Exploratory Data Analysis on Algerian Forest Fire dataset

Linkedin: https://www.linkedin.com/in/satya-nerurkar-9b0655190/
Github: https://github.com/SatyaNerurkar

Dataset Information

The dataset includes 244 instances that regroup a data of two regions of Algeria,namely the Bejaia region located in the northeast of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria.

There are 122 instances for each region.

- The period from June 2012 to September 2012.
- The dataset includes 11 attribues and 1 output attribue (class)
- The 244 instances have been classified into fire (138 classes) and not fire (106 classes) classes.

Dataset can be downloaded from below link:
https://archive.ics.uci.edu/ml/machine-learning-databases/00547/

Import Data and Required Packages

In [1]:
```
# Importing Pandas, Numpy, Matplotlib, Seaborn, plotly and Warings Library.
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
import warnings
warnings.filterwarnings("ignore")
import colorama
from colorama import Fore

# Display enitre dataset in output cell.
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
```

Download and Import the CSV Data as Pandas DataFrame

In [2]:
```
# Importing top 122 rows from CSV file that contain data for Bejaia Region.

Bejaia_df = pd.read_csv('C:\\Users\\vishw\\OneDrive\\Documents\\Satya\\DS\\ineuron\\EDA\\I
                header=1,nrows=122)

# Creating Region column and assigning value Bejaia for first 122 rows.
Bejaia_df['Region'] = 'Bejaia'
```

In [3]:
```
# Importing rest of data from CSV file that contain data for Sidi-Bel Abbes Region.
SidiBel_Abbes_df = pd.read_csv('C:\\Users\\vishw\\OneDrive\\Documents\\Satya\\DS\\ineuron\
header=125)
```

```
# Creating Region column and assigning value Sidi-Bel Abbes for remaining rows.
SidiBel_Abbes_df['Region'] = 'Sidi-Bel Abbes'
```

In [4]:
```
# performed concat operation along columns to get final dataframe.

df = pd.concat([Bejaia_df, SidiBel_Abbes_df], axis=0, ignore_index=True)
```

In [5]:
```
df['date'] = pd.to_datetime(df[['day', 'month', 'year']])
```

In [6]:
```
# Validating first 3 rows from dataframe.

df.head(3)
```

Out[6]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region	date
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	Bejaia	2012-06-01
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	Bejaia	2012-06-02
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	Bejaia	2012-06-03

In [7]:
```
# Validating last 3 rows from dataframe.

df.tail(3)
```

Out[7]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region	date
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not fire	Sidi-Bel Abbes	2012-09-28
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not fire	Sidi-Bel Abbes	2012-09-29
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not fire	Sidi-Bel Abbes	2012-09-30

In [8]:
```
# Shape of the dataset

print(Fore.BLUE+"This dataset contains {} rows and {} columns.".format(df.shape[0],df.shap
```

```
This dataset contains 244 rows and 16 columns.
```

In [9]:
```
# Check Null and Dtypes

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 16 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   day          244 non-null    int64
```

```
 1   month        244 non-null    int64
 2   year         244 non-null    int64
 3   Temperature  244 non-null    int64
 4    RH          244 non-null    int64
 5    Ws          244 non-null    int64
 6   Rain         244 non-null    float64
 7   FFMC         244 non-null    float64
 8   DMC          244 non-null    float64
 9   DC           244 non-null    object
 10  ISI          244 non-null    float64
 11  BUI          244 non-null    float64
 12  FWI          244 non-null    object
 13  Classes      243 non-null    object
 14  Region       244 non-null    object
 15  date         244 non-null    datetime64[ns]
dtypes: datetime64[ns](1), float64(5), int64(6), object(4)
memory usage: 30.6+ KB
```

Attribute Information:

```
01. Date : (DD/MM/YYYY)Day, month('june' to 'september'), year(2012) Weather data
observations
02. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
03. RH : Relative Humidity in %: 21 to 90
04. Ws : Wind speed in km/h: 6 to 29
05. Rain: total day in mm: 0 to 16.8 FWI Components
06. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
07. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
08. Drought Code (DC) index from the FWI system: 7 to 220.4
09. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
10. Buildup Index (BUI) index from the FWI system: 1.1 to 68
11. Fire Weather Index (FWI) Index: 0 to 31.1
12. Classes: two classes, namely Fire and not Fire
```

Additional Information about given features.

- Fine Fuel Moisture Code: The Fine Fuel Moisture Code (FFMC) is a numeric rating of the moisture content of litter and other cured fine fuels. This code is an indicator of the relative ease of ignition and the flammability of fine fuel.
- Duff Moisture Code: The Duff Moisture Code (DMC) is a numeric rating of the average moisture content of loosely compacted organic layers of moderate depth. This code gives an indication of fuel consumption in moderate duff layers and medium-size woody material.
- Drought Code: The Drought Code (DC) is a numeric rating of the average moisture content of deep, compact organic layers. This code is a useful indicator of seasonal drought effects on forest fuels and the amount of smoldering in deep duff layers and large logs.
- Initial Spread Index: The Initial Spread Index (ISI) is a numeric rating of the expected rate of fire spread. It is based on wind speed and FFMC. Like the rest of the FWI system components, ISI does not take fuel type into account. Actual spread rates vary between fuel types at the same ISI.
- Buildup Index: The Buildup Index (BUI) is a numeric rating of the total amount of fuel available for combustion. It is based on the DMC and the DC. The BUI is generally less than twice the DMC value, and moisture in the DMC layer is expected to help prevent burning in material deeper down in the available fuel.
- Fire Weather Index: The Fire Weather Index (FWI) is a numeric rating of fire intensity. It is based on the ISI and the BUI, and is used as a general index of fire danger throughout the forested areas of Canada.

Data cleaning

In [10]:
```
# Renaming column names so as to remove white spaces

df['Classes  '] = df['Classes  '].str.strip()

df.rename(columns = {'Classes  ':'Classes', ' RH':'RH',' Ws':'Ws', 'Rain ':'Rain'}, inplac
```

In [11]:
```
# Removing row that contains null data.

df = df.dropna()
```

In [12]:
```
# No null values present in the dataset.

df.isnull().sum()
```

Out[12]:
```
day            0
month          0
year           0
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        0
Region         0
date           0
dtype: int64
```

Exploring Data

Profile of the dataset

In [13]:
```
# Display summary statistics for a numerical features from dataframe.

df.describe().T
```

Out[13]:

	count	mean	std	min	25%	50%	75%	max
day	243.0	15.761317	8.842552	1.0	8.00	16.0	23.00	31.0
month	243.0	7.502058	1.114793	6.0	7.00	8.0	8.00	9.0
year	243.0	2012.000000	0.000000	2012.0	2012.00	2012.0	2012.00	2012.0
Temperature	243.0	32.152263	3.628039	22.0	30.00	32.0	35.00	42.0
RH	243.0	62.041152	14.828160	21.0	52.50	63.0	73.50	90.0
Ws	243.0	15.493827	2.811385	6.0	14.00	15.0	17.00	29.0
Rain	243.0	0.762963	2.003207	0.0	0.00	0.0	0.50	16.8
FFMC	243.0	77.842387	14.349641	28.6	71.85	83.3	88.30	96.0
DMC	243.0	14.680658	12.393040	0.7	5.80	11.3	20.80	65.9

	count	mean	std	min	25%	50%	75%	max
ISI	243.0	4.742387	4.154234	0.0	1.40	3.5	7.25	19.0
BUI	243.0	16.690535	14.228421	1.1	6.00	12.4	22.65	68.0

In [14]:
```
# Display summary for a categorical features from dataframe.

df.describe(include = 'object').T
```

Out[14]:

	count	unique	top	freq
DC	243	212	8.2	4
FWI	243.0	160.0	0.5	7.0
Classes	243	2	fire	137
Region	243	2	Bejaia	122

In [15]:
```
df['Classes'].value_counts()
```

Out[15]:
```
fire        137
not fire    106
Name: Classes, dtype: int64
```

In [16]:
```
# The Drought Code (DC) and Fire Weather Index (FWI) are numeric columns
# hence converting them into float datatype
df['DC'] = df['DC'].astype('float64')
df['FWI'] = df['FWI'].astype('float64')
```

Numeric and Categorical columns

In [17]:
```
# define numerical columns
numeric_features = [feature for feature in df.columns if df[feature].dtype != 'O']

# print numerical columns
print('We have {} numerical features : {}'.format(len(numeric_features), numeric_features)
```

```
We have 14 numerical features : ['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rai
n', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'date']
```

In [18]:
```
# define categorical columns
categorical_features = [feature for feature in df.columns if df[feature].dtype == 'O']

# print categorical columns
print('We have {} categorical features : {}'.format(len(categorical_features), categorical
```

```
We have 2 categorical features : ['Classes', 'Region']
```

In [19]:
```
# Highest temperature in the dataset.
highest_temp = df.sort_values(by='Temperature', ascending=False)[['month', 'day', 'Rain',

# Lowest temperature in the dataset.
lowest_temp =  df.sort_values(by='Temperature', ascending=True)[['month', 'day', 'Rain', '

print("Highest Temperature")

print(highest_temp)
```

```
print('*'*35)
print("Lowest Temperature")
print(lowest_temp)
```

```
Highest Temperature
     month  day  Rain  Temperature
199      8   17   0.0           42
193      8   11   0.0           40
184      8    2   0.0           40
198      8   16   0.1           40
176      7   25   1.2           39
**********************************
Lowest Temperature
     month  day  Rain  Temperature
105      9   14   8.3           22
93       9    2  10.1           22
243      9   30   0.2           24
242      9   29   0.1           24
106      9   15   0.4           24
```

In [20]:

```
# Highest Rainfall in the dataset.
highest_rain = df.sort_values(by='Rain', ascending=False)[['month', 'day', 'Rain', 'Temper

# Highest Rainfall in the dataset.
lowest_rain =  df.sort_values(by='Rain', ascending=True)[['month', 'day', 'Rain', 'Tempera

print("Highest Rainfall")

print(highest_rain)
print('*'*35)
print("Lowest Rainfall")
print(lowest_rain)
```

```
Highest Rainfall
     month  day  Rain  Temperature
91       8   31  16.8           28
2        6    3  13.1           26
93       9    2  10.1           22
139      6   18   8.7           33
105      9   14   8.3           22
**********************************
Lowest Rainfall
     month  day  Rain  Temperature
0        6    1   0.0           29
203      8   21   0.0           36
202      8   20   0.0           36
96       9    5   0.0           29
200      8   18   0.0           37
```

In [21]:

```
# Highest Fine Fuel Moisture Code values in dataset
highest_FFMC = df.sort_values(by='FFMC', ascending=False)[['month', 'day', 'Rain', 'Temper

# Lowest Fine Fuel Moisture Code values in dataset
lowest_FFMC =  df.sort_values(by='FFMC', ascending=True)[['month', 'day', 'Rain', 'Tempera

print("Highest Fine Fuel Moisture Code")

print(highest_FFMC)
print('*'*35)
print("Lowest Fine Fuel Moisture Code")
print(lowest_FFMC)
```

```
Highest Fine Fuel Moisture Code
     month  day  Rain  Temperature  FFMC
```

```
199      8   17   0.0           42  96.0
200      8   18   0.0           37  94.3
193      8   11   0.0           40  94.2
229      9   16   0.0           33  93.9
172      7   21   0.0           36  93.9
**********************************
Lowest Fine Fuel Moisture Code
     month  day  Rain  Temperature  FFMC
3        6    4   2.5           25  28.6
93       9    2  10.1           22  30.5
15       6   16   0.7           29  36.1
16       6   17   0.6           30  37.3
214      9    1   0.0           29  37.9
```

In [22]:

```
# Highest Buildup Index (BUI) values in dataset
highest_BUI = df.sort_values(by='BUI', ascending=False)[['month', 'day', 'Rain', 'Temperat

# Lowest Buildup Index (BUI) values in dataset
lowest_BUI =  df.sort_values(by='BUI', ascending=True)[['month', 'day', 'Rain', 'Temperatu

print("Highest Buildup Index")

print(highest_BUI)
print('*'*35)
print("Lowest Buildup Index")
print(lowest_BUI)
```

```
Highest Buildup Index
     month  day  Rain  Temperature   BUI
209      8   27   0.0           36  68.0
89       8   29   0.0           35  67.4
208      8   26   0.0           33  64.0
88       8   28   0.0           34  62.9
207      8   25   0.0           34  59.5
**********************************
Lowest Buildup Index
     month  day  Rain  Temperature  BUI
93       9    2  10.1           22  1.1
214      9    1   0.0           29  1.4
106      9   15   0.4           24  1.4
16       6   17   0.6           30  1.6
105      9   14   8.3           22  1.6
```

In [23]:

```
# Highest Fire Weather Index (FWI) values in dataset
highest_FWI = df.sort_values(by='FWI', ascending=False)[['month', 'day', 'Temperature', 'F

# Lowest Fire Weather Index (FWI) values in dataset
lowest_FWI =  df.sort_values(by='FWI', ascending=True)[['month', 'day', 'Temperature', 'BU

print("Highest Fire Weather Index")

print(highest_FWI)
print('*'*35)
print("Lowest Fire Weather Index")
print(lowest_FWI)
```

```
Highest Fire Weather Index
     month  day  Temperature   FWI
207      8   25           34  31.1
208      8   26           33  30.3
89       8   29           35  30.2
172      7   21           36  30.0
206      8   24           35  26.9
**********************************
```

```
Lowest Fire Weather Index
     month  day  Temperature  BUI
104      9   13           25  1.8
3        6    4           25  1.7
240      9   27           28  6.2
93       9    2           22  1.1
94       9    3           25  1.7
```

Initial Analysis report

- August month is the hottest month followed by july in the given data with highest recorded temperature is 42°C and September month is colder month with lowest recorded temperature is 22°C.
- September and June month received more rainfall than July and August month.
- Fine Fuel Moisture Code, Fire Weather Index, Buildup Index is high in August month when temperature in higher and low in September month when temperature is lower.

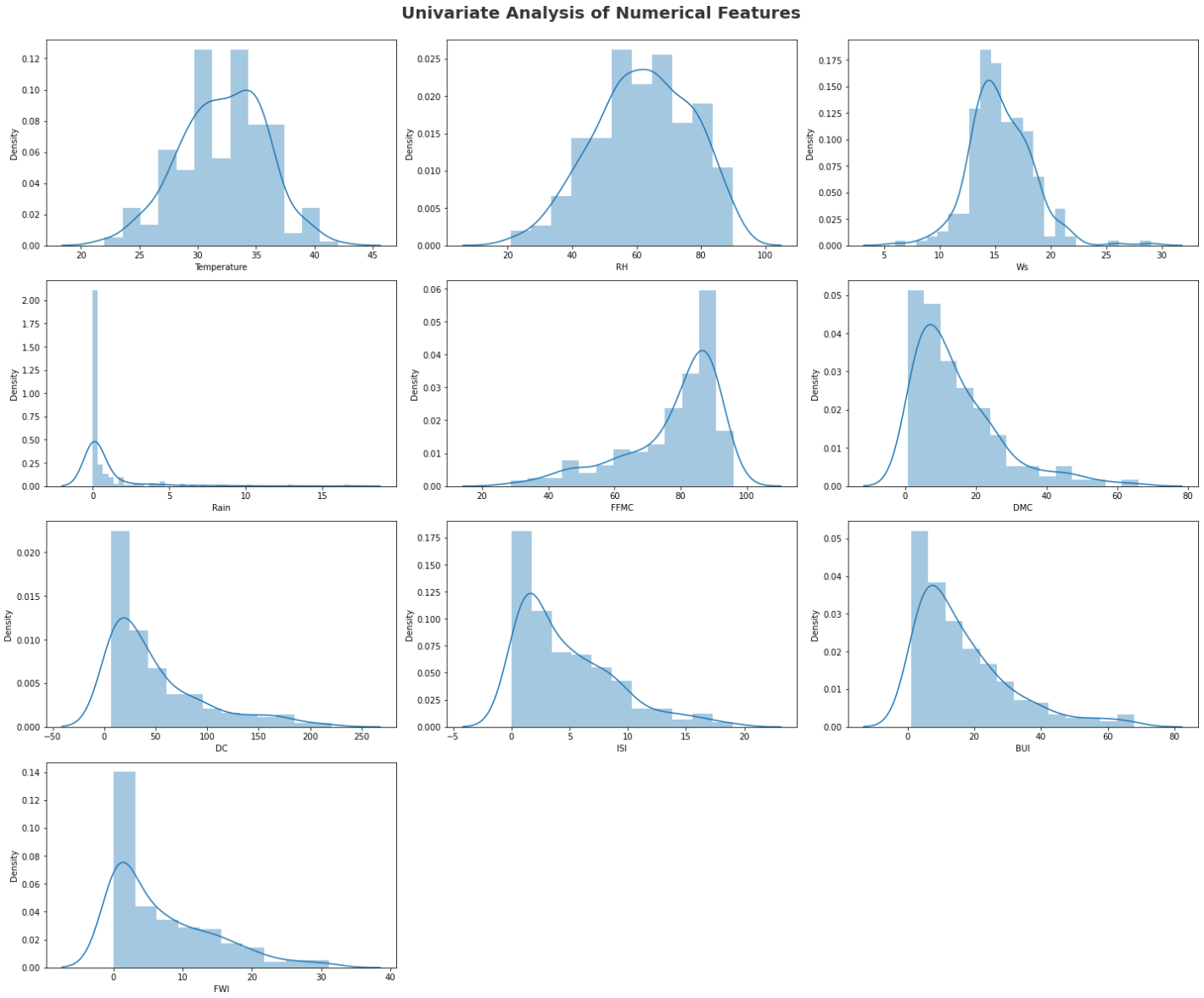
Visualization

Univariate Analysis

In [24]:
```
# Displaying Skewness in the features.

df.skew()
```

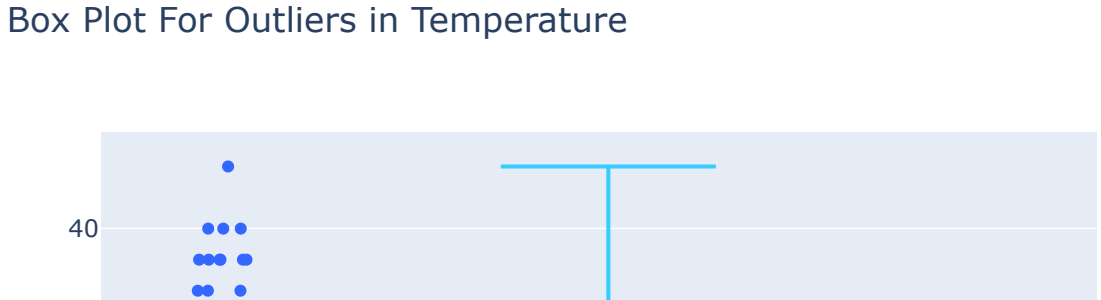
Out[24]:
```
day            0.000365
month         -0.005207
year           0.000000
Temperature   -0.191327
RH            -0.242790
Ws             0.555586
Rain           4.568630
FFMC          -1.320130
DMC            1.522983
DC             1.473460
ISI            1.140243
BUI            1.452745
FWI            1.147593
dtype: float64
```

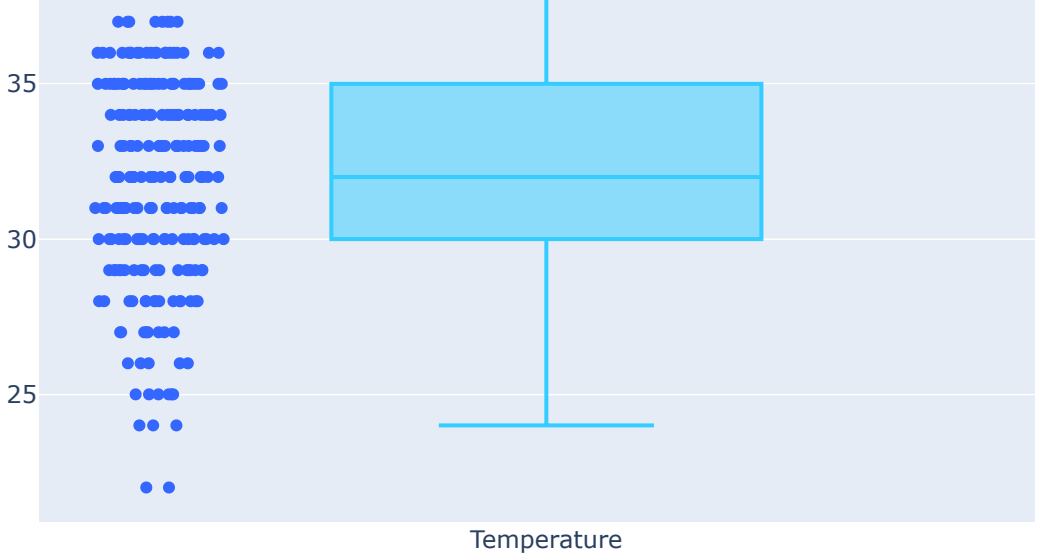
In [25]:
```
plt.figure(figsize=(20, 20))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontweight='bold',
numeric_cols =['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI'

for i in range(0, len(numeric_cols)):
    plt.subplot(5, 3, i+1)
    sns.distplot(x=df[numeric_cols[i]],kde=True)
    plt.xlabel(numeric_cols[i])
    plt.tight_layout()
```



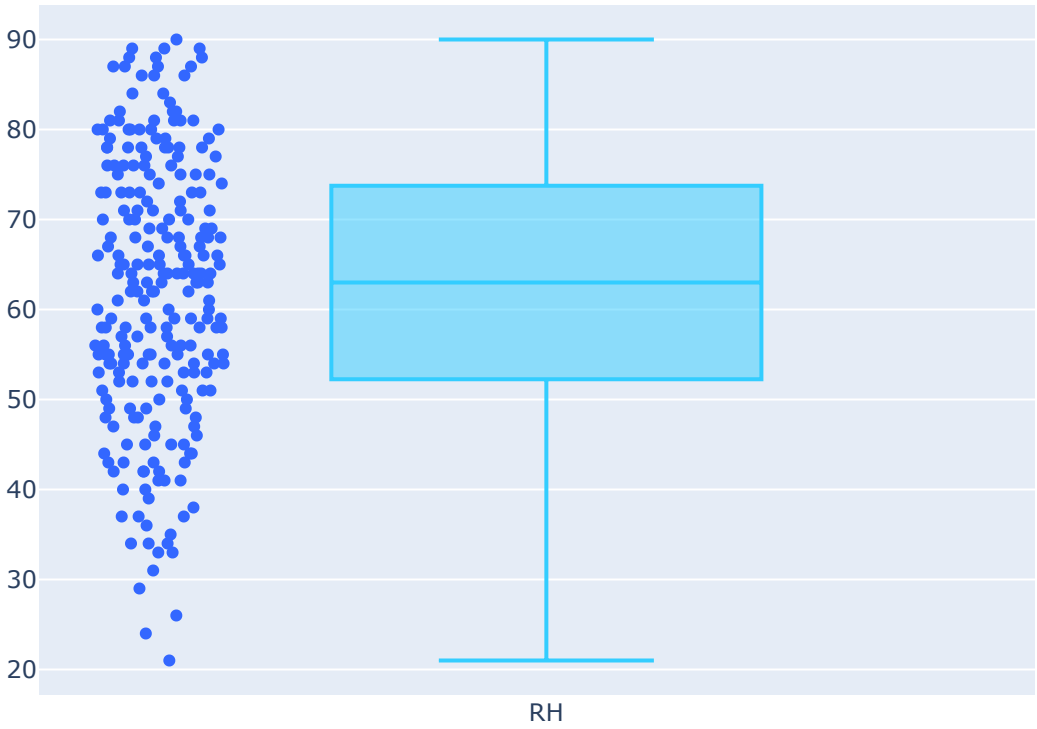
In [26]:

```
for feature in numeric_cols:
    fig = go.Figure()

    fig.add_trace(go.Box(
    y=df[feature],
    name=feature,
    jitter=0.3,
    pointpos=-1.8,
    boxpoints='all', # represent all points
    marker_color='rgb(51, 103, 255)',
    line_color='rgb(51, 205, 255)'))

    fig.update_layout(title_text="Box Plot For Outliers in "+feature)
    fig.show()
```

