Data

Metadata and Data Considerations

Data is from the National Water and Climate Center (NWCC)

Data is csv format by state. For `AZ` , `CA` , CO, NM, NV, UT, WY Data needs to be cleaned such that it only includes data for the Colorado River Basin. Data contains many metrics. PCA may be necessary to reduce dimensionality of the dataset.

Default format = Date | Station | Metric 1 | Metric 2 | ... | Metric n

Data split into multiple files per state as a result of the data acquisition process. Master dataset should include all data for the Colorado River Basin.
File schema as follows:

Snow_*.csv

- Station Name
- Station ID
- Snow Water Equivalent
- Elevation
- Latitude
- Longitude

Data may differ significantly over the period of record because of the effects of climate change in the region. We will attempt to use all period of record, but failing that, we will truncate the data. Data earlier than 2010 is likely not needed for predictions in following years and is likely too enstranged from current weather regimes to be useful and may instead present more error.

Target parameter is `Tot_water`, which is an engineered binary or trinary parameter that will use predicted the amount of water available to the water system after withdrawals. In the case of the binary target a `0` represents water below operating depth and a `1` represents water above operating depth. In the case of the trinary target a `0` represents a number below the dead-pool threshhold, a `1` represents non-operable water with flow-through potential, and a `2` represents water at operable depths.

According to research, targeting SWE directly is more effective than targeting snow depth. We will attempt to include meteorological data as well as soil temperature measurements and elevation.

Because we are comparing with water withdrawals and water stores, reservoir data is required to compare snowpack data to determine whether water is sufficient. Water data is taken from NWCC's RESERVOIR dataset that includes reservoir stages and storage volumes.

Water_*.csv

- Station Name
- Station ID
- Reservoir Storage Volume (dam^3) Start of Day Values
- Elevation
- Latitude
- Longitude

Notes and Caveates

Snow and water data was clipped geographically using a Colorado River Basin shapefile and ESRI ArcGIS Pro on WGS 1984 Mercator Auxiliary Sphere projection.

CA Water and Snow data lies outside the basin boundary and will be excluded from the analysis. We will do some more research into the water resource draw CA puts on the basin system to include at the end.

Some NV snow data lies within the basin boundary. NV Water reservoirs lie outside the basin boundary. Water resource draw by NV will have to be assessed similarly to CA.

System setup and Information

In [1]:

```
# Import general libraries
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
import numpy as np
from sklearn.pipeline import Pipeline
from src.functs import dicky_fuller_test, fix_na, del_unnamed, format_water_data
```

Import Data from File, Explore and Format

Here we will Import and Format the data from file and perform some cursory analysis of the original data.

In [2]:
```python
# Importing snow files into dataframes
snow_states = ['AZ', 'CO', 'NM', 'NV', 'UT', 'WY']
raw_snow = {}

for i in snow_states:
    raw_snow[i] = pd.read_csv(f'../00_Source_Data/Snowpack/{i}/Snow_{i}_Clip.csv'


# Importing water storage files into dataframes
water_states = ['AZ', 'CO', 'NM', 'UT', 'WY']
raw_water = {}

for i in water_states:
    raw_water[i] = pd.read_csv(f'../00_Source_Data/Snowpack/{i}/Water_{i}_Clip.cs
```

In [3]:
```python
raw_snow['AZ'].head()
```

Out[3]:

	Date	Station Name	Station Id	Snow Water Equivalent (mm) Start of Day Values	Snow Depth (cm) Start of Day Values	Snow Density (pct) Start of Day Values	Precipitation Accumulation (mm) Start of Day Values	Snow Rain Ratio (unitless)	Air Temperature Average (degC)	W Sp Aver (kn
0	1978-09-30	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	0.0	
1	1978-10-01	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	0.0	
2	1978-10-02	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	0.0	
3	1978-10-03	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	0.0	
4	1978-10-04	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	0.0	

In [4]:
```
# Standardizing column names for snow data.
column_names = {'Station_Name' : 'Station Name',
                'Station_Id' : 'Station ID',
                'Snow_Water_Equivalent__mm__Start_of_Day_Values' : 'SWE',
                'Snow_Depth__cm__Start_of_Day_Values' : 'Snow Depth',
                'Elevation__ft_' : 'Elevation',
                'Station Id' : 'Station ID',
                'Snow Water Equivalent (mm) Start of Day Values' : 'SWE',
                'Snow Depth (cm) Start of Day Values' : 'Snow Depth',
                'Snow Density (pct) Start of Day Values' : 'Snow Density',
                'Precipitation Accumulation (mm) Start of Day Values' : 'Precip Ac
                'Snow Rain Ratio (unitless)' : 'Snow / Rain',
                'Air Temperature Average (degC)' : 'Average Air Temperature',
                'Wind Speed Average (km/hr)' : 'Average Wind Speed',
                'Elevation (ft)' : 'Elevation'}

for i in snow_states:
    raw_snow[i] = raw_snow[i].rename(columns=column_names)

# Standardizing column names for water storage data.
wa_column_names = {'Station_Name' : 'Station Name',
                   'Station_Id' : 'Station ID',
                   'Station Id' : 'Station ID',
                   'Reservoir Storage Volume (dam^3) Start of Day Values' : 'Wate
                   'Reservoir_Storage_Volume__dam_3__Start_of_Day_Values' : 'Wate
                   'Elevation (ft)' : 'Elevation',
                   'Elevation__ft_' : 'Elevation'}

for i in water_states:
    raw_water[i] = raw_water[i].rename(columns=wa_column_names)
```

In [5]:
```
# Combine the dataframes into one dataframe for snow data.
snow_data = pd.concat(raw_snow, axis=0)
water_data = pd.concat(raw_water, axis=0)
```

In [6]:
```
water_data
```

Out[6]:

		Date	Station Name	Station ID	Water Storage	Elevation	Latitude	Longitude	OID_
AZ	0	1964-12-21	Cragin Dam Reservoir	9398300.0	0.0	6620.0	34.55528	-111.18333	NaN
	1	1964-12-22	Cragin Dam Reservoir	9398300.0	NaN	6620.0	34.55528	-111.18333	NaN
	2	1964-12-23	Cragin Dam Reservoir	9398300.0	NaN	6620.0	34.55528	-111.18333	NaN
	3	1964-12-24	Cragin Dam Reservoir	9398300.0	NaN	6620.0	34.55528	-111.18333	NaN
	4	1964-12-25	Cragin Dam Reservoir	9398300.0	NaN	6620.0	34.55528	-111.18333	NaN
...	...	...	...	...	...	...	...	...	...
WY	59795	2022-03-29	Meeks Cabin Reservoir	9218400.0	15393.0	8673.0	41.02583	-110.58067	NaN
	59796	2022-03-30	Meeks Cabin Reservoir	9218400.0	15470.0	8673.0	41.02583	-110.58067	NaN
	59797	2022-03-31	Meeks Cabin Reservoir	9218400.0	15556.0	8673.0	41.02583	-110.58067	NaN
	59798	2022-04-01	Meeks Cabin Reservoir	9218400.0	15642.0	8673.0	41.02583	-110.58067	NaN
	59799	2022-04-02	Meeks Cabin Reservoir	9218400.0	15706.0	8673.0	41.02583	-110.58067	NaN

