DIU-framework

January 27, 2026

[1]:
```
%load_ext autoreload
%autoreload 2
```

[3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso, LassoCV
import statsmodels.api as sm
from sklearn.preprocessing import StandardScaler
from datetime import datetime, timedelta
from IPython.display import display, Math
import re
from arch import arch_model
from arch.univariate import ZeroMean, GARCH, Normal
import pickle
import scipy.stats as stats
from statsmodels.graphics.tsaplots import plot_acf
```

[4]:
```
import preprocessing as preproc
```

[5]:
```
def cfs_to_af(cfs_day):
    """
    Convert 'CFS-days' to acre-feet:

    acre-ft = cfs_day / 1.9835
    """
    return cfs_day / 1.9835


def af_to_m3(acft):
    """Convert acre-feet to cubic metres (1 af = 1233.48 m³)."""
    return acft * 1233.48

def ft_to_m(ft):
    return ft / 3.281
```

```
def kcfs_to_m3hr(kcfs):
    """(1000 cfs = 1kcfs = 28.32 m³/s --> m3/hr """
    return kcfs * 28.32 * 3600
```

[6]:
```
def replace_outliers(data, max_val=1e8):
    """Replace values outside [-max_val, max_val] with average of nearest valid␣
↪neighbors"""
    arr = np.array(data, dtype=float)
    outlier_count = 0

    for i in range(len(arr)):
        if arr[i] > max_val or arr[i] < -max_val:
            outlier_count += 1
            # Find left neighbor
            left = None
            for j in range(i-1, -1, -1):
                if -max_val <= arr[j] <= max_val:
                    left = arr[j]
                    break

            # Find right neighbor
            right = None
            for j in range(i+1, len(arr)):
                if -max_val <= arr[j] <= max_val:
                    right = arr[j]
                    break

            # Replace with average of neighbors
            if left is not None and right is not None:
                arr[i] = (left + right) / 2
            elif left is not None:
                arr[i] = left
            elif right is not None:
                arr[i] = right
            else:
                arr[i] = 0

    print(f"Found and replaced {outlier_count} outliers")
    return arr
```

[11]:
```
def timeseries_to_matrix(df):
    df['Date Time'] = pd.to_datetime(df['Date Time'])

    # Remove Feb 29
    df_no_leap = df[~((df['Date Time'].dt.month == 2) & (df['Date Time'].dt.day␣
↪== 29))].copy()
```

```python
    # Use original dayofyear but shift after Feb 29 removal
    df_no_leap['Year'] = df_no_leap['Date Time'].dt.year
    df_no_leap['Month'] = df_no_leap['Date Time'].dt.month
    df_no_leap['Day'] = df_no_leap['Date Time'].dt.day

    # Create day of year: Jan 1 = 1, Dec 31 = 365 (after removing Feb 29)
    df_no_leap['DayOfYear'] = df_no_leap['Date Time'].dt.dayofyear

    # Adjust for leap day removal: if after Feb 28, subtract 1 in leap years
    leap_years = df_no_leap['Year'] % 4 == 0
    after_feb28 = (df_no_leap['Month'] > 2)
    df_no_leap.loc[leap_years & after_feb28, 'DayOfYear'] -= 1

    matrix = df_no_leap.pivot_table(
        index='Year',
        columns='DayOfYear',
        values='Daily Inflow',
        aggfunc='first'
    )

    return matrix
```

[13]:
```python
def clean_variable_name(feature):
    '''Clean up variable names for LaTeX display'''
    # Replace inflow_m3hr_ with y
    if feature.startswith('inflow_m3hr_'):
        clean_name = feature.replace('inflow_m3hr_', 'y')
    # Replace outflow_m3hr_ with x
    elif feature.startswith('outflow_m3hr_'):
        clean_name = feature.replace('outflow_m3hr_', 'x')
    else:
        clean_name = feature

    # Handle Lag_n pattern - convert to subscript t-n
    lag_pattern = r'Lag_(\d+)'
    if re.search(lag_pattern, clean_name):
        # Extract the lag number
        lag_match = re.search(lag_pattern, clean_name)
        lag_num = lag_match.group(1)
        # Replace Lag_n with _{t-n}
        clean_name = re.sub(lag_pattern, f'_{{t-{lag_num}}}', clean_name)

    # Escape remaining underscores for LaTeX
    #clean_name = clean_name.replace('_', '\\_')

    return clean_name
```

1 Model Train Mode

[19]:
```
framework = "DIU"
# framework = "DDU"
```

2 Data Load

[30]:
```
bon_path = "/Users/elizacohn/Desktop/cascaded-hydro/streamflow-data-raw/
↪bonneville/"
tda_path = "/Users/elizacohn/Desktop/cascaded-hydro/streamflow-data-raw/dalles/"
```

2.1 Seasonal Analysis

[33]:
```
bon_daily = pd.read_csv(bon_path + "bon-daily-inflow-calc.csv")
```

[35]:
```
daily_inflow_col = 'BON.Flow-In.Ave.~1Day.1Day.CBT-REV [kcfs]'
bon_daily = bon_daily.rename(columns={daily_inflow_col: "Daily Inflow"})
```

[37]:
```
bon_daily.head()
```

[37]:

	Date Time	Daily Inflow
0	31-Jul-1960 23:00	185.3
1	01-Aug-1960 23:00	170.9
2	02-Aug-1960 23:00	184.1
3	03-Aug-1960 23:00	168.9
4	04-Aug-1960 23:00	194.9

[39]:
```
# Transform matrix in 365 x N years

inflow_matrix = timeseries_to_matrix(bon_daily)

print(f"Matrix shape: {inflow_matrix.shape}")
print(f"Years: {inflow_matrix.index.min()} to {inflow_matrix.index.max()}")
print(f"Days: {inflow_matrix.columns.min()} to {inflow_matrix.columns.max()}")
```

```
Matrix shape: (66, 365)
Years: 1960 to 2025
Days: 1 to 365
```

[41]:
```
inflow_matrix.head()
```

[41]:

DayOfYear	1	2	3	4	5	6	7	8	9	\
Year										
1960	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1961	106.7	98.2	97.4	98.2	99.3	124.2	110.8	122.4	134.8	
1962	89.6	90.8	100.0	99.5	93.3	94.6	103.9	103.4	107.4	
1963	127.2	130.0	140.1	139.9	137.5	142.4	128.0	128.0	135.4	

```
1964          95.5  104.3   91.6   98.9   97.8  101.1   94.0  103.3  103.7

DayOfYear     10   …    356    357    358    359    360    361    362    363  \
Year               …
1960          NaN  …  109.1   97.3   97.1   98.5   98.2  101.9   96.2   96.9
1961        123.7  …  110.4  110.8  113.2  107.4   95.1   97.8   95.9   97.9
1962        144.7  …  146.6  150.6  152.2  140.8  142.6  128.7  128.3  128.4
1963        133.0  …   94.6   96.5   93.3   95.3   97.9  101.2   93.4   98.4
1964        103.9  …  224.4  386.4  419.9  432.4  342.9    NaN  284.3  245.4

DayOfYear    364    365
Year
1960       103.7  100.0
1961        94.0   94.2
1962       136.5  139.1
1963        97.5   99.1
1964       190.1  186.9

[5 rows x 365 columns]
```

[43]:
```python
## Calculate daily averages

daily_averages = inflow_matrix.mean(axis=0, skipna=True)

# Create a single-row DataFrame for the averages
avg_row = pd.DataFrame([daily_averages], index=['Average'],␣
 ↪columns=inflow_matrix.columns)

# Concatenate original matrix with average row
inflow_matrix_with_avg = pd.concat([inflow_matrix, avg_row], axis=0)
```

[45]:
```python
## Identify DoY with min and max flow

# Get the average row
daily_averages = avg_row.loc['Average']

# Find day with minimum average inflow
min_day = daily_averages.idxmin()
min_value = daily_averages.min()

# Find day with maximum average inflow
max_day = daily_averages.idxmax()
max_value = daily_averages.max()
```

[47]:
```python
def day_to_date(day_of_year):
    # Create a date using pandas
```

```
    date = pd.to_datetime(f"2023-01-01") + pd.Timedelta(days=int(day_of_year) -␣
↪1)
    return date.strftime("%B %d")

# Now this should work
print(f"Minimum inflow day: Day {min_day} ({day_to_date(min_day)}) = {min_value:
↪.2f} kcfs")
print(f"Maximum inflow day: Day {max_day} ({day_to_date(max_day)}) = {max_value:
↪.2f} kcfs")
```

```
Minimum inflow day: Day 275 (October 02) = 104.72 kcfs
Maximum inflow day: Day 157 (June 06) = 329.75 kcfs
```

[49]:

```
## Identify Seasons

dry_start = (min_day - 45 - 1) % 365 + 1
dry_end = (min_day + 45 - 1) % 365 + 1
print(f"90-Day Dry season: Day {dry_start} ({day_to_date(dry_start)}) to Day␣
↪{dry_end} ({day_to_date(dry_end)})")

wet_start = (max_day - 45 - 1) % 365 + 1
wet_end = (max_day + 45 - 1) % 365 + 1
print(f"90-Day Wet season: Day {wet_start} ({day_to_date(wet_start)}) to Day␣
↪{wet_end} ({day_to_date(wet_end)})")
```

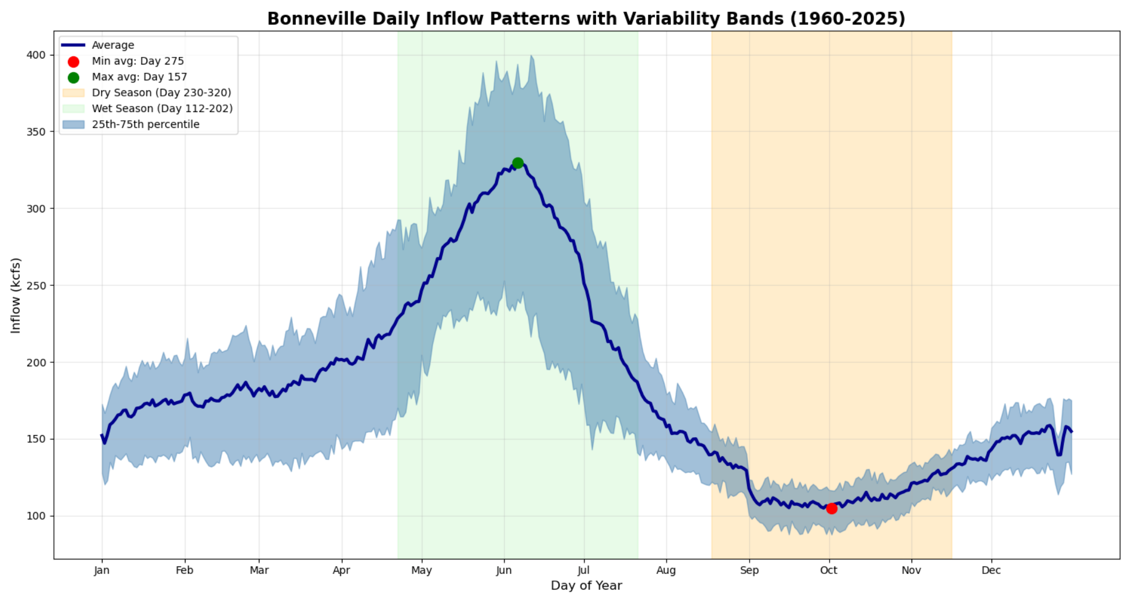
```
90-Day Dry season: Day 230 (August 18) to Day 320 (November 16)
90-Day Wet season: Day 112 (April 22) to Day 202 (July 21)
```

[51]:

```
# Create date labels for x-axis (using 2023 as reference year)
def create_date_labels():
    dates = []
    date_labels = []
    base_date = datetime(2023, 1, 1)

    for day in range(1, 366):  # Days 1-365
        current_date = base_date + timedelta(days=day - 1)
        dates.append(day)
        date_labels.append(current_date)

    return dates, date_labels

days, date_labels = create_date_labels()


# Alternative: More detailed plot with confidence intervals
def plot_with_percentiles():
```

```
    month_starts = [1, 32, 60, 91, 121, 152, 182, 213, 244, 274, 305, 335]  #␣
↪Approximate month starts
    month_labels = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                    'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']

    """Plot with percentile bands showing variability"""

    plt.figure(figsize=(15, 8))

    # Calculate percentiles for each day (excluding the average row)
    original_data = inflow_matrix_with_avg.iloc[:-1]  # Exclude 'Average' row
    p25 = original_data.quantile(0.25, axis=0)
    p75 = original_data.quantile(0.75, axis=0)
    p10 = original_data.quantile(0.10, axis=0)
    p90 = original_data.quantile(0.90, axis=0)

    # Plot average line
    plt.plot(days, daily_averages.values, linewidth=3, color='darkblue',␣
↪label='Average')

    # Highlight extremes
    plt.scatter([min_day], [min_value], color='red', s=100, zorder=5,␣
↪label=f'Min avg: Day {min_day}')
    plt.scatter([max_day], [max_value], color='green', s=100, zorder=5,␣
↪label=f'Max avg: Day {max_day}')

    # Add shaded regions for wet and dry seasons
    if dry_start > dry_end:  # Wraps around year
        plt.axvspan(dry_start, 365, alpha=0.2, color='orange', label=f'Dry␣
↪Season (Day {dry_start}-365, 1-{dry_end})')
        plt.axvspan(1, dry_end, alpha=0.2, color='orange')
    else:
        plt.axvspan(dry_start, dry_end, alpha=0.2, color='orange', label=f'Dry␣
↪Season (Day {dry_start}-{dry_end})')

    if wet_start > wet_end:  # Wraps around year
        plt.axvspan(wet_start, 365, alpha=0.2, color='lightgreen', label=f'Wet␣
↪Season (Day {wet_start}-365, 1-{wet_end})')
        plt.axvspan(1, wet_end, alpha=0.2, color='lightgreen')
    else:
        plt.axvspan(wet_start, wet_end, alpha=0.2, color='lightgreen',␣
↪label=f'Wet Season (Day {wet_start}-{wet_end})')

    # Plot percentile bands
    # plt.fill_between(days, p10.values, p90.values, alpha=0.2,␣
↪color='lightblue', label='10th-90th percentile')
```

```
    plt.fill_between(days, p25.values, p75.values, alpha=0.5,␣
 ↪color='steelblue', label='25th-75th percentile')


    plt.title('Bonneville Daily Inflow Patterns with Variability Bands␣
 ↪(1960-2025)', fontsize=16, fontweight='bold')
    plt.xlabel('Day of Year', fontsize=12)
    plt.ylabel('Inflow (kcfs)', fontsize=12)
    plt.grid(True, alpha=0.3)
    plt.legend()
    plt.xticks(month_starts, month_labels)
    plt.tight_layout()
    plt.show()

plot_with_percentiles()
```



2.2 AR Time Series Data Load

[54]:
```
## Load Bonneville Data
# Manually fixing timezone (from PST)

bon = pd.read_csv(bon_path + "bon-fullflow.csv")
# bon = pd.read_excel(bon_path + "bon-inflow-calc.xlsx")
bon['Date Time'] = pd.to_datetime(bon['Date Time'])
bon['Date Time'] = bon['Date Time'] + pd.Timedelta(hours=4)
```

[56]:
```
bon.head()
```

[56]:
```
            Date Time  BON.Flow-Gen.Ave.1Hour.1Hour.CBT-REV [kcfs]  \
0 2018-01-01 00:00:00                                        170.3
1 2018-01-01 01:00:00                                        171.6
2 2018-01-01 02:00:00                                        172.2
3 2018-01-01 03:00:00                                        171.5
4 2018-01-01 04:00:00                                        172.3

   BON.Flow-In.Inst.~6Hours.0.RFC-FCST [kcfs]  \
0                                         NaN
1                                         NaN
2                                         NaN
3                                         NaN
4                                         NaN

   BON.Flow-Out.Ave.1Hour.1Hour.CBT-REV [kcfs]  \
0                                        173.8
1                                        175.1
2                                        175.7
3                                        175.0
4                                        175.8

   BON.Flow-Spill.Ave.1Hour.1Hour.CBT-REV [kcfs]
0                                            0.0
1                                            0.0
2                                            0.0
3                                            0.0
4                                            0.0
```

[58]:
```python
## Load Dalles Data
# Manually fixing timezone (from PST)

tda = pd.read_csv(tda_path + "tda-fullflow.csv")
tda['Date Time'] = pd.to_datetime(tda['Date Time'])
tda['Date Time'] = tda['Date Time'] + pd.Timedelta(hours=4)
```

[60]:
```python
tda.head()
```

[60]:
```
            Date Time  TDA.Flow-Gen.Ave.1Hour.1Hour.CBT-REV [kcfs]  \
0 2018-01-01 00:00:00                                        162.6
1 2018-01-01 01:00:00                                        161.9
2 2018-01-01 02:00:00                                        163.6
3 2018-01-01 03:00:00                                        161.9
4 2018-01-01 04:00:00                                        148.4

   TDA.Flow-In.Inst.~6Hours.0.RFC-FCST [kcfs]  \
0                                         NaN
1                                         NaN
```

```
2                                                  NaN
3                                                  NaN
4                                                  NaN

   TDA.Flow-Out.Ave.1Hour.1Hour.CBT-REV [kcfs]  \
0                                        163.7
1                                        162.9
2                                        164.7
3                                        162.9
4                                        149.4

   TDA.Flow-Spill.Ave.1Hour.1Hour.CBT-REV [kcfs]
0                                            0.0
1                                            0.0
2                                            0.0
3                                            0.0
4                                            0.0
```

2.3 Merge Datasets

[63]:
```
inflow_col = "BON.Flow-In.Inst.~6Hours.0.RFC-FCST [kcfs]"
# inflow_col = "Calculated Hourly Inflow [kcfs]"
outflow_col = "TDA.Flow-Out.Ave.1Hour.1Hour.CBT-REV [kcfs]"
```

[65]:
```
# Gather Bonneville 6-Hr inflow and convert to m3/hr
flow = bon[["Date Time", inflow_col]].dropna().rename(columns={inflow_col:␣
 ↪"inflow_kcfs"})
flow['inflow_m3hr'] = flow['inflow_kcfs'].apply(lambda x: kcfs_to_m3hr(x))

# Merge in with Dalles total outflow data
flow = flow.merge(tda[["Date Time", outflow_col]], how='inner', on='Date Time').
 ↪rename(columns={outflow_col: "outflow_kcfs"})
flow['outflow_m3hr'] = flow['outflow_kcfs'].apply(lambda x: kcfs_to_m3hr(x))

# Drop kcfs columns
flow = flow.drop(['inflow_kcfs', 'outflow_kcfs'], axis=1)
```

[67]:
```
# flow['inflow_m3hr'] = replace_outliers(flow['inflow_m3hr'])
```

[69]:
```
flow.head()
```

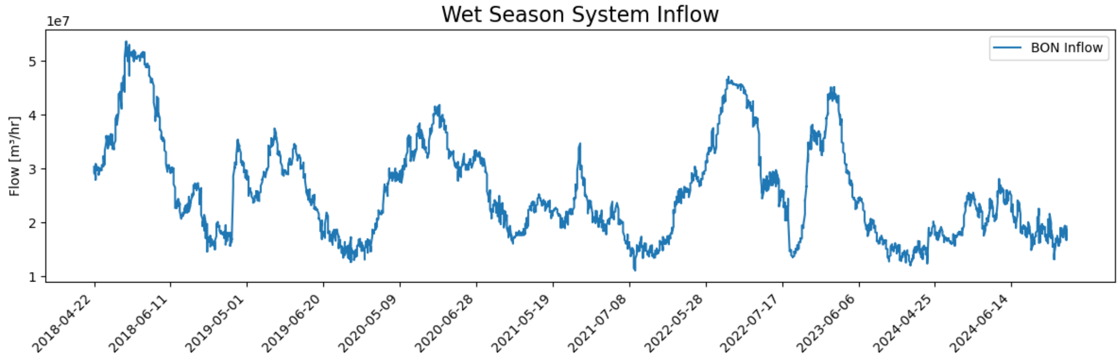
[69]:
```
            Date Time   inflow_m3hr  outflow_m3hr
0 2018-01-05 02:00:00  1.881769e+07    18371750.4
1 2018-01-05 08:00:00  1.868770e+07     9940320.0
2 2018-01-05 14:00:00  1.891240e+07    21165235.2
3 2018-01-05 20:00:00  1.906584e+07    19656345.6
4 2018-01-06 02:00:00  1.879455e+07    19381075.2
```

2.4 Extract Seasonal Datasets

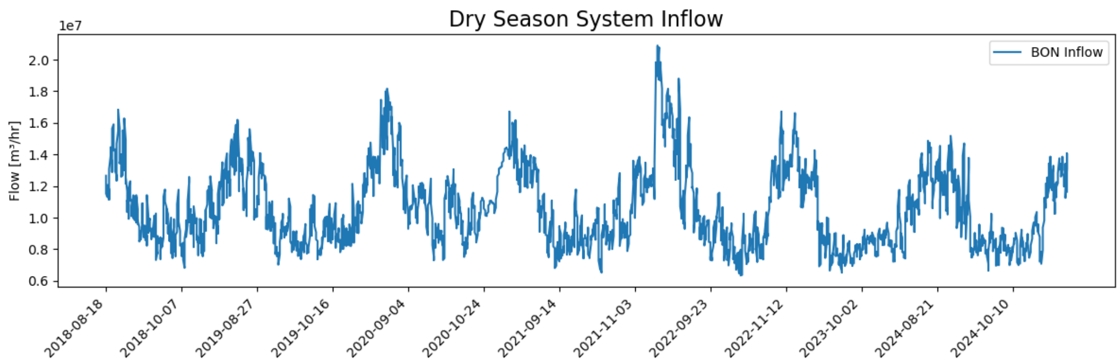
[72]:
```
# Remove 2025 data (ncomplete seasons)
flow = flow[flow["Date Time"].dt.year < 2025]

# Create DoY column
doy = flow["Date Time"].dt.dayofyear

# Wet season mask
wet_mask = (doy >= wet_start) & (doy <= wet_end)

# Dry season mask
dry_mask = (doy >= dry_start) & (doy <= dry_end)

# Build the dataframes
wet_flow = flow[wet_mask].copy()
dry_flow = flow[dry_mask].copy()
```

[88]:
```
# Visualize Flow Datasets

def plot_flow(df, tick_stride, season):
    plt.figure(figsize=(12, 4))

    # convert to strings for categorical x-axis
    x = df['Date Time'].dt.strftime("%Y-%m-%d")

    # plt.plot(x, df['outflow_m3hr'], label="TDA Outflow")
    plt.plot(x, df['inflow_m3hr'], label="BON Inflow")

    plt.title(f"{season} Season System Inflow", fontsize = 16)
    plt.ylabel('Flow [m³/hr]')
    plt.legend()

    # control tick density: show only every nth label
    plt.xticks(x[::tick_stride], rotation=45, ha='right')

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

[90]:
```
plot_flow(wet_flow, 200, "Wet")
```




```
[92]: plot_flow(dry_flow, 200, "Dry")
```



3 Seasonal OLS Models

3.1 Preprocessing

3.1.1 Normalize Data (Z-Score)

```
[97]: ## Wet Season

wet_scaler = StandardScaler() # removes mean and converts to unit variance for␣
 ↪each column
wet_flow_norm = wet_scaler.fit_transform(wet_flow.copy().drop(['Date Time'],␣
 ↪axis=1))
wet_flow_norm = pd.DataFrame(wet_flow_norm, columns=wet_flow.columns[1:])
```

```
[99]: print(f"{'Feature':<20} {'Mean':>12} {'Std Dev':>12} {'Variance':>12}")
print("-" * 58)
for i, col in enumerate(wet_flow.columns[1:]):
```

```
    print(f"{col:<20} {wet_scaler.mean_[i]:>12.2e} {wet_scaler.scale_[i]:>12.
 ↪2e} {wet_scaler.var_[i]:>12.2e}")
```

```
Feature                      Mean      Std Dev     Variance
----------------------------------------------------------
inflow_m3hr              2.58e+07     9.21e+06     8.49e+13
outflow_m3hr             2.37e+07     9.12e+06     8.32e+13
```

[101]:
```
## Dry Season

dry_scaler = StandardScaler() # removes mean and converts to unit variance for␣
 ↪each column
dry_flow_norm = dry_scaler.fit_transform(dry_flow.copy().drop(['Date Time'],␣
 ↪axis=1))
dry_flow_norm = pd.DataFrame(dry_flow_norm, columns=dry_flow.columns[1:])
```

[103]:
```
print(f"{'Feature':<20} {'Mean':>12} {'Std Dev':>12} {'Variance':>12}")
print("-" * 58)
for i, col in enumerate(dry_flow.columns[1:]):
    print(f"{col:<20} {dry_scaler.mean_[i]:>12.2e} {dry_scaler.scale_[i]:>12.
 ↪2e} {dry_scaler.var_[i]:>12.2e}")
```

```
Feature                      Mean      Std Dev     Variance
----------------------------------------------------------
inflow_m3hr              1.06e+07     2.47e+06     6.10e+12
outflow_m3hr             9.69e+06     2.79e+06     7.80e+12
```

3.1.2 Lag Features

[112]:
```
p = 4 + 1
up_feat = False
down_feat = True
x_col_name = 'outflow_m3hr'
y_col_name = 'inflow_m3hr'
```

[114]:
```
## Wet Season

wet_flow_lag, feature_cols = preproc.create_lag_features_colname(wet_flow_norm.
 ↪copy(), p, x_col_name, y_col_name, up_feat, down_feat)

# Add back in Date Time as index
wet_flow_lag.index = wet_flow["Date Time"]

# Drop rows with NaN values resulting from creating lag features
wet_flow_lag.dropna(inplace=True)
```

[116]:
```
wet_flow_lag.head()
```

[116]:
```
                     inflow_m3hr  outflow_m3hr  inflow_m3hr_Lag_1  \
Date Time
2018-04-23 02:00:00     0.314129      0.284386           0.368393
2018-04-23 08:00:00     0.283256      0.083247           0.314129
2018-04-23 14:00:00     0.231272      0.494464           0.283256
2018-04-23 20:00:00     0.553028      0.544749           0.231272
2018-04-24 02:00:00     0.476324      0.516813           0.553028

                     inflow_m3hr_Lag_2  inflow_m3hr_Lag_3  inflow_m3hr_Lag_4
Date Time
2018-04-23 02:00:00           0.472174           0.428079           0.494493
2018-04-23 08:00:00           0.368393           0.472174           0.428079
2018-04-23 14:00:00           0.314129           0.368393           0.472174
2018-04-23 20:00:00           0.283256           0.314129           0.368393
2018-04-24 02:00:00           0.231272           0.283256           0.314129
```

[118]:
```python
## Dry Season

dry_flow_lag, feature_cols = preproc.create_lag_features_colname(dry_flow_norm.
 ↪copy(), p, x_col_name, y_col_name, up_feat, down_feat)

# Add back in Date Time as index
dry_flow_lag.index = dry_flow["Date Time"]

# Drop rows with NaN values resulting from creating lag features
dry_flow_lag.dropna(inplace=True)
```

[120]:
```python
dry_flow_lag.head()
```

[120]:
```
                     inflow_m3hr  outflow_m3hr  inflow_m3hr_Lag_1  \
Date Time
2018-08-19 02:00:00     0.291111      0.182363           0.381574
2018-08-19 08:00:00     0.327404      0.182363           0.291111
2018-08-19 14:00:00     0.438675     -0.011127           0.327404
2018-08-19 20:00:00     0.606140     -0.003826           0.438675
2018-08-20 02:00:00     0.496479      0.029031           0.606140

                     inflow_m3hr_Lag_2  inflow_m3hr_Lag_3  inflow_m3hr_Lag_4
Date Time
2018-08-19 02:00:00           0.642226           0.591607           0.842928
2018-08-19 08:00:00           0.381574           0.642226           0.591607
2018-08-19 14:00:00           0.291111           0.381574           0.642226
2018-08-19 20:00:00           0.327404           0.291111           0.381574
2018-08-20 02:00:00           0.438675           0.327404           0.291111
```

3.2 Train / Test Split

[123]:
```
train_start_year = '2018'
test_start_year = '2024'
```

[125]:
```
## Enforce Framework
if framework == "DDU":
    feature_cols = ['inflow_m3hr_Lag_1', 'outflow_m3hr_Lag_1']

if framework == "DIU":
    feature_cols = ['inflow_m3hr_Lag_1'] #, 'inflow_m3hr_Lag_2']

print(feature_cols)
```

```
['inflow_m3hr_Lag_1']
```

[127]:
```
## Split the data into training and testing sets

def split_train_test(flow_lag, feature_cols, y_col_name, test_start_year,␣
↪season):
    # Train/test split
    train_data = flow_lag[flow_lag.index < test_start_year]
    test_data = flow_lag[flow_lag.index >= test_start_year]

    # Features + target
    X_train = train_data[feature_cols]
    y_train = train_data[y_col_name]
    X_test = test_data[feature_cols]
    y_test = test_data[y_col_name]

    # Return dictionary with season-prepended keys
    return {
        f"{season}_train_data": train_data,
        f"{season}_test_data": test_data,
        f"{season}_X_train": X_train,
        f"{season}_y_train": y_train,
        f"{season}_X_test": X_test,
        f"{season}_y_test": y_test,
    }
```

[129]:
```
wet_splits = split_train_test(wet_flow_lag, feature_cols, y_col_name,␣
↪test_start_year, "wet")
dry_splits = split_train_test(dry_flow_lag, feature_cols, y_col_name,␣
↪test_start_year, "dry")
```

[131]:
```
wet_splits["wet_X_train"].head()
```

[131]:
```
                     inflow_m3hr_Lag_1
Date Time
2018-04-23 02:00:00           0.368393
2018-04-23 08:00:00           0.314129
2018-04-23 14:00:00           0.283256
2018-04-23 20:00:00           0.231272
2018-04-24 02:00:00           0.553028
```

3.3 Wet Season OLS Model

[134]:
```python
# Step 1: Add constant (intercept)
wet_X_train_const = sm.add_constant(wet_splits["wet_X_train"])

# Step 2: Fit OLS model
wet_model = sm.OLS(wet_splits["wet_y_train"], wet_X_train_const).
 ↪fit(cov_type='HC1') # Heteroskedasticity-consistent

# Step 3: View summary
print(wet_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            inflow_m3hr   R-squared:                       0.990
Model:                            OLS   Adj. R-squared:                  0.990
Method:                 Least Squares   F-statistic:                 1.979e+05
Date:                Tue, 27 Jan 2026   Prob (F-statistic):               0.00
Time:                        11:34:19   Log-Likelihood:                 1836.4
No. Observations:                2179   AIC:                            -3669.
Df Residuals:                    2177   BIC:                            -3657.
Df Model:                           1
Covariance Type:                  HC1
================================================================================
=====
                        coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                -0.0004      0.002     -0.159      0.874      -0.005
0.004
inflow_m3hr_Lag_1     0.9954      0.002    444.827      0.000       0.991
1.000
==============================================================================
Omnibus:                      364.026   Durbin-Watson:                   2.141
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6683.016
Skew:                           0.139   Prob(JB):                         0.00
Kurtosis:                      11.575   Cond. No.                         1.12
==============================================================================
```

```
Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```

[136]:

```
# Extract coefficients and p-values into a tidy DataFrame
coef_df = pd.DataFrame({
    'feature': wet_model.params.index,
    'coefficient': wet_model.params.values
    #'p_value': model.pvalues.values,
    #'t_value': model.tvalues.values
})

# Optional: sort by absolute coefficient size
coef_df = coef_df.reindex(coef_df['coefficient'].abs().
 ↪sort_values(ascending=False).index)

print(coef_df)
```

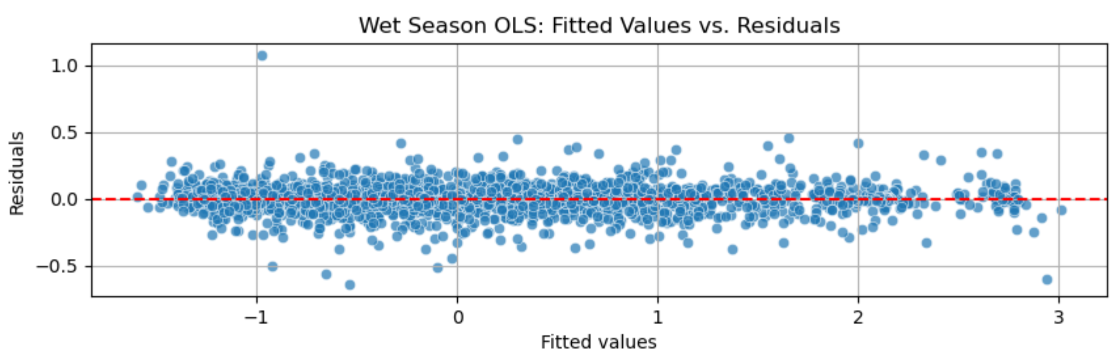
```
             feature  coefficient
1  inflow_m3hr_Lag_1     0.995421
0              const    -0.000354
```

[138]:

```
wet_residuals = wet_model.resid
wet_fitted_vals = wet_model.fittedvalues
```

[140]:

```
# Checking for Heteroskedasticity

preproc.plot_variance("Wet Season OLS", wet_fitted_vals, wet_residuals,␣
 ↪bounds=False)
```



[142]:

```
# Display Equation

params = wet_model.params
latex_eq = f"\\hat{{y}} = {params.iloc[0]:.4f}"
for coef, feature in zip(params.iloc[1:], feature_cols):
    sign = "+" if coef >= 0 else "-"
```

```
    coef_abs = abs(coef)
    clean_feature = clean_variable_name(feature)
    latex_eq += f" {sign} {coef_abs:.3f} {clean_feature}"
```

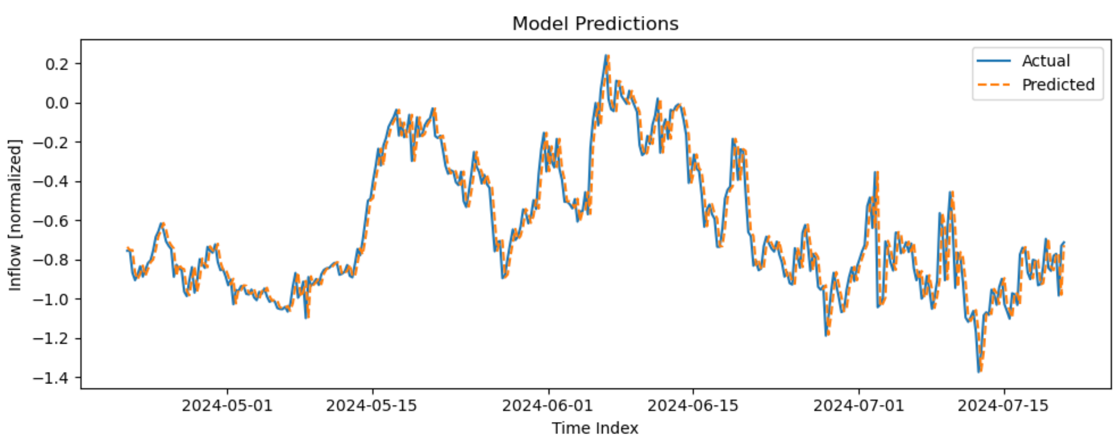
[144]:
```
display(Math(latex_eq))
```

$\hat{y} = -0.0004 + 0.995 y_{t-1}$

3.3.1 Evaluation

[147]:
```
wet_X_test_const = sm.add_constant(wet_splits["wet_X_test"])  # Add intercept␣
 ↪term
wet_X_test_const['const'] = np.ones(len(wet_splits["wet_X_test"]))
wet_X_test_const = pd.DataFrame(wet_X_test_const, columns=wet_model.model.
 ↪exog_names)
wet_y_pred = wet_model.predict(wet_X_test_const)
```

[149]:
```
# Dropping the first predicted value since not enough lag info

preproc.plot_inflow_forecasts(wet_splits["wet_y_test"].iloc[1:], wet_y_pred.
 ↪iloc[1:])
```

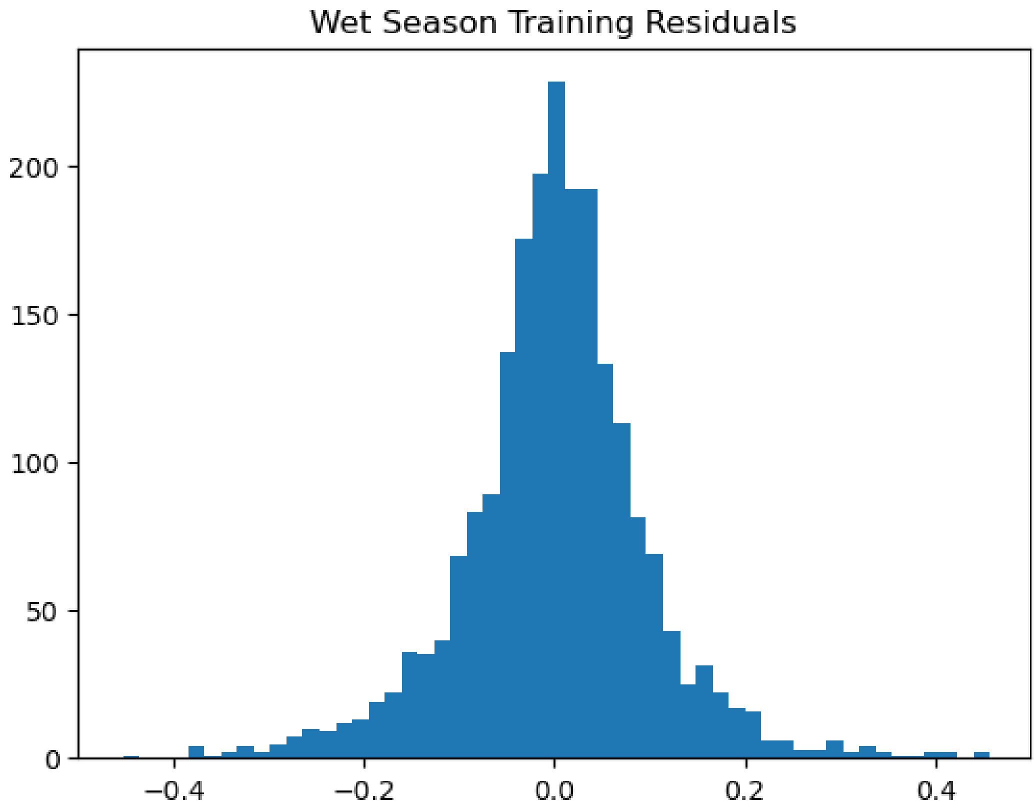


[151]:
```
# Calculate model performance without the first predicted value

preproc.print_test_stats(wet_splits["wet_y_test"].iloc[1:], wet_y_pred.iloc[1:])
```

```
RMSE: 0.105
MAE: 0.075
R²: 0.900
```

3.3.2 Residuals

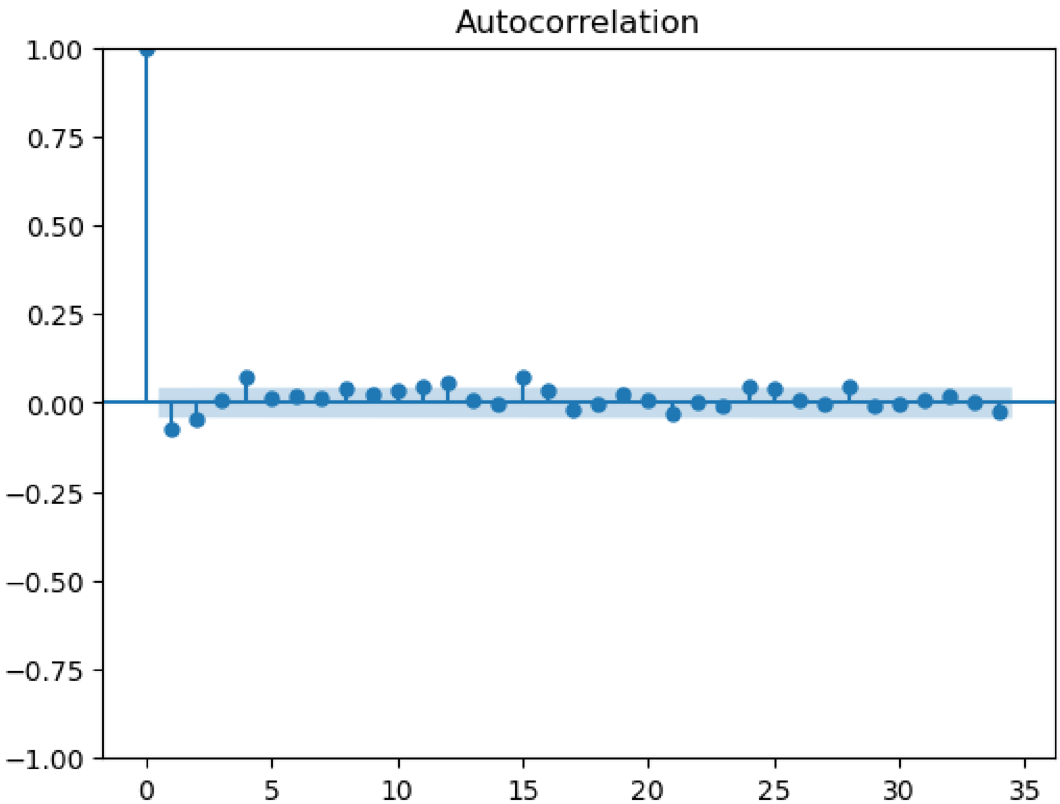
[154]:
```
plt.hist(wet_residuals, bins = 100)
plt.title('Wet Season Training Residuals')
plt.xlim([-.5, .5])
plt.show()
```



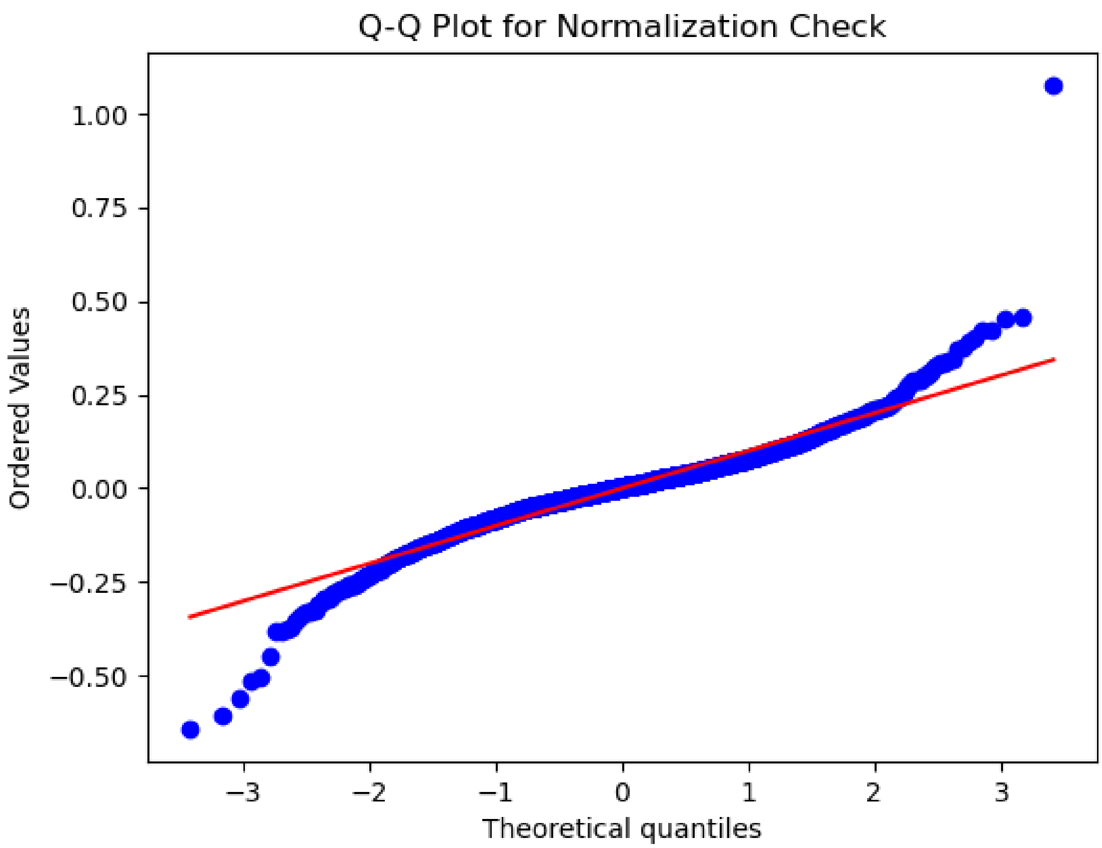
[156]:
```
mean = wet_residuals.mean()
std = wet_residuals.std()
(round(mean,3), round(std, 4))
```

[156]: (0.0, 0.1042)

[158]:
```
plot_acf(wet_residuals)
plt.show()
```



[160]:
```
stats.probplot(wet_residuals, dist="norm", plot=plt)
plt.title("Q-Q Plot for Normalization Check")
plt.show()
```



3.3.3 Data Export

[74]:
```
if framework == "DDU":
    wet_data_to_save = {
        "data": wet_splits,
        "y_pred": wet_y_pred,
        "residuals": wet_residuals,
    }

    # Save to pickle
    with open("wet_ols_model.pkl", "wb") as f:
        pickle.dump(wet_data_to_save, f)

    print("Saved")
```

Saved

3.4 Dry Season OLS Model

[163]:
```
# Step 1: Add constant (intercept)
dry_X_train_const = sm.add_constant(dry_splits["dry_X_train"])

# Step 2: Fit OLS model
dry_model = sm.OLS(dry_splits["dry_y_train"], dry_X_train_const).
 ↪fit(cov_type='HC1') # Heteroskedasticity-consistent

# Step 3: View summary
print(dry_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             inflow_m3hr   R-squared:                       0.901
Model:                             OLS   Adj. R-squared:                  0.901
Method:                  Least Squares   F-statistic:                 1.645e+04
Date:                 Tue, 27 Jan 2026   Prob (F-statistic):               0.00
Time:                         11:34:50   Log-Likelihood:                -597.40
No. Observations:                 2174   AIC:                             1199.
Df Residuals:                     2172   BIC:                             1210.
Df Model:                            1
Covariance Type:                   HC1
================================================================================
=====
                        coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                 0.0025      0.007      0.371      0.711      -0.011
0.016
inflow_m3hr_Lag_1     0.9502      0.007    128.257      0.000       0.936
0.965
==============================================================================
Omnibus:                       380.752   Durbin-Watson:                   2.124
Prob(Omnibus):                   0.000   Jarque-Bera (JB):             3037.768
Skew:                            0.593   Prob(JB):                         0.00
Kurtosis:                        8.668   Cond. No.                         1.03
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)
```

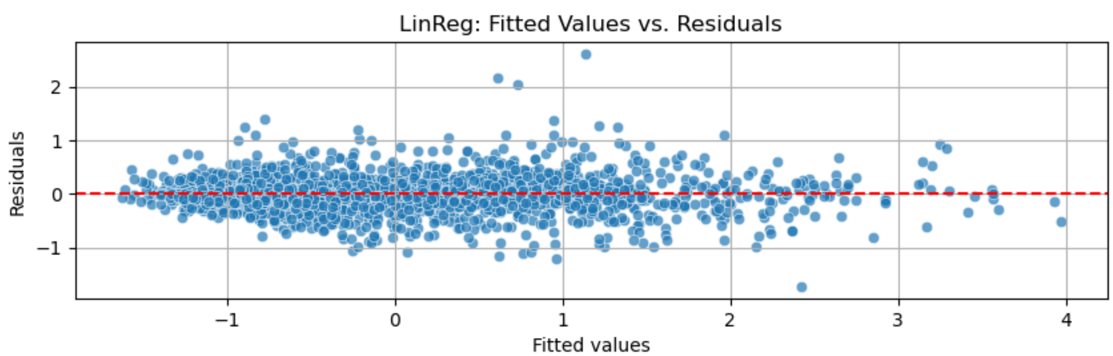
[165]:
```
# Extract coefficients and p-values into a tidy DataFrame
coef_df = pd.DataFrame({
    'feature': dry_model.params.index,
    'coefficient': dry_model.params.values
    #'p_value': model.pvalues.values,
```

```python
    #'t_value': model.tvalues.values
})

# Optional: sort by absolute coefficient size
coef_df = coef_df.reindex(coef_df['coefficient'].abs().
    sort_values(ascending=False).index)

print(coef_df)
```

```
             feature  coefficient
1  inflow_m3hr_Lag_1     0.950187
0              const     0.002509
```

[167]:
```python
dry_residuals = dry_model.resid
dry_fitted_vals = dry_model.fittedvalues
```

[169]:
```python
# Checking for Heteroskedasticity

preproc.plot_variance("LinReg", dry_fitted_vals, dry_residuals, bounds=False)
```



[171]:
```python
# Display Equation

params = dry_model.params
latex_eq = f"\\hat{{y}} = {params.iloc[0]:.4f}"
for coef, feature in zip(params.iloc[1:], feature_cols):
    sign = "+" if coef >= 0 else "-"
    coef_abs = abs(coef)
    clean_feature = clean_variable_name(feature)
    latex_eq += f" {sign} {coef_abs:.3f} {clean_feature}"
```

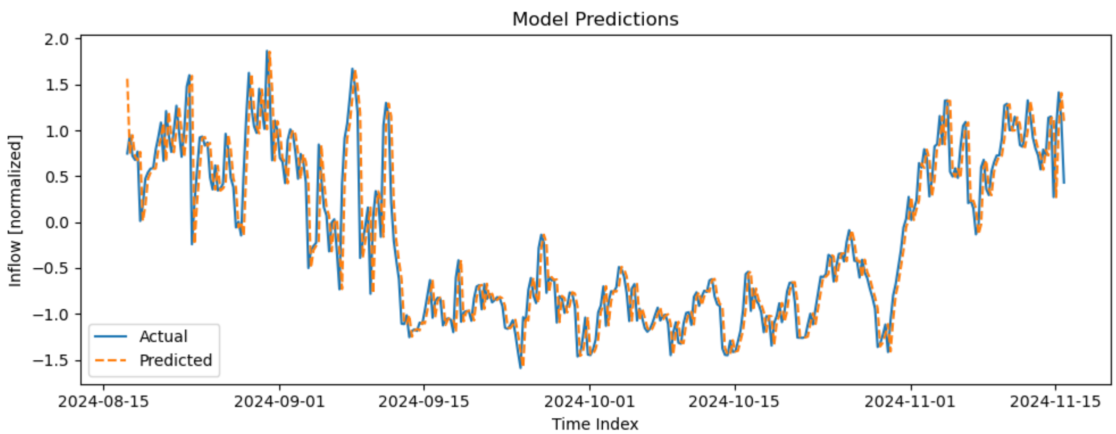
[173]:
```python
display(Math(latex_eq))
```

$\hat{y} = 0.0025 + 0.950 y_{t-1}$

3.4.1 Evaluation

[176]:
```
dry_X_test_const = sm.add_constant(dry_splits["dry_X_test"])  # Add intercept␣
↪term
dry_X_test_const['const'] = np.ones(len(dry_splits["dry_X_test"]))
dry_X_test_const = pd.DataFrame(dry_X_test_const, columns=dry_model.model.
↪exog_names)
dry_y_pred = wet_model.predict(dry_X_test_const)
```

[178]:
```
# Dropping the first predicted value since not enough lag info

preproc.plot_inflow_forecasts(dry_splits["dry_y_test"].iloc[1:], dry_y_pred.
↪iloc[1:])
```

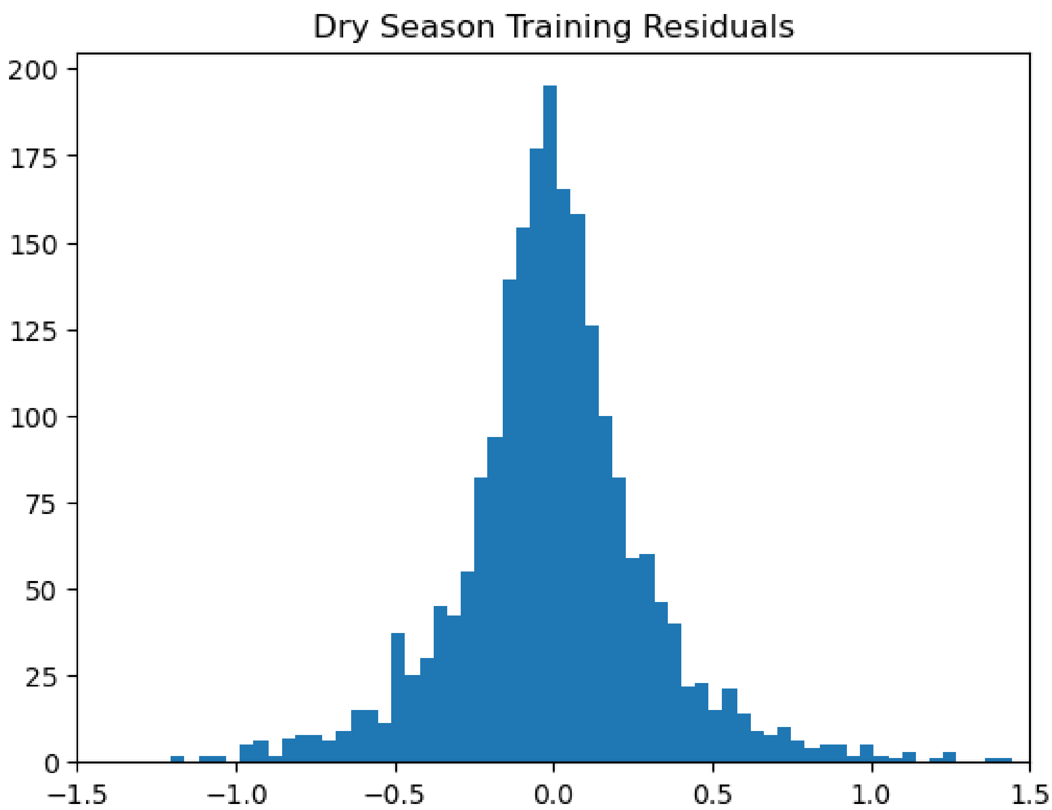


[180]:
```
# Calculate model performance without the first predicted value

preproc.print_test_stats(dry_splits["dry_y_test"].iloc[1:], dry_y_pred.iloc[1:])
```

```
RMSE: 0.322
MAE: 0.221
R²: 0.866
```

3.4.2 Residuals

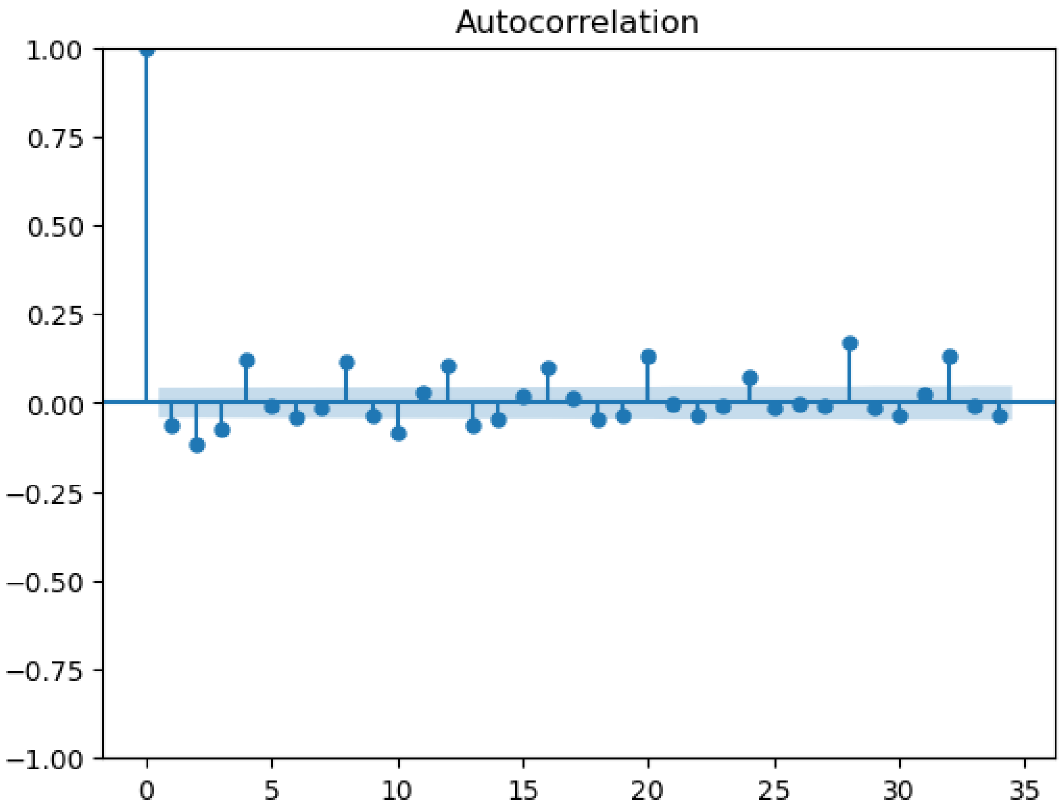
[183]:
```
plt.hist(dry_residuals, bins = 100)
plt.title('Dry Season Training Residuals')
plt.xlim([-1.5, 1.5])
plt.show()
```



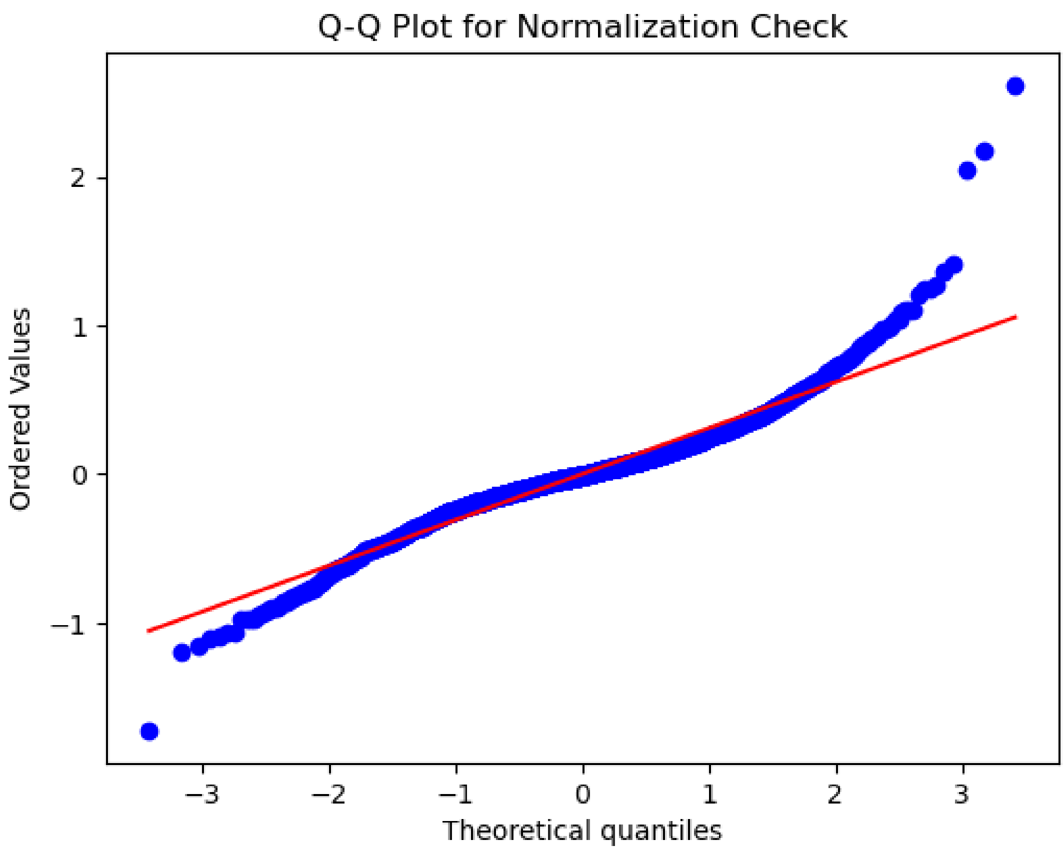
[185]:
```
mean = dry_residuals.mean()
std = dry_residuals.std()
(round(mean,3), round(std, 4))
```

[185]: (-0.0, 0.3186)

[187]:
```
plot_acf(dry_residuals)
plt.show()
```



[189]:
```
stats.probplot(dry_residuals, dist="norm", plot=plt)
plt.title("Q-Q Plot for Normalization Check")
plt.show()
```



[191]:
```
# plt.scatter(dry_splits["dry_y_train"], dry_residuals)
# plot moving window mean and you will see a bit of structure
# a nonlinear model (nearest neighbor or neural net will go away)
```

[193]:
```
if framework == "DDU":
    dry_data_to_save = {
        "data": dry_splits,
        "y_pred": dry_y_pred,
        "residuals": dry_residuals,
    }

    # Save to pickle
    with open("dry_ols_model.pkl", "wb") as f:
        pickle.dump(dry_data_to_save, f)

    print("Saved")
```

[ ]: