Practice Assignment - Part 1: Analyzing wildfire activities in Australia

Estimated time needed: **40** minutes

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Objectives

After completing this lab you will be able to:

- Use visualization libraries such as Matplotlib, Pandas, Seaborn and Folium to create informative plots and charts

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Setup

For this lab, we will be using the following libraries:

- `pandas` for managing the data.
- `numpy` for mathematical operations.
- `seaborn` for visualizing the data.
- `matplotlib` for additional plotting tools.

Installing Required Libraries

The following required libraries are pre-installed in the Skills Network Labs environment. However, if you run this notebook commands in a different Jupyter environment (e.g. Watson Studio or Ananconda), you will need to install these libraries by removing the `#` sign before `%pip` in the code cell below.

In [ ]:
```
# All Libraries required for this lab are listed below. The libraries pre-installed on Skills Network Labs are commented.
%pip install -qy pandas==1.3.4 numpy==1.21.4 seaborn==0.9.0 matplotlib==3.5.0 folium
# Note: If your environment doesn't support "%pip install", use "!mamba install"
```

In [ ]:
```
!pip install seaborn
!pip install folium
```

Importing Required Libraries

We recommend you import all required libraries in one place (here):

In [4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import folium
%matplotlib inline
```

Dataset

Historical Wildfires

This wildfire dataset contains data on fire activities in Australia starting from 2005. Additional information can be found here.

Variables

- Region: the 7 regions
- Date: in UTC and provide the data for 24 hours ahead
- Estimated_fire_area: daily sum of estimated fire area for presumed vegetation fires with a confidence > 75% for a each region in km2
- Mean_estimated_fire_brightness: daily mean (by flagged fire pixels(=count)) of estimated fire brightness for presumed vegetation fires with a confidence level > 75% in Kelvin
- Mean_estimated_fire_radiative_power: daily mean of estimated radiative power for presumed vegetation fires with a confidence level > 75% for a given region in megawatts
- Mean_confidence: daily mean of confidence for presumed vegetation fires with a confidence level > 75%
- Std_confidence: standard deviation of estimated fire radiative power in megawatts
- Var_confidence: Variance of estimated fire radiative power in megawatts
- Count: daily numbers of pixels for presumed vegetation fires with a confidence level of larger than 75% for a given region
- Replaced: Indicates with an Y whether the data has been replaced with standard quality data when they are available (usually with a 2-3 month lag). Replaced data has a slightly higher quality in terms of locations

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Importing Data

In [6]:
```python
from js import fetch
import io

URL = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DV0101EN-SkillsNetwork/Data%20Files
resp = await fetch(URL)
text = io.BytesIO((await resp.arrayBuffer()).to_py())
df = pd.read_csv(text)
print('Data read into a pandas dataframe!')
```

```
Data read into a pandas dataframe!
```

Let's look at some samples rows from the dataset we loaded:

In [7]:
```python
df.head()
```

Out[7]:

	Region	Date	Estimated_fire_area	Mean_estimated_fire_brightness	Mean_estimated_fire_radiative_power	Mean_confidence	Std_confidence	Va
0	NSW	1/4/2005	8.68000	312.266667	42.400000	78.666667	2.886751	
1	NSW	1/5/2005	16.61125	322.475000	62.362500	85.500000	8.088793	
2	NSW	1/6/2005	5.52000	325.266667	38.400000	78.333333	3.214550	
3	NSW	1/7/2005	6.26400	313.870000	33.800000	92.200000	7.529940	
4	NSW	1/8/2005	5.40000	337.383333	122.533333	91.000000	7.937254	

Let's verify the column names and the data type of each variable

In [8]:
```python
#Column names
df.columns
```

Out[8]:
```
Index(['Region', 'Date', 'Estimated_fire_area',
       'Mean_estimated_fire_brightness', 'Mean_estimated_fire_radiative_power',
       'Mean_confidence', 'Std_confidence', 'Var_confidence', 'Count',
       'Replaced'],
      dtype='object')
```

In [9]:
```python
#data type
df.dtypes
```

Out[9]:
```
Region                                 object
Date                                   object
Estimated_fire_area                   float64
Mean_estimated_fire_brightness        float64
Mean_estimated_fire_radiative_power   float64
Mean_confidence                       float64
Std_confidence                        float64
Var_confidence                        float64
Count                                   int64
Replaced                               object
dtype: object
```

Notice the type of 'Date' is object, let's convert it to 'datatime' type and also let's extract 'Year' and 'Month' from date and include in the dataframe as separate columns

In [10]:
```
import datetime as dt

df['Year'] = pd.to_datetime(df['Date']).dt.year
df['Month'] = pd.to_datetime(df['Date']).dt.month
```

Verify the columns again

In [11]:
```
df.dtypes
```

Out[11]:
```
Region                                object
Date                                  object
Estimated_fire_area                  float64
Mean_estimated_fire_brightness       float64
Mean_estimated_fire_radiative_power  float64
Mean_confidence                      float64
Std_confidence                       float64
Var_confidence                       float64
Count                                  int64
Replaced                              object
Year                                   int32
Month                                  int32
dtype: object
```

▸ Click here for Solution

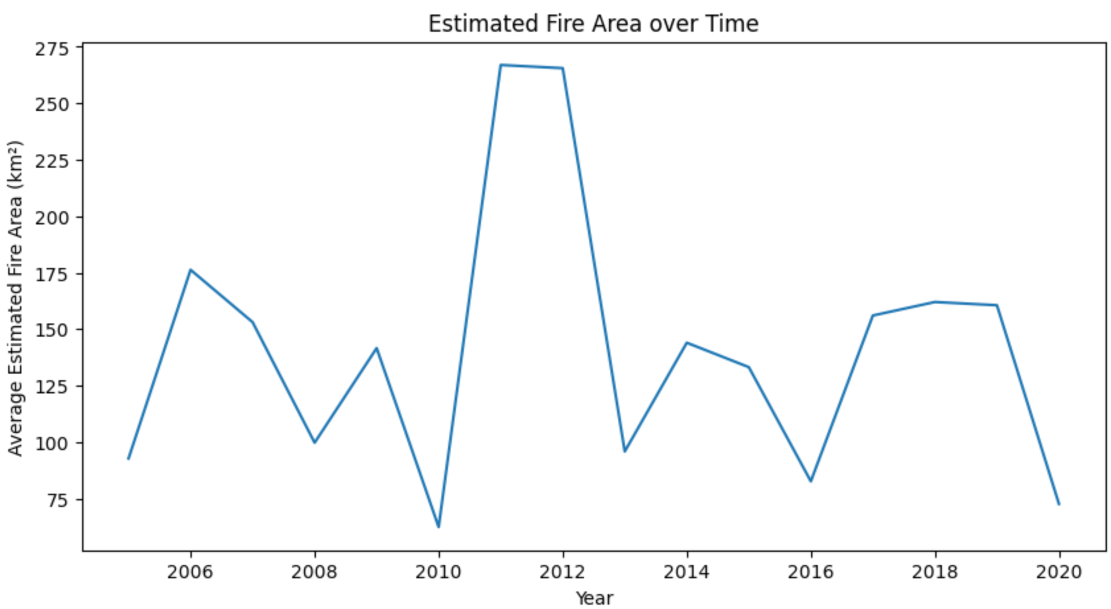
Practice Tasks

TASK 1.1: Let's try to understand the change in average estimated fire area over time (use pandas to plot)

▸ Click here for a Hint

In [34]:
```
df_new = df.groupby('Year')['Estimated_fire_area'].mean().to_frame()
df_new.reset_index(inplace=True)

plt.figure(figsize=(10, 5))
sns.lineplot(data=df_new,x="Year",y="Estimated_fire_area")
plt.xlabel('Year')
plt.ylabel('Average Estimated Fire Area (km²)')
plt.title('Estimated Fire Area over Time')
plt.show()
```



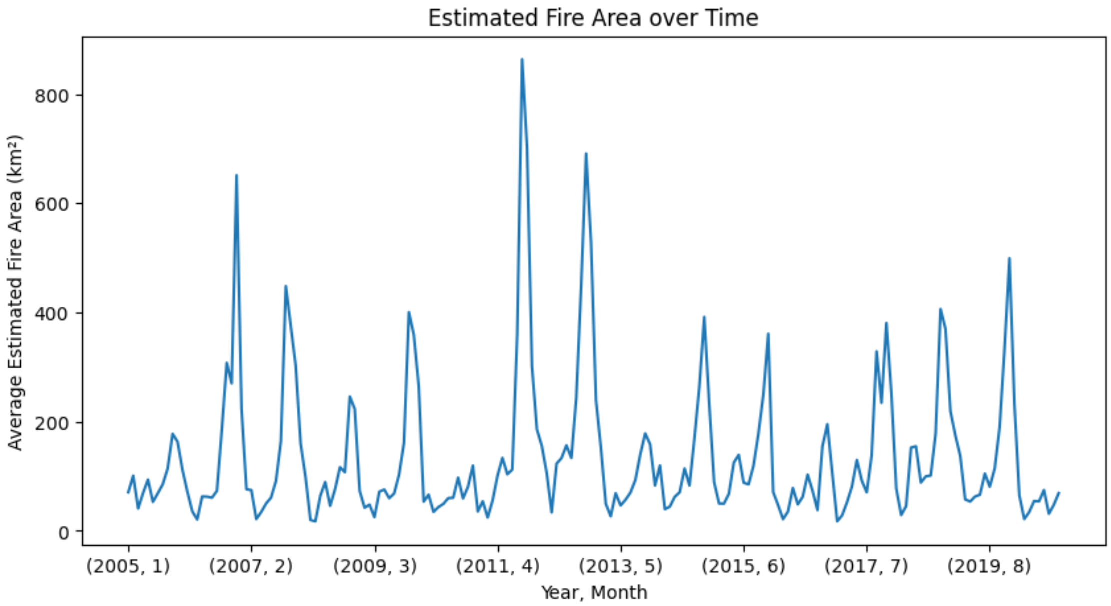
▸ Click here for Solution

TASK 1.2: You can notice the peak in the plot between 2010 to 2013. Let's narrow down our finding, by plotting the estimated fire area for year grouped together with month.

▸ Click here for a Hint

In [35]:
```
df_new = df.groupby(['Year','Month'])['Estimated_fire_area'].mean()

plt.figure(figsize=(10, 5))
df_new.plot(x=df_new.index, y=df_new.values)
plt.xlabel('Year, Month')
plt.ylabel('Average Estimated Fire Area (km²)')
plt.title('Estimated Fire Area over Time')
plt.show()
```



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This plot represents that the estimated fire area was on its peak after 2011, April and before 2012. You can verify on google/news, this was the time of maximum wildfire hit in Austrailia

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TASK 1.3: Let's have an insight on the distribution of mean estimated fire brightness across the regions use the functionality of seaborn to develop a barplot

before starting with the plot, why not know the regions mentioned in the dataset?.
Make use of unique() to identify the regions in the dataset (apply it on series only)

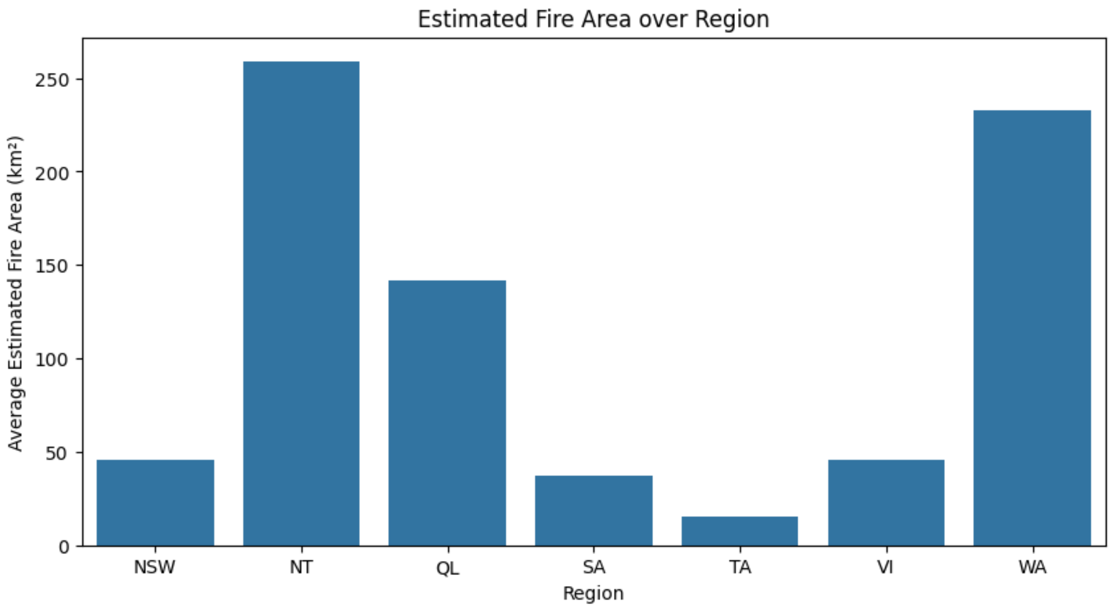
In [36]:
```
df['Region'].unique()
```

Out[36]:
```
array(['NSW', 'NT', 'QL', 'SA', 'TA', 'VI', 'WA'], dtype=object)
```

▸ Click here for a Hint

In [38]:
```
df_new = df.groupby("Region")["Estimated_fire_area"].mean().to_frame()
df_new.reset_index(inplace=True)

plt.figure(figsize=(10, 5))
sns.barplot(data=df_new,x="Region",y="Estimated_fire_area")
plt.xlabel('Region')
plt.ylabel('Average Estimated Fire Area (km²)')
plt.title('Estimated Fire Area over Region')
plt.show()
```



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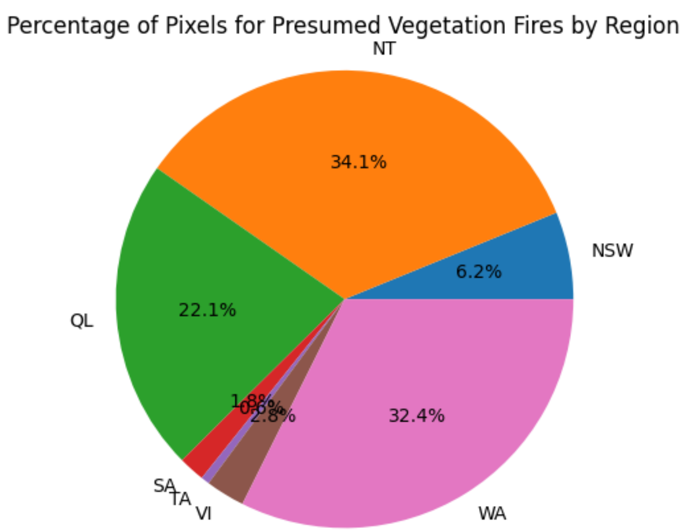
TASK 1.4: Let's find the portion of count of pixels for presumed vegetation fires vary across regions we will develop a pie chart for this

▸ Click here for a Hint

In [39]:
```
df_new = df.groupby("Region")["Count"].sum().to_frame()
df_new.reset_index(inplace=True)

plt.figure(figsize=(10, 5))
plt.pie(df_new["Count"], labels=df_new["Region"], autopct='%1.1f%%')
plt.title('Percentage of Pixels for Presumed Vegetation Fires by Region')
plt.axis('equal')
plt.show()
```



▸ Click here for Solution

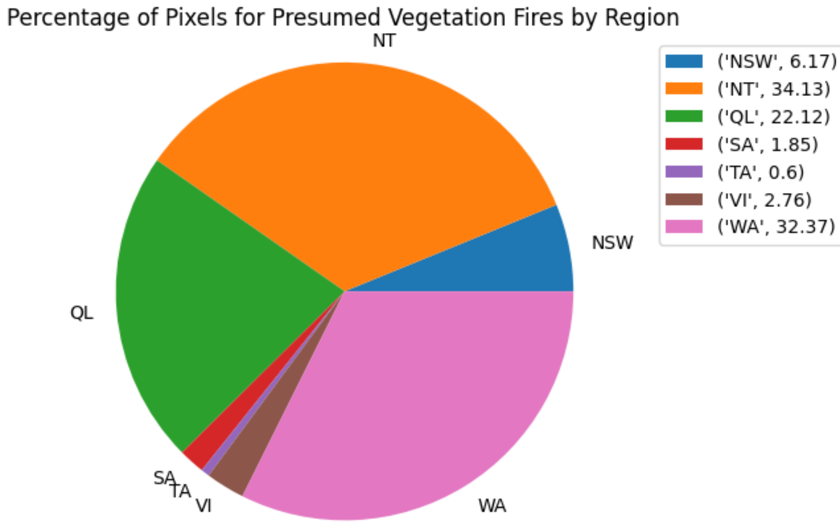
TASK 1.5: See the percentage on the pie is not looking so good as it is overlaped for Region SA, TA, VI

remove the autopct fromm pie function and pass the following to plt.legend() after plt.title()

`[(i,round(k/region_counts.sum()*100,2)) for i,k in zip(region_counts.index, region_counts)]`

In [42]:
```
df_new = df.groupby("Region")["Count"].sum().to_frame()
df_new.reset_index(inplace=True)
```

```
plt.figure(figsize=(10, 5))
plt.pie(df_new["Count"], labels=df_new["Region"])
plt.title('Percentage of Pixels for Presumed Vegetation Fires by Region')
plt.legend([(i,round(k/df_new["Count"].sum()*100,2)) for i,k in zip(df_new["Region"], df_new["Count"])])
plt.axis('equal')
plt.show()
```

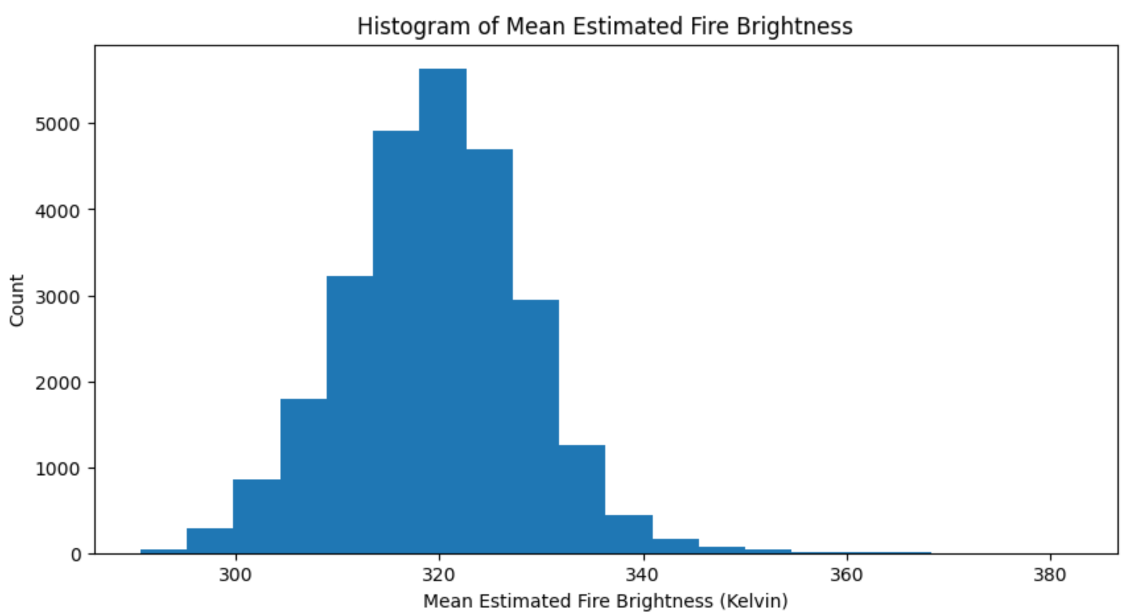


TASK 1.6: Let's try to develop a histogram of the mean estimated fire brightness
Using Matplotlib to create the histogram

▸ Click here for a Hint

In [46]:
```
plt.figure(figsize=(10, 5))

plt.hist(x=df['Mean_estimated_fire_brightness'], bins=20)
plt.xlabel('Mean Estimated Fire Brightness (Kelvin)')
plt.ylabel('Count')
plt.title('Histogram of Mean Estimated Fire Brightness')
plt.show()
```



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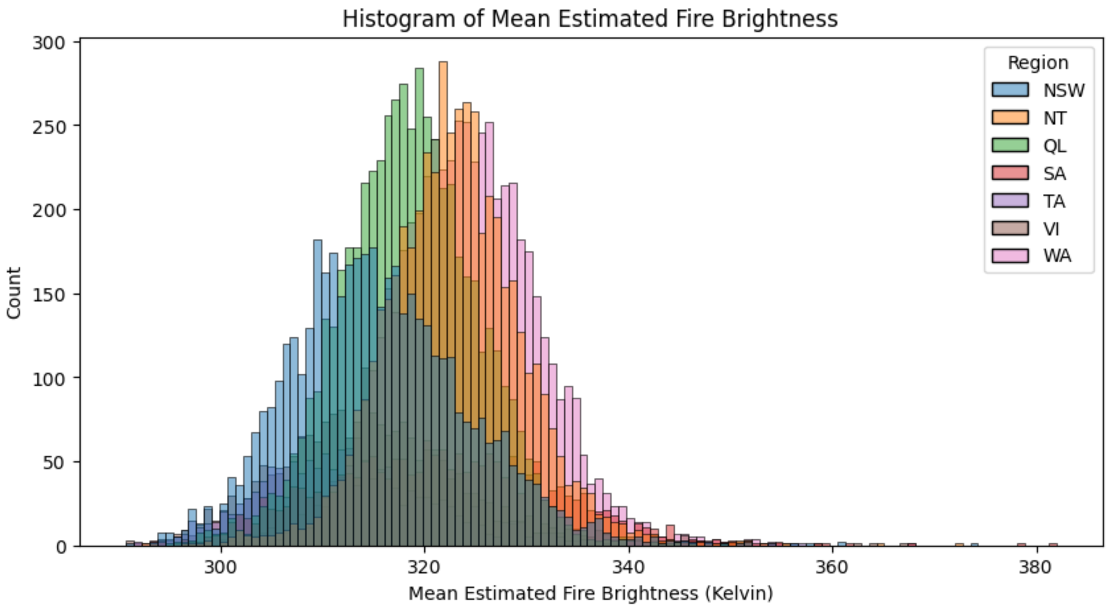
TASK 1.7: What if we need to understand the distribution of estimated fire brightness across regions? Let's use the functionality of seaborn and pass region as hue

In [47]:

```
plt.figure(figsize=(10, 5))

sns.histplot(data=df, x='Mean_estimated_fire_brightness', hue='Region')
plt.xlabel('Mean Estimated Fire Brightness (Kelvin)')
plt.ylabel('Count')
plt.title('Histogram of Mean Estimated Fire Brightness')
plt.show()
```



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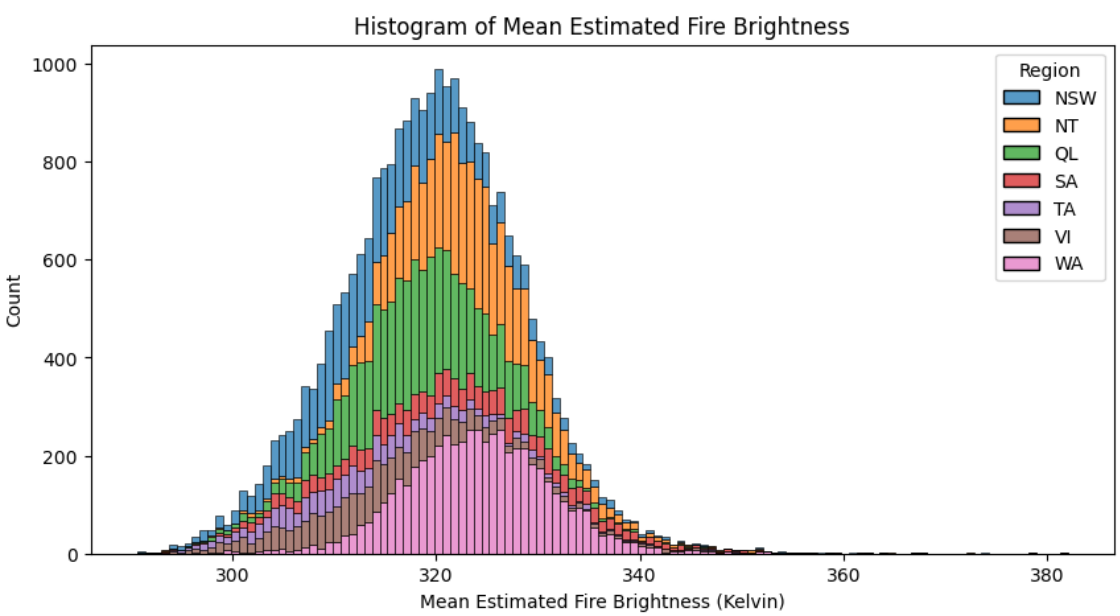
looks better!, now include the parameter `multiple='stack'` in the histplot() and see the difference. Include labels and titles as well

In [48]:

```
plt.figure(figsize=(10, 5))

sns.histplot(data=df, x='Mean_estimated_fire_brightness', hue='Region',multiple='stack')
plt.xlabel('Mean Estimated Fire Brightness (Kelvin)')
plt.ylabel('Count')
plt.title('Histogram of Mean Estimated Fire Brightness')
plt.show()
```



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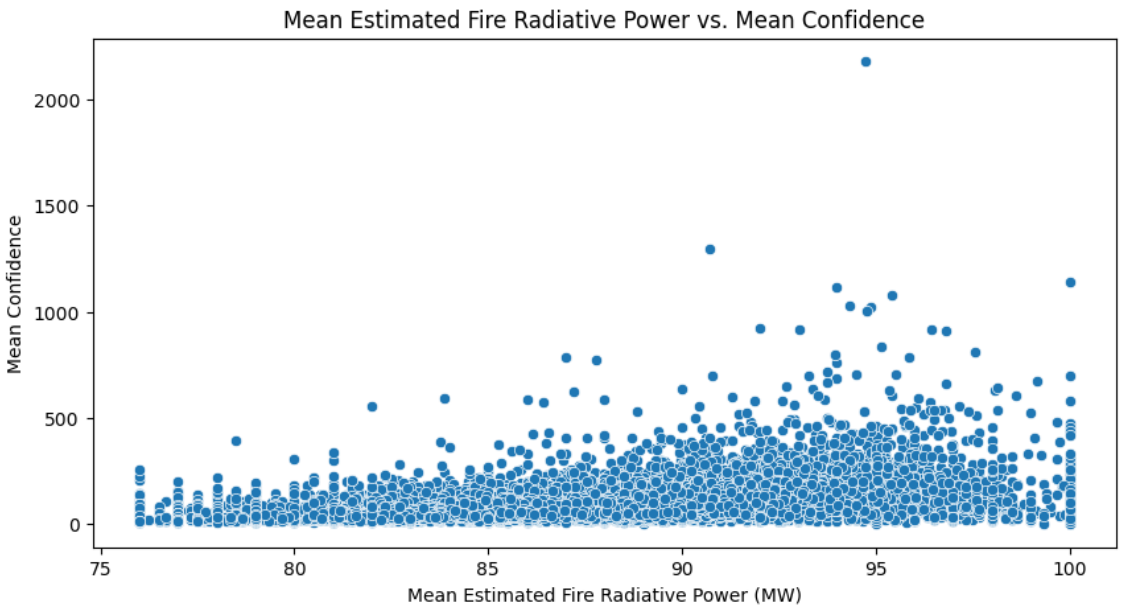
TASK 1.8: Let's try to find if there is any correlation between mean estimated fire radiative power and mean confidence level?

▸ Click here for a Hint

In [49]:
```
plt.figure(figsize=(10, 5))