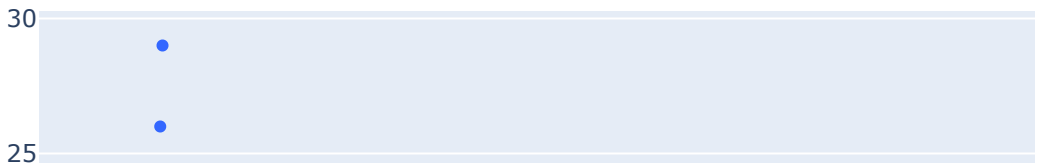


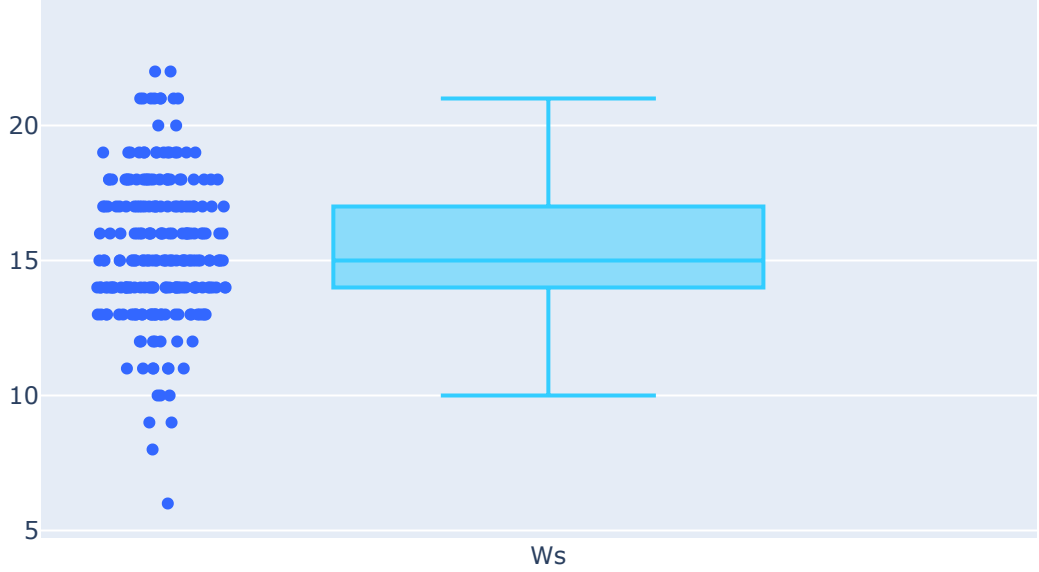


Box Plot For Outliers in RH

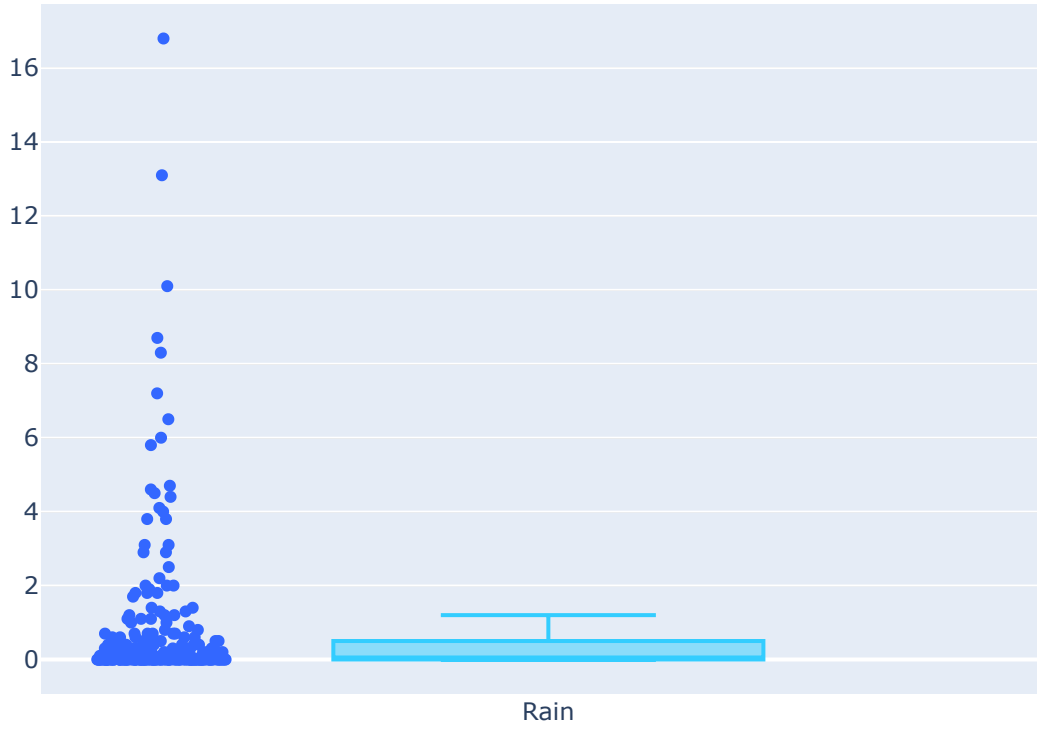


Box Plot For Outliers in Ws

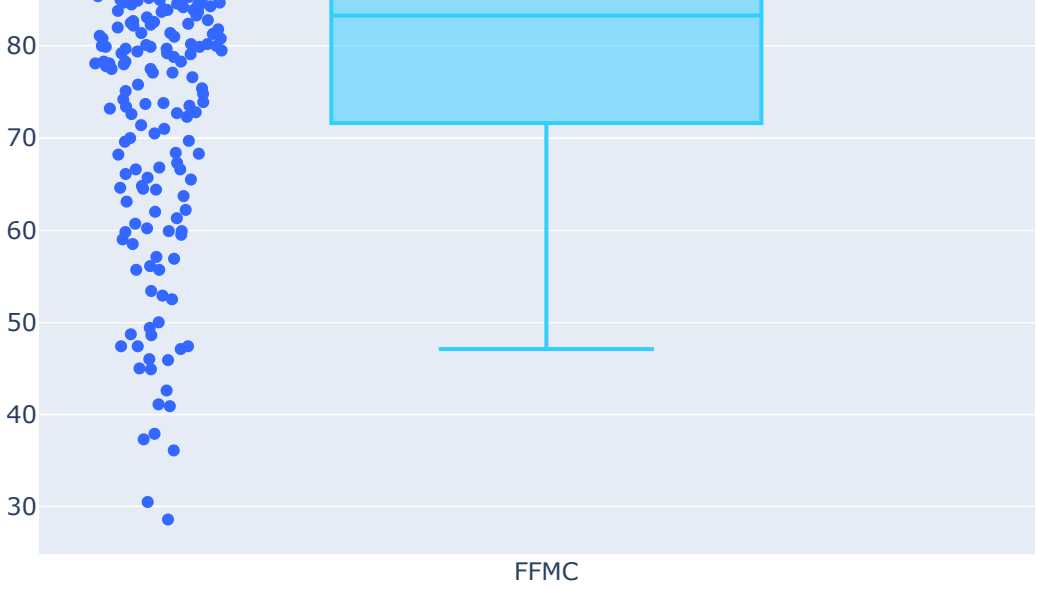




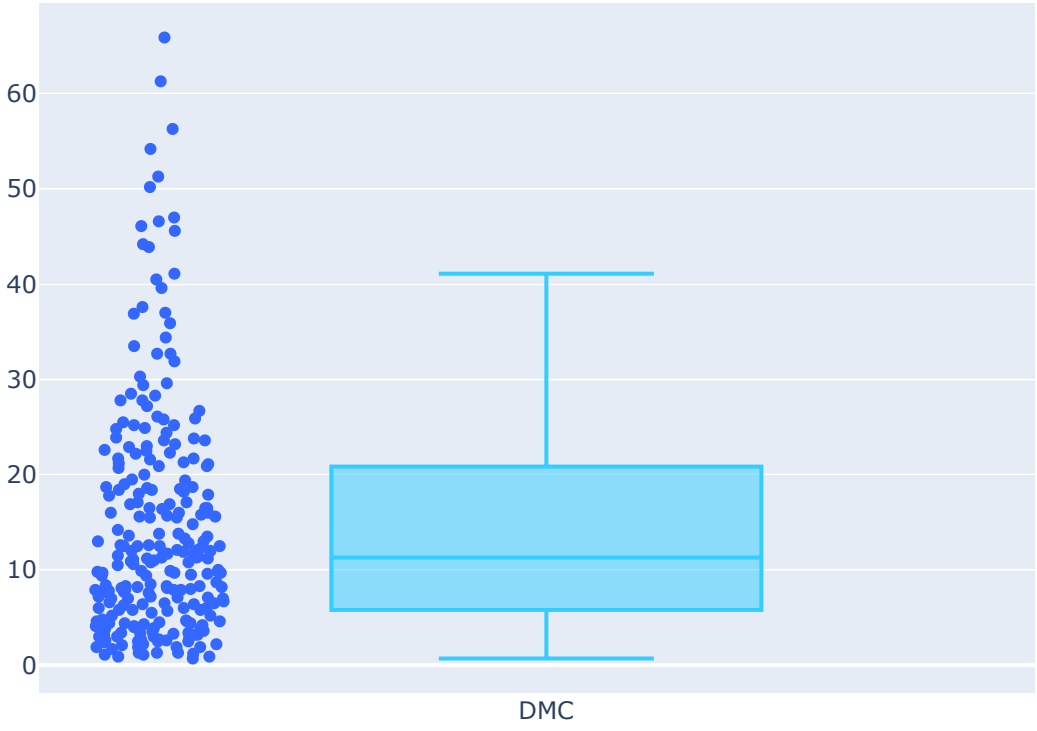
Box Plot For Outliers in Rain



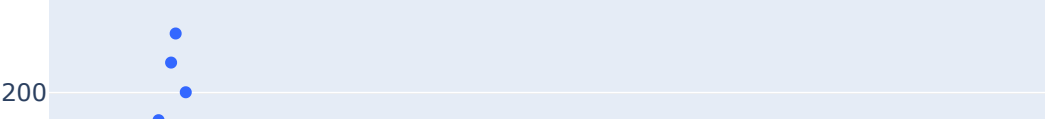
Box Plot For Outliers in FFMC

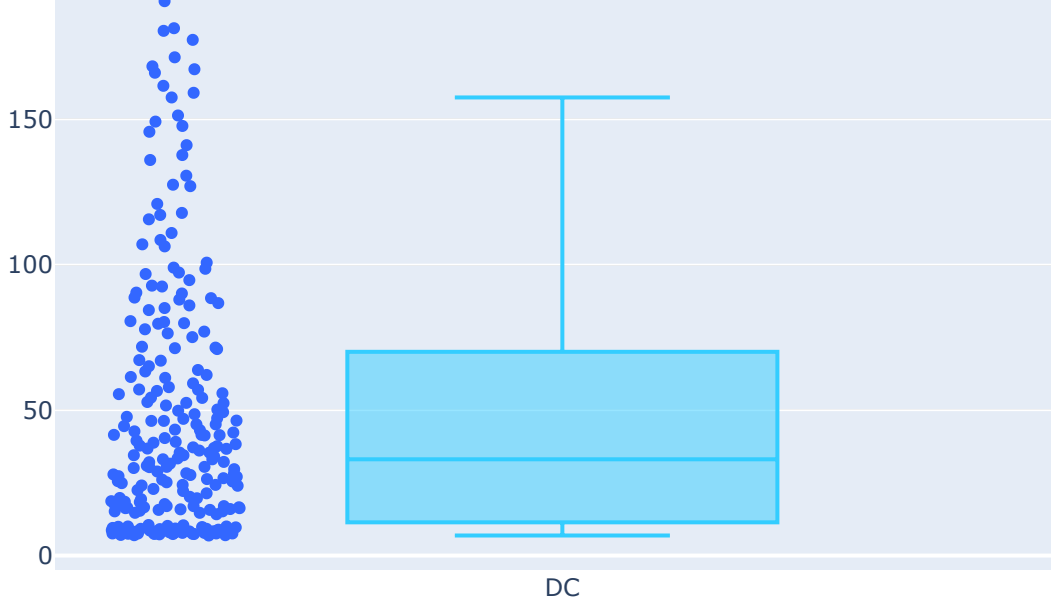


Box Plot For Outliers in DMC

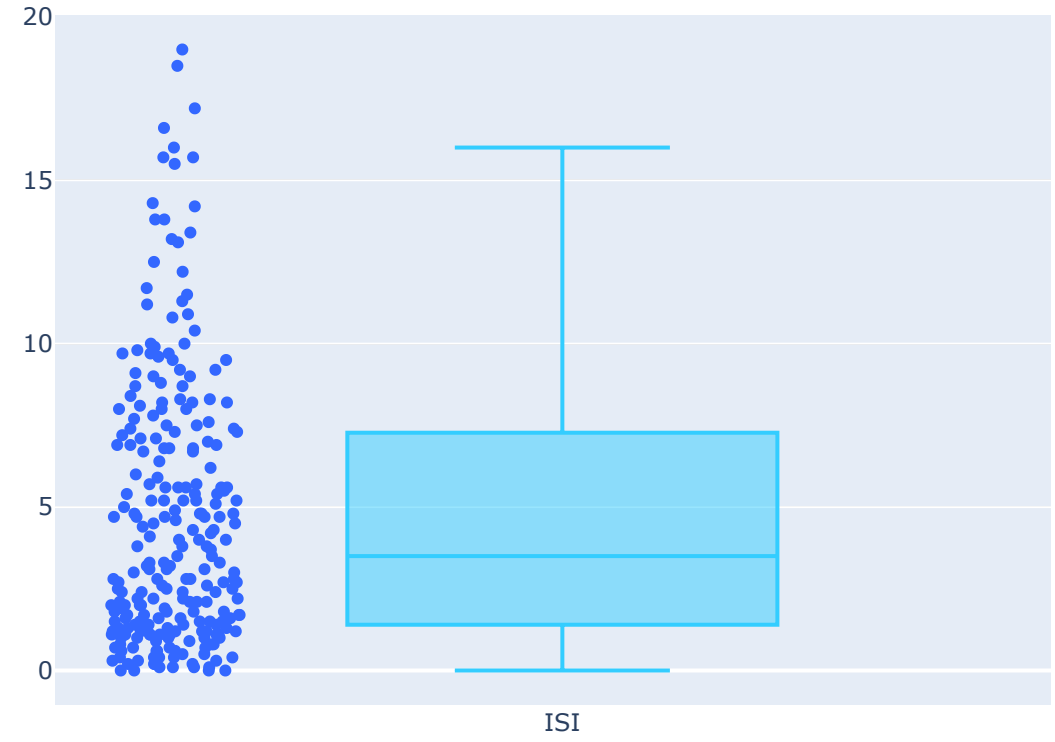


Box Plot For Outliers in DC

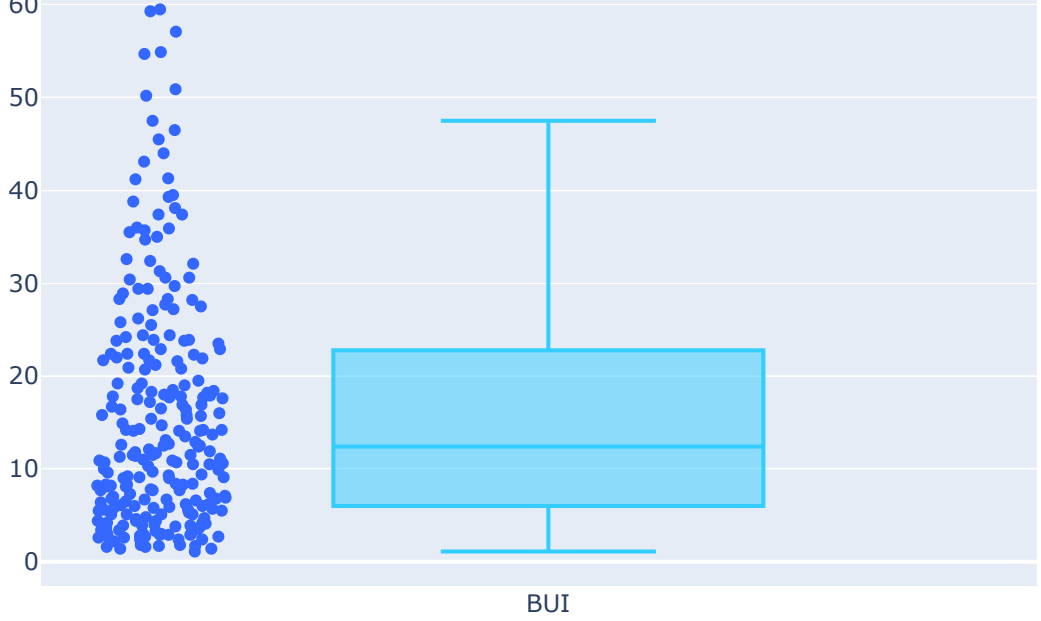




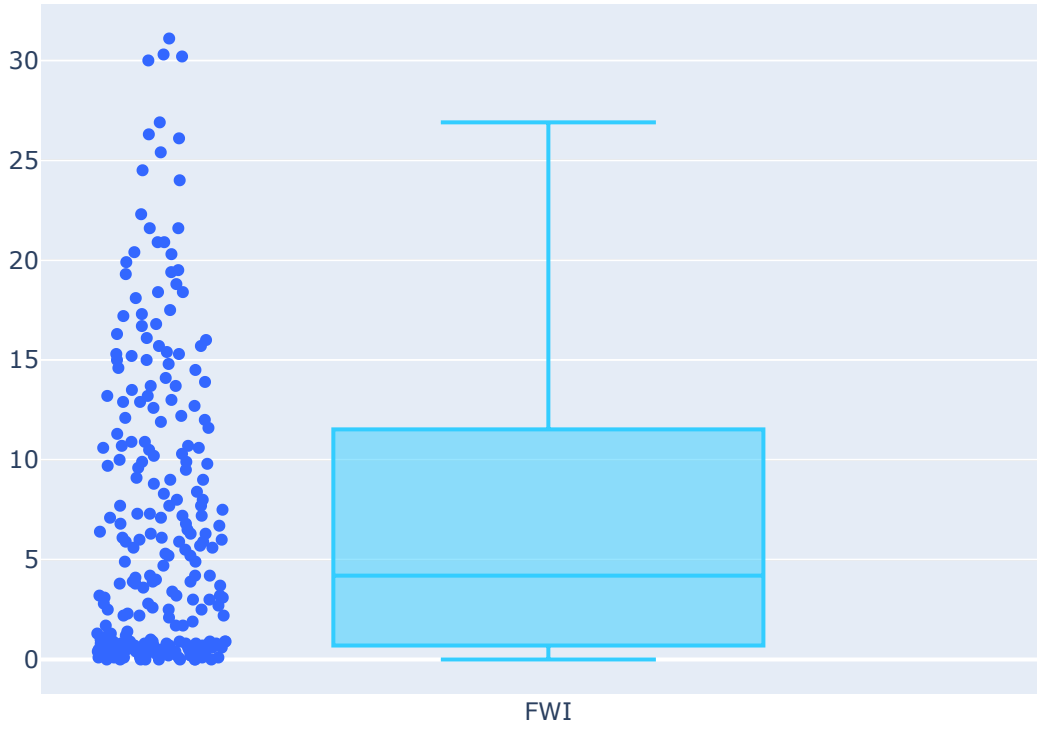
Box Plot For Outliers in ISI



Box Plot For Outliers in BUI



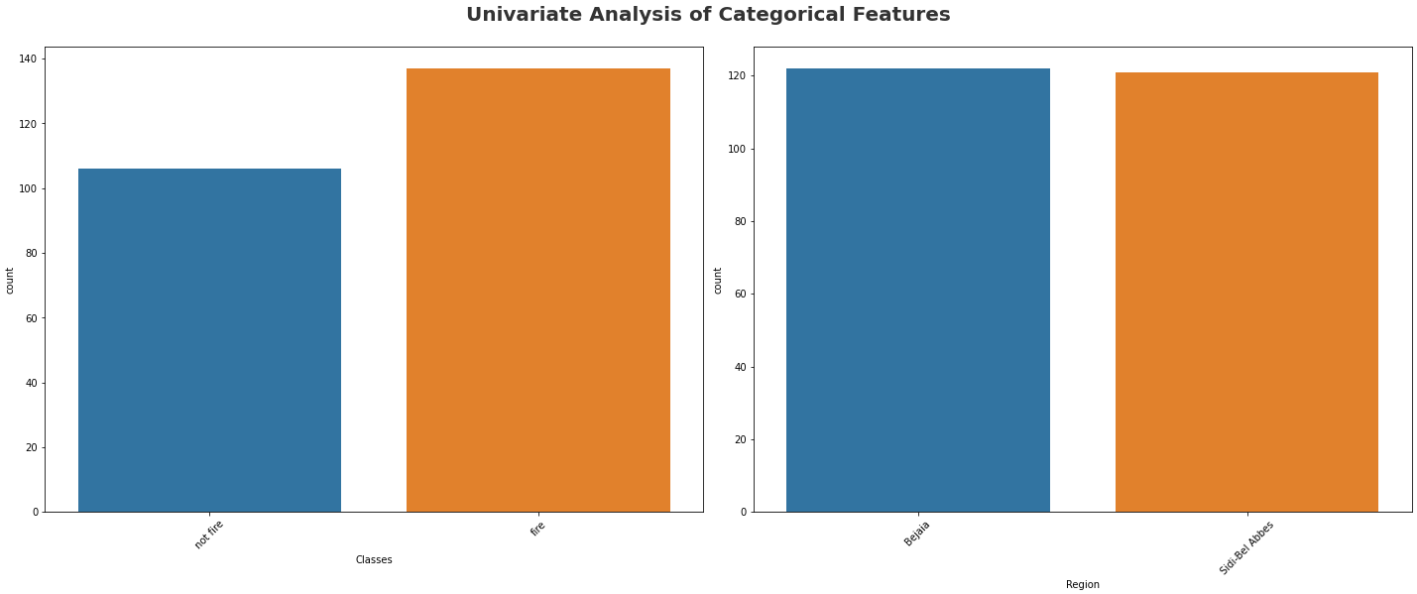
Box Plot For Outliers in FWI



In [27]:

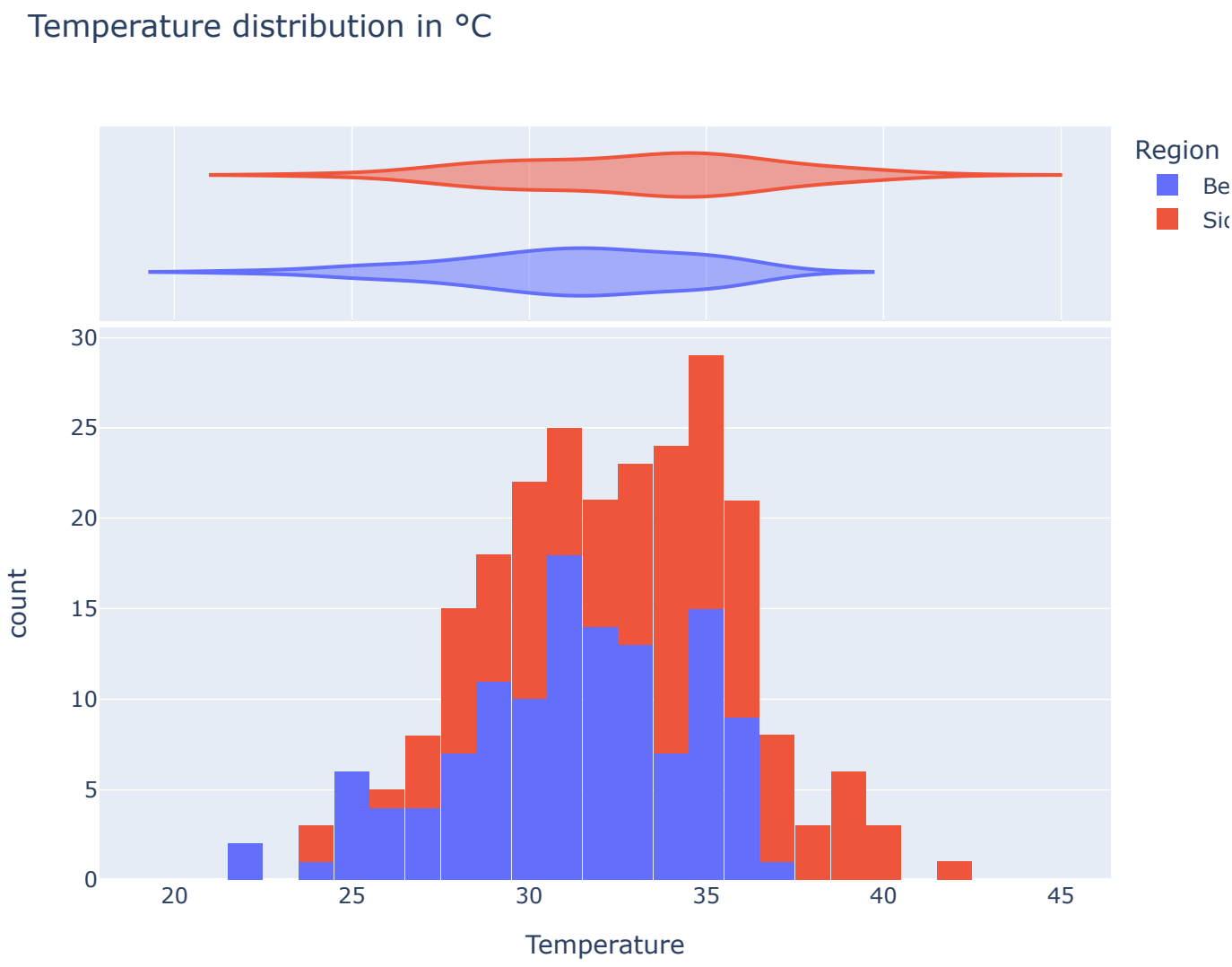
```
# categorical columns
plt.figure(figsize=(20, 15))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold'

for i in range(0, len(categorical_features)):
    plt.subplot(2, 2, i+1)
    sns.countplot(x=df[categorical_features[i]])
```

```
    plt.xlabel(categorical_features[i])
    plt.xticks(rotation=45)
    plt.tight_layout()
```



In [28]:

```
fig = px.histogram(df, x="Temperature", color="Region", marginal="violin",hover_data=df.co
                   title="Temperature distribution in °C", width=800, height=600)
fig.update_layout(bargap=0.02)
fig.show()
```



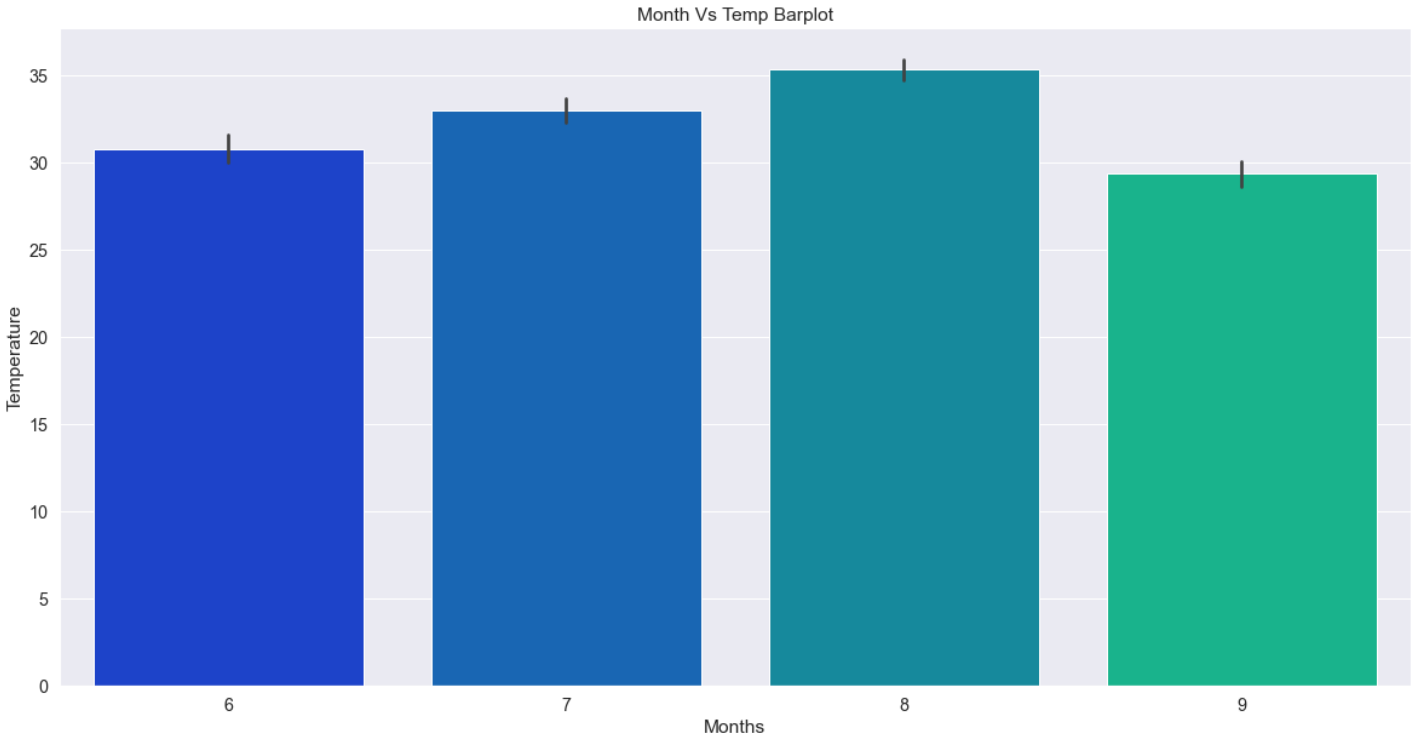
Observations:

- Rain, Duff Moisture Code (DMC), Drought Code (DC), Buildup Index (BUI) are are right skewed and postively skewed.
- Rain, Duff Moisture Code (DMC), Drought Code (DC), Buildup Index (BUI) has outliers.
- Temperature, Relative Humidity (RH), Wind speed (Ws) follow normal distribution

Bivariate analysis and multivariate analysis

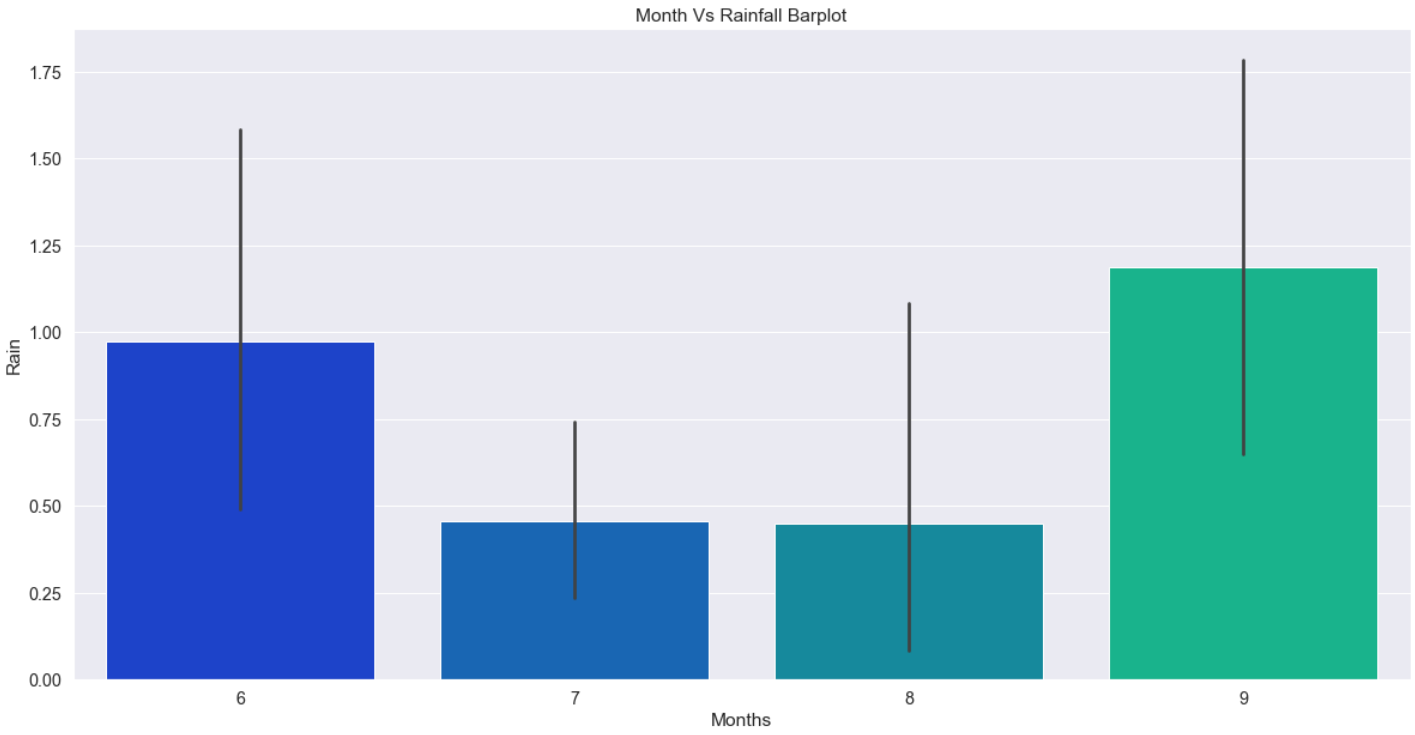
In [29]:
```
# setting parameters
plt.rcParams['figure.figsize'] = [20, 10]
sns.set(style = "darkgrid", font_scale = 1.3)
month_temp = sns.barplot(x = 'month', y = 'Temperature', data = df, palette = 'winter')
month_temp.set(title = "Month Vs Temp Barplot", xlabel = "Months", ylabel = "Temperature")
```

Out[29]:
```
[Text(0.5, 1.0, 'Month Vs Temp Barplot'),
 Text(0.5, 0, 'Months'),
 Text(0, 0.5, 'Temperature')]
```

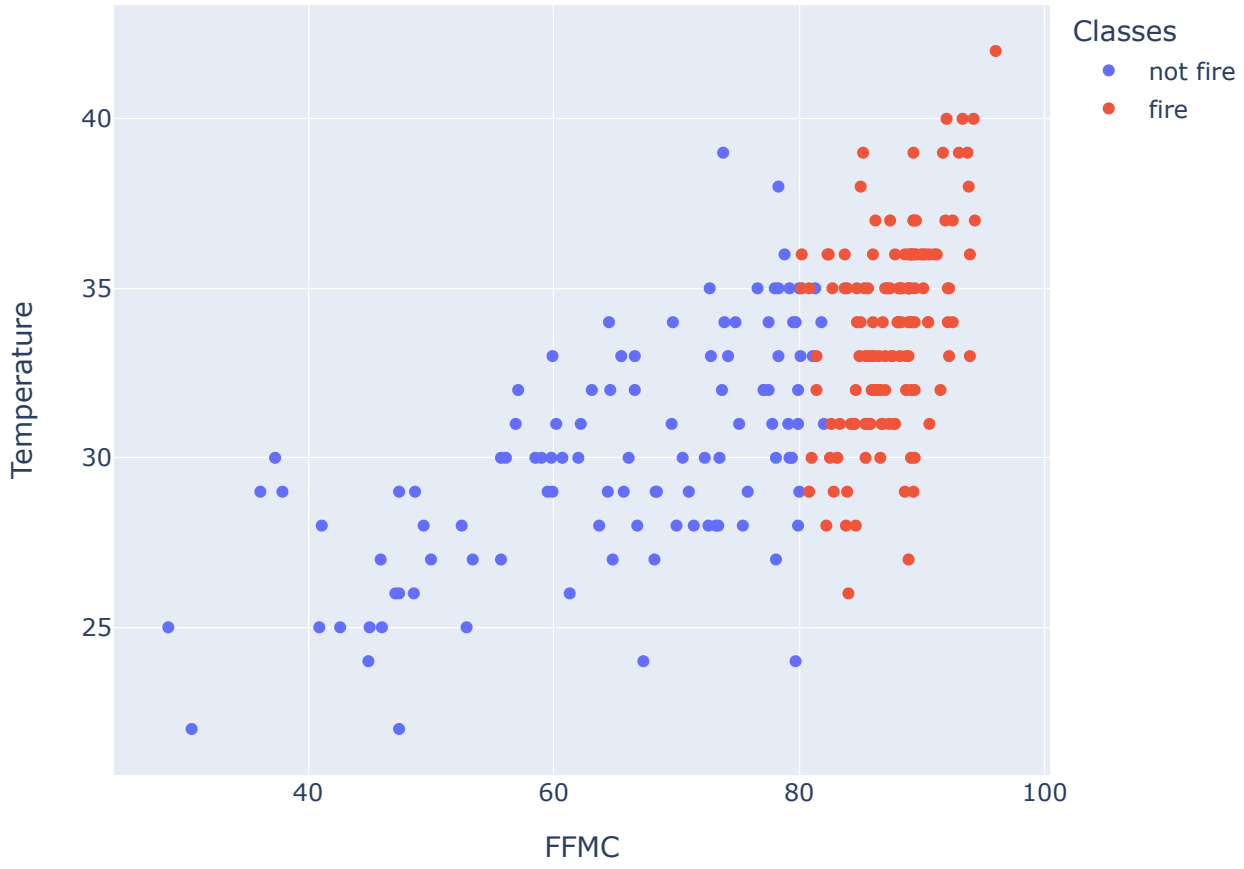


In [30]:
```
plt.rcParams['figure.figsize'] = [20, 10]
sns.set(style = "darkgrid", font_scale = 1.3)
month_temp = sns.barplot(x = 'month', y = 'Rain', data = df, palette = 'winter')
month_temp.set(title = "Month Vs Rainfall Barplot", xlabel = "Months", ylabel = "Rain")
```

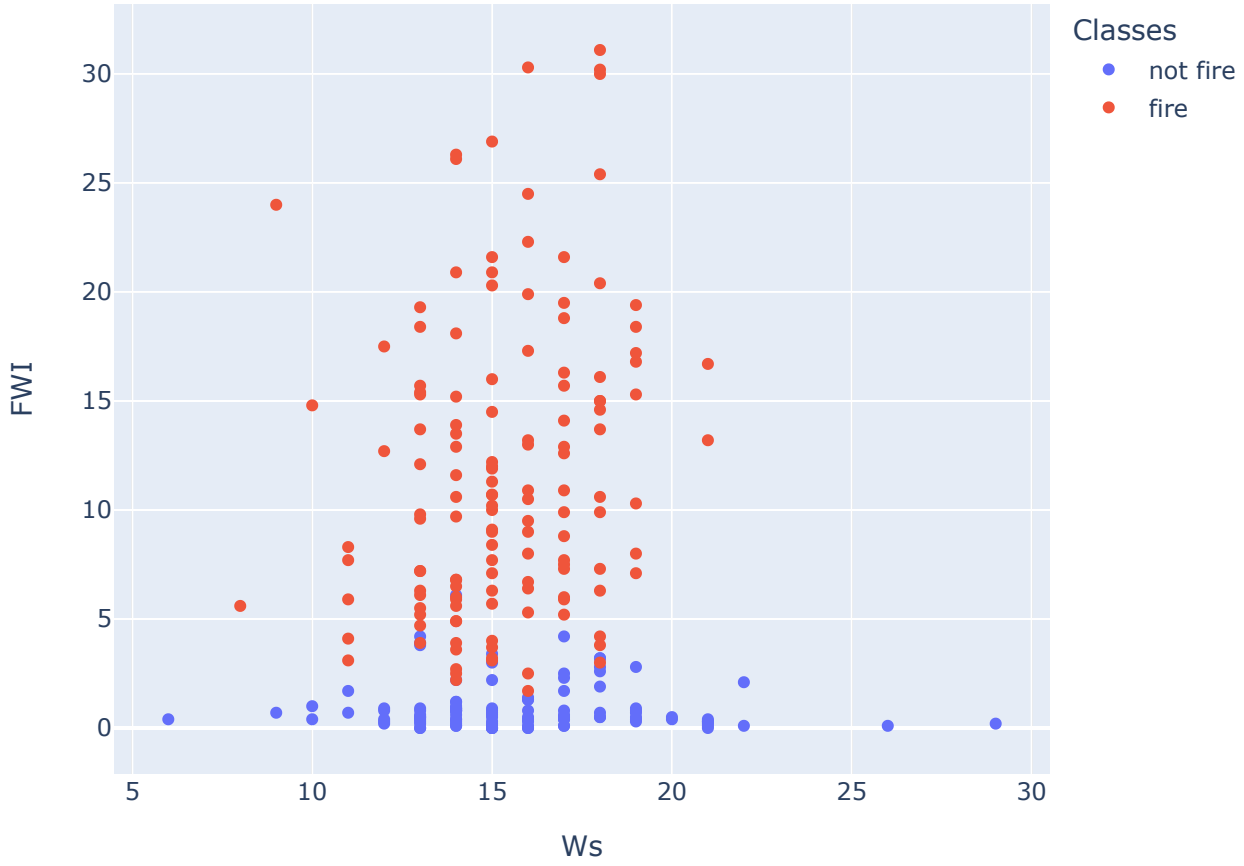
Out[30]:
```
[Text(0.5, 1.0, 'Month Vs Rainfall Barplot'),
 Text(0.5, 0, 'Months'),
 Text(0, 0.5, 'Rain')]
```



In [31]:
```
fig = px.scatter(df, x="FFMC", y="Temperature", color = 'Classes')
fig.show()
```

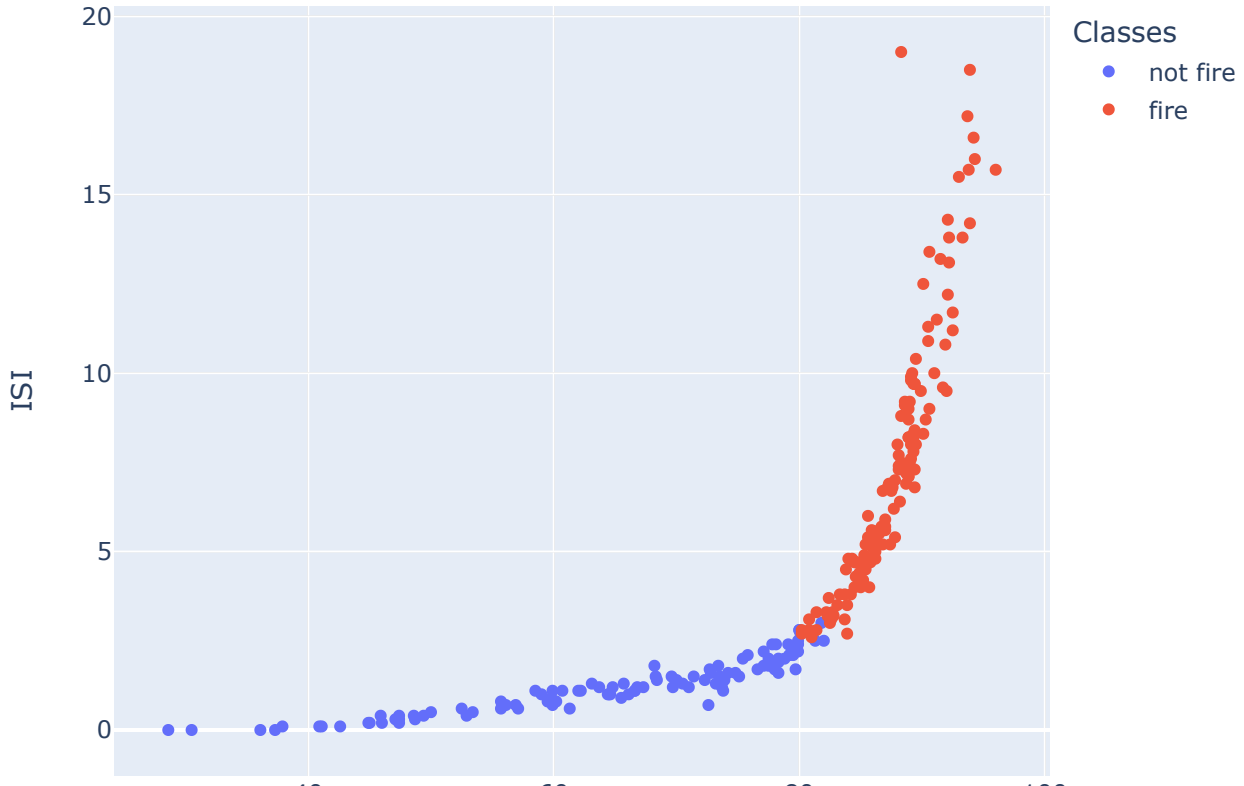


In [32]:
```
fig = px.scatter(df, x="Ws", y="FWI", color='Classes')
fig.show()
```

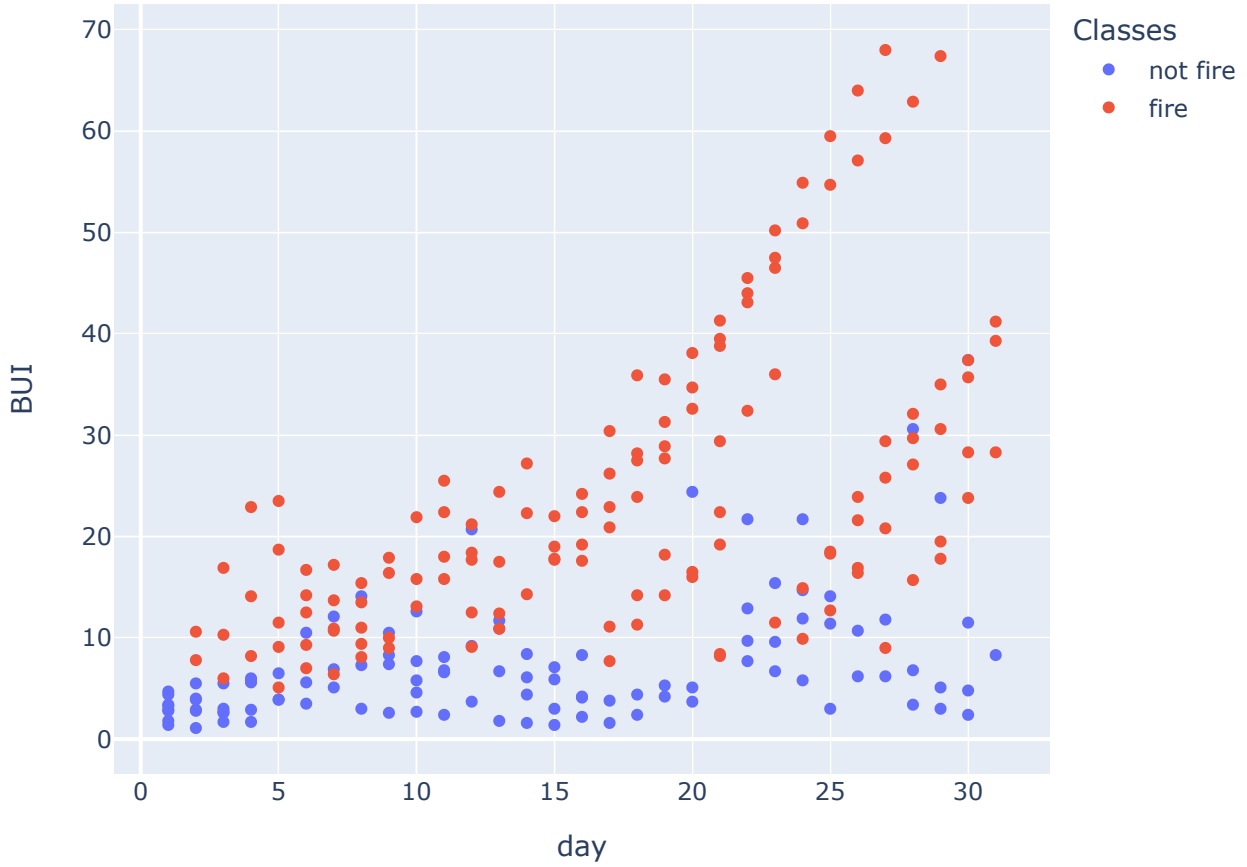


In [33]:

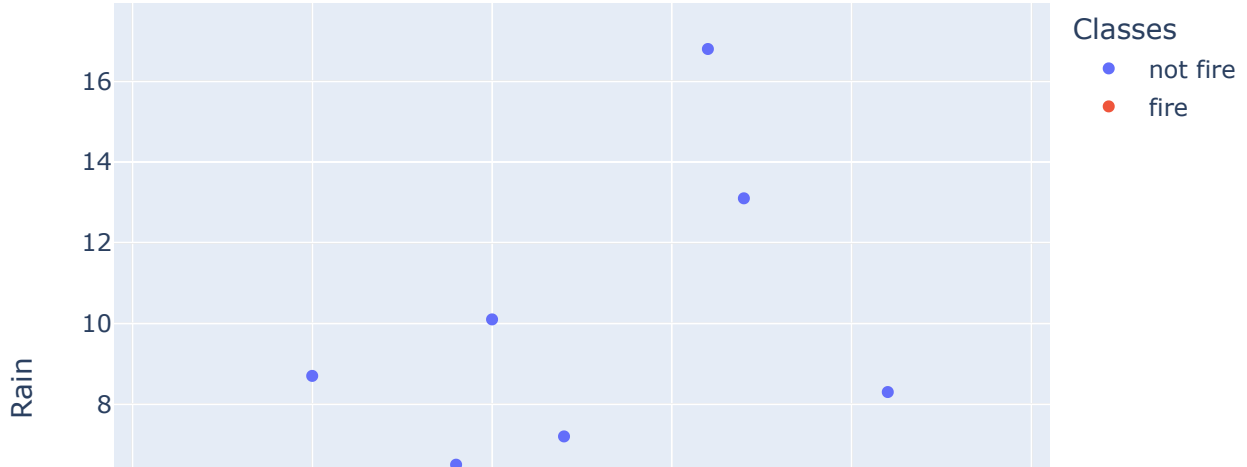
```
fig = px.scatter(df, x="FFMC", y="ISI", color='Classes')
fig.show()
```

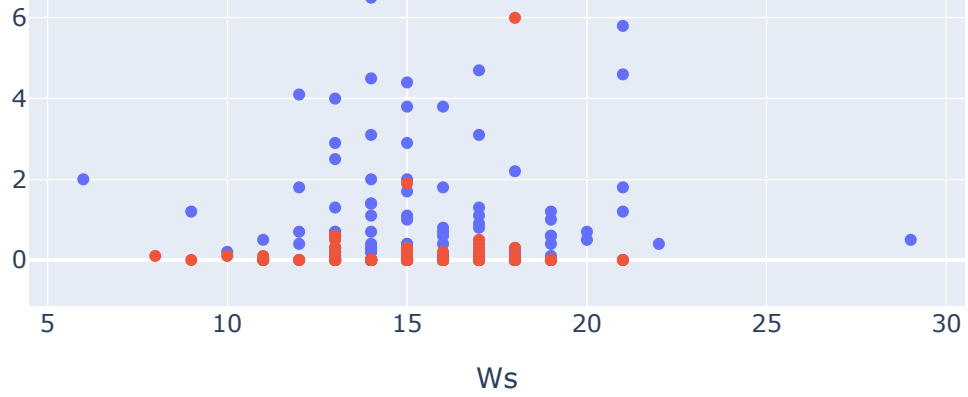


In [34]:
```
fig = px.scatter(df, x='day', y="BUI", hover_data=['month'] ,color='Classes')
fig.show()
```



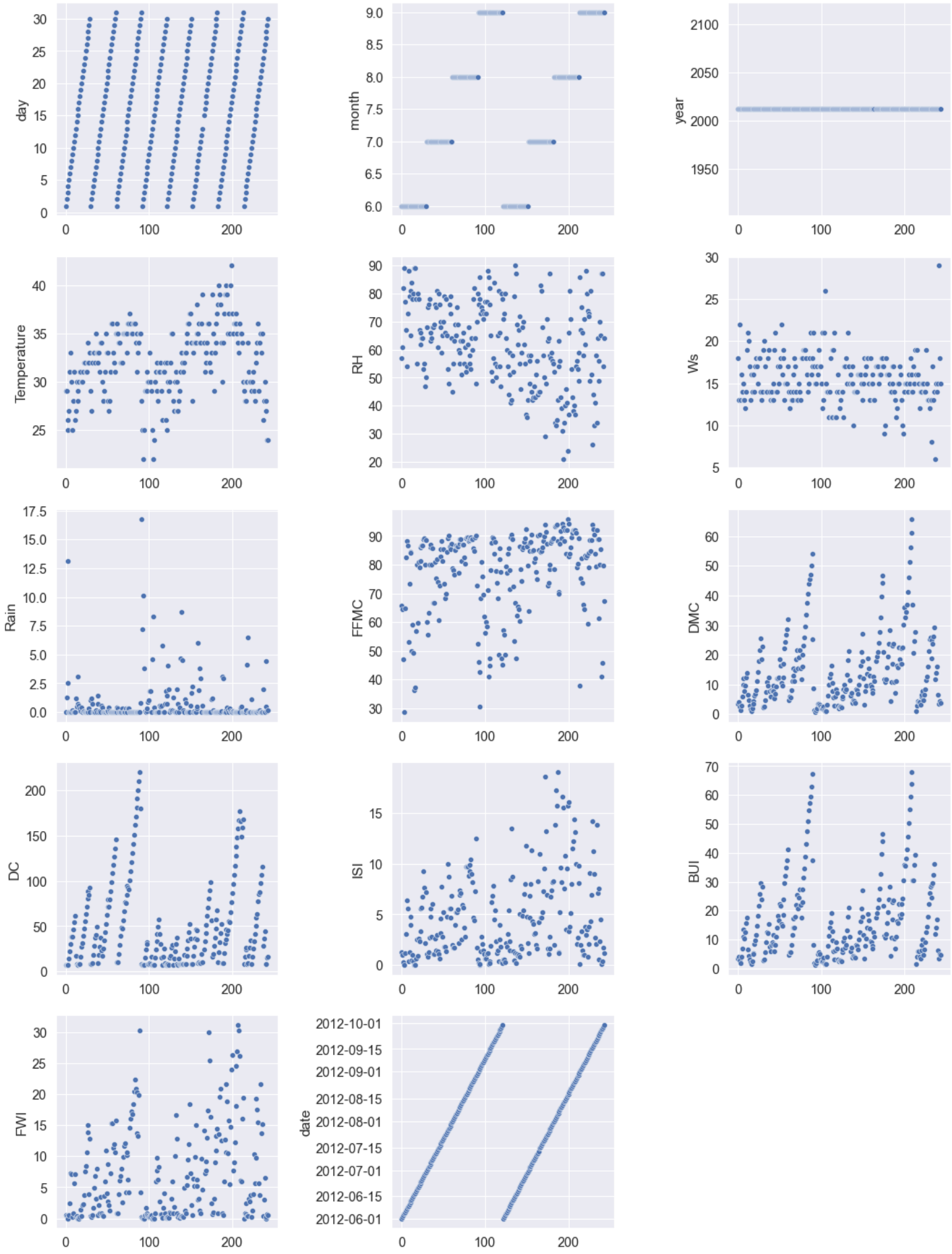
In [35]:
```
fig = px.scatter(df, x='Ws', y="Rain" ,color='Classes')
fig.show()
```





In [36]:

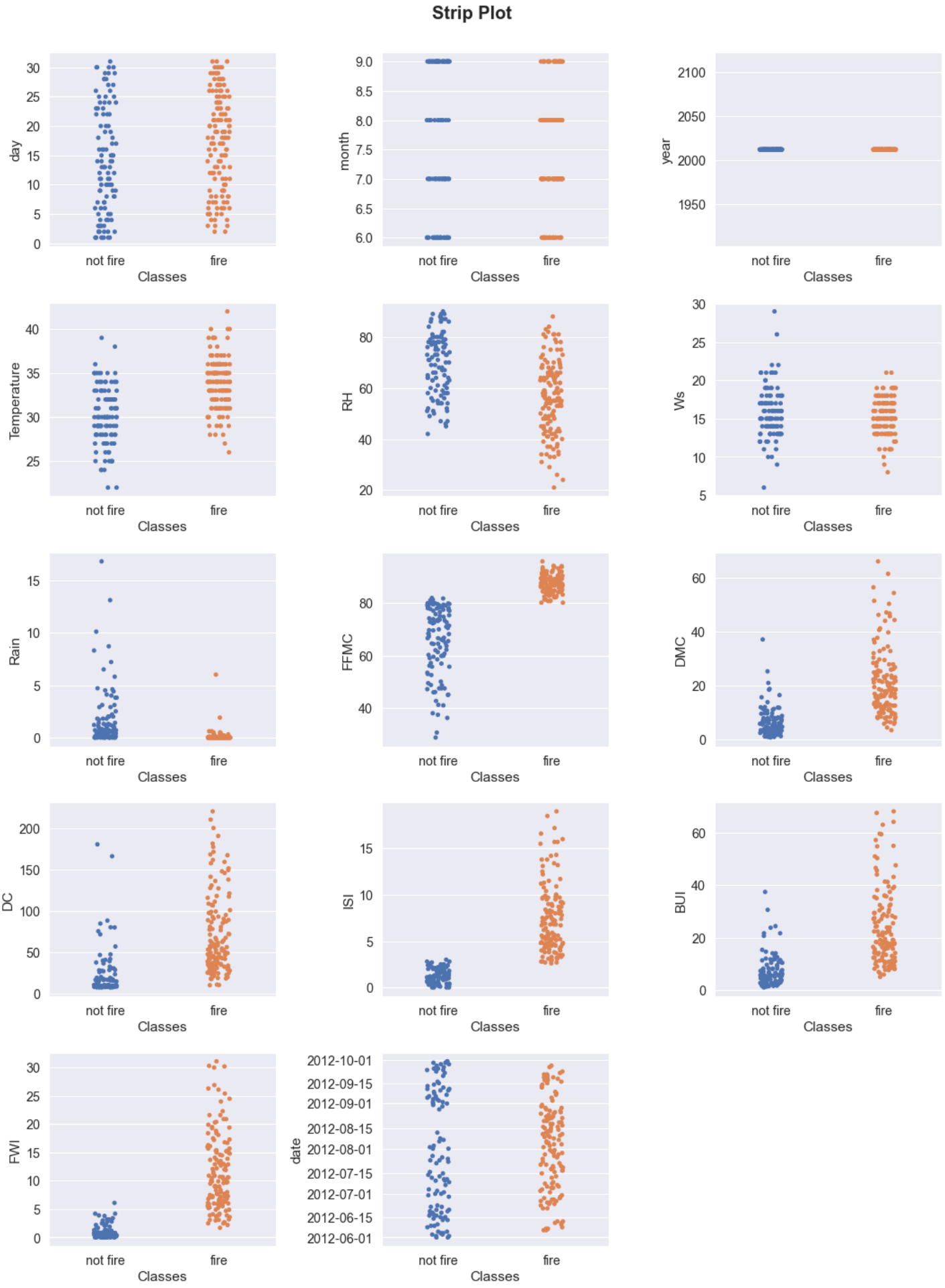
```
# scatter plot to see the trends in each numerical column

plt.figure(figsize=(15, 20))
plt.suptitle('scatter plot with each numerical feature to explore feature', fontsize=20, f

for i in range(0, len(numeric_features)):
    plt.subplot(5, 3, i+1)
    sns.scatterplot(y=numeric_features[i], x=df.index, data=df)
    plt.tight_layout()
```



In [37]:

```
# strip plot to see the relationship between numerical features and target
```

```
plt.figure(figsize=(15, 20))
plt.suptitle('Strip Plot', fontsize=20, fontweight='bold', alpha=1, y=1)

for i in range(0, len(numeric_features)):
    plt.subplot(5, 3, i+1)
    sns.stripplot(y=numeric_features[i], x='Classes', data=df)
    plt.tight_layout()
```



Observation:

- Temperature is higher in July and August month. This increases chances of forest fire in these months.

- Rainfall is higher in September month. From the chart above it is clear that temperature is relatively lower in this month. This decreases chances of forest fire in september month.
- Temperature greater than 25°C and Fine Fuel Moisture Code (FFMC) rating above 80 increases risk of forest fire.
- Wind speed between 10km/hr to 20km/hr and Fire Weather Index (FWI) index above 5 increases risk of forest fire.
- Fine Fuel Moisture Code (FFMC) rating greater than 80 and Initial Spread Index (ISI) index above 3 increases risk of forest fire.
- Buildup Index (BUI) is greater in August month which will increase risk of forest fire.

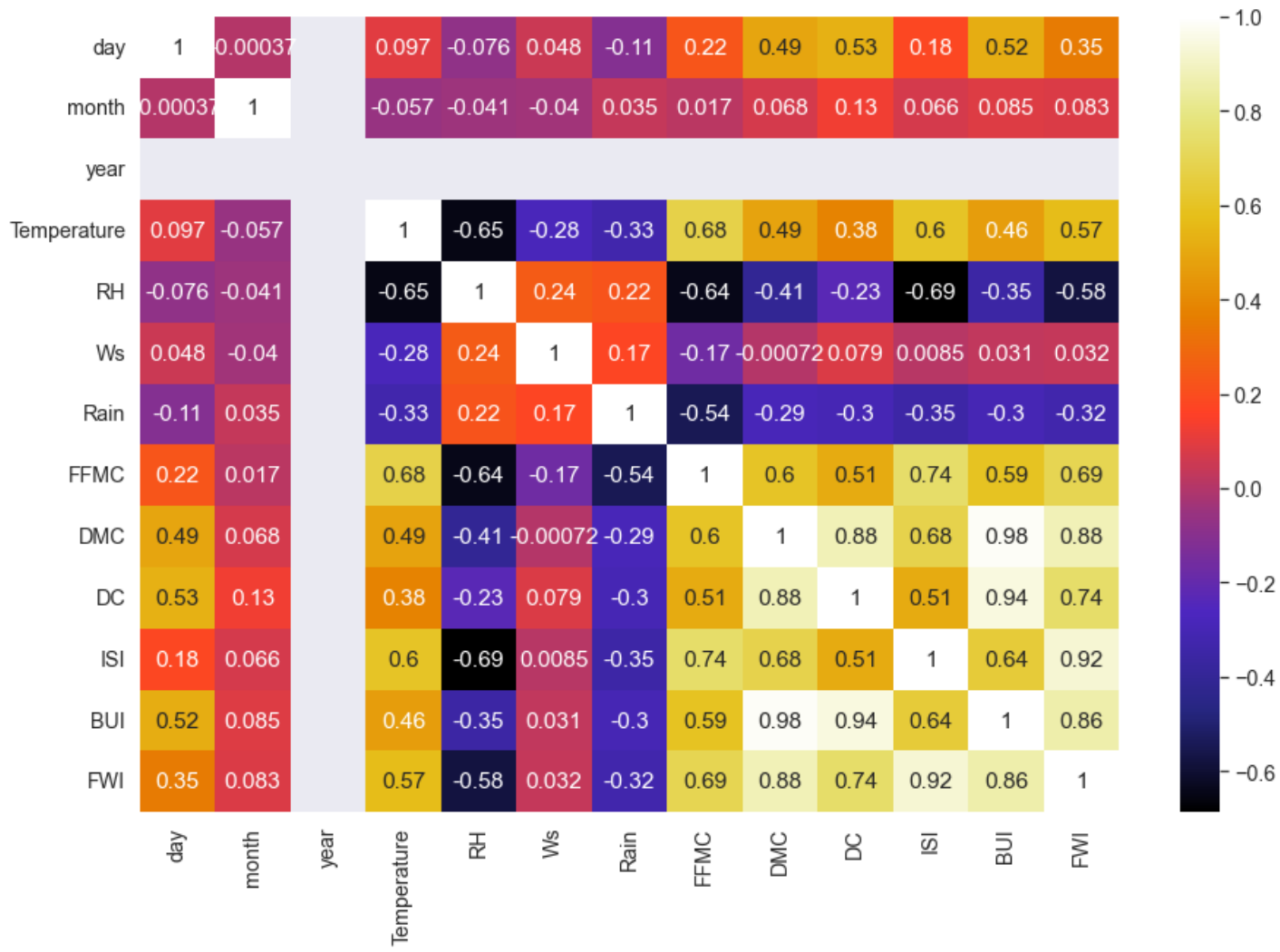
Multicolleniarity in numerical features

In [38]:
```
df.corr()
```

Out[38]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	D
day	1.000000	-0.000369	NaN	0.097227	-0.076034	0.047812	-0.112523	0.224956	0.491514	0.52795
month	-0.000369	1.000000	NaN	-0.056781	-0.041252	-0.039880	0.034822	0.017030	0.067943	0.12651
year	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
Temperature	0.097227	-0.056781	NaN	1.000000	-0.651400	-0.284510	-0.326492	0.676568	0.485687	0.37628
RH	-0.076034	-0.041252	NaN	-0.651400	1.000000	0.244048	0.222356	-0.644873	-0.408519	-0.22694
Ws	0.047812	-0.039880	NaN	-0.284510	0.244048	1.000000	0.171506	-0.166548	-0.000721	0.07913
Rain	-0.112523	0.034822	NaN	-0.326492	0.222356	0.171506	1.000000	-0.543906	-0.288773	-0.29802
FFMC	0.224956	0.017030	NaN	0.676568	-0.644873	-0.166548	-0.543906	1.000000	0.603608	0.50739
DMC	0.491514	0.067943	NaN	0.485687	-0.408519	-0.000721	-0.288773	0.603608	1.000000	0.87592
DC	0.527952	0.126511	NaN	0.376284	-0.226941	0.079135	-0.298023	0.507397	0.875925	1.00000
ISI	0.180543	0.065608	NaN	0.603871	-0.686667	0.008532	-0.347484	0.740007	0.680454	0.50864
BUI	0.517117	0.085073	NaN	0.459789	-0.353841	0.031438	-0.299852	0.592011	0.982248	0.94198
FWI	0.350781	0.082639	NaN	0.566670	-0.580957	0.032368	-0.324422	0.691132	0.875864	0.73952

In [39]:
```
plt.figure(figsize = (15,10))
sns.heatmap(df.corr(), cmap="CMRmap", annot=True)
plt.show()
```



observation -

- Highly positive correlated features are DMC and BUI, DC and BUI, ISI and PWI
- Highly negative correlated features are RH and Temp, RH and FFMC, RH and ICI

Final Report

There are three components needed for ignition and combustion to occur. A fire requires fuel to burn, air to supply oxygen, and a heat source to bring the fuel up to ignition temperature.

- Months like July and August with higher temperature has fire.
- Months like June and September with higher Rainfall helps lowering the temperature and provide more humidity in air thus decreasing risk of fire.
- High temperature along with wind speed provides more oxygen to the fire and may increase its intensity and spread.
- Factors such as temperature greater than 25°C, Fine Fuel Moisture Code (FFMC) rating above 80, Wind speed between 10km/hr to 20km/hr and Fire Weather Index (FWI) index above 5 increases risk of forest fire.