The claims from the New York Times

The New York times gave the following reasons for why the fire season during this time was so brutal:

1. A combination of record-breaking heat, drought and high wind conditions have dramatically amplified the recent fire season in Australia.
2. The last month of 2019 saw particularly low rainfall and the country recorded its hottest day yet.
3. Crystal A. Kolden, a wildfire researcher (formerly) at the University of Idaho says the combination of extremely dry and extremely hot conditions adds up to more powerful fires.

Lets see if these results match up with the data!

Our data

```
# Run once

tuesdata <- tidytuesdayR::tt_load('2020-01-07')
```

Our dataset consists of 11 files- but for the questions we're interested in answering, we will be using the `rainfall.csv` and `temperature.csv` datasets.

Shaping our data

Since we are going to look at the relationship between temperature and rainfall we're going to need to find a way to join these two datasets.

```
library(tidyverse)
rainfall <-tuesdata$rainfall
temperature<-tuesdata$temperature

glimpse(rainfall)
```

```
## Rows: 179,273
## Columns: 11
## $ station_code  "009151", "009151", "009151", "009151", "009151", "009151",
"009151", "009151", "...
## $ city_name     "Perth", "Perth", "Perth", "Perth", "Perth", "Perth",
"Perth", "Perth", "Perth", ...
## $ year          1967, 1967, 1967, 1967, 1967, 1967, 1967, 1967, 1967, 1967,
1967, 1967, 1967, 196...
## $ month         "01", "01", "01", "01", "01", "01", "01", "01", "01", "01",
"01", "01", "01", "01...
## $ day           "01", "02", "03", "04", "05", "06", "07", "08", "09", "10",
"11", "12", "13", "14...
## $ rainfall      NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ period        NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ quality       NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ lat           -31.96, -31.96, -31.96, -31.96, -31.96, -31.96, -31.96,
-31.96, -31.96, -31.96, -...
## $ long          115.79, 115.79, 115.79, 115.79, 115.79, 115.79, 115.79,
115.79, 115.79, 115.79, 1...
## $ station_name  "Subiaco Wastewater Treatment Plant", "Subiaco Wastewater
Treatment Plant", "Subi...
```

```
glimpse(temperature)
```

```
## Rows: 528,278
## Columns: 5
## $ city_name    "PERTH", "PERTH", "PERTH", "PERTH", "PERTH", "PERTH",
"PERTH", "PERTH", "PERTH", "...
## $ date         1910-01-01, 1910-01-02, 1910-01-03, 1910-01-04, 1910-01-05,
1910-01-06, 1910-01-0...
## $ temperature  26.7, 27.0, 27.5, 24.0, 24.8, 24.4, 25.3, 28.0, 32.6, 35.9,
33.9, 38.6, 35.1, 32.9...
## $ temp_type    "max", "max", "max", "max", "max", "max", "max", "max",
"max", "max", "max", "max"...
## $ site_name    "PERTH AIRPORT", "PERTH AIRPORT", "PERTH AIRPORT", "PERTH
AIRPORT", "PERTH AIRPORT...
```

Looking at these two datasets with the `glimpse` function, we see that we can possibly join our datasets by date and by city.

Before we can join our datasets by date, we are going to need to put our date data in the same form as the `date` field in the `temperature` dataset.

```
# Full date
rainfall$fulldate <- paste(rainfall$year,rainfall$month,rainfall$day, sep='-')
%>% as.Date()

glimpse(rainfall)
```

```
## Rows: 179,273
## Columns: 12
## $ station_code  "009151", "009151", "009151", "009151", "009151", "009151",
"009151", "009151", "...
## $ city_name     "Perth", "Perth", "Perth", "Perth", "Perth", "Perth",
"Perth", "Perth", "Perth", ...
## $ year          1967, 1967, 1967, 1967, 1967, 1967, 1967, 1967, 1967, 1967,
1967, 1967, 1967, 196...
## $ month         "01", "01", "01", "01", "01", "01", "01", "01", "01", "01",
"01", "01", "01", "01...
## $ day           "01", "02", "03", "04", "05", "06", "07", "08", "09", "10",
"11", "12", "13", "14...
## $ rainfall      NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ period        NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ quality       NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ lat           -31.96, -31.96, -31.96, -31.96, -31.96, -31.96, -31.96,
-31.96, -31.96, -31.96, -...
## $ long          115.79, 115.79, 115.79, 115.79, 115.79, 115.79, 115.79,
115.79, 115.79, 115.79, 1...
## $ station_name  "Subiaco Wastewater Treatment Plant", "Subiaco Wastewater
Treatment Plant", "Subi...
## $ fulldate      1967-01-01, 1967-01-02, 1967-01-03, 1967-01-04, 1967-01-05,
1967-01-06, 1967-01-...
```

Now that we have that taken care of we have to format our city names so that they can be joined together. This can be accomplished with the `stringr` package's `str_to_title` function.

```
library(stringr)

temperature$city_name_new<-temperature$city_name %>% str_to_title()

glimpse(temperature)
```

```
## Rows: 528,278
## Columns: 6
## $ city_name      "PERTH", "PERTH", "PERTH", "PERTH", "PERTH", "PERTH",
"PERTH", "PERTH", "PERTH",...
## $ date           1910-01-01, 1910-01-02, 1910-01-03, 1910-01-04,
1910-01-05, 1910-01-06, 1910-01...
## $ temperature    26.7, 27.0, 27.5, 24.0, 24.8, 24.4, 25.3, 28.0, 32.6,
35.9, 33.9, 38.6, 35.1, 32...
## $ temp_type      "max", "max", "max", "max", "max", "max", "max", "max",
"max", "max", "max", "ma...
## $ site_name      "PERTH AIRPORT", "PERTH AIRPORT", "PERTH AIRPORT", "PERTH
AIRPORT", "PERTH AIRPO...
```

```
## $ city_name_new  "Perth", "Perth", "Perth", "Perth", "Perth", "Perth",
"Perth", "Perth", "Perth",...
```

Now before we do the join lets view the cities listed in both datasets.

```
unique(rainfall$city_name)
```

```
## [1] "Perth"     "Adelaide"  "Brisbane"  "Sydney"    "Canberra"  "Melbourne"
```

```
unique(temperature$city_name_new)
```

```
## [1] "Perth"     "Port"      "Kent"      "Brisbane"  "Sydney"    "Canberra"
"Melbourne"
```

The `temperature` dataset accounts for Port an Kent, which aren't accounted for in the `rainfall` dataset; the `rainfall` dataset accounts for Adelaide which is not accounted for in the `temperature` dataset. Despite not having corresponding data, it would be insightful to look at the patterns for temperature and rainfall individually for these cities.

The challenge that I have with joining this data is that my machine is unable to allocate the memory to perform the join. So to slim down our data set lets filter our datasets to records from the 21st century. This way we can investigate the fires that took place from September 2019 to March 2020.

```
#' Datasets from the 21st Century and on

rainfall21<-filter(rainfall,fulldate >= "2000-01-01")
temperature21<-filter(temperature, date >= "2000-01-01")
```

Lets now join our data with using the `full_join` function from the `dplyr` package (this comes pre-loaded when we load `tidyverse`).

```
workingdf<-rainfall21[,c(2,6,7,8,11,12)] %>%
  full_join(temperature21,by=c("city_name"="city_name_new",
"fulldate"="date")) %>%
  group_by(fulldate)

glimpse(workingdf)
```

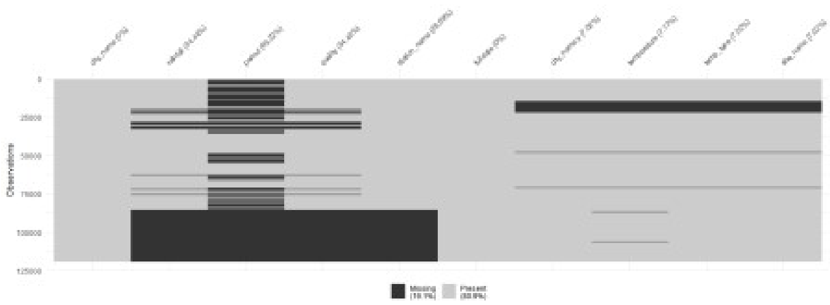
```
## Rows: 119,220
## Columns: 10
## Groups: fulldate [7,311]
## $ city_name     "Perth", "Perth", "Perth", "Perth", "Perth", "Perth",
"Perth", "Perth", "Perth", ...
## $ rainfall      0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0...
## $ period        NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
## $ quality       "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y",
"Y", "Y", "Y", "Y", "...
## $ station_name  "Subiaco Wastewater Treatment Plant", "Subiaco Wastewater
Treatment Plant", "Subi...
## $ fulldate      2000-01-01, 2000-01-01, 2000-01-02, 2000-01-02, 2000-01-03,
2000-01-03, 2000-01-...
```

```
## $ city_name.y   "PERTH", "PERTH", "PERTH", "PERTH", "PERTH", "PERTH",
"PERTH", "PERTH", "PERTH", ...
## $ temperature   36.5, 20.7, 37.2, 21.0, 36.3, 18.3, 37.4, 19.7, 37.2, 22.8,
35.4, 22.4, 34.5, 16....
## $ temp_type     "max", "min", "max", "min", "max", "min", "max", "min",
"max", "min", "max", "min...
## $ site_name     "PERTH AIRPORT", "PERTH AIRPORT", "PERTH AIRPORT", "PERTH
AIRPORT", "PERTH AIRPOR...
```

Missing data

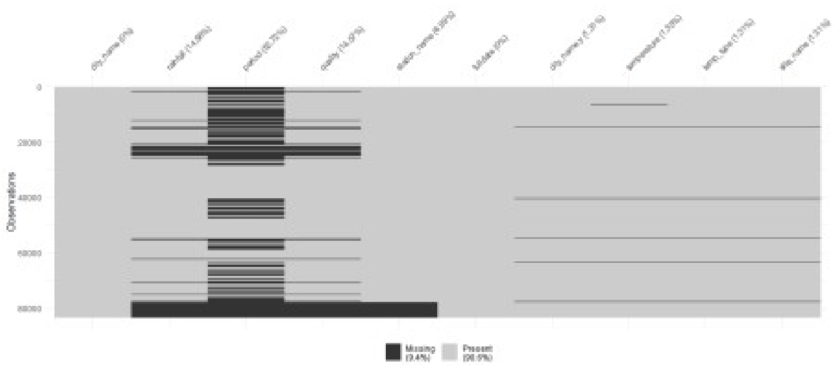
Having our joining and filtering taken care of doesn't mean we're done yet. Lets see what our missing data looks like. Thankfully the `naniar` package has a function that can help us with visualizing it, without being too labor intensive.

```
library(naniar)

vis_miss(workingdf,warn_large_data = FALSE)
```



Lets see what our dataset looks like when we remove the cities that are not commonly shared.

```
workingdf2<- workingdf %>%
  filter(city_name!="Port" & city_name !="Kent" & city_name != "Adelaide") %>%
  group_by(fulldate)

vis_miss(workingdf2,warn_large_data = FALSE)
```



Based on the numbers listed in the visualization, 9.7% of the missing data can be attributed to the cities not commonly shared by the rainfall and temperature datasets.

It looks like we are missing data about rainfall for 2019. But looks can be decieving. Lets confirm if there is no data on our area of interest.

```
workingdf3<- workingdf %>% filter(fulldate>="2018-09-01")
```

```
workingdf3
```

```
## # A tibble: 5,374 x 10
## # Groups:   fulldate [493]
##    city_name rainfall period quality station_name    fulldate   city_name.y
temperature temp_type site_name
##
##  1 Perth            0     NA N       Subiaco Wastew~ 2018-09-01 PERTH
19.3 max       PERTH AI~
##  2 Perth            0     NA N       Subiaco Wastew~ 2018-09-01 PERTH
9.1 min       PERTH AI~
##  3 Perth            0     NA N       Subiaco Wastew~ 2018-09-02 PERTH
20   max       PERTH AI~
##  4 Perth            0     NA N       Subiaco Wastew~ 2018-09-02 PERTH
6.6 min       PERTH AI~
##  5 Perth            0     NA N       Subiaco Wastew~ 2018-09-03 PERTH
20.5 max       PERTH AI~
##  6 Perth            0     NA N       Subiaco Wastew~ 2018-09-03 PERTH
4.9 min       PERTH AI~
##  7 Perth            6      1 N       Subiaco Wastew~ 2018-09-04 PERTH
18.3 max       PERTH AI~
##  8 Perth            6      1 N       Subiaco Wastew~ 2018-09-04 PERTH
11   min       PERTH AI~
##  9 Perth            5      1 N       Subiaco Wastew~ 2018-09-05 PERTH
16.2 max       PERTH AI~
## 10 Perth            5      1 N       Subiaco Wastew~ 2018-09-05 PERTH
9.7 min       PERTH AI~
## # ... with 5,364 more rows
```

Well, will you look at that! We actually have data on rainfall for 2019! I guess we learn from here that a picture can only tell so much, so always be sure to check the actual data to verify. Our visualization deceiving us can probably be due to the fact that our dataset is now only a little more than 5000 rows in a dataset which has 125,000. It probably is hard to scale this in a visualization, especially given the size of the data.

Understanding the nature of the data

What I really enjoy and find challenging about this dataset is that the data is multi-leveled. Thankfully we have the data dictionary (check out the readme.md) to look at for this dataset.

One of the variables that are important to note is the `temp_type` variable; this tells us what type of daily tempertature is recorded- be it the daily minimum or maximum; ***what is also important to see is that there is missing data present in this as well.***

(*Spoiler alert: I found a mistake in this blog before I published it*)

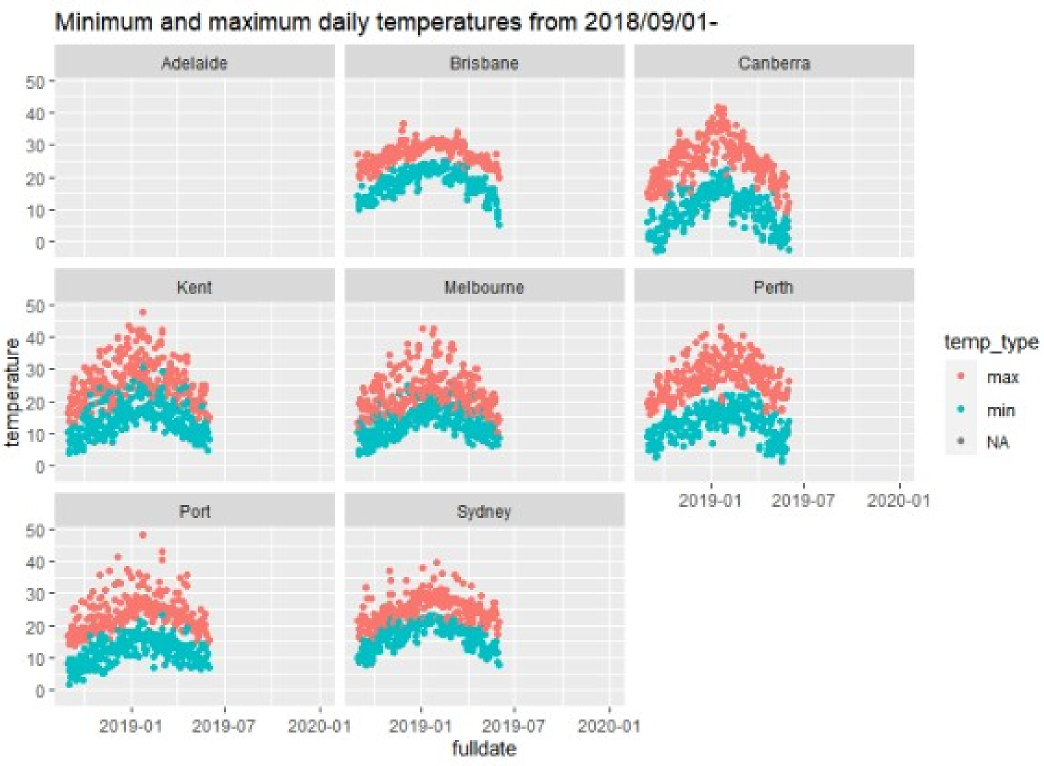
Visualizing the raw data

With this in mind we will make the following visualizations to account for this discrepancy.

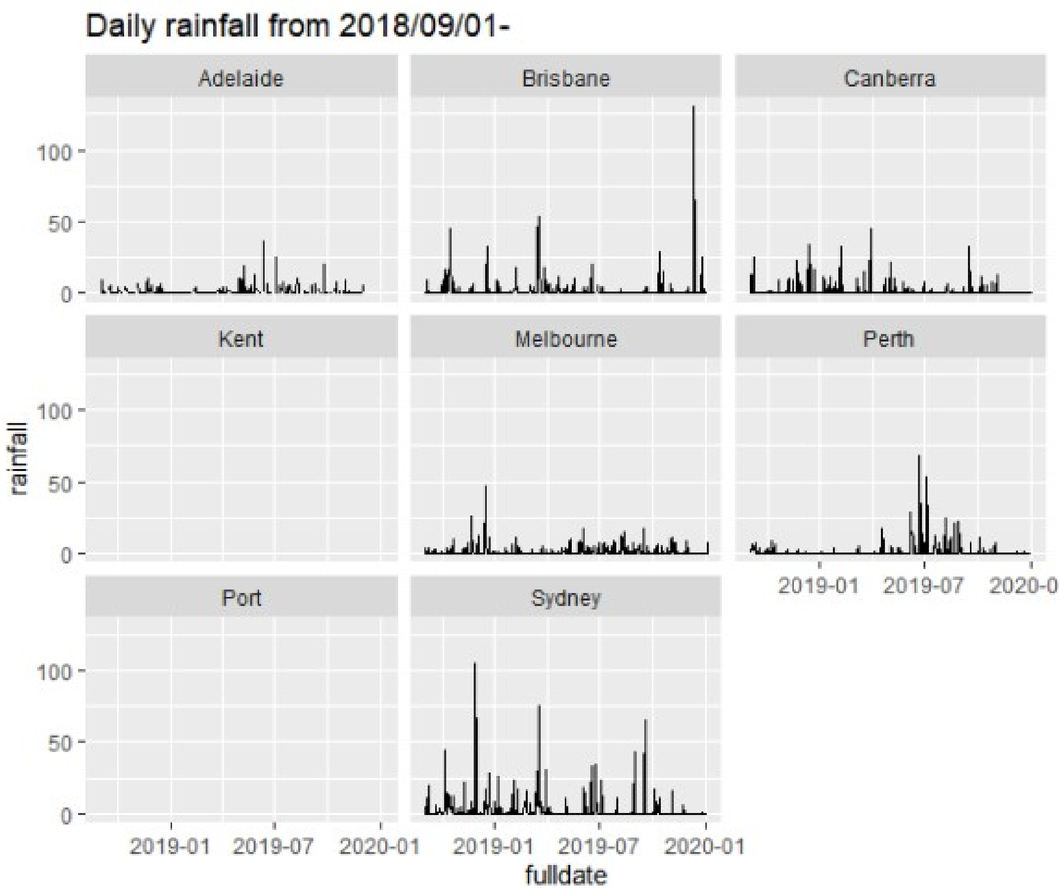
- plot minimum and maximum temperatures over time – faceting on city
- plot rainfall over time – faceting on city
- In addition to the above we will make some raw plots of the data on temperature and rainfall over time from the 21st Century.

```
ggplot(data=workingdf3,mapping=aes(x=fulldate,y=temperature,color=temp_type))+
  geom_point()+
```

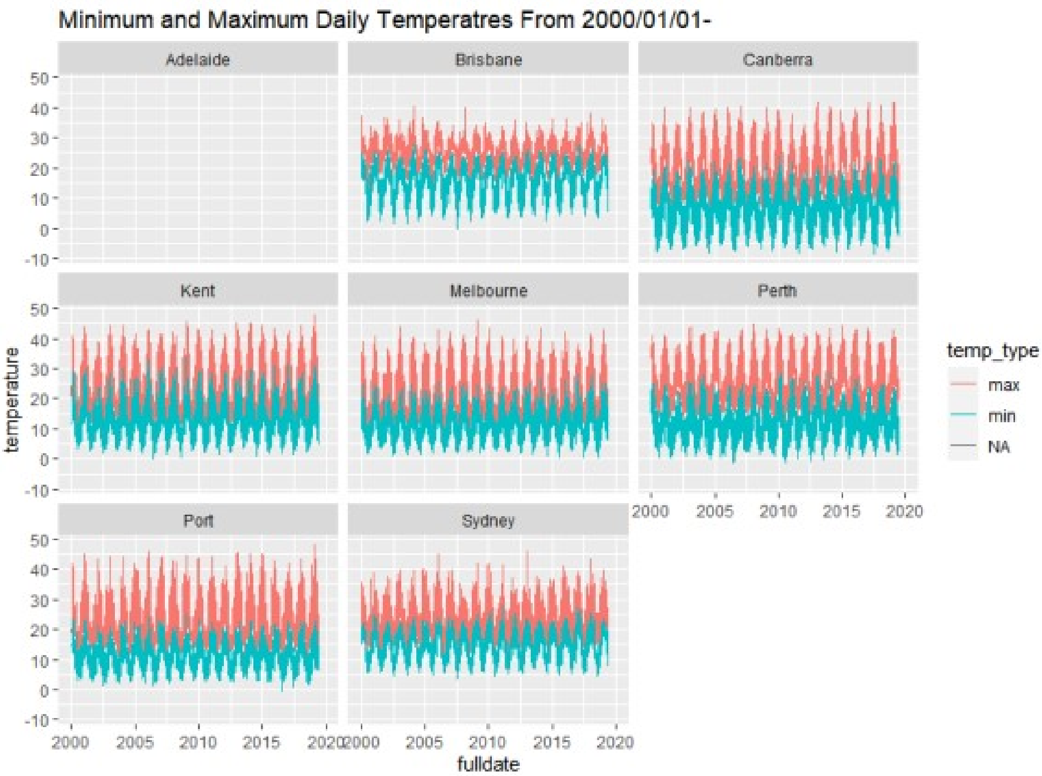
```
  facet_wrap(~city_name)+
  ggtitle("Minimum and maximum daily temperatures from 2018/09/01-")
```




```
ggplot(data=workingdf3,mapping=aes(x=fulldate,y=rainfall))+
  geom_line()+
  facet_wrap(~city_name)+
  ggtitle("Daily rainfall from 2018/09/01-")
```

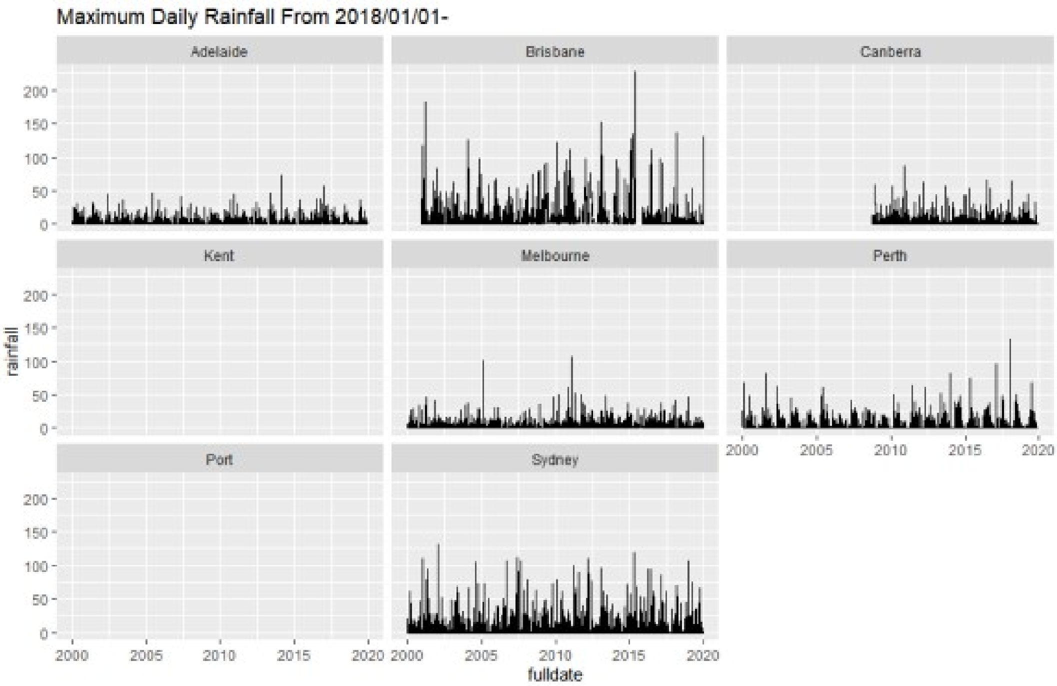



```
ggplot(data = workingdf) +
  geom_line(mapping = aes(x = fulldate, y = temperature,color=temp_type)) +
  ggtitle("Minimum and Maximum Daily Temperatres From 2000/01/01-")+
  facet_wrap(~city_name)
```




```
ggplot(data = workingdf) +
  geom_line(mapping = aes(x = fulldate, y = rainfall)) +
```

```
    ggtitle("Maximum Daily Rainfall From 2000/01/01-")+
    facet_wrap(~city_name)
```



From the visualizations here, temperature doesn't seem to be abnormal in 2019 over the years. This is because I'm looking at the general movement of the raw data and need to look at an annual and monthly statistic- like the mean- to note any abnormalities.

As far as rainfall is concerned, the given visualizations are not the best for showing if there has been a drop in rainfall. In this case too we will have to look at an annual/monthly statistic (like the mean) to see if there really has been a drop in rainfall during the time of the fires.

Looking at Annual measures of Temperature and Rainfall.

Statistical transformations

Before we plot our annual data, we are going to have to incorperate the `year` field into our dataset. Thankfully, we have this isolated in our original data set. But we can save time by using the `lubridate` package instead.

```
library(lubridate)

workingdf$year<- year(workingdf$fulldate)

glimpse(workingdf)
```

```
## Rows: 119,220
## Columns: 11
## Groups: fulldate [7,311]
## $ city_name     "Perth", "Perth", "Perth", "Perth", "Perth", "Perth",
"Perth", "Perth", "Perth", ...
## $ rainfall      0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0...
## $ period        NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, N...
```

```
## $ quality       "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y", "Y",
"Y", "Y", "Y", "Y", "...
## $ station_name  "Subiaco Wastewater Treatment Plant", "Subiaco Wastewater
Treatment Plant", "Subi...
## $ fulldate      2000-01-01, 2000-01-01, 2000-01-02, 2000-01-02, 2000-01-03,
2000-01-03, 2000-01-...
## $ city_name.y   "PERTH", "PERTH", "PERTH", "PERTH", "PERTH", "PERTH",
"PERTH", "PERTH", "PERTH", ...
## $ temperature   36.5, 20.7, 37.2, 21.0, 36.3, 18.3, 37.4, 19.7, 37.2, 22.8,
35.4, 22.4, 34.5, 16....
## $ temp_type     "max", "min", "max", "min", "max", "min", "max", "min",
"max", "min", "max", "min...
## $ site_name     "PERTH AIRPORT", "PERTH AIRPORT", "PERTH AIRPORT", "PERTH
AIRPORT", "PERTH AIRPOR...
## $ year          2000, 2000, 2000, 2000, 2000, 2000, 2000, 2000, 2000, 2000,
2000, 2000, 2000, 200...
```

The real work takes place when we are using `dplyr`, thankfully I am able to shape the data the way I like it because of what I learned while making my video on the pipe operator (*shameless plug*).

```
workingdfmaxtemp<- workingdf %>% filter(temp_type=="max")
workingdfmintemp<- workingdf %>% filter(temp_type=="min")


maxtempannualdf <- workingdfmaxtemp %>%
  group_by(city_name, year) %>%
  summarize(
    mean_rain = mean(rainfall, na.rm = T),
    mean_temperature_max = mean(temperature, na.rm = T)
  )


mintempannualdf <- workingdfmintemp %>%
  group_by(city_name, year) %>%
  summarize(
    mean_rain = mean(rainfall, na.rm = T),
    mean_temperature_min = mean(temperature, na.rm = T)
  )


annualtempdf <- mintempannualdf %>%
  full_join(maxtempannualdf)

glimpse(annualtempdf)
```

```
## Rows: 140
## Columns: 5
## Groups: city_name [7]
## $ city_name             "Brisbane", "Brisbane", "Brisbane", "Brisbane",
"Brisbane", "Brisbane", "...
## $ year                  2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007,
2008, 2009, 2010, 2011, 2...
## $ mean_rain             1.966667, 2.976616, 1.895862, 2.337047, 3.230380,
2.097305, 2.175346, 1.9...
## $ mean_temperature_min  15.084426, 15.183836, 15.074247, 15.109589,
```

```
15.322951, 15.936438, 15.4134...
## $ mean_temperature_max  25.08798, 25.71836, 25.85644, 25.24082, 25.94699,
25.79644, 25.51370, 25....
```

What Happened to Adelaide?

Whilst proofreading this to be posted I noticed that **Adelaide** is nowhere to be seen in this dataset. I first was looking at my joins and thought I was doing something wrong, but then I realized- we partitioned our data based on the `temp_type` variable! While we gained some precision for our temperature data, we lost data on an entire city that doesn't have any temperature data availible to it!

With this in mind we will have to make a separate analysis for Adelaide as we don't have any information about the temperature. Below is the code I used to prepare rainfall data of Adelaide.

```
workingdfAdelaide<-workingdf %>% filter(city_name =="Adelaide")

rainfalldfAdelaide <- workingdfAdelaide %>%
  group_by(city_name,year) %>%
  summarize(
    mean_rain = mean(rainfall, na.rm = T),
  )

rainfalldfAdelaide
```

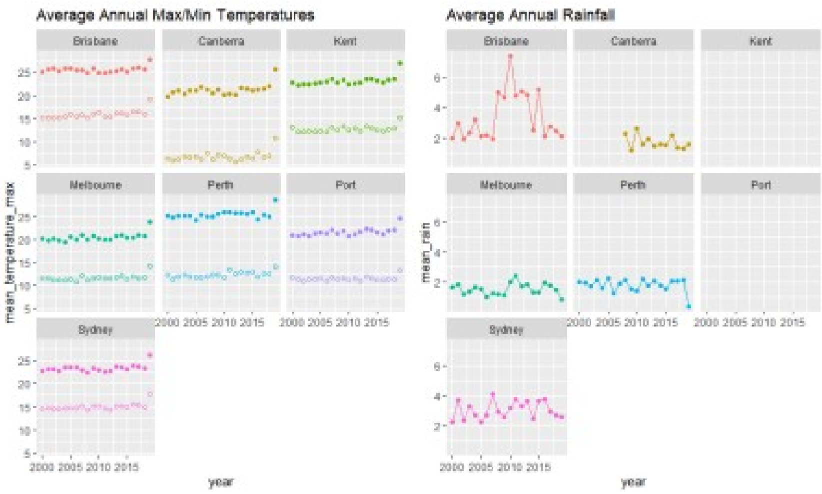
```
## # A tibble: 20 x 3
## # Groups:   city_name [1]
##    city_name  year mean_rain
##
##  1 Adelaide   2000     1.53
##  2 Adelaide   2001     1.71
##  3 Adelaide   2002     0.996
##  4 Adelaide   2003     1.49
##  5 Adelaide   2004     1.41
##  6 Adelaide   2005     1.61
##  7 Adelaide   2006     0.757
##  8 Adelaide   2007     1.27
##  9 Adelaide   2008     1.03
## 10 Adelaide   2009     1.34
## 11 Adelaide   2010     1.53
## 12 Adelaide   2011     1.45
## 13 Adelaide   2012     1.51
## 14 Adelaide   2013     1.50
## 15 Adelaide   2014     1.42
## 16 Adelaide   2015     1.06
## 17 Adelaide   2016     2.36
## 18 Adelaide   2017     1.58
## 19 Adelaide   2018     1.24
## 20 Adelaide   2019     1.16
```

Visualizing our transformed data.

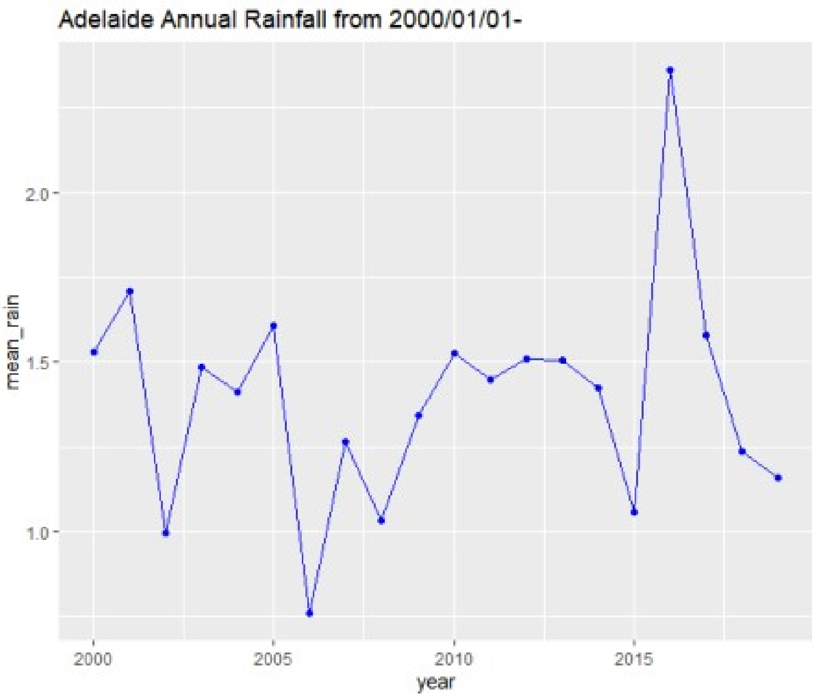
Now that we have shaped and calculated the available annual means for the cities listed in our dataset, we can come up with some visualizations.

```
library(gridExtra)
```

```
grid.arrange(
  ggplot(data = annualtempdf, mapping = aes(x = year, color = city_name)) +
    geom_point(mapping = aes(y = mean_temperature_max)) +
    geom_point(
      mapping = aes(y = mean_temperature_min),
      shape = 1
    ) +
    facet_wrap( ~ city_name) +
    ggtitle("Average Annual Max/Min Temperatures")+
    theme(legend.position = "none"),


  ggplot(data = annualtempdf, mapping = aes(x = year, color = city_name)) +
    geom_point(mapping = aes(y = mean_rain)) +
    geom_line(mapping = aes(y = mean_rain)) +
    facet_wrap( ~ city_name) +
    ggtitle("Average Annual Rainfall")+
    theme(legend.position = "none"),

  ncol=2
)
```




```
ggplot(data=rainfalldfAdelaide)+
  geom_point(mapping=aes(x=year,y=mean_rain),color="blue")+
  geom_line(mapping=aes(x=year,y=mean_rain),color="blue")+
  theme(legend.position = "none")+
  ggtitle("Adelaide Annual Rainfall")
```



It does look like that during this period **all** of our cities which we have data during this time experienced a jump in average annual maximum and minimum temperatures. Similarly with rainfall, while some cities did not experience an abnormally low average rainfall (like Sydney, Canberra, Brisbane and Adelaide), others did experience it (like Melbourne and Perth).

With this we have agreement with our first point that there was record breaking heat (at least in the past ~20 years) and drought present during the time of the fires. As far as high wind conditions, there is presently no data for that, so we can't verify if that was present (comment if you have a datasource for wind conditions!).

Looking at monthly measures of Temperature and Rainfall.

Now that we have verified the first claim of the New York Times, lets move on to the second one.

> "The last month of 2019 saw particularly low rainfall, and the country recorded its hottest day yet."

Well to do this we're going to have to group our data by month in a similar manner we grouped by year. Thankfully the `lubridate` package has the `format_ISO8601()` function (looks easy to remember) and to have that read as date data, we will pipe this to the `ym()` function.

```
workingdf$year_month<-workingdf$fulldate %>%  format_ISO8601(precision = 'ym') %>% ym()
```

Now we just need to run this code through the same `dplyr` code we wrote earlier (in "Statistical transformations") – but now grouping by `city` and `year_month`

```
# Because we are adding a new variable we need to rerun our maximum and minium temperature dataframes.

workingdfmaxtemp<- workingdf %>% filter(temp_type=="max")
workingdfmintemp<- workingdf %>% filter(temp_type=="min")


maxtempmonthdf <- workingdfmaxtemp %>%
```

```
  group_by(city_name, year_month) %>%
  summarize(
    mean_rain = mean(rainfall, na.rm = T),
    mean_temperature_max = mean(temperature, na.rm = T)
  )


mintempmonthdf <- workingdfmintemp %>%
  group_by(city_name, year_month) %>%
  summarize(
    mean_rain = mean(rainfall, na.rm = T),
    mean_temperature_min = mean(temperature, na.rm = T)
  )


# Add a filter to focus our dataset on data from 2019 and on

monthtempdf <- mintempmonthdf %>%
  full_join(maxtempmonthdf) %>%
  filter(year_month>= "2018-01-01")

glimpse(monthtempdf)
```

```
## Rows: 119
## Columns: 5
## Groups: city_name [7]
## $ city_name             "Brisbane", "Brisbane", "Brisbane", "Brisbane",
"Brisbane", "Brisbane", "...
## $ year_month            2018-01-01, 2018-02-01, 2018-03-01, 2018-04-01,
2018-05-01, 2018-06-01, ...
## $ mean_rain             0.9923077, 13.5904762, 5.0000000, 1.2000000,
0.8933333, 0.9733333, 0.8322...
## $ mean_temperature_min  21.2258065, 20.7678571, 20.5419355, 17.6666667,
13.0677419, 10.3900000, 9...
## $ mean_temperature_max  30.53226, 28.63929, 27.60968, 26.56000, 23.81290,
21.57667, 21.92903, 22....
```

For Adelaide, we write the following script.

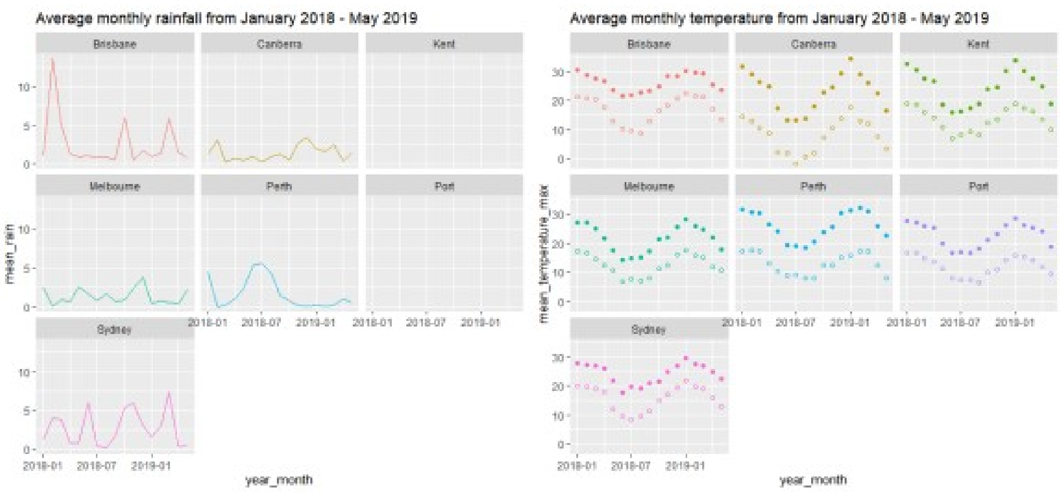
```
# Excuse the long name for the variable. I know its faux pas.

workingdfAdelaide$year_month<-workingdfAdelaide$fulldate %>%
format_ISO8601(precision = 'ym') %>% ym()

rainfalldfAdelaideMonthly<- workingdfAdelaide %>%
  group_by(city_name, year_month) %>%
  summarize(
    mean_rain = mean(rainfall, na.rm = T),
    mean_temperature_max = mean(temperature, na.rm = T)
  ) %>%
  filter(year_month >= "2018-01-01")
```

Now with that done lets get to visualizing our monthly data.

Visualizing our transformed data.

What is important to note from these visualizations is that we don't have data on rainfall, or temperature for the end of 2019. So what we can only look at how things were before the end of 2019.

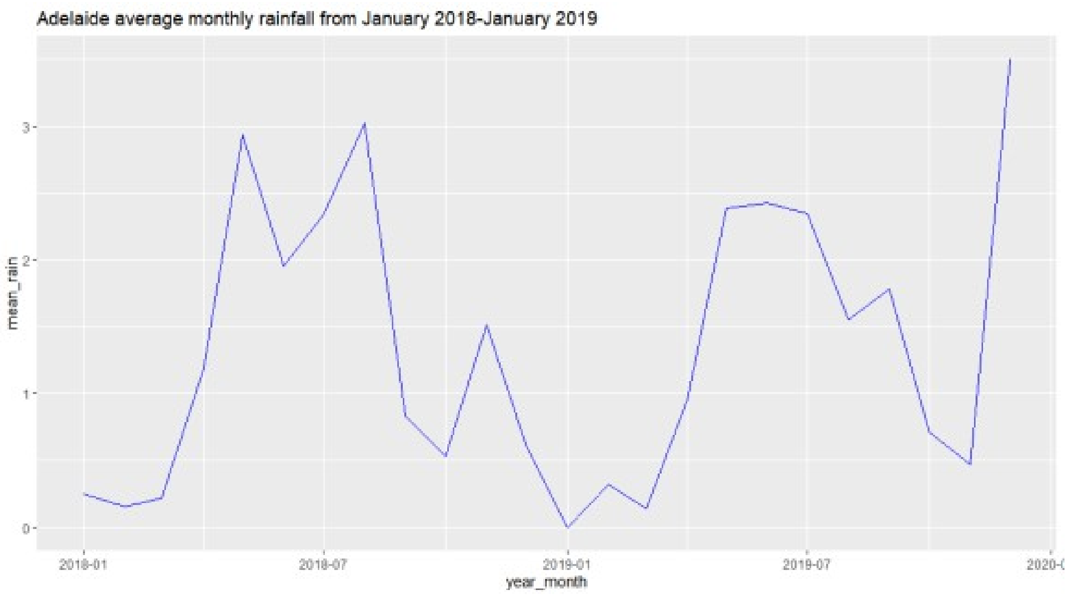
```
grid.arrange(
  ggplot(
    data = monthtempdf,
    mapping = aes(x = year_month, color = city_name)
  ) +
    geom_line(mapping = aes(y = mean_rain)) +
    facet_wrap( ~ city_name) +
    theme(legend.position = "none") +
    ggtitle("Average monthly rainfall from January 2018 - May 2019"),


  ggplot(
    data = monthtempdf,
    mapping = aes(x = year_month, color = city_name)
  ) +
    geom_point(mapping = aes(y = mean_temperature_max)) +
    geom_point(
      mapping = aes(y = mean_temperature_min),
      shape = 1
    ) +
    facet_wrap( ~ city_name) +
    theme(legend.position = "none") +
    ggtitle("Average monthly temperature from January 2018 - May 2019"),

  ncol = 2
)
```



For Adelaide we'll make a seperate visualization for its monthly rainfall. It should be grouped with the other rainfall data, but the other data needing to be split by temperature measurements makes the join awkward.

(Clearly, this part is after the fact)

```
ggplot(data= rainfalldfAdelaideMonthly, mapping=aes(x=year_month,mean_rain))+
  geom_line(color="blue")+
  ggtitle("Adelaide average monthly rainfall from January 2018-January 2019 ")
```



Analysis

Before we begin our discussion lets look at the rain season present in our plotted cities:
(**Disclaimer – I do not live in Austrailia and am relying on the internet to tell me when the rainy season is for these cities, if you see an error let me know!**)

- **Adelaide's** wet season lasts for 11 months, from January 22 to January 4 (source)
- **Brisbane's** rainy season is from December to February (source)
- **Canberra's** rainy season is from September to November (source)
- **Melbourne's** rainy season appears to be from September to November, but seems to get a pretty even spread of rainfall throughout the year (source)
- **Perth's** rainy season occurs from June to August (source)
- **Sydney's** doesn't really have a rainy season,but September and October are the months with the least amount of rain. (source)

Looking at the data, it apprears that Brisbane had significantly less rainfall in February 2019 (average 1.36 mm) than it did in 2018 (average 13.59 mm) which definitely looks telling even to someone without a background in meteorology of an onset to a drought. With Canberra, Melbourne, and Perth since we only have data up to March of 2019, we can't really make any inference about evidence for the onset of a drought. For Sydney, April and May of 2019 were dramatically lower in their rainfall (averages 0.37 mm and 0.47 mm) than they were in the previous year (averages 0.77 mm and 0.74) with drops in average rainfall being around 48% and 64% which can also be telling of an onset of a drought.

While we don't have any other data about the *last month* of 2019, we do have information about the onset of a drought occuring. I wish I could tell more, but thats what the data tells us!

As far as I can tell, with Adelaide, nothing looks off in terms of precipitation (do you see/know something? let me know!), the data that is plotted seems to agree with my internet search results.

One of the advantages of the Adelaide rainfall dataset is that we have data on rainfall going until the end of 2019. But as far as rainfall is concerned there is nothing abnormal to report as far as low rainfall is concerned.

Conclusion

As for the final claim from the New York times

> "[Crystal A. Kolden, a wildfire researcher (formerly) at the University of Idaho] says the combination of extremely dry and extremely hot conditions adds up to more powerful fires."