

What Can You Really Do With **\$5M** in Space?

A Bayesian Decision Model
for CubeSat Mission Design

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ESA-CNES Student Poster Challenge 2026
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EUROPEAN SPACE AGENCY

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1. CONTEXT

CubeSat missions exhibit extreme cost variability, ranging from less than 0.1M\$ to over 100M\$.

In the context of New Space, designing missions under strict budget constraints has become a central challenge.

Traditional cost estimation methods are often inaccessible in early design phases, especially in academic environments. This project explores how a data-driven and interpretable model can support early-stage decision-making.

Goal



Build a simple and interpretable model to estimate CubeSat mission cost and explore feasible designs under budget constraints.

2. DATASET

A curated dataset of ~100 CubeSat missions was constructed using public sources (ESA, CNES, scientific publications, mission reports)*. Data were manually curated and standardized from heterogeneous public sources.

Each mission is described using key design parameters:

- Platform size (1U to 16U)
- Orbit type (LEO, SSO, GEO, Deep Space)*
- Mission type
- Complexity score (constructed index)
- Total mission cost

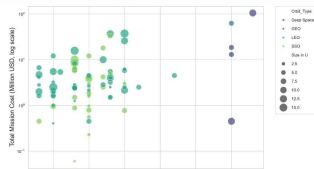


Fig 1 : Mission Cost vs Complexity Across Orbits

A mission complexity index was defined to approximate technological difficulty:

- Technology ~ 1.0
- Earth Observation ~ 1.5
- Science Missions ~ 2.0-2.3
- Deep Space ~ 3

This index takes into account the type of mission, the sending company, and the payload requirements (which depend on the mission).

3. MODEL

A Bayesian log-normal regression model was used to estimate mission cost with its uncertainties. It captures the multiplicative nature of cost drivers and the exponential scaling observed in space mission budgets, while ensuring strictly positive predictions. The goal is not precise prediction, but robust decision support under uncertainty.

Model formulation

$$\ln(\text{Cost}) = \alpha_{\text{orbit}} + \beta_{\text{size}} \cdot \text{Size} + \beta_{\text{complexity}} \cdot \text{Complexity} + \dots + \beta_{\text{year}} \cdot \text{Year} + \epsilon$$

Key characteristics

- Log-normal distribution (adapted to cost variability)
- Bayesian inference (uncertainty explicitly modeled)
- Interpretable parameters

Inputs

- Orbit (environment constraints)
- Size (platform scale)
- Complexity (technological difficulty)
- Commercial status (mission context)
- Temporal Control (Launch Year)

4. KEY RESULT

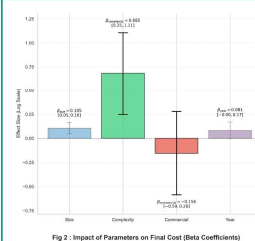


Fig 2 : Impact of Parameters on Final Cost (Beta Coefficients)

Role of Orbit :

Orbit introduces strong structural constraints on cost.

- LEO and SSO allow low-cost missions
- GEO / Deep Space require significantly higher baseline costs
- Cost sensitivity to size increases with orbital constraints

Why GEO and Deep Space are grouped ?

GEO and Deep Space missions were grouped due to limited data availability and similar cost structures.

Both environments require high communication capability, increased radiation protection, higher system reliability. They exhibit comparable cost scaling behavior.

Parameter influence : Complexity has the strongest and most significant impact on cost.

- $\beta_{\text{complexity}}$ is large and strictly positive
- β_{size} is positive but moderate, size has a secondary but consistent effect
- $\beta_{\text{commercial}}$ is weak and uncertain, commercial missions tend to be slightly cheaper (shared infrastructure)
- β_{year} shows no significant trend, Temporal trend is not statistically significant.

Complexity is the only consistently dominant cost driver across all scenarios.

***2.0 COST INCREASE
PER COMPLEXITY LEVEL**

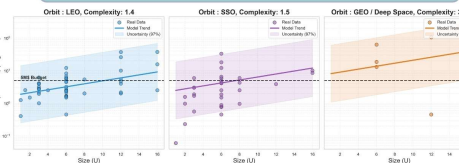


Fig 3 : Predictive Analysis by Destination

The model highlights non-linear cost escalation effects typical of space systems engineering.

Platform size has a secondary effect on cost:

- Increasing size raises cost moderately
- Increasing complexity triggers exponential growth

What the satellite does matters more than how big it is.

The model captures:

- Exponential cost growth with increasing complexity
- Higher uncertainty for extreme missions (Deep Space / GEO)
- Wide cost dispersion even for similar platform sizes

5. DECISION SCENARIO

CASE STUDY : 5M\$ BUDGET

Mission cost is estimated using the Bayesian model with:

- Platform size: 6U (standard CubeSat)
 - Commercial mission: Yes
 - Average complexity per mission type
 - Orbit-specific constraints included in the model
- Each mission scenario is evaluated using the trained model. Estimated costs are compared to a fixed 5M\$ budget.

MISSION	ORBIT	ESTIMATED COST (M\$)	FEASIBLE
Tech Demo (1.4)	LEO	1.15 - 8.62	✓ Yes
Earth Observation (1.5)	SSO	1.58 - 11.85	⚠ Limited
Science (2.2)	GEO / Deep Space	1.96 - 14.76	✗ No
Deep Space (3.6+)	GEO / Deep Space	5.12 - 38.51	✗ No

Ranges correspond to $\pm 1\sigma$ uncertainty (~68% credible interval)

Low-complexity missions remain feasible under strict budgets, while high-complexity missions rapidly exceed cost constraints. The transition from LEO to higher orbits significantly increases cost pressure. This approach can support early-phase mission design by rapidly identifying feasible configurations under budget constraints.

6. TAKEAWAY

- Complexity is the primary cost driver (*2.0 per level).
- Orbital environment strongly constrains mission feasibility.
- Data-driven models enable cost-aware mission design, simple Bayesian models can support early-stage mission design.
- The model captures cost uncertainty using probabilistic intervals.
- ~98% of real missions fall within predicted ranges ($\pm 2\sigma$).

7. LIMITATIONS & PERSPECTIVES

LIMITATIONS

- Limited dataset (~90 missions, few Deep Space cases).
- Complexity score is a constructed proxy (not directly measured).
- Simplified model (no real payload, power or subsystem-level variables).
- High cost dispersion reflects the intrinsic variability of space missions.

PERSPECTIVES

- Incorporate subsystem-level cost drivers (payload, ADCS*, power).
- Extend dataset with industrial and future mission data.
- Develop a full design-to-cost decision framework for CubeSat missions.



Even simple models can provide valuable insights for complex space systems.

*European Space Agency (ESA), Centre national d'études spatiales (CNES)

*Low earth orbit (LEO), Sun Synchronous Orbit (SSO), Geostationary orbit (GEO)

*Attitude Determination and Control System (ADCS)



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References :

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- Kulu, Erik. < CubeSat Tables > Nanosat Database. <https://www.nanosat.eu/table.html>. Accessed on April 23, 2024.

Finance the Report & Source Code with the QR CODE. Full references, model documentation, and raw data.



Early-stage mission cost estimation

Small spacecraft can have very different mission costs

Mission heterogeneity

Payload, destination and engineering requirements change the cost.

Early-stage uncertainty

A budget may be fixed before the mission architecture is fully defined.

Objective: an interpretable decision-support model

A manually curated public dataset

~90

CubeSat missions

1U-16U

Platform sizes

Size, orbit, mission type,
commercial status, year
and reported total cost

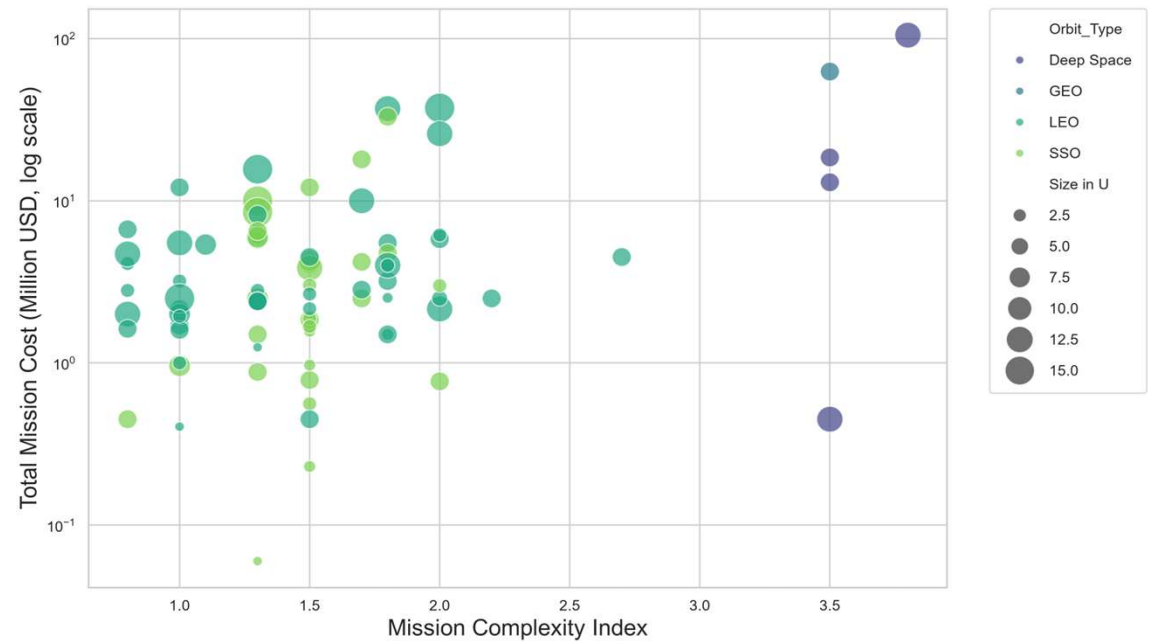


Fig 1 : Mission Cost vs Complexity Across Orbits

Cost increases exponentially with mission complexity

Public sources need currency normalization and manual checks.

The complexity score is a constructed proxy

Baseline + mission-type modifier + context adjustments

Mission type	Baseline score before context adjustments
Technology demonstration	1.0
Earth observation	1.5
Science / astronomy	2.0
Deep Space / GEO	3.0

Agency and manufacturing context can change the score.

The score summarizes qualitative information. Its definition is subjective. You will find the algorithm in the source code.

Bayesian log-normal regression

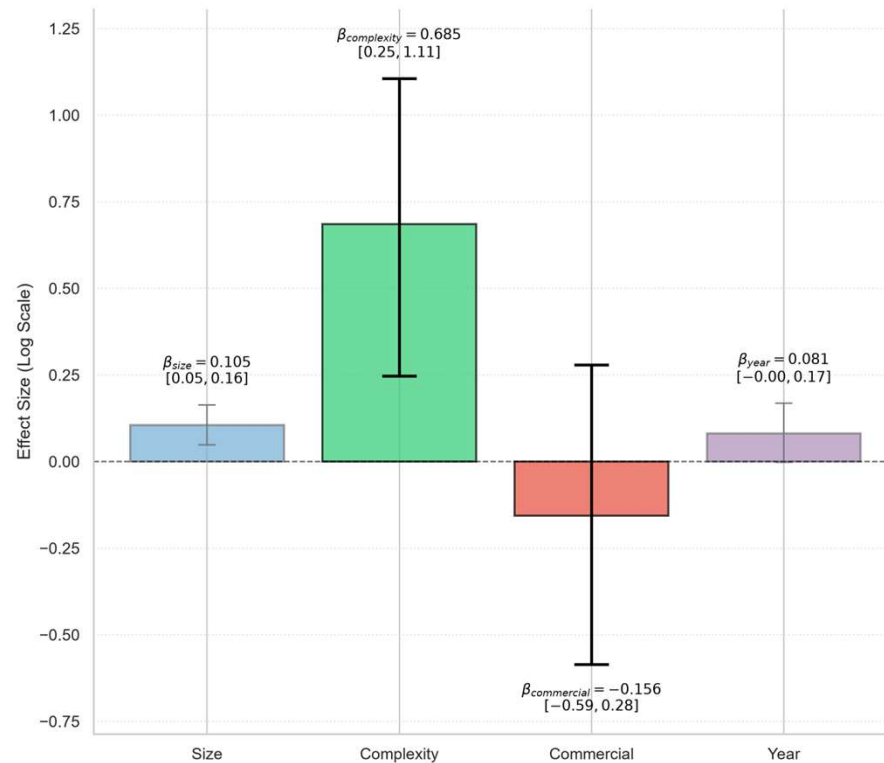
$$\ln(\text{Cost}) = \alpha_{\text{orbit}} + \beta_{\text{size}} \times \text{Size} + \beta_{\text{complexity}} \times \text{Complexity} \\ + \beta_{\text{commercial}} \times \text{Commercial} + \beta_{\text{year}} \times \text{Year} + \varepsilon$$

Why log-space?

Positive costs, right-skewed observations and multiplicative effects.

Bayesian inference carries parameter uncertainty into cost predictions.

Complexity has the strongest modeled cost effect



×2.0

Cost per additional complexity point

~12%

Cost per additional U

Fig 2 : Impact of Parameters on Final Cost (Beta Coefficients)

All else equal. Commercial status and year have weaker, uncertain effects.

Orbit changes the cost baseline

LEO / SSO

Generally lower-cost mission profiles
in this dataset

GEO / Deep Space

More demanding environments
can increase cost pressure

Communications, reliability, radiation and mission duration

The model groups GEO and Deep Space because the dataset contains few cases.
The grouping is a modeling simplification.

Predictive curves retain broad uncertainty

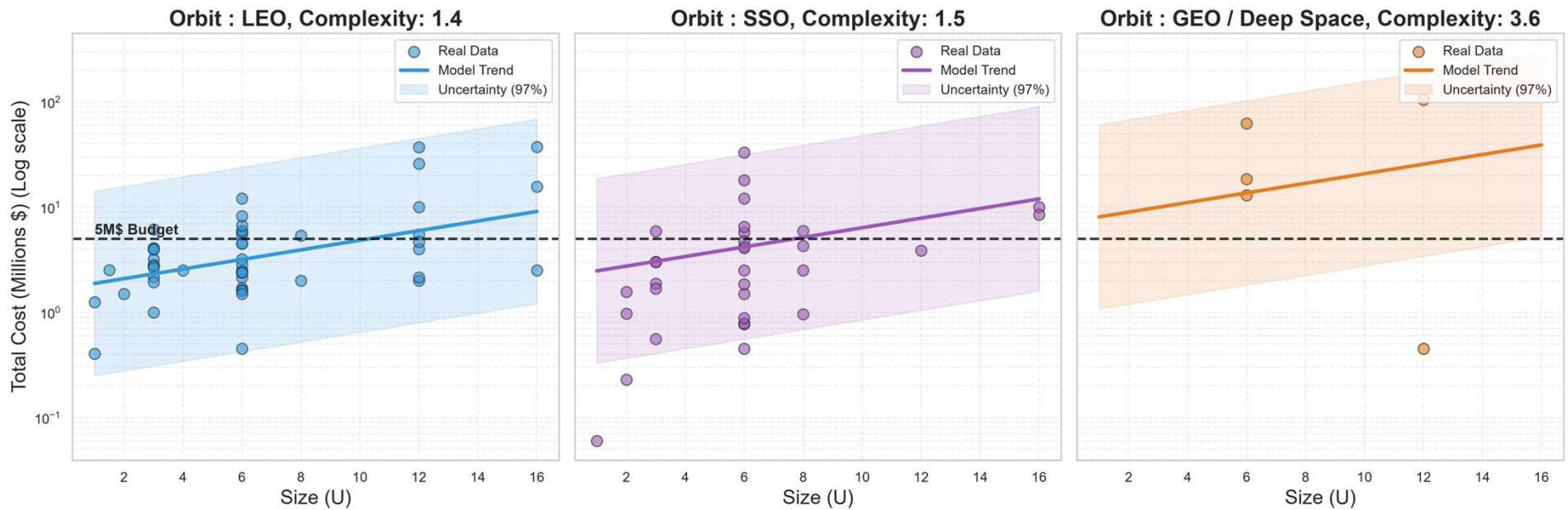


Fig 3 : Predictive Analysis by Destination with a uncertainty range (97% HDI)

Platform size raises cost moderately

Complexity drives stronger growth. Similar missions can still differ widely.

The \$5M scenario: four mission profiles

6U CubeSat Commercial context Year 2026

Mission profile	Orbit	Cost range (M\$)
Technology demonstration	LEO	1.15-8.62
Earth observation	SSO	1.58-11.85
Science	GEO / Deep Space	1.96-14.76
Demanding Deep Space	GEO / Deep Space	5.12-38.51

Ranges correspond to $\pm 1\sigma$ uncertainty, approximately 68%.

A fixed budget becomes a cost-risk question

\$5M

A fixed budget

**Several cost ranges cross
the budget threshold**

The decision depends on how much
budget risk the mission can accept.

$P(\text{Cost} \leq \$5\text{M} \text{ given the mission inputs})$

High coverage comes with limited precision

92.3%

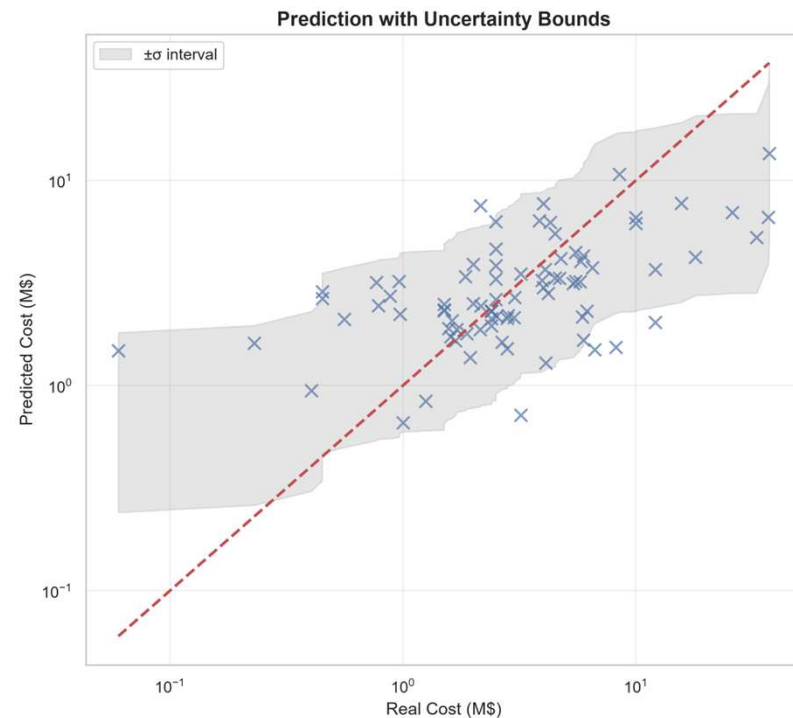
Observed costs within
approximate $\pm\sigma$ bounds

$R^2 \approx 0.29$

Fit on log-transformed costs

Wide intervals can cover observations while leaving substantial prediction uncertainty.

Actual Cost vs Prediction (Log-Log)



The model has important limits

A small and unbalanced dataset

About 90 missions, with few Deep Space examples.

A subjective complexity index

Different definitions of the score could produce different results.

Mission-level inputs

Payload, propulsion, ADCS and qualification requirements need more detail.

A design-to-cost framework

Given this budget, which mission architectures remain plausible?

Mission comparisons

Explore combinations of platform size, orbit and mission ambition.

Probability of satisfying the budget

Carry uncertainty into architecture choices and cost-risk decisions.

Three messages to take away

- 01** Complexity matters more than platform size in this model
- 02** Cost uncertainty belongs in the design decision
- 03** Simple models can support early mission design

Thank you. Questions?

Dataset and code: QR code on the poster

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Contact : Diego
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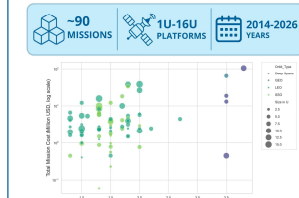


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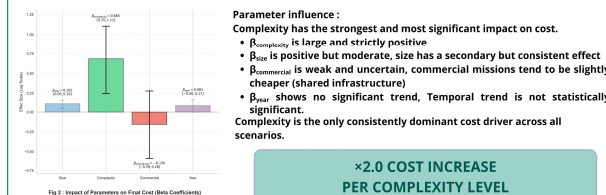
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Explores the Dataset & Source Code with the OR CODE, full references, model documentation, and raw data.

