In [4]:

```
import os
gee_files = [f for f in os.listdir('../Data/GEE') if f.endswith('.csv')]
print(gee_files)
```

```
['dewpoint_temperature_2m.csv', 'evaporation_from_vegetation_transpiration_sum.csv', 'potential_evaporation_sum.csv',
'prcp.csv', 'skin_temperature.csv', 'snow_depth.csv', 'snow_depth_water_equivalent.csv', 'soil_temperature_level_1.cs
v', 'soil_temperature_level_2.csv', 'soil_temperature_level_3.csv', 'soil_temperature_level_4.csv', 'srad.csv', 'sub_
surface_runoff_sum.csv', 'surface_latent_heat_flux_sum.csv', 'surface_net_solar_radiation_sum.csv', 'surface_net_ther
mal_radiation_sum.csv', 'surface_pressure.csv', 'surface_runoff_sum.csv', 'surface_solar_radiation_downwards_sum.cs
v', 'temperature_2m.csv', 'tmax.csv', 'tmin.csv', 'total_precipitation_sum.csv', 'u_component_of_wind_10m.csv', 'volu
metric_soil_water_layer_1.csv', 'volumetric_soil_water_layer_2.csv', 'vp.csv', 'v_component_of_wind_10m.csv']
```

In [1]:

```
import os
import pandas as pd

# Paths
gee_folder = '../Data/GEE'
discharge_folder = '../Data/Discharge'
output_folder = '../Data/Required Data'

# Create the output folder if it doesn't exist
os.makedirs(output_folder, exist_ok=True)

# Get list of GEE files
gee_files = [f for f in os.listdir(gee_folder) if f.endswith('.csv')]

# Extract column identifiers from GEE files
gee_column_identifiers = [col for col in pd.read_csv(os.path.join(gee_folder, gee_files[0])).columns if col.isdigit()

# Process each column identifier
for col_id in gee_column_identifiers:
    # Initialize a dataframe for this column identifier
    combined_data = pd.DataFrame()

    # Add Date column from any GEE file (Dates will be consistent across GEE files)
    first_gee_file = pd.read_csv(os.path.join(gee_folder, gee_files[0]))
    combined_data['Date'] = pd.to_datetime(first_gee_file['Date'], errors='coerce')

    # Load discharge file corresponding to the column identifier
    discharge_file_path = next((f for f in os.listdir(discharge_folder) if f.startswith(f"{col_id}. ")), None)
```

```python
    if not discharge_file_path:
        print(f"No discharge file found for column {col_id}")
        continue

    discharge_data = pd.read_csv(os.path.join(discharge_folder, discharge_file_path))
    discharge_data['Date'] = pd.to_datetime(discharge_data['Date'], errors='coerce')
    discharge_data['Q (ft3/s)'] = discharge_data['Q (ft3/s)'].str.replace(',', '', regex=True).astype(float, errors=
    discharge_data.rename(columns={'Q (ft3/s)': 'Discharge'}, inplace=True)

    # Merge Discharge data with the Date column from GEE files
    combined_data = pd.merge(combined_data, discharge_data[['Date', 'Discharge']], on='Date', how='left')

    # Add GEE parameters to the dataframe
    for gee_file in gee_files:
        param_name = os.path.splitext(gee_file)[0]  # Extract parameter name from file
        gee_data = pd.read_csv(os.path.join(gee_folder, gee_file))
        gee_data['Date'] = pd.to_datetime(gee_data['Date'], errors='coerce')

        # Merge with the combined dataframe based on Date
        combined_data = pd.merge(combined_data, gee_data[['Date', col_id]].rename(columns={col_id: param_name}),
                                 on='Date', how='left')

    # Save the combined data to a new CSV file
    output_path = os.path.join(output_folder, f'{col_id}.csv')
    combined_data.to_csv(output_path, index=False)
    print(f"Saved: {output_path}")

print("Processing complete!")
```

```
Saved: ../Data/Required Data\5.csv
Saved: ../Data/Required Data\6.csv
Saved: ../Data/Required Data\7.csv
Saved: ../Data/Required Data\8.csv
Saved: ../Data/Required Data\10.csv
Saved: ../Data/Required Data\11.csv
Processing complete!
```

In [2]:

```python
def look_multi_colinear(num):
    import seaborn as sns
    import matplotlib.pyplot as plt
    # Load the dataset
    file_path = f'../Data/Required Data/{num}.csv'  # Example file
```

```
data = pd.read_csv(file_path)

# Preprocessing for correlation analysis
data['Date'] = pd.to_datetime(data['Date'], errors='coerce')
data['day_of_year'] = data['Date'].dt.dayofyear  # Add day of year as a feature
data['month'] = data['Date'].dt.month  # Add month as a feature
data['week'] = data['Date'].dt.isocalendar().week  # Add week as a feature

# Drop the original Date column (if not needed) and rows with missing Discharge
data.drop(columns=['Date'], inplace=True)
data_clean = data.dropna(subset=['Discharge'])  # Only use rows with Discharge for correlation analysis

# Select only numeric columns
numeric_data = data_clean.select_dtypes(include=['number'])

# Compute correlation matrix
correlation_matrix = numeric_data.corr()

# Extract pairs with high correlations
high_corr_pairs = correlation_matrix.unstack().reset_index()
high_corr_pairs.columns = ['Feature1', 'Feature2', 'Correlation']

# Filter out duplicate pairs and self-correlations
high_corr_pairs = high_corr_pairs[
    (high_corr_pairs['Feature1'] != high_corr_pairs['Feature2']) &
    (abs(high_corr_pairs['Correlation']) > 0.95)
].drop_duplicates(subset=['Correlation'])

# Sort by absolute correlation value
high_corr_pairs = high_corr_pairs.sort_values(by='Correlation', ascending=False)

# Display the pairs
print("Highly Correlated Feature Pairs (|Correlation| > 0.95):")
print(high_corr_pairs)

# Save the result to a CSV file
#high_corr_pairs.to_csv('../Data/Required Data/high_correlation_pairs.csv', index=False)

# Plot correlation heatmap for visualization
plt.figure(figsize=(10, 8))
sns.heatmap(
    correlation_matrix,
```

```python
        annot=False,
        fmt=".2f",
        cmap="coolwarm",
        cbar=True,
        square=True,
        linewidths=0.5
    )
    plt.title("Feature Correlation Heatmap")
    plt.tight_layout()

    # Save the plot
    plt.savefig(f'../Figures/{num}_corr_heatmap.png')
```

In [3]:

```python
def clean_correlated(num):
    import pandas as pd
    # Load the dataset
    file_path = f'../Data/Required Data/{num}.csv'  # Example file
    data = pd.read_csv(file_path)

    # Columns to remove
    columns_to_remove = [
        'dewpoint_temperature_2m',
        'soil_temperature_level_1',
        'soil_temperature_level_2',
        'soil_temperature_level_3',
        'temperature_2m',
        'tmin',
        'month',
        'week',
        'volumetric_soil_water_layer_2'
    ]

    # Preprocessing for feature removal
    data['Date'] = pd.to_datetime(data['Date'], errors='coerce')
    data['day_of_year'] = data['Date'].dt.dayofyear  # Add day of year as a feature

    # Drop the specified columns
    data_cleaned = data.drop(columns=columns_to_remove, errors='ignore')

    # Save the cleaned dataset
    output_path = f'../Data/Required Data/{num}_cleaned.csv'
    data_cleaned.to_csv(output_path, index=False)
```

```python
    print(f"Cleaned dataset saved to {output_path}")
```

In [4]:
```python
def do_machine_learning(num):
    import pandas as pd
    from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

    # Step 1: Load the Cleaned Dataset
    file_path = f'../Data/Required Data/{num}_cleaned.csv'  # Cleaned dataset path
    data = pd.read_csv(file_path)

    data.drop(columns=['Date'], inplace=True)
    # Ensure Discharge is numeric
    data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
    # Drop Date column if not needed

    # Step 3: Setup PyCaret Regression Environment
    # Only use rows with valid 'Discharge' for training
    train_data = data.dropna(subset=['Discharge'])

    print("Setting up PyCaret environment...")
    regression_setup = setup(
        data=train_data,
        target='Discharge',
        session_id=42,
        normalize=True,        # Normalize features
        feature_selection=True, # Perform feature selection
        log_experiment=False,  # Disable experiment logging
    )

    # Step 4: Compare Models
    print("Comparing models...")
    best_model = compare_models()

    # Step 5: Tune the Best Model
    print("Tuning the best model...")
    tuned_model = tune_model(best_model)

    # Step 6: Finalize the Model
    print("Finalizing the model...")
    final_model = finalize_model(tuned_model)
```

```python
    # Step 7: Evaluate Model
    # Residual Plot
    print("Generating residual plot...")
    plot_model(final_model, plot='residuals', save=True)

    # Feature Importance Plot
    print("Generating feature importance plot...")
    plot_model(final_model, plot='feature', save=True)

    # Step 8: Predict Missing Values
    # Predict Discharge for rows with missing target values
    missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge
    missing_data.drop(columns = ['Discharge'], inplace = True)
    print("Predicting missing values...")
    predicted = predict_model(final_model, data=missing_data)

    # Assign predictions to the missing Discharge column
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv(f'../Data/Required Data/{num}_filled.csv', index=False)
    print(f"Saved the filled dataset as '../Data/Required Data/{num}_filled.csv'")
```

In [4]:

```python
def making_filled_plots(num):
    # File paths
    cleaned_file = f'../Data/Required Data/{num}_cleaned.csv'
    filled_file = f'../Data/Required Data/{num}_filled.csv'

    # Load datasets
    cleaned_data = pd.read_csv(cleaned_file)  # Original cleaned data with 'Date'
    filled_data = pd.read_csv(filled_file)    # Filled data without 'Date'

    # Ensure Discharge column is numeric in both datasets
    cleaned_data['Discharge'] = pd.to_numeric(cleaned_data['Discharge'], errors='coerce')
    filled_data['Discharge'] = pd.to_numeric(filled_data['Discharge'], errors='coerce')
```

```
# Check for remaining invalid or missing values in observed and filled datasets
#invalid_observed = cleaned_data[cleaned_data['Discharge'].isnull()]
#invalid_filled = filled_data[filled_data['Discharge'].isnull()]

# Print the number of invalid rows in each dataset
#print(f"Invalid rows in observed data: {len(invalid_observed)}")
#print(f"Invalid rows in filled data: {len(invalid_filled)}")

# Plotting (after ensuring 'Date' column exists in filled_data)
filled_data['Date'] = cleaned_data['Date']  # Add Date from cleaned_data if missing
filled_data['Date'] = pd.to_datetime(filled_data['Date'], errors='coerce')
cleaned_data['Date'] = pd.to_datetime(cleaned_data['Date'], errors='coerce')

# Separate observed and filled data
observed_data = cleaned_data
filled_data_nonnull = filled_data

# Plotting
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
plt.plot(observed_data['Date'], observed_data['Discharge'], label='Observed Data', marker='o', linestyle='-', alp
plt.plot(filled_data_nonnull['Date'], filled_data_nonnull['Discharge'], label='Machine Learning Prediction', mark
plt.title('Observed vs. Filled Discharge Time Series')
plt.xlabel('Date')
plt.ylabel('Discharge')
plt.legend()
plt.grid()
plt.tight_layout()

# Save the plot
plot_path = f'../Figures/{num}Observed_vs_Filled_Discharge_Cleaned.png'
plt.savefig(plot_path, dpi=300)
plt.show()

print(f"Time series plot saved to: {plot_path}")
```

In [6]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model
```

```python
numbers = ['5','6', '7', '8', '10', '11']
for num in numbers:
    look_multi_colinear(num)
```

```
Highly Correlated Feature Pairs (|Correlation| > 0.95):
                          Feature1                             Feature2  \
143               skin_temperature                       temperature_2m   
161                     snow_depth            snow_depth_water_equivalent   
897                    day_of_year                                month   
452  surface_net_solar_radiation_sum  surface_solar_radiation_downwards_sum   
225         soil_temperature_level_1             soil_temperature_level_2   
131               skin_temperature             soil_temperature_level_1   
236         soil_temperature_level_1                       temperature_2m   
145               skin_temperature                                 tmin   
610                 temperature_2m                                 tmin   
21           dewpoint_temperature_2m                                 tmin   
609                 temperature_2m                                 tmax   
19           dewpoint_temperature_2m                       temperature_2m   
4            dewpoint_temperature_2m                     skin_temperature   
238         soil_temperature_level_1                                 tmin   
144               skin_temperature                                 tmax   
898                    day_of_year                                 week   
929                          month                                 week   
677                           tmin                                   vp   
132               skin_temperature             soil_temperature_level_2   
267         soil_temperature_level_2                       temperature_2m   
269         soil_temperature_level_2                                 tmin   
243         soil_temperature_level_1                                   vp   
237         soil_temperature_level_1                                 tmax   

     Correlation  
143     0.999306  
161     0.997454  
897     0.996558  
452     0.996084  
225     0.991703  
131     0.985267  
236     0.982629  
145     0.981970  
610     0.979839  
21      0.979338  
609     0.978020  
19      0.975006  
4       0.973875  
238     0.973589  
144     0.973566  
```

```
898    0.971572
929    0.970187
677    0.966839
132    0.960553
267    0.956409
269    0.955277
243    0.954205
237    0.950341
Highly Correlated Feature Pairs (|Correlation| > 0.95):
                           Feature1                             Feature2  \
143                skin_temperature                       temperature_2m
452  surface_net_solar_radiation_sum  surface_solar_radiation_downwards_sum
161                      snow_depth            snow_depth_water_equivalent
897                     day_of_year                                month
131                skin_temperature              soil_temperature_level_1
225        soil_temperature_level_1              soil_temperature_level_2
236        soil_temperature_level_1                       temperature_2m
21          dewpoint_temperature_2m                                 tmin
145                skin_temperature                                 tmin
677                            tmin                                   vp
610                  temperature_2m                                 tmin
898                     day_of_year                                 week
609                  temperature_2m                                 tmax
929                           month                                 week
132                skin_temperature              soil_temperature_level_2
238        soil_temperature_level_1                                 tmin
144                skin_temperature                                 tmax
267        soil_temperature_level_2                       temperature_2m
4           dewpoint_temperature_2m                     skin_temperature
19          dewpoint_temperature_2m                       temperature_2m

     Correlation
143     0.999078
452     0.998583
161     0.998146
897     0.996515
131     0.991193
225     0.991091
236     0.988407
21      0.978428
145     0.975217
677     0.973405
```

```
610    0.971546
898    0.971113
609    0.970935
929    0.969746
132    0.967634
238    0.967270
144    0.964555
267    0.962979
4      0.961138
19     0.961125
Highly Correlated Feature Pairs (|Correlation| > 0.95):
                           Feature1                           Feature2  \
180                skin_temperature                     temperature_2m   
958                     day_of_year                              month   
265          soil_temperature_level_1           soil_temperature_level_2   
182                skin_temperature                               tmin   
662                  temperature_2m                               tmin   
499  surface_net_solar_radiation_sum  surface_solar_radiation_downwards_sum   
54           dewpoint_temperature_2m                               tmin   
661                  temperature_2m                               tmax   
199                      snow_depth        snow_depth_water_equivalent   
52           dewpoint_temperature_2m                     temperature_2m   
181                skin_temperature                               tmax   
37           dewpoint_temperature_2m                   skin_temperature   
959                     day_of_year                               week   
991                           month                               week   
168                skin_temperature           soil_temperature_level_1   
276          soil_temperature_level_1                     temperature_2m   
694                            tmax                               tmin   
278          soil_temperature_level_1                               tmin   
298          soil_temperature_level_2           soil_temperature_level_3   
283          soil_temperature_level_1                                 vp   
53           dewpoint_temperature_2m                               tmax   
277          soil_temperature_level_1                               tmax   
169                skin_temperature           soil_temperature_level_2   
826    volumetric_soil_water_layer_1      volumetric_soil_water_layer_2   

     Correlation  
180     0.999082  
958     0.996501  
265     0.993839  
182     0.989314  
```

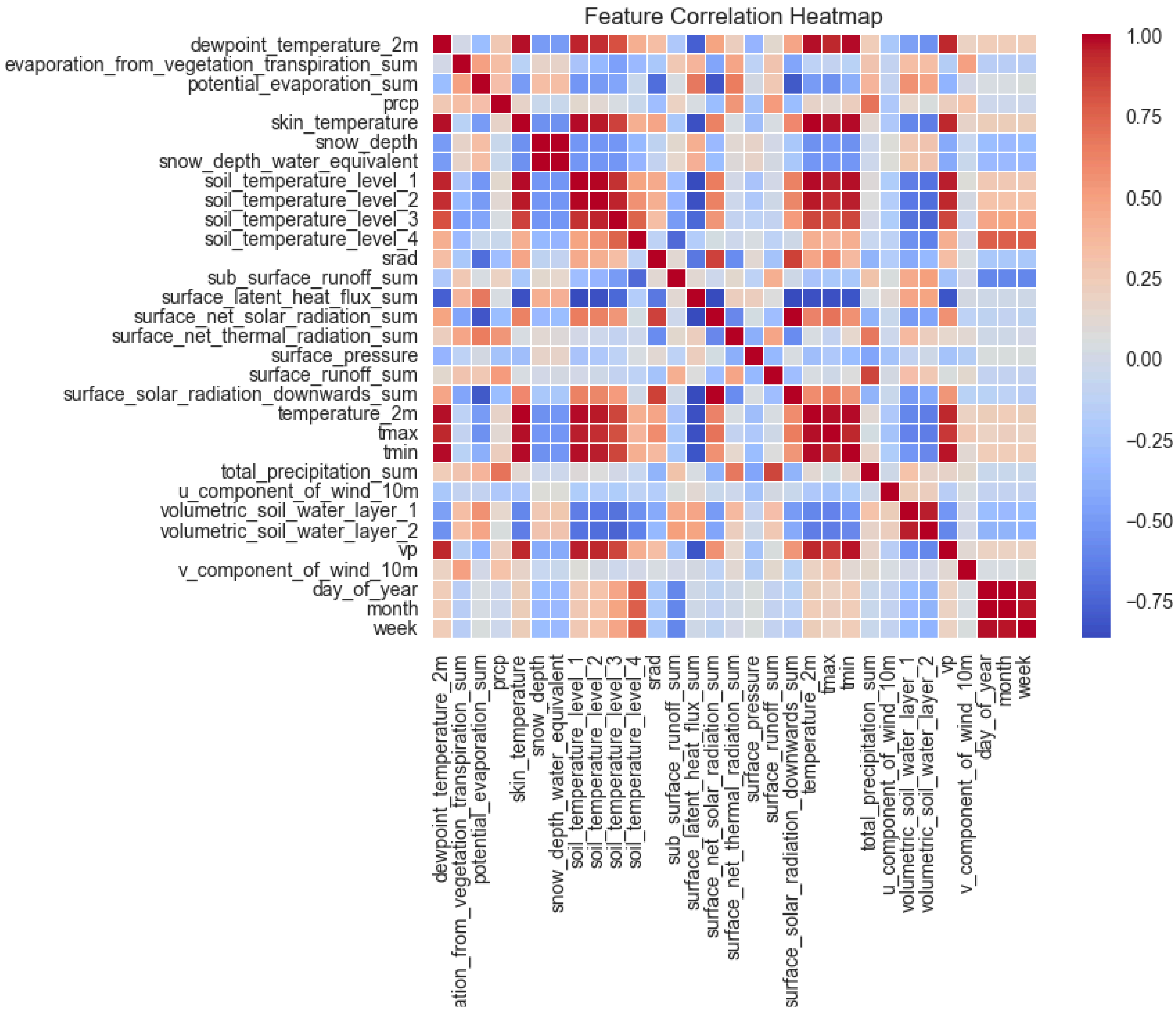
```
662    0.989216
499    0.986091
54     0.985914
661    0.984495
199    0.983972
52     0.982413
181    0.981860
37     0.979339
959    0.971759
991    0.970326
168    0.969528
276    0.966345
694    0.958508
278    0.955622
298    0.954393
283    0.954294
53     0.953172
277    0.952131
169    0.950609
826    0.950167
Highly Correlated Feature Pairs (|Correlation| > 0.95):
                           Feature1                             Feature2  \
143                skin_temperature                       temperature_2m
452  surface_net_solar_radiation_sum  surface_solar_radiation_downwards_sum
897                     day_of_year                                month
161                      snow_depth            snow_depth_water_equivalent
131                skin_temperature                 soil_temperature_level_1
225         soil_temperature_level_1                 soil_temperature_level_2
236         soil_temperature_level_1                       temperature_2m
677                            tmin                                   vp
145                skin_temperature                                 tmin
610                  temperature_2m                                 tmin
898                     day_of_year                                 week
609                  temperature_2m                                 tmax
929                           month                                 week
238         soil_temperature_level_1                                 tmin
132                skin_temperature                 soil_temperature_level_2
144                skin_temperature                                 tmax
21           dewpoint_temperature_2m                                 tmin
267         soil_temperature_level_2                       temperature_2m
237         soil_temperature_level_1                                 tmax
243         soil_temperature_level_1                                   vp
```

```
19          dewpoint_temperature_2m                          temperature_2m
150                skin_temperature                                      vp
769    volumetric_soil_water_layer_1          volumetric_soil_water_layer_2

     Correlation
143     0.999059
452     0.998983
897     0.996464
161     0.995594
131     0.993644
225     0.991504
236     0.989960
677     0.979391
145     0.978012
610     0.977600
898     0.973253
609     0.972997
929     0.971653
238     0.971259
132     0.971129
144     0.969117
21      0.968891
267     0.964849
237     0.953827
243     0.951607
19      0.951598
150     0.951326
769     0.951230
Highly Correlated Feature Pairs (|Correlation| > 0.95):
                           Feature1                               Feature2  \
180                skin_temperature                          temperature_2m
958                     day_of_year                                   month
265           soil_temperature_level_1                soil_temperature_level_2
662                  temperature_2m                                    tmin
182                skin_temperature                                    tmin
54          dewpoint_temperature_2m                                    tmin
661                  temperature_2m                                    tmax
499  surface_net_solar_radiation_sum  surface_solar_radiation_downwards_sum
168                skin_temperature                soil_temperature_level_1
181                skin_temperature                                    tmax
959                     day_of_year                                    week
52          dewpoint_temperature_2m                          temperature_2m
```

```
991                           month                               week
276          soil_temperature_level_1                     temperature_2m
199                      snow_depth           snow_depth_water_equivalent
37           dewpoint_temperature_2m                    skin_temperature
694                            tmax                               tmin
169                skin_temperature            soil_temperature_level_2
278          soil_temperature_level_1                               tmin
298          soil_temperature_level_2            soil_temperature_level_3
308          soil_temperature_level_2                     temperature_2m

     Correlation
180     0.997758
958     0.996472
265     0.994324
662     0.991089
182     0.989561
54      0.986072
661     0.984965
499     0.981267
168     0.979811
181     0.978556
959     0.973616
52      0.972311
991     0.972014
276     0.971884
199     0.971745
37      0.969459
694     0.965488
169     0.963794
278     0.962730
298     0.955285
308     0.954017
Highly Correlated Feature Pairs (|Correlation| > 0.95):
                          Feature1                            Feature2  \
180                skin_temperature                     temperature_2m
958                     day_of_year                              month
265          soil_temperature_level_1            soil_temperature_level_2
168                skin_temperature            soil_temperature_level_1
199                      snow_depth           snow_depth_water_equivalent
499  surface_net_solar_radiation_sum  surface_solar_radiation_downwards_sum
276          soil_temperature_level_1                     temperature_2m
662                  temperature_2m                               tmin
```

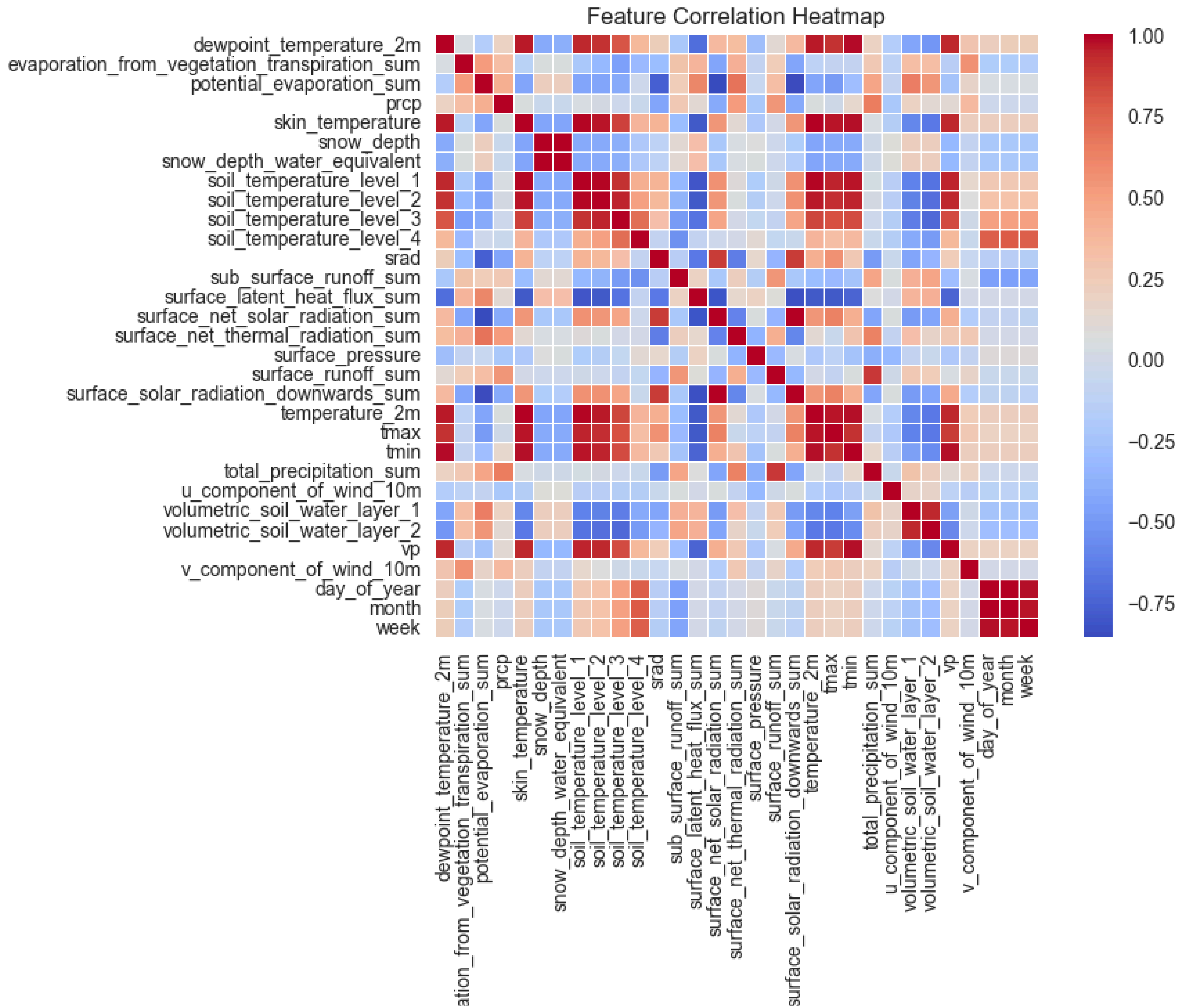
182	skin_temperature	tmin
278	soil_temperature_level_1	tmin
661	temperature_2m	tmax
169	skin_temperature	soil_temperature_level_2
54	dewpoint_temperature_2m	tmin
181	skin_temperature	tmax
308	soil_temperature_level_2	temperature_2m
959	day_of_year	week
310	soil_temperature_level_2	tmin
991	month	week
298	soil_temperature_level_2	soil_temperature_level_3
277	soil_temperature_level_1	tmax
731	tmin	vp

	Correlation
180	0.998012
958	0.996295
265	0.993986
168	0.992904
199	0.992236
499	0.991593
276	0.987795
662	0.985816
182	0.985283
278	0.979054
661	0.978226
169	0.977261
54	0.972807
181	0.971822
308	0.969231
959	0.962977
310	0.962856
991	0.961954
298	0.956736
277	0.955413
731	0.953812



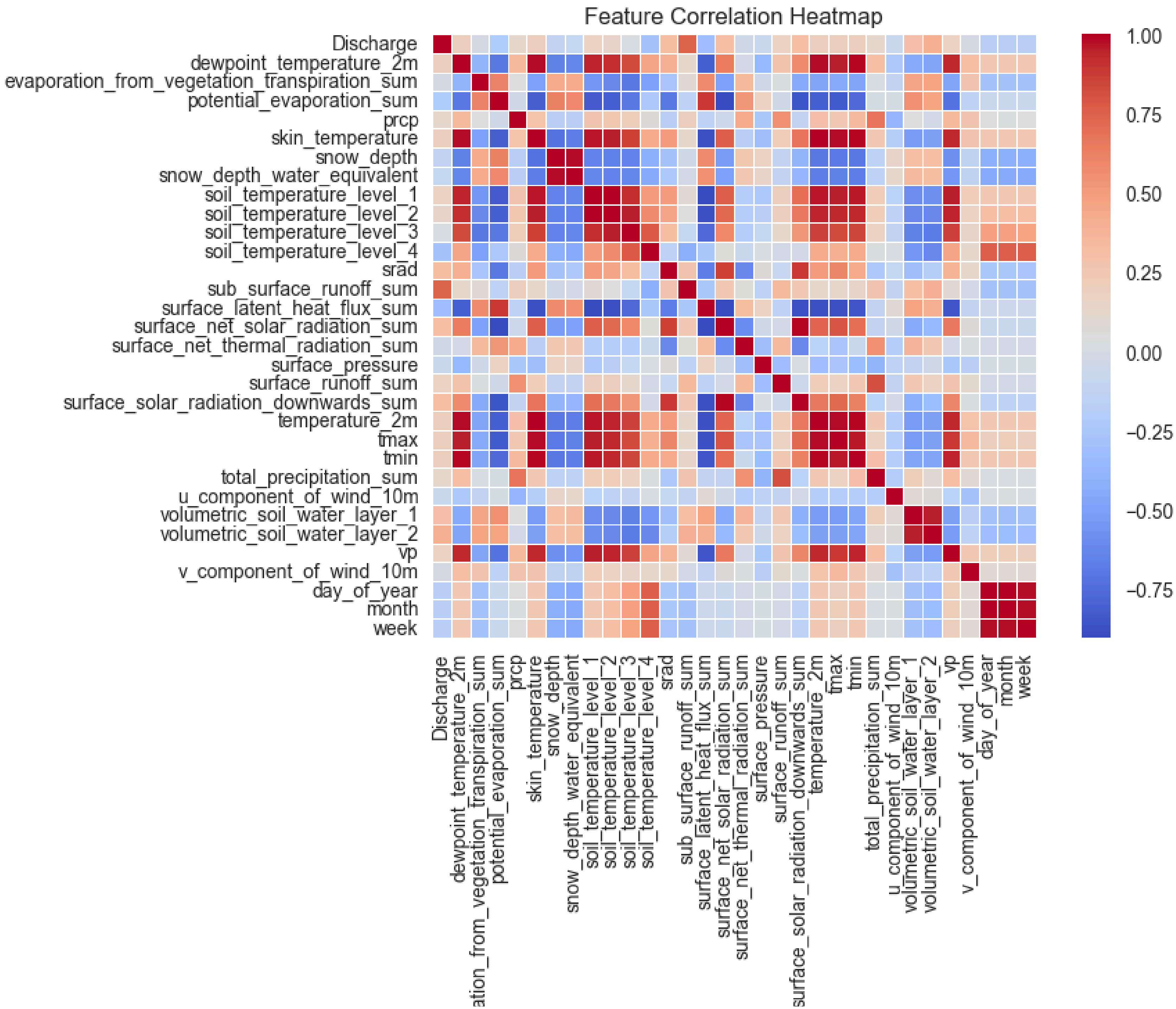
Feature Correlation Heatmap
dewpoint_temperature_2m
evaporation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

evapora



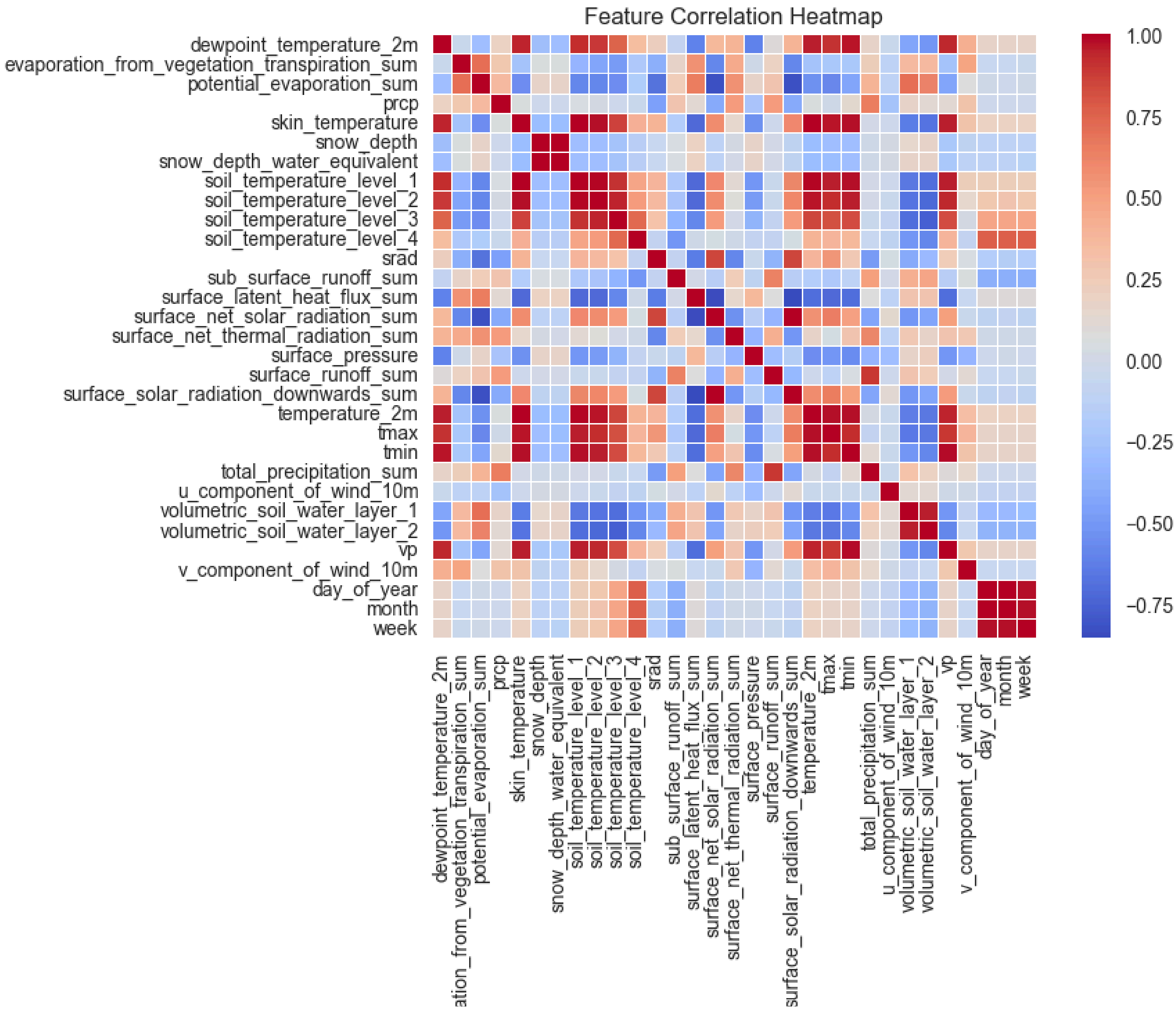
Feature Correlation Heatmap
dewpoint_temperature_2m
evaporation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
dewpoint_temperature_2m
ation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

evapora



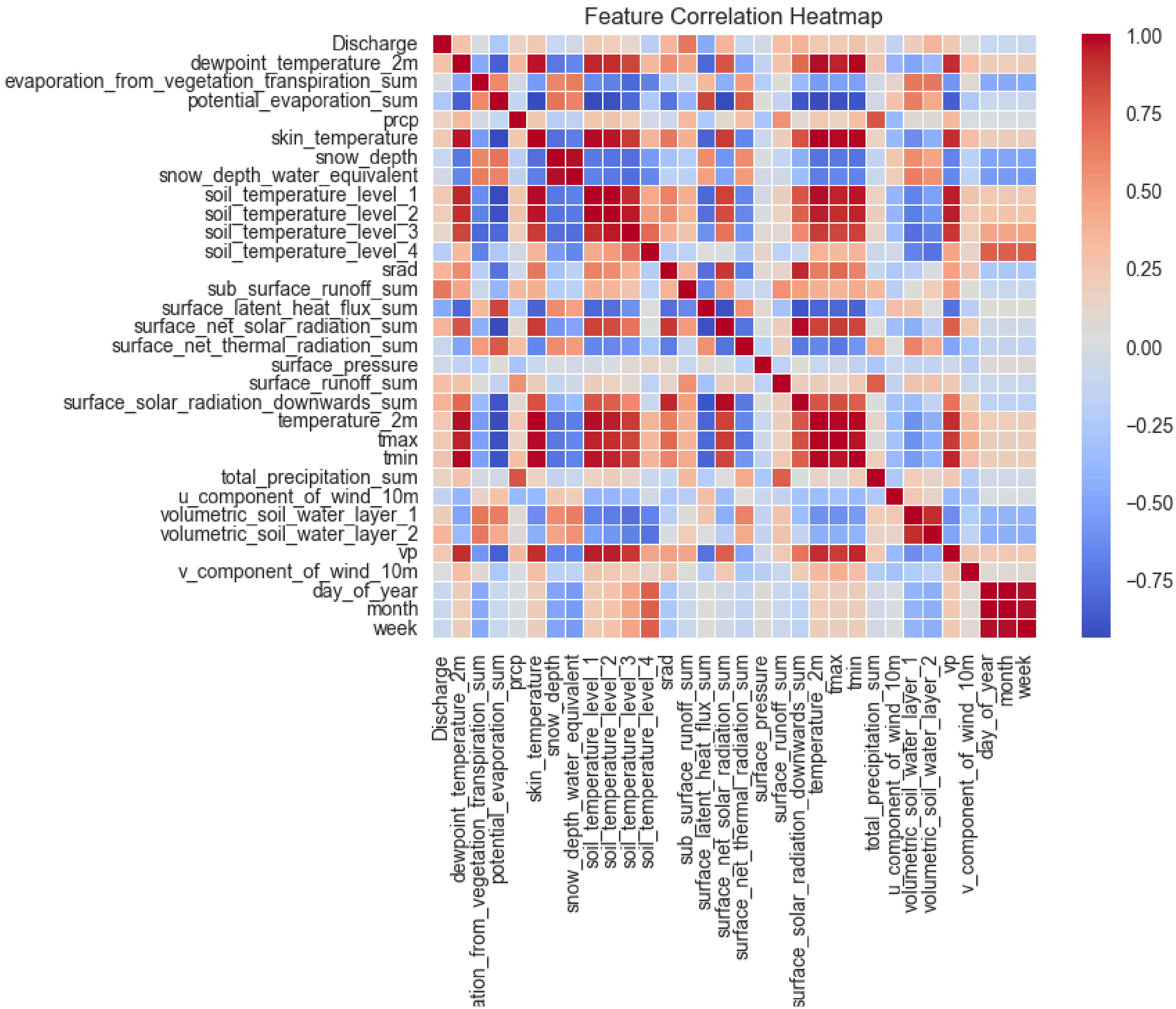
Feature Correlation Heatmap
Discharge
dewpoint_temperature_2m
evaporation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

evapora



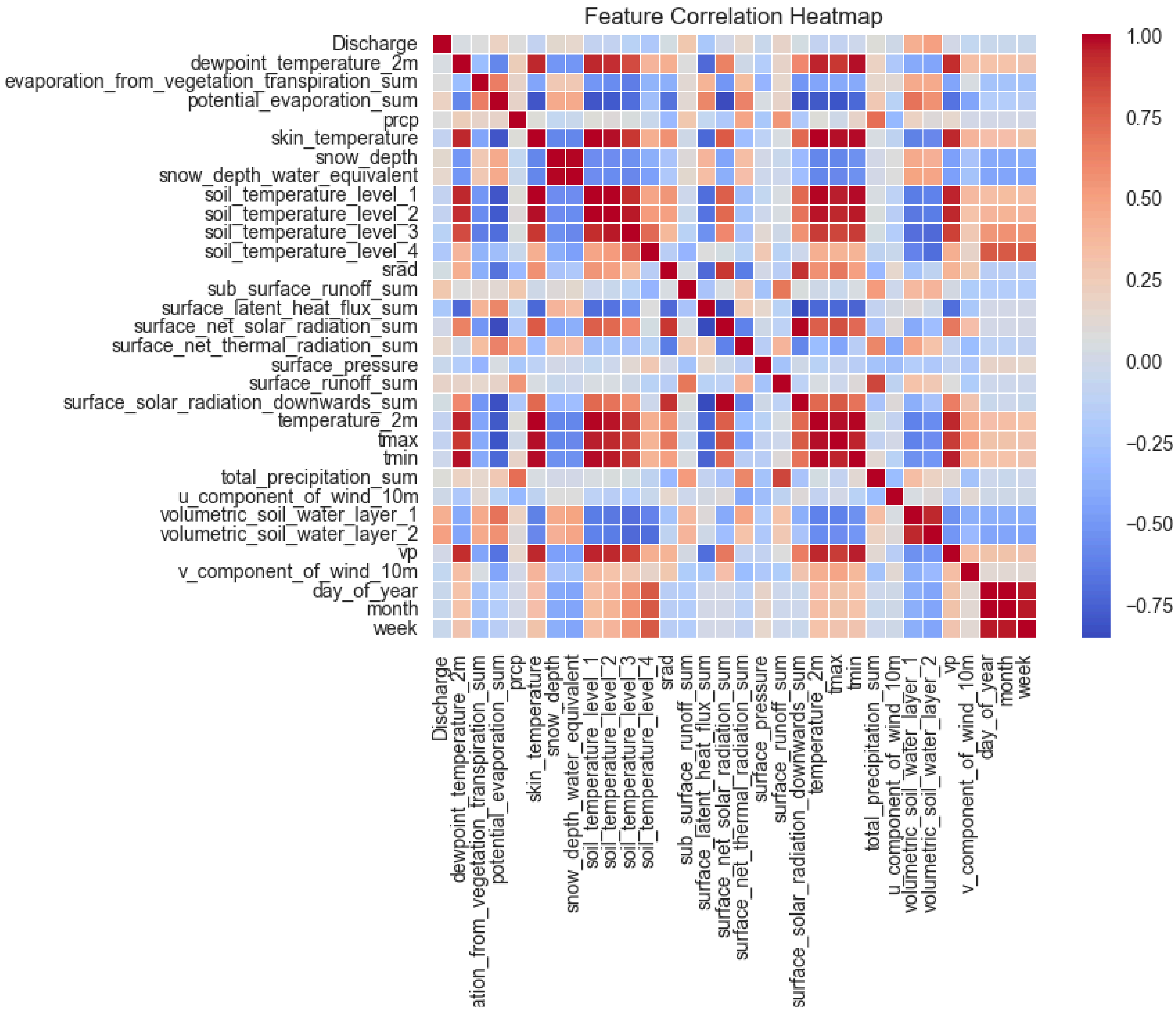
Feature Correlation Heatmap
dewpoint_temperature_2m
evaporation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

evapor



Feature Correlation Heatmap
Discharge
dewpoint_temperature_2m
evaporation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

evapora


Feature Correlation Heatmap
Discharge
dewpoint_temperature_2m
evaporation_from_vegetation_transpiration_sum
potential_evaporation_sum
prcp
skin_temperature
snow_depth
snow_depth_water_equivalent
soil_temperature_level_1
soil_temperature_level_2
soil_temperature_level_3
soil_temperature_level_4
srad
sub_surface_runoff_sum
surface_latent_heat_flux_sum
surface_net_solar_radiation_sum
surface_net_thermal_radiation_sum
surface_pressure
surface_runoff_sum
surface_solar_radiation_downwards_sum
temperature_2m
tmax
tmin
total_precipitation_sum
u_component_of_wind_10m
volumetric_soil_water_layer_1
volumetric_soil_water_layer_2
vp
v_component_of_wind_10m
day_of_year
month
week
ation_from_vegetation_transpiration_sum
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

evapor

In [7]:
```python
numbers = ['5','6', '7', '8', '10', '11']
for num in numbers:
    clean_correlated(num)
```

```
Cleaned dataset saved to ../Data/Required Data/5_cleaned.csv
Cleaned dataset saved to ../Data/Required Data/6_cleaned.csv
Cleaned dataset saved to ../Data/Required Data/7_cleaned.csv
Cleaned dataset saved to ../Data/Required Data/8_cleaned.csv
Cleaned dataset saved to ../Data/Required Data/10_cleaned.csv
Cleaned dataset saved to ../Data/Required Data/11_cleaned.csv
```

In [8]:
```python
import pandas as pd
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

# Step 1: Load the Cleaned Dataset
file_path = '../Data/Required Data/5_cleaned.csv'  # Cleaned dataset path
data = pd.read_csv(file_path)

data.drop(columns=['Date'], inplace=True)
# Ensure Discharge is numeric
data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
  # Drop Date column if not needed

# Step 3: Setup PyCaret Regression Environment
# Only use rows with valid 'Discharge' for training
train_data = data.dropna(subset=['Discharge'])

print("Setting up PyCaret environment...")
regression_setup = setup(
    data=train_data,
    target='Discharge',
    session_id=42,
    normalize=True,        # Normalize features
    feature_selection=True, # Perform feature selection
    log_experiment=False,  # Disable experiment logging
)

# Step 4: Compare Models
```

```python
print("Comparing models...")
best_model = compare_models()

# Step 5: Tune the Best Model
print("Tuning the best model...")
tuned_model = tune_model(best_model)

# Step 6: Finalize the Model
print("Finalizing the model...")
final_model = finalize_model(tuned_model)

# Step 7: Evaluate Model
# Residual Plot
print("Generating residual plot...")
plot_model(final_model, plot='residuals', save=True)

# Feature Importance Plot
print("Generating feature importance plot...")
plot_model(final_model, plot='feature', save=True)
```

```
Setting up PyCaret environment...
```

	Description	Value
0	Session id	42
1	Target	Discharge
2	Target type	Regression
3	Original data shape	(3715, 23)
4	Transformed data shape	(3715, 5)
5	Transformed train set shape	(2600, 5)
6	Transformed test set shape	(1115, 5)
7	Numeric features	22
8	Rows with missing values	0.1%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Normalize	True
14	Normalize method	zscore
15	Feature selection	True
16	Feature selection method	classic
17	Feature selection estimator	lightgbm
18	Number of features selected	0.200000
19	Fold Generator	KFold
20	Fold Number	10
21	CPU Jobs	-1

	Description	Value
22	Use GPU	False
23	Log Experiment	False
24	Experiment Name	reg-default-name
25	USI	f999

```
Comparing models...
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
et	Extra Trees Regressor	54885.6300	7053244082.5100	83568.0454	0.8809	0.2701	0.2157	0.1340
xgboost	Extreme Gradient Boosting	63410.6258	8864499968.0000	93870.7758	0.8503	0.2940	0.2391	0.2210
catboost	CatBoost Regressor	66176.8098	8932701878.2136	94124.5527	0.8494	0.2968	0.2507	0.3630
rf	Random Forest Regressor	63605.8277	8962408452.7192	94353.5927	0.8486	0.2943	0.2415	0.1520
lightgbm	Light Gradient Boosting Machine	69290.8177	9922395329.2040	99314.5920	0.8323	0.3101	0.2616	0.2240
knn	K Neighbors Regressor	78361.9844	12555371417.6000	111742.7133	0.7876	0.3516	0.3034	0.1160
gbr	Gradient Boosting Regressor	83602.7086	13298971524.2669	114996.4313	0.7755	0.3541	0.3143	0.1450
dt	Decision Tree Regressor	74212.6538	15231408588.4615	122818.3954	0.7413	0.3786	0.2793	0.1140
ada	AdaBoost Regressor	118692.3961	20380221314.9227	142565.3570	0.6550	0.5262	0.5891	0.1230
ridge	Ridge Regression	106919.9919	21171799229.7640	145340.7426	0.6415	0.4876	0.4042	0.3410
lasso	Lasso Regression	106916.8075	21172428831.7118	145342.5162	0.6415	0.4882	0.4042	0.3480
lar	Least Angle Regression	106916.8092	21172430711.5443	145342.5215	0.6415	0.4882	0.4042	0.1120
llar	Lasso Least Angle Regression	106916.8064	21172428924.0833	145342.5164	0.6415	0.4882	0.4042	0.1120
br	Bayesian Ridge	106929.1019	21170933328.3444	145338.6458	0.6415	0.4863	0.4043	0.1130
lr	Linear Regression	106916.8092	21172430711.5443	145342.5215	0.6415	0.4882	0.4042	0.3820
huber	Huber Regressor	105121.5995	21675950906.2372	146966.0327	0.6331	0.4772	0.3754	0.1130
par	Passive Aggressive Regressor	105054.1528	21769267673.3691	147326.0420	0.6317	0.4412	0.3661	0.1240
en	Elastic Net	113729.1387	23071678808.6841	151706.8344	0.6097	0.4517	0.4446	0.2410
omp	Orthogonal Matching Pursuit	120342.9829	25163007978.6819	158355.3986	0.5744	0.5157	0.5190	0.1150
dummy	Dummy Regressor	195191.7094	59221011660.8000	243184.2188	-0.0023	0.7860	0.9802	0.1050

```
Tuning the best model...
```

