Forest Fires

Abstract This is a difficult regression task, where the aim is to predict the burned area of forest fires, in the northeast region of Portugal, by using meteorological and other data

Dataset attributes information

1. X - x-axis spatial coordinate within the Montesinho park map: 1 to 9
2. Y - y-axis spatial coordinate within the Montesinho park map: 2 to 9
3. month - month of the year: 'jan' to 'dec'
4. day - day of the week: 'mon' to 'sun'
5. FFMC - FFMC index from the FWI system: 18.7 to 96.20
6. DMC - DMC index from the FWI system: 1.1 to 291.3
7. DC - DC index from the FWI system: 7.9 to 860.6
8. ISI - ISI index from the FWI system: 0.0 to 56.10
9. temp - temperature in Celsius degrees: 2.2 to 33.30
10. RH - relative humidity in %: 15.0 to 100
11. wind - wind speed in km/h: 0.40 to 9.40
12. rain - outside rain in mm/m2 : 0.0 to 6.4
13. area - the burned area of the forest (in ha): 0.00 to 1090.84

(this output variable is very skewed towards 0.0, thus it may make sense to model with the logarithm transform).

In [1]:

```
## importing libraries

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

In [4]:

```
#loading the data
df = pd.read_csv('forestfires.csv')
df.head()
```

Out[4]:

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
0	7	5	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0
1	7	4	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0
2	7	4	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0
3	8	6	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0
4	8	6	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0

In [5]:

```
#checking the dimensions of the data
df.shape
```

Out[5]:

```
(517, 13)
```

In [7]:

```
#let's look at the types of variables that we have in the dataset
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 13 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   X       517 non-null    int64  
 1   Y       517 non-null    int64  
 2   month   517 non-null    object 
 3   day     517 non-null    object 
 4   FFMC    517 non-null    float64
 5   DMC     517 non-null    float64
 6   DC      517 non-null    float64
 7   ISI     517 non-null    float64
 8   temp    517 non-null    float64
 9   RH      517 non-null    int64  
 10  wind    517 non-null    float64
 11  rain    517 non-null    float64
 12  area    517 non-null    float64
dtypes: float64(8), int64(3), object(2)
memory usage: 52.6+ KB
```

In [9]:

```
#statistical descriptions of data

df.describe().T    # T is to transform oppositly
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
X	517.0	4.669246	2.313778	1.0	3.0	4.00	7.00	9.00
Y	517.0	4.299807	1.229900	2.0	4.0	4.00	5.00	9.00
FFMC	517.0	90.644681	5.520111	18.7	90.2	91.60	92.90	96.20
DMC	517.0	110.872340	64.046482	1.1	68.6	108.30	142.40	291.30
DC	517.0	547.940039	248.066192	7.9	437.7	664.20	713.90	860.60
ISI	517.0	9.021663	4.559477	0.0	6.5	8.40	10.80	56.10
temp	517.0	18.889168	5.806625	2.2	15.5	19.30	22.80	33.30
RH	517.0	44.288201	16.317469	15.0	33.0	42.00	53.00	100.00
wind	517.0	4.017602	1.791653	0.4	2.7	4.00	4.90	9.40
rain	517.0	0.021663	0.295959	0.0	0.0	0.00	0.00	6.40
area	517.0	12.847292	63.655818	0.0	0.0	0.52	6.57	1090.84

In [13]:

```
# checking the missing values of dataset column wise
df.isna().sum()
```

Out[13]:

```
X        0
Y        0
month    0
day      0
FFMC     0
DMC      0
DC       0
ISI      0
temp     0
RH       0
wind     0
rain     0
area     0
dtype: int64
```

In [14]:

```
#our target is to predict the area so let's make it as a target variable

target = 'area'
```

checking the skweness and kurtosis of the target variable

SKEWNESS measures the lack of symmeety in data distribution.

- If the skewness is between -0.5 and 0.5, the data are fairly symmetrical.

- If the skewness is between -1 and -0.5(negatively skewed) or between 0.5 and 1(positively skewed), the data are moderately skewed.

- If the skewness is less than -1(negatively skewed) or greater than 1(positively skewed), the data are highly skewed.

Kurtosis is all about tails of distribution. it actually the "measure of outliers" present in the distribution

Kurtosis > 3: Distribution is longer, tails are fatter.

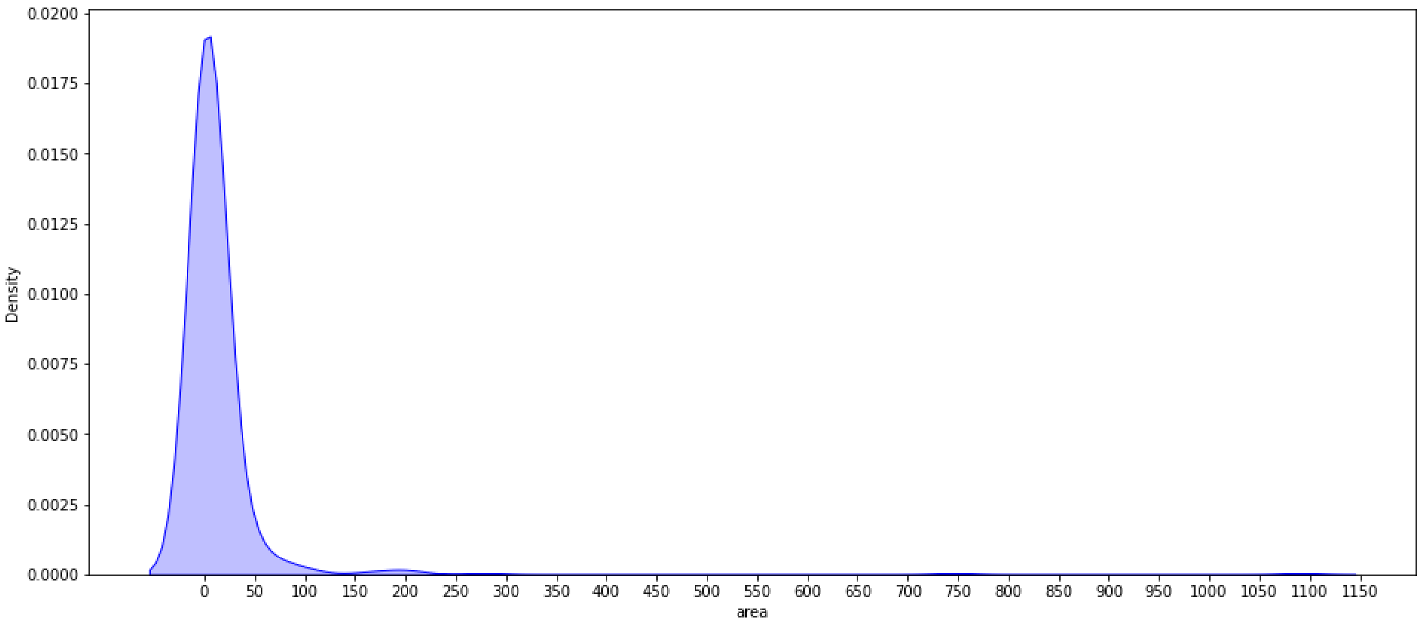
Kurtosis < 3: Distribution is shorter, tails are thinner than the normal distribution

In [25]:

```
#skewness and kurtosis

plt.figure(figsize=(16,7))
print("Skew: {}".format(df[target].skew()))
print("Kurtosis: {}".format(df[target].kurtosis()))
ax = sns.kdeplot(df[target],shade=True,color='b')
plt.xticks([i for i in range(0,1200,50)])
plt.show()
```

```
Skew: 12.846933533934868
Kurtosis: 194.1407210942299
```



Observations

- **the data is highly skewed with a value of +12.846 and kurtosis is very very high with a value of 194.14**
- **looking at the plot we can see that majority of the forest fires do not cover larger area, most of damaged area is under 50 hectares of land**

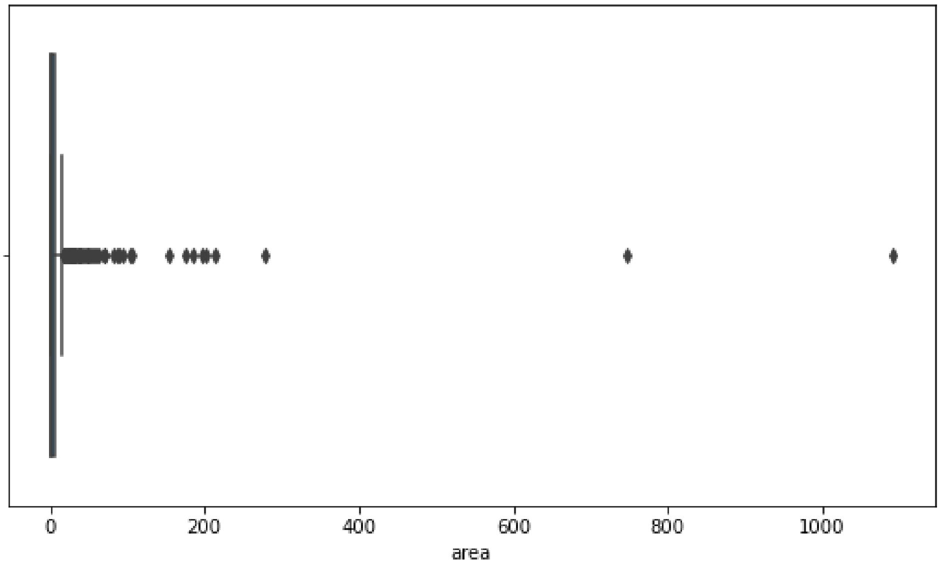
So we will scale the target variable to fix the skewness and kurtosis and at last we have to inverse transforms before submitting the outputs

In [37]:

```
#checking the outliers
plt.figure(figsize=(9,5))
sns.boxplot(x=df[target])
```

Out[37]:

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



By looking at the graph there are few outliers in the targer variable let's confirm validating with Z-score

Z-score describes any data point by finding their relationship with standard deviation and mean of the group of data point.

the data points which are too far from zero will be treated as outliers. In general threshold of 3 or -3 is used. if z > 3 or z < -3 respectively, the data point will be identified as outliers

In [38]:

```
#outliers detection
from scipy.stats import zscore

y_outliers = df[abs(zscore(df[target])) >= 3]

y_outliers
```

Out[38]:

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
237	1	2	sep	tue	91.0	129.5	692.6	7.0	18.8	40	2.2	0.0	212.88
238	6	5	sep	sat	92.5	121.1	674.4	8.6	25.1	27	4.0	0.0	1090.84
415	8	6	aug	thu	94.8	222.4	698.6	13.9	27.5	27	4.9	0.0	746.28
479	7	4	jul	mon	89.2	103.9	431.6	6.4	22.6	57	4.9	0.0	278.53

In [46]:

```
#let's look at the different type of variables
diff_data = df.drop(columns='area')
categorical = diff_data.select_dtypes(include = 'object').columns.tolist()
numericals = diff_data.select_dtypes(exclude = 'object').columns.tolist()
```

In [47]:

```
categorical,numericals
```

Out[47]:

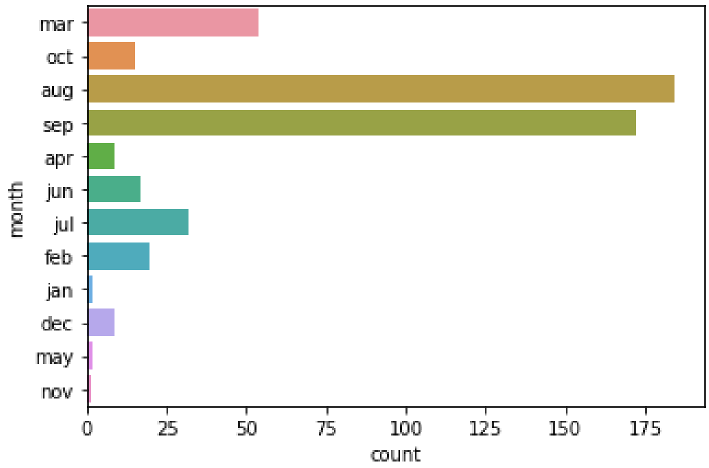
```
(['month', 'day'],
 ['X', 'Y', 'FFMC', 'DMC', 'DC', 'ISI', 'temp', 'RH', 'wind', 'rain'])
```

In [61]:

```
#checking which month have the more instances
sns.countplot(data=diff_data,y='month')
```

Out[61]:

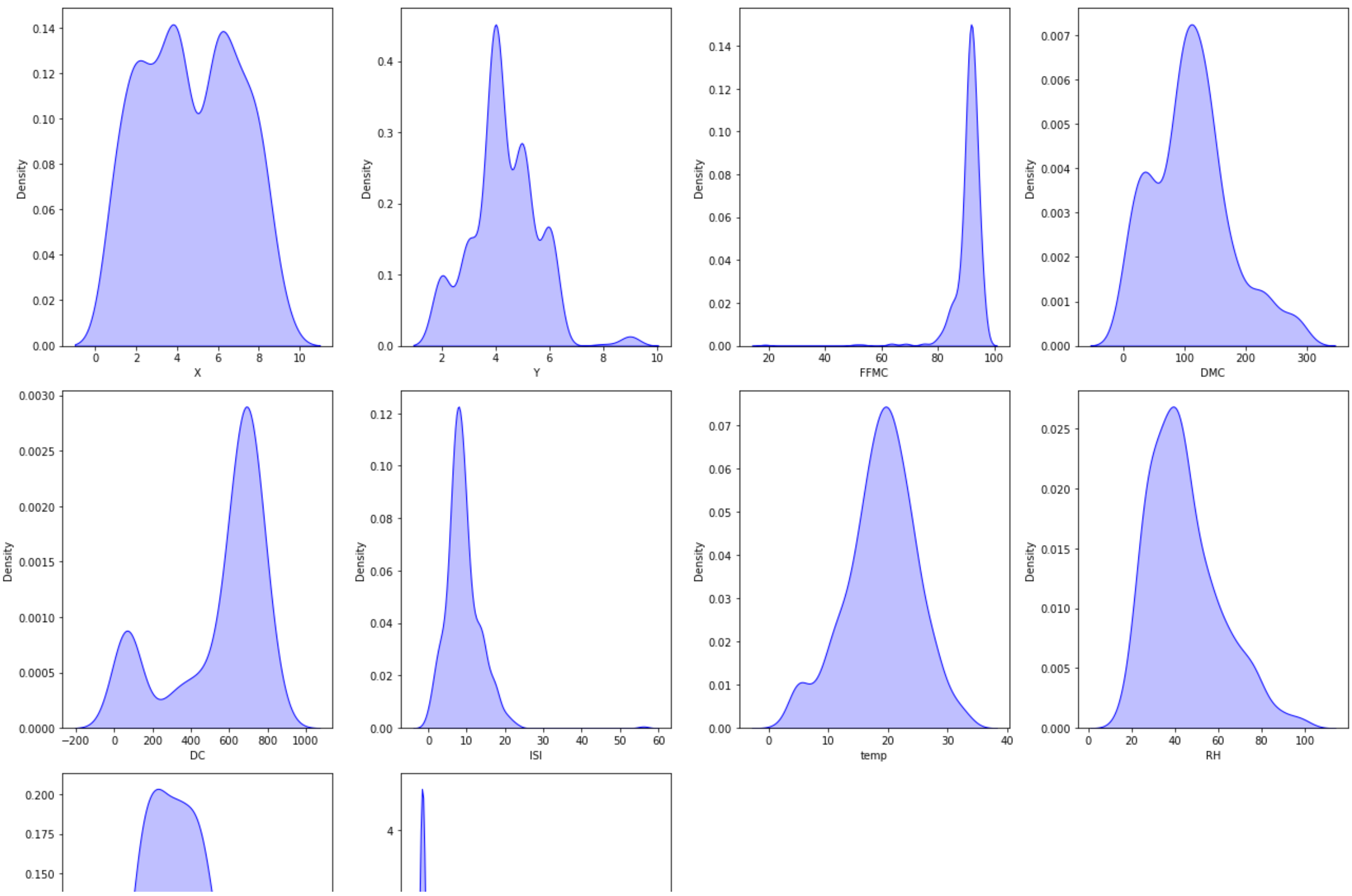
```
<AxesSubplot:xlabel='count', ylabel='month'>
```

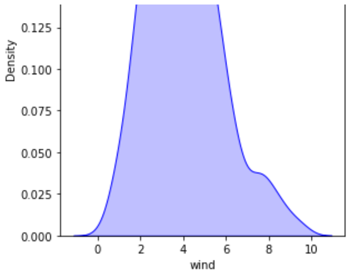


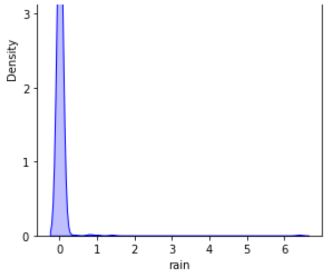
it looks that higher number of forest fires occurs in the month of August and September

In [62]:

```
plt.figure(figsize=(18,40))
for i,col in enumerate(numericals,1):
    plt.subplot(8,4,i)
    sns.kdeplot(df[col],color='b',shade=True)
plt.tight_layout()
plt.show()
num_data = df[numericals]
pd.DataFrame(data=[num_data.skew(),num_data.kurtosis()],index=['skewness','kurtosis'])
```







Out[62]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain
skewness	0.036246	0.417296	-6.575606	0.547498	-1.100445	2.536325	-0.331172	0.862904	0.571001	19.816344
kurtosis	-1.172331	1.420553	67.066041	0.204822	-0.245244	21.458037	0.136166	0.438183	0.054324	421.295964

from above graph, there is high postive or negative skweness and kurtosis was observed in the following columns.

1.rain

2.ISI

3.FFMC

Outliers Treatment

So far we observed outliers in 4 columns they are

1. **rain**
2. **ISI**
3. **FFMC**
4. **area**

In [66]:

```
outlier_columns = ['FFMC','ISI','rain','area']

#these outliers are not error values so we cannot remove it but in
#order to minimize the effect of outliers, we will transform above columns
```

Encoding categorical variables

In [ ]:

```
df = pd.get_dummies(df,columns =['day','month'],drop_first = True)
```

In [69]:

```
df.head()
```

Out[69]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	month_dec	month_feb	month_jan	month_jul	month_jun	month_
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	...	0	0	0	0	0	
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	...	0	0	0	0	0	
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	...	0	0	0	0	0	
3	8	6	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	...	0	0	0	0	0	
4	8	6	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	...	0	0	0	0	0	

5 rows × 28 columns

scaling the variables

In [73]:

```
#applying log transformation to the outlier variable and let's check
#the skewness and kurtosis again
np.log1p(df[outlier_columns]).skew(), np.log1p(df[outlier_columns]).kurtosis()
```

Out[73]:

```
(FFMC   -11.675394
 ISI     -0.937218
 rain    14.173028
 area     1.217838
 dtype: float64,
 FFMC    185.482383
 ISI       2.584588
 rain    234.240025
 area      0.945668
 dtype: float64)
```

by looking at above values, even after applying log transformation the skew and kurtosis of FFMC and rain are high. we cannot perform good with such high values so for FFMC we can remove the outliers in them using z-score method

In [74]:

```
#removing outliers in FFMC
fix_ffmc = df.loc[:,['FFMC']].apply(zscore).abs() < 3
```

In [75]:

```
fix_ffmc.head()
```

Out[75]:

	FFMC
0	True
1	True
2	True
3	True
4	True

In [76]:

```
df= df[fix_ffmc.values]
```

In [78]:

```
df.shape
```

Out[78]:

```
(510, 28)
```

In [ ]:

```
#transforming high skewed variables
outlier_columns.remove('rain')
df[outlier_columns] = np.log1p(df[outlier_columns])
```

In [81]:

```
df[outlier_columns].skew()
```

Out[81]:

```
FFMC    -1.803993
ISI     -0.434372
area     1.208492
dtype: float64
```

In [83]:

```python
#let's use this dataframe for machine learning model
df_ml = df.copy()
```

In [ ]:

```python
df_ml.copy()
```

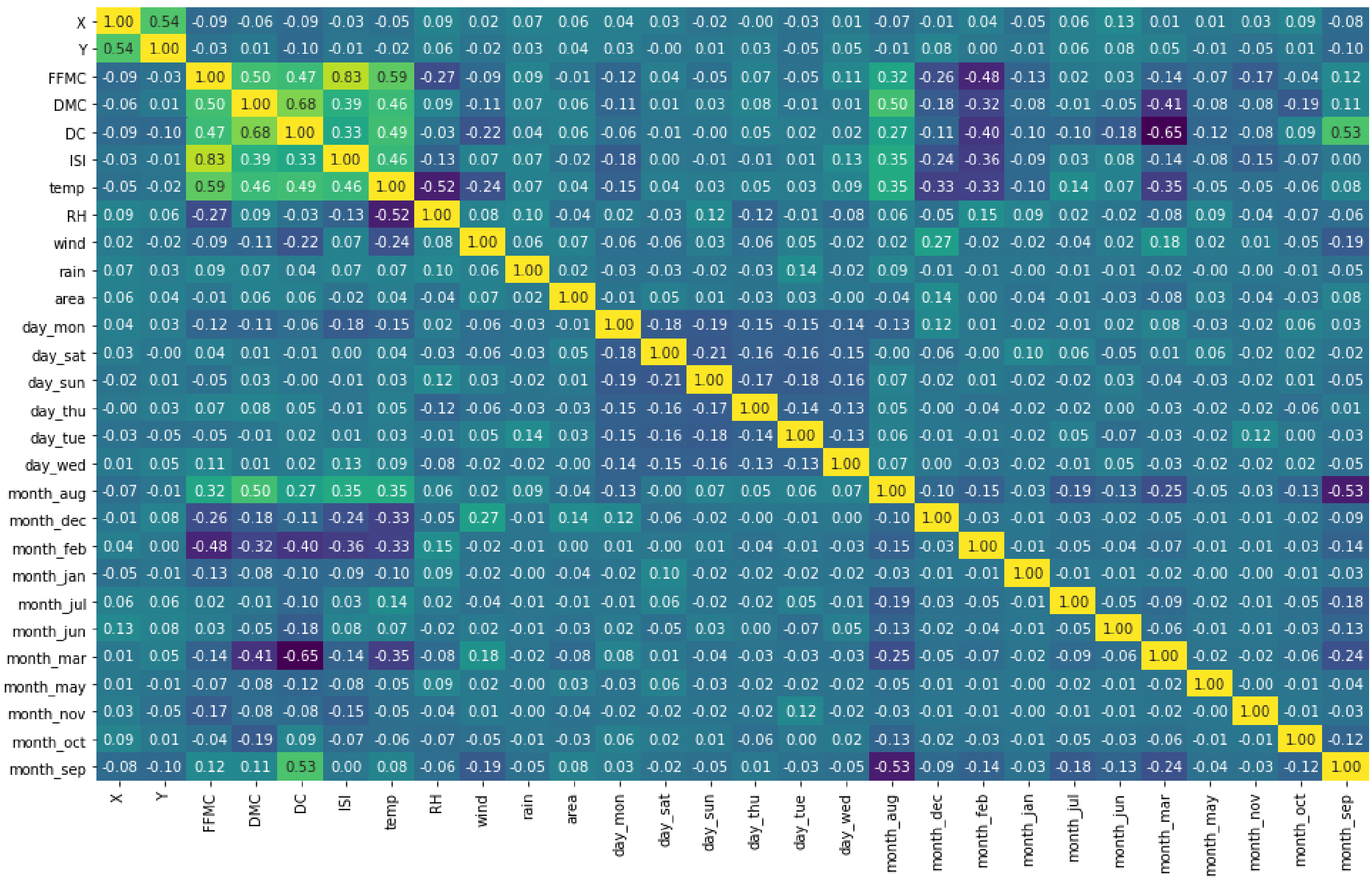
In [98]:

```python
# checking the correlation
plt.figure(figsize =(16,10))

sns.heatmap(df_ml.corr(),annot=True,cmap='viridis',fmt=".2f",cbar=False)
```

Out[98]:

```
<AxesSubplot:>
```



In [102]:

```python
#dividing the dataset

X = df.drop(columns=['area'])
y = df['area']
```

In [103]:

```python
X.head()
```

Out[103]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	month_dec	month_feb	month_jan	month_jul	month_jun
0	7	5	4.468204	26.2	94.3	1.808289	8.2	51	6.7	0.0	...	0	0	0	0	0
1	7	4	4.517431	35.4	669.1	2.041220	18.0	33	0.9	0.0	...	0	0	0	0	0
2	7	4	4.517431	43.7	686.9	2.041220	14.6	33	1.3	0.0	...	0	0	0	0	0
3	8	6	4.529368	33.3	77.5	2.302585	8.3	97	4.0	0.2	...	0	0	0	0	0
4	8	6	4.503137	51.3	102.2	2.360854	11.4	99	1.8	0.0	...	0	0	0	0	0

5 rows × 27 columns

In [104]:

```
y.head()
```

Out[104]:

```
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
Name: area, dtype: float64
```

In [124]:

```
#splitting data for model
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.2, random_state = 44)
```

Linear regression

In [125]:

```
#training the model to regression
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[125]:

```
LinearRegression()
```

In [126]:

```
#checkig the scores
print(f'Intercept: {regressor.intercept_}')
print(f'R^2 score: {regressor.score(X_train, y_train)}')
pd.DataFrame({"Coefficients": regressor.coef_}, index=X.columns)
```

```
Intercept: 1.4459065959355706
R^2 score: 0.019660820835479043
```

Out[126]:

	Coefficients
FFMC	0.010017
DMC	0.001366
DC	0.000215
ISI	-0.349481
temp	0.004511
RH	-0.006675
wind	0.081556

In [131]:

```
#dividing the dataset

X = df.drop(columns=['day_mon', 'day_sat', 'day_sun',
                     'day_thu', 'day_tue','day_wed', 'month_aug',
                     'month_dec', 'month_feb', 'month_jan','month_jul',
                     'month_jun', 'month_mar', 'month_may', 'month_nov',
                     'month_oct', 'month_sep','area'])
y = df['area']
```

In [132]:

```
#splitting data for model
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.2, random_state = 44)

#training the model to regression
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)

#checkig the scores
print(f'Intercept: {regressor.intercept_}')
print(f'R^2 score: {regressor.score(X_train, y_train)}')
```

```
Intercept: 0.44239945105705913
R^2 score: 0.024267880951563847
```

dropping outlier columns to check if there is any model improvement

In [147]:

```
#dividing the dataset

X = df.drop(columns=['day_mon', 'day_sat', 'day_sun',
                     'day_thu', 'day_tue','day_wed', 'month_aug',
                     'month_dec', 'month_feb', 'month_jan','month_jul',
                     'month_jun', 'month_mar', 'month_may', 'month_nov',
                     'month_oct', 'month_sep','area','FFMC','ISI','rain'])
y = df['area']

#splitting data for model
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.2, random_state = 44)

#training the model to regression
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)

#checkig the scores
print(f'Intercept: {regressor.intercept_}')
print(f'R^2 score: {regressor.score(X_train, y_train)}')
```

```
Intercept: 0.8489957707577935
R^2 score: 0.015496315662394289
```

In [ ]:

```

```

In [ ]:

```

```

polynomial regression

In [141]:

```
from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree = 4)
X_poly = poly_reg.fit_transform(X_train)
lin_reg_2 = LinearRegression()
lin_reg_2.fit(X_poly, y_train)
#checkig the scores
print(f'Intercept: {lin_reg_2.intercept_}')
print(f'R^2 score: {lin_reg_2.score(X_poly, y_train)}')
```

```
Intercept: 18.73168734737673
R^2 score: 0.9913685227111867
```

the data is not linear in nature hence a simple linear model will not help us in pumping the accuracy. So either we will have to introduce new features or use more complex models which can capture the non-linearity of the data.

In [ ]:

```
```