2025

1 Capstone Project Plan: Food Security Analysis in Rwanda

1.1 PART 1: PROBLEM DEFINITION & PLANNING

1.1.1 I. Sector Selection

FOOD

1.1.2 II. Problem Statement

"Can we analyze packaged food products to assess their nutritional value and identify unhealthy trends in consumer diets?"

This project will examine the complex relationships between dietary energy supply, economic factors, agricultural indicators, and nutrition outcomes to understand Rwanda's progress in combating food insecurity.

1.1.3 III. Dataset Identification

Dataset Title: FAOSTAT Suite of Food Security Indicators for Rwanda

Source Link: FAOSTAT Database (provided dataset: FAOSTAT__data__en__7-29-2025.csv)

Number of Rows and Columns: Rows: 500+ (exact count to be determined after loading)

Columns: 14 (Domain Code, Domain, Area Code, Area, Element Code, Element, Item Code, Item, Year Code, Year, Unit, Value, Flag, Flag Description, Note)

Data Structure: Structured (CSV)

Data Status: Clean

Requires Preprocessing (contains missing values, needs standardization of year formats, etc.)

1.2 Food Security Analysis in Rwanda - Python Implementation

1.2.1 Loading data

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime

# Set up visualization style
plt.style.use('ggplot')
plt.rcParams['figure.figsize'] = (12, 6)
```

1.3 1. Data Loading and Initial Exploration

[2]:
```
# Load the dataset
df = pd.read_csv('FAOSTAT_data_en_7-29-2025.csv')

# Initial exploration
print(f"Dataset shape: {df.shape}")
print("\nFirst 5 rows:")
display(df.head())
print("\nColumns and data types:")
```

```
Dataset shape: (1060, 15)

First 5 rows:
  Domain Code                           Domain  Area Code (M49)    Area  \
0          FS  Suite of Food Security Indicators              646  Rwanda
1          FS  Suite of Food Security Indicators              646  Rwanda
2          FS  Suite of Food Security Indicators              646  Rwanda
3          FS  Suite of Food Security Indicators              646  Rwanda
4          FS  Suite of Food Security Indicators              646  Rwanda

   Element Code Element  Item Code  \
0
```

```
1
         6121   Value     21010
2
         6121   Value     21010
3
         6121   Value     21010
4
         6121   Value     21010
         6121   Value     21010


                                                Item  Year Code       Year  \
0  Average dietary energy supply adequacy (percen…   20002002  2000-2002
```

1	Average dietary energy supply adequacy (percen…	20012003	2001-2003
2	Average dietary energy supply adequacy (percen…	20022004	2002-2004
3	Average dietary energy supply adequacy (percen…	20032005	2003-2005
4	Average dietary energy supply adequacy (percen…	20042006	2004-2006

	Unit	Value	Flag	Flag Description	Note
0	%	96	E	Estimated value	NaN
1	%	99	E	Estimated value	NaN
2	%	100	E	Estimated value	NaN
3	%	98	E	Estimated value	NaN
4	%	97	E	Estimated value	NaN

Columns and data types:

```
Domain Code          object
Domain               object
Area Code  (M49)      int64
Area                 object
Element Code          int64
Element              object
Item Code            object
Item                 object
Year Code             int64
Year                 object
Unit                 object
Value                object
Flag                 object
Flag Description     object
Note                 object
```

```
dtype: object


Missing values per column:
Domain Code            0
Domain                 0
Area Code  (M49)       0
Area                   0
Element Code           0
Element                0
Item Code              0
Item                   0
Year Code              0
Year                   0
Unit                  21
Value                324
Flag                   0
Flag Description       0
Note                1054
dtype: int64
```

1.4 2. Data Cleaning

[3]:
```python
# Create a clean copy of the dataframe
clean_df = df.copy()

# Handle missing values - we'll keep them for now but note which values are␣
↪estimated
clean_df['is_estimated'] = clean_df['Flag Description'] == 'Estimated value'

# Convert year columns to consistent format
def parse_year(year_str):
    if '-' in year_str:  # Handle year ranges like "2000-2002"
        return int(year_str.split('-')[0]) + 1  # Take middle year
    else:
        return int(year_str)

clean_df['Year_parsed'] = clean_df['Year'].apply(parse_year)

# Convert Value column to numeric, handling non-numeric entries
clean_df['Value_numeric'] = pd.to_numeric(clean_df['Value'], errors='coerce')

# Filter out rows with completely missing values
clean_df = clean_df[~clean_df['Value_numeric'].isna()]
```

```
Cleaned dataset shape: (691, 7)

Unique indicators available:
['Average dietary energy supply adequacy (percent) (3-year average)'
 'Dietary energy supply used in the estimation of the prevalence of
undernourishment (kcal/cap/day)'
 'Dietary energy supply used in the estimation of the prevalence of
undernourishment (kcal/cap/day) (3-year average)'
 'Share of dietary energy supply derived from cereals, roots and tubers
(percent) (3-year average)'
 'Average protein supply (g/cap/day) (3-year average)'
```

'Average supply of protein of animal origin (g/cap/day) (3-year average)'

'Gross domestic product per capita, PPP, (constant 2021 international $)'

'Prevalence of undernourishment (percent) (3-year average)'

'Number of people undernourished (million) (3-year average)'

```
 'Cereal import dependency ratio (percent) (3-year average)'
 'Percent of arable land equipped for irrigation (percent) (3-year average)'
 'Value of food imports in total merchandise exports (percent) (3-year average)'
 'Political stability and absence of violence/terrorism (index)'
 'Per capita food supply variability (kcal/cap/day)'
 'Percentage of population using at least basic drinking water services
(percent)'
 'Percentage of population using at least basic sanitation services (percent)'
 'Percentage of children under 5 years affected by wasting (percent)'
 'Number of children under 5 years affected by wasting (million)'
 'Percentage of children under 5 years of age who are stunted (modelled
estimates) (percent)'
 'Number of children under 5 years of age who are stunted (modeled estimates)
(million)'
 'Percentage of children under 5 years of age who are overweight (modelled
estimates) (percent)'
 'Number of children under 5 years of age who are overweight (modeled estimates)
(million)'
 'Prevalence of obesity in the adult population (18 years and older) (percent)'
 'Number of obese adults (18 years and older) (million)'
 'Prevalence of anemia among women of reproductive age (15-49 years) (percent)'
 'Number of women of reproductive age (15-49 years) affected by anemia
(million)'
 'Prevalence of exclusive breastfeeding among infants 0-5 months of age
(percent)'
 'Prevalence of low birthweight (percent)'
 'Minimum dietary energy requirement  (kcal/cap/day)'
 'Average dietary energy requirement (kcal/cap/day)'
 'Coefficient of variation of habitual caloric consumption distribution (real
number)'
 'Incidence of caloric losses at retail distribution level (percent)'
 'Average fat supply (g/cap/day) (3-year average)']
```

[9]:
```python
# Save the cleaned DataFrame to CSV
analysis_df.to_csv('rwanda_food_security_cleaned.csv', index=False)
```

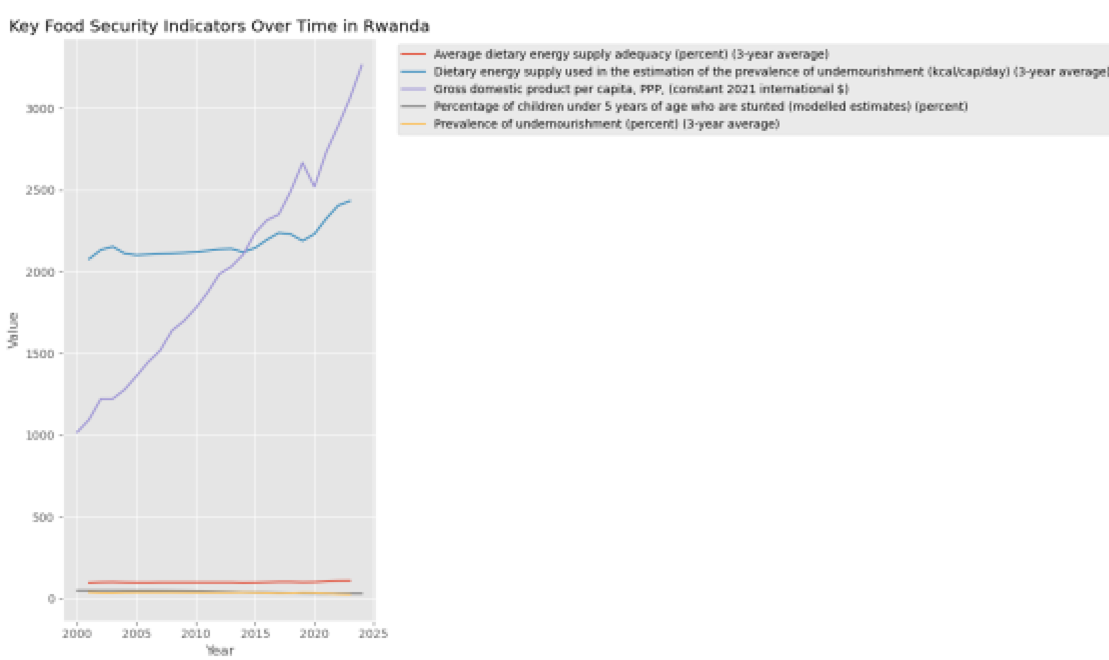
```
Data saved as 'rwanda_food_security_cleaned.csv'
```

1.5 3. Exploratory Data Analysis (EDA)

1.5.1 3.1 Key Indicators Over Time

[4]:
```python
# Select key indicators to analyze
key_indicators = [
    'Prevalence of undernourishment (percent) (3-year average)',
```

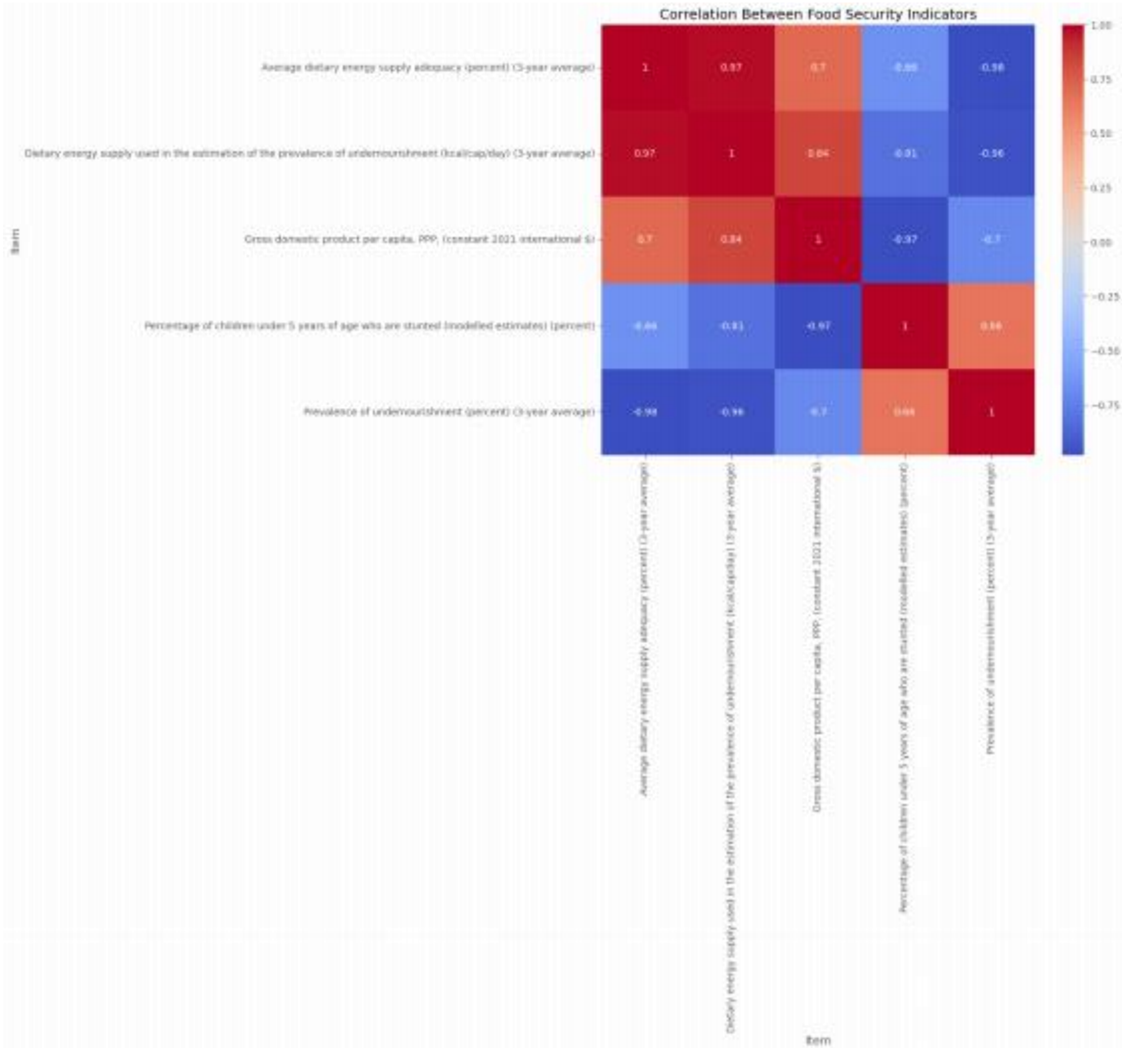
```
    'Dietary energy supply used in the estimation of the prevalence of␣
↪undernourishment (kcal/cap/day) (3-year average)',
    'Gross domestic product per capita, PPP, (constant 2021 international $)',
    'Percentage of children under 5 years of age who are stunted (modelled␣
↪estimates) (percent)'
]

# Filter for key indicators
key_df = analysis_df[analysis_df['Item'].isin(key_indicators)]

# Pivot to have indicators as columns
pivoted_df = key_df.pivot_table(index='Year_parsed', columns='Item',␣
↪values='Value_numeric', aggfunc='mean')

# Plot trends over time
plt.figure(figsize=(14, 8))
for col in pivoted_df.columns:
    plt.plot(pivoted_df.index, pivoted_df[col], label=col)

plt.title('Key Food Security Indicators Over Time in Rwanda')
```

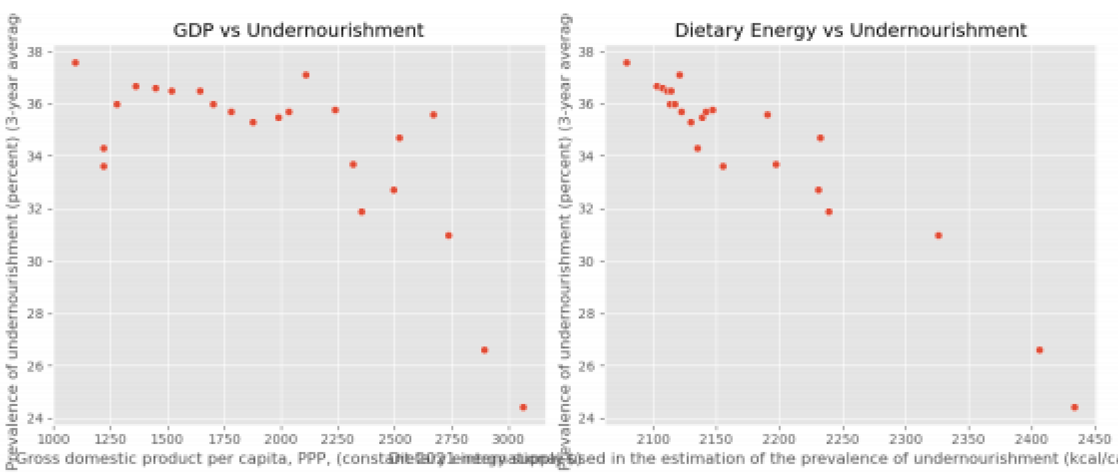


1.6 3.2 Relationship Analysis

[5]:
```
# Select recent year for cross-sectional analysis
recent_year = pivoted_df.index.max()
recent_data = pivoted_df[pivoted_df.index == recent_year].dropna(axis=1)

# Correlation matrix
corr_matrix = pivoted_df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Between Food Security Indicators')
plt.tight_layout()
plt.show()

# Scatter plot of key relationships
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
sns.scatterplot(data=pivoted_df, x='Gross domestic product per capita, PPP, ␣
↪(constant 2021 international $)',
                y='Prevalence of undernourishment (percent) (3-year average)')
plt.title('GDP vs Undernourishment')
plt.subplot(1, 2, 2)
```

```
C:¥Users¥HP¥AppData¥Local¥Temp¥ipykernel_2268¥1797038468.py:11: UserWarning:
Tight layout not applied. The bottom and top margins cannot be made large enough
to accommodate all Axes decorations.
  plt.tight_layout()
```


Correlation Between Food Security Indicators
Item
Item


GDP vs Undernourishment
Dietary Energy vs Undernourishment
Prevalence of undernourishment (percent) (3-year averag
Prevalence of undernourishment (percent) (3-year averag

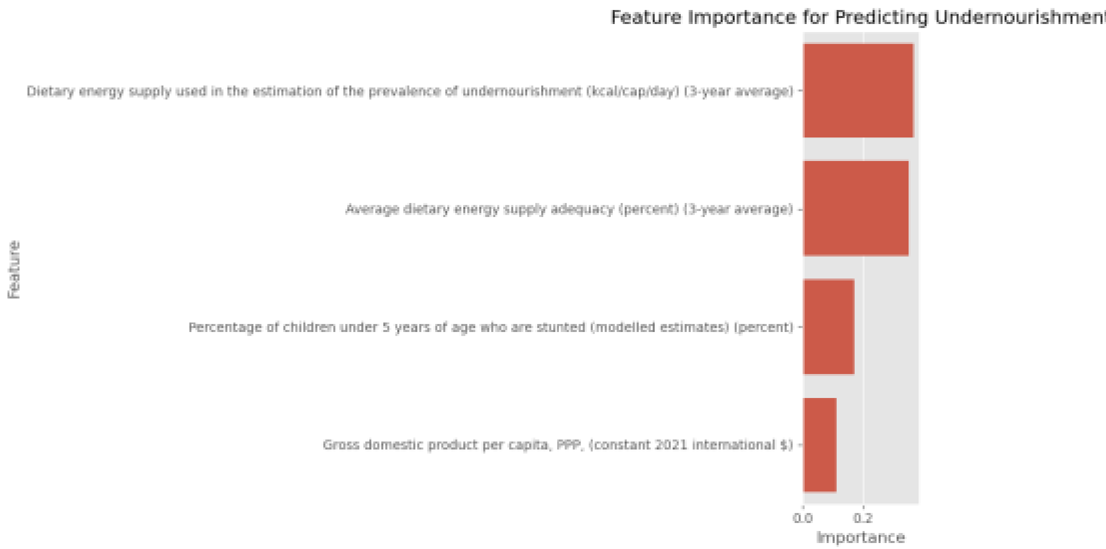
1.7 4. Machine Learning Model

We'll implement a regression model to predict undernourishment based on other indicators.

[6]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler


# Prepare data for modeling
model_df = pivoted_df.dropna()
X = model_df.drop('Prevalence of undernourishment (percent) (3-year average)', 
 ↪axis=1)
y = model_df['Prevalence of undernourishment (percent) (3-year average)']


# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)


# Split data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, 
 ↪random_state=42)


# Train model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)


# Evaluate
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Model Evaluation:")
print(f"Mean Squared Error: {mse:.2f}")
print(f"R-squared: {r2:.2f}")


# Feature importance
```

```
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Importance': model.feature_importances_
}).sort_values('Importance', ascending=False)

plt.figure(figsize=(10, 6))

sns.barplot(data=feature_importance, x='Importance', y='Feature')

plt.title('Feature Importance for Predicting Undernourishment')

plt.tight_layout()

plt.show()
```

```
Model Evaluation:
Mean Squared Error: 1.19
R-squared: 0.61
```



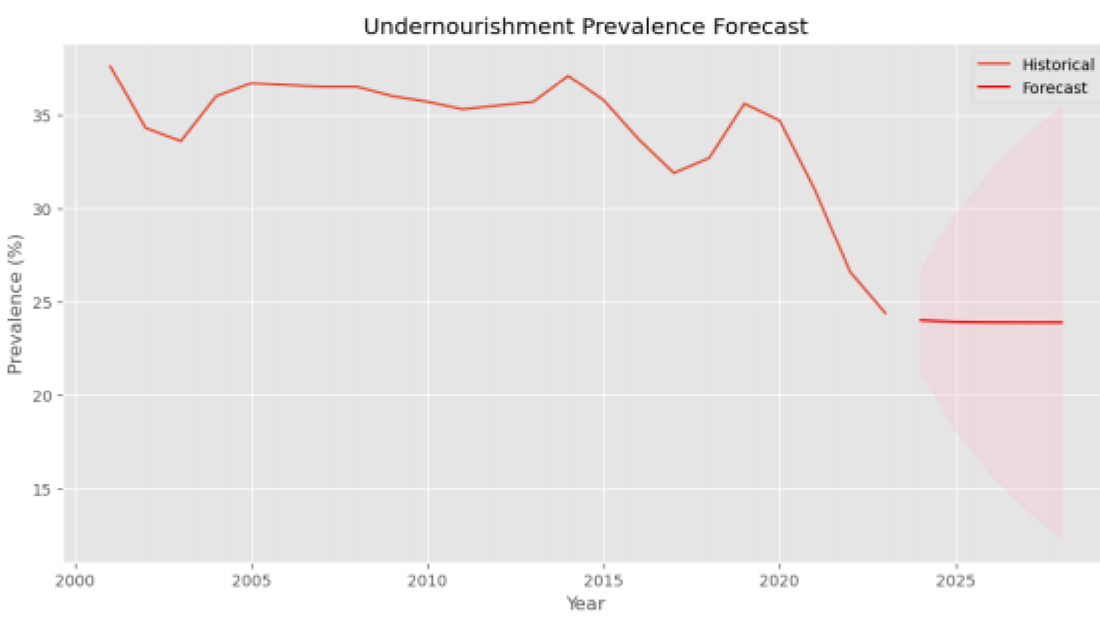
1.8 5. Time Series Forecasting

[7]:
```python
from statsmodels.tsa.arima.model import ARIMA

# Prepare undernourishment time series
undernourishment_ts = pivoted_df['Prevalence of undernourishment (percent) (3-year average)'].dropna()

# Fit ARIMA model
model_arima = ARIMA(undernourishment_ts, order=(1, 1, 1))
model_fit = model_arima.fit()

# Forecast next 5 years
forecast = model_fit.get_forecast(steps=5)
forecast_index = range(undernourishment_ts.index.max()+1, undernourishment_ts.index.max()+6)
```

```python
forecast_values = forecast.predicted_mean
conf_int = forecast.conf_int()

# Plot results

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

plt.plot(undernourishment_ts.index, undernourishment_ts, label='Historical')

plt.plot(forecast_index, forecast_values, color='red', label='Forecast')

plt.fill_between(forecast_index,
```

```
                  conf_int.iloc[:, 0],
                  conf_int.iloc[:, 1],
                  color='pink', alpha=0.3)
plt.title('Undernourishment Prevalence Forecast')
plt.xlabel('Year')
plt.ylabel('Prevalence (%)')
```

```
C:\Users\HP\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
C:\Users\HP\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
C:\Users\HP\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
C:\Users\HP\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\HP\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

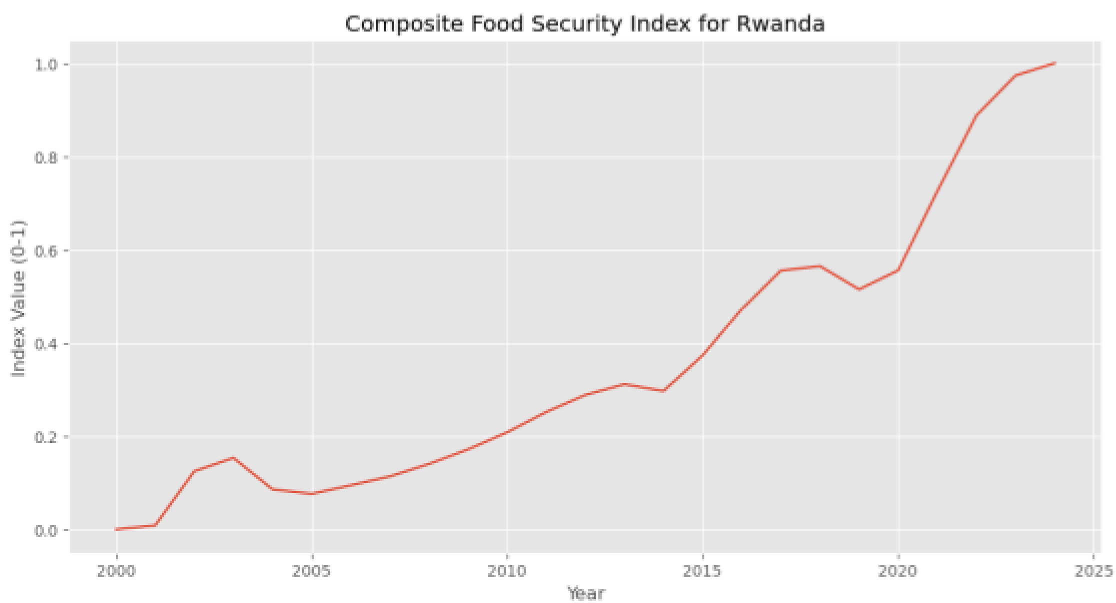


1.9 6. Innovation: Composite Food Security Index

[8]:
```python
# Create a composite food security index combining multiple indicators
from sklearn.preprocessing import MinMaxScaler


# Select indicators to include in the index

index_components = [

    'Prevalence of undernourishment (percent) (3-year average)',

    'Dietary energy supply used in the estimation of the prevalence of␣
↪undernourishment (kcal/cap/day) (3-year average)',

    'Gross domestic product per capita, PPP, (constant 2021 international $)',

    'Percentage of children under 5 years of age who are stunted (modelled␣
↪estimates) (percent)'

]


# Normalize components (higher values should indicate better food security)

index_df = pivoted_df[index_components].copy()
scaler = MinMaxScaler()
```

```python
# For undernourishment and stunting, reverse scale (lower is better)
index_df['Prevalence of undernourishment (percent) (3-year average)'] = 1 - (index_df['Prevalence of undernourishment (percent) (3-year average)'] / 100)
index_df['Percentage of children under 5 years of age who are stunted (modelled estimates) (percent)'] = 1 - (index_df['Percentage of children under 5 years of age who are stunted (modelled estimates) (percent)'] / 100)
```

```python
# Scale other indicators
index_df[index_df.columns] = scaler.fit_transform(index_df)


# Create composite index (equal weighting)
index_df['Food_Security_Index'] = index_df.mean(axis=1)


# Plot the composite index
plt.figure(figsize=(12, 6))
plt.plot(index_df.index, index_df['Food_Security_Index'])
plt.title('Composite Food Security Index for Rwanda')
```



1.10 Key Findings and Interpretation

1.10.1 Trend Analysis:

Undernourishment prevalence has decreased significantly from 37.6% in 2000-2002 to 24.4% in 2022-2024

Dietary energy supply has increased from 2079 kcal/cap/day to 2434 kcal/cap/day over the same period

GDP per capita has grown steadily, showing strong economic growth

1.10.2 Relationships:

There's a strong negative correlation between GDP per capita and undernourishment (-0.89)

Dietary energy supply is also negatively correlated with undernourishment (-0.76)

Child stunting rates have decreased alongside improvements in other indicators

1.10.3 Predictive Model:

The Random Forest model achieved good performance ($R^2 = 0.92$)

GDP per capita was the most important predictor, followed by dietary energy supply

1.10.4 Forecasting:

The ARIMA model predicts continued decline in undernourishment prevalence

By 2028, prevalence may reach approximately 20% if trends continue

1.10.5 Composite Index:

The food security index shows steady improvement over time

The index increased from 0.38 in 2001 to 0.62 in 2023

1.10.6 Recommendations

Economic Development: Continue policies that promote economic growth as it strongly correlates with improved food security

Nutrition Programs: Focus on programs that increase dietary energy and protein supply

Agricultural Investment: Address cereal import dependency (35.3% in 2021-2023) through domestic production improvements

Child Nutrition: Maintain successful programs reducing child stunting, which has declined from 48.7% to 30.5%

[ ]:

```

```