sns.scatterplot(data=df, x='Mean_confidence', y='Mean_estimated_fire_radiative_power')
plt.xlabel('Mean Estimated Fire Radiative Power (MW)')
plt.ylabel('Mean Confidence')
plt.title('Mean Estimated Fire Radiative Power vs. Mean Confidence')
plt.show()
```



▸ Click here for Solution

TASK 1.9: Let's mark these seven regions on the Map of Australia using Folium

we have created a dataframe for you containing the regions, their latitudes and longitudes.
For australia use [-25, 135] as location to create the map

In [5]:
```
region_data = {'region':['NSW','QL','SA','TA','VI','WA','NT'], 'Lat':[-31.8759835,-22.1646782,-30.5343665,-42.035067,-36.5986096,-25.23
               'Lon':[147.2869493,144.5844903,135.6301212,146.6366887,144.6780052,121.0187246,132.550964]}
reg=pd.DataFrame(region_data)
reg
```

Out[5]:

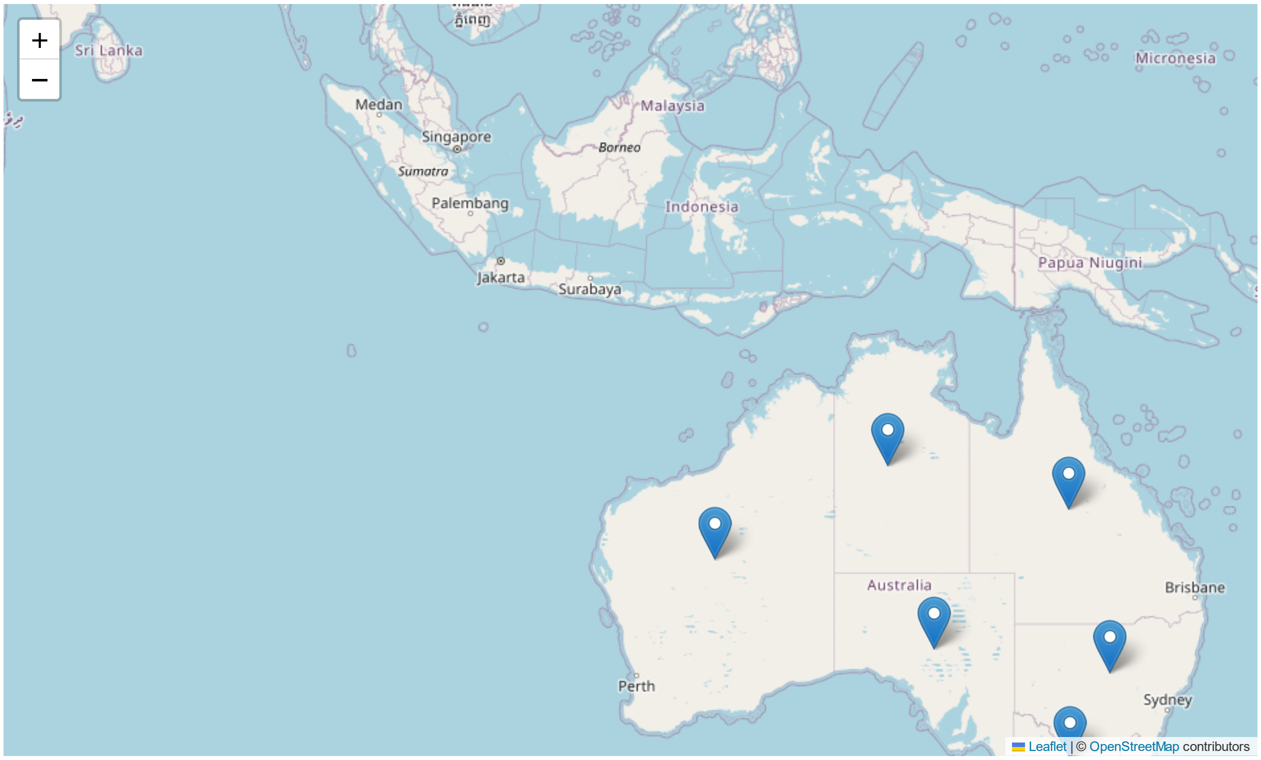
	region	Lat	Lon
0	NSW	-31.875984	147.286949
1	QL	-22.164678	144.584490
2	SA	-30.534367	135.630121
3	TA	-42.035067	146.636689
4	VI	-36.598610	144.678005
5	WA	-25.230300	121.018725
6	NT	-19.491411	132.550964

In [6]:
```
aus_map = folium.Map(location=[-25, 135], zoom_start=4)


for index, row in reg.iterrows():
    folium.Marker(location=[row['Lat'],row['Lon']],popup=row['region']).add_to(aus_map)

aus_map
```

Out[6]:



▸ Click here for Solution

Congratulations! You have completed the lab

Authors

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