1.

```
# import pandas
import pandas as pd
# import numpy
import numpy as np
# import matplotlib
from matplotlib import pyplot as plt
# make plots appear and be stored within the notebook
%matplotlib inline
Sig_Eqs = pd.read_csv("D:/earthquakes.tsv",sep='\t')
deaths_country = Sig_Eqs.groupby(['Country'])['Deaths'].sum().reset_index()
deaths_country
top_20_countries = deaths_country.nlargest(20, 'Deaths')
top_20_countries
```

	Country	Deaths
28	CHINA	2075947.0
141	TURKEY	1188881.0
65	IRAN	1011453.0
69	ITALY	498418.0
132	SYRIA	439224.0
58	HAITI	323478.0
10	AZERBAIJAN	317219.0
71	JAPAN	279607.0
6	ARMENIA	191890.0
103	PAKISTAN	145083.0
66	IRAQ	136200.0
40	ECUADOR	135496.0
142	TURKMENISTAN	117412.0
107	PERU	102169.0
68	ISRAEL	90388.0
110	PORTUGAL	83572.0
53	GREECE	80378.0
27	CHILE	64277.0
62	INDIA	63507.0
133	TAIWAN	57153.0

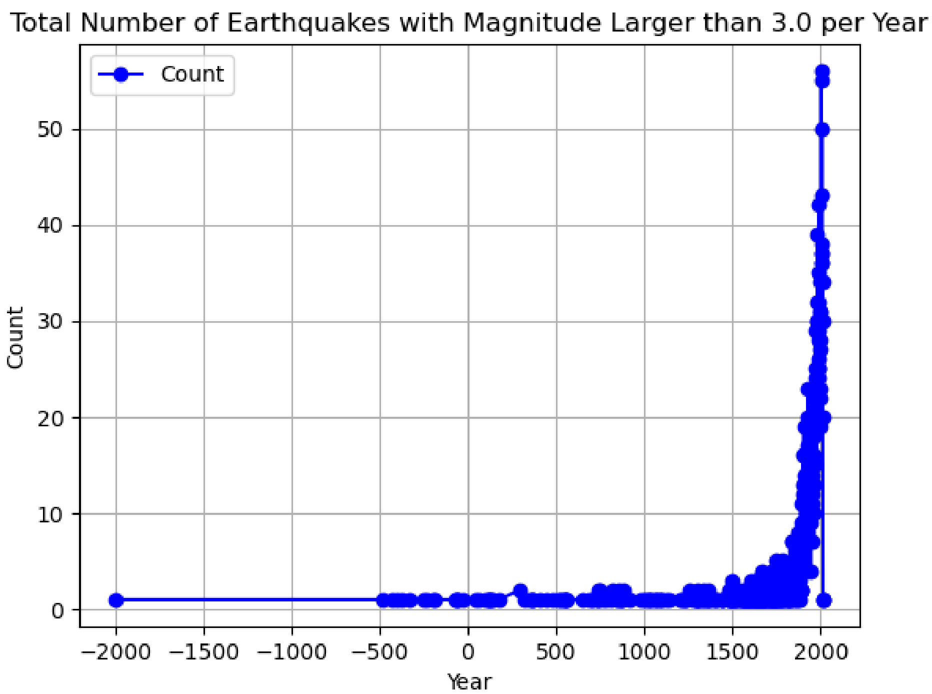
```
#1.2
total_number = Sig_Eqs.loc[Sig_Eqs['Ms'] > 3.0]
total_number2 = total_number.groupby(['Year'])['Ms'].count().reset_index()
total_number2
total_number2 = total_number2.rename(columns={'Ms': 'Count'})
total_number2.plot(x='Year', y='Count', marker='o', linestyle='-', color='blue')
plt.title('Total Number of Earthquakes with Magnitude Larger than 3.0 per Year')
plt.xlabel('Year')
plt.ylabel('Count')
plt.grid(True)
plt.show()
```

#The total number of earthquakes with magnitude larger than 3.0 (using column Ms as the magnitude) worldwide each year gradually increased after 1050, and has seen an exponential growth since 1500.

#Reason:Improvements in Seismic Detection: As technology has advanced, our ability to detect earthquakes has improved significantly. This means that earthquakes that may have gone unnoticed in the past are now being recorded.Population Growth and Urbanization: With an increasing global population and the expansion of urban areas, more people are living in seismically active regions, leading to more reported earthquakes.Industrial Activities: Certain human activities, such as mining, fracking, and the construction of large dams, can induce seismic activity. These activities have become more prevalent over time, potentially contributing to the increase in recorded earthquakes.

	Year	Ms
0	-2000.0	1
1	-479.0	1
2	-426.0	1
3	-400.0	1
4	-373.0	1
...	...	...
492	2012.0	34
493	2013.0	20
494	2015.0	1
495	2017.0	1
496	2019.0	1

497 rows × 2 columns



```
#1.3 (1)
import pandas as pd
def CountEq_LargestEq(country):
    # 筛选给定国家的地震
    country_eqs = Sig_Eqs[Sig_Eqs['Country'] == country]
    # 如果该国家没有地震记录，返回 None
    if country_eqs.empty:
        return None
    # 该国的地震总数
    total_eqs = len(country_eqs)
    total_eqs
    #(2)
    # 查找该国发生过的最大地震
    if not country_eqs['Ms'].dropna().empty:
        largest_eq_index = country_eqs['Ms'].dropna().idxmax()
        largest_eq = country_eqs.loc[largest_eq_index]
    else:
        return None   # 如果没有有效的震级数据，返回 None
    # 组装日期信息
    date_info = (largest_eq['Year'] if 'Year' in largest_eq else None,
                 largest_eq['Mo'] if 'Mo' in largest_eq else None,
                 largest_eq['Dy'] if 'Dy' in largest_eq else None)
    return total_eqs, date_info[0], date_info[1], date_info[2], largest_eq['Latitude'], largest_eq['Longitude']
# 对文件中的每个国家应用该函数，并按结果降序排列
results = []
for country in Sig_Eqs['Country'].unique():
    result = CountEq_LargestEq(country)
    if result:   # 确保 result 不是 None
        results.append(result)
# 将结果转换为 DataFrame
```

```
if results:    # 确保 results 不为空

    results_df = pd.DataFrame(results, columns=['Total_Earthquakes', 'Year', 'Mo', 'Dy', 'Latitude',
'Longitude'])

    # 按地震总数降序排列结果

    sorted_results = results_df.sort_values('Total_Earthquakes', ascending=False)

    # 显示结果

    print(sorted_results)

else:

    print("No data available.")
```

```
     Total_Earthquakes    Year    Mo    Dy  Latitude  Longitude
13                 623  1920.0  12.0  16.0    36.601    105.317
32                 419   869.0   7.0  13.0    38.500    143.800
65                 412  2004.0  12.0  26.0     3.295     95.982
6                  386   856.0  12.0  22.0    36.200     54.300
8                  337  1939.0  12.0  26.0    39.907     39.586
..                 ...     ...   ...   ...       ...        ...
121                  1  1993.0   3.0  12.0   -14.385   -178.252
122                  1  1993.0   8.0   1.0    15.385     31.690
88                   1  1848.0   7.0  12.0   -17.900   -149.900
83                   1  1819.0   8.0  31.0    66.416     12.850
104                  1  1914.0  10.0  23.0     6.000    132.500

[129 rows x 6 columns]
```

```
#2

import pandas as pd

import matplotlib.pyplot as plt

# 读取数据

data = pd.read_csv('D:/GitKraken/ese5023/assignment/Baoan_Weather_1998_2022.csv')

print(data.head())

# 拆分 TMP 列为 'Temperature' 和 'QC'

data[['Temperature', 'QC']] = data['TMP'].str.split(',', expand=True)

# 将 'Temperature' 转换为实际温度值，并将 'QC' 转换为整数类型

data['Temperature'] = pd.to_numeric(data['Temperature'], errors='coerce') / 10

data['QC'] = pd.to_numeric(data['QC'], errors='coerce')

# 过滤掉不符合质量标准的数据
```

```
data = data[(data['QC'] == 0) | (data['QC'] == 1 ) | (data['QC'] == 4 ) | (data['QC'] == 5)]
# 转换日期列为 datetime 格式
data['DATE'] = pd.to_datetime(data['DATE'], errors='coerce')
# 按照年月计算月平均温度
data['YearMonth'] = data['DATE'].dt.to_period('M')
monthly_avg_temp = data.groupby('YearMonth')['Temperature'].mean()
# 绘制结果
plt.figure(figsize=(12, 6))
monthly_avg_temp.plot()
plt.xlabel('Year-Month')
plt.ylabel('Monthly Average Temperature (°C)')
plt.title('Monthly Averaged Air Temperature in Shenzhen (1998-2022)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

#数据过滤：在数据过滤步骤中，代码只保留那些 QC 值为 0, 1, 4, 或 5 的数据行。这些 QC 值通常表示数据是可靠的或在可接受的质量标准内。

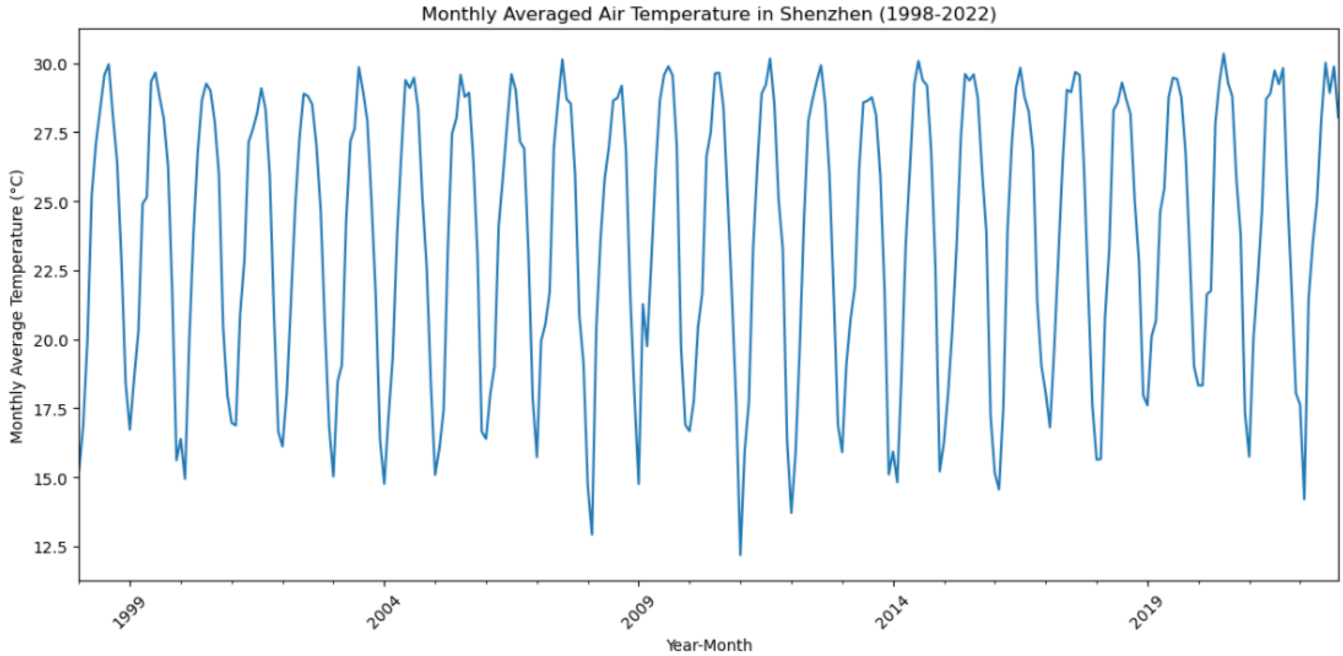
#过去 25 年的月平均气温趋势：月平均气温一年内通常先变大后变小，年际变化趋于平稳。

```
      STATION                 DATE  SOURCE REPORT_TYPE CALL_SIGN  \
0  59493099999  1998-01-01T00:00:00       4       SY-MT      ZGSZ
1  59493099999  1998-01-01T01:00:00       4       FM-15      ZGSZ
2  59493099999  1998-01-01T02:00:00       4       FM-15      ZGSZ
3  59493099999  1998-01-01T03:00:00       4       SY-MT      ZGSZ
4  59493099999  1998-01-01T04:00:00       4       FM-15      ZGSZ

  QUALITY_CONTROL          AA1  AA2  AA3    AG1  ... REPORT_TYPE.1  SA1  \
0            V020  06,0000,9,1  NaN  NaN  0,000  ...         SY-MT  NaN
1            V020          NaN  NaN  NaN  0,999  ...         FM-15  NaN
2            V020          NaN  NaN  NaN  0,999  ...         FM-15  NaN
3            V020          NaN  NaN  NaN  0,000  ...         SY-MT  NaN
4            V020          NaN  NaN  NaN  0,999  ...         FM-15  NaN

      SLP SOURCE.1      TMP  UA1  UG1            VIS WG1             WND
0  10184,1        4  +0186,1  NaN  NaN  008000,1,N,1 NaN  040,1,N,0040,1
1  99999,9        4  +0220,1  NaN  NaN  003300,1,N,1 NaN  130,1,N,0020,1
2  99999,9        4  +0240,1  NaN  NaN  003500,1,N,1 NaN  110,1,N,0020,1
3  10185,1        4  +0221,1  NaN  NaN  011000,1,N,1 NaN  090,1,N,0020,1
4  99999,9        4  +0240,1  NaN  NaN  005000,1,N,1 NaN  270,1,N,0030,1

[5 rows x 54 columns]
```



#3

#pd.read_csv: This is the function used to read a CSV file into a pandas DataFrame.

#usecols=range(17): This option specifies that only the first 17 columns of the CSV file should be read into the DataFrame. This is useful when you are only interested in a subset of the data or when the file contains unnecessary columns that you want to ignore.

#skiprows=[1, 2]: This option tells pandas to skip the first two rows of the file when reading it. This is often used when the file has header rows that are not needed in the DataFrame or when there are introductory rows that contain metadata or other non-data information.

#parse_dates=['ISO_TIME']: This option is used to parse a column as a datetime object. In this case, the 'ISO_TIME' column is being converted into a datetime format, which is useful for time series analysis and allows for easier manipulation of time data.

#na_values=['NOT_NAMED', 'NAME']: This option is used to specify custom missing or null values. Here, 'NOT_NAMED' and 'NAME' are being treated as missing values, which is useful for cleaning the data and ensuring that these specific strings are not 误 interpreted as actual data.

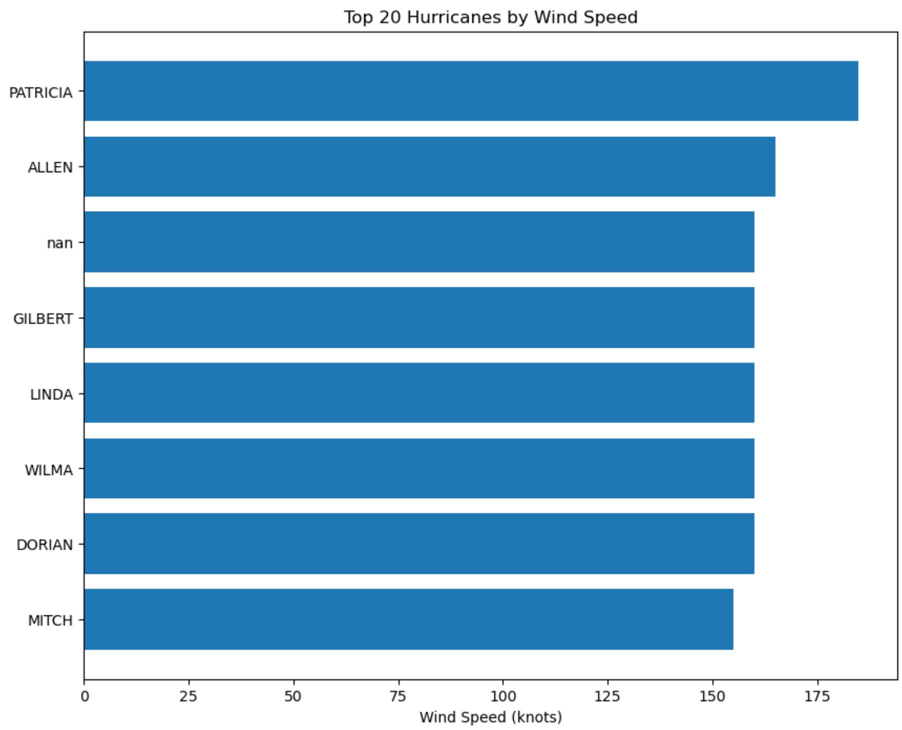
#After executing this code, df.head() is called to display the first five rows of the DataFrame, which is a quick way to inspect the initial data.

```
#3.1
import pandas as pd
# 加载数据集
df = pd.read_csv('D:/GitKraken/ese5023/assignment/ibtracs.ALL.list.v04r00.csv',
                 usecols=range(17),
                 skiprows=[1, 2],
                 parse_dates=['ISO_TIME'],
                 na_values=['NOT_NAMED', 'NAME'])
# 清理 WMO_WIND 列，移除空格，并转换为数值类型
df['WMO_WIND'] = df['WMO_WIND'].str.replace(' ', '')  # 移除空格
df['WMO_WIND'] = pd.to_numeric(df['WMO_WIND'], errors='coerce')  # 转换为数值类型
# 按照风速降序排序，并选择前 10 个飓风的名字
top_10_hurricanes = df.nlargest(10, 'WMO_WIND')[['NAME', 'WMO_WIND']]
print(top_10_hurricanes)
```

```
            NAME  WMO_WIND
665954  PATRICIA     185.0
665952  PATRICIA     180.0
665956  PATRICIA     180.0
427636     ALLEN     165.0
178209       NaN     160.0
178210       NaN     160.0
178212       NaN     160.0
482074   GILBERT     160.0
552459     LINDA     160.0
605746     WILMA     160.0
```

```
#3.2
import matplotlib.pyplot as plt
import pandas as pd
# 确保 WMO_WIND 列中没有空值
df = df.dropna(subset=['WMO_WIND'])
# 确保 NAME 列是字符串类型
df['NAME'] = df['NAME'].astype(str)
# 按照风速降序排序，并选择前 20 个飓风的风速
top_20_hurricanes = df.nlargest(20, 'WMO_WIND')[['NAME', 'WMO_WIND']]
top_20_hurricanes
# 制作条形图
plt.figure(figsize=(10, 8))
plt.barh(top_20_hurricanes['NAME'].astype(str), top_20_hurricanes['WMO_WIND'])
plt.xlabel('Wind Speed (knots)')
plt.title('Top 20 Hurricanes by Wind Speed')
plt.gca().invert_yaxis()  # 将条形图的顺序反转，使得最大的飓风在顶部
plt.show()
```

	NAME	WMO_WIND
665954	PATRICIA	185.0
665952	PATRICIA	180.0
665956	PATRICIA	180.0
427636	ALLEN	165.0
178209	nan	160.0
178210	nan	160.0
178212	nan	160.0
482074	GILBERT	160.0
552459	LINDA	160.0
605746	WILMA	160.0
689332	DORIAN	160.0
689333	DORIAN	160.0
427618	ALLEN	155.0
427634	ALLEN	155.0
427638	ALLEN	155.0
427648	ALLEN	155.0
482076	GILBERT	155.0
552457	LINDA	155.0
552461	LINDA	155.0
560437	MITCH	155.0



#3.3

按流域分组并计算每个流域的数据点数量

basin_counts = df['BASIN'].value_counts()

制作条形图

plt.figure(figsize=(10, 8))

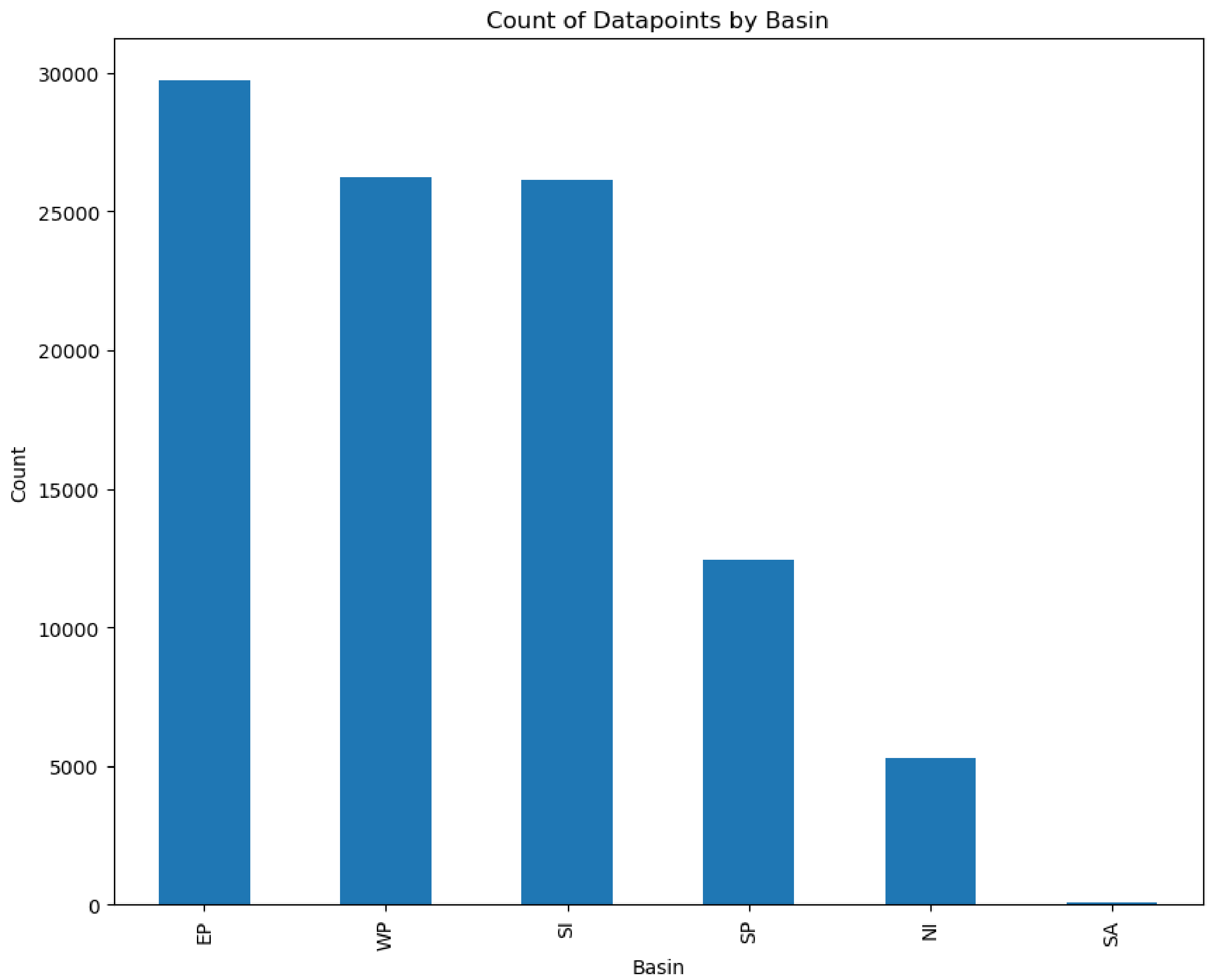
basin_counts.plot(kind='bar')

plt.xlabel('Basin')

plt.ylabel('Count')

plt.title('Count of Datapoints by Basin')

plt.show()



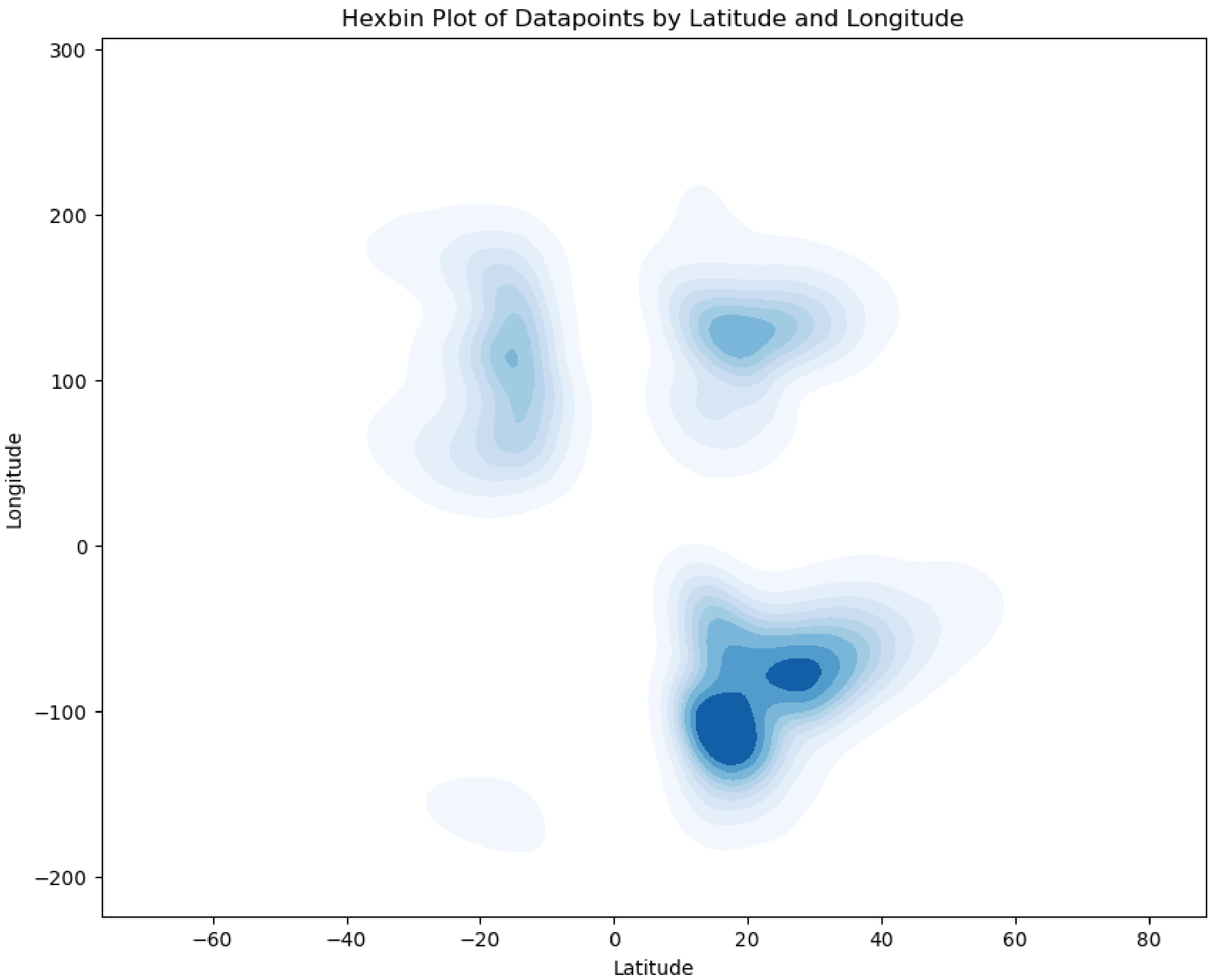
#3.4

import seaborn as sns

制作六边形图

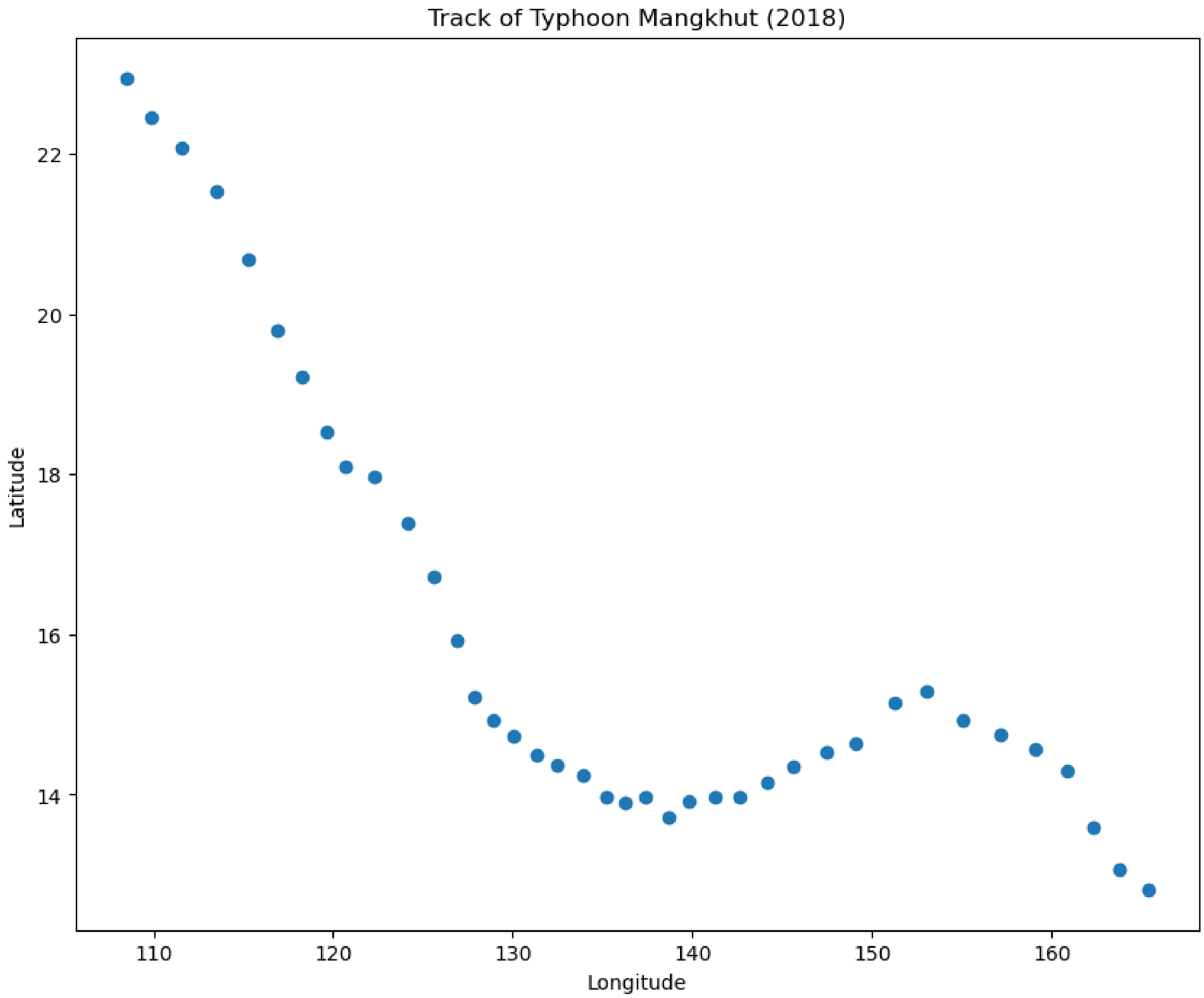
plt.figure(figsize=(10, 8))

```
sns.kdeplot(data=df, x='LAT', y='LON', cmap="Blues", fill=True)
plt.xlabel('Latitude')
plt.ylabel('Longitude')
plt.title('Hexbin Plot of Datapoints by Latitude and Longitude')
plt.show()
```




```
#3.5
import matplotlib.pyplot as plt
import pandas as pd
# 从 ISO_TIME 列中提取年份，并创建一个新的 YEAR 列
df['YEAR'] = pd.to_datetime(df['ISO_TIME']).dt.year
# 筛选出台风 Mangkhut 的数据
mangkhut = df[(df['NAME'] == 'MANGKHUT') & (df['YEAR'] == 2018)]
# 绘制散点图
plt.figure(figsize=(10, 8))
```

```
plt.scatter(mangkhut['LON'], mangkhut['LAT'])
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Track of Typhoon Mangkhut (2018)')
plt.show()
```

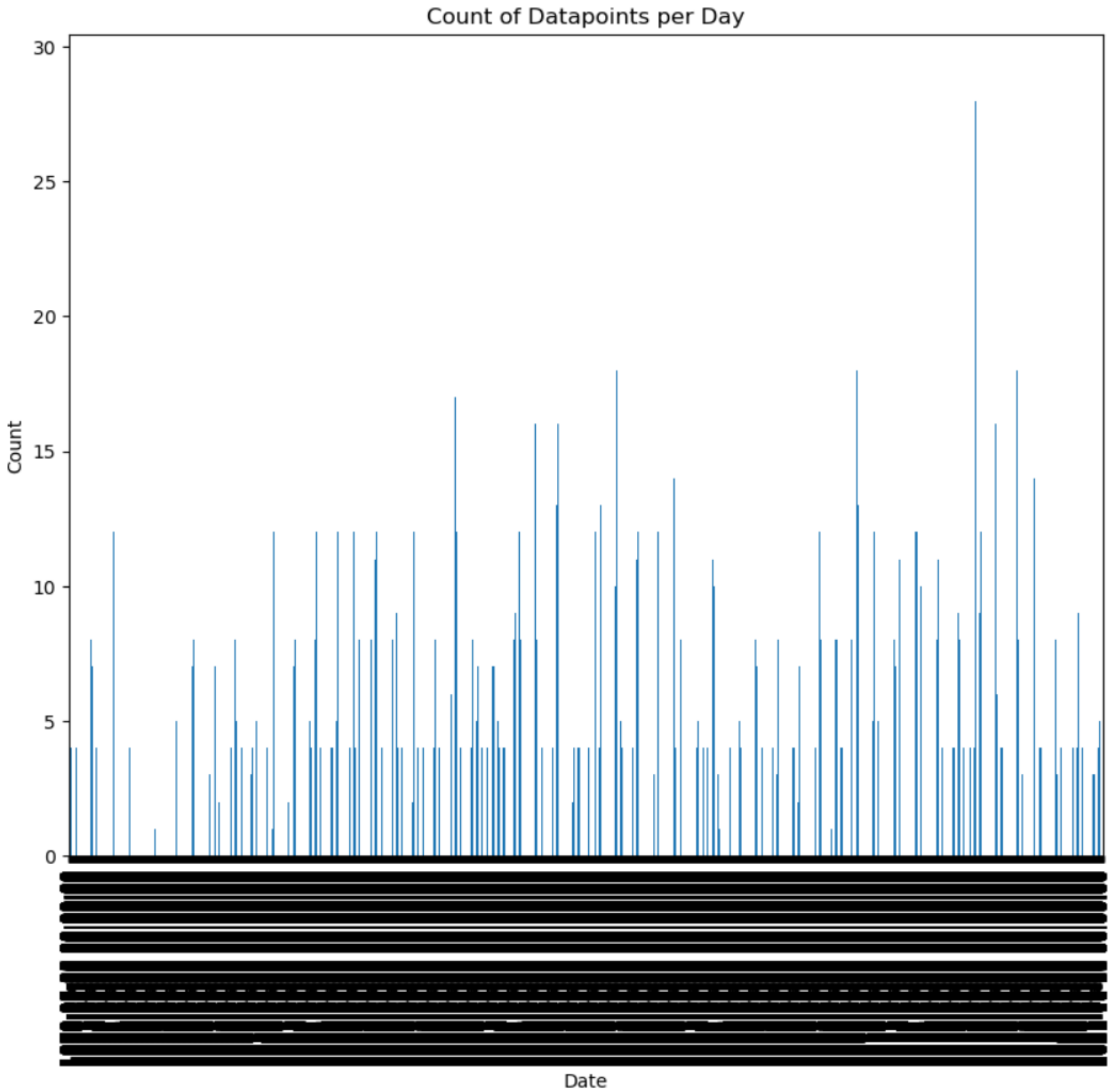



```
#3.6
# 筛选 1970 年以后的数据
western_pacific = df[(df['BASIN'] == 'WP') & (df['YEAR'] >= 1970)]
eastern_pacific = df[(df['BASIN'] == 'EP') & (df['YEAR'] >= 1970)]
# 合并两个流域的数据
pacific_data = pd.concat([western_pacific, eastern_pacific])
pacific_data
```

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE	LAT	LON	WMO_WIND	WMO_PRES	WMO_AGENCY
373698	1972316N05185	1972	124	WP	MM	RUBY	1972-11-14 06:00:00	TS	12.24800	179.976	70.0		cphc
405689	1977082N03165	1977	32	WP	MM	PATSY	1977-03-28 00:00:00	TS	5.81667	158.867	50.0	990	tokyo
405691	1977082N03165	1977	32	WP	MM	PATSY	1977-03-28 06:00:00	TS	6.26124	158.225	50.0	996	tokyo
405693	1977082N03165	1977	32	WP	MM	PATSY	1977-03-28 12:00:00	TS	6.71667	157.517	50.0	1000	tokyo
405695	1977082N03165	1977	32	WP	MM	PATSY	1977-03-28 18:00:00	TS	7.06540	156.765	45.0	1002	tokyo
...	...	...	...	...	...	...	...	...	...	...	...	...	...
703054	2021311N13248	2021	40	EP	MM	SANDRA	2021-11-09 00:00:00	TS	15.10000	-118.200	30.0	1008	hurdat_epa
703056	2021311N13248	2021	40	EP	MM	SANDRA	2021-11-09 06:00:00	TS	15.00000	-119.100	25.0	1009	hurdat_epa
703058	2021311N13248	2021	40	EP	MM	SANDRA	2021-11-09 12:00:00	TS	14.70000	-120.100	25.0	1010	hurdat_epa
703060	2021311N13248	2021	40	EP	MM	SANDRA	2021-11-09 18:00:00	DS	14.40000	-121.500	25.0	1010	hurdat_epa
703062	2021311N13248	2021	40	EP	MM	SANDRA	2021-11-10 00:00:00	DS	14.10000	-123.000	25.0	1010	hurdat_epa

52023 rows × 18 columns

```
#3.7
# 按天计数数据点
daily_counts = pacific_data.resample('D').size()
print(daily_counts)
# 绘制条形图
plt.figure(figsize=(10, 8))
daily_counts.plot(kind='bar')
plt.xlabel('Date')
plt.ylabel('Count')
plt.title('Count of Datapoints per Day')
plt.show()
```




```
# 3.8
xs, ys, lens = [], [], []
for k, v in daily_counts.resample('Y'):
    first = pd.Timestamp(f"{k.year}-01-01 00:00:00")
    v.index = (v.index - t).days
    # 获取每一年统计量的长度
    xs.append(first)
    ys.append(np.cumsum(v))
    lens.append(len(v))
```

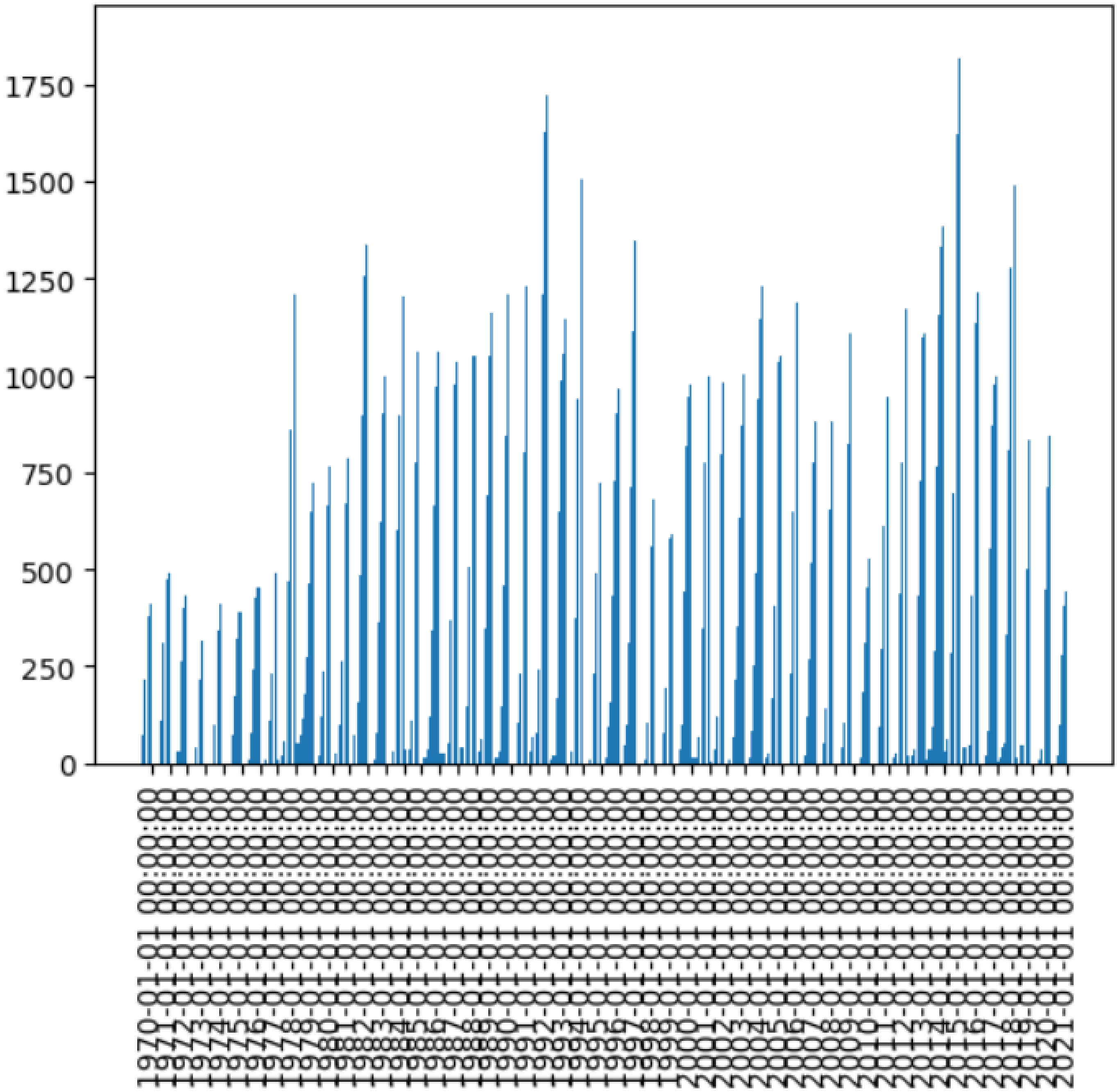
```
cum_lens = np.cumsum(lens)

cat_data = np.concatenate(ys)

#  绘制

_ = plt.xticks(cum_lens, xs, rotation=90)

plt.bar(np.arange(len(cat_data)), cat_data)
```




```
#3.9

#  计算异常值

anomalies = daily_counts - climatology
```

绘制异常值时间序列

plt.figure(figsize=(10, 8))

anomalies.plot()

plt.xlabel('Date')

plt.ylabel('Anomaly')

plt.title('Anomaly of Daily Counts from Climatology')

plt.show()

#3.10

重新采样至年分辨率

annual_anomalies = anomalies.resample('A').mean()

绘制条形图

plt.figure(figsize=(10, 8))

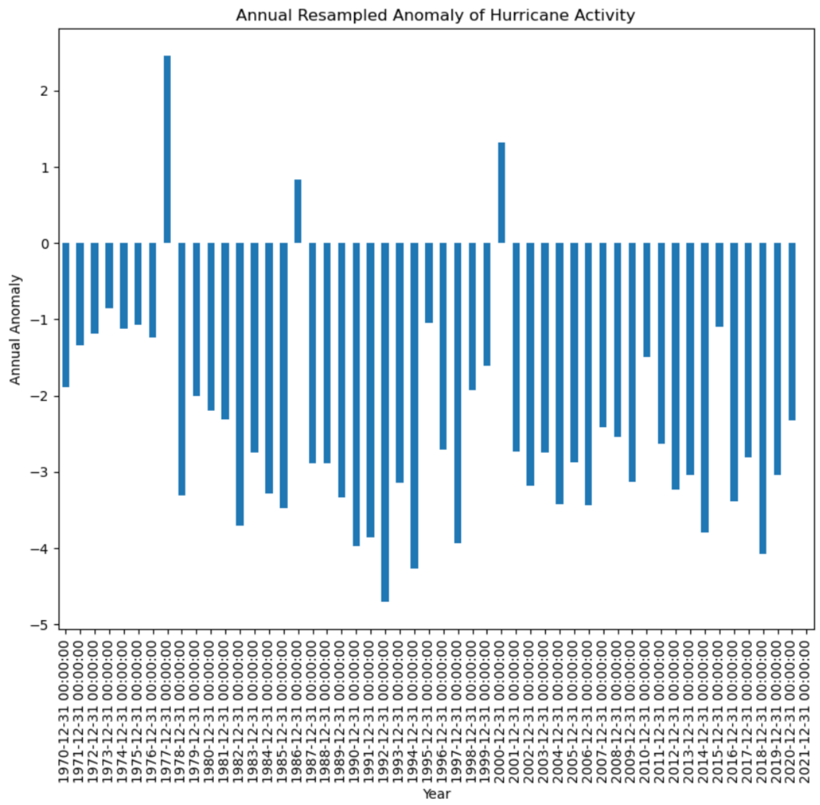
annual_anomalies.plot(kind='bar')

plt.xlabel('Year')

plt.ylabel('Annual Anomaly')

plt.title('Annual Resampled Anomaly of Hurricane Activity')

plt.show()



#4

#4.1

```
USC = pd.read_csv('D:/GitKraken/ese5023/assignment/USC00218450.csv').fillna(0)
USC
```

LONGITUDE	ELEVATION	NAME	CDSD	CDSD_ATTRIBUTES	CLDD	CLDD_ATTRIBUTES	...	PRCP	PRCP_ATTRIBUTES	SNOW	SNOW_ATTRIBUTES	TAVG
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	0.0	0	0.0	0	...	10.7	,,,Z	0.0	0	0.00
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	0.0	0	0.0	0	...	28.0	,,,Z	0.0	0	0.00
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	0.0	0	0.0	0	...	18.6	,,,Z	0.0	0	0.00
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	0.0	0	0.0	0	...	2.6	,,,Z	0.0	0	0.00
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	0.0	0	0.0	0	...	5.9	,,,Z	0.0	0	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	0.0	0	0.0	,7	...	97.9	,,,7	10.0	,,,7	8.12
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	10.0	0	10.0	,7	...	140.6	,,,7	0.0	,,,7	15.62
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	58.0	0	48.0	,7	...	202.9	,,,7	0.0	,T,,7	19.47
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	168.5	0	110.5	,7	...	122.2	,,,7	0.0	,,,7	21.82
-93.17995	295.7	UNIVERSITY OF MN ST. PAUL, MN US	248.2	0	79.7	,7	...	179.3	,,,7	0.0	,,,7	20.57

#4.2 绘制时间序列

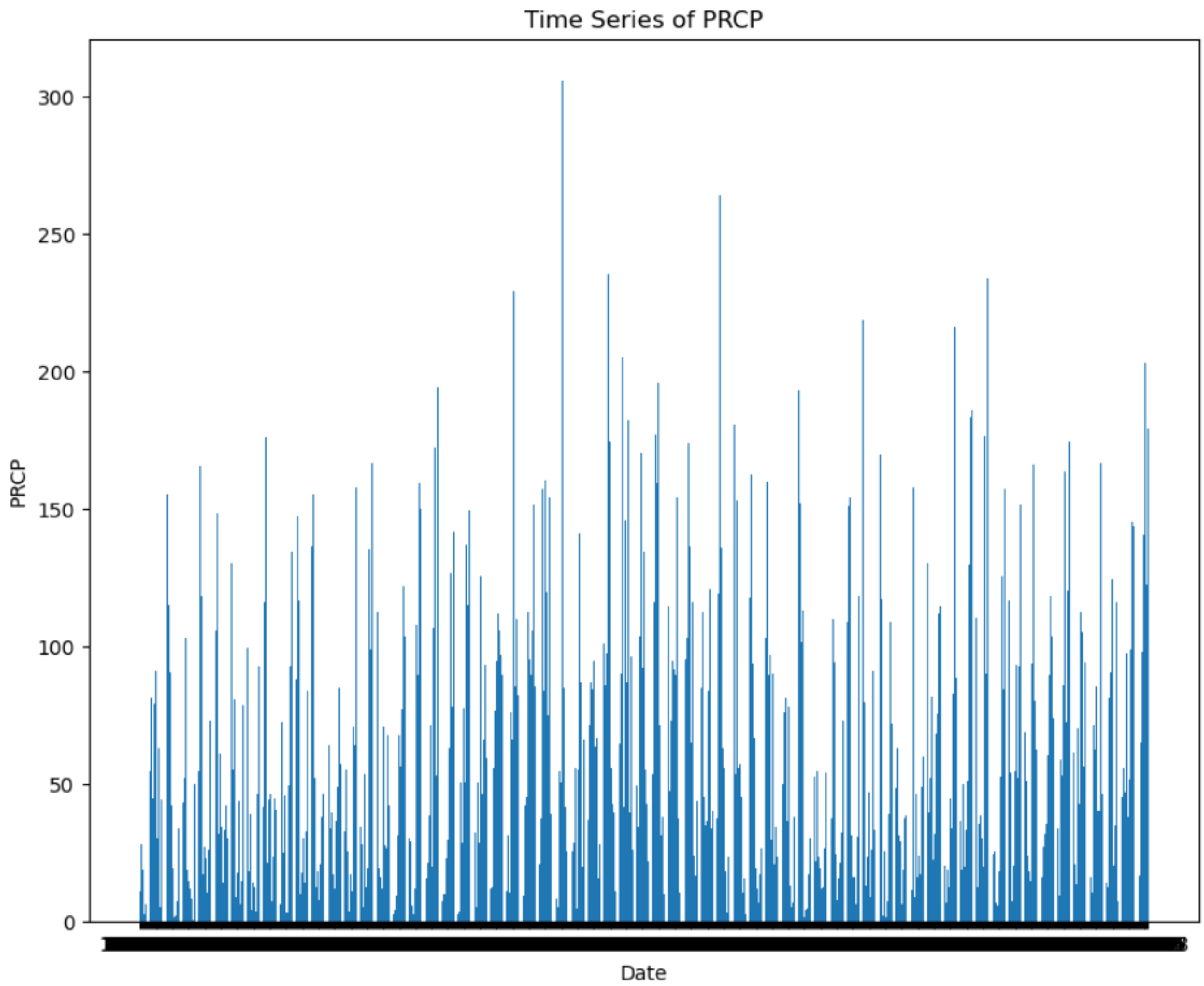
plt.figure(figsize=(10, 8))

plt.bar(USC['DATE'], USC['PRCP'])

plt.xlabel('Date')

plt.ylabel('PRCP')

plt.title('Time Series of PRCP')



#4.3

检查是否有缺失值

missing_values = df.isnull().sum()

print("缺失值情况：")

print(missing_values)

清理缺失值（如果对缺失值的处理方式有具体要求，可以在这里调整）

df_cleaned = df.dropna()

计算描述性统计量

desc_stats = USC['PRCP'].describe()

计算相关性

correlation = USC['PRCP'].corr(df['EMXP'])

计算标准差

std_dev = USC['PRCP'].std()

计算均值

mean_temp = USC['PRCP'].mean()

计算中位数

median_temp = USC['PRCP'].median()

报告发现

print("Descriptive Statistics:\n", desc_stats)

print("Correlation with Another Variable:", correlation)

print("Standard Deviation:", std_dev)

print("Mean Temperature:", mean_temp)

print("Median Temperature:", median_temp)

```
缺失值情况:
STATION            0
DATE               0
LATITUDE           0
LONGITUDE          0
ELEVATION          0
                  ..
TAVG_ATTRIBUTES    0
TMAX               0
TMAX_ATTRIBUTES    0
TMIN               0
TMIN_ATTRIBUTES    0
Length: 178, dtype: int64
Descriptive Statistics:
 count    767.000000
mean      64.783833
std       52.833345
min        0.000000
25%       22.850000
50%       51.600000
75%       93.900000
max      305.800000
Name: PRCP, dtype: float64
Correlation with Another Variable: nan
Standard Deviation: 52.83334480370376
Mean Temperature: 64.78383311603652
Median Temperature: 51.6
```