Oil Production Forecasting Using Machine Learning

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Import necessary libraries and Load the data

In [1]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import missingno as msno

# Load Volve production data from Excel file
volve_data = pd.read_excel('Volve production data.xlsx')
```

Performing Exploratory Data Analytics

In [2]:
```
volve_data.head()
```

Out[2]:

	DATEPRD	WELL_BORE_CODE	NPD_WELL_BORE_CODE	NPD_WELL_BORE_NAME	NPD_FIE
0	2014-04-07	NO 15/9-F-1 C	7405	15/9-F-1 C	
1	2014-04-08	NO 15/9-F-1 C	7405	15/9-F-1 C	
2	2014-04-09	NO 15/9-F-1 C	7405	15/9-F-1 C	
3	2014-04-10	NO 15/9-F-1 C	7405	15/9-F-1 C	
4	2014-04-11	NO 15/9-F-1 C	7405	15/9-F-1 C	

5 rows × 24 columns

In [3]:
```
# Print information about the data, including column names, data types, and nc
volve_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15634 entries, 0 to 15633
Data columns (total 24 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   DATEPRD                   15634 non-null  datetime64[ns]
 1   WELL_BORE_CODE            15634 non-null  object
 2   NPD_WELL_BORE_CODE        15634 non-null  int64
 3   NPD_WELL_BORE_NAME        15634 non-null  object
 4   NPD_FIELD_CODE            15634 non-null  int64
 5   NPD_FIELD_NAME            15634 non-null  object
 6   NPD_FACILITY_CODE         15634 non-null  int64
 7   NPD_FACILITY_NAME         15634 non-null  object
 8   ON_STREAM_HRS             15349 non-null  float64
 9   AVG_DOWNHOLE_PRESSURE     8980 non-null   float64
 10  AVG_DOWNHOLE_TEMPERATURE  8980 non-null   float64
 11  AVG_DP_TUBING             8980 non-null   float64
 12  AVG_ANNULUS_PRESS         7890 non-null   float64
 13  AVG_CHOKE_SIZE_P          8919 non-null   float64
 14  AVG_CHOKE_UOM             9161 non-null   object
 15  AVG_WHP_P                 9155 non-null   float64
 16  AVG_WHT_P                 9146 non-null   float64
 17  DP_CHOKE_SIZE             15340 non-null  float64
 18  BORE_OIL_VOL              9161 non-null   float64
 19  BORE_GAS_VOL              9161 non-null   float64
 20  BORE_WAT_VOL              9161 non-null   float64
 21  BORE_WI_VOL               5706 non-null   float64
 22  FLOW_KIND                 15634 non-null  object
 23  WELL_TYPE                 15634 non-null  object
dtypes: datetime64[ns](1), float64(13), int64(3), object(7)
memory usage: 2.9+ MB
```

In [4]:
```
# We can check the shape and columns of the data
print(volve_data.shape)
print(volve_data.columns)
```

```
(15634, 24)
Index(['DATEPRD', 'WELL_BORE_CODE', 'NPD_WELL_BORE_CODE', 'NPD_WELL_BORE_NAM
E',
       'NPD_FIELD_CODE', 'NPD_FIELD_NAME', 'NPD_FACILITY_CODE',
       'NPD_FACILITY_NAME', 'ON_STREAM_HRS', 'AVG_DOWNHOLE_PRESSURE',
       'AVG_DOWNHOLE_TEMPERATURE', 'AVG_DP_TUBING', 'AVG_ANNULUS_PRESS',
       'AVG_CHOKE_SIZE_P', 'AVG_CHOKE_UOM', 'AVG_WHP_P', 'AVG_WHT_P',
       'DP_CHOKE_SIZE', 'BORE_OIL_VOL', 'BORE_GAS_VOL', 'BORE_WAT_VOL',
       'BORE_WI_VOL', 'FLOW_KIND', 'WELL_TYPE'],
      dtype='object')
```

In [5]:
```
# We can also check the data types of each column
print(volve_data.dtypes)
```

```
DATEPRD                     datetime64[ns]
WELL_BORE_CODE                      object
NPD_WELL_BORE_CODE                   int64
NPD_WELL_BORE_NAME                  object
NPD_FIELD_CODE                       int64
NPD_FIELD_NAME                      object
NPD_FACILITY_CODE                    int64
NPD_FACILITY_NAME                   object
ON_STREAM_HRS                      float64
AVG_DOWNHOLE_PRESSURE              float64
AVG_DOWNHOLE_TEMPERATURE           float64
AVG_DP_TUBING                      float64
AVG_ANNULUS_PRESS                  float64
AVG_CHOKE_SIZE_P                   float64
AVG_CHOKE_UOM                       object
AVG_WHP_P                          float64
AVG_WHT_P                          float64
DP_CHOKE_SIZE                      float64
BORE_OIL_VOL                       float64
BORE_GAS_VOL                       float64
BORE_WAT_VOL                       float64
BORE_WI_VOL                        float64
FLOW_KIND                           object
WELL_TYPE                           object
dtype: object
```

In [6]:
```
null_counts = volve_data.isnull().sum()

# Print the result
print(null_counts)
```

```
DATEPRD                        0
WELL_BORE_CODE                 0
NPD_WELL_BORE_CODE             0
NPD_WELL_BORE_NAME             0
NPD_FIELD_CODE                 0
NPD_FIELD_NAME                 0
NPD_FACILITY_CODE              0
NPD_FACILITY_NAME              0
ON_STREAM_HRS                285
AVG_DOWNHOLE_PRESSURE       6654
AVG_DOWNHOLE_TEMPERATURE    6654
AVG_DP_TUBING               6654
AVG_ANNULUS_PRESS           7744
AVG_CHOKE_SIZE_P            6715
AVG_CHOKE_UOM               6473
AVG_WHP_P                   6479
AVG_WHT_P                   6488
DP_CHOKE_SIZE                294
BORE_OIL_VOL                6473
BORE_GAS_VOL                6473
BORE_WAT_VOL                6473
BORE_WI_VOL                 9928
FLOW_KIND                      0
WELL_TYPE                      0
dtype: int64
```

In [7]:
```
# Generate summary statistics of the data, including count, mean, standard dev
volve_data.describe()
```

Out[7]:

	NPD_WELL_BORE_CODE	NPD_FIELD_CODE	NPD_FACILITY_CODE	ON_STREAM_HRS
count	15634.000000	15634.0	15634.0	15349.000000
mean	5908.581745	3420717.0	369304.0	19.994093
std	649.231622	0.0	0.0	8.369978
min	5351.000000	3420717.0	369304.0	0.000000
25%	5599.000000	3420717.0	369304.0	24.000000
50%	5693.000000	3420717.0	369304.0	24.000000
75%	5769.000000	3420717.0	369304.0	24.000000
max	7405.000000	3420717.0	369304.0	25.000000

In [8]:
```
# Calculate the correlation between the different columns of the data
volve_data.corr()
```

Out[8]:

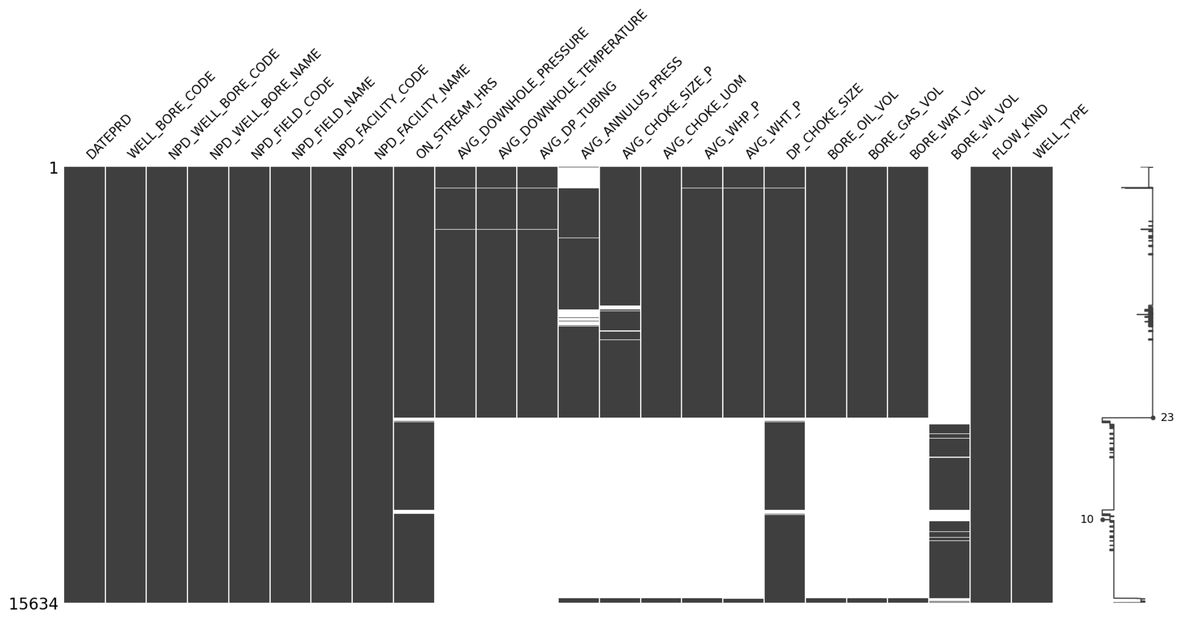
	NPD_WELL_BORE_CODE	NPD_FIELD_CODE	NPD_FACILITY_(
NPD_WELL_BORE_CODE	1.000000	NaN	
NPD_FIELD_CODE	NaN	NaN	
NPD_FACILITY_CODE	NaN	NaN	
ON_STREAM_HRS	-0.102270	NaN	
AVG_DOWNHOLE_PRESSURE	0.257481	NaN	
AVG_DOWNHOLE_TEMPERATURE	0.339509	NaN	
AVG_DP_TUBING	0.218243	NaN	
AVG_ANNULUS_PRESS	0.141756	NaN	
AVG_CHOKE_SIZE_P	-0.558461	NaN	
AVG_WHP_P	0.077946	NaN	
AVG_WHT_P	-0.519515	NaN	
DP_CHOKE_SIZE	0.237647	NaN	
BORE_OIL_VOL	-0.307645	NaN	
BORE_GAS_VOL	-0.310793	NaN	
BORE_WAT_VOL	-0.493591	NaN	
BORE_WI_VOL	-0.055894	NaN	

In [9]:
```
# Count the number of occurrences of each value in the 'WELL_BORE_CODE' colum
print(volve_data['WELL_BORE_CODE'].value_counts())
```

```
NO 15/9-F-4 AH    3327
NO 15/9-F-5 AH    3306
NO 15/9-F-12 H    3056
NO 15/9-F-14 H    3056
NO 15/9-F-11 H    1165
NO 15/9-F-15 D     978
NO 15/9-F-1 C      746
Name: WELL_BORE_CODE, dtype: int64
```

In [10]:
```
# Use the missingno library to visualize the missing data in the dataset
msno.matrix(volve_data)
```

Out[10]:
```
<AxesSubplot:>
```



In [11]:
```
print(volve_data['NPD_WELL_BORE_CODE'].value_counts())
```

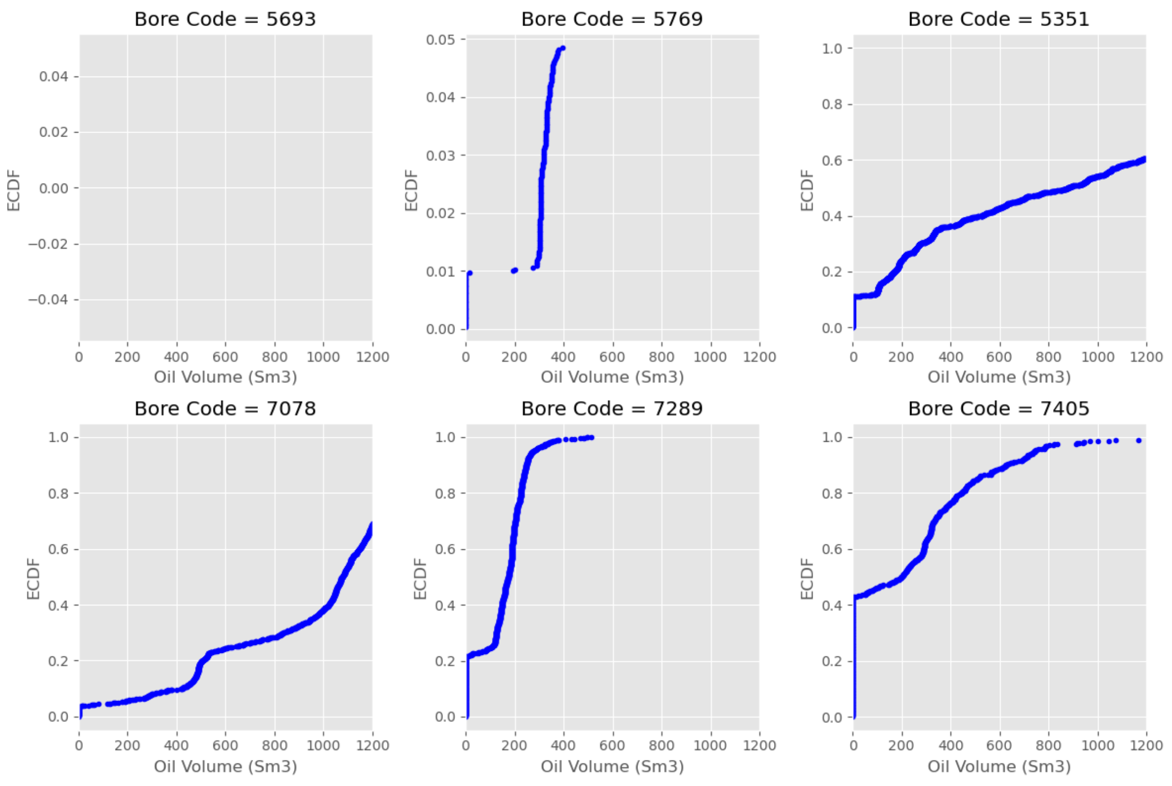
```
5693    3327
5769    3306
5599    3056
5351    3056
7078    1165
7289     978
7405     746
Name: NPD_WELL_BORE_CODE, dtype: int64
```

In [12]:
```
# Filter the data by selecting rows where the 'NPD_WELL_BORE_CODE' column matc
well_1_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 7405]
well_2_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 7078]
well_3_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 5599]
well_4_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 5351]
well_5_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 7289]
well_6_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 5693]
well_7_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == 5769]
```

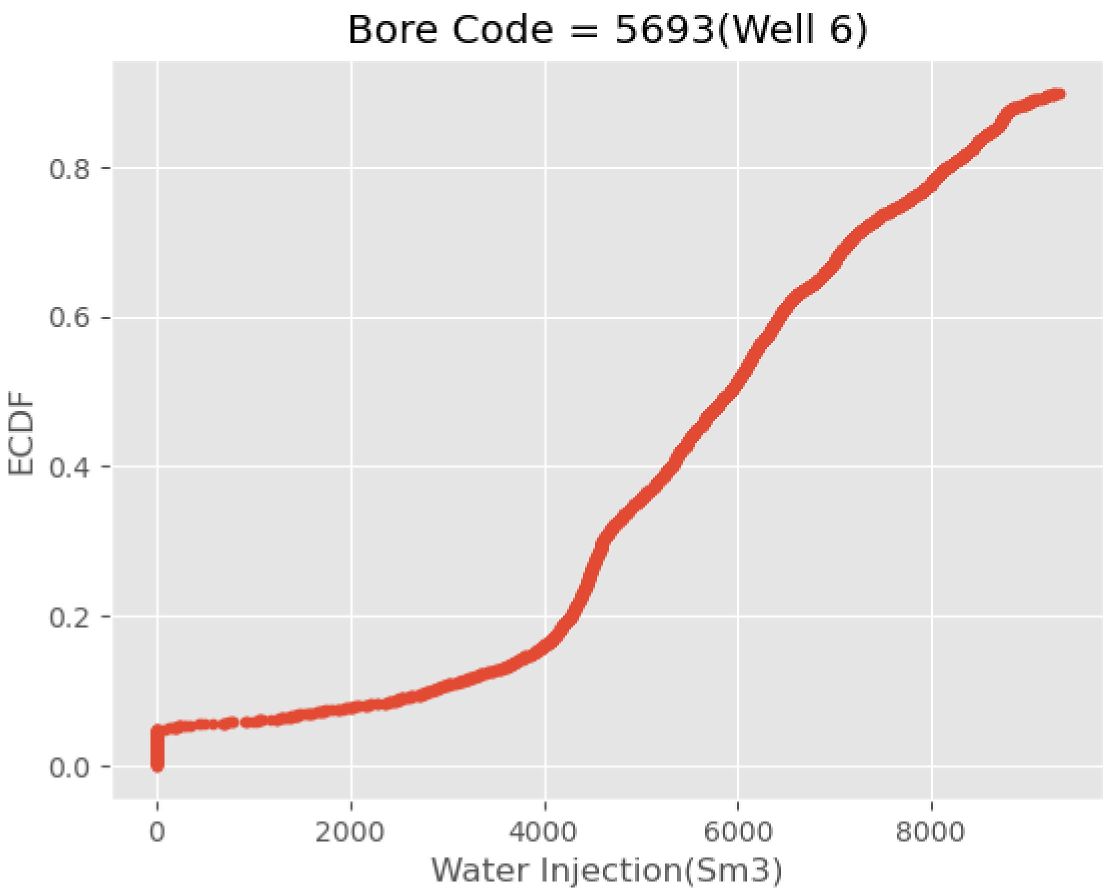
In [13]:
```
print("Information about well 1:")
print(well_1_data.info())
print("")

print("Information about well 2:")
print(well_2_data.info())
print("")

print("Information about well 3:")
print(well_3_data.info())
print("")

print("Information about well 4:")
print(well_4_data.info())
print("")

print("Information about well 5:")
print(well_5_data.info())
print("")

print("Information about well 6:")
print(well_6_data.info())
print("")

print("Information about well 7:")
print(well_7_data.info())
```

```
Information about well 1:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 746 entries, 0 to 745
Data columns (total 24 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   DATEPRD                   746 non-null    datetime64[ns]
 1   WELL_BORE_CODE            746 non-null    object
 2   NPD_WELL_BORE_CODE        746 non-null    int64
 3   NPD_WELL_BORE_NAME        746 non-null    object
 4   NPD_FIELD_CODE            746 non-null    int64
 5   NPD_FIELD_NAME            746 non-null    object
 6   NPD_FACILITY_CODE         746 non-null    int64
 7   NPD_FACILITY_NAME         746 non-null    object
 8   ON_STREAM_HRS             746 non-null    float64
 9   AVG_DOWNHOLE_PRESSURE     743 non-null    float64
 10  AVG_DOWNHOLE_TEMPERATURE  743 non-null    float64
 11  AVG_DP_TUBING             743 non-null    float64
 12  AVG_ANNULUS_PRESS         17 non-null     float64
```

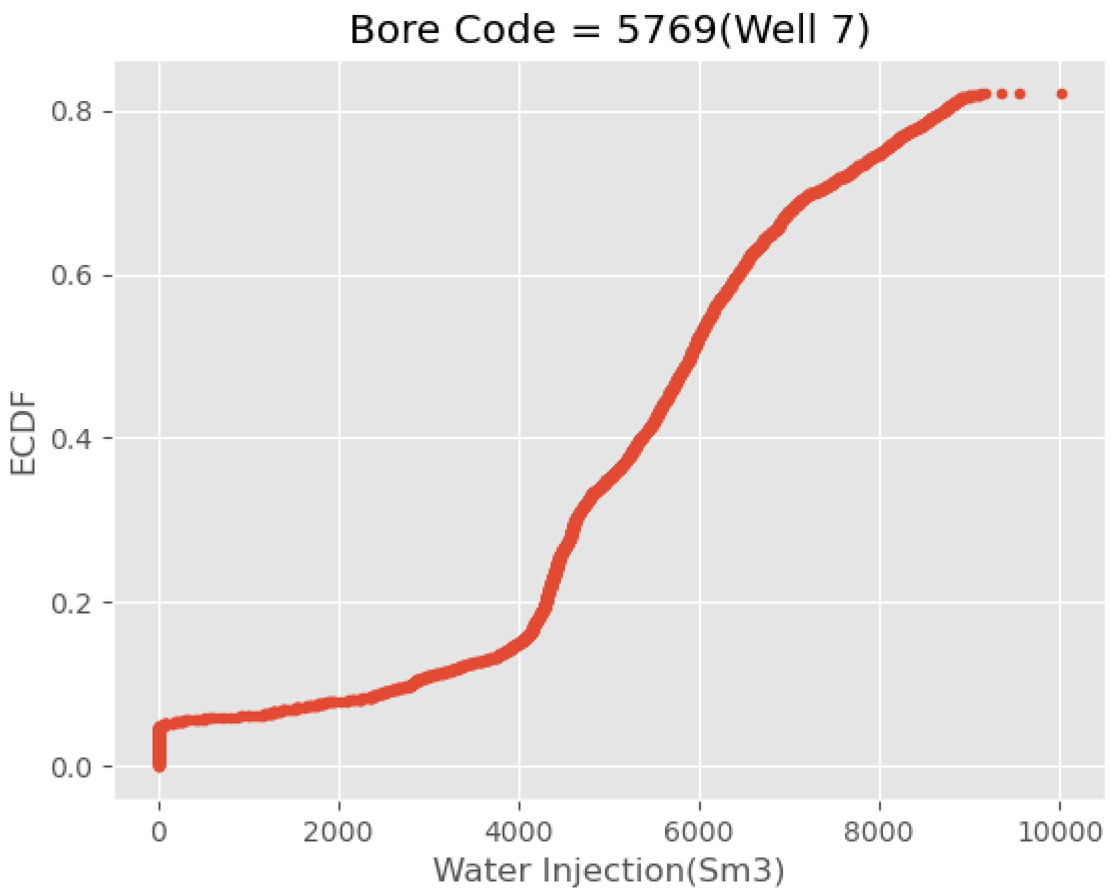
In [14]:
```
import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

# Define function for creating ECDF plot
def ecdf(data):
    n = len(data)
    x = np.sort(data)
    y = np.arange(1,n+1)/n
    return x,y

# Create subplots for all wells
fig, axs = plt.subplots(2, 3, figsize=(12, 8))
axs = axs.ravel()  # flatten the array of subplots

# Loop through wells and plot ECDF
wells = [5693, 5769, 5351, 7078, 7289, 7405]
for i, well in enumerate(wells):
    well_data = volve_data[volve_data['NPD_WELL_BORE_CODE'] == well]
    x_axis, y_axis = ecdf(well_data['BORE_OIL_VOL'])
    axs[i].plot(x_axis, y_axis, marker=".", linestyle="none", color='blue')
    axs[i].set_xlabel('Oil Volume (Sm3)')
    axs[i].set_ylabel('ECDF')
    axs[i].set_title(f'Bore Code = {well}')
    axs[i].set_xlim([0, 1200]) # set limit for x-axis

plt.tight_layout()
plt.show()
```



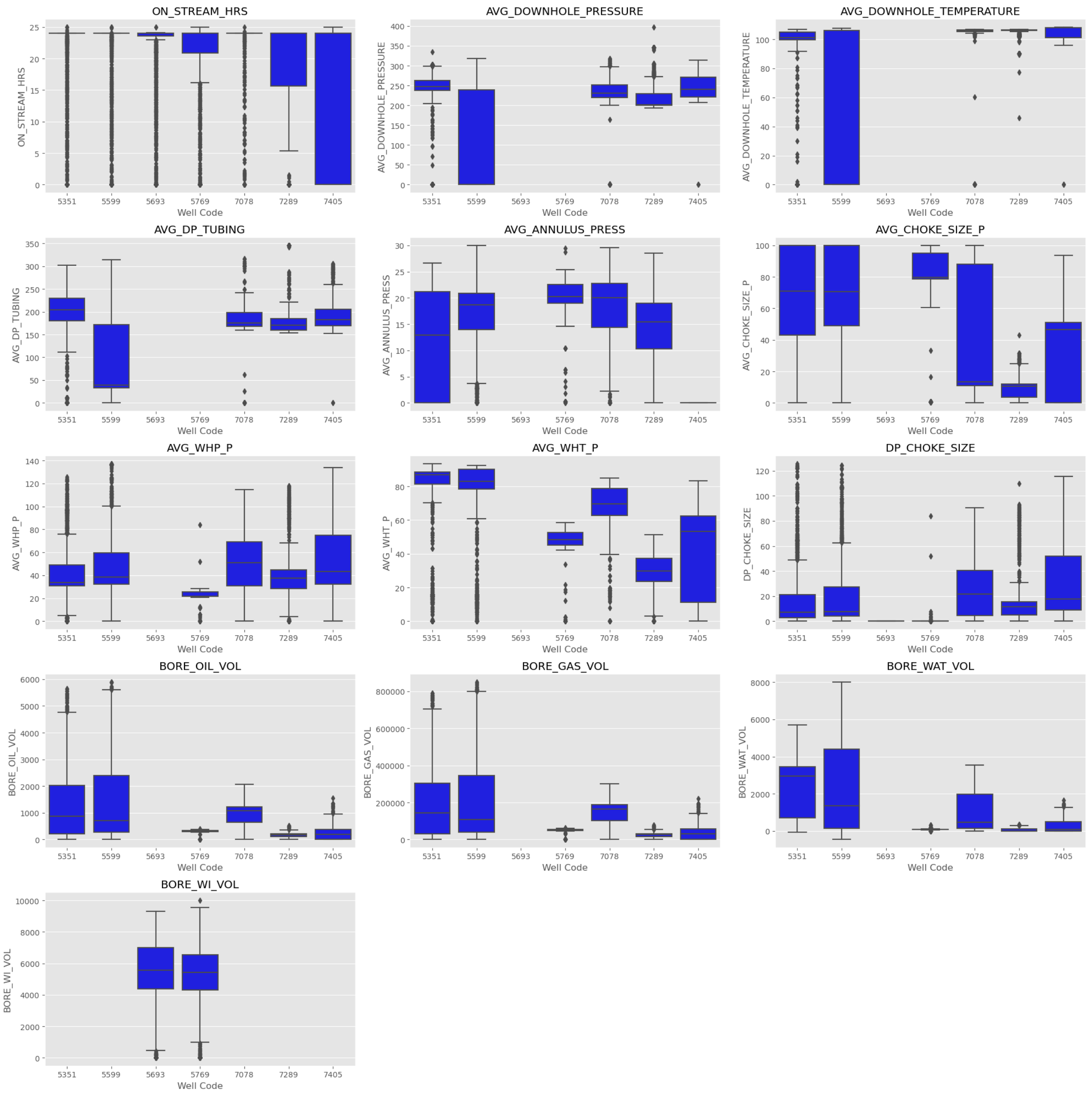
In [15]:
```
x_axis, y_axis = ecdf(well_6_data['BORE_WI_VOL'])
plt.plot(x_axis, y_axis, marker=".", linestyle="none")

#Labeling
plt.xlabel('Water Injection(Sm3)')
plt.ylabel('ECDF')
plt.title('Bore Code = 5693(Well 6)')

plt.show()
```



In [16]:
```
x_axis, y_axis = ecdf(well_7_data['BORE_WI_VOL'])
plt.plot(x_axis, y_axis, marker=".", linestyle="none")

#Labeling
plt.xlabel('Water Injection(Sm3)')
plt.ylabel('ECDF')
plt.title('Bore Code = 5769(Well 7)')

plt.show()
```

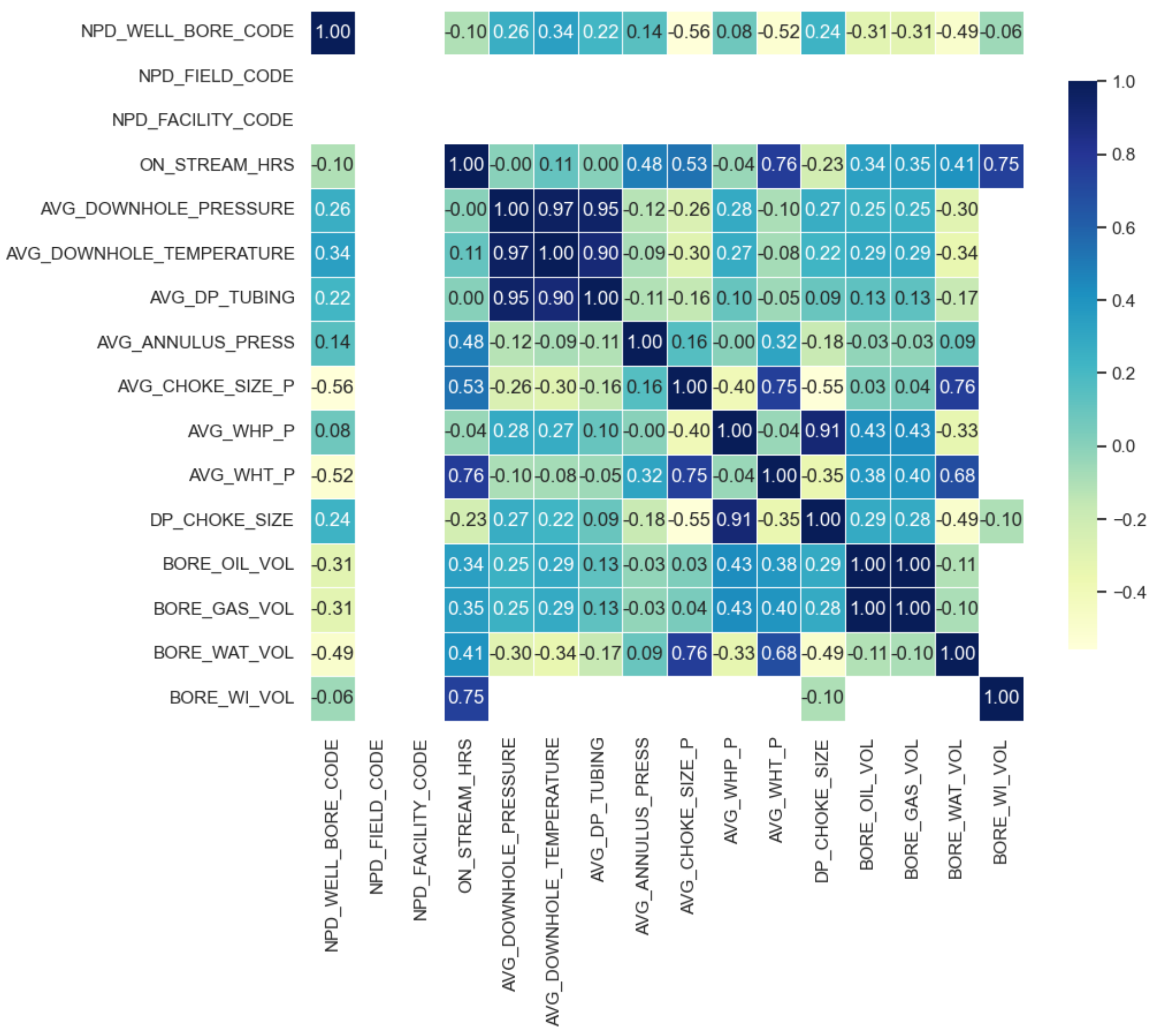


In [17]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(20,20))

columns = ['ON_STREAM_HRS', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DOWNHOLE_TEMPERATUR
           'AVG_DP_TUBING', 'AVG_ANNULUS_PRESS', 'AVG_CHOKE_SIZE_P',
           'AVG_WHP_P', 'AVG_WHT_P', 'DP_CHOKE_SIZE', 'BORE_OIL_VOL',
           'BORE_GAS_VOL', 'BORE_WAT_VOL', 'BORE_WI_VOL']

for i, col in enumerate(columns):
    plt.subplot(5, 3, i+1)
    sns.boxplot(x='NPD_WELL_BORE_CODE', y=col, data=volve_data, color='blue')
    plt.xlabel('Well Code')
    plt.ylabel(col)
    plt.title(col)

plt.tight_layout()
plt.show()
```



In [18]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt



# Calculate the correlation matrix
corr_matrix = volve_data.corr()

# Set up figure size and style
sns.set(style="white")
plt.figure(figsize=(10, 8))

# Create correlation plot
sns.heatmap(corr_matrix, cmap='YlGnBu', annot=True, fmt='.2f', linewidths=.5,
```

Out[18]:
```
<AxesSubplot:>
```



Performing Linear Regression

Import necessary libraries

In [19]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import math
from matplotlib import pyplot as plt
```

Load data

In [20]:
```
df = pd.read_excel('Volve production data.xlsx')
```

Round data to nearest integer

In [21]:
```
df = np.round(df)
```

Interpolate missing values

In [22]:
```
cols_to_interpolate = ['ON_STREAM_HRS', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DOWNHOL
                       'AVG_ANNULUS_PRESS', 'AVG_CHOKE_SIZE_P', 'AVG_WHP_P',
                       'BORE_OIL_VOL', 'BORE_GAS_VOL', 'BORE_WAT_VOL']
df[cols_to_interpolate] = df[cols_to_interpolate].interpolate(method='linear'
```

Drop unnecessary columns

In [23]:
```
cols_to_drop = ['WELL_BORE_CODE', 'NPD_WELL_BORE_NAME', 'NPD_FIELD_NAME', 'NPI
                'NPD_FACILITY_NAME', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DP_TUBING'
                'FLOW_KIND', 'WELL_TYPE', 'BORE_GAS_VOL']
df.drop(cols_to_drop, axis=1, inplace=True)
```

Scale dataset

In [24]:
```
cols_to_scale = ['ON_STREAM_HRS', 'AVG_DOWNHOLE_TEMPERATURE', 'AVG_ANNULUS_PR
                 'AVG_WHT_P']
scaler = MinMaxScaler()
df[cols_to_scale] = scaler.fit_transform(df[cols_to_scale])
```

Select data for wells 5599, 5351, 7078

In [25]:
```
df = df.loc[df['NPD_WELL_BORE_CODE'].isin([5599, 5351, 7078])]
```

Split data into training and testing sets

In [26]:
```
X = df.drop(['BORE_OIL_VOL'],axis=1)
y= df[['BORE_OIL_VOL','NPD_WELL_BORE_CODE']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rand
```

Train a linear regression model

In [27]:
```
reg_linear = LinearRegression()
x_train_final = X_train.drop(['DATEPRD','NPD_WELL_BORE_CODE'],axis = 1)
x_test_final = X_test.drop(['DATEPRD',"NPD_WELL_BORE_CODE"],axis = 1)
y_test_final = y_test['BORE_OIL_VOL']
y_train_final = y_train['BORE_OIL_VOL']
reg_linear.fit(x_train_final, y_train_final)
```

Out[27]:
```
LinearRegression()
```

Use the model to predict oil production for the test data

In [28]:
```
y_pred_linear = reg_linear.predict(x_test_final)
```

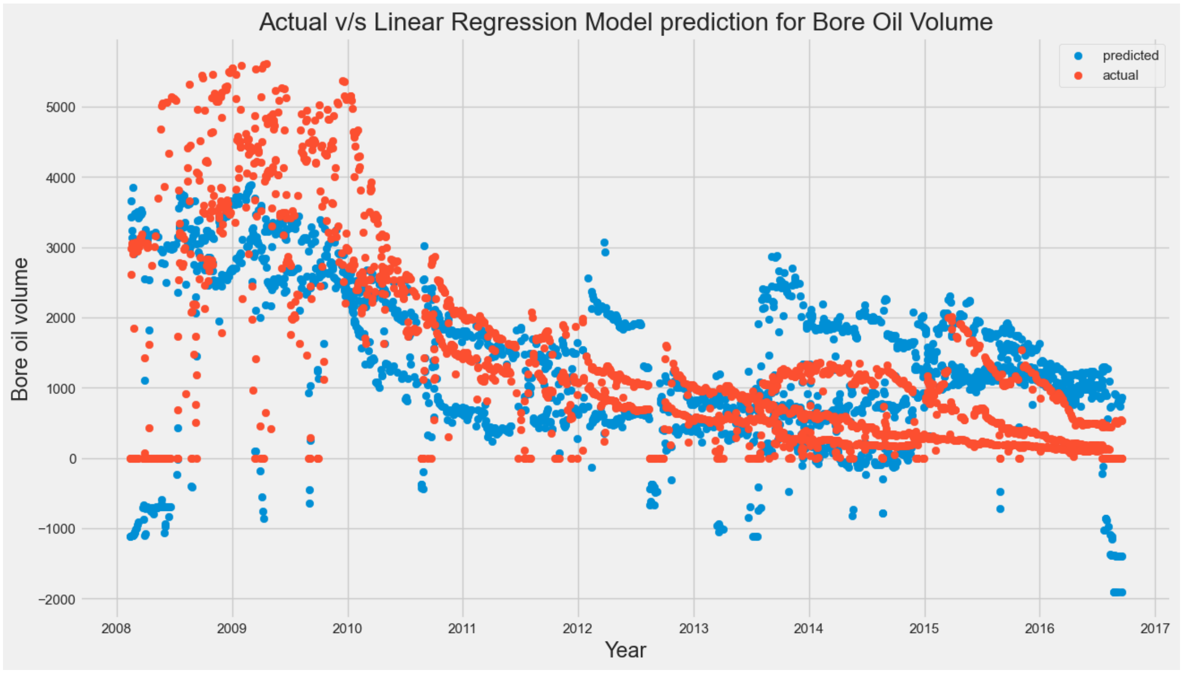
Calculate the Performance Metrics

In [29]:
```
# Calculate R-squared score to evaluate the model's performance
r2 = r2_score(y_test_final, y_pred_linear)
print('R-squared score of Linear Regression Model is :', r2)

# Calculate mean absolute error
mae = mean_absolute_error(y_test_final, y_pred_linear)
print('Mean absolute error of Linear Regression Model is :', mae)

# Calculate root mean squared error
rmse = math.sqrt(mean_squared_error(y_test_final, y_pred_linear))
print('Root mean squared error of linear Regression Model:', rmse)
# Calculate mean squared error
mse = mean_squared_error(y_test_final, y_pred_linear)
print('mean squared error of Linear Regression Model is :', mse)
```

```
R-squared score of Linear Regression Model is : 0.554546213401562
Mean absolute error of Linear Regression Model is : 705.8758754656305
Root mean squared error of linear Regression Model: 913.4242223150642
mean squared error of Linear Regression Model is : 834343.8099118797
```

Plot actual vs predicted values for Linear Regression Model

In [30]:
```
# Plot actual vs predicted values
plt.style.use('fivethirtyeight')
plt.figure(figsize = (14,8))
plt.scatter(X_test["DATEPRD"].tolist(), y_pred_linear, label='predicted')
plt.scatter(X_test["DATEPRD"].tolist(), y_test_final, label='actual')
plt.legend()
plt.xlabel("Year")
plt.ylabel("Bore oil volume")
plt.title('Actual v/s Linear Regression Model prediction for Bore Oil Volume'

# Show plot
plt.show()
```

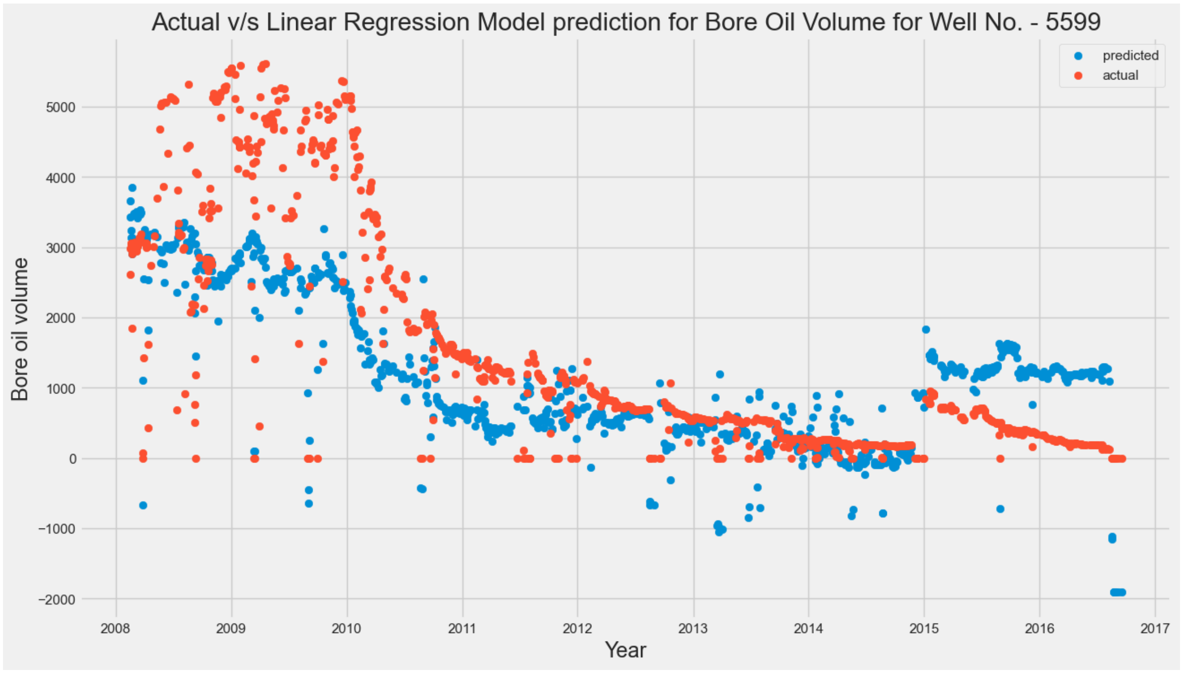


Plotting the actual vs Predicted values for Each Well Individually

Plot actual vs predicted values for 5599

```
In [31]: # Select data for well 5599
         X_test_5599 = X_test[X_test["NPD_WELL_BORE_CODE"] == 5599]
         y_test_5599 = y_test[y_test['NPD_WELL_BORE_CODE'] == 5599]
         x_test_5599final = X_test_5599.drop(['DATEPRD',"NPD_WELL_BORE_CODE"],axis = 1

         # Predict values
         y_pred_linear = reg_linear.predict(x_test_5599final)

         # Plot actual vs predicted values
         plt.style.use('fivethirtyeight')
         plt.figure(figsize = (14,8))
         plt.scatter(X_test_5599["DATEPRD"].tolist(),y_pred_linear,label='predicted')
         plt.scatter(X_test_5599["DATEPRD"].tolist(),y_test_5599['BORE_OIL_VOL'],label
         plt.legend()
         plt.xlabel("Year")
         plt.ylabel("Bore oil volume")
         plt.title('Actual v/s Linear Regression Model prediction for Bore Oil Volume 

         # Evaluate performance
         y_test_5599_final = y_test_5599['BORE_OIL_VOL']
         print("The R2 value for linear regression for oil volume production in well 5
```

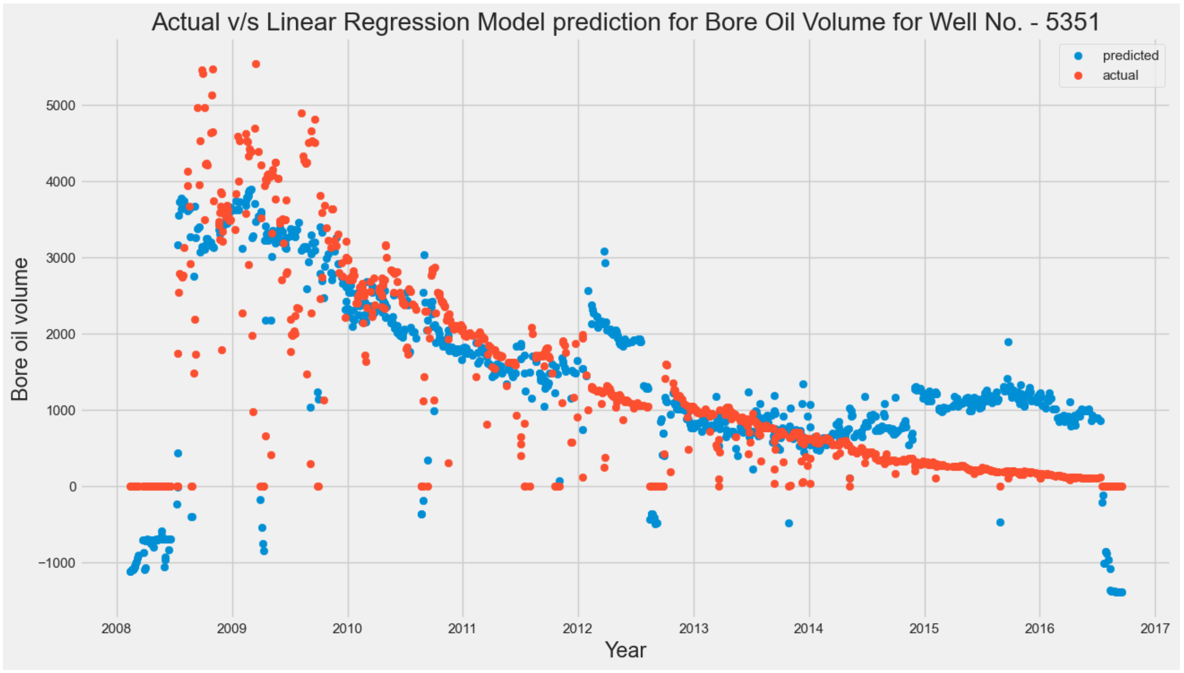
```
The R2 value for linear regression for oil volume production in well 5599 is
0.550247303910232
```



Plotting Actual vs predicted values for Well 5351

```
In [32]: # Select data for well 5351
         X_test_5351 = X_test[X_test["NPD_WELL_BORE_CODE"] == 5351]
         y_test_5351 = y_test[y_test['NPD_WELL_BORE_CODE'] == 5351]
         x_test_5351final = X_test_5351.drop(['DATEPRD',"NPD_WELL_BORE_CODE"],axis = 1

         # Predict values
         y_pred_linear = reg_linear.predict(x_test_5351final)

         # Plot actual vs predicted values
         plt.style.use('fivethirtyeight')
         plt.figure(figsize = (14,8))
         plt.scatter(X_test_5351["DATEPRD"].tolist(),y_pred_linear,label='predicted')
         plt.scatter(X_test_5351["DATEPRD"].tolist(),y_test_5351['BORE_OIL_VOL'],label
         plt.legend()
         plt.xlabel("Year")
         plt.ylabel("Bore oil volume")
         plt.title('Actual v/s Linear Regression Model prediction for Bore Oil Volume

         # Evaluate performance
         y_test_5351_final = y_test_5351['BORE_OIL_VOL']
         print("The R2 value for linear regression for oil volume production in well 5
```

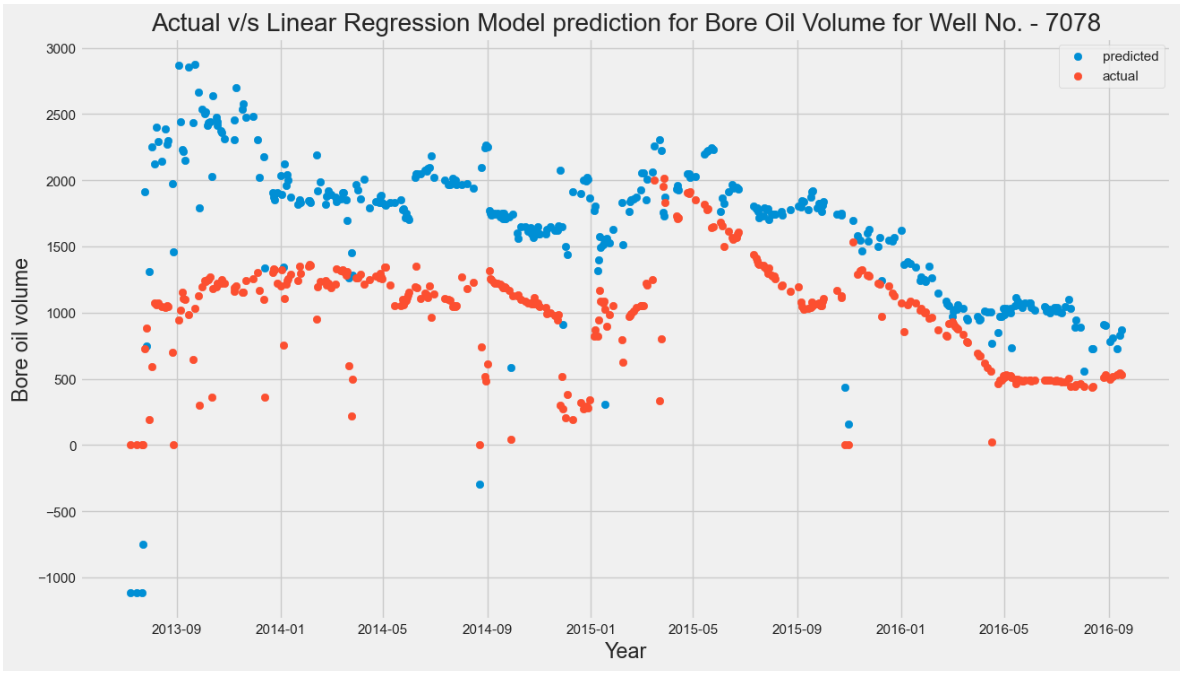
```
The R2 value for linear regression for oil volume production in well 5351 is
0.6742749337876078
```



Plotting Actual vs predicted values for Well 7078

In [33]:
```
# Select data for well 7078
X_test_7078 = X_test[X_test["NPD_WELL_BORE_CODE"] == 7078]
y_test_7078 = y_test[y_test['NPD_WELL_BORE_CODE'] == 7078]
x_test_7078final = X_test_7078.drop(['DATEPRD',"NPD_WELL_BORE_CODE"],axis = 1

# Predict using the trained model
y_pred_linear = reg_linear.predict(x_test_7078final)

# Plot actual vs predicted values
plt.style.use('fivethirtyeight')
plt.figure(figsize = (14,8))
plt.scatter(X_test_7078["DATEPRD"].tolist(), y_pred_linear, label='predicted'
plt.scatter(X_test_7078["DATEPRD"].tolist(), y_test_7078['BORE_OIL_VOL'], lab
plt.legend()
plt.xlabel("Year")
plt.ylabel("Bore oil volume")
plt.title('Actual v/s Linear Regression Model prediction for Bore Oil Volume
```

Out[33]:
```
Text(0.5, 1.0, 'Actual v/s Linear Regression Model prediction for Bore Oil V
olume for Well No. - 7078')
```



Polynomial regression

Importing any necessary libraries

In [34]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
```

Create polynomial features of degree 2

In [35]:
```
poly = PolynomialFeatures(degree=2)
x_train_poly = poly.fit_transform(x_train_final)
x_test_poly = poly.transform(x_test_final)
```

Fit linear regression model

In [36]:
```
reg_poly = LinearRegression()
reg_poly.fit(x_train_poly, y_train_final)
```

Out[36]:
```
LinearRegression()
```

Predict on test data

In [37]:
```
y_pred_poly = reg_poly.predict(x_test_poly)
```

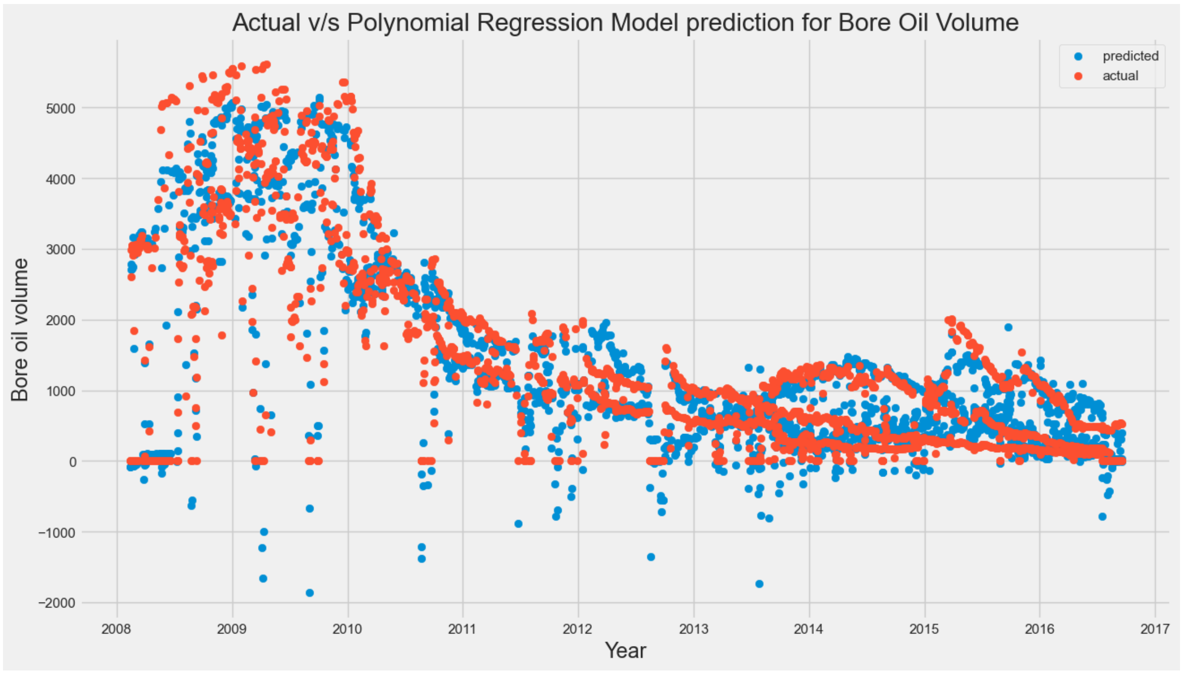
Calculating Performance metrics for Polynomial Regression

In [38]:
```
# Calculate R-squared score
r2_poly = r2_score(y_test_final, y_pred_poly)
print('R-squared score of Ploynomial Regression is :', r2_poly)

# Calculate mean absolute error
mae_poly = mean_absolute_error(y_test_final, y_pred_poly)
print('Mean absolute error of Ploynomial Regression is :', mae_poly)

#Calculate mean squared error
mse_poly = mean_squared_error(y_test_final, y_pred_poly)
print('Mean squared error of Ploynomial Regression is :', mse_poly)
# Calculate root mean squared error
rmse_poly = math.sqrt(mean_squared_error(y_test_final, y_pred_poly))
print('Root mean squared error of Ploynomial Regression is :', rmse_poly)
```

```
R-squared score of Ploynomial Regression is : 0.9301328617036829
Mean absolute error of Ploynomial Regression is : 250.37863563033665
Mean squared error of Ploynomial Regression is : 130862.54086855218
Root mean squared error of Ploynomial Regression is : 361.7492790159397
```

Plotting Actual vs Predicted values for Polynomial Regression

In [39]:
```
# Plot actual vs predicted values
plt.style.use('fivethirtyeight')
#plt.style.use('seaborn')
plt.figure(figsize=(14, 8))
plt.scatter(X_test['DATEPRD'], y_pred_poly, label='predicted')
plt.scatter(X_test['DATEPRD'], y_test_final, label='actual')
plt.legend()
plt.xlabel("Year")
plt.ylabel("Bore oil volume")
plt.title('Actual v/s Polynomial Regression Model prediction for Bore Oil Volu

# Show plot
plt.show()
```

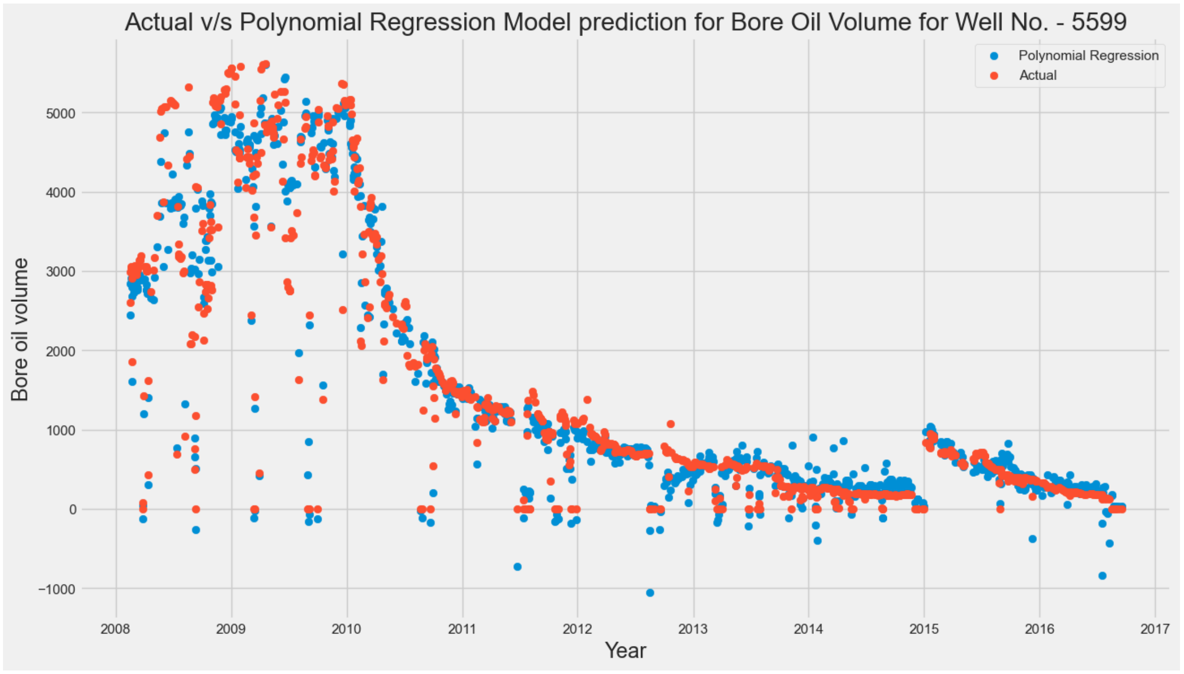


Plotting Actual vs predicted values for each Well

Plotting for well 5599

In [40]:
```
# Perform polynomial regression for well 5599
poly = PolynomialFeatures(degree=2)
x_poly_5599 = poly.fit_transform(x_test_5599final)
reg_poly = LinearRegression()
reg_poly.fit(x_poly_5599, y_test_5599_final)
y_pred_poly = reg_poly.predict(poly.fit_transform(x_test_5599final))

# Plot actual vs predicted values
plt.figure(figsize=(14, 8))
plt.scatter(X_test_5599["DATEPRD"].tolist(), y_pred_poly, label='Polynomial Re
plt.scatter(X_test_5599["DATEPRD"].tolist(), y_test_5599['BORE_OIL_VOL'], labe
plt.legend()
plt.xlabel("Year")
plt.ylabel("Bore oil volume")
plt.title('Actual v/s Polynomial Regression Model prediction for Bore Oil Volu
```

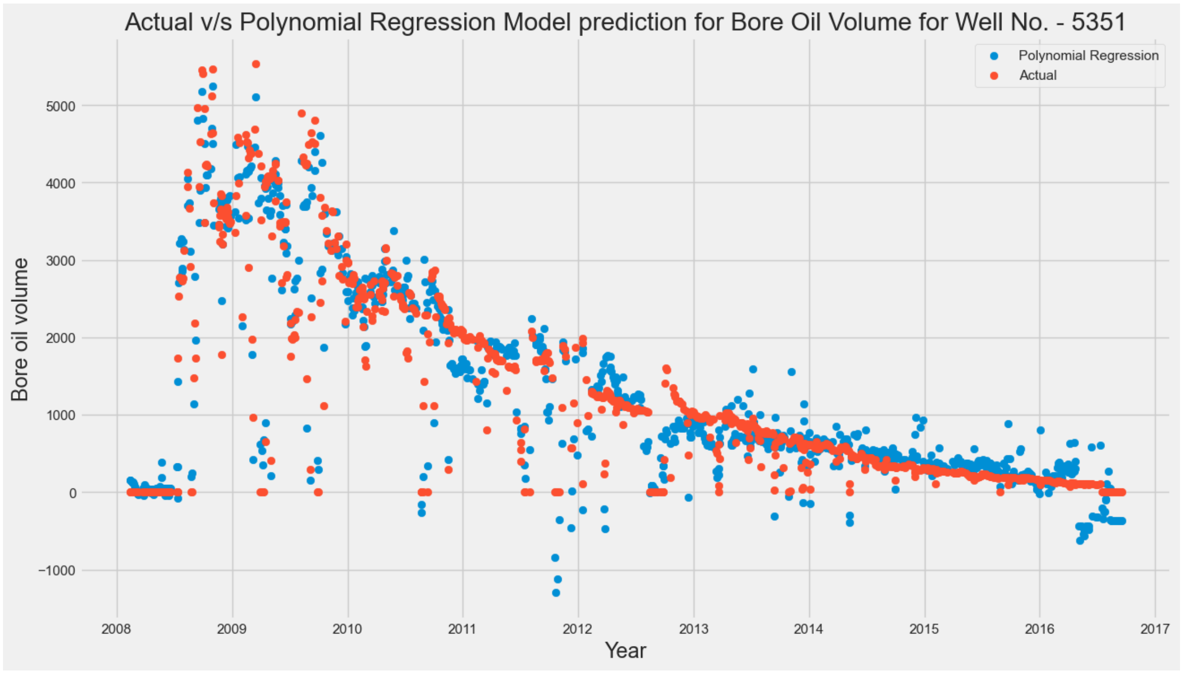
Out[40]:
```
Text(0.5, 1.0, 'Actual v/s Polynomial Regression Model prediction for Bore O
il Volume for Well No. - 5599')
```



Plotting for Well 5351

In [41]:
```
# Perform polynomial regression for well 5351
poly = PolynomialFeatures(degree=2)
x_poly_5351 = poly.fit_transform(x_test_5351final)
reg_poly = LinearRegression()
reg_poly.fit(x_poly_5351, y_test_5351_final)
y_pred_poly = reg_poly.predict(poly.fit_transform(x_test_5351final))

# Plot actual vs predicted values
plt.figure(figsize=(14, 8))
plt.scatter(X_test_5351["DATEPRD"].tolist(), y_pred_poly, label='Polynomial Re
plt.scatter(X_test_5351["DATEPRD"].tolist(), y_test_5351['BORE_OIL_VOL'], labe
plt.legend()
plt.xlabel("Year")
plt.ylabel("Bore oil volume")
plt.title('Actual v/s Polynomial Regression Model prediction for Bore Oil Volu
```

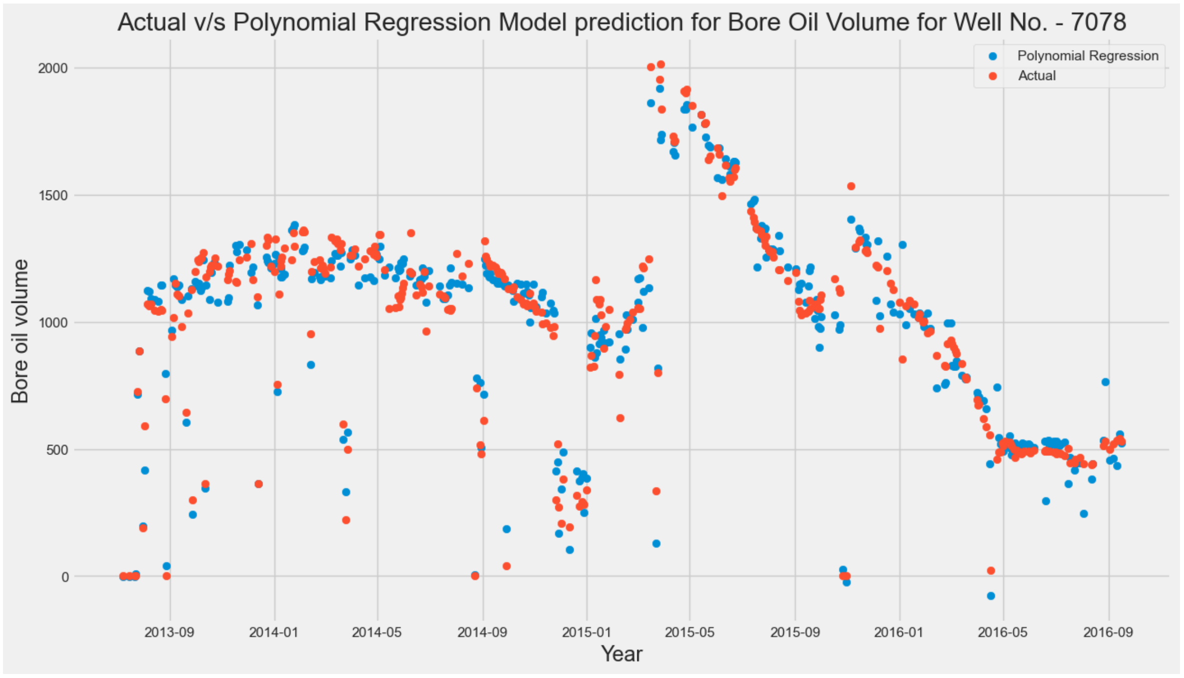
Out[41]:
```
Text(0.5, 1.0, 'Actual v/s Polynomial Regression Model prediction for Bore O
il Volume for Well No. - 5351')
```



Plotting for Well 7078

In [42]:
```
poly = PolynomialFeatures(degree=2)
y_test_7078_final = y_test_7078['BORE_OIL_VOL']
x_poly_7078 = poly.fit_transform(x_test_7078final)
reg_poly = LinearRegression()
reg_poly.fit(x_poly_7078, y_test_7078_final)
y_pred_poly = reg_poly.predict(poly.fit_transform(x_test_7078final))

# Plot actual vs predicted values
plt.figure(figsize=(14, 8))
plt.scatter(X_test_7078["DATEPRD"].tolist(), y_pred_poly, label='Polynomial Re
plt.scatter(X_test_7078["DATEPRD"].tolist(), y_test_7078['BORE_OIL_VOL'], labe
plt.legend()
plt.xlabel("Year")
plt.ylabel("Bore oil volume")
plt.title('Actual v/s Polynomial Regression Model prediction for Bore Oil Volu
```

Out[42]:
```
Text(0.5, 1.0, 'Actual v/s Polynomial Regression Model prediction for Bore O
il Volume for Well No. - 7078')
```



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XGBOOST

Import the Libraries

In [43]:
```
import pandas as pd
import numpy as np
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Load the data

In [44]:
```
df = pd.read_excel('Volve production data.xlsx')
```

Round data to nearest integer

In [45]:
```
# Round data to nearest integer
df = np.round(df)
```

Convert date to Unix timestamp

In [46]:
```
# Convert date to Unix timestamp
df['DATEPRD'] = pd.to_datetime(df['DATEPRD'])
df['DATEPRD'] = (df['DATEPRD'] - pd.Timestamp("1970-01-01")) // pd.Timedelta(
```

Interpolate missing values

In [47]:
```
# Interpolate missing values
cols_to_interpolate = ['ON_STREAM_HRS', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DOWNHOL
                       'AVG_ANNULUS_PRESS', 'AVG_CHOKE_SIZE_P', 'AVG_WHP_P',
                       'BORE_OIL_VOL', 'BORE_GAS_VOL', 'BORE_WAT_VOL']
df[cols_to_interpolate] = df[cols_to_interpolate].interpolate(method='linear'
```

Drop unnecessary columns

In [48]:
```
# Drop unnecessary columns
cols_to_drop = ['WELL_BORE_CODE', 'NPD_WELL_BORE_NAME', 'NPD_FIELD_NAME', 'NPI
                'NPD_FACILITY_NAME', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DP_TUBING'
                'FLOW_KIND', 'WELL_TYPE', 'BORE_GAS_VOL']
df.drop(cols_to_drop, axis=1, inplace=True)
```

Select data for wells 5599,5351,7078

In [49]:
```
# Select data for wells 2-4
df = df.loc[df['NPD_WELL_BORE_CODE'].isin([5599,5351,7078])]
```

Prepare data for training

In [50]:
```
# Prepare data for training
X = df.drop(['BORE_OIL_VOL'], axis=1)
y = df['BORE_OIL_VOL']

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

Train model

In [51]:
```
# Train model
model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.1, gamma=0, subsam
                         colsample_bytree=1, max_depth=7, random_state=42)
model.fit(X_train, y_train)
```

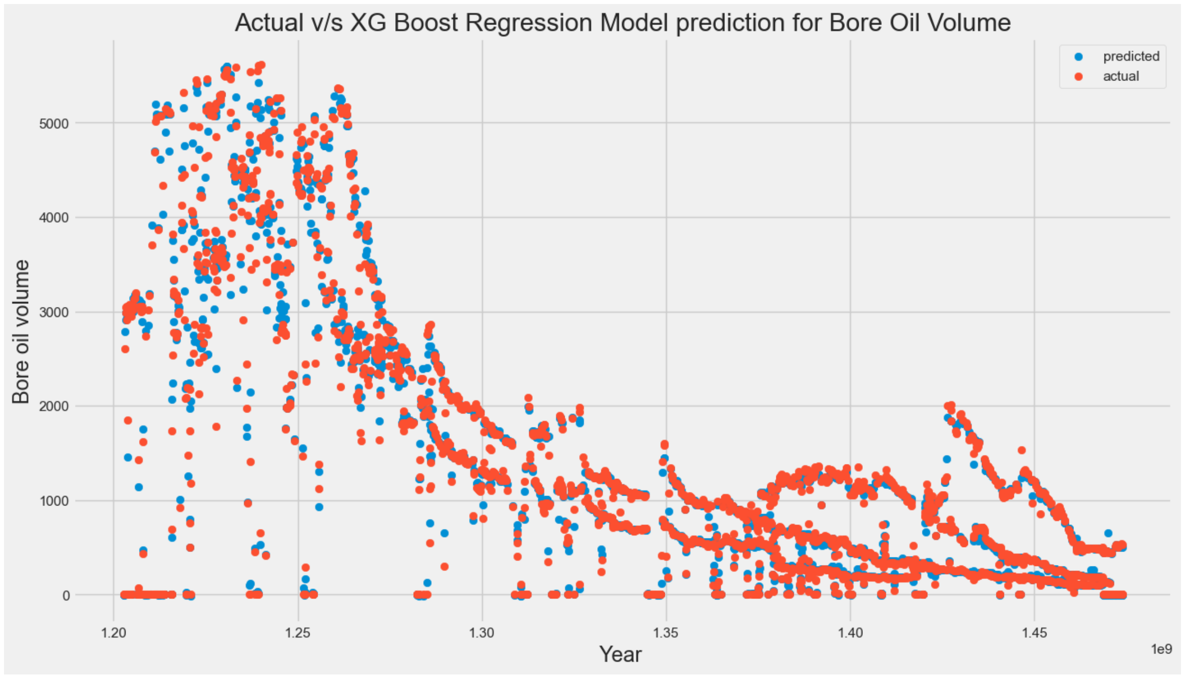
Out[51]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None, colsample_bytree
=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=None,
             grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=7, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=42, ...)
```

Predict on test set and calculate performance metrics

In [52]:
```
# Predict on test set and calculate performance metrics
y_pred_xgb = model.predict(X_test)
r2 = r2_score(y_test, y_pred_xgb)
mae = mean_absolute_error(y_test, y_pred_xgb)
mse = mean_squared_error(y_test, y_pred_xgb)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((y_test.replace(0, 1e-8) - y_pred_xgb) / y_test.replace

print("The R2 value for XGBoost Regression for oil volume production is", r2)
print("The mean absolute error (MAE) for XGBoost Regression is", mae)
print("The mean squared error (MSE) for XGBoost Regression is", mse)
print("The root mean squared error (RMSE) for XGBoost Regression is", rmse)
```

```
The R2 value for XGBoost Regression for oil volume production is 0.994066328
8525774
The mean absolute error (MAE) for XGBoost Regression is 53.5111157297474
The mean squared error (MSE) for XGBoost Regression is 11113.884180240848
The root mean squared error (RMSE) for XGBoost Regression is 105.42240834016
67
```

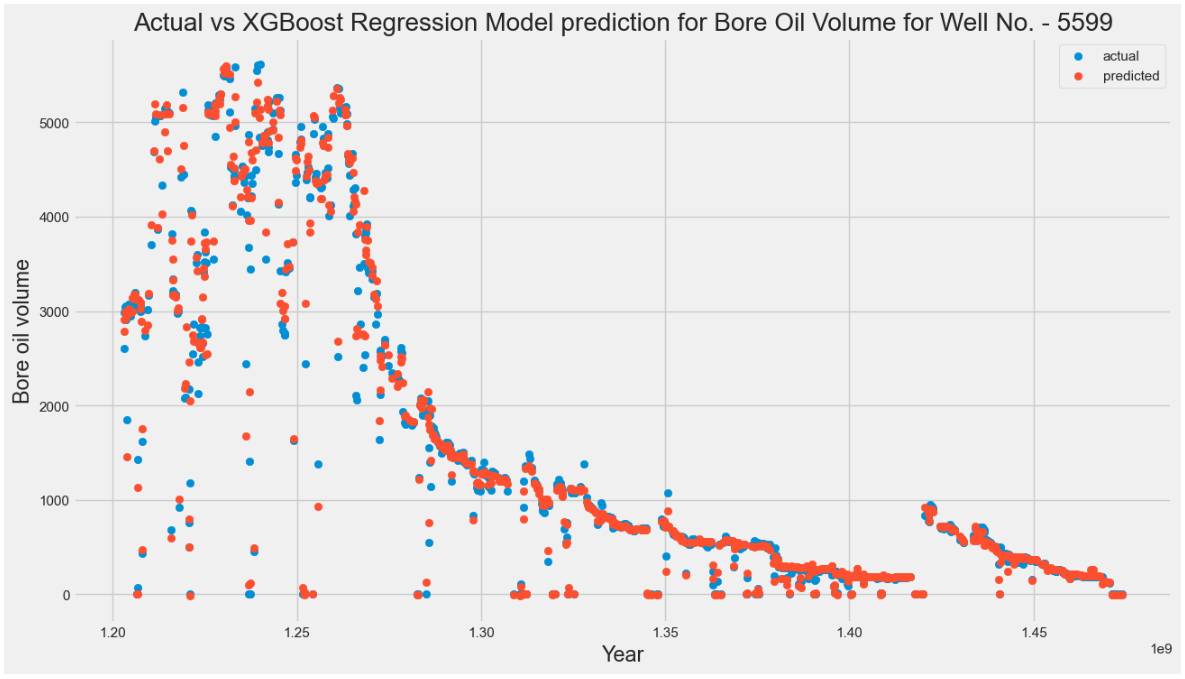
In [53]:
```
# Plot actual vs predicted values
plt.style.use('fivethirtyeight')
#plt.style.use('ggplot')
plt.figure(figsize=(14, 8))
plt.scatter(X_test['DATEPRD'], y_pred_xgb, label='predicted')
plt.scatter(X_test['DATEPRD'], y_test_final, label='actual')
plt.legend()
plt.xlabel("Year ")#represented in terms of 9th power of seconds as we are us
plt.ylabel("Bore oil volume")
plt.title('Actual v/s XG Boost Regression Model prediction for Bore Oil Volum

# Show plot
plt.show()
```

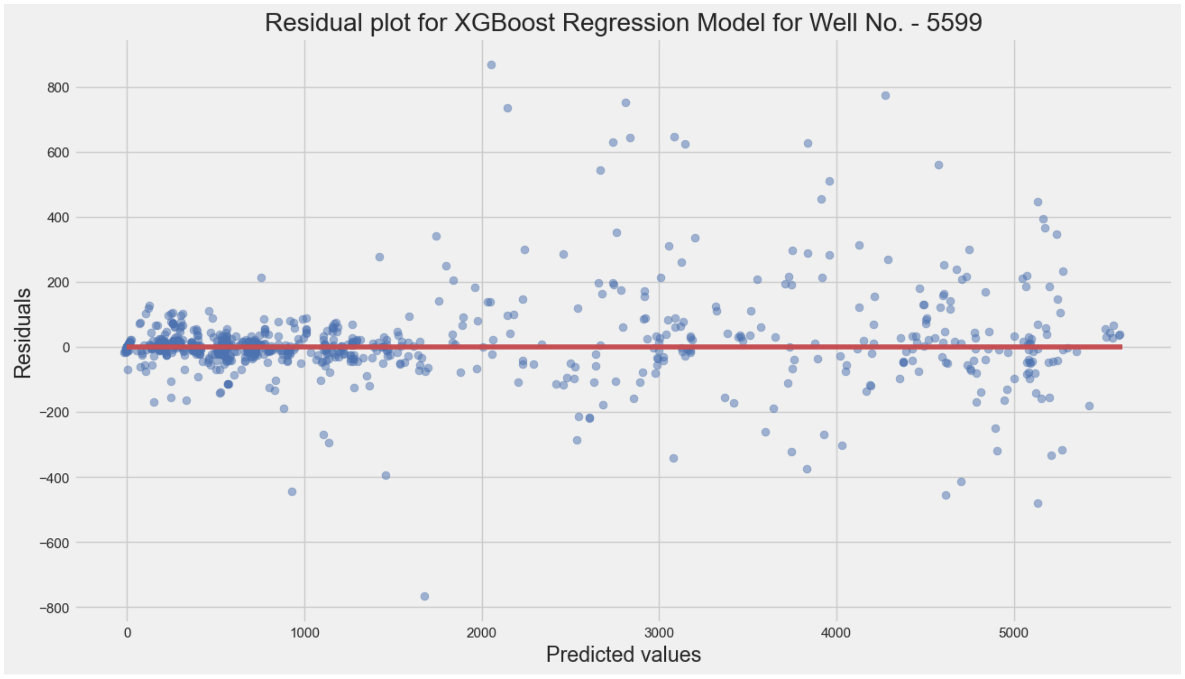


Plotting the Actual vs Predicted values for the wells using XGBoost Regression Model

Actual vs Predicted values for the well-5599

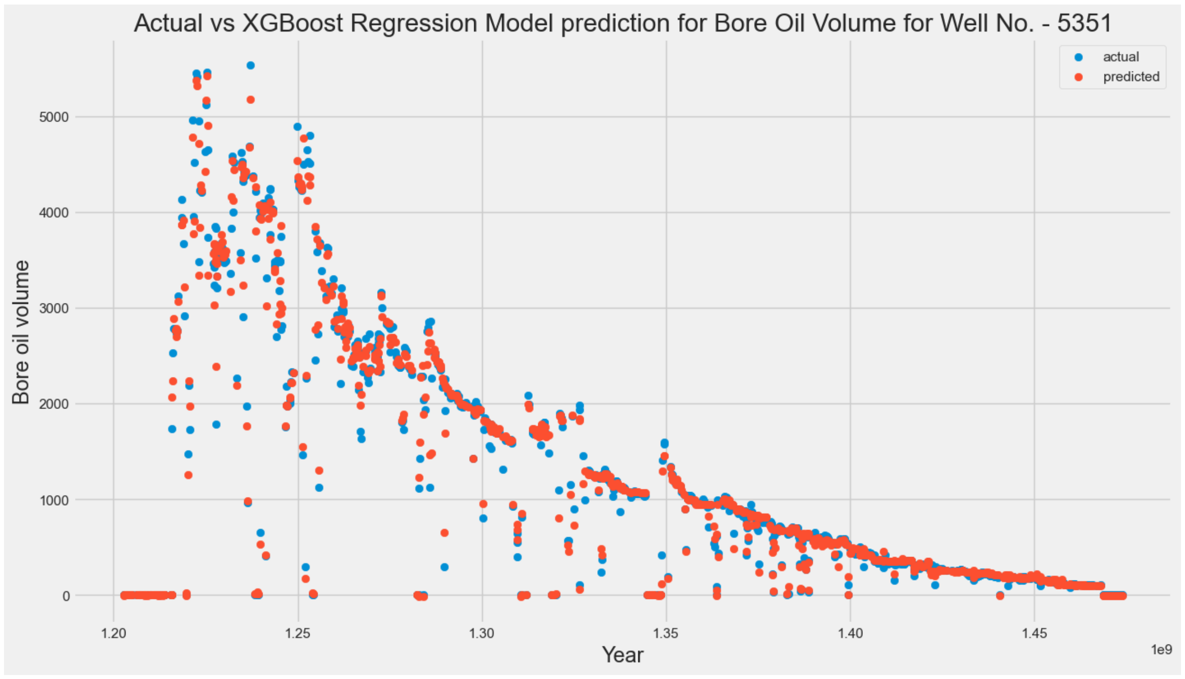
In [54]:
```
import matplotlib.pyplot as plt

# Select data for well 7405
X_test_5599 = X_test[X_test['NPD_WELL_BORE_CODE'] == 5599]
y_test_5599 = y_test[X_test['NPD_WELL_BORE_CODE'] == 5599]
y_pred_5599 = model.predict(X_test_5599)

# Plot predicted vs actual oil production
plt.figure(figsize=(14, 8))
plt.scatter(X_test_5599['DATEPRD'], y_test_5599, label='actual')
plt.scatter(X_test_5599['DATEPRD'], y_pred_5599, label='predicted')
plt.xlabel('Year')
plt.ylabel('Bore oil volume')
plt.title('Actual vs XGBoost Regression Model prediction for Bore Oil Volume 
plt.legend()
plt.show()

# Plot residual plot
plt.figure(figsize=(14, 8))
plt.scatter(y_pred_5599, y_pred_5599 - y_test_5599, c='b', s=40, alpha=0.5)
plt.hlines(y=0, xmin=0, xmax=max(y_test_5599), colors='r', zorder=3)
plt.xlabel('Predicted values')
plt.ylabel('Residuals')
plt.title('Residual plot for XGBoost Regression Model for Well No. - 5599')
plt.show()
```

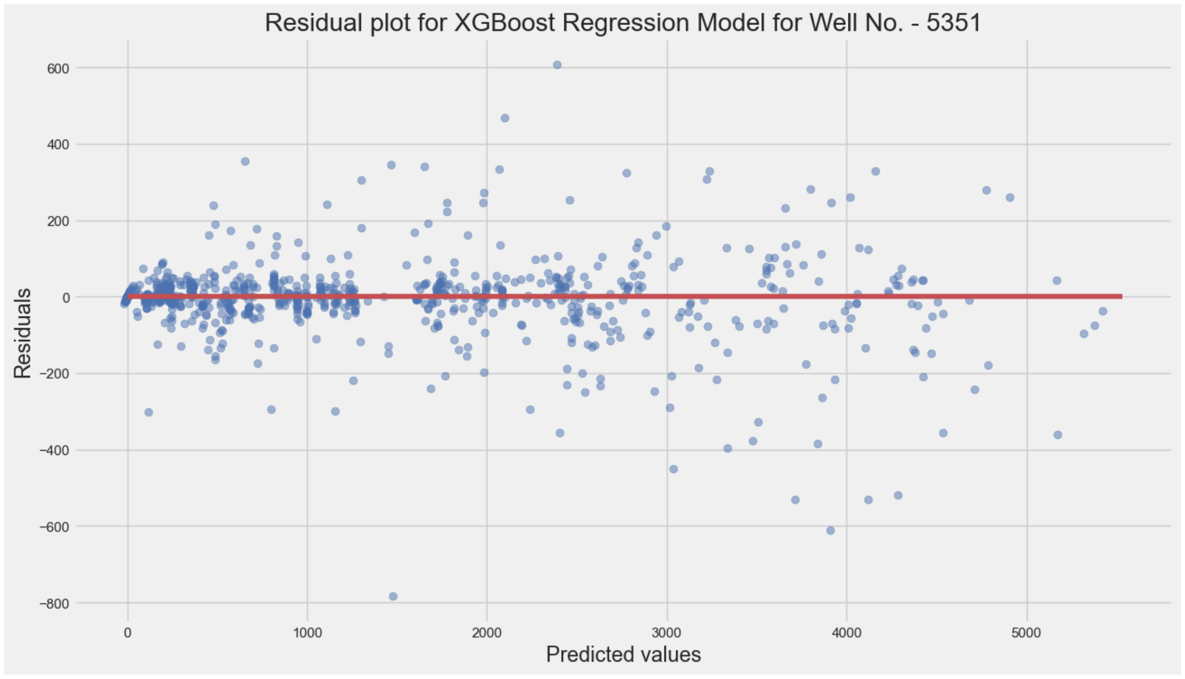




Actual vs Predicted values for the well-5351

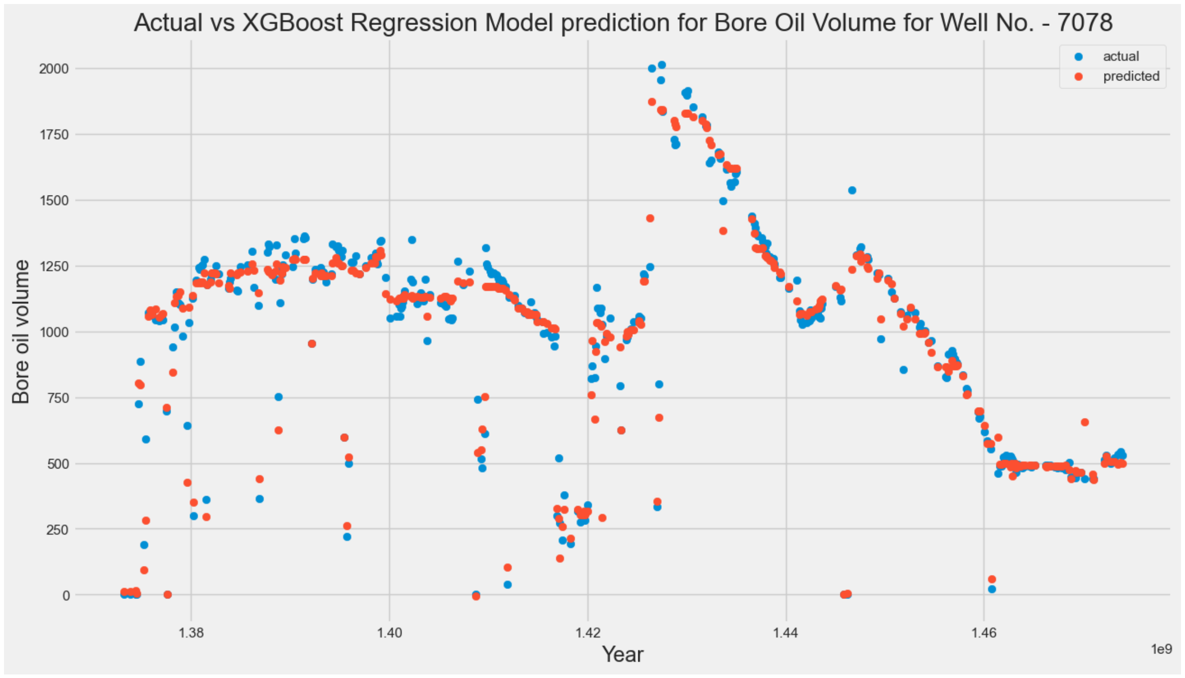
In [55]:
```
# Select data for well 5351
X_test_5351 = X_test[X_test['NPD_WELL_BORE_CODE'] == 5351]
y_test_5351 = y_test[X_test['NPD_WELL_BORE_CODE'] == 5351]
y_pred_5351 = model.predict(X_test_5351)

# Plot predicted vs actual oil production
plt.figure(figsize=(14, 8))
plt.scatter(X_test_5351['DATEPRD'], y_test_5351, label='actual')
plt.scatter(X_test_5351['DATEPRD'], y_pred_5351, label='predicted')
plt.xlabel('Year')
plt.ylabel('Bore oil volume')
plt.title('Actual vs XGBoost Regression Model prediction for Bore Oil Volume 
plt.legend()
plt.show()

# Plot residual plot
plt.figure(figsize=(14, 8))
plt.scatter(y_pred_5351, y_pred_5351 - y_test_5351, c='b', s=40, alpha=0.5)
plt.hlines(y=0, xmin=0, xmax=max(y_test_5351), colors='r', zorder=3)
plt.xlabel('Predicted values')
plt.ylabel('Residuals')
plt.title('Residual plot for XGBoost Regression Model for Well No. - 5351')
plt.show()
```



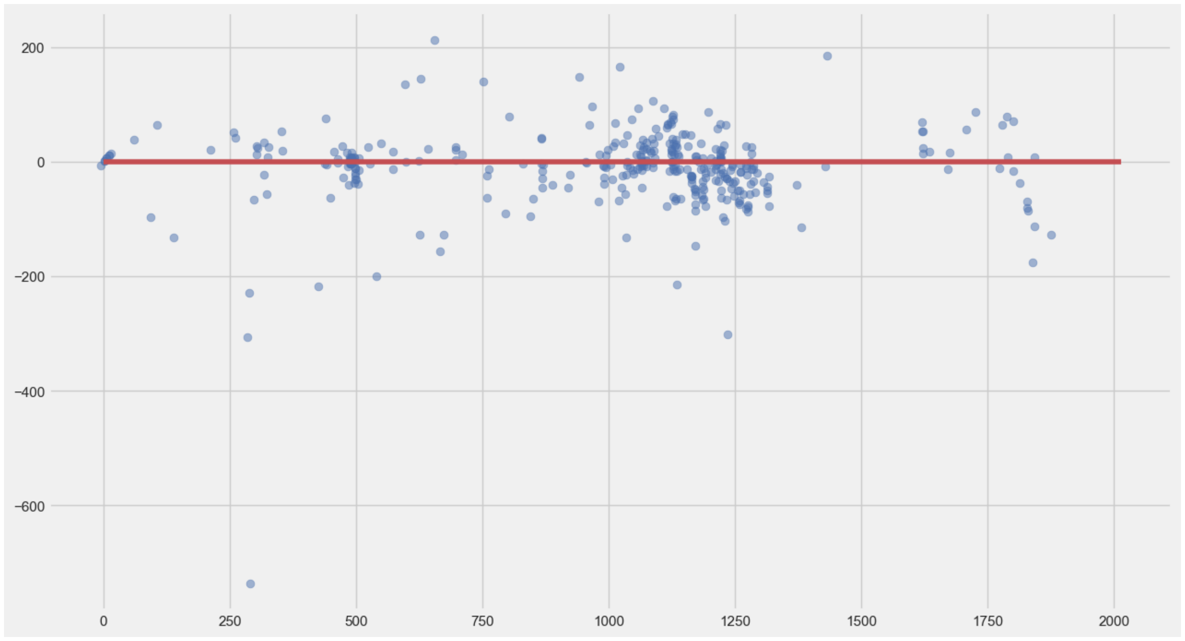


Actual vs Predicted values for the well-7078

In [56]:
```
# Select data for well 7078
X_test_7078 = X_test[X_test['NPD_WELL_BORE_CODE'] == 7078]
y_test_7078 = y_test[X_test['NPD_WELL_BORE_CODE'] == 7078]
y_pred_7078 = model.predict(X_test_7078)

# Plot predicted vs actual oil production
plt.figure(figsize=(14, 8))
plt.scatter(X_test_7078['DATEPRD'], y_test_7078, label='actual')
plt.scatter(X_test_7078['DATEPRD'], y_pred_7078, label='predicted')
plt.xlabel('Year')
plt.ylabel('Bore oil volume')
plt.title('Actual vs XGBoost Regression Model prediction for Bore Oil Volume 
plt.legend()
plt.show()

# Plot residual plot
plt.figure(figsize=(14, 8))
plt.scatter(y_pred_7078, y_pred_7078 - y_test_7078, c='b', s=40, alpha=0.5)
plt.hlines(y=0, xmin=0, xmax=max(y_test_7078), colors='r', zorder=3)
```



Out[56]:
```
<matplotlib.collections.LineCollection at 0x1f3846f3a30>
```



Random Forest

Importing the necessary libraries

In [57]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Load data

In [58]:
```
# Load data
df = pd.read_excel('Volve production data.xlsx')
```

Round data to nearest integer

In [59]:
```
df = np.round(df)
```

Convert date to Unix timestamp

In [60]:
```
df['DATEPRD'] = pd.to_datetime(df['DATEPRD'])
df['DATEPRD'] = (df['DATEPRD'] - pd.Timestamp("1970-01-01")) // pd.Timedelta(
```

Interpolate missing values

In [61]:
```
cols_to_interpolate = ['ON_STREAM_HRS', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DOWNHOL
                       'AVG_ANNULUS_PRESS', 'AVG_CHOKE_SIZE_P', 'AVG_WHP_P',
                       'BORE_OIL_VOL', 'BORE_GAS_VOL', 'BORE_WAT_VOL']
df[cols_to_interpolate] = df[cols_to_interpolate].interpolate(method='linear'
```

Drop unnecessary columns

In [62]:
```
cols_to_drop = ['WELL_BORE_CODE', 'NPD_WELL_BORE_NAME', 'NPD_FIELD_NAME', 'NPI
                'NPD_FACILITY_NAME', 'AVG_DOWNHOLE_PRESSURE', 'AVG_DP_TUBING'
                'FLOW_KIND', 'WELL_TYPE', 'BORE_GAS_VOL']
df.drop(cols_to_drop, axis=1, inplace=True)
```

Select data for wells 5351,5599,7078

In [63]:
```
df = df.loc[df['NPD_WELL_BORE_CODE'].isin([5351, 7078,5599])]
```

Prepare data for training

In [64]:
```
# Prepare data for training
X = df.drop(['BORE_OIL_VOL'], axis=1)
y = df['BORE_OIL_VOL']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, rand
```

Train model

In [65]:
```
rf_model = RandomForestRegressor(n_estimators=100, max_depth=7, random_state=
rf_model.fit(X_train, y_train)
```

Out[65]:
```
RandomForestRegressor(max_depth=7, random_state=42)
```

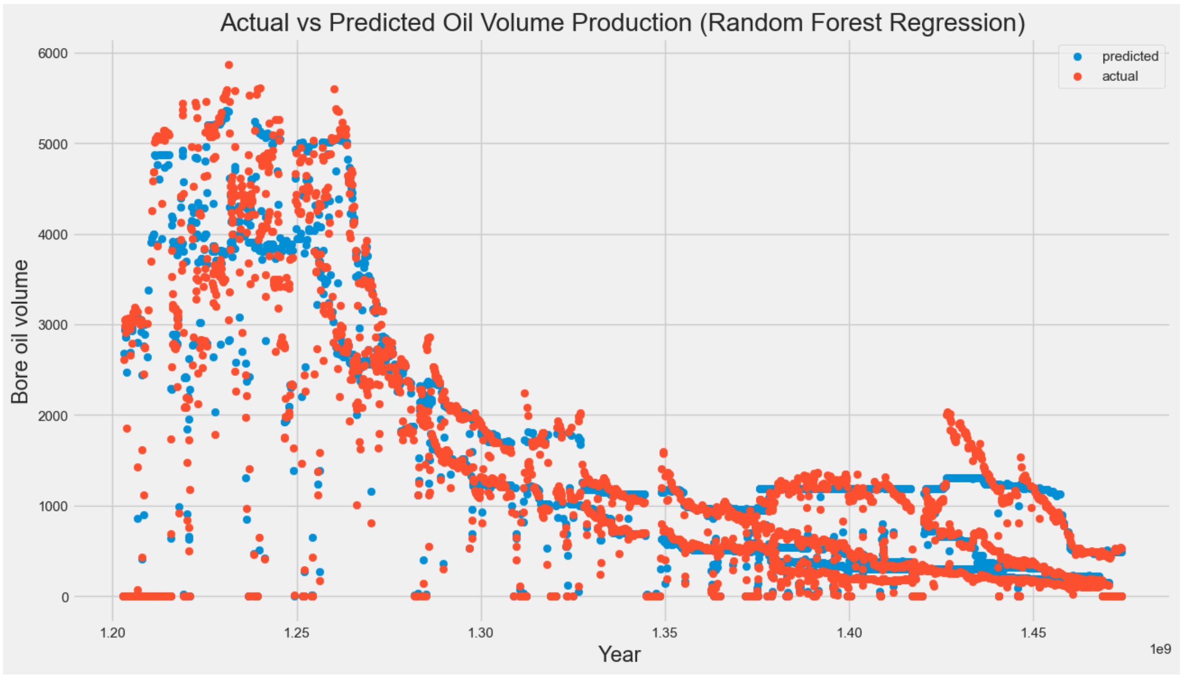
Predict on test set and calculate performance metrics

In [66]:
```
y_pred = rf_model.predict(X_test)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((y_test.replace(0, 1e-8) - y_pred) / y_test.replace(0, 

print("The R2 value for Random Forest Regression for oil volume production is
print("The mean absolute error (MAE) for Random Forest Regression is", mae)
print("The mean squared error (MSE) for Random Forest Regression is", mse)
print("The root mean squared error (RMSE) for Random Forest Regression is", r
```

```
The R2 value for Random Forest Regression for oil volume production is 0.975
5265282036907
The mean absolute error (MAE) for Random Forest Regression is 122.8333170751
7738
The mean squared error (MSE) for Random Forest Regression is 45689.433304144
76
The root mean squared error (RMSE) for Random Forest Regression is 213.75086
737635652
```

Plotting the actual vs Predicted values for random Forest Model

In [67]:
```
import matplotlib.pyplot as plt

# Plot actual vs predicted values
plt.style.use('fivethirtyeight')
#plt.style.use('dark_background')
plt.figure(figsize=(14, 8))
plt.scatter(X_test['DATEPRD'], y_pred, label='predicted')
plt.scatter(X_test['DATEPRD'], y_test, label='actual')
plt.legend()
plt.xlabel("Year ")#represented in terms of 9th power of seconds as we are us
plt.ylabel("Bore oil volume")
plt.title('Actual vs Predicted Oil Volume Production (Random Forest Regressio

# Show plot
plt.show()
```



In [ ]:

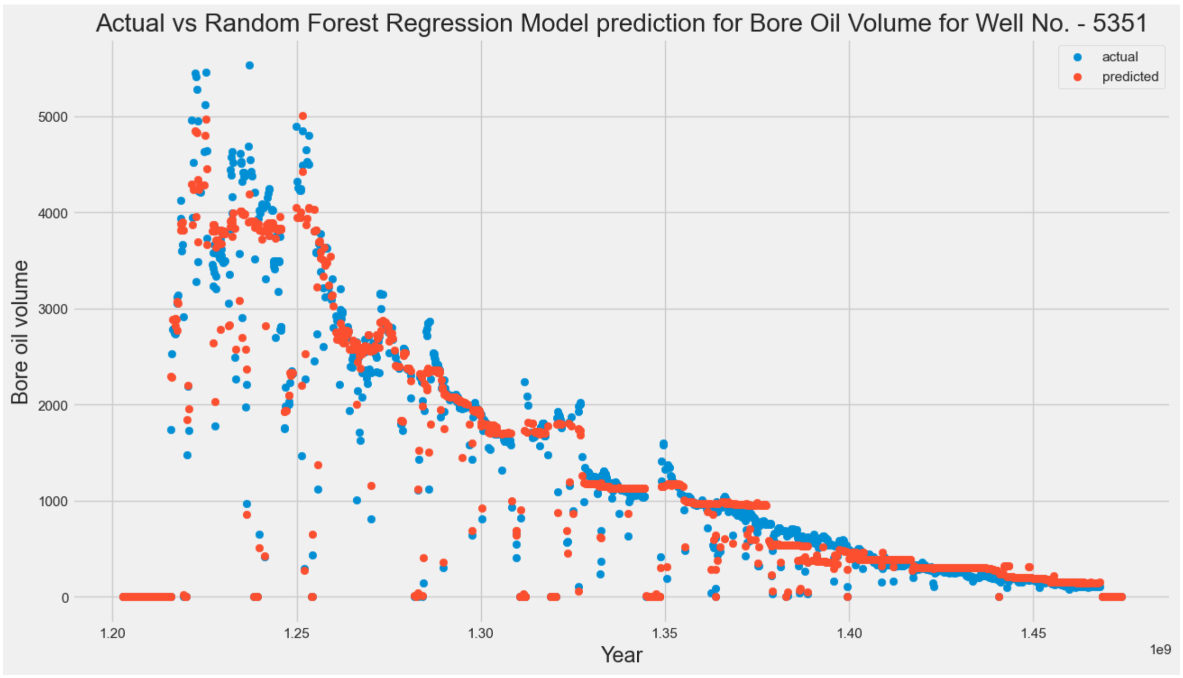
In [ ]:

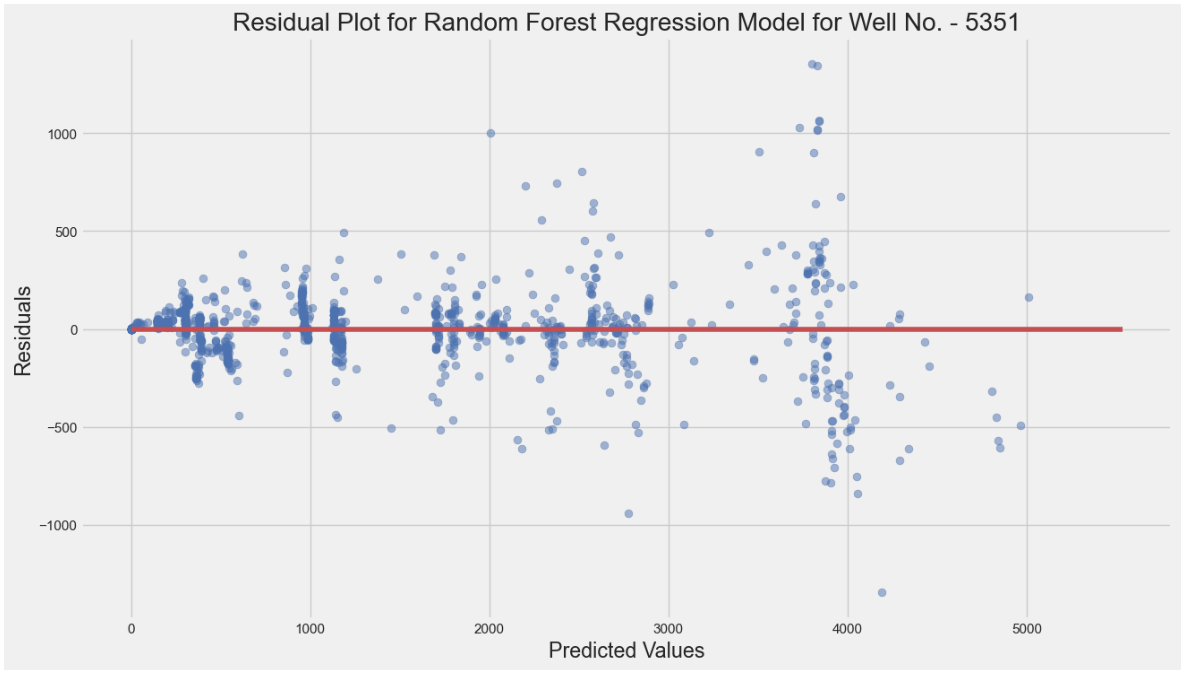
In [ ]:

Plotting the actual vs Predicted values for Each wells

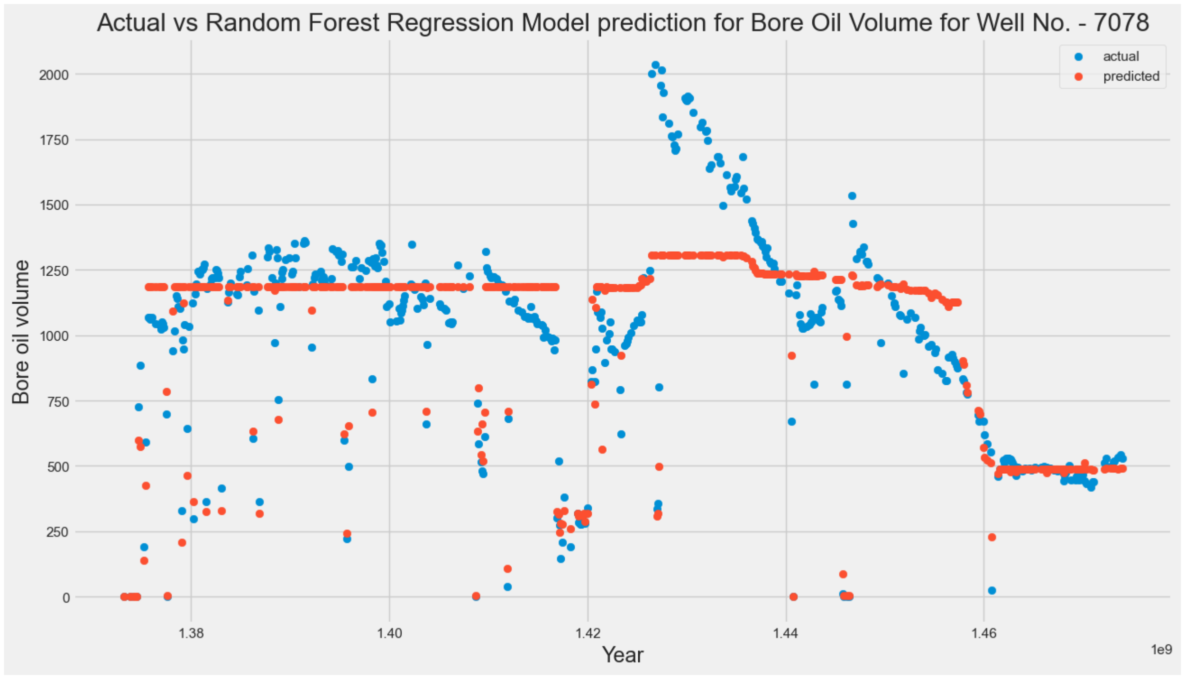
Actual VS Predicted values for well-5351

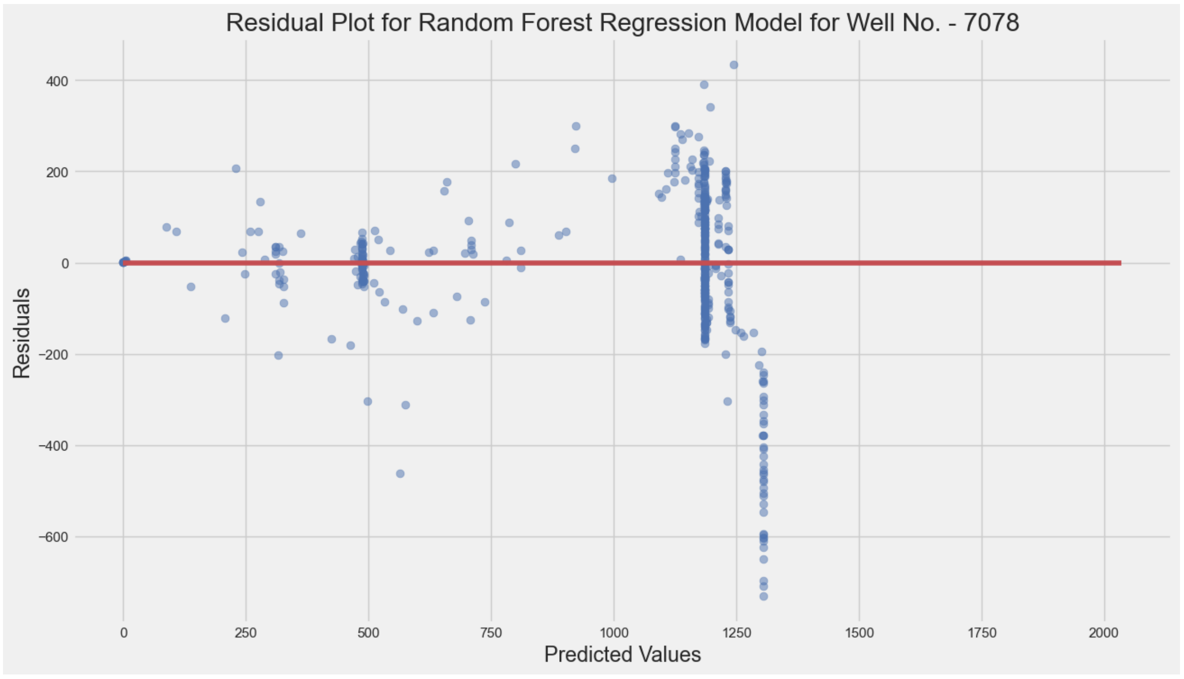
```
In [68]: # Select data for well 5351
         X_test_5351_rf = X_test[X_test['NPD_WELL_BORE_CODE'] == 5351]
         y_test_5351_rf = y_test[X_test['NPD_WELL_BORE_CODE'] == 5351]
         y_pred_5351_rf = rf_model.predict(X_test_5351_rf)

         # Plot predicted vs actual oil production
         plt.figure(figsize=(14, 8))
         plt.scatter(X_test_5351_rf['DATEPRD'], y_test_5351_rf, label='actual')
         plt.scatter(X_test_5351_rf['DATEPRD'], y_pred_5351_rf, label='predicted')
         plt.xlabel('Year')
         plt.ylabel('Bore oil volume')
         plt.title('Actual vs Random Forest Regression Model prediction for Bore Oil Vo
         plt.legend()
         plt.show()

         # Plot residual plot
         plt.figure(figsize=(14, 8))
         plt.scatter(y_pred_5351_rf, y_pred_5351_rf - y_test_5351_rf, c='b', s=40, alph
         plt.hlines(y=0, xmin=0, xmax=max(y_test_5351_rf), colors='r', zorder=3)
         plt.xlabel('Predicted Values')
         plt.ylabel('Residuals')
         plt.title('Residual Plot for Random Forest Regression Model for Well No. - 535
         plt.show()
```



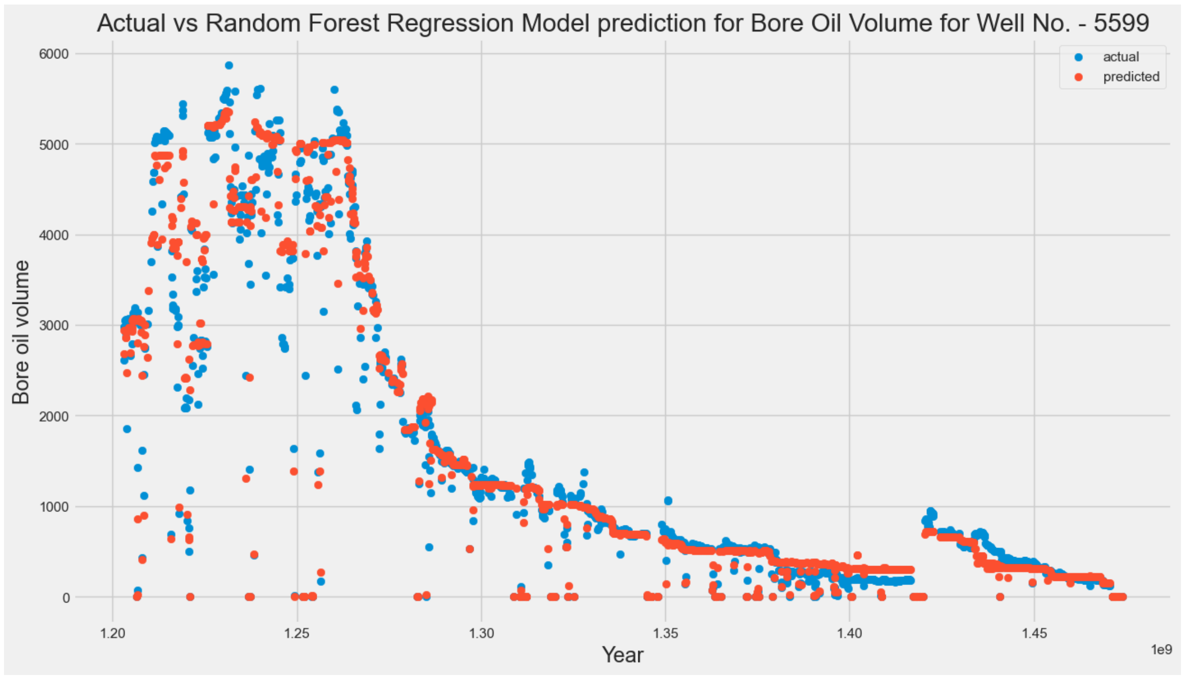

Residual Plot for Random Forest Regression Model for Well No. - 5351
Residuals
Predicted Values
1000
500
0
−500
−1000
0
1000
2000
3000
4000
5000

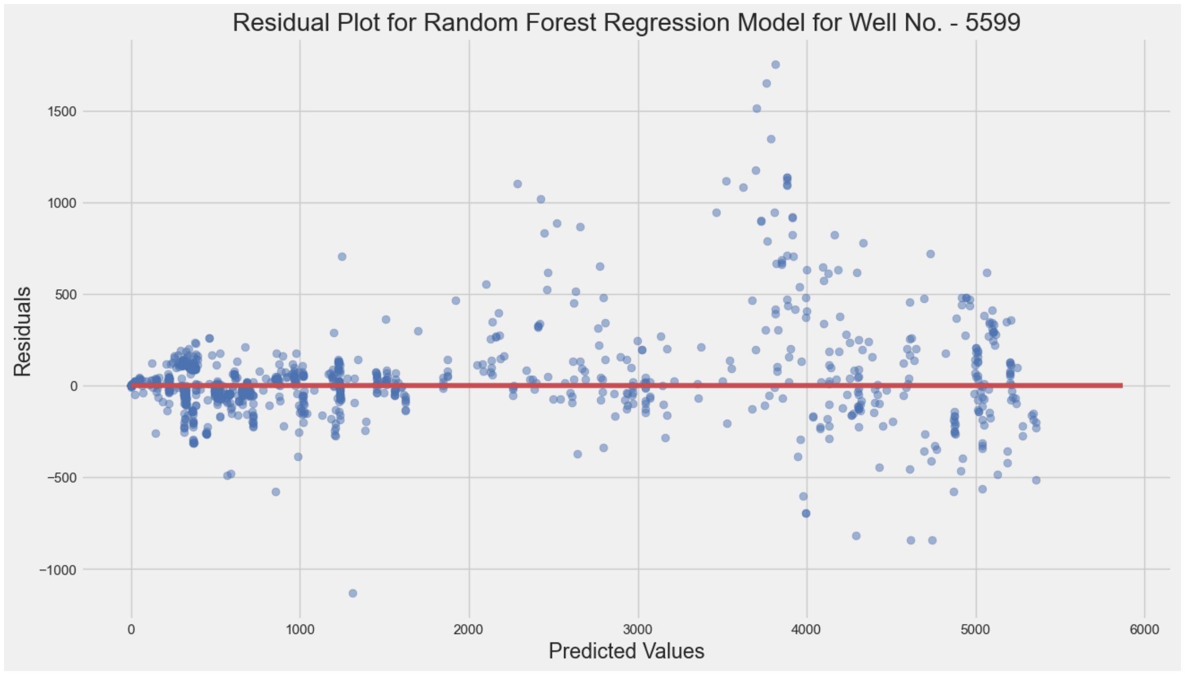
In [69]:
```
# Select data for well 7078
X_test_7078_rf = X_test[X_test['NPD_WELL_BORE_CODE'] == 7078]
y_test_7078_rf = y_test[X_test['NPD_WELL_BORE_CODE'] == 7078]
y_pred_7078_rf = rf_model.predict(X_test_7078_rf)

# Plot predicted vs actual oil production
plt.figure(figsize=(14, 8))
plt.scatter(X_test_7078_rf['DATEPRD'], y_test_7078_rf, label='actual')
plt.scatter(X_test_7078_rf['DATEPRD'], y_pred_7078_rf, label='predicted')
plt.xlabel('Year')
plt.ylabel('Bore oil volume')
plt.title('Actual vs Random Forest Regression Model prediction for Bore Oil Vo
plt.legend()
plt.show()

# Plot residual plot
plt.figure(figsize=(14, 8))
plt.scatter(y_pred_7078_rf, y_pred_7078_rf - y_test_7078_rf, c='b', s=40, alph
plt.hlines(y=0, xmin=0, xmax=max(y_test_7078_rf), colors='r', zorder=3)
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot for Random Forest Regression Model for Well No. - 707
plt.show()
```




Residual Plot for Random Forest Regression Model for Well No. - 7078
Residuals
Predicted Values
400
200
0
−200
−400
−600
0
250
500
750
1000
1250
1500
1750
2000

In [70]:
```
# Select data for well 7405
X_test_5599_rf = X_test[X_test['NPD_WELL_BORE_CODE'] == 5599]
y_test_5599_rf = y_test[X_test['NPD_WELL_BORE_CODE'] == 5599]
y_pred_5599_rf = rf_model.predict(X_test_5599_rf)

# Plot predicted vs actual oil production
plt.figure(figsize=(14, 8))
plt.scatter(X_test_5599_rf['DATEPRD'], y_test_5599_rf, label='actual')
plt.scatter(X_test_5599_rf['DATEPRD'], y_pred_5599_rf, label='predicted')
plt.xlabel('Year')
plt.ylabel('Bore oil volume')
plt.title('Actual vs Random Forest Regression Model prediction for Bore Oil Vo
plt.legend()
plt.show()

# Plot residual plot
plt.figure(figsize=(14, 8))
plt.scatter(y_pred_5599_rf, y_pred_5599_rf - y_test_5599_rf, c='b', s=40, alph
plt.hlines(y=0, xmin=0, xmax=max(y_test_5599_rf), colors='r', zorder=3)
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot for Random Forest Regression Model for Well No. - 559
plt.show()
```




Residual Plot for Random Forest Regression Model for Well No. - 5599
Residuals
1500
1000
500
0
−500
−1000
0
1000
2000
3000
4000
5000
6000
Predicted Values

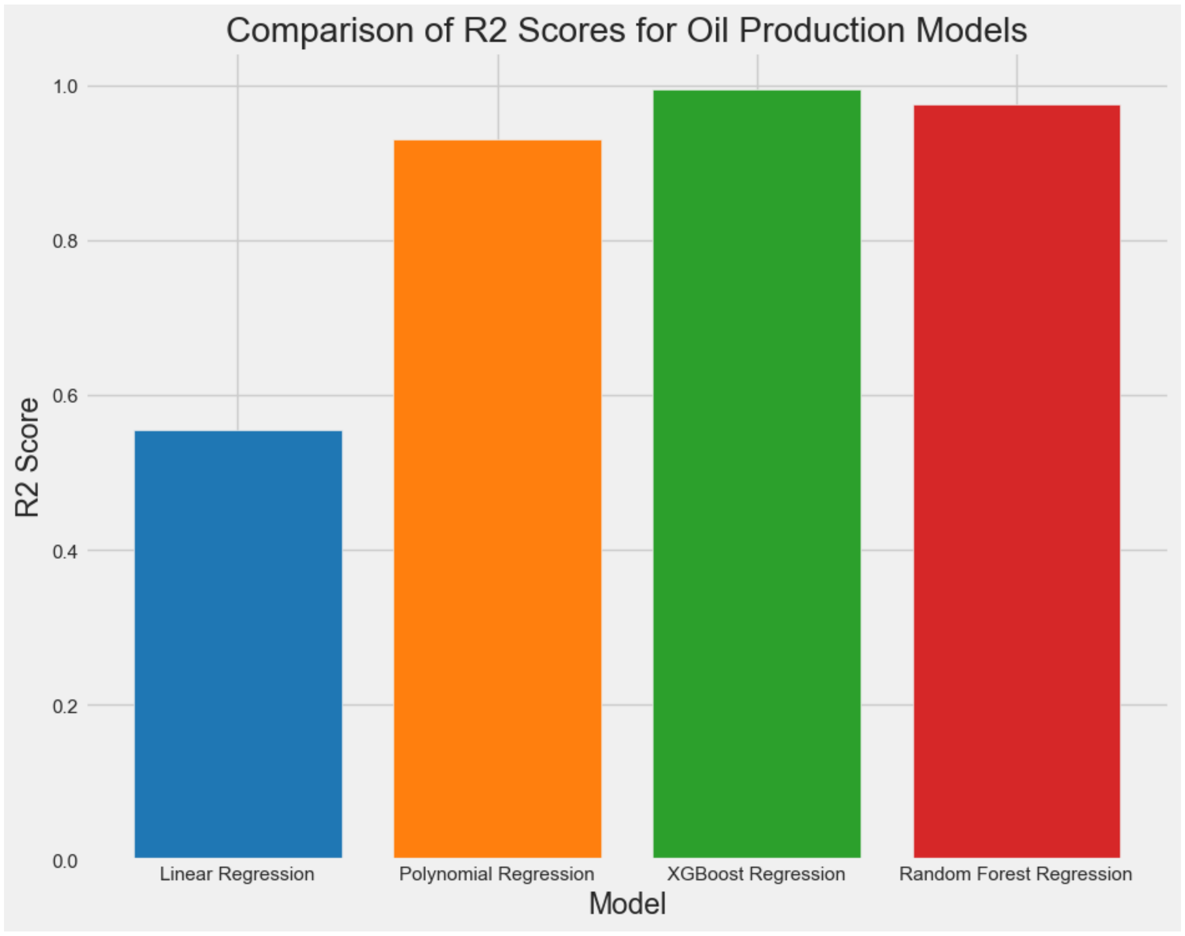
```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```

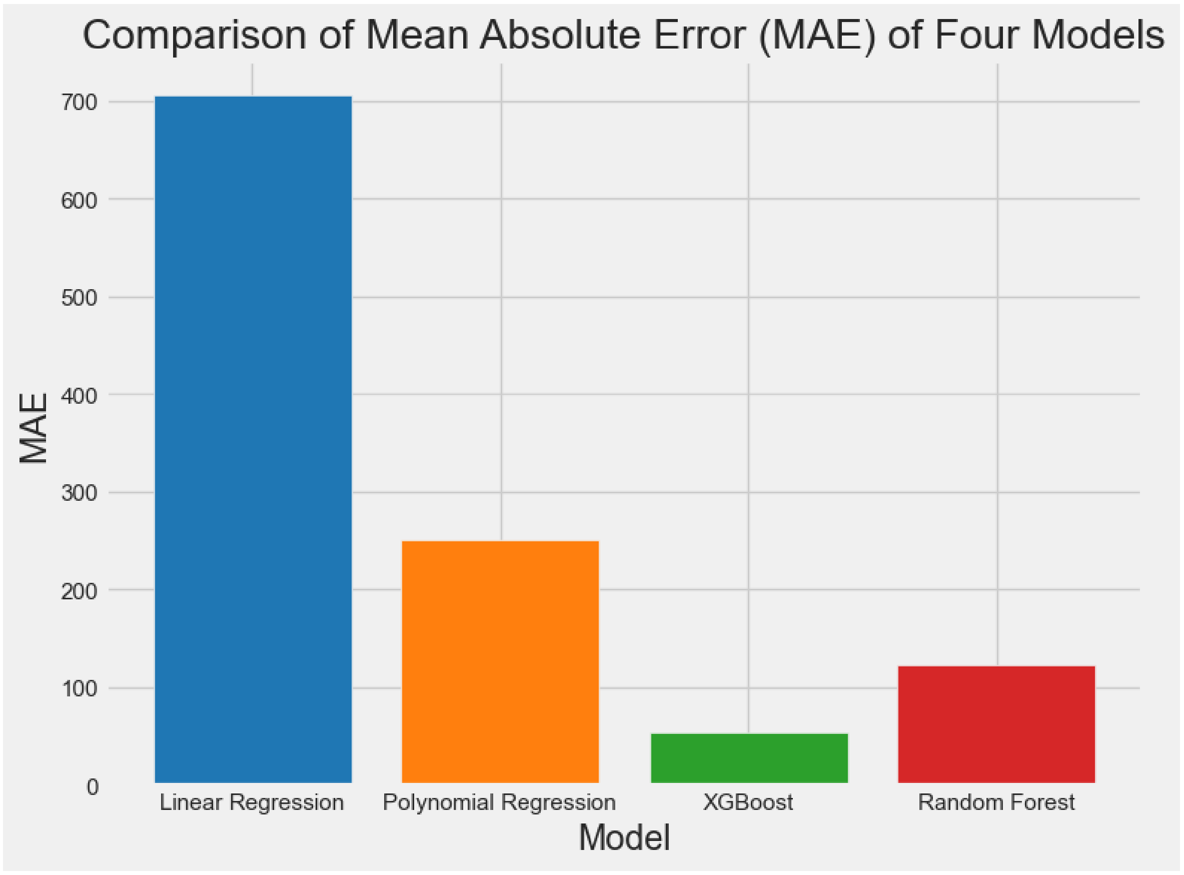
Comparison of R2 square values

In [71]:
```
import matplotlib.pyplot as plt

# Define data
models = ['Linear Regression', 'Polynomial Regression', 'XGBoost Regression',
r2_scores = [0.5545, 0.9301, 0.9941, 0.9755]

# Set figure size
fig, ax = plt.subplots(figsize=(10, 8))

# Define colors for each model
colors = ['blue', 'green', 'red', 'orange']

# Create bar chart
ax.bar(models, r2_scores, color=['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728'])

# Add labels and title
ax.set_xlabel('Model')
ax.set_ylabel('R2 Score')
ax.set_title('Comparison of R2 Scores for Oil Production Models')

# Display plot
plt.show()
```



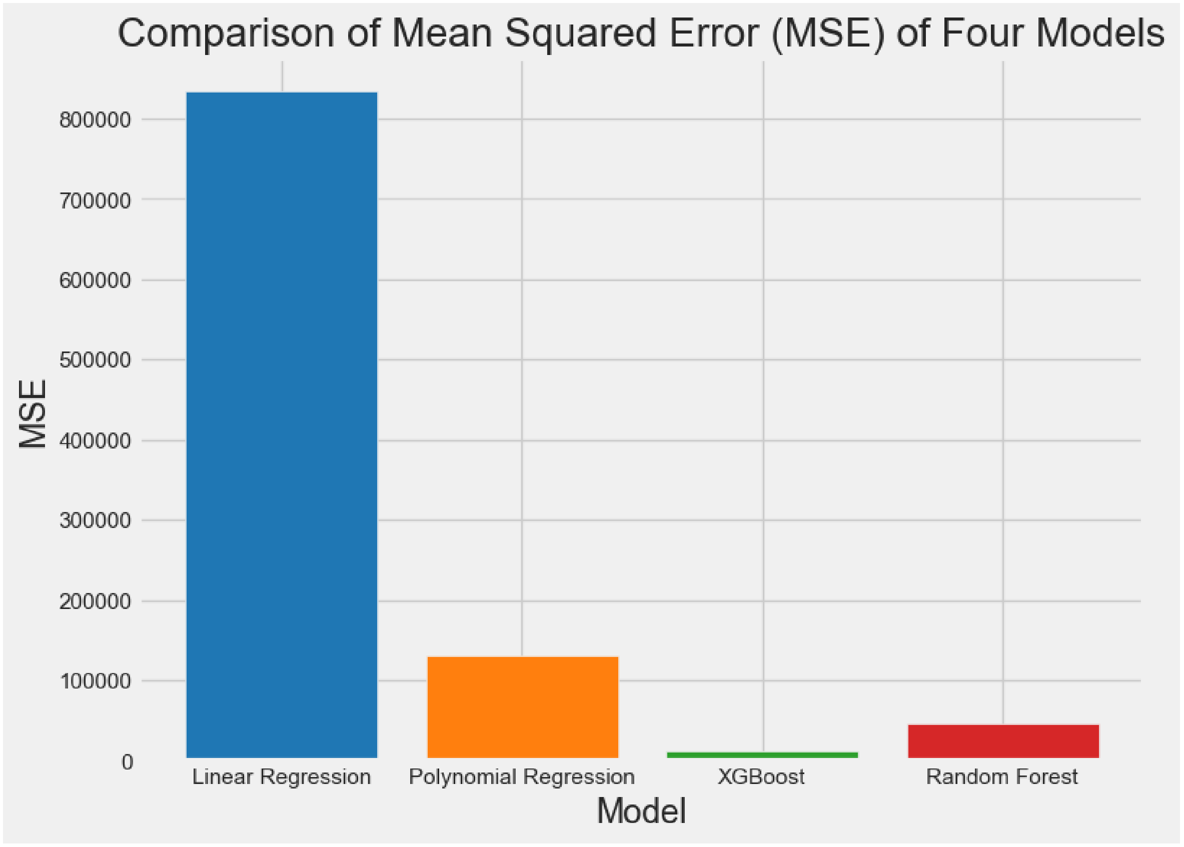
Comparing the Mean Absolute Errors Of the Machine Learning Models

In [72]:
```
models = ['Linear Regression', 'Polynomial Regression', 'XGBoost', 'Random Fo
mae = [705.8759, 250.3786, 53.5111, 122.8333]
colors = ['blue', 'green', 'red', 'orange']
fig, ax = plt.subplots(figsize=(8, 6))
ax.bar(models, mae, color=['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728'])
ax.set_title('Comparison of Mean Absolute Error (MAE) of Four Models')
ax.set_xlabel('Model')
ax.set_ylabel('MAE')
plt.show()
```

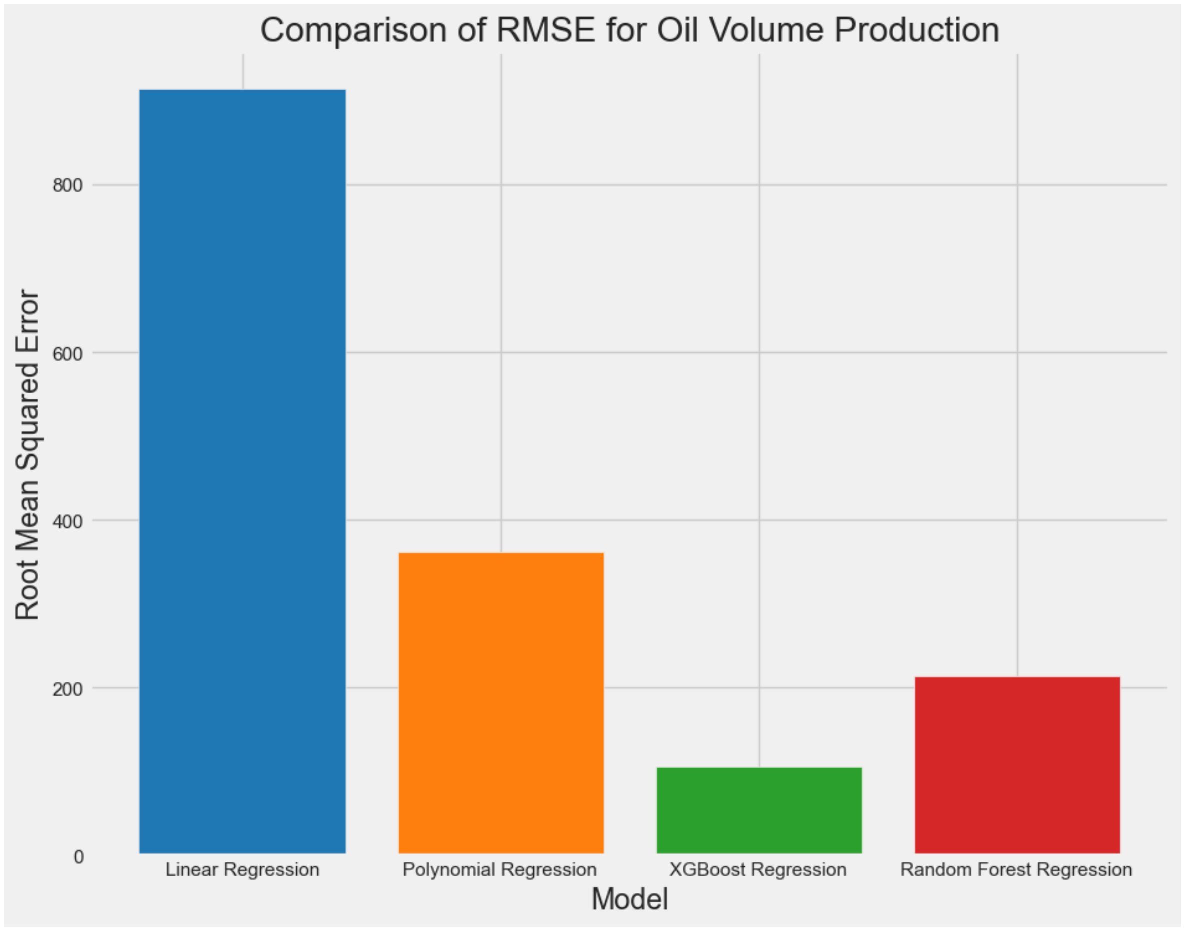


Comparing the Mean Squared Errors of the Machine Learning Models

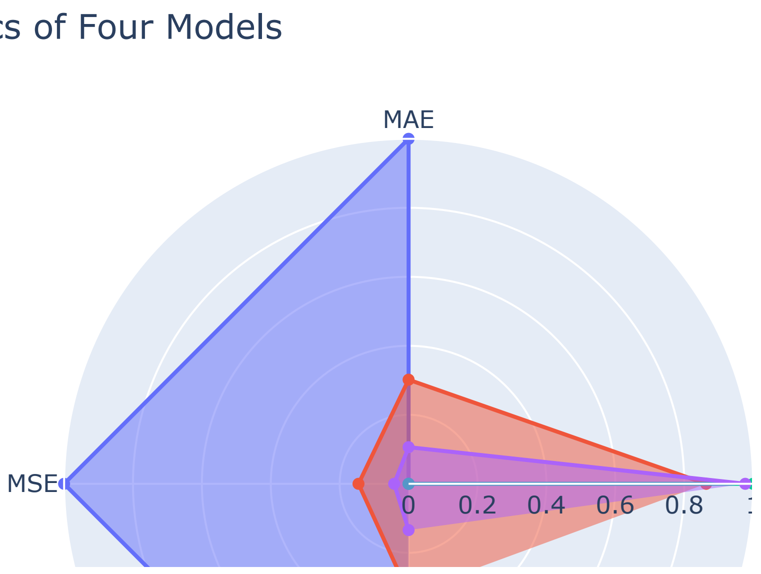
In [73]:
```
import matplotlib.pyplot as plt
import numpy as np

models = ['Linear Regression', 'Polynomial Regression', 'XGBoost', 'Random Fo
mse = [834343.8099, 130862.5409, 11113.8842, 45689.4333]
colors = ['blue', 'green', 'red', 'orange']

fig, ax = plt.subplots(figsize=(8, 6))
ax.bar(models, mse, color=['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728'])
ax.set_title('Comparison of Mean Squared Error (MSE) of Four Models')
ax.set_xlabel('Model')
ax.set_ylabel('MSE')
plt.show()
```



In [74]:
```python
import matplotlib.pyplot as plt

# define the data
models = ['Linear Regression', 'Polynomial Regression', 'XGBoost Regression',
rmse = [913.4242, 361.7493, 105.4224, 213.7509]

# set the figure size
plt.figure(figsize=(10, 8))

# create the bar chart
plt.bar(models, rmse, color=['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728'])

# add labels and title
plt.xlabel('Model')
plt.ylabel('Root Mean Squared Error')
plt.title('Comparison of RMSE for Oil Volume Production')

# display the plot
plt.show()
```



In [75]:
```
import plotly.graph_objects as go
import pandas as pd

# Create a dataframe with the performance metrics of the four models
data = {'Model': ['Linear Regression', 'Polynomial Regression', 'XGBoost Regr
        'R2 Score': [0.55, 0.93, 0.99, 0.98],
        'MAE': [705.88, 250.38, 53.51, 122.83],
        'MSE': [834343.81, 130862.54, 11113.88, 45689.43],
        'RMSE': [913.42, 361.75, 105.42, 213.75]}
df = pd.DataFrame(data)

# Normalize the metrics so they can be plotted on the same scale
df_norm = df.drop('Model', axis=1).apply(lambda x: (x - x.min()) / (x.max() -

# Create the radar chart
fig = go.Figure()

# Add a trace for each model
for model in df['Model']:
    fig.add_trace(go.Scatterpolar(
        r=df_norm.loc[df['Model'] == model].values.flatten().tolist(),
        theta=df_norm.columns.tolist(),
        fill='toself',
        name=model
    ))

# Set the title and layout
fig.update_layout(
    polar=dict(
        radialaxis=dict(
            visible=True,
            range=[0, 1]
        )
    ),
    showlegend=True,
    title='Performance Metrics of Four Models',
)

# Show the chart
fig.show()
```



```
In [ ]:
```

```
In [ ]:
```