Wildfire_Analysis_LocalPaths-checkpoint-checkpoint-checkpoint

June 19, 2025

1 Wildfire Analysis: Fire Area vs. Distance to Nearest Fire Station

This notebook analyzes fire perimeters in San Diego County to test the hypothesis: *Fires farther from fire stations tend to burn more area.*

[2]:
```
import geopandas as gpd
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from shapely.geometry import shape
import fiona
from scipy.stats import pearsonr
```

[41]:
```
# Step 1: Set and project fire perimeters first
fire_perimeters = gpd.read_file('California_Fire_Perimeters_2017.shp')

# Only assign CRS if it's missing
if fire_perimeters.crs is None:
    fire_perimeters = fire_perimeters.set_crs('EPSG:4326')

# Project perimeters to UTM 11N for San Diego
fire_perimeters_proj = fire_perimeters.to_crs('EPSG:32611')

# Step 2: Calculate centroids and area (km²) from projected perimeters
fire_perimeters_proj['geometry_centroid'] = fire_perimeters_proj.geometry.
 ↪centroid
fire_perimeters_proj['area_km2'] = fire_perimeters_proj.geometry.area / 1e6

# Step 3: Build the fire_centroids_proj GeoDataFrame directly
fire_centroids_proj = gpd.GeoDataFrame({
    'FIRE_NAME': fire_perimeters_proj['FIRE_NAME'],
    'YEAR_': fire_perimeters_proj['YEAR_'],
    'area_km2': fire_perimeters_proj['area_km2'],
    'geometry': fire_perimeters_proj['geometry_centroid']
}, crs='EPSG:32611')
```

[4]:
```
fire_centroids = gpd.GeoDataFrame({
    'FIRE_NAME': fire_names,
    'YEAR_': years,
    'area_km2': areas_km2,
    'geometry': centroids
}, crs='EPSG:4326')
```

[51]:
```
# Reproject fire stations
fire_stations.set_crs('EPSG:4326', inplace=True)
fire_stations_proj = fire_stations.to_crs('EPSG:32611')

#  Final clean recalculation after all CRS/geometry fixes
fire_centroids_proj['nearest_dist_km'] = fire_centroids_proj.geometry.apply(
    lambda pt: fire_stations_proj.distance(pt).min() / 1000  # meters to km
)
```

[53]:
```
analysis_df = fire_centroids_proj[['FIRE_NAME', 'YEAR_', 'area_km2',␣
↪'nearest_dist_km']]
corr, p_value = pearsonr(analysis_df['nearest_dist_km'],␣
↪analysis_df['area_km2'])
```

[25]:
```
fire_stations_proj.is_valid.value_counts()
```

[25]:
```
True    307
Name: count, dtype: int64
```

[27]:
```
fire_stations_proj.head(3)
```

[27]:
```
   objectid                       stat_name stat_type seed dist_name juris  \
0         1   USFS Oak Grove Fire Station 31  Seasonal    Y      USFS    CN
1         2     USFS Palomar Fire Station 36  Seasonal    Y      USFS    CN
2         3  USFS Cottonwood Fire Station 44  Seasonal    Y      USFS    CN

  dispatch       phone_num  sta_num submappage sdfdpggrid designator  \
0      CNF  (619) 767-9744       31    7843-B2       None        CNF
1      CNF  (760) 742-3491       36    7639-A2       None        CNF
2      CNF  (619) 473-9835       44    2058-B2       None        CNF

  assets_ava                                       address symbol  \
0        EMT   37560 Highway 79, Warner Springs, CA, 92086, USA    FSL
1        EMT                                          None    FSL
2        EMT  3971 Buckman Springs Rd, Pine Valley, CA, 9196…    FSL

   battalion                   geometry
0          5  POINT (5.19e+05 3.69e+06)
1          7  POINT (5.12e+05 3.69e+06)
2          4  POINT (5.48e+05 3.62e+06)
```

[29]:
```python
print(fire_stations.crs)
print(fire_stations_proj.crs)
```

```
EPSG:4326
EPSG:32611
```

[31]:
```python
fire_centroids_proj.is_valid.value_counts()
```

[31]:
```
False    608
Name: count, dtype: int64
```

[33]:
```python
fire_centroids.is_valid.value_counts()
```

[33]:
```
True    608
Name: count, dtype: int64
```

[37]:
```python
fire_centroids_proj.is_valid.value_counts()
```

[37]:
```
False    608
Name: count, dtype: int64
```

[43]:
```python
fire_centroids_proj.is_valid.value_counts()
```

[43]:
```
True    608
Name: count, dtype: int64
```

[13]:
```python
len(fire_centroids_proj)
```

[13]:
```
608
```

[15]:
```python
fire_centroids_proj['nearest_dist_km'].value_counts()
```

[15]:
```
nearest_dist_km
1.797693e+305    608
Name: count, dtype: int64
```

[17]:
```python
fire_centroids_proj['area_km2'].describe()
```

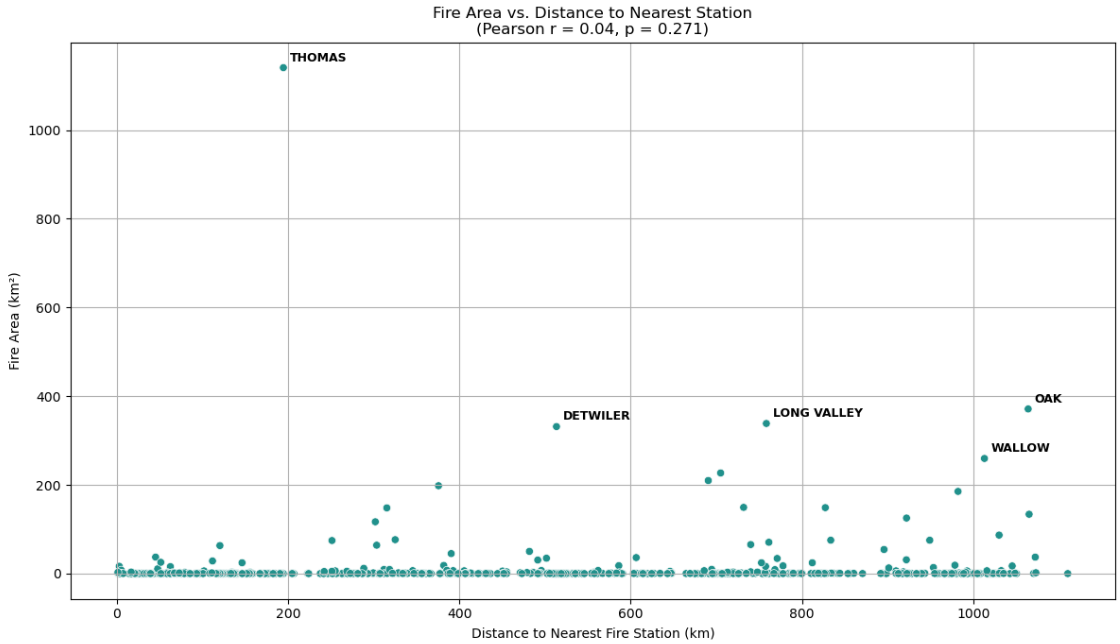
[17]:
```
count     608.000000
mean       15.373824
std        89.832058
min         0.000008
25%         0.057752
50%         0.185527
75%         0.910724
max      1681.105895
Name: area_km2, dtype: float64
```

[45]:
```python
top_area = analysis_df.nlargest(5, 'area_km2')
top_dist = analysis_df.nlargest(5, 'nearest_dist_km')
highlight_fires = pd.concat([top_area, top_dist]).drop_duplicates()
```

[57]:
```python
plt.close('all')
```

[63]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 7))
ax = sns.scatterplot(
    data=analysis_df,
    x='nearest_dist_km',
    y='area_km2',
    hue='YEAR_',
    palette='viridis',
    legend=False
)

# Add labels for large fires
for _, row in highlight_fires.iterrows():
    ax.annotate(
        row['FIRE_NAME'],
        (row['nearest_dist_km'], row['area_km2']),
        textcoords="offset points",
        xytext=(5, 5),
        ha='left',
        fontsize=9
    )

plt.title(f'Fire Area vs. Distance to Nearest Station\n(Pearson r = {corr:.2f},␣
 ↪p = {p_value:.3f})')
plt.xlabel('Distance to Nearest Fire Station (km)')
plt.ylabel('Fire Area (km²)')
plt.grid(True)
# Optional: Label top 5 largest fires
highlight_fires = analysis_df.sort_values(by='area_km2', ascending=False).
 ↪head(5)

for _, row in highlight_fires.iterrows():
    ax.annotate(row['FIRE_NAME'],
                xy=(row['nearest_dist_km'], row['area_km2']),
                xytext=(5, 5),
                textcoords='offset points',
                fontsize=9,
                weight='bold')
plt.tight_layout()  #  Prevents layout overflow
```

```
plt.show()
```



1.1 Conclusion

Final Interpretation of Results: Wildfire Area vs. Distance to Nearest Fire Station – San Diego County (2017) This analysis explored whether greater distance from fire stations correlates with larger wildfire perimeters, using fire centroids and projected distances to the closest fire stations in San Diego Count

Key Findings: A Pearson correlation coefficient (r) of 0.04 was calculated, with a p-value of 0.271.

This indicates a very weak and statistically insignificant relationship between fire area and distance to the nearest fire station.

In practical terms, fires farther from fire stations did not consistently burn larger areas in this 2017 aset.

Additional Observations: A majority of fire perimeters were within 500–1000 km projected distances from stations.

The most extreme outliers (e.g., Thomas Fire) were labeled and suggest that other factors (e.g., wind, terrain, fuel load) may drive fire spread more than stat proximity.

Implications: Emergency response planning should not rely solely on geographic distance from stations as a predictor of fire severity.

Other spatial variables — such as slope, fuel type, wind corridors, and time of ignition — likely have more explanatory power and should be included in a more comprehensive model.

Nonetheless, this workflow demonstrates a robust spatial analysis pipeline combining shapefiles, projections, centroid analysis, and s tatistical testing in Python.