

Satellite Imagery Analysis for Finance

1. Setup and Import Libraries

```
In [22]: !pip install linearmodels

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from linearmodels.panel import PanelOLS
import warnings

pd.set_option('display.max_columns', None)
pd.set_option('display.precision', 4)
warnings.filterwarnings('ignore')

plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette('husl')

print("Libraries imported successfully!")
```

Requirement already satisfied: linearmodels in /usr/local/lib/python3.12/dist-packages (7.0)

Requirement already satisfied: numpy<3,>=1.22.3 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (2.0.2)

Requirement already satisfied: pandas>=1.4.0 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (2.2.2)

Requirement already satisfied: scipy>=1.8.0 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (1.16.3)

Requirement already satisfied: statsmodels>=0.13.0 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (0.14.6)

Requirement already satisfied: mpy_extensions>=0.4 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (1.1.0)

Requirement already satisfied: pyhdfe>=0.1 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (0.2.0)

Requirement already satisfied: formulaic>=1.2.1 in /usr/local/lib/python3.12/dist-packages (from linearmodels) (1.2.1)

Requirement already satisfied: interface-meta>=1.2.0 in /usr/local/lib/python3.12/dist-packages (from formulaic>=1.2.1->linearmodels) (1.3.0)

Requirement already satisfied: narwhals>=1.17 in /usr/local/lib/python3.12/dist-packages (from formulaic>=1.2.1->linearmodels) (2.15.0)

Requirement already satisfied: typing-extensions>=4.2.0 in /usr/local/lib/python3.12/dist-packages (from formulaic>=1.2.1->linearmodels) (4.15.0)

Requirement already satisfied: wrapt>=1.0 in /usr/local/lib/python3.12/dist-packages (from formulaic>=1.2.1->linearmodels) (2.0.1)

Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.4.0->linearmodels) (2.9.0.post0)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.4.0->linearmodels) (2025.2)

Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.4.0->linearmodels) (2025.3)

Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.12/dist-packages (from statsmodels>=0.13.0->linearmodels) (1.0.2)

Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.12/dist-packages (from statsmodels>=0.13.0->linearmodels) (25.0)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2->pandas>=1.4.0->linearmodels) (1.17.0)

Libraries imported successfully!

2. Generate Synthetic Satellite and Financial Data

```
In [23]: np.random.seed(42)

regions = ['North America', 'Europe', 'Asia', 'Latin America', 'Africa']
n_regions = len(regions)
n_quarters = 40
dates = pd.date_range(start='2015-01-01', periods=n_quarters, freq='Q')

data_list = []
for region in regions:
    region_base_light = np.random.uniform(50, 100)
    region_base_vehicles = np.random.uniform(1000, 5000)
    region_base_port = np.random.uniform(20, 80)
    region_growth_trend = np.random.uniform(-0.2, 0.5)
```

```

for i, date in enumerate(dates):
    time_trend = i / n_quarters
    macro_shock = np.sin(2 * np.pi * i / 8) * 5

    light_intensity = (region_base_light +
                      region_growth_trend * time_trend * 50 +
                      macro_shock +
                      np.random.normal(0, 5))

    vehicle_count = (region_base_vehicles +
                    0.3 * light_intensity +
                    np.random.normal(0, 200))

    port_congestion = (region_base_port +
                      0.2 * light_intensity +
                      macro_shock * 2 +
                      np.random.normal(0, 8))

    gdp_growth = (1.5 +
                 0.03 * (light_intensity - region_base_light) +
                 0.02 * macro_shock +
                 np.random.normal(0, 1.5))

    stock_return = (5 +
                   0.5 * gdp_growth +
                   0.02 * (light_intensity - region_base_light) +
                   np.random.normal(0, 3))

    data_list.append({
        'region': region,
        'date': date,
        'light_intensity': light_intensity,
        'vehicle_count': vehicle_count,
        'port_congestion': port_congestion,
        'gdp_growth': gdp_growth,
        'stock_return': stock_return
    })

df = pd.DataFrame(data_list)

print(f"Generated dataset with {len(df)} observations")
print(f"Regions: {n_regions}, Time periods: {n_quarters}")
df.head(10)

```

Generated dataset with 200 observations
Regions: 5, Time periods: 40

Out[23]:

	region	date	light_intensity	vehicle_count	port_congestion	gdp_growth	stock_return
0	North America	2015-03-31	67.5562	4776.2967	90.0646	2.6160	4.8765
1	North America	2015-06-30	75.2492	4732.7484	82.3147	2.1293	0.4551
2	North America	2015-09-30	65.6501	4710.0947	78.9470	1.9791	3.2031
3	North America	2015-12-31	66.0225	5115.7937	82.3890	1.5909	1.4671
4	North America	2016-03-31	67.1004	4845.1719	68.1318	2.0147	4.1721
5	North America	2016-06-30	65.1021	4702.0465	84.6872	1.3003	2.4041
6	North America	2016-09-30	69.4827	4579.5333	69.4871	-1.5168	0.2721
7	North America	2016-12-31	68.0926	4970.9783	71.8380	1.2368	4.7021
8	North America	2017-03-31	63.5250	4677.9459	72.9395	2.9296	7.3911
9	North America	2017-06-30	65.9118	4887.4476	81.0924	0.4709	7.0141

3. Data Structure and Summary Statistics

```
In [24]: print("Dataset Information:")
print(df.info())

# Summary statistics
print("Summary Statistics:")
summary_stats = df.describe()
summary_stats
```

Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 7 columns):
Column Non-Null Count Dtype
--- -----
0 region 200 non-null object
1 date 200 non-null datetime64[ns]
2 light_intensity 200 non-null float64
3 vehicle_count 200 non-null float64
4 port_congestion 200 non-null float64
5 gdp_growth 200 non-null float64
6 stock_return 200 non-null float64
dtypes: datetime64[ns](1), float64(5), object(1)
memory usage: 11.1+ KB
None
Summary Statistics:

Out[24]:

	date	light_intensity	vehicle_count	port_congestion	gdp_growth	stock_return
count	200	200.0000	200.0000	200.0000	200.0000	200.0000
mean	2020-02-14 06:00:00	81.2486	3505.1937	66.1672	1.7075	5.8514
min	2015-03-31 00:00:00	40.8933	1894.7340	27.8726	-1.7434	-3.5552
25%	2017-09-07 00:00:00	68.0066	3214.8944	54.7984	0.6148	3.8888
50%	2020-02-14 12:00:00	79.8101	3477.3090	64.9762	1.7320	5.7197
75%	2022-07-23 00:00:00	93.2124	3752.3987	78.6557	2.6822	7.6753
max	2024-12-31 00:00:00	117.3496	5264.4183	111.3720	5.4121	13.7181
std	NaN	15.8057	847.7699	16.0548	1.4810	3.1492

In [25]:

```
print("Summary Statistics by Region (Light Intensity):")
df.groupby('region')['light_intensity'].describe()
```

Summary Statistics by Region (Light Intensity):

Out[25]:

	count	mean	std	min	25%	50%	75%	max
region								
Africa	40.0	90.5993	7.0351	74.5104	86.2808	91.5026	95.2788	104.7560
Asia	40.0	102.3860	7.7455	84.3918	97.4848	102.1648	108.0043	117.3496
Europe	40.0	78.1709	8.2187	62.4187	71.4580	79.6888	83.1796	99.5244
Latin America	40.0	62.1428	6.3386	40.8933	59.7706	62.9656	64.3345	76.5279
North America	40.0	72.9441	7.3988	54.4618	67.7007	74.0594	77.0890	95.4473

4. Exploratory Data Analysis (EDA)

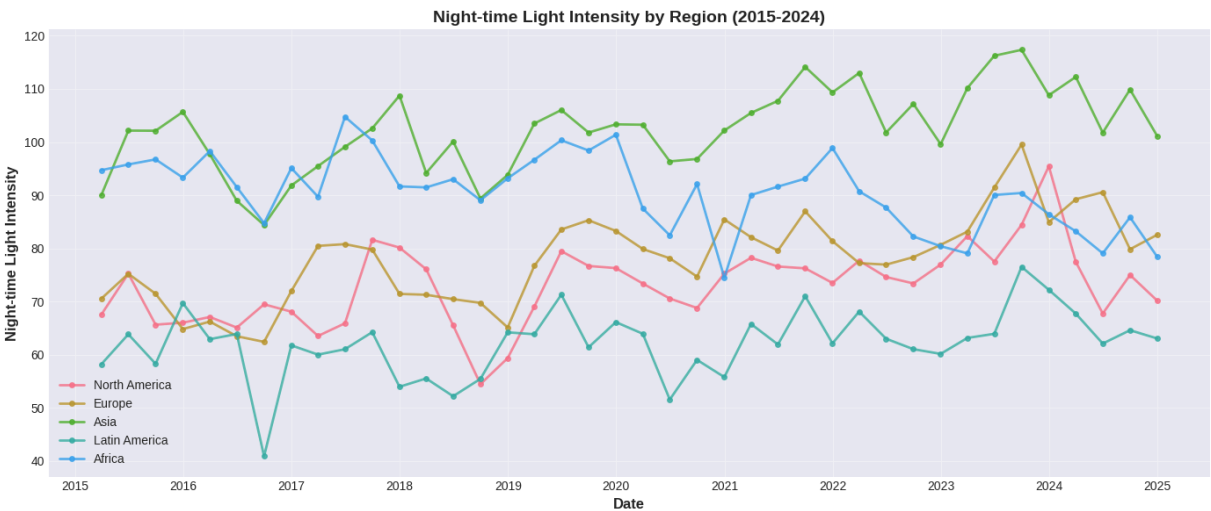
4.1 Time Series Visualization

In [26]:

```
fig, ax = plt.subplots(figsize=(14, 6))

for region in regions:
    region_data = df[df['region'] == region]
    ax.plot(region_data['date'], region_data['light_intensity'],
            marker='o', linewidth=2, markersize=4, label=region, alpha=0.8)

ax.set_xlabel('Date', fontsize=12, fontweight='bold')
ax.set_ylabel('Night-time Light Intensity', fontsize=12, fontweight='bold')
ax.set_title('Night-time Light Intensity by Region (2015-2024)',
            fontsize=14, fontweight='bold')
ax.legend(loc='best', fontsize=10)
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



```
In [27]: sample_region = 'Asia'
region_df = df[df['region'] == sample_region].copy()

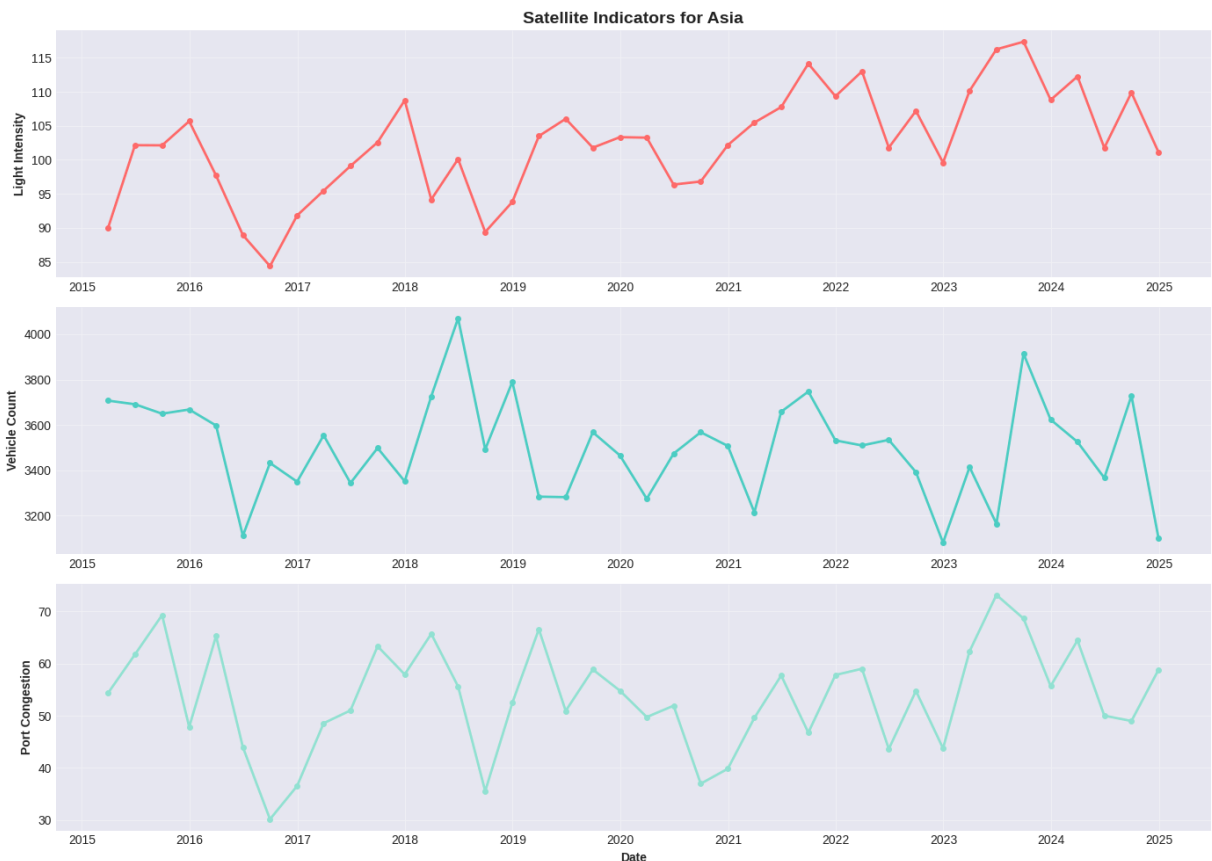
fig, axes = plt.subplots(3, 1, figsize=(14, 10))

# Light intensity
axes[0].plot(region_df['date'], region_df['light_intensity'],
             color='#FF6B6B', linewidth=2, marker='o', markersize=4)
axes[0].set_ylabel('Light Intensity', fontweight='bold')
axes[0].set_title(f'Satellite Indicators for {sample_region}',
                  fontsize=14, fontweight='bold')
axes[0].grid(True, alpha=0.3)

# Vehicle count
axes[1].plot(region_df['date'], region_df['vehicle_count'],
             color='#4ECDC4', linewidth=2, marker='o', markersize=4)
axes[1].set_ylabel('Vehicle Count', fontweight='bold')
axes[1].grid(True, alpha=0.3)

# Port congestion
axes[2].plot(region_df['date'], region_df['port_congestion'],
             color='#95E1D3', linewidth=2, marker='o', markersize=4)
axes[2].set_ylabel('Port Congestion', fontweight='bold')
axes[2].set_xlabel('Date', fontweight='bold')
axes[2].grid(True, alpha=0.3)

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



4.2 Distribution Analysis

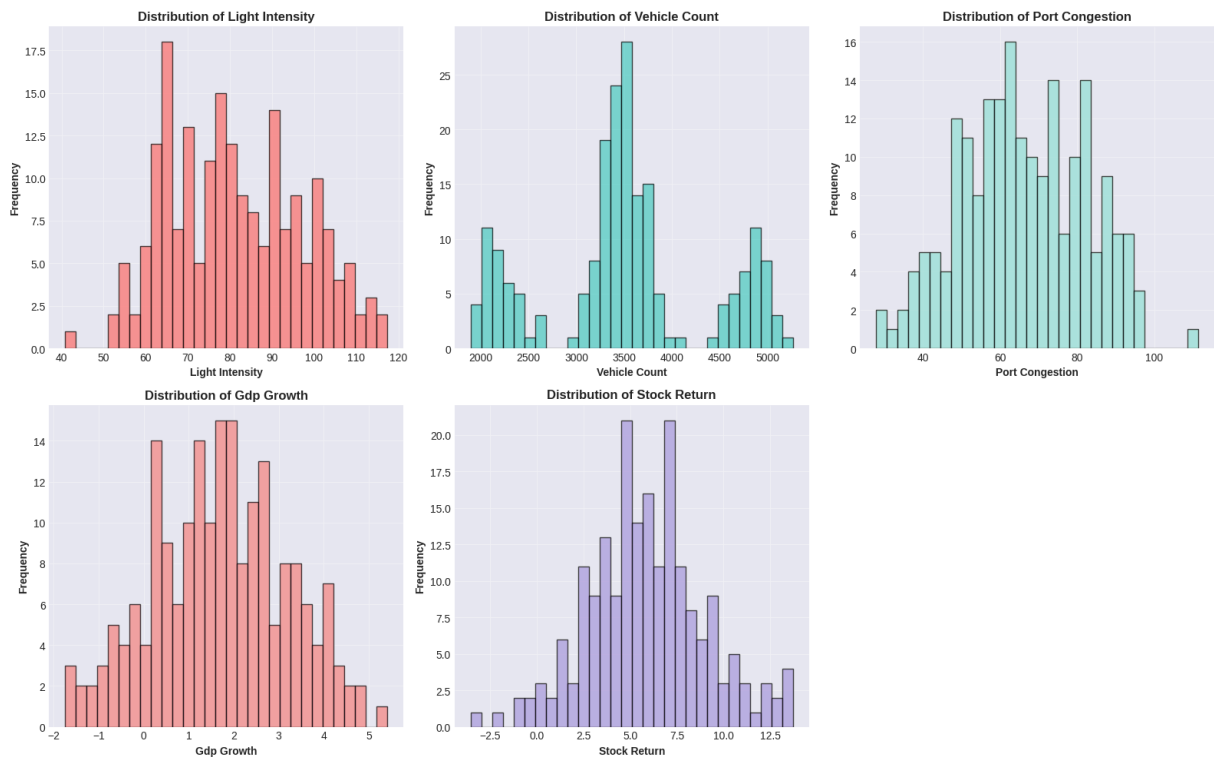
```
In [28]: fig, axes = plt.subplots(2, 3, figsize=(16, 10))
axes = axes.flatten()

variables = ['light_intensity', 'vehicle_count', 'port_congestion',
            'gdp_growth', 'stock_return']
colors = ['#FF6B6B', '#4ECDC4', '#95E1D3', '#F38181', '#AA96DA']

for idx, (var, color) in enumerate(zip(variables, colors)):
    axes[idx].hist(df[var], bins=30, color=color, alpha=0.7, edgecolor='black')
    axes[idx].set_xlabel(var.replace('_', ' ').title(), fontweight='bold')
    axes[idx].set_ylabel('Frequency', fontweight='bold')
    axes[idx].set_title(f'Distribution of {var.replace("_", " ").title()}',
                        fontweight='bold')
    axes[idx].grid(True, alpha=0.3)

fig.delaxes(axes[5])

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



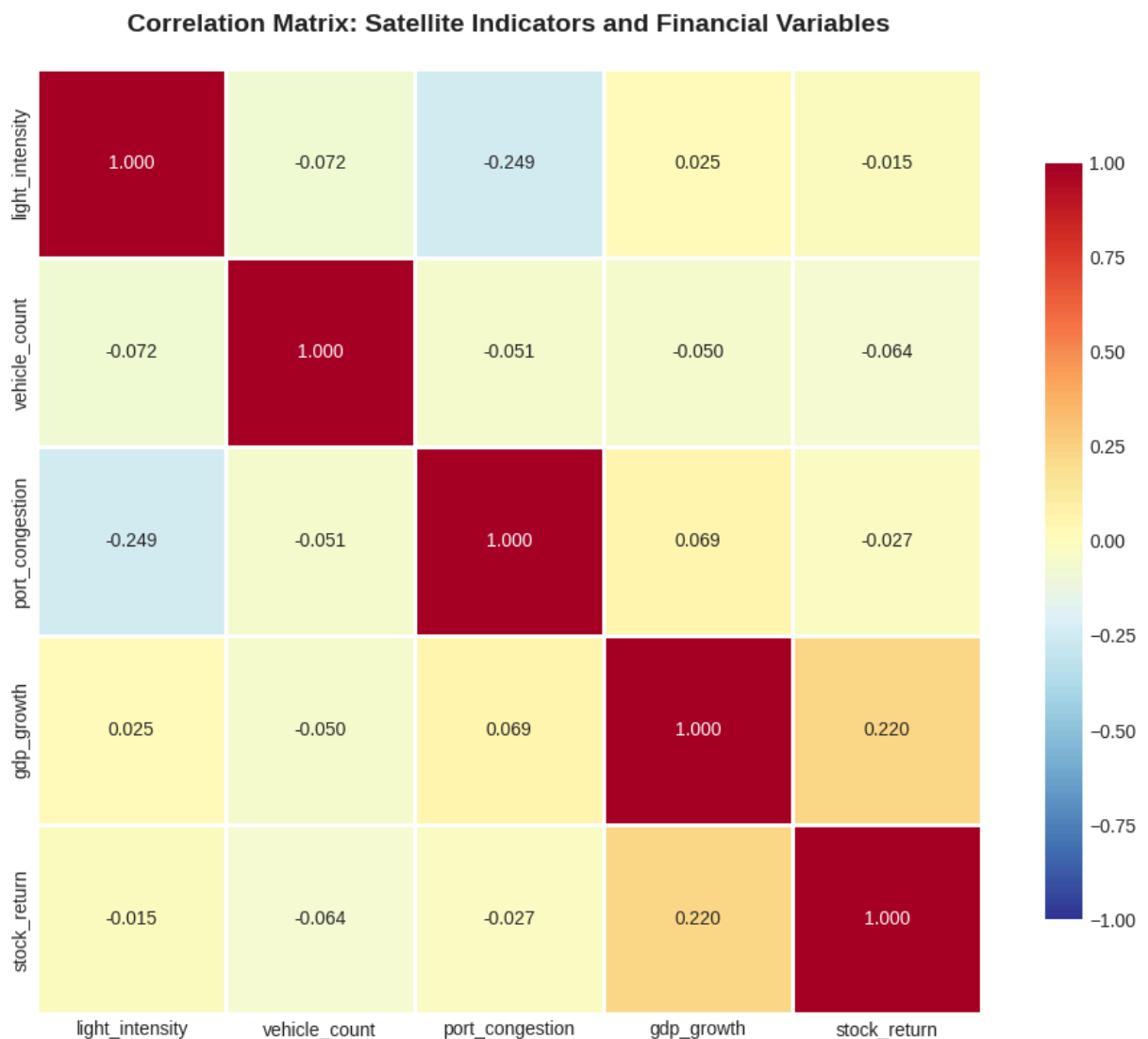
5. Correlation Analysis

Examining relationships between satellite indicators and traditional financial/economic variables.

```
In [29]: correlation_vars = ['light_intensity', 'vehicle_count', 'port_congestion',
                             'gdp_growth', 'stock_return']
corr_matrix = df[correlation_vars].corr()

fig, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt='.3f', cmap='RdYlBu_r',
            center=0, square=True, linewidths=1, cbar_kws={"shrink": 0.8},
            vmin=-1, vmax=1, ax=ax)
ax.set_title('Correlation Matrix: Satellite Indicators and Financial Variables',
            fontsize=14, fontweight='bold', pad=20)
plt.tight_layout()
plt.show()

print("\nCorrelation Matrix:")
print(corr_matrix)
```



Correlation Matrix:

	light_intensity	vehicle_count	port_congestion	gdp_growth	\
light_intensity	1.0000	-0.0717	-0.2494	0.0245	
vehicle_count	-0.0717	1.0000	-0.0512	-0.0504	
port_congestion	-0.2494	-0.0512	1.0000	0.0687	
gdp_growth	0.0245	-0.0504	0.0687	1.0000	
stock_return	-0.0148	-0.0640	-0.0267	0.2197	

	stock_return
light_intensity	-0.0148
vehicle_count	-0.0640
port_congestion	-0.0267
gdp_growth	0.2197
stock_return	1.0000

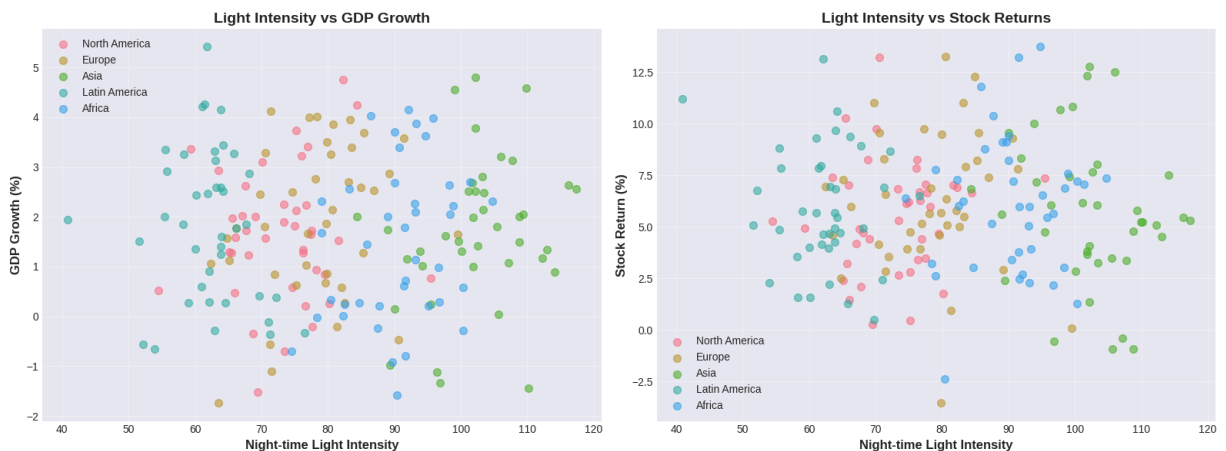
```
In [30]: fig, axes = plt.subplots(1, 2, figsize=(16, 6))
for region in regions:
    region_data = df[df['region'] == region]
    axes[0].scatter(region_data['light_intensity'], region_data['gdp_growth'],
                    label=region, alpha=0.6, s=50)

axes[0].set_xlabel('Night-time Light Intensity', fontsize=12, fontweight='bold')
axes[0].set_ylabel('GDP Growth (%)', fontsize=12, fontweight='bold')
axes[0].set_title('Light Intensity vs GDP Growth', fontsize=14, fontweight='bold')
axes[0].legend(loc='best')
axes[0].grid(True, alpha=0.3)

for region in regions:
    region_data = df[df['region'] == region]
    axes[1].scatter(region_data['light_intensity'], region_data['stock_return'],
                    label=region, alpha=0.6, s=50)

axes[1].set_xlabel('Night-time Light Intensity', fontsize=12, fontweight='bold')
axes[1].set_ylabel('Stock Return (%)', fontsize=12, fontweight='bold')
axes[1].set_title('Light Intensity vs Stock Returns', fontsize=14, fontweight='bold')
axes[1].legend(loc='best')
axes[1].grid(True, alpha=0.3)

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



6. Principal Component Analysis (PCA)

Extracting latent economic factors from multiple satellite indicators.

```
In [31]: satellite_features = ['light_intensity', 'vehicle_count', 'port_congestion']
X = df[satellite_features].values

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pca = PCA()
principal_components = pca.fit_transform(X_scaled)

pca_df = pd.DataFrame(data=principal_components,
                      columns=[f'PC{i+1}' for i in range(principal_components.shape[1])],
                      index=df.index)
pca_df['region'] = df['region'].values
pca_df['date'] = df['date'].values

print("PCA Results:")
print(f"Number of components: {pca.n_components_}")
print(f"\nExplained variance ratio:")
for i, var in enumerate(pca.explained_variance_ratio_):
    print(f"  PC{i+1}: {var:.4f} ({var*100:.2f}%)")
print(f"\nCumulative explained variance: {pca.explained_variance_ratio_.sum():.4f}")
```

PCA Results:

Number of components: 3

Explained variance ratio:

PC1: 0.4168 (41.68%)

PC2: 0.3421 (34.21%)

PC3: 0.2411 (24.11%)

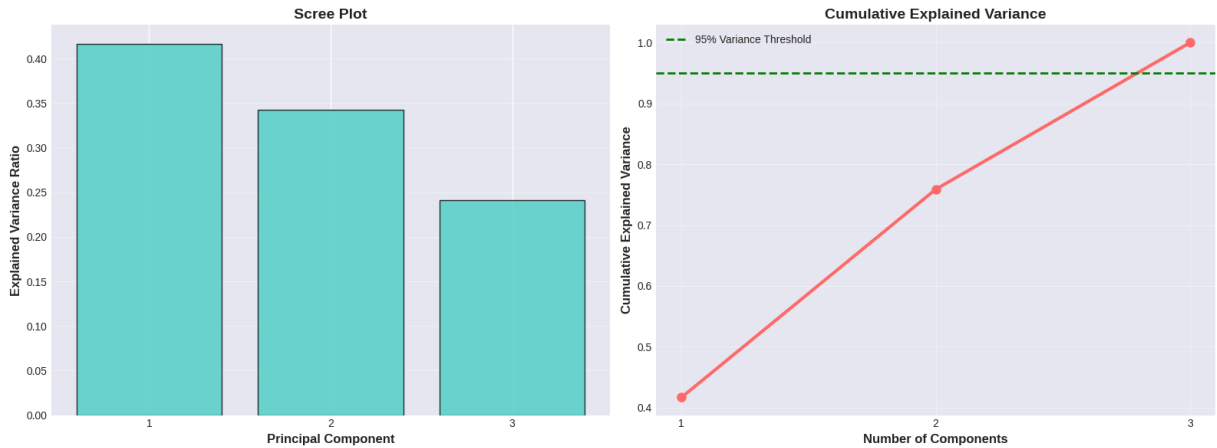
Cumulative explained variance: 1.0000

```
In [32]: fig, axes = plt.subplots(1, 2, figsize=(16, 6))

axes[0].bar(range(1, len(pca.explained_variance_ratio_) + 1),
            pca.explained_variance_ratio_, color='#4ECDC4', alpha=0.8, edgecolor='black')
axes[0].set_xlabel('Principal Component', fontsize=12, fontweight='bold')
axes[0].set_ylabel('Explained Variance Ratio', fontsize=12, fontweight='bold')
axes[0].set_title('Scree Plot', fontsize=14, fontweight='bold')
axes[0].set_xticks(range(1, len(pca.explained_variance_ratio_) + 1))
axes[0].grid(True, alpha=0.3, axis='y')
cumsum = np.cumsum(pca.explained_variance_ratio_)
axes[1].plot(range(1, len(cumsum) + 1), cumsum,
            marker='o', linewidth=3, markersize=8, color='#FF6B6B')
axes[1].axhline(y=0.95, color='green', linestyle='--', linewidth=2,
               label='95% Variance Threshold')
axes[1].set_xlabel('Number of Components', fontsize=12, fontweight='bold')
axes[1].set_ylabel('Cumulative Explained Variance', fontsize=12, fontweight='bold')
axes[1].set_title('Cumulative Explained Variance', fontsize=14, fontweight='bold')
axes[1].set_xticks(range(1, len(cumsum) + 1))
axes[1].legend(loc='best')
```

```
axes[1].grid(True, alpha=0.3)

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



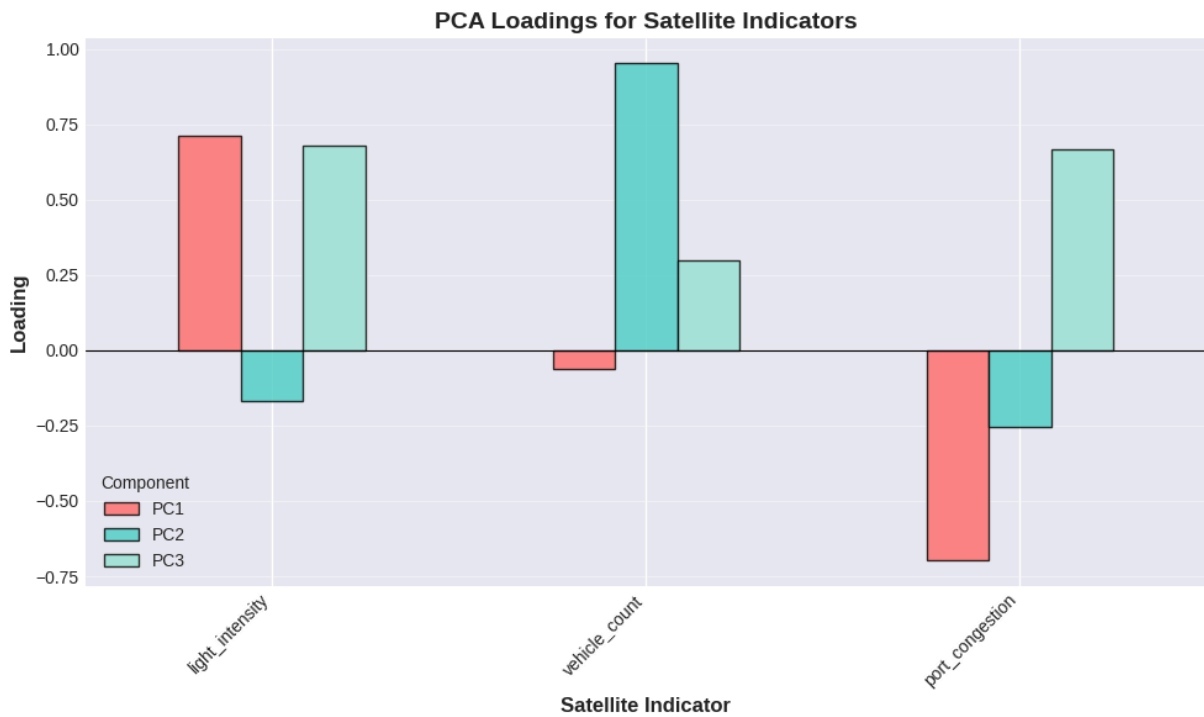
```
In [33]: loadings = pd.DataFrame(
    pca.components_.T,
    columns=[f'PC{i+1}' for i in range(pca.n_components_)],
    index=satellite_features
)

print("\nPrincipal Component Loadings:")
print(loadings)

fig, ax = plt.subplots(figsize=(10, 6))
loadings.plot(kind='bar', ax=ax, color=['#FF6B6B', '#4ECDC4', '#95E1D3'],
            edgecolor='black', alpha=0.8)
ax.set_xlabel('Satellite Indicator', fontsize=12, fontweight='bold')
ax.set_ylabel('Loading', fontsize=12, fontweight='bold')
ax.set_title('PCA Loadings for Satellite Indicators', fontsize=14, fontweight='bold')
ax.axhline(y=0, color='black', linewidth=0.8)
ax.legend(title='Component', fontsize=10)
ax.grid(True, alpha=0.3, axis='y')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

Principal Component Loadings:

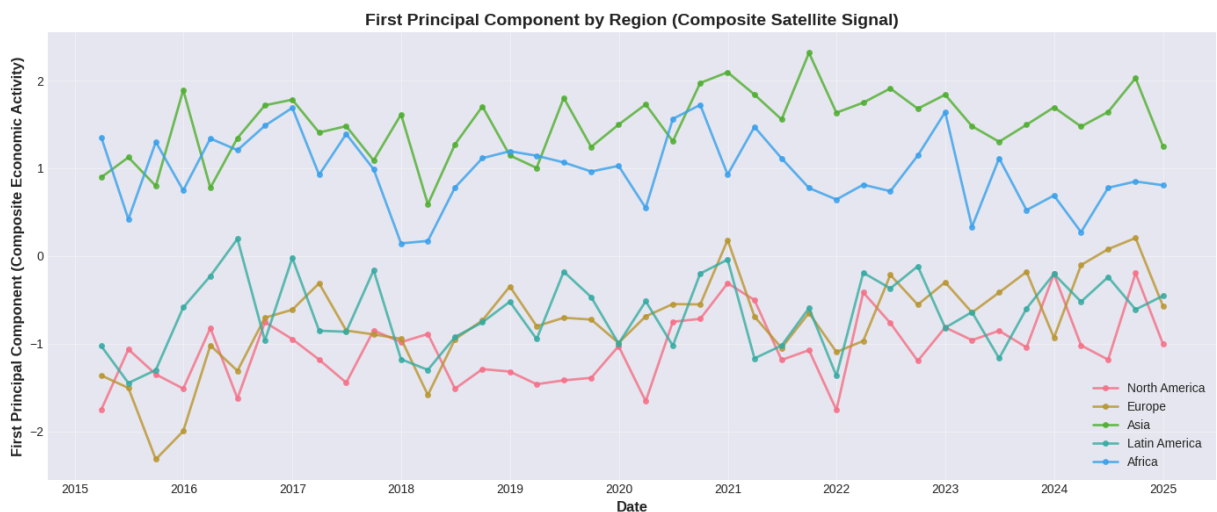
	PC1	PC2	PC3
light_intensity	0.7133	-0.1683	0.6804
vehicle_count	-0.0616	0.9519	0.3000
port_congestion	-0.6981	-0.2559	0.6687



```
In [34]: fig, ax = plt.subplots(figsize=(14, 6))

for region in regions:
    region_pca = pca_df[pca_df['region'] == region]
    ax.plot(region_pca['date'], region_pca['PC1'],
            marker='o', linewidth=2, markersize=4, label=region, alpha=0.8)

ax.set_xlabel('Date', fontsize=12, fontweight='bold')
ax.set_ylabel('First Principal Component (Composite Economic Activity)',
              fontsize=12, fontweight='bold')
ax.set_title('First Principal Component by Region (Composite Satellite Signal)',
             fontsize=14, fontweight='bold')
ax.legend(loc='best', fontsize=10)
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



7. Panel Regression Analysis

7.1 Pooled OLS (Baseline)

```
In [35]: panel_df = df.set_index(['region', 'date'])
from sklearn.linear_model import LinearRegression
from scipy import stats

X_pooled = df[['light_intensity']].values
y_pooled = df['gdp_growth'].values

pooled_model = LinearRegression()
pooled_model.fit(X_pooled, y_pooled)

y_pred = pooled_model.predict(X_pooled)
residuals = y_pooled - y_pred
ss_res = np.sum(residuals**2)
ss_tot = np.sum((y_pooled - np.mean(y_pooled))**2)
r_squared = 1 - (ss_res / ss_tot)

print("POOLED OLS REGRESSION")
print(f"Dependent Variable: GDP Growth")
print(f"Independent Variable: Light Intensity")
print(f"\nCoefficient: {pooled_model.coef_[0]:.4f}")
print(f"Intercept: {pooled_model.intercept_:.4f}")
print(f"R-squared: {r_squared:.4f}")
print(f"Number of observations: {len(y_pooled)}")
```

POOLED OLS REGRESSION

Dependent Variable: GDP Growth

Independent Variable: Light Intensity

Coefficient: 0.0023

Intercept: 1.5208

R-squared: 0.0006

Number of observations: 200

7.2 Fixed Effects Panel Regression

Controlling for region-specific (entity) and time-specific effects.

```
In [36]: print("ENTITY FIXED EFFECTS REGRESSION (Region FE)")

# Dependent and independent variables
y_panel = panel_df['gdp_growth']
X_panel = panel_df[['light_intensity']]

# Entity fixed effects model
entity_fe = PanelOLS(y_panel, X_panel, entity_effects=True)
entity_fe_results = entity_fe.fit(cov_type='clustered', cluster_entity=True)
```

```
print(entity_fe_results)
```

ENTITY FIXED EFFECTS REGRESSION (Region FE)

PanelOLS Estimation Summary

```
=====
Dep. Variable:          gdp_growth      R-squared:                0.0219
Estimator:              PanelOLS        R-squared (Between):      0.7355
No. Observations:       200             R-squared (Within):       0.0219
Date:                   Tue, Feb 03 2026 R-squared (Overall):      0.4333
Time:                   22:17:14        Log-likelihood            -358.55
Cov. Estimator:         Clustered

                               F-statistic:                4.3492
                               P-value                     0.0383
Entities:                5             Distribution:          F(1,194)
Avg Obs:                  40.000        F-statistic (robust):    5.4727
Min Obs:                  40.000        P-value                 0.0203
Max Obs:                  40.000        Distribution:          F(1,194)

Time periods:            40
Avg Obs:                  5.0000
Min Obs:                  5.0000
Max Obs:                  5.0000
=====
```

Parameter Estimates

```
=====
               Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
light_intensity    0.0299    0.0128    2.3394    0.0203    0.0047    0.0551
=====
```

F-test for Poolability: 1.5880

P-value: 0.1790

Distribution: F(4,194)

Included effects: Entity

```
In [37]: print("TIME FIXED EFFECTS REGRESSION")
```

```
time_fe = PanelOLS(y_panel, X_panel, time_effects=True)
time_fe_results = time_fe.fit(cov_type='clustered', cluster_time=True)

print(time_fe_results)
```

TIME FIXED EFFECTS REGRESSION

PanelOLS Estimation Summary

```

=====
Dep. Variable:          gdp_growth    R-squared:                0.0002
Estimator:              PanelOLS      R-squared (Between):      -0.1219
No. Observations:       200           R-squared (Within):       -0.0019
Date:                   Tue, Feb 03 2026 R-squared (Overall):      -0.0711
Time:                   22:17:14      Log-likelihood            -347.30
Cov. Estimator:         Clustered

                               F-statistic:                0.0300
                               P-value                     0.8628
Entities:                5           Distribution:          F(1,159)
Avg Obs:                 40.000      F-statistic (robust):    0.0337
Min Obs:                 40.000      P-value                 0.8546
Max Obs:                 40.000      Distribution:          F(1,159)

Time periods:            40
Avg Obs:                 5.0000
Min Obs:                 5.0000
Max Obs:                 5.0000

```

Parameter Estimates

```

=====
               Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
light_intensity  -0.0013    0.0069   -0.1836    0.8546   -0.0148    0.0123
=====

```

F-test for Poolability: 0.6353

P-value: 0.9512

Distribution: F(39,159)

Included effects: Time

```

In [38]: print("TWO-WAY FIXED EFFECTS REGRESSION (Region FE + Time FE)")

twoway_fe = PanelOLS(y_panel, X_panel, entity_effects=True, time_effects=True)
twoway_fe_results = twoway_fe.fit(cov_type='clustered', cluster_entity=True)

print(twoway_fe_results)

```

TWO-WAY FIXED EFFECTS REGRESSION (Region FE + Time FE)
PanelOLS Estimation Summary

=====			
Dep. Variable:	gdp_growth	R-squared:	0.0102
Estimator:	PanelOLS	R-squared (Between):	0.8740
No. Observations:	200	R-squared (Within):	0.0216
Date:	Tue, Feb 03 2026	R-squared (Overall):	0.5129
Time:	22:17:14	Log-likelihood	-345.06
Cov. Estimator:	Clustered		
		F-statistic:	1.5956
Entities:	5	P-value	0.2084
Avg Obs:	40.000	Distribution:	F(1,155)
Min Obs:	40.000		
Max Obs:	40.000	F-statistic (robust):	3.8767
		P-value	0.0507
Time periods:	40	Distribution:	F(1,155)
Avg Obs:	5.0000		
Min Obs:	5.0000		
Max Obs:	5.0000		

Parameter Estimates

=====						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI

light_intensity	0.0260	0.0132	1.9689	0.0507	-8.512e-05	0.0520
=====						

F-test for Poolability: 0.6559
P-value: 0.9462
Distribution: F(43,155)

Included effects: Entity, Time

7.3 Multiple Satellite Indicators Regression

```
In [39]: print("TWO-WAY FE: MULTIPLE SATELLITE INDICATORS")

X_multi = panel_df[['light_intensity', 'vehicle_count', 'port_congestion']]

multi_fe = PanelOLS(y_panel, X_multi, entity_effects=True, time_effects=True)
multi_fe_results = multi_fe.fit(cov_type='clustered', cluster_entity=True)

print(multi_fe_results)
```

TWO-WAY FE: MULTIPLE SATELLITE INDICATORS

PanelOLS Estimation Summary

```

=====
Dep. Variable:          gdp_growth    R-squared:                0.0119
Estimator:              PanelOLS      R-squared (Between):      0.8963
No. Observations:       200           R-squared (Within):       0.0192
Date:                   Tue, Feb 03 2026 R-squared (Overall):      0.5248
Time:                   22:17:14       Log-likelihood            -344.89
Cov. Estimator:         Clustered

                               F-statistic:                0.6129
                               P-value                     0.6076
Entities:                5           Distribution:          F(3,153)
Avg Obs:                  40.000
Min Obs:                  40.000
Max Obs:                  40.000
                               F-statistic (robust):          3.0314
                               P-value                     0.0312
Time periods:            40          Distribution:          F(3,153)
Avg Obs:                  5.0000
Min Obs:                  5.0000
Max Obs:                  5.0000

```

Parameter Estimates

```

=====
              Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
light_intensity    0.0274    0.0137    1.9926    0.0481    0.0002    0.0546
vehicle_count     2.652e-05    0.0008    0.0321    0.9744   -0.0016    0.0017
port_congestion   -0.0091    0.0101   -0.9002    0.3694   -0.0290    0.0108
=====

```

F-test for Poolability: 0.6216

P-value: 0.9647

Distribution: F(43,153)

Included effects: Entity, Time

```

In [41]: comparison_df = pd.DataFrame({
    'Model': ['Pooled OLS', 'Entity FE', 'Time FE', 'Two-Way FE', 'Multi Two-Way FE'],
    'R-squared': [
        r_squared,
        entity_fe_results.rsquared,
        time_fe_results.rsquared,
        twoway_fe_results.rsquared,
        multi_fe_results.rsquared
    ],
    'Light Coef': [
        pooled_model.coef_[0],
        entity_fe_results.params['light_intensity'],
        time_fe_results.params['light_intensity'],
        twoway_fe_results.params['light_intensity'],
        multi_fe_results.params['light_intensity']
    ],
    'Observations': [
        len(y_pooled),
        entity_fe_results.nobs,
        time_fe_results.nobs,
        twoway_fe_results.nobs,

```

```

        multi_fe_results.nobs
    ]
})

print("MODEL COMPARISON")

print(comparison_df.to_string(index=False))

```

MODEL COMPARISON

Model	R-squared	Light Coef	Observations
Pooled OLS	0.0006	0.0023	200
Entity FE	0.0219	0.0299	200
Time FE	0.0002	-0.0013	200
Two-Way FE	0.0102	0.0260	200
Multi Two-Way FE	0.0119	0.0274	200

```

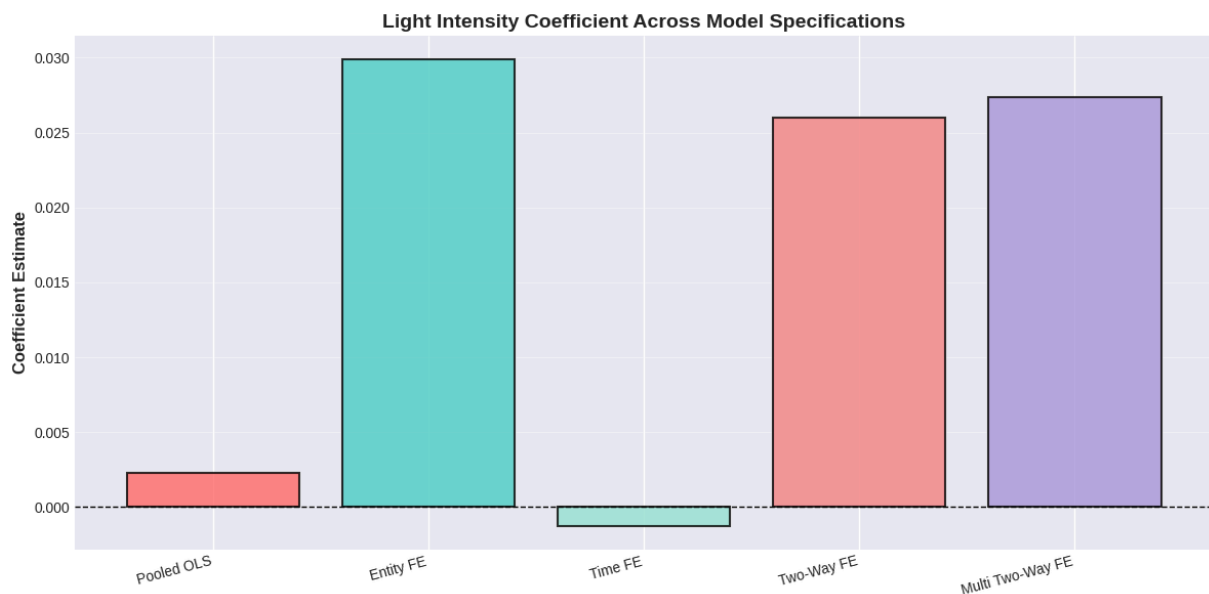
In [42]: # Visualize coefficient estimates across models
fig, ax = plt.subplots(figsize=(12, 6))

models = comparison_df['Model'].values
coefficients = comparison_df['Light Coef'].values

colors = ['#FF6B6B', '#4ECDC4', '#95E1D3', '#F38181', '#AA96DA']
bars = ax.bar(models, coefficients, color=colors, alpha=0.8, edgecolor='black', lin

ax.set_ylabel('Coefficient Estimate', fontsize=12, fontweight='bold')
ax.set_title('Light Intensity Coefficient Across Model Specifications',
             fontsize=14, fontweight='bold')
ax.axhline(y=0, color='black', linewidth=1, linestyle='--')
ax.grid(True, alpha=0.3, axis='y')
plt.xticks(rotation=15, ha='right')
plt.tight_layout()
plt.show()

```



8. Predictive Analysis: Stock Returns

Using satellite indicators to predict stock returns.

```
In [43]: print("PREDICTING STOCK RETURNS WITH SATELLITE DATA")

y_stock = panel_df['stock_return']
X_stock = panel_df[['light_intensity', 'vehicle_count', 'port_congestion']]

stock_fe = PanelOLS(y_stock, X_stock, entity_effects=True, time_effects=True)
stock_fe_results = stock_fe.fit(cov_type='clustered', cluster_entity=True)

print(stock_fe_results)
```

```
PREDICTING STOCK RETURNS WITH SATELLITE DATA
                        PanelOLS Estimation Summary
=====
Dep. Variable:          stock_return    R-squared:                0.0038
Estimator:              PanelOLS        R-squared (Between):      -1.4627
No. Observations:       200             R-squared (Within):       -0.0009
Date:                   Tue, Feb 03 2026 R-squared (Overall):     -1.1379
Time:                   22:17:55         Log-likelihood           -485.09
Cov. Estimator:         Clustered

                                F-statistic:          0.1954
Entities:                5                      P-value            0.8994
Avg Obs:                 40.000                 Distribution:      F(3,153)
Min Obs:                 40.000
Max Obs:                 40.000
                                F-statistic (robust):    0.1123
                                P-value                0.9528
Time periods:            40                     Distribution:      F(3,153)
Avg Obs:                 5.0000
Min Obs:                 5.0000
Max Obs:                 5.0000

                        Parameter Estimates
=====
              Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
light_intensity   -0.0282    0.0546   -0.5166    0.6062   -0.1361    0.0797
vehicle_count    -0.0001    0.0009   -0.1172    0.9068   -0.0020    0.0018
port_congestion  -0.0098    0.0424   -0.2322    0.8167   -0.0935    0.0739
=====

F-test for Poolability: 1.1052
P-value: 0.3234
Distribution: F(43,153)

Included effects: Entity, Time
```

```
In [ ]:
```