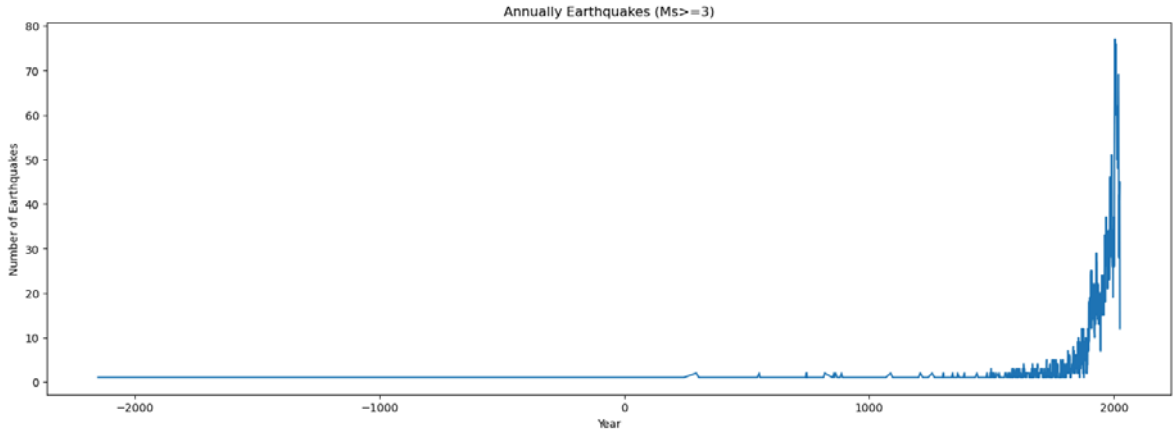
In [1]:
```
# import pandas
import pandas as pd
# import numpy
import numpy as np
# import matplotlib
from matplotlib import pyplot as plt
# make plots appear and be stored within the notebook
%matplotlib inline
import xarray as xr
```

In [2]:
```
#1.1 计算死亡总数
# Read the tsv file
Sig_Eqs = pd.read_csv("earthquakes-2024-10-31_09-53-06_+0800.tsv",sep='\t')

# Check information
#Sig_Eqs.info()
#Sig_Eqs.head()

#提取国家的名字
Sig_Eqs['Country'] = Sig_Eqs['Location Name'].str.split(':').str[0]
#分组算总数
Sig_Eqs_grouped = Sig_Eqs.groupby(['Country']).sum()
#去掉不相关列，输出国家及死亡总数
Sig_Eqs_grouped = Sig_Eqs_grouped[['Deaths']]
Sig_Eqs_grouped.sort_values('Deaths', ascending=False).head(20)
```

Out[2]:

TURKMENISTAN	117412.0
PERU	101461.0
PORTUGAL	83547.0
GREECE	80482.0
CHILE	64270.0
INDIA	61960.0
TAIWAN	57152.0

In [3]:
```
#1.2  Compute the total number of earthquakes with magnitude larger than 3.0
#筛选
Sig_Eqs_large = Sig_Eqs.loc[(Sig_Eqs['Mag'] >= 3)]

#分组并计数
Sig_Eqs_counts = Sig_Eqs_large.groupby(['Year']).size()

#作图
Sig_Eqs_counts.plot(kind='line',figsize=(18, 6))
plt.title('Annually Earthquakes (Ms>=3)')
plt.xlabel('Year')
plt.ylabel('Number of Earthquakes')
plt.show()
```



图中的前端出现了一条偶有波动的长实线，推测这是由于早年间没有成熟的地震监测技术，发生过的地震得不到良好的记录。 图中的后端出现了明显的升高，最高值达到80左右，推测原因有二，一是随着技术的进步，地震逐渐被检测并记录；二是地壳运动增强，导致其数量呈上升趋势。

In [140…

```python
#1.3 Write a function CountEq_LargestEq
#定义功能
def CountEq_LargestEq(country):
    Sig_Eqs = pd.read_csv("earthquakes-2024-10-31_09-53-06_+0800.tsv",sep='\t')

    #识别国家，地区，根据国家分组
    Sig_Eqs['Country'] = Sig_Eqs['Location Name'].str.split(':').str[0]
    Sig_Eqs['Location'] = Sig_Eqs['Location Name'].str.split(':').str[1]
    Sig_Eqs_country = Sig_Eqs.groupby(['Country']).size()

    #保证输入能被识别
    COUNTRY = country.upper()
    #识别不了就输出0
    total_eq = Sig_Eqs_country.get(COUNTRY, 0)

    #本来想输出一句话的，但后面要计算数据
    #print(f"The total number of earthquakes since 2150 B.C. in {COUNTRY} is {to

    #提取数字
    Sig_Eqs_set = Sig_Eqs.loc[(Sig_Eqs['Country'] == COUNTRY)]
    #排序
    Sig_Eqs_set.sort_values('Mag', ascending=False)

    #提取日期
    year = int(Sig_Eqs_set.iloc[0].get('Year'))
    month = Sig_Eqs_set.iloc[0].get('Month')
    day = Sig_Eqs_set.iloc[0].get('Day')
    Date_str = f"{year}"
    if month is not None:
        Date_str += f"-{month:02d}"
    if day is not None:
        Date_str += f"-{day:02d}"
    #print(f"The date of the largest earthquake ever happened in {COUNTRY} is {D

    #提取地点
    Loc_str = Sig_Eqs_set.iloc[0]['Location']
    #print(f"The location of the largest earthquake ever happened in {COUNTRY} i

    #输出
    return(COUNTRY,total_eq,Date_str,Loc_str)
```

```
#测试
#print(CountEq_LargestEq("Turkey"))

#读表格，读国家，建一个空list
Sig_Eqs = pd.read_csv("earthquakes-2024-10-31_09-53-06_+0800.tsv",sep='\t')
Sig_Eqs['Country'] = Sig_Eqs['Location Name'].str.split(':').str[0]
Sig_Eqs_country = Sig_Eqs.groupby(['Country']).size()
results_list = []

#用了循环从索引里找国家
for country in Sig_Eqs_country.index:
    result = CountEq_LargestEq(country)
    results_list.append(result)
#print(results_list)

#转化成df，排序
results_df = pd.DataFrame(results_list, columns=['Country', 'Total Earthquakes',
results_df = results_df.sort_values('Total Earthquakes', ascending=False)
print(results_df)
```

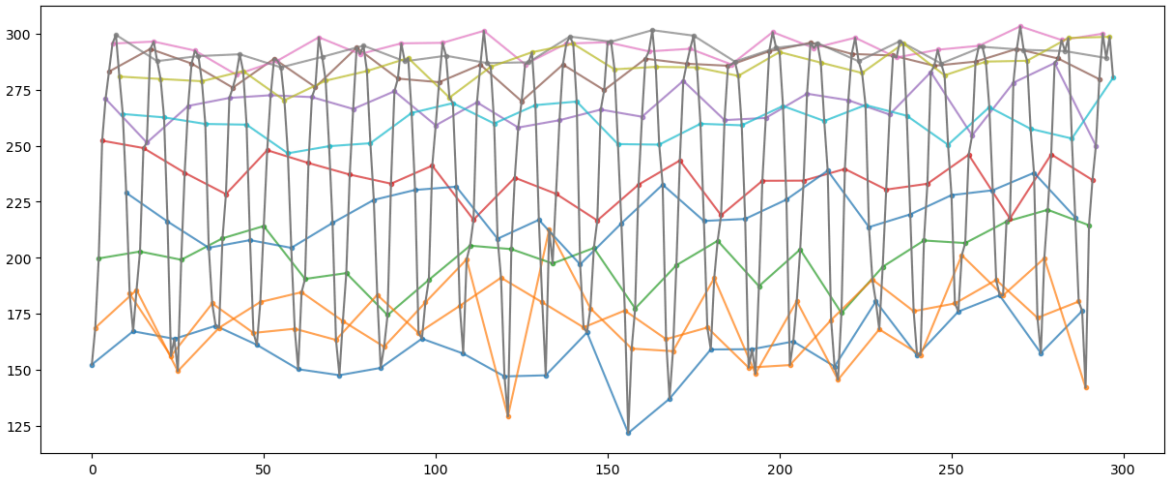
```
                          Country  Total Earthquakes   Date  \
58                          CHINA                623   -193
136                       INDONESIA                395   1629
140                            IRAN                386   -400
152                           JAPAN                359    684
148                           ITALY                332  -1450
..                              ...                ...    ...
117                         GUINEA                  1   1983
234         PAKISTAN-NW AFGHANISTAN                  1   1984
235                 PAKISTAN; INDIA                  1   2009
115  GUAM; NORTHERN MARIANA ISLANDS                  1   1825
349                         ZAMBIA                  1   2017

             Location
58      GANSU PROVINCE
136          BANDA SEA
140    REY,EIVAN-E-KAY
152                NaN
148       LACUS CIMINI
..                 ...
117     GAOUAL-KOUMBIA
234         HINDU KUSH
235            KASHMIR
115    LADRONES ISLAND
349             KAPUTA

[350 rows x 4 columns]
```

In [144…

```
# 2 Air temperature in Shenzhen
#设定筛选条件
strict = True

#读文件，把数据分成温度和质量
Baoan_TMP = pd.read_csv("Baoan_Weather_1998_2022.csv", usecols=['DATE', 'TMP'])
Baoan_TMP['QUA'] = Baoan_TMP['TMP'].str.split(',').str[1]
Baoan_TMP['TMP'] = Baoan_TMP['TMP'].str.split(',').str[0]

#根据筛选条件决定是否保留部分存疑数据
if strict:
```

```
    Baoan_TMP = Baoan_TMP.loc[ (Baoan_TMP['TMP'] != '+9999') & ((Baoan_TMP['QUA'
else:
    Baoan_TMP = Baoan_TMP.loc[ (Baoan_TMP['TMP'] != '+9999') & ((Baoan_TMP['QUA'
                                                                (Baoan_TMP['QUA'
                                                                (Baoan_TMP['QUA'
#把日期列分成容易读取的形式
Baoan_TMP['TIME'] = Baoan_TMP['DATE'].str.split('T').str[1]
Baoan_TMP['DATE'] = Baoan_TMP['DATE'].str.split('T').str[0]
Baoan_TMP['DAY'] = Baoan_TMP['DATE'].str.split('-').str[2]
Baoan_TMP['MON'] = Baoan_TMP['DATE'].str.split('-').str[1]
Baoan_TMP['YEAR'] = Baoan_TMP['DATE'].str.split('-').str[0]

#把各列转化一下格式
Baoan_TMP['TMP'] = pd.to_numeric(Baoan_TMP['TMP'])
Baoan_TMP['DAY'] = pd.to_numeric(Baoan_TMP['DAY'])
Baoan_TMP['MON'] = pd.to_numeric(Baoan_TMP['MON'])
Baoan_TMP['YEAR'] = pd.to_numeric(Baoan_TMP['YEAR'])

#分组计算平均值
Baoan_TMP_Mean = Baoan_TMP.groupby(['YEAR','MON'])['TMP'].mean().reset_index()

#转换待会x轴要用的数据（但后面生成图片的时候用的还是原来的index，没研究明白）
Baoan_TMP_Mean['DATE'] = Baoan_TMP_Mean['YEAR'].astype(str) + '-' + Baoan_TMP_Me
Baoan_TMP_Mean['date_column'] = pd.to_datetime(Baoan_TMP_Mean['DATE'], format='%

#表示出不同年份相同月的变化趋势
Baoan_TMP_Mean.groupby(['MON'])['TMP'].plot(x='date_column',alpha=0.7,markersize
#表示出月份的变化趋势
Baoan_TMP_Mean['TMP'].plot(x='date_column',kind='line',color = 'grey',figsize=(1
#Baoan_TMP_Mean.head()
```

Out[144… <Axes: >



从灰线，也就是所有数据之间的连线可以看出，温度的变化呈现出在一年之内先上升后下降的趋势。 从其它颜色线，也就是各年份之间的相同月份数据之间的连线可以看出，各年间相同月份温度变化没有明显规律，相对杂乱，但大多在一个2度左右的区间范围内变化。

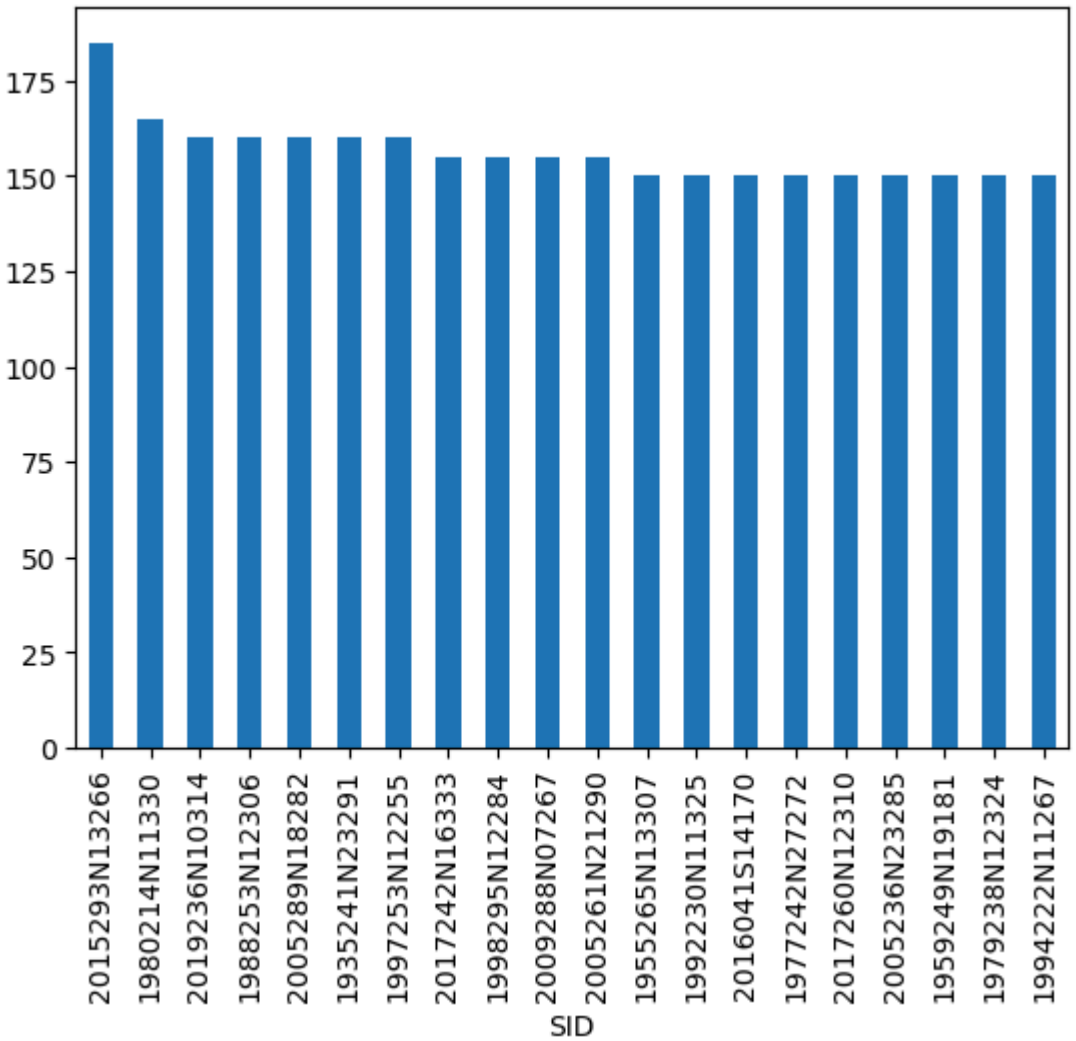
In [6]:

```
#3.1 生成最强的十个飓风
#读文件
Storms = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                     usecols=range(17),
                     skiprows=[1, 2],
                     parse_dates=['ISO_TIME'],
```

```
                  na_values=['NOT_NAMED', 'NAME'],
                  dtype={'NAME': str})

#转换一下风速列的格式
Storms['WMO_WIND'] = pd.to_numeric(Storms['WMO_WIND'], errors='coerce')

#去掉空值行
Storms_Speed = Storms.dropna(subset=['WMO_WIND'])
#Storms_Speed.head()

#分组，提取最大风速（之前试了一下平均值，怪怪的，还是用max吧）
Storms_SID_Speed = Storms_Speed.groupby(['SID'])['WMO_WIND'].max()
Storms_SID_Speed_Largest = Storms_SID_Speed.sort_values(ascending=False).head(10

输出结果
Name_of_Largest_Storms = []
for sid in Storms_SID_Speed_Largest['SID']:
    name = Storms.loc[Storms['SID'] == sid, 'NAME'].iloc[0]
    Name_of_Largest_Storms.append(name)
print(Name_of_Largest_Storms)
```

```
['PATRICIA', 'ALLEN', 'DORIAN', 'GILBERT', 'WILMA', nan, 'LINDA', 'IRMA', 'MITC
H', 'RICK']
```

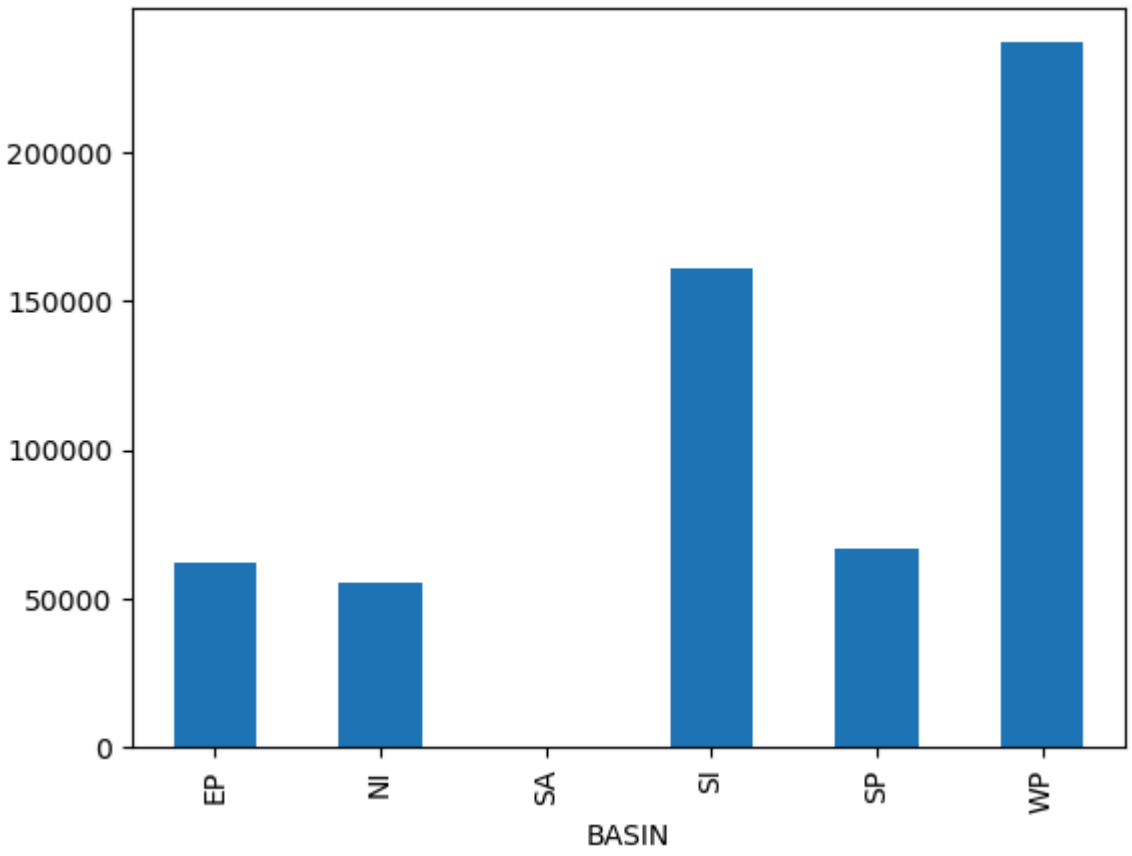
In [7]:
```
#3.2 飓风TOP20条形图
#把有编号没名字的飓风也保留了下来，毕竟有编号
Storms_SID_Speed_Largest = Storms_SID_Speed.sort_values(ascending=False).head(20
```



In [8]:
```
#3.3 生成不同流域数据点的数量
#读文件，这次只需要编号，名字和流域
Storms = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                     usecols=['SID','NAME','BASIN'],
                     skiprows=[1, 2],
                     #parse_dates=['ISO_TIME'],
                     na_values=['NOT_NAMED', 'NAME'],
                     dtype={'NAME': str})
#Storms.head()

#去掉流域不明的
Storms_Basein = Storms.loc[(Storms['BASIN'] != 'MM')]

#分组，计数
Storms_Basein_counts = Storms_Basein.groupby(['BASIN']).size()
print(Storms_Basein_counts)
Storms_Basein_counts.plot(kind='bar')
```

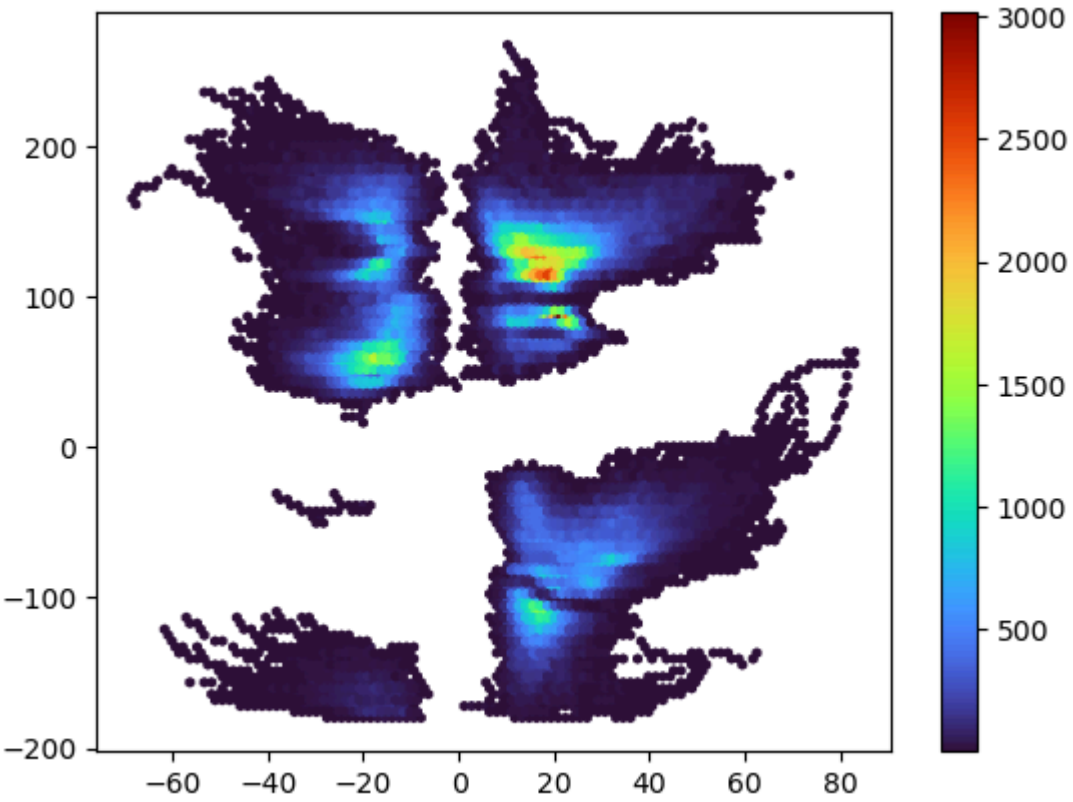
```
BASIN
EP     62412
NI     55401
SA       119
SI    160668
SP     67119
WP    236576
dtype: int64
```

Out[8]: <Axes: xlabel='BASIN'>



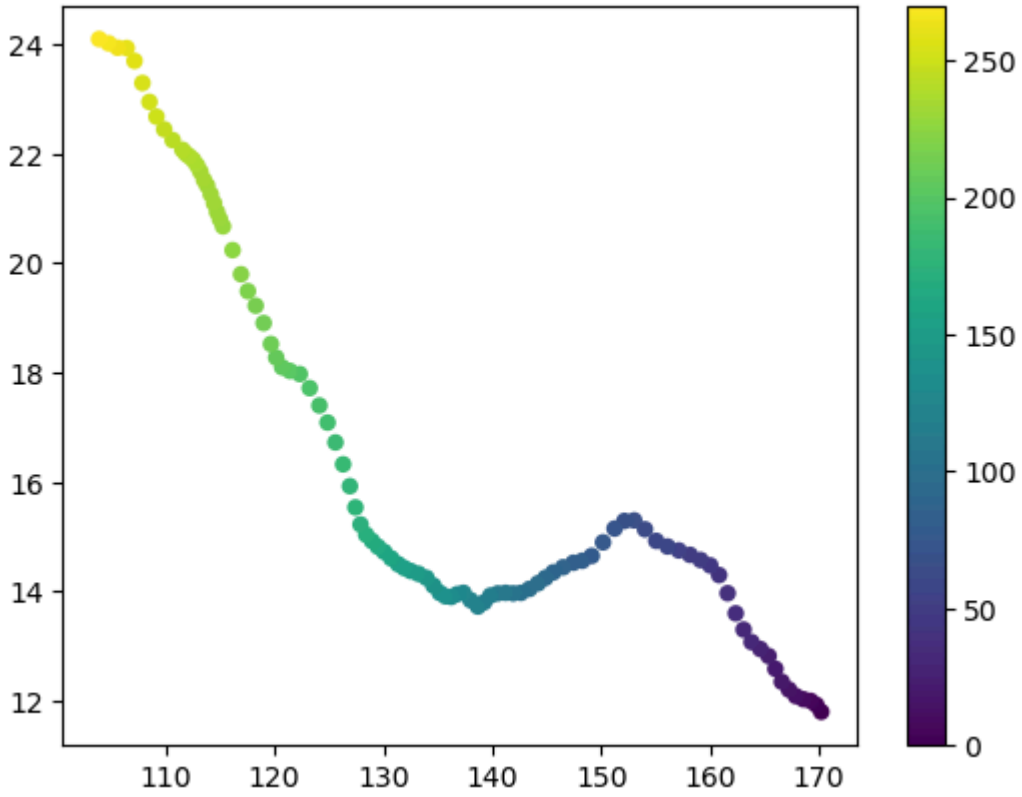
In [158…
```
#3.4 生成六边形图
#读文件，这次只要编号和经纬度
Storms = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                     usecols=['SID','LAT','LON'],
                     skiprows=[1, 2],
```

```
                #parse_dates=['ISO_TIME'],
                #na_values=['NOT_NAMED', 'NAME'],
                #dtype={'NAME': str}
                   )
#画图，试了一下，这样搭配看着清楚一点
hb = plt.hexbin(Storms['LAT'], Storms['LON'], gridsize=100, mincnt=1, cmap='turb
cb = plt.colorbar(hb)
plt.show()
```



