Introduction

This project encompasses an in-depth analysis and prediction model development for agricultural yield. The datasets which was utilized in this analysis include information regarding pesticides, temperature, rainfall, and historical yield data. It was gotten from Kaggle https://www.kaggle.com/datasets/patelris/crop-yield-prediction-dataset. The primary aim is to predict crop yield based on various factors such as temperature, pesticide usage, and environmental conditions. Although, we couldn't get data that speak to the Nigerian Ecosystem, we deem it necessary to use the available data to serve as a template for future work.

Importing the necessary libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error , mean_absolute_error , r2_score
```

Reading the dataset

In [2]:

```
df_pesticides = pd.read_csv("pesticides.csv")
df_yield_df = pd.read_csv("yield_df.csv")
df_yield = pd.read_csv("yield.csv")
df_temp= pd.read_csv("temp.csv")
df_rainfall = pd.read_csv("rainfall.csv")
```

Data Overview

The datasets used in this study comprise:

Pesticides Data Yield Data Temperature Data Rainfall Data

In [3]:

```
df_pesticides.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4349 entries, 0 to 4348
Data columns (total 7 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Domain   4349 non-null   object
 1   Area     4349 non-null   object
 2   Element  4349 non-null   object
 3   Item     4349 non-null   object
```

```
 4   Year     4349 non-null   int64  
 5   Unit     4349 non-null   object 
 6   Value    4349 non-null   float64
dtypes: float64(1), int64(1), object(5)
memory usage: 238.0+ KB
```

In [4]:

```
df_yield .info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56717 entries, 0 to 56716
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Domain Code   56717 non-null  object
 1   Domain        56717 non-null  object
 2   Area Code     56717 non-null  int64 
 3   Area          56717 non-null  object
 4   Element Code  56717 non-null  int64 
 5   Element       56717 non-null  object
 6   Item Code     56717 non-null  int64 
 7   Item          56717 non-null  object
 8   Year Code     56717 non-null  int64 
 9   Year          56717 non-null  int64 
 10  Unit          56717 non-null  object
 11  Value         56717 non-null  int64 
dtypes: int64(6), object(6)
memory usage: 5.2+ MB
```

In [5]:

```
df_temp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71311 entries, 0 to 71310
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   year      71311 non-null  int64  
 1   country   71311 non-null  object 
 2   avg_temp  68764 non-null  float64
dtypes: float64(1), int64(1), object(1)
memory usage: 1.6+ MB
```

In [6]:

```
df_rainfall.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6727 entries, 0 to 6726
Data columns (total 3 columns):
 #   Column                         Non-Null Count  Dtype 
---  ------                         --------------  ----- 
 0    Area                          6727 non-null   object
 1   Year                           6727 non-null   int64 
 2   average_rain_fall_mm_per_year  5953 non-null   object
dtypes: int64(1), object(2)
memory usage: 157.8+ KB
```

In [7]:

```
df_yield_df.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                     28242 non-null  int64  
 1   Area                           28242 non-null  object 
 2   Item                           28242 non-null  object 
 3   Year                           28242 non-null  int64  
 4   hg/ha_yield                    28242 non-null  int64  
 5   average_rain_fall_mm_per_year  28242 non-null  float64
 6   pesticides_tonnes              28242 non-null  float64
 7   avg_temp                       28242 non-null  float64
dtypes: float64(3), int64(3), object(2)
memory usage: 1.7+ MB
```

Inspecting the characteristics of the datasets, to know the available columns, unique values in certain columns, and potential columns for merging or joining datasets based on common their attributes.

In [8]:
```
print(df_yield.columns)
```

```
Index(['Domain Code', 'Domain', 'Area Code', 'Area', 'Element Code', 'Element',
       'Item Code', 'Item', 'Year Code', 'Year', 'Unit', 'Value'],
      dtype='object')
```

In [9]:
```
print(df_yield['Area'].nunique())
print(df_yield['Year'].nunique())
```

```
212
56
```

In [10]:
```
print(df_yield_df.columns)
```

```
Index(['Unnamed: 0', 'Area', 'Item', 'Year', 'hg/ha_yield',
       'average_rain_fall_mm_per_year', 'pesticides_tonnes', 'avg_temp'],
      dtype='object')
```

In [11]:
```
print(df_yield_df['Area'].nunique())
print(df_yield_df['Year'].nunique())
df_yield_df.drop(['Unnamed: 0'], axis = 1 ,inplace = True)
```

```
101
23
```

In [12]:
```
print(df_rainfall.columns)
```

```
Index([' Area', 'Year', 'average_rain_fall_mm_per_year'], dtype='object')
```

In [13]:
```
# Renaming the ' Area' column to remove the space before it for uniformity
df_rainfall.rename(columns = {' Area':'Area'},inplace = True) #

print(df_rainfall['Area'].nunique())
print(df_rainfall['Year'].nunique())
```

```
217
31
```

In [14]:

```
print(df_temp.columns)
```

```
Index(['year', 'country', 'avg_temp'], dtype='object')
```

In [15]:

```
# Renaming the ' year' column to 'Year' for uniformity
df_temp.rename(columns = {'year':'Year','country':'Area'},inplace = True)

print(df_temp['Area'].nunique())
print(df_temp['Year'].nunique())
print(df_temp.columns)
```

```
137
271
Index(['Year', 'Area', 'avg_temp'], dtype='object')
```

From the Analysis Above, it is clear that the Year and and Country(Area) columns are common to all , this will be used for merging the datasets on these columns.

In [16]:

```
df_temprain = pd.merge(df_rainfall,df_temp,on = ['Year','Area'])
df_temprainpest = pd.merge(df_temprain,df_pesticides , on = ['Year','Area'])
```

In [17]:

```
#Find common columns between df_trp and df_yield by iterating through their columns.
trplist =list(df_temprainpest.columns)
dfyield = list(df_yield.columns)
# Create a list (com1) containing column names present in both DataFrames.
com1 = [i for i in trplist if i in dfyield]
```

In [18]:

```
print(df_yield.columns)
print(df_yield_df.columns)



ly = [i for i in list(df_yield.columns) if i in (df_yield_df.columns)]
```

```
Index(['Domain Code', 'Domain', 'Area Code', 'Area', 'Element Code', 'Element',
       'Item Code', 'Item', 'Year Code', 'Year', 'Unit', 'Value'],
      dtype='object')
Index(['Area', 'Item', 'Year', 'hg/ha_yield', 'average_rain_fall_mm_per_year',
       'pesticides_tonnes', 'avg_temp'],
      dtype='object')
```

In [19]:

```
yield_df = pd.merge(df_yield_df,df_yield, on = ['Year','Area','Item'])
```

In [20]:

```
print(yield_df.shape)

print(yield_df.columns)
print(df_temprainpest.columns)
```

```
(28242, 16)
Index(['Area', 'Item', 'Year', 'hg/ha_yield', 'average_rain_fall_mm_per_year',
       'pesticides_tonnes', 'avg_temp', 'Domain Code', 'Domain', 'Area Code',
       'Element Code', 'Element', 'Item Code', 'Year Code', 'Unit', 'Value'],
      dtype='object')
Index(['Area', 'Year', 'average_rain_fall_mm_per_year', 'avg_temp', 'Domain',
       'Element', 'Item', 'Unit', 'Value'],
      dtype='object')
```

In [21]:

```
#Assuming your first dataframe is df1 and second dataframe is df2
years_df1 = set(yield_df['Year'].unique())
years_df2 = set(df_temprainpest['Year'].unique())

# Find the years in df2 that are not in df1
years_only_in_df2 = years_df2 - years_df1
```

In [22]:

```
# Print the result
print("Years present in df1 but not in df2:", years_only_in_df2)
```

```
Years present in df1 but not in df2: set()
```

This result shows that are no mismatch or missing years in terms of the 'Year' column when comparing the two dataframes.

In [23]:

```
area_df1 = set(yield_df['Year'].unique())
area_df2 = set(df_temprainpest['Year'].unique())
```

In [24]:

```
# Doing same for Area, checking if there are Areas in df2 that are not in df1
area_only_in_df1 = area_df2 - area_df1

# Print the result
print("Area present in df1 but not in df2:", area_only_in_df1)
```

```
Area present in df1 but not in df2: set()
```

EDA

In [25]:

```
yield_df.head()
```

Out[25]:

	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp	Do
0	Albania	Maize	1990	36613	1485.0	121.0	16.37	
1	Albania	Potatoes	1990	66667	1485.0	121.0	16.37	
2	Albania	Rice, paddy	1990	23333	1485.0	121.0	16.37	
3	Albania	Sorghum	1990	12500	1485.0	121.0	16.37	
4	Albania	Soybeans	1990	7000	1485.0	121.0	16.37	

In [26]:
```
print(yield_df['Item Code'].nunique())
print(yield_df['Item'].nunique())
## It has one unique value for each crop
```

```
10
10
```

In [27]:
```
print(yield_df['Domain'].nunique())
print(yield_df['Domain Code'].nunique())
```

```
1
1
```

In [28]:
```
print(yield_df['Area'].nunique())
print(yield_df['Area Code'].nunique())
```

```
101
101
```

In [29]:
```
print(yield_df['Element Code'].nunique())
print(yield_df['Element'].nunique())
print(yield_df['Unit'].nunique())
```

```
1
1
1
```

Based on these information , it is clear that the 'Year Code' and 'Domain Code' columns are redundant and unnecessary. The 'Area Code' column does not contribute meaningfully to drawing conclusions. Since the 'Domain' column has only one unique value, it is deemed irrelevant and is dropped. Additionally, 'Area Code' is mentioned twice, implying redundancy. The columns 'hg/ha_yield', 'Value', and 'Unit' are interrelated, and as a result, the last two columns are being dropped.

In [30]:
```
Yield_dfcopy = yield_df.copy()
```

In [31]:
```
Yield_dfcopy.drop(['Area Code','Year Code','Domain','Domain Code',
                   'Area Code','Item Code','Element','Element Code','Unit','Value']
                  axis = 1 , inplace = True)
```

In [32]:
```
Yield_dfcopy.head()
```

Out[32]:

	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
0	Albania	Maize	1990	36613	1485.0	121.0	16.37
1	Albania	Potatoes	1990	66667	1485.0	121.0	16.37
2	Albania	Rice, paddy	1990	23333	1485.0	121.0	16.37
3	Albania	Sorghum	1990	12500	1485.0	121.0	16.37
4	Albania	Soybeans	1990	7000	1485.0	121.0	16.37

In [33]:
```
Yield_dfcopy[Yield_dfcopy['Area'] == 'Ghana'].head()
```

Out[33]:

	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
9161	Ghana	Cassava	1990	84170	1187.0	65.8	26.73
9162	Ghana	Maize	1990	11889	1187.0	65.8	26.73
9163	Ghana	Plantains and others	1990	61890	1187.0	65.8	26.73
9164	Ghana	Rice, paddy	1990	16510	1187.0	65.8	26.73
9165	Ghana	Sorghum	1990	6310	1187.0	65.8	26.73

The dataset should include the average temperature in Celsius, calculated based on temperature values.

Feature Engineering: Splitting Items with Multiple Crops

The 'Item' column in Yield_final_data contains entries where multiple crops are listed using commas. To address this, the column is split using the comma as a delimiter, and the resulting lists are expanded into separate rows using the explode function. The index is then reset for clarity.

In [34]:
```
Yield_dfcopy['Item'] = Yield_dfcopy['Item'].str.split(', ')
Yield_dfcopy = Yield_dfcopy.explode('Item').reset_index(drop=True)
```

In [35]:
```
Yield_dfcopy.shape
```

Out[35]:
```
(31630, 7)
```

In [36]:
```
Yield_dfcopy.loc[Yield_dfcopy['Area'].str.len().sort_values().index].head(12)
```

Out[36]:

	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
17260	Iraq	Potatoes	1996	177576	216.0	616.00	23.96
17377	Iraq	paddy	2005	28879	216.0	873.01	19.96
17376	Iraq	Rice	2005	28879	216.0	873.01	19.96
17375	Iraq	paddy	2005	28879	216.0	873.01	23.58
17374	Iraq	Rice	2005	28879	216.0	873.01	23.58
17373	Iraq	Potatoes	2005	158431	216.0	873.01	19.96
17372	Iraq	Potatoes	2005	158431	216.0	873.01	23.58
17371	Iraq	Maize	2005	23079	216.0	873.01	19.96

	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
17370	Iraq	Maize	2005	23079	216.0	873.01	23.58
17369	Iraq	Wheat	2004	11898	216.0	828.62	20.00
17368	Iraq	Wheat	2004	11898	216.0	828.62	23.72
17367	Iraq	Soybeans	2004	10000	216.0	828.62	20.00

In [37]:

```
Yield_dfcopy['Item'].value_counts()
```

Out[37]:

```
Potatoes                4276
Maize                   4121
Wheat                   3857
Rice                    3388
paddy                   3388
Soybeans                3223
Sorghum                 3039
Sweet potatoes          2890
Cassava                 2045
Yams                     847
Plantains and others     556
Name: Item, dtype: int64
```

In [38]:

```
Yield_dfcopy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31630 entries, 0 to 31629
Data columns (total 7 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Area                           31630 non-null  object 
 1   Item                           31630 non-null  object 
 2   Year                           31630 non-null  int64  
 3   hg/ha_yield                    31630 non-null  int64  
 4   average_rain_fall_mm_per_year  31630 non-null  float64
 5   pesticides_tonnes              31630 non-null  float64
 6   avg_temp                       31630 non-null  float64
dtypes: float64(3), int64(2), object(2)
memory usage: 1.7+ MB
```

In [39]:

```
Yield_dfcopy.describe()
```

Out[39]:

	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
count	31630.000000	31630.000000	31630.000000	31630.000000	31630.000000
mean	2001.536895	73162.659437	1153.085267	37062.481868	20.620043
std	7.053614	81302.121833	712.805826	59771.245918	6.255367
min	1990.000000	50.000000	51.000000	0.040000	1.300000
25%	1995.000000	20918.000000	593.000000	1714.390000	16.780000
50%	2001.000000	37607.000000	1083.000000	17529.440000	21.550000
75%	2008.000000	94651.000000	1668.000000	48715.510000	26.030000

	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
max	2013.000000	501412.000000	3240.000000	367778.000000	30.650000

In [40]:

```
Yield_dfcopy.groupby(['Area'],sort = True)[['hg/ha_yield']].sum().nlargest(10, 'hg/ha_y
```

Out[40]:

	hg/ha_yield
Area	
India	342749968
Brazil	175935463
Mexico	139270288
Japan	133321962
Australia	121009524
Pakistan	80118288
Indonesia	75507330
Turkey	59531760
United Kingdom	55419990
Spain	51622833

In [41]:

```
Yield_dfcopy.groupby(['Item','Area'], sort=True)['hg/ha_yield'].sum().nlargest(20)
```

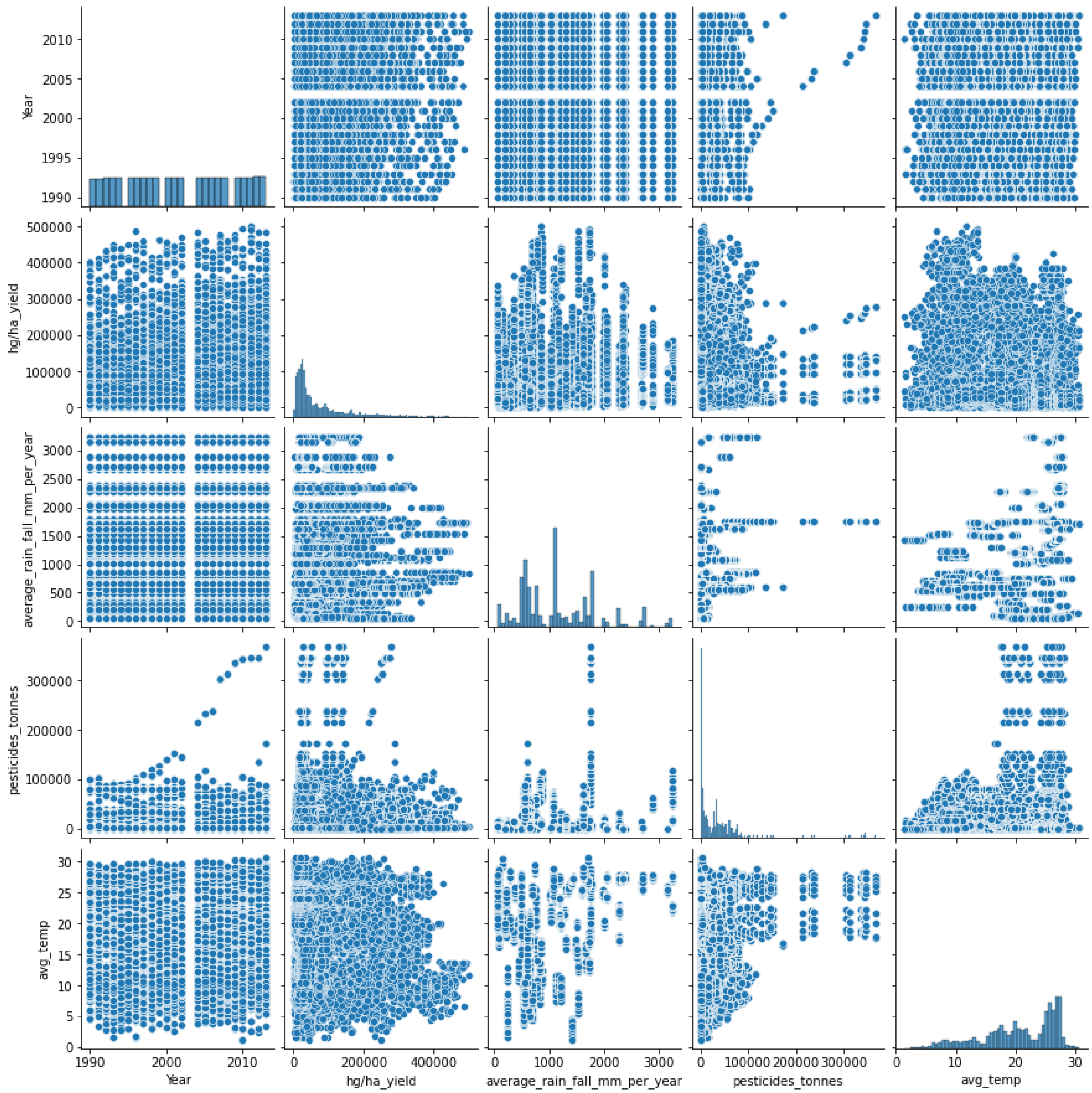
Out[41]:

```
Item            Area
Cassava         India             142810624
Potatoes        India              92122514
                Brazil             49602168
                United Kingdom     46705145
                Australia          45670386
Sweet potatoes  India              44439538
Potatoes        Japan              42918726
                Mexico             42053880
Sweet potatoes  Mexico             35808592
                Australia          35550294
Cassava         Brazil             33671231
Potatoes        Pakistan           32969754
Sweet potatoes  Japan              32794236
Potatoes        Turkey             30530955
Yams            Japan              29165394
Sweet potatoes  Brazil             28266502
Potatoes        South Africa       27341980
                Germany            26672181
Yams            Brazil             23472053
Sweet potatoes  Pakistan           21687615
Name: hg/ha_yield, dtype: int64
```

In [42]:

```
## Checking the pairplot between the columns
sns.pairplot(Yield_dfcopy)
```

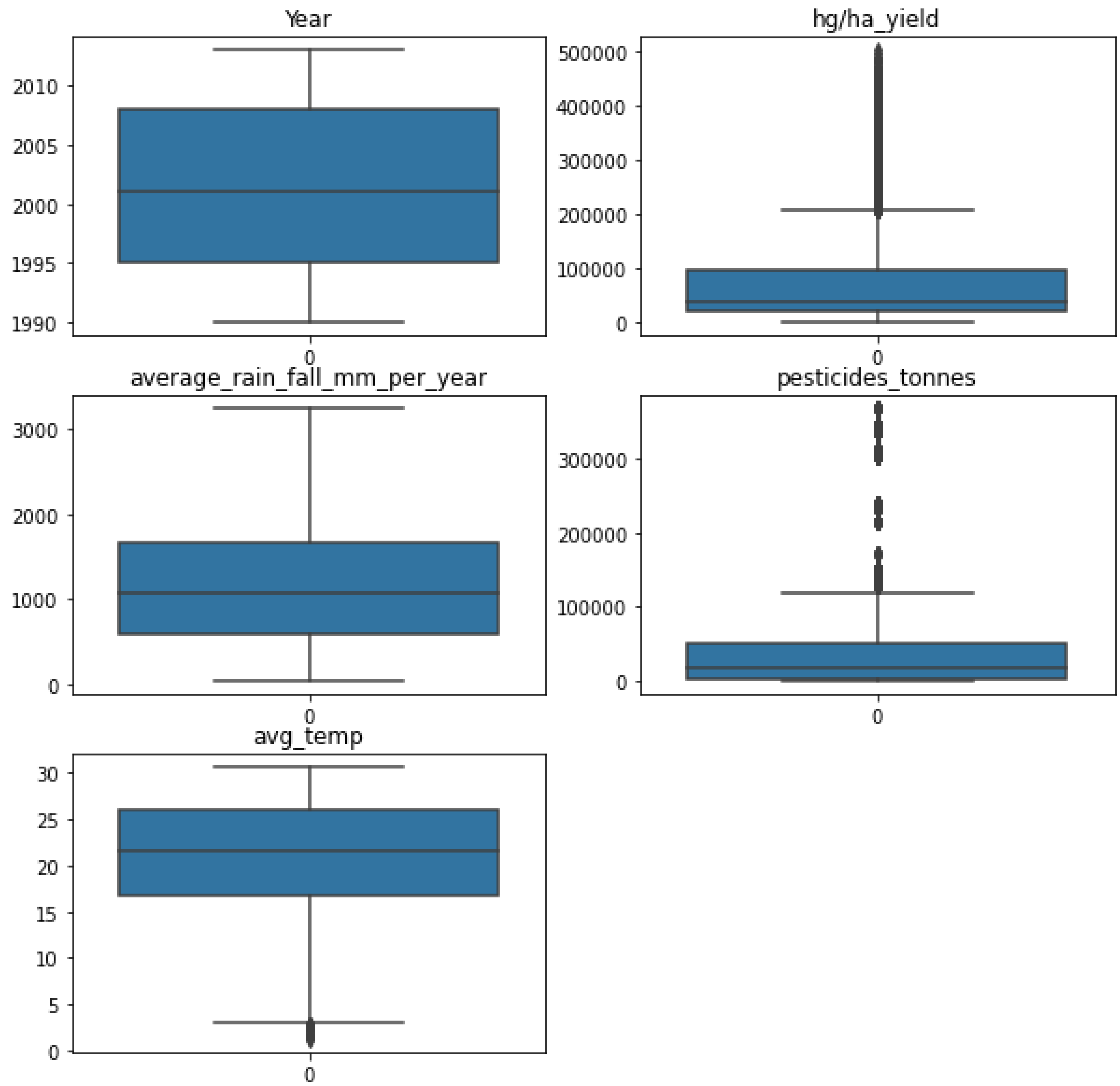
Out[42]: <seaborn.axisgrid.PairGrid at 0x22af69b8550>



In [43]:

```
# Checking the data for outliers

plt.figure(figsize = (10,10))

plt.subplot(3,2,1)
sns.boxplot(data= Yield_dfcopy['Year'])
plt.title('Year')


plt.subplot(3,2,2)
sns.boxplot(data= Yield_dfcopy['hg/ha_yield'])
plt.title('hg/ha_yield')

plt.subplot(3,2,3)
sns.boxplot(data= Yield_dfcopy['average_rain_fall_mm_per_year'])
plt.title('average_rain_fall_mm_per_year')
```

```
plt.subplot(3,2,4)
sns.boxplot(data= Yield_dfcopy['pesticides_tonnes'])
plt.title('pesticides_tonnes')

plt.subplot(3,2,5)
sns.boxplot(data= Yield_dfcopy['avg_temp'])
plt.title('avg_temp')

plt.show()
```



It has been observed that there are outliers in the 'avg_temp' and 'pesticides_tonnes' columns

In [ ]:

```
```

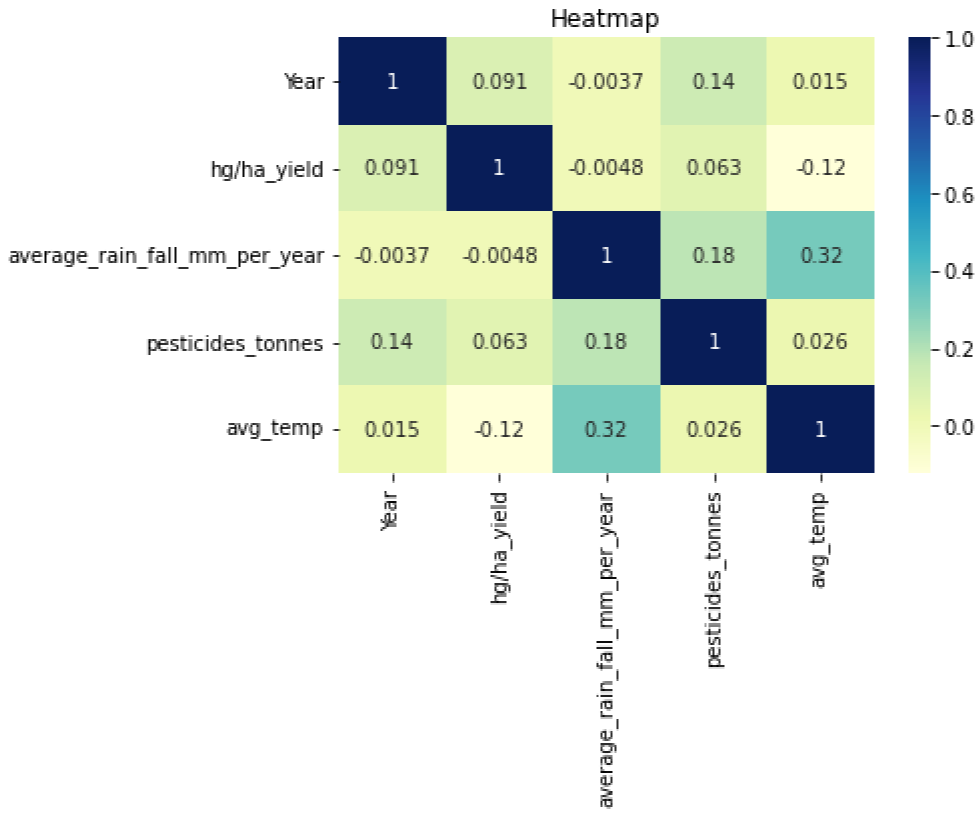
In [44]:

```
num_cor = Yield_dfcopy.select_dtypes(['int64','float64']).corr()
```

In [45]:

```
sns.heatmap(num_cor,cmap = 'YlGnBu',annot = True)
plt.title('Heatmap')
```

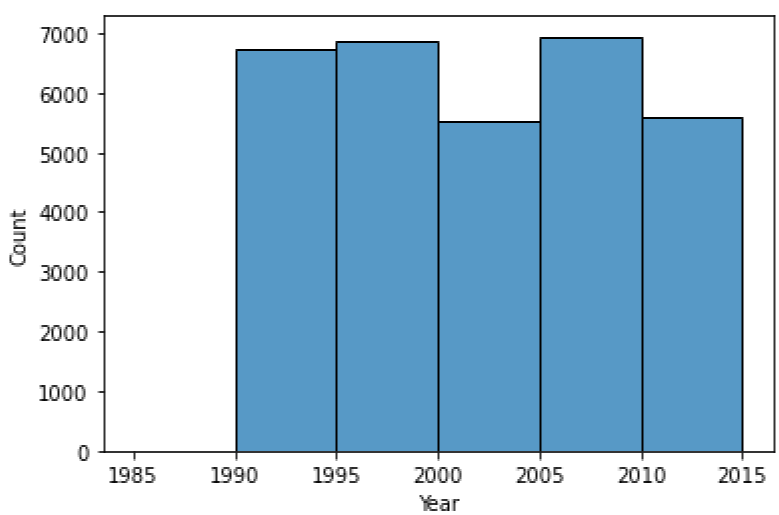
Out[45]:
```
Text(0.5, 1.0, 'Heatmap')
```



The plot visually indicates that there is no significant correlation observed among the columns. The absence of strong correlations suggests that the variables may not have a linear relationship or exhibit a direct influence on each other. Further statistical analysis may be conducted to explore any underlying patterns or relationships.

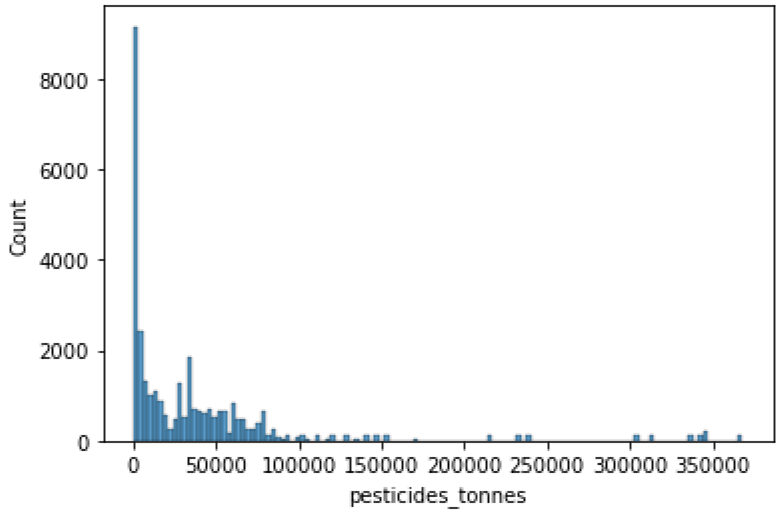
In [46]:
```
 #Checking the data distribution in the
sns.histplot(Yield_dfcopy, x = 'Year' , bins = range(1985, 2020, 5))
```

Out[46]:
```
<AxesSubplot:xlabel='Year', ylabel='Count'>
```



In [47]:
```
### Checking the pesticide usage data

## Checking the data distribution in the yield column
sns.histplot(Yield_dfcopy, x = 'pesticides_tonnes' )
```

Out[47]: <AxesSubplot:xlabel='pesticides_tonnes', ylabel='Count'>

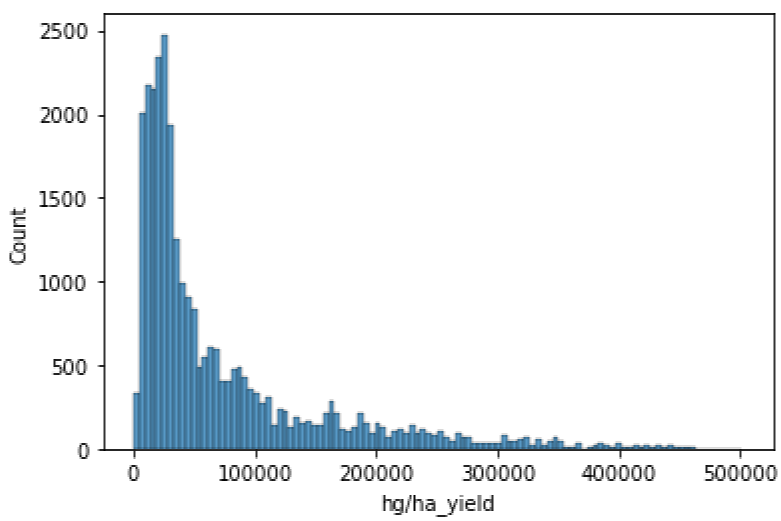


There are outlier points in the datasets, to maintain data integrity while addressing the impact of extreme values on the analysis, mitigating potential high variance by removing only the upper 10% of data points is needed.

In [48]:
```
Yield_dfcopy = Yield_dfcopy[Yield_dfcopy['pesticides_tonnes']
                                    <= Yield_dfcopy['pesticides_tonnes'].quantile(0.90)
```

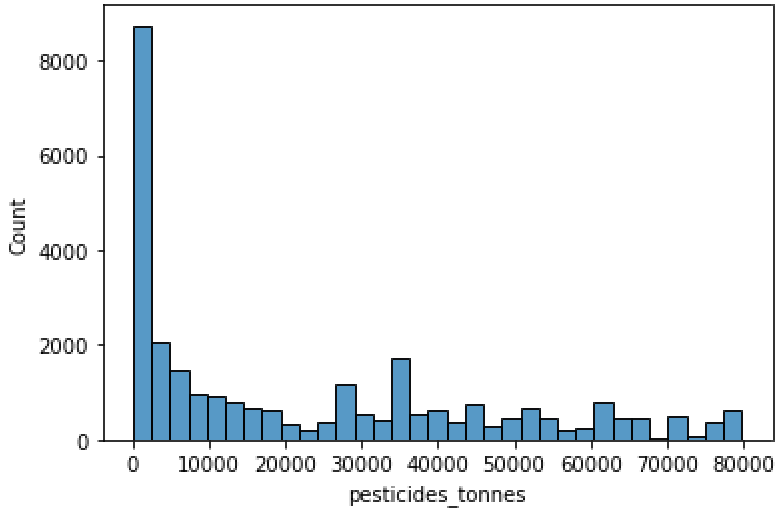
In [49]:
```
# Checking the data distribution in the yield column(if there have been any changes in 
sns.histplot(Yield_dfcopy, x = 'hg/ha_yield' )
```

Out[49]: <AxesSubplot:xlabel='hg/ha_yield', ylabel='Count'>



In [50]:
```
sns.histplot(Yield_dfcopy, x = 'pesticides_tonnes' )
```

Out[50]: <AxesSubplot:xlabel='pesticides_tonnes', ylabel='Count'>



In [51]:
```
Yield_dfcopy= pd.get_dummies(Yield_dfcopy,columns = ['Item','Area'], drop_first = True
```

In [ ]:

In [ ]:

Splitting the data

In [52]:
```
split_ratio = 0.25
split_index = int(len(Yield_dfcopy) * split_ratio)

# Get the 'Year' value at the split point
split_year = Yield_dfcopy['Year'].iloc[split_index]

print(f"Split Year: {split_year}")
```

```
Split Year: 2006
```

In [53]:
```
df_train = Yield_dfcopy[Yield_dfcopy['Year'] <= 2008]
df_test  = Yield_dfcopy[Yield_dfcopy['Year'] > 2008]
```

In [54]:
```
Yield_dfcopy.shape
```

Out[54]:
```
(28959, 115)
```

In [55]:
```
df_train = df_train.drop('Year',axis = 1)
df_test  = df_test.drop('Year',axis = 1)

X_train = df_train.drop('hg/ha_yield',axis = 1 )
y_train = df_train['hg/ha_yield']
X_test  = df_test.drop('hg/ha_yield', axis = 1)
y_test  = df_test['hg/ha_yield']

print(X_train.shape)
```

```
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(22632, 113)
(22632,)
(6327, 113)
(6327,)
```

In [56]:

```
y_train.values.reshape(-1,1)
y_test.values.reshape(-1,1)
```

Out[56]:

```
array([[ 55693],
       [219780],
       [ 16667],
       ...,
       [ 13142],
       [ 22222],
       [ 22888]], dtype=int64)
```

Scaling and Model training

In [57]:

```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Training: Training of model using Linear Regression

In [59]:

```
from sklearn.linear_model import LinearRegression
LR = LinearRegression()
LR.fit(X_train,y_train)
y_pred = LR.predict(X_test)

Model_perf = pd.DataFrame(columns=['Model_Name','MSE','R2_Score'])

LR_mse = mean_squared_error(y_test,y_pred)
LR_R2 = r2_score(y_test,y_pred)

new_row = {'Model_Name':'Linear Regression','MSE':LR_mse , 'R2_Score': LR_R2}
Model_perf = Model_perf.append(new_row,ignore_index = True)
```

In [60]:

```
from sklearn.preprocessing import PolynomialFeatures


# Create polynomial features
poly_features = PolynomialFeatures(degree=1)
X_poly = poly_features.fit_transform(X_train)

# Train the polynomial regression model
poly_regression = LinearRegression()
poly_regression.fit(X_poly, y_train)

# Predict using the trained model
```

```
X_test_poly = poly_features.transform(X_test)
y_pred = poly_regression.predict(X_test_poly)
print("Predicted values:", y_pred)
```

```
Predicted values: [ 22948.8125 174228.8125   2213.5625 ... -19339.5625  85013.875
 -12284.5625]
```

In [61]:

```
PR_mse = mean_squared_error(y_test,y_pred)
PR_R2 = r2_score(y_test,y_pred)

new_row = {'Model_Name':'Polynomial Regression(degree 1)','MSE':PR_mse , 'R2_Score': PR_
Model_perf = Model_perf.append(new_row,ignore_index = True)
```

In [ ]:

In [ ]:

Model Performance

In [62]:

```
Model_perf
```

Out[62]:

	Model_Name	MSE	R2_Score
0	Linear Regression	7.542342e+28	-8.749149e+18
1	Polynomial Regression(degree 1)	3.652341e+25	-4.236731e+15

Conclusion

This project aims to harness the power of data science to gain insights into agricultural trends, optimize crop yield predictions, and contribute to informed decision-making in the agricultural sector. Through careful analysis and modeling, we seek to provide valuable tools for farmers, policymakers, and stakeholders to enhance sustainable and efficient agricultural practices. Although, we couldn't get data that speak to the Nigerian Ecosystem, we deem it necessary to use the available data to serve as a template for future work.

Reccommendation

Acknowledging the limitation in obtaining data specific to the Nigerian ecosystem, leveraging the available dataset becomes pivotal as a template for future endeavors within the Nigerian agricultural landscape. Despite the absence of direct data, this project serves as a foundational framework, offering insights into methodologies, potential analyses, and model development that can be adapted and fine-tuned when specific Nigerian agricultural data becomes accessible.

By utilizing this existing dataset as a prototype, it provides a roadmap for structuring future data collection endeavors. It allows for the identification of essential variables, relevant features, and potential correlations that might be crucial within the Nigerian context.

Moreover, this groundwork helps in establishing methodologies for data preprocessing, outlier detection, feature engineering, and model selection, all of which are fundamental in any agricultural data analysis. These processes can serve as a starting point when integrating future Nigerian agricultural data, ensuring a more streamlined and efficient analysis pipeline.

In essence, while the current dataset might not directly represent the Nigerian ecosystem, the methodologies, approaches, and learnings gained through this project create a strong foundation. They stand as a valuable precursor, guiding future data collection efforts and analyses specifically tailored to the unique nuances of the Nigerian agricultural landscape.

In [ ]: