HFF Turbidity Analysis

Business Understanding

Henry's Fork Foundation aims to preserve and restore the natural water quality of the Henry's Fork of the Snake River and its watershed. While their responsibilities are many, one of their chief aims is to use modern scientific techniques to keep tabs on the river and ensure local industrial and commercial practices are not interfering with its overall health and aesthetics. In turn, the river provides habitat for local flora and fauna, not to mention a large portion of the tourism revenue for the surrounding towns in the form of sport fishing.

To ensure optimal fishing experience the water conditions must be within acceptable ranges. Turbidity is the measure of clarity of a liquid, and in this case is very important to this experience. According to my correspondence with their Senior Scientist, Rob Van Kirk, "Turbidity is the single biggest factor affecting fishing experience. Anglers can't see things like dissolved oxygen or nutrient concentrations, but they can see how clear or dirty the water is. By far the single biggest complaint I get about fishing conditions is how turbid the water is."

I have been tasked with assessing and modeling data from multiple sources to determine major factors and predictors that contribute to turbidity in the river. Using this analysis and its framework, future scientists may be able to forecast water clarity and even mitigate contributing factors.

Data Understanding

The first dataset comes from the publically available sonde data at HFF.org (https://henrysforkdata.shinyapps.io/scientific_website/). This data is updated every 15 minutes using an in-water monitoring device called a sonde. These devices measure water temperature, turbidity, dissolved oxygen, conductivity, phytoplankton, and cyanobacteria content. While the other factors can contribute to the turbidity of a system on their own, they do not provide a complete picture.

We chose the sonde at this location because it is the head of one of the best regarded fishing areas, and its location just a few hundred yards downstream from Island Park Dam makes turbidity there less predictable and of higher concern. Determining the contributing factors to water clarity here could prove valuable in understanding how activity and management at Island Park reservoir impact the downstream water conditions.

The second dataset comes from the US Bureau of Reclamation (https://www.usbr.gov/projects/index.php?id=151) and contains historical data regarding the water in island park reservoir, including in/outflow, elevation, and overall change in volume. While this data does not directly address the clarity of the water, the rate of flow in and out of the reservoir may kick up sediment and with the amount of exposed shoreline may affect the rate at which the shoreline erodes into the reservoir. This data dates back to 1929 which may be interesting to explore further once we have established the relevant tools for the job.

The third dataset comes from the USDA Snotel Natural Resources Conservation Service National Water and Climate Center (https://wcc.sc.egov.usda.gov/reportGenerator/view/customChartReport/daily/start_of_period/546:ID fitToScreen=false&useLogScale=false) which provides snow and climate monitoring at specific sites across the entire USA. The dataset we have is localized to our region, which we narrow further to sites that affect the watershed into the reservoir's tributaries. This has been collected since 1988 for this locale, which we again narrow into a timeframe we can use. The data includes the temperature at these sites, the daily and average precipitation, and the amount of water currently at the site in the form of snow.

Data Preparation

First we import relevant libraries and format the data to be readable as a timeseries. Then, in order to get the data into a time scale that is relevant to the other datasets we downsample to daily frequency and split the data into training and testing sets. The data is in a timeseries, which precludes traditional random train/test splitting, and must be done using values that are in sequence. In this case, we take the most recent year with relatively complete data as the test set, and the rest of the complete years as the training data.

In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
from matplotlib.pyplot import figure

import seaborn as sns

from sklearn.model_selection import TimeSeriesSplit
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler, Normalizer, Ordi

from sklearn.compose import ColumnTransformer
from sklearn.metrics import mean_squared_error


from statsmodels.tsa.stattools import adfuller
from statsmodels.regression.linear_model import OLS
from statsmodels.tsa.vector_ar.vecm import coint_johansen
from statsmodels.tsa.vector_ar.var_model import VAR
from statsmodels.tsa.seasonal import STL

from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

In [2]:
```
# Import raw Island Park Dam sonde data
ipe_df = pd.read_csv('data/15_min_data_HFF/IPE 15 min 2022-08-08.csv')
ipe_df
```

Out[2]:

	contTime	Turb_FNU	TurbDailyMn	TurbSamp_NTU	Chloro_RFU	ChloroDailyMn	BGA_RFU
0	2014-06-20 00:00:00	NaN	NaN	NaN	NaN	NaN	NaN
1	2014-06-20 00:15:00	NaN	NaN	NaN	NaN	NaN	NaN
2	2014-06-20 00:30:00	NaN	NaN	NaN	NaN	NaN	NaN
3	2014-06-20 00:45:00	NaN	NaN	NaN	NaN	NaN	NaN
4	2014-06-20 01:00:00	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...
285217	2022-08-07 23:00:00	5.48	NaN	NaN	0.34	NaN	0.02
285218	2022-08-07 23:15:00	5.74	NaN	NaN	0.27	NaN	0.03
285219	2022-08-07 23:30:00	6.37	NaN	NaN	0.29	NaN	0.03
285220	2022-08-07 23:45:00	6.40	NaN	NaN	0.34	NaN	0.02
285221	2022-08-08 00:00:00	5.79	NaN	NaN	0.31	NaN	0.04

285222 rows × 33 columns

In [3]:
```
# Convert date to index and DateTime format
ipe_df = ipe_df.rename(columns={'contTime': 'date'})
ipe_df['date'] = pd.to_datetime(ipe_df.date)
data = ipe_df.drop(['date'], axis=1)
data.index = ipe_df.date
```

In [4]:
```
# Downsample data to daily frequency
ipe_daily = data.resample('D').mean()
```

In [5]:
```
ipe_daily = ipe_daily.drop(['TurbDailyMn', 'TurbSamp_NTU',
       'ChloroDailyMn', 'BGADailyMn', 'ODODailyMn',
       'TempDailyMn', 'CondDailyMn', 'TDS_mgL',
       'TotalPres_psi', 'AshtonAirPres_psi', 'Depth_ft', 'Shift_psi',
       'Turb_FNU_raw', 'Chloro_RFU_raw', 'BGA_RFU_raw', 'ODO_mgL_raw',
       'Temp_C_raw', 'Cond_muSCm_raw', 'TDS_mgL_raw', 'TotalPres_psi_raw',
       'Turb_avdymn', 'Chlor_avdymn', 'Cyano_avdymn', 'Temp_avdymn',
       'ODO_avdymn', 'Cond_avdymn'], axis=1)
```

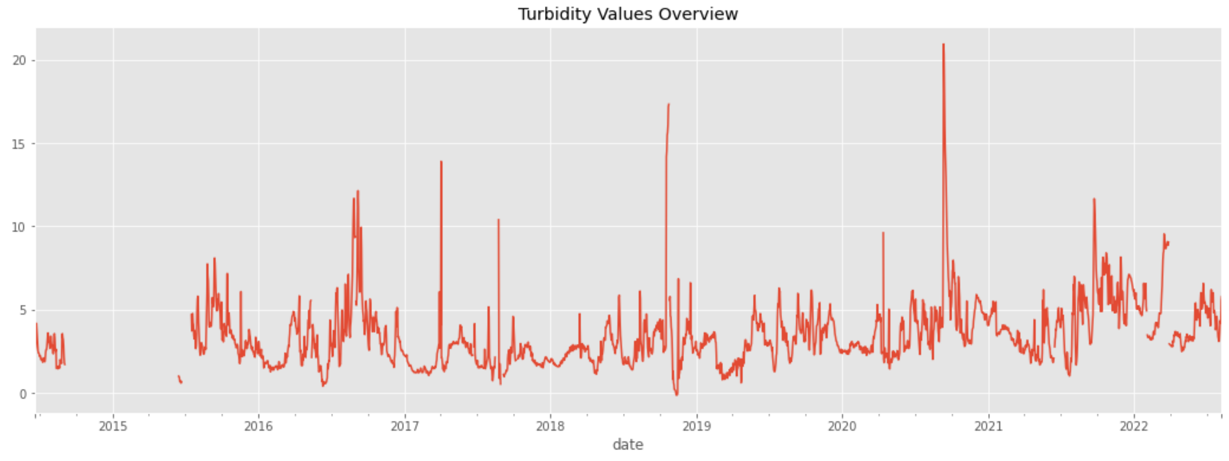
In [6]:
```
ipe_interp = ipe_daily.interpolate(method='spline', order=2)
```

In [7]:
```
ipe_train = ipe_interp['2016':'2020']
```

In [8]:
```
ipe_test = ipe_interp['2021']
```

```
C:\Users\harri\AppData\Local\Temp\ipykernel_29700\3605300567.py:1: FutureWarnin
g: Indexing a DataFrame with a datetimelike index using a single string to slic
e the rows, like `frame[string]`, is deprecated and will be removed in a future
version. Use `frame.loc[string]` instead.
  ipe_test = ipe_interp['2021']
```

In [9]:
```
ipe_daily['Turb_FNU'].plot(figsize=(18,6))
plt.title('Turbidity Values Overview');
```



When we inspect the turbidity values here, we see there is a rather large gap early on in the time series, and a few smaller ones later on. These may bee too large for simple interpolation, especially with the high variance in data values over a short period of time. For this reason we will later drop these sections. Other NaN values will be interpolated over using the splining method to attempt to anticipate the patterns before modeling.

In [10]:
```
# import island park dam hydrology data
hydro_df = pd.read_csv('data/IslandPark.TS.csv')

# set the datetime to the index
hydro_df['date'] = pd.to_datetime(hydro_df['date'])
hydro_df.set_index(['date'], inplace=True)
hydro_df.index.names = ['date']
hydro_df.columns
```

Out[10]:
```
Index(['elevation.ft', 'volume.af', 'smoothed.vol', 'smoothed.elev',
       'surfacearea.acres', 'net.evap.af', 'delta.V.af', 'regQ.cfs',
       'gain.cfs', 'smoothed.natQ.cfs'],
      dtype='object')
```

In [11]:
```
# drop redundant columns
hydro_df.drop(['volume.af', 'smoothed.vol', 'elevation.ft',
                   'smoothed.elev', 'surfacearea.acres'], axis=1, inplace=True)
```

In [12]:
```
hydro_df = hydro_df['2014':'2022']
```

In [13]:
```
# set the range of the data to the same as the sonde data
hydro_interp = hydro_df.interpolate(method='spline', order=2)
```

In [14]:
```
hydro_df_train = hydro_interp['2016':'2020']
```

In [15]:
```
hydro_df_test = hydro_interp['2021']
```

```
C:\Users\harri\AppData\Local\Temp\ipykernel_29700\1673822024.py:1: FutureWarnin
g: Indexing a DataFrame with a datetimelike index using a single string to slic
e the rows, like `frame[string]`, is deprecated and will be removed in a future
version. Use `frame.loc[string]` instead.
  hydro_df_test = hydro_interp['2021']
```

```
In [16]: climate_df = pd.read_csv('data/Clean.Climate.TS.csv')
         climate_df['Date'] = pd.to_datetime(climate_df['Date'])
         climate_df.set_index(['Date'], inplace=True)
         climate_df.drop(['GT.TAVE', 'GT.TMIN', 'GT.TMAX', 'GT.DP', 'GT.AP', 'GT.SWE', 'PE
                'PB.TMIN', 'PB.TMAX', 'PB.DP','HFW.AP', 'TR.SWE', 'FR.SWE', 'HF.SWE', 'HFW
                'HFW.Cum.P', 'AG.Cum.P', 'AG.Cum.ET', 'PB.AP', 'PB.SWE', 'BB.TAVE', 'BB.TM
                'BB.SWE', 'LL.TAVE', 'LL.TMIN', 'LL.TMAX', 'LL.DP', 'LL.AP', 'LL.SWE', 'GL
                'GL.TMIN', 'GL.TMAX', 'GL.DP', 'GL.AP', 'GL.SWE', 'PC.TAVE', 'PC.TMIN', 'P
                'PC.DP', 'PC.AP', 'PC.SWE', 'AL.TAVE', 'AL.TMIN', 'AL.TMAX', 'AL.DP', 'AL.
                'AS.TAVE', 'AS.TMIN', 'AS.TMAX', 'AS.DP', 'AS.AP', 'AS.ET', 'RX.TAVE',
                'RX.TMIN', 'RX.TMAX', 'RX.DP', 'RX.AP', 'RX.ET', 'TR.TAVE', 'FR.TAVE',
                'HF.TAVE', 'VA.TAVE', 'HFW.TAVE', 'TR.TMIN', 'FR.TMIN', 'HF.TMIN',
                'VA.TMIN', 'HFW.TMIN', 'TR.TMAX', 'FR.TMAX', 'HF.TMAX', 'VA.TMAX',
                'HFW.TMAX', 'TR.DP', 'FR.DP', 'HF.DP', 'VA.DP', 'HFW.DP', 'TR.AP',
                'FR.AP', 'HF.AP', 'VA.AP', 'WE.TMIN', 'WE.TMAX', 'CC.TMIN', 'CC.TMAX',
                'IP.TMIN', 'IP.TMAX'], axis=1, inplace=True)
         climate_df.index.names = ['date']
         climate_df.columns

Out[16]: Index(['WE.TAVE', 'WE.DP', 'WE.AP', 'WE.SWE', 'CC.TAVE', 'CC.DP', 'CC.AP',
                'CC.SWE', 'IP.TAVE', 'IP.DP', 'IP.AP', 'IP.SWE'],
               dtype='object')
```

```
In [17]: climate_df = climate_df['2014':'2022']
```

```
In [18]: clim_interp = climate_df.interpolate(method='spline', order=2)
```

```
In [19]: climate_df_train = clim_interp['2016':'2020']
```

```
In [20]: climate_df_test = clim_interp['2021']

         C:\Users\harri\AppData\Local\Temp\ipykernel_29700\3356747189.py:1: FutureWarnin
         g: Indexing a DataFrame with a datetimelike index using a single string to slic
         e the rows, like `frame[string]`, is deprecated and will be removed in a future
         version. Use `frame.loc[string]` instead.
           climate_df_test = clim_interp['2021']
```

Next, we combine the dataframes into their final training and testing sets, and inspect the resulting dataframe to ensure the structure looks correct, and there are no NaN values.

```
In [21]: # Merge to create training set
         final_train = pd.merge(climate_df_train, hydro_df_train, on=['date'])
         final_train = pd.merge(final_train, ipe_train, on=['date'])
```

```
In [22]: # Merge to create testing set
         final_test = pd.merge(climate_df_test, hydro_df_test, on=['date'])
         final_test = pd.merge(final_test, ipe_test, on=['date'])
```

In [23]:
```
# Inspect dataframe
final_test
```

Out[23]:

	WE.TAVE	WE.DP	WE.AP	WE.SWE	CC.TAVE	CC.DP	CC.AP	CC.SWE	IP.TAVE	IP.DP	...
date											
2021-01-01	16.0	0.0	8.2	7.3	19.0	0.0	4.0	3.6	23.0	0.0	...
2021-01-02	19.0	0.2	8.4	7.6	20.0	0.3	4.3	3.9	24.0	0.3	...
2021-01-03	22.0	0.4	8.8	7.9	24.0	0.1	4.4	4.0	27.0	0.3	...
2021-01-04	25.0	0.7	9.5	8.6	26.0	0.4	4.8	4.5	30.0	0.3	...
2021-01-05	23.0	0.6	10.1	9.0	25.0	0.2	5.0	4.7	29.0	0.4	...
...	...	...	...	...	...	...	...	...	...	...	...
2021-12-27	10.0	0.5	17.3	12.9	13.0	0.4	11.5	6.5	17.0	0.6	...
2021-12-28	2.0	0.0	17.3	13.0	3.0	0.0	11.5	6.5	9.0	0.0	...
2021-12-29	6.0	0.3	17.6	13.3	8.0	0.1	11.6	6.6	11.0	0.3	...
2021-12-30	10.0	0.4	18.0	13.7	11.0	0.1	11.7	6.7	16.0	0.3	...
2021-12-31	8.0	0.0	18.0	13.7	11.0	0.0	11.7	6.7	11.0	0.2	...

365 rows × 23 columns

In [24]:
```
# Check for NaNs
final_train.isna().sum()
```

Out[24]:
```
WE.TAVE              0
WE.DP                0
WE.AP                0
WE.SWE               0
CC.TAVE              0
CC.DP                0
CC.AP                0
CC.SWE               0
IP.TAVE              0
IP.DP                0
IP.AP                0
IP.SWE               0
net.evap.af          0
delta.V.af           0
regQ.cfs             0
gain.cfs             0
smoothed.natQ.cfs    0
Turb_FNU             0
Chloro_RFU           0
BGA_RFU              0
ODO_mgL              0
Temp_C               0
Cond_muSCm           0
dtype: int64
```

In [25]:
```
# Check for NaNs
final_test.isna().sum()
```

Out[25]:
```
WE.TAVE              0
WE.DP                0
WE.AP                0
WE.SWE               0
CC.TAVE              0
CC.DP                0
CC.AP                0
CC.SWE               0
IP.TAVE              0
IP.DP                0
IP.AP                0
IP.SWE               0
net.evap.af          0
delta.V.af           0
regQ.cfs             0
gain.cfs             0
smoothed.natQ.cfs    0
Turb_FNU             0
Chloro_RFU           0
BGA_RFU              0
ODO_mgL              0
Temp_C               0
Cond_muSCm           0
dtype: int64
```

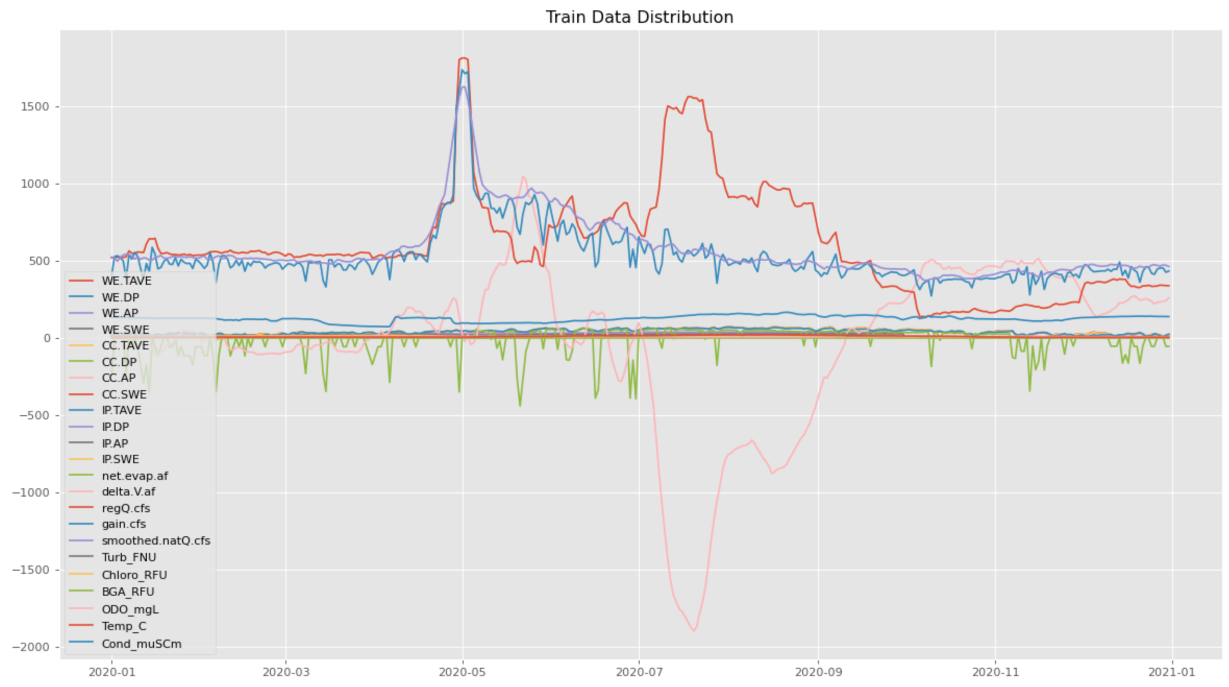
In [26]:
```
# determine the lowest negative value so we can add that to all values to make th
final_train.min()
```

Out[26]:
```
WE.TAVE                 -5.000000
WE.DP                    0.000000
WE.AP                    0.000000
WE.SWE                   0.000000
CC.TAVE                 -4.000000
CC.DP                    0.000000
CC.AP                    0.000000
CC.SWE                   0.000000
IP.TAVE                 -8.000000
IP.DP                    0.000000
IP.AP                    0.000000
IP.SWE                   0.000000
net.evap.af          -1486.560444
delta.V.af           -2171.061429
regQ.cfs                71.900000
gain.cfs               -64.733023
smoothed.natQ.cfs      295.220945
Turb_FNU                -0.118526
Chloro_RFU              -0.332188
BGA_RFU                 -0.453542
ODO_mgL                  3.373684
Temp_C                   2.639990
Cond_muSCm              71.887474
dtype: float64
```

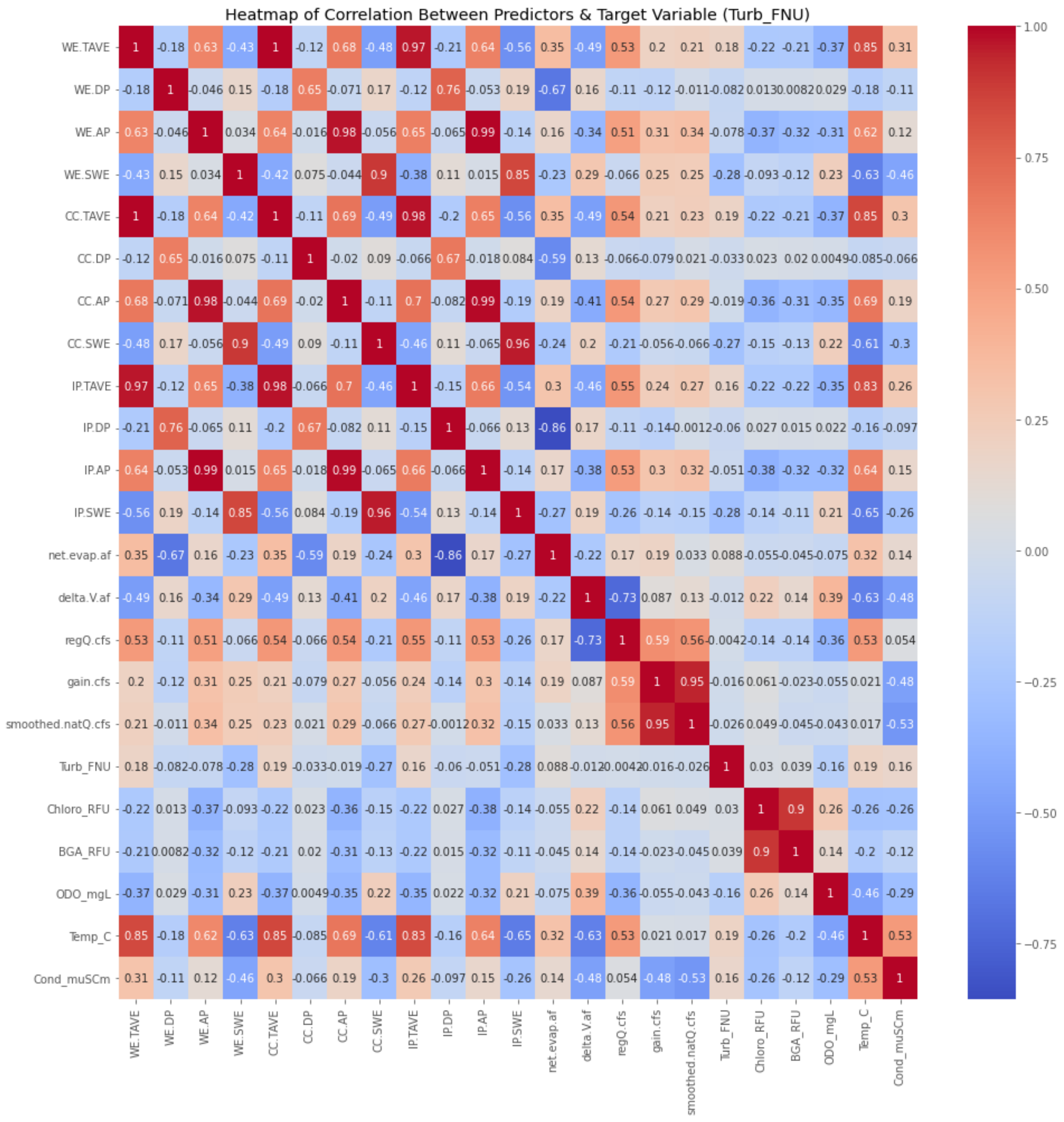
In [27]:
```
# Logarithmic transformation after subtracting the most negative value
final_train_log = np.log((final_train+2172))
final_test_log = np.log((final_test+2172))
```

```
In [28]: # Visualise train set for curiosity's sake
         plt.figure(figsize=(18,10), dpi=80)
         plt.plot(final_train['2020'])
         plt.legend(final_train)
         plt.title('Train Data Distribution');
```

```
C:\Users\harri\AppData\Local\Temp\ipykernel_29700\469378547.py:3: FutureWarnin
g: Indexing a DataFrame with a datetimelike index using a single string to slic
e the rows, like `frame[string]`, is deprecated and will be removed in a future
version. Use `frame.loc[string]` instead.
  plt.plot(final_train['2020'])
```



In [29]:
```
# set up figure size
fig, ax = plt.subplots(figsize=(16, 16))
# set up correlation matrix
corr = final_train.corr()
sns.heatmap(corr, cmap = 'coolwarm', annot = True)

# Customize the plot appearance
ax.set_title("Heatmap of Correlation Between Predictors & Target Variable (Turb_F
plt.show();
```



Here, we have a correlation matrix which shows the raw correlation between values in the dataset. This displays potential sources of collinearity where the correlation is high. It also shows that none of the variables are directly correlated very highly with turbidity, meaning more advanced regression is required to determine the relationships.

OLS Model

First, we determine feature importance for a simple model to give an idea of the weights of the explanatory variables on turbidity. An OLS model allows us to use multivariate regression to capture the variance in the data.

In [30]:
```
# Instantiate and fit the OLS model, and provide output
ols = OLS(exog=final_train.drop(['Turb_FNU'], axis=1), endog=final_train['Turb_FN
ols_model = ols.fit()
print(ols_model.summary())
```

```
                                 OLS Regression Results                                
=======================================================================================
=========
Dep. Variable:               Turb_FNU   R-squared (uncentered):                   
0.785
Model:                            OLS   Adj. R-squared (uncentered):              
0.782
Method:                 Least Squares   F-statistic:                              
299.4
Date:                Wed, 24 Aug 2022   Prob (F-statistic):                       
0.00
Time:                        22:47:10   Log-Likelihood:                           
-3565.4
No. Observations:                1827   AIC:                                      
7175.
Df Residuals:                    1805   BIC:                                      
7296.
Df Model:                          22                                                  
Covariance Type:            nonrobust                                                  
=======================================================================================
======
                     coef    std err          t      P>|t|      [0.025      
0.975]
---------------------------------------------------------------------------------------
------
WE.TAVE           -0.0733      0.031     -2.396      0.017      -0.133      
-0.013
WE.DP              0.0346      0.237      0.146      0.884      -0.431      
0.500
WE.AP             -0.3237      0.025    -12.705      0.000      -0.374      
-0.274
WE.SWE            -0.0094      0.013     -0.696      0.487      -0.036      
0.017
CC.TAVE            0.1330      0.036      3.664      0.000       0.062      
0.204
CC.DP              0.0690      0.300      0.230      0.818      -0.518      
0.656
CC.AP             -0.0490      0.035     -1.405      0.160      -0.117      
0.019
CC.SWE             0.1758      0.038      4.671      0.000       0.102      
0.250
IP.TAVE           -0.0367      0.013     -2.913      0.004      -0.061      
-0.012
IP.DP             -0.4351      0.560     -0.777      0.437      -1.533      
0.663
IP.AP              0.5372      0.060      8.888      0.000       0.419      
0.656
IP.SWE            -0.1669      0.034     -4.976      0.000      -0.233      
-0.101
net.evap.af       -0.0005      0.001     -0.471      0.637      -0.002      
0.002
delta.V.af         0.0010      0.001      1.743      0.081      -0.000      
```

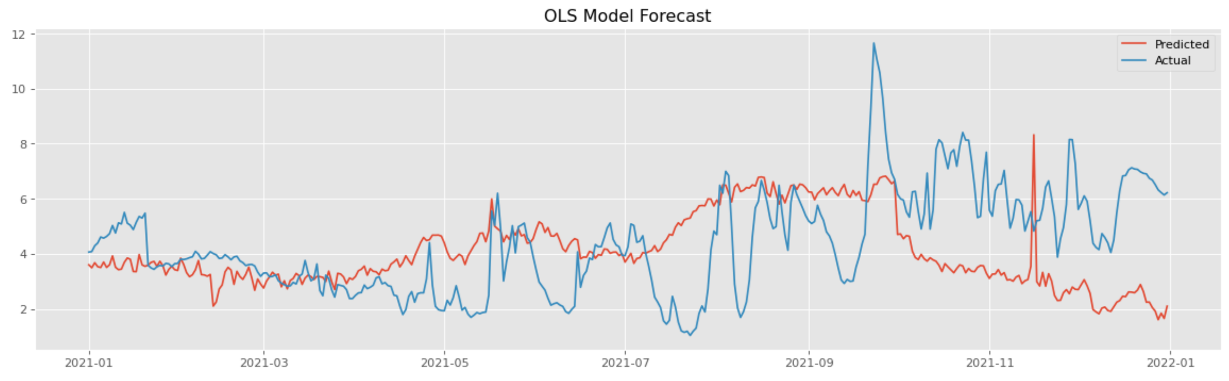
```
0.002
regQ.cfs            -0.0002      0.001     -0.163      0.870      -0.002
0.002
gain.cfs             0.0005      0.001      0.412      0.681      -0.002
0.003
smoothed.natQ.cfs    0.0006      0.001      0.932      0.351      -0.001
0.002
Chloro_RFU          -0.0026      0.054     -0.048      0.962      -0.109
0.104
BGA_RFU              0.1085      0.158      0.687      0.492      -0.201
0.418
ODO_mgL             -0.1605      0.035     -4.539      0.000      -0.230
-0.091
Temp_C               0.0483      0.032      1.521      0.128      -0.014
0.111
Cond_muSCm           0.0222      0.003      8.727      0.000       0.017
0.027
==============================================================================
Omnibus:                     1360.592   Durbin-Watson:                   0.291
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            34454.875
Skew:                           3.238   Prob(JB):                         0.00
Kurtosis:                      23.265   Cond. No.                     1.51e+04
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not cont
ain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[3] The condition number is large, 1.51e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [31]:
```
# Display standard deviations
final_train.std()
```

Out[31]:
```
WE.TAVE                16.602699
WE.DP                   0.278735
WE.AP                  17.329576
WE.SWE                 10.776551
CC.TAVE                16.611129
CC.DP                   0.193697
CC.AP                   9.495161
CC.SWE                  5.003882
IP.TAVE                16.159206
IP.DP                   0.169281
IP.AP                  10.288354
IP.SWE                  5.481206
net.evap.af           105.403773
delta.V.af            516.610946
regQ.cfs              336.144960
gain.cfs              219.347114
smoothed.natQ.cfs     235.757751
Turb_FNU                1.927556
Chloro_RFU              1.999588
BGA_RFU                 0.641085
ODO_mgL                 1.114011
Temp_C                  5.159372
Cond_muSCm             17.618043
dtype: float64
```

In [32]:
```
# Predict on the test set
ols_pred = ols_model.predict(final_test.drop(['Turb_FNU'], axis=1))
```

In [33]:
```
# Plot OLS model forecast
plt.figure(figsize=(18,5), dpi=80)
plt.plot(ols_pred, label='Predicted')
plt.plot(final_test['Turb_FNU'], label='Actual')
plt.rcParams["figure.figsize"] = (20,3)
plt.title('OLS Model Forecast')
plt.legend();
```



In [34]:
```
# Calculate RMSE
dibrinse = ((final_test['Turb_FNU'])-ols_pred)
dibb = dibrinse.sum()
mse = dibb/365
rmse = np.sqrt(mse)
rmse
```

Out[34]:
```
0.5311789017236513
```

This adjusted R2 value shows that the variance in the turbidity is about 79% captured by the explanatory variables according to this model. This does not necessarily mean our model can't get any better than this, but it may represent a loose ballpark for the upper bounds of how accurately we can predict the turbidity using basic methods. Additionally, multicollinearity is high here, which is to be expected. This can be mitigated by eliminating columns or using models that eliminate multicollinearity issues going forward.

The Durbin-Watson score here is low, implying the variance of the data is not constant throughout. This makes sense in this case, as even though the data is from the same time frame, it comes from three completely different sources. This is something to keep in mind and can be eliminated using a transformation.

The coefficients here represent the amount of change in turbidity for a one unit change in the explanatory variable in question. Higher values can denote a larger influence in this simple model, but it is important to take into mind the scale of the variable and compare, which is why the standard deviation is included for context. If the coefficient is large but the scale of the variable is also large, that might not mean as significant an influence.

The p values here also should be taken in with a grain of salt, as a p value lower than 0.05 should mean we can reject the null hypothesis that the variable has no influence on the turbidity, and the converse is also true, that if the p value is higher than 0.05 we can reject the alternative hypothesis that the variable does have a significant influence. Using our background knowledge however, we know that high amounts of chlorophyll and BGA are linked to higher turbidity, which does not seem to be the case in this regression.

From this, we see that the factors that have a direct impact via low p values and high coefficients relative to their scale are all temperatures at the Snotel sites, which are collinear, as well as the amount of snow at the Island Park and Crab Creek sites. As snow melts at the Crab Creek site, the turbidity increases at Island Park, and then as the amount of snow increases at Island Park, the turbidity also increases, reflecting the effects of increased inflow into the reservoir from this inlet and possibly the effects of inclement weather respectively, as in the latter the average precipitation also has a low p value. The amount of dissolved oxygen also negatively correlates with the turbidity, showing that the conditions that increase turbidity also decrease the amount of biologically available oxygen. The conductivity positively correlates with the turbidity, which tracks, as the amount of dissolved salts and other inorganic compounds could hamper water clarity.

RMSE value averages the square of all the errors, and then takes the square root to get the number back into the scale of the data. The RMSE for the predictions vs actual here is surprisingly low at 0.53, meaning given the information, this model is actually quite good.

The drawback of this model is that the data you provide it will often already contain the turbidity value, given the sonde. It can, however, be used to estimate the turbidity in cases where we have an idea going in of what the values for the predictors might be, as in the prediction for 2021. This means that this model cannot forecast very well without being given information about the future.

VAR Model

The VAR model is a multivariate timeseries model that allows us to quickly compare the past and present verisions of a dataset to examine their relationship. This model does well for recurring patterns by creating vectors out of the predictor variables relationships, and then continuing the patterns for all variables.

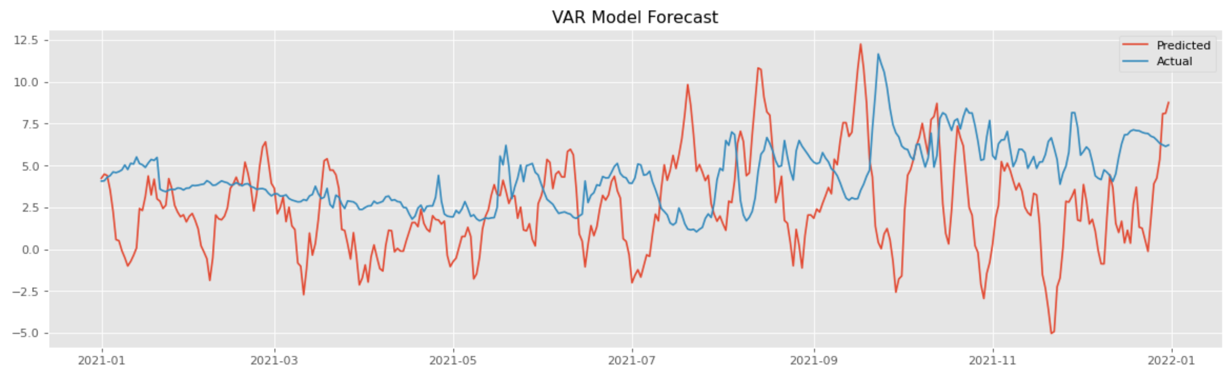
In [35]:
```
#creating the train and validation set
train = final_train_log
valid = final_test_log
```

In [36]:
```
#make final predictions
model = VAR(endog=train.dropna())
model_fit = model.fit(365)
yhat = model_fit.forecast(model_fit.endog, steps=365)
```

```
C:\Users\harri\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  self._init_dates(dates, freq)
```

In [37]:
```
# Untransform and reformat the predictions
yhat_unt = pd.DataFrame((np.exp(yhat))-2172)
yhat_unt.set_index(final_test.index, inplace=True)
yhat_unt.columns = final_test.columns
```

In [38]:
```
# Plot the predictions vs the actual values for 2021
plt.figure(figsize=(18,5), dpi=80)
plt.plot(yhat_unt['Turb_FNU'], label='Predicted')
plt.plot(final_test['Turb_FNU'], label='Actual')
plt.rcParams["figure.figsize"] = (20,3)
plt.title('VAR Model Forecast')
plt.legend();
```



In [39]:
```
# Calculate RMSE
dibrinse = ((final_test['Turb_FNU']**2)-yhat_unt['Turb_FNU'])
dibb = dibrinse.sum()
mse = dibb/365
rmse = np.sqrt(mse)
rmse
```

Out[39]:
```
4.463655258001275
```

The above is the predicted values for turbidity using VAR. This result is if we were to predict the entire year without knowing any of the values for the predictor variables for the year. This shows that although the explanatory variables do contribute to the turbidity value, they themselves are not predictable due to major contributing factors not explained by the data.

The RMSE here is much worse, at 4.5, as the forecast has no information about the future values for which it is predicting, explanatory variables or otherwise. That said, the overall variance gets larger as the year goes on in both the predicted and actual values much like the years prior. The highs also seems to match the nearby peaks in the actual data as well.

LSTM Neural Network

Long Short Term Memory(LSTM) networks are a style of Recurrent Neural Network(RNN). RNNs are machine learning models that use the previous values to help predict the future values, and are the neural networks generally best suited to dealing with time series values. This works in theory, but these models tend toward stasis as they try to forecast further into the future. This essentially means that while the most recent values still affect the model, as the old ones get further from the current prediction, they begin to lose importance.

LSTM networks alleviate this problem by selectively forgetting information that it deems unimportant, while retaining the information it deems important. It determines the importance of the previous input using a sigmoid function to and then uses the same function along with the current input to create a vector telling the model how much of the new information to include in the new memory state. This new memory state is then retained and considered in with the next input, and so on.

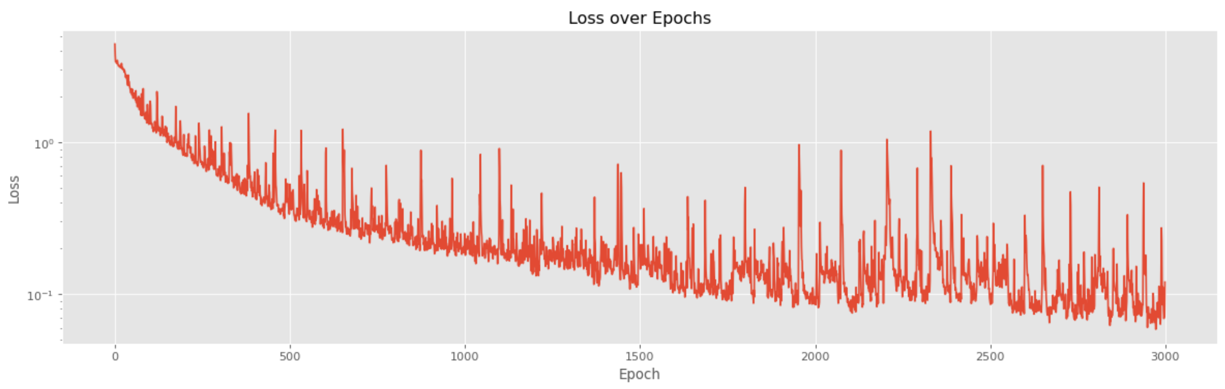
In [40]:
```
# Make train and test sets
X_train = final_train.drop(['Turb_FNU'], axis=1)
y_train = final_train.Turb_FNU
X_test = final_test.drop(['Turb_FNU'], axis=1)
y_test = final_test.Turb_FNU
```

In [41]:
```
# Build the LSTM Neural Network

m = Sequential()
m.add(LSTM(units=50, return_sequences=True,
          input_shape=(X_train.shape[1],1)))
m.add(Dropout(0.2))
m.add(LSTM(units=50))
m.add(Dropout(0.1))
m.add(Dense(units=1))
m.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

In [42]:
```
# Fit the model to the data
history = m.fit(X_train, y_train, epochs=3000, batch_size=25, verbose=1)
```

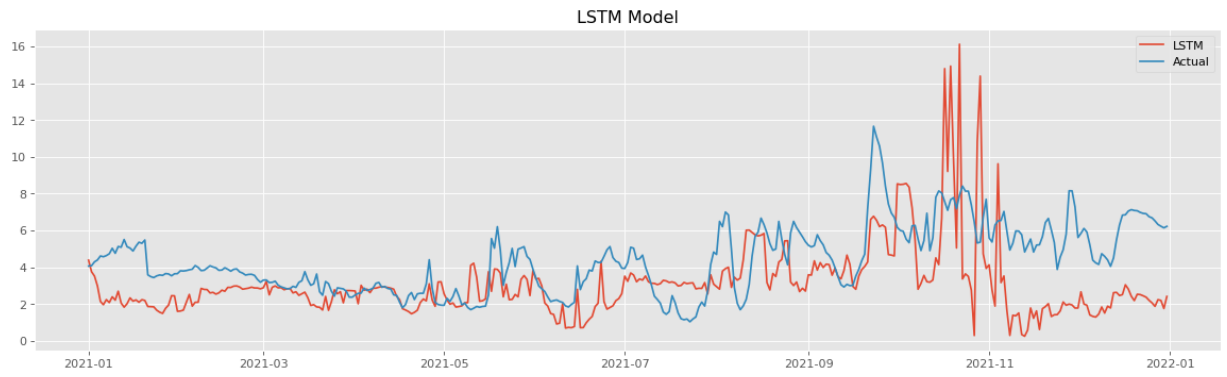
```
74/74 [==============================] - 1s 8ms/step - loss: 0.1992
Epoch 1584/3000
74/74 [==============================] - 1s 8ms/step - loss: 0.1987
Epoch 1585/3000
74/74 [==============================] - 1s 9ms/step - loss: 0.1457
Epoch 1586/3000
74/74 [==============================] - 1s 8ms/step - loss: 0.1429
Epoch 1587/3000
74/74 [==============================] - 1s 8ms/step - loss: 0.1231
Epoch 1588/3000
74/74 [==============================] - 1s 9ms/step - loss: 0.1083
Epoch 1589/3000
74/74 [==============================] - 1s 8ms/step - loss: 0.1266
Epoch 1590/3000
74/74 [==============================] - 1s 8ms/step - loss: 0.1903
Epoch 1591/3000
74/74 [==============================] - 1s 8ms/step - loss: 0.1235
Epoch 1592/3000
74/74 [==============================] - 1s 9ms/step - loss: 0.1156
Epoch 1593/3000
```

In [43]:
```
# Plot the loss of the model as each epoch passes
plt.figure(figsize=(18,5), dpi=80)
plt.ylabel('Loss'); plt.xlabel('Epoch')
plt.semilogy(history.history['loss'])
plt.title('Loss over Epochs');
```



```
In [44]: # Use the fitted LSTM to predict on the test set
         y_pred = m.predict(X_test)
         y_pred = pd.DataFrame(y_pred)
         y_pred.set_index(X_test.index, inplace=True)

         12/12 [==============================] - 1s 3ms/step
```

```
In [45]: # Plot the LSTM results
         plt.figure(figsize=(18,5), dpi=80)
         plt.plot(y_pred,label='LSTM')
         plt.plot(y_test,label='Actual')
         plt.title('LSTM Model')
         plt.legend();
```



```
In [46]: # Calculate correlation between predictions and actual values
         pd.DataFrame(y_test)['Turb_FNU'].corr(pd.DataFrame(y_pred)[0])

Out[46]: 0.367233411920398
```

```
In [47]: # Calculate RMSE
         dibrinse = (pd.DataFrame(y_test)['Turb_FNU']-pd.DataFrame(y_pred)[0])
         dibb = dibrinse.sum()
         mse = dibb/365
         rmse = np.sqrt(mse)
         rmse

Out[47]: 1.1373817719220303
```

The predicted and actual values for turbidity in 2021 are displayed in the graph above. Many of the peaks and valleys match up even though their magnitude may not always match. The RMSE here is relatively low, roughly a third of that of the VAR model, and shows that for any given point in time, the model is on average only off by 1.14.

While the RMSE for this model is not as high as that of the OLS model, this model stands to improve the most without considering new variables, given that the machine learning element of this model automatically picks up the signal, and that the loss is steadily decreasing, even after 3000 epochs.

Conclusions

All three models have their merits, and picking one requires knowledge of their underlying principles and the desired result. The fastest way to get a low variance prediction that is closest to the mean of forecasted values is the OLS regression. This model also has the added advantage of describing the relationship of the predictor variables to the turbidity, which is one of the major goals of this project. The most important factors are precipitation and snowmelt at White Elephant, which feeds rivers upstream in the Mack's Inn area, precipitation and snowmelt at the Island Park Dam, dissolved oxygen, which decreases as turbidity goes up, conductivity, with a positive correlation with turbidity, and temperature at both Island Park Dam and White Elephant. The disadvantage of this model is that it needs estimates for the future values of these explanatory variables in order to work.

The VAR model is possibly the best to use when you have no future data and this is its strongest point. The predictions it generates approximate the typical year of turbidity, with some flaws. The variance at the start of the year is a little too much, and the peaks do not line up exactly when they should happen, although this latter problem is likely caused by meteorological events not included in our data.

The LSTM model is the most adaptible, and can forecast with or without the explanatory variables provided. In this way it acts as sort of a blend of the previous two models, and with a relatively low RMSE it still predicts spikes in turbidity fairly wel, as opposed to the VAR model. Where the VAR is set up to forecast given no extra information out of the box, the LSTM could in the future use the predictions of the VAR model to provide more accurate results. As far as monitoring the turbidity, the best way to do that is the LSTM model with forecsats for the other variables provided.