From event to action: A reactive loop demonstrator for Earth Observation based on modular AI-driven components

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Abstract — **Operational needs in Earth Observation (EO) are increasingly demanding more responsive and autonomous systems, particularly for security and defense applications. This requires new architectures able to shorten the decision–action cycle through real-time event detection, adaptive tasking, and intelligent onboard analytics. The IRMA project, led by IRT Saint Exupéry, develops Artificial Intelligence (AI)-based technologies for mission planning and data processing of EO constellations (both on the ground and onboard satellites) to enhance reactivity and decision-making in realistic end-to-end scenarios. This paper presents the IRMA demonstrator, a modular platform emulating a complete EO system and integrating advanced technologies such as the adaptive multi-agent scheduler ATLAS2 and a YOLOX-based ship detection pipeline. It validates autonomy, robustness to operational constraints, and clarity of outputs for human operators, three key challenges for security / defense applications. The demonstrator executes fast-paced, end-to-end scenarios on real data, offering an engaging and operationally relevant user experience. It provides a testbed to mature AI building blocks, assess system-level reactivity, and explore the architecture of future EO systems combining ground and onboard intelligence. Its design supports modularity, standardized APIs and real-time visualization, and will soon integrate embedded processing hardware to enable hybrid ground/onboard workflows in line with security and defense requirements for autonomy and frugality.**

Keywords — ***Earth Observation, Reactive Systems, Mission Planning, Multi-Agent Systems, AI for Space, AI for Security and Defense, Onboard Processing, Edge Computing, Demonstrator, System Autonomy, Maritime Surveillance***

I. INTRODUCTION

The Earth Observation (EO) domain is undergoing a profound transformation, driven by the growing demand for more responsive, autonomous, and intelligent systems. In both civilian and defense contexts, users now expect satellite systems to move beyond data delivery and provide timely, actionable insights like detecting, interpreting, and reacting to events such as natural disasters, illegal activities, or military threats within minutes rather than hours. While current constellations already produce tens of terabytes of imagery daily [1], traditional EO workflows often introduce delays of several hours, sometimes a full day, before information reaches decision-makers.

This latency is increasingly incompatible with time-critical missions. In defense, space-based Intelligence, Surveillance, and Reconnaissance (ISR) relies on fast detection and re-tasking. The European Defense Fund's SPIDER project directly addresses this challenge by promoting autonomous planning, short revisit cycles, and minimal end-to-end latency [2], [3]. In the civil domain, NASA's Earth Science to Action strategy similarly calls for reducing the gap between observation and response, prioritizing decision-ready information [4]. These converging priorities are further amplified by the rise of New Space and the growing availability of agile, multi-sensor constellations, reinforcing the need for integrated, low-latency decision-action loops — both on the ground and onboard satellites.

The necessary transformation to meet this challenge impacts all components of EO systems. In particular, institutional, commercial, and industrial strategies increasingly converge on a set of key enabling technologies:

- *Artificial Intelligence (AI)*, for high-level reasoning and interpretation of multi-modal data (optical, radar);
- *Edge Computing on-board satellites*, enabling early detection, filtering/prioritization and autonomous decision-making (e.g. triggering follow-on actions), as demonstrated by missions like Phi-Sat 2 [5] and CogniSAT-6 [6];
- *Inter-operability and orchestration*, to federate heterogeneous multi-mission assets and coordinate them under tight timing and mission constraints;
- *Low-latency and seamless communication infrastructures*, including Ground Station as a Service and optical or radiofrequency Inter-Satellite Links (ISL), to enable real-time feedback loops and ensure global system reactivity.

These technological directions are echoed in the strategic roadmaps of major space stakeholders—including the European Union, ESA, CEOS, and NASA—as highlighted in recent reports and white papers [7][8][9][10][11][12][13][14].

Collectively, these efforts signal a structural shift from linear, siloed EO systems toward distributed, intelligent, and reactive architectures. Such a shift is essential to meet the evolving requirements of both civilian operations and time-critical defense applications. Fig. 1 illustrates this shift from traditional architectures to the next generation of responsive EO systems.

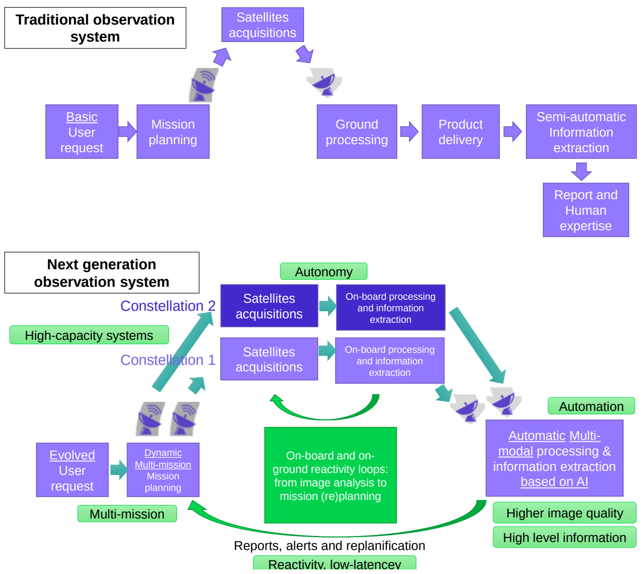

Fig. 1. From traditional EO systems to intelligent, reactive architectures.

The IRMA project (Image processing for a Responsive Mission with AI) led by IRT Saint Exupéry [15], contributes to this transition through AI and edge computing core technologies by developing a suite of AI-based technological building blocks for intelligent and reactive mission planning and data processing, on ground as well as on board.

IRMA is also developing a demonstrator in order to validate and quantify, through realistic and illustrative end-to-end scenarios, the added value of these technologies in terms of system reactivity and autonomy. This demonstrator is a modular hardware and software platform that integrates IRMA technologies into an architecture emulating the main operational components of EO systems.

The idea of more agile and intelligent EO architectures has been discussed in the scientific community for at least a decade. In 2015, Golkar presented a federated Satellite systems paradigm [16] envisioning heterogeneous spacecraft cooperating by sharing resources and services to enhance efficiency and resilience. Denis et al. [17] later examined potential disruptions in Earth Observation systems and markets, highlighting how New Space constellations, data-as-a-service models, and platform-based business approaches could fundamentally reshape EO value chains. More recent works have proposed mission and system architectures supporting persistent and multi-sensor monitoring [18], or demonstrated how autonomous onboard intelligence can improve the exploitation of high-dimensional EO data [19].

In parallel, several European initiatives are translating these concepts into concrete system developments. DOMINO-X [20] is a collaborative effort to modernize EO ground segments through modular building blocks and standardized interfaces. Building on that groundwork, DOMINO-E introduces a multi-mission federation layer to orchestrate sensors across mission boundaries and optimize reactivity through advanced scheduling [21]. Other projects also illustrate this paradigm shift. For example, LEONSEGS [22] explores federated multi-mission ground segments, CALLISTO [23] integrates Copernicus DIAS (Data and Information Access Services) data with heterogeneous sources through AI and big data processing; and RapidAI4EO [24] develops spatiotemporal AI models for high-cadence land monitoring. At the same time, on-board AI demonstrations (ESA Φ-sat-1/-2, OPS-SAT) show practical pathways to filter, prioritize, and act on data at the edge, from cloud-screening [25] to anomaly detection experiments in-orbit [26].

While these initiatives are actively addressing future Earth observation system needs in Europe, most efforts still either work on defining high-level flexible architectures or target isolated technological bricks. The IRMA demonstrator takes a complementary and original approach by bridging system architecture and operational concepts with the integration of concrete, state-of-the-art technologies enhancing key system functions both on ground and on board. It provides a unique environment to assess how these technologies interact within full-system workflows and how they jointly contribute to complex performance indicators such as system reactivity and autonomy.

The remainder of this paper is structured as follows. Section II introduces the main requirements of the IRMA demonstrator and the adopted development approach. Section III presents the demonstrator architecture and the integration of its core components. Section IV details the AI-based technological building blocks integrated into the system. Section V illustrates a representative use-case scenario, highlighting the reactivity loop and dynamic coordination between modules. Finally, Section VI concludes the paper by emphasizing the demonstrator's contributions and outlining perspectives for future developments.

II. REQUIREMENTS AND DEVELOPMENT APPROACH

A. *Operational Context*

The main goal of the IRMA demonstrator is to illustrate, through "live" demonstration sessions, reactive system loops on realistic scenarios, where high-level User Requests (UR) trigger adaptive acquisitions, processing and reprogramming actions based on AI-driven insights.

An effort was undertaken to identify Earth Observation use-cases requiring high responsiveness, in which traditional EO systems fall short due to long processing and reaction cycles. This analysis is summarized in TABLE I and provides a foundation for aligning system functionalities with real-world operational needs.

At maturity, the IRMA demonstrator is expected to support complex scenarios such as the following:

A high-resolution multispectral satellite is tasked to acquire images over a conflict area. Thanks to its on-board processing capabilities, it detects the spectral signature of polymer materials (e.g., plastics) within a densely vegetated area indicating a potential camouflage material. An alert and a lightweight report are immediately transmitted to the ground through a low bandwidth channel. On board, the alert also leads to the prioritization of that image's downlink on the next ground-station overpass.

On ground, the alert automatically triggers the urgent re-tasking of a high-resolution radar satellite to acquire a follow-up image over the same area. Upon reception, the radar image is processed and reveals a metallic echo at the exact location previously flagged, confirming the likely presence of a concealed material. Further exploitation of the radar signature may allow for coarse classification of the object (vehicle, structure or other material), depending on image characteristics and target dimensions.

This example highlights how the demonstrator bridges operational needs with enabling technological capabilities.

TABLE I.
EARTH OBSERVATION USE-CASES AND THEIR TYPICAL REACTIVITY NEEDS

ID	Theme	Expected Latency
1	Maritime surveillance – Oil spills	< 1h
2	Maritime surveillance – Algae, sediments	< 3h
3	Maritime surveillance – Illegal activities	< 1h
4	Port or Airport monitoring	< 1h
5	Natural disaster (Earthquakes, Floods, Hurricanes…) / War zone monitoring	< 30min
6	Wildfires	< 15min
7	Search & Rescue	< 15min
8	Monitoring of critical or military industrial sites	30min – 1 day
9	Monitoring of large areas (e.g., deforestation, borders)	30min – 1 day
10	Soil analysis / Precision farming	< 24h
11	Camouflage detection	30min – 6h
12	Air quality monitoring – Methane	< 1h

B. Key System-Level Requirements

The illustrative scenario described in the previous paragraph is representative of the end-to-end reactivity that IRMA aims to support. To achieve this, the demonstrator is designed to integrate AI technologies into a simulated EO system comprising at least the following components and interfaces:

- Space segment that is configurable with the number of satellites and their main parameters: agility, orbit type (sun-synchronous (SSO), inclined, etc.), and payload modalities (optical, IR, SAR, hyperspectral);
- Smart mission planning function;
- On-ground and on-board data processing;
- Reactivity service, to close the loop between data processing and mission planning;
- Simulation of communication links, with configurable number and location of ground stations (including Ground Stations as a Service), as well as additional links such as low-bandwidth RF channels or Inter-Satellite Links (ISL).

During scenario execution, IRMA AI technologies must be run in real time on real data. On-board processing must be executed on a real edge device with embedded hardware. For live demonstrations, the system must compress the execution of an operational scenario (normally spanning 6–24 h) into less than 10 min, with real-time visualization of key events and performance metrics.

The demonstrator shall showcase as many of the following capabilities as possible:

Event tracking and automatic reprogramming through a feedback loop between image analysis (on-ground or on-board) and mission planning.
Optimal constellation planning, maximizing mission capacity (number of images), revisit frequency, and information freshness.
Mission reactivity for dynamic planning of urgent requests.
Semantic information extraction from mono- and multi-modal images via ground-based processing.
Semantic information extraction from mono-modal images via on-board processing.
Selective processing (on-ground or on-board) depending on acquisition request characteristics.
Ability to follow the user request status from definition to completion.
Prioritization of satellite downlink schedules based on urgency and the semantic content of on-board processed images.
Ability to update on-board processing algorithms during the system's lifetime.
Automatic backup acquisition to replace failed attempts (e.g., due to weather or anomalies).
Capability to program a multi-mission system.

C. Development Challenges and Strategy

Designing such a demonstrator poses several key challenges, including the integration of heterogeneous software bricks of varying levels of maturity and origin (R&T developments, industrial partners and legacy projects), their interoperability within a streamlined yet representative EO system architecture, and the need to combine real-time execution with offline or embedded components while ensuring consistent interface management and temporal synchronization. Additional challenges include providing a positive and engaging User Experience (UX) during live demonstrations, as well as ensuring maintainability and modularity for future expansions.

To address these challenges, the team adopted an agile, incremental development approach, allowing step-by-step integration and testing of components as well as iterative refinement based on user feedback and UX evaluations. A model-based systems engineering (MBSE) methodology using Capella [27] was also employed to support high-level architectural specification, functional decomposition, and traceability of system requirements. The demonstrator architecture was aligned with the principles of DOMINO-X [20], which defines a modular ground segment for next-generation EO systems. This architecture has been tailored to the IRMA demonstrator scope, focusing on components where AI brings operational value.

III. SYSTEM ARCHITECTURE

A. Software and Functional Architecture

In its current version, the IRMA demonstrator emulates a realistic EO architecture, as illustrated in Fig. 2. It relies on a central orchestrator designed to coordinate the simulation timeline, manage time-sensitive interactions, and trigger key events (e.g., acquisitions, downlinks, processing). This mechanism ensures deterministic temporal control and smooth integration, while remaining consistent with the principles of DOMINO-X promoting modular, event-driven and loosely coupled architecture. Our approach and used technologies also echoes NASA's NOS-T (New Observing Strategies Testbed) prototyping platform for distributed space missions [28].

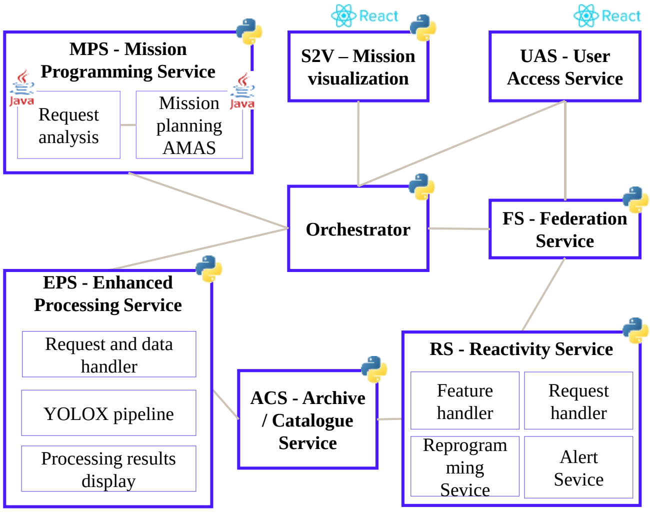

Fig. 2. Simplified overview of the high-level software architecture of the current IRMA demonstrator. The primary programming language used for each component is indicated by its corresponding icon.

The architecture includes the key components defined in DOMINO-X, complemented by a few additional modules (indicated with a *) specific to the demonstrator:

- User Access Service (UAS): The main human-machine interface for defining and visualizing user requests as well as the scenario timeline.
- Mission Programming Service (MPS): Performs meshing and analyzes the feasibility of an acquisition request, then uses an AI-based Adaptive Multi-Agent Planner (AMAS) for dynamic scheduling.
- Enhanced Processing Service (EPS): Performs AI-based image analysis in response to the user request (e.g., ship detection with a YOLOX model).
- Reactivity Service (RS): Manages event follow-up and makes decisions (such as triggering an alert or (re)programming an acquisition) based on comparison between EPS outputs and user request criteria (rule-based engine).
- FS (Federation Service): The central orchestrator in the Domino-X architecture, responsible for unified management of user requests and workflows across multiple systems. In the IRMA demonstrator, it is implemented as a simplified function focused on request handling.
- Archive & Catalog Service (ACS): Indexes raw and processed products using OGC STAC standards. Implemented with minimal functions supporting other components.
- Orchestrator (*): Drives the simulation, coordinates components, manages the mission timeline, and enables observability.
- Mission Visualization Tool (*): A Cesium-based application, referred to as S2V (Scenario to Visualization), acting as the main HMI for dynamic scenario rendering. It provides real-time visualization of satellite operations, orbital tracks, and ground stations in both 2D and 3D environments.

The demonstrator leverages standardized, well-established technologies. All components are containerized with Docker and expose interoperable REST/OGC interfaces for smooth integration and scalability. Communication between services relies on modern frameworks such as FastAPI and MQTT, enabling real-time interaction, responsiveness, and advanced visualization. The entire stack supports automated deployment through Docker Compose or Swarm, reinforcing maintainability and enabling future extensions to more complex or operational deployments. Although the current demonstrator focuses on ground-based components, the architecture is designed to integrate on-board processing modules via a dedicated compute board in the next release.

B. Hardware architecture

Physically, the demonstrator is hosted in a modular flight case with three interconnected hardware stations, each with its own display representing a key part of the simulated EO system, as shown in Fig. 3.

Allocation of system components and HMI to Hardware components is shown in TABLE II.

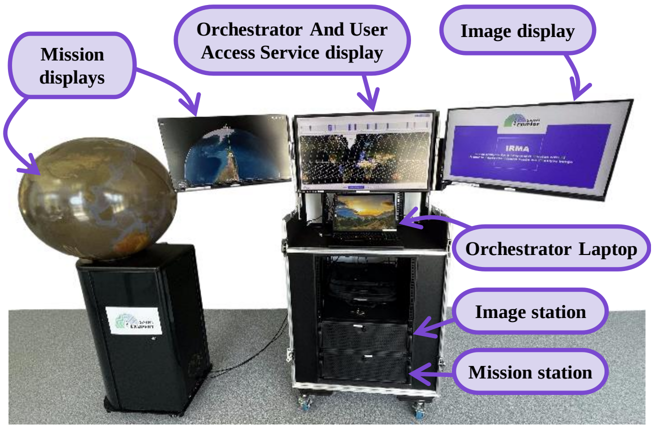

Fig. 3. Hardware setup of the IRMA demonstrator. Upcoming versions will include an embedded target to emulate on-board processing.

TABLE II.
HARDWARE LIST AND SOFTWARE COMPONENTS / HMI ALLOCATION

Hardware station	Software components	Visual Interface
Mission	MPS, S2V	AMAS internal acquisition request status, ***global vision of the constellation***.
Image	EPS, ACS, RS	***Images and outputs from EPS*** (e.g. detection bounding boxes).
Orchestrator	Orchestrator, UAS, FS	***Scenario timeline***, ***User Request selection/validation*** and follow-up, alerts, reports and suggested reprogramming request, reactivity dashboard.
Spherical screen	S2V	Global vision of the constellation.
Edge target	(Upcoming): On-board processing and reactivity.	

[a] Interactive HMIs in ***bold italics***

The demonstrator also includes a spherical screen displaying Earth and constellation dynamic evolution (from

S2V) to increase UX. Additionally, in a close future an embedded hardware target will be connected to the demonstrator enabling real-time on-board processing for illustration of new, more reactive, operational scenarios.

IV. Technological Building Blocks

The demonstrator integrates key AI-based technologies into an architecture emulating the main operational components of EO systems. It validates their integration, illustrates their added value within a responsive system loop, and supports TRL progression through interoperable, standardized interfaces. It enables system-level evaluation of autonomy, alignment with operational constraints, and clarity of outputs for human decision-making, three central challenges for security / defense applications.

The IRMA project develops multiple AI-based technological bricks at varying maturity levels, including multi-modal image processing (e.g., object detection, segmentation, image enhancement), representation learning (e.g., image retrieval, captioning), foundation models, and unsupervised anomaly detection on both imagery and time series. For mission planning, a legacy Adaptive Multi-Agent Planner (AMAS) is being upgraded. The project also investigates several embedded platforms (AMD, Intel, Nvidia), leveraging vendor-specific toolchains to deploy and benchmark IRMA algorithms, with a focus on improving the robustness of AI models when processing raw remote sensing data directly on board satellites.

In its current version, the demonstrator integrates two flagship AI-based technologies, described in the following paragraphs: adaptive and reactive mission planning with AMAS, and ship detection and recognition with YOLOX.

A. *Adaptive and Reactive Scheduling with AMAS*

A central component of the IRMA demonstrator is the Mission Programming Service (MPS), which handles the planning and scheduling of satellite acquisitions. This component integrates an AI-based planner grounded in the Adaptive Multi-Agent System (AMAS) paradigm [29]. More specifically, the AMAS implemented in the MPS is a redesigned version, called ATLAS2, which enhances the responsiveness of Earth observation systems by supporting feedback loops from image analysis to mission planning [30].

In contrast to traditional greedy algorithms still widely used in operational systems, ATLAS2 enables real-time and dynamic planning, supporting the insertion of last-minute or high-priority requests without restarting the entire planning process. The agent-based design models satellites, user requests and acquisitions as cooperative agents capable of negotiating conflicts and adapting to evolving constraints. More precisely, the main intelligence of the multi-agent system lies in the way acquisition agents negotiate with each other to resolve the non-cooperative conflict situation, perceived by a satellite agent, where a required time slot is already booked by another acquisition agent. The negotiation is based on the criticality of the request (e.g. its priority) and on the scheduling cost of this request across all available satellite resources. This flexibility makes the system particularly well-suited for reactive Earth Observation scenarios such as disaster response, environmental monitoring, or maritime surveillance.

In [30], benchmarks on realistic scenarios with agile satellites constellations in demonstrate that ATLAS2 can lead to up to a 30% improvement in the number of planned requests compared to a state-of-the-art hierarchical greedy algorithm, particularly in complex, resource-constrained situations (e.g., two-satellite systems with thousands of requests). It also shows faster and more robust integration of urgent requests, as illustrated in Fig. 4, typically re-planning within less than one minute, and resolves scheduling conflicts more effectively through local negotiation mechanisms.

Finally, ATLAS2's decentralized nature provides inherent scalability to multi-constellation systems, and its “any-time” behavior makes it suitable for use in continuous planning loops with feedback from image analysis. These properties are key enablers for future architectures where on-ground and on-board mission planning must coexist and interact seamlessly.

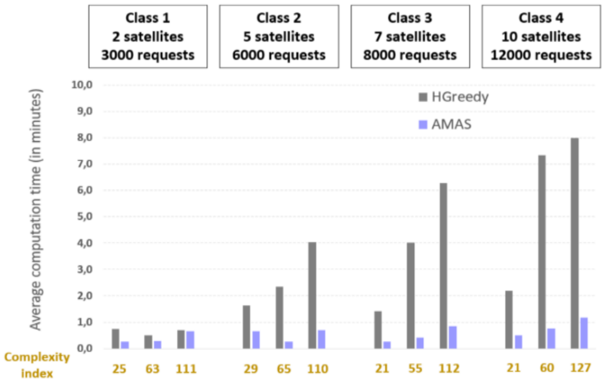

Fig. 4. Time to plan an urgent request with the AMAS algorithm (purple) compared with HGreedy (gray) for scenario classes of increasing complexity (excerpt from [30])

B. *Ship detection and recognition with YOLOX*

Another core component integrated in the IRMA demonstrator is the on-ground Enhanced Processing Service (EPS), which hosts AI-based image analysis capabilities. In the current setup, this service includes a real-time ship detection and recognition module based on YOLOX, a member of the “You Only Look Once” family of detectors [31], deployed on standard GPU-based hardware.

This Convolutional Neural Network (CNN) module builds upon prior work carried out by IRT Saint Exupéry in the CIAR project and presented at CAID in 2022 [32], where a YOLOv3-based solution had been implemented and assessed for its suitability for on-board deployment and low-latency detection of vessels from high-resolution satellite imagery. Building on this experience, a YOLOX-S network (S for “Small” backbone) was selected for the IRMA demonstrator due to its improved balance between detection accuracy, model size, and computational efficiency. This exploration of lightweight embedded models directly addresses the need for frugality and constrained-resource environments, a critical concern in security and defense systems.

YOLOX was trained and validated on a unique, high-quality dataset specifically created for IRT, consisting of over 24,000 annotated ships across 46 classes, including small vessels, military ships, and commercial cargo ships. The dataset, derived from high-resolution (30-50 cm GSD) MAXAR imagery, was labeled by expert photointerpreters from GEO4I. It contains 24,000 patches of 640 × 640 pixels.

YOLOX detection/recognition and hardware performance results are summarized in TABLE III. Evaluation shows that YOLOX-S achieves F1-scores above 40% and a mean

Average Precision (mAP) of around 30% on unseen test images. These global figures are penalized by lower performance on underrepresented ship classes, but despite this imbalance, excellent precision and recall (both above 90%) are achieved for dominant categories such as fishing vessels, sailboats, and leisure craft, with promising generalization to less represented types. Overall, this level of performance is considered sufficient for the demonstrator.

Inference tests on an AMD FPGA confirm that YOLOX-S is lighter and faster than YOLOv3, making it a suitable candidate for future integration in the demonstrator's embedded hardware.

TABLE III.
YOLOX PERFORMANCE SUMMARY ON OUR CUSTOM SHIP DATASET

Complexity				
Model size	65 MB			
Complexity	26.8 Gflops			
Performance on compute station				
Performance on test dataset	Precision: 41.5%	Recall: 41.6%	F1-Score: 41.55%	mAP: 29.7%
Performance on Xilinx ZCU104 FPGA (deployed with VITISAI 3.0)				
Performance on test dataset	Precision: 38.1%	Recall: 37.5%	F1-Score: 37.8%	mAP: 27.6%
Hardware performance (batchsize=1)	Latency: 29ms		Throughput: 14Mpx/s	

To meet the needs of the demonstrator scenario, which must operate on full real images (and not only small patches from datasets), YOLOX has been integrated into a complete ship detection pipeline capable of processing large remote sensing images. The pipeline includes image tiling and dynamic range adaptation as pre-processing steps, and detection map reconstruction at image scale as post-processing.

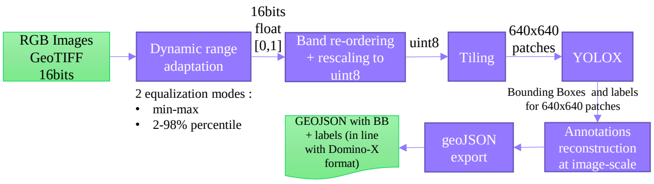

Fig. 5. Complete ship detection and recognition pipeline based on YOLOX integrated into the EPS.

Once integrated into the EPS, the delay between the start of the processing pipeline and the display of the results remains under one minute for demonstration images ranging from 100 to 700 megapixels. This latency is acceptable for demonstration purposes, with most of the time being spent on launching the YOLOX Docker container and handling data transfers.

V. ILLUSTRATIVE SCENARIO: MARITIME SURVEILLANCE

A. *Use-case Selection and Simulated EO System*

In this section, we illustrate the demonstrator's execution on a representative scenario. Among the use-cases listed in TABLE I, illegal fishing detection was selected as the first demonstrator scenario for several reasons:

- It requires rapid response loops for effective interdiction and acts as a proxy for time-critical security / defense missions.
- It builds on existing IRMA capabilities and previous projects, notably the YOLOX-based ship detection models and annotated datasets [32].
- It produces visual and interpretable outcomes, useful for validation and demonstration purposes.

A realistic EO system was configured alongside the use-case selection, composed of three satellites and two ground stations. The space segment includes one Very High Resolution (VHR) optical satellite (30 cm GSD) in Sun-Synchronous Orbit (SSO) and two High-Resolution (HR) optical satellites (70 cm GSD) in inclined orbits to increase revisit frequency at mid-latitudes. All satellites have high agility. The ground segment includes uplink/downlink stations in Kiruna (Sweden) and Toulouse (France). The scenario spans a 24-hour period from June 21 to June 22, 2025. This is summarized in TABLE IV.

To maintain operational realism, the orchestrator injects latencies related to telecommunications and non-simulated operations (e.g., primary ground processing for sensor correction and georeferencing). These values are predefined, based on typical performance in EO systems and operational partner feedback.

TABLE IV.
MAIN PARAMETERS OF THE SIMULATED SYSTEM

Parameters	**Value**
# of Satellites	3 satellites with high agility
Satellite 1	VHR optical @30cm GSD, 19km swath
Satellite 2 & 3	HR optical @70cm GSD, 19km swath
Orbits	- Sat. 1: 550km; Sun-Synchronous (SSO) - Sat 2&3: 550km; Inclined
Scenario duration	24h from 21/06/2025 to 22/06/2025
Ground stations	Kiruna (SWE) + Toulouse (FRA) (both for uplink and downlink)

At scenario start, the system is pre-loaded with 1,000 background acquisition requests of type SPOT (19×19 km) or STRIP (19×[20–200] km), distributed globally. Up to 2,000 additional requests may arrive during execution. These requests are not tied to specific use-cases but simulate a realistic workload and stress-test for the ATLAS2 multi-agent planning system.

In parallel, several high-priority User Requests (URs) represent the selected use-case. Their format, inspired by DOMINO-X [20] preliminary definition, has been largely improved to cope with the needs of our scenarios (in terms of reactivity and processing needs) and with our mission planning tool interfaces. When selected by the user, a UR triggers a full end-to-end reactive loop, activating the different AI technological bricks within a realistic operational context, thereby validating their proper functioning and illustrating their operational relevance.

During scenario execution, the user can freely adjust time acceleration. However, all IRMA technologies are executed in real time to showcase their actual performance, requiring strict synchronization by the orchestrator.

B. *Scenario Execution and Functional Chain Validation*

In this maritime surveillance scenario, the reactive loop is initiated when the user selects and validates a pre-defined UR in the UAS. This activates the full end-to-end functional chain of the demonstrator, summarized in Fig. 6. An alert is triggered if at least one fishing vessel is detected in the image (assuming the area is a prohibited fishing zone).

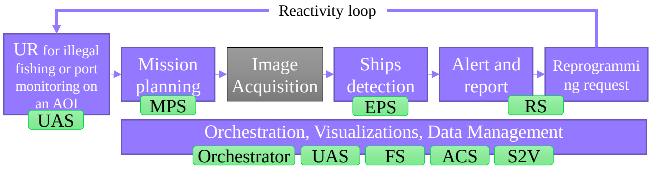

Fig. 6. Simplified functional chain of the maritime surveillance scenario

Illustrative outputs from the demonstrator, generated during an illegal fishing detection scenario over the Golfe du Morbihan (France), are shown in Fig. 7 on the next page. The screenshots illustrate, in order (left to right, bottom to top):

- *UAS: Locations of predefined User Requests.* Initial state of the scenario, with the system already processing background requests and waiting for a high-priority one.
- *UAS: Selection of an illegal fishing UR.* The user chooses among several predefined requests, each triggering a reactive loop that showcases the role of AI in enhancing responsiveness.
- *UAS: Selected UR parameters.* User-defined acquisition, processing, and reactivity parameters are displayed.
- *UAS: UR follow-up interface.* Once a UR is selected from the HMI, it is sent to the Federation Service (FS), which dispatches its elements to other components. At each major event, the UR status and scenario timeline are updated in the UAS.
- *MPS: ATLAS2 acquisition requests internal state.* It shows how the mission planner schedules acquisitions, prioritizing high-priority requests.
- *S2V: Dynamic mission visualization.* The user can follow the scenario's space segment activities in real time. When a satellite passes over the ground station, the orchestrator simulates plan upload and data download while S2V shows corresponding communications with ground stations.
- *EPS: Ship detection and recognition with YOLOX.* Once the UR image is acquired and downloaded, the EPS retrieves and processes it, displaying both the image and detection results.
- *RS/UAS: Detection report and reprogramming request.* When a ship is detected in a non-fishing area, the RS generates an alert, a report, and a suggested reprogramming request, all displayed in the UAS for user validation.

This scenario validates the end-to-end integration of IRMA technologies and demonstrates their relevance in a realistic maritime surveillance context. It also shows how AI-driven autonomy can accelerate decision-making.

VI. Conclusion and Perspectives

The IRMA demonstrator provides a unique environment to validate reactive system loops in Earth Observation, bridging system architecture, operational concepts, and state-of-the-art AI technologies. It offers a tangible and operationally relevant platform to mature technologies, validate functional integration, and test interoperability between components. These objectives align with European strategic initiatives such as the Earth Observation Governmental Service (EOGS), currently under ESA and EU study contracts, and the upcoming ERS-EO program, both aiming to enable resilient and responsive EO capabilities for security and defense applications.

By integrating concrete capabilities such as adaptive multi-agent planning and real-time ship detection with YOLOX, IRMA demonstrator shows how autonomous decision loops can be implemented and evaluated under realistic conditions. It thus accelerates the maturation of key AI components, enforces standardized interfaces, and highlights their operational value through interpretable, user-oriented outputs. Future developments will extend its scope to additional use-cases, multi-sensor configurations, and onboard intelligence.

Lessons learned from IRMA also address broader security / defense challenges. The demonstrator illustrates how autonomy can be enabled through closed-loop reactivity, how robustness can be strengthened by testing AI on representative scenarios, and how explainability can be enhanced by providing transparent outputs at every stage of the loop; all aspects fully aligned with the challenges emphasized by CAID 2025. The forthcoming integration of FPGA platforms also contributes to frugality, a critical requirement for space-based and defense-oriented applications.

In addition to serving as a communication and integration tool, the demonstrator paves the way for a future end-to-end performance simulation framework. Such a tool is increasingly needed to quantify reactivity performance, now a key decision factor for institutional and commercial EO users. Unlike classical metrics such as revisit time, which only reflect acquisition capability, reactivity is a system-level metric that depends on the coordinated behavior of satellites, ground segments, communication links, and processing both on board and on ground. Enhancing global system reactivity therefore requires progress across almost all EO system domains and is intrinsically tied to automation and autonomy.

As the next steps unfold, the IRMA demonstrator will continue to act as a catalyst for advancing the design and evaluation of intelligent, responsive EO systems, while contributing to the development of next-generation autonomous security / defense architectures.

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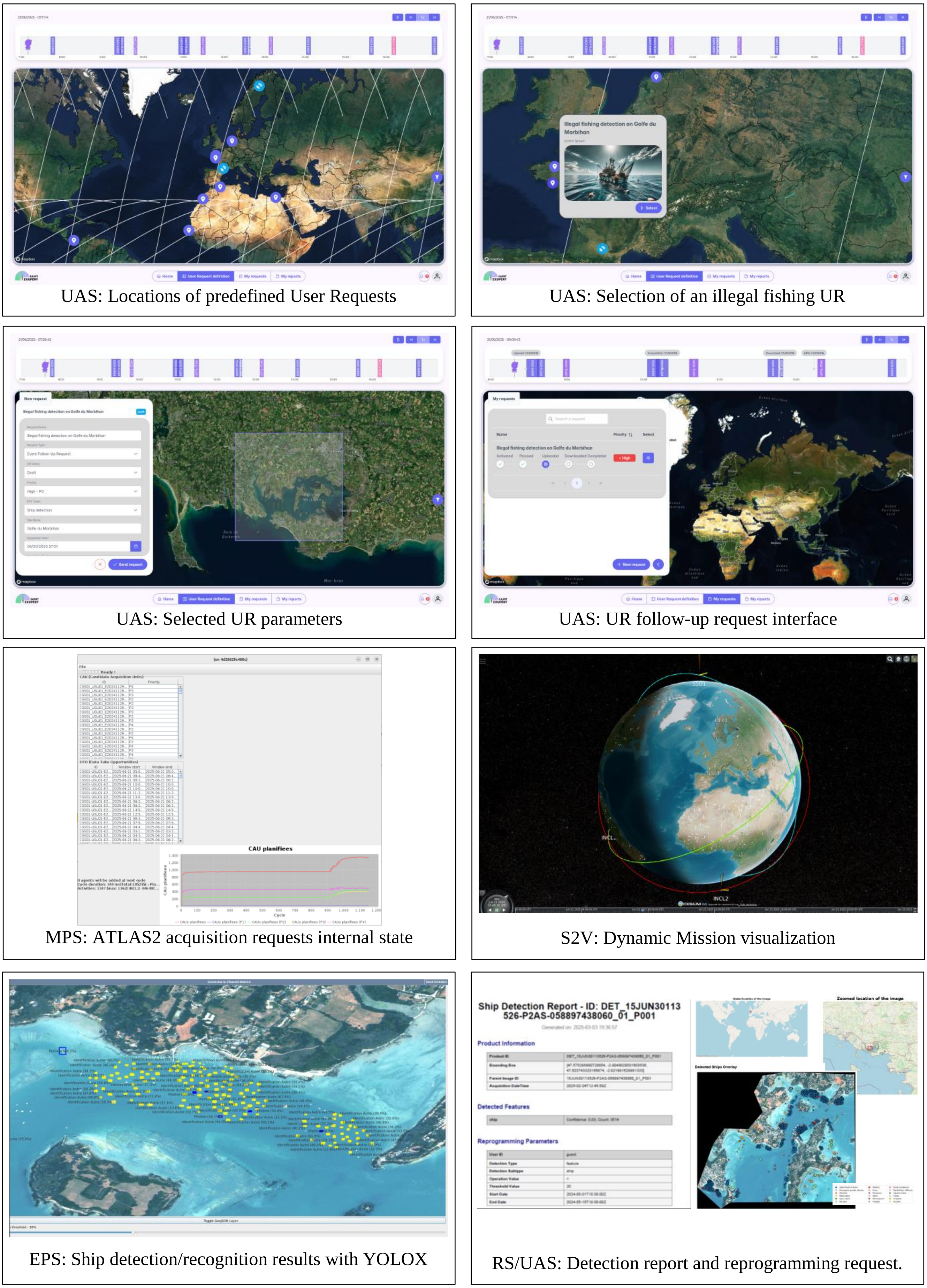

UAS: Locations of predefined User Requests

UAS: Selection of an illegal fishing UR

UAS: Selected UR parameters

UAS: UR follow-up request interface

MPS: ATLAS2 acquisition requests internal state

S2V: Dynamic Mission visualization

EPS: Ship detection/recognition results with YOLOX

RS/UAS: Detection report and reprogramming request.

Fig. 7. Simplified functional chain of the maritime surveillance scenario. (Satellite images: Maxar Imagery Product © 2015 Maxar Technologies Technologies.)

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