

# CAPSTONE 3

# SATELLITE

Group 1

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03

# KEY FEATURES



1

Introduction

2

Compliance Role

3

Technical Role

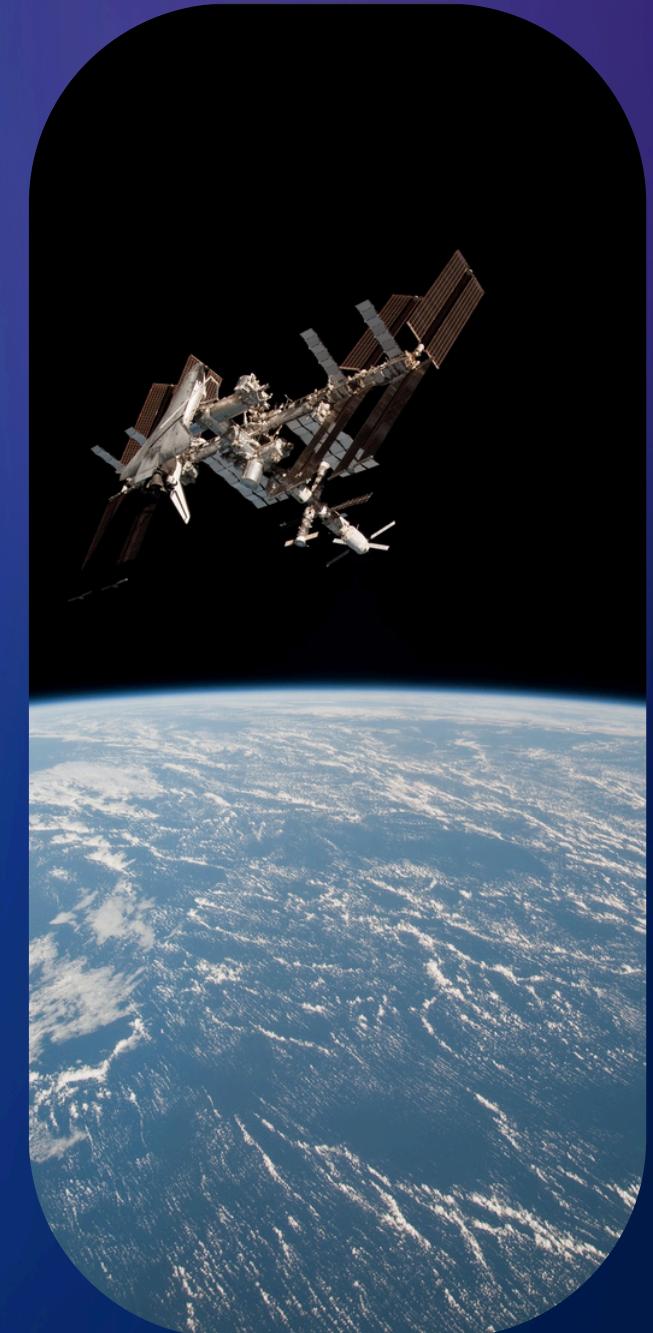
4

Business Role



# INTRODUCTION

This project aims to leverage the UCS Satellite Database to explore satellite data through three distinct lenses: technical, compliance, and business roles.





# PROBLEM DEFINITION

- The satellite industry is faced with the challenge of optimizing satellite performance and longevity
- This project seeks to address this gap by conducting a comprehensive analysis of these factors and developing predictive models to forecast satellite lifetimes based on technical specifications.

# DATA COLLECTION



LUIS\_EMILIANI · 8MO AGO · 6,066 VIEWS

## Exploring the UCS satellite database

Python · UCS Satellite Database (Excel version)

Notebook   Input   Output   Logs   Comments (0)

Run   4.5s   ⌚ Version 35 of 35

Science and Technology   Exploratory Data Analysis   Data Cleaning   Linear Regression   pandas   Seaborn

Exploring the UCS satellite database



## Natural Satellites

A small or secondary planet which revolves around a larger one.

## Artificial Satellites

There are 171 moons, or natural satellites that orbit the planets in our solar system.

A man-made object placed in orbit around an astronomical body.

Geostationary Satellite/  
Communication Satellite

Types

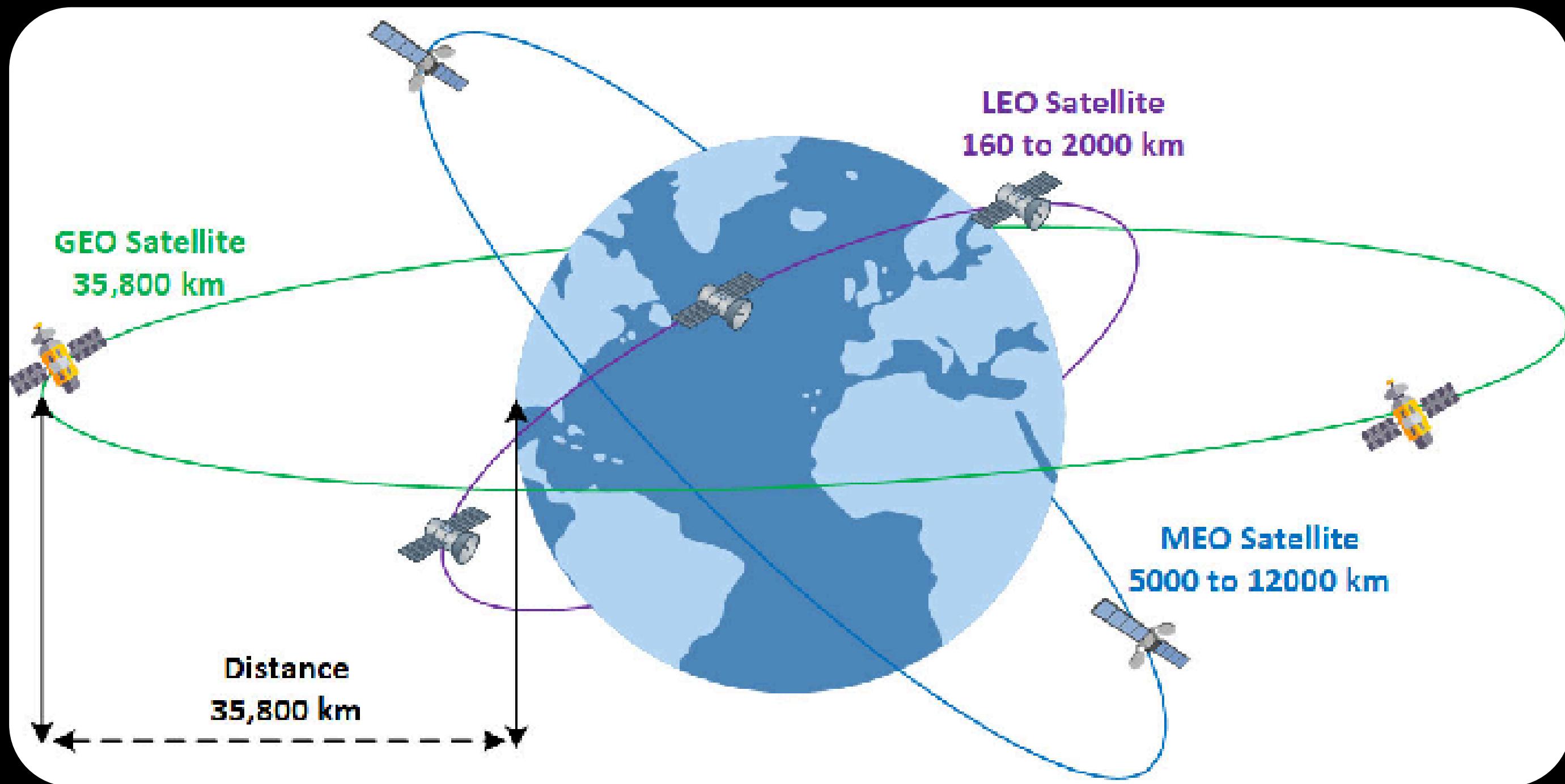
an earth-orbiting satellite, take 24 hours to orbit the Earth

used to provide visible and infrared images of Earth's surface and atmosphere for weather observation, oceanography, and atmospheric tracking.

Polar Satellite

polar orbits, takes approximately 90 minutes to complete one orbit

used for monitoring the weather, military applications (spying) and taking images of Earth's surface



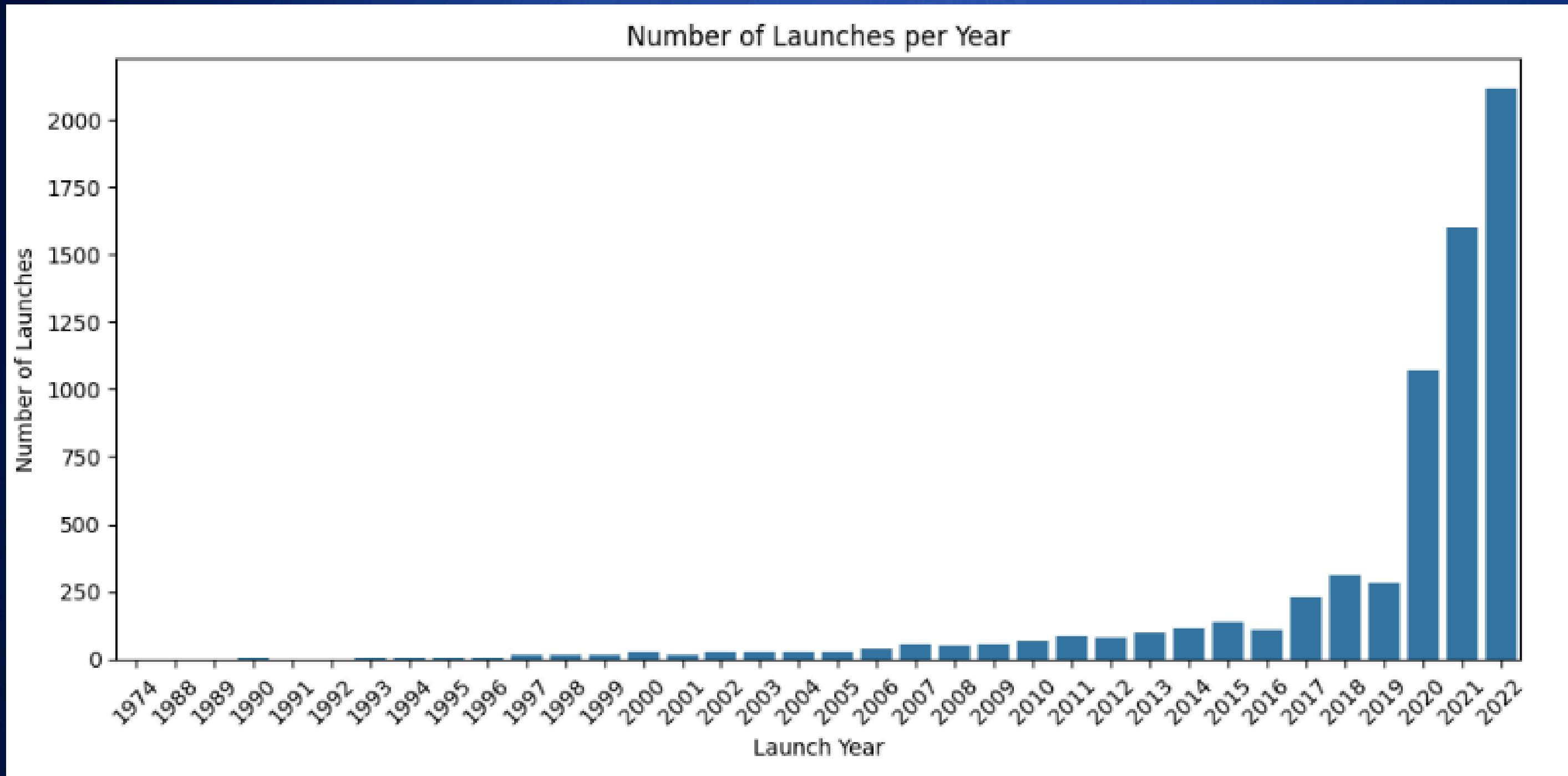


# SATELLITE COMPLIANCE ANALYSIS

1. Analyze Launch and Ownership Trends
2. Examine Launch Vehicle Usage

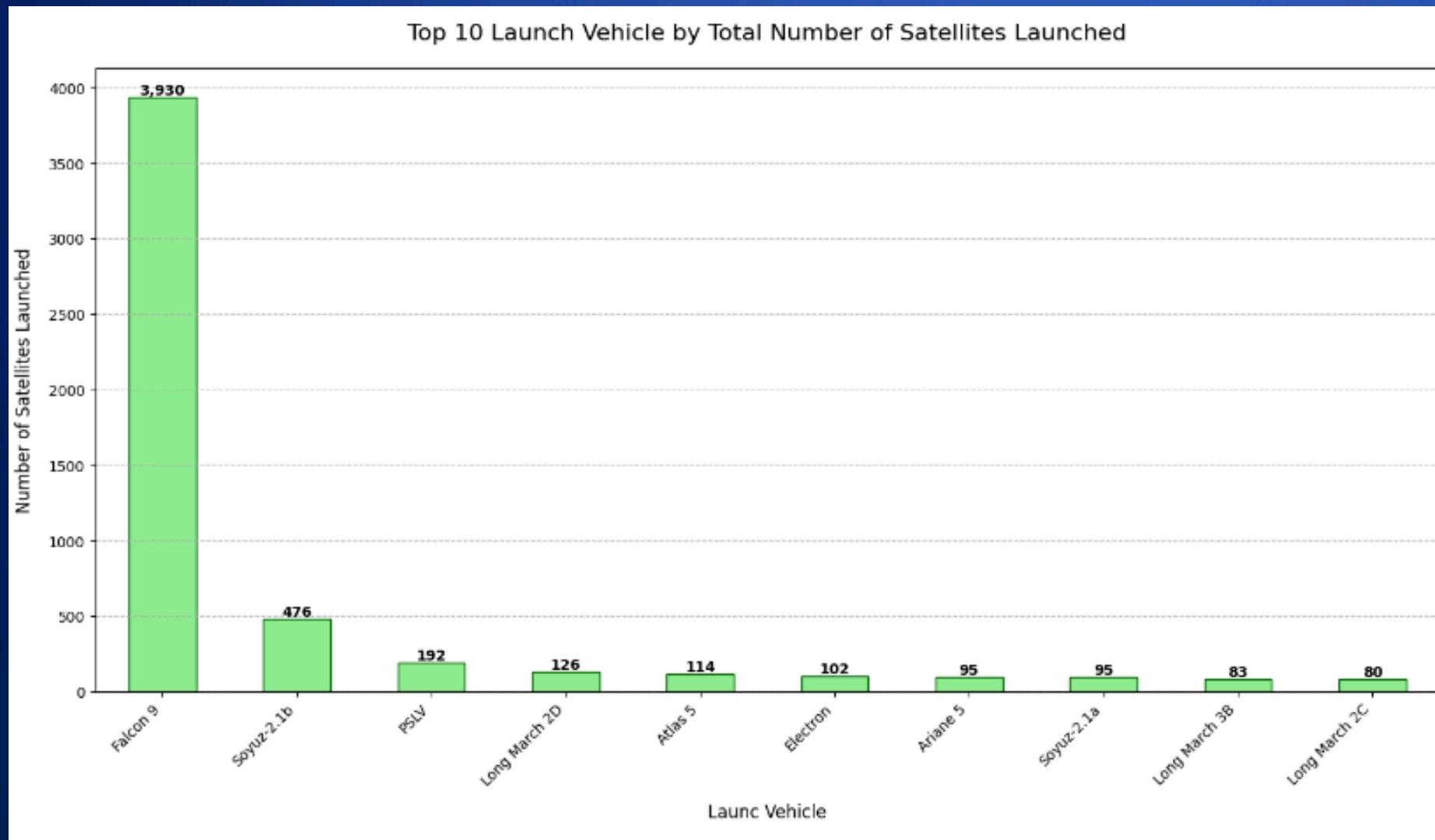
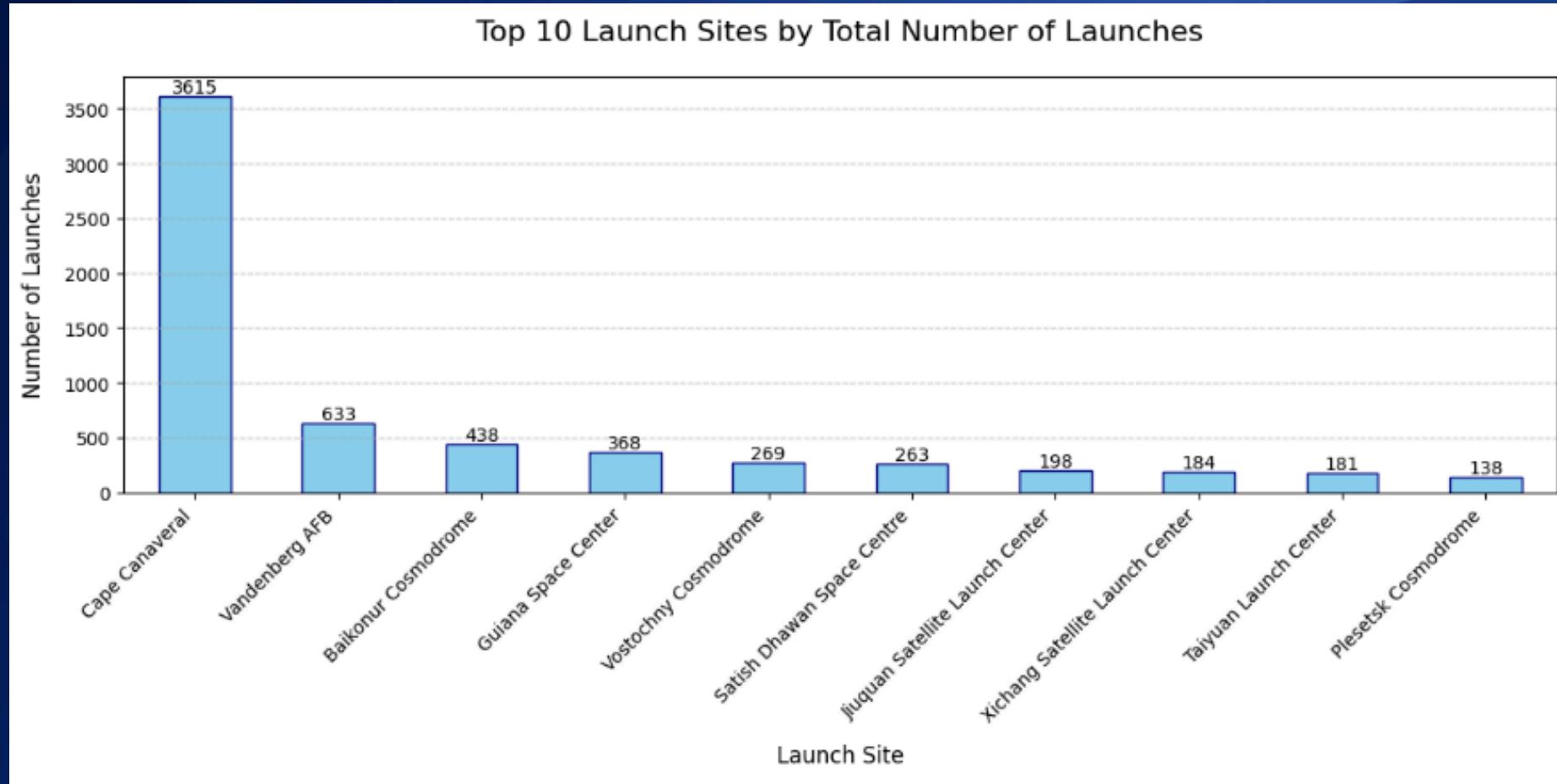


## COMPLIANCE ROLE

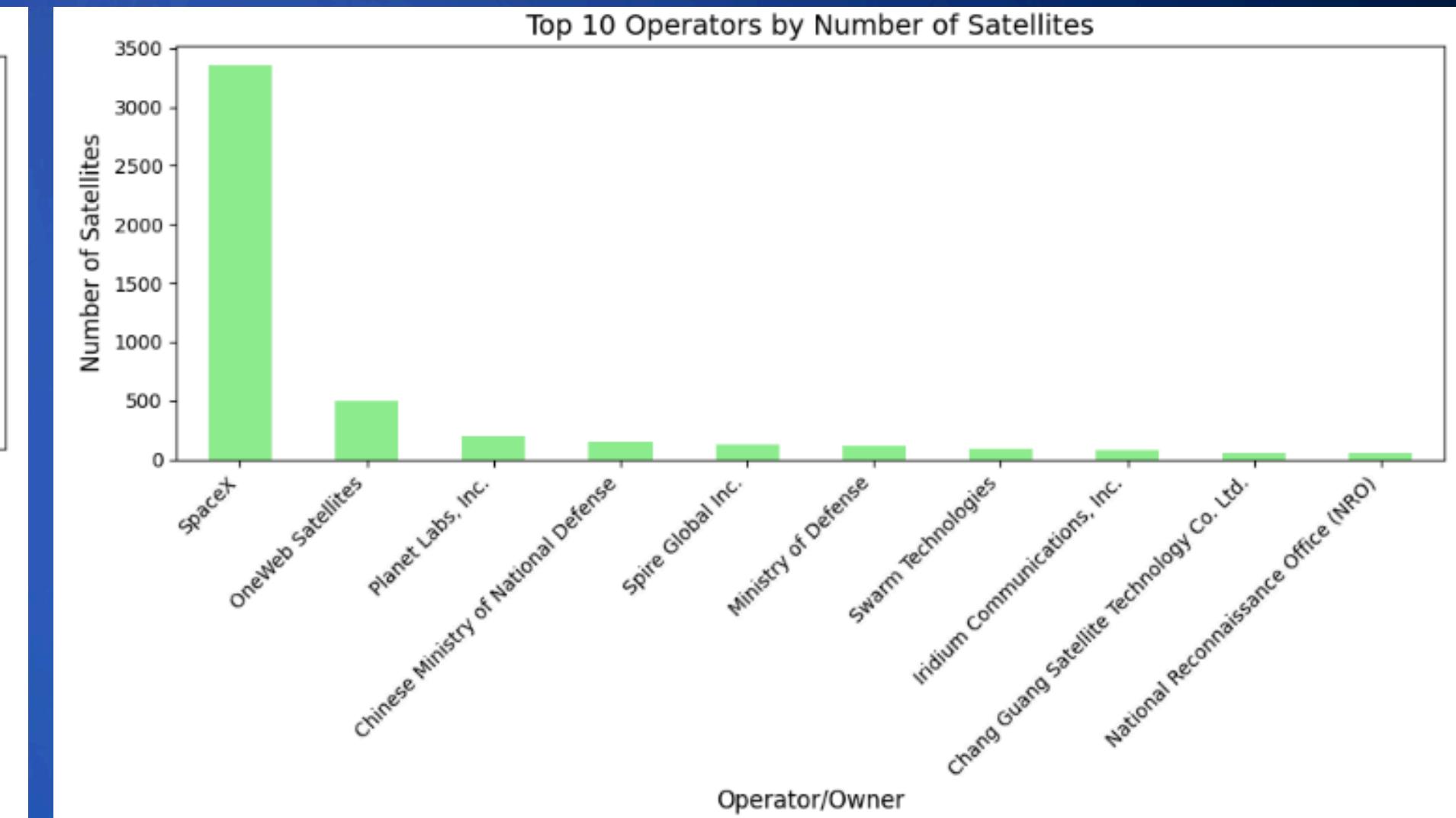
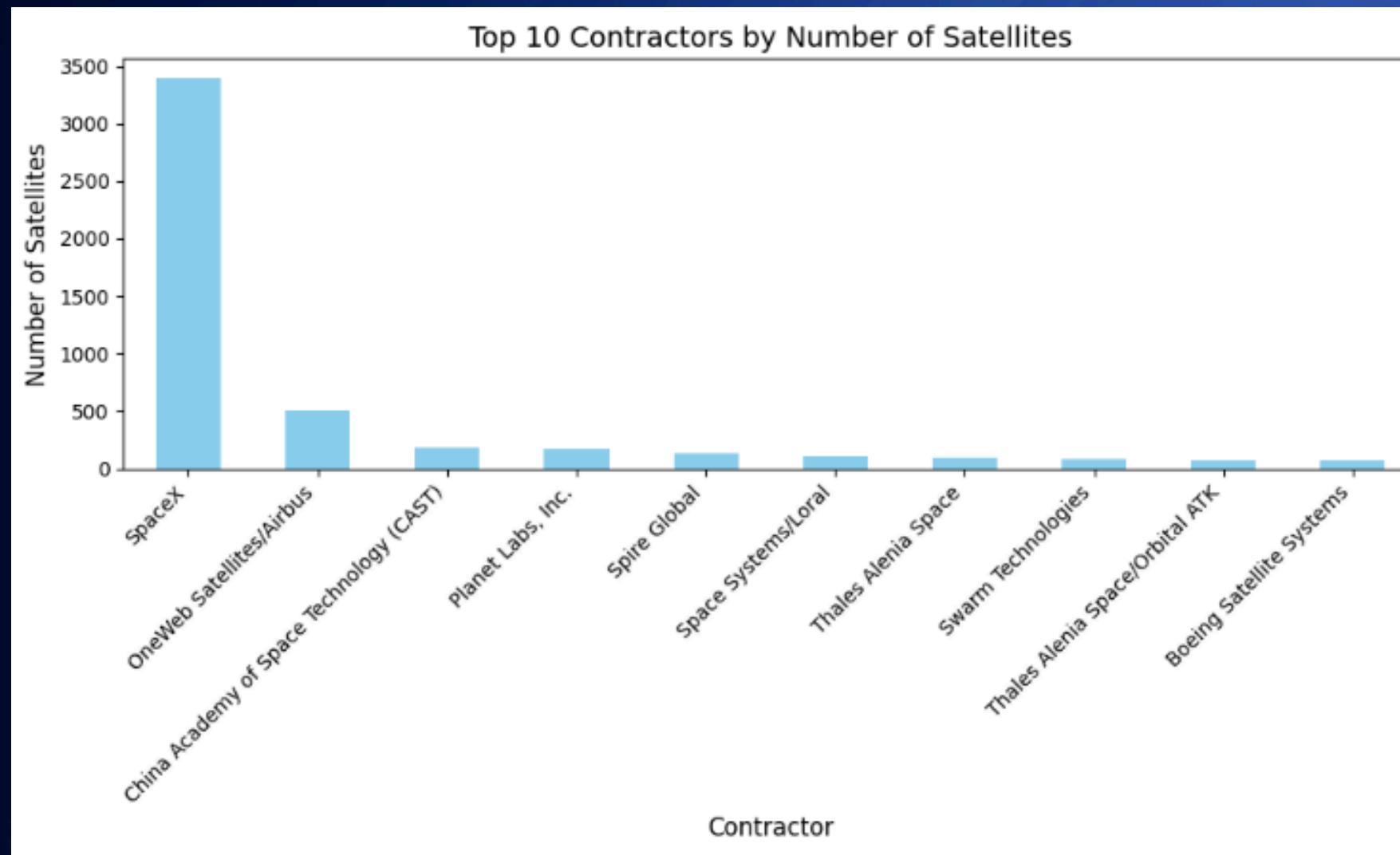


Launch  
Trend  
Analysis

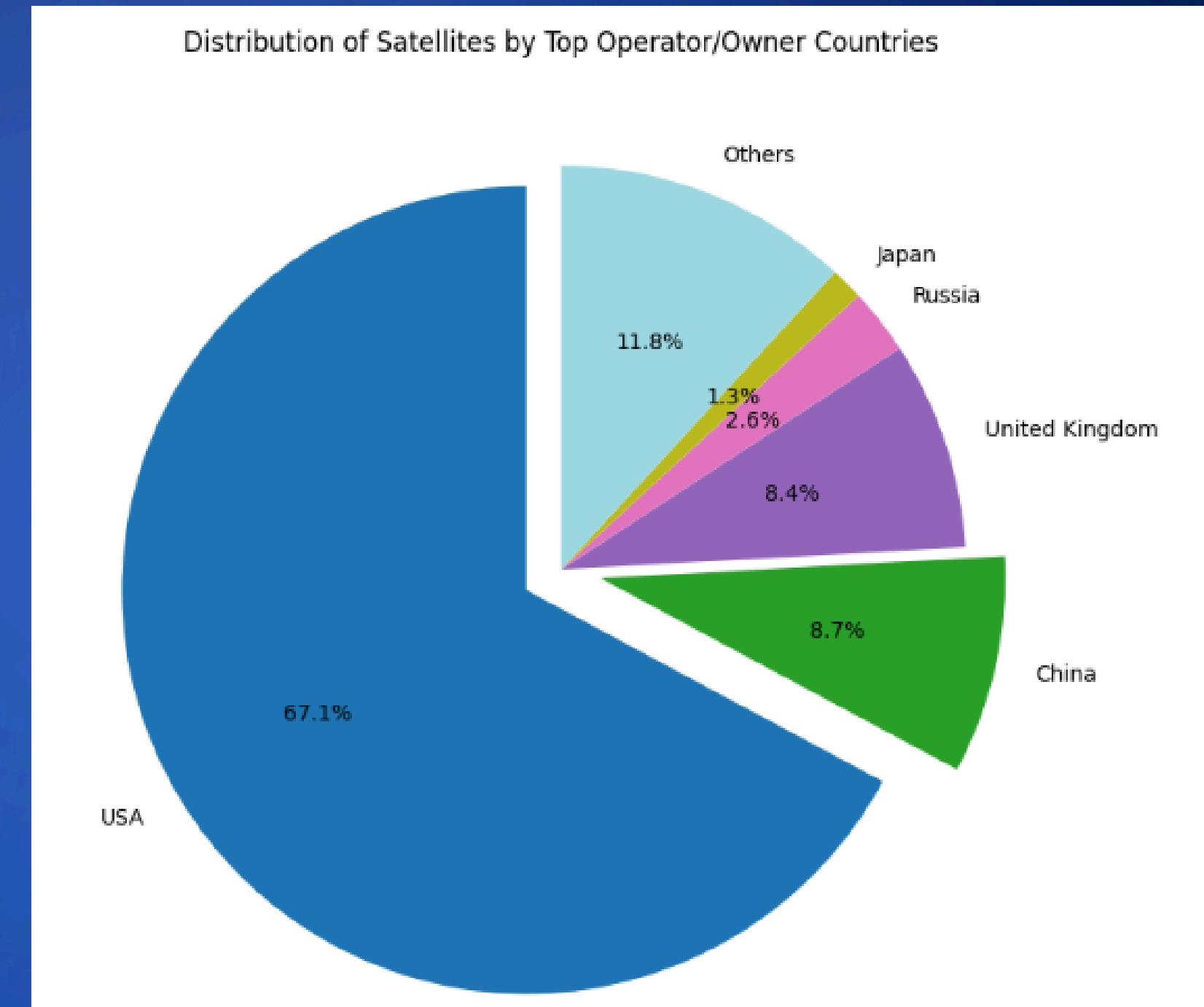
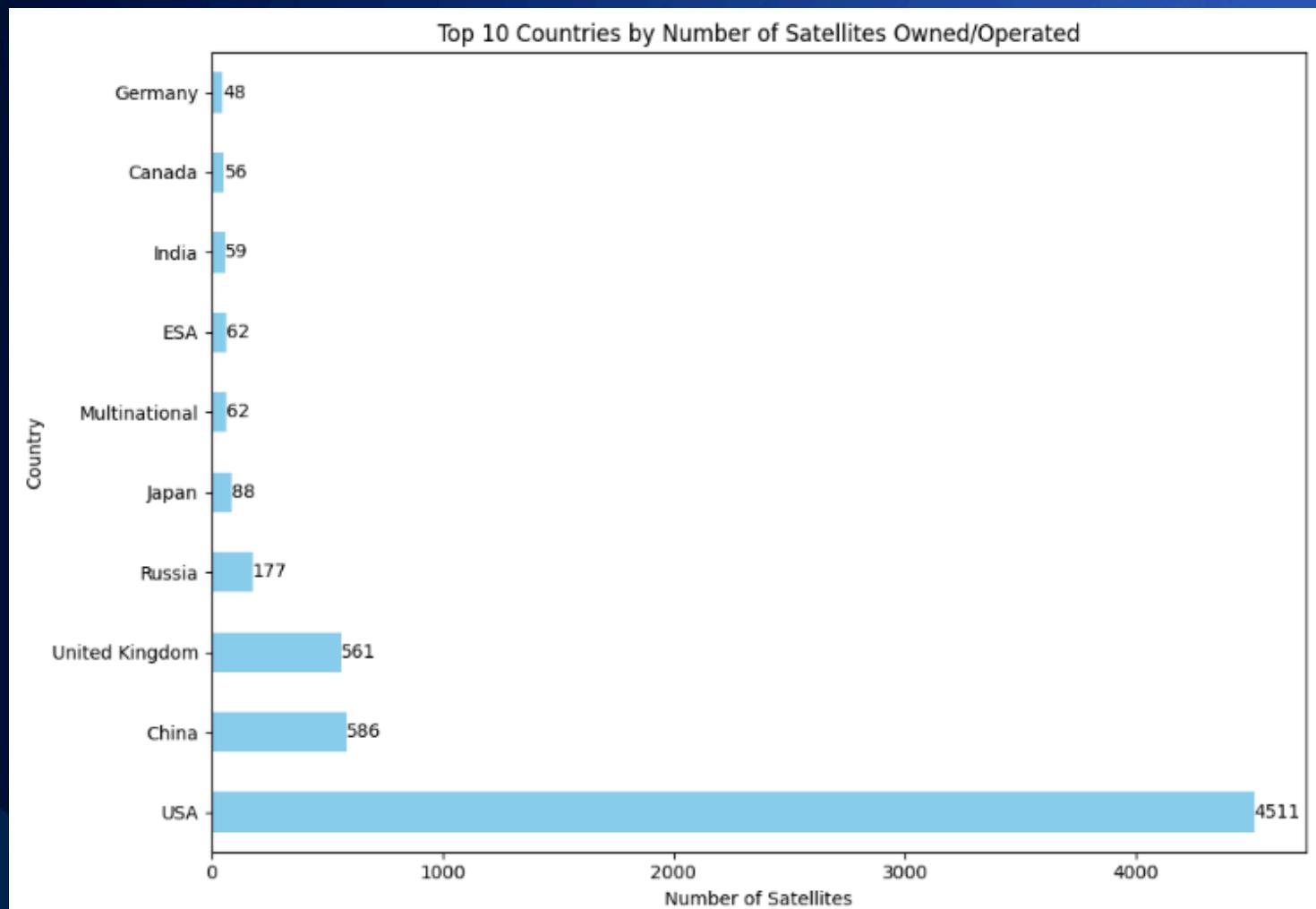
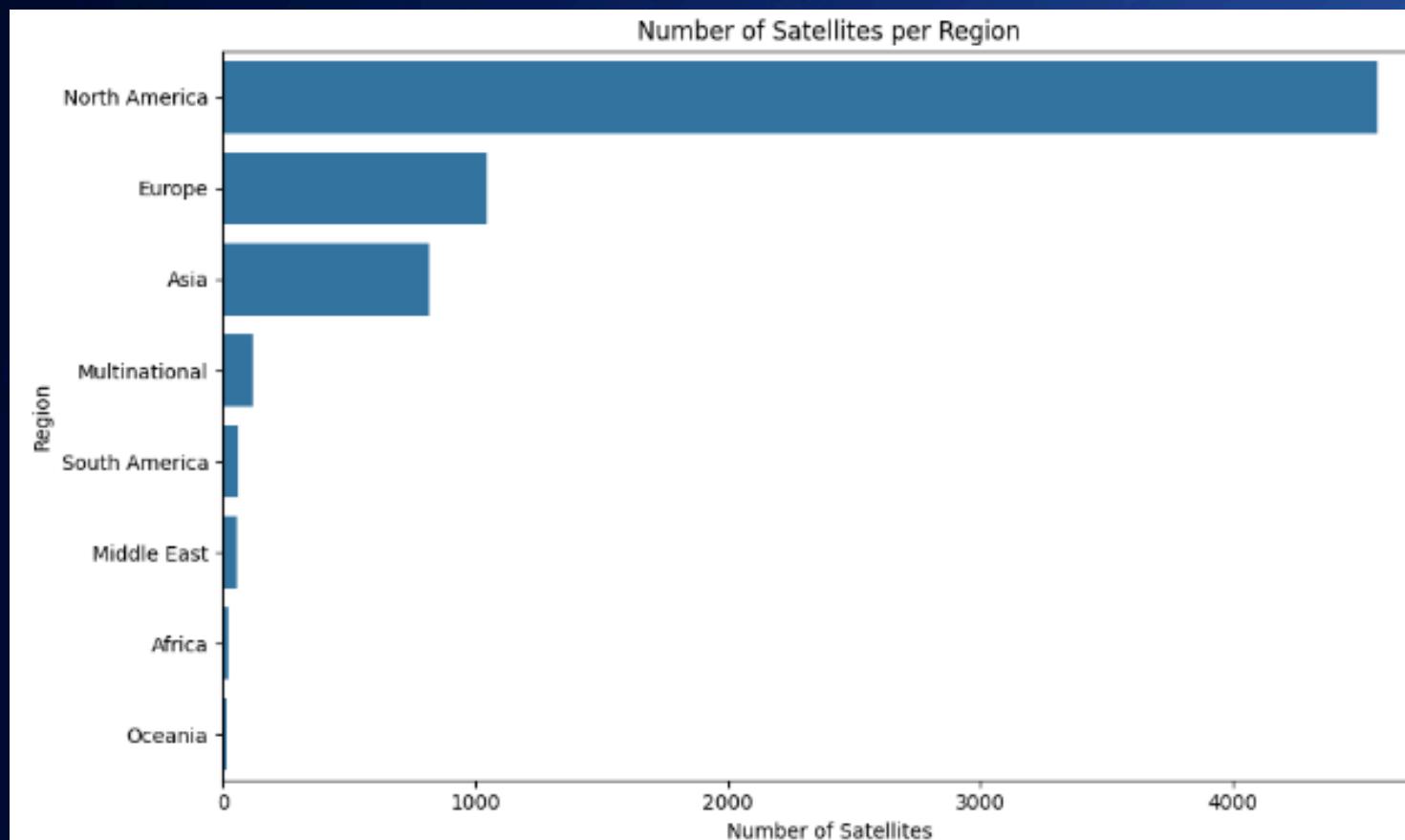
## Launch Trend Analysis



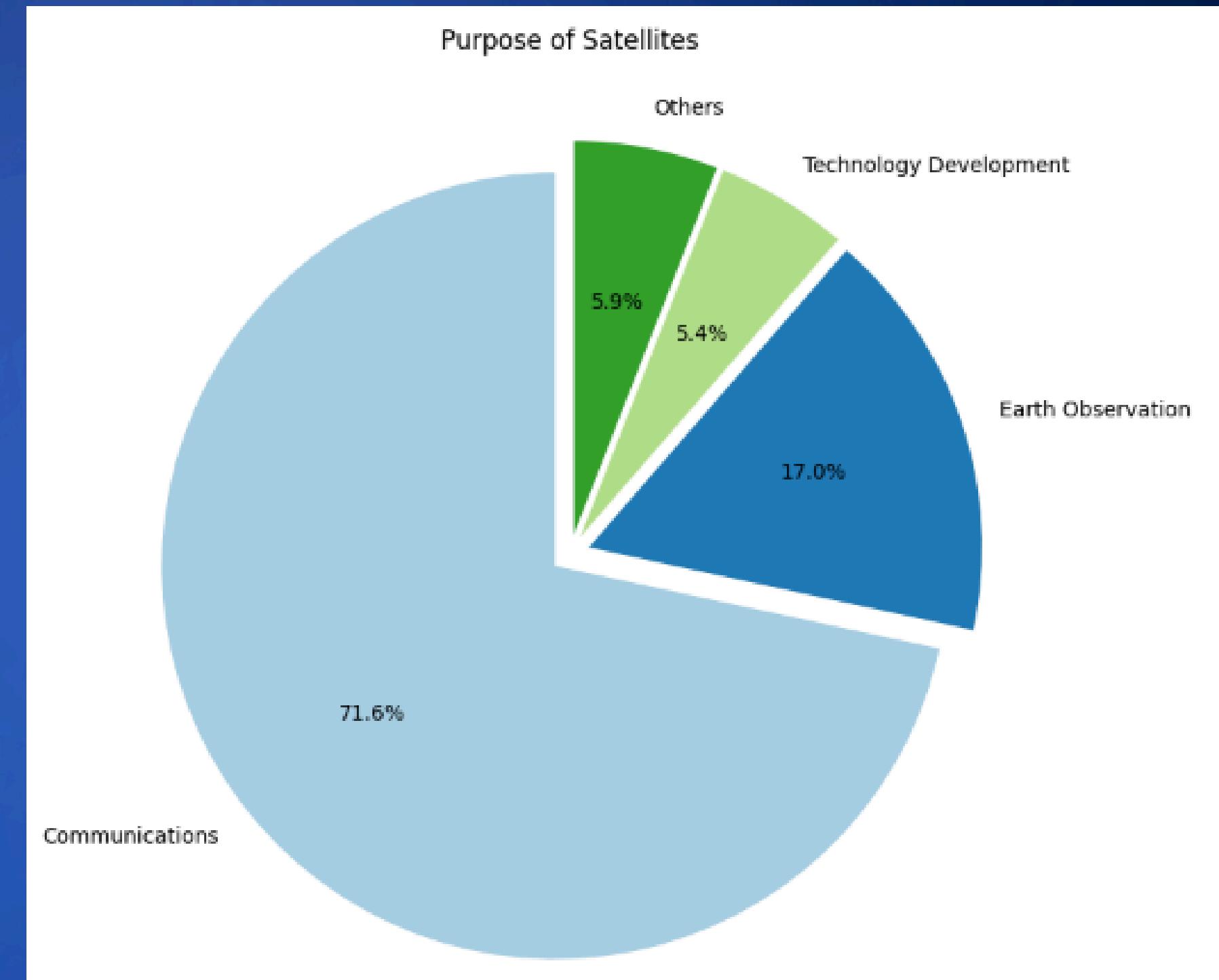
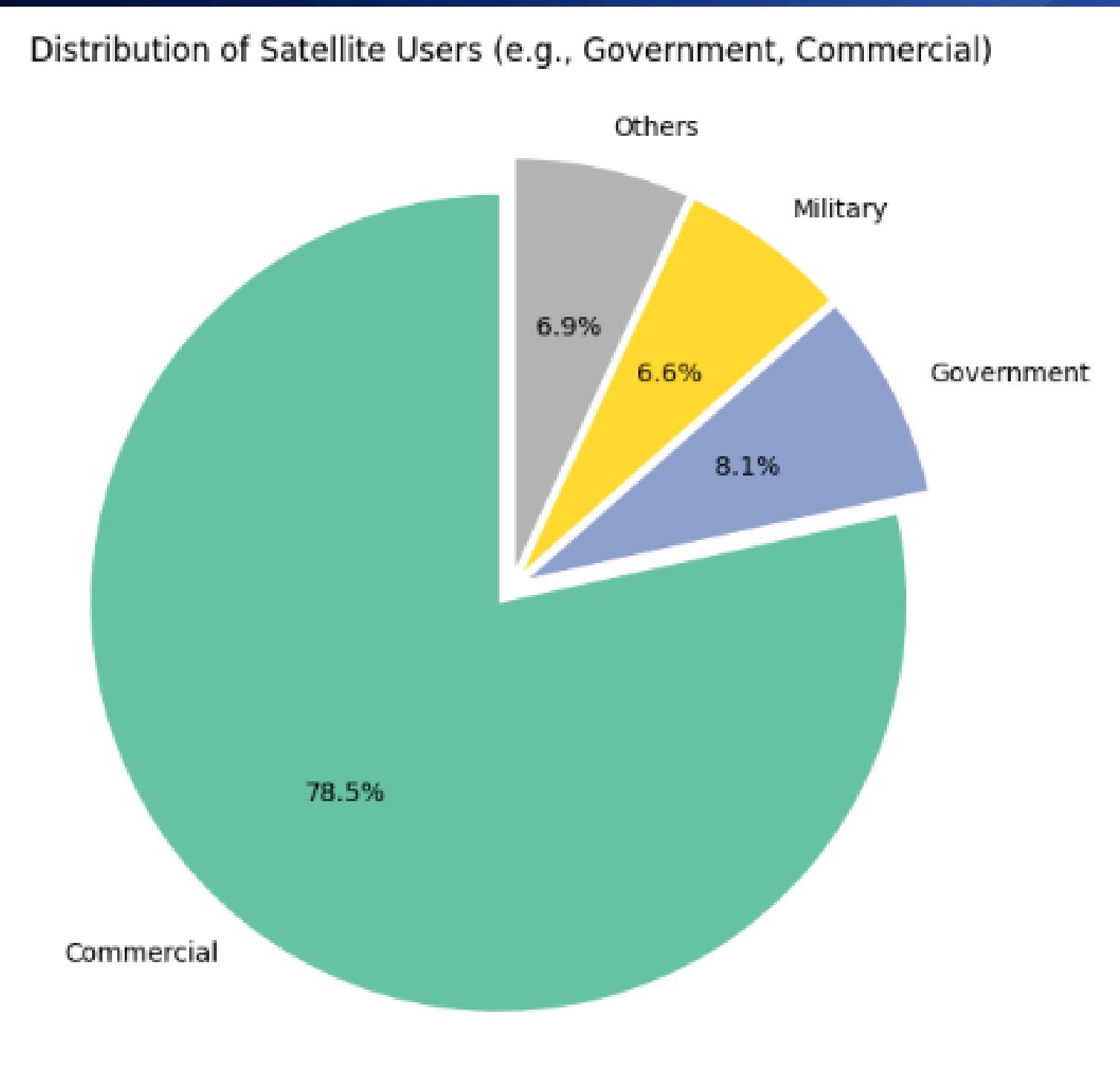
## COMPLIANCE ROLE

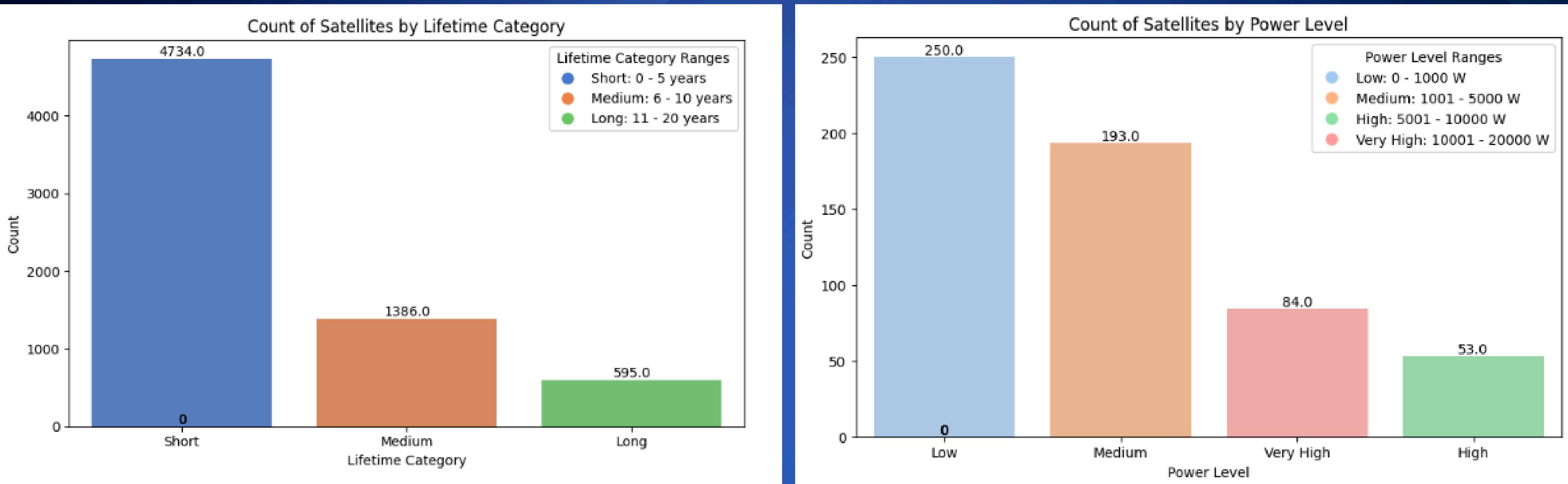


# OWNERSHIP



# PURPOSE





# GENERAL SATELLITE LIFESPANS & POWER

# MALAYSIAN SATELLITE



Current Official Name of Satellite	Country/Org of UN Registry	Country of Operator/Owner	Operator/Owner	Users	Purpose	Detailed Purpose	Class of Orbit	Type of Orbit	Longitude of GEO (degrees)	Launch Site	Launch Vehicle
1126 INNOSat-2	NR	Malaysia	Astronautic Technology Sdn. Bhd (ATSB)	Government	Technology Development	Unknown	LEO	Sun-Synchronous	0.0	Satish Dhawan Space Centre	PSLV
1598 Measat 3A	Malaysia	Malaysia	MEASAT Satellite Systems Sdn. Bhd.	Commercial	Communications	Unknown	GEO	Unknown	91.5	Baikonur Cosmodrome	Zenit 3SLB
1599 Measat 3B	Malaysia	Malaysia	MEASAT Satellite Systems Sdn. Bhd.	Commercial	Communications	Unknown	GEO	Unknown	91.5	Guiana Space Center	Ariane 5 ECA
1600 Measat 3D	NR (9/22)	Malaysia	MEASAT Satellite Systems Sdn. Bhd.	Commercial	Communications	Unknown	GEO	Unknown	91.5	Guiana Space Center	Ariane 5

```
# Filter for SpaceX satellites
spacex_satellites = satellite[satellite['Operator/Owner'].str.contains('SpaceX', na=False)]

# Calculate the mean expected Lifetime for Malaysian satellites and SpaceX satellites
mean_lifetime_malaysia = malaysian_satellites['Expected Lifetime (yrs.)'].mean()
mean_lifetime_spacex = spacex_satellites['Expected Lifetime (yrs.)'].mean()

print(f"Mean Expected Lifetime of Malaysian Satellites: {mean_lifetime_malaysia} years")
print(f"Mean Expected Lifetime of SpaceX Satellites: {mean_lifetime_spacex} years")
```

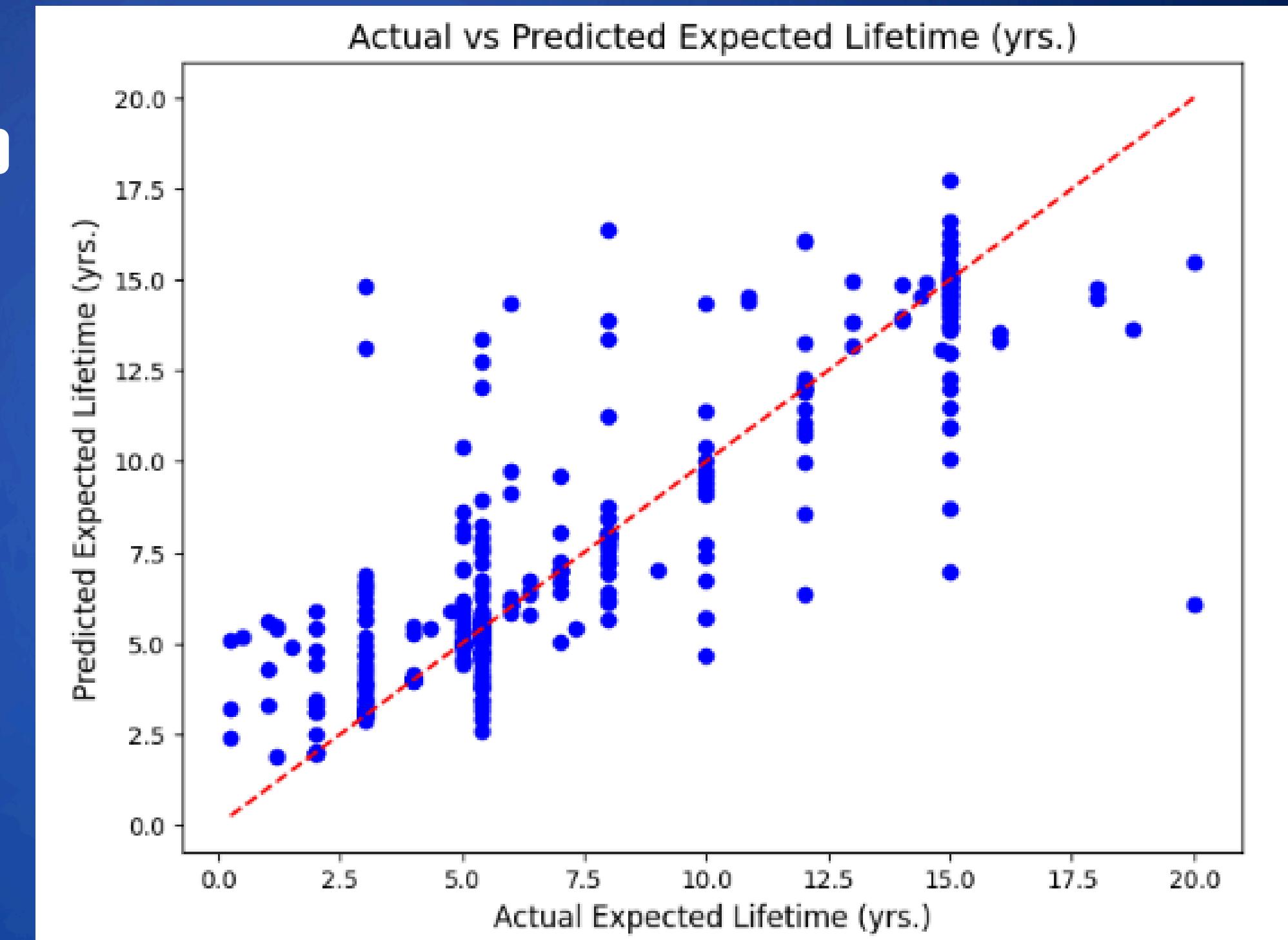
Mean Expected Lifetime of Malaysian Satellites: 12.599068371932006 years  
 Mean Expected Lifetime of SpaceX Satellites: 4.0 years

# PREDICTING EXPECTED LIFETIME USING LINEAR REGRESSION (RANDOM FOREST REGRESSOR)

Explanation of the visualization:

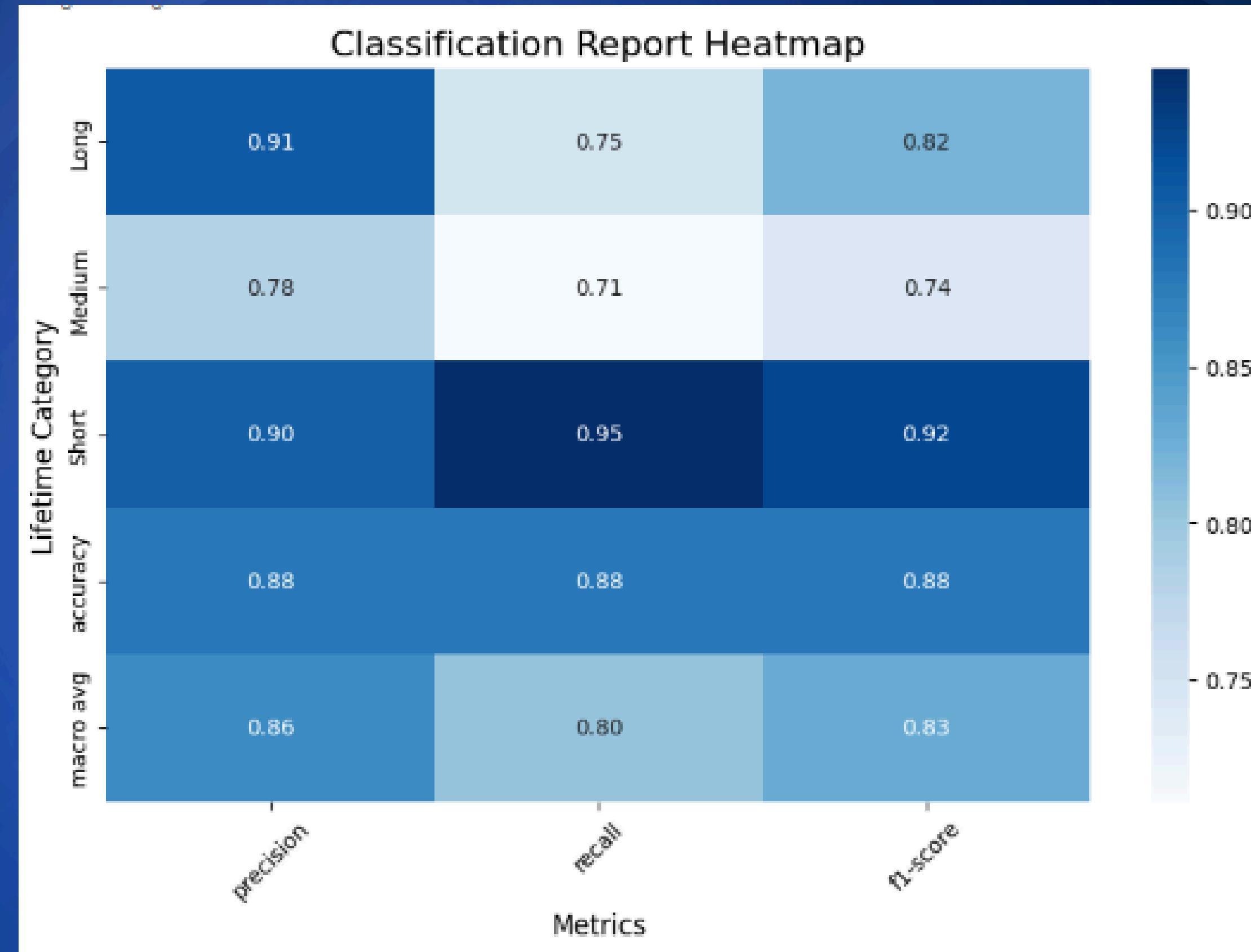
- Blue dots represent the actual vs. predicted values.
- The red dashed line represents the ideal scenario where predicted values exactly match the actual values (i.e., perfect prediction).
- Dots close to the line indicate better predictions, while dots farther away indicate larger errors.

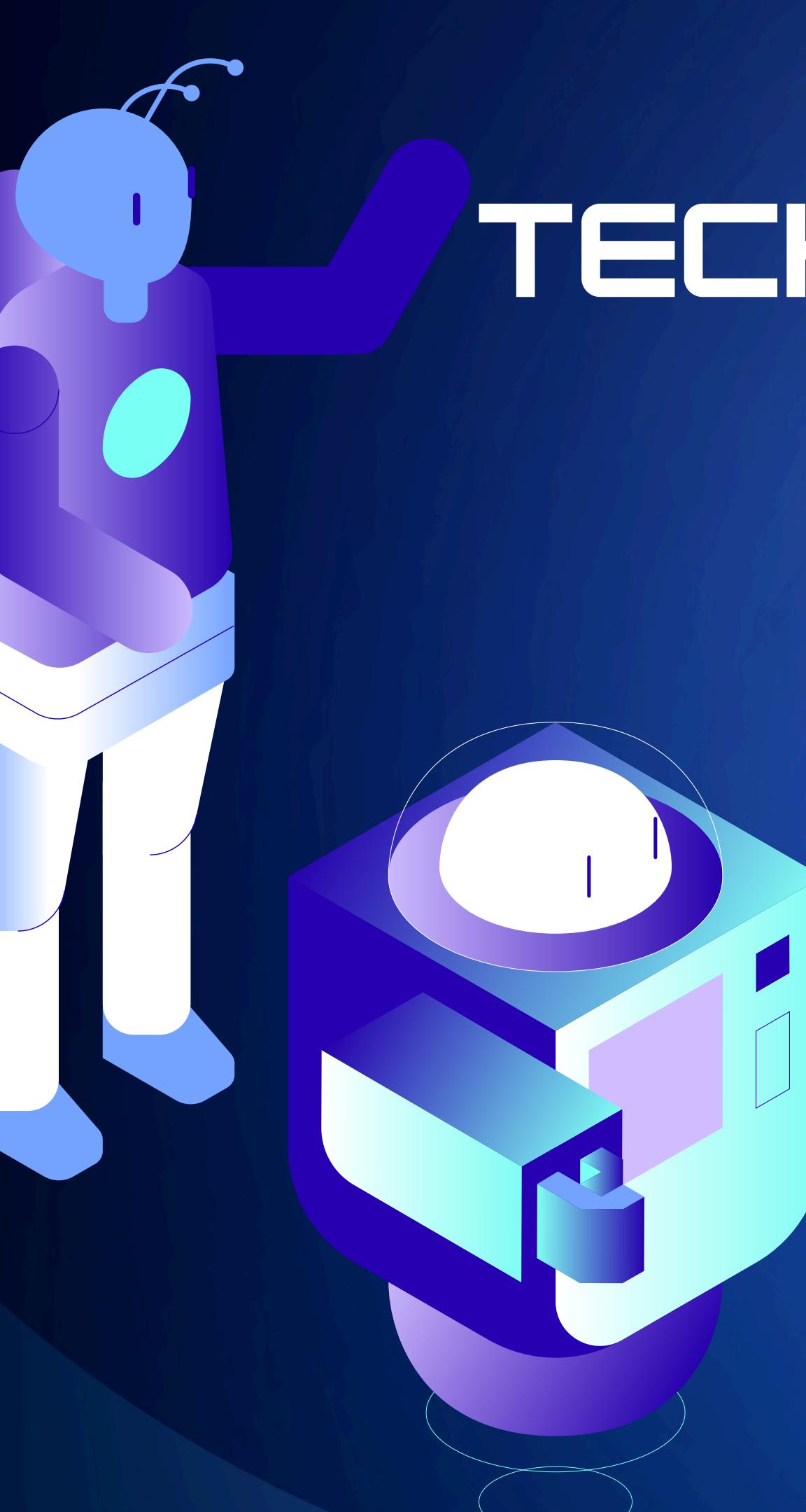
```
# Features and target variable
features = ['Launch Mass (kg.)', 'Power (watts)', 'Perigee (km)', 'Apogee (km)', 'Inclination (degrees)']
target = 'Expected Lifetime (yrs.)'
```



# PERFORMANCE ANALYSIS USING RANDOM FOREST CLASSIFIER

- Overall Performance: 88% accuracy in predicting satellite lifetimes across all categories.
- Long: 91% of predicted Long satellites have a true class of Long, misses about 25% of actual satellites.
- Medium: 78% of predicted Medium satellites are actually Medium.
- Short: 90% of predicted Short satellites are indeed Short



A large, semi-transparent watermark of a robotic arm is positioned on the left side of the slide. The robot has a white head with a blue visor, a purple torso, and white arms. It is holding a hexagonal object with a circular sensor or camera mounted on top.

# TECHNICAL ANALYSIS

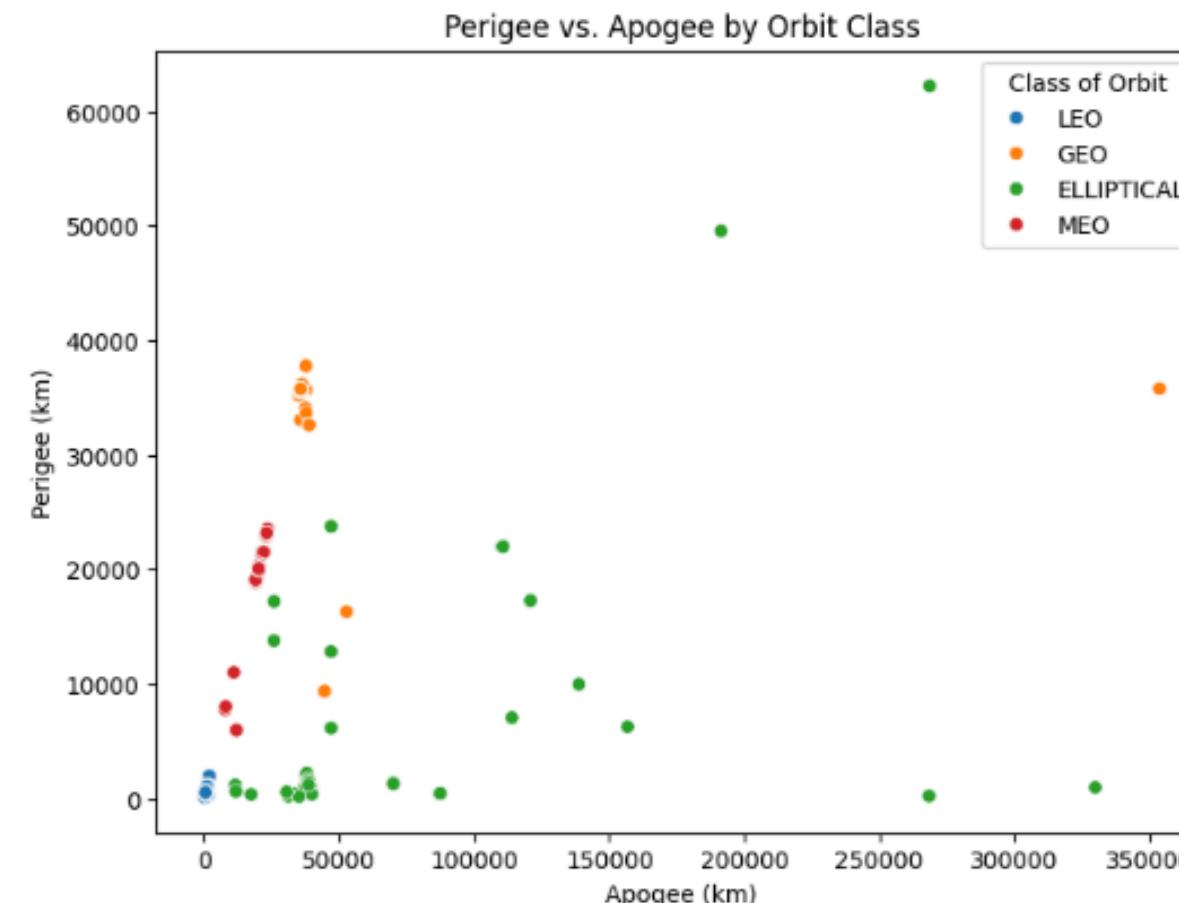
1. Analyze Technical Parameters
2. Apply Machine Learning for Classification

- Analyze Mean Orbital Speed

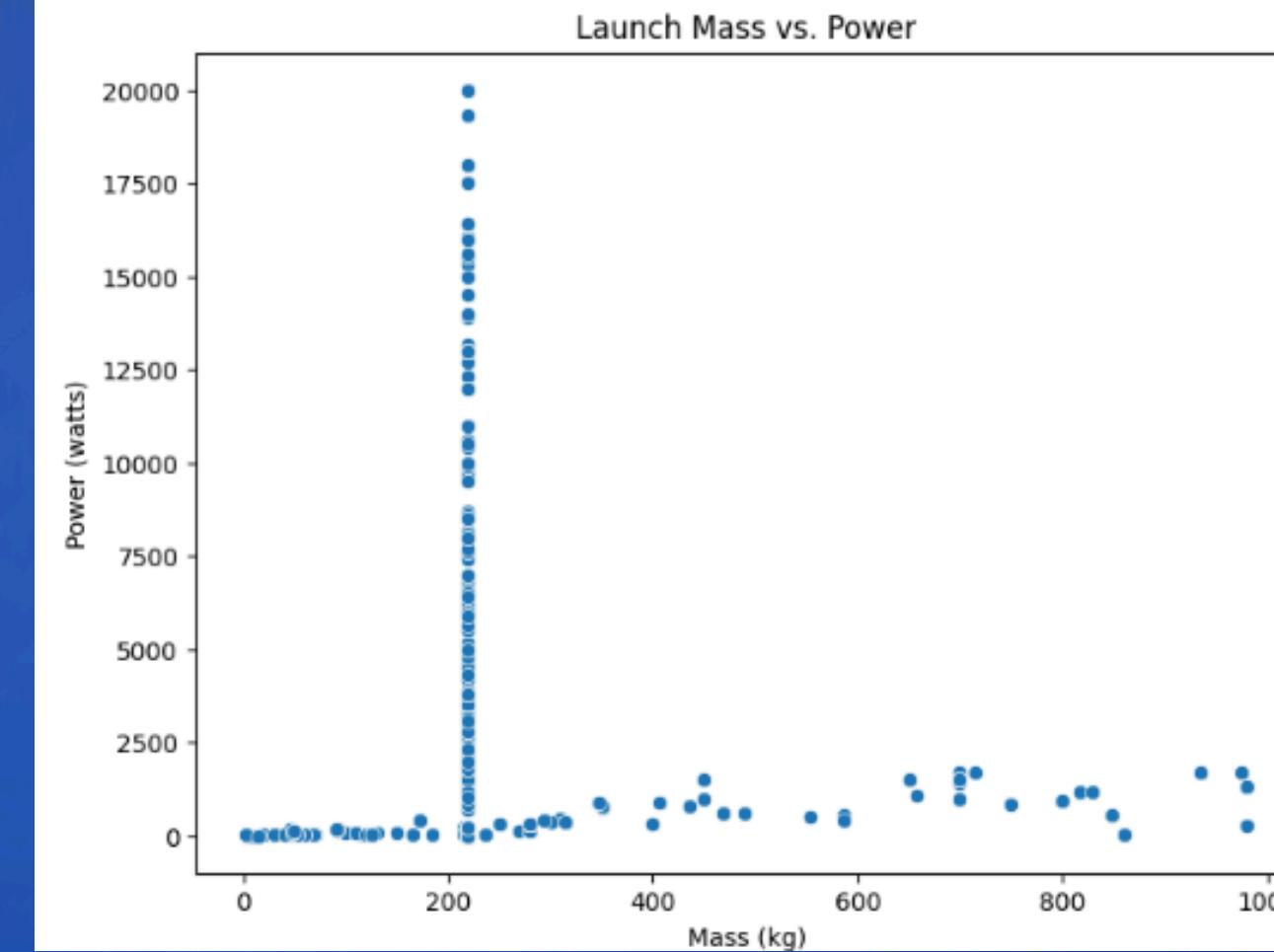
```
--> Mean orbital speed: descriptive statistics LEO
count    5931.000000
mean     7.584568
std      1.088282
min     0.495287
25%     7.574980
50%     7.594084
75%     7.624774
max     81.200424
Mean orbital speed for LEO satellites with complete parameter set in UCSDDB: 7.58 km/sec.
--> Mean orbital speed: descriptive statistics MEO
count    142.000000
mean     4.198047
std      2.154475
min     1.169184
25%     3.773108
50%     3.873711
75%     3.952928
max     28.762194
Mean orbital speed for MEO satellites with complete parameter set in UCSDDB: 4.20 km/sec.
--> Mean orbital speed: descriptive statistics GEO
count    580.000000
mean     3.242707
std      2.222474
min     2.265962
25%     3.074585
50%     3.074628
75%     3.074684
max     44.917812
Mean orbital speed for GEO satellites with complete parameter set in UCSDDB: 3.24 km/sec.
Current Official Name of Satellite Class of Orbit \
0          1HOPSAT-TD      LEO
1          Aalto-1         LEO
2          AAIt-4          LEO
3          ABS-2           GEO
4          ABS-2A          GEO
5          ABS-3A          GEO
Mean Orbital Speed (km/sec)
0          7.574047
1          7.613647
2          7.581165
3          3.074705
4          3.068321
5          3.075498
```

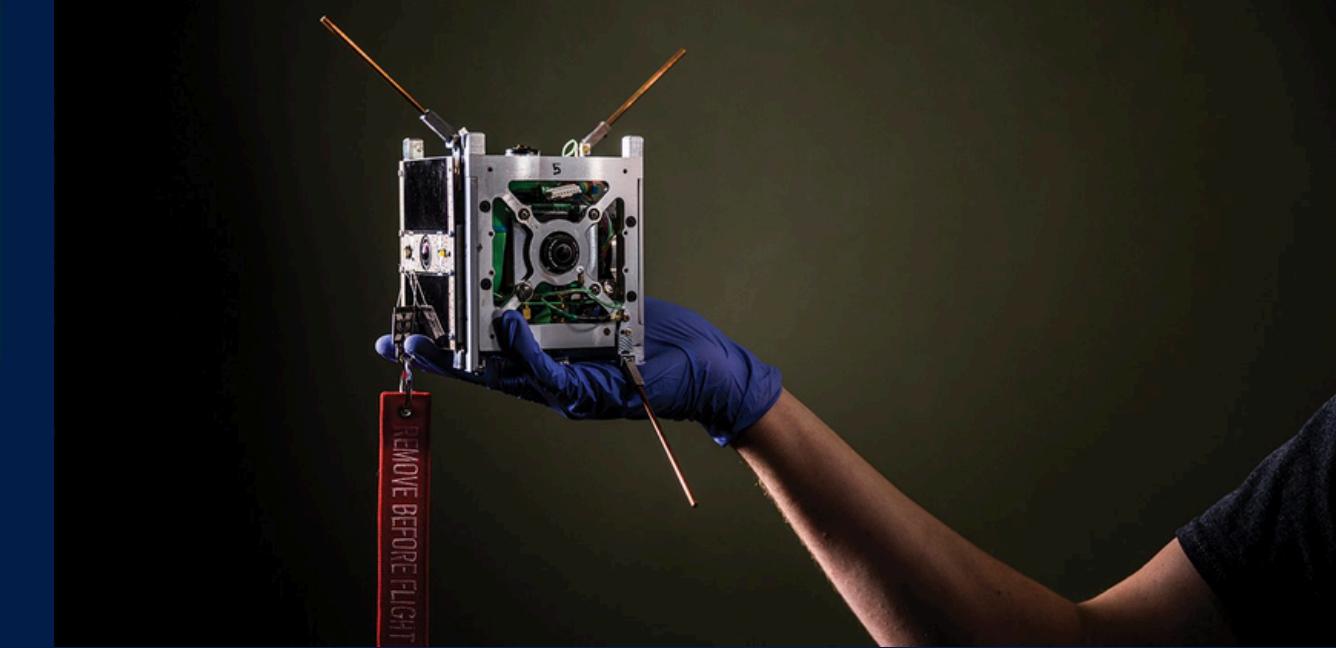
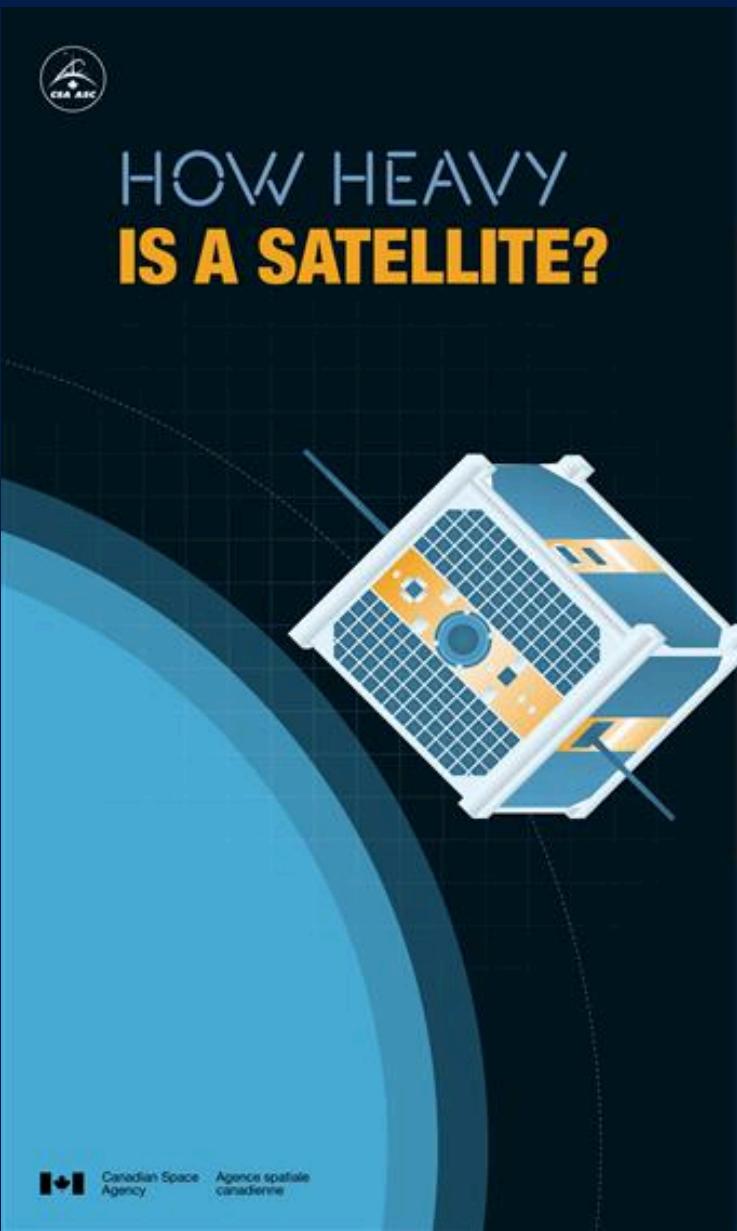
# TECH LEAD

```
# Scatter plot for Perigee vs. Apogee
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Apogee (km)', y='Perigee (km)', hue='Class of Orbit', data=satellite)
plt.title('Perigee vs. Apogee by Orbit Class')
plt.xlabel('Apogee (km)')
plt.ylabel('Perigee (km)')
plt.show()
```



```
# Scatter plot for Mass vs. Power
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Launch Mass (kg.)', y='Power (watts)', data=satellite)
plt.title('Launch Mass vs. Power')
plt.xlabel('Mass (kg)')
plt.ylabel('Power (watts)')
plt.show()
```

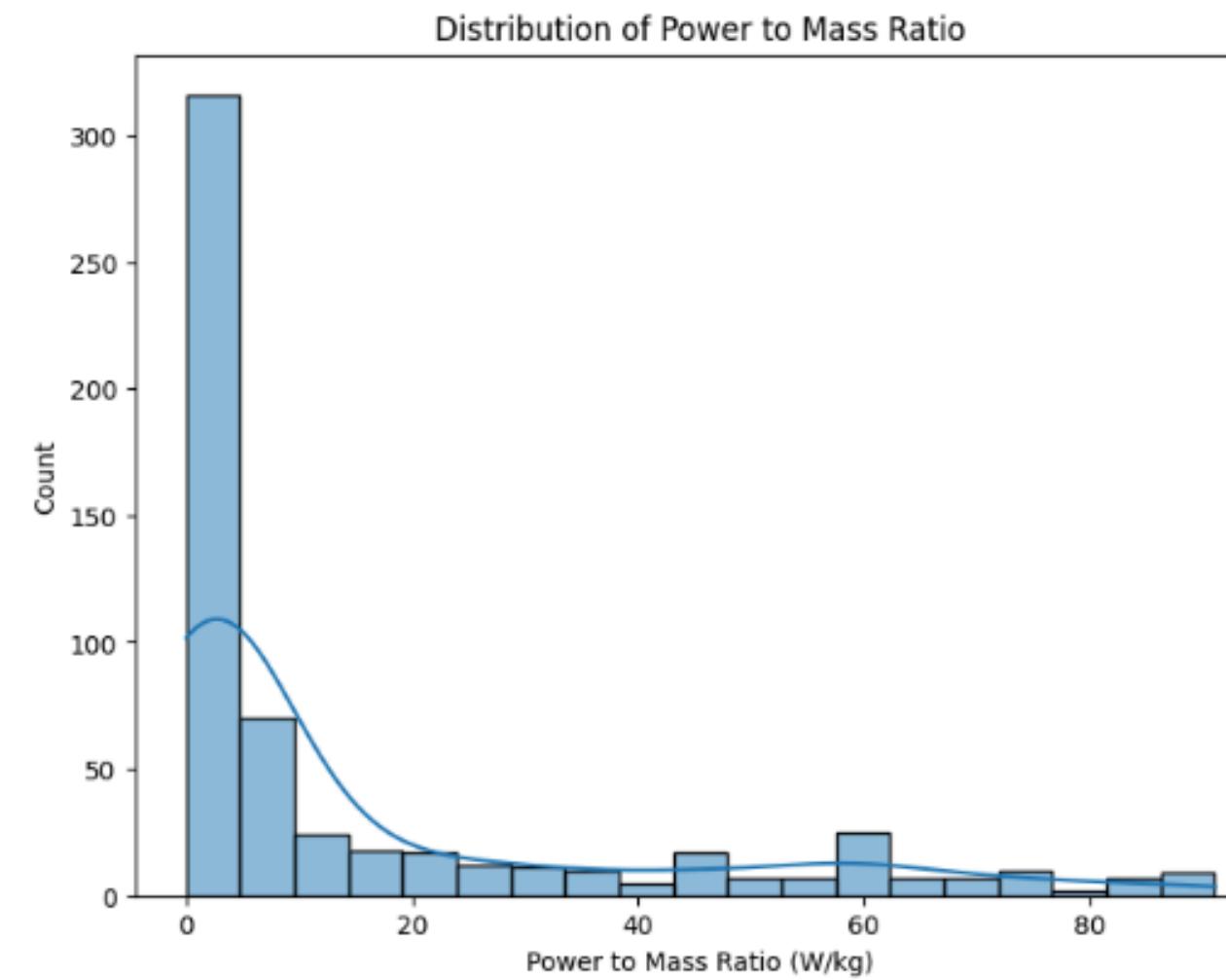




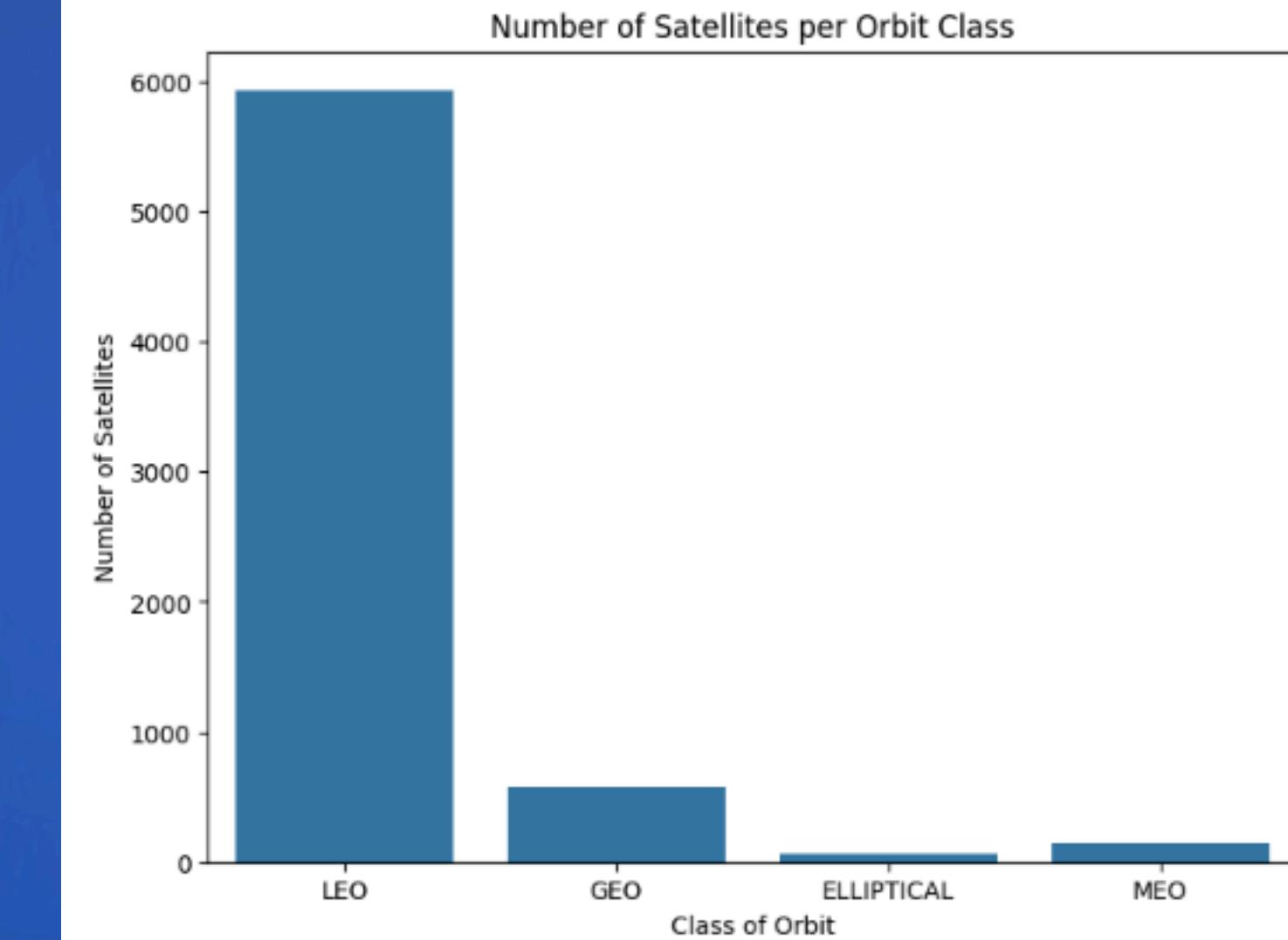
## TECH LEAD

```
# Calculate Power to Mass Ratio
satellite['Power to Mass Ratio'] = satellite['Power (watts)'] / satellite['Launch Mass (kg.)']

# Plot the Power to Mass Ratio
plt.figure(figsize=(8, 6))
sns.histplot(satellite['Power to Mass Ratio'], kde=True)
plt.title('Distribution of Power to Mass Ratio')
plt.xlabel('Power to Mass Ratio (W/kg)')
plt.show()
```



```
# Bar plot of the number of satellites per orbit class
plt.figure(figsize=(8, 6))
sns.countplot(x='Class of Orbit', data=satellite)
plt.title('Number of Satellites per Orbit Class')
plt.xlabel('Class of Orbit')
plt.ylabel('Number of Satellites')
plt.show()
```



## TECH LEAD

### FLAT TREND FOR MASS:

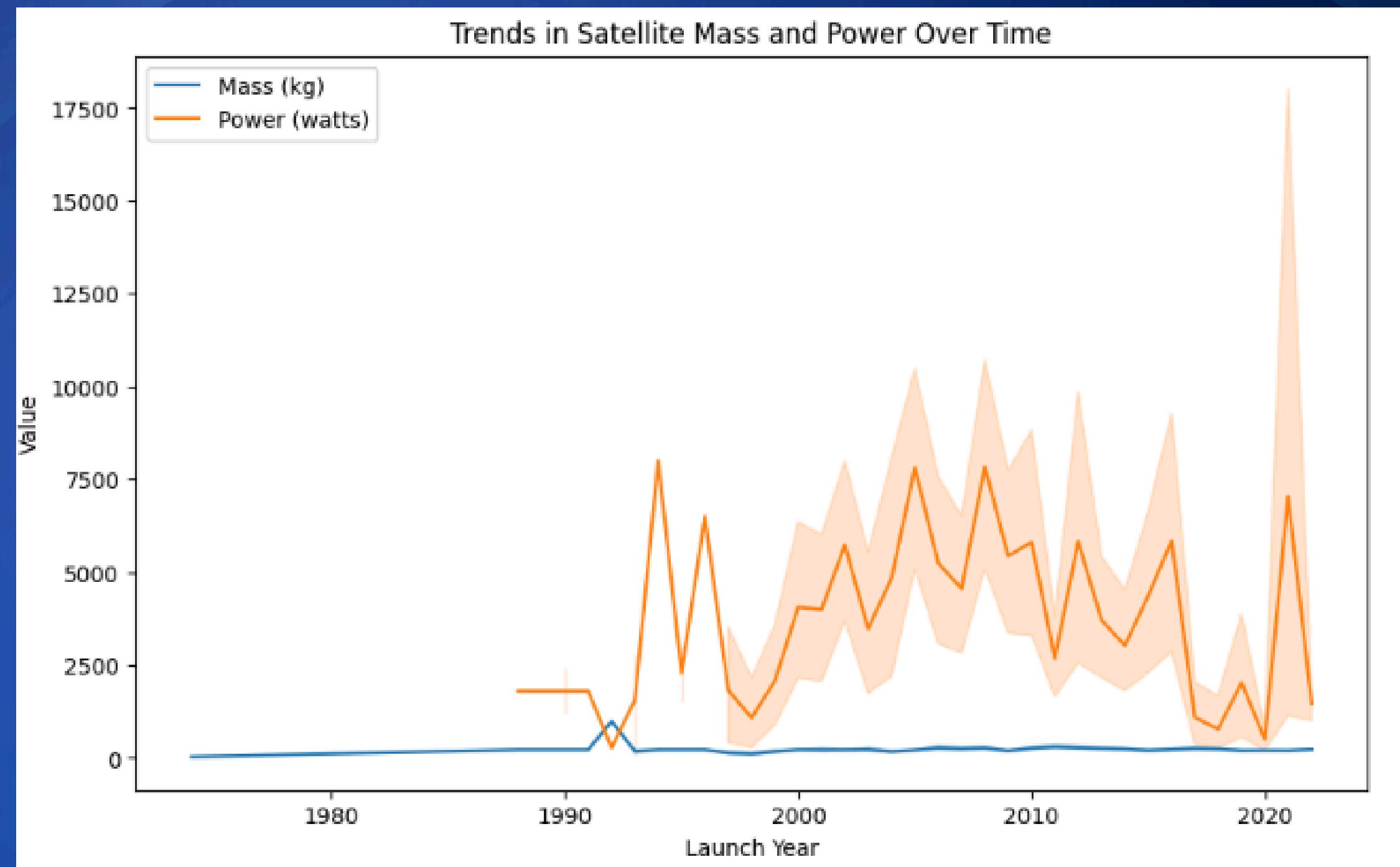
- SATELLITE MASS (BLUE LINE) HAS STAYED STABLE, WITH A SMALL RISE IN THE LATE 1990S AND AFTER 2020.
- THIS SUGGESTS SATELLITE DESIGNS HAVEN'T DRastically CHANGED IN WEIGHT DESPITE TECHNOLOGY ADVANCEMENTS, LIkELY DUE TO STRUCTURAL INTEGRITY REQUIREMENTS.

### FLUCTUATING POWER TREND:

- POWER (ORANGE LINE) VARIES MORE, WITH SPIKES IN THE 1990s AND POST-2010, SHOWING INCREASING ENERGY DEMANDS.
- THE SHARP RISE AFTER 2020 SUGGESTS NEW TECHNOLOGIES OR SATELLITE CONSTELLATIONS THAT NEED MORE POWER.

### ERROR BANDS (SHADEd AREAS):

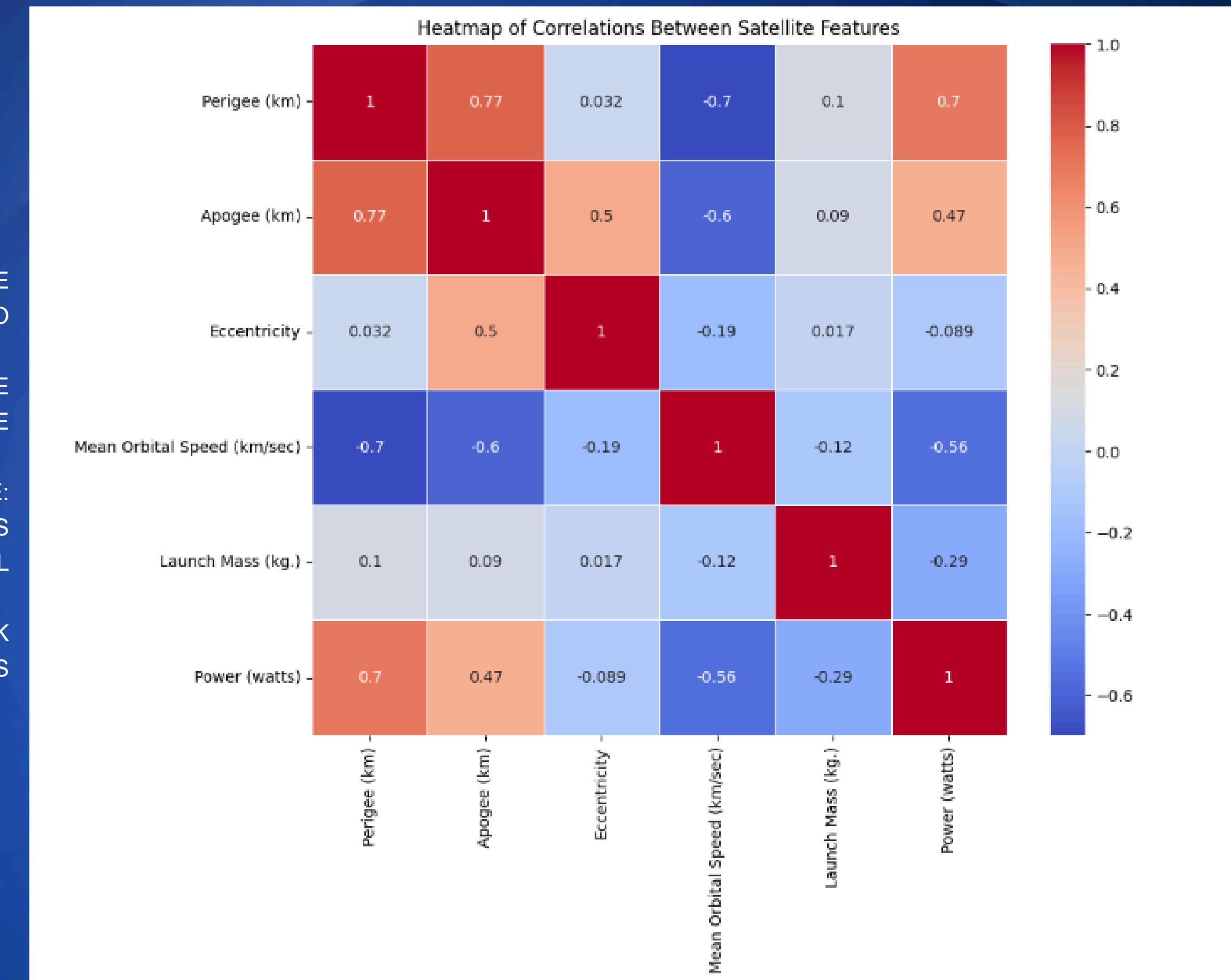
- POWER VALUES SHOW WIDER VARIABILITY, ESPECIALLY AFTER 1990, REFLECTING DIVERSE SATELLITE MISSIONS.
- MASS SHOWS NARROWER VARIABILITY, MEANING SATELLITE WEIGHTS ARE MORE CONSISTENT.



## TECH LEAD

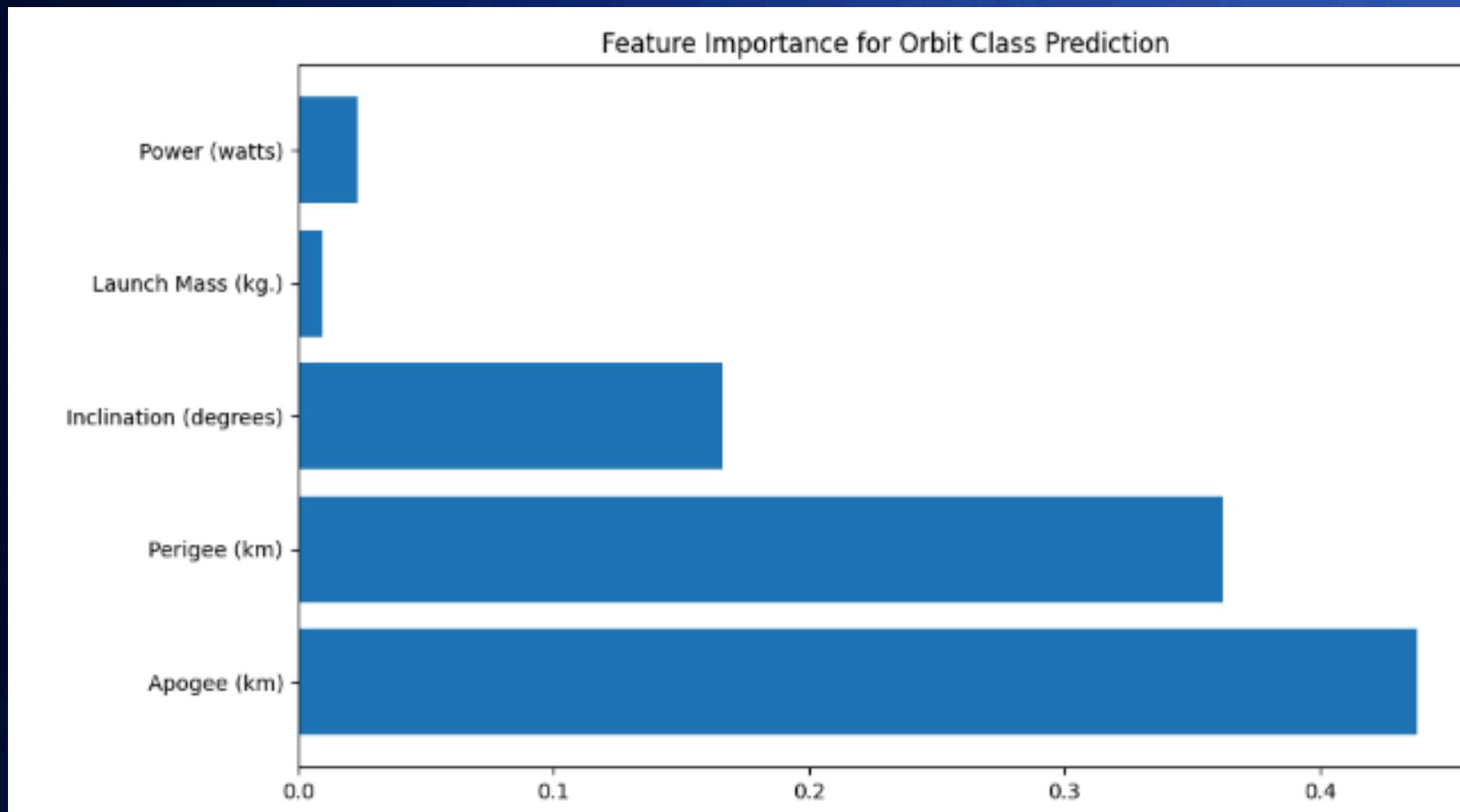
### KEY OBSERVATIONS:

- PERIGEE AND POWER (0.7): STRONG POSITIVE CORRELATION—SATELLITES CLOSER TO EARTH TEND TO USE MORE POWER.
- ECCENTRICITY AND APOGEE (0.5): MODERATE POSITIVE CORRELATION—HIGHER APOGEES ARE LINKED TO MORE ECCENTRIC ORBITS.
- MEAN ORBITAL SPEED VS. PERIGEE AND APOGEE: NEGATIVE CORRELATION—SATELLITES IN HIGHER ORBITS MOVE MORE SLOWLY, CONSISTENT WITH ORBITAL MECHANICS.
- LAUNCH MASS AND OTHER VARIABLES: WEAK CORRELATIONS WITH MOST FEATURES, MEANING MASS DOESN'T STRONGLY AFFECT THESE CHARACTERISTICS.

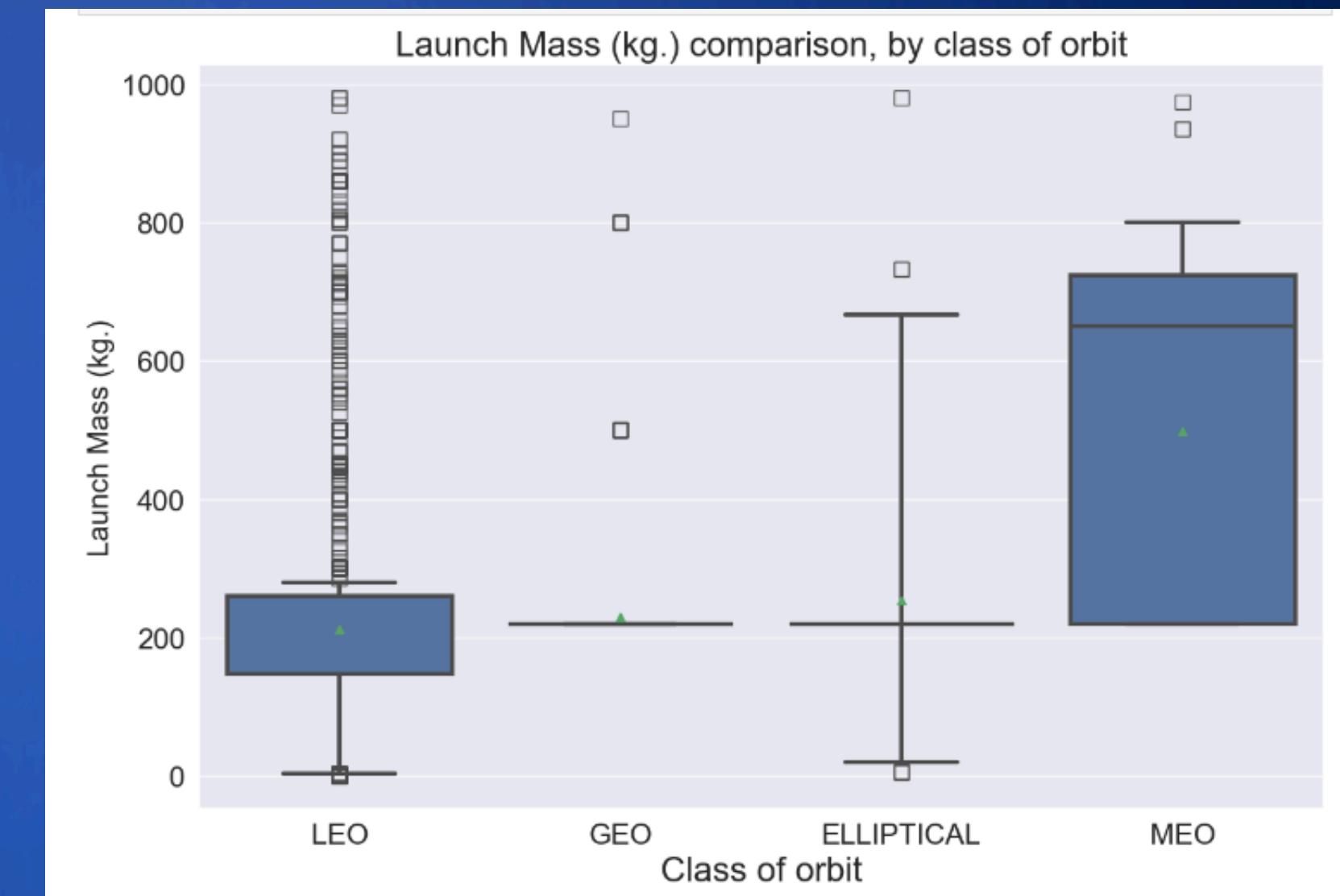


## TECH LEAD

### • Machine Learning



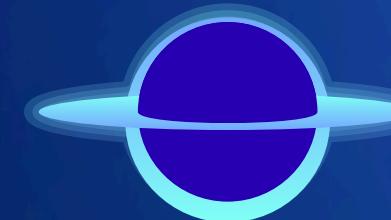
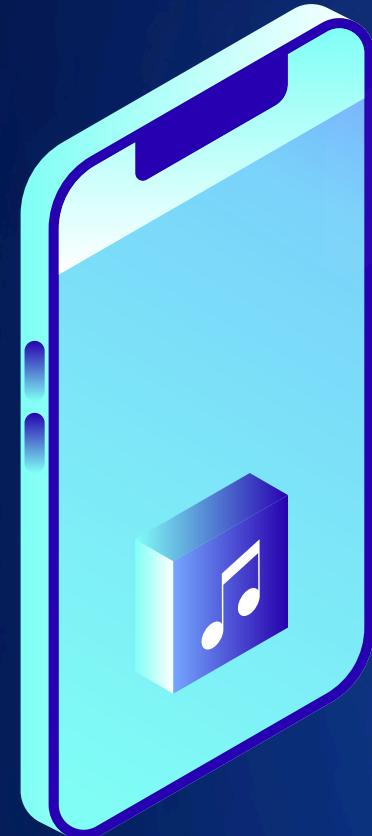
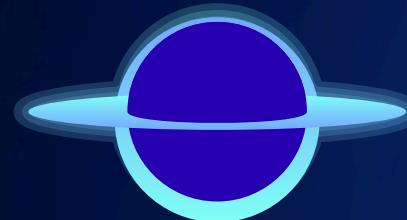
- LEO SATELLITES SHOW THE WIDEST RANGE OF LAUNCH MASSES, INDICATING THAT BOTH SMALL AND LARGE SATELLITES ARE COMMONLY DEPLOYED INTO LEO.
- MEO SATELLITES TEND TO BE HEAVIER THAN THOSE IN OTHER ORBITS, POSSIBLY DUE TO THE NEED FOR LARGER PAYLOADS OR SPECIFIC MISSION REQUIREMENTS.
- GEO SATELLITES ARE CONSISTENTLY LIGHT IN THIS DATASET, LIKELY BECAUSE GEOSTATIONARY SATELLITES ARE MORE SPECIALIZED AND REQUIRE LESS MASS FOR THEIR PARTICULAR ORBITS.
- ELLIPTICAL ORBIT SATELLITES ARE USUALLY LIGHT, BUT A FEW LARGE SATELLITES EXIST, SHOWN BY THE OUTLIERS



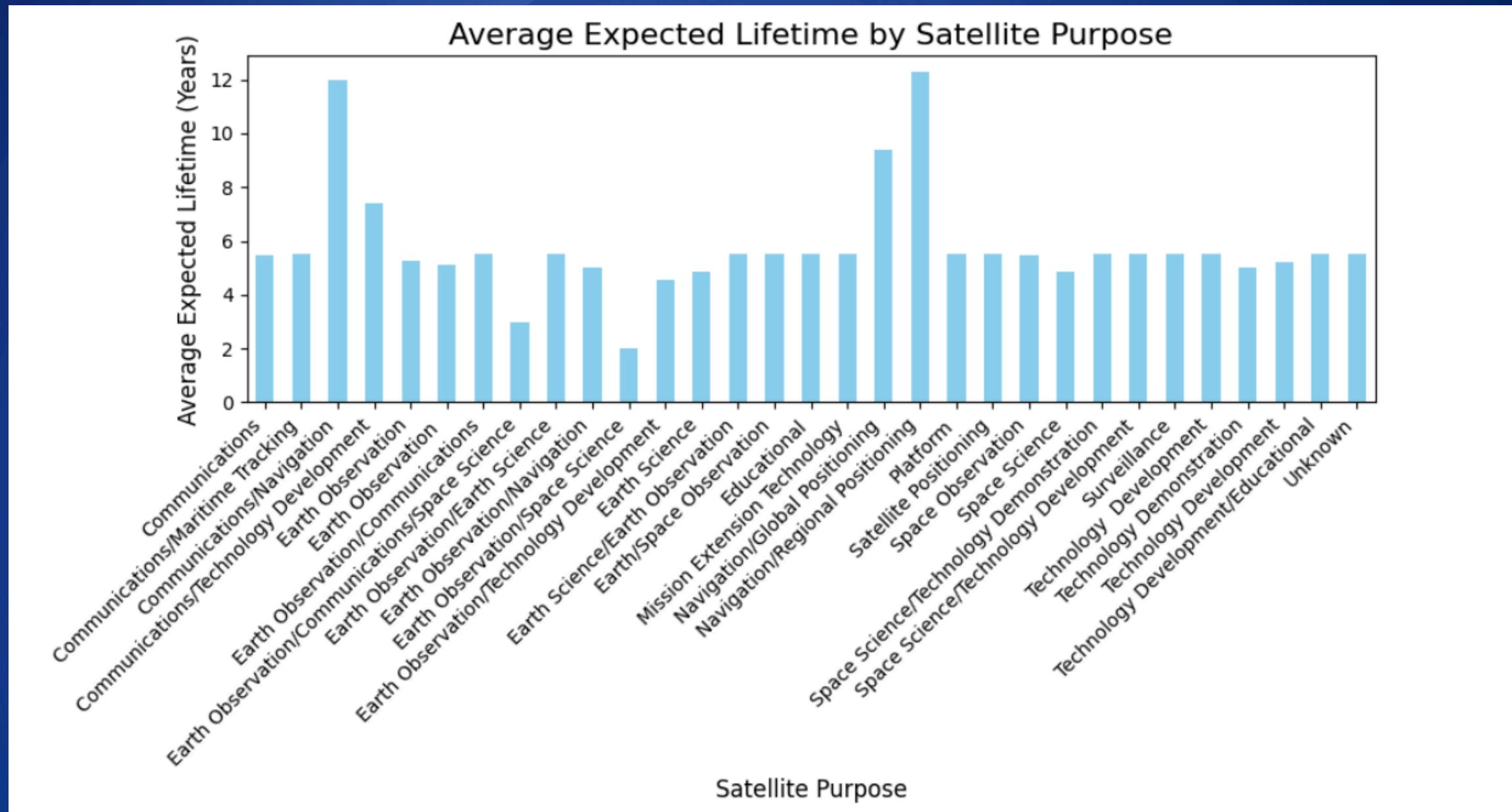
06

## BUSINESS ROLE

1. Analyze key factors influencing satellite lifespan.
2. Develop machine learning models to predict satellite lifespans and classify satellites based on their expected lifetime, power consumption, and technical specifications.

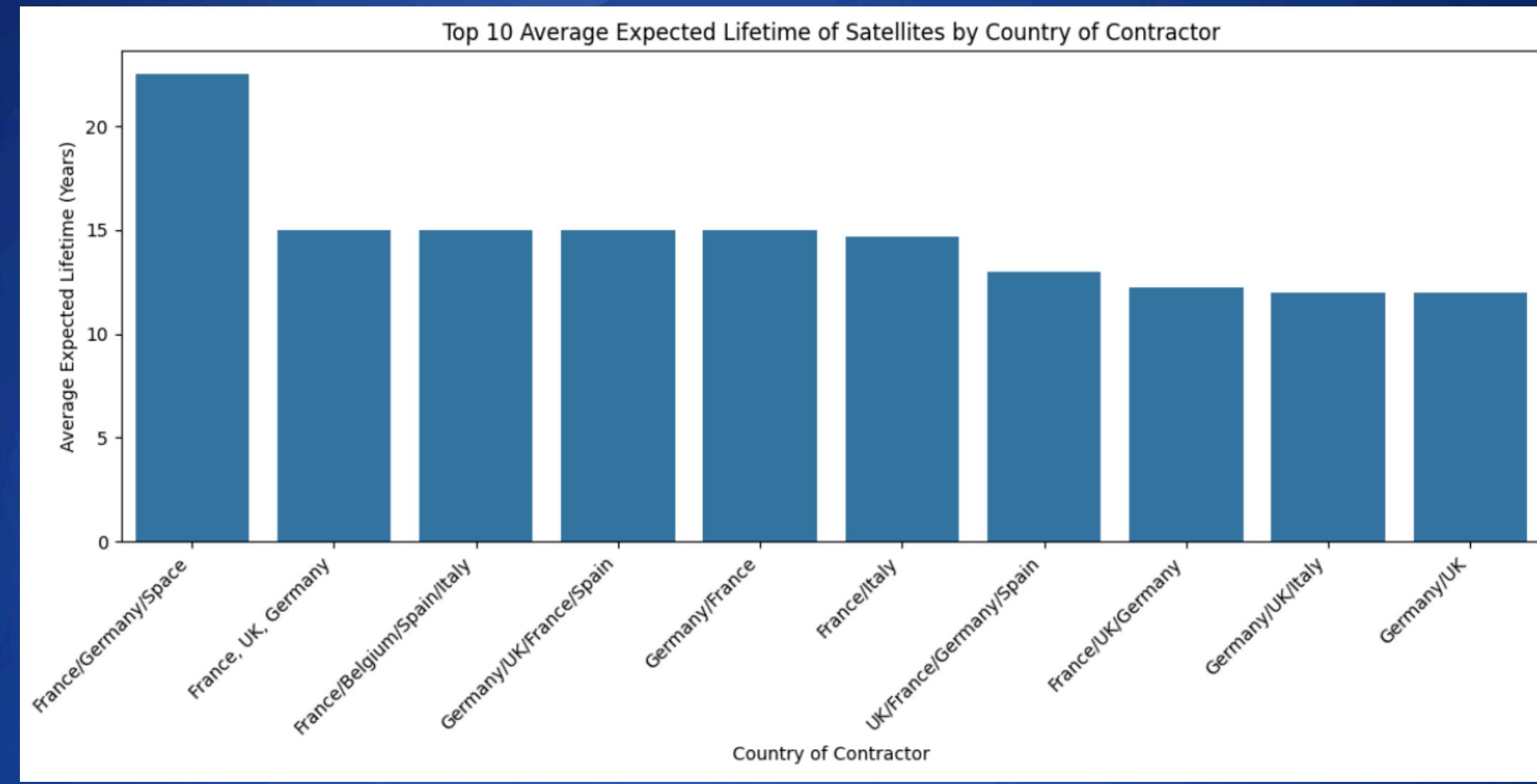


Factors  
influence  
satellite  
lifespan



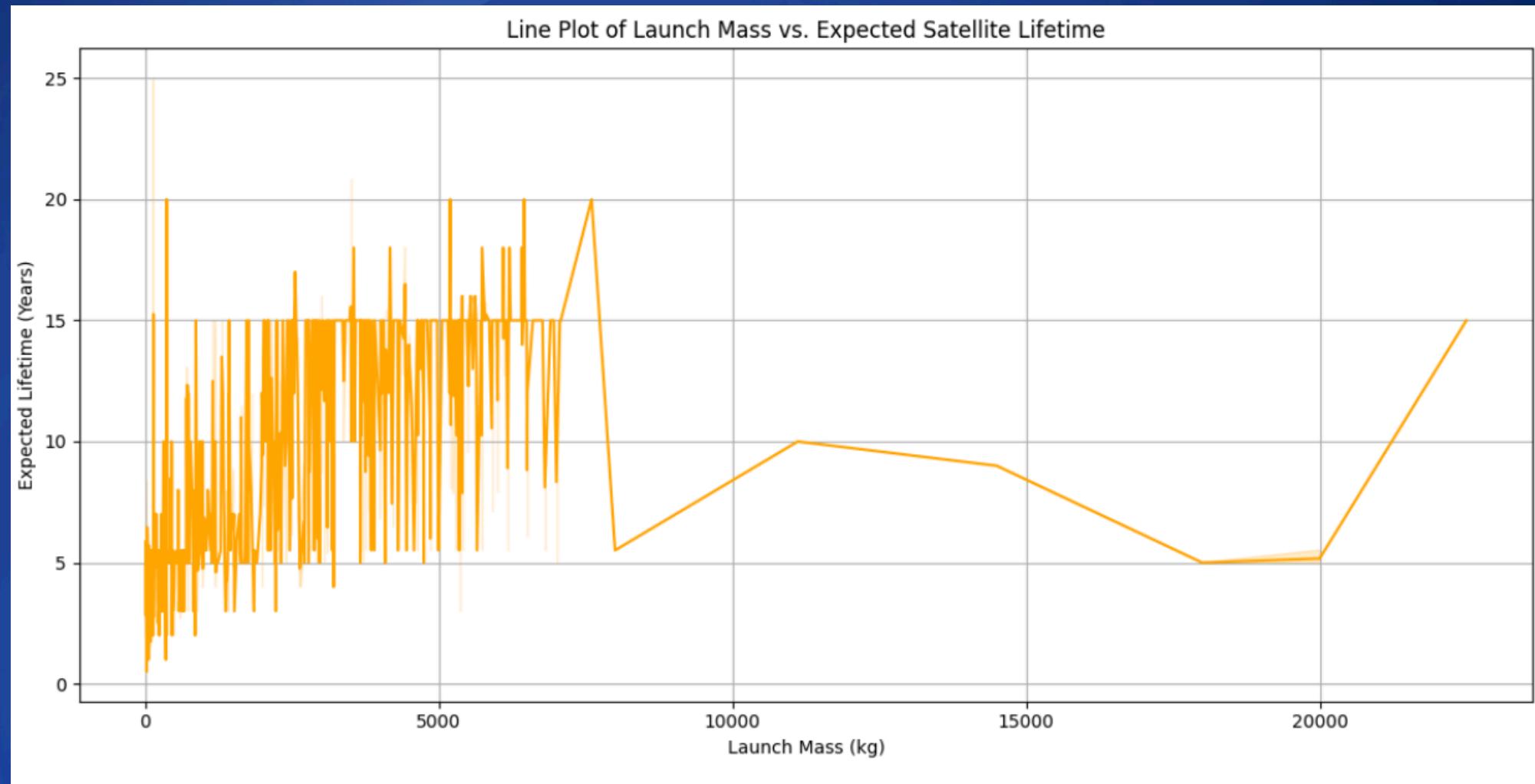
- Bar chart illustrates the Average Expected Lifetime of Satellites across different Satellite Purposes.
- Navigational/Regional Positioning purpose has the highest expected lifetime
- Earth Observation/Space Science purpose has the lowest expected lifetime

Factors  
influence  
satellite  
lifespan



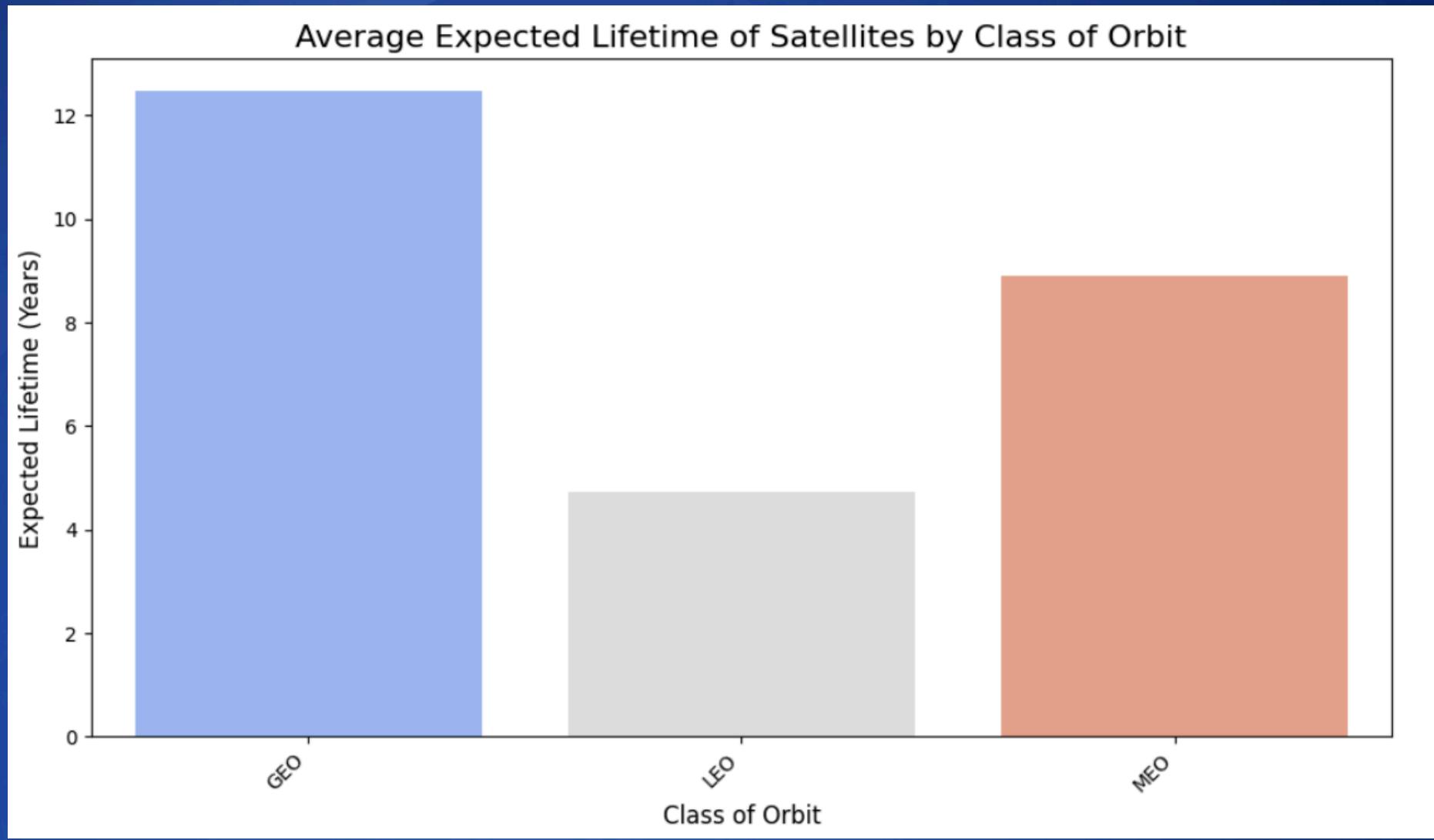
- This variance in satellite lifespan can indicate differences in quality of materials used by different countries and space agencies
- High materials quality lead to potential long-term revenue streams and reduced costs of replacement or maintenance
- Important to evaluate the risk of working with contractors from different regions

Factors  
influence  
satellite  
lifespan



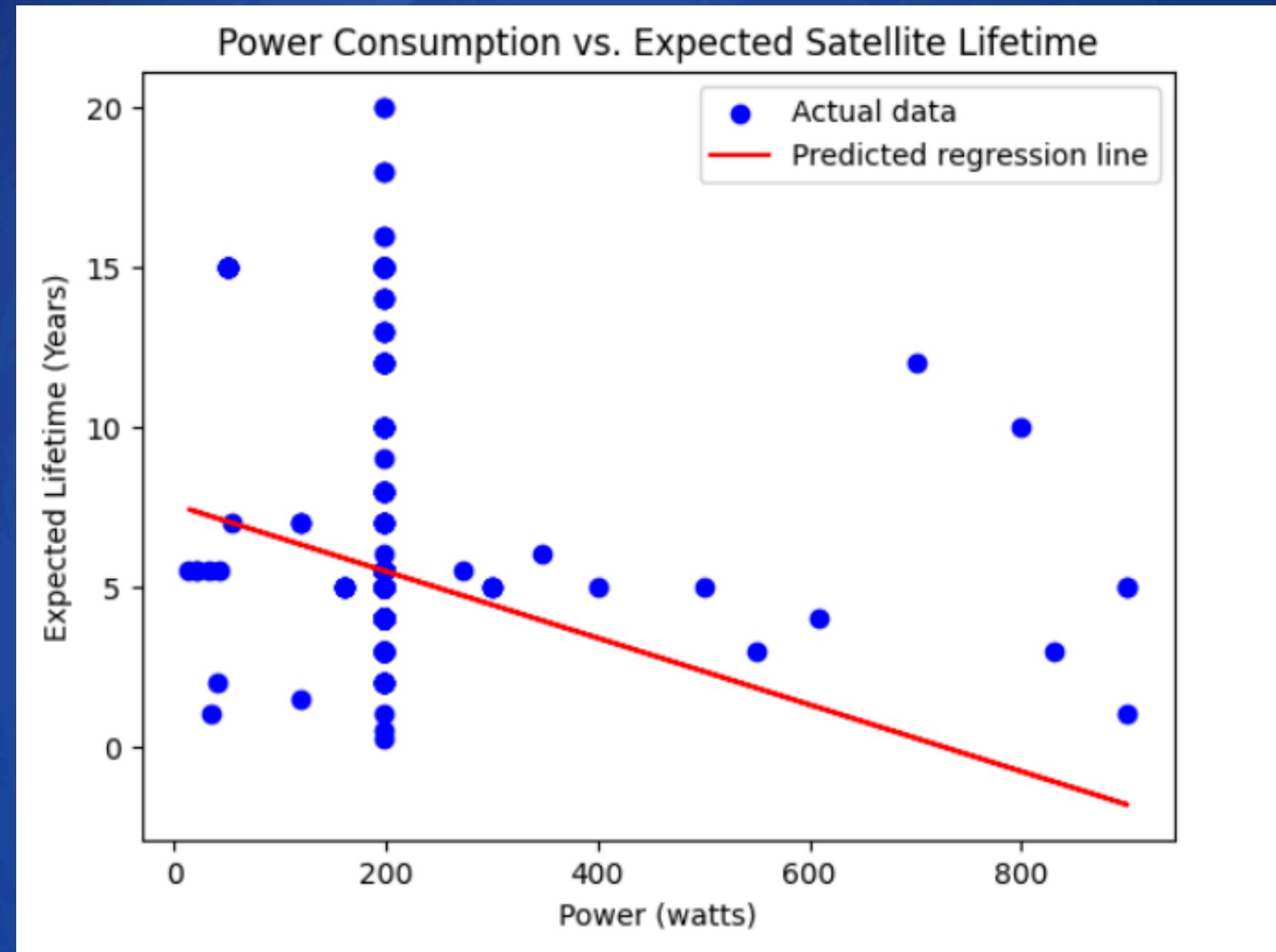
- For small satellites (less than 5,000 kg), there is a wide variation in their expected lifetime, indicating that other factors besides mass might significantly influence satellite longevity
- For large satellites (close to or above 20,000 kg), there is a notable increase in their expected lifetime.

Factors  
influence  
satellite  
lifespan



- The bar chart illustrates the average expected lifetime of satellites based on their class of orbit.
- Satellites in GEO orbits last much longer can reduce cost because they don't need to be replaced as often.
- LEO satellites have a shorter lifespan, meaning they need to be replaced more frequently and lead to higher costs over time.

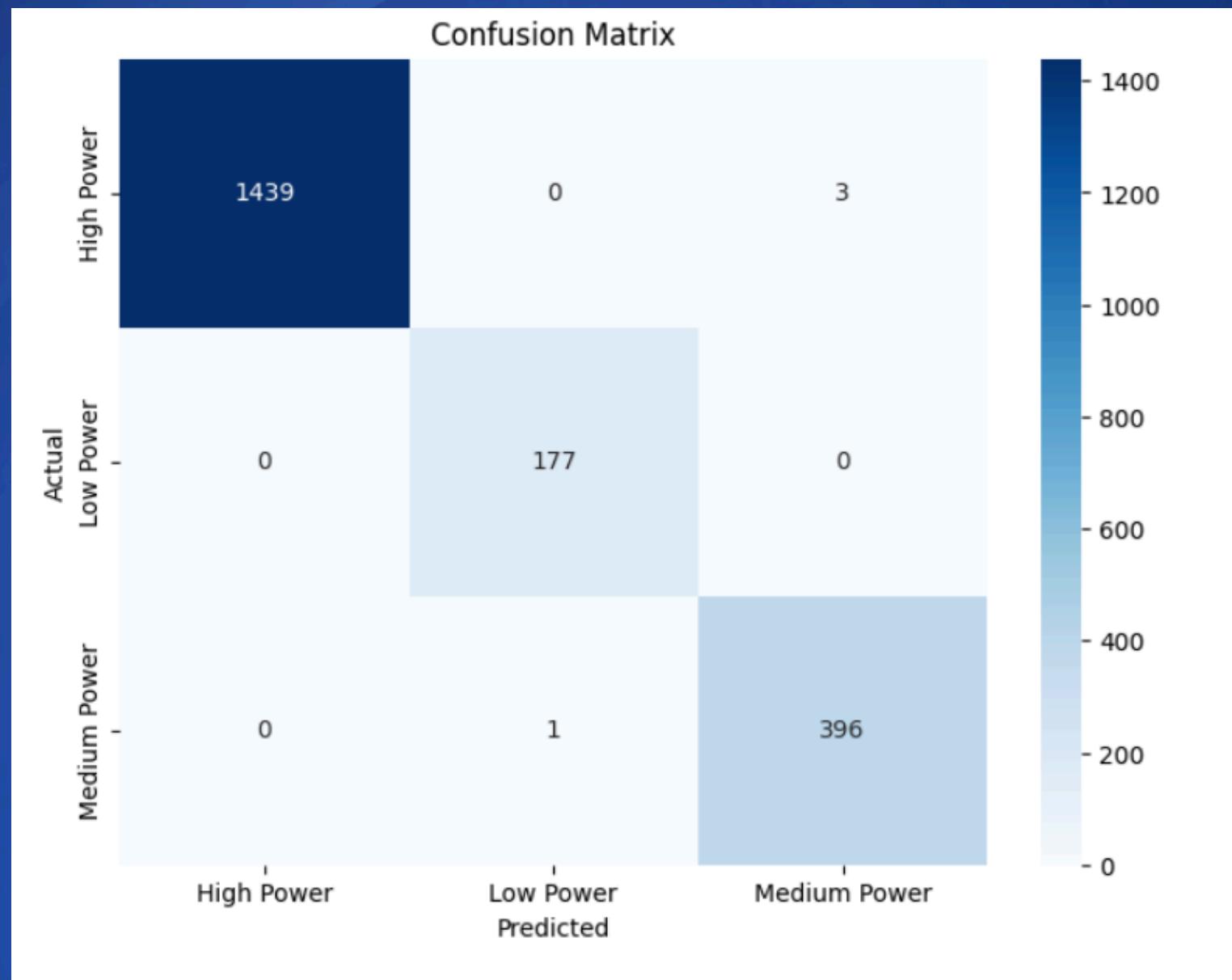
## 1) Linear Regression Model



- Model show the satellite lifetimes decrease as power consumption increases
- Increased power consumption could lead to overheating, further shortening the satellite's operational lifespan
- Satellites with lower power consumption are likely more optimized for longer-term, less demanding missions

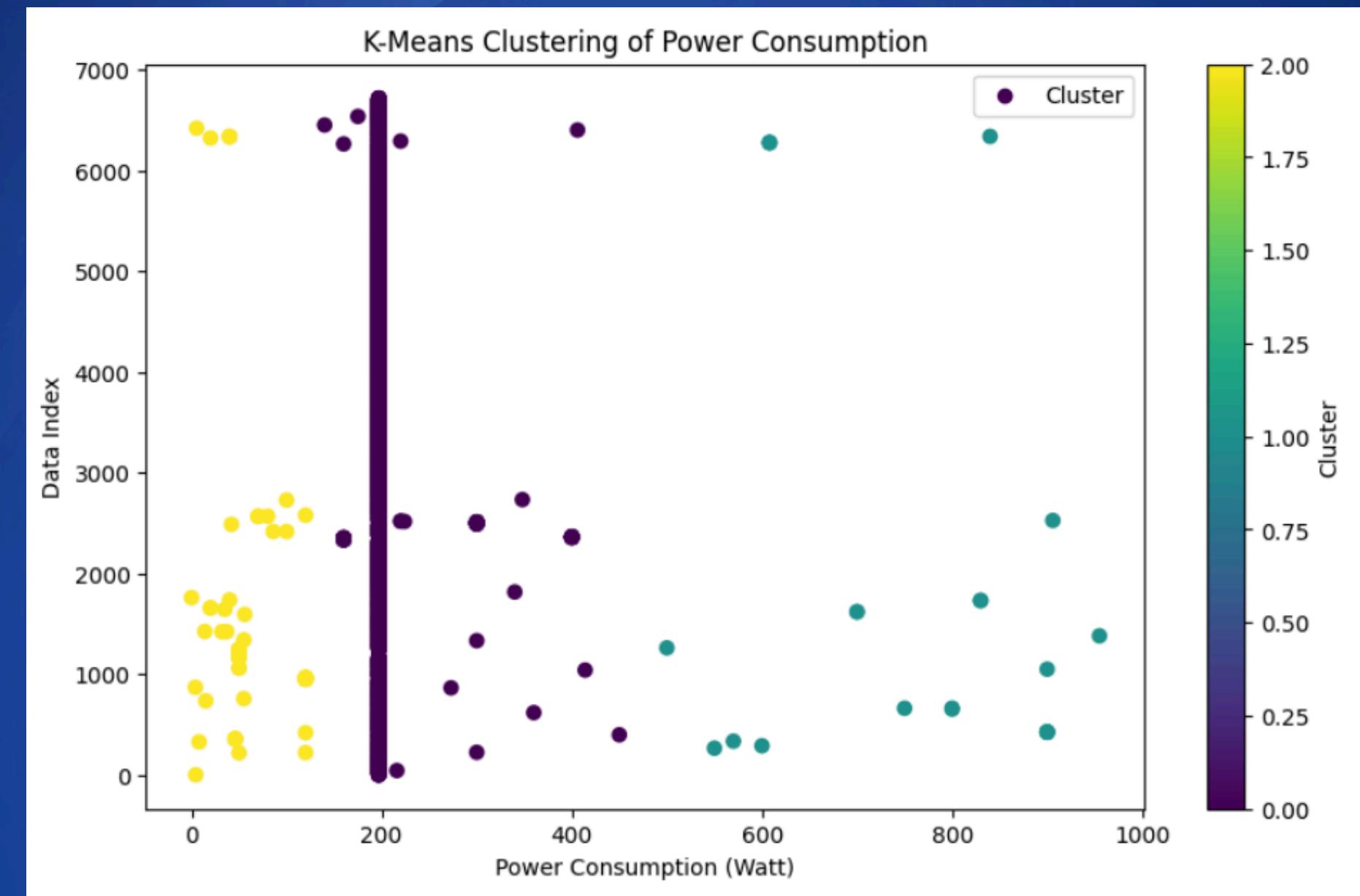


## 2) K-Nearest Neighbors (KNN)



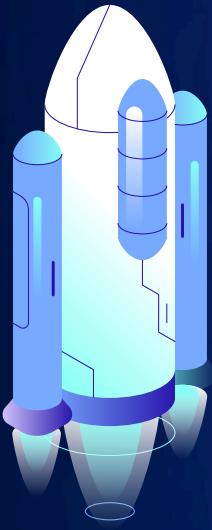
- The matrix shows the actual class (rows) vs. the predicted class (columns)
- High Power: 1439 were correctly predicted, and 3 were misclassified
- Low Power: All 177 actual low power points were correctly predicted
- Medium Power: 396 were correctly predicted, and 1 were misclassified
- KNN model performs well in this case, with very few misclassifications, as shown by the high numbers in the diagonal cells.

### 3) K-Means Clustering



- Graph represent clusters of satellites based on power consumption
- Yellow cluster may consist of satellites with low power consumption, possibly used for long-term missions
- Blue cluster could represent high-power satellites, like those used in large-scale communication

# CONCLUSION

- 
1. In conclusion, our project showed how technical, compliance and business roles can use different analysis and models to make better decisions about satellites.
  2. By looking at things like how long satellites last, how much power they use, and where they are in space, businesses can plan smarter, save money, and keep their satellites working longer.



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Ku Muhamad Aminhaikal (Haikal) Bin Ku MHD Zaki  
(He/Him) [Verify now](#)  
Bachelor of Communications Engineering (Honours) || International Islamic University Malaysia (IIUM) || Alumni Peneraju Tunas BRIDGE Karisma  
Kuala Lumpur, Federal Territory of Kuala Lumpur, Malaysia · [Contact info](#)

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Tuan Muhammad Aidiel (He/Him) · 1st  
Fresh Graduate | Bachelor of Communications Engineering (Honours) | IIUM | Machine Learning  
Segamat, Johore, Malaysia · [Contact info](#)

105 connections

Muhamad Irfan Shahid, Mohamad Asri, and 63 other mutual connections

[Message](#) [More](#)

Mohd Rahmat Bin Adar (He/Him) · 1st  
Mechanical-Automotive Engineering Student at International Islamic University Malaysia (IIUM)  
Gombak District, Selangor, Malaysia · [Contact info](#)

27 connections

Mohamad Asri, Amzar Sukri, and 16 other mutual connections

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# THANK YOU

Thank you for taking the time to learn about our Capstone 3 Project. If you have any questions or are interested in getting involved, please don't hesitate to contact us. Together, let's build the future of digital interaction.

