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_va
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 [2]:
```python
!jupyter nbconvert 5291 Project.ipynb --to pdf
```

```
[NbConvertApp] WARNING | pattern '5291' matched no files
[NbConvertApp] WARNING | pattern 'Project.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and i
nclude the error message in the cell output (the default behaviour is to abort
conversion). This flag is only relevant if '--execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with
default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False --NbConvertApp.expo
rt_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False --NbConvertApp.expo
rt_format=notebook --FilesWriter.build_directory= --ClearOutputPreprocessor.en
abled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True --TemplateExp
orter.exclude_output_prompt=True]
--no-input
```

```
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True --TemplateEx
porter.exclude_input=True --TemplateExporter.exclude_input_prompt=True]
--allow-chromium-download
    Whether to allow downloading chromium if no suitable version is found on t
he system.
    Equivalent to: [--WebPDFExporter.allow_chromium_download=True]
--disable-chromium-sandbox
    Disable chromium security sandbox when converting to PDF..
    Equivalent to: [--WebPDFExporter.disable_sandbox=True]
--show-input
    Shows code input. This flag is only useful for dejavu users.
    Equivalent to: [--TemplateExporter.exclude_input=False]
--embed-images
    Embed the images as base64 dataurls in the output. This flag is only usefu
l for the HTML/WebPDF/Slides exports.
    Equivalent to: [--HTMLExporter.embed_images=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN', 'ERROR',
'CRITICAL']
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown', 'notebook', 'p
df', 'python', 'rst', 'script', 'slides', 'webpdf']
            or a dotted object name that represents the import path for an
            ``Exporter`` class
    Default: ''
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_name]
--template-file=<Unicode>
    Name of the template file to use
    Default: None
    Equivalent to: [--TemplateExporter.template_file]
--theme=<Unicode>
    Template specific theme(e.g. the name of a JupyterLab CSS theme distribute
d
    as prebuilt extension for the lab template)
    Default: 'light'
    Equivalent to: [--HTMLExporter.theme]
--writer=<DottedObjectName>
    Writer class used to write the
                                        results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                        results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
```

```
--output=<Unicode>
    overwrite base name use for output files.
                can only be used when converting one notebook at a time.
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each notebook.
To recover
                                  previous default behaviour (outputting to th
e current
                                  working directory) use . as the flag value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url pointing to a
copy
            of reveal.js.
            For speaker notes to work, this must be a relative path to a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of the
            current directory (from which the server is run).
            See the usage documentation
            (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-h
tml-slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb --to html

            Options include ['asciidoc', 'custom', 'html', 'latex', 'markdow
n', 'notebook', 'pdf', 'python', 'rst', 'script', 'slides', 'webpdf'].

            > jupyter nbconvert --to latex mynotebook.ipynb

            Both HTML and LaTeX support multiple output templates. LaTeX inclu
des
            'base', 'article' and 'report'.  HTML includes 'basic', 'lab' and
            'classic'. You can specify the flavor of the format used.

            > jupyter nbconvert --to html --template lab mynotebook.ipynb

            You can also pipe the output to stdout, rather than a file

            > jupyter nbconvert mynotebook.ipynb --stdout

            PDF is generated via latex
```

```
                > jupyter nbconvert mynotebook.ipynb --to pdf

                You can get (and serve) a Reveal.js-powered slideshow

                > jupyter nbconvert myslides.ipynb --to slides --post serve

                Multiple notebooks can be given at the command line in a couple of
                different ways:

                > jupyter nbconvert notebook*.ipynb
                > jupyter nbconvert notebook1.ipynb notebook2.ipynb

                or you can specify the notebooks list in a config file, containin
g::

                    c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

                > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.
```

In [3]:

```
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]:

```
# Load data
citibike_df = pd.read_csv(citibike_path)
weather_df = pd.read_csv(weather_path)
```

In [6]:

```
# 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]:

```
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]:

```
# Compute average daily temperature
weather_df['temperature_avg'] = (weather_df['temperature_2m_max'] + weather_df
```

In [6]:

```
# 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]:

```
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').dr
```

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_su
0	0	2015-01-01	5317	801.806658	4263206	-1.00	(
1	1	2015-01-02	11304	731.240977	8265948	1.45	(
2	2	2015-01-03	4478	655.284279	2934363	1.75	16
3	3	2015-01-04	7849	679.554211	5333821	10.00	'
4	4	2015-01-05	14506	637.811802	9252098	1.55	(

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', 'su
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:

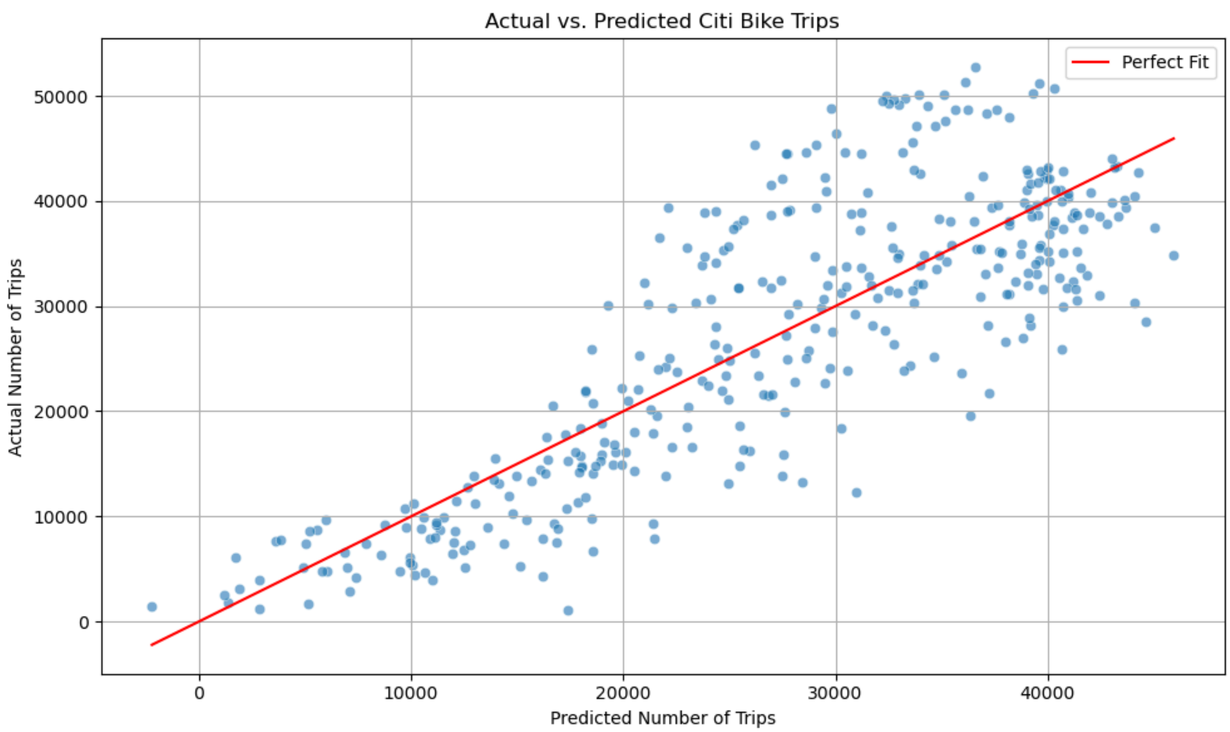
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.52e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Visualization

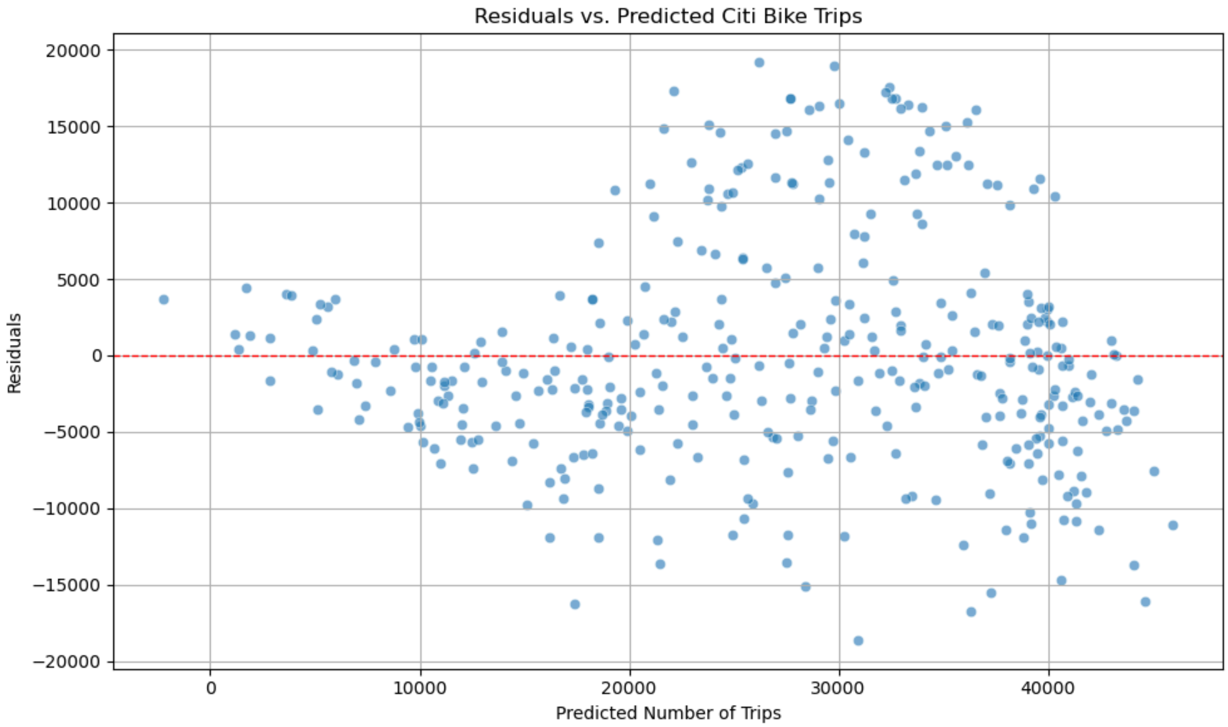
In [18]:
```
# Predict values using the fitted model
merged_df['predicted_trips'] = model.predict(X)
```

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',
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()
```

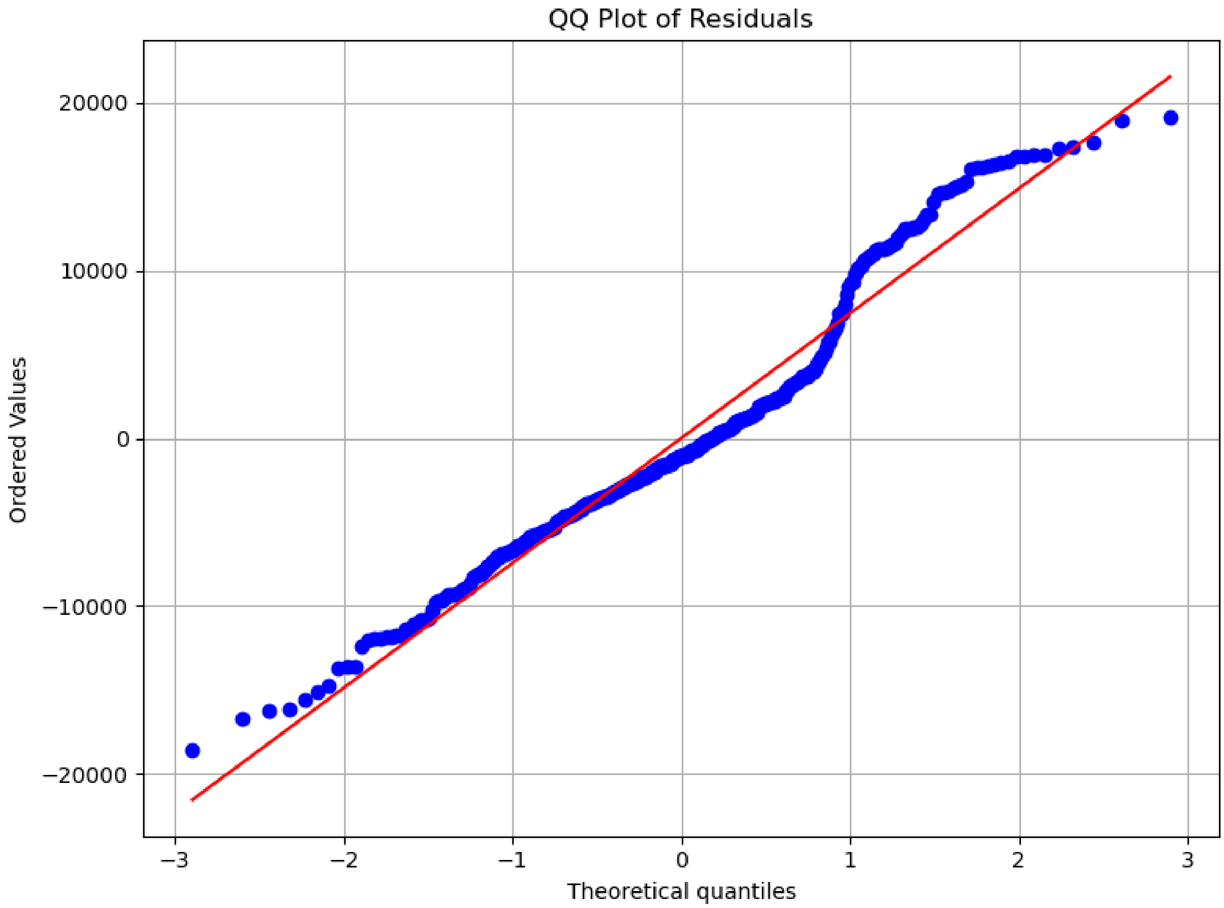


In [20]:
```
# Calculate residuals
merged_df['residuals'] = merged_df['num_trips'] - merged_df['predicted_trips']
```

In [21]:
```
# 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]:
```
# 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'] - merg
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_windspe
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.

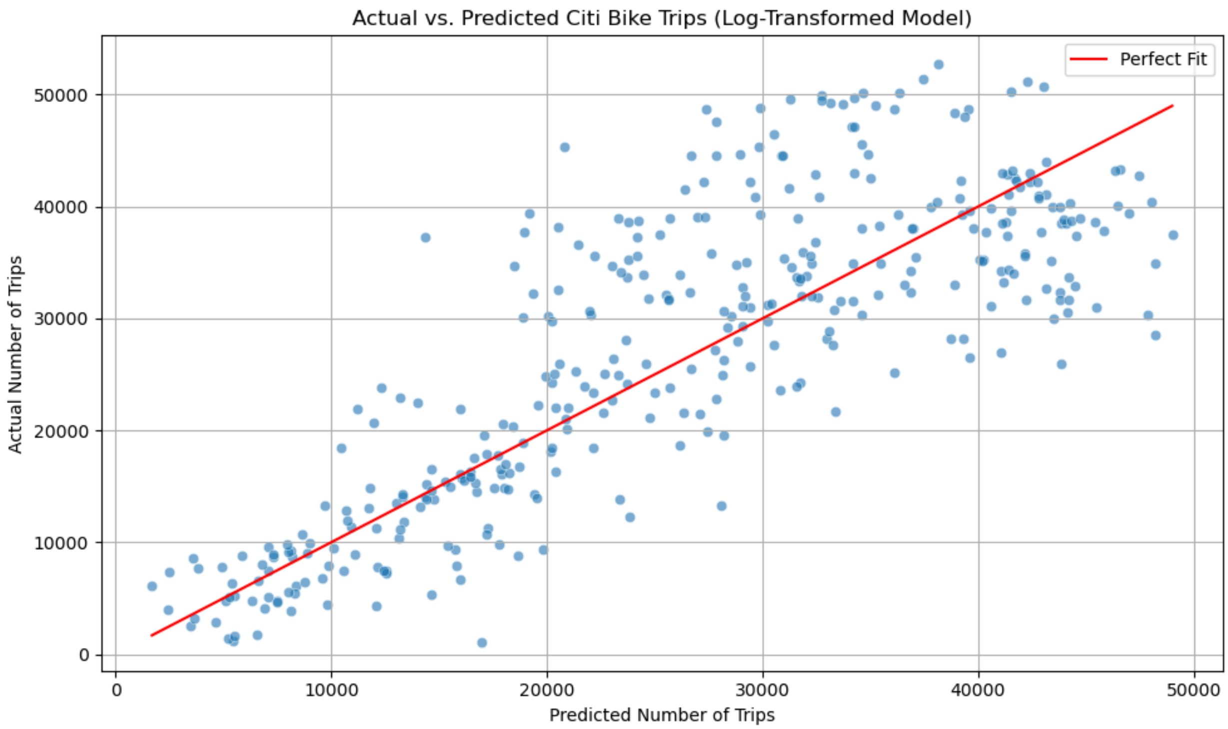
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

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_predicte
```

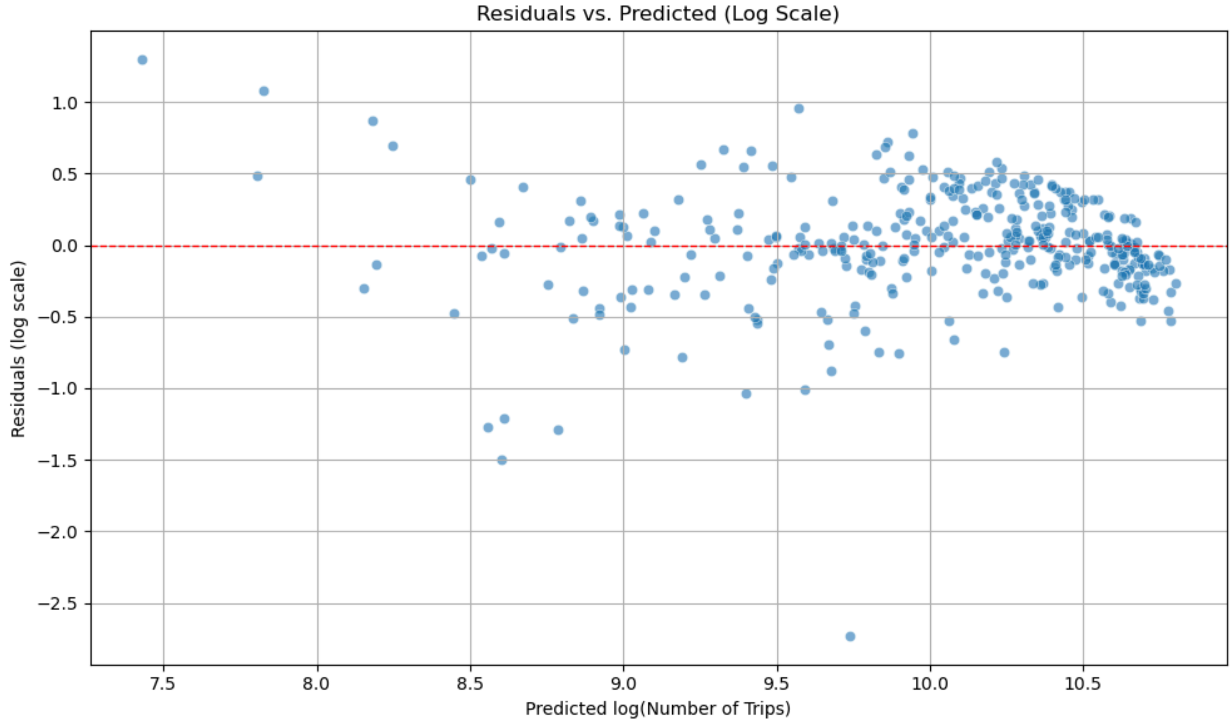
In [26]:
```
# Plot actual vs. predicted (original scale)
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x='backtransformed_predicted_trips',
    y='num_trips',
    data=merged_df,
    alpha=0.6
)
sns.lineplot(
    x='backtransformed_predicted_trips',
```

```
    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()
```

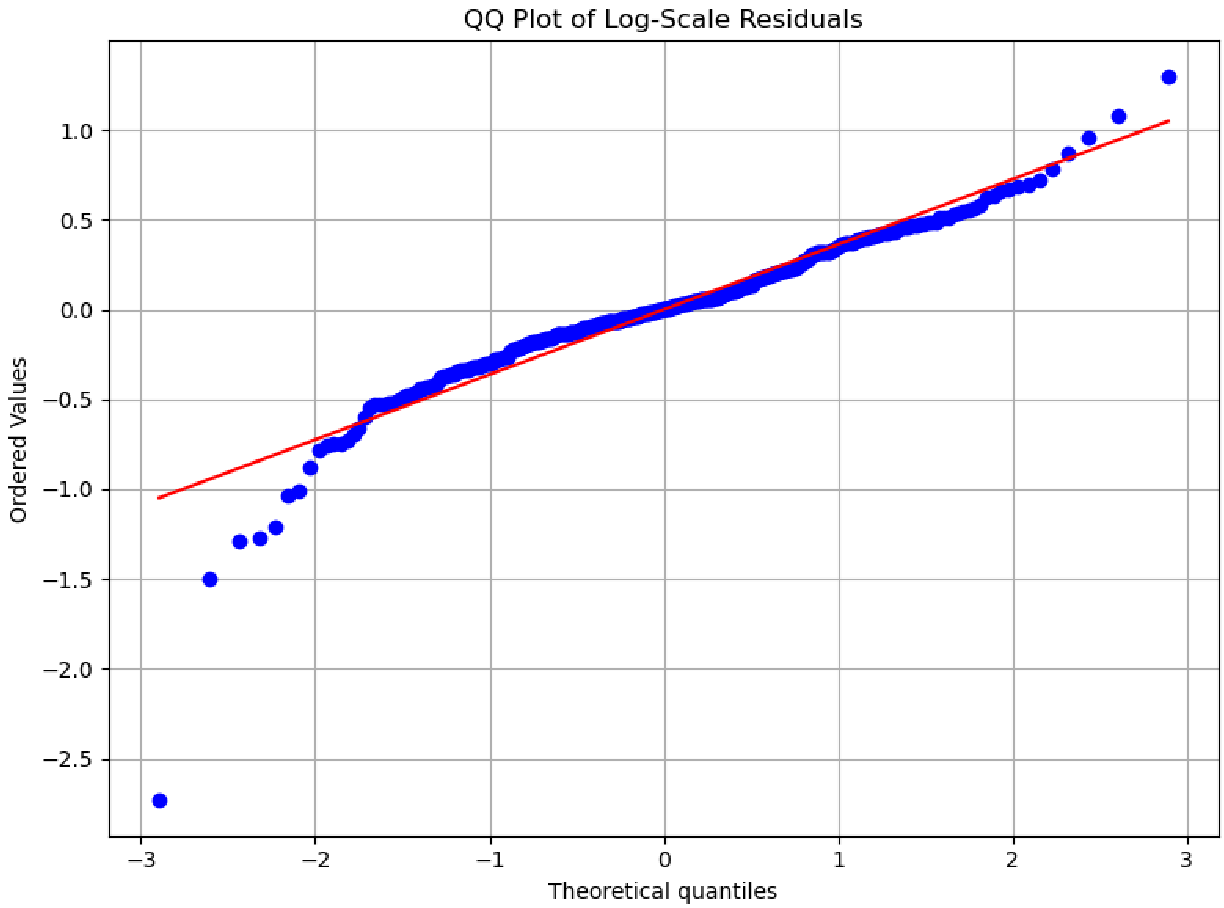


In [27]:
```
# Calculate residuals in log scale
merged_df['log_residuals'] = merged_df['log_num_trips'] - merged_df['log_predi
```

In [28]:
```
# 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]:
```
# 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

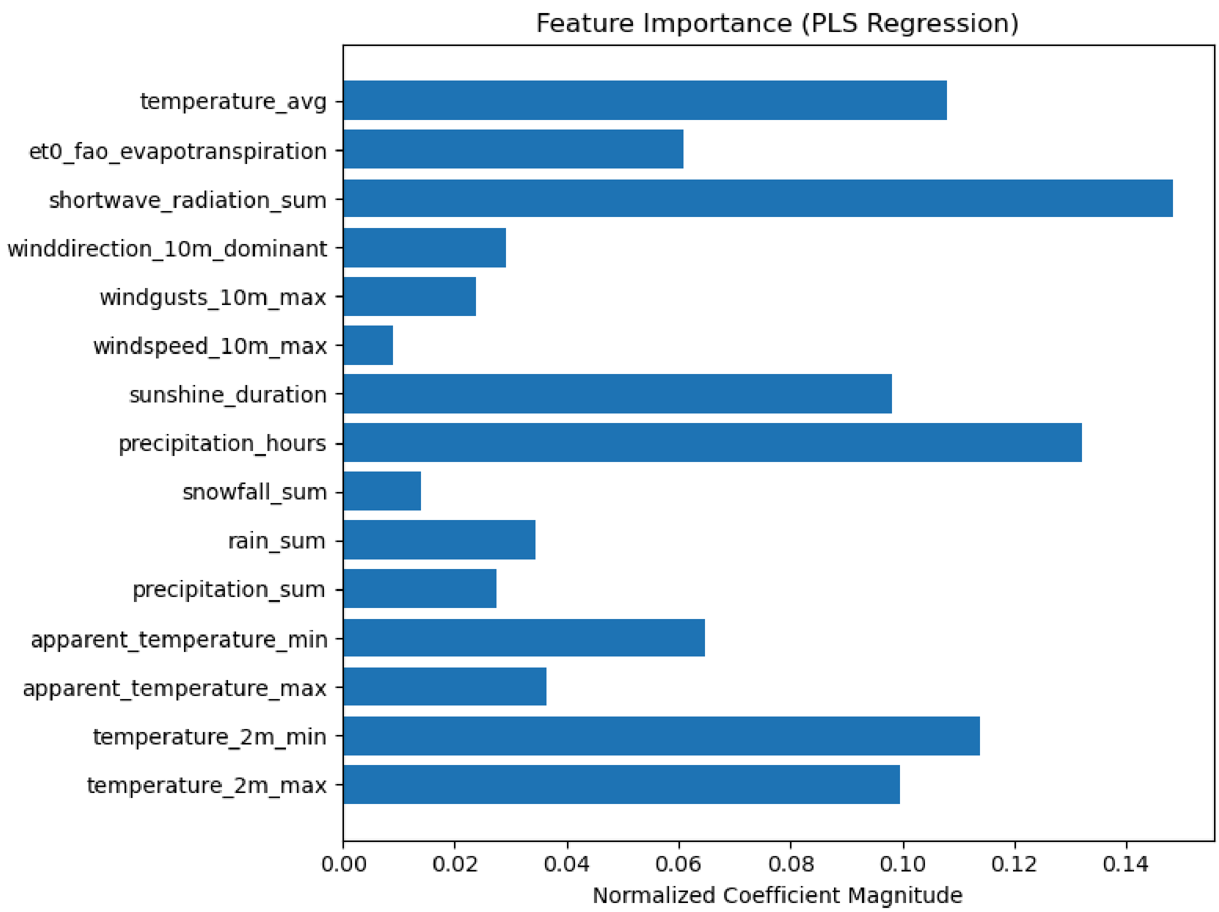
In [10]:
```
merged_df_pp = pd.merge(citibike_df, weather_df, on='date', how='inner').dropna
```

In [11]:
```
features = [
    'temperature_2m_max', 'temperature_2m_min', 'apparent_temperature_max', 'ap
    'precipitation_sum', 'rain_sum', 'snowfall_sum', 'precipitation_hours',
    'sunshine_duration', 'windspeed_10m_max', 'windgusts_10m_max', 'winddirecti
    '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,
```

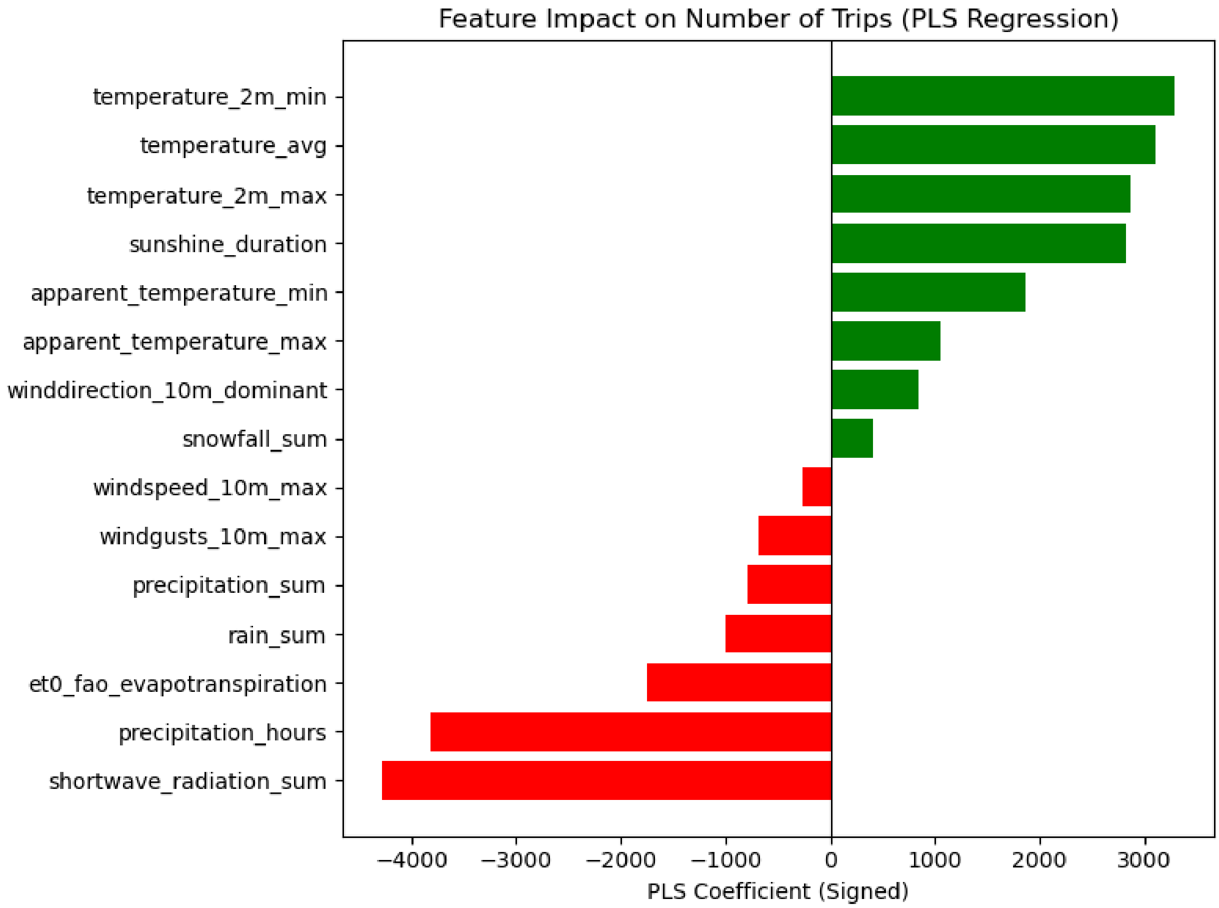
In [32]:
```
pls = PLSRegression(n_components=5)
pls.fit(X_train_scaled, y_train)

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['Coeffic
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()
```

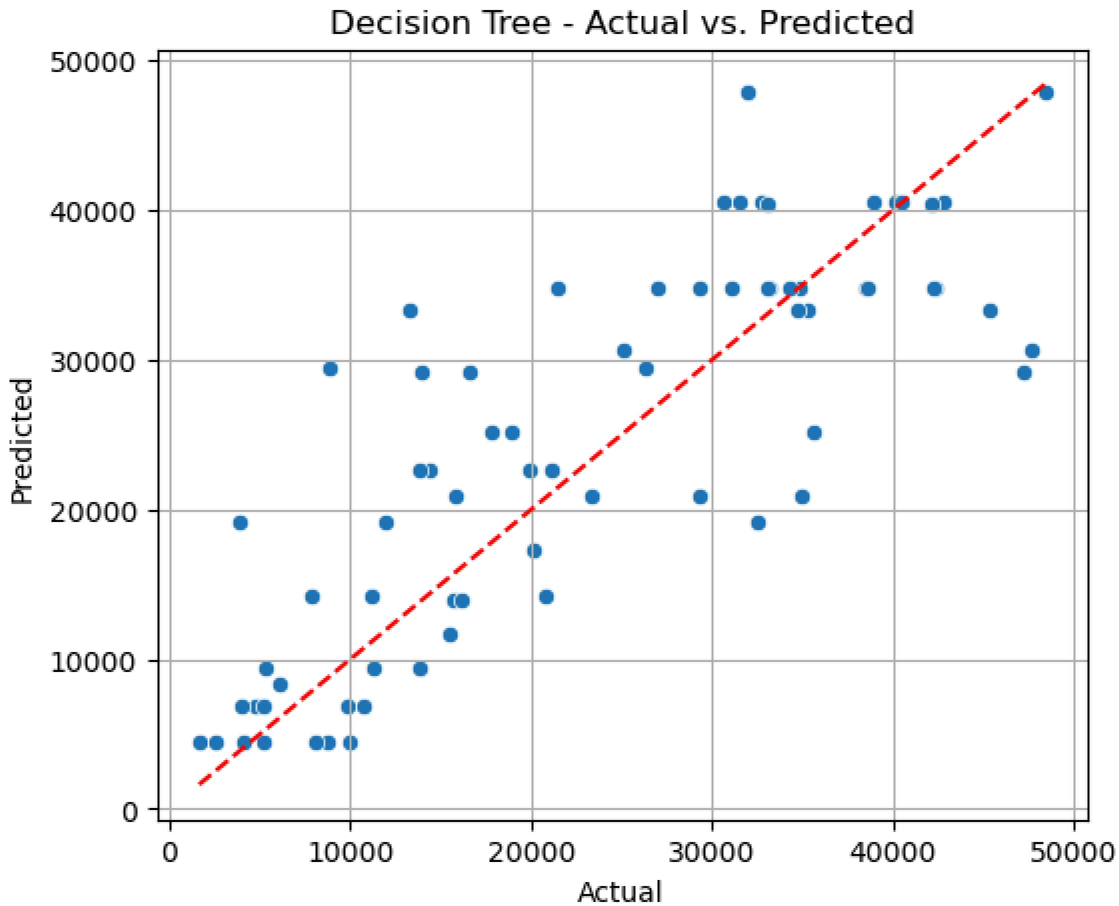
Decision Tree

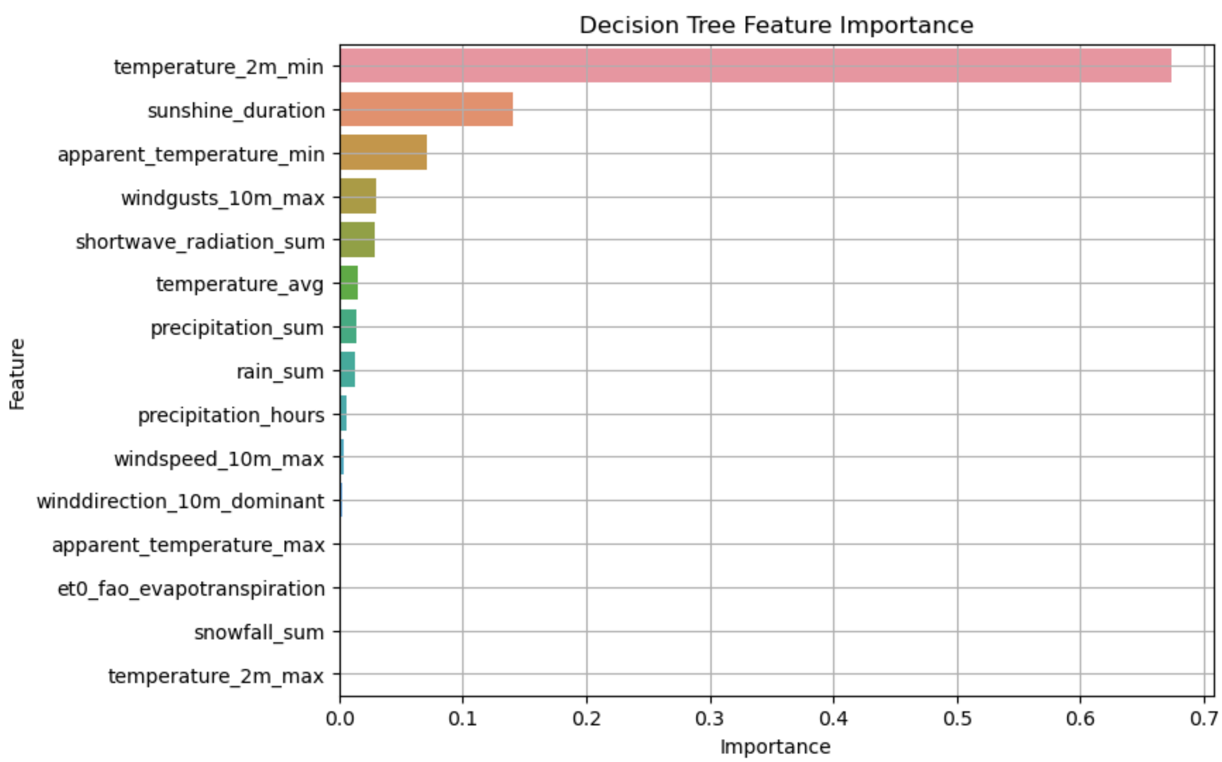
In [18]:
```
dt_param_dist = {
    'max_depth': randint(2, 20),
    'min_samples_split': randint(2, 20),
    'min_samples_leaf': randint(1, 10)
}

dt = DecisionTreeRegressor(random_state=42)
dt_search = RandomizedSearchCV(dt, dt_param_dist, n_iter=50, cv=5, scoring='r2
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_sample
s_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),
```

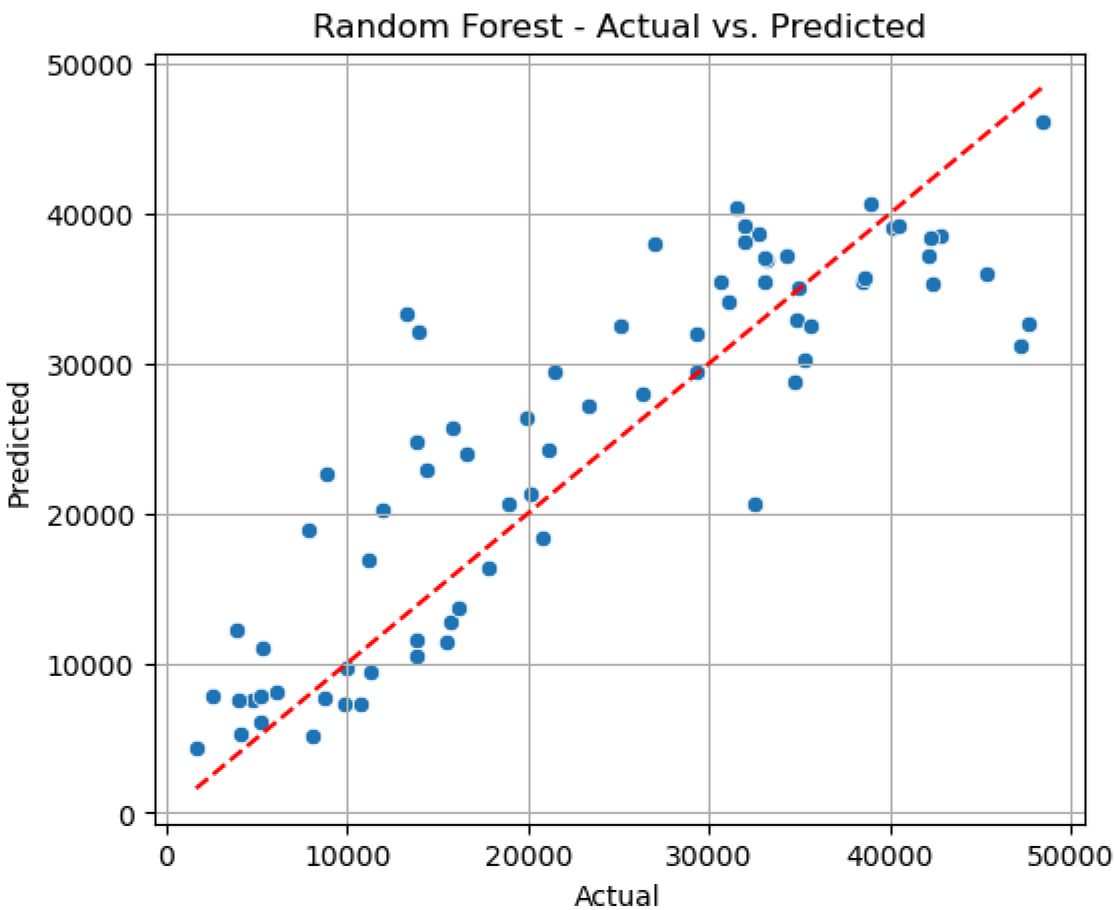
```
    'max_depth': randint(5, 30),
    'min_samples_split': randint(2, 10),
    'min_samples_leaf': randint(1, 10),
    'max_features': ['sqrt', 'log2']
}

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

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

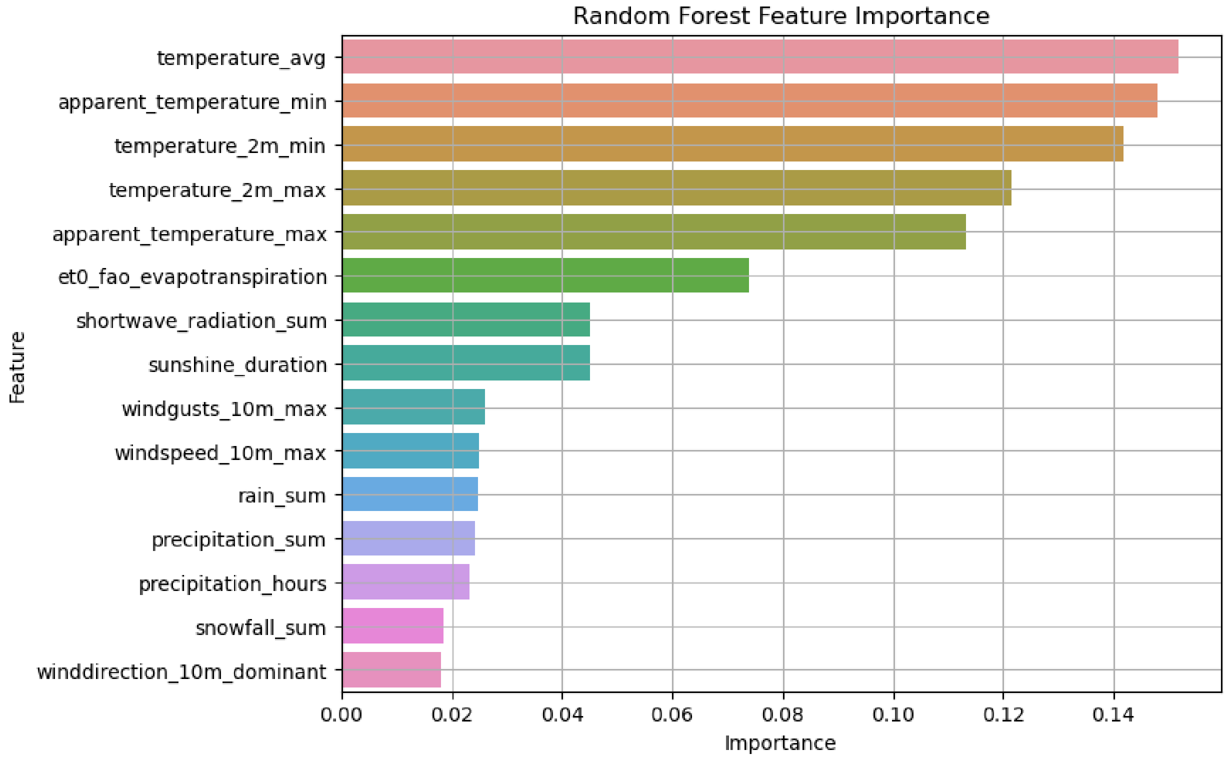
```
Best Random Forest Params: {'max_depth': 10, 'max_features': 'log2', 'min_samp
les_leaf': 1, 'min_samples_split': 2, 'n_estimators': 173}
```

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
```





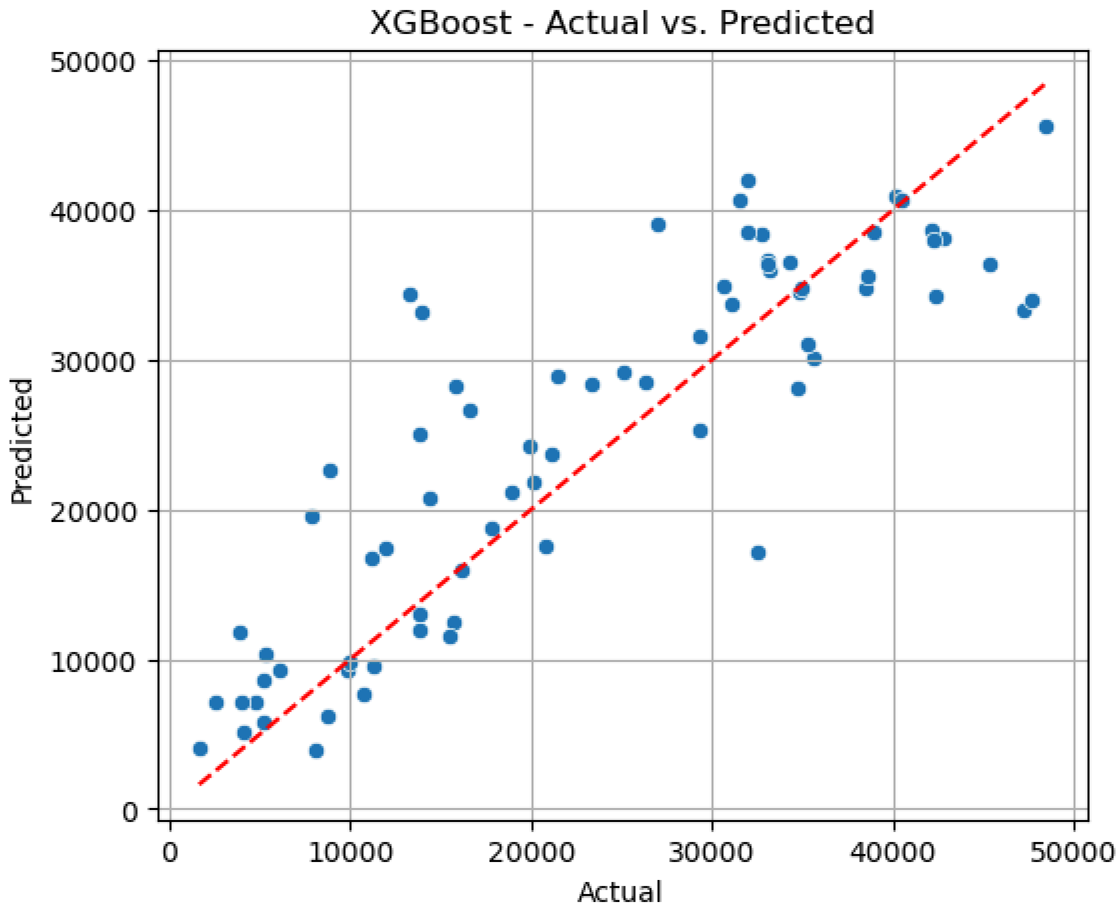
XGBoost

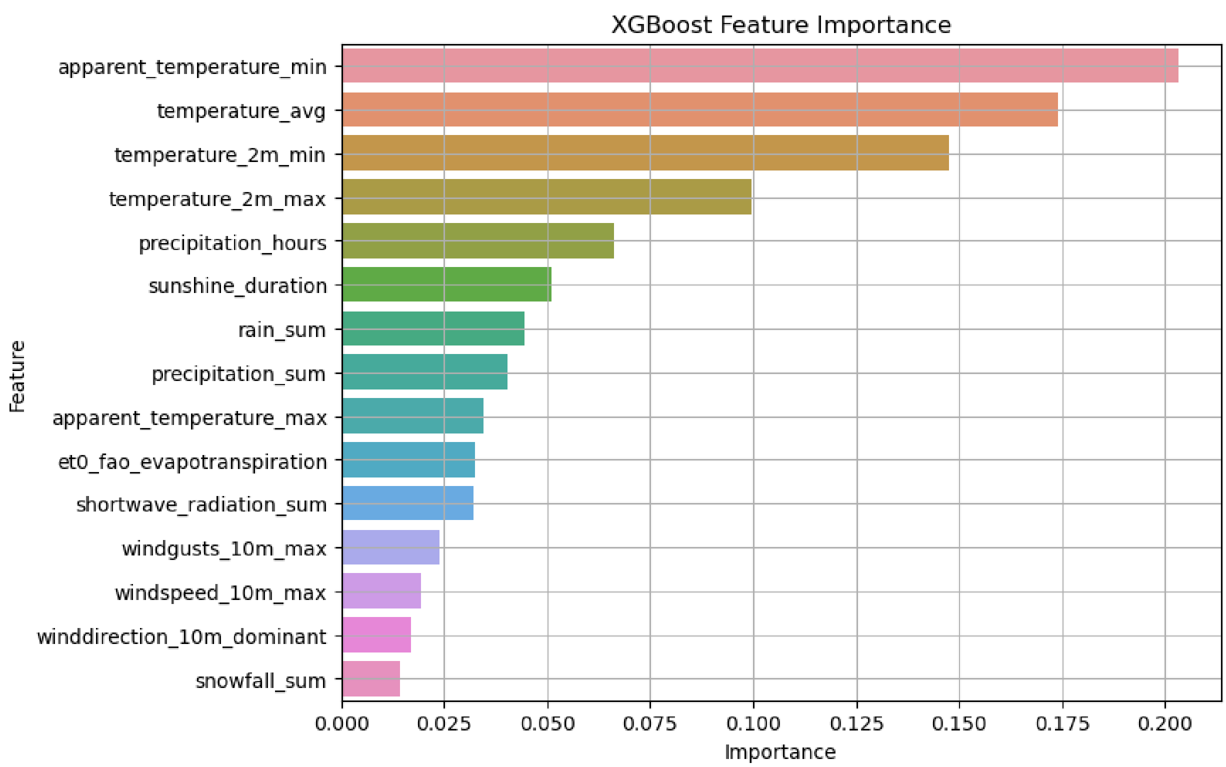
In [23]:
```
xgb_param_dist = {
    'n_estimators': randint(50, 200),
    'max_depth': randint(3, 15),
    'learning_rate': uniform(0.01, 0.3),
    'subsample': uniform(0.5, 0.5),
    'colsample_bytree': uniform(0.5, 0.5),
    'gamma': uniform(0, 5)
}

xgb = XGBRegressor(random_state=42, verbosity=0)
xgb_search = RandomizedSearchCV(xgb, xgb_param_dist, n_iter=50, cv=5, scoring=
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': 1.44875
72645688402, 'learning_rate': 0.058366386176201324, 'max_depth': 4, 'n_estimat
ors': 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
```





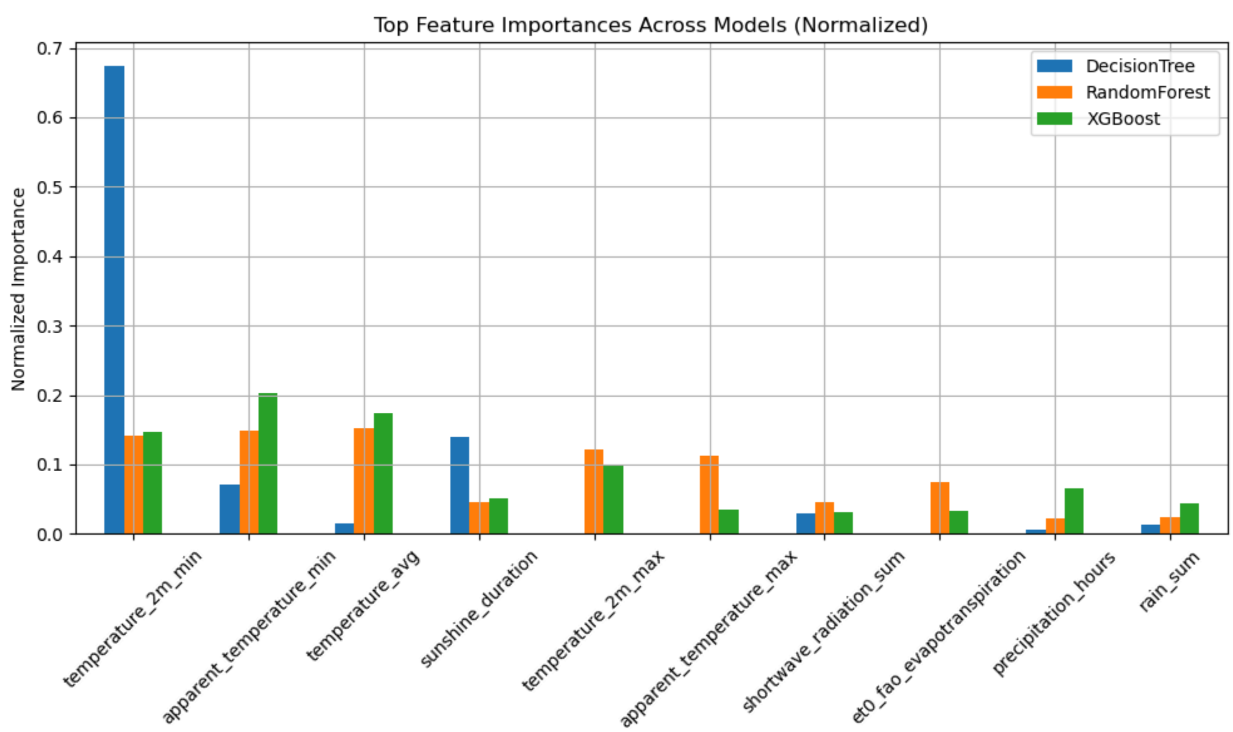
In [26]:
```
dt_importance = pd.Series(best_dt.feature_importances_, index=features, name='I
rf_importance = pd.Series(best_rf.feature_importances_, index=features, name='I
xgb_importance = pd.Series(best_xgb.feature_importances_, index=features, name=

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

```python
# 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_t
emperature_min', 'temperature_avg', 'sunshine_duration', 'temperature_2m_max']
```

In [27]:

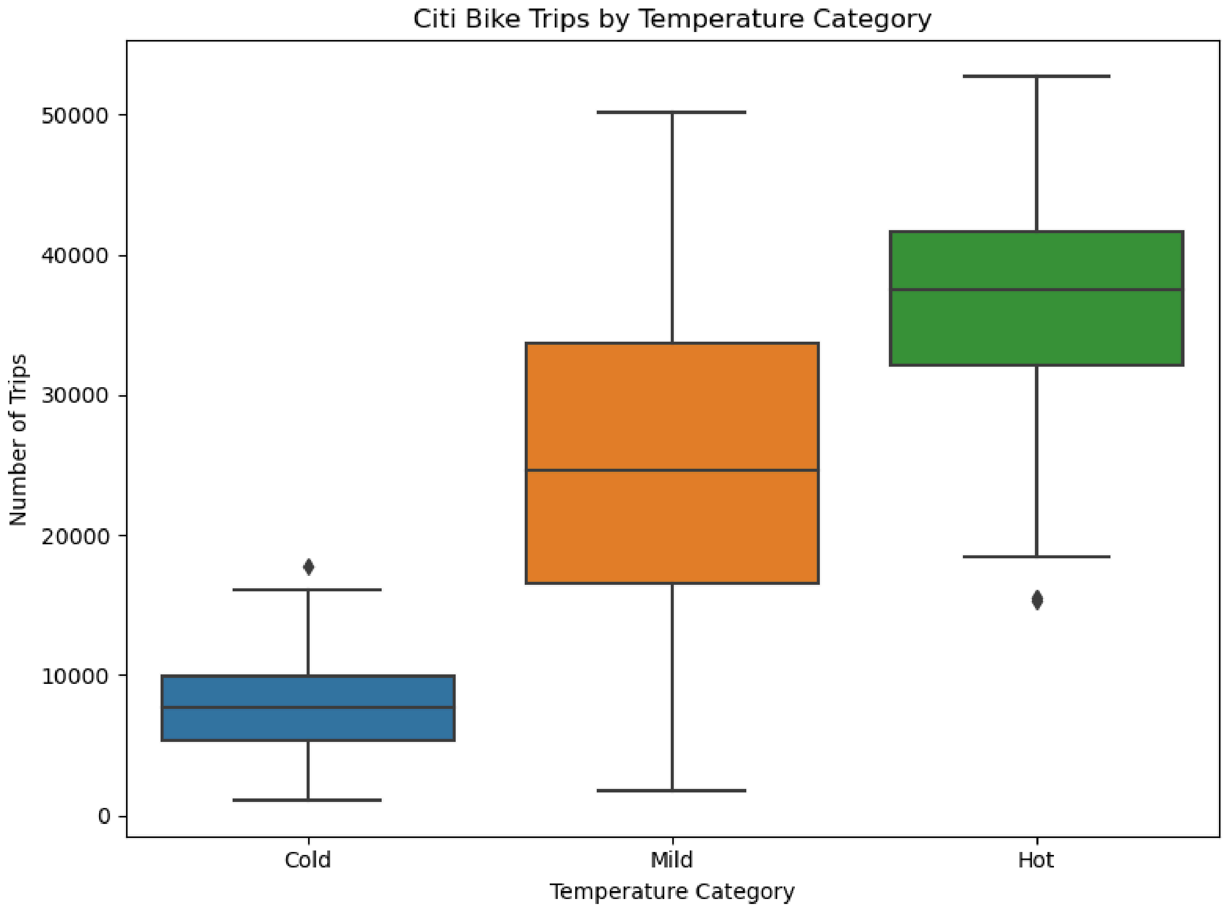
```python
top_n = 10
top_plot_df = normalized_df.sort_values('Mean', ascending=False).head(top_n)

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

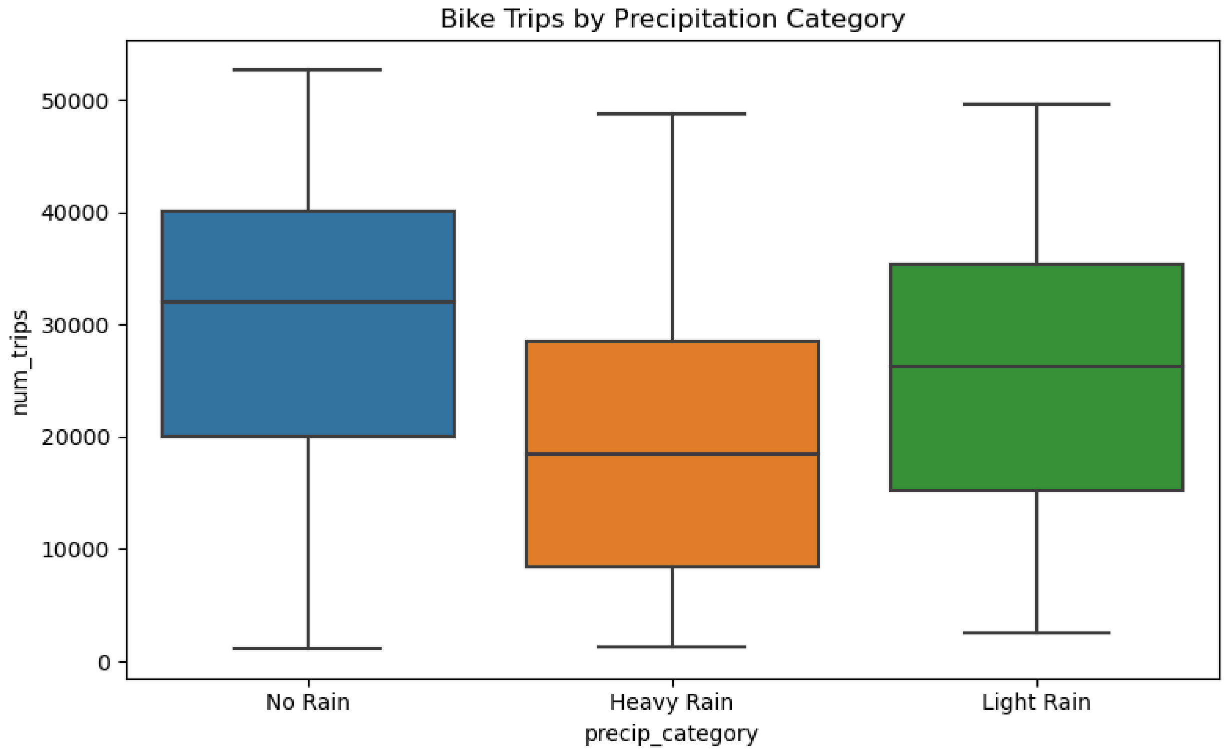
In [37]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import f_oneway
from statsmodels.stats.multicomp import pairwise_tukeyhsd

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

merged_df["temp_category"] = merged_df["temperature_2m_max"].apply(categorize_t

# 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_result)

# 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=9.84392
3705640121e-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]:
```
# 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_

# 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=3.0933
15843297417e-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
--------------------------------------------------------------------
```

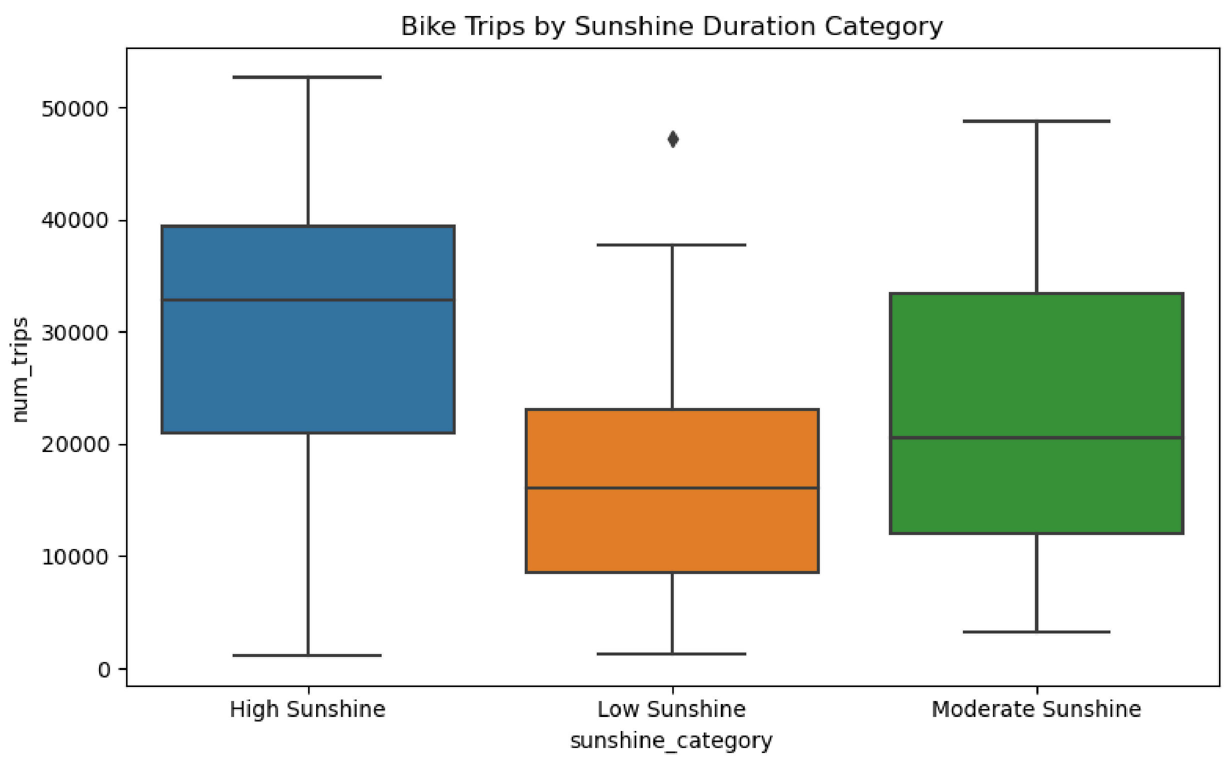


In [39]:

```
# 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(categori

# ANOVA for Sunshine
sunshine_groups = merged_df.groupby("sunshine_category")["num_trips"].apply(li
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    rejec
t
------------------------------------------------------------------------------
-
High Sunshine      Low Sunshine -12750.547    0.0 -17123.4046 -8377.6893   Tru
e
High Sunshine Moderate Sunshine -6559.2737 0.0049 -11447.7829 -1670.7646   Tru
e
 Low Sunshine Moderate Sunshine  6191.2733 0.0427    160.6584 12221.8881   Tru
e
------------------------------------------------------------------------------
-
```



In [ ]: