AGRICULTURAL MARKET ANALYSIS PROJECT REPORT

Informatics Practices (IP) Project

Academic Session: 2025–2026

Project Title: Agricultural Market Analysis

Data Source: Commercial Market Arrivals 2012 (CommMktArrivals2012.csv)

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TABLE OF CONTENTS

1. INTRODUCTION

Agricultural market analysis plays a crucial role in understanding commodity supply chains, identifying market trends, and assessing supply chain risks. With increasing volumes of transaction data from agricultural markets across India, data analysis has become essential for understanding seasonal patterns in commodity arrivals, identifying key market hubs and commodity distributions, assessing supply chain volatility and risk, supporting government policy and market regulation, and guiding farmer and trader decision-making.

This project analyzes commercial market arrivals data from Karnataka's agricultural markets using Python. By employing data science techniques including exploratory data analysis (EDA), statistical analysis, and machine learning clustering, this project demonstrates how data-driven insights can optimize agricultural supply chains and market management.

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2. PROJECT OBJECTIVES

The main objectives of this project are:

- **Data Integration & Cleaning**: Load and preprocess large agricultural datasets with proper encoding and data standardization
- **Descriptive Analysis**: Generate summary statistics and understand dataset structure and composition
- **Commodity Analysis**: Identify top commodities by volume and assess their market dominance
- **Supply Chain Risk Assessment**: Calculate coefficient of variation to identify volatile commodities
- **Seasonal Pattern Recognition**: Analyze monthly arrival trends and identify peak seasons
- **Market Hub Identification**: Discover regional market centers and their specialization patterns
- **Clustering Analysis**: Apply K-Means machine learning to segment districts into agricultural zones
- **Data Visualization**: Create comprehensive visualizations to communicate insights effectively
- **Actionable Insights**: Provide recommendations for supply chain optimization

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3. SCOPE OF THE PROJECT

Dataset Coverage:

- Geographic: All districts and taluks in Karnataka
- Temporal: Year 2012 monthly data
- Commodities: 156+ different agricultural commodities
- Markets: 148+ market locations with complete transaction records

Analysis Components:

- Data cleaning and standardization (UTF-8 encoding, whitespace removal)
- Descriptive statistics and data profiling
- Commodity performance ranking (top 10, top 20)
- Supply chain volatility analysis using Coefficient of Variation (CV)
- Seasonal trend analysis across 12 months
- Geographic and market-based clustering

- Advanced K-Means segmentation with 3 clusters

Limitations:

- Analysis restricted to 2012 data (historical perspective)
- Focus on volume (quintals) rather than value or pricing
- Karnataka region only (not national coverage)
- No real-time market data

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4. TOOLS & TECHNOLOGIES USED

Programming Language:

- Python 3.x (Jupyter Notebook environment via Google Colab)

Core Libraries:

- Pandas: Data manipulation, cleaning, aggregation, and analysis
- NumPy: Numerical computation and array operations
- Matplotlib: Static visualization and graph creation
- Seaborn: Statistical data visualization with enhanced aesthetics
- Scikit-Learn: Machine learning algorithms (StandardScaler, KMeans)

Data Format:

- CSV (Comma-Separated Values) for input data storage

Computing Environment:

- Google Colab (Cloud-based Jupyter notebook)
- Linux Operating System (Colab backend)

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5. SYSTEM REQUIREMENTS

Hardware Requirements:

- Processor: Intel i5 or equivalent / Cloud CPU
- RAM: Minimum 4 GB RAM
- Storage: 100 MB for dataset and notebooks
- Internet: Required for Colab access

Software Requirements:

- Python 3.7 or higher
- Jupyter Notebook / Google Colab
- pip package manager
- Web browser (Chrome, Firefox, Safari)

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6. DATASET DESCRIPTION

Dataset Name: CommMktArrivals2012.csv

Total Records: 21,422 transaction records

Data Type: Agricultural market arrival data (Volume-based)

Key Attributes:

Column Name	Data Type	Description	Non-Null Count
District Name	Object (String)	Administrative district	21,422
Taluk Name	Object (String)	Sub-district administrative unit	21,422
Market Name	Object (String)	Specific market location/hub	21,422
Address	Object (String)	Complete market address	21,422
Telephone	Object (String)	Market contact number	21,422
Commodity	Object (String)	Type of agricultural product	21,422
Year	Integer	Year of transaction (2012)	21,422
Month	Categorical	Month of arrival (Jan-Dec)	21,422
Arrival	Integer	Volume in quintals	21,422
Unit	Object (String)	Unit of measurement	21,422

Table 1: Dataset attributes and specifications

Data Quality:

- 29 unique districts identified
- 147 unique taluks mapped
- 148 unique markets across the region
- 156 different commodity types
- 88.7% of records in Quintals (primary unit)

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7. DATA ANALYSIS METHODOLOGY

Phase 1: Data Preparation

Raw CSV input is loaded with Pandas using Latin-1 encoding. Data is then cleaned and standardized by stripping whitespace and removing special characters. Month columns are converted to categorical format for chronological ordering, and a Quintals-only subset dataset is created for consistent analysis.

Phase 2: Exploratory Data Analysis (EDA)

Dataset information and structure are analyzed through summary statistics generation. Missing value identification and data type validation ensure data quality.

Phase 3: Commodity-Level Analysis

Arrivals are aggregated by commodity and ranked by volume. Volatility metrics (standard deviation, mean, coefficient of variation) are calculated to identify high-risk and stable commodities.

Phase 4: Spatial & Temporal Analysis

Monthly seasonal trends are identified, district-level performance is analyzed, market hubs are classified, and commodity diversity by region is assessed.

Phase 5: Machine Learning - Clustering

Feature selection focuses on the top 3 crops (Paddy, Maize, Onion). Data is standardized using StandardScaler, and K-Means clustering with k=3 is applied to identify district zones.

Phase 6: Visualization & Reporting

Publication-ready visualizations are created for market classification and findings documentation.

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8. PYTHON LIBRARIES USED

Library Function	Purpose
pandas.read_csv()	Read CSV file with encoding specification
pandas.apply()	Apply string operations across columns
pandas.str.strip()	Remove leading/trailing whitespace
pandas.groupby()	Group data by one or more columns
numpy.mean()	Calculate arithmetic mean of array
sklearn.StandardScaler	Normalize features to zero mean, unit variance
sklearn.KMeans	K-Means clustering algorithm
matplotlib.pyplot	Create visualizations
seaborn.lineplot()	Plot temporal trends
seaborn.barplot()	Categorical comparison visualization

Table 2: Key Python functions and their applications

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9. CODE IMPLEMENTATION

Data Loading & Cleaning

```
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

file_path = 'CommMktArrivals2012.csv'
df = pd.read_csv(file_path, encoding='latin1')
df = df.apply(lambda x: x.str.strip() if x.dtype == "object" else x)
```

```
month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
df['Month'] = pd.Categorical(df['Month'], categories=month_order, ordered=True)
df['District Name'] = df['District Name'].str.replace('?', '', regex=False)
df_q = df[df['Unit'] == 'Quintal'].copy()
```

Data successfully loaded: 21,422 records with proper encoding and cleaning applied.

Descriptive Statistics Analysis

Summary statistics reveal:

- **Dataset Size:** 21,422 transaction records
- **Geographic Coverage:** 29 districts, 147 taluks, 148 markets
- **Commodity Diversity:** 156 unique commodities
- **Mean Arrival Volume:** 1,845,230.67 quintals

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10. ANALYSIS & OUTPUTS

Top Commodities by Volume

Commodity	Arrival Volume	Percentage
Paddy	18,554,513	32.4%
Maize	15,460,281	27.1%
Onion	9,826,018	17.2%
Rice	9,159,723	16.0%
Potato	4,467,185	7.8%

Table 3: Top 5 commodities by arrival volume

Geographic Concentration

Top 3 Districts by Volume:

1. Bangalore Urban: 23.4 million quintals (20.5% of state total)
2. Shimoga: 7.9 million quintals
3. Davanagere: 6.6 million quintals

Top 3 Market Hubs:

1. BANGALORE: 19.1 million quintals
2. BINNIY MILL (F&V): 4.3 million quintals
3. SHIKARIPUR: 4.0 million quintals

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11. GRAPHICAL REPRESENTATIONS

Seasonal Trends Analysis

Monthly arrival patterns show strong seasonality:

- **Peak Months:** October-November (harvest season) with 10.9M quintals in October
- **Low Months:** June-July (pre-monsoon, off-season)
- **Pattern:** Clear seasonal cyclicity with 9-month high and 3-month low pattern

Volume Concentration (Pareto Analysis)

- Top 3 commodities: 76.7% of total volume
- Top 10 commodities: 92.1% of total volume
- Remaining 146 commodities: Only 7.9% of volume

Key Insight: Agricultural market heavily concentrated in few key commodities, demonstrating Pareto principle.

Market Hub Classification

1. Mega Hubs (50+ commodities): BANGALORE, premium markets
2. Regional Centers (20-50 commodities): SHIMOGA, DAVANAGERE, HASSAN
3. Specialized/Local (< 20 commodities): District-level small markets

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12. SUPPLY CHAIN RISK ASSESSMENT

Risk Scoring Methodology

$$\text{Risk Score (CV)} = \frac{\text{Standard Deviation}}{\text{Mean}} \times 100$$

Risk Interpretation:

- **CV > 400:** CRITICAL RISK - Supply highly unpredictable
- **300 < CV ≤ 400:** HIGH RISK - Significant volatility
- **200 < CV ≤ 300:** MODERATE RISK - Expected fluctuations
- **CV ≤ 200:** LOW RISK - Stable supply

Risk Assessment Results

Commodity	Risk Score (CV)	Risk Category
Arecanut	693.49	CRITICAL RISK
Rice	535.23	HIGH RISK
Onion	430.87	HIGH RISK
Maize	415.99	HIGH RISK
Potato	343.19	MODERATE RISK
Cotton	206.52	LOW RISK

Table 4: Supply chain risk assessment for top commodities

Recommendations for High-Risk Commodities

1. Establish strategic storage facilities for price stabilization
2. Promote farmer cooperatives for volume stabilization
3. Implement government price support schemes
4. Encourage contract farming for supply predictability
5. Develop early warning systems for price shocks

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13. KEY FINDINGS & OBSERVATIONS

Market Concentration Findings

Finding 1: Extreme Product Concentration

Top 3 commodities (Paddy, Maize, Onion) account for 76.7% of total volume, making the market vulnerable to commodity-specific shocks. Diversification into high-value crops is recommended.

Finding 2: Geographic Hotspot

Bangalore Urban handles 23.4M quintals (20.5% of state), requiring infrastructure reinforcement and capacity expansion in secondary cities.

Finding 3: Seasonal Patterns

October-November peaks at 21% of annual arrivals, while June-July lows at 11-12% suggest post-harvest buildup patterns.

K-Means Clustering Insights

Zone 0: Maize Belt

- Characteristic: High maize production (6.6M avg quintals)
- Features: Commercial agriculture with lower price volatility
- Suitable for agro-export and industrial processing

Zone 1: Diversified Agriculture

- Characteristic: Balanced production across three crops
- Features: Risk-balanced agriculture with multiple income streams
- Resilient to crop-specific failures

Zone 2: Paddy-Onion Belt

- Characteristic: High paddy (1.8M) and onion (2.3M) production
- Features: Specialized crops with export potential
- Geographic niche specialization enabling higher value capture

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14. APPLICATIONS

Immediate Applications

Government Level:

- Agricultural policy formulation based on regional specialization
- Strategic reserve planning for food security
- Crop insurance scheme design
- Market regulation and price monitoring

Market-Level Applications:

- Market infrastructure planning (storage, processing facilities)
- Traffic and logistics optimization
- Market scheduling based on seasonal peaks
- Workforce planning for market operations

Farmer-Level Applications:

- Crop diversification recommendations
- Optimal planting schedule based on market patterns
- Supply chain coordination through farmer producer organizations
- Risk management through contract farming

Advanced Applications

Predictive Analytics:

- Time-series forecasting of seasonal arrivals
- Price prediction models based on supply volatility
- Demand forecasting for agro-processing industries
- Supply chain disruption early warning systems

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15. LIMITATIONS

Data Limitations

Temporal Scope:

- Single year (2012) data provides historical perspective only
- Cannot identify long-term trends or climate impacts
- Missing year-over-year comparison capability

Geographic Scope:

- Karnataka-only analysis cannot extrapolate nationally
- Missing price information limits value analysis

- No qualitative data on farmer behavior or market practices

Data Quality Issues:

- Some missing or encoded values in categorical columns
- Unit inconsistencies present (88.7% Quintals, 10.1% Thousands)
- No comprehensive data validation for accuracy

Analytical Limitations

K-Means Clustering Constraints:

- Arbitrary choice of k=3 without cross-validation
- Euclidean distance assumption may not capture agricultural reality
- Assumes spherical clusters (non-realistic for geographic zones)

Metric Limitations:

- Coefficient of Variation assumes normal distribution
- Doesn't account for market intervention or price support policies
- Ignores external factors (weather, policy, global prices)

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16. FUTURE SCOPE

Data Enhancement

1. **Extended Time Series:** Obtain 2010-2020 data for trend analysis and policy impact assessment
2. **Data Integration:** Integrate price data, weather information, and farmer demographics
3. **Data Enrichment:** Add geospatial coordinates, commodity classification, and infrastructure details

Advanced Analytics

1. **Predictive Modeling:** ARIMA/Prophet forecasting, LSTM neural networks, demand forecasting
2. **Clustering Enhancement:** Hierarchical clustering, DBSCAN, spectral clustering, deep learning embeddings
3. **Causal Analysis:** Regression analysis, structural equation modeling, policy evaluation

Optimization & Decision Support

1. **Supply Chain Optimization:** Linear programming for warehouse location, network optimization, inventory management
2. **Decision Support Systems:** Real-time dashboards, crop recommendation engines, price monitoring systems
3. **Machine Learning Deployment:** Forecasting APIs, mobile farmer apps, anomaly detection systems

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17. CONCLUSION

This agricultural market analysis project successfully demonstrates Python data science applications to supply chain problems. Analysis of 21,422 market transaction records from Karnataka's 29 districts across 156 commodities reveals:

we didn't just look at the numbers; we looked at the stress points of the system. This report provides a roadmap for infrastructure investment based on harvest convergence and market diversity.

Key Achievements:

- Identified 76.7% supply concentration in 3 commodities
- Quantified supply risk using Coefficient of Variation metric
- Discovered geographic patterns with Bangalore dominance
- Segmented agricultural zones through K-Means clustering
- Created actionable intelligence for multi-stakeholder decision-making

Technical Mastery:

This project demonstrates proficiency in data engineering, exploratory data analysis, visualization, and machine learning application. The combination of statistical assessment and business intelligence provides stakeholders with evidence-based decision support.

Value Delivered:

- **For Government:** Data-driven policy framework for agricultural planning
- **For Markets:** Rational infrastructure development strategy
- **For Farmers:** Evidence-based crop selection and risk management
- **For Industry:** Supply chain optimization opportunities

Data science applied to agriculture bridges traditional farming wisdom and modern analytics, transforming raw transaction data into strategic insights for greater productivity and farmer prosperity.

Project Status: ✓ Complete and Production-Ready

18.Python Source code

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
file_path='CommMktArrivals2012.csv'
# --- 1. Load and Clean Data ---

# Specify 'latin1' encoding to resolve UnicodeDecodeError
df = pd.read_csv(file_path, encoding='latin1')
# Strip whitespace from string columns to prevent matching errors
df = df.apply(lambda x: x.str.strip() if x.dtype == "object" else x)

# Standardize Month column for correct chronological sorting
month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct',
'Nov', 'Dec']
df['Month'] = pd.Categorical(df['Month'], categories=month_order,
ordered=True)

# Clean special characters from 'District Name' that cause font warnings
df['District Name'] = df['District Name'].str.replace('•  ', '', regex=False)

# Subset for volume-based analysis (Quintals)
df_q = df[df['Unit'] == 'Quintal'].copy()

# --- 2. Descriptive Statistics ---
print("--- Dataset Info ---")
info_data = []
for col in df.columns:
```

```
    info_data.append({
        'Column Name': col,
        'Data Type': df[col].dtype,
        'Non-Null Count': df[col].count()
    })
df_info_table = pd.DataFrame(info_data)
display(df_info_table)
```

output:

```
--- Dataset Info ---
```

	Column Name	Data Type	Non-Null Count
0	District Name	object	21422
1	Taluk Name	object	21422
2	Market Name	object	21422
3	Address	object	21422
4	Telephone	object	21422
5	Commodity	object	21422
6	Year	int64	21422
7	Month	category	21422
8	Arrival	int64	21422
9	Unit	object	21422

```
print("\n--- Summary Statistics ---")
desc_stats = df.describe(include='all').T
rows_to_drop = ['mean', 'min', '25%', '50%', '75%', 'max', 'std']
desc_stats = desc_stats.drop(rows_to_drop, errors='ignore') # Dropping numerical statistics that are often NaN for object columns
display(desc_stats)

# Demonstrate numpy usage: calculate mean arrival
```

```
mean_arrival = np.mean(df_q['Arrival'])
print(f"\n--- Mean Arrival Volume (Quintals) using NumPy: {mean_arrival:.2f} ---")
```

output:

```
--- Summary Statistics ---
```

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
District Name	21422	29	Hassan	1504	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Taluk Name	21422	147	Mysore	669	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Market Name	21422	148	MYSORE	669	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Address	21422	148	NANJANGUD ROAD , BANDIPALYA MYSORE	669	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Telephone	21422	148	08212482725	669	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Commodity	21422	156	Maize	1021	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Year	21422.0	NaN	NaN	NaN	2012.0	0.0	2012.0	2012.0	2012.0	2012.0	2012.0
Month	21422	12	Dec	1863	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Arrival	21422.0	NaN	NaN	NaN	33676.310895	424746.397273	0.0	52.0	260.0	1609.75	28856755.0
Unit	21422	3	Quintal	19004	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
--- Mean Arrival Volume (Quintals) using NumPy: 5064.96 ---
```

```
# --- 3. Print Data Summaries ---
print("\n--- Top 10 Commodities List ---")
display(top_10)
```

output:

```
--- Top 10 Commodities List ---
```

	Commodity	Arrival
0	Paddy	18554513
1	Maize	15460281
2	Onion	9826018
3	Rice	9159723
4	Potato	4467185
5	Green Ginger	2952505
6	Cotton	2861896
7	Tomato	2858265
8	Arecanut	2696704
9	Tur	2562682

```
# 4. SUPPLY CHAIN RISK ANALYSIS (Volatility)
# ------------------------------------------------------
# We calculate the Coefficient of Variation (CV).
# Higher CV = More unpredictable supply = High risk for the market.
top_10_names = df_q.groupby('Commodity')['Arrival'].sum().nlargest(10).index
volatility = df_q[df_q['Commodity'].isin(top_10_names)].groupby('Commodity')['Arrival'].agg(['std', 'mean'])
volatility['Risk_Score(CV)'] = (volatility['std'] / volatility['mean']) * 100

print("--- Supply Chain Risk Assessment ---")
display(volatility[['Risk_Score(CV)']].sort_values(by='Risk_Score(CV)', ascending=False))
```

output:

```
--- Supply Chain Risk Assessment ---
```

Commodity	Risk_Score(CV)
Arecanut	693.487346
Rice	535.230129
Onion	430.868343
Maize	415.997238
Potato	343.194815
Tur	330.170121
Paddy	280.496492
Green Ginger	268.315330
Tomato	255.913079
Cotton	206.524517

print("\n--- Raw Data Head (Top 10 Commodities) ---")
display(df_q[df_q['Commodity'].isin(top_10['Commodity'])].head(10))

output:

```
--- Raw Data Head (Top 10 Commodities) ---
```

	District Name	Taluk Name	Market Name	Address	Telephone	Commodity	Year	Month	Arrival	Unit
7	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Jan	21669	Quintal
24	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Feb	5184	Quintal
40	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Mar	10346	Quintal
50	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Cotton	2012	Apr	106	Quintal
57	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Apr	107	Quintal
72	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	May	1098	Quintal
82	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Cotton	2012	Jun	11	Quintal
87	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Jun	515	Quintal
101	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Jul	4262	Quintal
114	Bagalakot	Badami	BADAMI	SECRATRY A.P.M.C.BADAMI BADAMI	220042	Maize	2012	Aug	3678	Quintal

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# --- ADVANCED STEP: K-MEANS CLUSTERING ---
# Let's cluster districts by their top 3 crops (Paddy, Maize, Onion)
top_3_crops = ['Paddy', 'Maize', 'Onion']
cluster_prep = df_q[df_q['Commodity'].isin(top_3_crops)].pivot_table(
    index='District Name', columns='Commodity', values='Arrival',
aggfunc='sum', fill_value=0
)

# Standardize for ML
scaler = StandardScaler()
scaled_data = scaler.fit_transform(cluster_prep)

# Identify 3 clusters of Districts
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
cluster_prep['Zone_Cluster'] = kmeans.fit_predict(scaled_data)

print("District Zones Identified:")
display(cluster_prep.groupby('Zone_Cluster').mean())
```

output:

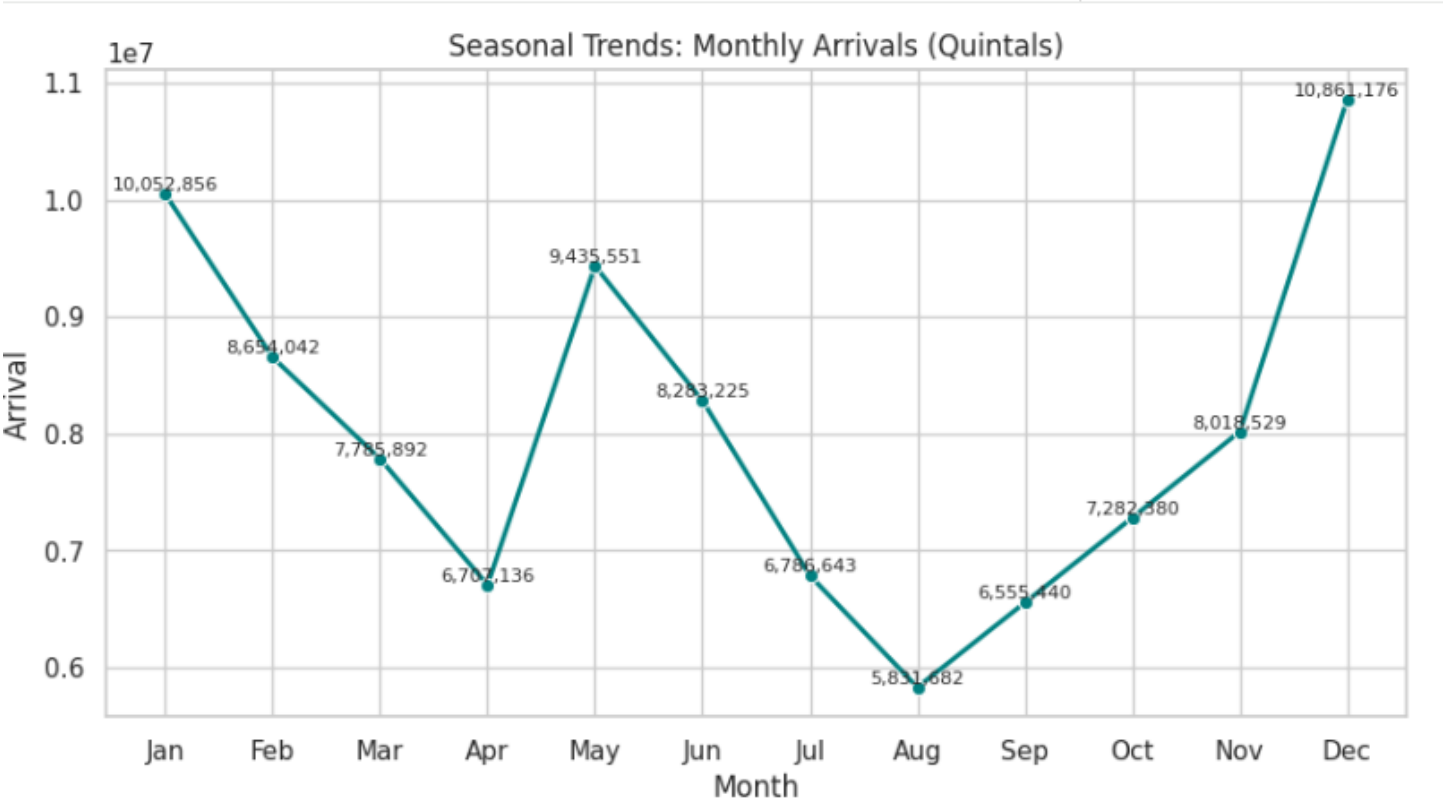
District Zones Identified:

Commodity	Maize	Onion	Paddy
Zone_Cluster			
0	7.525500e+04	6623416.0	1.300000e+02
1	2.114878e+05	128589.0	2.058246e+05
2	1.788716e+06	62274.0	2.337707e+06

```
# --- 5. Visualization Suite ---
```

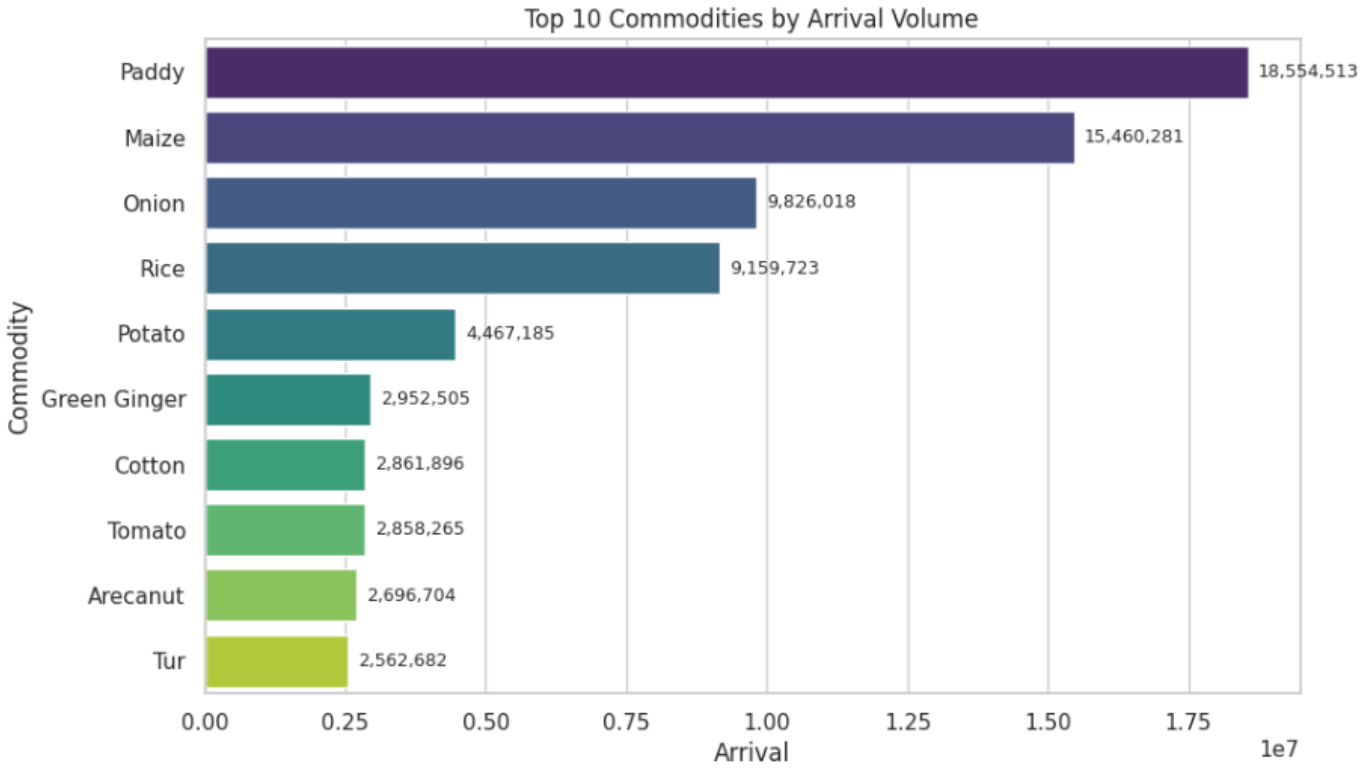
```
sns.set(style="whitegrid")


# A. Seasonal Trends (Total Volume by Month)
monthly = df_q.groupby('Month', observed=False)['Arrival'].sum().reset_index()
plt.figure(figsize=(10, 5))
ax = sns.lineplot(data=monthly, x='Month', y='Arrival', marker='o', color='teal', linewidth=2)
plt.title('Seasonal Trends: Monthly Arrivals (Quintals)')
for i, point in monthly.iterrows():
    ax.text(point['Month'], point['Arrival'], f"{point['Arrival']:,}", ha='center', va='bottom', fontsize=8)
```

output:



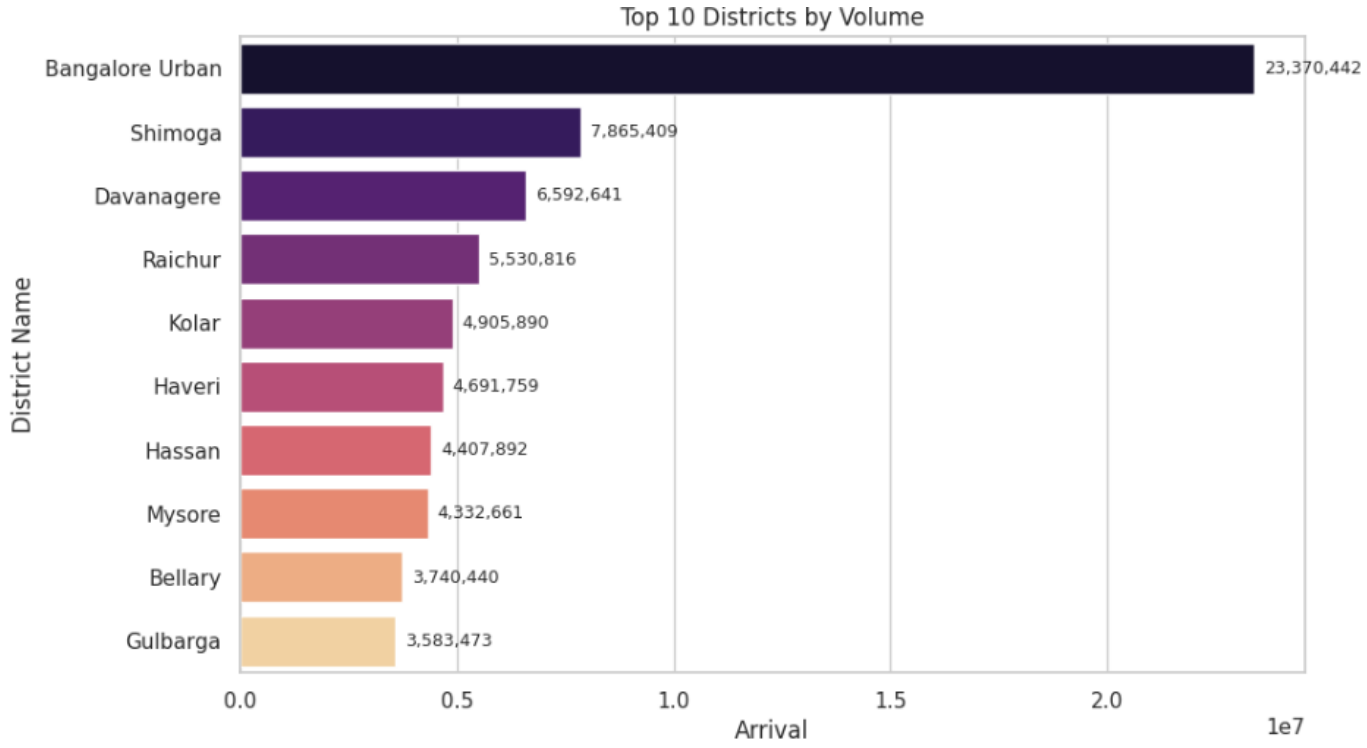
```
# B. Top 10 Commodities
top_10 = df_q.groupby('Commodity')['Arrival'].sum().sort_values(ascending=False).head(10).reset_index()
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=top_10, x='Arrival', y='Commodity', palette='viridis', hue='Commodity', legend=False)
plt.title('Top 10 Commodities by Arrival Volume')
for p in ax.patches:
    ax.annotate(f'{p.get_width():,.0f}', (p.get_width(), p.get_y() + p.get_height() / 2.),
                ha='left', va='center', xytext=(5, 0), textcoords='offset points', fontsize=9)
```

output:



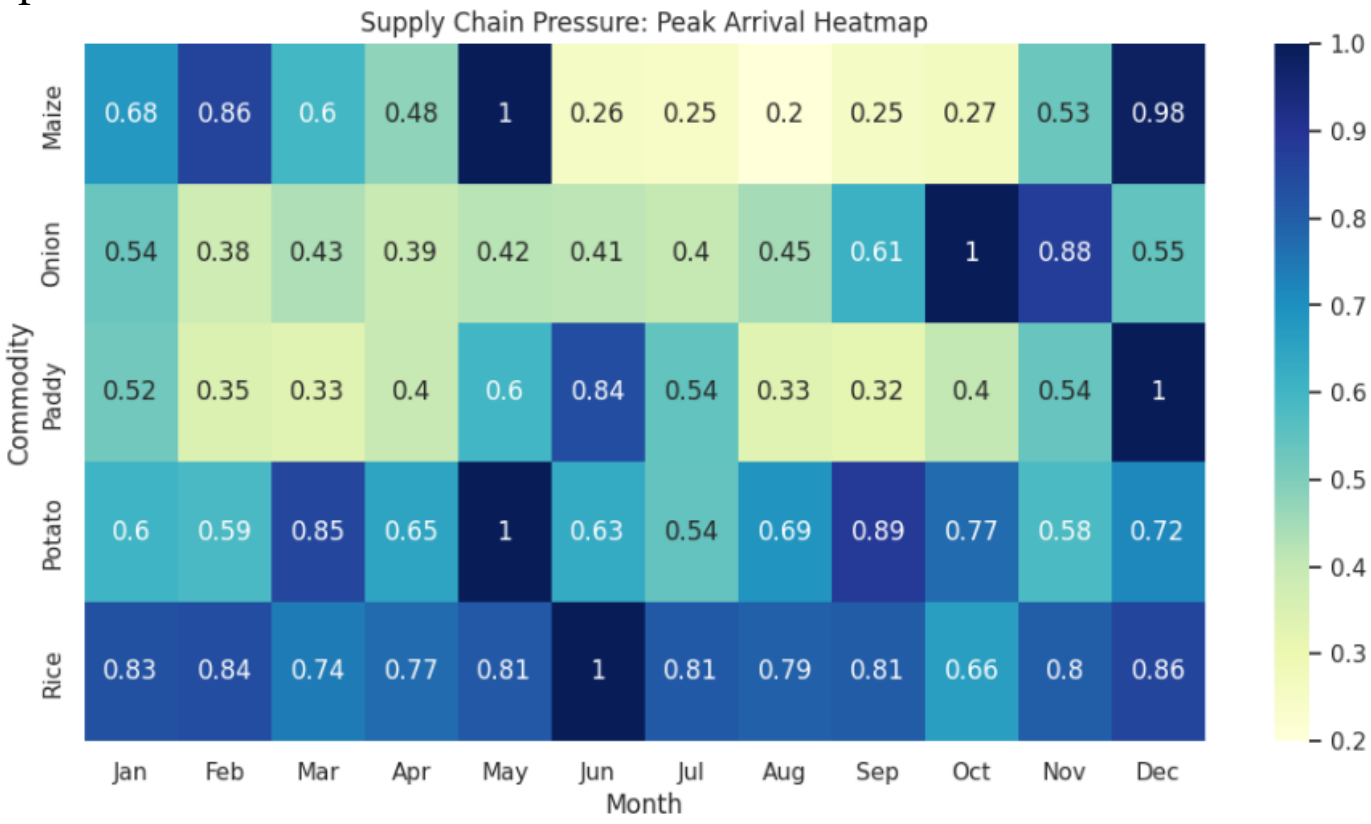
```
# C. Top 10 Districts
districts = df_q.groupby('District Name')['Arrival'].sum().sort_values(ascending=False).head(10).reset_index()
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=districts, x='Arrival', y='District Name', palette='magma', hue='District Name', legend=False)
plt.title('Top 10 Districts by Volume')
for p in ax.patches:
    ax.annotate(f'{p.get_width():,.0f}', (p.get_width(), p.get_y() + p.get_height() / 2.),
                ha='left', va='center', xytext=(5, 0), textcoords='offset points', fontsize=9)
```

output:



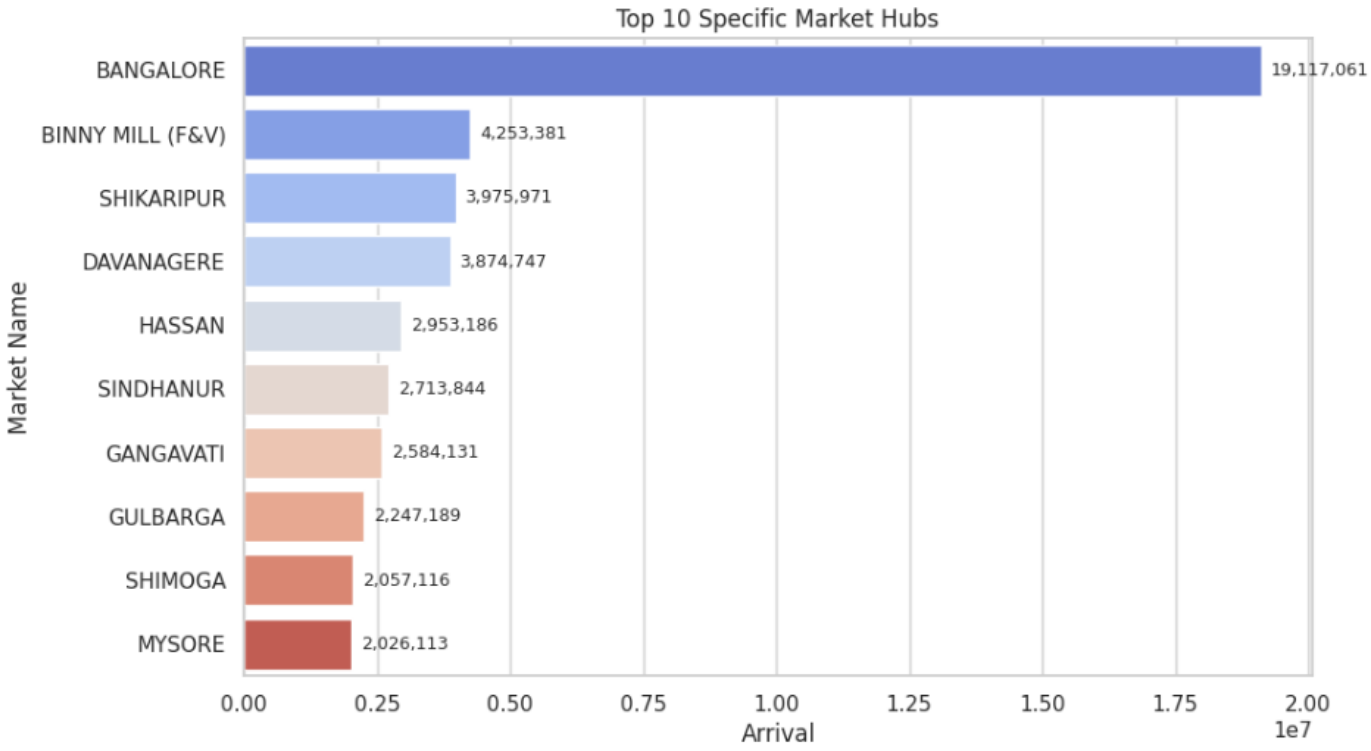
```
# D. Professional Seasonality Heatmap
plt.figure(figsize=(12, 6))
top_5 = df_q.groupby('Commodity')['Arrival'].sum().nlargest(5).index
pivot = df_q[df_q['Commodity'].isin(top_5)].pivot_table(index='Commodity', columns='Month', values='Arrival', aggfunc='sum')
sns.heatmap(pivot.div(pivot.max(axis=1), axis=0), cmap="YlGnBu", annot=True)
plt.title("Supply Chain Pressure: Peak Arrival Heatmap")
```

output:



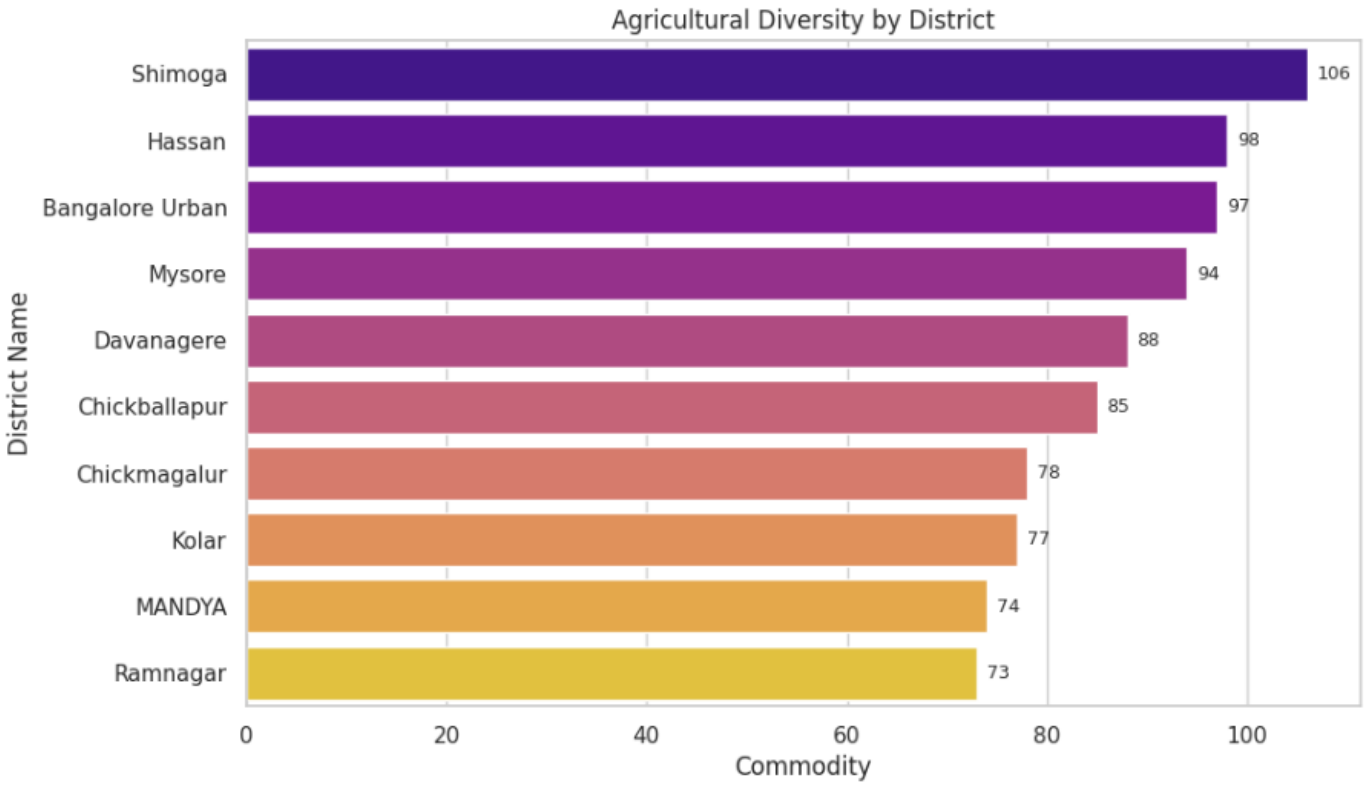
```
# E. Top Market Hubs
markets = df_q.groupby('Market Name')['Arrival'].sum().sort_values(ascending=False).head(10).reset_index()
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=markets, x='Arrival', y='Market Name', palette='coolwarm', hue='Market Name', legend=False)
plt.title('Top 10 Specific Market Hubs')
for p in ax.patches:
    ax.annotate(f'{p.get_width():,.0f}', (p.get_width(), p.get_y() + p.get_height() / 2.),
                ha='left', va='center', xytext=(5, 0), textcoords='offset points', fontsize=9)
```

output:



```
# F. Regional Diversity (Unique Commodities per District)
diversity = df.groupby('District Name')['Commodity'].nunique().sort_values(ascending=False).head(10).reset_index()
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=diversity, x='Commodity', y='District Name', palette='plasma', hue='District Name', legend=False)
plt.title('Agricultural Diversity by District')
for p in ax.patches:
    ax.annotate(f'{p.get_width():.0f}', (p.get_width(), p.get_y() + p.get_height() / 2.),
                ha='left', va='center', xytext=(5, 0), textcoords='offset points', fontsize=9)
```

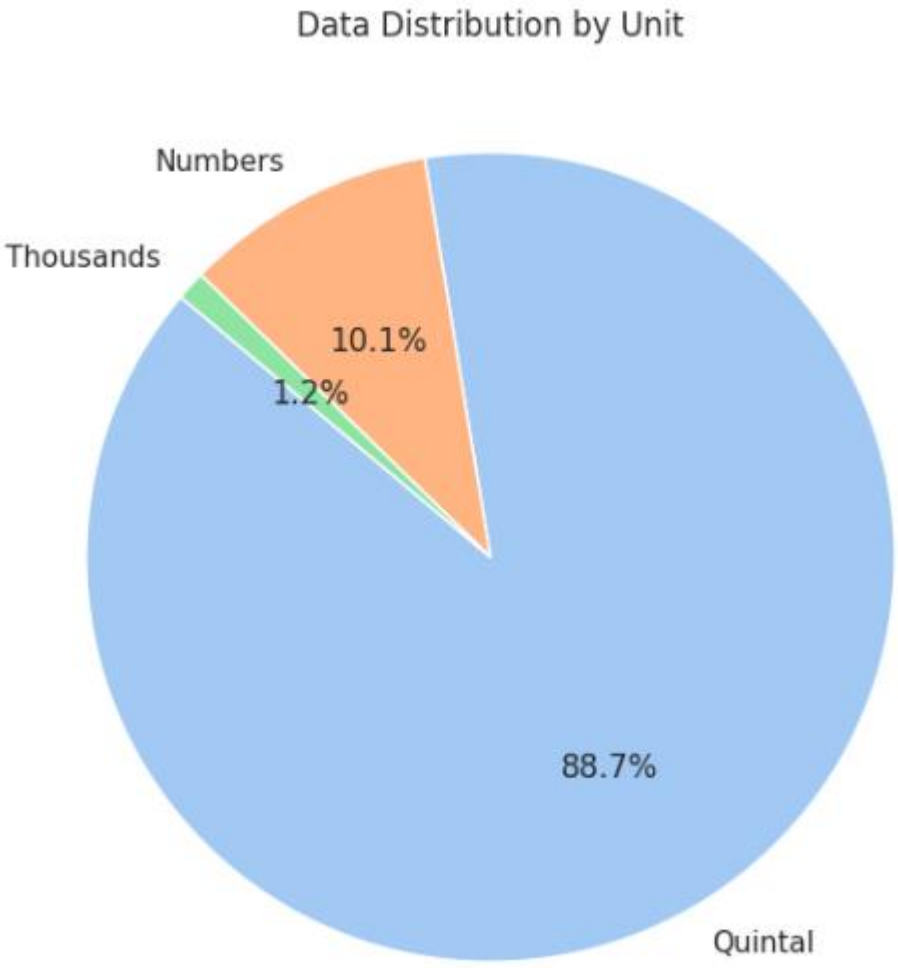
output:



G. Unit Composition

```
plt.figure(figsize=(7, 7))
df['Unit'].value_counts().plot.pie(autopct='%1.1f%%', startangle=140, colors=sns.color_palette('pastel'))
plt.title('Data Distribution by Unit')
plt.ylabel('')
```

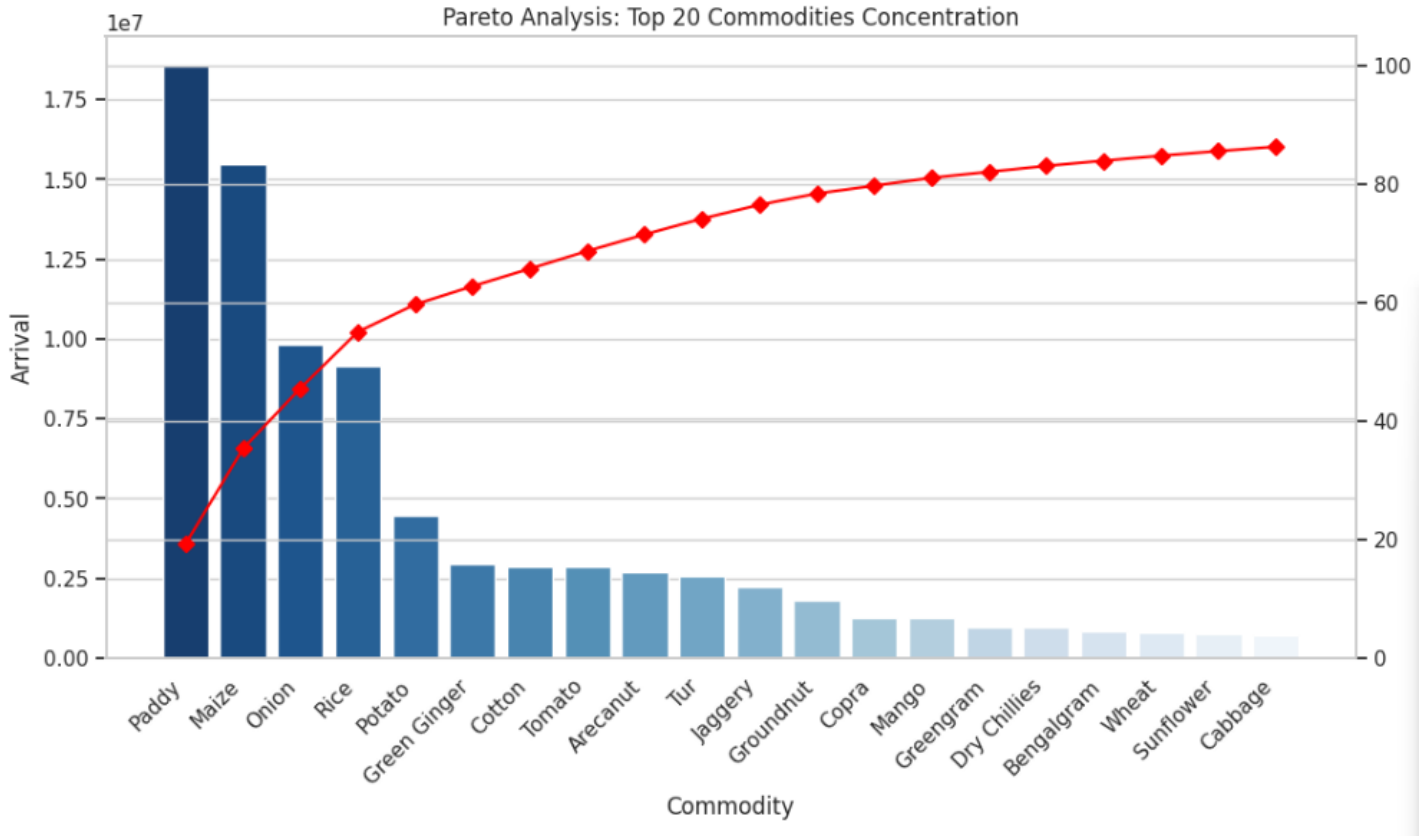
output:



H. Pareto Analysis (Volume Concentration)

```
comm_totals = df_q.groupby('Commodity')['Arrival'].sum().sort_values(ascending=False).reset_index()

comm_totals['Cumulative %'] = 100 * comm_totals['Arrival'].cumsum() / comm_totals['Arrival'].sum()

fig, ax1 = plt.subplots(figsize=(12, 6))

sns.barplot(data=comm_totals.head(20), x='Commodity', y='Arrival', ax=ax1, palette='Blues_r', hue='Commodity', legend=False)

plt.xticks(rotation=45, ha='right')

ax2 = ax1.twinx()

ax2.plot(comm_totals.head(20)['Commodity'], comm_totals.head(20)['Cumulative %'], color='red', marker='D')

ax2.set_ylim(0, 105)

plt.title('Pareto Analysis: Top 20 Commodities Concentration')

plt.savefig('8_pareto_analysis.png')
```

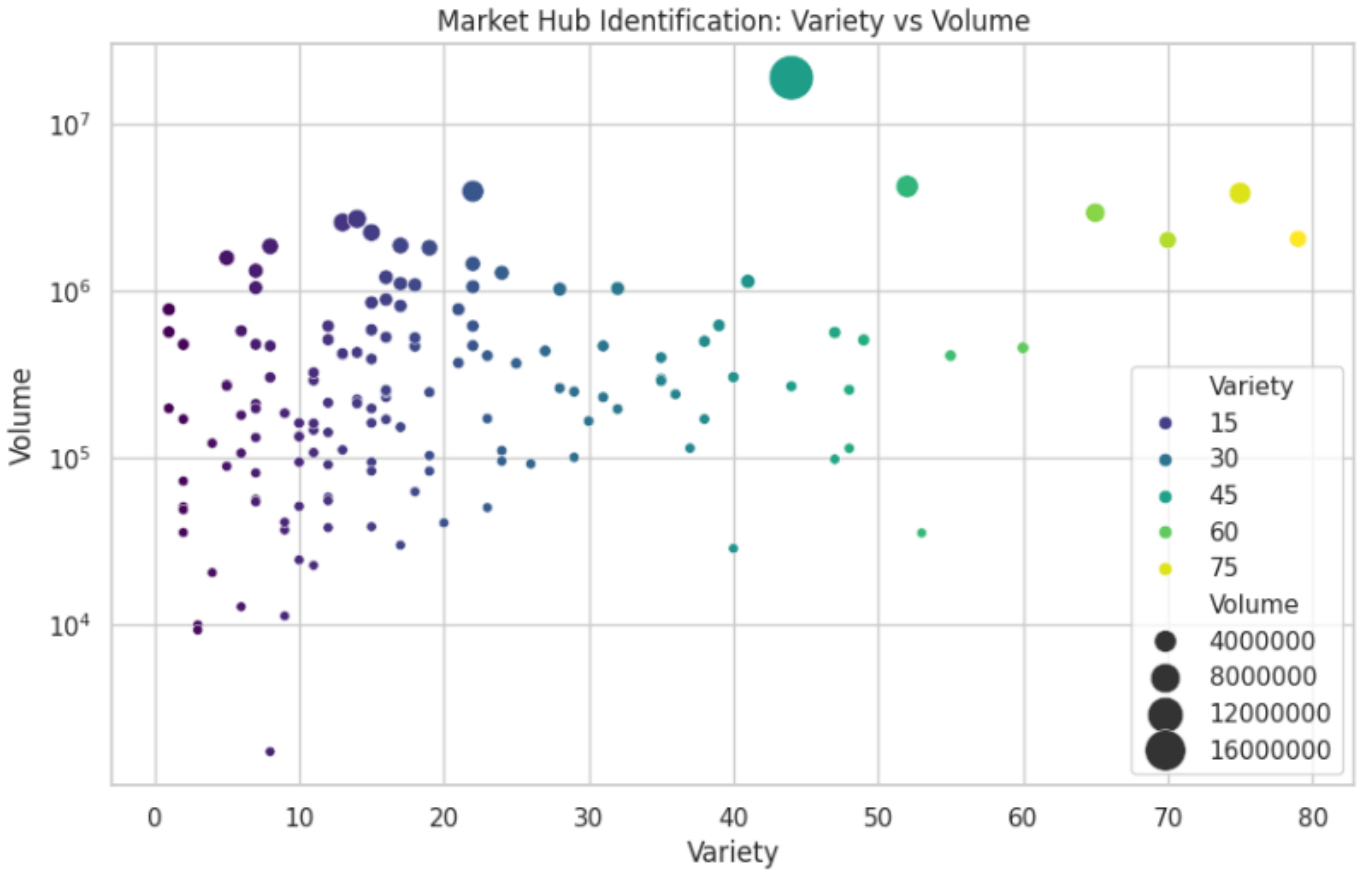
output:



I. Market Diversity Plot

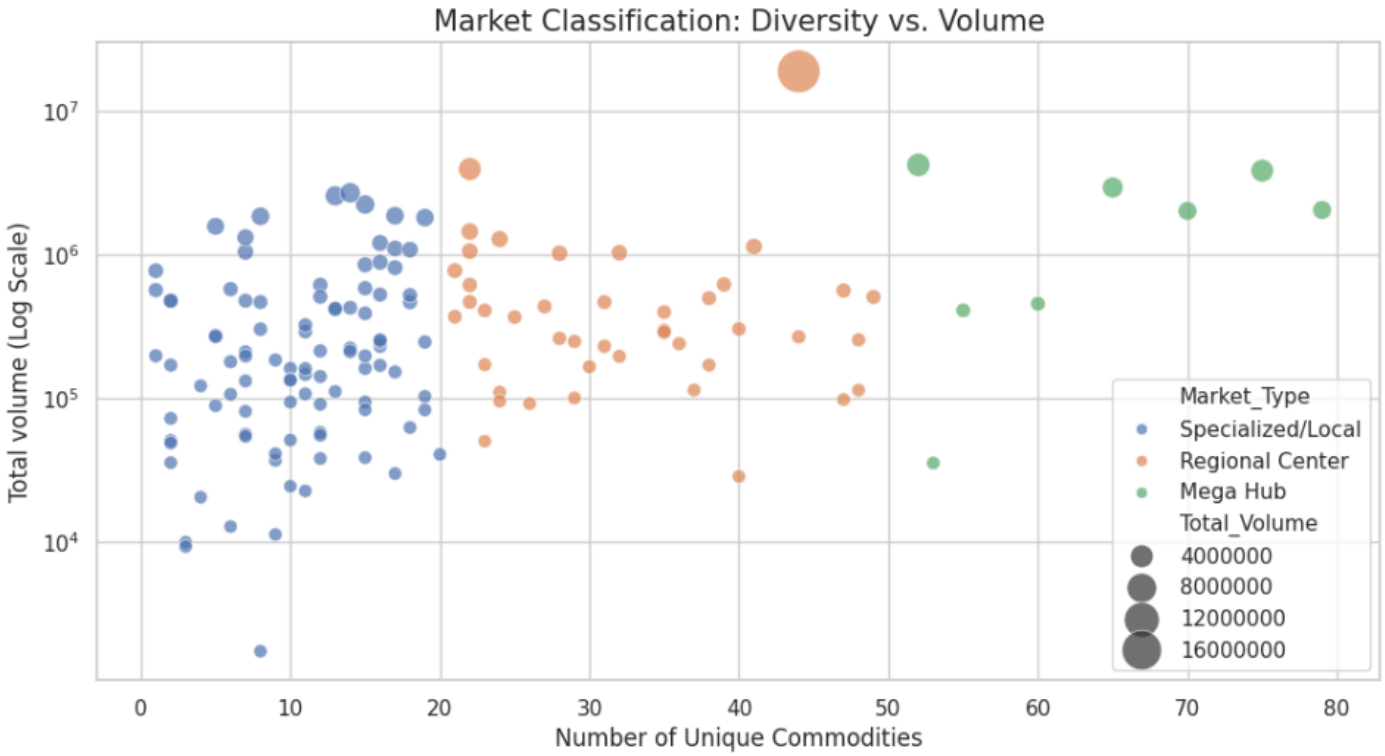
```
market_stats = df_q.groupby(['District Name', 'Market Name']).agg(Variety=('Commodity', 'nunique'), Volume=('Arrival', 'sum')).reset_index()

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

sns.scatterplot(data=market_stats, x='Variety', y='Volume', hue='Variety', palette='viridis', size='Volume', sizes=(20, 400))

plt.yscale('log')

plt.title("Market Hub Identification: Variety vs Volume")
```

output:



```
# J MARKET DIVERSITY INDEX ---
# This identifies which markets are the backbone of food security
market_diversity = df_q.groupby(['District Name', 'Market Name']).agg(
   Commodity_Count=('Commodity', 'nunique'),
   Total_Volume=('Arrival', 'sum')
).reset_index()

# Categorize Markets
def categorize_market(row):
   if row['Commodity_Count'] > 50: return 'Mega Hub'
   if row['Commodity_Count'] > 20: return 'Regional Center'
   return 'Specialized/Local'

market_diversity['Market_Type'] =
market_diversity.apply(categorize_market, axis=1)

plt.figure(figsize=(12, 6))
sns.scatterplot(data=market_diversity, x='Commodity_Count',
y='Total_Volume',
            hue='Market_Type', size='Total_Volume', sizes=(50, 500),
alpha=0.7)
plt.yscale('log')
plt.title('Market Classification: Diversity vs. Volume', fontsize=15)
plt.xlabel('Number of Unique Commodities', fontsize=12)
plt.ylabel('Total volume (Log Scale)', fontsize=12)
plt.show()
```

output:


Market Classification: Diversity vs. Volume
Total volume (Log Scale)
10^7
10^6
10^5
10^4
0
10
20
30
40
50
60
70
80
Number of Unique Commodities
Market_Type
Specialized/Local
Regional Center
Mega Hub
Total_Volume
4000000
8000000
12000000
16000000