Fold	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	81155.8427	11835335956.7429	108790.3303	0.8043	0.3456	0.3102
1	80671.2066	12541369687.1477	111988.2569	0.7993	0.3512	0.2969
2	77978.5897	10776937865.3658	103812.0314	0.7901	0.3486	0.3152
3	84113.6663	13800955129.9666	117477.4665	0.7574	0.3516	0.3193
4	74423.6201	10612416203.7911	103016.5822	0.8103	0.3361	0.3030
5	77833.1201	11417398283.6982	106852.2264	0.8060	0.3148	0.2805
6	81268.4350	12040938858.9725	109731.2119	0.7928	0.3107	0.2737
7	90386.1520	16142178405.2562	127051.8729	0.7398	0.3909	0.3606
8	87391.1128	12692647530.3097	112661.6507	0.7744	0.3654	0.3465
9	91239.5648	15397325577.1495	124085.9604	0.7750	0.3504	0.3246
Mean	82646.1310	12725750349.8400	112546.7589	0.7849	0.3465	0.3130
Std	5282.0789	1767430145.9630	7679.6745	0.0218	0.0219	0.0256

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tune
d model (not the original one).
Finalizing the model...
Generating residual plot...
Generating feature importance plot...
```

Out[8]: 'Feature Importance.png'

In [9]:

```
# Step 8: Predict Missing Values
# Predict Discharge for rows with missing target values
missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge

if missing_data.empty:
    print("No missing values to predict.")
else:
    missing_data.drop(columns = ['Discharge'], inplace = True)
```

```
    print("Predicting missing values...")

    # Use PyCaret's predict_model to predict missing values
    predicted = predict_model(final_model, data=missing_data)

    # Check for the prediction column and assign values
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv('../Data/Required Data/5_filled.csv', index=False)
    print("Saved the filled dataset as '../Data/Required Data/5_filled.csv'")
```

```
Predicting missing values...
Saved the filled dataset as '../Data/Required Data/5_filled.csv'
```

In [10]:

```
import pandas as pd
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

# Step 1: Load the Cleaned Dataset
file_path = '../Data/Required Data/6_cleaned.csv'  # Cleaned dataset path
data = pd.read_csv(file_path)

data.drop(columns=['Date'], inplace=True)
# Ensure Discharge is numeric
data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
  # Drop Date column if not needed

# Step 3: Setup PyCaret Regression Environment
# Only use rows with valid 'Discharge' for training
train_data = data.dropna(subset=['Discharge'])

print("Setting up PyCaret environment...")
regression_setup = setup(
    data=train_data,
    target='Discharge',
```

```python
    session_id=42,
    normalize=True,        # Normalize features
    feature_selection=True, # Perform feature selection
    log_experiment=False,  # Disable experiment logging
)

# Step 4: Compare Models
print("Comparing models...")
best_model = compare_models()

# Step 5: Tune the Best Model
print("Tuning the best model...")
tuned_model = tune_model(best_model)

# Step 6: Finalize the Model
print("Finalizing the model...")
final_model = finalize_model(tuned_model)

# Step 7: Evaluate Model
# Residual Plot
print("Generating residual plot...")
plot_model(final_model, plot='residuals', save=True)

# Feature Importance Plot
print("Generating feature importance plot...")
plot_model(final_model, plot='feature', save=True)
```

```
Setting up PyCaret environment...
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.001325 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 5602
[LightGBM] [Info] Number of data points in the train set: 1306, number of used features: 22
[LightGBM] [Info] Start training from score 64967.764165
```

	Description	Value
0	Session id	42
1	Target	Discharge
2	Target type	Regression
3	Original data shape	(1867, 23)
4	Transformed data shape	(1867, 5)
5	Transformed train set shape	(1306, 5)
6	Transformed test set shape	(561, 5)
7	Numeric features	22
8	Rows with missing values	0.1%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Normalize	True
14	Normalize method	zscore
15	Feature selection	True
16	Feature selection method	classic
17	Feature selection estimator	lightgbm
18	Number of features selected	0.200000
19	Fold Generator	KFold
20	Fold Number	10
21	CPU Jobs	-1

	Description	Value
22	Use GPU	False
23	Log Experiment	False
24	Experiment Name	reg-default-name
25	USI	6407

```
Comparing models...
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
et	Extra Trees Regressor	12659.5997	595555425.0883	24004.7215	0.8097	0.2668	0.2002	0.1350
catboost	CatBoost Regressor	14697.4373	674507200.2571	25606.5211	0.7839	0.3013	0.2380	0.3280
xgboost	Extreme Gradient Boosting	14434.2301	721625865.6000	26591.5438	0.7707	0.3098	0.2367	0.1510
rf	Random Forest Regressor	14593.6359	750964679.6191	27066.9409	0.7603	0.3026	0.2320	0.1450
lightgbm	Light Gradient Boosting Machine	16317.1010	822689314.9751	28406.0007	0.7364	0.3292	0.2620	0.2340
gbr	Gradient Boosting Regressor	17916.8413	919257471.3496	30103.7514	0.7070	0.3532	0.2930	0.1300
knn	K Neighbors Regressor	19055.5597	1231328499.2000	34846.2090	0.6165	0.3532	0.2861	0.1190
dt	Decision Tree Regressor	16512.9859	1247170416.9701	34469.5480	0.6069	0.3811	0.2595	0.1330
br	Bayesian Ridge	25503.9205	1781513468.9456	42054.7425	0.4374	0.4592	0.4141	0.1170
lr	Linear Regression	25481.6632	1781643221.6252	42053.3495	0.4373	0.4587	0.4132	0.1080
lasso	Lasso Regression	25481.7851	1781631332.6777	42053.2453	0.4373	0.4587	0.4132	0.1130
lar	Least Angle Regression	25481.6632	1781643221.6252	42053.3495	0.4373	0.4587	0.4132	0.1300
llar	Lasso Least Angle Regression	25481.7857	1781631336.8641	42053.2453	0.4373	0.4587	0.4132	0.1150
ridge	Ridge Regression	25486.5331	1781526742.8979	42052.6676	0.4373	0.4588	0.4134	0.1180
omp	Orthogonal Matching Pursuit	25835.9168	1784977081.3814	42114.1922	0.4370	0.4668	0.4208	0.1170
huber	Huber Regressor	23894.9337	1845275211.3966	42831.6053	0.4194	0.4362	0.3266	0.1160
par	Passive Aggressive Regressor	23839.9961	1852397455.2435	42916.9631	0.4174	0.4367	0.3215	0.1160
ada	AdaBoost Regressor	33323.3325	1871191516.1738	42932.2539	0.4158	0.5984	0.7293	0.1220
en	Elastic Net	28117.8596	1940365191.4971	43946.4939	0.3942	0.5059	0.4893	0.1170
dummy	Dummy Regressor	40398.2145	3224343731.2000	56653.2766	-0.0023	0.7008	0.7732	0.1030

```
Tuning the best model...
```

Fold	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	18895.6438	1024573734.2998	32008.9633	0.7626	0.3216	0.2867
1	18473.0991	910075915.3727	30167.4645	0.7018	0.3321	0.2964
2	15912.0626	709944372.5568	26644.7813	0.7518	0.3254	0.2764
3	20237.3497	936849803.0444	30608.0023	0.6556	0.3606	0.3155
4	22427.8679	1153593740.1507	33964.5954	0.6595	0.4252	0.4126
5	18159.0944	828647043.7215	28786.2301	0.7110	0.3491	0.3107
6	23033.2077	1158687597.9309	34039.5006	0.5829	0.4087	0.3931
7	17968.6049	975397981.9146	31231.3622	0.7147	0.3151	0.2676
8	19603.3030	1339529417.7604	36599.5822	0.6021	0.3585	0.2770
9	20246.9808	1159235200.5764	34047.5432	0.6598	0.3528	0.3155
Mean	19495.7214	1019653480.7328	31809.8025	0.6802	0.3549	0.3151
Std	2015.0530	176726848.8511	2791.0473	0.0562	0.0347	0.0469

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tune
d model (not the original one).
Finalizing the model...
Generating residual plot...
Generating feature importance plot...
```

Out[10]: 'Feature Importance.png'

In [11]:

```
# Step 8: Predict Missing Values
# Predict Discharge for rows with missing target values
missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge

if missing_data.empty:
    print("No missing values to predict.")
else:
    missing_data.drop(columns = ['Discharge'], inplace = True)
```

```python
    print("Predicting missing values...")

    # Use PyCaret's predict_model to predict missing values
    predicted = predict_model(final_model, data=missing_data)

    # Check for the prediction column and assign values
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv('../Data/Required Data/6_filled.csv', index=False)
    print("Saved the filled dataset as '../Data/Required Data/6_filled.csv'")
```

```
Predicting missing values...
Saved the filled dataset as '../Data/Required Data/6_filled.csv'
```

In [12]:

```python
import pandas as pd
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

# Step 1: Load the Cleaned Dataset
file_path = '../Data/Required Data/7_cleaned.csv'  # Cleaned dataset path
data = pd.read_csv(file_path)

data.drop(columns=['Date'], inplace=True)
# Ensure Discharge is numeric
data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
  # Drop Date column if not needed

# Step 3: Setup PyCaret Regression Environment
# Only use rows with valid 'Discharge' for training
train_data = data.dropna(subset=['Discharge'])

print("Setting up PyCaret environment...")
regression_setup = setup(
    data=train_data,
    target='Discharge',
```

```python
    session_id=42,
    normalize=True,         # Normalize features
    feature_selection=True, # Perform feature selection
    log_experiment=False,  # Disable experiment logging
)

# Step 4: Compare Models
print("Comparing models...")
best_model = compare_models()

# Step 5: Tune the Best Model
print("Tuning the best model...")
tuned_model = tune_model(best_model)

# Step 6: Finalize the Model
print("Finalizing the model...")
final_model = finalize_model(tuned_model)

# Step 7: Evaluate Model
# Residual Plot
print("Generating residual plot...")
plot_model(final_model, plot='residuals', save=True)

# Feature Importance Plot
print("Generating feature importance plot...")
plot_model(final_model, plot='feature', save=True)
```

```
Setting up PyCaret environment...
```

	Description	Value
0	Session id	42
1	Target	Discharge
2	Target type	Regression
3	Original data shape	(16071, 23)
4	Transformed data shape	(16071, 5)
5	Transformed train set shape	(11249, 5)
6	Transformed test set shape	(4822, 5)
7	Numeric features	22
8	Rows with missing values	0.1%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Normalize	True
14	Normalize method	zscore
15	Feature selection	True
16	Feature selection method	classic
17	Feature selection estimator	lightgbm
18	Number of features selected	0.200000
19	Fold Generator	KFold
20	Fold Number	10
21	CPU Jobs	-1

	Description	Value
22	Use GPU	False
23	Log Experiment	False
24	Experiment Name	reg-default-name
25	USI	9a4a

```
Comparing models...
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
et	Extra Trees Regressor	41095.2506	4332172750.4051	65736.1580	0.8125	0.2359	0.1767	0.2080
rf	Random Forest Regressor	45730.4228	4978060200.8868	70479.5837	0.7845	0.2560	0.1980	0.3140
catboost	CatBoost Regressor	54317.0143	5975993750.0672	77287.0110	0.7412	0.2890	0.2406	0.5570
xgboost	Extreme Gradient Boosting	53476.0936	6065836100.9620	77849.2357	0.7374	0.2921	0.2354	0.1750
lightgbm	Light Gradient Boosting Machine	56472.3412	6451198101.9890	80290.0680	0.7207	0.2975	0.2494	0.2530
knn	K Neighbors Regressor	54992.4544	6753745188.3608	82134.4453	0.7074	0.2996	0.2398	0.1190
gbr	Gradient Boosting Regressor	63164.5833	7702474004.4043	87748.1930	0.6665	0.3243	0.2780	0.2380
dt	Decision Tree Regressor	54342.8561	9125617381.1973	95405.2226	0.6043	0.3446	0.2306	0.1220
lar	Least Angle Regression	73182.1888	9958689667.6073	99758.0529	0.5691	0.3724	0.3374	0.1170
ridge	Ridge Regression	73183.4273	9958688466.9593	99758.0456	0.5691	0.3724	0.3375	0.1280
llar	Lasso Least Angle Regression	73182.2780	9958689643.7035	99758.0523	0.5691	0.3724	0.3374	0.1290
br	Bayesian Ridge	73185.8409	9958688932.7525	99758.0453	0.5691	0.3725	0.3375	0.1140
lasso	Lasso Regression	73182.2765	9958689641.3316	99758.0523	0.5691	0.3724	0.3374	0.1140
lr	Linear Regression	73182.1888	9958689667.6073	99758.0529	0.5691	0.3724	0.3374	0.1150
omp	Orthogonal Matching Pursuit	74055.8888	10179411100.1151	100855.9278	0.5597	0.3801	0.3444	0.1320
huber	Huber Regressor	70470.6856	10184936990.3806	100887.3683	0.5593	0.3584	0.2937	0.1210
par	Passive Aggressive Regressor	70079.0350	10394277938.0883	101920.6066	0.5502	0.3581	0.2796	0.1390
en	Elastic Net	81484.1204	11473817825.7480	107073.6774	0.5039	0.4274	0.4143	0.1240
ada	AdaBoost Regressor	99272.9959	13574026775.4658	116364.9308	0.4133	0.5079	0.5781	0.1580
dummy	Dummy Regressor	120955.9593	23137470644.9114	152068.5269	-0.0004	0.6108	0.6569	0.1130

```
Tuning the best model...
```

	MAE	MSE	RMSE	R2	RMSLE	MAPE
Fold						
0	61424.4693	6900195573.9468	83067.4158	0.7069	0.3107	0.2779
1	59759.3640	6890293525.7369	83007.7920	0.6669	0.3204	0.2763
2	62841.4627	7385914704.3927	85941.3446	0.6706	0.3296	0.2922
3	64054.4813	7890857182.7767	88830.4969	0.6608	0.3307	0.2914
4	61374.8924	6981181990.4807	83553.4679	0.6981	0.3183	0.2819
5	63226.2262	7422785328.9456	86155.5879	0.6991	0.3273	0.2938
6	62394.1126	7443496033.3356	86275.6978	0.6683	0.3217	0.2796
7	61762.4251	7522717513.5144	86733.6008	0.6738	0.3151	0.2767
8	61975.6577	7331610491.6051	85624.8240	0.6879	0.3257	0.2858
9	62424.4332	7474673800.2628	86456.1958	0.6959	0.3268	0.2856
Mean	62123.7525	7324372614.4997	85564.6424	0.6828	0.3226	0.2841
Std	1114.1986	299446455.9690	1750.5978	0.0157	0.0062	0.0063

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tune
d model (not the original one).
Finalizing the model...
Generating residual plot...
Generating feature importance plot...
```

Out[12]: 'Feature Importance.png'

In [13]:

```python
# Step 8: Predict Missing Values
# Predict Discharge for rows with missing target values
missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge

if missing_data.empty:
    print("No missing values to predict.")
else:
    missing_data.drop(columns = ['Discharge'], inplace = True)
```

```python
    print("Predicting missing values...")

    # Use PyCaret's predict_model to predict missing values
    predicted = predict_model(final_model, data=missing_data)

    # Check for the prediction column and assign values
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv('../Data/Required Data/7_filled.csv', index=False)
    print("Saved the filled dataset as '../Data/Required Data/7_filled.csv'")
```

```
No missing values to predict.
```

In [14]:

```python
import pandas as pd
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

# Step 1: Load the Cleaned Dataset
file_path = '../Data/Required Data/8_cleaned.csv'  # Cleaned dataset path
data = pd.read_csv(file_path)

data.drop(columns=['Date'], inplace=True)
# Ensure Discharge is numeric
data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
  # Drop Date column if not needed

# Step 3: Setup PyCaret Regression Environment
# Only use rows with valid 'Discharge' for training
train_data = data.dropna(subset=['Discharge'])

print("Setting up PyCaret environment...")
regression_setup = setup(
    data=train_data,
    target='Discharge',
    session_id=42,
```

```python
    normalize=True,         # Normalize features
    feature_selection=True, # Perform feature selection
    log_experiment=False,  # Disable experiment logging
)

# Step 4: Compare Models
print("Comparing models...")
best_model = compare_models()

# Step 5: Tune the Best Model
print("Tuning the best model...")
tuned_model = tune_model(best_model)

# Step 6: Finalize the Model
print("Finalizing the model...")
final_model = finalize_model(tuned_model)

# Step 7: Evaluate Model
# Residual Plot
print("Generating residual plot...")
plot_model(final_model, plot='residuals', save=True)

# Feature Importance Plot
print("Generating feature importance plot...")
plot_model(final_model, plot='feature', save=True)
```

```
Setting up PyCaret environment...
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000626 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 5601
[LightGBM] [Info] Number of data points in the train set: 5035, number of used features: 22
[LightGBM] [Info] Start training from score 556473.088381
```

	Description	Value
0	Session id	42
1	Target	Discharge
2	Target type	Regression
3	Original data shape	(7194, 23)
4	Transformed data shape	(7194, 5)
5	Transformed train set shape	(5035, 5)
6	Transformed test set shape	(2159, 5)
7	Numeric features	22
8	Rows with missing values	0.1%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Normalize	True
14	Normalize method	zscore
15	Feature selection	True
16	Feature selection method	classic
17	Feature selection estimator	lightgbm
18	Number of features selected	0.200000
19	Fold Generator	KFold
20	Fold Number	10
21	CPU Jobs	-1

	Description	Value
22	Use GPU	False
23	Log Experiment	False
24	Experiment Name	reg-default-name
25	USI	cd77

```
Comparing models...
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
et	Extra Trees Regressor	70365.6709	12586366028.4313	112123.0722	0.8480	0.2073	0.1460	0.1530
rf	Random Forest Regressor	82960.0298	15795902717.0337	125619.8590	0.8090	0.2311	0.1716	0.1890
catboost	CatBoost Regressor	100029.2435	18981885065.3489	137740.6267	0.7709	0.2611	0.2130	0.4630
xgboost	Extreme Gradient Boosting	96536.9977	19485711872.0000	139543.7859	0.7649	0.2584	0.2006	0.1380
lightgbm	Light Gradient Boosting Machine	105835.8586	20864306991.1988	144408.3321	0.7479	0.2723	0.2250	0.2470
knn	K Neighbors Regressor	105935.2906	22702836531.2000	150575.2516	0.7260	0.2897	0.2324	0.1150
gbr	Gradient Boosting Regressor	125958.2541	28265359212.8189	168076.9680	0.6590	0.3107	0.2663	0.1550
dt	Decision Tree Regressor	94418.9877	29993201379.8163	172679.8945	0.6369	0.3115	0.1900	0.1050
ada	AdaBoost Regressor	153226.8233	36226990520.9609	190303.3658	0.5628	0.3555	0.3398	0.1190
ridge	Ridge Regression	161184.0684	45355874548.4038	212834.0435	0.4536	0.3906	0.3546	0.1160
lasso	Lasso Regression	161182.2050	45355955883.4688	212834.2010	0.4536	0.3906	0.3546	0.1160
lar	Least Angle Regression	161182.1114	45355958737.6257	212834.2062	0.4536	0.3906	0.3546	0.0940
llar	Lasso Least Angle Regression	161182.2073	45355955885.8773	212834.2010	0.4536	0.3906	0.3546	0.1090
br	Bayesian Ridge	161195.6719	45355529668.4440	212833.4402	0.4536	0.3907	0.3547	0.1110
lr	Linear Regression	161182.1114	45355958737.6257	212834.2062	0.4536	0.3906	0.3546	0.1050
huber	Huber Regressor	157112.8584	46933407950.8842	216378.3038	0.4349	0.3745	0.3207	0.1250
par	Passive Aggressive Regressor	156864.0084	47607449947.4426	217927.7492	0.4267	0.3726	0.3116	0.1170
en	Elastic Net	169302.1052	47639035304.1352	218177.7296	0.4260	0.4121	0.3867	0.1110
omp	Orthogonal Matching Pursuit	179319.2038	53635023284.5941	231505.6075	0.3537	0.4227	0.3953	0.1080
dummy	Dummy Regressor	237152.6453	83332943052.8000	288533.5000	-0.0023	0.5623	0.5906	0.1080

```
Tuning the best model...
```

	MAE	MSE	RMSE	R2	RMSLE	MAPE
Fold						
0	122680.5552	25786330972.5506	160581.2286	0.7267	0.2959	0.2607
1	123596.5201	26497630726.0432	162780.9286	0.6770	0.3075	0.2718
2	115372.6428	24220347831.2023	155628.8785	0.6896	0.2868	0.2467
3	123735.3725	26266509340.0279	162069.4584	0.6995	0.2928	0.2529
4	122726.6129	26821262401.9262	163771.9830	0.6638	0.2925	0.2472
5	123377.6950	25597571034.6899	159992.4093	0.6619	0.3136	0.2742
6	118963.4416	23305418400.4535	152661.1228	0.7093	0.2925	0.2578
7	124176.4313	26176807406.3422	161792.4825	0.6965	0.3071	0.2711
8	129855.7846	27927739150.3466	167115.9452	0.6541	0.3230	0.2847
9	123534.2538	26306525895.2368	162192.8664	0.6973	0.3019	0.2695
Mean	122801.9310	25890614315.8819	160858.7303	0.6876	0.3014	0.2637
Std	3520.8709	1238967949.5791	3883.7088	0.0219	0.0108	0.0119

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tune
d model (not the original one).
Finalizing the model...
Generating residual plot...
Generating feature importance plot...
```

Out[14]: 'Feature Importance.png'

In [15]:
```
# Step 8: Predict Missing Values
# Predict Discharge for rows with missing target values
missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge

if missing_data.empty:
    print("No missing values to predict.")
else:
    missing_data.drop(columns = ['Discharge'], inplace = True)
```

```python
    print("Predicting missing values...")

    # Use PyCaret's predict_model to predict missing values
    predicted = predict_model(final_model, data=missing_data)

    # Check for the prediction column and assign values
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv('../Data/Required Data/8_filled.csv', index=False)
    print("Saved the filled dataset as '../Data/Required Data/8_filled.csv'")
```

```
Predicting missing values...
Saved the filled dataset as '../Data/Required Data/8_filled.csv'
```

In [16]:

```python
import pandas as pd
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

# Step 1: Load the Cleaned Dataset
file_path = '../Data/Required Data/10_cleaned.csv'  # Cleaned dataset path
data = pd.read_csv(file_path)

data.drop(columns=['Date'], inplace=True)
# Ensure Discharge is numeric
data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
  # Drop Date column if not needed

# Step 3: Setup PyCaret Regression Environment
# Only use rows with valid 'Discharge' for training
train_data = data.dropna(subset=['Discharge'])

print("Setting up PyCaret environment...")
regression_setup = setup(
    data=train_data,
    target='Discharge',
```

```python
    session_id=42,
    normalize=True,         # Normalize features
    feature_selection=True, # Perform feature selection
    log_experiment=False,  # Disable experiment logging
)

# Step 4: Compare Models
print("Comparing models...")
best_model = compare_models()

# Step 5: Tune the Best Model
print("Tuning the best model...")
tuned_model = tune_model(best_model)

# Step 6: Finalize the Model
print("Finalizing the model...")
final_model = finalize_model(tuned_model)

# Step 7: Evaluate Model
# Residual Plot
print("Generating residual plot...")
plot_model(final_model, plot='residuals', save=True)

# Feature Importance Plot
print("Generating feature importance plot...")
plot_model(final_model, plot='feature', save=True)
```

```
Setting up PyCaret environment...
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000852 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 5600
[LightGBM] [Info] Number of data points in the train set: 6072, number of used features: 22
[LightGBM] [Info] Start training from score 94096.245059
```

	Description	Value
0	Session id	42
1	Target	Discharge
2	Target type	Regression
3	Original data shape	(8675, 23)
4	Transformed data shape	(8675, 5)
5	Transformed train set shape	(6072, 5)
6	Transformed test set shape	(2603, 5)
7	Numeric features	22
8	Rows with missing values	0.1%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Normalize	True
14	Normalize method	zscore
15	Feature selection	True
16	Feature selection method	classic
17	Feature selection estimator	lightgbm
18	Number of features selected	0.200000
19	Fold Generator	KFold
20	Fold Number	10
21	CPU Jobs	-1

	Description	Value
22	Use GPU	False
23	Log Experiment	False
24	Experiment Name	reg-default-name
25	USI	b39c

```
Comparing models...
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
et	Extra Trees Regressor	18014.0343	1043026258.8662	32219.5301	0.7559	0.2819	0.2076	0.1660
rf	Random Forest Regressor	20342.6810	1209321058.5772	34683.8514	0.7179	0.3046	0.2344	0.2160
catboost	CatBoost Regressor	22798.9704	1288527268.5939	35837.7260	0.6992	0.3256	0.2694	0.4830
xgboost	Extreme Gradient Boosting	22263.3520	1296628089.6000	35952.7965	0.6976	0.3255	0.2605	0.1330
lightgbm	Light Gradient Boosting Machine	24142.9326	1456396085.7014	38103.6996	0.6604	0.3397	0.2827	0.2570
knn	K Neighbors Regressor	24027.8230	1612262080.0000	40089.7727	0.6236	0.3466	0.2768	0.1180
gbr	Gradient Boosting Regressor	27437.5182	1742942040.2837	41673.1570	0.5939	0.3758	0.3252	0.1970
dt	Decision Tree Regressor	24154.1820	2232314332.2504	47091.9734	0.4804	0.4009	0.2656	0.1180
lar	Least Angle Regression	33791.3233	2304532409.1416	47918.4558	0.4628	0.4547	0.4341	0.1060
ridge	Ridge Regression	33792.5520	2304531148.1052	47918.4584	0.4628	0.4547	0.4341	0.1190
llar	Lasso Least Angle Regression	33791.4679	2304532511.4635	47918.4606	0.4628	0.4547	0.4341	0.1230
br	Bayesian Ridge	33796.9138	2304534953.8522	47918.5516	0.4628	0.4548	0.4342	0.1100
lasso	Lasso Regression	33791.4674	2304532509.2228	47918.4606	0.4628	0.4547	0.4341	0.1050
lr	Linear Regression	33791.3233	2304532409.1416	47918.4558	0.4628	0.4547	0.4341	0.1010
huber	Huber Regressor	31762.8321	2391971376.1777	48812.9338	0.4425	0.4250	0.3528	0.1260
omp	Orthogonal Matching Pursuit	34953.6466	2421595537.0078	49135.2060	0.4355	0.4636	0.4451	0.1190
par	Passive Aggressive Regressor	31552.0808	2470437356.8410	49609.7602	0.4241	0.4238	0.3307	0.1240
en	Elastic Net	37148.0551	2526478759.8053	50190.6891	0.4121	0.4978	0.5028	0.1100
ada	AdaBoost Regressor	49125.8956	3508054241.4083	59077.2330	0.1775	0.6159	0.7655	0.1580
dummy	Dummy Regressor	50155.2215	4315202329.6000	65600.8117	-0.0029	0.6413	0.6968	0.0910

```
Tuning the best model...
```

Fold	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	27151.2572	1724852006.6060	41531.3376	0.5829	0.3635	0.3173
1	29141.7283	2043609230.4188	45206.2964	0.5127	0.4095	0.3709
2	27695.2781	1657665207.8639	40714.4349	0.6167	0.3715	0.3334
3	28314.2956	1739906284.6580	41712.1839	0.6159	0.3628	0.3193
4	26309.4512	1535865326.5894	39190.1177	0.6209	0.3766	0.3387
5	28127.1664	1746477512.5288	41790.8783	0.6593	0.3621	0.3242
6	25476.2100	1511070217.7017	38872.4866	0.6243	0.3741	0.3387
7	24532.7064	1280604324.1712	35785.5323	0.6453	0.3478	0.3073
8	28554.8351	1918985889.9832	43806.2312	0.6189	0.3787	0.3368
9	27886.5332	1591801013.8256	39897.3810	0.6013	0.3862	0.3565
Mean	27318.9461	1675083701.4347	40850.6880	0.6098	0.3733	0.3343
Std	1384.3296	204012460.0730	2510.9742	0.0380	0.0158	0.0180

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tune
d model (not the original one).
Finalizing the model...
Generating residual plot...
Generating feature importance plot...
```

Out[16]: 'Feature Importance.png'

In [17]:

```
# Step 8: Predict Missing Values
# Predict Discharge for rows with missing target values
missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge

if missing_data.empty:
    print("No missing values to predict.")
else:
    missing_data.drop(columns = ['Discharge'], inplace = True)
```

```
    print("Predicting missing values...")

    # Use PyCaret's predict_model to predict missing values
    predicted = predict_model(final_model, data=missing_data)

    # Check for the prediction column and assign values
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv('../Data/Required Data/10_filled.csv', index=False)
    print("Saved the filled dataset as '../Data/Required Data/10_filled.csv'")
```

```
Predicting missing values...
Saved the filled dataset as '../Data/Required Data/10_filled.csv'
```

In [1]:

```
import pandas as pd
from pycaret.regression import setup, compare_models, tune_model, finalize_model, predict_model, plot_model

# Step 1: Load the Cleaned Dataset
file_path = '../Data/Required Data/11_cleaned.csv'  # Cleaned dataset path
data = pd.read_csv(file_path)

data.drop(columns=['Date'], inplace=True)
# Ensure Discharge is numeric
data['Discharge'] = pd.to_numeric(data['Discharge'], errors='coerce')
  # Drop Date column if not needed

# Step 3: Setup PyCaret Regression Environment
# Only use rows with valid 'Discharge' for training
train_data = data.dropna(subset=['Discharge'])

print("Setting up PyCaret environment...")
regression_setup = setup(
    data=train_data,
    target='Discharge',
```

```python
    session_id=42,
    normalize=True,        # Normalize features
    feature_selection=True, # Perform feature selection
    log_experiment=False,  # Disable experiment logging
)

# Step 4: Compare Models
print("Comparing models...")
best_model = compare_models()

# Step 5: Tune the Best Model
print("Tuning the best model...")
tuned_model = tune_model(best_model)

# Step 6: Finalize the Model
print("Finalizing the model...")
final_model = finalize_model(tuned_model)

# Step 7: Evaluate Model
# Residual Plot
'''
print("Generating residual plot...")
plot_model(final_model, plot='residuals', save=True)

# Feature Importance Plot
print("Generating feature importance plot...")
plot_model(final_model, plot='feature', save=True)
'''
```

```
Setting up PyCaret environment...
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000460 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 5604
[LightGBM] [Info] Number of data points in the train set: 957, number of used features: 22
[LightGBM] [Info] Start training from score 22166.060606
```

	Description	Value
0	Session id	42
1	Target	Discharge
2	Target type	Regression
3	Original data shape	(1368, 23)
4	Transformed data shape	(1368, 5)
5	Transformed train set shape	(957, 5)
6	Transformed test set shape	(411, 5)
7	Numeric features	22
8	Rows with missing values	0.1%
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Normalize	True
14	Normalize method	zscore
15	Feature selection	True
16	Feature selection method	classic
17	Feature selection estimator	lightgbm
18	Number of features selected	0.200000
19	Fold Generator	KFold
20	Fold Number	10
21	CPU Jobs	-1

	Description	Value
22	Use GPU	False
23	Log Experiment	False
24	Experiment Name	reg-default-name
25	USI	d479

```
Comparing models...
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
et	Extra Trees Regressor	5618.8222	107207870.1966	10095.5470	0.7798	0.3866	0.3462	0.1190
catboost	CatBoost Regressor	6123.6250	109203658.2289	10253.8379	0.7719	0.4142	0.3710	0.3300
rf	Random Forest Regressor	6126.8337	124367308.2096	10929.2190	0.7436	0.4064	0.3638	0.1290
xgboost	Extreme Gradient Boosting	6042.7813	122734648.0000	10911.9280	0.7397	0.3910	0.3396	0.1800
lightgbm	Light Gradient Boosting Machine	6599.4307	133578413.4739	11347.7636	0.7227	0.4265	0.3837	0.2110
gbr	Gradient Boosting Regressor	8063.5306	163542860.9951	12656.2050	0.6581	0.5020	0.5030	0.1150
knn	K Neighbors Regressor	7933.2484	188439511.2000	13557.7296	0.6080	0.4921	0.4841	0.1110
dt	Decision Tree Regressor	6662.3566	207610702.4803	14069.2332	0.5793	0.4563	0.3477	0.0980
ada	AdaBoost Regressor	11983.0291	241848836.3326	15465.4817	0.4911	0.7391	1.0048	0.1210
br	Bayesian Ridge	13947.5948	364797759.3496	18995.7558	0.2409	0.8816	1.0085	0.1030
llar	Lasso Least Angle Regression	13968.4742	364691057.0135	18994.5470	0.2407	0.8551	1.0110	0.1060
lr	Linear Regression	13968.6568	364689367.6628	18994.5150	0.2407	0.8552	1.0110	0.3830
lasso	Lasso Regression	13968.4643	364691191.3971	18994.5527	0.2407	0.8551	1.0110	0.3400
lar	Least Angle Regression	13968.6568	364689367.6628	18994.5150	0.2407	0.8552	1.0110	0.1050
ridge	Ridge Regression	13966.2293	364696239.9465	18994.5487	0.2407	0.8542	1.0107	0.3380
en	Elastic Net	14135.8135	383640812.5192	19453.0781	0.2090	0.8211	1.0677	0.2320
omp	Orthogonal Matching Pursuit	14384.8636	401185225.5814	19920.4516	0.1673	0.8927	1.0448	0.1030
huber	Huber Regressor	12662.3610	422452184.8332	20342.2752	0.1416	0.7287	0.6665	0.0980
par	Passive Aggressive Regressor	12598.1583	451733547.2481	21022.1369	0.0841	0.7283	0.5801	0.1010
dummy	Dummy Regressor	16416.6977	493256568.0000	22071.7953	-0.0176	0.9954	1.4519	0.0980

```
Tuning the best model...
```

Fold	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	11229.2062	266633084.8938	16328.9034	0.5440	0.6222	0.7520
1	9414.7895	188306467.1222	13722.4804	0.6127	0.5566	0.6151
2	5624.3746	73176311.0647	8554.3153	0.6914	0.4114	0.4062
3	8539.4971	159373921.4370	12624.3385	0.6898	0.5105	0.5451
4	9863.2616	216630543.6717	14718.3744	0.6257	0.5930	0.6750
5	8170.4965	146848733.4444	12118.1159	0.6384	0.5294	0.5941
6	9676.6679	219595314.5689	14818.7488	0.6223	0.5414	0.6014
7	9775.4712	248063874.7775	15750.0436	0.5370	0.5015	0.5002
8	8506.2738	202746132.5812	14238.8951	0.6356	0.4639	0.4412
9	9076.4225	184210705.6213	13572.4245	0.5290	0.5755	0.6583
Mean	8987.6461	190558508.9183	13644.6640	0.6126	0.5305	0.5789
Std	1396.0276	52414313.9818	2093.2401	0.0557	0.0592	0.1018

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tune
d model (not the original one).
Finalizing the model...
```

Out[1]:
```
'\nprint("Generating residual plot...")\nplot_model(final_model, plot=\'residuals\', save=True)\n\n# Feature Importa
nce Plot\nprint("Generating feature importance plot...")\nplot_model(final_model, plot=\'feature\', save=True)\n'
```

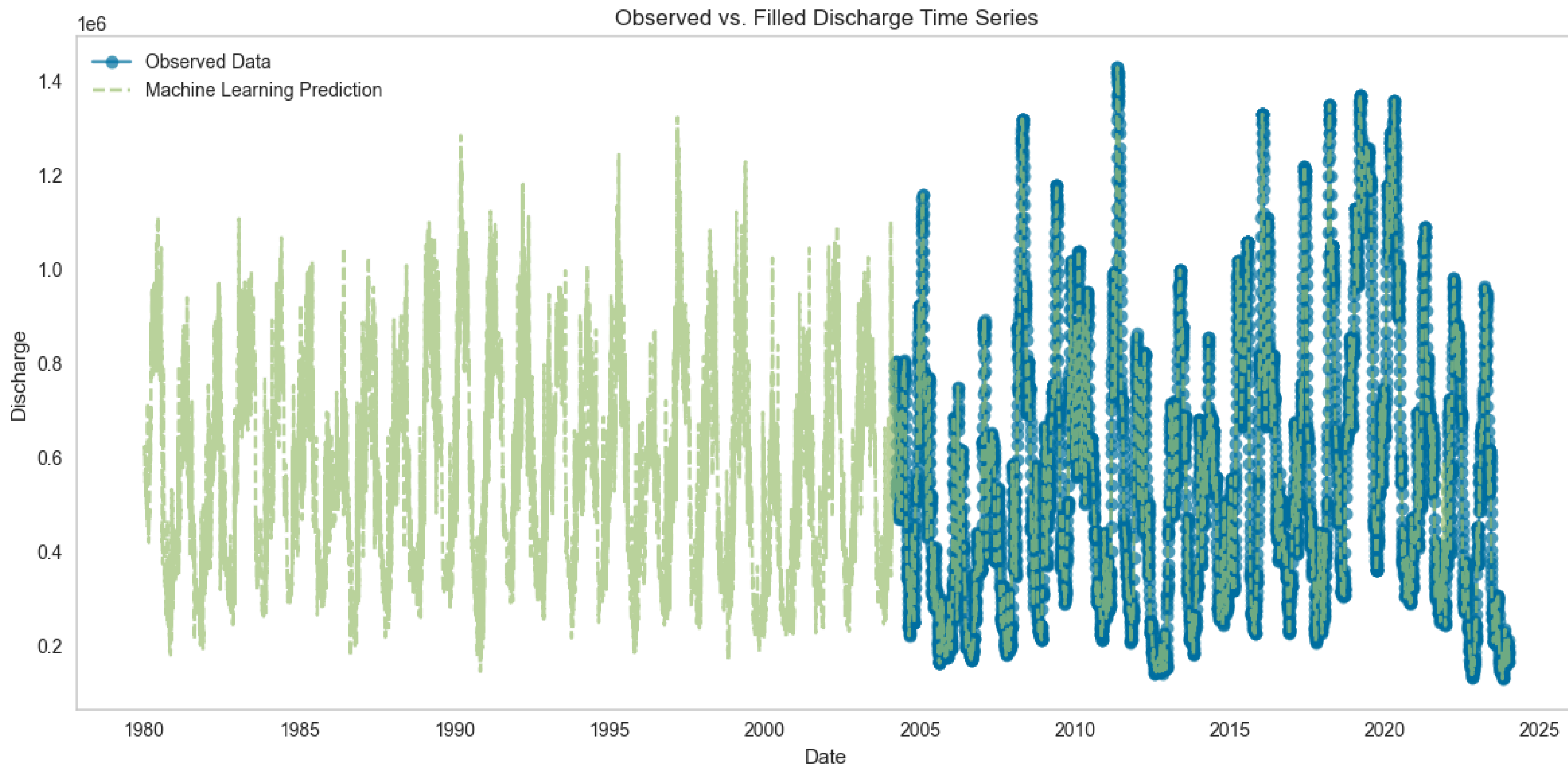
In [2]:
```
# Step 8: Predict Missing Values
# Predict Discharge for rows with missing target values
missing_data = data[data['Discharge'].isnull()]  # Extract rows with missing Discharge

if missing_data.empty:
    print("No missing values to predict.")
else:
    missing_data.drop(columns = ['Discharge'], inplace = True)
    print("Predicting missing values...")
```

```
    # Use PyCaret's predict_model to predict missing values
    predicted = predict_model(final_model, data=missing_data)

    # Check for the prediction column and assign values
    if 'prediction_label' in predicted.columns:
        missing_data['Discharge'] = predicted['prediction_label']
    else:
        print(predicted.head())  # Debugging: Show a sample of the output
        raise KeyError("No valid prediction column ('prediction_label') found in the output of predict_model.")

    # Combine predicted rows with the original dataset
    filled_data = pd.concat([train_data, missing_data]).sort_index()

    # Save the filled dataset
    filled_data.to_csv('../Data/Required Data/11_filled.csv', index=False)
    print("Saved the filled dataset as '../Data/Required Data/11_filled.csv'")
```

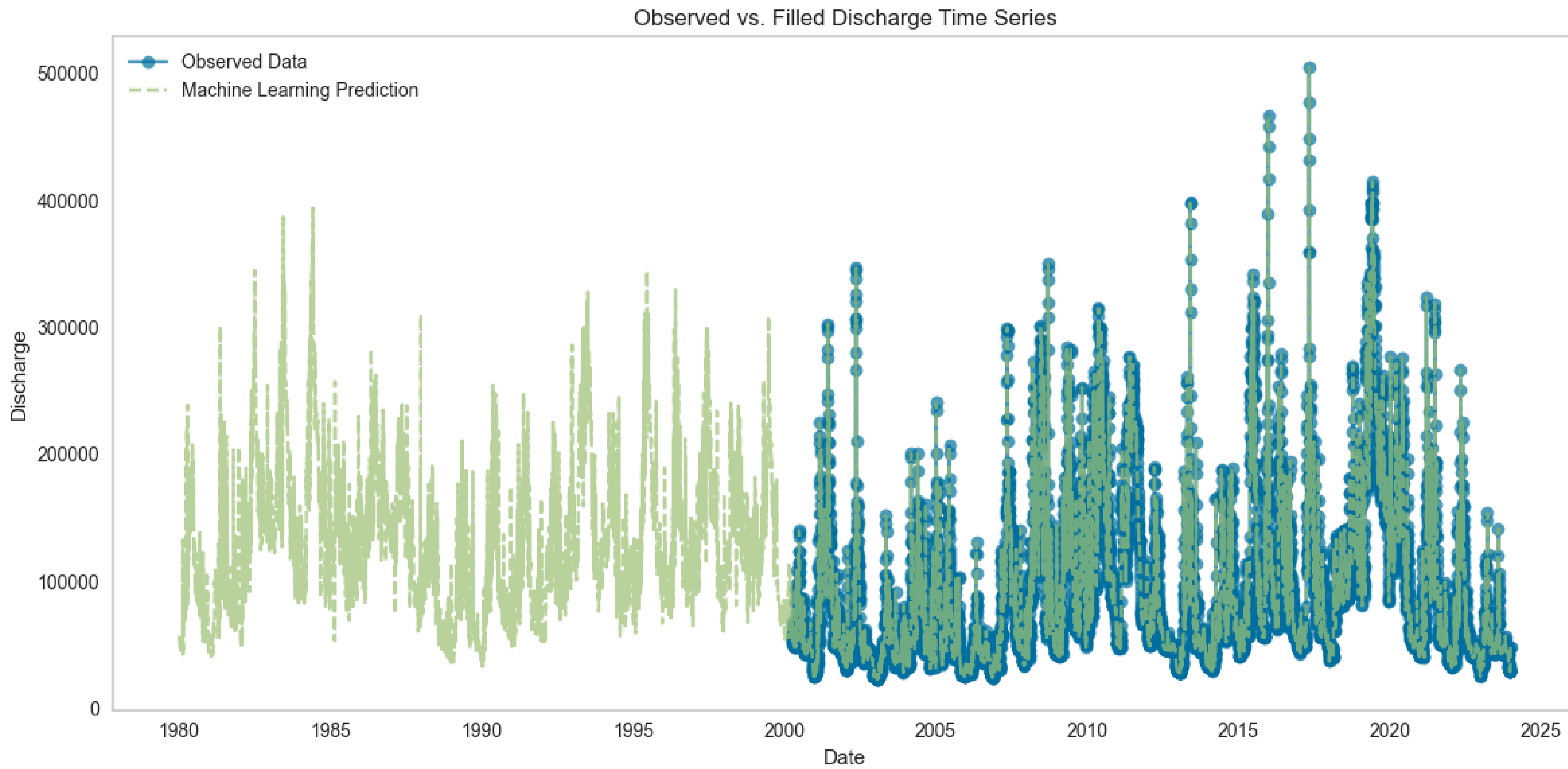
```
Predicting missing values...
Saved the filled dataset as '../Data/Required Data/11_filled.csv'
```

In [5]:

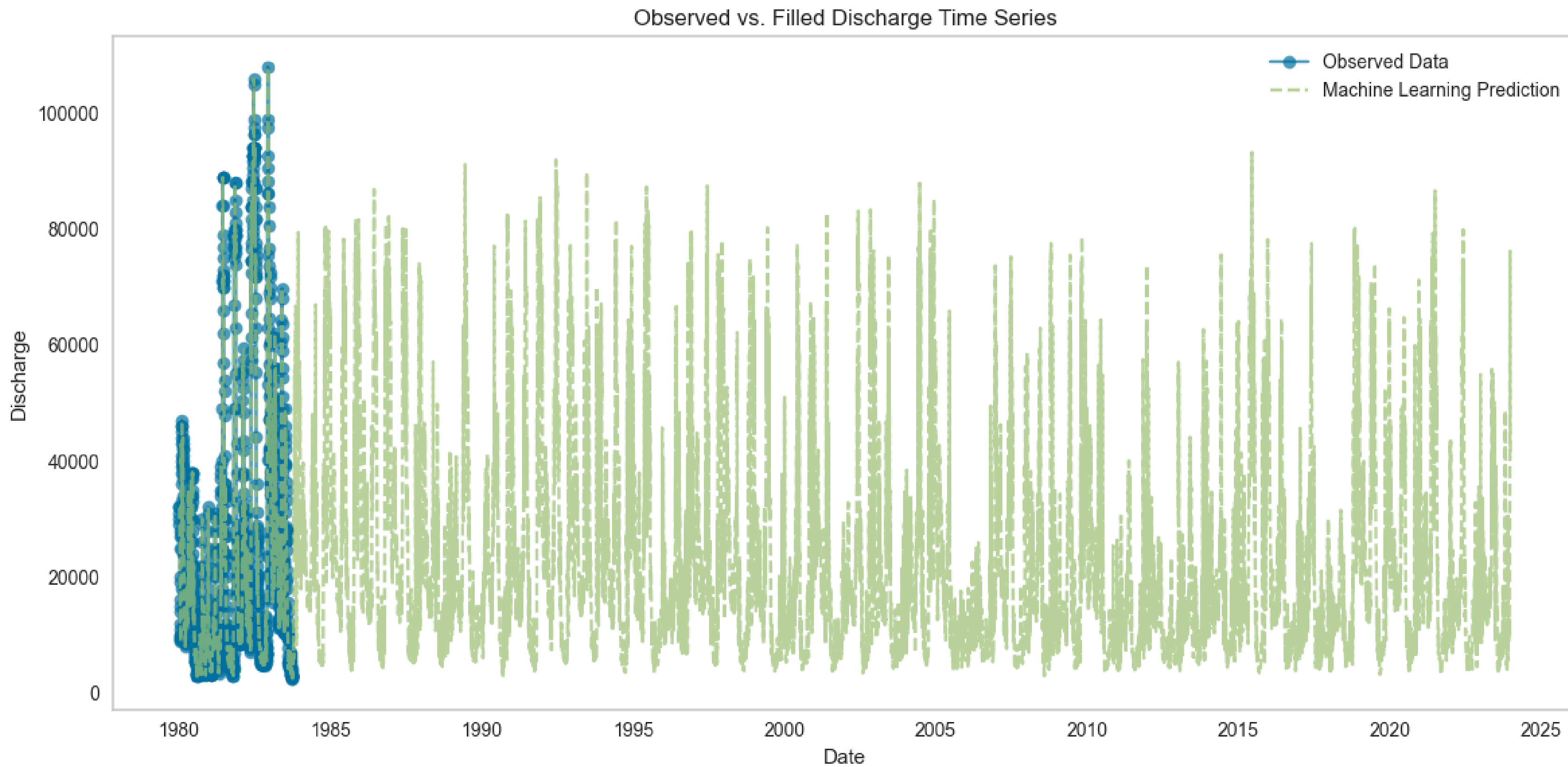
```
numbers = ['8', '10', '11']
for num in numbers:
    making_filled_plots(num)
```




```
Time series plot saved to: ../Figures/8Observed_vs_Filled_Discharge_Cleaned.png
```




```
Time series plot saved to: ../Figures/10Observed_vs_Filled_Discharge_Cleaned.png
```




```
Time series plot saved to: ../Figures/11Observed_vs_Filled_Discharge_Cleaned.png
```

```
In [ ]:
```