HW 2

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In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

1. Significant earthquakes since 2150 B.C.

> The Significant Earthquake Database contains information on destructive earthquakes from 2150 B.C. to the present. On the top left corner, select all columns and download the entire significant earthquake data file in .tsv format by clicking the Download TSV File button. Click the variable name for more information. Read the file (e.g., earthquakes-2022-10-18*09-17-48*+0800.tsv) as an object and name it Sig_Eqs.

1.1 [5 points] Compute the total number of deaths caused by earthquakes since 2150 B.C. in each country, and then print the top 20 countries along with the total number of deaths.

In [ ]:
```
data1 =pd.read_table('earthquakes-2022-10-20_21-52-40_+0800.tsv')

data1[['Country','location']] =data1['Location Name'].str.split(':',n=1, expand=True)
total_deaths_city =data1.groupby(['Country']).sum().Deaths
print('The top 20 countries along with the total number of deaths is as follow:\n',tot
```

```
The top 20 countries along with the total number of deaths is as follow:
 Country
CHINA          2075019.0
TURKEY         1094479.0
IRAN            995403.0
ITALY           498477.0
SYRIA           369224.0
HAITI           323474.0
AZERBAIJAN      317219.0
JAPAN           277142.0
ARMENIA         191890.0
ISRAEL          160120.0
PAKISTAN        145080.0
ECUADOR         135479.0
IRAQ            120200.0
TURKMENISTAN    117412.0
PERU            101511.0
PORTUGAL         83506.0
GREECE           79278.0
CHILE            64269.0
INDIA            61940.0
TAIWAN           57134.0
Name: Deaths, dtype: float64
```

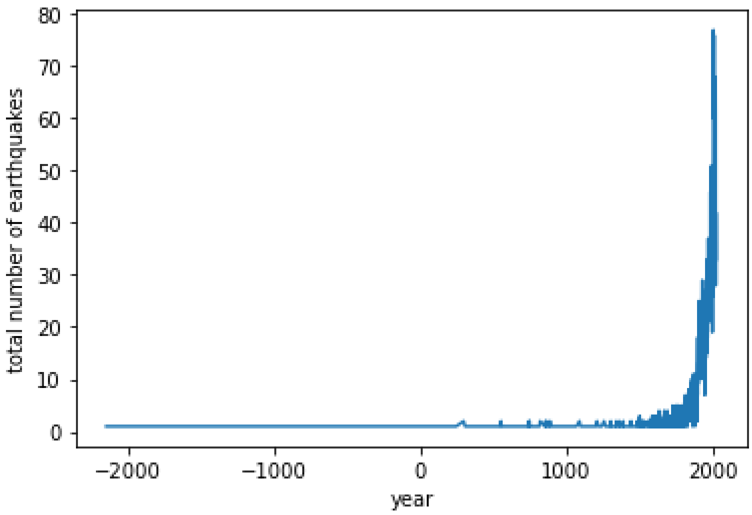
1.2 [10 points] Compute the total number of earthquakes with magnitude larger than 3.0 (use column Ms as the magnitude) worldwide each year, and then plot the time series. Do you observe any trend? Explain why or why not?

In [ ]:
```
total_earth_mag30 =data1[data1.Mag >3.0].groupby('Year').count()
```

```
plt.plot(total_earth_mag30.index,total_earth_mag30['Location Name'])
plt.ylabel('total number of earthquakes')
plt.xlabel('year')
```

Out[ ]:

```
Text(0.5, 0, 'year')
```



There is a increasing trend of total number of the earthquakes along time, and shows a sharply upwards in recent years. This may because of the number of evidences the researchers can find, the later the richer

1.3 [10 points] Write a function CountEq_LargestEq that returns (1) the total number of earthquakes since 2150 B.C. in a given country AND (2) date and location of the largest earthquake ever happened in this country. Apply CountEq_LargestEq to every country in the file, report your results in a descending order.

In [ ]:

```
def CountEq_LargestEq(country,df):
    data_country =df.loc[df.Country ==country.upper(),['Year','Mo','Dy','Hr','locatic
    if data_country.Mag.isnull().all():
        return len(data_country),'',''
    else:
        max_ind =data_country.loc[data_country.Mag.idxmax()].fillna('')

        total_number_eq = len(data_country)
        largest_date =str(max_ind['Year'])+'-'+str(max_ind['Mo'])+'-'\
                        +str(max_ind['Dy'])+'-'+str(max_ind['Hr'])
        largest_loca =max_ind['location'].lstrip()

        return total_number_eq,largest_date,largest_loca
```

In [ ]:

```
CountEq_LargestEq('china',data1)
print(data1.Mag.loc[data1.Country =='SYRIAN COASTS'])
```

```
7      NaN
520    NaN
Name: Mag, dtype: float64
```

In [ ]:

```
all_country =[]
countries =data1.Country.drop_duplicates(keep='first').drop(0,axis=0)
for i in countries:
    if i == i:
        num,date,loca =CountEq_LargestEq(i,data1)
        all_country.append([i,data1.Mag.max(),num,date,loca])
```

```
all_countries =pd.DataFrame(all_country, columns=['country','mag','num','date','loca'
print(all_countries.country)
```

```
0                          JORDAN
1                BRITISH COLUMBIA
2                           KENYA
3                  ISRAEL; JORDAN
4               CALIFORNIA, MEXICO
                   ...
339                    COSTA RICA
340    W. LUZON ISLAND, PHILIPPINES
341    E. LUZON ISLAND, PHILIPPINES
342                    BANGLADESH
343                NORTH CAROLINA
Name: country, Length: 344, dtype: object
```

2. Air temperature in Shenzhen during the past 25 years

In this problem set, we will examine how air temperature changes in Shenzhen during the past 25 years using the hourly weather data measured at the BaoAn International Airport. The data set is from NOAA Integrated Surface Dataset. Download the file Baoan_Weather_1998_2022.csv, move the .csv file to your working directory.

Read page 10-11 (POS 88-92 and POS 93-93) of the comprehensive user guide for the detailed format of the air temperature data (use column TMP). Explain how you filter the data in your report.

[10 points] Plot monthly averaged air temperature against the observation time. Is there a trend in monthly averaged air temperature in the past 25 years?

In [ ]:

```
data2 =pd.read_csv('Baoan_Weather_1998_2022.csv')
```

```
c:\ProgramData\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3444: Dtyp
eWarning: Columns (4,8,9,10,11,14,15,24,25,27,29,31,34,37,38,40,41,45,49,50) have mixe
d types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

3. Global collection of hurricanes

The International Best Track Archive for Climate Stewardship (IBTrACS) project is the most complete global collection of tropical cyclones available. It merges recent and historical tropical cyclone data from multiple agencies to create a unified, publicly available, best-track dataset that improves inter-agency comparisons. IBTrACS was developed collaboratively with all the World Meteorological Organization (WMO) Regional Specialized Meteorological Centres, as well as other organizations and individuals from around the world.

In this problem set, we will use all storms available in the IBTrACS record since 1842. Download the file ibtracs.ALL.list.v04r00.csv, move the .csv file to your working directory. Read Column Variable Descriptions for variables in the file. Examine the first few lines of the file.

Below we provide an example to load the file as a pandas dataframe. Think about the options being used and why, and modify when necessary.

In [ ]:
```
data3 =pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                   usecols=range(17), # only choose useful columns, here we choose 0-16
                   skiprows=[1, 2], # skip the rows, which will not exist in read datase
                   parse_dates=['ISO_TIME'], # set the date form
                   na_values=['NOT_NAMED', 'NAME']) # replace two terms into NAN
data3
```

```
c:\ProgramData\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3444: Dtyp
eWarning: Columns (5) have mixed types.Specify dtype option on import or set low_memor
y=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Out[ ]:

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE	LA
0	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 06:00:00	NR	10.870
1	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 09:00:00	NR	10.843
2	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 12:00:00	NR	10.818
3	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 15:00:00	NR	10.800
4	1842298N11080	1842	1	NI	AS	NaN	1842-10-25 18:00:00	NR	10.788
...	...	...	...	...	...	...	...	...	...
707171	2022284N16268	2022	79	NaN	GM	KARL	2022-10-12 21:00:00	TS	22.279
707172	2022284N16268	2022	79	NaN	GM	KARL	2022-10-13 00:00:00	TS	22.400
707173	2022286N15151	2022	80	WP	MM	NaN	2022-10-12 12:00:00	NR	15.200
707174	2022286N15151	2022	80	WP	MM	NaN	2022-10-12 15:00:00	NR	15.050
707175	2022286N15151	2022	80	WP	MM	NaN	2022-10-12 18:00:00	NR	14.900

707176 rows × 17 columns

3.1 [5 points] Group the data on Storm Identifie (SID), report names (NAME) of the 10 largest hurricanes according to wind speed (WMO_WIND).

In [ ]:

```
data3_SID =data3.groupby('SID', as_index=False).max().sort_values('WMO_WIND', ascend
print('10 largest hurricanes according to wind speed after group by storm identifie ar
```

```
10 largest hurricanes according to wind speed after group by storm identifie are :
 11015            RHONDA
11909            TALIM
11865            PERCY
11867           INGRID
11872    ADELINE:JULIET
11877            NESAT
11887            EMILY
11888          HAITANG
11905            MAWAR
11908          KATRINA
Name: NAME, dtype: object
C:\Users\duck\AppData\Local\Temp/ipykernel_16592/1194367031.py:1: FutureWarning: Dropp
ing invalid columns in DataFrameGroupBy.max is deprecated. In a future version, a Type
Error will be raised. Before calling .max, select only columns which should be valid f
or the function.
  data3_SID =data3.groupby('SID', as_index=False).max().sort_values('WMO_WIND', ascend
ing=False)
```

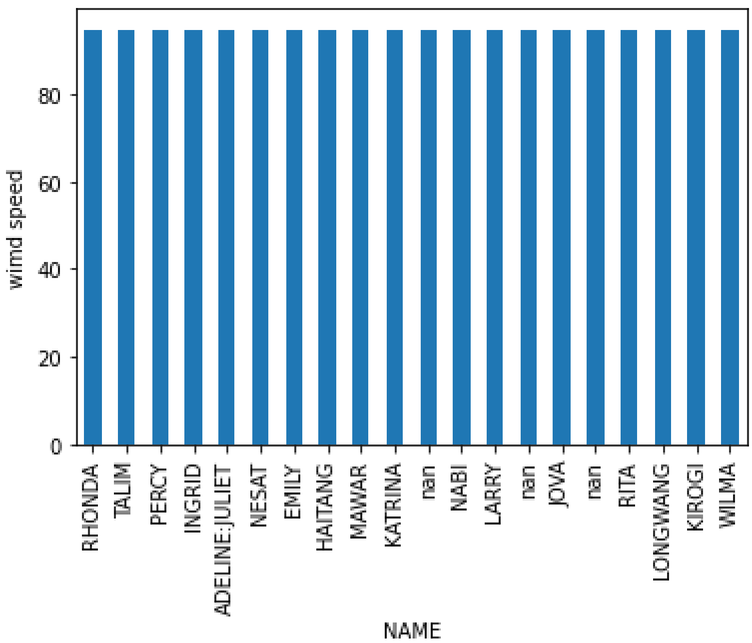
3.2 [5 points] Make a bar chart of the wind speed (WMO_WIND) of the 20 strongest-wind hurricanes.

> assume data processed on Q1 can be used here

In [ ]:

```
data3_lg20 =pd.to_numeric(data3_SID.WMO_WIND.head(20))
data3_lg20.index =data3_SID.NAME.head(20)
data3_lg20.plot.bar(ylabel ='wimd speed')
```

Out[ ]: <AxesSubplot:xlabel='NAME', ylabel='wimd speed'>

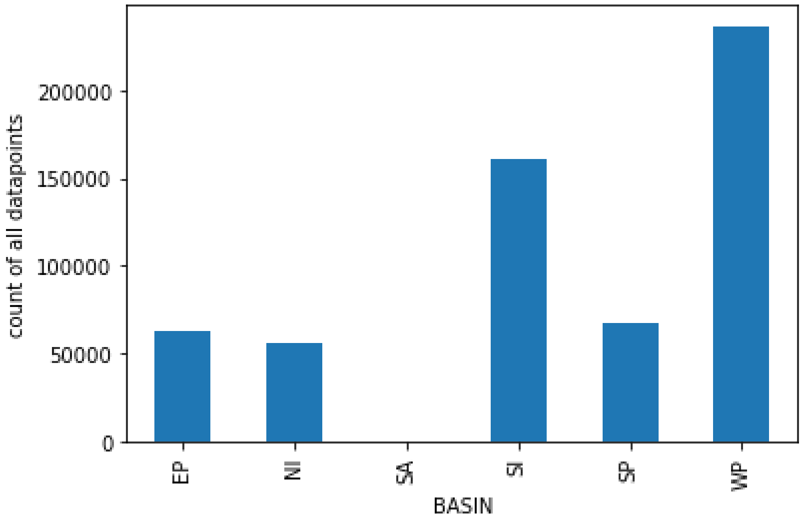


3.3 [5 points] Plot the count of all datapoints by Basin as a bar chart.

In [ ]:

```
basin =data3.groupby('BASIN').count().SID
basin.plot.bar(ylabel ='count of all datapoints')
```

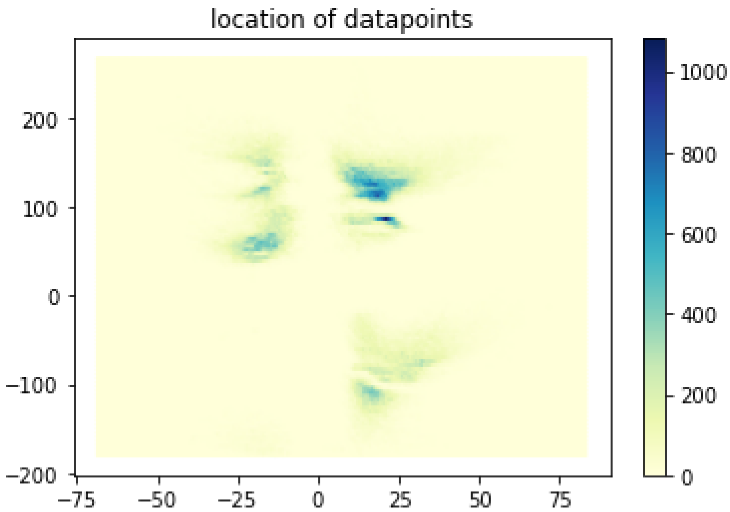
Out[ ]: <AxesSubplot:xlabel='BASIN', ylabel='count of all datapoints'>



3.4 [5 points] Make a hexbin plot of the location of datapoints in Latitude and Longitude.

In [ ]:

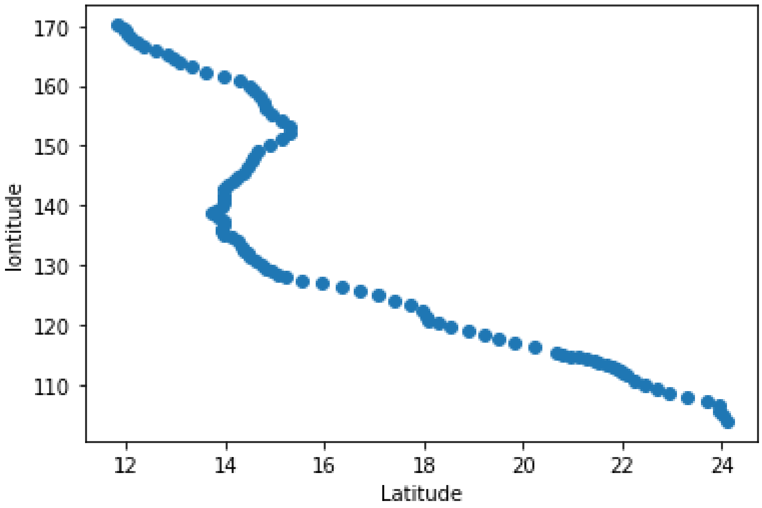
```
hb =plt.hexbin(data3.LAT, data3.LON, gridsize= 180,cmap ='YlGnBu')
plt.colorbar(hb)
plt.title('location of datapoints')
plt.show()
```



3.5 [5 points] Find Typhoon Mangkhut (from 2018) and plot its track as a scatter plot.

In [ ]:

```
mangkhut =data3.loc[(data3.NAME == 'MANGKHUT') & (data3.SEASON ==2018)]
plt.scatter(mangkhut.LAT,mangkhut.LON)
plt.xlabel('Latitude')
plt.ylabel('lontitude')
plt.show()
```



3.6 [5 points] Create a filtered dataframe that contains only data since 1970 from the Western North Pacific ("WP") and Eastern North Pacific ("EP") Basin. Use this for the rest of the problem set.

In [ ]:

```
data3_6 =data3.loc[((data3.BASIN =='WP')|(data3.BASIN =='EP'))&(data3.ISO_TIME >='19
data3_6
```

Out[ ]:

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE	I
350393	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 00:00:00	TS	7.00
350394	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 03:00:00	TS	7.24
350395	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 06:00:00	TS	7.50
350396	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 09:00:00	TS	7.75
350397	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 12:00:00	TS	8.00
...	...	...	...	...	...	...	...	...	
707084	2022275N10316	2022	76	EP	MM	JULIA	2022-10-10 15:00:00	TS	13.99
707085	2022275N10316	2022	76	EP	MM	JULIA	2022-10-10 18:00:00	NR	14.50
707173	2022286N15151	2022	80	WP	MM	NaN	2022-10-12 12:00:00	NR	15.20
707174	2022286N15151	2022	80	WP	MM	NaN	2022-10-12 15:00:00	NR	15.05

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE	I
707175	2022286N15151	2022	80	WP	MM	NaN	2022-10-12 18:00:00	NR	14.90

176352 rows × 17 columns

3.7 [5 points] Plot the number of datapoints per day.

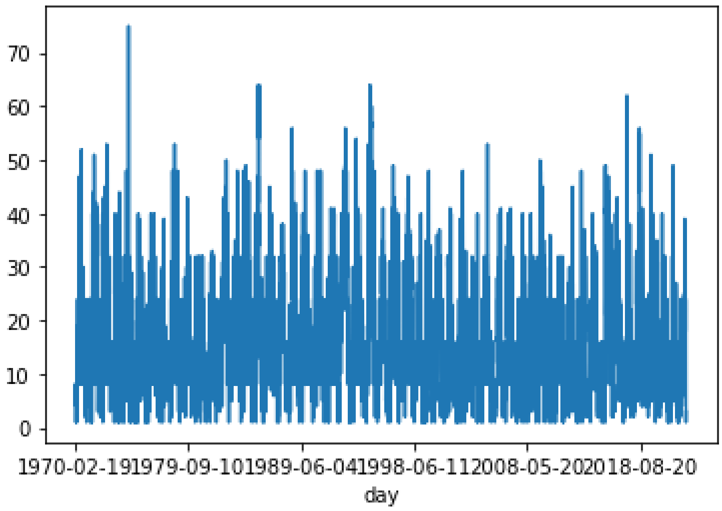
In [ ]:

```
data3_6['day'] =data3_6.ISO_TIME.dt.strftime('%Y-%m-%d')
datapiont_day =data3_6.groupby('day').count()
datapiont_day.SID.plot()
```

```
C:\Users\duck\AppData\Local\Temp/ipykernel_16592/2140946348.py:1: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  data3_6['day'] =data3_6.ISO_TIME.dt.strftime('%Y-%m-%d')
```

Out[ ]: <AxesSubplot:xlabel='day'>



3.8 [5 points] Calculate the climatology of datapoint counts as a function of day of year. The day of year is the sequential day number starting with day 1 on January 1st.

In [ ]:

```
import numpy as np
def day_of_year(date):
    sum= 0
    y,m,d =date.split('-')

    arr = np.array([0, 31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31])
    if (int(y) % 4 == 0 and int(y) % 100 != 0) or int(y) % 400 == 0:
        arr[2] = 29
    else:
        arr[2] = 28

    for i in range(1 , int(m)) :
        sum = sum + arr[i]
    sum = sum + int(d)
    return sum
```

In [ ]:

```
data3_6['day_of_year'] =data3_6.apply(lambda x: day_of_year(x.day),axis=1)
```

```
C:\Users\duck\AppData\Local\Temp/ipykernel_16592/3118200995.py:1: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  data3_6['day_of_year'] =data3_6.apply(lambda x: day_of_year(x.day),axis=1)
```

3.9 [5 points] Calculate the anomaly of daily counts from the climatology.

In [ ]:

```
day_anomaly =data3_6.groupby('day_of_year').count()
day_anomaly['anomaly'] =day_anomaly['SID']-day_anomaly.SID.mean()
day_anomaly
```

Out[ ]:

day_of_year	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE	LAT	LON
1	83	83	83	83	83	72	83	83	83	83
2	72	72	72	72	72	64	72	72	72	72
3	74	74	74	74	74	58	74	74	74	74
4	93	93	93	93	93	57	93	93	93	93
5	105	105	105	105	105	65	105	105	105	105
...	...	...	...	...	...	...	...	...	...	...
362	158	158	158	158	158	118	158	158	158	158
363	132	132	132	132	132	93	132	132	132	132
364	104	104	104	104	104	81	104	104	104	104
365	93	93	93	93	93	77	93	93	93	93
366	13	13	13	13	13	8	13	13	13	13

366 rows × 19 columns

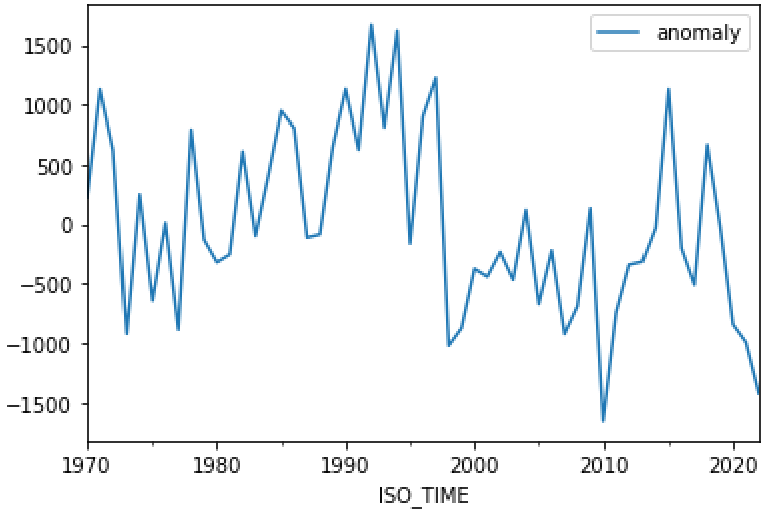
3.10 [5 points] Resample the anomaly timeseries at annual resolution and plot. So which years stand out as having anomalous hurricane activity?

In [ ]:

```
data3_resample =data3_6.resample('Y',on ='ISO_TIME').count()[['SID']]
data3_resample['anomaly'] =data3_resample['SID']-data3_resample.SID.mean()
data3_resample[['anomaly']].plot()
```

Out[ ]:

```
<AxesSubplot:xlabel='ISO_TIME'>
```



In [ ]:

```
print('The year that stand out as having anomalous hurricane activity is:',data3_resam
```

```
The year that stand out as having anomalous hurricane activity is: 1992-12-31 00:00:00
```

4

download data from https://www.ncei.noaa.gov/access/search/data-search/global-summary-of-the-month?pageNum=2, WATTON 2 WSW, MI US(USC00208706.csv)

In [ ]:

```
data4 =pd.read_csv('USC00208706.csv',
                   parse_dates=['DATE'],
                   index_col= 'DATE'
                   )
```

In [ ]:

```
data4
```

Out[ ]:

	STATION	LATITUDE	LONGITUDE	ELEVATION	NAME	CDSD	CDSD_ATTRIBUTES	CLDI
DATE								
2005-07-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	49.
2005-08-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	38.
2005-09-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	18.
2005-10-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	6.
2005-11-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	0.
...	...	...	...	...	...	...	...	.

	STATION	LATITUDE	LONGITUDE	ELEVATION	NAME	CDSD	CDSD_ATTRIBUTES	CLDI
DATE								
2022-05-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	11.7	NaN	11.
2022-06-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	46.7	NaN	35.
2022-07-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	Na
2022-08-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	27.
2022-09-01	USC00208706	46.52664	-88.64243	424.9	WATTON 2 WSW, MI US	NaN	NaN	10.

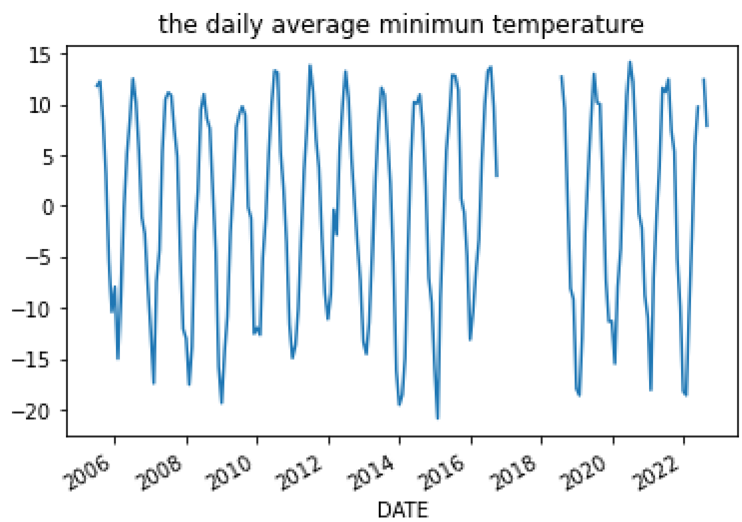
190 rows × 117 columns

4.2 [5 points] Plot the time series of a certain variable.

In [ ]:

```
data4.TMIN.plot(title= 'the daily average minimun temperature')
```

Out[ ]: <AxesSubplot:title={'center':'the daily average minimun temperature'}, xlabel='DATE'>



4.3 [5 points] Conduct at least 5 simple statistical checks with the variable, and report your findings.

In [ ]:

```
# check the basic destribution of the number of cooling days
print(data4['CLDD'].describe())
```

```
count    185.000000
mean       9.860000
std       16.944379
min        0.000000
25%        0.000000
50%        0.000000
```

```
75%         13.000000
max         81.200000
Name: CLDD, dtype: float64
```

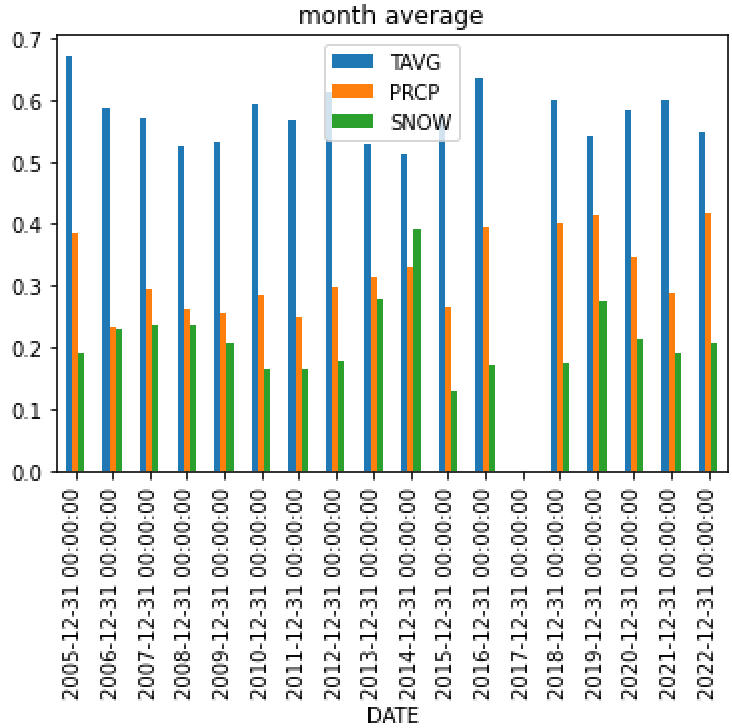
In [ ]:

```
# normalization data
data4_std =data4[['TAVG','PRCP','SNOW']].apply(lambda x: (x - np.min(x)) / (np.max(x
# calculate mouthly statistic value
month_avg =data4_std.resample('Y').mean()
month_max =data4_std.resample('Y').max()
month_min =data4_std.resample('Y').min()
```

In [ ]:

```
# plot three main variables
month_avg[['TAVG','PRCP','SNOW']].plot(title='month average', kind='bar')
# report the average, maximun and minimun of monthly data
print('The maximun annual average temperature year is:',month_avg[['TAVG']].idxmax()[(
print('The maximun annual average precipitation year is:',month_avg[['PRCP']].idxmax()
print('The maximun annual average snow depth year is:',month_avg[['SNOW']].idxmax()[0]
```

```
The maximun annual average temperature year is: 2005
 The minimun annual average temperature year is: 2014
The maximun annual average precipitation year is: 2022
 The minimun annual average precipitation year is: 2006
The maximun annual average snow depth year is: 2014
 The minimun annual average snow depth year is: 2015
```



In [ ]:

```
month_max[['TAVG','PRCP','SNOW']].plot(title='month maximun')
print('The maximun annual maximan year is:',month_max[['TAVG']].idxmax()[0].year,'\n',
```

```
The maximun annual maximan year is: 2020
 The minimun annual maximun year is: 2009
```


month maximun
1.0
0.9
0.8
0.7
0.6
0.5
0.4
2006
2008
2010
2012
2014
2016
2018
2020
2022
DATE
TAVG
PRCP
SNOW

```
In [ ]:
```