VICTORIA FOREST FIRE OCCURRENCES AND LAND SURFACE TEMPERATURE ANOMALIES

```
## Linking to GEOS 3.9.1, GDAL 3.2.3, PROJ 7.2.1; sf_use_s2() is TRUE

## terra 1.5.21

## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following object is masked from 'package:terra':
##
##     time<-

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## rts 1.1-3 (2021-10-16)

##
## Attaching package: 'gdalUtils'

## The following object is masked from 'package:sf':
##
##     gdal_rasterize

## Please note that rgdal will be retired by the end of 2023,
## plan transition to sf/stars/terra functions using GDAL and PROJ
## at your earliest convenience.
##
## rgdal: version: 1.5-28, (SVN revision 1158)
## Geospatial Data Abstraction Library extensions to R successfully loaded
## Loaded GDAL runtime: GDAL 3.2.3, released 2021/04/27
## Path to GDAL shared files: /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/rgdal
## GDAL binary built with GEOS: TRUE
## Loaded PROJ runtime: Rel. 7.2.1, January 1st, 2021, [PJ_VERSION: 721]
## Path to PROJ shared files: /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/rgdal
## PROJ CDN enabled: FALSE
## Linking to sp version:1.4-6
## To mute warnings of possible GDAL/OSR exportToProj4() degradation,
## use options("rgdal_show_exportToProj4_warnings"="none") before loading sp or rgdal.
## Overwritten PROJ_LIB was /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/rgdal/p

##
## Attaching package: 'rgdal'

## The following object is masked from 'package:terra':
##
##     project
```

```
##
## Attaching package: 'ggplot2'

## The following object is masked from 'package:terra':
##
##     arrow

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:raster':
##
##     intersect, select, union

## The following objects are masked from 'package:xts':
##
##     first, last

## The following objects are masked from 'package:terra':
##
##     intersect, src, union

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

##
## Attaching package: 'tidyr'

## The following object is masked from 'package:raster':
##
##     extract

## The following object is masked from 'package:RCurl':
##
##     complete

## The following object is masked from 'package:terra':
##
##     extract

## Loading required package: lattice

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:raster':
##
##     intersect, union

## The following objects are masked from 'package:terra':
##
##     intersect, union

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v tibble  3.1.6     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x ggplot2::arrow()         masks terra::arrow()
## x lubridate::as.difftime() masks base::as.difftime()
## x tidyr::complete()        masks RCurl::complete()
## x lubridate::date()        masks base::date()
## x tidyr::extract()         masks raster::extract(), terra::extract()
## x dplyr::filter()          masks stats::filter()
## x dplyr::first()           masks xts::first()
## x readr::guess_encoding()  masks rvest::guess_encoding()
## x lubridate::intersect()   masks raster::intersect(), terra::intersect(), base::intersect()
## x dplyr::lag()             masks stats::lag()
## x dplyr::last()            masks xts::last()
## x dplyr::select()          masks raster::select()
## x lubridate::setdiff()     masks base::setdiff()
## x dplyr::src()             masks terra::src()
## x lubridate::union()       masks raster::union(), terra::union(), base::union()

##
## Attaching package: 'lmtest'

## The following object is masked from 'package:RCurl':
##
##     reset

##
## Attaching package: 'nlme'

## The following object is masked from 'package:dplyr':
##
##     collapse

## The following object is masked from 'package:raster':
##
##     getData

##
## Attaching package: 'ape'

## The following objects are masked from 'package:raster':
##
##     rotate, zoom

## The following objects are masked from 'package:terra':
##
##     rotate, trans, zoom

##
## Attaching package: 'FRK'

## The following objects are masked from 'package:STRbook':
##
##     LinePlotTheme, NOAA_df_1990

## The following object is masked from 'package:raster':
##
```

```
##     distance
## The following object is masked from 'package:terra':
##
##     distance
##
## Attaching package: 'knitr'
## The following object is masked from 'package:terra':
##
##     spin
##
## Please cite as:
##  Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.
##  R package version 5.2.3. https://CRAN.R-project.org/package=stargazer
```

Introduction :

Researchers have observed that land surface temperature anomalies could be the reason of lower moisture content of vegetations and could increase the possibility of fire.

Objective

The objective for this paper is:

Assess the relationship between land surface temperature(LST) anomalies and forest fire occurrence as well as further exploring related fire prediction factors.

Hypothesis

Null Hypothes :Land surface temperature anomaly has no relationship with Fire occurrences. Alternate Hypothesis: Land surface temperature anomaly has some relationship with Fire occurrences.

Study Area:

Victoria, as one of the states which has suffered most from wildfires in Australia, has also been affected by cause of climate change (Commissioner for Environmental Sustainability Victoria, 2018).

The province of Victoria comprises a total land surface area of 227,416 km2, located in south east Australia (141°–150°E, 34°–39°S) (Stewart & Nitschke, 2017). The area is composed of Australian Alps and plains, dominated by woody perennial vegetation (hardwood, softwood cover and large shrubs), with woody horticulture, grassland, urban and lakes. Forest cover accounts for over 25%, approximately 64 000 km2 including fire-intensive forest types like grassland, woody cover especially Eucalyptus regnans (Commissioner for Environmental Sustainability Victoria, 2018). The Victorian climate has been continuously warming since 2000s in the central and southern parts of the state, which causes a greater amount of fire occurrence (Stewart & Nitschke, 2017).

Data

1. MODIS LST Dataset

A dataset of daily gridded Terra-MODIS LST data (product MOD11A1, collection 6) from 2001 to 2019 retrieved from the Land Processes Distributed Active Archive Centre (LP DAAC, https://e4ftl01.cr.usgs.gov/) has been used for this study. The MOD11A1 V6 product provides daily land surface temperature (LST) values in a 1200 x 1200 kilometer grid.

Choosing diurnal instead of nocturnal data, and Terra-MODIS rather than Aqua-MODIS. MODIS Terra Satellite daily datasets could be calculated mean LST anomalies, standard deviation from January in each fire season peaks during the previous 20 years.

2. Fire Ignition Dataset:

This dataset describes recorded fire's spatial information since 2001 to 2019, covering bushfires and DELWP (Department of Environment, Land, Water and Planning) planned burn information in state of Victoria. CFA data on fires occurring on private land has been covered from 2009. The dataset includes fire ignition, recorded date and time of fire extinction, and presumed causes (Department of Environment, Land, Water & Planning of Victoria, 2015).

Fire causes summary in January from 2001 to 2019

3. Variables :

Response : (derived variable)(Fire(0/1) binary variable. If (number of fires)Firenum_lodate >0, Fire =1 else Fire =0 Predictor: Land Surface Temprature anomaly(LST), latitude(lat), longitude(lon), t(derived variable: time sequence) Spatial location : Victoria, Australia (Bounding box: xmin: 140.9617 ymin: -39.13396 xmax: 149.9763 ymax: -33.99605)(use ozmap 'R' function) Time : Month of January across 2001 to 2019

Methodology

1. Study the LST Data

Read the data from tiff files.(Tiff files are data stored as images)

i) Read the Land Surface Temprature data from two tiff files for the month of January from 2001 - 2019 as “Raster object”.
ii) There are two raster objects LST1_15 and LST1_16.
iii) Each raster object has multiple raster layers and a projection string.
iv) Since both the tiff files are for Victoria, Australia their coordinate reference system are same.
v) LST1_15 has(15 x 19 layers : Each layer has data for a single date) and LST16_31 has(16x 19) layers.
vi) Extract all the layers and stack them and convert the stack into a data frame. Since data frames are easy to analyse.

2. Study the Fire data

a. Study the distribution of fire data across different Fire causes and across all years.

4. Merge the LST Data and Fire Data.

a. Assign the coordinate reference system(crs) of LST data to Fire data.

b. Match(overlay on) the coordinates Fire data with LST data using ‘Nearest neighbor coordinate matching’.

c. Aggregate the data by month.

d. Study the aggregated merged data set.

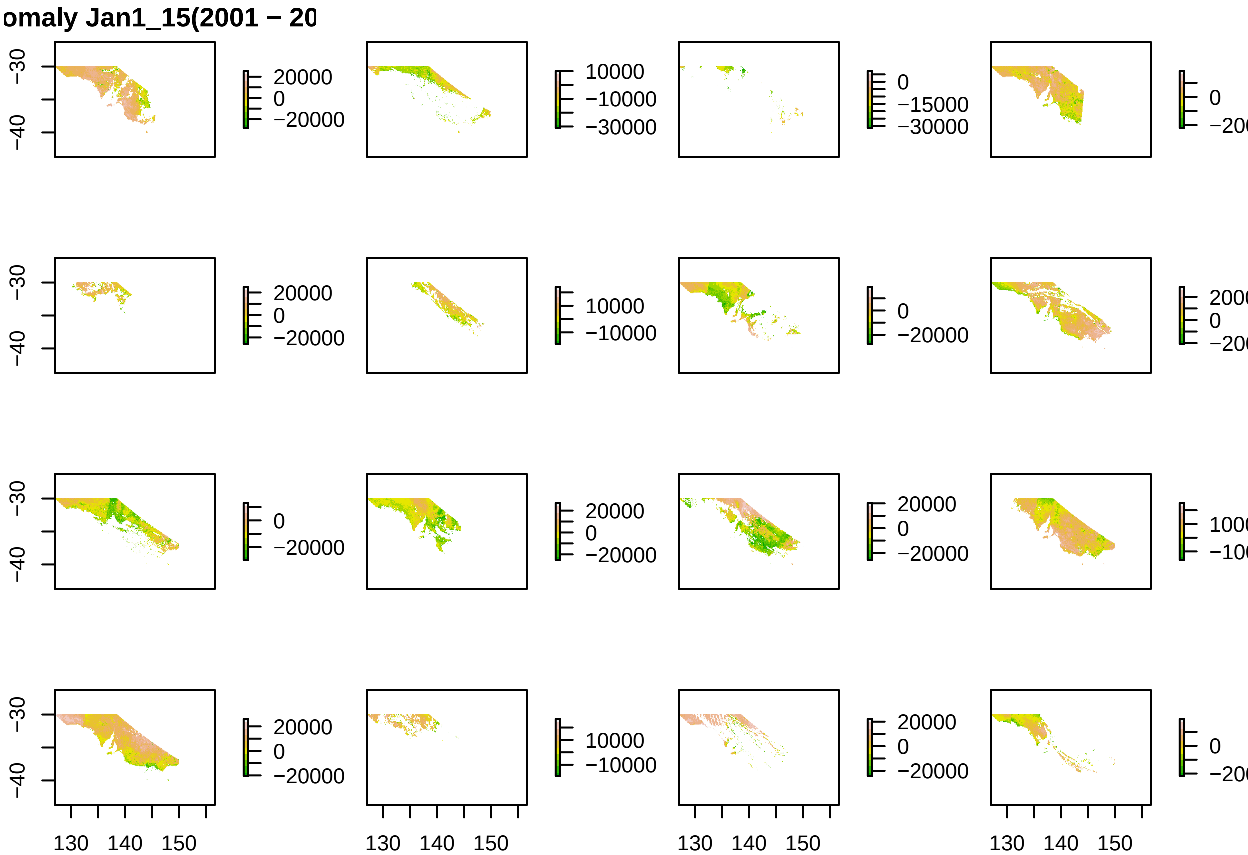
e. Study the Empirical Spatial and temporal LST mean.

f. Empirical ST Covariogram :Study the covariabillity in the LST data as a function of temporal lags and spatial lags.

5. Modelling

a. Study the LST and Fire relationship : Pixelwise binary regression to study the relation between LST and Fire.
b. Forecasting: Predict Fire incidents using temporal basis and spatial random effects.

Raw Land Surface Temprature Data stored in Tiff files

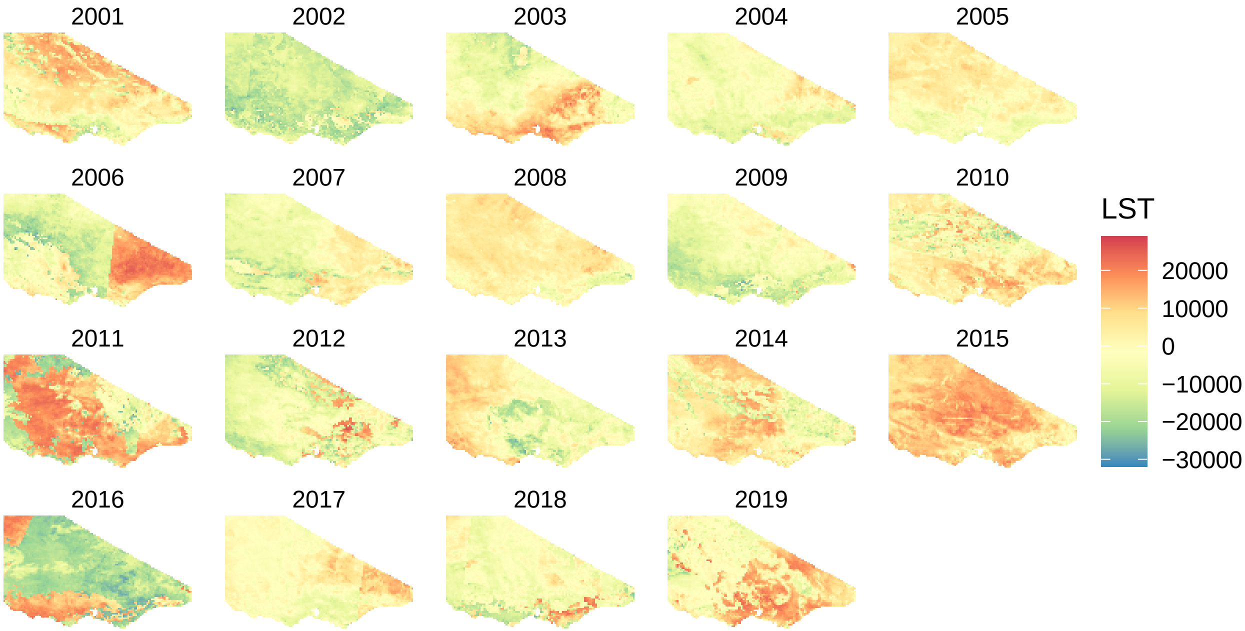


Since summer is at the peak in Australia in the month of January. Temperature is on the higher side. [Input data is LST for entire Australia. I will subset the information for the state of Victoria for further analysis].

Each plot has data for one day of the month of January accorss all years. Therefore, the first plot is the LST input data for January 1 for all the 19 years from 2001 to 2019

There are some blank spaces in the input data(no colors) implying missing data.

Victoria, Australia - xmin: 140.9617 ymin: -39.13396 xmax: 149.9763 ymax: -33.99605



Fire data stored in shape files.[Saptialpoint objects]

The fire data has location(longitude,latitude), date, fire causes and number of fires.

There are 24 known causes of fires. Here is the summary of Fire Causes.

```
## [1] 0
```

```
## # A tibble: 24 x 2
##    CAUSE                                          FIRE_INCIDENTS
##    <chr>                                                   <dbl>
##  1 LIGHTNING                                               59965
##  2 UNATTENDED CAMPFIRE - CONTAINED WITHIN BOUNDARY         31426
##  3 CAMPFIRE, BARBEQUE                                      31357
##  4 UNKNOWN                                                 19698
##  5 DELIBERATE LIGHTING (MALICIOUS)                         15686
##  6 BURNING VEHICLE, MACHINE                                 6269
##  7 OTHER                                                    5834
##  8 EXHAUST, OTHER                                           1774
##  9 POWER TRANSMISSION                                       1609
## 10 PIPE, CIGARETTE, MATCH                                   1273
## # ... with 14 more rows
```

59965(highest across all fire cause)number of fires reported due to "Lightning".

LST Anomalies Calculation:

To analyse each year's LST variation I have chosen January data between the year 2001 and 2019 as the fire season peaks in January.

LST anomalies = $\frac{x_{DOY} - \bar{x}_{DOY}}{\sigma_{DOY}}$

where:

x_{DOY} is observed LST for pixel x,y on day of year in year y

$\bar{x}_{DOY}$ is mean LST of day of year over 19 years

σ_{DOY} is standard deviation of LST of day of year over 19 years

Summary : Fire count across years

```
## # A tibble: 19 x 2
##    `year(FIRE_START)` FIRE_INCIDENTS
##                 <dbl>          <dbl>
##  1               2019          38287
##  2               2018          24464
##  3               2015          17140
##  4               2014          16126
##  5               2017          12308
##  6               2016          12033
##  7               2003           7496
##  8               2006           6329
##  9               2013           5361
## 10               2001           5177
## 11               2010           5018
## 12               2008           4658
## 13               2009           4613
## 14               2007           4356
## 15               2005           4286
## 16               2004           3618
## 17               2002           3496
## 18               2012           3268
## 19               2011            268
```


```
## # A tibble: 19 x 2
##    `year(FIRE_START)` FIRE_INCIDENTS
##                 <dbl>          <dbl>
##  1               2019          38287
##  2               2018          24464
##  3               2015          17140
##  4               2014          16126
##  5               2017          12308
##  6               2016          12033
##  7               2003           7496
##  8               2006           6329
##  9               2013           5361
## 10               2001           5177
## 11               2010           5018
## 12               2008           4658
## 13               2009           4613
## 14               2007           4356
## 15               2005           4286
## 16               2004           3618
## 17               2002           3496
## 18               2012           3268
## 19               2011            268
```


38287(highest in the year in entire Victoria region)number of fires reported in 2019.

Summary : 2019 Fire causes Summary

```
## # A tibble: 13 x 2
##    CAUSE                                          TotalFire
##    <chr>                                              <dbl>
##  1 UNATTENDED CAMPFIRE - CONTAINED WITHIN BOUNDARY     14963
```

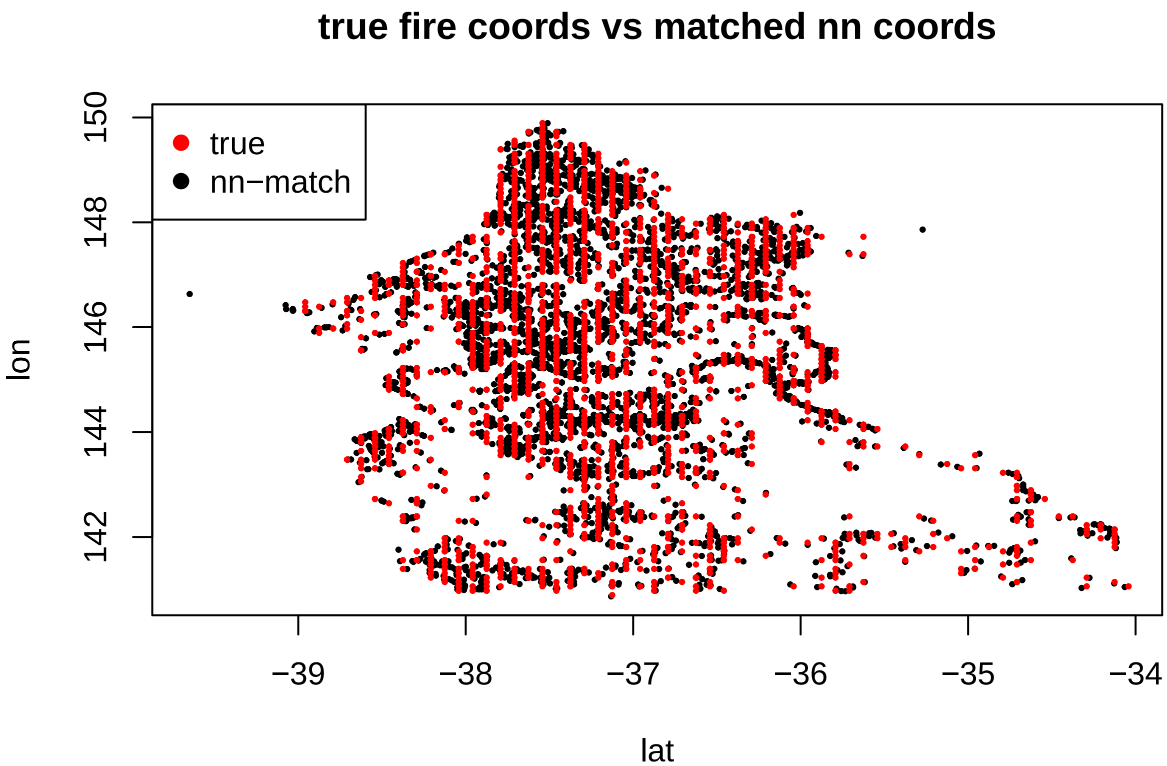
```
##  2 LIGHTNING                                                13247
##  3 CAMPFIRE, BARBEQUE                                        4178
##  4 UNKNOWN                                                   2638
##  5 BURNING VEHICLE, MACHINE                                  1503
##  6 DELIBERATE LIGHTING (MALICIOUS)                            646
##  7 OTHER                                                      575
##  8 PIPE, CIGARETTE, MATCH                                     168
##  9 EXHAUST, OTHER                                             121
## 10 FIREWORKS                                                   81
## 11 BURNING OFF, WINDROW, HEAP                                  63
## 12 POWER TRANSMISSION                                          55
## 13 BURNING BUILDING                                            49
```

14963 number of fires reported in 2019 due to 'Unattended Camp Fire - contained within boundary.' In 2019, 575 fires were due to unknown reasons.

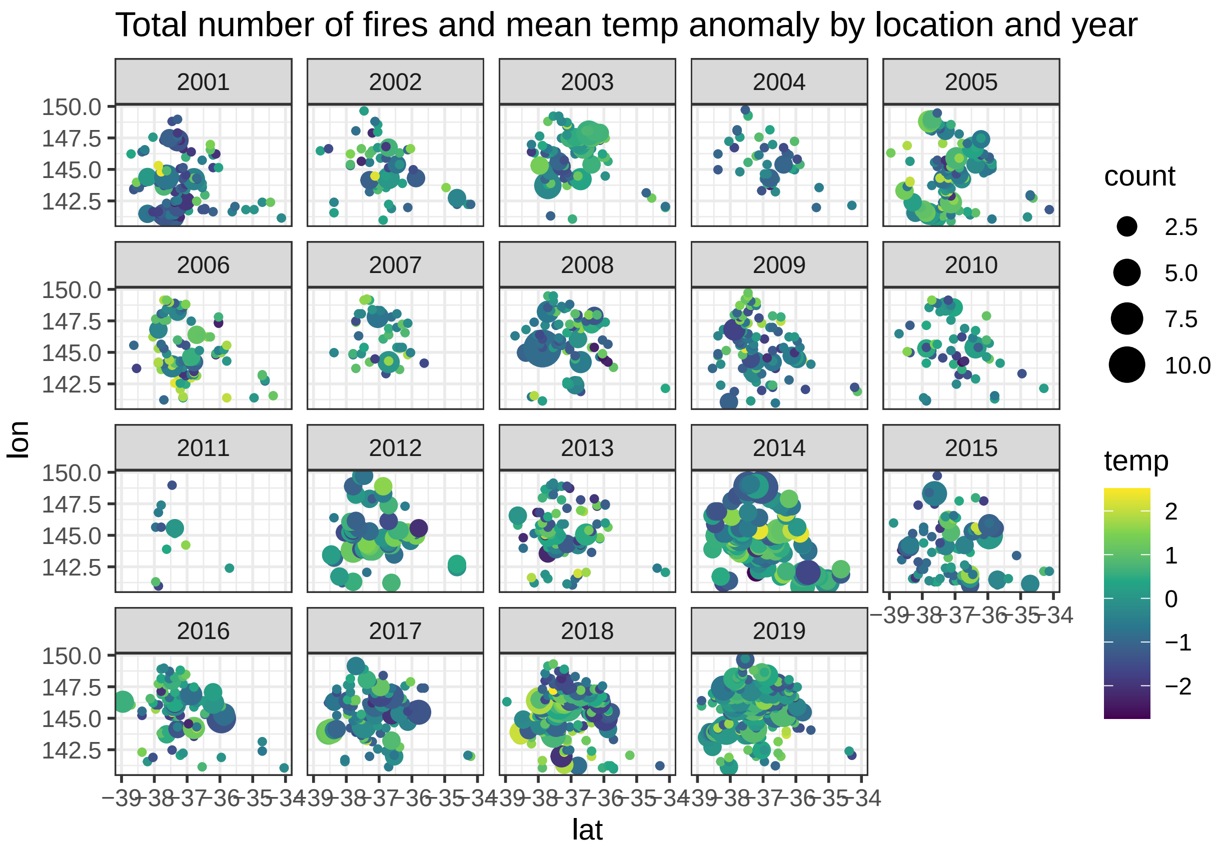
Connect Fires and the Land Surface Temperature Data : Nearest Neighbor coordinate matching

```
## [1] 0
```

The plot shows coordinate matching of Land Surface Temperature Data and Fire Data. using 'nearest neighbor coordinate matching'.



There are two outliers in the the data.I will remove these two outliers. Fire data is difficult to report the exact origin of Fire. It is reported where it was first observed.



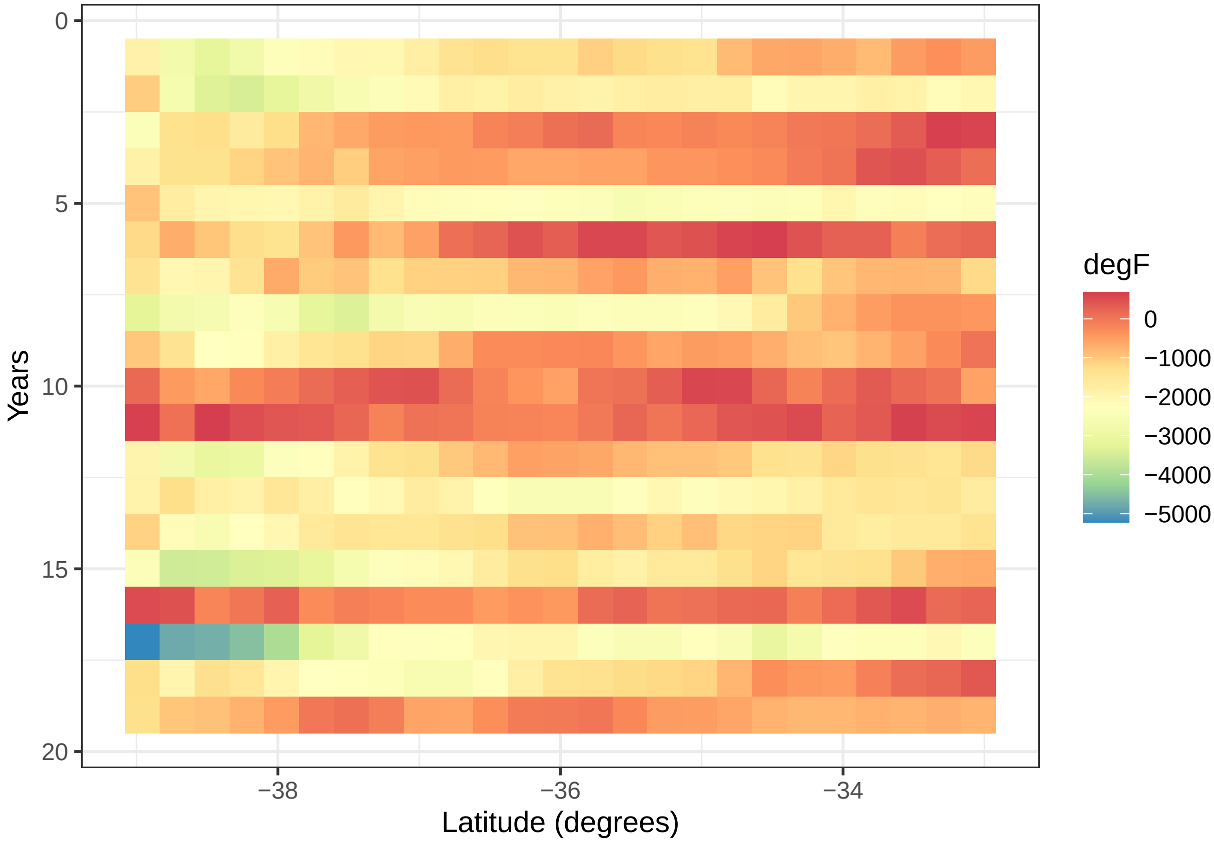

```
## [1] 2087000
```

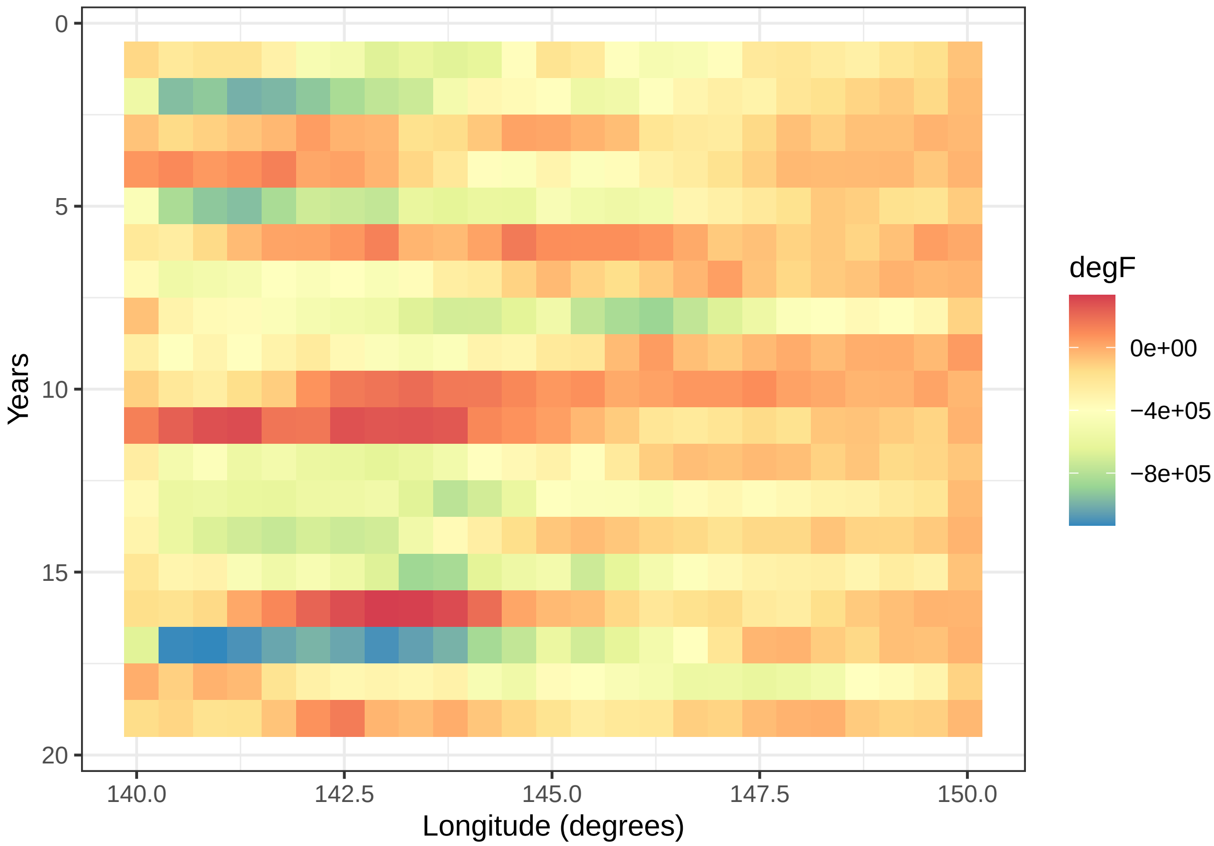
```
## [1] 0
```

From the Spatial mean plot for Land surface temperature and Fire data it appears that the southern Victoria is the overall most affected part due to average rise in temperature over the period of 19 years(our study time period.)

Hovmoller Plot : Temprature Anomalies for all years across Latitude and Longitude

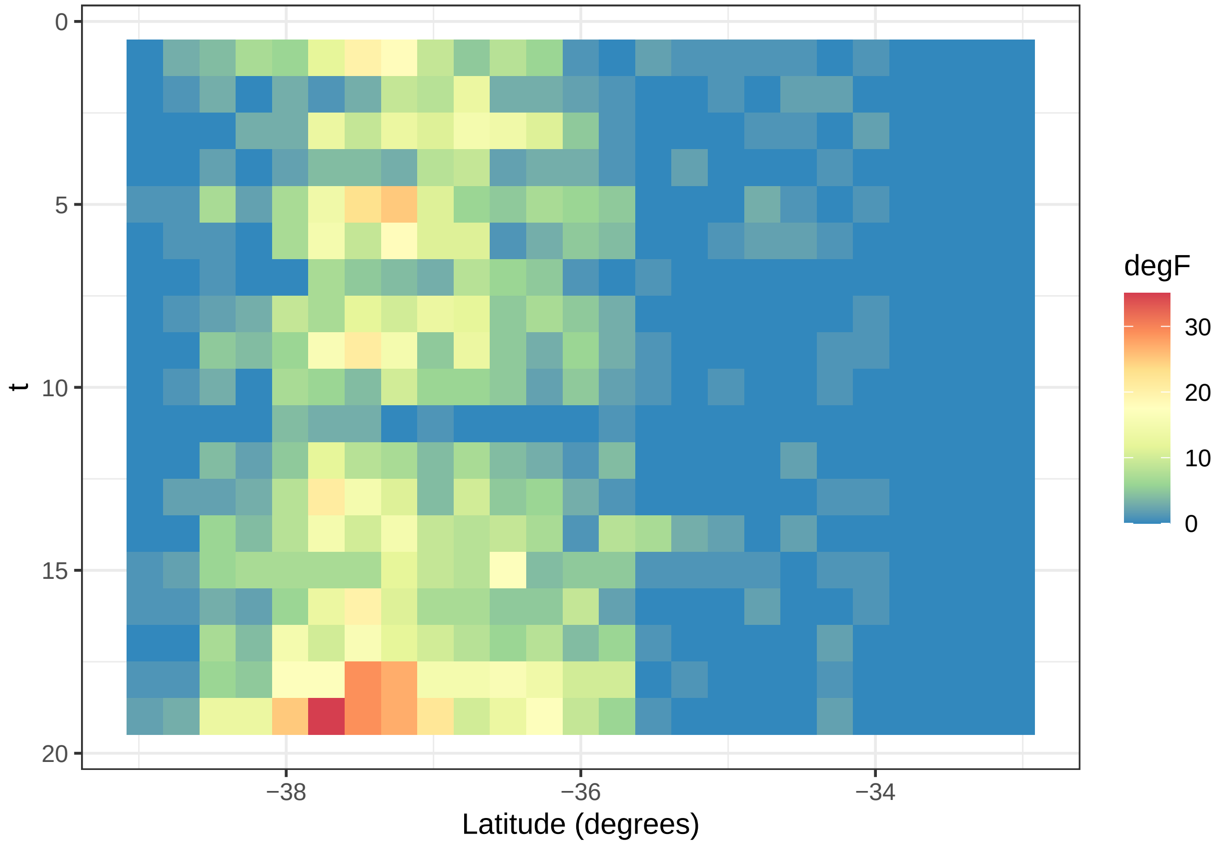
```
## NULL
```

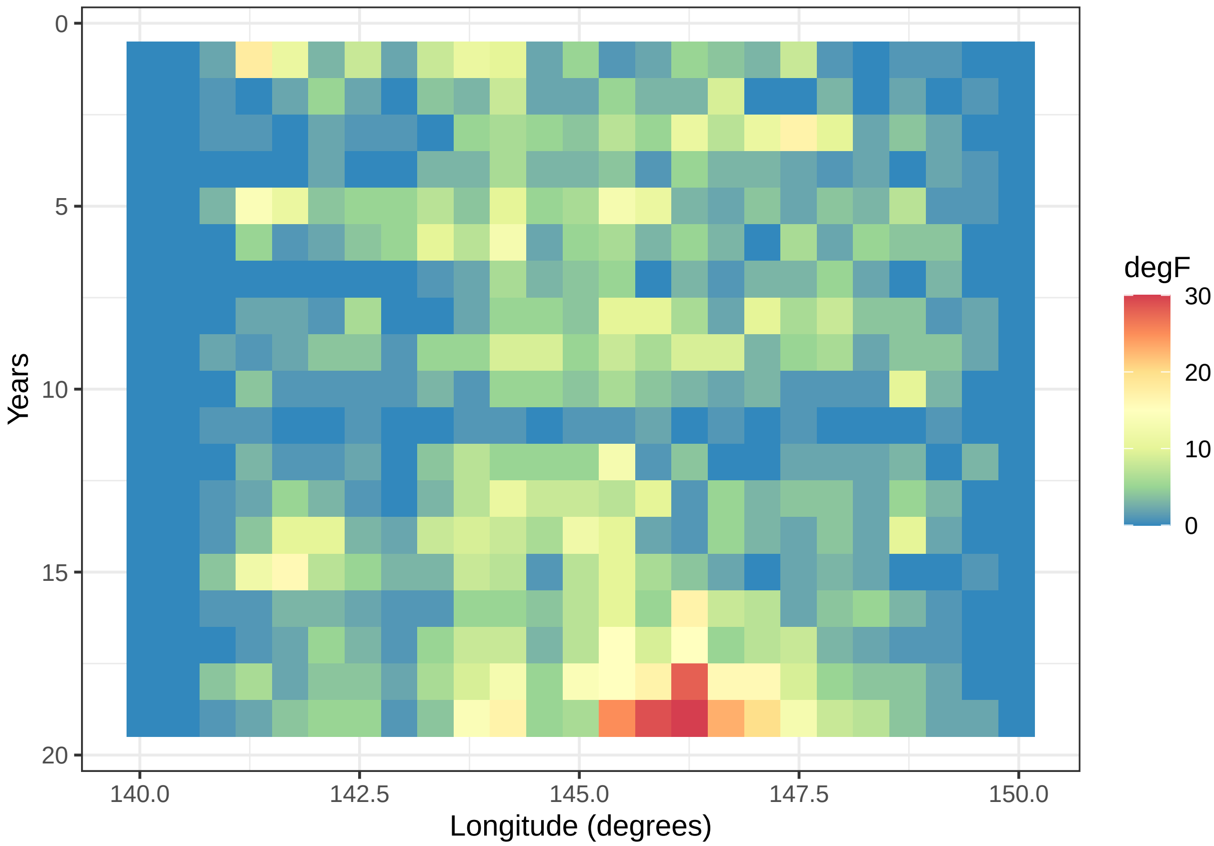



0
5
10
15
20
Years
140.0
142.5
145.0
147.5
150.0
Longitude (degrees)
degF
0e+00
−4e+05
−8e+05

Hovmoller Plot : Fire for all years across Latitude and Longitude

```
## NULL
```




0
5
10
15
20
Years
140.0
142.5
145.0
147.5
150.0
Longitude (degrees)
degF
30
20
10
0

Modelling

Fitting a GLS model and comparing to LS estimates

Adding spatial basis functions to create X matrix

Variable Selection

The method implemented in the `leaps` package for best subsets can be found in the function `regsubsets`

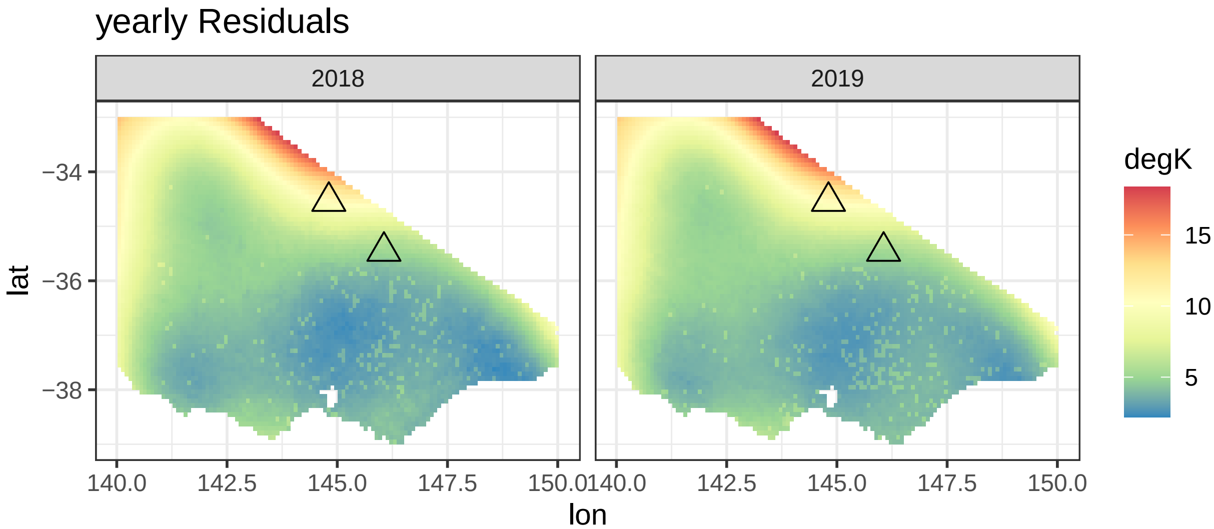
```
##   adj.r2 CP BIC
## 1      7  7   7
```

```
##   (Intercept)             t            B3            B4            B8
## -0.0055090068 -0.0077033238  0.0100710953 -0.0122029189  0.0217065061
##            B9           B14         lat:t
##  0.0523495403 -0.1089822224 -0.0002340878
```

The best model is the one including all terms when using adjusted R-squared and Mallows-CP, I'll go with that one.

```
##
## Call:
## glm(formula = Fire ~ temp + (lon + lat + t)^2 + ., family = "binomial",
##     data = data11)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.4901  -0.2126  -0.1375  -0.0499   3.7592
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.273e+04  1.774e+03   7.174 7.31e-13 ***
## temp        -9.784e-05  1.662e-05  -5.888 3.90e-09 ***
## lon         -9.040e+01  1.245e+01  -7.263 3.77e-13 ***
## lat          3.430e+02  4.745e+01   7.230 4.84e-13 ***
## t           -3.838e-01  4.060e-01  -0.945   0.3445
## B1           3.574e+01  3.700e+00   9.658  < 2e-16 ***
## B2           1.297e+01  2.367e+00   5.479 4.27e-08 ***
## B3           1.353e+01  2.729e+00   4.957 7.15e-07 ***
## B4           5.589e+00  2.824e+00   1.979   0.0478 *
## B5           6.134e-01  4.318e+00   0.142   0.8870
## B6           1.936e+01  2.818e+00   6.871 6.39e-12 ***
## B7          -1.785e+00  2.700e+00  -0.661   0.5087
## B8           3.336e+01  3.772e+00   8.844  < 2e-16 ***
## B9           1.032e+00  4.036e+00   0.256   0.7982
## B10          5.326e+01  7.233e+00   7.364 1.79e-13 ***
## B11          7.610e-01  5.658e+00   0.134   0.8930
## B12          4.713e+01  5.523e+00   8.533  < 2e-16 ***
## B13         -6.580e+00  6.789e+00  -0.969   0.3324
## B14          6.711e+01  1.018e+01   6.589 4.42e-11 ***
## B15         -9.462e+00  1.368e+01  -0.692   0.4892
## lon:lat     -2.425e+00  3.323e-01  -7.296 2.96e-13 ***
## lon:t        4.619e-04  2.542e-03   0.182   0.8558
## lat:t       -8.800e-03  6.489e-03  -1.356   0.1750
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 14731  on 97272  degrees of freedom
## Residual deviance: 13190  on 97250  degrees of freedom
## AIC: 13236
##
## Number of Fisher Scoring iterations: 11
```



The plot seems to show both spatial and temporal dependence. i.e., points that are close to each other in space and time tend to have similar residuals. Next, I formally test for dependence using Moran's I (for spatial dependence) and the Durbin-Watson (for temporal dependence).

First up: Moran's I.

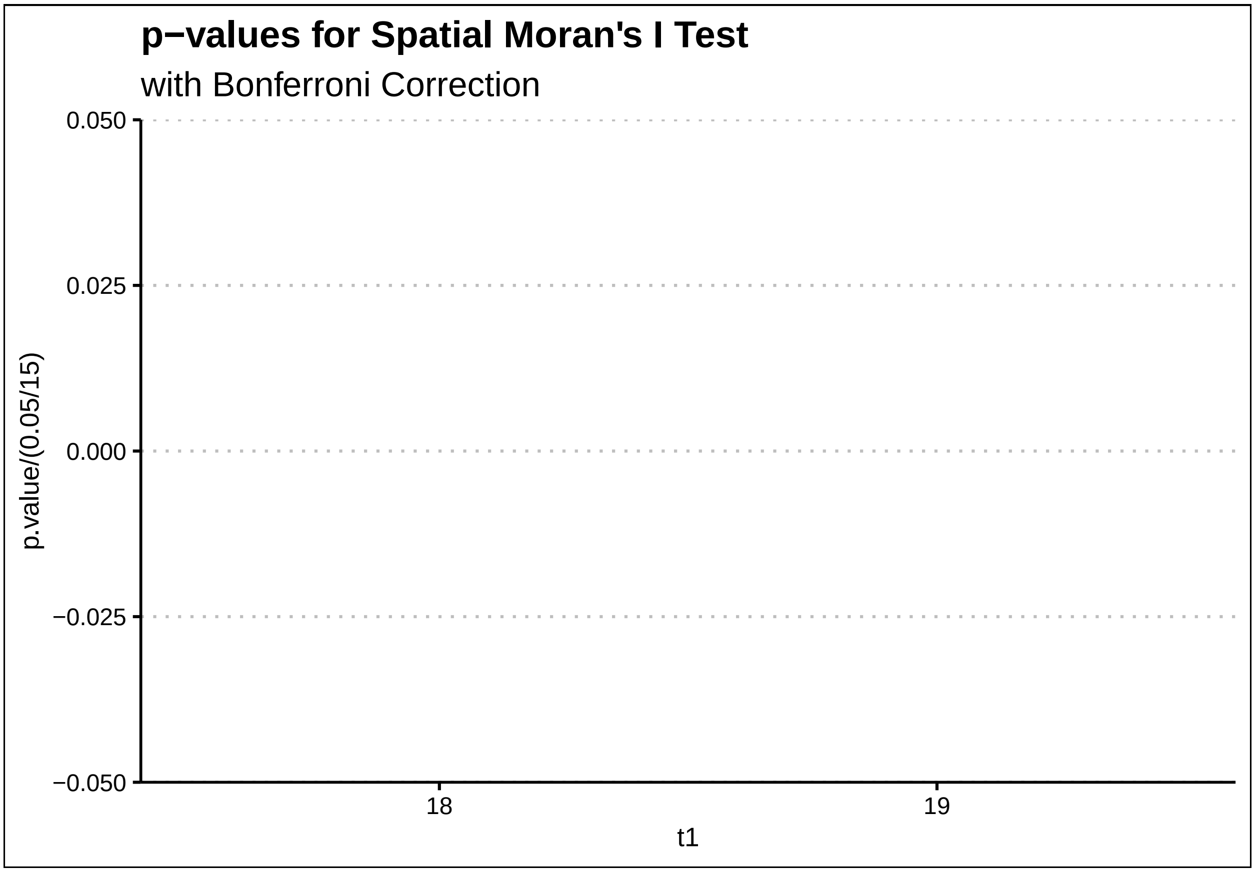
Moran's I

Create function for calculating Moran's I:

Get Moran's I test statistics and p-values for the last 5 years in my analysis (2015-2019); plot with Bonferonni adjustment:

Table 1: Moran's I Results

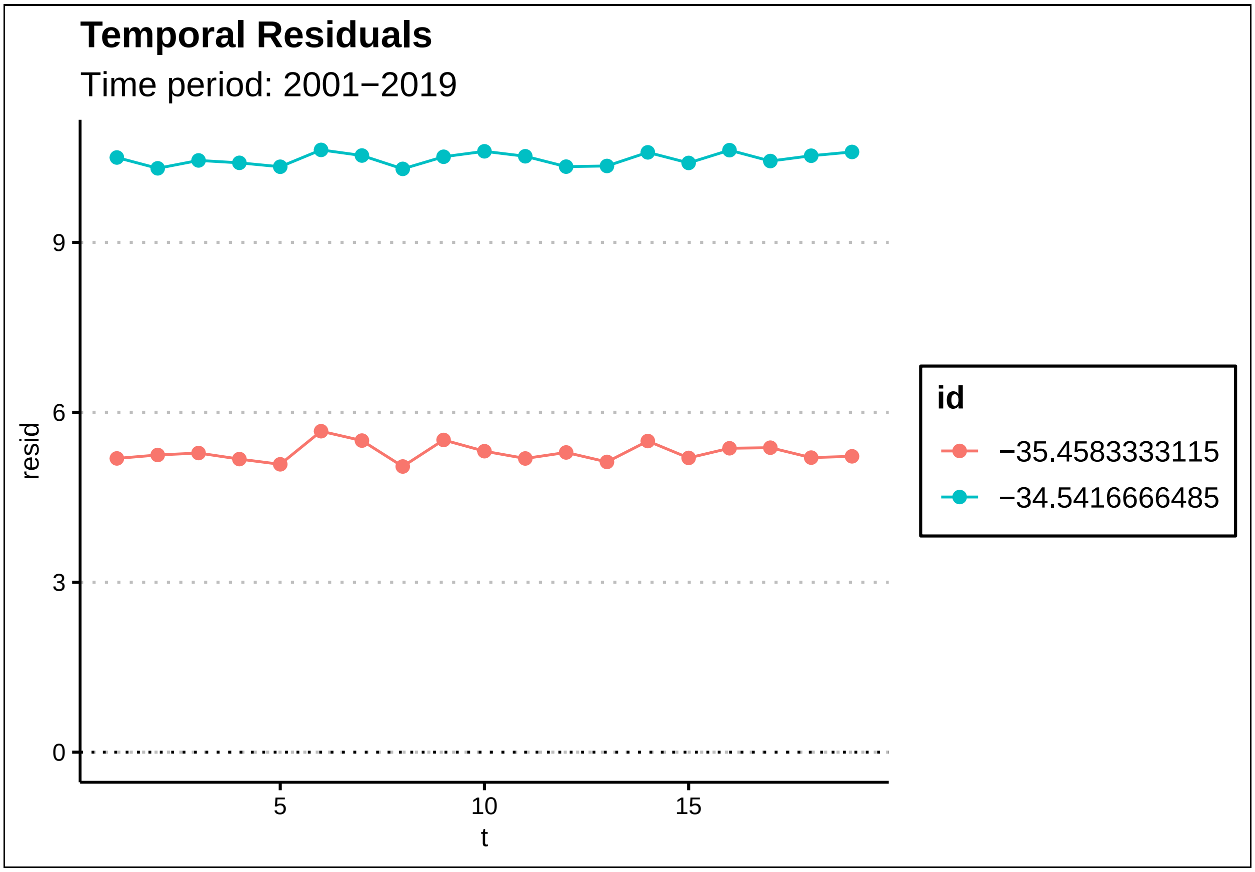
observed	expected	sd	p.value
0.2898483	-0.0001748	0.0003364	0
0.2821791	-0.0001748	0.0003364	0



The p-values for all years appear to be exactly zero. This implies that there is evidence for some spatial dependence within the spatial locations at each year.

Temporal Residuals

Let's visualize the temporal component for the location id :23369 and 19438. These are the same locations that were denoted by triangles in the spatial residuals plot.



DW-statistic The temporal dependence present in the residuals can be analyzed one location point at a time

```
## # A tibble: 6 x 3
## # Groups:   lon, lat [6]
##     lon   lat data
##   <dbl> <dbl> <list>
## 1  140. -33.0 <tibble [19 x 22]>
## 2  140. -33.0 <tibble [19 x 22]>
## 3  140. -33.0 <tibble [19 x 22]>
## 4  140. -33.0 <tibble [19 x 22]>
## 5  140. -33.0 <tibble [19 x 22]>
## 6  140. -33.0 <tibble [19 x 22]>
```

```
## # A tibble: 1 x 4
##   statistic p.value method             alternative
##       <dbl>   <dbl> <chr>              <chr>
## 1      1.76   0.299 Durbin-Watson test true autocorrelation is greater than 0
```

```
## # A tibble: 6 x 8
## # Groups:   lon, lat [6]
##     lon   lat data               dwtest  statistic p.value method    alternative
##   <dbl> <dbl> <list>             <list>      <dbl>   <dbl> <chr>     <chr>
## 1  140. -33.0 <tibble [19 x 22]> <htest>      1.76  0.299  Durbin-W~ true autoc~
## 2  140. -33.0 <tibble [19 x 22]> <htest>      1.39  0.0825 Durbin-W~ true autoc~
## 3  140. -33.0 <tibble [19 x 22]> <htest>      1.35  0.0706 Durbin-W~ true autoc~
## 4  140. -33.0 <tibble [19 x 22]> <htest>      1.30  0.0538 Durbin-W~ true autoc~
```

```
## 5  140. -33.0 <tibble [19 x 22]> <htest>      1.05  0.0126 Durbin-W~ true autoc~
## 6  140. -33.0 <tibble [19 x 22]> <htest>      1.17  0.0262 Durbin-W~ true autoc~
```

Percentage of coordinates with signif p.vals after Bonferroni correction

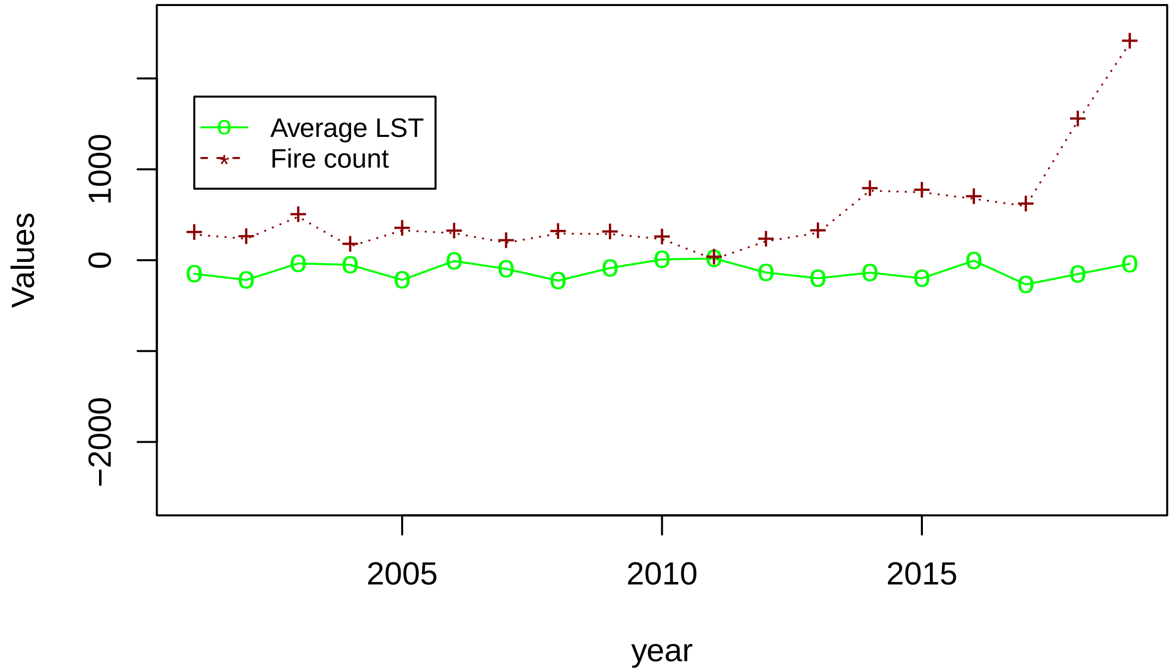
```
## [1] 0.01747641
```

```
## [1] 5722
```

Out of the 2261 distinct coordinates, about 1.747% of them had significant p-values, meaning that in about 1.747% of the coordinates, I would reject the hypothesis of temporal independence (they display serial correlation).

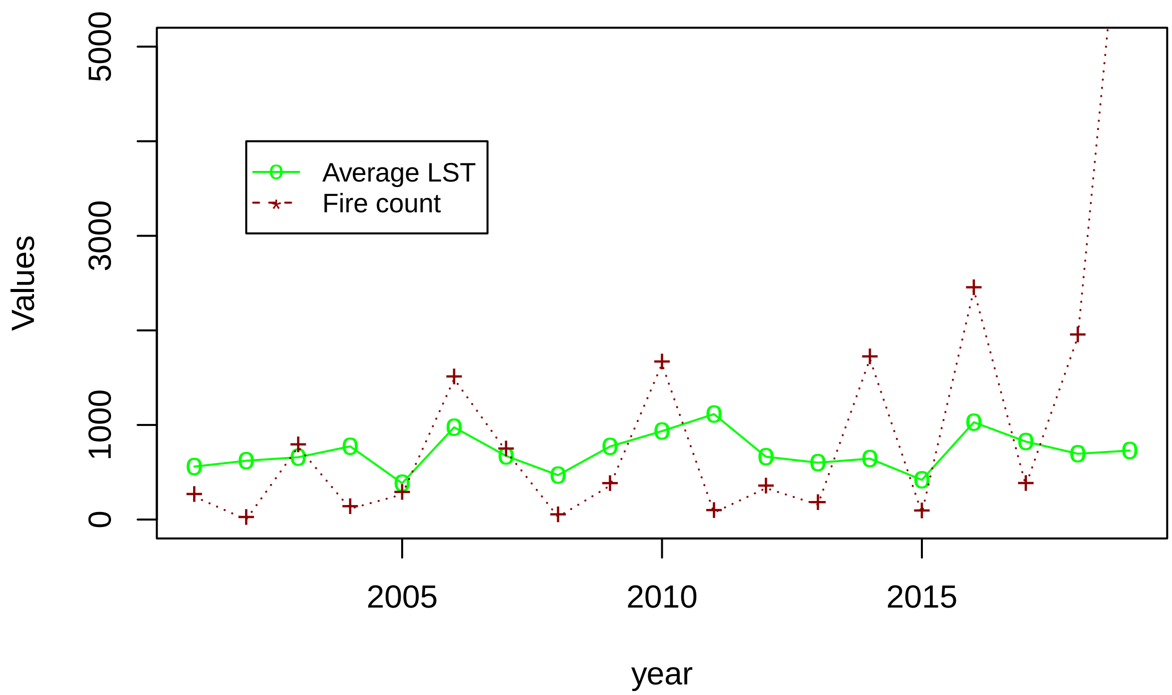
Land Surface Temperature anomaly and Fire across years

1. All Anomalies



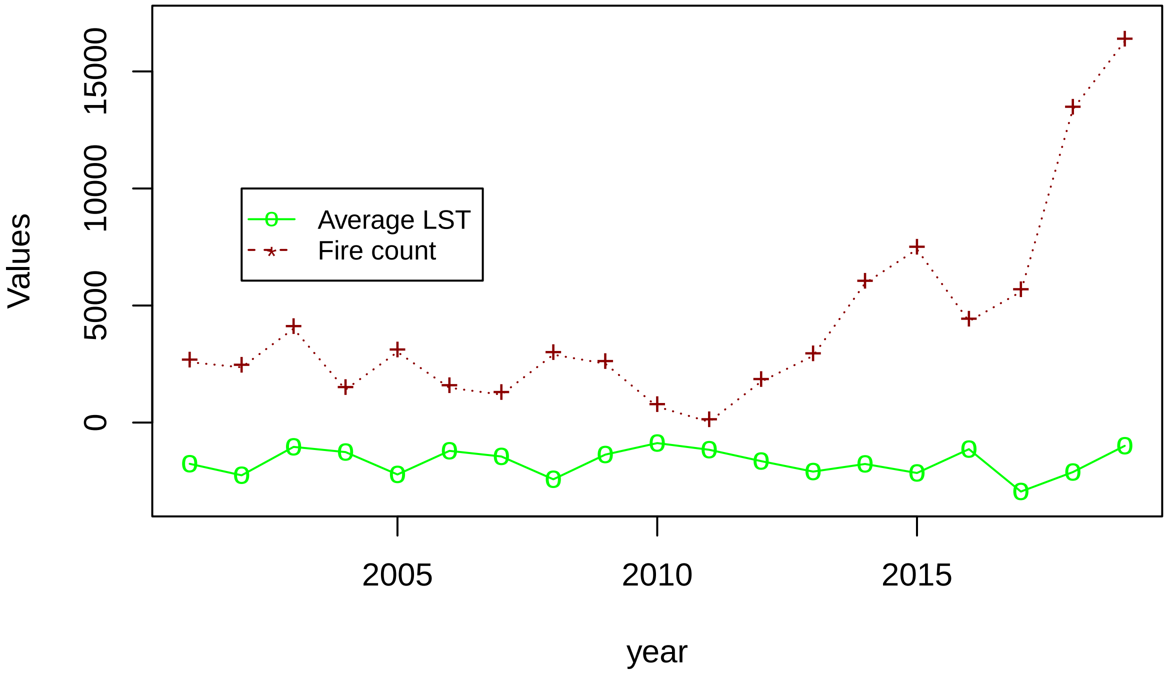
2. Positive Anomalies

```
## [1] 0
```



3. Negative Anomalies

```
## [1] 0
```



The line plot for Positive and Negative Fire anomalies looks similar.

SUMMARY

1.Fire count has increased with time. Firecount for 2018 and 2019 are alomost double the count for 2017.

2. There is a baseline shift in the Fire count from 2011. From 2001 to 2010 the line plot is almost flat. In 2011 the Fire count is the lowest.
3. Locations with fire split wr.to LST anomaly: almost 1:1 for positive and negative anomalies.
4. Th positive and negative anomalies show a similar relation with fire count.

5.I got weak relation between Land Surface Temperature anomaly and Fire occurrences.However, the data is not sufficient to confirm the relationship. Also, the point 4 doesn't seem to align with the relation.

Next steps

1. Take 2001 -2010 as baseline model.
2. Study the Fire causes.Add them in the model as categorical variables.
3. Study the lower fire count in 2011.

THANK YOU