Pharmaceutical Supply Chain Inventory Optimization: Predicting Energy Consumption

Business Overview/Problem

PharmaCorp faces a significant business challenge related to the optimization of its pharmaceutical supply chain inventory. The primary issues include:

A. Overproduction and Losses: PharmaCorp often produces medications in quantities that exceed market demand. This overproduction leads to substantial financial losses due to expired shelf-life and the need for disposal of unsold products.

B. Shelf Life Management: Managing the varying shelf lives of different pharmaceutical products is a complex task. Failure to sell products before their expiration date not only results in financial losses but also poses potential risks to patient safety.

C. Market Trends: The pharmaceutical industry is highly dynamic, with market trends and demand patterns constantly evolving. PharmaCorp struggles to align its production schedules with these ever-changing market dynamics.

D. Competitive Pressures: PharmaCorp faces intense competition from other pharmaceutical companies. Efficient inventory management is crucial to maintaining a competitive edge and optimizing costs.

Rationale for the Project

Rationale for the Project Supply Chain Inventory Optimization is the process of managing inventory levels in a supply chain to minimize costs while meeting customer demand. It is crucial in the pharmaceutical industry because of the perishable nature of drugs and the need to maintain a high level of quality control. The significance of initiating this project lies in several compelling reasons:

A. Cost Reduction: PharmaCorp incurs significant financial losses due to overproduction and inventory mismanagement. Optimizing inventory based on shelf life and market trends can lead to substantial cost reductions.

B. Enhanced Profitability: Reducing losses from overproduction and minimizing waste will directly impact PharmaCorp's profitability, allowing resources to be allocated more efficiently.

C. Competitive Advantage: Efficient inventory management will provide PharmaCorp with a competitive advantage by allowing the company to respond more effectively to market trends and customer demands.

D. Sustainability: Reducing overproduction and waste aligns with PharmaCorp's commitment to sustainability and responsible business practices.

Aim of the Project

The project aims to achieve the following objectives:

- Reduce Overproduction: Implement an inventory optimization strategy that significantly reduces overproduction of pharmaceutical products.

- Minimize Losses: Minimize financial losses associated with expired products by aligning inventory with shelf life.

- Improve Forecasting: Enhance demand forecasting accuracy by incorporating market trends and historical sales data.

Data Description

The dataset available from the company contains the following information:

- Product ID: Product unique identifier, for each product.
- Shelf Life Days: Shelf life of the pharmaceutical product in days.
- Sales 2021: Total number of sales of that product in 2021.
- Sales 2022: Total number of sales of that product in 2022.
- Market Trend Factor: An index that measures factors like market trends, consumer preferences, competitor actions, and other external factors.
- Compliance Status: This is an indication of whether or not a drug is compliant with regulation. Can be either of two things ‘Compliant’ or ‘Non-compliant’.

Tools

Programming Language

- Python

Libraries and Packages

- Pandas
- NumPy

Data Visualization

- Matplotlib
- Seaborn

Machine Learning:

- Scikit-learn (Sklearn)
- DecisionTreeRegressor
- LabelEncoder
- Metrics (mean_absolute_error, mean_squared_error, mean_absolute_percentage_error

1. Import Packages

In [47]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import (mean_absolute_error,
                             mean_absolute_percentage_error,
                             mean_squared_error)

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

2. Data Exploration and preprocessing

In [2]:
```
df = pd.read_csv('Dataset.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	Product_ID	Shelf_Life_Days	Sales_2021	Sales_2022	Market_Trend_Factor	Compliance_Status	Supplier_ID	Manufacturing_Location
0	Product_1	277	602.6	545	0.906303	Compliant	Supplier_2	Location_B
1	Product_2	343	359.4	345	0.972500	Compliant	Supplier_1	Location_C
2	Product_3	291	983.0	915	1.026074	Non-compliant	Supplier_5	Location_C
3	Product_4	298	789.4	751	0.911503	Compliant	Supplier_8	Location_C
4	Product_5	260	326.8	430	1.052617	Compliant	Supplier_10	Location_A

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Product_ID                0
Shelf_Life_Days           0
Sales_2021                0
Sales_2022                0
Market_Trend_Factor       0
Compliance_Status         0
Supplier_ID               0
Manufacturing_Location    0
Product_Category          0
Safety_Stock_Days         0
Storage_Location          0
dtype: int64
```

In [5]:
```
1 df.describe()
```

Out[5]:

	Shelf_Life_Days	Sales_2021	Sales_2022	Market_Trend_Factor	Safety_Stock_Days
count	19381.000000	19381.000000	19381.000000	19381.000000	19381.000000
mean	301.737939	618.423250	618.798256	0.999851	21.327073
std	25.576353	239.313199	220.590729	0.257548	7.090764
min	260.000000	80.000000	234.000000	0.078110	6.000000
25%	278.000000	429.000000	429.000000	0.823775	16.000000
50%	302.000000	619.200000	621.000000	1.000239	21.000000
75%	326.000000	811.200000	809.000000	1.175179	27.000000
max	344.000000	1155.400000	999.000000	1.909161	42.000000

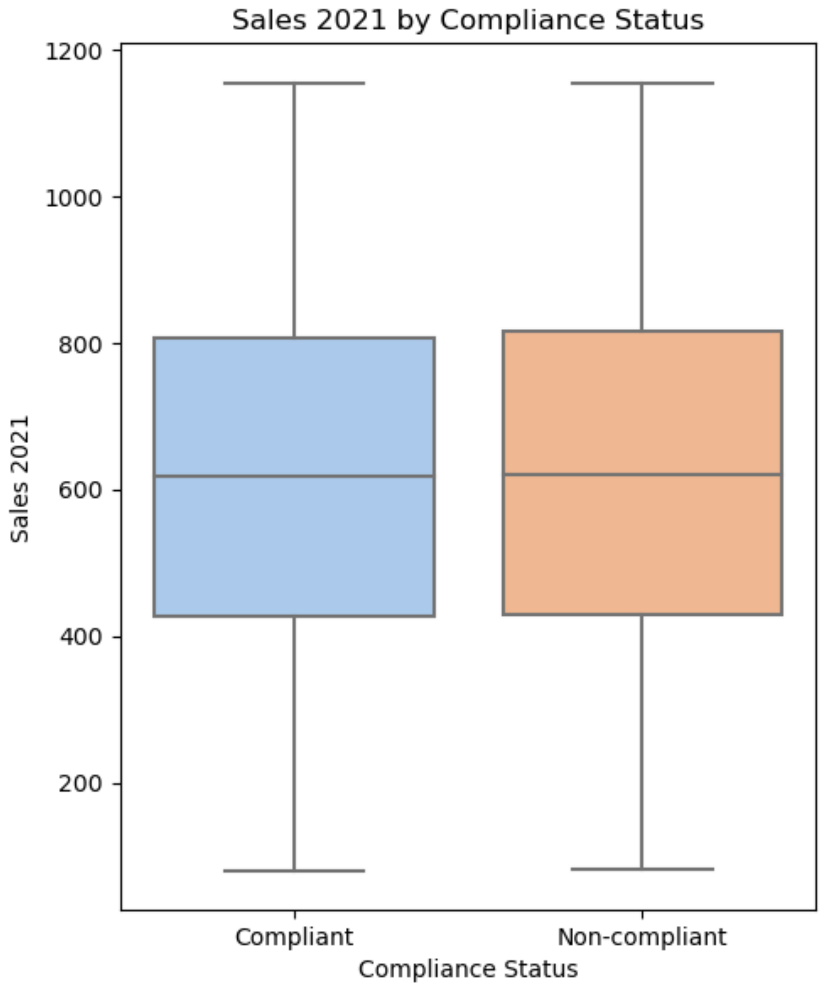
In [6]:
```
1 df.duplicated().all()
```

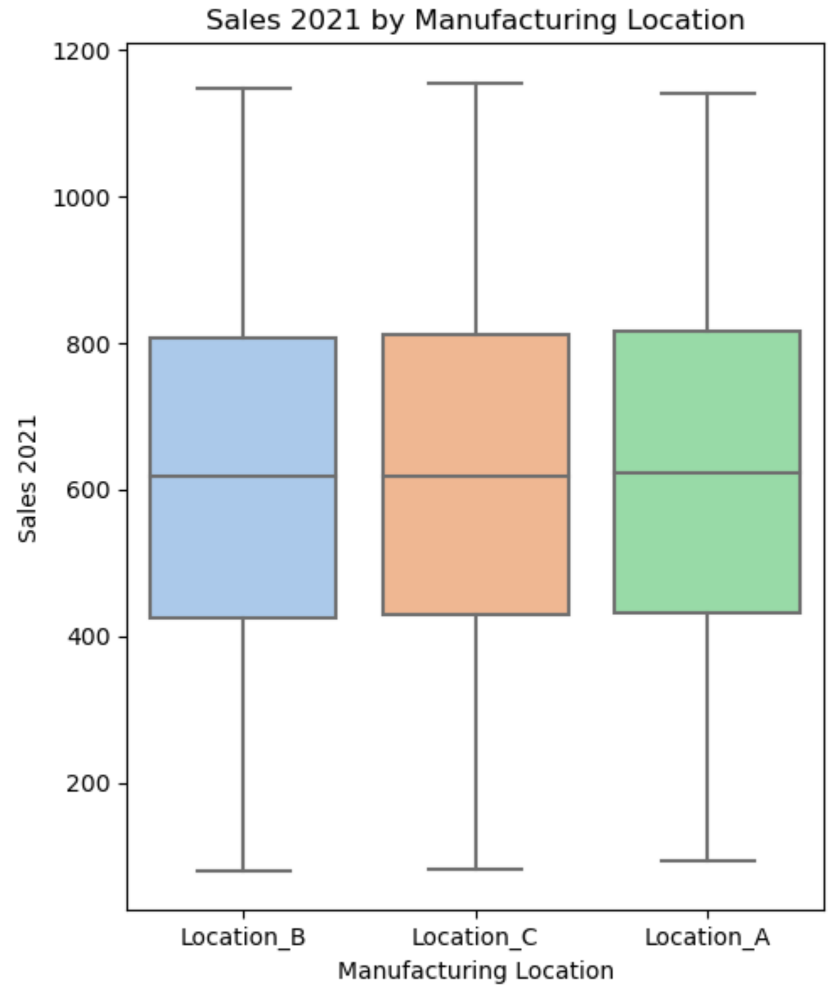
Out[6]: False

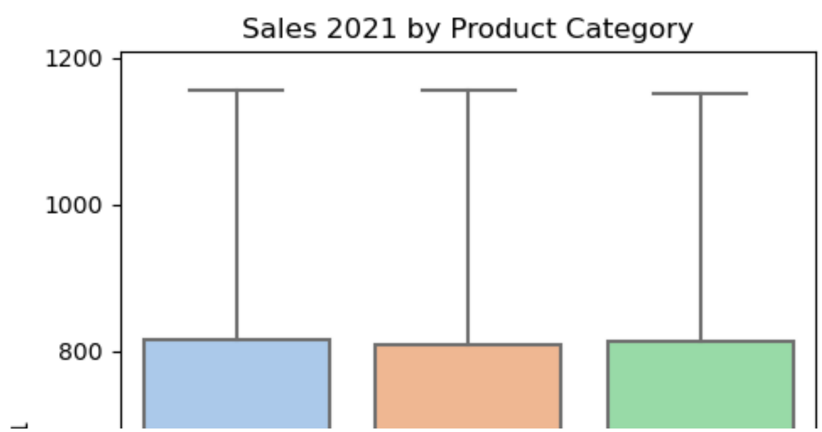
2.2 Bivariate Analysis

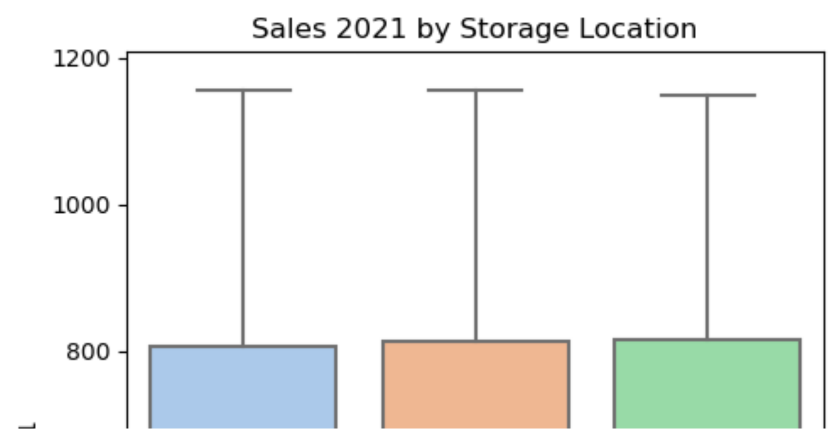
In [7]:

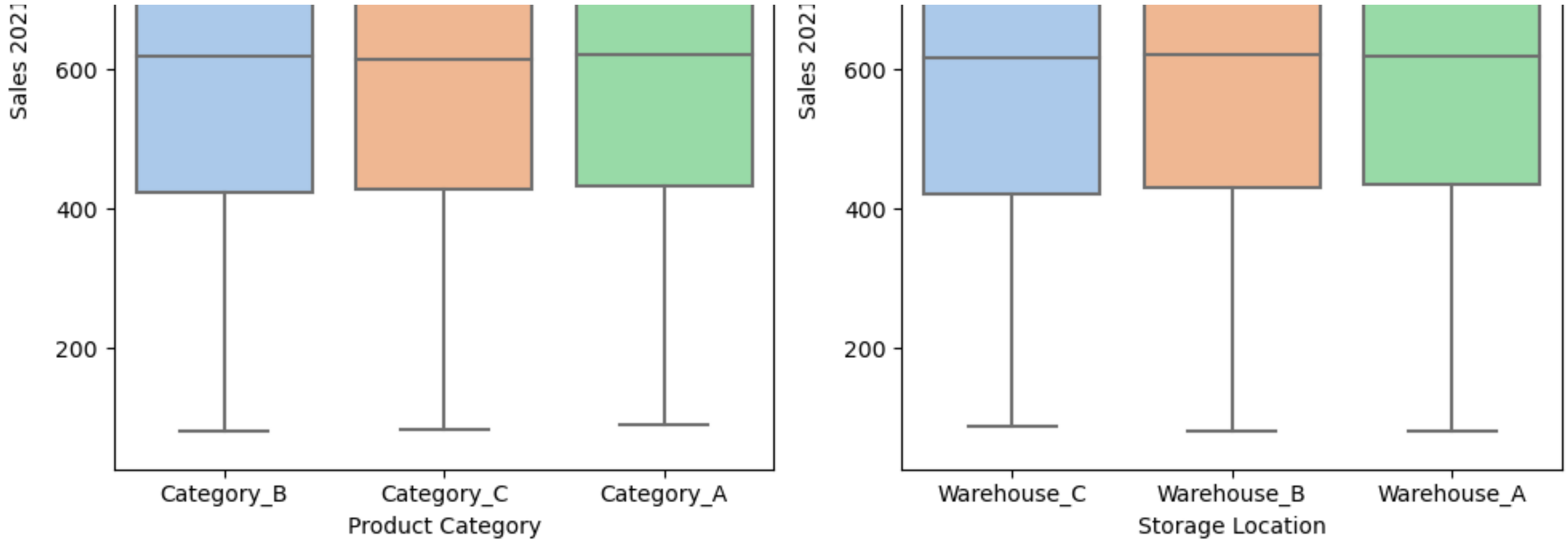
```
import matplotlib.pyplot as plt
import seaborn as sns

fig, ax = plt.subplots(2, 2, figsize=(10, 12))

# Sales 2021 against Compliance Status
sns.boxplot(data=df, x='Compliance_Status', y='Sales_2021', ax=ax[0, 0], palette='pastel')
ax[0, 0].set_title('Sales 2021 by Compliance Status')
ax[0, 0].set_xlabel('Compliance Status')
ax[0, 0].set_ylabel('Sales 2021')

# Sales 2021 against Manufacturing Location
sns.boxplot(data=df, x='Manufacturing_Location', y='Sales_2021', ax=ax[0, 1], palette='pastel')
ax[0, 1].set_title('Sales 2021 by Manufacturing Location')
ax[0, 1].set_xlabel('Manufacturing Location')
ax[0, 1].set_ylabel('Sales 2021')

# Sales 2021 against Product Category
sns.boxplot(data=df, x='Product_Category', y='Sales_2021', ax=ax[1, 0], palette='pastel')
ax[1, 0].set_title('Sales 2021 by Product Category')
ax[1, 0].set_xlabel('Product Category')
ax[1, 0].set_ylabel('Sales 2021')

# Sales 2021 against Storage Location
sns.boxplot(data=df, x='Storage_Location', y='Sales_2021', ax=ax[1, 1], palette='pastel')
ax[1, 1].set_title('Sales 2021 by Storage Location')
ax[1, 1].set_xlabel('Storage Location')
ax[1, 1].set_ylabel('Sales 2021')

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


Sales 2021 by Compliance Status
Sales 2021
1200
1000
800
600
400
200
Compliant
Non-compliant
Compliance Status


Sales 2021 by Manufacturing Location
Sales 2021
1200
1000
800
600
400
200
Location_B
Location_C
Location_A
Manufacturing Location


Sales 2021 by Product Category
1200
1000
800

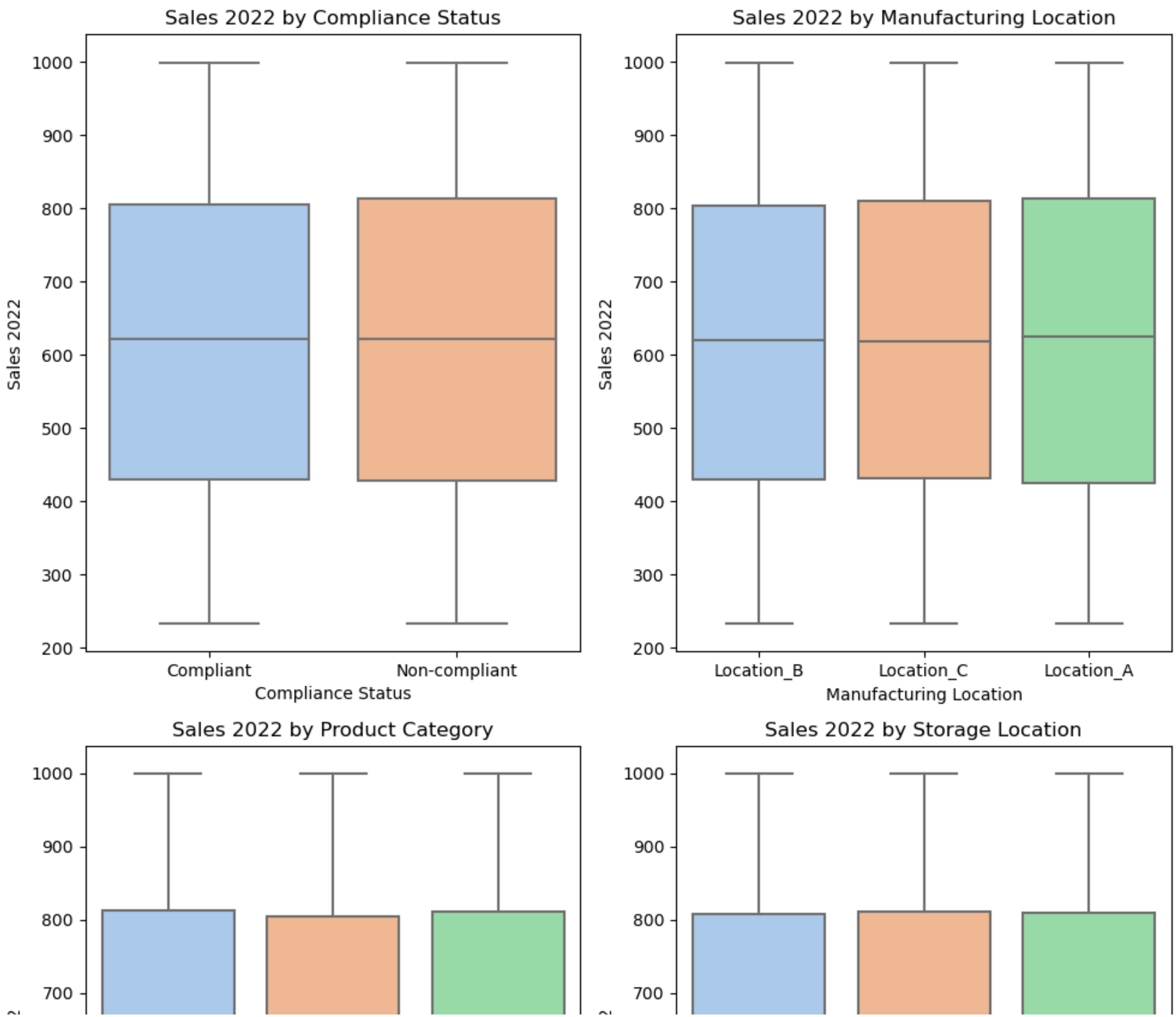

Sales 2021 by Storage Location
1200
1000
800

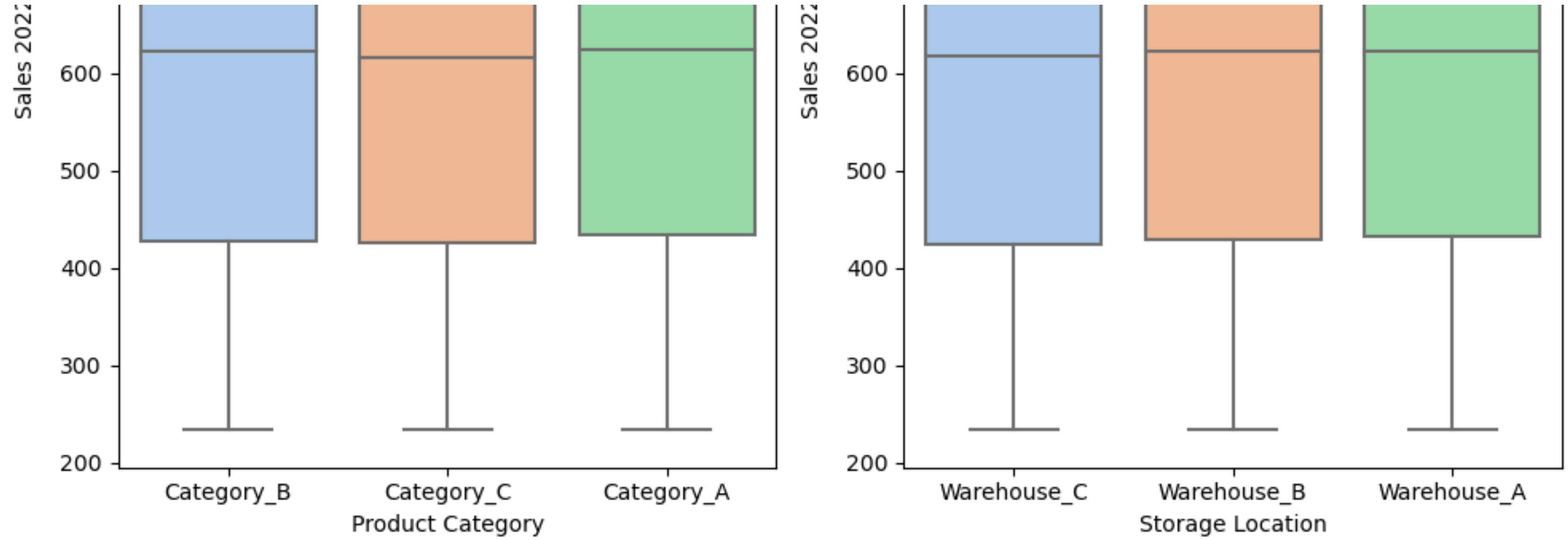


2.2.1 Sales 2022 against Categorical Variables

In [8]:

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

fig, ax = plt.subplots(2, 2, figsize=(10, 12))

# Sales 2022 against Compliance Status
sns.boxplot(data=df, x='Compliance_Status', y='Sales_2022', ax=ax[0, 0], palette='pastel')
ax[0, 0].set_title('Sales 2022 by Compliance Status')
ax[0, 0].set_xlabel('Compliance Status')
ax[0, 0].set_ylabel('Sales 2022')

# Sales 2022 against Manufacturing Location
sns.boxplot(data=df, x='Manufacturing_Location', y='Sales_2022', ax=ax[0, 1], palette='pastel')
ax[0, 1].set_title('Sales 2022 by Manufacturing Location')
ax[0, 1].set_xlabel('Manufacturing Location')
ax[0, 1].set_ylabel('Sales 2022')

# Sales 2022 against Product Category
sns.boxplot(data=df, x='Product_Category', y='Sales_2022', ax=ax[1, 0], palette='pastel')
ax[1, 0].set_title('Sales 2022 by Product Category')
ax[1, 0].set_xlabel('Product Category')
ax[1, 0].set_ylabel('Sales 2022')

# Sales 2022 against Storage Location
sns.boxplot(data=df, x='Storage_Location', y='Sales_2022', ax=ax[1, 1], palette='pastel')
ax[1, 1].set_title('Sales 2022 by Storage Location')
ax[1, 1].set_xlabel('Storage Location')
ax[1, 1].set_ylabel('Sales 2022')

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


Sales 2022 by Compliance Status
Sales 2022
1000
900
800
700
600
500
400
300
200
Compliant
Non-compliant
Compliance Status
Sales 2022 by Manufacturing Location
Location_B
Location_C
Location_A
Manufacturing Location
Sales 2022 by Product Category
Sales 2022 by Storage Location

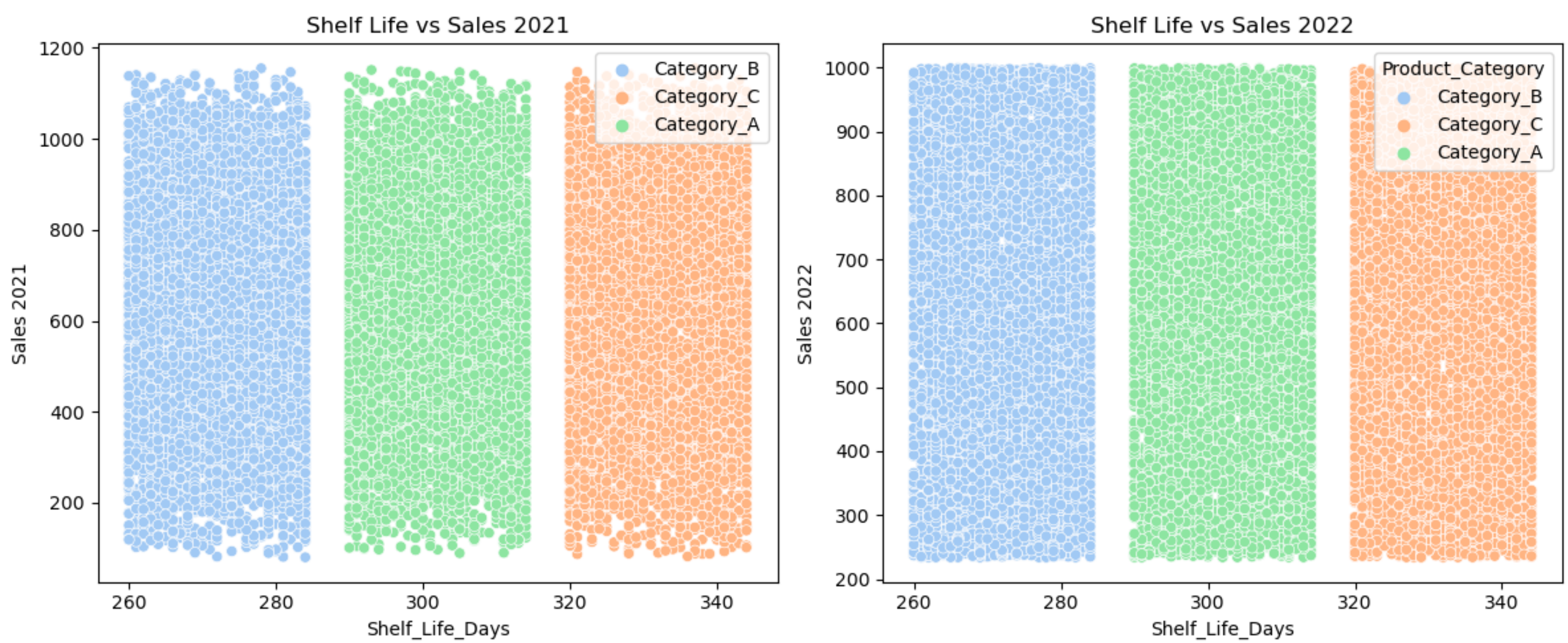


2.2.2 Bivariariate Analysis: sales against Numerical Variables

Sales against "Shelf_life_Days" and Market_Trend_Factor

In [9]:

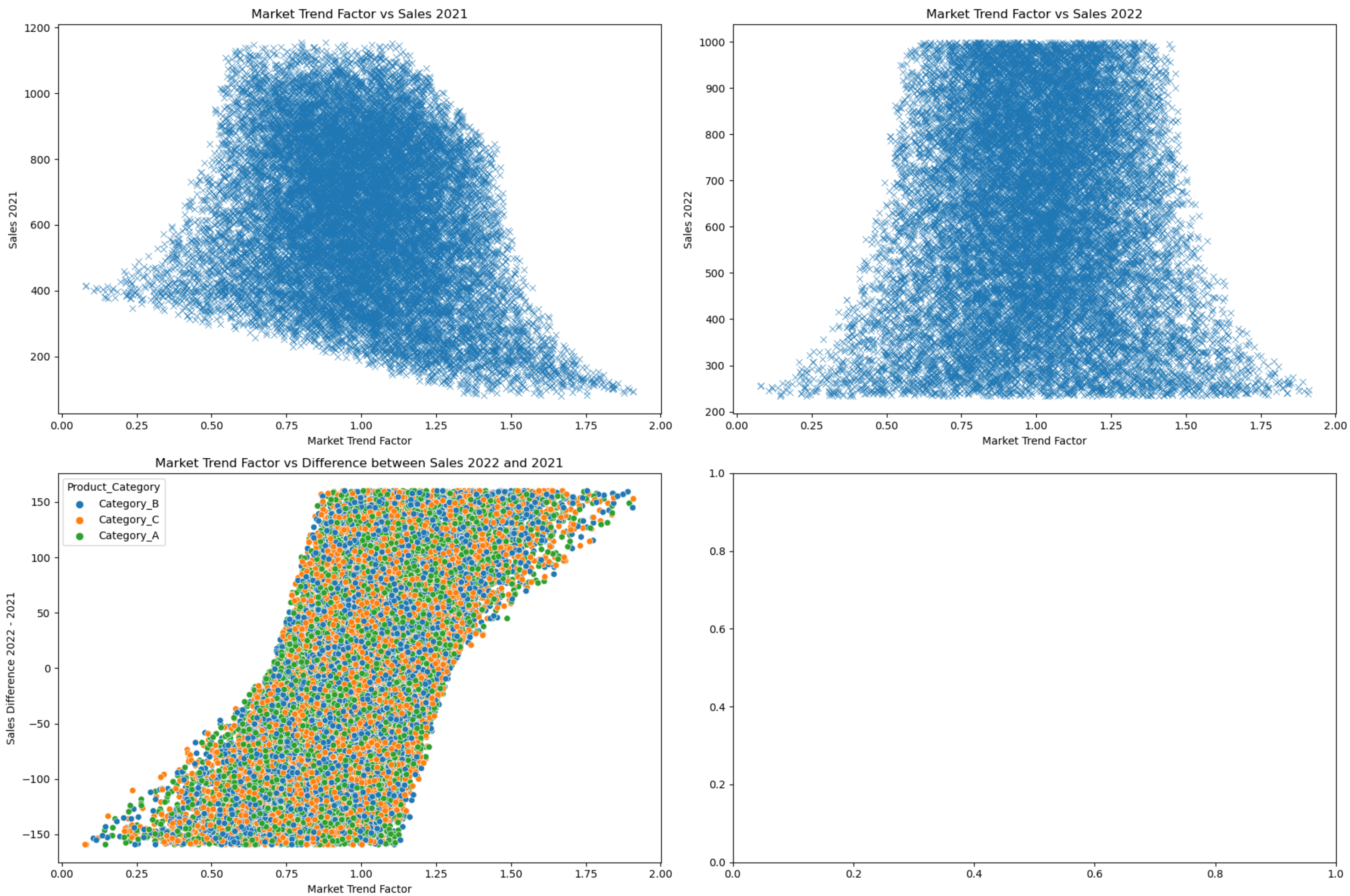
```
fig, ax = plt.subplots(1, 2, figsize= (12, 5))

# shelf Life Days against Sales 2021
sns.scatterplot(data=df, x='Shelf_Life_Days', y='Sales_2021', ax=ax[0], hue= 'Product_Category', palette=
ax[0].set_title('Shelf Life vs Sales 2021')
ax[0].set_xlabel('Shelf_Life_Days')
ax[0].set_ylabel('Sales 2021')
ax[0].legend(loc = 'upper right')


# shelf Life Days against Sales 2022
sns.scatterplot(data=df, x='Shelf_Life_Days', y='Sales_2022', ax=ax[1], hue = 'Product_Category', palette
ax[1].set_title('Shelf Life vs Sales 2022')
ax[1].set_xlabel('Shelf_Life_Days')
ax[1].set_ylabel('Sales 2022')
ax[0].legend(loc = 'upper right')

plt.tight_layout()
plt.show()

```



Next Plot for Sales_2021, Sales_2022, Market_Trend_Factor

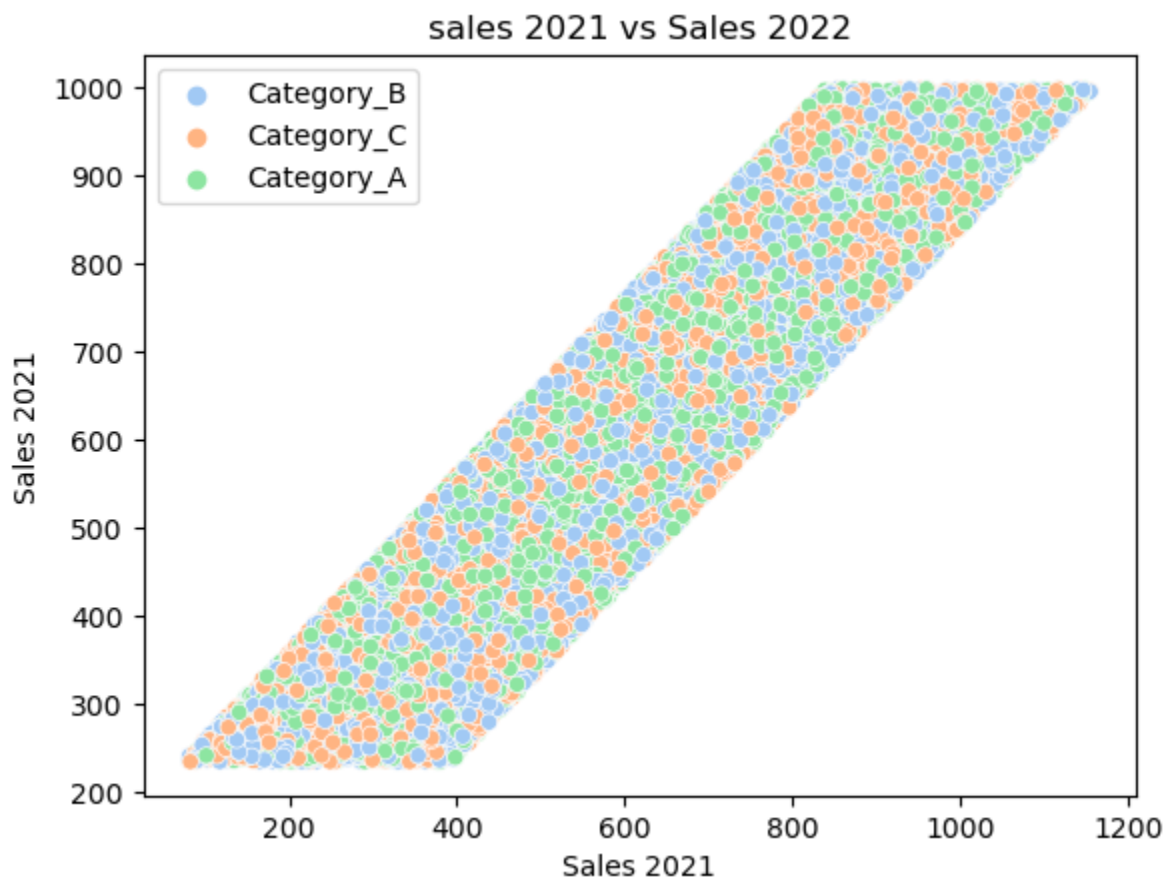
In [10]:

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

fig, ax = plt.subplots(2, 2, figsize=(18, 12))

# Market Trend Factor against Sales 2021
sns.scatterplot(data=df, x='Market_Trend_Factor', y='Sales_2021', ax=ax[0, 0], marker='x')
ax[0, 0].set_title('Market Trend Factor vs Sales 2021')
ax[0, 0].set_xlabel('Market Trend Factor')
ax[0, 0].set_ylabel('Sales 2021')

# Market Trend Factor against Sales 2022
sns.scatterplot(data=df, x='Market_Trend_Factor', y='Sales_2022', ax=ax[0, 1], marker='x')
ax[0, 1].set_title('Market Trend Factor vs Sales 2022')
ax[0, 1].set_xlabel('Market Trend Factor')
ax[0, 1].set_ylabel('Sales 2022')

# Market Trend Factor against difference between sales 2022 and 2021
df['Sales_2022-sales_2021'] = df['Sales_2022'] - df['Sales_2021']
sns.scatterplot(data=df, x='Market_Trend_Factor', y='Sales_2022-sales_2021', ax=ax[1, 0], hue='Product_Ca
ax[1, 0].set_title('Market Trend Factor vs Difference between Sales 2022 and 2021')
ax[1, 0].set_xlabel('Market Trend Factor')
ax[1, 0].set_ylabel('Sales Difference 2022 - 2021')

plt.tight_layout()
plt.show()

```



Bivariate Analysis: Sales for 2021 and 2022

In [11]:
```
sns.scatterplot(data=df, x='Sales_2021', y='Sales_2022', hue= 'Product_Category', palette='pastel')
plt.title('sales 2021 vs Sales 2022')
plt.xlabel('Sales 2021')
plt.ylabel('Sales 2021')
plt.legend(loc='upper left')
plt.show()
```



This is a positive correlation

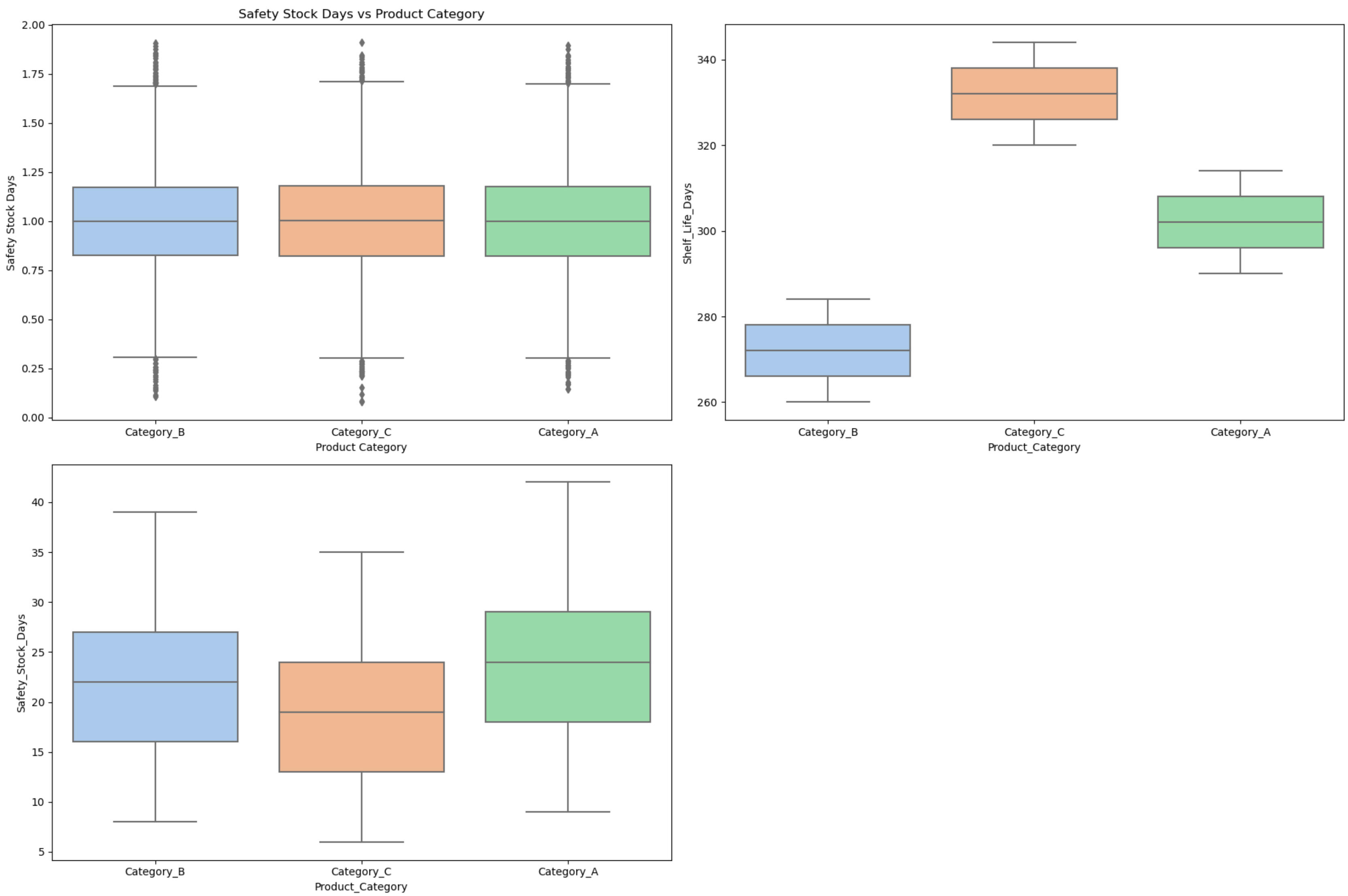
Bivariate Analysis: Other pairs of variables

Product_Category against

- 'Market_Trend_Days',
- 'Safety_StockDays'

In [12]:

```
fig, ax = plt.subplots(2,2, figsize=(18, 12))

# Market Trend Factor and Product Category
sns.boxplot(data=df, x='Product_Category', y='Market_Trend_Factor', ax=ax[0,0], palette= 'pastel')
ax[0,0].set_title('Market Trend Factor vs Product Category')
ax[0,0].set_xlabel('Product Category')
ax[0,0].set_ylabel('Market Trend Factor')


# Shelf Life days and Product Category
sns.boxplot(data=df, x='Product_Category', y='Shelf_Life_Days', ax=ax[0,1], palette= 'pastel')
ax[0,0].set_title('Shelf Life Days vs Product Category')
ax[0,0].set_xlabel('Product Category')
ax[0,0].set_ylabel('Shelf Life Days')


# Safety Stock Days and Product Category
sns.boxplot(data=df, x='Product_Category', y='Safety_Stock_Days', ax=ax[1,0], palette= 'pastel')
ax[0,0].set_title('Safety Stock Days vs Product Category')
ax[0,0].set_xlabel('Product Category')
ax[0,0].set_ylabel('Safety Stock Days')

ax[1,1].remove()

plt.tight_layout()
plt.show()

```


Safety Stock Days vs Product Category
Safety Stock Days
Product Category
Category_B
Category_C
Category_A
Shelf_Life_Days
Product_Category
Safety_Stock_Days
Product_Category

In [13]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19381 entries, 0 to 19380
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Product_ID              19381 non-null  object 
 1   Shelf_Life_Days         19381 non-null  int64  
 2   Sales_2021              19381 non-null  float64
 3   Sales_2022              19381 non-null  int64  
 4   Market_Trend_Factor     19381 non-null  float64
 5   Compliance_Status       19381 non-null  object 
 6   Supplier_ID             19381 non-null  object 
 7   Manufacturing_Location  19381 non-null  object 
 8   Product_Category        19381 non-null  object 
 9   Safety_Stock_Days       19381 non-null  int64  
 10  Storage_Location        19381 non-null  object 
 11  Sales_2022-sales_2021   19381 non-null  float64
dtypes: float64(3), int64(3), object(6)
memory usage: 1.8+ MB
```

3. Demand Forecasting and Inventory Optimization

-Using 'Market_Trend_Factor' and Sales_2022

3.1 Demnd Forecasting and Inventory Optimization; Using Market trend Factor

Market_Trend_Factor' and Sales_2022

Feature Engineering

In [14]:
```
df_mtf = df.copy()

df_mtf['Projected_Sales_2023'] = df_mtf['Sales_2022'] * df_mtf['Market_Trend_Factor']
df_mtf['Projected_Sales_2023'] = df_mtf['Projected_Sales_2023'].apply(lambda x: x if x >=0 else 0)
```

Encoding The Categorical Variables

In [15]:
```
from sklearn.preprocessing import LabelEncoder



# Columns to encode
cols = ['Compliance_Status', 'Supplier_ID', 'Manufacturing_Location', 'Product_Category', 'Storage_Locati

# Label encoding
label_encoder = {}

for column in cols:
    le = LabelEncoder()
    df_mtf[column] = le.fit_transform(df_mtf[column])
    label_encoder[column] = le
```

In [16]:
```
df_mtf.head()
```

Out[16]:

	Product_ID	Shelf_Life_Days	Sales_2021	Sales_2022	Market_Trend_Factor	Compliance_Status	Supplier_ID	Manufacturing_Location
0	Product_1	277	602.6	545	0.906303	0	2	1
1	Product_2	343	359.4	345	0.972500	0	0	2
2	Product_3	291	983.0	915	1.026074	1	5	2
3	Product_4	298	789.4	751	0.911503	0	8	2
4	Product_5	260	326.8	430	1.052617	0	1	0

3.1.2 Prepare X and Y data

In [17]:
```
# Splitting into features and target
x = df_mtf.drop(columns=['Product_ID', 'Projected_Sales_2023'])
y = df_mtf['Projected_Sales_2023']
```

In [18]:
```
from sklearn.model_selection import train_test_split

# Splitting the data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)
```

In [19]:
```
# Initialize and train the model
model = DecisionTreeRegressor(random_state=42)
model.fit(x_train, y_train)

# Make predictions
y_pred = model.predict(x_test)

mae = mean_absolute_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred) * 100


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

```
MAE: 6.221055387690978
RMSE: 70.98980614116753
MAPE: 1.1952156870085173
```

3.1.3 Inventory Optimization

Get average daily sales

In [20]:
```
df_mtf['Average_Daily_Sales'] = (df_mtf['Sales_2021'] + df_mtf['Sales_2022']) / (2 * 365)
```

Get Safety Stock

In [21]:
```
df_mtf['Safety_Stock'] = df_mtf['Safety_Stock_Days'] * df_mtf['Average_Daily_Sales']
```

Optimal Inventory For 2023

In [22]:
```
df_mtf['Optimal_Inventory_2023'] = df_mtf['Projected_Sales_2023'] + df_mtf['Safety_Stock']
```

Including Shelf Life In Our Estimation

In [23]:
```
df_mtf['Optimal_Inventory_2023'] = df_mtf.apply(lambda row: min(row['Optimal_Inventory_2023'],
                                                                row['Shelf_Life_Days'] * row['Average_Dail
```

3.2. Demand Forecasting And I nventory Optimization: Linear Projection

3.2.1 Feature Engineering

Generally, the formula is: $y = y_0 + Slope * (x_1 - x_0)$

$x = YEAR, y = SALES$

Generally, Slope is : $Slope = \frac{y_1 - y_0}{x_1 - x_0}$

So, for our usecase:

$$Projected\_Sales\_2023 = Sales\_2021 + Slope$$
$$= (2023 - 2021)$$

Type *Markdown* and LaTeX: α^2

In [27]:
```python
df_lp = df.copy()

slope = df_lp['Sales_2022'] - df_lp['Sales_2021']

df_lp['Projected_Sales_2023'] = df_lp['Sales_2021'] + 2 * slope

df_lp['Projected_Sales_2023'] = df_lp['Projected_Sales_2023'].apply(lambda x: x if x >= 0 else 0)
```

Encode the bcategorical variables

In [28]:
```python
cols = ['Compliance_Status',
       'Supplier_ID',
        'Manufacturing_Location',
        'Product_Category',
        'Storage_Location']

label_encoders = {}

for column in cols:
    le = LabelEncoder()
    df_lp[column] = le.fit_transform(df_lp[column])
    label_encoders[column] = le
```

In [29]:
```python
df_lp.head()
```

Out[29]:

	Product_ID	Shelf_Life_Days	Sales_2021	Sales_2022	Market_Trend_Factor	Compliance_Status	Supplier_ID	Manufacturing_Location
0	Product_1	277	602.6	545	0.906303	0	2	1
1	Product_2	343	359.4	345	0.972500	0	0	2
2	Product_3	291	983.0	915	1.026074	1	5	2
3	Product_4	298	789.4	751	0.911503	0	8	2
4	Product_5	260	326.8	430	1.052617	0	1	0

In [31]:
```python
x = df_lp.drop(columns=['Product_ID', 'Projected_Sales_2023'])
y = df_lp['Projected_Sales_2023']
```

In [33]:
```python
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(
    x,
    y,
    test_size=0.3,
    random_state=42
)
```

3.2.2 Demand Forecasting

Build the model.

In [34]:
```python
model = DecisionTreeRegressor()
model.fit(x_train, y_train)

y_pred = model.predict(x_test)

mae = mean_absolute_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
mape = mean_absolute_percentage_error(y_test, y_pred) * 100


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

```
MAE: 4.609733447979364
RMSE: 5.928638395485055
MAPE: 0.9320903139629664
```

3.2.3. Inventory Optimization

Get Average Daily Sales

In [35]:
```
df_lp['Average_Daily_Sales'] = (df_lp['Sales_2021'] + df_lp['Sales_2022']) / (2 * 365)
```

Get The Safety Stock

In [36]:
```
df_lp['Safety_Stock'] = df_lp['Safety_Stock_Days'] * df_lp['Average_Daily_Sales']
```

Optimal Inventory for 2023

In [37]:
```
df_lp['Optimal_Inventory_2023'] = df_lp['Projected_Sales_2023'] + df_lp['Safety_Stock']
```

Adjust this value to account for shelf life

In [39]:
```
df_lp['Optimal_Inventory_2023'] = df_lp.apply(lambda row: row['Shelf_Life_Days'] * row['Average_Daily_Sal

```

4. Conclusion

Results form Market Trend factor and Sales 2022

In [40]:
```
df_mtf[['Product_ID', 'Projected_Sales_2023', 'Safety_Stock', 'Optimal_Inventory_2023']].head()
```

Out[40]:

	Product_ID	Projected_Sales_2023	Safety_Stock	Optimal_Inventory_2023
0	Product_1	493.935278	34.585205	435.459178
1	Product_2	335.512507	23.158356	330.971507
2	Product_3	938.857721	62.400000	756.600000
3	Product_4	684.538694	42.202740	628.820822
4	Product_5	452.625369	21.770959	269.545205

Result from Linear PRojection: Sales 2021 and Sales 2022

In [41]:

```
df_lp[['Product_ID', 'Projected_Sales_2023', 'Safety_Stock', 'Optimal_Inventory_2023']].head()
```

Out[41]:

	Product_ID	Projected_Sales_2023	Safety_Stock	Optimal_Inventory_2023
0	Product_1	487.4	34.585205	435.459178
1	Product_2	330.6	23.158356	330.971507
2	Product_3	847.0	62.400000	756.600000
3	Product_4	712.6	42.202740	628.820822
4	Product_5	533.2	21.770959	269.545205

In [46]:

```
from sklearn.metrics import mean_squared_error

columns = ['Projected_Sales_2023', 'Optimal_Inventory_2023']

errors = dict()

for col in columns:
    mtf, lp = df_mtf[col], df_lp[col]

    mae = mean_absolute_error(mtf, lp)
    rmse = mean_squared_error(mtf, lp,)  # Correcting RMSE calculation
    mape = mean_absolute_percentage_error(mtf, lp) * 100

    errors[col] = [mae, rmse, mape]

pd.DataFrame(errors, index=['MAE', 'RMSE', 'MAPE'])

```

Out[46]:

	Projected_Sales_2023	Optimal_Inventory_2023
MAE	92.516408	21.767899
RMSE	12873.965456	3190.923775
MAPE	16.661423	7.636946

5. Recommendations

1. Implement an Advanced Predictive Analytics System Action: Adopt a state-of-the-art predictive analytics system that leverages machine learning models to forecast demand accurately. Benefit: This will enable PharmaCorp to anticipate market demand more effectively, reduce overproduction, and minimize the risk of stockouts, leading to more efficient inventory management.
2. Develop a Dynamic Shelf Life Management Program Action: Create a dynamic shelf life management program using real-time tracking technologies such as RFID and IoT sensors. Benefit: This program will help PharmaCorp monitor the expiration dates of products more closely, prioritize the sale of near-expiry items, and reduce financial losses due to expired inventory.
3. Enhance Supplier Collaboration and Integration Action: Establish stronger collaboration and data integration with suppliers to synchronize supply chain activities. Benefit: Improved communication and data sharing with suppliers can lead to better alignment of production schedules, reduced lead times, and more responsive supply chain operations, ensuring that inventory levels are optimized.
4. Adopt Lean Inventory Management Practices Action: Implement lean inventory management practices, such as Just-In-Time (JIT) inventory and continuous improvement (Kaizen) processes. Benefit: These practices will help PharmaCorp reduce excess inventory, lower carrying costs, and enhance operational efficiency by ensuring that inventory levels are closely aligned with actual demand.
5. Invest in Employee Training and Development Action: Provide ongoing training and development programs for the supply chain management team on the latest inventory optimization techniques and tools. Benefit: A well-trained team will be better equipped to make data-driven decisions, utilize advanced analytics tools effectively, and continuously improve inventory management processes, leading to enhanced performance and productivity.

In [ ]: