Temperature Prediction for Algerian Forest Fires Dataset Data Set

Life cycle of Machine learning Project

- Understanding the Problem Statement
- Data Collection
- Exploratory data analysis
- Data Cleaning
- Data Pre-Processing
- Model Training

1) Problem statement.

- The dataset includes 244 instances that regroup a data of two regions of Algeria
- We have to predict temperature based on features

2) Data Collection.

- The Dataset is collected from uci machine learning repository ([https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++ (https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++)](https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++))
- 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.
- 122 instances for each region.
- The dataset includes 11 attribues and 1 output attribue (class)

2.1 Import Data and Required Packages

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
df = pd.read_csv("Algerian_forest_fires_dataset_UPDATE.csv", skiprows=[0,124,125,126])
```

Attribute Information:

1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations
2. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
3. RH : Relative Humidity in %: 21 to 90
4. Ws :Wind speed in km/h: 6 to 29
5. Rain: total day in mm: 0 to 16.8 FWI Components
6. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
7. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
8. Drought Code (DC) index from the FWI system: 7 to 220.4
9. 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

Top 5 records in dataset

In [3]:
```
df.head()
```

Out[3]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0	not fire
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire

Last 5 records in dataset

In [4]:
```
df.tail()
```

Out[4]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
239	26	9	2012	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	fire
240	27	9	2012	28	87	15	4.4	41.1	6.5	8	0.1	6.2	0	not fire
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not fire
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not fire
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not fire

Sample 5 records in dataset

In [5]:
```
df.sample(5)
```

Out[5]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
118	27	9	2012	31	66	11	0.0	85.7	8.3	24.9	4.0	9.0	4.1	fire
14	15	6	2012	28	80	17	3.1	49.4	3.0	7.4	0.4	3.0	0.1	not fire
211	29	8	2012	35	53	17	0.5	80.2	20.7	149.2	2.7	30.6	5.9	fire
97	6	9	2012	29	74	19	0.1	75.8	3.6	32.2	2.1	5.6	0.9	not fire
21	22	6	2012	31	67	17	0.1	79.1	7.0	39.5	2.4	9.7	2.3	not fire

Dataype in dataset

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 14 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 
dtypes: float64(5), int64(6), object(3)
memory usage: 26.8+ KB
```

Observations

1. there are missing values in Classes column
2. FWI column has data type as object
3. DC column has data type as object

3. EDA

In [7]:
```python
df['FWI'].unique()
```

Out[7]:
```
array(['0.5', '0.4', '0.1', '0', '2.5', '7.2', '7.1', '0.3', '0.9', '5.6',
       '7.1 ', '0.2', '1.4', '2.2', '2.3', '3.8', '7.5', '8.4', '10.6',
       '15', '13.9', '3.9', '12.9', '1.7', '4.9', '6.8', '3.2', '8',
       '0.6', '3.4', '0.8', '3.6', '6', '10.9', '4', '8.8', '2.8', '2.1',
       '1.3', '7.3', '15.3', '11.3', '11.9', '10.7', '15.7', '6.1', '2.6',
       '9.9', '11.6', '12.1', '4.2', '10.2', '6.3', '14.6', '16.1',
       '17.2', '16.8', '18.4', '20.4', '22.3', '20.9', '20.3', '13.7',
       '13.2', '19.9', '30.2', '5.9', '7.7', '9.7', '8.3', '0.7', '4.1',
       '1', '3.1', '1.9', '10', '16.7', '1.2', '5.3', '6.7', '9.5', '12',
       '6.4', '5.2', '3', '9.6', '4.7', 'fire   ', '14.1', '9.1', '13',
       '17.3', '30', '25.4', '16.3', '9', '14.5', '13.5', '19.5', '12.6',
       '12.7', '21.6', '18.8', '10.5', '5.5', '14.8', '24', '26.3',
       '12.2', '18.1', '24.5', '26.9', '31.1', '30.3', '26.1', '16',
       '19.4', '2.7', '3.7', '10.3', '5.7', '9.8', '19.3', '17.5', '15.4',
       '15.2', '6.5'], dtype=object)
```

In [8]:
```python
# handling FWI row having alphabetical values
```

In [9]:
```python
df[df['FWI'] == 'fire   ']
```

Out[9]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
165	14	7	2012	37	37	18	0.2	88.9	12.9	14.6 9	12.5	10.4	fire	NaN

In [10]:
```python
df.iloc[165]
```

Out[10]:
```
day                14
month               7
year             2012
Temperature        37
 RH                37
 Ws                18
Rain              0.2
FFMC             88.9
DMC              12.9
DC             14.6 9
ISI              12.5
BUI              10.4
FWI           fire   
Classes           NaN
Name: 165, dtype: object
```

In [11]:
```
# dropping row having alphabetical values
df = df.drop(df.index[165])
```

In [12]:
```
df
```

Out[12]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0	not fire
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
239	26	9	2012	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	fire
240	27	9	2012	28	87	15	4.4	41.1	6.5	8	0.1	6.2	0	not fire
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not fire
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not fire
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not fire

243 rows × 14 columns

In [13]:
```
df['FWI'].str.isnumeric().sum()
```

Out[13]: 28

In [14]:
```
# coverting datatype to float
df['FWI'] = df['FWI'].astype('float')
```

In [15]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 243 entries, 0 to 243
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   day          243 non-null    int64  
 1   month        243 non-null    int64  
 2   year         243 non-null    int64  
 3   Temperature  243 non-null    int64  
 4    RH          243 non-null    int64  
 5    Ws          243 non-null    int64  
 6   Rain         243 non-null    float64
 7   FFMC         243 non-null    float64
 8   DMC          243 non-null    float64
 9   DC           243 non-null    object 
 10  ISI          243 non-null    float64
 11  BUI          243 non-null    float64
 12  FWI          243 non-null    float64
 13  Classes      243 non-null    object 
dtypes: float64(6), int64(6), object(2)
memory usage: 28.5+ KB
```

In [16]:

```
1 df['DC'].unique()
```

Out[16]:

```
array(['7.6', '7.1', '6.9', '14.2', '22.2', '30.5', '38.3', '38.8',
       '46.3', '54.3', '61.4', '17', '7.8', '7.4', '8', '16', '27.1',
       '31.6', '39.5', '47.7', '55.8', '63.8', '71.8', '80.3', '88.5',
       '84.4', '92.8', '8.6', '8.3', '9.2', '18.5', '27.9', '37', '40.4',
       '49.8', '9.3', '18.7', '27.7', '37.2', '22.9', '25.5', '34.1',
       '43.1', '52.8', '62.1', '71.5', '79.9', '71.3', '79.7', '88.7',
       '98.6', '108.5', '117.8', '127', '136', '145.7', '10.2', '10',
       '19.8', '29.7', '39.1', '48.6', '47', '57', '67', '77', '75.1',
       '85.1', '94.7', '92.5', '90.4', '100.7', '110.9', '120.9', '130.6',
       '141.1', '151.3', '161.5', '171.3', '181.3', '190.6', '200.2',
       '210.4', '220.4', '180.4', '8.7', '7.5', '7', '15.7', '24', '32.2',
       '30.1', '8.4', '8.9', '16.6', '7.3', '24.3', '33.1', '41.3',
       '49.3', '57.9', '41.4', '30.4', '15.2', '7.7', '16.3', '24.9',
       '8.8', '8.2', '15.4', '17.6', '26.3', '28.9', '14.7', '22.5',
       '37.8', '18.4', '25.6', '34.5', '43.3', '52.4', '36.7', '8.5',
       '17.8', '27.3', '36.8', '46.4', '45.1', '35.4', '9.7', '9.9',
       '9.5', '19.4', '10.4', '24.1', '42.3', '51.6', '61.1', '71',
       '80.6', '90.1', '99', '56.6', '15.9', '19.7', '28.3', '37.6',
       '47.2', '57.1', '67.2', '10.5', '21.4', '32.1', '42.7', '52.5',
       '9.1', '9.8', '20.2', '30.9', '41.5', '55.5', '54.2', '65.1',
       '76.4', '86.8', '96.8', '107', '117.1', '127.5', '137.7', '147.7',
       '157.5', '167.2', '177.3', '166', '149.2', '159.1', '168.2',
       '26.6', '17.7', '26.1', '25.2', '33.4', '50.2', '59.2', '63.3',
       '77.8', '86', '88', '97.3', '106.3', '115.6', '28.1', '36.1',
       '44.5', '7.9', '16.5'], dtype=object)
```

In [17]:

```
1 df['DC'].str.isnumeric().sum()
```

Out[17]:

```
27
```

In [18]:
```
df['DC'].value_counts()
```

Out[18]:
```
8        5
7.6      4
7.8      4
8.4      4
7.5      4
        ..
92.5     1
90.4     1
100.7    1
110.9    1
16.5     1
Name: DC, Length: 197, dtype: int64
```

In [19]:
```
df['DC'].str.isalpha().sum()
```

Out[19]:
```
0
```

In [20]:
```
# coverting datatype to float
df['DC'] = df['DC'].astype('float')
```

In [21]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 243 entries, 0 to 243
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   day          243 non-null    int64  
 1   month        243 non-null    int64  
 2   year         243 non-null    int64  
 3   Temperature  243 non-null    int64  
 4    RH          243 non-null    int64  
 5    Ws          243 non-null    int64  
 6   Rain         243 non-null    float64
 7   FFMC         243 non-null    float64
 8   DMC          243 non-null    float64
 9   DC           243 non-null    float64
 10  ISI          243 non-null    float64
 11  BUI          243 non-null    float64
 12  FWI          243 non-null    float64
 13  Classes      243 non-null    object 
dtypes: float64(7), int64(6), object(1)
memory usage: 28.5+ KB
```

In [22]:
```
# handling missing values
df.isnull().sum()
```

Out[22]:
```
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
dtype: int64
```

In [23]:

```
df.describe()
```

Out[23]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI
count	243.000000	243.000000	243.0	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000
mean	15.761317	7.502058	2012.0	32.152263	62.041152	15.493827	0.762963	77.842387	14.680658	49.430864	4.742387	16.690535
std	8.842552	1.114793	0.0	3.628039	14.828160	2.811385	2.003207	14.349641	12.393040	47.665606	4.154234	14.228421
min	1.000000	6.000000	2012.0	22.000000	21.000000	6.000000	0.000000	28.600000	0.700000	6.900000	0.000000	1.100000
25%	8.000000	7.000000	2012.0	30.000000	52.500000	14.000000	0.000000	71.850000	5.800000	12.350000	1.400000	6.000000
50%	16.000000	8.000000	2012.0	32.000000	63.000000	15.000000	0.000000	83.300000	11.300000	33.100000	3.500000	12.400000
75%	23.000000	8.000000	2012.0	35.000000	73.500000	17.000000	0.500000	88.300000	20.800000	69.100000	7.250000	22.650000
max	31.000000	9.000000	2012.0	42.000000	90.000000	29.000000	16.800000	96.000000	65.900000	220.400000	19.000000	68.000000

Observations

1. year column has 0 standard deviation
2. Rain, DC column has very high max value, looks like presence of outliers

Check for duplicates

In [24]:

```
df[df.duplicated()]
```

Out[24]:

day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes

In [25]:

```
df.corr()
```

Out[25]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI
day	1.000000	-0.000369	NaN	0.097227	-0.076034	0.047812	-0.112523	0.224956	0.491514	0.527952	0.180543	0.517117	0.350781
month	-0.000369	1.000000	NaN	-0.056781	-0.041252	-0.039880	0.034822	0.017030	0.067943	0.126511	0.065608	0.085073	0.082639
year	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Temperature	0.097227	-0.056781	NaN	1.000000	-0.651400	-0.284510	-0.326492	0.676568	0.485687	0.376284	0.603871	0.459789	0.566670
RH	-0.076034	-0.041252	NaN	-0.651400	1.000000	0.244048	0.222356	-0.644873	-0.408519	-0.226941	-0.686667	-0.353841	-0.580957
Ws	0.047812	-0.039880	NaN	-0.284510	0.244048	1.000000	0.171506	-0.166548	-0.000721	0.079135	0.008532	0.031438	0.032368
Rain	-0.112523	0.034822	NaN	-0.326492	0.222356	0.171506	1.000000	-0.543906	-0.288773	-0.298023	-0.347484	-0.299852	-0.324422
FFMC	0.224956	0.017030	NaN	0.676568	-0.644873	-0.166548	-0.543906	1.000000	0.603608	0.507397	0.740007	0.592011	0.691132
DMC	0.491514	0.067943	NaN	0.485687	-0.408519	-0.000721	-0.288773	0.603608	1.000000	0.875925	0.680454	0.982248	0.875864
DC	0.527952	0.126511	NaN	0.376284	-0.226941	0.079135	-0.298023	0.507397	0.875925	1.000000	0.508643	0.941988	0.739521
ISI	0.180543	0.065608	NaN	0.603871	-0.686667	0.008532	-0.347484	0.740007	0.680454	0.508643	1.000000	0.644093	0.922895
BUI	0.517117	0.085073	NaN	0.459789	-0.353841	0.031438	-0.299852	0.592011	0.982248	0.941988	0.644093	1.000000	0.857973
FWI	0.350781	0.082639	NaN	0.566670	-0.580957	0.032368	-0.324422	0.691132	0.875864	0.739521	0.922895	0.857973	1.000000

In [26]:

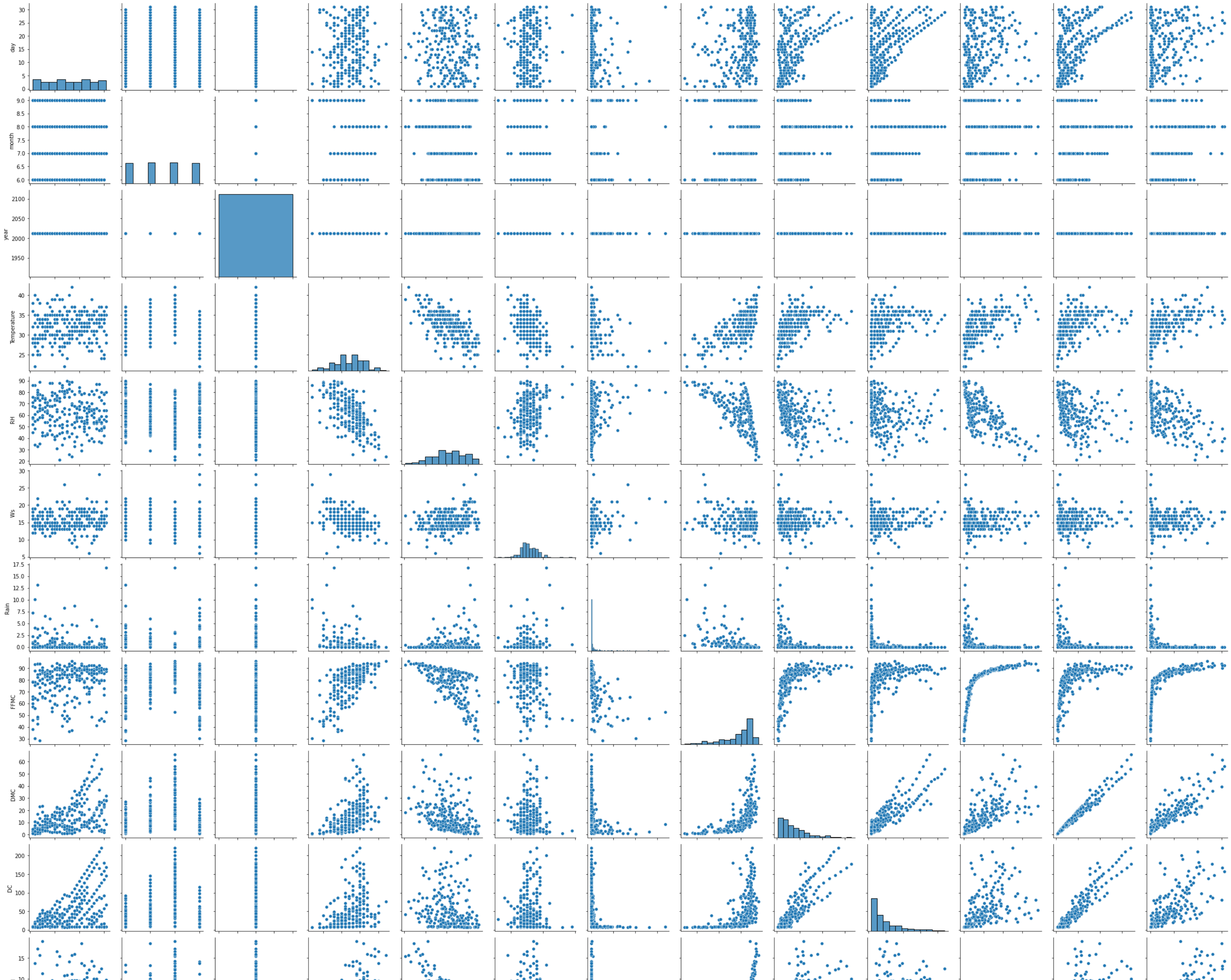
```
df['year'].unique()
```

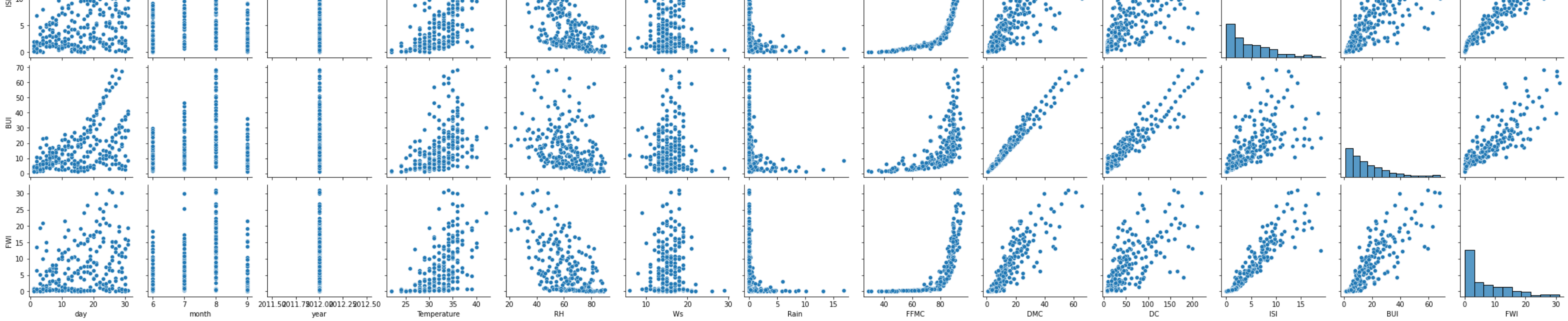
Out[26]:

```
array([2012], dtype=int64)
```

In [27]:
```
sns.pairplot(df)
```

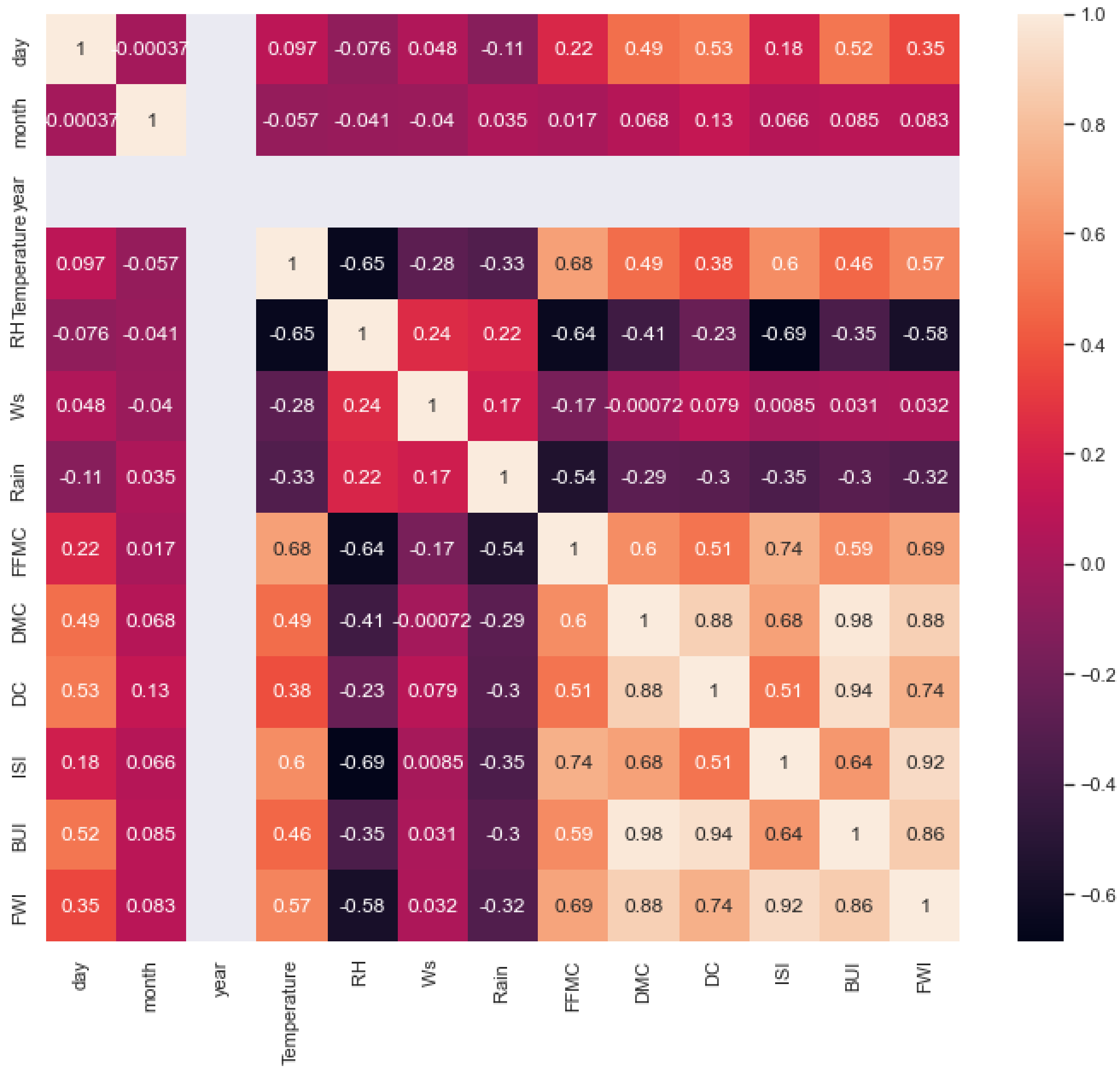
Out[27]: <seaborn.axisgrid.PairGrid at 0x17b2055cd60>




ISI
BUI
FWI
day
month
year
Temperature
RH
Ws
Rain
FFMC
DMC
DC
ISI
BUI
FWI

In [28]:
```
sns.set(rc={'figure.figsize':(12,10)})
sns.heatmap(df.corr(), annot=True)
```

Out[28]: <AxesSubplot:>



Observations:

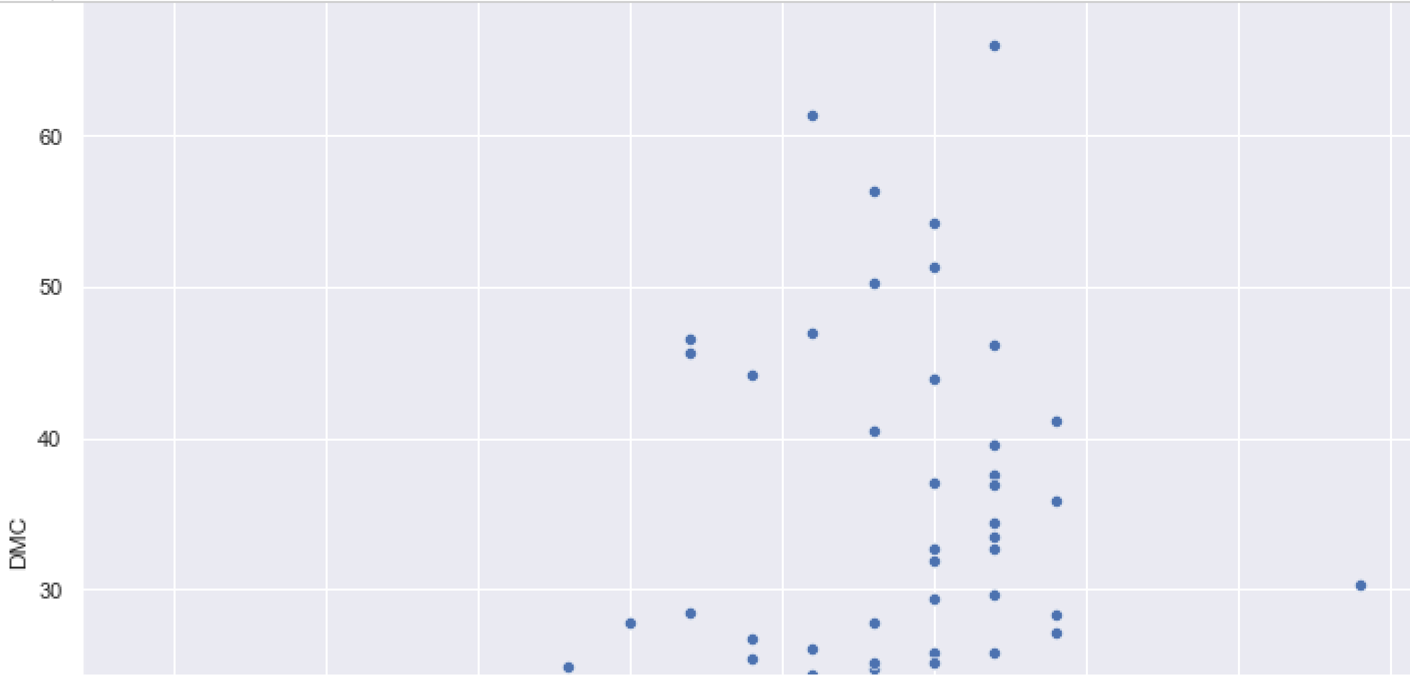
1. DMC, BUI highly correlated
2. ISI, FWI highly correlated

Checking correlation with Temperature and above columns

In [29]:
```
df.columns
```

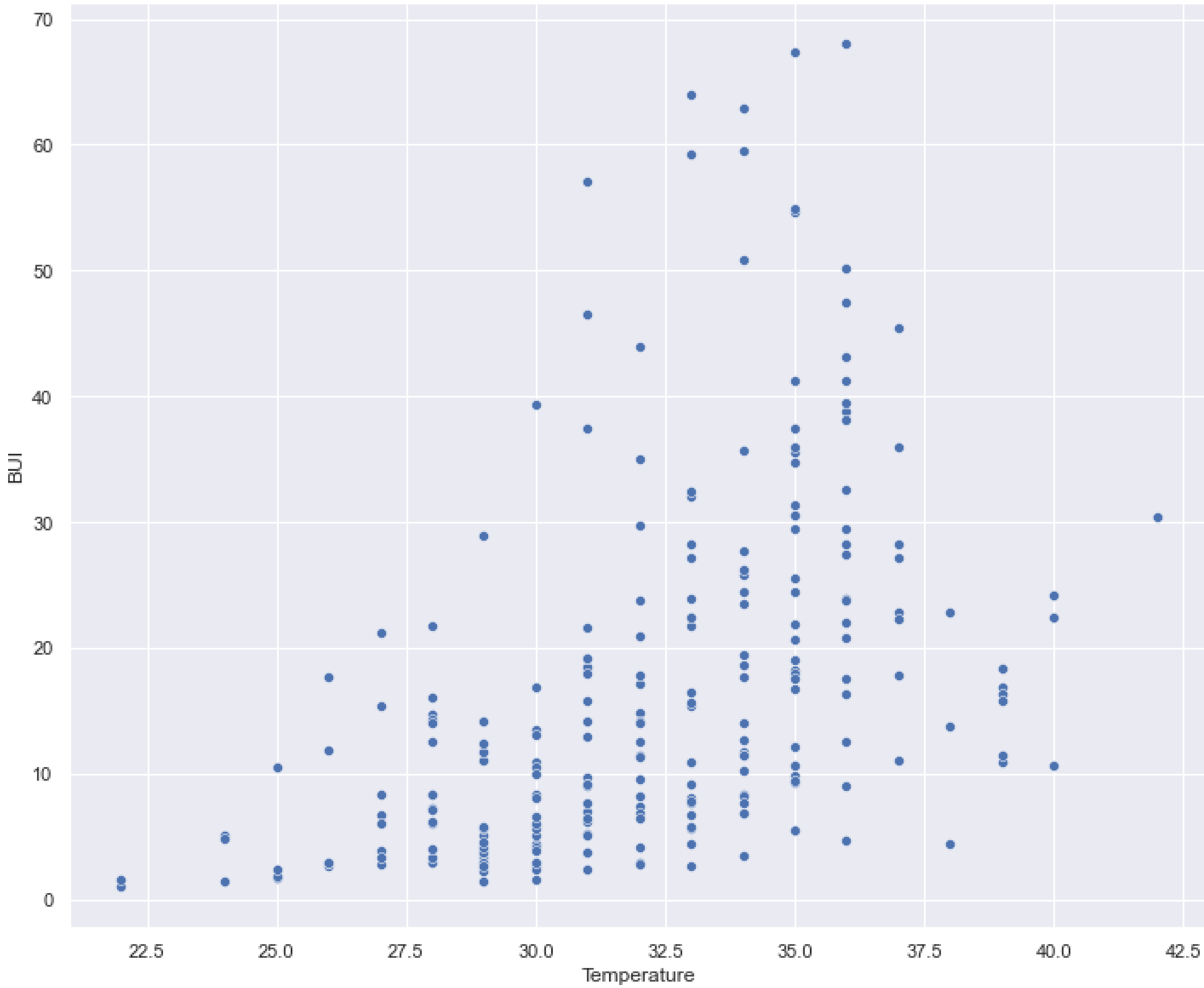
Out[29]:
```
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes  '],
      dtype='object')
```

In [30]:
```
sns.scatterplot(x='Temperature', y='DMC', data=df)
```



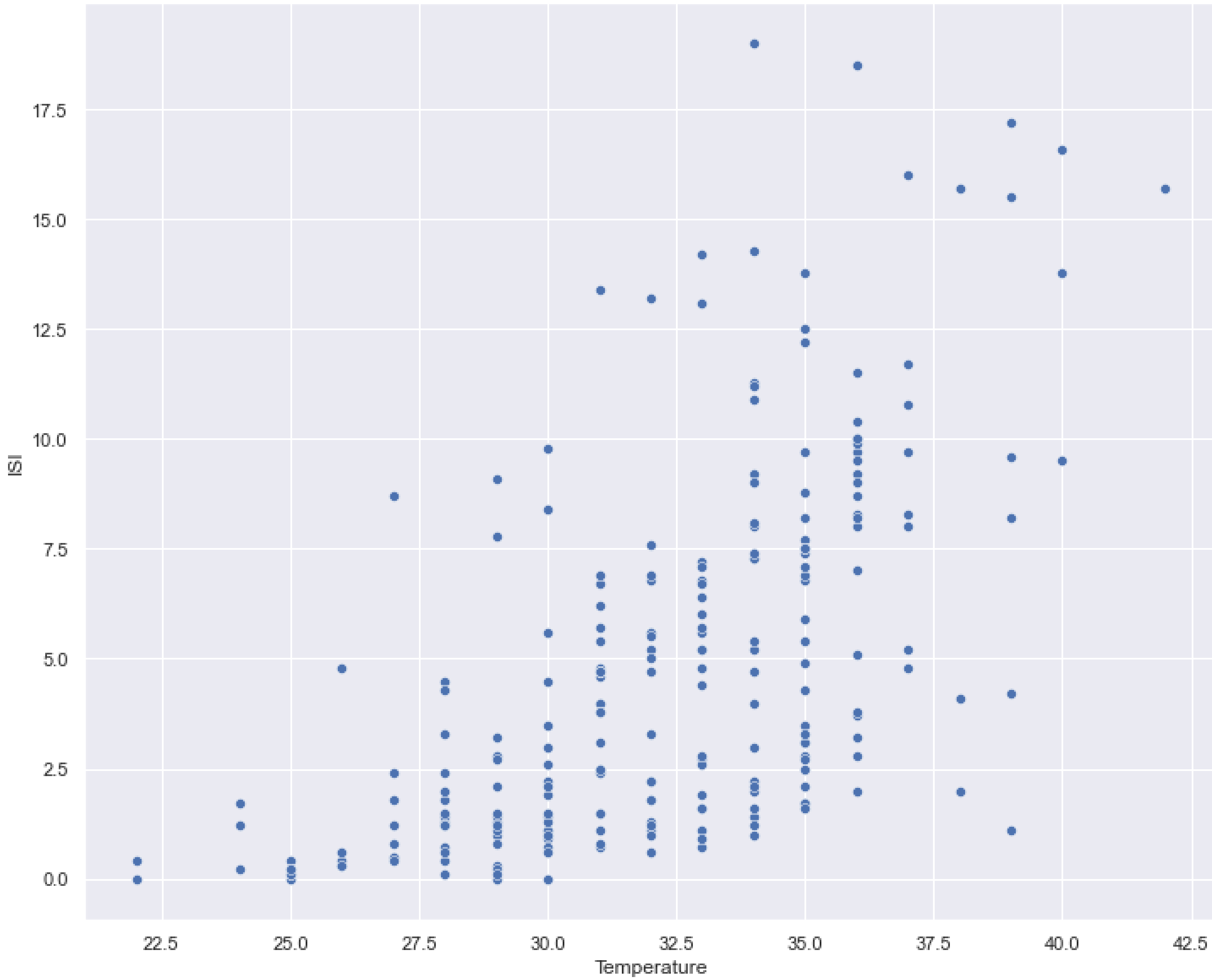
In [31]:
```
sns.scatterplot(x='Temperature', y='BUI', data=df)
```

Out[31]: <AxesSubplot:xlabel='Temperature', ylabel='BUI'>



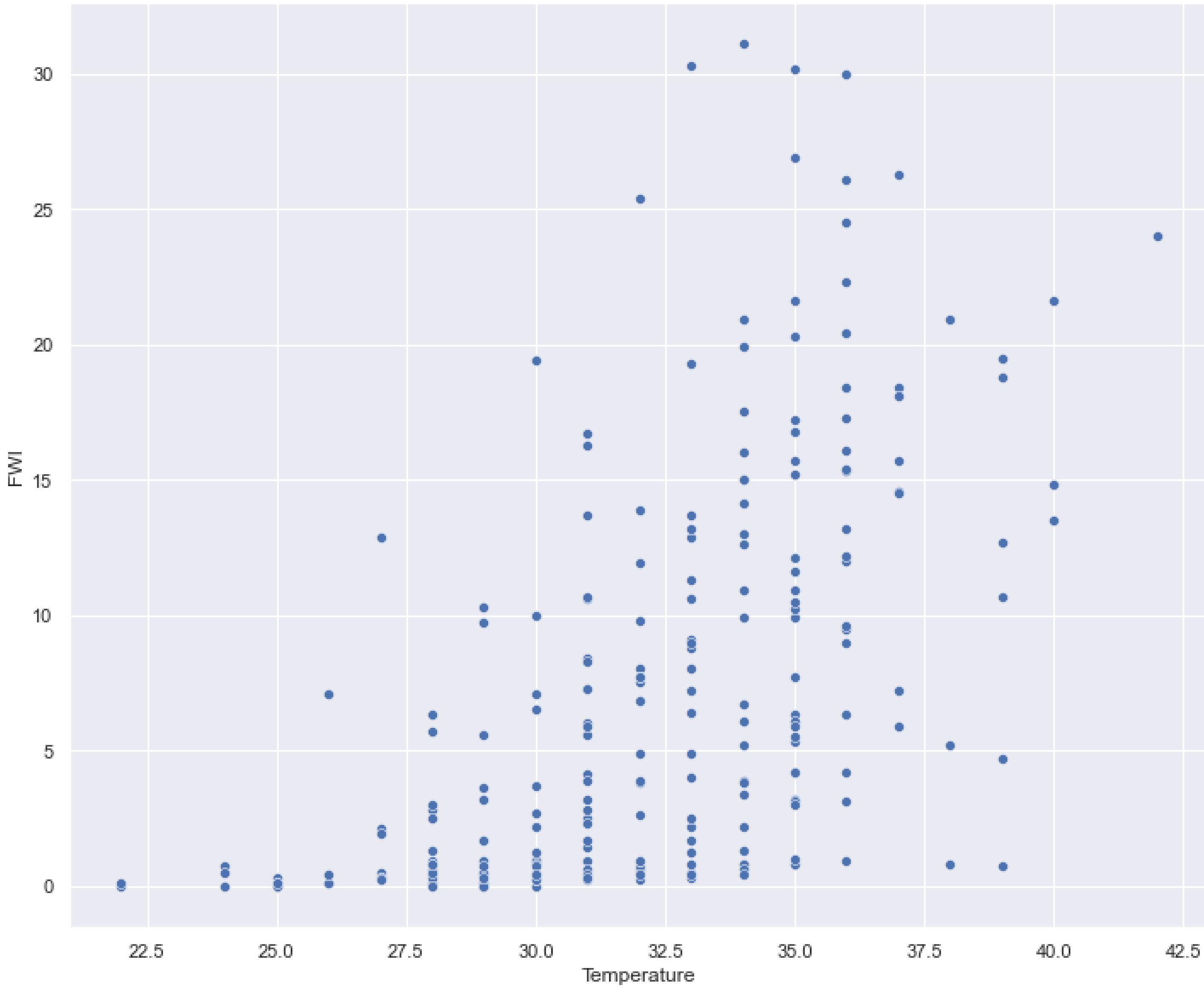
In [37]:
```
sns.scatterplot(x='Temperature', y='ISI', data=df)
```

Out[37]: <AxesSubplot:xlabel='Temperature', ylabel='ISI'>



In [35]:
```
sns.scatterplot(x='Temperature', y='FWI', data=df)
```

Out[35]: <AxesSubplot:xlabel='Temperature', ylabel='FWI'>

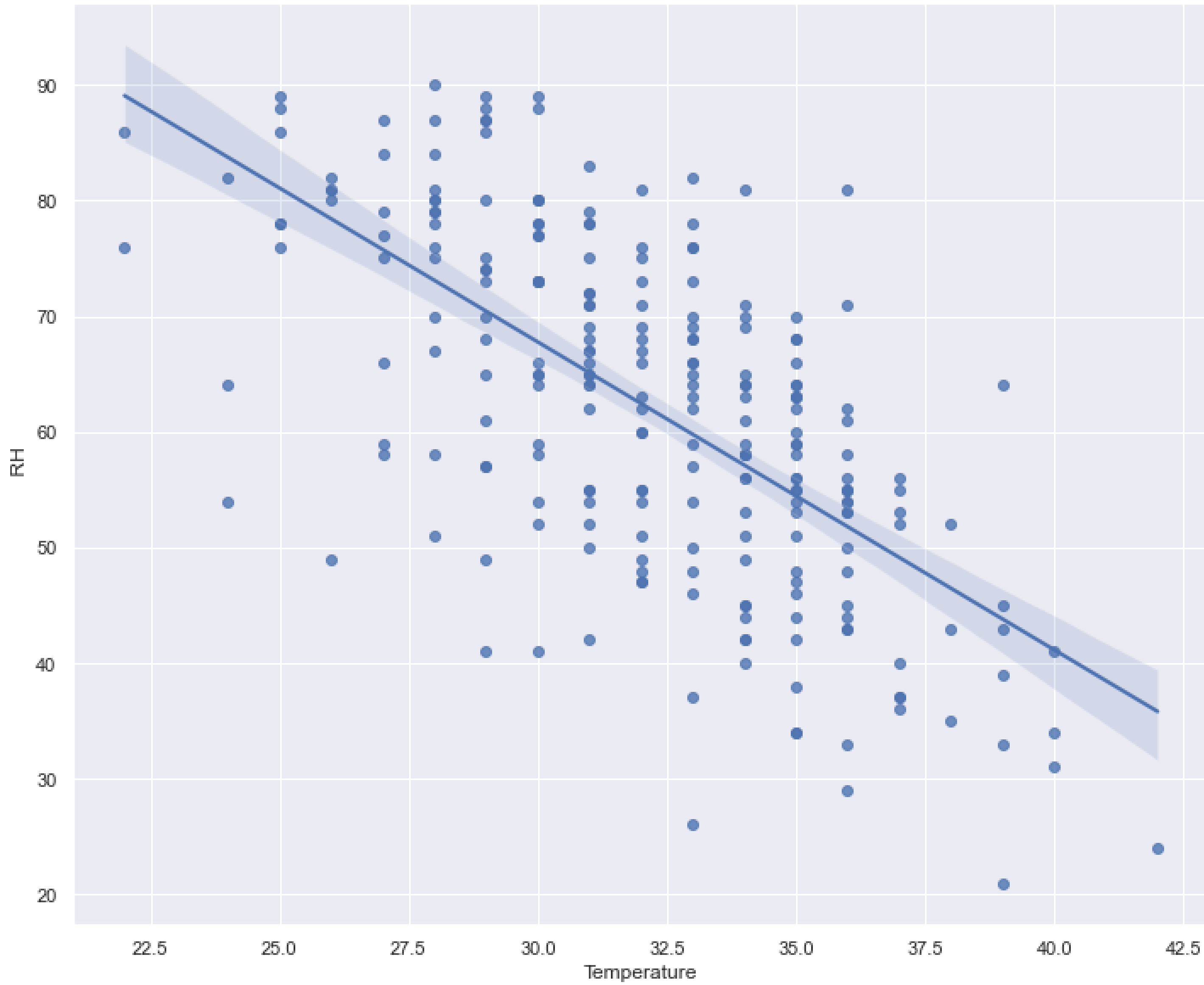


Observations:

1. ISI and FWI have almost similar correlation with Temperature column
2. BUI and DMC have almost similar correlation with Temperature column

In [36]:
```
sns.regplot(x='Temperature', y=' RH', data=df)
```

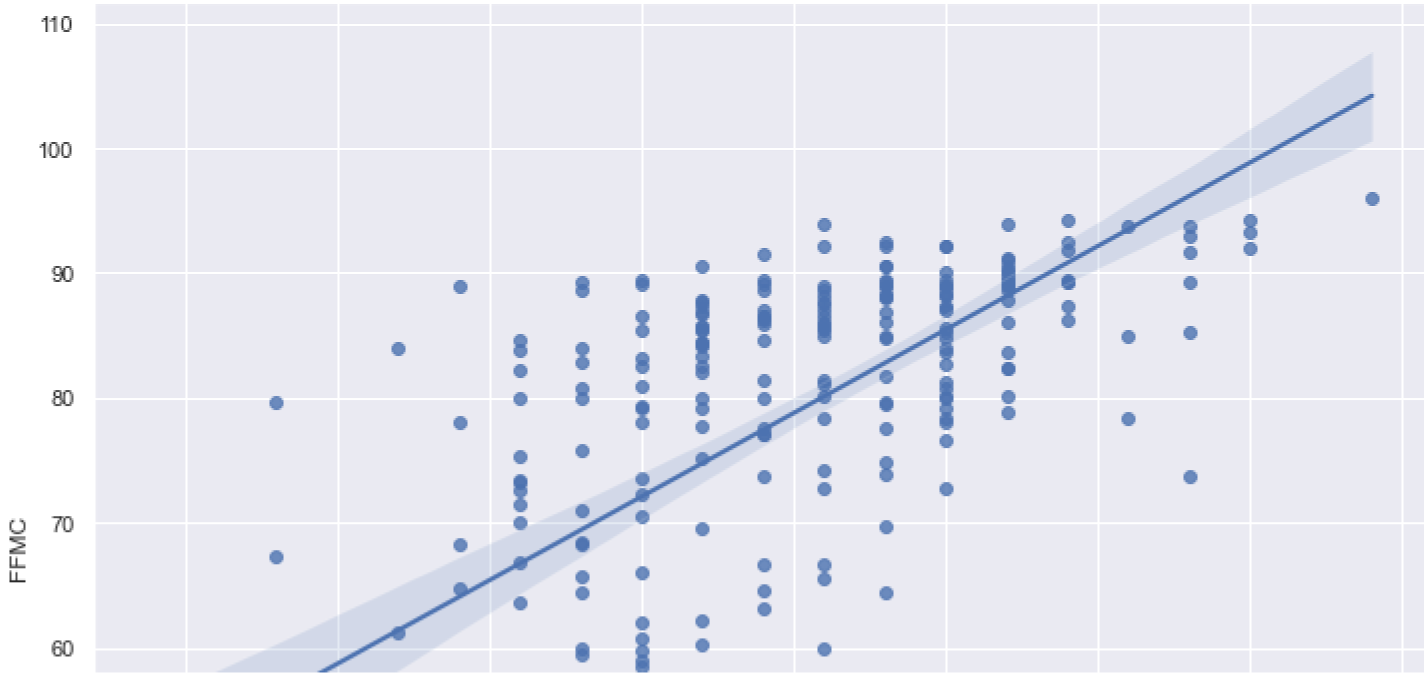
Out[36]: <AxesSubplot:xlabel='Temperature', ylabel=' RH'>



Observation:

Temperature is inversely proportional to Relative Humidity

In [40]:
```
sns.regplot(x='Temperature', y='FFMC', data=df)
```



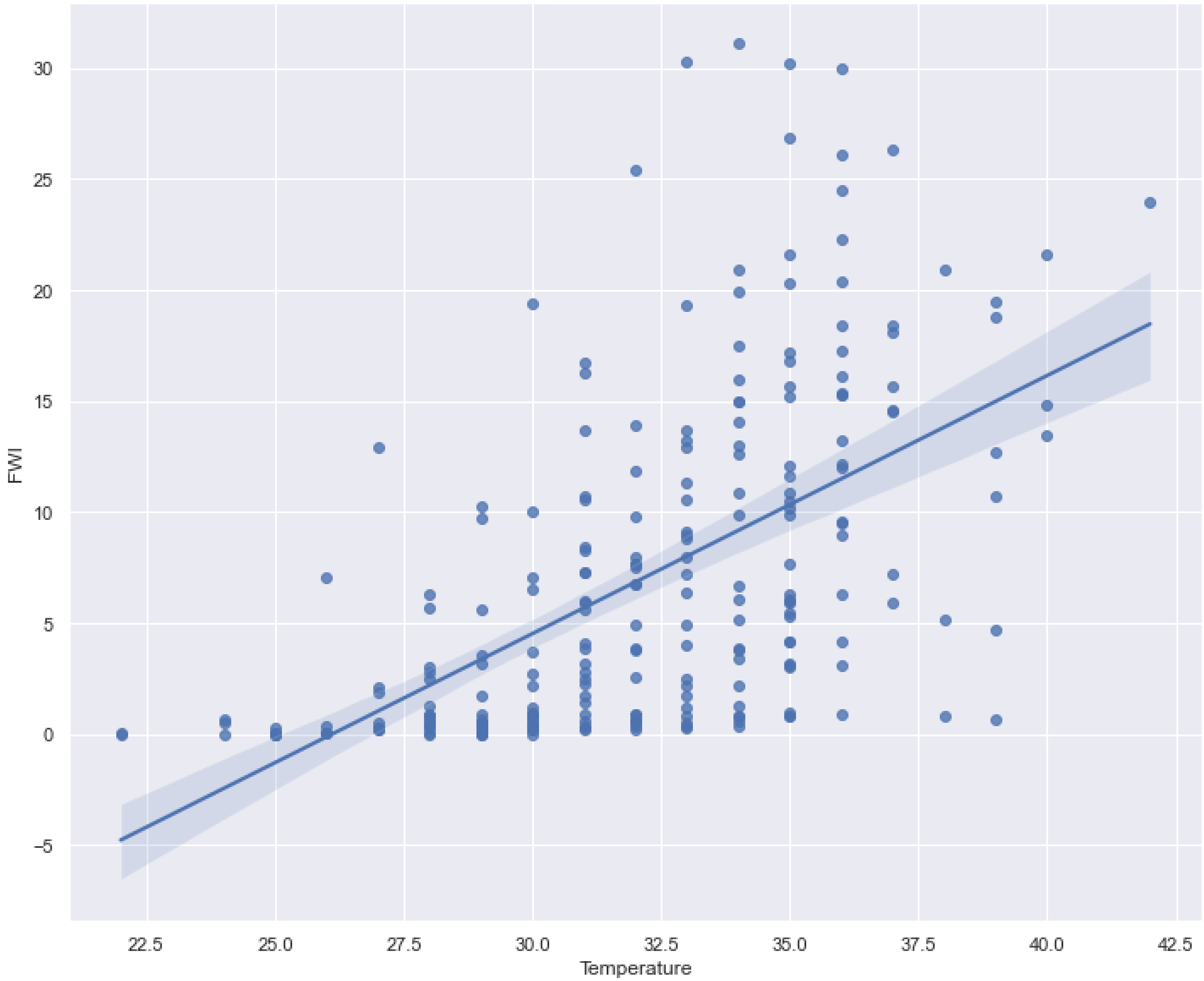
Observation:

Temperature is directly proportional to Fine Fuel Moisture Code (FFMC) index

In [41]:

```
sns.regplot(x='Temperature', y='FWI', data=df)
```

Out[41]: <AxesSubplot:xlabel='Temperature', ylabel='FWI'>



Observation:

Temperature is directly proportional to Fire Weather Index (FWI)

Checking Outliers

In [45]:

```
sns.boxplot(df['DC'])
```

```
C:\Users\pc\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a key
word arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without
an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[45]:

```
<AxesSubplot:xlabel='DC'>
```

Handling Categorical Variables

In [71]:

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

In [72]:
```
df['Classes  '].unique()
```
Out[72]:
```
array(['not fire', 'fire'], dtype=object)
```

In [ ]:
```
replace = []
```

In [75]:
```
df['Classes  '] = df['Classes  '].replace(['not fire', 'fire'], [0,1])
```

In [77]:
```
df.sample(5)
```
Out[77]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
83	23	8	2012	36	53	16	0.0	89.5	37.6	161.5	10.4	47.5	22.3	1
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0
226	13	9	2012	29	49	19	0.0	88.6	11.5	33.4	9.1	12.4	10.3	1
194	12	8	2012	39	21	17	0.4	93.0	18.4	41.5	15.5	18.4	18.8	1
66	6	8	2012	32	75	14	0.0	86.4	13.0	39.1	5.2	14.2	6.8	1

Independent and Dependent Features

In [80]:
```
df.head()
```
Out[80]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0

In [81]:
```
X = df.drop(columns='Temperature')
```

In [82]:
```
X
```

Out[82]:

	day	month	year	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0
1	2	6	2012	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0
2	3	6	2012	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0
3	4	6	2012	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0
4	5	6	2012	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
239	26	9	2012	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1
240	27	9	2012	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	0
241	28	9	2012	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	0
242	29	9	2012	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0
243	30	9	2012	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	0

243 rows × 13 columns

In [83]:
```
y = df['Temperature']
```

In [84]:
```
y
```

Out[84]:
```
0      29
1      29
2      26
3      25
4      27
       ..
239    30
240    28
241    27
242    24
243    24
Name: Temperature, Length: 243, dtype: int64
```

split data into training and test set

In [85]:
```python
from sklearn.model_selection import train_test_split
```

In [86]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [87]:
```python
X_train
```

Out[87]:

	day	month	year	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
29	30	6	2012	50	14	0.0	88.7	22.9	92.8	7.2	28.3	12.9	1
120	29	9	2012	80	16	1.8	47.4	2.9	7.7	0.3	3.0	0.1	0
114	23	9	2012	54	11	0.5	73.7	7.9	30.4	1.2	9.6	0.7	0
242	29	9	2012	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0
5	6	6	2012	67	14	0.0	82.6	5.8	22.2	3.1	7.0	2.5	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
106	15	9	2012	82	15	0.4	44.9	0.9	7.3	0.2	1.4	0.0	0
14	15	6	2012	80	17	3.1	49.4	3.0	7.4	0.4	3.0	0.1	0
92	1	9	2012	76	17	7.2	46.0	1.3	7.5	0.2	1.8	0.1	0
180	29	7	2012	59	16	0.0	88.1	19.5	47.2	7.4	19.5	10.9	1
102	11	9	2012	77	21	1.8	58.5	1.9	8.4	1.1	2.4	0.3	0

170 rows × 13 columns

In [88]:
```python
X_train.shape
```

Out[88]: (170, 13)

In [89]:
```
X_test
```

Out[89]:

	day	month	year	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
24	25	6	2012	64	15	0.0	86.7	14.2	63.8	5.7	18.3	8.4	1
6	7	6	2012	54	13	0.0	88.2	9.9	30.5	6.4	10.9	7.2	1
152	1	7	2012	58	18	2.2	63.7	3.2	8.5	1.2	3.3	0.5	0
233	20	9	2012	58	13	0.2	79.5	18.7	88.0	2.1	24.4	3.8	0
239	26	9	2012	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
195	13	8	2012	34	16	0.2	88.3	16.9	45.1	7.5	17.5	10.5	1
104	13	9	2012	86	21	4.6	40.9	1.3	7.5	0.1	1.8	0.0	0
109	18	9	2012	49	11	0.0	89.4	9.8	33.1	6.8	11.3	7.7	1
191	9	8	2012	43	12	0.0	91.7	16.5	30.9	9.6	16.4	12.7	1
79	19	8	2012	62	19	0.0	89.4	23.2	120.9	9.7	31.3	17.2	1

73 rows × 13 columns

In [90]:
```
X_test.shape
```

Out[90]:
```
(73, 13)
```

In [91]:
```
y_train
```

Out[91]:
```
29     33
120    26
114    32
242    24
5      31
       ..
106    24
14     28
92     25
180    34
102    30
Name: Temperature, Length: 170, dtype: int64
```

In [92]:
```
y_train.shape
```
Out[92]:
```
(170,)
```

In [93]:
```
y_test
```
Out[93]:
```
24     31
6      33
152    28
233    34
239    30
       ..
195    35
104    25
109    32
191    39
79     35
Name: Temperature, Length: 73, dtype: int64
```

In [94]:
```
y_test.shape
```
Out[94]:
```
(73,)
```

Feature Scaling

In [95]:
```
from sklearn.preprocessing import StandardScaler
```

In [96]:
```
scaler = StandardScaler()
```

In [97]:
```
X_train = scaler.fit_transform(X_train)
```

In [98]:
```
X_test = scaler.transform(X_test)
```

In [99]:
```
X_train
```

Out[99]:
```
array([[ 1.56765151, -1.30687831,  0.        , ...,  0.75507842,
         0.74777936,  0.90992142],
       [ 1.45605153,  1.39153439,  0.        , ..., -0.94987343,
        -0.91039641, -1.098996  ],
       [ 0.78645164,  1.39153439,  0.        , ..., -0.50510338,
        -0.83266942, -1.098996  ],
       ...,
       [-1.66874796,  1.39153439,  0.        , ..., -1.03074071,
        -0.91039641, -1.098996  ],
       [ 1.45605153, -0.40740741,  0.        , ...,  0.16205169,
         0.48868939,  0.90992142],
       [-0.55274815,  1.39153439,  0.        , ..., -0.99030707,
        -0.88448741, -1.098996  ]])
```

In [100]:
```
X_test
```

```
         9.09921419e-01],
       [ 1.67925149e+00, -4.07407407e-01,  0.00000000e+00,
         8.39147711e-02,  5.55707612e-01, -3.85823876e-01,
         6.82141084e-01,  1.31398887e+00,  1.93071213e+00,
         4.79526983e-01,  1.62440169e+00,  1.11050531e+00,
         9.09921419e-01],
       [ 3.40051709e-01, -1.30687831e+00,  0.00000000e+00,
        -5.24566744e-01,  1.73236786e-01, -3.40052726e-01,
         1.70390942e-01, -8.11427023e-01, -7.00737215e-01,
        -5.22858561e-01, -7.94877806e-01, -7.41987934e-01,
        -1.09899600e+00],
       [-1.22234804e+00, -1.30687831e+00,  0.00000000e+00,
        -1.86521458e-01, -5.91704866e-01, -2.94281575e-01,
        -2.58967840e-02, -6.95072139e-01, -6.68275234e-01,
        -6.86037603e-01, -7.14010525e-01, -8.06760425e-01,
        -1.09899600e+00],
       [-1.22234804e+00,  1.39153439e+00,  0.00000000e+00,
         8.27614401e-01,  1.73236786e-01, -3.85823876e-01,
         2.33483425e-01, -8.96753939e-01, -5.38427309e-01,
        -4.52924686e-01, -8.08355686e-01, -7.03124439e-01,
```

Model Training

In [101]:
```python
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
```

In [102]:
```
regression = LinearRegression()
lasso = Lasso()
ridge = Ridge()
elasticnet = ElasticNet()
```

In [103]:
```
models = [regression, lasso, ridge, elasticnet]
```

In [105]:
```
regression.fit(X_train, y_train)
```

Out[105]:
```
▾ LinearRegression
LinearRegression()
```

print coefficients and intercept

In [106]:
```
regression.coef_
```

Out[106]:
```
array([-5.80896121e-01, -2.69620725e-01,  2.99760217e-15, -9.57968404e-01,
       -7.84242778e-01,  4.24923494e-01,  1.55454106e+00,  3.50343864e+00,
        2.70599802e+00,  4.94774573e-01, -5.04327581e+00, -3.18139966e-01,
       -1.16724927e-01])
```

In [107]:
```
regression.intercept_
```

Out[107]:
```
32.04117647058823
```

prediction for test data

In [108]:
```
y_pred = regression.predict(X_test)
```

In [109]:
```
y_pred
```

Out[109]:
```
array([32.79641075, 35.02274903, 30.63350595, 33.12299224, 31.94283052,
       32.23833383, 31.30709182, 34.64596675, 31.96124513, 30.82888561,
       28.35059241, 39.73626564, 34.37012538, 34.46787268, 34.06057298,
       32.84166182, 32.99177473, 25.89504057, 32.81746314, 34.91043925,
       31.04033313, 28.47749154, 33.24853634, 28.98216672, 36.63268857,
       33.89017314, 33.48485866, 33.53634489, 26.95658767, 33.53120014,
       29.6252971 , 32.30899838, 32.1633019 , 32.96925253, 32.05849405,
       32.9839793 , 31.01781389, 34.31315509, 26.67234481, 20.88467142,
       34.28671884, 32.75694265, 34.19553275, 25.0935279 , 36.4189878 ,
       32.71875823, 30.86736383, 30.67971234, 33.15003874, 28.26380837,
       37.19062884, 35.21819978, 33.66102279, 34.75102604, 33.28117209,
       32.31620419, 32.31942747, 32.54349773, 31.79147197, 36.22333466,
       33.20847127, 30.11380025, 29.12870902, 36.78820367, 31.57165732,
       31.46204735, 33.1511071 , 34.41965372, 35.04570101, 24.471576  ,
       34.64175337, 35.89062008, 33.18548941])
```

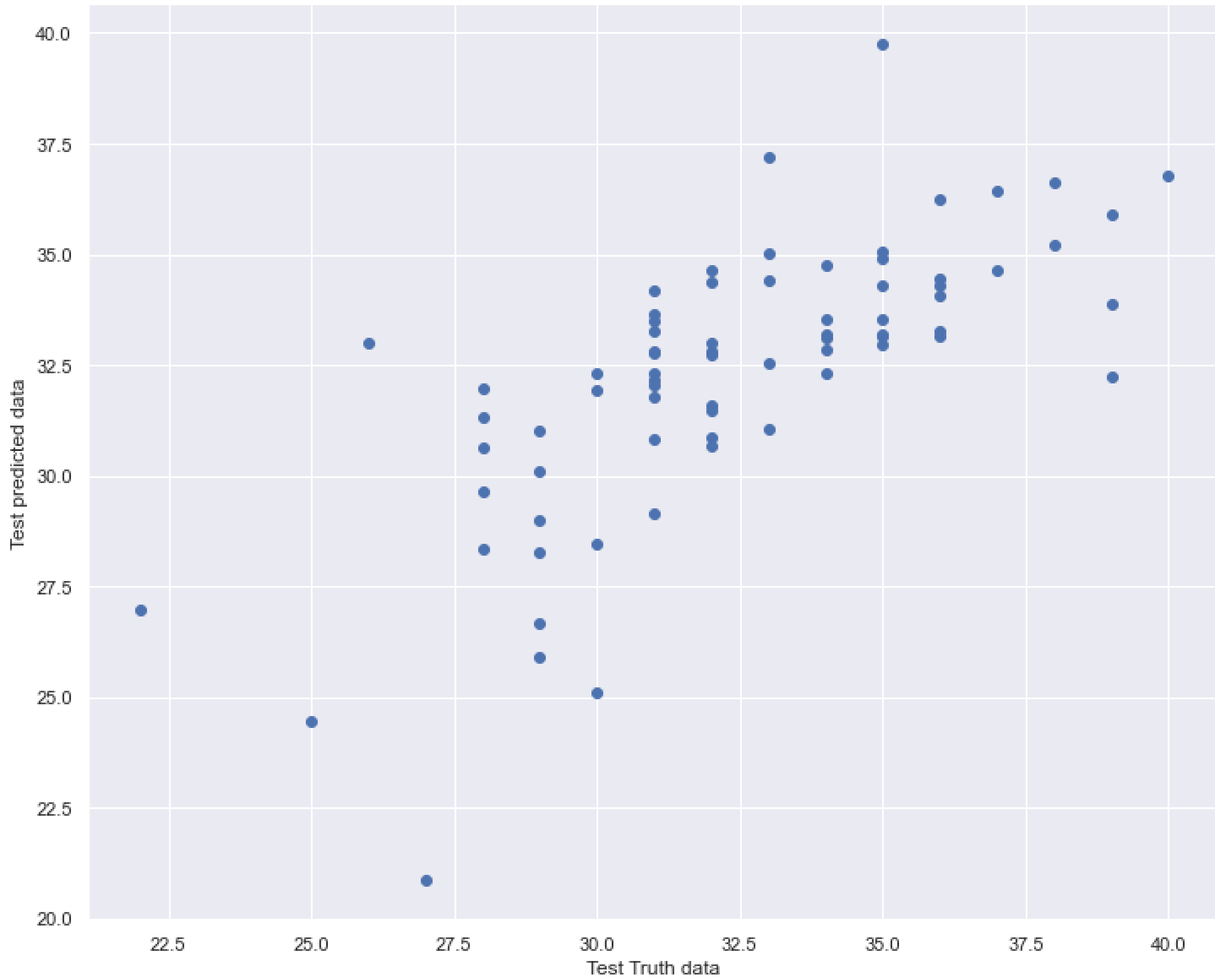
Checking Assumptions

1. linear relationship between test and predicted values

In [111]:

```
plt.scatter(y_test, y_pred)
plt.xlabel("Test Truth data")
plt.ylabel("Test predicted data")
```

Out[111]: Text(0, 0.5, 'Test predicted data')



Observation

- test values are directly proportional to predicted values
- model is good fit

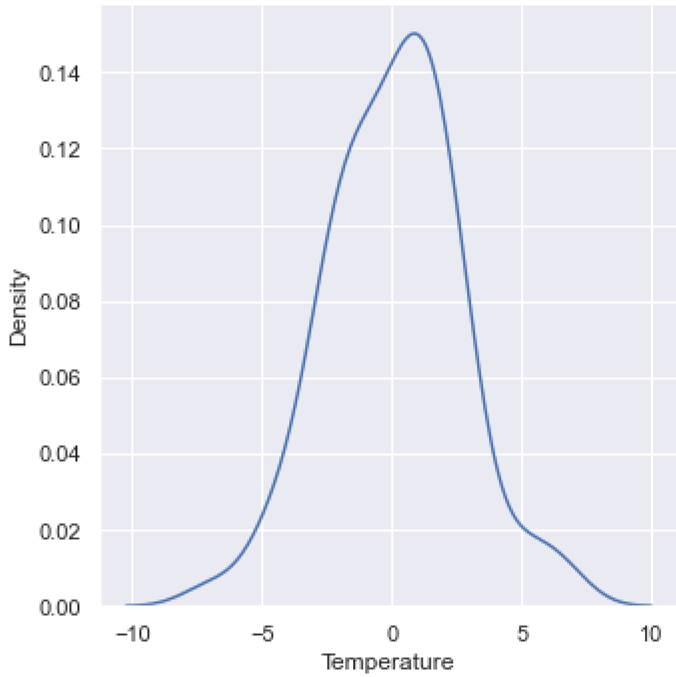
2. residuals should be normally distributed

In [112]:
```
residuals = y_test - y_pred
```

In [113]:
```
residuals
```

Out[113]:
```
24    -1.796411
6     -2.022749
152   -2.633506
233    0.877008
239   -1.942831
         ...
195   -0.045701
104    0.528424
109   -2.641753
191    3.109380
79     1.814511
Name: Temperature, Length: 73, dtype: float64
```

In [114]:
```
sns.displot(residuals,kind='kde');
```



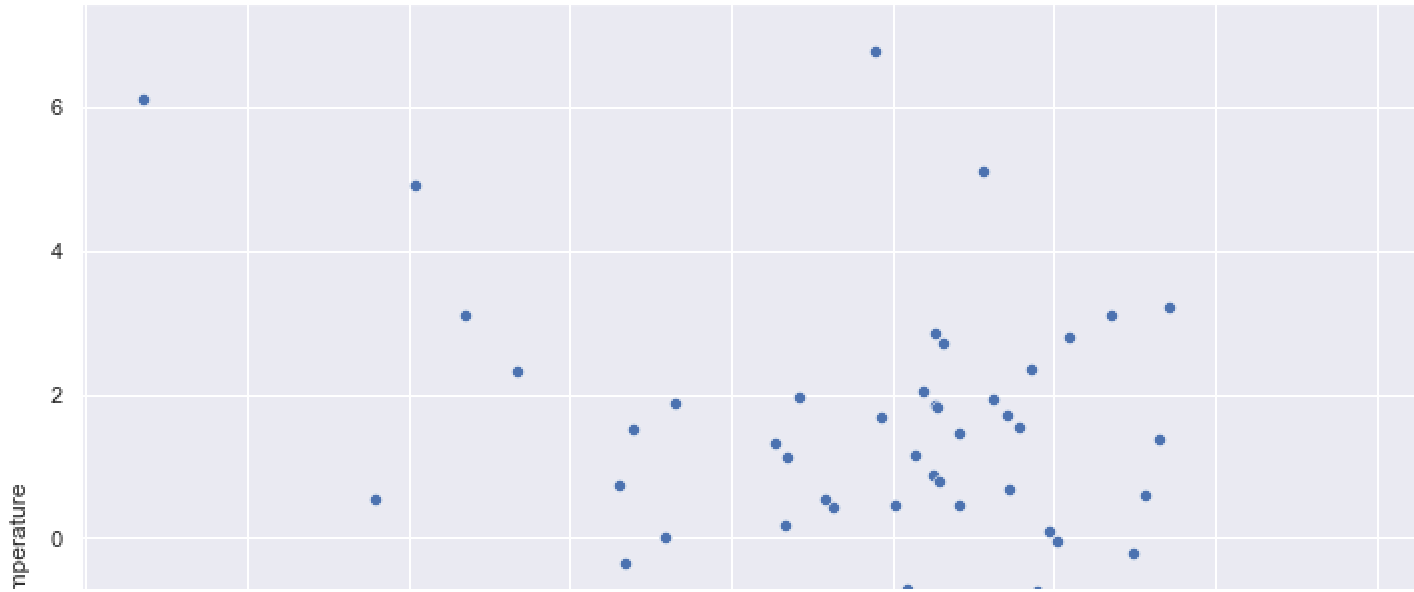
Observation

- residuals are normally distributed
- model is good fit

3. Homoscedasticity

In [115]:
```
sns.scatterplot(x = y_pred, y=residuals)
```

Out[115]: <AxesSubplot:ylabel='Temperature'>



Observation:

- residuals are uniformly spread
- model is good fit

Performanc Matrix

In [116]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

In [120]:
```
print(f"Mean Squared Error: {mean_squared_error(y_test, y_pred)}")
```

```
Mean Squared Error: 6.399727193150853
```

In [121]:
```
print(f"Root Mean Squared Error: {np.sqrt(mean_squared_error(y_test, y_pred))}")
```

```
Root Mean Squared Error: 2.5297682093723237
```

In [122]:
```
print(f"Mean Absolute Error: {mean_absolute_error(y_test, y_pred)}")
```

```
Mean Absolute Error: 2.0093401158864626
```

R Squarred and Adjusted R Squarred

In [123]:
```
from sklearn.metrics import r2_score
```

In [124]:
```
score = r2_score(y_test, y_pred)
```

In [125]:
```
print(f"R Squarred: {score}")
```

```
R Squarred: 0.47488457776767024
```

In [127]:
```
adj_rsquare = 1 - (1-score)*(len(y_test) - 1) /(len(y_test) - X_test.shape[1] - 1)
print(f"Adjusted R Squarred: {adj_rsquare}")
```

```
Adjusted R Squarred: 0.35918117964868235
```

Checking Performance of Model for Ridge, Lasso and ElasticNet

In [135]:
```
def evaluation(model, X_train, X_test,y_train, y_test) :
    model.fit(X_train, y_train)
    print(f"Coefficient: \n{model.coef_}")
    print(f"Intercept: {model.intercept_}")
    y_pred = model.predict(X_test)
    print(f"\n{'*'*25} Evaluation for {model} model {'*'*25}\n")
    print(f"Mean Squarred Error: {mean_squared_error(y_test, y_pred)}")
    print(f"Root Mean Squarred Error: {np.sqrt(mean_squared_error(y_test, y_pred))}")
    print(f"Mean Absolute Error: {mean_absolute_error(y_test, y_pred)}")

    score = r2_score(y_test, y_pred)
    print(f"\nR Squarred: {score}")
    adj_rsquare = 1 - (1-score)*(len(y_test) - 1) /(len(y_test) - X_test.shape[1] - 1)
    print(f"Adjusted R Squarred: {adj_rsquare}")
    print()
```

In [136]:

```python
for model in models :
    evaluation(model, X_train, X_test,y_train, y_test)
```

```
Coefficient:
[-5.80896121e-01 -2.69620725e-01  2.99760217e-15 -9.57968404e-01
 -7.84242778e-01  4.24923494e-01  1.55454106e+00  3.50343864e+00
  2.70599802e+00  4.94774573e-01 -5.04327581e+00 -3.18139966e-01
 -1.16724927e-01]
Intercept: 32.04117647058823

************************* Evaluation for LinearRegression() model *************************

Mean Squared Error: 6.399727193150853
Root Mean Squared Error: 2.5297682093723237
Mean Absolute Error: 2.0093401158864626

R Squared: 0.47488457776767024
Adjusted R Squared: 0.35918117964868235

Coefficient:
[ 0.         -0.          0.         -0.65210487 -0.         -0.
  1.08755359  0.          0.          0.          0.          0.
  0.        ]
Intercept: 32.04117647058823

************************* Evaluation for Lasso() model *************************

Mean Squared Error: 6.6495770305009945
Root Mean Squared Error: 2.5786773800731635
Mean Absolute Error: 2.123185084516282

R Squared: 0.4543837034530257
Adjusted R Squared: 0.3341631635358957

Coefficient:
[-0.57163213 -0.24486263  0.         -0.97026732 -0.7811602   0.38521533
  1.48287006  0.45825186  1.03142175  0.51435613 -0.46476688 -0.31517238
 -0.1118449 ]
Intercept: 32.04117647058823

************************* Evaluation for Ridge() model *************************

Mean Squared Error: 5.93403273310624
Root Mean Squared Error: 2.435987014149755
Mean Absolute Error: 1.9296082189973855

R Squared: 0.5130961039213632
```

```
Adjusted R Squarred: 0.4058121946159008

Coefficient:
[-0.          -0.           0.          -0.62675812 -0.22498622 -0.
  0.69959647  0.09593062  0.           0.26773045  0.06300842  0.17640915
  0.117818  ]
Intercept: 32.04117647058823

************************ Evaluation for ElasticNet() model ************************

Mean Squarred Error: 6.184150209485093
Root Mean Squarred Error: 2.4867951683814034
Mean Absolute Error: 2.007985784009525

R Squarred: 0.4925732690797576
Adjusted R Squarred: 0.3807673792159755
```

Feature Selection

In [138]:
```
df.columns
```

Out[138]:
```
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes  '],
      dtype='object')
```

1. Variance Threshold

In [140]:
```
from sklearn.feature_selection import VarianceThreshold
```

In [157]:
```
variance_threshold = VarianceThreshold(threshold=0)
variance_threshold.fit(df)
```

Out[157]:
```
VarianceThreshold
VarianceThreshold(threshold=0)
```

In [158]:
```
variance_threshold.get_support()
```
Out[158]:
```
array([ True,  True, False,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True])
```
In [159]:
```
df.columns[variance_threshold.get_support()]
```
Out[159]:
```
Index(['day', 'month', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC', 'DMC',
       'DC', 'ISI', 'BUI', 'FWI', 'Classes  '],
      dtype='object')
```

finding colunns having zero standard deviation

In [147]:
```
constant_columns = [column for column in df.columns if column not in df.columns[variance_threshold.get_support()]]
```
In [148]:
```
print(len(constant_columns))
```
```
1
```
In [149]:
```
for feature in constant_columns :
    print(feature)
```
```
year
```
In [167]:
```
df = df.drop(constant_columns,axis=1)
```

In [168]:
```
df
```

Out[168]:

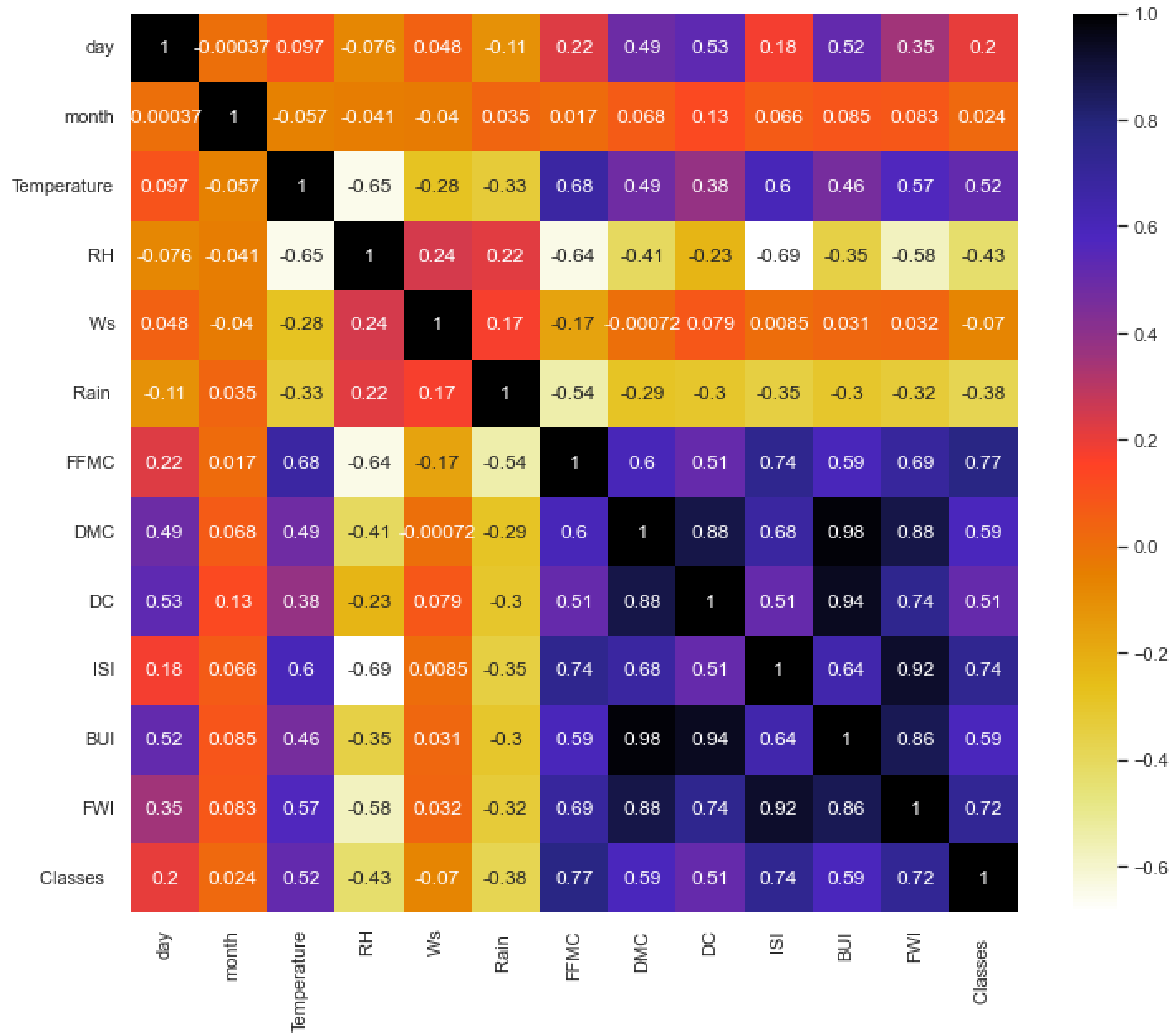
	day	month	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0
1	2	6	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0
2	3	6	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0
3	4	6	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0
4	5	6	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
239	26	9	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1
240	27	9	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	0
241	28	9	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	0
242	29	9	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0
243	30	9	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	0

243 rows × 13 columns

2. Correlation

In [169]:
```python
sns.set(rc={'figure.figsize':(12,10)})
sns.heatmap(df.corr(), annot=True, cmap=plt.cm.CMRmap_r)
```

Out[169]: <AxesSubplot:>



In [170]:
```python
# with the following function we can select highly correlated features
# it will remove the first feature that is correlated with anything other feature

def correlation(dataset, threshold):
    col_corr = set()  # Set of all the names of correlated columns
    corr_matrix = df.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold: # we are interested in absolute coeff value
                colname = corr_matrix.columns[i]  # getting the name of column
                col_corr.add(colname)
    return col_corr
```

In [171]:
```python
corr_features = correlation(df, 0.85)
len(set(corr_features))
```

Out[171]: 3

In [172]:
```python
corr_features
```

Out[172]: {'BUI', 'DC', 'FWI'}

In [176]:
```python
df = df.drop(corr_features,axis=1)
```

In [177]:
```
df
```

Out[177]:

	day	month	Temperature	RH	Ws	Rain	FFMC	DMC	ISI	Classes
0	1	6	29	57	18	0.0	65.7	3.4	1.3	0
1	2	6	29	61	13	1.3	64.4	4.1	1.0	0
2	3	6	26	82	22	13.1	47.1	2.5	0.3	0
3	4	6	25	89	13	2.5	28.6	1.3	0.0	0
4	5	6	27	77	16	0.0	64.8	3.0	1.2	0
...	...	...	...	...	...	...	...	...	...	...
239	26	9	30	65	14	0.0	85.4	16.0	4.5	1
240	27	9	28	87	15	4.4	41.1	6.5	0.1	0
241	28	9	27	87	29	0.5	45.9	3.5	0.4	0
242	29	9	24	54	18	0.1	79.7	4.3	1.7	0
243	30	9	24	64	15	0.2	67.3	3.8	1.2	0

243 rows × 10 columns

In [179]:
```
df = df.drop(columns=['day', 'month'], axis=1)
```

In [180]:
```
df
```

Out[180]:

	Temperature	RH	Ws	Rain	FFMC	DMC	ISI	Classes
0	29	57	18	0.0	65.7	3.4	1.3	0
1	29	61	13	1.3	64.4	4.1	1.0	0
2	26	82	22	13.1	47.1	2.5	0.3	0
3	25	89	13	2.5	28.6	1.3	0.0	0
4	27	77	16	0.0	64.8	3.0	1.2	0
...	...	...	...	...	...	...	...	...
239	30	65	14	0.0	85.4	16.0	4.5	1
240	28	87	15	4.4	41.1	6.5	0.1	0
241	27	87	29	0.5	45.9	3.5	0.4	0
242	24	54	18	0.1	79.7	4.3	1.7	0
243	24	64	15	0.2	67.3	3.8	1.2	0

243 rows × 8 columns

repeating same procedure to find model performance

In [181]:
```
X = df.drop(columns='Temperature')
```

In [182]:
```
X
```

Out[182]:

	RH	Ws	Rain	FFMC	DMC	ISI	Classes
0	57	18	0.0	65.7	3.4	1.3	0
1	61	13	1.3	64.4	4.1	1.0	0
2	82	22	13.1	47.1	2.5	0.3	0
3	89	13	2.5	28.6	1.3	0.0	0
4	77	16	0.0	64.8	3.0	1.2	0
...	...	...	...	...	...	...	...
239	65	14	0.0	85.4	16.0	4.5	1
240	87	15	4.4	41.1	6.5	0.1	0
241	87	29	0.5	45.9	3.5	0.4	0
242	54	18	0.1	79.7	4.3	1.7	0
243	64	15	0.2	67.3	3.8	1.2	0

243 rows × 7 columns

In [183]:
```
y = df['Temperature']
```

In [184]:
```
y
```

Out[184]:
```
0      29
1      29
2      26
3      25
4      27
       ..
239    30
240    28
241    27
242    24
243    24
Name: Temperature, Length: 243, dtype: int64
```

split data into training and test set

split data into training and test set

In [185]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [186]:
```
X_train
```

Out[186]:

	RH	Ws	Rain	FFMC	DMC	ISI	Classes
29	50	14	0.0	88.7	22.9	7.2	1
120	80	16	1.8	47.4	2.9	0.3	0
114	54	11	0.5	73.7	7.9	1.2	0
242	54	18	0.1	79.7	4.3	1.7	0
5	67	14	0.0	82.6	5.8	3.1	1
...	...	...	...	...	...	...	...
106	82	15	0.4	44.9	0.9	0.2	0
14	80	17	3.1	49.4	3.0	0.4	0
92	76	17	7.2	46.0	1.3	0.2	0
180	59	16	0.0	88.1	19.5	7.4	1
102	77	21	1.8	58.5	1.9	1.1	0

170 rows × 7 columns

In [187]:
```
X_train.shape
```

Out[187]:
```
(170, 7)
```

In [188]:
```
X_test
```

Out[188]:

	RH	Ws	Rain	FFMC	DMC	ISI	Classes
24	64	15	0.0	86.7	14.2	5.7	1
6	54	13	0.0	88.2	9.9	6.4	1
152	58	18	2.2	63.7	3.2	1.2	0
233	58	13	0.2	79.5	18.7	2.1	0
239	65	14	0.0	85.4	16.0	4.5	1
...	...	...	...	...	...	...	...
195	34	16	0.2	88.3	16.9	7.5	1
104	86	21	4.6	40.9	1.3	0.1	0
109	49	11	0.0	89.4	9.8	6.8	1
191	43	12	0.0	91.7	16.5	9.6	1
79	62	19	0.0	89.4	23.2	9.7	1

73 rows × 7 columns

In [189]:
```
X_test.shape
```

Out[189]:
```
(73, 7)
```

In [190]:
```
y_train
```

Out[190]:
```
29     33
120    26
114    32
242    24
5      31
       ..
106    24
14     28
92     25
180    34
102    30
Name: Temperature, Length: 170, dtype: int64
```

In [191]:
```
y_train.shape
```

Out[191]:
```
(170,)
```

In [192]:
```
y_test
```

Out[192]:
```
24     31
6      33
152    28
233    34
239    30
       ..
195    35
104    25
109    32
191    39
79     35
Name: Temperature, Length: 73, dtype: int64
```

In [193]:
```
y_test.shape
```

Out[193]:
```
(73,)
```

Feature Scaling

In [194]:
```
from sklearn.preprocessing import StandardScaler
```

In [195]:
```
scaler = StandardScaler()
```

In [196]:
```
X_train = scaler.fit_transform(X_train)
```

In [197]:
```
X_test = scaler.transform(X_test)
```

In [198]:
```
X_train
```

Out[198]:
```
array([[-0.86261203, -0.59170487, -0.38582388, ...,  0.61585956,
         0.57277215,  0.90992142],
       [ 1.16565969,  0.17323679,  0.43805684, ..., -0.9355389 ,
        -1.03570698, -1.098996  ],
       [-0.5921758 , -1.73911734, -0.15696812, ..., -0.54768929,
        -0.82590535, -1.098996  ],
       ...,
       [ 0.89522346,  0.55570761,  2.90969898, ..., -1.05965078,
        -1.05901827, -1.098996  ],
       [-0.25413052,  0.17323679, -0.38582388, ...,  0.35212182,
         0.61939473,  0.90992142],
       [ 0.96283252,  2.08559091,  0.43805684, ..., -1.01310882,
        -0.84921665, -1.098996  ]])
```

In [199]:
```
X_test
```

```
       [ 1.63037138e-02, -2.09234040e-01, -3.85823876e-01,
         6.68120532e-01,  3.13336859e-01,  2.69725358e-01,
         9.09921419e-01],
       [ 1.57131403e+00, -2.09234040e-01,  4.23706235e+00,
        -3.29268536e+00, -1.10619273e+00, -1.10564085e+00,
        -1.09899600e+00],
       [-3.21739572e-01,  9.38178437e-01, -3.85823876e-01,
         7.38223292e-01, -1.05540725e-01,  7.59262484e-01,
         9.09921419e-01],
       [ 1.43609592e+00,  9.38178437e-01, -3.85823876e-01,
         4.43791703e-01, -1.13297717e-01, -5.66327264e-02,
         9.09921419e-01],
       [-3.21739572e-01, -1.35664652e+00,  1.49079330e+00,
        -7.97027136e-01, -8.50211985e-01, -8.72527937e-01,
        -1.09899600e+00],
       [ 8.39147711e-02,  9.38178437e-01, -3.85823876e-01,
         6.54099981e-01,  2.20252952e-01,  4.56215692e-01,
         9.09921419e-01],
       [ 8.39147711e-02,  5.55707612e-01, -3.85823876e-01,
         6.82141084e-01,  1.31398887e+00,  4.79526983e-01,
```

Model Training

In [200]:
```python
from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet
```

In [201]:

```python
regression = LinearRegression()
lasso = Lasso()
ridge = Ridge()
elasticnet = ElasticNet()
```

In [202]:

```python
models = [regression, lasso, ridge, elasticnet]
```

In [203]:

```python
for model in models :
    evaluation(model, X_train, X_test,y_train, y_test)
```

```
Intercept: 32.04117647058823

************************ Evaluation for Ridge() model ************************


Mean Squared Error: 5.7797092049513905
Root Mean Squared Error: 2.4041025778762832
Mean Absolute Error: 1.9559622622376804

R Squared: 0.5257587787825893
Adjusted R Squared: 0.47468664726686804

Coefficient:
[-0.643625   -0.21571403 -0.          0.71828381  0.18822364  0.32893064
  0.14715384]
Intercept: 32.04117647058823

************************ Evaluation for ElasticNet() model ************************

Mean Squared Error: 6.186738102315899
```

In [ ]:

```python

```