In [16]:
```python
# Import packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cross_decomposition import PLSRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split, cross_val_score, cross_val_predict, KFold, GridSearchCV,
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from scipy.optimize import minimize
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.linear_model import LassoCV
from collections import Counter
from scipy.stats import randint, uniform
```

In [16]:
```python
!jupyter nbconvert 5291_Project.ipynb --to html
```

```
[NbConvertApp] Converting notebook 5291_Project.ipynb to html
[NbConvertApp] Writing 1772301 bytes to 5291_Project.html
```

In [3]:
```python
import os
curr_path = os.getcwd()
citibike_path = os.path.join(curr_path, "citibike_day.csv")
weather_path = os.path.join(curr_path, "nyc_Weather_2013_2023.csv")
```

In [4]:
```python
# Load data
citibike_df = pd.read_csv(citibike_path)
weather_df = pd.read_csv(weather_path)
```

In [6]:
```python
# Display basic information
citibike_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365 entries, 0 to 364
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Unnamed: 0      365 non-null    int64  
 1   date            365 non-null    object 
 2   num_trips       365 non-null    int64  
 3   avg_duration    365 non-null    float64
 4   total_duration  365 non-null    int64  
dtypes: float64(1), int64(3), object(1)
memory usage: 14.4+ KB
```

In [7]:
```python
weather_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4017 entries, 0 to 4016
Data columns (total 15 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   time                      4017 non-null   object 
 1   temperature_2m_max        4017 non-null   float64
 2   temperature_2m_min        4017 non-null   float64
 3   apparent_temperature_max  4017 non-null   float64
 4   apparent_temperature_min  4017 non-null   float64
 5   precipitation_sum         4017 non-null   float64
 6   rain_sum                  4017 non-null   float64
 7   snowfall_sum              4017 non-null   float64
 8   precipitation_hours       4017 non-null   float64
 9   sunshine_duration         4017 non-null   float64
 10  windspeed_10m_max         4017 non-null   float64
 11  windgusts_10m_max         4017 non-null   float64
 12  winddirection_10m_dominant  4017 non-null   int64  
 13  shortwave_radiation_sum   4017 non-null   float64
 14  et0_fao_evapotranspiration  4017 non-null   float64
dtypes: float64(13), int64(1), object(1)
memory usage: 470.9+ KB
```

In [5]:
```python
# Compute average daily temperature
weather_df['temperature_avg'] = (weather_df['temperature_2m_max'] + weather_df['temperature_2m_min']) / 2
```

In [6]:
```python
# Rename 'time' to 'date' and convert to datetime
weather_df = weather_df.rename(columns={'time': 'date'})
weather_df['date'] = pd.to_datetime(weather_df['date'])
citibike_df['date'] = pd.to_datetime(citibike_df['date'])
```

In [10]:
```python
weather_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4017 entries, 0 to 4016
Data columns (total 16 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   date                        4017 non-null   datetime64[ns]
 1   temperature_2m_max          4017 non-null   float64
 2   temperature_2m_min          4017 non-null   float64
 3   apparent_temperature_max    4017 non-null   float64
 4   apparent_temperature_min    4017 non-null   float64
 5   precipitation_sum           4017 non-null   float64
 6   rain_sum                    4017 non-null   float64
 7   snowfall_sum                4017 non-null   float64
 8   precipitation_hours         4017 non-null   float64
 9   sunshine_duration           4017 non-null   float64
 10  windspeed_10m_max           4017 non-null   float64
 11  windgusts_10m_max           4017 non-null   float64
 12  winddirection_10m_dominant  4017 non-null   int64
 13  shortwave_radiation_sum     4017 non-null   float64
 14  et0_fao_evapotranspiration  4017 non-null   float64
 15  temperature_avg             4017 non-null   float64
dtypes: datetime64[ns](1), float64(14), int64(1)
memory usage: 502.3 KB
```

In [7]:
```
# Select and rename relevant columns
weather_selected = weather_df[[
    'date',
    'temperature_avg',
    'precipitation_sum',
    'windspeed_10m_max',
    'sunshine_duration'
]]
```

In [8]:
```
# Merge with Citi Bike data
merged_df = pd.merge(citibike_df, weather_selected, on='date', how='inner').dropna()
```

In [9]:
```
# Display first few rows of the merged dataset
merged_df.head()
```

Out[9]:

	Unnamed: 0	date	num_trips	avg_duration	total_duration	temperature_avg	precipitation_sum	windspeed_10m_max	sunshine_duration
0	0	2015-01-01	5317	801.806658	4263206	-1.00	0.0	21.3	29236.59
1	1	2015-01-02	11304	731.240977	8265948	1.45	0.0	19.9	29150.96
2	2	2015-01-03	4478	655.284279	2934363	1.75	16.5	15.8	6444.89
3	3	2015-01-04	7849	679.554211	5333821	10.00	7.2	22.3	0.00
4	4	2015-01-05	14506	637.811802	9252098	1.55	0.0	26.8	29161.29

In [14]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365 entries, 0 to 364
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         365 non-null    int64
 1   date               365 non-null    datetime64[ns]
 2   num_trips          365 non-null    int64
 3   avg_duration       365 non-null    float64
 4   total_duration     365 non-null    int64
 5   temperature_avg    365 non-null    float64
 6   precipitation_sum  365 non-null    float64
 7   windspeed_10m_max  365 non-null    float64
 8   sunshine_duration  365 non-null    float64
dtypes: datetime64[ns](1), float64(5), int64(3)
memory usage: 25.8 KB
```

Regression Analysis

In [15]:
```
# Define response and predictors
X = merged_df[['temperature_avg', 'precipitation_sum', 'windspeed_10m_max', 'sunshine_duration']]
y = merged_df['num_trips']
```

In [16]:
```
# Add constant to predictors
X = sm.add_constant(X)

# Fit the regression model
```

```
model = sm.OLS(y, X).fit()
```

In [17]:

```
# Show regression summary
model.summary()
```

Out[17]:

OLS Regression Results

Dep. Variable:	num_trips	**R-squared:**	0.687
Model:	OLS	**Adj. R-squared:**	0.684
Method:	Least Squares	**F-statistic:**	197.9
Date:	Fri, 18 Apr 2025	**Prob (F-statistic):**	1.59e-89
Time:	13:39:26	**Log-Likelihood:**	-3775.7
No. Observations:	365	**AIC:**	7561.
Df Residuals:	360	**BIC:**	7581.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.186e+04	1778.374	12.290	0.000	1.84e+04	2.54e+04
temperature_avg	950.7864	42.906	22.160	0.000	866.409	1035.164
precipitation_sum	-554.2002	72.091	-7.688	0.000	-695.972	-412.428
windspeed_10m_max	-266.0749	81.373	-3.270	0.001	-426.102	-106.048
sunshine_duration	-0.0039	0.034	-0.114	0.909	-0.070	0.062

Omnibus:	13.958	**Durbin-Watson:**	0.629
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	14.860
Skew:	0.494	**Prob(JB):**	0.000593
Kurtosis:	2.989	**Cond. No.**	1.52e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.52e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

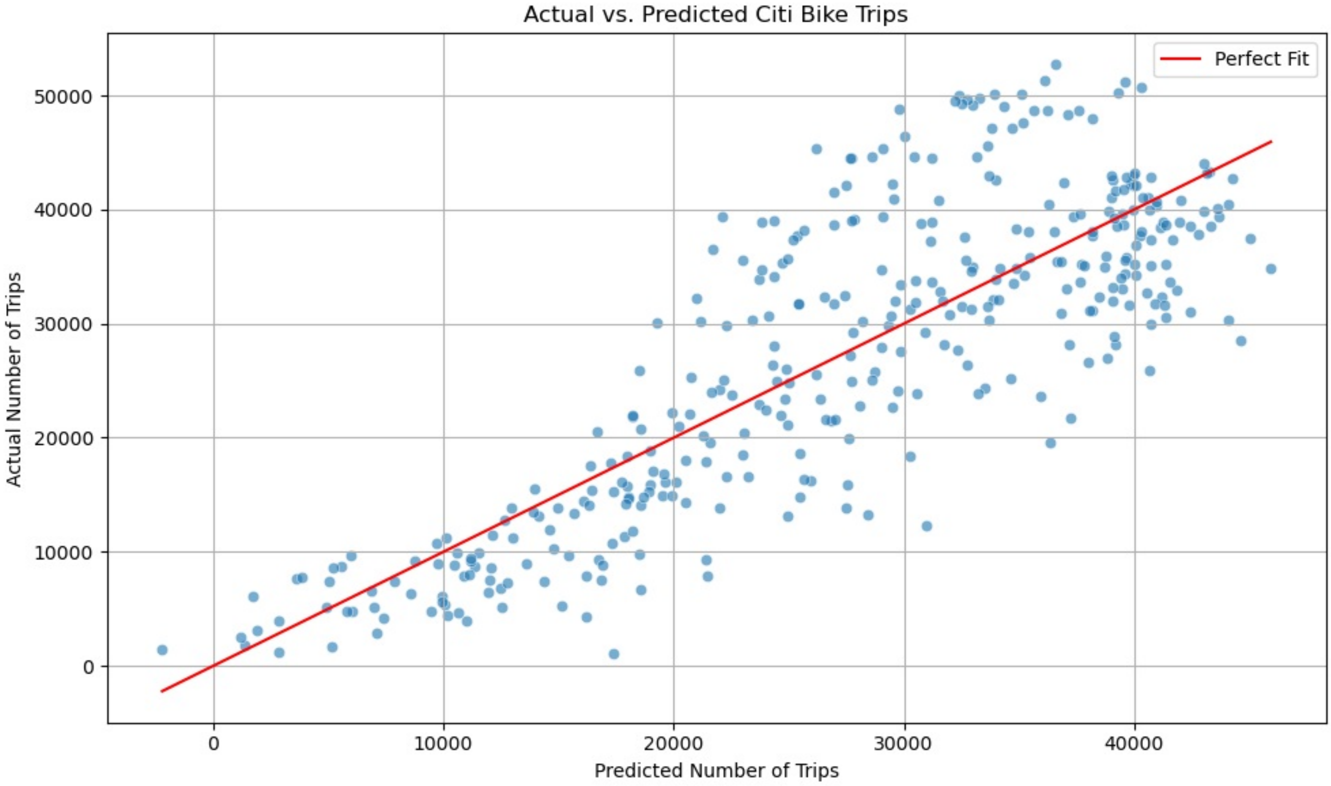
Visualization

In [18]:

```
# Predict values using the fitted model
merged_df['predicted_trips'] = model.predict(X)
```

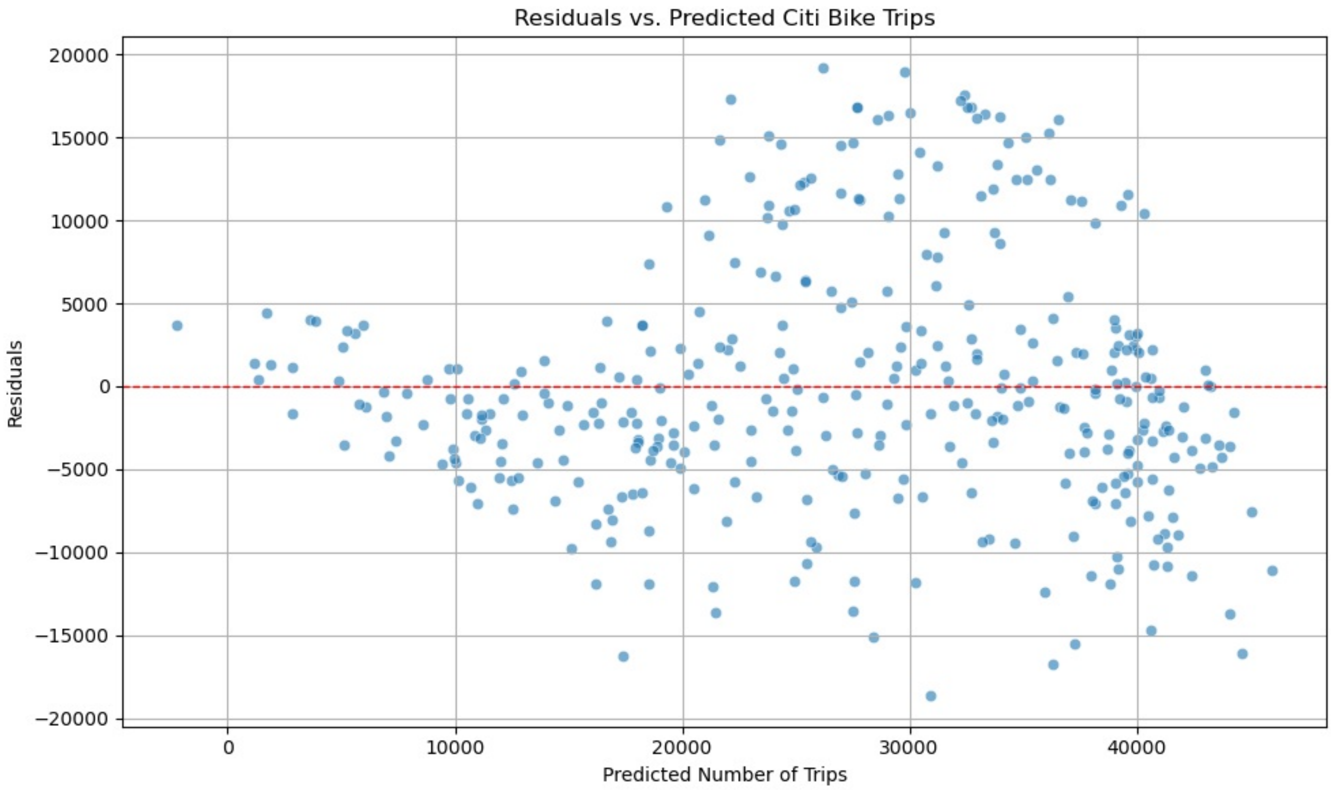
In [19]:

```
# Create a new DataFrame just for plotting
plot_df = merged_df[['num_trips', 'predicted_trips']].copy()

# Plot actual vs. predicted values with a perfect fit line
plt.figure(figsize=(10, 6))
sns.scatterplot(data=plot_df, x='predicted_trips', y='num_trips', alpha=0.6)
sns.lineplot(data=plot_df.sort_values('predicted_trips'), x='predicted_trips', y='predicted_trips', color='red'
plt.title('Actual vs. Predicted Citi Bike Trips')
plt.xlabel('Predicted Number of Trips')
plt.ylabel('Actual Number of Trips')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

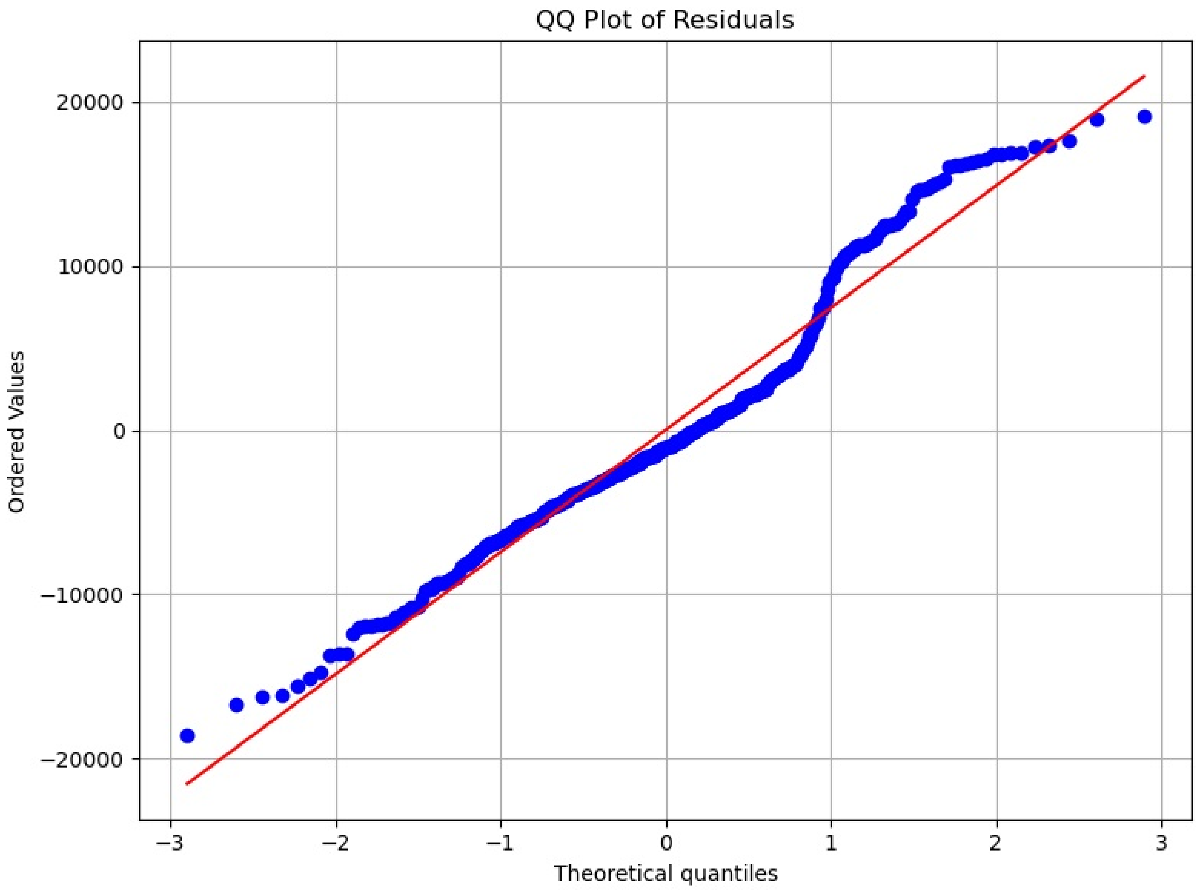


In [20]:
```python
# Calculate residuals
merged_df['residuals'] = merged_df['num_trips'] - merged_df['predicted_trips']
```

In [21]:
```python
# Plot residuals vs. predicted values
plt.figure(figsize=(10, 6))
sns.scatterplot(x='predicted_trips', y='residuals', data=merged_df, alpha=0.6)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title('Residuals vs. Predicted Citi Bike Trips')
plt.xlabel('Predicted Number of Trips')
plt.ylabel('Residuals')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [22]:
```python
# Generate QQ plot of residuals
plt.figure(figsize=(8, 6))
stats.probplot(merged_df['residuals'], dist="norm", plot=plt)
plt.title('QQ Plot of Residuals')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Log-transforming

In [23]:
```
# Add log-transformed features
merged_df['log_num_trips'] = np.log1p(merged_df['num_trips'])  # log(1 + trips)
merged_df['log_temperature_avg'] = np.log1p(merged_df['temperature_avg'] - merged_df['temperature_avg'].min() +
merged_df['log_precipitation_sum'] = np.log1p(merged_df['precipitation_sum'])
merged_df['log_windspeed_10m_max'] = np.log1p(merged_df['windspeed_10m_max'])
merged_df['log_sunshine_duration'] = np.log1p(merged_df['sunshine_duration'])
```

In [24]:
```
# Define new model predictors and response
X_log = merged_df[['log_temperature_avg', 'log_precipitation_sum', 'log_windspeed_10m_max', 'log_sunshine_durat
y_log = merged_df['log_num_trips']
X_log = sm.add_constant(X_log)

# Fit the log-transformed model
model_log = sm.OLS(y_log, X_log).fit()

# Show summary of the log-transformed model
model_log.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	log_num_trips	**R-squared:**	0.734
Model:	OLS	**Adj. R-squared:**	0.731
Method:	Least Squares	**F-statistic:**	248.5
Date:	Fri, 18 Apr 2025	**Prob (F-statistic):**	3.63e-102
Time:	13:39:30	**Log-Likelihood:**	-162.49
No. Observations:	365	**AIC:**	335.0
Df Residuals:	360	**BIC:**	354.5
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.7365	0.272	24.805	0.000	6.202	7.271
log_temperature_avg	1.0576	0.039	27.011	0.000	0.981	1.135
log_precipitation_sum	-0.1957	0.024	-8.024	0.000	-0.244	-0.148
log_windspeed_10m_max	-0.1194	0.072	-1.666	0.097	-0.260	0.022
log_sunshine_duration	0.0330	0.009	3.794	0.000	0.016	0.050

Omnibus:	137.200	**Durbin-Watson:**	1.050
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1162.070
Skew:	-1.334	**Prob(JB):**	4.57e-253
Kurtosis:	11.324	**Cond. No.**	151.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

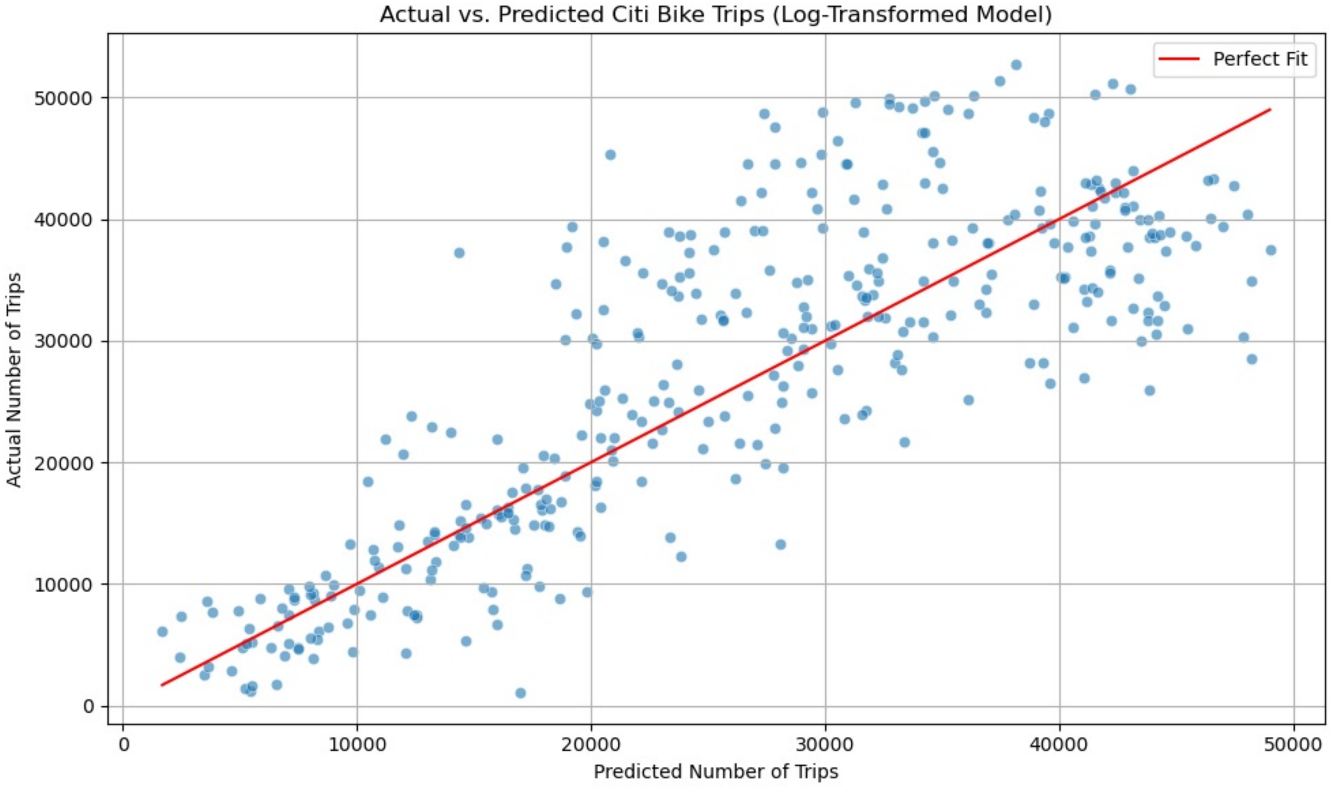
Visualization

In [25]:

```
# Predict log(num_trips) and back-transform to original scale
merged_df['log_predicted_trips'] = model_log.predict(X_log)
merged_df['backtransformed_predicted_trips'] = np.expm1(merged_df['log_predicted_trips'])
```

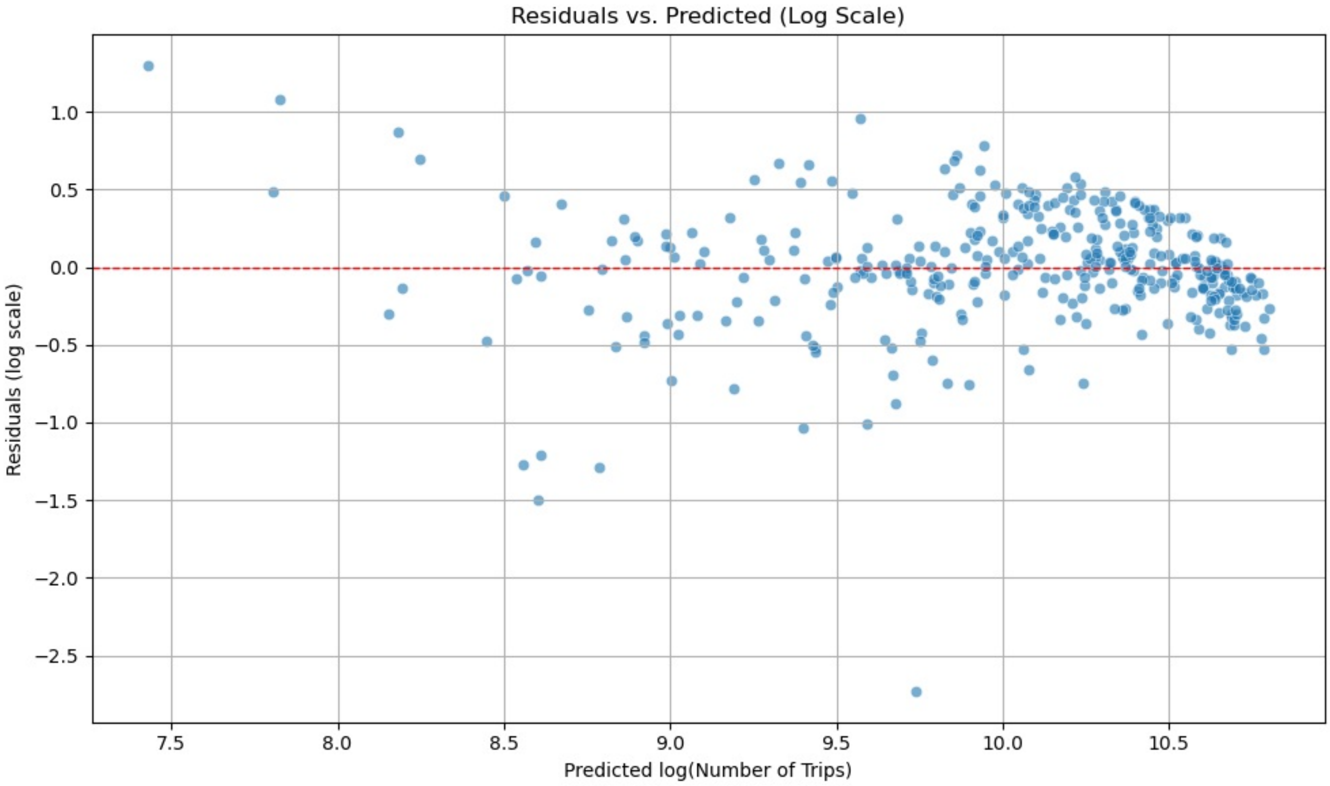
In [26]:

```
# Plot actual vs. predicted (original scale)
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x='backtransformed_predicted_trips',
    y='num_trips',
    data=merged_df,
    alpha=0.6
)
sns.lineplot(
    x='backtransformed_predicted_trips',
    y='backtransformed_predicted_trips',
    data=merged_df.sort_values('backtransformed_predicted_trips'),
    color='red',
    label='Perfect Fit'
)
plt.title('Actual vs. Predicted Citi Bike Trips (Log-Transformed Model)')
plt.xlabel('Predicted Number of Trips')
plt.ylabel('Actual Number of Trips')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



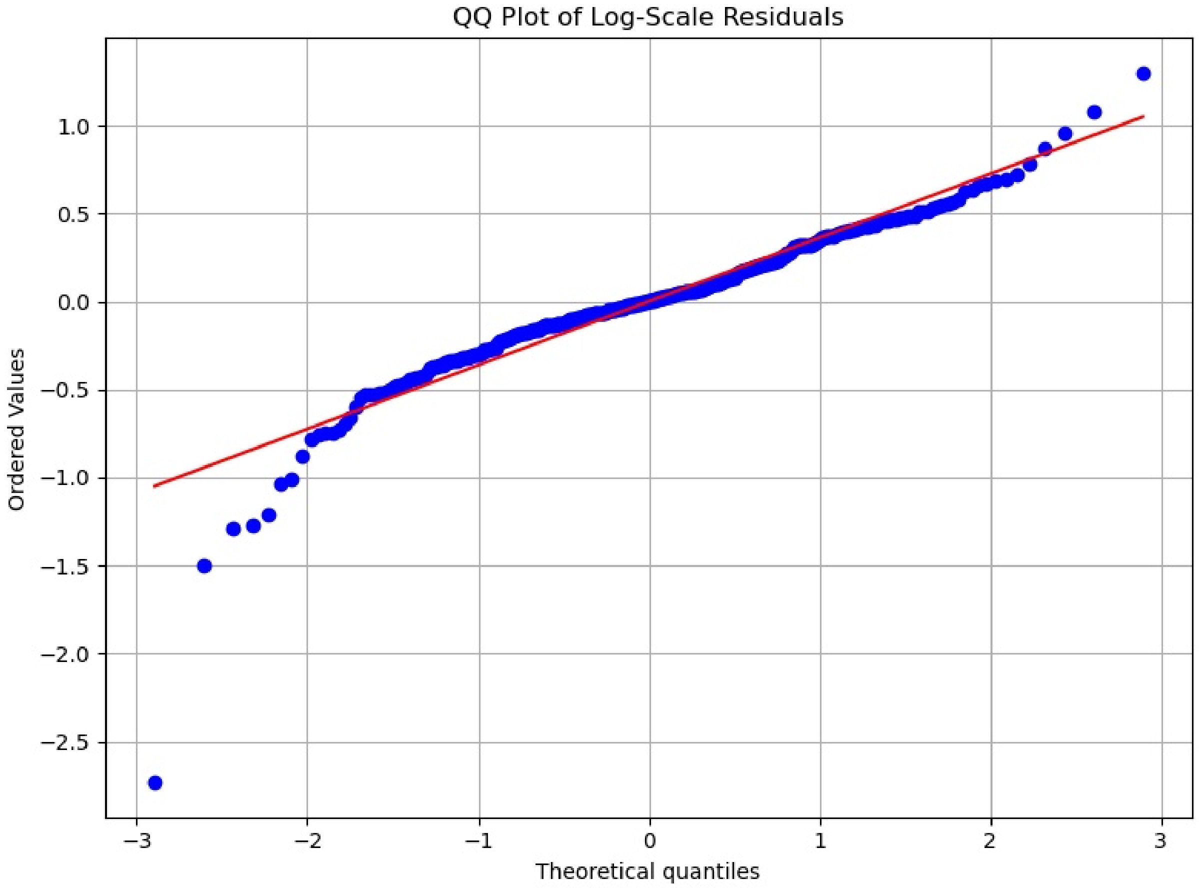
In [27]:
```python
# Calculate residuals in log scale
merged_df['log_residuals'] = merged_df['log_num_trips'] - merged_df['log_predicted_trips']
```

In [28]:
```python
# Residual plot: log residuals vs. predicted (log scale)
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x='log_predicted_trips',
    y='log_residuals',
    data=merged_df,
    alpha=0.6
)
plt.axhline(0, color='red', linestyle='--', linewidth=1)
plt.title('Residuals vs. Predicted (Log Scale)')
plt.xlabel('Predicted log(Number of Trips)')
plt.ylabel('Residuals (log scale)')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [29]:
```python
# QQ plot for log residuals
plt.figure(figsize=(8, 6))
```

```
stats.probplot(merged_df['log_residuals'], dist="norm", plot=plt)
plt.title('QQ Plot of Log-Scale Residuals')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Partial Least Squares Regression

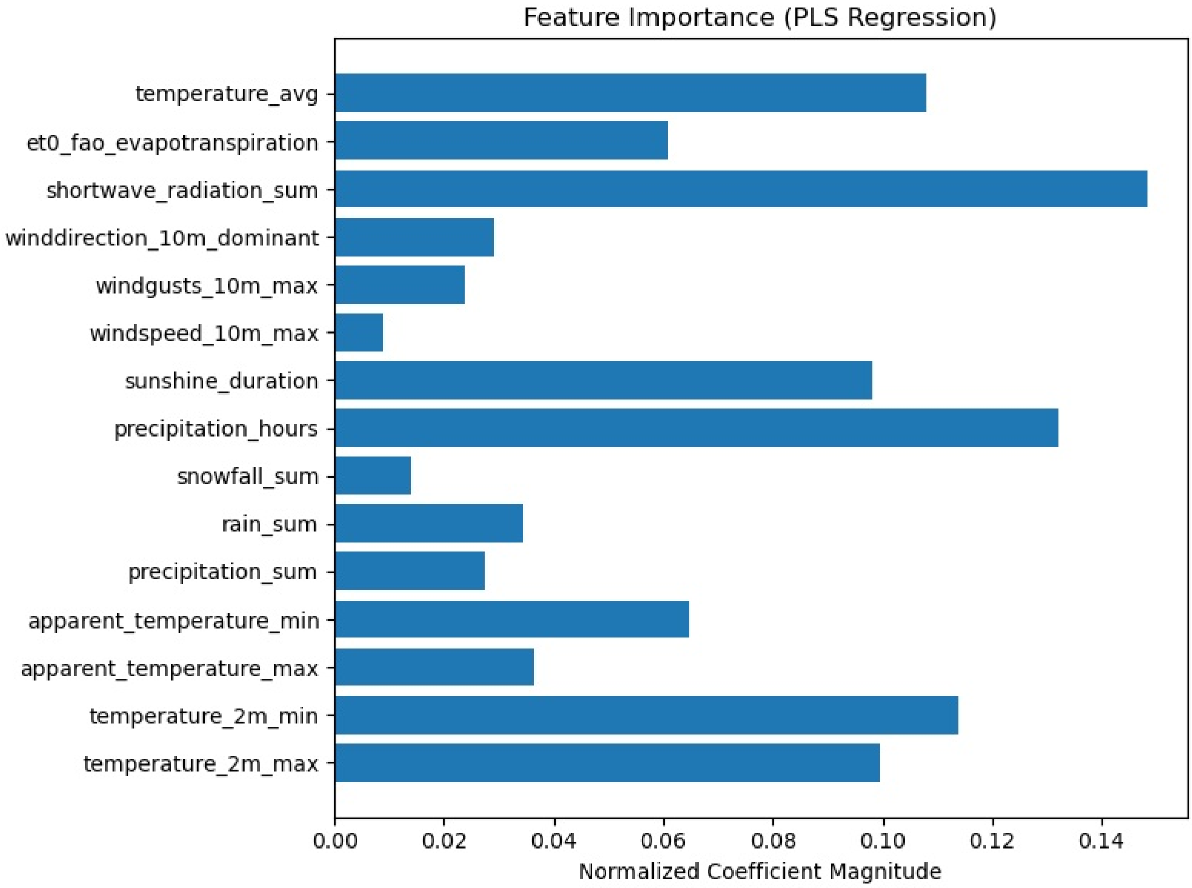
In [10]:
```
merged_df_pp = pd.merge(citibike_df, weather_df, on='date', how='inner').dropna()
```

In [11]:
```
features = [
    'temperature_2m_max', 'temperature_2m_min', 'apparent_temperature_max', 'apparent_temperature_min',
    'precipitation_sum', 'rain_sum', 'snowfall_sum', 'precipitation_hours',
    'sunshine_duration', 'windspeed_10m_max', 'windgusts_10m_max', 'winddirection_10m_dominant',
    'shortwave_radiation_sum', 'et0_fao_evapotranspiration', 'temperature_avg'
]
X = merged_df_pp[features]
y = merged_df_pp['num_trips']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train_scaled, X_test_scaled, y_train, y_test = train_test_split(X_scaled, y, test_size = 0.2, random_state= 4
```

In [32]:
```
pls = PLSRegression(n_components=5)
pls.fit(X_train_scaled, y_train)

y_pred = pls.predict(X_test_scaled)

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print("RMSE:", rmse)
print("R²:", r2)
```

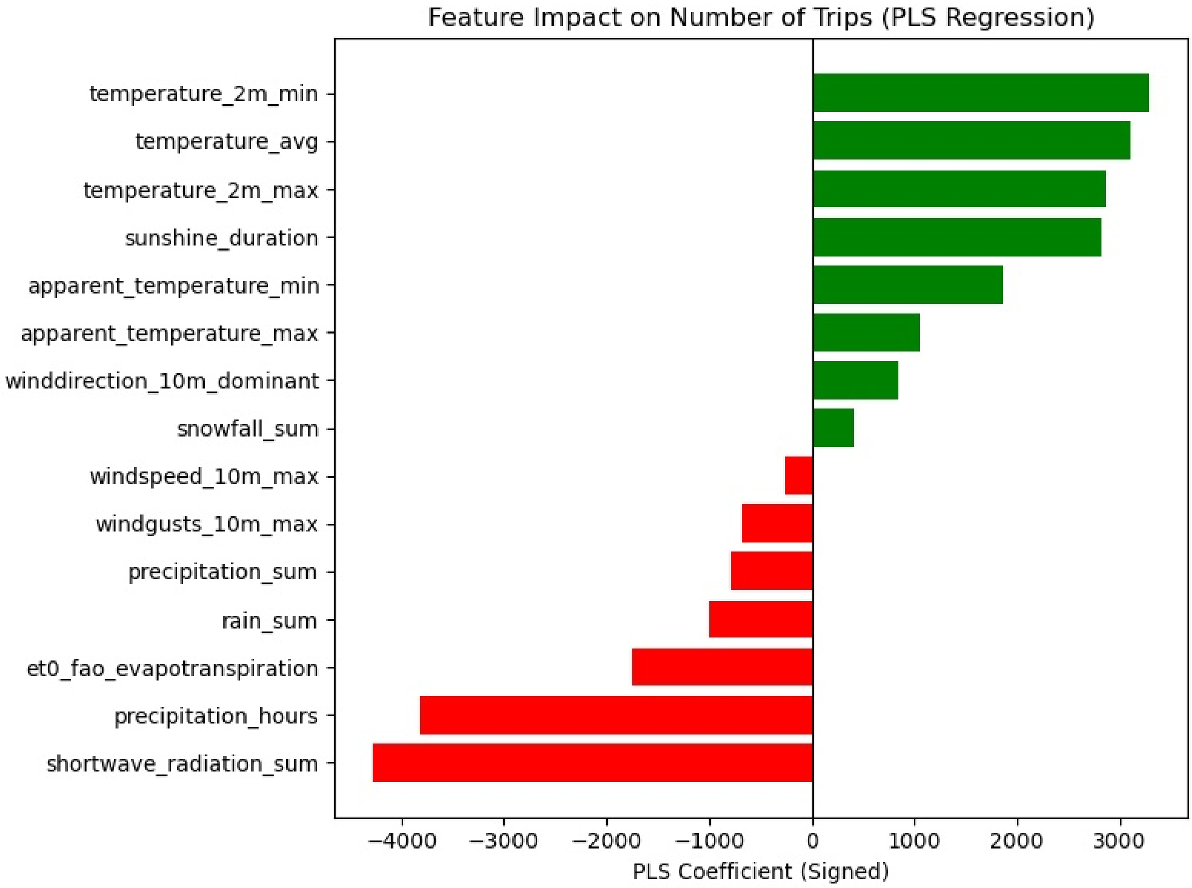
```
RMSE: 6759.398624717034
R²: 0.745126140393312
```

In [33]:
```
coeffs = np.abs(pls.coef_).flatten()
coeffs /= np.sum(coeffs)

plt.figure(figsize=(8, 6))
plt.barh(X.columns, coeffs)
plt.xlabel("Normalized Coefficient Magnitude")
plt.title("Feature Importance (PLS Regression)")
plt.tight_layout()
plt.show()
```



In [34]:

```
coeffs_signed = pls.coef_.flatten()
impact_df = pd.DataFrame({
    'Feature': features,
    'Coefficient': coeffs_signed
}).sort_values(by='Coefficient', ascending=True)

plt.figure(figsize=(8, 6))
bars = plt.barh(impact_df['Feature'], impact_df['Coefficient'],
                color=['green' if c > 0 else 'red' for c in impact_df['Coefficient']])
plt.axvline(0, color='black', linewidth=0.8)
plt.xlabel("PLS Coefficient (Signed)")
plt.title("Feature Impact on Number of Trips (PLS Regression)")
plt.tight_layout()
plt.show()
```



Tree-Based Model & Feature Importance Analysis

In [17]:

```
def evaluate_model(model, X_test, y_test, title="Model"):
    y_pred = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    r2 = r2_score(y_test, y_pred)

    print(f"{title} RMSE: {rmse:.4f}")
    print(f"{title} R²: {r2:.4f}")

    # Plot actual vs. predicted
    plt.figure(figsize=(6, 5))
    sns.scatterplot(x=y_test, y=y_pred)
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
    plt.xlabel("Actual")
    plt.ylabel("Predicted")
    plt.title(f"{title} - Actual vs. Predicted")
    plt.grid(True)
    plt.show()

    return y_pred

def plot_feature_importance(model, feature_names, title="Feature Importance"):
    importances = model.feature_importances_
    indices = np.argsort(importances)[::-1]

    plt.figure(figsize=(8, 6))
    sns.barplot(x=importances[indices], y=np.array(feature_names)[indices])
    plt.title(title)
    plt.xlabel("Importance")
    plt.ylabel("Feature")
    plt.grid(True)
    plt.show()
```

Decision Tree

In [18]:

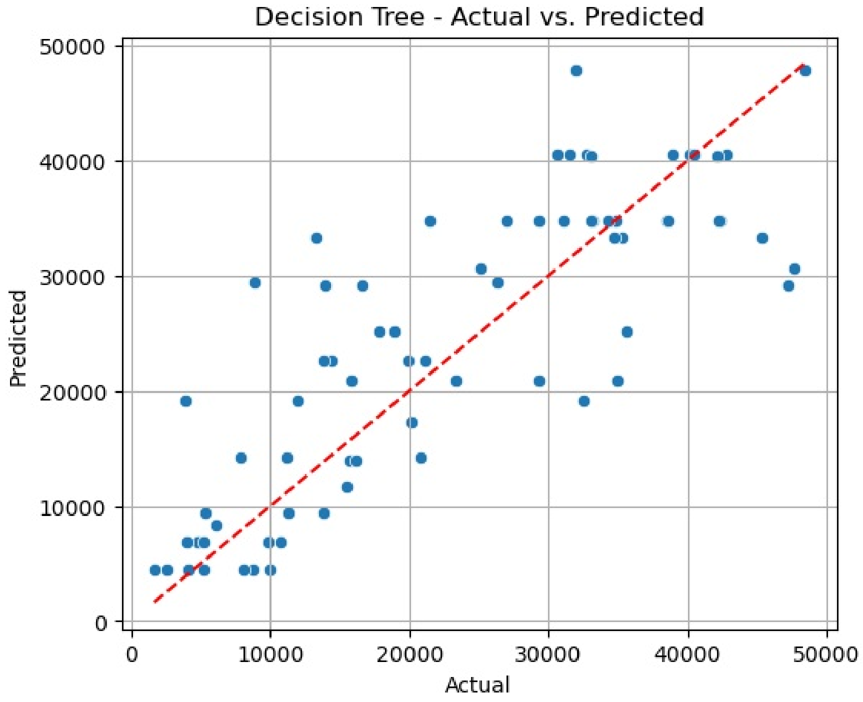
```
dt_param_dist = {
    'max_depth': randint(2, 20),
    'min_samples_split': randint(2, 20),
    'min_samples_leaf': randint(1, 10)
}

dt = DecisionTreeRegressor(random_state=42)
dt_search = RandomizedSearchCV(dt, dt_param_dist, n_iter=50, cv=5, scoring='r2', n_jobs=-1, random_state=42)
dt_search.fit(X_train_scaled, y_train)
```

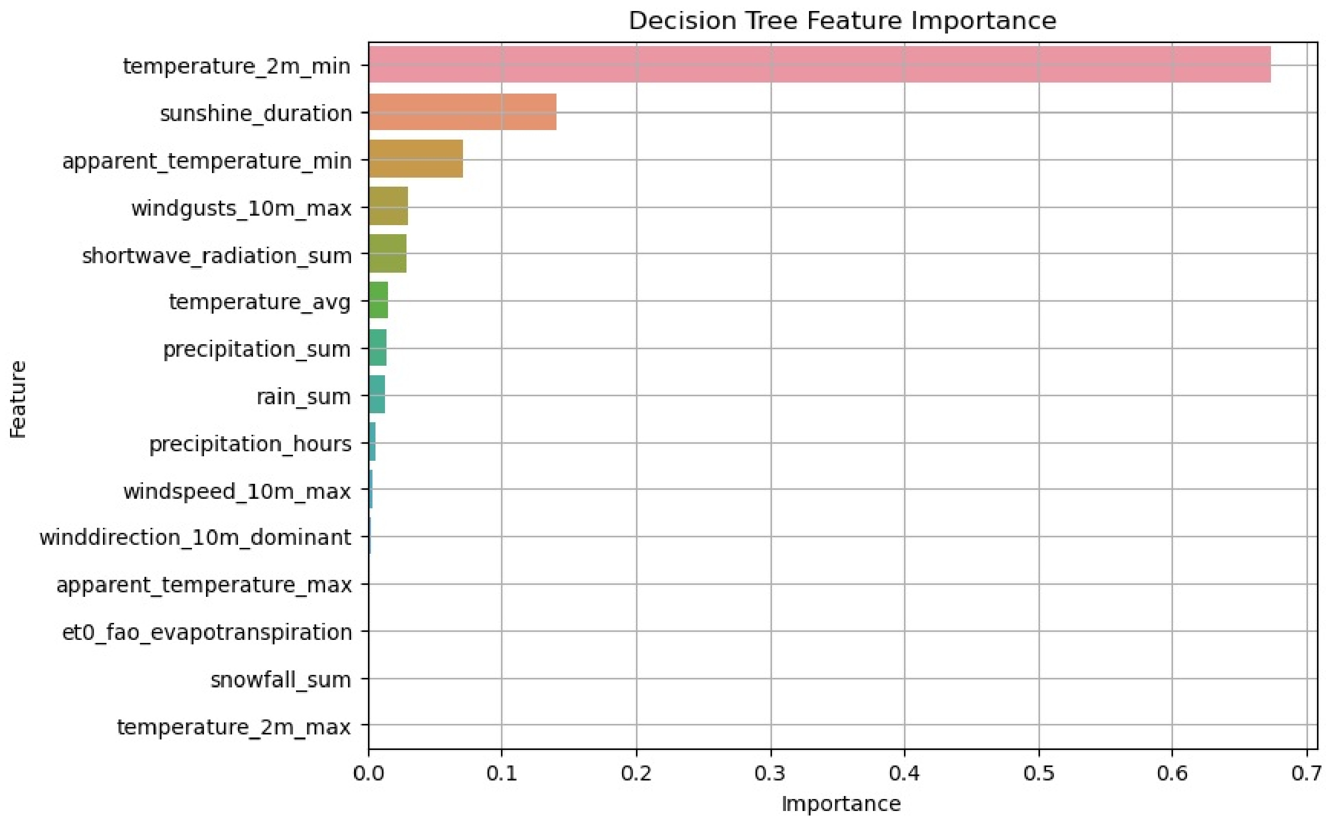
```
print("Best Decision Tree Params:", dt_search.best_params_)
best_dt = dt_search.best_estimator_
```

Best Decision Tree Params: {'max_depth': 6, 'min_samples_leaf': 7, 'min_samples_split': 8}

In [19]:
```
evaluate_model(best_dt, X_test_scaled, y_test, "Decision Tree")
plot_feature_importance(best_dt, features, "Decision Tree Feature Importance")
```

Decision Tree RMSE: 8008.7662
Decision Tree R²: 0.6422





Random Forest

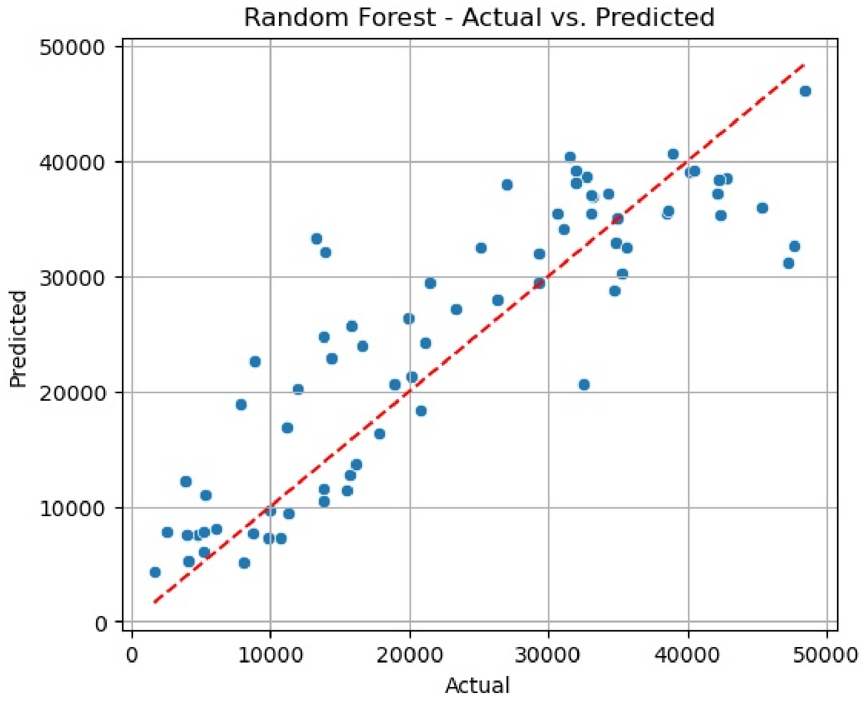
In [21]:
```
rf_param_dist = {
    'n_estimators': randint(50, 200),
    'max_depth': randint(5, 30),
    'min_samples_split': randint(2, 10),
    'min_samples_leaf': randint(1, 10),
    'max_features': ['sqrt', 'log2']
}

rf = RandomForestRegressor(random_state=42)
rf_search = RandomizedSearchCV(rf, rf_param_dist, n_iter=50, cv=5, scoring='r2', n_jobs=-1, random_state=42)
rf_search.fit(X_train_scaled, y_train)
```

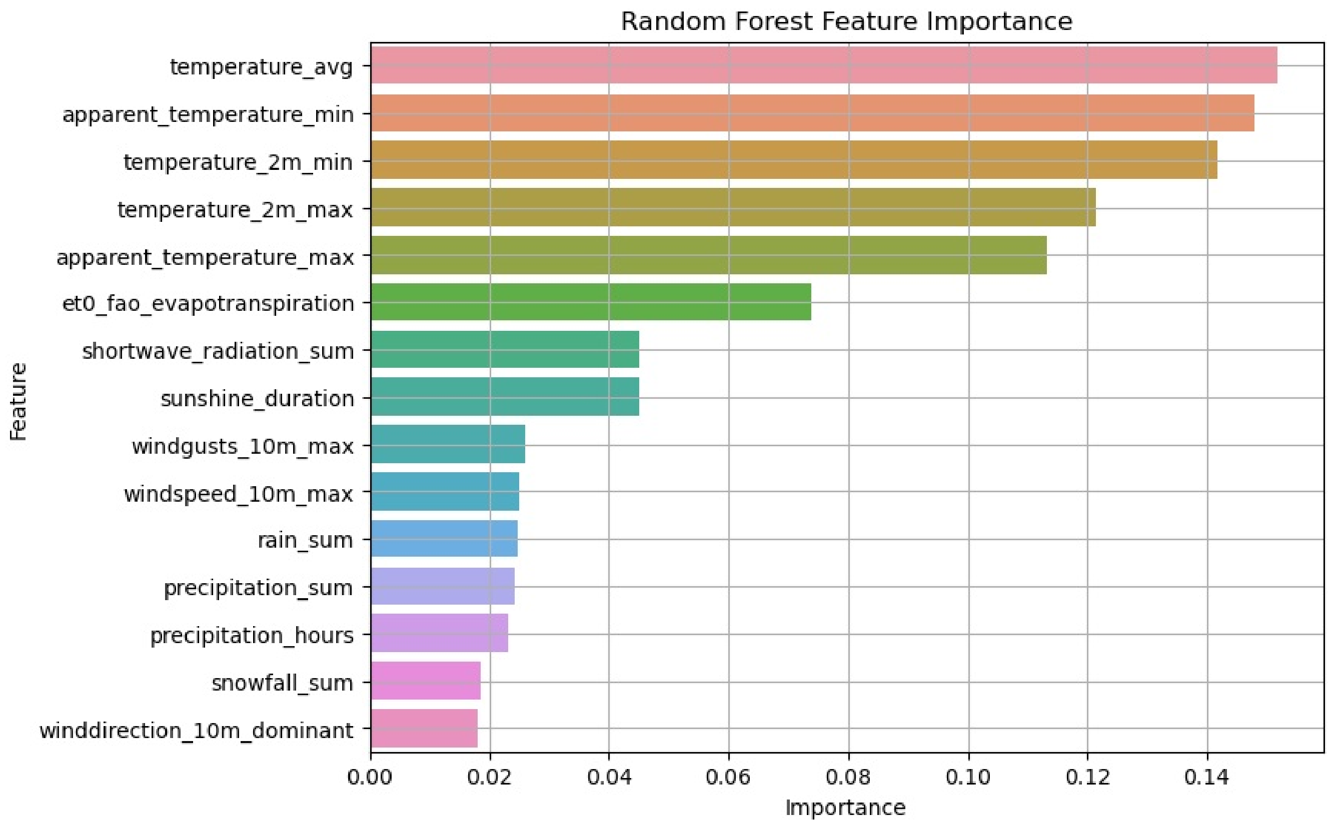
```
print("Best Random Forest Params:", rf_search.best_params_)
best_rf = rf_search.best_estimator_
```

```
Best Random Forest Params: {'max_depth': 10, 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split'
: 2, 'n_estimators': 173}
```

In [22]:
```
evaluate_model(best_rf, X_test_scaled, y_test, "Random Forest")
plot_feature_importance(best_rf, features, "Random Forest Feature Importance")
```

```
Random Forest RMSE: 6682.8512
Random Forest R²: 0.7509
```





XGBoost

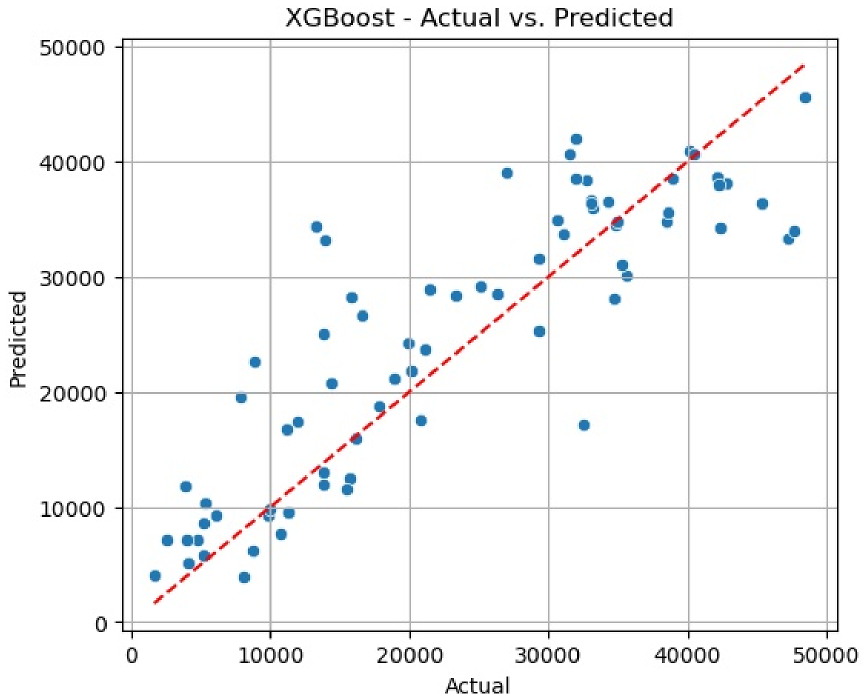
In [23]:
```
xgb_param_dist = {
    'n_estimators': randint(50, 200),
    'max_depth': randint(3, 15),
    'learning_rate': uniform(0.01, 0.3),
    'subsample': uniform(0.5, 0.5),
    'colsample_bytree': uniform(0.5, 0.5),
    'gamma': uniform(0, 5)
}
```

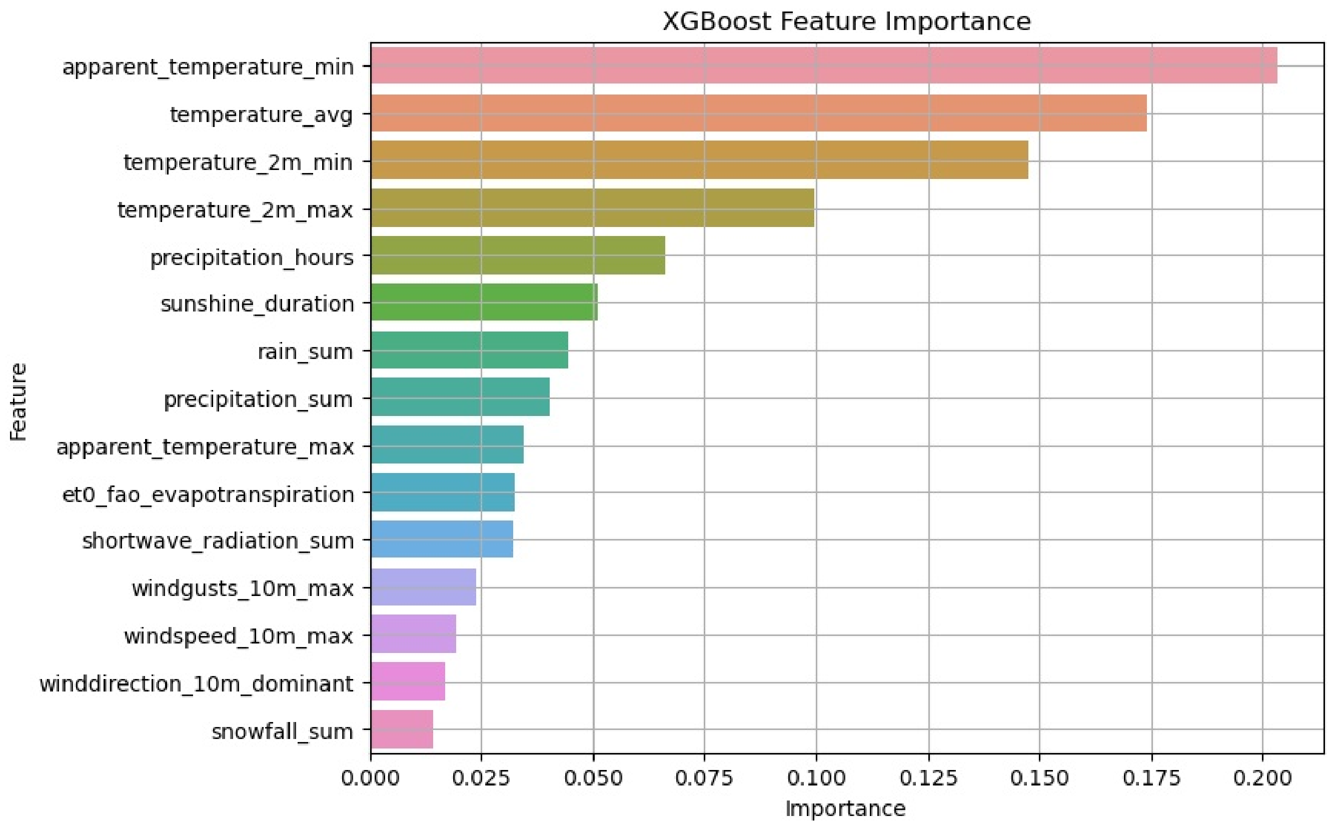
```
xgb = XGBRegressor(random_state=42, verbosity=0)
xgb_search = RandomizedSearchCV(xgb, xgb_param_dist, n_iter=50, cv=5, scoring='r2', n_jobs=-1, random_state=42)
xgb_search.fit(X_train_scaled, y_train)

print("Best XGBoost Params:", xgb_search.best_params_)
best_xgb = xgb_search.best_estimator_
```

```
Best XGBoost Params: {'colsample_bytree': 0.5384899549143964, 'gamma': 1.4487572645688402, 'learning_rate': 0.0
58366386176201324, 'max_depth': 4, 'n_estimators': 94, 'subsample': 0.647816842918857}
```

In [24]:
```
evaluate_model(best_xgb, X_test_scaled, y_test, "XGBoost")
plot_feature_importance(best_xgb, features, "XGBoost Feature Importance")
```

```
XGBoost RMSE: 6847.1848
XGBoost R²: 0.7385
```





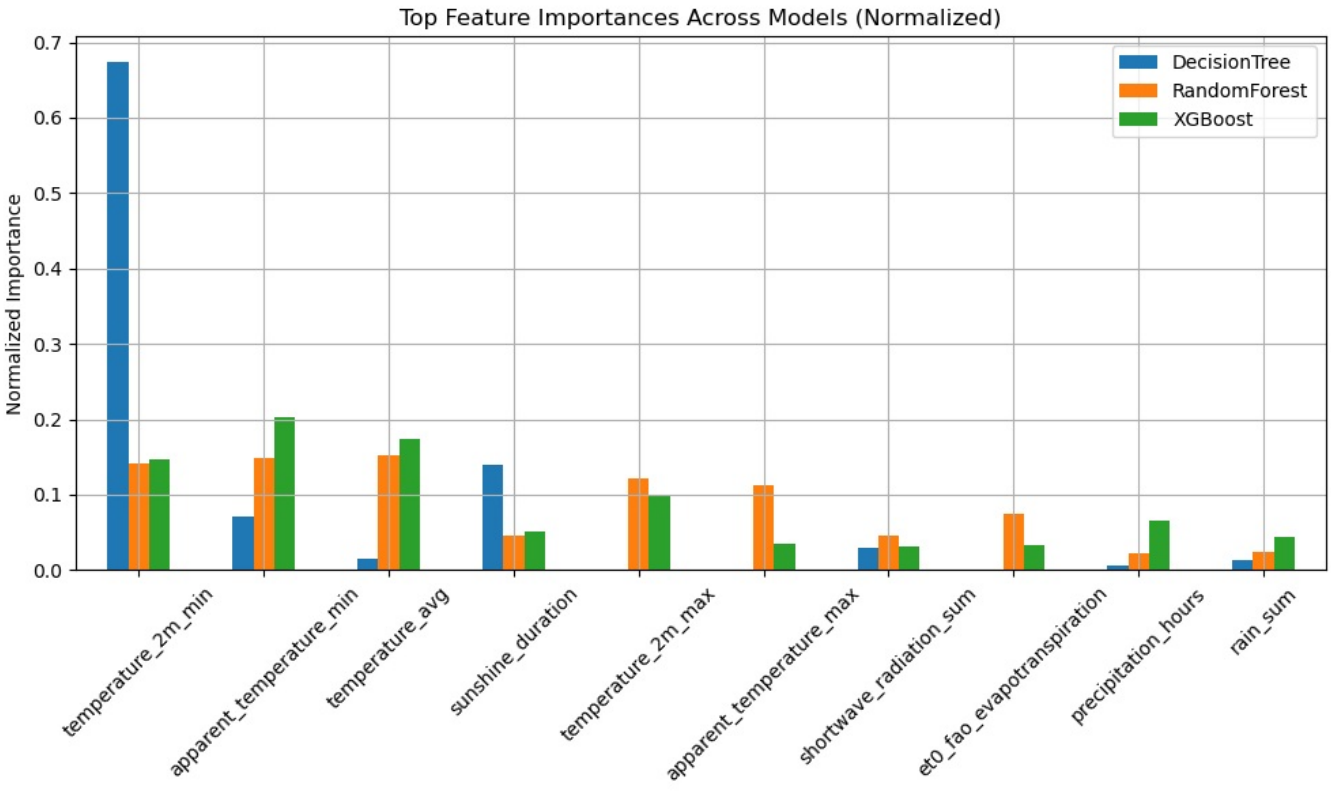
In [26]:
```
dt_importance = pd.Series(best_dt.feature_importances_, index=features, name='DecisionTree')
rf_importance = pd.Series(best_rf.feature_importances_, index=features, name='RandomForest')
xgb_importance = pd.Series(best_xgb.feature_importances_, index=features, name='XGBoost')

# Combine into a single DataFrame
importance_df = pd.concat([dt_importance, rf_importance, xgb_importance], axis=1)

# Option A: Normalize
normalized_df = importance_df.div(importance_df.sum(axis=0), axis=1)
```

```
# Option B: Rank
rank_df = importance_df.rank(ascending=False)

# Aggregated importance
normalized_df['Mean'] = normalized_df.mean(axis=1)
rank_df['MeanRank'] = rank_df.mean(axis=1)

# Sort by importance or rank
top_features_by_importance = normalized_df.sort_values('Mean', ascending=False)
top_features_by_rank = rank_df.sort_values('MeanRank')

# Choose top 5
selected_features = top_features_by_importance.head(5).index.tolist()
print("Selected Top Features (by mean importance):", selected_features)
```

```
Selected Top Features (by mean importance): ['temperature_2m_min', 'apparent_temperature_min', 'temperature_avg
', 'sunshine_duration', 'temperature_2m_max']
```

In [27]:

```
top_n = 10
top_plot_df = normalized_df.sort_values('Mean', ascending=False).head(top_n)

top_plot_df[top_plot_df.columns[:-1]].plot(kind='bar', figsize=(10, 6))
plt.title("Top Feature Importances Across Models (Normalized)")
plt.ylabel("Normalized Importance")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



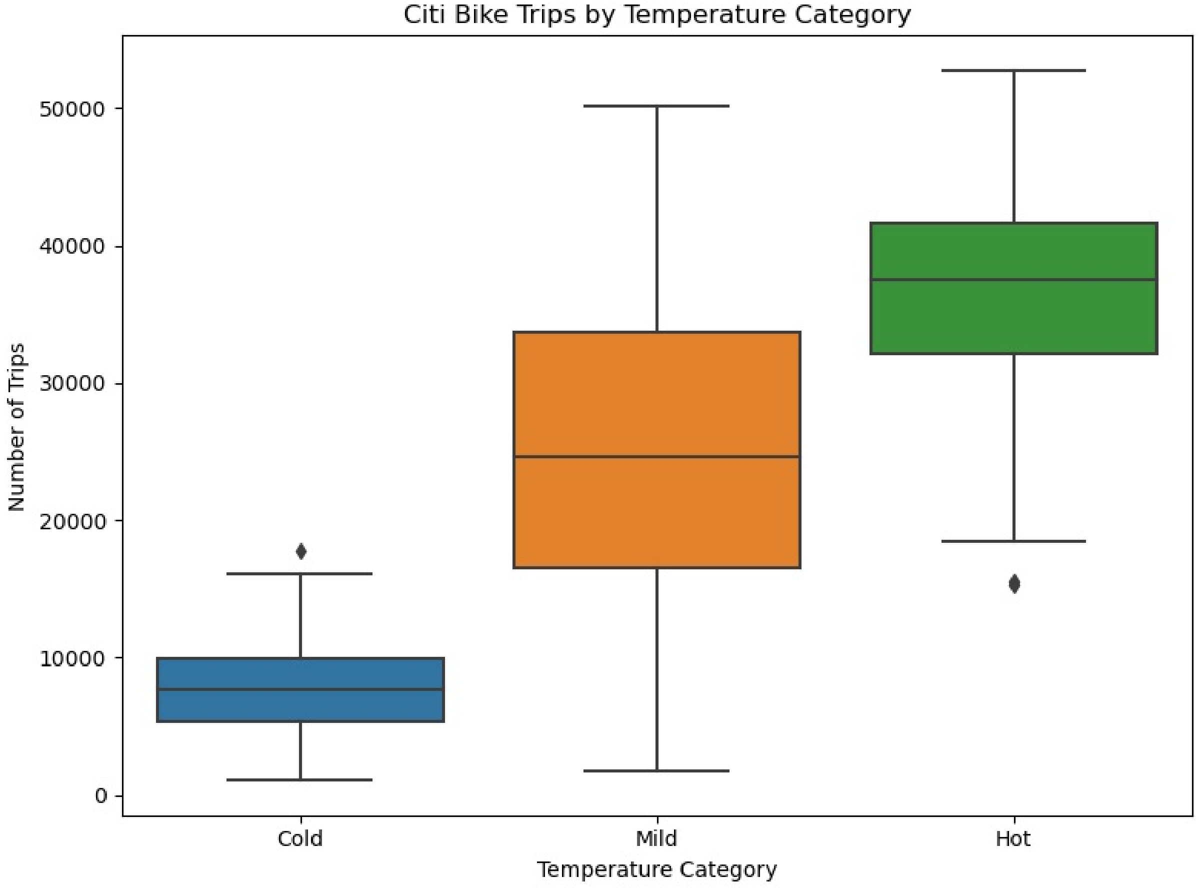
Statistical Testing

In [ ]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import f_oneway
from statsmodels.stats.multicomp import pairwise_tukeyhsd

# Load data
weather_df = pd.read_csv("nyc_weather_2013_2023.csv")
bike_df = pd.read_csv("citibike_day.csv")

# Convert date columns
weather_df["time"] = pd.to_datetime(weather_df["time"])
bike_df["date"] = pd.to_datetime(bike_df["date"])

# Merge
merged_df = pd.merge(bike_df, weather_df, left_on="date", right_on="time")

# Temperature category
def categorize_temp(temp):
    if temp < 5:
        return "Cold"
```

```python
    elif 5 <= temp <= 20:
        return "Mild"
    else:
        return "Hot"

merged_df["temp_category"] = merged_df["temperature_2m_max"].apply(categorize_temp)

# ANOVA
temp_groups = merged_df.groupby("temp_category")["num_trips"].apply(list)
temp_anova = f_oneway(*temp_groups)
print("Temperature ANOVA:", temp_anova)

# Tukey HSD for Temperature
tukey_temp = pairwise_tukeyhsd(
    endog=merged_df["num_trips"],
    groups=merged_df["temp_category"],
    alpha=0.05
)
print(tukey_temp)

# Boxplot
plt.figure(figsize=(8, 6))
sns.boxplot(x="temp_category", y="num_trips", data=merged_df)
plt.title("Citi Bike Trips by Temperature Category")
plt.xlabel("Temperature Category")
plt.ylabel("Number of Trips")
plt.tight_layout()
plt.show()
```

```
Temperature ANOVA: F_onewayResult(statistic=248.93908429347974, pvalue=9.843923705640121e-69)
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
==============================================================
group1 group2   meandiff  p-adj    lower      upper    reject
--------------------------------------------------------------
  Cold    Hot  28598.0609   0.0  25560.4613 31635.6605   True
  Cold   Mild  17507.4512   0.0  14447.9848 20566.9176   True
   Hot   Mild -11090.6097   0.0 -13476.9897 -8704.2297   True
--------------------------------------------------------------
```

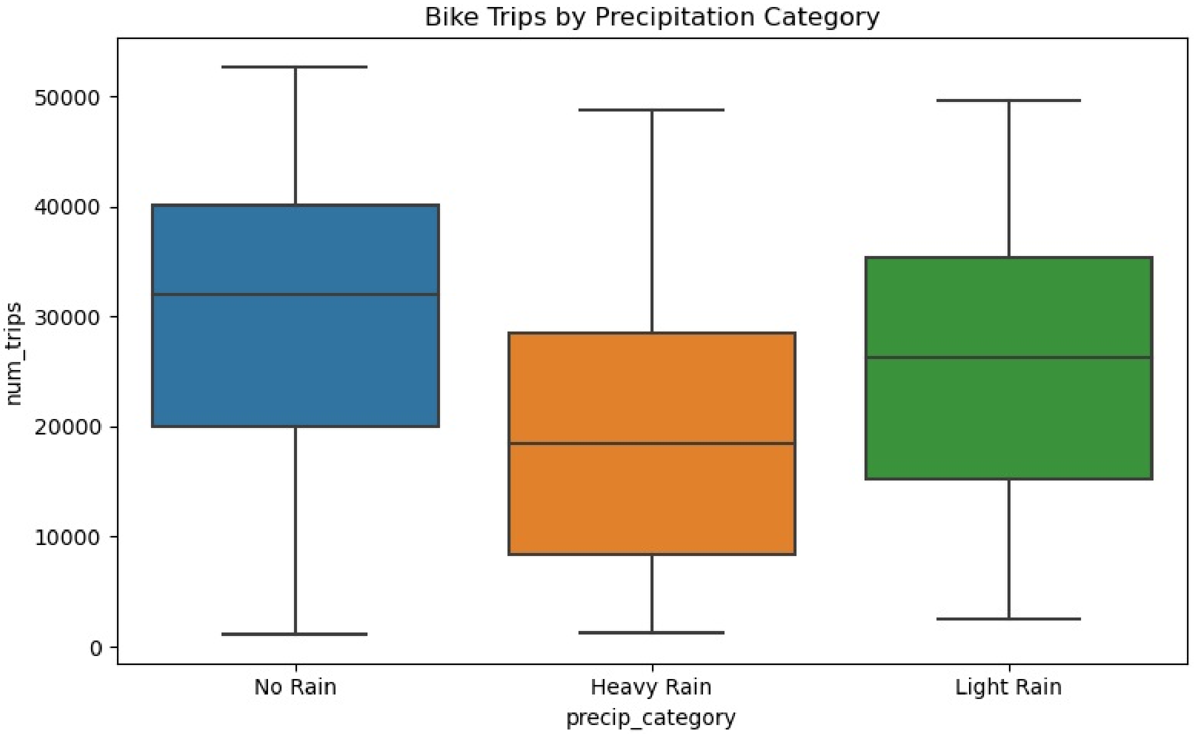


In [38]:

```python
# Precipitation category
def categorize_precip(p):
    if p == 0:
        return "No Rain"
    elif p <= 5:
        return "Light Rain"
    else:
        return "Heavy Rain"

merged_df["precip_category"] = merged_df["precipitation_sum"].apply(categorize_precip)

# ANOVA for Precipitation
precip_groups = merged_df.groupby("precip_category")["num_trips"].apply(list)
```

```
precip_anova = f_oneway(*precip_groups)
print("Precipitation ANOVA:", precip_anova)

# Tukey HSD for Precipitation
tukey_precip = pairwise_tukeyhsd(
    endog=merged_df["num_trips"],
    groups=merged_df["precip_category"],
    alpha=0.05
)
print(tukey_precip)

# Boxplot
plt.figure(figsize=(8, 5))
sns.boxplot(x="precip_category", y="num_trips", data=merged_df)
plt.title("Bike Trips by Precipitation Category")
plt.tight_layout()
plt.show()
```

```
Precipitation ANOVA: F_onewayResult(statistic=15.62696766833985, pvalue=3.093315843297417e-07)
        Multiple Comparison of Means - Tukey HSD, FWER=0.05
===================================================================
  group1     group2    meandiff  p-adj    lower      upper    reject
-------------------------------------------------------------------
Heavy Rain Light Rain  6250.2382 0.0125 1101.9523 11398.5242   True
Heavy Rain    No Rain 10601.1689    0.0 5987.9472 15214.3906   True
Light Rain    No Rain  4350.9307 0.0176  614.8757  8086.9856   True
-------------------------------------------------------------------
```

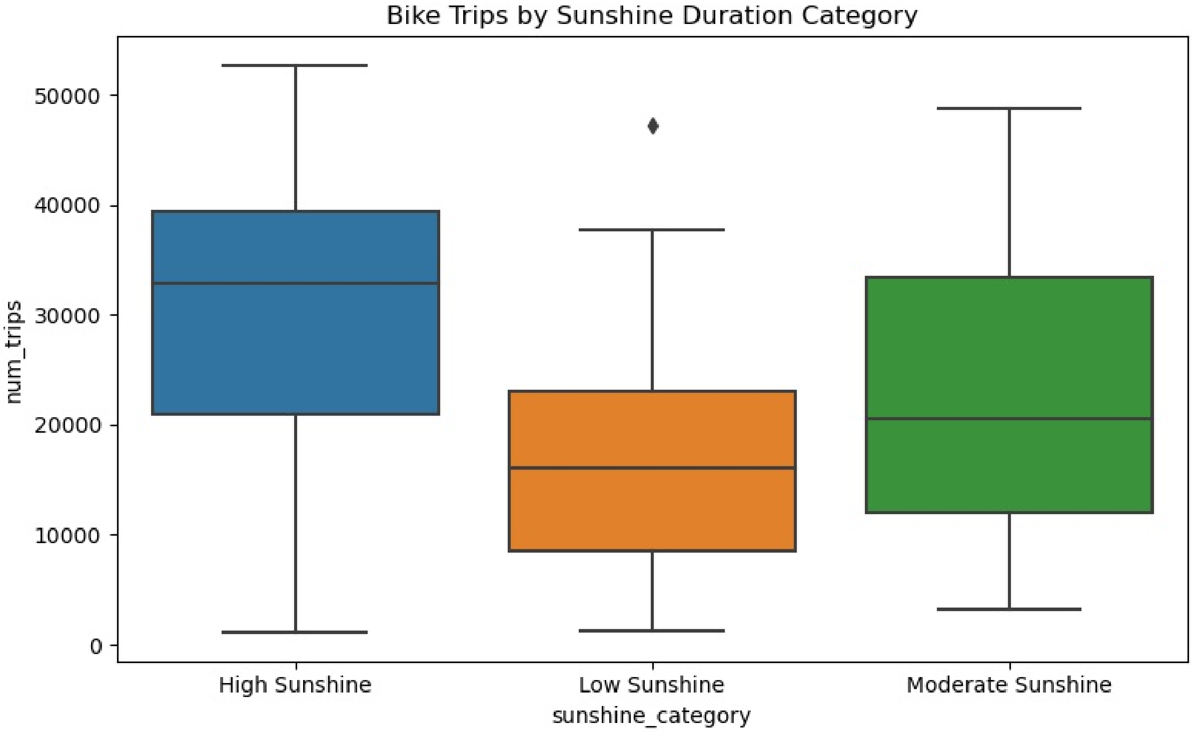


In [39]:

```
# Sunshine Duration category
def categorize_sunshine(sun):
    if sun < 10000:
        return "Low Sunshine"
    elif 10000 <= sun < 25000:
        return "Moderate Sunshine"
    else:
        return "High Sunshine"

merged_df["sunshine_category"] = merged_df["sunshine_duration"].apply(categorize_sunshine)

# ANOVA for Sunshine
sunshine_groups = merged_df.groupby("sunshine_category")["num_trips"].apply(list)
sunshine_anova = f_oneway(*sunshine_groups)
print("Sunshine Duration ANOVA:", sunshine_anova)


# Tukey HSD for Sunshine Duration
tukey_sun = pairwise_tukeyhsd(
    endog=merged_df["num_trips"],
    groups=merged_df["sunshine_category"],
    alpha=0.05
)
print(tukey_sun)

# Boxplot
plt.figure(figsize=(8, 5))
sns.boxplot(x="sunshine_category", y="num_trips", data=merged_df)
plt.title("Bike Trips by Sunshine Duration Category")
plt.tight_layout()
```

```
plt.show()
```

```
Sunshine Duration ANOVA: F_onewayResult(statistic=25.782967460505027, pvalue=3.401338631787172e-11)
              Multiple Comparison of Means - Tukey HSD, FWER=0.05
===============================================================================
    group1          group2       meandiff  p-adj     lower      upper    reject
-------------------------------------------------------------------------------
High Sunshine      Low Sunshine -12750.547    0.0 -17123.4046 -8377.6893   True
High Sunshine Moderate Sunshine -6559.2737 0.0049 -11447.7829 -1670.7646   True
 Low Sunshine Moderate Sunshine  6191.2733 0.0427    160.6584 12221.8881   True
-------------------------------------------------------------------------------
```



In [ ]:

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