occurrences, the precision is 92%, highlighting that false alarms are rare, while the recall is slightly lower at 79%, meaning that some actual wildfires are missed.

The overall accuracy of 86% reflects the model's strong performance across both classes, with balanced macro-average precision, recall, and F1-scores of approximately 0.86. These numbers show the model's reliability, though the lower recall for wildfires shows room for improvement.

Impact:

The predictive models developed in this project have the potential to serve as a tool for fire risk assessment. It could be utilized to send early warning systems or to improve resource allocation strategies for firefighting efforts. This can highlight the areas that will be at higher risk, so they can plan accordingly. For a real-world application, fire departments could use the model to prioritize areas for surveillance or pre-deploy resources during high-risk periods. This approach could reduce response times and limit wildfire damage. It could be used for preventative measures and to set protocols on ways to protect communities. However, the model's performance highlights the need for further refinement. This could include additional data sources, such as real-time weather data for dynamic predictions. These additions could improve the model's accuracy and applicability.

Summary:

The models were trained using data from meteorological sources (NOAA), historical fire incidents, and weather conditions. By examining how past fire patterns relate to climate factors, the models aimed to predict future wildfire risks. Though human activity plays a significant role in wildfire ignition, this project focused on the natural factors influencing fire occurrence.

Model Performance

- Linear Regression: This model proved ineffective due to missing data and a small dataset. High mean squared error (MSE) and low R^2 values indicated poor predictive accuracy.
- Gradient Boosting Classifier (GBC): GBC delivered more refined predictions, learning iteratively from previous errors. However, it is prone to overfitting, requiring careful tuning. Despite this, it outperformed other models in terms of prediction accuracy.
- Random Forest: This model effectively handled nonlinear relationships and class imbalances, achieving a high AUC of 0.93. It identified temperature, precipitation, and wind speed as key predictors of wildfire risk, though recall for wildfires could be improved.

Random Forest and GBC performed better than Linear Regression, with GBC showing superior accuracy when tuned. For this application, the recall was prioritized over the accuracy, as minimizing false negatives (missed wildfires) is crucial for wildfire risk prediction. These models can improve wildfire prediction, resource allocation, and response planning. Future improvements could include integrating real-time data and expanding the models to account for human activity, further enhancing prediction accuracy and equity in wildfire management.

Linear Regression Model

In [9]:
```
#Linear Regression
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

#this version of data processing uses years 2016 - 2018

# File paths
file1 = '/Users/aydaozisik/Downloads/monthly_precipitation.csv'  # (2016 - 2022)
file2 = '/Users/aydaozisik/Downloads/full_year_2018.csv'  # (only 2018)
file3 = '/Users/aydaozisik/Downloads/Filtered_Fire_Incidents.csv'  # (2013 - 2020)
file4 = '/Users/aydaozisik/Downloads/full_year_2016.csv'  # (only 2016)
file5 = '/Users/aydaozisik/Downloads/full_year_2017.csv'  # (only 2017)


rain = pd.read_csv(file1)
fire_incidents = pd.read_csv(file3)
noaa_18 = pd.read_csv(file2)
noaa_16 = pd.read_csv(file4)
noaa_17 = pd.read_csv(file5)

#filter rain and fire datasets to include only the years 2016-2018
rain['DATE'] = pd.to_datetime(rain['DATE'], format='%Y-%m')
rain = rain[rain['DATE'].dt.year.between(2016, 2018)]  # Filter for 2016-2018


#remove rows where both LATITUDE and LONGITUDE = 0
fire_incidents = fire_incidents[~((fire_incidents['LATITUDE'] == 0) & (fire_incidents['LONGITUDE'] == 0))]

fire_incidents['DATE'] = pd.to_datetime(fire_incidents['DATE'], format='%Y-%m')  # Adjust format if necessary
fire_incidents = fire_incidents[fire_incidents['DATE'].dt.year.between(2016, 2018)]  # Filter for 2016-2018

rain['LATITUDE'] = rain['LATITUDE'].round(2)
rain['LONGITUDE'] = rain['LONGITUDE'].round(2)

fire_incidents['LATITUDE'] = fire_incidents['LATITUDE'].round(2)
fire_incidents['LONGITUDE'] = fire_incidents['LONGITUDE'].round(2)

noaa_16['LATITUDE'] = noaa_16['LATITUDE'].round(2)
noaa_16['LONGITUDE'] = noaa_16['LONGITUDE'].round(2)

noaa_17['LATITUDE'] = noaa_17['LATITUDE'].round(2)
noaa_17['LONGITUDE'] = noaa_17['LONGITUDE'].round(2)

noaa_18['LATITUDE'] = noaa_18['LATITUDE'].round(2)
noaa_18['LONGITUDE'] = noaa_18['LONGITUDE'].round(2)

#merge rain and fire datasets
merged_rain_fire = pd.merge(rain, fire_incidents, on=['LATITUDE', 'LONGITUDE'], how='inner')

#merged rain and fire data with the multiple NOAA datasets for respective years (2016-2018)
merged_all = pd.merge(merged_rain_fire, noaa_16, on=['LATITUDE', 'LONGITUDE'], how='left', suffixes=('', '_16'))
merged_all = pd.merge(merged_all, noaa_17, on=['LATITUDE', 'LONGITUDE'], how='left', suffixes=('', '_17'))
merged_all = pd.merge(merged_all, noaa_18, on=['LATITUDE', 'LONGITUDE'], how='left', suffixes=('', '_18'))


merged_all = merged_all.drop(columns=['STATION', 'NAME', 'ELEVATION'])


X = merged_all[['TotalPrecipitation', 'PRCP', 'TAVG']]  # Independent variables
y = merged_all['AcresBurned']  # Dependent variable (target)

# 7. Handle missing values (fill with 0 or another imputation method)
X = X.fillna(0)  # Fill missing feature values with 0
y = y.fillna(0)  # Fill missing target values with 0

# 8. Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 9. Create the linear regression model and train it
model = LinearRegression()
model.fit(X_train, y_train)
```

```python
# 10. Predict on the test set
y_pred = model.predict(X_test)

# 11. Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the results
print("Mean Squared Error:", mse)
print("R²:", r2)
```

```
Mean Squared Error: 110.46847596370779
R²: 0.002402376360975622
```

The second filtering method only uses the year 2018 from all three data sets:

In [10]:
```python
# Load the datasets
full_year = pd.read_csv('/Users/aydaozisik/Downloads/full_year_2018.csv')
fire_occurrences = pd.read_csv('/Users/aydaozisik/Downloads/Filtered_Fire_Incidents.csv')
rain = pd.read_csv('/Users/aydaozisik/Downloads/monthly_precipitation.csv')

#covnert to DATE format, although this was already done in csv files
full_year['DATE'] = pd.to_datetime(full_year['DATE'], format='%Y-%m')  # Convert full_year DATE column
fire_occurrences['DATE'] = pd.to_datetime(fire_occurrences['DATE'], format='%Y-%m')
rain['DATE'] = pd.to_datetime(rain['DATE'], format='%Y-%m')

# Filter fire_occurrences and rain datasets for 2018
fire_occurrences = fire_occurrences[fire_occurrences['DATE'].dt.year == 2018]
rain = rain[rain['DATE'].dt.year == 2018]

# Round LATITUDE and LONGITUDE to 1 decimal place for both datasets
full_year['LATITUDE'] = full_year['LATITUDE'].round(2)
full_year['LONGITUDE'] = full_year['LONGITUDE'].round(2)

fire_occurrences['LATITUDE'] = fire_occurrences['LATITUDE'].round(2)
fire_occurrences['LONGITUDE'] = fire_occurrences['LONGITUDE'].round(2)

rain['LATITUDE'] = rain['LATITUDE'].round(2)
rain['LONGITUDE'] = rain['LONGITUDE'].round(2)

#filter columns
rain = rain[['LATITUDE', 'LONGITUDE', 'DATE', 'TotalPrecipitation']]
full_year = full_year[['LATITUDE', 'LONGITUDE', 'DATE', 'EVAP', 'AWND', 'TAVG', 'PRCP', 'WDMV']]
fire_occurrences = fire_occurrences[['LATITUDE', 'LONGITUDE', 'DATE', 'AcresBurned']]

#merge full_year with fire_occurrences on LATITUDE, LONGITUDE, and DATE
merged_data = pd.merge(
    full_year,
    fire_occurrences,
    on=['LATITUDE', 'LONGITUDE', 'DATE'],
    how='left'
)

#merge rain data with LATITUDE, LONGITUDE, and DATE
merged_data = pd.merge(
    merged_data,
    rain,
    on=['LATITUDE', 'LONGITUDE', 'DATE'],
    how='left'
)

# fill missing values in the dataset with 0
# this most like creates immense inaccuracy?
merged_data_v2 = merged_data.fillna(0)

# predicting AcresBurned
x = merged_data_v2[['TAVG', 'PRCP', 'AWND', 'WDMV','EVAP', 'TotalPrecipitation']]  # Independent variables
y = merged_data_v2['AcresBurned']  # Dependent variable (continuous: AcresBurned)



#split into training and testing
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

#train linear model
model = LinearRegression()
model.fit(X_train, y_train)

# predictions on test set
y_pred = model.predict(X_test)
```

```python
#find mean squared error and R²
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse:.4f}")
print(f"R²: {r2:.4f}")
```

```
Mean Squared Error: 18.7016
R²: -0.0005
```

In [11]:
```python
merged_data_v2
```

Out[11]:

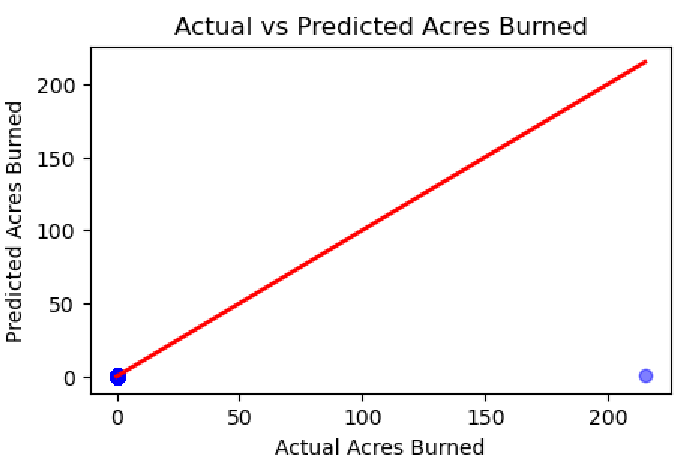
	LATITUDE	LONGITUDE	DATE	EVAP	AWND	TAVG	PRCP	WDMV	AcresBurned	TotalPrecipitation
0	39.02	-122.41	2018-01-01	0.0	0.0	49.3	0.00	0.0	0.0	0.0
1	39.02	-122.41	2018-02-01	0.0	0.0	51.3	0.00	0.0	0.0	0.0
2	39.02	-122.41	2018-03-01	0.0	0.0	49.4	0.00	0.0	0.0	0.0
3	39.02	-122.41	2018-04-01	0.0	0.0	56.7	0.00	0.0	0.0	0.0
4	41.87	-120.16	2018-01-01	0.0	0.0	38.4	1.63	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...
12353	39.74	-121.49	2018-09-01	0.0	0.0	73.4	0.00	0.0	0.0	0.0
12354	39.74	-121.49	2018-10-01	0.0	0.0	64.5	0.00	0.0	0.0	0.0
12355	39.74	-121.49	2018-12-01	0.0	0.0	44.9	0.00	0.0	0.0	0.0
12356	34.05	-118.94	2018-09-01	0.0	0.0	66.6	0.00	0.0	0.0	0.0
12357	34.05	-118.94	2018-10-01	0.0	0.0	66.5	0.00	0.0	0.0	0.0

12358 rows × 10 columns

In [13]:
```python
# I dont think VIF function is necessary since we are missing a lot of values
#add constant term for the intercept
X = sm.add_constant(X)

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

#OLS regression results
print(model.summary())

#VIF (Variance Inflation Factor)
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Calculate VIF for each feature in X
vif_data = pd.DataFrame()
vif_data["Feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

# Display VIF values
print("\nVIF results:")
print(vif_data)
```

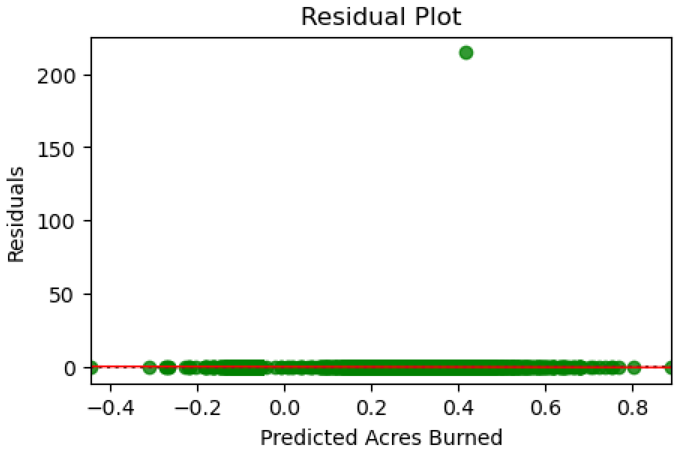
```
                            OLS Regression Results
==============================================================================
Dep. Variable:            AcresBurned   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.9101
Date:                Fri, 13 Dec 2024   Prob (F-statistic):              0.486
Time:                        20:35:01   Log-Likelihood:                -45442.
No. Observations:               12358   AIC:                         9.090e+04
Df Residuals:                   12351   BIC:                         9.095e+04
Df Model:                           6
Covariance Type:            nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
const                 -0.0475      0.143     -0.333      0.739      -0.327       0.232
EVAP                  -0.0365      0.162     -0.225      0.822      -0.354       0.281
AWND                   0.0152      0.053      0.286      0.775      -0.089       0.119
TAVG                   0.0061      0.003      2.025      0.043       0.000       0.012
PRCP                  -0.0065      0.036     -0.181      0.856      -0.077       0.064
WDMV               -4.308e-05      0.001     -0.055      0.956      -0.002       0.001
TotalPrecipitation    -0.0492      0.108     -0.457      0.648      -0.260       0.162
==============================================================================
Omnibus:                    47365.895   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):      39190333345.028
Skew:                          89.113   Prob(JB):                         0.00
Kurtosis:                    8725.287   Cond. No.                         277.
==============================================================================

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

VIF results:
              Feature       VIF
0               const  2.750194
1                EVAP  1.783333
2                AWND  1.225906
3                TAVG  1.167263
4                PRCP  1.100303
5                WDMV  1.775397
6  TotalPrecipitation  1.172663
```

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

#linear regression
plt.figure(figsize=(5, 3))
plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', lw=2)

# Labels and title
plt.xlabel('Actual Acres Burned')
plt.ylabel('Predicted Acres Burned')
plt.title('Actual vs Predicted Acres Burned')
plt.show()
```



In [16]:
```
#linear regression
residuals = y_test - y_pred
plt.figure(figsize=(5, 3))
sns.residplot(x=y_pred, y=residuals, lowess=True, color="g", line_kws={'color': 'red', 'lw': 1})
plt.xlabel('Predicted Acres Burned')
```

```python
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()
```



In [ ]:

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.model_selection import train_test_split, KFold, GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, roc_curve, auc, classification_report,
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
#Load the datasets.
full_year = pd.read_csv("/Users/jojihun/Desktop/full_year_2018_sorted.csv")
fire_occurrences = pd.read_csv("/Users/jojihun/Desktop/Fire_Occurrences_2018_sorted

#Remove time from 'DATE'column and 'DISCOVERYDATETIME'column to merge two datasets
full_year['DATE'] = full_year['DATE'].apply(lambda x: x.split(' ')[0])
fire_occurrences['DATE'] = fire_occurrences['DISCOVERYDATETIME'].apply(lambda x: x.

#Make a new column 'YEAR_MONTH' on both datasets
full_year['YEAR_MONTH'] = full_year['DATE'].apply(lambda x: '-'.join(x.split('-')[:
fire_occurrences['YEAR_MONTH'] = fire_occurrences['DATE'].apply(lambda x: '-'.join(

#Since the locations on the both datasets are represented as very detailed latitude
#I will round latitude and longitude values to one decimal point for matching.
full_year['LATITUDE'] = full_year['LATITUDE'].round(1)
full_year['LONGITUDE'] = full_year['LONGITUDE'].round(1)
fire_occurrences['X'] = fire_occurrences['X'].round(1)
fire_occurrences['Y'] = fire_occurrences['Y'].round(1)

#Select relevant columns from the datasets for merging.
full_year = full_year[['LATITUDE', 'LONGITUDE', 'YEAR_MONTH', 'EVAP', 'AWND', 'TAVG
fire_occurrences = fire_occurrences[['X', 'Y', 'YEAR_MONTH', 'TOTALACRES']]

#Merge the datasets on latitude/longitude and YEAR_MONTH.
merged_data = pd.merge(
    full_year,
    fire_occurrences,
    left_on=['LATITUDE', 'LONGITUDE', 'YEAR_MONTH'],
    right_on=['Y', 'X', 'YEAR_MONTH'],
    how='left'
)

#Create a binary column 'FIRE_OCCURRED' to indicate if a fire occurred or not.
merged_data['FIRE_OCCURRED'] = (merged_data['TOTALACRES'] > 0).astype(int)

#Drop unnecessary columns 'X' and 'Y' after merging.
merged_data = merged_data.drop(columns=['X', 'Y'])

#Display the distribution of the target variable('FIRE_OCCURRED').
merged_data['FIRE_OCCURRED'].value_counts()

#Fill the remaining missing values with 0 to model the dataset later.
merged_data_v1 = merged_data.fillna(0)
```

```
merged_data_v1
```

Out[2]:

	LATITUDE	LONGITUDE	YEAR_MONTH	EVAP	AWND	TAVG	PRCP	WDMV	TOTA
0	39.0	-122.4	2018-01	0.0	0.0	49.3	0.00	0.0	
1	37.6	-119.0	2018-01	0.0	0.0	34.0	1.93	0.0	
2	38.4	-123.0	2018-01	0.0	0.0	49.6	11.18	0.0	
3	39.3	-121.6	2018-01	0.0	0.0	0.0	4.57	0.0	
4	41.6	-122.9	2018-01	0.0	0.0	39.6	0.00	0.0	
...	...	...	...	...	...	...	...	...	
12436	35.7	-118.5	2018-12	0.0	0.0	45.0	0.00	0.0	
12437	36.4	-121.6	2018-12	0.0	0.0	0.0	3.49	0.0	
12438	41.0	-122.0	2018-12	0.0	0.0	0.0	8.64	0.0	
12439	41.8	-122.0	2018-12	0.0	0.0	33.2	0.00	0.0	
12440	38.4	-122.0	2018-12	0.0	5.6	48.8	0.93	0.0	

12441 rows × 10 columns

In [3]:

```
#Boosting

#Evaporation (EVAP)
#Average Wind Speed (AWND)
#Average Temperature (TAVG)
#Precipitation (PRCP)
#Wind Movement (WDMV)

#Load and preprocess the dataset.
x = merged_data_v1[['EVAP', 'AWND', 'TAVG', 'PRCP', 'WDMV']]
y = merged_data_v1['FIRE_OCCURRED']

#Split the dataset into training and testing sets(80:20).
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_sta

#Standardize the training and test features using mean and standard deviation of th
mean_train = x_train.mean()
std_train = x_train.std()
x_train_sc = (x_train - mean_train) / std_train
x_test_sc = (x_test - mean_train) / std_train

#Use KFold Cross-Validation for model evaluation and define model hyperparameters.
kf = KFold(n_splits = 10, shuffle = True, random_state = 2018)
n_estimators = 100
max_leaf_nodes = 10

#Store indices for each fold in cross-validation.
```

```
kfold_index = []
for index in kf.split(x_train_sc):
    kfold_index.append(index)

#CV loop to compute CV accuracy scores.
cv_scores = []
for train_index, val_index in kf.split(x_train_sc):
    x_kf_train, x_kf_val = x_train_sc.iloc[train_index], x_train_sc.iloc[val_index]
    y_kf_train, y_kf_val = y_train.iloc[train_index], y_train.iloc[val_index]

    #Train Gradient Boosting Classifier.
    gbm = GradientBoostingClassifier(n_estimators = n_estimators, max_leaf_nodes =
    gbm.fit(x_kf_train, y_kf_train)

    #Compute cv accuracy scores.
    y_val_pred = gbm.predict(x_kf_val)
    val_accuracy = accuracy_score(y_kf_val, y_val_pred)
    cv_scores.append(val_accuracy)

#Mean CV Accuracy result
mean_cv_accuracy = np.mean(cv_scores)
print("Mean CV Accuracy:", mean_cv_accuracy)

#Train the final model on the entire training set.
final_gbm = GradientBoostingClassifier(n_estimators = n_estimators, max_leaf_nodes
final_gbm.fit(x_train_sc, y_train)

#Gradient Boosting Classifier Test Accuracy result
y_pred_test = final_gbm.predict(x_test_sc)
gbm_model = accuracy_score(y_test, y_pred_test)
print("GBC Test Accuracy:", gbm_model)
print(classification_report(y_test, y_pred_test))
```

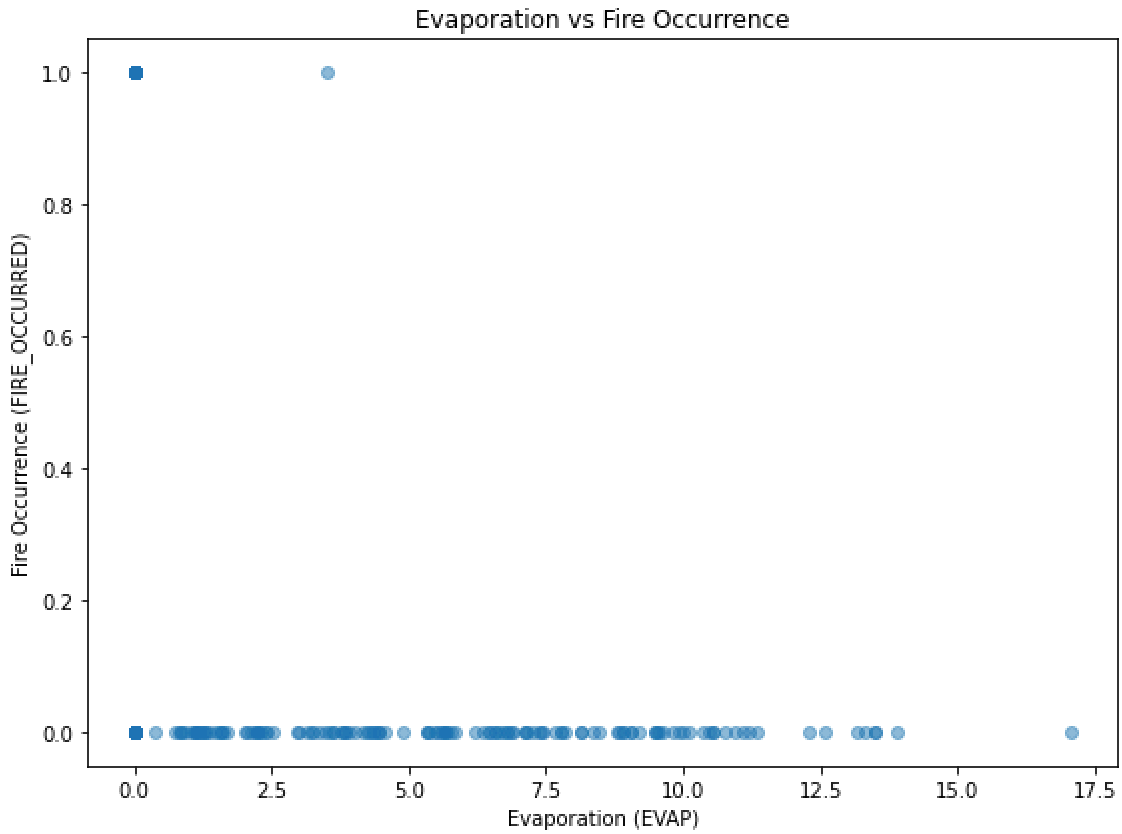
```
Mean CV Accuracy: 0.967945651954552
GBC Test Accuracy: 0.9682603455202893
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      2412
           1       0.33      0.03      0.05        77

    accuracy                           0.97      2489
   macro avg       0.65      0.51      0.52      2489
weighted avg       0.95      0.97      0.95      2489
```

In [4]:
```
mse = mean_squared_error(y_test, y_pred_test)
r2 = r2_score(y_test, y_pred_test)
print(f"\nMean Squared Error (MSE): {mse:.4f}")
print(f"R² Score: {r2:.4f}")
```

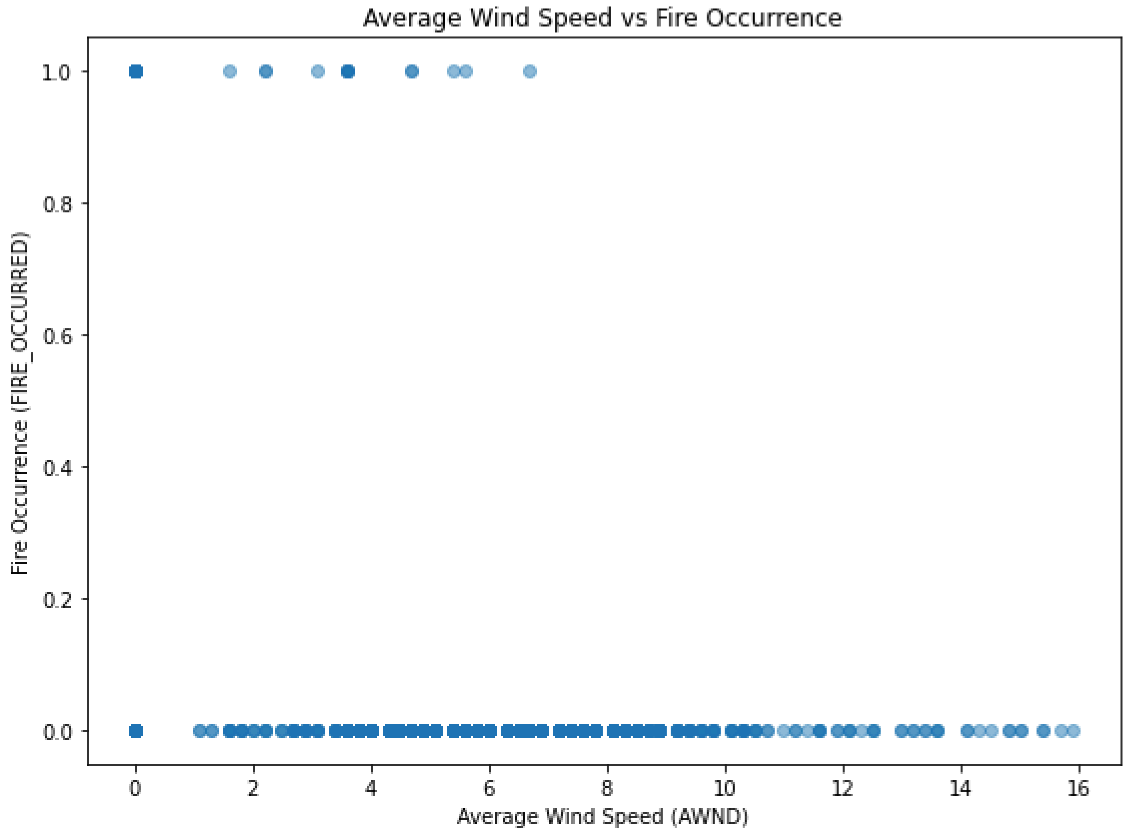
```
Mean Squared Error (MSE): 0.0317
R² Score: -0.0587
```

In [5]:
```
plt.figure(figsize=(8, 6))
plt.scatter(merged_data_v1['EVAP'], merged_data_v1['FIRE_OCCURRED'], alpha=0.5)
plt.xlabel('Evaporation (EVAP)')
plt.ylabel('Fire Occurrence (FIRE_OCCURRED)')
```

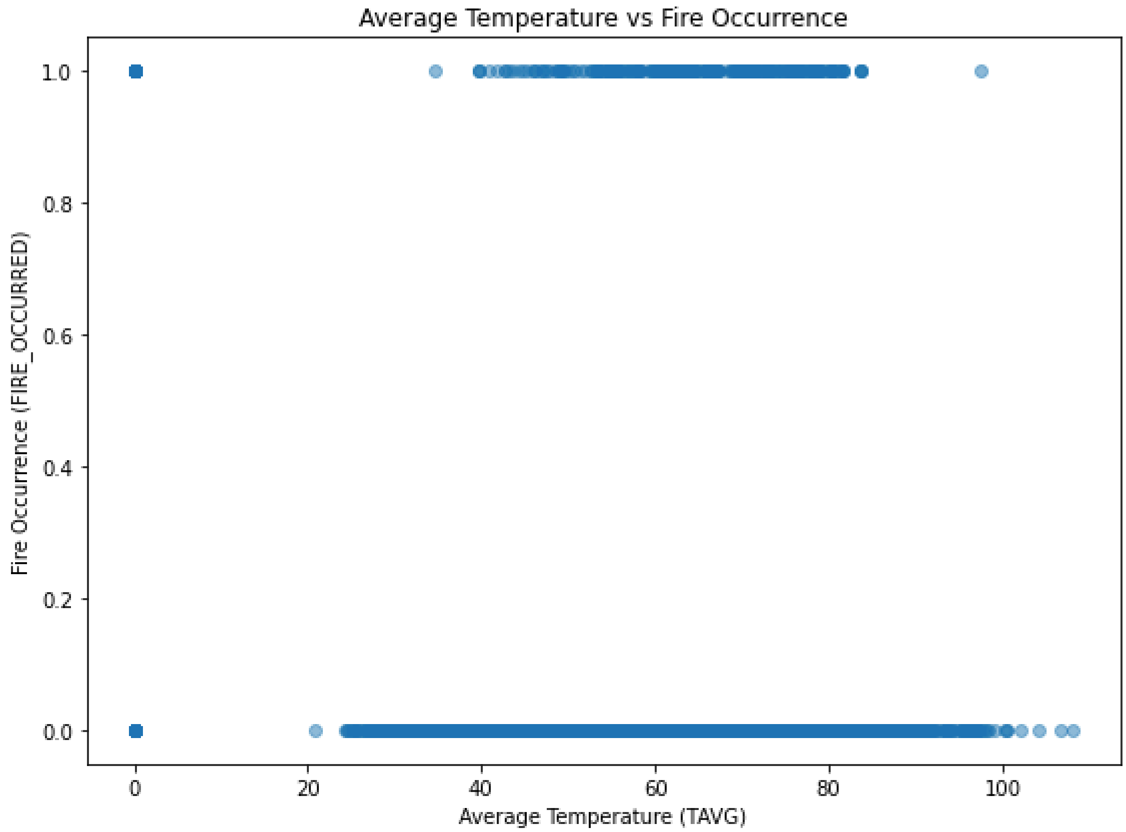
```
plt.title('Evaporation vs Fire Occurrence')
plt.tight_layout()
plt.savefig('Evaporation_vs_Fire_Occurrence.png')
plt.show()
```



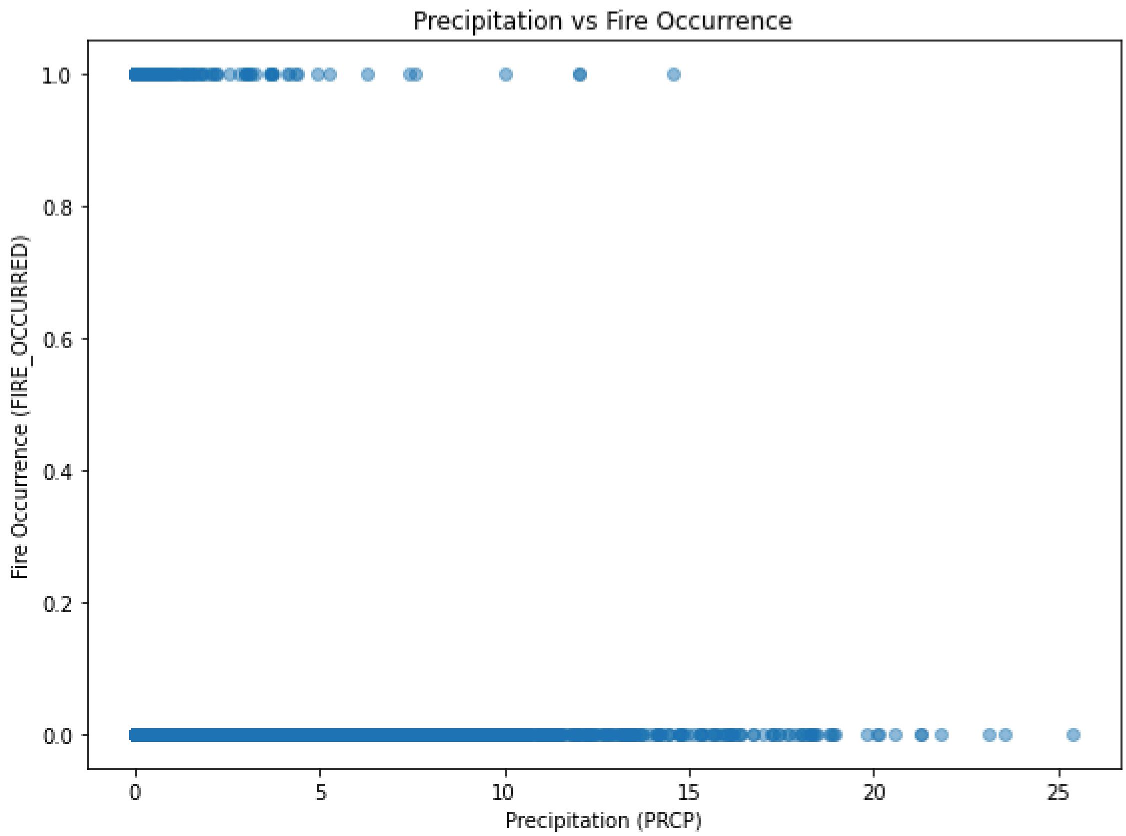
In [6]:
```
plt.figure(figsize=(8, 6))
plt.scatter(merged_data_v1['AWND'], merged_data_v1['FIRE_OCCURRED'], alpha=0.5)
plt.xlabel('Average Wind Speed (AWND)')
plt.ylabel('Fire Occurrence (FIRE_OCCURRED)')
plt.title('Average Wind Speed vs Fire Occurrence')
plt.tight_layout()
plt.savefig('Average_Wind_Speed_vs_Fire_Occurrence.png')
plt.show()
```



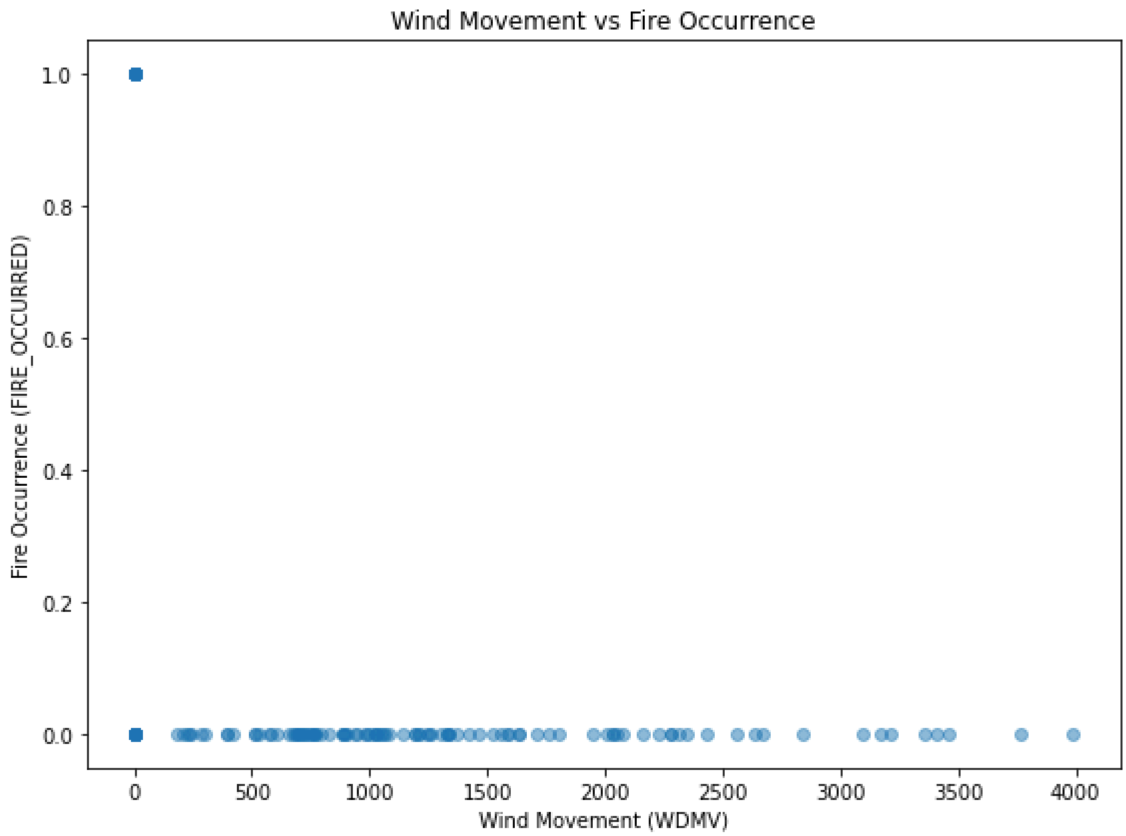
In [7]:
```
plt.figure(figsize=(8, 6))
plt.scatter(merged_data_v1['TAVG'], merged_data_v1['FIRE_OCCURRED'], alpha=0.5)
plt.xlabel('Average Temperature (TAVG)')
plt.ylabel('Fire Occurrence (FIRE_OCCURRED)')
plt.title('Average Temperature vs Fire Occurrence')
plt.tight_layout()
plt.savefig('Average_Temperature_vs_Fire_Occurrence.png')
plt.show()
```



In [8]:
```
plt.figure(figsize=(8, 6))
plt.scatter(merged_data_v1['PRCP'], merged_data_v1['FIRE_OCCURRED'], alpha=0.5)
plt.xlabel('Precipitation (PRCP)')
plt.ylabel('Fire Occurrence (FIRE_OCCURRED)')
plt.title('Precipitation vs Fire Occurrence')
plt.tight_layout()
plt.savefig('Precipitation_vs_Fire_Occurrence.png')
plt.show()
```



In [9]:
```
plt.figure(figsize=(8, 6))
plt.scatter(merged_data_v1['WDMV'], merged_data_v1['FIRE_OCCURRED'], alpha=0.5)
plt.xlabel('Wind Movement (WDMV)')
plt.ylabel('Fire Occurrence (FIRE_OCCURRED)')
plt.title('Wind Movement vs Fire Occurrence')
plt.tight_layout()
plt.savefig('Wind Movement_vs_Fire_Occurrence.png')
plt.show()
```



In [10]:

```
feature_importances = final_gbm.feature_importances_

feature_names = x.columns
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importances
})

print("\nFeature importances:")
print(feature_importances)
plt.figure(figsize=(8, 6))
plt.bar(importance_df['Feature'], importance_df['Importance'], alpha=0.7)
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance')
plt.show()
```

```
Feature importances:
[2.10732360e-02 1.08745034e-01 6.39046997e-01 2.30678991e-01
 4.55741831e-04]
```