Assessment 1: Group 6

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In [ ]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

import pycountry
import pycountry_convert as pc
import plotly.express as px
```

In [ ]:
```
# This can help us see all the columns when checking the dataframe
pd.set_option('display.max_columns', None)
```

Part 1: Data Wrangling

Data Cleaning

Loading Datasets

In [ ]:
```
# Load FAO dataset
df_fao = pd.read_csv('FAO.csv', encoding='iso-8859-1')

# Load FAOSTAT dataset
df_faostat = pd.read_csv('FAOSTAT.csv')
```

In [ ]:
```
df_fao.sample(3)
```

Out[ ]:

	Area Abbreviation	Area Code	Area	Item Code	Item	Element Code	Element	Unit	latitu
2169	BOL	19	Bolivia (Plurinational State of)	2515	Rye and products	5142	Food	1000 tonnes	-16
11454	LBR	123	Liberia	2744	Eggs	5142	Food	1000 tonnes	6
6066	ECU	58	Ecuador	2619	Dates	5142	Food	1000 tonnes	-1

In [ ]:
```
df_faostat.sample(3)
```

Out[ ]:

	Domain Code	Domain	Area Code	Area	Element Code	Element	Item Code	Item	Year Code	Ye
2	OA	Annual population	4	Algeria	511	Total Population - Both sexes	3010	Population - Est. & Proj.	2017	20
199	OA	Annual population	212	Syrian Arab Republic	511	Total Population - Both sexes	3010	Population - Est. & Proj.	2017	20
205	OA	Annual population	218	Tokelau	511	Total Population - Both sexes	3010	Population - Est. & Proj.	2017	20

Data Dictionary

In [ ]:
```
def generate_data_dictionary(df, desc_list):
    data_dict = {
        'Column Name': [],
        'Data Type': [],
        'Description': []
    }

    for i, column in enumerate(df.columns):
        data_dict['Column Name'].append(column)
        data_dict['Data Type'].append(df[column].dtype)

        # Provide a description based on the description list or a default value
        description = desc_list[i] if i < len(desc_list) else 'N/A'

        # If the column name starts with 'Y' and is a year, format accordingly
        if column.startswith('Y') and column[1:].isdigit():
```

```
            description = f'Data for the year {column[1:]}'
        data_dict['Description'].append(description)

    return pd.DataFrame(data_dict)
```

FAO Dataset

In [ ]:
```
fao_description_list = [
    "Abbreviation of Area",
    "Full name of the country or region",
    "ISO country code or region abbreviation",
    "Numeric code for the country or region",
    "Numeric code for the item",
    "Name of the item",
    "Numeric code for the element",
    "Type of data recorded",
    "Measurement unit for the recorded data",
    "Latitude coordinate of the location",
    "Longitude coordinate of the location",
]
```

In [ ]:
```
# Generate data dictionary for FAO
fao_data_dict = generate_data_dictionary(df_fao, fao_description_list)
fao_data_dict
```

Out[ ]:

	Column Name	Data Type	Description
0	Area Abbreviation	object	Abbreviation of Area
1	Area Code	int64	Full name of the country or region
2	Area	object	ISO country code or region abbreviation
3	Item Code	int64	Numeric code for the country or region
4	Item	object	Numeric code for the item
...	...	...	...
58	Y2009	float64	Data for the year 2009
59	Y2010	float64	Data for the year 2010
60	Y2011	float64	Data for the year 2011
61	Y2012	int64	Data for the year 2012
62	Y2013	int64	Data for the year 2013

63 rows × 3 columns

FAOSTAT Dataset

In [ ]:
```
faostat_description_list=[
    "Numeric Code for Domain",
    "Population Type",
```

```
    "Numeric code for the country or region",
    "Full name of the country or region",
    "Numeric code for the element",
    "Element Type",
    "Numeric code for the item",
    "Object of focus",
    "Code for the Year",
    "Time of the Year",
    "Quantity of item",
    "Value of the item",
    "Flag",
    "Sources of item",
    "Note for item",
]
```

In [ ]:

```
# Generate data dictionary for FAOSTAT
faostat_data_dict = generate_data_dictionary(df_faostat, faostat_description_list)
faostat_data_dict
```

Out[ ]:

	Column Name	Data Type	Description
0	Domain Code	object	Numeric Code for Domain
1	Domain	object	Population Type
2	Area Code	int64	Numeric code for the country or region
3	Area	object	Full name of the country or region
4	Element Code	int64	Numeric code for the element
5	Element	object	Element Type
6	Item Code	int64	Numeric code for the item
7	Item	object	Object of focus
8	Year Code	int64	Code for the Year
9	Year	int64	Time of the Year
10	Unit	object	Quantity of item
11	Value	float64	Value of the item
12	Flag	object	Flag
13	Flag Description	object	Sources of item
14	Note	object	Note for item

Handling Missing Values

In [ ]:

```
# Check rows with null value per column
fao_null_values = {col: df_fao[col].isnull().sum() for col in df_fao.columns if df_

fao_null_values
```

Out[ ]:
```
{'Y1961': 3539,
 'Y1962': 3539,
 'Y1963': 3539,
 'Y1964': 3539,
 'Y1965': 3539,
 'Y1966': 3539,
 'Y1967': 3539,
 'Y1968': 3539,
 'Y1969': 3539,
 'Y1970': 3539,
 'Y1971': 3539,
 'Y1972': 3539,
 'Y1973': 3539,
 'Y1974': 3539,
 'Y1975': 3539,
 'Y1976': 3539,
 'Y1977': 3539,
 'Y1978': 3539,
 'Y1979': 3539,
 'Y1980': 3539,
 'Y1981': 3539,
 'Y1982': 3539,
 'Y1983': 3539,
 'Y1984': 3539,
 'Y1985': 3539,
 'Y1986': 3539,
 'Y1987': 3539,
 'Y1988': 3539,
 'Y1989': 3539,
 'Y1990': 3415,
 'Y1991': 3415,
 'Y1992': 987,
 'Y1993': 612,
 'Y1994': 612,
 'Y1995': 612,
 'Y1996': 612,
 'Y1997': 612,
 'Y1998': 612,
 'Y1999': 612,
 'Y2000': 349,
 'Y2001': 349,
 'Y2002': 349,
 'Y2003': 349,
 'Y2004': 349,
 'Y2005': 349,
 'Y2006': 104,
 'Y2007': 104,
 'Y2008': 104,
 'Y2009': 104,
 'Y2010': 104,
 'Y2011': 104}
```

In [ ]:
```
null_cols = df_fao.isnull().sum()
null_cols[null_cols > 0].index
```

Out[ ]:
```
Index(['Y1961', 'Y1962', 'Y1963', 'Y1964', 'Y1965', 'Y1966', 'Y1967', 'Y1968',
       'Y1969', 'Y1970', 'Y1971', 'Y1972', 'Y1973', 'Y1974', 'Y1975', 'Y1976',
       'Y1977', 'Y1978', 'Y1979', 'Y1980', 'Y1981', 'Y1982', 'Y1983', 'Y1984',
       'Y1985', 'Y1986', 'Y1987', 'Y1988', 'Y1989', 'Y1990', 'Y1991', 'Y1992',
       'Y1993', 'Y1994', 'Y1995', 'Y1996', 'Y1997', 'Y1998', 'Y1999', 'Y2000',
       'Y2001', 'Y2002', 'Y2003', 'Y2004', 'Y2005', 'Y2006', 'Y2007', 'Y2008',
       'Y2009', 'Y2010', 'Y2011'],
      dtype='object')
```

In [ ]:
```python
print(f'Number of rows with null values: {len(df_fao[df_fao.isnull().any(axis=1)])}
```

```
Number of rows with null values: 3539
```

In [ ]:
```python
faostat_null_values = {col: df_faostat[col].isnull().sum() for col in df_faostat.co

faostat_null_values
```

Out[ ]:
```
{}
```

Explanation & Justification:

> We handled missing data in the `FAO` and `FAOSTAT` dataset specifically for the years 1961 - 1991 by retaining the null values rather than replacing them with -1. Since the "y{YEAR_NUM}" columns are the only ones with null values, it is acceptable to leave these nulls as they are. Replacing these nulls with -1 could affect the summarization of statistics and affect the accuracy of visualizations.

> Retaining null values preserves the integrity of our statistical summaries, such as mean and standard deviation calculations, which could be skewed by arbitrary replacement values like -1. By keeping nulls, we avoid misrepresenting missing data as zeroes, thus ensuring that our plots and analyses accurately reflect the data's true nature and maintain clarity in our visualizations.

Removing & Checking Duplicates

In [ ]:
```python
# Check duplicates in FAO
dupe_fao_sum= df_fao.duplicated().sum()

print(f'Total number of duplicated rows in FAO: {dupe_fao_sum}')
```

```
Total number of duplicated rows in FAO: 0
```

In [ ]:
```python
# Check duplicates in FAOSTAT
dupe_faostat_sum = df_faostat.duplicated().sum()

print(f'Total number of duplicated rows in FAOSTAT: {dupe_faostat_sum}')
```

```
Total number of duplicated rows in FAOSTAT: 0
```

Explanation & Justification:

> To remove and check duplicates in both the `FAO` and `FAOSTAT` datasets, the *duplicated* Pandas method is utilized.

> By default, the *duplicated* Pandas method returns a boolean series that denotes duplicate rows. To have a numerical representation of the number of duplicates, we added the *sum* Pandas method, that denotes its total instead.

Standardize Column Names

In [ ]:
```
df_fao.columns = (
    df_fao.columns
    .str.lower()                                  # Convert to lowercase
    .str.replace(' ', '_')                        # Replace spaces with underscores
    .str.replace(r'[^a-z0-9_]', '', regex=True)  # Remove special characters
)
```

In [ ]:
```
df_faostat.columns = (
    df_faostat.columns
    .str.lower()
    .str.replace(' ', '_')
    .str.replace(r'[^a-z0-9_]', '', regex=True)
)
```

Explanation & Justification:

> To standardize the column names of the `FAO` and `FAOSTAT` datasets, we first converted the column names to lowercase and replaced any spaces with underscores. This ensures consistency in case and format, helping to avoid potential issues related to case sensitivity.

> Additionally, we removed any special characters from the column names, leaving only lowercase letters, numbers, and underscores.

> These standardization steps enhance data consistency, making the datasets easier to work with and reducing the likelihood of errors during data processing.

In [ ]:
```
# Rename similar columns in the dataframe
df_faostat.rename(columns={
    'item'        : 'population_item',
    'item_code'   : 'population_item_code',
    'element'     : 'population_element',
    'element_code': 'population_element_code',
    'unit'        : 'population_unit'
}, inplace=True)

df_faostat.columns
```

Out[ ]:
```
Index(['domain_code', 'domain', 'area_code', 'area', 'population_element_code',
       'population_element', 'population_item_code', 'population_item',
       'year_code', 'year', 'population_unit', 'value', 'flag',
       'flag_description', 'note'],
      dtype='object')
```

Explanation & Justification:

> The `FAO` and `FAOSTAT` datasets share similar column names and merging them could lead to confusion or errors. Thus, we renamed such columns to ensure clarity and avoid potential conflicts during analysis.

> We renamed specific columns in the `FAOSTAT` dataset to make them more descriptive and aligned with the dataset's focus on population data. The columns renamed include:
>
> - 'item' to 'population_item': This clarifies that the column refers specifically to the population data item (e.g., "Population - Estimated and Projected").
> - 'item_code' to 'population_item_code': By adding "population," it specifies that the code is related to population items.
> - 'element' to 'population_element': This indicates that the column pertains to a specific element within the population data (e.g., "Total Population - Both sexes").
> - 'element_code' to 'population_element_code': This specifies that the code relates to population elements (e.g., "511").
> - 'unit' to 'population_unit': This clearly shows that the column represents the unit of measurement for the population data (e.g., "1000 persons").

Data Merging

In [ ]:
```python
df_fao.merge(
    df_faostat,
    how='inner',
    on=['area_code', 'area']
).sample(3)
```

Out[ ]:

	area_abbreviation	area_code	area	item_code	item	element_code	elemei
18977	TGO	217	Togo	2642	Cloves	5142	Foc
9880	ITA	106	Italy	2633	Cocoa Beans and products	5142	Foc
14070	NZL	156	New Zealand	2918	Vegetables	5521	Fee

In [ ]:
```python
len_merged_df = len(
    df_fao.merge(
        df_faostat,
        how='inner',
        on=['area_code', 'area']
    )
)

print(f'Number of rows of FAO dataframe: {len(df_fao)}')
print(f'Number of rows of FAOSTAT dataframe: {len(df_faostat)}')
print(f'Number of rows of merged dataframe: {len_merged_df}')
```

```
Number of rows of FAO dataframe: 21477
Number of rows of FAOSTAT dataframe: 231
Number of rows of merged dataframe: 21230
```

Explanation & Justification:

> We merged the two dataframes on both 'area_code' and 'area' not only because these columns are present in both datasets, but also provide a more unique identifier for each row in the merged result.

> We chose an *inner join* for this merge to avoid introducing null values, since there are combinations of 'area_code' and 'area' that do not exist in the `FAO` and `FAOSTAT` dataframes.

> An inner join allows us to retain only the rows where there is a match in both datasets based on the specified columns. This is crucial for ensuring data consistency and accuracy, as it filters out any records that do not have corresponding matches in both dataframes.

> Unlike other types of joins, such as left or right joins, which would include

> unmatched records from one side or the other, resulting in null values, the inner join provides a focused dataset with only the relevant records that exist in both sources. This approach not only enhances the accuracy of the match but also improves the uniqueness and reliability of each row in the final merged dataset.

Create New Dataframe

In [ ]:
```
merged_df = df_fao.merge(
    df_faostat,
    how='inner',
    on=['area_code', 'area'])

merged_df.sample(3)
```

Out[ ]:

	area_abbreviation	area_code	area	item_code	item	element_code	element
8017	GRD	86	Grenada	2737	Fats, Animals, Raw	5142	Food
6615	ETH	238	Ethiopia	2744	Eggs	5142	Food
13162	MAR	143	Morocco	2733	Pigmeat	5142	Food

Explanation & Justification:

> We merged the `FAO` and `FAOSTAT` datasets into a single dataframe, `merged_df,` using an inner join based on the common columns area_code and area.

> This operation ensures that only the rows with matching 'area_code' and 'area' values from both datasets are included in the final merged dataframe.

Feature Engineering

Column: Years Existing

In [ ]:
```
# Create a list for year columns that will be useful throughout the analysis
```

```
year_cols = [col for col in merged_df.columns if col.startswith('y') and col[1:].is
```

In [ ]:
```
# Create a new column by adding the number of year columns that do not have a null
merged_df['years_existing'] = merged_df[year_cols].notnull().sum(axis=1)

merged_df[['area_code', 'area', 'years_existing']].sample(3)
```

Out[ ]:

	area_code	area	years_existing
2240	19	Bolivia (Plurinational State of)	53
2231	19	Bolivia (Plurinational State of)	53
20014	229	United Kingdom	53

Explanation & Justification:

> We created a new column for *years existing* to count the number of years for which valid (non-negative) data exists per record in the dataset.

Column: Average Production

In [ ]:
```
# Create a new column by getting the mean of year columns' values
merged_df['average_production'] = merged_df[year_cols].mean(axis=1)

merged_df[['area', 'years_existing', 'average_production']].sample(3)
```

Out[ ]:

	area	years_existing	average_production
8665	Honduras	53	0.018868
280	Algeria	53	101.660377
14216	Niger	53	40.622642

Explanation & Justification:

> We created a new column for *average production* to calculate the mean production over a specified range of years within the dataset. It summarizes production levels over time per record.

Column: Value per Capita

In [ ]:
```
# Convert the value of the population unit to digits only (e.g 1000 persons to 1000
merged_df['population_unit'] = merged_df['population_unit'].str.extract('(\d+)').as

merged_df['population_unit'].unique()
```

Out[ ]:
```
array([1000])
```

In [ ]:
```
merged_df[['population_unit', 'value']].sample(3)
```

Out[ ]:

	population_unit	value
20139	1000	57310.019
1135	1000	9827.589
4985	1000	4189.353

In [ ]:
```
# Create a new column by dividing the value by the population unit
merged_df['value_per_capita'] = merged_df['value'] / merged_df['population_unit']

merged_df[['value', 'population_unit', 'value_per_capita']].sample(3)
```

Out[ ]:

	value	population_unit	value_per_capita
16279	12208.407	1000	12.208407
10142	127484.450	1000	127.484450
10127	127484.450	1000	127.484450

Explanation & Justification:

> We created a new column for *value per capita* by dividing the 'value' by the 'population_unit.'

Column: ISO Alpha-3 Country Code

In [ ]:
```
# Create a function to get the iso_alpha_3 of a country using the PyCountry library

def get_iso_alpha3(country_name):
    try:
        return pycountry.countries.lookup(country_name).alpha_3
    except:
        return 'INVALID'

merged_df['iso_alpha3'] = merged_df['area'].apply(get_iso_alpha3)
merged_df[['area', 'iso_alpha3']].drop_duplicates().sample(3)
```

Out[ ]:

	area	iso_alpha3
5780	Dominica	DMA
20631	Venezuela (Bolivarian Republic of)	INVALID
18700	Thailand	THA

In [ ]:
```
# Check if there are areas that has 'INVALID' iso_alpha3
merged_df[merged_df['iso_alpha3'] == 'INVALID'][['area', 'iso_alpha3']].drop_duplic
```

Out[ ]:

	area	iso_alpha3
2162	Bolivia (Plurinational State of)	INVALID
3866	China, Hong Kong SAR	INVALID
3999	China, Macao SAR	INVALID
4120	China, mainland	INVALID
4266	China, Taiwan Province of	INVALID
9293	Iran (Islamic Republic of)	INVALID
15658	Republic of Korea	INVALID
19275	Turkey	INVALID
20631	Venezuela (Bolivarian Republic of)	INVALID

In [ ]:

```
# Manually set the ISO alpha-3 of these countries
manual_iso_mapping = {
    'Bolivia (Plurinational State of)': 'BOL',
    'China, Hong Kong SAR': 'HKG',
    'China, Macao SAR': 'MAC',
    'China, mainland': 'CHN',
    'China, Taiwan Province of': 'TWN',
    'Iran (Islamic Republic of)': 'IRN',
    'Republic of Korea': 'KOR',
    'Turkey': 'TUR',
    'Venezuela (Bolivarian Republic of)': 'VEN',
}

merged_df['iso_alpha3'] = merged_df['area'].map(manual_iso_mapping).fillna(merged_d

merged_df[merged_df['iso_alpha3'] == 'INVALID'][['area', 'iso_alpha3']].drop_duplic
```

Out[ ]:

area	iso_alpha3

In [ ]:

```
merged_df[['area', 'iso_alpha3']].drop_duplicates().sample(3)
```

Out[ ]:

	area	iso_alpha3
8766	Hungary	HUN
1830	Belize	BLZ
9293	Iran (Islamic Republic of)	IRN

Explanation & Justification:

> We created a new column for *iso_alpha3* using `pycountry_convert` library to assign continent for each country.

> In the case of some areas (like Timor-Leste), we manually assigned its continent. This column will be useful for future analysis based on continents.

Column: Continent

In [ ]:
```
def country_to_continent(country_alpha3):
    try:
        country_alpha2 = pc.country_alpha3_to_country_alpha2(country_alpha3)
        country_continent_code = pc.country_alpha2_to_continent_code(country_alpha2
        country_continent_name = pc.convert_continent_code_to_continent_name(countr
    except:
        return 'Invalid'

    return country_continent_name

merged_df['continent'] = merged_df['iso_alpha3'].apply(country_to_continent)
merged_df[['area', 'iso_alpha3', 'continent']].drop_duplicates().sample(3)
```

Out[ ]:

	area	iso_alpha3	continent
15114	Peru	PER	South America
10825	Kyrgyzstan	KGZ	Asia
19403	Turkmenistan	TKM	Asia

In [ ]:
```
# Check if there are continents that has 'INVALID' value
merged_df[merged_df['continent'] == 'Invalid'][['area', 'iso_alpha3', 'continent']]
```

Out[ ]:

	area	iso_alpha3	continent
18831	Timor-Leste	TLS	Invalid

In [ ]:
```
# Manually assign continent for Timor-Leste
merged_df.loc[merged_df['iso_alpha3'] == 'TLS', 'continent'] = 'Asia'

merged_df[merged_df['continent'] == 'Invalid'][['area', 'iso_alpha3', 'continent']]
```

Out[ ]:

area	iso_alpha3	continent

Explanation & Justification:

> We created a new column for *continent* using `pycountry` library to assign ISO alpha-3 for each country.

> In the case of some areas that were not recognized by the library, we manually assigned their respective ISO alpha-3 based on our research for those countries.

> This column will be essential when creating a choropleth maps.

Final Merged Dataframe

In [ ]:
```
merged_df.sample(3)
```

Out[ ]:

	area_abbreviation	area_code	area	item_code	item	element_code	elemen
3524	CAN	33	Canada	2961	Aquatic Products, Other	5142	Foo
13095	MAR	143	Morocco	2516	Oats	5142	Foo
16836	SAU	194	Saudi Arabia	2515	Rye and products	5521	Fee

In [ ]:
```
# Check if there are rows with null values (excluding the year columns)
non_year_columns = merged_df.columns.difference(year_cols)
merged_df[merged_df[non_year_columns].isnull().any(axis=1)].head()
```

Out[ ]:

area_abbreviation	area_code	area	item_code	item	element_code	element	unit	latitu

Explanation & Justification:

> We created a new column for *value per capita* by dividing the `value` by the `population_unit` .

Part 2: Data Exploration

Descriptive Statistics

Summarize Statistics

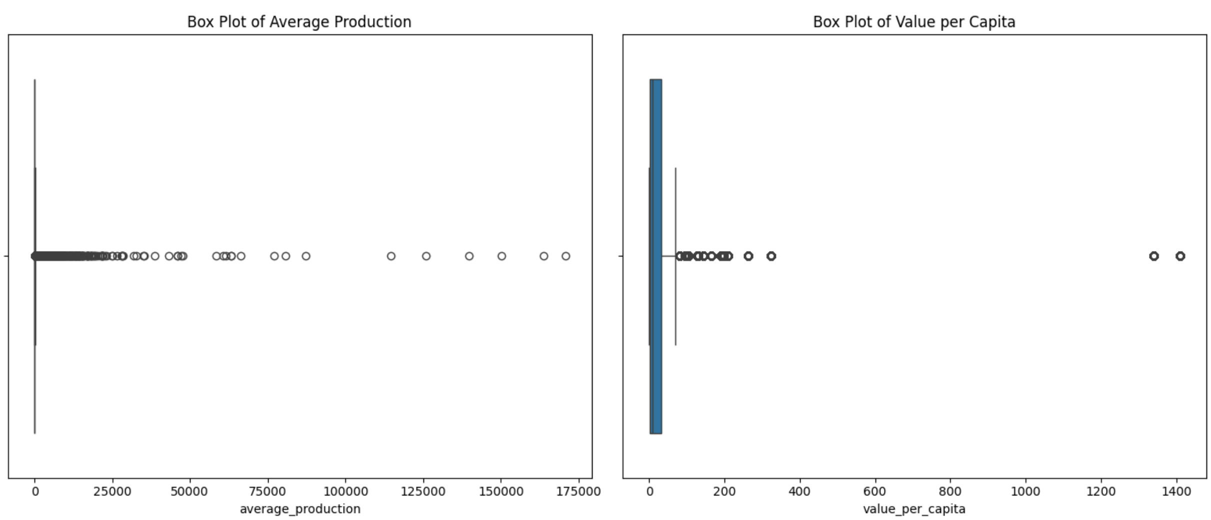
In [ ]:
```
# Generate summary statistics
merged_df.describe()
```

Out[ ]:

	area_code	item_code	element_code	latitude	longitude	y196
count	21230.000000	21230.000000	21230.000000	21230.000000	21230.000000	17821.0000
mean	124.814131	2694.205417	5211.712435	20.579903	15.671588	196.5233
std	72.990946	148.967495	146.840747	24.468235	66.383070	1870.1686
min	1.000000	2511.000000	5142.000000	-40.900000	-172.100000	0.0000
25%	63.000000	2561.000000	5142.000000	6.430000	-14.450000	0.0000
50%	119.000000	2640.000000	5142.000000	20.590000	18.730000	1.0000
75%	185.000000	2782.000000	5142.000000	41.150000	47.480000	21.0000
max	276.000000	2961.000000	5521.000000	64.960000	179.410000	112227.0000

In [ ]:

```python
# Plot to check the outliers in the average production and value per capita

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14, 6))

sns.boxplot(x=merged_df['average_production'], ax=axes[0])
axes[0].set_title('Box Plot of Average Production')

sns.boxplot(x=merged_df['value_per_capita'], ax=axes[1])
axes[1].set_title('Box Plot of Value per Capita')

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



Group-Based Statistics

Group by area

In [ ]:

```python
merged_df.groupby('area').agg({
    'average_production': ['mean', 'min', 'max', 'median', 'std'],
})
```

Out[ ]:

	average_production				
	mean	min	max	median	std
area					
Afghanistan	156.663333	0.0	3266.811321	14.433962	475.311572
Albania	36.386256	0.0	547.698113	2.622642	100.213216
Algeria	232.899117	0.0	4771.132075	10.603774	681.038196
Angola	122.211528	0.0	2350.792453	8.150943	348.506708
Antigua and Barbuda	0.716981	0.0	10.396226	0.000000	1.866105
...	...	...	...	...	...
Venezuela (Bolivarian Republic of)	194.598403	0.0	2293.566038	21.556604	428.648377
Viet Nam	531.120305	0.0	10144.452830	75.528302	1441.316038
Yemen	72.900745	0.0	1976.301887	5.452830	228.312172
Zambia	49.636321	0.0	1183.792453	1.679245	163.471642
Zimbabwe	54.747076	0.0	1469.811321	4.886792	174.326752

172 rows × 5 columns

In [ ]:

```
merged_df.groupby('area').agg({
    'value_per_capita': ['mean', 'min', 'max', 'median', 'std']
})
```

Out[ ]:

	value_per_capita				
	mean	min	max	median	std
area					
Afghanistan	35.530081	35.530081	35.530081	35.530081	0.0
Albania	2.930187	2.930187	2.930187	2.930187	0.0
Algeria	41.318142	41.318142	41.318142	41.318142	0.0
Angola	29.784193	29.784193	29.784193	29.784193	0.0
Antigua and Barbuda	0.102012	0.102012	0.102012	0.102012	0.0
...	...	...	...	...	...
Venezuela (Bolivarian Republic of)	31.977065	31.977065	31.977065	31.977065	0.0
Viet Nam	95.540800	95.540800	95.540800	95.540800	0.0
Yemen	28.250420	28.250420	28.250420	28.250420	0.0
Zambia	17.094130	17.094130	17.094130	17.094130	0.0
Zimbabwe	16.529904	16.529904	16.529904	16.529904	0.0

172 rows × 5 columns

Group by continent

In [ ]:
```
merged_df.groupby('continent').agg({
    'average_production': ['mean', 'min', 'max', 'median', 'std']
})
```

Out[ ]:

	average_production				
	mean	min	max	median	std
continent					
Africa	137.094308	0.0	18081.981132	3.641509	666.732046
Asia	622.694665	0.0	170690.452830	9.009434	5328.369857
Europe	381.951031	0.0	35149.590909	13.846913	1582.509259
North America	367.167041	0.0	139783.094340	1.471698	4049.862584
Oceania	52.403154	0.0	4642.830189	0.566038	282.879666
South America	314.121381	0.0	20385.754717	12.188679	1363.204292

In [ ]:
```
merged_df.groupby('continent').agg({
    'value_per_capita': ['mean', 'min', 'max', 'median', 'std']
})
```

Out[ ]:

	value_per_capita				
	mean	min	max	median	std
continent					
Africa	27.083160	0.204327	190.886311	17.094130	35.602057
Asia	109.277925	0.428697	1409.517397	20.876917	298.448881
Europe	20.159273	0.335025	143.989754	8.735453	29.686296
North America	27.061767	0.055345	324.459463	4.098587	72.187064
Oceania	3.925730	0.116398	24.450561	0.283007	7.849592
South America	37.065123	0.563402	209.288278	18.054726	56.484878

Insights:

> In relation to 'value_per_capita,' Asia stands out with the highest mean and maximum values, indicating significant economic output - which is likely due to its larger agricultural base and focus.

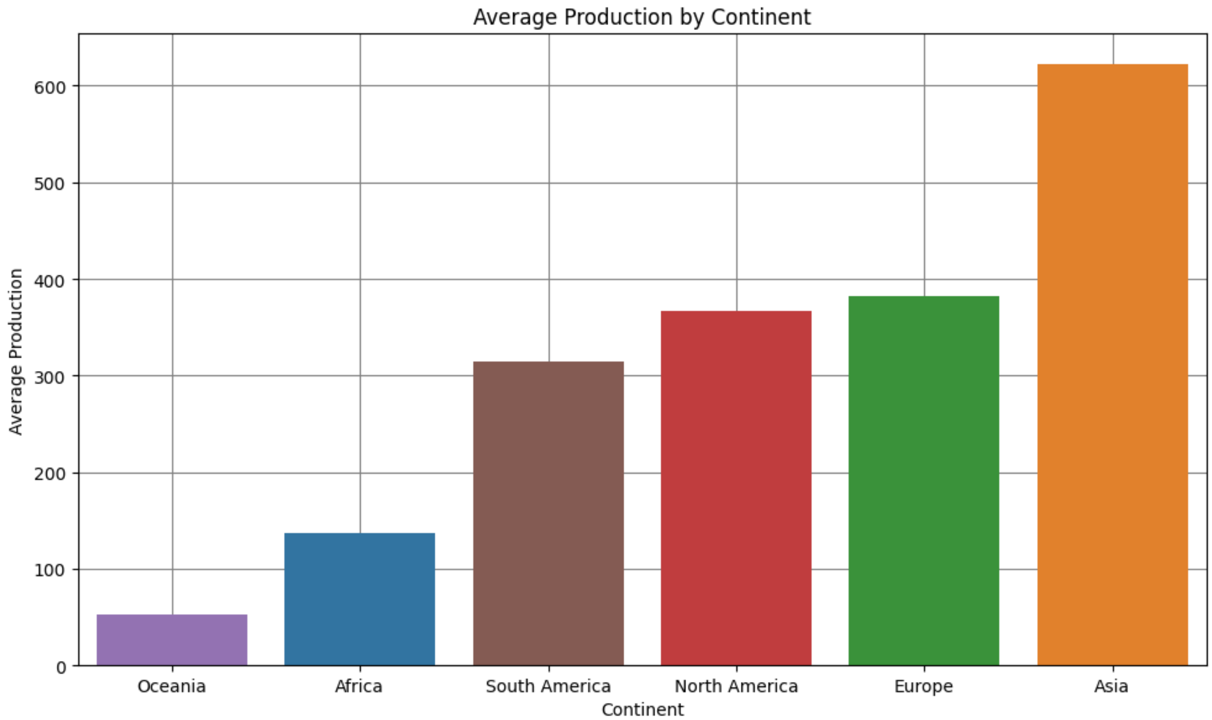
> The standard deviation is notably high in Asia and North America, suggesting a wide range of values that could be attributed to the 'values' in the dataset.

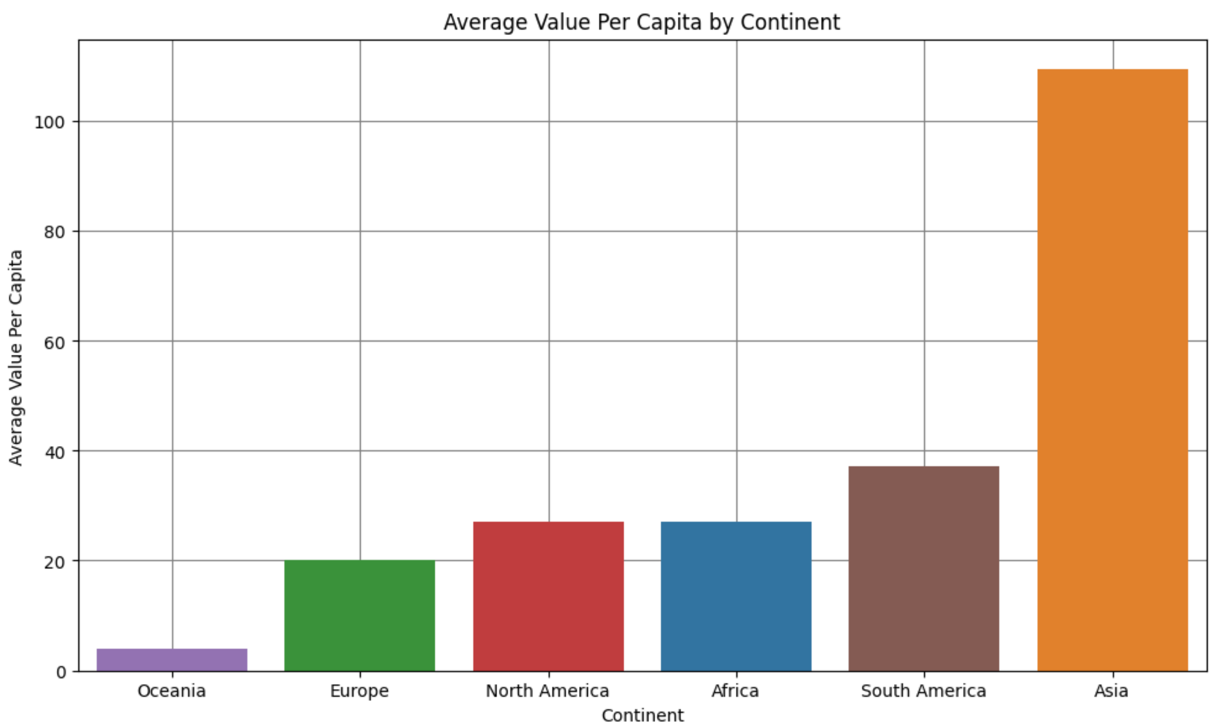
> Oceania shows the lowest mean and maximum values, which reflects lesser agricultural activities in contrast to Asia.

In [ ]:

```
# Calculate the average production
ave_production_continent = merged_df.groupby('continent')['average_production'].mea

# Calculate the average value per capita
vpc_continent = merged_df.groupby('continent')['value_per_capita'].mean().sort_valu

# Palette
col_continent = {
    'Africa': '#1f77b4',            # blue
    'Asia': '#ff7f0e',              # orange
    'Europe': '#2ca02c',            # green
    'North America': '#d62728',     # red
    'Oceania': '#9467bd',           # purple
    'South America': '#8c564b'      # brown
}

fig, axes = plt.subplots(nrows=2, ncols=1, figsize=(10, 12))

sns.barplot(
    x=ave_production_continent.index,
    y=ave_production_continent.values,
    hue=ave_production_continent.index,
    palette=col_continent,
    ax=axes[0]
```

```
)

axes[0].set_title('Average Production by Continent')
axes[0].set_xlabel('Continent')
axes[0].set_ylabel('Average Production')
axes[0].grid(True, color='gray', zorder=2)
axes[0].set_axisbelow(True)

sns.barplot(
    x=vpc_continent.index,
    y=vpc_continent.values,
    hue=vpc_continent.index,
    palette=col_continent,
    ax=axes[1]
)
axes[1].set_title('Average Value Per Capita by Continent')
axes[1].set_xlabel('Continent')
axes[1].set_ylabel('Average Value Per Capita')
axes[1].grid(True, color='gray', zorder=2)
axes[1].set_axisbelow(True)

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





Insights:

> Asia leads significantly in average production, more than five times higher than Africa and nearly twice that of Europe.

> Oceania has the lowest production figures, which may reflect smaller agricultural sectors or less intensive farming practices compared to other regions.

> North America and Europe have comparable production levels, suggesting

> similar capabilities or resources dedicated to agricultural output.

> Asia stands out with a notably higher value per capita compared to other continents, indicating a stronger economic return per person from agriculture.

> In contrast, Oceania exhibits the lowest value, suggesting limited agricultural productivity.

> Europe, North America, and South America show moderate values, with South America slightly higher.

Correlation Analysis

Correlation Matrix

In [ ]:

```
# Only include columns that are relevant to correlation matrix
numeric_cols = year_cols + ['value', 'value_per_capita','average_production']

# Create correlation matrix using existing method from Pandas
correlation_matrix = merged_df[numeric_cols].corr()
correlation_matrix
```

Out[ ]:

	y1961	y1962	y1963	y1964	y1965	y1966	y1967
y1961	1.000000	0.996953	0.991819	0.982617	0.986427	0.982623	0.981941
y1962	0.996953	1.000000	0.996036	0.988794	0.991423	0.989008	0.987950
y1963	0.991819	0.996036	1.000000	0.997223	0.995657	0.993844	0.993042
y1964	0.982617	0.988794	0.997223	1.000000	0.994727	0.992247	0.992647
y1965	0.986427	0.991423	0.995657	0.994727	1.000000	0.997595	0.996960
y1966	0.982623	0.989008	0.993844	0.992247	0.997595	1.000000	0.998595
y1967	0.981941	0.987950	0.993042	0.992647	0.996960	0.998595	1.000000
y1968	0.983367	0.989043	0.994558	0.993602	0.996640	0.997968	0.998135
y1969	0.984125	0.989106	0.991925	0.989727	0.996408	0.997283	0.997749
y1970	0.971267	0.978507	0.984254	0.984811	0.992271	0.995408	0.996461
y1971	0.971904	0.978209	0.983963	0.984729	0.993649	0.994224	0.995178
y1972	0.969788	0.975131	0.981964	0.984012	0.992194	0.991738	0.993798
y1973	0.965995	0.972906	0.978619	0.979481	0.988771	0.992135	0.993942
y1974	0.948810	0.959183	0.967759	0.970780	0.976828	0.984107	0.985504
y1975	0.951767	0.962277	0.971316	0.975003	0.979773	0.986215	0.988152
y1976	0.948360	0.957805	0.969184	0.974360	0.978650	0.983488	0.985692
y1977	0.946692	0.957064	0.965907	0.970853	0.976725	0.981503	0.984506
y1978	0.945641	0.955960	0.965373	0.970161	0.976856	0.981638	0.984200
y1979	0.938790	0.948376	0.961242	0.968651	0.973106	0.976213	0.979382
y1980	0.922141	0.935169	0.948206	0.957048	0.961199	0.965225	0.968589
y1981	0.926234	0.936979	0.951578	0.961329	0.962771	0.965110	0.968972
y1982	0.919876	0.930890	0.945120	0.955131	0.959222	0.960132	0.963748
y1983	0.901895	0.914825	0.930415	0.942673	0.943331	0.946263	0.950482
y1984	0.902069	0.913413	0.929373	0.941510	0.941875	0.943031	0.947392
y1985	0.898378	0.910413	0.927254	0.940145	0.937522	0.936416	0.940320
y1986	0.902297	0.911732	0.926688	0.938387	0.936254	0.933276	0.937974
y1987	0.901603	0.911627	0.925401	0.936302	0.933948	0.931783	0.936487
y1988	0.877996	0.889605	0.904598	0.917282	0.909939	0.909412	0.915035
y1989	0.882493	0.893715	0.907974	0.920430	0.913703	0.912129	0.918011
y1990	0.891423	0.900342	0.914034	0.924700	0.921660	0.920371	0.925011

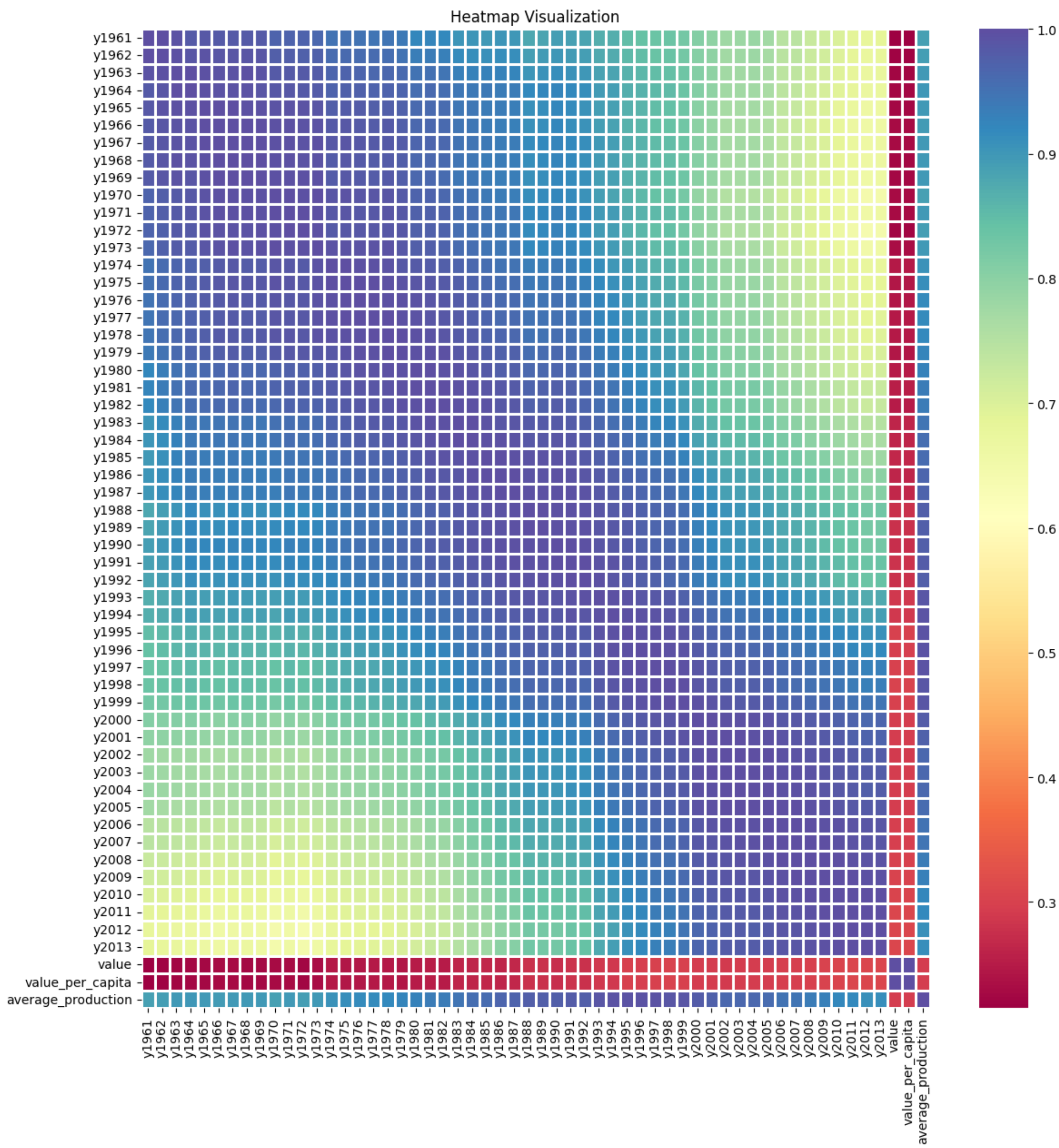
	y1961	y1962	y1963	y1964	y1965	y1966	y1967
y1991	0.886957	0.895342	0.907892	0.918397	0.914733	0.913318	0.918854
y1992	0.882953	0.890341	0.901639	0.911330	0.907868	0.905594	0.911365
y1993	0.868424	0.875133	0.886130	0.894968	0.890784	0.889998	0.895732
y1994	0.868348	0.873124	0.882643	0.890499	0.887430	0.884616	0.890489
y1995	0.846943	0.852833	0.862569	0.870491	0.865589	0.864953	0.870733
y1996	0.842994	0.847451	0.856210	0.863423	0.859015	0.856213	0.862549
y1997	0.837243	0.840026	0.847073	0.853356	0.848928	0.845267	0.851437
y1998	0.835312	0.838312	0.844745	0.850750	0.846337	0.843308	0.849304
y1999	0.825464	0.827274	0.831834	0.836092	0.832062	0.828609	0.834504
y2000	0.806910	0.805770	0.806967	0.808016	0.803403	0.799298	0.805005
y2001	0.797262	0.795246	0.795269	0.795379	0.791050	0.786504	0.792150
y2002	0.778486	0.775849	0.774626	0.773762	0.768969	0.764512	0.769871
y2003	0.780499	0.777274	0.775611	0.774378	0.769868	0.764892	0.770206
y2004	0.783211	0.779450	0.777161	0.775377	0.771424	0.765978	0.771490
y2005	0.773558	0.769491	0.766702	0.764581	0.760267	0.754695	0.760212
y2006	0.748388	0.744181	0.742272	0.740976	0.733543	0.727626	0.733263
y2007	0.744814	0.739777	0.737603	0.736026	0.728148	0.721852	0.727655
y2008	0.726683	0.721495	0.719147	0.717103	0.708937	0.703701	0.709180
y2009	0.717692	0.712528	0.710189	0.708294	0.699476	0.694303	0.699767
y2010	0.701682	0.696496	0.694271	0.692414	0.682986	0.678566	0.684115
y2011	0.689817	0.684632	0.683303	0.681788	0.672057	0.668633	0.674108
y2012	0.678682	0.672916	0.671622	0.669820	0.660128	0.657036	0.662273
y2013	0.684139	0.677957	0.676580	0.674684	0.665559	0.662202	0.667684
value	0.214798	0.220389	0.223071	0.226653	0.224395	0.227185	0.227408
value_per_capita	0.214798	0.220389	0.223071	0.226653	0.224395	0.227185	0.227408
average_production	0.887841	0.890565	0.895783	0.898981	0.895961	0.893899	0.898577

Insights:

> The data accross years, from 1961 to 2013 show a high correlation, often close to 1. It indicates that production values are fairly consistent or stable, which means that agricultural practices remain effective over time.

> The 'value' and and 'value_per_capita' metrics show a lower correlation with the yearly data. It may indicate that in spite of production being stable, the economic value derive does not increase - in direct proportion.

In [ ]:
```
# Generate the heatmap
plt.figure(figsize=(14, 14))
sns.heatmap(correlation_matrix, cmap='Spectral', linewidths=1)
plt.title('Heatmap Visualization')
plt.show()
```



Insights:

> The heatmap shows that each year is highly correlated with itself (represented by the purple diagonal), there is also a noticeable shift around the mid-1990s.

> Before this period, the correlations between different years (moving away from the purple diagonal) remain relatively strong.

> However, around y1994, the correlation between different years starts to decrease more rapidly, this is indicated by the quicker transition from purple to green and yellow tones. This suggests that the relationship between years weakens more significantly during the mid-1990s, indicating a change in the data trends.

Part 3: Data Visualization

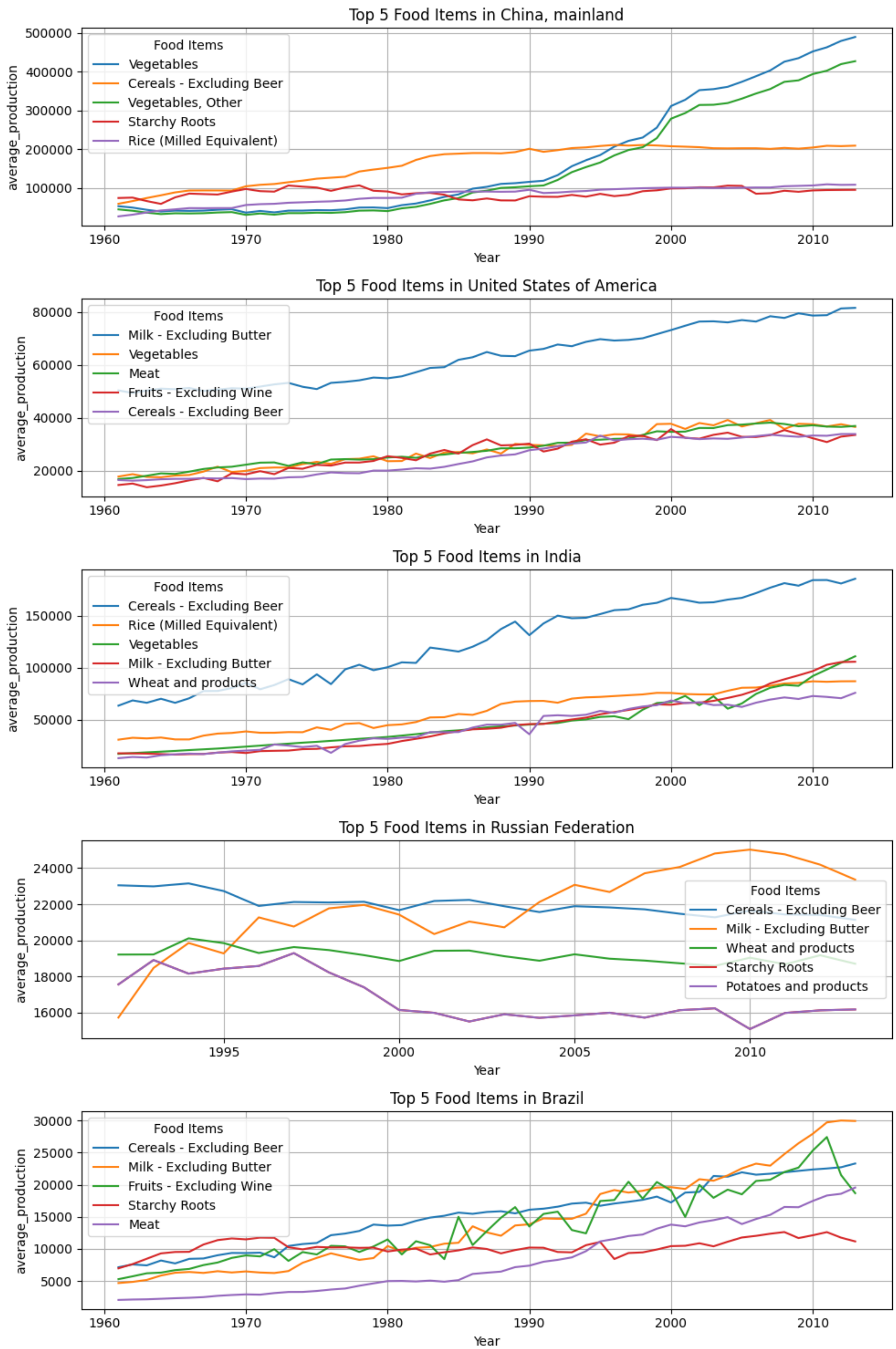
Time-Series Analysis

Line Plot

In [ ]:
```
def line_plot(df, location, top_location, value, top_value, element):
    # Group by specific location (area or continent), calculate their mean and sele
    top_locations = df.groupby(location)[value].mean().nlargest(top_location).index

    _, axes = plt.subplots(nrows=len(top_locations), figsize=(10, 15))

    for i, loc in enumerate(top_locations):
        # Filter the current location and element and get the top items by average
        data = df[(df[location] == loc) & (df['element'] == element)]
        top_items = data.groupby('item')[value].mean().nlargest(top_value).index

        for item in top_items:
            # Filter the data for current item and calculate the mean across the ye
            item_data = data[data['item'] == item][year_cols].mean()
            item_data.index = item_data.index.str[1:].astype(int)

            axes[i].plot(item_data.index, item_data.values, label=item)

        axes[i].set_title(f'Top {top_value} {element} Items in {loc}')
        axes[i].set_xlabel('Year')
        axes[i].set_ylabel(value)
        axes[i].legend(title=f'{element} Items')
        axes[i].grid(True)

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

In [ ]:
```
# Line plot for Food items in the top 5 areas in average production
line_plot(
    df=merged_df,
    location='area',
    top_location=5,
    value='average_production',
    top_value=5,
    element='Food'
```

```
)
```


Top 5 Food Items in China, mainland
Food Items
Vegetables
Cereals - Excluding Beer
Vegetables, Other
Starchy Roots
Rice (Milled Equivalent)
average_production
Year
Top 5 Food Items in United States of America
Food Items
Milk - Excluding Butter
Vegetables
Meat
Fruits - Excluding Wine
Cereals - Excluding Beer
average_production
Year
Top 5 Food Items in India
Food Items
Cereals - Excluding Beer
Rice (Milled Equivalent)
Vegetables
Milk - Excluding Butter
Wheat and products
average_production
Year
Top 5 Food Items in Russian Federation
Food Items
Cereals - Excluding Beer
Milk - Excluding Butter
Wheat and products
Starchy Roots
Potatoes and products
average_production
Year
Top 5 Food Items in Brazil
Food Items
Cereals - Excluding Beer
Milk - Excluding Butter
Fruits - Excluding Wine
Starchy Roots
Meat
average_production
Year

Insights:

> The graph illustrates the top 5 food items in China, the United States, India, the Russian Federation, and Brazil, over time.

`For Food:`

> **China, mainland:** Vegetables dominate as the top food item, with a sharp increase in value starting from the late 1990s. Cereals (excluding beer) also rank highly but plateaued around the same time. Starchy roots and rice show consistent values without significant growth or decline. The possible rise in vegetable consumption from the late 1990s may be because of China's economic reforms and rapid urbanization at that time - which led to changes in dietary habits and preferences. A noticeable plataeu in Cereals- Excluding Beer could be because of a shift towards other food sources, as the Chinese diversified its diet.

> **United States of America:** Milk (excluding butter) shows the highest values and a steady increase, indicating its significant importance. Other food items like vegetables, meat, fruits (excluding wine), and cereals (excluding beer) also show growth but at a lower pace. The prominence of milk shows the country's strength in the dairy industry, as well as its importance in their dietary culture. Additionally, the growth of other food items suggests a balanced diet that includes a variety of food groups, reflecting the country's agricultural diversity and food availability.

> **India:** Cereals (excluding beer) is the top food product in India by a significant margin. In similarity to the United States, the rest of the food items, e.g., Rice (milled equivalent), vegetables, milk (excluding butter), and wheat and products, are closely growing together. However, it is noticeable that Rice (milled equivalent) is seemingly approaching a plataeu. Whilst the rest of the products is still yet to reach their peak.

> **Russian Federation:** Food items in Russia show similar growth trends, with most products closely aligned in value.

> **Brazil:** Milk (excluding butter) is the top food product in recent years in Brazil. It is followed by fruits (excluding wine) and cereals (excluding butter). The rest of the food items, e.g., meat and starchy roots, are relatively close with one another, however, it is noticeable that the value of starchy roots still remain the same over the decades.

`Conclusion`

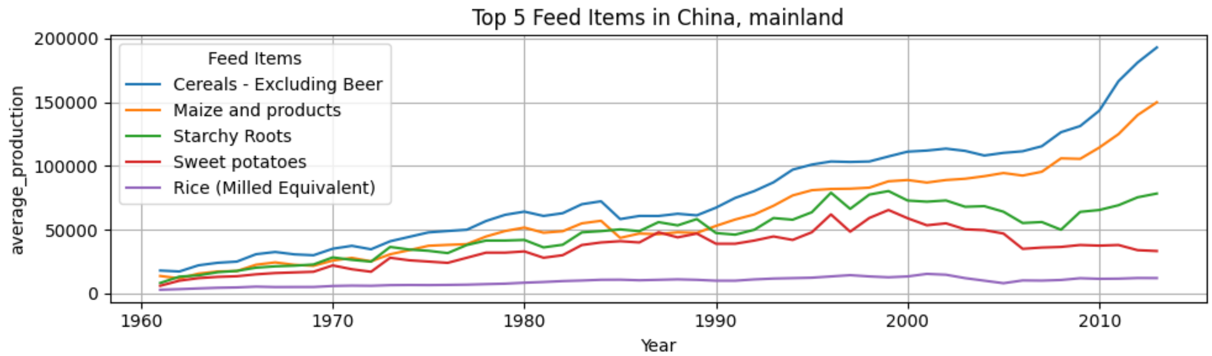
> The analysis of top food items over time in China, the United States, India, Russia, and Brazil reveals distinct national trends influenced by economic,

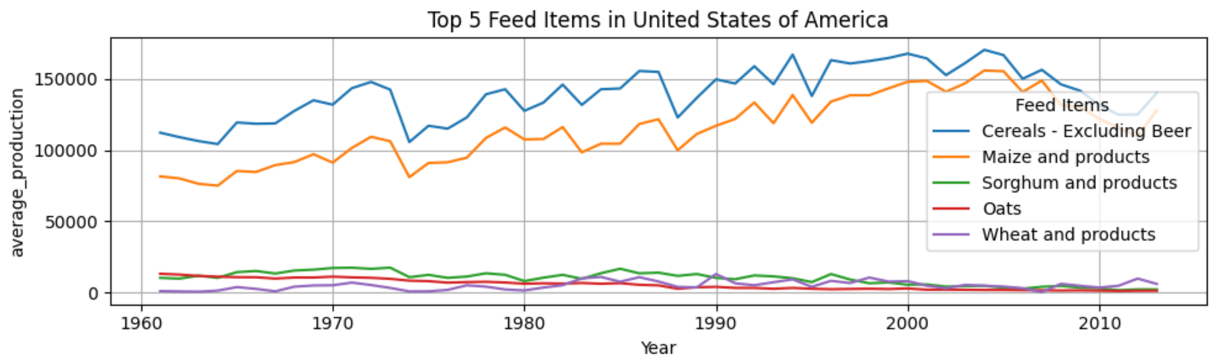
> cultural, and environmental factors. In China, rapid urbanization and economic reforms have led to increased vegetable consumption, while in the United States, steady growth in milk consumption underscores its cultural and dietary significance. India's focus on cereals highlights its staple food reliance, contrasting with Brazil's diverse but stable food item production.

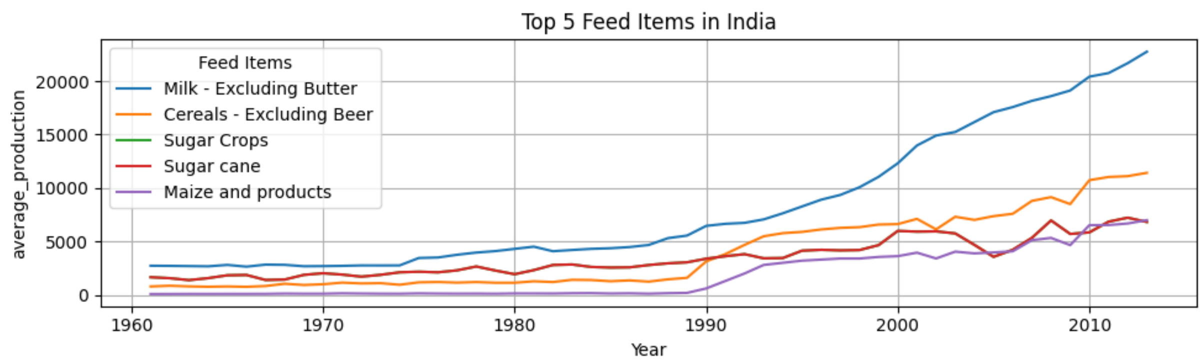
> **Diversification of Crop Production:** Given the plateau in certain staple crops like cereals in China and rice in India, it is advisable for these countries to continue diversifying their agricultural production. This could include enhancing support for alternative crops that might better meet changing dietary preferences and economic conditions.

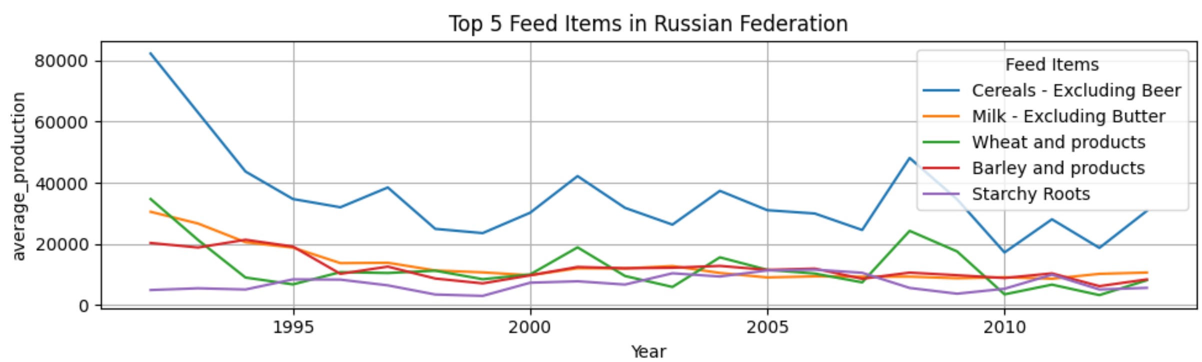
In [ ]:

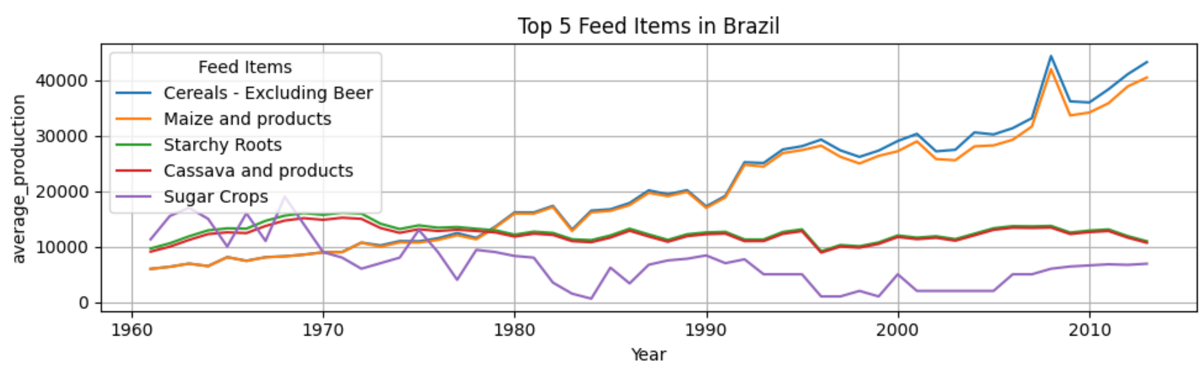
```
# Line plot for Feed items in the top 5 areas in average production
line_plot(
    df=merged_df,
    location='area',
    top_location=5,
    value='average_production',
    top_value=5,
    element='Feed'
)
```


Top 5 Feed Items in China, mainland
Feed Items
Cereals - Excluding Beer
Maize and products
Starchy Roots
Sweet potatoes
Rice (Milled Equivalent)
average_production
Year
0
50000
100000
150000
200000
1960
1970
1980
1990
2000
2010


Top 5 Feed Items in United States of America
Feed Items
Cereals - Excluding Beer
Maize and products
Sorghum and products
Oats
Wheat and products
average_production
Year
0
50000
100000
150000
1960
1970
1980
1990
2000
2010


Top 5 Feed Items in India
Feed Items
Milk - Excluding Butter
Cereals - Excluding Beer
Sugar Crops
Sugar cane
Maize and products
average_production
Year
0
5000
10000
15000
20000
1960
1970
1980
1990
2000
2010


Top 5 Feed Items in Russian Federation
Feed Items
Cereals - Excluding Beer
Milk - Excluding Butter
Wheat and products
Barley and products
Starchy Roots
average_production
Year
0
20000
40000
60000
80000
1995
2000
2005
2010


Top 5 Feed Items in Brazil
Feed Items
Cereals - Excluding Beer
Maize and products
Starchy Roots
Cassava and products
Sugar Crops
average_production
Year
0
10000
20000
30000
40000
1960
1970
1980
1990
2000
2010

Insights:

> The graph illustrates the top 5 feed items in China, the United States, India, the Russian Federation, and Brazil, in a given period of time. Cereals (excluding beer) are a dominant feed item across all these countries, highlighting their importance in global livestock feeding practices. Maize is also significant, especially in countries like the United States, China, and Brazil.

`For Feed:`

> **China, mainland:** In relation to trends, there is a clear upward trend in the use of Cereals - excluding beer and Maize and Products, especially after and around the year 2000. Sweet Potatoes and Starchy Roots remain relatively stable, with slight increase in the recent years. As mentioned and similar to earlier, the strong increase in cereals and maize can be attributed to the rapid industrialization and urbanization of China, leading to higher demand for livestock feed to meet the growing consumption of meat.

> **United States of America:** The graph shows consistent high values for cereals - excluding beer and maize and products. Wheat and products, as well as other feed items, show relatively lower and more stable values. The consistent high values for cereals and maize reflect the importance of these crops in the U.S. agricultural system, especially for feeding livestock.

> **India:** There is a steady increase in the use of milk (excluding butter) particularly after the 1990s. Maize and sugar cane show relatively stable trends with a slight upward movement. The rise in milk as a feed item is closely related to the country;s strong dairy industry, which is one of the largest in the world.

> **Russian Federation:** The graphs for Russia show a sharp decline in cereals, and a more subtle decline in milk, and other feed items after the dissolution of the Soviet Union in the early 1990s, with some stabilization afterward. Hence, such event could affect the decline of feed value - which could shortly distabilize agricultural productivity.

> **Brazil:** Brazil's feed items show a gradual increase, with cereals and maize leading the trends. Starchy roots and cassava also show growth, at lower levels. Sugar crops seemingly was the top feed item, but slowly went on a decline in terms of its value.

`Conclusion:`

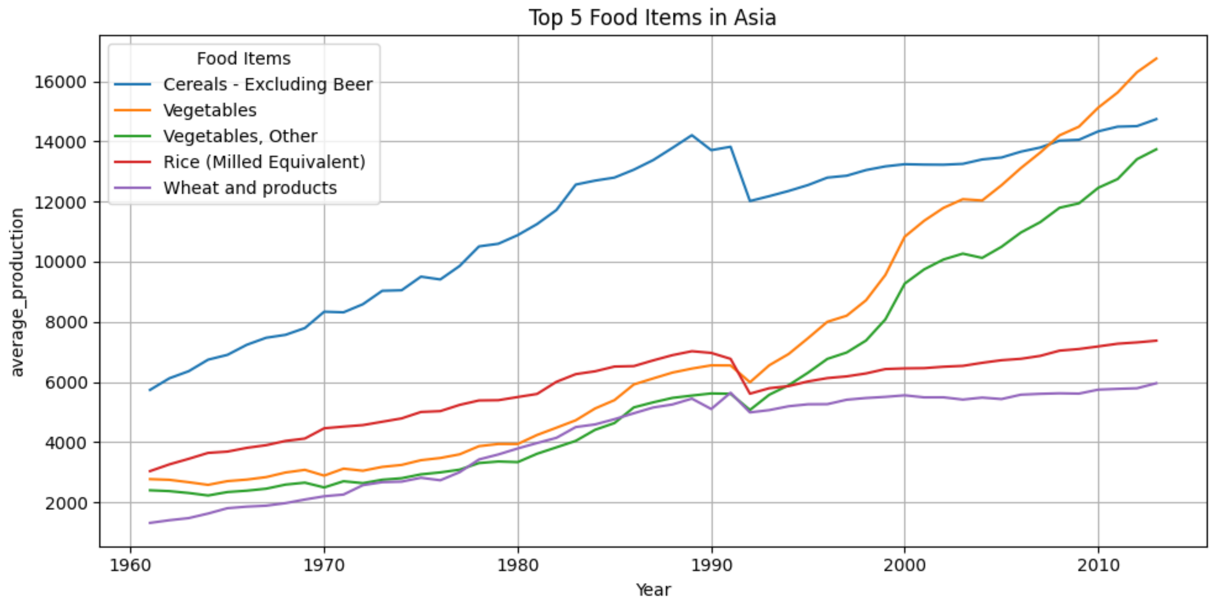
> The comparative analysis of feed item production across China, the United States, India, Russia, and Brazil highlights the pivotal role of cereals and maize in sustaining global livestock or feed industries. The varied trajectories in each country, from steady growth in Brazil to fluctuating trends in Russia post-

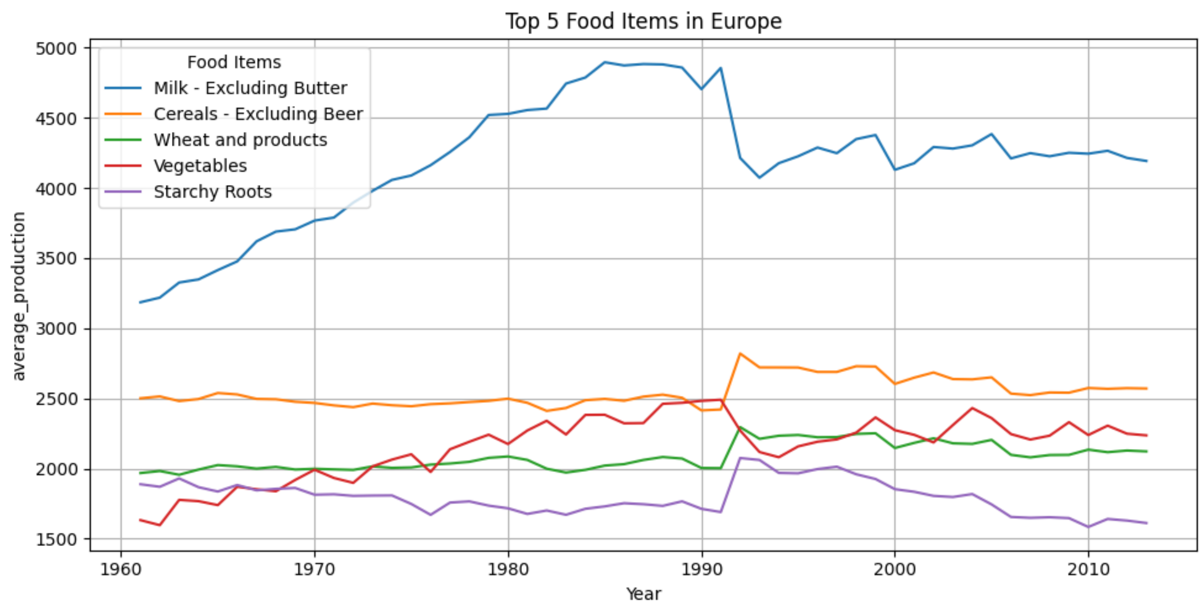
> Soviet Union dissolution, illustrate the complex interplay of economic, political, and agricultural dynamics shaping global feed production.

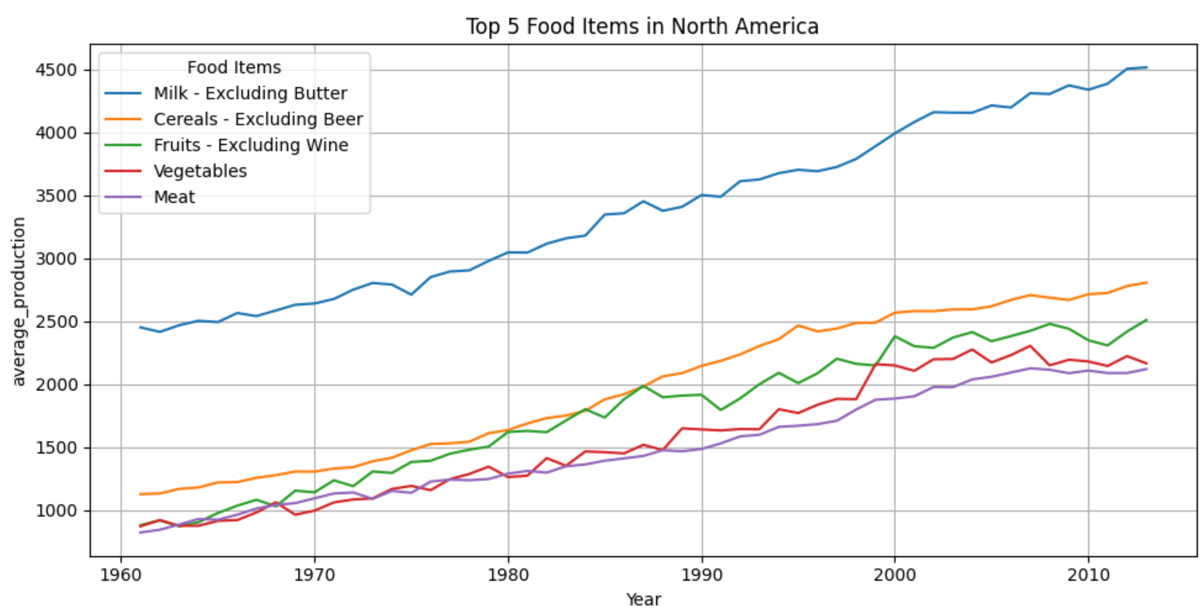
> **Strengthen Agricultural Infrastructure:** Invest in agricultural infrastructure improvements, such as storage facilities, transportation, and market access, particularly in countries like Russia and India where feed production has shown fluctuation or decline.

In [ ]:

```
# Line plot for Food items in the top 3 continents in average production
line_plot(
    df=merged_df,
    location='continent',
    top_location=3,
    value='average_production',
    top_value=5,
    element='Food'
)
```


Top 5 Food Items in Asia
Food Items
Cereals - Excluding Beer
Vegetables
Vegetables, Other
Rice (Milled Equivalent)
Wheat and products
average_production
Year
2000
4000
6000
8000
10000
12000
14000
16000
1960
1970
1980
1990
2000
2010


Top 5 Food Items in Europe
Food Items
Milk - Excluding Butter
Cereals - Excluding Beer
Wheat and products
Vegetables
Starchy Roots
average_production
Year
1500
2000
2500
3000
3500
4000
4500
5000
1960
1970
1980
1990
2000
2010


Top 5 Food Items in North America
Food Items
Milk - Excluding Butter
Cereals - Excluding Beer
Fruits - Excluding Wine
Vegetables
Meat
average_production
Year
1000
1500
2000
2500
3000
3500
4000
4500
1960
1970
1980
1990
2000
2010

Insights:

> These line plots illustrate the top 5 food items top 3 leading continents: Asia, Europe, and North America. Each line represents the line trend of each food item throughout the years.

For Food:

> **Asia:** A steady increase for production of all food items are seen from 1960s - early 1990s, and a steady increase afterwards in the production of rice, wheat, and vegetables. This rise reflects the growing population's need for these staples, particularly cereals like rice, and a likely shift toward healthier diets and better farming methods.

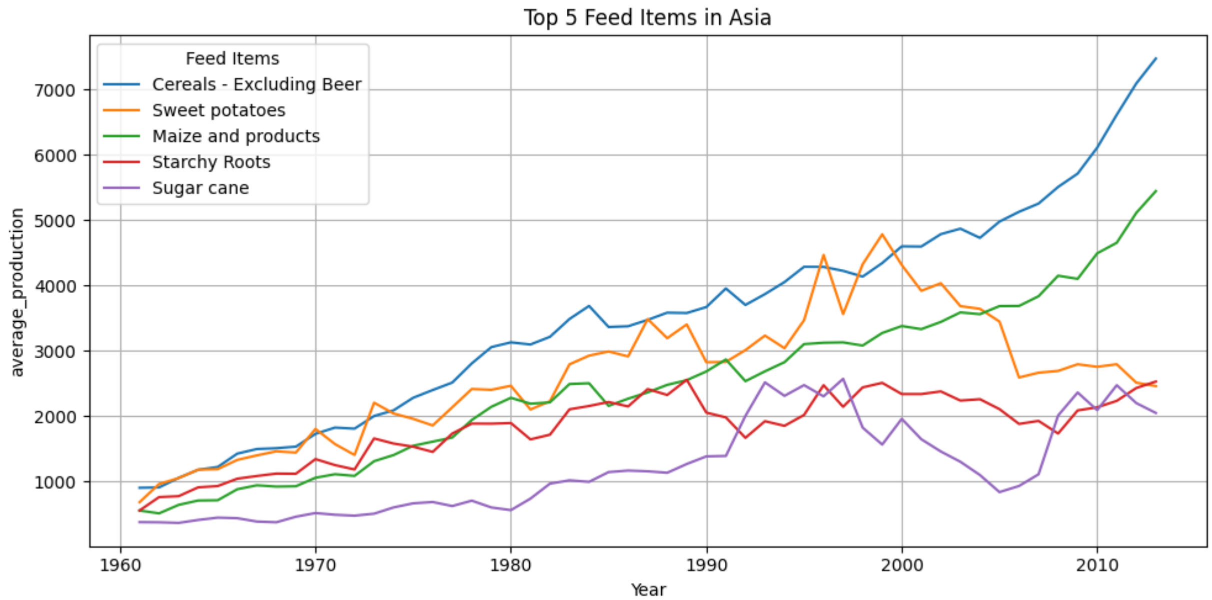
> **Europe:** In Europe, milk and dairy productions has been growing consistently, showing the importance of livestock and dairy industries possibly also because of Europe's favorable climate conditions for raising dairy cattle. Cereal production, especially wheat, has remained steady, reflecting stable farming practices and traditional diets. While, the production of starchy roots like potatoes has slightly declined, likely due to shifts in the region's dietary preferences.

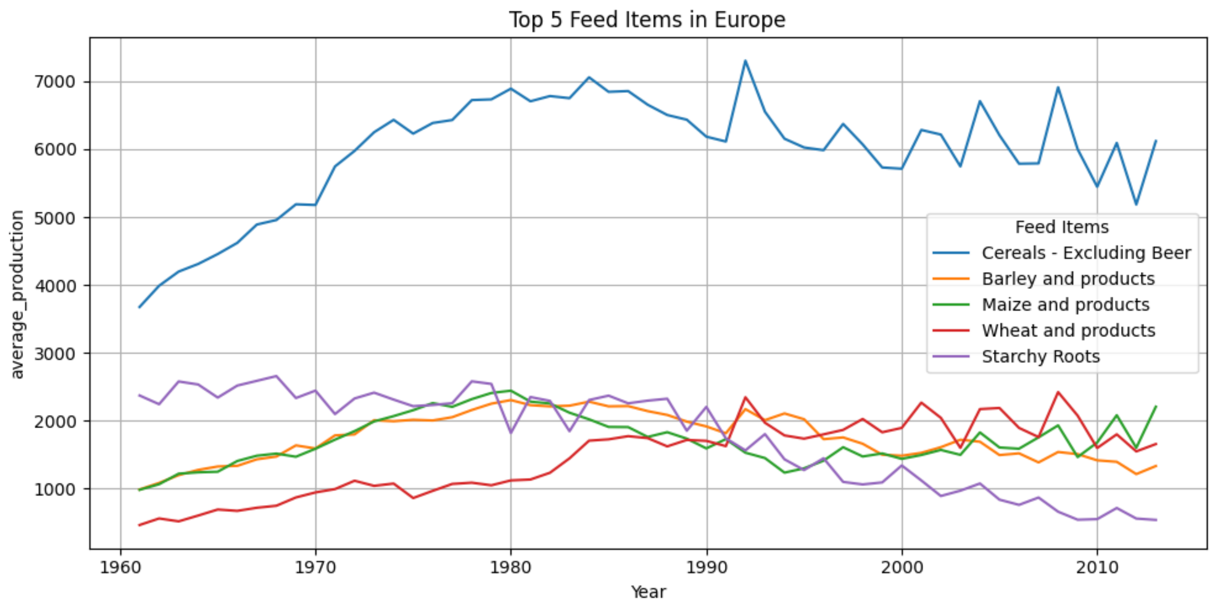
> **North America:** All food items in the graph show consistent production increases, likely due to expanded farmland and improved farming techniques. Milk production has surged from 2,500 in 1960 to 4,500 in 2010, reflecting substantial growth driven by increased demand and advancements in dairy farming. In contrast, other food items have seen more modest increases, from under 1,500 in 1960 to under 3,000 in 2010, indicating slower growth in these sectors.

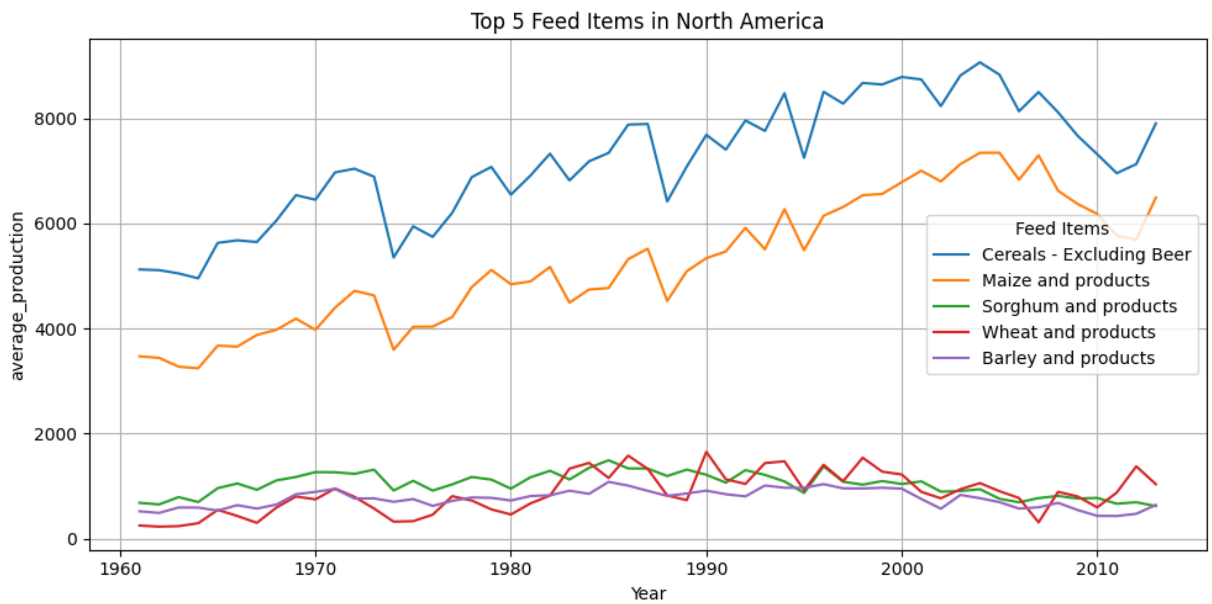
Conclusion

> Asia's dramatic increase in the production of staples like vegetables and cereals aligns with its growing population and a shift towards more sustainable farming methods. In contrast, Europe shows steady growth in milk and dairy due to favorable conditions and traditional diets, while North America demonstrates overall growth in food production.

In [ ]:
```python
# Line plot for Feed items in the top 3 continents in average production
line_plot(
    df=merged_df,
    location='continent',
    top_location=3,
    value='average_production',
    top_value=5,
    element='Feed'
)
```


Top 5 Feed Items in Asia
Feed Items
Cereals - Excluding Beer
Sweet potatoes
Maize and products
Starchy Roots
Sugar cane
average_production
Year


Top 5 Feed Items in Europe
Feed Items
Cereals - Excluding Beer
Barley and products
Maize and products
Wheat and products
Starchy Roots
average_production
Year


Top 5 Feed Items in North America
Feed Items
Cereals - Excluding Beer
Maize and products
Sorghum and products
Wheat and products
Barley and products
average_production
Year

Insights:

> These line plots illustrate the top 5 feed items top 3 leading continents: Asia, Europe, and North America. Each line represents the line trend of each food item throughout the years.

```
For Food:
```

> **Asia:** Cereals (excluding beer) have seen a consistent rise, peaking sharply around early 2010 - and still rising seemingly. Maize and products have grown steadily, particularly after 1980. Sweet potatoes and starchy roots also show steady growth, although starchy roots saw a decline post-1990. Sugar cane, while consistently low, shows a slight upward trend in recent years.

> **Europe:** Cereals (excluding beer) dominate, showing strong growth until around 1990, followed by fluctuations. Barley and wheat products exhibit relatively stable trends with minor fluctuations. Maize products show gradual growth, while starchy roots see a decline from the mid-1980s onwards.

> **North America:** Cereals (excluding beer) and maize products have strong upward trends, with cereals leading. Sorghum shows an early increase, followed by a decline after the mid-1980s. Wheat and barley products have relatively flat trends, with barley declining slightly after 1990.

```
Conclusion
```

> Cereals (excluding beer) consistently lead as the top feed item across all three continents, with Asia and North America showing significant growth, particularly in the last two decades. In Europe, cereals peaked around 1990 but have since fluctuated, while maize and other grains have grown steadily in North America.

Comparison Plot

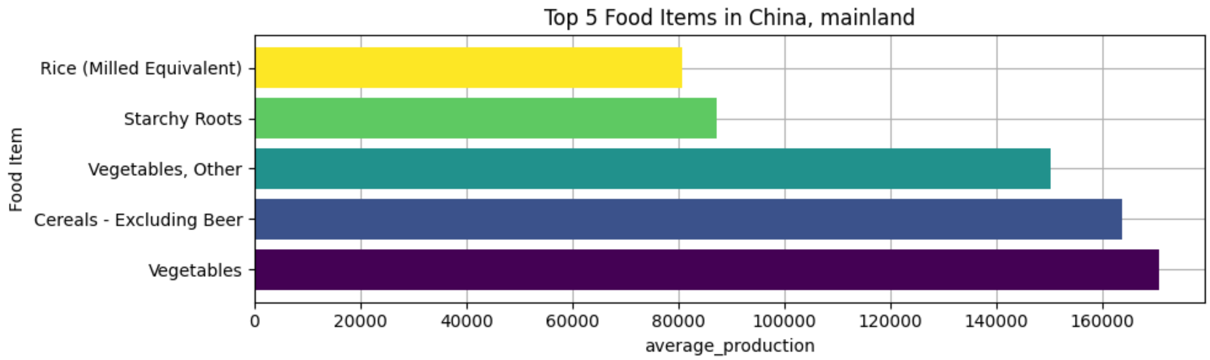
Plot Creation

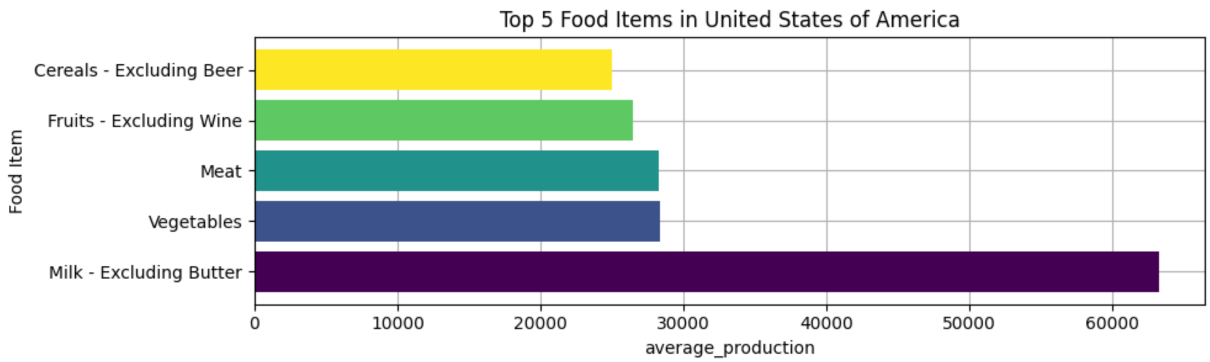
In [ ]:
```
def comparison_plot(df, location, top_location, value, top_value, element):
    # Get the top locations by average value
    top_locations = df.groupby(location)[value].mean().nlargest(top_location).index

    # Filter by the given element and top locations
    data = df[df[location].isin(top_locations) & (df['element'] == element)]

    # Get the top items for each location
    top_items = data.groupby([location, 'item'])[value].mean()
    top_items = top_items.groupby(location).nlargest(top_value).reset_index(level=0

    # Create subplots
    _, axes = plt.subplots(nrows=len(top_locations), figsize=(10, 15))
```

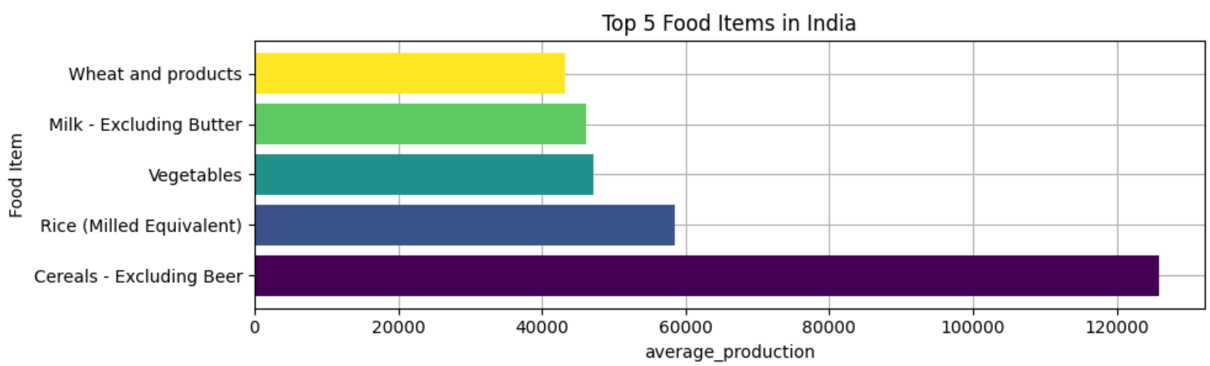
```
    cmap = plt.colormaps.get_cmap('viridis')

    for i, loc in enumerate(top_locations):
        data = top_items[top_items[location] == loc]
        color_list = cmap(np.linspace(0, 1, top_value))

        axes[i].barh(data['item'], data[value], color=color_list)
        axes[i].set_title(f'Top {top_value} {element} Items in {loc}')
        axes[i].set_xlabel(value)
        axes[i].set_ylabel(f'{element} Item')
        axes[i].set_axisbelow(True)
        axes[i].grid(True, zorder=0)

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

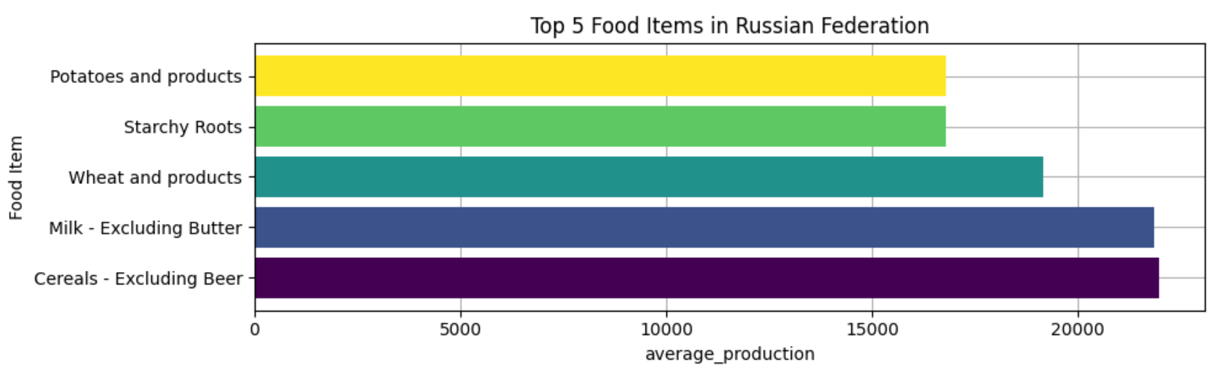
In [ ]:

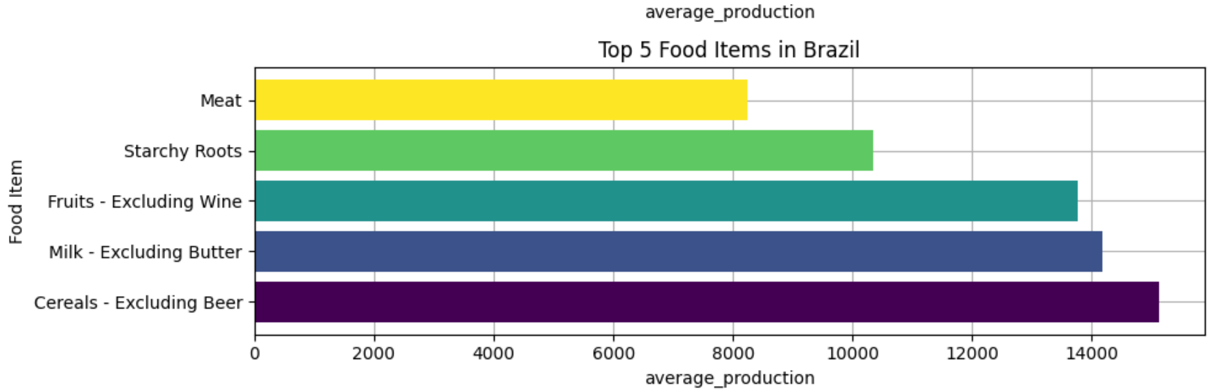
```
# Comparison plot for Food items in the top 5 areas in average production
comparison_plot(
    df=merged_df,
    location='area',
    top_location=5,
    value='average_production',
    top_value=5,
    element='Food'
)
```


Top 5 Food Items in China, mainland
Food Item
Rice (Milled Equivalent)
Starchy Roots
Vegetables, Other
Cereals - Excluding Beer
Vegetables
0
20000
40000
60000
80000
100000
120000
140000
160000
average_production


Top 5 Food Items in United States of America
Food Item
Cereals - Excluding Beer
Fruits - Excluding Wine
Meat
Vegetables
Milk - Excluding Butter
0
10000
20000
30000
40000
50000
60000
average_production


Top 5 Food Items in India
Food Item
Wheat and products
Milk - Excluding Butter
Vegetables
Rice (Milled Equivalent)
Cereals - Excluding Beer
0
20000
40000
60000
80000
100000
120000
average_production


Top 5 Food Items in Russian Federation
Food Item
Potatoes and products
Starchy Roots
Wheat and products
Milk - Excluding Butter
Cereals - Excluding Beer
0
5000
10000
15000
20000
average_production


Top 5 Food Items in Brazil
Food Item
Meat
Starchy Roots
Fruits - Excluding Wine
Milk - Excluding Butter
Cereals - Excluding Beer
0
2000
4000
6000
8000
10000
12000
14000
average_production

Insights:

> The graph shows the top 5 food items by average production in China, the United States, India, Russia, and Brazil. Cereals (excluding beer) are particularly prevalent across several countries, including Brazil, Russia, and India.

`For Food:`

> **China, mainland:** The top food items are vegetables, cereals, starchy roots, and rice. Vegetables is the most produced food item, reflecting its central role in the Chinese diet. Other vegetables and cereals (excluding beer) also have high production levels, indicating a mix of grains and fresh produce. Starchy roots and rice have lower production, likely due to a shift in diets.

> **United States of America:** Cereals (excluding beer) leads in production, highlighting the importance of dairy for American diet and agriculture. Vegetables and meat follow, suggesting a focus on greens and poultry products.

> **India:** Their top 5 food items are cereals, rice, vegetables, and wheat, highlighting the central role of grains in the Indian diet. The absence of meat in the top 5 can be attributed to cultural and religious factors, such as Hinduism's promotion of vegetarianism and Islam's dietary restrictions. For further insight, milk (excluding butter) and cereals (excluding beer) lead in feed production, showing a balanced reliance on both animal-based and plant-based feed sources. Sugar crops and maize also play a significant role, though to a slightly lesser extent.

> **Russian Federation:** Cereals and milk are the leading food items in terms of production, with their average production levels closely matching each other. This possibly indicates the country's importance to both items pertaining to the country's food production strategy. Additionally, it is noteworthy that potatoes and starchy roots, despite having the lowest average production among the top food items, exhibit a similar production mean as well.

> **Brazil:** Cereals (excluding beer) and maize are the most produced feed items, reflecting their critical role in Brazilian agriculture. Starchy roots and cassava are also important but have lower production averages. Sugar crops have the lowest production among the top feed items. This diversity underscores Brazil's extensive agricultural resources and favorable tropical and subtropical climates, which support a wide range of crops.

`Conclusion`

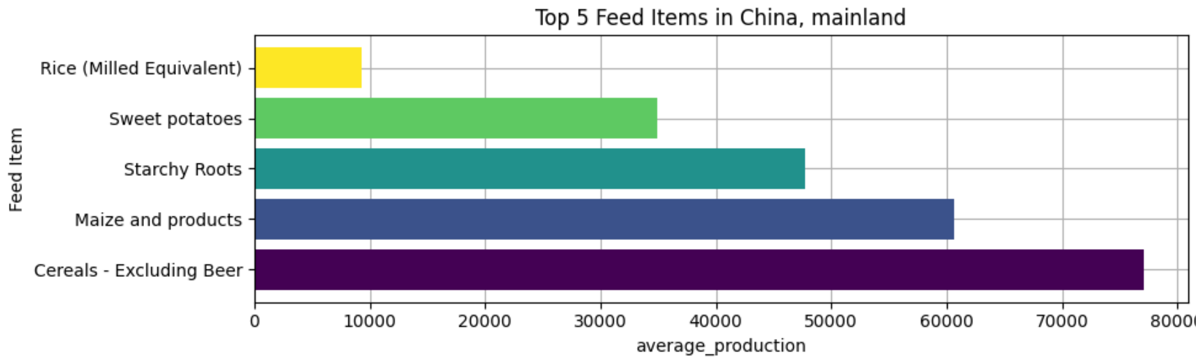
> The analysis reveals a strong emphasis on cereals across all examined countries, highlighting their significance as food. Variations in the top food items, such as the prominence of vegetables in China and the absence of meat

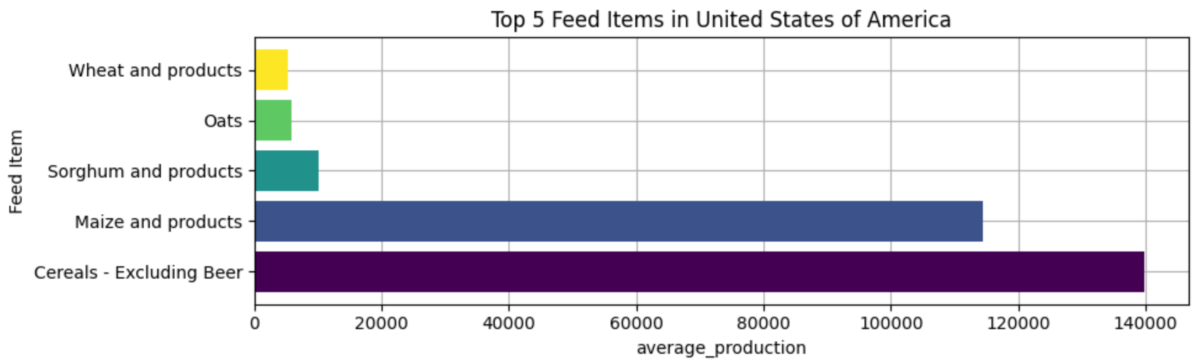
> in India's top production, reflect diverse cultural dietary practices and agricultural focuses.

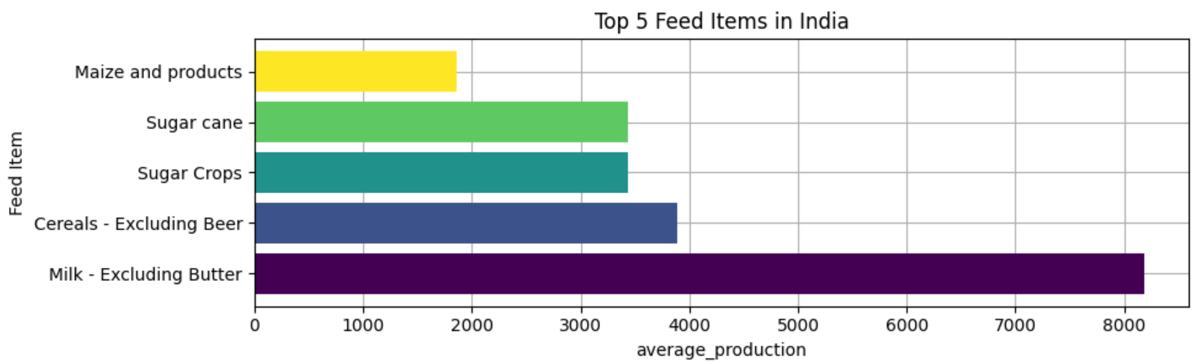
> **Promote Crop Rotation and Sustainable Farming Practices:** Given the heavy reliance on cereals in countries like India, Russia, and Brazil, promoting crop rotation and other sustainable agriculture practices could help maintain soil health and boost productivity.

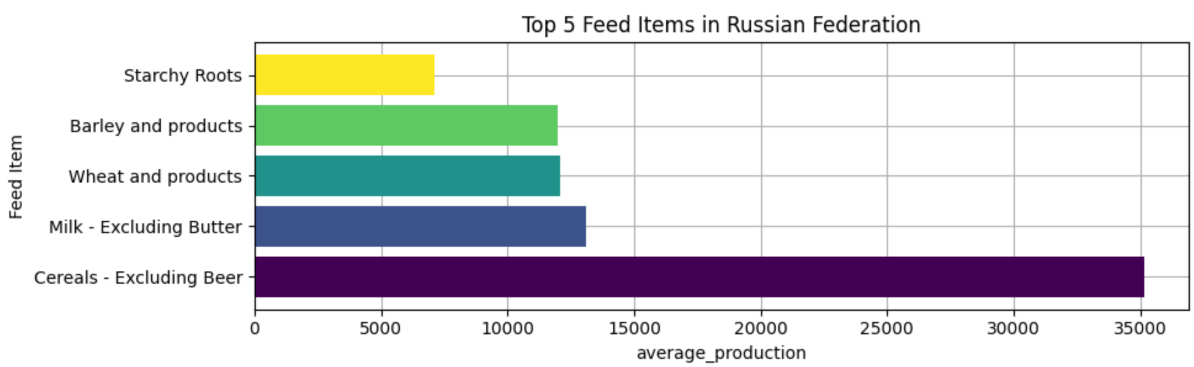
In [ ]:

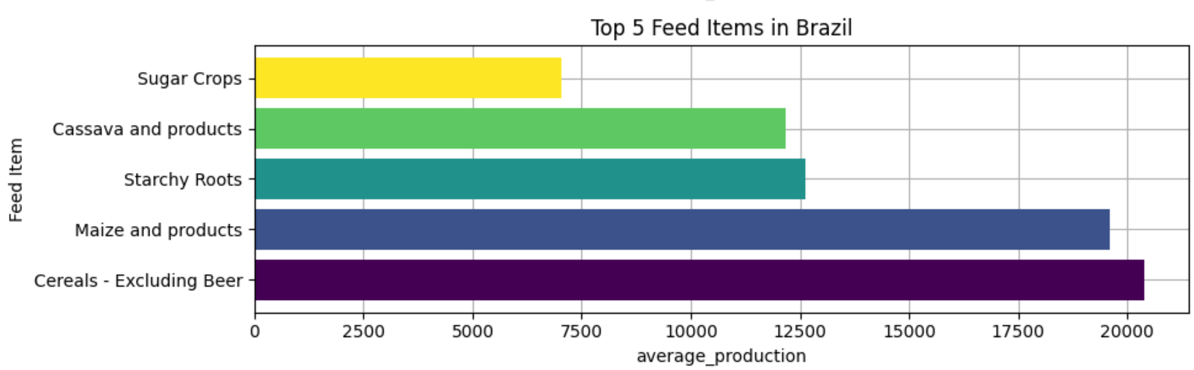
```
# Comparison plot for Feed items in the top 5 areas in average production
comparison_plot(
    df=merged_df,
    location='area',
    top_location=5,
    value='average_production',
    top_value=5,
    element='Feed'
)
```


Top 5 Feed Items in China, mainland
Rice (Milled Equivalent)
Sweet potatoes
Starchy Roots
Maize and products
Cereals - Excluding Beer
Feed Item
0 10000 20000 30000 40000 50000 60000 70000 80000
average_production


Top 5 Feed Items in United States of America
Wheat and products
Oats
Sorghum and products
Maize and products
Cereals - Excluding Beer
Feed Item
0 20000 40000 60000 80000 100000 120000 140000
average_production


Top 5 Feed Items in India
Maize and products
Sugar cane
Sugar Crops
Cereals - Excluding Beer
Milk - Excluding Butter
Feed Item
0 1000 2000 3000 4000 5000 6000 7000 8000
average_production


Top 5 Feed Items in Russian Federation
Starchy Roots
Barley and products
Wheat and products
Milk - Excluding Butter
Cereals - Excluding Beer
Feed Item
0 5000 10000 15000 20000 25000 30000 35000
average_production


Top 5 Feed Items in Brazil
Sugar Crops
Cassava and products
Starchy Roots
Maize and products
Cereals - Excluding Beer
Feed Item
0 2500 5000 7500 10000 12500 15000 17500 20000
average_production

Insights:

> These comparison plots illustrate the top 5 feed items by average production in the top 5 leading countries: China, United States, India, the Russian Federation, and Brazil. Each bar represents the average production quantity for a specific food or feed item within each country.

```
For Feed:
```

> **China and United States:** Both countries are top producers of maize and cereals for animal feed, highlighting how crucial these grains are for their large livestock industries, which are essential for meeting high domestic demand for meat and dairy products.

> **India:** Maize and cereals are also prominent in feed production, supporting the large livestock sector, which plays a crucial role in the rural economy. Using grain-based feed helps maintain a big livestock population, especially in a country where milk and dairy products are highly valued

> **Russian Federation:** he focus on wheat, barley, and cereals for feed emphasizes the use of grain-based feed for animals. This is essential in a country with long, cold winters, where livestock needs substantial feed supplies to survive the harsh conditions.

> **Brazil:** Large production of maize, cereals, and starchy roots supports its large agricultural sector geared toward livestock. As one of the world's top meat exporters, especially beef, Brazil has a high demand for feed to support its extensive livestock industry.

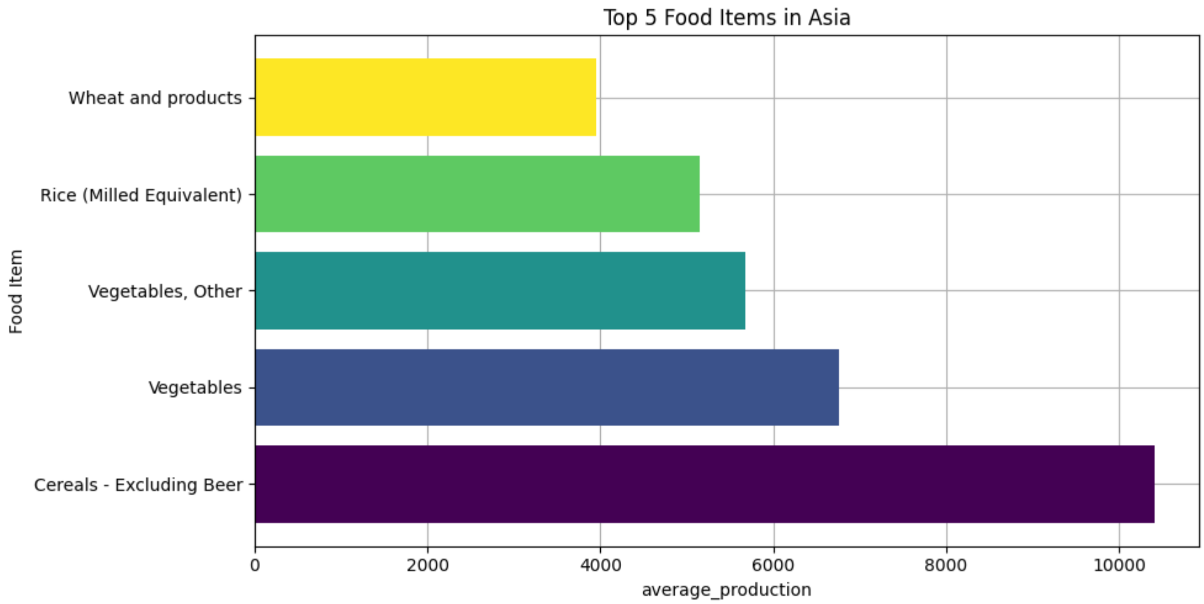
```
Conclusion
```

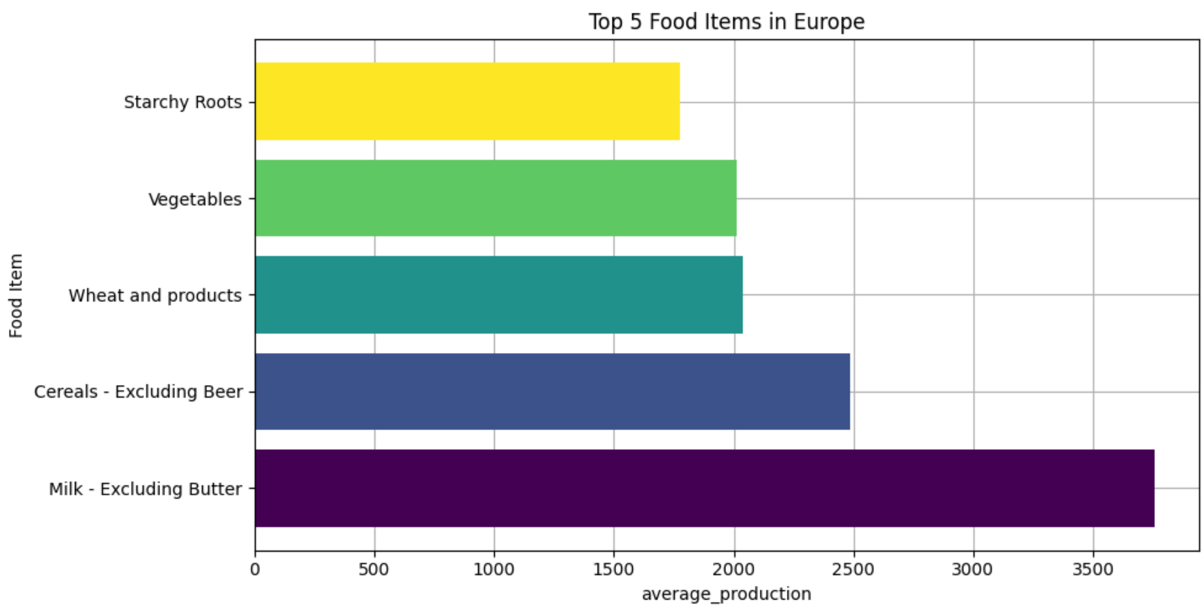
> The data shows how cultural, religious, and climatic factors affect the types of food and feed produced in each country. For example, India’s cultural preferences result in a diet rich in grains with less focus on meat, while Russia’s climate requires the cultivation of hardy crops. In the U.S. and Brazil, strong livestock industries lead to high production of feed, especially maize and cereals. These factors influence each country’s agricultural practices and food security, highlighting the link between culture, climate, and agriculture.

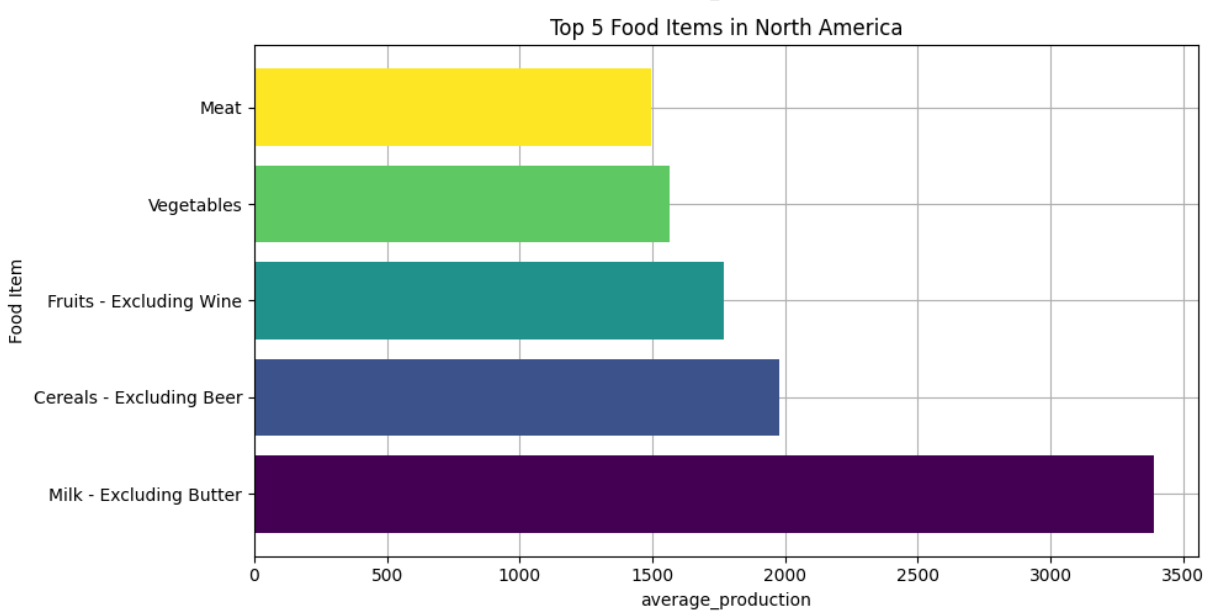
> **Development for other Possible Feed Alternatives:** Given the heavy reliance on cereals and milk for animal feed in major agricultural countries, investing in research for sustainable and alternative feed sources as well.

In [ ]:
```
# Comparison plot for Food items in the top 3 continents in average production
comparison_plot(
    df=merged_df,
    location='continent',
    top_location=3,
```

```
    value='average_production',
    top_value=5,
    element='Food'
)
```


Top 5 Food Items in Asia
Wheat and products
Rice (Milled Equivalent)
Vegetables, Other
Vegetables
Cereals - Excluding Beer
Food Item
0
2000
4000
6000
8000
10000
average_production


Top 5 Food Items in Europe
Starchy Roots
Vegetables
Wheat and products
Cereals - Excluding Beer
Milk - Excluding Butter
Food Item
0
500
1000
1500
2000
2500
3000
3500
average_production


Top 5 Food Items in North America
Meat
Vegetables
Fruits - Excluding Wine
Cereals - Excluding Beer
Milk - Excluding Butter
Food Item
0
500
1000
1500
2000
2500
3000
3500
average_production

Insights:

> The graph shows the top 5 food items by average production in China, the United States, India, Russia, and Brazil. Cereals (excluding beer) are particularly prevalent across several countries, including Brazil, Russia, and India.

```
For Food:
```

> **Asia:** Asia's leading role in cereal production, especially rice and wheat, may be likely due to its large population and reliance on staple foods essential to traditional diets. Countries like China and India use extensive agricultural land for growing cereals to meet the needs of its large population. Furthermore, rice is a central part of cultural practices and cuisines in many Asian countries. This also applies in the high production of vegetables wherein, it is incorporated into a variety of dishes.

> **Europe:** In Europe, dairy industries helps produce a lot of milk, especially in Germany, France, and the Netherlands. The mild weather in Europe is good for growing cereals and wheat, which are important for foods like bread and pasta. Europe's different climates and fertile soil also support growing various vegetables and starchy foods like potatoes, which are key parts of many European meals.

> **North America:** North America has a strong dairy industry, with the U.S. being in the top 10 largest milk producing countries. The vast agricultural lands in the U.S. and Canada support large-scale cereal production, including maize, wheat, and barley, which are used for food and livestock feed. The diverse climates in North America also allow for growing a wide range of fruits and vegetables. Additionally, large-scale livestock farming in North America, especially for beef, pork, and poultry, makes meat an important part of the diet in the U.S. and Canada.

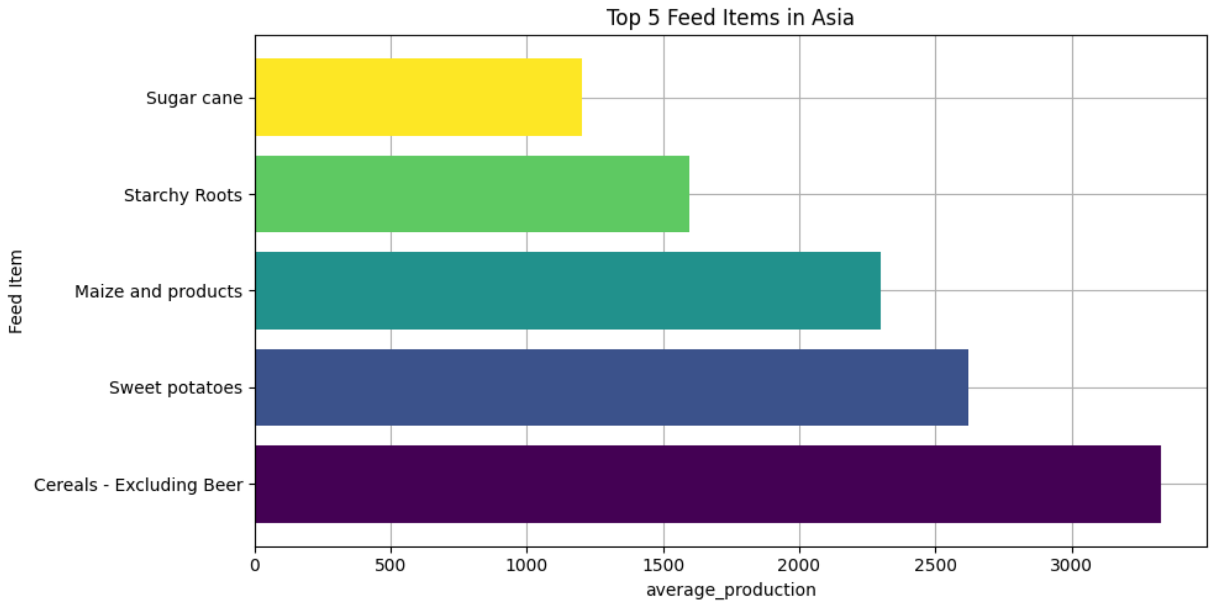
```
Conclusion:
```

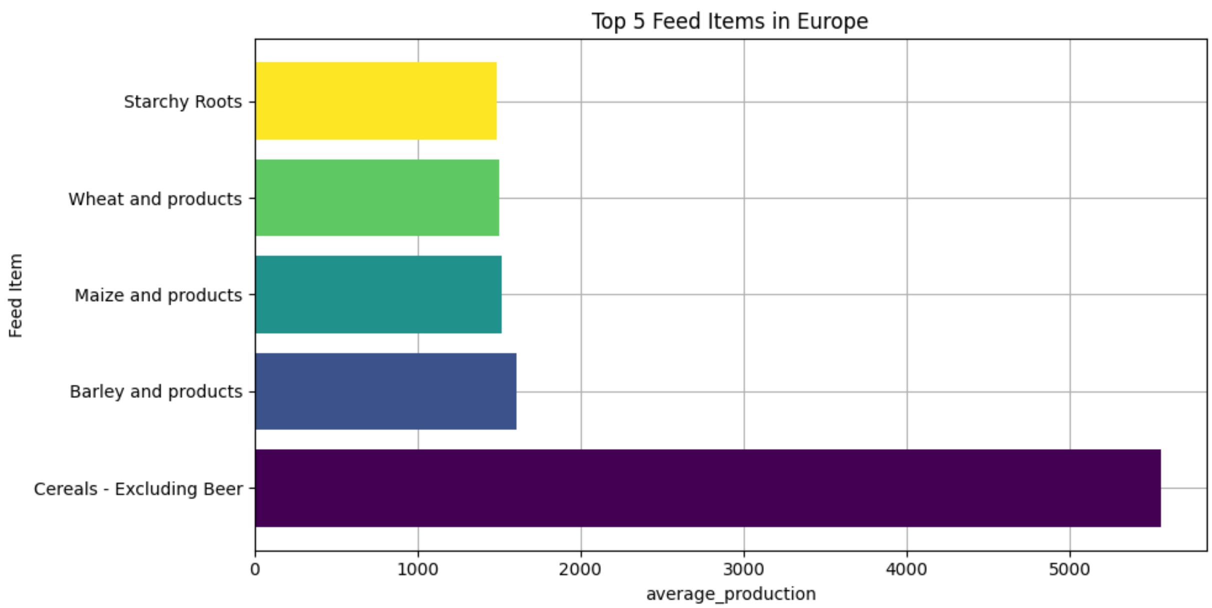
> **Infrastructure Development:** Based on the bar plot of average production by continent, we can see that africa and oceania have signigicantly lower average agricultural production compared to other continents. This indicate that these continents are behind in agricultural productivity compared to other continents. Policymakers should prioritize implementing targeted agricultural development programs in Africa and Oceania. Solutions like investing in infrastructures and modern farming can help increase their production and also contribute to food security and poverty reduction in these regions.

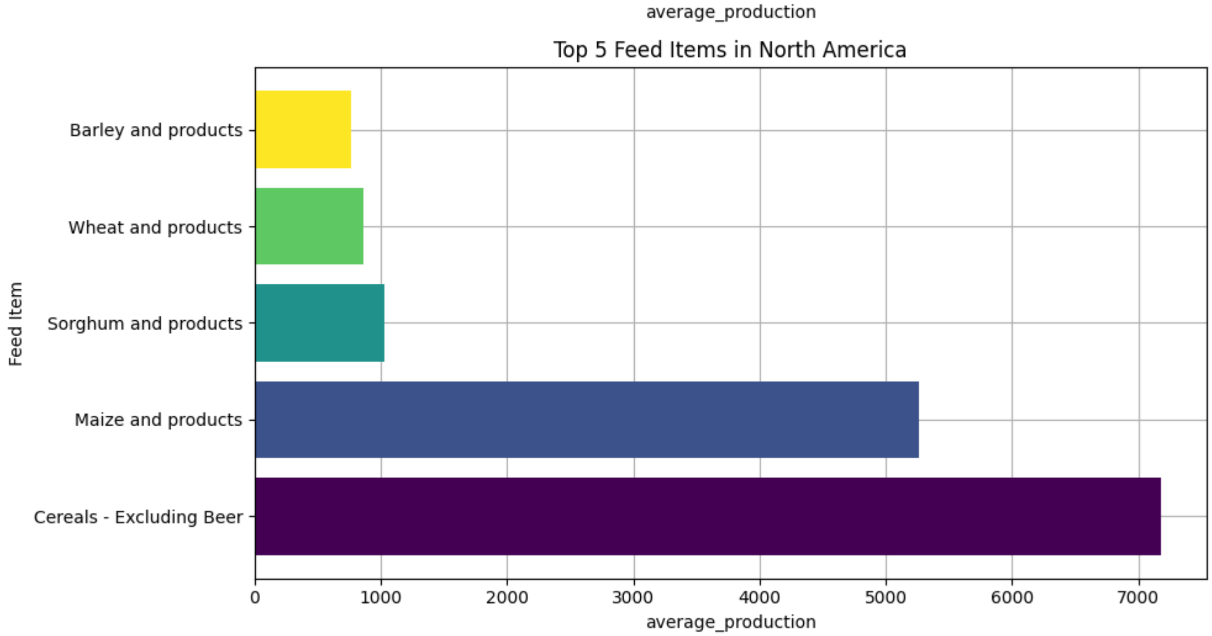
> **Market Diversification:** Even though europe has the 2nd highest average production among continents, it has the 2nd lowest average value per capita. This shows despite high production levels, they cannot maximize the

> economic value of their products. It could also mean that the agricultural market in Europe could be saturated. It is recommended to expand their market by exploring new export markets which can help increase their products' value.

In [ ]:
```
# Comparison plot for Feed items in the top 3 continents in average production
comparison_plot(
    df=merged_df,
    location='continent',
    top_location=3,
    value='average_production',
    top_value=5,
    element='Feed'
)
```


Top 5 Feed Items in Asia
Sugar cane
Starchy Roots
Maize and products
Sweet potatoes
Cereals - Excluding Beer
Feed Item
0
500
1000
1500
2000
2500
3000
average_production


Top 5 Feed Items in Europe
Starchy Roots
Wheat and products
Maize and products
Barley and products
Cereals - Excluding Beer
Feed Item
0
1000
2000
3000
4000
5000
average_production


Top 5 Feed Items in North America
Barley and products
Wheat and products
Sorghum and products
Maize and products
Cereals - Excluding Beer
Feed Item
0
1000
2000
3000
4000
5000
6000
7000
average_production

Insights:

> These comparison plots illustrate the top 5 food and feed items by average production in the top 3 leading continents: Asia, Europe, and North America. Each bar represents the average production quantity for a specific food or feed item within each continent.

`For Feed:`

> **Asia:** In Asia, cereals like rice and wheat as the leading feed items likely reflects the continent's agricultural focus and dietary habits. Starchy roots, such as cassava and sweet potatoes, also play a significant role, possibly due to their versatility and ability to thrive in tropical climates.

> **Europe:** In Europe, wheat and barley are the main feed components, showing the continent's agricultural methods and food preferences. Although starchy roots are present, they are less significant compared to Asia, possibly due to varying climate conditions or economic factors.

> **North America:** In North America, especially in the U.S., a lot of cereal crops are grown for animal feed, supporting the livestock industry. Maize is a key feed crop, important for both meat and dairy. Sorghum is used as a drought-resistant feed in drier areas. While, wheat is used for feed in Canada and the northern U.S., and barley is important for feeding cattle in the northern plains.

`Conclusion`

> The data reveals how cultural, climatic, and economic factors shape food and feed production across Asia, Europe, and North America. Asia’s prominence on rice and wheat reflects its population size and dietary habits, while starchy roots thrive in its tropical climates. Europe’s varied climates support its strong dairy and cereal industries, with potatoes and vegetables also being significant. In North America, extensive agricultural lands and diverse climates enable large-scale cereal production for both food and feed, including key crops like maize and sorghum. These patterns illustrate how regional factors influence agricultural practices and food systems.

Geographical Visualization

Choropleth Map

In [ ]:
```
# Get the mean of the important columns that will be used in choropleth map
avg_data_per_country = merged_df.groupby(['iso_alpha3', 'area'], as_index=False).ag
    'value_per_capita': 'mean',
    'average_production': 'mean'
})
```

```
avg_data_per_country
```

Out[ ]:

	iso_alpha3	area	value_per_capita	average_production
0	AFG	Afghanistan	35.530081	156.663333
1	AGO	Angola	29.784193	122.211528
2	ALB	Albania	2.930187	36.386256
3	ARE	United Arab Emirates	9.400145	34.384687
4	ARG	Argentina	44.271041	503.171192
...	...	...	...	...
167	WSM	Samoa	0.196440	2.329665
168	YEM	Yemen	28.250420	72.900745
169	ZAF	South Africa	56.717156	329.053100
170	ZMB	Zambia	17.094130	49.636321
171	ZWE	Zimbabwe	16.529904	54.747076

172 rows × 4 columns

In [ ]:

```
fig = px.choropleth(
    avg_data_per_country,
    locations='iso_alpha3',
    color='value_per_capita',
    hover_name='area',
    color_continuous_scale=px.colors.sequential.Plasma,
    projection='equirectangular',
    title='Value per Capita by Country'
)

fig.show()
```

In [ ]:

```
fig = px.choropleth(
    avg_data_per_country,
    locations='iso_alpha3',
    color='average_production',
    hover_name='area',
    color_continuous_scale=px.colors.sequential.Plasma,
    projection='equirectangular',
    title='Average Production by Country'
)

fig.show()
```

Analysis:

> Some countries in North America, Europe, and parts of Asia tend to have higher value per capita, value, and average production. These are represented

> by lighter colored hues, while some regions in Africa, South America, and parts of Asia exhibit lower values.

> The overall distribution of colors on the map reveals regional disparities. For example, there appears to be a concentration of higher values in developed countries and regions with strong economies, while lower values are more prevalent in developing countries and regions facing economic challenges.

Part 4: Drawing Conclusions

Analysis Summary

Summary Report

`Key Findings`

> **Average Production by Continent:** Asia has the highest average production, significantly outperforming other continents. It is followed by Europe and North America. Oceania has the lowest average production.

> **Average Value per Capita by Continent:** Asia also leads in average value per capita, with a huge gap compared to other continents. This indicates that Asia is performing the best in both agriculture production and value return.

> **Top Food and Feed Items in China:** Vegetables and cereals (excluding beer) dominate production. Feed production is similarly dominated by cereals.

> **USA:** Milk (excluding butter) is the top food item, with cereals (excluding beer) is leading the feed item.

> **India:** Cereals (excluding beer) and rice are the top food items, with milk gaining importance in feed production.

> **Russian Federation:** Milk and cereals dominate both food and feed production, but there is a noticable decline in some feed items over time.

> **Brazil:** Cereals and maize and products both lead in food and feed items.

> **Heatmap Visualization:** The correlation heatmap shows strong correlations between years and production metrics, suggesting consistent trends over time.

`Trends`

> **Rising Production in Asia:** Asia dominated in both production and value per

> capita which indicates their rapid agricultural growth, driven by cereals and staple crops like rice.

> **Diverse Food Production Trends:** Countries like Brazil and India are producing a wider range of food items, instead of relying heavily on just one or two types of crops.

Insights & Trends

> The key insights we gained from our plot analysis reveal how cultural, climatic, and economic factors influence global food and feed production, as well as how dietary preferences evolve over time in different countries and continents.

> Culture plays a significant role, as seen in how dietary practices shape food production; for example, India's focus on cereals rather than meat is driven by cultural and religious reasons.

> Climatic factors are also crucial: Russia's cold winters favor the cultivation of hardy crops like potatoes, while Brazil’s tropical climate supports a diverse range of crops.

> Economic factors, particularly livestock farming, significantly impact feed production, as observed in the substantial maize and cereal production in North America and Brazil.

> Additionally, the plot highlights how dietary preferences change over time, reflecting possible shifts in economic conditions, cultural trends, and urbanization, as seen in the increasing and decreasing trend in the line plots.

Actionable Recommendations

Recommendations

Investment in Agriculture in Asia:

> **Recommendation:** Asia's agricultural sector has shown remarkable growth, particularly in terms of both production levels and value per capita. To maintain and enhance this success, it is crucial to continue supporting and investing on their innovation.

> **Justification:** Asia leads the world in agricultural production, especially in staple crops like rice and cereals. They also deliver high value per capita, which indicate that they generate large economic value through agriculture. They also established strong growth potential as seen in the time-series analysis.

Encourage Diversification of Agricultural Products for Other Continents:

> **Recommendation:** North America and Europe have traditionally focused on staple crops and well-established agricultural products like wheat, corn, and soybeans. However, these regions face challenges in matching Asia's high production levels and economic returns. To enhance their competitiveness and market reach, it is recommended that these regions to expand their range of crops and agricultural products.

> **Justification:** While North America and Europe benefit from stable agricultural sectors, this stability can lead to market saturation and limited growth opportunities. By diversifying, these regions can tap into a broader consumer base and reduce the economic risks of depending on a limited set of crops.

Contextual Relevance

Introduction

`Background Information`

> The Food and Agriculture Organization (FAO) serves as a specialized agency of the United Nations, aiming to eliminate hunger and improve nutrition and food security worldwide (FAO, n.d.). One of its primary data can be found in the FAO and FAOSTAT database, which offers extensive data on food and agriculture. The data holds information also from a vast number of countries.

> This dataset is quite useful for researchers, policymakers, and governments, since it provides reliable statistics that can help formulate informed decisions on food production and sustainability.

> It is from the analysis of these datasets that data analysts and stakeholders can generate patterns and propose solutions to challenges facing food distribution. Thus, the significance of this data goes far beyond just being numbers; it impacts policies internationally and helps in fighting hunger and poverty (FAO, n.d.).

`Global Implications`

> The insights derived from this analysis are vital for crafting robust agricultural policies aimed at further enhancing the production count and value of food and feed items in the world.

> For instance, the bar graph that shows the average production by continent illustrates that Asia has the largest yields in production. This could be due to

> warmer temperatures around this region. Moreover, the relatvely warmer regions, e.g., Africa and South America, may struggle to produce more feed and food because of their geographical location and climate.
>
> > Africa and Oceania have significantly lower average agricultural production compared to other continents, indicating lagging agricultural productivity. Policymakers should focus on enhancing agricultural development in these regions. Investments in infrastructure and modern farming techniques could boost production, contributing to food security and poverty reduction in Africa and Oceania.

`Task Importance`

> Analyzing agricultural data, in relation to food production and values, are vital for enhancing global food security and productivity. This in turn, help support economic stability among countries and public health for its citizens.

> Furthermore, as populations grow and environmental issues, e.g., *climate change*, continues to impact agriculture, the urgency for data-driven solutions in policy-making becomes important than ever.

`Objective of the Analysis`

> The primary objective of this analysis is to understand trends and patterns in agricultural production and its values using the FAO and FAOSTAT datasets among countries.

> Whereas, by assessing these trends, the analysis aims to understand the impact of different agricultural practices on global food security - based on recorded data.

> Whereas, this focused analysis will provide insights that can help shape effective agricultural strategies.

Contextual Evidence

`Dataset Description`

> **FAO:** It is data sourced by the Food and Agriculture Organization (FAO) from its member nations, offers a comprehensive overview of global food production patterns. It contains detailed annual data spanning from 1961 to 2013, covering a wide range of metrics, e.g., production values. Each entry in the dataset is categorized by various attributes including area (with both abbreviation and full name), item (including food items or products), and element (detailing the type of data recorded, such as production or

> consumption). The dataset also integrates geographical data, providing latitude and longitude coordinates for each country or region.

> **FAOSTAT:** It is another dataset that goes along with FAO, in which it provides a record of agricultural production as well. It includes data elements such as the population type, area (with numerical codes and full names of countries or regions), and item details (including food items or products identified by numeric codes). Also, additional metadata in the dataset includes flags and descriptions indicating the sources and reliability of the data.

`Data Analysis Tools Used`

> **Pandas:** A tool for data manipulation and analysis, enabling the cleaning, transforming, and organizing of complex datasets like those from FAO and FAOSTAT.

> **Matplotlib:** A library that provides capabilities for creating static data visualizations in Python - crucial for the task of illustrating trends and patterns in the given datasets.

> **Seaborn:** A library similar to Matplotlib that provides attractive and informative statistical graphics.

> **Numpy:** A tool that supports large, multi-dimensional arrays and matrices, along with a vast collection of high-level mathematical functions to operate on these arrays.

> **PyCountry:** A library that provides accessible ISO country codes or names - that is used to help standardize data in FAO and FAOSTAT.

> **Plotly.Express:** A tool that helps in the creation of interactive plots for dynamic data visualization, like its use in the choropleth graph.

Data Analysis Steps and Context

`Data Cleaning and Merging`

> **Data Loading:** Both the FAO and FAOSTAT datasets are imported and loaded using Pandas.

> **Data Dictionary Creation:** Use of functions to generate data dictionaries for each dataset, clarifying column details and ensuring transparency.

> **Null Value and Duplicates Check:** Null values are identified and quantified to assess data completeness.
>
> - Duplicates are detected and counted to ensure data integrity.

> **Data Standardization:** Column names are standardized by converting to lowercase, replacing spaces with underscores, and removing special characters to facilitate data handling.
>
> **Column Renaming:** Similar columns are renamed for consistency, aiding in accurate dataset merging.
>
> **Data Merging:** The datasets are merged on common columns ('area_code' and 'area'), with checks performed to validate the merge process.
>
> - New dataframe is exported as a CSV file for convenient loading of merged data.

`Feature Engineering and Data Wrangling`

> **Active Years Calculation:** A new column, years_existing, is created to indicate the number of years for which data exists for each entry.
>
> **Average Production Computation:** The dataset now includes an average_production column, calculated as the mean of values across all year columns.
>
> **Population Unit Standardization:** The population_unit column is parsed to retain only numeric values, standardizing the unit representation and facilitating numerical operations.
>
> **Per Capita Values:** A new column, value_per_capita, is derived by dividing total values by the standardized population unit.
>
> **ISO Code Conversion:** Utilizing the PyCountry library, each country's name is converted to its respective ISO alpha-3 code.
>
> - **ISO Code Validation:** An initial check identifies areas with invalid ISO codes, which are then manually corrected based on a predefined mapping.
>
> **Continent Assignment:** Each country's ISO alpha-3 code is further mapped to its corresponding continent using a combination of PyCountry and manual adjustments.
>
> - **Continent Validation and Adjustment:** Continents with 'Invalid' values are identified and corrected manually where necessary.

References

FAO. (n.d.). *About FAO*. https://www.fao.org/about/about-fao/en/