# Sniffing from the Stratosphere: How HAPS Can Unmask the Dark Fleet?

Kalamkas Zhagyparova, *Student Member, IEEE,* Osama Amin, *Senior Member, IEEE,*
Nour Kouzayha, *Member, IEEE,* Tareq Y. Al-Naffouri, *Fellow, IEEE* and Basem Shihada, *Senior Member, IEEE,*

***Abstract*—The "Dark Fleet"—vessels that disable their Automatic Identification Systems (AIS) to engage in illegal activities—poses a serious challenge to global maritime security. Traditional satellite surveillance is limited by persistent cloud cover and orbital revisit times. This article explores how High-Altitude Platform Systems (HAPS), operating in the stratosphere, can serve as opportunistic "sniffers." By intercepting the uplink signals transmitted from vessel terminals to Low Earth Orbit (LEO) satellites, HAPS can analyze the traffic patterns of these "dark" targets. We show that this non-cooperative passive stratospheric approach achieves a vessel classification accuracy of $80.3\%$, outperforming cooperative satellite-based baselines by exploiting more favorable signal geometry.**

***Index Terms*—marine communication, vessel type identification, channel state information, satellite, high altitude platforms**

## THE DARK FLEET PROBLEM

Maritime Domain Awareness is the cornerstone of ocean governance, essential for countering Illegal, Unreported, and Unregulated fishing, piracy, and smuggling operations. While cooperative tracking systems such as the Automatic Identification System (AIS) provide real-time situational awareness for compliant vessels, they are vulnerable to manipulation, as malicious actors routinely disable AIS transponders or spoof their coordinates to drop off official monitoring [1]. This has produced a "dark fleet" that has grown to an estimated $3,000$ vessels, now comprising $10\%$ of the global tanker market capacity for ships over $5,000$ deadweight tonnes [2]. Because these tactics easily bypass traditional monitoring mechanisms, maritime security agencies need non-cooperative surveillance capabilities that can detect, track, and classify vessels without relying on their voluntary participation.

Current non-cooperative tracking methods face significant physical and operational limitations. Terrestrial technologies, such as coastal high-frequency radars, are constrained by the curvature of the Earth, leaving vast expanses of exclusive economic zones unmonitored. Space-based solutions, while offering global reach, suffer from their own blind spots: optical sensors are rendered ineffective by persistent cloud cover [3], while Synthetic Aperture Radar (SAR) satellites face low revisit rates and high tasking costs [4]. Acoustic methods, though operating on a different principle entirely, are challenged by environmental noise and high attenuation in open waters [5].

At the same time, a parallel shift in maritime communication offers a way to reduce this gap. The rapid proliferation of LEO satellite constellations (e.g., Starlink Maritime, OneWeb) has ubiquitously connected vessels to the global internet [6]. Dark vessels are no exception: while they disable AIS to conceal their identity, they remain active users of these satellite links, as total radio silence is not a viable operational choice [7]. This dependency creates two fundamentally distinct opportunities for surveillance: analyzing the satellite signals that *reflect* off a vessel's hull or intercepting the signals that a vessel actively *transmits*.

To date, both industry standards and academic research have predominantly focused on the former. For instance, recent studies have attempted to exploit satellite constellations for surveillance through passive bistatic radar, using LEO satellites as "illuminators of opportunity" to detect targets by analyzing the satellite downlinks that bounce off a ship's hull [8], [9]. Parallel to this academic research, the telecommunications industry is formalizing this reflection-based approach through Integrated Sensing and Communications (ISAC) as a pillar for future 6G non-terrestrial architectures [10]. Within the latest 3GPP Release 19 standards, ISAC is being actively studied to allow Non-Terrestrial Networks (NTN) to perform "native" sensing by reusing communication signals for radar-like detection [11].

However, whether using opportunistic bistatic radar or standardized ISAC, this approach faces a fundamental physical limitation when applied to the non-cooperative "dark fleet": it treats the vessel as a passive reflector. The resulting "echo" is weak compared to the background noise, limiting these systems to presence detection or velocity estimation, often failing to distinguish a small fishing boat from a large cargo ship.

### *Listening from the Stratosphere*

To overcome the limitations of traditional maritime surveillance, we shift from active radar tracking to passive signal interception. We introduce an *Opportunistic Stratospheric Sensing Framework* that uses HAPS as passive RF sensors. By intercepting the uplink emissions transmitted directly from a vessel's UE to satellite networks, we can extract side-channel information that fingerprints a vessel's spectral footprint.

This article explores three key insights:

- The Geometry Advantage: We show that the non-cooperative stratospheric vantage point provides better

K. Zhagyparova, O. Amin, N. Kouzayha, T. Y. Al-Naffouri and B. Shihada are with the Electrical and Computer Engineering Program, Division of Computer, Electrical and Mathematical Sciences and Engineering (CEMSE), King Abdullah University of Science and Technology (KAUST) ({kalamkas.zhagyparova, osama.amin, nour.kouzayha, tareq.alnaffouri, basem.shihada}@kaust.edu.sa).

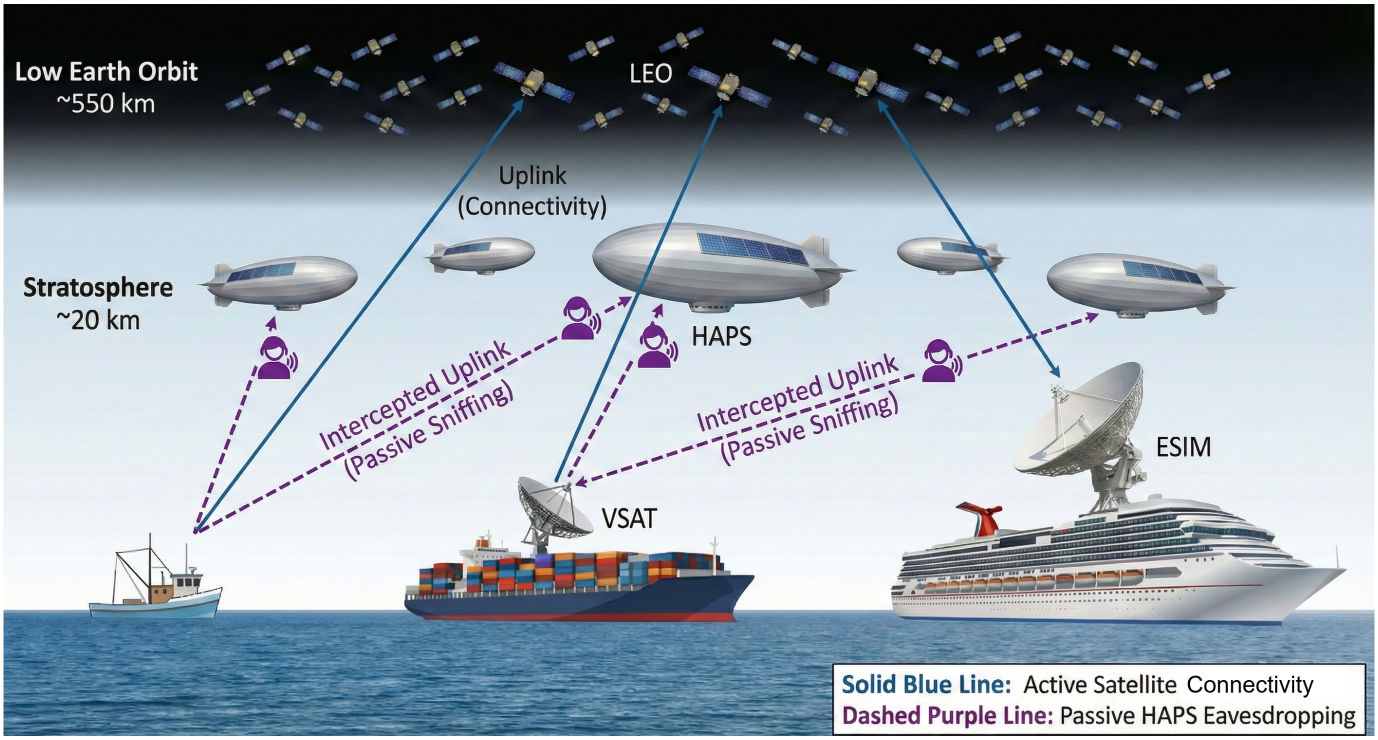


Fig. 1. NTN System Architecture

observation stability and link budgets compared to cooperative satellite receivers, retaining signal metrics that are often lost or fragmented at orbital altitudes.

- Behavioral Classification: We introduce a method to classify vessels (Passenger, Cargo, Fishing) based solely on their statistical traffic signatures, the "user behavior" rather than the hull shape.
- *Federated training:* we report a HAPS-as-client FedAvg variant of the classifier and show that it reduces uplink bandwidth by over two orders of magnitude while remaining within a few percentage points of the centralized accuracy at small constellations.

The remainder of this article is organized as follows. First, we describe the proposed Opportunistic Stratospheric Sensing Framework and its geometric and spectral advantages over satellite receivers. We then present the feasibility case study, including the simulation environment, the channel model, and the classification protocol, and report results for HAPS and cooperative satellite baselines. Finally, we discuss practical challenges and outline future work, including federated learning, 6G integration, and AoA-based localization.

## The Stratospheric Observer

As depicted in Fig. 1, we deploy HAPS [12], solar-powered aircraft or balloons operating in the stratosphere, as Bistatic Sniffers. By intercepting the uplink signals transmitted from a vessel's UE to a satellite network, we redefine non-cooperative surveillance. This approach eliminates the need to crack link encryption; instead, we analyze physical side-channel information by accessing L1 and L2 control packets. This metadata includes the vessel's unique "loudness" via Received Signal Reference Power (RSRP), timing and synchronization metadata such as Timing Advance (TA), and traffic rhythms derived from packet inter-arrival times and bandwidth usage. By characterizing these physical-layer properties, we can classify the vessel type, while maintaining the privacy of the communication payload.

Sensing is only one role of a HAPS payload. Modern HAPS are converging communication, sensing, and computation into a single stratospheric node, evolving into what recent literature terms Data Center-Enabled HAPS [13]. In this paradigm, HAPS can simultaneously provide broadband connectivity to underserved maritime regions, intercept uplink emissions for surveillance, and execute onboard edge inference to classify vessels in real time without offloading raw data to terrestrial servers. Since the HAPS is already deployed to facilitate maritime 6G connectivity, the opportunistic sniffing of "dark" signals becomes a secondary task performed at a limited additional infrastructure and deployment costs. Because solar power is abundant and uninterrupted at stratospheric altitudes above the cloud layer, the energy budget is favorable enough to power continuous flight, payload operation, and computation for months, making HAPS a highly sustainable alternative for persistent ocean monitoring [13].

Beyond energy sustainability, HAPS occupy a strategic "sweet spot" in the Earth's atmosphere—too high for terrestrial constraints, yet low enough to outperform satellites. They operate above the weather, covering a vast service radius unaffected by rain or sea clutter. Crucially, they sit far below the orbital noise floor. This proximity yields a physical advantage in signal interception, while their ability to loiter provides longer observation persistence compared to fast-moving space-

TABLE I
COMPARISON OF THE PASSIVE HAPS SENSOR AGAINST STANDARD SATELLITE RECEIVERS.

| **Metric** | **HAPS (Proposed)** | **LEO (Target)** | **MEO (Target)** | **GEO (Target)** |
|---|---|---|---|---|
| **Role** | Passive sniffer | Active relay | Active relay | Active relay |
| Altitude | 20 km | 550 km | 8,063 km | 35,786 km |
| Relative speed | $\approx$ 0 km/s | 7.6 km/s | 5.25 km/s | 0 km/s |
| Observation time | Continuous | Minutes | Hours | Continuous |
| Path loss Exp. | Low (strong signal) | High | Higher | Very high |
| Rx antenna gain | 30 dBi | 35 dBi | 40 dBi | 45 dBi |
| Handover rate | Near zero | Frequent | Moderate | Zero |
| *Target link parameters (Uplink interception)* | | | | |
| Frequency | Ku-Band (12 GHz) / Ka-Band (20 GHz) | | | |
| Bandwidth | 100 MHz | 100 MHz | 216 MHz | 33 MHz |
| Rx noise figure | 3 dB | 4 dB | 5 dB | 5 dB |

*Target Vessel Gains:* The classification relies on the distinct ”Loudness” of the vessel’s transmitter: **Fishing** (10–20 dBi), **Cargo** (15–30 dBi), and **Passenger** (20–35 dBi).

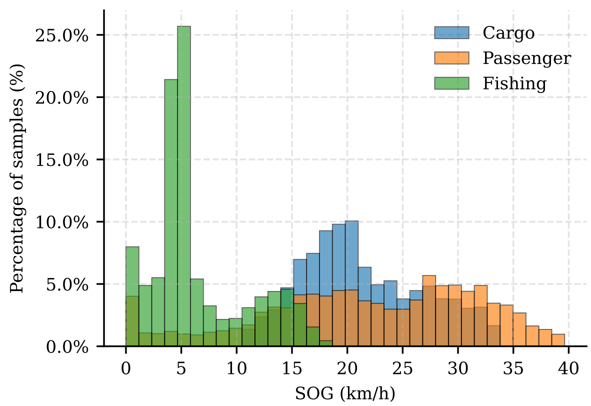


Fig. 2. Histogram of SOG for Passenger, Cargo and Fishing vessels

based constellations.

## FEASIBILITY CASE STUDY

To validate the robustness of the proposed HAPS sensing framework, we conducted a simulation grounded in real-world maritime data. We constructed a “digital twin” of the maritime environment to benchmark the passive stratospheric sensor against active, cooperative LEO, MEO, and GEO satellite baselines (representing direct data access at the intended receiver). The simulator is a custom Python pipeline that ingests AIS trajectories, applies a stochastic NTN channel model to generate per-sample RF observations for each platform configuration, and runs a stateful handover process before feature extraction and classification.

### *Ground Truth: Recreating the Maritime Environment*

The simulation is based on real-world vessel movement. We leveraged AIS data provided by the Danish Maritime Authority [14] to generate realistic vessel trajectories. The raw dataset was filtered to isolate open-ocean scenarios, excluding coastal regions where terrestrial networks might interfere.

The resulting simulation tracks 2,412 unique vessels across three categories—Passenger, Cargo, and Fishing—over varying sea states and months, with approximately 25.6 million per-second snapshots. AIS records are used only offline to define vessel trajectories and class labels for simulation and evaluation; the classifier itself uses only the RF, timing, and handover-derived features listed in Table II

For multi-HAPS configurations, platform locations are not assumed a priori. We obtain them by running $K$-means clustering on a sub-sample of the AIS positions in the study area, which places each HAPS over a region of high vessel density. Each vessel is then associated to the platform that provides the best instantaneous signal, subject to a hysteresis-based handover rule (implemented in Numba) that suppresses ping-ponging between platforms with comparable received power. Inter-HAPS handover events are recorded and become a feature of the classifier (HO rate in Table II) rather than being treated as noise.

An important component of this distinction lies in the speed-over-ground (SOG) profiles. As shown in Fig. 2, each vessel class exhibits distinct operational patterns: fishing vessels typically maintain lower speeds, passenger vessels operate across a broader velocity range, and cargo vessels occupy the intermediate range. By simulating RF emissions as originating from UE at these specific coordinates, we leverage these physical characteristics to generate realistic Doppler shifts and handover profiles. This approach allows us to determine if a vessel’s type can be inferred exclusively from its intercepted spectral footprint rather than its self-reported data.

### *Signal Sources: Class-specific Transmitters*

An important detail in our model is that the transmitter is not the ship’s hull, but its specific satellite terminal. To capture this, we mapped each vessel class to a representative hardware profile (see Table I), defining the “loudness” and behavior of their uplink signals:

- Fishing Vessels: Modeled using handheld satellite phones (e.g., Iridium/Thuraya) or low-profile trackers. These utilize low-gain antennas (~10–20 dBi) with broad beams, resulting in the weakest radiated power.
- Cargo Ships: Equipped with standard Maritime VSAT dishes (60–100 cm). These provide stable, medium-gain (~15–30 dBi) connectivity for operational logistics.

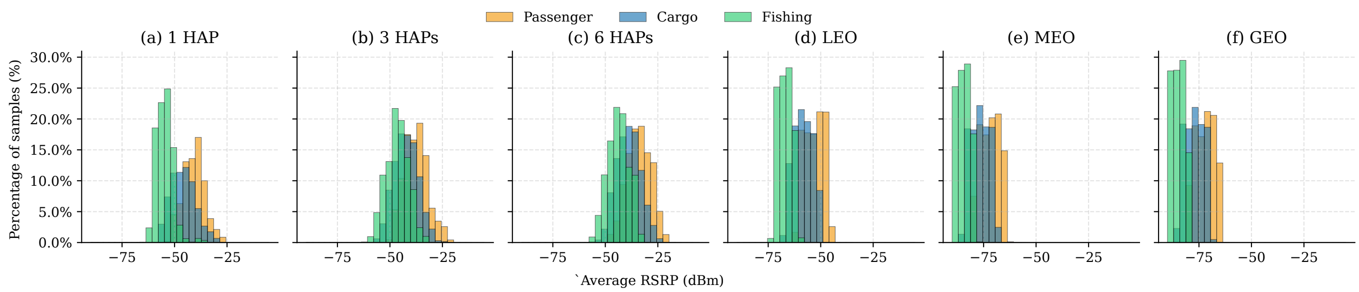


Fig. 3. Histograms of RSRP for Passenger, Cargo, and Fishing vessels under different NTN configurations: (a) 1 HAP, (b) 3 HAPS, (c) 6 HAPS, (d) LEO, (e) MEO, (f) GEO.

- Passenger Vessels: Modeled as carrying high-performance Earth Stations in Motion (ESIM). These generate high-gain (∼20–35 dBi) pencil beams to support the heavy, bursty data loads of hundreds of passengers.

*The Physics of Interception: Signal Strength and Fading*

To accurately model the interception link, we replaced simplified free-space calculations with a Rician Fading Model [6], which captures a dominant Line-of-Sight signal mixed with multipath reflections bouncing off the ocean surface.

The simulation computes the RSRP by accounting for three physical factors:

1) Path Loss Geometry: Active signals traveling to a co-operative LEO satellite weaken significantly, and those aimed at higher MEO and GEO orbits suffer from even higher attenuation. The passive HAPS sensor intercepts them with at least 20–30 dB less attenuation than even the closest orbital constellations.
2) Doppler Dynamics: We account for the frequency shifts caused by relative motion. Cooperative LEO and MEO satellites induce large Doppler shifts due to their rapid orbital velocities [15]. While GEO platforms share the Doppler stability of our quasi-stationary HAPS, their utility is offset by the severe path loss mentioned above. In contrast, HAPS uniquely combines a highly stable frequency profile with strong signal interception.
3) Atmospheric Shadowing: We incorporate log-normal shadowing to model random environmental obstructions.

The resulting signal profiles in Fig. 3 validate the model: Passenger vessels consistently saturate the receiver, while fishing vessels hover near the noise floor, producing class-dependent order of received power that aids classification.

Fig. 3 compares RSRP histograms across the six platform configurations. In panels (a)–(c) (1, 3, and 6 HAPS), all three vessel classes occupy distinct regions of the RSRP axis: passenger ESIMs cluster at the upper end (-35 to -25 dBm), cargo VSAT terminals occupy the middle range, and fishing handheld terminals are pushed toward -75 dBm, and below. This ordering is the physical signature exploited by the classifier. In panels (d)–(f) (LEO, MEO, GEO), the additional path loss to the orbital receiver compresses all three classes toward the noise floor and the per-class modes overlap, which explains the lower classification accuracy in Table III. Although Fig. 3 focuses on RSRP for visualization, classification uses the full feature vector in Table II, including RSSI, timing, and handover-derived statistics over 300-s windows.

*Geometry as a Feature: Stability and Propagation Delay*

Beyond raw signal strength, we extract features derived from the unique geometry of the observer.

- Handovers (HO): In a wide-area surveillance network, platform mobility produces handovers, i.e., the abrupt transfer of a target's signal from one observing node to another. However, the nature of these handovers differs between the two modes. In the cooperative satellite baseline, a LEO satellite moves across the sky at 7.6 km/s and observes a target for only minutes which fragments the received traffic flow. Conversely, in the proposed non-cooperative framework, a quasi-stationary HAPS loiters in the stratosphere and maintains a constant view of the same area. Because each HAPS loiters over a fixed region, its handover rate is one to two orders of magnitude lower than that of a fast-moving cooperative LEO baseline (Table III: ∼1–2 HO/min for HAPS versus ∼16 HO/min for LEO), even when the constellation has multiple platforms. This continuous passive observation window is important for capturing the long-duration traffic statistics required for accurate classification. Furthermore, because the passive HAPS is continuously receiving the uplink, it can detect when a target vessel actively switches its connection from one intended LEO satellite to another by monitoring abrupt shifts in the intercepted transmission characteristics.
- Timing-Advance (TA): Finally, this geometry directly impacts how we measure propagation delay, which we analyze through two distinct lenses. First, the HAPS observe the effective TA applied by the vessel from the timing of the intercepted uplink relative to the expected slot grid. The satellites use TA to synchronize transmissions across vast, shifting orbital distances, therefore, this delay fluctuates rapidly and predictably as the spacecraft moves across the sky.
  Simultaneously, the HAPS records its own absolute propagation delay—the actual time it takes for that intercepted uplink signal to travel from the vessel to the stratospheric sensor. Because HAPS are stationary relative to the Earth, the signal's time-of-flight from the surface to the

TABLE II
LIST OF CSI FEATURES EXTRACTED FOR CLASSIFICATION.

| Raw Data | | Extracted Features | |
|---|---|---|---|
| 1 | RSRP | 5 | Moving Average RSRP |
| 2 | RSSI | 6 | Moving Variance RSRP |
| 3 | Handover (HO) | 7 | Moving Average RSSI |
| 4 | Timing advance (TA) | 8 | Moving Variance RSSI |
| | | 9 | Moving Average HO |
| | | 10 | HO rate |

stratosphere remains stable. By tracking this difference in timing advance, our classifier can easily filter out the geometric noise introduced by orbital mechanics.

## FEATURE EXTRACTION AND CLASSIFICATION

To reduce the impact of instantaneous fading and capture long-term behaviors (e.g., the bursty internet browsing vs. the periodic pattern of telemetry), we do not rely on single data points. Instead, we aggregate statistics over a sliding window of 300 seconds.

As summarized in Table II, we extract a vector of ten statistical features—including Moving Averages and Variances of RSRP, RSSI, and Handover counts. These aggregated features are passed to a gradient-boosted decision-tree classifier - XGBoost configured with 300 estimators, maximum depth 6, learning rate 0.05, and a multiclass soft-probability objective over the three vessel categories. To prevent vessel leakage between the training and test sets, we use a grouped 70/30 split with the vessel MMSI as the group key. The unique MMSIs are partitioned before feature-window generation, and each 300-s window inherits the split of its corresponding MMSI. Hence, no MMSI appears in both the training and testing sets. Class imbalance across the three categories is handled using per-sample weights. and a fixed random seed is used for reproducibility. The reported accuracies in Table III are evaluated on the held-out 30% vessel-disjoint test set.

We assume that the per-vessel feature vectors observed by each HAPS are aggregated at a central node (one designated HAPS or a ground gateway), where the classifier is trained and evaluated. A distributed variant in which model updates rather than raw features are exchanged across HAPS (federated learning) is also explored. Because gradient-boosted decision trees do not admit the parameter averaging used by FedAvg, the federated variant replaces XGBoost with a small multilayer perceptron trained on the same feature vector and the same vessel-disjoint split. The same MLP is also reported in the centralized setting in Table III, so that the federated-vs-centralized comparison is not confounded with the choice of classifier. In this federated configuration, each HAPS plays the role of a single client and trains on the rows it serves at end-of-window, with sample-weighted aggregation over 60 rounds and 2 local epochs per round.

## RESULTS FROM THE STRATOSPHERE

The performance comparison between the non-cooperative and cooperative modes, encompassing accuracy, coverage, latency, and stability, is summarized in Table III. The results show a trade-off between the global reach of active satellite networks and the identification accuracy of passive HAPS. As shown in Table III, our experiments demonstrated that a constellation of just three HAPS platforms achieves an optimal trade-off for non-cooperative surveillance in our setting. This configuration delivered a classification accuracy of 80.3% while maintaining 95.8% coverage of the target zone. A two-HAPS configuration reaches a higher accuracy (82.4%) but only 92.7% coverage, and increasing the constellation beyond three platforms brings more uncovered-area windows into the analysis and gradually erodes accuracy down to 78.2% at six HAPS.

The main driver of this performance is the platform's stability. As detailed in Table III, the geometric stability of HAPS results in a low handover rate (just 1.62 for three HAPS compared to 16.14 for LEO) and sub-millisecond propagation delays (0.6 ms for three HAPS). This persistence enables the sensor to maintain an observation window capturing the patterns of the data traffic to easily distinguish the bursty internet usage of a passenger ferry from the steady telemetry of a cargo ship.

In contrast, the cooperative space-based baselines offered 100% global coverage but struggled with identification despite having direct access to the transmissions. LEO satellites were the most competitive cooperative option (69.8% accuracy), but their rapid orbital velocity fragmented the observation window, making it difficult to capture long-term behavioral patterns. Higher orbits fared worse. MEO and GEO platforms suffered from excessive path loss and high propagation delays (up to 279 ms). This signal attenuation caused the RF features of different vessel classes to collapse toward the noise floor, keeping these baselines at ~66% accuracy—noticeably below the HAPS results in the same table.

The FedAvg column of Table III reports the federated variant. At 2 HAPS, FedAvg reaches 79.0% accuracy, essentially matching the centralized MLP baseline of 80.3%. For larger constellations, the gap widens: FedAvg lands in the 66-69% range, while the centralized MLP holds in the 74-78% range. This is the expected consequence of non-IID class skew across HAPS clients, since per-HAPS data concentrates traffic and class composition. Despite this gap, the federated formulation reduces HAPS-to-ground uplink by more than two orders of magnitude (around 1.4 GB per HAPS for centralized training versus a few MB total for 60 FedAvg rounds), which is also consistent with the privacy considerations discussed later.

## PRACTICAL CHALLENGES AND THE ROAD AHEAD

While the physics favors HAPS, deployment faces practical hurdles. A primary concern is privacy. However, our proposed framework adheres to "privacy by design." The system does not decrypt the payload (the emails or messages being sent). It relies exclusively on physical layer metrics (power, timing, frequency) and traffic statistics. This allows security agencies to identify the *type* of vessel and its location without violating the privacy of the communication content.

Beyond the technical 'privacy by design' argument, passive interception of RF emissions sits in a non-trivial legal landscape. Reception of radio emissions and access to their content

TABLE III
PERFORMANCE COMPARISON: CENTRALIZED XGB, CENTRALIZED MLP, AND FEDAVG ACCURACIES, WITH COVERAGE, LATENCY, AND HANDOVER STABILITY.

| Platform | XGB Acc. | MLP Acc. | FedAvg Acc. | Cov. (%) | Delay (ms) | HO Rate |
|---|---|---|---|---|---|---|
| 1 HAP | 0.771 | — | — | 74.96 | 0.9 | 0.00 |
| 2 HAPS | 0.824 | 0.803 | 0.790 | 92.66 | 0.7 | 0.77 |
| **3 HAPS** | **0.803** | **0.777** | **0.662** | **95.76** | **0.6** | **1.62** |
| 4 HAPS | 0.802 | 0.771 | 0.675 | 97.97 | 0.5 | 1.82 |
| 5 HAPS | 0.795 | 0.764 | 0.664 | 99.04 | 0.5 | 2.00 |
| 6 HAPS | 0.782 | 0.739 | 0.688 | 99.65 | 0.4 | 2.21 |
| **LEO** | **0.698** | — | — | **100.00** | **5.6** | **16.14** |
| MEO | 0.669 | — | — | 100.00 | 73.4 | 12.38 |
| GEO | 0.667 | — | — | 100.00 | 279.4 | 16.75 |

All three accuracy columns (XGB, MLP, FedAvg) for the HAPS rows are evaluated on the same vessel-disjoint test set after dropping windows with no serving HAPS

are treated differently by the ITU Radio Regulations and by national frameworks, and the boundary between metadata-only observation and unlawful interception varies across jurisdictions and operator status (state authority vs. private entity). We therefore position the proposed framework as a capability for state-authorized maritime security agencies operating under existing national law, rather than as a turnkey commercial product.

Spectrum allocation is a further bottleneck for the deployment of new aerospace technologies. Because the proposed HAPS payload is entirely passive, it operates without transmitting signals. This avoids the spectrum licensing burdens, interference mitigation requirements, and emission regulations associated with active radar systems. This passive sensing approach can significantly accelerate the regulatory approval process required for full-scale operational deployment.

Economic feasibility is another concern. HAPS are not yet ubiquitous and are not currently deployed at a scale that provides global maritime coverage. However, stratospheric platforms are in active development [12] and are increasingly considered within NTN and future 6G architectures [10]. The proposed framework does not require a dedicated stratospheric constellation; rather, it can be integrated as an additional passive-sensing payload on HAPS deployed primarily for connectivity [13]. This requires adding a passive receiver and onboard inference capability, so the incremental infrastructure burden is expected to be lower than that of deploying a dedicated active-radar constellation. As shown in Table III, even a small constellation of three HAPS provides more than 95% coverage in our simulated regional target zone, suggesting that the framework can be instrumented incrementally and regionally rather than requiring immediate global HAPS coverage.

This framework also aligns naturally with ongoing 3GPP standardization efforts. As 6G matures, HAPS are increasingly envisioned not just as relays but as native nodes within a multi-layered NTN. Our concept complements existing ISAC initiatives by reusing the ubiquitous cellular emissions for localization and classification. Standard communications platforms can also serve as surveillance assets, enabling comprehensive maritime monitoring without the need to deploy additional active radars.

Several technical milestones remain. Future work must resolve the synchronization challenges between passive HAPS sensors and active satellite constellations to optimize signal interception and minimize interference. Furthermore, while this study focused on single-antenna metrics, future HAPS equipped with massive MIMO antenna arrays could utilize Angle of Arrival (AoA) estimation to localize of "dark" vessels with higher precision.

Closing the non-IID accuracy gap reported in Table III for the federated variant is an open direction. Candidate fixes that we have not yet evaluated include FedProx-style proximal regularization, adaptive learning-rate schedules, and warm-starting from the centralized MLP weights.

Finally, advancing the signal processing pipeline will require the integration of deep learning architectures. Implementing models such as Convolutional Neural Networks for RF spectrogram analysis or Recurrent Neural Networks to track temporal traffic patterns could improve vessel classification accuracy in dynamic, noisy maritime environments.

## CONCLUSION: SECURING THE SEAS OF TOMORROW

The "Dark Fleet" has long relied on the vastness of the ocean to operate without attribution. As satellite connectivity becomes ubiquitous, these vessels still need to communicate, and the resulting uplink emissions are observable. This article demonstrates that HAPS can serve as undetectable observers, using the uplink transmissions these vessels depend on into a beacon for their own detection.

Instead of relying on easily manipulated cooperative systems like AIS or cloud-obscured optical imagery, our proposed Passive Stratospheric Sensing Framework introduces a new approach for Maritime Domain Awareness. By utilizing HAPS as "opportunistic sniffers," we can intercept and classify the uplink transmissions of non-cooperative vessels. We validated that distinct hardware profiles—from the low-power handheld trackers of fishing boats to the high-gain ESIM domes of passenger ferries—generate unique, persistent RF signatures.

By shifting surveillance from orbit down to the stratosphere, we obtain the geometric persistence and signal stability required to capture long-term traffic patterns. Our simulations prove that HAPS achieve an identification accuracy of 80.3 percent, outperforming intended LEO satellite receivers. By exploiting existing commercial satellite traffic, this approach reduces the dependence of maritime security on voluntary reporting. The Dark Fleet can turn off their transponders, but they cannot hide their spectral footprints from the stratosphere.

## References


[1] B. Tetreault, "Use of the Automatic Identification System (AIS) for maritime domain awareness (MDA)," in *Proceedings of OCEANS 2005 MTS/IEEE*, 2005, pp. 1590–1594 Vol. 2.

[2] Kpler, "The Expanding Role of the Grey Fleet," Kpler Maritime Risk and Compliance, Whitepaper, March 2025. [Online]. Available: https://marketing.kpler.com/hubfs/Tofu%20Content/Grey_Fleet_whitepaper___March_25.pdf

[3] U. Kanjir, H. Greidanus, and K. Oštir, "Vessel detection and classification from spaceborne optical images: A literature survey," *Remote sensing of environment*, vol. 207, pp. 1–26, 2018.

[4] R. W. Jansen, R. G. Raj, L. Rosenberg, and M. A. Sletten, "Practical multichannel SAR imaging in the maritime environment," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 7, pp. 4025–4036, 2018.

[5] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: research challenges," *Ad Hoc Networks*, vol. 3, no. 3, pp. 257–279, 2005.

[6] F. S. Alqurashi, A. Trichili, N. Saeed, B. S. Ooi, and M.-S. Alouini, "Maritime communications: A survey on enabling technologies, opportunities, and challenges," *IEEE Internet of Things Journal*, vol. 10, no. 4, pp. 3525–3547, 2022.

[7] R. Hopcraft, "Developing maritime digital competencies," *IEEE Communications Standards Magazine*, vol. 5, no. 3, pp. 12–18, 2021.

[8] A. G. Stove, M. S. Gashinova, S. Hristov, and M. Cherniakov, "Passive maritime surveillance using satellite communication signals," *IEEE Transactions on aerospace and electronic systems*, vol. 53, no. 6, pp. 2987–2997, 2017.

[9] D. A. Bosma and K. T. J. Klein, "Exploiting ICEYE Satellites as Illuminator of Opportunity for Passive Radar Target Detection," in *2025 IEEE Radar Conference (RadarConf25)*, 2025, pp. 835–840.

[10] M. A. Jamshed, A. Kaushik, M. Dajer, A. Guidotti, F. Parzysz, E. Lagunas, M. Di Renzo, S. Chatzinotas, and O. A. Dobre, "Non-terrestrial networks for 6G: Integrated, intelligent and ubiquitous connectivity," *IEEE Communications Standards Magazine*, 2025.

[11] 3GPP, "Feasibility Study on Integrated Sensing and Communication," 3rd Generation Partnership Project (3GPP), Technical Report (TR) 22.837, 2024, version 19.4.0, Release 19. [Online]. Available: https://www.3gpp.org/dynareport/22837.html

[12] G. Karabulut Kurt, M. G. Khoshkholgh, S. Alfattani, A. Ibrahim, T. S. J. Darwish, M. S. Alam, H. Yanikomeroglu, and A. Yongacoglu, "A Vision and Framework for the High Altitude Platform Station (HAPS) Networks of the Future," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 729–779, 2021.

[13] W. Abderrahim, O. Amin, and B. Shihada, "How to leverage high altitude platforms in green computing?" *IEEE Communications Magazine*, vol. 61, no. 7, pp. 134–140, 2023.

[14] Danish Maritime Authority, "AIS Data," https://dma.dk/safety-at-sea/navigational-information/ais-data, accessed: November 30, 2025.

[15] X. Li, W. Feng, Y. Chen, C.-X. Wang, and N. Ge, "Maritime coverage enhancement using UAVs coordinated with hybrid satellite-terrestrial networks," *IEEE Transactions on Communications*, vol. 68, no. 4, pp. 2355–2369, 2020.


## BIOGRAPHIES


**KALAMKAS ZHAGYPAROVA** (Student Member, IEEE) (kalamkas.zhagyparova@kaust.edu.sa) is a Ph.D. Student at King Abdullah University of Science and Technology (KAUST). Her research focuses on machine learning applications in wireless communications, particularly indoor and outdoor localization using cellular signals, transportation mode recognition, and evaluating the impact of weather on networks. She is the developer of the CellMob dataset for 4G LTE cellular measurements.

**OSAMA AMIN** (Senior Member, IEEE) (osama.amin@kaust.edu.sa) is a Senior Research Scientist at King Abdullah University of Science and Technology (KAUST). His research focuses on next-generation communication networks, optical wireless communications, and bio-compatible systems. With a broad background in signal processing and optimization, he aims to improve global connectivity, enhance energy efficiency, and advance healthcare monitoring technologies.

**NOUR KOUZAYHA** (Member, IEEE) (nour.kouzayha@kaust.edu.sa) is a research scientist with the Information Theory Lab, King Abdullah University of Science and Technology (KAUST). Her research explores wireless communications, energy-efficient Internet of Things (IoT) architectures, stochastic geometry, and non-terrestrial networks.

**TAREQ Y. AL-NAFFOURI** (Fellow, IEEE) (tareq.alnaffouri@kaust.edu.sa) is a Professor at King Abdullah University of Science and Technology (KAUST). His research investigates sparse, adaptive, and statistical inference with applications to wireless communications, localization, and smart cities. An IEEE Senior Member with over 370 publications, he received the 2022 Abdul Hameed Shoman Prize for Innovative Research in IoT.

**BASEM SHIHADA** (Senior Member, IEEE) (basem.shihada@kaust.edu.sa) is a Professor of Computer Science at King Abdullah University of Science and Technology (KAUST). His expertise includes developing next-generation wireless systems across intelligent, underwater, and non-terrestrial networks. A founding KAUST faculty member, he spearheaded Aqua-Fi, the first underwater Wi-Fi system, and currently serves as a Senior Editor for IEEE Communication Letters.