ClassiFire

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Table of Contents

Notes:

Use checkpoints to skip parts dataset creation, each checkpoint contains hyperlink to prvious cells that need to be run, run imports before continuing

▶ Quick Links

Project Overview

Project Overview

The goal of this project is to develop a classification model that can predict the fire management complexity level of a wildfire. Fire management complexity represents the highest management level utilized to manage a wildland fire. This target provides valuable insights into the resources needed and the potential scale, size and impact of a fire.

This classification model analyzes various features associated with the a wildfire incident, including meteorological data, bureaucratic data, and locational data. The developed classification model will enable fire management agencies to anticipate the resources required should a wildfire occur based on the location and current meteorological data. This model doesn't replace the realtime complex decision of determining fire management complexity level (like evaluating the risk to the firefighters). However this model can aid in helping predict if a new wildfire incident will be a large scale/impacting event based on the predicted fire management complexity.

Business Understanding

Wildfires pose a significant risks to life, property, and the environment. Effective fire management is crucial for mitigating these risks and minimizing the impact of wildfires. Predicted fire management complexity level evaluates if a location is at risk of being resource intensive or potentially large threat to life and property should a wildfire occur. This can help identify regions that need to be on high alert and preparedness to minimize the impact of a wildfire.

The fire agencies administrator is responsible for setting the fire managment complexity level. Their decision follows a set of standarized and subjective guidelines. Some of these guidelines are utilized as features in this project.

Fire management agencies, administrators, and other personnel responsible for allocating resources and planning fire response strategies would benefit from being able to accurately and efficiently predict the fire management complexity level of wildland fire incidents. This allows for them to anticipate the required resources, as well as assess the potential scale and impact of a fire. This information is crucial for fire management agencies to make informed decisions and ensured preparedness for faster fire response times.

Data Understanding

- [Target]
- [Data Sources]
- [Data Directory]
- [Key Features]

Target

Target

- FireMgmtComplexity (Defined here)

  Factors contributing to the fire management complexity level:
- Area involved
- Threat to life and property
- Political sensitivity
- Organizational complexity
- Jurisdictional boundaries
- Values at risk
- Fire behavior
- Strategy and tactics
- Agency policy

Source:
https://gacc.nifc.gov/swcc/management_admin/Agency_Administrator/AA_Guidelines/pdf_file
(https://gacc.nifc.gov/swcc/management_admin/Agency_Administrator/AA_Guidelines/pdf_file

FireMgmtComplexity Classes:

The levels of wildfire fire incidents range from Type 5 to Type 1. Each level represents a specific level of complexity

- Type 5:
  - lowest class
  - local resources
  - 2-6 firefighters
  - quickly contained
  - low impact risk
- Type 4
  - Local resources
  - low impact risk
  - slight increase in scale compared to Type 5
- Type 3
  - Mix of local and regional resources used
  - increased scale and risk
  - action plan created
- Type 2
  - large scale 200+ firefighters
  - Many units required
  - regular planning and briefing
- Type 1
  - highest class
  - Same characteristics of type 2 incident
  - 500+ firefighters
  - aircraft and aviation is used
  - Greater access to resources
  - larger scale and impact

Data Sources

The data used in this project comes from the following sources below:

- Wildfire Occurrences
  - https://data-nifc.opendata.arcgis.com/datasets/nifc::wildland-fire-incident-locations/about (https://data-nifc.opendata.arcgis.com/datasets/nifc::wildland-fire-incident-locations/about)
  - This dataset gets updated daily and contains data going back to roughly 2014
- Live RAWS Data (Remote Access Weather Stations)
  - https://data-nifc.opendata.arcgis.com/datasets/nifc::public-view-interagency-remote-automatic-weather-stations-raws/about (https://data-nifc.opendata.arcgis.com/datasets/nifc::public-view-interagency-remote-automatic-weather-stations-raws/about)
  - Dataset of live RAWS data
- Historical RAWS Data
  - https://raws.dri.edu/ (https://raws.dri.edu/)
  - Contains historical data for around 3k RAWS
- Elevation data:
  - open elevation api

Data Directory

Data	Curation	Utilization	Additiona
station_list.csv	web_scraper.ipynb	post_request.ipynb	RAWS 4
threshold_year.pickle	web_scraper.ipynb	EDA1.ipynb	RAWS cod final year s collectec
nessid.csv	web_scraper.ipynb	EDA1.ipynb	NESSII RAWS
RAWS_Historical_Full	post_request.ipynb	EDA1.ipynb	Json files into 4
RAWS.csv	Live RAWS download	Modeling.ipynb	
stations_dates.csv.zip	EDA1.ipynb	Modeling.ipynb	correspond day, cc represe RAWS. Mi data for a F on a specifi is denot
RAWS_stations.csv.zip	EDA1.ipynb	Modeling.ipynb	This is sp into 1,2 a pd.concat([1 axis note
Wildland_Fire_Incident_Locations.csv.zip	Wildfire Occurrences download	Modeling.ipynb	

clean_fire_data.csv.zip	Modeling.ipynb	Modeling.ipynb	
fire_elevation.csv	Modeling.ipynb	Modeling.ipynb	Elevation of fire inc
fire_model_data.csv	Modeling.ipynb	Modeling.ipynb	Final da used to M drop unwa column b moc

Key Features

Below are the key features used in this project. Several features in the dataset have corresponding features that contained the same or similar data. These features were utilized to fill in missing values whenever possible. There are many more features then what is listed here, refer to source websites for an indepth overview.

Fire Incidents:

Definitions provided by source

- **FireMgmtComplexity:** The highest management level utilized to manage a wildland fire
- **FinalAcres:** Final burn acres, nulls filled in with IncidentSize
- **site:** Created in Modeling.ipynb, closest RAWS that has at least 50% data coverage over the duration of a fire incident.
    - It is used as a reference point for analyzing weather conditions during the fire event.
- **DispatchCenterID:** A unique identifier for a dispatch center responsible for supporting the incident. Nulls filled in with POODispatchCenterID
- **POODispatchCenterID:** A unique identifier for the dispatch center that intersects with the incident point of origin (point where fire incident occured)
- **POOJurisdictionalAgency:** The agency having land and resource management responsibility for a fire incident as provided by federal, state or local law
- **POOFips:** Code identifies counties and county equivalents. The first two digits are the FIPS State code and the last three are the county code within the state.
- **FireDiscoveryDateTime:** The date and time a fire was reported as discovered or confirmed to exist
- **FireOutDateTime:** The date and time when a fire is declared out
- **OBJECTID:** Incident ID for dataset
- **EstimatedFinalCost:** Nulls filled in with EstimatedCostTodate
- **elevation:** Elevation of fire incident (meters)

  ## RAWS data:

  For each fire incident, all meteorological metrics were computed as averages of the fire duration.

    - **NESSID:** NESS ID for identifying RAWS
    - **X:** Longitude
    - **Y:** Latitude
    - **date:** date when data was collected, if null then no data collected on that day
    - **total_solar_radiation_lv:** Solar radiation

- **total_solar_radiation_ly:** Solar radiation
- **ave_mean_wind_speed_mph:** Average wind speed (mph)
- **ave_mean_wind_direction_deg:** Average wind direction (degree)
- **max_maximum_wind_gust_mph:** Maximum wind gust (mph)
- **ave_average_air_temperature_deg_f:** Average air temperature (°F)
- **ave_average_relative_humidity:** Average relative humidity
- **total_precipitation_in:** Total precipitation (inches)

Data Set length: over 250K and the final model dataset has a length of 7731 RAWS: There are roughly 2252 RAWS sites with usable data, aaround 3k in total

Live RAWS Dataset EDA

- Completed prior to webscraping
- What stations have nulls?
- What ID should be used, NESSID, WXID, NWSID, Station ID?

In [654]:

```
import pandas as pd
import numpy as np
pd.set_option('display.max_columns', 35)
import matplotlib.pyplot as plt
from scipy.spatial import Voronoi, voronoi_plot_2d
import time
from sklearn.model_selection import train_test_split, cross_val_score,
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.pipeline import Pipeline
```

```
from imblearn.pipeline import Pipeline as ImPipeline
from sklearn.compose import ColumnTransformer, TransformedTargetRegres
from sklearn.metrics import plot_confusion_matrix, classification_repo
                            plot_roc_curve, precision_score, recall_sc
                            roc_auc_score, roc_curve
from sklearn.ensemble import RandomForestClassifier, GradientBoostingC
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from imblearn.over_sampling import SMOTE
from sklearn.impute import SimpleImputer
from sklearn.svm import SVC
from datetime import datetime, timedelta
from joblib import Parallel, delayed
import requests
import seaborn as sns
import matplotlib as mpl
from matplotlib.ticker import StrMethodFormatter
```

In [655]:
```
# Importing live IRAWS Stations data
df1 = pd.read_csv('Data/RAWS.csv')

# There are duplicates but Object Id column prevents .duplicated() fro
df1.drop(columns='OBJECTID', inplace=True)

# several rows contain a NO DATA value, here i replace those with null
df1.replace("NO DATA", np.nan, inplace=True)
```

In [656]:
```
df1['NESSID'].value_counts()
```

Out[656]:
```
325515EE    15
32416F08    14
326F772A    12
328B27E6    10
FF1041BA     9
            ..
3266B468     1
326DE7BC     1
326116A4     1
0800C6DC     1
D680125A     1
Name: NESSID, Length: 2495, dtype: int64
```

In [657]:
```
def unique_stations(df):
    # Find column with the most letters, return the length
    column_width = max(len(column) for column in df.columns)
    # header, sets space to fit the longest column name
    print(f"\033[1m{'Columns':<{column_width}} | {'Length':<15} | Null
    print(f"{'':<{column_width +1}}|\033[31m (Unique Values) \033[0m|"
    print(f"{'-'*40}")

    # Columns length
    for column in df.columns:
        length = len(df[column].value_counts())
        print(f"{column:<{column_width}} | {length:<15} | {df[column].
```

```
unique_stations(df1)
```

```
Columns             | Length           | Nulls
                    | (Unique Values)  |
----------------------------------------
X                   | 2916             | 7
Y                   | 2912             | 7
StationName         | 2708             | 0
WXID                | 6487             | 570
ObservedDate        | 3737             | 0
NESSID              | 2495             | 570
NWSID               | 2026             | 1742
Elevation           | 2036             | 580
SiteDescription     | 1775             | 3448
Latitude            | 2705             | 570
Longitude           | 2707             | 570
State               | 53               | 570
County              | 723              | 967
Agency              | 10               | 570
Region              | 89               | 621
Unit                | 486              | 855
SubUnit             | 822              | 2797
Status              | 4                | 570
RainAccumulation    | 2787             | 59
WindSpeedMPH        | 90               | 75
WindDirDegrees      | 377              | 1911
AirTempStandPlace   | 172              | 84
FuelTemp            | 120              | 4212
RelativeHumidity    | 259              | 46
BatteryVoltage      | 42               | 1927
FuelMoisture        | 265              | 4283
WindDirPeak         | 398              | 1925
WindSpeedPeak       | 75               | 1995
SolarRadiation      | 859              | 2135
StationID           | 7057             | 0
```

In [658]:

```
# This project doesn't use IRAWS stationos as they do not have a NESSI
# they can be added but more data will need pulled through post reques
df1[df1['StationName']== 'IRAWS 3']
```

Out[658]:

	X	Y	StationName	WXID	ObservedDate	NESSID	NWSID	Elevation	Si
51	-123.10313	41.24443	IRAWS 3	NaN	2022/02/16 12:45:00+00	NaN	NaN	NaN	
3935	-116.20833	43.56500	IRAWS 3	NaN	2022/05/03 18:14:59+00	NaN	NaN	NaN	
6136	-116.20833	43.56500	IRAWS 3	NaN	2023/02/02 14:45:00+00	NaN	NaN	NaN	
					2023/02/02				

6174	-116.20833	43.56500	IRAWS 3	NaN	[illegible] 21:30:00+00	NaN	NaN	NaN

In [659]:

```python
# Data Frame containning rows where NESSID is null.
# Checking the NESSID column for nulls
# This indicates that for rows missing NESSID, they have key informati
# Evalute further before dropping
print(df1[df1['NESSID'].isna() == True].info())
df1[df1['NESSID'].isna() == True]
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 570 entries, 51 to 7072
Data columns (total 30 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   X                  568 non-null    float64
 1   Y                  568 non-null    float64
 2   StationName        570 non-null    object 
 3   WXID               0 non-null      float64
 4   ObservedDate       570 non-null    object 
 5   NESSID             0 non-null      object 
 6   NWSID              0 non-null      object 
 7   Elevation          0 non-null      float64
 8   SiteDescription    0 non-null      object 
 9   Latitude           0 non-null      float64
 10  Longitude          0 non-null      float64
 11  State              0 non-null      object 
 12  County             0 non-null      object 
 13  Agency             0 non-null      object 
 14  Region             0 non-null      object 
 15  Unit               0 non-null      object 
 16  SubUnit            0 non-null      object 
 17  Status             0 non-null      object 
 18  RainAccumulation   570 non-null    object 
 19  WindSpeedMPH       570 non-null    object 
 20  WindDirDegrees     0 non-null      object 
 21  AirTempStandPlace  570 non-null    object 
 22  FuelTemp           0 non-null      object 
 23  RelativeHumidity   570 non-null    object 
 24  BatteryVoltage     0 non-null      object 
 25  FuelMoisture       0 non-null      object 
 26  WindDirPeak        0 non-null      object 
 27  WindSpeedPeak      0 non-null      object 
 28  SolarRadiation     0 non-null      object 
 29  StationID          570 non-null    int64  
dtypes: float64(6), int64(1), object(23)
memory usage: 138.0+ KB
None
```

Out[659]:

	X	Y	StationName	WXID	ObservedDate	NESSID	NWSID	Elevation	Si
51	-123.10313	41.24443	IRAWS 3	NaN	2022/02/16 12:45:00+00	NaN	NaN	NaN	
63	-109.98161	31.87208	RO PORTABLE	NaN	2022/04/03 16:28:00+00	NaN	NaN	NaN	

			#4		10:28:00+00				
72	-80.49248	36.35649	PILOT MOUNTAIN	NaN	2022/03/15 13:02:59+00	NaN	NaN	NaN	
97	-105.05300	35.82131	IRAWS 1 (RIO MORA)	NaN	2022/05/11 06:45:00+00	NaN	NaN	NaN	
162	-114.73650	48.41300	SWANEY	NaN	2022/12/05 14:39:00+00	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	...	
7054	-107.48400	37.30422	SAN JUAN PORTABLE #2	NaN	2023/05/05 09:46:00+00	NaN	NaN	NaN	
7061	-109.57233	43.43539	SHF5 PORTABLE	NaN	2023/05/05 10:08:00+00	NaN	NaN	NaN	
7063	-116.20833	43.56500	PRAWS 4	NaN	2023/05/05 10:20:00+00	NaN	NaN	NaN	
7068	-114.58861	46.78111	LOLO PORTABLE #6	NaN	2023/05/04 17:13:00+00	NaN	NaN	NaN	
7072	-108.48333	37.51228	DOLORES D5 PORTABLE	NaN	2023/05/04 21:09:00+00	NaN	NaN	NaN	

570 rows × 30 columns

In [660]:

```
# Majority of the IRAWS have nulls for the NESSID stations
df2 = df1[df1['NESSID'].isna() == True]
print(f"Number of IRAWS stations total: {len(df1[df1['StationName'].st
print(f"Number of PRAWS stations total: {len(df1[df1['StationName'].st
print(f"Of the {len(df1[df1['StationName'].str.contains('IRAWS')])} IR
{len(df2[df2['StationName'].str.contains('IRAWS')])} Contain no NESSID

df2[df2['StationName'].str.contains('IRAWS')]
```

```
Number of IRAWS stations total: 238
Number of PRAWS stations total: 75
Of the 238 IRAWS stations, 196 Contain no NESSID
```

Out[660]:

	X	Y	StationName	WXID	ObservedDate	NESSID	NWSID	Elevation	Si
51	-123.10313	41.24443	IRAWS 3	NaN	2022/02/16 10:45:00+00	NaN	NaN	NaN	

					12:45:00+00				
97	-105.05300	35.82131	IRAWS 1 (RIO MORA)	NaN	2022/05/11 06:45:00+00	NaN	NaN	NaN
188	-116.20861	43.55972	IRAWS 39	NaN	2022/03/15 18:03:00+00	NaN	NaN	NaN
292	-112.32306	45.99556	IRAWS 36	NaN	2022/03/02 15:33:00+00	NaN	NaN	NaN
329	-104.93564	36.34879	IRAWS 7 (DP90)	NaN	2022/05/03 19:46:00+00	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...
6978	-116.20833	43.56500	IRAWS 44	NaN	2023/04/27 12:19:00+00	NaN	NaN	NaN
6980	-116.20833	43.56500	IRAWS 42	NaN	2023/04/27 12:19:00+00	NaN	NaN	NaN
7001	-116.20833	43.56500	IRAWS 54	NaN	2023/05/01 11:19:59+00	NaN	NaN	NaN
7023	-116.20833	43.56500	IRAWS 52	NaN	2023/05/03 15:19:00+00	NaN	NaN	NaN
7050	-116.20833	43.56500	IRAWS 55	NaN	2023/05/03 15:20:00+00	NaN	NaN	NaN

196 rows × 30 columns

After looking at documentation NWS ID represents (WIMS Station ID) Unique six-digit identification number assigned to the weather station.

Upon further evaluation there are roughly 1700 nulls for this while NESSID only has around 570

In [661]:
```
# Checking duplicates
df1.duplicated().sum()
```
Out[661]: 18

In [662]:
```
def duplicates(df, output=None):# locating duplicate
    '''
    Located number of duplicates
    set output= any value to display the non-duplicated
    '''
    print(f'Number of Duplicates: {df.duplicated().sum()}')
    if output:
        display(df.loc[df.duplicated() == False])
    else:
        display(df.loc[df.duplicated() == True])
duplicates(df1)
```
```
Number of Duplicates: 18
```

	X	Y	StationName	WXID	ObservedDate	NESSID	NWSID	Ele
4881	-105.57236	40.79281	REDFEATHER	16927282.0	2022/11/16 16:33:00+00	323610D2	050505	8
4882	-95.09472	30.51806	COLDSPRINGS	17294878.0	2023/04/24 18:03:00+00	3288B58A	414201	
4883	-105.22694	40.57083	REDSTONE	17066030.0	2023/05/05 09:57:00+00	3335E6FA	050508	6
4884	-74.31611	40.09861	JACKSON	17392930.0	2022/10/25 21:11:00+00	FF1041BA	280291	
4885	-74.49417	40.40722	NEW MIDDLESEX COUNTY	17392680.0	2022/12/27 15:11:00+00	FF10372A	280231	
4886	-119.06140	37.66182	INF05 PORTABLE	17407304.0	2022/11/01 01:12:59+00	32878682	NaN	9
4887	-123.89645	40.64000	CALFIRE PORTABLE 12	17226578.0	2023/04/24 19:25:00+00	CA49643C	NaN	2
4888	-114.38161	45.75567	BITTERROOT QD#1 - PORT	17129304.0	2022/10/17 20:18:00+00	326D044E	241598	5
4889	-112.00758	38.65989	FISHLAKE D4 PT #4	18048571.0	2022/11/01 18:01:59+00	32D3D786	NaN	9
4890	-105.57236	40.79281	REDFEATHER	16927282.0	2022/11/16 16:33:00+00	323610D2	050505	8
4891	-95.09472	30.51806	COLDSPRINGS	17294878.0	2023/04/24 18:03:00+00	3288B58A	414201	
4892	-105.22694	40.57083	REDSTONE	17066030.0	2023/05/05 09:57:00+00	3335E6FA	050508	6
4893	-74.31611	40.09861	JACKSON	17392930.0	2022/10/25 21:11:00+00	FF1041BA	280291	
4894	-74.49417	40.40722	NEW MIDDLESEX COUNTY	17392680.0	2022/12/27 15:11:00+00	FF10372A	280231	
4895	-119.06140	37.66182	INF05 PORTABLE	17407304.0	2022/11/01 01:12:59+00	32878682	NaN	9
4896	-123.89645	40.64000	CALFIRE PORTABLE 12	17226578.0	2023/04/24 19:25:00+00	CA49643C	NaN	2
4897	-114.38161	45.75567	BITTERROOT QD#1 - PORT	17129304.0	2022/10/17 20:18:00+00	326D044E	241598	5
4898	-112.00758	38.65989	FISHLAKE D4 PT #4	18048571.0	2022/11/01 18:01:59+00	32D3D786	NaN	9

Checking if all station names are in all caps or not

- only 2 are not in all caps, these don't have a id and will likley end up not being a match anyways

In [663]:
```
# Checking the capitalization of station names
df1['StationName'].str.isupper().value_counts()
```

Out[663]:
```
True     7073
False       2
Name: StationName, dtype: int64
```

In [664]:
```
df1[~df1['StationName'].str.isupper()]
```

Out[664]:

	X	Y	StationName	WXID	ObservedDate	NESSID	NWSID	Elevation	Si
287	-80.97806	26.30472	FLSEA_Port1	NaN	2022/03/15 13:05:59+00	NaN	NaN	NaN	
3549	-116.20806	43.59944	Depot Test 210	NaN	2022/03/15 13:25:00+00	NaN	NaN	NaN	

In [665]:
```
def contains(dfs, column, string, upc=False):
    '''
    Function searchs input column for the input string or numeric
    df: input dataframe
    column : column to search for string
    string : Words to search for, if a int or float, inupt numbers
    upc : False, if True will apply all caps to input string and searc

    if integer or float, it will need the full value not just part of
     Strings use .contains, while numbers use a .loc == int
    '''
    df = dfs.copy()
    df.dropna(subset=[column], inplace=True)
    try:
        if upc:
            print('Searching for Uppercase strings')
            display(df[df[column].str.contains(string.upper())])
        else:
            display(df[df[column].str.contains(string, case=False)])
    except Exception as e:
        print(f'ERROR: {e}')
        display(df[df[column]== string])
```

In [666]:
```
contains(df1, 'StationName', 'holli')
```

	X	Y	StationName	WXID	ObservedDate	NESSID	NWSID	Elevat
395	-121.36216	36.8422	HOLLISTER	17375525.0	2023/03/22 19:12:59+00	CA25B1FA	044406	40
3984	-121.36216	36.8422	HOLLISTER	17375524.0	2022/03/15 13:12:59+00	CA25B1FA	044406	40
6546	-121.36216	36.8422	HOLLISTER	17375526.0	2023/05/05 10:12:59+00	CA25B1FA	044406	40

Removing Duplicate NESSID Values

In [667]:
```
# Creating a new df where there are no duplicated NESSID values
df_set = df1[~df1['NESSID'].duplicated()]
df_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2496 entries, 0 to 7038
Data columns (total 30 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   X                2493 non-null   float64
 1   Y                2493 non-null   float64
 2   StationName      2496 non-null   object 
 3   WXID             2495 non-null   float64
 4   ObservedDate     2496 non-null   object 
 5   NESSID           2495 non-null   object 
 6   NWSID            2012 non-null   object 
 7   Elevation        2487 non-null   float64
 8   SiteDescription  1302 non-null   object 
 9   Latitude         2495 non-null   float64
 10  Longitude        2495 non-null   float64
 11  State            2495 non-null   object 
 12  County           2304 non-null   object 
 13  Agency           2495 non-null   object 
 14  Region           2465 non-null   object 
```

```
 15  Unit               2348 non-null   object
 16  SubUnit            1540 non-null   object
 17  Status             2495 non-null   object
 18  RainAccumulation   2477 non-null   object
 19  WindSpeedMPH       2468 non-null   object
 20  WindDirDegrees     1926 non-null   object
 21  AirTempStandPlace  2467 non-null   object
 22  FuelTemp           1138 non-null   object
 23  RelativeHumidity   2482 non-null   object
 24  BatteryVoltage     1918 non-null   object
 25  FuelMoisture       1109 non-null   object
 26  WindDirPeak        1919 non-null   object
 27  WindSpeedPeak      1884 non-null   object
 28  SolarRadiation     1829 non-null   object
 29  StationID          2496 non-null   int64
dtypes: float64(6), int64(1), object(23)
memory usage: 604.5+ KB
```

In [668]:

```python
duplicates(df1['NESSID'], True)
# 4579 duplicates
# 2496 unique ID's
```

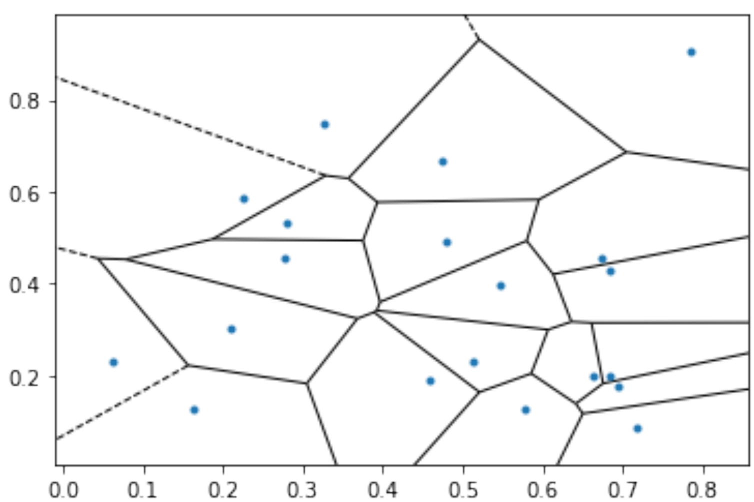
```
Number of Duplicates: 4579

0       8376139A
1       FA6321D4
2       325AE3F8
3       CA28F196
4       32941370
          ...
6955    339054E2
6966    3239463C
6979    3248D408
7016    52109588
7038    328084B6
Name: NESSID, Length: 2496, dtype: object
```

Thiessen Polygons

1. Create Voronoi polygons with stations points
   - For visual purposes, ended up not using due to issues with boundaries and

- For visual purposes, ended up not using due to issues with boundaries and polygons being created doesn't match the number of input stations

In [27]:
```
# EXAMPLE
# random points
points = np.random.rand(20, 2)

# Voronoi
thiessen = Voronoi(points)

fig, ax = plt.subplots(figsize=(6,4))
voronoi_plot_2d(thiessen, ax=ax, show_vertices=False);
```



In [676]:
```
fireplot(df, X, Y, stations=None, site=None, color='red', sp=False):
'''
```

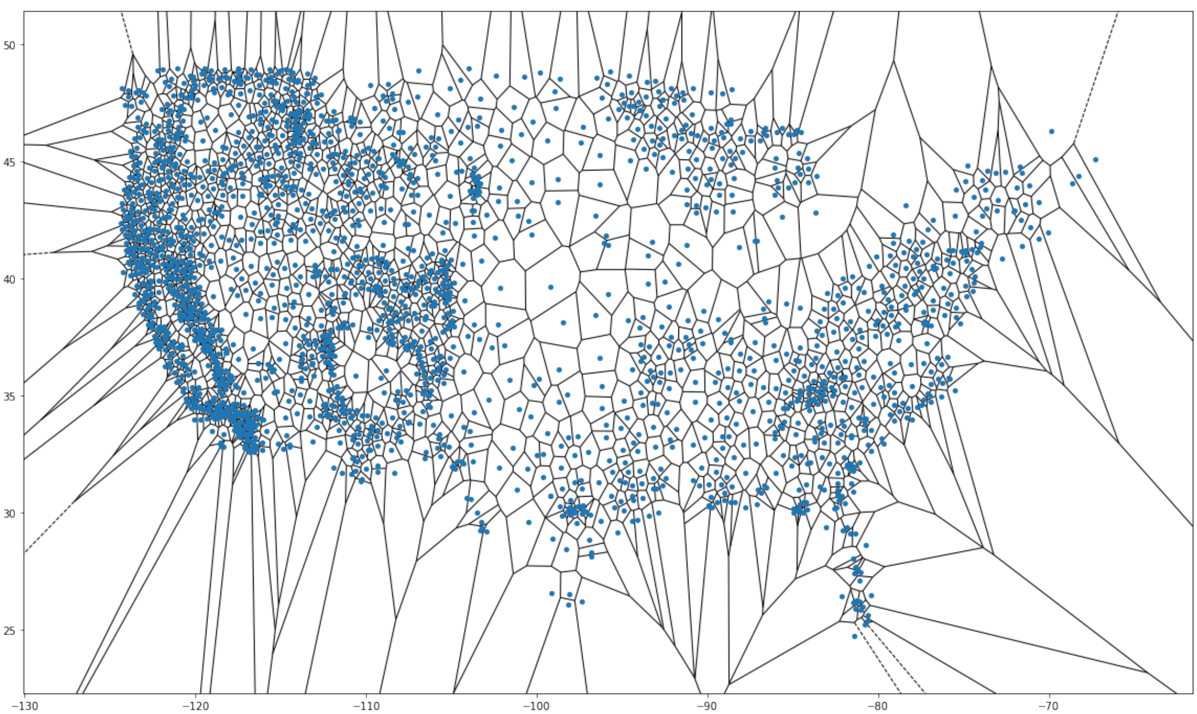
```
Function creates a plot of fires, RAWS stations, Thiessen polygons for
df : dataframe
Y = Latitude
X = Longitude
sp = False  - show_points, this is for the voronoi_plot, set to True t
'''
dfc = df.copy()
st = time.time()
# min and max lat aand long for contiguous USA
# Create boundary
maxLat, minLat = 49.384358, 24.396308
maxLong, minLong = -66.934570, -125.000000

dfc[Y] = dfc[Y].apply(lambda y: None if y > maxLat or y < minLat else
dfc[X]= dfc[X].apply(lambda x: None if x > maxLong or x < minLong else

dfc.dropna(subset=[X, Y], inplace= True)

# PLOT
fig, ax = plt.subplots(figsize=(20, 12))

dfc.plot(x=X, y=Y, ax=ax, kind='scatter', c= 'b', label='Fires');

if site:
    nid = stations[stations['NESSID'].isin(list(df['site'].dropna().va
    nid.plot(x=X, y=Y, ax=ax, kind='scatter', c='black', label='RAWS S
    ax.legend();
      Draw lines between fire and station points
    distances = []
    for index, row in nid.iterrows():
        nessid, x, y = row['NESSID'], row[X], row[Y]
        dfc_row = dfc[dfc['site'] == nessid]
        # Create grey and red lines
        for index, dfc_point in dfc_row.iterrows():
            distance = np.sqrt((x - dfc_point[X]) ** 2 + (y - dfc_poin
            distances.append(distance)
            percentile = np.percentile(distances, 99)
            line_color = color if distance > percentile else 'grey'
            ax.plot([x, dfc_point[X]], [y, dfc_point[Y]], c=line_color

    # attempt to run in parallel
      def distance_check(row, nid):
          X = row['X']
          Y = row['Y']
          # pull raw row
          raw_site  = nid[nid['NESSID']==row['site']]

          # fire
          point = np.array([X, Y])
          site_points = np.array(raw_site[['X', 'Y']])

          # Elucidian Distance
          distances = np.linalg.norm(site_points - point, axis=1)
            nearest_index = np.argmin(distances)
          return {row['OBJECTID'] : {'distance':distances[0], 'X1':raw_
```

```
    from joblib import Parallel, delayed
    presult = Parallel(n_jobs=-1, verbose=1)(
        delayed(distance_check)(row, nid) for index, row in dfc.iter

    result_dict = {key: value for r in presult for key, value in r.i

    for key, values in result_dict.items():
        # Find the row index with matching 'OBJECTIID' value
        index = dfc[dfc['OBJECTID'] == key].index

        # Check if a matching row was found
        if not index.empty:
            # Update the row with new column values
            dfc.loc[index, 'distance'] = values['distance']
            dfc.loc[index, 'X1'] = values['X1']
            dfc.loc[index, 'Y1'] = values['Y1']

    def line(row):

        # Determine the line color based on the distance value
        line_color = 'red' if row['distance'] >0 else 'grey'

        # Draw a line between the points (X, Y) and (X1, Y1)
        return [[row['X'], row['X1']], [row['Y'], row['Y1']], line_c

    presult2 = Parallel(n_jobs=-1, verbose=1)(
        delayed(line)(row) for index, row in dfc.iterrows())
      return presult2
    for pr in presult2:
        ax.plot(pr[0], pr[1], c=pr[2])

elif isinstance(stations, pd.DataFrame):
    vor = thiessen(stations, 'X', 'Y', plot=None)
    voronoi_plot_2d(vor, ax=ax, show_vertices=False, show_points=sp);
print(time.time() - st)
  plt.savefig('fire_site_map.png', dpi=100, bbox_inches='tight')
```

In [30]:
```
def thiessen(df, X, Y, plot=True):
    '''
    df : Dataframe
    Y = Latitude
    X = Longitude
    plot : True, set to False to remove plot
    '''
    dfc = df.copy()

    maxLat, minLat = 49.384358, 24.396308
    maxLong, minLong = -66.934570, -125.000000

    dfc[Y] = dfc[Y].apply(lambda y: pd.NA if y > maxLat or y < minLat
    dfc[X]= dfc[X].apply(lambda x: pd.NA if x > maxLong or x < minLong

    dfc.dropna(subset=[X, Y], inplace =True)
```

```python
    # Pull list of points
    points = list(zip(dfc[X], dfc[Y]))

    # Voronoi
    thiessen = Voronoi(points)

    if plot:
        fig, ax = plt.subplots(figsize=(20, 12))
        voronoi_plot_2d(thiessen, ax=ax, point_size=8, show_vertices=F
    else:
        return thiessen
```

In [31]:
```python
thiessen(df_set, 'X', 'Y')
```

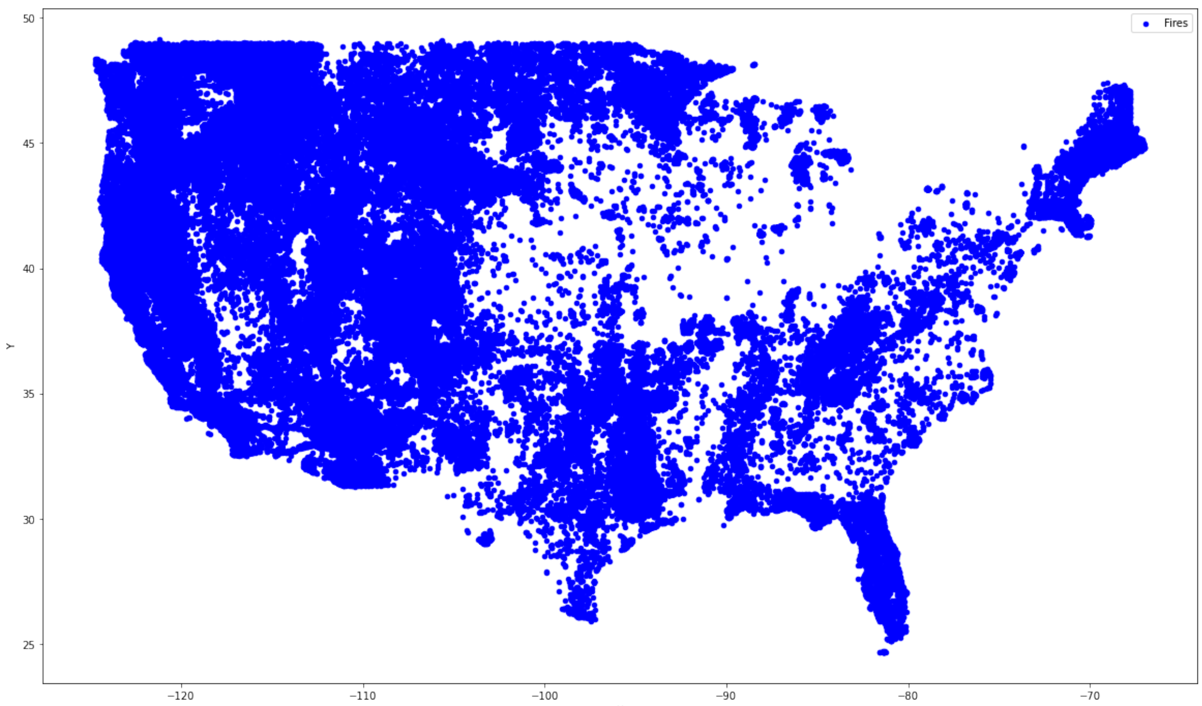


In [689]:
```python
# Loading in Fire locations dataset
fire_sites = pd.read_csv('Data/Wildland_Fire_Incident_Locations.csv.zi
```

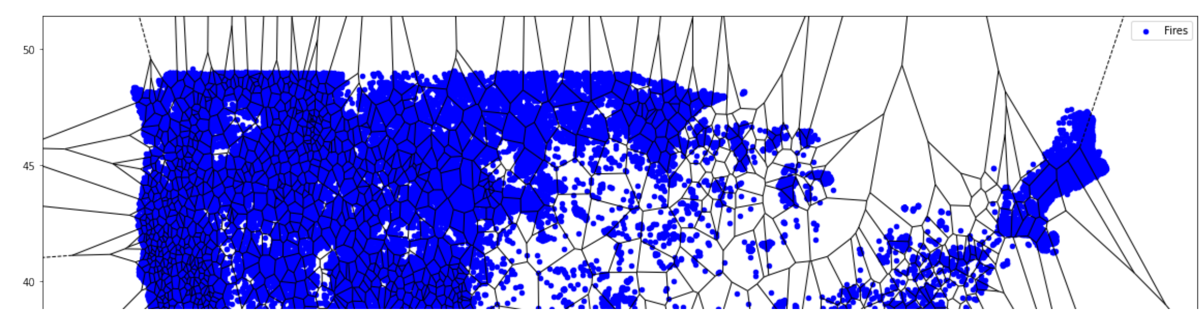
In [ ]:
```python
fire_sites.info()
```

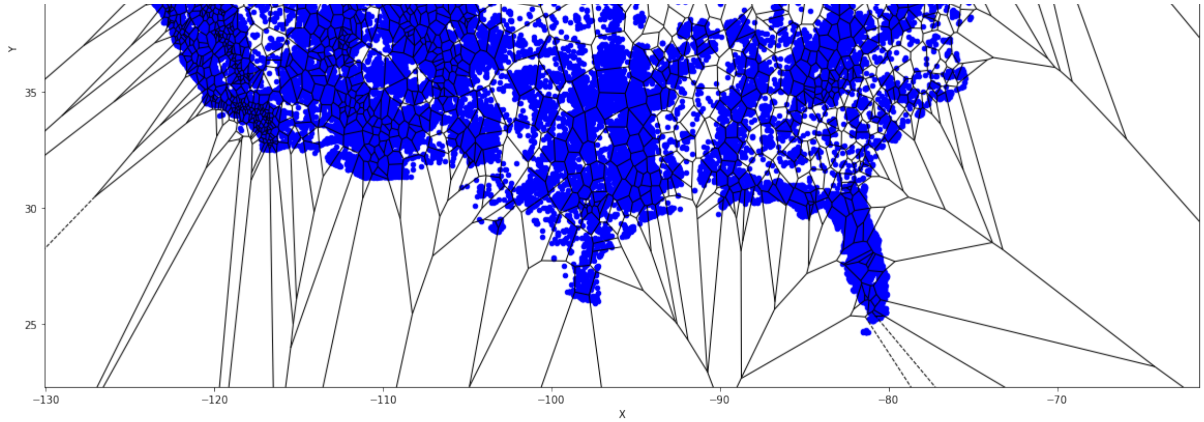
In [ ]:
```python
# Finding Wild Fire in Boulder, 2021
# US-CO
contains(fire_sites[fire_sites['POOState']== 'US-CO'], 'IncidentName'.
```

In [33]:
```
fireplot(fire_sites, 'X', 'Y')
```



In [34]:
```
fireplot(fire_sites, 'X', 'Y', df_set)
```





Loading in RAWS Stations

    - stations_df is the IRAWS with metric data
    - stations_dates is the IRAWS but just the dates

In [38]:
```
stations_df = pd.read_csv('RAWS_stations.csv', header = [0,1], low_mem
```

In [39]:
```
stations_df['32574066'].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3393 entries, 0 to 3392
Data columns (total 15 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   date                             3313 non-null   object 
 1   year                             3393 non-null   int64  
 2   day_of_year                      3393 non-null   int64  
 3   day_of_run                       3393 non-null   int64  
 4   total_solar_radiation_ly         3313 non-null   float64
 5   ave_mean_wind_speed_mph          3313 non-null   float64
 6   ave_mean_wind_direction_deg      3313 non-null   float64
 7   max_maximum_wind_gust_mph        3313 non-null   float64
 8   ave_average_air_temperature_deg_f 3313 non-null   float64
 9   max_average_air_temperature_deg_f 3313 non-null   float64
 10  min_average_air_temperature_deg_f 3313 non-null   float64
 11  ave_average_relative_humidity    3313 non-null   float64
 12  max_average_relative_humidity    3313 non-null   float64
 13  min_average_relative_humidity    3313 non-null   float64
 14  total_precipitation_in           3313 non-null   float64
dtypes: float64(11), int64(3), object(1)
memory usage: 397.7+ KB
```

