Trisha Manandhar 0369859

```
# Imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import time
import statsmodels.api as sm
from sklearn.model_selection import train_test_split, GridSearchCV,
cross_val_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score, confusion_matrix
from sklearn.dummy import DummyRegressor
from joblib import Parallel, delayed
import warnings
warnings.filterwarnings('ignore')

#Load dataset
df = pd.read_csv('wildfire.csv')
print("Data Shape:", df.shape)
df.head()
```

```
Data Shape: (55367, 43)

   Unnamed: 0.1  Unnamed: 0 fire_name  fire_size fire_size_class  \
0             0           0       NaN       10.0               C
1             1           1       NaN        3.0               B
2             2           2       NaN       60.0               C
3             3           3    WNA  1        1.0               B
4             4           4       NaN        2.0               B

    stat_cause_descr   latitude   longitude state disc_clean_date  ...
\
0  Missing/Undefined  18.105072  -66.753044    PR       2/11/2007  ...

1              Arson  35.038330  -87.610000    TN      12/11/2006  ...

2              Arson  34.947800  -88.722500    MS       2/29/2004  ...

3     Debris Burning  39.641400 -119.308300    NV        6/6/2005  ...

4      Miscellaneous  30.700600  -90.591400    LA       9/22/1999  ...


  Wind_cont Hum_pre_30 Hum_pre_15  Hum_pre_7   Hum_cont Prec_pre_30  \
0  3.250413  78.216590  76.793750  76.381579  78.724370         0.0
```

```
1  2.122320  70.840000  65.858911  55.505882  81.682678        59.8
2  3.369050  75.531629  75.868613  76.812834  65.063800       168.8
3  0.000000  44.778429  37.140811  35.353846   0.000000        10.4
4 -1.000000  -1.000000  -1.000000  -1.000000  -1.000000        -1.0

   Prec_pre_15 Prec_pre_7 Prec_cont  remoteness
0          0.0        0.0       0.0    0.017923
1          8.4        0.0      86.8    0.184355
2         42.2       18.1     124.5    0.194544
3          7.2        0.0       0.0    0.487447
4         -1.0       -1.0      -1.0    0.214633

[5 rows x 43 columns]
```

```
print('Columns:', df.columns.tolist())
```

```
Columns: ['Unnamed: 0.1', 'Unnamed: 0', 'fire_name', 'fire_size',
'fire_size_class', 'stat_cause_descr', 'latitude', 'longitude',
'state', 'disc_clean_date', 'cont_clean_date', 'discovery_month',
'disc_date_final', 'cont_date_final', 'putout_time', 'disc_date_pre',
'disc_pre_year', 'disc_pre_month', 'wstation_usaf', 'dstation_m',
'wstation_wban', 'wstation_byear', 'wstation_eyear', 'Vegetation',
'fire_mag', 'weather_file', 'Temp_pre_30', 'Temp_pre_15',
'Temp_pre_7', 'Temp_cont', 'Wind_pre_30', 'Wind_pre_15', 'Wind_pre_7',
'Wind_cont', 'Hum_pre_30', 'Hum_pre_15', 'Hum_pre_7', 'Hum_cont',
'Prec_pre_30', 'Prec_pre_15', 'Prec_pre_7', 'Prec_cont', 'remoteness']
```

```
print("\nBasic Info:")
print(df.info())

print("\nSummary Statistics:")
print(df.describe())
```

```
Basic Info:
<class 'pandas.core.frame.DataFrame'>
Index: 18918 entries, 3 to 55351
Data columns (total 40 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   fire_size          18918 non-null  float64
 1   fire_size_class    18918 non-null  object
 2   stat_cause_descr   18918 non-null  int64
 3   latitude           18918 non-null  float64
 4   longitude          18918 non-null  float64
 5   state              18918 non-null  int64
 6   cont_clean_date    18918 non-null  object
 7   discovery_month    18918 non-null  object
 8   disc_date_final    18918 non-null  object
 9   cont_date_final    18918 non-null  object
 10  putout_time        18918 non-null  object
```

```
 11  disc_date_pre     18918 non-null  object 
 12  disc_pre_year     18918 non-null  int64  
 13  disc_pre_month    18918 non-null  object 
 14  wstation_usaf     18918 non-null  object 
 15  dstation_m        18918 non-null  float64
 16  wstation_wban     18918 non-null  int64  
 17  wstation_byear    18918 non-null  int64  
 18  wstation_eyear    18918 non-null  int64  
 19  Vegetation        18918 non-null  int64  
 20  fire_mag          18918 non-null  float64
 21  weather_file      18918 non-null  object 
 22  Temp_pre_30       18918 non-null  float64
 23  Temp_pre_15       18918 non-null  float64
 24  Temp_pre_7        18918 non-null  float64
 25  Temp_cont         18918 non-null  float64
 26  Wind_pre_30       18918 non-null  float64
 27  Wind_pre_15       18918 non-null  float64
 28  Wind_pre_7        18918 non-null  float64
 29  Wind_cont         18918 non-null  float64
 30  Hum_pre_30        18918 non-null  float64
 31  Hum_pre_15        18918 non-null  float64
 32  Hum_pre_7         18918 non-null  float64
 33  Hum_cont          18918 non-null  float64
 34  Prec_pre_30       18918 non-null  float64
 35  Prec_pre_15       18918 non-null  float64
 36  Prec_pre_7        18918 non-null  float64
 37  Prec_cont         18918 non-null  float64
 38  remoteness        18918 non-null  float64
 39  year              18918 non-null  int32  
dtypes: float64(22), int32(1), int64(7), object(10)
memory usage: 5.8+ MB
None

Summary Statistics:
           fire_size  stat_cause_descr      latitude     longitude  \
count   18918.000000      18918.000000  18918.000000  18918.000000   
mean     4391.650101          2.575959     38.554115    -99.752638   
std     21714.729933          2.515652      7.468966     17.595707   
min         0.510000          0.000000     17.983333   -165.116700   
25%         1.500000          1.000000     33.350100   -113.044236   
50%         5.000000          2.000000     36.409683    -95.482900   
75%       100.000000          3.000000     42.855000    -85.158516   
max    538049.000000         12.000000     69.047200    -67.047639   

              state  disc_pre_year    dstation_m  wstation_wban  \
count  18918.000000   18918.000000  18918.000000   18918.000000   
mean      14.696638    2005.281848  44036.211132   59517.271487   
std        9.885414       7.053115  27845.948388   40262.762699   
min        0.000000    1991.000000    128.528883     100.000000   
```

```
25%        5.000000    1999.000000   23282.882862   14943.000000
50%       14.000000    2006.000000   38779.144670   63885.000000
75%       22.000000    2011.000000   58628.418048   99999.000000
max       49.000000    2015.000000  224153.661800   99999.000000

       wstation_byear  wstation_eyear  ...    Hum_pre_30    Hum_pre_15
\
count    18918.000000    18918.000000  ...  18918.000000  18918.000000

mean      1981.839306     2016.309916  ...     51.878355     49.112908

std         23.910196        6.339265  ...     22.921503     24.062070

min       1931.000000     1993.000000  ...      0.000000      0.000000

25%       1973.000000     2015.000000  ...     40.394013     36.034394

50%       1984.000000     2020.000000  ...     60.122327     57.431148

75%       2006.000000     2020.000000  ...     68.396226     67.168916

max       2014.000000     2020.000000  ...     94.000000     94.000000


          Hum_pre_7      Hum_cont   Prec_pre_30   Prec_pre_15
Prec_pre_7  \
count  18918.000000  18918.000000  18918.000000  18918.000000
18918.000000
mean      47.364133     13.906023     34.976081     16.559948
6.886949
std       24.437431     23.264780    124.014866     79.681293
42.267077
min        0.000000      0.000000      0.000000      0.000000
0.000000
25%       33.280263      0.000000      0.000000      0.000000
0.000000
50%       54.415067      0.000000      0.500000      0.000000
0.000000
75%       66.023454     28.547078     30.200000      9.700000
1.300000
max       95.240000     92.000000   3267.000000   2527.000000
1638.000000

          Prec_cont    remoteness          year
count  18918.000000  18918.000000  18918.000000
mean       1.746358      0.259709   2005.321334
std       13.796265      0.161475      7.063931
min        0.000000      0.000390   1992.000000
25%        0.000000      0.142429   1999.000000
50%        0.000000      0.207152   2006.000000
```

```
75%          0.000000      0.377674   2011.000000
max        591.600000      0.988892   2015.000000

[8 rows x 30 columns]

# Datacleaning
df.drop(columns=['Unnamed: 0', 'Unnamed: 0.1', 'fire_name',
'disc_clean_date'], errors='ignore', inplace=True)
df.replace(-1.0, np.nan, inplace=True)
df.dropna(inplace=True)

#Categorical encoding
df['stat_cause_descr'] = pd.factorize(df['stat_cause_descr'])[0]
df['state'] = pd.factorize(df['state'])[0]

# Feature Engineering
X = df.drop(columns=['fire_size'])
y = df['fire_size']
X = X.select_dtypes(include=[np.number])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

#Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Model 1: Linear Regression
lr_model = LinearRegression()
start = time.time()
lr_model.fit(X_train_scaled, y_train)
lr_train_time = time.time() - start
y_pred_lr = lr_model.predict(X_test_scaled)

# Model 2: Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, max_depth=20,
random_state=42, n_jobs=-1)
start = time.time()
rf_model.fit(X_train_scaled, y_train)
rf_train_time = time.time() - start
y_pred_rf = rf_model.predict(X_test_scaled)

# Baseline: Dummy Regressor
dummy_model = DummyRegressor(strategy="mean")
start = time.time()
dummy_model.fit(X_train_scaled, y_train)
dummy_train_time = time.time() - start
y_dummy = dummy_model.predict(X_test_scaled)
```

```python
# Evaluation Function
def evaluate_model(name, y_true, y_pred, train_time=None):
    print(f"\n {name}")
    print("MAE:", mean_absolute_error(y_true, y_pred))
    print("RMSE:", np.sqrt(mean_squared_error(y_true, y_pred)))
    print("R²:", r2_score(y_true, y_pred))
    if train_time:
        print(f"Training Time: {train_time:.4f} seconds")

# Evaluate Models
evaluate_model("Linear Regression", y_test, y_pred_lr, lr_train_time)
evaluate_model("Random Forest", y_test, y_pred_rf, rf_train_time)
evaluate_model("Dummy Regressor", y_test, y_dummy, dummy_train_time)
```

```
 Linear Regression
MAE: 4925.116963320564
RMSE: 16575.806397551492
R²: 0.24124971667218387
Training Time: 0.3835 seconds

 Random Forest
MAE: 3553.1760385430775
RMSE: 15613.97228539606
R²: 0.3267500290362758
Training Time: 12.7714 seconds

 Dummy Regressor
MAE: 6822.52938940741
RMSE: 19033.2988441466
R²: -0.00040917974944720825
Training Time: 0.0029 seconds
```

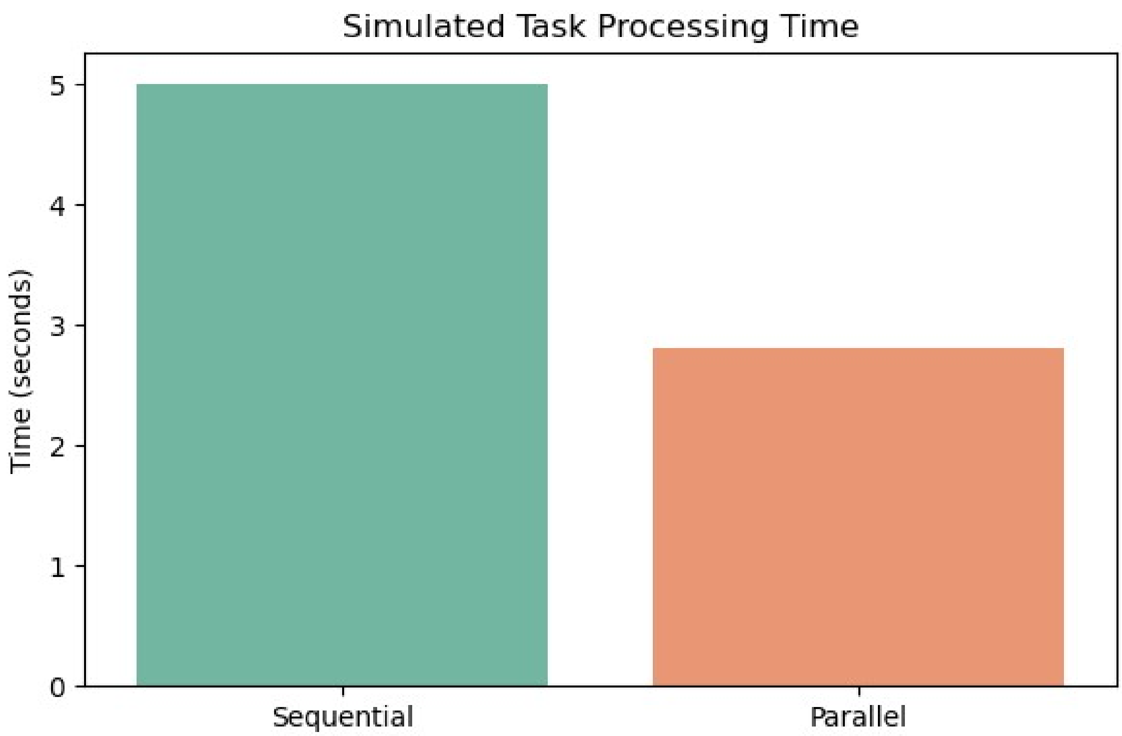
```python
# OLS Summary
X_train_ols = sm.add_constant(X_train_scaled)
ols = sm.OLS(y_train, X_train_ols).fit()
print(ols.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:              fire_size   R-squared:
0.209
Model:                            OLS   Adj. R-squared:
0.207
Method:                 Least Squares   F-statistic:
142.2
Date:                Thu, 17 Jul 2025   Prob (F-statistic):
0.00
Time:                        12:31:50   Log-Likelihood:            -
```

```
1.7125e+05
No. Observations:                 15134   AIC:
3.426e+05
Df Residuals:                     15105   BIC:
3.428e+05
Df Model:                            28

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const       4468.6443    161.668     27.641      0.000    4151.755
4785.534
x1          -133.9676    165.173     -0.811      0.417    -457.726
189.791
x2          1854.3969    242.091      7.660      0.000    1379.868
2328.925
x3           722.6235    370.558      1.950      0.051      -3.715
1448.962
x4          -386.1987    172.897     -2.234      0.026    -725.098
-47.299
x5           461.3081    222.098      2.077      0.038      25.969
896.647
x6           203.1649    179.488      1.132      0.258    -148.653
554.983
x7           -62.1871    164.183     -0.379      0.705    -384.007
259.632
x8          -106.2265    191.457     -0.555      0.579    -481.505
269.052
x9           135.6719    191.147      0.710      0.478    -238.999
510.343
x10         -117.8080    174.269     -0.676      0.499    -459.396
223.780
x11         1.018e+04    241.906     42.083      0.000    9706.051
1.07e+04
x12         -431.8429    661.557     -0.653      0.514   -1728.575
864.889
x13          704.6670    947.890      0.743      0.457   -1153.312
2562.646
x14          -23.2321    645.539     -0.036      0.971   -1288.567
1242.103
x15          526.1176    369.579      1.424      0.155    -198.302
1250.538
x16         -921.9204    501.866     -1.837      0.066   -1905.638
61.797
```

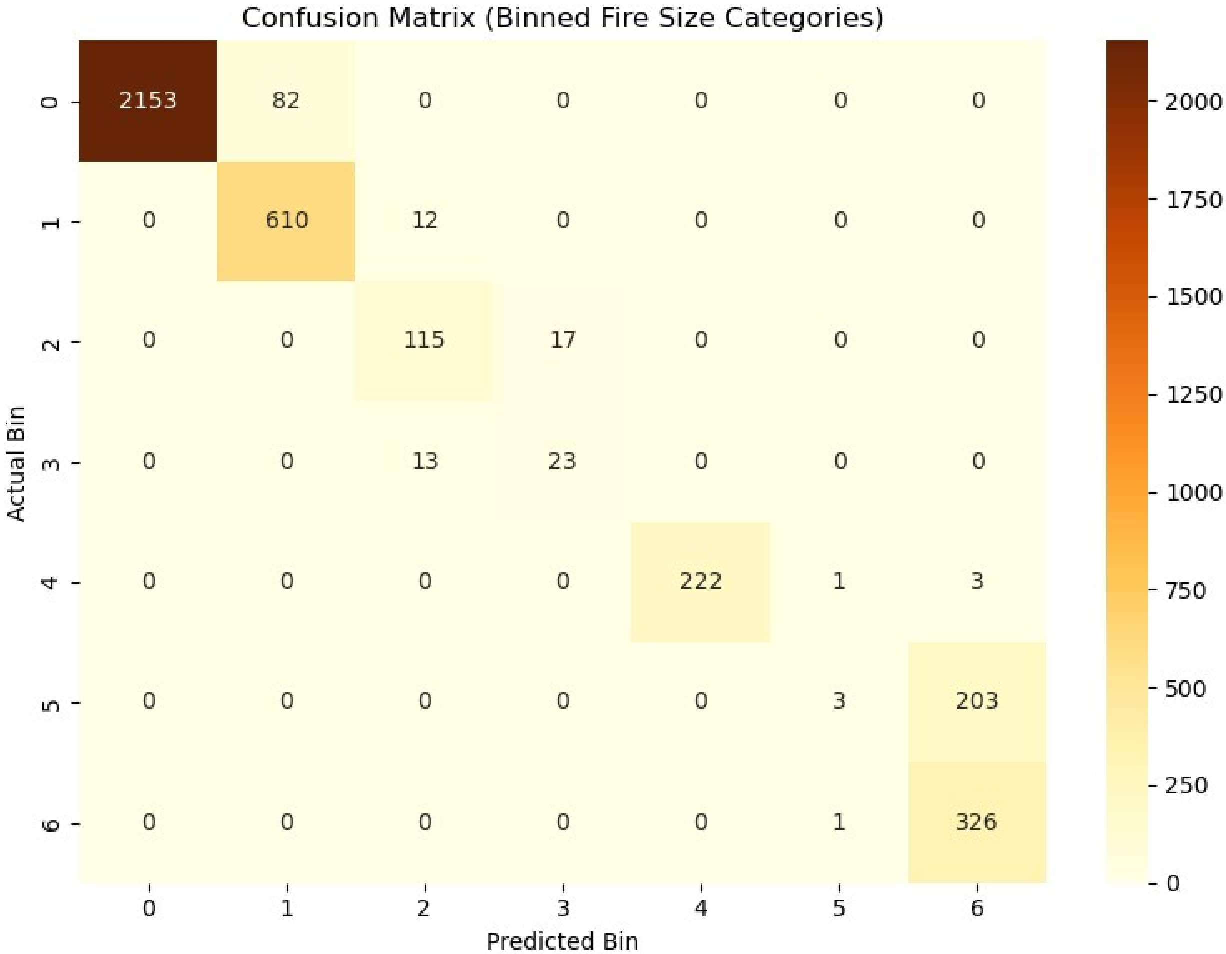
```
x17          -254.0529    662.689     -0.383      0.701   -1553.003
1044.897
x18           732.2471    437.940      1.672      0.095    -126.169
1590.663
x19         -1217.7301    324.893     -3.748      0.000   -1854.559
-580.901
x20          1114.9167    442.035      2.522      0.012     248.475
1981.358
x21          -200.7520    675.199     -0.297      0.766   -1524.224
1122.720
x22          -499.0648    534.080     -0.934      0.350   -1545.927
547.797
x23          -434.2482    316.497     -1.372      0.170   -1054.620
186.124
x24            50.0717    346.893      0.144      0.885    -629.881
730.024
x25            20.6085    424.185      0.049      0.961    -810.845
852.062
x26             3.8672    275.468      0.014      0.989    -536.084
543.818
x27           -48.0369    167.814     -0.286      0.775    -376.972
280.898
x28          1384.8564    268.645      5.155      0.000     858.280
1911.433
======================================================================
========
Omnibus:                    27028.654   Durbin-Watson:
1.979
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
35391793.628
Skew:                          12.979   Prob(JB):
0.00
Kurtosis:                     238.482   Cond. No.
16.3
======================================================================
========

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

# Parallel Computing – Simulation
def simulate_training(delay=1):
    time.sleep(delay)
    return delay

seq_start = time.time()
for _ in range(5):
    simulate_training(1)
seq_time = time.time() - seq_start
```

```
par_start = time.time()
Parallel(n_jobs=5)(delayed(simulate_training)(1) for _ in range(5))
par_time = time.time() - par_start

# Compare Sequential vs Parallel
plt.figure(figsize=(6, 4))
sns.barplot(x=['Sequential', 'Parallel'], y=[seq_time, par_time],
palette='Set2')
plt.title("Simulated Task Processing Time")
plt.ylabel("Time (seconds)")
plt.tight_layout()
plt.show()
```




```
# Confusion Matrix-like View (Regression Binning)
bins = [0, 10, 100, 500, 1000, 5000, 10000, np.inf]
y_test_binned = pd.cut(y_test, bins=bins, labels=False)
y_pred_binned = pd.cut(y_pred_rf, bins=bins, labels=False)
cm = confusion_matrix(y_test_binned, y_pred_binned)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title("Confusion Matrix (Binned Fire Size Categories)")
plt.xlabel("Predicted Bin")
plt.ylabel("Actual Bin")
```

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



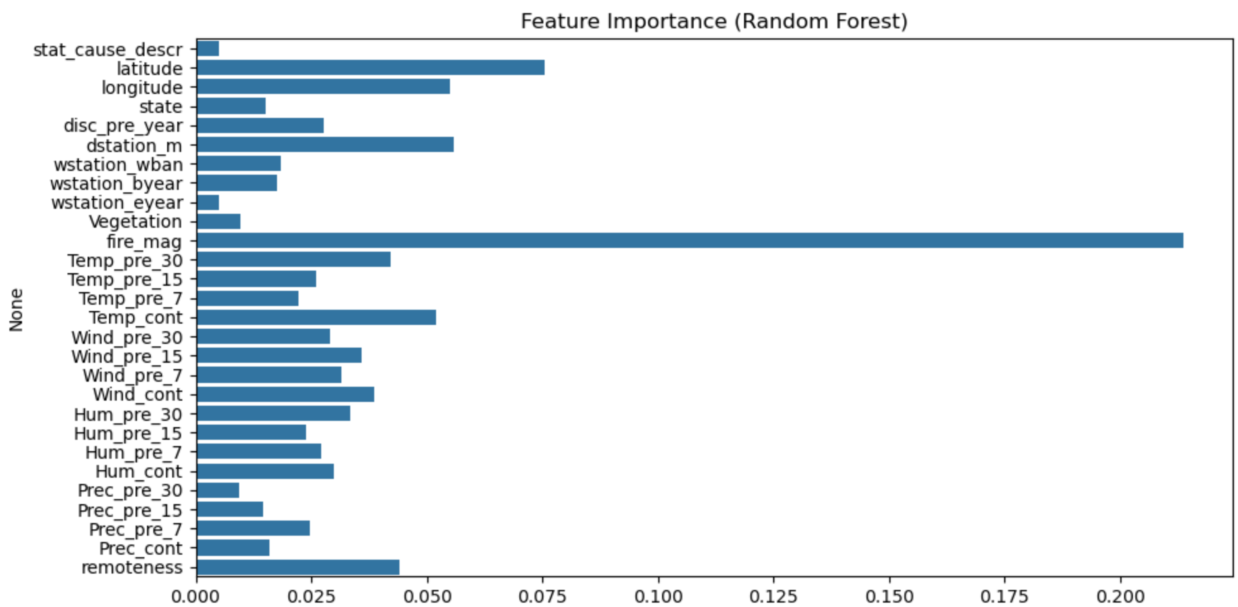

```
# Parallel Training of Multiple Models
def train_one_model(seed):
    model = RandomForestRegressor(n_estimators=50, max_depth=10,
random_state=seed)
    model.fit(X_train_scaled, y_train)
    return model.score(X_test_scaled, y_test)

scores = Parallel(n_jobs=4)(delayed(train_one_model)(s) for s in
range(4))
print("Parallel RF Models R²:", scores)
print("Average R²:", np.mean(scores))
```

```
Parallel RF Models R²: [0.3362560144763683, 0.3318771302019403,
0.29202003162291357, 0.3216524678166113]
Average R²: 0.3204514110294584
```

```python
# Grid Search
param_grid = {'n_estimators': [50, 100], 'max_depth': [10, 20]}
grid_search = GridSearchCV(RandomForestRegressor(random_state=42),
param_grid, cv=3, n_jobs=-1)
start = time.time()
grid_search.fit(X_train_scaled, y_train)
end = time.time()
print("Grid Best Params:", grid_search.best_params_)
print("Best CV R²:", grid_search.best_score_)
print("Grid Search Time:", round(end - start, 2), "seconds")
```

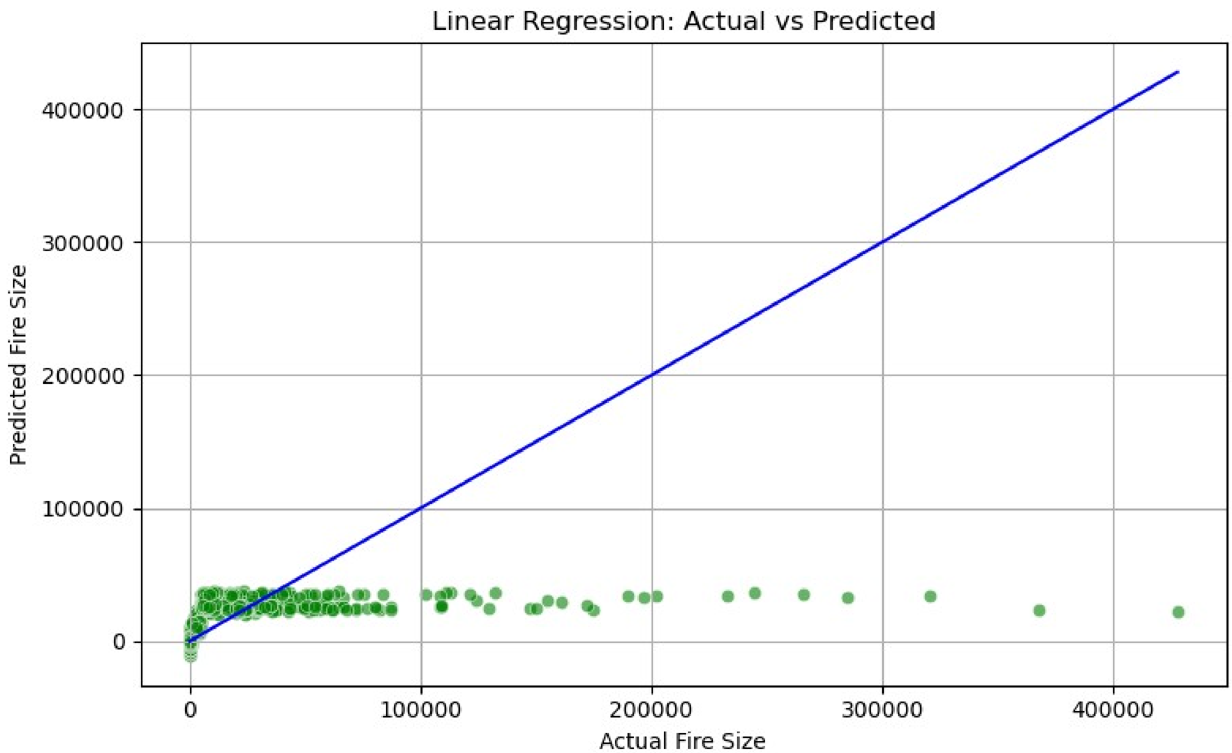
```
Grid Best Params: {'max_depth': 10, 'n_estimators': 100}
Best CV R²: 0.2389664115468015
Grid Search Time: 120.28 seconds
```

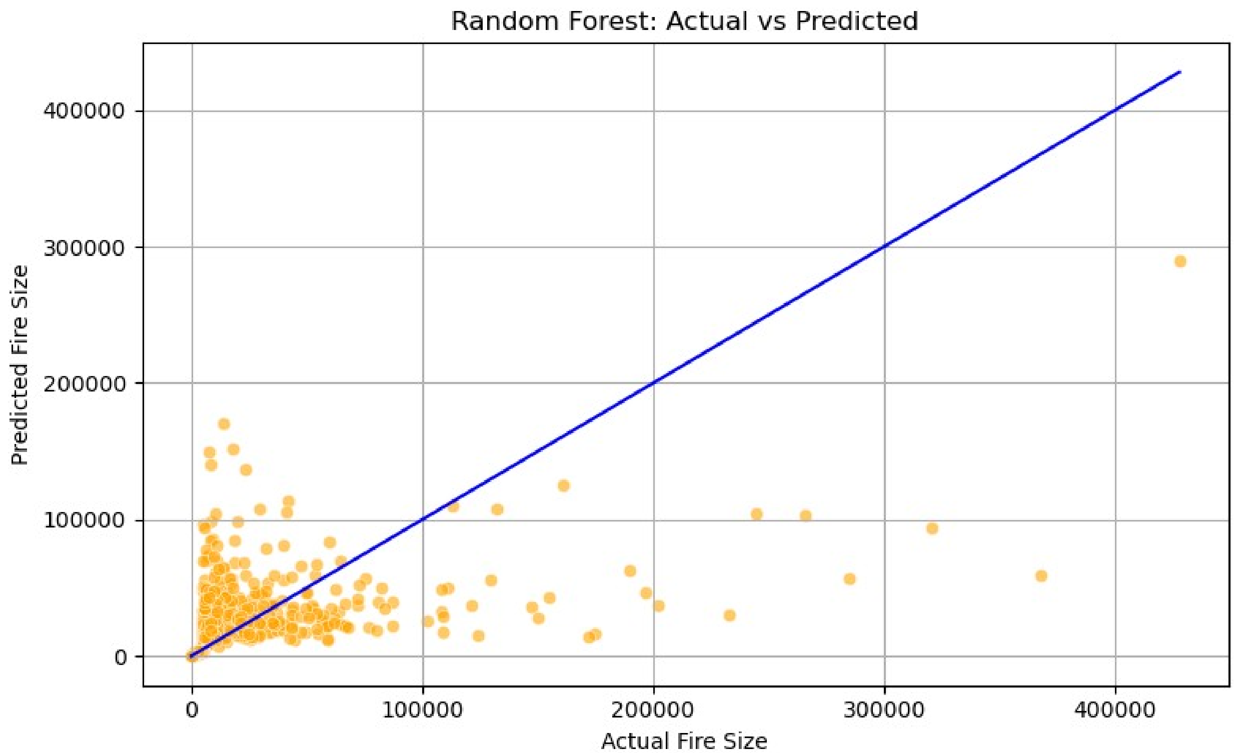
```python
# Feature Importance
feature_importances = rf_model.feature_importances_
features = X.columns
plt.figure(figsize=(10, 5))
sns.barplot(x=feature_importances, y=features)
plt.title("Feature Importance (Random Forest)")
plt.tight_layout()
plt.show()
```



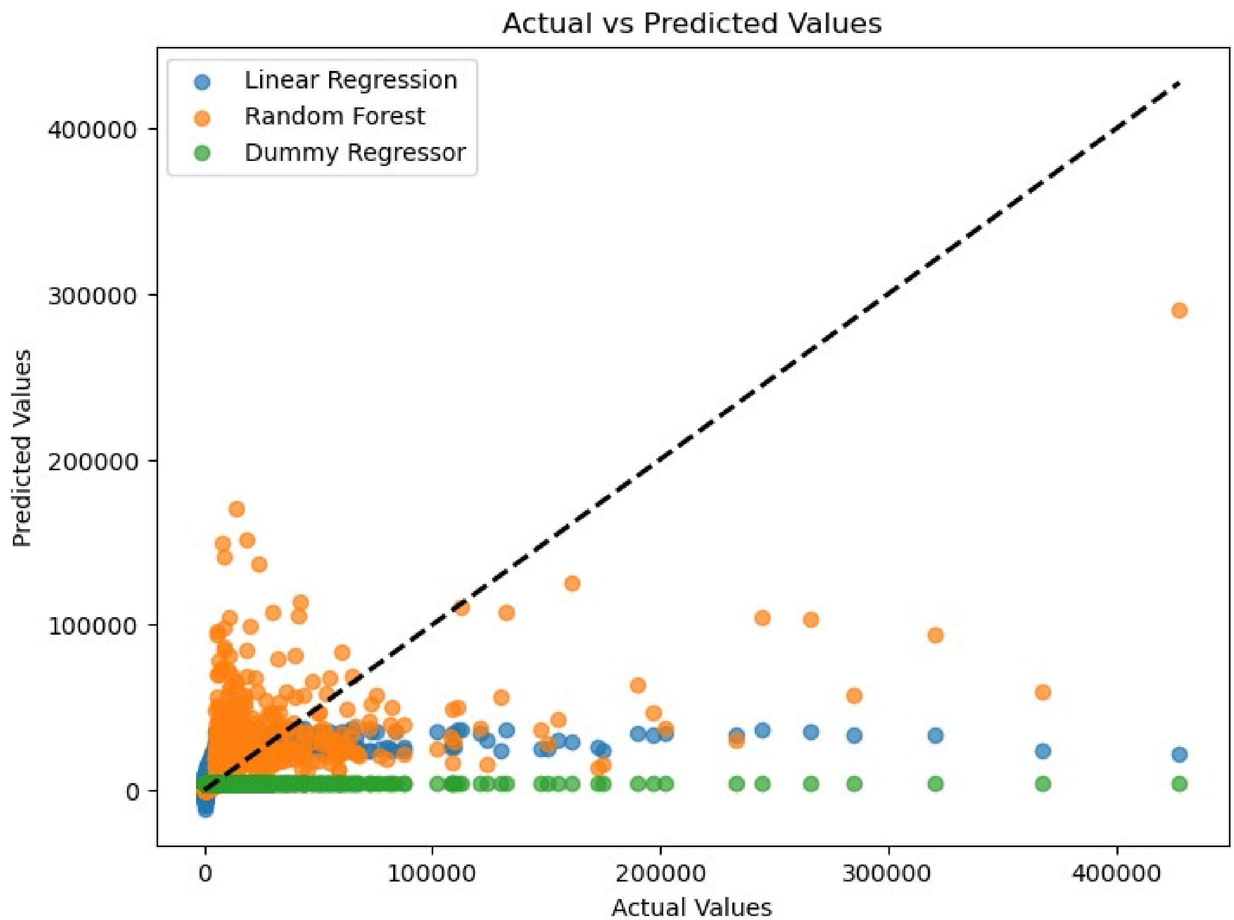

```python
# Actual vs Predicted Plots
def plot_actual_vs_predicted(y_true, y_pred, title, color):
    plt.figure(figsize=(8, 5))
    sns.scatterplot(x=y_true, y=y_pred, alpha=0.6, color=color)
    sns.lineplot(x=y_true, y=y_true, color='blue')
    plt.title(title)
```

```
    plt.xlabel("Actual Fire Size")
    plt.ylabel("Predicted Fire Size")
    plt.grid(True)
    plt.tight_layout()
    plt.show()

plot_actual_vs_predicted(y_test, y_pred_lr, "Linear Regression: Actual
vs Predicted", "green")
plot_actual_vs_predicted(y_test, y_pred_rf, "Random Forest: Actual vs
Predicted", "orange")
```

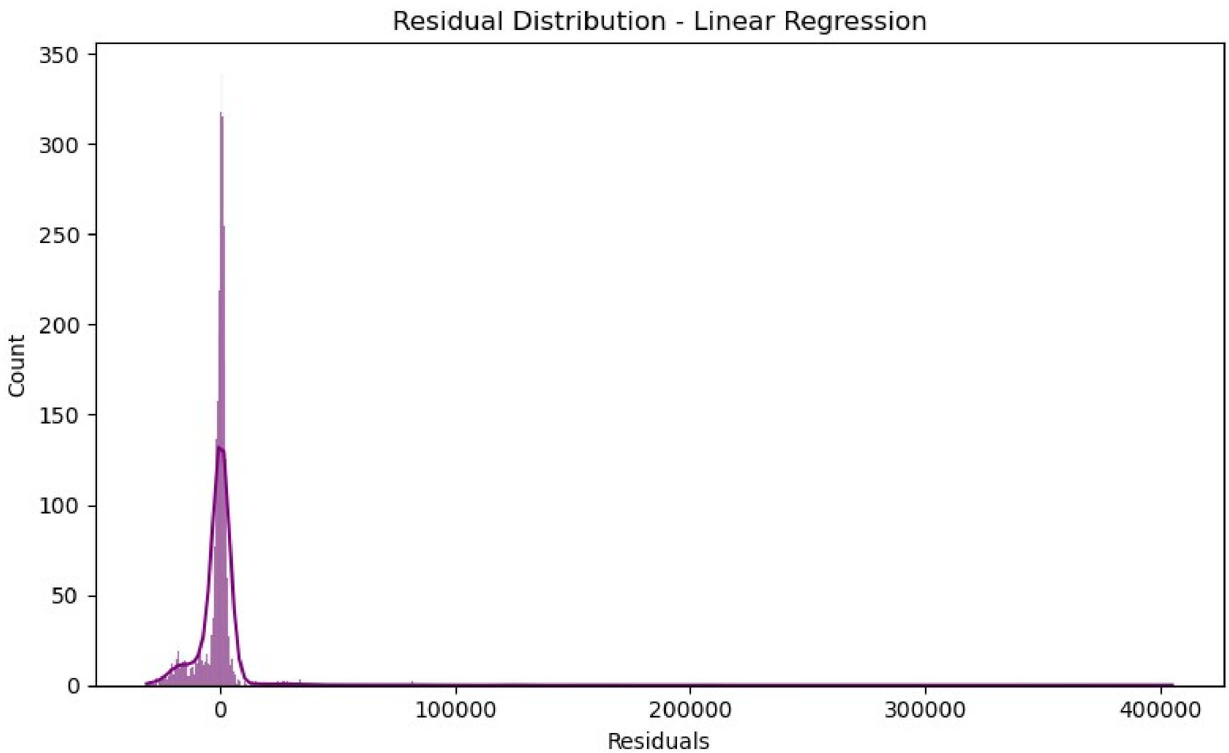


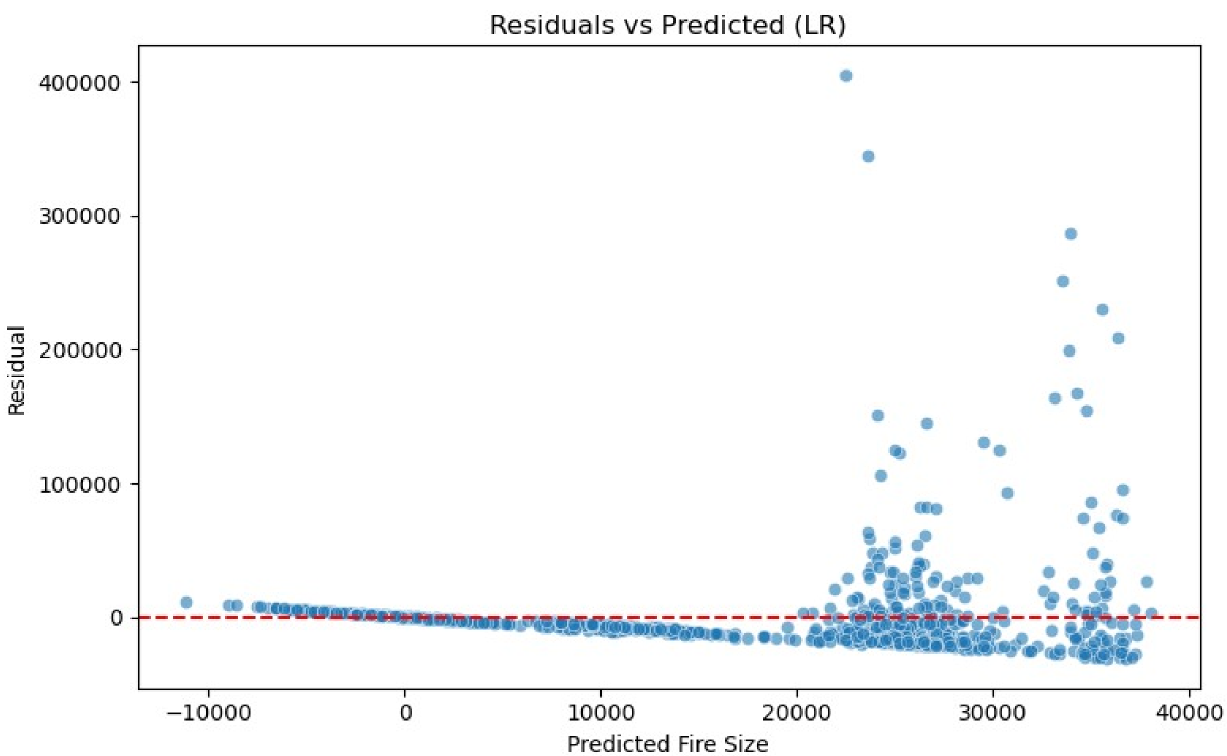



```
#Scatter plot comparing actual vs predicted values for each model.
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred_lr, alpha=0.7, label='Linear Regression')
plt.scatter(y_test, y_pred_rf, alpha=0.7, label='Random Forest')
plt.scatter(y_test, y_dummy, alpha=0.7, label='Dummy Regressor')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
'k--', lw=2)  # diagonal line for perfect prediction
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs Predicted Values")
plt.legend()
plt.show()
```



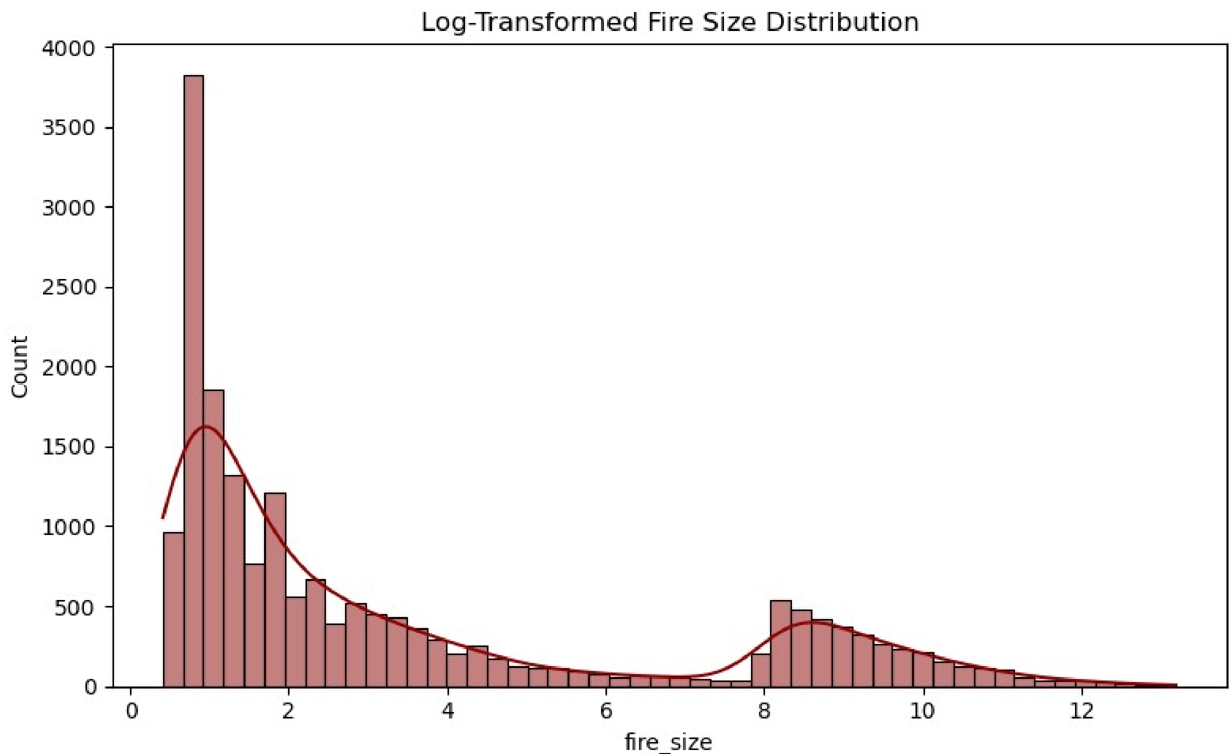

```python
# Linear Regression Residual Plot
residuals_lr = y_test - lr_model.predict(X_test_scaled)

plt.figure(figsize=(8, 5))
sns.histplot(residuals_lr, kde=True, color='purple')
plt.title("Residual Distribution - Linear Regression")
plt.xlabel("Residuals")
plt.tight_layout()
plt.show()

# Residuals vs Predicted
plt.figure(figsize=(8, 5))
sns.scatterplot(x=lr_model.predict(X_test_scaled), y=residuals_lr,
alpha=0.6)
plt.axhline(0, color='red', linestyle='--')
plt.title("Residuals vs Predicted (LR)")
plt.xlabel("Predicted Fire Size")
plt.ylabel("Residual")
plt.tight_layout()
plt.show()
```

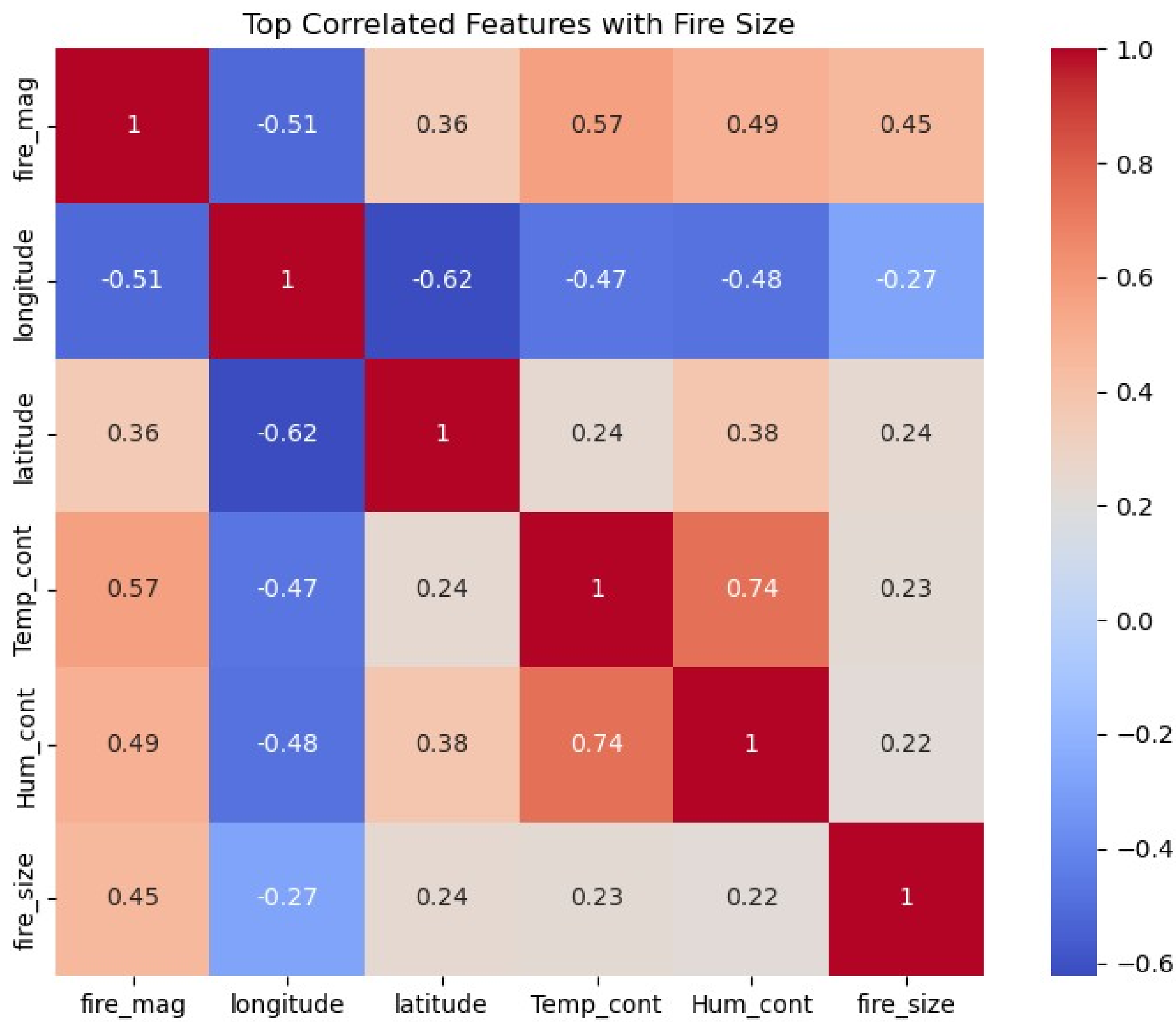





```
# Distribution & Correlation
plt.figure(figsize=(8, 5))
sns.histplot(np.log1p(df['fire_size']), bins=50, kde=True,
```

```
color='darkred')
plt.title("Log-Transformed Fire Size Distribution")
plt.tight_layout()
plt.show()

corr = df.select_dtypes(include=[np.number]).corr()
top_corr =
corr['fire_size'].abs().sort_values(ascending=False).index[1:6].tolist
() + ['fire_size']
plt.figure(figsize=(8, 6))
sns.heatmap(corr.loc[top_corr, top_corr], annot=True, cmap='coolwarm',
square=True)
plt.title("Top Correlated Features with Fire Size")
plt.tight_layout()
plt.show()
```

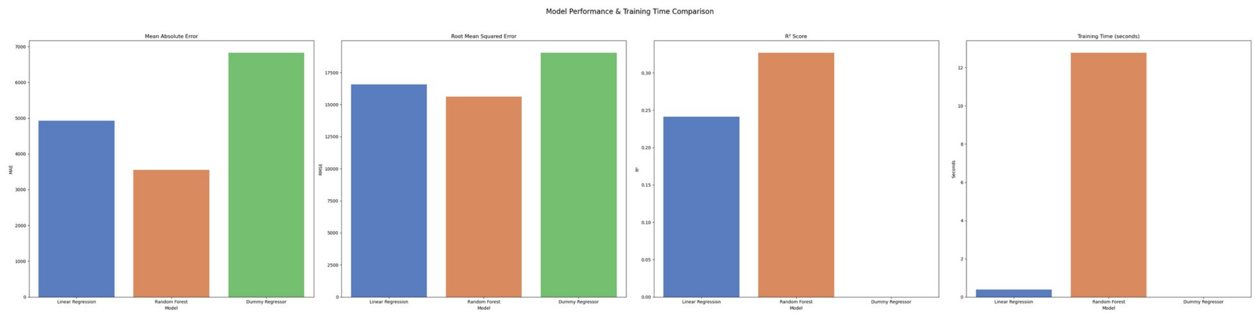




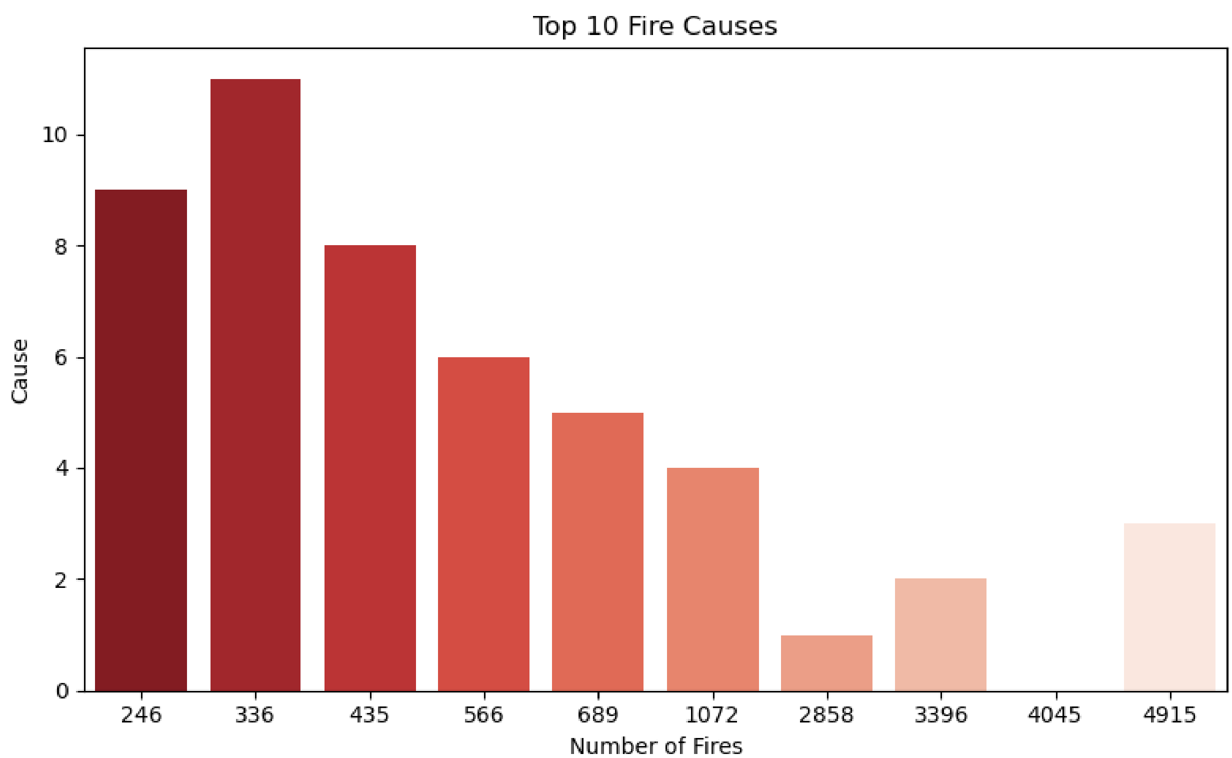

```python
# Cross-validation Scores
cv_scores_lr = cross_val_score(lr_model, X_train_scaled, y_train,
cv=5, scoring='r2')
cv_scores_rf = cross_val_score(rf_model, X_train_scaled, y_train,
cv=5, scoring='r2')

cv_df = pd.DataFrame({
    'Model': ['Linear Regression'] * 5 + ['Random Forest'] * 5,
    'Fold': list(range(1, 6)) * 2,
    'R2 Score': list(cv_scores_lr) + list(cv_scores_rf)
})

plt.figure(figsize=(8, 5))
sns.boxplot(data=cv_df, x='Model', y='R2 Score', palette='pastel')
plt.title("Cross-Validation R² Scores")
plt.tight_layout()
plt.show()
```


```
#Model Comparison Table
print("\nModel Comparison Table:")
print(f"{'Model':<20}{'MAE':<10}{'RMSE':<10}{'R²':<10}{'Train
Time(s)':<15}")
print(f"{'Linear Regression':<20}{mean_absolute_error(y_test,
y_pred_lr):<10.2f}{np.sqrt(mean_squared_error(y_test,
y_pred_lr)):<10.2f}{r2_score(y_test, y_pred_lr):<10.2f}
{lr_train_time:<15.4f}")
print(f"{'Random Forest':<20}{mean_absolute_error(y_test,
y_pred_rf):<10.2f}{np.sqrt(mean_squared_error(y_test,
y_pred_rf)):<10.2f}{r2_score(y_test, y_pred_rf):<10.2f}
{rf_train_time:<15.4f}")
print(f"{'Dummy Regressor':<20}{mean_absolute_error(y_test,
y_dummy):<10.2f}{np.sqrt(mean_squared_error(y_test, y_dummy)):<10.2f}
{'N/A':<10}{dummy_train_time:<15.4f}")


Model Comparison Table:
Model               MAE       RMSE      R²        Train Time(s)
Linear Regression   4925.12   16575.81  0.24      0.3835
Random Forest       3553.18   15613.97  0.33      12.7714
Dummy Regressor     6822.53   19033.30  N/A       0.0029

# Model Comparison Visualization
metrics_df = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest', 'Dummy
```

```
Regressor'],
    'MAE': [
        mean_absolute_error(y_test, y_pred_lr),
        mean_absolute_error(y_test, y_pred_rf),
        mean_absolute_error(y_test, y_dummy)
    ],
    'RMSE': [
        np.sqrt(mean_squared_error(y_test, y_pred_lr)),
        np.sqrt(mean_squared_error(y_test, y_pred_rf)),
        np.sqrt(mean_squared_error(y_test, y_dummy))
    ],
    'R2': [
        r2_score(y_test, y_pred_lr),
        r2_score(y_test, y_pred_rf),
        np.nan
    ],
    'Train Time (s)': [lr_train_time, rf_train_time, dummy_train_time]
})

fig, axs = plt.subplots(1, 4, figsize=(40, 10))

sns.barplot(x='Model', y='MAE', data=metrics_df, ax=axs[0],
palette='muted')
axs[0].set_title("Mean Absolute Error")
axs[0].set_ylabel("MAE")

sns.barplot(x='Model', y='RMSE', data=metrics_df, ax=axs[1],
palette='muted')
axs[1].set_title("Root Mean Squared Error")
axs[1].set_ylabel("RMSE")

sns.barplot(x='Model', y='R2', data=metrics_df, ax=axs[2],
palette='muted')
axs[2].set_title("R² Score")
axs[2].set_ylabel("R²")

sns.barplot(x='Model', y='Train Time (s)', data=metrics_df, ax=axs[3],
palette='muted')
axs[3].set_title("Training Time (seconds)")
axs[3].set_ylabel("Seconds")

plt.suptitle("Model Performance & Training Time Comparison",
fontsize=16)
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```

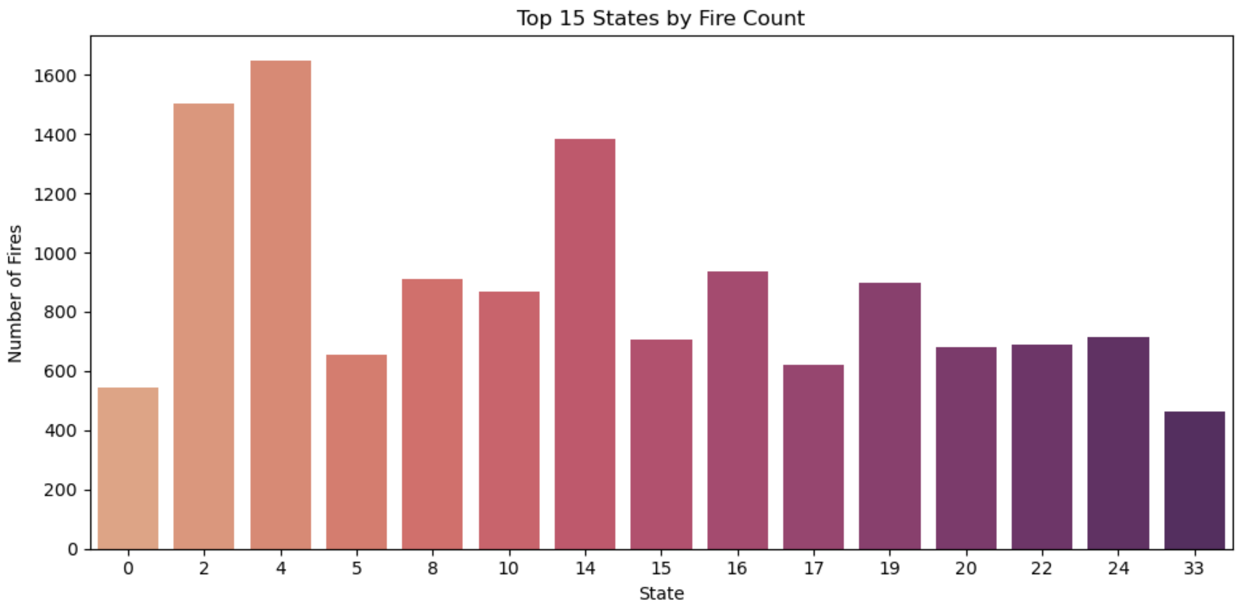



```python
# Top 10 Fire Causes
cause_counts = df['stat_cause_descr'].value_counts().head(10)
plt.figure(figsize=(8, 5))
sns.barplot(x=cause_counts.values, y=cause_counts.index,
palette='Reds_r')
plt.title("Top 10 Fire Causes")
plt.xlabel("Number of Fires")
plt.ylabel("Cause")
plt.tight_layout()
plt.show()
```

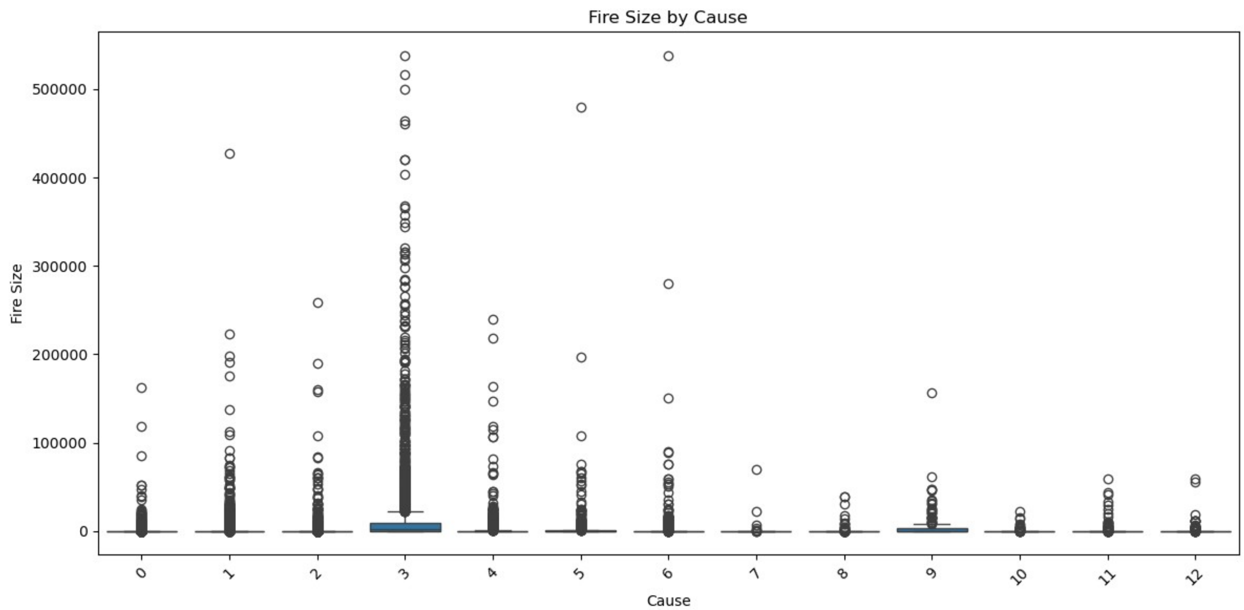



```python
#Fire by states
state_counts = df['state'].value_counts().head(15)
plt.figure(figsize=(10, 5))
sns.barplot(x=state_counts.index, y=state_counts.values,
palette='flare')
```

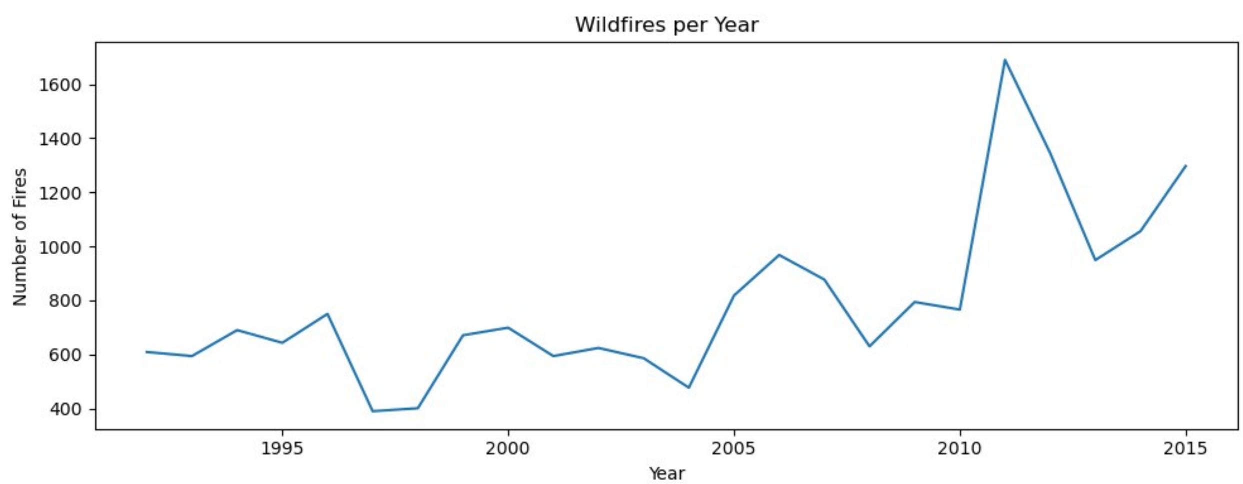
```
plt.title("Top 15 States by Fire Count")
plt.xlabel("State")
plt.ylabel("Number of Fires")
plt.tight_layout()
plt.show()
```




```
#Fire size by cause
plt.figure(figsize=(12, 6))
sns.boxplot(data=df, x='stat_cause_descr', y='fire_size')
plt.title("Fire Size by Cause")
plt.xlabel("Cause")
plt.ylabel("Fire Size")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```




```
# Temporal Analysis: Fires by Year
df['year'] = pd.to_datetime(df['disc_date_final']).dt.year
fires_per_year = df['year'].value_counts().sort_index()
plt.figure(figsize=(10, 4))
sns.lineplot(x=fires_per_year.index, y=fires_per_year.values)
plt.title("Wildfires per Year")
plt.xlabel("Year")
plt.ylabel("Number of Fires")
plt.tight_layout()
plt.show()
```




```
#Feature Distribution
numeric_cols = df.select_dtypes(include=np.number).columns.tolist()
df[numeric_cols].hist(figsize=(15, 12), bins=30, color='skyblue')
plt.suptitle("Feature Distributions", fontsize=16)
```

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