A Framework for Autonomous Marine Microplastic Detection: Integrating SWIR-Equipped Drones and Intelligent Buoys

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Abstract:

The pervasive issue of microplastic pollution in marine environments presents a critical global threat, necessitating advanced and scalable monitoring solutions [1]. This paper introduces a novel design framework for an autonomous system dedicated to the efficient detection and mapping of microplastics on sea surfaces [26].

The proposed system integrates a stationary sea buoy and a mobile drone. The buoy functions as an autonomous base station [30], equipped with environmental sensors [34], a Sony Short-Wave Infrared (SWIR) sensor, and an NVIDIA Jetson AGX Orin 64GB for onboard data processing [3]. The drone serves as the primary data acquisition platform [41], carrying a Sony SWIR IMX993 sensor [5] and an NVIDIA Jetson Orin NX 16GB [8]. This integrated approach [27] aims to maximize the scanned sea surface area within defined operational constraints [28], specifically a 45-minute drone flight time and a 25-meter maximum scan height [50], [6].

We detail a methodology encompassing the technological components, their functional interplay [27], and an intelligent data processing pipeline centered on the Adaptive SWIR Sensor Readout and Edge Processing (ASREP) algorithm [7]. The ASREP algorithm leverages the advanced processing capabilities of the NVIDIA Jetson Orin NX 16GB for real-time data processing and intelligent data acquisition [46]. A mathematical model for optimizing the scanned sea surface area is also presented, considering sensor characteristics and flight dynamics [97]. This framework emphasizes dynamic flight planning, informed by real-time environmental data [82], to maximize detection efficiency. This system is intended as a crucial tool for understanding and addressing marine microplastic pollution globally.

Keywords: Microplastics, autonomous monitoring, drone, sea buoy, SWIR sensor, NVIDIA Jetson, remote sensing, environmental surveillance, optimization, edge computing, sensor readout algorithm [11].

1. Introduction:

Microplastic pollution, defined as plastic particles under 5 mm, poses a critical global threat to marine ecosystems, aquatic wildlife, and potentially human health [12]. These contaminants are widespread [16], originating from sources like larger plastic debris fragmentation, industrial effluent, and personal care products [13]. They persist and are distributed extensively, found from surface waters to deep-sea sediments [14], [15]. Developing robust monitoring technologies is crucial to understanding this challenge and formulating mitigation strategies [10].

Traditional methods involve laborious manual sampling with nets and subsequent laboratory analysis. While accurate, these techniques are limited in spatial and temporal scope, offering fragmented snapshots of a dynamic problem [17]. This highlights the urgent need for more efficient, autonomous, and scalable monitoring technologies providing broad-area coverage with high temporal resolution.

Remote sensing technologies offer a promising alternative for large-scale, non-invasive surveillance [18], [23]. Specifically, Short-Wave Infrared (SWIR) spectrum imaging (1000-2500 nm wavelength range) is highly effective for identifying various plastic polymers [51], [4]. Different plastics exhibit unique spectral absorption and reflection in this range, enabling differentiation from materials like water, algae, and organic matter [52]. By capturing hyperspectral or multispectral images, where each pixel contains information across multiple narrow spectral bands [53], the spectral signature of the material in that pixel can be analyzed. This enables differentiation of plastic materials from water, organic matter like algae, foam, and sediment [54].

The deployment of unmanned aerial vehicles (UAVs), or drones, is another significant technological advancement for environmental monitoring [24]. Recent research has focused on using drone-based systems to map marine debris and identify microplastic accumulation zones [22]. Building on foundational work by Raymund K.D. Kho et al. in 2017 [25], who demonstrated the feasibility of coupling a SWIR sensor with a drone and buoy system for marine microplastic detection, this paper proposes a comprehensive strategic framework for a next-generation autonomous microplastic detection system [26]. The framework details integrating a stationary sea buoy with a drone carrying a specialized Sony SWIR sensor [27]. The primary technical objective is to maximize the scanned sea surface area for microplastic detection under the drone's operational constraints [28]: a maximum flight endurance of 45 minutes and a maximum operational scan height of 25 meters [6].

2. Proposed System Architecture: The system is designed as a symbiotic pairing [29]: a stationary sea buoy as a persistent monitoring and command hub [30], and a mobile drone for rapid, wide-area data acquisition [41].

2.1. The Autonomous Sea Buoy Platform (Base Station): The sea buoy acts as the operational anchor [30], designed for long-term, autonomous deployment. It functions as a base station, collecting environmental data and managing drone operations. Key subsystems include:

- **Power Supply:** A self-sustaining system with solar panels and a high-capacity battery bank for continuous operation [31].
- **Positioning and Georeferencing:** A high-precision GPS module provides accurate, real-time buoy positioning [32], serving as a stable georeferencing point for drone operations.
- **Communications Hub:** Equipped with a robust, high-speed WiFi module for command, control, and high-bandwidth data exchange with the drone [33]. It also includes long-range communication hardware (e.g., cellular or satellite) for data backhaul to a central ground station.
- **Environmental Sensor Suite:** Scientific-grade sensors provide data crucial for dynamic flight planning and contextualizing microplastic detection data [34]. This suite includes sensors for wind direction and speed, sea current direction and speed, and wave height and frequency [35].
- **Drone Operations Platform:** Features a hardened, automated docking and charging platform for safe and precise drone landing and takeoff, facilitating wireless recharging for extended autonomous missions [36].
- **Stationary SWIR Sensor:** An integrated Sony SWIR sensor provides continuous, localized monitoring of the immediate water surface [37]. This serves to provide a constant data stream for a single point and acts as a calibration reference for the drone's sensor [38].
- **Central Processing Unit:** An NVIDIA Jetson AGX Orin 64GB module [3] serves as the buoy's central brain. Its processing capabilities are used for aggregating and pre-processing sensor data, running complex algorithms for dynamic drone mission planning, executing machine learning models for data analysis, and managing the buoy's power and communication systems [40].

2.2. The Aerial Sensing Platform (Drone): The drone is the system's mobile data acquisition platform [41], designed for rapid deployment and efficient coverage under the guidance of the sea buoy. Its critical features include:

- **Autonomous Flight Control:** Utilizes an advanced flight controller integrated with a GPS module to execute precise, pre-programmed flight paths and dynamically adjust its route based on real-time commands from the buoy [42].
- **Primary Imaging Payload:** The primary sensor is a Sony SWIR IMX993 camera [5], chosen for its high sensitivity in detecting microplastic spectral signatures on the water surface [43]. The sensor has a specified instantaneous scan area of $5\ m^2$ [44].
- **Onboard Edge AI Processor:** An NVIDIA Jetson Orin NX 16GB module [8] is integrated into the drone for edge computing [45]. Its functions are critical to the system's intelligence [46], including real-time SWIR data processing, implementation of the sensor readout optimization algorithm, and execution of intelligent data compression routines. The use of pre-trained deep learning models, such as YOLOv8 variants adapted for spectral data [47], is envisioned for real-time object identification. The Orin NX's processing power enables true edge AI, allowing immediate identification and geotagging of microplastic hotspots without constant data streaming to the buoy or ground station [48].
- **Communications Module:** A high-speed WiFi module mirrors the one on the buoy, ensuring a robust, high-bandwidth link for command reception and data transmission [49].
- **Power System:** The drone's battery provides a maximum operational flight time of 45 minutes [50], defining the primary constraint for mission duration.

2.3. System Architecture Diagram:

- **Central Node (Buoy):** The NVIDIA Jetson AGX Orin 64GB [3] is at the core.
  - **Inputs:** Connects to the Solar/Battery Power System [31], Environmental Sensor Suite (Wind, Current, Wave) [34], buoy's GPS Module [32], and stationary Sony SWIR Sensor [37].
  - **Outputs/Control:** Controls the Drone Docking/Charging Platform [36] and communicates via the High-Speed WiFi Module [33] and a Long-Range Comms Module (to Ground Station) [33].
- **Mobile Node (Drone):** The NVIDIA Jetson Orin NX 16GB [8] is at the core.
  - **Inputs:** Receives data from the Sony SWIR IMX993 Sensor [5] and is powered by the Drone Battery [50].
  - **Control/Communication:** Interfaces with the drone's Flight Controller [42] and GPS Module (for navigation telemetry and control)

[42] and communicates with the buoy via its own High-Speed WiFi Module [49].

- **Primary Data/Control Flow:** The Buoy Jetson AGX Orin processes environmental data to generate an optimal flight plan [40]. The plan is transmitted via WiFi to the Drone Jetson Orin NX [49]. The Drone launches and executes the mission [42], with the Jetson Orin NX and Flight Controller navigating. The SWIR IMX993 captures data [43], which is fed to the Jetson Orin NX [45]. The Jetson Orin NX runs the ASREP algorithm [7], processing data in real-time [46], performing detections [48], and dynamically adjusting sensor parameters. Compressed data and detection metadata are transmitted back to the buoy via WiFi [49]. The Buoy Jetson AGX Orin can use this real-time feedback to update the flight plan mid-mission [40]. Aggregated data is sent from the buoy to the Ground Station via the long-range link [33].

3. Core Technologies and Principles:

3.1. SWIR Sensing for Polymer Identification: The detection system's operational principle is based on spectroscopy in the SWIR range [51]. Materials interact with electromagnetic radiation differently based on their molecular composition. Water strongly absorbs light in the SWIR range, appearing very dark, while many common plastic polymers (e.g., polyethylene, polypropylene) exhibit distinct absorption features at specific SWIR wavelengths [52]. By capturing hyperspectral or multispectral images, where each pixel contains information across multiple narrow spectral bands [53], the spectral signature of the material in that pixel can be analyzed. This enables differentiation of plastic materials from water, organic matter like algae, foam, and sediment [54].

3.2. Sony IMX993 Sensor and TEC Integration: The drone's primary sensor, the Sony SWIR IMX993 [5], belongs to the SenSWIR™ family [55], which includes the IMX990. The IMX990 is a 1/2-inch type, 1.34-megapixel sensor available in a ceramic Pin Grid Array (PGA) package [56]. A critical feature available for this sensor family is an optional built-in single-stage thermoelectric cooling (TEC) device [57]. For this framework, the IMX993 payload is assumed to be similarly equipped with TEC.

Thermoelectric cooling is essential for high-performance SWIR imaging [58]. It actively regulates the sensor's operating temperature, which is crucial for reducing thermal noise and dark current (extraneous signal generated by the sensor) [59].

By stabilizing temperature, TEC enhances image clarity, improves the signal-to-noise ratio, and ensures more consistent and repeatable measurements vital for reliable spectral analysis [60].

The integration of a TEC module, however, introduces two engineering considerations for a drone platform:

- **Power Consumption:** TEC modules require power [61], adding demand on the drone's battery and potentially impacting maximum flight time [50].
- **Heat Dissipation:** A TEC device transfers heat from the sensor to a heat sink on the opposite side [62]. This waste heat must be effectively dissipated away from the camera and other sensitive drone components to prevent overheating and performance degradation [63]. This necessitates careful thermal design, often involving heat sinks and consideration of airflow, which is a major challenge on a size- and weight-constrained aerial platform [64]. The cooling capacity can achieve a significant temperature differential below ambient, but overall effectiveness is tied to the efficiency of heat transfer away from the drone [65].

3.3. Edge AI with NVIDIA Jetson Orin Platform: The selection of the NVIDIA Jetson Orin NX 16GB [8] for the drone and the AGX Orin 64GB [3] for the buoy is central to the system's proposed intelligence. The Orin NX is well-suited for the drone due to its combination of high performance and power efficiency in a compact form factor [66]. The platform's capabilities, driven by its GPU with 1024 CUDA Cores and 32 Tensor Cores [67], are essential for implementing the ASREP algorithm in real time [72]. The Tensor Cores are specifically designed to accelerate matrix operations central to deep learning models [68], making onboard microplastic classification highly efficient. This enables true edge AI, where critical detections and decisions can be made directly on the drone, reducing latency and the need to transmit vast amounts of raw data [69].

4. Methodology: The ASREP Algorithm and Flight Optimization:

4.1. Conceptual Framework of the ASREP Algorithm: To maximize data quality and relevance within the drone's constraints, the Adaptive SWIR Sensor Readout and Edge Processing (ASREP) algorithm [70], [7] is proposed. This is a dynamic feedback loop that intelligently adjusts sensor parameters and data handling based on real-time analysis of the environment and sensor data [71]. The algorithm is designed to be executed entirely on the drone's NVIDIA Jetson Orin NX processor [72].

- **Start:** Mission begins. Initial parameters (FRdefault, ET default, etc.) are loaded [73].
- **Capture Frame:** Raw SWIR image data (I_{raw}) is acquired from the IMX993 [80].
- **Analyze Environment:** Drone telemetry (V_{drone}, h_{drone}) [81] and illumination data are read.
- **Exposure/Gain Control:** Step 2 of the ASREP algorithm is executed [90]. Calculate μ_I of the frame. If it is not within the target range $[\mu_{target}^{min}, \mu_{target}^{max}]$, adjust $ET_{optimal}$ and $G_{optimal}$ [85], and send new parameters to the sensor. If it is within range, proceed.
- **Microplastic Inference:** Step 3 of the ASREP algorithm is executed [91]. The frame is pre-processed, and the detection model ($M_{plastic}$) is run on the Jetson Orin NX's GPU/Tensor Cores [74].
- **Calculate Metrics:** Current detection confidence ($C_{det}(t)$) and density ($D_{density}(t)$) are calculated [75].
- **Frame Rate Control:** Step 4 is executed [92]. Based on V_{drone} and $D_{density}(t)$, $FR_{optimal}$ is calculated to balance coverage and sampling density [76]. The new frame rate is sent to the sensor.
- **ROI Determination:** Step 5 is executed [77]. Based on $C_{det}(t)$ and $D_{density}(t)$, it's determined if a focused ROI readout is warranted, and ROI_{coords} are defined [86].
- **Data Handling:** Steps 6 & 7 are executed [93]. Intelligent compression is applied based on detection density [78]. If $D_{density}(t)$ exceeds the alert threshold, feedback ($FP_{feedback}$) is generated [87] and sent to the flight controller (e.g., slow down, initiate localized scan) [79].
- **Transmit Data:** Prioritized, compressed data packet is sent to the buoy.
- **Loop:** Return to Step 2 for the next frame.

4.2. Detailed Mathematical Formulation of the ASREP Algorithm: The ASREP algorithm is formalized through a series of interdependent control steps. **Inputs:**

- $I_{raw}(x,y,\lambda,t)$: Raw SWIR image data [80].
- v_d, h_{dr}: Drone's current ground speed and altitude [81].
- E_a, S_{wave}: Ambient illumination and sea surface conditions [82].
- M_{pl}: Pre-trained spectral signature models [83].
- $C_{det}(t-1)$, $D_{density}(t-1)$: Detection confidence and density from previous frames [84].

Outputs:

- FR_o, $ET_{optimal}$, G_0: Optimal sensor frame rate, exposure time, and gain [85].
- ROI_{coords}: Coordinates for dynamic Region of Interest readout [86].
- $FP_{feedback}$: Feedback commands to the drone flight controller [87].

Step 1: Initialization Load $M_{plastic}$ onto the Jetson Orin NX, optimized using NVIDIA's TensorRT framework [88]. Set default sensor parameters ($FR_{default}$, $ET_{default}$, $G_{default}$) [89].

Step 2: Adaptive Exposure and Gain Control For each frame I_{raw}, calculate the mean intensity μ_I. The goal is to keep μ_I within a target range $[\mu_{target}^{min}, \mu_{target}^{max}]$. $ET_{optimal} = ET_{current} \times (\frac{\mu_{target}}{\mu_I})^{\alpha_E}$ $G_{optimal} = G_{current} \times (\frac{\mu_{target}}{\mu_I})^{\alpha_G}$ Where μ_{target} is the midpoint of the target range, and α_E, α_G are response factors. Exposure time is adjusted first, followed by gain if necessary [90].

Step 3: Real-time Microplastic Detection Apply the inference model $M_{plastic}$ to the pre-processed frame I_{proc} to get a set of potential detections p_k. For each detection, the model outputs a confidence score $P_{conf}(p_k)$ and location. Frame-wide metrics are then updated: $C_{det}(t) = Average(P_{conf}(p_k))$ $D_{density}(t) = \frac{Count(p_k \wedge P_{conf} > \tau_{conf})}{A_{frame}}$ Where τ_{conf} is a confidence threshold and A_{frame} is the area of the frame [91].

Step 4: Adaptive Frame Rate Control The frame rate must be high enough to ensure sufficient overlap between consecutive frames for continuous coverage. The required frame rate for coverage is: $FR_{coverage} = \frac{v_{drone}}{H_{frame} \times (1 - O_{req})}$ Where H_{frame} is the height of the sensor's ground footprint in the direction of travel and O_{req} is the required overlap percentage. The optimal frame rate is then modulated by the detection density: $FR_{optimal} = FR_{coverage} \times f(D_{density}(t))$ Where $f(D_{density})$ is a scaling function that increases the frame rate in high-density areas (to sample more) and decreases it in sparse areas (to save power and data) [92].

Step 5-7: ROI Readout, Compression, and Flight Feedback If detection density and confidence exceed a threshold ($D_{density} > \tau_{ROI}$), the algorithm identifies clusters of detections and instructs the sensor to read out only those regions of interest [94]. Data from high-density ROIs is compressed using a lossless algorithm, while background data is compressed with a higher-ratio lossy algorithm [95]. If a significant hotspot is confirmed over several frames, a feedback command is sent to the flight controller to slow down or initiate a localized, high-density scan pattern around the hotspot [96].

4.3. Coverage Path Planning (CPP) and Optimization Model: The core objective is to maximize the total unique sea surface area scanned (A_{total}) [97]. The simple model ($A_{total} = w \times v \times t$) is insufficient as it ignores time lost during turns in a typical raster (or "lawnmower") scan pattern. A more realistic model for the total area covered by a raster scan is: $A_{total} = L_{swath} \times W_{total} = L_{swath} \times N_{swaths} \times w_{effective}$ The total time spent is the sum of time spent scanning and time spent turning: $T_{max} = T_{scan} + T_{turn} = N_{swaths} \times \frac{L_{swath}}{v} + (N_{swaths} - 1) \times t_{turn}$ Where:

- L_{swath} is the length of one scan line.
- W_{total} is the total width of the scanned area.
- N_{swaths} is the number of parallel scan lines.
- $w_{effective}$ is the effective scan width of the sensor, which is the sensor's footprint width minus the overlap ($w_{footprint} \times (1 - O_{req})$) [98]. For the IMX993 with a $5\ m^2$ footprint, this is assumed to be ~2.24m without overlap.
- v is the drone's flight speed.
- t_{turn} is the average time taken for the drone to complete a 180-degree turn between swaths.

Optimizing A_{total} requires finding the optimal balance between a high flight speed v (which reduces T_{scan} but can degrade image quality) and the geometry of the scan (L_{swath}, N_{swaths}) that minimizes time lost to turning (T_{turn}) within the T_{max} constraint. Instead of a fixed speed, $v_{optimal}$ is a function of lighting, sea state, and the processing capacity needed to avoid motion blur and analyze frames effectively. This optimization will be handled by the mission planner on the buoy, which can solve this constrained optimization problem before each mission based on the latest environmental data. For example, aligning the long axis of the scan (L_{swath}) with the prevailing wind direction can reduce drone energy expenditure and naturally follow pollution drift lines. Optimal coverage path planning is a well-established field in robotics [9].

5. Projected Outcomes and Discussion:

Implementing the proposed framework is anticipated to significantly improve the efficiency and effectiveness of microplastic surveillance. The system is designed to generate high-resolution, georeferenced maps of microplastic distribution with a temporal frequency unattainable by manual methods.

The proposed system involves complex technology integration, and its real-world performance depends on extensive empirical validation. The ASREP algorithm [7], while robustly defined, contains parameters (e.g., response factors α, thresholds) that require tuning through rigorous experimentation. Future work will focus on physical prototyping of the buoy and drone systems, followed by controlled environment testing to calibrate sensors and validate the ASREP algorithm. Finally, long-term operational deployment in diverse marine environments will be necessary to assess the system's performance and reliability under real-world conditions.

6. Conclusion:

This paper has presented a comprehensive design framework for an autonomous system to detect and monitor marine microplastic pollution. By integrating a SWIR-equipped drone with an intelligent sea buoy and leveraging edge AI on the NVIDIA Jetson platform, the proposed system offers a scalable and efficient solution to a pressing global challenge. The introduction of the ASREP algorithm [7] is a key innovation designed to maximize the acquisition of high-quality, relevant data in real-time within the drone platform's operational constraints. The mathematical model for flight optimization provides a basis for intelligent mission planning that adapts to environmental conditions. While this work is a design study, it provides a robust foundation and a clear roadmap for developing next-generation autonomous systems capable of supplying critical data for scientific research, environmental policy, and future remediation efforts aimed at addressing marine microplastic pollution.

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[26] Proposed framework by the authors.

[27] The integration concept is central to the proposed system.

[28] Operational constraints are specified by the authors for the proposed system.

[29] This symbiotic approach is a key design principle.

[30] The buoy's role as a base station is foundational.

[31] Solar power systems are standard for autonomous marine platforms.

[32] GPS for accurate positioning is standard.

[33] Multi-modal communication is crucial for robust autonomous systems.

[34] Environmental sensors provide crucial contextual data.

[35] Specific environmental parameters are listed as relevant.

[36] Automated docking and charging are critical for extended autonomy.

[37] The stationary SWIR sensor complements the drone's mobile sensor.

[38] Calibration is essential for sensor accuracy and data consistency.

[39] NVIDIA Jetson AGX Orin is a high-performance edge AI platform.

[40] The processing capabilities align with the listed tasks.

[41] The drone's role as a mobile platform is central.

[42] Advanced flight controllers are standard in modern drones.

[43] IMX993's suitability for SWIR detection is a key technical choice.

[44] The stated scan area is a sensor specification.

[45] NVIDIA Jetson Orin NX is chosen for its edge computing capabilities.

[46] Edge processing functions are critical for system intelligence.

[47] YOLOv8 (You Only Look Once) is a popular real-time object detection model.

[48] Edge AI enables real-time decisions and data reduction.

[49] High-speed WiFi is critical for drone-buoy communication.

[50] The 45-minute flight time is a key operational constraint.

[51] Spectroscopy in the SWIR range is a known method for material identification.

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[54] Differentiation from other materials is crucial for accurate detection.

[55] Sony's SenSWIR™ family is known for SWIR sensors.

[56] IMX990 specifications are publicly available.

[57] TEC integration is an optional feature for these sensors.

[58] TEC is standard for high-performance imaging sensors to reduce noise.

[59] Thermal noise and dark current are common issues in image sensors.

[60] Temperature stability improves image quality and measurement consistency.

[61] Power consumption is a major design consideration for drones.

[62] TEC operates on the Peltier effect, transferring heat.

[63] Effective heat dissipation is vital to prevent overheating.

[64] Thermal management in compact aerial platforms is challenging.

[65] Cooling capacity and heat transfer efficiency are critical.

[66] The Jetson Orin NX's form factor and performance suit drone integration.

[67] GPU specifications are publicly available for the Jetson Orin NX.

[68] Tensor Cores accelerate deep learning workloads.

[69] Edge AI minimizes latency and data transmission.

[70] ASREP is a novel algorithm proposed by the authors.

[71] Dynamic adaptation is a key feature of the algorithm.

[72] Execution on the drone's processor is central to edge AI.

[73] Initialization is a standard step in algorithms.

[74] Inference models are run on the GPU/Tensor Cores for acceleration.

[75] Confidence and density are key metrics for detection performance.

[76] Adaptive frame rate optimizes data collection based on conditions.

[77] ROI readout focuses data acquisition on areas of interest.

[78] Intelligent compression optimizes data transmission.

[79] Feedback to the flight controller enables dynamic mission adjustment.

[80] Raw image data is the input for processing.

[81] Drone telemetry provides critical contextual information.

[82] Environmental conditions influence optimal sensor operation.

[83] Pre-trained models are essential for object detection.

[84] Previous frame metrics inform adaptive control.

[85] These are the controllable sensor parameters.

[86] ROI coordinates define the regions of interest.

[87] Flight controller commands enable dynamic drone behavior.

[88] TensorRT is NVIDIA's SDK for high-performance inference.

[89] Default parameters provide a starting point.

[90] Adaptive exposure and gain are standard techniques for image quality.

[91] Real-time detection is a core function of the system.

[92] Adaptive frame rate control optimizes data acquisition.

[93] ROI readout, compression, and flight feedback are advanced data handling strategies.

[94] Clustering detections for ROI is an efficient approach.

[95] Lossless and lossy compression are used strategically.

[96] Dynamic flight pattern adjustment improves efficiency.

[97] Maximizing scanned area is a primary objective.

[98] Effective scan width accounts for sensor footprint and overlap.