

australian-fires-data-visualizations

December 2, 2023

```
[10]: import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import numpy as np1
import pandas as pd
import plotly.graph_objects as go
import matplotlib.pyplot as plt
import plotly.express as px
import os
```

1 Data columns

- Field name Description
- latitude Center of 1km fire pixel but not necessarily the actual location of the fire as one or more fires can be detected within the 1km pixel.
- longitude Center of 1km fire pixel but not necessarily the actual location of the fire as one or more fires can be detected within the 1km pixel.
- brightness Brightness temperature 21 (Kelvin): Channel 21/22 brightness temperature of the fire pixel measured in Kelvin.
- scan Along Scan pixel size: The algorithm produces 1km fire pixels but MODIS pixels get bigger toward the edge of scan. Scan and track reflect actual pixel size.
- track Along Track pixel size: The algorithm produces 1km fire pixels but MODIS pixels get bigger toward the edge of scan. Scan and track reflect actual pixel size.
- acq_date Date of MODIS acquisition.
- acq_time Acquisition Time: Time of acquisition/overpass of the satellite (in UTC).
- satellite Satellite: A = Aqua and T = Terra.
- instrument Instrument: Constant value for MODIS.
- confidence Confidence (0-100%): This value is based on a collection of intermediate algorithm quantities used in the detection process.
- version Version: Algorithm version used to process the data.
- bright_t31 Brightness temperature 31 (Kelvin): Channel 31 brightness temperature of the fire pixel measured in Kelvin.
- frp Fire Radiative Power (FRP) in Megawatts (MW): FRP is the radiant heat power emitted by the fire, as measured by the MODIS sensor.
- daynight Day/Night: Flag indicating whether the fire was detected during the day (D) or night (N).

Load data

```
[17]: df = pd.read_csv("fire_archive_M6_96619.csv")
```

Show first five rows of data

```
[19]: df.head()
```

```
[19]:
```

	latitude	longitude	brightness	scan	track	acq_date	acq_time	\
0	-11.8070	142.0583	313.0	1.0	1.0	2019-08-01	56	
1	-11.7924	142.0850	319.3	1.0	1.0	2019-08-01	56	
2	-12.8398	132.8744	311.6	3.1	1.7	2019-08-01	57	
3	-14.4306	143.3035	310.1	1.1	1.1	2019-08-01	57	
4	-12.4953	131.4897	310.3	4.0	1.9	2019-08-01	57	

	satellite	instrument	confidence	version	bright_t31	frp	daynight	type
0	Terra	MODIS	48	6.3	297.3	6.6	D	0
1	Terra	MODIS	71	6.3	297.3	11.3	D	0
2	Terra	MODIS	42	6.3	298.7	23.1	D	0
3	Terra	MODIS	33	6.3	296.1	6.5	D	0
4	Terra	MODIS	36	6.3	298.8	27.6	D	0

Information about data

```
[22]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36011 entries, 0 to 36010
Data columns (total 15 columns):
#   Column          Non-Null Count  Dtype
---  -
0   latitude        36011 non-null  float64
1   longitude        36011 non-null  float64
2   brightness       36011 non-null  float64
3   scan            36011 non-null  float64
4   track           36011 non-null  float64
5   acq_date        36011 non-null  object
6   acq_time        36011 non-null  int64
7   satellite       36011 non-null  object
8   instrument      36011 non-null  object
9   confidence      36011 non-null  int64
10  version         36011 non-null  float64
11  bright_t31      36011 non-null  float64
12  frp             36011 non-null  float64
13  daynight        36011 non-null  object
14  type            36011 non-null  int64
dtypes: float64(8), int64(3), object(4)
memory usage: 4.1+ MB
```

```
[24]: min(df['acq_date'])
```

```
[24]: '2019-08-01'
```

```
[26]: max(df['acq_date'])
```

```
[26]: '2019-09-30'
```

2 Seasonal Variation:

Plot: Line plot showing the number of fires over time, grouped by seasons. Seasonal variation could be an indicator of natural factors like dry seasons. Geographical Distribution:

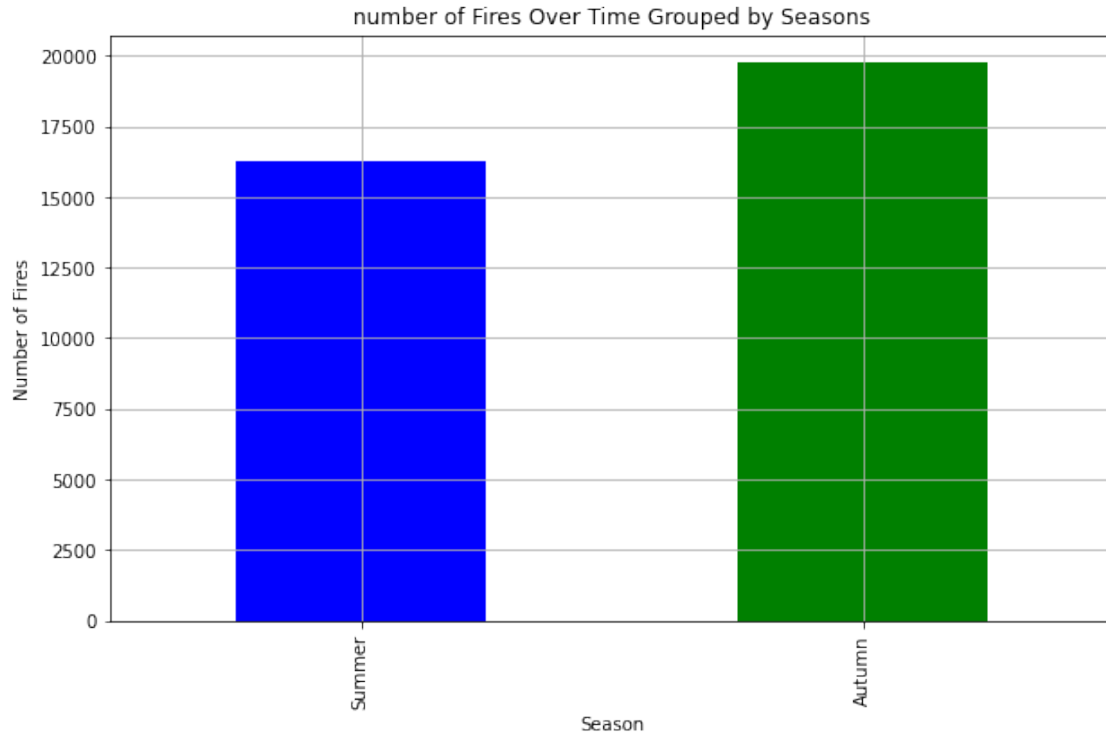
```
[29]: # assuming 'acq_date' is in datetime format in your DataFrame
# If not, convert it using df['acq_date'] = pd.to_datetime(df['acq_date'])
df['acq_date'] = pd.to_datetime(df['acq_date'])

# create a new column for the season based on the month
df['season'] = df['acq_date'].dt.month.apply(lambda x: (x % 12 + 3) // 3)

# group by season and count the number of fires
seasonal_fires = df.groupby('season').size()

# map season numbers to names
season_names = {1: 'Winter', 2: 'Spring', 3: 'Summer', 4: 'Autumn'}
seasonal_fires.index = seasonal_fires.index.map(season_names)
```

```
[31]: # Plotting
plt.figure(figsize=(10, 6))
#plt.plot(seasonal_fires#.index, seasonal_fires, marker='o', kind='bar', linestyle='-', color='b', markerfacecolor='r')
seasonal_fires.plot(kind='bar', stacked=True, color=['blue', 'green'])
plt.title('number of Fires Over Time Grouped by Seasons')
plt.xlabel('Season')
plt.ylabel('Number of Fires')
plt.grid(True)
plt.show()
```



3 Result

Winter and autumn are the fire seasons in many parts of the world because these seasons are typically associated with drier conditions and increased winds, which can make it easier for fires to start and spread.

Factors that contribute to wildfires in winter and autumn include:

- Drier conditions
- Increased winds
- Leaves on the ground
- Low humidity
- Human activity
- Lightning

4 Reference

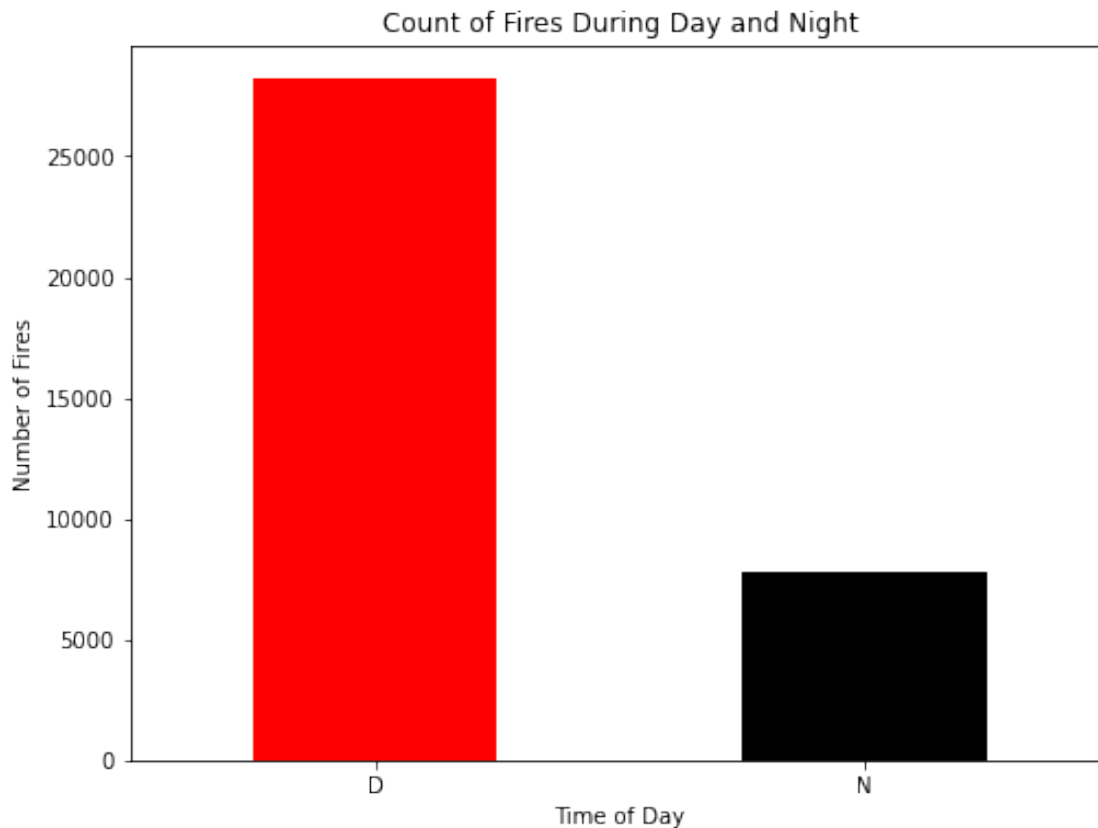
<https://en.wikipedia.org/wiki/Wildfire>

5 Time of Day:

Plot: Bar plot showing the count of fires during the day and night. This might indicate if human activities play a role in fire occurrences.

```
[35]: day_night = df['daynight'].value_counts().sort_index()
```

```
[37]: plt.figure(figsize=(8, 6))
day_night.plot(kind='bar', color=['red', 'black'])
plt.title('Count of Fires During Day and Night')
plt.xlabel('Time of Day')
plt.ylabel('Number of Fires')
plt.xticks(rotation=0)
plt.show()
```



6 Result

- The data shows that a higher percentage of fires occur during the day (61.80%) than at night (38.19%). This suggests that human activities may play a role in fire occurrences, as people are more likely to be using tools and equipment that could spark fires during the day.

7 Refrence

- Human-caused wildfires in Australia: <https://www.environment.gov.au/resource/wildfires/human-cause>

8 Geographical Distribution:

Plot: Scatter plot of latitude vs longitude, color-coded by the number of fires in each region. This could help identify regions with a higher frequency of fires.

```
[41]: import pandas as pd
import plotly.express as px

# Assuming 'brightness', 'longitude', 'latitude', and 'acq_date' are columns in
# your DataFrame
# If not, replace them with the correct column names

# Convert 'acq_date' to string
df['acq_date_str'] = df['acq_date'].astype(str)

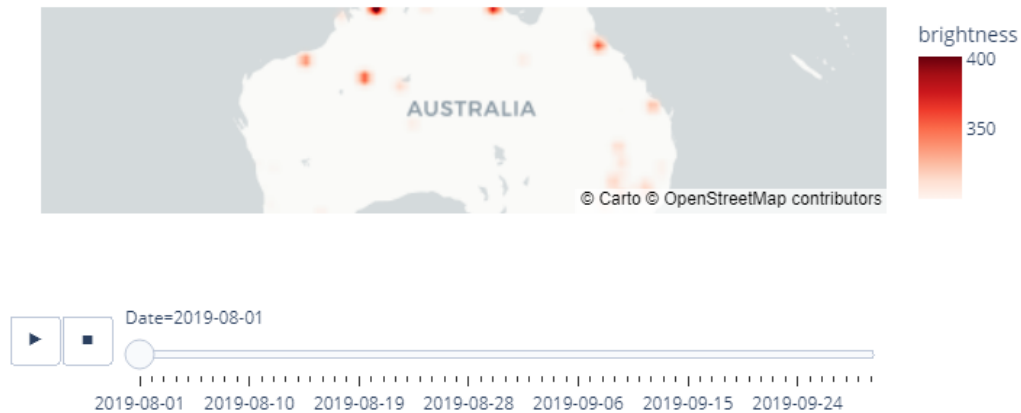
# Sorting DataFrame by 'acq_date'
df1 = df.sort_values(by='acq_date', ascending=True)

# Creating the animated density map
fig = px.density_mapbox(
    df1,
    lon='longitude',
    lat='latitude',
    z='brightness',
    radius=8,
    center=dict(lon=134, lat=-25),
    zoom=2.4,
    mapbox_style='carto-positron',
    color_continuous_scale='reds',
    animation_frame='acq_date_str', # Use the string version
    labels={"acq_date_str": "Date"}
)

# Updating layout
fig.update_layout(
    title='Australian Fires: From 2019/10/01 to 2020/01/11',
    title_font=dict(size=18, color='FireBrick'),
    title_x=0.5
)

# Show the figure
fig.show()
```

Australian Fires: From 2019/10/01 to 2020/01/11



9 Result and analysis

- Regions with a higher frequency of wildfires in Australia: Southeast Australia, Northeast Australia, and Southwest Australia.
- Regions with a lower frequency of wildfires in Australia: Northern Territory and Central Australia.
- Factors that drive the geographical distribution of wildfires in Australia: Climate, vegetation, land use, and topography.
- Types of vegetation or land use patterns that increase wildfire risk: Eucalypt forests, dry grasslands and savannas, cleared or fragmented forests, and areas with a history of fire.

The data shows the locations(lat long) and density(number of cases) of the australia bushfires as seen from satellite images