RyanAveryHW2

November 5, 2017

1 Part 1a) Importing Time Series for Flow, Precip, and Temp

2 b) Creating single dataframes with pandas

3 c) Converting to proper datetime formate with to_timestamp()

In [1]:
```
############################## this data is from ulmo###########################
import ulmo
import pandas as pd

mangoflow_u = ulmo.usgs.nwis.get_site_data(site_code='50055750', start='01/01/2000', en
valencianoflow_u = ulmo.usgs.nwis.get_site_data(site_code='50056400', start='01/01/200
loizaflow_u = ulmo.usgs.nwis.get_site_data(site_code='50050900', start='01/01/2000', en

mango_values_dict = mangoflow_u['00060:00003']['values']
valenciano_values_dict = valencianoflow_u['00060:00003']['values']
loiza_values_dict = loizaflow_u['00060:00003']['values']


mangoDF = pd.DataFrame(mango_values_dict)
mangoDF['name'] = mangoflow_u['00060:00003']['site']['name']
valencianoDF = pd.DataFrame(valenciano_values_dict)
valencianoDF['name'] = valencianoflow_u['00060:00003']['site']['name']
loizaDF = pd.DataFrame(loiza_values_dict)
loizaDF['name'] = loizaflow_u['00060:00003']['site']['name']


flowDFlist = [mangoDF, valencianoDF, loizaDF]

allflow = pd.concat(flowDFlist)
allflow['value'] = [float(thisValue) for thisValue in allflow['value']]

with pd.HDFStore('data/flow.h5', mode='w') as flowhdf:
    flowhdf.put('d1', allflow, format='table', data_columns=True)
    # head doesn't just print out the first five for some reason
```

```
/home/anaconda3/lib/python3.6/site-packages/ulmo/twc/kbdi/core.py:20: FutureWarning: pandas.tsl
You can access Timestamp as pandas.Timestamp
  CSV_SWITCHOVER = pandas.tslib.Timestamp('2016-10-01')
/home/anaconda3/lib/python3.6/site-packages/ulmo/usgs/nwis/core.py:252: FutureWarning: to_date
  start_datetime = util.convert_datetime(start)
/home/anaconda3/lib/python3.6/site-packages/ulmo/usgs/nwis/core.py:255: FutureWarning: to_date
  end_datetime = util.convert_datetime(end)
processing data from request: https://waterservices.usgs.gov/nwis/dv/?format=waterml&site=5005
processing data from request: https://nwis.waterservices.usgs.gov/nwis/iv/?format=waterml&site
processing data from request: https://waterservices.usgs.gov/nwis/dv/?format=waterml&site=5005
processing data from request: https://nwis.waterservices.usgs.gov/nwis/iv/?format=waterml&site
processing data from request: https://waterservices.usgs.gov/nwis/dv/?format=waterml&site=5005
processing data from request: https://nwis.waterservices.usgs.gov/nwis/iv/?format=waterml&site
```

In [2]:
```python
import pandas as pd
with pd.HDFStore('data/flow.h5',  mode='r') as newstore:
    flowdf = newstore.select('d1')
flowdf.head
```

Out[2]:
```
<bound method NDFrame.head of                       datetime qualifiers  value  \
0      2000-01-01T00:00:00          A   27.0
1      2000-01-02T00:00:00          A   21.0
2      2000-01-03T00:00:00          A   76.0
3      2000-01-04T00:00:00          A   64.0
4      2000-01-05T00:00:00          A   98.0
5      2000-01-06T00:00:00          A   73.0
6      2000-01-07T00:00:00          A  100.0
7      2000-01-08T00:00:00          A   32.0
8      2000-01-09T00:00:00          A   26.0
9      2000-01-10T00:00:00          A   20.0
10     2000-01-11T00:00:00          A   18.0
11     2000-01-12T00:00:00          A   17.0
12     2000-01-13T00:00:00          A   16.0
13     2000-01-14T00:00:00          A   17.0
14     2000-01-15T00:00:00          A   17.0
15     2000-01-16T00:00:00          A   87.0
16     2000-01-17T00:00:00          A   20.0
17     2000-01-18T00:00:00          A   16.0
18     2000-01-19T00:00:00          A   15.0
19     2000-01-20T00:00:00          A   13.0
20     2000-01-21T00:00:00          A   12.0
21     2000-01-22T00:00:00          A   12.0
22     2000-01-23T00:00:00          A   12.0
23     2000-01-24T00:00:00          A   11.0
24     2000-01-25T00:00:00          A   14.0
25     2000-01-26T00:00:00          A   15.0
26     2000-01-27T00:00:00          A   13.0
```

```
27    2000-01-28T00:00:00          A   16.0
28    2000-01-29T00:00:00          A   16.0
29    2000-01-30T00:00:00          A   14.0
...                   ...        ...    ...
5812  2016-12-01T00:00:00          A   21.2
5813  2016-12-02T00:00:00          A  193.0
5814  2016-12-03T00:00:00          A   62.8
5815  2016-12-04T00:00:00          A   35.5
5816  2016-12-05T00:00:00          A   29.4
5817  2016-12-06T00:00:00          A   27.0
5818  2016-12-07T00:00:00          A   24.0
5819  2016-12-08T00:00:00          A   22.0
5820  2016-12-09T00:00:00          A   20.6
5821  2016-12-10T00:00:00          A   19.5
5822  2016-12-11T00:00:00          A   19.5
5823  2016-12-12T00:00:00          A   21.2
5824  2016-12-13T00:00:00          A   49.1
5825  2016-12-14T00:00:00          A   30.0
5826  2016-12-15T00:00:00          A   19.7
5827  2016-12-16T00:00:00          A   17.5
5828  2016-12-17T00:00:00          A   18.9
5829  2016-12-18T00:00:00          A   18.8
5830  2016-12-19T00:00:00          A   21.8
5831  2016-12-20T00:00:00          A   37.5
5832  2016-12-21T00:00:00          A   19.2
5833  2016-12-22T00:00:00          A   16.7
5834  2016-12-23T00:00:00          A   16.2
5835  2016-12-24T00:00:00          A   46.6
5836  2016-12-25T00:00:00          A   21.5
5837  2016-12-26T00:00:00          A   16.7
5838  2016-12-27T00:00:00          A   16.2
5839  2016-12-28T00:00:00          A   16.7
5840  2016-12-29T00:00:00          A   25.3
5841  2016-12-30T00:00:00          A   37.4

                                            name
0                     RIO GURABO BLW EL MANGO, PR
1                     RIO GURABO BLW EL MANGO, PR
2                     RIO GURABO BLW EL MANGO, PR
3                     RIO GURABO BLW EL MANGO, PR
4                     RIO GURABO BLW EL MANGO, PR
5                     RIO GURABO BLW EL MANGO, PR
6                     RIO GURABO BLW EL MANGO, PR
7                     RIO GURABO BLW EL MANGO, PR
8                     RIO GURABO BLW EL MANGO, PR
9                     RIO GURABO BLW EL MANGO, PR
10                    RIO GURABO BLW EL MANGO, PR
11                    RIO GURABO BLW EL MANGO, PR
```

```
12                    RIO GURABO BLW EL MANGO, PR
13                    RIO GURABO BLW EL MANGO, PR
14                    RIO GURABO BLW EL MANGO, PR
15                    RIO GURABO BLW EL MANGO, PR
16                    RIO GURABO BLW EL MANGO, PR
17                    RIO GURABO BLW EL MANGO, PR
18                    RIO GURABO BLW EL MANGO, PR
19                    RIO GURABO BLW EL MANGO, PR
20                    RIO GURABO BLW EL MANGO, PR
21                    RIO GURABO BLW EL MANGO, PR
22                    RIO GURABO BLW EL MANGO, PR
23                    RIO GURABO BLW EL MANGO, PR
24                    RIO GURABO BLW EL MANGO, PR
25                    RIO GURABO BLW EL MANGO, PR
26                    RIO GURABO BLW EL MANGO, PR
27                    RIO GURABO BLW EL MANGO, PR
28                    RIO GURABO BLW EL MANGO, PR
29                    RIO GURABO BLW EL MANGO, PR
...                                           ...
5812  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5813  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5814  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5815  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5816  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5817  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5818  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5819  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5820  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5821  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5822  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5823  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5824  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5825  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5826  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5827  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5828  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5829  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5830  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5831  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5832  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5833  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5834  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5835  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5836  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5837  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5838  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5839  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5840  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
```

```
5841  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR

[18260 rows x 4 columns]>
```

```
In [3]: # now get noaa ncdc temp and precip

        ponce_ncdc = ulmo.ncdc.ghcn_daily.get_data('RQC00667292', as_dataframe=True)
        piedras_ncdc = ulmo.ncdc.ghcn_daily.get_data('RQC00668306', as_dataframe=True)
        roosevelt_ncdc = ulmo.ncdc.ghcn_daily.get_data('RQW00011630', as_dataframe=True)

        def getallvar(d1,d2,d3, measure, startdate, enddate):

            listd = [d2, d3]
            listnames = ['Ponce', 'Piedras', 'Roosevelt Roads']
            tmin = d1[measure]
            tmin['value'] = [float(thisValue)/10 for thisValue in tmin['value']]
            tmin['name'] = listnames[0]
            tmin = tmin[startdate:enddate]
            index = 1
            for d in listd:
                tmintoadd = d[measure]
                tmintoadd['value'] = [float(thisValue)/10 for thisValue in tmintoadd['value']]
                tmintoadd['name'] = listnames[index]
                tmintoadd = tmintoadd[startdate:enddate]
                tmin = pd.concat([tmin,tmintoadd])
                index += 1
            #converts to datetime
            tmin.index = tmin.index.to_timestamp()
            tmin = tmin.reset_index()
            return tmin

        alltmin = getallvar(ponce_ncdc, piedras_ncdc, roosevelt_ncdc,'TMIN','2000-01-01','2016-
        with pd.HDFStore('data/tmin.h5', mode='w') as tminhdf:
            tminhdf.put('d1', alltmin, format='table', data_columns=True)

        allprecip = getallvar(ponce_ncdc, piedras_ncdc, roosevelt_ncdc,'PRCP', '2000-01-01','20
        allprecip['value'] = [float(thisValue)*10 for thisValue in allprecip['value']]
        with pd.HDFStore('data/precip.h5', mode='w') as preciphdf:
            preciphdf.put('d1', allprecip, format='table', data_columns=True)
```

```
/home/anaconda3/lib/python3.6/site-packages/ulmo/ncdc/ghcn_daily/core.py:89: SettingWithCopyWa
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: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  axis=1)
/home/anaconda3/lib/python3.6/site-packages/ulmo/ncdc/ghcn_daily/core.py:95: FutureWarning:
.resample() is now a deferred operation
```

```
You called index(...) on this deferred object which materialized it into a dataframe
by implicitly taking the mean.  Use .resample(...).mean() instead
  daily_index = element_df.resample('D').index.copy()
/home/anaconda3/lib/python3.6/site-packages/ulmo/ncdc/ghcn_daily/core.py:111: SettingWithCopyWa
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  dataframe[column_name][dates] = element_df[col][months]
```

```
In [3]: with pd.HDFStore('data/tmin.h5',  mode='r') as newtmin:
            tmindf = newtmin.select('d1')
        # tmindf.drop(axis=1,columns=['mflag', 'qflag', 'sflag']) this errors, couldn't debug
```

```
In [4]: with pd.HDFStore('data/precip.h5',  mode='r') as newprecip:
            precipdf = newprecip.select('d1')
        precipdf.head
```

```
Out[4]: <bound method NDFrame.head of       month_period  value mflag qflag sflag            r
        0       2000-01-01   30.0   NaN   NaN     0           Ponce
        1       2000-01-02    0.0   NaN   NaN     0           Ponce
        2       2000-01-03    0.0   NaN   NaN     0           Ponce
        3       2000-01-04    0.0   NaN   NaN     0           Ponce
        4       2000-01-05   13.0   NaN   NaN     0           Ponce
        5       2000-01-06    0.0   NaN   NaN     0           Ponce
        6       2000-01-07    0.0   NaN   NaN     0           Ponce
        7       2000-01-08    0.0   NaN   NaN     0           Ponce
        8       2000-01-09    0.0   NaN   NaN     0           Ponce
        9       2000-01-10    0.0   NaN   NaN     0           Ponce
        10      2000-01-11    0.0   NaN   NaN     0           Ponce
        11      2000-01-12    0.0   NaN   NaN     0           Ponce
        12      2000-01-13    0.0   NaN   NaN     0           Ponce
        13      2000-01-14    0.0   NaN   NaN     0           Ponce
        14      2000-01-15    0.0   NaN   NaN     0           Ponce
        15      2000-01-16    0.0   NaN   NaN     0           Ponce
        16      2000-01-17    0.0   NaN   NaN     0           Ponce
        17      2000-01-18    0.0   NaN   NaN     0           Ponce
        18      2000-01-19    0.0   NaN   NaN     0           Ponce
        19      2000-01-20    0.0   NaN   NaN     0           Ponce
        20      2000-01-21    0.0   NaN   NaN     0           Ponce
        21      2000-01-22    0.0   NaN   NaN     0           Ponce
        22      2000-01-23    0.0   NaN   NaN     0           Ponce
        23      2000-01-24    0.0   NaN   NaN     0           Ponce
        24      2000-01-25   10.0   NaN   NaN     0           Ponce
        25      2000-01-26   69.0   NaN   NaN     0           Ponce
        26      2000-01-27    3.0   NaN   NaN     0           Ponce
        27      2000-01-28    0.0   NaN   NaN     0           Ponce
        28      2000-01-29    0.0   NaN   NaN     0           Ponce
```

```
29       2000-01-30    3.0   NaN   NaN     0            Ponce
...             ...    ...   ...   ...   ...              ...
18597    2016-12-01   91.0   NaN   NaN     W  Roosevelt Roads
18598    2016-12-02  102.0   NaN   NaN     W  Roosevelt Roads
18599    2016-12-03   33.0   NaN   NaN     W  Roosevelt Roads
18600    2016-12-04    3.0   NaN   NaN     W  Roosevelt Roads
18601    2016-12-05    8.0   NaN   NaN     W  Roosevelt Roads
18602    2016-12-06    3.0   NaN   NaN     W  Roosevelt Roads
18603    2016-12-07    0.0     T   NaN     W  Roosevelt Roads
18604    2016-12-08    0.0   NaN   NaN     W  Roosevelt Roads
18605    2016-12-09    0.0     T   NaN     W  Roosevelt Roads
18606    2016-12-10    5.0   NaN   NaN     W  Roosevelt Roads
18607    2016-12-11    8.0   NaN   NaN     W  Roosevelt Roads
18608    2016-12-12   10.0   NaN   NaN     W  Roosevelt Roads
18609    2016-12-13   64.0   NaN   NaN     W  Roosevelt Roads
18610    2016-12-14   15.0   NaN   NaN     W  Roosevelt Roads
18611    2016-12-15    0.0     T   NaN     W  Roosevelt Roads
18612    2016-12-16    0.0   NaN   NaN     W  Roosevelt Roads
18613    2016-12-17  109.0   NaN   NaN     W  Roosevelt Roads
18614    2016-12-18   15.0   NaN   NaN     W  Roosevelt Roads
18615    2016-12-19  226.0   NaN   NaN     W  Roosevelt Roads
18616    2016-12-20  193.0   NaN   NaN     W  Roosevelt Roads
18617    2016-12-21    0.0   NaN   NaN     W  Roosevelt Roads
18618    2016-12-22    0.0     T   NaN     W  Roosevelt Roads
18619    2016-12-23   10.0   NaN   NaN     W  Roosevelt Roads
18620    2016-12-24   33.0   NaN   NaN     W  Roosevelt Roads
18621    2016-12-25    8.0   NaN   NaN     W  Roosevelt Roads
18622    2016-12-26    5.0   NaN   NaN     W  Roosevelt Roads
18623    2016-12-27   53.0   NaN   NaN     W  Roosevelt Roads
18624    2016-12-28    0.0   NaN   NaN     W  Roosevelt Roads
18625    2016-12-29    0.0     T   NaN     W  Roosevelt Roads
18626    2016-12-30    0.0   NaN   NaN     W  Roosevelt Roads

[18627 rows x 6 columns]>
```

3.1 Part 1d) Sorting by datetime

In [51]:
```
flowdf.columns
```

Out[51]:
```
Index(['datetime', 'qualifiers', 'value', 'name'], dtype='object')
```

In [5]:
```
flowdf.sort_values('datetime', ascending=True)
tmindf.sort_values('month_period', ascending=True)
precipdf.sort_values('month_period', ascending=True)
```

Out[5]:
```
      month_period  value mflag qflag sflag             name
0       2000-01-01   30.0   NaN   NaN     0            Ponce
12418   2000-01-01    NaN   NaN   NaN   NaN  Roosevelt Roads
6209    2000-01-01    NaN   NaN   NaN   NaN          Piedras
```

1	2000-01-02	0.0	NaN	NaN	0	Ponce
12419	2000-01-02	NaN	NaN	NaN	NaN	Roosevelt Roads
6210	2000-01-02	NaN	NaN	NaN	NaN	Piedras
2	2000-01-03	0.0	NaN	NaN	0	Ponce
12420	2000-01-03	NaN	NaN	NaN	NaN	Roosevelt Roads
6211	2000-01-03	NaN	NaN	NaN	NaN	Piedras
3	2000-01-04	0.0	NaN	NaN	0	Ponce
12421	2000-01-04	NaN	NaN	NaN	NaN	Roosevelt Roads
6212	2000-01-04	NaN	NaN	NaN	NaN	Piedras
12422	2000-01-05	NaN	NaN	NaN	NaN	Roosevelt Roads
6213	2000-01-05	NaN	NaN	NaN	NaN	Piedras
4	2000-01-05	13.0	NaN	NaN	0	Ponce
6214	2000-01-06	NaN	NaN	NaN	NaN	Piedras
5	2000-01-06	0.0	NaN	NaN	0	Ponce
12423	2000-01-06	NaN	NaN	NaN	NaN	Roosevelt Roads
6215	2000-01-07	NaN	NaN	NaN	NaN	Piedras
6	2000-01-07	0.0	NaN	NaN	0	Ponce
12424	2000-01-07	NaN	NaN	NaN	NaN	Roosevelt Roads
6216	2000-01-08	NaN	NaN	NaN	NaN	Piedras
12425	2000-01-08	NaN	NaN	NaN	NaN	Roosevelt Roads
7	2000-01-08	0.0	NaN	NaN	0	Ponce
12426	2000-01-09	NaN	NaN	NaN	NaN	Roosevelt Roads
6217	2000-01-09	NaN	NaN	NaN	NaN	Piedras
8	2000-01-09	0.0	NaN	NaN	0	Ponce
12427	2000-01-10	NaN	NaN	NaN	NaN	Roosevelt Roads
6218	2000-01-10	NaN	NaN	NaN	NaN	Piedras
9	2000-01-10	0.0	NaN	NaN	0	Ponce
...	...	...	...	...	...	...
6199	2016-12-21	0.0	NaN	NaN	7	Ponce
18617	2016-12-21	0.0	NaN	NaN	W	Roosevelt Roads
12408	2016-12-21	NaN	NaN	NaN	NaN	Piedras
6200	2016-12-22	10.0	NaN	NaN	7	Ponce
18618	2016-12-22	0.0	T	NaN	W	Roosevelt Roads
12409	2016-12-22	NaN	NaN	NaN	NaN	Piedras
12410	2016-12-23	NaN	NaN	NaN	NaN	Piedras
6201	2016-12-23	0.0	NaN	NaN	7	Ponce
18619	2016-12-23	10.0	NaN	NaN	W	Roosevelt Roads
12411	2016-12-24	NaN	NaN	NaN	NaN	Piedras
6202	2016-12-24	NaN	NaN	NaN	NaN	Ponce
18620	2016-12-24	33.0	NaN	NaN	W	Roosevelt Roads
18621	2016-12-25	8.0	NaN	NaN	W	Roosevelt Roads
6203	2016-12-25	NaN	NaN	NaN	NaN	Ponce
12412	2016-12-25	NaN	NaN	NaN	NaN	Piedras
12413	2016-12-26	NaN	NaN	NaN	NaN	Piedras
18622	2016-12-26	5.0	NaN	NaN	W	Roosevelt Roads
6204	2016-12-26	NaN	NaN	NaN	NaN	Ponce
12414	2016-12-27	NaN	NaN	NaN	NaN	Piedras
18623	2016-12-27	53.0	NaN	NaN	W	Roosevelt Roads

```
6205     2016-12-27    NaN    NaN    NaN    NaN             Ponce
12415    2016-12-28    NaN    NaN    NaN    NaN           Piedras
18624    2016-12-28    0.0    NaN    NaN      W  Roosevelt Roads
6206     2016-12-28    NaN    NaN    NaN    NaN             Ponce
18625    2016-12-29    0.0      T    NaN      W  Roosevelt Roads
6207     2016-12-29    NaN    NaN    NaN    NaN             Ponce
12416    2016-12-29    NaN    NaN    NaN    NaN           Piedras
12417    2016-12-30    NaN    NaN    NaN    NaN           Piedras
6208     2016-12-30    NaN    NaN    NaN    NaN             Ponce
18626    2016-12-30    0.0    NaN    NaN      W  Roosevelt Roads

[18627 rows x 6 columns]
```

3.2 2) Resampling Time Series Data with Split-Apply-Combine

```
In [6]: flowdf['datetime'] = [pd.to_datetime(thisDate) for thisDate in flowdf['datetime']]
        flowdf['year'] = [thisDate.year for thisDate in flowdf['datetime']]
        precipdf['year'] = [thisDate.year for thisDate in precipdf['month_period']]
        tmindf['year'] = [thisDate.year for thisDate in tmindf['month_period']]
```

```
In [7]: flowdf['month'] = [thisDate.month for thisDate in flowdf['datetime']]
        precipdf['month'] = [thisDate.month for thisDate in precipdf['month_period']]
        tmindf['month'] = [thisDate.month for thisDate in tmindf['month_period']]
```

```
In [8]: flowdf['day'] = [thisDate.dayofyear for thisDate in flowdf['datetime']]
        precipdf['day'] = [thisDate.dayofyear for thisDate in precipdf['month_period']]
        tmindf['day'] = [thisDate.dayofyear for thisDate in tmindf['month_period']]
```

```
In [10]: print(flowdf)
```

```
      datetime qualifiers  value                                  name  \
0   2000-01-01          A   27.0                 RIO GURABO BLW EL MANGO, PR
1   2000-01-02          A   21.0                 RIO GURABO BLW EL MANGO, PR
2   2000-01-03          A   76.0                 RIO GURABO BLW EL MANGO, PR
3   2000-01-04          A   64.0                 RIO GURABO BLW EL MANGO, PR
4   2000-01-05          A   98.0                 RIO GURABO BLW EL MANGO, PR
5   2000-01-06          A   73.0                 RIO GURABO BLW EL MANGO, PR
6   2000-01-07          A  100.0                 RIO GURABO BLW EL MANGO, PR
7   2000-01-08          A   32.0                 RIO GURABO BLW EL MANGO, PR
8   2000-01-09          A   26.0                 RIO GURABO BLW EL MANGO, PR
9   2000-01-10          A   20.0                 RIO GURABO BLW EL MANGO, PR
10  2000-01-11          A   18.0                 RIO GURABO BLW EL MANGO, PR
11  2000-01-12          A   17.0                 RIO GURABO BLW EL MANGO, PR
12  2000-01-13          A   16.0                 RIO GURABO BLW EL MANGO, PR
13  2000-01-14          A   17.0                 RIO GURABO BLW EL MANGO, PR
14  2000-01-15          A   17.0                 RIO GURABO BLW EL MANGO, PR
15  2000-01-16          A   87.0                 RIO GURABO BLW EL MANGO, PR
16  2000-01-17          A   20.0                 RIO GURABO BLW EL MANGO, PR
17  2000-01-18          A   16.0                 RIO GURABO BLW EL MANGO, PR
```

```
18   2000-01-19          A   15.0                RIO GURABO BLW EL MANGO, PR
19   2000-01-20          A   13.0                RIO GURABO BLW EL MANGO, PR
20   2000-01-21          A   12.0                RIO GURABO BLW EL MANGO, PR
21   2000-01-22          A   12.0                RIO GURABO BLW EL MANGO, PR
22   2000-01-23          A   12.0                RIO GURABO BLW EL MANGO, PR
23   2000-01-24          A   11.0                RIO GURABO BLW EL MANGO, PR
24   2000-01-25          A   14.0                RIO GURABO BLW EL MANGO, PR
25   2000-01-26          A   15.0                RIO GURABO BLW EL MANGO, PR
26   2000-01-27          A   13.0                RIO GURABO BLW EL MANGO, PR
27   2000-01-28          A   16.0                RIO GURABO BLW EL MANGO, PR
28   2000-01-29          A   16.0                RIO GURABO BLW EL MANGO, PR
29   2000-01-30          A   14.0                RIO GURABO BLW EL MANGO, PR
...         ...        ...    ...                                        ...
5812 2016-12-01          A   21.2  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5813 2016-12-02          A  193.0  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5814 2016-12-03          A   62.8  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5815 2016-12-04          A   35.5  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5816 2016-12-05          A   29.4  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5817 2016-12-06          A   27.0  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5818 2016-12-07          A   24.0  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5819 2016-12-08          A   22.0  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5820 2016-12-09          A   20.6  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5821 2016-12-10          A   19.5  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5822 2016-12-11          A   19.5  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5823 2016-12-12          A   21.2  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5824 2016-12-13          A   49.1  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5825 2016-12-14          A   30.0  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5826 2016-12-15          A   19.7  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5827 2016-12-16          A   17.5  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5828 2016-12-17          A   18.9  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5829 2016-12-18          A   18.8  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5830 2016-12-19          A   21.8  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5831 2016-12-20          A   37.5  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5832 2016-12-21          A   19.2  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5833 2016-12-22          A   16.7  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5834 2016-12-23          A   16.2  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5835 2016-12-24          A   46.6  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5836 2016-12-25          A   21.5  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5837 2016-12-26          A   16.7  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5838 2016-12-27          A   16.2  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5839 2016-12-28          A   16.7  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5840 2016-12-29          A   25.3  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
5841 2016-12-30          A   37.4  RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR
```

```
      year  month  day
0     2000      1    1
1     2000      1    2
2     2000      1    3
```

3	2000	1	4
4	2000	1	5
5	2000	1	6
6	2000	1	7
7	2000	1	8
8	2000	1	9
9	2000	1	10
10	2000	1	11
11	2000	1	12
12	2000	1	13
13	2000	1	14
14	2000	1	15
15	2000	1	16
16	2000	1	17
17	2000	1	18
18	2000	1	19
19	2000	1	20
20	2000	1	21
21	2000	1	22
22	2000	1	23
23	2000	1	24
24	2000	1	25
25	2000	1	26
26	2000	1	27
27	2000	1	28
28	2000	1	29
29	2000	1	30
...	...	...	...
5812	2016	12	336
5813	2016	12	337
5814	2016	12	338
5815	2016	12	339
5816	2016	12	340
5817	2016	12	341
5818	2016	12	342
5819	2016	12	343
5820	2016	12	344
5821	2016	12	345
5822	2016	12	346
5823	2016	12	347
5824	2016	12	348
5825	2016	12	349
5826	2016	12	350
5827	2016	12	351
5828	2016	12	352
5829	2016	12	353
5830	2016	12	354
5831	2016	12	355

```
5832  2016      12  356
5833  2016      12  357
5834  2016      12  358
5835  2016      12  359
5836  2016      12  360
5837  2016      12  361
5838  2016      12  362
5839  2016      12  363
5840  2016      12  364
5841  2016      12  365

[18260 rows x 7 columns]
```

```
In [11]: print(precipdf)
```

```
      month_period  value mflag qflag sflag            name  year  month  day
0       2000-01-01   30.0   NaN   NaN     0           Ponce  2000      1    1
1       2000-01-02    0.0   NaN   NaN     0           Ponce  2000      1    2
2       2000-01-03    0.0   NaN   NaN     0           Ponce  2000      1    3
3       2000-01-04    0.0   NaN   NaN     0           Ponce  2000      1    4
4       2000-01-05   13.0   NaN   NaN     0           Ponce  2000      1    5
5       2000-01-06    0.0   NaN   NaN     0           Ponce  2000      1    6
6       2000-01-07    0.0   NaN   NaN     0           Ponce  2000      1    7
7       2000-01-08    0.0   NaN   NaN     0           Ponce  2000      1    8
8       2000-01-09    0.0   NaN   NaN     0           Ponce  2000      1    9
9       2000-01-10    0.0   NaN   NaN     0           Ponce  2000      1   10
10      2000-01-11    0.0   NaN   NaN     0           Ponce  2000      1   11
11      2000-01-12    0.0   NaN   NaN     0           Ponce  2000      1   12
12      2000-01-13    0.0   NaN   NaN     0           Ponce  2000      1   13
13      2000-01-14    0.0   NaN   NaN     0           Ponce  2000      1   14
14      2000-01-15    0.0   NaN   NaN     0           Ponce  2000      1   15
15      2000-01-16    0.0   NaN   NaN     0           Ponce  2000      1   16
16      2000-01-17    0.0   NaN   NaN     0           Ponce  2000      1   17
17      2000-01-18    0.0   NaN   NaN     0           Ponce  2000      1   18
18      2000-01-19    0.0   NaN   NaN     0           Ponce  2000      1   19
19      2000-01-20    0.0   NaN   NaN     0           Ponce  2000      1   20
20      2000-01-21    0.0   NaN   NaN     0           Ponce  2000      1   21
21      2000-01-22    0.0   NaN   NaN     0           Ponce  2000      1   22
22      2000-01-23    0.0   NaN   NaN     0           Ponce  2000      1   23
23      2000-01-24    0.0   NaN   NaN     0           Ponce  2000      1   24
24      2000-01-25   10.0   NaN   NaN     0           Ponce  2000      1   25
25      2000-01-26   69.0   NaN   NaN     0           Ponce  2000      1   26
26      2000-01-27    3.0   NaN   NaN     0           Ponce  2000      1   27
27      2000-01-28    0.0   NaN   NaN     0           Ponce  2000      1   28
28      2000-01-29    0.0   NaN   NaN     0           Ponce  2000      1   29
29      2000-01-30    3.0   NaN   NaN     0           Ponce  2000      1   30
...            ...    ...   ...   ...   ...             ...   ...    ...  ...
```

```
18597   2016-12-01   91.0  NaN  NaN    W  Roosevelt Roads  2016    12  336
18598   2016-12-02  102.0  NaN  NaN    W  Roosevelt Roads  2016    12  337
18599   2016-12-03   33.0  NaN  NaN    W  Roosevelt Roads  2016    12  338
18600   2016-12-04    3.0  NaN  NaN    W  Roosevelt Roads  2016    12  339
18601   2016-12-05    8.0  NaN  NaN    W  Roosevelt Roads  2016    12  340
18602   2016-12-06    3.0  NaN  NaN    W  Roosevelt Roads  2016    12  341
18603   2016-12-07    0.0    T  NaN    W  Roosevelt Roads  2016    12  342
18604   2016-12-08    0.0  NaN  NaN    W  Roosevelt Roads  2016    12  343
18605   2016-12-09    0.0    T  NaN    W  Roosevelt Roads  2016    12  344
18606   2016-12-10    5.0  NaN  NaN    W  Roosevelt Roads  2016    12  345
18607   2016-12-11    8.0  NaN  NaN    W  Roosevelt Roads  2016    12  346
18608   2016-12-12   10.0  NaN  NaN    W  Roosevelt Roads  2016    12  347
18609   2016-12-13   64.0  NaN  NaN    W  Roosevelt Roads  2016    12  348
18610   2016-12-14   15.0  NaN  NaN    W  Roosevelt Roads  2016    12  349
18611   2016-12-15    0.0    T  NaN    W  Roosevelt Roads  2016    12  350
18612   2016-12-16    0.0  NaN  NaN    W  Roosevelt Roads  2016    12  351
18613   2016-12-17  109.0  NaN  NaN    W  Roosevelt Roads  2016    12  352
18614   2016-12-18   15.0  NaN  NaN    W  Roosevelt Roads  2016    12  353
18615   2016-12-19  226.0  NaN  NaN    W  Roosevelt Roads  2016    12  354
18616   2016-12-20  193.0  NaN  NaN    W  Roosevelt Roads  2016    12  355
18617   2016-12-21    0.0  NaN  NaN    W  Roosevelt Roads  2016    12  356
18618   2016-12-22    0.0    T  NaN    W  Roosevelt Roads  2016    12  357
18619   2016-12-23   10.0  NaN  NaN    W  Roosevelt Roads  2016    12  358
18620   2016-12-24   33.0  NaN  NaN    W  Roosevelt Roads  2016    12  359
18621   2016-12-25    8.0  NaN  NaN    W  Roosevelt Roads  2016    12  360
18622   2016-12-26    5.0  NaN  NaN    W  Roosevelt Roads  2016    12  361
18623   2016-12-27   53.0  NaN  NaN    W  Roosevelt Roads  2016    12  362
18624   2016-12-28    0.0  NaN  NaN    W  Roosevelt Roads  2016    12  363
18625   2016-12-29    0.0    T  NaN    W  Roosevelt Roads  2016    12  364
18626   2016-12-30    0.0  NaN  NaN    W  Roosevelt Roads  2016    12  365

[18627 rows x 9 columns]
```

```
In [12]: print(tmindf)
```

```
      month_period  value mflag qflag sflag             name  year  month  day
0       2000-01-01   18.3   NaN   NaN     0            Ponce  2000      1    1
1       2000-01-02   21.7   NaN   NaN     0            Ponce  2000      1    2
2       2000-01-03   21.1   NaN   NaN     0            Ponce  2000      1    3
3       2000-01-04   20.0   NaN   NaN     0            Ponce  2000      1    4
4       2000-01-05   18.3   NaN   NaN     0            Ponce  2000      1    5
5       2000-01-06   20.0   NaN   NaN     0            Ponce  2000      1    6
6       2000-01-07   19.4   NaN   NaN     0            Ponce  2000      1    7
7       2000-01-08   18.3   NaN   NaN     0            Ponce  2000      1    8
8       2000-01-09   18.9   NaN   NaN     0            Ponce  2000      1    9
9       2000-01-10   18.3   NaN   NaN     0            Ponce  2000      1   10
10      2000-01-11   17.8   NaN   NaN     0            Ponce  2000      1   11
```

11	2000-01-12	17.8	NaN	NaN	0	Ponce	2000	1	12
12	2000-01-13	17.2	NaN	NaN	0	Ponce	2000	1	13
13	2000-01-14	18.3	NaN	NaN	0	Ponce	2000	1	14
14	2000-01-15	18.9	NaN	NaN	0	Ponce	2000	1	15
15	2000-01-16	18.3	NaN	NaN	0	Ponce	2000	1	16
16	2000-01-17	18.9	NaN	NaN	0	Ponce	2000	1	17
17	2000-01-18	15.6	NaN	NaN	0	Ponce	2000	1	18
18	2000-01-19	13.3	NaN	NaN	0	Ponce	2000	1	19
19	2000-01-20	15.0	NaN	NaN	0	Ponce	2000	1	20
20	2000-01-21	17.8	NaN	NaN	0	Ponce	2000	1	21
21	2000-01-22	18.9	NaN	NaN	0	Ponce	2000	1	22
22	2000-01-23	18.3	NaN	NaN	0	Ponce	2000	1	23
23	2000-01-24	20.0	NaN	NaN	0	Ponce	2000	1	24
24	2000-01-25	22.2	NaN	NaN	0	Ponce	2000	1	25
25	2000-01-26	21.1	NaN	NaN	0	Ponce	2000	1	26
26	2000-01-27	21.1	NaN	NaN	0	Ponce	2000	1	27
27	2000-01-28	20.0	NaN	NaN	0	Ponce	2000	1	28
28	2000-01-29	21.1	NaN	NaN	0	Ponce	2000	1	29
29	2000-01-30	20.0	NaN	NaN	0	Ponce	2000	1	30
...	...	...	...	...	...	...	...	...	...
18597	2016-12-01	22.8	NaN	NaN	W	Roosevelt Roads	2016	12	336
18598	2016-12-02	23.3	NaN	NaN	W	Roosevelt Roads	2016	12	337
18599	2016-12-03	23.3	NaN	NaN	W	Roosevelt Roads	2016	12	338
18600	2016-12-04	22.2	NaN	NaN	W	Roosevelt Roads	2016	12	339
18601	2016-12-05	22.8	NaN	NaN	W	Roosevelt Roads	2016	12	340
18602	2016-12-06	25.0	NaN	NaN	W	Roosevelt Roads	2016	12	341
18603	2016-12-07	25.6	NaN	NaN	W	Roosevelt Roads	2016	12	342
18604	2016-12-08	25.6	NaN	NaN	W	Roosevelt Roads	2016	12	343
18605	2016-12-09	25.6	NaN	NaN	W	Roosevelt Roads	2016	12	344
18606	2016-12-10	25.0	NaN	NaN	W	Roosevelt Roads	2016	12	345
18607	2016-12-11	25.6	NaN	NaN	W	Roosevelt Roads	2016	12	346
18608	2016-12-12	25.0	NaN	NaN	W	Roosevelt Roads	2016	12	347
18609	2016-12-13	23.3	NaN	NaN	W	Roosevelt Roads	2016	12	348
18610	2016-12-14	23.3	NaN	NaN	W	Roosevelt Roads	2016	12	349
18611	2016-12-15	22.2	NaN	NaN	W	Roosevelt Roads	2016	12	350
18612	2016-12-16	22.8	NaN	NaN	W	Roosevelt Roads	2016	12	351
18613	2016-12-17	22.2	NaN	NaN	W	Roosevelt Roads	2016	12	352
18614	2016-12-18	22.8	NaN	NaN	W	Roosevelt Roads	2016	12	353
18615	2016-12-19	21.1	NaN	NaN	W	Roosevelt Roads	2016	12	354
18616	2016-12-20	21.7	NaN	NaN	W	Roosevelt Roads	2016	12	355
18617	2016-12-21	24.4	NaN	NaN	W	Roosevelt Roads	2016	12	356
18618	2016-12-22	24.4	NaN	NaN	W	Roosevelt Roads	2016	12	357
18619	2016-12-23	23.9	NaN	NaN	W	Roosevelt Roads	2016	12	358
18620	2016-12-24	23.3	NaN	NaN	W	Roosevelt Roads	2016	12	359
18621	2016-12-25	23.9	NaN	NaN	W	Roosevelt Roads	2016	12	360
18622	2016-12-26	23.9	NaN	NaN	W	Roosevelt Roads	2016	12	361
18623	2016-12-27	22.2	NaN	NaN	W	Roosevelt Roads	2016	12	362
18624	2016-12-28	22.2	NaN	NaN	W	Roosevelt Roads	2016	12	363

```
18625   2016-12-29   23.9   NaN   NaN     W  Roosevelt Roads  2016     12  364
18626   2016-12-30   20.6   NaN   NaN     W  Roosevelt Roads  2016     12  365

[18627 rows x 9 columns]
```

3.3 2b) Calculate and Plot Long-Term Daily and Monthly Mean/Medians

```
In [9]: flow_monthname_med = flowdf.groupby(['month', 'name']).median()
        flow_dayname_med = flowdf.groupby(['day', 'name']).median()
        flow_yearname_med = flowdf.groupby(['year','name']).median()
```

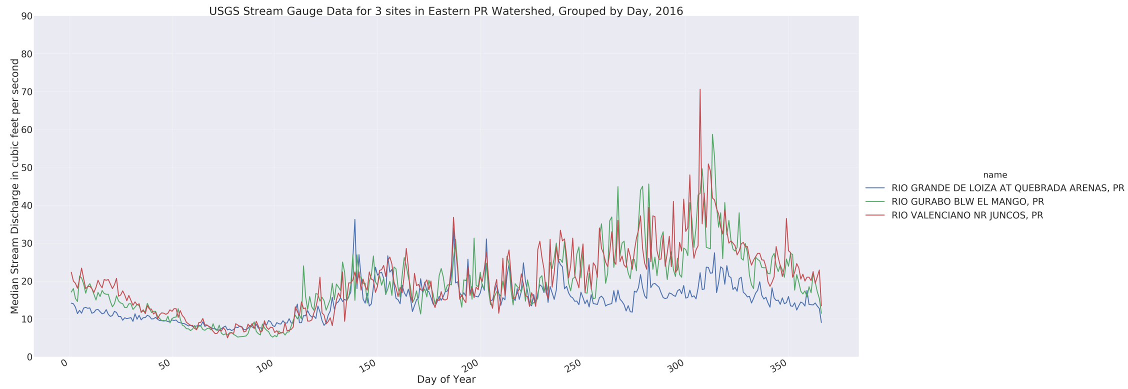
```
In [10]: tmin_monthname_mean = tmindf.groupby(['month', 'name']).mean()
         tmin_dayname_mean = tmindf.groupby(['day', 'name']).mean()
         tmin_yearname_mean = tmindf.groupby(['year','name']).mean()
```

```
In [11]: precip_monthname_mean = precipdf.groupby(['month', 'name']).mean()
         precip_dayname_mean = precipdf.groupby(['day', 'name']).mean()
         precip_yearname_mean = precipdf.groupby(['year','name']).mean()
```

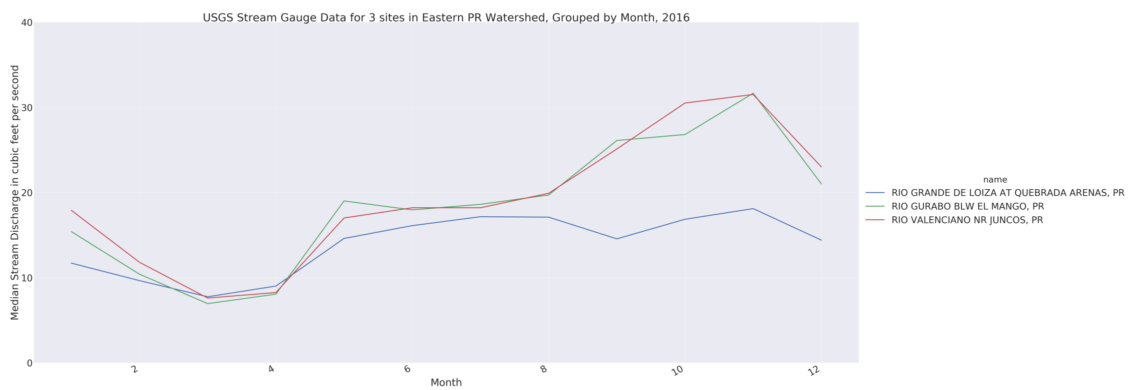
```
In [12]: import seaborn as sn
         import matplotlib.pyplot as plt

         def plotgroupsdays(df, ticklist, timestep='day', xtext='Day of Year', ytext='Median St
             sn.set(font_scale=6, rc={"lines.linewidth": 6})
             f = sn.FacetGrid(df.reset_index(), hue='name', size=40, aspect=2)
             f.map(plt.plot, timestep, 'value').add_legend()
             f.ax.set(xlabel=xtext,
                     ylabel=ytext,
                     title=titletext)
             f.fig.autofmt_xdate()
             f.set(yticks=ticklist)
             plt.show()

         def plotgroupsmonths(df, ticklist, timestep='month', xtext='Month', ytext='Median Stre
             sn.set(font_scale=6, rc={"lines.linewidth": 6})
             f = sn.FacetGrid(df.reset_index(), hue='name', size=40, aspect=2)
             f.map(plt.plot, timestep, 'value').add_legend()
             f.ax.set(xlabel='Month',
                     ylabel=ytext,
                     title=titletext)
             f.fig.autofmt_xdate()
             f.set(yticks=ticklist)
             plt.show()

         def plotgroupsyears(df, ticklist, timestep='year', ytext='Median Stream Discharge in c
             sn.set(font_scale=6, rc={"lines.linewidth": 6})
             f = sn.FacetGrid(df.reset_index(), hue='name', size=40, aspect=2)
             f.map(plt.plot, timestep, 'value').add_legend()
```

```
        f.ax.set(xlabel='Year',
                 ylabel=ytext,
                 title=titletext)
        f.fig.autofmt_xdate()
        f.set(yticks=ticklist)
        plt.show()
```

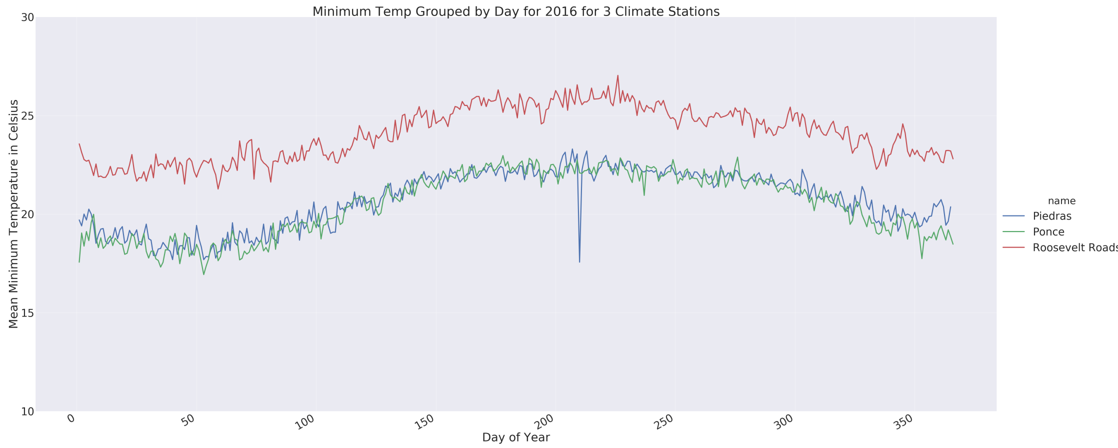
In [19]:
```
yticksdaysflow = list(range(0,100,10))
plotgroupsdays(flow_dayname_med, yticksdaysflow)
```



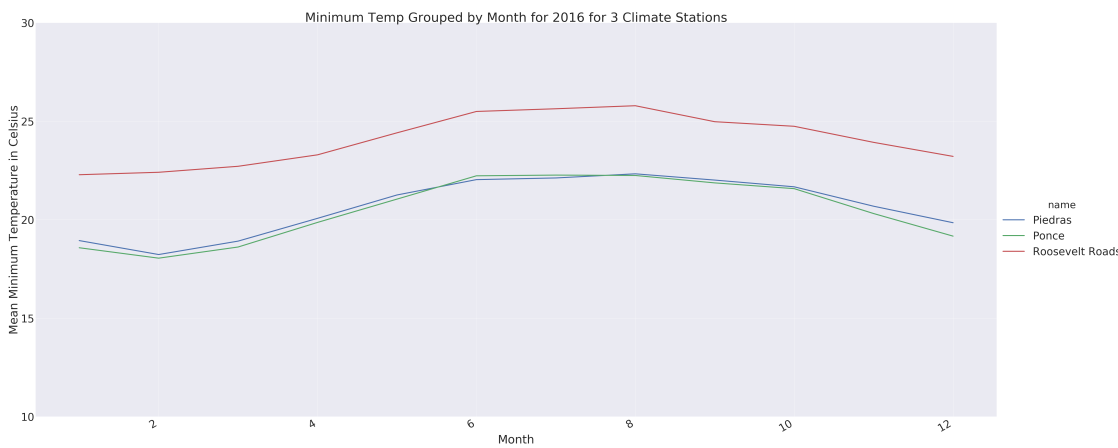
In [22]:
```
yticksmonthsflow = list(range(0,50,10))
plotgroupsmonths(flow_monthname_med, yticksmonthsflow)
```



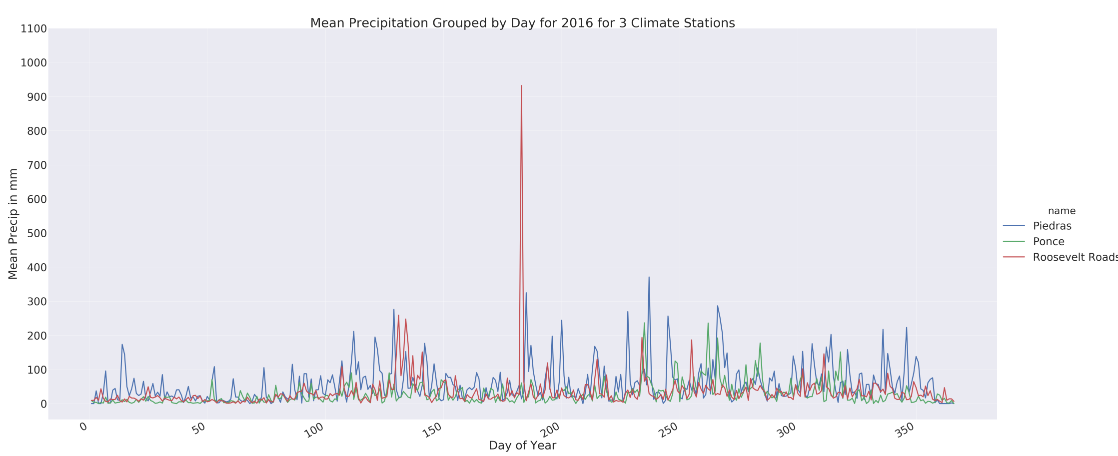
In [26]:
```
yticksdaystmin = list(range(10,35,5))
plotgroupsdays(tmin_dayname_mean, yticksdaystmin, ytext='Mean Minimum Temperature in C
```



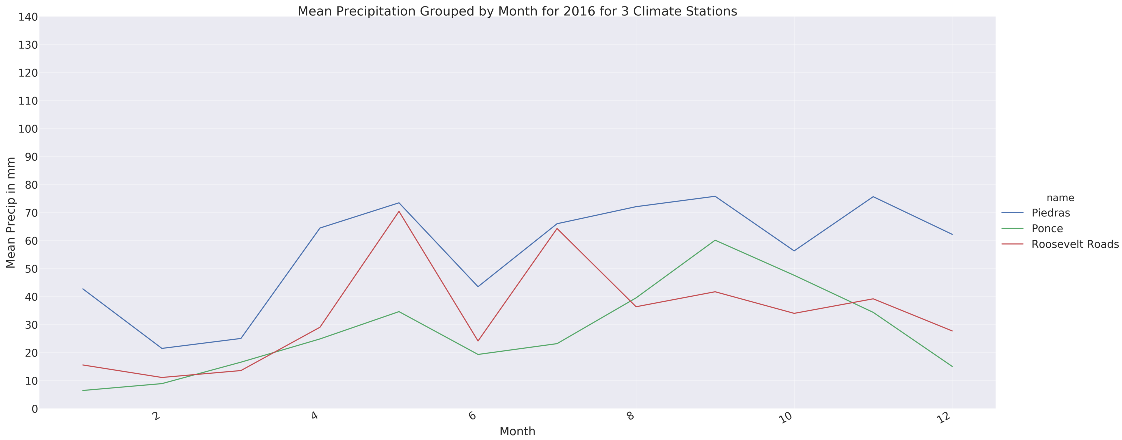

```
In [27]: plotgroupsmonths(tmin_monthname_mean, yticksdaystmin, ytext='Mean Minimum Temperature
```




```
In [29]: yticksdaysprecip = list(range(0,1101,100))
         plotgroupsdays(precip_dayname_mean, yticksdaysprecip, ytext='Mean Precip in mm',title
```

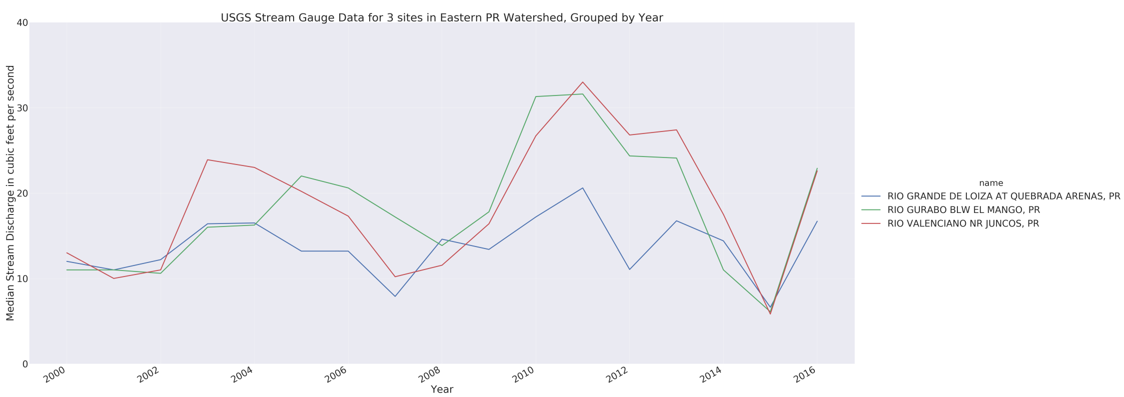


```
In [30]: yticksmonthsprecip = list(range(0,141,10))
         plotgroupsmonths(precip_monthname_mean, yticksmonthsprecip, ytext='Mean Precip in mm'
```

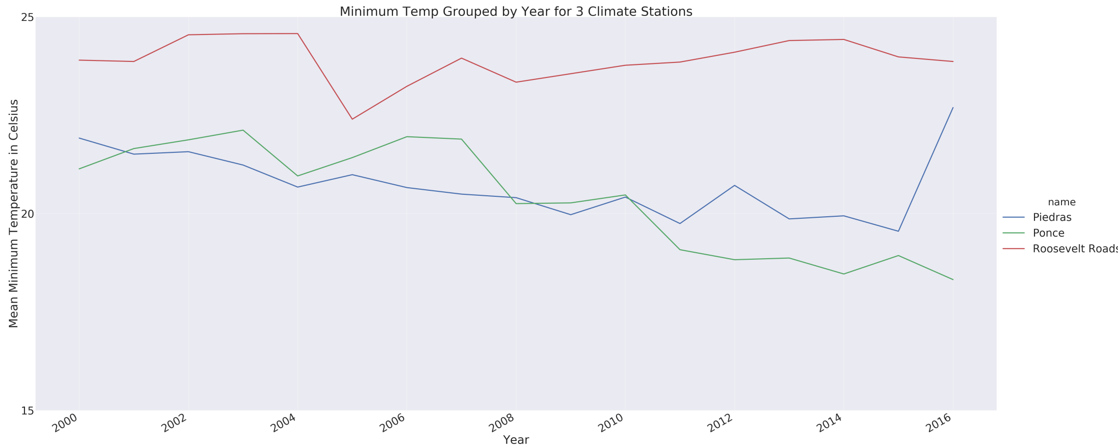


3.4 2c) Calculate Annual Mean/Median Values

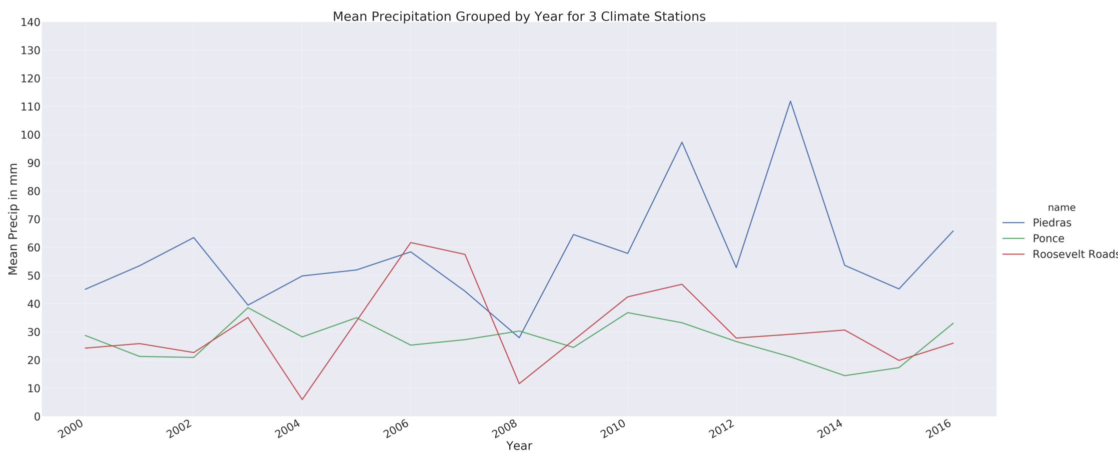
```
In [33]: yticksflowyear = list(range(0, 41, 10))
         plotgroupsyears(flow_yearname_med, yticksflowyear)
```




```
In [38]: ytickstminyear = list(range(15,30,5))
         plotgroupsyears(tmin_yearname_mean, ytickstminyear, ytext='Mean Minimum Temperature i
```




```
In [40]: ytickspreciyear = list(range(0,141,10))
         plotgroupsyears(precip_yearname_mean, ytickspreciyear,ytext='Mean Precip in mm',title
```



3.5 Calculate Seasonal Mean/Median

```
In [13]: flowdf['quarter'] = [month%4+1 for month in flowdf['month']]
         tmindf['quarter'] = [month%4+1 for month in tmindf['month']]
         precipdf['quarter'] = [month%4+1 for month in precipdf['month']]
```

```
In [14]: flow_seasons = flowdf.groupby(['year', 'quarter', 'name']).median()
         tmin_seasons = tmindf.groupby(['year', 'quarter', 'name']).mean()
         precip_seasons = precipdf.groupby(['year', 'quarter', 'name']).mean()
         flow_seasons = flow_seasons.reset_index()
         tmin_seasons = tmin_seasons.reset_index()
         precip_seasons = precip_seasons.reset_index()
```

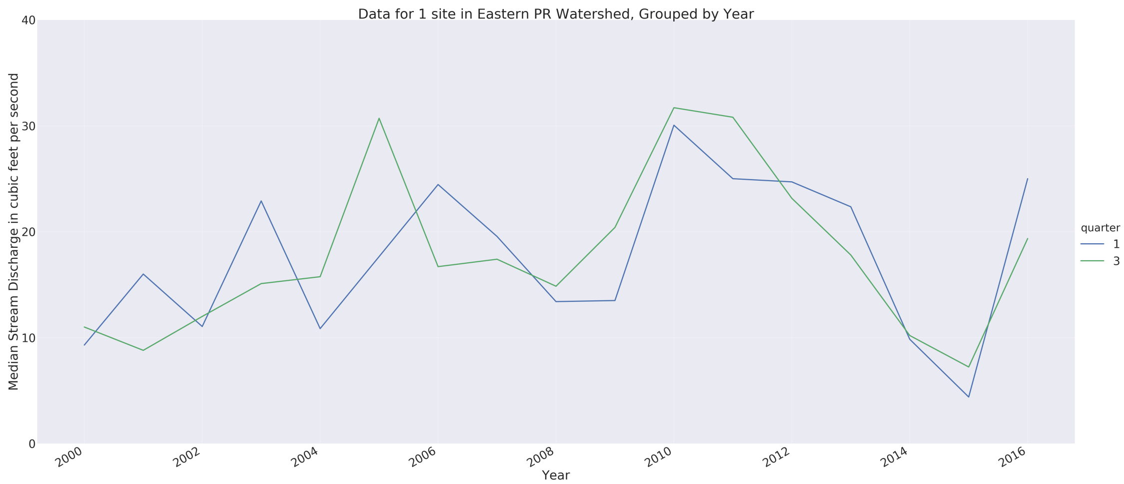
```
def plotgroupsseasons(df, ticklist, timestep='year', ytext='Median Stream Discharge in
    sn.set(font_scale=6, rc={"lines.linewidth": 6})
    f = sn.FacetGrid(df.reset_index(), hue='quarter', size=40, aspect=2)
    f.map(plt.plot, timestep, 'value').add_legend()
    f.ax.set(xlabel='Year',
            ylabel=ytext,
            title=titletext)
    f.fig.autofmt_xdate()
    f.set(yticks=ticklist)
    plt.show()
```

```
In [69]: flow_seasons_subset.name.unique()
```

```
Out[69]: array(['RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR',
                'RIO GURABO BLW EL MANGO, PR', 'RIO VALENCIANO NR JUNCOS, PR'], dtype=object)
```

```
In [70]: flow_seasons_subset = flow_seasons[flow_seasons.quarter != 2]
         flow_seasons_subset = flow_seasons_subset[flow_seasons_subset.quarter != 4]
         flow_seasons_subset = flow_seasons_subset[flow_seasons_subset.name != 'RIO GRANDE DE L
         flow_seasons_subset = flow_seasons_subset[flow_seasons_subset.name != 'RIO VALENCIANO
```

```
In [88]: yticksseasonsflow = list(range(0,50,10))
         plotgroupsseasons(flow_seasons_subset, yticksseasonsflow)
```



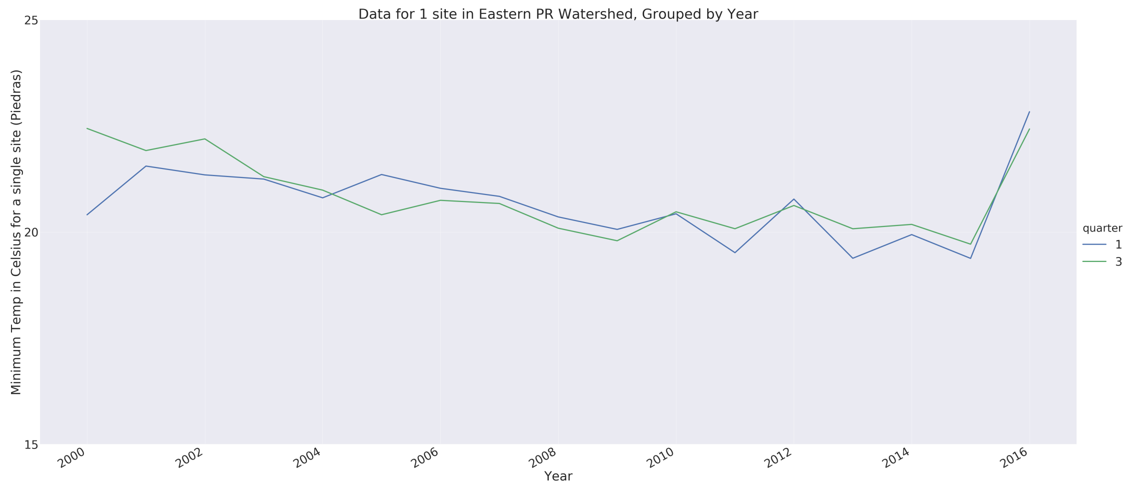

```
In [77]: tmin_seasons.name.unique()
```

```
Out[77]: array(['Piedras', 'Ponce', 'Roosevelt Roads'], dtype=object)
```

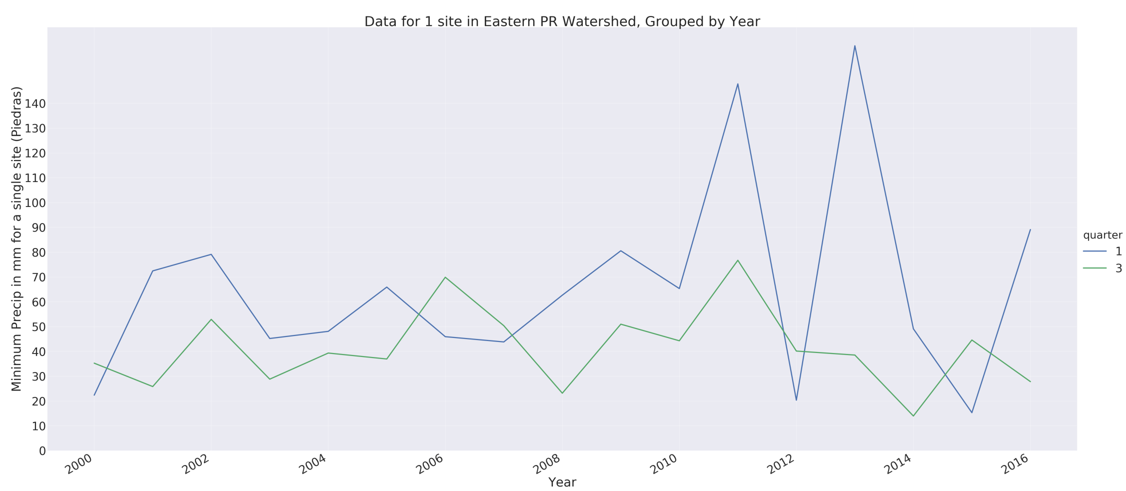
```
In [15]: def subset_stations(df):
             seasons_subset = df[df.quarter != 2]
             seasons_subset = seasons_subset[seasons_subset.quarter != 4]
```

```
        seasons_subset = seasons_subset[seasons_subset.name != 'Ponce']
        seasons_subset = seasons_subset[seasons_subset.name != 'Roosevelt Roads']
        return seasons_subset
    tmin_seasons_subset = subset_stations(tmin_seasons)
    precip_seasons_subset = subset_stations(precip_seasons)
```

```
In [89]: plotgroupsseasons(tmin_seasons_subset, ytickstminyear, ytext='Minimum Temp in Celsius
```




```
In [90]: plotgroupsseasons(precip_seasons_subset, yticksprecipyear, ytext='Minimum Precip in mm
```



3.6 2e Reflection

Because Puerto Rico is in a tropical climate, it has a relative lack of seasons. Temperature does not varry much between JFM and JJA and the same goes for stream flow. There is quite a large amount of variation in stream flow throught the years for both seasons. Precipitation on the other hand does show some variation between seasons, and we see that there was consistently more precip in JFM than JJA. It's interesting that the second lowest year in terms of precip occurred between the two highest years of prcip for JFM. I wonder if this was caused by any significant storm events, as our group by day plot above shows that a particular day between Day 1 and Day 25 exhibited double the precip of days surrounding it averaged over 16 years. The seasonal plot and the day plot indicate that some large storm events in JFM 2011 or 2013 may have influenced that gauge reading.

3.7 3a Fitting a Trend

In [27]:
```
flow_yearname_med
```

Out[27]:

```
                                                   value  month    day
year name
2000 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  12.000    7.0  183.5
     RIO GURABO BLW EL MANGO, PR                 11.000    7.0  183.5
     RIO VALENCIANO NR JUNCOS, PR                13.000    7.0  183.5
2001 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  11.000    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 11.000    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                10.000    7.0  183.0
2002 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  12.200    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 10.600    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                11.000    7.0  183.0
2003 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  16.400    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 16.000    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                23.900    7.0  183.0
2004 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  16.500    7.0  183.5
     RIO GURABO BLW EL MANGO, PR                 16.250    7.0  183.5
     RIO VALENCIANO NR JUNCOS, PR                23.000    7.0  183.5
2005 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  13.200    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 22.000    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                20.200    7.0  183.0
2006 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  13.200    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 20.600    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                17.300    7.0  183.0
2007 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR   7.895    5.0  136.5
     RIO GURABO BLW EL MANGO, PR                 17.200    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                10.200    7.0  183.0
2008 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  14.600   11.0  320.0
     RIO GURABO BLW EL MANGO, PR                 13.850    7.0  183.5
     RIO VALENCIANO NR JUNCOS, PR                11.550    7.0  183.5
2009 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  13.400    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 17.800    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                16.400    7.0  183.0
2010 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  17.200    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 31.300    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                26.700    7.0  183.0
```

```
2011 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  20.600    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 31.600    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                33.000    7.0  183.0
2012 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  11.050    7.0  183.5
     RIO GURABO BLW EL MANGO, PR                 24.350    7.0  183.5
     RIO VALENCIANO NR JUNCOS, PR                26.800    7.0  183.5
2013 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  16.750    7.0  183.5
     RIO GURABO BLW EL MANGO, PR                 24.100    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                27.400    7.0  183.0
2014 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  14.400    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 11.000    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                17.500    7.0  183.0
2015 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR   6.630    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                  6.100    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                 5.830    7.0  183.0
2016 RIO GRANDE DE LOIZA AT QUEBRADA ARENAS, PR  16.700    7.0  183.0
     RIO GURABO BLW EL MANGO, PR                 22.900    7.0  183.0
     RIO VALENCIANO NR JUNCOS, PR                22.600    7.0  183.0
```

In [31]:
```python
import statsmodels.formula.api as smf
valenciano_flow_med = flow_yearname_med.reset_index()[flow_yearname_med.reset_index()
xi = valenciano_flow_med.year
y = valenciano_flow_med.value
y = [int(val) for val in y]
model = smf.OLS(y,xi).fit()
model.summary()
```

```
/home/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1334: UserWarning: kurtosiste
  "anyway, n=%i" % int(n))
```

Out[31]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.866
Model:                            OLS   Adj. R-squared:                  0.857
Method:                 Least Squares   F-statistic:                     103.2
Date:                Sun, 05 Nov 2017   Prob (F-statistic):           2.20e-08
Time:                        15:35:14   Log-Likelihood:                -57.191
No. Observations:                  17   AIC:                             116.4
Df Residuals:                      16   BIC:                             117.2
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           0.0088      0.001     10.161      0.000       0.007       0.011
```

```
==============================================================================
Omnibus:                        0.676   Durbin-Watson:                   0.977
Prob(Omnibus):                  0.713   Jarque-Bera (JB):                0.698
Skew:                           0.361   Prob(JB):                        0.705
Kurtosis:                       2.319   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
"""
```

```
In [38]: xi = tmin_seasons_subset.year[tmin_seasons_subset.quarter == 1]
         y = tmin_seasons_subset.value[tmin_seasons_subset.quarter == 1]
         y = [int(val) for val in y]
         model = smf.OLS(y,xi).fit()
         model.summary()
```

```
/home/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1334: UserWarning: kurtosiste
  "anyway, n=%i" % int(n))
```

```
Out[38]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.998
Model:                            OLS   Adj. R-squared:                  0.998
Method:                 Least Squares   F-statistic:                     8468.
Date:                Sun, 05 Nov 2017   Prob (F-statistic):           3.14e-23
Time:                        15:57:40   Log-Likelihood:                -21.890
No. Observations:                  17   AIC:                             45.78
Df Residuals:                      16   BIC:                             46.61
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           0.0100      0.000     92.024      0.000       0.010       0.010
==============================================================================
Omnibus:                        0.556   Durbin-Watson:                   1.221
Prob(Omnibus):                  0.757   Jarque-Bera (JB):                0.584
Skew:                           0.098   Prob(JB):                        0.747
Kurtosis:                       2.113   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
"""
```

```
In [39]: xi = precip_seasons_subset.year[precip_seasons_subset.quarter == 1]
         y = precip_seasons_subset.value[precip_seasons_subset.quarter == 1]
         y = [int(val) for val in y]
         model = smf.OLS(y,xi).fit()
         model.summary()
```

```
/home/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1334: UserWarning: kurtosistes
  "anyway, n=%i" % int(n))
```

```
Out[39]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                     OLS Regression Results
         ==============================================================================
         Dep. Variable:                      y   R-squared:                       0.739
         Model:                            OLS   Adj. R-squared:                  0.723
         Method:                 Least Squares   F-statistic:                     45.36
         Date:                Sun, 05 Nov 2017   Prob (F-statistic):           4.79e-06
         Time:                        15:58:00   Log-Likelihood:                -86.296
         No. Observations:                  17   AIC:                             174.6
         Df Residuals:                      16   BIC:                             175.4
         Df Model:                           1
         Covariance Type:            nonrobust
         ==============================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
         ------------------------------------------------------------------------------
         year           0.0325      0.005      6.735      0.000       0.022       0.043
         ==============================================================================
         Omnibus:                        7.340   Durbin-Watson:                   2.672
         Prob(Omnibus):                  0.025   Jarque-Bera (JB):                4.467
         Skew:                           1.168   Prob(JB):                        0.107
         Kurtosis:                       3.923   Cond. No.                         1.00
         ==============================================================================

         Warnings:
         [1] Standard Errors assume that the covariance matrix of the errors is correctly spec
         """
```

3.8 Comments on Regression

The fit for the temperature data was the best since the temperature data has the least variance, as noted in 2e. The linear model for this data has an R-squared of .998. It also passes a left and right sided significance test (with alpha = .01). All regression tests pass with an alpha = .1.