In [ ]:

```
import numpy as np
import pandas as pd
import re
from matplotlib import pyplot as plt
%matplotlib inline
import cartopy.crs as ccrs
from cartopy.io import shapereader as shpreader
from cartopy.feature import ShapelyFeature
from cartopy.mpl.ticker import LongitudeFormatter,LatitudeFormatter
```

1.自2150BC以来的重大地震

In [33]:

```
#读取文件
Sig_Eqs=pd.read_csv('earthquakes-2022-10-26_16-51-28_+0800.tsv',skiprows=[1],sep='\t')
```

1.1 计算自2150BC以来每个国家因地震死亡的的总人数，并打印出来死亡人数最多的前20个国家

In [6]:

```
df1=Sig_Eqs.groupby('Country')['Deaths'].sum()# 对country进行聚类，并对每个country的Deaths求和
df2=df1.sort_values(ascending=False)[0:20]# 排序取前20
print(df2)
```

```
IRAN           1011446.0
ITALY           498477.0
SYRIA           439224.0
HAITI           323474.0
AZERBAIJAN      317219.0
JAPAN           278142.0
ARMENIA         191890.0
PAKISTAN        145083.0
IRAQ            136200.0
ECUADOR         135479.0
TURKMENISTAN    117412.0
PERU            102219.0
ISRAEL           90388.0
PORTUGAL         83531.0
GREECE           79174.0
CHILE            64276.0
INDIA            63491.0
TAIWAN           57135.0
Name: Deaths, dtype: float64
```

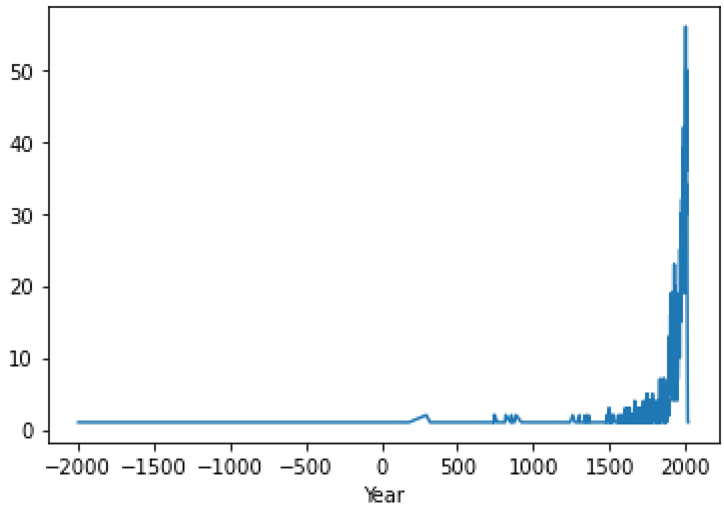
1.2 计算全球每年震级大于3的地震总次数，并画出时间序列。写观察到的趋势并解释。

In [27]:

```
df3=Sig_Eqs[Sig_Eqs['Ms']>3]#先筛选出表面波Ms等级大于3的dataframe
df3.groupby('Year').size().plot()#对df3关于Year进行聚类。size返回每一类的计数，也就是每一年有多少次震
```

Out[27]:

<AxesSubplot:xlabel='Year'>



观察到的趋势：自1500年地震次数显著增加

1.3 写一个函数叫CountEq_LargestEq（1）给定一个国家AND，返回它自2150BC以来的的地震总次数。（2）该国家发生的最大一次地震的日期和地点。将这个函数用于每一个国家，并写出结果（降序）。

In [67]:

```
def CountEq_LargestEq(AND):
    global largest_location
    Eq_number=Sig_Eqs['Country'].str.contains(AND).sum()#国家发生的地震次数
    Index_largest=Sig_Eqs[Sig_Eqs['Country'].str.contains(AND)==True].sort_values(['Mag','Mw','Mw',
    largest_location=Sig_Eqs.loc[[Index_largest]][['Country','Year','Mo','Dy','Location Name','Mag']
    largest_location['Eq_number']=Eq_number
    return largest_location

CountEq_LargestEq('CHINA')
```

Out[67]:

	Country	Year	Mo	Dy	Location Name	Mag	Eq_number
977	CHINA	1668	7.0	25.0	CHINA: SHANDONG PROVINCE	8.5	616

In [70]:

```
All_country=Sig_Eqs['Country'].unique()#找出一共有多少个国家
new_df=pd.DataFrame()#创建一个空的dataframe
#将函数用于每一个国家，并添加到new_df
for AND in All_country:
    nw=CountEq_LargestEq(AND)
    new_df=pd.concat([new_df,nw])
new_df.sort_values('Mag',ascending=False).head(10)#对'Mag'进行降序排序，并返回前十个
```

Out[70]:

	Country	Year	Mo	Dy	Location Name	Mag	Eq_number
3830	CHILE	1960	5.0	22.0	CHILE: PUERTO MONTT, VALDIVIA	9.5	198
3942	USA	1964	3.0	28.0	ALASKA	9.2	311
5326	INDONESIA	2004	12.0	26.0	INDONESIA: SUMATRA: ACEH: OFF WEST COAST	9.1	405
5728	JAPAN	2011	3.0	11.0	JAPAN: HONSHU	9.1	411
3645	RUSSIA	1952	11.0	4.0	RUSSIA: KAMCHATKA PENINSULA	9.0	152
1122	PERU	1716	2.0	6.0	PERU: PUEBLO DE TORATA IN TACNA	8.8	190
2464	PHILIPPINES	1897	9.0	21.0	PHILIPPINES: MINDANAO, ZAMBOANGA, SULU, ISABELA	8.7	222
3599	INDIA	1950	8.0	15.0	INDIA-CHINA	8.6	102
1262	PORTUGAL	1755	11.0	1.0	PORTUGAL: LISBON	8.5	26
977	CHINA	1668	7.0	25.0	CHINA: SHANDONG PROVINCE	8.5	616

2.过去25年深圳的空气温度

在这个习题集中，我们将利用在宝安国际机场测量的每小时天气数据来研究深圳在过去25年的气温变化。数据集来自NOAA综合地表数据集。下载文件Baoan_Weather_1998_2022.CSV，移动CSV文件到您的工作目录。阅读综合用户指南的第的10 - 11页(pos88 -92和pos93 -93)，以获得空气温度数据的详细格式(使用TMP列)。解释如何在报告中筛选数据。

用月平均气温与观测时间作图。过去25年的月平均气温有变化趋势吗?

In [9]:

```
#### 如何在报告中筛选数据呢？
####本题只用到TMP和DATA，其中这两列中的部分信息对于计算是无用的，可以通过正则进行匹配并返回匹配值，在
#### TMP 处理：从'+ABCD，X'中提取出'+ABCD'转化为int形式，并除以10，'X'，可以判断数据的数据的质量状态，
#### DATE 处理：从'年-月-日T小时：分钟：秒'中提取出'年-月-日'
```

In [160]:

```
Baoan_Weather=pd.read_csv('Baoan_Weather_1998_2022.csv',usecols=['DATE','TMP'])#读取文件
```

In [161]:

```
#使用apply()和lambda进行提取，并将提取的内容添加到新的列
Baoan_Weather['Ymd']= Baoan_Weather['DATE'].apply(lambda x:re.findall('(\d+-\d+)-\d+',x)[0])
Baoan_Weather['T_celsius']=Baoan_Weather['TMP'].apply(lambda x:re.findall('(.\d+).\d+',x)[0]).astyp
Baoan_Weather['T_type']=Baoan_Weather['TMP'].apply(lambda x:re.findall('.\d+.(\d+)',x)[0]).astype(i
```

In [162]:

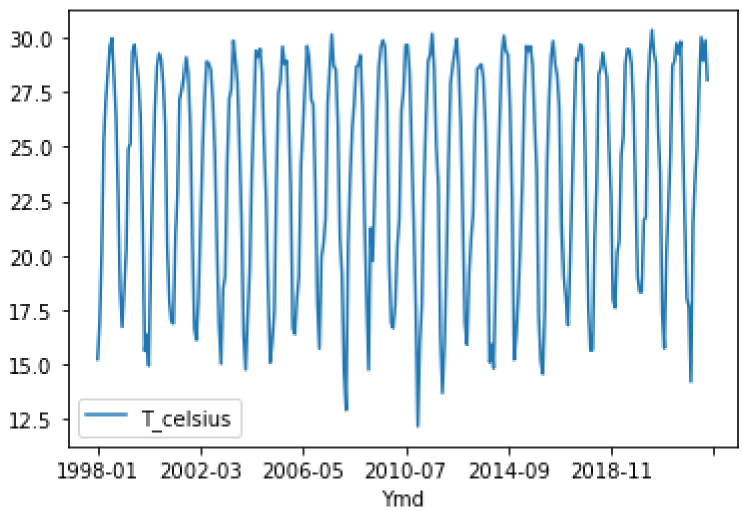
```
Baoan_Weather['T_type'].unique()## 有四种类型1,2,5,9，在本题当中我打算去除9：missing values
Baoan_Weather=Baoan_Weather.loc[Baoan_Weather['T_type']!=9]
Baoan_Weather=Baoan_Weather.drop(['T_type'],axis=1)#去除这一列，这样后面画图就不用选择画哪一列，可以
```

In [163]:

```
Baoan_Weather.groupby('Ymd').mean().plot()#对年进行聚类，求每一类的平均值后画图
```

Out[163]:

<AxesSubplot:xlabel='Ymd'>



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 [2]:

```
df = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                 usecols=range(17),
                 skiprows=[1, 2],
                 parse_dates=['ISO_TIME'],
                 na_values=[' ','WMO_WIND','NOT_NAMED', 'NAME'])
df.head()
##运行这几行代码，我发现只读取了前17列，并且跳过了2和3行，设置'ISO_TIME'列为时间格式，并且我们把'WMO
```

```
D:\anaconda3\envs\Python3\lib\site-packages\IPython\core\interactiveshell.py:3457: D
typeWarning: Columns (5,12) have mixed types.Specify dtype option on import or set l
ow_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Out[2]:

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE	LAT
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

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 [15]:

```
#是先对SID 进行聚类，求每一类当中WMO_WIND的最大值，并返回最大值的名字吗
headhur=df.groupby(['SID','NAME'])['WMO_WIND'].max().sort_values(ascending=False)
headhur.head(10)
```

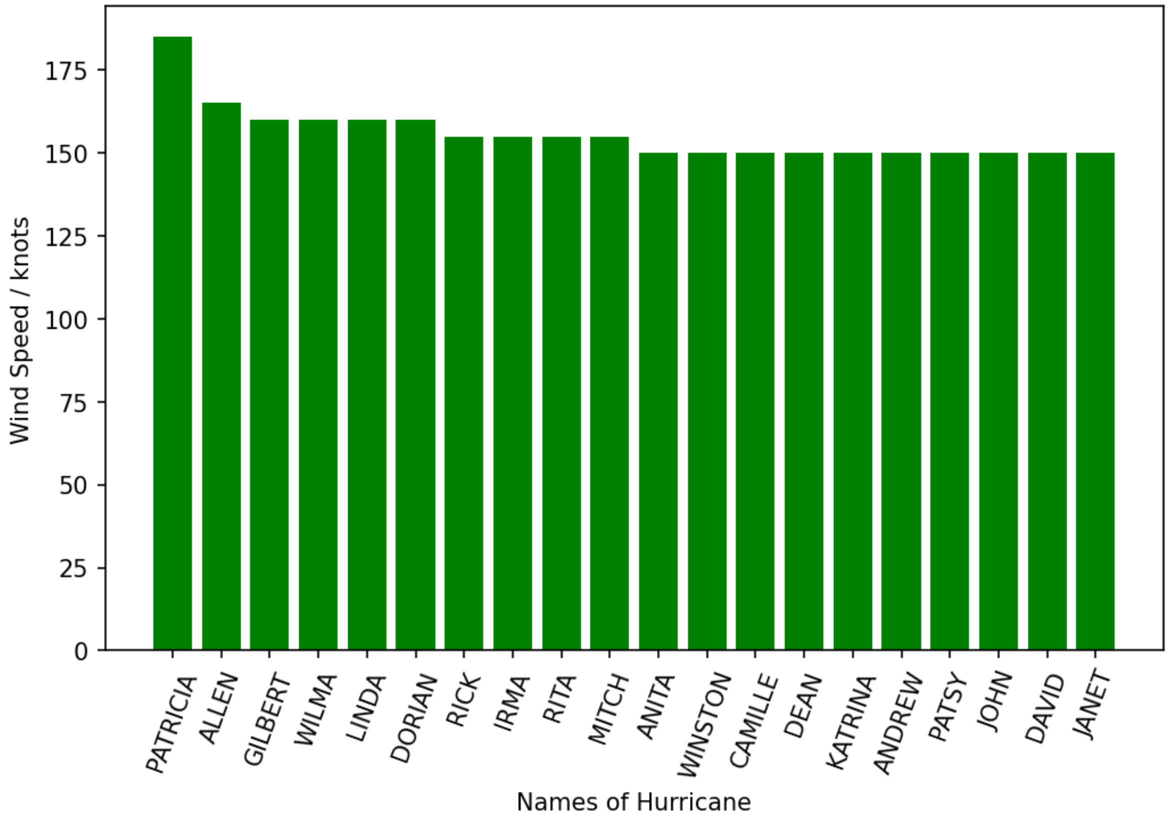
Out[15]:

```
SID            NAME
2015293N13266  PATRICIA    185.0
1980214N11330  ALLEN       165.0
1988253N12306  GILBERT     160.0
2005289N18282  WILMA       160.0
1997253N12255  LINDA       160.0
2019236N10314  DORIAN      160.0
2009288N07267  RICK        155.0
2017242N16333  IRMA        155.0
2005261N21290  RITA        155.0
1998295N12284  MITCH       155.0
Name: WMO_WIND, dtype: float64
```

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

In [16]:

```
headhur= headhur.reset_index()
headhur20=headhur.head(20)
fig, ax = plt.subplots(figsize=(8,5),dpi=150)
ax.bar(headhur20['NAME'],headhur20['WMO_WIND'],color = 'g')
ax.set_xlabel('Names of Hurricane')
ax.set_ylabel('Wind Speed / knots')
ax.xaxis.set_tick_params(rotation=70)
```



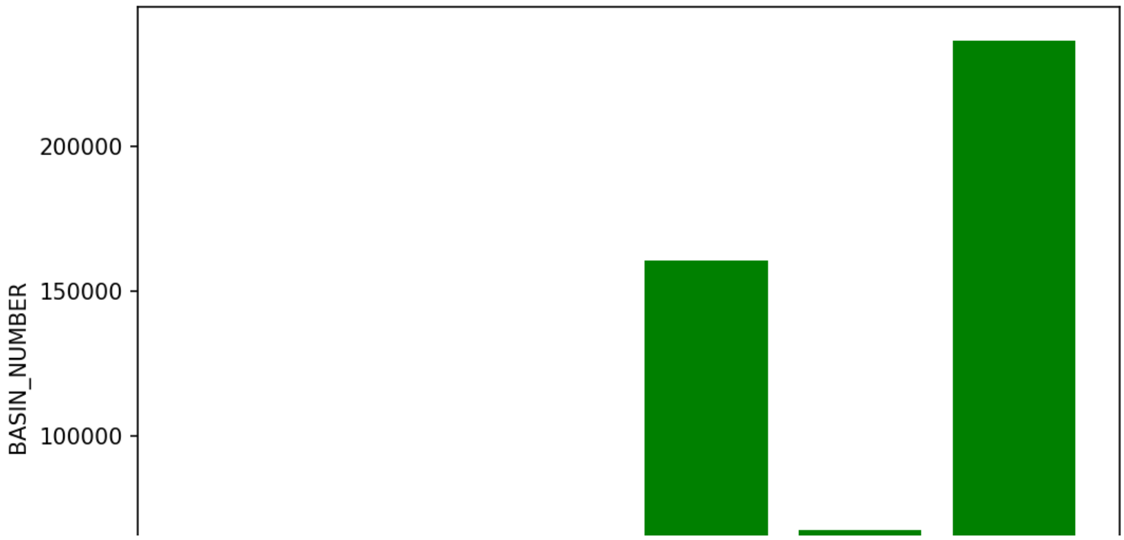
3.3 [5 points] Plot the count of all datapoints by Basin as a bar chart.

In [17]:

```
BASIN_NUMBER = df.groupby(['BASIN']).count()
fig, ax = plt.subplots(figsize=(4,3),dpi=150)
ax.bar(BASIN_NUMBER.index,BASIN_NUMBER['SID'],color='g')
ax.set_xlabel('BASIN_TYPE')
ax.set_ylabel('BASIN_NUMBER')
```

Out[17]:

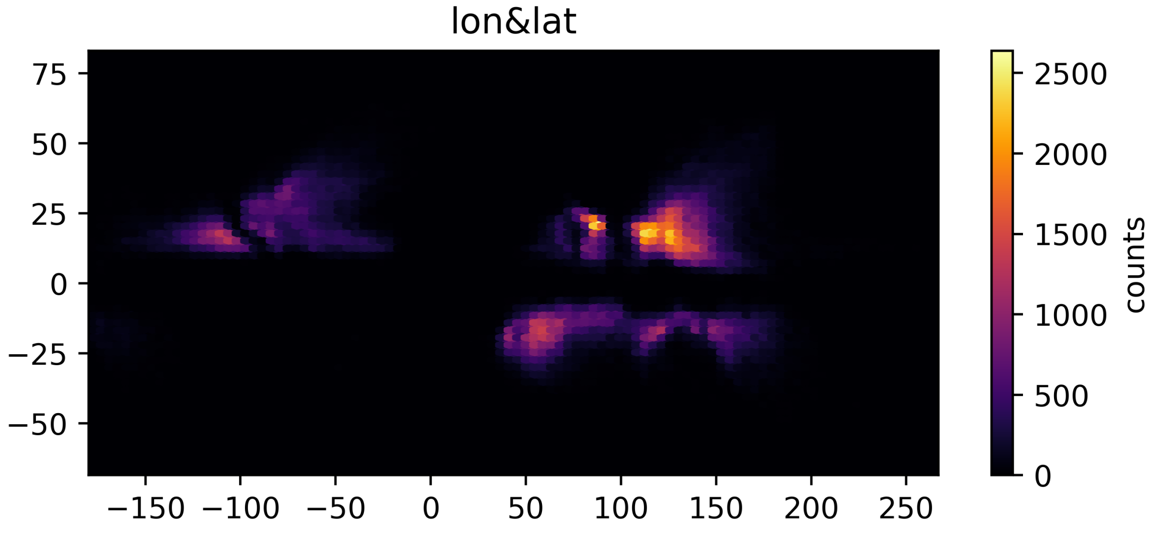
```
Text(0, 0.5, 'BASIN_NUMBER')
```



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

In [18]:

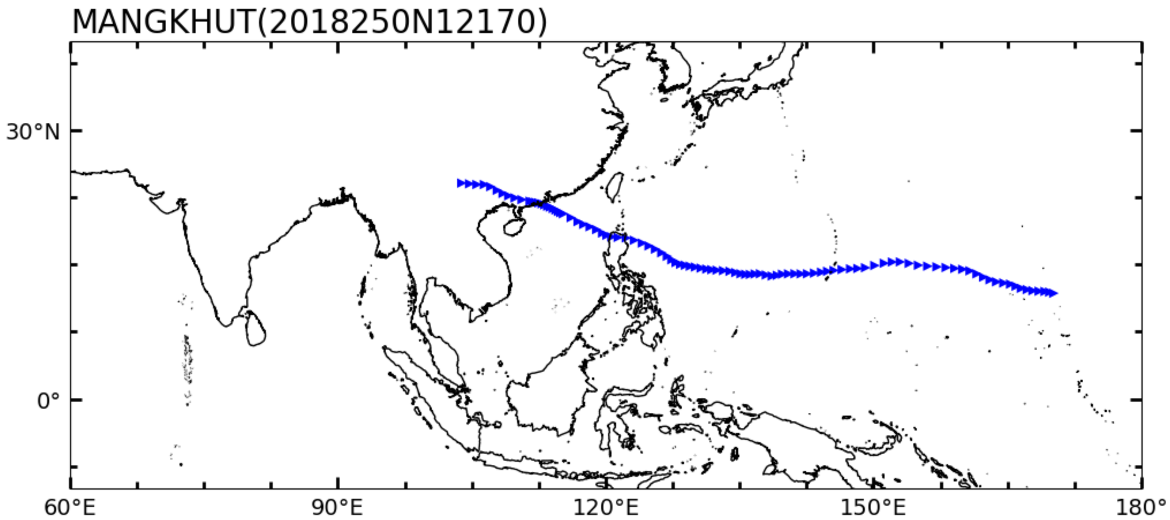
```
x = df['LON']
y = df['LAT']
xmin = x.min()
xmax = x.max()
ymin = y.min()
ymax = y.max()
fig=plt.figure(figsize=(5,2),dpi=500)#添加画布
ax1=fig.add_axes([0,0,1,1])#添加子图
hb = ax1.hexbin(x, y, cmap='inferno')
ax1.set(xlim=(xmin, xmax), ylim=(ymin, ymax))
ax1.set_title("lon&lat")
cb = fig.colorbar(hb, ax=ax1)
cb.set_label('counts')
plt.show()
```



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

In [4]:

```
mangkhut  =  df.loc[df['NAME'] == 'MANGKHUT']
mangkhut  =  df.loc[df['SID'] == '2018250N12170']
lon  = mangkhut['LON']
lat  = mangkhut['LAT']
time = mangkhut['ISO_TIME']
fig,ax7=plt.subplots(figsize=(12,20),nrows=1,ncols=1,subplot_kw=dict(projection=ccrs.PlateCarree())
plt.subplots_adjust(wspace=0.18,hspace=0.18)
plt.rcParams['xtick.direction']='in'
plt.rcParams['ytick.direction']='in'
shape_feature_1=ShapelyFeature(shpreader.Reader('10m_coastline.shp').geometries(),ccrs.PlateCarree()
ax7.set_adjustable(adjustable='box',share=True)
ax7.set_xticks([-180,-150,-120,-90,-60,-30,0,30,60,90,120,150,180])
ax7.set_yticks([-90,-60,-30,0,30,60,90])
ax7.xaxis.set_major_formatter(LongitudeFormatter())
ax7.yaxis.set_major_formatter(LatitudeFormatter())
ax7.tick_params(axis='both',which='major',labelsize=14,length=7,width=2,pad=5,top=True,right=True)
ax7.minorticks_on()
ax7.tick_params(axis='both',which='minor',length=4,width=2,top=True,right=True)
cd1=ax7.scatter(lon,lat,transform=ccrs.PlateCarree(),marker = '>',linewidth=0.01,linestyle=':', col
ax7.set_title('MANGKHUT(2018250N12170)',loc='left',fontsize =20)
ax7.add_feature(shape_feature_1)
plt.grid(False)
plt.xlim(60,180)
plt.ylim(-10,40)
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 [30]:

```
data=  df.loc[(df['SEASON'] >= 1970)&((df['BASIN'] == 'WP') | (df['BASIN'] == 'EP'))]
data.head()
```

Out[30]:

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NATURE
350393	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 00:00:00	TS
350394	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 03:00:00	TS
350395	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 06:00:00	TS
350396	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 09:00:00	TS
350397	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 12:00:00	TS

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

In [61]:

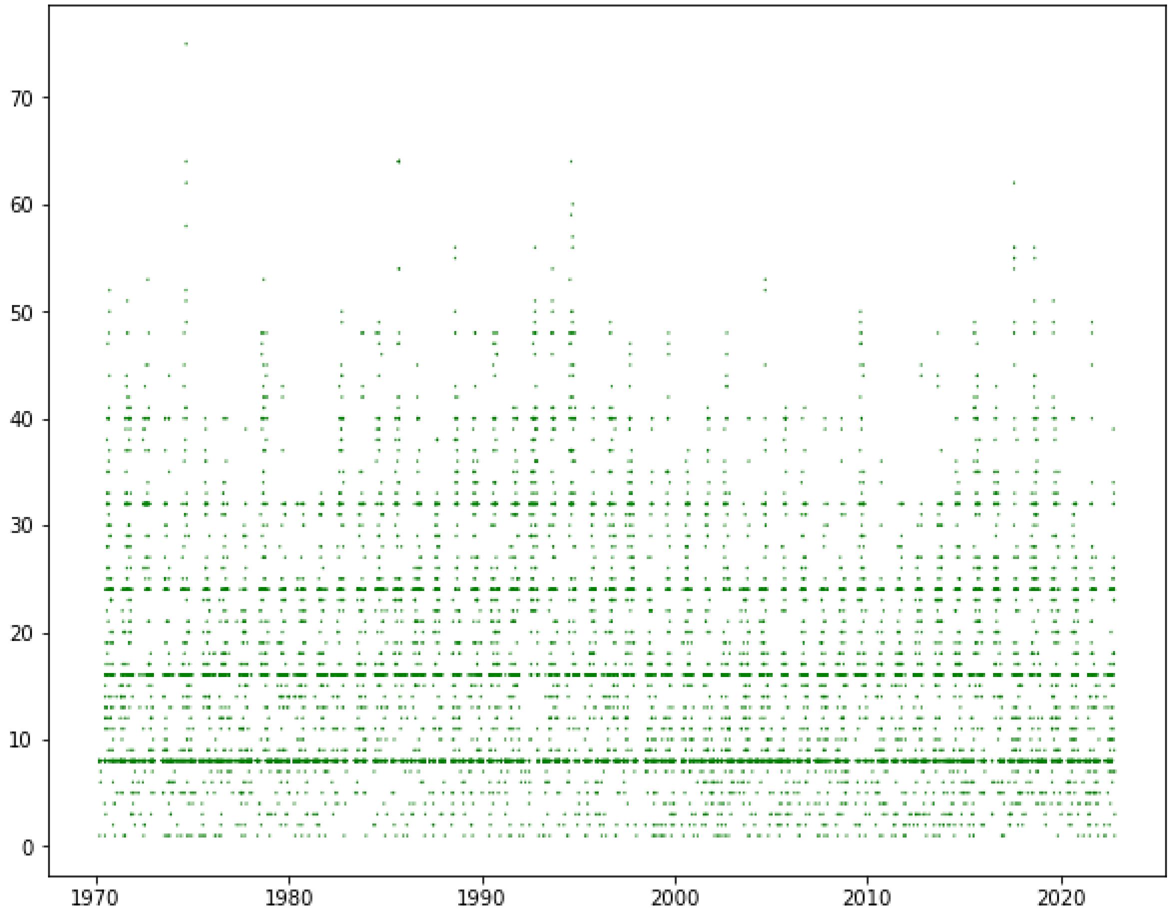
```
e = data['ISO_TIME'].dt.date
result1 = e.value_counts(sort = False)
```

In [62]:

```
fig,ax1=plt.subplots(figsize=(10,8))
ax1.scatter(result1.index,result1,s=0.5, color = 'g',linewidth=1,linestyle=':')
```

Out[62]:

```
<matplotlib.collections.PathCollection at 0x23924210310>
```



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 [65]:

```
f = data['ISO_TIME'].dt.strftime('%m-%d')# %m 十进制表示的月份 %d 十进制表示的每月的第几天
result2 = f.value_counts(sort = False)
result2
```

Out[65]:

```
02-19    52
02-20    48
02-21    43
02-22    33
02-23    27
         ..
02-16    33
02-17    38
02-18    50
02-11    24
02-12    21
Name: ISO_TIME, Length: 366, dtype: int64
```

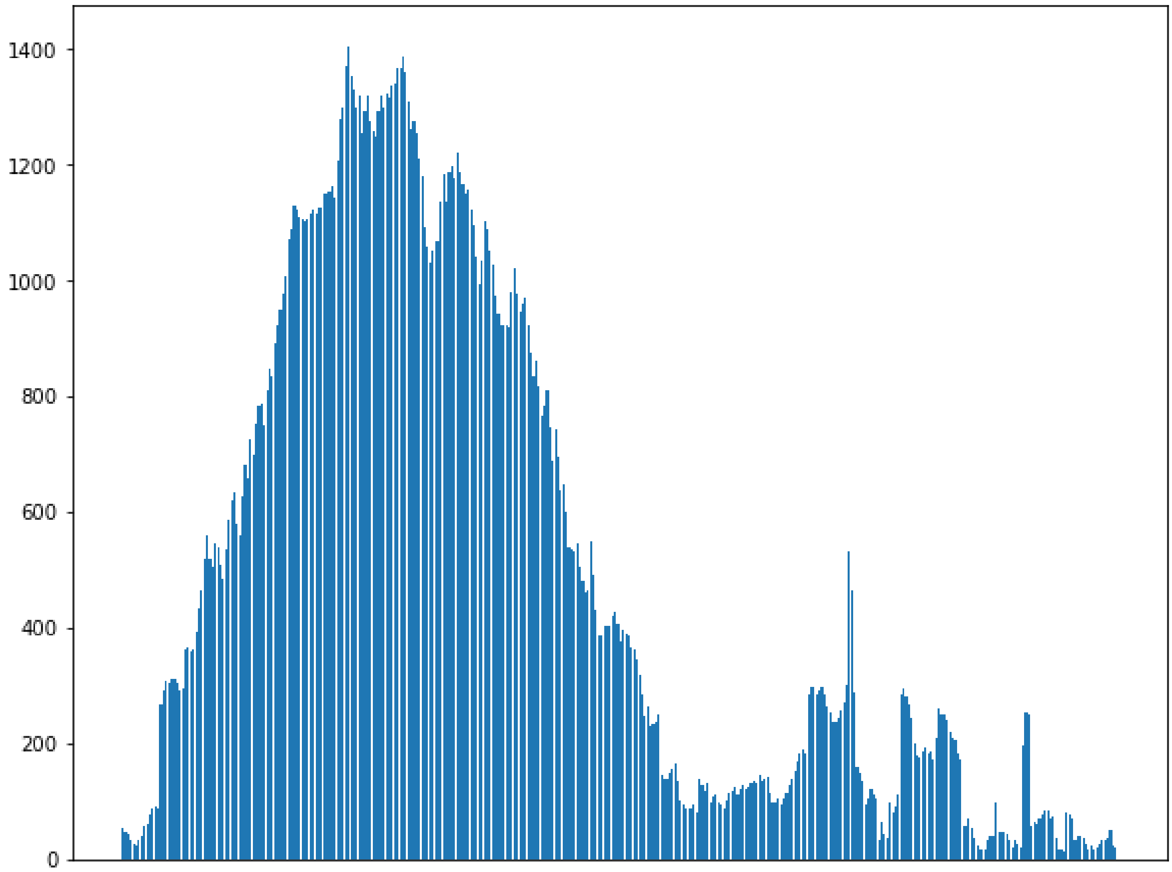
In [66]:

```
fig,ax1=plt.subplots(figsize=(10,8))
ax1.bar(result2.index,result2)
plt.xticks([])
```

```
C:\Users\nicol\AppData\Local\Temp\ipykernel_11152\1767751263.py:3: MatplotlibDeprecationWarning: Support for passing numbers through unit converters is deprecated since 3.5 and support will be removed two minor releases later; use Axis.convert_units instead.
  plt.xticks([])
```

Out[66]:

```
([], [])
```



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

In [ ]:

```
#不会
```

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

In [46]:

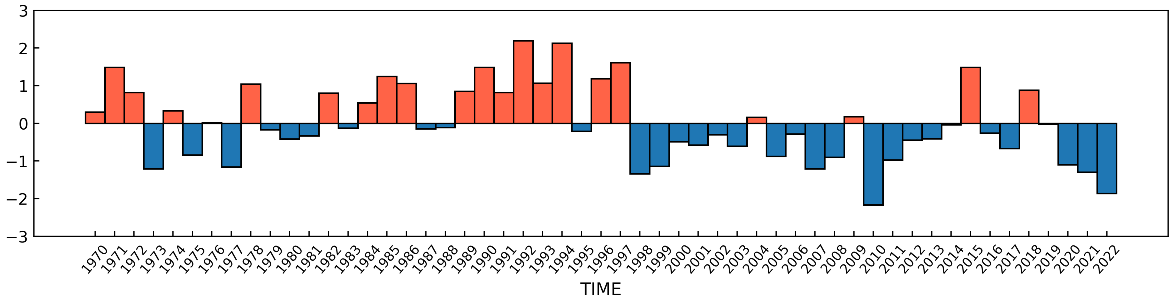
```
g = pd.DatetimeIndex(data['ISO_TIME']).year
```

In [47]:

```
result3= g.value_counts(sort = False)
from sklearn import preprocessing
z = preprocessing.scale(result3)#将序列标准化
```

In [49]:

```
fig=plt.figure(figsize=(10,2),dpi=500)
ax1=fig.add_axes([0,0,1,1])
x=range(53)
bar1 = ax1.bar(x,z,color=np.where(z>0,'tomato','tab:blue'),edgecolor='k',width=1)
ax1.set_ylim(-3,3)
ax1.tick_params(axis='both',which='both',direction='in')
ax1.tick_params(axis='both',which='both',direction='in')
ax1.set_xticks(x)
ax1.set_xticklabels(result3.index ,rotation = 50,fontsize = 'small')
ax1.set_xlabel('TIME',fontsize=11)
plt.show()
```



In [50]:

```
print('异常的年份为：')
for i in range(53):
    if(z[i]<=-1 or z[i]>=1):
        print("                ",result3.index[i])
```

```
异常的年份为：
                 1971
                 1973
                 1977
                 1978
                 1985
                 1986
                 1990
                 1992
                 1993
                 1994
                 1996
                 1997
                 1998
                 1999
                 2007
                 2010
                 2015
                 2020
                 2021
                 2022
```

4. Explore a data set

Browse the National Centers for Environmental Information (NCEI) or Advanced Global Atmospheric Gases Experiment (AGAGE) website. Search and download a data set you are interested in. You are also welcome to use data from your group in this problem set. But the data set should be in csv, XLS, or XLSX format, and have temporal information.

In [ ]:

```
#这个数据集是2018年某污水处理厂的进水流量和水质数据，一共有339天的数据。污水处理厂一般有两条线路，数
#水质数据集的的处理比较简单，大多是对一些空值进行处理，或者是对数据的格式进行处理以便能够进行运算
```

4.1 [5 points] Load the csv, XLS, or XLSX file, and clean possible data points with missing values or bad quality.

In [99]:

```
#读取文件
data = pd.read_csv("data1.csv",encoding='gbk')#
data.head()

#对时间进行处理
data['Date'] =pd.to_datetime(data['Date'])#转化为时间格式
data['month']=data['Date'].dt.month#添加新的一列月份

#，碱度一列是空值，但是不打算分析碱度，所以我打算去除这一列。对于水质我们更关心COD的浓度，列表中给了
data=data.drop(['ALK'],axis=1)
data['TCOD']=data['CBOD5']*2.1

#流量是字符串的形式，不能进行运算，要把它转化为float 的格式。再添加新的一列'total_flow'总流量
data['Flow_ST']=pd.DataFrame(data['Flow_ST'],dtype=np.float)
data['Flow_NT']=pd.DataFrame(data['Flow_NT'],dtype=np.float)
data['total_flow']=data['Flow_ST']+data['Flow_NT']

data.head()
```

```
C:\Users\nicol\AppData\Local\Temp\ipykernel_40432\1271037299.py:14: DeprecationWarni
ng: `np.float` is a deprecated alias for the builtin `float`. To silence this warnin
g, use `float` by itself. Doing this will not modify any behavior and is safe. If yo
u specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/r
elease/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/1.20.0-note
s.html#deprecations)
  data['Flow_ST']=pd.DataFrame(data['Flow_ST'],dtype=np.float)
C:\Users\nicol\AppData\Local\Temp\ipykernel_40432\1271037299.py:15: DeprecationWarni
ng: `np.float` is a deprecated alias for the builtin `float`. To silence this warnin
g, use `float` by itself. Doing this will not modify any behavior and is safe. If yo
u specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/r
elease/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/1.20.0-note
s.html#deprecations)
  data['Flow_NT']=pd.DataFrame(data['Flow_NT'],dtype=np.float)
```

Out[99]:

	Date	Day	TSS	CBOD5	TKN	NH3	Nitrates/Nitrites	Flow_ST	Flow_NT	month
0	2018-01-01 00:35:00	1	224	130	38.0	34.6	0.02	38908.16110	43608.16076	1
1	2018-01-02 00:25:00	2	98	100	39.8	34.0	0.02	38908.16110	43608.16076	1
2	2018-01-03 00:30:00	3	230	160	45.6	34.0	0.02	39270.35305	46488.81711	1
3	2018-01-04 00:30:00	4	202	89	44.3	32.4	0.02	38728.58436	49848.70029	1
4	2018-01-05 00:30:00	5	226	110	42.3	32.9	0.02	38492.46720	48197.44245	1

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

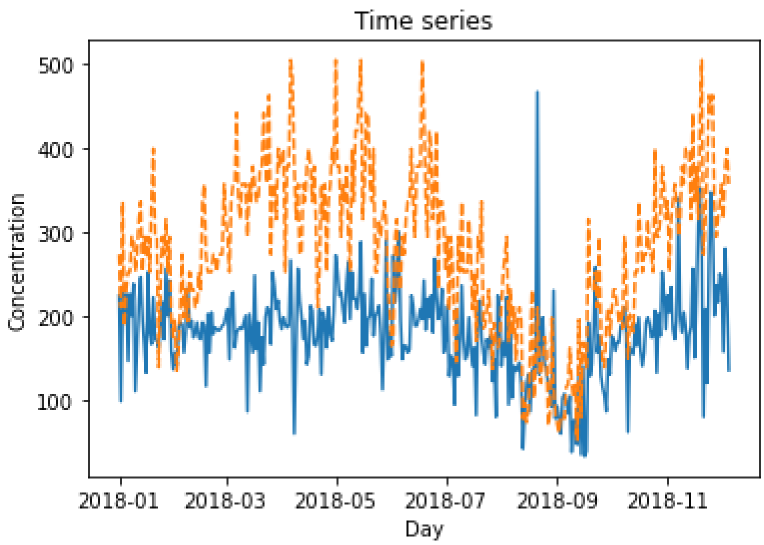
In [117]:

```
#TSS和COD是两个重要的水质指标
plt.plot(data['Date'],data['TSS'])
plt.plot(data['Date'],data['TCOD'],ls='--')
plt.title('Time series')#设置标题
plt.ylabel('Concentration')#设置y轴坐标名称
plt.xlabel('Day')#设置y轴坐标名称

plt.show
```

Out[117]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



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

In [104]:

```
#频率分析 主要用于查看数据基本分布特征，数据清晰，各种统计量、基本报告数据源等
#由于有的月份的数据少，有的月份的数据多，我打算看看每一个月的数据量各是多少
M=data.groupby('month')['Day'].count()
M
##从结果可以看出，12月份的数据只有五天，如果进行月份之间的分析，12月份明显不靠谱
```

Out[104]:

```
month
1     31
2     28
3     31
4     30
5     31
6     30
7     31
8     31
9     30
10    31
11    30
12     5
Name: Day, dtype: int64
```

In [113]:

```
#数据探索 探索性分析主要是从统计的角度查看统计量来评估数据分布，主要用于异常值侦测、正态分布检验、数
#在污水处理厂中通常要根据进水水量和水质，确定加药量、曝气量
#而对于曝气来说，当溶解氧的量低于某个值时，开始曝气，高于某个值的时候，曝气结束。
#所以数据分段比较有用，但是暂时没有溶解氧含量的记录，所以，我打算对TSS进行控制
#采用比例积分控制
TSS=data['TSS']
for tss in TSS:
    set_Tss=200
    err_tss=set_Tss-tss
    #偏差占总KLA的百分比
    mbias=50
    #比例系数
    kc=1.1
    #控制器需要调节的量
    controller_Tss=mbias+kc*err_tss

    if controller_Tss>100:
        controller_Tss=100
    elif controller_Tss<100:
        controller_Tss=0

    tss=tss+controller_Tss

tss
```

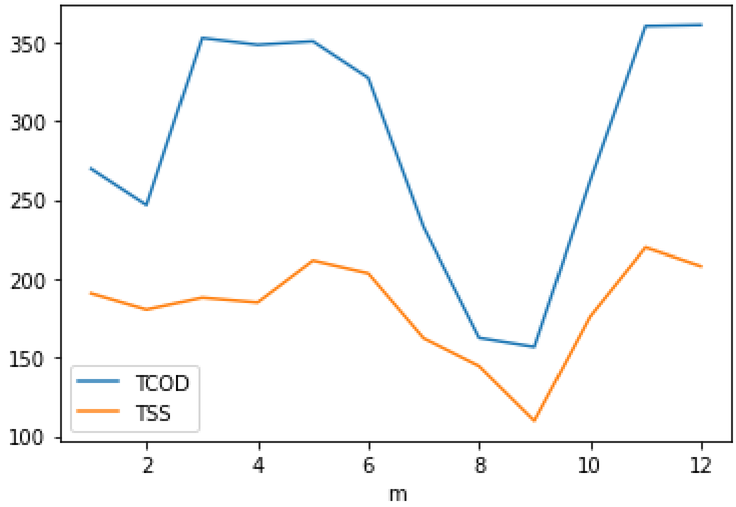
Out[113]:

```
235
```

In [75]:

```
#求每月进水TSS,TCOD的平均值,并画图
M=data.groupby('m')['TCOD','TSS'].mean().plot()
##可以看出夏季的进水水质浓度比较低，秋冬的进水水质浓度较高，可能和夏季用水量大，经常下雨有关
```

```
C:\Users\nicol\AppData\Local\Temp\ipykernel_40432\1945591314.py:1: FutureWarning: In
dexing with multiple keys (implicitly converted to a tuple of keys) will be deprecat
ed, use a list instead.
  M=data.groupby('m')['TCOD','TSS'].mean().plot() #求每月进水TSS,TCOD的平均值,并画图
```



In [114]:

```
##对变量进行相关性分析
data.corr(method='pearson')#相关系数用来衡量两个变量的数据集是否在一条直线上
##从结果可以看出TKN和NH3相关性较好，大于0.8
```

Out[114]:

	Day	TSS	CBOD5	TKN	NH3	Nitrates/Nitrites	Flow_ST
Day	1.000000	-0.107371	-0.146689	-0.177543	-0.412390	0.041310	-0.284607
TSS	-0.107371	1.000000	0.568497	0.568448	0.464763	0.064755	-0.279140
CBOD5	-0.146689	0.568497	1.000000	0.694600	0.728762	-0.017108	-0.343460
TKN	-0.177543	0.568448	0.694600	1.000000	0.819711	-0.062726	-0.327827
NH3	-0.412390	0.464763	0.728762	0.819711	1.000000	-0.077275	-0.314824
Nitrates/Nitrites	0.041310	0.064755	-0.017108	-0.062726	-0.077275	1.000000	-0.007862
Flow_ST	-0.284607	-0.279140	-0.343460	-0.327827	-0.314824	-0.007862	1.000000
Flow_NT	0.313757	-0.333367	-0.579624	-0.606397	-0.727437	-0.008399	0.445347
month	0.995903	-0.110904	-0.149576	-0.183598	-0.412595	0.035871	-0.293745
TCOD	-0.146689	0.568497	1.000000	0.694600	0.728762	-0.017108	-0.343460
total_flow	0.056890	-0.362976	-0.557296	-0.566651	-0.638952	-0.009577	0.811134

In [115]:

```
data.corr(method='kendall')#用于反映分类变量相关性的指标，即针对无序序列的相关系数，非正太分布的数据
##从结果可以看出，TKN和NH3相关性最大，为0.6665
```

Out[115]:

	Day	TSS	CBOD5	TKN	NH3	Nitrates/Nitrites	Flow_ST
Day	1.000000	-0.098856	-0.079788	-0.141327	-0.272788	0.012854	-0.257196
TSS	-0.098856	1.000000	0.416843	0.380866	0.340060	-0.017240	-0.169214
CBOD5	-0.079788	0.416843	1.000000	0.512806	0.519723	-0.011010	-0.239280
TKN	-0.141327	0.380866	0.512806	1.000000	0.666515	-0.051987	-0.187274
NH3	-0.272788	0.340060	0.519723	0.666515	1.000000	-0.052014	-0.151303
Nitrates/Nitrites	0.012854	-0.017240	-0.011010	-0.051987	-0.052014	1.000000	-0.017210
Flow_ST	-0.257196	-0.169214	-0.239280	-0.187274	-0.151303	-0.017210	1.000000
Flow_NT	0.253182	-0.215992	-0.398961	-0.438131	-0.527712	-0.002915	0.249277
month	0.956116	-0.106644	-0.093209	-0.162851	-0.300573	0.008670	-0.269941
TCOD	-0.079788	0.416843	1.000000	0.512806	0.519723	-0.011010	-0.239280
total_flow	-0.036553	-0.233630	-0.429731	-0.380992	-0.426774	-0.012884	0.597731

In [135]:

```
##异常值排查
#数据为在线数据，仪器可能收精度或者突发情况的影响，测量数据会有异常值，所以对明显不符合常规的数值进行
#首先我们先看一下data数据
data.describe()
#
```

Out[135]:

	Day	TSS	CBOD5	TKN	NH3	Nitrates/Nitrites	Flow_S
count	339.000000	339.000000	339.000000	339.000000	339.000000	339.000000	337.0000
mean	170.000000	179.654867	133.545723	39.386726	28.327729	0.026077	37577.0920
std	98.005102	53.988620	44.904832	7.542038	5.872219	0.083586	9750.1768
min	1.000000	33.000000	25.000000	17.000000	10.100000	0.020000	19760.8180
25%	85.500000	152.000000	100.000000	34.150000	24.450000	0.020000	31342.7754
50%	170.000000	184.000000	140.000000	40.100000	28.900000	0.020000	35749.1375
75%	254.500000	208.000000	170.000000	44.450000	33.150000	0.020000	41194.4674
max	339.000000	466.000000	240.000000	68.400000	39.700000	1.490000	93813.8459

In [146]:

```
#去除TSS大于300和小于150的行
data=data.drop(data.loc[(data['TSS']>400)|(data['TSS']<100)].index)
data.describe()
```

Out[146]:

	Day	TSS	CBOD5	TKN	NH3	Nitrates/Nitrites	Flow_S
count	311.000000	311.000000	311.000000	311.000000	311.000000	311.000000	309.0000
mean	165.096463	188.025723	139.099678	40.213505	29.021543	0.026302	36899.6719
std	99.012595	42.529451	41.369613	6.637300	5.257488	0.087097	8883.1185
min	1.000000	102.000000	33.000000	20.500000	10.100000	0.020000	19760.8180
25%	80.500000	159.000000	110.000000	35.050000	25.200000	0.020000	31181.1455
50%	159.000000	187.000000	140.000000	41.000000	29.300000	0.020000	35178.7264
75%	253.500000	210.000000	170.000000	44.750000	33.500000	0.020000	41026.8492
max	339.000000	352.000000	240.000000	64.800000	39.700000	1.490000	93813.8459

In [ ]:

```

```