1. Import neccessery libraries

In [13]:
```
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn import metrics
import seaborn as sns
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
from sklearn.decomposition import PCA
from mlxtend.plotting import plot_decision_regions

import warnings
```

Problem

Classify the SizeCategorie using SVM

2. Import data

In [3]:
```
fire_data = pd.read_csv('forestfires.csv')
```

Out[3]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	monthfeb	monthjan
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	...	0	0
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	...	0	0
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	...	0	0
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	...	0	0
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	...	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
512	aug	sun	81.6	56.7	665.6	1.9	27.8	32	2.7	0.0	...	0	0
513	aug	sun	81.6	56.7	665.6	1.9	21.9	71	5.8	0.0	...	0	0
514	aug	sun	81.6	56.7	665.6	1.9	21.2	70	6.7	0.0	...	0	0
515	aug	sat	94.4	146.0	614.7	11.3	25.6	42	4.0	0.0	...	0	0
516	nov	tue	79.5	3.0	106.7	1.1	11.8	31	4.5	0.0	...	0	0

517 rows × 31 columns

Data understanding

In [4]:
```
fire_data.shape
```

Out[4]: (517, 31)

In [5]:

Out[5]:

```
month             object
day               object
FFMC             float64
DMC              float64
DC               float64
ISI              float64
temp             float64
RH                 int64
wind             float64
rain             float64
area             float64
dayfri             int64
daymon             int64
daysat             int64
daysun             int64
daythu             int64
daytue             int64
daywed             int64
monthapr           int64
monthaug           int64
monthdec           int64
monthfeb           int64
monthjan           int64
monthjul           int64
monthjun           int64
monthmar           int64
monthmay           int64
monthnov           int64
monthoct           int64
monthsep           int64
size_category     object
dtype: object
```

In [7]:

Out[7]:

	count	mean	std	min	25%	50%	75%	max
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 [8]:

Out[8]:

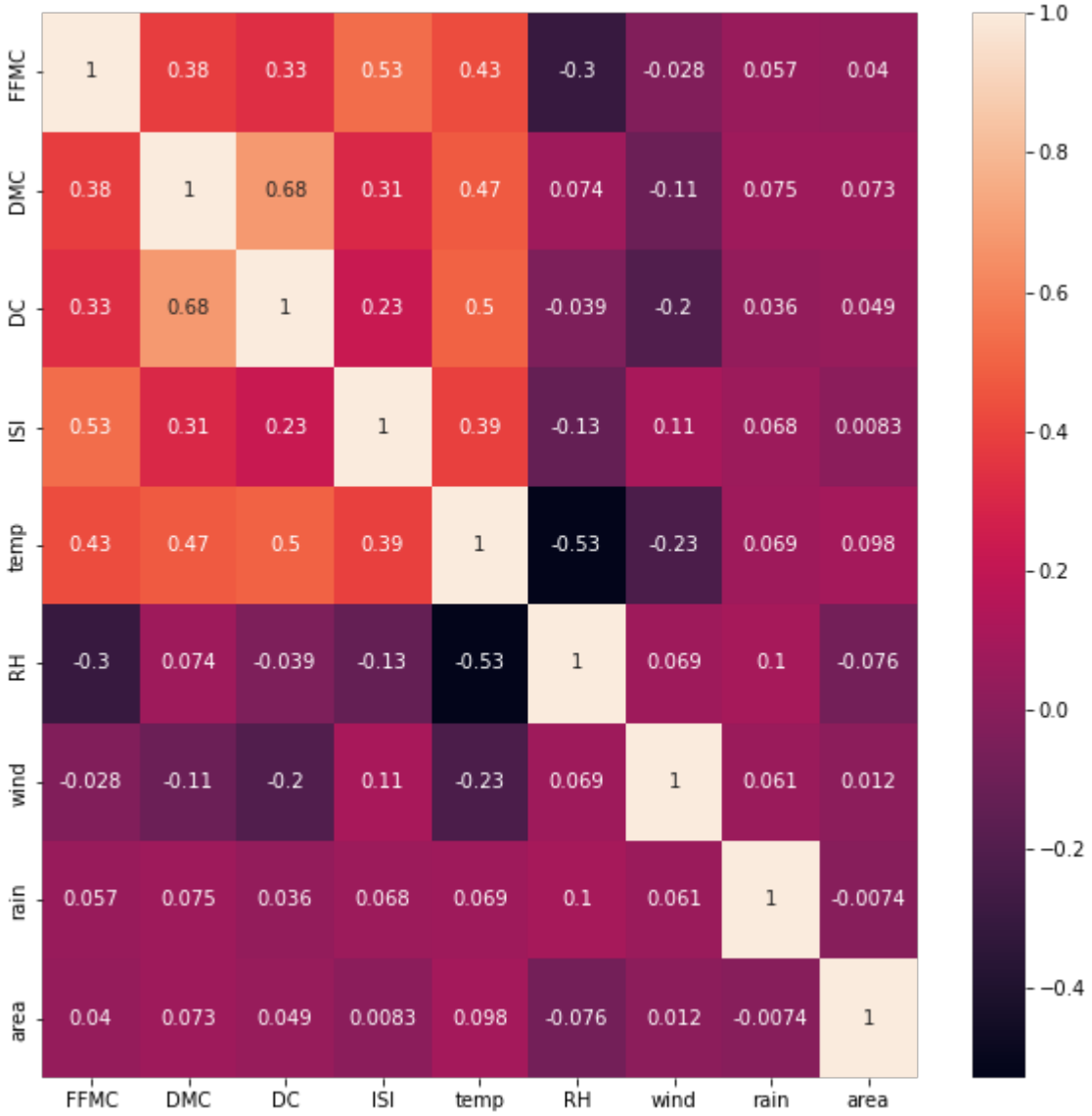
```
month      0
day        0
FFMC       0
DMC        0
DC         0
ISI        0
temp       0
RH         0
```

Finding Correlation

In [9]:

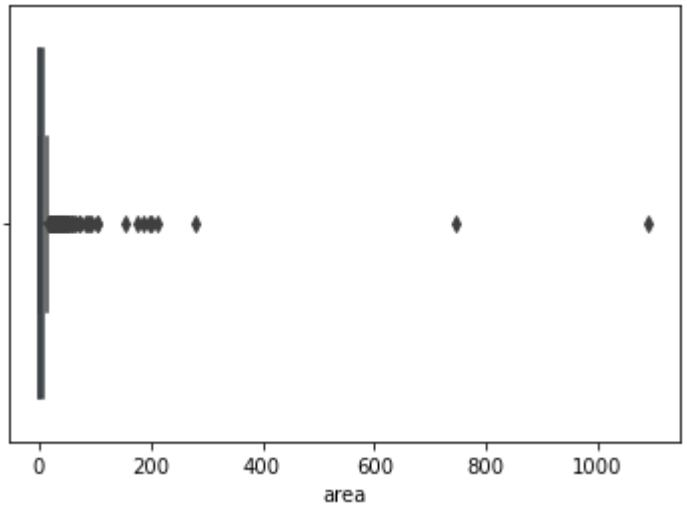
In [10]:
```
plt.figure(figsize=(10,10))
```

Out[10]: <AxesSubplot:>



Outlier Check

In [14]:

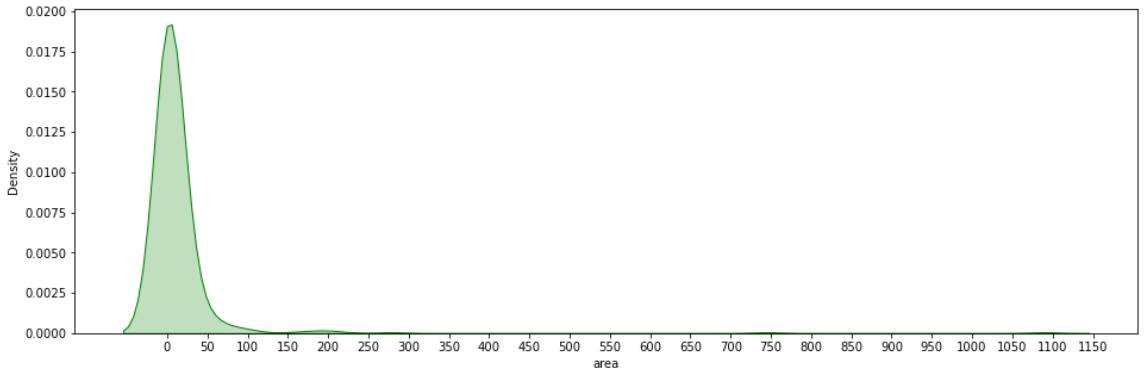


There are 3 Outlier instances in our data

In [15]:

In [17]:
```
plt.figure(figsize=(16,5))
print("Skew: {}".format(fire_data['area'].skew()))
print("Kurtosis: {}".format(fire_data['area'].kurtosis()))
ax = sns.kdeplot(fire_data['area'],shade=True,color='g')
plt.xticks([i for i in range(0,1200,50)])
```

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



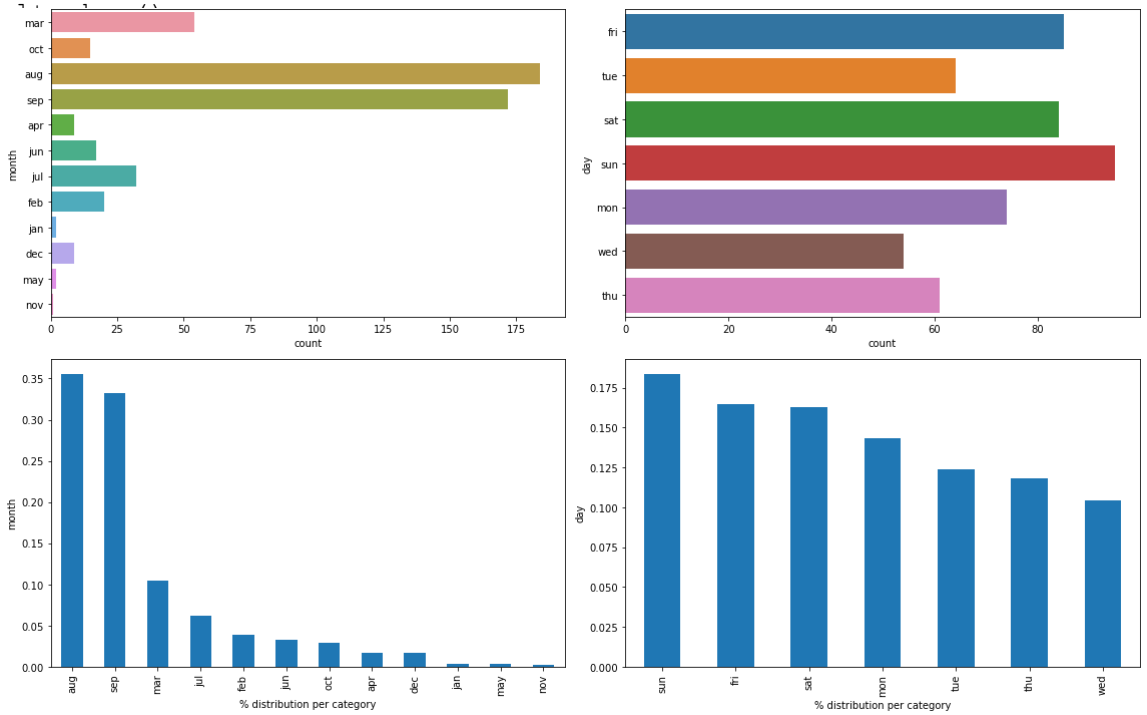
The Data is highly skewed and has large kurtosis value

Majority of the forest fires do not cover a large area, most of the damaged area is under 100 hectares of land

In [18]:
```
dfa = fire_data[fire_data.columns[0:10]]
month_colum = dfa.select_dtypes(include='object').columns.tolist()
```

In [19]:
```
plt.figure(figsize=(16,10))
for i,col in enumerate(month_colum,1):
    plt.subplot(2,2,i)
```

```
    sns.countplot(data=dfa,y=col)
    plt.subplot(2,2,i+2)
    fire_data[col].value_counts(normalize=True).plot.bar()
    plt.ylabel(col)
    plt.xlabel('% distribution per category')
plt.tight_layout()
```

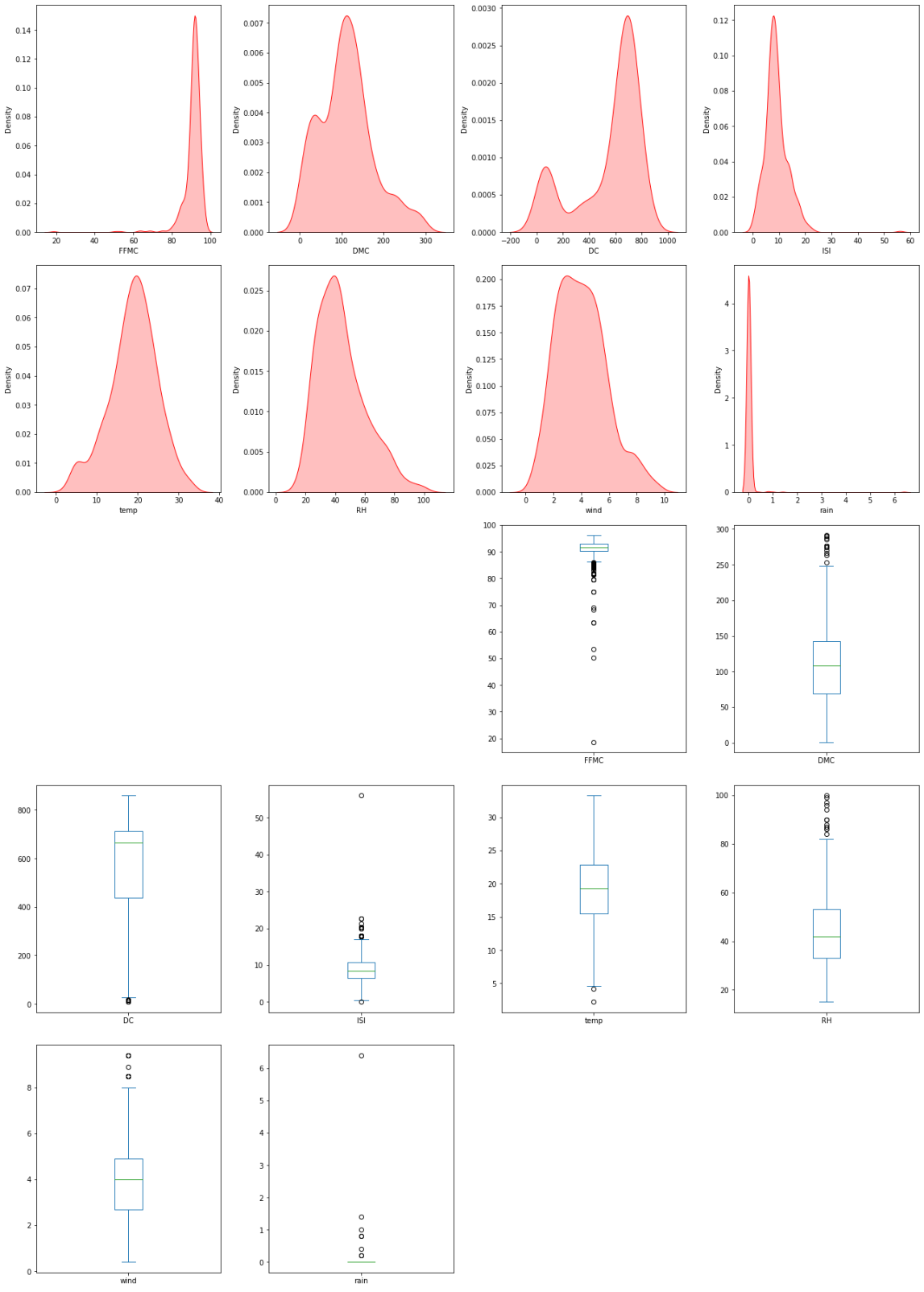


Majority of the fire accors in the month Aug and Sep

For Days Sun and Fri have recoreded the most cases

In [20]:
```
num_columns = dfa.select_dtypes(exclude='object').columns.tolist()
```

In [21]:
```
plt.figure(figsize=(18,40))
for i,col in enumerate(num_columns,1):
    plt.subplot(8,4,i)
    sns.kdeplot(fire_data[col],color='r',shade=True)
    plt.subplot(8,4,i+10)
    fire_data[col].plot.box()
plt.tight_layout()
plt.show()
num_data = fire_data[num_columns]
pd.DataFrame(data=[num_data.skew(),num_data.kurtosis()],index=['skewnes
```



Out[21]:

FFMC	DMC	DC	ISI	temp	RH	wind	r

	FFMC	DMC	DC	ISI	temp	RH	wind	ra
skewness	-6.575606	0.547498	-1.100445	2.536325	-0.331172	0.862904	0.571001	19.8163

3. SVM

In [23]:
```
X = fire_data.iloc[:,2:30]
```

In [24]:
```

```

In [25]:
```

```

In [26]:
```
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size = 0.20,
```

3.1 Linear

In [27]:
```
model_linear = SVC(kernel = "linear")
model_linear.fit(x_train,y_train)
pred_test_linear = model_linear.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, pred_test_linear))
```

```
Accuracy: 0.9807692307692307
```

3.2 Poly

In [28]:
```
model_poly = SVC(kernel = "poly")
model_poly.fit(x_train,y_train)
pred_test_poly = model_poly.predict(x_test)
```

```
Accuracy: 0.7403846153846154
```

3.3 RBF

In [29]:
```
model_rbf = SVC(kernel = "rbf")
model_rbf.fit(x_train,y_train)
pred_test_rbf = model_rbf.predict(x_test)
```

```
Accuracy: 0.7403846153846154
```

3.4 Sigmoid

In [30]:
```
model_sigmoid = SVC(kernel = "sigmoid")
model_sigmoid.fit(x_train,y_train)
pred_test_sigmoid = model_sigmoid.predict(x_test)
print("Accuracy:",metrics.accuracy_score(y_test, pred_test_sigmoid))
```

```
Accuracy: 0.6346153846153846
```

4 - Conclusion

Linear Model gives the best accuracy

Below is an exmaple on how we can plot the data. I used PCA to select only 2 variables

In [31]:

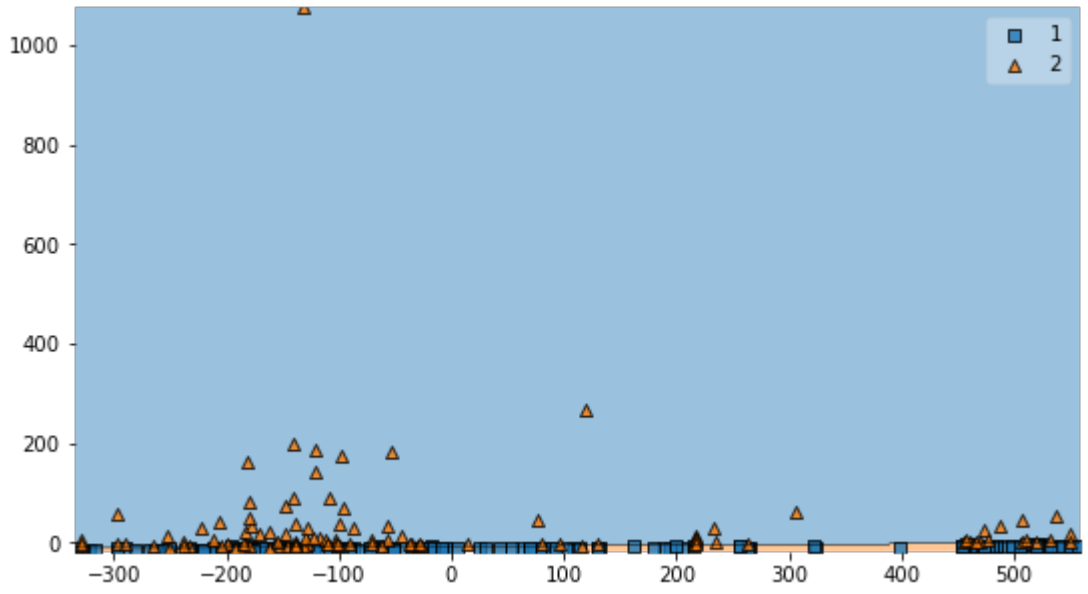
In [32]:

In [33]:

In [35]:

Out[35]: SVC(kernel='linear')

In [39]:
```
plot_decision_regions(x_train2,yt, clf=model_linear)
```



In [ ]: