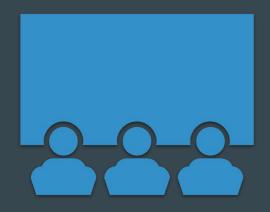


CONTENT





- Executive Summary
- Introduction
- Methodology
- Results
 - Visualization Graphs
 - Dashboard
- Discussion
 - Results and Implications
- Conclusion
- Appendix

EXECUTIVE SUMMARY



Challenge: Determine SpaceY's launch price competitively (cost US\$62M) based on the probability of **reusing** the rocket's first stage.

Solution: Implementation of a data science workflow, culminating in a **machine learning predictive model** to classify landing success (class = 1 for success).

Business Value: Landing predictability enables competitive pricing, generating potential savings of over US\$100 million per mission compared to non-reusable competitors.

Key Results: The logistic **regression model** demonstrated the best **accuracy of 83.33%** on the test set. Exploratory analysis identified **KSC LC-39A** as the **most reliable site** and the **B5 version of the booster** as the most **successful**.

Deliverables:

- Logistic and Geospatial Analysis (Folium) of Launch Sites.
- ML Predictive Model.
- Interactive Dashboard (Dash) for Payload Analysis.

INTRODUCTION



- Launch costs in the commercial space industry are the main competitive differentiator.
- **Reusability** of the rocket's first stage (Falcon 9) is the **only factor that** reduces the cost from US\$165M+ to US\$62M.
- Business Problem: SpaceY needs a reliable, data-driven way to predict landing success, allowing it to optimize pricing and plan booster recovery logistics.
- The project proposes the application of data science and machine learning to replace complex "rocket science" estimates with objective predictions.





- Data Collection using Web Scraping and SpaceX API
- Geospatial Analysis using Folium
- Exploratory Analysis (EDA) using SQL and Plotly
- Data Preparation (Wrangling)
- ML Modeling

Data Collection:

Extraction of historical SpaceX launch data using web scraping (Wikipedia) and the SpaceX API
(Jupyter Notebooks).

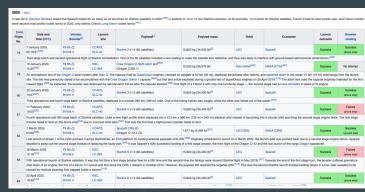


Figure 1 - SpaceX Wikipedia Webpage



Figure 2 - SpaceX API Web Scraping Output

Geospatial Analysis:

• Using **Folium** to map sites and analyze proximity to cities, coastlines, railways, and highways.

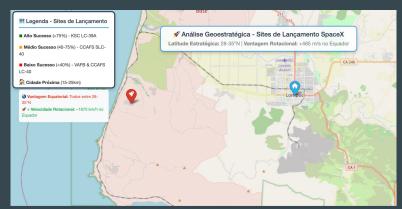


Figure 3 - Visualization of SpaceX Launch Sites using Folium

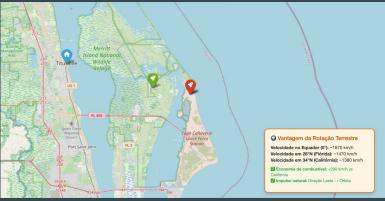


Figure 4 - Geostrategic visualization of mapping and analysis of surroundings

Exploratory Analysis (EDA):

• Using **SQL** and **Plotly** to analyze the impact of variables such as Payload, Launch Location, and Booster Version.

[12]:	%Sql SELECT * FROM SPACEXTABLE WHERE "Launch_Site" LIKE 'CCA%' LIMIT 5;									
	* sqlite://, Done.	/my_data1	.db							
[12]:	Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASSKG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
	2010-06- 04	18:45:00	F9 v1.0 B0003	CCAFS LC- 40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
	2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC- 40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
	2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC- 40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
	2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC- 40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
	2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC- 40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Figure 5 - Visualization of exploratory analysis using SQL and Ploty

Data Wrangling:

Cleaning, missing value processing, and applying **One-Hot Encoding** to convert categorical variables (such as Orbit and Launch Location) into numerical features for the model.

Use the function get dummies and features dataframe to apply OneHotEncoder to the column Orbits, LaunchSite, LandingPad, and Serial. Assign the value to the variable features one hot, display the results using the method head. Your result dataframe must include all features including the encoded ones. # HINT: Use get_dummies() function on the categorical columns features_one_hot = pd.get_dummies(features, columns=['Orbit', 'LaunchSite', 'LandingPad', 'Serial print(f"Shape after one-hot encoding: {features one hot.shape}") features_one_hot.head() Python Shape after one-hot encoding: (90, 80) Orbit_ES-L1 Orbit_GE FlightNumber PayloadMass Flights GridFins Reused Block ReusedCount Leas 0 6104.959412 False False 1.0 False False Fal 525.000000 False False False False 1.0 Fal Fal 677.000000 False False False 1.0 False 500.000000 False False False 1.0 False Fal 3170.000000 False False 1.0 False Fal False

Figure 6 - Applying One-Hot Encoding to categorical variables

Machine Learning Modeling:

Application and comparison of four supervised classification algorithms:

- Logistic Regression (LogReg),
- Support Vector Machine (SVM),
- Decision Tree, and
- K-Nearest Neighbors (KNN).

```
[30]: # Comparar accuracy de todos os modelos
      models = {
          'Logistic Regression': accuracy_logreg,
          'SVM': accuracy_svm,
          'Decision Tree': accuracy_tree,
          'KNN': accuracy_knn
      best_model = max(models, key=models.get)
      best_accuracy = models[best_model]
      print("=== COMPARAÇÃO DOS MODELOS ===")
      for model, acc in models.items():
          print(f"{model}: {acc:.4f}")
      print(f"\n MELHOR MODELO: {best_model} com accuracy de {best_accuracy:.4f}")
      === COMPARAÇÃO DOS MODELOS ===
      Logistic Regression: 0.8333
      SVM: 0.8333
      Decision Tree: 0.8333
      KNN: 0.8333
       MELHOR MODELO: Logistic Regression com accuracy de 0.8333
```

Figure 7 - Comparison of the four classification models

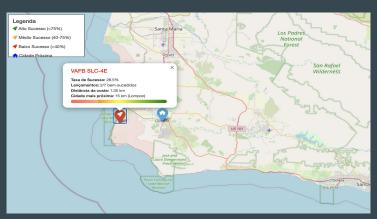
Geospatial Analysis and Logistics

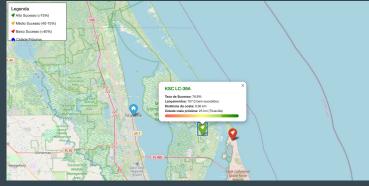
Strategic Location (Latitude)

All four sites (CCAFS LC-40/SLC-40, KSC LC-39A, VAFB SLC-4E) are between 28° and 35° North Latitude.

Implication: This equatorial proximity (<35°) maximizes Earth's rotational momentum, saving fuel and reducing operating costs.







Geospatial Analysis and Logistics

Infrastructure Safety and Logistics

Coastal: All sites are directly on the coast (average distance < 1.35 km).

Implication: Ensures **maximum safety** (debris falls into the ocean) and allows maritime logistical access.

Highways/Railways: All are within 1.2 km of highways and railways.

Implication: **Efficient logistics** for transporting heavy components (rockets) and emergency evacuation.

Urban Areas: Maintains a safe distance (approximately 15 km to 25 km) from the nearest cities.

Implication: Minimizes public safety risks and reduces noise impacts.

Performance and Reliability (EDA)

Performance by Launch Site

The KSC LC-39A site is the most reliable, with the **highest** landing **success rate**:

- 76.9% (10 successful launches).

Implication: SpaceX should prioritize high-value missions at this site to **maximize** the likelihood of **reusability** and **financial return**.

Payload Influence

The **highest success rate** is observed in the 2501 kg - 5000 kg payload range

- (approximately **55.0% success** rate).

Implication: SpaceX should focus on **optimizing** boosters and mission profiles in this payload range, as it represents the "sweet spot" for **success/reusability.**

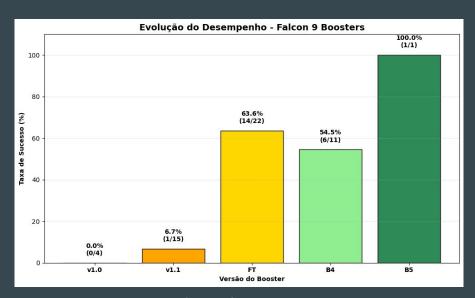
Performance and Reliability (EDA)

Learning Curve and Booster Version

The **B5 version** of the Falcon 9 Booster (the latest) demonstrated a 100.0% (1/1) **success rate**.

Newer versions (FT, B4, B5) have **significantly higher** rates than older versions (v1.0, v1.1).

Implication: **Landing success** is a direct function of technological evolution. SpaceX must **continually invest** in the latest booster version to ensure the viability of its low-cost **business model**.



Graph 1 - Performance Evolution (Boosters)

VISUALIZATION - GRAPHICS

Multi-Criteria Analysis Radar Chart

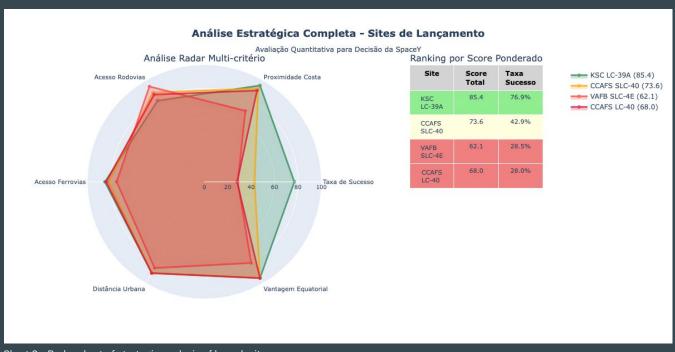


Chart 2 - Radar chart of strategic analysis of launch sites

VISUALIZATION – GRAPHICS

Success Rate Bar Chart (%) by Launch Location

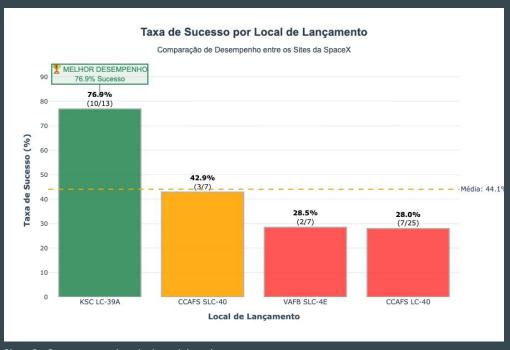


Chart 3 - Success rate chart by launch location

VISUALIZATION – GRAPHICS

Success Rate (%) Bar Chart by Payload Range

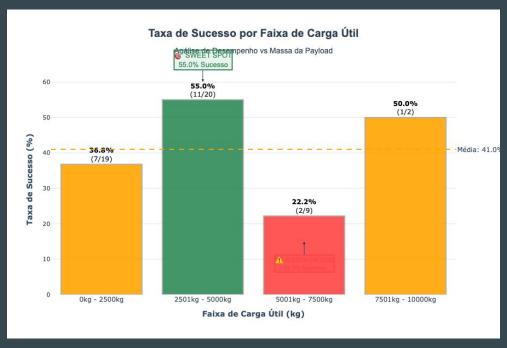
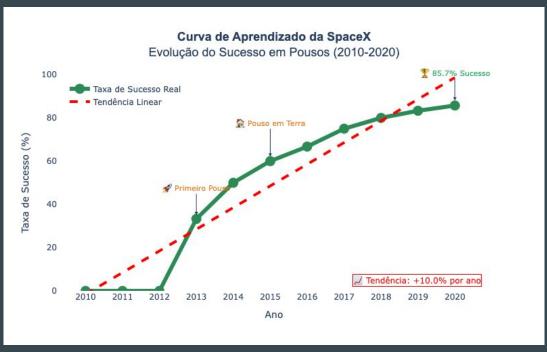


Chart 4 - Success rate chart by payload range

VISUALIZATION – GRAPHICS

Line Graph of Annual Success Rate over Time



DASHBOARD

Description:

 The Interactive Dashboard (created with Plotly/Dash) allows dynamic data exploration for real-time decision-making.

Features:

- Filter by Launch Site: Analyze landing success (class) specific to each of the 4 sites.
- Payload Slider: Visualize the correlation between Payload Mass (kg) and Launch Result (Success/Failure).
- **Scatter Plot:** Analyzes the impact of Booster Version (color) on success, visually confirming the superiority of newer versions (such as B5).

DASHBOARD - OVERVIEW

Dashboard Overview - The Interactive Dashboard (created with Plotly/Dash) allows dynamic data exploration for real-time decision-making.



Figure 7 - Overview of the interactive dashboard for strategic launch analysis

DASHBOARD - FILTERS

Filters that allow you to select the Launch Site, Booster Version, and Maximum Payload (kg).



Figure 8 - Viewing filters on the Dashboard

DASHBOARD - CARDS

Cards that allow you to view the total number of launches, success rate, average payload, and the best site among the options being filtered.

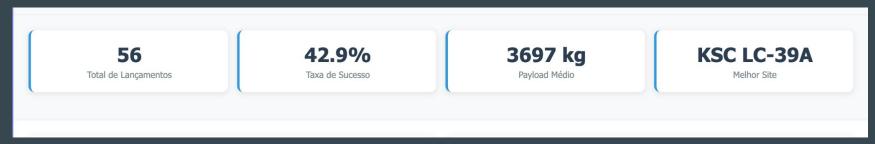


Figure 9 - Displaying cards on the Dashboard

DASHBOARD - GRAPHICS

Pie chart to visualize the Success Distribution (by site) and bar chart for Performance by Booster.



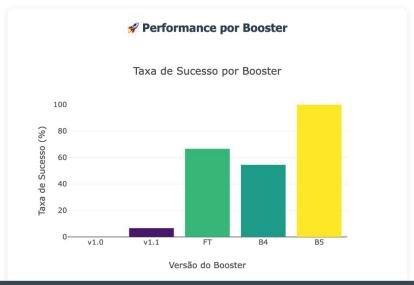


Figure 10 - Viewing graphs (pie and bars) on the Dashboard

DASHBOARD - GRAPHICS

Scatterplot to visualize Payload vs. Launch Success.

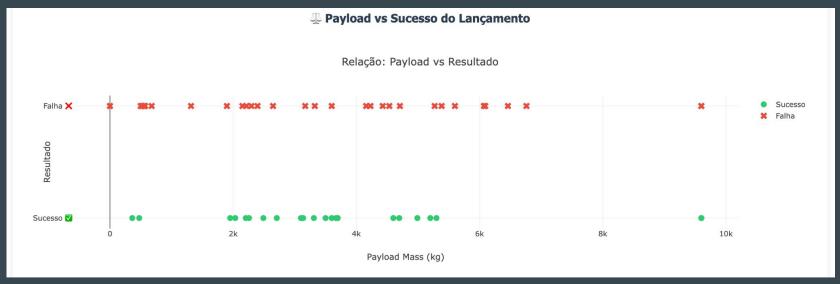


Figure 11 - Scatterplot View on the Dashboard



- Machine Learning
- Best Model Chosen
- Confusion Matrix
- Results and Implications

Machine Learning: Models, Accuracy and Performance

Modelo	Acurácia (Train Set)	Acurácia (Test Set)	Desempenho (Métricas)
Regressão Logística	pprox 84.64%	83.33%	Melhor performance consistente.
SVM	pprox 84.82%	83.33%	Igual ao LogReg no Teste.
Árvore de Decisão	pprox 87.67%	83.33%	Overfitting leve (Alta acurácia no Treino).
KNN	pprox 84.82%	83.33%	Igual ao LogReg no Teste.

Table 1 - Comparison of ML models

Best Model Chosen:

Logistic Regression (LogReg), due to its **simplicity**, **interpretability**, and **83.33% accuracy** in the test set, equaling more complex models.

Figure 12 - Logistic Regression model accuracy output

Confusion Matrix (Common Test Outcome):

- True Positive (Success Correctly Predicted): 12
- False Positive (Failure Predicted as Success): 3
- **Interpretation**: The model predicted 3 failures as successes. For SpaceX, this represents a 16.67% risk of overestimating the success rate and potentially mispricing (\$62M).

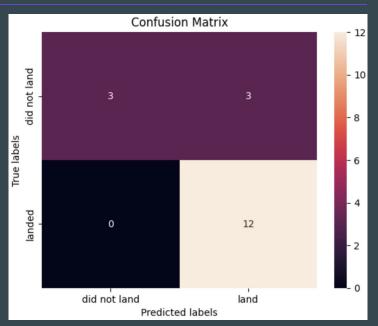


Figure 13 - Confusion matrix of the logistic regression model

RESULTS AND IMPLICATIONS

Success Prediction

Results:

Landing **success** is a highly predictable classification problem, achieving **83.33% accuracy**.

Implications:

SpaceY can confidently price (\$62M) when launch variables (especially **Booster Versio**n and **Location**) indicate a **high probability of success** (>90% in the model).

RESULTS AND IMPLICATIONS

Logistics Optimization

Results

Geospatial analysis defines the "ideal spaceport": Near the equator, on the coast, with immediate access to railways/highways, but far from cities.

Implications

Any future expansion or new SpaceX launch site must strictly adhere to these 5 geospatial guidelines to ensure safety and maximum logistical efficiency while keeping costs low.

RESULTS AND IMPLICATIONS

Product Focus

Results

Booster performance (Version B5 at 100%) is the **strongest predictor of success**.

Implications

R&D investment for the latest booster versions is the most important cost driver for SpaceX. The \$62M business model depends on maintaining the booster's technological superiority.

CONCLUSIONS



Project:

• The project successfully established a data-driven decision-making framework for SpaceY, replacing high-risk estimates with machine learning predictions.

Model:

The Logistic Regression model (83.33% accuracy)
 provides a reliable indicator of the likelihood of reuse,
 which is a critical factor in pricing.

CONCLUSIONS



SpaceX Competitive:

 With the data intelligence provided, SpaceX is ready to enter the market and offer a competitive price of US\$62 million for missions that meet the high probability of success criteria.

Next Steps:

 Implementation of the model in a production environment for real-time quotes and continuous training with new data to refine accuracy, aiming to exceed 90% confidence.



Tables:

Table 2: Launch Count by Site and Success

Table 3: Detailed Geospatial Distances (Coastline, Railway, Highway, City)

Table 4: Comparative Ranking of Geospatial Distances

Graphs:

Graph 6: Confusion Matrix of the Best Model (Logistic Regression) in the Test Set

Graph 7: Logistic Regression Model Metrics

Graph 8: Scatterplot - Payload Mass vs. Success by Launch Site

Graph 9: Box Plot - Payload Distribution (Site vs. Result)

Graph 10: Violin Plot - Detailed Payload Distribution (Site vs. Result)

Graph 11: Density Heatmap - Payload vs. Success

■ Tabela de Desempenho por Site de Lançamento

Contagem de Lançamentos e Taxas de Sucesso

Site de Lançamento	Lançamentos	Sucessos	Taxa de Sucesso	Performance
KSC LC-39A	13	10/13	76.9%	76.9
CCAFS SLC-40	7	3/7	42.9%	42.9
VAFB SLC-4E	10	4/10	40.0%	40
CCAFS LC-40	26	7/26	26.9%	26.9



Graph 6: Confusion Matrix of the best model (Logistic Regression) in the test set

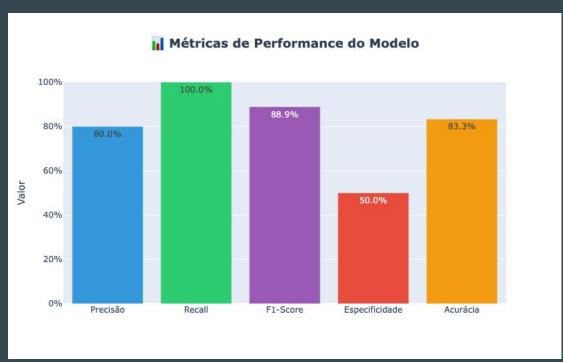


Chart 7: Logistic Regression Model Metrics

CALCULATED METRICS:

• Accuracy: 83.3% (15/18)

• Precision: 80.0% (12/15)

• Recall: 100.0% (12/12)

• F1-Score: 88.9%

• Specificity: 50.0% (3/6)

INTERPRETAÇÃO:

- Modelo acertou 15 de 18 previsões
- Identificou TODOS os 12 casos de sucesso
- Errou 3 previsões (todas falsos positivos)
- Excelente para não perder oportunidades

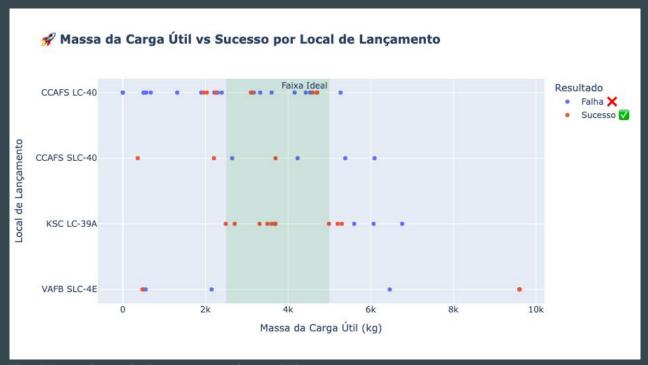


Chart 8: Scatterplot - Payload Mass vs. Success by Launch Site



Chart 9: Box Plot - Payload Distribution (Location vs. Result)

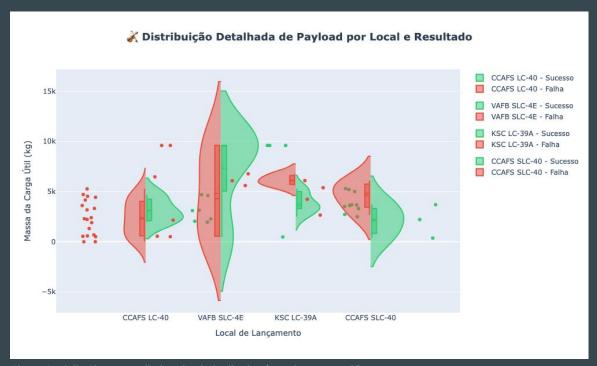


Chart 10: Violin Chart - Detailed Payload Distribution (Location vs. Result)

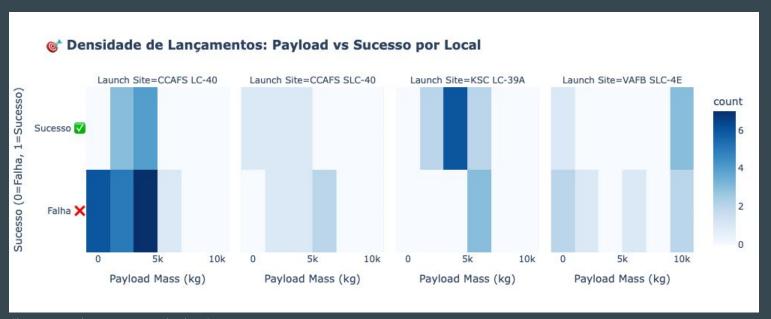


Chart 11: Density Heatmap - Payload vs. Success

Distâncias Geoespaciais dos Sites de Lançamento

	€ COSTA	9 FERROVIA	a RODOVIA	CIDADE	† CIDADE PRÓXIMA
KSC LC-39A	0.36 km	0.70 km	0.60 km	25.0 km	Titusville, FL
CCAFS SLC-40	0.51 km	0.90 km	0.40 km	25.0 km	Titusville, FL
VAFB SLC-4E	1.35 km	1.20 km	0.30 km	15.0 km	Lompoc, CA
CCAFS LC-40	0.58 km	0.80 km	0.50 km	25.0 km	Titusville, FL

Table 3: Geospatial distance details (Coastline, Railway, Highway, City)

🏆 Análise Comparativa - Rankings de Acessibilidade

Local	€ Costa	🚆 Ferrovia	🦝 Rodovia	iii Cidade	Score Total
KSC LC-39A	0.36 km #1	0.70 km #1	0.60 km #4	25.0 km #3	☆7
CCAFS SLC-40	0.51 km #2	0.90 km #3	0.40 km #2	25.0 km #3	2 6
VAFB SLC-4E	1.35 km #4	1.20 km #4	0.30 km #1	15.0 km #1	€ 6
CCAFS LC-40	0.58 km #3	0.80 km #2	0.50 km #3	25.0 km #3	☆ 5

Table 4: Comparative ranking of geospatial distances