project

February 22, 2023

1 CST 383: Predicting Water Suface Elevation in Ground Water

1.1 Preliminary work on data preparation

[45]:
```
# imported required libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

[46]:
```
# set default figure size
plt.rcParams['figure.figsize'] = [8.0, 6.0]
```

[82]:
```
# code in this cell from:
# https://stackoverflow.com/questions/27934885/
 ↪how-to-hide-code-from-cells-in-ipython-notebook-visualized-with-nbviewer
from IPython.display import HTML

HTML('''<script>
code_show=true;
function code_toggle() {
 if (code_show){
 $('div.input').hide();
 } else {
 $('div.input').show();
 }
 code_show = !code_show
}
$( document ).ready(code_toggle);
</script>
<form action="javascript:code_toggle()"><input type="submit" value="Click here␣
 ↪to display/hide the code."></form>''')
```

[82]:
```
<IPython.core.display.HTML object>
```

1.1.1 Reading the Data

[48]:
```
data = "https://data.cnra.ca.gov/dataset/618c73fe-b28c-4399-a824-43d0278fe974/
 ↪resource/16f256f8-35a4-4cab-ae02-399a2914c282/download/gwl-monthly.csv"
df = pd.read_csv(data)
```

[49]:
```
stations = pd.read_csv("https://data.cnra.ca.gov/dataset/
 ↪618c73fe-b28c-4399-a824-43d0278fe974/resource/
 ↪03967113-1556-4100-af2c-b16a4d41b9d0/download/gwl-stations.csv")
quality_codes = pd.read_csv("https://data.cnra.ca.gov/dataset/
 ↪618c73fe-b28c-4399-a824-43d0278fe974/resource/
 ↪06437a09-ac72-4d5b-91a7-e5963349b486/download/gwl-quality_codes.csv")
```

[50]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 81764 entries, 0 to 81763
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   STATION     81764 non-null  object
 1   MSMT_DATE   81764 non-null  object
 2   WLM_RPE     81534 non-null  float64
 3   WLM_RPE_QC  81764 non-null  int64
 4   WLM_GSE     81191 non-null  float64
 5   WLM_GSE_QC  81764 non-null  int64
 6   RPE_WSE     66399 non-null  float64
 7   RPE_WSE_QC  81764 non-null  int64
 8   GSE_WSE     65884 non-null  float64
 9   GSE_WSE_QC  81764 non-null  int64
 10  WSE         66183 non-null  float64
 11  WSE_QC      81764 non-null  int64
dtypes: float64(5), int64(5), object(2)
memory usage: 7.5+ MB
```

[51]:
```
df.describe()
```

[51]:

	WLM_RPE	WLM_RPE_QC	WLM_GSE	WLM_GSE_QC	RPE_WSE	\
count	81534.00000	81764.000000	81191.000000	81764.000000	66399.000000	
mean	340.04853	9.166357	339.019729	9.420405	36.407878	
std	970.08112	27.466726	971.953454	28.743207	33.688272	
min	-0.57000	1.000000	-3.170000	1.000000	-11.949000	
25%	45.01000	1.000000	44.580000	1.000000	12.893000	
50%	132.45000	1.000000	129.300000	1.000000	25.993000	
75%	208.22000	1.000000	207.430000	1.000000	49.389000	

```
max     5495.26000    255.000000   5492.010000    255.000000    316.157000

         RPE_WSE_QC       GSE_WSE    GSE_WSE_QC           WSE        WSE_QC
count  81764.000000  65884.000000  81764.000000  66183.000000  81764.000000
mean      47.971687     34.638727     55.309439    300.674951     54.736547
std       96.876386     33.829700     97.045280    981.511909     96.938959
min        1.000000    -14.749000      1.000000   -165.659000      1.000000
25%        1.000000     11.359250      1.000000     20.449500      1.000000
50%        1.000000     24.202000      1.000000     94.775000      1.000000
75%        1.000000     47.762000     70.000000    147.962500     70.000000
max      255.000000    314.037000    255.000000   5491.840000    255.000000
```

1.1.2 Missing Data

[52]:
```
# print the number of null values in each column of the DataFrame 'df'
print(df.isnull().sum())
```

```
STATION           0
MSMT_DATE         0
WLM_RPE         230
WLM_RPE_QC        0
WLM_GSE         573
WLM_GSE_QC        0
RPE_WSE       15365
RPE_WSE_QC        0
GSE_WSE       15880
GSE_WSE_QC        0
WSE           15581
WSE_QC            0
dtype: int64
```

[53]:
```
# filter the DataFrame 'df' to show only the rows where the 'RPE_WSE',␣
 ↪'GSE_WSE' and 'WSE' columns are null
df[df.RPE_WSE.isnull() & df.GSE_WSE.isnull() & df.WSE.isnull()].head()
```

[53]:

	STATION	MSMT_DATE	WLM_RPE	WLM_RPE_QC	WLM_GSE	WLM_GSE_QC	\
0	01N04E36Q001M	2005-04-01	9.1	1	6.9	1	
37	01N04E36Q001M	2008-05-01	9.1	1	6.9	1	
38	01N04E36Q001M	2008-06-01	9.1	1	6.9	1	
39	01N04E36Q001M	2008-07-01	9.1	1	6.9	1	
40	01N04E36Q001M	2008-08-01	9.1	1	6.9	1	

	RPE_WSE	RPE_WSE_QC	GSE_WSE	GSE_WSE_QC	WSE	WSE_QC
0	NaN	255	NaN	255	NaN	255
37	NaN	255	NaN	255	NaN	255
38	NaN	255	NaN	255	NaN	255
39	NaN	255	NaN	255	NaN	255

```
40      NaN         255      NaN         255  NaN     255
```

We can drop the na values for now? Its a fraction of the data.

[54]:
```
# show total rows before cleaning null values
print("Total rows with NA values: ",len(df))
```

```
Total rows with NA values:  81764
```

[55]:
```
df = df.dropna()
print("Total clean rows: ", len(df))
```

```
Total clean rows:  65884
```

[56]:
```
# check for null values
print(df.isnull().sum())
```

```
STATION       0
MSMT_DATE     0
WLM_RPE       0
WLM_RPE_QC    0
WLM_GSE       0
WLM_GSE_QC    0
RPE_WSE       0
RPE_WSE_QC    0
GSE_WSE       0
GSE_WSE_QC    0
WSE           0
WSE_QC        0
dtype: int64
```

1.1.3 Station Info

[57]:
```
stations.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 567 entries, 0 to 566
Data columns (total 20 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   STATION      567 non-null    object
 1   SITE_CODE    556 non-null    object
 2   STNAME       567 non-null    object
 3   WELL_NAME    567 non-null    object
 4   LATITUDE     567 non-null    float64
 5   LONGITUDE    567 non-null    float64
 6   LLDATUM      567 non-null    object
 7   POSACC       567 non-null    object
```

```
 8   ELEV          567 non-null    float64
 9   ELEVDATUM     103 non-null    object
 10  ELEVACC       567 non-null    object
 11  COUNTY_NAME   567 non-null    object
 12  BASIN_CODE    536 non-null    object
 13  BASIN_NAME    536 non-null    object
 14  WELL_DEPTH    523 non-null    float64
 15  WELL_USE      526 non-null    object
 16  WELL_TYPE     536 non-null    object
 17  WCR_NO        398 non-null    object
 18  WDL           567 non-null    object
 19  COMMENT       205 non-null    object
dtypes: float64(4), object(16)
memory usage: 88.7+ KB
```

1.1.4 Quality Control Info

[58]:
```
quality_codes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46 entries, 0 to 45
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   QUALITY_CODE  46 non-null     int64
 1   DESCRIPTION   46 non-null     object
dtypes: int64(1), object(1)
memory usage: 864.0+ bytes
```

1.2 Preliminary work on data exploration and visualization

1.2.1 Helper Functions to filter by date

[59]:
```
def get_mst_by_year(df, year):
    return df[df['MSMT_DATE'].str.startswith(year)]

def get_mst_by_month(df, month):
    return df[df['MSMT_DATE'].str[5:].str.startswith(month)]

def get_mst_by_month_year(df, month, year):
    return df[df['MSMT_DATE'].str.startswith(year + '-' + month)]
```

1.2.2 Highest water level recorded in 2005

[60]:
```
y2005 = get_mst_by_year(df, '2005')
y2005.max()
```

[60]:
```
STATION       48N05E26D001M
MSMT_DATE        2005-12-01
WLM_RPE             5495.26
WLM_RPE_QC               70
WLM_GSE             5492.01
WLM_GSE_QC               70
RPE_WSE             203.254
RPE_WSE_QC               70
GSE_WSE             201.284
GSE_WSE_QC               70
WSE                5489.487
WSE_QC                   70
dtype: object
```

1.2.3 Highest Recorded Water Level in December

[61]:
```
dec = get_mst_by_month(df, '12')
dec.max()
```

[61]:
```
STATION       48N05E36A002M
MSMT_DATE        2022-12-01
WLM_RPE             5495.26
WLM_RPE_QC              130
WLM_GSE             5492.01
WLM_GSE_QC              130
RPE_WSE             249.449
RPE_WSE_QC              120
GSE_WSE             246.829
GSE_WSE_QC              130
WSE                5491.607
WSE_QC                  130
dtype: object
```

1.2.4 Max Level in December 2005

[62]:
```
dec_2005 = get_mst_by_month_year(df, '12', '2005')
dec_2005.max()
```

[62]:
```
STATION       48N05E26D001M
MSMT_DATE        2005-12-01
WLM_RPE             5495.26
WLM_RPE_QC               70
WLM_GSE             5492.01
WLM_GSE_QC               70
RPE_WSE             149.485
RPE_WSE_QC               10
GSE_WSE             147.985
```

```
GSE_WSE_QC               70
WSE                5489.487
WSE_QC                   70
dtype: object
```

1.3 Water level of station 48N05E26D001M over 2005

[63]:
```
get_mst_by_year(df[df['STATION'] == '48N05E26D001M'], '2005')[['MSMT_DATE',␣
↪'WSE', 'WSE_QC']]
```

[63]:

	MSMT_DATE	WSE	WSE_QC
81695	2005-01-01	4011.179	1
81696	2005-02-01	4011.453	1
81697	2005-03-01	4011.560	1
81698	2005-04-01	4011.785	1
81699	2005-05-01	4012.024	1
81700	2005-06-01	3989.853	1
81701	2005-07-01	4011.226	1
81702	2005-08-01	4011.034	1
81703	2005-09-01	4010.845	1
81704	2005-10-01	4010.657	1
81705	2005-11-01	4010.468	1
81706	2005-12-01	4010.279	1

1.4 View Number of yearly measurements per station.

[64]:
```
get_mst_by_month(df, '01')[['STATION', 'MSMT_DATE', 'WSE', 'WSE_QC']].
↪value_counts('STATION').head(10)
```

[64]:
```
STATION
21N02E26E005M    52
11N04E04N004M    29
09N03E08C001M    29
09N03E08C003M    29
11N04E04N003M    28
11N04E04N002M    28
09N03E08C002M    27
11N01E24Q005M    27
09N03E08C004M    27
11N01E24Q007M    25
dtype: int64
```

1.5 View Station 21N02E26E005M

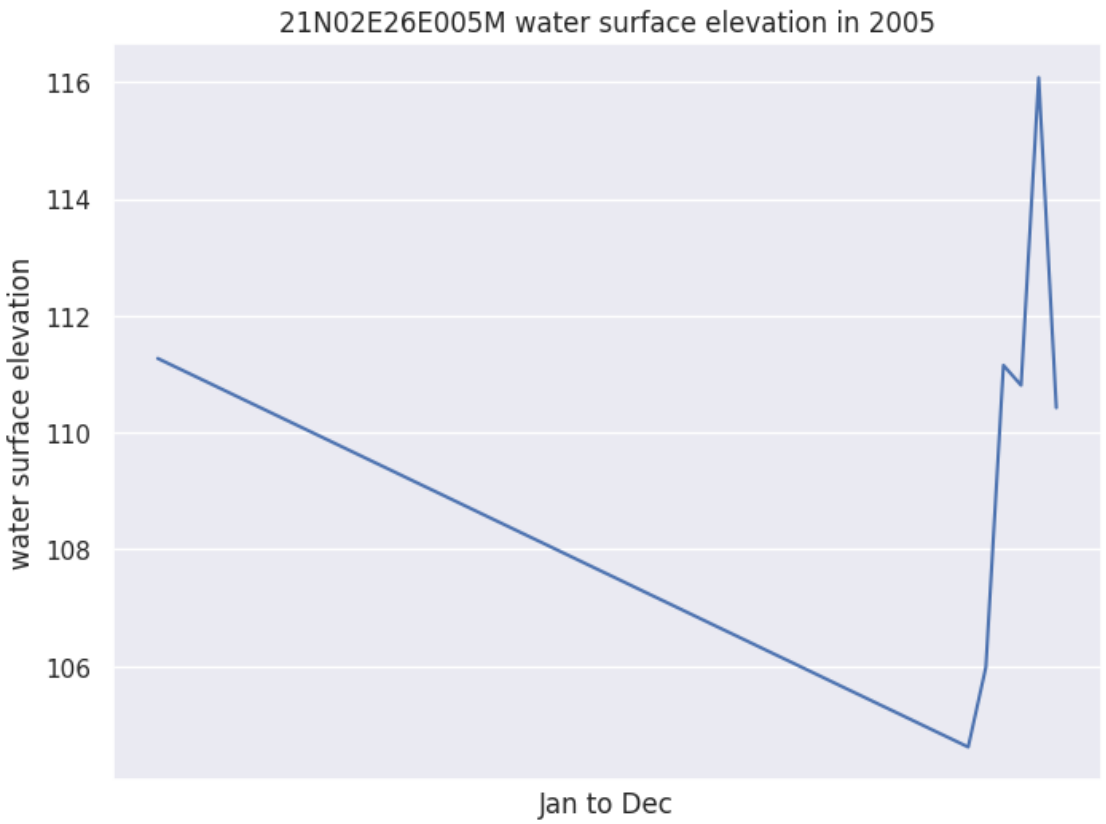
[65]:
```
historic_station_levels = get_mst_by_month(df[df['STATION'] ==␣
 ↪'21N02E26E005M'], '01')
print(historic_station_levels)
plt.xticks([])
plt.title('21N02E26E005M water surface elevation in 2005')
plt.ylabel('water surface elevation')
plt.xlabel('Jan to Dec')
plt.plot(get_mst_by_month(df[df['STATION'] == '21N02E26E005M'],␣
 ↪'01')['MSMT_DATE'], get_mst_by_month(df[df['STATION'] == '21N02E26E005M'],␣
 ↪'01')['WSE'])
plt.show()
```

	STATION	MSMT_DATE	WLM_RPE	WLM_RPE_QC	WLM_GSE	WLM_GSE_QC	\
47213	21N02E26E005M	1970-01-01	184.44	10	182.26	10	
47225	21N02E26E005M	1971-01-01	184.44	10	182.26	10	
47237	21N02E26E005M	1972-01-01	184.44	10	182.26	10	
47249	21N02E26E005M	1973-01-01	184.44	10	182.26	10	
47261	21N02E26E005M	1974-01-01	184.44	10	182.26	10	
47273	21N02E26E005M	1975-01-01	184.44	10	182.26	10	
47285	21N02E26E005M	1976-01-01	184.44	10	182.26	10	
47297	21N02E26E005M	1977-01-01	184.44	10	182.26	10	
47309	21N02E26E005M	1978-01-01	184.44	10	182.26	10	
47321	21N02E26E005M	1979-01-01	184.44	10	182.26	10	
47333	21N02E26E005M	1980-01-01	184.44	10	182.26	10	
47345	21N02E26E005M	1981-01-01	184.44	10	182.26	10	
47357	21N02E26E005M	1982-01-01	184.44	10	182.26	10	
47369	21N02E26E005M	1983-01-01	184.44	10	182.26	10	
47381	21N02E26E005M	1984-01-01	184.44	10	182.26	10	
47393	21N02E26E005M	1985-01-01	184.44	10	182.26	10	
47405	21N02E26E005M	1986-01-01	184.44	10	182.26	10	
47417	21N02E26E005M	1987-01-01	184.44	10	182.26	10	
47429	21N02E26E005M	1988-01-01	184.44	10	182.26	10	
47441	21N02E26E005M	1989-01-01	184.44	10	182.26	10	
47453	21N02E26E005M	1990-01-01	184.44	10	182.26	10	
47465	21N02E26E005M	1991-01-01	184.44	10	182.26	10	
47477	21N02E26E005M	1992-01-01	184.44	10	182.26	10	
47489	21N02E26E005M	1993-01-01	184.44	10	182.26	10	
47501	21N02E26E005M	1994-01-01	184.44	10	182.26	10	
47513	21N02E26E005M	1995-01-01	184.44	10	182.26	10	
47525	21N02E26E005M	1996-01-01	184.44	10	182.26	10	
47537	21N02E26E005M	1997-01-01	184.44	10	182.26	10	
47549	21N02E26E005M	1998-01-01	184.44	10	182.26	10	
47561	21N02E26E005M	1999-01-01	184.44	10	182.26	10	
47573	21N02E26E005M	2000-01-01	184.44	10	182.26	10	
47585	21N02E26E005M	2001-01-01	184.44	10	182.26	10	
47597	21N02E26E005M	2002-01-01	184.44	10	182.26	10	

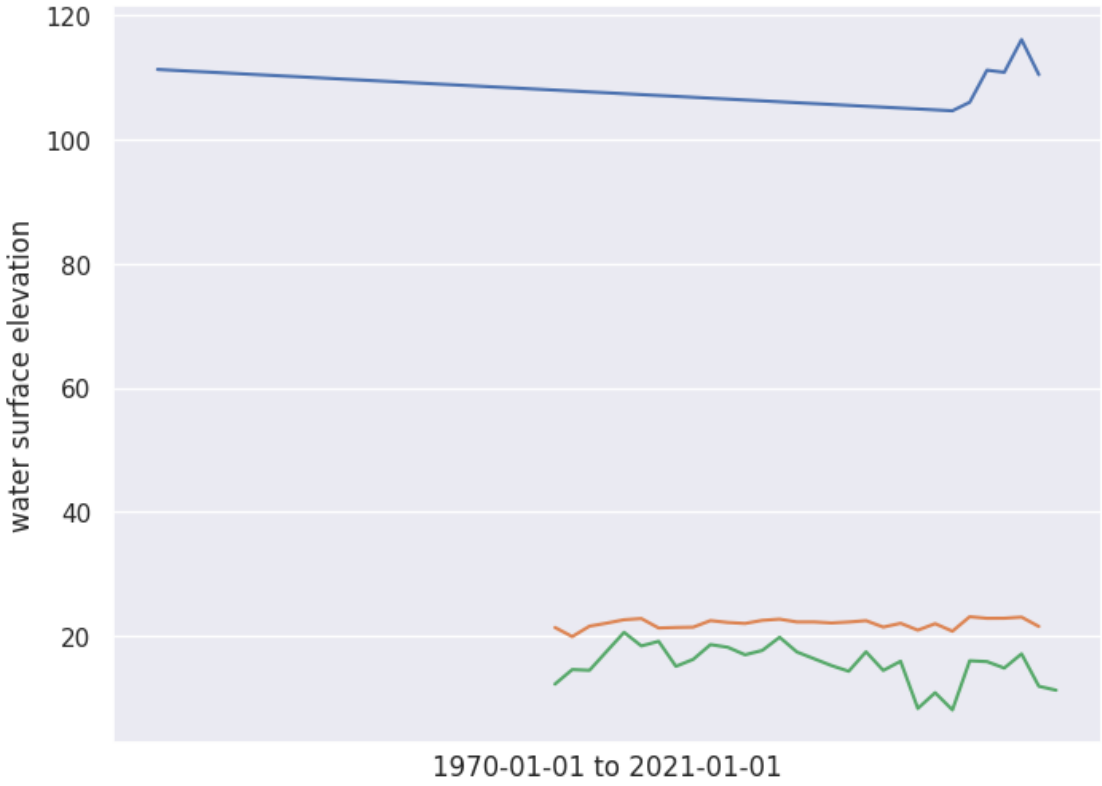
47609	21N02E26E005M	2003-01-01	184.44	10	182.26	10
47621	21N02E26E005M	2004-01-01	184.44	10	182.26	10
47633	21N02E26E005M	2005-01-01	184.44	10	182.26	10
47645	21N02E26E005M	2006-01-01	184.44	10	182.26	10
47657	21N02E26E005M	2007-01-01	184.44	10	182.26	10
47669	21N02E26E005M	2008-01-01	184.44	10	182.26	10
47681	21N02E26E005M	2009-01-01	184.44	10	182.26	10
47693	21N02E26E005M	2010-01-01	184.44	10	182.26	10
47705	21N02E26E005M	2011-01-01	184.44	10	182.26	10
47717	21N02E26E005M	2012-01-01	184.44	10	182.26	10
47729	21N02E26E005M	2013-01-01	184.44	10	182.26	10
47741	21N02E26E005M	2014-01-01	184.44	10	182.26	10
47753	21N02E26E005M	2015-01-01	184.44	10	182.26	10
47765	21N02E26E005M	2016-01-01	184.44	10	182.26	10
47777	21N02E26E005M	2017-01-01	184.44	10	182.26	10
47789	21N02E26E005M	2018-01-01	184.44	10	182.26	10
47801	21N02E26E005M	2019-01-01	184.44	10	182.26	10
47813	21N02E26E005M	2020-01-01	184.44	10	182.26	10
47825	21N02E26E005M	2021-01-01	184.44	10	182.26	10

	RPE_WSE	RPE_WSE_QC	GSE_WSE	GSE_WSE_QC	WSE	WSE_QC
47213	73.171	1	70.991	10	111.269	10
47225	73.316	1	71.136	10	111.124	10
47237	73.460	1	71.280	10	110.980	10
47249	73.605	1	71.425	10	110.835	10
47261	73.750	1	71.570	10	110.690	10
47273	73.895	1	71.715	10	110.545	10
47285	74.039	1	71.859	10	110.401	10
47297	74.184	1	72.004	10	110.256	10
47309	74.329	1	72.149	10	110.111	10
47321	74.473	1	72.293	10	109.967	10
47333	74.618	1	72.438	10	109.822	10
47345	74.763	1	72.583	10	109.677	10
47357	74.908	1	72.728	10	109.532	10
47369	75.052	1	72.872	10	109.388	10
47381	75.197	1	73.017	10	109.243	10
47393	75.342	1	73.162	10	109.098	10
47405	75.486	1	73.306	10	108.954	10
47417	75.631	1	73.451	10	108.809	10
47429	75.776	1	73.596	10	108.664	10
47441	75.921	1	73.741	10	108.519	10
47453	76.065	1	73.885	10	108.375	10
47465	76.210	1	74.030	10	108.230	10
47477	76.354	1	74.174	10	108.086	10
47489	76.499	1	74.319	10	107.941	10
47501	76.644	1	74.464	10	107.796	10
47513	76.789	1	74.609	10	107.651	10
47525	76.933	1	74.753	10	107.507	10

47537	77.078	1	74.898	10	107.362	10
47549	77.223	1	75.043	10	107.217	10
47561	77.367	1	75.187	10	107.073	10
47573	77.512	1	75.332	10	106.928	10
47585	77.657	1	75.477	10	106.783	10
47597	77.802	1	75.622	10	106.638	10
47609	77.946	1	75.766	10	106.494	10
47621	78.091	1	75.911	10	106.349	10
47633	78.236	1	76.056	10	106.204	10
47645	78.380	1	76.200	10	106.060	10
47657	78.525	1	76.345	10	105.915	10
47669	78.670	1	76.490	10	105.770	10
47681	78.815	1	76.635	10	105.625	10
47693	78.959	1	76.779	10	105.481	10
47705	79.104	1	76.924	10	105.336	10
47717	79.248	1	77.068	10	105.192	10
47729	79.393	1	77.213	10	105.047	10
47741	79.538	1	77.358	10	104.902	10
47753	79.682	1	77.502	10	104.758	10
47765	79.827	1	77.647	10	104.613	10
47777	78.462	1	76.282	10	105.978	10
47789	73.289	1	71.109	10	111.151	10
47801	73.631	1	71.451	10	110.809	10
47813	68.362	1	66.182	10	116.078	10
47825	74.016	1	71.836	10	110.424	10



[66]:
```
plt.xticks([])
plt.ylabel('water surface elevation')
plt.plot(get_mst_by_month(df[df['STATION'] == '21N02E26E005M'],␣
 ↪'01')['MSMT_DATE'], get_mst_by_month(df[df['STATION'] == '21N02E26E005M'],␣
 ↪'01')['WSE'])
plt.plot(get_mst_by_month(df[df['STATION'] == '09N03E08C001M'],␣
 ↪'01')['MSMT_DATE'], get_mst_by_month(df[df['STATION'] == '09N03E08C001M'],␣
 ↪'01')['WSE'])
plt.plot(get_mst_by_month(df[df['STATION'] == '09N03E08C003M'],␣
 ↪'01')['MSMT_DATE'], get_mst_by_month(df[df['STATION'] == '09N03E08C003M'],␣
 ↪'01')['WSE'])
plt.xlabel(get_mst_by_month(df[df['STATION'] == '21N02E26E005M'],␣
 ↪'01')['MSMT_DATE'].iloc[0] + ' to ' + get_mst_by_month(df[df['STATION'] ==␣
 ↪'21N02E26E005M'], '01')['MSMT_DATE'].iloc[-1])
plt.show()
```

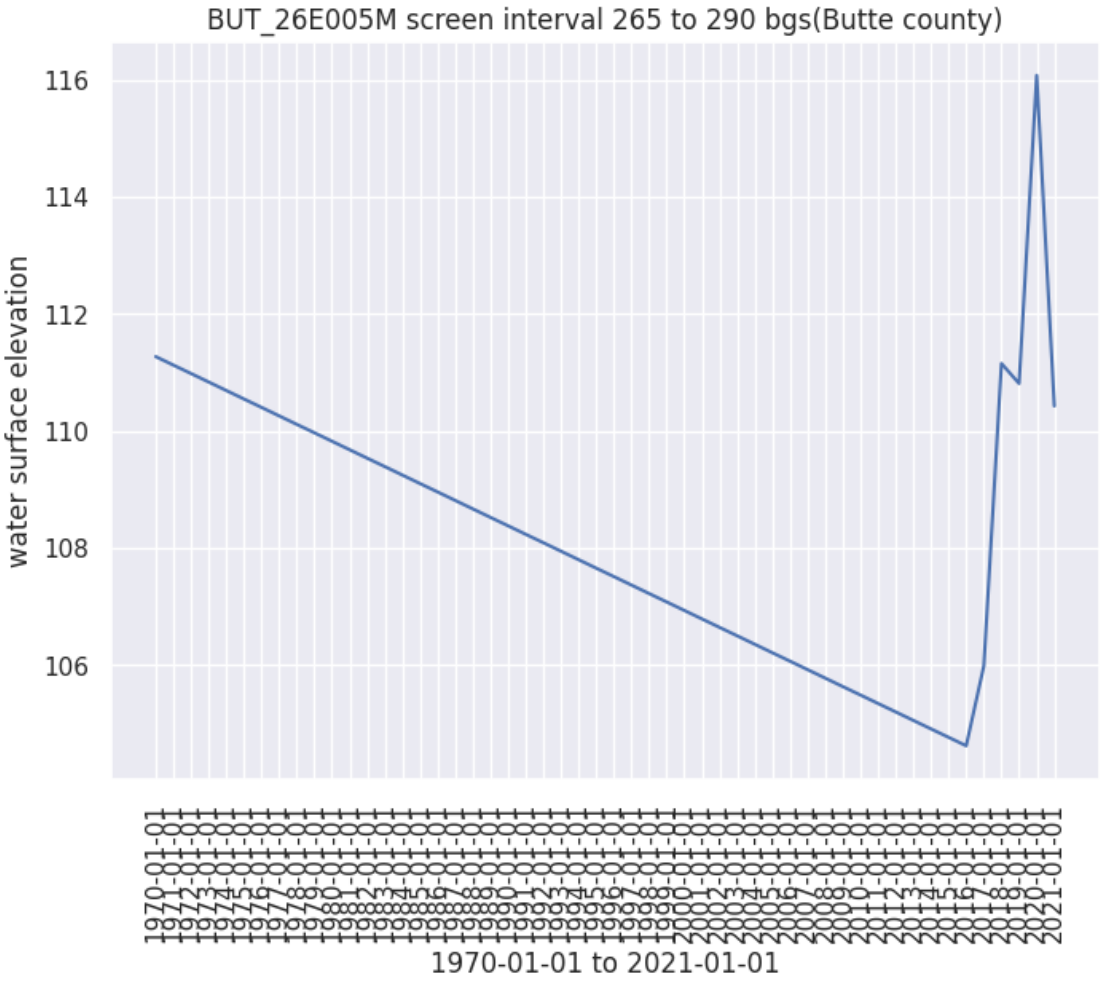


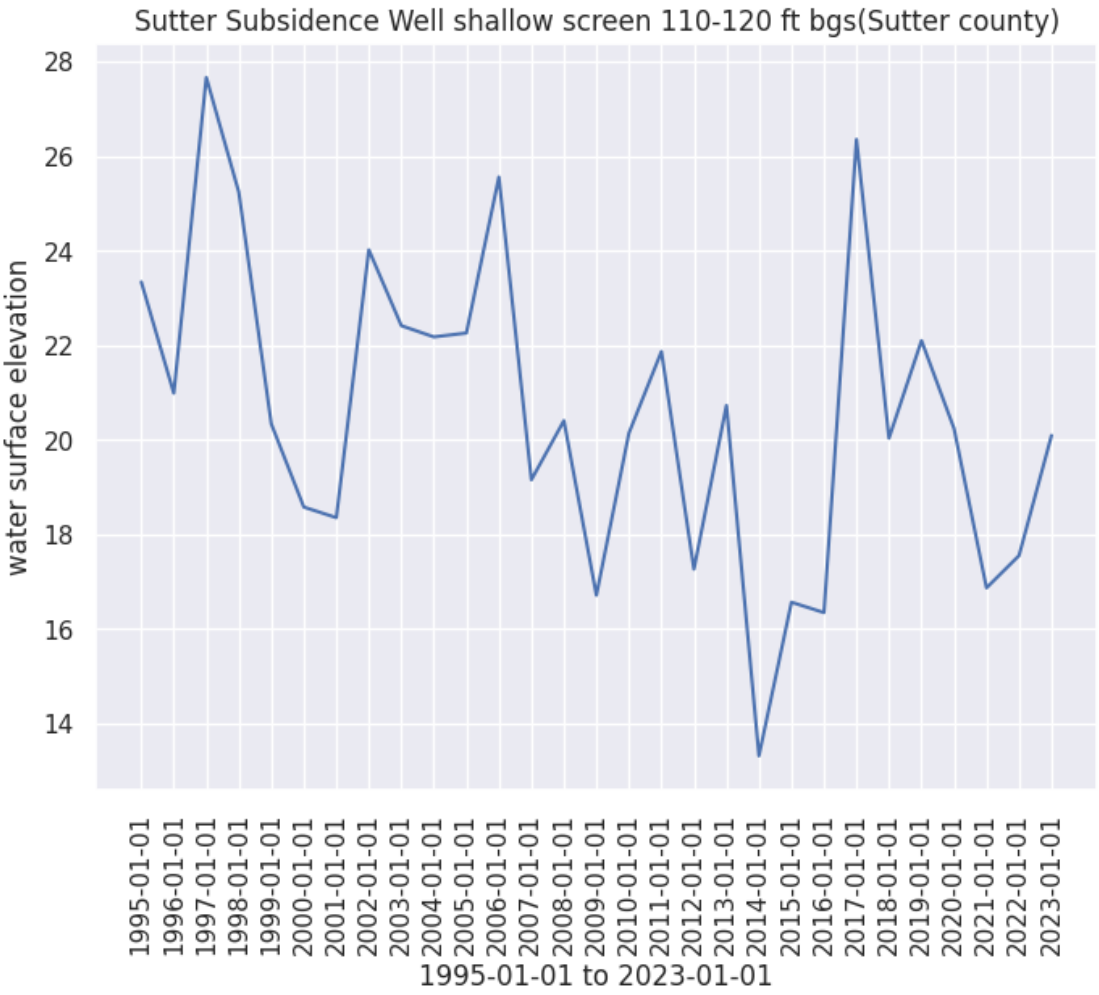
1.6 Graping the water Levels

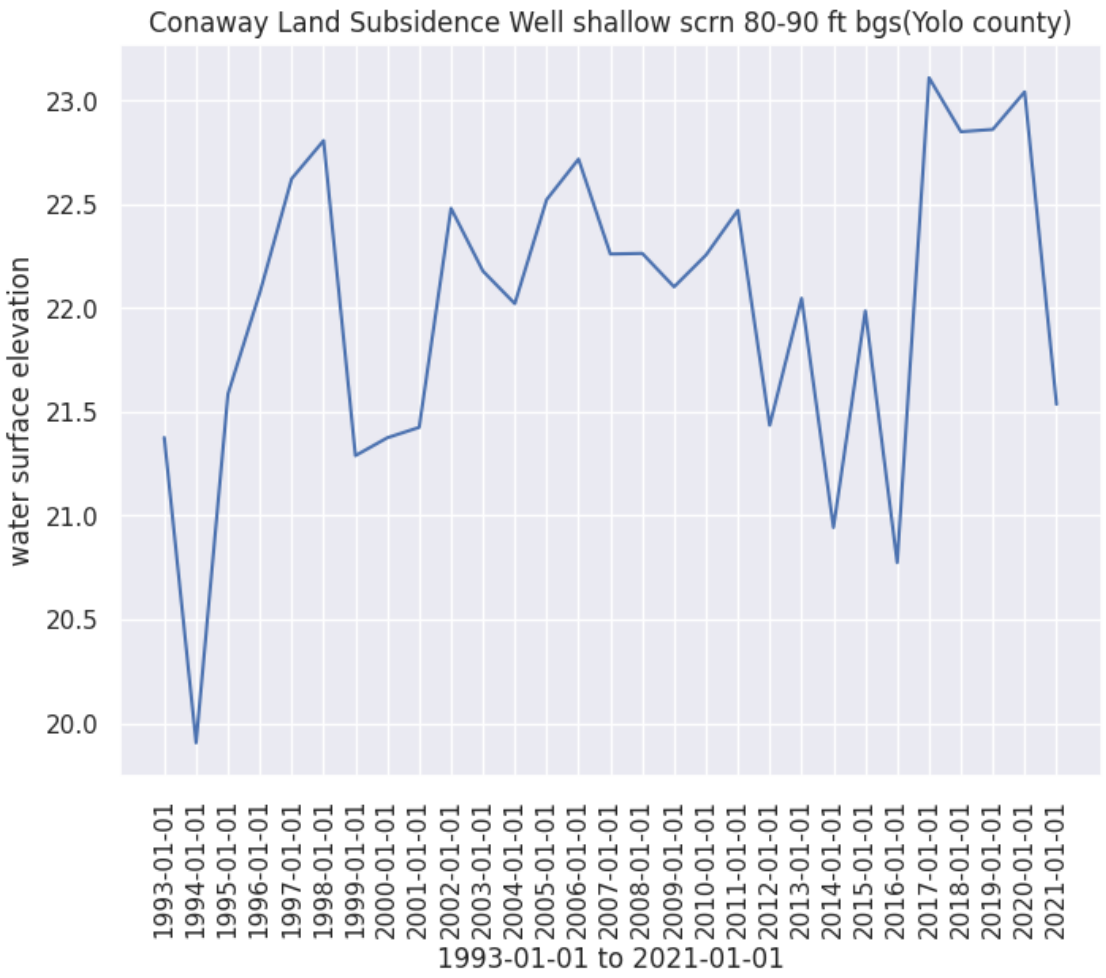
View Water Levels over the lifetime of measurements. Only looking at places that have 28+ years of measurements.

[67]:
```
jan_meas = get_mst_by_month(df, '01').copy()

count = jan_meas.value_counts('STATION')
for station in count[count >= 28].index:
    st_info = stations[stations['STATION'] == station]
    stn = jan_meas[jan_meas['STATION'] == station]
    title = st_info['STNAME'].iloc[0] + '(' + st_info['COUNTY_NAME'].iloc[0] +␣
 ↪' county)'
    xlabel = stn['MSMT_DATE'].iloc[0] + ' to ' + stn['MSMT_DATE'].iloc[-1]
    plt.title(title)
    plt.plot(stn['MSMT_DATE'], stn['WSE'])
    plt.xticks(stn['MSMT_DATE'], rotation='vertical')
    plt.ylabel('water surface elevation')
    plt.xlabel(xlabel)
    plt.show()
```


BUT_26E005M screen interval 265 to 290 bgs(Butte county)
water surface elevation
116
114
112
110
108
106
1970-01-01 to 2021-01-01


Sutter Subsidence Well shallow screen 110-120 ft bgs(Sutter county)
water surface elevation
28
26
24
22
20
18
16
14
1995-01-01
1996-01-01
1997-01-01
1998-01-01
1999-01-01
2000-01-01
2001-01-01
2002-01-01
2003-01-01
2004-01-01
2005-01-01
2006-01-01
2007-01-01
2008-01-01
2009-01-01
2010-01-01
2011-01-01
2012-01-01
2013-01-01
2014-01-01
2015-01-01
2016-01-01
2017-01-01
2018-01-01
2019-01-01
2020-01-01
2021-01-01
2022-01-01
2023-01-01
1995-01-01 to 2023-01-01


Conaway Land Subsidence Well shallow scrn 80-90 ft bgs(Yolo county)
water surface elevation
23.0
22.5
22.0
21.5
21.0
20.5
20.0
1993-01-01
1994-01-01
1995-01-01
1996-01-01
1997-01-01
1998-01-01
1999-01-01
2000-01-01
2001-01-01
2002-01-01
2003-01-01
2004-01-01
2005-01-01
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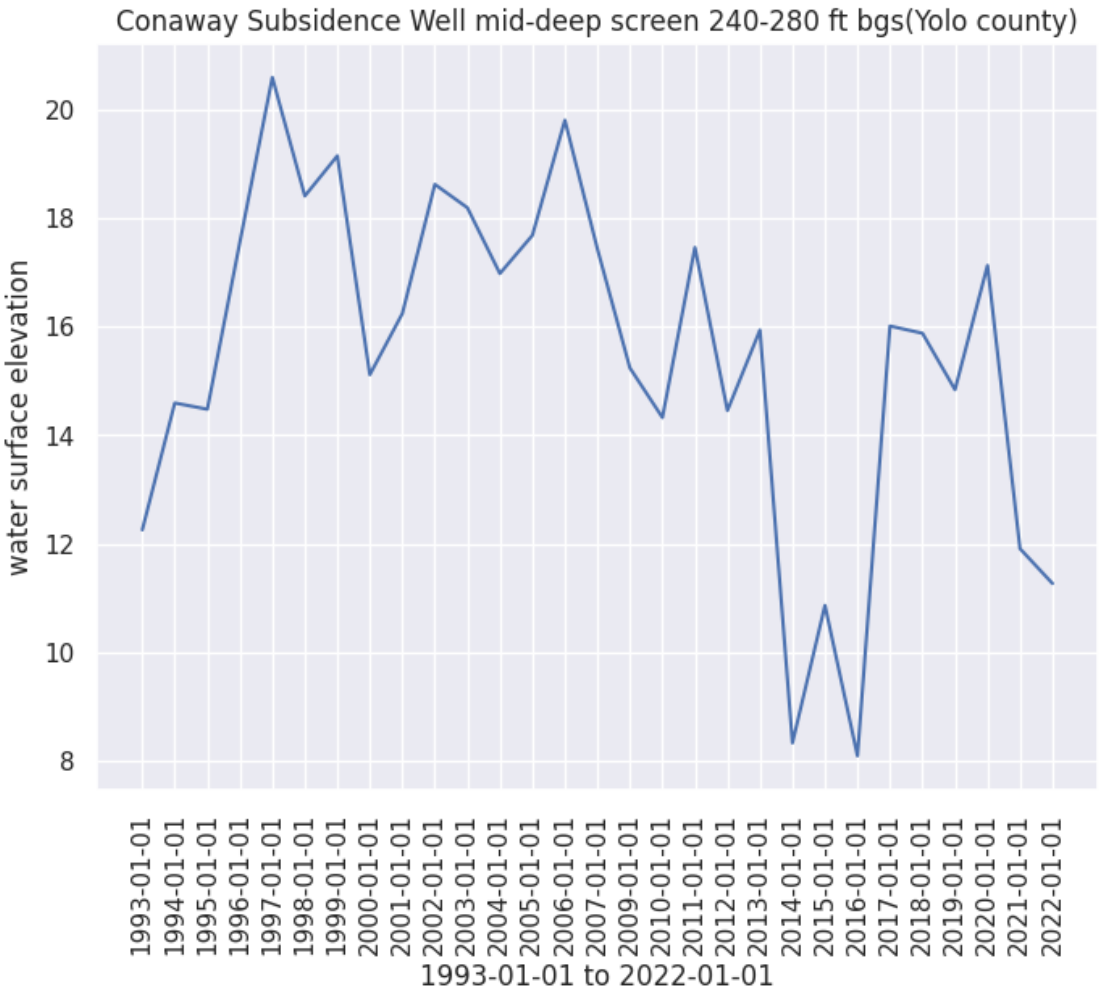
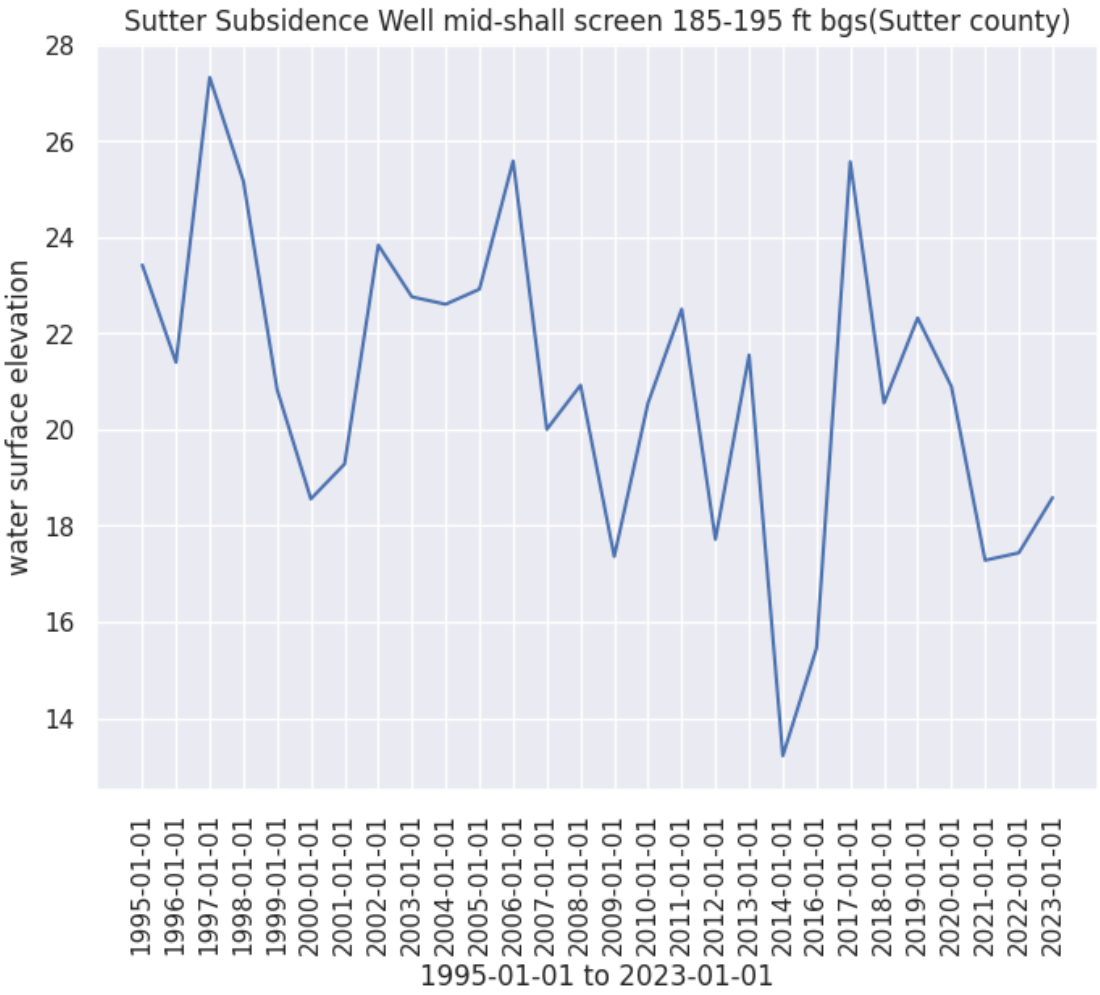
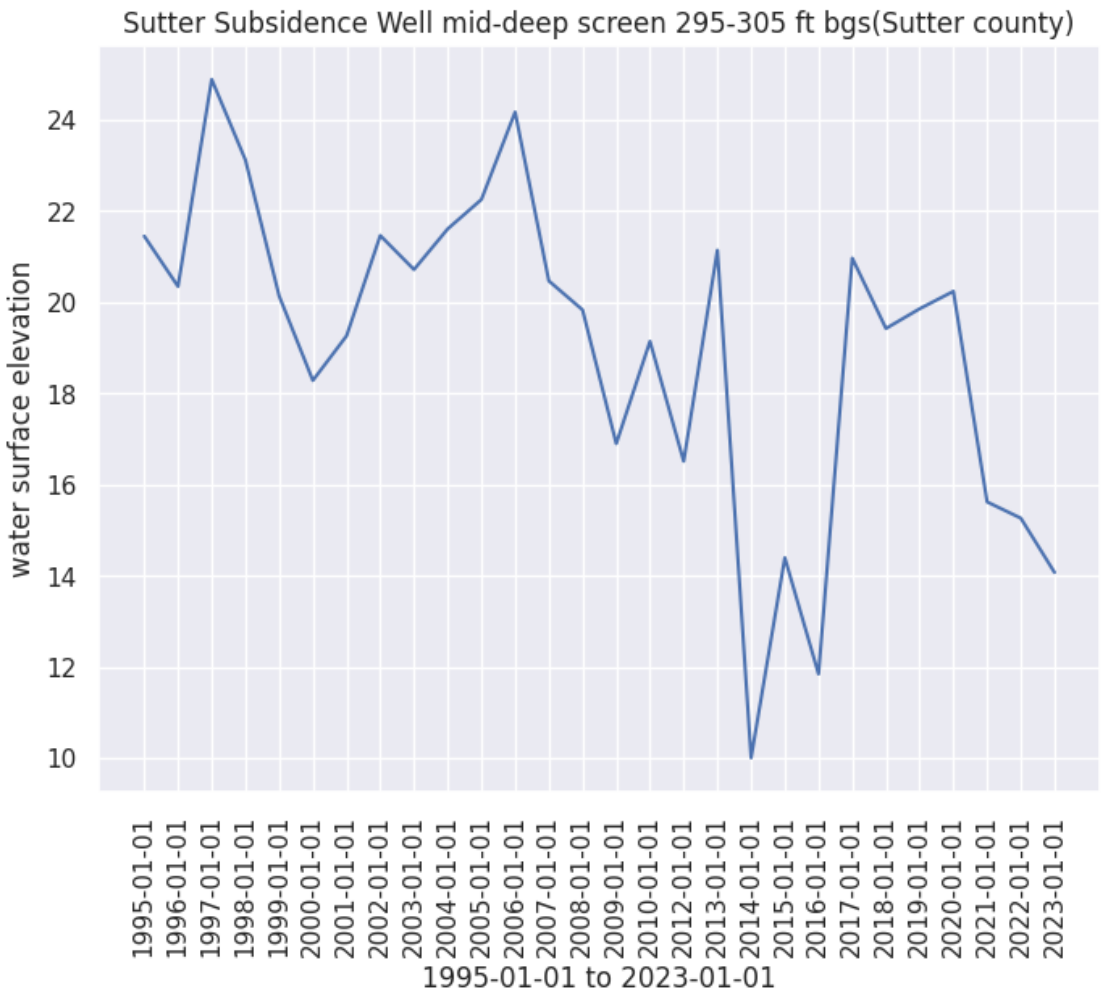
2007-01-01
2008-01-01
2009-01-01
2010-01-01
2011-01-01
2012-01-01
2013-01-01
2014-01-01
2015-01-01
2016-01-01
2017-01-01
2018-01-01
2019-01-01
2020-01-01
2021-01-01
1993-01-01 to 2021-01-01


Conaway Subsidence Well mid-deep screen 240-280 ft bgs(Yolo county)
water surface elevation
20
18
16
14
12
10
8
1993-01-01
1994-01-01
1995-01-01
1996-01-01
1997-01-01
1998-01-01
1999-01-01
2000-01-01
2001-01-01
2002-01-01
2003-01-01
2004-01-01
2005-01-01
2006-01-01
2007-01-01
2009-01-01
2010-01-01
2011-01-01
2012-01-01
2013-01-01
2014-01-01
2015-01-01
2016-01-01
2017-01-01
2018-01-01
2019-01-01
2020-01-01
2021-01-01
2022-01-01
1993-01-01 to 2022-01-01


Sutter Subsidence Well mid-shall screen 185-195 ft bgs(Sutter county)
water surface elevation
28
26
24
22
20
18
16
14
1995-01-01
1996-01-01
1997-01-01
1998-01-01
1999-01-01
2000-01-01
2001-01-01
2002-01-01
2003-01-01
2004-01-01
2005-01-01
2006-01-01
2007-01-01
2008-01-01
2009-01-01
2010-01-01
2011-01-01
2012-01-01
2013-01-01
2014-01-01
2016-01-01
2017-01-01
2018-01-01
2019-01-01
2020-01-01
2021-01-01
2022-01-01
2023-01-01
1995-01-01 to 2023-01-01



1.7 Preliminary work on machine learning to make predictions

We are going to use the `jan_meas` variable to perform the predictions

1.7.1 Convert MSMT_Date to Timestamp

[68]:
```
jan_meas = get_mst_by_month(df, '01').copy()

jan_meas['MSMT_TIMESTAMP'] = pd.to_datetime(jan_meas['MSMT_DATE'],␣
↪format='%Y-%m-%d').astype(int)
jan_meas['STATION_IDX'] = jan_meas.apply(lambda x: stations[stations['STATION']␣
↪== x['STATION']].index[0] if len(stations[stations['STATION'] ==␣
↪x['STATION']].index) > 0 else None, axis=1)
```

[69]:
```
jan_meas.describe()
```

[69]:
```
           WLM_RPE   WLM_RPE_QC      WLM_GSE   WLM_GSE_QC      RPE_WSE  \
count  5560.000000  5560.000000  5560.000000  5560.000000  5560.000000
mean    337.260949     8.685791   335.403631     8.280396    32.601100
std     977.666585    24.343446   977.565067    24.052238    31.216816
min      -0.570000     1.000000    -3.170000     1.000000   -11.806000
25%      38.830000     1.000000    37.081000     1.000000    11.662250
50%     122.680000     1.000000   119.880000     1.000000    22.940500
75%     205.890000     1.000000   204.420000     1.000000    42.104000
max    5495.260000   130.000000  5492.010000   130.000000   241.365000

        RPE_WSE_QC      GSE_WSE  GSE_WSE_QC          WSE       WSE_QC  \
count  5560.000000  5560.000000  5560.00000  5560.000000  5560.000000
mean      1.722302    30.743781     9.25018   304.659853     9.221403
std       7.185703    31.291370    25.00618   979.378738    25.009904
min       1.000000   -14.606000     1.00000   -98.033000     1.000000
25%       1.000000    10.036250     1.00000    24.030500     1.000000
50%       1.000000    20.922500     1.00000    99.537000     1.000000
75%       1.000000    40.266000     1.00000   155.448750     1.000000
max     120.000000   238.745000   130.00000  5491.813000   130.000000

       MSMT_TIMESTAMP  STATION_IDX
count    5.560000e+03  5560.000000
mean     1.374386e+18   266.152158
std      1.942721e+17   145.206354
min      0.000000e+00     0.000000
25%      1.262304e+18   142.000000
50%      1.388534e+18   267.000000
75%      1.514765e+18   383.000000
max      1.672531e+18   566.000000
```

[70]:
```
# for repeatability
np.random.seed(42)

predictors = ['MSMT_TIMESTAMP', 'STATION_IDX']
target = 'WSE'

X = jan_meas[predictors].values
y = jan_meas[target].values

# Split the data into training and test sets, and scale
scaler = StandardScaler()

# unscaled version (note that scaling is only used on predictor variables)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,␣
 ↪random_state=42)
```

[71]:
```
X_train.shape
```

[71]: (3892, 2)

[72]:
```
X_train[:3]
```

[72]:
```
array([[1546300800000000000,                 145],
       [1293840000000000000,                 424],
       [1514764800000000000,                 495]])
```

[73]:
```
def rmse(predicted, actual):
    return np.sqrt(((predicted - actual)**2).mean())
```

[74]:
```
reg = KNeighborsRegressor(algorithm='brute')
reg.fit(X_train, y_train)
predict = reg.predict(X_test)
RMSE = rmse(predict, y_test)
print('test RMSE, default hyperparameters: ', RMSE)
```

```
test RMSE, default hyperparameters:  1067.4543175586887
```

[75]:
```
def get_train_test_rmse(regr, X_train, X_test, y_train, y_test):
    regr.fit(X_train, y_train)
    predict = regr.predict(X_test)
    rmse_te = rmse(predict, y_test)

    regr.fit(X_train, y_train)
    predict = regr.predict(X_train)
    rmse_tr = rmse(predict, y_train)
    return rmse_tr, rmse_te
```

[76]:
```
n = 30
test_rmse = []
train_rmse = []
ks = np.arange(1, n+1, 2)
for k in ks:
    print(k, ' ', end='')
    regr = KNeighborsRegressor(n_neighbors=k, algorithm='brute')
    rmse_tr, rmse_te = get_train_test_rmse(regr, X_train, X_test, y_train,␣
 ↪y_test)
    train_rmse.append(rmse_tr)
    test_rmse.append(rmse_te)
print('done')
```

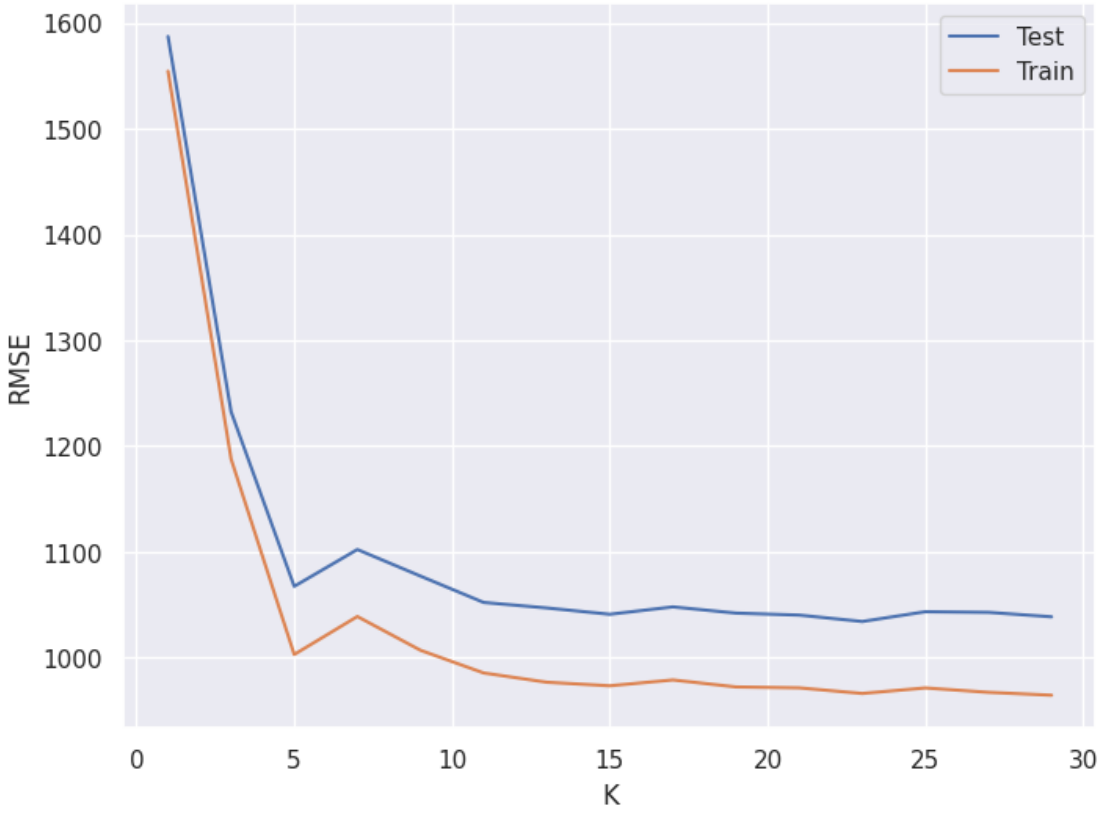
```
1  3  5  7  9  11  13  15  17  19  21  23  25  27  29  done
```

[77]:
```
def get_best(ks, rmse):
    min_k = 1
    min = np.array(rmse)[0]
```

```
    for idx in range(len(ks)):
        if np.array(rmse)[idx] < min:
            min_k = ks[idx]
            min = np.array(rmse)[idx]
    return min_k, min

best_k, best_rmse = get_best(ks, test_rmse)
print('best k = {}, best test RMSE: {:0.1f}'.format(best_k, best_rmse))
```

```
best k = 23, best test RMSE: 1034.2
```

[78]:
```
plt.plot(ks, test_rmse, label='Test')
plt.plot(ks, train_rmse, label='Train')
plt.xlabel('K')
plt.ylabel('RMSE')
plt.legend()
plt.show()
```



1.8 Comments

So far the training data does not look quite right. Could be from the cyclic data or that the index/timestamp predictors do not fit this model well. It could also be because the data is somewhat erratic.

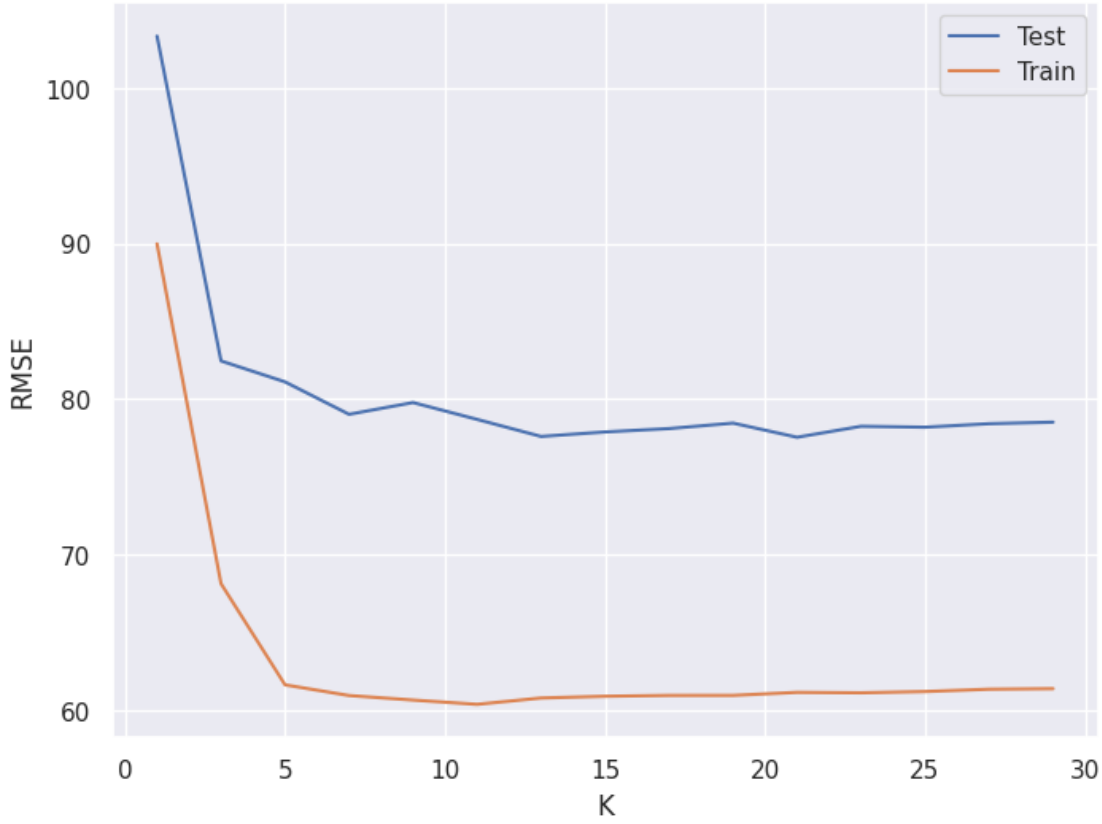
1.9 Testing Unscaled vs Scaled

1.9.1 Unscaled knn regressor

[79]:
```
jan_meas = get_mst_by_month(df, '01').copy()
jan_meas = jan_meas[jan_meas['STATION'].map(jan_meas['STATION'].value_counts())␣
 ↪> 20]
jan_meas['MSMT_TIMESTAMP'] = pd.to_datetime(jan_meas['MSMT_DATE'],␣
 ↪format='%Y-%m-%d').astype(int)
jan_meas['STATION_IDX'] = jan_meas.apply(lambda x: stations[stations['STATION']␣
 ↪== x['STATION']].index[0] if len(stations[stations['STATION'] ==␣
 ↪x['STATION']].index) > 0 else None, axis=1)

predictors = ['MSMT_TIMESTAMP', 'STATION_IDX']
target = 'WSE'

X = jan_meas[predictors].values
y = jan_meas[target].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,␣
 ↪random_state=42)

n = 30
test_rmse = []
train_rmse = []
ks = np.arange(1, n+1, 2)
for k in ks:
    print(k, ' ', end='')
    regr = KNeighborsRegressor(n_neighbors=k, algorithm='brute')
    rmse_tr, rmse_te = get_train_test_rmse(regr, X_train, X_test, y_train,␣
 ↪y_test)
    train_rmse.append(rmse_tr)
    test_rmse.append(rmse_te)
print('done')
best_k, best_rmse = get_best(ks, test_rmse)
print('best k = {}, best test RMSE: {:0.1f}'.format(best_k, best_rmse))

plt.plot(ks, test_rmse, label='Test')
plt.plot(ks, train_rmse, label='Train')
plt.xlabel('K')
plt.ylabel('RMSE')
plt.legend()
```

```
plt.show()
```

```
1  3  5  7  9  11  13  15  17  19  21  23  25  27  29  done
best k = 21, best test RMSE: 77.5
```



1.9.2 Scaled knn regressor

[80]:
```
jan_meas = get_mst_by_month(df, '01').copy()
# jan_meas = df.copy()
jan_meas = jan_meas[jan_meas['STATION'].map(jan_meas['STATION'].value_counts())␣
 ↪> 20]
jan_meas = jan_meas[jan_meas['WSE_QC'] == 1]

print(jan_meas.value_counts('WSE_QC'))

jan_meas['MSMT_TIMESTAMP'] = pd.to_datetime(jan_meas['MSMT_DATE'],␣
 ↪format='%Y-%m-%d').astype(int)
jan_meas['STATION_IDX'] = jan_meas.apply(lambda x: stations[stations['STATION']␣
 ↪== x['STATION']].index[0] if len(stations[stations['STATION'] ==␣
 ↪x['STATION']].index) > 0 else None, axis=1)
```

```
predictors = ['MSMT_TIMESTAMP', 'STATION_IDX']
target = 'WSE'

X = jan_meas[predictors].values
y = jan_meas[target].values

scaler = StandardScaler()

X_train_raw, X_test_raw, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪30, random_state=42)

X_train = scaler.fit_transform(X_train_raw)
X_test = scaler.transform(X_test_raw)

n = 30
test_rmse = []
train_rmse = []
ks = np.arange(1, n+1, 2)
for k in ks:
    print(k, ' ', end='')
    regr = KNeighborsRegressor(n_neighbors=k, algorithm='brute')
    rmse_tr, rmse_te = get_train_test_rmse(regr, X_train, X_test, y_train,␣
 ↪y_test)
    train_rmse.append(rmse_tr)
    test_rmse.append(rmse_te)
print('done')
best_k, best_rmse = get_best(ks, test_rmse)
print('best k = {}, best test RMSE: {:0.1f}'.format(best_k, best_rmse))

plt.plot(ks, test_rmse, label='Test')
plt.plot(ks, train_rmse, label='Train')
plt.xlabel('K')
plt.ylabel('RMSE')
plt.legend()
plt.show()
```

```
WSE_QC
1    81
dtype: int64
1  3  5  7  9  11  13  15  17  19  21  23  25  27  29  done
best k = 9, best test RMSE: 6.5
```


Test
Train
RMSE
K
0
5
10
15
20
25
30