In [162…

```
#3.5 18年山竹轨迹图
#读文件
Storms = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                usecols=['ISO_TIME','NAME','LAT','LON','WMO_WIND'],
                skiprows=[1, 2],
                parse_dates=['ISO_TIME'],
                na_values=['NOT_NAMED', 'NAME'],
                dtype={'NAME': str}
                   )

#筛出符合条件的山竹，排除掉其他年份的
Storms_Mangkhut = Storms.loc[(Storms['NAME'] == 'MANGKHUT') & (Storms['ISO_TIME'

#生成一列表示台风生成时间
first_time = Storms_Mangkhut['ISO_TIME'].iloc[0]
Storms_Mangkhut.loc[:,'duration'] = (Storms_Mangkhut['ISO_TIME'] - first_time).d

#生成散点图，通过颜色变化看台风方向
scatter = plt.scatter(Storms_Mangkhut['LON'], Storms_Mangkhut['LAT'], c=Storms_M
cb = plt.colorbar(scatter)
plt.show()
```



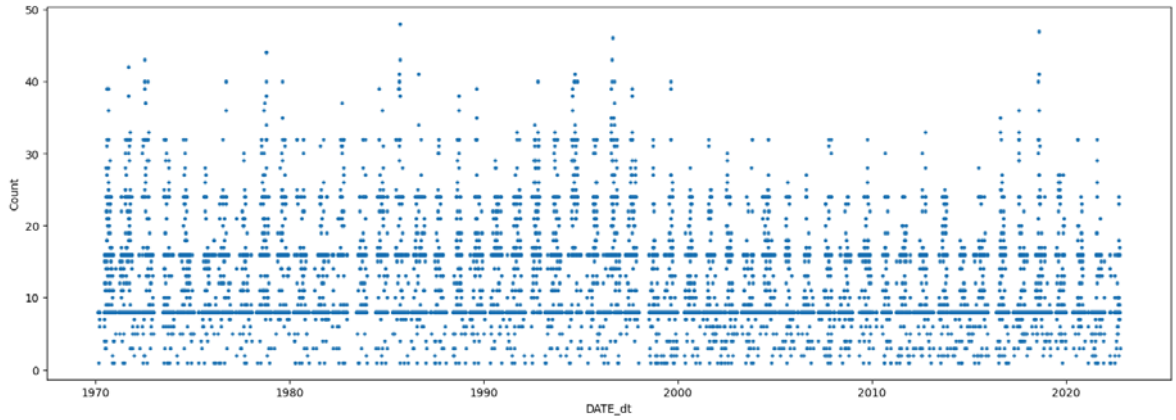
In [3]:
```
#3.6 保留特定流域数据
#读文件
Storms_3_6 = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                 usecols=range(17),
                 skiprows=[1, 2],
                 parse_dates=['ISO_TIME'],
                 na_values=['NOT_NAMED', 'NAME'],
                 dtype={'NAME': str})

#根据要求筛数据
Storms_WEP = Storms_3_6.loc[((Storms_3_6['BASIN'] == 'WP') | (Storms_3_6['BASIN'
print(Storms_WEP)
```

```
                  SID  SEASON  NUMBER BASIN SUBBASIN   NAME  \
350393  1970050N07151    1970      22    WP       MM  NANCY
350394  1970050N07151    1970      22    WP       MM  NANCY
350395  1970050N07151    1970      22    WP       MM  NANCY
350396  1970050N07151    1970      22    WP       MM  NANCY
350397  1970050N07151    1970      22    WP       MM  NANCY
...               ...     ...     ...   ...      ...    ...
706972  2022271N22132    2022      74    WP       MM   ROKE
706973  2022271N22132    2022      74    WP       MM   ROKE
707173  2022286N15151    2022      80    WP       MM    NaN
707174  2022286N15151    2022      80    WP       MM    NaN
707175  2022286N15151    2022      80    WP       MM    NaN

                  ISO_TIME NATURE       LAT      LON WMO_WIND WMO_PRES  \
350393 1970-02-19 00:00:00     TS   7.00000  151.400              1006
350394 1970-02-19 03:00:00     TS   7.24752  151.205
350395 1970-02-19 06:00:00     TS   7.50000  151.000              1002
350396 1970-02-19 09:00:00     TS   7.75747  150.772
350397 1970-02-19 12:00:00     TS   8.00000  150.500               998
...                    ...    ...       ...      ...      ...       ...
706972 2022-10-03 15:00:00     NR  37.17000  159.759
706973 2022-10-03 18:00:00     NR  37.29560  159.906
707173 2022-10-12 12:00:00     NR  15.20000  151.300
707174 2022-10-12 15:00:00     NR  15.05000  151.325
707175 2022-10-12 18:00:00     NR  14.90000  151.350

       WMO_AGENCY   TRACK_TYPE  DIST2LAND LANDFALL           IFLAG
350393      tokyo         main       1088     1088  _OO____________
350394                    main       1109     1109  _PP____________
350395      tokyo         main       1143     1143  _OO____________
350396                    main       1171     1168  _PP____________
350397      tokyo         main       1182     1179  _OO____________
...           ...          ...        ...      ...             ...
706972            PROVISIONAL       1253     1250  P_______________
706973            PROVISIONAL       1250          O_______________
707173            PROVISIONAL       1985     1974  O_______________
707174            PROVISIONAL       1974     1952  P_______________
707175            PROVISIONAL       1954          O_______________

[122301 rows x 17 columns]
```

In [164…

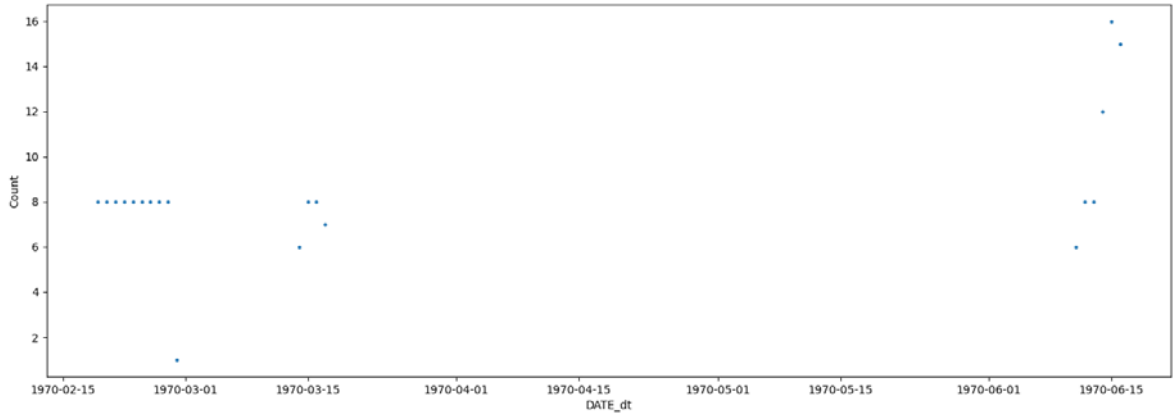
```
#3.7 计数并作图
Storms_WEP.loc[:, 'YEAR'] = Storms_WEP['ISO_TIME'].dt.year
Storms_WEP.loc[:, 'MON'] = Storms_WEP['ISO_TIME'].dt.month
Storms_WEP.loc[:, 'DAY'] = Storms_WEP['ISO_TIME'].dt.day
#print(Storms_WEP)

#分组，计数
Storms_WEP_DAY_counts = Storms_WEP.groupby(['YEAR', 'MON', 'DAY']).size().reset_
#print(Storms_WEP_DAY_counts)

#整理格式
Storms_WEP_DAY_counts.loc[:, 'DATE'] = Storms_WEP_DAY_counts['YEAR'].astype(str)
Storms_WEP_DAY_counts.rename(columns={0: 'Count'}, inplace=True)
#print(Storms_WEP_DAY_counts)
Storms_WEP_DAY_counts.loc[:, 'DATE_dt'] = pd.to_datetime(Storms_WEP_DAY_counts['

#画图
Storms_WEP_DAY_counts.plot(kind='scatter', x='DATE_dt',y='Count',s = 5,figsize=(
```

Out[164… <Axes: xlabel='DATE_dt', ylabel='Count'>



In [166…
```
#试一下日期之间的点是否连续
Storms_WEP_DAY_counts.head(20).plot(kind='scatter', x='DATE_dt',y='Count',s = 5,
```

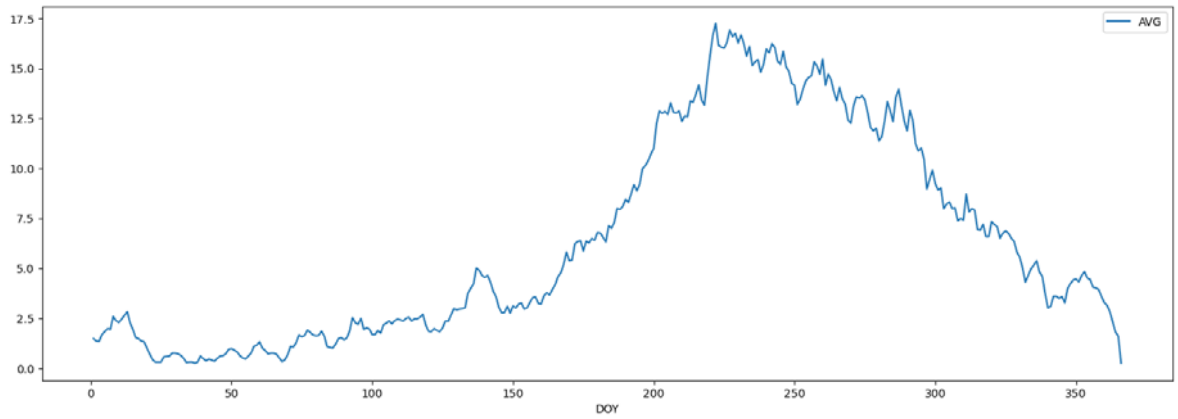
Out[166… <Axes: xlabel='DATE_dt', ylabel='Count'>



从这里可以发现，日期并不连续，而没有数据点记录的日期对应的计数点是“无”，但在实际情况中，没有数据点记录的日期对应的计数点还存在为“0”的可能.

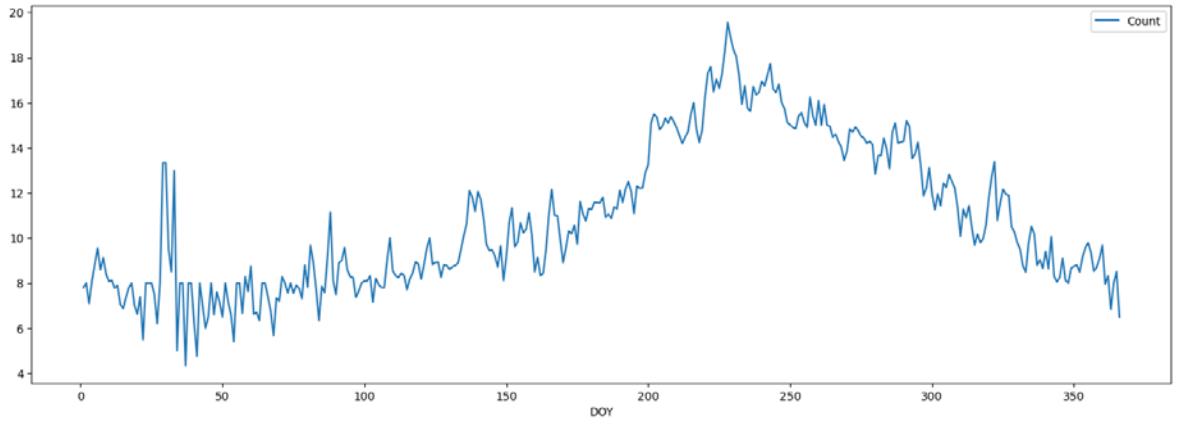
In [68]:
```
#3.8 年积日计算及作图
#生成年积日
Storms_WEP_DAY_counts.loc[:, 'DOY'] = Storms_WEP_DAY_counts['DATE_dt'].dt.dayofy
#print(Storms_WEP_DAY_counts)

#试一下看看同一个年积日有几年有数据
#test = Storms_WEP_DAY_counts.loc[Storms_WEP_DAY_counts['DOY'] == 56]
#print(test)

#分组，计算计数点总和再求平均，作图
Storms_WEP_DOY_counts_avg = Storms_WEP_DAY_counts.groupby('DOY')['Count'].sum().
Storms_WEP_DOY_counts_avg.loc[:, 'AVG'] = Storms_WEP_DOY_counts_avg['Count']/(20
#print(Storms_WEP_DOY_counts)
Storms_WEP_DOY_counts_avg.plot(kind='line',x='DOY',y='AVG',figsize=(18, 6))
```

Out[68]: <Axes: xlabel='DOY'>



In [66]:
```
#直接分组求平均，作图
Storms_WEP_DOY_counts_mean = Storms_WEP_DAY_counts.groupby('DOY')['Count'].mean(
Storms_WEP_DOY_counts_mean.plot(kind='line',x='DOY',y='Count',figsize=(18, 6))
```

Out[66]: <Axes: xlabel='DOY'>



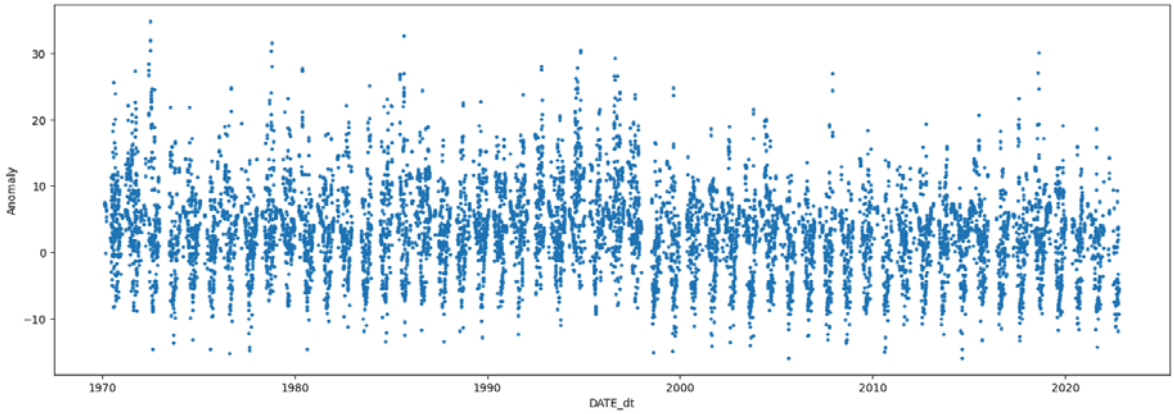
因为上一个发现，在这里做了两种计算。第一种计算对应的是数据点为“0”的情况，先计算了同一年积日记录的所有数据点总和，再除以年份之间的差值，也就是说，如果10年里面有3年的1月1号分别记录了8个数据点，那么年积日为1对应计算出来的平均数为2.4。第二种计算对应的是数据点为“无”的情况，也就是说，如果10年里面有3年的1月1号分别记录了8个数据点，那么年积日为1对应计算出来的平均数为8。 观察两张图片可以发现，第二张图片的波动更杂乱，尤其是年积日为30到年积日为50时，出现了明显的峰段；而第一张图片的虽然也有波动，但基本反映出了该流域的飓风季集中在一年中的下半年这一现象，而年积日为30到年积日为50时，并没有像第二张图里面那样明显的峰段。 综上考虑，在这次作业中，没有数据点记录的日期对应的计数点被考虑为“0”.

In [70]:
```
#3.9 计算差值，作图

#检查数据
#print(Storms_WEP_DAY_counts)
#print(Storms_WEP_DOY_counts_avg)

#合并表格，根据年积日匹配计数点及平均数，这里用的是先求和再求的平均
merged_WEP_counts = pd.merge(Storms_WEP_DAY_counts, Storms_WEP_DOY_counts_avg, l
#print(merged_WEP_counts)
Storms_WEP_DAY_counts_full = Storms_WEP_DAY_counts.copy()
Storms_WEP_DAY_counts_full.loc[:, 'AVG'] = merged_WEP_counts['AVG']
#print(Storms_WEP_DAY_counts_full)

#计算计数点和平均数之间的差值，作图
```

```
Storms_WEP_DAY_counts_full.loc[:, 'Anomaly'] = Storms_WEP_DAY_counts_full['Count
#print(Storms_WEP_DAY_counts_full)
Storms_WEP_DAY_counts_full.plot(kind='scatter', x='DATE_dt',y='Anomaly',s = 5,fi
print(Storms_WEP_DAY_counts_full)
```

	YEAR	MON	DAY	Count	DATE	DATE_dt	DOY	AVG	Anomaly
0	1970	2	19	8	1970-2-19	1970-02-19	50	0.981132	7.018868
1	1970	2	20	8	1970-2-20	1970-02-20	51	0.905660	7.094340
2	1970	2	21	8	1970-2-21	1970-02-21	52	0.811321	7.188679
3	1970	2	22	8	1970-2-22	1970-02-22	53	0.622642	7.377358
4	1970	2	23	8	1970-2-23	1970-02-23	54	0.509434	7.490566
...	...	...	...	...	...	...	...	...	...
9720	2022	9	30	8	2022-9-30	2022-09-30	273	13.509434	-5.509434
9721	2022	10	1	8	2022-10-1	2022-10-01	274	13.641509	-5.641509
9722	2022	10	2	8	2022-10-2	2022-10-02	275	13.415094	-5.415094
9723	2022	10	3	7	2022-10-3	2022-10-03	276	12.792453	-5.792453
9724	2022	10	12	3	2022-10-12	2022-10-12	285	12.339623	-9.339623

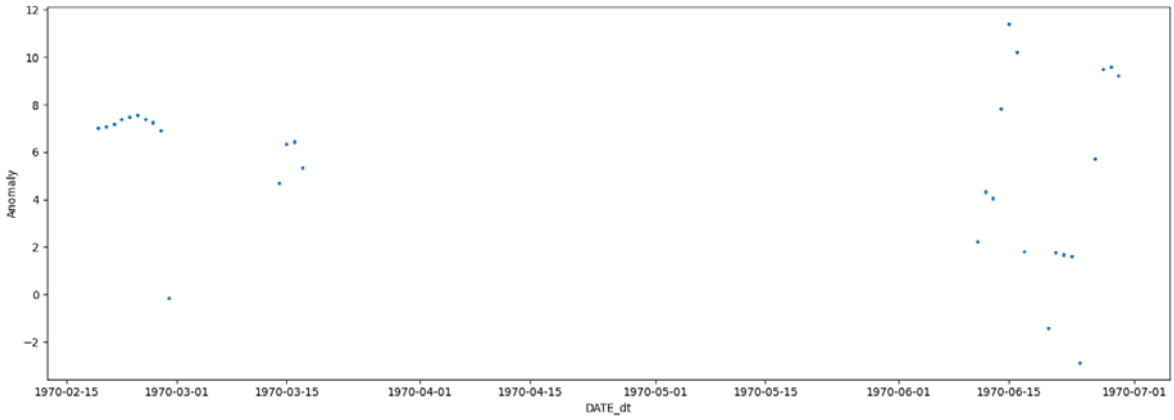
[9725 rows x 9 columns]



这里画的是有数据点记录的日期对应的差值，没把其他日期列入图中。

In [44]:
```
#试一下日期之间的差值点是否连续
Storms_WEP_DAY_counts_full.head(30).plot(kind='scatter', x='DATE_dt',y='Anomaly'
```

Out[44]: <Axes: xlabel='DATE_dt', ylabel='Anomaly'>

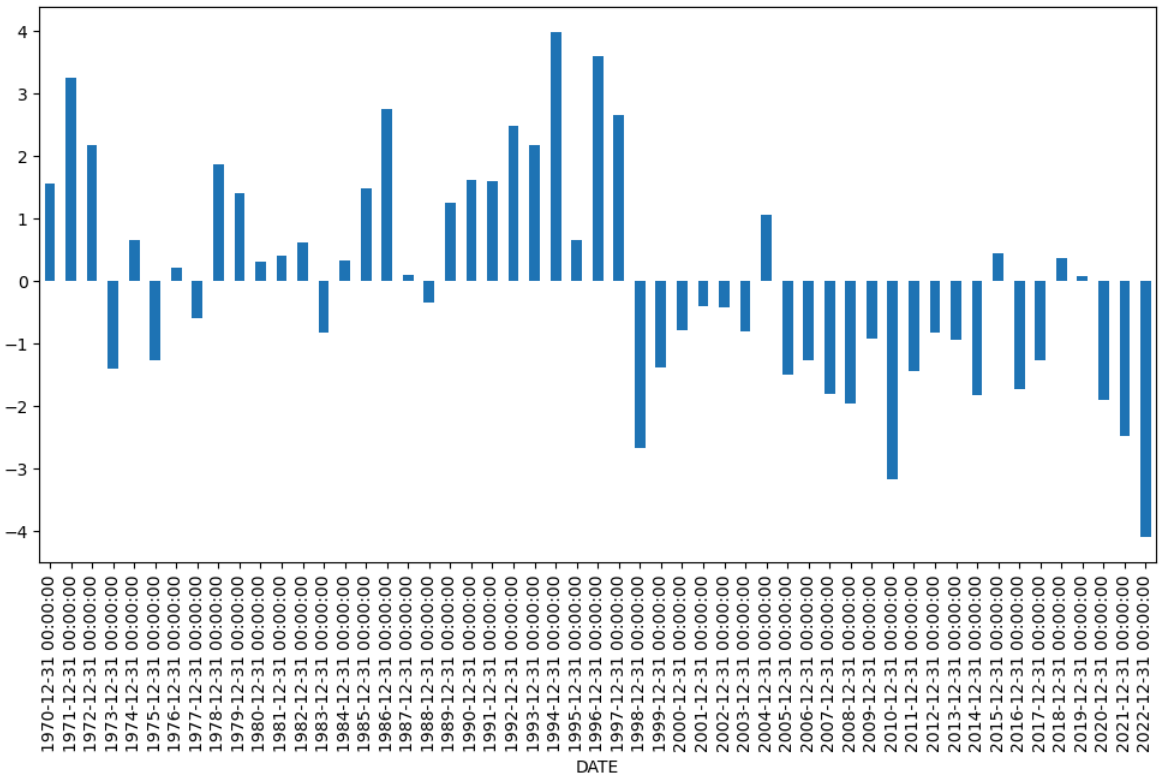


依旧不连续

In [118...
```
#3.10 resample
#之前的题目里面发现日期是不连续的，但这些不连续的日期里，计数点不应该是“无”，而应

#创建一个count全为0的表格，但日期完全的表格
start_date = datetime(1970, 2, 19)
```

```
end_date = datetime(2022, 10, 22)
date_range = pd.date_range(start=start_date, end=end_date)
Storms_WEP_DAY_counts_zero = pd.DataFrame()
Storms_WEP_DAY_counts_zero['DATE'] = date_range
Storms_WEP_DAY_counts_zero['YEAR'] = Storms_WEP_DAY_counts_zero['DATE'].dt.year
Storms_WEP_DAY_counts_zero['MON'] = Storms_WEP_DAY_counts_zero['DATE'].dt.month
Storms_WEP_DAY_counts_zero['DAY'] = Storms_WEP_DAY_counts_zero['DATE'].dt.day
Storms_WEP_DAY_counts_zero['Count'] = 0
#Storms_WEP_DAY_counts_zero.head()

#将表格合并，使得没有计数点存在的日期计数点表示为0
Storms_WEP_DAY_counts['DATE'] = pd.to_datetime(Storms_WEP_DAY_counts['DATE'])
Storms_WEP_DAY_counts['YEAR'] = Storms_WEP_DAY_counts['YEAR'].astype(int)
merged_Storms_WEP_DAY_counts_full = pd.merge(Storms_WEP_DAY_counts_zero, Storms_
merged_Storms_WEP_DAY_counts_full['Count'] = merged_Storms_WEP_DAY_counts_full['

#简化表格
merged_Storms_WEP_DAY_counts_full_sim = merged_Storms_WEP_DAY_counts_full.copy()
merged_Storms_WEP_DAY_counts_full_sim.drop(['Count_1','YEAR_2', 'MON_2','DAY_2',
merged_Storms_WEP_DAY_counts_full_sim.loc[:, 'DOY'] = merged_Storms_WEP_DAY_coun
#merged_Storms_WEP_DAY_counts_full_sim.head(30)

#将表格合并，在原有表格基础上根据DOY添加计数点平均值
merged_WEP_counts_full_year = pd.merge(merged_Storms_WEP_DAY_counts_full_sim, St
merged_WEP_counts_full_year.drop(['Count_y'], axis=1,inplace=True)
merged_WEP_counts_full_year.loc[:, 'Anomaly'] = merged_WEP_counts_full_year['Cou
#merged_WEP_counts_full_year.tail(30)

#resample，从日到年，作图
merged_WEP_counts_full_year_dtindex = merged_WEP_counts_full_year.copy()
merged_WEP_counts_full_year_dtindex.set_index(merged_WEP_counts_full_year['DATE'
yearly_mean = merged_WEP_counts_full_year_dtindex['Anomaly'].resample('YE').mean
#print(yearly_mean)
yearly_mean.plot(kind='bar',figsize=(12, 6))
```

Out[118… <Axes: xlabel='DATE'>



将0纳入考量后发现，飓风活动较为活跃的时期聚集在20世纪90年代，具体较突出的年份为1994年。

In [122…

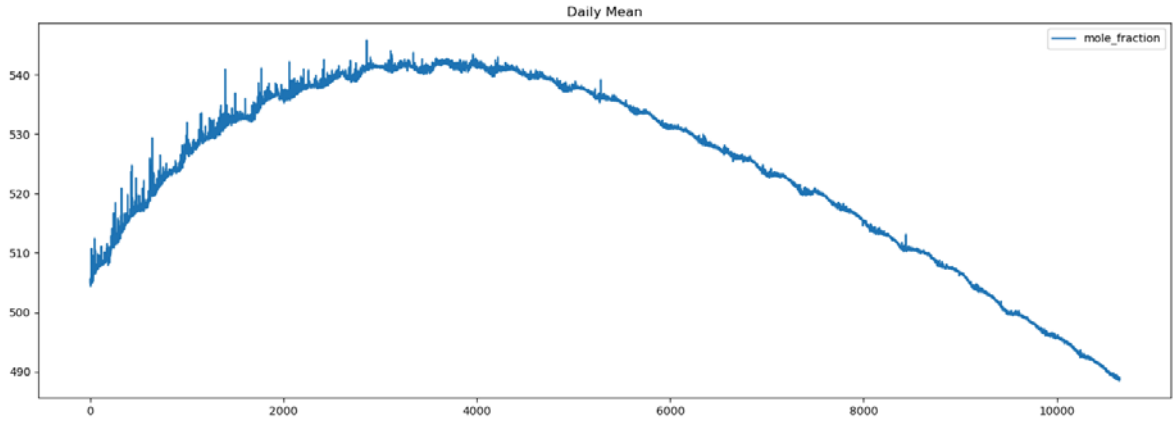
```
#4.1 读取数据
#抓取的数据是txt格式的，列与列之间分隔符是数量不等的空格，且前面有一串readme，读取
CFC_12 = pd.read_csv('AGAGE-GCMD_CGO_cfc-12.txt', delimiter='\\s+', skiprows=ran
#数据清洗，洗掉空值
CFC_12 = CFC_12.loc[(CFC_12['flag'] != '-')]
CFC_12.info()
```

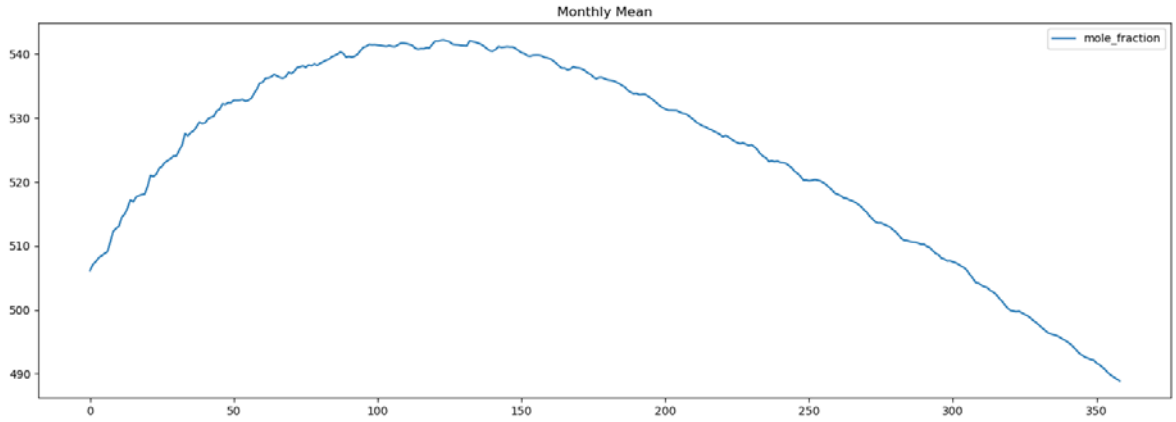
```
<class 'pandas.core.frame.DataFrame'>
Index: 308074 entries, 0 to 329113
Data columns (total 9 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   time           308074 non-null  float64
 1   DD             308074 non-null  int64  
 2   MM             308074 non-null  int64  
 3   YYYY           308074 non-null  int64  
 4   hh             308074 non-null  int64  
 5   mm             308074 non-null  int64  
 6   mole_fraction  308074 non-null  float64
 7   repeability    308074 non-null  float64
 8   flag           308074 non-null  object 
dtypes: float64(3), int64(5), object(1)
memory usage: 23.5+ MB
```

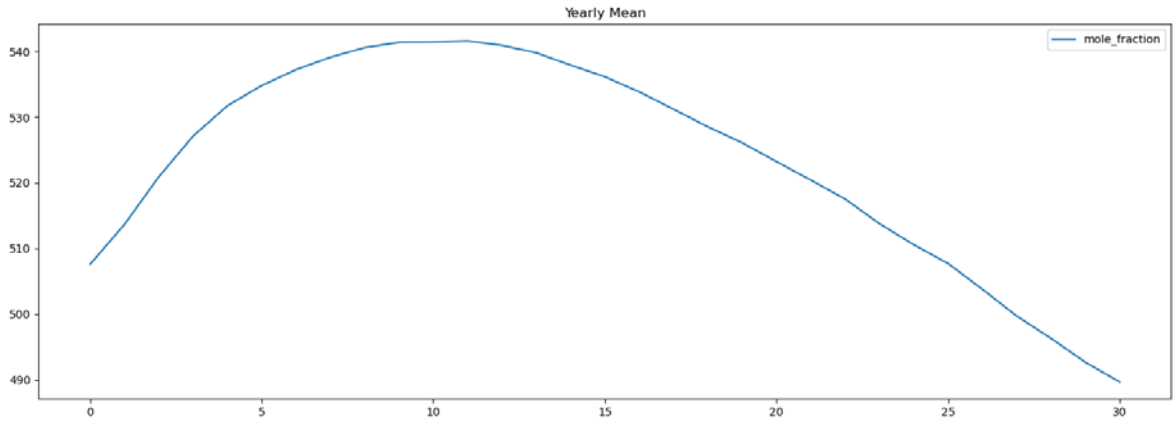
这里使用的数据来源于这个网址：
https://agage2.eas.gatech.edu/data_archive/agage/gc-md/event/capegrim/ascii/AGAGE-GCMD_CGO_cfc-12.txt%E3%80%82

In [170…

```
#4.2 计算每天、每月、每年的平均值，按时间序列作图
CFC_12_daily = CFC_12.groupby(['YYYY', 'MM','DD'])['mole_fraction'].mean().reset
CFC_12_monthly = CFC_12.groupby(['YYYY', 'MM'])['mole_fraction'].mean().reset_in
CFC_12_yearly = CFC_12.groupby(['YYYY'])['mole_fraction'].mean().reset_index()
#print(CFC_12_monthly)

CFC_12_daily.plot(kind='line',y='mole_fraction',figsize=(18, 6))
plt.title('Daily Mean')
plt.show()

CFC_12_monthly.plot(kind='line',y='mole_fraction',figsize=(18, 6))
plt.title('Monthly Mean')
plt.show()

CFC_12_yearly.plot(kind='line',y='mole_fraction',figsize=(18, 6))
plt.title('Yearly Mean')
plt.show()
```

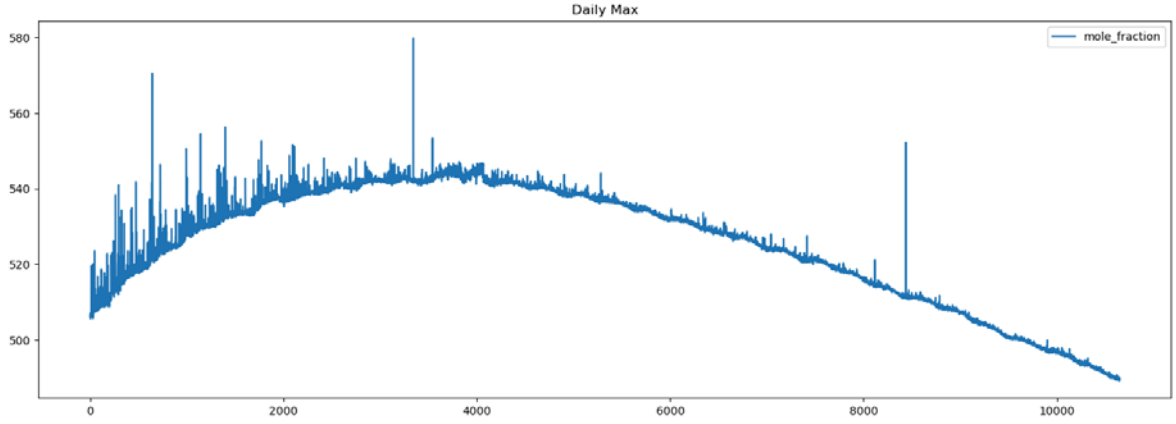






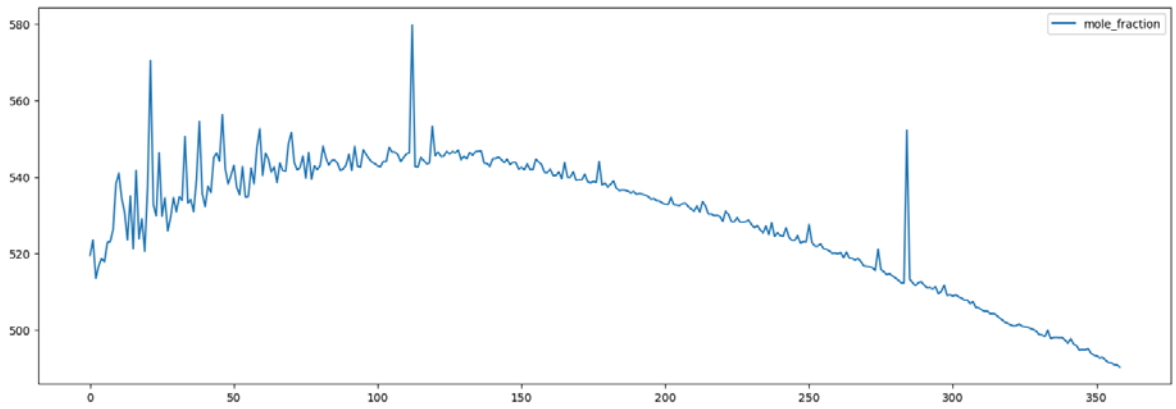
In [168…

```
#4.3.1 提取每天的最大值，按时间序列作图
CFC_12_daily_max = CFC_12.groupby(['YYYY', 'MM','DD'])['mole_fraction'].max().re
#print(CFC_12_daily_max)
CFC_12_daily_max.plot(kind='line',y='mole_fraction',figsize=(18, 6))
plt.title('Daily Max')
plt.show()
```



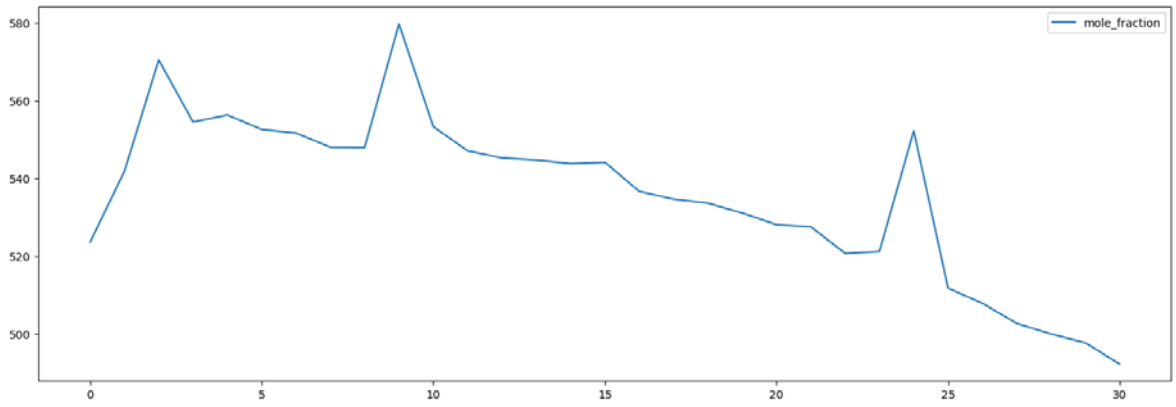
In [126…
```
#4.3.2 提取每月的最大值，按时间序列作图
CFC_12_monthly_max = CFC_12.groupby(['YYYY', 'MM'])['mole_fraction'].max().reset
#print(CFC_12_monthly_max)
CFC_12_monthly_max.plot(kind='line',y='mole_fraction',figsize=(18, 6))
```

Out[126… <Axes: >



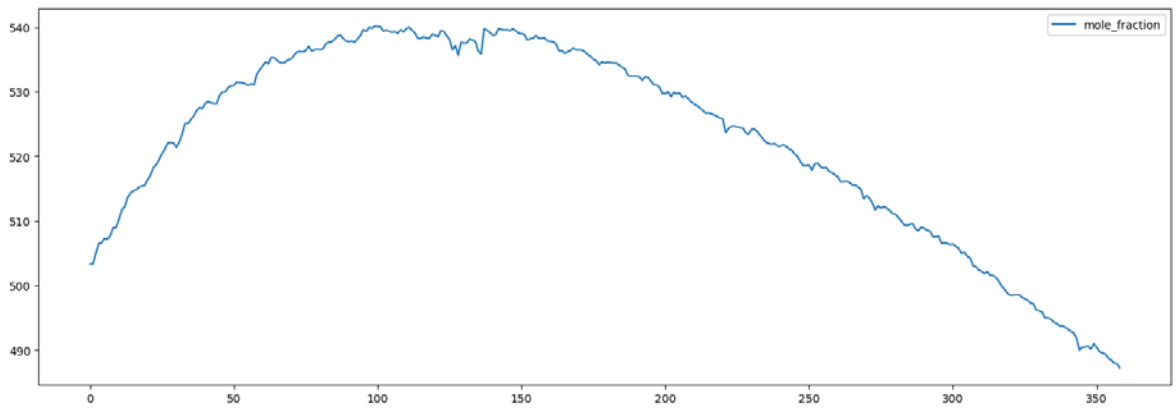
In [128…
```
#4.3.3 提取每年的最大值，按时间序列作图
CFC_12_yearly_max = CFC_12.groupby(['YYYY'])['mole_fraction'].max().reset_index(
#print(CFC_12_monthly_max)
CFC_12_yearly_max.plot(kind='line',y='mole_fraction',figsize=(18, 6))
```

Out[128… <Axes: >



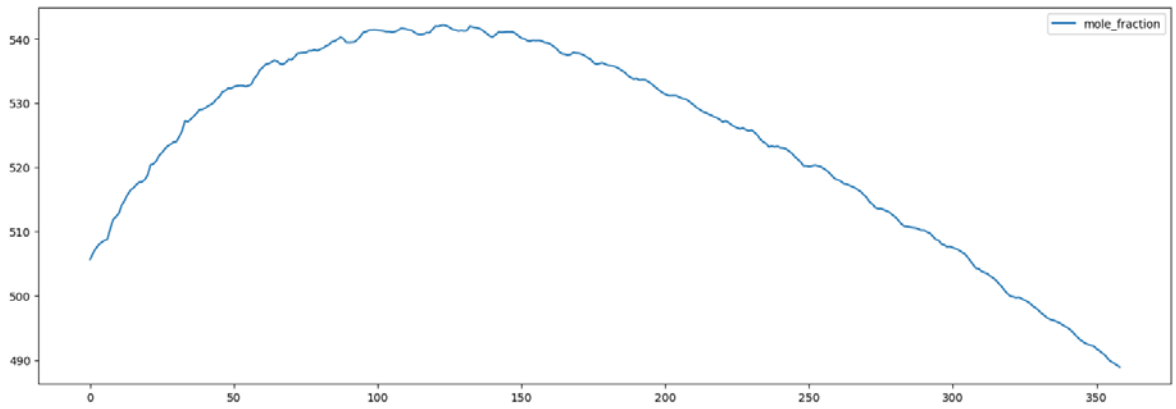
In [21]:
```
#4.3.4 提取每月的最小值，按时间序列作图
CFC_12_monthly_min = CFC_12.groupby(['YYYY', 'MM'])['mole_fraction'].min().reset
#print(CFC_12_monthly_min)
CFC_12_monthly_min.plot(kind='line',y='mole_fraction',figsize=(18, 6))
```

Out[21]: <Axes: >



In [136…
```
#4.3.5 提取每月的中位数，按时间序列作图
CFC_12_monthly_median = CFC_12.groupby(['YYYY', 'MM'])['mole_fraction'].median()
#print(CFC_12_monthly_min)
CFC_12_monthly_median.plot(kind='line',y='mole_fraction',figsize=(18, 6))
```

Out[136…
```
<Axes: >
```



画了五张图，分别采用了不同的时间序列和不同的数值。 每一张图都呈现出了先上升再下降的趋势，只是曲线的平滑程度有区别。 在不同三个时间尺度的比较中，平均值曲线反映出的趋势的平滑程度呈现出年>月>日的规律，而峰值曲线呈现出日>月>年的规律。 而在相同时间尺度下，曲线的平滑程度呈现出中位数>最小值>最大值的规律。