1010474 rows × 8 columns

In [7]:
```
# Column Selection for master snow dataset
junk_columns = ['Station ID', 'Snow Density', 'Precip Accumulation', 'Snow / Rair
                'Average Wind Speed', 'Elevation', 'Latitude', 'Longitude', 'OID_

snow_data.drop(columns=junk_columns, inplace=True)

# Column Selection for master water storage dataset
water_data.drop(columns=['Station ID', 'Elevation', 'Latitude', 'Longitude', 'OID
```

In [8]:
```
# Date time formatting
snow_data.index = pd.to_datetime(snow_data['Date'], infer_datetime_format=True)
snow_data.drop(columns='Date', inplace=True)

water_data.index = pd.to_datetime(water_data['Date'], infer_datetime_format=True)
water_data.drop(columns='Date', inplace=True)
```

In [10]:
```
snow_data
```

Out[10]:

Date	Station Name	SWE	Snow Depth
1978-09-30	Baker Butte	NaN	NaN
1978-10-01	Baker Butte	NaN	NaN
1978-10-02	Baker Butte	NaN	NaN
1978-10-03	Baker Butte	NaN	NaN
1978-10-04	Baker Butte	NaN	NaN
...	...	...	...
2022-03-31	Whiskey Park	569.0	155.0
2022-04-01	Whiskey Park	569.0	152.0
2022-04-02	Whiskey Park	574.0	150.0
2022-04-03	Whiskey Park	572.0	147.0
2022-04-04	Whiskey Park	582.0	147.0

1963530 rows × 3 columns

In [19]:
```
print(f"Number of Stations in snow data: {len(pd.unique(snow_data['Station Name']
```

```
Number of Stations in snow data: 172
```

We will backfill and interpolate to fix `NaN` values, then aggregate by date to create values for the entire basin.

In [14]:
```
water_data
```

Out[14]:

Date	Station Name	Water Storage
1964-12-21	Cragin Dam Reservoir	0.0
1964-12-22	Cragin Dam Reservoir	NaN
1964-12-23	Cragin Dam Reservoir	NaN
1964-12-24	Cragin Dam Reservoir	NaN
1964-12-25	Cragin Dam Reservoir	NaN
...	...	...
2022-03-29	Meeks Cabin Reservoir	15393.0
2022-03-30	Meeks Cabin Reservoir	15470.0
2022-03-31	Meeks Cabin Reservoir	15556.0
2022-04-01	Meeks Cabin Reservoir	15642.0
2022-04-02	Meeks Cabin Reservoir	15706.0

In [20]:
```
print(f"Number of Stations in water data: {len(pd.unique(water_data['Station Name
```

```
Number of Stations in water data: 55
```

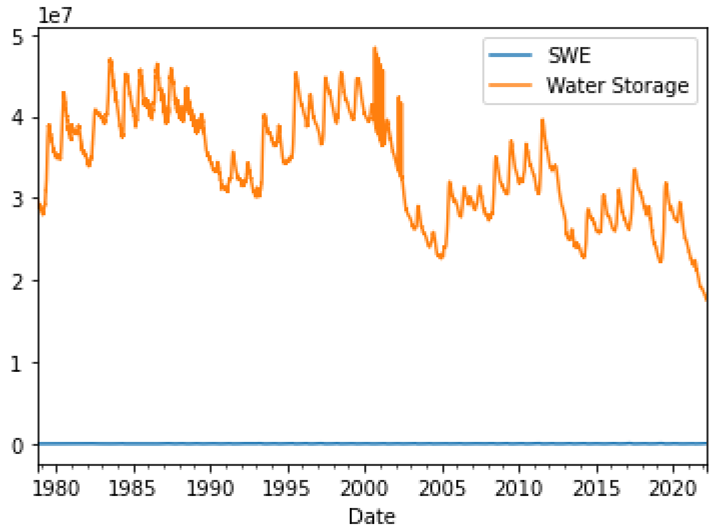
Imputing and aggregating:

In [18]:
```
fill_snow = fix_na(snow_data)
fill_water = fix_na(water_data)

ag_snow = snow_data.groupby(fill_snow.index).aggregate({'SWE' : 'median'})
ag_water = water_data.groupby(fill_water.index).aggregate({'Water Storage' : 'sum
```

In [15]:
```
masterdata = ag_snow.join(ag_water, how='left', on=ag_snow.index)
masterdata = fix_na(masterdata)
```

In [16]:
```
masterdata.plot()
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f957e833e50>



Without interpolating SWE over the areas between stations where snow accumulates, the values of SWE don't match or compare with the changes in water storage. Thus we may look at water storage and water withdrawals directly.

In [17]:
```
# Bringing in water withdrawal data

aquaculture_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CR
commercial_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRE
hydropower_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRE
irrigation_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRE
livestock_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRB_
mining_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRB_HUC
public_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRB_HUC
ss_domestic_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CR
ss_industrial_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/
thermoelectric_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage
wastewater_withdrawals = pd.read_csv(f'../00_Source_Data/Snowpack/Water Usage/CRE
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2882: D
typeWarning: Columns (3,7) have mixed types.Specify dtype option on import or s
et low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

In [19]:
```
# Remove all artifact columns from all withdrawal datasets

aquaculture_withdrawals = del_unnamed(aquaculture_withdrawals)
commercial_withdrawals = del_unnamed(commercial_withdrawals)
hydropower_withdrawals = del_unnamed(hydropower_withdrawals)
irrigation_withdrawals = del_unnamed(irrigation_withdrawals)
livestock_withdrawals = del_unnamed(livestock_withdrawals)
mining_withdrawals = del_unnamed(mining_withdrawals)
public_withdrawals = del_unnamed(public_withdrawals)
ss_domestic_withdrawals = del_unnamed(ss_domestic_withdrawals)
ss_industrial_withdrawals = del_unnamed(ss_industrial_withdrawals)
thermoelectric_withdrawals = del_unnamed(thermoelectric_withdrawals)
wastewater_withdrawals = del_unnamed(wastewater_withdrawals)
```

Each dataset has differing columns but the premise of how to put it all together is relatively simple. The total amount of consumed water is subtracted from total water storage. Water reclaimed is added to water storage. Each time period is treated as independant from the previous as the resulting storage is actual and thus should already include the values in the withdrawals data sets.

Most dams have a minimum water level they maintain, so we will reduce the total storage per time figure by an amount equal to a percentage of the maximum (estimated by maximum in our dataset) to account for minimum operating depths in reservoirs and hydroelectric dams.

In [20]:
```
# doing some quick math because facts are in different scales.
# Depth is in feet.

total_water_depth = 710
min_operating = 3490
dead_pool = 3370
lake_elevation = 3700

per_to_dead = (lake_elevation - dead_pool)/total_water_depth
per_to_non_op = (lake_elevation - min_operating)/total_water_depth

print(f'Glen Canyon Dam has a minimum operating depth of {round(per_to_non_op*10
print(f'Glen Canyon Dam has a minimum flow-through depth of {round(per_to_dead*1
```

```
Glen Canyon Dam has a minimum operating depth of 30% of the full depth.
Glen Canyon Dam has a minimum flow-through depth of 46% of the full depth. Also
called the "dead pool" depth.
```

We will use Glen Canyon as our model dam, as it is difficult to find information on the dead pool and minimum operating depths of most other dams and reservoirs on the Colorado.

Thus, we can generalize that all water storage cannot drop below 46% percent of the maximum idealy. Dropping below 30% of the maximum storage is dire.

Formatting procedures

- Index to year as datetime.
- groupby date and aggregate total consumptive water withdrawal and total water reclaimed

Columns of interest by dataframe (units in TAF unless stated otherwise):

- Aquaculture: `'AQ-WTotl'` total fresh and saline withdrawals
- Commercial: `'CO-WFrTotl'` total water usage fresh
- Hydro power: `'HY-ToUse'` total instream and offstream water withdrawals defined by producer

```
  - Not differentiated between consumed and reclaimed.
  - Assuming all hydro power 'withdrawals' are flowthrough and not c
onsumptive
```

- Irrigation: `'IR-WFrTo'` total fresh water withdrawls

```
  - Not differentiated between consumptive, conveyance losses, and e
vap.
```

- Livestock: `'LS-WTotl'` total fresh water withdrawals

```
  - Saline withdrawals not included.
```

- Mining: `'MI-WTotl'` total fresh and saline withdrawals
- Public: `'PS-WTotl'` total fresh and saline withdrawals

```
  - Public water totals appear to be delivered and included in other
categories.
```

- SS Domestic: `'DO-WTotl'` total self-supplied withdrawals
- SS Industrial: `'IN-WTotl'` total self-supplied fresh and saline withdrawals
- Thermoelectric: `'PT-CUTot'` total fresh and saline consumptive use
- Wastewater: `'WW-PuRet'` total return flow

```
aquaculture_withdrawals.index = pd.to_datetime(aquaculture_withdrawals['YEAR'],
format='%Y', infer_datetime_format=True)
```

In [22]:
```
# format water withdrawal data
aq_totls = format_water_data(aquaculture_withdrawals, 'AQ-WTotl')
com_totls = format_water_data(commercial_withdrawals, 'CO-WFrTotl')
hydro_totls = format_water_data(hydropower_withdrawals, 'HY-ToUse')
irr_totls = format_water_data(irrigation_withdrawals, 'IR-WFrTo')
ls_totls = format_water_data(livestock_withdrawals, 'LS-WTotl')
mi_totls = format_water_data(mining_withdrawals, 'MI-WTotl')
pub_totls = format_water_data(public_withdrawals, 'PS-WTotl')
ss_dom_totls = format_water_data(ss_domestic_withdrawals, 'DO-WTotl')
ss_ind_totls = format_water_data(ss_industrial_withdrawals, 'IN-WTotl')
te_totls = format_water_data(thermoelectric_withdrawals, 'PT-CUTot')
ww_totls = format_water_data(wastewater_withdrawals, 'WW-PuRet')
```

In [23]:
```
water_withdrawals = aq_totls.join([com_totls, hydro_totls, irr_totls, ls_totls, m
                                   pub_totls, ss_dom_totls, ss_ind_totls, te_totl
```

In [24]:
```
water_withdrawals
```

Out[24]:

YEAR	AQ-WTotl	CO-WFrTotl	HY-ToUse	IR-WFrTo	LS-WTotl	MI-WTotl	PS-WTotl	DO-WTotl	IN-WTotl	PT-CUTot	WW-PuRet
2000-01-01	154.62	22.29	52485.04	14975.81	45.54	231.62	1910.20	66.68	33.00	235.90	1786.04
2005-01-01	142.15	26.94	43617.69	14818.85	41.35	183.30	1988.93	75.60	31.35	332.57	1699.78
2010-01-01	151.35	30.49	46076.89	13648.80	43.77	176.37	2096.00	69.44	31.67	328.20	1753.24

In [25]:
```
# turn withdrawals into negative numbers and returns into positive numbers.

if water_withdrawals['AQ-WTotl'][0] > 0:
    for i in water_withdrawals.columns:
        water_withdrawals[i] = water_withdrawals[i]*-1

if water_withdrawals['WW-PuRet'][0] < 0:
    water_withdrawals['WW-PuRet'] = water_withdrawals['WW-PuRet']*-1
```

In [26]:
```
water_withdrawals
```

Out[26]:

YEAR	AQ-WTotl	CO-WFrTotl	HY-ToUse	IR-WFrTo	LS-WTotl	MI-WTotl	PS-WTotl	DO-WTotl	IN-WTotl	PT-CUTot	P
2000-01-01	-154.62	-22.29	-52485.04	-14975.81	-45.54	-231.62	-1910.20	-66.68	-33.00	-235.90	178
2005-01-01	-142.15	-26.94	-43617.69	-14818.85	-41.35	-183.30	-1988.93	-75.60	-31.35	-332.57	169
2010-01-01	-151.35	-30.49	-46076.89	-13648.80	-43.77	-176.37	-2096.00	-69.44	-31.67	-328.20	175

```
                                         water_withdrawals['HY-ToUse'] + \
                                         water_withdrawals['PS-WTotl'] + \
```

In [27]:
```
water_withdrawals['Total Withdrawals'] = water_withdrawals['AQ-WTotl'] + \
                                         water_withdrawals['CO-WFrTotl'] + \
                                         water_withdrawals['IR-WFrTo'] + \
                                         water_withdrawals['LS-WTotl'] + \
                                         water_withdrawals['MI-WTotl'] + \
                                         water_withdrawals['DO-WTotl'] + \
                                         water_withdrawals['IN-WTotl'] + \
                                         water_withdrawals['PT-CUTot'] + \
                                         water_withdrawals['WW-PuRet']
```

In [28]:
```
water_withdrawals
```

Out[28]:

	AQ-WTotl	CO-WFrTotl	HY-ToUse	IR-WFrTo	LS-WTotl	MI-WTotl	PS-WTotl	DO-WTotl	IN-WTotl	PT-CUTot	P
YEAR											
2000-01-01	-154.62	-22.29	-52485.04	-14975.81	-45.54	-231.62	-1910.20	-66.68	-33.00	-235.90	178
2005-01-01	-142.15	-26.94	-43617.69	-14818.85	-41.35	-183.30	-1988.93	-75.60	-31.35	-332.57	169
2010-01-01	-151.35	-30.49	-46076.89	-13648.80	-43.77	-176.37	-2096.00	-69.44	-31.67	-328.20	175

Addressing differences in units

The master dataset has water in dam^3 and our water withdrawals are in TAFs.

So, we will convert our withdrawals to dam^3.

$$\frac{1233.48\text{dam}^3}{1000\text{acre-feet}}$$

so simply multiply the rows by 1233.48

In [29]:
```
for i in water_withdrawals.columns:
        water_withdrawals[i] = water_withdrawals[i]*1233.48
```

Now all measurements of water are in cubic decameters (dam^3)

Resampling and visualizing

In [30]:
```
graphing = masterdata.join(water_withdrawals.drop(columns=['HY-ToUse', 'PS-WTotl'
```

In [31]:
```
graphing = graphing.fillna(value=None, method='backfill', axis=None, limit=None,
graphing = graphing.fillna(value=None, method='ffill', axis=None, limit=None, dow
```

In [32]:
```
graphing
```

Out[32]:

	SWE	Water Storage	AQ-WTotl	CO-WFrTotl	IR-WFrTo	LS-WTotl	MI-WTotl	
Date								
1978-09-30	0.0	29913012.0	-190720.6776	-27494.2692	-1.847236e+07	-56172.6792	-285698.6376	-8
1978-10-01	2354.0	29894823.0	-190720.6776	-27494.2692	-1.847236e+07	-56172.6792	-285698.6376	-8
1978-10-02	0.0	29800335.0	-190720.6776	-27494.2692	-1.847236e+07	-56172.6792	-285698.6376	-8
1978-10-03	0.0	29826110.0	-190720.6776	-27494.2692	-1.847236e+07	-56172.6792	-285698.6376	-8
1978-10-04	0.0	29754881.0	-190720.6776	-27494.2692	-1.847236e+07	-56172.6792	-285698.6376	-8
...	...	...	...	...	...	...	...	
2022-03-31	45372.0	17685824.0	-186687.1980	-37608.8052	-1.683552e+07	-53989.4196	-217548.8676	-8
2022-04-01	45536.0	17639916.0	-186687.1980	-37608.8052	-1.683552e+07	-53989.4196	-217548.8676	-8
2022-04-02	44888.0	17641640.0	-186687.1980	-37608.8052	-1.683552e+07	-53989.4196	-217548.8676	-8
2022-04-03	44031.0	17641640.0	-186687.1980	-37608.8052	-1.683552e+07	-53989.4196	-217548.8676	-8
2022-04-04	42545.0	17641640.0	-186687.1980	-37608.8052	-1.683552e+07	-53989.4196	-217548.8676	-8

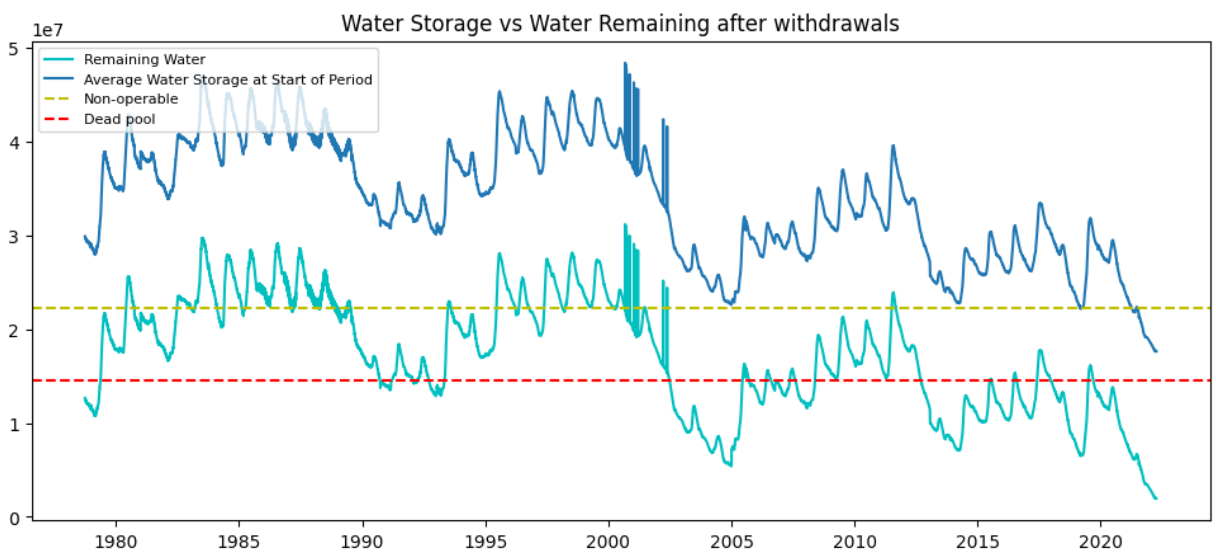
15893 rows × 12 columns

In [33]:
```
graphing['Remaining Water'] = graphing['Water Storage'] + graphing['Total Withdra
```

In [34]:
```
graphing['Remaining Water']
```

Out[34]:
```
Date
1978-09-30    1.266968e+07
1978-10-01    1.265149e+07
1978-10-02    1.255700e+07
1978-10-03    1.258278e+07
1978-10-04    1.251155e+07
                  ...
2022-03-31    1.987509e+06
2022-04-01    1.941601e+06
2022-04-02    1.943325e+06
2022-04-03    1.943325e+06
2022-04-04    1.943325e+06
Freq: D, Name: Remaining Water, Length: 15893, dtype: float64
```

In [35]:
```
# Plot
plt.figure(figsize=(12,5), dpi=100)
plt.plot(graphing['Remaining Water'], label='Remaining Water', color = 'c' )
plt.plot(graphing['Water Storage'], label='Average Water Storage at Start of Peri
#plt.plot(graphing['Total Withdrawals'], label='Withdrawals', color='r')
plt.axhline(graphing['Water Storage'].max()*0.46, color='y', linestyle='--', labe
plt.axhline(graphing['Water Storage'].max()*0.30, color='r', linestyle='--', labe
plt.title('Water Storage vs Water Remaining after withdrawals')
plt.legend(loc='upper left', fontsize=8)
plt.show();
```



Creating a target columns

Definitions for Trinary targets

- 0 = Dead pool
- 1 = Non-op for hydroelectric dams
- 2 = Enough water for operation

Definitions for Binary targets

- 0 = Dead pool
- 1 = Enough water for operation

In [36]:
```
nonop = graphing['Water Storage'].max()*0.46
dead = graphing['Water Storage'].max()*0.30

graphing['target_binary'] = np.where(graphing['Remaining Water'] > dead, 1, 0)

graphing['target_trinary'] = np.where(graphing['Remaining Water'] > nonop, 2,
                                      np.where(graphing['Remaining Water'] > deac
```

In [37]:
```
graphing.target_trinary.value_counts()
```

Out[37]:
```
1    6196
0    5732
2    3965
Name: target_trinary, dtype: int64
```

Modeling

Metrics of interest

We are interested in precision because we are discussing water resources

Train-test split

Performing train test split by time.

Train will contain 80% of the oldest data.

Test will contain 20% of the newest data.

This ratio may change for future models if stuff gets weird.

In [38]:
```
# importing relevant libraries
from sklearn.model_selection import train_test_split
```

In [39]:
```
# We will use 20% of the most recent data as a test set
cutoff = round(graphing.shape[0]*0.8)

# splitting train and test
time_train = graphing[:cutoff]
time_test = graphing[cutoff:]

# Second train-test split for logistic regression
# splitting into dataframes with predictors and dataframes with targets
#X = graphing.drop(columns=['Remaining Water', 'target_binary', 'target_trinary',
X = graphing[['Water Storage', 'SWE']]

y = graphing[['target_binary', 'target_trinary']]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, randon
```

In [40]:
```
# scoring function
def score(model, target, predictor):
    mod_type = str(model).split('(')[0]
    print(f'Our {mod_type} model has a precision of: \
      {round(precision_score(target, model.predict(predictor), average = "weighte
```

Dummy Model

In [41]:
```
# Importing dummy model library
from sklearn.dummy import DummyClassifier
from sklearn.metrics import precision_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
```

Binary target

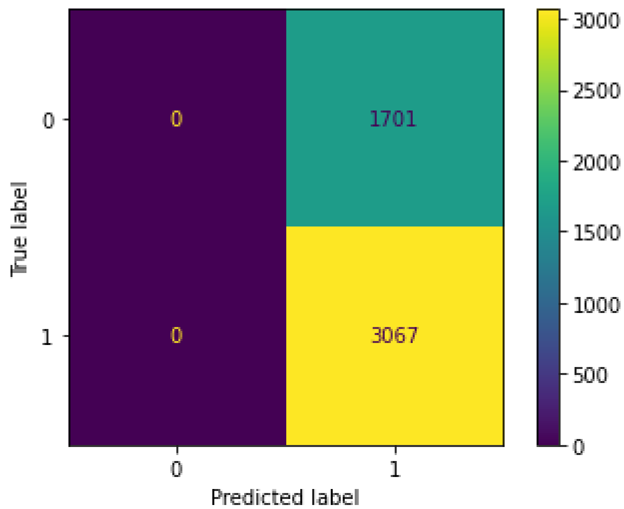
In [42]:
```
# instantiate the dummy model
b_model_0 = DummyClassifier(random_state=42, strategy='most_frequent')

# Fit the model to the training set
b_model_0.fit(X_train, y_train['target_binary'])
```

Out[42]:
```
DummyClassifier(random_state=42, strategy='most_frequent')
```

In [43]:
```
score(b_model_0, y_test['target_binary'], X_test)
```

```
Our DummyClassifier model has a precision of:       41.4%
```

In [44]:
```
ConfusionMatrixDisplay(confusion_matrix(y_test['target_binary'],b_model_0.predict
```
Out[44]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f957ffb599
0>
```



Trinary target

In [45]:
```python
# instantiate the dummy model
t_model_0 = DummyClassifier(random_state=42, strategy='most_frequent')

# Fit the model to the training set
t_model_0.fit(X_train, y_train['target_trinary'])
```
Out[45]:
```
DummyClassifier(random_state=42, strategy='most_frequent')
```

In [46]:
```python
score(t_model_0, y_test['target_trinary'], X_test)
```
```
Our DummyClassifier model has a precision of:       15.6%
```

First Simple Model (FSM)

We will do a simple logistic regression to model the status of water in the Colorado Basin

In [47]:
```python
# importing relevant libraries
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
```

Scaling predictors

In [48]:
```
ss = StandardScaler()

X_tr_scaled = ss.fit_transform(X_train)
X_te_scaled = ss.transform(X_test)
```

Binary Target

In [49]:
```
# instantiate the logistic model
b_model_1 = LogisticRegression(random_state=42, solver='newton-cg')

# Fit the model to the training set
b_model_1.fit(X_tr_scaled, y_train['target_binary'])
```

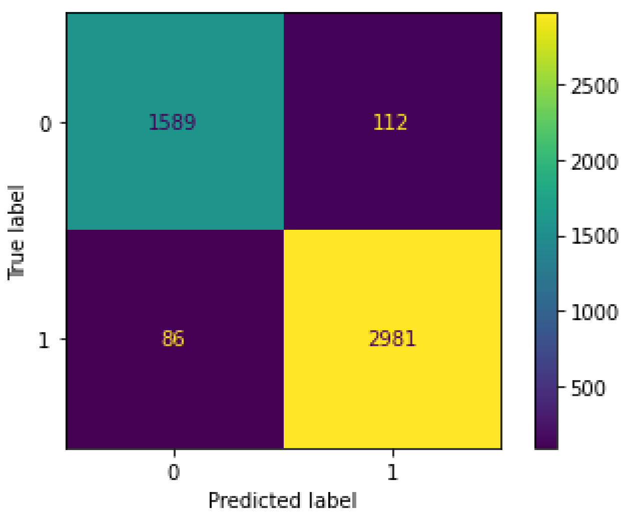
Out[49]:
```
LogisticRegression(random_state=42, solver='newton-cg')
```

In [50]:
```
# Score the model
score(b_model_1, y_test['target_binary'], X_te_scaled)
```

```
Our LogisticRegression model has a precision of:       95.8%
```

In [51]:
```
ConfusionMatrixDisplay(confusion_matrix(y_test['target_binary'],b_model_1.predict
```

Out[51]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f9577488c5
0>
```



Trinary Target

In [52]:
```
# instantiate the logistic model
t_model_1 = LogisticRegression(multi_class='multinomial',
                               solver='newton-cg')

# Fit the model to the training set
t_model_1.fit(X_tr_scaled, y_train['target_trinary'])
```

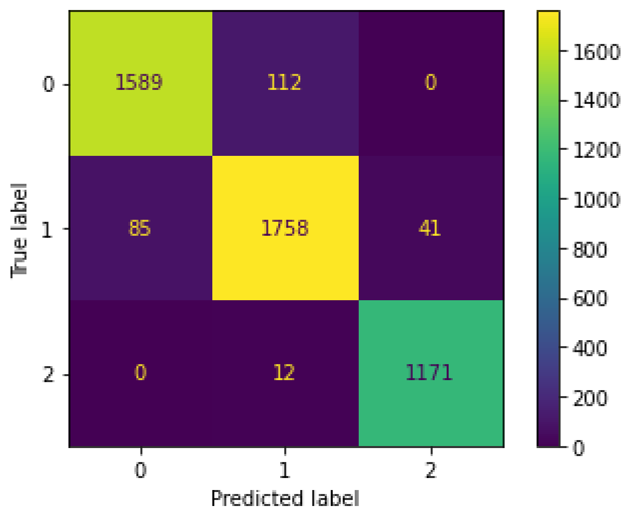
Out[52]:
```
LogisticRegression(multi_class='multinomial', solver='newton-cg')
```

In [53]:
```
# Score the model
print('Train Score:')
score(t_model_1, y_train['target_trinary'], X_tr_scaled)
print('Test Score:')
score(t_model_1, y_test['target_trinary'], X_te_scaled)
```

```
Train Score:
Our LogisticRegression model has a precision of:       94.39999999999999%
Test Score:
Our LogisticRegression model has a precision of:       94.69999999999999%
```

In [54]:
```
ConfusionMatrixDisplay(confusion_matrix(y_test['target_trinary'],t_model_1.predic
```

Out[54]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f957785625
0>
```



While this model seems to do an excellent job with precision, we worry that this model's accuracy may be a result of colinearity. We will perform a grid search with several L1 and L2 penalty values to evaluate what may be best.

Model 2

In [55]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

Given that the scale of our data is largely different, we should standardize the scale of our data for the purpose of this model.

In [57]:
```python
# Create param grid.

pipe = Pipeline([('classifier', RandomForestClassifier())])

param_grid = [
    {'classifier' : [LogisticRegression()],
     'classifier__penalty' : ['l1', 'l2'],
     'classifier__C' : np.logspace(-4, 4, 20),
     'classifier__solver' : ['liblinear']},
    {'classifier' : [KNeighborsClassifier()],
     'classifier__n_neighbors' : list(range(10,20,1)),
     'classifier__n_jobs': [-1]},
    {'classifier' : [RandomForestClassifier()],
     'classifier__n_estimators' : list(range(1,101,20)),
     'classifier__max_depth' : list(range(1, 31, 5))}
]


# Create a gridsearch object

scaled_clf = GridSearchCV(pipe, param_grid = param_grid, cv = 5, verbose=3, n_jot


# Second attempt on scaled data

best_scaled_clf = scaled_clf.fit(X_tr_scaled, y_train['target_trinary'])

print(f'Best parameters: {best_scaled_clf.best_params_}')
```

```
Fitting 5 folds for each of 80 candidates, totalling 400 fits
Best parameters: {'classifier': RandomForestClassifier(max_depth=11, n_estimato
rs=81), 'classifier__max_depth': 11, 'classifier__n_estimators': 81}
```

So, our Random Forest did better than both a logistic regression and a KNN model, with a resulting score of 98.4% with the parameters listed above. Our final model will look like the below such that we are not running tuning algorithms each time.

In [58]:
```python
# run the pipeline scaled without the optimized parameters
pipe.fit(X_tr_scaled, y_train['target_trinary'])

print('Training set score: ' + str(pipe.score(X_tr_scaled,y_train['target_trinary
print('Test set score: ' + str(pipe.score(X_te_scaled,y_test['target_trinary'])))
```

```
Training set score: 1.0
Test set score: 0.9794463087248322
```

In [66]:
```python
best_scaled_clf.best_estimator_
```

Out[66]:
```
Pipeline(steps=[('classifier',
                 RandomForestClassifier(max_depth=11, n_estimators=81))])
```

In [67]:
```
# run the pipeline scaled and with the optimized parameters

pipe = Pipeline([('classifier' , best_scaled_clf.best_estimator_)])

pipe.fit(X_tr_scaled, y_train['target_trinary'])

print('Training set score: ' + str(pipe.score(X_tr_scaled,y_train['target_trinary
print('Test set score: ' + str(pipe.score(X_te_scaled,y_test['target_trinary'])))
```

```
Training set score: 0.9946067415730337
Test set score: 0.9828020134228188
```

Model 3: Adding time series elements

Here we will try a Time Series Forest model from the PyTS library. Our previous models were not time series models and thus excluded the presence of time and the relationship in the data that comes with time. This next model should relate better to the data because the original data is a time series and thus relationships between the data and time not overlooked by the simplicity of the model.

This model was developed specifically for doing classification with time series data. Citation below.

Johann Faouzi and Hicham Janati. pyts: A python package for time series classification. Journal of Machine Learning Research, 21(46):1−6, 2020.

In [68]:
```
# Install PyTS
!pip install pyts
```

```
Requirement already satisfied: pyts in /usr/local/lib/python3.7/dist-packages
(0.12.0)
Requirement already satisfied: scipy>=1.3.0 in /usr/local/lib/python3.7/dist-pa
ckages (from pyts) (1.4.1)
Requirement already satisfied: joblib>=0.12 in /usr/local/lib/python3.7/dist-pa
ckages (from pyts) (1.1.0)
Requirement already satisfied: scikit-learn>=0.22.1 in /usr/local/lib/python3.
7/dist-packages (from pyts) (1.0.2)
Requirement already satisfied: numpy>=1.17.5 in /usr/local/lib/python3.7/dist-p
ackages (from pyts) (1.21.5)
Requirement already satisfied: numba>=0.48.0 in /usr/local/lib/python3.7/dist-p
ackages (from pyts) (0.51.2)
Requirement already satisfied: llvmlite<0.35,>=0.34.0.dev0 in /usr/local/lib/py
thon3.7/dist-packages (from numba>=0.48.0->pyts) (0.34.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-pack
ages (from numba>=0.48.0->pyts) (57.4.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.
7/dist-packages (from scikit-learn>=0.22.1->pyts) (3.1.0)
```

In [70]:
```
# Import the model
from pyts.classification import TimeSeriesForest
```

In [73]:
```
# create a pipeline object for the classification model

time_pipe = Pipeline([('classifier', TimeSeriesForest())])

# Create a param grid for tuning

param_grid = [
              {'classifier' : [TimeSeriesForest()],
               'classifier__n_estimators' : list(range(500, 1000, 100)),
               'classifier__n_windows' : [0.1, 0.5, 1],
               'classifier__max_depth' : [None] + list(range(10, 100, 15)),}
]
```

In [74]:
```
# First attempt without tuning or scaling

time_pipe.fit(X_train, y_train['target_trinary'])

print('Training set score: ' + str(time_pipe.score(X_train,y_train['target_trinar
print('Test set score: ' + str(time_pipe.score(X_test,y_test['target_trinary'])))
```

```
Training set score: 1.0
Test set score: 0.9635067114093959
```

In [75]:
```
# First attempt without tuning but scaled

time_pipe.fit(X_tr_scaled, y_train['target_trinary'])

print('Training set score: ' + str(time_pipe.score(X_tr_scaled,y_train['target_tr
print('Test set score: ' + str(time_pipe.score(X_te_scaled,y_test['target_trinary
```

```
Training set score: 1.0
Test set score: 0.9786073825503355
```

Without any parameters, the timeseriesforest overfits, but still has good score of 95% accuracy and appears to be somewhat overfit. With the scaled data, accuracy rises to 97% but is also overfit.

Lets perform a grid search to optomize some of these parameters.

In [76]:
```
# Create new gridsearch object

scaled_tsf = GridSearchCV(time_pipe, param_grid = param_grid, cv = 5, verbose=3,

# run gridsearch on scaled train data

best_scaled_tsf = scaled_tsf.fit(X_tr_scaled, y_train['target_trinary'])

print(f'Best parameters: {best_scaled_tsf.best_params_}')
```

```
Fitting 5 folds for each of 105 candidates, totalling 525 fits
Best parameters: {'classifier': TimeSeriesForest(max_depth=10, n_estimators=60
0, n_windows=0.5), 'classifier__max_depth': 10, 'classifier__n_estimators': 60
0, 'classifier__n_windows': 0.5}
```

Our final optimized model and an unoptimized comparison are below.

In [77]:
```
# run the pipeline scaled without the optimized parameters
time_pipe.fit(X_tr_scaled, y_train['target_trinary'])

print('Training set score: ' + str(time_pipe.score(X_tr_scaled,y_train['target_tr
print('Test set score: ' + str(time_pipe.score(X_te_scaled,y_test['target_trinary
```

```
Training set score: 1.0
Test set score: 0.9786073825503355
```

In [79]:
```
# run the pipeline scaled and with the optimized parameters

time_pipe_opt = Pipeline([('classifier', best_scaled_tsf.best_estimator_)])

time_pipe_opt.fit(X_tr_scaled, y_train['target_trinary'])

print('Training set score: ' + str(time_pipe_opt.score(X_tr_scaled,y_train['targe
print('Test set score: ' + str(time_pipe_opt.score(X_te_scaled,y_test['target_tri
```

```
Training set score: 0.9760898876404495
Test set score: 0.9651845637583892
```

For the sake of curiousity, lets see what the difference is in the model if we use a MinMax scaler (less susceptible to outliers).

In [80]:
```
# Import minmax scaler
from sklearn.preprocessing import MinMaxScaler
```

In [82]:
```
# create pipeline for MinMax scaler and TimeSeriesForest
time_pipe_minmax = Pipeline([('scaler', MinMaxScaler()), ('classifier', best_scal

time_pipe_minmax.fit(X_train, y_train['target_trinary'])

print('Training set score: ' + str(time_pipe_minmax.score(X_train, y_train['targe
print('Test set score: ' + str(time_pipe_minmax.score(X_test, y_test['target_trin
```

```
Training set score: 0.9849887640449438
Test set score: 0.9714765100671141
```

While the accuracy of the model dropped a minute amount, we feel that reducing the sensitivity of the model to outliers provides more sound results.

Conclusion and Future Considerations

While this model generalizes over the entirety of the Colorado River Basin, it does provide a proof of concept for future models of its type. We feel that the use of models like these on a more granular scale and customized for the differing water depth phases of each individual dam or reservoir by the teams managing those water resources is the best approach. Water incomes and withdrawals can then be evaluated at an upstream level for each water storage center to provide more accurate outcomes with respect to those individual stations. This process can also be applied to other basins to assist and inform water regulation and use policies for the following year. Models such as these can integrate weather station system datas for live updates on the predictions of next year's water availability based on current and emerging weather conditions.

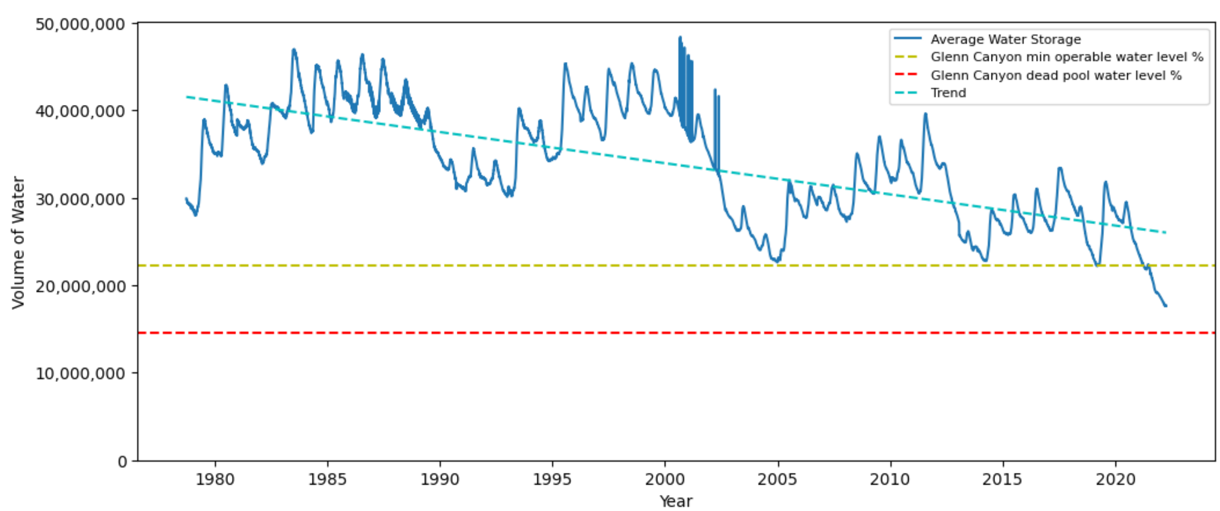
Finalizing Visualizations

Water Storage Visuals

In [83]:

```
#import dates module
import matplotlib.dates as mdates
from IPython.display import display, Math
import matplotlib.ticker as ticker


# Set trendline values
x = mdates.date2num(graphing.index)
y = graphing['Water Storage']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)

# Plot time series of water storage
plt.figure(figsize=(12,5), dpi=100)
plt.plot(graphing['Water Storage'], label='Average Water Storage')
plt.axhline(graphing['Water Storage'].max()*0.46, color='y', linestyle='--', labe
plt.axhline(graphing['Water Storage'].max()*0.30, color='r', linestyle='--', labe
plt.title(display(Math(r'\text{Volume of Water Stored in CRB Dams }(dam^3)')))
plt.xlabel('Year')
plt.ylabel('Volume of Water')
plt.plot(x, p(x), "c--", label='Trend')
plt.gca().yaxis.set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}'))
plt.ylim(ymin=0)
plt.legend(loc='upper right', fontsize=8)
#plt.savefig(f'../images/water_storage_ts.png', bbox_inches='tight', transparent=
plt.show();
```

Volume of Water Stored in CRB Dams (dam^3)



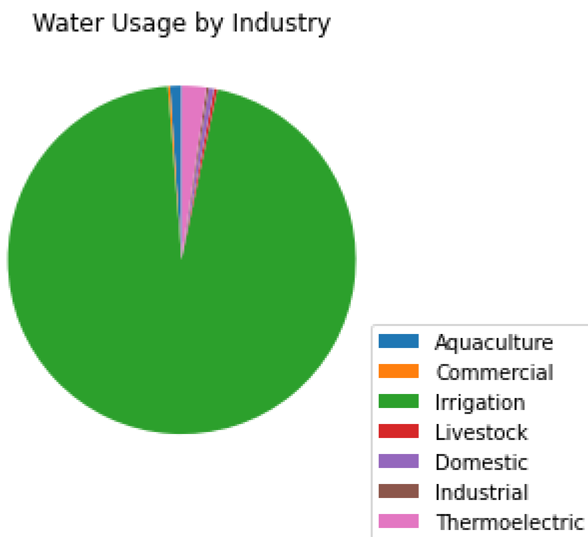
Water Usage Visuals

In [84]:
```
# Recompile water usage data
# List of interested columns
useage = ['AQ-WTotl','CO-WFrTotl', 'IR-WFrTo', 'LS-WTotl', 'DO-WTotl', 'IN-WTotl'
names = ['Aquaculture', 'Commercial', 'Irrigation', 'Livestock', 'Domestic', 'Inc

water_usage = water_withdrawals[useage] * -1
water_usage = water_usage.transpose()

#creating dict for renaming of columns
columns = water_usage.columns.to_list()
items = [2000, 2005, 2010]

col_dict = dict(zip(useage, names))

water_usage = water_usage.rename(col_dict)

water_usage
```

Out[84]:

YEAR	2000-01-01	2005-01-01	2010-01-01
Aquaculture	1.907207e+05	1.753392e+05	1.866872e+05
Commercial	2.749427e+04	3.322995e+04	3.760881e+04
Irrigation	1.847236e+07	1.827876e+07	1.683552e+07
Livestock	5.617268e+04	5.100440e+04	5.398942e+04
Domestic	8.224845e+04	9.325109e+04	8.565285e+04
Industrial	4.070484e+04	3.866960e+04	3.906431e+04
Thermoelectric	2.909779e+05	4.102184e+05	4.048281e+05

In [85]:
```
# Pie chart to show overwhelming wateruse by irrigation
labels=water_usage.index.to_list()

plt.gca().axis("equal")
pie = plt.pie(water_usage['2010-01-01'], startangle=90)
plt.legend(pie[0],labels, bbox_to_anchor=(1,0), loc="lower right",
                          bbox_transform=plt.gcf().transFigure)
plt.title('Water Usage by Industry')
#plt.savefig(f'../images/water_usage_pie.png', bbox_inches='tight', transparent=T
plt.show();
```



In [86]:
```
# Breakdown of Irrigation

junk = ['STATECODE', 'HUC4CODE', 'HUC8CODE', 'HUCNAME']
ir_types = ['IR-IrSpr', 'IR-IrMic', 'IR-IrSur']
ir_withdrawals = ['IR-WGWFr', 'IR-WSWFr']

ir_breakdown = irrigation_withdrawals.dropna().drop(columns=junk).reset_index(dro
```

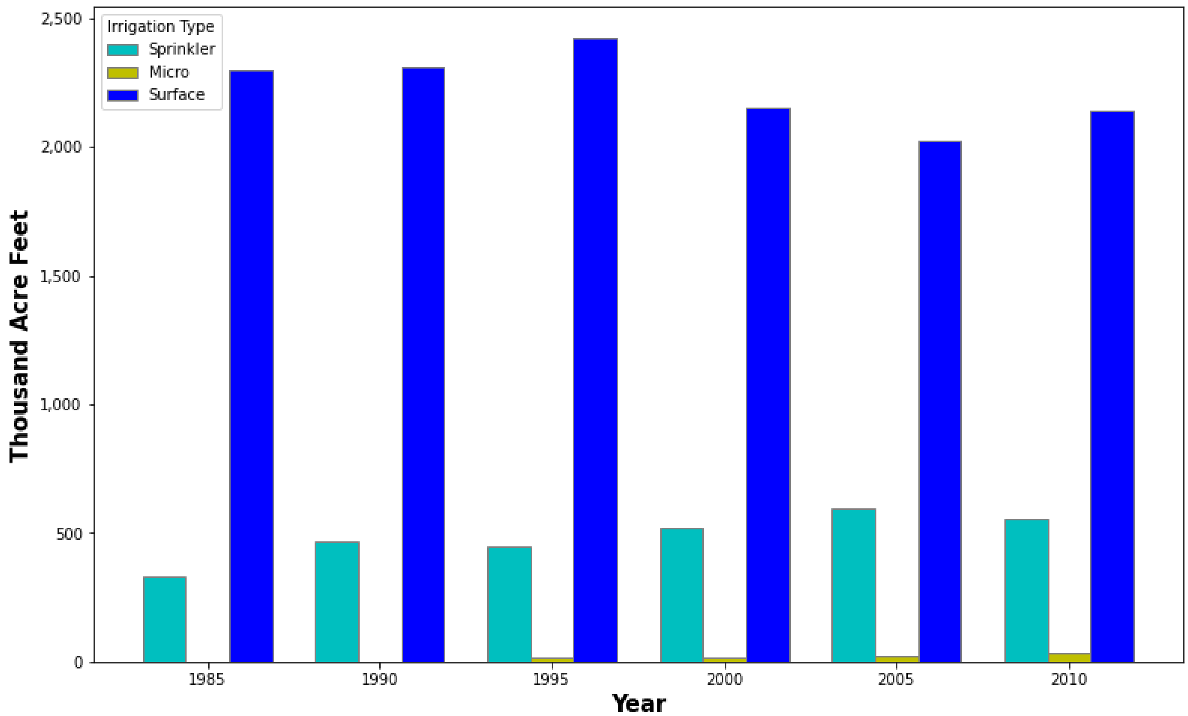
In [87]:
```
# set up labels
types_labels = ['Sprinkler Irrigation', 'Micro-irrigation', 'Surface Irrigation']
withdr_labels = ['Fresh Ground Water', 'Fresh Surface Water']

ir_bd_sum = ir_breakdown.groupby('YEAR').sum()

ir_bd_sum.rename(columns=dict(zip(ir_types,types_labels)), inplace=True)
ir_bd_sum.rename(columns=dict(zip(ir_withdrawals,withdr_labels)), inplace=True)
ir_bd_sum.drop(columns= ['IR-WFrTo', 'IR-CUsFr', 'IR-CLoss', 'IR-IrTot'], inplace
ir_bd_sum
```

Out[87]:

YEAR	Fresh Ground Water	Fresh Surface Water	Sprinkler Irrigation	Micro-irrigation	Surface Irrigation
1985.0	2943.53	12089.84	334.38	0.00	2301.41
1990.0	2550.87	11636.03	466.36	0.00	2308.40
1995.0	2462.45	12088.18	450.37	16.46	2424.34
2000.0	2923.23	12052.45	519.17	14.33	2155.55
2005.0	2828.28	11990.79	596.72	21.49	2021.70
2010.0	2058.26	11576.59	553.88	33.22	2141.88

In [88]:

```
# Plot irrigation types

# set width of bar
barWidth = 0.25
fig = plt.subplots(figsize =(13, 8))

# set height of bar
spr = ir_bd_sum['Sprinkler Irrigation'].to_list()
mic = ir_bd_sum['Micro-irrigation'].to_list()
sur = ir_bd_sum['Surface Irrigation'].to_list()

# Set position of bar on X axis
br1 = np.arange(len(spr))
br2 = [x + barWidth for x in br1]
br3 = [x + barWidth for x in br2]

# Make the plot
plt.bar(br1, spr, color ='c', width = barWidth,
        edgecolor ='grey', label ='Sprinkler')
plt.bar(br2, mic, color ='y', width = barWidth,
        edgecolor ='grey', label ='Micro')
plt.bar(br3, sur, color ='b', width = barWidth,
        edgecolor ='grey', label ='Surface')

# Adding Xticks
plt.gca().yaxis.set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}'))
plt.xlabel('Year', fontweight ='bold', fontsize = 15)
plt.ylabel('Thousand Acre Feet', fontweight ='bold', fontsize = 15)
plt.xticks([r + barWidth for r in range(len(spr))],
        [int(x) for x in ir_bd_sum.index.to_list()])

plt.legend(title="Irrigation Type", loc='upper left')
#plt.savefig(f'../images/water_usage_bar.png', bbox_inches='tight', transparent=T
plt.show();
```


Irrigation Type
Sprinkler
Micro
Surface
Thousand Acre Feet
0
500
1,000
1,500
2,000
2,500
1985
1990
1995
2000
2005
2010
Year

In [88]: