Load and Explore the Dataset

```
import pandas as pd
```

```
df = pd.read_csv('Crop Production data.csv')
df.head(10)
```

	State_Name	District_Name	Crop_Year	Season	Crop	Area	Production
0	Andaman and Nicobar Islands	NICOBARS	2000.0	Kharif	Arecanut	1254.0	2000.0
1	Andaman and Nicobar Islands	NICOBARS	2000.0	Kharif	Other Kharif pulses	2.0	1.0
2	Andaman and Nicobar Islands	NICOBARS	2000.0	Kharif	Rice	102.0	321.0
3	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Banana	176.0	641.0
4	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Cashewnut	720.0	165.0
5	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Coconut	18168.0	65100000.0
6	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Dry ginger	36.0	100.0
7	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Sugarcane	1.0	2.0
8	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Sweet potato	5.0	15.0
9	Andaman and Nicobar Islands	NICOBARS	2000.0	Whole Year	Tapioca	40.0	169.0

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15831 entries, 0 to 15830
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   State_Name     15831 non-null  object
 1   District_Name  15830 non-null  object
 2   Crop_Year      15830 non-null  float64
 3   Season         15830 non-null  object
 4   Crop           15830 non-null  object
 5   Area           15830 non-null  float64
 6   Production     15760 non-null  float64
dtypes: float64(3), object(4)
memory usage: 865.9+ KB
```

	Crop_Year	Area	Production
count	15830.000000	15830.000000	1.576000e+04
mean	2006.075237	9677.251678	1.168658e+06
std	5.125498	37736.103854	2.183598e+07
min	1997.000000	0.200000	0.000000e+00
25%	2002.000000	126.000000	1.957500e+02
50%	2006.000000	727.000000	1.251000e+03
75%	2011.000000	4000.000000	8.794000e+03
max	2014.000000	877029.000000	7.801620e+08

Data Cleaning and Preprocessing

Handling Missing Values

```
# Checking for missing values
missing_values = df.isnull().sum()
print(missing_values)
```

```
State_Name        0
District_Name     1
Crop_Year         1
Season            1
Crop              1
Area              1
Production       71
dtype: int64
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

```
from sklearn.preprocessing import LabelEncoder
```

```
label_encoders = {}
for column in df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le
```

```
import numpy as np

# Filling missing values with the mean for numeric columns only
numeric_cols = df.select_dtypes(include=np.number).columns
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].mean())
```

Outlier Detection and Handling

```
from scipy import stats

# Z-score method to detect outliers
z_scores = stats.zscore(df.select_dtypes(include=[float, int]))
abs_z_scores = abs(z_scores)
filtered_entries = (abs_z_scores < 3).all(axis=1)
df_clean = df[filtered_entries]
```

```
print("Original dataset shape:", df.shape)
print("Dataset shape after removing outliers:", df_clean.shape)
```

```
Original dataset shape: (15831, 7)
Dataset shape after removing outliers: (15515, 7)
```

Feature Engineering

Creating New Features

```
df_clean['Yield_per_Hectare'] = df_clean['Production'] / df_clean['Area']
```

```
<ipython-input-8-d595a56ec854>:1: SettingWithCopyWarning:
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/stable/user_guide/indexing.html#returning-a-view-versus
  df_clean['Yield_per_Hectare'] = df_clean['Production'] / df_clean['Area']
```

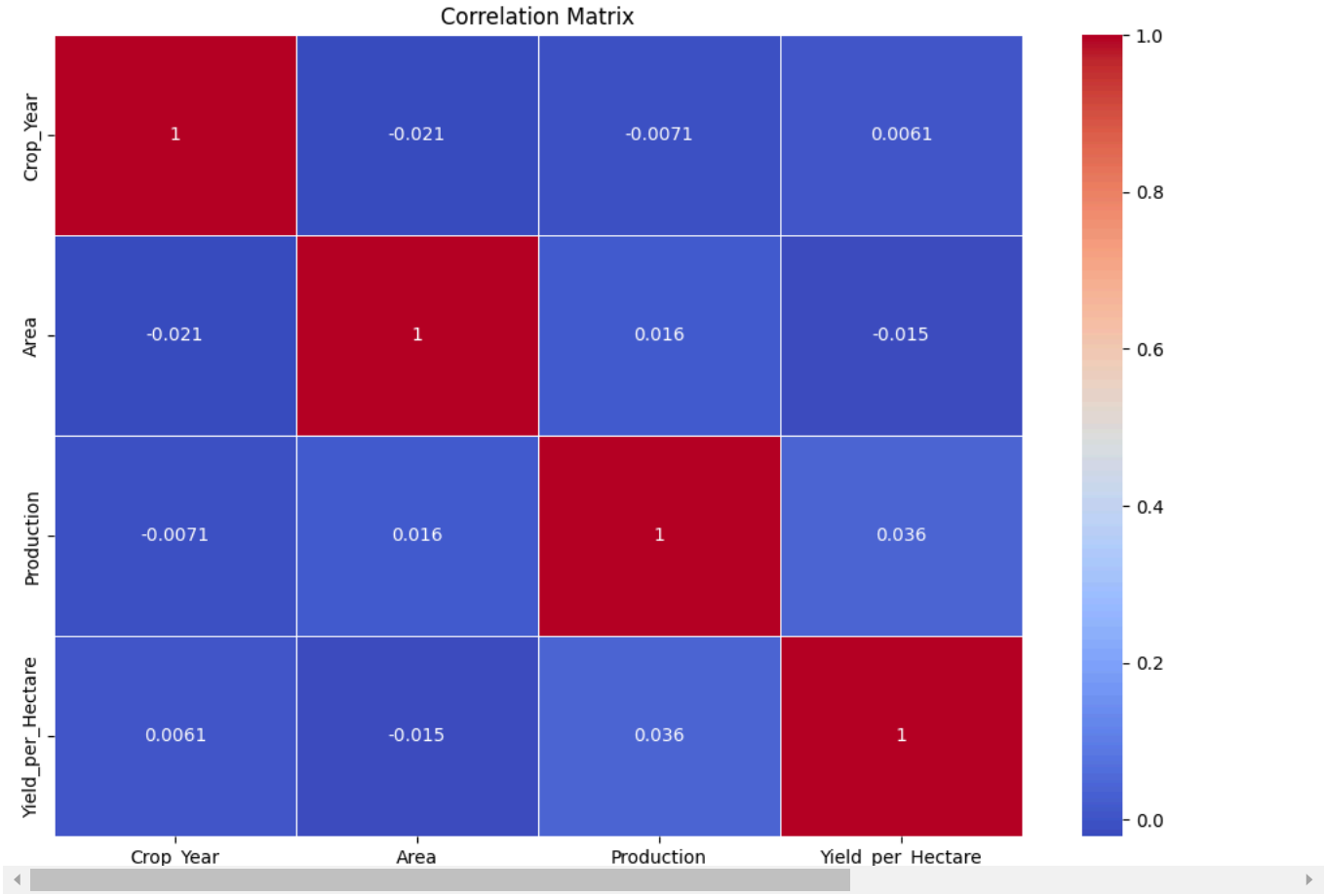
Exploratory Data Analysis (EDA)

Correlation Matrix and Heatmap

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

# Identify non-numeric columns
non_numeric_cols = df_clean.select_dtypes(exclude=['number']).columns
print("Non-numeric columns:", non_numeric_cols)


df_numeric = df_clean.drop(non_numeric_cols, axis=1)
```

```
plt.figure(figsize=(12, 8))
if 'df_numeric' in locals():
    correlation_matrix = df_numeric.corr()
else:
    correlation_matrix = df_clean.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```

```
Non-numeric columns: Index(['State_Name', 'District_Name', 'Season', 'Crop'], dtype='object')
```




```
Start coding or generate with AI.
```

Crop Production Trends Over the Years

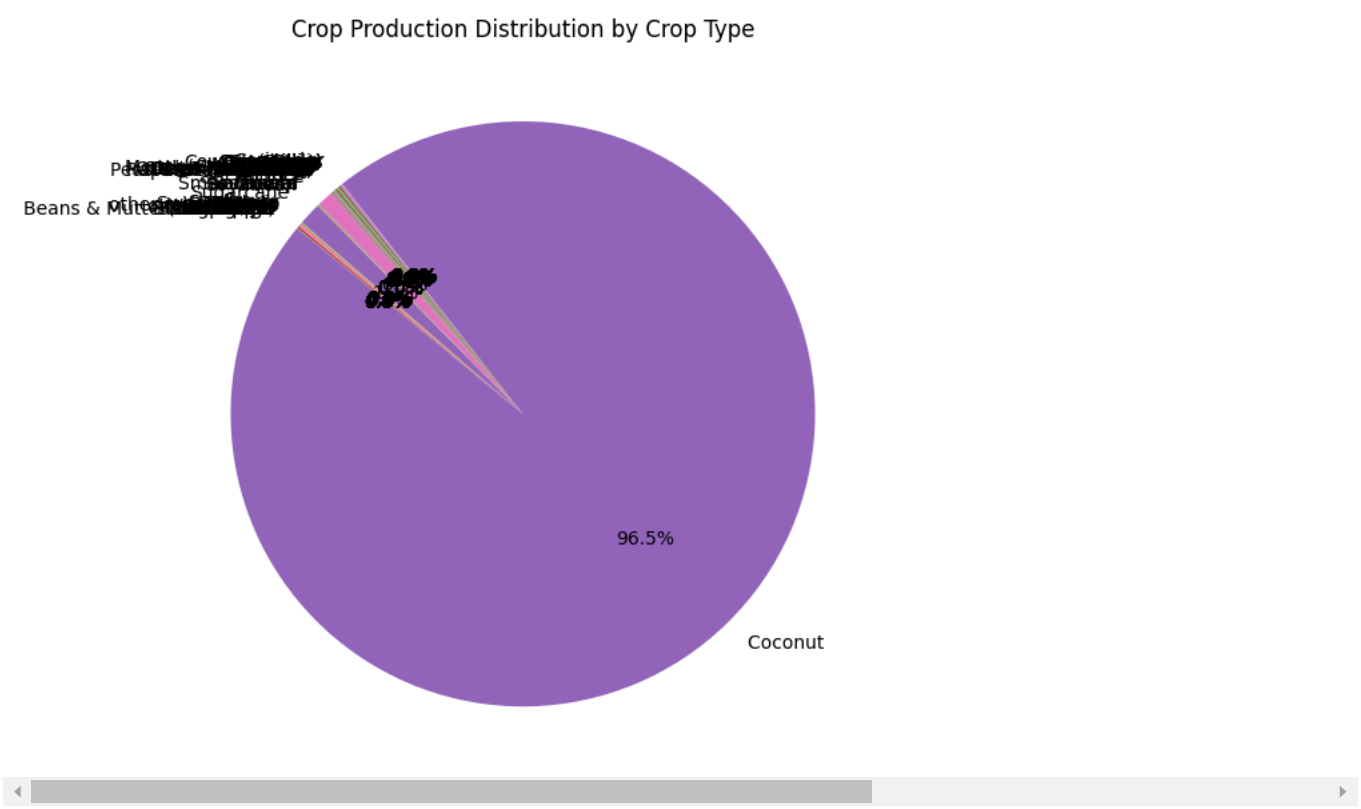
Analyze how crop production has changed over time.

```
print(df_clean.columns)

if 'Year' in df_clean.columns:
    print(df_clean['Crop_Year'].dtype)
else:
    print("The 'Year' column does not exist in the DataFrame.")
```

```
Index(['State_Name', 'District_Name', 'Crop_Year', 'Season', 'Crop', 'Area',
       'Production', 'Yield_per_Hectare'],
      dtype='object')
The 'Year' column does not exist in the DataFrame.
```

Pie Chart: Crop Production Distribution by Crop Type

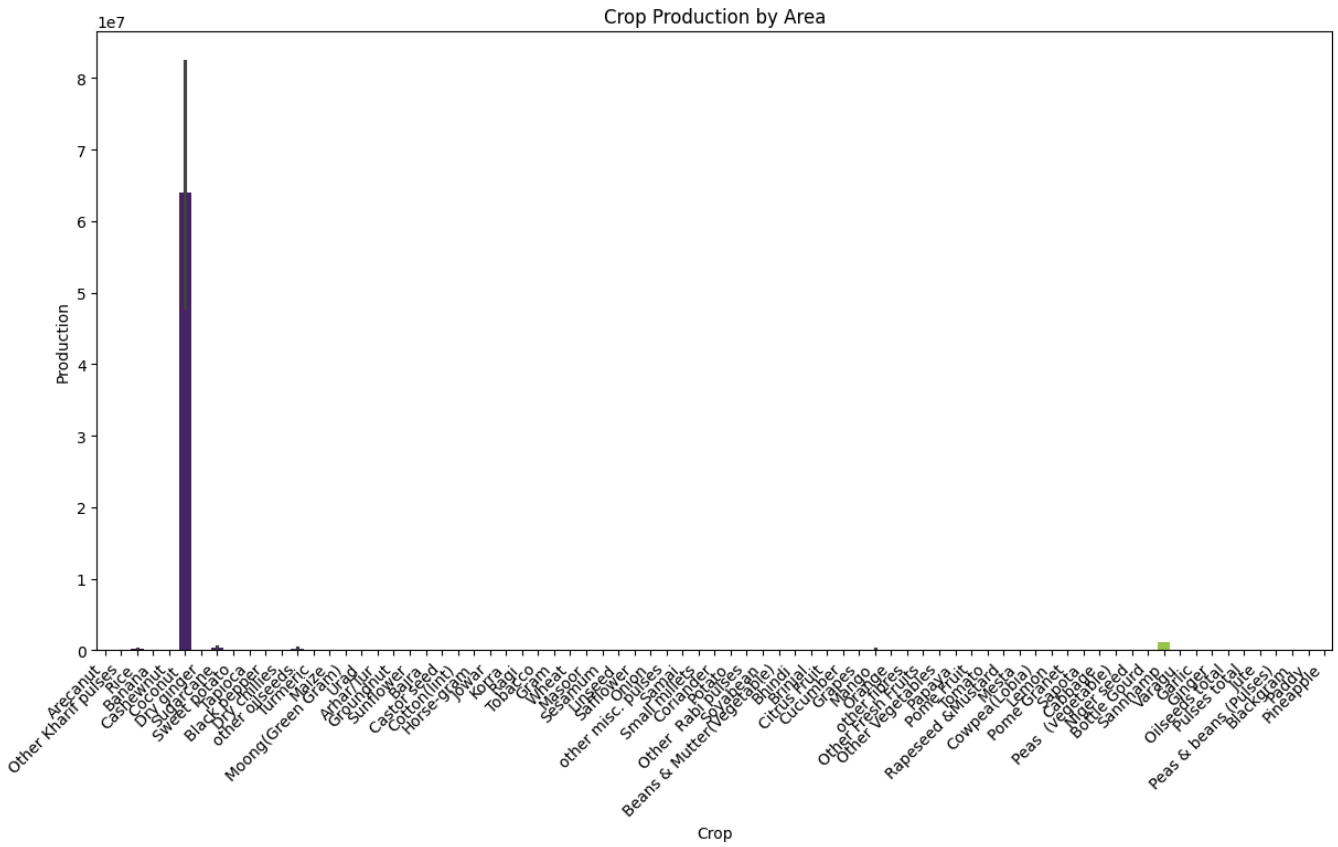
```
crop_production = df.groupby('Crop')['Production'].sum()
plt.figure(figsize=(10, 6))
plt.pie(crop_production, labels=crop_production.index, autopct='%1.1f%%', startangle=140, labeldistance=1.1)
plt.title('Crop Production Distribution by Crop Type')
plt.tight_layout()
plt.show()
```



Crop Production by Area

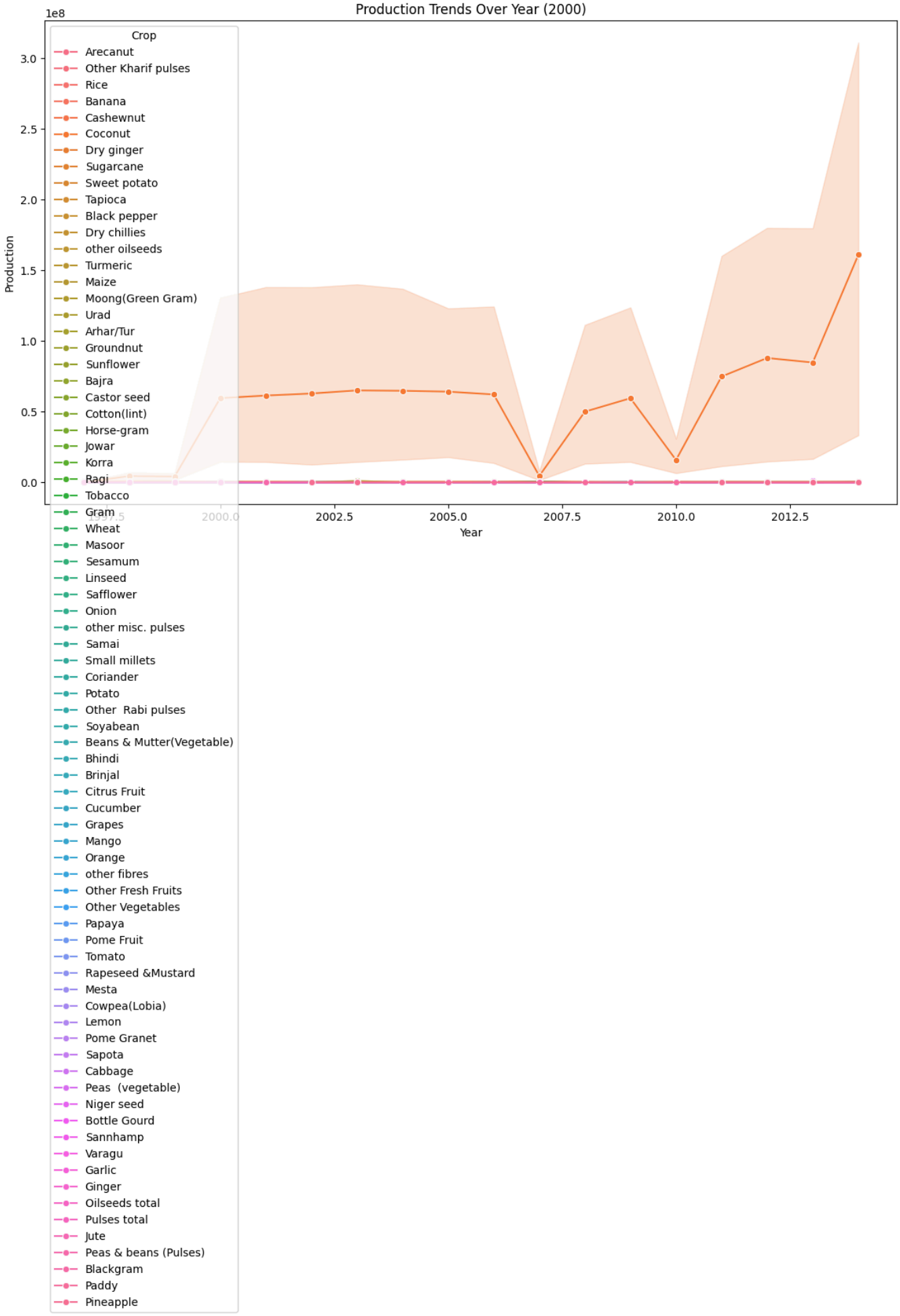
```
plt.figure(figsize=(14, 8))
sns.barplot(x=df['Crop'], y=df['Production'], palette='viridis')
plt.title('Crop Production by Area')
plt.xlabel('Crop')
plt.ylabel('Production')
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.subplots_adjust(left=0.1, right=0.9, top=0.9, bottom=0.2)  # Adjust layout
plt.show()
```

```
<ipython-input-17-f06d6bfb0128>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.barplot(x=df['Crop'], y=df['Production'], palette='viridis')
```



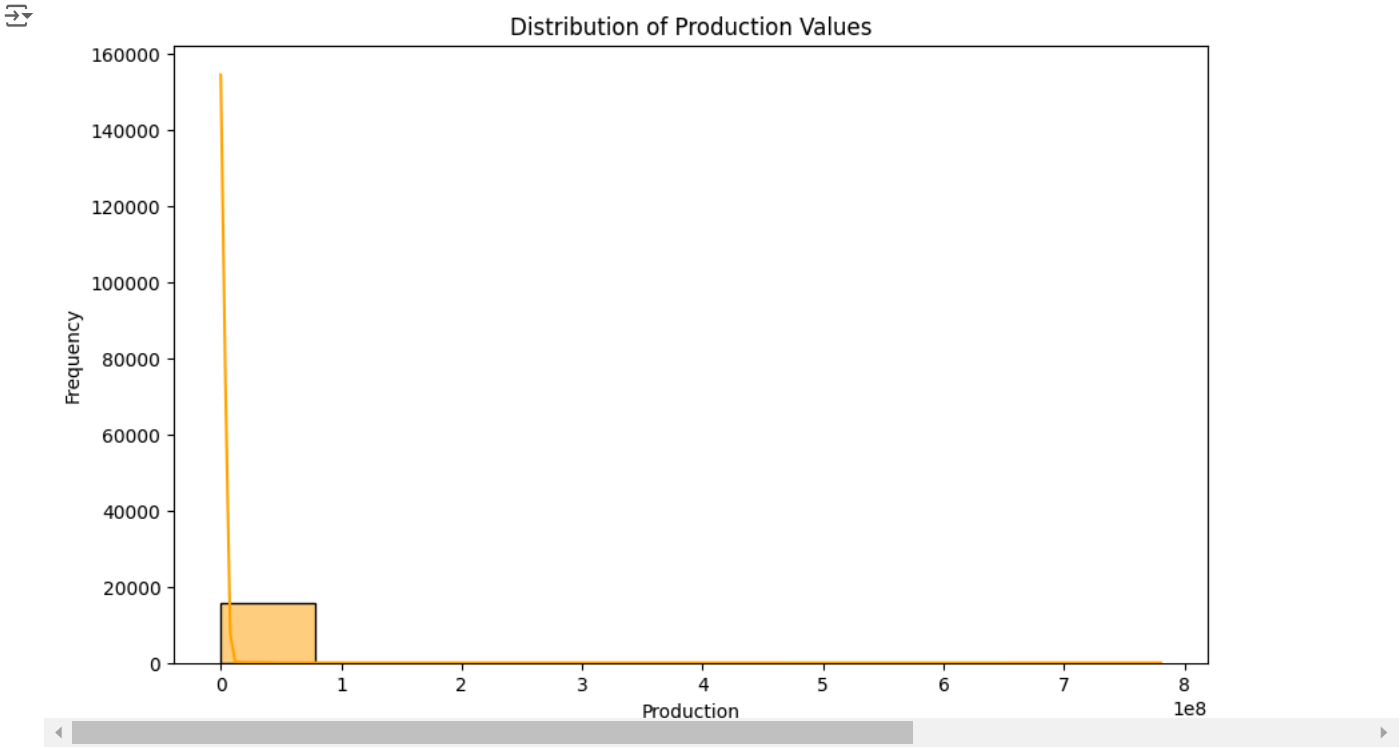
Production Trends Over Years

```
plt.figure(figsize=(14, 8))
sns.lineplot(x='Crop_Year', y='Production', hue='Crop', data=df, marker='o')
plt.title('Production Trends Over Year (2000)')
plt.xlabel('Year')
plt.ylabel('Production')
plt.show()
```


Production Trends Over Year (2000)
1e8
Production
Year
Crop
Arecanut
Other Kharif pulses
Rice
Banana
Cashewnut
Coconut
Dry ginger
Sugarcane
Sweet potato
Tapioca
Black pepper
Dry chillies
other oilseeds
Turmeric
Maize
Moong(Green Gram)
Urad
Arhar/Tur
Groundnut
Sunflower
Bajra
Castor seed
Cotton(lint)
Horse-gram
Jowar
Korra
Ragi
Tobacco
Gram
Wheat
Masoor
Sesamum
Linseed
Safflower
Onion
other misc. pulses
Samai
Small millets
Coriander
Potato
Other Rabi pulses
Soyabean
Beans & Mutter(Vegetable)
Bhindi
Brinjal
Citrus Fruit
Cucumber
Grapes
Mango
Orange
other fibres
Other Fresh Fruits
Other Vegetables
Papaya
Pome Fruit
Tomato
Rapeseed &Mustard
Mesta
Cowpea(Lobia)
Lemon
Pome Granet
Sapota
Cabbage
Peas (vegetable)
Niger seed
Bottle Gourd
Sannhamp
Varagu
Garlic
Ginger
Oilseeds total
Pulses total
Jute
Peas & beans (Pulses)
Blackgram
Paddy
Pineapple

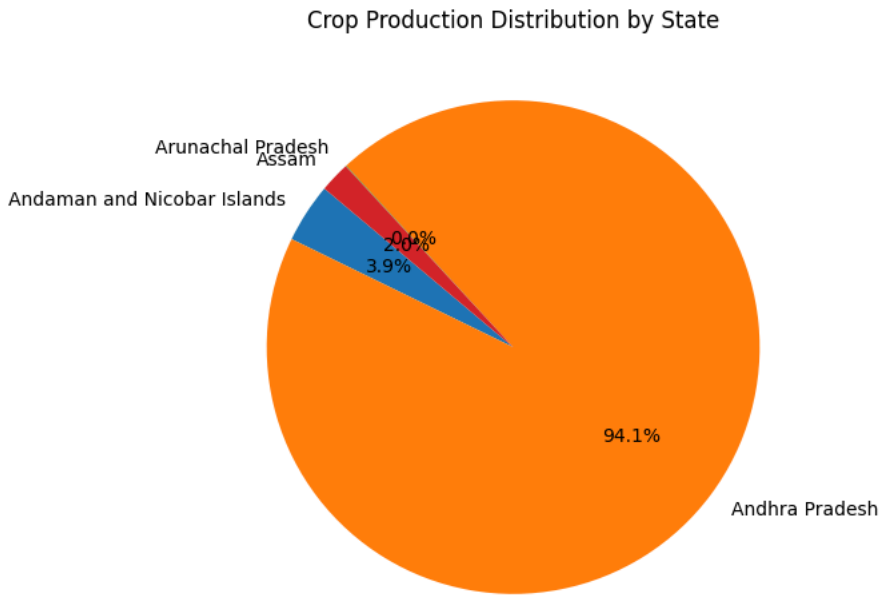
Histogram: Distribution of Production Values

```
plt.figure(figsize=(10, 6))
sns.histplot(df['Production'], bins=10, kde=True, color='orange')
plt.title('Distribution of Production Values')
plt.xlabel('Production')
plt.ylabel('Frequency')
plt.show()
```



Crop Production Distribution by State

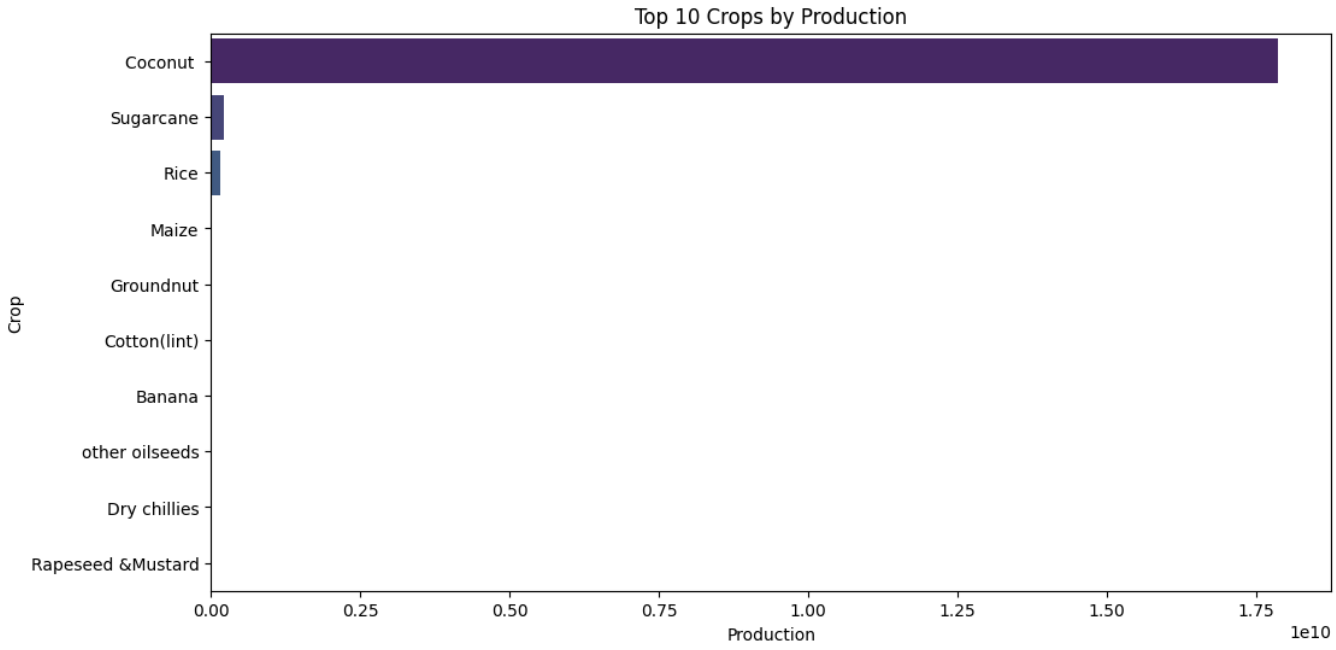
```
state_production = df.groupby('State_Name')['Production'].sum()

# Plotting the pie chart
plt.figure(figsize=(10, 6))
plt.pie(state_production, labels=state_production.index, autopct='%1.1f%%', startangle=140)
plt.title('Crop Production Distribution by State')
plt.show()
```



Top 10 Crops by Production

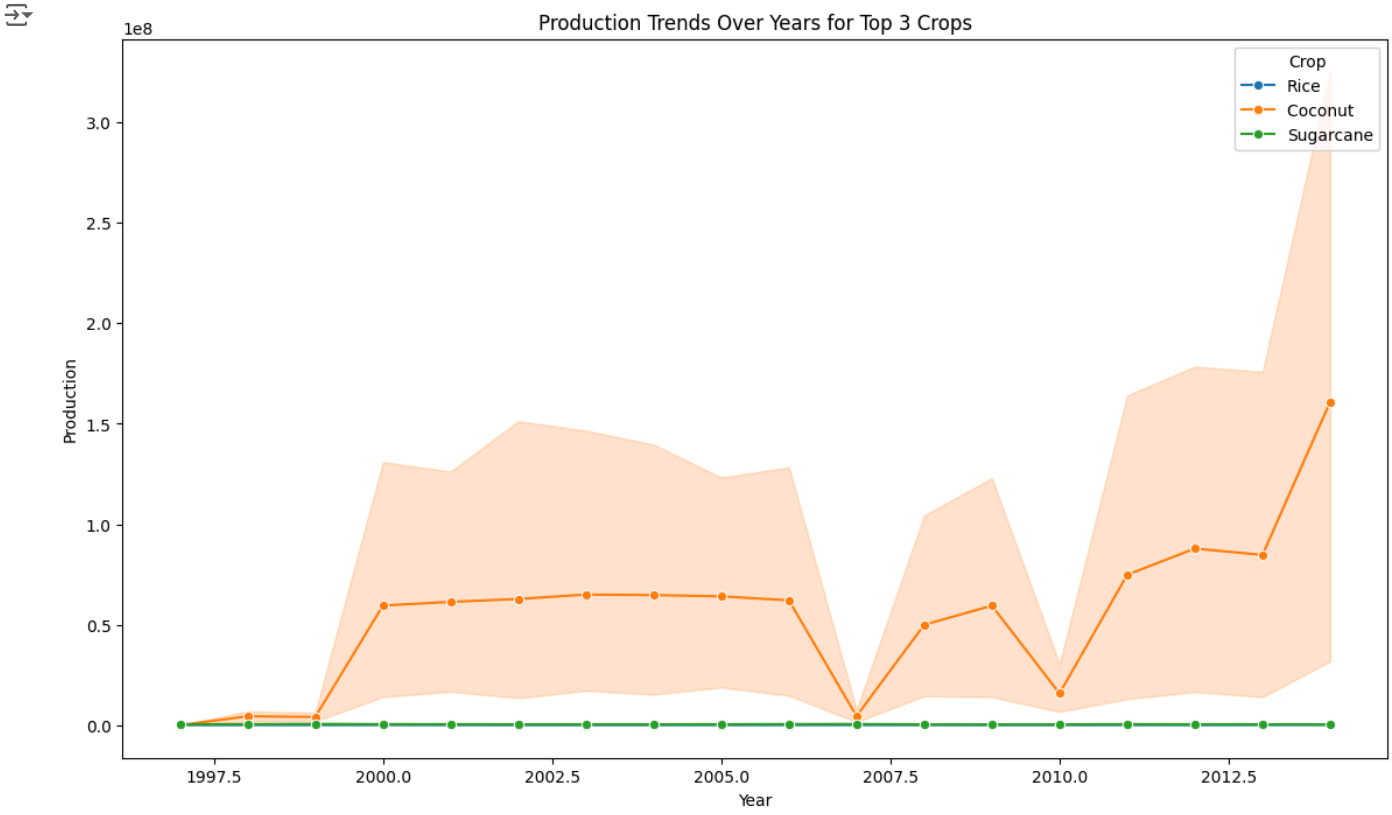
```
import seaborn as sns

# Aggregate production by crop
crop_production = df.groupby('Crop')['Production'].sum().sort_values(ascending=False).head(10)

# Plotting the bar plot
plt.figure(figsize=(12, 6))
sns.barplot(x=crop_production.values, y=crop_production.index, palette='viridis')
plt.title('Top 10 Crops by Production')
plt.xlabel('Production')
plt.ylabel('Crop')
plt.show()
```

```
<ipython-input-21-53fb524caefa>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `le

  sns.barplot(x=crop_production.values, y=crop_production.index, palette='viridis')
```



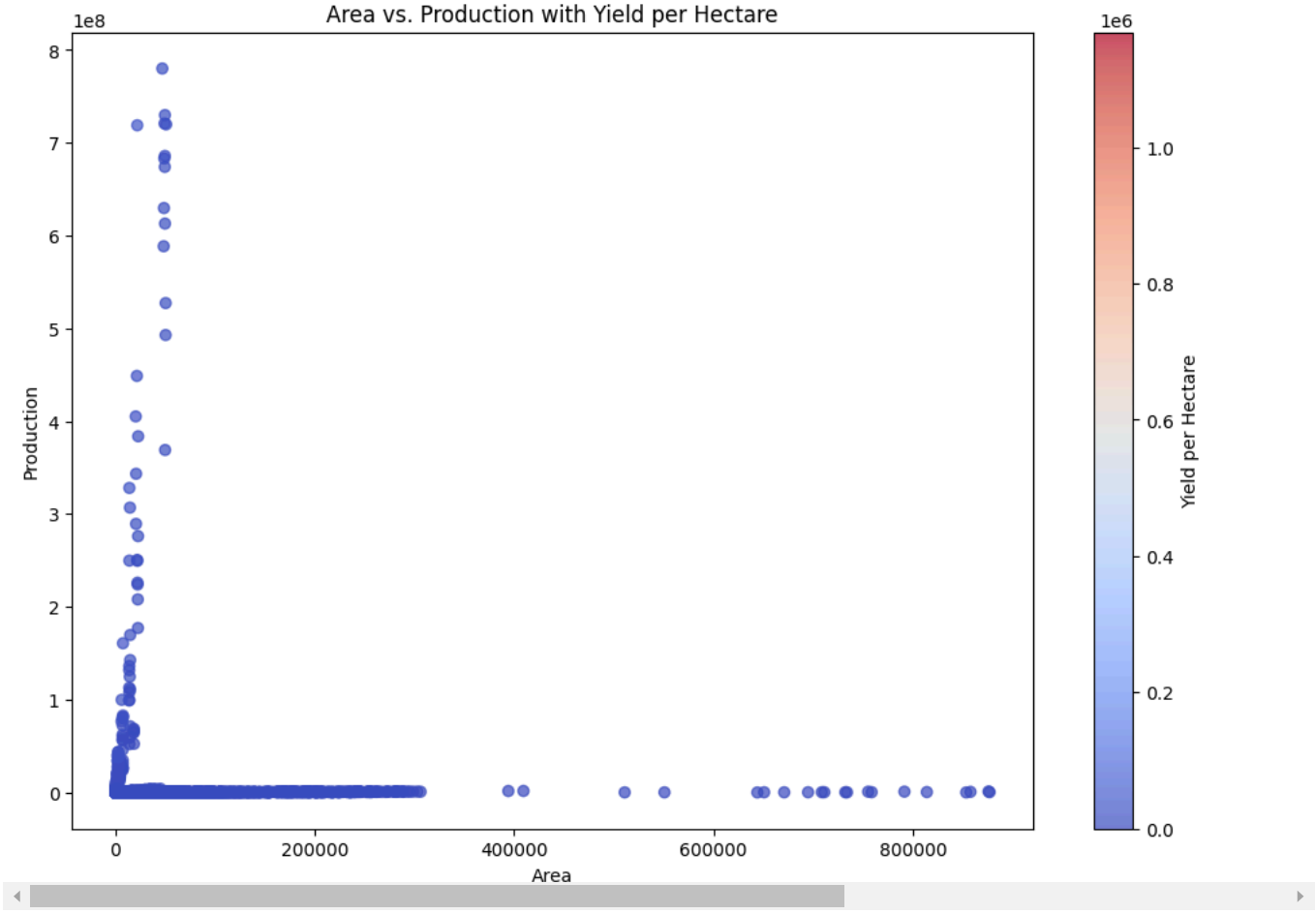
Production Trends Over Years for Top 3 Crops

```
# Select top 3 crops
top_crops = crop_production.index[:3]
df_top_crops = df[df['Crop'].isin(top_crops)]

# Plotting the line plot
plt.figure(figsize=(14, 8))
sns.lineplot(x='Crop_Year', y='Production', hue='Crop', data=df_top_crops, marker='o')
plt.title('Production Trends Over Years for Top 3 Crops')
plt.xlabel('Year')
plt.ylabel('Production')
plt.show()
```



Area vs. Production with Yield per Hectare as Color

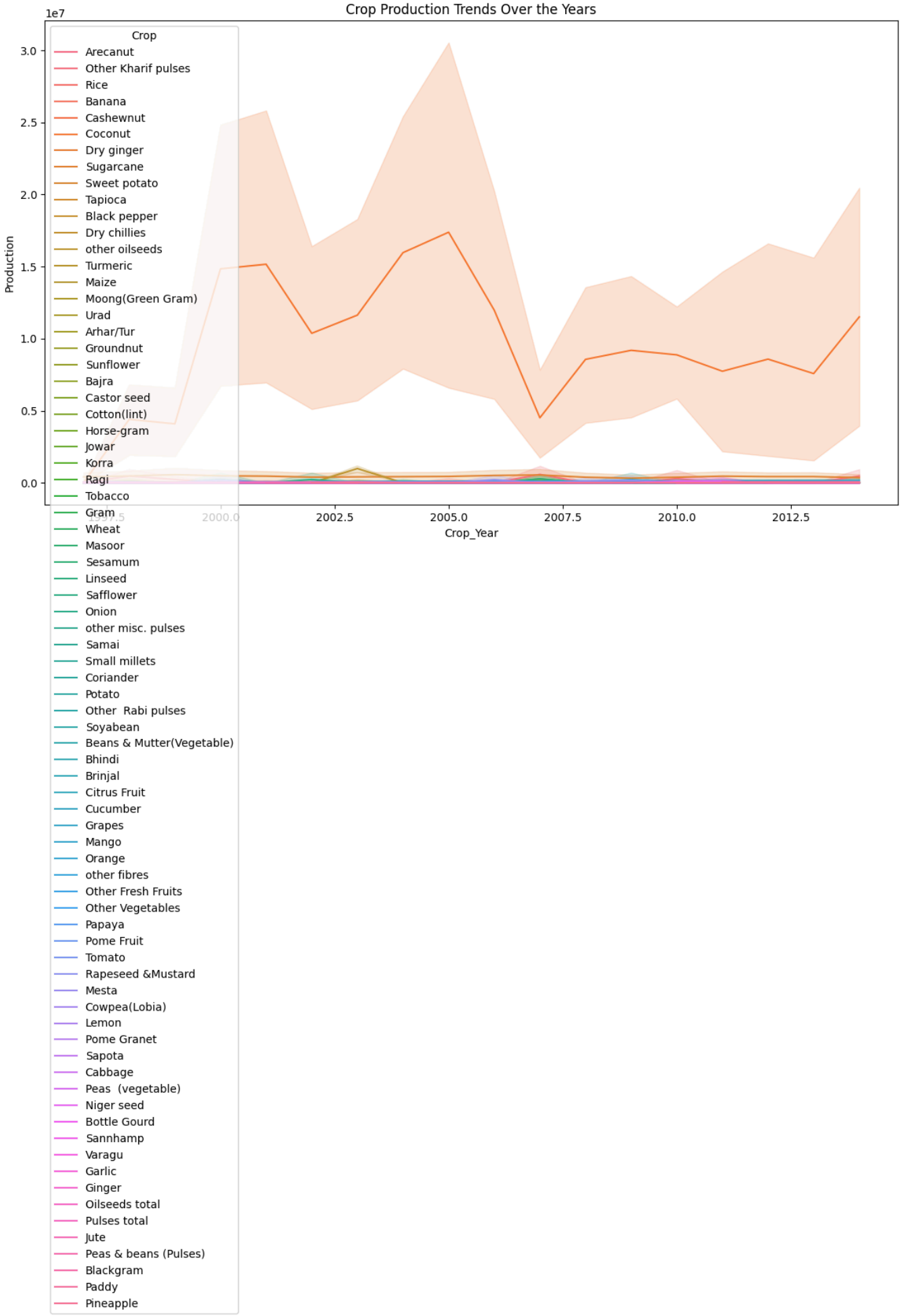
```
# Calculate yield per hectare
df['Yield_per_Hectare'] = df['Production'] / df['Area']

# Scatter plot with yield per hectare as color
plt.figure(figsize=(12, 8))
scatter = plt.scatter(df['Area'], df['Production'], c=df['Yield_per_Hectare'], cmap='coolwarm', alpha=0.7)
plt.colorbar(scatter, label='Yield per Hectare')
plt.title('Area vs. Production with Yield per Hectare')
plt.xlabel('Area')
plt.ylabel('Production')
plt.show()
```



Crop Production Trends Over the Years

```
print(df_clean.columns)


plt.figure(figsize=(14, 8))
sns.lineplot(x='Crop_Year', y='Production', hue='Crop', data=df_clean)
plt.title('Crop Production Trends Over the Years')
plt.show()
```

```
Index(['State_Name', 'District_Name', 'Crop_Year', 'Season', 'Crop', 'Area',
       'Production', 'Yield_per_Hectare'],
      dtype='object')
```



Predictive Modeling

Preparing the Data for Modeling

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
import pandas as pd
import numpy as np
```

Example dataset (replace with your actual data)

Assuming df is your DataFrame and you have 'features' and 'target' columns

Example:

df = pd.read_csv('your_data.csv')

X = df[['feature1', 'feature2', 'feature3']] # Feature columns

y = df['target'] # Target column

```
np.random.seed(42)
X = np.random.rand(100, 5)
y = np.random.rand(100)
```

```
# Splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Training a Random Forest model
model = RandomForestRegressor(n_estimators=100, max_depth=10, random_state=42)
model.fit(X_train, y_train)
```

```
RandomForestRegressor
RandomForestRegressor(max_depth=10, random_state=42)
```

```
# Predict and evaluate
y_pred = model.predict(X_test)
rmse = mean_squared_error(y_test, y_pred, squared=False)
print('RMSE (Random Forest):', rmse)
```

```
RMSE (Random Forest): 0.38741500892466685
```

```
# Training a Linear Regression model (for comparison)
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

```
LinearRegression
LinearRegression()
```

```
# Predict and evaluate for Linear Regression
y_pred_lr = lr_model.predict(X_test)
rmse_lr = mean_squared_error(y_test, y_pred_lr, squared=False)
print('RMSE (Linear Regression):', rmse_lr)
```

```
RMSE (Linear Regression): 0.35203465547983964
```


```
# Predict and evaluate for Linear Regression
y_pred_lr = lr_model.predict(X_test)
rmse_lr = mean_squared_error(y_test, y_pred_lr, squared=False)
print('RMSE (Linear Regression):', rmse_lr)
```

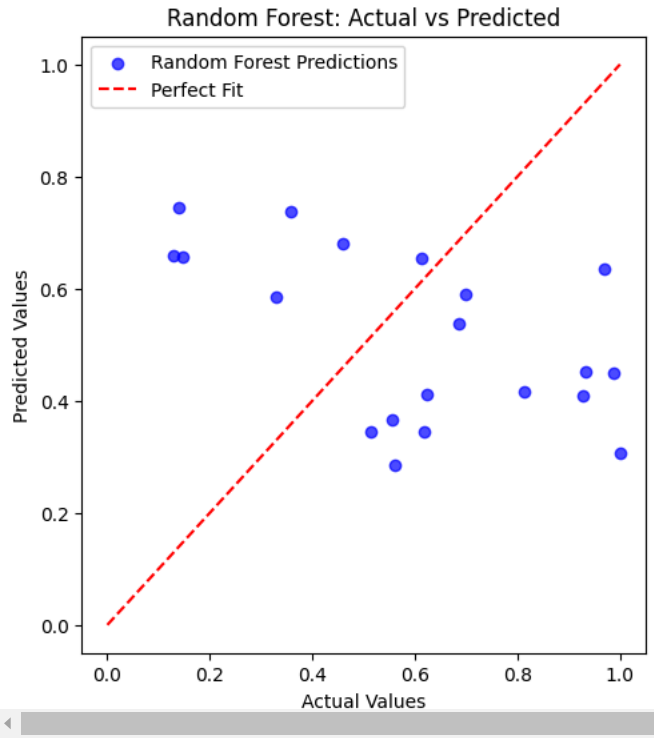
```
RMSE (Linear Regression): 0.35203465547983964
```


Plotting the Results

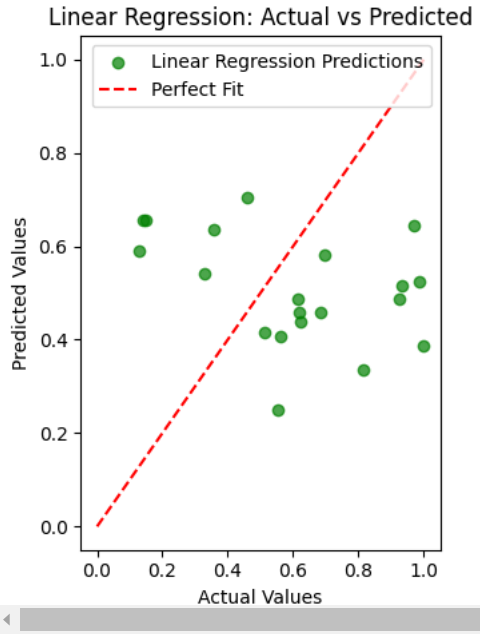
Plot Predictions vs. Actual Values

```
plt.figure(figsize=(12, 6))

# Plot Random Forest Predictions
plt.subplot(1, 2, 1)
plt.scatter(y_test, y_pred, color='blue', alpha=0.7, label='Random Forest Predictions')
plt.plot([0, 1], [0, 1], color='red', linestyle='--', label='Perfect Fit')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Random Forest: Actual vs Predicted')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7ae36f100940>
```



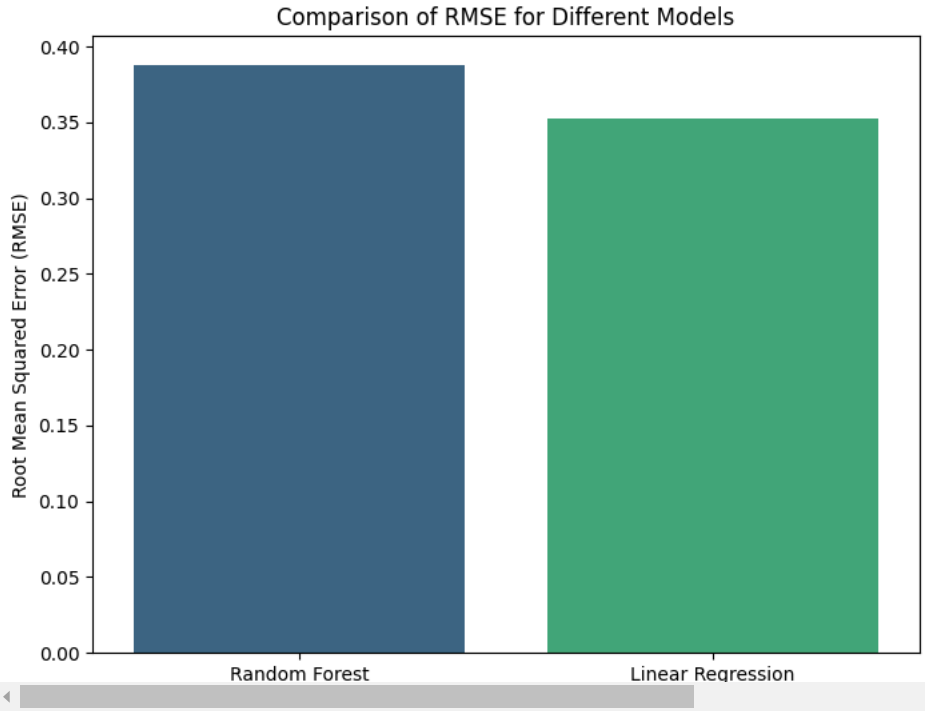

```
# Plot Linear Regression Predictions
plt.subplot(1, 2, 2)
plt.scatter(y_test, y_pred_lr, color='green', alpha=0.7, label='Linear Regression Predictions')
plt.plot([0, 1], [0, 1], color='red', linestyle='--', label='Perfect Fit')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Linear Regression: Actual vs Predicted')
plt.legend()

plt.tight_layout()
plt.show()
```



Plot RMSE Comparison

```
# RMSE values
models = ['Random Forest', 'Linear Regression']
rmses = [rmse, rmse_lr]

plt.figure(figsize=(8, 6))
sns.barplot(x=models, y=rmses, palette='viridis')
plt.ylabel('Root Mean Squared Error (RMSE)')
plt.title('Comparison of RMSE for Different Models')
plt.show()
```

```
<ipython-input-59-1c425b6fff17>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.barplot(x=models, y=rmses, palette='viridis')
```



CONCLUSION:

Based on the RMSE values and the plots:

(i).RMSE (Random Forest): Displays how well the Random Forest model performed on the test set. Lower RMSE indicates better performance.

(ii).RMSE (Linear Regression): Displays how well the Linear Regression model performed on the test set. In the Conclusion Section: