Advancing Space Domain Awareness through Data Science

Tracking, Characterizing, and Anticipating Satellite Maneuvers

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Introduction

Acknowledgements

Thank you to my advisor and committee members.

Support provided by my employers: time, access, travel, inspiration

- US Military Academy (previous assignment)
- US Space Command (current assignment)
- US Army (employer)

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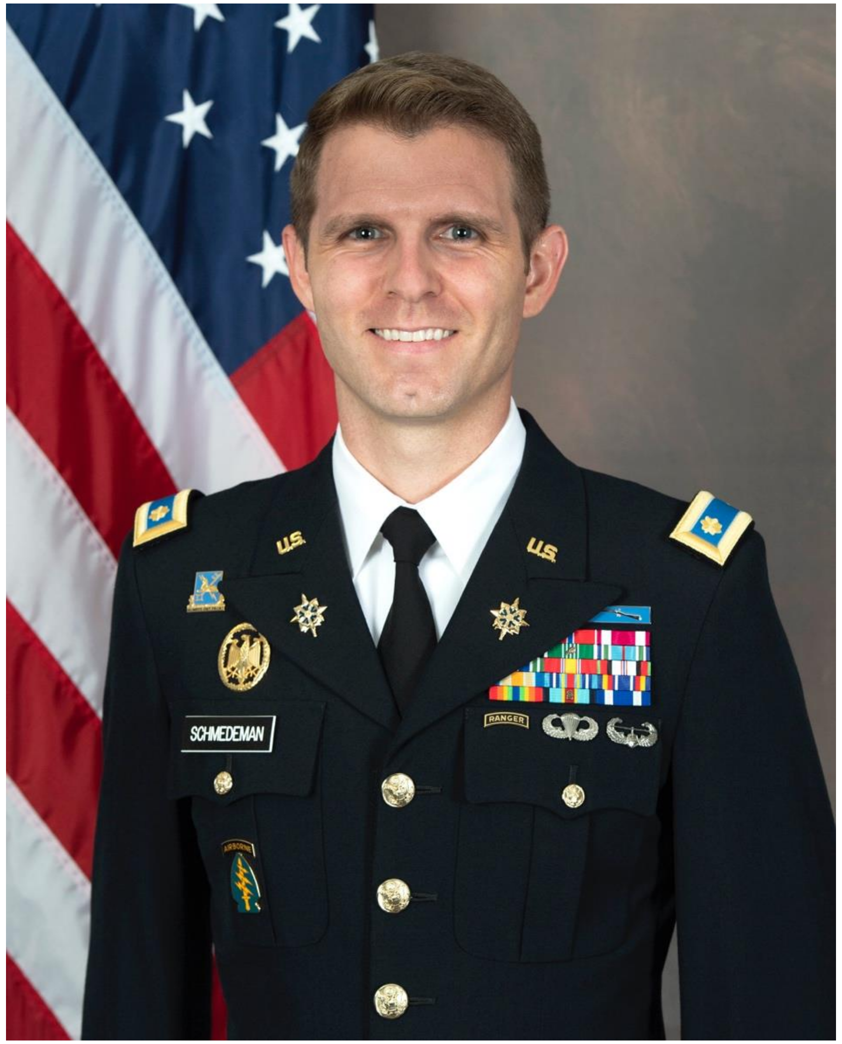
Phillip Schmedeman, Major, US Army



BS from West Point; MS from MIT

Deployments to Afghanistan, Turkey, and Syria as an Infantry and Military Intel officer

Current career field is Operations Research / Data Scientist

2021 - 2025: Instructor / Assistant Professor in the Sys Eng Dept at West Point

2025 - Present: Deputy Branch Chief, Advanced Analytics, US Space Command

Recent publications (2025: 4 conference papers; 2 journal papers)

- **P. Schmedeman**, A. Pfluger, “Evaluating Anaerobic Co-digestion and Biogas Production Potential for Energy Security on Military Installations,” *Journal of Cleaner Production*, vol. 535, Dec. 2025.
- **P. Schmedeman**, J. Gerber, D. Herber, “A Mission-Oriented Framework for Evaluating Space Situational Awareness Data,” *Advanced Maui Optical and Space Surveillance Technologies Conference (AMOS)*, Maui, Hawaii, USA, Sep. 2025.
- E. Lim, T. Larson, L. Johnston, K. Johnston, A. Garton, L. Langou, **P. Schmedeman**, K. Hood, W. Koch, “Exploring Leading Indicators of Satellite Maneuvers in Geosynchronous Orbit,” *IEEE International Systems Conference (SysCon)*, Montreal, Quebec, Canada, Apr. 2025.

Agenda

- Background
- Research Questions & Tasks
  - Data Evaluation for Space Awareness
  - Satellite Pattern-of-Life Characterization
  - Satellite Maneuver Detection
- Work to Date
- Timeline
- Research Contributions
- Conclusions

Satellite launch on a Falcon 9 by the US Space Force [1]

Background

The Increasing Complexity of Space Operations

- ~12,500 active satellites currently tracked [2]
- Rapid growth driven by commercial constellations, reduced launch costs
- Diverse operators: governments, militaries, commercial, and academic
- Specific regimes (LEO, GEO) increasingly congested

Multiple satellites crossing the night sky [3]

Elevated Risks in a Contested Domain

- Collision risks: Iridium 33/Kosmos-2251 (2009) → 23,000+ debris fragments [4]
- Anti-satellite testing: COSMOS 1408 (2021) → 1,700+ fragments [5]
- Strategic value: communications, navigation, Earth observation, national security
- Adversarial threats: electronic warfare, cyber attacks, proximity operations

Space Domain Awareness / Space Situational Awareness

Space Domain Awareness (**SDA**) is “the timely, relevant, and actionable understanding of the operational environment that allows military forces to plan, integrate, execute, and assess space operations.” [6]

- SDA = operational understanding for decision-making

Space Situational Awareness (**SSA**) is a **subset of SDA** defined as “the requisite foundational, current, and predictive knowledge and characterization of space objects within the space domain.” [6]

- SSA = foundational technical picture

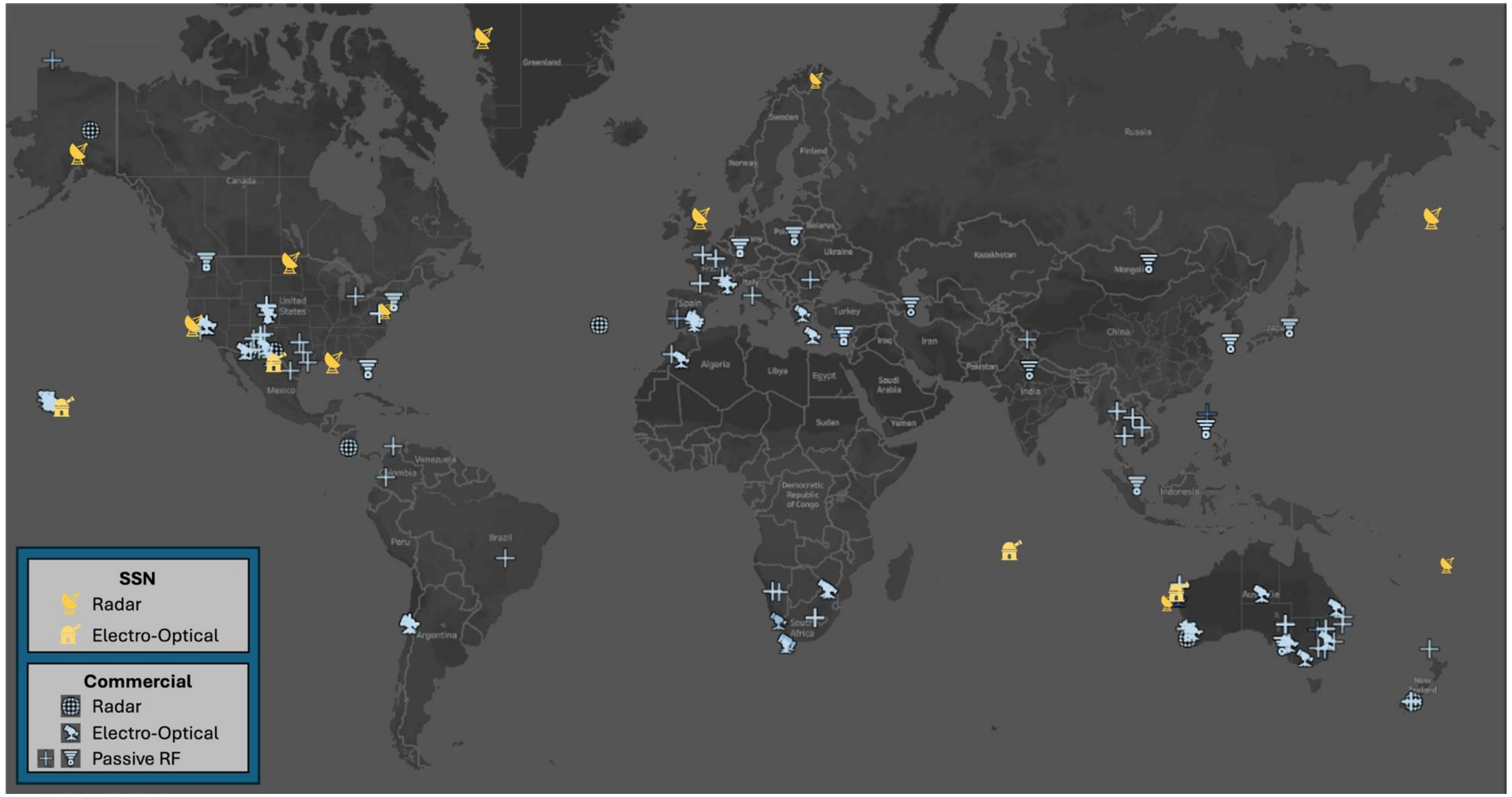
The SSA Ecosystem

Space Surveillance Network (SSN): Decades of operation, well-characterized sensors

US Space Force (USSF) Commercial Space Strategy (2024): “The USSF seeks capabilities from the commercial sector that can contribute to the holistic generation of SSA.” [7]

Joint Commercial Operations (JCO)

- 150+ commercial sensors
- ~800 high-interest satellites
- 1M+ observations daily

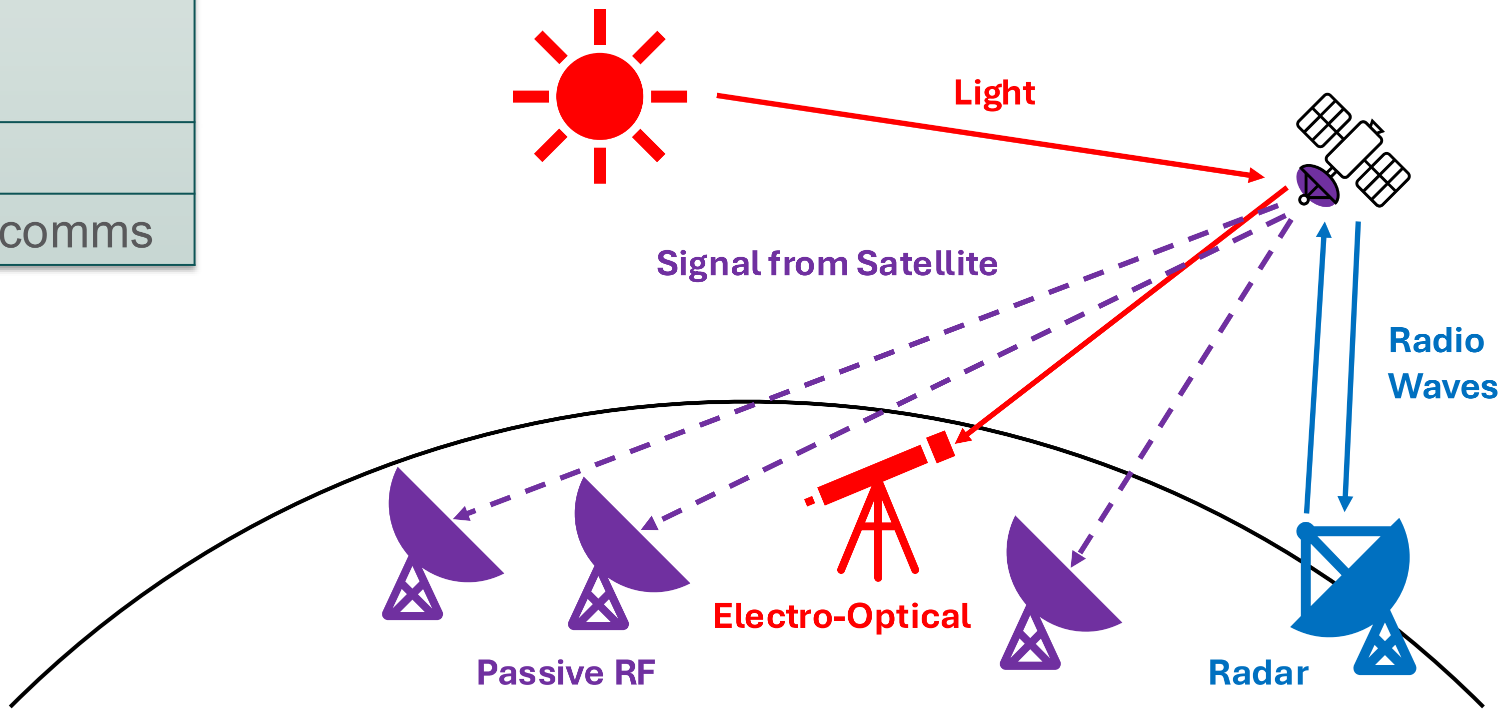


Commercial sensor locations contracted by the JCO in blue overlayed with SSN locations in yellow [8].

Primary SSA Sensor Types

Characteristic	Radar	EO	Passive RF
Weather-independent	✓	✗	✓
Daytime operation	✓	Limited	✓
Range measurement	✓	✗	✓
Cost	High	Low	Moderate
Best for	LEO	GEO	Persistent comms

Radar, Electro Optical (EO), and Passive RF (TDOA/FDOA) are the most common types of terrestrial SSA sensors.



SSA Sensor Evaluation

SSA evaluation has progressed from single-sensor characterization toward integrated, mission-oriented assessment of heterogeneous architectures.

Focus Area	Key Finding	Reference
Radar performance	Detecting 1m² object at 2,000km requires specific frequency, antenna gain, and power combinations; radar complements optical systems	Choi et al. [9]
Ground vs. space-based optical	Hybrid architectures reduce detection latency and broaden coverage	Ackermann et al. [10]
Architecture optimization	Hybrid ground + polar GEO satellites reduced system cost by 22.4%	Felten [11]
Mission-driven design	Network optimization tripled observation capacity, reduced catalog gaps by 50%	Harris [12]
Multi-objective optimization	Integrating commercial providers achieved 3× capacity, 55% coverage improvement	Vasso et al. [13]

Existing research focuses on technical evaluation or optimization of specific technologies or architectures.

Characterizing How Satellites Operate

Satellite Pattern-of-Life (PoL): Behaviors observed over time that reflect characteristics such as mission, operating mode, procedures, or hardware

Key question: What can we learn about satellites by observing them over time?

Supports

- Mission type inference
- Operational baselines
- Anomaly detection
  - Malfunction
  - Operator error
  - Adversarial action

Prior Work: Satellite Pattern-of-Life Characterization

- Prior work demonstrates that both unsupervised clustering and supervised classification can reveal satellite behaviors, but studies have relied predominantly on **maneuver-based features from trajectory data alone**.
- Propulsion type has been used as interpretive context—never as a prediction target.

Unsupervised Learning for Behavioral Discovery

Approach	Key Finding	Reference
Spatiotemporal clustering (k-means, DBSCAN)	Grouped GEO satellites by position evolution; cluster transitions indicate anomalies	Mital et al. [14]
Behavioral mode framework	Defined PoL nodes (initializing, adjusting, ending drifts); 6 distinct clusters from longitudinal histories	Roberts et al. [15, 16]
Deep learning + DBSCAN	Masked autoencoders enabled LEO characterization; identified constellation-specific patterns	Guimaraes et al. [17]

Supervised Learning for Classification

Approach	Key Finding	Reference
Photometric classification	Random forests achieved 99% satellite ID accuracy, 91% bus type classification	Lane et al. [18]
Maneuver type classification	Neural networks distinguish E-W SK, N-S SK, and transfer maneuvers with probability distributions	DiBona et al. [19]
CNN on light curves	Deep learning extracts discriminative features without explicit human-designed engineering	Furfaro et al. [20]

Why Maneuver Detection Matters

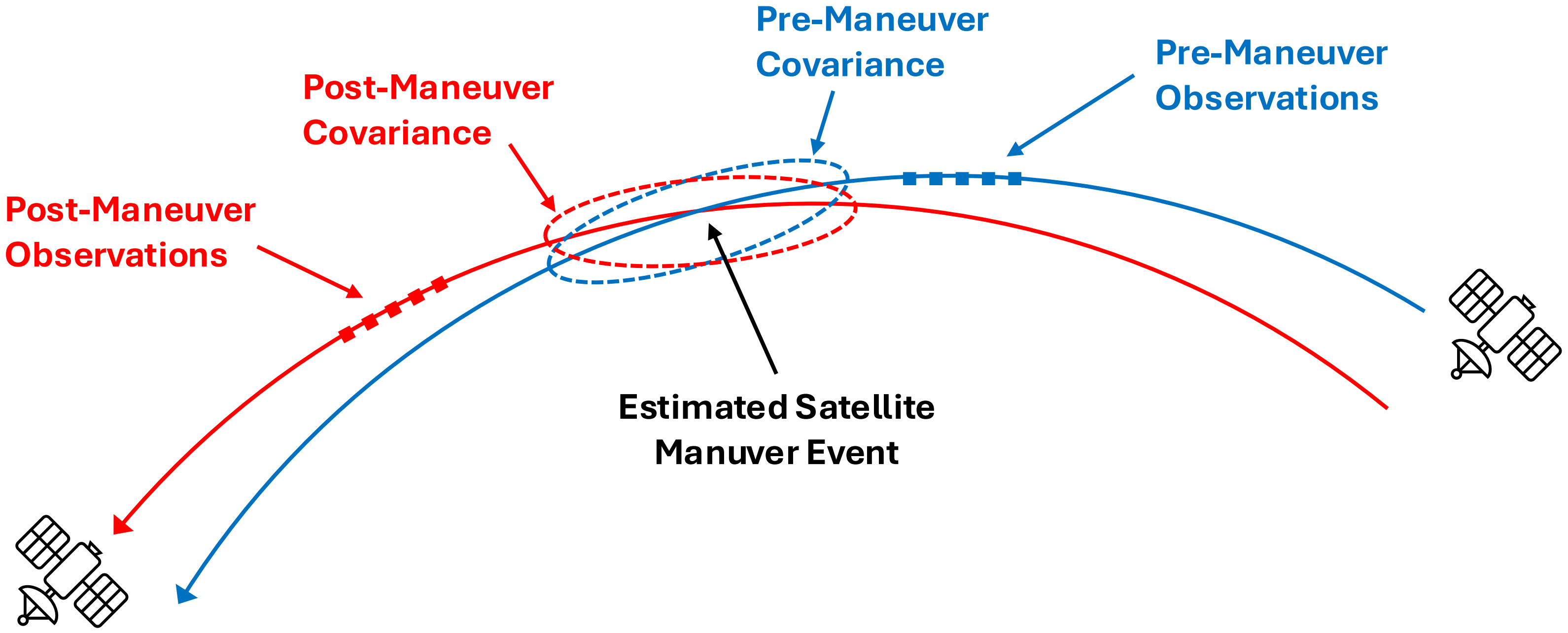
Maneuver purposes: Station-keeping, orbit-alteration, collision avoidance, proximity operations

Operational need: Rapid detection enables:

- Conjunction assessment
- Operator coordination
- Evasive actions

Propulsion types affect observability:

- Chemical: Short, high-thrust burns
- Electric: Extended, low-thrust burns



Physics-based approach to maneuver detection, which involves cross propagating the pre- and post-maneuver states. Figure adapted from T. Kelecy and M. Jah [21].

Prior Work: Satellite Maneuver Detection

Era	Focus	Representative Studies
2008-2010	Physics-based foundations	Folcik [22], Kelecy [21]
2014-2015	Statistical/adaptive methods	Lemmens [23], Goff [24]
2016	First/only prediction attempt	Shabarekh [25]
2019	Machine learning emergence	Bai [26], DiBona [27]
2021-2022	Sensor diversification + Deep learning	Beer [28], Roberts [29], Perovich [30]
2023-2024	Sequence modeling	Cipollone [31], Li [32]
2024-2025	Robustness/generalization	Tian [33], Wu [34], Gui [35]
Gap	**Deep learning + Multimodal fusion + Real-world validation + Propulsion-specific modeling**	**None**

Limitations of Current Methods

- Evaluation frameworks focus on specific technologies or architectures
  - Emphasize accuracy, but neglect other mission-relevant metrics
  - Not broadly applicable
- Satellite PoL characterization overlooks non-maneuver attributes
  - No means to classify propulsion system from observables
- Physics-based and classical methods are reactive
  - Require orbital deviation to accumulate
  - Detection latencies range from hours to days
- Machine learning approaches show promise but:
  - Limited incorporation of multi-modal data
  - Labeled truth data rarely available
- **Goal**: Shift from reactive detection → proactive anticipation

Three Critical Gaps in Current SDA Knowledge

1. **SSA Data Evaluation** – No framework for comparing SSA data providers using diverse sensor types and architectures

2. **Satellite Characterization** – Limited multi-modal fusion; no propulsion classification from observables

3. **Maneuver Detection** – Single-modality and classical approaches are insufficient in terms of accuracy and timeliness; lacking validation against labeled truth data

Research Questions & Tasks

Research Question 1 – SSA Data Evaluation

What quantitative metrics effectively characterize the operational value of SSA data from diverse sensor types and provider architectures for custody maintenance and maneuver detection?

Objectives

- Develop mission-oriented evaluation framework
- Compare providers across radar, EO, passive RF
- Enable evidence-based procurement decisions

Tasks

- T1: Elicit stakeholder requirements (Space Command, National Space Defense Center)
- T2: Develop quantitative metrics (custody + maneuver detection)
- T3: Conduct empirical evaluation on multi-provider dataset
- T4: Present results and characterize provider performance & trade-offs

Research Question 2 – Satellite Characterization

How does multimodal sensor fusion enable the characterization of satellite operational behaviors and propulsion system types in GEO?

Two complementary dimensions

- Behavioral patterns (unsupervised) → *How* satellites operate
- Propulsion classification (supervised) → *What* hardware they possess

Modality	Proposed Features
Photometric (EO)	Change point freq, variability
Signal (RF)	TDOA/FDOA stability, transmission patterns, bandwidth variations
Maneuver	Inter-maneuver intervals, ΔV distributions, frequency, duration, drift

Tasks

- T1: Acquire and prepare dataset for satellite characterization
- T2: Engineer multimodal features for satellite characterization
- T3: Discover unsupervised PoL patterns through clustering
- T4: Develop supervised propulsion system classification models
- T5: Interpret results, validate findings, and develop operational recommendations

Research Question 3 – Maneuver Detection Enhancement

How does multimodal sensor fusion and feature engineering affect the performance of satellite maneuver detection models?

Motivation

- Current providers: low detection rate (<50%) OR high false positives (>50%)
- Median detection times: 2.7 – 21.7 hours
- Operational requirement: <2 hours

Tasks

- T1: Compile truth dataset from cooperative operators
- T2: Engineer features for maneuver detection across sensor modalities
- T3: Develop supervised models and establish baseline performance
- T4: Conduct systematic feature ablation analysis and propulsion-specific modeling

Features: same as RQ2 + propulsion type

Key question: Which sensor modalities improve detection accuracy and reduce latency?

Work to Date

Preliminary Research Progress

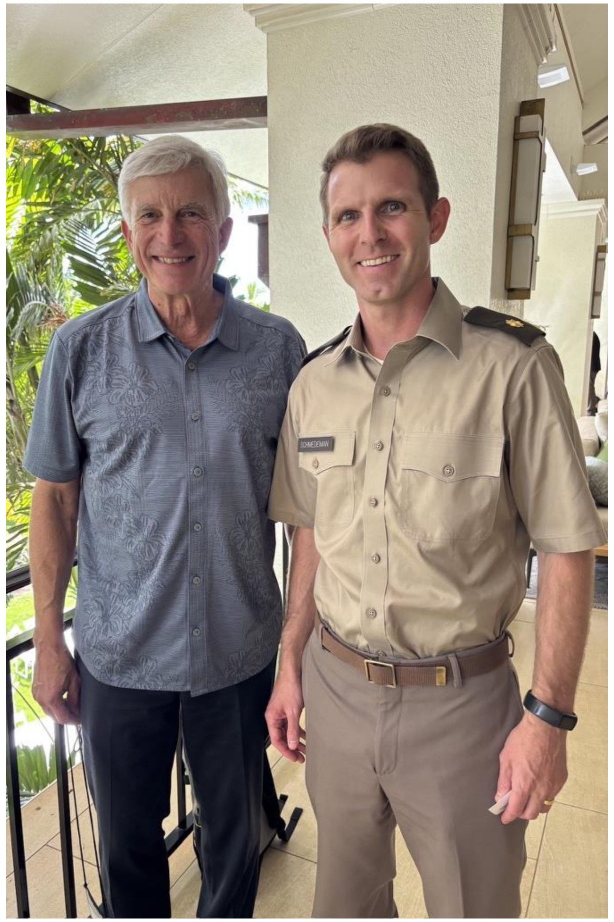
Q1: Evaluation	RQ2: Characterization	RQ3: Detection
✓ COMPLETED	◐ IN PROGRESS	◐ IN PROGRESS
Mission-oriented framework for evaluating SSA data (AMOS 2025 Paper [8]) + Implementation at JCO	Preliminary multi-modal feature engineering (CAS 2025 Paper [36]) + Dataset + Input from SSA/SDA experts	Leading indicators study (IEEE SysCon 2025 Paper [37]) + Dataset + Benchmarking

Mission-Oriented Evaluation Framework (RQ1)

- **Published:** AMOS Conference, September 2025 [8]
- Evaluated 17 providers over 31 days
- 14M+ observations, 3.2M+ derived products

Key metric categories

- **Custody:** Persistence, Violation Time, Unique Coverage
- **Maneuver:** Detection Rate, False Positives, Time to Detect



Photos from AMOS 2025, Maui, Hawaii

RQ1 Methods - Key Metrics

Total Violation Time

Violation time $V_{i,j}$ is defined as the excess duration beyond the threshold:

$$V_{i,j} = \begin{cases} \Delta t_{i,j} - T_{\text{threshold}}, & \Delta t_{i,j} > T_{\text{threshold}} \\ 0, & \text{otherwise} \end{cases} \qquad (1)$$

where $\Delta t_{i,j}$ is the interval between consecutive observations and $T_{threshold}$ is the revisit threshold based on satellite rank.

Unique Observation Capability

A provider is considered to satisfy a satellite-bin (s,b) if it contributes at least three observations within that temporal bin, ensuring sufficient evidence for a usable orbital update within the time window. Let C_p denote the set of satellite bins covered by provider p. A satellite-bin is "unique" to provider p if p satisfies the bin and no other provider does:

$$U_p = \{(s,b) \in C_p : C_q \cap \{(s,b)\} = \emptyset \text{ for all } q \neq p\} \qquad (2)$$

Maneuver Detection Rate and False Positives

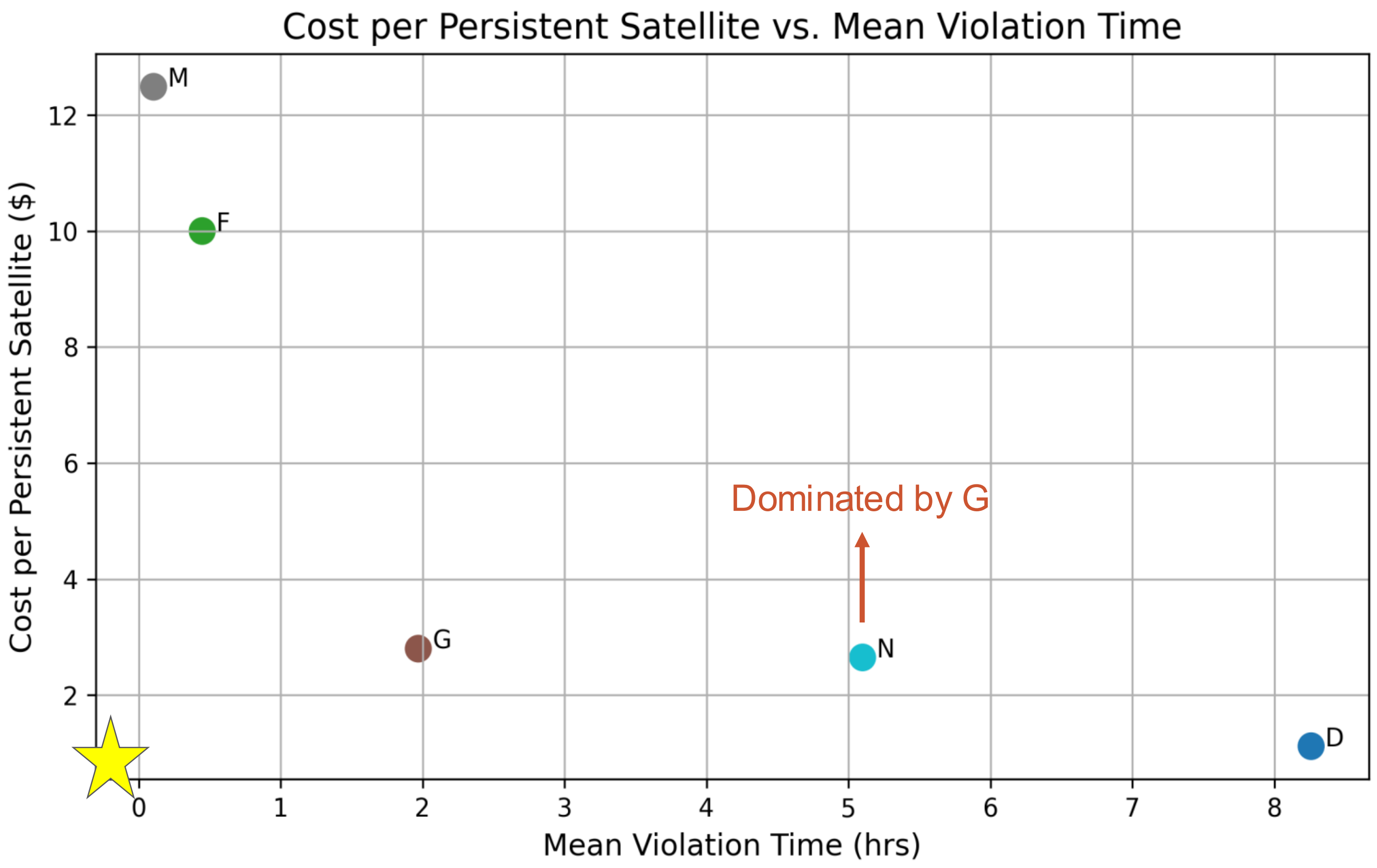
Let $N_{reported}$ represent the number of maneuver reports issued by a provider within 24 hours of a known maneuver (from reference data), and $N_{maneuvers}$ the total number of maneuver events in the reference set. False positives (N_{false}) occur when a provider reports a maneuver not corresponding to any verified event.

$$\text{Detection Rate (\%)} = \frac{N_{\text{reported}}}{N_{\text{maneuvers}}} \times 100 \qquad (3)$$

$$\text{False Positive Ratio} = \frac{N_{\text{false}}}{N_{\text{total reports}}} \qquad (4)$$

RQ1 Key Findings

- Wide performance variation across providers
- Little correlation between high persistence and accurate maneuver reporting
- Framework enables evidence-based procurement



Cost versus mean violation time for SSA data providers, based on artificial demonstration data. Providers near the origin notionally represent an ideal cost-performance balance.

AMOS Response

Subject: AMOS Conference Presentation - Follow up

MAJ Schmedeman - I'd like to introduce you to [redacted]. We saw you presentation at AMOS and [redacted] was interested in a follow up meeting and introduction to understand/discuss your metrics and perhaps get a copy of your research paper. Thank you!

Good morning Maj Schmedeman,

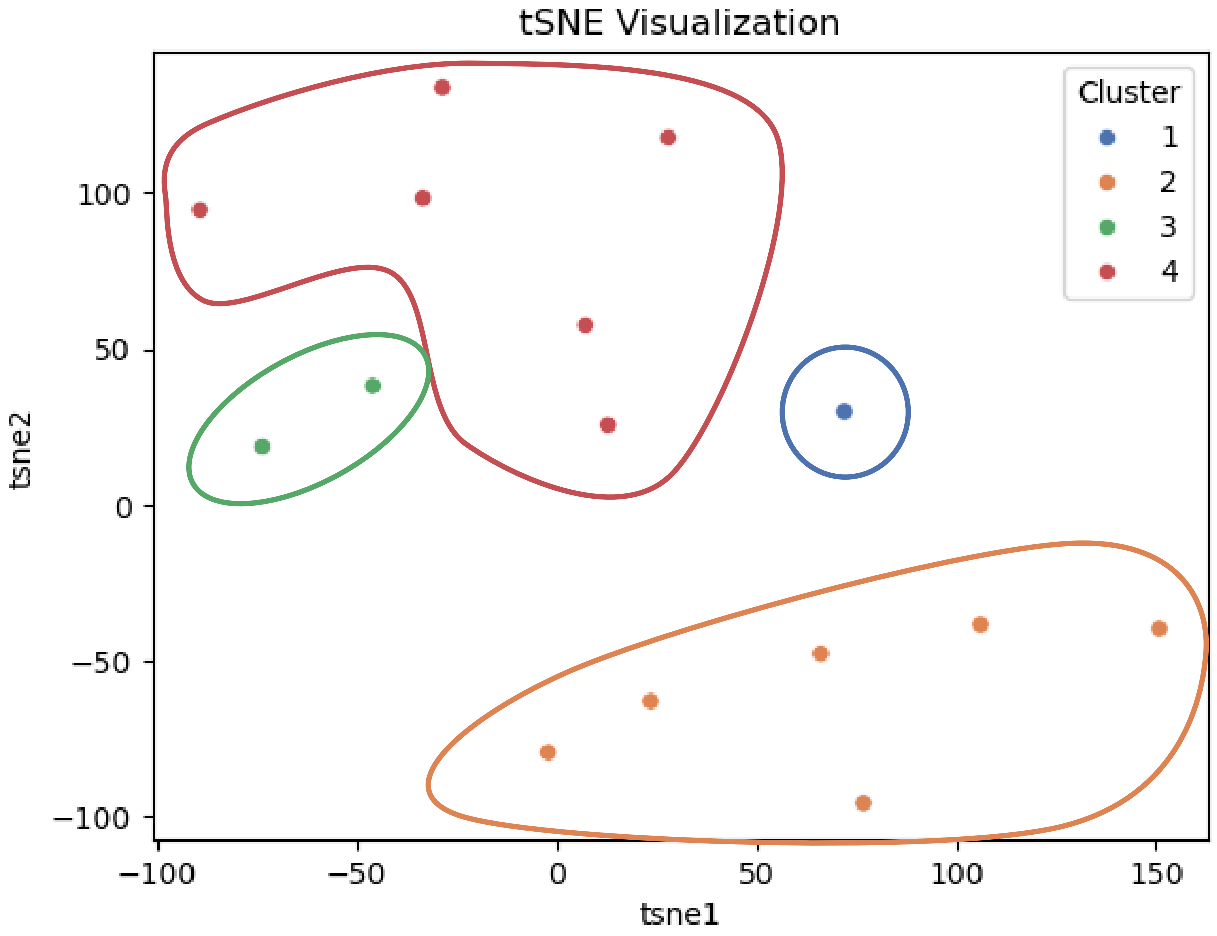
[redacted]

[redacted] is developing spaceborne radar capability for space-domain awareness and intelligence mission areas. I'm interested in understanding the metrics you presented and evaluating how we contribute to the mission.

MAJ Schmedeman—great to virtually meet you, Sir. As I mentioned, [redacted] team has been referencing your *"Mission-Oriented Framework for Evaluating Space Situational Awareness Data"* as we support SSC/COMSO on the CASR Mission Area Analysis. It's an excellent piece of work and aligns closely with some of our ongoing modeling and assessment activities. If you're open to it, I'd love to set up a short sync to compare notes and discuss potential alignment points between your framework and our current analysis threads. Please just let me know what your schedule looks like over the next week or so.

Behavioral Pattern Discovery (RQ2)

- Published: Complex Adaptive Systems Conference, April 2025 [36]
- 15 GEO satellites, 4 distinct behavioral clusters
- Integrated: maneuvers + photometric changes + RF signals
- Satellites from same operator often cluster together



Dimension reduction (tSNE) visualization for 15 satellites with 4 clusters indicated by color [36]. Real-world data.

Exploring Leading Indicators (RQ3)

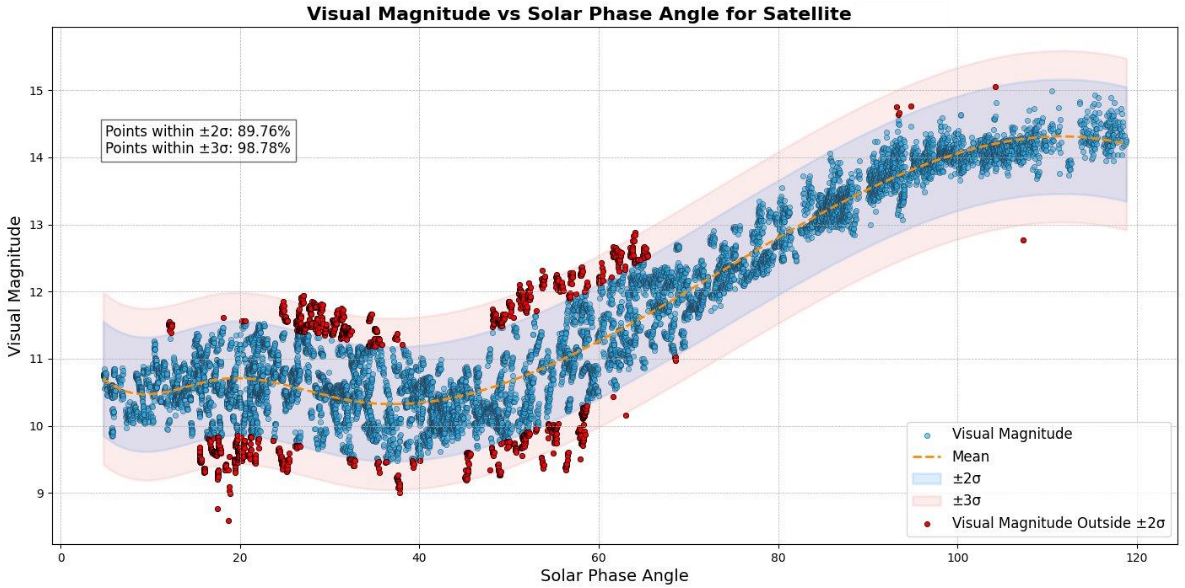
Content

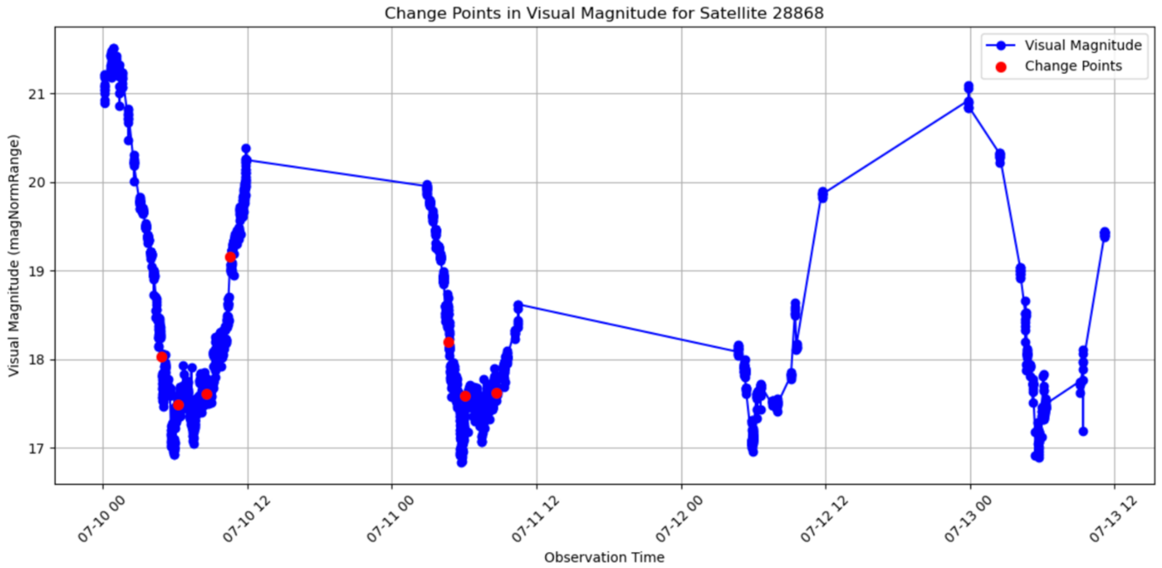
- Published: IEEE SysCon, April 2025 [37]
- Applied statistics to photometric time series
- Finding: Photometric changes alone are insufficient

Confounding factors

- Solar panel rotations
- Antenna repositioning
- Glinting effects
- Earth shadow entry/exit

Conclusion: Multi-modal fusion required





Identifying change points in visual magnitude to evaluate its potential as an early indicator of satellite maneuver [37]. Real-world data.

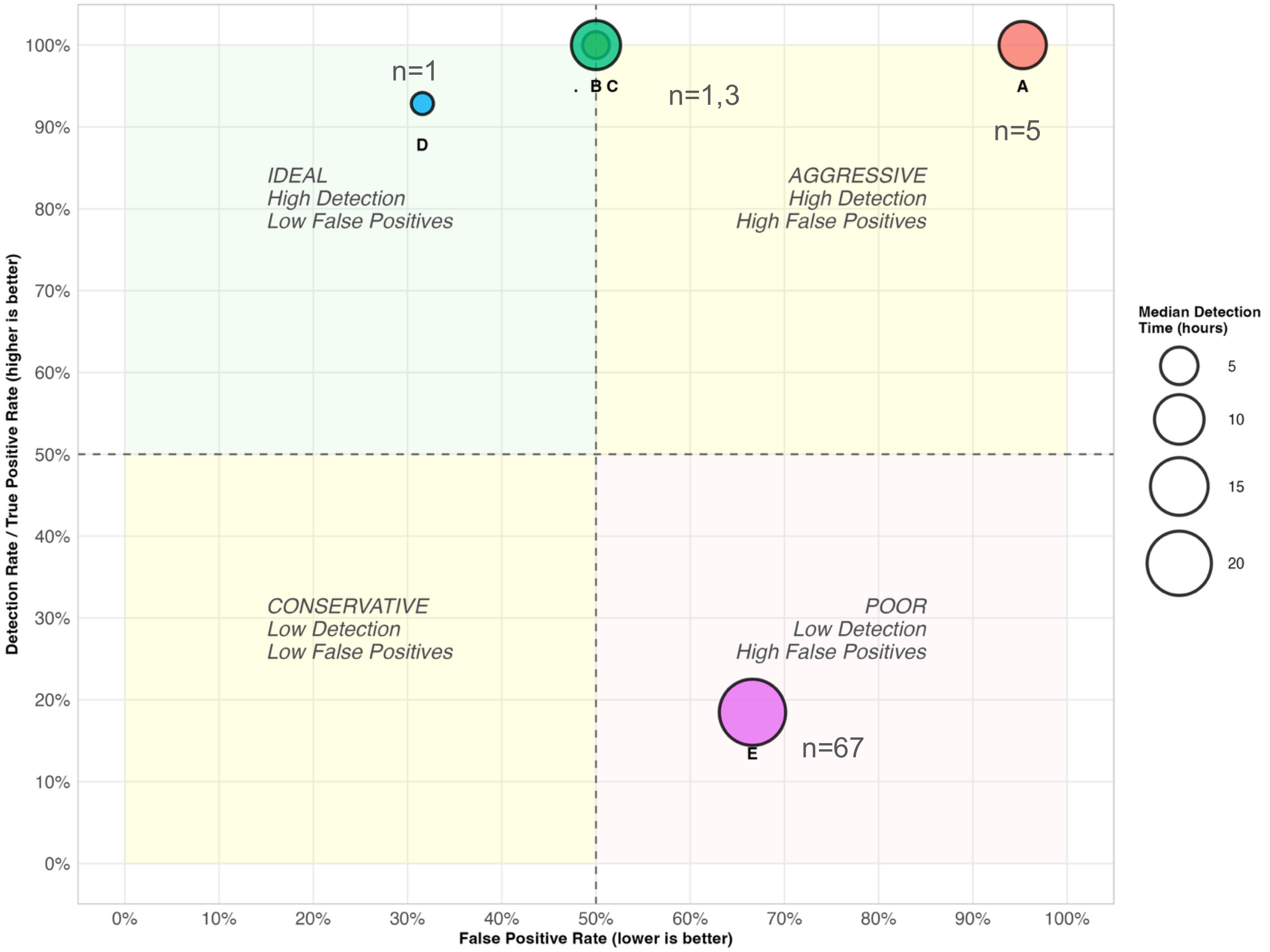
"Ground Truth" Dataset

- Satellite Operators: INTELSAT, NASA
- 67 satellites (66 GEO, 1 LEO)
- ~9,000 validated maneuvers over six months
- 5 propulsion types:
  - Chemical
  - Xenon Ion Propulsion System (XIPS)
  - Stationary Plasma Thruster (SPT)
  - Electro-thermal Hydrazine Thruster (EHT)
  - ArcJet

Significance: Enables first-ever supervised propulsion classification from observables and propulsion-informed maneuver detection

Current Detection Capabilities Fall Short

- Best detection rate (on limited satellites): 92.9-100%
- Broadest coverage provider: Only 18.5% detection
- False positive rates: 31.6% – 95.3%
- Median detection times: 2.7 – 21.7 hours



Evaluation of 5 commercial providers on real-world data.

Current methods do not simultaneously achieve high detection, low false positives, and broad coverage.

Timeline

Key Dates

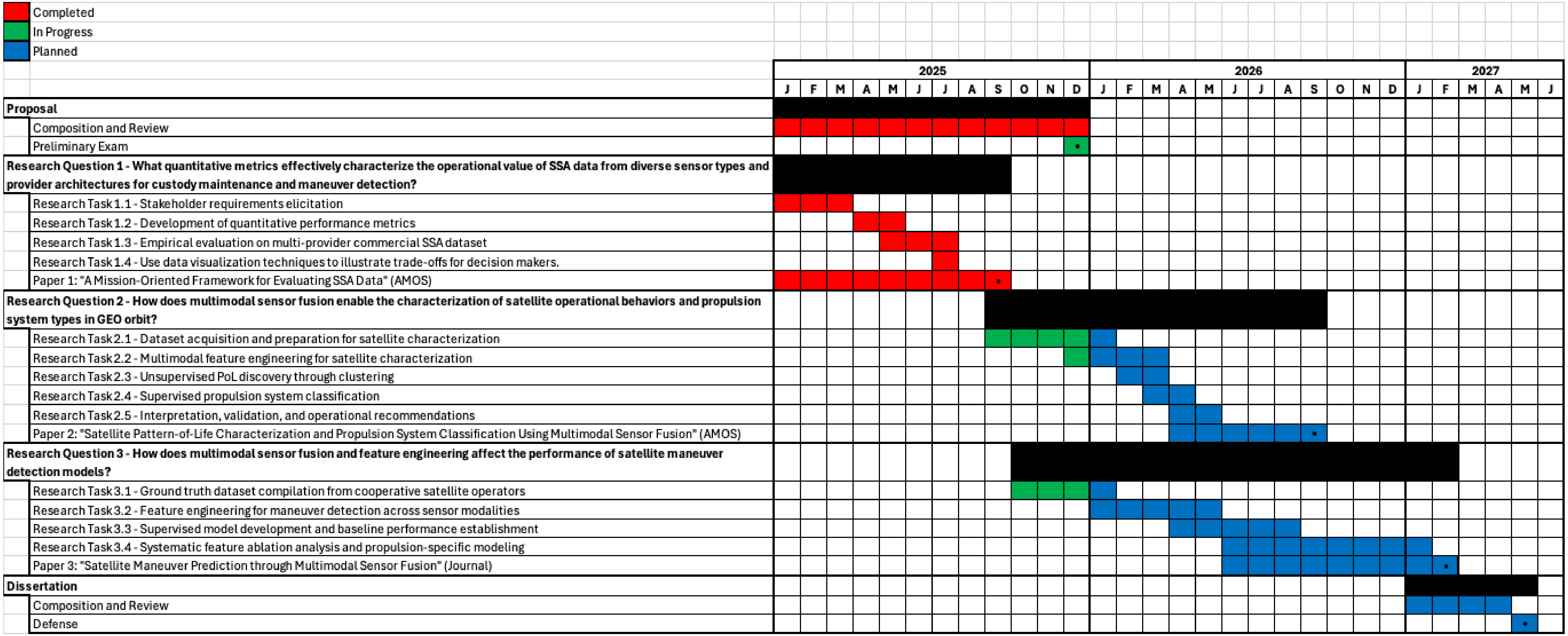
Preliminary Exam: December 2025

Paper 2 (RQ2): AMOS 2026 (Abstract March, Paper August, Conference September)

Paper 3 (RQ3): Journal submission August 2026 - Acta Astronautica (Elsevier)

Dissertation Defense: May 2027

Timeline of Research Questions and Tasks



Research Contributions

Expected Research Contributions

1. Integrated analytical framework connecting evaluation → characterization → prediction
2. Mission-oriented evaluation framework for SSA providers with empirical trade-off analysis
3. Validated truth dataset (67 satellites, 9,000 maneuvers, 5 propulsion types)
4. Systematic assessment of multimodal sensor fusion value for behavioral characterization
5. Novel propulsion classification methodology from observable signatures
6. Empirically-grounded understanding of leading indicator features for maneuver detection
7. Comparative ML architecture analysis for maneuver detection with performance benchmarks

Conclusion

Summary & Path Forward

Three-part research progression:

Phase	Focus	Impact
Evaluate	Commercial SSA providers	Evidence-based procurement
Characterize	Behavioral patterns + propulsion	Non-cooperative satellite assessment
Detect	Multimodal maneuver detection	Proactive vs. reactive SDA

Advancing SDA from reactive observation to proactive anticipation through multimodal sensor fusion and machine learning.

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Thank you!

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