In [40]:
```python
stations_dates = pd.read_csv('stations_dates.csv', low_memory=False)
```

In [41]:
```python
stations_dates.head()
```

Out[41]:

	3234455A	4870D3B2	324AD1FC	323FA500	CA41F5F8	327BC600	02609414	323361
0	02/01/2014	02/01/2014	02/01/2014	02/01/2014	02/01/2014	02/01/2014	02/01/2014	02/01/20
1	02/02/2014	02/02/2014	02/02/2014	02/02/2014	02/02/2014	02/02/2014	02/02/2014	02/02/20
2	02/03/2014	02/03/2014	02/03/2014	02/03/2014	02/03/2014	02/03/2014	02/03/2014	02/03/20
3	02/04/2014	02/04/2014	02/04/2014	02/04/2014	02/04/2014	02/04/2014	02/04/2014	02/04/20
4	02/05/2014	02/05/2014	02/05/2014	02/05/2014	02/05/2014	02/05/2014	02/05/2014	02/05/20

5 rows × 1939 columns

In [42]:
```python
stations_dates.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3393 entries, 0 to 3392
Columns: 1939 entries, 3234455A to 88400776
dtypes: object(1939)
memory usage: 50.2+ MB
```

Cleaning RAWS data

In [43]:
```python
# Number of stations
def number_of_stations(df, Return=True):
    '''
    Returns the number of columns in a multilevel index, at level 0,
    also returns a list of the columns
    '''
    col = df.columns.get_level_values(0).unique().tolist()
    print(f'Number of Stations: {len(col)}')
    if Return:
        return col
```

In [44]:
```python
# should be 1939, missing 4 stations
raw_stations_list = number_of_stations(stations_df)
```

```
Number of Stations: 1935
```

In [45]:
```
def columCheck(df, inputs=False, Return=False):
    '''
    Returns the number of columns in a multilevel index at level 1,
    also returns a list of the columns
    '''
    # list of every column at level1
    col = df.columns.get_level_values(1).unique().tolist()
    print(f'Number of Stations: {len(col)}')
    display(col)
    # list of columns that contain the input
    if inputs:
        i = inputs
    else:
        i = input('Select name from list: ')
    if i:
        val = [l for l in df.columns if i in l[1]]
        print(f'Stations with {i}\n {val}')

    print('\nFull list\n')
    total_val = set()
    for c in col[15:]:
        val = [l[0] for l in df.columns if c in l[1]]
        total_val.update(val)
    print(f'Stations with incorrect columns:\n {total_val}')


    if Return:
        return col, list(total_val)
```

In [46]:
```
ccc, bad_columns= columCheck(stations_df, Return=True)
```

```
Number of Stations: 60

['date',
 'year',
 'day_of_year',
 'day_of_run',
 'total_solar_radiation_ly',
 'ave_mean_wind_speed_mph',
```

```
 'ave_mean_wind_speed_mph',
 'ave_mean_wind_direction_deg',
 'max_maximum_wind_gust_mph',
 'ave_average_air_temperature_deg_f',
 'max_average_air_temperature_deg_f',
 'min_average_air_temperature_deg_f',
 'ave_average_relative_humidity',
 'max_average_relative_humidity',
 'min_average_relative_humidity',
 'total_precipitation_in',
 'date.1',
 'year.1',
 'day_of_year.1',
 'day_of_run.1',
 'total_solar_radiation_ly.1',
 'ave_mean_wind_speed_mph.1',
 'ave_mean_wind_direction_deg.1',
 'max_maximum_wind_gust_mph.1',
 'ave_average_air_temperature_deg_f.1',
 'max_average_air_temperature_deg_f.1',
 'min_average_air_temperature_deg_f.1',
 'ave_average_relative_humidity.1',
 'max_average_relative_humidity.1',
 'min_average_relative_humidity.1',
 'total_precipitation_in.1',
 'date.2',
 'year.2',
 'day_of_year.2',
 'day_of_run.2',
 'total_solar_radiation_ly.2',
 'ave_mean_wind_speed_mph.2',
 'ave_mean_wind_direction_deg.2',
 'max_maximum_wind_gust_mph.2',
 'ave_average_air_temperature_deg_f.2',
 'max_average_air_temperature_deg_f.2',
 'min_average_air_temperature_deg_f.2',
 'ave_average_relative_humidity.2',
 'max_average_relative_humidity.2',
 'min_average_relative_humidity.2',
 'total_precipitation_in.2',
 'date.3',
 'year.3',
 'day_of_year.3',
 'day_of_run.3',
 'total_solar_radiation_ly.3',
 'ave_mean_wind_speed_mph.3',
 'ave_mean_wind_direction_deg.3',
 'max_maximum_wind_gust_mph.3',
 'ave_average_air_temperature_deg_f.3',
 'max_average_air_temperature_deg_f.3',
 'min_average_air_temperature_deg_f.3',
 'ave_average_relative_humidity.3',
 'max_average_relative_humidity.3',
 'min_average_relative_humidity.3',
 'total_precipitation_in.3']

Select name from list:
```

```
Select name from list:

Full list

Stations with incorrect columns:
 {'08007552', 'nan'}
```

In [47]:
```python
stations_df['08007552'].head()
```

Out[47]:

	date	year	day_of_year	day_of_run	total_solar_radiation_ly	ave_mean_wind_speed_r
0	02/01/2014	2014.0	32.0	1.0	34.0	
1	02/02/2014	2014.0	33.0	2.0	44.0	
2	02/03/2014	2014.0	34.0	3.0	70.0	
3	02/04/2014	2014.0	35.0	4.0	44.0	
4	02/05/2014	2014.0	36.0	5.0	69.0	

In [48]:
```python
stations_df['nan'].head()
```

Out[48]:

	date	year	day_of_year	day_of_run	total_solar_radiation_ly	ave_mean_wind_speed_r
0	02/01/2014	2014.0	32.0	1.0	NaN	1
1	02/02/2014	2014.0	33.0	2.0	NaN	2
2	02/03/2014	2014.0	34.0	3.0	NaN	1
3	02/04/2014	2014.0	35.0	4.0	NaN	1
4	02/05/2014	2014.0	36.0	5.0	NaN	

5 rows × 60 columns

In [49]:
```python
stations_dates['08007552']
```

Out[49]:
```
0       02/01/2014
1       02/02/2014
2       02/03/2014
3       02/04/2014
4       02/05/2014
           ...
3388           NaN
3389           NaN
3390           NaN
3391           NaN
3392           NaN
Name: 08007552, Length: 3393, dtype: object
```

In [50]:
```
# Convert lists back to sets
set1 = set(raw_stations_list)
set2 = set(stations_dates.columns)

# Find the extra values
set2_extra = set2 - set1
set1_extra = set1 - set2


print(f"set2:{list(set2_extra)}\nset1:{list(set1_extra)}")
```

```
set2:['Unnamed: 1517', 'Unnamed: 103', 'Unnamed: 1330', '08007552.1',
'Unnamed: 1554']
set1:['nan']
```

In [56]:
```
# From dates_df the  08007552 need to be dropped as well as all the ot
#extra staations that i dont actually have data for
# stations_dates doesn't have a nan so we can just ignore that

stations_dates.drop(columns= ['08007552.1', 'Unnamed: 1517', 'Unnamed:
                              'Unnamed: 103', 'Unnamed: 1330', '080075
                   inplace= True)
```

Missing stations explained

The above 2 stations for some reason contains 6 stations total, thats the 4 missing stations

- Going to just drop all 6 stations

In [57]:
```
stations_df1 = stations_df.copy()
```

In [58]:
```python
stations_df1['nan']
```

Out[58]:

	date	year	day_of_year	day_of_run	total_solar_radiation_ly	ave_mean_wind_spee
0	02/01/2014	2014.0	32.0	1.0	NaN	
1	02/02/2014	2014.0	33.0	2.0	NaN	
2	02/03/2014	2014.0	34.0	3.0	NaN	
3	02/04/2014	2014.0	35.0	4.0	NaN	
4	02/05/2014	2014.0	36.0	5.0	NaN	
...	...	...	...	...	...	
3388	NaN	NaN	NaN	NaN	NaN	
3389	NaN	NaN	NaN	NaN	NaN	
3390	NaN	NaN	NaN	NaN	NaN	
3391	NaN	NaN	NaN	NaN	NaN	
3392	NaN	NaN	NaN	NaN	NaN	

3393 rows × 60 columns

In [59]:
```python
def adjust_column_names(df):
    '''
    Modifies the DataFrame columns at level 0 of the multi-level index
    '''
    header = ['date', 'year', 'day_of_year', 'day_of_run', 'total_sola
              'ave_mean_wind_speed_mph', 'ave_mean_wind_direction_deg', 'm
              'ave_average_air_temperature_deg_f', 'max_average_air_temper
              'min_average_air_temperature_deg_f', 'ave_average_relative_h
              'max_average_relative_humidity', 'min_average_relative_humic

    col = df.columns.get_level_values(0).unique().tolist()
    try:
        for c in col:
            df[c].set_axis(header, axis=1, inplace=True)
        return df
    except Exception as e:
        print(e)
```

In [60]:
```python
adjust_column_names(stations_df1)
```

```
Length mismatch: Expected axis has 60 elements, new values have 15 el
ements
```

The above failed, just going to drop the stations with this issue

In [61]:
```python
bad_columns
```

Out[61]:
```
['08007552', 'nan']
```

In [62]:
```python
stations_df1.drop(columns= bad_columns, level=0, inplace= True)
```

In [63]:
```python
# Checking if dropping the bad columns worked
columCheck(stations_df1)
```

```
Number of Stations: 15

['date',
 'year',
 'day_of_year',
 'day_of_run',
 'total_solar_radiation_ly',
 'ave_mean_wind_speed_mph',
 'ave_mean_wind_direction_deg',
 'max_maximum_wind_gust_mph',
 'ave_average_air_temperature_deg_f',
 'max_average_air_temperature_deg_f',
 'min_average_air_temperature_deg_f',
 'ave_average_relative_humidity',
 'max_average_relative_humidity',
 'min_average_relative_humidity',
 'total_precipitation_in']

Select name from list:

Full list

Stations with incorrect columns:
 set()
```

In [64]:
```python
# Get the list of unique level 0 column names
col = stations_df1.columns.get_level_values(0).unique().tolist()

# Convert 'date' column to datetime
for c in col:
    stations_df1[(c, 'date')] = pd.to_datetime(stations_df1[(c, 'date'
```

In [65]:
```python
# Drop specified columns
columns_to_drop = ['year', 'day_of_year', 'day_of_run', 'max_average_a
                   'min_average_air_temperature_deg_f', 'max_average_r
                   'min_average_relative_humidity']
```

```python
stations_df1.drop(columns=columns_to_drop, level=1, inplace=True)
```

In [66]:
```python
stations_df1['3234455A'].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3393 entries, 0 to 3392
Data columns (total 8 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   date                               3371 non-null   datetime64[ns
]
 1   total_solar_radiation_ly           3371 non-null   float64
 2   ave_mean_wind_speed_mph            3371 non-null   float64
 3   ave_mean_wind_direction_deg        3371 non-null   float64
 4   max_maximum_wind_gust_mph          3371 non-null   float64
 5   ave_average_air_temperature_deg_f  3371 non-null   float64
 6   ave_average_relative_humidity      3371 non-null   float64
 7   total_precipitation_in             3371 non-null   float64
dtypes: datetime64[ns](1), float64(7)
memory usage: 212.2 KB
```

In [67]:
```python
stations_df1.head()
```

Out[67]:

	date	total_solar_radiation_ly	ave_mean_wind_speed_mph	ave_mean_wind_direction_deg	ma
0	2014-02-01	270.0	0.42	93.0	
1	2014-02-02	207.0	3.50	146.0	
2	2014-02-03	114.0	0.96	232.0	
3	2014-02-04	237.0	5.71	120.0	
4	2014-02-05	294.0	4.92	122.0	

5 rows × 15464 columns

Fire Occurrences EDA

- Using dataFrame fire_sites

[Go to Top](#)

In [684]:
```
# various columns in fire_sites, Ended up using all that is selected
keep = ['IncidentSize', 'EstimatedCostToDate', 'FinalAcres', 'FireCaus
        'EstimatedFinalCost', 'IncidentName']

maybe = ['FireCauseGeneral', 'FireCauseSpecific', 'DiscoveryAcres', 'F
         'IncidentShortDescription']

keep1 = ['X','Y', 'OBJECTID','ContainmentDateTime','ControlDateTime','
                                'FireOutDateTime']

keep3 = ['DispatchCenterID', 'ABCDMisc', 'FireCode', 'FireDepartmentID
         'POOCounty','POOFips', 'POOJurisdictionalAgency', 'POOJurisdi

fire_test = fire_sites[keep1 + maybe + keep + keep3]
fire_test.head()
```

...

In [69]:
```
fire_test.isna().sum()
```

Out[69]:
```
X                                0
Y                                0
OBJECTID                         0
ContainmentDateTime         102796
ControlDateTime             118401
FireDiscoveryDateTime            0
FireOutDateTime             109938
FireCauseGeneral            201737
FireCauseSpecific           241832
DiscoveryAcres               65383
FireMgmtComplexity          234285
IncidentShortDescription    247801
IncidentSize                 76637
EstimatedCostToDate         242591
FinalAcres                  238393
FireCause                    31610
PrimaryFuelModel            240503
EstimatedFinalCost          255773
IncidentName                     9
DispatchCenterID             37378
ABCDMisc                    244544
FireCode                    127669
FireDepartmentID            246920
GACC                            61
POODispatchCenterID          77599
POOCounty                      161
POOFips                        168
POOJurisdictionalAgency     147810
POOJurisdictionalUnit        92977
POOState                         0
dtype: int64
```

In [70]:
```python
print(f'Over 50% Are Nulls:\n{"-"*45}\n{fire_test.isna().sum() > (len(
```

```
Over 50% Are Nulls:
---------------------------------------------
X                               False
Y                               False
OBJECTID                        False
ContainmentDateTime             False
ControlDateTime                 False
FireDiscoveryDateTime           False
FireOutDateTime                 False
FireCauseGeneral                 True
FireCauseSpecific                True
DiscoveryAcres                  False
FireMgmtComplexity               True
IncidentShortDescription         True
IncidentSize                    False
EstimatedCostToDate              True
FinalAcres                       True
FireCause                       False
PrimaryFuelModel                 True
EstimatedFinalCost               True
IncidentName                    False
DispatchCenterID                False
ABCDMisc                         True
FireCode                        False
FireDepartmentID                 True
GACC                            False
POODispatchCenterID             False
POOCounty                       False
POOFips                         False
POOJurisdictionalAgency          True
POOJurisdictionalUnit           False
POOState                        False
dtype: bool
```

In [71]:
```python
# checking length of target
len(fire_test[~fire_test['FireMgmtComplexity'].isna()])
```

Out[71]:
```
23340
```

Fire Acres contains many nulls, below I evaluate the column called incidentsize to determine if it is the same units or similar to final acres

In [72]:
```
fire_size = fire_test[(~fire_test['FinalAcres'].isna()) & (~fire_test[
fire_size = fire_size[['FinalAcres', 'IncidentSize']]
fire_size
```

Out[72]:

	FinalAcres	IncidentSize
9215	0.00	0.00
36489	0.00	0.00
70726	0.00	0.00
72652	492.30	400.10
72914	0.01	0.01
...	...	...
257568	5.00	5.00
257570	0.50	0.50
257574	1.00	1.00
257602	2.00	2.00
257615	3.00	3.00

13575 rows × 2 columns

- many of the values are similar aand i have good reason to believe incident size is in acres,
- all values missing acres but has incidentsize will be used

In [73]:

```
# replace null acres with their incident size
fire_test['FinalAcres'].fillna(fire_test['IncidentSize'], inplace=True
fire_test.drop(columns='IncidentSize', inplace=True)
```

```
/Users/keanan/opt/anaconda3/envs/flatiron-env/lib/python3.8/site-pack
ages/pandas/core/series.py:4517: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  return super().fillna(
/Users/keanan/opt/anaconda3/envs/flatiron-env/lib/python3.8/site-pack
ages/pandas/core/frame.py:4163: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  return super().drop(
```

In [74]:

```
# Rechecking the nulls
```

```
fire_test.isna().sum()
```

Out[74]:
```
X                                0
Y                                0
OBJECTID                         0
ContainmentDateTime         102796
ControlDateTime             118401
FireDiscoveryDateTime            0
FireOutDateTime             109938
FireCauseGeneral            201737
FireCauseSpecific           241832
DiscoveryAcres               65383
FireMgmtComplexity          234285
IncidentShortDescription    247801
EstimatedCostToDate         242591
FinalAcres                   70980
FireCause                    31610
PrimaryFuelModel            240503
EstimatedFinalCost          255773
IncidentName                     9
DispatchCenterID             37378
ABCDMisc                    244544
FireCode                    127669
FireDepartmentID            246920
GACC                            61
POODispatchCenterID          77599
POOCounty                      161
POOFips                        168
POOJurisdictionalAgency     147810
POOJurisdictionalUnit        92977
POOState                         0
dtype: int64
```

In [75]:
```
# Renaming all columns with date that shouldn't be datetime
fire_test.rename(columns={'EstimatedCostToDate': 'EstimatedCostTodate'
```

```
/Users/keanan/opt/anaconda3/envs/flatiron-env/lib/python3.8/site-pack
ages/pandas/core/frame.py:4296: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  return super().rename(
```

In [76]:
```
# Setting datetime
def datetimes(df, dates=None, normal=True):
    '''
```

```
    df : dataframe
    dates : list of columns to perform datetime on, if none only colum
    normal : True, False will not use format='%Y-%m-%d'
    '''
    if not dates:
        dates = list(df.columns[df.columns.str.contains('Date')])
    if normal:
        for t in dates:
            df[t] = pd.to_datetime(df[t], errors='coerce', format='%Y-
            df[t] = df[t].dt.tz_localize(None)
            print('Used Format Y-m-d')
    else:
        for t in dates:
            df[t] = pd.to_datetime(df[t], errors='coerce')

datetimes(fire_test)
```

```
<ipython-input-76-c499f70d71c7>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df[t] = pd.to_datetime(df[t], errors='coerce', format='%Y-%m-%d')#.
dt.normalize()
<ipython-input-76-c499f70d71c7>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df[t] = df[t].dt.tz_localize(None)

Used Format Y-m-d
Used Format Y-m-d
Used Format Y-m-d
Used Format Y-m-d
```

In [77]:
```
# Setting all columns as date time
datetimes(stations_dates, list(stations_dates.columns), normal=False)
```

In [78]:
```




def fixer(df):
    '''
    Function to further clean fire occurences dataset
    '''
    # remove any year thats older then 2014 (dataset is only supposed
```

```
    datetime_columns = list(df.select_dtypes(['datetime64[ns, UTC]', '

    # Replace missing FireOutDateTime values with ContainmentDateTime
    dropped = []
    for dc in datetime_columns:
        df['year'] = df[dc].dt.year
        dropped.extend(df[df['year'] < 2014].values)
        df = df[df['year'] >= 2014]
#          dropped.extend(df[df['year'] < 2014].index)
    df.drop(columns='year', inplace=True)


    # Replacing null fireoutdatetime with containment datetime
    df['FireOutDateTime'].fillna(df['ContainmentDateTime'], inplace=Tr

    # Drop any fire out day that is after the current date, as thats i
    from datetime import datetime
    # Todays date
    today = datetime.now().date()

    # Drop rows where FireOutDateTime is greater then today
    dropped.extend(df[df['FireOutDateTime'].dt.date > today].values)
    df = df[df['FireOutDateTime'].dt.date <= today]

    # Drop rows where FireOutDateTime is greater then FireDiscoveryDat
    dropped.extend(df[df['FireOutDateTime'].dt.date >= df['FireDiscove
    df = df[df['FireOutDateTime'].dt.date >= df['FireDiscoveryDateTime


    # Final drop
    df.drop(columns=['ContainmentDateTime','ControlDateTime'], inplace

    return df, dropped

fire_test, dropped_rows = fixer(fire_test)
fire_test.head()
```

```
<ipython-input-78-e1039468ab7e>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df['year'] = df[dc].dt.year
<ipython-input-78-e1039468ab7e>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df['year'] = df[dc].dt.year
```

Out[78]:

	X	Y	OBJECTID	FireDiscoveryDateTime	FireOutDateTime	FireCaus
371	-107.464712	45.622997	372	2022-09-19 06:08:00	2022-11-07 18:04:59	
670	-108.840411	37.245426	671	2022-08-09 21:32:00	2022-08-15 20:39:00	
1817	-121.604615	47.638906	1818	2022-09-02 20:08:00	2022-12-16 21:13:00	
5842	-110.770411	33.117105	5843	2022-03-14 20:25:00	2022-03-15 02:00:00	
12572	-108.972811	38.758058	12575	2022-07-17 23:48:59	2022-12-20 17:19:59	
...	...	...	...	...	...	
257521	-116.656414	47.613426	307102	2023-05-04 18:32:00	2023-05-04 19:55:00	
257539	-111.490511	32.712385	307122	2023-05-04 19:50:59	2023-05-05 14:35:00	
257557	-95.855345	47.085820	307143	2023-05-04 22:05:00	2023-05-05 23:48:59	
257590	-114.248212	35.382985	307191	2023-05-05 03:45:43	2023-05-05 04:40:00	
257593	-116.966714	48.457256	307195	2023-05-05 01:23:00	2023-05-05 02:40:00	

128906 rows × 27 columns

Duration

Calculating duration to for RAWS site pulling, this is used to check if a RAWS has data for atleast 50% of the duration a fire occurs

In [79]:

```
# duration of each fire
fire_test['duration'] = fire_test['FireOutDateTime'] - fire_test['Fire
fire_test['duration'] = fire_test['duration'].dt.days
```

In [80]:

```
def findfire(day):
    '''
    Function: Locates fires occurences based on input year
    '''
    fire_test1 = fire_test.copy()
    fire_test1.reset_index(inplace=True)

    return fire_test1[fire_test1['FireOutDateTime'].dt.date == pd.to_d
```

In [81]:
```
findfire('2023')
```
Out[81]:

	index	X	Y	OBJECTID	FireDiscoveryDateTime	FireOutDateTime
11963	97892	-119.065715	48.766786	102122	2022-08-01 04:24:09	2023-01-01 07:59:00
103506	217152	-122.012615	46.461046	253772	2022-11-17 21:11:43	2023-01-01 00:00:00
126462	247648	-94.566597	35.720216	292902	2023-01-01 00:30:00	2023-01-01 02:00:00

Dropping all points outside of the contiguous USA

This is done to reduce size and risk of irregularities along islands and other points that appear to be in the oceaan

In [669]:
```
# Pulling nessid for each site,
nessid_df = df_set[['NESSID', 'X', 'Y']]#.set_index('NESSID')
```
In [83]:
```
def conti(site):
    '''
    This function assumes lat and long are X and Y
    limits dataset to only contiguous USA
    '''
    max_lat, min_lat = 49.384358, 24.396308
    max_long, min_long = -66.934570, -125.000000

    site['Y'] = site['Y'].apply(lambda y: np.nan if y > max_lat or y <
    site['X'] = site['X'].apply(lambda x: np.nan if x > max_long or x
    site.dropna(subset=['X', 'Y'], inplace =True)
    return site
fire_test = conti(fire_test)
```
In [84]:
```
fire_test1 = fire_test.copy()
```
In [86]:
```
def set_index(dfs):
    '''
    Set index to be a list of dates
    dfs : dataframe

    Input should be a dataframe with all values as dates, assumes each
    Redundancy statement checks for this.
    '''
    df = dfs.copy()
    dates = []
```

```
    dates = []

    # Iterate over each row in DataFrame
    for index, row in df.iterrows():
        # Find the date value in the row
        date_value = pd.to_datetime(row.values, errors='coerce')

        # Check if the date value is unique in the row, Redundancy che
        if date_value.nunique() != 1:
            print(f"Non-unique date value found in row {index}")

        # Add date value to the list
        dates.append(date_value[0])

    # set index to be list of days in DataFrame
    df.index = dates
    return df
stations_dates5 = set_index(stations_dates)
```

In [87]:
```
# setting dates to dt.date for fire dataset
fire_test1['FireDiscoveryDateTime'] = fire_test1['FireDiscoveryDateTim
fire_test1['FireOutDateTime'] = fire_test1['FireOutDateTime'].dt.date
```

Fire Incidents RAWS

For each fire duration, data from remote access weather stations that provided data for 50% or more of the duration were collected. The closest weather station was then assigned to the fire incident. The assigned weather station's average values for each parameter were used to represent the meteorological characteristics over the entire duration.

In [88]:
```
def poly_site(row ,site, nessid):
    '''
    x : X coordinate (longitude)
    y : Y coordinate (latitude)
    row : dataframe row as a series
    site : RAWS dates dataframe, all values should be dates, index als
    nessid : RAWS with nessid, X and Y

    Function:
    Find RAWS closest to Fire incident that has data for atleast 50% c

    1. Pulls all RAWS between fire start and end date, if more then ha
    2. If start or end date doesn't exsit in site data, then reduce du
    3. pull all rows in nessid that are in filtered site, columns in s
    4. pull all X and Y for filtered nessid, find site closest to fire
    5. return fire objectid and site nessid
    '''
    X = row['X']
    Y = row['Y']
    obid = row['OBJECTID']
    start, end = row['FireDiscoveryDateTime'], row['FireOutDateTime']
    duration = row['duration']
```

```
    # pulling all sites between start and end dates
    # Recursive function will adjust start and end date if current dat
    def recursive_time(site, start, end, duration):
        try:
            filtered_data = site.loc[start:end].dropna(axis=1, thresh=
            return filtered_data
        except Exception as e:
            if e.args[0].date() == end:
                end = end - timedelta(days=1)
            elif e.args[0].date() == start:
                start = start + timedelta(days=1)

            return recursive_time(site, start, end, duration)
    # if duration <= 1 day , then drop RAWS if null
    if duration <= 1:
        try:
            filtered_data = site.loc[start:end].dropna(axis=1)
        except:
            # if it fails then there is no site with data for this day
            return {obid : np.nan}
    else:
        filtered_data = recursive_time(site, start, end, duration)

    nid = nessid[nessid['NESSID'].isin(filtered_data.columns)].reset_i
#     return nid
    # Create arrays for elucidian calculation
    point = np.array([X, Y])
    site_points = np.array(nid[['X', 'Y']])

    # Elucidian Distance
    distances = np.linalg.norm(site_points - point, axis=1)
    nearest_index = np.argmin(distances)

    return {obid : nid.iloc[nearest_index]['NESSID']}
```

In [89]:

```
# Running poly_site function with parallel processing

# Use Parallel
results = Parallel(n_jobs=-1, verbose=1)(
    delayed(poly_site)(row, stations_dates5, nessid_df) for index, row
)

# create one dict, from the nest
result_dict = {key: value for r in results for key, value in r.items()
# Add sites to new column
fire_test1['site'] = fire_test1['OBJECTID'].map(result_dict)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
```

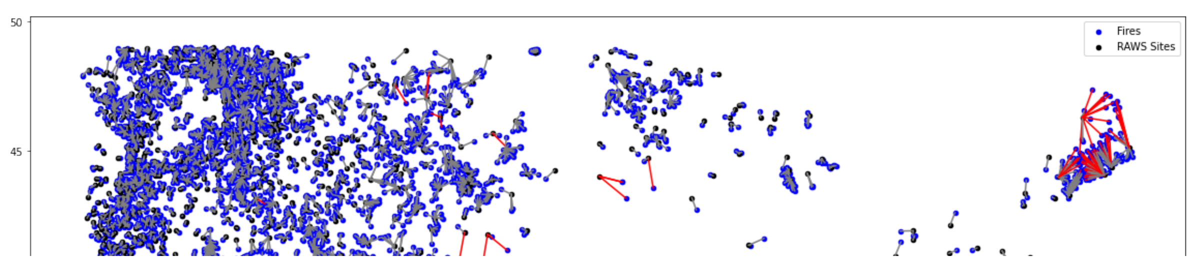
```
rkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done 976 tasks      | elapsed:    3.7s
[Parallel(n_jobs=-1)]: Done 2976 tasks      | elapsed:    7.8s
[Parallel(n_jobs=-1)]: Done 5776 tasks      | elapsed:   13.7s
[Parallel(n_jobs=-1)]: Done 9376 tasks      | elapsed:   22.1s
[Parallel(n_jobs=-1)]: Done 13776 tasks      | elapsed:   32.0s
[Parallel(n_jobs=-1)]: Done 18976 tasks      | elapsed:   43.5s
[Parallel(n_jobs=-1)]: Done 24976 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 31776 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 39376 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 47776 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 56976 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 66976 tasks      | elapsed:  2.8min
[Parallel(n_jobs=-1)]: Done 77776 tasks      | elapsed:  3.3min
[Parallel(n_jobs=-1)]: Done 89376 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done 101776 tasks      | elapsed:  4.2min
[Parallel(n_jobs=-1)]: Done 114976 tasks      | elapsed:  4.7min
[Parallel(n_jobs=-1)]: Done 124387 out of 124387 | elapsed:  5.1min f
inished
```

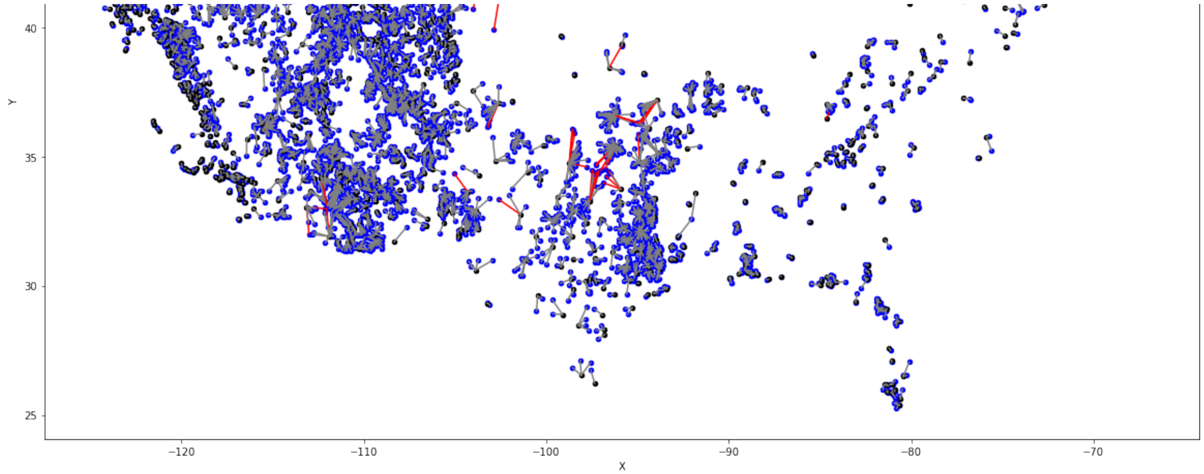
In [90]:
```python
# number of missing sites
fire_test1['site'].isna().sum()
```

Out[90]: 18

In [91]:
```python
# Plot showing fire incidents and the closest usable RAW
# Red line indicates farther then 99% of the other pairs
st = time.time()
fireplot(fire_test1[:10000], 'X', 'Y', nessid_df, True)
time.time() - st
```

Out[91]: 13.713191986083984





Pulling the mean values for each fire

Go to Top

In [92]:
```
# drop all nulls in subset site
fire_test1.dropna(subset=['site'], inplace=True)
```

In [93]:
```
# check for nulls
fire_test1['site'].isna().sum()
```

Out[93]:
```
0
```

In [94]:
```
# create df for all used RAWS stations
final_raws = stations_df1[set(r for r in list(fire_test1['site']) if r
number_of_stations(final_raws, Return=False)
```

```
Number of Stations: 1512
```

In [95]:
```
final_raws.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3393 entries, 0 to 3392
Columns: 12096 entries, ('327307B8', 'date') to ('3287439C', 'total_p
recipitation_in')
dtypes: datetime64[ns](1512), float64(9937), int64(647)
memory usage: 313.1 MB
```

In [96]:
```
def final_eda(row, site):
    '''
    row : fire incident dataframe rows
    site : RAWS stations full dataframe, multilevel index
    For each fire incident, locate RAWS (nessid) and calculate the mea
    returns dictionary with objectid and dataframe with the mean value
    '''
```

```
    start, end = row['FireDiscoveryDateTime'], row['FireOutDateTime']

    # pull the site dataframe
    picked_site = site[row['site']]
    # pull all rows between start and end date
    picked_site = picked_site[(picked_site['date'].dt.date >= start) &

    return {row['OBJECTID'] : picked_site.mean(numeric_only=True)} #nu
```

In [99]:
```
fire_final = fire_test1.copy()
```

In [103]:
```
# Using parallel processing to run final_eda
results_eda = Parallel(n_jobs=-1, verbose=1)(
    delayed(final_eda)(row, final_raws) for index, row in fire_final.i
)

st = time.time()
# create one dict, from the nest
result_dict = {key: value for r in results_eda for key, value in r.ite
print(f"Total Run Time: {time.time()- st}")

# take output dict and add to dataframe
st = time.time()
for key, value in result_dict.items():
    fire_final.loc[fire_final['OBJECTID'] == key, value.index] = value
print(f"Total Run Time: {time.time()- st}")
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
```

```
rkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.6s
[Parallel(n_jobs=-1)]: Done 1800 tasks      | elapsed:    3.8s
[Parallel(n_jobs=-1)]: Done 5800 tasks      | elapsed:   11.4s
[Parallel(n_jobs=-1)]: Done 11400 tasks      | elapsed:   21.5s
[Parallel(n_jobs=-1)]: Done 18600 tasks      | elapsed:   32.6s
[Parallel(n_jobs=-1)]: Done 27400 tasks      | elapsed:   44.9s
[Parallel(n_jobs=-1)]: Done 37800 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 49800 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 63400 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 78600 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 95400 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 113800 tasks      | elapsed:  2.9min
[Parallel(n_jobs=-1)]: Done 124369 out of 124369 | elapsed:  3.1min f
inished

Total Run Time: 0.30333423614501953
Total Run Time: 445.47034335136414
```

Final dataset EDA

In [106]:
```
# Checking for nulls in meteorological
fire_final.isna().sum()
```

Out[106]:
```
X                                    0
Y                                    0
OBJECTID                             0
FireDiscoveryDateTime                0
FireOutDateTime                      0
FireCauseGeneral                 91013
FireCauseSpecific               113574
DiscoveryAcres                   15656
FireMgmtComplexity              112376
IncidentShortDescription        119780
EstimatedCostTodate             117767
FinalAcres                        6247
FireCause                         1855
PrimaryFuelModel                116933
EstimatedFinalCost              122988
IncidentName                         0
DispatchCenterID                 11755
```

```
ABCDMisc                               112721
FireCode                                44952
FireDepartmentID                       122006
GACC                                       29
POODispatchCenterID                     43910
POOCounty                                   7
POOFips                                    12
POOJurisdictionalAgency                 61851
POOJurisdictionalUnit                   31589
POOState                                    0
duration                                    0
site                                        0
total_solar_radiation_ly                  835
ave_mean_wind_speed_mph                   116
ave_mean_wind_direction_deg               112
max_maximum_wind_gust_mph                 283
ave_average_air_temperature_deg_f          12
ave_average_relative_humidity             234
total_precipitation_in                     14
dtype: int64
```

In [108]:
```
fire_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 124369 entries, 371 to 257593
Data columns (total 36 columns):
 #   Column                                 Non-Null Count   Dtype
---  ------                                 --------------   -----
 0   X                                      124369 non-null  float64
 1   Y                                      124369 non-null  float64
 2   OBJECTID                               124369 non-null  int64
 3   FireDiscoveryDateTime                  124369 non-null  object
 4   FireOutDateTime                        124369 non-null  object
 5   FireCauseGeneral                       33356 non-null   object
 6   FireCauseSpecific                      10795 non-null   object
 7   DiscoveryAcres                         108713 non-null  float64
 8   FireMgmtComplexity                     11993 non-null   object
 9   IncidentShortDescription               4589 non-null    object
 10  EstimatedCostTodate                    6602 non-null    float64
 11  FinalAcres                             118122 non-null  float64
 12  FireCause                              122514 non-null  object
 13  PrimaryFuelModel                       7436 non-null    object
```

```
 14  EstimatedFinalCost                  1381 non-null    float64
 15  IncidentName                        124369 non-null  object
 16  DispatchCenterID                    112614 non-null  object
 17  ABCDMisc                            11648 non-null   object
 18  FireCode                            79417 non-null   object
 19  FireDepartmentID                    2363 non-null    object
 20  GACC                                124340 non-null  object
 21  POODispatchCenterID                 80459 non-null   object
 22  POOCounty                           124362 non-null  object
 23  POOFips                             124357 non-null  object
 24  POOJurisdictionalAgency             62518 non-null   object
 25  POOJurisdictionalUnit               92780 non-null   object
 26  POOState                            124369 non-null  object
 27  duration                            124369 non-null  int64
 28  site                                124369 non-null  object
 29  total_solar_radiation_ly            123534 non-null  float64
 30  ave_mean_wind_speed_mph             124253 non-null  float64
 31  ave_mean_wind_direction_deg         124257 non-null  float64
 32  max_maximum_wind_gust_mph           124086 non-null  float64
 33  ave_average_air_temperature_deg_f   124357 non-null  float64
 34  ave_average_relative_humidity       124135 non-null  float64
 35  total_precipitation_in              124355 non-null  float64
dtypes: float64(13), int64(2), object(21)
memory usage: 35.1+ MB
```

In [110]:

```
# dropping rows that have null weather values
fire_final.dropna(subset=['total_solar_radiation_ly', 'ave_mean_wind_s
'max_maximum_wind_gust_mph', 'ave_average_air_temperature_deg_f', 'ave
'total_precipitation_in'], inplace=True)
```

Data Checkpoint

In [535]:

```
# Saving fire to a final dataset
# fire_final.to_csv('clean_fire_data.csv', index=False)
fire_final = pd.read_csv('Data/clean_fire_data.csv.zip', low_memory=Fa
```

In [536]:

```
fire_final
```

Out[536]:

peed_mph	ave_mean_wind_direction_deg	max_maximum_wind_gust_mph	ave_average_air_temper
6.524400	165.300000	20.340000	
4.630000	135.428571	23.714286	
2.549245	119.792453	15.160377	
6.355000	222.000000	23.500000	
5.863248	199.337580	22.853503	
...	...	...	
7.960000	39.000000	39.000000	
5.145000	274.000000	18.500000	
8.580000	217.000000	23.500000	
7.000000	206.000000	22.000000	
1.350000	79.000000	8.000000	

Modeling

Go to Top

In [114]:
```
# Checking feature similarity
fire_cost = fire_final[(~fire_final['EstimatedCostTodate'].isna()) & (
fire_cost[['EstimatedCostTodate', 'EstimatedFinalCost']]
# going to try filling in final cost nulls with costtodate and then dr
```

Out[114]:

	EstimatedCostTodate	EstimatedFinalCost
1817	2000000.0	3100000.0
13105	1525000.0	3000000.0
52351	21089080.0	21000000.0
57692	20000.0	500000.0
69603	17600000.0	20000000.0
...	...	...
246815	4275000.0	5400000.0

246827	712000.0	1000000.0
247008	35000.0	100000.0
250886	480000.0	500000.0
254564	500000.0	500000.0

1109 rows × 2 columns

In [115]:
```
# Number of different RAWS used
fire_final['site'].value_counts()
```

Out[115]:
```
707026AA    1303
32D7C1CA    1263
327C34B0    1200
3252C1B2    1195
326BA478    1108
            ...
CA421104       1
53705306       1
CA2537EE       1
CA424178       1
0800252E       1
Name: site, Length: 1500, dtype: int64
```

Checking the mean acre size for each target class

In [117]:
```
fire_final[fire_final['FireMgmtComplexity'] == 'Type 5 Incident']['Fir
```

Out[117]:
```
564.7606086779662
```

In [118]:
```
fire_final[fire_final['FireMgmtComplexity'] == 'Type 4 Incident']['Fir
```

Out[118]:
```
4091.429750692521
```

In [119]:
```
fire_final[fire_final['FireMgmtComplexity'] == 'Type 3 Incident']['Fir
```

Out[119]:
```
8433.43902415459
```

In [120]:
```
fire_final[fire_final['FireMgmtComplexity'] == 'Type 2 Incident']['Fir
```

Out[120]:
```
14398.560229007633
```

In [121]:
```
fire_final[fire_final['FireMgmtComplexity'] == 'Type 1 Incident']['Fir
```

Out[121]:
```
24025.013815789473
```

Note the trend between acres and fire complexity

Model Dataset

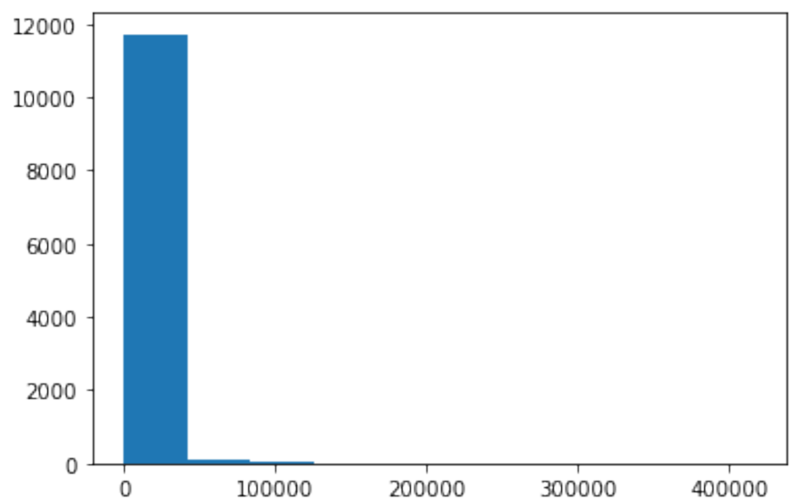
Go to Top

In [7]:
```
f_keep2 = ['FinalAcres', 'site', 'total_solar_radiation_ly', 'FireMgmt
           'ave_mean_wind_speed_mph', 'ave_mean_wind_direction_deg', 'm
           'ave_average_air_temperature_deg_f', 'ave_average_relative_h
           'DispatchCenterID', 'POOJurisdictionalAgency', 'POOFips']

drop3 = ['FireDiscoveryDateTime', 'FireOutDateTime',
        'FireCauseGeneral', 'FireCauseSpecific', 'DiscoveryAcres','Inci
          'EstimatedCostTodate', 'FireCause', 'PrimaryFuelModel','Estim
        'IncidentName','duration', 'FireDepartmentID', 'ABCDMisc', 'Fir

# Target
target ='FireMgmtComplexity'
# target = 'FinalAcres'


# copy
fire_final1 = fire_final.copy()

fire_final1.drop(columns=drop3, inplace=True)
# fire_final1 = fire_final1[f_keep2]



try:
    # moving and dropping estimated cost to date
    fire_final1['EstimatedFinalCost'].fillna(fire_final1['EstimatedCos
    fire_final1.drop(columns='EstimatedCostTodate', inplace=True)
except:
    pass

try:
# POODispatchCenterID and DispatchCenterID are the same, going to keep
    fire_final1['DispatchCenterID'].fillna(fire_final1['POODispatchCen
    fire_final1.drop(columns='POODispatchCenterID', inplace=True)
except:
    pass

#droping nulls if in target or weather data
fire_final1.dropna(subset=[target,'total_solar_radiation_ly'], inplace


# Create bins if target is arces
if target == 'FinalAcres':
    fire_final1 = fire_final1[(fire_final1['FinalAcres']> 0.0) | (fire
    class5 = fire_final1[fire_final1['FireMgmtComplexity'] == 'Type 5
    class4 = fire_final1[fire_final1['FireMgmtComplexity'] == 'Type 4
    class3 = fire_final1[fire_final1['FireMgmtComplexity'] == 'Type 3
```

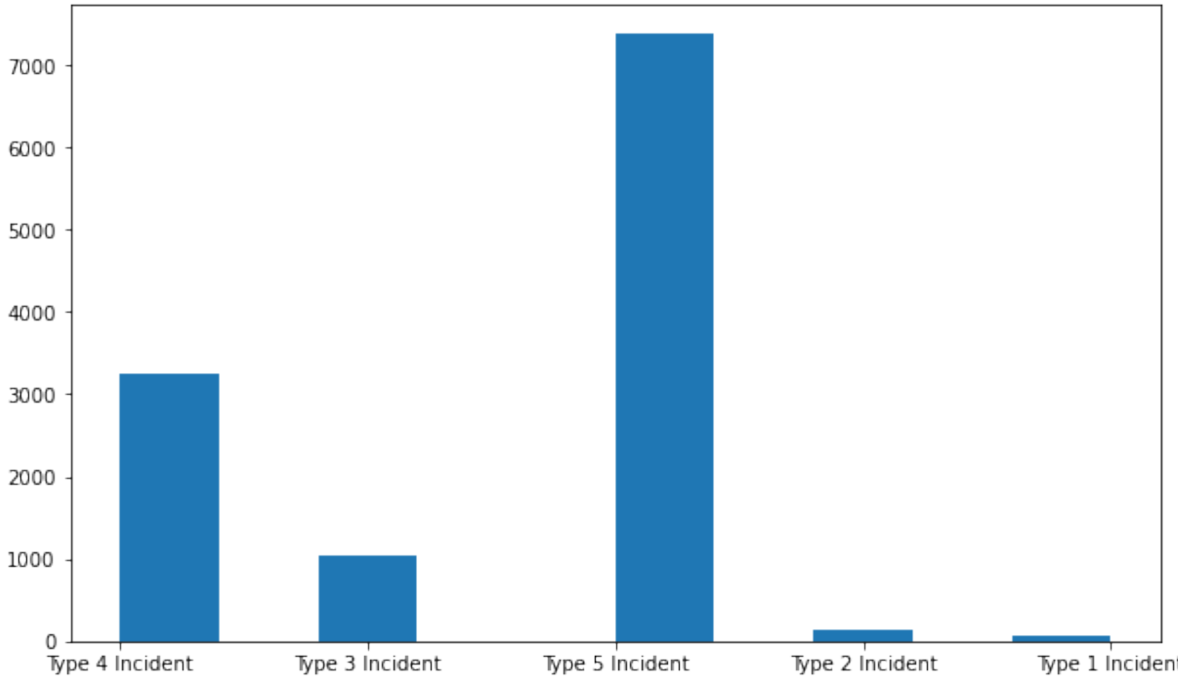
```
    class2 = fire_final1[fire_final1['FireMgmtComplexity'] == 'Type 2
    class1 = fire_final1[fire_final1['FireMgmtComplexity'] == 'Type 1
    top = fire_final1[target].max() +1
    bot = fire_final1[target].min() -1
    b= [bot, class5, class4, top]

    fire_final1['FinalAcresBin'] = pd.cut(fire_final1[target], bins=b,

    print(f"\nBin Size & Counts:\n\n{pd.cut(fire_final1[target], bins=

elif target == 'FireMgmtComplexity':
#     Droping prescribed fire incidents
    fire_final1 = fire_final1[fire_final1['FireMgmtComplexity'] != 'Ty

#     fire_final1['FireMgmtComplexity'].replace({'Type 1 Incident': 'T
#     fire_final1['FireMgmtComplexity'].replace({'Type 2 Incident': 'T

    print(fire_final1[target].value_counts())
```

```
Type 5 Incident    7375
Type 4 Incident    3249
Type 3 Incident    1035
Type 2 Incident     131
Type 1 Incident      76
Name: FireMgmtComplexity, dtype: int64
```

In [10]:
```
# Clear class imbalance
plt.hist(fire_final1['FinalAcres'],bins=10);#, bins=10, range=(0, 10))

# fire_final1.drop(columns='FinalAcres', inplace=True)
```



In [34]:
```
fig, ax = plt.subplots(figsize = (10,6))
if target == 'FireMgmtComplexity':
    plt.hist(fire_final1['FireMgmtComplexity'])
try:
    plt.hist(fire_final1['FinalAcresBin'])#, bins=10, range=(0, 10));
except Exception as e:
    e
```



In [ ]:

```
# List of functions
%whos function
```

Modeling Class

Go to Top

The Class below is used to create train test split, build pipeline, model, and evalaute

Pipeline

- one hot encoder for categoricals
- Standard Scaler for numerical features
- SMOTE is used to resolve the large class imbalance

In [461]:

```
class model():
    '''
    This class is used to create test, split, modeling, model validati
    '''
    def __init__(self, X, y, model=None, **kwargs):
        '''
        X : DataFrame with Target removed
        y : Series containing the Target
```

```
        Mdoel: if external model is used, already has random forest, c
        **kwargs for train test split, like train_size, or test_size
        This is for classification models
        '''
        self.model = model
        if not isinstance(y,pd.core.series.Series):
            return 'y must be a series, containing the target'
        if y.name in X.columns:
            return 'Target (y) must be removed from X'

        self.__y = y
        self.__X = X

        self.X_train, self.X_test, self.y_train, self.y_test = train_t

        if model:
            self.score = self.model.score(self.X_test, self.y_test)
            self.y_pred_train = self.model.predict(self.X_train)
            self.y_pred_test = self.model.predict(self.X_test)

    def models(self, mtype, test=None, **kwargs):
        '''
        Function runs model through pipeline,
        Classification models only
        mtype options: 'rfc' = RandomForest, 'trees' = Decision tree,
        **kwargs : For the models additional parameters
        verbose  = 0, auto set to 0
        '''
        # Numerics for scaling
        df_num = list(self.__X.select_dtypes(include='number').columns
        # categoricals for one hot encoder
        df_cat = list(self.__X.select_dtypes(include='object').columns

        # pipeline
        subpipe_num = Pipeline(steps=[('ss', StandardScaler())])

        subpipe_cat = Pipeline(steps=[('ohe', OneHotEncoder(sparse=Fal

        subpipe_smote = Pipeline(steps=[('smote', SMOTE(random_state=4

        smote = SMOTE(sampling_strategy='auto', random_state=42, n_job

        CT = ColumnTransformer(transformers=[('subpipe_num', subpipe_r
                                             ('subpipe_cat', subpi
                               remainder='passthrough')
        self.CT= CT
        self.df_num = df_num
        self.df_cat = df_cat
        # Model types ------------------------------------------------
        # Random forest
        if mtype == 'rfc':

            self.model = ImPipeline(steps=[('ct', CT,),
                                           ('smote', smote),
                                          ('rfc', RandomForestClass
```

```
            self.model.fit(self.X_train, self.y_train)
        # Logistic regression
        if mtype == 'log':
            self.model = ImPipeline(steps=[('ct', CT),
                                           ('smote', smote),
                                         ('logreg', LogisticRegression(ranc
                                                                       n_jc

            self.model.fit(self.X_train, self.y_train)
        # Decision trees
        if mtype == 'trees':
            self.model = Pipeline(steps=[('ct', CT),
                                        ('dt', DecisionTreeClassifier(randc
            self.model.fit(self.X_train, self.y_train)

        if mtype == 'svc':
            check = input("Are you sure you want to run this? It may t
            if check == 'yes':
                self.model = ImPipeline(steps=[('ct', CT,),
                                                   ('smote', smote),
                                                 ('svm', SVC(random_st

                self.model.fit(self.X_train, self.y_train)
            else:
                return 'Execution Stopped'

        # General return
        self.y_pred_test = self.model.predict(self.X_test)
        if test:
            self.score = self.model.score(self.X_test, self.y_test)
            return print(f'Test Score: {self.score}\nTrain Score: {sel
        else:
            return print(f"Train Score: {self.model.score(self.X_trair
    def gridsearch(self, params_grid, **kwargs):
        '''
        **kwargs:
            estimator,
            param_grid,
            *,
            scoring=None,
            n_jobs=None,
            iid='deprecated',
            refit=True,
            cv=None,
            verbose=0,
            pre_dispatch='2*n_jobs',
            error_score=nan,
            return_train_score=False

            RandomForestClassifier options:
                    n_estimators=100,
                    criterion='gini',
                    max_depth=None,
                    min_samples_split=2,
```

```
                    min_samples_leaf=1,
                    min_weight_fraction_leaf=0.0,
                    max_features='auto',
                    max_leaf_nodes=None,
                    min_impurity_decrease=0.0,
                    min_impurity_split=None,
                    bootstrap=True,
                    oob_score=False,
                    n_jobs=None,
                    random_state=None,
                    verbose=0,
                    warm_start=False,
                    class_weight=None,
                    ccp_alpha=0.0,
                    max_samples=None
        '''
        self.gsmodel = GridSearchCV(estimator=self.model,
                 param_grid= params_grid, n_jobs=-1, **kwargs)

        self.gsmodel.fit(X_train, y_train)
        return self.gsmodel.best_params_ , self.gsmodel.best_score_

    def scoringHelp(self):
        '''Scoring options, no inputs'''
        from sklearn.metrics import SCORERS
        print(f'List of Scoring options:{list(SCORERS.keys())}')

    def cross_validate(self, **kwargs):
        '''
        **kwargs:
                estimator,
                X,
                y=None,
                *,
                groups=None,
                scoring=None,
                cv=None,
                n_jobs=None,
                verbose=0,
                fit_params=None,
                pre_dispatch='2*n_jobs',
                error_score=nan

        For scoring run .scoringHelp to view options
        '''
        self.cvs_results = cross_val_score(X=self.X_train, y=self.y_tr
                                          **kwargs).mean()
#         self.cv_results = cross_validate(X=self.X_train, y=self.y_tr
#                                          cv=cv_input,return_train_sc
        print(f'CV Results: {self.cvs_results}')

    def test_report(self, Return=False, **kwargs):
        '''
        Returns claassiciation report for y_test and y_pred_test
        **kwargs for addtional arguments like output_dict=True if you
        Saving: set Return = True
```

```python
        '''
        if Return:
            return classification_report(self.y_test, self.y_pred_test
        else:
            print(classification_report(self.y_test, self.y_pred_test,


    def aprf(self, test=None, **kwargs):
        '''
        test : return test scores, if test = 'full' then predicts on X
        '''
        # Accuracy, Precision, Recall, and F1-Score
        if test == 'full':
            print('Predicting X, full dataset')
            y_pred_train = self.model.predict(self.X_train)
            y_pred_full = self.model.predict(self.__X)
        else:
            y_pred_train = self.model.predict(self.X_train)
            y_pred_test = self.model.predict(self.X_test)
            y_pred_full = None
        try:
            #accuracy
            self.train_accuracy = accuracy_score(self.y_train, y_pred_
            if test == 'full':
                self.test_accuracy = accuracy_score(self.__y, y_pred_f
            else:
                self.test_accuracy = accuracy_score(self.y_test, y_pre
            print(f'Training Accuracy: {self.train_accuracy}')
            if test:
                print(f'Testing Accuracy: {self.test_accuracy}')

            # Precision
            print(f'Training Precision: {precision_score(self.y_train,
            if test:
                if test == 'full':
                    print(f'Testing Precision: {precision_score(self._
                else:
                    print(f'Testing Precision: {precision_score(self.y

            # Recall
            self.train_recall = recall_score(self.y_train, y_pred_trai
            if test == 'full':
                self.test_recall = recall_score(self.__y, y_pred_full,
            else:
                self.test_recall = recall_score(self.y_test, y_pred_te
            print(f'Training Recall: {self.train_recall}')
            if test:
                print(f'Testing Recall: {self.test_recall}')

            # F1-Score
            self.train_f1 = f1_score(self.y_train, y_pred_train, **kwa
            if test == 'full':
                self.test_f1 = f1_score(self.__y, y_pred_full, **kwarg
            else:
                self.test_f1 = f1_score(self.y_test, y_pred_test, **kw
```

```
            print(f'Training F1-Score: {self.train_f1}')
            if test:
                print(f'Testing F1-Score: {self.test_f1}')

        except Exception as e:
            print("An error occurred:", e)
```

- [Go to Data Checkpoint 2]

In [36]:
```
fire_final1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11866 entries, 2 to 122951
Data columns (total 20 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   X                               11866 non-null  float64
 1   Y                               11866 non-null  float64
 2   OBJECTID                        11866 non-null  int64  
 3   FireMgmtComplexity              11866 non-null  object 
 4   FinalAcres                      11866 non-null  float64
 5   DispatchCenterID                11601 non-null  object 
 6   GACC                            11866 non-null  object 
 7   POOCounty                       11866 non-null  object 
 8   POOFips                         11866 non-null  object 
 9   POOJurisdictionalAgency         7731 non-null   object 
 10  POOJurisdictionalUnit           9501 non-null   object 
 11  POOState                        11866 non-null  object 
 12  site                            11866 non-null  object 
 13  total_solar_radiation_ly        11866 non-null  float64
 14  ave_mean_wind_speed_mph         11866 non-null  float64
 15  ave_mean_wind_direction_deg     11866 non-null  float64
 16  max_maximum_wind_gust_mph       11866 non-null  float64
 17  ave_average_air_temperature_deg_f  11866 non-null  float64
 18  ave_average_relative_humidity   11866 non-null  float64
 19  total_precipitation_in          11866 non-null  float64
dtypes: float64(10), int64(1), object(9)
memory usage: 1.9+ MB
```

Elevation

[Go to Top]

In [543]:

```
def elevation(row, counts=0):
    '''
    This function inputs a dataframe row,  takes X and Y and pulls ele
    Required columns:
    X : Longitude
    Y : Latitude
    OBJECTID : objectid

    Notes:
    This is designed to run in with joblib, works best running ~ 2000
    '''
    # URL for Open-Elevation API
    url = 'https://api.open-elevation.com/api/v1/lookup'

    # latitude and longitude values
    lat = row['Y']
    lon = row['X']
    obid = row['OBJECTID']

    # API request
    request_url = f'{url}?locations={lat},{lon}'

    # GET request
    response = requests.get(request_url)

    # Check if the request was successful, will try 15 times before re
    if response.status_code == 200:
        # Extract elevation from the response
        elevations = response.json()['results'][0]['elevation']
        return { obid: elevations}

    else:
        exc = []
        def retry(counts):
            try:
                elevations = response.json()['results'][0]['elevation'
                return {obid : elevations}
            except Exception as e:
                if counts <15:
                    counts+=1
                    return elevation(row,counts)
```

```
                else:
                    return {obid : np.nan}

        retried = retry(counts)
        return retried
```

In [663]:

```
# Code to run elevation function in parallel with joblib
results_e = Parallel(n_jobs=-1, verbose=1)(
    delayed(elevation)(row) for index, row in fire_final1.iterrows())

st = time.time()
# create one dict, from the nest
result_dict = {key: value for r in results_e for key, value in r.items
print(f"Total Run Time: {time.time()- st}")

# take output dict and add to dataframe
st = time.time()
# Updating elevation column in fire_final1
fire_final1['elevation'] = fire_final1['OBJECTID'].map(result_dict).fi
print(f"Total Run Time: {time.time()- st}")
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.

Total Run Time: 0.00015687942504882812
Total Run Time: 0.007983207702636719

[Parallel(n_jobs=-1)]: Done  14 out of  14 | elapsed:    3.8s remaini
ng:    0.0s
[Parallel(n_jobs=-1)]: Done  14 out of  14 | elapsed:    3.8s finishe
d
```

In [664]:

```
# Null index checker, use to check what rows needs to be run again
num = 11866
if len(np.where(fire_final1[0:num]['elevation'].isna())[0].tolist()) <
    print(np.where(fire_final1[0:num]['elevation'].isna())[0].tolist()

print(fire_final1[0:num]['elevation'].isna().sum())
fire_final1[0:num][fire_final1[0:num]['elevation'].isna()]#.sum()
```

```
[]
0
```

Out[664]:

X	Y	OBJECTID	FireMgmtComplexity	DispatchCenterID	GACC	POOCounty	POOFips	POC

In [1414]:
```
fire_final1
```

Out[1414]:

	X	Y	OBJECTID	FireMgmtComplexity	DispatchCenterID	GACC	PC
1817	-121.604615	47.638906	1818	Type 4 Incident	WAPSC	NWCC	
13105	-117.058714	48.648346	13108	Type 4 Incident	IDCDC	NRCC	Pe
52351	-122.050314	43.363345	52366	Type 3 Incident	ORRICC	NWCC	
57692	-120.684915	47.963556	57710	Type 5 Incident	WACWC	NWCC	
69603	-120.897615	47.882316	69625	Type 5 Incident	WACWC	NWCC	
...	...	...	...	...	...	...	
256442	-83.144794	37.232427	305668	Type 5 Incident	KYKIC	SACC	
256452	-83.692464	36.744317	305681	Type 5 Incident	KYKIC	SACC	
256461	-83.666022	37.714499	305700	Type 5 Incident	KYKIC	SACC	
256490	-83.160804	37.338307	305748	Type 5 Incident	KYKIC	SACC	
256783	-100.475158	34.150797	306139	Type 5 Incident	TXTIC	SACC	

11866 rows × 20 columns

In [667]:
```
# saving elevation dataset
fire_elevation = fire_final1[['OBJECTID','elevation']]
# fire_elevation.to_csv('fire_elevation.csv', index=False)
```

In [894]:
```
# saving final model data
# fire_final1.to_csv('fire_model_data.csv', index=False)
```

Data Checkpoint 2

Go to Top

Run These Cells:

- Modeling Class

In [20]:

```
# Load fire_final2
fire_final2 = pd.read_csv('Data/fire_model_data.csv')
# fire_final2 = fire_final1.copy()


# Dropping columns deemed to be not useful
fire_final2.drop(columns=['X', 'Y', 'OBJECTID', 'GACC', 'POOCounty', '
                          'POOState'], inplace=True)
```

In [21]:

```
# setting target and dropping finalacres if present
target2 = 'FireMgmtComplexity'

try:
    fire_final2.drop(columns=['FinalAcres'], inplace=True)
except:
    pass
```

- Jurisdictional unit is at too micro of a level
- County, state, fips, and GACC are redundent metrics that lower the resolution of the model

Instantiating Model class

In [473]:

```
# Creating model
fire_final2.dropna(inplace=True)
X = fire_final2.drop(columns= target2)
y = fire_final2[target2]

fire_model = model(X,y)
```

In [532]:
```
fire_final2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7731 entries, 0 to 11865
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   FireMgmtComplexity              7731 non-null   object 
 1   DispatchCenterID                7731 non-null   object 
 2   POOJurisdictionalAgency         7731 non-null   object 
 3   site                            7731 non-null   object 
 4   total_solar_radiation_ly        7731 non-null   float64
 5   ave_mean_wind_speed_mph         7731 non-null   float64
 6   ave_mean_wind_direction_deg     7731 non-null   float64
 7   max_maximum_wind_gust_mph       7731 non-null   float64
 8   ave_average_air_temperature_deg_f 7731 non-null   float64
 9   ave_average_relative_humidity   7731 non-null   float64
 10  total_precipitation_in          7731 non-null   float64
 11  elevation                       7731 non-null   float64
dtypes: float64(8), object(4)
memory usage: 785.2+ KB
```

In [475]:
```
# saving x and y train and test
X_train, X_test, y_train, y_test = fire_model.X_train, fire_model.X_te
y_train.value_counts(normalize=1)
```

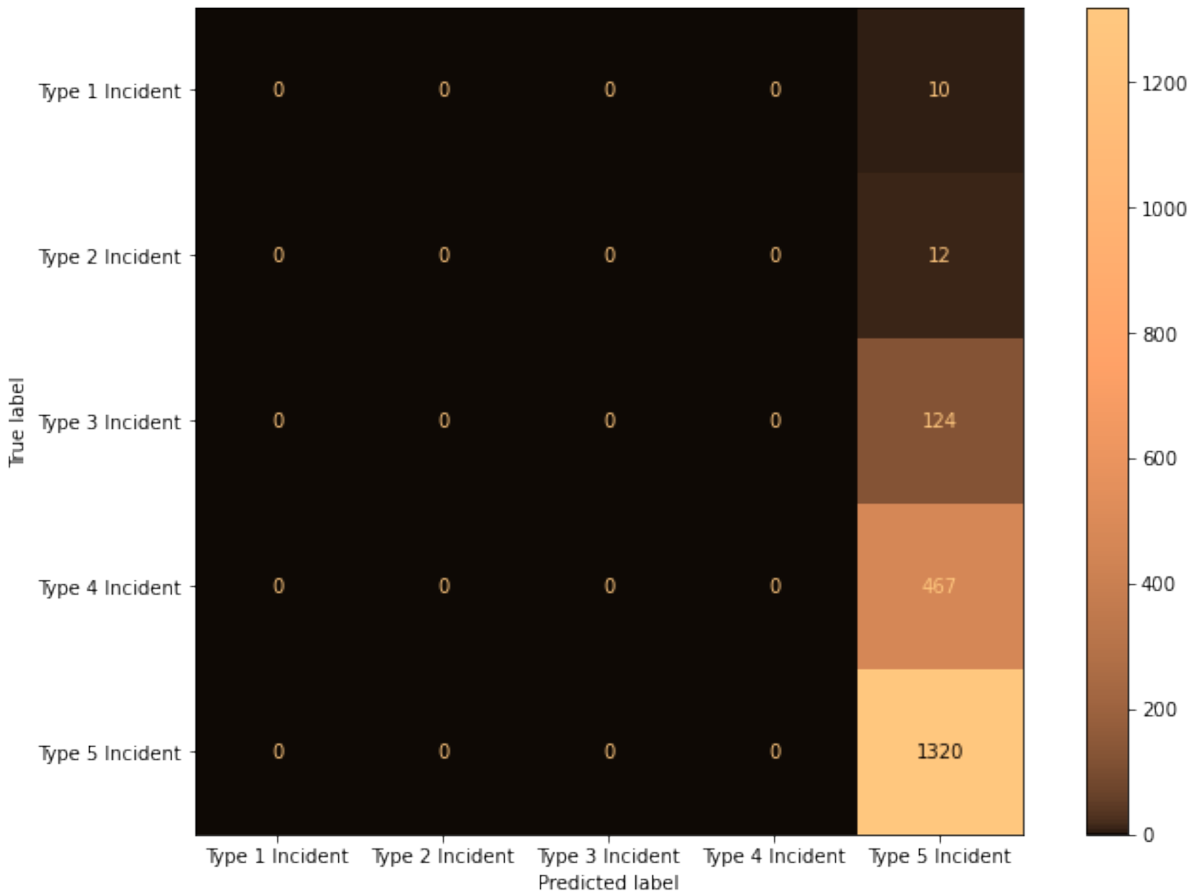
Out[475]:
```
Type 5 Incident    0.674543
Type 4 Incident    0.240773
Type 3 Incident    0.071921
Type 2 Incident    0.008451
Type 1 Incident    0.004312
Name: FireMgmtComplexity, dtype: float64
```

In [476]:
```
dummy_model = DummyClassifier(strategy='most_frequent')
dummy_model.fit(X_train, y_train)
y_pred = dummy_model.predict(X_train)
```

In [477]:
```
cv_results = cross_val_score(dummy_model, X_train, y_train, cv=5)
cv_results.mean()
```

Out[477]:
```
0.6745430067537412
```

In [693]:
```
# copper
cmap = mpl.cm.copper
colors = cmap(np.linspace(.05, 1, cmap.N))

cmap_modified = mpl.colors.ListedColormap(colors)
gradient_cmap = mpl.colors.LinearSegmentedColormap.from_list('gradient

fig, ax = plt.subplots(figsize=(12, 8))
plot_confusion_matrix(dummy_model, X_test, y_test, ax=ax, cmap=gradier
```



In [479]:
```
baseline = model(X, y, dummy_model)
baseline.cross_validate()
```

```
CV Results: 0.6745430067537412
```

In [480]:
```
baseline.aprf(average='weighted')
```

```
Training Accuracy: 0.6745429458433942
Training Precision: 0.4550081857870843
Training Recall: 0.6745429458433942
Training F1-Score: 0.5434416440814739

/Users/keanan/opt/anaconda3/envs/flatiron-env/lib/python3.8/site-pack
ages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predi
cted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Random Forest

Go to Top

In [156]:
```
fire_model.models('rfc')
```

```
Train Score: 0.9996550534667127
```

In [157]:
```
# accuracy
fire_model.cross_validate(n_jobs=-1)
```

```
CV Results: 0.8104525304215882
```

In [1018]:
```
fire_model.scoringHelp()
```

```
List of Scoring options:['explained_variance', 'r2', 'max_error', 'ne
g_median_absolute_error', 'neg_mean_absolute_error', 'neg_mean_square
d_error', 'neg_mean_squared_log_error', 'neg_root_mean_squared_error'
, 'neg_mean_poisson_deviance', 'neg_mean_gamma_deviance', 'accuracy',
'roc_auc', 'roc_auc_ovr', 'roc_auc_ovo', 'roc_auc_ovr_weighted', 'roc
_auc_ovo_weighted', 'balanced_accuracy', 'average_precision', 'neg_lo
g_loss', 'neg_brier_score', 'adjusted_rand_score', 'homogeneity_score
', 'completeness_score', 'v_measure_score', 'mutual_info_score', 'adj
usted_mutual_info_score', 'normalized_mutual_info_score', 'fowlkes_ma
llows_score', 'precision', 'precision_macro', 'precision_micro', 'pre
cision_samples', 'precision_weighted', 'recall', 'recall_macro', 'rec
all_micro', 'recall_samples', 'recall_weighted', 'f1', 'f1_macro', 'f
1_micro', 'f1_samples', 'f1_weighted', 'jaccard', 'jaccard_macro', 'j
accard_micro', 'jaccard_samples', 'jaccard_weighted']
```

In [158]:
```
# Perform cross-validation with F1 score
fire_model.cross_validate(n_jobs=-1, scoring = 'f1_weighted') # f1_wei
```

```
CV Results: 0.8075472717534069
```

In [159]:
```
# Recall
fire_model.cross_validate(n_jobs=-1, scoring = 'recall_weighted') # f1
```

```
CV Results: 0.8104525304215882
```

In [160]:
```
fire_model.aprf(average='weighted')
```

```
Training Accuracy: 0.9996550534667127
Training Precision: 0.9996566999895447
Training Recall: 0.9996550534667127
Training F1-Score: 0.9996554219713732
```

Decision Tree

In [77]:
```
fire_model.models('trees')
```

```
Train Score: 0.9996765847347995
```

In [58]:
```
fire_model.cross_validate(n_jobs=-1,scoring = 'f1_weighted')
```

```
CV Results: 0.7650126935530464
```

In [59]:
```
fire_model.cross_validate(n_jobs=-1, scoring = 'recall_weighted')
```

```
CV Results: 0.7643925302106307
```

In [78]:
```
fire_model.aprf(average='weighted')
```

```
Training Accuracy: 0.9996765847347995
Training Precision: 0.9996780548041867
Training Recall: 0.9996765847347995
Training F1-Score: 0.9996769144217802
```

After runninig the models with the final set of data, Random Forest returned the best model, Both models fit well to the training data

Grid Search

In [79]:
```
fire_model.models('rfc')
```

```
Train Score: 0.9996765847347995
```

In [1046]:
```
params_grid = {"rfc__criterion": ["gini", "entropy"],
               "rfc__max_depth": [10, 20, 30, 40, 50],
               "rfc__min_samples_split": [2, 5, 10],
               "rfc__min_samples_leaf": [1, 5, 10, 15, 30, 50]
              }
fire_model.gridsearch(params_grid, scoring='f1_weighted', verbose=1)
```

```
Fitting 5 folds for each of 180 candidates, totalling 900 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  6.6min
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed: 17.0min
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed: 29.7min
[Parallel(n_jobs=-1)]: Done 900 out of 900 | elapsed: 34.5min finishe
d
```

Out[1046]:
```
({'rfc__criterion': 'entropy',
  'rfc__max_depth': 50,
  'rfc__min_samples_leaf': 1,
  'rfc__min_samples_split': 2},
 0.8091065271810889)
```

It appears that max depth value is likely higher, going to run another general grid search but expand the values for max depth and increase the resolution for the other parameters

In [1075]:
```
params_grid = {"rfc__n_estimators" :[50,100,150,200],
               "rfc__criterion": ["gini", "entropy"],
               "rfc__max_depth": [10, 40, 50, 60, 70, 80],
               "rfc__min_samples_split": [2, 3, 4],
               "rfc__min_samples_leaf": [1, 2, 3, 4, 5]
              }
fire_model.gridsearch(params_grid, scoring='f1_weighted', verbose=1)
```

```
Fitting 5 folds for each of 720 candidates, totalling 3600 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  5.5min
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed: 16.2min
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed: 33.5min
[Parallel(n_jobs=-1)]: Done 1234 tasks      | elapsed: 56.5min
[Parallel(n_jobs=-1)]: Done 1784 tasks      | elapsed: 85.0min
[Parallel(n_jobs=-1)]: Done 2434 tasks      | elapsed: 111.4min
[Parallel(n_jobs=-1)]: Done 3184 tasks      | elapsed: 149.6min
[Parallel(n_jobs=-1)]: Done 3600 out of 3600 | elapsed: 170.8min fini
shed
```

Out[1075]:
```
({'rfc__criterion': 'entropy',
  'rfc__max_depth': 80,
  'rfc__min_samples_leaf': 1,
  'rfc__min_samples_split': 4,
  'rfc__n_estimators': 100},
 0.8122947935953431)
```

Max depth can still go higher, min sample leafs is likely 1 , and min samples split als seemed to have found sweet spot as 4

In [1077]:
```
# setting n estimators to default 100, setting min samples leaf to def
params_grid = {"rfc__criterion": ["entropy"],
               "rfc__max_depth": [70, 80, 90, 100, 120, 140],
               "rfc__min_samples_split": [2, 3, 4, 5, 6, 7],
              }
fire_model.gridsearch(params_grid, scoring='f1_weighted', verbose=1)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 180 out of 180 | elapsed:  8.3min finishe
d
```

Out[1077]:
```
({'rfc__criterion': 'entropy',
  'rfc__max_depth': 120,
  'rfc__min_samples_split': 4},
 0.8123104803276566)
```

I think this grid search found the best parameters, i am going to run one more with higher resolution around mid depth = 120

In [1078]:
```
# last grid search increasing number of folds
params_grid = {"rfc__criterion": ["entropy"],
               "rfc__max_depth": [100, 110, 120, 130, 140],
               "rfc__min_samples_split" : [2, 3, 4, 5, 6, 7],
              }
fire_model.gridsearch(params_grid, scoring='f1_weighted', cv=10, verbo
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed: 10.6min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 17.0min finishe
d
```

Out[1078]:
```
({'rfc__criterion': 'entropy',
  'rfc__max_depth': 110,
  'rfc__min_samples_split': 4},
 0.8122706666618329)
```

This grid search performed worse with 10 folds. Going to stick with the previous grid search and keep folds to 5

Grid Search Evaluation

- The second to last grid search performed the best, with 5 folds. Overall each grid search got better and the parameters became more fine tuned

---

Best Parameters

That are not default values:

- criterion = 'entropy',
- max_depth = 120,
- min_samples_split = 4,

Final Model

[Go to Top]

In [481]:
```
fire_model.models('rfc',
                  criterion= 'entropy',
                  max_depth= 120,
                  min_samples_split= 4, test=True)
```

```
                   min_samples_split= 4, test=True)
```

```
Test Score: 0.8380755302638386
Train Score: 0.9932735426008968
```

In [106]:

```
# Model Tree
fire_model.model
```

Out[106]:

```
Pipeline(steps=[('ct',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('subpipe_num',
                                                  Pipeline(steps=[('s
s',
                                                                   St
andardScaler())]),
                                                  ['total_solar_radia
tion_ly',
                                                   'ave_mean_wind_spe
ed_mph',
                                                   'ave_mean_wind_dir
ection_deg',
                                                   'max_maximum_wind_
gust_mph',
                                                   'ave_average_air_t
emperature_deg_f',
                                                   'ave_average_relat
ive_humidity',
                                                   'total_precipitati
on_in',
                                                   'elevation']),
                                                 ('subpipe_cat',
                                                  Pipeline(steps=[('o
he',
                                                                   On
eHotEncoder(handle_unknown='ignore',

sparse=False))]),
                                                  ['DispatchCenterID'
,
                                                   'POOJurisdictional
Agency',
                                                   'site'])])),
                ('smote', SMOTE(n_jobs=-1, random_state=42)),
                ('rfc',
                 RandomForestClassifier(criterion='entropy', max_dept
h=120,
                                        min_samples_split=4, n_jobs=-
1,
                                        random_state=42))])
```

In [464]:

```
fire_model.test_report()
```

```
                 precision    recall  f1-score   support
```

```
Type 1 Incident       0.75      0.60      0.67        10
Type 2 Incident       0.11      0.08      0.10        12
Type 3 Incident       0.39      0.25      0.30       124
Type 4 Incident       0.65      0.81      0.72       467
Type 5 Incident       0.96      0.91      0.94      1320

       accuracy                           0.84      1933
      macro avg       0.57      0.53      0.54      1933
   weighted avg       0.84      0.84      0.84      1933
```

In [163]:
```
fire_model.cross_validate(n_jobs=-1, scoring = 'f1_weighted') # f1_wei
```

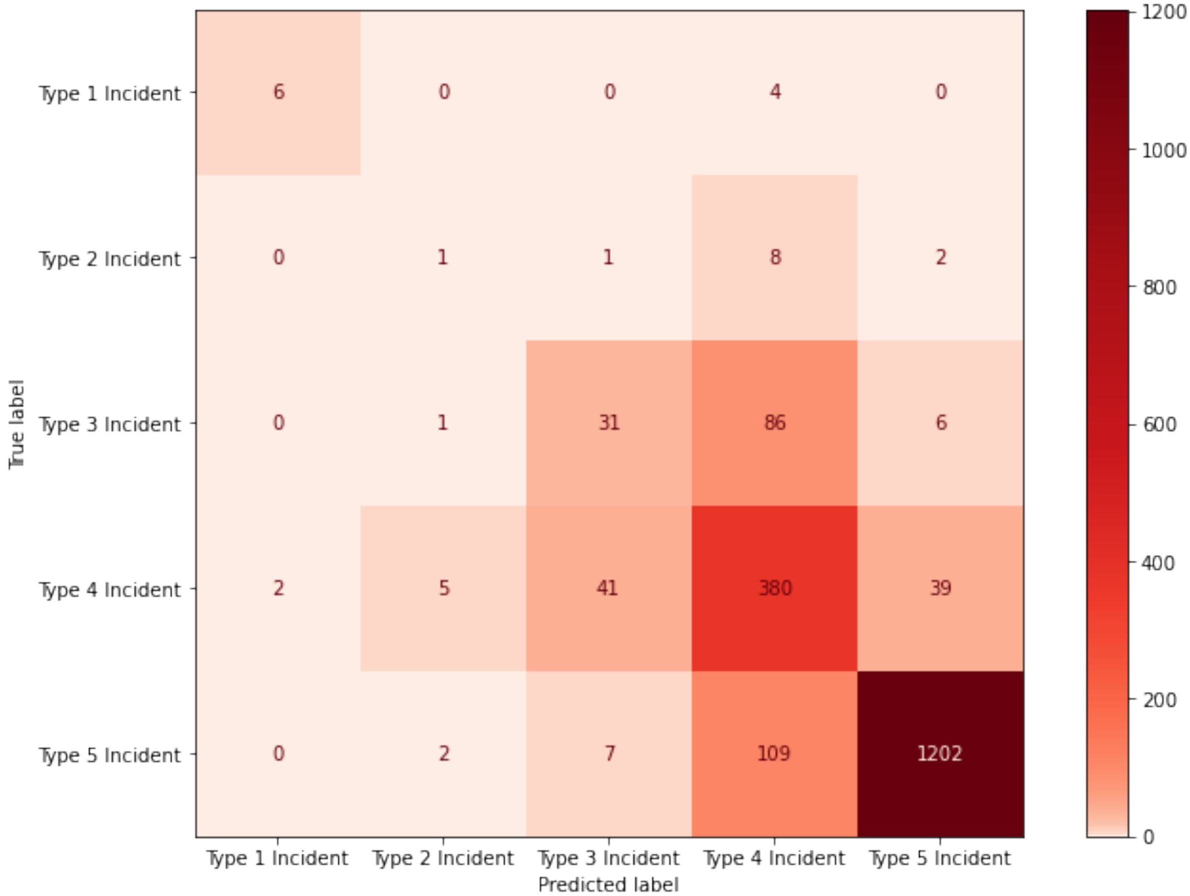
```
CV Results: 0.8123104803276566
```

In [489]:
```
fire_model.aprf(test=True, average='weighted')
```

```
Training Accuracy: 0.9932735426008968
Testing Accuracy: 0.8380755302638386
Training Precision: 0.9932782416512479
Testing Precision: 0.8430048946512145
Training Recall: 0.9932735426008968
Testing Recall: 0.8380755302638386
Training F1-Score: 0.9932738139763453
Testing F1-Score: 0.8367573570291799
```

In [435]:
```
# copper
cmap = mpl.cm.Reds
colors = cmap(np.linspace(.05, 1, cmap.N))

cmap_modified = mpl.colors.ListedColormap(colors)
gradient_cmap = mpl.colors.LinearSegmentedColormap.from_list('gradient
```

```
fig, ax = plt.subplots(figsize=(12, 8))
plot_confusion_matrix(fire_model.model, fire_model.X_test, fire_model.

# plt.savefig('matrix_red.png', dpi=100, bbox_inches='tight')
```



The model is able to predict majority of each type accuraatly except for type 2 incidents. This could be due to the fact that type 2 incidents appear to be a stepping stone or place holder level before moving up to type 5.

Model Evaluation

In [487]:
```
fire_model.aprf(test='full', average='weighted')
```

```
Predicting X, full dataset
Training Accuracy: 0.9932735426008968
Testing Accuracy: 0.954469020825249
Training Precision: 0.9932782416512479
Testing Precision: 0.9554598028141272
Training Recall: 0.9932735426008968
Testing Recall: 0.954469020825249
```

```
Testing Recall: 0.9544690206825249
Training F1-Score: 0.9932738139763453
Testing F1-Score: 0.9545859912049014
```

The above evaluation on the entire dataset is eexpected to run better due to it already seeing 70% of the data. The confusion matrix from the test data shows fairly high accuracy. For type 1 incidents it predicted 60% incidents correctly while the other 40% where predicted to be type 4 incidents. This is likley due to missing information such as remoteness or fire incidents location to populated areas, drought data, and other meterics that had to bbe droped such as acres or the ecconomic costs. Continuing with the testing evalutation, the model has a 81.2% cross validation score compared to the first model of 80% so after the grid searach we have a slight inmprovment. Type 5 incidents have the highest f1 score at 94%, type 4 at 72%, type 3 at 30%, type 2 at 10% and finally type 1 incidents at 67%.

Interpreting Results

In [167]:
```
# Pulling transformed categorical features
tf_names = fire_model.CT.named_transformers_['subpipe_cat']['ohe'].get

# Creating full list of features
features_t = fire_model.df_num.copy()
features_t.extend(tf_names)
```

In [168]:
```
# creating important features
important_featured = {name: score
                      for name, score
                         in zip(features_t, fire_model.model['rfc'].f
#                           in zip(X_train.columns, rfc_model_final['

# Sorting list of important features
sorted_if = sorted(important_featured.items(), key= lambda x: x[1], re

# Top 15 Important Features
im_df = pd.DataFrame(sorted_if[:15], columns=['Feature Name','Feature
```

In [169]:
```
# Get the OneHotEncoder from the pipeline
one_hot_encoder = fire_model.model.named_steps['ct'].named_transformer

# Get the original feature names
original_feature_names = one_hot_encoder.get_feature_names(input_featu

# Create a dictionary to map one-hot encoded names to original names
feature_mapping = {feature_encoded: feature_original for feature_encoc
                   feature_original in zip(one_hot_encoder.get_feature
```

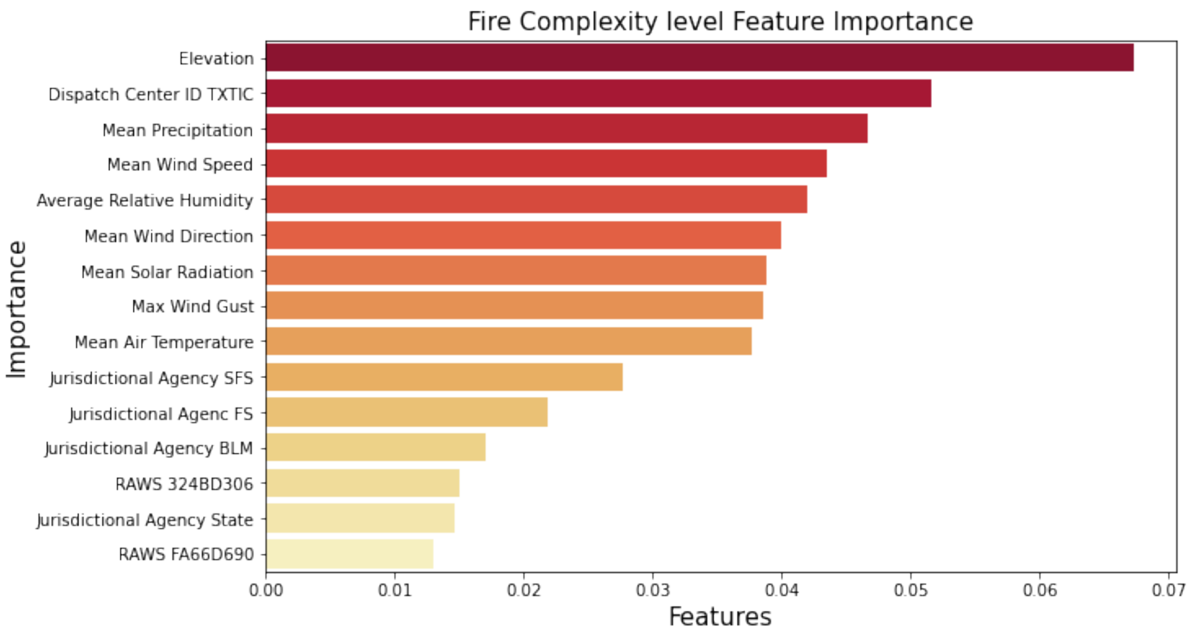
```
# Map the one-hot encoded names in 'im_df' to original names dictionar
im_df['Original Name'] = im_df['Feature Name'].map(feature_mapping)

# if original name is nan then use Feature name
im_df['Original Name'].fillna(im_df['Feature Name'], inplace=True)
```

In [698]:
```
im_df['Original Name'].values
```

Out[698]:
```
array(['elevation', 'DispatchCenterID_TXTIC', 'total_precipitation_in
',
       'ave_mean_wind_speed_mph', 'ave_average_relative_humidity',
       'ave_mean_wind_direction_deg', 'total_solar_radiation_ly',
       'max_maximum_wind_gust_mph', 'ave_average_air_temperature_deg_
f',
       'POOJurisdictionalAgency_SFS', 'POOJurisdictionalAgency_FS',
       'POOJurisdictionalAgency_BLM', 'site_324BD306',
       'POOJurisdictionalAgency_State', 'site_FA66D690'], dtype=objec
t)
```

In [699]:
```
# Ploting Feature Importance
# import branca.colormap as cm
fig, ax = plt.subplots(figsize=(10,6))

ax = sns.barplot(x=im_df['Feature Importance'], y=im_df['Original Name
ax.set_title('Fire Complexity level Feature Importance', fontsize=15)
ax.set_xlabel('Features', fontsize=15)
ax.set_ylabel('Importance', fontsize=15);

# Changing Feature names

new_names = ['Elevation', 'Dispatch Center ID TXTIC', 'Mean Precipitat
```

```
new_names = ['Elevation', 'Dispatch Center ID TXTIC', 'Mean Precipitat
       'Mean Wind Speed', 'Average Relative Humidity',
       'Mean Wind Direction', 'Mean Solar Radiation',
       'Max Wind Gust', 'Mean Air Temperature',
       'Jurisdictional Agency SFS', 'Jurisdictional Agenc FS',
       'Jurisdictional Agency BLM', 'RAWS 324BD306',
       'Jurisdictional Agency State', 'RAWS FA66D690']


ax.set_yticklabels(new_names);

plt.savefig('feature_importance.png', dpi=100, bbox_inches='tight')
```

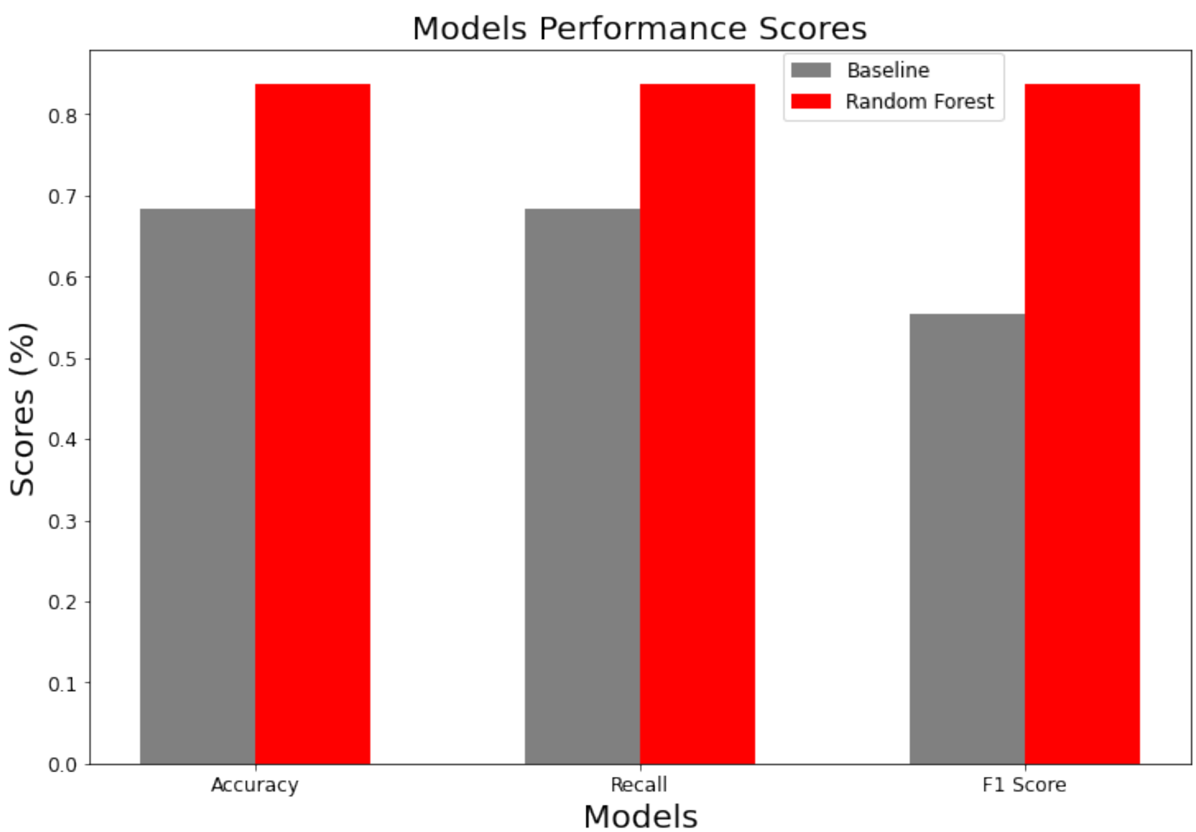


In [491]:

```
fig, ax = plt.subplots(figsize= (12,8))

fire_model.aprf(test=True, average='weighted')

width = .3

f1 = np.arange(3)
f2 = [x + width for x in f1]

ax.bar(f1, [baseline.test_recall, baseline.test_accuracy, baseline.tes

ax.bar(f2, [fire_model.test_recall, fire_model.test_accuracy, fire_moc
       width, label='Random Forest', color='red')
```

```
# Add labels and title
ax.set_xlabel('Models',fontsize=20)
ax.set_ylabel('Scores (%)',fontsize=20)
ax.set_title('Models Performance Scores',fontsize=20)

ax.set_xticks(f1 + width/2)
ax.set_xticklabels(['Accuracy', 'Recall','F1 Score'])
ax.tick_params(axis='both', which='major', labelsize=12)
ax.legend(fontsize=12,loc=(.63,.9));

plt.savefig('scores.png', dpi=100, bbox_inches='tight')
```

```
Training Accuracy: 0.9932735426008968
Testing Accuracy: 0.8380755302638386
Training Precision: 0.9932782416512479
Testing Precision: 0.8430048946512145
Training Recall: 0.9932735426008968
Testing Recall: 0.8380755302638386
Training F1-Score: 0.9932738139763453
Testing F1-Score: 0.8367573570291799
```



In [465]:
```
final_scores = fire_model.test_report(Return=True)
final_scores
```

Out[465]:
```
{'Type 1 Incident': {'precision': 0.75,
  'recall': 0.6,
  'f1-score': 0.6666666666666665,
```

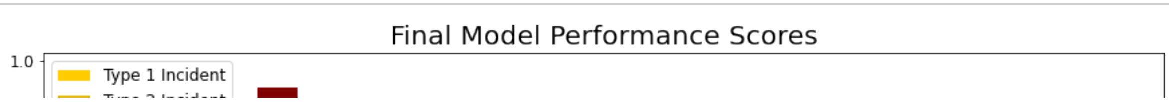
```
 'support': 10},
'Type 2 Incident': {'precision': 0.1111111111111111,
 'recall': 0.08333333333333333,
 'f1-score': 0.09523809523809525,
 'support': 12},
'Type 3 Incident': {'precision': 0.3875,
 'recall': 0.25,
 'f1-score': 0.303921568627451,
 'support': 124},
'Type 4 Incident': {'precision': 0.6473594548551959,
 'recall': 0.8137044967880086,
 'f1-score': 0.7210626185958254,
 'support': 467},
'Type 5 Incident': {'precision': 0.9623698959167334,
 'recall': 0.9106060606060606,
 'f1-score': 0.9357726741922927,
 'support': 1320},
'accuracy': 0.8380755302638386,
'macro avg': {'precision': 0.5716680923766081,
 'recall': 0.5315287781454805,
 'f1-score': 0.5445323246640662,
 'support': 1933},
'weighted avg': {'precision': 0.8430048946512145,
 'recall': 0.8380755302638386,
 'f1-score': 0.8367573570291799,
 'support': 1933}}
```

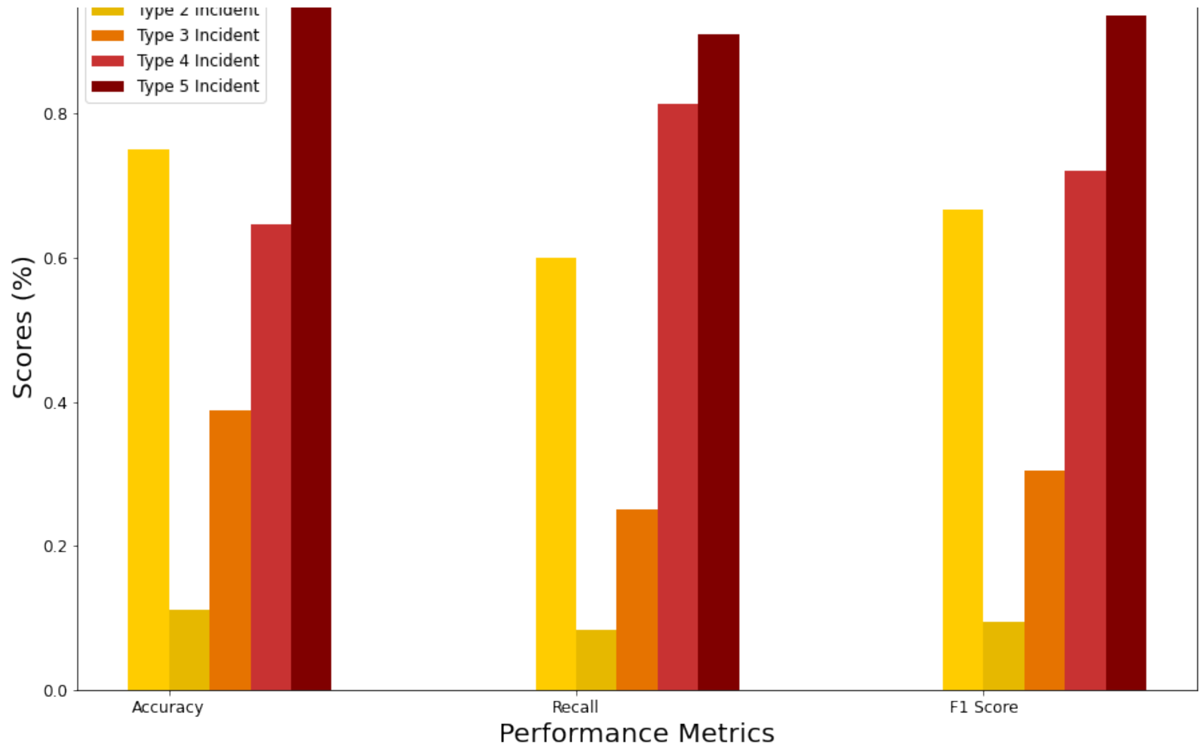
In [468]:
```python
final_scores['Type 1 Incident']#['precision']
```

Out[468]:
```
0.75
```

In [692]:
```python
fig, ax = plt.subplots(figsize= (15,10))

final_scores = fire_model.test_report(Return=True)
metrics = ['precision', 'recall', 'f1-score', 'support']
labels = ['Type 1 Incident', 'Type 2 Incident', 'Type 3 Incident', 'Ty

width = .1

f1 = np.arange(3)
f2 = [x + width for x in f1]
f3 = [x + width for x in f2]
f4 = [x + width for x in f3]
f5 = [x + width for x in f4]

type1 = final_scores['Type 1 Incident']
type2 = final_scores['Type 2 Incident']
type3 = final_scores['Type 3 Incident']
type4 = final_scores['Type 4 Incident']
type5 = final_scores['Type 5 Incident']
```

```
# ax.bar(f1, [type1['precision'], type1['recall'],
#              type1['f1-score']], width, label='Type 1 Incident', colo

# ax.bar(f2, [type2['precision'], type2['recall'],
#              type2['f1-score']], width, label='Type 2 Incident', colo

# ax.bar(f3, [type3['precision'], type3['recall'],
#              type3['f1-score']], width, label='Type 3 Incident', colo

# ax.bar(f4, [type4['precision'], type4['recall'],
#              type4['f1-score']], width, label='Type 4 Incident', colo

# ax.bar(f5, [type5['precision'], type5['recall'],
#              type5['f1-score']], width, label='Type 5 Incident', colo

ax.bar(f1, [type1['precision'], type1['recall'],
            type1['f1-score']], width, label='Type 1 Incident', color=

ax.bar(f2, [type2['precision'], type2['recall'],
            type2['f1-score']], width, label='Type 2 Incident', color=

ax.bar(f3, [type3['precision'], type3['recall'],
            type3['f1-score']], width, label='Type 3 Incident', color=

ax.bar(f4, [type4['precision'], type4['recall'],
            type4['f1-score']], width, label='Type 4 Incident', color=

ax.bar(f5, [type5['precision'], type5['recall'],
            type5['f1-score']], width, label='Type 5 Incident', color=

# Add labels and title
ax.set_xlabel('Performance Metrics',fontsize=20)
ax.set_ylabel('Scores (%)',fontsize=20)
ax.set_title('Final Model Performance Scores',fontsize=20)

ax.set_xticks(f1 + width/2)
ax.set_xticklabels(['Accuracy', 'Recall','F1 Score'])
ax.tick_params(axis='both', which='major', labelsize=12)
ax.legend(fontsize=12,loc='best');

# # color set to white for presentation plot
# ax.set_xlabel('Performance Metrics', fontsize=20, color='white')
# ax.set_ylabel('Scores (%)', fontsize=20, color='white')
# ax.set_title('Final Model Performance Scores', fontsize=20, color='w

# ax.set_xticks(f1 + width/2)
# ax.set_xticklabels(['Accuracy', 'Recall', 'F1 Score'], color='white'
# ax.tick_params(axis='both', which='major', labelsize=12, colors='whi
# ax.legend(fontsize=12, loc='best')


# plt.savefig('Incident_scores.png', dpi=100, bbox_inches='tight')
```

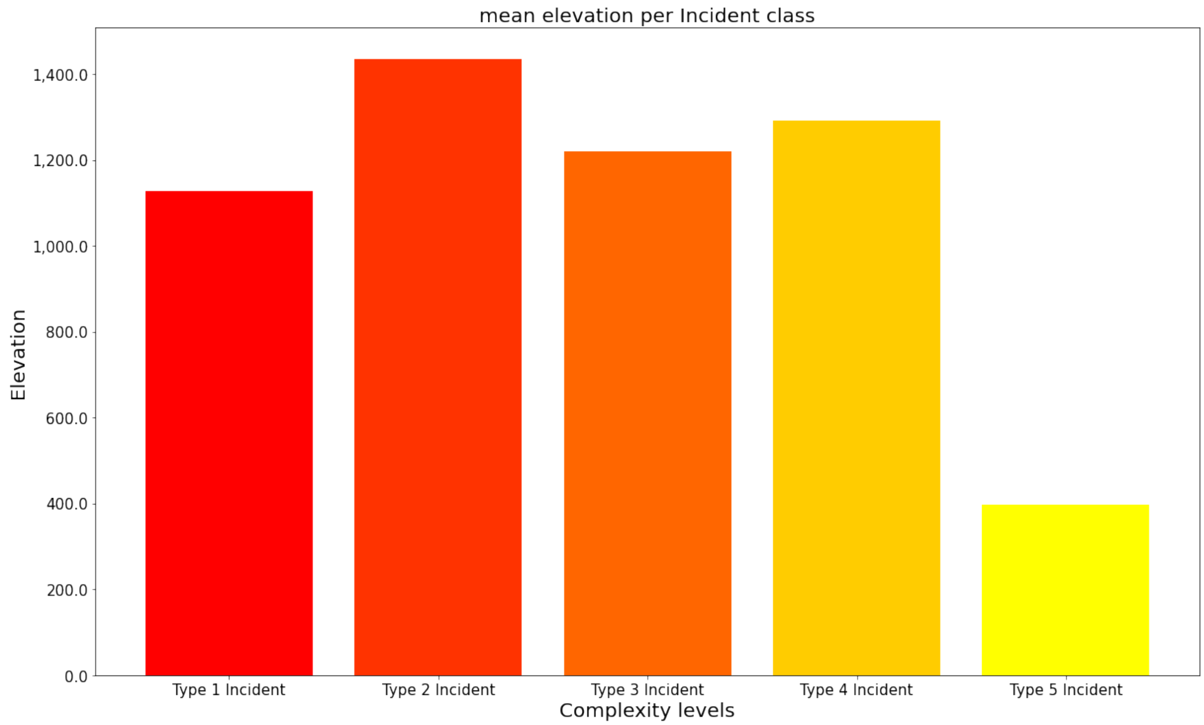




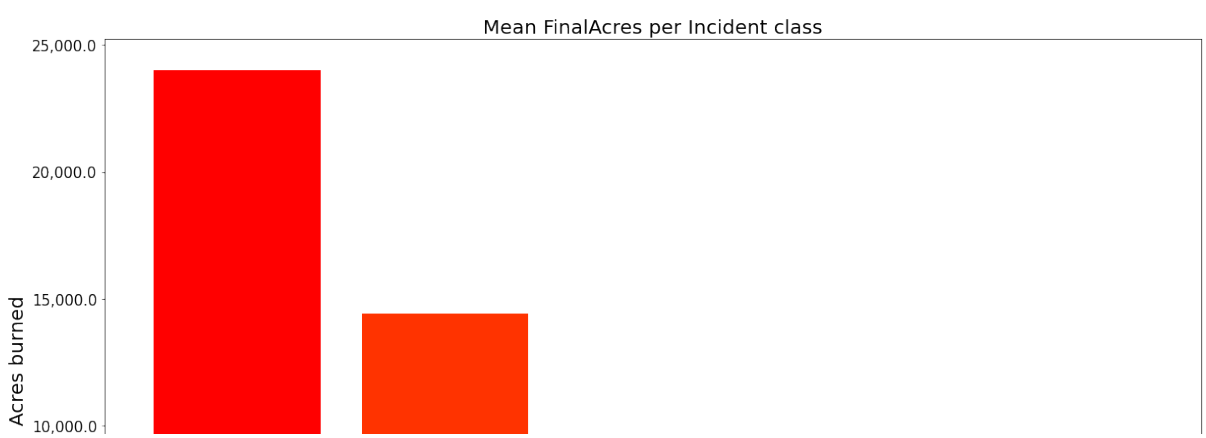
In [682]:

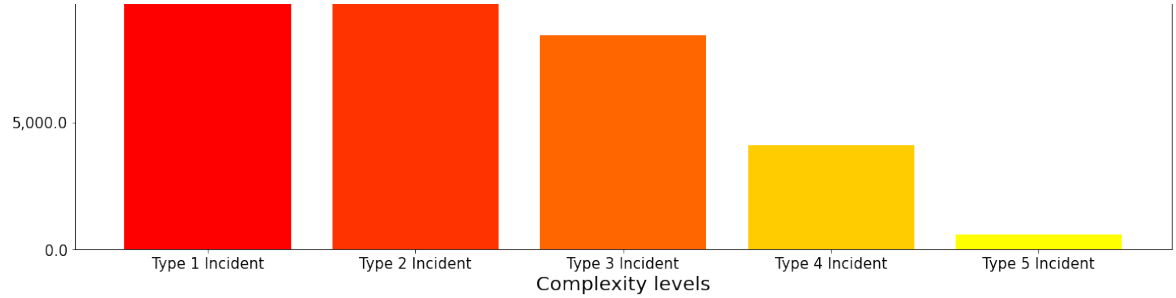
```
from matplotlib.ticker import StrMethodFormatter
def bar_plot(dfs, column, ylabel, aggregates):
    '''
    Bar plot function for evalutating how different features compare t
    dfs : dataframe
    column : column to compare to target
    ylabel : set y label
    aggregates : mean, sum, or max
    '''
    df = dfs.copy()
    fig, ax = plt.subplots(figsize=(20,12))
    df.sort_values(by=column, inplace=True)
    df.dropna(subset=['FireMgmtComplexity', column], inplace=True)
#     colors = ['grey']*3+['red']*1

    if aggregates == 'mean':
        mean_values = df.groupby('FireMgmtComplexity')[column].mean()
        try:
            mean_values = mean_values.drop('Type 1 Prescribed Fire')
        except:
            pass

        colors = ['yellow', '#FFCC00', '#FF6600', '#FF3300', 'red'][::

    if aggregates == 'sum':
        aggregates = 'Total'
        mean_values = df.groupby('FireMgmtComplexity')[column].sum()
        try:
            mean_values = mean_values.drop('Type 1 Prescribed Fire')
        except:
            pass
        colors = ['red' if idx == mean_values.idxmax() else 'grey' for
```

```
    if aggregates == 'max':
        aggregates = 'Max'
        mean_values = df.groupby('FireMgmtComplexity')[column].max()
        try:
            mean_values = mean_values.drop('Type 1 Prescribed Fire')
        except:
            pass
        colors = ['red' if idx == mean_values.idxmax() else 'grey' for

    ax.bar(mean_values.index, mean_values.values, color=colors)

    ax.set_xlabel('Complexity levels',fontsize=20)
    ax.set_ylabel(ylabel, fontsize=20)
    ax.set_title(f'{aggregates} {column} per Incident class', fontsize
    ax.yaxis.set_major_formatter(StrMethodFormatter('{x:,}'))
    ax.tick_params(axis='both', which='major', labelsize=15);

#     plt.savefig('Target_Acres_max.png',dpi=300)
bar_plot(fire_final2, fire_final2['elevation'].name, 'Elevation','mear
```

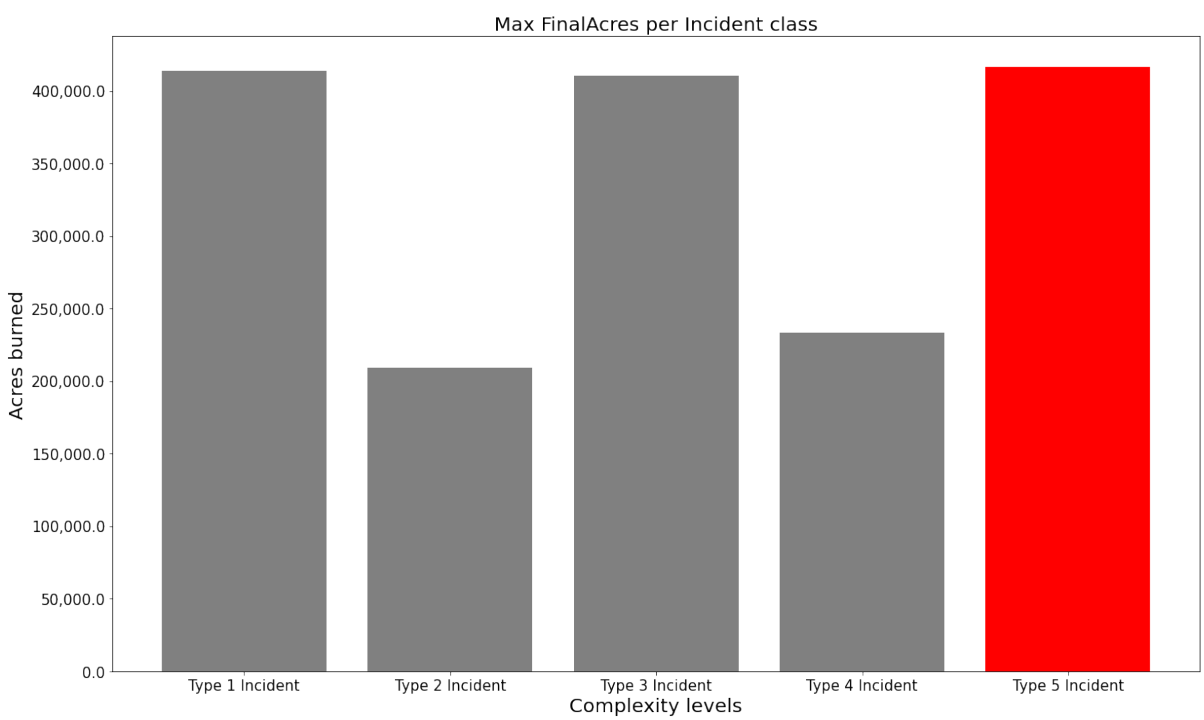


In [632]:
```
bar_plot(fire_final, 'FinalAcres', 'Acres burned','mean')
```

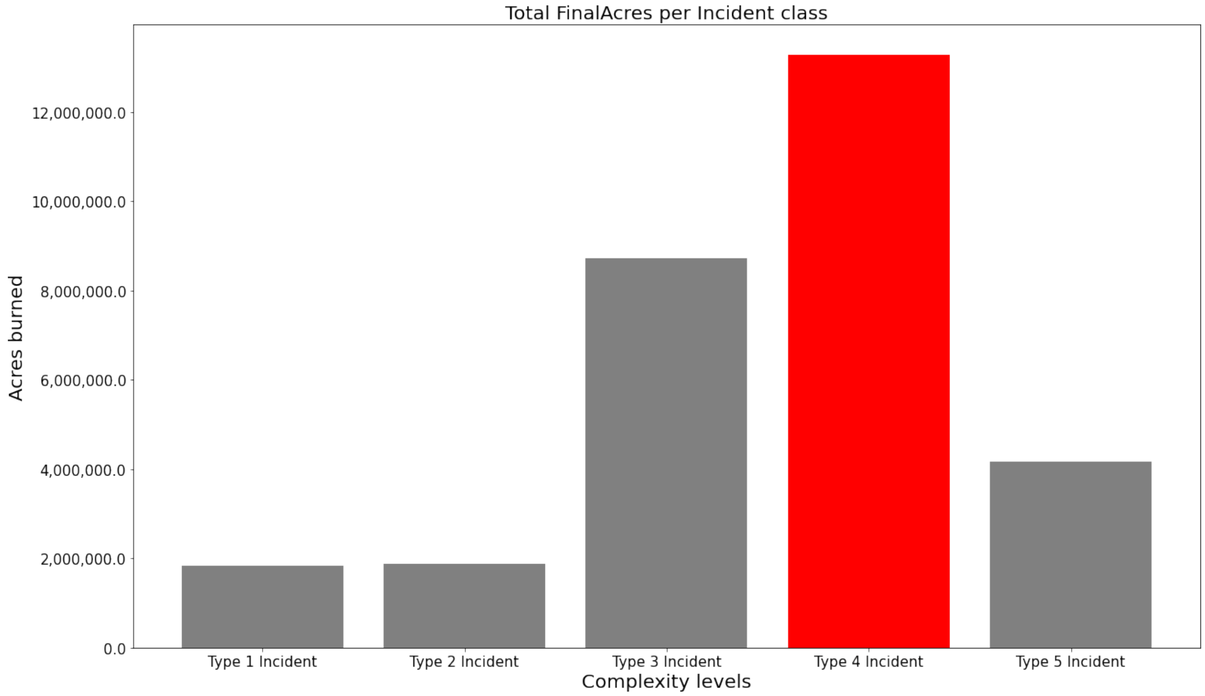




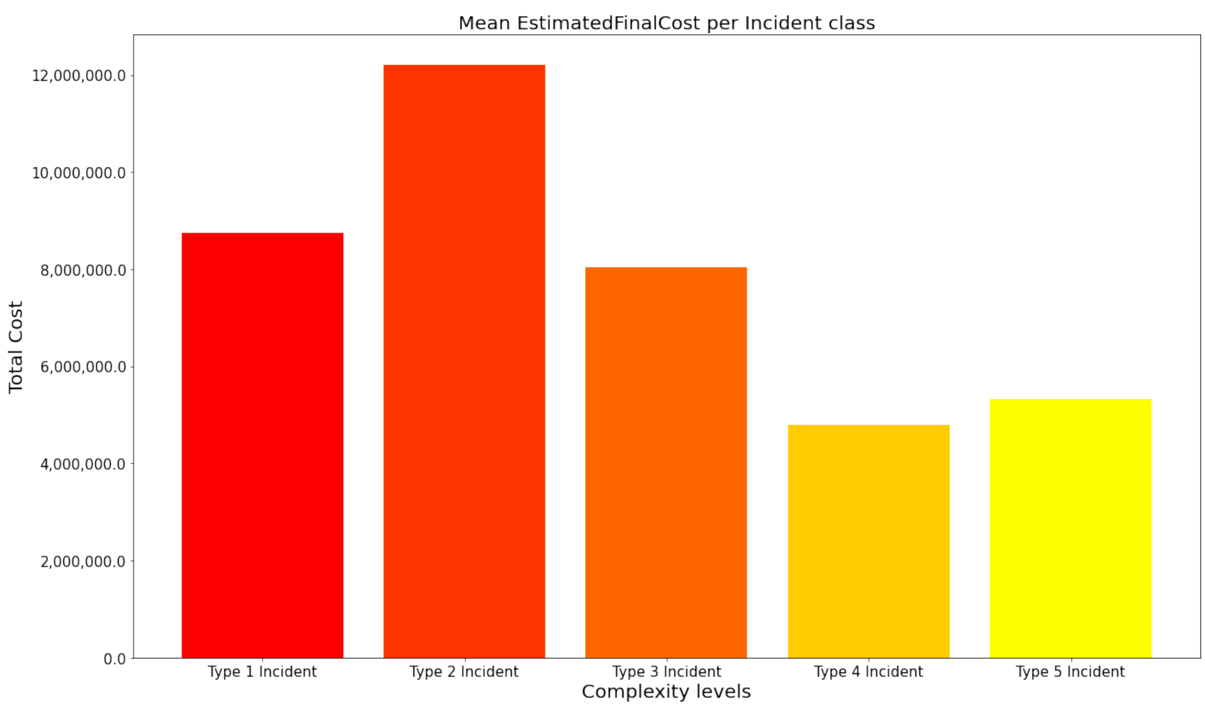
In [681]:
```
bar_plot(fire_final, 'FinalAcres', 'Acres burned','max')
```



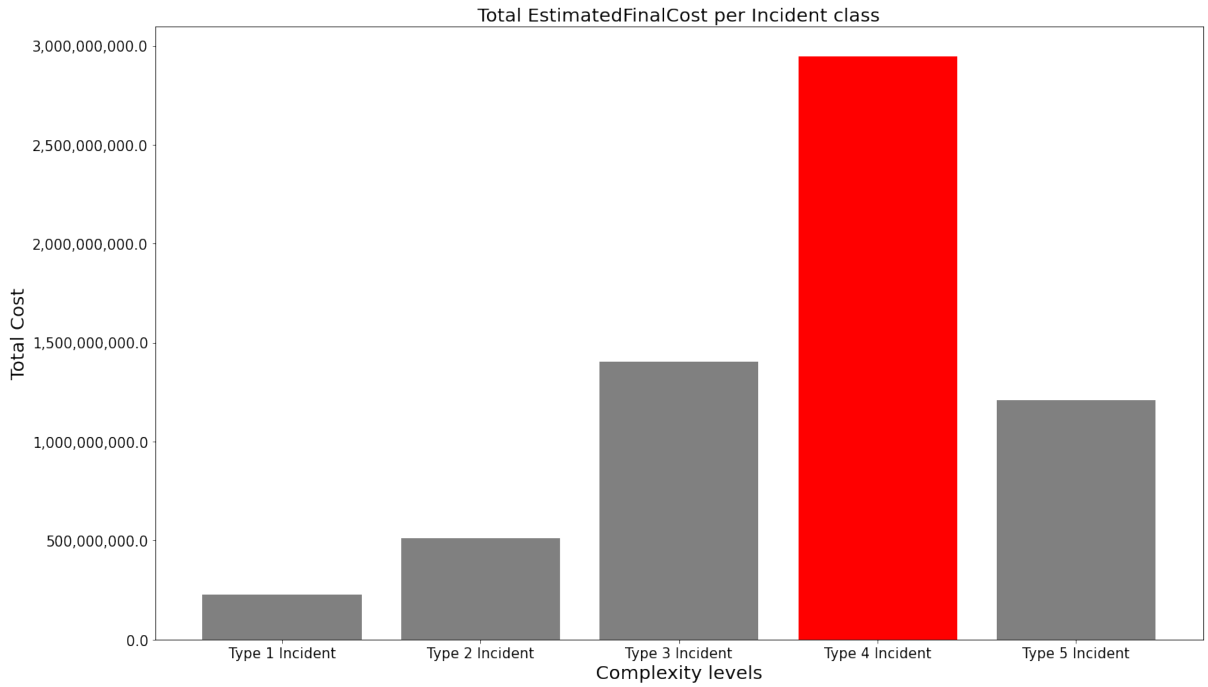
```
In [646]: bar_plot(fire_final, 'FinalAcres', 'Acres burned','sum')
```




```
In [633]: bar_plot(fire_final, fire_final['EstimatedFinalCost'].name, 'Total Cos
```




```
In [644]: bar_plot(fire_final, fire_final['EstimatedFinalCost'].name, 'Total Cos
```



Conclusion

The final model scores:

Complexity level	precision	recall	f1-score	support
Type 1 Incident	0.75	0.60	0.67	10
Type 2 Incident	0.11	0.08	0.10	12
Type 3 Incident	0.39	0.25	0.30	124
Type 4 Incident	0.65	0.81	0.72	467
Type 5 Incident	0.96	0.91	0.94	1320
accuracy			0.84	1933
macro avg	0.57	0.53	0.54	1933
weighted avg	0.84	0.84	0.84	1933

The final model performs best at predicting type 5 incidents, even though I used smote, the majority of wildfires occur at the type 5 incident. This means that most fires are put out within a few days and or only require a few firefighters. Type 4 incident is one level up and type 1 incidents have the next best performance. With type 2 and 3 performing poorly. Looking at the usability of this model it is more significant to be able to predict both extremes well. If a fire incident is 1 day old it is likely still at type 5, this model will be able to use current and forecasted meteorological data, and bureaucratic features such as agency and dispatch center to predict the fire incidents fire complexity level. Further evaluation shows that the highest mean acres burned and economic cost correlate with type 1 incidents, This for one confirms that fire complexity levels do correlate with fire scale and impact. However, this is not absolute, when evaluating the max acres burned for each level types 1, 3, and 5 all share close max acres burned. This could be an error in the data or Possibly more underlying factors influencing the fire complexity level. One speculation is that large fires occurring in heavily remote regions are less of a risk to people and communities. Further analysis also shows that type 4 incidents have the largest cumulative acres burned and economic costs. This is likely due to just the class imbalance as the mean shows that type 1 incidents are significantly higher in both features.

Next Steps

Looking at the next steps, I am looking to further improve model performance by adding additional features such as calculating drought data, remoteness index, and improving RAWS site selection. After this, I am looking to build a streamlit deployment of the model. This will involve setting up APIs and pulling current RAWS data, and potentially forecasted Meteorological data.

In [ ]:
```

```