH', 'clivi') + getEns('MH', 'clwvi') + getEns('MH', 'prw')</pre>
```

```
pred.vars.mh <- sapply(1:12, function(x){</pre>
  brick(t2m[[x]], msl[[x]], tcw[[x]], cp[[x]], lsp[[x]], elev, dco) %>%
    setNames(c('t2m', 'msl', 'tcw', 'cp', 'lsp', 'elev', 'dco'))
})
Make predictions for the Mid Holocene.
tmean.mh <- sapply(1:12, function(x){</pre>
    predict(pred.vars.mh[[x]], tmean.gam)
  }) %>% brick
prec.occur.mh <- sapply(1:12, function(x){</pre>
    predict(pred.vars.mh[[x]], p.occur.gam, type = 'response')
  }) %>% brick %>% is_weakly_greater_than(.5)
prec.mh <- sapply(1:12, function(x){</pre>
    predict(pred.vars.mh[[x]], prcp.gam, type = 'response')
  }) %>% brick %>% mask(prec.occur.mh, maskvalue = 0, updatevalue = 0)
LGM
Repeat for the LGM
t2m <- getEns('LGM', 'tas')
msl <- getEns('LGM', 'psl')</pre>
cp <- getEns('LGM', 'prc') %>% multiply_by(86.4)
lsp <- (getEns('LGM', 'pr') %>% multiply_by(86.4)) - cp
tcw <- getEns('LGM', 'clivi') + getEns('LGM', 'clwvi') + getEns('LGM', 'prw')</pre>
pred.vars.lgm <- sapply(1:12, function(x){</pre>
  brick(t2m[[x]], msl[[x]], tcw[[x]], cp[[x]], lsp[[x]], elev, dco) %>%
    setNames(c('t2m', 'msl', 'tcw', 'cp', 'lsp', 'elev', 'dco'))
})
tmean.lgm <- sapply(1:12, function(x){</pre>
    predict(pred.vars.lgm[[x]], tmean.gam)
  }) %>% brick
prec.occur.lgm <- sapply(1:12, function(x){</pre>
    predict(pred.vars.lgm[[x]], p.occur.gam, type = 'response')
  }) %>% brick %>% is_weakly_greater_than(.5)
prec.lgm <- sapply(1:12, function(x){</pre>
    predict(pred.vars.lgm[[x]], prcp.gam, type = 'response')
  }) %>% brick %>% mask(prec.occur.lgm, maskvalue = 0, updatevalue = 0)
```

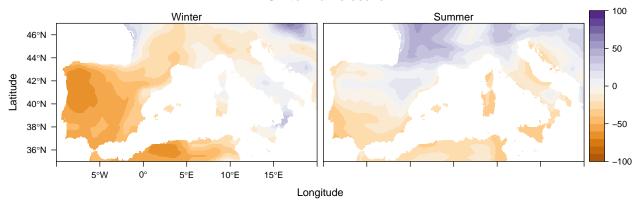
Analysis of Spatial Patterns

Use the downscaled ensemble data to estimate how the spatial patterns of climate variability have changed over time, and to test for consistency with the transient TraCE simulation.

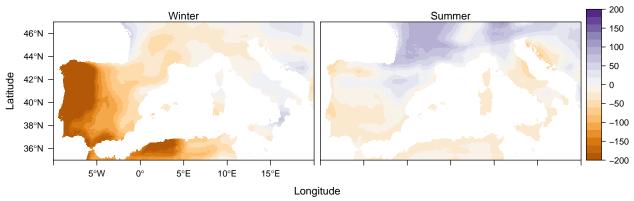
First crop the downscaled data to the West Mediterranean.

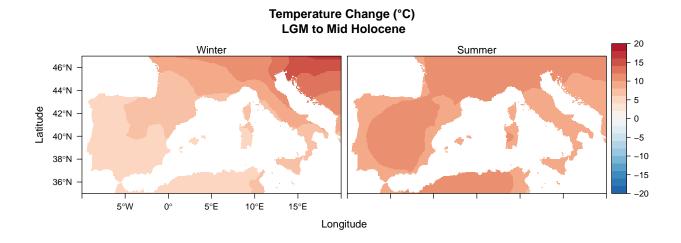
```
bbox <- extent(c(-10, 20, 35, 47))
lgm.prc <- prec.lgm %>% crop(bbox)
mh.prc <- prec.mh %>% crop(bbox)
lgm.tmp <- tmean.lgm %>% crop(bbox)
mh.tmp <- tmean.mh %>% crop(bbox)
Calculate changes in seasonal precipitation and temperature.
bySeason <- function(x, season, var){</pre>
  if(season == 'djf') \{ids <- c(1,2,12)\}
  if(season == 'jja') {ids <- c(6,7,8)}
 if(var == 'tmp') return(mean(x[[ids]]))
 if(var == 'prc') return(sum(x[[ids]]))
}
prc.change.map <- brick(c(</pre>
  bySeason(mh.prc, 'djf', 'prc') - bySeason(lgm.prc, 'djf', 'prc'),
  bySeason(mh.prc, 'jja', 'prc') - bySeason(lgm.prc, 'jja', 'prc')))
prc.change.map[prc.change.map < -200] <- -200 # so the plot isn't washed out by large precip values
prc.change.map.percent <- brick(c(</pre>
  (bySeason(mh.prc, 'djf', 'prc') - bySeason(lgm.prc, 'djf', 'prc')) * 100 / bySeason(lgm.prc, 'djf', 'prc'),
  (bySeason(mh.prc, 'jja', 'prc') - bySeason(lgm.prc, 'jja', 'prc')) * 100 / bySeason(lgm.prc, 'jja', 'prc'))
tmp.change.map <- brick(c(</pre>
  bySeason(mh.tmp, 'djf', 'tmp') - bySeason(lgm.tmp, 'djf', 'tmp'),
  bySeason(mh.tmp, 'jja', 'tmp') - bySeason(lgm.tmp, 'jja', 'tmp')))
Plot the results
levelplot(prc.change.map.percent, margin = F, names.attr = c('Winter', 'Summer'),
          main = 'Precipitation Change (%)\n LGM to Mid Holocene',
          par.settings = PuOrTheme(),
          at = seq(-100, 100, 10))
```

Precipitation Change (%) LGM to Mid Holocene



Precipitation Change (mm) LGM to Mid Holocene

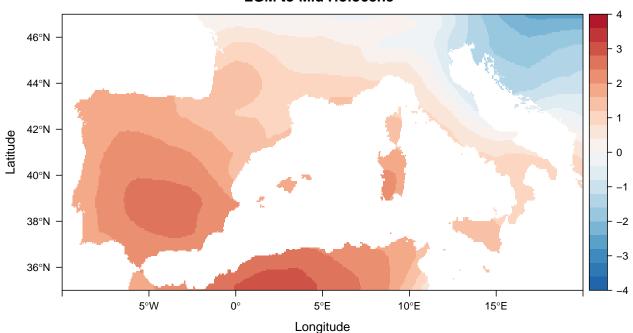




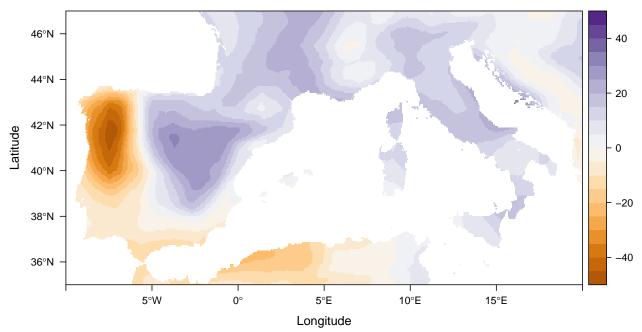
Now we can calculate changes in seasonality. For temperature, this is just the standard deviation of all 12 monthly averages. For precipitation, we will use the coefficient of variation.

```
tmp.seasonality <- calc(mh.tmp, sd) - calc(lgm.tmp, sd)
prc.seasonality <- cv(mh.prc) - cv(lgm.prc)
Plot the results.</pre>
```





Change in precipitation seasonality (CV) LGM to Mid Holocene



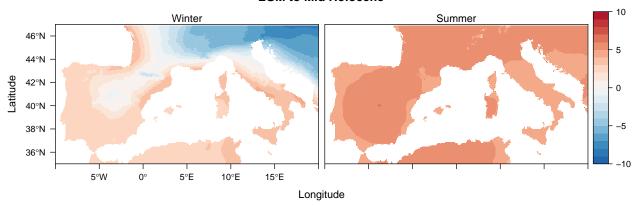
What about changes in spatial hetergeneity? First define a 5x5 weights matrix within which to sample

the climate maps

```
Temperature
tmp.hetero <- brick(c(</pre>
 bySeason(mh.tmp, 'djf', 'tmp') %>%
   focal(w = wts, sd, na.rm = T) %>%
   subtract(
     bySeason(lgm.tmp, 'djf', 'tmp') %>%
       focal(w = wts, sd, na.rm = T)),
 bySeason(mh.tmp, 'jja', 'tmp') %>%
   focal(w = wts, sd, na.rm = T) %>%
   subtract(
     bySeason(lgm.tmp, 'jja', 'tmp') %>%
       focal(w = wts, sd, na.rm = T)))) %>%
 mask(mh.tmp[[1]]) # clip buffer added by window
levelplot(tmp.hetero, margin = F, names.attr = c('Winter', 'Summer'),
        main = 'Temperature heterogeneity (SD in 25km radius) change\n LGM to Mid Holocene'.
```

Temperature heterogeneity (SD in 25km radius) change LGM to Mid Holocene

par.settings = BuRdTheme(), at = seq(-10, 10, 1))



Same for precipitaiton.

```
prc.hetero.sd <- brick(c(
   bySeason(mh.prc, 'djf', 'prc') %>%
   focal(w = wts, sd, na.rm = T) %>%
   subtract(
      bySeason(lgm.prc, 'djf', 'prc') %>%
      focal(w = wts, sd, na.rm = T)),
   bySeason(mh.prc, 'jja', 'prc') %>%
   focal(w = wts, sd, na.rm = T) %>%
   subtract(
      bySeason(lgm.prc, 'jja', 'prc') %>%
```

0

-20

-40

42°N

40°N

38°N

36°N

5°W

0°

5°E

10°E

15°E

Longitude