Beyond Constellations: Revealing Natural Satellite Groups in Multi-GNSS Landscape

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INTRODUCTION & GOAL

- Empirical orbit and solar radiation pressure (SRP) parameters estimated in precise orbit determination (e.g., Empirical CODE Orbit Model terms and constant-per-revolution, CPR) capture distinct dynamical signatures of each GNSS satellite.
- These parameters encode effects of spacecraft design, attitude control, SRP response, and orbital plane specifics, forming a stable "fingerprint" that distinguishes satellites across constellations and generations.
- Data-driven grouping of these parameter signatures reveals natural satellite families that go beyond official labels (e.g., the IGS satellite metadata file), highlighting physically meaningful structure in the constellations.

- Identify natural clusters of satellites across multi-GNSS constellations based on shared patterns in empirical orbit/SRP parameters.
- Evaluate cluster quality using cohesion and separation metrics, and verify robustness across epochs and solar geometries.
- Detect stable structures and temporal changes, flag outliers and transitions, and verify the physical interpretability of clusters.
- Provide actionable insights for GNSS applications.

Table 1. Summary of SRP modeling applied in the analyzed solutions.

	DLR (German Aerospace Center)	ESA (European Space Agency)
GPS	ECOM (D0, Y0, B0, BS, BC) CPRA0, CPRAS, CPRAC	BOX-WING ECOM (D0, Y0, B0, BS, BC) CPRA0, CPRAS, CPRAC
GLO	ECOM2 (D0, Y0, B0, BS, BC, D2C, D2S)	
BEI	ECOM (D0, Y0, B0, BS, BC)	
GAL	BOX-WING ECOM (D0, Y0, B0, BS, BC) CPRA0, CPRAS, CPRAC	

DATASET

- Two different orbit solutions used: DLR (German Aerospace Center), ESA (European Space Agency).
- The a priori expectation is that, due to the absence of a box-wing model for DLR (except for Galileo), the patterns in the ECOM parameters will be sharper, thus more easily clusterable. On the other hand, for ESA, the identified groups should highlight deficiencies in the box-wing model for specific satellite subgroups.

METHODOLOGY

PREPROCESSING: EXTRACT RELEVANT PARAMETERS (*ECOM/CPR*) → *FEATURE ENGINEERING*: STATISTICAL PROFILES (SP) / CURVE-BASED FEATURE EXTRACTION (CB) → *LINKAGE*: WARD → INTERNAL EVALUATION / EXTERNAL EVALUATION

CLUSTERIZATION

- **Statistical Profiles (SP)** For each satellite and parameter, we compute statistical summaries (mean, median, standard deviation, IQR, mode, percentiles) to capture central tendency, spread, and typical behavior. These profiles are generated for the full beta range.
- **Curve-based features (CB)**: model each parameter with the mean and standard deviation aggregating over β bins **(Fig. 1)**. These capture the physical SRP-driven signature beyond simple statistics. Pairwise curve distances yield the distance matrix that serves as input for clustering. Finally, a symmetric distance matrix is composed calculating the average over all the distances.
- Apply agglomerative hierarchical clustering with Ward linkage on the feature matrix. Ward's criterion minimizes within-cluster variance, favoring compact, well-separated, physically interpretable groups.

Each satellite is its own cluster → Compute pairwise distances between all clusters → Merge the pair of clusters that causes the smallest increase in total variance → Repeat until all are merged into one tree

FEATURE ENGINEERING - SP

	D0 MEAN	D0 STD	Y0 MEAN	Y0 STD	...
E101	0.012	0.003	-0.045	0.005	...
E102	0.018	0.004	-0.040	0.006	...
E103	0.015	0.002	-0.048	0.007	...
E201	0.021	0.006	-0.050	0.009	...
E202	0.019	0.003	-0.042	0.006	...
...	...	...	...	...	...

WARD DISTANCE

$$D(A,B) = \frac{n_A n_B}{n_A + n_B} \|\boldsymbol{\mu}_A - \boldsymbol{\mu}_B\|^2$$

- n_A, n_B → Number of points in clusters A and B
- $\boldsymbol{\mu}_A, \boldsymbol{\mu}_B$ → Centroids (means) of A and B
- $\|\cdot\|$ → Euclidean norm (distance)

FEATURE ENGINEERING - CB

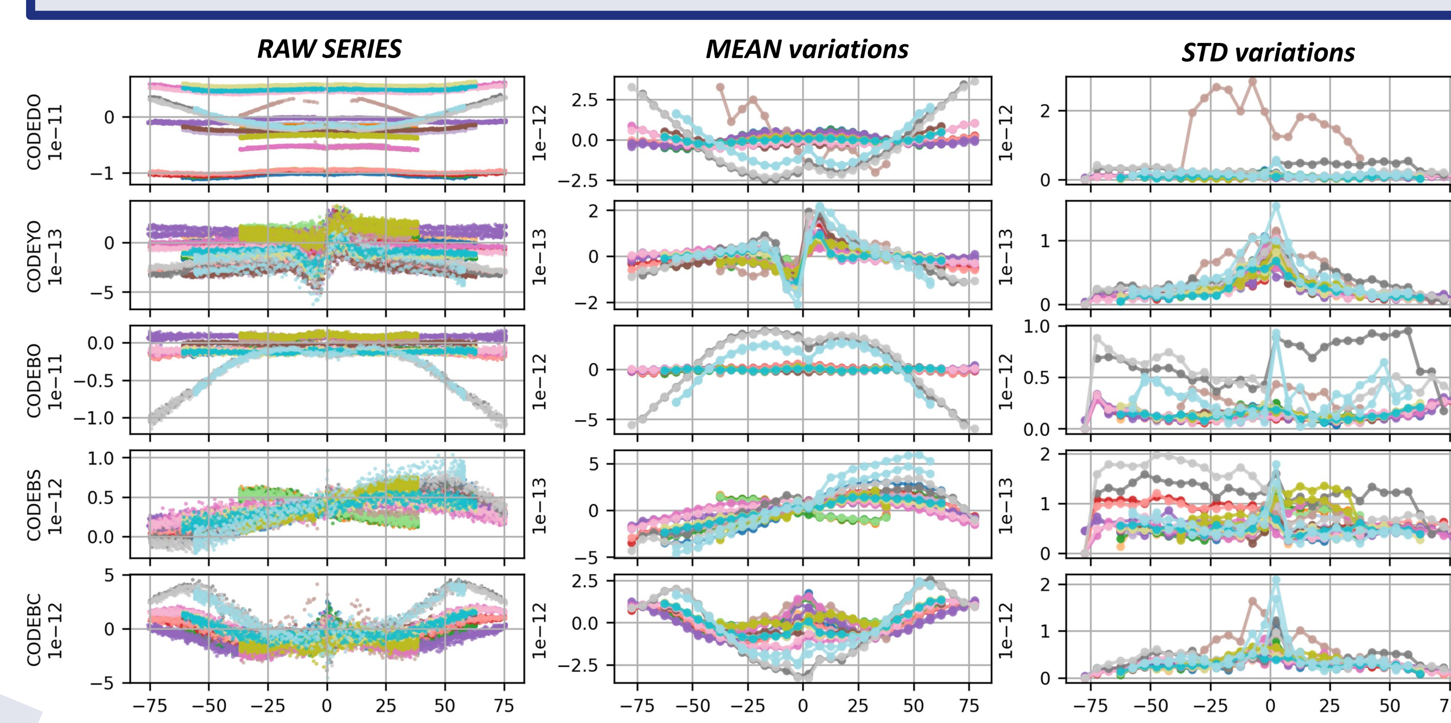

Fig. 1. Exemplary procedure for converting raw ECOM estimates of individual satellites into curves of mean and standard deviation of binned data points. Example of BDS satellites.

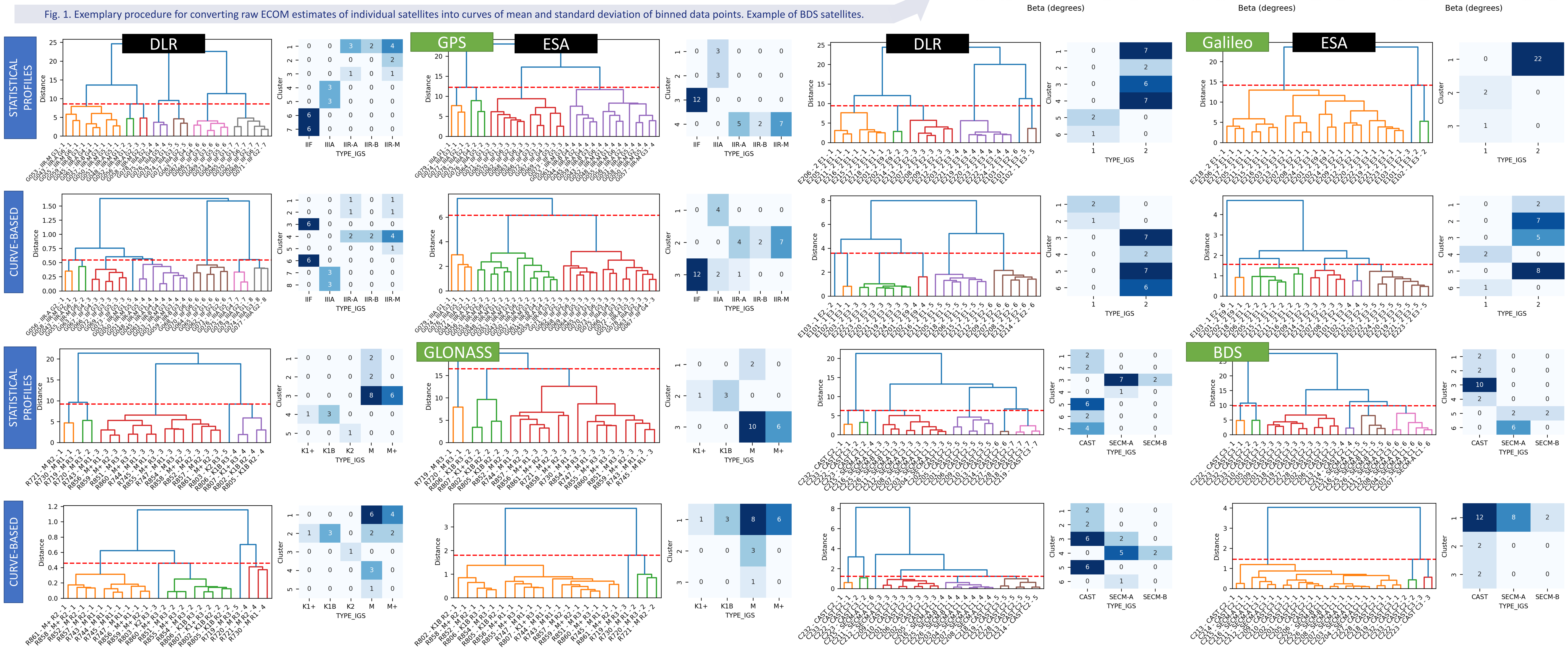

Fig. 2. Dendrograms of GPS (top left), GLONASS (bottom left), Galileo (top right), and BDS (bottom right) satellites after clustering in two modes: SP (STATS) and CB (CURVES), using two datasets: DLR (inner left) and ESA (inner right), together with their correspondence to IGS metadata types.

CLUSTERIZATION

Table 2. Assessment of clustering quality based on selected metrics.

	Solution	Method	Clusters	SH	D-B	C-H
BDS	DLR	CB	6	0.351	0.874	11.48
	DLR	SP	7	0.456	0.632	18.2
	ESA	CB	3	0.397	0.707	9.56
	ESA	SP	6	0.347	0.921	12.97
GLONASS	DLR	CB	5	0.151	1.047	7.52
	DLR	SP	5	0.368	0.768	14.55
	ESA	CB	3	0.238	1.096	5.17
	ESA	SP	3	0.325	0.972	9.19
GPS	DLR	CB	8	0.142	1.263	8.87
	DLR	SP	7	0.190	1.234	10.45
	ESA	CB	3	0.158	1.697	6.51
	ESA	SP	4	0.208	1.422	8.96
Galileo	DLR	CB	6	0.416	0.712	16.1
	DLR	SP	6	0.416	0.712	16.1
	ESA	CB	6	0.199	1.111	8.38
	ESA	SP	3	0.468	0.545	8.77
SH — Silhouette Score		The closer to 1 the better	How well each satellite fits within its cluster. Low values (near 0) suggest poor cohesion or separation.			
D-B — Davies-Bouldin Index		The closer to 0 the better	Penalizes overlapping or dispersed clusters. Lower = more distinct and compact.			
C-H — Calinski-Harabasz Index		Higher is better	Measures between-cluster separation vs. within-cluster compactness.			

- The methodology successfully recovered natural satellite groups with strong within-cluster cohesion and between-cluster separation. **(Fig. 2)**
- Constellation separability ranks Galileo > BeiDou > GLONASS > GPS, confirmed by best case SH (0.468[ESA_SP]/0.416[DLR_SP], 0.456[DLR_SP], 0.368[DLR_SP], 0.208[ESA_SP]) and consistent trends in DB and CH.
  - BeiDou (BDS): Strongest and most diverse cluster structure with high cohesion and clear separation, reflecting differences in satellite construction and in-orbit behavior.
  - Galileo (GAL): Clean, method-stable clusters that align with consistent design families (GAL-2 and GAL-1), even able to recover orbital planes.
  - GLONASS (GLO): Moderately defined clusters indicating modest internal variability across vehicles.
  - GPS: Weak clusters; however, successfully separated satellite blocks.
- DLR yields clearer separation overall (SH 0.311 vs 0.292, DB 0.905 vs 1.059, CH 12.909 vs 8.689), capturing richer dynamical behavior than ESA. BeiDou shows the cleanest structure with DLR outperforming ESA across SH/DB/CH; Galileo, GLONASS and GPS are more mixed, with DLR often better on DB and CH despite ESA sometimes having slightly higher SH.
- DLR ECOM parameters are 20–60% more scattered than those from ESA products, which results from using a priori box-wing model only for GAL. **(Fig.3)**

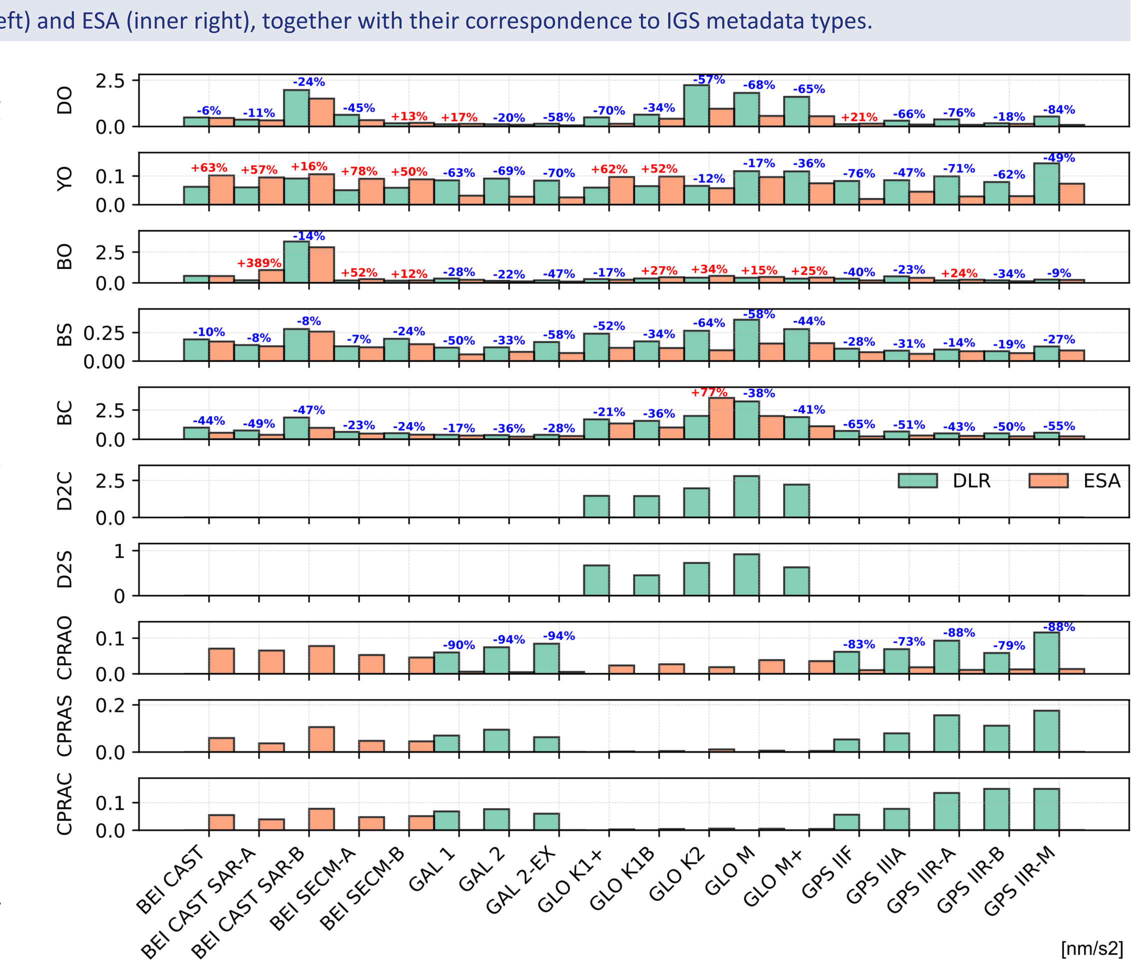

Fig. 3. Standard deviation of ECOM and CPR estimated from DLR and ESA solutions.

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