1 Importing the libraries

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

2 Data

The data is related with the different factors of the crop. The classification goal is to predict the production of the yield.

In [4]:
```
crop=pd.read_csv(r"C:\Users\DD\Desktop\yield\yield.csv")    #importing the data
```

In [5]:
```
crop
```

Out[5]:

	Unnamed: 0	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesti
0	0.0	Albania	Maize	1990.0	36613	1485.0	
1	1.0	Albania	Potatoes	NaN	NaN	NaN	
2	2.0	Albania	Rice, paddy	NaN	NaN	1485.0	
3	3.0	Albania	Sorghum	1990.0	12500	1485.0	
4	4.0	Albania	Soybeans	1990.0	7000	1485.0	
...	...	...	...	...	...	...	
28237	28237.0	Zimbabwe	Rice, paddy	NaN	NaN	NaN	
28238	28238.0	Zimbabwe	Sorghum	NaN	NaN	NaN	
28239	28239.0	Zimbabwe	Soybeans	2013.0	13142	657.0	
28240	28240.0	Zimbabwe	Sweet potatoes	2013.0	22222	657.0	
28241	28241.0	Zimbabwe	Wheat	2013.0	22888	657.0	

28242 rows × 8 columns

3 Data Preprocessing

In [4]:
```
crop.head(3)
```

Out[4]:

	Unnamed: 0	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_to
0	0.0	Albania	Maize	1990.0	36613	1485.0	
1	1.0	Albania	Potatoes	NaN	NaN	NaN	
2	2.0	Albania	Rice, paddy	NaN	NaN	1485.0	

In [5]:
```
crop.tail(3)
```

Out[5]:

	Unnamed: 0	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesti
28239	28239.0	Zimbabwe	Soybeans	2013.0	13142	657.0	
28240	28240.0	Zimbabwe	Sweet potatoes	2013.0	22222	657.0	
28241	28241.0	Zimbabwe	Wheat	2013.0	22888	657.0	

In [6]:
```
crop.info
```

Out[6]:
```
<bound method DataFrame.info of        Unnamed: 0      Area            Item
Year hg/ha_yield  \
0             0.0   Albania           Maize  1990.0       36613
1             1.0   Albania        Potatoes     NaN         NaN
2             2.0   Albania     Rice, paddy     NaN         NaN
3             3.0   Albania         Sorghum  1990.0       12500
4             4.0   Albania        Soybeans  1990.0        7000
...           ...       ...             ...     ...         ...
28237     28237.0  Zimbabwe     Rice, paddy     NaN         NaN
28238     28238.0  Zimbabwe         Sorghum     NaN         NaN
28239     28239.0  Zimbabwe        Soybeans  2013.0       13142
28240     28240.0  Zimbabwe  Sweet potatoes  2013.0       22222
28241     28241.0  Zimbabwe           Wheat  2013.0       22888

       average_rain_fall_mm_per_year  pesticides_tonnes  avg_temp
0                             1485.0             121.00       NaN
1                                NaN                NaN     16.37
2                             1485.0             121.00     16.37
3                             1485.0             121.00     16.37
4                             1485.0                NaN     16.37
...                              ...                ...       ...
28237                            NaN                NaN       NaN
28238                            NaN                NaN       NaN
28239                          657.0            2550.07     19.76
28240                          657.0            2550.07     19.76
28241                          657.0            2550.07     19.76

[28242 rows x 8 columns]>
```

In [7]:
```
crop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28242 entries, 0 to 28241
Data columns (total 8 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   Unnamed: 0                      28079 non-null  float64
 1   Area                            27359 non-null  object 
 2   Item                            27096 non-null  object 
 3   Year                            26716 non-null  float64
 4   hg/ha_yield                     26285 non-null  object 
 5   average_rain_fall_mm_per_year   25539 non-null  float64
 6   pesticides_tonnes               26287 non-null  float64
 7   avg_temp                        25806 non-null  float64
dtypes: float64(5), object(3)
memory usage: 1.7+ MB
```

In [8]:
```
crop.shape
```

Out[8]:
```
(28242, 8)
```

In [9]:
```
crop.describe(include='all')
```

Out[9]:

	Unnamed: 0	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year
count	28079.000000	27359	27096	26716.000000	26285	25539.000000
unique	NaN	101	10	NaN	10489	NaN
top	NaN	India	Potatoes	NaN	10000	NaN
freq	NaN	4039	4070	NaN	94	NaN
mean	14127.489120	NaN	NaN	2001.551243	NaN	1165.771330
std	8157.195199	NaN	NaN	7.045317	NaN	712.639125
min	0.000000	NaN	NaN	1990.000000	NaN	51.000000
25%	7051.500000	NaN	NaN	1995.000000	NaN	593.000000
50%	14128.000000	NaN	NaN	2001.000000	NaN	1083.000000
75%	21200.500000	NaN	NaN	2008.000000	NaN	1668.000000
max	28241.000000	NaN	NaN	2013.000000	NaN	3240.000000

In [10]:
```
crop.nunique()
```

Out[10]:
```
Unnamed: 0                      28079
Area                              101
Item                               10
Year                               23
hg/ha_yield                     10489
average_rain_fall_mm_per_year      99
pesticides_tonnes                1606
avg_temp                         1785
dtype: int64
```

In [11]:
```
(crop.isnull().sum()/(len(crop)))*100
```

Out[11]:
```
Unnamed: 0                        0.577155
Area                              3.126549
Item                              4.057786
Year                              5.403300
hg/ha_yield                       6.929396
average_rain_fall_mm_per_year     9.570852
pesticides_tonnes                 6.922314
avg_temp                          8.625451
dtype: float64
```

In [12]:
```
crop.isnull().sum()
```

Out[12]:
```
Unnamed: 0                         163
Area                               883
Item                              1146
Year                              1526
hg/ha_yield                       1957
average_rain_fall_mm_per_year     2703
pesticides_tonnes                 1955
avg_temp                          2436
dtype: int64
```

In [13]:
```
# Number of years (1990 - 2016)
len(crop.Year.unique())
```

Out[13]:
```
24
```

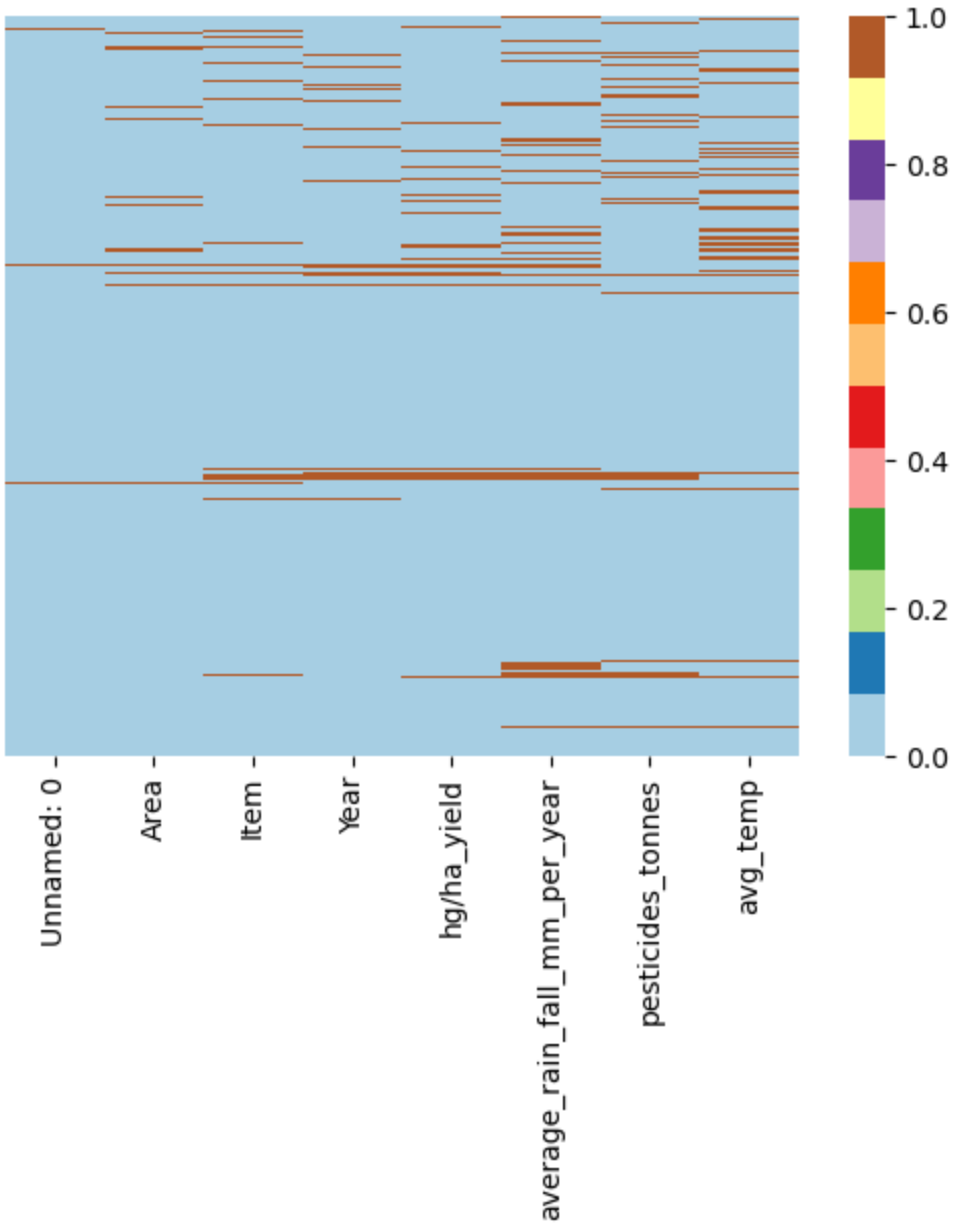
In [14]:
```
# Number of countries
len(crop.Area.unique())
```

Out[14]:
```
102
```

Heatmap show the missing values in data

In [15]:
```
sns.heatmap(crop.isnull(),yticklabels=False,cmap="Paired")
```

Out[15]: <Axes: >



In [16]:
```
crop['Area'].value_counts()   #returns object containing counts of unique value
```

Out[16]:
```
India          4039
Brazil         2136
Mexico         1472
Pakistan       1449
Japan           966
               ...
Estonia          42
Belgium          39
Bahrain          29
Sudan            28
Montenegro       24
Name: Area, Length: 101, dtype: int64
```

In [17]:
```
crop.rename({"Unnamed: 0":"Number","Item":"Crop Name","hg/ha_yield":"Yield (hg/
             "average_rain_fall_mm_per_year":"Rainfall (mm)",
             "avg_temp":"Temperature (Celsius)"}, axis=1, inplace=True)
```

In [18]:
```
crop
```

Out[18]:

	Number	Area	Crop Name	Year	Yield (hg/ha)	Rainfall (mm)	pesticides_tonnes	Temperature (Celsius)
0	0.0	Albania	Maize	1990.0	36613	1485.0	121.00	NaN
1	1.0	Albania	Potatoes	NaN	NaN	NaN	NaN	16.37
2	2.0	Albania	Rice, paddy	NaN	NaN	1485.0	121.00	16.37
3	3.0	Albania	Sorghum	1990.0	12500	1485.0	121.00	16.37
4	4.0	Albania	Soybeans	1990.0	7000	1485.0	NaN	16.37
...	...	...	...	...	...	...	...	...
28237	28237.0	Zimbabwe	Rice, paddy	NaN	NaN	NaN	NaN	NaN
28238	28238.0	Zimbabwe	Sorghum	NaN	NaN	NaN	NaN	NaN
28239	28239.0	Zimbabwe	Soybeans	2013.0	13142	657.0	2550.07	19.76
28240	28240.0	Zimbabwe	Sweet potatoes	2013.0	22222	657.0	2550.07	19.76
28241	28241.0	Zimbabwe	Wheat	2013.0	22888	657.0	2550.07	19.76

28242 rows × 8 columns

In [19]:
```
crop.isnull().sum()
```

Out[19]:
```
Number                  163
Area                    883
Crop Name              1146
Year                   1526
Yield (hg/ha)          1957
Rainfall (mm)          2703
pesticides_tonnes      1955
Temperature (Celsius)  2436
dtype: int64
```

In [20]:
```
crop.dropna(subset=["Number"],inplace=True)
crop.dropna(subset=["Area"],inplace=True)
crop["Crop Name"].fillna(crop["Crop Name"].mode()[0],inplace=True)
crop["Temperature (Celsius)"].fillna(crop["Temperature (Celsius)"].median(),inp
crop["Rainfall (mm)"].fillna(crop["Rainfall (mm)"].median(),inplace=True)
crop["pesticides_tonnes"].fillna(crop["pesticides_tonnes"].median(),inplace=Tru
crop["Year"].ffill(axis=0,inplace=True)
crop["Yield (hg/ha)"].ffill(axis=0,inplace=True)
```

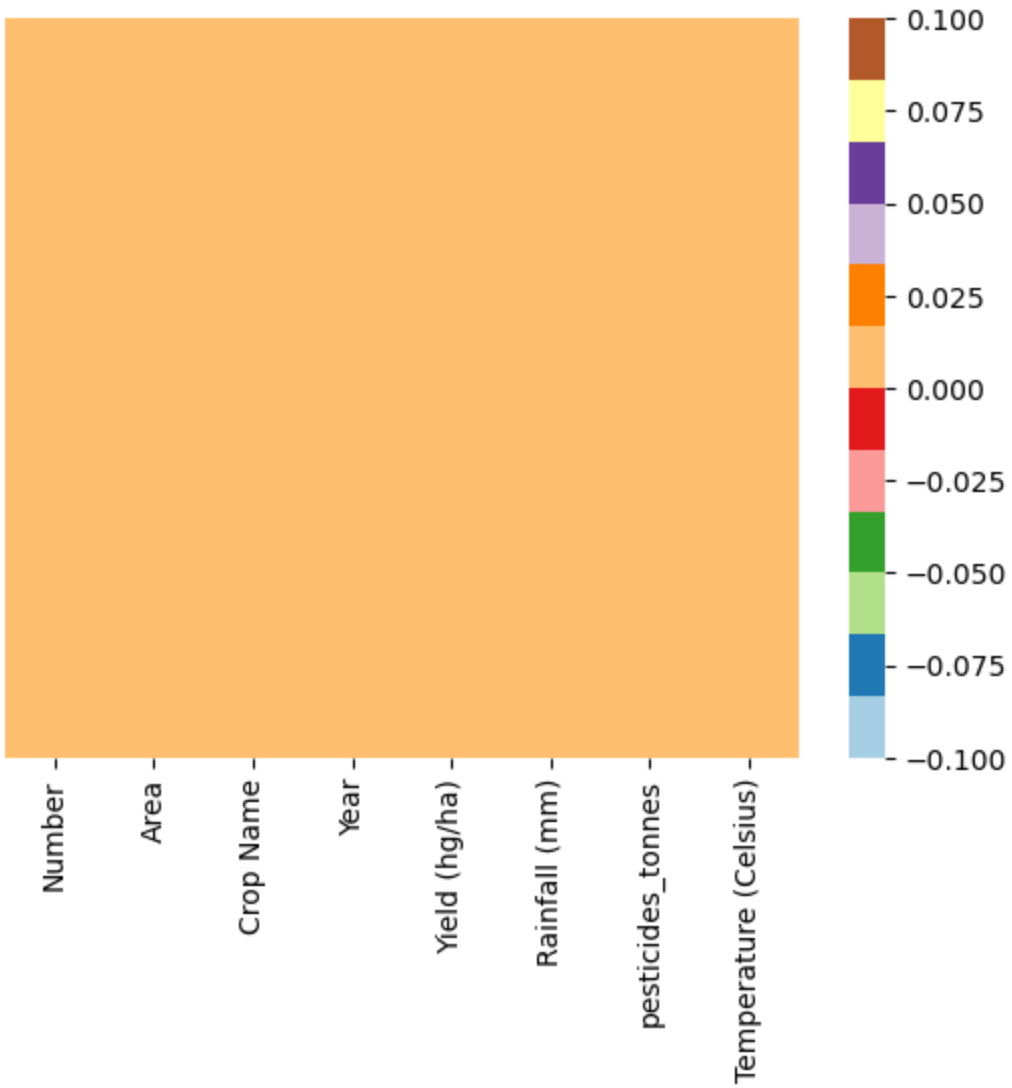
In [21]:
```
crop.isnull().sum()
```

Out[21]:
```
Number                  0
Area                    0
Crop Name               0
Year                    0
Yield (hg/ha)           0
Rainfall (mm)           0
pesticides_tonnes       0
Temperature (Celsius)   0
dtype: int64
```

After treatment their is no missing values in data

In [22]:
```
sns.heatmap(crop.isnull(),yticklabels=False,cmap="Paired")
```

Out[22]:
```
<Axes: >
```



In [23]:
```
crop.drop(["Number"],axis=1,inplace=True)
```

In [24]:
```
crop
```

Out[24]:

	Area	Crop Name	Year	Yield (hg/ha)	Rainfall (mm)	pesticides_tonnes	Temperature (Celsius)
0	Albania	Maize	1990.0	36613	1485.0	121.00	21.69
1	Albania	Potatoes	1990.0	36613	1083.0	17529.44	16.37
2	Albania	Rice, paddy	1990.0	36613	1485.0	121.00	16.37
3	Albania	Sorghum	1990.0	12500	1485.0	121.00	16.37
4	Albania	Soybeans	1990.0	7000	1485.0	17529.44	16.37
...	...	...	...	...	...	...	...
28237	Zimbabwe	Rice, paddy	2013.0	165714	1083.0	17529.44	21.69
28238	Zimbabwe	Sorghum	2013.0	165714	1083.0	17529.44	21.69
28239	Zimbabwe	Soybeans	2013.0	13142	657.0	2550.07	19.76
28240	Zimbabwe	Sweet potatoes	2013.0	22222	657.0	2550.07	19.76
28241	Zimbabwe	Wheat	2013.0	22888	657.0	2550.07	19.76

27339 rows × 7 columns

In [25]:
```
cat_data=crop.select_dtypes(include=object)     # show catogorical data column
num_data=crop.select_dtypes(exclude=object)     # show numerical data in columr
```

In [26]:
```
cat_data
```

Out[26]:

	Area	Crop Name	Yield (hg/ha)
0	Albania	Maize	36613
1	Albania	Potatoes	36613
2	Albania	Rice, paddy	36613
3	Albania	Sorghum	12500
4	Albania	Soybeans	7000
...	...	...	...
28237	Zimbabwe	Rice, paddy	165714
28238	Zimbabwe	Sorghum	165714
28239	Zimbabwe	Soybeans	13142
28240	Zimbabwe	Sweet potatoes	22222
28241	Zimbabwe	Wheat	22888

27339 rows × 3 columns

In [27]:
```
num_data
```

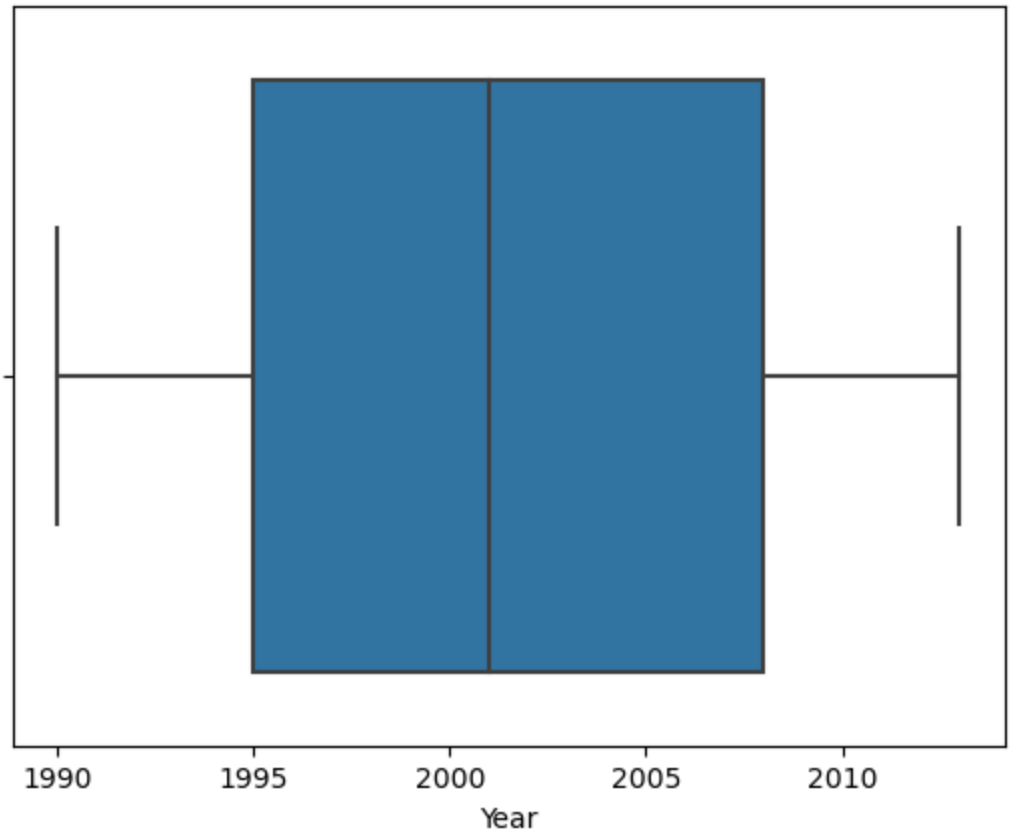
Out[27]:

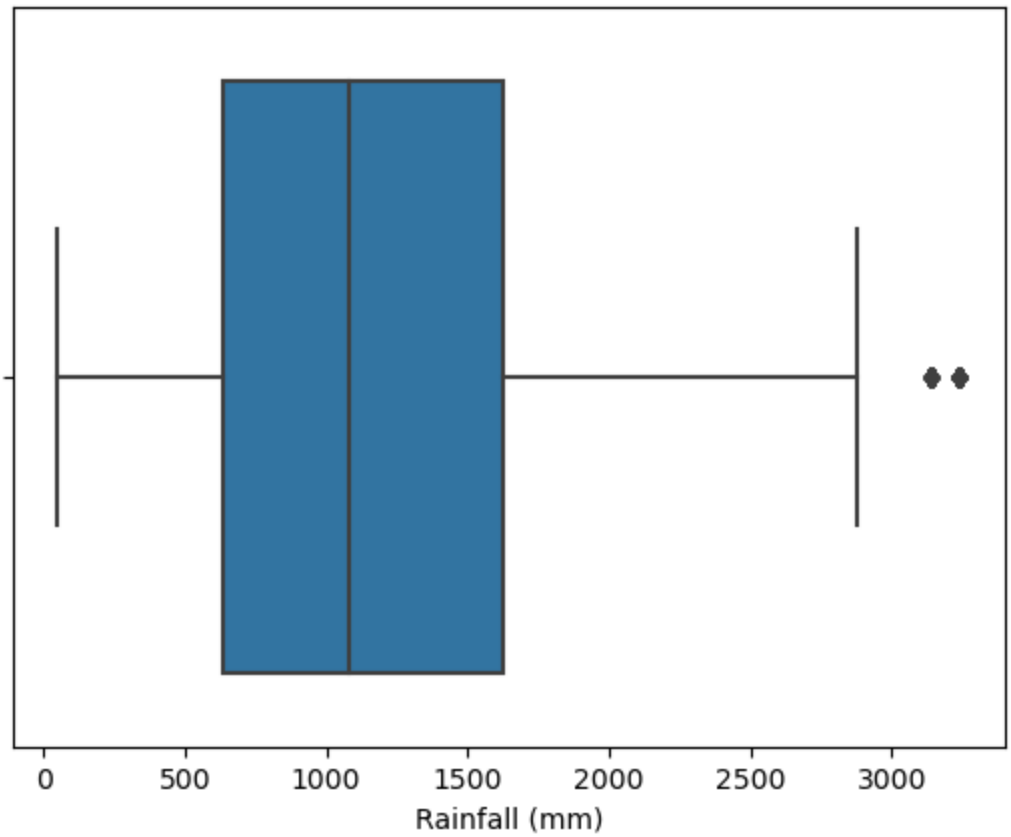
	Year	Rainfall (mm)	pesticides_tonnes	Temperature (Celsius)
0	1990.0	1485.0	121.00	21.69
1	1990.0	1083.0	17529.44	16.37
2	1990.0	1485.0	121.00	16.37
3	1990.0	1485.0	121.00	16.37
4	1990.0	1485.0	17529.44	16.37
...	...	...	...	...
28237	2013.0	1083.0	17529.44	21.69
28238	2013.0	1083.0	17529.44	21.69
28239	2013.0	657.0	2550.07	19.76
28240	2013.0	657.0	2550.07	19.76
28241	2013.0	657.0	2550.07	19.76

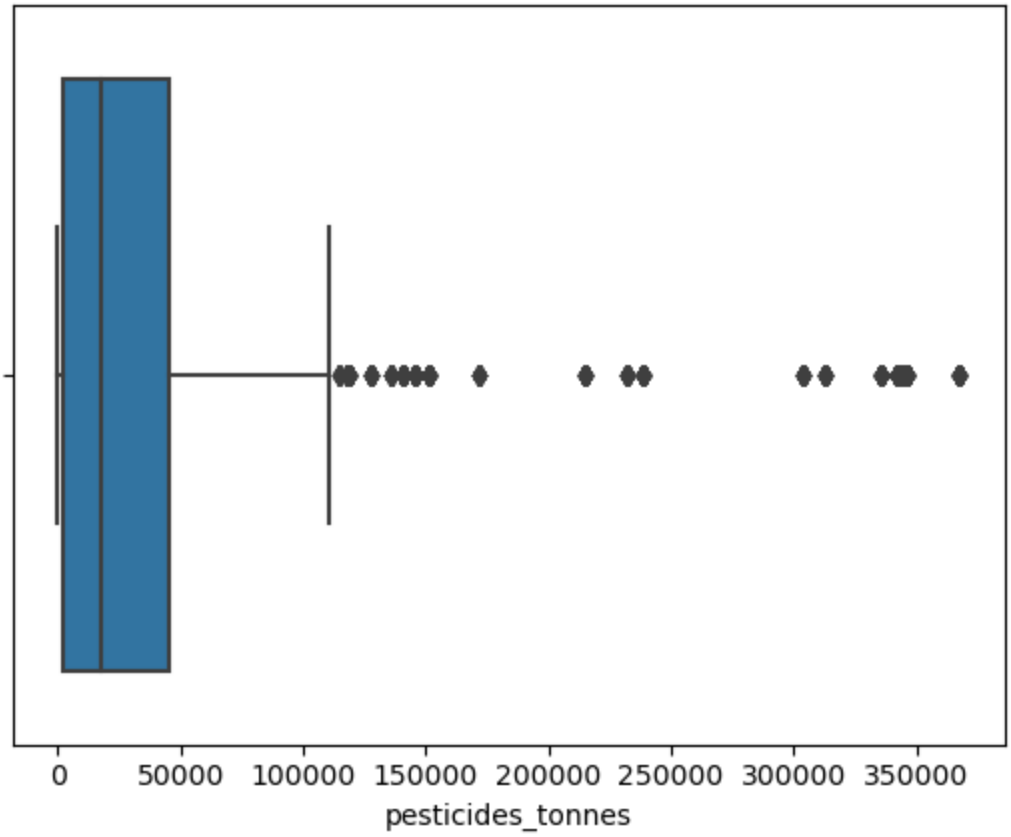
27339 rows × 4 columns

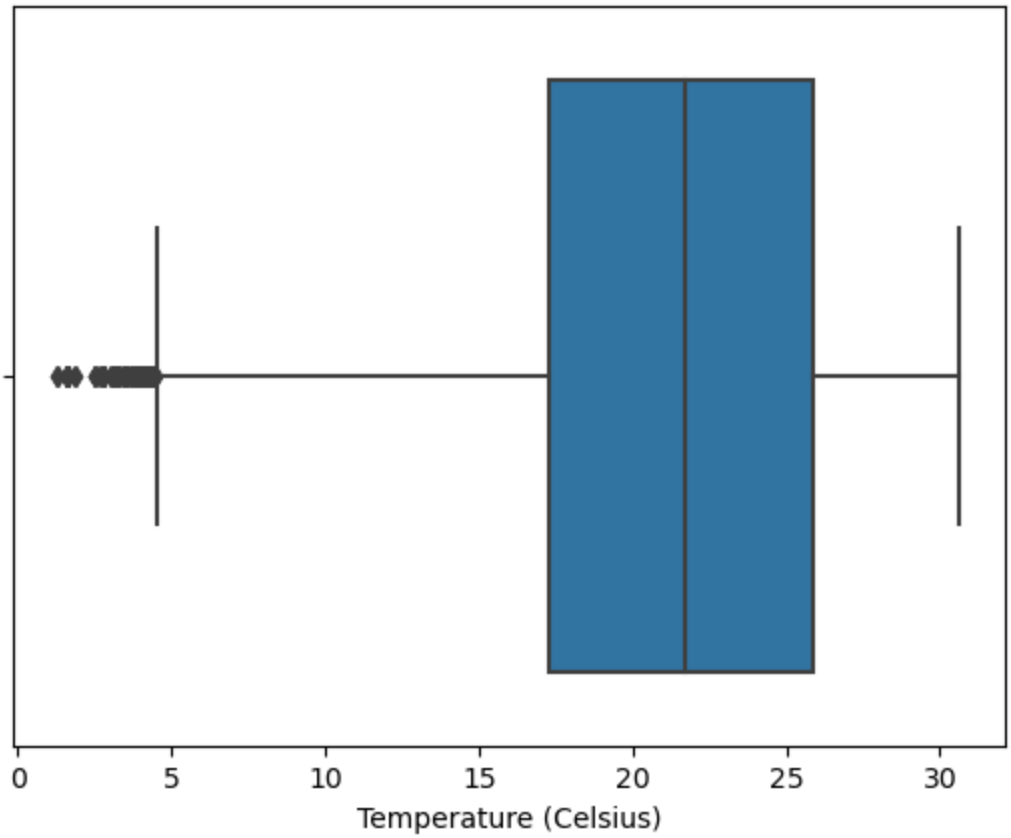
4 Exploratory Data Analysis (EDA)

In [28]:
```
for i in num_data.columns:
    sns.boxplot(x=crop[i])   #Boxplot show Numeric data
    plt.show()
```

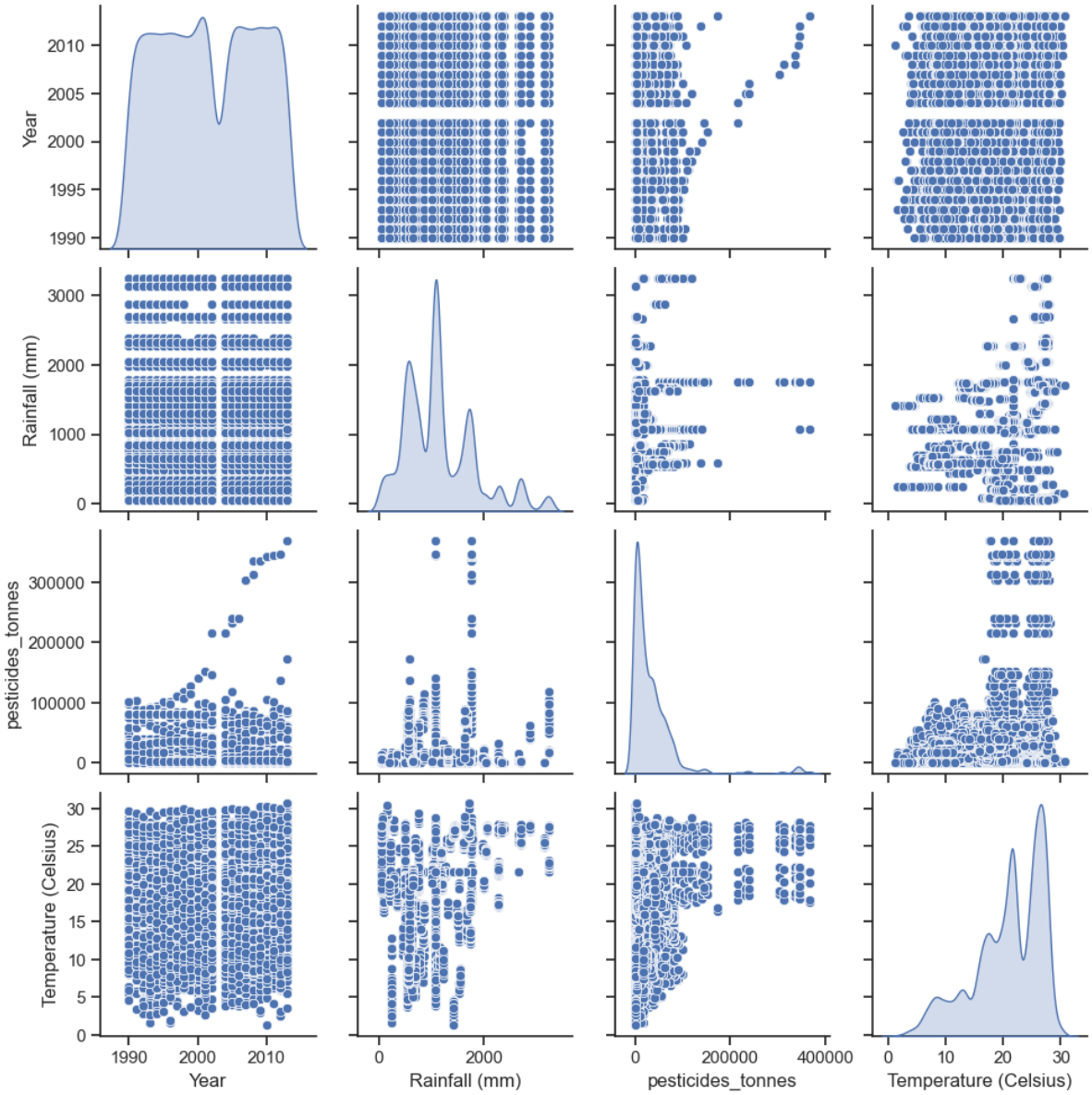




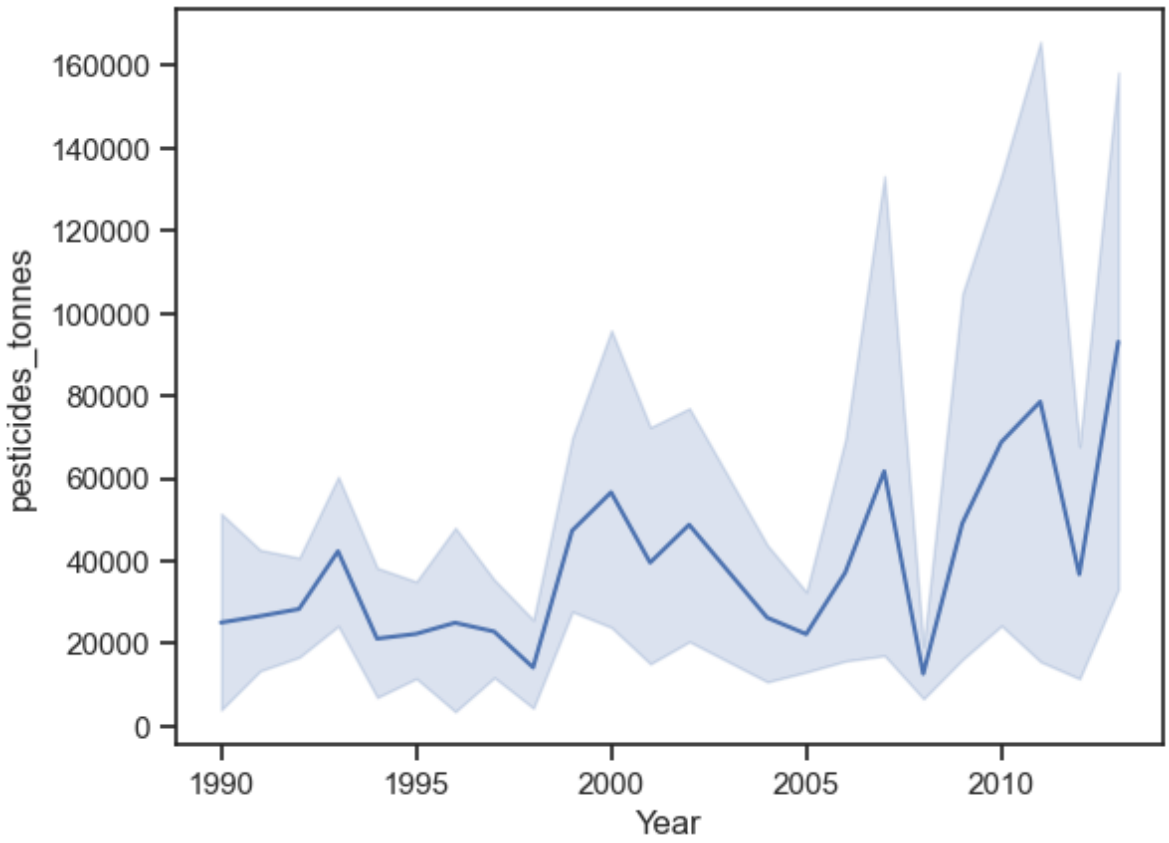

0
50000
100000
150000
200000
250000
300000
350000
pesticides_tonnes


0
5
10
15
20
25
30
Temperature (Celsius)

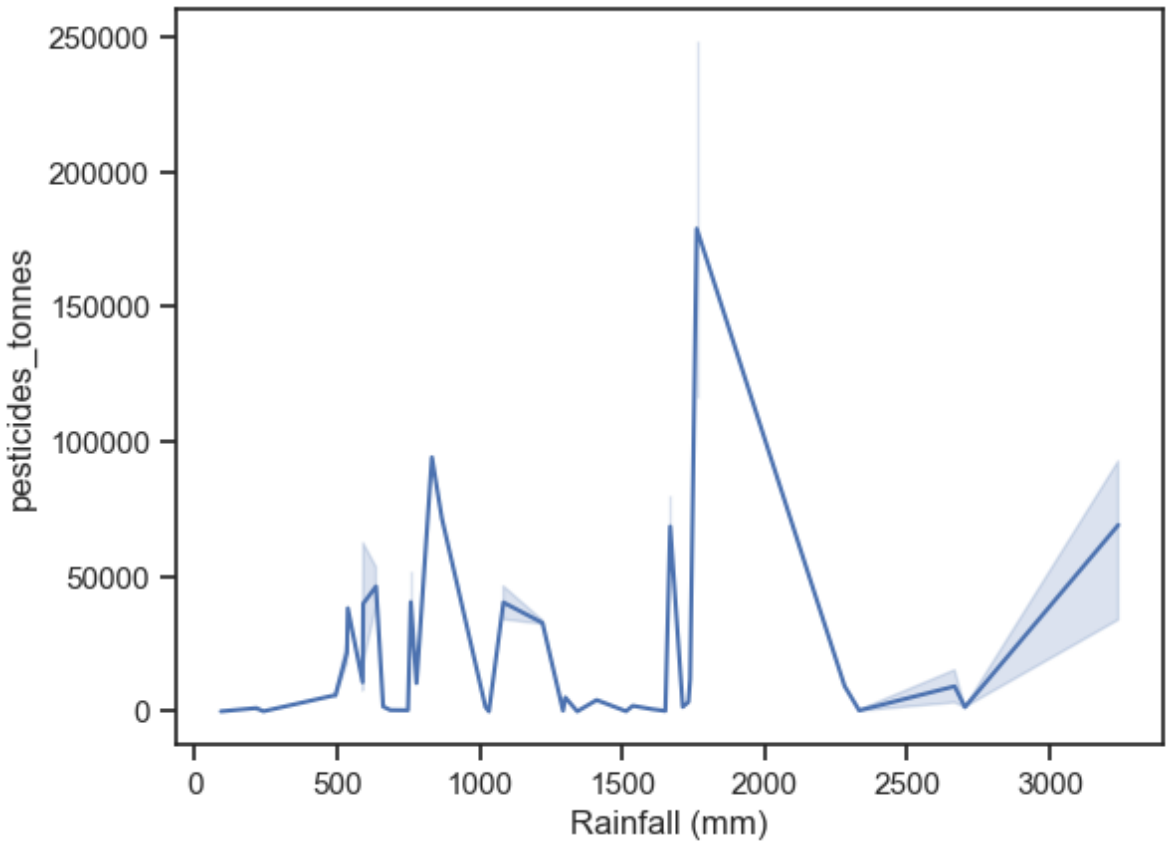
In [29]:
```
sns.set(style="ticks")
sns.pairplot(crop, diag_kind="kde", markers="o")
plt.show()
```



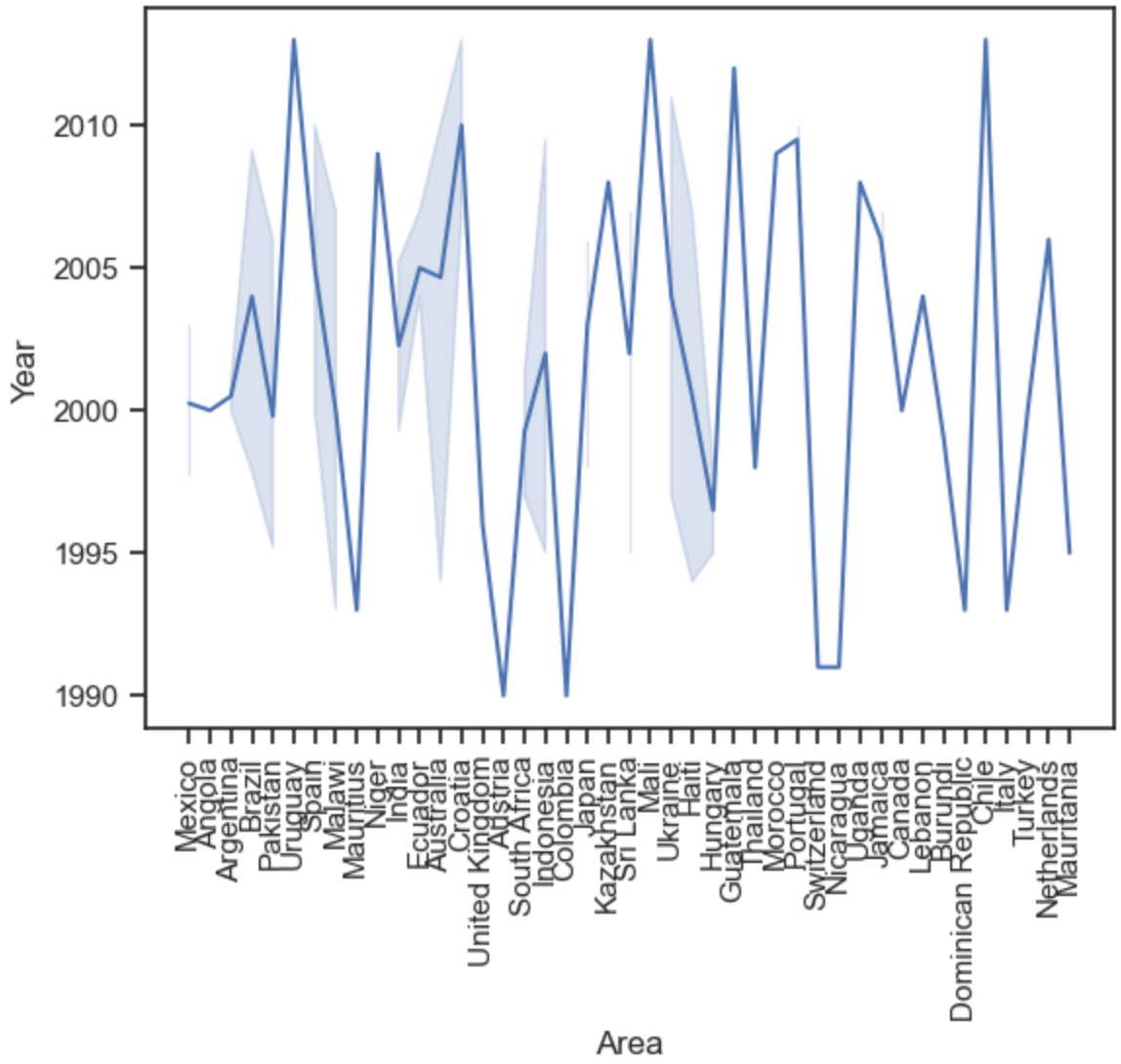
In [30]:
```
a=crop.sample(250)
sns.lineplot(x="Year",y="pesticides_tonnes",data=a)
plt.show()
```



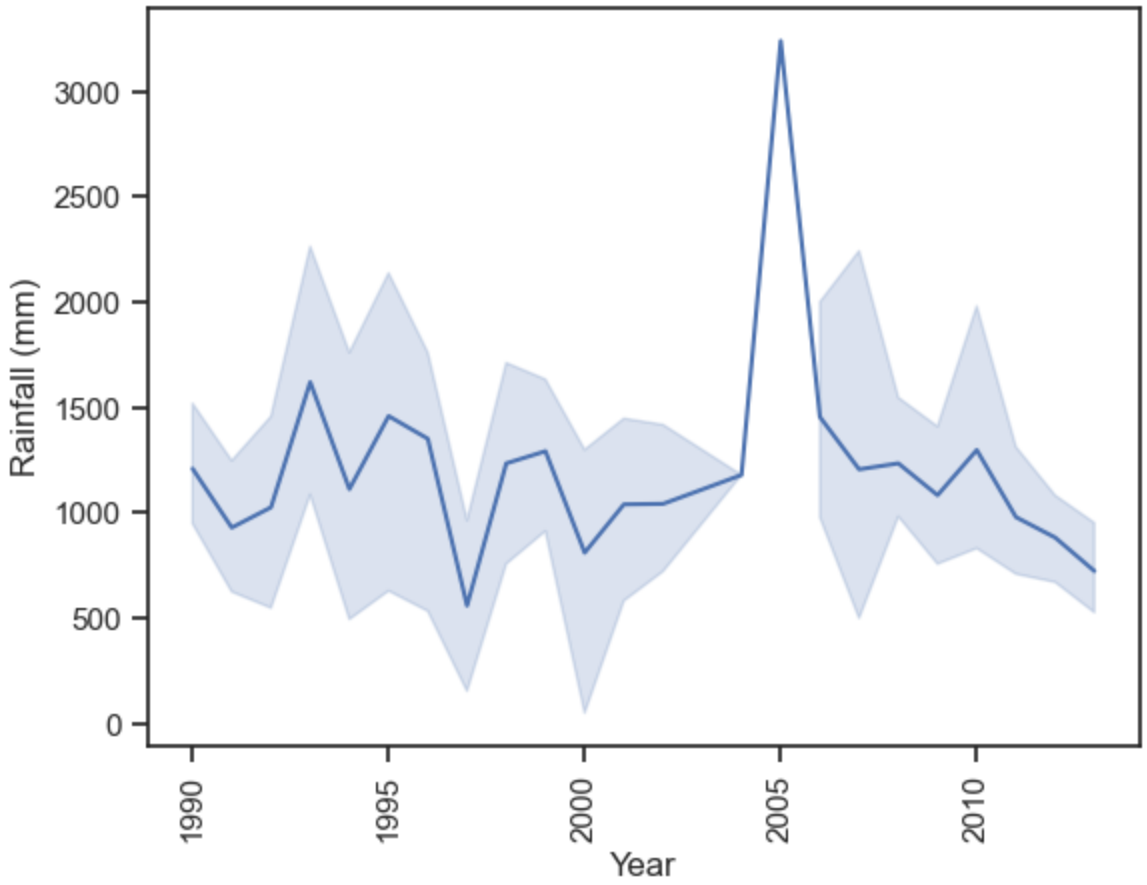
In [31]:
```
a=crop.sample(105)
sns.lineplot(x="Rainfall (mm)",y="pesticides_tonnes",data=a)
plt.show()
```



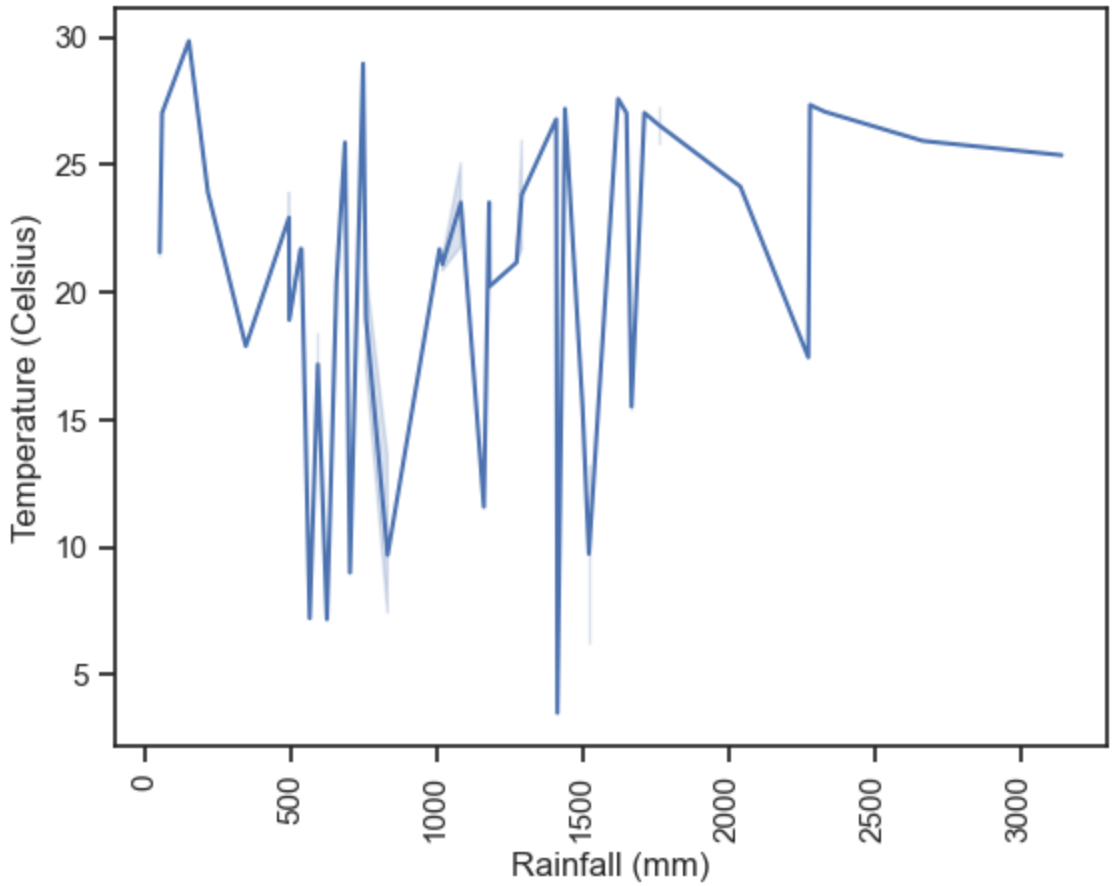
In [32]:
```
a=crop.sample(99)
figsize=(22,10)
sns.lineplot(x="Area",y="Year",data=a)
plt.xticks(rotation=90)
plt.show()
```



In [33]:
```
a=crop.sample(99)
figsize=(22,10)
sns.lineplot(x="Year",y="Rainfall (mm)",data=a)
plt.xticks(rotation=90)
plt.show()
```

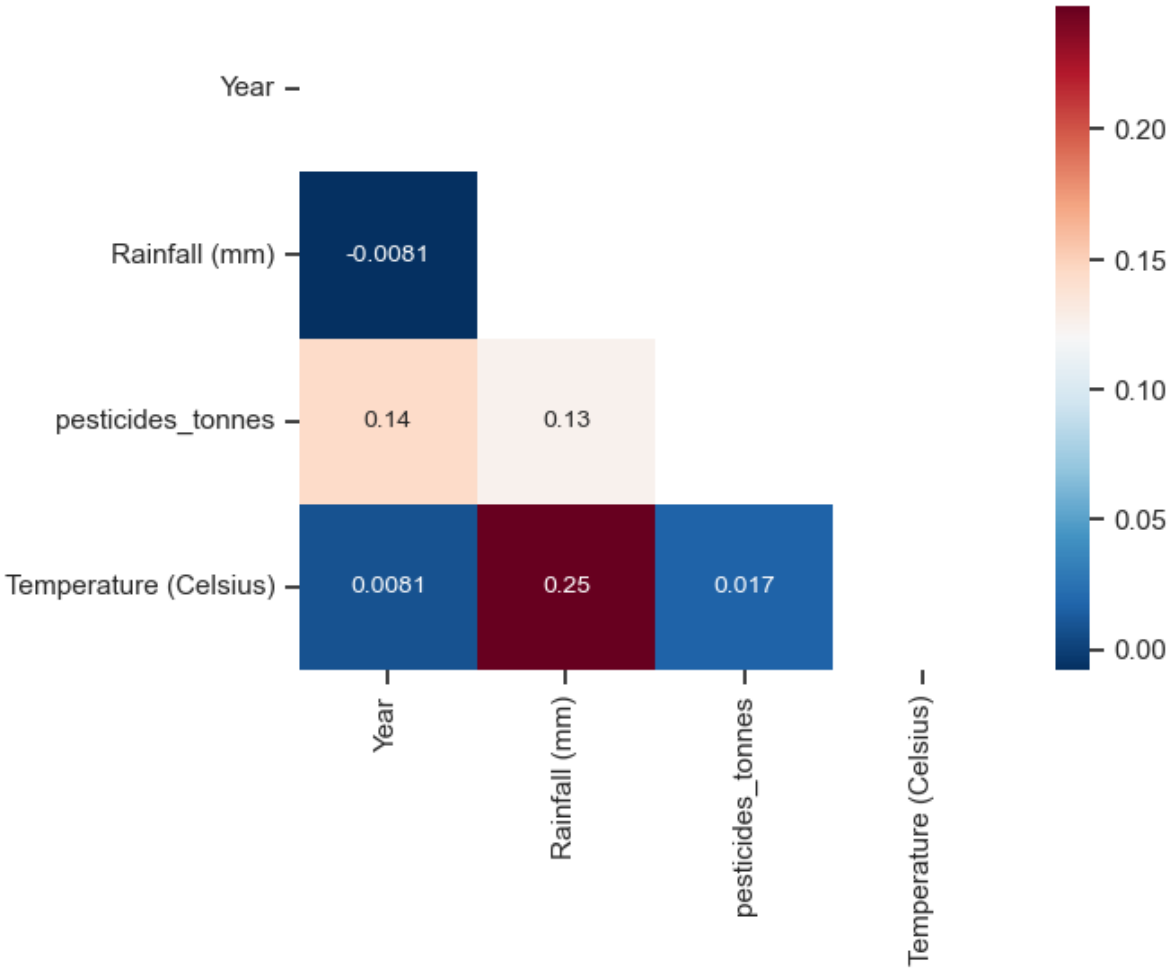


In [34]:
```
a=crop.sample(99)
figsize=(50,30)
sns.lineplot(x="Rainfall (mm)",y="Temperature (Celsius)",data=a)
plt.xticks(rotation=90)
plt.show()
```



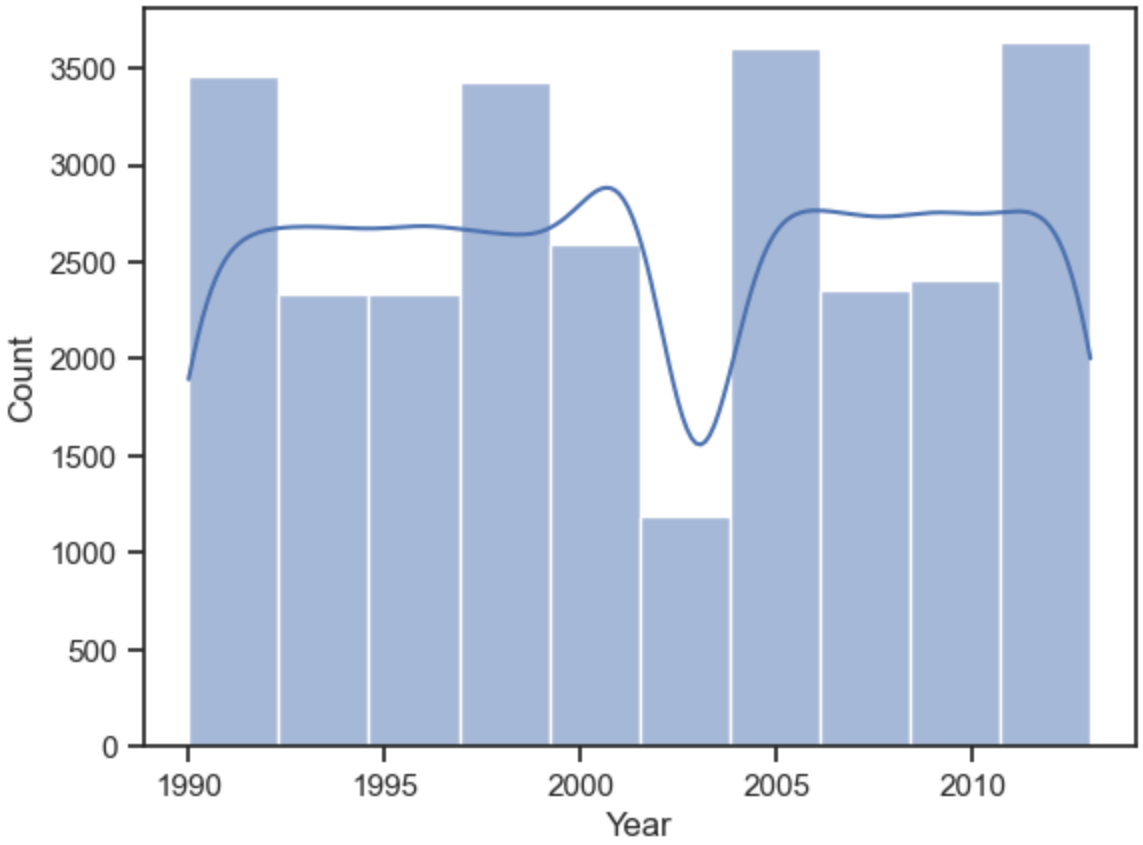
In [35]:
```
corr=num_data.corr()
msk = np.triu(np.ones_like(corr))
sns.heatmap(corr,cmap=plt.cm.RdBu_r,annot=True,annot_kws={'size':10},mask=msk)
```

Out[35]: <Axes: >

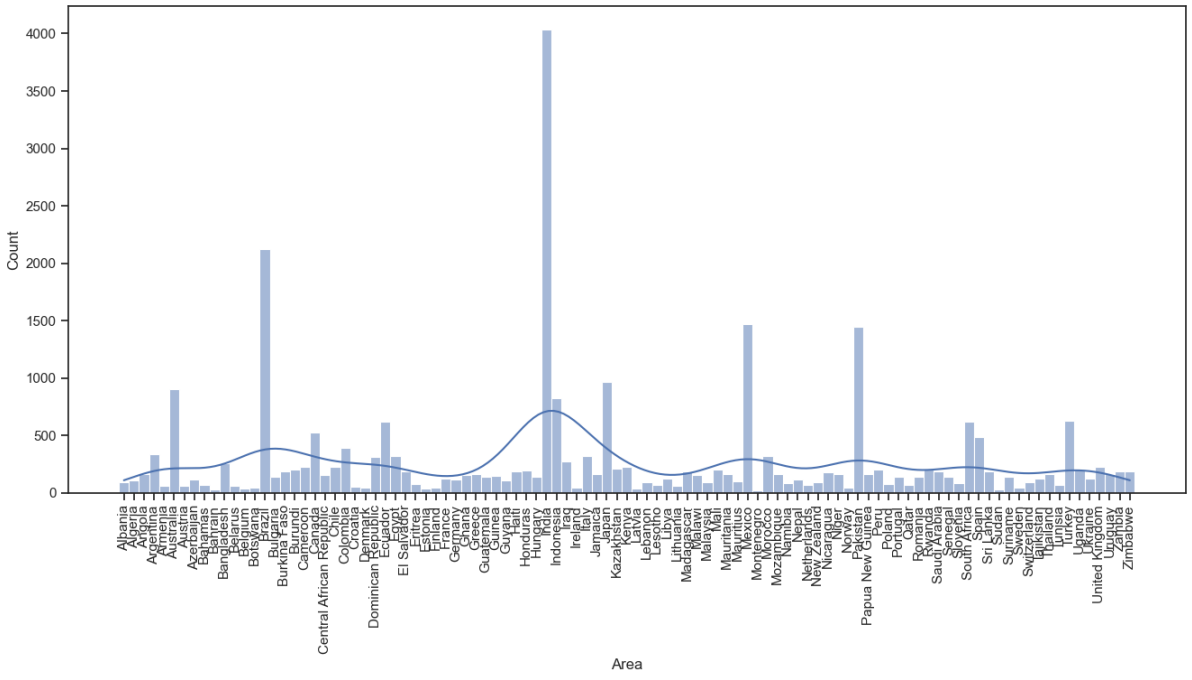


In [36]:
```
sns.histplot(crop["Year"],bins=10,kde=True)
```

Out[36]:
```
<Axes: xlabel='Year', ylabel='Count'>
```

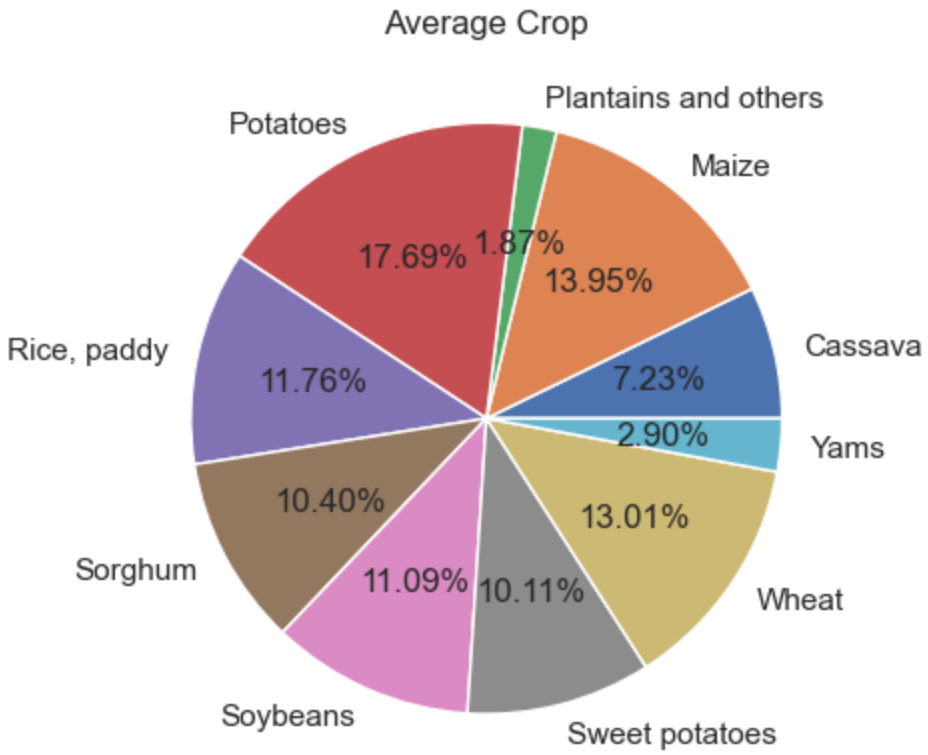


In [37]:
```
plt.figure(figsize=(16,7))
sns.histplot(crop["Area"],bins=10,kde=True)
plt.xticks(rotation=90)
plt.show()
```



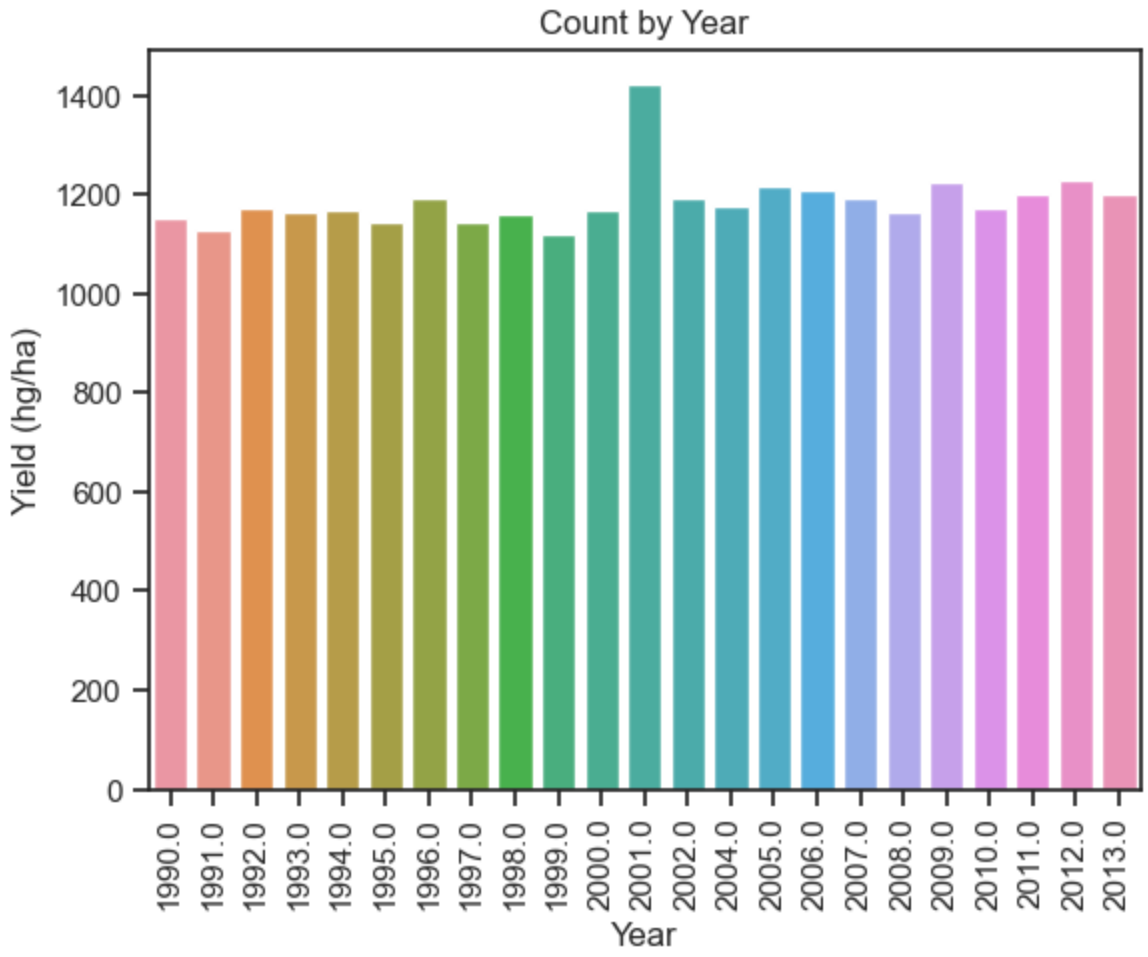
In [38]:
```
b=crop.groupby("Crop Name")["Crop Name"].count()
```

In [39]:
```
plt.pie(b,labels=b.index,autopct="%.2f%%")
plt.xticks(rotation=90)
plt.title("Average Crop")
plt.show()
```

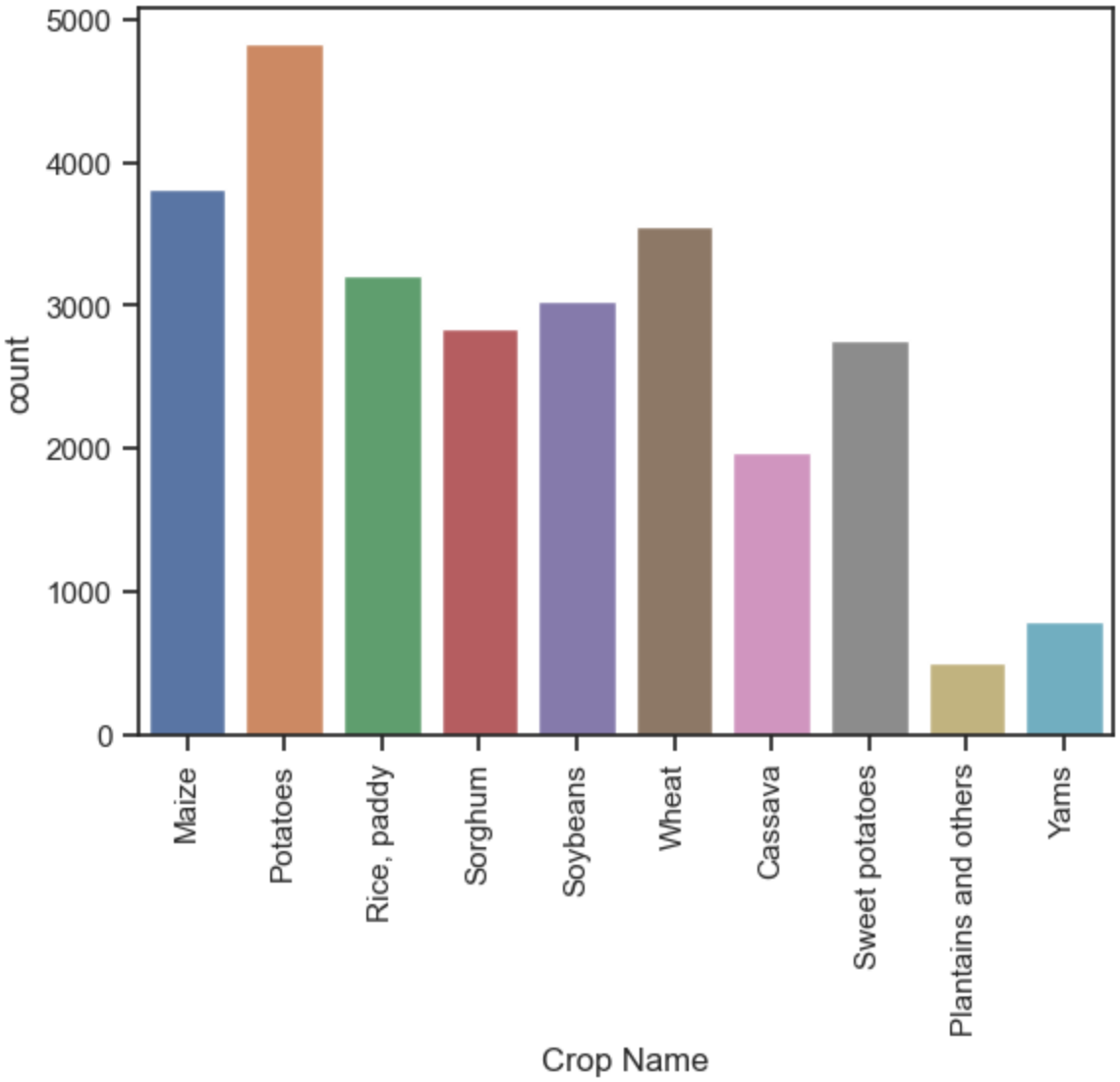


In [42]:
```
b=crop.groupby("Year")["Year"].count()
```

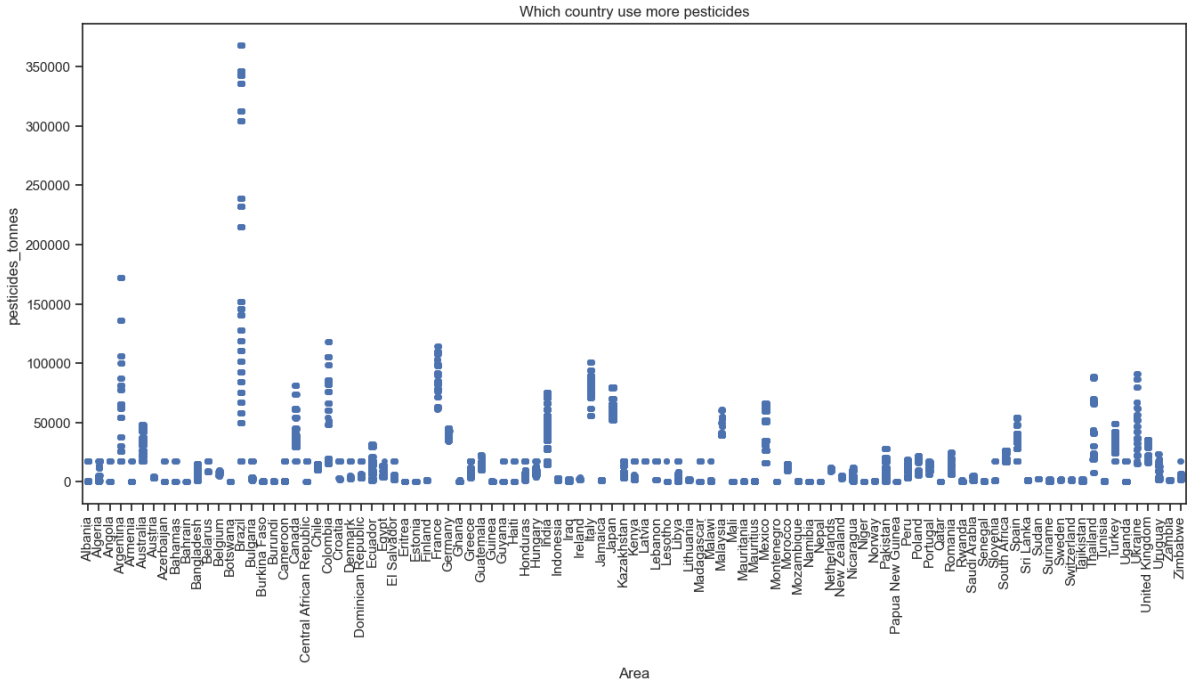
In [43]:
```
sns.barplot(x=b.index,y=b.values)
plt.xticks(rotation=90)
plt.title("Count by Year")
plt.xlabel("Year")
plt.ylabel("Yield (hg/ha)")
plt.show()
```



In [44]:
```
sns.countplot(x='Crop Name',data=crop)
plt.xticks(rotation=90)
plt.show()
```

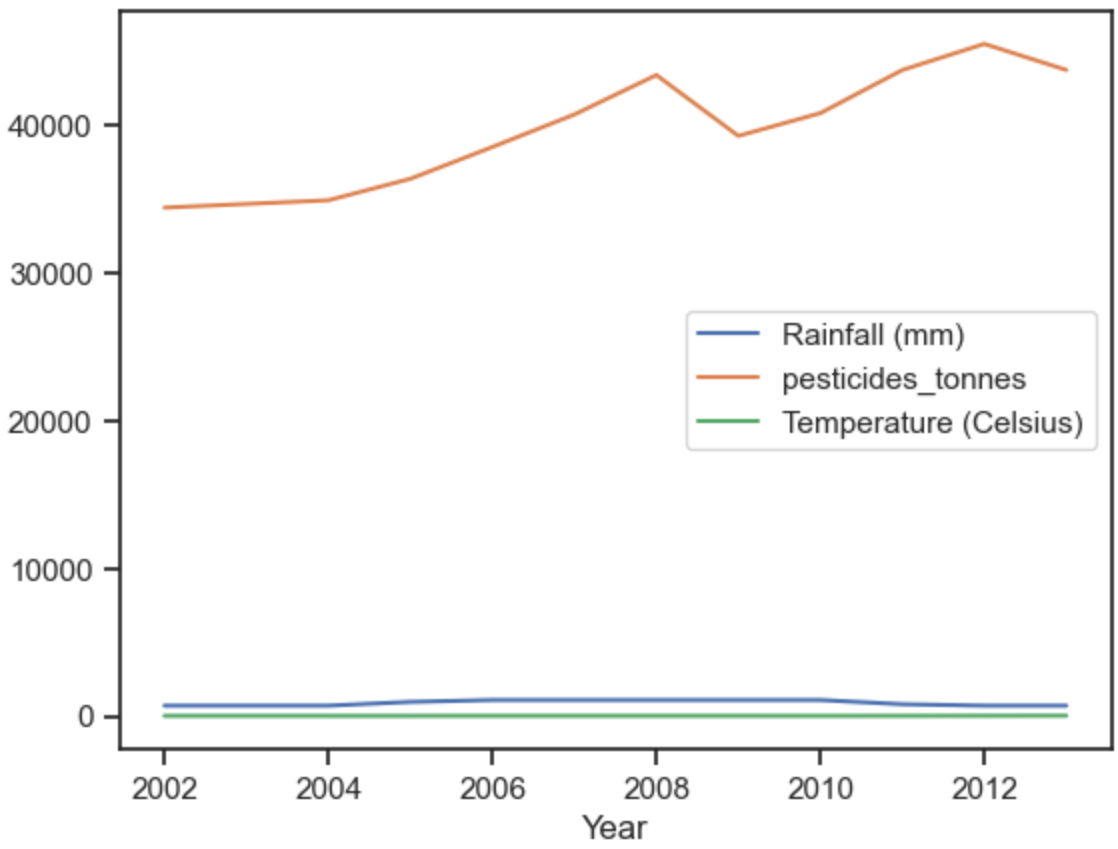


In [45]:
```
plt.figure(figsize=(16,7))
sns.stripplot(x="Area",y="pesticides_tonnes",data=crop)
plt.title("Which country use more pesticides")
plt.xticks(rotation=90)
plt.show()
```



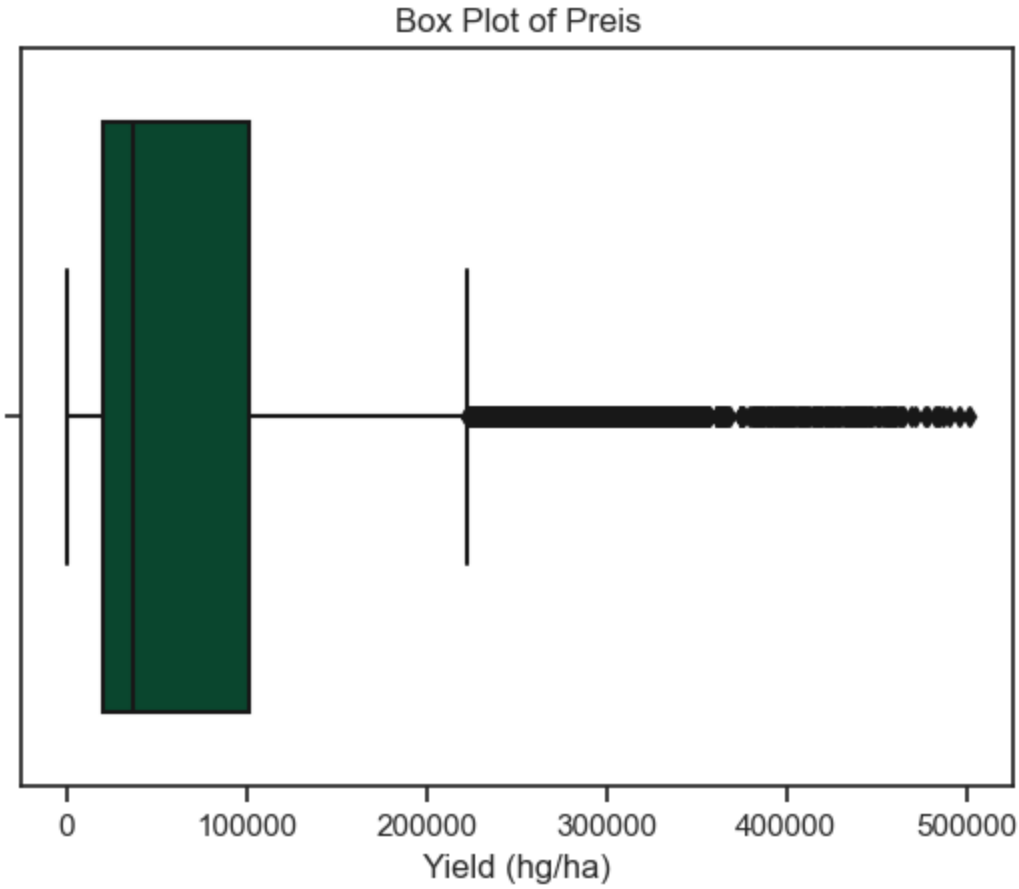
In [46]:
```
crop.loc[crop['Area'] == 'Germany'].groupby('Year').mean().plot()
plt.show()
```

```
C:\Users\DD\AppData\Local\Temp\ipykernel_6992\362564267.py:1: FutureWarning:
The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In
a future version, numeric_only will default to False. Either specify numeric_
only or select only columns which should be valid for the function.
  crop.loc[crop['Area'] == 'Germany'].groupby('Year').mean().plot()
```

