Agricultural Product Distribution Forecasting: Predicting Demand to Optimize Harvest Schedules

1. Project Overview

1.1 Rationale for the Project

- Enhancing Efficiency: Maximize resource utilization with accurate demand forecasting and optimized harvest schedules.
- Reducing Food Waste: Align harvest times with demand predictions to minimize waste.
- Improved Profit Margins: Enhance profit margins through efficient distribution, reduced wastage, and meeting customer demand.
- Competitive Advantage: Stay ahead of market trends and consistently deliver fresh produce.

1.2 Aim of the Project

- Develop a robust demand forecasting model to predict product demand based on historical data, weather conditions, and market trends.
- Identify key parameters that affect production demand.

2. Business Overview/Problem

GreenSeason Farms faces several challenges:

- Inefficient Harvesting: Underutilization of resources due to reliance on traditional seasonal patterns.
- Demand Variability: Difficulty in predicting demand fluctuations, leading to overstocking or understocking.
- Shelf Life Management: Ensuring products reach customers at peak freshness.
- Transportation Optimization: Finding optimal routes and delivery schedules to minimize transportation costs.

2.1 Tech Stack

- Pandas
- NumPy

- SciPy
- Matplotlib
- Seaborn
- Statsmodels
- Prophet
- ARIMA
- Scikit-learn

2.2 Project Scope

- Data Collection & Preparation
- Exploratory Data Analysis
- Model Evaluation
- Demand Forecasting Mode

3. Data Collection and Preparation

Import Packages

In [87]:
```
#pip install prophet
```

In [44]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from prophet import Prophet
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error, mean_squared_error

import warnings
warnings.filterwarnings('ignore')
```

Data Collection

In [45]:

```
df = pd.read_csv(r'C:\Users\Admin\OneDrive\Documents\Amdari\Agricultural Product\Dataset.csv')
```

In [46]:

```
df.head()
```

Out[46]:

	Date	Product	Quantity_Sold	Revenue	Temperature_Celsius	Rainfall_mm	Location	Transportation_Cost	Labor_Cost
0	2015-01-01	Strawberries	690.0	70.298339	9.680289	0.077279	Field C	20	13.771809
1	2015-01-01	Apples	354.0	599.863944	9.680289	0.077279	Field A	50	9.702670
2	2015-01-01	Tomatoes	275.0	199.249505	9.680289	0.077279	Field C	20	22.356498
3	2015-01-01	Apples	1079.0	1136.111770	9.680289	0.077279	Field A	50	15.691418
4	2015-01-01	Strawberries	1008.0	111.653303	9.680289	0.077279	Field B	30	17.473353

In [47]:
```
df.describe()
```

Out[47]:

	Quantity_Sold	Revenue	Temperature_Celsius	Rainfall_mm	Transportation_Cost	Labor_Cost	Quality_Score	Inventory_Le
count	28382.000000	28388.000000	28377.000000	28377.000000	28388.000000	28388.000000	28388.000000	28382.000
mean	609.197097	405.584444	20.024600	7.393332	33.465901	17.573430	0.835909	2617.164
std	316.521726	485.206130	8.701719	4.316396	12.466448	7.232465	0.047362	1189.840
min	41.000000	3.546003	5.011709	0.003963	20.000000	5.000083	0.769340	66.000
25%	334.000000	94.572138	12.435564	3.621238	20.000000	11.289710	0.769340	1621.000
50%	607.500000	256.513966	20.124216	7.358936	30.000000	17.586134	0.861953	2630.000
75%	884.000000	513.624224	27.544882	11.062843	50.000000	23.869033	0.876056	3597.000
max	1195.000000	3382.034941	34.985404	14.997572	50.000000	29.998989	0.876056	5172.000

In [48]:
```
missing_values = df.isnull().sum()

missing_values
```

Out[48]:
```
Date                   0
Product                0
Quantity_Sold          6
Revenue                0
Temperature_Celsius   11
Rainfall_mm           11
Location               0
Transportation_Cost    0
Labor_Cost             0
Customer               0
Quality_Score          0
Inventory_Level        6
dtype: int64
```

Check for Outliers

In [49]:

```
cols = ('Quantity_Sold', 'Temperature_Celsius', 'Rainfall_mm', 'Inventory_Level')

for col in cols:
    z = np.abs(stats.zscore(df[col], nan_policy='omit'))
    outliers = df[col][z>3]
    print(f'{col} has {len(outliers)} outliers')
```

```
Quantity_Sold has 0 outliers
Temperature_Celsius has 0 outliers
Rainfall_mm has 0 outliers
Inventory_Level has 0 outliers
```

CHeck For Skewness

In [50]:

```
for col in cols:
    skew = df[col].skew()
    print(f'{col} has a skewness of {skew}')
```

```
Quantity_Sold has a skewness of 0.007049968334628765
Temperature_Celsius has a skewness of -0.005244633606917498
Rainfall_mm has a skewness of 0.017580193058957767
Inventory_Level has a skewness of -0.006928239182168006
```

Handle Missing Values

In [51]:

```
for col in cols:
    df[col].fillna(df[col].mean(), inplace = True)
```

Confirm that there are no more missing numbers

In [52]:
```
missing_values = df.isnull().sum()

missing_values
```

Out[52]:
```
Date                   0
Product                0
Quantity_Sold          0
Revenue                0
Temperature_Celsius    0
Rainfall_mm            0
Location               0
Transportation_Cost    0
Labor_Cost             0
Customer               0
Quality_Score          0
Inventory_Level        0
dtype: int64
```

4. Exploratory Data Analysis (EDA)

Univariate Analysis

Analysing the distribution of variables individually, for

- numerical variables,
- categorical Variables

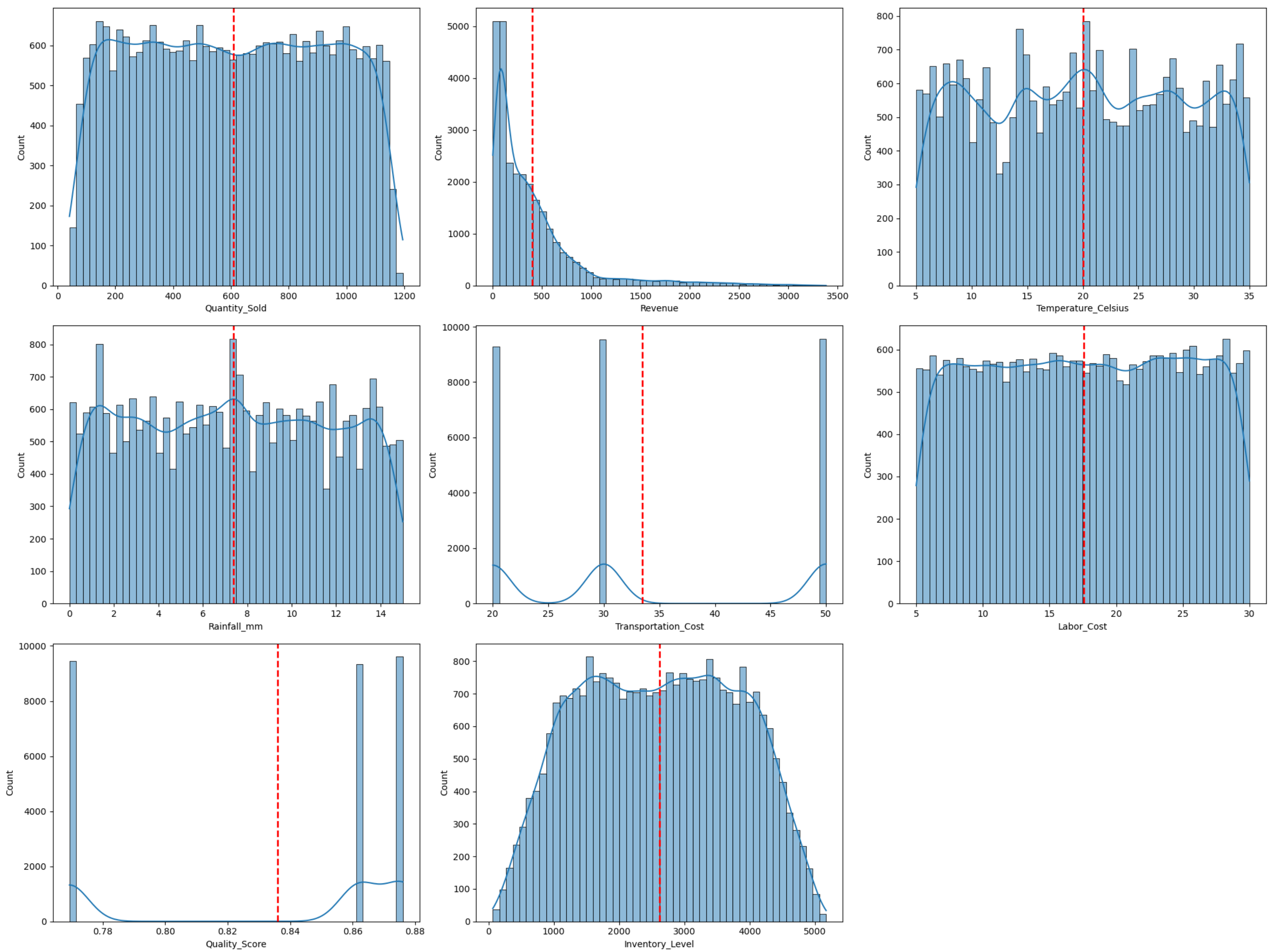
Univariate Analysis: Numerical Variables

In [53]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28388 entries, 0 to 28387
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Date                  28388 non-null  object 
 1   Product               28388 non-null  object 
 2   Quantity_Sold         28388 non-null  float64
 3   Revenue               28388 non-null  float64
 4   Temperature_Celsius   28388 non-null  float64
 5   Rainfall_mm           28388 non-null  float64
 6   Location              28388 non-null  object 
 7   Transportation_Cost   28388 non-null  int64  
 8   Labor_Cost            28388 non-null  float64
 9   Customer              28388 non-null  object 
 10  Quality_Score         28388 non-null  float64
 11  Inventory_Level       28388 non-null  float64
dtypes: float64(7), int64(1), object(4)
memory usage: 2.6+ MB
```

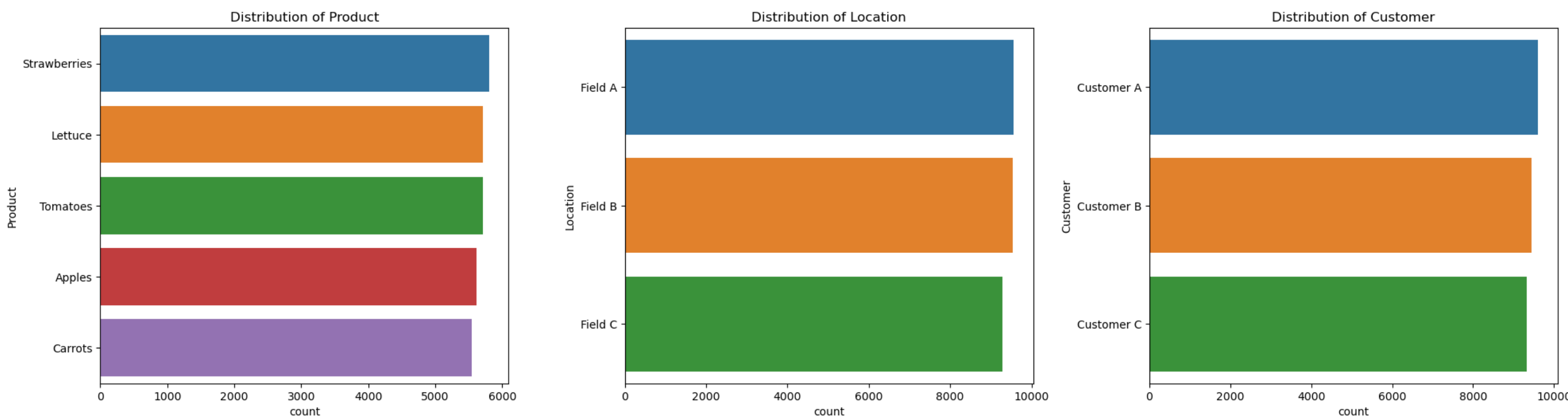
In [54]:

```
plt.figure(figsize=(20, 15))

numeric_vars = ['Quantity_Sold',
                'Revenue',
                'Temperature_Celsius',
                'Rainfall_mm',
                'Transportation_Cost',
                'Labor_Cost',
                'Quality_Score',
                'Inventory_Level']

for i, var in enumerate(numeric_vars, 1):
    plt.subplot(3, 3, i)
    sns.histplot(df[var], bins=50, kde=True)
    plt.axvline(df[var].mean(), color='red', linestyle='dashed', linewidth =2)


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



Univariate Analysis: Categorical Variables

In [55]:
```
plt.figure(figsize=(20, 10))

categorical_vars = ['Product',
                    'Location',
                    'Customer',]

for i, var in enumerate(categorical_vars, 1):
    plt.subplot(2, 3, i)
    sns.countplot(data=df, y=var,order=df[var].value_counts().index)
    plt.title(f'Distribution of {var}')

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



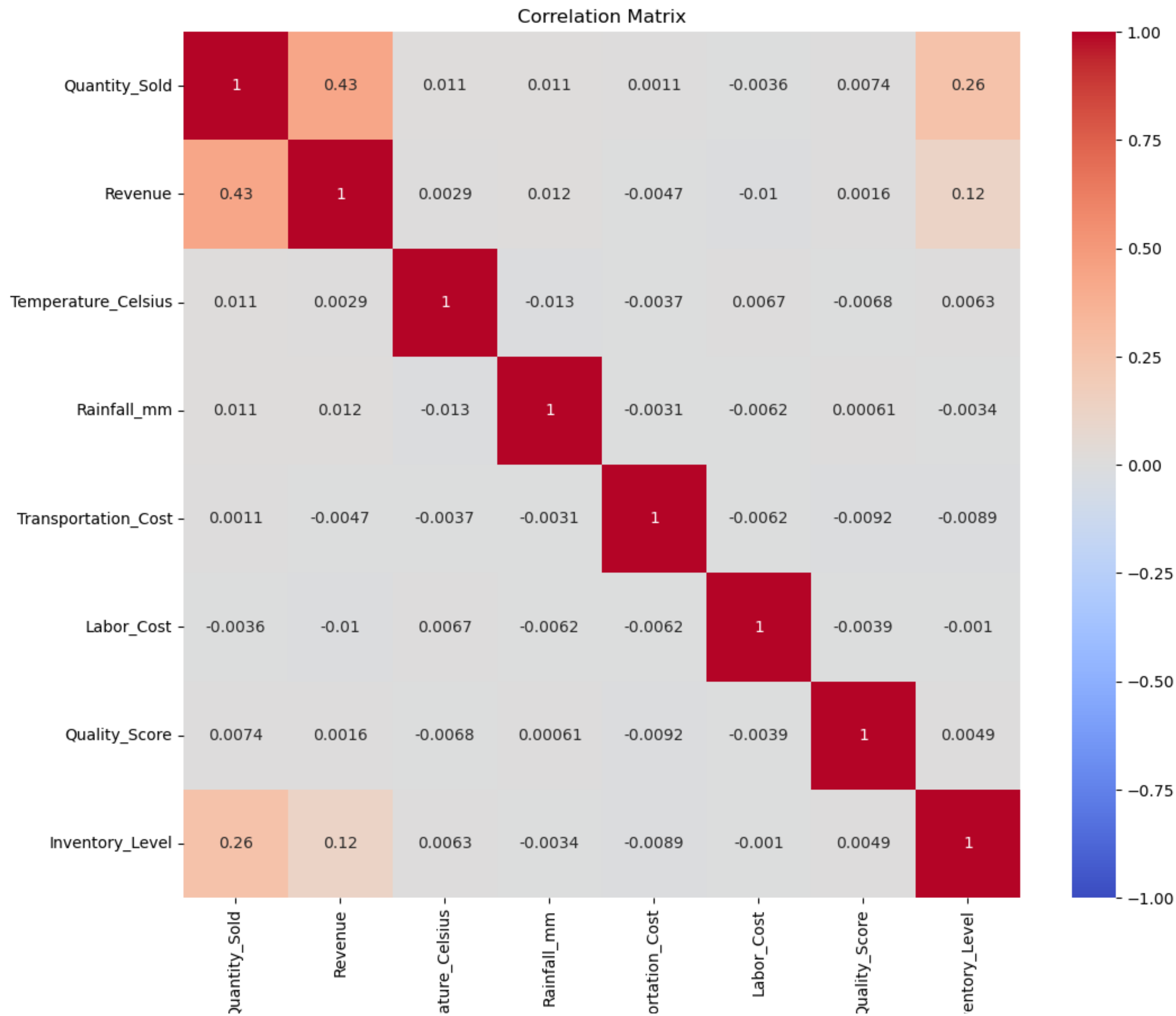
Bivariate Analysis

We look at pairs of variables, by looking at: - pairs of numerical variabls - numerical and categorical variables - pairs of categorical variables

Bivariate Analysis: Numerical Variables

Starting with Correlation matrix

In [56]:
```
correlation_matrix = df.select_dtypes(include=np.number).corr()

plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
Quantity_Sold
Revenue
Temperature_Celsius
Rainfall_mm
Transportation_Cost
Labor_Cost
Quality_Score
Inventory_Level
1 0.43 0.011 0.011 0.0011 -0.0036 0.0074 0.26
0.43 1 0.0029 0.012 -0.0047 -0.01 0.0016 0.12
0.011 0.0029 1 -0.013 -0.0037 0.0067 -0.0068 0.0063
0.011 0.012 -0.013 1 -0.0031 -0.0062 0.00061 -0.0034
0.0011 -0.0047 -0.0037 -0.0031 1 -0.0062 -0.0092 -0.0089
-0.0036 -0.01 0.0067 -0.0062 -0.0062 1 -0.0039 -0.001
0.0074 0.0016 -0.0068 0.00061 -0.0092 -0.0039 1 0.0049
0.26 0.12 0.0063 -0.0034 -0.0089 -0.001 0.0049 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

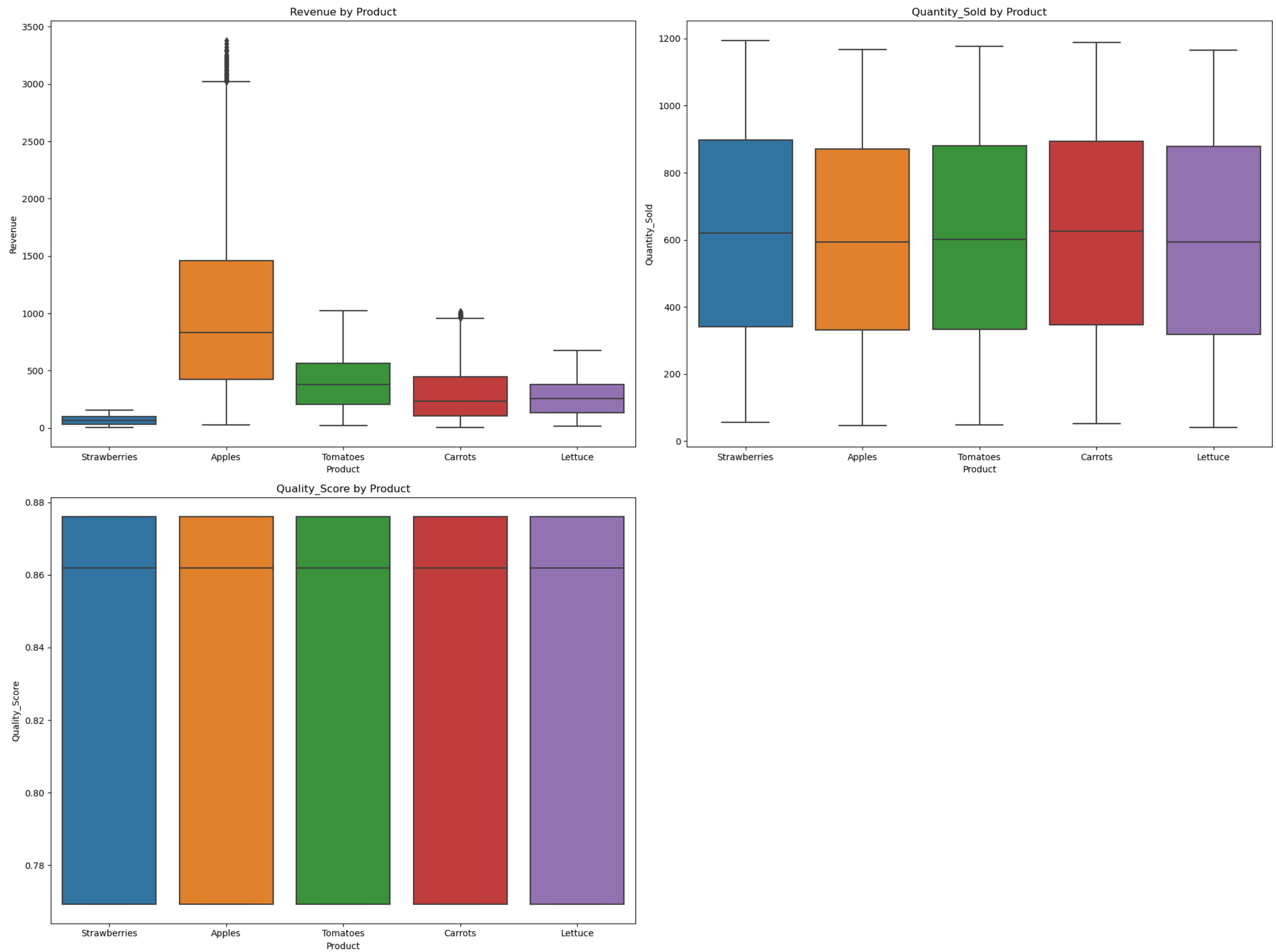
Bivariate Analysis: Numerical and Categorical Variables

Analysing 'Product' against:

- 'Revenue'
- 'Quantity_Sold'
- 'Quality_Score'

In [57]:

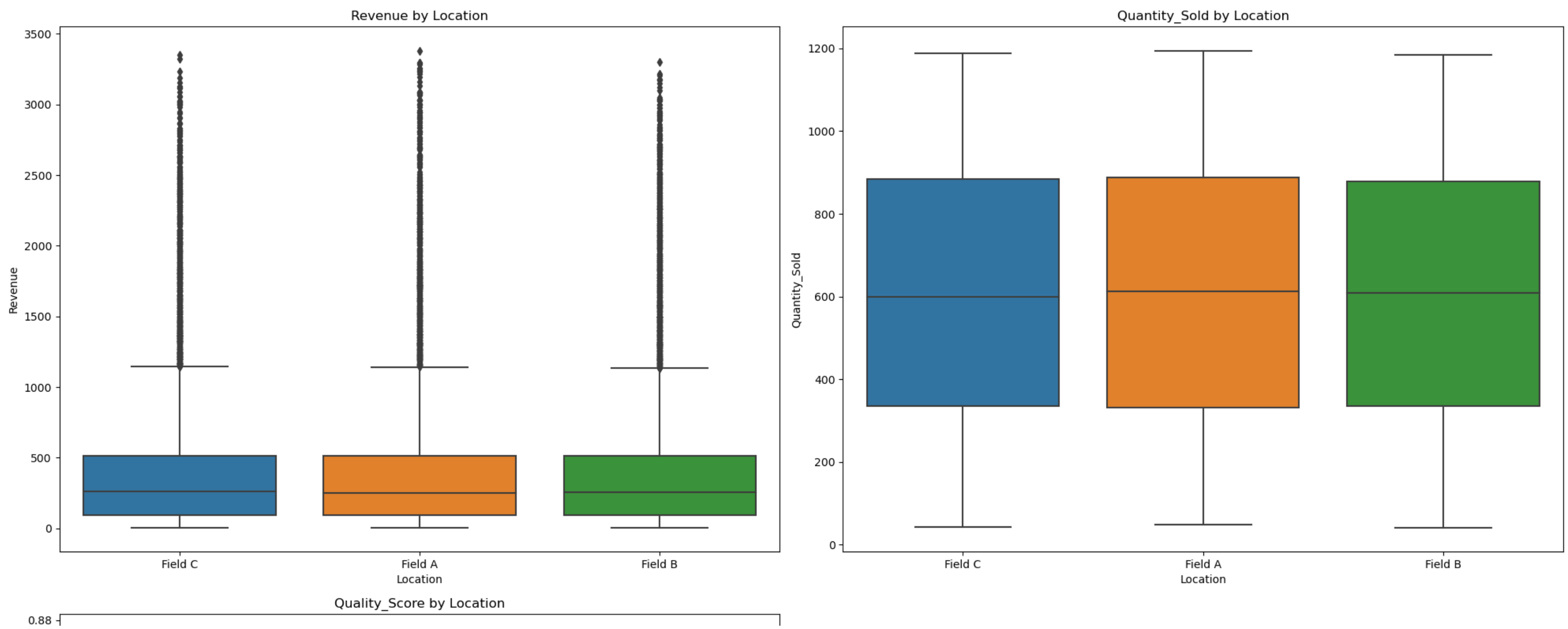
```
plt.figure(figsize= (20, 15))

key_numeric_vars = ['Revenue', 'Quantity_Sold', 'Quality_Score']

for i,var in enumerate(key_numeric_vars,1):
    plt.subplot(2, 2, i)
    sns.boxplot(data=df, x='Product', y=var)
    plt.title(f'{var} by Product')


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



"Field" Vs the same key Variables

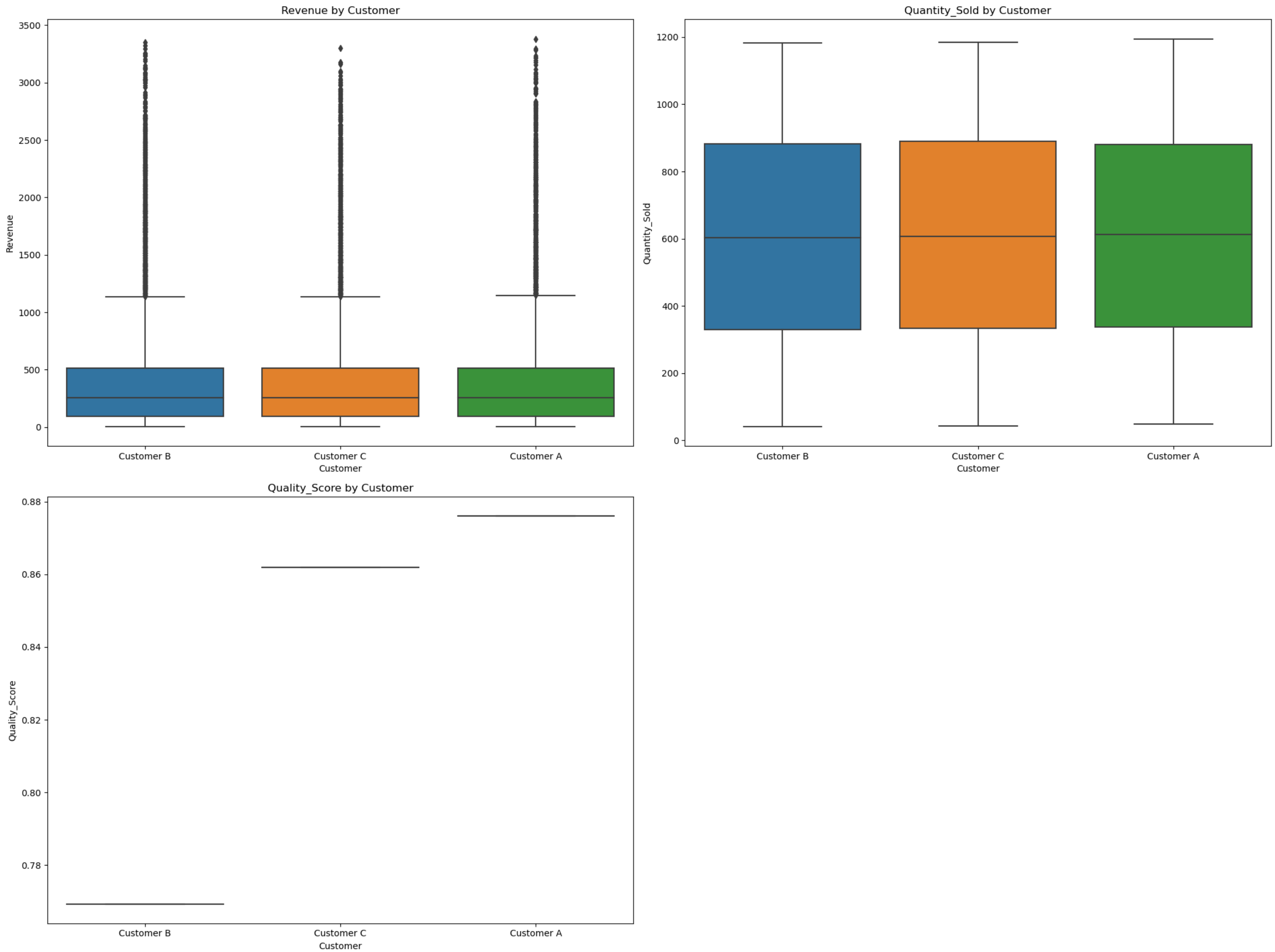
In [58]:

```
plt.figure(figsize=(20,15))

for i, var in enumerate(key_numeric_vars, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(data=df, x='Location', y=var)
    plt.title(f'{var} by Location')

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



Relationship between 'Customer' and the key parameters

In [59]:
```
plt.figure(figsize= (20, 15))

for i,var in enumerate(key_numeric_vars,1):
    plt.subplot(2, 2, i)
    sns.boxplot(data=df, x='Customer', y=var)
    plt.title(f'{var} by Customer')


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



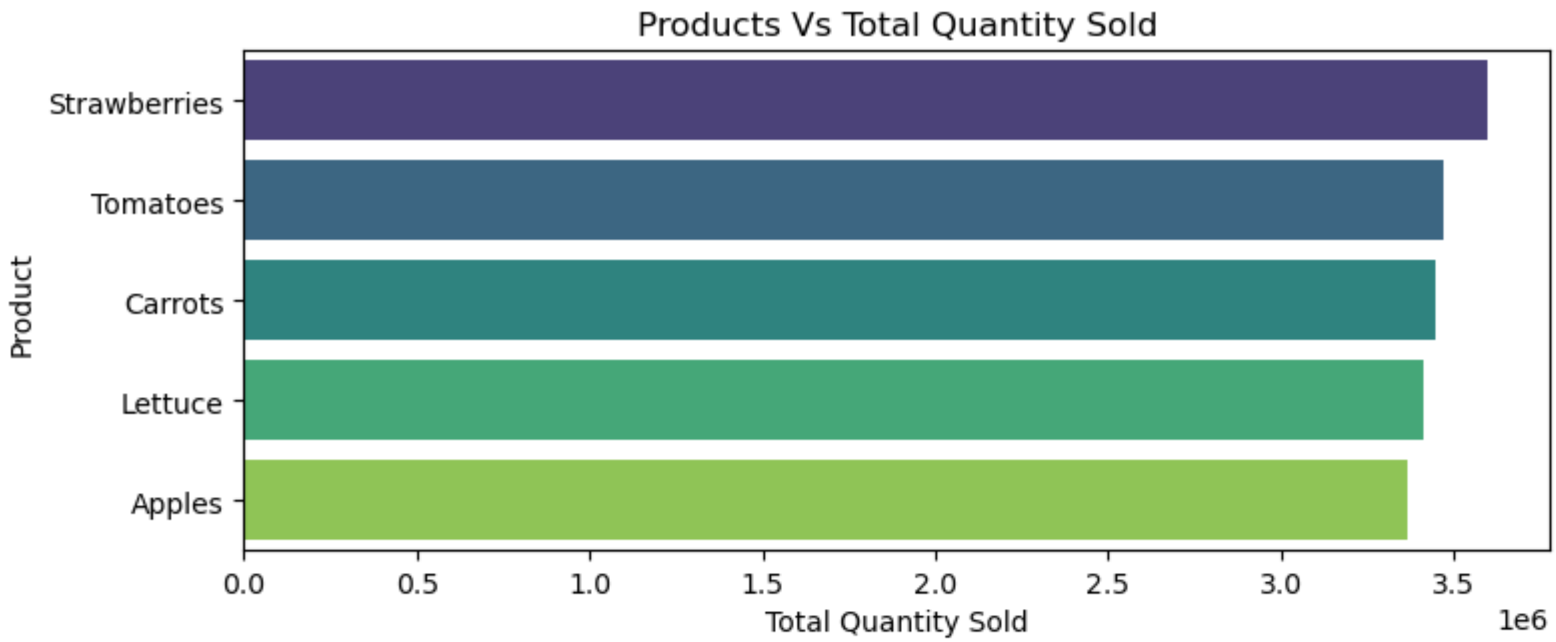
Visualise

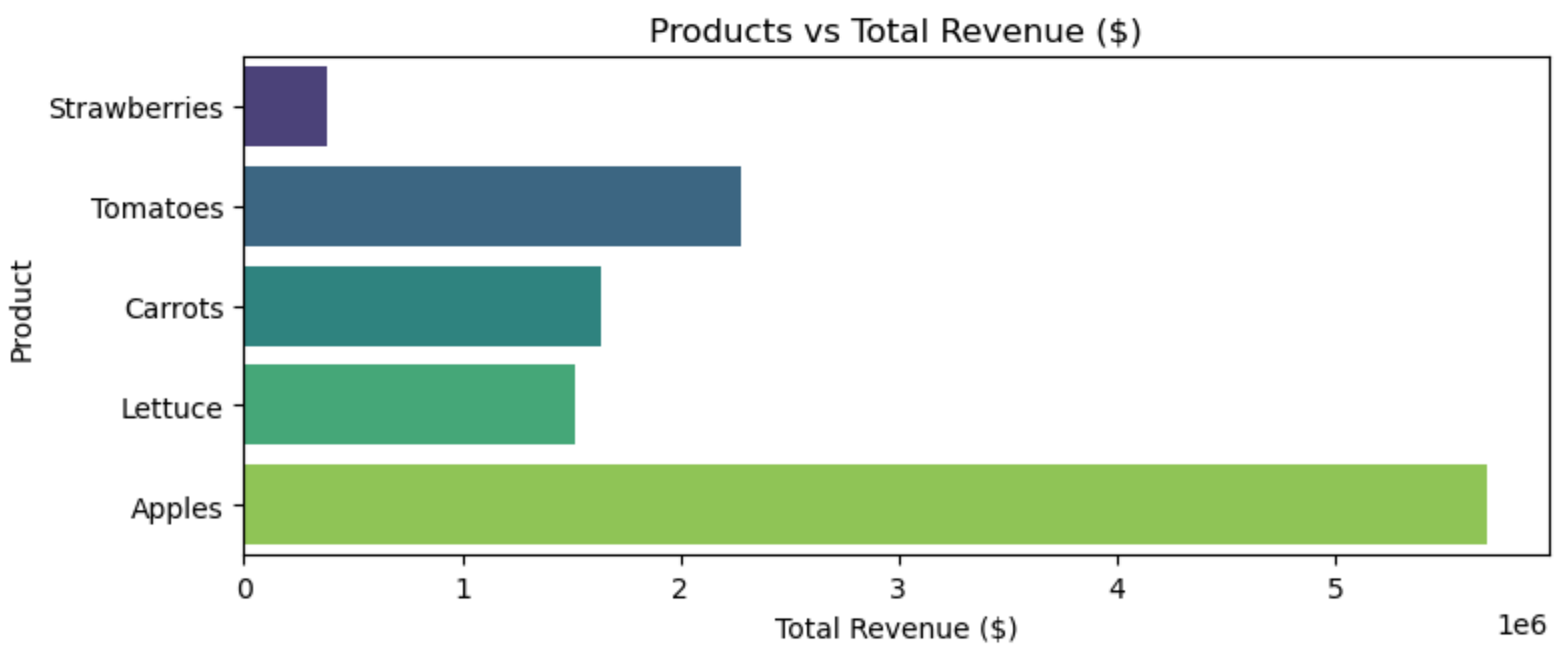
- Total 'Quantity_Sold' per product,

- Total 'Revenue' per product
- Quality_Score per product

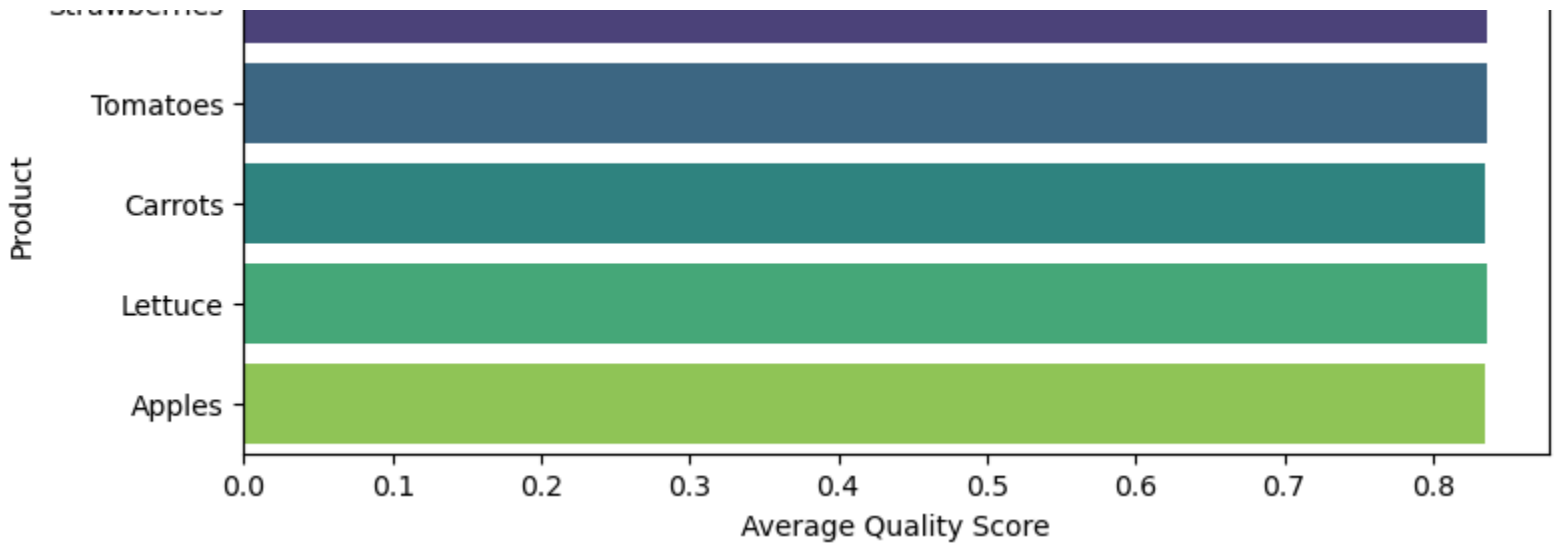
In [60]:

```
# Aggregate data by product
product_data = df.groupby('Product').agg({'Quantity_Sold': 'sum',
                                          'Revenue': 'sum',
                                          'Quality_Score': 'mean'}).reset_index()

# Sort the product data by total quantity sold
product_data = product_data.sort_values(by='Quantity_Sold', ascending=False)

# Create subplots
fig, ax = plt.subplots(3, 1, figsize=(8, 10))

# Products vs Total Quantity Sold
sns.barplot(data=product_data, x='Quantity_Sold', y='Product', ax=ax[0], palette='viridis')
ax[0].set_title('Products Vs Total Quantity Sold')
ax[0].set_xlabel('Total Quantity Sold')
ax[0].set_ylabel('Product')

# Products vs Total Revenue
sns.barplot(data=product_data, x='Revenue', y='Product', ax=ax[1], palette='viridis')
ax[1].set_title('Products vs Total Revenue ($)')
ax[1].set_xlabel('Total Revenue ($)')
ax[1].set_ylabel('Product')

# Products vs Average Quality Score
sns.barplot(data=product_data, x='Quality_Score', y='Product', ax=ax[2], palette='viridis')
ax[2].set_title('Products vs Average Quality Score')
ax[2].set_xlabel('Average Quality Score')
ax[2].set_ylabel('Product')

# Adjust layout for better visualization
plt.tight_layout()
plt.show()
```


Products Vs Total Quantity Sold
Product
Strawberries
Tomatoes
Carrots
Lettuce
Apples
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Total Quantity Sold
1e6


Products vs Total Revenue ($)
Product
Strawberries
Tomatoes
Carrots
Lettuce
Apples
0
1
2
3
4
5
Total Revenue ($)
1e6


Products vs Average Quality Score
Strawberries

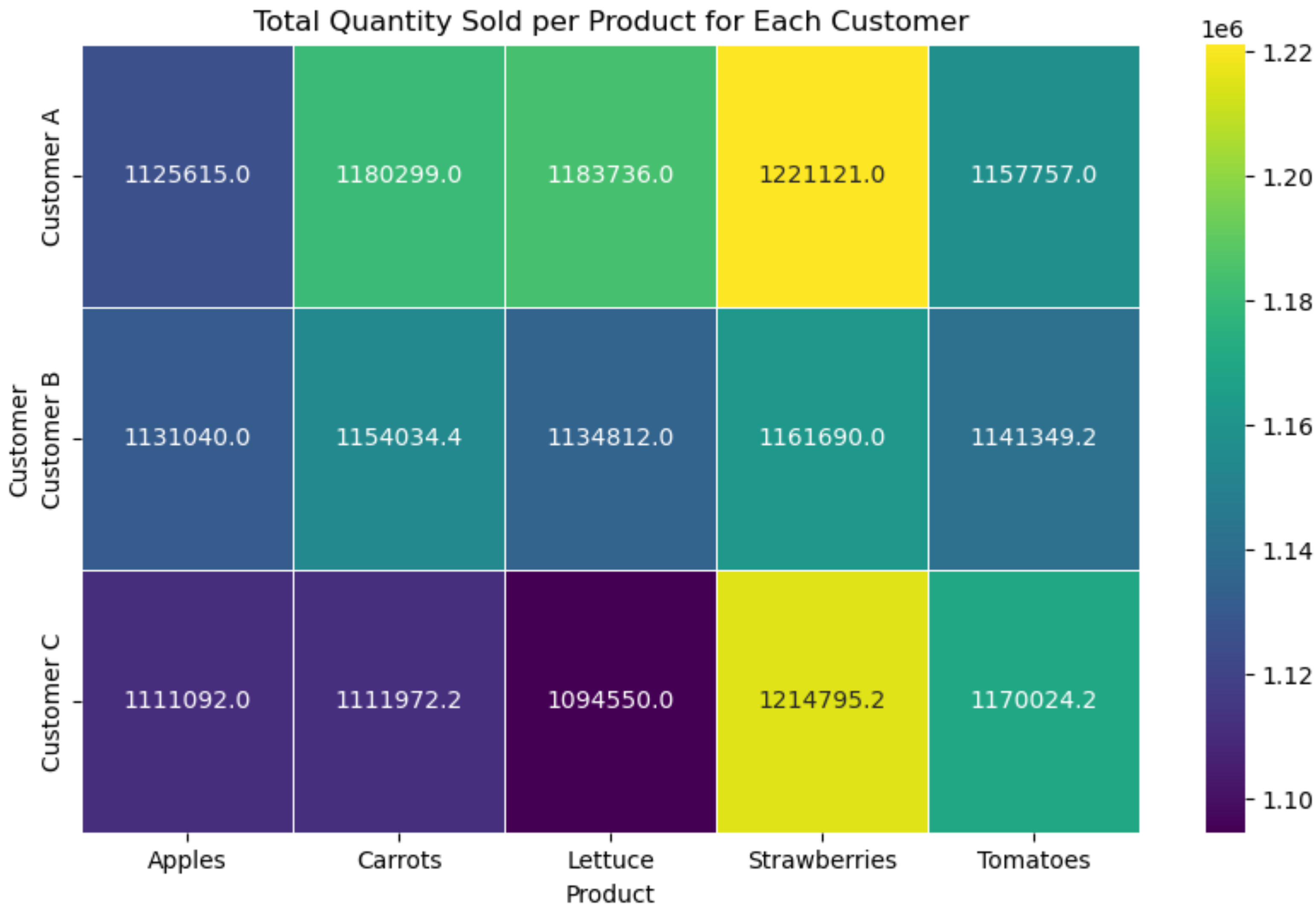


In [ ]:

Total Quantity sold for each product per customer.

In [61]:

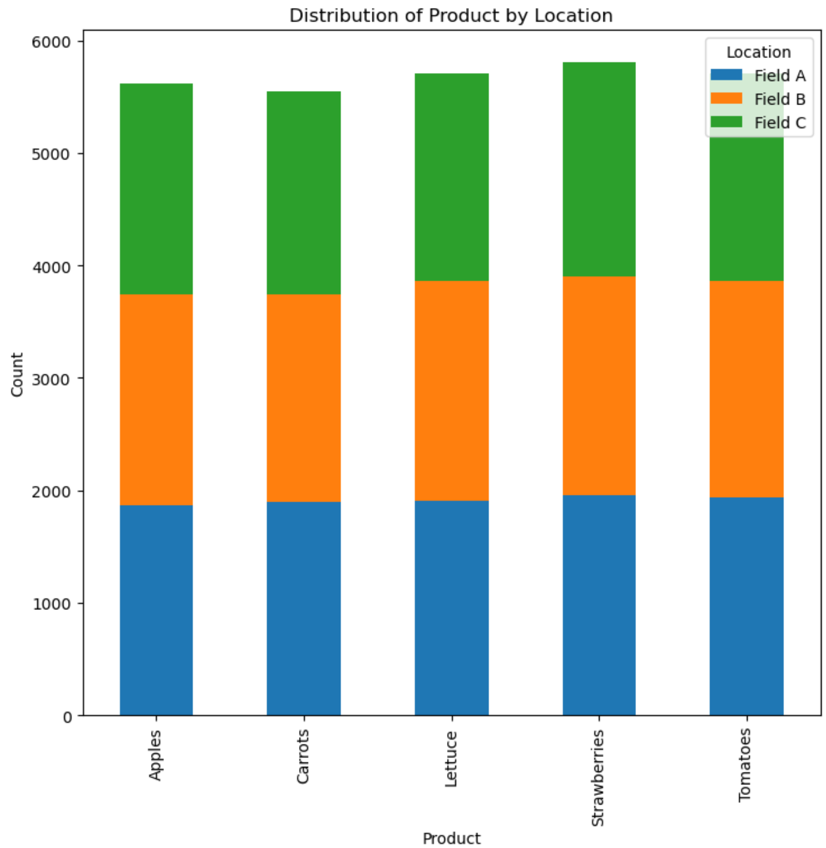
```
customer_data = df.groupby(['Customer', 'Product']).agg({'Quantity_Sold': 'sum',
                                                          'Revenue': 'sum',
                                                          'Quality_Score': 'mean'}).reset_index()
customer_pivot = customer_data.pivot(index='Customer', columns='Product', values='Quantity_Sold')

plt.figure(figsize=(10, 6))
sns.heatmap(customer_pivot, annot=True, cmap='viridis', fmt='.1f', linewidth=.5)
plt.title('Total Quantity Sold per Product for Each Customer')
plt.ylabel('Customer')
plt.xlabel('Product')
plt.show()
```

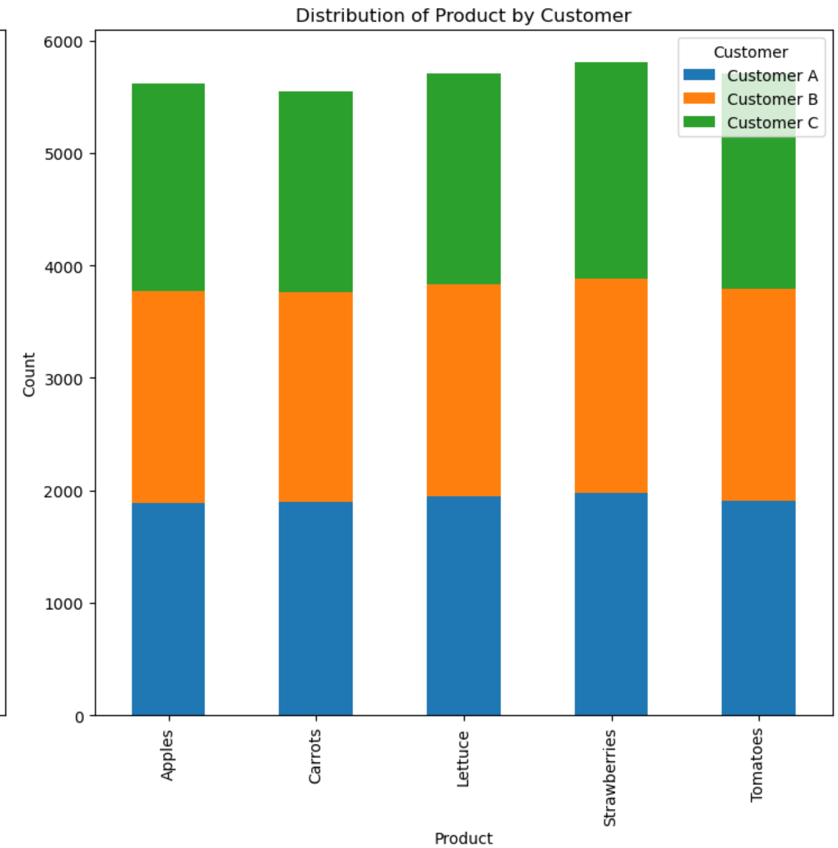


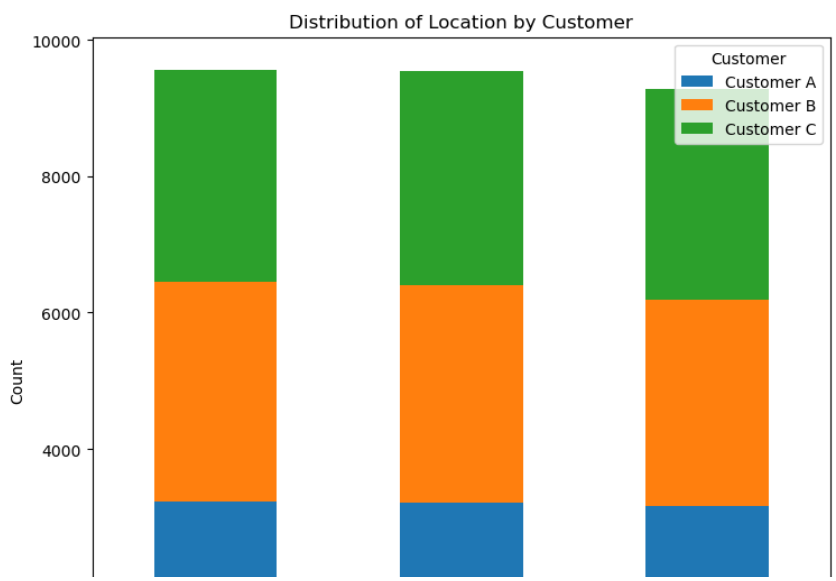
Bivariate Analysis: Two Categorical Variables

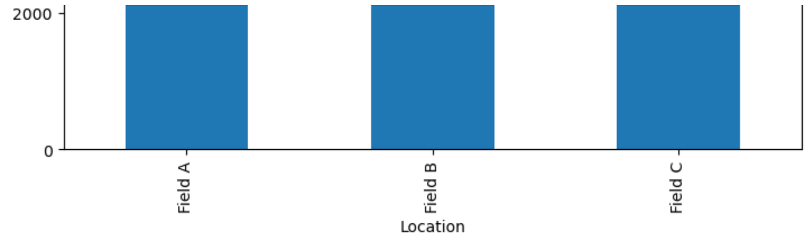
In [62]:

```
plt.figure(figsize=(15, 15))

pairs = [('Product', 'Location'),
         ('Product', 'Customer'),
         ('Location', 'Customer')]
for i, (p1, p2) in enumerate(pairs):
    contigency_table = pd.crosstab(df[p1], df[p2])

    ax = plt.subplot(2, 2, i + 1)
    contigency_table.plot(kind='bar', stacked=True, ax=ax)
    plt.title(f'Distribution of {p1} by {p2}')
    plt.ylabel('Count')
    plt.xlabel(p1)

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


Distribution of Product by Location
Location
Field A
Field B
Field C
Count
0
1000
2000
3000
4000
5000
6000
Apples
Carrots
Lettuce
Strawberries
Tomatoes
Product

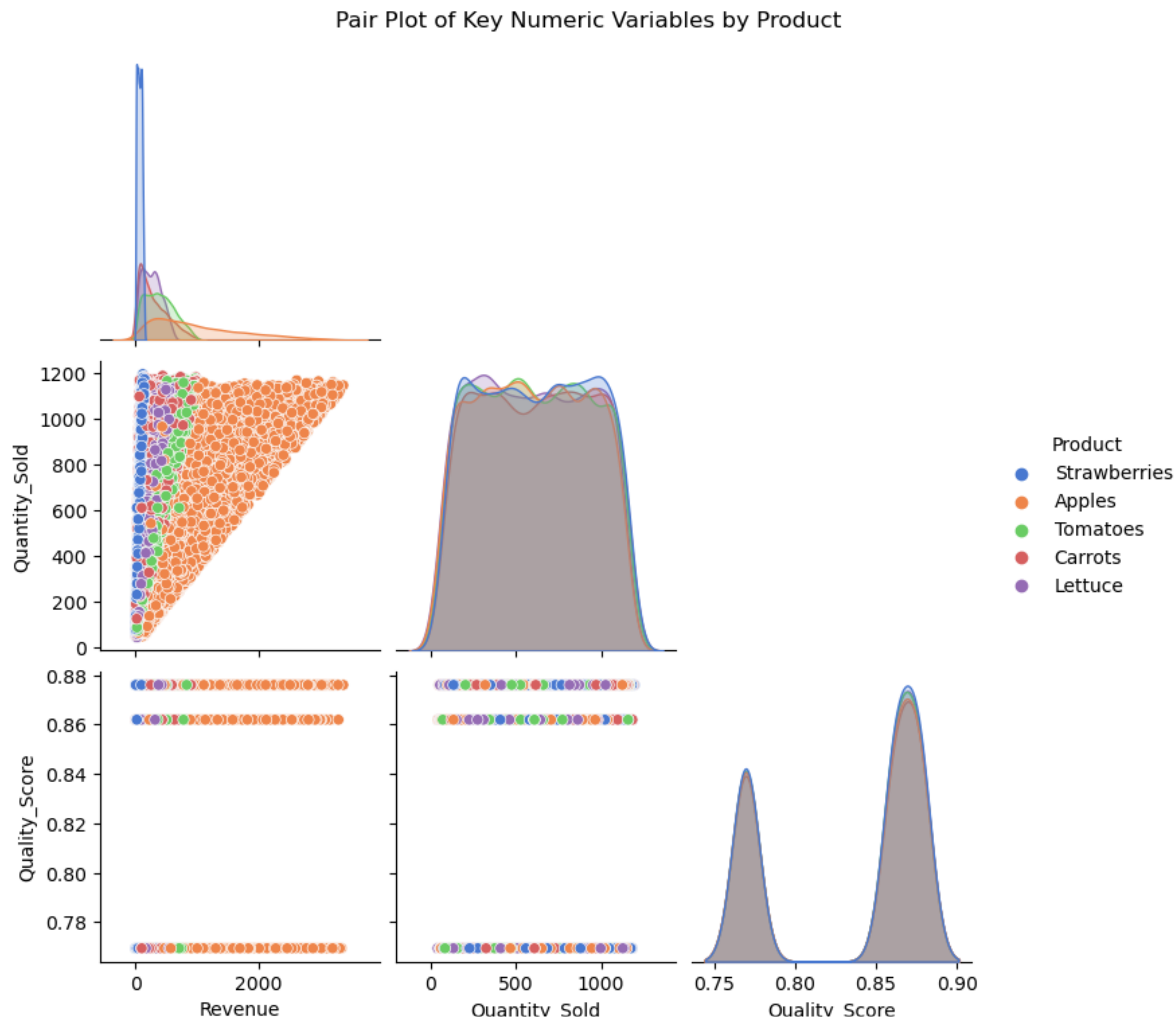

Distribution of Product by Customer
Customer
Customer A
Customer B
Customer C
Count
0
1000
2000
3000
4000
5000
6000
Apples
Carrots
Lettuce
Strawberries
Tomatoes
Product


Distribution of Location by Customer
Customer
Customer A
Customer B
Customer C
Count
4000
6000
8000
10000



Multvariate Analysis

In [63]:
```
pair_plot = sns.pairplot(df, hue='Product', vars=key_numeric_vars, palette='muted', corner=True)
pair_plot.fig.suptitle('Pair Plot of Key Numeric Variables by Product', y=1.02)

plt.show()
```

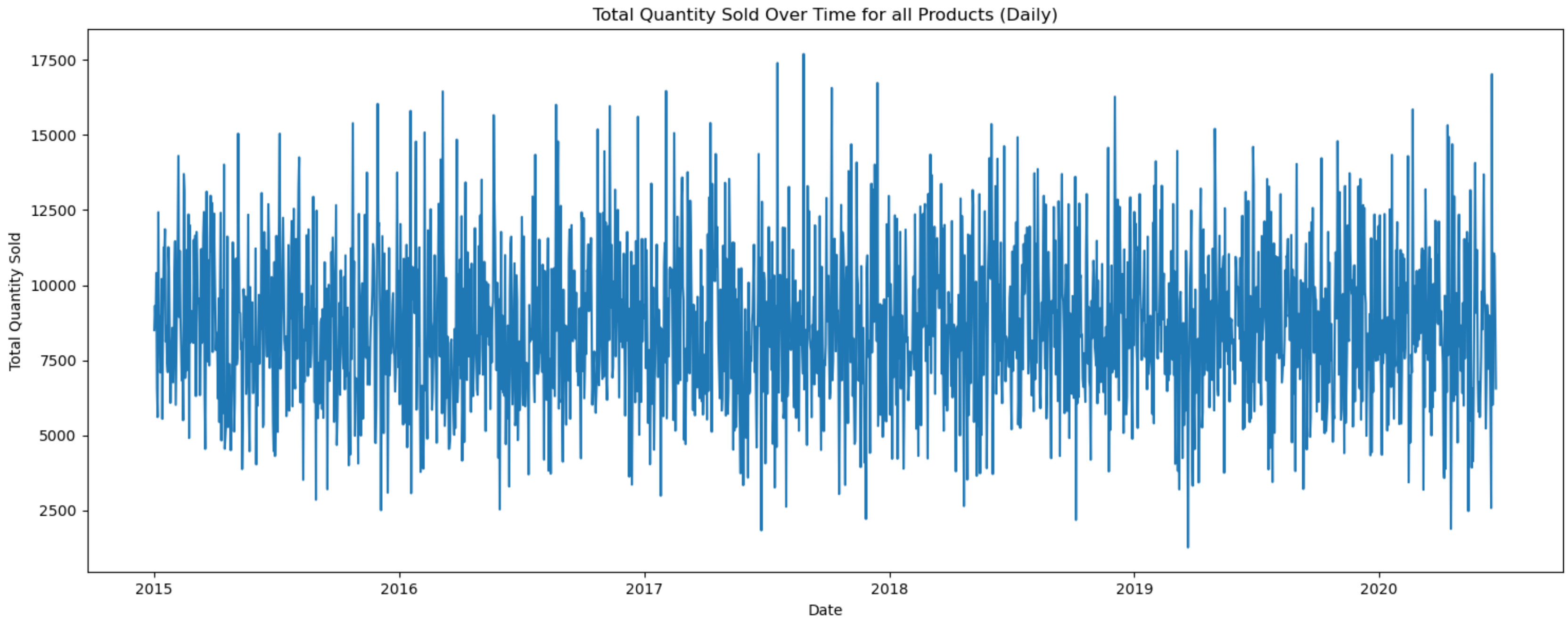

Pair Plot of Key Numeric Variables by Product
Quantity_Sold
Quality_Score
Revenue
Quantity_Sold
Quality_Score
Product
Strawberries
Apples
Tomatoes
Carrots
Lettuce

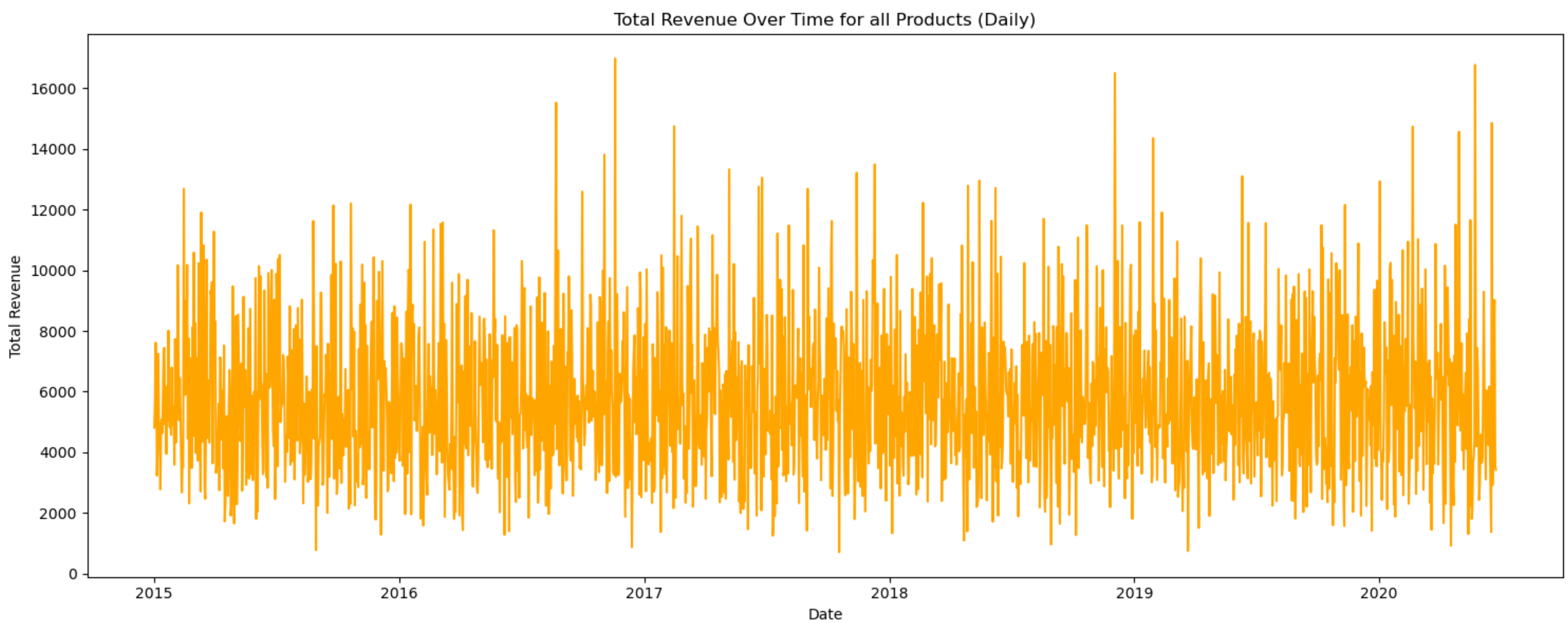
Temporal Analysis

How the Quantity_Sold and Revenue vary daily

In [64]:

```

# Convert 'Date' column to datetime
df['Date'] = pd.to_datetime(df['Date'])

# Group by 'Date' and aggregate 'Quantity_Sold' and 'Revenue'
time_based_data = df.groupby('Date').agg({'Quantity_Sold': 'sum', 'Revenue': 'sum'}).reset_index()

# Plotting the aggregated data
fig, ax = plt.subplots(2, 1, figsize=(15, 12))

# Quantity Sold Over Time
sns.lineplot(data=time_based_data, x='Date', y='Quantity_Sold', ax=ax[0])
ax[0].set_title('Total Quantity Sold Over Time for all Products (Daily)')
ax[0].set_ylabel('Total Quantity Sold')

# Revenue over Time
sns.lineplot(data=time_based_data, x='Date', y='Revenue', ax=ax[1], color='orange')
ax[1].set_title('Total Revenue Over Time for all Products (Daily)')
ax[1].set_ylabel('Total Revenue')

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

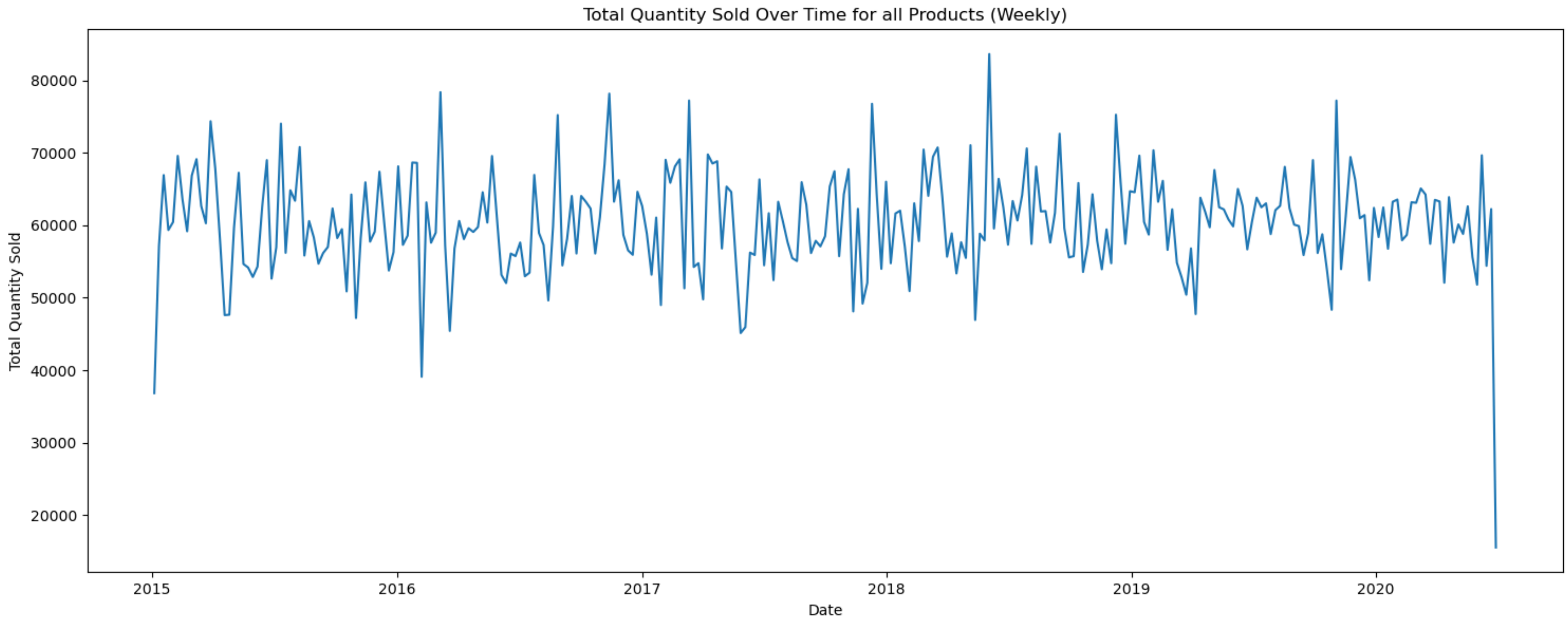

Total Quantity Sold Over Time for all Products (Daily)
Total Quantity Sold
17500
15000
12500
10000
7500
5000
2500
2015
2016
2017
2018
2019
2020
Date


Total Revenue Over Time for all Products (Daily)
Total Revenue
16000
14000
12000
10000
8000
6000
4000
2000
0
2015
2016
2017
2018
2019
2020
Date

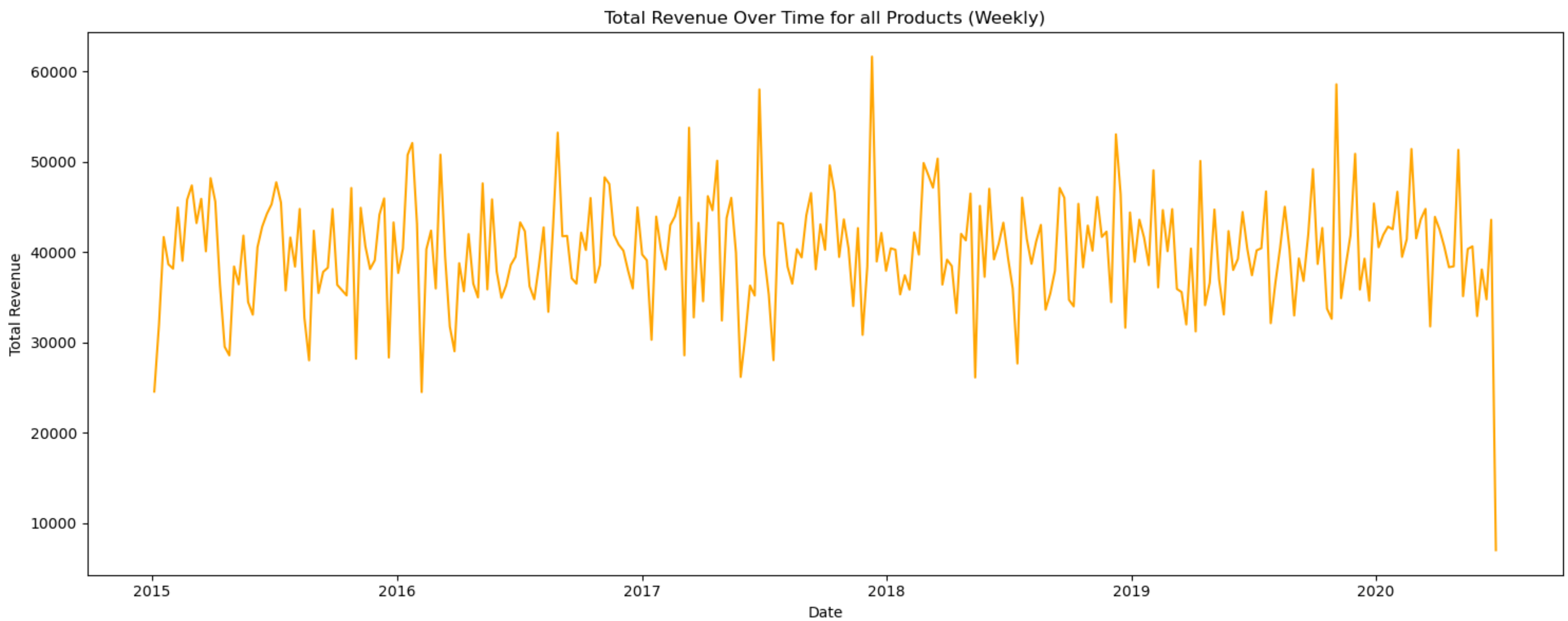
Make the Same Plot weekly

In [65]:

```
time_based_data = df.groupby('Date').agg({'Quantity_Sold': 'sum',
                                          'Revenue': 'sum'}).reset_index()

time_based_data = time_based_data.set_index('Date').resample('W').sum().reset_index()

fig, ax = plt.subplots(2, 1, figsize=(15,12))

#Quantity  Sold over Time
sns.lineplot(data=time_based_data, x='Date', y='Quantity_Sold', ax=ax[0])
ax[0].set_title('Total Quantity Sold Over Time for all Products (Weekly)')
ax[0].set_ylabel('Total Quantity Sold')


# Revenue over Time
sns.lineplot(data=time_based_data, x='Date', y='Revenue', ax=ax[1], color='orange')
ax[1].set_title('Total Revenue Over Time for all Products (Weekly)')
ax[1].set_ylabel('Total Revenue')

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



Total Quantity Sold Over Time for all Products (Weekly)
Total Quantity Sold
Date

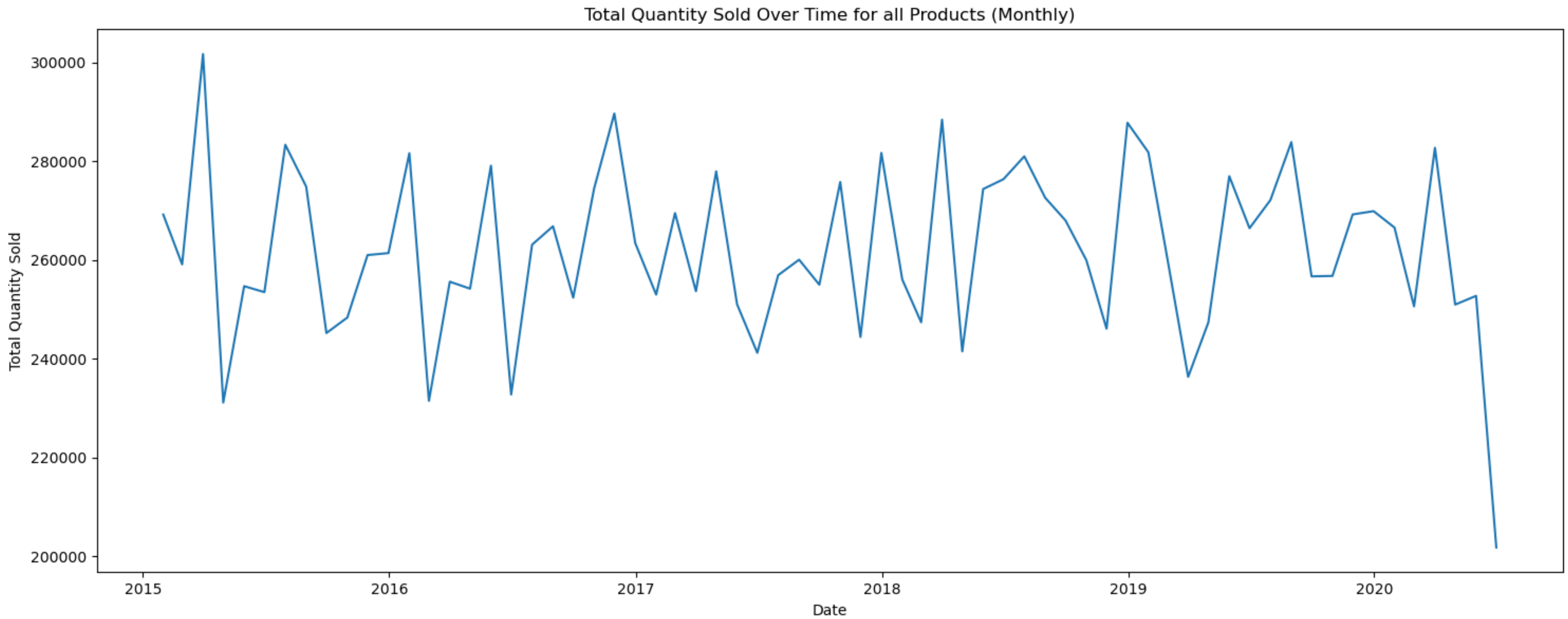


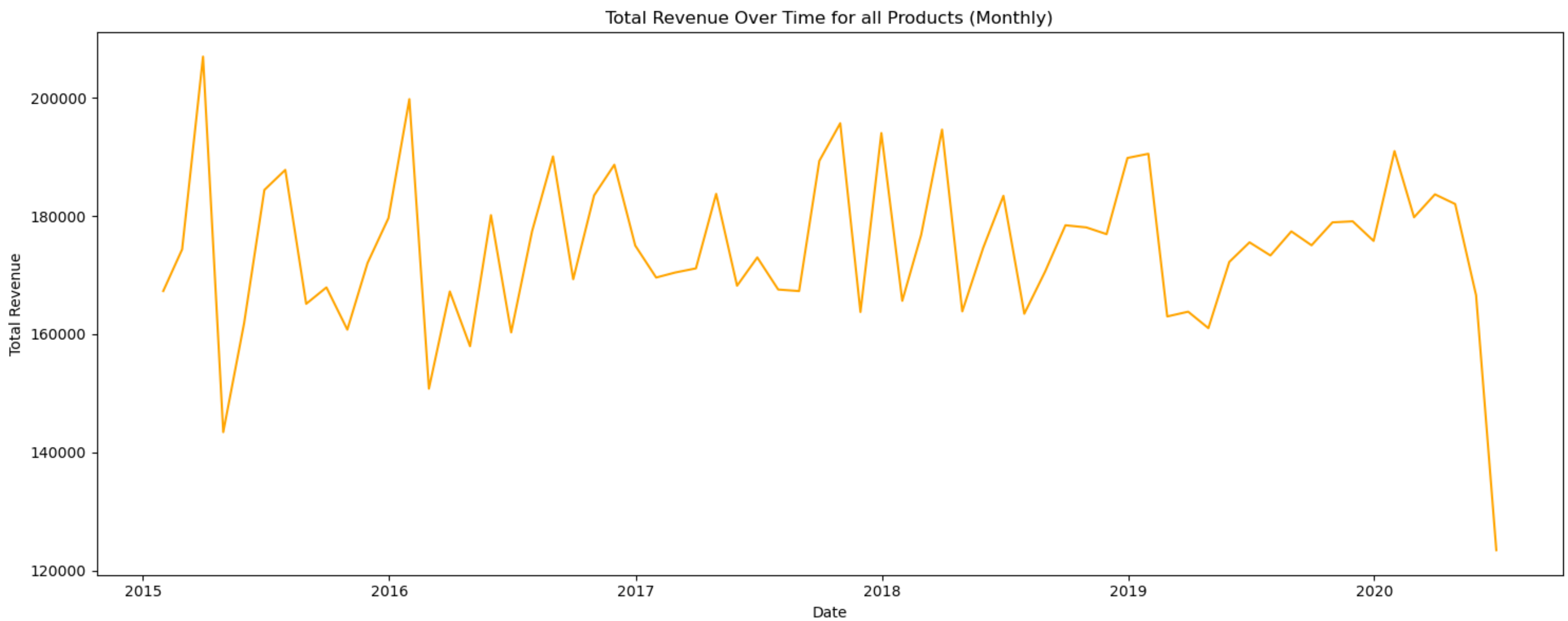
Total Revenue Over Time for all Products (Weekly)
Total Revenue
Date

Same plot Monthly

In [66]:

```
time_based_data = df.groupby('Date').agg({'Quantity_Sold': 'sum',
                                          'Revenue': 'sum'}).reset_index()

time_based_data = time_based_data.set_index('Date').resample('M').sum().reset_index()

fig, ax = plt.subplots(2, 1, figsize=(15,12))

#Quantity  Sold over Time
sns.lineplot(data=time_based_data, x='Date', y='Quantity_Sold', ax=ax[0])
ax[0].set_title('Total Quantity Sold Over Time for all Products (Monthly)')
ax[0].set_ylabel('Total Quantity Sold')


# Revenue over Time
sns.lineplot(data=time_based_data, x='Date', y='Revenue', ax=ax[1], color='orange')
ax[1].set_title('Total Revenue Over Time for all Products (Monthly)')
ax[1].set_ylabel('Total Revenue')

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

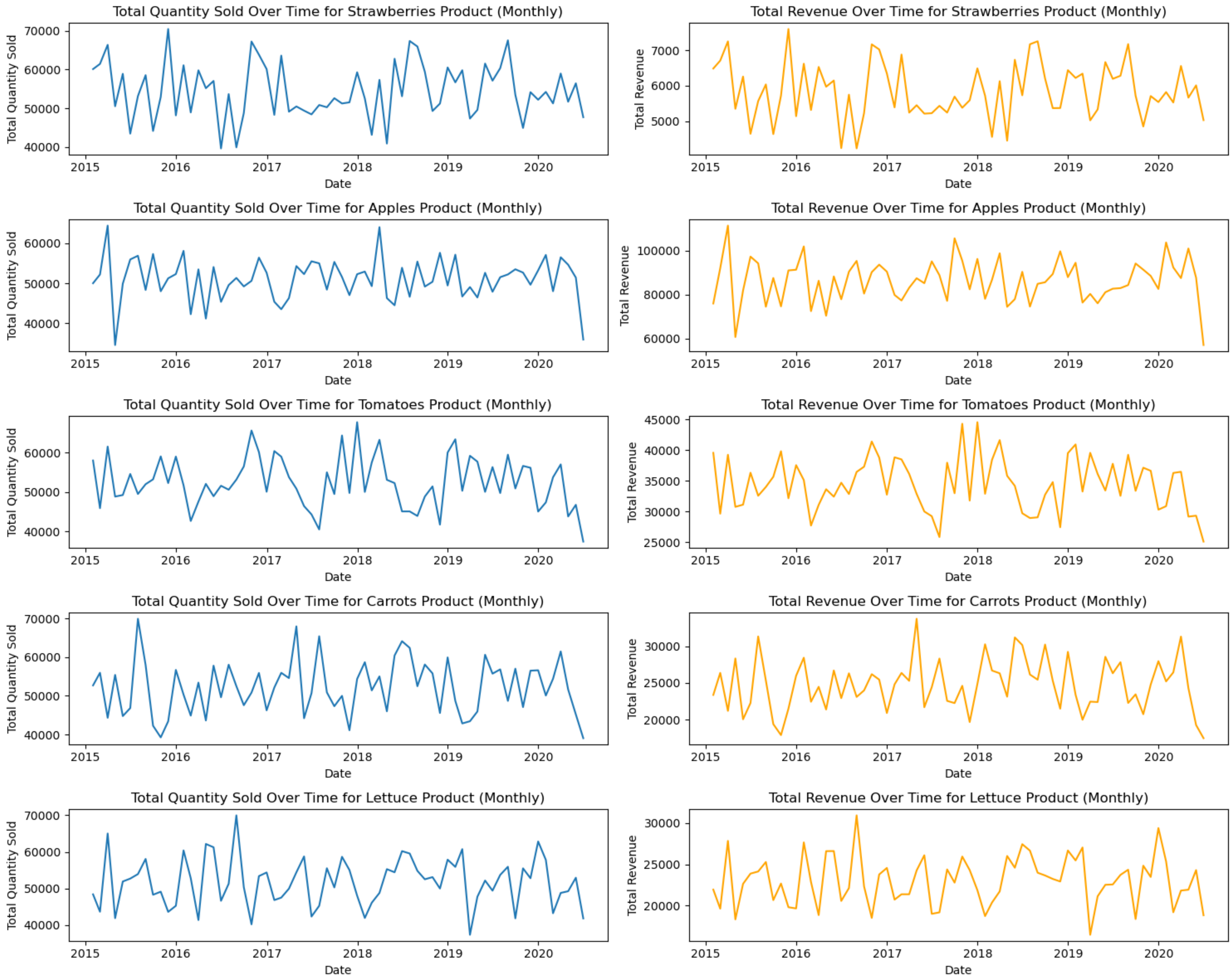

Total Quantity Sold Over Time for all Products (Monthly)
Total Quantity Sold
Date
300000
280000
260000
240000
220000
200000
2015
2016
2017
2018
2019
2020


Total Revenue Over Time for all Products (Monthly)
Total Revenue
Date
200000
180000
160000
140000
120000
2015
2016
2017
2018
2019
2020

PLot qunatity sold and revenue per product

In [67]:

```

products = df['Product'].unique()

fig, ax = plt.subplots(len(products), 2, figsize=(15, 12))

for i, product in enumerate(products):
    time_based_data = df[df['Product'] == product]

    time_based_data = time_based_data.groupby('Date').agg({'Quantity_Sold': 'sum', 'Revenue': 'sum'}).res

    time_based_data = time_based_data.set_index('Date').resample('M').sum().reset_index()

    # Quantity Sold over Time
    sns.lineplot(data=time_based_data, x='Date', y='Quantity_Sold', ax=ax[i, 0])
    ax[i, 0].set_title(f'Total Quantity Sold Over Time for {product} Product (Monthly)')
    ax[i, 0].set_ylabel('Total Quantity Sold')

    # Revenue over Time
    sns.lineplot(data=time_based_data, x='Date', y='Revenue', ax=ax[i, 1], color='orange')
    ax[i, 1].set_title(f'Total Revenue Over Time for {product} Product (Monthly)')
    ax[i, 1].set_ylabel('Total Revenue')

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


Total Quantity Sold Over Time for Strawberries Product (Monthly)
Total Revenue Over Time for Strawberries Product (Monthly)
Total Quantity Sold Over Time for Apples Product (Monthly)
Total Revenue Over Time for Apples Product (Monthly)
Total Quantity Sold Over Time for Tomatoes Product (Monthly)
Total Revenue Over Time for Tomatoes Product (Monthly)
Total Quantity Sold Over Time for Carrots Product (Monthly)
Total Revenue Over Time for Carrots Product (Monthly)
Total Quantity Sold Over Time for Lettuce Product (Monthly)
Total Revenue Over Time for Lettuce Product (Monthly)
Total Quantity Sold
Total Revenue
Date

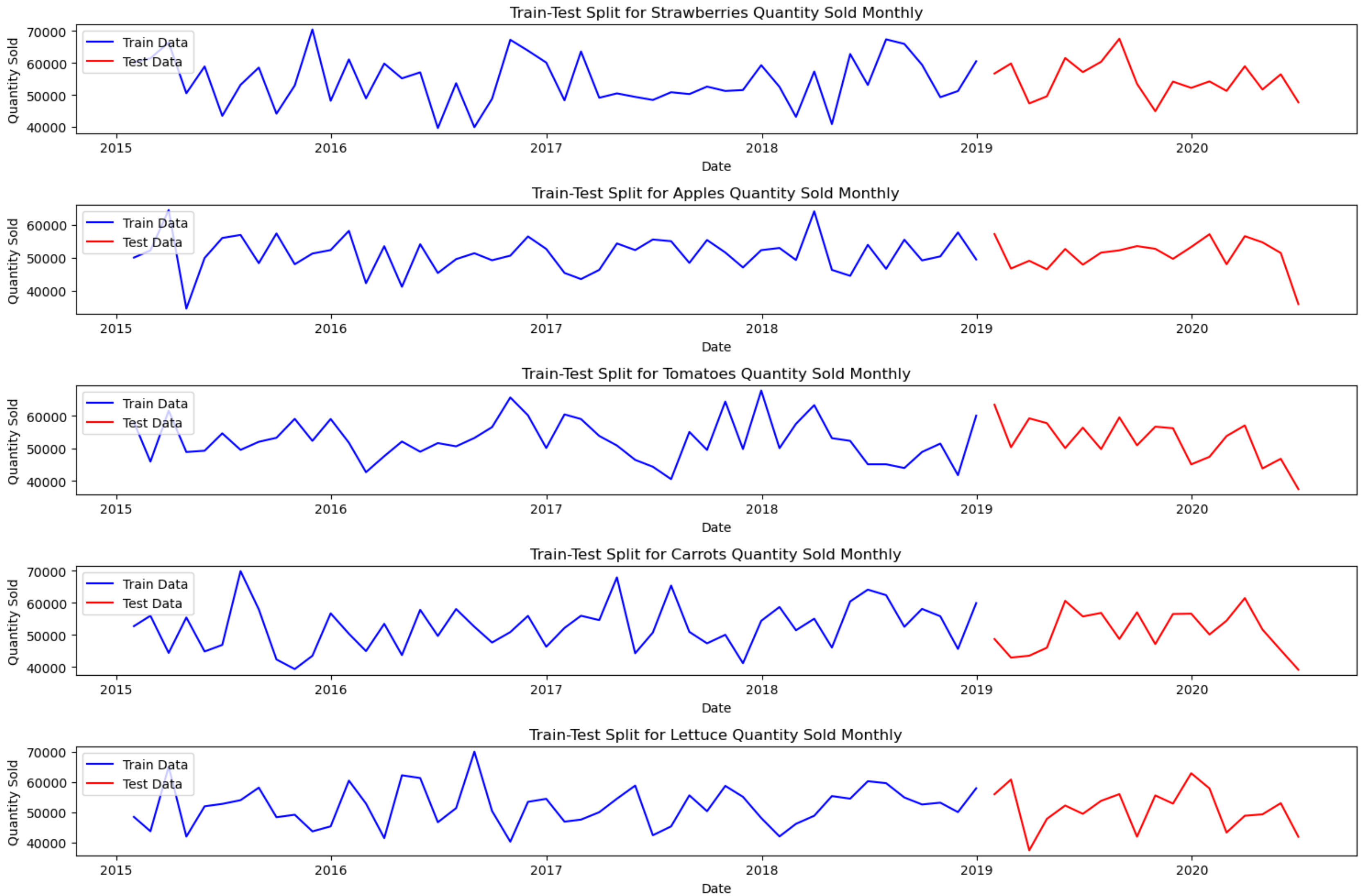
Feature Engineering

Splitting Dataset into train And test sets

In [68]:
```
train_data = dict()
test_data = dict()

for product in products:
    df_product = df[df['Product'] == product]

    df_product = df_product.groupby('Date').agg({'Quantity_Sold': 'sum',
                                                 'Revenue': 'sum'}).reset_index()

    df_product = df_product.set_index('Date').resample('M').sum().reset_index()

    train_data[product] = df_product[df_product['Date'].dt.year < 2019].reset_index()
    test_data[product] = df_product[df_product['Date'].dt.year >= 2019].reset_index()
```

Visualize the split

In [69]:
```
fig, ax = plt.subplots(len(products), 1, figsize=(15, 10))

for i, product in enumerate(products):
    ax[i].plot(train_data[product]['Date'],
               train_data[product]['Quantity_Sold'],
               color='blue')

    ax[i].plot(test_data[product]['Date'],
               test_data[product]['Quantity_Sold'],
               color='red')
    ax[i].set_title(f'Train-Test Split for {product} Quantity Sold Monthly')
    ax[i].set_xlabel('Date')
    ax[i].set_ylabel('Quantity Sold')
    ax[i].legend(['Train Data', 'Test Data'], loc='upper left')

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



5. Modelling

The models that will be used include: - ARIMA - Prophet, - RandomForestRegressor.

For evaluation, we will be using:

- Mean Absolute Error (MAE),
- Root Mean Square Error (RMSE).

Forecasting with ARIMA

Stattionarity test

In [70]:

```python
def adf_test(series):
    result = adfuller(series)
    dfoutput = pd.Series(result[0:4], index=['Test Statistic',
                                             'p-value',
                                             '#lags used',
                                             'number of observations'])

    for key, value in result[4].items():
        dfoutput[f'Critical Value ({key})'] = value

    return dfoutput
```

Performing the Sationarity test.

In [71]:

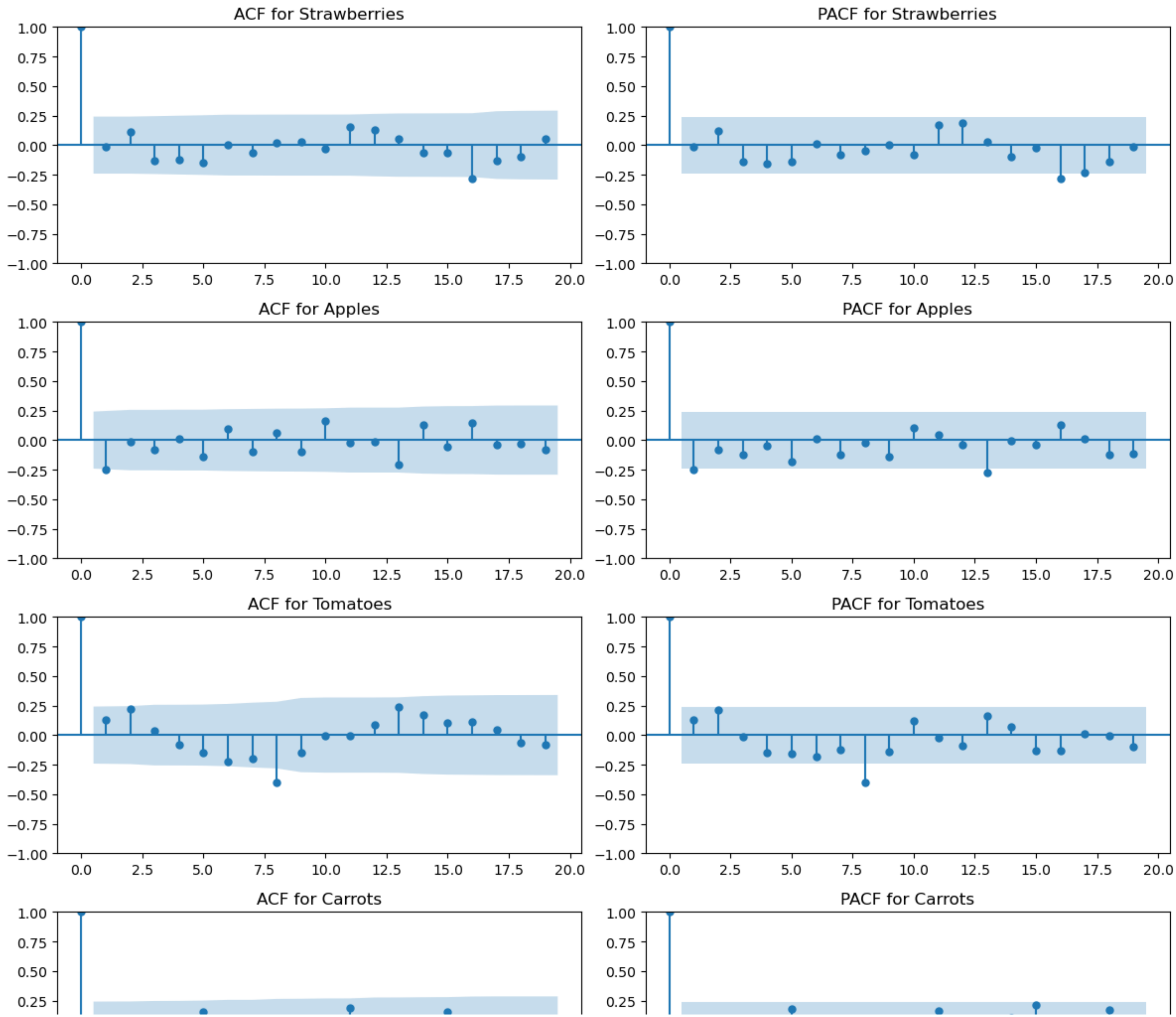
```
stationarity_test = dict()

for product in products:
    product_data = pd.concat([train_data[product], test_data[product]])
    stationarity_test[product] = adf_test(product_data['Quantity_Sold'])

pd.DataFrame(stationarity_test)
```

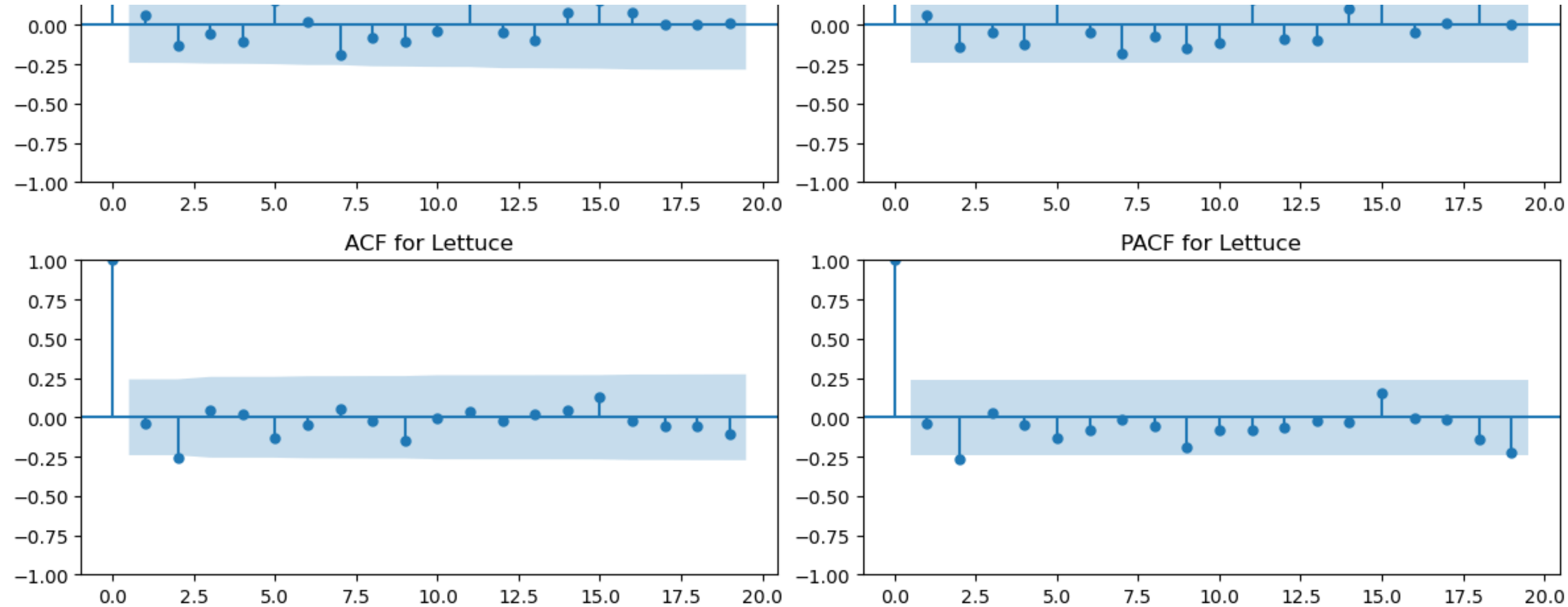
Out[71]:

	Strawberries	Apples	Tomatoes	Carrots	Lettuce
Test Statistic	-5.058980	-9.876209e+00	-4.368359	-7.209263e+00	-7.433840e+00
p-value	0.000017	3.876435e-17	0.000338	2.257203e-10	6.258368e-11
#lags used	2.000000	0.000000e+00	8.000000	0.000000e+00	1.000000e+00
number of observations	63.000000	6.500000e+01	57.000000	6.500000e+01	6.400000e+01
Critical Value (1%)	-3.538695	-3.535217e+00	-3.550670	-3.535217e+00	-3.536928e+00
Critical Value (5%)	-2.908645	-2.907154e+00	-2.913766	-2.907154e+00	-2.907887e+00
Critical Value (10%)	-2.591897	-2.591103e+00	-2.594624	-2.591103e+00	-2.591493e+00

Plot ACF and PACF

In [72]:
```
fig, ax = plt.subplots(len(products), 2, figsize=(12, 15))

for i, product in enumerate(products):
    product_data = pd.concat([train_data[product], test_data[product]])

    plot_acf(product_data['Quantity_Sold'], ax=ax[i][0])
    ax[i][0].set_title(f'ACF for {product}')

    plot_pacf(product_data['Quantity_Sold'], ax=ax[i][1])
    ax[i][1].set_title(f'PACF for {product}')

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


ACF for Strawberries
PACF for Strawberries
ACF for Apples
PACF for Apples
ACF for Tomatoes
PACF for Tomatoes
ACF for Carrots
PACF for Carrots



Build the models, and evaluate them

In [73]:

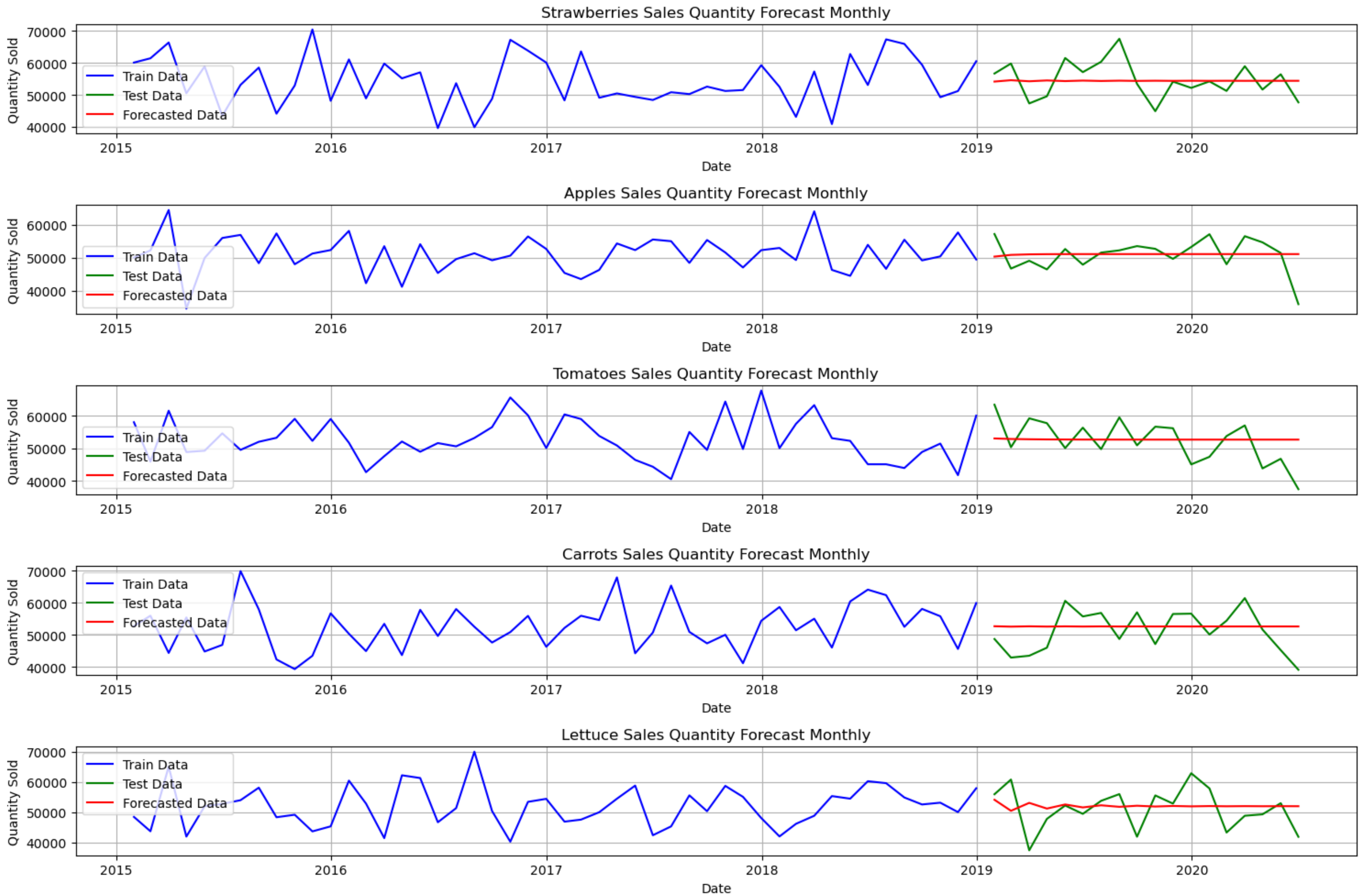
```python
mae, rmse, mape = 0, 0, 0
arima_mape_scores = dict()

arima_forecasts = dict()

for product in products:
    train = train_data[product]['Quantity_Sold'].values
    test = test_data[product]['Quantity_Sold'].values

    model = ARIMA(train, order=(1, 0, 1))
    model_fit = model.fit()

    forecast = model_fit.forecast(steps=len(test))
    arima_forecasts[product] = forecast

    product_mae = mean_absolute_error(test, forecast)
    product_rmse = mean_squared_error(test, forecast, squared=False)
    product_mape = mean_absolute_percentage_error(test, forecast) * 100

    mae += product_mae
    rmse += product_rmse
    mape += product_mape

    arima_mape_scores[product] = product_mape

n_products = len(products)

mae /= n_products
rmse /= n_products
mape /= n_products

print('MAE:', mae)
print('RMSE:', rmse)
print('MAPE:', mape)
```

```
MAE: 4915.419962117331
RMSE: 6059.511862209205
MAPE: 9.971574059237227
```

Plot the train, test and forecast data.

In [74]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(15, 10))

for i, product in enumerate(products):
    plt.subplot(len(products), 1, i + 1)

    plt.plot(train_data[product]['Date'],
             train_data[product]['Quantity_Sold'],
             label='Actual Quantity Sold (Train Data)',
             color='blue')
    plt.plot(test_data[product]['Date'],
             test_data[product]['Quantity_Sold'],
             label='Actual Quantity Sold (Test Data)',
             color='green')
    plt.plot(test_data[product]['Date'],
             arima_forecasts[product],
             label='Forecasted Quantity to be Sold',
             color='red',
             linestyle='-')
    plt.title(f'{product} Sales Quantity Forecast Monthly')
    plt.xlabel('Date')
    plt.ylabel('Quantity Sold')
    plt.legend(['Train Data', 'Test Data', 'Forecasted Data'])
    plt.grid(True)

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



Forecasting With Prophet

With prophet, Train and Evaluate the Models

In [82]:

```python

mae, rmse, mape = 0, 0, 0

prophet_models = dict()
prophet_forecasts = dict()
prophet_mape_scores = dict()

for product in products:
    train = train_data[product][['Date', 'Quantity_Sold']]
    test = test_data[product][['Date', 'Quantity_Sold']]

    train.columns = ['ds', 'y']
    test.columns = ['ds', 'y']

    model_prophet = Prophet(yearly_seasonality=True, daily_seasonality=False)
    model_prophet.fit(train)
    prophet_models[product] = model_prophet

    future_dates = model_prophet.make_future_dataframe(periods=len(test), freq='M')

    all_forecast = model_prophet.predict(future_dates)
    prophet_forecasts[product] = all_forecast

    test_forecast = all_forecast[-len(test):]

    product_mae = mean_absolute_error(test['y'], test_forecast['yhat'])
    product_rmse = mean_squared_error(test['y'], test_forecast['yhat'], squared=False)
    product_mape = mean_absolute_percentage_error(test['y'], test_forecast['yhat']) * 100

    prophet_mape_scores[product] = product_mape

    mae += product_mae
    rmse += product_rmse
    mape += product_mape

n_products = len(products)

mae /= n_products
rmse /= n_products
mape /= n_products

```

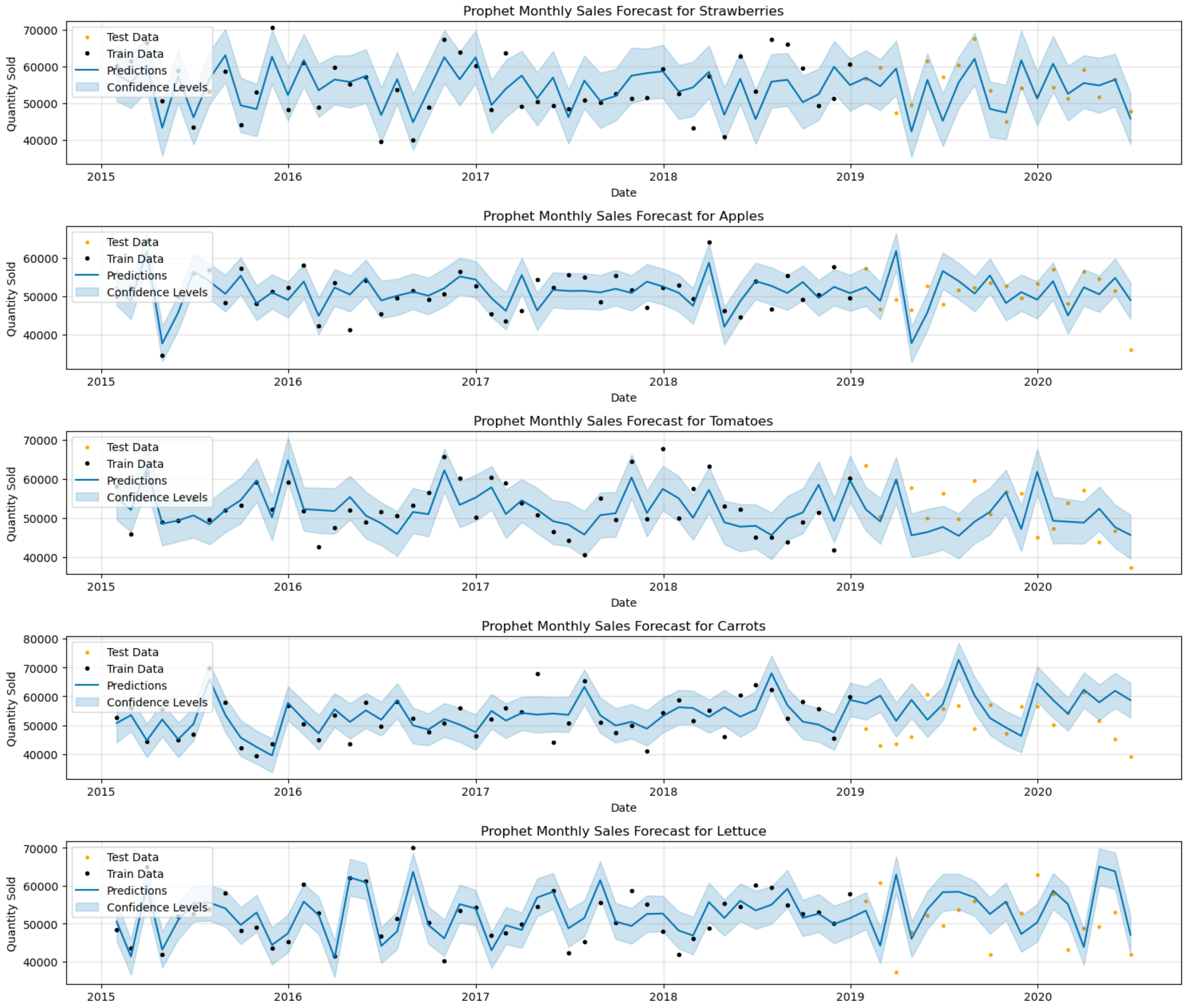
```python
print('\nMAE:', mae)
print('RMSE:', rmse)
print('MAPE:', mape)
```

```
10:38:28 - cmdstanpy - INFO - Chain [1] start processing
10:38:29 - cmdstanpy - INFO - Chain [1] done processing
10:38:29 - cmdstanpy - INFO - Chain [1] start processing
10:38:29 - cmdstanpy - INFO - Chain [1] done processing
10:38:30 - cmdstanpy - INFO - Chain [1] start processing
10:38:30 - cmdstanpy - INFO - Chain [1] done processing
10:38:30 - cmdstanpy - INFO - Chain [1] start processing
10:38:30 - cmdstanpy - INFO - Chain [1] done processing
10:38:31 - cmdstanpy - INFO - Chain [1] start processing
10:38:31 - cmdstanpy - INFO - Chain [1] done processing


MAE: 6557.378688869758
RMSE: 8136.562065696507
MAPE: 13.280854877120092
```

Visualization Of the Result

In [83]:

```python

# Create subplots for each product
fig, axes = plt.subplots(len(products), 1, figsize=(15, 13))

if len(products) == 1:
    axes = [axes]  # Ensure axes is always a list

for i, product in enumerate(products):
    axes[i].scatter(test_data[product]['Date'],
                    test_data[product]['Quantity_Sold'],
                    color='orange',
                    s=6)

    category_plot = prophet_models[product].plot(prophet_forecasts[product],
                                                 ax=axes[i],
                                                 figsize=(15, 7))

    axes[i].set_title(f'Prophet Monthly Sales Forecast for {product}')
    axes[i].set_xlabel('Date')
    axes[i].set_ylabel('Quantity Sold')

    axes[i].legend(['Test Data', 'Train Data', 'Predictions', 'Confidence Levels'], loc='upper left')

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


Prophet Monthly Sales Forecast for Strawberries
Prophet Monthly Sales Forecast for Apples
Prophet Monthly Sales Forecast for Tomatoes
Prophet Monthly Sales Forecast for Carrots
Prophet Monthly Sales Forecast for Lettuce
Test Data
Train Data
Predictions
Confidence Levels
Quantity Sold
Date

Forecasting With RandomForestRegressor

Train And Evaluate the models

In [84]:

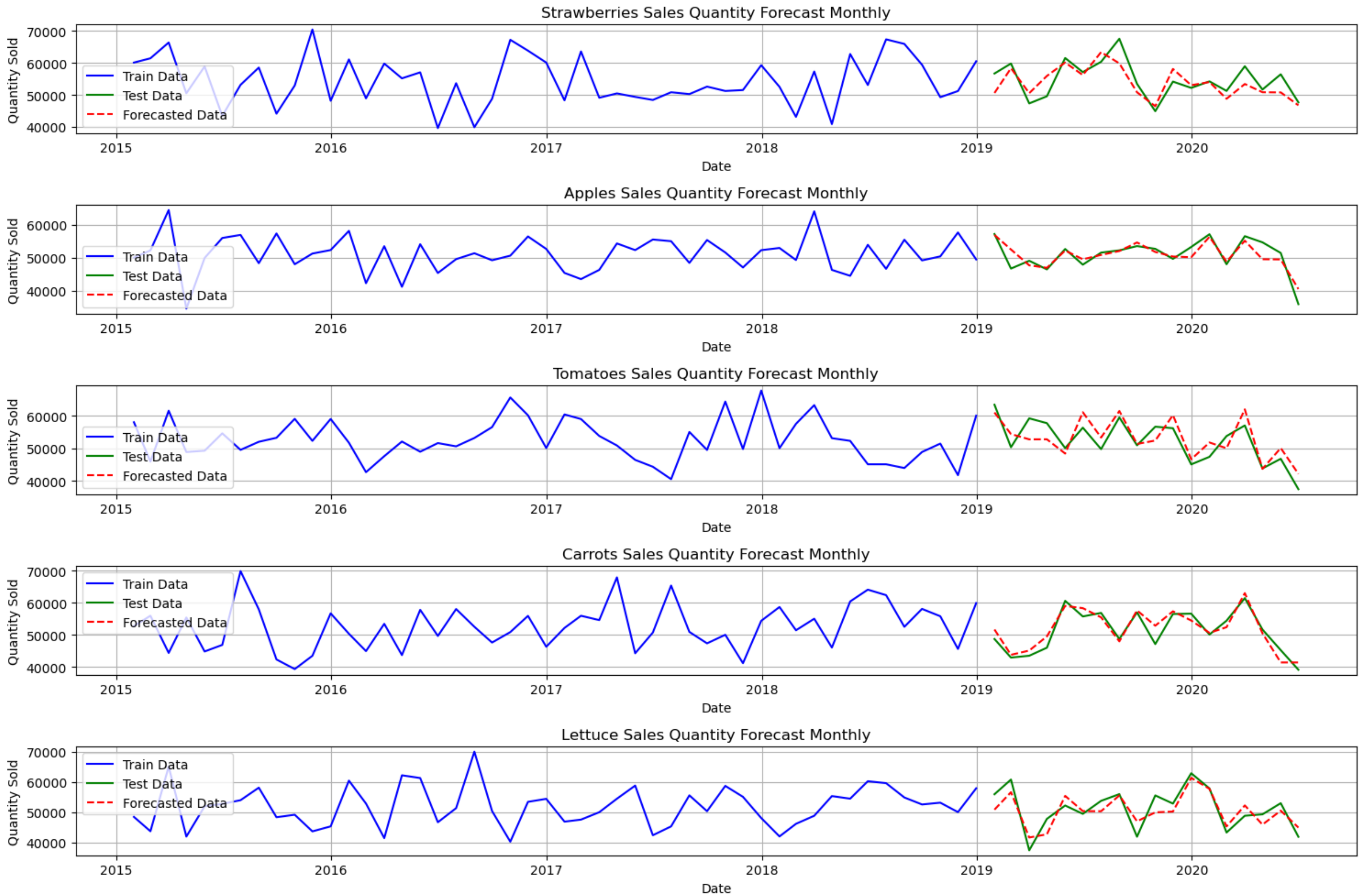
```python

# Initialize variables for evaluation metrics
rf_mae, rf_rmse, rf_mape = 0, 0, 0

# Dictionaries to store models and forecasts
rf_mape_scores = dict()
rf_X_train_dates = dict()
rf_X_test_dates = dict()
rf_y_train = dict()
rf_y_test = dict()
rf_forecasts = dict()

for product in products:
    df_product = df[df['Product'] == product]

    df_product = pd.get_dummies(df_product, drop_first=True)

    df_product = df_product.set_index('Date').resample('M').sum().reset_index()

    df_product['Year'] = df_product['Date'].dt.year
    df_product['Month'] = df_product['Date'].dt.month
    df_product['Day'] = df_product['Date'].dt.day
    df_product['WeekOfYear'] = df_product['Date'].dt.isocalendar().week

    # Prepare the data
    train = df_product[df_product['Year'] < 2019].reset_index()
    test = df_product[df_product['Year'] >= 2019].reset_index()

    rf_X_train_dates[product] = train['Date']
    rf_X_test_dates[product] = test['Date']

    train = train.drop(columns=['Date'])
    test = test.drop(columns=['Date'])

    X_train = train.drop(columns=['Quantity_Sold', 'Revenue'])
    y_train = train['Quantity_Sold']

    X_test = test.drop(columns=['Quantity_Sold', 'Revenue'])
    y_test = test['Quantity_Sold']

    rf_y_train[product] = y_train
```

```
    rf_y_test[product] = y_test

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

    forecast = model.predict(X_test)
    rf_forecasts[product] = forecast

    product_mae = mean_absolute_error(y_test, forecast)
    product_rmse = mean_squared_error(y_test, forecast, squared=False)
    product_mape = mean_absolute_percentage_error(y_test, forecast) * 100

    rf_mae += product_mae
    rf_rmse += product_rmse
    rf_mape += product_mape

    rf_mape_scores[product] = product_mape

# Calculate average metrics
n_products = len(products)
rf_mae /= n_products
rf_rmse /= n_products
rf_mape /= n_products

print('Random Forest MAE:', rf_mae)
print('Random Forest RMSE:', rf_rmse)
print('Random Forest MAPE:', rf_mape)
```

```
Random Forest MAE: 2661.934684588824
Random Forest RMSE: 3177.6926944638376
Random Forest MAPE: 5.203538526320775
```

In [85]:

```

plt.figure(figsize=(15, 10))

for i, product in enumerate(products):
    plt.subplot(n_products, 1, i + 1)

    if product in rf_X_train_dates and product in rf_y_train:
        # Plot actual vs forecast
        plt.plot(rf_X_train_dates[product], rf_y_train[product], color='blue', label='Actual Quantity Sol
        plt.plot(rf_X_test_dates[product], rf_y_test[product], color='green', label='Actual Quantity Sold
        plt.plot(rf_X_test_dates[product], rf_forecasts[product], color='red', linestyle='dashed', label=

        plt.title(f'{product} Sales Quantity Forecast Monthly')
        plt.xlabel('Date')
        plt.ylabel('Quantity Sold')
        plt.legend(['Train Data', 'Test Data', 'Forecasted Data'])
        plt.grid(True)
    else:
        print(f"Data for '{product}' not found in rf_X_train_dates or rf_y_train.")

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



Strawberries Sales Quantity Forecast Monthly
Apples Sales Quantity Forecast Monthly
Tomatoes Sales Quantity Forecast Monthly
Carrots Sales Quantity Forecast Monthly
Lettuce Sales Quantity Forecast Monthly
Train Data
Test Data
Forecasted Data
Quantity Sold
Date
2015
2016
2017
2018
2019
2020

Conclusion

In [86]:

```python
arima_mape_scores['--Average--'] = np.mean([v for k, v in arima_mape_scores.items()])
prophet_mape_scores['--Average--'] = np.mean([v for k,v in prophet_mape_scores.items()])
rf_mape_scores['--Average--'] = np.mean([v for k, v in rf_mape_scores.items()])


pd.DataFrame({'ARIMA':arima_mape_scores,
              'Prophet': prophet_mape_scores,
              'RandomForestRegressor': rf_mape_scores})
```

Out[86]:

	ARIMA	Prophet	RandomForestRegressor
Strawberries	8.252509	8.665478	5.482484
Apples	7.672138	10.521305	3.627103
Tomatoes	11.009154	12.012712	6.526076
Carrots	11.643805	18.719716	4.069554
Lettuce	11.280264	16.485064	6.312475
--Average--	9.971574	13.280855	5.203539

Findings

1. Demand Patterns:

- Seasonality significantly influences demand, with certain months showing peaks.

2. Key Influencers:

- Weather conditions, particularly temperature and rainfall, have a strong correlation with demand.

3. Product Variability:

- Different products exhibit varied demand patterns and seasonal peaks.

Recommendations

1. Adjust Harvest Schedules:

- Use demand forecasts to adjust harvest schedules, ensuring alignment with market demand.

2. Diversify Product Offering:

- Consider diversifying the product range to stabilize revenue throughout the year.

3. Enhance Data Collection:

- Improve data collection methods for more accurate and comprehensive forecasting.

4. Leverage the Best Performing Model:

- The RandomForestRegressor consistently outperformed ARIMA and Prophet across all products. Thus, it is recommended to primarily use the RandomForestRegressor for demand forecasting.

5. Tailor Strategies to Product-Specific Insights:

- Strawberries:
  - With the lowest error rate, focus on refining the model to maintain accuracy.
  - Implement strategies to optimize strawberry production based on accurate forecasts.
- Apples:
  - Continue using RandomForestRegressor due to its high accuracy.
  - Consider exploring additional features to improve the model further.
- Tomatoes, Carrots, and Lettuce:
  - Despite higher error rates compared to strawberries and apples, the RandomForestRegressor still outperforms other models.
  - Focus on data quality and potentially additional features specific to these crops to reduce errors.

6. Model Improvement and Maintenance:

- Regularly monitor the performance of the RandomForestRegressor to ensure its predictive accuracy remains high.
- Periodically retrain the model with new data to adapt to changing market conditions and trends.

7. Data Collection Enhancements:

- Improve the quality and granularity of data collected, particularly for products with higher prediction errors, to enhance model accuracy.
- Consider additional data points such as soil conditions, pest infestations, and more detailed weather patterns.

Future Work

1. Incorporate More Variables:

- Include additional factors like market trends and competitor data for more robust forecasting.

2. Continuous Model Improvement:

- Regularly update and refine models to adapt to changing market conditions.

3. Real-time Forecasting:

- Implement real-time data processing and forecasting to enable more responsive decision-making.

In [ ]:

```
```