Water Resources

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

Here we mount a google drive and check the system's physical attributes.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mou
```

```
# Import general libraries
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
import numpy as np
from sklearn.pipeline import Pipeline
```

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.

```
# 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'/content/drive/MyDrive/Flatiron_capstone/00_Source_Data/Snowp


# 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'/content/drive/MyDrive/Flatiron_capstone/00_Source_Data/Snow
```

```
raw_snow['AZ'].head()
```

	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)	Temp
0	1978-09-30	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	
1	1978-10-01	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	
2	1978-10-02	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	
3	1978-10-03	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	
4	1978-10-04	Baker Butte	308	NaN	NaN	NaN	NaN	NaN	

```
# 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 Accumulation',
               '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' : 'Water Storage',
                   'Reservoir_Storage_Volume__dam_3__Start_of_Day_Values' : 'Water Storage',
                   'Elevation (ft)' : 'Elevation',
                   'Elevation__ft_' : 'Elevation'}

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

```
# 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)
```

```
water_data
```

		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
...	**...**	...	...	...	...	...	...	...	...

```
# Column Selection for master snow dataset
```

```
junk_columns = ['Station ID', 'Snow Density', 'Precip Accumulation', 'Snow / Rain', 'Average
                '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_'], inplace
```

```
# 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)
```

```
snow_data
```

	Station Name	SWE	Snow Depth
Date			
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

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

```
water_data
```

	Station Name	Water Storage
Date		
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

```
from statsmodels.tsa.stattools import adfuller

def dicky_fuller_test(data, alpha):
    is_stationary = adfuller(data)[1] < alpha
    if is_stationary == True:
        print(f'The data is stationary with a fuller score of {round(adfuller(data)[1],3)}')
    else:
        print(f'The data is not stationary with a fuller score of {round(adfuller(data)[1],3
    return
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
  import pandas.util.testing as tm
```

Imputing and aggregating:

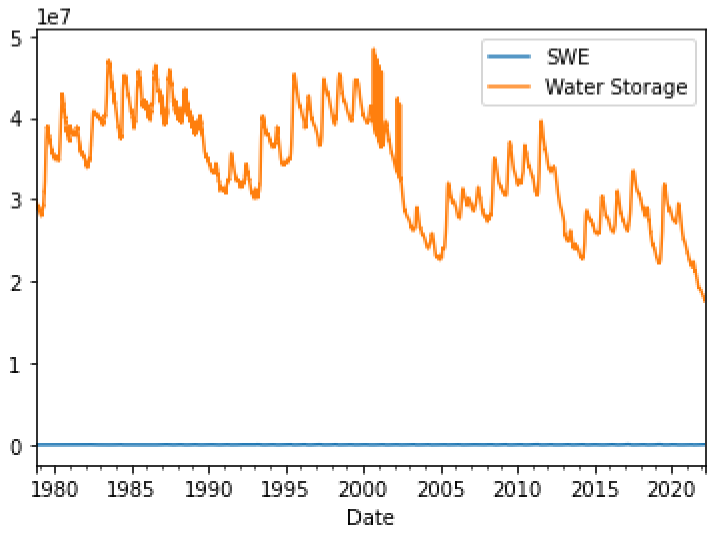
```
def fix_na(df, interpolation_method='linear', fill_method='backfill'):
    # interpolate and backfill

    df = df.interpolate(method='linear').fillna(value=None, method='backfill', axis=None, lin
    return df
```

```
fill_snow = fix_na(snow_data)
fill_water = fix_na(water_data)

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

```
masterdata = ag_snow.join(ag_water, how='left', on=ag_snow.index)
masterdata = fix_na(masterdata)
```

```
masterdata.plot()
```

```
<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.

```
# Bringing in water withdrawal data

aquaculture_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Da
commercial_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Dat
hydropower_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Dat
irrigation_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Dat
livestock_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Data
mining_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Data/Sr
public_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Data/Sr
ss_domestic_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Da
ss_industrial_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_
thermoelectric_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source
wastewater_withdrawals = pd.read_csv(f'/content/drive/MyDrive/Flatiron_capstone/00_Source_Dat
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2882: DtypeWarn
  exec(code_obj, self.user_global_ns, self.user_ns)
```

```
# Define a function to remove XLS file artifacts from dataframes.

def del_unnamed(df):
    cols = df.columns.tolist()
    to_remove = []

    for i in cols:
        if i.startswith('Unnamed'):
            to_remove.append(i)
    return df.drop(columns=to_remove)
```

```
# 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.

```
# 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*100)}% of the f
print(f'Glen Canyon Dam has a minimum flow-through depth of {round(per_to_dead*100)}% of the
```

```
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
```

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 consumptive
  ```

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

  ```
  - Not differentiated between consumptive, conveyance losses, and evap.
  ```

- 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

↳ *10 cells hidden*

[ ]

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

[ ] ↳ *2 cells hidden*

Resampling and visualizing

[ ] ↳ *6 cells hidden*

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

[ ] ↳ *2 cells hidden*

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.

[ ] ↳ *3 cells hidden*

Dummy Model

[ ] ↳ *8 cells hidden*

First Simple Model (FSM)

[ ] ↳ *13 cells hidden*

Model 2

```
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.

```
# 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_jobs=-1, error_
# 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_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.

```
# 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
```

```
best_scaled_clf.best_estimator_
```

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

```
# 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.

```
# 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-packages (
Requirement already satisfied: joblib>=0.12 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: scikit-learn>=0.22.1 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: numpy>=1.17.5 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: numba>=0.48.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: llvmlite<0.35,>=0.34.0.dev0 in /usr/local/lib/python3.7/
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-pa
```

```
# Import the model
from pyts.classification import TimeSeriesForest
```

```
# 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)),}
]
```

```
# 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_trinary'])))
print('Test set score: ' + str(time_pipe.score(X_test,y_test['target_trinary'])))
```

```
Training set score: 1.0
```

```
Test set score: 0.9635067114093959
```

```
# 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_trinary'])))
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.

```
# Create new gridsearch object

scaled_tsf = GridSearchCV(time_pipe, param_grid = param_grid, cv = 5, verbose=3, n_jobs=-1, e

# 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=600, n_wind
```

Our final optimized model and an unoptimized comparison are below.

```
# 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_trinary'])))
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
```

```
# 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['target_trinary']
print('Test set score: ' + str(time_pipe_opt.score(X_te_scaled,y_test['target_trinary'])))
```

```
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).

```
# Import minmax scaler
from sklearn.preprocessing import MinMaxScaler
```

```
# create pipeline for MinMax scaler and TimeSeriesForest
time_pipe_minmax = Pipeline([('scaler', MinMaxScaler()), ('classifier', best_scaled_tsf.best_

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

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

```
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.

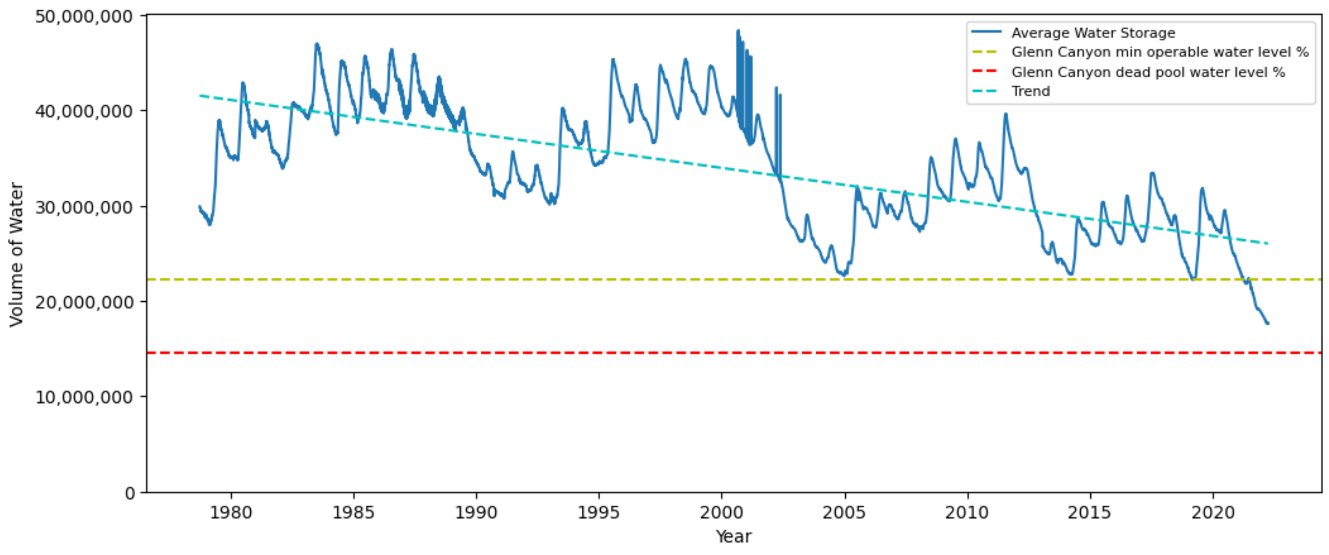
Finalizing Visualizations

Water Storage Visuals

```
#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='--', label= 'Glenn Ca
plt.axhline(graphing['Water Storage'].max()*0.30, color='r', linestyle='--', label= 'Glenn Ca
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=True)
plt.show();
```

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



Water Usage Visuals

```
# Recompile water usage data
# List of interested columns
useage = ['AQ-WTotl','CO-WFrTotl', 'IR-WFrTo', 'LS-WTotl', 'DO-WTotl', 'IN-WTotl', 'PT-CUTot'
names = ['Aquaculture', 'Commercial', 'Irrigation', 'Livestock', 'Domestic', 'Industrial', 'T

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
```

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

```
# 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=True)
plt.show();
```

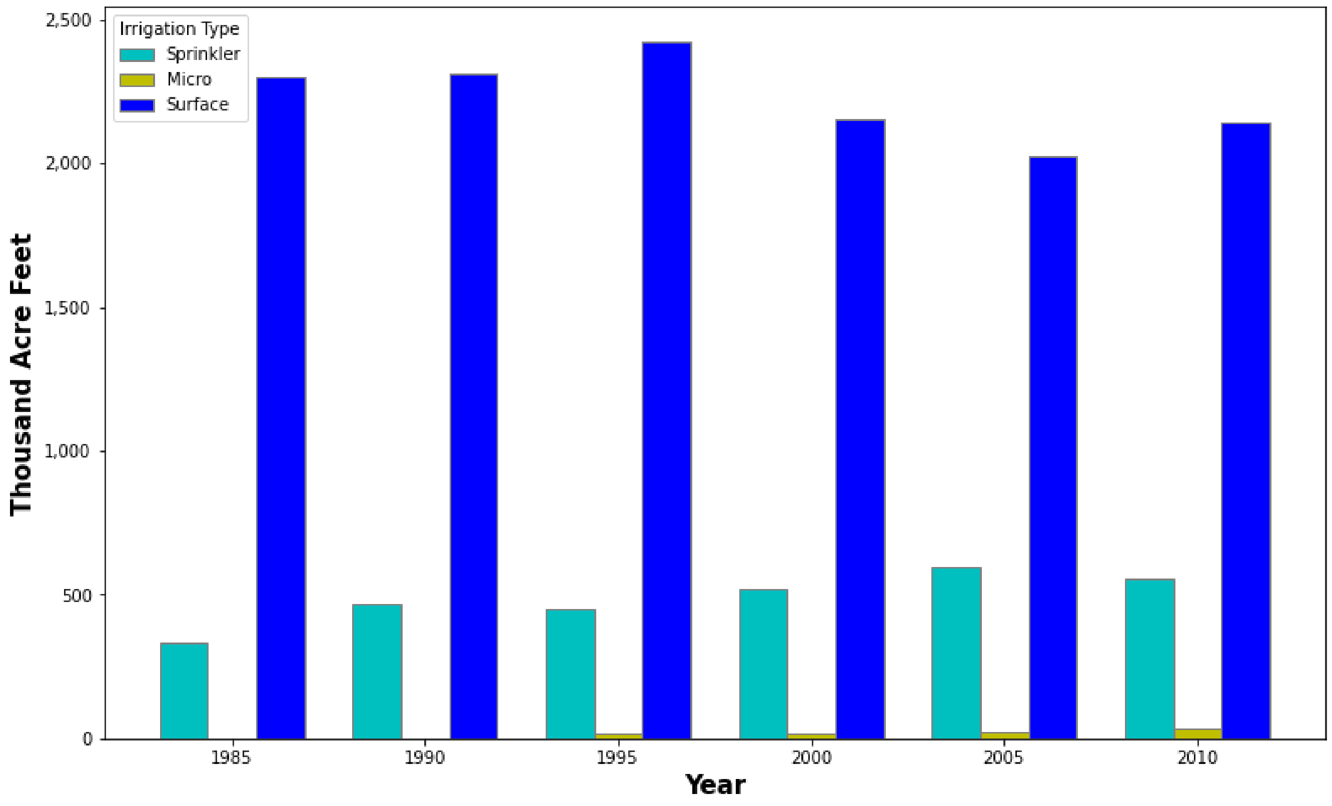
```
# Breakdown of Irrigation

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(drop=True)
```

```
# 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=True)
ir_bd_sum
```

	Fresh Ground Water	Fresh Surface Water	Sprinkler Irrigation	Micro-irrigation	Surface Irrigation
YEAR					
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

```
# 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=True)
plt.show();
```



✓ 0s completed at 7:54 PM