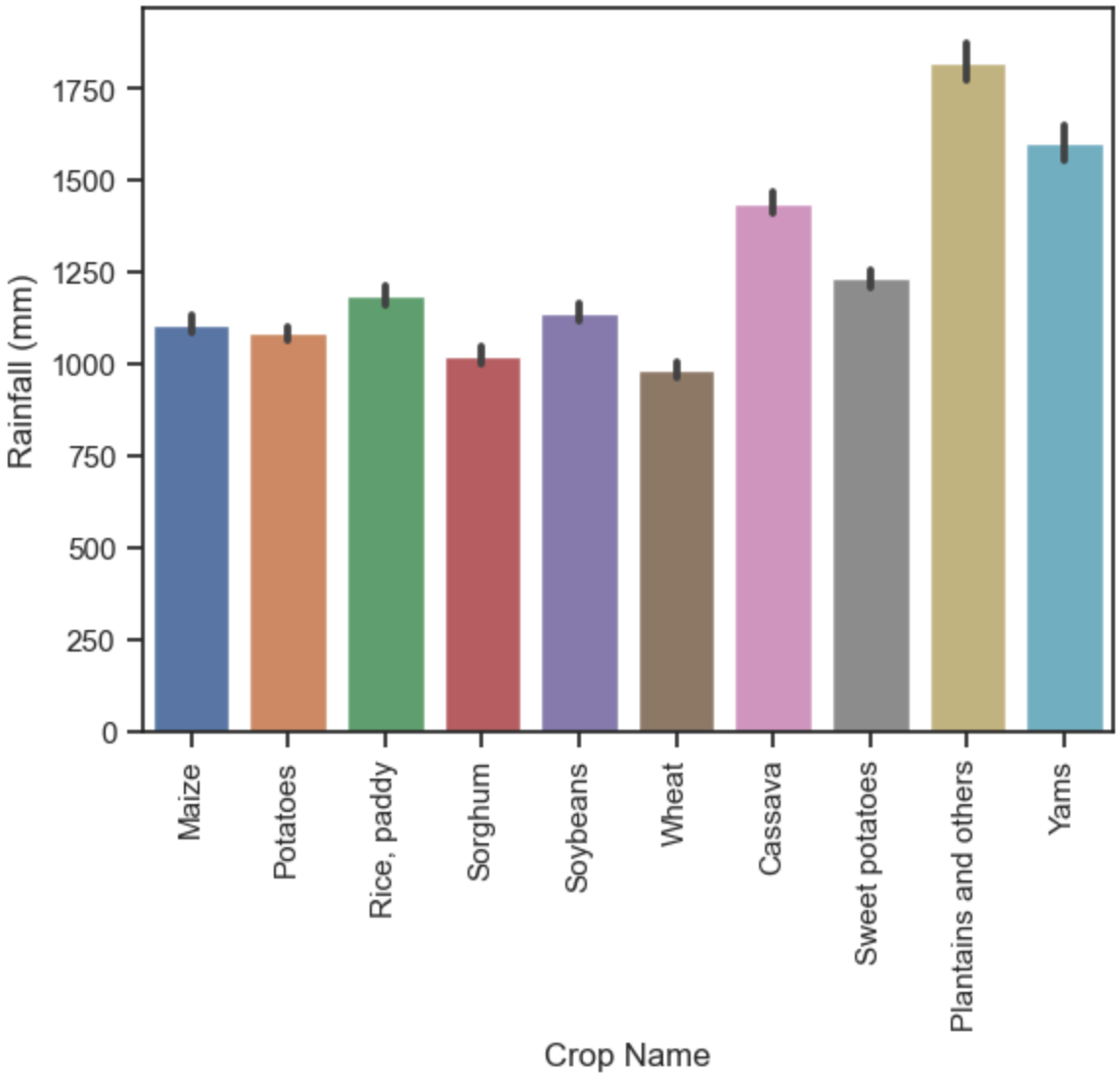


In [113]:
```
sns.boxplot(x=df_new['Yield (hg/ha)'],color='#005030')
plt.title(f'Box Plot of Preis')
```

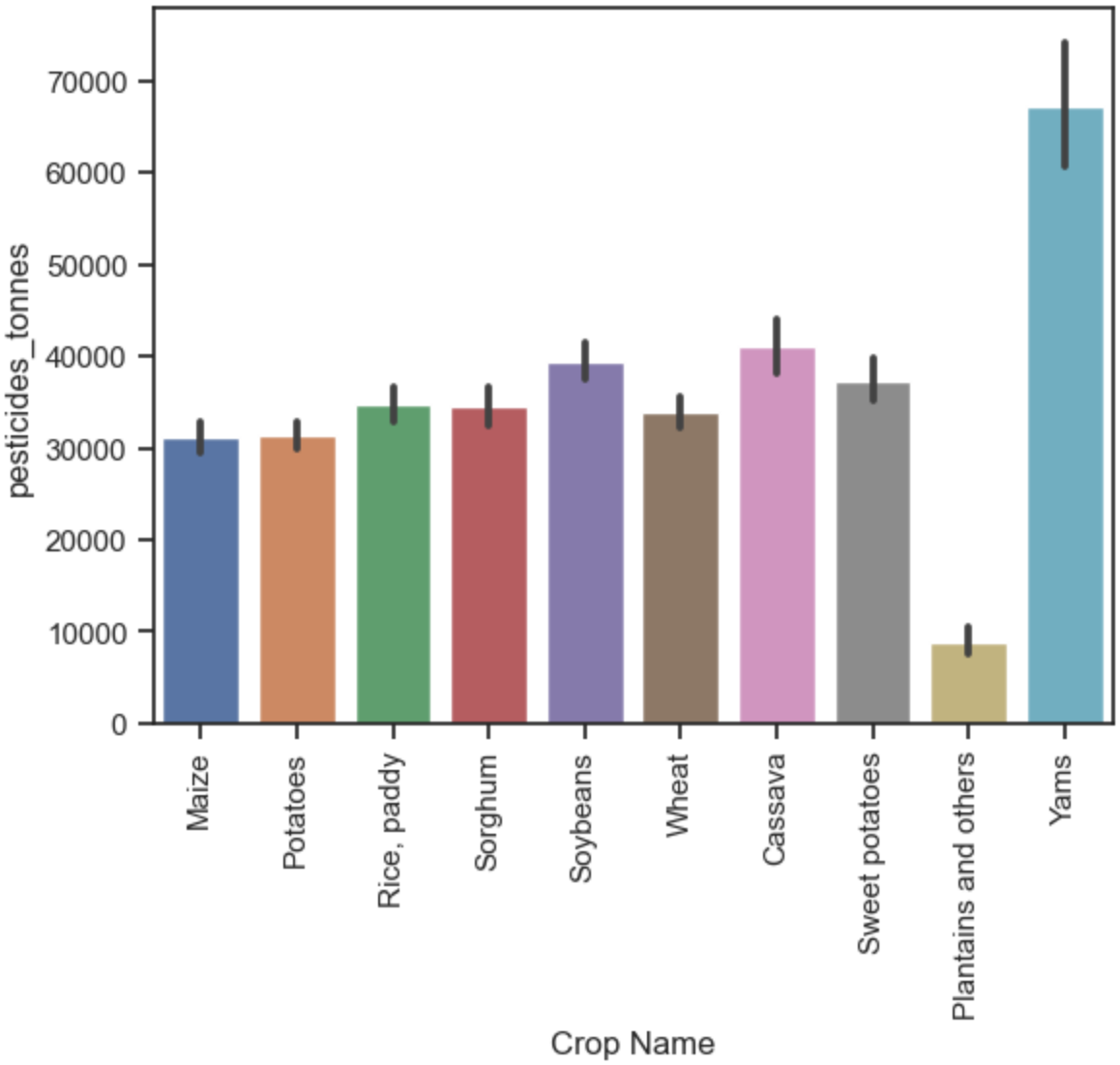
Out[113]:
```
Text(0.5, 1.0, 'Box Plot of Preis')
```



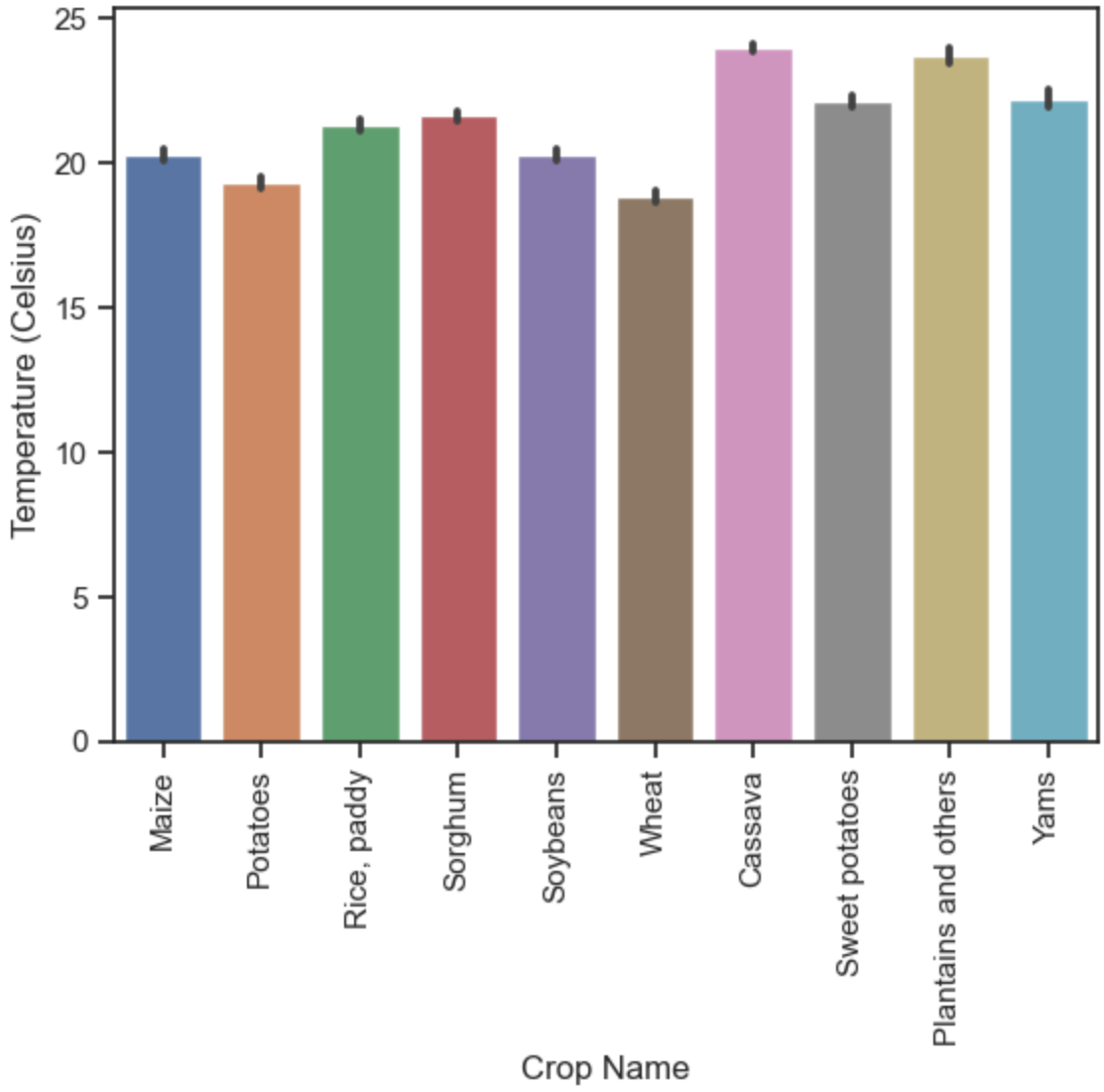
In [120]:
```
sns.barplot(x='Crop Name', y='Rainfall (mm)', data=crop, orient='v')
plt.xticks(rotation=90)
plt.show()
```



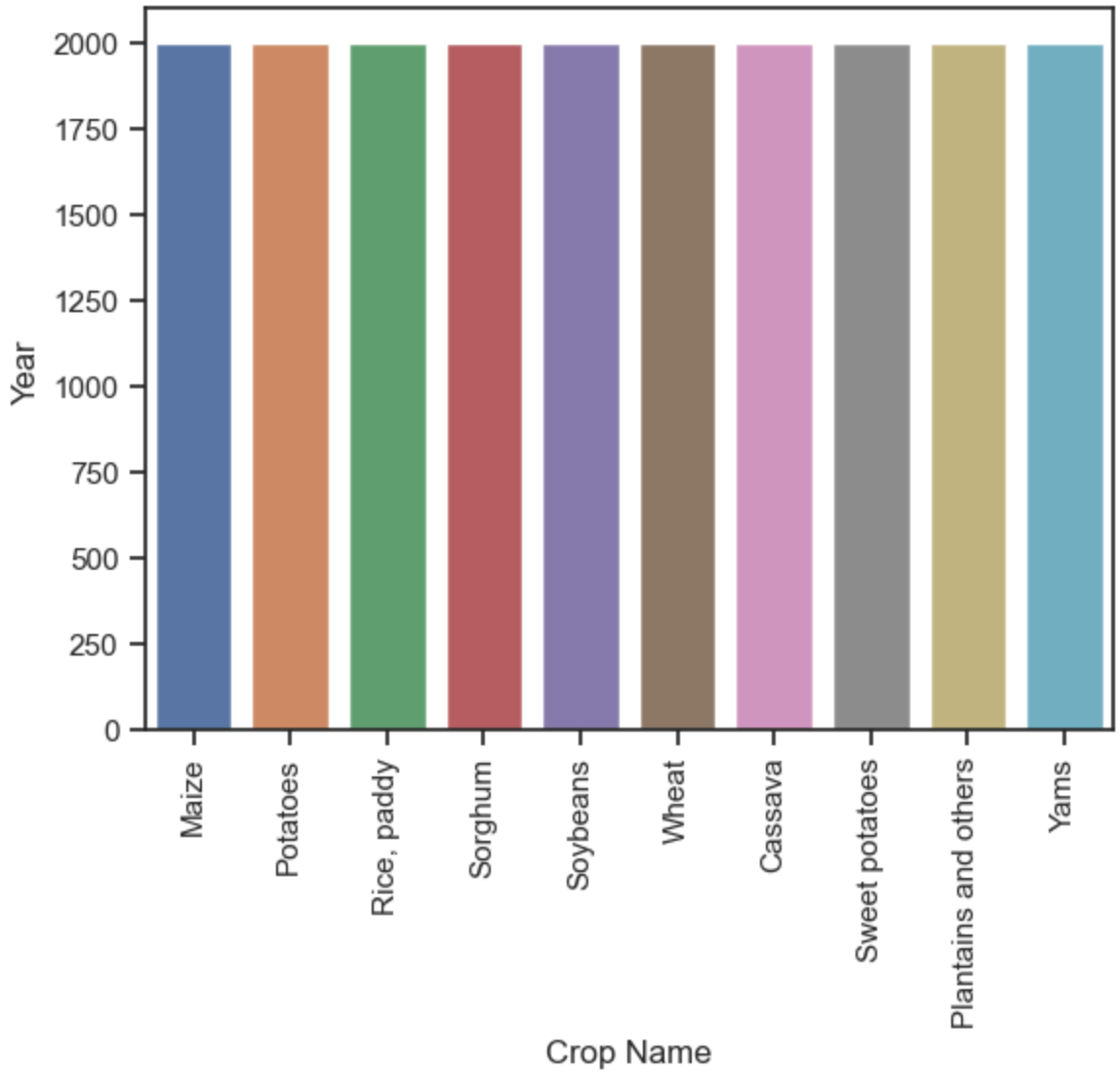
In [121]:
```
sns.barplot(x='Crop Name', y='pesticides_tonnes', data=crop, orient='v')
plt.xticks(rotation=90)
plt.show()
```



In [122]:
```
sns.barplot(x='Crop Name', y='Temperature (Celsius)', data=crop, orient='v')
plt.xticks(rotation=90)
plt.show()
```

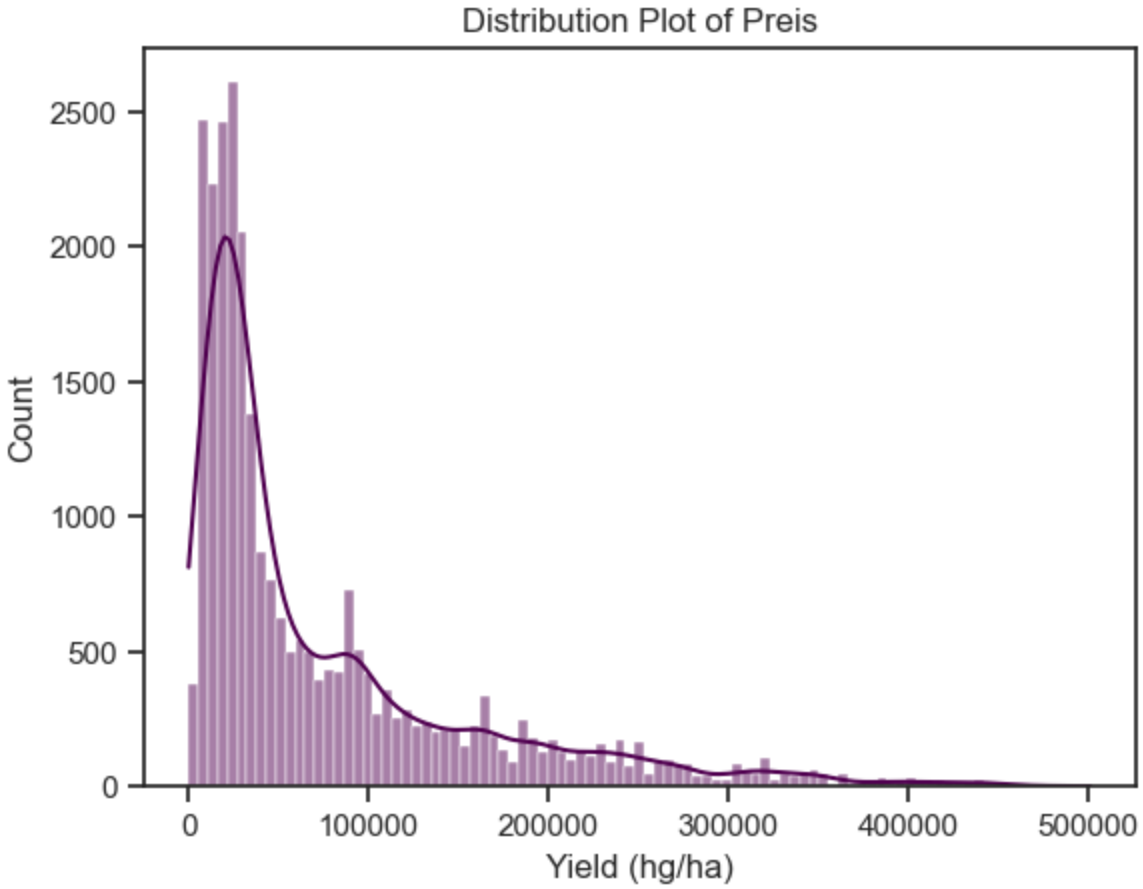


In [123]:
```
sns.barplot(x='Crop Name', y='Year', data=crop, orient='v')
plt.xticks(rotation=90)
plt.show()
```

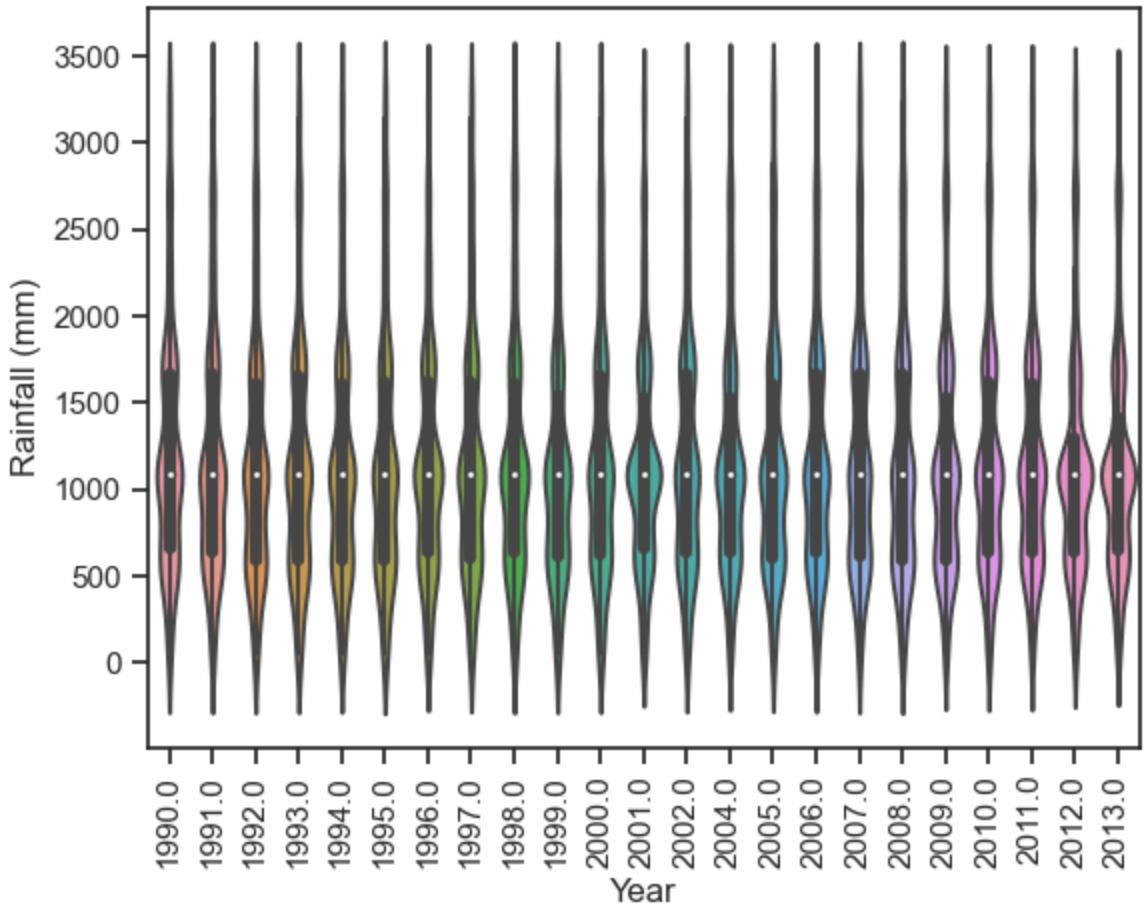


In [114]:
```
sns.histplot(x=df_new['Yield (hg/ha)'], color='#500050', kde=True)
plt.title(f'Distribution Plot of Preis')
```

Out[114]:
```
Text(0.5, 1.0, 'Distribution Plot of Preis')
```



In [47]:
```
sns.violinplot(x="Year",y="Rainfall (mm)",data=crop)
plt.xticks(rotation=90)
plt.show()
```



5 Outlier detection and removal

In [53]:
```
new_df
```

Out[53]:

	Area	Crop Name	Year	Yield (hg/ha)	Rainfall (mm)	pesticides_tonnes	Temperature (Celsius)
0	Albania	Maize	1990.0	36613	1485.0	121.00	21.69
1	Albania	Potatoes	1990.0	36613	1083.0	17529.44	16.37
2	Albania	Rice, paddy	1990.0	36613	1485.0	121.00	16.37
3	Albania	Sorghum	1990.0	12500	1485.0	121.00	16.37
4	Albania	Soybeans	1990.0	7000	1485.0	17529.44	16.37
...	...	...	...	...	...	...	...
28237	Zimbabwe	Rice, paddy	2013.0	165714	1083.0	17529.44	21.69
28238	Zimbabwe	Sorghum	2013.0	165714	1083.0	17529.44	21.69
28239	Zimbabwe	Soybeans	2013.0	13142	657.0	2550.07	19.76
28240	Zimbabwe	Sweet potatoes	2013.0	22222	657.0	2550.07	19.76
28241	Zimbabwe	Wheat	2013.0	22888	657.0	2550.07	19.76

26946 rows × 7 columns

In [54]:
```
z_scores=stats.zscore(new_df["Temperature (Celsius)"])
z_score_outlier=(z_scores<-3)|(z_scores>3)
```

In [55]:
```
z_score_outlier_row=new_df[z_score_outlier]
print("outliers detected by Z-score:",z_score_outlier_row)
```

```
outliers detected by Z-score:              Area    Crop Name    Year Yield (h
g/ha)  Rainfall (mm)  \
17150  Kazakhstan        Maize  1992.0         31214          250.0
17152  Kazakhstan     Potatoes  1992.0        105923          250.0
17154  Kazakhstan  Rice, paddy  1992.0         39915          250.0
17156  Kazakhstan      Sorghum  1992.0         11765          250.0
17158  Kazakhstan     Soybeans  1992.0         11919          250.0
17160  Kazakhstan        Wheat  1992.0         13324          250.0
17162  Kazakhstan        Maize  1993.0         32677          250.0
17164  Kazakhstan     Potatoes  1993.0         96200          250.0
17166  Kazakhstan  Rice, paddy  1993.0         36871          250.0
17168  Kazakhstan      Sorghum  1993.0         12500          250.0
17170  Kazakhstan     Soybeans  1993.0         11269          250.0
17172  Kazakhstan        Wheat  1993.0          9178          250.0
17198  Kazakhstan        Maize  1996.0         16795          250.0
17200  Kazakhstan     Potatoes  1996.0         88347          250.0
17202  Kazakhstan  Rice, paddy  1996.0         26155          250.0
17204  Kazakhstan      Sorghum  1996.0          8255          250.0
17206  Kazakhstan     Soybeans  1996.0          8437          250.0
17208  Kazakhstan        Wheat  1996.0          6835          250.0
17382  Kazakhstan  Rice, paddy  2012.0         37712          250.0
17384  Kazakhstan      Sorghum  2012.0          2750          250.0
17386  Kazakhstan     Soybeans  2012.0         20128          250.0
17388  Kazakhstan        Wheat  2012.0          7929          250.0
21662      Norway     Potatoes  1993.0        249602         1414.0
21663      Norway        Wheat  1993.0         51096         1414.0
21664      Norway     Potatoes  1994.0        230846         1414.0
21665      Norway        Wheat  1994.0         28362         1414.0
21668      Norway     Potatoes  1996.0        231321         1414.0
21669      Norway        Wheat  1996.0         45258         1414.0
21678      Norway     Potatoes  2001.0        262878         1414.0
21679      Norway        Wheat  2001.0         40738         1414.0
21694      Norway     Potatoes  2010.0        251662         1414.0
21695      Norway        Wheat  2010.0         45975         1414.0

       pesticides_tonnes  Temperature (Celsius)
17150           17182.00                  2.78
17152           17182.00                  2.78
17154           17182.00                  2.78
17156           17182.00                  2.78
17158           17182.00                  2.78
17160           17182.00                  2.78
17162           17182.00                  1.63
17164           17182.00                  1.63
17166           17182.00                  1.63
17168           17182.00                  1.63
17170           17182.00                  1.63
17172           17182.00                  1.63
17198           13047.00                  1.61
17200           13047.00                  1.61
17202           13047.00                  1.61
17204           13047.00                  1.61
17206           13047.00                  1.61
17208           13047.00                  1.61
17382            8674.58                  2.50
17384            8674.58                  2.50
17386            8674.58                  2.50
```

```
17388          8674.58                2.50
21662           749.00                2.72
21663           749.00                2.72
21664           848.00                2.74
21665           848.00                2.74
21668           698.25                1.88
21669           698.25                1.88
21678           512.66                2.68
21679           512.66                2.68
21694           698.98                1.30
21695           698.98                1.30
```

In [56]:
```
p=(z_scores>-3)&(z_scores<3)
df_new=new_df[p]
```

In [57]:
```
df_new
```

Out[57]:

	Area	Crop Name	Year	Yield (hg/ha)	Rainfall (mm)	pesticides_tonnes	Temperature (Celsius)
0	Albania	Maize	1990.0	36613	1485.0	121.00	21.69
1	Albania	Potatoes	1990.0	36613	1083.0	17529.44	16.37
2	Albania	Rice, paddy	1990.0	36613	1485.0	121.00	16.37
3	Albania	Sorghum	1990.0	12500	1485.0	121.00	16.37
4	Albania	Soybeans	1990.0	7000	1485.0	17529.44	16.37
...	...	...	...	...	...	...	...
28237	Zimbabwe	Rice, paddy	2013.0	165714	1083.0	17529.44	21.69
28238	Zimbabwe	Sorghum	2013.0	165714	1083.0	17529.44	21.69
28239	Zimbabwe	Soybeans	2013.0	13142	657.0	2550.07	19.76
28240	Zimbabwe	Sweet potatoes	2013.0	22222	657.0	2550.07	19.76
28241	Zimbabwe	Wheat	2013.0	22888	657.0	2550.07	19.76

26914 rows × 7 columns

Linear Regression

In [58]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.compose import ColumnTransformer
import joblib
```

In [59]:
```
categorical_cols=['Crop Name']
encoder=OneHotEncoder(drop='first',sparse=False)
encoder_cols=pd.DataFrame(encoder.fit_transform(df_new[categorical_cols]),colum
numerical_cols=['Year','Temperature (Celsius)','Rainfall (mm)','pesticides_tonn
scaler=StandardScaler()
scaled_cols=pd.DataFrame(scaler.fit_transform(df_new[numerical_cols]),columns=s
```

```
C:\Users\DD\AppData\Local\anaconda3\Lib\site-packages\sklearn\preprocessing\_
encoders.py:972: FutureWarning: `sparse` was renamed to `sparse_output` in ve
rsion 1.2 and will be removed in 1.4. `sparse_output` is ignored unless you l
eave `sparse` to its default value.
  warnings.warn(
```

In [60]:
```
encoder_cols
```

Out[60]:

	Crop Name_Maize	Crop Name_Plantains and others	Crop Name_Potatoes	Crop Name_Rice, paddy	Crop Name_Sorghum	Cr Name_Soybea
0	1.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	1.0	0.0	0.0	
2	0.0	0.0	0.0	1.0	0.0	
3	0.0	0.0	0.0	0.0	1.0	
4	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
26909	0.0	0.0	0.0	1.0	0.0	
26910	0.0	0.0	0.0	0.0	1.0	
26911	0.0	0.0	0.0	0.0	0.0	
26912	0.0	0.0	0.0	0.0	0.0	
26913	0.0	0.0	0.0	0.0	0.0	

26914 rows × 9 columns

In [61]:
```
scaled_cols
```

Out[61]:

	Year	Temperature (Celsius)	Rainfall (mm)	pesticides_tonnes
0	-1.642466	0.158301	0.563857	-0.609567
1	-1.642466	-0.739669	-0.068228	-0.305626
2	-1.642466	-0.739669	0.563857	-0.609567
3	-1.642466	-0.739669	0.563857	-0.609567
4	-1.642466	-0.739669	0.563857	-0.305626
...	...	...	...	...
26909	1.624805	0.158301	-0.068228	-0.305626
26910	1.624805	0.158301	-0.068228	-0.305626
26911	1.624805	-0.167466	-0.738050	-0.567156
26912	1.624805	-0.167466	-0.738050	-0.567156
26913	1.624805	-0.167466	-0.738050	-0.567156

26914 rows × 4 columns

In [80]:
```
Y=df_new['Yield (hg/ha)'] = pd.to_numeric(df_new['Yield (hg/ha)'], errors='coer
```

```
C:\Users\DD\AppData\Local\Temp\ipykernel_6992\1488642903.py:1: SettingWithCop
yWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  Y=df_new['Yield (hg/ha)'] = pd.to_numeric(df_new['Yield (hg/ha)'], errors
='coerce')
```

In [81]:
```
Y.isnull().sum()
```

Out[81]:
```
0
```

In [63]:
```
X=pd.concat([encoder_cols,scaled_cols],axis=1)
```

In [64]:
```
X
```

Out[64]:

	Crop Name_Maize	Crop Name_Plantains and others	Crop Name_Potatoes	Crop Name_Rice, paddy	Crop Name_Sorghum	Name_Soyl
0	1.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	1.0	0.0	0.0	
2	0.0	0.0	0.0	1.0	0.0	
3	0.0	0.0	0.0	0.0	1.0	
4	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
26909	0.0	0.0	0.0	1.0	0.0	
26910	0.0	0.0	0.0	0.0	1.0	
26911	0.0	0.0	0.0	0.0	0.0	
26912	0.0	0.0	0.0	0.0	0.0	

In [82]:
```
Y
```

Out[82]:
```
0         36613.0
1         36613.0
2         36613.0
3         12500.0
4          7000.0
           ...
28237    165714.0
28238    165714.0
28239     13142.0
28240     22222.0
28241     22888.0
Name: Yield (hg/ha), Length: 26914, dtype: float64
```

In [83]:
```
X_train,X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2,random_st
```

In [84]:
```
model=LinearRegression()
model.fit(X_train,Y_train)
y_pred=model.predict(X_test)
```

In [85]:
```
print(model.intercept_) #y-intercept of the model
```

```
156851.2271362113
```

In [86]:
```
print(model.coef_)
```

```
[-121538.88647677  -42346.96499459   13155.10385344 -113686.42327323
 -136539.98901586 -141092.94767476  -37676.58155463 -129555.73508792
  -44732.47751622    8054.82380194  -11850.92087513   -1870.24920727
    4421.3268142 ]
```

In [87]:
```
mae = mean_absolute_error(Y_test,y_pred)
mse= mean_squared_error(Y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(Y_test, y_pred)
print('Mean Absolute Error',mae)
print('Mean Squared Error',mse)
print('Root Mean Absolute Error',rmse)
print('R2 Score',r2)
```

```
Mean Absolute Error 35547.97408069165
Mean Squared Error 3206317258.1390595
Root Mean Absolute Error 56624.35216529245
R2 Score 0.5294891887453548
```

In [93]:
```
#adjusted_r2=1-[(1-r2)*(n-1)/(n-k-1)]
adjusted_r2=1-((1-0.52948)*(10169-1)/(10169-13-1))
print('adjusted r2 is :',adjusted_r2)
```

```
adjusted r2 is : 0.5288776602658789
```

In [89]:
```
y_mean=np.mean(Y_test)
SSR = np.sum((y_pred - y_mean) ** 2)
SSR
```

Out[89]:
```
20685991271390.867
```

In [90]:
```
SST = np.sum((Y_test - y_mean) ** 2)
SST
```

Out[90]:
```
36682697586775.5
```

In [91]:
```
SSE=SST-SSR
SSE
```

Out[91]:
```
15996706315384.633
```

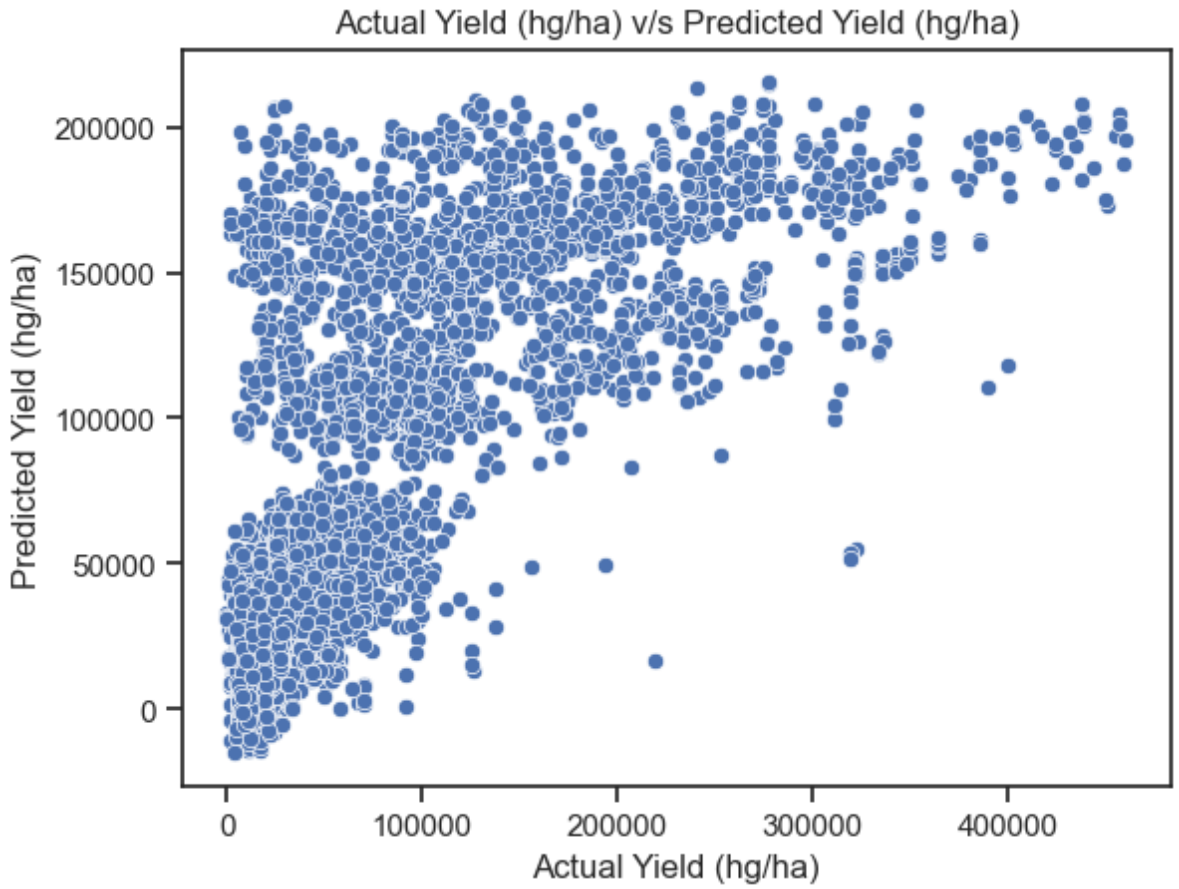
In [92]:
```
b=pd.DataFrame({"Actual":Y_test,"Predicted":y_pred})
b
```

Out[92]:

	Actual	Predicted
16402	323558.0	176208.541345
12133	175712.0	159766.670615
8677	97147.0	161492.604764
18737	5856.0	-2383.350356
3713	19488.0	33362.476789
...	...	...
25276	70170.0	2861.511256
5155	57576.0	105.566153
12927	88588.0	111160.234690
17013	27612.0	46429.186531
10169	13185.0	10792.463800

5383 rows × 2 columns

In [95]:
```
sns.scatterplot(x=Y_test,y=y_pred)
plt.xlabel('Actual Yield (hg/ha)')
plt.ylabel('Predicted Yield (hg/ha)')
plt.title('Actual Yield (hg/ha) v/s Predicted Yield (hg/ha)')
plt.show()
```



import some libraries cross val score, GridSearchCV, Ridge, Lasso

In [97]:
```
from sklearn.model_selection import cross_val_score,GridSearchCV
from sklearn.linear_model import Ridge,Lasso
```

In [98]:
```
lr_model=LinearRegression()
lr_scores=cross_val_score(lr_model,X_train,Y_train,cv=5)
```

In [99]:
```
lasso_model=Lasso(alpha=1.0)
lassso_scores=cross_val_score(lasso_model,X_train,Y_train,cv=5)
```

In [100]:
```
ridge_model=Ridge(alpha=1.0)
ridge_scores=cross_val_score(ridge_model,X_train,Y_train,cv=5)
```

In [101]:
```
lr_model.fit(X_train,Y_train)
lr_prediction =lr_model.predict(X_test)
lr_mae =mean_absolute_error(Y_test,lr_prediction)
lr_mse =mean_squared_error(Y_test,lr_prediction)
lr_rmse = np.sqrt(lr_mse)
lr_r2 = r2_score(Y_test,lr_prediction)
```

In [102]:
```
print('Linear mae',lr_mae)
print('Linear mse',lr_mse)
print('Linear rmse',lr_rmse)
print('Linear r2',lr_r2)
```

```
Linear mae 35547.97408069165
Linear mse 3206317258.1390595
Linear rmse 56624.35216529245
Linear r2 0.5294891887453548
```

L1(Lasso)

In [103]:
```
lasso_model.fit(X_train,Y_train)
lasso_prediction =lasso_model.predict(X_test)
lasso_mae =mean_absolute_error(Y_test,lasso_prediction)
lasso_mse =mean_squared_error(Y_test,lasso_prediction)
lasso_rmse = np.sqrt(lasso_mse)
lasso_r2 = r2_score(Y_test,lr_prediction)
```

In [104]:
```
print("LASSO MAE=",lasso_mae)
print("LASSO MSE=",lasso_mse)
print("LASSO R2=",lasso_r2)
```

```
LASSO MAE= 35546.35588145759
LASSO MSE= 3206405016.1985655
LASSO R2= 0.5294891887453548
```

L2 (Ridge)

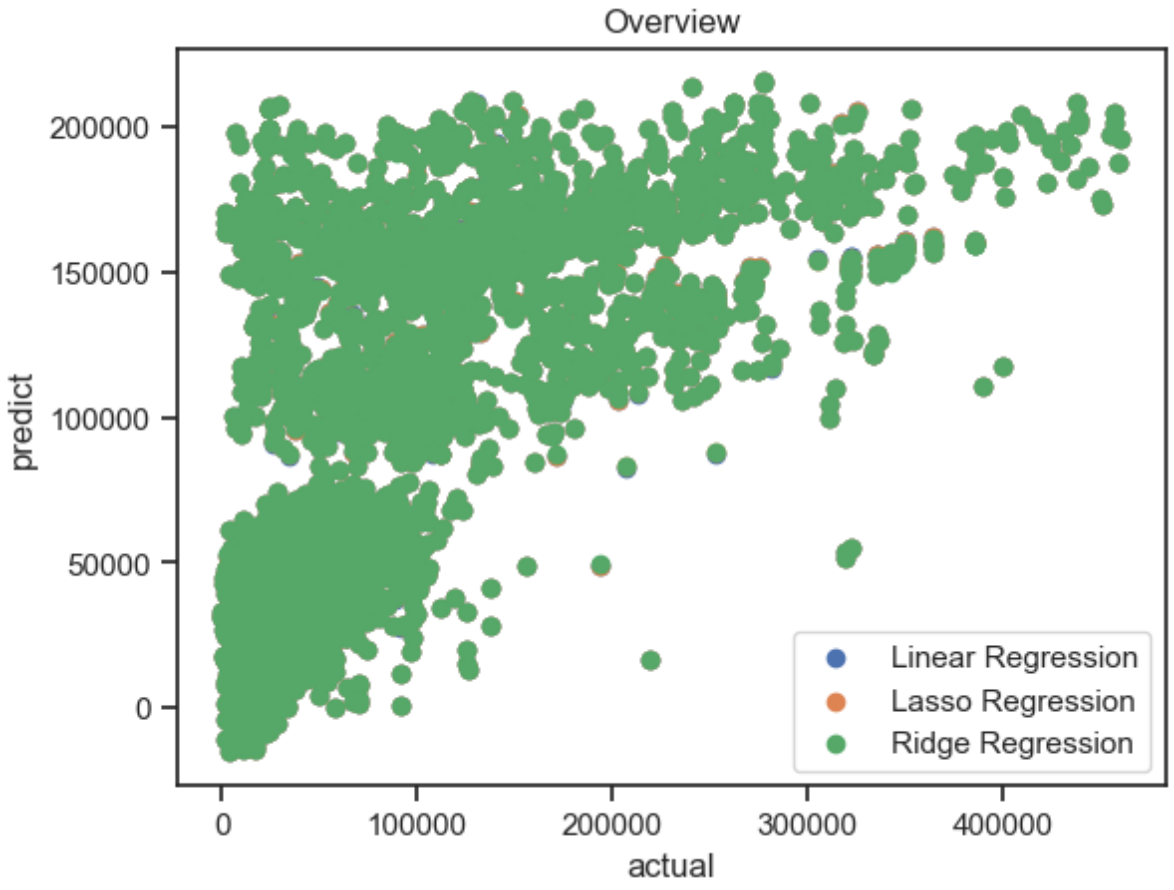
In [105]:
```
ridge_model.fit(X_train,Y_train)
ridge_prediction =ridge_model.predict(X_test)
ridge_mae =mean_absolute_error(Y_test,ridge_prediction)
ridge_mse =mean_squared_error(Y_test,ridge_prediction)
ridge_rmse = np.sqrt(ridge_mse)
ridge_r2 = r2_score(Y_test,ridge_prediction)
```

In [106]:
```
print('ridge mae',ridge_mae)
print('ridge mse',ridge_mse)
print('ridge rmse',ridge_rmse)
print('ridge r2',ridge_r2)
```

```
ridge mae 35538.53022624312
ridge mse 3206764831.5847526
ridge rmse 56628.3041560027
ridge r2 0.5294235096100495
```

In [107]:
```
plt.scatter(Y_test,lr_prediction,alpha=1.0,label='Linear Regression')
plt.scatter(Y_test,lasso_prediction,alpha=1.0,label='Lasso Regression')
plt.scatter(Y_test,ridge_prediction,alpha=1.0,label='Ridge Regression')
plt.xlabel('actual')
plt.ylabel('predict')
plt.title('Overview')
plt.legend()
```

Out[107]: <matplotlib.legend.Legend at 0x209b860c5d0>



Robust Techniques

Huber Regression

In [108]:
```
# MM estimator:huberregression
from sklearn.linear_model import HuberRegressor
X_scaled = scaler.fit_transform(X_test)
huber = HuberRegressor(epsilon=1.35)
huber.fit(X_scaled, Y_test)
huber_prediction = huber.predict(X_scaled)
huber_mae =mean_absolute_error(Y_test,huber_prediction)
huber_mse =mean_squared_error(Y_test,huber_prediction)
huber_rmse = np.sqrt(huber_mse)
huber_r2 = r2_score(Y_test,huber_prediction)
print('huber mae:',huber_mae)
print('huber mse:',huber_mse)
print('huber rmse:',huber_rmse)
print('huber r2:',huber_r2)
```

```
huber mae: 33451.99171642028
huber mse: 3346774072.1736135
huber rmse: 57851.310029882756
huber r2: 0.5088778629790464
```

RANSAC regression

In [109]:
```
# MM estimate: RANSAC regression
from sklearn.linear_model import RANSACRegressor
from sklearn.datasets import make_regression
ransac = RANSACRegressor()
mm= ransac.fit(X_test, Y_test)
mm_estimate_coeff = ransac.estimator_.coef_
mm_estimate_intercept = ransac.estimator_.intercept_
mm_prediction = ransac.predict(X_test)
print("MM Estimate Coefficients:", mm_estimate_coeff)
print("MM Estimate Intercept:", mm_estimate_intercept)
mm_mae =mean_absolute_error(Y_test,mm_prediction)
mm_mse =mean_squared_error(Y_test,mm_prediction)
mm_rmse = np.sqrt(mm_mse)
mm_r2 = r2_score(Y_test,huber_prediction)
print('mm mae:',mm_mae)
print('mm mse:',mm_mse)
print('mm rmse:',mm_rmse)
print('mm r2:',mm_r2)
```

```
MM Estimate Coefficients: [-9.97334772e+04 -6.55673669e+03  6.29931872e+03 -
9.25340752e+04
 -1.11540580e+05 -1.10192131e+05  1.18199138e+05 -1.03320208e+05
 -9.72602008e+01  1.14568157e+03 -2.66245230e+03 -1.36837117e+03
  2.83075773e+03]
MM Estimate Intercept: 125463.67892256746
mm mae: 43403.221712379804
mm mse: 5231053852.033473
mm rmse: 72326.0247216275
mm r2: 0.5088778629790464
```

ITS estimate

In [110]:
```
# lts estimate
from sklearn.linear_model import RANSACRegressor
ransac = RANSACRegressor()

ransac.fit(X_test, Y_test)

lts_estimate_coeff = ransac.estimator_.coef_
lts_estimate_intercept = ransac.estimator_.intercept_

print("LTS Estimate Coefficients:", lts_estimate_coeff)
print("LTS Estimate Intercept:", lts_estimate_intercept)

lts_prediction = ransac.predict(X_test)
lts_mae =mean_absolute_error(Y_test,lts_prediction)
lts_mse =mean_squared_error(Y_test,lts_prediction)
lts_rmse = np.sqrt(lts_mse)
lts_r2 = r2_score(Y_test,huber_prediction)
print('lts mae:',lts_mae)
print('lts mse:',lts_mse)
print('lts rmse:',lts_rmse)
print('lts r2:',lts_r2)
```

```
LTS Estimate Coefficients: [-17289.44040168   4620.84160864 -18293.88393828
-6283.85399667
 -26229.75251551 -24974.10657743  47670.97992475 -13454.68735647
  39921.20926608    531.24113705  -1189.69880663   2622.32053759
   2381.95719322]
LTS Estimate Intercept: 39535.4441124448
lts mae: 49299.86008848798
lts mse: 8156187058.658424
lts rmse: 90311.61087400903
lts r2: 0.5088778629790464
```

theil sen regressor

In [111]:
```
# theil sen regressor
from sklearn.linear_model import TheilSenRegressor

# Create a Theil-Sen estimator model
theil_sen = TheilSenRegressor()

# Fit the model to the data
theil_sen.fit(X_test, Y_test)

# Get the Theil-Sen estimate of the coefficients
theil_sen_estimate_intercept = theil_sen.intercept_
theil_sen_estimate_coefficient = theil_sen.coef_[0]
print("Theil-Sen Estimate Intercept:", theil_sen_estimate_intercept)
print("Theil-Sen Estimate Coefficient:", theil_sen_estimate_coefficient)

ts_prediction = theil_sen.predict(X_test)
ts_mae =mean_absolute_error(Y_test,ts_prediction)
ts_mse =mean_squared_error(Y_test,ts_prediction)
ts_rmse = np.sqrt(ts_mse)
ts_r2 = r2_score(Y_test,ts_prediction)
print('ts mae:',ts_mae)
print('ts mse:',ts_mse)
print('ts rmse:',ts_rmse)
print('ts r2:',ts_r2)
```

```
Theil-Sen Estimate Intercept: 97994.38002196976
Theil-Sen Estimate Coefficient: -52795.71671417082
ts mae: 39738.459992126
ts mse: 3735502536.107464
ts rmse: 61118.75764532083
ts r2: 0.45183393057996646
```

One Hot Encoding

In [132]:
```
crop.shape
```

Out[132]: (27339, 7)

In [133]:
```
from sklearn.preprocessing import OneHotEncoder

df_onehot = pd.get_dummies(crop, columns=['Area', 'Crop Name'], prefix=['Area',
crop = df_onehot.loc[:, df_onehot.columns != 'Yield (hg/ha)']
crop['Yield (hg/ha)'] = df_onehot['Yield (hg/ha)']
```

In [134]:
```
crop.shape
```

Out[134]: (27339, 116)