In [ ]:
```
%%html
<!--Script block to left align Markdown Tables-->
<style>
  table {margin-left: 0 !important;}
</style>
```

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Laboratory 24: "Predictor-Response Data Models"

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ENGR 1330 Laboratory 24

Exercise: Watershed Response Metrics

Background

Rainfall-Runoff response prediction is a vital step in engineering design for mitigating flood-induced infrastructure failure. One easy to measure characteristic of a watershed is its drainage area. Harder to quantify are its characteristic response time, and its conversion (of precipitation into runoff) factor.

Study Database

The watersheds.csv dataset contains (measured) drainage area for 92 study watersheds in Texas from Cleveland, et. al., 2006, and the associated data:

Columns	Info.
STATION_ID	USGS HUC-8 Station ID code
TDA	Total drainage area (sq. miles)
RCOEF	Runoff Ratio (Runoff Depth/Precipitation Depth)
TPEAK	Characteristic Time (minutes)
FPEAK	Peaking factor (same as NRCS factor)
QP_OBS	Observed peak discharge (measured)
QP_MOD	Modeled peak discharge (modeled)

:

Using the following steps, build a predictor-response type data model.

Step 1:

Read the "watersheds.csv" file as a dataframe. Explore the dataframe and in a markdown cell briefly describe the summarize the dataframe.

In [42]:
```
# import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import math

df = pd.read_csv("watersheds.csv")
# read data file
# summarize contents + markdown cell as needed
df.describe()
```

Out[42]:

	TDA	RCOEF	TPEAK	FPEAK	QP_OBS	QP_MOD
count	92.000000	92.000000	92.000000	92.000000	92.000000	92.000000
mean	16.809130	0.321473	234.292174	4.228043	0.007499	0.004811
std	29.272612	0.162198	211.798151	2.997854	0.005721	0.004245
min	0.260000	0.011400	18.000000	1.310000	0.000393	0.000089
25%	3.037500	0.183400	88.767500	2.455000	0.002800	0.001830
50%	6.965000	0.308000	189.735000	3.365000	0.005720	0.003250
75%	13.815000	0.424450	282.222500	4.617500	0.010575	0.006713
max	166.000000	0.712900	1150.500000	17.940000	0.023000	0.022400

In [12]:
```
df.head()
```

Out[12]:

	STATION_ID	TDA	RCOEF	TPEAK	FPEAK	QP_OBS	QP_MOD
0	08158920	6.3	0.3083	127.43	1.61	0.00932	0.005150
1	08158930	19.0	0.2108	190.44	3.69	0.00521	0.002680
2	08158970	27.6	0.1838	339.06	5.59	0.00454	0.001910
3	08154700	22.3	0.1803	266.64	2.86	0.00498	0.003080
4	08155200	89.7	0.1876	722.50	2.25	0.00184	0.000745

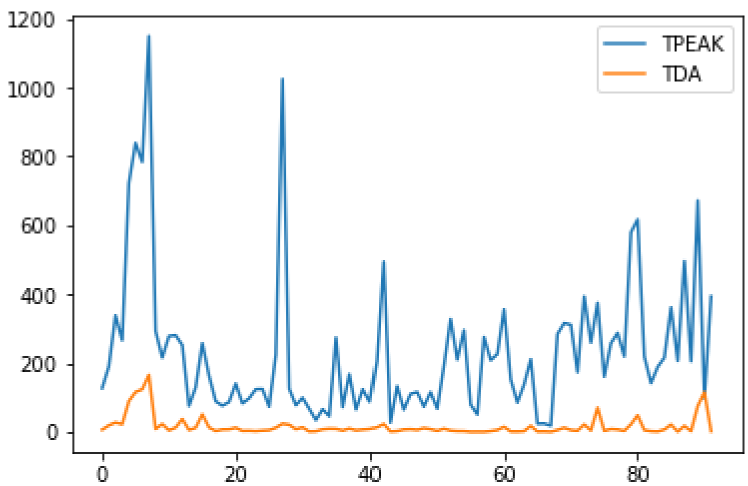
the data ub watersheds.csv has 92 entries of 6 columnds each, the first being an id integer and the rest being floats (measurements)

Step 2:

Make a data model using **TDA** as a predictor of **TPEAK** ($T_{peak} = \beta_{0}+\beta_{1}*TDA$) Plot your model and the data on the same plot. Report your values of the parameters.

In [30]:
```
#
fig, ax = plt.subplots()
tdaSet = np.array(df['TDA'])
tpeakSet = np.array(df['TPEAK'])

data = pd.DataFrame({'TPEAK':tpeakSet, 'TDA':tdaSet})

data.plot(ax=ax)
tdaSet
```

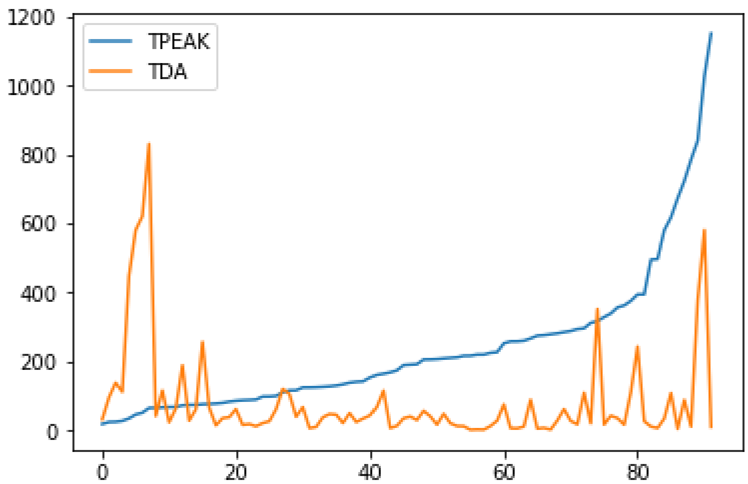
Out[30]:
```
array([  6.3 ,  19.  ,  27.6 ,  22.3 ,  89.7 , 116.  , 124.  , 166.  ,
         8.24,  23.1 ,   4.61,  12.6 ,  37.71,   5.57,  12.1 ,  51.3 ,
        13.1 ,   2.79,   7.03,   7.56,  12.3 ,   3.12,   3.58,   2.31,
         4.13,   5.22,  12.2 ,  24.  ,  21.  ,   7.83,  13.42,   1.22,
         1.94,   7.51,   9.42,   9.03,   4.17,   9.94,   4.75,   6.77,
         8.5 ,  13.4 ,  23.  ,   1.25,   2.53,   6.92,   7.98,   5.91,
        11.26,   8.05,   3.26,   9.54,   4.05,   2.45,   2.33,   0.26,
         0.45,   0.33,   2.43,   5.57,  15.  ,   1.19,   1.08,   2.15,
        17.7 ,   0.97,   1.35,   0.38,   5.64,  12.3 ,   5.41,   3.42,
        21.8 ,   4.02,  70.4 ,   3.29,   8.43,   7.01,   3.18,  22.2 ,
        48.6 ,   5.25,   2.14,   1.26,   6.82,  21.6 ,   0.77,  17.6 ,
         2.1 ,  75.5 , 116.  ,   1.94])
```



In [41]:
```
b0 = int(input('Please enter an input for b0'))
b1 = int(input('Please enter an input for b1'))

sorted_df = df.sort_values(by = 'TPEAK')
sorted_df.head()

#print(range(0,len(sorted_df)))

fig, ax = plt.subplots()
sortedTdaPeakSet = np.array(sorted_df['TPEAK'])

sortedTdaSet = [] #np.array(sorted_df['TDA'])

for i in (range(0 , len(sorted_df))):
```

```
    #print(i)
    #print(sorted_df['TDA'][i])

    sortedTdaSet.append(b0 + b1* sorted_df['TDA'][i])
data = pd.DataFrame({'TPEAK':sortedTdaPeakSet, 'TDA':sortedTdaSet})

data.plot(ax=ax)
```

Out[41]: <AxesSubplot:>



Step 3:

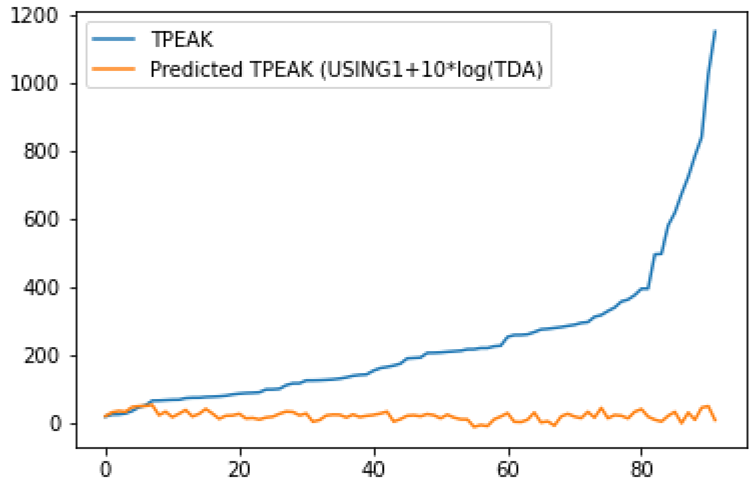
Make a data model using **log(TDA)** as a predictor of **TPEAK** ($T_{peak} = \beta_{0}+\beta_{1}*log(TDA)$)

In your opinion which mapping of **TDA** (arithmetic or logarithmic) produces a more useful graph?

In [45]:

```
b0 = int(input('Please enter an input for b0'))
b1 = int(input('Please enter an input for b1'))

sorted_df = df.sort_values(by = 'TPEAK')
sorted_df.head()

#print(range(0,len(sorted_df)))

fig, ax = plt.subplots()
sortedTdaPeakSet = np.array(sorted_df['TPEAK'])

sortedTdaSet = [] #np.array(sorted_df['TDA'])

for i in (range(0 , len(sorted_df))):
    #print(i)
    #print(sorted_df['TDA'][i])

    sortedTdaSet.append(b0 + b1*math.log(sorted_df['TDA'][i]))
data = pd.DataFrame({'TPEAK':sortedTdaPeakSet, 'Predicted TPEAK (USING'+ str(b0)+ '+'+s

data.plot(ax=ax)
```

Out[45]: <AxesSubplot:>



In [ ]:
```
It appears the logbased it more useful.
```